

$$H(Z|X) = \underbrace{P(X=6)}_{1/2} \cdot H(Z|X=6) + \underbrace{P(X=26)}_{1/2} \cdot H(Z|X=26)$$

$Z \setminus X$	①	②
1	$1-y(x)$	$y(x)$
2	$y(x)$	$1-y(x)$

$$H(Z|X) = \frac{1}{2} \left[ H\left(\frac{e^{-6}}{e^{-6}+e^6}\right) + H\left(\frac{e^{-26}}{e^{-6}+e^{26}}\right) \right]$$

$$= \frac{1}{2} \left[ H(L) + H(R) \right]$$

$$x = \frac{z^e}{e^{-z} + e^z}$$

$$y = \frac{e^{-26}}{e^{-6} + e^{26}}$$

$$P(Z=X_2) = P(X=1) \cdot P(Z=X_2|X=1) + P(X=2) \cdot P(Z=X_2|X=2)$$

$$= \frac{1}{2} \frac{e^e}{e^6 + e^6} + \frac{1}{2} \left( 1 - \frac{e^{-26}}{e^{-6} + e^{26}} \right)$$

$$P(Z=X) = P(X) \cdot P(Z=X|X) + P(Y) \cdot P(Z=X|Y)$$

$$= \frac{e^{2e}}{2} \left( 1 - y(x) \right) + \frac{1}{2} y(x)$$

$$M_1 = \frac{e^{-26} + e^{26}}{e^{-6} + e^6} = \frac{1}{2}$$

$$\frac{e^{-26}}{e^{-6} + e^6} = \frac{e^{-26}}{2(e^{-6} + e^6)} + \frac{e^{-26}}{2(e^{-6} + e^6)}$$

$$\frac{e^{-6}}{2(e^{-6} + e^6)} = \frac{e^{-26}}{2(e^{-6} + e^6)}$$

$$\frac{1}{e^{-6} + e^6} = \frac{e^{-26}}{e^{-6} + e^6} \quad e^{-26} + e^{26} = e^{-26} + 1$$

$$e^{26} = 1 \quad 26 \ln e = 0 \quad \Rightarrow [6=0]$$

$$W(\beta, \eta) = \sum_{i=1}^2 \eta(x_i) \cdot \ln \theta(x_i) + \sum_{i=1}^2 \eta(x_i) \cdot \ln \beta(x_i) =$$

$$= \left( \frac{1}{2} \ln 1 + \frac{1}{2} \ln 2 \right) + \frac{1}{2} \ln \frac{e^{-6}}{e^{-6} + e^6} + \frac{1}{2} \ln \frac{e^{-26}}{e^{-6} + e^{26}}$$

$$\frac{1}{n} \ln S_n = \frac{1}{n} \ln \Pi S(x) = \frac{1}{n} \sum \ln S(x) \rightarrow E[\ln S(x)] = W(\eta, \beta)$$

$$S_n = 2^n \cdot W(\eta, \beta)$$

$$b=1$$

$$\begin{aligned} W(x,y) &= \frac{1}{2} + \frac{1}{2} \ln \frac{e^{-x}}{e^{-x}+e^x} + \frac{1}{2} \ln \frac{e^{-2}}{e^{-2}+e^2} = \\ &= \frac{1}{2} + \frac{1}{2} \ln \left( \frac{1}{1+e^{2x}} \cdot \frac{1}{1+e^4} \right) = \\ &= \frac{e^{-x}}{e^{-x}+e^x} \cdot \frac{e^{-2}}{e^{-2}+e^2} = \frac{1}{1+e^{2x}} \cdot \frac{1}{1+e^4} = \\ &= \frac{1}{(1+x^b)} \cdot \frac{1}{(1+x^{2b})} \quad (a=e^2) \\ &= \frac{1}{1+a^{2x}+a^b+a^{3x}} = \frac{1}{1+a^x+a^{2x}+a^{3x}} > \frac{1}{\sum_{n=0}^{\infty} e^{2b \cdot n}} \\ &= \frac{1}{\frac{1}{1-e^{2b}}} = 1 - e^{2b} \end{aligned}$$

$$\begin{aligned} W(b,q) &= \frac{1}{2} + \frac{1}{2} \ln \frac{e^{-x}}{e^{-x}+e^x} + \frac{1}{2} \ln \left( 1 - \frac{e^{-x}}{e^{-x}+e^x} \right) \\ &= \frac{1}{2} + \frac{1}{2} \ln \frac{e^{-x}}{e^{-x}+e^x} + \frac{1}{2} \ln \frac{e^x}{e^{-x}+e^x} = \\ &= \frac{1}{2} + \frac{1}{2} \ln \frac{1}{(e^{-x}+e^x)^2} = \frac{1}{2} + \ln \frac{1}{e^{-x}+e^x} \\ &= \frac{1}{2} + \ln(e^{-x}+e^x) = \frac{1}{2} - \ln e^x (1+e^{2x}) = \\ &= \frac{1}{2} + x \ln e - \ln(1+e^{2x}) \end{aligned}$$

• Edition 2 Solutions

$$\begin{aligned} (b) \quad E[X|X] &= P(X=x) \cdot E[X|X=x] + P(X=y) \cdot E[X|X=y] \\ &= \frac{1}{2} \cdot 2x + \frac{1}{2} \cdot \frac{x}{2} = x + \frac{x}{4} = \frac{5x}{4} \end{aligned}$$

$$\begin{aligned} E[X|X=x] &= \sum_{Y \in \Omega} Y \cdot P(Y|X=x) = 2x \cdot \frac{1}{2} + \frac{x}{2} \cdot \frac{1}{2} = \\ &= x + \frac{x}{4} = \frac{5x}{4} \end{aligned}$$

(c) Conditioned on  $J=1$   $X=26$ , probability

that  $Z=X$  i.e.  $J'=1$  is  $y(26)$ .

- Similarly conditioned on  $J=1$   $X=6 \Rightarrow$  prob

$J'=1$  is  $\underline{1-y(6)}$

$$\begin{aligned}
 P(J'=1|J=1) &= P(X=6|J=1) P(J'=1|J=1, X=6) \\
 &+ P(X=26|J=1) P(J'=1|J=1, X=26) = \\
 &= \frac{1}{2} [1-y(6)] + \frac{1}{2} \cdot y(26) = \frac{1}{2} + \frac{1}{2} [y(26)-y(6)] \\
 &> \frac{1}{2} \Rightarrow J \text{ \& } J' \text{ ARE NOT INDEPENDENT.}
 \end{aligned}$$

SINCE CONDITIONAL DISTRIBUTION IS NOT EQUAL TO THE UNCONDITIONAL DISTRIBUTION

$$P(J') = \left\{ \frac{1}{2}, \frac{1}{2} \right\}$$

VJE OSNOV NA OVA REZESNA DENA  
 $y(J'=1|J=1) < \frac{1}{2}$

$$y(6) \geq y(26) \quad \forall 6 > 26 \quad \text{VIOL MARK}$$

$$\begin{aligned}
 (d) E[Z|J=1] &= P(X=6|J=1) E[Z|X=6, J=1] + \\
 &+ P(X=26|J=1) \cdot E[Z|X=26, J=1] = \frac{1}{2} E[Z|X=6, J=1] + \\
 &+ \frac{1}{2} E[Z|X=26, J=1] =
 \end{aligned}$$

$$E[Z|X=6, J=1] = \int y(x) + x \cdot (1-y(x)) =$$

$$= 26 y(26) + 6 [1-y(6)]$$

$$E[Z|X=26, J=1] = x \cdot (1-y(x)) + \int y(x) =$$

$$= 26 [1-y(26)] + 6 y(6)$$

$$\begin{aligned}
 &= \frac{1}{2} P(J'=1|X=6, J=1) \cdot E[Z|J'=1, X=6, J=1] + \\
 &+ \frac{1}{2} P(J'=2|X=6, J=1) \cdot E[Z|J'=2, X=6, J=1] + \\
 &+ \frac{1}{2} P(J'=1|X=26, J=1) \cdot E[Z|J'=1, X=26, J=1] + \\
 &+ \frac{1}{2} P(J'=2|X=26, J=1) \cdot E[Z|J'=2, X=26, J=1] =
 \end{aligned}$$

$$= \frac{1}{2} [1 - \gamma(b)] \cdot \underbrace{E[Z | J=1, X=b, J=1]}_b + \frac{1}{2} [\gamma(b)] \cdot \underbrace{E[Z | J=2, X=b, J=1]}_{2b}$$

$$+ \frac{1}{2} \gamma(2b) \cdot \underbrace{E[Z | J=1, X=2b, J=1]}_{2b} + \frac{1}{2} [1 - \gamma(2b)] \cdot \underbrace{E[Z | J=2, X=2b, J=1]}_b$$

$$= \frac{1}{2} (1 - \gamma(b)) \cdot 2b + \frac{1}{2} \gamma(b) \cdot b + \frac{1}{2} \gamma(2b) \cdot 2b + \frac{1}{2} [1 - \gamma(2b)] \cdot b$$

JAK NEKAJKA ROKA NEKAJ VANA: [MA 5 ZADANJE] [VNA 90] [KREDAKAR!!!]

$$= \frac{1}{2} (1 + \gamma(b)) \cdot b + \frac{1}{2} \gamma(b) \cdot 2b + \frac{1}{2} [1 - \gamma(2b)] \cdot 2b + \frac{1}{2} \gamma(2b) \cdot b$$

$$= \frac{b}{2} - \frac{\gamma(b) \cdot b}{2} + b \cdot \gamma(b) + \frac{2b}{2} - 2b \cdot \gamma(2b) + \frac{b}{2} \gamma(2b) =$$

$$= \frac{3b}{2} + \frac{b \gamma(b)}{2} - \frac{3b}{2} \gamma(2b) = \frac{3b}{2} + \frac{b}{2} [\gamma(b) - 3\gamma(2b)]$$

→ REVISITED (SEGA ZAPISUJAM DOVA J POUKOV-VA MA VROBLEMOTO PLINO I ROKA ZA SORNA VIKROSTA O NEKONOT (ZBOR)

$$E[Z | J=1] = \frac{1}{2} P(J=1 | X=b, J=1) \cdot E[Z | J=1, X=b, J=1] + \frac{1}{2} P(J=2 | X=b, J=1) \cdot E[Z | J=2, X=b, J=1] + \frac{1}{2} P(J=1 | X=2b, J=1) \cdot E[Z | J=1, X=2b, J=1] + \frac{1}{2} P(J=2 | X=2b, J=1) \cdot E[Z | J=2, X=2b, J=1]$$

$$= \frac{1}{2} [1 - \gamma(b)] \cdot 2b + \frac{1}{2} \gamma(b) \cdot b + \frac{1}{2} [1 - \gamma(2b)] \cdot 2b + \frac{1}{2} \gamma(2b) \cdot b =$$

OSTANNA MA 2 I POSIVA      SWITCH-VA MA SE ZASTAVA      OSTANNA POSIVA      SWITCH-VA 9VA1

$$= b - \gamma(b) \cdot b + \frac{1}{2} \gamma(b) \cdot b + 2b - 2b \gamma(2b) + \frac{b}{2} \gamma(2b) =$$

$$= 2b - \frac{1}{2} \gamma(b) \cdot b - \frac{1}{2} \gamma(2b) \cdot b = 2b - \frac{b}{2} [\gamma(b) + \gamma(2b)]$$

$$\Rightarrow 2b - \frac{b}{2} = \frac{3b}{2} \quad (E[Z | J=1] > \frac{3b}{2} = E[X] \leq 1 \text{ (VIA MALE)})$$

(C) REVISITED:  $P(J=1 | J=1) = P(X=b | J=1) \cdot P(J=1 | X=b, J=1) + P(X=2b | J=1) \cdot P(J=1 | X=2b, J=1) = \frac{1}{2} \cdot [1 - \gamma(b)] + \frac{1}{2} [1 - \gamma(2b)] = 1 - \frac{1}{2} [\gamma(b) + \gamma(2b)] > \frac{1}{2}$  (ZA  $b \neq 0$ )

$\leq 1$  (VIA MALE)

→ NEMA ZAVISLOTI POMBIV REMATOR VERA I MAMENT-MA POKAZA (INDEX) MA POKAZUOTO PLINO.

$P(J=1 | J=1) > \frac{1}{2} = P(J') = P(J'') \Rightarrow$  J & J' ARE NOT INDEPENDENT

**PROBLEM - 2**

JAMACING. FIND HOUSE WIN PROBABILITIES.  $q_1, q_2, \dots, q_n$

(a) MAXIMIZE THE DOUBLING RATE FOR GIVEN FIXED KNOWN ODDS.

(b) MINIMIZE THE DOUBLING RATE FOR GIVEN FIXED ODDS.

$$\begin{aligned}
 W(b, p) &= \sum_x \gamma(x) \cdot \ln \beta(x) \cdot \ln \alpha(x) \\
 &= \sum_x \gamma(x) \cdot \ln \frac{1}{\alpha(x)} - \sum_x \gamma(x) \cdot \ln \frac{1}{\beta(x)} \\
 &= \sum_x \gamma(x) \cdot \ln \frac{1}{\alpha(x)} - \sum_x \gamma(x) \cdot \ln \frac{p(x)}{\gamma(x)} = \sum_x \gamma(x) \cdot \ln \frac{\gamma(x)}{\alpha(x)} - \sum_x \gamma(x) \cdot \ln \frac{p(x)}{\gamma(x)}
 \end{aligned}$$

$$W(b, p) = D(\gamma || \alpha) - D(\gamma || \beta)$$

Lagrange estimate

max  $[W(b, p)] = W^*(b, p) = D(\gamma || \gamma)$  i.e.  $\underline{p = \alpha}$

(b) min  $[W(b, p)] = 0$   $b = \alpha$  THE DOUBLING RATE IS MINIMAL I.E. 0 IF YOU BET ACCORDING BAKER'S ESTIMATE

- DA HVA METE NEGATIVA NA TIDE DOUBLING RATE AND BAKER'S ESTIMATE AT POINT OF MAXIMUM DISTANCE I.E. AND

$\gamma = \alpha$  i.e.  $\left[ \gamma_i = \frac{1}{\alpha_i} \right]$

NO FOR SLOTT

$$\boxed{W^*(b, p) = D(\gamma || \alpha) - D(\gamma || b) = - D(\gamma || b)}$$

$D(\gamma || b)$  e CONSTANT FOR ALL  $p$

$$D(\gamma || b) = \sum \gamma \ln \frac{\gamma}{b} \quad \left. \vphantom{\sum} \right\} \text{DA SE MAXIMIZATA}$$

$$\begin{aligned}
 \frac{d D(\gamma || b)}{d b_i} &= 0 & \nabla D(\gamma || b) + \lambda \nabla \sum b &= 0 \\
 \frac{d}{d b_i} \left( \gamma \ln \frac{\gamma}{b_i} \right) + \lambda &= 0
 \end{aligned}$$

$$\frac{d}{db_i} \left( y \ln \frac{y}{b_i} \right) = - \frac{d}{db_i} \left( y \cdot \frac{\ln b_i}{\ln 2} \right) = \frac{y}{\ln 2} \cdot \frac{1}{b_i}$$

$$\frac{p_i}{\ln 2 b_i} = \lambda$$

$$b_i = \frac{p_i}{\lambda \cdot \ln 2}$$

$$\sum_i \frac{p_i}{\lambda \cdot \ln 2} = 1$$

$$\frac{1}{\lambda \cdot \ln 2} = 1 \quad \left( \lambda = \frac{1}{\ln 2} \right)$$

$$\Rightarrow b_i = p_i \quad ?$$

$$W_*(b, y) = - D(y \| b) = - \sum p \ln \frac{y}{b} =$$

$$= - \sum y \ln \frac{1}{b} - \sum y \ln y = - \sum y \ln \frac{1}{b} + H(y) =$$

$$\left( b = \frac{1}{y} \right) = - \ln y + H(y) < - \ln y + \ln y = 0$$

$$H(y) < \ln y$$

$$\Rightarrow W_*(y, p) < 0$$

MINIMAR DOVAJUNG, KATV!

- Završiti, kao bookie-to za verovatnoću i koristiti p(x) a ti se koristi uniformno to znači će biti vo naravno ya zadržati vo naravno da i lučim ti ova na se koristi kao bookie-to za na b. b. s. a "0".

$$\text{[EDITON 2 SOLUTIONS]} \quad W^*(y, b) = \sum p_i \ln \frac{y}{b_i}$$

$$= \sum p_i \ln \frac{y}{b_i} - \sum p_i \ln \frac{1}{p_i} = \sum p_i \ln \frac{y}{b_i} - H(y)$$

$$= \sum p_i \ln \frac{y}{b_i} = \sum p_i \ln \frac{p_i}{b_i} \cdot \frac{1}{\sum p_i} =$$

$$= \sum p_i \ln \frac{p_i}{b_i} = \sum p_i \ln \frac{1}{\sum p_i} =$$

$$\left( p_i = \frac{1}{b_i} \right) = \sum p_i \ln \frac{p_i}{p_i} = \ln \sum \frac{1}{b_i}$$

$$\text{[ } p_i = \frac{1}{b_i} \text{]} \quad W^*(y, b) = - \ln \sum \frac{1}{b_i}$$

• MAXIMUM profit rate occurs when horse with maximum value win in all races, i.e.  $p_i = 1$  for horse that provides maximum odds

And also when we know so best at horse or its opponent

**PROBLEM 6.13** DUCH BOOK. CONSIDER THE HOUSE RAC WITH  $n=2$  HORSES:

$$x = 1, 2 \quad P = \left\{ \frac{1}{2}, \frac{1}{2} \right\} \quad O = \{10, 30\}$$

$$Q = \left\{ \frac{1}{6}, 1-6 \right\}$$

THE ODDS ARE SUPERFAIR.

(a) THERE IS A SET  $G$  THAT GUARANTEES THE SAME TAKE OFF REGARDLESS OF WHICH HORSE WINS. SUCH SET IS CALLED DUCH BOOK. FIND THIS SET AND ASSOCIATED WEALTH FACTOR  $S(x)$ .

(b) WHAT IS THE MAXIMUM PROFIT RATE OF THE HOUSE FOR OPTIMAL CHOICE OF  $G$ ? IS THERE A SET FOR THE DUCH BOOK.

$$S(x) = G(x) \cdot O(x) \quad G \cdot 10 = (1-G) \cdot 30$$

$$10G = 30 - 30G \quad 40G = 30 \quad G = \frac{3}{4}$$

$$S(x) = 10 \cdot \frac{3}{4} = \frac{30}{4} = 30 \left(1 - \frac{3}{4}\right) = 30 \cdot \frac{1}{4} = \frac{30}{4}$$

$$W_D = \frac{1}{2} \cdot \frac{3}{4} \cdot 10 + \frac{1}{2} \cdot \frac{1}{4} \cdot 30 = \frac{30}{4} = 2.9$$

(c)  $G(x) = P(x)$   $G = \frac{1}{2}$

$$W^*(G, P) = \sum_P P(x) \cdot O(x) = P\left(\frac{1}{2}\right) = \frac{1}{2} \cdot 10 + \frac{1}{2} \cdot 30 = 20 = 4 \cdot 11 - 1 = 3$$

$$W^* = \left\{ E[O \cdot S(x)] \right\} \quad S_H = 2$$

$$E[O \cdot \frac{3}{4}] = 2.9 \quad W_D = 2.9 < 3.11 = W^*$$

MAXIMUM PROFIT RATE IS ASSOCIATED SO MAXIMUM RATE.

$$\frac{1}{4} \cdot 30 = \frac{1}{4} \cdot 30 \cdot P(S(x)) = \frac{1}{4} \cdot \sum O \cdot S(x)$$

$$E[O \cdot S(x)] = W(x) \quad W(y, G) = E[O \cdot S(x)]$$

$$S_H = 2 \quad S_H = 2 \cdot 3.11 = 3.66$$

**PROBLEM 6.14**

**HORSE RACE**

PROBABILITIES OF  $u$  HORSES WIN  
 ( $o_1, o_2, \dots, o_u$ ) YEAR HIGHER OUTFIELDING RATE  
 THEN ( $o'_1, o'_2, \dots, o'_u$ )?

$$W(y) = \sum y_i \cdot b_i \cdot o_i$$

$$W(y, \beta) = \sum y_i \cdot b_i \cdot o'_i$$

$$W(y, \beta) - W(y) = \sum y_i \cdot b_i \cdot o_i - \sum y_i \cdot b_i \cdot o'_i =$$

$$= \left[ \sum y_i \cdot b_i \cdot o_i - \sum y_i \cdot b_i \cdot o'_i \right] = \sum y_i \cdot b_i \cdot \frac{o_i}{o'_i} \cdot \frac{1}{y} =$$

$$= \sum y_i \cdot b_i \cdot \frac{1}{r_i} - \sum y_i \cdot b_i \cdot \frac{1}{y_i} = D(y \parallel r_i) - D(y \parallel y_i) > 0$$

$$\left( D(y \parallel r_i) > D(y \parallel y_i) \right) \iff \left( E[\log o_i] > E[\log o'_i] \right)$$

**PROBLEM 6.15**

**ENTROPY OF A FAIR HORSE RACE**

LET  $X \sim \gamma(x)$ ,  $x = 1, 2, \dots, u$ ,  
 DENOTE THE WINNER OF A HORSE RACE.  
 SUPPOSE THAT THE ODDS  $o(x)$  ARE FAIR WITH  
 RESPECT TO  $\gamma(x)$  [i.e.  $o(x) = \frac{1}{\gamma(x)}$ ]. LET

$b(x)$  BE THE AMOUNT BET ON HORSE  $x$ . ALSO  
 $\sum_1^u b(x) = 1$ . THEN THE RESULTING WEALTH FACTOR  
 IS  $S(x) = o(x) \cdot b(x)$  WITH PROBAB.:  $\gamma(x)$ .

- (a) FIND  $E[S(x)]$  (EXPECTED WEALTH)
- (b) FIND  $W^*$  OPTIMAL GROWTH RATE OF WEALTH.
- (c) SUPPOSE:  $r = \begin{cases} 1 & x=1 \text{ OR } 2 \\ 0 & \text{OTHERWISE} \end{cases}$

IF THIS SIDE INFORMATION IS AVAILABLE BEFORE  
 THE BET. HOW MUCH DOES IT INCREASE THE  
 GROWTH RATE  $W^*$ !

(d) FIND  $I(x; r)$

$$(1) E[S(x)] = \sum \gamma(x) \cdot S(x) = \sum \gamma(x) \cdot b(x) \cdot o(x) =$$

$$= \sum_x \gamma(x) \cdot b(x) \cdot \frac{1}{\gamma(x)} = \sum_1^u b(x) = 1$$

$$(2) W^* = \sum_x \gamma(x) \cdot b(x) \cdot o(x) = \sum_x \gamma(x) \cdot b(x) \cdot \frac{1}{\gamma(x)}$$

$$\nabla W^*(\beta) \rightarrow \nabla b(x) = 0 \quad \frac{\partial}{\partial b_i} \left( y_i \cdot b_i \cdot \frac{1}{y_i} \right) = y_i \cdot \frac{1}{b_i \cdot y_i}$$



$$\frac{p_i^2}{b_i} - \lambda = 0 \quad p_i^2 = \lambda \cdot b_i \quad b_i = \frac{p_i^2}{\lambda}$$

$$\sum_i b_i = \sum_i \frac{p_i^2}{\lambda} = \frac{1}{\lambda} \sum_i p_i^2 = 1$$

$$p_i^2 = \left\{ \frac{1}{2}, \frac{1}{4}, \frac{1}{4} \right\} \cdot \left\{ \frac{1}{2}, \frac{1}{4}, \frac{1}{4} \right\} = \left\{ \frac{1}{4}, \frac{1}{16}, \frac{1}{16} \right\}$$

$$\sum p_i^2 = \frac{1}{4} + 2 \cdot \frac{1}{16} = \frac{1}{4} + \frac{1}{8} = \frac{3}{8}$$

$$\boxed{\lambda = \sum p_i^2} \quad \sum p_i^2 = E[p_i] \quad \boxed{b_i = \frac{p_i^2}{\sum p_i^2}}$$

$$W = \sum_x p(x) \cdot b_d \cdot \frac{1}{\sum p(x)} = \sum_x p(x) b_d \cdot \frac{p(x)}{\sum p^2(x)}$$

$$= \sum p(x) \cdot b_d \cdot \frac{1}{\sum p(x)} = H(x)$$

$$W = \sum_i p_i \cdot b_d \cdot \frac{b_i}{p_i} = H(x) + \sum_i p_i \cdot b_d \cdot b_i$$

$$W = - \sum p_i \cdot b_d \cdot \frac{p_i^2}{b_i} = -D(p||b) \rightarrow \frac{p=b \Rightarrow W^* = 0 \text{ (OPTIMAL)}}$$

GROWTH RATE.

Is there more so  $\lambda = 1$  = MULTIFACTOR:

$$\nabla W(b, \lambda) = \lambda \nabla b(x) \quad W(b, \lambda) = \sum p(x) b_d b(x) + H(x)$$

$$\nabla W(b, \lambda) \nabla b_i \quad \frac{d}{d b_i} \sum p(x) b_d b(x) - \lambda = 0$$

$$\boxed{p_i \cdot \frac{1}{b_i} = \lambda} \quad b_i = \frac{p_i}{\lambda} \quad \sum_i \frac{p_i}{\lambda} = 1 \Rightarrow \lambda = 1$$

$\Rightarrow p_i = b_i$  } OPTIMAL SOLUTION.

$$(c) \quad \lambda = \begin{cases} 1 & \text{for } 2 \\ 0 & \text{otherwise} \end{cases}$$

$$W(x|\lambda) = \sum p(x) \cdot b_d \cdot \alpha(x) = b_d \cdot \lambda \Rightarrow$$

$$W^*(x|\lambda) = \sum p(x) \cdot b_d \cdot \alpha(x) \cdot p(x) = \sum p(x) \cdot b_d \cdot \alpha(x) + \sum p(x) \cdot \frac{1}{p(x)} = H(x) + H(x|p)$$

$$W^*(x) = \sum \gamma(\tau) \cdot \delta \alpha(\tau) \gamma(\tau) = \sum \gamma(\tau) \delta \alpha(\tau) = H(x)$$

$$W^*(x|\tau) - W^*(x) = \sum \gamma(\tau) \delta \alpha(\tau) - H(x|\tau) =$$

$$- \sum \gamma(\tau) \delta \alpha(\tau) + H(x) = H(x) - H(x|\tau) = \underline{\underline{I(x; \tau)}}$$

$$(b) H(x) = \sum_{i=1}^m p_i \delta \frac{1}{\gamma_i}$$

$$H(x|\tau) = \gamma(\tau=1) \cdot H(x|\tau=1) + \gamma(\tau=0) \cdot H(x|\tau=0)$$

$$= \gamma(\tau=1) \cdot H(x_1, x_2) + \gamma(\tau=0) \cdot H(x_3, \dots)$$

$$= \gamma(\tau=1) \cdot H(x_1^2) + [1 - \gamma(\tau=1)] \cdot H(x_2^2)$$

$$\therefore I(x; \tau) = H(x_1^2) - \gamma(\tau=1) H(x_1^2) - H(x_2^2) + \gamma(\tau=1) H(x_2^2)$$

$$I(x; \tau) = \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} - \gamma(\tau=1) \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} - \sum_{i=3}^m p_i \delta \frac{1}{\gamma_i}$$

$$+ \gamma(\tau=1) \sum_{i=3}^m p_i \delta \frac{1}{\gamma_i} = \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} - \gamma(\tau=1) \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i}$$

$$+ \gamma(\tau=1) \sum_{i=3}^m p_i \delta \frac{1}{\gamma_i} = \underbrace{p(\tau=0) \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i}}_2 +$$

$$+ \gamma(\tau=1) \sum_{i=3}^m p_i \delta \frac{1}{\gamma_i} = \gamma(\tau=0) \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} +$$

$$+ \gamma(\tau=1) \left[ H(x) - \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} \right] =$$

$$= \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} [\gamma(\tau=0) - \gamma(\tau=1)] + \gamma(\tau=1) H(x) =$$

$$p(\tau=1) = p(x=x_1) + \gamma(x=x_2)$$

$$= [1 - p(\tau=1) - \gamma(x=x_2)] \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} + \gamma(\tau=1) H(x) =$$

$$= [1 - 2(p_1 + p_2)] \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} + (\gamma_1 + \gamma_2) H(x)$$

$$= [1 - (p_1 + p_2)] \sum_{i=1}^2 p_i \delta \frac{1}{\gamma_i} + (\gamma_1 + \gamma_2) \sum_{i=1}^m p_i \delta \frac{1}{\gamma_i}$$

$$= \sum_{i=3}^m p_i \cdot \sum_{j=1}^2 p_j \log \frac{1}{p_j} + \sum_{i=1}^2 p_i \cdot \sum_{j=3}^m p_j \log \frac{1}{p_j}$$

$[p_1, p_2, p_3]$

$$p_3 \cdot \sum_{j=1}^2 p_j \log \frac{1}{p_j} + (p_1 + p_2) p_3 \log \frac{1}{p_3} =$$

$$= p_1 p_3 \log \frac{1}{p_1} + p_2 p_3 \log \frac{1}{p_2} + p_1 p_3 \log \frac{1}{p_3} + p_2 p_3 \log \frac{1}{p_3}$$

$$= p_1 p_3 \left( \log \frac{1}{p_1} + \log \frac{1}{p_3} \right) + p_2 p_3 \left( \log \frac{1}{p_2} + \log \frac{1}{p_3} \right)$$

$$I(x; \tau) = p \cdot \sum_{i=1}^2 p_i \log \frac{1}{p_i} + (1-p) \sum_{i=3}^m p_i \log \frac{1}{p_i}$$

$$\boxed{p = P(\tau=1)}$$

IF

$$\boxed{p = \frac{1}{2}}$$

$$I(x; \tau) = \frac{1}{2} \sum_{i=1}^2 p_i \log \frac{1}{p_i} = \frac{1}{2} H(x)$$

Example 2 solution

$$(c) (d) \quad q = P(\tau=1) = p(x_1) + p(x_2)$$

$$I(x; \tau) = H(x) - H(x|\tau) = H(\tau) - H(\tau|x)$$

$\tau$  is a function of  $x$  and vice versa

$$I(x; \tau) = H(\tau) = q \log \frac{1}{q} + (1-q) \log \frac{1}{1-q} = H(q)$$

**PROBLEM 6.16** NEGATIVE HORSE RACE. CONSIDER A HORSE RACE WITH  $m$  HORSES WITH WIN PROBABILITIES:  $p_1, p_2, \dots, p_m$ . THERE ARE  $m$  GAMBLERS NOTED THAT GIVEN HORSE WILL LOSE. THE GAMBLERS DEVS  $(b_1, b_2, \dots, b_m)$  ON THE HORSES, LOSES HIS BET  $b_i$  IF HORSE  $i$  WINS AND RETAINS THE REST OF HIS BETS. (NO ODDS) — thus,  $S = \sum b_i$  WITH PROBABILITIES  $p_i$ , AND ONE WISHES TO MAXIMIZE  $\sum p_i \log(1 - b_i)$  subject to

TO CONSTRAINT:  $\sum b_i = 1$

(a) FIND THE GROWTH RATE OPTIMAL INVESTMENT STRATEGY  $b^*$  DO NOT CONSTRAINT THE  $b_i$  TO BE POSITIVE, BUT DO CONSTRAINT THE  $b_i$  TO SUM TO 1. (THIS EFFECTIVELY ALLOWS SHORT SELLING AND MARGIN.)

(b) WHAT IS THE OPTIMAL GROWTH RATE?

(a)  $S(x) = 1 - b(x)$  } DERIVATIVE IS TO BE POSITIVE & OF A CONSTANT SIZE

$$W(b, \lambda) = \sum_{i=1}^n \gamma_i \cdot b_i \cdot S(x) = \sum_{i=1}^n \gamma_i \cdot b_i (1 - b_i)$$

$$\sum_{i=1}^n b_i = 1 \quad \frac{d}{db_i} \gamma_i b_i (1 - b_i) + \lambda = 0$$

$$-\frac{\gamma_i}{b_i^2} (1 - b_i) + \lambda = 0$$

$$\lambda = \frac{\gamma_i / b_i^2}{1 - b_i}$$

$$\sum_{i=1}^n b_i = 1$$

$$1 - b_i = \frac{\gamma_i / b_i^2}{\lambda} \quad b_i = \left(1 - \frac{\gamma_i}{\lambda}\right)$$

$$\sum_{i=1}^n \left(1 - \frac{\gamma_i}{\lambda}\right) = 1 \quad \Rightarrow \quad n - \frac{1}{\lambda} \sum_{i=1}^n \gamma_i = 1$$

$$n - \frac{1}{\lambda} = 1$$

$$n - 1 = \frac{1}{\lambda} \sum_{i=1}^n \gamma_i$$

$$\left[ \frac{1}{\lambda} = \frac{2}{n-1} \right]$$

$$b_i = 1 - \frac{\gamma_i / b_i^2}{1 / (b_i^2 \cdot (n-1))} \quad \leftarrow \quad \lambda = \frac{1}{b_i^2 \cdot (n-1)}$$

$$b_i = 1 - \gamma_i (n-1)$$

(b)  $W^*(\gamma, b) = \sum \gamma_i b_i (1 - b_i) = \sum \gamma_i b_i (1 - \gamma_i (n-1))$

$$W^*(\gamma, b) = \sum \gamma_i b_i (1 - \gamma_i (n-1)) = b_i (n-1) - H(\gamma)$$

OPTION 2 SOLUTION

$$b_i' = 1 - b_i$$

$$\sum_{i=1}^n b_i' = n - 1$$

$$z_i = \frac{b_i'}{\sum b_i'} = \frac{b_i'}{n-1}$$

$$W = \sum \gamma_i b_i (1 - b_i) =$$

$$= \sum \gamma_i b_i b_i' = \sum \gamma_i b_i (n-1) z_i = b_i (n-1) + \sum \gamma_i b_i z_i$$

$$= b_i (n-1) + \sum \gamma_i b_i \frac{\gamma_i}{\gamma_i} z_i = b_i (n-1) - D(\gamma | z) - H(\gamma)$$

$(\gamma = z) \Rightarrow$  MAXIMIZE  $W$

$$\frac{b_i'}{n-1} = p \quad \frac{1 - b_i}{n-1} = p$$

$$[G_s = 1 - \gamma(m-1)] \Rightarrow D(\gamma, 1) = 0 \Rightarrow$$

$$W^*(0, \gamma) = \frac{1}{\gamma} - \frac{1}{\gamma(m-1)}$$

**PROBLEM 6.17** St. Petersburg Lottery Game

190 IN AN ENTIRE ST. PETERSBURG THE FOLLOWING  
 GAME TAKING 100,000,000 - USED GREAT CONTRIBUTION.  
 FOR THE ENTRY FEE OF  $C$  UNITS A GAMBLER  
 RECEIVES A PAYOFF OF  $2^k$  UNITS WITH PROBABILITY  
 $2^{-k}$ ,  $k = 1, 2, \dots$

(a) SHOW THAT EXPECTED PAYOFF FOR THIS GAME IS  
 INFINITE. FOR THIS REASON, IT WAS ASSUMED  
 THAT  $C = \infty$  WAS A FAIR PRICE TO PAY  
 TO PLAY THIS GAME. MOST PEOPLE FIND THIS  
 ANSWER ASSURD.

(b) SUPPOSE THAT GAMBLER CAN BUY A SHARE  
 OF THE GAME FOR  $\epsilon$  UNITS. IF HE INVESTS  
 $C/2$  UNITS IN THE GAME, HE RECEIVES  $1/2$   
 A SHARE OF A PAYOFF  $2^k$  WHERE  $P(A=2^k) =$   
 $2^{-k}$ ,  $k = 1, 2, \dots$ . SUPPOSE THAT  $X_1, X_2, \dots$  ARE  
 I.I.D. ACCORDING TO THIS DISTRIBUTION, AND THAT  
 THE GAMBLER REINVESTS ALL HIS WEALTH  
 EACH TIME. THUS HIS WEALTH  $S_n$  AT TIME  
 $n$  IS GIVEN BY:

$$S_n = \prod_{i=1}^n \frac{X_i}{C}$$

SHOW THAT THIS LIMITING  
 PROPERTY OF A GAMBLER  
 $C \rightarrow \infty$  IDENTIFY THE  
 MORE NEARLY TO THE  
 ALLOWED TO REPLY

$G = 1 - B$   
 OF HIS MONEY IN THE MARKET AND INVEST THE  
 REST IN ST. PETERSBURG GAME. HIS WEALTH AT  
 TIME  $n$  IS THEN:

$$S_n = \prod_{i=1}^n \left( \frac{1}{2} + \frac{B 2^k}{C} \right)$$

LET:  $W(B, C) = \sum_{k=1}^{\infty} 2^{-k} C \left( \frac{1}{2} + \frac{B 2^k}{C} \right)$

WE HAVE:  $S_n \leq 2^{-n} W(B, C)$  ,  $\lim_{n \rightarrow \infty} W^*(C) = \lim_{B \rightarrow 1} W(B, C)$

- HERE ARE SOME QUESTIONS ABOUT  $W^*(C)$
  - (a) FOR WHAT VALUE OF THE ENTRY FEE  $C$  DOES THE  
 OPTIMIZING VALUE  $B^*$  FALL BELOW  $1/2$ ?
  - (b) HOW DOES  $B^*$  VARY WITH  $C$ ?
  - (c) HOW DOES  $W^*(C)$  FALL OFF WITH  $C$ ?
- NOTE THAT SINCE  $W^*(C) > 0$  FOR  $B \leq 1$  WE CAN CONCLUDE  
 THAT AN ENTRY FEE  $C = 1$  IS FAIR.

$$(9) \quad W = \sum p(\pi) \cdot \ln O(\pi) \cdot B(\pi) \quad O(x) = \frac{1}{2^k} \quad k=1, 2, \dots$$

$$W = \sum p(\pi) \cdot \ln O(\pi) = H(\pi)$$

$$W = \sum \frac{1}{2^k} \cdot \ln 2^{-k} = - \sum_{k=1}^{\infty} \frac{k}{2^k} = \frac{2}{(1-2)^2} = -2 \quad \left| 2 = \frac{1}{2} \right.$$

$$S = \sum_{x=1}^{\infty} \frac{x}{2^x} = \sum_{x=1}^{\infty} x \cdot 2^{-x} \quad \int a^x dx = \frac{a^{x+1}}{x+1}$$

$$S = 2 \sum_{x=1}^{\infty} x \cdot 2^{-(x+1)}$$

$$S = \sum_{x=1}^{\infty} 2^x \quad \frac{dS}{d2} = \sum_{x=1}^{\infty} x \cdot 2^{x-1}$$

$$\frac{dS}{d2} = 2 \sum_{x=1}^{\infty} x \cdot 2^{x-1}$$

$$S = \frac{1}{1-2}$$

$$\frac{dS}{d2} = \left( \frac{1}{1-2} \right)' = \frac{1}{(1-2)^2}$$

$$\frac{1}{(1-2)^2} = 2 \sum_{x=1}^{\infty} x \cdot 2^{x-1}$$

$$S = \sum_{x=1}^{\infty} x \cdot 2^x = \frac{x}{1-2}$$

$$\sum_{x=1}^{\infty} x^2 = 1 + 4 + 9 + 16 + \dots = \frac{1}{1-2}$$

$$\sum_{x=1}^{\infty} x^3 = \frac{1}{1-2} = \sum_{x=1}^{\infty} x^2 + 1 = \sum_{x=1}^{\infty} x^2 + 1$$

$$\frac{dS}{dx} = \frac{x}{(1-x)^2} + \frac{1}{(1-x)^2} = \frac{1-x+x}{(1-x)^2} = \frac{1}{(1-x)^2}$$

$$\frac{d}{dx} \sum_{x=1}^{\infty} x^2 = \sum_{x=1}^{\infty} 2x = \frac{1}{1-x^2} = \frac{1}{(1-x)^2}$$

$$\sum_{x=1}^{\infty} x^2 = \frac{x}{(1-x)^2}$$

$$W = \frac{1}{2} \cdot \frac{1}{(1-2)^2} = H(\pi) = \frac{1}{2} \cdot \frac{1}{1} = 2 = H(\pi)$$

$$S_n = 2^{n \cdot W} \quad \max [H(r)] = n \cdot \frac{1}{4} \ln 2 = \ln 2$$

$$S(x) = 2^k = G(x) \cdot D(x)$$

$$E[S(x)] = \sum_{k=1}^{\infty} \frac{1}{2^k} \cdot \ln 2 \cdot 2^k = \sum_{k=1}^{\infty} \frac{k}{2^k} = 2 = W$$

$$S_n = 2^{n \cdot W} = 2^{2n} \quad \lim_{n \rightarrow \infty} S_n = \infty$$

- VARIÁVELS NA TERÇA É! Hora (1) INDA

$$E[x] = E[S(x)] = \sum_{k=1}^{\infty} \frac{1}{2^k} \cdot 2^k = \sum_{k=1}^{\infty} 1 = \infty$$

VALOR É DEFINIDO NO NÚMERO!!!

(6) GAMBALER INVESTS  $\frac{c}{2}$  UNITS IN THE GAME AND RECEIVES  $\frac{1}{2} \cdot x$  SHARE AND A RETURN  $\frac{x}{2}$

$$Pr(x=2^k) = 2^{-k} \quad k=1, 2, \dots$$

$$x_1, x_2, \dots \quad x_i \leftarrow \text{i.i.d.} \quad S_n = \prod_{i=1}^n \frac{x_i}{c}$$

$$S(x_1) = \frac{x_1}{2} \quad S(x_2) = \frac{x_2}{2} = \frac{1}{2} \cdot \frac{x_1}{2}$$

$$S(x_3) = \frac{x_3}{2} = \frac{1}{2} \cdot \frac{x_2}{2} = \frac{1}{2} \cdot \frac{1}{2} \cdot \frac{x_1}{2}$$

$$S(x_n) = \frac{x_n}{2^n}$$

$$S_n = \prod_{i=1}^n \frac{x_i}{c} = \prod_{i=1}^n S(x_i)$$

$$\textcircled{4} \rightarrow \sum_{i=0}^{\infty} \frac{1}{2^i} = \frac{1}{2} \sum_{i=0}^{\infty} \frac{1}{2^{i-1}} = \frac{1}{2} \sum_{i=0}^{\infty} \frac{1}{2^i} = \frac{1}{2} \cdot \frac{1}{1-\frac{1}{2}} = \frac{1}{2} \cdot 2 = 1$$

$$\frac{1}{4} \ln S_n = \frac{1}{4} \ln \prod_{i=1}^n S(x_i) = \frac{1}{4} \ln \prod_{i=1}^n \frac{x_i}{c} = \frac{1}{4} \sum_{i=1}^n \ln \left( \frac{x_i}{c} \right)$$

$$\sum_{i=1}^n Pr(x_i) \cdot \ln \left( \frac{x_i}{c} \right) =$$

$$= \sum_{i=1}^{\infty} \frac{1}{2^i} \cdot \ln \frac{2^i}{c} =$$

$$= \sum_{i=1}^{\infty} \frac{i}{2^i} \ln 2 - \sum_{i=1}^{\infty} \frac{1}{2^i} \ln c = \frac{1}{2} \ln 2 - \ln c =$$

$$= 2 - \ln c \left( \sum_{i=1}^{\infty} \frac{1}{2^i} \right) = 2 - (\ln c) \cdot 1 = |c=2| = 0$$

$$1 \leq c \leq 2 \quad W = 2 - \ln c \rightarrow \frac{1}{4} \ln S_n$$

$$S_n = 2^n \cdot W = 2^n \cdot (2 - cdc) \quad \boxed{c^* = 4}$$

$$\boxed{C > C^* = 4} \Rightarrow S_n = 2^{-n} \cdot |cdc - 2|$$

$$n \rightarrow \infty \quad S_n \rightarrow 0 \quad \boxed{W = 2 - cdc}$$

$$1 \leq \boxed{C < C^* = 4} \quad S_n = 2^n \cdot |2 - ldc| \rightarrow \infty$$

• MORE REALISTICALLY  $\bar{b} = 1 - b$  KEEPING PROPORT.

$$S_n = \prod_{i=1}^n \left( \bar{b} + \frac{b2^i}{c} \right)$$

$$\boxed{W(b, c) = \sum_{k=1}^{\infty} 2^{-k} \text{ld} \left( 1 - b + \frac{b2^k}{c} \right) =}$$

$$= \sum_{k=1}^{\infty} 2^{-k} \text{ld} \left( 1 - b + \frac{b2^k}{c} \right) = \textcircled{*}$$

$$W^*(c) = \max_{0 \leq b \leq 1} W(b, c)$$

NEED  $\lambda = 20170$   
 NEED DEFINITION CONDIT.  
 INT  $\sum b = 1$

$$\frac{d}{db} \left[ 2^{-k} \text{ld} \left( 1 - b + \frac{b2^k}{c} \right) \right] + \lambda = 0$$

$$\frac{2^k}{b+2} \cdot \frac{1}{\left( 1 - b + \frac{b2^k}{c} \right)} \cdot \left( -1 + \frac{2^k}{c} \right) = 0$$

$$\frac{2^k \cdot c}{b+2(c-bc+b \cdot 2^k)} \cdot \left( \frac{2^k}{c} - 1 \right) = 0$$

$$\frac{2^k}{c} - 1 = 0 \quad \frac{2^k}{c} = 1$$

$$\frac{1}{c-bc+b2^k} \cdot \left( \frac{2^k}{c} - 1 \right) = 0$$

$$\boxed{c = 2^k} \Rightarrow W(b, 2^k) = 0$$

$$\textcircled{*} = \sum_{k=1}^{\infty} 2^{-k} \text{ld} \left[ \left( 1 - b + \frac{b2^k}{c} \right) \frac{2^{-k}}{2^{-k}} \right] = \sum_{k=1}^{\infty} 2^{-k} \text{ld} \frac{2^{-k}}{\left( 1 - b + \frac{b2^k}{c} \right)}$$

$$+ \sum_{k=1}^{\infty} 2^{-k} \text{ld} \frac{1}{2^{-k}} = \sum_{k=1}^{\infty} 2^{-k} \text{ld} \frac{2^{-k}}{\left( 1 - b + \frac{b2^k}{c} \right)}$$

$$+ \sum_{k=1}^{\infty} 2^{-k} \cdot k = \sum_{k=1}^{\infty} 2^{-k} \text{ld} \frac{2^{-k}}{\left( 1 - b + \frac{b2^k}{c} \right)} - \frac{1}{2}$$

$$= \sum_{k=1}^{\infty} 2^{-k} \text{ld} \frac{2^{-k}}{\left( 1 - b + \frac{b2^k}{c} \right)} - 2 = D(\frac{1}{2} || \frac{1}{2}) - 2$$



$$\frac{d}{dc} \left[ 2^{-k} \ln \left( 1-b + \frac{b2^k}{c} \right) \right] = \frac{2^{-k}}{\ln 2} \frac{1}{1-b + \frac{b2^k}{c}} \cdot \frac{b \cdot 2^k}{c^2} = 0$$

$$A = \frac{b}{\frac{b}{c} 2^k - b + 1} = 0$$

$$A = \frac{b-c}{b(2^k-1) + c} = 0$$

$$\frac{b \cdot 2^k}{b(2^k-1) + c} = 0$$

$$\frac{b}{b(1-2^k) + 1} = 0$$

$$\lim_{c \rightarrow \infty} A = \lim_{c \rightarrow \infty} \frac{b-c}{b(c-1) + c} = \lim_{c \rightarrow \infty} \frac{b-c}{bc+c-b} =$$

$$\lim_{c \rightarrow \infty} \frac{bc}{c(b+1)-b} = \frac{b}{b+1} = 0?$$

$$1-b + \frac{b \cdot 2^k}{c} \rightarrow \infty$$

• KHUN - ruckel conditions?

• GRADIENT 2 SOLUTIONS [PART (c)]

$$W(b,c) = \sum_{k=1}^{\infty} 2^{-k} \ln \left( 1-b + \frac{b2^k}{c} \right)$$

$$\boxed{b=0} \quad W(b,c) = \sum_{k=1}^{\infty} 2^{-k} \ln(1) = 0$$

$$\boxed{b=1} \quad W(b,c) = \sum_{k=1}^{\infty} 2^{-k} \ln \frac{2^k}{c} = \sum_{k=1}^{\infty} \frac{k}{2^k} - \sum_{k=1}^{\infty} \frac{\ln c}{2^k} =$$

$$\boxed{W = 2 - \ln c} \quad \frac{\partial W(b,c)}{\partial b} = \sum_{k=1}^{\infty} 2^{-k} \frac{1}{1-b + \frac{b2^k}{c}} \left( \frac{b2^k}{c} - 1 \right)$$

$$\boxed{b=1} \quad \frac{\partial W(b,c)}{\partial b} = \sum_{k=1}^{\infty} 2^{-k} \frac{1}{\frac{2^k}{c}} \cdot \left( \frac{2^k}{c} - 1 \right) = \sum_{k=1}^{\infty} 2^{-2k} \cdot c \left( \frac{2^k}{c} - 1 \right)$$

$$= \sum_{k=1}^{\infty} \left( \frac{2^k}{c} - \frac{c}{2^{2k}} \right) = \sum_{k=1}^{\infty} 2^{-k} - \sum_{k=1}^{\infty} \frac{c}{2^{2k}} = \frac{1}{2} \frac{1}{1-\frac{1}{2}} - c \frac{1}{4} \frac{1}{1-\frac{1}{4}}$$

$$= \frac{1}{2} \cdot 2 - c \cdot \frac{1}{3} \cdot \frac{4}{1} = 1 - \frac{4c}{3} \geq 0 \quad \text{FOR } \boxed{c \leq 3}$$

$$\sum_{k=1}^{\infty} 2^{-k} \frac{\frac{b2^k}{c}}{1-b + \frac{b2^k}{c}} - \sum_{k=1}^{\infty} \frac{c}{2^{2k}} = 0$$

$$\sum_{k=1}^{\infty} \frac{2^{-k}}{1-b + \frac{b \cdot 2^k}{c}} \left( \frac{b \cdot 2^k}{c} - 1 \right) = \sum_{k=1}^{\infty} \frac{\left( \frac{b}{c} - 2^{-k} \right)}{1-b + \frac{b \cdot 2^k}{c}} =$$

$$= \sum_{k=1}^{\infty} \frac{(b - c \cdot 2^{-k})}{(1-b) \cdot c + b \cdot 2^k} = \sum_{k=1}^{\infty} \frac{\left( b - \frac{c}{2^k} \right)}{(1-b) \cdot c + b \cdot 2^k}$$

$$c=0 \quad dw = \sum_{k=1}^{\infty} \frac{b}{b \cdot 2^k} = \frac{1}{2} \cdot \frac{1}{1-\frac{1}{2}} = 1$$

07-08-2017

**PROBLEM 6.18**

SIMILAR ST. PETERSBURG FINANCY WE

WHILE  $P_k(x = 2^k) = 2^{-k}$ ,  $k=1, 2, \dots$  THERE IS A  
 SELECTED LOG-WEIGHT IS INFINITE FOR ALL  $b > 0$ ,  
 FOR ALL  $c$  AND THE GROWTHS WEIGHT GROWS  
 TO INFINITE FASTER THAN EXPONENTIAL FOR ALL  $b > 0$ .  
 BUT THAT DOESN'T MEAN THAT ALL INVESTMENT  
 INTO  $c^2$  ARE EQUALLY GOOD. TO SEE THIS  
 WE WISH TO MAXIMIZE THE RELATIVE GROWTH  
 RATE WITH RESPECT TO SOME OTHER PORTFOLIO,  
 SAY,  $b = (\frac{1}{2}, \frac{1}{2})$ . SHOW THAT THERE EXISTS  
 A UNIQUE  $b$  OPTIMIZING:

$$E \left[ \ln \frac{b + b + c}{\frac{1}{2} + \frac{1}{2} \frac{c}{2}} \right] \quad \text{[apply] UNLESS}$$

AND INTERPRET THE ANSWER.

$$E[\ln S(x)] = \sum_{k=1}^{\infty} \frac{1}{2^k} \ln 2^k = \sum_{k=1}^{\infty} \frac{2^k}{2^k} = \sum_{k=1}^{\infty} \frac{1}{2^{-2k}}$$

$$= \frac{1}{4} \sum_{k=0}^{\infty} \frac{1}{4^k} = \frac{1}{4} \cdot \frac{1}{1-\frac{1}{4}} = \frac{1}{4} \cdot \frac{4}{3} = \frac{1}{3}$$

$$S(x) = \frac{2^k}{c} \Rightarrow E[\ln S(b)] = \sum_{k=1}^{\infty} \frac{1}{2^k} \ln \frac{2^k}{c} =$$

$$= \frac{1}{3} - \left( \frac{1}{2} \sum_{k=0}^{\infty} \frac{1}{2^k} \right) \ln c = \frac{1}{3} - \frac{1}{2} \cdot 2 \cdot \ln c = \frac{1}{3} - \ln c$$

$$W = \sum_{k=1}^{\infty} \frac{1}{2^k} \ln \left( \frac{1-b + \frac{b \cdot 2^k}{c}}{\frac{1}{2} + \frac{1}{2} \frac{c}{2^k}} \right) = \sum_{k=1}^{\infty} \frac{1}{2^k} \ln \left( \frac{1-b + \frac{b \cdot 2^k}{c}}{\frac{1}{2} + \frac{c}{2^k}} \right)$$

$$\frac{dW}{db} = \frac{1}{2^k} \frac{\frac{1}{2} + \frac{c}{2^k}}{1-b + \frac{b \cdot 2^k}{c}} \cdot \left( -1 + \frac{2^k}{c} \right)$$

$$\frac{2^k}{c} = 1$$

$$c = 2^k$$

$$\frac{dW}{dc} = \frac{\frac{1}{2} + \frac{2^{2k}}{2c}}{1-b + \frac{b \cdot 2^{2k}}{c}} \cdot \left( -\frac{b \cdot 2^{2k}}{c^2} \right) \left( \frac{1}{2} + \frac{2^{2k}}{2c} \right) +$$

$$+ \left( 1-b + \frac{b \cdot 2^{2k}}{c} \right) \frac{2^{2k}}{c^2} \cdot 2c = 0$$

$$\left( \frac{1}{2} + \frac{2^{2k}}{2c} \right) = 0 \Rightarrow \frac{2^{2k}}{2c} = -\frac{1}{2} \quad c = -2^{2k}$$

$$-\frac{b \cdot 2^{2k}}{2c^2} + \frac{b \cdot 2^{2k} \cdot 2^{2k}}{2c^3} + \frac{2^{2k}}{c^2} - \frac{b \cdot 2^{2k}}{c^2} + \frac{b \cdot 2^{2k} \cdot 2}{c^3} = 0$$

$$-\frac{3b \cdot 2^{2k}}{2c^2} - \frac{b \cdot 2^{2k}}{2c^3} + \frac{2^{2k}}{c^2} = 0$$

$$\frac{2^{2k}}{c^2} \left( 1 - \frac{3b}{2} - \frac{b \cdot 2^{2k}}{2c} \right) = 0$$

$$\left( 1 - \frac{3b}{2} - \frac{b}{2} \right) = 0 \quad \left( 1 - \frac{4b}{2} \right) = 0 \quad (1 - 2b) = 0 \quad \boxed{b = \frac{1}{2}}$$

$$W(b, c) \quad \boxed{W\left(\frac{1}{2}, c\right) = 0}$$

PROBLEM 6 (REVISITED)

$$W(b, c) = \sum_{k=1}^{\infty} 2^{-k} b \left( 1 - b + \frac{b \cdot 2^k}{c} \right)$$

$$\frac{dW(b, c)}{db} = \sum_{k=1}^{\infty} 2^{-k} \left( \frac{-1 + \frac{2^k}{c}}{1 - b + \frac{b \cdot 2^k}{c}} \right) = 0$$

$$b=1 \quad dW = \sum_{k=1}^{\infty} 2^{-k} \frac{\frac{2^k}{c} - 1}{\frac{2^k}{c}} = \sum_{k=1}^{\infty} 2^{-k} \frac{2^k - c}{2^k} = \sum_{k=1}^{\infty} \frac{1 - c \cdot 2^{-k}}{2^k}$$

$$= \sum_{k=1}^{\infty} \frac{1}{2^k} - c \sum_{k=1}^{\infty} \frac{1}{4^k} = \frac{1}{2} \frac{1}{1-1/2} - c \frac{1}{4} \frac{1}{1-1/4} = 1 - \frac{c}{4} \cdot \frac{4}{3}$$

$$\boxed{dW = 1 - \frac{c}{3}}$$

$$dW = - \sum_{k=1}^{\infty} \frac{2^{-k}}{1 - b + \frac{b \cdot 2^k}{c}} + \sum_{k=1}^{\infty} \frac{1}{c} \frac{1}{1 - b + \frac{b \cdot 2^k}{c}}$$

$$S_1 = \sum_{k=1}^{\infty} \frac{1}{c \cdot 2^k (1-b) + b} = -c \sum_{k=1}^{\infty} \frac{1}{2^k \cdot c(1-b) + b} = -c \sum_{k=1}^{\infty} \frac{1}{c + b \cdot 2^k}$$

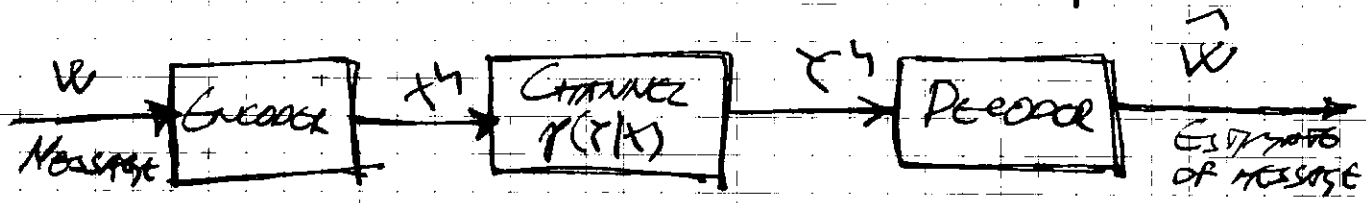
$$S_2 = \frac{1}{c} \sum_{k=1}^{\infty} \frac{1}{c(1-b) + b \cdot 2^k} = \frac{1}{c} \sum_{k=1}^{\infty} \frac{1}{c + b \cdot 2^k}$$

$$E[U] = \sum_{k=1}^{\infty} \frac{[\log_2(w + 2^{k-1}) - \log_2(w)]}{2^k} < \infty$$

↑ EXPECTED UTILITY OF THE LOTTERY

## CHAPTER 7: CHANNEL CAPACITY

X5TECH



DEFINITION: We define "INFORMATION" CHANNEL CAPACITY OF THE DISCRETE MEMORYLESS CHANNEL AS:

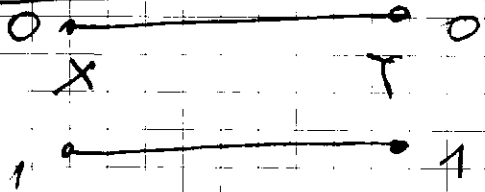
$$C = \max_{p(x)} I(x; y)$$

WHERE THE MAXIMUM IS TAKEN OVER ALL POSSIBLE INPUT DISTRIBUTIONS.

OPERATIONAL DEFINITION: CHANNEL CAPACITY IS THE HIGHEST BIT RATE OF WHICH INFORMATION CAN BE SENT WITH ARBITRARILY LOW PROBABILITY OF ERROR.

### 7.1 EXAMPLES OF CHANNEL CAPACITY

#### 7.1.1 NOISELESS BINARY CHANNEL



$$C = 1$$

INFORMATION CAPACITY:  $C = \max I(x; y) = 1$

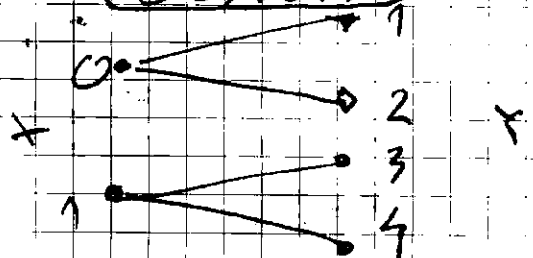
$H(y|x) = 0$  NO UNCERTAINTY REMAINS

$$I(x, y) = H(x) - \underbrace{H(x|y)}_0 = H(y) - H(y|x)$$

ONE-TO-ONE MAPPING

$H(x) = \log_2 2 = 1$  FOR  $p(x) = \begin{bmatrix} 1 & 1 \\ 2 & 2 \end{bmatrix}$

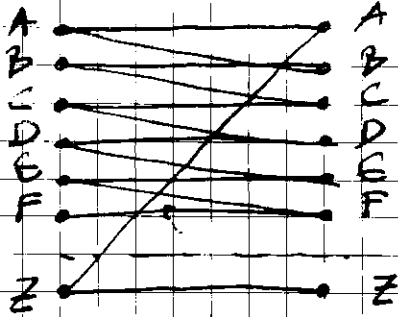
#### 7.1.2 NOISE CHANNEL WITH NON-DISCRETE OUTPUTS



$$H(x|y) = p(y=1) \cdot H(x|y=1) + p(y=2) \cdot H(x|y=2) + p(y=3) \cdot H(x|y=3) + p(y=4) \cdot H(x|y=4)$$

$$= 0 \cdot H(x|y=1) + 1 \cdot H(x|y=2) + 1 \cdot H(x|y=3) + 0 \cdot H(x|y=4)$$

### 7.1.3 NOISE TYPE WRITER;



IN THIS CASE CHANNEL INPUT IS EITHER RECEIVED UNCHANGED AT THE OUTPUT WITH PROBABILITY  $1/2$  OR IS TRANSFORMED INTO THE NEXT LETTER WITH PROBABILITY  $1/2$ .

$$C = \max [I(X, Y)] = \max [H(Y) - H(Y|X)] =$$

$$H(Y|X) = P(X=A) H(Y|X=A) + P(X=B) H(Y|X=B) + \dots + P(X=Z) H(Y|X=Z)$$

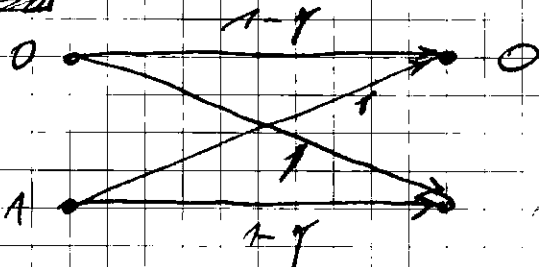
$$H(Y|X=A) = H(Y|X=B) = \dots = H(Y|X=Z) = \frac{1}{2} \log 2 + \frac{1}{2} \log 2 = 1$$

$$C = \max [H(Y) - 1] = \max [H(Y)] - 1 = \log 26 - 1$$

$$C = \log 26 - 1 = \log 26 - \log 2 = \log 13$$

FOR  $H(Y) = 1$  UNIFORM.

### 7.1.4 BINARY SYMMETRIC CHANNEL



$$I(X, Y) = H(Y) - H(Y|X) = H(Y) - \sum_x p(x) H(Y|X=x)$$

$$= H(Y) - p(x=0) \cdot H(Y|X=0) - p(x=1) \cdot H(Y|X=1)$$

$$= H(Y) - p(x=0) \cdot \left[ -p \log \frac{p}{p+q} - (1-p) \log \frac{1-p}{p+q} \right] - p(x=1) \cdot \left[ -p \log \frac{p}{p+q} - (1-p) \log \frac{1-p}{p+q} \right]$$

$$= H(Y) - p(x=0) \cdot \left[ (1-q) \log \frac{1}{1-q} + q \log \frac{1}{q} \right] - p(x=1) \cdot \left[ p \log \frac{1}{p} + (1-p) \log \frac{1}{1-p} \right]$$

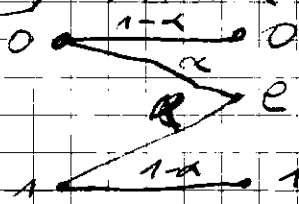
$$= H(Y) - p(x=0) \cdot H(q) - p(x=1) \cdot H(p) = H(Y) - H(q)$$

$$\leq \log 2 - H(q) = 1 - H(q)$$

$$\max I(X, Y) = 1 - H(q)$$

$$C = 1 - H(q)$$

### 7.1.5 BINARY ERASURE CHANNEL



$$H(Y|X) = \sum_{x=0,1} p(x) H(Y|X=x) = \frac{1}{2} \cdot H(q) + \frac{1}{2} \cdot H(q) = H(q)$$

$$I(X, Y) = H(Y) - H(Y|X) = \log 2 - H(q) = 1 - H(q)$$

$$H(Y|X) = H(\alpha)$$

$$H(Y) = P(Y=0) \cdot \log \frac{1}{P(Y=0)} +$$

$$+ P(Y=1) \cdot \log \frac{1}{P(Y=1)} + P(Y=e) \cdot \log \frac{1}{P(Y=e)} =$$

$$= \cancel{2(1-\alpha)} \log \frac{1}{\cancel{2(1-\alpha)}} + \cancel{2\alpha} \log \frac{1}{\cancel{2\alpha}} = 2 - 2\alpha + 2\alpha = 2 \quad ?$$

$$= \frac{(1-\alpha)}{2} \log \frac{2}{1-\alpha} + \alpha \log \frac{2}{\alpha} + \frac{1-\alpha}{2} \log \frac{2}{1-\alpha}$$

$$2 \cdot \frac{1-\alpha}{2} + \alpha = 1 - \alpha + \alpha = 1$$

$$= (1-\alpha) \log \frac{2}{1-\alpha} + \alpha \log \frac{2}{\alpha} = \underline{\underline{(1-\alpha) + H(\alpha)}}$$

$$I(X;Y) = H(Y) - H(Y|X) = 1 - \alpha + H(\alpha) - H(\alpha) = \underline{\underline{1-\alpha}}$$

Conceal Proof:  $H(Y) = H(Y, E) = H(Y) + H(E|Y) =$   
 $= H(Y) + 0 = \underline{\underline{H(E) + H(Y|E)}}$

$E \rightarrow$  event  $Y=e$

$H(Y) = ? \quad H(E) = ? \quad [P(Y=1) = \pi]$

$H(Y, E) = H(Y) = H\left(\underbrace{(1-\pi)}_{P(Y=1)}, (1-\alpha), \alpha, 0, (1-\alpha)\right) =$

$$= -\left[ (1-\pi)(1-\alpha) \log \frac{1}{(1-\pi)(1-\alpha)} + \alpha \log \frac{1}{\alpha} + \pi(1-\alpha) \log \frac{1}{\pi(1-\alpha)} \right]$$

$$= -\left[ (1-\pi)(1-\alpha) \log \frac{1}{(1-\pi)(1-\alpha)} + (1-\alpha) \log \frac{1}{1-\alpha} + \alpha \log \frac{1}{\alpha} + \pi(1-\alpha) \log \frac{1}{\pi(1-\alpha)} \right]$$

$$= -\left[ (1-\alpha) \left[ (1-\pi) \log \frac{1}{(1-\pi)(1-\alpha)} + \pi \log \frac{1}{\pi(1-\alpha)} \right] + \alpha \log \frac{1}{\alpha} \right] + H(\alpha) =$$

$$= (1-\alpha) \cdot H(\bar{\pi}) + H(\alpha)$$

$$H(Y, E) = \sum_{Y, E} P(Y, E) \log \frac{1}{P(Y, E)} = -\left[ P(Y=1, \bar{E}) \log \frac{1}{P(Y=1, \bar{E})} \right.$$

$$\left. + P(Y=0, \bar{E}) \log \frac{1}{P(Y=0, \bar{E})} + P(E) \log \frac{1}{P(E)} \right] =$$

$$= H(\bar{\pi}(1-\alpha), (1-\pi) \cdot (1-\alpha), \alpha)$$

$$P(E) = P(E|X=1) \cdot P(X=1) + P(E|X=0) \cdot P(X=0) =$$

$$= \pi \cdot \alpha + \alpha \cdot (1-\pi) = \pi \alpha + \alpha - \alpha \pi = \alpha$$

$$I(X;Y) = H(Y) - H(Y|X) = (1-\alpha)H(X) + H(\alpha) - H(\alpha)$$

$$I(X;Y) = (1-\alpha)H(X)$$

$$C = \lim_{T \rightarrow \infty} \frac{1}{T} H(Y)$$

$$\pi = P(X=1) = \frac{1}{2}$$

$$C = (1-\alpha) \cdot H\left(\frac{1}{2}\right) = (1-\alpha)$$

(\*)

	$P(Y E)$			
$E \setminus Y$	0	1		$P(E)$
0	$\alpha$	$1-\alpha$		$\alpha$
1	$1-\alpha$	$\alpha$		$1-\alpha$
	$\alpha$	$1-\alpha$		

$$H(Y,E) = -P(0,E) \log P(0,E) - P(1,E) \log P(1,E) - P(E,0) \log P(E,0) - P(E,1) \log P(E,1) - P(E) \log P(E)$$

... AND ...

THE EXTENSION FOR THE CAPACITY HAS SOME INTUITIVE MEANING: SINCE THE RECEPTION OF  $\alpha$ 'S OF THE BITS ARE LOST IN THE CHANNEL WE CAN COVER AT MOST A FRACTION  $(1-\alpha)$  OF THE ...

HENCE THE CAPACITY IS AT MOST  $(1-\alpha)$ .

AND ...

$$D = 10^{-8}$$

$$\alpha = (1 - 10^{-8})^{10^6}$$

... OF ...

AND ...

$$K = (1 - 10^{-8}) \cdot 10^6 = 10^6 - 10^{-2} = 1,000,000 - 0.01$$

$$\approx 999,999.99$$

... = 999.7 k...

FEEDBACK DOESN'T INCREASE THE CAPACITY OF THE MEMORYLESS CHANNEL

### 7.2 SYMMETRIC CHANNELS

$$Y(X) = X \begin{bmatrix} 0.3 & 0.2 & 0.5 \\ 0.5 & 0.7 & 0.2 \\ 0.2 & 0.5 & 0.7 \end{bmatrix}$$

EACH COLUMN AND ...

$$Z = X + Z \pmod{C}$$

$$Z \in \{0, 1, 2, \dots, C-1\}$$

... AS ...

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} \Rightarrow Y = P X$$

$$Y_i = p_{i1}X_1 + p_{i2}X_2 + p_{i3}X_3$$

$$\begin{bmatrix} Y_1 \\ Y_2 \\ Y_3 \end{bmatrix} = \begin{bmatrix} X_1 \\ X_2 \\ X_3 \end{bmatrix} \times \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix}$$

OVER  
POLYGRAPH  
KREMLIN  
Pij

r - ROW OF THE TRANSITION MATRIX

$$I(X; Y) = H(Y) - H(Y|X)$$

$$Y(Y) = \sum_{i=1}^n p(Y_i) \cdot \log \frac{1}{p(Y_i)}$$

$p(Y_i) = P_{ij}$

$$H(Y|X) = \sum_x p(x) H(Y|X=x) = \sum_{x,y} p(x) \sum_{c=1}^n p_{rc} \log \frac{1}{p_{rc}} = H(Y)$$

EA SMOZKA PERICA E ISTO JA IZGUBWA GRED SUMATA  $\rightarrow H(Y)$

$$I(X; Y) = H(Y) - H(Y|X) \leq H(X) - H(Y)$$

•  $p(x) = \frac{1}{|X|} \Rightarrow$  ACHIEVES UNIFORM DISTRIBUTION FOR  $X$

$$I(X; Y) = \sum_{x \in X} p(x) \cdot \log \frac{1}{p(x)} = \frac{1}{|X|} \sum_{x \in X} \log \frac{1}{p(x)} = \frac{C}{|X|} = \frac{1}{|X|}$$

C = SUM OF PROBABILITIES IN ONE COLUMN OF THE PROBABILITY TRANSITION MATRIX.  
TRUS THE CHANNEL IN 7.17 HAS CAPACITY:

$$C = \max_{p(x)} I(X; Y) = \log 4 - H(0.5, 0.3, 0.2)$$

DEFINITION: A CHANNEL IS SAID TO BE SYMMETRIC IF THE ROWS OF THE CHANNEL TRANSITION MATRIX  $P(Y|X)$  ARE PERMUTATIONS OF EACH OTHER AND THE COLUMNS ARE PERMUTATIONS OF EACH OTHER. THE CHANNEL IS SAID TO BE WEAKLY SYMMETRIC IF EVERY ROW OF THE TRANSITION MATRIX  $P(Y|X)$  IS A PERMUTATION OF EVERY OTHER ROW AND THE COLUMNS SUM  $\sum_x p(x)$  ARE EQUAL.

$$P(Y|X) = \begin{pmatrix} \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & \frac{1}{2} & \frac{1}{2} \end{pmatrix} \Rightarrow$$

WEAKLY SYMMETRIC CHANNEL.

THEOREM 7.2.1

FOR A WEAKLY SYMMETRIC CHANNEL  $C = \log |X| - H(\text{ROW OF TRANSITION MATRIX})$

THAT IS ACHIEVED FOR THE UNIFORM DISTRIB OF  $X$  AND ALPHABET.

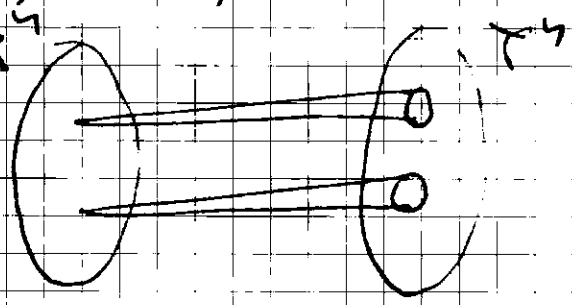


### 7.3 PROPERTIES OF CHANNEL CAPACITY

1.  $C > 0$  since  $I(x; y) \geq 0$
  2.  $C \leq C(x)$  since  $C = \max I(x; y) \leq \max H(x) = C(x)$
  3.  $C \leq C(y)$  for the same reason
  4.  $I(x; y)$  is continuous function of  $p(x)$
  5.  $I(x; y)$  is concave function of  $p(x)$ .
- (THEOREM 2.7.4)

### 7.4 REVIEW OF THE CHANNEL CODING THEORY

- For each (TYPICAL) INPUT SEQUENCE, there are  $2^{nH(y)}$  possible  $Y$  SEQUENCES, ALL OF THEM EQUALLY LIKELY (FIG. 7.7)



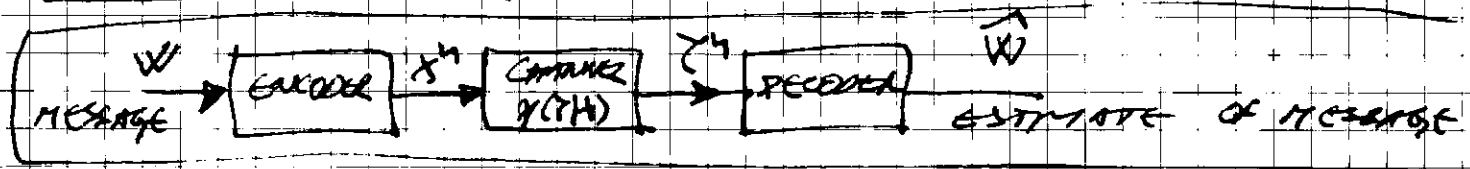
• THE TOTAL NUMBER OF POSSIBLE (TYPICAL)  $Y$  SEQUENCES IS  $= 2^{nH(y)}$ . THIS SET HAS TO BE DIVIDED IN SETS OF SIZE  $2^{nH(x|y)}$  CORRESPONDING TO THE DIFFERENT  $2^{nH(x)}$  INPUT  $X$  SEQUENCES.

- TOTAL NUMBER OF DISTINCT SETS IS LESS THAN OR EQUAL TO:

$$2^{n(H(x) - H(x|y))} = 2^{nI(x; y)}$$

THUS WE CAN SEND AT MOST  $2^{nI(x; y)}$  DISTINGUISHABLE SEQUENCES OF LENGTH  $n$ .

### 7.5 DEFINITIONS



- A MESSAGE  $W$  DRAWN FROM THE INDEX  $\{1, 2, \dots, M\}$  RESULTS IN THE SEQUENCE  $X^n(W)$  WHICH IS RECEIVED BY THE RECEIVER AS A NOISY SEQUENCE:

$$X^n \sim y(y^n | x^n)$$

THE RECEIVER THEN SUCCESSFULLY RECOVERS THE INDEX  $W$  BY APPROPRIATE DECODING RULE:  $\hat{W} = g(Z^n)$

THE RECEIVER MAKES AN ERROR IF  $\hat{w}$  IS NOT THE SAME AS THE INDEX  $w$  THAT WAS TRANSMITTED.

**DEFINITION** A discrete channel, denoted by  $(\mathcal{X}, \mathcal{Y}, \{p(y|x)\})$  consists of two finite sets  $\mathcal{X}$  and  $\mathcal{Y}$ , and a collection of probability mass functions  $p(y|x)$ , one for each  $x \in \mathcal{X}$  such that for every  $x$  and  $y$ ,  $p(y|x) \geq 0$ , and for every  $x$ ,  $\sum_y p(y|x) = 1$ , with the interpretation that  $\mathcal{X}$  is the input and  $\mathcal{Y}$  is the output of the channel.

**DEFINITION** The  $n$ -th extension of the discrete memoryless channel (DMC) is the channel  $(\mathcal{X}^n, \mathcal{Y}^n, \{p(y^n|x^n)\})$  where  $p(y_k|x^n, y^{n-1}) = p(y_k|x_k)$   $k=1, 2, \dots, n$

**REMARK** IF THE CHANNEL IS USED WITHOUT FEEDBACK (I.E. IF THE INPUT SYMBOLS DO NOT DEPEND ON THE PAST SYMBOLS, NAMELY  $p(x_k|x^{k-1}, y^{k-1}) = p(x_k|x^{k-1})$ ) THE CHANNEL TRANSITION PROBABILITIES REDUCE TO:

$$p(y^n|x^n) = \prod_{i=1}^n p(y_i|x_i)$$

**DEFINITION:** An  $(M, n)$  CODE FOR CHANNEL  $(\mathcal{X}, \mathcal{Y}, \{p(y|x)\})$  CONSISTS OF FOLLOWING:

1. AN INDEX SET  $\{1, 2, \dots, M\}$
2. AN ENCODING FUNCTION  $\mathcal{X}^n: \{1, 2, \dots, M\} \rightarrow \mathcal{X}^n$  YIELDING CODEWORDS  $x^n(1), x^n(2), \dots, x^n(M)$ . THE SET OF CODEWORDS IS CALLED CODEBOOK.
3. A DECODING FUNCTION:  $\mathcal{Y}^n \rightarrow \{1, 2, \dots, M\}$  IS DETERMINISTIC RULE THAT ASSIGNS A GUESS TO EACH POSSIBLE RECEIVED VECTOR.

**DEFINITION:** (CONDITIONAL PROBABILITY OF ERROR) LET  $\lambda_i = P_e(g(x^n) \neq i | x^n = x^n(i)) = \sum_{y^n} p(y^n|x^n(i)) I(g(y^n) \neq i)$

BE THE CONDITIONAL PROBABILITY OF ERROR GIVEN THAT  $i$  WAS SENT WHERE  $I(\cdot)$  IS THE INDICATOR FUNCTION (VERIFYING  $I(\text{TRUE}) = 1$ )

$$\lambda^n = \max_{i \in \{1, 2, \dots, M\}} \lambda_i$$

DEFINITION: (AVERAGE PROBABILITY OF ERROR)  $P_e^{(n)}$  FOR AN  $(M, n)$  CODE IS DEFINED AS:

$$P_e^{(n)} = \frac{1}{M} \sum_{i=1}^M p_i$$

- IF THE INDEX IS CHOSEN ACCORDING TO UNIFORM DISTRIBUTION OVER SET  $\{1, 2, \dots, M\}$  AND  $X^n = X^n(\omega)$  THEN:

$$P_e^{(n)} = P_r(\cup_{j \neq i} F_j(\omega))$$

i.e.  $P_e^{(n)}$  IS PROBABILITY OF ERROR. ALSO NOTED:

$$P_e^{(n)} \leq \lambda^{(n)}$$

DEFINITION: THE RATE  $R$  OF AN  $(M, n)$  CODE IS:

$$R = \frac{\log M}{n} \quad \text{BITS PER TRANSMISSION}$$

DEFINITION: A RATE  $R$  IS SAID TO BE ACHIEVABLE IF THERE EXISTS A SEQUENCE OF  $(\lfloor 2^{nR} \rfloor, n)$  CODES SUCH THAT THE MAXIMUM PROBABILITY OF ERROR  $\lambda^{(n)}$  TENDS TO 0 AS  $n \rightarrow \infty$ .  
 IN FACT, WE WRITE  $(\lfloor 2^{nR} \rfloor, n)$  CODES TO MEAN  $(\lfloor 2^{nR} \rfloor, n)$  CODES. THIS WILL SIMPLIFY THE NOTATION.

DEFINITION: THE CAPACITY OF THE CHANNEL IS SUPREMACY OF ALL ACHIEVABLE RATES.

THEREFORE RATES LESS THAN CAPACITY CAN BE ACHIEVED WITH SMALL PROBABILITY OF ERROR FOR SUFFICIENTLY LARGE BLOCK LENGTHS.

$$-n(H+\epsilon) \leq \log 2 \leq -n(H-\epsilon)$$

JOINTLY TYPICAL SEQUENCES

WE DECODE THE CHARACTER  $x_i$  AS THE  $i$ -TH INDEX IF THE CODEWORD  $x^i(i)$  IS JOINTLY TYPICAL WITH RECEIVED SIGNAL  $z^n$

DEFINITION: THE SET  $A_{\epsilon}^{(n)}$  OF JOINTLY TYPICAL SEQUENCES  $\{(x^n, z^n)\}$  WITH RESPECT TO THE DISTRIBUTION  $p(x, y)$  IS THE SET OF SEQUENCES WITH EMPIRICAL ENTROPIES  $\epsilon$ -CLOSE TO THE TRUE ENTROPIES:

$$A_{\epsilon}^{(n)} = \{ (x^n, z^n) \in X^n \times Z^n : \left| -\frac{1}{n} \log p(x^n) - H(X) \right| < \epsilon$$

$$\left| -\frac{1}{n} \log p(z^n) - H(Z) \right| < \epsilon \quad \left| -\frac{1}{n} \log p(x^n, z^n) - H(X, Z) \right| < \epsilon$$

$$\rightarrow -n(H+\epsilon) \leq \log p(x^n) \leq -n(H-\epsilon)$$

$$-n(H-\epsilon) \leq \log p(z^n) \leq -n(H+\epsilon) \quad \left| -\epsilon \leq -\frac{1}{n} \log p(x^n, z^n) - H(X, Z) \leq \epsilon \right|$$

$$H+\epsilon \geq -\frac{1}{n} \log p(x^n) \geq H-\epsilon \quad H-\epsilon \leq -\frac{1}{n} \log p(z^n) \leq H+\epsilon$$

WHERE:  $y(x^N, \gamma^N) = \prod_{i=1}^N y(x_i, \gamma_i)$

**THEOREM 7-6.1 (JOINT AEP)** Let  $(x^N, \gamma^N)$  be sequences of length  $N$  drawn i.i.d. according to  $y(x, \gamma) = \prod_{i=1}^N y(x_i, \gamma_i)$ . THEN:

- 1.)  $\Pr[(x^N, \gamma^N) \in A_\epsilon^{(N)}] \rightarrow 1$  as  $N \rightarrow \infty$
- 2.)  $|A_\epsilon^{(N)}| \leq 2^{N(H(x, \gamma) + \epsilon)}$
- 3.) If  $\tilde{x}^N, \tilde{\gamma}^N \sim y(x^N), y(\gamma^N)$  THAT IS  $\tilde{x}^N$  &  $\tilde{\gamma}^N$  ARE INDEPENDENT WITH THE SAME MARGINALS:  $y(x, \gamma)$ , THEN:

$$\Pr((\tilde{x}^N, \tilde{\gamma}^N) \in A_\epsilon^{(N)}) \leq 2^{-N(H(x, \gamma) - 3\epsilon)}$$

ALSO FOR SUFFICIENTLY LARGE  $N$ :

$$\Pr((\tilde{x}^N, \tilde{\gamma}^N) \in A_\epsilon^{(N)}) \geq (1-\epsilon) 2^{-N(H(x, \gamma) + 3\epsilon)}$$

**PROOF:**  $-\frac{1}{N} \log y(x^N) \rightarrow -E[\log y(x)] = H(x)$  IN PROBABILITY

Hence given  $\epsilon > 0$ , there exist  $N_1$  such that all  $N > N_1$

$$\Pr\left(\left| -\frac{1}{N} \log y(x^N) - H(x) \right| \geq \epsilon\right) < \frac{\epsilon}{3}$$

- SIMILARLY BY THE WEAK LAW

$$-\frac{1}{N} \log y(\gamma^N) \rightarrow E[\log y(\gamma)] = H(\gamma) \text{ IN PROBABILITY}$$

AND:

$$-\frac{1}{N} \log y(x^N, \gamma^N) \rightarrow E[\log y(x, \gamma)] = H(x, \gamma)$$

AND THERE EXIST  $N_2 \leq N_1$  SUCH AS:

$$\Pr\left(\left| -\frac{1}{N} \log y(\gamma^N) - H(\gamma) \right| \geq \epsilon\right) < \frac{\epsilon}{3}, \quad N \geq N_2$$

$$\Pr\left(\left| -\frac{1}{N} \log y(x^N, \gamma^N) - H(x, \gamma) \right| \geq \epsilon\right) < \frac{\epsilon}{3}, \quad N \geq N_3$$

- CHOOSING  $N > \max\{N_1, N_2, N_3\}$

$\Rightarrow$  FOR SUFFICIENTLY LARGE  $N \Rightarrow$

$$\Pr\{A_\epsilon^{(N)}\} \Rightarrow 1 \quad \text{i.e.} \quad \Pr\{A_\epsilon^{(N)}\} = 1 - \epsilon$$

2) PROOF OF SECOND PART:

$$1 = \sum_{(x^y, y^y)} p(x^y, y^y) \geq \sum_{A_\epsilon^{(y)}} p(x^y, y^y) \geq |A_\epsilon^{(y)}| \cdot 2^{-y(H(x|y) + \epsilon)}$$

$$2 \leq p(x^y, y^y) \leq 2^{-y(H(x) - \epsilon)}$$

$$|A_\epsilon^{(y)}| \leq 2^{y(H(x, y) + \epsilon)}$$

РЕЧКА КОММУНИКАЦИОННАЯ  
[246285513]

$$3) P_1((\tilde{x}^y, \tilde{y}^y) \in A_\epsilon^y) = \sum_{(x^y, y^y) \in A_\epsilon^{(y)}} p(x^y) p(y^y) \leq$$

$$\leq 2^{y(H(x, y) + \epsilon)} \cdot 2^{-y(H(x) - \epsilon)} \cdot 2^{-y(H(y) - \epsilon)} =$$

$$= 2^{y(H(x) + H(y|x) + 4\epsilon - yH(x) + 4\epsilon - yH(y) + 4\epsilon)}$$

$$= 2^{-y[H(y) - H(x|y)] + 4\epsilon} = 2^{-y[H(x, y) - 3\epsilon]}$$

- FOR SUFFICIENTLY LARGE  $n$   $P_1(A_\epsilon^{(y)}) \geq 1 - \epsilon$  AND THEREFORE:

$$1 - \epsilon \leq \sum_{(x^y, y^y) \in A_\epsilon^{(y)}} p(x^y, y^y) \leq |A_\epsilon^{(y)}| \cdot 2^{-y(H(x, y) - \epsilon)}$$

$$|A_\epsilon^{(y)}| \geq (1 - \epsilon) \cdot 2^{y(H(x, y) - \epsilon)}$$

ОСНОВНАЯ ЛЕММА ТЕОРЕМЫ 3.12

$$P_1((\tilde{x}^y, \tilde{y}^y) \in A_\epsilon^y) = \sum_{(x^y, y^y) \in A_\epsilon^{(y)}} p(x^y) \cdot p(y^y) \geq$$

$$\geq (1 - \epsilon) \cdot 2^{y(H(x, y) + \epsilon)} \cdot 2^{-y(H(x) + \epsilon)} \cdot 2^{-y(H(y) + \epsilon)}$$

$$= (1 - \epsilon) \cdot 2^{y(H(x, y) - 4\epsilon - yH(x) - 4\epsilon - yH(y) - 4\epsilon)}$$

$$= (1 - \epsilon) \cdot 2^{y[H(x) + H(y|x)] - 3y\epsilon - yH(x) - yH(y)}$$

$$= (1 - \epsilon) \cdot 2^{-y[H(y) - H(x|y)] - 3y\epsilon} = (1 - \epsilon) \cdot 2^{-y[H(x, y) - 3\epsilon]}$$

ТЕОРЕМЫ 7.6.1 В АКАДЕМИИ НАУК 3.12

$$p(y) - \epsilon \leq p(x^y) \leq H(y) + \epsilon \quad 2^{-y(H(y) - \epsilon)} \leq p(x^y) \leq 2^{-y(H(y) - \epsilon)}$$

$$1) P_1\{A_\epsilon^{(y)}\} = 1 - \epsilon$$

$$2) |A_\epsilon^{(y)}| \leq 2^{y(H(x) + \epsilon)}$$

$$3) |A_\epsilon^{(y)}| \geq (1 - \epsilon) \cdot 2^{y(H(x, y) - \epsilon)}$$

ОСНОВНАЯ ЛЕММА ТЕОРЕМЫ 3.12

There are about  $2^{nH(X)}$  typical  $X$  sequences and about  $2^{nH(Y)}$  typical  $Y$  sequences. However since there are only  $2^{n(H(X,Y))}$  jointly typical sequences, not all pairs of typical  $X^n$  and typical  $Z^n$  are also jointly typical.

Probability that any randomly chosen pair is jointly typical is about  $2^{-nI(X;Y)}$ .

This suggests that there are about  $2^{nI(X;Y)}$  distinguishable signals  $X^n$ .

For the fixed output sequence  $Z^n$  there are about  $2^{nH(X|Y)}$  conditional typical input  $X^n$ 's. The probability that some randomly chosen (other) input sequence is jointly typical with  $Z^n$  is about:

$$\frac{2^{nH(X|Y)}}{2^{nH(X)}} = 2^{-n(H(X) - H(X|Y))} = 2^{-nI(X;Y)}$$

Hence we can choose  $2^{nI(X;Y)}$  codewords  $X^n(w)$  before one of this codewords will get confused with the codeword that caused the output  $Z^n$ .

Lemma

$$2^{-n(H(X;Y)+\epsilon)} \leq P(X^n, Y^n) \leq 2^{-n(H(X;Y)-\epsilon)}$$

$$1) \Pr[(X^n, Y^n) \in A_\epsilon^{(n)}] \rightarrow 1 \text{ as } n \rightarrow \infty$$

$$2) |A_\epsilon^{(n)}| \leq 2^{n(H(X;Y)+\epsilon)}$$

$$3) \exists n \text{ s.t. } \Pr[(\tilde{X}^n, \tilde{Y}^n) \in A_\epsilon^{(n)}] \leq 2^{-n(I(X;Y)-3\epsilon)}$$

$$\exists n \text{ s.t. } \Pr[(\tilde{X}^n, \tilde{Y}^n) \in A_\epsilon^{(n)}] \geq (1-\epsilon) 2^{-n(I(X;Y)-3\epsilon)}$$

$$(2) 1 = \sum_{A_\epsilon^{(n)}} P(X^n, Y^n) \geq |A_\epsilon^{(n)}| \cdot 2^{-n(H(X;Y)+\epsilon)} \Rightarrow$$

$$|A_\epsilon^{(n)}| \leq 2^{n(H(X;Y)+\epsilon)}$$

$$(3) \Pr[(\tilde{X}^n, \tilde{Y}^n) \in A_\epsilon^{(n)}] = \sum_{A_\epsilon^{(n)}} P(X^n, Y^n) \leq |A_\epsilon^{(n)}| \cdot 2^{-n(H(X)-\epsilon)} \cdot 2^{-n(H(Y)-\epsilon)}$$

$$= 2^{n(H(X;Y)+\epsilon) - nH(X) + n\epsilon - nH(Y) + n\epsilon}$$

$$= 2^{n(H(X;Y) + 4\epsilon - H(X) - H(Y))} = 2^{-n(I(X;Y) - 3\epsilon)}$$

$$= 2^{-n(I(X;Y) - 3\epsilon)}$$

$$\exists \epsilon \quad 1 - \epsilon \leq \sum_{A_\epsilon^{(n)}} \gamma(x^y, z^y) \leq |A_\epsilon^{(n)}| \cdot 2^{-n[H(A, X) - \epsilon]}$$

$$|A_\epsilon^{(n)}| \geq (1 - \epsilon) 2^{n[H(A, X) - \epsilon]}$$

$$\begin{aligned} \sum_{A_\epsilon^{(n)}} \gamma(x^y, z^y) &\geq |A_\epsilon^{(n)}| \cdot 2^{-n[H(X) + \epsilon]} \cdot 2^{-n[H(Z) + \epsilon]} \\ &\geq (1 - \epsilon) 2^{n[H(A, X) + H(X, Z) - \epsilon]} \cdot 2^{-n[H(X) + \epsilon]} \cdot 2^{-n[H(Z) + \epsilon]} \\ &= (1 - \epsilon) 2^{n[H(A, X) + H(X, Z) - H(X) - H(Z) - \epsilon]} \\ &= (1 - \epsilon) 2^{-n[H(X) - H(X|A)] - 3\epsilon} \\ P_r[\tilde{x}^y, \tilde{z}^y \in A_\epsilon^{(n)}] &\geq (1 - \epsilon) 2^{-n[H(X|A) - 3\epsilon]} \end{aligned}$$

**7.7. CHANNEL CODING THEORY**

**THEOREM 7.1 (SHANNON CODING THEOREM)**

FOR A DISCRETE MEMORYLESS CHANNEL ALL RATES BELOW CHANNEL CAPACITY ARE ACHIEVABLE. SPECIFICALLY FOR EVERY RATE  $R < C$ , THERE EXIST SEQUENCES OF  $(2^{nR}, n)$  CODES WITH VANISHING ERROR PROBABILITY OF ERROR:

$$P_e^{(n)} \rightarrow 0$$

CONVERSELY, ANY SEQUENCE OF  $(2^{nR}, n)$  CODES WITH  $P_e^{(n)} \rightarrow 0$  MUST HAVE  $R \leq C$ .

**ACHIEVABILITY:** Fix  $\epsilon > 0$ . GENERATE A  $(2^{nR}, n)$  CODE AT RANDOM ACCORDING TO DISTRIBUTION  $p(x)$ . SPECIFICALLY WE GENERATE  $2^{nR}$  CODEWORDS INDEPENDENTLY ACCORDING TO THE DISTRIBUTION:

$$p(x^n) = \prod_{i=1}^n p(x_i)$$

$$\begin{bmatrix} x_1(1) & x_2(1) & \dots & x_n(1) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(2^{nR}) & x_2(2^{nR}) & \dots & x_n(2^{nR}) \end{bmatrix}$$

THE PROBABILITY THAT WE GENERATE A PARTICULAR CODE  $c$  IS:

$$P_i(c) = \prod_{i=1}^n \prod_{u=1}^{2^{nR}} \gamma(x_i(u), c)$$

CONSIDER FOLLOWING SEQUENCE OF EVENTS:

- 1.) A RANDOM CODE IS GENERATED AS DESCRIBED IN 19.3.2. ACCORDING TO  $\gamma(\xi)$ .
- 2.) THE CODE IS REVEALED TO BOTH SENDER AND RECEIVER. BOTH THE SENDER AND THE RECEIVER ARE ALSO ASSUMED TO KNOW THE CHANNEL TRANSITION MATRIX  $\gamma(x|t)$  FOR CHANNEL.

- 3.) A MESSAGE  $W$  IS CHOSEN ACCORDING TO A UNIFORM DISTRIBUTION.

$$P_W(W=w) = 2^{-nR} \quad w = 1, 2, \dots, 2^{nR}$$

- 4.) THE  $w$ -TH CODEWORD  $x^n(w)$  CORRESPONDS TO THE  $w$ -TH ROW OF  $C$ , & SENT OVER THE CHANNEL.

- 5.) THE RECEIVER RECEIVES A SEQUENCE  $y^n$  ACCORDING TO THE DISTRIBUTION

$$P(y^n | x^n(w)) = \prod_{i=1}^n \gamma(y_i | x_i(w))$$

- 6.) THE RECEIVER GUESSES WHICH MESSAGE WAS SENT. THE OPTIMUM PROCEDURE TO MINIMIZE THE PROBABILITY OF ERROR IS MAXIMUM LIKELIHOOD DECODING (I.E. THE RECEIVER SHOULD CHOOSE THE POSTERIORI MOST LIKELY MESSAGE.)

INSTEAD (DUE TO COMPLEXITY) WE USE JOINTLY TYPICAL DECODING. THE RECEIVER RECEIVES  $y^n$  AND FINDS THE INDEX  $\hat{w}$  WAS SENT IF THE FOLLOWING ~~AND~~ CONDITIONS ARE SATISFIED:

- $(x^n(\hat{w}), y^n)$  IS JOINTLY TYPICAL
  - THERE IS NO OTHER INDEX  $w' \neq \hat{w}$  SUCH THAT  $(x^n(w'), y^n) \in A_{\epsilon}^{(n)}$
- (IF ~~THERE~~ NO SUCH  $\hat{w}$  EXIST OR THERE IS MORE THAN ONE SUCH AN INDEX IS DECLARED. (WE ASSUME THAT THE RECEIVER OUTPUTS DEFAULT SYMBOL IN THIS CASE (E.G. 0))

- 7.) THERE IS DECODING ERROR IF  $\hat{w} \neq w$ . LET  $E$  BE THE EVENT  $\{\hat{w} \neq w\}$ .

ANALYSIS OF THE PROBABILITY OF ERROR:

FOR TYPICAL CODING, THERE ARE TWO DIFFERENT SOURCES OF ERROR WHEN WE USE JOINTLY TYPICAL DECODING: EITHER THE OUTPUT  $y^n$  IS NOT JOINTLY TYPICAL WITH TRANSMITTED CODWORD OR



THERE IS SOME OTHER WAY THAT A SOURCE TRANSMITS WITH  $\tau^n$ . THE PROBABILITY THAT THE TRANSMITTED CODEWORD AND THE RECEIVED SEQUENCE ARE JOINTLY TYPICAL GOES TO 1, AS SHOWN BY THE JOINT ACP. FOR ANY OTHER CODEWORD, THE PROBABILITY THAT IT IS JOINTLY TYPICAL WITH THE RECEIVED SEQUENCE IS APPROXIMATELY  $2^{-nI}$  AND HENCE WE CAN USE ABOUT  $2^{nI}$  CODEWORDS AND STILL HAVE LOW PROBABILITY OF ERROR.

### DETAILED CALCULATION OF PROBABILITY OF ERROR

WE LET  $W$  BE DRAWN ACCORDING TO UNIFORM DISTRIBUTION OVER  $\{1, 2, \dots, 2^{nR}\}$  AND USE JOINTLY TYPICAL DECODING  $W(\tau^n)$ .

LET:  $E = \{W(\tau^n) \neq W\}$  DENOTE THE ERROR EVENT

WE WILL CALCULATE THE AVERAGE PROBABILITY OF ERROR AVERAGED OVER ALL CODEWORDS AND THE CODEWORDS AND OVER ALL CODEWORDS:

$$P_r(E) = \sum_C P_r(C) \lambda_w(C) = \sum_C P_r(C) \sum_{w=1}^{2^{nR}} \lambda_w(C) = \frac{1}{2^{nR}} \sum_{w=1}^{2^{nR}} \sum_C P_r(C) \lambda_w(C)$$

BY THE SYMMETRY OF THE CODE CONSTRUCTION, THE AVERAGE PROBABILITY OF ERROR AVERAGED OVER ALL CODES DOES NOT DEPEND ON THE PARTICULAR INDEX THAT WAS SENT (I.E.,  $\sum_C P_r(C) \lambda_w(C)$  DOES NOT DEPEND ON  $w$ ). THUS

WE CAN ASSUME THAT  $w=1$  MESSAGE WAS SENT

$$P_r(E) = \frac{1}{2^{nR}} \sum_{w=1}^{2^{nR}} \sum_C P_r(C) \lambda_w(C) = \sum_C P_r(C) \lambda_1(C) = P_r(E|W=1)$$

DEFINE THE FOLLOWING EVENTS:

$$E_i = \{(x^n(i), \tau^n) \notin A_\epsilon^{(n)}\}, \quad i \in \{1, 2, \dots, 2^{nR}\}$$

WHERE  $E_i$  IS THE EVENT THAT THE  $i$ TH CODEWORD  $x^n(i)$  AND  $\tau^n$  ARE JOINTLY TYPICAL. THEN ERROR OCCURS IF EITHER  $E_1$  OCCURS (THE TRANSMITTED CODEWORD AND THE RECEIVED SEQUENCE ARE NOT JOINTLY TYPICAL) OR  $E_2 \cup E_3 \cup \dots \cup E_{2^{nR}}$  OCCURS (WHEN THE WRONG CODE IS JOINTLY TYPICAL WITH RECEIVED SEQUENCE.)

$$P_r(E|W=1) = P(E_1 \cup E_2 \cup E_3 \cup \dots \cup E_{2^{nR}} | W=1) \leq P(E_1 | W=1) + \sum_{i=2}^{2^{nR}} P(E_i | W=1)$$

$$P(A \cup B) = P(A+B) = P(A) + P(B) - P(A \cap B) \Rightarrow \text{① H.S.}$$

At the point AEP,  $P(E_1^c | W=1) \rightarrow 0$

$P(E_1^c | W=1) \leq \epsilon$  for sufficiently large  $n$

Since at code generation process  $X^*(1)$  and  $X^*(i)$  are independent for  $i \neq 1$  so the  $X^*(1)$  and  $X^*(i)$  hence the probability that  $X^*(1)$  and  $X^*(i)$  are jointly typical is  $\leq 2^{-n(I(X;Y) - 3\epsilon)}$  at the point AEP.

$$2^{-n(I(X;Y) - 3\epsilon)}$$

$$\frac{1}{n} \log Y(X^n) = \frac{1}{n} \sum_{i=1}^n \log y(X_i) \rightarrow -E[\log(X) = H(X)]$$

$$Y(X^n) \rightarrow 2^{-n \cdot H(X)}$$

$$P(\epsilon) = P_0(\epsilon | W=1) \leq P(E_1^c | W=1) + \sum_{i=2}^{2^{nR}} P(E_i | W=1) =$$

$$= \epsilon + (2^{nR} - 1) 2^{-n[I(X;Y) - 3\epsilon]} \leq$$

$$\leq \epsilon + 2^{nR} \cdot 2^{-n[I(X;Y) - 3\epsilon]} = \epsilon + 2^{3n\epsilon} \cdot 2^{-n[I(X;Y) - R]} \leq 2\epsilon$$

if  $n$  is sufficiently large and:

$$R \leq I(X;Y) - 3\epsilon$$

$$2^{3n\epsilon} \cdot 2^{-n[R + I(X;Y) - 3\epsilon]} \leq 2\epsilon$$

$$-R + I(X;Y) + 3\epsilon \geq 0$$

$$R \leq I(X;Y) - 3\epsilon$$

if  $n$  is sufficiently large and  $2^{3n\epsilon} \cdot 2^{-n[R + I(X;Y) - 3\epsilon]} \leq 2\epsilon$

Hence if  $R \leq I(X;Y)$ , we can choose  $\epsilon$  and  $n$  so that the average probability of error, averaged over codewords and codewords is less than  $2\epsilon$ .

1) Choose  $p(x)$  in the proof to be  $q^*(x)$ , a distribution of  $X$  that achieves capacity. Then the condition  $R \leq I(X;Y)$  can be replaced by the achievability condition:  $R \leq C$

2) Since message probability of error over codewords is small ( $\leq 2\epsilon$ ), there exists at least one codeword  $C^*$  with a small average probability of error. Thus:

$$P(\epsilon | C^*) \leq 2\epsilon$$

$$P(\epsilon | C^*) = \frac{1}{2^{nR}} \sum_{i=1}^{2^{nR}} \lambda_i(C^*)$$

HOWEVER, THE WORST HALF OF THE WORDS ARE THE BEST CODEBOOK  $C^*$ . SINCE ARITHMETIC MEAN PROBABILITIES OF ERROR  $P_e^{(n)}(C^*)$  FOR THIS CODE IS LESS THAN  $2\epsilon$ , WE HAVE:

$$P_e(C^*) \leq \frac{1}{2^{nr}} \sum N_i(C^*) \leq 2\epsilon$$

WHICH IMPLIES THAT AT LEAST HALF THE INDICES  $i$  AND THEIR ASSOCIATED CODEWORDS  $X^i(n)$  MUST HAVE CONDITIONAL PROBABILITIES  $P_i$  LESS THAN  $4\epsilon$  (OTHERWISE, THE CODEWORDS THEMSELVES WOULD CONTRIBUTE MORE THAN  $2\epsilon$  TO THE LHS).

$$\frac{1}{2^{nr-1}} \cdot \frac{1}{2} \sum N_i(C^*) \leq 2\epsilon \quad "B."$$

$$\frac{1}{2^{nr-1}} \sum N_i(C^*) \leq 4\epsilon$$

HENCE THE BEST HALF OF THE CODEWORDS HAVE MAXIMAL PROBABILITY OF ERROR LESS THAN  $4\epsilon$ . THROWING OUT THE HALF OF THE WORDS (CODES) THE RATE:

$$R \geq \frac{nr}{n} = \frac{r(n-1)}{n} = \frac{nr-1}{n} = R - \frac{1}{n}$$

WE HAVE CONSTRUCTED CODE WITH RATE  $R' = R - \frac{1}{n}$  WITH MAXIMAL PROBABILITY OF ERROR  $P_e^{(n)} \leq 4\epsilon$ . THIS PROVES THE RELIABILITY OF ANY RATE BELOW CAPACITY.

$$\frac{1}{2^{nr}} \sum N_i(C^*) \leq$$

$$\frac{2^{nr-1} \cdot 4\epsilon}{2^{nr}} = \frac{4\epsilon}{2} \leq 2\epsilon$$

NO MAXIMIZATION SINCE NO SIZE FOR  $i$  ERROR VIA  $P_i \leq 4\epsilon$

## 7.8 ZERO-ERROR CODES

$$X \rightarrow Y \rightarrow Z$$

$$I(X; Y) \geq I(X; Z)$$

$$H(Z|X, Y) = H(Z|Y)$$

$$I(X; Y, Z) = I(X; Y) + I(X; Z|Y) = I(X; Z)$$

$$I(X; Z|Y) = H(Z|Y) - H(Z|X, Y) = H(Z|Y) - H(Z|X)$$

$$I(X; Y, Z) = I(X; Z) + I(X; Y|Z) = I(X; Y)$$

$$\neq 0 \quad [I(X; Y) \geq I(X; Z)]$$

• WE WILL NOW PROVE THAT  $P_e^{(n)} = 0$  IMPLIES THAT  $R \leq C$ . ASSUME THAT WE HAVE  $(2^{nr}, n)$  CODE WITH ZERO PROBABILITY OF ERROR. [I.E. THE DECODED MESSAGE  $\hat{y}(z^n)$  IS

EQUAL TO THE INPUT INDEX  $W$  WITH PROBABILITY 1. THEN THE INPUT INDEX  $W$  IS REPEATED BY THE OUTPUT SEQUENCE [i.e.  $H(W|Z) = 0$ ].

NOW TO OBTAIN STRONG BOUND, WE TEMPORARILY ASSUME THAT  $W$  IS UNIFORMLY DISTRIBUTED OVER  $\{1, 2, \dots, 2^R\}$ . THUS  $H(W) = R$ .

$$\begin{aligned}
 R &= H(W) = H(W|Z) + H(W) - H(W|Z) = \\
 &= H(W|Z) + H(W; Z) = I(W; Z) \cdot I(W; Z) \\
 &\stackrel{(a)}{\leq} I(X; Z) \stackrel{(b)}{\leq} \sum_{i=1}^n I(X_i; Z_i) \leq nC
 \end{aligned}$$

(a) DATA PROCESSING INEQUALITY  $W \rightarrow X \rightarrow Z$  FOR MARKOV CHAIN

$$I(W) \geq I(W; Z) \quad I(X; Z) \geq I(W; Z)$$

$$I(X; Z) = I(X; Y) + I(X; Z|Y) = I(X; Y) + I(X; Z|Y)$$

$$I(Y; X, Z) = I(X; Y) + I(Y; Z|X) = I(Y; Z) + I(Y; X|Z)$$

$$I(X; Y) = I(Y; X|Z)$$

$$I(Z; X, Y) = I(Z; X) + I(Z; Y|X) =$$

$$= I(X; Z) + I(Y; Z|X) = I(Z; Y) + I(Z; X|Y) =$$

$$= I(Y; Z) + I(X; Z|Y) \Rightarrow I(Y; Z) \geq I(X; Z)$$

$$\begin{aligned}
 I(X; Z|Y) &= H(X|Y) - H(X|Y, Z) = H(Z|Y) - H(Z|X, Y) = \\
 &= H(Z|Y) - H(Z|Y)
 \end{aligned}$$

$$P(X, Z|Y) = \frac{P(X, Y, Z)}{P(Y)} = \frac{P(X|Y) \cdot P(Z|X, Y)}{P(Y)}$$

$$= \frac{P(X|Y) \cdot P(Z|Y)}{P(Y)} = \frac{P(Y) \cdot P(X|Y) \cdot P(Z|Y)}{P(Y)}$$

$$= P(X|Y) \cdot P(Z|Y) \quad P(Z|X) = \frac{P(X, Y, Z)}{P(Y) \cdot P(X|Y)} = P(Z|Y)$$

(b) WILL BE QUANTIFIED IN THE COM 7.9.2 USING DISCRETE TOTAL-LESS ASSUMPTION.

(c) FOLLOWS FROM THE DEFINITION OF REDUNDANCY CAPACITY.

Hence FOR ANY ZERO-ERROR  $(2^R, \gamma)$  CODE FOR ALL  $n \geq 1$

$$K \leq C$$

$$H(X, Z) = H(X) + H(Z|X)$$

7.9

### STRONGER NEGATIVE AND THE CONVERSE OF THE CODING THEOREM.

WE NOW EXTEND THE PROOF THAT WAS GIVEN FOR ZERO-ERROR TO THE CASE OF CODES WITH VERY SMALL PROBABILITY OF ERROR.

$$X \rightarrow Y \rightarrow \hat{X} \quad \epsilon = \begin{cases} 1 & \hat{X} \neq X \\ 0 & \hat{X} = X \end{cases} \quad P(\epsilon) = \begin{cases} p_e \\ 1-p_e \end{cases}$$

$$\begin{aligned} H(X|Y, \epsilon) &= P(\epsilon=0) \cdot H(X|Y, \epsilon=0) + P(\epsilon=1) \cdot H(X|Y, \epsilon=1) \\ &= (1-p_e) \cdot 0 + p_e \cdot H(X|Y, \epsilon=1) \leq p_e \cdot H(X|Y) \leq p_e H(X) \\ &\leq p_e \ell_d(X) \end{aligned}$$

$$\begin{aligned} H(X|Y) &= H(\epsilon, X|Y) = H(X|Y) + H(\epsilon|X, Y) \\ &= H(\epsilon|Y) + H(X|Y, \epsilon) \leq H(\epsilon) + p_e \ell_d(X) \\ &= P(\hat{X} \neq X) \cdot H(\epsilon|\hat{X} \neq X) + P(\hat{X} = X) \cdot H(\epsilon|\hat{X} = X) \end{aligned}$$

$$H(\epsilon|Y) \leq H(\epsilon) = H(p_e) = p_e \log \frac{1}{p_e} + (1-p_e) \log \frac{1}{1-p_e}$$

$$H(X|Y) \leq H(p_e) + p_e \ell_d(X) \leq 1 + p_e \ell_d(X)$$

$$p_e \geq \frac{H(X|Y) - 1}{\ell_d(X)} \quad (-1) \Rightarrow p_e \leq \frac{1 - H(X|Y)}{\ell_d(X)}$$

• STRONGER NEGATIVE:  $H(X|Y, \epsilon) \leq p_e \ell_d(X-1)$

$$p_e \leq \frac{1 - H(X|Y)}{\ell_d(X-1)} \quad p_e \geq \frac{H(X|Y) - 1}{\ell_d(X-1)}$$

• MARKOV'S INEQUALITY + DATA PROCESSING INEQUALITY:

$$\begin{aligned} I(X; X) &\leq I(X; Y) \quad H(X) - H(X|Y) \leq H(X) - H(X|\hat{X}) \\ H(X) - H(X|Y) &\leq H(X) - H(X|\hat{X}) \quad H(X|Y) \geq H(X|\hat{X}) \end{aligned}$$

$$\begin{aligned} H(X|Y) &\leq 1 + p_e \ell_d(X) \quad H(X|\hat{X}) \leq 1 + p_e \ell_d(X) \\ p_e &\leq \frac{1 - H(X|\hat{X})}{\ell_d(X)} \end{aligned}$$

- The index is uniformly distributed on the set  $W = \{1, 2, \dots, 2^{nR}\}$  and sequence  $Z^n$  is related probabilistically to  $W$ .

From  $Z^n$  we estimate the user  $W$  that was sent. Let the estimate be  $\hat{W} = f(Z^n)$ .

Thus:  $W \rightarrow X^n(W) \rightarrow Z^n \rightarrow \hat{W}$  forms Markov chain. Probability of error is:

$$P_e = P(\hat{W} \neq W) = \frac{1}{2^{nR}} \sum_i \lambda_i = P_e^{(n)}$$

**Lemma 7.9.1 (Fano's Inequality)** For a discrete memoryless channel with codebook  $C$  and the input message  $W$  uniformly distributed over  $2^{nR}$ , we have:

$$H(W|\hat{W}) \leq 1 + P_e^{(n)} \cdot nR$$

**Proof:**  $W \sim$  uniform, distrib + apply Fano's inequality  $P_e^{(n)} = P(\hat{W} \neq W)$

- Capacity of transmission is not increased if we use a discrete memoryless channel many times.

**Lemma 7.9.2** Let  $Z^n$  be the result of passing  $X^n$  through a discrete memoryless channel of capacity  $C$ . Then:

$$I(X^n; Z^n) \leq nC \quad \text{for all } n$$

**Proof:**  $I(X^n; Z^n) = H(Z^n) - H(Z^n|X^n) = H(Z^n) - \sum_{i=1}^n H(Z_i|Z_1^{i-1}, X^n) = H(Z^n) - \sum_{i=1}^n H(Z_i|X_i)$

Since by definition of the discrete memoryless channel  $H(Z_i|X_i)$  depends only on  $X_i$  and is conditional independent of other bits.

$$I(X^n; Z^n) = H(Z^n) - \sum_{i=1}^n H(Z_i|X_i) \leq \left( \sum_{i=1}^n H(Z_i) \right) - \sum_{i=1}^n H(Z_i|X_i) = \sum_{i=1}^n I(X_i; Z_i) \leq nC$$

Entropy of collection of random variables is less than the sum of individual entropies:

$$H(Z^n) = \sum_{i=1}^n H(Z_i|Z_1^{i-1}) \leq \sum_{i=1}^n H(Z_i)$$

conditioning reduces entropy

$$W \rightarrow X^N \rightarrow Y^N \rightarrow \hat{W} \quad \left\{ I(W, X^N) \geq I(W, Y^N) \right\}$$

$$I(W, X^N, Y^N) \geq I(W, \hat{W})$$

$$I(W, X^N, Y^N) = I(X^N, Y^N; W) = I(X^N; W) + I(X^N, W | Y^N)$$

$$I(X^N; W) \geq I(W, \hat{W}) \quad I(W; Y^N) \geq I(W, \hat{W})$$

$$I(X^N; W) + 0 = I(X^N; W) + I(X^N; W | \emptyset)$$

$$I(W, X^N, Y^N) = I(W; Y^N) + I(X^N; W | Y^N) = I(X^N; Y^N) + I(W; Y^N | X^N) \Rightarrow I(X^N; Y^N) \geq I(W; Y^N)$$

$$I(X^N; Y^N) \geq I(W; Y^N) \geq I(W, \hat{W})$$

$I(X^N; Y^N) \geq I(W, \hat{W})$

MMV

Let  $W$  be drawn according to uniform distribution  $\{1, 2, \dots, 2^{nR}\}$

$$Pr(W \neq \hat{W}) = P_e^{(n)} = \frac{1}{2^{nR}} \sum_{\hat{w} \neq w} \sum_{w} 2^{-nR} = H(W) - H(W | \hat{W})$$

$$nR = H(W) = H(W | \hat{W}) + I(W; \hat{W}) \leq 1 + P_e^{(n)} \log 2^{nR} + I(W; \hat{W})$$

$$= 1 + P_e^{(n)} \cdot nR + I(W; \hat{W}) \leq 1 + P_e^{(n)} nR + I(X^N; Y^N) \leq 1 + P_e^{(n)} nR + nC$$

$$\leq 1 + P_e^{(n)} nR + nC$$

$$R \leq \frac{1}{n} + P_e^{(n)} R + C \quad \text{IF } n \rightarrow \infty \quad R \leq C$$

$P_e^{(n)} \geq 1 - \frac{1}{nR} - \frac{C}{R}$

IF  $R > C$

PROBABILITY OF ERROR IS BOUNDED AWAY FROM 0 FOR SUFFICIENTLY LARGE  $n$ . HENCE WE CANNOT ACHIEVE AN ARBITRARILY LOW PROBABILITY OF ERROR AT RATES ABOVE CAPACITY. THIS CONVERSE IS CALLED WEAK CONVERSE TO THE CHANNEL CODING THEOREM. IT IS ALSO POSSIBLE TO PROVE A STRONG CONVERSE WHICH STATES THAT FOR RATES ABOVE CAPACITY, PROBABILITY OF ERROR GOES TO 1.

HENCE CAPACITY IS A VERY CLEAR DIVIDING POINT -  
 AT RATES BELOW CAPACITY  $P_e \rightarrow 0$  ASYMPTOTICALLY  
 AND AT RATES ABOVE CAPACITY  $P_e \rightarrow 1$  ASYMPTOTICALLY.

**7.10 EQUATION IN THE CONVERSE TO THE CHANNEL CODING THEOREM**

- We repeat the steps of the prove of the converse  $P_e = 0$  WITH MORE IT WILL GIVE SOME IDEAS FOR THE CODES THAT ACHIEVE CAPACITY.

$$H(Z) = H(W) = \underbrace{H(W|\bar{W})}_{\text{NO CORRELATION} = 0} + I(W; \bar{W}) = I(W; \bar{W})$$

$$\begin{aligned} (a) \quad & I(X^n; Z^n) = H(Z^n) - H(Z^n|X^n) = H(Z^n) - \\ & - \sum_{i=1}^n H(Z_i|Z_1^{i-1}, X^n) = H(Z^n) - \sum_{i=1}^n H(Z_i|X_i) \leq \\ & \leq \sum_{i=1}^n H(Z_i) - \sum_{i=1}^n H(Z_i|X_i) = \sum_{i=1}^n I(X_i; Z_i) \\ & \leq nC \end{aligned}$$

(a) DATA PROCESSING

EQUATION IF: (\*)  $I(X^n, Z^n) = I(W; Z^n) + I(X^n, Z^n|W)$

$$I(X^n, Z^n, \bar{W}) = I(X^n, \bar{W}) + I(X^n, Z^n | \bar{W}) \stackrel{\text{TREAT } W = \emptyset}{=} 0$$

$$= I(X^n, \bar{W}) + I(Z^n, \bar{W} | X^n)$$

$$I(X^n, Z^n, \bar{W}) = I(X^n, Z^n) + I(X^n, \bar{W} | Z^n) \stackrel{\text{TREAT } W = \emptyset}{=} 0$$

$$= I(X^n, \bar{W}) + I(X^n, Z^n | \bar{W})$$

$$I(X^n, Z^n) = I(X^n, \bar{W}) + I(X^n, Z^n | \bar{W})$$

$$I(W, X^n, Z^n, \bar{W}) \stackrel{\text{TREAT } W = \emptyset}{=} I(X^n, Z^n, \bar{W}) + I(W, \bar{W} | X^n, Z^n) =$$

$$= I(W, \bar{W}) + I(X^n, Z^n, \bar{W} | W) \stackrel{\text{TREAT } W = \emptyset}{=} I(Z^n, \bar{W} | W)$$

(\*)  $I(X^n, Z^n, \bar{W}) = I(Z^n, \bar{W})$

$I(Z^n, \bar{W}) = I(W, \bar{W}) + I(X^n, Z^n, \bar{W} | W)$  (\*)



$$I(W, X^4; Z^4, \hat{W}) = I(X^4; Z^4, \hat{W}) + I(W; Z^4, \hat{W} | X^4) \\ = I(X^4; Z^4) + I(W; Z^4, \hat{W} | X^4)$$

$$\textcircled{2} \quad I(Z^4; \hat{W}) = I(W; \hat{W}) + I(Z^4; \hat{W} | W) \\ I(Z^4; \hat{W}) - I(Z^4; \hat{W} | W) = I(W; \hat{W})$$

$$I(X^4; Z^4, W, \hat{W}) = I(X^4; Z^4) + I(X^4; W | Z^4) + I(X^4, \hat{W} | Z^4, W) \\ \text{solution} \downarrow \\ I(W, X^4; Z^4, \hat{W}) = I(X^4; Z^4, \hat{W}) + I(W; Z^4, \hat{W} | X^4) \\ = I(W, X^4; Z^4) + I(W, X^4; \hat{W} | Z^4) = \textcircled{3}$$

$$I(X^4; Z^4, \hat{W}) = I(W, X^4; Z^4) = I(X^4; Z^4) \quad \text{proved!}$$

$$\textcircled{3} = I(W; Z^4, \hat{W}) + I(X^4; Z^4, \hat{W} | W) = \\ = I(W, X^4; \hat{W}) + I(W, X^4; Z^4 | \hat{W})$$

$$I(X^4; Z^4) - I(W, X^4; Z^4, \hat{W}) = I(W; Z^4, \hat{W}) + I(X^4; Z^4 | W)$$

$$I(W; Z^4, \hat{W}) = I(W; \hat{W}) + I(W; Z^4 | \hat{W}) = \\ = I(W; Z^4) + I(W; \hat{W} | Z^4)$$

$$I(X^4; Z^4) = I(W; \hat{W}) + I(W, Z^4; \hat{W}) + I(X^4; Z^4 | W)$$

$$\textcircled{2} = I(W; \hat{W}) = I(W | \hat{W}, Z^4) + I(X^4) - I(X^4 | W, Z^4) \\ \text{no cancel!!} \quad \text{no cancel!!} \quad I(X^4; Z^4 | W)$$

$$I(X^4; Z^4) = I(W; \hat{W}) + I(X^4; Z^4 | W) \\ I(X^4; Z^4) = I(W; \hat{W}) \quad \text{if } I(X^4; Z^4 | W) = 0$$

$$I(X^4; Z^4) = I(W, X^4; Z^4, \hat{W}) = I(W, X^4; \hat{W}) + I(X^4; Z^4 | \hat{W}) \\ = I(W; \hat{W}) + I(X^4; \hat{W} | W) + I(X^4; Z^4 | \hat{W}) = I(W; \hat{W}) + I(X^4; Z^4 | W) \\ I(X^4; \hat{W} | W) = I(\hat{W} | W) + I(\hat{W} | W, X^4) \quad \text{no cancel!!} \quad \textcircled{2}$$

$$I(x_n; z_n) = I(w; \bar{w}) \quad \text{IF} \quad I(x_n; z_n | \bar{w}) = 0$$

PREVIOUS CONDITION WAS  $I(x_n; z_n | w) = 0$

(a) WE HAVE INEQUALITY IF ONLY  $I(x; z | w) = I(x'; z' | \bar{w}) = 0$

WHICH IS TRUE IF ~~ONLY~~ ALL THE CODEWORDS ARE DISTINCT AND IF  $\bar{w}$  IS SUFFICIENT STATISTIC FOR DECODING.

(b) WE HAVE ~~ONLY~~ EQUALITY IF  $y_i$ 'S ARE INDEPENDENT

(c) WE HAVE EQUALITY ONLY IF THE DISTRIBUTION OF  $x_i$  IS  $y^*(x)$  THE DISTRIBUTION OF  $x$  THAT ACHIEVES THAT CAPACITY.

THIS INDICATES THAT A CAPACITY-ACHIEVING ZERO-RATE CODE HAS DISTINCT CODEWORDS AND THE DISTRIBUTION OF THE  $y_i$ 'S MUST BE I.I.D WITH

$$y^*(y) = \sum y^*(x) p(y|x)$$

THE DISTRIBUTION OF  $y$  INDUCED BY THE OPTIMUM DISTRIBUTION OF  $x$ .

$$p(x_i, y_i) = \frac{1}{2^{nr}} \sum_{w=1}^{2^{nr}} I(x_i(w) = x_i) p(y_i | x_i)$$

$$R \leq p_e \cdot R + \frac{1}{n} + c$$

$$p_e \geq 1 - \frac{1}{en} - \frac{c}{R}$$

### 7.11 HAMMING CODES

THE CHANNING CODING THEOREM PROVES THE EXISTENCE OF BLOCK CODES THAT WILL ALLOW US TO TRANSMIT INFORMATION AT RATES BELOW CAPACITY WITH AN ARBITRARILY SMALL PROBABILITY OF ERROR IF THE ~~CODE~~ BLOCK LENGTH IS ~~SUFFICIENTLY~~ LARGE ENOUGH.

$$H = \begin{bmatrix} 0 & 0 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 & 1 & 0 & 1 \end{bmatrix}$$

i-th column

$$z = \begin{bmatrix} 1 & 1 & 1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 1 & 1 & 0 & 0 \\ 0 & 1 & 0 & 1 & 0 & 1 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 & 1 \end{bmatrix}$$

ONE OF MANY METHODS  
 $H \cdot z = 0$

SINCE THE SET OF CODEWORDS IS THE NULL SPACE OF A MATRIX IT IS LINEAR IN THE SENSE THAT THE SUM OF ANY TWO CODEWORDS IS ALSO A CODEWORD.

THE MINIMUM NUMBER OF 1'S IN ANY CODEWORD IS 3. THIS IS CALLED MINIMUM WEIGHT

OF THE CODE. MINIMUM DISTANCE (Hamming) IS EQUAL TO THE MINIMUM WEIGHT OF THE LINEAR CODE.

SINCE THE CODE IS LINEAR THE DIFFERENCE BETWEEN TWO CODEWORDS IS ALSO A CODEWORD, AND HENCE ANY TWO CODEWORDS DIFFER IN AT LEAST THREE PLACES.

FOR THE CODE ABOVE THE MINIMUM DISTANCE IS 3. HENCE IF THE CODEWORD  $C \in$  IS CORRUPTED IN ONLY ONE PLACE IT WILL DIFFER FROM ANY OTHER WORD IN AT LEAST TWO PLACES, AND HENCE IT WILL BE CORRUPTED TO  $C' \neq C$  THEN TO ANY OTHER CODEWORD.

THE MATRIX  $H$  IS THE CHECK MATRIX. THE THE MATRIX  $H \cdot C = 0$  FOR EVERY CODEWORD  $C$ .

LET  $e_i$  BE A VECTOR OF LENGTH  $n$  WITH A 1 IN THE  $i$ TH POSITION AND 0 ELSEWHERE. IT IS CALLED AN ERROR VECTOR.

$$H \cdot r = H \cdot (C + e_i) = H \cdot C + H \cdot e_i = H \cdot e_i$$

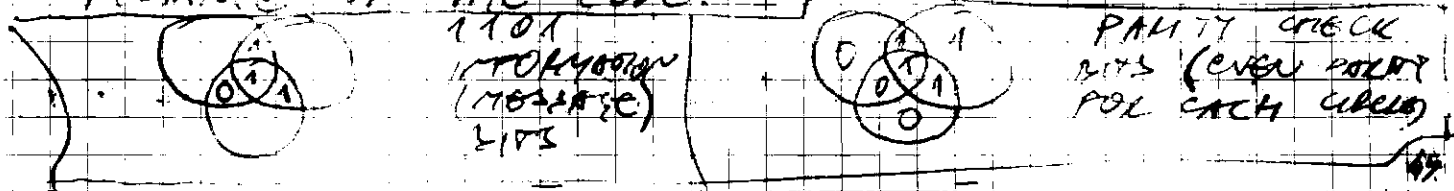
HENCE LOOKING AT  $H \cdot r$  WE CAN FIND WHICH POSITION OF THE VECTOR WAS CORRUPTED. FINDING THIS SET WILL GIVE US THE CODEWORD.

WE HAVE CONSTRUCTED 16 CODEWORDS OF LENGTH 7 WHICH CAN CORRECT UP TO ONE ERROR. THIS CODE IS CALLED HAMMING CODE.

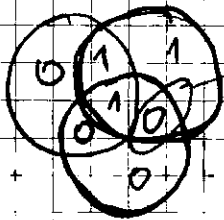
0000000	0100101	1000011	1100110
0001111	0101010	1001100	1101001
0010110	0110111	1010101	1110000
0011001	0111100	1011010	1111111

$k$  - BITS REPRESENT THE MESSAGE.  
 $n-k$  - BITS OF THE CODEWORD REPRESENT THE PARITY CHECK BITS. SUCH CODE IS CALLED A SYSTOLIC CODE.

THE ABOVE CODE IS CALLED (7,4) HAMMING CODE (I.E.  $n=7, k=4, d=3$ ).  $d$  - MINIMUM DISTANCE OF THE CODE.



- Assuming one bit is changed



- Efficient bit (insert in value) so random parity check - bit 3 to value 10 so random parity check.

• Generalization of Hamming code:

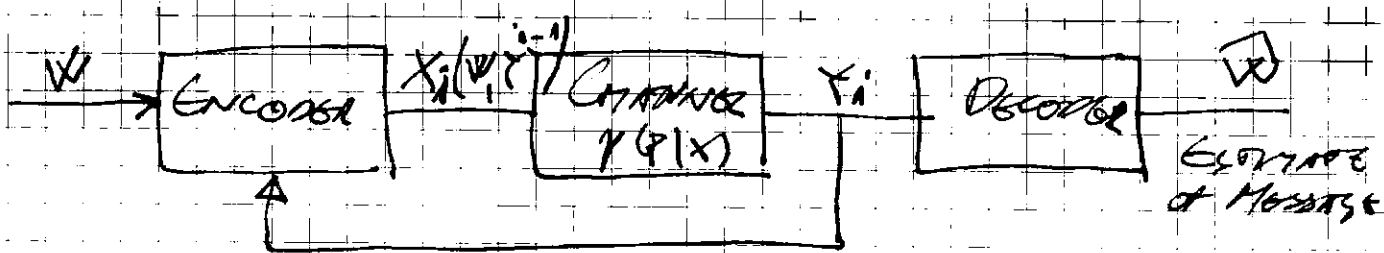
$$n = 2^l - 1 \quad k = 2^l - l - 1 \quad \text{AND MINIMUM DISTANCE } (3)$$

$l$  - NUMBER OF ROWS IN  $H$  MATRIX

eg.  $l=3$       $n = 2^3 - 1 = 7$       $k = 2^3 - 3 - 1 = 8 - 4 = 4$

1 1 1 1 1

## 7.12 FEEDBACK CAPACITY



WE DEFINE A  $(2^{rN}, n)$  feedback code as a sequence of mappings  $X_i(W, Z^{i-1})$  where each  $X_i$  is a function over the message

$W \in 2^{rN}$  AND PREVIOUS RECEIVED VALUES:

$Z_1, Z_2, \dots, Z_{i-1}$  AND A SEQUENCE OF DECODING FUNCTIONS  $g: Z^i \rightarrow \{1, 2, \dots, 2^{rN}\}$

$$P_e^{(n)} = P_r \{ g(Z^n) = W \}$$

where  $W$  is UNIFORMLY DISTRIBUTED OVER  $\{1, 2, \dots, 2^{rN}\}$

**DEFINITION** THE CAPACITY WITH FEEDBACK  $C_{FB}$  OF THE DISCRETE MEMORYLESS CHANNEL IS THE SUPRENUM OF ALL RATES ACHIEVABLE BY FEEDBACK CODES.

### THEOREM 7.12.1 (FEEDBACK CAPACITY)

$$C_{FB} = C = \max_{p(x)} I(x; Y)$$

**PROOF:** LET  $W$  BE UNIFORMLY DISTRIBUTED OVER  $\{1, 2, 3, \dots, 2^{rN}\}$ . THEN  $P_r(W \neq \hat{W}) = P_e^{(n)}$

$$nR = H(W) = H(W|W) + I(W; \vec{W}) \xrightarrow{\text{chain rule}} H(W) - H(W|W) \\ 1 + P_e^{(n)} nR + I(W; \vec{W}) \stackrel{(6)}{\leq} 1 + P_e^{(n)} nR + I(W; \gamma^n)$$

(a) Fano inequality

(b) PASTA-PROCESSING INEQUALITY

$$I(W; \gamma^n) = H(\gamma^n) - H(\gamma^n|W) \leq$$

$$\leq H(\gamma^n) - \sum_{i=1}^n H(\gamma_i | \gamma_1, \gamma_2, \dots, \gamma_{i-1}, W) =$$

$$= \sum_{i=1}^n \left( H(\gamma_i | \gamma_1, \gamma_2, \dots, \gamma_{i-1}) - H(\gamma_i | \gamma_1, \gamma_2, \dots, \gamma_{i-1}, W) \right) =$$

$$H(z|x, \gamma) \quad x = f(\gamma)$$

$$H(x, z|x, \gamma) = H(x|x, \gamma) + H(z|x, \gamma) =$$

$$\Rightarrow H(z|x, \gamma) = H(z|\gamma) + H(x|\gamma, z) \quad \boxed{H(z|x, \gamma) = H(z|\gamma)}$$

$$= H(\gamma^n) - \sum_{i=1}^n H(\gamma_i | x_i)$$

$$W \rightarrow \gamma^n \rightarrow \gamma^n \quad \text{MARKOV CHAIN} \quad H(\gamma^n | x, W) = H(\gamma^n | x)$$

$$I(W; \gamma^n) = H(\gamma^n) - \sum_{i=1}^n H(\gamma_i | x_i) \leq \sum_{i=1}^n H(\gamma_i) - \sum_{i=1}^n H(\gamma_i | x_i) = \sum_{i=1}^n I(\gamma_i, x_i) \leq nC$$

$$nR \leq P_e^{(n)} nR + 1 + nC \quad / n$$

$$R \leq P_e^{(n)} R + \frac{1}{n} + C \xrightarrow{n \rightarrow \infty} 0 + 0 + C$$

$$\boxed{R \leq C}$$

THUS WE CANNOT ACHIEVE ANY HIGHER RATES WITH FEEDBACK THAN WE CAN WITHOUT FEEDBACK, AND

$$\boxed{C_{FB} = C}$$

• AS WE HAVE SEEN IN THE EXAMPLE OF THE BINARY ERASURE CHANNEL FEEDBACK GIVES HELP ENORMOUSLY IN SIGNALING, ENCODING AND DECODING. HOWEVER IT CANNOT INCREASE THE CAPACITY OF THE CHANNEL

# 7.13 SOURCE-CHANNEL SEPARATION THEOREM

$$H(X) \leq \frac{E[L(X)]}{n} \leq \frac{H(X) + 1}{n}$$

$$R = \frac{CnM}{n} = \frac{Cn2^{nR}}{n} \leq C$$

IT IS NOW TIME TO COMBINE THE TWO MAIN RESULTS THAT WE HAVE PROVED SO FAR:

- DATA COMPRESSION  $R > H$  (THEOREM 5.4.2)
- DATA TRANSMISSION  $R < C$  (THEOREM 7.7.1)

↳ THE CONDITION  $H < C$  NECESSARY AND SUFFICIENT FOR SENDING THE SOURCE OVER THE CHANNEL.

WE CAN CONSIDER THE DESIGN OF ~~THE~~ A COMMUNICATION SYSTEM AS A COMBINATION OF TWO PARTS, SOURCE CODING AND CHANNEL CODING. WE CAN DESIGN SOURCE CODES FOR THE MOST EFFICIENT REPRESENTATION OF THE DATA WE CAN, SEPARATELY AND INDEPENDENTLY DESIGN CHANNEL CODES APPROPRIATE FOR THE CHANNEL. THE COMBINATION WILL BE AS EFFICIENT AS ANYTHING WE COULD DESIGN BY CONSIDERING BOTH PROBLEMS TOGETHER.

LET US DEFINE ~~SETUP~~ UNDER CONSIDERATION. WE HAVE A SOURCE  $V$  THAT GENERATES SYMBOLS FROM AN ALPHABET  $\mathcal{V}$ . THE STOCHASTIC PROCESS GENERATED BY  $V$  IS FROM FINITE ALPHABET AND SATISFIES AEP. (E.G. SEQUENCE OF I.I.D RANDOM VARIABLES AND THE SEQUENCE OF STATES OF A STATIONARY IRREDUCIBLE MARKOV CHAIN).

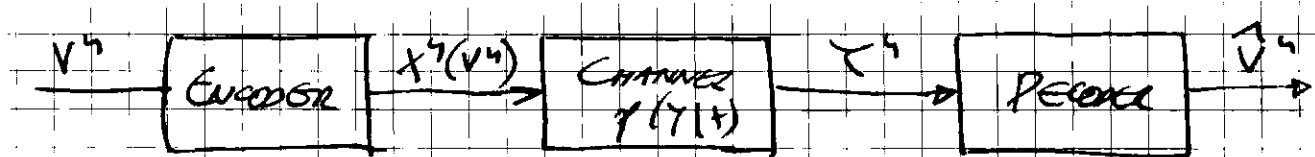
ANY STATIONARY ergodic SOURCE SATISFIES AEP  
 - WE WANT TO SEND SEQUENCE OF SYMBOLS:

$$V^n = V_1, V_2, \dots, V_n$$

OVER THE CHANNEL, SO THAT THE RECEIVER CAN RECONSTRUCT THE SEQUENCE. WE MAP THE SEQUENCE ONTO A CODEWORD  $\gamma(V^n)$  AND SEND THE CODEWORD OVER THE CHANNEL. THE RECEIVER LOOKS AT HIS RECEIVED SEQUENCE

$Z^n$  AND MAKES ESTIMATE  $\hat{V}^n$ . ERROR IS DECLARED IF  $V^n \neq \hat{V}^n$ . WE DEFINE:

$$P_e(V^n \neq \hat{V}^n) = \sum_{V^n} \sum_{\hat{V}^n} \gamma(V^n) \gamma(\hat{V}^n) I(\gamma(V^n) \neq \gamma(\hat{V}^n))$$



### Theorem 7.13.1 (Joint Source-Channel Coding Theorem)

If  $V_1, V_2, \dots, V^n$  is a finite alphabet stochastic process that satisfies the AEP and  $H(V) < C$  there exists a source-channel code with probability of error  $P_e(V^n \neq \hat{V}^n) \rightarrow 0$ . Conversely, if  $H(V) > C$ , the number of bits is bounded away from zero, and it is not possible to send the process over the channel with arbitrarily low probability of error.

Proof Achievability Since we have assumed that the stochastic process satisfies the AEP, it implies that there exists a typical set:

$$A_\epsilon^{(n)} \text{ of size } \leq 2^{n(H(V) + \epsilon)}$$

We will send ~~the~~ only the source sequence belonging to the typical set, all other sequences will result in error.

Since there are at most  $2^{n(H(V) + \epsilon)}$  such sequences  $n(H(V) + \epsilon)$  bits suffice to index them.

We can transmit the desired index to the receiver with probability of error less than  $\epsilon$  if:

$$H(V) + \epsilon = R < C$$

$$P(V^n \neq \hat{V}^n) \leq P(V^n \notin A_\epsilon^{(n)}) + P(g(Y^n) \neq V^n | V^n \in A_\epsilon^{(n)}) \leq \epsilon + \epsilon = 2\epsilon$$

For sufficiently large  $n$ . Hence we can reconstruct the sequence with low  $P_e$  for sufficiently large  $n$  if:

$$H(V) < C$$

Converse We wish to show that  $P_e(V^n \neq \hat{V}^n) \rightarrow 0$  implies that  $H(V) \leq C$  for any sequence of source-channel codes:

$$x^n(v^n): V^n \rightarrow X^n \quad g_n(Y^n): Y^n \rightarrow \hat{V}^n$$

$$H(V^n | \hat{V}^n) \leq 1 + P_e(V^n \neq \hat{V}^n) \log |V^n| = 1 + P_e(V^n \neq \hat{V}^n) \cdot n \log |V|$$

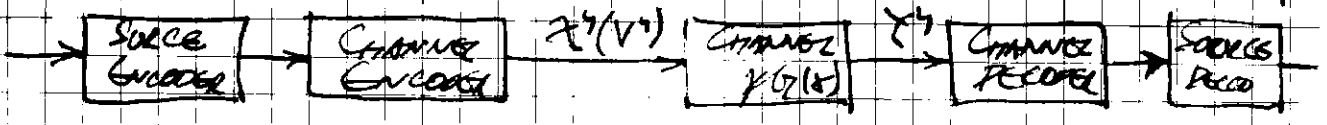
$$\begin{aligned}
 H(V) &\stackrel{(a)}{\leq} \frac{H(V_1, V_2, \dots, V_n)}{n} = \frac{H(V^n)}{n} = \frac{1}{n} H(V^n | \hat{V}^n) + \\
 &+ \frac{1}{n} I(V^n; \hat{V}^n) \stackrel{(b)}{\leq} \frac{1}{n} (1 + P_e(\hat{V}^n \neq V^n) \cdot n \log |V|) + \frac{1}{n} I(V^n; \hat{V}^n) \\
 &\stackrel{(c)}{\leq} \frac{1}{n} (1 + P_e(\hat{V}^n \neq V^n) \cdot n \log |V|) + \frac{1}{n} I(V^n; \hat{V}^n) \stackrel{(d)}{\leq} \frac{1}{n} + \\
 &+ P_e(\hat{V}^n \neq V^n) \log |V| + C
 \end{aligned}$$

Now letting  $n \rightarrow \infty$  we have:

$$H(V) \leq C$$

Hence we can transmit a stationary ergodic source over a channel if and only if its entropy rate is less than the capacity of the channel.

The source coder tries to find the most efficient representation of the source, and the channel coder encodes the message to combat the noise and errors introduced by the channel.



The ~~data compression~~ ~~theorem~~ is consequence to a set which shows that there exist codes set  $\{k^n\}$  that we can represent the source with ~~small probability~~ small probability of error using  $n$  bits per symbol. The ~~rate transmission~~ ~~theorem~~ is used on point ~~set~~. It uses the fact that for long block lengths, the output sequence of the channel is very likely to be jointly typical with input codeword while any other ~~sequence~~ codeword is jointly typical with the ~~channel~~  $\epsilon = 2^{-n^2}$ . Hence we can use  $2^{nI}$  codewords and still have negligible probability of error.

**SUMMARY**

**Channel Capacity** The logarithm of the number of distinguishable inputs is given by

$$C = \max_{p(x)} I(X; Y)$$

**EXAMPLES:**

- BINARY SYMMETRIC CHANNEL:  $C = 1 - H(p)$
- BINARY ERASURE CHANNEL:  $C = 1 - \alpha$
- SYMMETRIC CHANNEL:  $C = \log |V| - H(\text{row of transition matrix})$

**PROPERTIES OF C**



1)  $0 \leq C \leq \min\{C(x), C(y)\}$

2)  $I(x; y)$  is a CONTINUOUS CONCAVE FUNCTION OF  $\gamma(x)$

JOINT TYPICALITY: THE SET  $A_\epsilon^{(n)}$  OF JOINTLY TYPICAL SEQUENCES  $\{(x^n, y^n)\}$  WITH RESPECT TO THE DISTRIBUTION  $\gamma(x, y)$  IS GIVEN BY:

$$A_\epsilon^{(n)} = \left\{ (x^n, y^n) \in \mathcal{X}^n \times \mathcal{Y}^n : \left| -\frac{1}{n} \log \gamma(x^n) - H(x) \right| < \epsilon, \right. \\ \left. \left| -\frac{1}{n} \log \gamma(y^n) - H(y) \right| < \epsilon, \left| -\frac{1}{n} \log \gamma(x^n, y^n) - H(x, y) \right| < \epsilon \right\}$$

WHERE:  $\gamma(x^n, y^n) = \prod_{i=1}^n \gamma(x_i, y_i)$

JOINT AEP LET  $\{(x_i, y_i)\}_{i=1}^n$  BE SEQUENCE OF I.I.D. ACCORDING TO:

$\gamma(x_i, y_i) = \prod_{i=1}^n \gamma(x_i, y_i)$  THEN:

1.  $P_n((x^n, y^n) \in A_\epsilon^{(n)}) \rightarrow 1$  as  $n \rightarrow \infty$

2.  $|A_\epsilon^{(n)}| \leq 2^{n(H(x, y) + \epsilon)}$

3. IF  $(\tilde{x}^n, \tilde{y}^n) \sim \gamma(x^n) \gamma(y^n)$  THEN  $P_n((\tilde{x}^n, \tilde{y}^n) \in A_\epsilon^{(n)}) \leq 2^{-n(I(x, y) - 3\epsilon)}$

CHANNEL CODING THEOREM: ALL RATES BELOW  $C$  ARE ACHIEVABLE, AND ALL RATES ABOVE CAPACITY ARE NOT; THAT IS, FOR ALL RATES  $R < C$ , THERE EXIST SEQUENCE  $\{(x^n, y^n)\}$  CODES WITH PROBABILITY OF ERROR  $\rightarrow 0$ . CONVERSELY, FOR RATES  $R > C$ ,  $\lambda^n$  IS BOUNDED AWAY FROM 0.

FEEDBACK CAPACITY FEEDBACK DOES NOT INCREASE CAPACITY FOR DISCRETE MEMORYLESS CHANNELS (I.E.  $C_{FB} = C$ )

SOURCE-CHANNEL THEOREM: A STOCHASTIC PROCESS WITH ENTROPY RATE  $H$  CANNOT BE SENT RELIABLY OVER A DISCRETE MEMORYLESS CHANNEL IF  $H > C$ . CONVERSELY, IF THE PROCESS SATISFIES AEP, THE SOURCE CAN BE TRANSMITTED RELIABLY IF  $H < C$ .

RECALL:  $\lambda^n \geq \sum \gamma(x^n, y^n) \geq |A_\epsilon^{(n)}| \cdot 2^{-n(H(x, y) + \epsilon)}$

$|A_\epsilon^{(n)}| \leq 2^{n(H(x, y) + \epsilon)}$   $\Rightarrow 2^{-n(H(x, y) + \epsilon)} \leq \gamma(x^n, y^n) \leq 2^{-n(H(x, y) - \epsilon)}$

$$1 = \sum_{x^1, \dots, x^n} \gamma(x^1, \dots, x^n) \geq \sum_{(x^1, \dots, x^n) \in A_\epsilon^{(n)}} \gamma(x^1, \dots, x^n) \geq 2^{-n(H(x, z) + \epsilon)}$$

$$\Pr((\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}) = \sum_{(\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}} \gamma(\tilde{x}_n) \cdot \gamma(\tilde{z}_n) \leq |A_\epsilon^{(n)}| \cdot 2^{-n(H(z) - \epsilon)}$$

$$\circledast = n \cdot (H(x) + H(x|z)) + 3n\epsilon - nH(z) - nH(z) = -n(H(x) - H(x|z)) + 3n\epsilon$$

$$\Pr((\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}) \leq 2^{-n[I(x; z) - 3\epsilon]}$$

$$(1 - \epsilon) \leq \sum_{x^1, \dots, x^n \in A_\epsilon^{(n)}} \gamma(x^1, \dots, x^n) \leq |A_\epsilon^{(n)}| \cdot 2^{-n(H(x, z) - \epsilon)}$$

$$|A_\epsilon^{(n)}| \geq (1 - \epsilon) 2^{n(H(x, z) - \epsilon)}$$

$$\Pr((\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}) = \sum_{\tilde{x}_n, \tilde{z}_n \in A_\epsilon^{(n)}} \gamma(\tilde{x}_n) \cdot \gamma(\tilde{z}_n) \geq (1 - \epsilon) 2^{n(H(z) - \epsilon)}$$

$$\Pr[(\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}] \geq (1 - \epsilon) 2^{-n[H(x; z) + 3\epsilon]}$$

THEOREM 7.7.1 (REVISED)

$$C = \begin{bmatrix} x_1(1) & x_2(1) & \dots & x_n(1) \\ \vdots & \vdots & \ddots & \vdots \\ x_1(2^{nr}) & x_2(2^{nr}) & \dots & x_n(2^{nr}) \end{bmatrix}$$

$$W = \{1, 2, \dots, 2^{nr}\}$$

$$\Pr(C) = \prod_{w=1}^{2^{nr}} \prod_{i=1}^n \Pr(x_i(w))$$

$$\Pr(W=w) = 2^{-nr}$$

$$\Pr(y_i | x_i(w)) = \prod_{i=1}^n \Pr(y_i | x_i(w))$$

$$\begin{aligned}
 P_r(\mathcal{E}) &= \sum_C P_r(C) P_{\mathcal{E}}^{(M)}(C) = \sum_C P_r(C) \frac{1}{2^{4R}} \sum_{w=1}^{2^{4R}} \lambda_w(C) = \\
 &= \frac{1}{2^{4R}} \sum_C P_r(C) \sum_{w=1}^{2^{4R}} \lambda_w(C) = \frac{1}{2^{4R}} \sum_{w=1}^{2^{4R}} \sum_C P_r(C) \lambda_w(C) = \\
 &= \frac{1}{2^{4R}} \cdot 2^{4R} \sum_C P_r(C) \lambda_1(C) = \sum_C P_r(C) \cdot \lambda_1(C) = P_r(\mathcal{E} | W=1)
 \end{aligned}$$

$$\mathcal{E}_i = \left\{ (X^N(i), \tau^N) \text{ is in } A_{\mathcal{E}}^{(N)} \right\}, \quad i \in \{1, 2, \dots, 2^{4R}\}$$

$$\begin{aligned}
 P_r(\mathcal{E} | W=1) &= P(\mathcal{E}_1^c \cup \mathcal{E}_2 \cup \mathcal{E}_3 \cup \dots \cup \mathcal{E}_{2^{4R}} | W=1) \leq \\
 &\leq P(\mathcal{E}_1^c | W=1) + \sum_{i=2}^{2^{4R}} P(\mathcal{E}_i | W=1)
 \end{aligned}$$

$$\begin{aligned}
 P_r(\mathcal{E}) = P_r(\mathcal{E} | W=1) &\leq P(\mathcal{E}_1^c | W=1) + \sum_{i=2}^{2^{4R}} P(\mathcal{E}_i | W=1) \leq \\
 \mathcal{E} + \sum_{i=2}^{2^{4R}} 2^{-4(I(X; \tau) - \beta \mathcal{E})} &= \mathcal{E} + (2^{4R} - 1) 2^{-4(I(X; \tau) - \beta \mathcal{E})}
 \end{aligned}$$

$$= \mathcal{E} + 2^{4R} \cdot 2^{-4(I(X; \tau) - \beta \mathcal{E})} = 2^{4R} \cdot 2^{-4(I(X; \tau) - \beta \mathcal{E})} \leq$$

$$\leq \mathcal{E} + 2^{4R} \mathcal{E} \cdot 2^{-4(I(X; \tau) - \beta \mathcal{E})} \leq 2\mathcal{E}$$

IF  $\gamma \rightarrow$  SUFFICIENTLY LARGE AND  $\beta < I(X; \tau)$

$$\bullet P(\mathcal{E} | \mathcal{C}^*) \leq 2\mathcal{E}$$

$$P_r(\mathcal{E} | \mathcal{C}^*) = \frac{1}{2^{4R}} \sum_{i=1}^4 \lambda_i(\mathcal{C}^*)$$

$$\begin{aligned}
 \lambda_i &= P_r(\mathcal{E} | x_n(W=i)) = \sum_{\tau^N} \gamma(\tau^N | x^N(i)) I(g(\tau^N) \neq i) \\
 &= P_r(g(\tau^N) \neq i | X^N = x^N(i))
 \end{aligned}$$

$$H(W) = \sum \frac{1}{2^{4R}} \cdot \log \frac{1}{2^{4R}} = 2^{4R} \cdot \frac{1}{2^{4R}} \cdot \log 2^{4R} = 4R$$

$$H(W | \bar{W}) \leq 1 + P_{\mathcal{E}}^{(M)} \log 2^{4R} \leq 1 + P_{\mathcal{E}}^{(M)} \cdot 4R$$

$$I(X^{(1)}, \tau^{(1)}) \leq 4 \cdot C$$

$$I(X^{(1)}, \tau^{(1)}) = H(\tau^{(1)}) - H(\tau^{(1)} | X^{(1)}) = H(\tau^{(1)}) - \sum_{i=1}^4 H(\tau^{(1)} | X^{(1)} = x_i)$$

$$= H(\tau^{(1)}) - \sum_{i=1}^4 H(\tau^{(1)} | x_i) \leq \sum_{i=1}^4 H(\tau^{(1)}) - \sum_{i=1}^4 H(\tau^{(1)} | x_i) =$$

$$= \sum_{i=1}^4 H(\tau^{(1)} | x_i) - H(\tau^{(1)} | x_i) = \sum_{i=1}^4 I(X_i; \tau^{(1)}) \leq 4 \cdot C$$

$$\begin{aligned} \eta R &= H(W) = H(W|\bar{W}) + I(W; \bar{W}) \leq 1 + P_e^{(\eta)} \cdot \eta R + I(W; \bar{W}) \\ &\leq 1 + P_e^{(\eta)} \cdot \eta R + I(X; \bar{X}) \leq 1 + P_e^{(\eta)} \cdot \eta R + \eta C \\ \eta R &\leq 1 + P_e^{(\eta)} \cdot \eta R + \eta C \quad R \leq \frac{1}{\eta} + P_e^{(\eta)} R + C \end{aligned}$$

$$\eta \rightarrow \infty \quad \boxed{R \leq C}$$

$$P_e^{(\eta)} \geq 1 - \frac{1}{\eta R} - \frac{C}{R}$$

### PROBLEMS

**7.1** PREPROCESSING THE OUTPUT. ONE IS GIVEN A COMMUNICATION CHANNEL WITH TRANSITION PROBABILITIES  $p(y|x)$  AND CHANNEL CAPACITY  $C = \max_{p(x)} I(x; y)$ . A HECKFUL STATISTICIAN PREPROCESSES THE OUTPUT BY FORMING  $\tilde{y} = g(y)$ . HE CLAIMS THIS WILL STRICTLY IMPROVE THE CAPACITY.

- (a) SHOW THAT HE IS WRONG  
 (b) UNDER WHAT CONDITIONS DOES HE NOT STRICTLY DECREASE THE CAPACITY

(a)  $I(x; y) = H(x) - H(x|y) = H(y) - H(y|x) \leq H(y) - H(g(y)|x)$

$$I(x; g(y)) = H(x) - H(x|g(y)) = H(g(y)) - H(g(y)|x)$$

$$H(x; g(y)) = H(x) + \underbrace{H(g(y)|x)}_{\geq 0} = \underbrace{H(g(y))}_{\geq 0} + \underbrace{H(x|g(y))}_{\geq 0}$$

$$\boxed{H(x) \geq H(g(y))} \quad \text{⊕}$$

$$I(x; g(y)) = \underline{H(g(y))} - H(g(y)|x) \leq H(x) - \underline{H(g(y)|x)}$$

$$H(x, g(y)|x) = H(x|x) + \underbrace{H(g(y)|x, x)}_{\geq 0} =$$

$$= H(g(y)|x) + H(x|x, g(y))$$

$$H(x|x) \geq H(g(y)|x) \quad ?$$

$$I(x; g(y)) \leq H(x) - H(g(y)|x) \geq H(x) - H(x|x)$$

$$\boxed{x \rightarrow \tilde{y} \rightarrow y} \quad \underline{I(x; \tilde{y})} \geq \underline{I(x; y)}$$

$$I(x; y) \leq H(y) - H(y|x)$$

$$I(x; g(z)) \leq H(y) - H(y|x)$$

DATA PROCESSING  
EQUATION

$$x \rightarrow y \rightarrow \tilde{y}$$

$\tilde{y} = g(z)$

$$I(x; y) \geq I(x; \tilde{y})$$

ZA DICO VANOVA  
IZBOR NA  $g(x)$   
 $\max_{1 \leq i \leq n} I(x; y) \geq \max_{1 \leq i \leq n} I(x; \tilde{y})$

(b) " " KOTI IMAGE " "

$$I(x; \tilde{y}) = H(\tilde{y}) - H(\tilde{y}|x) = H(x) - H(x|\tilde{y})$$

$$I(x; y) \leq H(y) - H(y|x)$$

$$H(y, \tilde{y}|x) = H(y|x) + H(\tilde{y}|x, y) = H(\tilde{y}|x) + H(y|x, \tilde{y})$$

IF  $\tilde{y} = g(z)$  ONE-TO-ONE MAPPING

$$\Rightarrow H(y|\tilde{y}, x) = 0 \Rightarrow H(y|x) = H(\tilde{y}|x)$$

$$\text{ALSO: } H(y) = H(\tilde{y}) + H(y|\tilde{y}) = H(\tilde{y})$$

$$0 \text{ (ONE-TO-ONE MAPPING)} \Rightarrow I(x; y) = I(x; \tilde{y})$$

Solutions Ed 1

$$x \rightarrow \tilde{y} \rightarrow y$$

$$x \rightarrow y \rightarrow \tilde{y}$$

$$I(x; \tilde{y}) \geq I(x; y)$$

$$I(x; y) \geq I(x; \tilde{y})$$

A KA VARTI I PVEZE

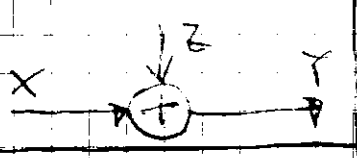
$$I(x; y) = I(x; \tilde{y})$$

DVA VARI ANO:  $H(\tilde{y}) = H(y) \text{ \& } H(y|x) = H(\tilde{y}|x)$

A TOA VARI ANO  $\tilde{y} = g(z)$  E ONE-TO-ONE

**7.2** ADDITIVE NOISE CHANNEL. FIND THE CHANNEL

CAPACITY OF THE FOLLOWING DISCRETE MEMORYLESS CHANNEL:



WHILE  $P\{Z=0\} = P\{Z=a\} = \frac{1}{2}$

THE ALPHABET FOR X IS  $\mathcal{X} = \{0, 1\}$ . ASSUME THAT

Z IS INDEPENDENT OF X. OBSERVE THAT THE CHANNEL CAPACITY DEPENDS ON THE VALUE OF 'a'

$$Y = X + Z$$

$$I(x; \tau) = ?$$

$$I(x; x+z) = ?$$

$$\max_{p \in (0,1)} I(x; \tau)$$

$$x = \{0, 1\} \quad p(x) = \{p, 1-p\}$$

$$z = \{0, a\}$$

$$p(\tau=0) = p(x=0) \cdot p(z=0) = p/2$$

$$p(\tau=1) = p(x=0) \cdot p(z=a) = (1-p) \cdot p/2$$

$$p(\tau=a) = p(x=1) \cdot p(z=0) = p \cdot 1/2$$

$$p(\tau=1+a) = p(x=1) \cdot p(z=a) = (1-p) \cdot 1/2$$

$$I(x; \tau) = H(x) - H(x|\tau) = H(\tau) - H(\tau|x)$$

$$H(\tau) = - \sum_{\tau} p(\tau) \log_2 p(\tau) = - \left[ \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)p}{2} \log_2 \frac{(1-p)p}{2} + \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)}{2} \log_2 \frac{(1-p)}{2} \right]$$

$$H(\tau|x) = p(x=0) \cdot H(\tau|x=0) + p(x=1) \cdot H(\tau|x=1)$$

$$H(\tau|x=0) = - \sum_{\tau} p(\tau|x=0) \log_2 p(\tau|x=0) = - \left[ \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)}{2} \log_2 \frac{(1-p)}{2} \right] = 1$$

$$p \in \{0, a\} \quad p(\tau|x=0) = \left\{ \frac{p}{2}, \frac{(1-p)}{2} \right\}$$

$$H(\tau|x=1) = - \sum_{\tau} p(\tau|x=1) \log_2 p(\tau|x=1) = - \left[ \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)}{2} \log_2 \frac{(1-p)}{2} \right] = 1$$

$$p \in \{1, 1+a\} \quad p(\tau|x=1) = \left\{ \frac{p}{2}, \frac{(1-p)}{2} \right\}$$

$$H(\tau|x) = p \cdot 1 + (1-p) \cdot 1 = 1$$

$$I(x; \tau) = - \left[ \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)p}{2} \log_2 \frac{(1-p)p}{2} \right] - 1$$

$$0 = \frac{p}{2} \log_2 \frac{p}{2} + \frac{(1-p)p}{2} \log_2 \frac{(1-p)p}{2} - \frac{p^2}{2} \log_2 \frac{(1-p)p}{2} - 1$$

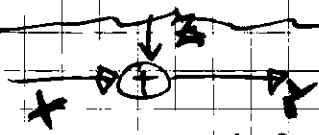
$$\frac{d}{dp} \left( \frac{p}{4} \log_2 \frac{(1-p)p^2}{2} - \frac{p^2}{2} \log_2 \frac{(1-p)p}{2} \right) = 0 \quad p = 0.59506$$

$$*(0.59506) = -1.77639$$

$$\max_{p \in (0,1)} I(x; \tau) = +1.77639$$

SECRET

$$Y = \text{mod}(X+Z)$$



$X \in \{0,1\}$   
 $Z \in \{0,1\}$

$$I(X; Z) = ? \quad I(X; Z) = H(Z) - H(Z|X)$$

$$I(X, Z; Y) = I(X; Y) + I(Z; Y|X) = I(Z; Y) + I(X; Y|Z)$$

$$I(Z; Y|X) = H(Y|X) - H(Y|X, Z)$$

ako si znas  
 $X, Z$  znas  $Y$

$$I(Z; Y|X) = H(Y|X) - H(Y|X, Z) \quad I(X, Z; Y) = I(X; Y) + H(Z|X)$$

$$I(X; Z) = H(Z) - H(Z|X)$$

$$I(X, Z; Y) = H(Z) - H(Z|X) + H(Z|X) = H(Z)$$

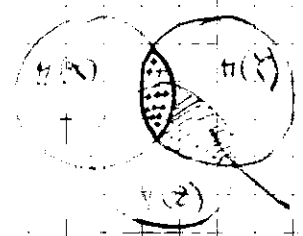
$$I(X; Z|Y) = H(Z|Y) - H(Z|X, Y)$$

$$I(X, Z; Y) = I(Z; Y) + I(X; Y|Z) = I(Z; Y) + H(Z|Z) = H(Z) - H(Z|Y) + H(Z)$$

$$+ H(Z|Z) = H(Z)$$

$$I(Z; Y) + H(Z|Z) = I(X; Y) + H(Z|X)$$

$H(X, Z)$



$$H(X, Z) = H(X) + H(Z|X)$$

$$I(X, Z; Y) = I(X; Y) + I(Z; Y|X)$$

$I(Z; Y|X)$

log 100

$$I(X, Z; Y) = H(Z)$$

ako si znas  
 $X, Z$  znas  $Y$

$$I(X, Z; Y) = I(X; Y) + I(X, Z; Y|X) = I(X; Y) + I(X; Z|Y)$$

$$I(X; Z|Y) = H(Z) - H(Z|X, Y) = H(Z) - H(Z|X, Y)$$

$$Y = \text{mod}(X+Z)$$

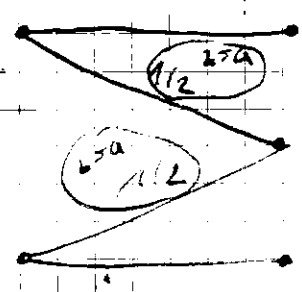
Y	Z	X
0	0	0
0	1	1
1	0	1
1	1	0

CO NAROV  $X = Z$  znas  $Y$  i  $Z$

$$H(Z|Z) = H(X|Z)$$

$X, Z$  znas  $Y$  znas  $Y$

$$H(X|Z) = H(X)$$



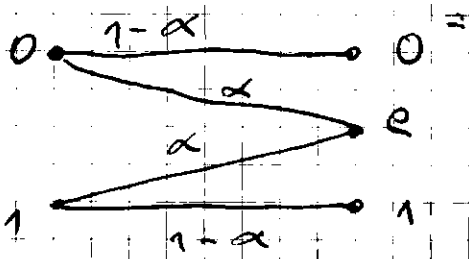
$$I(Z; Y|X) = H(Y|X) - H(Y|X, Z) = H(Z|X)$$

$$I(Z; Y|X) = H(Z|X) - H(Z|X, Y)$$

$$H(Z|X) = H(Z|X)$$

$$I(X; Z) = H(Z) - H(Z|X) = H(Z) - H(Z|X) = H(Z) - H(Z) = 0$$

MMV



$$I(x; z) = H(x) - H(x|z) = H(z) - H(z|x)$$

$$H(z|x) = P(x=0) \cdot H(z|x=0) + P(x=1) \cdot H(z|x=1) = \pi \cdot H(z|x=0) + (1-\pi) \cdot H(z|x=1)$$

$$= \pi \left[ (1-\alpha) \log(1-\alpha) + \alpha \log \alpha \right] + (1-\pi) \left[ (1-\alpha) \log(1-\alpha) + \alpha \log \alpha \right]$$

$$= [\pi + (1-\pi)] H(\alpha) = H(\alpha)$$

$$I(x; z) = H(z) - H(\alpha)$$

$$\max_{x(z)} I(x; z) = (1-\alpha) H(\alpha) - H(\alpha) = -H(\alpha)$$

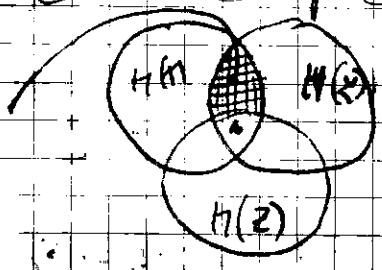
$$\alpha = \frac{1}{2}$$

$$\max I(x; z) = 1 - \frac{1}{2} = 1/2$$

$H(z) \geq H(x)$      $H(z) \geq H(x)$   
 $I(x, z; z) = H(z) = I(z; z) + I(x; z|z) = I(z; z) + H(x)$   
 $I(x; z|z) = H(x|z) - H(x|z, z) = H(x) - 0$   
 $H(z) = I(z; z) + H(x) \Rightarrow H(z) \geq H(x)$

$z = x + \gamma$      $I(x; z) = H(z) - H(z|x) = H(z) - H(\gamma|x) = H(z) - H(\gamma)$   
 $H(z|x) = H(\gamma|x)$

$H(f(x), x) = H(x) + H(f(x)|x) = H(f(x)) + H(x|f(x))$   
 $H(x) \geq H(f(x))$   
 $H(x) = H(f(x))$  IF THE MAPPING IS ONE-TO-ONE



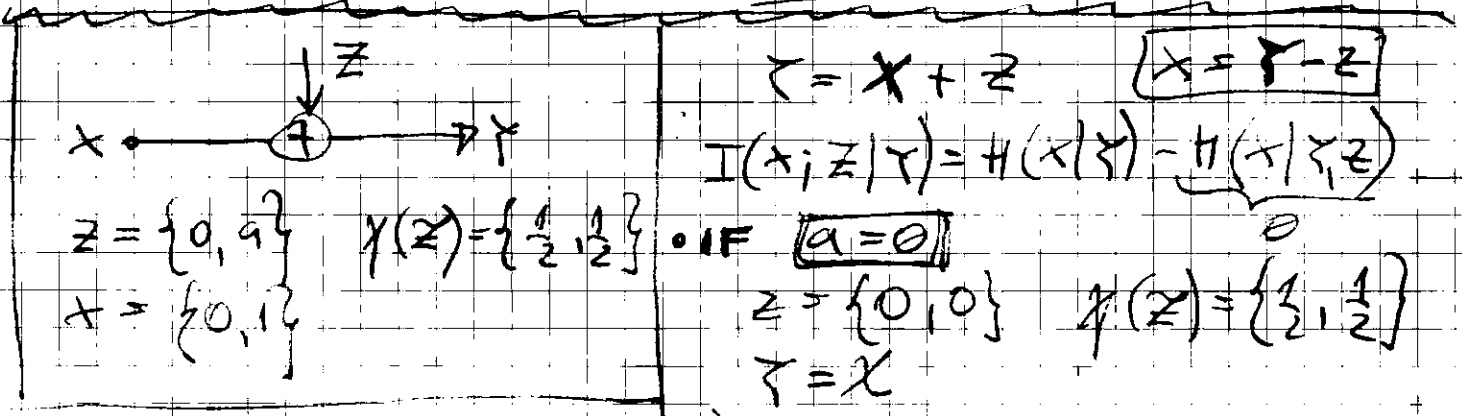
$z = (x+\gamma) \bmod 2$      $\gamma = (z-x) \bmod 2$   
 $I(x; z|z) = 1$   
 $I(z, z; x) = I(x; z) + I(x; z|z)$   
 $I(x; z) = 0 \Rightarrow A = -1$



$$I(X; Z|Y) = H(X|Z) - \underbrace{H(X|Y, Z)}_0 = \underline{H(X|Z)} \quad \begin{matrix} Y = (Z-X) \text{ mod } 2 \\ X = (Z-Y) \text{ mod } 2 \end{matrix}$$

$$H(X|Z) = \sum_{z \in \mathcal{Z}} \gamma(z) \cdot H(X|Z=z) = \frac{\gamma(z=0)}{1/2} \left[ \underbrace{\gamma(x=0|0)}_{1/2} \log \frac{1}{\gamma(0,0)} + \underbrace{\gamma(x=1|0)}_{1/2} \log \frac{1}{\gamma(0,0)} \right] + \frac{\gamma(z=1)}{1/2} \left[ \underbrace{\gamma(x=0|1)}_{1/2} \log \frac{1}{\gamma(0,1)} + \underbrace{\gamma(x=1|1)}_{1/2} \log \frac{1}{\gamma(1,1)} \right]$$

$$= \frac{1}{2} \left[ 2 \cdot \frac{1}{2} \cdot \log 2 \right] + \frac{1}{2} \left[ 2 \cdot \frac{1}{2} \cdot \log 2 \right] = \frac{1}{2} + \frac{1}{2} = 1 \text{ bit}$$



$$I(X; Z) = H(X) - H(X|Z) = H(X) \Rightarrow$$

• IF  $\boxed{a=1}$      $I(X; Z) = H(Z) - H(Z|X) = H(Z) - 1 = H(X) - H(Z)$

$$I(X; Z) = H(Z) - H(Z|X) = H(Z) - \underbrace{H(Z|X)}_{\text{same as } H(Z|X)}$$

$$H(Z|X) = H(Z|X) \quad \boxed{Z = Y - X}$$

$$\underline{H(Z|X)} = \sum_x \gamma(x) H(Z|Z=x) = \sum_x \gamma(x) H(Z+x|X) = \sum_x \gamma(x) \sum_z \underbrace{f(z+x|x)}_{\text{same as } f(z|x)} \log \frac{1}{\gamma(z+x, x)} = \sum_x \gamma(x) H(Z|x) = H(Z|x)$$

$$I(X, Z; Y) = I(X; Y) + I(Z; Y|X)$$

$$I(Z; Y|X) = H(Z|X) - \underbrace{H(Z|X, Y)}_0 = H(Z|X) - H(Y|X, Z) \Rightarrow \boxed{H(Z|X) = H(Y|X)}$$

$$I(X; Z) = H(Z) - H(Z|X) = H(X) - H(Z|X) = H(X) - H(Z)$$

$$I(Y; Z; X) = \underbrace{I(Y; X)}_0 - \underbrace{I(Z; X|Y)}_0 = I(X; Y) - H(Z|X) + H(Z|X, Y)$$

$$I(Z; X|Y) = H(Z|X) + 0 - H(X|Y, Z) = H(X|Y)$$

$$I(x; \tau) = \begin{cases} H(x) & a=0 \\ H(x) - \frac{H(z)}{1} & a=1 \end{cases}$$

$$C = \max_{Y(X)} I(x; \tau) = \begin{cases} 1 & a=0 \\ 1-1=0 & a=1 \end{cases}$$

$$C = \begin{cases} 1 & a=0 \\ 0 & a=1 \end{cases}$$

CHANNEL CAPACITY DEPENDS ON THE VALUE OF  $a$

**Example 1 section:**

$a=0$   $\tau=x \Rightarrow I(x; \tau) = H(x)$

$$C = \max_{Y(X)} I(x; \tau) = \log_2 2 = 1$$

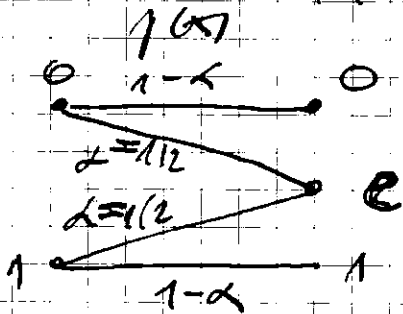
$a \neq 0, \neq 1$   $\tau \in \{0, 1, \alpha, 1+\alpha\}$

Knowing  $\tau$  we know  $x$ :

$$I(x; \tau) = H(x) - \frac{H(x|\tau)}{1} = H(x)$$

$$C = \max_{Y(X)} H(x) = 1$$

$a=1$



$$C = 1 - \alpha = 1 - \frac{1}{2} = \frac{1}{2}$$

$$I(\tau; x) = H(\tau) - H(\tau|x)$$

$$H(\tau|x) = \sum_{\tau \in \mathcal{R}} p(x) H(\tau|x=x) = p(0) \cdot H(\tau|x=0) +$$

$$+ p(1) \cdot H(\tau|x=1) = p(0) \cdot H(\alpha) + p(1) \cdot H(\alpha) = H(\alpha)$$

$$H(\tau) = -H(\alpha) + 1 - \alpha$$

$$I(\tau; x) = -H(\alpha) + 1 - \alpha - H(\alpha) = 1 - \alpha - 2H(\alpha)$$

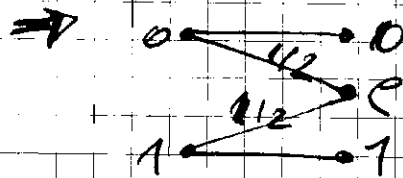
$$I(\tau; x) = 1 - \frac{1}{2} = \frac{1}{2} \quad \text{(BITS PER TRANSMISSION)}$$

$a=-1$

$\tau \in \{-1, 0, 1\}$

$$I(x; \tau) = 1 - \alpha = \frac{1}{2}$$

bits/transmission



$$H(\tau) = \frac{(1-\alpha)}{2} \log \left[ \frac{(1-\alpha)}{2} \right]^{-1} + \alpha \log \alpha^{-1} + \frac{1-\alpha}{2} \log \left( \frac{2}{1-\alpha} \right)$$

$$= (1-\alpha) \log \frac{2}{1-\alpha} + \alpha \log \frac{1}{\alpha} = (1-\alpha) \log 2 + (1-\alpha) \log \frac{1}{1-\alpha} + \alpha \log \frac{1}{\alpha} = (1-\alpha) + H(\alpha)$$

$$H(\tau) = H(\tau, \epsilon) = H(\tau) + \underbrace{H(\epsilon|\tau)}_{=0} = H(\epsilon) + \underbrace{H(\tau|\epsilon)}_{=0}$$

$$H(\tau, \epsilon) = H((1-\pi)(1-\alpha), \alpha, \pi(1-\alpha)) = \left[ (1-\pi)(1-\alpha) \log \frac{1}{(1-\pi)(1-\alpha)} + \alpha \log \frac{1}{\alpha} + \pi(1-\alpha) \log \frac{1}{\pi(1-\alpha)} \right]$$

$$= (1-\pi)(1-\alpha) \log \frac{1}{(1-\pi)} + (1-\pi)(1-\alpha) \log \frac{1}{(1-\alpha)} + \alpha \log \frac{1}{\alpha} + \pi(1-\alpha) \log \frac{1}{\pi} + \pi(1-\alpha) \log \frac{1}{(1-\alpha)}$$

$$= (1-\alpha) \left[ (1-\pi) \log \frac{1}{1-\pi} + \pi \log \frac{1}{\pi} \right] + H(\alpha) = (1-\alpha) H(\pi) + H(\alpha)$$

$\tau = \frac{1}{2}$       $H(\tau) = (1-\alpha) + H(\alpha)$

$$I(x; \tau) = H(\tau) - H(\tau|x) = (1-\alpha) + H(\alpha) - H(\alpha) = (1-\alpha)$$

$$I(x; \tau) = 1-\alpha \quad \forall \quad C = 1-\alpha$$

CHARACTER OF BINARY CHANNEL WITH CLIPPING

**PROBLEM 7.3** CHANNELS WITH MEMORY HAVE HIGHER CAPACITY. CONSIDER BINARY SYMMETRIC CHANNEL WITH  $Z_i = X_i \oplus Z_i$   $X_i, Z_i \in \{0,1\}$ . SUPPOSE THAT  $\{Z_i\}$  HAS CONSTANT MARGINAL PROBABILITIES.

$P\{Z_i=1\} = \gamma = 1 - P\{Z_i=0\}$  BUT THAT  $Z_1, Z_2, \dots, Z_n$  ARE NOT NECESSARILY INDEPENDENT. ASSUME THAT  $Z_1$  IS INDEPENDENT FROM  $Z_2$ .

LET  $C = 1 - H(\gamma, 1-\gamma)$ . SHOW THAT

$$\max_{\gamma(x_1, x_2, \dots, x_n)} I(x_1, x_2, \dots, x_n; z_1, z_2, \dots, z_n) \geq nC$$

$$R \leq p_e^{(n)} R + \frac{1}{n} + C$$

$p_e^{(n)} = P\{g(\tau^n) \neq W\}$       $C_{FB} = C = \max_{\gamma \in [0,1]} I(\tau; \tau)$

$$nR = H(W) = H(W; \hat{W}) + I(W; \hat{W}) \leq 1 + P_e nR + I(W; \hat{W})$$

$$\Leftrightarrow n + P_e nR \leq I(W; \hat{W})$$

$$I(W; \hat{W}) = H(\hat{W}) - H(\hat{W}|W) = H(\hat{W}) - \sum_{i=1}^n H(\hat{w}_i | \hat{w}_1^{i-1}, W)$$

$$\stackrel{X_i = g(\hat{w}_1^{i-1}, W)}{=} H(\hat{W}) - \sum_{i=1}^n H(\hat{w}_i | \hat{w}_1^{i-1}, W, X_i) =$$

$$= H(\hat{W}) - \sum_{i=1}^n H(\hat{w}_i | X_i) \leq \sum_{i=1}^n H(\hat{w}_i) + \sum_{i=1}^n H(\hat{w}_i | X_i)$$

$$= \sum_{i=1}^n I(\hat{w}_i; X_i) \leq n \cdot C$$

$$nR \leq n + P_e nR + n \cdot C \quad \left[ R \leq \frac{1}{n} + P_e R + C \right]$$

$$n \rightarrow \infty \quad \left[ R \leq C \right] \quad \left[ C \geq C \right]$$

$$P(V \neq \hat{V}) = \sum_{V^u} \sum_{V^d} P(V^u) P(V^d | V^u) I(g(V^u) \neq V^d)$$

$$\left[ H(V) + \epsilon = R \leq C \right] \quad V^u \rightarrow X^u \rightarrow \hat{V}^u \rightarrow \hat{V}^d$$

$$H(V) \leq H(V^u) = H(V | \hat{V}) + I(V; \hat{V}) \leq \frac{1}{n} (1 + P(V \neq \hat{V}) \cdot n \cdot C)$$

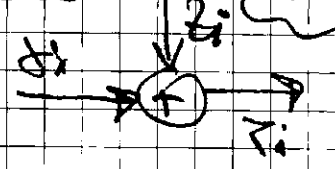
$$+ I(V; \hat{V}) \leq \frac{1}{n} + P(V \neq \hat{V}) \cdot C + \frac{1}{n} I(X^u; \hat{V}^u) \leq$$

$$\leq \frac{1}{n} + P(V \neq \hat{V}) \cdot C + C \leq n \cdot C$$

$$n \rightarrow \infty \quad \left[ H(V) \leq C \right]$$

$$I(X^u; \hat{V}^u) = H(\hat{V}^u) - H(\hat{V}^u | X^u) = H(\hat{V}^u) - \sum_{i=1}^n H(\hat{v}_i | \hat{v}_1^{i-1}, X^u)$$

$$= H(\hat{V}^u) - \sum_{i=1}^n H(\hat{v}_i | \hat{v}_1^{i-1}, X^u) = H(\hat{V}^u) - \sum_{i=1}^n H(\hat{v}_i | X^u)$$



$$I(\hat{v}_i; \hat{v}_i) = H(\hat{v}_i) - H(\hat{v}_i | X^u) =$$

$$= H(\hat{v}_i) - H(\hat{v}_i | X^u) = H(\hat{v}_i) - H(\hat{v}_i | X^u)$$

$$= H(\hat{v}_i) - H(\hat{v}_i)$$

$$\left[ I(\hat{v}_i; \hat{v}_i) = H(\hat{v}_i) - H(\hat{v}_i) \right]$$

~~Handwritten scribbles and crossed-out text at the bottom of the page.~~

$$H(x_i | x_i) = \sum_{x_i} \gamma(x_i) \cdot H(\tilde{x}_i | x_i = x_i)$$

$$H(z_i | x_i) = \sum_{x_i} \gamma(x_i) H(z_i | x_i = x_i) = \sum_{x_i} \gamma(x_i) H(\underbrace{z_i + x_i}_{\tilde{x}_i} | x_i = x_i)$$

$$= \sum_{x_i} \gamma(x_i) H(\tilde{x}_i | x_i = x_i) = H(\tilde{x}_i | x_i)$$

$$I(x^N, z^N) = H(x^N) - \sum_{i=1}^N H(x_i | z_1^{i-1}, x^N) \stackrel{\text{①}}{=} H(x^N) - \sum_{i=1}^N H(x_i | z_1^{i-1}, x^N)$$

$$H(x^N | x^N) = H(z^N | x^N)$$

$$\text{①} = H(x^N) - H(z^N | x^N) \geq H(x^N) - H(z^N)$$

$$\Rightarrow H(z^N) = \sum_{i=1}^N H(z_i | z_i^i) \leq H(z) \cdot N$$

$$\Rightarrow H(x^N) - N \cdot H(z) = N \cdot H(x) - N \cdot H(z) = N \cdot (H(x) - H(z))$$

$$H(x^N) = \sum_{x^N} H(x_i | z_1^{i-1}, x^N) = N \cdot H(x)$$

INDEPENDENT

$$= N \cdot I(x; z) = N \cdot C$$

→ OVA e derivativo ⇒ zorro 370

$$H(z^N) = \sum_{z^N} H(z_i | z_1^{i-1}) < \sum_{z_i} H(z_i) = N \cdot H(z)$$

$$H(z) = 1 - H(p) \Rightarrow$$

$$I(x^N; z^N) \geq N \cdot C = N \cdot (1 - H(p))$$

Exam 1 Solution (or also no plow  $x^N$ ):

$$I(x^N, z^N) = H(x^N) - H(x^N | z^N) = H(x^N) - H(z^N | x^N) = 0$$

$$H(x^N | z^N) = H(z^N | x^N) \quad \tilde{z}_i = z_i - x_i \text{ const}$$

$$H(x^N | z^N) = \sum_{x^N} \gamma(x_i^N) H(x^N | z^N = \tilde{x}_i^N) =$$

$$= \sum_{y_i} p(y_i) \cdot H(y_i - x_i^y | y_i) = \sum_{y_i} p(y_i) H(z_i^y | y_i)$$

$$\text{p63 } \Rightarrow H(x^y) - H(z^y) = H(x^y) - \sum_{i=1}^4 H(z_i | z_i^{y-1}) \geq$$

$$\geq H(x^y) - \sum_{i=1}^4 H(z_i) = H(x^y) - 4 \cdot H(z) =$$

$$= H(x^y) - 4 \cdot H(x) = 4 \cdot H(x) - 4 \cdot H(x)$$

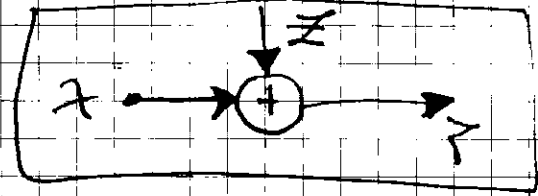
$$H(x^y) = \sum H(x_i | x_i^{y-1}) = H(x) = 4 \cdot (1 - H(x))$$

$$H(x) \leq \log_2 4 = 2 = 1$$

$$= 4 \cdot C \Rightarrow I(x^y; z^y) \geq 4 \cdot C \quad \text{PROVED!!!}$$

**PROBLEM 7.4** CHANNEL CAPACITY. CONSIDER THE DISCRETE MEMORYLESS CHANNEL  $Y = X + Z \pmod{11}$  WHERE:

$$Z = \begin{pmatrix} 1 & 2 & 3 \\ \frac{1}{3} & \frac{1}{2} & \frac{1}{2} \end{pmatrix}$$



AND  $X \in \{0, 1, \dots, 10\}$ . ASSUME THAT  $Z$  IS INDEPENDENT OF  $X$ .

- (a) FIND THE CAPACITY.
- (b) WHAT IS MAXIMIZING  $I^*(X)$ ?

$$\begin{aligned} \text{(a)} \quad I(X; Z) &= H(Z) - H(Z|X) = H(Z) - H(Z|X) = \\ &= H(Z) - H(Z) = \log_2 4 - H\left(\frac{1}{3}, \frac{1}{2}, \frac{1}{2}\right) = \\ &= \log_2(4 - 3 \cdot \frac{1}{2} \cdot \log_2) = \log_2(4 - \log_2 3) = \log_2 \frac{11}{2} = \underline{\underline{1.88}} \end{aligned}$$

$$\begin{aligned} \text{(b)} \quad I(X; Z) &= H(X) - H(X|Z) = H(X) - H(Z|X) = \\ &= H(X) - H(Z) = \log_2 11 - \log_2 4 = \log_2 11 - \log_2 4 \end{aligned}$$

at max p(x)  $I(X; Z) = C = \log_2 11$  FOR  $p(x) = \frac{1}{11}$

$$p(x=i) = \frac{1}{11} \quad i=0,1,\dots,10$$

**PROBLEM 7.5** USING TWO CHANNELS AT ONCE. CONSIDER TWO DISCRETE MEMORYLESS CHANNELS  $(\mathcal{X}_1, p(y_1|x_1), \mathcal{Z}_1)$

$(\mathcal{X}_2, p(y_2|x_2), \mathcal{Z}_2)$  WITH CAPACITIES  $C_1$  AND  $C_2$ , RESPECTIVELY. A NEW CHANNEL

$(\mathcal{X}_1 \times \mathcal{X}_2, p(y_1|x_1) \times p(y_2|x_2), \mathcal{Z}_1 \times \mathcal{Z}_2)$  IS

FORMED IN WHICH  $x_1 \in \mathcal{X}_1$  AND  $x_2 \in \mathcal{X}_2$  ARE SENT SIMULTANEOUSLY, RESULTING IN  $(y_1, y_2)$ . FIND THE CAPACITY OF THIS CHANNEL.

$$= \max_{p(x)} I(x; z) = H(x) - H(x|z) = H(z) - H(z|x)$$

$$C_1 = \max_{p(x_1)} I(x_1; z_1) = H(z_1) - H(z_1|x_1)$$

$$C_2 = \max_{p(x_2)} I(x_2; z_2) = H(z_2) - H(z_2|x_2)$$

$$\mathcal{X} = \mathcal{X}_1 \times \mathcal{X}_2 \quad \mathcal{Z} = \mathcal{Z}_1 \times \mathcal{Z}_2$$

$$p(x) = p(x_1) \cdot p(x_2) \quad x_1, x_2 \text{ independent}$$

$$\mathcal{Z} = \mathcal{Z}_1 \times \mathcal{Z}_2 \quad p(z) = p(z_1) \cdot p(z_2) = p(z_1) p(z_2)$$

$$H(x) = H(x_1) + H(x_2)$$

$$H(z) = H(z_1) + H(z_2)$$

$$H(z|x) = H(z_1 \times z_2 | x_1 \times x_2)$$

$$H(z_1 \times z_2 | x_1 \times x_2) = \sum_{x_1 \times x_2} p(x_1 \times x_2) H(z_1 \times z_2 | x_1 \times x_2)$$

$$= \sum_{x_1 \times x_2} p(x_1 \times x_2) \sum_{z_1 \times z_2} p(z_1 \times z_2 | x_1 \times x_2) \cdot \log \frac{1}{p(z_1 \times z_2 | x_1 \times x_2)}$$

$$= \sum_{\substack{x_1 \times x_2 \\ y_1 \times y_2}} p(x_1 \times x_2, y_1 \times y_2) \log \frac{1}{p(y_1 \times y_2 | x_1 \times x_2)} =$$

$$= \sum_{\substack{x_1 \times x_2 \\ y_1 \times y_2}} p(x_1 \times x_2, y_1 \times y_2) \log p(y_1 | x_1) \cdot p(y_2 | x_2) =$$

$$= \sum_{\substack{x_1 \times x_2 \\ y_1 \times y_2}} p(x_1 \times x_2, y_1 \times y_2) \log p(y_1 | x_1) + \sum_{\substack{x_1 \times x_2 \\ y_1 \times y_2}} p(x_1 \times x_2, y_1 \times y_2) \log p(y_2 | x_2) = H(z_1|x_1) + H(z_2|x_2) \text{ as}$$

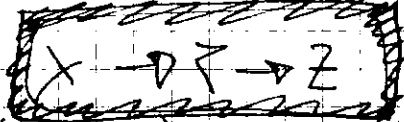
$$C = \max_{\gamma(t_1), \gamma(t_2)} [ \pi(z_1) + \pi(z_2) - \pi(z_1|t_1) - \pi(z_2|t_2) ]$$

$$= \max_{\gamma(t_1), \gamma(t_2)} [ \pi(z_1) - \pi(z_1|t_1) ] + \max_{\gamma(t_2)} [ \pi(z_2) - \pi(z_2|t_2) ]$$

$$= \max_{\gamma(t_1)} I(z_1; t_1) + \max_{\gamma(t_2)} I(z_2; t_2) = C_1 + C_2$$

$$C = C_1 + C_2$$

EDITION 1 SOLUTION



MARKOVITZ:

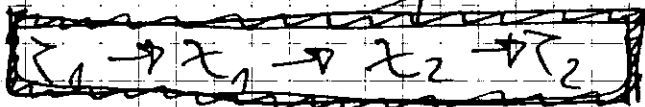
$$p(x, z | \tau) = \frac{p(x, z, \tau)}{p(\tau)} = \frac{p(x, \tau) \cdot p(z | x, \tau)}{p(\tau)}$$

$$= \frac{p(x, \tau) \cdot p(z | \tau)}{p(\tau)} = \frac{p(\tau) \cdot p(x | \tau) \cdot p(z | \tau)}{p(\tau)}$$

$$p(x, z | \tau) = p(x | \tau) \cdot p(z | \tau)$$

$$p(\tau, z | x) = \frac{p(x, \tau, z)}{p(\tau)} = \frac{p(x, \tau) \cdot p(z | x, \tau)}{p(\tau)}$$

$$= \frac{p(x) \cdot p(\tau | x) \cdot p(z | \tau)}{p(\tau)} = p(\tau | x) \cdot p(z | \tau)$$



$$p(\tau_1, \tau_2 | x_1, z_1) = \frac{p(x_1, z_1, \tau_1, \tau_2)}{p(\tau_1, \tau_2)}$$

$$= \frac{p(x_1, \tau_1) \cdot p(z_1 | x_1, \tau_1) \cdot p(\tau_2 | x_1, z_1, \tau_1)}{p(\tau_1, \tau_2)} = \frac{p(\tau_1, \tau_2) \cdot p(z_1 | \tau_1)}{p(\tau_1, \tau_2)}$$

$$= \frac{p(z_1 | \tau_1)}{p(\tau_1)} = p(z_1) \cdot p(\tau_1 | z_1) = p(\tau_1) \cdot p(z_1 | \tau_1)$$

$$= \frac{p(x_1) \cdot p(\tau_1 | x_1) \cdot p(\tau_2) \cdot p(z_1 | \tau_2)}{p(x_1, \tau_2)} = \frac{p(\tau_1, \tau_2) \cdot p(z_1 | \tau_2)}{p(x_1, \tau_2)}$$

$$\frac{p(x_1, z_1, \tau_1, \tau_2)}{p(x_1, \tau_2)} = p(\tau_1 | x_1) \cdot p(\tau_2 | z_1) = p(\tau_1, \tau_2 | x_1, z_1)$$



$$p(x_1, x_2, \gamma_1, \gamma_2) = p(x_1, x_2) \cdot p(\gamma_1 | x_1) \cdot p(\gamma_2 | x_2)$$

$$p(\gamma_1, \gamma_2 | x_1, x_2) = p(\gamma_1 | x_1) \cdot p(\gamma_2 | x_2)$$

$$I(x_1, x_2; \gamma_1, \gamma_2) = H(x_1, x_2) - H(\gamma_1, \gamma_2 | x_1, x_2) = \textcircled{*}$$

$$H(\gamma_1, \gamma_2 | x_1, x_2) = H(\gamma_1 | x_1, x_2) + H(\gamma_2 | x_1, x_2) =$$

$$= \underbrace{H(\gamma_1 | x_1)}_{\textcircled{*}} + H(\gamma_2 | x_2) = \underbrace{H(\gamma_1 | x_1)}_{\textcircled{*}} + H(\gamma_2 | x_2)$$

we are done

$$H(\gamma_1 | x_1, x_2) = ? \quad H(x_1, \gamma_1 | x_2) = H(x_1 | x_2) + H(\gamma_1 | x_2, x_1)$$

$$= H(\gamma_1 | x_2) + H(x_1 | \gamma_1, x_2)$$

$$p(\gamma_1 | x_1, x_2) = \frac{p(x_1, x_2, \gamma_1)}{p(x_1, x_2)} = \frac{p(x_1, \gamma_1) \cdot p(x_2 | x_1, \gamma_1)}{p(x_1) \cdot p(x_2)}$$

$$= \frac{p(x_1) \cdot p(\gamma_1 | x_1) \cdot p(x_2 | x_1, \gamma_1)}{p(x_1) \cdot p(x_2)} \quad \left( p(x_2 | x_1) = p(\gamma_1 | x_1) \cdot p(x_2 | x_1, \gamma_1) \right)$$

$$H(\gamma_1 | x_1, x_2) = \sum_{x_1, x_2, \gamma_1} \frac{p(\gamma_1 | x_1, x_2) \cdot p(x_1, x_2)}{p(x_1, x_2)} \log \frac{p(x_1, x_2)}{p(\gamma_1 | x_1, x_2) \cdot p(x_1, x_2)}$$

$$\textcircled{*} = H(x_1, x_2) - H(\gamma_1 | x_1, x_2) - H(\gamma_2 | x_1, x_2) \leq H(x_1) + H(x_2) - H(\gamma_1 | x_1) - H(\gamma_2 | x_2) = I(x_1; \gamma_1) + I(x_2; \gamma_2)$$

$$C = \min_{p(x_1, x_2)} I(x_1, x_2; \gamma_1, \gamma_2) \leq \min_{p(x_1, x_2)} I(x_1; \gamma_1) + \min_{p(x_1, x_2)} I(x_2; \gamma_2)$$

$$+ \max_{p(x_1, x_2)} I(x_1; \gamma_1) + \max_{p(x_1, x_2)} I(x_2; \gamma_2) = \max_{p(x_1)} I(x_1; \gamma_1) + \max_{p(x_2)} I(x_2; \gamma_2)$$

$$= C_1 + C_2 \quad \left( C = C_1 + C_2 \right)$$

$$\textcircled{\blacksquare} \quad X \rightarrow Z \rightarrow Y \quad H(Z | X, Y) = H(Z | Y) \quad / \cdot H(X, Y)$$

$$H(X, Y) \cdot H(Z | X, Y) = H(X, Y) \cdot H(Z | Y)$$

$$H(X, Y, Z) = H(Z) \cdot H(X | Z) \cdot H(Y | Z) = H(X | Z) \cdot H(Z) \cdot H(Y | Z)$$

$$\boxed{H(X | Y, Z) = H(X | Z)} \quad \text{DOWNSIDE !!!}$$

$$(1-p-q)^2 = (1-q)^2 - 2(1+q)q + q^2$$

$$(1-q-p)^2 = (1-q)^2 - 2(1+q)q + q^2$$

$$\frac{1}{2} (1 - (1-2q)^n)$$

No MATRAN POSIV:

$[V D] = \text{eig}(A)$       $V = \begin{bmatrix} 1 & -1 \\ 1 & 1 \end{bmatrix}$       $D = \begin{bmatrix} 1 & 0 \\ 0 & 1-2q \end{bmatrix}$

$A^n = V \cdot D^n \cdot V^{-1}$

$D^n = \begin{bmatrix} 1 & 0 \\ 0 & (1-2q)^n \end{bmatrix}$

$A^n = \begin{bmatrix} \frac{1}{2}(1+(1-2q)^n) & \frac{1}{2}(1-(1-2q)^n) \\ \frac{1}{2}(1-(1-2q)^n) & \frac{1}{2}(1+(1-2q)^n) \end{bmatrix}$

$P_e = \frac{1}{2} (1 - (1-2q)^n)$

EXACTION 1 SOLUTION: PROBABILITY OF ERROR FOR CASCADE CHANNEL IS SUM OF ODD TERMS OF BINOMIAL EXPANSION:

WITH  $x=q$       $z=1-q$

$$\frac{1}{2} (x+z)^n - \frac{1}{2} (z-x)^n = \frac{1}{2} (q+1-q)^n - \frac{1}{2} (1-q-q)^n =$$

$$= \frac{1}{2} (1 - (1-2q)^n)$$

NUOQU ZAH FXTA MMV

**Problem 7.8** Z-CHANNEL THE Z CHANNEL HAS INPUT AND OUTPUT ALPHABETS AND TRANSITION PROBABILITIES  $P(y|x)$  GIVEN BY THE FOLLOWING MATRIX:

$$Q = \begin{bmatrix} 1 & 0 \\ \alpha & \alpha \end{bmatrix} \quad x, y \in [0, 1]$$

FIND THE CAPACITY OF THE Z CHANNEL AND MAXIMIZING INPUT PROBABILITY DISTRIBUTION.

$$C = \max_{p(x)} I(x; y) = H(y) - H(y|x)$$

$$H(y|x) = \sum_x p(x) \cdot H(y|x=x)$$

(69)

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1/2 & 1/2 \end{bmatrix}^T \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix}^T \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} \quad \begin{matrix} X_1 \in \{x_1, x_2\} \\ X_2 \in \{x_1, x_2\} \end{matrix}$$

$$Y_1 = p_{11}X_1 + p_{12}X_2 \quad Y_2 = p_{21}X_1 + p_{22}X_2$$

$$H(Y|X=x_1) = p_{11} \log \frac{1}{p_{11}} + p_{21} \log \frac{1}{p_{21}}$$

$$H(Y|X=x_2) = p_{12} \log \frac{1}{p_{12}} + p_{22} \log \frac{1}{p_{22}}$$

$$H(Y|X=x_1) = 1 \log \frac{1}{1} = 0$$

$$H(Y|X=x_2) = \frac{1}{2} \log \frac{1}{1/2} + \frac{1}{2} \log \frac{1}{1/2} = 1$$

$$H(Y|X) = \sum p(x) H(Y|X=x) = p(x_1) H(Y|X=x_1) +$$

$$p(x_2) H(Y|X=x_2) = 0 + p(x_2)$$

$$C = H(Y) - p(x_2)$$

$$\max H(Y) = \log 2 = \log 2 = 1$$

$$C = 1 - p(x_2)$$

$$p(x_2) = \frac{1}{2} \quad \text{UNIFORM DISTR}$$

$$C = 1 - 1/2 = 1/2$$

**EXERCISE 2 SOLUTION**

$$H(Y|X) = p(x_2) = P_r(Z=x_2) = P_r(Z=1) = x$$

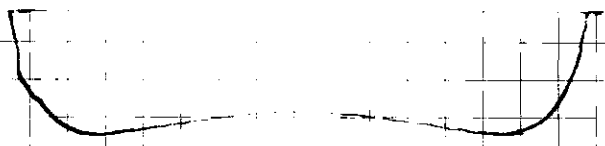
$$H(Y) = \underbrace{P_r(Z=x_1)}_0 \log \frac{1}{P_r(Z=x_1)} + \underbrace{P_r(Z=x_2)}_x \log \frac{1}{P_r(Z=x_2)} =$$

$$H(Y) = H(P_r(Z=1)) = H(P_r(X=x_2) P_r(Z=x_2|X=x_2)) =$$

$$\cancel{H(P_r(X=x_2))} = H(P_r(X=x_2)) = H\left(\frac{P_r(X=x_2)}{2}\right) = H\left(\frac{x}{2}\right)$$

$$I(x, Y) = H(Y) - x = \frac{x}{2} \log \left(\frac{2}{x}\right) - x$$

$$\frac{dI(x, Y)}{dx} = \frac{1}{2} \log \frac{2}{x} + \frac{x}{2} \cdot \frac{-1}{x} - 1 = \frac{1}{2} \log \frac{2}{x} - \frac{1}{2} - 1$$



(70)

$$\begin{bmatrix} Y_1 \\ Y_2 \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1/2 & 1/2 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix} = \begin{bmatrix} 1 & 1/2 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}$$

$$H(\tau|x) = P_1(X=X_2) = P_1(X=1) = x$$

$$H(\tau) = P_1(\tau=Y_1) \ln P_1(\tau=Y_1) - P_1(\tau=Y_2) \ln P_1(\tau=Y_2)$$

$$\begin{aligned} P_1(\tau=Y_1) &= P_1(X=X_1) \cdot P_1(\tau=Y_1|X=X_1) + P_1(X=X_2) \cdot P_1(\tau=Y_1|X=X_2) \\ P_1(\tau=Y_2) &= P_1(X=X_1) \cdot P_1(\tau=Y_2|X=X_1) + P_1(X=X_2) \cdot P_1(\tau=Y_2|X=X_2) \\ &= (1-x) \cdot p_{22} + x \cdot p_{22} = \frac{1}{2}(1-x) + 0 \end{aligned}$$

$$P_1(\tau=Y_1) = x + (1-x) \cdot \frac{1}{2} = \frac{x}{2} + \frac{1-x}{2} = \frac{1+x}{2}$$

$$\begin{aligned} P_1(\tau=Y_1) + P_1(\tau=Y_2) &= \frac{1}{2}(1-x) + \frac{1}{2}(x+1) = \\ &= \frac{1}{2} - \frac{x}{2} + \frac{x}{2} + \frac{1}{2} = 1 \end{aligned}$$

$$H(\tau) = - \frac{x+1}{2} \ln \frac{x+1}{2} - \frac{1-x}{2} \ln \frac{1-x}{2}$$

$$= - \left[ \frac{x}{2} \ln \frac{x+1}{2} + \frac{1}{2} \ln \frac{x+1}{2} + \frac{1-x}{2} \ln \frac{1-x}{2} + \frac{1}{2} \ln \frac{1-x}{2} \right]$$

$$= - \left[ \frac{x}{2} \ln \frac{x+1}{1-x} + \frac{1}{2} \ln \frac{x+1}{1-x} \right] = \frac{x+1}{2} \ln \frac{x+1}{1-x}$$

$$I(x, \tau) = - \frac{x+1}{2} \ln \frac{x+1}{1-x} - x = \frac{x+1}{2} \ln \frac{1-x}{x+1} - x$$

$$\frac{\partial I(x, \tau)}{\partial x} = \frac{1}{2} \ln \frac{1-x}{x+1} + \frac{x+1}{2} \cdot \frac{-1}{x+1} - 1 = \frac{1}{2} \ln \frac{1-x}{x+1} - 1$$

$$= \frac{1}{2} \ln \frac{1-x}{x+1} + \frac{1}{2} \frac{-x-1-1-x}{\ln 2} - 1 = \frac{1}{2} \ln \frac{1-x}{x+1} - \frac{1}{\ln 2} - 1$$

$$= \frac{1}{2} \ln \frac{1-x}{x+1} - \frac{\ln e}{\ln 2} - 1 = \frac{1}{2} \ln \frac{1-x}{x+1} - \ln e - 1$$

(T1)

$$P(Y=Y_1) = (1-x) + x \cdot \frac{1}{2} = 1 - \frac{x}{2}$$

$$P(Y=Y_2) = x \cdot \frac{1}{2} + (1-x) \cdot \frac{1}{2} = \frac{x}{2}$$

$$H(x) = H(\pi) = H\left(\frac{x}{2}\right)$$

NA SCETHIYANASTA SYKHA  
IMOV GRESHA !!!  
IMOV ZEMEND!  
 $P(X=x) = x, \pi$   
TAKA  $P(X=x_2) = x$

$$I(x, \pi) = \frac{1}{2} \log \frac{2}{x} + \left(1 - \frac{x}{2}\right) \log \frac{2}{2-x} - x =$$

$$= \frac{x}{2} \log \frac{2}{x} - \frac{x}{2} \log \frac{2}{2-x} + \log \frac{2}{2-x} - x =$$

$$= \frac{1}{2} \log \frac{2}{x} \frac{2-x}{2} + \log \frac{2}{2-x} - x = \frac{1}{2} \log \frac{2-x}{x} + \log \frac{2}{2-x} - x$$

$$\frac{dI(x, \pi)}{dx} = \frac{1}{2} \log \frac{2-x}{x} + \frac{1}{2} \frac{x}{2-x} \cdot \frac{-1 \cdot x - (2-x)}{x^2 (1/2)} + \frac{2(2-x)(2-x)^{-2} - 1}{2(2-x)}$$

$$= \frac{1}{2} \log \frac{2-x}{x} + \frac{x - 2 + x}{2 \cdot 2(2-x)} + \frac{(2-x)}{2 \cdot 2(2-x)^2} - 1 =$$

$$= \frac{1}{2} \log \frac{2-x}{x} + \frac{1}{2 \cdot 2(2-x)} + \frac{1}{2 \cdot 2(2-x)} - 1 =$$

$$= \frac{1}{2} \log \frac{2-x}{x} - 1 = \frac{1}{2} \log \left( \frac{1 - \frac{x}{2}}{\frac{x}{2}} \right) - 1 = 0$$

~~Handwritten scribbles and crossed-out equations.~~

$$\frac{1}{2} \log \frac{1 - \frac{x}{2}}{\frac{x}{2}} = 1 \quad \log \frac{1 - \frac{x}{2}}{\frac{x}{2}} = 2$$

$$\frac{1 - \frac{x}{2}}{\frac{x}{2}} = 4 \quad 1 - \frac{x}{2} = 2x \quad 2x + \frac{x}{2} = 1$$

$$\frac{5x}{2} = 1$$

$$x = \frac{2}{5}$$

$$C = \max_{Y|X} I(x, \pi) = H\left(\frac{2}{5}, \frac{1}{2}\right) - \frac{2}{5}$$

$$H\left(\frac{2}{5}\right) = \frac{1}{5} \log 5 + \frac{4}{5} \log \frac{5}{4} = 0.922$$

$$C = H\left(\frac{2}{5}\right) - \frac{2}{5} = 0.322$$

IT IS REDUNDANT THAT  $P(X=1) = \frac{1}{2}$  BECAUSE  $X=1$  IS THE NOISE.

NPU TO THE CHANNELS

**Fig 7.9 SUBOPTIMAL CODES** FOR THE Z-CHANNEL OF PROBLEM 7.8, ASSUME THAT WE CHOOSE  $(2^{nL})$  CODES AT RANDOM WHERE EACH CODEWORD IS A SEQUENCE OF FAIR COIN TOSSES. THIS WILL NOT ACHIEVE CAPACITY. FIND THE MAXIMUM RATE  $R$  SUCH THAT THE PROBABILITY OF ERROR  $P_e^{(n)}$  AVERAGED OVER THE RANDOMLY GENERATED CODES TENDS TO ZERO AS THE BLOCK LENGTH  $n \rightarrow \infty$ .

$$nR = H(W) = H(W|\bar{W}) + I(W; \bar{W}) \leq \underbrace{1 + P_e^{(n)}}_{\text{Fano}} nR + nC$$

$$P_e^{(n)} = \frac{1}{2^{nR}} \sum_{i=1}^M \lambda(i)$$

$n=2$

00	10
01	11

$n=3$

000	100
001	101
010	110
011	111

$$\frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2^2} = \frac{1}{4}$$

$$\frac{1}{2} \cdot \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{2^3}$$

$$Q = \begin{bmatrix} 1 & 0 \\ 1/2 & 1/2 \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \quad \begin{bmatrix} \gamma_{11} & \gamma_{21} \\ \gamma_{12} & \gamma_{22} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1 & 1/2 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} 0 \\ 1 \end{bmatrix}$$

$13.5 = 10 \log \frac{P}{12W}$        $10^{1.35} 12W \approx P$        $(P = 22.4W)$

$$I(W; \bar{W}) \leq I(X^n; Y^n) = H(Y^n) - \sum_{i=1}^n H(Y_i | X_i)$$

$$\leq \sum_{i=1}^n H(Y_i) - \sum_{i=1}^n H(Y_i | X_i) = \sum_{i=1}^n H(X_i, Y_i) \leq nC$$

$$\lambda_i = P(g(Y^n) \neq i | X^n = X^n(i)) = \sum_{Y^n} P(Y^n | X^n(i)) \cdot I(g(Y^n) \neq i)$$

$$P_e^{(n)} = \sum_{i=1}^M \underbrace{p(X^n(i))}_{\text{UNIFORM}} \cdot \lambda_i = \frac{1}{2^{nR}} \sum_{i=1}^M \lambda_i$$

$$P(Y^n | X^n(i)) = P(Y_1 | X^n(i)) \cdot P(Y_2 | Y_1, X^n(i)) \cdots P(Y_n | Y_1^{n-1}, X^n(i))$$

$$= P(Y_1 | X_1) \cdot P(Y_2 | X_2) \cdots P(Y_n | X_n)$$

(7)

$$\begin{bmatrix} P(X=0) \\ P(X=1) \end{bmatrix} = \begin{bmatrix} 1 & 1/2 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} P(Z=0) \\ P(Z=1) \end{bmatrix}$$

$$P(Z=0) = P(X=0) \cdot P(Z=0|X=0) + P(X=1) \cdot P(Z=0|X=1)$$

$$P(Z=1) = P(X=0) \cdot P(Z=1|X=0) + P(X=1) \cdot P(Z=1|X=1)$$

- Ako znamo da je  $0$  na izlazu signala počinamo da se zove  $0$  na ulazu signala  $0$  i  $1$  na ulazu signala  $1$ .

- Ako znamo da je  $1$  na ulazu signala  $0$  i  $1$  na ulazu signala  $1$  sa verovatnošću  $1/2$ .

• Vrednosti  $0$  na ulazu signala  $0$  i  $1$  na ulazu signala  $1$  su  $2^4$

• Vrednosti  $1$  na ulazu signala  $0$  i  $1$  na ulazu signala  $1$  su  $1$

$$\binom{n}{1} = n$$

$$P(Z=1|X=1) = \frac{1}{2}$$

$$\lambda_1 = \binom{n}{1} \cdot P(Z=1|X=1) = \binom{n}{1} \cdot \frac{1}{2^1}$$

$$\lambda_2 = \binom{n}{2} \cdot P(Z=1|X=2) = \binom{n}{2} \cdot \frac{1}{2^2}$$

$$\lambda_n = \binom{n}{n} \cdot \frac{1}{2^n}$$

$$\lambda_k = \binom{n}{k} \cdot \frac{1}{2^k}$$

MAKE!

$$P_e = \frac{1}{2^n} \sum_{i=1}^n \binom{n}{i} \frac{1}{2^i} \quad P_e = \frac{1}{2^n} \left( \left(\frac{3}{2}\right)^n - 1 \right)$$

$$P_e = 0 \quad \frac{1}{2^n} \left( \frac{3^n}{2^n} - 1 \right) = \frac{3^n}{2^{2n}} - 1$$

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$$P_e = \frac{3^n}{2^{(n+1)R}} - \frac{1}{2^{nR}}$$

$$\frac{3^n}{2^{(n+1)R}} = \frac{1}{2^{nR}}$$

$$2^2 = 3 / 4$$

$$R = \log_2 3$$

CONTINUE FROM 88

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ZERO-ERROR CAPACITY. A CHANNEL WITH ALPHABET  $\{0, 1, 2, 3, 4\}$  HAS TRANSITION PROBABILITIES OF FORM

$$p(y|x) = \begin{cases} 1/2 & y = (x \pm 1) \pmod{5} \\ 0 & \text{OTHERWISE} \end{cases}$$

ANALOGY TO NOISE FREE W/ PBT.

- (a) COMPUTE THE CAPACITY OF THIS CHANNEL IN BITS
- (b) THE ZERO-ERROR CAPACITY OF A CHANNEL IS THE NUMBER OF BITS PER CHANNEL USE THAT CAN BE TRANSMITTED WITH ZERO PROBABILITY OF ERROR. CLEARLY, THE ZERO-ERROR CAPACITY OF THIS PENTAGONAL CHANNEL IS AT LEAST 1 BIT (TRANSMIT 0 OR 1 WITH PROBABILITIES 1/2). FIND A BLOCK CODE THAT SHOWS THAT ZERO-ERROR CAPACITY IS GREATER THAN 1 BIT. CAN YOU ESTIMATE THE EXACT VALUE OF THE ZERO-ERROR CAPACITY? (HINT: CONSIDER CODES OF LENGTH 2 FOR THIS CHANNEL) THE ZERO-ERROR CAPACITY OF THIS CHANNEL WAS FINALLY FOUND BY LOVASZ [365].

$$nR = H(W) = H(W|W) + I(W, W) \leq 1 + P_e \cdot nR + I(x^{\pm 1}; x) \leq 1 + P_e \cdot nR + nC \quad \text{ZERO-ERROR}$$

$R \leq C$

	0	1	2	3	4
0	0	1/2	0	0	1/2
1	1/2	0	1/2	0	0
2	0	1/2	0	1/2	0
3	0	0	1/2	0	1/2
4	1/2	0	0	1/2	0

$$y = (x \pm 1) \pmod{5}$$

$$\Gamma =$$

0	1/2	0	0	1/2
1/2	0	1/2	0	0
0	1/2	0	1/2	0
0	0	1/2	0	1/2
1/2	0	0	1/2	0

$$\begin{aligned} p(y_1) &= p_{21} p_2 + p_{51} p_5 \\ p(y_2) &= p_{12} p_1 + p_{32} p_3 \\ p(y_3) &= p_{13} p_1 + p_{43} p_4 \end{aligned}$$



75

$$C = \max_{\gamma(x)} I(X, Z) = \max_{\gamma(x)} (H(Z) - H(Z|X))$$

$$\begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ \gamma(x_3) \end{bmatrix} = \begin{bmatrix} 0 & 1/2 & 0 & 0 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ \dots & \dots & \dots & \dots & \dots \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} 1/5 \\ 1/5 \\ 1/5 \\ 1/5 \\ 1/5 \end{bmatrix} = \begin{bmatrix} 1/5 \\ 1/5 \\ 1/5 \\ 1/5 \\ 1/5 \end{bmatrix}$$

$$\max H(Z) = \sum \frac{1}{5} \log 5 = \log 5$$

$$H(Z|X) = \sum_x \gamma(x) H(Z|X=x) = \sum_x \gamma(x) \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right] = 1$$

$$C = \log 5 - 1 = 2.3219 - 1 = 1.3219$$

MA PP PR SG ROONK  
ISTOT KOKKAT MO  
ZA HOIYEDPO Y(X)

$$(b) \log R \leq 1 + P_e \log R + \eta C$$

$$R \leq \frac{1}{\eta} + P_e R + C$$

$$W = \{0, 1, 2, 3, 4\}$$

$$X^2 = \{0, 1, 00, 01, 10\}$$

$$X^3 = \{0, 1, 01, 10, 11\}$$

$\gamma(x)$	$C(x)$	$l(x)$
0.4	0.1	2
0.2	0.00	3
0.2	0.01	2
0.2	1.0	2
0.2	1.1	2

$$E[l] = \frac{1}{5} (6+6) = \frac{12}{5} = 2.4$$

$$X^4 = \{14, 02, 13, 24, 03\}$$

$$W = \{0, 1, 2, 3, 4\}$$

$$X^4 = \{00, 11, 22, 33, 44\}$$

$$\begin{aligned} \gamma(x_1) &= \gamma_{21} \gamma(x_2) + \gamma_{51} \gamma(x_5) = (\gamma_{21} + \gamma_{51}) \cdot \frac{1}{5} \\ \gamma(x_2) &= \gamma_{12} \gamma(x_1) + \gamma_{32} \gamma(x_3) \\ \gamma(x_3) &= \gamma_{23} \gamma(x_2) + \gamma_{43} \gamma(x_4) \\ \gamma(x_4) &= \gamma_{24} \gamma(x_3) + \gamma_{54} \gamma(x_5) \\ \gamma(x_5) &= \gamma_{45} \gamma(x_4) + \gamma_{15} \gamma(x_1) \end{aligned}$$

$$X^n = \{14, 02, 13, 24, 03\}$$

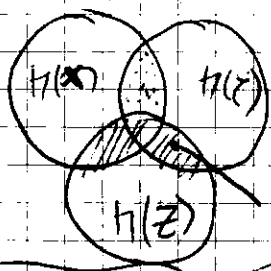
$$W = \{0, 1, 2, 3, 4\}$$

$$H_2 = \underbrace{H(W|X^n)}_{\text{zero error}} + I(W, X^n) \leq I(X^n, Z^n) \leq n \cdot C$$

$$I(X^n, Z^n) = I(X_1, X_2; Y_1, Z_2) = I(X_1, Z_2) + I(X_2, Z_2 | X_1)$$

$$I(X_1, X_2; Y) = I(X_1; Y) + I(X_2; Y | X_1)$$

$$I(X; Y; Z) = I(X; Z) + I(Y; Z | X)$$



$$I(X_2, Z_1, Z_2 | X_1) = H(X_2 | X_1) - \underbrace{H(X_2 | X_1, Z_1, Z_2)}_{\text{zero error}}$$

$$H(X_2 | X_1) = \sum_{x_1} p(x_1) \cdot H(X_2 | X_1 = x_1) =$$

$$= p(X_1=1) \cdot H(X_2 | X_1=1) + p(X_1=0) \cdot H(X_2 | X_1=0) + p(X_1=2) \cdot$$

$$H(X_2 | X_1=2) = \frac{2}{5} \left( \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right) + \frac{2}{5} \cdot 1 + \frac{1}{5} \cdot \log 5 = 4/5$$

$$I(X_1, Z_1, Z_2) = I(X_1, X_1) + I(Z_2, X_1 | Z_1)$$

$$I(X_1, Z_1) = H(X_1) - H(Z_1 | X_1) = H(X_1) - H(X_1 | Z_1)$$

$$I(X_1, Z_2) = I(X_1, Z_1, Z_2) = H(X_1) - \underbrace{H(X_1 | Z_1, Z_2)}_{\text{zero error}}$$

$$I(X^n, Z^n) = H(X_1) + H(X_2 | X_1) = H(X_2, X_1)$$

$$H(X_1) = p(X_1=1) \log \frac{1}{p(X_1=1)} + p(X_1=2) \log \frac{1}{p(X_1=2)} + p(X_1=0) \log \frac{1}{p(X_1=0)}$$

$$\log \frac{1}{p(X_1=0)} = \frac{2}{5} \log \frac{5}{2} + \frac{1}{5} \log 5 + \frac{2}{5} \log \frac{5}{2} = \frac{4}{5} \log \frac{5}{2} + \frac{1}{5} \log 5$$

$$= \frac{4}{5} \log 5 - \frac{4}{5} \log 2 + \frac{1}{5} \log 5 = \log 5 - \frac{4}{5}$$

$$I(X^n, Z^n) = \log 5 - \frac{4}{5} + \frac{4}{5} = \log 5$$

$$\begin{bmatrix} P(Y_1) \\ P(Y_2) \\ P(Y_3) \\ P(Y_4) \\ P(Y_5) \end{bmatrix} = \begin{bmatrix} 0 & 1/2 & 0 & 0 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} P(X_1) \\ P(X_2) \\ P(X_3) \\ P(X_4) \\ P(X_5) \end{bmatrix}$$

$$P(g(Y) = 0) = \left( \frac{1}{2} P(X_2) + \frac{1}{2} P(X_5) \right) + \left( \frac{1}{2} P(X_2) + \frac{1}{2} P(X_5) \right)$$

$$P(g(Y) = 0) = P(Y_1 = 1, Y_2 = 1, 4) = \frac{1}{2} P(X_2) \cdot \frac{1}{2} P(X_5)$$

$$I(X^N, Y^N) = H(X^N) - \underbrace{H(Y^N | X^N)}_{= 0} \quad (\text{ZERO CORREL})$$

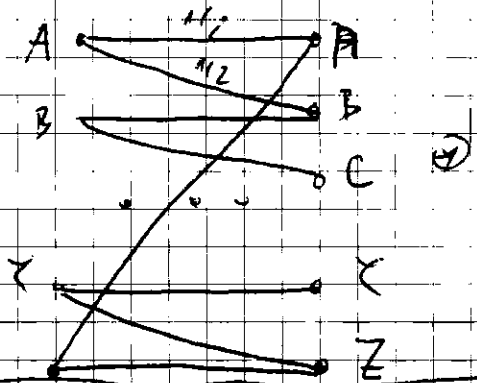
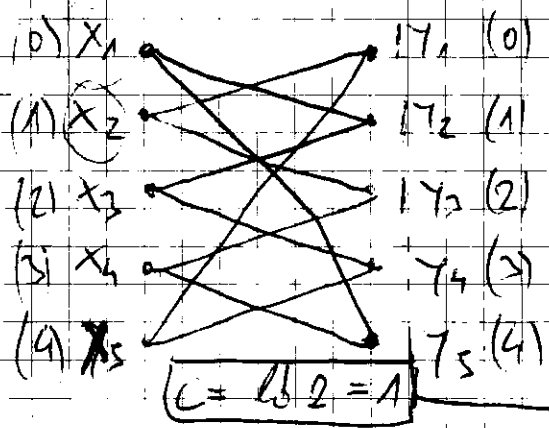
$$H(Y^N) = ? \quad H(Y^N) = P(Y^N = 14) \log \frac{1}{P(Y^N = 14)} + P(Y^N = 03) \log \frac{1}{P(Y^N = 03)}$$

$$P(Y^N = 14) = 1 - P(Y^N = 11) - P(Y^N = 44) - P(Y^N = 41) =$$

$Y_1 = 1 \quad Y_2 = 4$

$$P(g(Y) = 0) = P(\text{XXXXXXXXXX})$$

$$P(\text{XXXXXXXXXX}) = P(X_2) \cdot P(X_5) = \frac{1}{2} \cdot \frac{1}{2}$$



$C = \log 2 = 1$  CAPACITY IS LOGARITHM OF THE NUMBER OF RECOGNIZABLE INPUTS !!!

$$\begin{aligned} (*) \text{max } I(X, Y) &= \text{max } H(Y) - H(Y|X) = \log 26 - H(Y|X) \\ H(Y|X) &= \sum_x P(X=x) H(Y|X=x) = P(X=A) H(Y|X=A) + \\ &+ P(X=B) H(Y|X=B) + \dots + P(X=Z) H(Y|X=Z) = \\ &= \frac{1}{26} \left( \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right) + \dots + \frac{1}{26} (1) = 26 \cdot \frac{1}{26} = 1 \text{ bit} \end{aligned}$$

$$C = \log 26 - 1 = \log 26 - \log 2 = \log 13$$

$$\begin{bmatrix} P(Y_1) \\ P(Y_2) \\ P(Y_3) \\ P(Y_4) \\ P(Y_5) \end{bmatrix} = \begin{bmatrix} 0 & 1/2 & 0 & 0 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix} \cdot \begin{bmatrix} P(X_1) \\ P(X_2) \\ P(X_3) \\ P(X_4) \\ P(X_5) \end{bmatrix}$$

$$C = P(S) - H(Z|X)$$

$$H(Z|X) = \sum P(X) H(Z|X=X) =$$

$$= P(X_1) \left[ P(Z=Z_2|X_1) \log \frac{1}{P(Z=Z_2|X_1)} + \right.$$

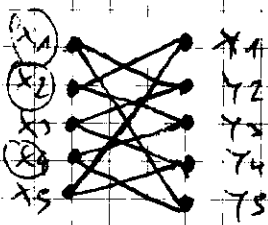
$$\left. + P(Z=Z_3|X_1) \log \frac{1}{P(Z=Z_3|X_1)} \right] + P(X_2) [\dots] + P(X_3) [\dots] + P(X_4) [\dots] + P(X_5) [\dots] =$$

$$= P(X_1) \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right] + P(X_2) + \dots + P(X_5) = 1$$

$$\boxed{H(Z|X) = 1} \quad \left[ C = P(S) - 1 = 1.3219 \right]$$

LSOTO OD PG FS NO ZA MOZVORO g(X)

$$W = \{0, 1, 2, 3, 4\} \quad X = \left\{ \begin{matrix} 2 & 1 & 2 \\ x_1 x_1 & x_2 x_2 & x_3 x_3 \\ 00 & 11 & \dots \end{matrix} \right\}$$



$$\boxed{C = \log 3 = 1.6}$$

DA NO DA KONJANI OVA E ETROKSS

$$I(X^1 X^2; Y^1 Z^2) =$$

$$H(Y|X_1=0) = \frac{1}{2} \log 2 + \frac{1}{2} \log 2 = 1 = P(Y=Z_2|X_1=0) \log \frac{1}{P(Y=Z_2|X_1=0)}$$

$$+ P(Y=Z_4|X_1=0) \log \frac{1}{P(Y=Z_4|X_1=0)} = 1$$

$$H(Y^1 | X_1^1=00) = ? = P(Y^1=Z^1_2 | X_1^1=00) \log \frac{1}{P(Y^1=Z^1_2 | X_1^1=00)}$$

$$+ \left[ \log(P(Y^1=Z^1_4 | X_1^1=00)) \right]^{-1} P(Y^1=Z^1_4 | X_1^1=00) + P(Y^1=Z^1_2 | X_1^1=00) \log \frac{1}{P(Y^1=Z^1_2 | X_1^1=00)}$$

$$+ P(Y^1=Z^1_4 | X_1^1=00) \log \frac{1}{P(Y^1=Z^1_4 | X_1^1=00)} = \left( \frac{1}{4} \cdot \log 4 \right) 4 = 2 \quad (?)$$

$$I(X^1 X^2; Y^1 Z^2) = H(Y^1 Z^2) - H(Y^1 Z^2 | X^1 X^2)$$

$$H(Y^1 Z^2 | X^1 X^2) = \sum_{x^1 x^2} P(x^1 x^2) H(Y^1 Z^2 | X^1 X^2 = x^1 x^2)$$

$$H(Y^1 Z^2 | X^1 X^2 = 00) = - \sum_{y^1 z^2} P(y^1 z^2 | 00) \log P(y^1 z^2 | 00) = 4 \cdot \frac{1}{4} \log 4 = 2$$

79a

$$H(\tau_2 \tau_4 | x^1 x^2 = 00) = \left(\frac{1}{4} \cdot 4\right) \cdot 4 = 2 \quad H(\tau_1 \tau_3 | 00) = 4 \cdot \frac{1}{4} \cdot 4 = 2$$

$$H(\tau^4 | x_1 x_2) = ? \quad \tau^4 = (\tau_2 \tau_4, \tau_1 \tau_2, \tau_3 \tau_5)$$

$$H(\tau^4 | x^1 x^2) = \sum_{x^1 x^2} p(x^1 x^2) \cdot H(\tau^4 | x^1 x^2 = x^1 x^2)$$

$$H(\tau^4 | x_4 x_5) = ?$$

$$x^4 = \{x_1 x_1, x_2 x_2, x_4 x_4\}$$

$$H(\tau^4 | 00) = p(\tau^4 = \tau_2 \tau_4) \cdot 4 + p(\tau^4 = \tau_1 \tau_2 | 00) + p(\tau^4 = \tau_3 \tau_5 | 00)$$

$$= p(\tau^4 = \tau_2 \tau_4) \cdot 4 + p(\tau^4 = \tau_1 \tau_2 | 00) + p(\tau^4 = \tau_3 \tau_5 | 00)$$

$$= p(\tau^4 = \tau_2 \tau_4 | 00) \cdot 4 + p(\tau^4 = \tau_1 \tau_2 | 00) + p(\tau^4 = \tau_3 \tau_5 | 00)$$

OVA MORE DA GO U ENERKA  $x_1 - x_2$

$$H(\tau^4 | x^1 = x_1 x_1) = 4 \cdot \frac{1}{4} \cdot 4 = 2 \quad H(\tau^4 | x^1 = x_2 x_2) = 2$$

$$H(\tau^4 | x_4 x_5) = p(\tau^4 = \tau_3 \tau_5 | x_4 x_5) \cdot 4 + p(\tau^4 = \tau_2 \tau_4 | x_4 x_5) + p(\tau^4 = \tau_1 \tau_2 | x_4 x_5) + p(\tau^4 = \tau_3 \tau_5 | x_4 x_5)$$

$$= p(\tau^4 = \tau_3 \tau_5 | x_4 x_5) \cdot 4 + p(\tau^4 = \tau_2 \tau_4 | x_4 x_5) + p(\tau^4 = \tau_1 \tau_2 | x_4 x_5)$$

OVA VON VON OPERKA III ① || ② || ③ || ④ || ⑤ ||

$$\tau^4 = \{14, 02, 13, 24, 05\} = \{x_2 x_5; x_1 x_3, x_2 x_4, x_3 x_5, x_1 x_4\}$$

$$e.g. \tau^4 = (x_2 x_5) \rightarrow \tau^4 \in (\tau_1 \vee \tau_3, \tau_1 \vee \tau_4) = (\tau_1 \tau_1, \tau_1 \tau_4, \tau_3 \tau_1, \tau_3 \tau_4)$$

$$x^4 = (x_1 x_2) \rightarrow \tau^4 \in (\tau_2 \vee \tau_5, \tau_2 \vee \tau_4) = (\tau_2 \tau_2, \tau_2 \tau_4, \tau_5 \tau_2, \tau_5 \tau_4)$$

$$x^4 = (x_1 x_4) \rightarrow \tau^4 \in (\tau_1 \vee \tau_3, \tau_3 \vee \tau_5) = (\tau_1 \tau_3, \tau_1 \tau_5, \tau_3 \tau_3, \tau_3 \tau_5)$$

$$x^4 = (x_5 x_3) \rightarrow \tau^4 \in (\tau_1 \vee \tau_4, \tau_2 \vee \tau_4) = (\tau_1 \tau_2, \tau_1 \tau_4, \tau_4 \tau_2, \tau_4 \tau_4)$$

$$x^4 = (x_1 x_3) \rightarrow \tau^4 \in (\tau_2 \vee \tau_5, \tau_3 \vee \tau_5) = (\tau_2 \tau_3, \tau_2 \tau_5, \tau_5 \tau_3, \tau_5 \tau_5)$$

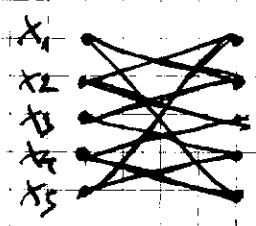
$$x^4 = (x_5 x_2) \rightarrow \tau^4 \in (\tau_1 \vee \tau_4, \tau_1 \vee \tau_3) = (\tau_1 \tau_1, \tau_1 \tau_3, \tau_4 \tau_1, \tau_4 \tau_3)$$

200

$$X^1 = \{14, 02, 13, 24, 03\}$$

$$X^2 = \{15, 20, 31, 42, 03\}$$

$x_2 x_5 \quad x_3 x_1 \quad x_4 x_2 \quad x_5 x_3 \quad x_1 x_4$



	$w$	
$(x_2 x_5) \rightarrow \tau^1 = (\tau_1 \vee \tau_2, \tau_2 \vee \tau_4) = \tau_1 \tau_1, \tau_2 \tau_4, \tau_3 \tau_2, \tau_4 \tau_4$	0	
$(x_3 x_1) \rightarrow \tau^2 = (\tau_2 \vee \tau_4, \tau_2 \vee \tau_5) = \tau_2 \tau_2, \tau_2 \tau_5, \tau_4 \tau_2, \tau_4 \tau_5$	1	
$(x_4 x_2) \rightarrow \tau^3 = (\tau_3 \vee \tau_5, \tau_1 \vee \tau_2) = \tau_3 \tau_1, \tau_3 \tau_2, \tau_5 \tau_1, \tau_5 \tau_2$	2	
$(x_5 x_3) \rightarrow \tau^4 = (\tau_1 \vee \tau_5, \tau_2 \vee \tau_4) = \tau_1 \tau_2, \tau_1 \tau_4, \tau_5 \tau_2, \tau_5 \tau_4$	3	
$(x_1 x_4) \rightarrow \tau^5 = (\tau_2 \vee \tau_5, \tau_3 \vee \tau_3) = \tau_2 \tau_3, \tau_2 \tau_5, \tau_5 \tau_3, \tau_5 \tau_5$	4	

$y(1)$	0	1/2	0	0	1/2	$y(1)$
$y(2)$	1/2	0	1/2	0	0	$y(2)$
$y(3)$	0	1/2	0	1/2	0	$y(3)$
$y(4)$	0	0	1/2	0	1/2	$y(4)$
$y(5)$	1/2	0	0	1/2	0	$y(5)$

(25), (13), (24), (35), (14)  
 $x_1 \quad x_2 \quad x_3 \quad x_4 \quad x_5$

RETURN FROM NAG. 108

10 IZVEŠČANJE ZA  $H(\tau^4 | x^2)$

$H(x^2 | x_2 x_5) = H(\tau^4 | x_4 x_2) = H(\tau^4 | x_1 x_4)$

$H(\tau^4 | x_3 x_1) = H(\tau^4 | x_4 x_2) = \frac{0.22}{2} = 0.16$

SUM  
 = 0

SEMAK IMATI 40 VO PREDVID IZVEŠČANJE 90% KMO  
 NA NAG. 98 IZVEŠČANJE DEKA (x2 x5) (x5 x3)  
 ISTO MATI MATA GLEJUA T.E

$H(\tau^4 | x_2 x_5) = H(\tau^4 | x_5 x_3) = \frac{0.22}{2} = 0.16$

SAMO  $H(\tau^4 | x_4 x_2)$  NEMA GLEJUA T.E

$H(\tau^4 | x_4 x_2) = 0$

$C_2 = H(\tau^4) - 4 \cdot 0.16 = H(\tau^4) - 0.64$

$C_2 = 1.65 - 0.64 = 1.013 = 1.7$

$C = \frac{1.7}{2} = 0.85 = 1$

VRELO E DEZAVRTO SO 2<sup>o</sup> CO TOA 40 PODIVAS  
 IZVEŠČANJE KANALOT NA KANALOT SE CILNI TAVIA  
 20% ZA EDEN IZVEŠČANJE SEMPOL PA SE  
 DENOD. I.A ILLAVNO SE IZVEŠČANJE DVA VIZI  
 SEMPOL T.E DVE VISITEDI NA KANALOT.

• EDITION 1 COLUTIONS WE WILL PICK 5 WORDS  
 WITH DISTINCT FIRST SEMIPOL {0a, 1b, 2c, 3d, 4e}

Primer

$$C = \{M, N\}$$

$$v = (n + 1) \bmod 5$$

$$M=0 \\ M=1$$

$$v = 3 \bmod 5 = 3 \\ v = 4 \bmod 5 = 4$$

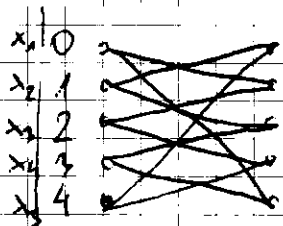
$$M=2 \\ M=3$$

$$v = 5 \bmod 5 = 0 \\ v = 6 \bmod 5 = 1$$

$$n=4 \quad v = (n+1) \bmod 5 = 2$$

$$\rightarrow \{0, 14, 20, 31, 42\}$$

$$f(y|x) = \begin{cases} 1/2 & y = (x+1) \bmod 5 \\ 0 & \text{otherwise} \end{cases}$$



$$\begin{matrix} 0 & y_1 \\ 1 & y_2 \\ 2 & y_3 \\ 3 & y_4 \\ 4 & y_5 \end{matrix} \quad \begin{matrix} f(y_1) \\ f(y_2) \\ f(y_3) \\ f(y_4) \\ f(y_5) \end{matrix} = \begin{bmatrix} 0 & 1/2 & 0 & 0 & 1/2 \\ 1/2 & 0 & 1/2 & 0 & 0 \\ 0 & 1/2 & 0 & 1/2 & 0 \\ 0 & 0 & 1/2 & 0 & 1/2 \\ 1/2 & 0 & 0 & 1/2 & 0 \end{bmatrix} \begin{bmatrix} y(0) \\ y(1) \\ y(2) \\ y(3) \\ y(4) \end{bmatrix}$$

$$\begin{matrix} (x_2 x_5) & x_2 x_5 & x_2 x_4 & x_3 x_5 & x_4 x_5 \\ (14, 02) & 13 & 24 & 03 \\ (14, 20) & 31 & 42 & 03 \\ (x_2 x_1) & x_3 x_1 & x_4 x_2 & x_5 x_3 & x_1 x_4 \end{matrix}$$

$$\begin{aligned} (x_2 x_5) &\rightarrow (y_2 \vee y_3, y_2 \vee y_4) \rightarrow y_2 y_3, y_2 y_4, y_3 y_2, y_3 y_4 \\ (x_3 x_1) &\rightarrow (y_2 \vee y_4, y_2 \vee y_5) \rightarrow y_2 y_4, y_2 y_5, y_4 y_2, y_4 y_5 \\ (x_4 x_2) &\rightarrow (y_3 \vee y_5, y_3 \vee y_2) \rightarrow y_3 y_5, y_3 y_2, y_5 y_3, y_5 y_2 \\ (x_5 x_3) &\rightarrow (y_4 \vee y_4, y_2 \vee y_4) \rightarrow y_4 y_4, y_4 y_4, y_4 y_2, y_4 y_4 \\ (x_1 x_4) &\rightarrow (y_2 \vee y_5, y_3 \vee y_5) \rightarrow y_2 y_5, y_2 y_5, y_3 y_5, y_3 y_5 \end{aligned}$$

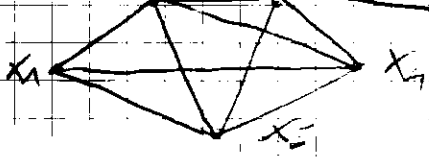
-  $V_0 = IS$  TVODIT NEMA  $H(C^m \times 4) = \emptyset$

$$C = \begin{pmatrix} 1 \\ 2 \end{pmatrix} \bmod 5$$

ZERO ERROR CAPACITY

$$\begin{matrix} x_1 x_1 & \rightarrow & (y_2 \vee y_5, y_2 \vee y_5) \\ x_2 x_3 & \rightarrow & (y_4 \vee y_3, y_2 \vee y_4) \\ x_3 x_5 & \rightarrow & (y_3 \vee y_4, y_1 \vee y_4) \\ x_4 x_2 & \rightarrow & (y_3 \vee y_5, y_3 \vee y_2) \\ x_5 x_4 & \rightarrow & (y_1 \vee y_4, y_3 \vee y_5) \end{matrix}$$

$$\begin{matrix} 2x2x2 & 2x2x2 & 2x2x2 & 2x2x2 \\ NA & NA & NA & NA \\ y_2 y_2 & y_2 y_5 & y_5 y_2 & y_5 y_5 \\ y_4 y_2 & y_4 y_4 & y_5 y_2 & y_5 y_5 \\ y_1 y_1 & y_2 y_4 & y_4 y_1 & y_4 y_4 \\ y_3 y_1 & y_3 y_3 & y_5 y_4 & y_5 y_3 \\ y_1 y_5 & y_4 y_5 & y_4 y_3 & y_4 y_5 \end{matrix}$$



OVA JE PRAVILAN KOD !!!  
OVO JE KOD NEMA DA GREŠI!  
GO NAPOUV OD CLANKOV NA ZOVASE.

**7.11**

TIME-VARYING DISCRETE CHANNELS CONSIDER TIME-VARYING DISCRETE MEMORY-LESS CHANNELS

LET  $Z_1, Z_2, \dots, Z_n$  BE CONDITIONALLY INDEPENDENT GIVEN  $X_1, X_2, \dots, X_n$  WITH CONDITIONAL DISTRIBUTION GIVEN BY:

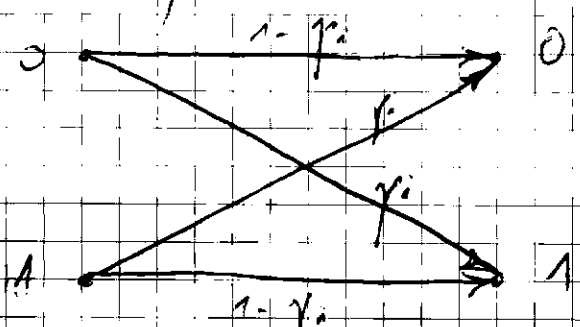
$$p(z|x) = \prod_{i=1}^n p(z_i | x_i)$$

LET  $X = (X_1, X_2, \dots, X_n)$   $Z = (Z_1, Z_2, \dots, Z_n)$   
 FIND  $\max_{p(x)} I(X; Z)$

$$I(X; Z) = H(Z^n) - H(Z^n | X^n)$$

$$H(Z^n | X^n) = \sum_{i=1}^n H(Z_i | X_1^n, X_2^n, \dots, X_{i-1}^n) = \sum_{i=1}^n H(Z_i | X_i)$$

$$H(X_1, X_2, \dots, X_n) = \sum_{i=1}^n H(X_i | X_1^{i-1}) = H(X_n) + H(X_2 | X_1) + H(X_3 | X_1, X_2) + \dots + H(X_n | X_1^{n-1})$$



$$I(X_i; Z_i) = H(Z_i) - H(Z_i | X_i) = 1 - H(Z_i | X_i)$$

$$H(Z_i | X_i) = p(X_i=0) H(Z_i | X_i=0) + p(X_i=1) H(Z_i | X_i=1)$$

$$H(Z_i | X_i) = H(p_i)$$

$$I(X_i; Z_i) = 1 - H(p_i)$$

MARKOV CHAIN  $X \rightarrow Z \rightarrow Z$

$$p(x, z | y) = \frac{p(x, y, z)}{p(y)} = \frac{p(x|y) \cdot p(z|x, y)}{p(y)}$$

$$= p(x|y) \cdot p(z|y) \quad p(x, z | x) = \frac{p(x, z)}{p(x)} = \frac{p(x) p(z)}{p(x)} = p(z)$$



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$$H(x, z, \tau) = H(x) + H(\tau|x) + H(z|x, \tau) = H(A) + H(B|A) + H(z)$$

$$H(x) = \lim_{n \rightarrow \infty} \frac{H(x_n)}{n} = \lim_{n \rightarrow \infty} \frac{H(x_2|x_1)}{n} = H(A_2|A_1)$$

TIME INVARIANT

$$H(x) = \lim_{n \rightarrow \infty} H(x_n | x_{n-1}) = H(A_n | A_{n-1}) = H(A_2 | A_1)$$

$$I(x, \tau) = H(\tau|x) - \sum_{i=1}^n H(\tau_i | x_i)$$

$$I(x, \tau) = H(\tau|x) - \sum_{i=1}^n H(\tau_i) \leq \sum_{i=1}^n H(\tau_i) - \sum_{i=1}^n H(\tau_i) \leq \sum_{i=1}^n I(x_i, \tau_i) = \sum_{i=1}^n (1 - H(\tau_i))$$

$$I(x, \tau) \leq \sum_{i=1}^n I(x_i, \tau_i) \quad I(x, \tau) \leq n - \sum_{i=1}^n H(\tau_i) \leq n$$

$H(\tau_i) = 0$  FOR  $\tau_i = 0$  OR  $\tau_i = 1$

$$C = n$$

$$C = \max_{q(x)} I(x, \tau)$$

EDITION 1 SOLUTION

$$C = \sum_{i=1}^n (1 - H(\tau_i))$$

Problem 7.12

UNUSED SYMBOLS. SHOW THAT CAPACITY OF THE CHANNEL WITH PROBABILITY TRANSITION MATRIX

$$P_{Y|X} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & \frac{1}{3} & \frac{2}{3} \end{bmatrix}$$

IS ACHIEVED BY A DISTRIBUTION THAT PLACES ZERO PROBABILITY ON ONE OF INPUT SYMBOLS. WHAT IS THE CAPACITY OF THIS CHANNEL?

GIVE AN INTUITIVE REASON WHY THAT LETTER IS USED.

$$\begin{bmatrix} q(y_1) \\ q(y_2) \\ q(y_3) \end{bmatrix} = \begin{bmatrix} \frac{1}{3} & \frac{1}{3} & 0 \\ \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ 0 & \frac{1}{3} & \frac{2}{3} \end{bmatrix} \begin{bmatrix} p(x_1) \\ p(x_2) \\ p(x_3) \end{bmatrix}$$

$$\begin{bmatrix} p(x_1) \\ p(x_2) \\ p(x_3) \end{bmatrix} = \begin{bmatrix} 2/3 & 1/3 & 0 \\ 1/3 & 1/3 & 1/3 \\ 0 & 1/3 & 2/3 \end{bmatrix} \begin{bmatrix} p(y_1) \\ p(y_2) \\ p(y_3) \end{bmatrix}$$

$$I(x; \tau) = H(\tau) - H(\tau|X)$$

$$H(\tau|X) = \sum_x p(x) H(\tau|x)$$

$$= p(x_1) \cdot H(\tau|x_1) + p(x_2) \cdot H(\tau|x_2) + p(x_3) \cdot H(\tau|x_3)$$

$$= p(x_1) \left[ \frac{1}{3} \log 3 + \frac{2}{3} \log \frac{3}{2} \right] + p(x_2) \left[ 3 \cdot \frac{1}{3} \log 3 \right] +$$

$$p(x_3) \left[ \frac{1}{3} \log 3 + \frac{2}{3} \log \frac{3}{2} \right]$$

$$= p(x_1) \left[ \frac{1}{3} \log 3 + \frac{2}{3} \log 3 - \frac{2}{3} \right] + p(x_2) \left[ \log 3 \right] +$$

$$+ p(x_3) \left[ \log 3 - \frac{2}{3} \right]$$

$$\min_x [H(\tau|X)] = [p(x_1) + p(x_3)] \cdot \left( \log 3 - \frac{2}{3} \right) \quad \text{for } p(x_2) = 0$$

$$C = \max_{p(x)} I(x; \tau) = H(\tau) - \log 3 + \frac{2}{3} = \log 3 - \log 3 + \frac{2}{3}$$

$$C = 2/3$$

$$p(x_1) = p(x_3) = \frac{1}{2}$$

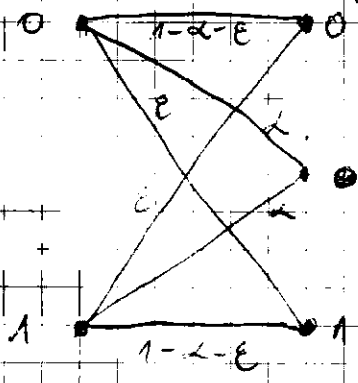
UNIFORM

$$p(\tau) = \left[ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$$

UNIFORM

**PROBLEM 7.13**

ERASURES AND ERRORS IN A BINARY CHANNEL  
 CONSIDER A CHANNEL WITH INPUT WORDS THAT HAS BOTH ERRORS AND ERASURES. LET THE PROBABILITY OF ERROR BE  $\epsilon$  AND THE PROBABILITY OF ERASURE BE  $\alpha$ , SO THE CHANNEL IS AS FOLLOWS.



- (a) FIND THE CAPACITY OF THIS CHANNEL
- (b) SPECIFY TO THE CASE OF THE BINARY SYMMETRIC CHANNEL ( $\alpha = 0$ )
- (c) SPECIFY TO THE CASE OF THE BINARY ERASURE CHANNEL ( $\epsilon = 0$ )

$$(a) I(x; \tau) = H(\tau) - H(\tau|X)$$

$$H(\tau) = p(\tau=0) \cdot \log p(\tau=0) + p(\tau=1) \cdot \log p(\tau=1) + p(\tau=\emptyset) \cdot \log p(\tau=\emptyset)$$

$$p(\tau=0) = p(x=0) \cdot (1-\alpha-\epsilon) + p(x=1) \cdot \epsilon = 1-\alpha-\epsilon+\epsilon = 1-\alpha$$

$$p(\tau=1) = p(x=1) \cdot (1-\alpha-\epsilon) + p(x=0) \cdot \epsilon = (1-\alpha)/2$$

$$p(\tau=\emptyset) = p(x=0) \cdot \alpha + p(x=1) \cdot \alpha = \alpha$$



$$H(\tau) = \alpha \log \frac{1}{\alpha} + \frac{1-\alpha}{2} \log \left( \frac{1-\alpha}{2} \right) + \left( \frac{2(1-\alpha-\epsilon) - (1-\alpha-2\epsilon)}{2} \right)$$

$$\cdot \log \left[ \frac{2(1-\alpha) - 2\epsilon - (1-\alpha) + 2\epsilon}{2} \right]^{-1} = \alpha \log \frac{1}{\alpha} + \frac{1-\alpha}{2} \log \left[ \frac{1-\alpha}{2} \right]^{-1} + \frac{1-\alpha}{2} \log \left[ \frac{1-\alpha}{2} \right]^{-1} = \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{2}{(1-\alpha)}$$

$$H(\tau) = \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{2}{(1-\alpha)}$$

• (570) SE POSIWIKA SO PIRIWIKA STATISTIČNA DEKA  
 $f(x=0) = f(x=1) = 1/2$

$$H(\tau) = \alpha \log \frac{1}{\alpha} + \frac{1-\alpha}{2} \log \frac{2}{1-\alpha} + \frac{1-\alpha}{2} \log \frac{2}{1-\alpha}$$

$$H(\tau|x) = \sum p(x) \cdot H(\tau|x=x) = p(x=0) \cdot H(\tau|x=0) +$$

$$p(x=1) \cdot H(\tau|x=1) = \frac{1}{2} \left[ \frac{(1-\alpha-\epsilon) \log (1-\alpha-\epsilon)^{-1} + \alpha \log 2^{-1} + \epsilon \log \epsilon^{-1}}{2} \right] \cdot 2 = (1-\alpha-\epsilon) \log \frac{1}{1-\alpha-\epsilon} + \alpha \log \frac{1}{2} + \epsilon \log \frac{1}{\epsilon}$$

$$= \log \frac{1}{1-\alpha-\epsilon} - \alpha \log \frac{1}{1-\alpha-\epsilon} - \epsilon \log \frac{1}{1-\alpha-\epsilon} + \alpha \log \frac{1}{2} + \epsilon \log \frac{1}{\epsilon} =$$

$$= \log \frac{1}{1-\alpha-\epsilon} + \alpha \log \left( \frac{1-\alpha-\epsilon}{\alpha} \right) + \epsilon \log \left( \frac{1-\alpha-\epsilon}{\epsilon} \right)$$

$$I(x, \tau) = \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{2}{1-\alpha} - \log \frac{1}{1-\alpha-\epsilon} - \alpha \log \left( \frac{1-\alpha-\epsilon}{\alpha} \right)$$

$$- \epsilon \log \left( \frac{1-\alpha-\epsilon}{\epsilon} \right) \quad C = I(x; \tau) - \log \frac{1}{1-\alpha-\epsilon}$$

(b)  $\alpha=0$   $C = ?$

$$C = \alpha \log (1-\alpha-\epsilon)^{-1} + (1-\alpha) \log \frac{2}{1-\alpha} - \epsilon \log \left( \frac{1-\alpha-\epsilon}{\epsilon} \right) = 0 + \log 2 - \epsilon \log \left( \frac{1-\epsilon}{\epsilon} \right) =$$

$$= 1 - \epsilon \log \frac{1}{\epsilon} - \epsilon \log (1-\epsilon) - \log \frac{1}{1-\epsilon} = 1 - \epsilon \log \frac{1}{\epsilon} + \epsilon \log \frac{1}{1-\epsilon} - \log \frac{1}{1-\epsilon}$$

$$= 1 - \epsilon \log e^{-1} - (1-\epsilon) \log \frac{1}{1-\epsilon} = 1 - H(\epsilon)$$

(c)  $\boxed{E=0}$   $C = \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} - \log \frac{1}{1-\alpha} - \alpha \log \left( \frac{1-\alpha}{\alpha} \right)$   
 $= \underbrace{\alpha \log \frac{1-\alpha-\alpha}{\alpha}}_{A=0} + \underbrace{(1-\alpha) \log \frac{1}{1-\alpha}}_{A=0} - \log \frac{1}{1-\alpha} - \alpha \log \left( \frac{1-\alpha}{\alpha} \right)$   
 $A = \alpha \log \frac{1}{\alpha} - \alpha \log (1-\alpha)$   
 $\lim_{\alpha \rightarrow 0} (\alpha \log \frac{1}{\alpha}) = \lim_{\alpha \rightarrow 0} \frac{\alpha \ln \frac{1}{\alpha}}{\ln 2}$

$\lim_{x \rightarrow 0} x \ln x = - \lim_{x \rightarrow 0} \frac{\ln x}{\frac{1}{x}} \left( \frac{-\infty}{-\infty} \right) = \lim_{x \rightarrow 0} \frac{\frac{1}{x}}{-\frac{1}{x^2}} = - \lim_{x \rightarrow 0} \frac{x^2}{1}$   
 $= - \lim_{x \rightarrow 0} \frac{1}{1} = -1$

$C = \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} + (1-\alpha) \log \frac{1}{2} - \log \frac{1}{1-\alpha} - \alpha \log \left( \frac{1-\alpha}{\alpha} \right)$   
 $= \alpha \log \frac{1}{1-\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} + (1-\alpha) - \log \frac{1}{1-\alpha} =$   
 $= - (1-\alpha) \log \frac{1}{1-\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} + (1-\alpha) = 1-\alpha$

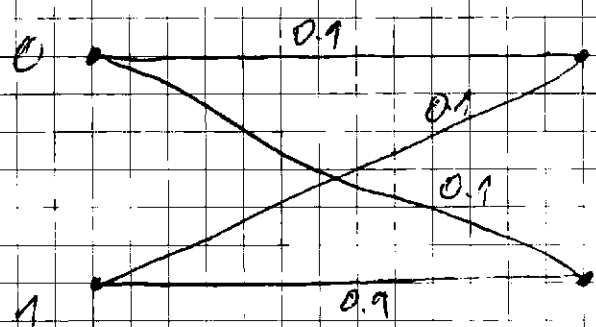
**7.14** CHANNEL WITH DEPENDENCE BETWEEN LETTERS.  
 CONSIDER THE FOLLOWING CHANNEL OVER A FINITE ALPHABET THAT TAKES IN 2-BIT SYMBOLS AND PRODUCES A 2-BIT OUTPUT AS DETERMINED BY THE FOLLOWING MAPPING:  $00 \rightarrow 01$ ,  $01 \rightarrow 10$ ,  $10 \rightarrow 11$  AND  $11 \rightarrow 00$ .  
 THUS, IF THE TWO BIT SEQUENCE  $01$  IS THE INPUT TO THE CHANNEL, THE OUTPUT IS  $10$  WITH PROBABILITY 1. LET  $X_1, X_2$  DENOTE THE TWO INPUT SYMBOLS AND  $Y_1, Y_2$  DENOTE THE CORRESPONDING OUTPUT SYMBOLS.

- (a) CALCULATE THE MUTUAL INFORMATION  $I(X_1, X_2; Y_1, Y_2)$  AS A FUNCTION OF THE INPUT DISTRIBUTION ON THE FOUR POSSIBLE PAIRS OF INPUTS.
- (b) SHOW THAT THE CAPACITY OF THIS CHANNEL IS 2 BITS.
- (c) SHOW THAT UNDER THE MAXIMIZING INPUT DISTRIBUTION  $I(X_1, X_2; Y_1, Y_2) = 2$ . THIS DISTRIBUTION ON THE INPUT SEQUENCE THAT ACHIEVES CAPACITY DOES NOT NECESSARILY MAXIMIZE MUTUAL INFORMATION BETWEEN INDIVIDUAL SYMBOLS AND THEIR CORRESPONDING OUTPUTS.

CONTINUE FROM 122!

**PROBLEM 7.15**

**JOINTLY TYPICAL SEQUENCES.** AS WE DID IN PROBLEM 3.15 FOR THE TYPICAL SET FOR A SINGLE RANDOM VARIABLE, WE WILL CALCULATE THE JOINTLY TYPICAL SET FOR A PAIR OF RANDOM VARIABLES CONNECTED BY A BINARY SYMMETRIC CHANNEL AND THE PROBABILITY OF ERROR FOR JOINTLY TYPICAL DECODING FOR SUCH A CHANNEL.



WE CONSIDER A BINARY SYMMETRIC CHANNEL WITH CROSSED PROBABILITIES 0.1. THE INPUT DISTRIBUTION THAT ACHIEVES CAPACITY IS THE UNIFORM DISTRIBUTION  $p(x) = \{ \frac{1}{2}, \frac{1}{2} \}$  FOR WHICH THIS CHANNEL YIELDS THE JOINT DISTRIBUTION  $p(x, y)$ .

WHICH YIELDS THE JOINT DISTRIBUTION:

$x \backslash y$	0	1	$p(x)$
0	0.45	0.05	0.5
1	0.05	0.45	0.5
$p(y)$	0.5	0.5	

THE MARGINAL DISTRIBUTION OF  $y$  IS:  $p(y) = \{ \frac{1}{2}, \frac{1}{2} \}$

- (a) CALCULATE  $p(x)$ ,  $p(y)$ ,  $p(x, y)$  AND  $I(x; y)$  FOR JOINT DISTRIBUTION ABOVE
- (b) LET  $x^n$  BE DRAWN ACCORDING BERNOULLI  $(1/2)$  DISTRIBUTION OF THE  $2^n$  POSSIBLE "INPUT" SEQUENCES OF LENGTH  $n$  WHICH OF THEM ARE TYPICAL [I.E. MEMBER OF  $A_\epsilon^{(n)}(x)$  FOR  $\epsilon = 0.2$ ]? WHICH ARE THE TYPICAL SEQUENCES IN  $A_\epsilon^{(n)}(y)$ ?

(c) THE JOINTLY TYPICAL SET  $A_\epsilon^{(n)}(x, y)$  IS DEFINED AS THE SET OF SEQUENCES THAT SATISFY EQUATIONS (7.25 - 7.27). THE FIRST TWO EQUATIONS CORRESPOND TO THE CONDITIONS THAT  $x^n$  AND  $y^n$  ARE IN  $A_\epsilon^{(n)}(x)$  AND  $A_\epsilon^{(n)}(y)$ , RESPECTIVELY. CONSIDER THE LAST CONDITION, WHICH CAN BE REWRITTEN TO STATE THAT

$$-\frac{1}{n} \log p(x^n, y^n) \in (H(x, y) - \epsilon, H(x, y) + \epsilon).$$

LET  $k$  BE THE NUMBER OF PLACES IN WHICH THE SEQUENCE  $x^n$  DIFFERS FROM  $y^n$  ( $k$  IS A FUNCTION OF THE TWO SEQUENCES). THEN WE CAN WRITE

$$p(x^n, y^n) = \prod_{i=1}^n p(x_i, y_i) = (0.45)^{n-k} (0.05)^k = \left(\frac{1}{2}\right)^n (1.9)^{-k}$$

AN ALTERNATIVE WAY OF LOOKING AT THIS PROBABILITY IS

TO LOOK AT THE BSC AS AN ADDITIVE CHANNEL  
~~UNIQUE~~  $X = X \oplus Z$ , WHERE  $Z$  IS BINARY RANDOM  
 VARIABLE THAT IS EQUAL TO 1 WITH PROBABILITY  
 $p$  AND IS INDEPENDENT OF  $X$ .  
 IN THIS CASE,

$$p(x^y, y^y) = p(x^y) p(y^y | x^y) = p(x^y) \cdot p(z^y | x^y) =$$

$$= p(x^y) p(z^y) = \left(\frac{1-p}{2}\right)^k \cdot \left(\frac{1-p}{2}\right)^{n-k} = \left(\frac{1-p}{2}\right)^n$$

SHOW THAT THE CONDITION THAT  $(x^y, y^y)$  BEING  
 JOINTLY TYPICAL IS EQUIVALENT TO THE CONDITION THAT  
 $x^y$  IS TYPICAL AND  $z^y = y^y - x^y$  IS TYPICAL.

(d) WE NOW CALCULATE THE SIZE OF  $A_{\epsilon}^{(n)}(Z)$  FOR  $n=25$   
 AND  $\epsilon=0.2$  AS IN PROBLEM 3.13, HERE IS TABLE  
 OF THE PROBABILITIES AND NUMBER OF SEQUENCES  
 WITH  $k$  ONES:

$k$	$\binom{n}{k}$	$\binom{n}{k} p^k (1-p)^{n-k}$	$\frac{1}{n} \log p(k^y)$
0	1	0.071790	0.152005
1	25	0.199416	0.278800
2	300	0.265858	0.405597
3	2300	0.226497	0.532394

[SEQUENCES WITH MORE THAN 12 ONES ARE OMITTED  
 SINCE THEIR TOTAL PROBABILITY IS NEGLIGIBLE  
 (AND THEY ARE NOT IN THE TYPICAL SET).]

WHAT IS THE SIZE OF THE SET  $A_{\epsilon}^{(n)}(Z)$ ?

(e) NOW CONSIDER RANDOM CODING FOR THE CHANNEL AS IN  
 THE FIRST OF THE CHANNEL CODING THEOREMS. ASSUME  
 THAT OUR CODEWORDS  $x^y(1), x^y(2), \dots, x^y(2^n)$  ARE  
 CHOSEN UNIFORMLY OVER THE  $2^n$  POSSIBLE BINARY  
 SEQUENCES OF LENGTH  $n$ . ONE OF THE CODEWORDS  
 IS CHOSEN AND SENT OVER THE CHANNEL. THE  
 RECEIVER LOOKS AT THE RECEIVED SEQUENCE AND  
 TRIES TO FIND A CODEWORD IN THE CODE THAT IS  
 JOINTLY TYPICAL WITH RECEIVED SEQUENCE. AS  
 ASSUMED ABOVE, THIS CORRESPONDS TO FINDING A CODEWORD  
 $x^y(i)$  SUCH THAT  $z^y - x^y(i) \in A_{\epsilon}^{(n)}(Z)$ . FOR A  
 FIXED CODEWORD  $x^y(i)$ , WHAT IS THE PROBABILITY  
 THAT THE RECEIVED SEQUENCE  $y^y$  IS SUCH  
 THAT  $(x^y(i), y^y)$  IS JOINTLY TYPICAL.

(f) NOW CONSIDER A PARTICULAR RECEIVED SEQUENCE  $y^n = 000000 \dots 0$  SAY. ASSUME THAT WE CHOSE A SEQUENCE  $x^n$  AT RANDOM, UNIFORMLY DISTRIBUTED AMONG ALL THE  $2^n$  POSSIBLE OTHER  $n$ -SEQUENCES. WHAT IS THE PROBABILITY THAT THE CHOSEN SEQUENCE IS JOINTLY TYPICAL WITH  $y^n$ ? HINT: THIS IS THE PROBABILITY OF ALL SEQUENCES  $x^n$  SUCH THAT:

$$y^n - x^n \in A_{\epsilon}^{(n)}(\mathbb{Z})$$

(g) NOW CONSIDER A CODE WITH  $Q = 3/2$  CODE-WORDS OF LENGTH 12, CHOSEN AT RANDOM, UNIFORMLY DISTRIBUTED AMONG ALL THE  $194$  SEQUENCES OF LENGTH  $n = 25$ . ONE OF THESE CODEWORDS, SAY THE ONE CORRESPONDING TO  $x = A$ , IS CHOSEN AND SENT OVER THE CHANNEL AS DESCRIBED IN PART (e). THE RECEIVED SEQUENCE  $y^n$  WITH HIGH PROBABILITY IS JOINTLY TYPICAL WITH THE CODEWORD THAT WAS SENT. WHAT IS THE PROBABILITY THAT ONE OR MORE OF THE <sup>OTHER</sup> CODEWORDS (WHICH WERE CHOSEN AT RANDOM INDEPENDENT OF THE SENT CODEWORD) IS JOINTLY TYPICAL WITH THE RECEIVED SEQUENCE? HINT: YOU COULD USE THE UNION BOUND, BUT YOU COULD ALSO CALCULATE THE PROBABILITY EXACTLY, USING THE RESULT OF PART (f) AND INDEPENDENCE OF THE CODE-WORDS.

(h) GIVEN THAT A PARTICULAR WORD WAS SENT, THE PROBABILITY OF ERROR (AVERAGED OVER THE PROBABILITY DISTRIBUTION OF THE CHANNEL AND OVER THE RANDOM CHOICE OF OTHER CODEWORDS) CAN BE WRITTEN AS:

$$P(E | x^n \text{ sent}) = \sum_{y^n \text{ cases error}} P(y^n | x^n)$$

THERE ARE TWO TYPES OF ERROR: (1) RECEIVED SEQUENCE  $y^n$  IS NOT JOINTLY TYPICAL WITH THE TRANSMITTED CODEWORD. (2) THERE IS ANOTHER CODEWORD JOINTLY TYPICAL WITH THE RECEIVED SEQUENCE. USING THE RESULTS OF THE PREVIOUS PARTS, CALCULATE THE PROBABILITY OF ERROR. BY THE SYMMETRY OF THE RANDOM CODING ARGUMENT, THIS DOESN'T DEPEND ON WHICH CODEWORD WAS SENT.



(9) AE

$$-y(H+\epsilon) \leq \gamma(x_i^*) \leq y(H-\epsilon) \quad | \quad \underline{AE}$$

$$Pr(x \in A_\epsilon^*) \geq 1-\epsilon \quad | \quad \underline{AE} \leq 2^{-y(H+\epsilon)} \quad | \quad |A_\epsilon^*| \geq (1-\epsilon) 2^{y(H-\epsilon)}$$

$$-y(H+\epsilon) \leq \frac{1}{y} \log \gamma(x_i^*) \leq -y(H-\epsilon) \quad | \quad -y(H-\epsilon) \leq \frac{1}{y} \log \gamma(x_i^*) \leq -y(H+\epsilon)$$

$$-y \leq -H - \frac{1}{y} \log \gamma(x_i^*) \leq y \quad | \quad | -H - \frac{1}{y} \log \gamma(x_i^*) | \leq y$$

CONTINUE FROM 16E

(f)  $\gamma = 0.000000 \dots 0$   
 MISLAKAN DEKHA AN  $\epsilon$  KE  $\geq 0.01$  (g) DO JONT AEF  
 KESET WATE  $x_i^*, \gamma$  SE NEETVANI

$$2 \cdot (1-\epsilon) \leq Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) \leq 2^{-y(I(x, \gamma) - 3\epsilon)}$$

$|I(x, \gamma) = 0.5331|$

$y=25$        $2.5 \cdot 10^{-11} \leq Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) \leq 0.00021$

$y=100$        $1.6 \cdot 10^{-18} \leq Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) \leq 6.6 \cdot 10^{-15}$

$y=1000$        $2.6 \cdot 10^{-24} \leq Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) \leq 4.1 \cdot 10^{-23}$

(h)  $Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) = \sum_{x_i^* \in A_\epsilon^*} \gamma(x_i^*) \cdot p(\gamma)$

$\gamma = 0.00 \dots 0$        $\gamma_i$  KEWA SURA NA SITE  $x_i^*$  KEI  
 SE KEBAI WATE  $y=40$       1, 2, 3, 4 KEWA

$$Pr = \sum_{A_\epsilon^*} \frac{1}{2^y} = |A_\epsilon^*| \cdot \frac{1}{2^y}$$

$y=25$        $Pr = \frac{15275}{2^{25}} = 0.00046$

$\sum_{k=1}^y \binom{y}{k} = 2^y - 1$

(g)  $Pr(\tilde{x}_n, \tilde{\gamma} \in A_\epsilon^*) = \frac{|A_\epsilon^*|}{2^y} = \frac{15275}{2^{25}} = 0.00046$

$\sum_{k=1}^9 \binom{9}{k} = 2^9 - 1 = 511$

924

$$\left| -\frac{1}{4} p^k (1-p)^{12-k} - 0.469 \right| \leq \epsilon = 0.2$$

TRUE  $k=2, 3, 4, 5$

$$Pr[(\tilde{x}, \tilde{z}) \in A_{\epsilon}^{(k)}] = \frac{781}{2^{12}} = 0.19$$

$$\sum_{k=2}^5 \binom{12}{k} = \sum_{k=2}^5 \binom{12}{k} = 781$$

$$\sum_{k=2}^5 \binom{12}{k} p^k (1-p)^{12-k} = 0.631$$

VIC solution of (6)

$$2 \leq 2^k \leq 2^{12} = 4096$$

$$1.2 \leq \dots \leq 0.8 \quad / \frac{1}{4}$$

$$1.2 \geq 1 \geq 0.8$$

$0.8 < 1 < 1.2$  } NO OVERLAP

solution of (6)

$$\left| -\frac{1}{4} \log \gamma(x, z) - \pi(x, z) \right| \leq \epsilon$$

$$H(x, z) = H(x) + H(x|z) = H(x) + H(z)$$

$$\left| -\frac{1}{4} \log \gamma(x, z) - H(x) - H(z) \right| =$$

$$\equiv \left| -\frac{1}{4} \log 2^k - \frac{1}{4} \log \gamma(z) - 1 - H(z) \right| =$$

$$\equiv \left| 1 - \frac{1}{4} \log \gamma(z) - H(z) \right| = \left| -\frac{1}{4} \log \gamma(z) - H(z) \right| \leq \epsilon$$

solution of (9)

$$Pr(\cup A_n) \leq \sum Pr(A_n)$$

THE PROBABILITY THAT AT LEAST ONE OF THIS 512 COPIES OF FILES IN THE SET IS NOT GREATER THAN THE SUM OF PROBABILITIES THAT EACH COPIED FILE IN SET OF FILES IS NOT

RELEVANT SOLUTION ON N16.00

$$Pr(\cup A_n) \leq 512 \times 0.00046 = 512 \cdot \frac{19275}{10^8} = 0.23308$$

$$(h) Pr(\text{Error} | X^4) = \sum_{\text{77 errors}} p(\gamma^k | x^4) = 1 - Pr(x^4, z^4 \in A_{\epsilon}^{(k)})$$

$$Pr[(\tilde{x}, \tilde{z}) \in A_{\epsilon}^{(k)}] =$$

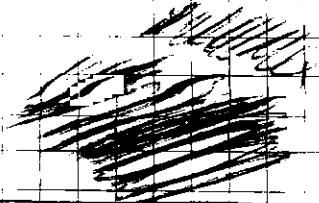
ANOTHER COPIES IS 10 INVT TRACZ WITH REC. PER

(x, z) ARE NOT 20 INVT TRACZ

$$= 1 - \sum_{k=2}^5 \binom{12}{k} p^k (1-p)^{12-k} + 512 \cdot \frac{19275}{10^8} = 1 - 0.631 + 0.23308$$

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$$P(\text{error} | X^n(a)) = 0.17 + 0.23 = 0.4$$



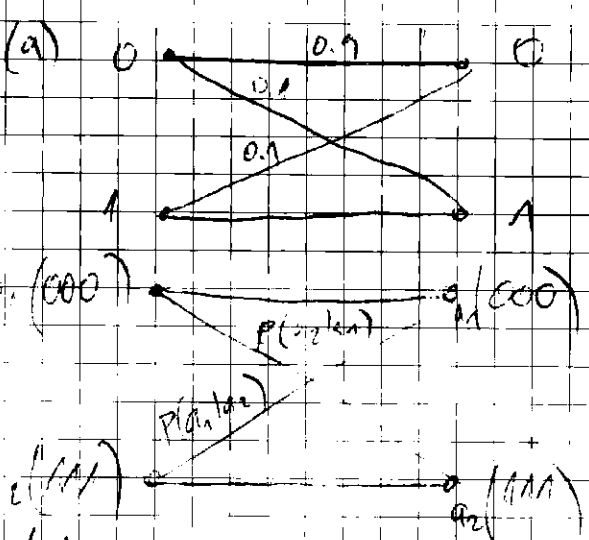
We have error if received sequence is not jointly typical with the transmitted word or if encoder word is jointly typical with received sequence.

if  $\text{error} \& \text{justifica na plesymkatha na kintatost na baska}$

**Problem 7.16** ENCODER AND DECODER AS PART OF THE CHANNEL

CONSIDER A BINARY SYMMETRIC CHANNEL WITH CROSSOVER PROBABILITY 0.1. A SIMPLE CODING SCHEME FOR THE CHANNEL WITH TWO CODEWORDS OF LENGTH 3 IS TO ENCODE MESSAGE  $a_1$  AS 000 AND  $a_2$  AS 111. WITH THIS CODING SCHEME WE CAN CONSIDER THE COMBINATION OF ENCODER CHANNEL AND DECODER AS FORMING A NEW BSC WITH TWO INPUTS  $a_1$  AND  $a_2$  AND TWO OUTPUTS  $a_1$  AND  $a_2$ .

- (a) CALCULATE A SPECIFIC PROBABILITY OF THIS CHANNEL
- (b) WHAT IS THE CAPACITY OF THIS CHANNEL?
- (c) WHAT IS THE CAPACITY OF BINARY BSC WITH CROSSOVER PROBABILITY 0.1?
- (d) GIVE A GENERAL RESULT THAT FOR ANY CHANNEL, COMBINING THE ENCODER CHANNEL AND DECODER TOGETHER AS A NEW CHANNEL FROM MESSAGES TO ESTIMATED MESSAGES WILL NOT INCREASE THE CAPACITY IN ITS FULL TRANSMISSION OF THE ORIGINAL CHANNEL.



$$\begin{aligned}
 (a) \quad & P(1|0) = 0.1 \\
 & P(a_1) = 0.1 \\
 & P(a_2|a_1) = P(111|000) + P(110|000) \\
 & P(110|000) = \frac{1}{10^3} + \frac{1}{10^2} = \frac{11}{10^3} \\
 & P(a_1|a_2) = P(000|111) + P(001|111) \\
 & = \frac{1}{10^3} + \frac{1}{10^2} = \frac{11}{10^3}
 \end{aligned}$$

(b)  $C = \max_{P(X)} I(X; Y)$ ,  $I(A; B) = H(A) - H(A|B)$  □

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$$P(a_2|a_1) = \frac{11}{10^3} = P(a_1|a_2) = 0.01100$$

$$P(X|Z) = P(X) \cdot P(Z|X)$$

X \ Z	a1	a2
a1	0.989	0.011
a2	0.011	0.989

X \ Z	a1	a2	P(Z)
a1	0.4945	0.0055	0.5
a2	0.0055	0.4945	0.5
P(Z)	0.5	0.5	

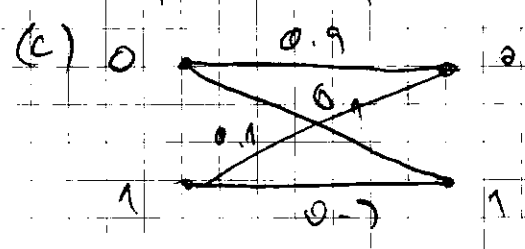
$$H(X) = \left(\frac{1}{2} \log 2\right) \cdot 2 = 1$$

$$H(Z) = \left(\frac{1}{2} \log 2\right) = 1$$

$$H(X|Z) = ? \quad H(Z|X) = ?$$

$$H(Z|X) = - \sum P(X) \log P(Z|X) = - [0.4945 (\log 0.989) \cdot 2 + 0.0055 (\log 0.011) \cdot 2] = - [0.989 (\log 0.989) + 0.011 (\log 0.011)] = 0.08735$$

$$I(X,Z) = H(X) - H(Z|X) = 1 - 0.08735 = 0.91265$$



X \ Z	0	1
0	0.9	0.1
1	0.1	0.9
P(Z X)		

X \ Z	0	1	P(X)
0	0.45	0.05	0.5
1	0.05	0.45	0.5
P(Z)	0.5	0.5	

$$C = 1 - H(Z|X)$$

$$H(Z|X) = - [0.45 (\log 0.9) \cdot 2 + 0.05 (\log 0.1) \cdot 2] = - [0.9 (\log 0.9) + 0.1 (\log 0.1)] = 0.4690$$

$$C = 1 - 0.4690 = \underline{0.531}$$

(d)  $\frac{0.91265}{3} = 0.30422 \text{ bit/transmission} \leq 0.531$

-NB & DOXA PŘESMETKAMA NA ČÍSLOVÉ PROBITNÍKTY. G. I. MAM MOUŠTENO DVOUČTE KOMPARACI OD SEKVENCÍ.

(B) REVISITARE

$$P(a_2|a_1) = P(111|000) = P(111|000) + P(110|000) + P(101|000) + P(011|000) = \left(\frac{1}{10}\right)^3 + \binom{3}{2} \left(\frac{1}{10}\right)^2 \cdot \frac{9}{10} = 0.031$$

$$\binom{3}{2} = \frac{3!}{(3-2)! \cdot 2!} = \frac{6}{2} = 3$$

2. 0.4849

X \ Y	a <sub>1</sub>	a <sub>2</sub>
a <sub>1</sub>	0.969	0.031
a <sub>2</sub>	0.031	0.969

$$H(T|X) = 0.969 \cdot (-\log_2 0.969) + 0.031 \cdot (-\log_2 0.031) = 0.19938$$

$$C = 1 - 0.19938 = 0.80062$$

$$\frac{C}{3} = 0.26687 \text{ Bits/trans}$$

- VO GENERALIZAZIONE:

$$P(a_2|a_1) = P(\underbrace{11\dots 1}_n | \underbrace{00\dots 0}_n) = \binom{n}{\lfloor \frac{n}{2} \rfloor} \left(\frac{1}{10}\right)^{\lfloor \frac{n}{2} \rfloor} \left(\frac{9}{10}\right)^{\lceil \frac{n}{2} \rceil}$$

$$n = 2k+1, \quad k = 1, 2, \dots$$

$$n = 3, 5, 7, \dots$$

$$P(a_2|a_1) = \sum_{i=0}^{\lfloor \frac{n}{2} \rfloor} \binom{n}{n-i} \frac{1}{10^{n-1}} \quad \rightarrow 0 \quad n \rightarrow \infty$$

→ VOI VO GENERALIZZAZIONE: "n" È UNA CROSSOVER PROBABILITÀ TERRE CON "0"

$$H(T|X) = - [P(a_2|a_1) \log_2 P(a_2|a_1) + (1 - P(a_2|a_1)) \log_2 (1 - P(a_2|a_1))]$$

$$C = 1 - H(T|X)$$

$$C_n = \frac{1 - H(T|X)}{n} \rightarrow 0 \quad n \rightarrow \infty$$

VIDI MATE!!!

• NOMELO (3) MOSES DA OBIÈ SO:

$$P(a_2|a_1) = \sum_{i=0}^{\lfloor \frac{n}{2} \rfloor} \binom{n}{n-i} \frac{1}{10^{n-1}}$$

JOHN HOPKINS SOLUTION

(a) 1ST TRY RECON SUM 90 1ND 2ND SUM  
 PROBABILITY OF ERROR 0.9

$$P(a_2|a_1) = (0.1)^3 + 3(0.1)^2(0.9) = 0.02800$$

0.9 is prob of error

GENERALIZED

$$P(a_2|a_1) = \sum_{i=0}^{n-1} \binom{n}{i} \frac{1}{10^{n-i}} \left(\frac{9}{10}\right)^i$$

(b)  $C_3 = \frac{1}{3} (1 - H(P(a_2|a_1))) = \frac{1}{3} (1 - H(0.028)) = \frac{0.81574}{3} = 0.272$

(c)  $C = 1 - H(0.1) = 0.531$

(d)  $C = \max_{q(x^i)} I(x^i, \tau^i)$

$$I(x^i, \tau^i) = H(x^i) - H(\tau^i|x^i) = H(\tau^i) - \sum_{x^i} p(x^i) H(\tau^i|x^i)$$

$$\leq H(\tau^i) - \sum_{k=1}^n H(\tau_k|x_k) = \sum_{k=1}^n (H(\tau_k) - H(\tau_k|x_k))$$

$$= \sum_{k=1}^n I(x_k, \tau_k) = n \cdot I(x_k, \tau_k) \leq n \cdot C$$

$$C(x^i, \tau^i) = \frac{I(x^i, \tau^i)}{n} \leq C(x_k, \tau_k)$$

More directly  
 OR see conclusion of  
 LEMMA 7.9.2.  
 ALSO  
 $C(3) = 0.27; \frac{C(5)}{5} = 0.18; \frac{C(7)}{7} = 0.14$

7.17 CODES OF LENGTH 3 FOR BSC AND BEC. IN PROBLEM

7.16 THE PROBABILITY OF ERROR WAS CALCULATED FOR A CODE WITH TWO CODEWORDS OF LENGTH 3 (000 AND 111) SENT OVER A BINARY SYMMETRIC CHANNEL WITH CROSOVER PROBABILITY  $\epsilon$ . FOR THIS PROBLEM TAKE  $\epsilon = 0.1$ .

(a) FIND THE BEST CODE OF LENGTH 3 WITH FOUR CODEWORDS FOR THIS CHANNEL. WHAT IS THE PROBABILITY OF ERROR FOR THIS CHANNEL. NOTE THAT

ALL POSSIBLE RECEIVED SEQUENCES SHOULD BE MAPPED ONTO POSSIBLE CODEWORDS

(b) WHAT IS THE PROBABILITY OF ERROR IF WE USED ALL EIGHT POSSIBLE SEQUENCES OF LENGTH 3 AS CODEWORDS?

(c) NOW CONSIDER A BINARY ERASURE CHANNEL. ERASURE PROBABILITY 0.1. AGAIN, IF WE USED THE TWO-CODEWORD CODE '000' AND '111', RECEIVED SEQUENCES 00E, 0E0, E00, 0EE, E0E, EE0 WILL ALL BE DECODED AS '0' AND SIMILARLY, WE WOULD DECODE 11E, 1E1, E11, 1EE, E1E, EE1 AS '1'.

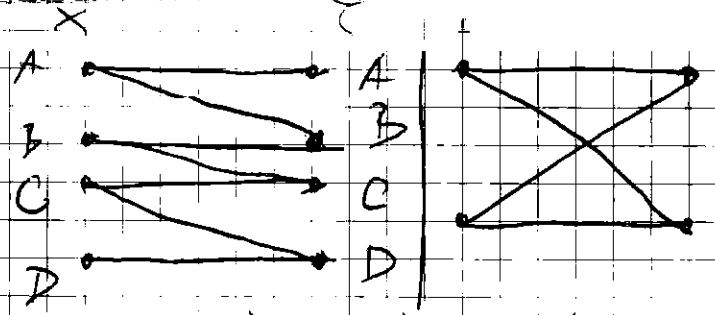
IF WE RECEIVED THE SEQUENCE EEE, WE WOULD NOT KNOW IF IT WAS '000' OR '111' THAT WAS SENT, SO WE CHOOSE ONE OF THESE TWO AT RANDOM, AND ARE WRONG HALF THE TIME. WHAT IS THE PROBABILITY OF ERROR FOR CODES IN (a) OVER THE ERASURE CHANNEL?

(d) WHAT IS THE PROBABILITY OF ERROR FOR CODES IN PART (a) AND (b) WHEN USED OVER THE ERASURE CHANNEL?

(a)

X	Z	Y	W
1	000	000	A
	<del>000</del>	001	
2	010	010	2
	<del>010</del>	011	
3	100	100	3
	<del>100</del>	101	
4	110	110	4
	<del>110</del>	111	

NOISE FREE



$$C = I(X; Z) = H(Z) - H(Z|X)$$

$$H(Z) = \log_2 6$$

$$H(Z|X) = \sum_x p(x) H(Z|x) =$$

$$= p(x=A) H(Z|x=A) + p(x=D) H(Z|x=D) + \dots$$

$$H(Z|x=A) = -[P(Z=A|x=A) \log_2 P(Z=A|x=A) + P(Z=D|x=A) \log_2 P(Z=D|x=A)] =$$

$$= -\frac{1}{2} \log_2 \frac{1}{2} - \frac{1}{2} \log_2 \frac{1}{2} = 1$$

$$C = I(X; Z) = \log_2 6 - 1 = \log_2 6 - 1 = \log_2 3$$

$$P(\text{Error} | W=000) = P(010) + P(011) + P(100) + P(101) + P(110) + P(111)$$

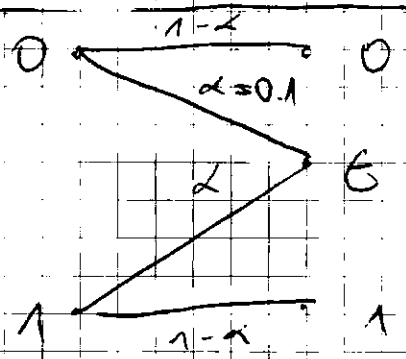
$$= (0.1)^2 \times (0.1) + (0.1)^2 \times (0.1) + (0.1) \times (0.1)^2 + (0.1) \times (0.1)^2 + (0.1)^2 \times (0.1) + (0.1)^2 \times (0.1)$$

$$\begin{aligned}
 (a) \quad P(\text{Ere} | 000) &= P(000) + P(001) + P(100) + P(101) + P(110) + P(111) \\
 &= (0.1)(0.9)^2 + (0.1)^2 \cdot 0.9 + (0.1)^2 \cdot 0.9 + (0.1)^3 + (0.1)(0.9)^2 + (0.1)^2 \cdot 0.9 \\
 &= (0.1)^3 + 3 \cdot (0.1)^2 \cdot 0.9 + 2 \cdot (0.1)(0.9)^2 = 0.19
 \end{aligned}$$

$$P(E) = \sum_x P(x) P(\text{Ere} | x) = \left( \frac{1}{4} \cdot 0.19 \right) \cdot 4 = 0.19$$

$$(b) \quad P(\text{Ere} | 000) = \sum_{i=1}^3 P(i^?) = 1 - (0.9)^3 = 0.271$$

$$P(E) = \sum_x P(x) P(\text{Ere} | x) = 8 \cdot \frac{1}{8} \cdot 0.271 = 0.271$$



$$C = I(x, \tau) = H(x) - H(\tau|x)$$

$$\boxed{H(\tau) = P(\tau=0) \log_2 P(\tau=0) + P(\tau=1) \log_2 P(\tau=1) + P(\tau=e) \log_2 P(\tau=e)}$$

$$P(\tau=0) = P(x=0) \cdot P(0|0) = \frac{1}{2} (1-x)$$

$$P(\tau=1) = \frac{1}{2} (1-x) \quad P(\tau=e) = P(x=0) P(e|0) +$$

$$P(x=1) \cdot P(e|1) = \frac{1}{2} x + \frac{1}{2} x = x$$

$$\sum P(\tau) = \frac{1}{2} (1-x) \cdot 2 + x = 1-x+x = 1$$

$$H(\tau) = -2 \left( \frac{1-x}{2} \log_2 \frac{1-x}{2} \right) - x \log_2 x = (1-x) \log_2 \frac{2}{1-x} - x \log_2 x$$

$$H(\tau|x) = \sum_x P(x) H(\tau|x) \quad H(\tau|x=0) = H(x)$$

$$H(\tau|x=1) = H(x) \quad H(\tau|x) = 2 \cdot \frac{1}{2} H(x) = H(x)$$

$$C = (1-x) \log_2 \frac{2}{1-x} + (1-x) + x \log_2 \frac{2}{x} - H(x) = 1-x$$

$$P("1"|"0") = 1 - P("0"|"0") = 1 - [P(00e|000) + P(0e0|000) + P(e00|000) + P(0ee|000) + P(ee0|000)] - P(eee) - P(000)$$



$$P("1"|"0") = 1 - P("0"|"0") = 1 - (3x - 3x^2 + \frac{1}{2}9x^3) = 1 - (3 \cdot 0.1 - 3 \cdot 0.1^2 + \frac{1}{2} \cdot 9 \cdot 0.1^3) = 1 - (0.3 - 0.3 + 0.045) = 0.655$$

000	eee	<del>eee</del>	01e
001	ee1	<del>ee1</del>	0e1
010	e1e	<del>e1e</del>	10e
011	e11	<del>e11</del>	1e0
100	1ee	<del>1ee</del>	e01
101	1e1	<del>1e1</del>	e10
110	11e	<del>11e</del>	
111	111	<del>111</del>	
8	7	6	0

12 + 8 + 7 = 27 = 3<sup>3</sup>

$$P("1"|"0") = 1 - [3(1-x)^2x + 3(1-x)x^2 + \frac{x^3}{2} + (1-x)^3] = 1 - (1 - \frac{x^3}{2}) = \frac{x^3}{2}$$

$$P(x) = \frac{x^3}{2} \quad P(0.1) = (0.1)^3 / 2 = 0.0005$$

$$P(e) = P(x="0") \cdot P("1"|"0") + P(x="1") \cdot P("0"|"1") = \frac{x^3}{2}$$

$$P(e) = |x=0.1|^{1/2} = \frac{(0.1)^3}{2} = 0.0005$$

MMV

(d) (e)  $P(\text{err}|1000) = 1 - (0.9)^3 = 0.271$

w	x <sup>w</sup>	x <sup>w</sup>	x <sup>w</sup>
1	000	000 00e	
2	010	010 01e	
3	100	100 10e	
4	110	110 11e	

000 → 000  
00e  
010 → 010  
01e  
100 → 100  
10e  
110 → 110  
11e

$$P(\text{err}|1000) = P(010) + P(01e) + P(100) + P(10e) + P(110) + P(11e) = 0.9^2 + 0.9^2 \cdot 0.1 + \dots$$

$$P(\text{err}|1000) = P(eee) + P(0e0) + P(0ee) + P(e0e) + P(ee0) = 0.1^3 + 0.1 \cdot 0.9^2 + 0.1^2 \cdot 0.9 + 0.1^2 \cdot 0.9 + 0.1^2 \cdot 0.1 = 0.1^3 + 2 \cdot 0.1 \cdot 0.9^2 + 3 \cdot 0.1^2 \cdot 0.9 = 0.19$$

$$P(e) = \sum P(x) P(\text{err}|x=x) = \frac{1}{4} \cdot 0.19 \cdot 4 = 0.19$$

(d) (e)  $P(e) = 1 - 0.9^3 = 0.271$

JOHN HOPKINS UNIVERSITY SOLUTIONS

(d) (a)

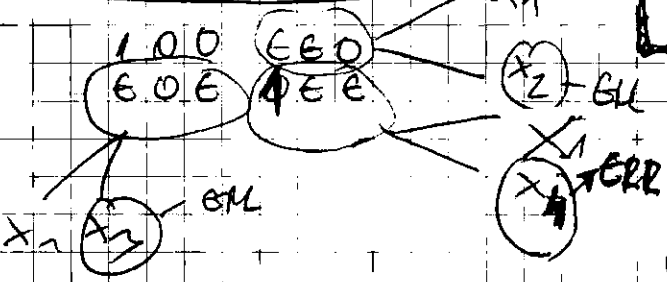
	X			W
X <sub>1</sub>	100	100	000	1
		100	100	
X <sub>2</sub>	010	010	010	2
		000	010	
X <sub>3</sub>	001	001	001	3
		001	000	
X <sub>4</sub>	111	111	111	4
		100	111	

• WITH ONE ERASURE BITS RECEIVED

$$P_1(E|100) = 1 - [P(000) + P(100) + P(100) + P(100)] = 1 - 2(1-p)^2 - (1-p)^3 - 2(1-p)^2 - 2(1-p)^2 = 1 - 3(1-p)^2 - (1-p)^3$$

NO ERROR 111

• WITH TWO ERASURE BITS



$$P_2(E|100) = \frac{(1-p) \cdot 2 \cdot 3}{2}$$

$$P(E|100) = P(P(E|000)) + P(P(E|000)) + P(P(E|000)) = (1-p)^2 \cdot \frac{1}{2} + \frac{1}{2}(1-p)^2 + \frac{1}{2}(1-p)^2 = \frac{3}{2}(1-p)^2$$

ANY

• WITH THREE ERASURE BITS RECEIVED

$$P_3(E|100) = 3 \cdot P(000) = 3 \cdot \frac{1}{4} = \frac{3}{4}$$

$$P(E) = \sum_x P(X) P_3(E|x) = \frac{1}{4} \cdot P_3(E|1) = \frac{3}{4} \cdot P(000) = \frac{3}{4} \cdot \frac{1}{4}$$

$$P_3(E) = \frac{3 \cdot 2^3}{4}$$

$$P(E) = P_1(E) + P_2(E) + P_3(E) = \frac{3(1-p)^2}{2} + \frac{3}{4} \cdot 2^3$$

(d) (b)

000	100
001	101
010	110
011	111

• ONE ERASED BIT

$$P(E|000) = P(000) + P(000) + P(000) = 3 \cdot \frac{1}{2} = \frac{3}{2}$$

"0" V "1" } WITH 1/2 PROBABILITY

$$P(E|000) = 2(1-p)^2 \cdot 3$$

$$P(E) = \frac{1}{8} \cdot 8 \cdot P(E|000) \cdot 2$$

• TWO ERASED BITS

$$P_2(E|000) = P(000) + P(000) + P(000) = \frac{3}{4}(1-p)^2 + \frac{3}{4}(1-p)^2 + \frac{3}{4}(1-p)^2 = \frac{9}{4}(1-p)^2$$

• THREE ERASED BITS

$$P_3(E|000) = \frac{7}{8} \cdot \frac{3}{4} \cdot 2^3 = \frac{7}{8} \cdot \frac{3}{4} \cdot 8 = \frac{21}{4}$$

$$P(E) = \frac{3 \cdot 2(1-p)^2}{2} + \frac{3}{4} \cdot 2(1-p)^2 + \frac{7}{8} \cdot \frac{3}{4} \cdot 8 = 0.1426$$

**7.18** CHANNEL CAPACITY OF THE FOLLOWING CHANNELS

capacity of

(a)  $X = Z = \{0, 1, 2\}$

$$p(z|x) = \begin{bmatrix} 1/3 & 1/3 & 1/3 \\ 1/3 & 1/3 & 1/3 \end{bmatrix}$$

(b)  $X = Z = \{0, 1, 2\}$

$$p(z|x) = \begin{bmatrix} 1/2 & 1/2 & 0 \\ 0 & 1/2 & 1/2 \\ 1/2 & 0 & 1/2 \end{bmatrix}$$

(c)  $X = Z = \{0, 1, 2, 3\}$

$$p(z|x) = \begin{bmatrix} \gamma & 1-\gamma & 0 & 0 \\ 0 & 0 & \gamma & 1-\gamma \\ 0 & 0 & 1-\gamma & \gamma \end{bmatrix}$$

(a)  $C = \max I(X; Z) = H(Z) - H(Z|X) = 1.585 - H(Z|X)$

$$H(Z|X) = \sum p(x) H(Z|Z=x) = \frac{1}{3} p(0) H(Z|Z=0) + \frac{1}{3} p(1) H(Z|Z=1) + \frac{1}{3} p(2) H(Z|Z=2) = \frac{1}{3} [ \frac{1}{3} \log_2 \frac{1}{3} ] \cdot 3 = 1.585$$

$C = 1.585 - 1.585 = 0$

(b)  $H(Z|X) = \frac{1}{2} [ (\frac{1}{2} \log_2 \frac{1}{2}) \cdot 2 ] \cdot 2 = 1.585$

$C = 1.585 - 1.585 = 0.58496 \text{ bits}$

(c)  $H(Z|X) = \frac{1}{4} [ \gamma \log_2 \frac{\gamma}{\gamma} + (1-\gamma) \log_2 \frac{1-\gamma}{1-\gamma} ] \cdot 2 + \frac{1}{4} [ 2 \log_2 \frac{1}{2} + (1-\gamma) \log_2 \frac{1-\gamma}{1-\gamma} ]$

$H(Z|X) = \frac{1}{2} H(\gamma) + \frac{1}{2} H(2) \quad C = 1.585 - \frac{1}{2} [ H(\gamma) + H(2) ]$

$C = 2 - \frac{1}{2} [ H(\gamma) + H(2) ]$

$$H(x) = x H(p) + (1-x) H(q)$$

$$H(x) = p(x_1) \log \frac{1}{p(x_1)} + p(x_2) \log \frac{1}{p(x_2)} + p(x_3) \log \frac{1}{p(x_3)} + p(x_4) \log \frac{1}{p(x_4)} = ?$$

$$p(x_1) + p(x_2) = x \quad p(x_1) = p \quad p(x_2) = x - p$$

$$p \log \frac{1}{p} + (x-p) \log \frac{1}{x-p} = p \log \frac{1}{p} + x \log \frac{1}{x-p}$$

$$-p \log \frac{1}{x-p} = p \log \frac{x-p}{p} + x \log \frac{1}{x-p} =$$

$$= p \log \frac{x-p}{p} + x \log \frac{1}{x-p} - x \log \frac{1}{x-p} =$$

$$= p \log \frac{x-p}{p} - x \log \frac{x-p}{p} - x \log \frac{1}{x-p} = (p-x) \log \frac{x-p}{p} + \frac{x \log p}{p}$$

$$H(x) = x \log \frac{x}{x} + \frac{x}{2} \log \frac{x}{x} + 2 \frac{x-x}{2} \log \frac{x}{1-x} =$$

$$= x \log \frac{x}{x} + (1-x) \log \frac{x}{1-x}$$

$$C = \max_x I(x; \pi) = x \log \frac{x}{x} + (1-x) \log \frac{x}{1-x} - x H(p) - (1-x) H(q)$$

$$= x \log \frac{x}{x} + x \log \frac{x}{x} + (1-x) \log \frac{x}{1-x} + (1-x) \log \frac{1}{x} - x H(p) - (1-x) H(q)$$

$$\frac{dC}{dx} = \frac{d}{dx} \left[ x \log \frac{x}{x} + (1-x) \log \frac{x}{1-x} \right] - H(p) + H(q) =$$

$$= \log \frac{x}{x} + \frac{1/\ln 2}{x} + -\log \frac{x}{1-x} + (1-x) \frac{1/\ln 2}{1-x} - H(p) + H(q)$$

$$= \log \frac{x}{x} - \frac{2}{\ln 2} - \log \frac{x}{1-x} - H(p) + H(q)$$

$$\frac{d}{dx} \left[ x \log \frac{x}{x} + (1-x) \log \frac{x}{1-x} \right] = -\left[ \log \frac{x}{x} + x \frac{1}{x \ln 2} - 1 \cdot \log \frac{x}{1-x} + (1-x) \frac{1}{(1-x) \ln 2} \right]$$

$$\begin{aligned}
 \textcircled{*} &= - \left[ \log x - \log(1-x) + \frac{2}{\ln 2} \right] = - \left[ \log \left( \frac{x}{1-x} \right) + \frac{2}{\ln 2} \right] = \\
 &= - \frac{\log \left( \frac{x}{1-x} \right) + 2}{\ln 2} \quad \frac{d}{dx} \left[ 2 \log x - 2 \log(1-x) + \log(1-x) \right] = \\
 &= \log x + x \cdot \frac{1}{x \cdot \ln 2} - \log(1-x) - 2 \frac{(-1)}{(1-x) \ln 2} + \frac{-1}{(1-x) \ln 2} = \\
 &= \log x + \frac{1}{\ln 2} - \log(1-x) + \frac{2}{(1-x) \ln 2} - \frac{1}{(1-x) \ln 2} = \\
 &= \log x + \frac{1}{\ln 2} - \log(1-x) + \frac{(1-x)}{(1-x) \ln 2} = \log \frac{x}{1-x}
 \end{aligned}$$

~~Handwritten scribbles and crossed-out text.~~

$$\textcircled{*} = - \log \frac{x}{1-x} - \log \frac{(1-x)}{x}$$

$$\frac{dL}{dx} = \log \frac{(1-x)}{x} - H(1) + H(2) = 0$$

$$\log \frac{1-x}{x} = H(1) - H(2)$$

$$\frac{1-x}{x} = 2^{H(1) - H(2)}$$

$$1-x = x \cdot 2$$

$$1 = x(1+2)$$

$$x = \frac{1}{1 + 2^{H(1) - H(2)}} = \frac{1}{1 + \frac{2^{H(1)}}{2^{H(2)}}} = \frac{2^{H(2)}}{2^{H(1)} + 2^{H(2)}}$$

$$\begin{aligned}
 &= 1 - x \log x - (1-x) \log(1-x) - \frac{2^{H_2}}{2^{H_1} + 2^{H_2}} H(1) - \\
 &= \frac{2^{H_1}}{2^{H_1} + 2^{H_2}} H(2) = 1 - \frac{2^{H_2}}{2^{H_1} + 2^{H_2}} \log \frac{2^{H_2}}{2^{H_1} + 2^{H_2}} - \frac{2^{H_1}}{2^{H_1} + 2^{H_2}} \log \frac{2^{H_1}}{2^{H_1} + 2^{H_2}} \\
 &= \frac{2^{H_1} H(1) + 2^{H_1} H(2)}{2^{H_1} + 2^{H_2}} = 1 - \frac{2^{H_2}}{2^{H_1} + 2^{H_2}} \log 2^{H_2} - \frac{2^{H_1}}{2^{H_1} + 2^{H_2}} \log 2^{H_1} \\
 &+ \frac{2^{H_2} \cdot 2^{H_1} + 2^{H_2}}{2^{H_1} + 2^{H_2}} \log(2^{H_1} + 2^{H_2}) - \frac{2^{H_2}}{2^{H_1} + 2^{H_2}}
 \end{aligned}$$

$$C = 1 - \frac{H_2 2^{H_2} + H_1 2^{H_1}}{2^{H_1} + 2^{H_2}} + \log(2^{H_1} + 2^{H_2})$$

$$- \frac{H_1 2^{H_1} + H_2 2^{H_2}}{2^{H_1} + 2^{H_2}} = 1 - H_1 - H_2 + \log(2^{H_1} + 2^{H_2})$$

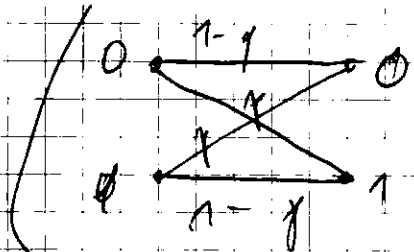
$$C = \log 2 + \log 2^{-H_1} 2^{-H_2} + \log(2^{H_1} + 2^{H_2}) =$$

$$= \log [2^{1-H_1-H_2} (2^{H_1} + 2^{H_2})] = \log [2^{1-H_2} + 2^{1-H_1}]$$

$$2^C = 2^{1-H_2} + 2^{1-H_1}$$

$$2^C = 2^{C_1} + 2^{C_2}$$

$$C_1 = 1 - H(\gamma) \quad C_2 = 1 - H(\rho)$$



$$C = 1 - H(\tau(X)) = 1 - P(0) [H(\rho)] - P(1) [H(\gamma)] = 1 - H(\gamma)$$

~~КОНДИЦИОНАЛНА ДВА НЕЗАВИСИМИ ВАРИАБЕЛИ~~

$$C = \log [2^{C_1} + 2^{C_2}]$$

IF  $C_1 = C_2 = 1$   
 $C = 2$

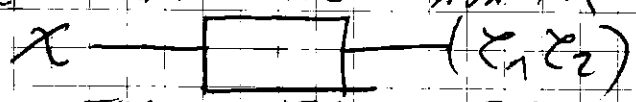
IF:  $C_1 = 3 \quad C_2 = 3 \quad C = \log [8 + 8] = \log 16 = 4$

**PROBLEM 7.20**

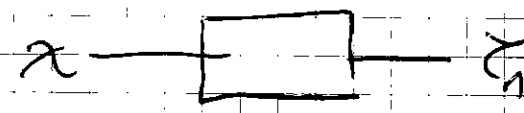
CHANNEL WITH TWO INDEPENDENT LOOKS AT INDEPENDENT AND DISCRETELY DISTRIBUTED. LET  $Z_1$  AND  $Z_2$  BE CONDITIONALY INDEPENDENT GIVEN  $X$ . IDENTICAL.

(a) SHOW THAT  $I(X, Z_1, Z_2) = 2I(X, Z_1) - I(Z_1, Z_2)$

(b) CONCLUDE THAT THE CAPACITY OF THE CHANNEL



IS LESS THEN TWICE THE CAPACITY OF THE CHANNEL.



$$(a) I(x; \tau_1, \tau_2) = I(x; \tau_1) + I(x; \tau_2 | \tau_1)$$

$$I(x; \tau_2 | \tau_1) = H(x | \tau_1) - H(x | \tau_1, \tau_2) =$$

$$= H(\tau_2 | \tau_1) - \underbrace{H(\tau_2 | \tau_1, x)}_{= H(\tau_2 | x)} = \underbrace{H(\tau_2 | \tau_1) - H(\tau_2 | x)}_{\text{INDEPENDENT GIVEN } x}$$

$$= \underbrace{-H(\tau_2) + H(\tau_2 | \tau_1)}_{-I(\tau_1; \tau_2)} + \underbrace{H(\tau_2) - H(\tau_2 | x)}_{I(x; \tau_2)}$$

$$I(x; \tau_1, \tau_2) = \underbrace{I(x; \tau_1)}_{I(x; \tau_1)} + \underbrace{I(x; \tau_2)}_{I(x; \tau_2)} - \underbrace{I(\tau_1; \tau_2)}_{I(\tau_1; \tau_2)}$$

$\tau_1, \tau_2$  ARE IDENTICALLY DISTRIBUTED

$$I(x; \tau_1) = H(\tau_1) - H(\tau_1 | x)$$

$$H(\tau_1 | x) = H(\tau_2 | x)$$

$$I(x; \tau_2) = H(\tau_2) - H(\tau_2 | x)$$

$$H(\tau_1) = H(\tau_2)$$

IDENTICALLY DISTRIBUTED

$$I(x; \tau_1) = I(x; \tau_2)$$

$$\rightarrow I(x; \tau_1, \tau_2) = 2I(x; \tau_1) - I(\tau_1; \tau_2)$$

$$(b) C_2 = \max_{y \in \mathcal{Y}} I(x; \tau_1, \tau_2) = \underbrace{2 \max_{y \in \mathcal{Y}} (I(x; \tau_1))}_{2C_1} - \underbrace{I(\tau_1; \tau_2)}_{\text{CONSTANT OF } x}$$

$$\Rightarrow C_2 = 2C_1 - I(\tau_1; \tau_2)$$

$$C_2 \leq 2C_1$$

ALTERNATE SOLUTION:

$$I(x; \tau_1, \tau_2) = H(\tau_1, \tau_2) - H(\tau_1, \tau_2 | x) = H(\tau_1) + H(\tau_2) -$$

$$- H(\tau_1 | x) - H(\tau_2 | x) = I(x; \tau_1) + I(x; \tau_2) - I(\tau_1; \tau_2)$$

$$H(\tau_1, \tau_2) = H(\tau_1) + H(\tau_2 | \tau_1) = H(\tau_1) - H(\tau_2) + H(\tau_2 | \tau_1) + H(\tau_2)$$

$$= H(\tau_1) + H(\tau_2) - I(\tau_1; \tau_2)$$

**PROBLEM 7.21**

TALL FAT PEOPLE. SUPPOSE THAT THE AVERAGE HEIGHT OF PEOPLE IN A ROOM IS 5 FEET. ALSO THAT THE AVERAGE WEIGHT IS 100 LB. THE HEIGHT THAT NO ONE IS SHORTER THAN ONE-THIRD OF THE POPULATION IS 15 FEET TALL.

(b) FIND WHAT FRACTION OF THE 300 LB 10-FOOTERS IN THE ROOM.

$$\bar{h} = 5 \text{ feet} = 152 \text{ cm}$$

$$\bar{w} = 100 \text{ lb} = 45 \text{ kg}$$

(a)  $\bar{h} = 5$        $h\left(\frac{4}{3}\right) = 15$  feet

$$\frac{1}{n} (h_1 + h_2 + \dots + h_n) = 5$$

$n_3 = \frac{4}{3}$

$$\frac{1}{n_3} \sum_{i=1}^{n_3} h_{ii} \leq 15$$

IF  $n_3 = \left(\frac{4}{3} + 1\right) \Rightarrow \left(\frac{4}{3} + 1\right) \cdot 15 = 5n + 15$

OVA JE PODOLGO OD VNEKATERA ~~TOGA~~ VNEKATERA OD SITE  
 LUPE VO SODATA PA ZATOA VO SODATA  
 NE MOJE DA MA POVECE OD  $\frac{4}{3}$  LUPE  
 SO VESNA POVECE OD 15 feet-1.

(b)  $\bar{w} = 100$  lb

$$\frac{1}{n} (w_1 + w_2 + \dots + w_n) = 100$$

$$\sum_{i=1}^n w_i = 100n$$

$n_2 = 300 \leq 100n$

$$n_2 \leq \frac{n}{3}$$

NE POVECE OD  $\frac{4}{3}$  LUPE MAAT 300 lb.

$\lim_{n \rightarrow \infty} H(h_1, h_2, \dots, h_n) = H(h) = \lim_{n \rightarrow \infty} H(h_n | h_1^{n-1})$

$H(x) = \lim_{n \rightarrow \infty} \frac{H(x_1, x_2, \dots, x_n)}{n(H(h, w) + \epsilon)}$

$|A_\epsilon^{(n)}| \leq 2^{n(H(h, w) + \epsilon)}$        $H(h, w) = H(h) + H(w)$

$2^{-n(H(h, w) + \epsilon)} \leq \Pr[(\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}] \leq 2^{-n(H(h, w) - \epsilon)}$

$\Pr[(\tilde{x}_n, \tilde{z}_n) \in A_\epsilon^{(n)}] \approx 2^{-n I(x; z)}$

$H(h, w) = H(h) + H(w) = H(h) + H(w) \leq L_{h,w} + L_{w,h}$

$H(h, w) = 1 + L_{h,w}$

PAOT NA PRIZICI MOZICI  
 VISINI NA LUPE KAND  
 PRIZICI NA LUPE.



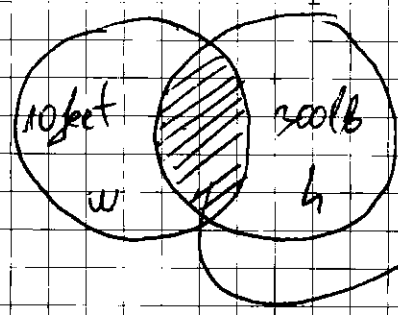
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$$\mu_1 \cdot 10(\text{foot}) \leq 5 \cdot \mu_1$$

$$\mu_1 \leq \frac{5 \cdot \mu_1}{10} = \frac{\mu_1}{2}$$

$$\mu_1 \leq \frac{\mu_1}{2}$$

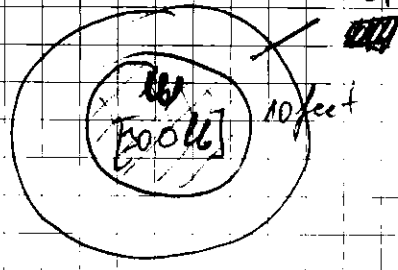
VO SODAJA NE MORE DA  
IMA POVECE OD SOGA LICE 401  
SE 10VISOKI OD 10feet = 3m



$$I(w, h)$$

$$I(w, h) = f(w) - f(w|h)$$

Upper bound is site 300 lb or  
10 feet - i.e.



VO OVO? SLUCA?  $f(w|h) = 0$   
 $I(w, h) = f(w)$

Upper bound of 300 lb - 10 feet is  
equal to  $\max(\mu_1, \mu_2)$  i.e.

$$U.B = \max(\mu_1, \mu_2) = \frac{\mu_1}{2}$$

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### Stackoverflow solutions

Markov inequality

$$P(X \geq c) \leq \frac{\mu}{c}$$

$$P(X > 15) \leq \frac{5}{15}$$

$$P(X \geq c) = \sum_{x \geq c} P(X) \leq \sum_x x P(X)$$

- Proof of Markov's inequality

$I_E = 1$  if  $E$  occurs  $I_E = 0$  otherwise

$$I(x \geq a) = \begin{cases} 1 & x \geq a \\ 0 & x < a \end{cases}$$

$$a I(x \geq a) \leq X$$
  
 $a \cdot 0 \leq X$

if  $x \geq a$   $a \cdot 1 \leq X$

$I(X \geq a) \leq X \quad (E[\cdot]) \quad E[a I(X \geq a)] \leq E[X]$

$E[a I(X \geq a)] = a [1 \cdot P(X \geq a) + 0 \cdot P(X < a)] = a P(X \geq a)$   
 $\boxed{a P(X \geq a) \leq E[X]} \quad \boxed{P(X \geq a) \leq \frac{E[X]}{a}}$

• Chebyshev inequality

$P_r[(X - \mu)^2 > \epsilon^2] \leq P_r[(X - \mu) \geq \epsilon] \leq \frac{E[(X - \mu)^2]}{\epsilon^2}$   
 $= \frac{\sigma^2}{\epsilon^2}$   
 WE MARKOV'S INEQUALITY !!!

(b)  $P(X > 300 \text{ lb}) = \frac{100 \text{ lb}}{300} = \frac{1}{3}$   
 (c)  $P(\tau \geq 10 \text{ f}) = \frac{40 \text{ s}}{10} = \frac{1}{2}$   
 MAX SI POSITIVN  
 IS TIE FAKTA  
 STO SI POSIVN  
 SVAZANO

- So slozimo zavorot za solemi n'ocvi; srednja vredost na primoznot ter ee kon stati izivata s'pna vredost

- $\frac{1}{3}$  Lude ic dimat so tera perocna od 300 lb
- $\frac{1}{2}$  Lude ic dimat so v'iska > od 10f.

$P(X > 300 \text{ lb}, \tau \geq 10 \text{ f}) = \left| \begin{matrix} X \\ \tau \end{matrix} \right| =$   
 $= P(X > 300) \cdot P(\tau \geq 10) = \frac{1}{3} \cdot \frac{1}{2} = \frac{1}{6}$

OTUKA:  $\frac{1}{6}$  Lude se 1 potesni od 300 lb i pov'ok od 10f.

TRDA IN NOVEAM SO MORE-CALC SIMULACIJA

**PROBLEM F22**

CAN SIGNAL DERIVATIVES LOWER CAPACITY? SHOW THAT TDDING A ROW TO A CHANNEL TRANSMISSION MATRIX DOESN'T DECREASE CAPACITY.

$\begin{bmatrix} y(t_1) \\ y(t_2) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{22} & p_{22} \end{bmatrix} \begin{bmatrix} x(t_1) \\ x(t_2) \end{bmatrix}$   
 $C = \max I(A, \tau)$   
 $I(A, \tau) = H(\tau) - H(E[A])$

10/3/24

$$\begin{aligned}
 \gamma(x_1) &= \gamma_{11} \gamma(x_1) + \gamma_{21} \gamma(x_2) \\
 \gamma(x_2) &= \gamma_{12} \gamma(x_1) + \gamma_{22} \gamma(x_2)
 \end{aligned}$$

$$H(z) = \gamma(x_1) \delta(z_1) + \gamma(x_2) \delta(z_2)$$

$$\Pi = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \quad \Pi_1 = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix}$$

$$\begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \gamma_{21} \\ \gamma_{12} & \gamma_{22} & \gamma_{22} \end{bmatrix} \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ \gamma(x_2) \end{bmatrix} \quad \sum_{i=1}^2 \gamma(x_i | x_i) = 1$$

$$\gamma(x_1) = \gamma_{11} \gamma(x_1) + \gamma_{21} \gamma(x_2) + \gamma_{21} \gamma(x_2)$$

$$c = Id_m - H(z|x) \rightarrow \text{OVA EVTS !!!}$$

$$H(z|x) = \sum_x \gamma(x) \cdot H(z|x=x)$$

$$\begin{aligned}
 H(z|x=x_1) &= \gamma_{11} \delta(z_1) + \gamma_{12} \delta(z_2) \\
 &= \sum_{i=1}^2 \gamma_{1i} \delta(z_i)
 \end{aligned}$$

$$H(z|x) = \sum_{i=1}^2 \sum_{j=1}^2 \gamma_{ji} \delta(z_j)$$

$$H(z|x) = \sum_{i=1}^2 \sum_{j=1}^2 \gamma_{ji} \delta(z_j) \quad \left\{ \begin{array}{l} 2 \times 2 \text{ TRANSITION} \\ \text{MATRIX} \end{array} \right.$$

$$\begin{aligned}
 H(z|x=x_2) &= \gamma_{21} \delta(z_1) + \gamma_{22} \delta(z_2) \\
 H(z|x=x_1) &= \gamma_{11} \delta(z_1) + \gamma_{12} \delta(z_2)
 \end{aligned}$$

• TRANSITION PROBABILITY MATRIX FOR GENOTYPE CHANGE

$$\Pi = \begin{bmatrix} 1-f & f & 0 \\ 0 & f & 1-f \end{bmatrix} \quad z = \Pi^T x \quad \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ \gamma(x_2) \end{bmatrix} = \begin{bmatrix} 1-f & 0 \\ f & 1-f \end{bmatrix} \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \end{bmatrix}$$

$$z = \Pi^T x$$

$$\begin{bmatrix} \gamma(z_1) \\ \gamma(z_2) \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{12} \\ \gamma_{21} & \gamma_{22} \end{bmatrix} \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ 0 \end{bmatrix} =$$

$$= \begin{bmatrix} \gamma_{11} & \gamma_{21} & \gamma_{31} \\ \gamma_{12} & \gamma_{22} & \gamma_{32} \end{bmatrix} \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ 0 \end{bmatrix}$$

$$\gamma(z_1) = \gamma_{11} \gamma(x_1) + \gamma_{21} \gamma(x_2)$$

$$\gamma(z_2) = \gamma_{12} \gamma(x_1) + \gamma_{22} \gamma(x_2)$$

$$H(z) = H(x) = - \sum_{i=1}^2 \gamma(z_i) \log \gamma(z_i)$$

$$C = \max_x I(x, z) = H(z) - H(z|x)$$

$$H(z|x) = \sum_{i=1}^2 \gamma(x_i) H(z|x_i) = \gamma(x_1) \cdot H(z|x_1) + \gamma(x_2)$$

$$+ \gamma(x_2) \cdot H(z|x_2) = \sum_{i=1}^2 \gamma(x_i) H(z|x_i)$$

$$H(z|x_1) = \gamma_{11} \log \gamma_{11} + \gamma_{21} \log \gamma_{21}$$

$$H(z|x_2) = \gamma_{12} \log \gamma_{12} + \gamma_{22} \log \gamma_{22}$$

Vo generalizar a unica:

$$H(z) = \sum_{i=1}^n \gamma(z_i) \log \gamma(z_i)$$

$$\Pi = \begin{bmatrix} \gamma_{11} & \gamma_{12} & \dots & \gamma_{1n} \\ \gamma_{21} & \gamma_{22} & \dots & \gamma_{2n} \\ \dots & \dots & \dots & \dots \\ \gamma_{m1} & \gamma_{m2} & \dots & \gamma_{mn} \end{bmatrix}$$

$$\gamma'(z_1) = \sum_{i=1}^{m+1} \gamma_{i1} \cdot \gamma(x_i) = \sum_{i=1}^m \gamma_{i1} \gamma(x_i) + \gamma_{m+1,1} \gamma(x_{m+1})$$

$$\gamma(z_1) = \sum_{i=1}^{m+1} \gamma_{i1} \cdot \gamma(x_i) \quad \left. \begin{array}{l} \text{ESTA VAZIO ZA KESSOR XIA} \\ \text{MEMO X KENATA} \end{array} \right\}$$

$$H(z|x) = \sum_{i=1}^n \gamma(x_i) H(z|x_i) = \sum_{i=1}^n \gamma(x_i) \cdot H(z|x_i) +$$

$$+ \gamma(x_{m+1}) \cdot H(z|x_{m+1}) = \sum_{i=1}^n \gamma(x_i) H(z|x_i) \quad \left. \begin{array}{l} \text{IZTO VAZIO KORO} \\ \text{ZA NESLOJICE} \\ \text{MATA MASTICA} \end{array} \right\}$$

$$H(z|x_1) = \gamma_{11} \log \gamma_{11} + \gamma_{12} \log \gamma_{12} + \dots + \gamma_{1n} \log \gamma_{1n} \quad \left. \begin{array}{l} \text{TRANZICIONE} \\ \text{ENTRIGIJE} \\ \text{SE MENJAVATI} \end{array} \right\}$$

**Problem 7.23**

SWIFT MULTIPLIER CHANNEL

- (a) Consider the channel  $Z = XZ$  where  $X$  and  $Z$  are independent binary variables that take on values 0 and 1.  $Z$  is Bernoulli( $\alpha$ ) [ $P(Z=1)=\alpha$ ].  
 (b) Now suppose that the receiver can observe  $Z$  as well as  $Y$ . What is the capacity?

Find the capacity of this channel and the maximizing distribution on  $X$ .

$Z \backslash X$	0	1
0	0	0
1	0	1

$$K(x) = \begin{cases} 1 & x=1, z=1 \\ 0 & \text{otherwise} \end{cases}$$

$$p(z) = \{ p(x=1) p(z=1), p(x=1) p(z=0) + p(x=0) p(z=1) + p(x=0) p(z=0) \}$$

$Z \backslash X$	0	1	$P(Z X)$
0	1	0	
1	$1-\alpha$	$\alpha$	

$$P(Z=0|X=0) = 1$$

$$P(Z=1|X=1) = \frac{P(Z=1)}{P(X=1)} = \frac{\alpha}{1} = \alpha$$

$$P(Z=0|X=1) = P(Z=0) = 1-\alpha$$

$$C = \left[ H(Z) - H(Z|X) \right] = 1 - H(Z|X) = 1 - p(x=0) H(Z|X=0) - p(x=1) H(Z|X=1) = 1 - \frac{1}{2} \cdot 0 - H(\alpha)$$

$C = 1 - H(\alpha)$

$C = 1 - \frac{1}{2} \cdot 0 - \frac{1}{2} \cdot 0 = 1$

$Z \backslash X$	0	1
0	1	0
1	$1-\beta$	$\beta$

Berkeley Section

$$H(X|Y) = H(X) - p(x=0) H(Z|X=0) - p(x=1) H(Z|X=1) = H(X) - (1-\beta) \cdot 0 - \beta \cdot H(\alpha) = H(X) - \beta H(\alpha)$$

$$p(z) = \{ \beta \cdot \alpha, \beta(1-\alpha) + (1-\beta)\alpha + (1-\beta) \cdot H(\alpha) \}$$

$$= \{ \beta \cdot \alpha, \beta - \beta \alpha + \alpha - \alpha \beta + 1 - \alpha + \beta \alpha + \alpha \beta \} = \{ \alpha \beta, 1 - \alpha \beta \}$$

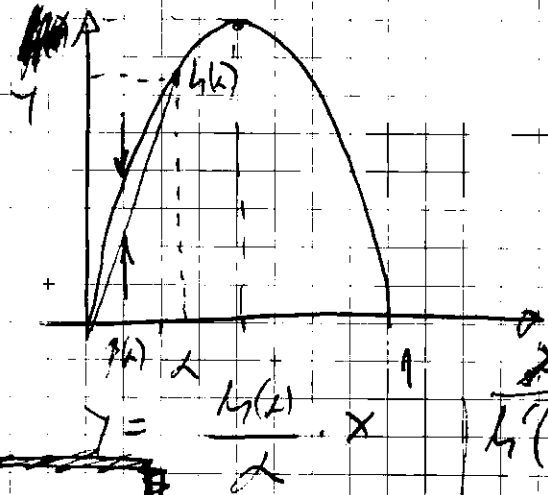
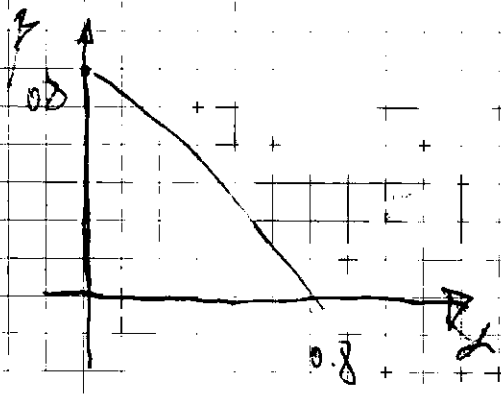
$$- H(Z) = \beta \log \beta + (1-\beta) \log(1-\beta)$$

1049

$$I(x, \gamma) = H(\gamma) - \beta \cdot H(x)$$

$$H(\gamma) = H(\alpha \beta)$$

$$I(x, \gamma) = H(\alpha \beta) - \beta \cdot H(x)$$



$$L'(f(x) \cdot x) = \frac{L(x)}{x}$$

$$C = L(f(x) \cdot x) - f(x) \cdot L(x)$$

$$z = x \cdot z \quad f'(z) = \begin{cases} \alpha & z=1 \\ 1-\alpha & z=0 \end{cases}$$

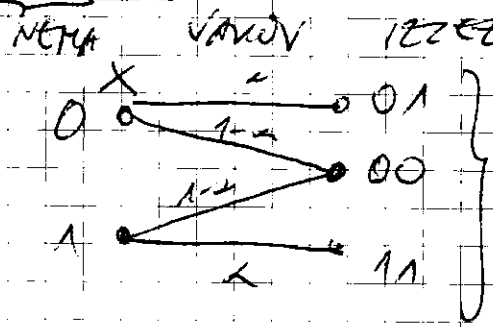
(6)

	$z$	00	01	10	11
$x$	0	$1-\alpha$	$\alpha$	0	0
	1	$\alpha$	0	0	$\alpha$

$$P(00|1) = P(z=0) = 1-\alpha$$

$$P(10|1) = \alpha$$

	$z$	00	01	11
$x$	0	$1-\alpha$	$\alpha$	0
	1	$1-\alpha$	0	$\alpha$



NETA VAVOV IZETEN SYMBOOL  
 10 MARK  
 GRAFUR E CHANNEL

$$C = (1-\alpha)H(\alpha) = 1-\alpha' = \alpha' = 1-\alpha = 1-\alpha + \alpha = \alpha$$

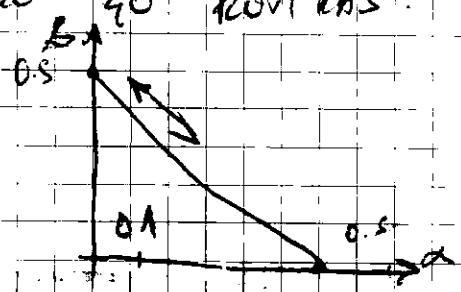
$$C = \alpha$$

WE HAVE DISCOVERED THAT  $\alpha \geq H(f(x) \cdot x) - f(x) \cdot H(x)$

• OD GRAFIKUT VO MAPLE ZA VO 1/2 SE  
 PORIVA PEA KOMPONENT E MAXIMIZEN ZA  
 $\alpha = 0.4$

• AVO 40 ROVENS:

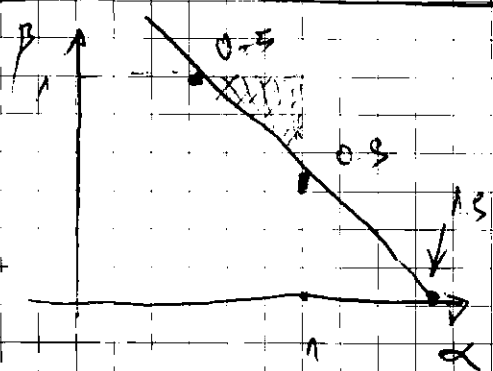
$$f(x, \gamma) = x \gamma W(x, \gamma) + (1-x) \gamma W(1, \gamma)$$



$$\gamma = -x + \frac{1}{2}$$

$$\gamma = -\frac{1}{10} + \frac{1}{2} = \frac{-1+5}{10} = \frac{4}{10} = \frac{2}{5}$$

12a



③ 
$$y = -x + 1.5$$

$x=1$	$y=0.5$
$x=0.5$	$y=1$

NA OVA  
MVA A A  
X & Y

ZA NILO VOI  $y \in [0, 1]$  PRESHETANI SO ③  
 $H(x) = 1$  T.E. MAXIMIZOVAN

$C = 1 - p(x) \cdot H(x)$

$y = (-x) + 1.5$

IF  $x = \frac{1}{2}$

$\Rightarrow p = 1$

$C = 1 - H(x)$

$C = 0$

BIMORE  
SMETKICE  
OPANICE

IF  $x = 1$

$y = +1.5 - 1 = 0.5$

$y \in [0, 1]$   
 $x \in [0, 1]$

ONE VIEWPOINT POINT KON MAXIMIZOVAN  $H(x, y)$

$C = 1 - \frac{1}{2} H(\frac{1}{2}) = 1 - \frac{1}{2} = \frac{1}{2}$

AVO  $x=1$  CELO VIEME T.E.  $x=1 \Rightarrow p=0.5$

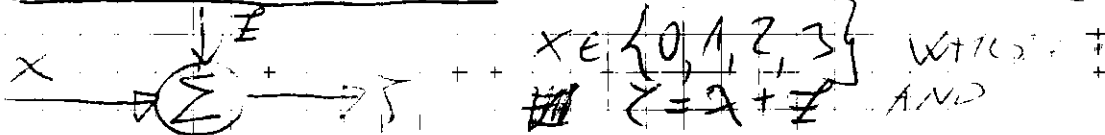
$C = 1 - \frac{1}{2} \cdot 0 = 1$

VO OVO SE VIDA SE  
POZIVA MAXIMIZOVAN VODITEL

VAO GO ZGOLYUVA	$x \in [0, 1]$	TAM COO
VLEME SE ZGOLYUVA	VAPACITETOT ZA VAPACIT	
A NEGOVOT	MAXIMUM	STOJAT C ZA $p = 1/2$
T.P. ZA	UNIFORMNA	VASHI OVA NA NEKITE
SIMBOL	(VOI ZIKH VO MABE)	

PROBLEM 7.24

YOUR WANTS (CONSIDER THE GRAPH)



$I$  IS UNIFORMLY DISTRIBUTED OVER THREE DISTINCT INTEGER VALUES  $Z = \{z_1, z_2, z_3\}$

(a) WHAT IS THE MAXIMUM CAPACITY OVER ALL CHOICES OF THE ACIPHER? GIVE DISTINCT INTEGER VALUES  $z_1, z_2, z_3$  AND A DISTRIBUTION ON  $x$  ACHIEVING THIS.

1129

(B) What is the minimum capacity over all codes for the  $\mathbb{Z}$  channel? Give distinct integer values  $Z_1, Z_2, Z_3$  and a distribution on  $X$  achieving this.

(a) ~~1129~~  $I(X; Z) = H(Z) - H(Z|X) = H(Z) - \sum_x p(x) H(Z|x)$   
 $= H(Z) - \sum_x p(x) H(X+Z/x) = H(Z) - H(Z)$   
 $Z = \{Z_1, Z_2, Z_3\}$   $p(Z) = \left\{ \frac{1}{2}, \frac{1}{3}, \frac{1}{6} \right\}$   
 $H(Z) = 1.63$   $I(X; Z) = H(Z) - 1.63$

1130

$X \setminus Z$	$0+Z$	$1+Z$	$2+Z$	$3+Z$
0	$Z_1, Z_2, Z_3$	$Z_1, Z_2, Z_3$	$Z_1, Z_2, Z_3$	$Z_1, Z_2, Z_3$
1				
2				
3				

$Z = \{0, 1, 2\}$   $p(Z) = \left\{ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right\}$

$X \setminus Z$	$Z_1$	$Z_2$	$Z_3$	$Z_4$
0	1, 3, 5	2, 4, 6	3, 5, 7	4, 6, 8
1	3, 5, 9	4, 6, 10	5, 7, 11	6, 8, 12
2	4, 2, 3	2, 3, 4	3, 4, 5	4, 5, 6
3				

- $\{0, 1, 2\}$
- $\{1, 3, 5\}$
- $\{3, 5, 9\}$
- $\{1, 2, 3\}$

$1^0$   $0=5$   $N=6$   $2^0$   $1=8$   $N=8$   $3^0$   $3=12$   $N=10$   
 $4^0$   $1=6$   $N=6$

$P(Z_0=1) = P(X=0) P(Z=1) = \frac{1}{4} \cdot \frac{1}{3} = \frac{1}{12}$   
 $P(Z_0=2) = P(X=0) P(Z=2) + P(X=1) P(Z=1) = \frac{1}{6}$   
 $P(Z_0=3) = P(X=0) P(Z=3) + P(X=1) P(Z=2) + P(X=2) P(Z=1) = \frac{1}{4}$   
 $P(Z_0=4) = (1, 3) + (2, 2) + (3, 1) = \frac{1}{4}$   
 $P(Z_0=5) = (2, 3) + (3, 2) = \frac{1}{6}$   
 $P(Z=6) = \frac{1}{12}$   
 $P = \frac{1}{12} + 8 \cdot \frac{1}{6} + 2 \cdot \frac{1}{4} = \frac{1}{6} + \frac{1}{3} + \frac{1}{2} = \frac{4+2+3}{6} = 1$

$H(Z) = 2 \cdot \frac{1}{12} \log_2 12 + 2 \cdot \frac{1}{6} \log_2 6 + 2 \cdot \frac{1}{4} \log_2 4 = \frac{1}{6} \log_2 12 + \frac{1}{3} \log_2 6 + 1$   
 $= \frac{1}{6} \log_2 12 + \frac{1}{3} \log_2 6 + 1 = \frac{1}{6} (\log_2 12 \cdot 6) + 1$   
 $= \frac{1}{6} \log_2 72 + 1 = 2.5 + 1 = 3.5$   
 $C = 2.5 - 1.6 = 0.9$



Alga

MAXIMIZIRAN KAPACITET SE DOBIVA IMA NE POTOCI  
PRESEK MEĐU  $X$  I  $Z$  TOČNI SU DOIMATI  
12 NEKAVI 12227 ZA  $\tau$ .

ZNAJI REŠENJE ZA (9) S IMA  $X$  I  $Z$   
SE UNIFORMNO ZASTUPENI IMA IMA NEK  
PRESEK MEĐU MV VO TOČI (4UET)

$$f(\tau) = \left(\frac{1}{12} \cdot 12\right) \cdot 12 = 12$$

$$I(x, \tau) = C_{max} = 12 \cdot \frac{12}{3} = 12 \cdot 4 = 48$$

$$C \in [0.9, 2]$$

handout 9 SOLUTION 3

DO INT KARLING  
RTO. MOŠTO  
REŠENJE SO  
NAPINE PRESEK: E: TOČI-  
MEĐU !!!

MAX. TOČI 0 MOŠTO. IMA IMA IMA

MIN. MOŠTO  $Z = \{0, 1, 2\}$   $f(x) = \begin{pmatrix} 1 & 0 & 0 \\ 2 & 1 & 1 \end{pmatrix}$

$$P(Z=0) = \binom{2}{2} \cdot P(Z=0) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

$$P(Z=1) = \frac{1}{2} \cdot P(Z=1) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

$$P(Z=2) = \binom{2}{2} \cdot P(Z=2) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

$$P(Z=3) = \binom{2}{2} \cdot P(Z=3) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

$$P(Z=4) = \binom{2}{2} \cdot P(Z=4) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

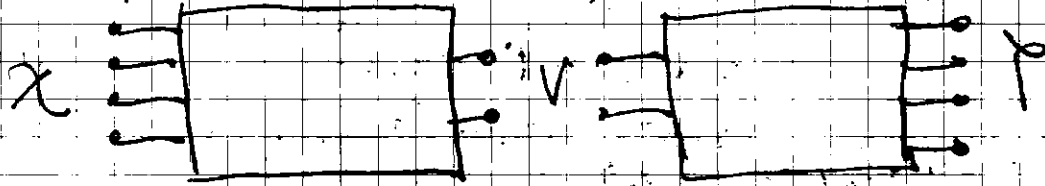
$$P(Z=5) = \binom{2}{2} \cdot P(Z=5) = \frac{1}{2} \cdot \frac{1}{3} = \frac{1}{6}$$

$$f(\tau) = \left(\frac{1}{6} \cdot 6\right) \cdot 6 = 6 \quad I(x, \tau) = 6 \cdot 6 = 36$$

$$I(x, \tau) = \left(\frac{1}{6} \cdot 6\right) = 6 \cdot 2 = 12 = C_{max}$$

PROBLEM 7.25 BOTTLENECK CHANNEL. SUPPOSE

THAT A  $\lambda \in X = \{1, 2, \dots, m\}$  GOES  
THROUGH INTERVENING TRANSITION  $X \rightarrow V \rightarrow Y$



⑩ WHERE  $X = \{1, 2, \dots, n\}$   $Y = \{1, 2, \dots, m\}$   
 AND  $U = \{1, 2, \dots, k\}$ . FIRST  $P(X|U)$  AND  $P(Y|U)$   
 ARE ADDITIVE AND THE CHANNEL HAS TRANSITION  
 PROBABILITIES:

$$P(Y|X) = \sum_U P(X|U) P(Y|U)$$

SHOW THAT  $C \leq \log k$

**PROBLEM 7.26** (CONTINUE FROM N16.6)

(C)  $X \in \{0, 1, 2, 3, 4\}$   $Z \in \{A, B\}$   $C = ?$

$$P(Z|X) = P(Z=z|X=x) = \sum_{Z=z_0} P(Z=z_0|Z=x)$$

X \ Z	A	B
0	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
1	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
2	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
3	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$

Z \ X	A	B
0	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
1	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
2	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$
3	$\frac{1}{4}, \frac{1}{4}$	$\frac{1}{4}, \frac{1}{4}$

$$I(X;Z) = H(Z) - H(Z|X)$$

$$C = 1 - H(Z|X)$$

$$P(Z=A) = \sum_{i=1}^4 P_{ij}$$

$$= \sum_{i=1}^4 (P_{i1} + P_{i2})$$

$$P(Z=B) = \sum_{i=1}^4 (P_{i3} + P_{i4})$$

$$- H(Z) = \left[ \sum_{i=1}^4 (P_{i1} + P_{i2}) \right] \log \sum_{i=1}^4 (P_{i1} + P_{i2})$$

$$+ \left[ \sum_{i=1}^4 (P_{i3} + P_{i4}) \right] \log \left[ \sum_{i=1}^4 (P_{i3} + P_{i4}) \right]$$

TRANSITION PROBAB

$$P_{ij} = \frac{P_{ij}}{P(i)}$$

$$H(Z|Z) = \sum_X P(X) \cdot H(Z|Z=X)$$

$$H(Z|Z=0) = - \left[ (P_{11} + P_{12}) \cdot \log(P_{11} + P_{12}) + (P_{21} + P_{22}) \cdot \log(P_{21} + P_{22}) \right]$$

$$P(X=0) \cdot H(Z|Z=0) = - (P_{11} + P_{12}) \cdot \log \frac{(P_{11} + P_{12})}{P(X=0)} + (P_{21} + P_{22}) \cdot \log \frac{(P_{21} + P_{22})}{P(X=0)}$$

X \ Z	A	B
0	$\frac{1}{2}, \frac{1}{2}$	$0, 0$
1	$0, \frac{1}{2}, \frac{1}{2}$	$0, 0$
2	$0, 0$	$\frac{1}{2}, \frac{1}{2}$
3	$\frac{1}{2}, 0$	$0, \frac{1}{2}$

$$H(Z|X=0) = - \left[ 1 \cdot \log 1 + 1 \cdot \log 1 \right]$$

$$H(Z|X=1) = - \left[ P(Z=A|X=1) \log P(Z=A|X=1) + P(Z=B|X=1) \log P(Z=B|X=1) \right]$$

$$= - \left[ \frac{1}{2} \log \frac{1}{2} + \frac{1}{2} \log \frac{1}{2} \right] = 1$$

$$H(Z|X=2) = P(Z=1|X=2) \cdot 1 + P(Z=2|X=2) \cdot 0 = 1 \cdot 1 + 0 = 1$$

$$H(Z|X=3) = P(Z=1|X=3) \cdot 1 + P(Z=2|X=3) \cdot 0 = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 0 = \frac{1}{2}$$

$$H(Z|X) = P(X=0) \cdot 0 + P(X=1) \cdot 1 + P(X=2) \cdot 0 + P(X=3) \cdot \frac{1}{2}$$

$$C = \max_{X|Y} [I(X;Y)] = 1 - H(Z|X) = 1 - [P(X=1) + P(X=3) \cdot \frac{1}{2}]$$

$$C = P(X=0) + P(X=2) \quad \text{①}$$

(b) REVISITED:

		0	1	2	3
X \ Z	0	1	2	3	
0	0	0	0	0	
1	0	1/4	1/4	0	
2	0	0	0	0	
3	1/4	0	0	1/4	
P(X)	1/2	1/2			

Tab. 2

$$P(X=1) = P(X=3) = \frac{1}{2}$$

$$H(Z|X=0) = 0$$

$$H(Z|X=2) = 0$$

$$H(Z|X=1) = P(Z=1|X=1) \cdot 1 + P(Z=2|X=1) \cdot 0 = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 0 = \frac{1}{2}$$

$$H(Z|X=1) = \frac{1}{4} \cdot 1 + \frac{1}{4} \cdot 1 = \frac{1}{2} + \frac{1}{2} = 1$$

$$H(Z|X) = P(X=1) \cdot H(Z|X=1) + P(X=3) \cdot H(Z|X=3) = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot \frac{1}{2} = \frac{3}{4}$$

$$I(X;Y) = H(Z) - H(Z|X)$$

$$H(Z) = H\left(\frac{1}{2}, \frac{1}{2}\right) = 1$$

$$H(Z) = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 1 = 1$$

$$I(X;Y) = 1 - \frac{3}{4} = \frac{1}{4}$$

		0	1	2	3
X \ Z	0	1	2	3	
0	1/4	1/4	0	0	
1	0	0	0	0	
2	0	0	1/4	1/4	
3	0	0	0	0	

$$P(X=0) = P(X=2) = \frac{1}{2}$$

$$H(Z|X) = \sum P(X) H(Z|X=X) = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 0 = \frac{1}{2}$$

$$I(X;Y) = H(Z) - H(Z|X) = 1 - \frac{1}{2} = \frac{1}{2}$$

OBSERVED FORMULA ① FUNCTIONAL FORMULA 1. 2A ② 1. 3A ③

b) Does  $X \rightarrow Z \rightarrow Y$  FORM MARKOV CHAIN?

$$P(Z, Y|X) = \frac{P(X, Y, Z)}{P(X)} = \frac{P(X, Z) P(Y|X, Z)}{P(X)} = P(Z|X) P(Y|Z)$$

$$I(X, Z; Y) = I(Z; Y) + I(X; Z|Z) \cdot I(X; Y|Z) = I(Z; Y) = H(Y|Z) = 1 - H(Z|Y) = 1 - \frac{1}{2} = \frac{1}{2}$$

$$-H(Z|X, Y) = I(Y|Z) - I(X|Z) = 0 = 0$$

(11)  $I(x, z; z) = I(x; z) + I(x; z | z) = 0$

$I(x; z | z) = H(z | z) - H(z | x, z) = H(z | z) - H(z | z) = 0$

$H(z | z) = ?$       $H(z | z=A) = P(z=0 | z=A) \cdot \log P(z=0 | z=A) + P(z=1 | z=A) \cdot \log P(z=1 | z=A) = \left(\frac{1}{2} \log 2\right) \cdot 2 = 1$

$H(x | z) = P(z=A) \cdot 1 + P(z=B) \cdot 1 = \frac{1}{2} + \frac{1}{2} = 1$

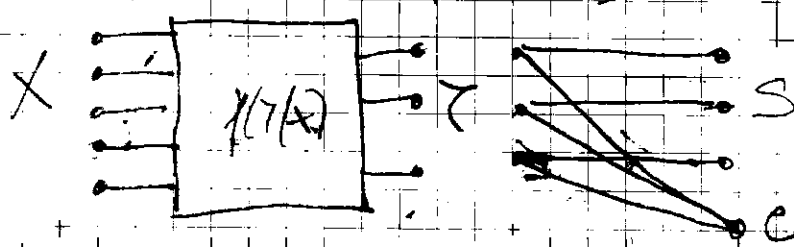
$H(z | x, z) = ?$       $H(z | 0A) = 0$       $H(z | 0B) = 0$

$H(z | 1A) = 0$ ;      $H(z | 1B) = 0$ ;      $H(z | 2A) = 0$ ;  
 $H(z | 2B) = 0$ ;      $H(z | 3A) = 0$ ;      $H(z | 3B) = 0$

AND SO Z HAS 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, 31, 32, 33, 34, 35, 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46, 47, 48, 49, 50, 51, 52, 53, 54, 55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112, 113, 114, 115, 116, 117, 118, 119, 120, 121, 122, 123, 124, 125, 126, 127, 128, 129, 130, 131, 132, 133, 134, 135, 136, 137, 138, 139, 140, 141, 142, 143, 144, 145, 146, 147, 148, 149, 150, 151, 152, 153, 154, 155, 156, 157, 158, 159, 160, 161, 162, 163, 164, 165, 166, 167, 168, 169, 170, 171, 172, 173, 174, 175, 176, 177, 178, 179, 180, 181, 182, 183, 184, 185, 186, 187, 188, 189, 190, 191, 192, 193, 194, 195, 196, 197, 198, 199, 200, 201, 202, 203, 204, 205, 206, 207, 208, 209, 210, 211, 212, 213, 214, 215, 216, 217, 218, 219, 220, 221, 222, 223, 224, 225, 226, 227, 228, 229, 230, 231, 232, 233, 234, 235, 236, 237, 238, 239, 240, 241, 242, 243, 244, 245, 246, 247, 248, 249, 250, 251, 252, 253, 254, 255, 256, 257, 258, 259, 260, 261, 262, 263, 264, 265, 266, 267, 268, 269, 270, 271, 272, 273, 274, 275, 276, 277, 278, 279, 280, 281, 282, 283, 284, 285, 286, 287, 288, 289, 290, 291, 292, 293, 294, 295, 296, 297, 298, 299, 300, 301, 302, 303, 304, 305, 306, 307, 308, 309, 310, 311, 312, 313, 314, 315, 316, 317, 318, 319, 320, 321, 322, 323, 324, 325, 326, 327, 328, 329, 330, 331, 332, 333, 334, 335, 336, 337, 338, 339, 340, 341, 342, 343, 344, 345, 346, 347, 348, 349, 350, 351, 352, 353, 354, 355, 356, 357, 358, 359, 360, 361, 362, 363, 364, 365, 366, 367, 368, 369, 370, 371, 372, 373, 374, 375, 376, 377, 378, 379, 380, 381, 382, 383, 384, 385, 386, 387, 388, 389, 390, 391, 392, 393, 394, 395, 396, 397, 398, 399, 400, 401, 402, 403, 404, 405, 406, 407, 408, 409, 410, 411, 412, 413, 414, 415, 416, 417, 418, 419, 420, 421, 422, 423, 424, 425, 426, 427, 428, 429, 430, 431, 432, 433, 434, 435, 436, 437, 438, 439, 440, 441, 442, 443, 444, 445, 446, 447, 448, 449, 450, 451, 452, 453, 454, 455, 456, 457, 458, 459, 460, 461, 462, 463, 464, 465, 466, 467, 468, 469, 470, 471, 472, 473, 474, 475, 476, 477, 478, 479, 480, 481, 482, 483, 484, 485, 486, 487, 488, 489, 490, 491, 492, 493, 494, 495, 496, 497, 498, 499, 500, 501, 502, 503, 504, 505, 506, 507, 508, 509, 510, 511, 512, 513, 514, 515, 516, 517, 518, 519, 520, 521, 522, 523, 524, 525, 526, 527, 528, 529, 530, 531, 532, 533, 534, 535, 536, 537, 538, 539, 540, 541, 542, 543, 544, 545, 546, 547, 548, 549, 550, 551, 552, 553, 554, 555, 556, 557, 558, 559, 560, 561, 562, 563, 564, 565, 566, 567, 568, 569, 570, 571, 572, 573, 574, 575, 576, 577, 578, 579, 580, 581, 582, 583, 584, 585, 586, 587, 588, 589, 590, 591, 592, 593, 594, 595, 596, 597, 598, 599, 600, 601, 602, 603, 604, 605, 606, 607, 608, 609, 610, 611, 612, 613, 614, 615, 616, 617, 618, 619, 620, 621, 622, 623, 624, 625, 626, 627, 628, 629, 630, 631, 632, 633, 634, 635, 636, 637, 638, 639, 640, 641, 642, 643, 644, 645, 646, 647, 648, 649, 650, 651, 652, 653, 654, 655, 656, 657, 658, 659, 660, 661, 662, 663, 664, 665, 666, 667, 668, 669, 670, 671, 672, 673, 674, 675, 676, 677, 678, 679, 680, 681, 682, 683, 684, 685, 686, 687, 688, 689, 690, 691, 692, 693, 694, 695, 696, 697, 698, 699, 700, 701, 702, 703, 704, 705, 706, 707, 708, 709, 710, 711, 712, 713, 714, 715, 716, 717, 718, 719, 720, 721, 722, 723, 724, 725, 726, 727, 728, 729, 730, 731, 732, 733, 734, 735, 736, 737, 738, 739, 740, 741, 742, 743, 744, 745, 746, 747, 748, 749, 750, 751, 752, 753, 754, 755, 756, 757, 758, 759, 760, 761, 762, 763, 764, 765, 766, 767, 768, 769, 770, 771, 772, 773, 774, 775, 776, 777, 778, 779, 780, 781, 782, 783, 784, 785, 786, 787, 788, 789, 790, 791, 792, 793, 794, 795, 796, 797, 798, 799, 800, 801, 802, 803, 804, 805, 806, 807, 808, 809, 810, 811, 812, 813, 814, 815, 816, 817, 818, 819, 820, 821, 822, 823, 824, 825, 826, 827, 828, 829, 830, 831, 832, 833, 834, 835, 836, 837, 838, 839, 840, 841, 842, 843, 844, 845, 846, 847, 848, 849, 850, 851, 852, 853, 854, 855, 856, 857, 858, 859, 860, 861, 862, 863, 864, 865, 866, 867, 868, 869, 870, 871, 872, 873, 874, 875, 876, 877, 878, 879, 880, 881, 882, 883, 884, 885, 886, 887, 888, 889, 890, 891, 892, 893, 894, 895, 896, 897, 898, 899, 900, 901, 902, 903, 904, 905, 906, 907, 908, 909, 910, 911, 912, 913, 914, 915, 916, 917, 918, 919, 920, 921, 922, 923, 924, 925, 926, 927, 928, 929, 930, 931, 932, 933, 934, 935, 936, 937, 938, 939, 940, 941, 942, 943, 944, 945, 946, 947, 948, 949, 950, 951, 952, 953, 954, 955, 956, 957, 958, 959, 960, 961, 962, 963, 964, 965, 966, 967, 968, 969, 970, 971, 972, 973, 974, 975, 976, 977, 978, 979, 980, 981, 982, 983, 984, 985, 986, 987, 988, 989, 990, 991, 992, 993, 994, 995, 996, 997, 998, 999, 1000

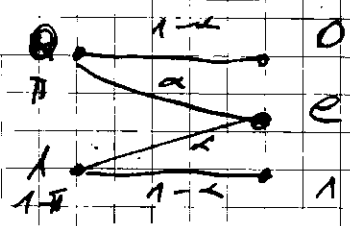
OD THE 2 P.P.MB  
 ZASMO DEUT AND E  
 PAVENO Z  
 X NA NUMER AND ZSA Y MORE OR  
 PIPE "1" SO VERODKOROST "1/2" A MORE  
 PA PIPE "3" NO VERODKOROST "1/2"  
 VO KVIOT SCOTA Z=1 A VO VOTIOT Z=3  
 (TAB. 1)  
 Z Y Z Y: FOLYIRA MASHIN  
 AND SO ZASB Y Z  
 X NE ZAVISI OD X NA PRIMER, AND  
 ZSA Y MORE OR PIPE 0 1 1 1 SO  
 VERODKOROST "1/2" (TAB. 1) NO NE ZAVISI OD  
 X ZAVISI X SVOBODI E = 0.

**PROBLEM 7.17** ERASURE CHANNEL. Let  $\{X, P(x)\}$  be a discrete memoryless channel with capacity  $C$ . Suppose that the channel is cascaded immediately with a noise channel  $\{Y, P(y|x), S\}$  that erases  $L$  of its symbols.



SPECIFICALLY,  $S = \{s_1, s_2, \dots, s_m, e\}$  AND  
 $P_V\{S = s_i | Z = z\} = \alpha P(s_i | X)$ ,  $s_i \in S$   
 $P_V\{S = e | X = x\} = \alpha$

DETERMINE THE CAPACITY OF THIS CHANNEL.



$$I(x; z) = H(z) - H(z|x)$$

$$H(z) = \left\{ \pi \cdot (1-\alpha), \pi \cdot \alpha + (1-\pi) \cdot \alpha, (1-\pi)(1-\alpha) \right\}$$

$$= H\left(\frac{z}{2}\right) = \left\{ \frac{1-\alpha}{2}, \alpha, \frac{1-\alpha}{2} \right\}$$

$$H(z) = 2 \left(\frac{1-\alpha}{2}\right) \cdot \log \frac{2}{1-\alpha} + \alpha \log \frac{1}{\alpha} = (1-\alpha) \log \frac{1}{1-\alpha} + \alpha \log \frac{1}{\alpha}$$

$$H(z|x) = (1-\pi) H(\alpha) + \pi \cdot H(\alpha) + (1-\pi) H(\alpha) = H(\alpha)$$

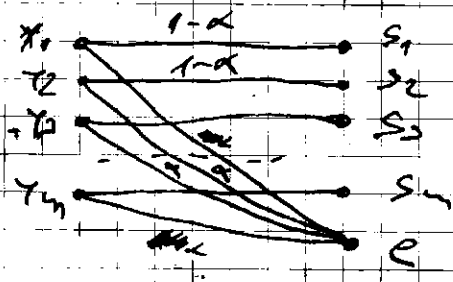
$$I(x; z) = H(z) - H(z|x) = H(\alpha) + (1-\alpha) - H(\alpha) = 1-\alpha$$

$$I(x; z; z) = I(x; z) + I(x; z|z) = I(x; z) + 0 = I(x; z)$$

$$I(x; z) = H(z|x) - H(z|x, x) = H(z|x) - H(z|x) = 0$$

$$I(x; z) \leq I(z; z)$$

$$C = \max_x I(x; z) = I(z; z)$$



$$I(z; s) = H(s) - H(s|z)$$

$$H(s|z) = \sum_{\tau} p(\tau) H(s|\tau) = \sum_{\tau} p(\tau) H(\alpha) = H(\alpha)$$

$$H(s) = ? \quad p(s) = \{ p(\tau_1)(1-\alpha), p(\tau_2)(1-\alpha), \dots, p(\tau_m)(1-\alpha), \alpha \}$$

$$H(s) = - \sum_i p(s_i) \log p(s_i) = - \left[ \sum_{\tau} p(\tau) (1-\alpha) \log [p(\tau) (1-\alpha)] + \alpha \log \alpha \right]$$

$$= - \left[ \sum_{\tau} p(\tau) (1-\alpha) \log p(\tau) + \dots + p(\tau_m) (1-\alpha) \log p(\tau_m) \right] - \alpha \log \alpha$$

$$= - \left[ p(\tau_1) \log p(\tau_1) + \dots + p(\tau_m) \log p(\tau_m) \right] + (1-\alpha) H(\tau) - \alpha \log \alpha$$

$$= (1-\alpha) H(\tau) - (1-\alpha) \log(1-\alpha) - \alpha \log \alpha = (1-\alpha) H(\tau) + H(\alpha)$$

$$C = (1-\alpha) H(\tau) + H(\alpha) - H(\alpha) = (1-\alpha) H(\tau)$$

①  $H(\tau) = ?$

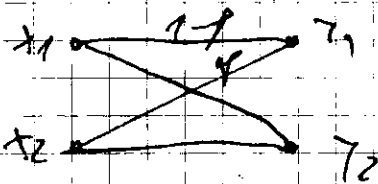
$$\begin{bmatrix} \gamma(\tau_1) \\ \gamma(\tau_2) \\ \vdots \\ \gamma(\tau_n) \end{bmatrix} = \begin{bmatrix} \gamma_{11} & \gamma_{21} & \dots & \gamma_{n1} \\ \gamma_{21} & \gamma_{22} & & \gamma_{n2} \\ & & & \\ \gamma_{n1} & \gamma_{n2} & & \gamma_{nn} \end{bmatrix} \begin{bmatrix} \gamma(x_1) \\ \gamma(x_2) \\ \vdots \\ \gamma(x_n) \end{bmatrix}$$

$$\gamma(\tau_i) = \sum_j \gamma_{ij} \cdot \gamma(x_j) \quad \gamma(\tau_j) = \sum_i \gamma_{ij} \gamma(x_i)$$

$$H(\tau) = \sum_i \gamma(\tau_i) \log \gamma(\tau_i) = \left[ - \sum_i \sum_j \gamma_{ij} \gamma(x_j) \log \sum_j \gamma_{ij} \gamma(x_j) \right]$$

• Критерий на дискретен меморелес канал:

$$C = \max_{\gamma(x)} I(x; \tau) = H(\tau) - H(\tau|x)$$



$$H(\tau|x) = - \sum_{x, \tau} \gamma(x, \tau) \log \gamma(\tau|x) \\ = - \sum_{x, \tau} \gamma(x) \gamma(\tau|x) \log \gamma(\tau|x)$$

$$H(\tau) = C + H(\tau|x)$$

• University of Toronto Solutions (sol 4.5)

$$I(x; \tau, s) = I(x; s) + I(x; \tau | s) = I(x; \tau) + I(x; s | \tau)$$

$$I(x; s) = I(x; \tau) - I(x; \tau | s) = H(\tau) - H(\tau|x) - I(x; \tau | s)$$

$$I(x; \tau | s) = H(x|s) - H(x|\tau, s)$$

$$H(x|s) = \sum \gamma(s) H(x|s=s) = (1-\alpha) H(x|s=e) + \alpha H(x|s=\tau)$$

$$H(x|\tau, s) = \sum_s \gamma(s) H(x|\tau, s=s) = (1-\alpha) H(x|\tau) + \alpha H(x|\tau, s=e)$$

$$I(x; \tau | s) = H(\tau | s=e) - H(\tau | \tau, s)$$

КОГА НЕМА ГРЕШКА S=τ

$$H(\tau | s=e) = \sum \gamma(s) H(\tau | s=s) = \gamma(s=e) \cdot H(\tau | s=e) + \gamma(s=\tau) \cdot H(\tau | s=\tau) \\ = \alpha \cdot H(\tau | s=e) + (1-\alpha) H(\tau | s=\tau) \\ = \alpha \cdot H(x|s=e) \quad \text{①}$$

$$H(X|XS) = \sum_{s \in \mathcal{S}} p(s) \cdot H(Z|X, S=s) = p(e) H(Z|X, S=e) + p(c) \cdot H(Z|X, S=c) = \alpha H(Z|X, S=e) \quad (*)$$

~~$$I(X; Z|S) = H(Z|S=e) + (1-\alpha) H(Z) + \alpha H(Z|X, S=e) + H(Z|X) + \alpha H(Z|X)$$

$$I(X; S) = H(Z) - H(Z|X) - \alpha H(Z|S=e) - (1-\alpha) H(Z) + \alpha H(Z|X, S=e) + H(Z|X) - \alpha H(Z|X) = H(Z) - H(Z|X) - \alpha H(Z|S=e) + H(Z) + \alpha H(Z|X, S=e) - \alpha H(Z|X) + \alpha H(Z|X)$$

$$I(X; S) = H(Z) - H(Z|X) - \alpha H(Z|S=e) + \alpha H(Z|X, S=e)$$~~

$$I(X; S) = \alpha H(Z|S=e) - \alpha H(Z|X, S=e)$$

$$I(X; S) = H(Z) - H(Z|X) - \alpha H(Z|S=e) + \alpha H(Z|X, S=e)$$

$$= H(Z) - H(Z|X) - \alpha H(Z) + \alpha H(Z|X) = (1-\alpha) H(Z) - (1-\alpha) H(Z|X) = (1-\alpha) I(X; Z)$$

$$C = \max_{p(s)} I(X; S) = \max_{p(s)} H(Z) - (1-\alpha) H(Z|X) = \max_{p(s)} H(Z) - (1-\alpha) H(Z|X)$$

$$I(X; S) = (1-\alpha) H(Z) - (1-\alpha) H(Z|X) = (1-\alpha) I(X; Z)$$

VALUATA FORMA VERDE DICI NA METODO ORIGINALI  
 LEGGIE NA 116.118

**Problem 7.28** CHOICE OF CHANNELS. FIND THE CAPACITY OF THE UNION OF TWO CHANNELS

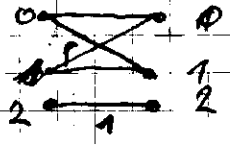
$(X_1, Y_1(Z_1|X_1), Z_1)$  AND  $(X_2, Y_2(Z_2|X_2), Z_2)$

WHERE AT EACH TIME ONE CAN SEND A SYMBOL OVER CHANNEL 1 OR CHANNEL 2 BUT NOT BOTH. ASSUME THAT THE OUTPUT ALPHABETS ARE DISTINCT AND DON'T INTERSECT.

(a) SHOW THAT  $2^C = 2^{C_1} + 2^{C_2}$ . THUS,  $2^C$  IS EFFECTIVE ALPHABET SIZE OF A CHANNEL WITH CAPACITY C.

(b) COMPARE WITH PROBLEM 2.10 WHERE  $2^H = 2^{H_1} + 2^{H_2}$  AND INTERPRET (a) IN TERMS OF BINARY TREE SYMBOLS.

(c) USE THE ABOVE RESULT TO CALCULATE THE CAPACITY OF THE FOLLOWING CHANNEL.



(12A)  $H(W) = \underbrace{H(W, \bar{W})}_{\text{ld } 2^{2R}} + H(W | \bar{W})$

FAKNO:  $H(W | \bar{W}) \leq 1 + P_e \cdot \text{ld } |W|$

$nR \leq 1 + P_e \cdot nR + I(X^N; Z^N) \leq 1 + P_e \cdot nR + nC$

$R \leq \frac{1}{n} + P_e \cdot R + C \quad n \rightarrow \infty \quad \boxed{R \rightarrow C}$

or  $P_e^N \Rightarrow nR - 1 - nC \quad \boxed{P_e^N \geq 1 - \frac{C}{R} - \frac{1}{nR}}$   
 $R > C \Rightarrow P_e^N$  IS BOUNDED AWAY FROM  $0^2$

(9)  $2^C = 2^{C_1} + 2^{C_2}$

$2^C = 2^{1-H(Y)} + 1$

$C_1 = 1 - H(Y)$

$C_2 = 0$

$C = \text{ld} [2^{1-H(Y)} + 1]$

$C = \text{ld} \left[ \frac{2 + 2^{H(Y)}}{2^{H(Y)}} \right]$

(a)

$$\begin{bmatrix} p(x_1) \\ p(x_2) \\ \vdots \\ p(x_n) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & \dots & p_{1n} \\ p_{21} & p_{22} & \dots & p_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ p_{n1} & p_{n2} & \dots & p_{nn} \end{bmatrix} \begin{bmatrix} p(x_1^1) \\ p(x_1^2) \\ \vdots \\ p(x_1^n) \\ p(x_2^1) \\ p(x_2^2) \\ \vdots \\ p(x_2^n) \end{bmatrix} \begin{matrix} (1) \\ (2) \\ \vdots \\ (n-k) \\ (k) \end{matrix}$$

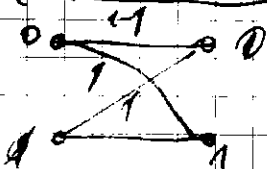
$I(X; Z) = H(Z) - H(Z|X)$

$H(Z) = \left( \frac{z}{y} \right) \text{ld} \frac{y}{z} + \left( \frac{1-z}{y} \right) \text{ld} \frac{y}{1-z}$

UNIFORM DISTRIBUTION GIVES MAXIMUM  $C^2$

$H(Z) = z \text{ld} \frac{z}{y} + (1-z) \text{ld} \frac{1-z}{y}$

$H(Z|X) = z H(Z_1|X_1) + (1-z) H(Z_2|X_2)$



$H(Z|X) = p(+0) \cdot H(q) + p(+1) \cdot H(q) = H(q)$

(A)  $\begin{cases} C_1 = \max_{p(x_1)} H(Z_1) - H(Z_1|X_1) = \text{ld } y - H(Z_1|X_1) \\ C_2 = \max_{p(x_2)} H(Z_2) - H(Z_2|X_2) = \text{ld } y - H(Z_2|X_2) \end{cases}$



$$I(x, \alpha) = -\alpha \log \frac{\alpha}{1-\alpha} - (1-\alpha) \log \frac{1-\alpha}{\alpha} - \alpha H(\tau_1 | A_1) - (1-\alpha) H(\tau_2 | A_2)$$

$$\frac{dI(x, \alpha)}{d\alpha} = 0 = \log \left( \frac{1-\alpha}{\alpha} \right) - H(\tau_1 | A_1) + H(\tau_2 | A_2)$$

$$\log \left( \frac{1-\alpha}{\alpha} \right) = \underbrace{H(\tau_1 | A_1)}_{H_1} - \underbrace{H(\tau_2 | A_2)}_{H_2} \quad \frac{1-\alpha}{\alpha} = 2^{H_1 - H_2} \cdot 2$$

$$1-\alpha = \alpha \cdot 2^{H_1 - H_2} \quad 1 = \alpha \left( 1 + \frac{2^{H_1}}{2^{H_2}} \right) \quad \alpha = \frac{2^{H_2}}{2^{H_1} + 2^{H_2}}$$

$$C = \log \left[ 2^{1-H_2} + 2^{1-H_1} \right] \quad 2^C = 2^{1-H_2} + 2^{1-H_1} \quad \text{--- (2)}$$

$$\boxed{2^C = 2^{C_1} + 2^{C_2}}$$

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(b) COMPARE WITH  $\boxed{2^{H_1}}$

$$I(x, \alpha) = -\alpha \log \alpha - (1-\alpha) \log (1-\alpha) + \alpha \log \frac{1}{\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} - \alpha H(\tau_1 | A_1) - (1-\alpha) H(\tau_2 | A_2)$$

$$= -\alpha \log \alpha - (1-\alpha) \log (1-\alpha) - \alpha H(\tau_1 | A_1) - (1-\alpha) H(\tau_2 | A_2)$$

$$2^{H(x)} \leq 2^{H(x_1)} + 2^{H(x_2)}$$

**UNIVERSITY OF TORONTO SOLUTION**

$\mathcal{X} = \{x_1 \cup x_2\}$   
 $\mathcal{Z} = \{z_1 \cup z_2\}$

$Z \in \{1, 2\}$       $Z=1$  CHANNEL 1  
 $Z=2$  CHANNEL 2

$$(a) \Rightarrow I(x, Z; \alpha) = H(Z, X) - H(X, Z | \alpha) = H(Z) + H(X|Z) - H(X | \alpha) - H(Z | X, \alpha)$$

$$= H_2(\alpha) + \alpha H(x_1) + (1-\alpha) H(x_2) - \alpha H(x_1 | \alpha) - (1-\alpha) H(x_2 | \alpha)$$

$$= H_2(\alpha) + \alpha I(x_1; \alpha) + (1-\alpha) I(x_2; \alpha)$$

$$\boxed{C = \max_{\alpha} H_2(\alpha) + \alpha C_1 + (1-\alpha) C_2}$$

$$H_2(\alpha) = \alpha \log \frac{1-\alpha}{\alpha} + (1-\alpha) \log \frac{1}{1-\alpha} \quad \frac{dH_2(\alpha)}{d\alpha} = \log \left( \frac{1-\alpha}{\alpha} \right)$$

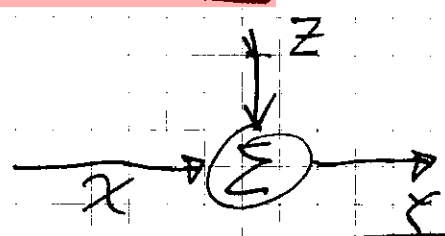
$$\frac{d}{d\alpha} \left[ \alpha \log \frac{1-\alpha}{\alpha} + C_1 - C_2 \right] = \log \frac{1-\alpha}{\alpha} = C_2 - C_1 \quad \frac{1-\alpha}{\alpha} = 2^{C_2 - C_1}$$

$$1-\alpha = \alpha \cdot 2^{C_2 - C_1} \quad 1 = \alpha \left( 1 + 2^{C_2 - C_1} \right) \quad \alpha = \frac{2^{C_1}}{2^{C_1} + 2^{C_2}}$$

$$\Rightarrow \boxed{C = 2^{C_1} + 2^{C_2}}$$

**PROBLEM 7.29**

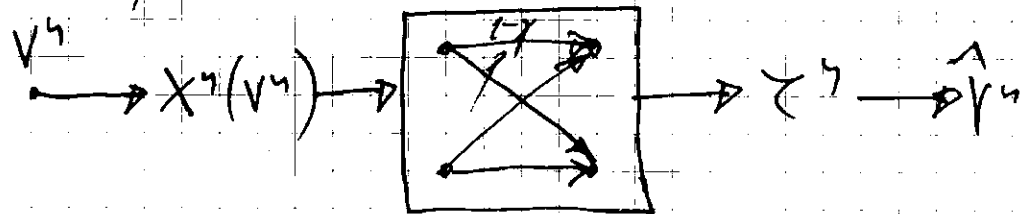
NOISE ADAPTERS. CONSIDER CHANNEL (29)



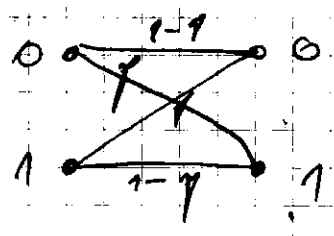
$\mathcal{X} = \{0, 1, 2, 3\}$   $\mathcal{Y} = \mathcal{X} + \mathcal{Z}$   
 AND  $\mathcal{Z}$  IS UNIFORMELY DISTRIBUTED.  
 15TH WANO 7.24

**PROBLEM 7.31**

WE WISH TO ENCODE A DETERMINISTIC PROCESS  $V^n$  FOR TRANSMISSION OVER A BINARY SYMMETRIC CHANNEL, WITH CROSSOVER PROBABILITY  $p$ .



FIND CONDITIONS ON  $\alpha^n$  AND  $p^n$  SO THAT THE PROBABILITY OF ERROR  $P(V^n \neq \hat{V}^n)$  CAN BE MADE TO GO TO ZERO AS  $n \rightarrow \infty$ .



$C_2 = H(X) - H(Y)$   
 $I(X; Y) = H(Y) - H(Y|X)$   
 $\max_{p \in [0, 1]} I(X; Y) = \max_{p \in [0, 1]} H(Y) - H(Y|X)$

$I(X^n; Z^n) \leq n \cdot I(X; Y)$

$n \cdot R \leq n + n \cdot p \cdot n \cdot R + nC$

$R \leq \frac{1}{n} + pR + C$

$C = H(X) - H(Y)$

$R(1 - pe) \leq \frac{1}{n} + H(X) - H(Y)$

$1 - pe \leq \frac{1}{nR} + \frac{H(X) - H(Y)}{R}$

$pe \geq 1 - \frac{1}{nR} - \frac{H(X) - H(Y)}{R}$

$n \rightarrow \infty \quad pe \geq 1 - \frac{H(X) - H(Y)}{R} \rightarrow 0 \Rightarrow$

$[H(X) - H(Y) = R]$

eg.  $\alpha = \frac{1}{2} \quad 1 - H(\frac{1}{2}) = R$

$p = 0.1 \Rightarrow H(p) = 0.469$

$R = 1 - 0.469 = 0.531$

$H(X) - H(Y) \leq R$  (BSC max R = 1)

$[H(X) \leq 1 - H(Y)]$  IS NOT NECESSARY

$H(X) - H(Y) \leq 1$

GO TO GO DOOR  $\checkmark$  VO KESERETO VO VIC.

# Solution University of Illinois Chicago

We can transmit a stationary ergodic source over a channel if and only if its entropy rate is less than the capacity of the channel.

$$H(V) < C$$

$$H(V) = \lim_{n \rightarrow \infty} \frac{1}{n} H(V_1, V_2, \dots, V_n) = \frac{H(X)}{n} = H(X)$$

$$H(X) < 1 - H(Y)$$

CIBC

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15th MAR  
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## PROBLEM 7.32 RANDOM 2D QUESTIONS. Let $X$ be

UNIFORMLY DISTRIBUTED OVER  $\{1, 2, \dots, m\}$ . Assume THAT  $m = 2^n$ . We ask random questions IS  $X \in S_1$ ? IS  $X \in S_2$ ? UNTIL ONE INTEGER REMAINS. ALL  $2^m$  SUBSETS  $S$  OF  $\{1, 2, \dots, m\}$  ARE EQUALLY LIKELY.

(a) HOW MANY DETERMINING QUESTIONS ARE NEEDED TO DETERMINE  $X$ ?

(b) WITHOUT LOSS OF GENERALITY, SUPPOSE THAT  $X=1$  IS THE RANDOM OBJECT. WHAT IS THE PROBABILITY THAT OBJECT 2 YIELDS THE SAME ANSWER AS OBJECT 1 FOR  $k$  QUESTIONS.

(c) WHAT IS THE EXPECTED NUMBER OF OBJECTS IN  $\{2, 3, \dots, m\}$  THAT HAVE THE SAME ANSWERS TO THE QUESTIONS AS THOSE OF THE COLLECT OBJECT 1?

(d) SUPPOSE THAT WE ASK WITH  $n$  RANDOM QUESTIONS. WHAT IS THE EXPECTED NUMBER OF WRONG OBJECTS AGREEING WITH ANSWERS?

(e) USE MARKOV INEQUALITY  $P\{X \geq tm\} \leq 1/t$  TO SHOW THAT PROBABILITY OF ERROR (ONE OR MORE WRONG OBJECTS REMAINING) GOES TO ZERO AS  $n \rightarrow \infty$ .

## PROBLEM 7.36 CHANNEL WITH MEMORY. CONSIDER THE DISCRETE MEMORYLESS CHANNEL $Z_i = Z_i X_i$ WITH INPUT ALPHABET $X_i \in \{-1, 1\}$

(a) WHAT IS THE CAPACITY OF THIS CHANNEL WHEN  $\{Z_i\}$  IS I.I.D.  $Z_i = \begin{cases} 1 & p=0.5 \\ -1 & p=0.5 \end{cases}$ ?

(15) NOW CONSIDER THE CHANNEL WITH MEMORY.  
 BEFORE TRANSMISSION BEGINS  $Z$  IS RANDOMLY CHOSEN AND FIXED FOR ALL TIME. THUS  $Z = Z_0$

(b) WHAT IS THE CHANNEL I.F.:

$$Z = \begin{cases} 1 & p=0.5 \\ -1 & q=0.5 \end{cases}$$

adding  
memory

(a)  $Z_i = X_i - Z_i$

$I(X; Z) = ?$

$P(X, Z, Y)$	$P(X, Z)$		
$X, Z$	-1	1	$P(X, Z)$
-1	0	1/4	1/4
1	1/4	0	1/4
$P(Z)$	1/2	1/2	

$I(X; Z) = H(Z) - H(Z|X)$

$H(Z) = \log_2 2 = 1$   
 $H(Z|X) = P(+ = -1) \cdot H(Z|+ = -1) + P(+ = 1) \cdot H(Z|+ = 1) = \frac{1}{2} \left( \frac{1}{4} \log_2 \frac{1}{4} \right) \cdot 2 + \frac{1}{2} \left( \frac{1}{4} \log_2 \frac{1}{4} \right) \cdot 2 = \frac{1}{2} + \frac{1}{2} = 1$

NA AND MAIN RESULT POSSIBLE PROBS OF 0.5

$I(X; Y) = 0$

$P(Z) = \left\{ \frac{1}{2}, \frac{1}{2} \right\}$

also:  $P(X) = \{p, 1-p\}$

$X, Z$	-1	1	$P(X, Z)$
-1	0	p/2	p/2
1	0	(1-p)/2	(1-p)/2
$P(Z)$	1/2	1/2	

$H(Z) = \frac{1}{2} \log_2 2 = 1$   
 $H(Z|X) = p \cdot \left( \frac{p}{2} \log_2 \frac{p}{2} \right) \cdot 2 + (1-p) \cdot \left( \frac{1-p}{2} \log_2 \frac{1-p}{2} \right) \cdot 2 = \frac{p^2}{1-p} \log_2 \frac{p}{2} + \frac{(1-p)^2}{1-p} \log_2 \frac{1-p}{2}$

$I(X; Z) = 1 - \left[ \frac{p^2}{1-p} \log_2 \frac{p}{2} + \frac{(1-p)^2}{1-p} \log_2 \frac{1-p}{2} \right]$

GUESSE!!!  
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 FA VERIFICAÇÃO  
 DA SE ZERAR.  
 Y.O DA DUIS  
 SO Y(X)  
 VIPY  
 PR 128

$\frac{d(I(X; Z))}{dp} = 0$   
 $2p \ln \left( \frac{1-p}{p} \cdot 2 \right) = \ln \left[ \left( \frac{1-p}{p} \right)^2 \cdot 2 \right] \Rightarrow \left[ \frac{2(1-p)}{p} \right]^2 = \left( \frac{1-p}{p} \right)^2 \Rightarrow Y = 1$

- So PLOT VO MAKE ZA (8) SE DOORVA (26)

MAXIMUM:  $p = 0.128$   $f(y) = 1 - p^2 \log \frac{2}{y} + (1-p)^2 \log \frac{2}{1-y}$   
 $f(y) = 0.024388$

$-2y \ln \frac{2}{y} + 2(1-y) \ln \left( \frac{2}{1-y} \right) - 1 + 2p = 0$   
 $-2y \ln \frac{2}{y} + 2 \ln \frac{2}{1-y} - 2y \ln \frac{2}{1-y} - 1 + 2p = 0$

$-2y \left( \ln \frac{2}{y} + \ln \frac{2}{1-y} - 1 \right) = 1 - 2 \ln \frac{2}{1-y}$   
 $2y \ln \frac{2 \cdot 2}{y(1-y)} \cdot \frac{1}{2} = \ln 2 - \ln \frac{4}{(1-y)^2} = \ln 2 \cdot \frac{(1-y)^2}{4}$   
 $\left[ \frac{y(1-y)}{2} \right]^{2y} = \frac{(1-y)^2}{2}$   $\left( \frac{y(1-y)}{2} \right)^y = \frac{1-y}{\sqrt{2}}$   $\left[ \begin{matrix} y=0.5 \\ p=1 \end{matrix} \right]$

(6)  $I(x^y, y) = I(x_1^y, y_1^y) = H(z_1^y) = H(z_1^y | x_1^y)$   
 $H(z_1^y) = H(z_1) + H(z_2 | z_1) + H(z_3 | z_1 z_2) + \dots + H(z_n | x_1^{n-1})$   
 $H(z_1^y | x_1^y) = H(z_1 | x_1^y) + H(z_2 | x_1^y z_1) + \dots + H(z_n | x_1^y z_1^{n-1})$   
 $= H(z_1 | x_1) + H(z_2 | x_2) + \dots + H(z_n | x_n)$   
 (MA sum!!) NEVA sum!!! SRO

$H(z_1 | x_1) = p^2 \log \frac{2}{1} + (1-p)^2 \log \frac{2}{1-p}$

$I(x^y, y) = y \cdot 1 - H(z_1 | x_1) = y - p^2 \log \frac{2}{1} - (1-p)^2 \log \frac{2}{1-p}$

$I(x, y) = \sum_{i=1}^y I(x_i, y_i) = 1 - p^2 \log \frac{2}{1} + (1-p)^2 \log \frac{2}{1-p} + \dots$   
 $+ \sum_{i=2}^y I(x_i, y_i) = 1 - p^2 \log \frac{2}{1} - (1-p)^2 \log \frac{2}{1-p} + \sum_{i=2}^y H(y_i)$

$= y - p^2 \log \frac{2}{1} - (1-p)^2 \log \frac{2}{1-p}$   
 $C_m = \frac{1}{y} \left( y - p^2 \log \frac{2}{1} - (1-p)^2 \log \frac{2}{1-p} \right)$   
 $(y \rightarrow \infty \quad C \rightarrow 1)$

CHANGE CAPACITY FOR y TIMES USAGE OF THE CHANNEL

• AVO ZEMEI DEKA  $y(x) = \left\{ \frac{1}{2}, \frac{1}{2} \right\} \rightarrow \text{(\$)} \rightarrow$   
 $H(z_1 | x_1) = 1 \Rightarrow I(x^y, y) \leq y - 1$   
 $C = \lim_{y \rightarrow \infty} \frac{y-1}{y} = 1$

$$z_i = (x_i + z_i) \bmod 2$$

$$I(x, z) = H(z) - H(z|x) = H(z) - \sum \gamma(x) H(z|x=z=x)$$

$$= H(z) - \sum \gamma(x) H((x+z) \bmod 2 | x) = H(z) - H(z)$$

$$I(x, z) = H(z) - H(z) \quad [C = 1 - H(z) = 1 - H(y)]$$

X \ Z	0	1	P(z)
0 0	1/2	0	(1-p)/2
0 1	0	p/2	p/2
1 0	0	(1-p)/2	(1-p)/2
1 1	p/2	0	p/2
P(x)	1/2	1/2	

P(x, z, y)

$$I(x, z) = H(z) - H(z|x) = H(y) - P(x=0) H(z|x=0) - P(x=1) H(z|x=1)$$

$$= H(y) - H(y) [P(x=0) + P(x=1)] = H(z) - H(y) \Rightarrow C = 1 - H(y)$$

Z \ X	0	1	P(x)
0 0	1-p	0	
0 1	0	p	
1 0	(1-p)	0	
1 1	0	p	

NA MODA NA ODISI SO METIOTAVNA.  $\gamma(x) = \begin{cases} 1 & 1 \\ 0 & 0 \end{cases}$  SODNO JE IZSLEDUJE NA P(Z|X) JE KRAJOT.

P(x, z, z)

X \ Z	0	1	H(z)
0 0	1-p	0	p(1-p)
0 1	0	p	p
1 0	0	(1-p)	p(1-p)
1 1	p	0	p
P(z)	p(1-p)	p	

X \ Z	0	1
0 0	1-p	0
0 1	0	p
1 0	0	1-p
1 1	p	0

NA OVO NAČIN ENKAPISUJE SE POVAZUVA.  $\star$  **DMV**

THIS IS DIRECT SYMMETRIC CHANNEL WITH CROSSOVER PROBABILITY  $p$ .

$$C(K) = \frac{1}{K} \max_{P(x)} \frac{I(x^K, z^K)}{K} = \frac{1}{K} \max_{P(x)} [H(x^K) - H(x^K|z^K)]$$

$$= \frac{1}{K} \max_{P(x)} [H(x^K) - \sum \gamma(x) H((x_i - z_i) \bmod 2 | x_i)] = H(z)$$

$$= \frac{1}{K} [K - H(z)] = 1 - \frac{H(z)}{K} = 1 - \frac{H(y)}{K}$$

THE CHANNEL WITH MEMORY LENGTH "K" HAS CAPACITY

CAPACITY RELATED TO THE MEMORYLESS CHANNEL. (12)

PROBLEM 7.369 REVISITED:

$P(Y Z)$			
$X \backslash Y$	1	1	
1	0	1/2	
1	1/2	0	
1	1/2	0	
1	0	1/2	

~~$$P(Z) = P_1 \left( \frac{1}{2} \right) + P_2 \left( \frac{1}{2} \right) = \frac{1}{2} + \frac{1}{2} = 1$$

$$P(Z=1) = P_1 \left( \frac{1}{2} \right) + P_2 \left( \frac{1}{2} \right) = \frac{1}{2} + \frac{1}{2} = 1$$~~

$$P(Z=1) = P_1 \left( \frac{1}{2} \right) + P_2 \left( \frac{1}{2} \right) = 1$$

ZNACH - PP. 125 (4) VARI NO OBT SWOR

$$I(X; Z) = 1 - 1 = 0 \quad C = 0$$

(6) REVISITED  $P(Z_1 | X_1) = 1 \Rightarrow$

$$I(X_1; Z_1) = 1 \cdot 1 - 1 = 0 \quad I(X_1; Z_1) \leq 1 \cdot C$$

$$C \geq \frac{I(X_1; Z_1)}{1} \rightarrow \lim_{n \rightarrow \infty} \left( \frac{1}{n} \right) = 0$$

**PROBLEM 7.37**

JOINT TYPICALITY. Let  $(X_i, Y_i, Z_i)$  be

i.i.d. according to  $p(x, y, z)$ . We will say that  $(x^n, y^n, z^n)$  is JOINTLY TYPICAL [WRITTEN]

- $(x^n, y^n, z^n) \in A_\epsilon^{(n)}$  IF:
- $p(x^n) \in 2^{-n(H(X) \pm \epsilon)}$ ;  $p(y^n) \in 2^{-n(H(Y) \pm \epsilon)}$ ;  $p(z^n) \in 2^{-n(H(Z) \pm \epsilon)}$
  - $p(x^n, y^n) \in 2^{-n(H(X, Y) \pm \epsilon)}$ ;  $p(x^n, z^n) \in 2^{-n(H(X, Z) \pm \epsilon)}$ ;  $p(y^n, z^n) \in 2^{-n(H(Y, Z) \pm \epsilon)}$
  - $p(x^n, y^n, z^n) \in 2^{-n(H(X, Y, Z) \pm \epsilon)}$

Now suppose that  $(\tilde{x}^n, \tilde{y}^n, \tilde{z}^n)$  is drawn according to  $p(x^n) \cdot p(y^n) \cdot p(z^n)$ . Thus  $\tilde{x}^n, \tilde{y}^n, \tilde{z}^n$  have the same marginals as  $p(x^n, y^n, z^n)$  but are independent. Find bounds on  $P\{(\tilde{x}^n, \tilde{y}^n, \tilde{z}^n) \in A_\epsilon^{(n)}\}$  in terms of entropies  $H(X), H(Y), H(Z), H(X, Y), H(X, Z), H(Y, Z)$ , and  $H(X, Y, Z)$ .

$P\{(\tilde{x}^n, \tilde{y}^n, \tilde{z}^n) \in A_\epsilon^{(n)}\} = ?$   $p(x^n, y^n) \in 2^{-n(H(X, Y) \pm \epsilon)}$

$$1 = \sum_{(x^n, y^n, z^n) \in A_\epsilon^{(n)}} p(x^n, y^n, z^n) \geq \sum_{(x^n, y^n) \in A_\epsilon^{(n)}} p(x^n, y^n) \geq \sum_{(x^n, y^n) \in A_\epsilon^{(n)}} 2^{-n(H(X, Y) - \epsilon)}$$

$$\frac{1}{2^{-n(H(X, Y) - \epsilon)}} \leq p(x^n, y^n) \leq 2^{-n(H(X, Y) - \epsilon)} \geq |A_\epsilon^{(n)}| \cdot 2^{-n(H(X, Y) - \epsilon)}$$

$$|A_\epsilon^y| \leq 2^{n(H(x|\gamma)+\epsilon)}$$

$$Pr((x, \gamma) \in A_\epsilon^y) \geq 1 - \epsilon \quad (12)$$

$$Pr((\tilde{x}_n, \tilde{\gamma}_n) \in A_\epsilon^y) \leq 2^{-n(H(x|\gamma)+3\epsilon)}$$

$$(1-\epsilon) \leq \sum_{x, \gamma \in A_\epsilon^y} \gamma(x, \gamma) \leq |A_\epsilon^y| \cdot 2^{-n(H(x|\gamma)-\epsilon)}$$

$$|A_\epsilon^y| \geq (1-\epsilon) 2^{n(H(x|\gamma)-\epsilon)} = \gamma(\tilde{x}_n, \tilde{\gamma}_n)$$

$$Pr((\tilde{x}_n, \tilde{\gamma}_n) \in A_\epsilon^y) = \sum_{\tilde{x}_n, \tilde{\gamma}_n \in A_\epsilon^y} \gamma(\tilde{x}_n) \cdot \gamma(\tilde{\gamma}_n) \leq \sum_{\tilde{x}_n, \tilde{\gamma}_n \in A_\epsilon^y} 2^{-n(H(x|\gamma)-\epsilon)} \cdot 2^{-n(H(x|\gamma)+\epsilon)}$$

$$\leq \sum_{\tilde{x}_n, \tilde{\gamma}_n \in A_\epsilon^y} 2^{-n(H(x|\gamma)+4\epsilon)} \leq 2^{-n(H(x|\gamma)+4\epsilon)} \cdot |A_\epsilon^y|$$

$$= 2^{-n(H(x|\gamma)+4\epsilon)} \cdot 2^{n(H(x|\gamma)-\epsilon)} = 2^{-n(H(x|\gamma)+5\epsilon)}$$

$$Pr[(\tilde{x}_n, \tilde{\gamma}_n) \in A_\epsilon^y] \leq 2^{-n(H(x|\gamma)+5\epsilon)}$$

$$Pr[(\tilde{x}_n, \tilde{\gamma}_n) \in A_\epsilon^y] = \sum_{\tilde{x}_n, \tilde{\gamma}_n \in A_\epsilon^y} \gamma(\tilde{x}_n) \cdot \gamma(\tilde{\gamma}_n) \geq (1-\epsilon) 2^{n(H(x|\gamma)-\epsilon)}$$

$$2^{-n(H(x|\gamma)+5\epsilon)} \geq (1-\epsilon) 2^{n(H(x|\gamma)-\epsilon)}$$

$$2^{-n(H(x|\gamma)+5\epsilon)} \geq (1-\epsilon) 2^{-n(H(x|\gamma)+3\epsilon)}$$

$$Pr[(\tilde{x}_n, \tilde{\gamma}_n) \in A_\epsilon^y] \geq (1-\epsilon) 2^{-n(H(x|\gamma)+3\epsilon)}$$

$$Pr[(\tilde{x}_n, \tilde{\gamma}_n, \tilde{z}_n) \in A_\epsilon^y] = \sum_{\tilde{x}_n, \tilde{\gamma}_n, \tilde{z}_n \in A_\epsilon^y} \gamma(\tilde{x}_n, \tilde{\gamma}_n, \tilde{z}_n) = \left[ \sum_{\tilde{x}_n, \tilde{\gamma}_n, \tilde{z}_n \in A_\epsilon^y} \gamma(\tilde{x}_n) \gamma(\tilde{\gamma}_n) \gamma(\tilde{z}_n) \right] \leq$$

$$|A_\epsilon^y| \cdot 2^{-n(H(x|\gamma)-\epsilon)} \cdot 2^{-n(H(\gamma)-\epsilon)} \cdot 2^{-n(H(z|\gamma)+\epsilon)}$$

$$\leq 2^{-n(H(x|\gamma, \gamma, z)+\epsilon)} = 2^{-n(H(x|\gamma)+H(\gamma)+H(z|\gamma)+\epsilon)}$$

$$\leq 2^{-n(H(x|\gamma, \gamma, z)+\epsilon)}$$



$$1 = \sum_{(x,y,z) \in A_\epsilon^3} \gamma(x,y,z) \leq \sum_{(x,y,z) \in A_\epsilon^3} \frac{\gamma(x,y,z)}{2^{-n(H(x,y,z) - \epsilon)}} \leq |A_\epsilon^3| \cdot 2^{-n(H(x,y,z) - \epsilon)}$$

$$|A_\epsilon^3| \leq 2^{n(H(x,y,z) + \epsilon)}$$

$$P_r((X,Y,Z) \in A_\epsilon^3) \geq 1 - \epsilon$$

$$(1 - \epsilon) \leq \sum_{(x,y,z) \in A_\epsilon^3} \gamma(x,y,z) \leq |A_\epsilon^3| \cdot 2^{-n(H(x,y,z) - \epsilon)}$$

$$(1 - \epsilon) \leq |A_\epsilon^3| \cdot 2^{-n(H(x,y,z) - \epsilon)} \implies |A_\epsilon^3| \geq (1 - \epsilon) \cdot 2^{n(H(x,y,z) - \epsilon)}$$

$$\textcircled{4} \implies P_r[(\tilde{X}_n, \tilde{Y}_n, \tilde{Z}_n) \in A_\epsilon^3] \leq 2^{-n[-H(x,y,z) + H(x) + H(y) + H(z) - 3\epsilon]}$$

$$P_r[(\tilde{X}_n, \tilde{Y}_n, \tilde{Z}_n) \in A_\epsilon^3] = \sum_{(\tilde{x}_n, \tilde{y}_n, \tilde{z}_n) \in A_\epsilon^3} \gamma(\tilde{x}_n) \gamma(\tilde{y}_n) \gamma(\tilde{z}_n) \geq (1 - \epsilon) \cdot 2^{n(H(x,y,z) - \epsilon)}$$

$$2^{-n(H(x,y,z) - \epsilon) - n[H(x) + H(y) + H(z) - 3\epsilon]} = (1 - \epsilon) \cdot 2^{n[H(x,y,z) - H(x) - H(y) - H(z) + 3\epsilon]}$$

$$P_r[(\tilde{X}_n, \tilde{Y}_n, \tilde{Z}_n) \in A_\epsilon^3] \geq (1 - \epsilon) \cdot 2^{n[H(x,y,z) - H(x) - H(y) - H(z) + 3\epsilon]}$$

$$P_r[(\tilde{X}_n, \tilde{Y}_n, \tilde{Z}_n) \in A_\epsilon^3] \geq (1 - \epsilon) \cdot 2^{-n[-H(x,y,z) + H(x) + H(y) + H(z) + 3\epsilon]}$$

$$-H(x,y,z) + H(x) + H(y) + H(z)$$

$$\lambda_i = P_r[g(\tilde{Z}_n) \neq i | \tilde{X}_n = \tilde{X}(i)] = \sum_{y^n} P(y^n | \tilde{X}(i)) \mathbf{I}[g(\tilde{Z}_n) \neq i]$$

**PROBLEM 7.15 REVISITED (3)**

$P_v = 4.6 \cdot 10^{-4}$  ANT SEQUENCE TO BE JOINTLY TYPICAL WITH  $Z^n$ . THE PROBABILITY THAT NONE OF 511 CODEWORDS ARE JOINTLY TYPICAL WITH RECEIVED SEQUENCE IS THEREFORE:

$$(1 - 4.552 \cdot 10^{-4})^{511} = 0.792$$

THE PROBABILITY THAT AT LEAST ONE IS JOINTLY TYPICAL WITH RECEIVED SEQUENCE IS:

$$1 - 0.792 = 0.208$$

PROBABLE THE PROBABILITY WORKING AT A OF 410M AROUND (0.233)

# CHAPTER 8 (CONTINUE FROM N.16c)

$h(\phi_k) \geq h(g)$        $\phi_k$  - GAUSSIAN DENSITY  $N(0, k)$

IN PARTICULAR GAUSSIAN DISTRIBUTION MAXIMIZES THE ENTROPY OVER ALL DISTRIBUTIONS WITH SAME VARIANCE. THIS LEADS TO THE ESTIMATION LOWER BOUND TO FANO'S INEQUALITY. LET  $X$  BE A RANDOM VARIABLE WITH DIFFERENTIABLE DENSITY  $h(x)$ . LET  $\hat{x}$  BE AN ESTIMATE OF  $X$ , AND LET  $E(x - \hat{x})^2$  BE THE EXPECTED PREDICTION ERROR. LET  $p_e$  BE IN A.D.S.

RECALL FANO INEQUALITY:  $h(x|\hat{x}) \leq 1 + p_e \log(1/p_e)$   
 $x \in \{0, 1\}$        $\hat{x} \in \{0, 1\}$

$$h(x|\hat{x}) = P(\hat{x}=0) \cdot h(x|\hat{x}=0) + P(\hat{x}=1) \cdot h(x|\hat{x}=1)$$

$$= P(\hat{x}=0) [ P(x=0|\hat{x}=0) \cdot \log P(x=0|\hat{x}=0) + P(x=1|\hat{x}=0) \cdot \log P(x=1|\hat{x}=0) ]$$

$$+ P(\hat{x}=1) [ P(x=0|\hat{x}=1) \cdot \log P(x=0|\hat{x}=1) + P(x=1|\hat{x}=1) \cdot \log P(x=1|\hat{x}=1) ]$$

$$p_e = P(x=0) \cdot P(\hat{x}=1|x=0) + P(x=1) \cdot P(\hat{x}=0|x=1)$$

$$h(x, \hat{x}) = h(x) + h(\hat{x}|x) = h(\hat{x}) + h(x|\hat{x})$$

$$e = \begin{cases} 1 & \hat{x} \neq x \\ 0 & \hat{x} = x \end{cases} \quad p_e = P(\hat{x} \neq x)$$

$$h(e, x|\hat{x}) = h(e|\hat{x}) + h(x|e\hat{x}) = P(\hat{x}=0) \cdot h(e|\hat{x}=0) + P(\hat{x}=1) \cdot h(e|\hat{x}=1)$$

$$= P(\hat{x}=0) [ P(e=1|\hat{x}=0) \cdot \log P(e=1|\hat{x}=0) + P(e=0|\hat{x}=0) \cdot \log P(e=0|\hat{x}=0) ]$$

$$h(e, x|\hat{x}) = h(x|\hat{x}) + h(e|x, \hat{x}) = h(x|\hat{x}) = h(e|\hat{x}) + h(x|e\hat{x}) \leq h(e) + p_e \log(1/p_e)$$

(1)  $h(e|\hat{x}) \leq h(e) = h(p_e)$

$$h(x|\hat{x}) = \frac{p_e}{1-p_e} \cdot h(x|e=0, \hat{x}) + P(e=1) \cdot h(x|e=1, \hat{x})$$

$$= p_e \cdot h(x|e=1, \hat{x}) \leq p_e \cdot h(x) \leq p_e \log(1/p_e)$$

(1.92)  $H(X|F) \leq \frac{H(X)}{1 + P_e C_d(X)}$   $e = \{1, 0\}$   $P(e) = \{P_e, 1-P_e\}$

$$H(e, X|F) = H(X|F) + \underbrace{H(e|X, F)}_0 = \underbrace{H(e|F)}_{\leq H(e) = P_e} + H(X|e, F) =$$

$$H(X|e, F) = P(e=0) \cdot H(X|e=0, F) + \underbrace{P(e=1)}_{P_e} H(X|e=1, F)$$

$$H(X|e, F) \leq P_e H(X) \leq P_e C_d(X)$$

$$\underline{H(X|F)} \leq H(P_e) + P_e \cdot C_d(X) \leq \underline{1 + P_e C_d(X)}$$

$$X \rightarrow Y \rightarrow \hat{X}$$

$$I(X; Y) \geq I(X; \hat{X})$$

$$I(X; Y) \geq I(Y; \hat{X})$$

$$I(X; Y) = H(X) - H(Y|X) \geq I(X; \hat{X}) = H(X) - H(Y|\hat{X})$$

$$H(Y|\hat{X}) \leq H(X|\hat{X}) \leq 1 + P_e C_d(X)$$

$$\boxed{H(Y|\hat{X}) \leq 1 + P_e C_d(X)} \leq \underline{1 + P_e C_d(X-1)}$$

**THEOREM 8.6.6** (ESTIMATION ERROR AND DIFFERENTIAL ENTROPY)  
 FOR A CONTINUOUS RANDOM VARIABLE  $X$  AND ESTIMATION ERROR  $X - \hat{X}$

$$\boxed{E(X - \hat{X})^2 \geq \frac{1}{2\pi e} e^{2h(X)}}$$

WITH EQUALITY IF AND ONLY IF  $X$  IS GAUSSIAN AND  $\hat{X}$  IS THE MEAN OF  $X$ .

PROOF:  $E(X - \hat{X})^2 \geq \min_{\hat{X}} E[X - \hat{X}]^2 = E[X - E(X)]^2$   
 $= \text{var}(X) \geq \frac{1}{2\pi e} e^{2h(X)}$

$$h(X) \leq h(\phi) = \frac{1}{2} \ln(2\pi e \sigma^2) \quad \text{with} \quad h(X) = \frac{1}{2} \ln(2\pi e)^{|K|}$$

$$\boxed{\sigma^2 \geq \frac{1}{2\pi e} e^{2h(X)}}$$

(\*)  $\Rightarrow$  FOLLOWS FROM THE FACT THAT THE MEAN OF  $X$  IS THE BEST ESTIMATOR FOR  $X^2$

COROLLARY: GIVEN SAME FORMATION  $\tau$  AND ESTIMATION ERROR  $\hat{X}(\tau)$  IT FOLLOWS THAT  $E(X - \hat{X}(\tau))^2 \geq \frac{1}{2\pi e} e^{2h(X|\tau)}$   $h(X) >$

**SUMMARY**

$$h(x) = h(f) = - \int f(x) \ln f(x) dx$$

$$h(x^n) = 2^{-n} h(x)$$

$$\text{Vol}(A_e^{(n)}) = 2^{-n} h(x)$$

$$h([X]_2^n) = h(x) + n$$

$$h(N(0, \sigma^2)) = \frac{1}{2} \ln 2\pi e \sigma^2$$

$$h(N(\mu, \sigma^2)) = \frac{1}{2} \ln [(2\pi e)^{-1} |K|]$$

$$D(f||g) = \int f \ln \frac{f}{g} \geq 0$$

$$h(x_1, x_2, \dots, x_n) = \sum_{i=1}^n h(x_i | x_1^{i-1})$$

$$h(x|Y) \leq h(x)$$

$$h(aX) = h(x) + \ln |a|$$

$$I(x, Y) = \int f(x, Y) \ln \frac{f(x, Y)}{f(x) \cdot f(Y)} \geq 0$$

$$\max_{\text{EXIT}=K} h(x) = \frac{1}{2} \ln (2\pi e)^{-1} |K|$$

$$E[x - F(Y)]^2 \geq \frac{1}{2\pi e} e^{2h(x|Y)}$$

- $2^{-n} h(x) \rightarrow$  is the effective alphabet size of discrete random variable.
- $2^{-n} h(x) \rightarrow$  is the effective alphabet size for a continuous random variable.
- $2^C \rightarrow$  is the effective alphabet size of a channel of capacity  $C$ .

CONTINUE FROM N/6a

$$f(x_1) = \frac{1}{\sigma_1 \sqrt{2\pi}} e^{-\frac{(x_1 - \mu_1)^2}{2\sigma_1^2}}$$

$$f(x_2) = \frac{1}{\sigma_2 \sqrt{2\pi}} e^{-\frac{(x_2 - \mu_2)^2}{2\sigma_2^2}}$$

$$x = x_1 + x_2$$

$$f(x) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2\sigma^2}}$$

$$\begin{aligned} \mu &= \mu_1 + \mu_2 \\ \sigma &= \sigma_1 + \sigma_2 \end{aligned}$$

$$h(x) = \frac{1}{2} \ln 2\pi e \sigma^2$$

$$\begin{aligned} \mu &= \mu_1 + \mu_2 \\ \sigma^2 &= \sigma_1^2 + \sigma_2^2 \end{aligned}$$

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$$h(x) = \frac{1}{2} \ln [2\pi e^{-(x-\mu)^2/\sigma^2}]$$

$$f(x) = \frac{dF(x)}{dx}$$

$$F(x) = \int_{-\infty}^x f(t) dt$$

$$M(s) = \int f(x) e^{-sx} dx$$

$$M(s) = \mathcal{L}[f(x)]$$

$$\mathcal{L}\left[\frac{dF(x)}{dx}\right] = M(s)$$

$$\mathcal{L}\left[\frac{dF(x)}{dx}\right] = s \mathcal{L}[F(x)]$$

$$s \hat{F}(s) = M(s)$$

$$\hat{F}(s) = \frac{M(s)}{s}$$

$$F(x) = \mathcal{L}\left[\frac{M(s)}{s}\right]$$

$$p(x) = \frac{1}{(\sqrt{2\pi})^k} e^{-\frac{x^T K^{-1} x}{2}}$$

**Problem 8.2** CONCAVITY OF DETERMINANTS. Let  $K_1$  AND  $K_2$  BE TWO SYMMETRIC NON-NEGATIVE DEFINITE  $n \times n$  MATRICES. FROM THE RESULT OF  $K_1$  FOR [1997]:

$$|\lambda K_1 + \bar{\lambda} K_2| \geq |K_1|^\lambda |K_2|^{\bar{\lambda}} \text{ FOR } 0 \leq \lambda \leq 1; \bar{\lambda} = 1 - \lambda;$$

WHERE  $|K|$  DENOTES THE DETERMINANT OF  $K$ .

[HINT: Let  $Z = X_\theta$ ,  $X_1 \sim N(0, K_1)$ ,  $X_2 \sim N(0, K_2)$  AND  $\theta = \text{BERNOULLI}(\lambda)$ . THEN USE  $h'(Z|\theta) \leq h(Z)$ ]

$$\begin{aligned} h(Z|\theta) &= p(\theta=1) \cdot h(Z|\theta=1) + p(\theta=2) \cdot h(Z|\theta=2) = \\ &= \lambda h(Z|\theta=1) + (1-\lambda) h(Z|\theta=2) = \lambda h(x_1) + (1-\lambda) h(x_2) \\ h(x_1) &= \frac{1}{2} \ln(2\pi e)^n |K_1| \quad h(x_2) = \frac{1}{2} \ln(2\pi e)^n |K_2| \end{aligned}$$

CONCAVITY OF RELATIVE ENTROPY

$$\begin{aligned} D(\lambda p_1 + (1-\lambda)p_2 \| \lambda \gamma_1 + (1-\lambda)\gamma_2) &\leq \lambda D(p_1 \| p_2) + \\ &+ (1-\lambda) D(p_2 \| p_2) \quad \text{CONCAVITY OF RELATIVE ENTROPY} \\ H(\lambda \gamma_1 + (1-\lambda)\gamma_2) &\geq \lambda H(\gamma_1) + (1-\lambda) H(\gamma_2) \quad \text{CONCAVITY OF ENTROPY!} \end{aligned}$$

$$Z = X_\theta \quad H(Z) \geq H(Z|\theta) = p(\theta=1) \cdot H(Z|\theta=1) + p(\theta=2) \cdot H(Z|\theta=2)$$

$$H(Z) \geq \lambda H(x_1) + (1-\lambda) H(x_2)$$

$$\lambda h(x_1) + (1-\lambda) h(x_2) = \frac{\lambda}{2} \ln(2\pi e)^n |K_1| + \frac{(1-\lambda)}{2} \ln(2\pi e)^n |K_2| \leq h(Z)$$

1.5  $h(z) =$   $z = \begin{cases} x_1 & \lambda \\ x_2 & 1-\lambda \end{cases} \rightarrow$  DISJOINT MIXTURE

$z = \lambda x_1 + (1-\lambda)x_2$   $E[z] = E[\lambda x_1] + E[(1-\lambda)x_2]$   
 $E[z] = \lambda \mu_1 + (1-\lambda) \mu_2$

$G_1 = \int \lambda x_1 \gamma(x_1) dx_1$

$\gamma(z_1) = ?$

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$z_1 = \lambda x_1$

$\gamma(z_1) = \frac{\gamma(x_1)}{\frac{dx_1}{dz_1}} \Big|_{x_1 = \frac{z_1}{\lambda}}$

$\gamma(z_1) = \frac{\gamma(\frac{z_1}{\lambda})}{\lambda} = \frac{1}{\lambda} \frac{1}{(2\pi)^n \sqrt{|K|}} e^{-\frac{1}{2} (\frac{z_1}{\lambda} - \mu_1)^T K^{-1} (\frac{z_1}{\lambda} - \mu_1)}$

$h(z) \equiv h(z|\theta) = \lambda h(x_1) + (1-\lambda) h(x_2) = \frac{\lambda}{2} \ln((2\pi e)^n |K_1|) + \frac{1-\lambda}{2} \ln((2\pi e)^n |K_2|)$   
 $h(z) \approx \frac{\lambda}{2} \ln((2\pi e)^n |K_1|) + \frac{1-\lambda}{2} \ln((2\pi e)^n |K_2|)$

$\gamma(z_1) = \frac{1}{\lambda} \frac{1}{(2\pi)^n \sqrt{|K|}} e^{-\frac{1}{2\lambda^2} (z_1 - \lambda \mu_1)^T K^{-1} (z_1 - \lambda \mu_1)}$

$\gamma(z_1) = \frac{1}{(2\pi)^n \sqrt{|K|} \cdot \lambda^2} e^{-\frac{1}{2} (z_1 - \lambda \mu_1)^T (\lambda^2 K)^{-1} (z_1 - \lambda \mu_1)}$

$\gamma(z_1) = \mathcal{N}(\lambda \mu_1, \lambda^2 |K|)$   $\gamma(z_2) = \mathcal{N}((1-\lambda) \mu_2, (1-\lambda)^2 |K|)$

$z = z_1 + z_2$   $\gamma(z) = \mathcal{N}(E[z_1] + E[z_2], \text{var}(z_1) + \text{var}(z_2))$

$p(z) = \mathcal{N}(\lambda \mu_1 + (1-\lambda) \mu_2, \lambda^2 |K_1| + (1-\lambda)^2 |K_2|)$

$h(z) = \frac{1}{2} \ln[(2\pi e)^n (\lambda^2 |K_1| + (1-\lambda)^2 |K_2|)]$

$\frac{1}{2} \ln[(2\pi e)^n (\lambda^2 |K_1| + (1-\lambda)^2 |K_2|)] \approx \frac{\lambda}{2} \ln((2\pi e)^n |K_1|) + \frac{1-\lambda}{2} \ln((2\pi e)^n |K_2|)$

$\frac{1}{2} \ln[(2\pi e)^n (\lambda^2 |K_1| + (1-\lambda)^2 |K_2|)] \approx \frac{\lambda}{2} \ln[(2\pi e)^n |K_1|] + \frac{1-\lambda}{2} \ln[(2\pi e)^n |K_2|]$

$(2\pi e)^n (\lambda^2 |K_1| + (1-\lambda)^2 |K_2|) \approx (2\pi e)^{n\lambda} |K_1|^\lambda \cdot (2\pi e)^{n(1-\lambda)} |K_2|^{1-\lambda}$

$$(\lambda e)^4 (\lambda^2 |k_1| + (1-\lambda)^2 |k_2|) \geq (\lambda e)^{2\lambda+2(1-\lambda)} \cdot |k_1|^\lambda \cdot |k_2|^{1-\lambda}$$

$$(\lambda^2 |k_1| + (1-\lambda)^2 |k_2|) \geq |k_1|^\lambda \cdot |k_2|^{1-\lambda}$$

$$|\lambda k_1 + (1-\lambda)k_2| \quad \begin{bmatrix} \lambda a & \lambda c \\ \lambda e & \lambda d \end{bmatrix} + \begin{bmatrix} (1-\lambda)e & (1-\lambda)f \\ (1-\lambda)g & (1-\lambda)h \end{bmatrix} =$$

$$= \begin{bmatrix} \lambda a + (1-\lambda)e & \lambda c + (1-\lambda)f \\ \lambda e + (1-\lambda)g & \lambda d + (1-\lambda)h \end{bmatrix} = \begin{matrix} \lambda^2 ad + \lambda a(1-\lambda)h + \lambda d(1-\lambda)e + (1-\lambda)^2 eh \\ - \lambda bc - \lambda b(1-\lambda)f - \lambda c(1-\lambda)g - (1-\lambda)^2 fh \end{matrix}$$

$$= \lambda^2 \underbrace{(ad - bc)}_{|k_1|} + (1-\lambda)^2 \underbrace{(eh - fh)}_{|k_2|} + \lambda(1-\lambda) \underbrace{[ah + de - bg - cf]}_{\textcircled{A}}$$

POSITIVE DEFINITE

$$\begin{bmatrix} 1 & 1 \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \begin{bmatrix} a+c & b+d \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \underline{a+c+b+d} > 0$$

$$\begin{bmatrix} 1 & 2 \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 \\ 2 \end{bmatrix} = \begin{bmatrix} a+2c & b+2d \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} = \underline{a+2c+b+2d} >$$

$$\begin{bmatrix} 1 & e \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} 1 \\ e \end{bmatrix} = \begin{bmatrix} a+be \\ c+de \end{bmatrix} = \begin{matrix} a+be > -c-e^2 \\ c+de > -a-e^2 \\ e(a+be) > -e(c+de) \end{matrix}$$

IF:  $\textcircled{A} \quad ah + de - bg - cf > 0 \quad \text{i.e.} \quad \underline{ah + de > bg + cf}$

$$\Rightarrow \lambda^2 |k_1| + (1-\lambda)^2 |k_2| + \lambda(1-\lambda) \textcircled{A} \geq \lambda^2 |k_1| + (1-\lambda)^2 |k_2| \geq |k_1|^\lambda |k_2|^{1-\lambda}$$

$$\textcircled{A}, \textcircled{B} \Rightarrow |\lambda k_1 + (1-\lambda)k_2| \geq |k_1|^\lambda |k_2|^{1-\lambda}$$

(REMARK SOLUTIONS (sch - 4-227-1107-96/))

$$E[Z Z^T] = E[E[Z Z^T] | \theta] = E[|k_1| | \theta=1 + |k_2| | \theta=2] = \lambda |k_1| + \bar{\lambda} |k_2| = E[E[X_1 X_1^T] | \theta=1 + E[X_2 X_2^T] | \theta=2]$$

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix} \begin{bmatrix} a & b \\ c & d \end{bmatrix} = \begin{bmatrix} a^2+bc & ab+bd \\ ac+bd & b^2+d^2 \end{bmatrix} \quad \begin{bmatrix} a & e \\ c & d \end{bmatrix} \begin{bmatrix} a & c \\ b & d \end{bmatrix} = \begin{bmatrix} a^2+bc & ab+bd \\ ac+bd & c^2+dc \end{bmatrix}$$

$$|\lambda k_1 + (1-\lambda)k_2| = \lambda^2(ad-bc) + (1-\lambda)^2(eh-fg) + \lambda(1-\lambda)[ah+de-bf-cg]$$

$k_1$  &  $k_2$  are symmetric  $\Rightarrow$

$$b=c \quad f=g$$

$$|\lambda k_1 + (1-\lambda)k_2| = \lambda^2 |k_1| + (1-\lambda)^2 |k_2| + \lambda(1-\lambda)[ah+de-g-g]$$

$$= \lambda^2 |k_1| + (1-\lambda)^2 |k_2| + \lambda(1-\lambda)[ah+de-2cg]$$

$$MGF(N(\mu, \sigma^2)) = e^{t\mu + \frac{\sigma^2 t^2}{2}} \quad \text{[Lecture 21]}$$

$(X_1, X_2, \dots, X_n)$  are joint Gaussian

$$M(t_1, t_2, \dots, t_n) = \exp(t_1 \mu_1 + \dots + t_n \mu_n) \exp\left(\frac{1}{2} \sum_{i,j=1}^n t_i a_{ij} t_j\right)$$

$$M(\underline{t}) = \exp(\underline{t}' \underline{\mu}) \exp\left(\frac{1}{2} \underline{t}' \underline{A} \underline{t}\right) \quad \text{a - COLUMN VECTOR}$$

**21.2 THEOREM** JOINT GAUSSIAN RANDOM VARIABLES  
 THESE FROM NON-SIMULTANEOUS LINEAR  
 TRANSFORMATIONS ON INDEPENDENT RANDOM VARIABLES  
 VECTOR

PROOF:  $X_1, \dots, X_n$  are independent with  $X_i \sim N(0, \lambda_i)$

$\underline{X} = (X_1, \dots, X_n)'$ . Let  $\underline{Z} = \underline{B} \underline{X} + \underline{\mu}$  where  $\underline{B}$  is nonsingular then  $\underline{Z}$  is Gaussian.

$$M_{\underline{Z}}(\underline{t}) = E[\exp(\underline{t}' \underline{Z})] = E[\exp(\underline{t}' \underline{B} \underline{X}) \exp(\underline{t}' \underline{\mu})]$$

$$E[\exp(\underline{t}' \underline{X})] = \prod_{i=1}^n E[\exp(t_i X_i)] = \exp\left(\sum_{i=1}^n \lambda_i \frac{t_i^2}{2}\right) = \exp\left(\frac{1}{2} \underline{t}' \underline{D} \underline{t}\right)$$

$$[M_1 M_2] \begin{bmatrix} \lambda_1 & 0 \\ 0 & \lambda_2 \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} = [\lambda_1 M_1 \quad \lambda_2 M_2] \begin{bmatrix} t_1 \\ t_2 \end{bmatrix} = \lambda_1 t_1^2 + \lambda_2 t_2^2$$

$$\underline{M}' = \underline{B}' \underline{t} \quad \underline{M} = \underline{t}' \underline{B}$$

$$M_{\underline{Z}}(\underline{t}) = \exp(\underline{t}' \underline{\mu}) \cdot \exp\left(\frac{1}{2} \underline{t}' \underline{B} \underline{D} \underline{B}' \underline{t}\right) \quad \underline{B} \underline{D} \underline{B}' \text{ is}$$

symmetric and positive definite matrix  $\Rightarrow \underline{Z}$  is Gaussian.

$$M_{\underline{Z}}(\underline{t}) = \exp(\underline{t}' \underline{\mu}) \cdot \exp\left(\frac{1}{2} \underline{t}' \underline{A} \underline{t}\right)$$



• DA 40 PROBLEME 12 ERZÖT M 135 \* ZA ANWENDUNG.

$$f(x) = \frac{1}{\sqrt{2\pi} |K|^{1/2}} e^{-\frac{x^T K^{-1} x}{2}}$$

$$|K| = \sigma_1^2 \sigma_2^2 - \rho^2$$

$$K = \begin{bmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix}$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\sigma_{12} = \text{Cov}(x_1, x_2)$$

$$f(x_1, x_2) = \frac{1}{\sqrt{2\pi} \sigma_1 \sigma_2 \sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)} \left[ \frac{x_1^2}{\sigma_1^2} - 2\rho \frac{x_1}{\sigma_1} \frac{x_2}{\sigma_2} + \frac{x_2^2}{\sigma_2^2} \right]\right)$$

$$|K| = \sigma_1^2 \sigma_2^2 - \rho^2 \sigma_1^2 \sigma_2^2 = \sigma_1^2 \sigma_2^2 (1-\rho^2)$$

$$z = \lambda \cdot x \quad f(z) = ?$$

$$y_1 = \lambda x_1 \quad y_2 = \lambda x_2$$

$$J = \begin{vmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} \end{vmatrix} = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix} = \lambda^2$$

$$f(z) = \frac{f(x)}{|J|} \quad x = \frac{z}{\lambda}$$

$$f(y_1, y_2) = \frac{1}{\lambda^2} \frac{1}{\sqrt{2\pi} \sigma_1 \sigma_2 \sqrt{1-\rho^2}} \exp\left(-\frac{1}{2(1-\rho^2)} \left[ \frac{y_1^2}{\lambda^2 \sigma_1^2} - 2\rho \frac{y_1 y_2}{\lambda^2 \sigma_1 \sigma_2} + \frac{y_2^2}{\lambda^2 \sigma_2^2} \right]\right)$$

$$|K_z| = \lambda^2 \sigma_1 \sigma_2 \sqrt{1-\rho^2} \quad |K_y| = \lambda^4 \sigma_1^2 \sigma_2^2 (1-\rho^2)$$

$$K_z = \lambda \begin{bmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix} = \begin{bmatrix} \lambda \sigma_1^2 & \lambda \rho \sigma_1 \sigma_2 \\ \lambda \rho \sigma_1 \sigma_2 & \lambda \sigma_2^2 \end{bmatrix} = \begin{bmatrix} \lambda \sigma_1^2 & \lambda \rho \sigma_1 \sigma_2 \\ \lambda \rho \sigma_1 \sigma_2 & \lambda \sigma_2^2 \end{bmatrix}$$

$$|K_z| = \lambda^2 (\sigma_1^2 \sigma_2^2 - \rho^2 \sigma_1^2 \sigma_2^2) = \lambda^2 (\sigma_1^2 \sigma_2^2 (1-\rho^2)) = \lambda^2 \sigma_1^2 \sigma_2^2 (1-\rho^2)$$

$$K_z^{-1} = \frac{1}{\lambda^2 \sigma_1^2 \sigma_2^2 (1-\rho^2)} \begin{bmatrix} \lambda \sigma_2^2 & -\lambda \rho \sigma_1 \sigma_2 \\ -\lambda \rho \sigma_1 \sigma_2 & \lambda \sigma_1^2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix}$$

$$\frac{1}{2\pi} \begin{bmatrix} y_1 & y_2 \end{bmatrix} \begin{bmatrix} \lambda \sigma_2^2 & -\lambda \rho \sigma_1 \sigma_2 \\ -\lambda \rho \sigma_1 \sigma_2 & \lambda \sigma_1^2 \end{bmatrix} \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \frac{1}{2\pi} \begin{bmatrix} \lambda \sigma_2^2 y_1^2 - \lambda \rho \sigma_1 \sigma_2 y_1 y_2 \\ -\lambda \rho \sigma_1 \sigma_2 y_1 y_2 + \lambda \sigma_1^2 y_2^2 \end{bmatrix}$$

$$= \frac{1}{2\pi} (\lambda \sigma_2^2 y_1^2 - \lambda \rho \sigma_1 \sigma_2 y_1 y_2 - \lambda \rho \sigma_1 \sigma_2 y_1 y_2 + \lambda \sigma_1^2 y_2^2) = \frac{1}{2\pi} (\lambda \sigma_2^2 y_1^2 - 2\rho \lambda \sigma_1 \sigma_2 y_1 y_2 + \lambda \sigma_1^2 y_2^2) = \frac{1}{2(1-\rho^2)} \left[ \frac{y_1^2}{\lambda^2 \sigma_1^2} - \frac{2\rho y_1 y_2}{\lambda^2 \sigma_1 \sigma_2} + \frac{y_2^2}{\lambda^2 \sigma_2^2} \right]$$

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$$\begin{bmatrix} \frac{\gamma_1}{\lambda} & \frac{\gamma_2}{\lambda} \end{bmatrix} \begin{bmatrix} \sigma_2^2 - \rho \sigma_1 \sigma_2 & -\rho \sigma_1 \sigma_2 \\ -\rho \sigma_1 \sigma_2 & \sigma_1^2 \end{bmatrix} \begin{bmatrix} \frac{\gamma_1}{\lambda} \\ \frac{\gamma_2}{\lambda} \end{bmatrix} = \frac{1}{\lambda} (|\kappa_1| = \sigma_1 \sigma_2^2 (1 - \rho^2))$$

$$\frac{1}{2\lambda} \begin{bmatrix} \frac{\sigma_2^2 \gamma_1}{\lambda} - \frac{\rho \sigma_1 \sigma_2 \gamma_2}{\lambda} & -\frac{\rho \sigma_1 \sigma_2 \gamma_1}{\lambda} + \frac{\sigma_1^2 \gamma_2}{\lambda} \end{bmatrix} \begin{bmatrix} \frac{\gamma_1}{\lambda} \\ \frac{\gamma_2}{\lambda} \end{bmatrix} =$$

$$\frac{1}{2\lambda} \begin{bmatrix} \frac{\sigma_2^2 \gamma_1^2}{\lambda^2} - \frac{\sigma_1 \sigma_2 \gamma_1 \gamma_2}{\lambda^2} - \frac{\rho \sigma_1 \sigma_2 \gamma_1 \gamma_2}{\lambda^2} + \frac{\sigma_1^2 \gamma_2^2}{\lambda^2} \end{bmatrix}$$

$$= \frac{1}{2(1-\rho^2)} \left[ \frac{\gamma_1}{\lambda \sigma_1^2} - \frac{2\gamma_1 \gamma_2}{\sigma_1 \sigma_2 - \lambda^2} + \frac{\gamma_2^2}{\sigma_2^2 \lambda^2} \right]$$

$$= \frac{1}{\sigma_1} = \lambda \sigma_{x_1} \quad \sigma_{x_2} = \lambda \sigma_{x_2} =$$

1st term used 139

$$= \frac{1}{2(1-\rho^2)} \left[ \frac{\gamma_1}{\sigma_1^2} - \frac{2\gamma_1 \gamma_2}{\sigma_1 \sigma_2} + \frac{\gamma_2^2}{\sigma_2^2} \right]$$

$$\kappa_2 = \begin{bmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix} = \lambda^2 \begin{bmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{bmatrix}$$

$$|\kappa_2| = \lambda^4 \sigma_1^2 \sigma_2^2 - \lambda^4 \sigma_1^2 \sigma_2^2 \rho^2 = \lambda^4 (1 - \rho^2) \sigma_1^2 \sigma_2^2$$

$$\gamma = \frac{1}{\sqrt{2\pi} \sqrt{|\kappa_2|}} e^{-\frac{1}{2} \gamma^T \kappa_2^{-1} \gamma} = \frac{1}{\lambda^2 2\pi \sigma_1 \sigma_2 \sqrt{1-\rho^2}} e^{-\frac{1}{2} \gamma^T \kappa_2^{-1} \gamma}$$

$$|\kappa_2| = \lambda^4 |\kappa_1|$$

ЗНАЧИМО:  $Z = \lambda X_1 + (1-\lambda) X_2$  DISJOINT (FROM NOGU MS & ZA DISJOINT. TUKA KEBA LEJENOTO MA MODCENOT.

$$Z = \lambda X_1 + (1-\lambda) X_2 \rightarrow$$

$$P(Z) = N(\lambda \mu_1 + (1-\lambda) \mu_2, \lambda^2 |\kappa_1| + (1-\lambda)^2 |\kappa_2|)$$

СМАК ЗАДАЧА 6 ЗА DISJOINT  $Z = \begin{cases} X_1 & \lambda \\ X_2 & 1-\lambda \end{cases}$

PROBLEM 8.7

DIFFERENTIAL ENTROPY (CONTINUE FROM N/60)  
BOUND ON DISCRETE ENTROPY

$x \in \{a_1, a_2, \dots, a_n, \dots\}$   
 $x' \in \{1, 2, \dots, n, \dots\}$   
 $z = x' + v$

$p(x) = \{p_1, p_2, \dots\}$   
 $p(x') = \{p_1, p_2, \dots\}$

$h(x) = h(x')$

0	0.5	→ 0
0.5	1	→ 1

$I(x'; z) = \underbrace{h(x')}_{=h(x)} - h(x'|z) = h(z) - h(z|x') = h(z) - h(v)$

$z \in [1\sqrt{2}, 2\sqrt{2}, \dots, n\sqrt{2}, \dots]$        $z = \{z_1, z_2, \dots, z_n, \dots\}$

$h(z) = \lim_{n \rightarrow \infty} \frac{1}{n} h(z_1, z_2, \dots, z_n) = \frac{1}{n} h(z_i) = h(z_i)$

$h(z_i) = ?$        $z_i = \begin{cases} x' & n=0 \\ x'+1 & n=1 \end{cases}$        $h(z_i) = \frac{1}{2} \log 2 + \frac{1}{2} \log 2 = 1$

$h(z) = 1$        $\Rightarrow h(x) - h(x'|z) = h(z) = 1$

$h(x) = 1 + h(x'|z)$ ;       $h(x'|z) = p(z_i=x) \cdot h(x'|z_i=x) + p(z_i=x+1) \cdot h(x'|z_i=x+1) = \frac{1}{2} \cdot 1 + \frac{1}{2} \cdot 1 = 1$

$h(x) = 1 + 1 = 2$

$E[(x-\bar{x})^2] \geq \min (x-\bar{x})^2 = (x-\bar{x})^2 = \text{var } x = \sigma^2$

$h(x) \leq \frac{1}{2} \log (2\pi e) \sigma^2$        $\sigma^2 \geq \frac{e}{(2\pi e)}$

$E[(x-\bar{x})^2] \geq \frac{e}{(2\pi e)} \cdot \frac{1}{2} \log (2\pi e) \sigma^2$        $h(x|z) = h(x|z)$   
 $\sigma^2 \geq \frac{e}{(2\pi e)} = \frac{e}{2\pi e} = \frac{1}{2\pi}$

$E[(x-\bar{x})^2] = E[x^2] - \bar{x}^2 = E[x^2] - E[x]^2 = \sum_{i=1}^n i^2 p_i - \left(\sum_{i=1}^n i p_i\right)^2$

$E[x] = \sum_{i=1}^{\infty} a_i p_i = a_1 p_1 + a_2 p_2 + \dots$

$E[x^2] = \sum_{i=1}^{\infty} i^2 p_i = 1 \cdot p_1 + 2 \cdot p_2 + \dots$

$h(x) = h(x') \leq \frac{1}{2} \log (2\pi e) \left[ \sum_{i=1}^{\infty} i^2 p_i - \left(\sum_{i=1}^{\infty} i p_i\right)^2 \right]$

(111)

$Y = X + U$

$E[(Y - \bar{Y})^2] = ?$

$f(x, u) = f(x)$

$f(x, u) = \int_{t=0}^1 p(t-x) \cdot \underbrace{q(x)}_{1=0 \dots 1} dx$

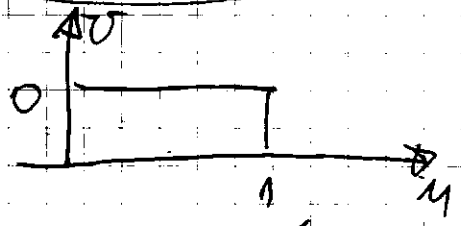
$f(t) = \int_0^1 p(t-x) dx = 1$

$p(x) = \{p_1, p_2, p_3, \dots, p_n, \dots, \infty\}$

$H(u) + \ln \Delta = \underbrace{h(u)}_0$

$H(u^0) = -\ln \Delta$   
 $H(u^0) = -\ln(2^y)^{-1}$

$H(u^0) = \ln \frac{1}{2^y} = h$



$var(u) = \int (u - \bar{u})^2 p(u) du$

$\bar{u} = \int u p(u) du = \frac{4 \frac{u^2}{2}}{2} = \frac{1}{2}$

$var(u) = \int_0^1 (u - \frac{1}{2})^2 du = \int_0^1 (u^2 - 2u + \frac{1}{4}) du = \left[ \frac{u^3}{3} - \frac{u^2}{2} + \frac{1}{4}u \right]_0^1 = \left( \frac{1}{3} - \frac{1}{2} + \frac{1}{4} \right) = \frac{4-6+3}{12} = \frac{1}{12}$

$E[(Y - \bar{Y})^2] = ?$

solust. yof

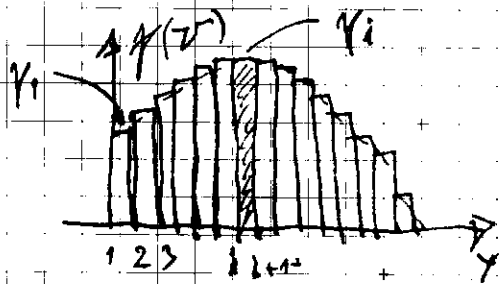
POSSIBLE SOLUTIONS:  $Y = X + U$  AND THEREFORE THE DISTRIBUTION OF  $Y$  HAS THE SAME OF A DISCRETE (I.E.  $f_Y(y) = p_i$  FOR  $1 \leq i \leq n$ )

$H(X) = H(Y)$  SINCE DISCRETE ENTROPYES DEPENDS ON THE AMPLITUDES AND NOT ON THE VALUES OF THE OUTCOMES.

$H(X) = - \sum_{i=1}^n p_i \ln p_i = - \sum_{i=1}^n \left( \int f_X(x) dx \right) \ln \left( \int f_X(x) dx \right)$   
 $= - \sum_{i=1}^n p_i \ln p_i = - \sum_{i=1}^n p_i \ln p_i = - \sum_{i=1}^n p_i \ln p_i = - \int_1^n f_X(x) \ln f_X(x) dx =$

$$= h(z)$$

$$h(x) = h(x^{-}) = h(z)$$



$$h(z) \leq \frac{1}{2} \log \left( \frac{2\pi e}{\sigma_x^2} \right) = \frac{1}{2} \log \left( \frac{2\pi e}{\sigma_x^2 + \sigma_y^2} \right) = \frac{1}{2} \log \left( \frac{2\pi e}{\sum_{i=1}^n i^2 p_i + \frac{1}{12}} \right)$$

Since entropy is invariant with respect to permutations

$$h(z) \leq \frac{1}{2} \log \left( \frac{2\pi e}{\sum_{i=1}^n i^2 p_i - \left( \sum_{i=1}^n i p_i \right)^2 + \frac{1}{12}} \right)$$

• Parameter is  $\sigma_z^2 = \sigma_x^2 + \sigma_y^2$  ?

Spoken Bivariate Formula for  $\sigma_z^2$

$$\text{Var}(\bar{x}) = \text{Var} \left( \frac{1}{n} \sum_{i=1}^n x_i \right) = \frac{1}{n^2} \sum_{i=1}^n \text{Var}(x_i) = \frac{1}{n^2} \sum_{i=1}^n \sigma_x^2 = \frac{\sigma_x^2}{n}$$

$$\iint \left[ (x+y)^2 - (\bar{x} + \bar{y}) \right]^2 p(x,y) dx dy =$$

$$\iint (x+y)^2 p(x,y) dx dy - \int (\bar{x} + \bar{y}) p(x,y) dx dy =$$

$$\int (\bar{x} + \bar{y})^2 p(x,y) dx dy = \text{Cov}(x,y) = (\bar{x} - \mu_x)(\bar{y} - \mu_y)$$

$$= \int x^2 p(x,y) dx dy + 2 \int xy p(x,y) dx dy - (\bar{x} + \bar{y}) \int (x+y) p(x,y) dx dy + (\bar{x} + \bar{y})^2 = E[x^2] + E[y^2] + 2E[xy] - (\bar{x} + \bar{y})^2 = E[x^2] + E[y^2] + 2E[xy] - \bar{x}^2 - \bar{y}^2 - 2\bar{x}\bar{y} = E[x^2] + E[y^2] + 2E[xy] - \bar{x}^2 - \bar{y}^2 - 2\bar{x}\bar{y} = 0$$

**Problem 8.9** (Continue from N(bk)) UIC solution

$$x \rightarrow z \rightarrow z \quad (x,z) \stackrel{p_A}{\rightarrow} (z,z) \stackrel{p_B}{\rightarrow} z \quad I(x; z) = ?$$

$$I(x; z) = h(x) - h(x|z) = |h(x,z) = h(z) + h(x|z)| = h(x) - h(x,z) + h(z)$$

Since  $x, z, z$  are jointly Gaussian, hence

(145) X AND Z ARE JOINTLY GAUSSIAN

$$K = \begin{bmatrix} \sigma_x^2 & \rho_{xz} \sigma_x \sigma_z \\ \rho_{xz} \sigma_x \sigma_z & \sigma_z^2 \end{bmatrix} \quad I(x; z) = h(x) + h(z) - h(x, z)$$

$$I(x; z) = \frac{1}{2} \log(\sigma_x \sigma_z) \sigma_x^2 + \frac{1}{2} \log(\sigma_x \sigma_z) \sigma_z^2 - \frac{1}{2} \log(\sigma_c)^2$$

$$\begin{aligned} \therefore \sigma_x^2 \sigma_z^2 (1 - \rho_{xz}^2) &= \frac{1}{4} \log(\sigma_x \sigma_z) + \frac{1}{2} \log(\sigma_x^2 + \sigma_z^2) - \\ &- \frac{1}{2} \log(\sigma_x \sigma_z) - \frac{1}{2} \log(\sigma_x^2 \sigma_z^2) - \frac{1}{2} \log(1 - \rho_{xz}^2) = -\frac{1}{2} \log(1 - \rho_{xz}^2) \end{aligned}$$

$\rho_{xz} = ?$  BY USING MARKOVITE:

$$p(x, z | \gamma) = p(x | \gamma) p(z | \gamma)$$

$$p(z | x) = \frac{p(x, z | \gamma)}{p(x | \gamma)} = \frac{p(x | \gamma) p(z | \gamma)}{p(x | \gamma)} = p(z | \gamma)$$

~~$$p(x, z) = p(x) p(z)$$~~

$$p(z | x) = \frac{p(x, z)}{p(x)} = \frac{p(x) p(z)}{p(x)} = p(z)$$

$$p(z | x) = p(z | \gamma) \cdot p(\gamma | z)$$

$$\rho_{xz} = \frac{E[x, z]}{\sigma_x \sigma_z} = \frac{E[(x, z | \gamma)]}{\sigma_x \sigma_z} = \frac{E[E[x | \gamma] E[z | \gamma]]}{\sigma_x \sigma_z}$$

SINCE X, Z ARE JOINTLY GAUSSIAN

$$E[x | \gamma] = \frac{\sigma_x \rho_{x\gamma}}{\sigma_\gamma} \gamma \quad E[z | \gamma] = \frac{\sigma_z \rho_{z\gamma}}{\sigma_\gamma} \gamma$$

$$E[E[x | \gamma] E[z | \gamma]] = E\left[ \frac{\sigma_x \rho_{x\gamma}}{\sigma_\gamma} E[\gamma] \cdot \frac{\sigma_z \rho_{z\gamma}}{\sigma_\gamma} E[\gamma] \right]$$

$$\rho_{xz} = \frac{1}{\sigma_x \sigma_z} \frac{\sigma_x \sigma_z \rho_{x\gamma} \rho_{z\gamma}}{\sigma_\gamma^2} E[E[\gamma]^2] = \frac{\rho_{x\gamma} \rho_{z\gamma}}{\sigma_\gamma^2} \sigma_\gamma^2 = \rho_{x\gamma} \rho_{z\gamma}$$

$$\rho_{xz} = \rho_{x\gamma} \rho_{z\gamma} \Rightarrow I(x; z) = -\frac{1}{2} \log(1 - \rho_{x\gamma}^2 \rho_{z\gamma}^2) = -\frac{1}{2} \log(1 - \rho_{xz}^2)$$

$$\begin{aligned} p(x, z | \gamma) &= \frac{p(x, z)}{p(\gamma)} = \frac{p(x) p(z)}{p(\gamma)} = \frac{p(x | \gamma) p(z | \gamma)}{p(\gamma)} \\ &= p(x | \gamma) p(z | \gamma) \end{aligned}$$

$$E[(x, z) | z] = \iint x z P(x, z | z) dx dz$$

**PROBLEM 8.10** STATE OF THE TYPICAL SET,

LET  $x_i$  BE I.I.D  $\sim f(x)$  WHERE

$$f(x) = c e^{-x^4}$$

LET  $h = -\int f \ln f$ . DESCRIBE THE STATE (OUTPUT) OF THE TYPICAL SET:  $A_\epsilon^{(n)} = \{x^i \in \mathcal{R}^n : f(x^i) \in [2^{-n(h \pm \epsilon)}]\}$

$$h(x) - \epsilon \leq \frac{1}{n} \ln f(x) \leq h(x) + \epsilon \quad \Rightarrow \quad -n(h(x) + \epsilon) \leq f(x) \leq -n(h(x) - \epsilon)$$

$$2 \cdot (1 - \epsilon) \leq \text{Vol} \{A_\epsilon^{(n)}\} \leq 2^{+n(h(x) + \epsilon)}$$

$$h(c) = \frac{1}{2} \frac{c \ln(c) \pi \sqrt{2}}{\Gamma(\frac{3}{4})} + \frac{1}{8} \frac{c \pi \sqrt{2}}{\Gamma(\frac{3}{4})} = \frac{1}{2} \frac{c \pi \sqrt{2}}{\Gamma(\frac{3}{4})} \left( \ln c + \frac{1}{4} \right)$$

$$h(c) = \frac{c \pi}{\sqrt{2} \Gamma(\frac{3}{4})} \ln(c e^{\frac{1}{4}})$$

$$\text{Vol} \{A_\epsilon^{(n)}\} = 2^{+n h(x)}$$

n-DIMENSIONAL VOLUME

$$\text{side length} = \left( 2^{+n h(x)} \right)^{\frac{1}{n}} = 2^{h(x)} = 2^{\frac{c \pi}{\sqrt{2} \Gamma(\frac{3}{4})} \ln(c e^{\frac{1}{4}})}$$

$$= (c e^{\frac{1}{4}})^{\frac{c \pi}{\sqrt{2} \Gamma(\frac{3}{4})}} = (c e^{\frac{1}{4}})^{\frac{1}{4} \frac{c \pi}{\sqrt{2} \Gamma(\frac{3}{4})}}$$

UNIVERSITY OF TORONTO SOLUTION:

$$f(x^n) = c^n e^{-(x_1^4 + x_2^4 + \dots + x_n^4)}$$

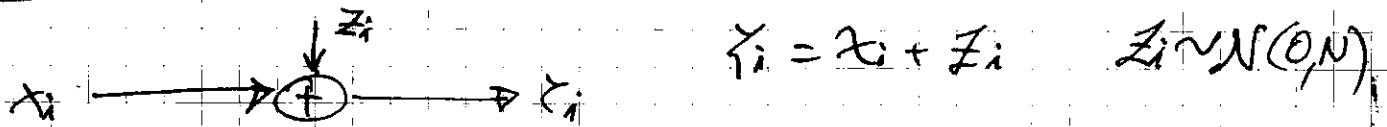
$$2^{-n(h(x) + \epsilon)} \leq c^n e^{-\sum_{i=1}^n x_i^4} \leq 2^{-n(h(x) - \epsilon)}$$

$$-n(h(x) + \epsilon) \ln 2 \leq \ln c + \sum_{i=1}^n x_i^4 \leq -n(h(x) - \epsilon) \ln 2$$

$$A_\epsilon^{(n)} = \{x^i \in \mathcal{R}^n : n[h(x) - \epsilon] \ln 2 + \ln c \leq \sum_{i=1}^n x_i^4 \leq n[h(x) + \epsilon] \ln 2 + \ln c\}$$

THIS IS REMINISCENT OF THE FACT THAT TYPICAL SET OF A GAUSSIAN DISTRIBUTION IS A THIN SPHERICAL SHELL. IN THIS CASE, THE SHELL HAS BEEN ROTATED AT A STATE OF FORM:  $x_1^4 + x_2^4 + \dots + x_n^4 = V$ , BUT THE THIN SHELL PROPERTY REMAINS.

# CHAPTER 9: GAUSSIAN CHANNELS



We assume an average power constraint for the codeword  $(x_1, x_2, \dots, x_n)$  transmitted over the channel, we require that

$$\frac{1}{n} \sum_{i=1}^n x_i^2 \leq P$$

i.e. the most common limitation on the input is energy or power const.

$$P_e = \frac{1}{2} P_r(z < 0 | x = P) + \frac{1}{2} P_r(z > 0 | x = -P) =$$

$$= \frac{1}{2} P_r(z < -P | x = P) + \frac{1}{2} P_r(z > P | x = -P) =$$

$$= P_r(z > P) = 1 - \int_{-\infty}^P \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{z^2}{2\sigma^2}} dz = 1 - \Phi\left(\frac{P}{\sigma}\right)$$

$$= 1 - \Phi\left(\frac{P}{N}\right)$$

$$\Phi(x) = \int_{-\infty}^x \frac{e^{-\frac{z^2}{2\sigma^2}}}{\sigma \sqrt{2\pi}} dz$$

## PROBLEM 9.4

EXPONENTIAL NOISE CHANNELS.  $r_i = x_i + z_i$  where  $z_i$  is i.i.d. exponential distributed noise with mean  $\mu$ . Assume that we have a power constraint on the signal ( $\sum x_i \leq \lambda$ ). Show that capacity of such channel is:  $C = \log\left(1 + \frac{\lambda}{\mu}\right)$

$$I(x^n; z^n) = H(z^n) - H(z^n | x^n) \leq \sum_{i=1}^n H(z_i) - \sum_{i=1}^n H(z_i | x_i)$$

$$\leq \sum_{i=1}^n \int_{-\infty}^{\infty} \lambda e^{-\lambda x} \log \lambda dx \leq \sum_{i=1}^n \frac{1}{2} \log(2\pi e) \left( \sigma_{x_i}^2 + \left[ \frac{z_i}{\lambda} \right]^2 \right)$$

$$h(z) = \frac{1 - \log \lambda}{\log 2} = \log e - \log \lambda = \log e + \log \mu = \log e \mu = \frac{1}{2} \log(2\pi e)$$

$$I(x^n; z^n) \leq \sum_{i=1}^n \frac{1}{2} \log(2\pi e) \left( \sigma_x^2 + \frac{\lambda^2}{\mu^2} \right)$$

$$\leq \sum_{i=1}^n \frac{1}{2} \log\left(\frac{2\pi e}{\mu^2}\right) \left[ \frac{\sigma_x^2 + \lambda^2}{\mu^2} \right] = \log\left(\frac{2\pi e}{\mu^2}\right) \left[ \frac{\sigma_x^2 + \lambda^2}{\mu^2} \right]$$

$$\sigma_y^2 = \sigma_x^2 + \sigma_z^2 \quad E[z_i] = \frac{1}{\lambda} \mu \lambda$$

$$\sigma_x^2 = E[(x - \lambda)^2] = E[x^2] - 2\lambda E[x] + \lambda^2 = E[x^2] - \lambda^2$$



$$\sigma_x^2 = E[x^2] - \lambda^2 \quad \text{---} \quad \textcircled{*} = \sum_{i=1}^n \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) \dots \approx \ln \sqrt{2\pi} - \lambda^2 \frac{e}{\mu^2} = \textcircled{*}$$

Jensen inequality:

$$E[f(x)] \geq f(E[x]) \quad f(x) = x^2 \quad \text{---} \quad \text{CONVEX - PROVA}$$

$$E[x] \leq \lambda \quad E^2[x_i] \leq \lambda \quad E^2[x_i] \leq E[x_i^2]$$

$$\textcircled{*} = \frac{1}{2} \cdot \frac{1}{n} \sum_{i=1}^n \ln\left(-E[x_i^2] - \lambda^2 + \mu^2\right) + \frac{1}{2} \sum_{i=1}^n \ln\left(\frac{2\pi}{e}\right) \leq \frac{1}{2} \ln \dots$$

$$\leq \frac{1}{2} \ln \left[ \sum_{i=1}^n \left(-E[x_i^2] - \lambda^2 + \mu^2\right) \right] + \frac{1}{2} \ln \dots$$

MARKOV'S INEQUALITY:  $P_r(x > a) \leq \frac{E[x]}{a}$

$$J(p_i^*) = - \sum_{i=1}^n p_i^* \ln p_i^* - \ln(E[\mu]) + \lambda \sum_{i=1}^n x_i p_i^*$$

$$C = \max_{p_i^* \sum_{i=1}^n p_i^* \leq 1} J(x_i, p_i^*)$$

$$J_{\max} = \sum_{i=1}^n \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) \cdot (E[x_i^2] + \mu^2)$$

$$\frac{dJ(p_i^*)}{dp_i} = - \sum_{i=1}^n \frac{1}{2} \frac{d}{dp_i} \left[ \ln\left(\frac{2\pi}{e}\right) (\sigma_x^2 + \mu^2) \right] + \lambda x_i = 0$$

$$J(\lambda; \mu) \leq \sum_{i=1}^n h(\tilde{x}_i) - \sum_{i=1}^n h(\tilde{z}_i) = \sum_{i=1}^n \left( \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) (\sigma_x^2 + \mu^2) - h(\tilde{z}_i) \right)$$

$$\leq \left( \text{GAUSSIAN DISTRO MAXIMIZES ENTROPY} \right) = \sum_{i=1}^n \left[ \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) (\sigma_x^2 + \mu^2) - \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) \mu^2 \right] = \sum_{i=1}^n \frac{1}{2} \ln\left(\frac{2\pi}{e}\right) \sigma_x^2$$

$\sigma = X + Z$  AND METODOS PARA ENCONTRAR  $\lambda \in \dots$

$$f(x) = \gamma \cdot e^{-\gamma x} \quad E[X] = \frac{1}{\gamma} = \lambda \quad E[(X-\lambda)^2] = \frac{1}{\gamma^2} = \lambda^2$$

$$\text{PROVA } X, Z \text{ SE ENCONTRAMOS DISTRIBUICAO (TIP)} \quad E[X^2] = E[X^2] + E[Z^2] \quad \sigma_y^2 = \sigma_x^2 + \sigma_z^2 = \lambda^2 + \mu^2$$

$$\leq \frac{1}{2} \sum_{i=1}^n \ln\left(\frac{2\pi}{e}\right) \frac{\sigma_x^2 + \mu^2}{\mu^2} = \sum_{i=1}^n \ln\left(1 + \frac{\lambda^2}{\mu^2}\right) = n \cdot \ln\left(1 + \frac{\lambda^2}{\mu^2}\right) \quad \text{---} \quad \text{lets}$$

$$\mathbb{E}(x^2) = \sum_{i=1}^n h(\tau_i) - \sum_{i=1}^n h(z_i) =$$

$$= \sum_{i=1}^n \frac{1}{2} \log(\sigma^2 + \mu^2) - \sum_{i=1}^n \frac{1}{2} \log(\mu^2)$$

$$J = \frac{1}{2} \log(\sigma^2 + \mu^2) - \sum x^2$$

$$\frac{dJ}{d\sigma^2} = 0 \Rightarrow \frac{d}{d\sigma^2} \left[ \frac{1}{2} \log \left( \int_{-\infty}^{\infty} (x^2 - \lambda^2) p(x) dx + \mu^2 \right) - \sum x^2 \right] = 0$$

AD SO SUMA PARAMETRO

$$\frac{d}{d\sigma^2} \left[ \frac{1}{2} \log \left( \sum_{i=1}^n (x_i^2 - \lambda^2) + \mu^2 \right) \right] - \sum x^2 = 0$$

$$\frac{1}{2} \frac{\sum (x^2 - \lambda^2)}{\sum (x^2 - \lambda^2) + \mu^2} \cdot \frac{1}{\sigma^2} - \sum x^2 = 0$$

CHERNOFF BOUND:

$$\Pr(Y \geq a) \leq M(s) \cdot e^{-sa}$$

PARAMETRO E SIGMA: SOMMA  $Y \sim N(\mu, \sigma^2)$   
 TOGA NOTA DISTRIBUZIONE  $Y(x)$  CONVOLUZIONE SO  
 E' ADENGA DISTRIBUZIONE CE DAPPE  
 GAUSSOVA TRASLADATA

$$p(x) \sim N(\mu, \sigma^2) \iff Y(x) \otimes p(z)$$

$$M(s) = \mathbb{E}[e^{sz}] = \left( \frac{\lambda}{-\lambda + s} \right) = \left( \frac{\lambda + \lambda}{-\lambda + \lambda} \right) = \left( \frac{\lambda - s}{\lambda} \right) = \left( 1 - \frac{s}{\lambda} \right)^{-1}$$

$$M_x = M_x \cdot M_z \quad M_x = \frac{M_x}{M_z} = \frac{M_x}{\left( 1 - \frac{s}{\lambda} \right)^{-1}}$$

$$M(-s) = \int p(x) e^{-sx} dx = \mathcal{L}[p(x)]$$

$$p(x) = \mathcal{L}^{-1}[M(-s)]$$

$$M_x(s) = e^{\frac{1}{2}s(s\sigma^2 + 2\mu)}$$

$$M_z(s) = \frac{\lambda}{\lambda - s}$$

$$M_x = \frac{\lambda - s}{\lambda} \cdot e^{\frac{1}{2}s(s\sigma^2 + 2\mu)} = e^{\frac{1}{2}s(s\sigma^2 + 2\mu)} \cdot \frac{s e^{-s \cdot \lambda}}{\lambda}$$

$$p(x) = p(y) + \frac{1}{\lambda} \frac{d}{dy} [p(y)] \quad (\text{PROVA NA SLOVAKA STRANA})$$

$$\mathcal{L}[p(x)] = M_x(-s) = e^{s(s\sigma^2 - 2\mu)/2} \quad \mathcal{L}[q(x)] = M_x(-s) = \frac{\lambda}{s + \lambda}$$

$$Y(x) = \mathcal{L}^{-1} [M_x(-s) \cdot M_x(-s)] = \mathcal{L}^{-1} \left[ \frac{s + \lambda}{\lambda} e^{s(s\sigma^2 - 2\mu)/2} \right]$$

$$= \frac{1}{\lambda} \mathcal{L}^{-1} [s \cdot M_x(-s)] + p(x) = \frac{1}{\lambda} \frac{d}{dx} Y(x) + Y(x)$$

$$\mathcal{L} \left[ \frac{d}{dt} f(t) \right] = s \cdot F(s) - f(0) \quad \frac{d}{dt} f(t) = \mathcal{L}^{-1} [s F(s)] - \mathcal{L}^{-1} [f(0)]$$

$$Y(x) = \frac{1}{\lambda} \frac{dY(x)}{dx} + \frac{Y(0)}{\lambda} + Y(x) = \frac{1}{\lambda} \frac{dY(x)}{dx} + \frac{Y(0) - Y(x)}{\lambda}$$

$$Y(x) = -\frac{1}{\sqrt{2}} \left( \frac{-\mu - \lambda\sigma^2}{\sqrt{\pi} \lambda \sigma^2} \right) \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} + \frac{1}{\sqrt{2}} \frac{1}{\sigma\sqrt{\pi}} \cdot e^{-\frac{x^2}{2\sigma^2}}$$

$$Y(x) = \frac{\lambda\sigma^2 + \mu - x}{\lambda\sigma^3\sqrt{2\pi}} \cdot e^{-\frac{(x-\mu)^2}{2\sigma^2}} + \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}}$$

$$Y(x) = \frac{(\lambda\sigma^2 + \mu)}{\lambda\sigma^3\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} + \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} - \frac{x}{\lambda\sigma^3\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$Y(x) = \frac{(\lambda\sigma^2 + \mu)}{\lambda\sigma^3\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} + \frac{1}{\lambda\sigma\sqrt{\pi}} e^{-\frac{x^2}{2\sigma^2}} - \frac{x}{\lambda\sigma^3\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

$$E[x^2] = \frac{(\mu + \lambda\sigma^2)(\lambda^2 + \sigma^2)}{\lambda^2\sigma^2} + 0 = \frac{\mu(\mu + 3\sigma^2)}{\lambda\sigma^2} = \frac{2\mu}{\lambda} + \frac{\mu^2 + \sigma^2}{\lambda\sigma^2}$$

$$E[x] = \frac{\mu + \lambda\sigma^2 - 1}{\lambda\sigma^2} \quad \sigma_x^2 = E[x^2] - E[x]^2 = \left( \frac{\mu^2}{\sigma^2} \right) - \frac{1}{\lambda^2\sigma^2} = \frac{\mu^2 - 1}{\lambda^2\sigma^2}$$

$$E[x] \leq \lambda_x \quad \frac{\mu + \lambda\sigma^2 - 1}{\lambda\sigma^2} \leq \lambda_x$$

$$\lambda_x(\mu - \lambda_x) \leq \mu - \mu_x$$

$$\lambda_x \leq \frac{1}{\mu - \lambda_x}$$

$$E[x] = \mu - \mu_x \leq \lambda_x \quad I(+i\epsilon) \leq \sum_{i=1}^n \frac{1}{2} \ln(2\pi e) \sigma_i^2 - \sum_{i=1}^n \frac{1}{2} \ln(e^{\mu_i})$$

$$\leq \frac{1}{2} \sum_{i=1}^n \ln(2\pi e) \frac{\sigma_i^2}{e^{\mu_i}} = \frac{1}{2} \sum_{i=1}^n \ln(2\pi e) \frac{\sigma_i^2 + \mu_i^2}{e^{\mu_i + \mu_i^2}} = \frac{1}{2} \sum_{i=1}^n \ln(2\pi e) \frac{(\sigma_i + \mu_i)^2}{e^{\mu_i + \mu_i^2}}$$

⑩  $E[X] = \mu_1 - \mu_2$        $\sigma_x^2 = \frac{\sigma^2}{\lambda^2} - \mu_2^2$        $\sigma_z^2 = \frac{1}{\lambda^2} = \mu_2^2$

$$I(x; z) \leq \frac{1}{2} \sum_{i=1}^{\infty} \left( d \left( \frac{2\sigma_i}{c} \right) \cdot \left( 1 + \frac{\sigma_i^2}{\mu_2^2} \right) \right)$$

$$\mu_1 - \mu_2 \leq \lambda$$

$$E[X] = \mu_1 - \mu_2 = \lambda$$

$$E[X^2] = -\frac{2\mu_1}{\lambda^2} + \mu_1^2 + \sigma^2 \quad ; \quad \mu_1 = \mu_2 \rightarrow E[X] = 0$$

$$E[X^2] = \sigma^2$$

$$E[X^2] = -2\mu_1 \cdot \mu_2 + \mu_1^2 + \sigma^2 \quad ; \quad \mu_1 = \lambda + \mu_2$$

$$E[X^2] = -2(\lambda + \mu_2)\mu_2 + (\lambda + \mu_2)^2 + \sigma^2 =$$

$$= -2\lambda\mu_2 - 2\mu_2^2 + \lambda^2 + 2\lambda\mu_2 + \mu_2^2 + \sigma^2 = \lambda^2 + \sigma^2 - \mu_2^2$$

$$\sigma_x^2 = E[X^2] - E[X]^2 = \lambda^2 + \sigma^2 - \lambda^2 = \sigma^2 - \mu_2^2$$

$$I(x; z) \leq \frac{1}{2} \sum_{i=1}^{\infty} \left( d \left( \frac{2\sigma_i}{c} \right) \left( 1 + \frac{\sigma_i^2 - \mu_2^2}{\mu_2^2} \right) \right) = \frac{1}{2} \sum_{i=1}^{\infty} d \left( \frac{2\sigma_i}{c} \right) \left( \frac{\sigma_i^2}{\mu_2^2} \right)$$

$$\boxed{\mu_1 - \mu_2 \leq \lambda}$$

BERNOLLI RANDOM:  $p(z) = \frac{1}{2} e^{-z/\alpha}$

$$h(z) = - \int_{-\infty}^{\infty} p(z) \ln p(z) = \underline{1 + \ln \alpha}$$

$\alpha = \mu$   
MEAN OF EXPONENTIAL.

• Among all nonnegative random variables having density and having mean  $\alpha$ , the exponential density with mean  $\alpha$  has the maximum entropy.

Let  $f(x)$  be density (with support of nonnegative values) having mean  $\alpha$ :

$$0 \leq D(f(x) \parallel \frac{1}{2} e^{-x/\alpha}) = \int f(x) \ln \frac{f(x)}{\frac{1}{2} e^{-x/\alpha}} dx$$

$$= \int f(x) \ln f(x) - \int f(x) \ln \left( \frac{1}{2} e^{-x/\alpha} \right) dx =$$

$$= -h(f(x)) - \int f(x) \left[ -\frac{x}{\alpha} \ln e - \ln 2 \right] dx =$$

$$= -h(f(x)) + \frac{1}{\alpha} \int x f(x) dx + \ln 2 = -h(f(x)) + \frac{1}{\alpha} \cdot \alpha + \ln 2$$

$$= -h(f(x)) + 1 + \ln 2 \Rightarrow \boxed{h(f(x)) \leq 1 + \ln 2}$$

$$C = \max_{p(z)} I(x; z); \quad I(x; z) = h(z) - h(z|x) =$$

$$= h(z) - h(z) = h(z) - (1 + \log \mu) \leq$$

EXHAUSTIVE  
DISTRO MATCH-  
MIZES D(x|z)  
EAT EX

$$\leq (1 + \log(\mu + 1)) - (1 + \log \mu) = 1 + \log(\frac{\mu+1}{\mu}) = 1 + \log(1 + \frac{1}{\mu})$$

$$= \log(\frac{\mu+1}{\mu}) = \log(1 + \frac{1}{\mu})$$

THE EXHAUSTIVE DISTRIBUTION OF A GIVEN MEAN MAXIMIZES THE DIFFERENTIAL ENTROPY AMONG ALL NONNEGATIVE DENSITIES HAVING THAT MEAN

$$D(q||z) = \sum_{x,y} q \log \frac{q}{z} \quad I(x; z) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)}$$

$$I(x; z) = D(p(x,y)||p(x)p(y));$$

$$I(x; z) = \sum_{x,y} p(x,y) \log \frac{1}{p(x)p(y)} + \sum_{x,y} p(x,y) \log p(x,y)$$

$$= \sum_x \log \frac{1}{p(x)} \sum_y p(y) = H(x|z)$$

$$= H(x) + H(z) - H(xz) = H(x) - H(x|z)$$

$$M_z(s) = \int_0^\infty e^{-sz} \frac{1}{z} e^{-\frac{z}{\lambda}} dz = \frac{1}{s + \frac{1}{\lambda}} = \frac{\lambda}{1 + \lambda s}$$

$$M_z(-s) \cdot \frac{1}{1 + \lambda s} = \frac{1}{1 + (\lambda + \mu)s} \quad \boxed{\lambda = \lambda}$$

$$M_z(-s) = \frac{\lambda s}{1 + (\lambda + \mu)s} + \frac{1}{1 + (\lambda + \mu)s} = \frac{\lambda s}{1 + (\lambda + \mu)s} + \frac{1}{1 + (\lambda + \mu)s}$$

convert  $\left( \frac{1 + \lambda s}{1 + (\lambda + \mu)s}, \text{frac}, s \right) = \frac{\lambda}{\lambda + \mu} + \frac{\mu}{(\lambda + \mu)(1 + (\lambda + \mu)s)}$

$$f(z) = \mathcal{L}^{-1}[M_z(-s)] = \frac{\lambda}{\lambda + \mu} \delta(z) + \frac{\mu}{\lambda + \mu} \frac{1}{\lambda + \mu} e^{-\frac{z}{\lambda + \mu}}$$

**PROBLEM 7.5** FADING CHANNELS. Consider an ADDITIVE NOISE FADING CHANNEL. Consider an ADDITIVE NOISE FADING CHANNEL.  $Y = X \cdot V + Z$  WHERE  $Z$  IS ADDITIVE NOISE,  $V$  IS RANDOM VARIANCE BEING FADING, AND  $Z$  AND  $V$  ARE INDEPENDENT

OF EACH OTHER AND OF  $X$ . ARGUE THAT KNOWLEDGE OF THE NOISING FACTOR  $V$  IMPROVES CHANNEL AS SMOKING TIPS

$$I(x; z|v) \geq I(x; z)$$

$$z = x \cdot v + z \quad I(x; z|v) = H(z) - H(z|xv)$$

$$H(z|xv) = \sum_{xv} p(x, v) H(xv + z / x=x, v=v)$$

$$I(x; z|v) = H(z) - H(z) \quad [H(z) = I(x; z|v) + H(z)]$$

$$I(x; z) = H(z) - \sum_x p(x) H(z|x=x)$$

$$= H(z) - \sum_x p(x) H(x \cdot v + z | x) = H(z) - H(v+z)$$

$$[ \psi = v + z ] \quad H(v+z) = \sum_{\psi} p(\psi) \log \frac{1}{p(\psi)}$$

$$H(\psi) \leq \frac{1}{2} \log (\pi e) \sigma_{\psi}^2 \quad \sigma_{\psi}^2 = \sigma_v^2 + \sigma_z^2$$

$$I(x; z) \geq H(z) - \frac{1}{2} \log (\pi e) [\sigma_v^2 + \sigma_z^2]$$

$$I(x; z|v) = H(z) - \frac{1}{2} \log (\pi e) [\sigma_z^2]$$

$$[ H(z) = I(x; z|v) + \frac{1}{2} \log (\pi e) \sigma_z^2 ]$$

$$I(x; z) = I(x; z|v) + \frac{1}{2} \log (\pi e) \sigma_z^2 - H(\psi)$$

$$H(z) - H(\psi) \geq H(z) - \frac{1}{2} \log (\pi e) \sigma_{\psi}^2$$

$$I(x; z|v) = I(x; z) + H(\psi) - \frac{1}{2} \log (\pi e) \sigma_z^2$$

$$[ H(\psi) \geq \frac{1}{2} \log (\pi e) \sigma_z^2 ]$$

$$H(\psi) \leq H(v, z) = H(z) + H(v|z) = H(z) + H(v) \quad (\$)$$

$$I(x; z) = H(z) - H(\psi) \geq H(z) - H(z) - H(v|z)$$

$$I(x; z) \geq I(x; z|v) + H(z) - H(z) - H(v|z) \geq I(x; z|v) - H(v|z)$$

$$[ I(x; z|v) \leq I(x; z) + H(v|z) ] = I(x; z) + H(v) \quad [ v, z \text{ indep. } ]$$

$$I(v; \psi) = H(\psi) - H(\psi|v) = H(\psi) - H(z)$$

$$I(V; \Psi) = -H(V; \Psi) + H(V) + H(\Psi)$$

$$= -H(\Psi|V) - H(V; \Psi) + H(V) + H(\Psi|V)$$

$$\Psi = V + Z$$

$$I(V; \Psi) = H(V) - H(Z) \geq 0 \quad H(V) \geq H(Z)$$

$$I(V; \Psi) = H(V) + H(\Psi) - H(V; \Psi)$$

$$- H(Z) = H(V) + H(\Psi) - H(V; \Psi) \quad H(Z) \geq H(V)$$

$$z = x + y \quad I(x; z) = H(z) - H(z|x) \geq 0 \quad H(z) \geq H(x)$$

$$H(z|x) = H(z) + H(x|z) = H(x) + H(z|x)$$

$$I(x, y; z) = I(x; z) - I(y; z|x)$$

$$I(y; z|x) = H(z) - H(z|y|x) = H(z) - H(x) \geq 0 \quad H(z) \geq H(x)$$

$$\Rightarrow I(x; z|V) \geq I(x; z) \quad [H(V|z) = H(V) > 0]$$

$$\Psi = f(x, z) \quad \Psi = f(\xi)$$

$$H(\Psi, \xi) = H(\Psi) + H(\xi|\Psi) = H(\xi) + H(\Psi|\xi)$$

$$H(\xi) \geq H(\Psi) \geq H(\xi|\Psi)$$

FUNCTION DECREASES ENTROPY

$$I(x; z|V) = H(z) - H(z|x) \quad I(x; z) = H(z) - H(V+z)$$

$$(V+z) = f(V, z) \quad H(f(V, z)) \leq H(V, z)$$

$$I(x; z) = H(z) - H(z|V, z) \geq H(z) - H(V, z) =$$

$$= H(z) - H(V) - H(z|V) = H(z) - H(V) - H(z)$$

$$I(x; z|V) = H(z) - H(z|x)$$

$$I(x; z) \geq H(z) - H(V) - H(z)$$

ДОПОЛНИТЕЛЬНАЯ ИНФОРМАЦИЯ НЕ ДОБАВЛЯЕТСЯ

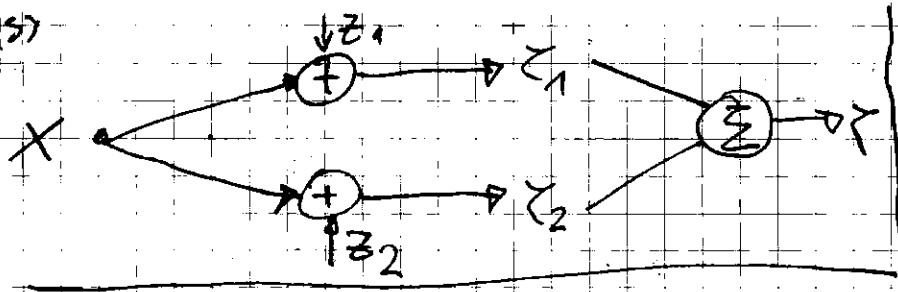
$$H(V+z, \Psi) = H(\Psi) + H(V+z|\Psi) = H(V+z) + H(\Psi|V+z)$$

? да и нет

### 2. MULTIPATH GAUSSIAN CHANNEL

GAUSSIAN NOISE CHANNEL WITH POWER CONSTRAINT  $P$ , WHERE THE SIGNAL TAKES TWO DIFFERENT PATHS AND THE RECEIVED NOISE SIGNALS ARE ADDED TOGETHER AT THE ANTENNA.

15)



(a) FIND THE CAPACITY OF THIS CHANNEL IF  $Z_1$  AND  $Z_2$  ARE JOINTLY GAUSSIAN WITH COVARIANCE MATRIX:

$$K_Z = \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix}$$

(b) WHAT IS THE CAPACITY FOR  $\rho = 0$ ,  $\rho = 1$  AND  $\rho = -1$

$$K_Z = \begin{bmatrix} P+N & N\rho \\ N\rho & P+N \end{bmatrix} \Rightarrow (P+N)^2 - N^2\rho^2 = P^2 + 2PN + N^2 - N^2\rho^2 = N^2(1-\rho^2) + 2P(P+N)$$

$$K_Z = \begin{bmatrix} P+N & P+N\rho \\ P+N\rho & P+N \end{bmatrix} \Rightarrow (P+N)^2 - (P+N\rho)^2 = P^2 + 2PN + N^2 - P^2 - 2PN\rho - N^2\rho^2 = 2PN(1-\rho) + N^2(1-\rho^2)$$

$$Z = Z_1 + Z_2 = X + Z_1 + X + Z_2 = 2X + Z_1 + Z_2$$

$$C = \frac{1}{2} \log \frac{(2\pi e)^2 |K_Z|}{(2\pi e)^2 |K_X|}$$

$$I(X; Z) = H(Z) - H(Z|X) \leq H(Z) - H(Z|X)$$

$$I(X; Z) = H(Z_1 + Z_2) - H(Z|X) \leq H(Z_1, Z_2) - H(Z|X)$$

$$H(Z|X) = H(Z_1 + Z_2 | X) = H(2X + Z_1 + Z_2 | X) = H(Z_1 + Z_2)$$

$$I(X; Z) \leq H(Z_1, Z_2) - H(Z_1 + Z_2)$$

$$\begin{cases} \xi = Z_1 + Z_2 \\ \eta = Z_1 \end{cases}$$

TOOJNA  
MPOKHA  
BOYKCT.

$$\begin{bmatrix} \frac{\partial(z_1, z_2)}{\partial \xi} & \frac{\partial z_1}{\partial \xi} \\ \frac{\partial(z_1, z_2)}{\partial \eta} & \frac{\partial z_1}{\partial \eta} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix} = 1$$

$$p(z_1, z_2) = |j| p(\xi, \eta)$$

$$p(\xi, \eta) = \frac{p(z_1, z_2)}{|j|} \quad \begin{cases} z_1 = \eta \\ z_2 = \xi - \eta \end{cases}$$

$$p(\xi, \eta) = p(\eta, \xi - \eta)$$

$$p(\xi) = \int p(\xi, \eta) d\eta =$$

$$= \int p(\eta, \xi - \eta) d\eta = \int p(\eta) \cdot p(\xi - \eta) d\eta \quad p(\xi) = p(\eta) * p(\xi)$$

$$p(z_1 + z_2) = \int p(z_1, z_2 - z_1) dz_1 =$$

$$p(z_1 + z_2) \sim N(0, N(\sigma^2 + \rho^2\sigma^2))$$

$$\frac{e^{-\frac{1}{2} \frac{z^2}{N(\sigma^2 + \rho^2\sigma^2)}}}{N \sigma^2}$$

GAUSSIAN  
MIMLE



$$h(z_1 + z_2) = \frac{1}{2} \log(2\pi e N(5+4g))$$

$$\circ \rightarrow I(x; z) \leq \underline{h(z_1, z_2)} - h(z_1 + z_2) = \underline{h(z_1, z_2)} - \frac{1}{2} \log(2\pi e N(5+4g))$$

$$I(x; z) \leq \frac{1}{2} \log(2\pi e (4P + N(5+4g))) - \frac{1}{2} \log(2\pi e N(5+4g))$$

$$I(x; z) \leq \frac{1}{2} \log \left( 1 + \frac{4P}{N(5+4g)} \right) = \frac{1}{2} \log \left[ 1 + \frac{4P}{N(5+4g)} \right]$$

$$(g) C(p=0) = \frac{1}{2} \log \left[ 1 + \frac{4P}{5N} \right]; \quad C(p=1) = \frac{1}{2} \log \left[ 1 + \frac{4P}{9N} \right]$$

$$C(p=-1) = \frac{1}{2} \log \left[ 1 + \frac{4P}{N} \right]$$

UNIVERSITY OF TORONTO SOLUTION (solns 5.90e)

$$I(x; z) = h(z) - h(z|x) = h(z_1 + z_2) - h(z_1, z_2)$$

GAUSSIAN DISTRO OF  $\vec{z}$  MAXIMIZES ENTROPY

$$C = \frac{1}{2} \log(2\pi e) E[(2x + z)^2] - \frac{1}{2} \log(2\pi e) E[z^2]$$

$$E[(2x + z)^2] = 4E[x^2] + E[z^2] = 4P + E[(z_1 + z_2)^2]$$

$$E[(z_1 + z_2)^2] = E[z_1^2 + 2z_1z_2 + z_2^2] = E[z_1^2] + 2E[z_1z_2] + E[z_2^2]$$

WE MAKE SE INDEPENDENT REFS:

$$E[z_1z_2] = 0; \quad E[z_1^2] = N; \quad E[z_2^2] = N; \quad E[z_1^2 + z_2^2] = 2N$$

$$E[(z_1 + z_2)^2] = N + 2 \cdot 0 + N = 2N + 2gN = 2N(1+g)$$

$$C = \frac{1}{2} \log(2\pi e) [4P + 2N(1+g)] - \frac{1}{2} \log(2\pi e) [2N(1+g)]$$

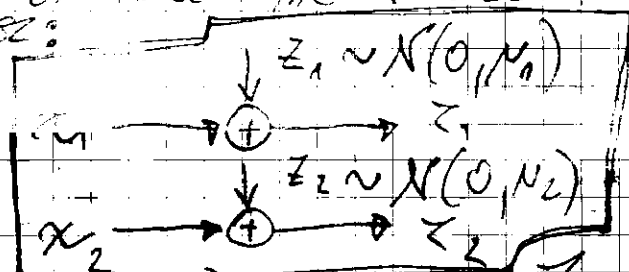
$$C = \frac{1}{2} \log \left( 1 + \frac{4P}{2N(1+g)} \right) \quad N = b^2$$

$$(g) g=0; \quad C = \frac{1}{2} \log \left( 1 + \frac{2P}{N} \right); \quad [g=1] \quad C = \frac{1}{2} \log \left( 1 + \frac{P}{N} \right)$$

$$[g=-1] \quad C = \frac{1}{2} \log \left( 1 + \frac{2P}{0} \right) \rightarrow \infty \quad \text{NOISE CANCELS ITSELF}$$

IN  $g=0$  THE NOISE POWER IS DIVIDED AND IN CASE  $g=1$  THE NOISE POWER IS 4 TIMES CAPSED THEN IN THE CASE OF SINGLE NOISE CHANNEL.

**PROBLEM 9.8** CONSIDER THE FOLLOWING CHANNEL MODEL:



WHERE  $z_1 \sim N(0, N_1)$  AND  $z_2 \sim N(0, N_2)$  ARE INDEPENDENT GAUSSIAN RANDOM VARIABLES AND:

(19)  $Z_i = \sum_{k=1}^K \lambda_k Z_{ik}$   
 We wish to reallocate power to the two  
 interferer channels. Let  $P_1$  and  $P_2$  be fixed.  
 Consider total cost constraint  $P_1 P_1 + P_2 P_2 \leq P$   
 where  $P_i$  is power allocated to the  $i$ th  
 channel and  $P_i$  is the cost per unit power  
 in that channel. Thus  $P_1 \geq 0$  and  $P_2 \geq 0$   
 can be chosen subject to the cost constraints

(a) For what value of  $P$  does the channel  
 stop acting like pair of channels?

(b) Evaluate the capacity and find  $P_1$  and  $P_2$   
 that achieve capacity. For  $P_1=1, P_2=2$   
 $N_1=3, N_2=2$  and  $P=10$ .

$$I(x; z) = h(x) - h(z|x) = h(z) - h(x|z) \leq \sum_{i=1}^2 h(z_i) - \sum_{i=1}^2 h(x_i) \leq \sum_{i=1}^2 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right)$$

$$C = \sum_{i=1}^2 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right) \quad \sum P_i \leq P$$

$$\frac{\partial J}{\partial P_i} = 0 \quad J = \sum_{i=1}^2 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right) + \lambda \sum_{i=1}^2 P_i$$

$$\frac{1}{2} \frac{1}{1 + \frac{P_i}{N_i}} \frac{1}{N_i} + \lambda = 0 \quad \frac{1}{2} \frac{1}{P_i + N_i} + \lambda = 0$$

$$\frac{1}{P_i + N_i} = -2\lambda \quad P_i + N_i = -\frac{1}{2\lambda} \quad P_i = -\frac{1}{2\lambda} - N_i$$

$$P_i = P - N_i \quad P_1 + P_2 \leq P \quad N_1 - N_2 \leq P$$

$$P + N_1 = P \Rightarrow N_1 = P$$

$$V = P_2 + N_2 \quad [P + N_2 \geq N_1] \quad [P \geq N_1 - N_2]$$

DO NOT MISTAKE  
 100% NAVA OR 50% NAVA WOULD  
 BE OK WOULD

$$C = \sum_{i=1}^2 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right) \quad \sum P_i P_i \leq P \quad P_i = \frac{1}{2\lambda P_i} - N_i$$

$$\frac{1}{2} \frac{1}{P_i + N_i} + \lambda \cdot P_i = 0 \quad \frac{1}{P_i + N_i} = 2\lambda \cdot P_i$$

$$P_i + N_i = \frac{1}{2\lambda \cdot P_i} \quad N_1 = \frac{1}{2\lambda P_1} \quad \lambda = \frac{1}{2N_1 P_1}$$

$$P_2 + N_2 = \frac{1}{2\lambda P_2} \quad P_2 + N_2 = \frac{1}{2 \cdot \frac{1}{2N_1 P_1} \cdot P_2} = N_1 \cdot \frac{P_1}{P_2}$$

$P_2 \leq \frac{P_1}{P_2} \cdot N_1 - N_2 \Rightarrow$  CHANNEL STOPS ACTING LIKE  
 A PAIR OF CHANNELS.

$$p_1 \cdot r_1 + p_2 \cdot r_2 \leq \beta$$

$$p_1 \cdot N_1 + p_2 \cdot N_2 \leq \beta$$

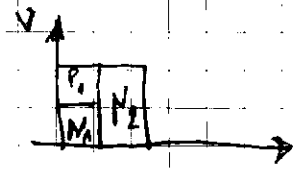
(B)  $p_1, p_2 = ?$        $N_1 = 3$     $N_2 = 2$        $p_1 = 1$     $p_2 = 2$     $\beta = 10$

$$P_1 = \frac{1}{p_1} (\beta - p_1 N_1 + p_2 N_2) = (10 - 3 + 2 \cdot 2) = 10 - 1 = 9$$

$$P_2 = \frac{p_1}{p_2} N_1 - N_2 = \frac{1}{2} \cdot 3 - 2 = 1.5 - 2 = -0.5$$

$$1 \cdot (11) + 1 \cdot 3 - 2 \cdot 2 = 11 + 3 - 4 = 11 - 1 = 10$$

- ОБЛАСТЬ СРЕДНЕЙ ЧАСТИ НЕГАТИВНА СЛУЖИ



$$P_1 + N_1 = \frac{1}{2 \lambda p_1}$$

$$N_2 = \frac{1}{2 \lambda p_2}$$

$$\lambda = \frac{1}{2 N_2 p_2}$$

$$P_1 + N_1 = \frac{1}{2 \lambda p_1}$$

$$P_1 + N_1 = \frac{1}{2 \cdot \frac{1}{2 N_2 p_2} \cdot p_1} = \frac{p_2}{p_1} \cdot N_2$$

$$P_1 = \frac{p_2}{p_1} N_2 - N_1$$

$$P_1 = 2 N_2 - N_1$$

$$P_1 = 4 - 3 = 1$$

$$P_2 = \frac{1}{p_2} (\beta - p_1 P_1) = \frac{1}{2} (10 - 1 \cdot 1) = \frac{9}{2} = 4.5$$

$$p_1 p_1 + p_2 p_2 \leq \beta$$

$$p_1 = 1 + 2 \cdot p_2 = 10 \quad p_2 = \frac{10 - 1}{2} = 4.5$$

$$p_1 = 1 \quad p_2 = 4.5$$

$$p_2 N_2 - p_1 N_1 + p_2 p_2 = \beta$$

$$p_1 p_1 + p_2 p_2 = 1 \cdot 1 + 2 \cdot 4.5 = 1 + 9 = 10 = \beta$$

$$C = \frac{1}{2} \log \left( 1 + \frac{p_1}{N_1} \right) + \frac{1}{2} \log \left( 1 + \frac{p_2}{N_2} \right) = \frac{1}{2} \log \left( 1 + \frac{p_1}{N_1} \right) \left( 1 + \frac{p_2}{N_2} \right)$$

$$= \frac{1}{2} \log \left( 1 + \frac{1}{3} \right) \cdot \left( 1 + \frac{4.5}{2} \right) = \frac{1}{2} \log \left( \frac{4}{3} \right) \cdot \left( \frac{2 + 4.5}{2} \right)$$

$$C = \frac{1}{2} \log \left( \frac{4 \cdot 6.5}{6} \right) = \frac{1}{2} \log \left( \frac{26.0}{6} \right) = \frac{1}{2} \log \left( \frac{13}{3} \right)$$

$$C = 0.5 \log(4.33) = 1.058 \text{ bits/sec use}$$

$$C = \frac{1}{2} \log \left( 1 + \frac{5.5}{3} \right) \left( 1 + \frac{2.25}{2} \right) = \frac{1}{2} \log \left( \frac{8.5 \cdot 4.25}{6} \right) = 1.27$$

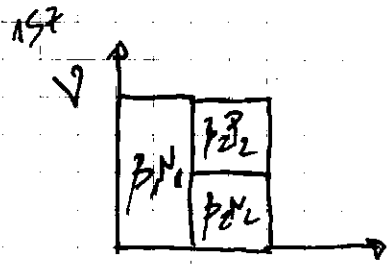
UNIVERSITY OF ILLINOIS. SOLUTIONS (HW8: PDP)

$$p_1 = 5.5 \quad p_2 = 2.25$$

- ЗА ДА 40 КОДЕТИС ВИСЕ ПОВИНОУ ИАСТА ДА СЕ СВЕДЕ НА (1) ПА ЗАТОА (4) 90 ПОВИНОУ ВО СЛЕДНА ВА ПОЛМА:

$$p_1 p_1 + p_2 p_2 = \frac{1}{2} = \beta \quad (\beta = \text{CONST})$$

(\*) МОДОТ ПУСТА НЕ Е ДЕКА ЗЕТО (\*) НЕ Е КОНСТ.

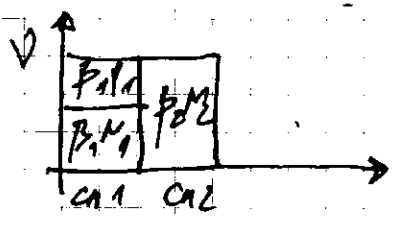


$$p_1 N_1 = Y \quad p_2 P_2 + p_2 N_2 = V$$

$$p_2 P_2 + p_2 N_2 = p_1 N_1$$

$$p_2 P_2 = p_1 N_1 - p_2 N_2$$

$p_2 P_2 \geq p_1 N_1 - p_2 N_2$  } VO OVOJ ZUCIOJ IMAME DVA KONACI  
 (6)  $p_1 N_1 = 1 \cdot 3 = 3$   $p_2 N_2 = 2 \cdot 2 = 4$   
 ZNAZI OSLOBOGO OVAKA:



$$p_1 N_1 \geq p_2 N_2 - p_1 N_1 \quad \left. \vphantom{p_1 N_1} \right\} 2 \text{ CHAN.}$$

$$p_1 P_1 \geq p_2 N_2 - p_1 N_1$$

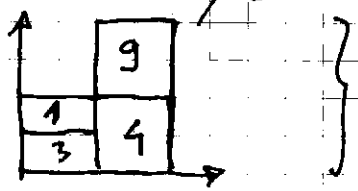
$$p_2 N_2 - p_1 N_1 + p_2 P_2 = \beta$$

$$4 - 3 + p_2 P_2 = 10 \quad p_1 P_1$$

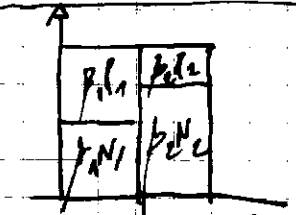
$$p_2 P_2 = 10 - 1 = 9$$

$$P_2 = \frac{9}{p_2} = \frac{9}{2} = 4.5$$

$$P_1 = 1 \quad \text{MINIMIZIRAJ } p_1 P_1$$



OVAKA JE ISKLEPA OVO ODAJ  
 KO MICALIČASTA VEKOST NA  
 $p_1 P_1 = 1$  NO NE SO ISKOLIVATI  
 TAKA USLOVOT SIVATA SA SIVATA  
 NA SIVOT I SIVAZOT SA  
 DIOG KONSTANTA ZA OVAJA KONACI.



$$I \quad p_1 N_1 + p_1 N_2 = p_2 P_2 + p_2 N_2$$

OVAKA  
 PIVKALA  
 MI PIVKALI!

$$p_1 = (p_2 P_2 + p_2 N_2 - p_1 N_1) / p_1$$

$$P_2 = \frac{1}{p_2} (p - p_1 P_1) = \frac{p}{p_2} - \frac{p_1 P_1}{p_2}$$

$$II \quad p_1 N_1 + p_2 P_2 = \beta$$

$$P_1 = \left( \beta - p_1 P_1 + p_2 N_2 - p_1 N_1 \right) \frac{1}{p_1} = \frac{\beta}{p_1} - P_1 + \frac{p_2 N_2 - N_1}{p_1}$$

$$2P_1 = \left( \frac{\beta}{p_1} + \frac{p_2 N_2 - N_1}{p_1} \right) \quad P_1 = \frac{1}{2} \left( \frac{\beta}{p_1} + \frac{p_2 N_2 - N_1}{p_1} \right)$$

$$EP_1 = \frac{1}{2} \left( \frac{10}{1} + \frac{2}{1} \cdot 2 - 3 \right) = \frac{1}{2} (10 + 4 - 3) = \frac{11}{2} = 5.5$$

$$P_2 = \frac{1}{2} (10 - 5.5) = \frac{1}{2} (4.5) = 2.25$$

$$10 = 1 \cdot 5.5 + 2 \cdot 2.25 = 5.5 + 4.5 = 10$$

**SOLUCION**

**Problem 9.11** (continue from N16n)  $x \rightarrow z \rightarrow Z$

$$I(x, r; Z) = H(Z) - H(Z|x, r) = H(Z) - H(Z|r)$$

$$= \frac{1}{2} \ln(2\pi\sigma^2) - H(Z|r); \quad H(Z|r) = ?$$

$$I(x, z; z) = I(x; z) - I(z; z|x) = I(x; z) \quad \text{since } H(z|x) = H(z)$$

$$I(z; z|x) = H(z|x) - H(z|x, z) = H(z|x) - H(z|x) = 0$$

$$I(x; z) = \frac{1}{2} \log(2\pi e) \sigma_z^2 - H(z|z) \quad H(z|z) = H(z) - H(z|x)$$

$$K = \begin{bmatrix} \sigma_x^2 & \rho \sigma_x \sigma_z & 0 \\ \rho \sigma_x \sigma_z & \sigma_z^2 & \rho \sigma_x \sigma_z \\ 0 & \rho \sigma_x \sigma_z & \sigma_x^2 \end{bmatrix} = \begin{bmatrix} P & \rho P & 0 \\ \rho P & P & \rho P \\ 0 & \rho P & P \end{bmatrix}$$

$$H(z|z) = ?$$

$$\frac{z^2 - 2z\rho\sigma_z + 2z\rho\sigma_z^2 - \rho^2 z^2}{2P(1-\rho^2)}$$

$$f(z|x) = \frac{f(z, z)}{f(z)} = \frac{1}{\sqrt{2\pi(1-\rho^2)P}} e^{-\frac{z^2 - 2z\rho\sigma_z + 2z\rho\sigma_z^2 - \rho^2 z^2}{2P(1-\rho^2)}}$$

$$\textcircled{2} = \frac{z^2 - 2z\rho\sigma_z - \rho^2 z^2}{2P(1-\rho^2)}$$

$$h(z|x) = - \int f(z, z) \ln f(z, z) dz dz$$

10000 Gleichung  
 10000 Gleichung  
 10000 Gleichung  
 10000 Gleichung  
 $h(z|x)$   
 $h(x) - h(z|x) = I(x; z) - h(x)$   
 $+ h(z|x) = I(x; z) - h(x) + h(z|x)$   
 $= I(x; z) - h(x) + h(z|x)$

$$h(z|x) = \frac{1}{2} \ln(2\pi e) (1-\rho^2) P + \frac{1}{2} \ln(2\pi e) (1-\rho^2) P + \frac{1}{2} \ln(2\pi e) (1-\rho^2) P$$

$$\begin{bmatrix} P & \rho P \\ \rho P & P \end{bmatrix} = P^2 - \rho^2 P^2 = P^2(1-\rho^2) = |K_{z|x}|$$

$$I(x; z) = \frac{1}{2} \log(2\pi e) \sigma_z^2 - \frac{1}{2} \ln(2\pi e) (1-\rho^2) P - \frac{1}{2} \ln e$$

$$I(x; z) = \frac{1}{2} \log \frac{1}{e} \left( \frac{1}{1-\rho^2} \right) = -\frac{1}{2} \log(1-\rho^2) \frac{1}{e}$$

$$I(x; z) = H(z) - H(z|x) = H(z) - (H(z|x) + H(x)) = H(z) - H(z|x) - H(x) = H(z) - H(z|x) - H(x)$$

$$= H(z) - H(z|x) - H(x) = \frac{1}{2} \log(2\pi e) \sigma_z^2 - \frac{1}{2} \log(2\pi e) \sigma_z^2 + \frac{1}{2} \log(2\pi e) |K_{z|x}| = \frac{1}{2} \log(2\pi e) \sigma_z^2 - \frac{1}{2} \log(2\pi e) \sigma_z^2 + \frac{1}{2} \log(2\pi e) P(1-\rho^2)$$

US Problem 8.9 solution

$$I(x; z) = h(x) - h(x|z) \quad h(x, z) = h(z) + h(x|z)$$

$$h(x|z) = h(x, z) - h(z) \quad I(x; z) = h(x) + h(z) - h(x, z)$$

$$I(x; z) = 0.5 \log(2\pi e \sigma_x^2) + 0.5 \log(2\pi e \sigma_z^2) - \frac{1}{2} \log(2\pi e) |K_{x,z}|$$

$$K_{x,z} = \begin{bmatrix} \sigma_x^2 & \rho \sigma_x \sigma_z & \rho \sigma_x \sigma_z \\ \rho \sigma_x \sigma_z & \sigma_x^2 & \sigma_x^2 \\ \rho \sigma_x \sigma_z & \sigma_x^2 & \sigma_z^2 \end{bmatrix} = \sigma_x^2 \sigma_z^2 - \rho^2 \sigma_x^2 \sigma_z^2 = \sigma_x^2 \sigma_z^2 (1-\rho^2)$$

$$I(x; z) = 0.5 \log(2\pi e \sigma_x^2) + 0.5 \log(2\pi e \sigma_z^2) - \frac{1}{2} \log(2\pi e) \sigma_x^2 \sigma_z^2 (1-\rho^2)$$

199  $f(x, z | \gamma) = f(x | \gamma) \cdot \gamma(z | \gamma)$   $E[xz] = \rho_1 \rho_2 \sigma_x \sigma_z$

$h(x, z | \gamma) = h(x | \gamma) + h(z | x, \gamma)$

$\rho_{xz} = \frac{E[xz]}{\sigma_x \sigma_z} = \frac{E_{xz}[xz]}{\sigma_x \sigma_z} = \frac{E_x[E[xz | \gamma]]}{\sigma_x \sigma_z} = \frac{E_x[\rho_1 \rho_2 \sigma_x \sigma_z]}{\sigma_x \sigma_z}$

$E_z[z | \gamma] = \int_{-\infty}^{\infty} z \gamma(z | \gamma) dz \stackrel{\text{MARE}}{=} \rho_2 \sigma_z$  (if  $\sigma_x = \sigma_z$ )

IF  $\sigma_x \neq \sigma_z$  MARE

$\sigma_z[z | \gamma] = \frac{\rho_2 \sigma_x \sigma_z}{\sigma_x}$

$\sigma_x[x | \gamma] = \frac{\rho_1 \sigma_x \sigma_z}{\sigma_x}$

$E_x \left[ \frac{\rho_2 \sigma_x \sigma_z}{\sigma_x} \cdot \frac{\rho_1 \sigma_x \sigma_z}{\sigma_x} \right] = \frac{\rho_1 \rho_2 \sigma_x \sigma_z}{\sigma_x^2} E_x[\gamma^2] = \rho_1 \rho_2 \sigma_x \sigma_z$

$\rho_{xz} = \rho_1 \rho_2$   $I(x, z) = 0.5 \log \left( \frac{2\pi \sigma_x^2 \sigma_z^2}{1 - \rho_1^2 \rho_2^2} \right) - \frac{1}{2} \log \left( \frac{2\pi \sigma_x^2 \sigma_z^2}{1 - \rho_1^2 \rho_2^2} \right)$

$I(x, z) = \frac{1}{2} \log \left( \frac{(2\pi \sigma_x^2 \sigma_z^2)^2}{(2\pi \sigma_x^2 \sigma_z^2)^2 (1 - \rho_1^2 \rho_2^2)} \right) = -0.5 \log(1 - \rho_1^2 \rho_2^2)$

= OD ZADACANA NA VEŠN. VO DOLA. SMECI SE MI VEKTA O NEVA DOKA GLAVA 8 (MODEL 8.9) NAJON

$h(z | \gamma) = \frac{1}{2} + \frac{1}{2} \ln 2\pi (1 - \rho_2^2) \rho = \frac{1}{2} \ln(2\pi) (1 - \rho_2^2) \rho$

$h(x | \gamma) = \frac{1}{2} \ln(2\pi) (1 - \rho_1^2) \rho$

$I(x, z) = I(x, \gamma) + I(x, z | \gamma) = I(x, z) + I(x, \gamma | z)$

$I(x, z | \gamma) = h(x | \gamma) - h(x | \gamma, z) = 0$

$I(x, z) = I(x, \gamma) - I(x, \gamma | z) = I(x, \gamma) - h(x | \gamma, z) + h(x | \gamma)$

$= I(x, \gamma) - h(\gamma | z) + h(\gamma | x) = I(x, \gamma) - h(\gamma | z) + h(\gamma | x)$

$h(\gamma | z) = \frac{1}{2} \ln 2\pi \rho (1 - \rho_2^2) + 1/2$   $h(\gamma | x) = \frac{1}{2} \ln 2\pi \rho (1 - \rho_1^2) + 1/2$

$I(x, z) = \frac{1}{2} \log \left( \frac{(2\pi \sigma_x^2 \sigma_z^2)^2 \rho^2 (1 - \rho_1^2)}{1 - \rho_1^2 \rho_2^2} \right) - \frac{1}{2} \ln 2\pi \rho (1 - \rho_2^2) + \frac{1}{2} \ln 2\pi \rho (1 - \rho_1^2)$

$I(x, z) = \frac{1}{2} \log \left( \frac{(2\pi \sigma_x^2 \sigma_z^2)^2 \rho^2 (1 - \rho_1^2) (1 - \rho_1^2)}{(1 - \rho_1^2 \rho_2^2)} \right)$

$I(x, z) = h(z) - h(z | x) \quad I(x, z) = h(z) - h(z | x) - h(z | \gamma) + h(z | \gamma, x)$

$$h(\tau, z) = \frac{1}{2} \log((\tau e)^2 + \rho(1-\rho z^2)) = h(\tau|z) + h(z|\tau)$$

$$h(\tau|z) = h(\tau, z) - h(z) = -\frac{1}{2} \log(2\pi\rho) - \frac{1}{2} \log(\tau^2 e^2 + \rho(1-\rho z^2))$$

$$= -\frac{1}{2} \log(\tau^2 e^2) - \frac{1}{2} \log(1 + \frac{\rho(1-\rho z^2)}{\tau^2 e^2})$$

$$= -\frac{1}{2} \log(\tau^2 e^2) - \frac{1}{2} \log(1 + \frac{\rho(1-\rho z^2)}{\tau^2 e^2})$$

→ MED TO STD EPOCH TO INTERPOL TO MAKE IDEAL

**9.12** TIME-VARYING CHANNEL. A TRAIN PULL

OUT OF THE STATION AT THE CONSTANT VELOCITY. THE RECEIVED SIGNAL ENERGY TAKES PLACE OF WITH TIME AS  $\lambda t^2$ . THE TOTAL RECEIVED SIGNAL AT TIME  $t = 1$  IS:

$$Y_1 = \sum_{i=1}^N X_i + Z_1$$

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WHERE  $Z_1, Z_2, \dots$  ARE I.I.D  $\sim N(0, N)$ . THE TRANSMITTER CONSTANT FOR BLOCK LENGTH  $N$  IS

$$\frac{1}{N} \sum_{i=1}^N X_i^2(\omega) \leq P \quad \omega \in \{\omega_1, \omega_2, \dots, \omega_{2^R}\}$$

USING FANO INEQUALITY, SHOW THAT THE CAPACITY IS EQUAL TO ZERO FOR THIS CHANNEL.

$$I(X_1; Y_1) = H(Y_1) - H(Z_1 | X_1) = H(Y_1) - H(Z_1)$$

$$H(Y_1 | X_1) \leq 1 - \rho e \log 2^{NR} \leq 1 - \rho e \cdot NR$$

$$E = \begin{cases} 1 & \omega \neq \bar{\omega} \\ 0 & \omega = \bar{\omega} \end{cases} \quad \begin{matrix} \rho e \\ \text{error} \end{matrix}$$

~~$H(X_1, Y_1) = H(X_1) + H(Y_1 | X_1) = H(X_1) + H(Z_1 | X_1)$~~

$$H(E, \bar{\omega}) = H(\bar{\omega}) + H(E | \bar{\omega}) = H(\bar{\omega})$$

$$= H(E | \bar{\omega}) + H(\bar{\omega} | E) \leq H(E) + \rho e \cdot H(\bar{\omega})$$

$$H(\bar{\omega} | E) = P(E=0) H(\bar{\omega} | E=0) + P(E=1) H(\bar{\omega} | E=1)$$

$$H(\bar{\omega} | \bar{\omega}) \leq H(E) + \rho e H(\bar{\omega}) \leq H(E) + \rho e \log 2^N$$

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} 1 \\ \frac{1}{2} \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

$$C = \frac{1}{2} \log \left( \frac{\frac{1}{2} \sigma_x^2 + \sigma_z^2}{\sigma_x^2} \right)$$

$$= \sum_{i=1}^N \frac{1}{2} \log \left( 1 + \frac{\sigma_z^2}{\sigma_x^2} \right)$$

(16)

$$Y_i = \frac{1}{\lambda} z_i + Z_i$$

$$I(x_1^y; x_1^z) = H(z_1^y) - H(z_1^y | x_1^y)$$

$n=3$

$$H(z_1^y | x_1^y) = H(z_1 | x_1 z_2 z_3) + H(z_2 | x_1^y z_3) + H(z_3 | x_1^y z_2)$$
  
$$= H(z_1 | x_1) + H(z_2 | x_2) + H(z_3 | x_3)$$

$$H(z_1 | x_1) = H(\frac{1}{\lambda} x_1 + z_1 | x_1) = H(z_1)$$

$$H(z_2 | x_2) = H(\frac{1}{\lambda} x_2 + z_2 | x_2) = H(z_2)$$

$$I(x_1^y; x_1^z) = H(z_1^y) - H(z_1^y) = H(z_1^y) - \sum_{i=1}^3 H(z_i)$$

$$H(z_1^y) = ? \quad H(z_1^y) = H(z_1) + H(z_2 | z_1) + H(z_3 | z_2 z_1)$$

$$H(W | \omega) = H(p_e) + p_e \cdot \log(W) = H(p_e) + p_e \cdot \log R$$

$$\star I(x_1^y; z_1^y) = H(z_1^y) - \sum_{i=1}^3 H(z_i) \leq \sum_{i=1}^3 [H(z_i) - H(z_i)]$$
  
$$\leq \sum_{i=1}^3 [H(z_i) - \log R]$$

$$[z_1, z_2] \quad z_1 = x_1 + z_1 \quad z_2 = \frac{1}{2} x_2 + z_2$$

$$x_2' = \frac{1}{2} x_2 \quad \gamma(x_2') = \frac{f(x_2)}{\frac{dx_2'}{dx_2}} \Big|_{x_2 = 2x_2'} = 2f(2x_2')$$

$$f(x_2) = \frac{1}{\sigma \sqrt{2\pi}} e^{-\frac{x_2^2}{2\sigma^2}} \quad \frac{dx_2'}{dx_2} = \frac{1}{2} \quad e^{-\frac{x_2^2}{2\sigma^2}} = e^{-\frac{(2x_2')^2}{2\sigma^2}}$$

$$f(x_2') = \frac{2}{\sigma \sqrt{2\pi}} e^{-\frac{(2x_2')^2}{2\sigma^2}} = \frac{1}{\frac{\sigma}{2} \sqrt{2\pi}} e^{-\frac{x_2'^2}{2(\frac{\sigma}{2})^2}}$$

$$\sigma_{x_2'} = \frac{\sigma}{2}$$

$$\sigma_{x_2'}^2 = \frac{\sigma^2}{4}$$

$$\sigma_{z_2'}^2 = \frac{\sigma_{x_2}^2}{4} + \sigma_{z_2}^2$$

$$\sigma_{z_1'}^2 = \frac{\sigma_{x_1}^2}{\lambda^2} + \sigma_{z_1}^2$$

$$I(x_1^y; z_1^y) \leq \sum_{i=1}^3 \frac{1}{2} \log \frac{\sigma_{x_i}^2}{\sigma_{z_i'}^2}$$
  
$$= \sum_{i=1}^3 \frac{1}{2} \log \left( 1 + \frac{\sigma_{x_i}^2}{\lambda^2 \sigma_{z_i}^2} \right) = \frac{1}{2} \log \left( 1 + \frac{\sigma_{x_i}^2}{\sigma_{z_i}^2} \right)$$

$$J = \sum_{i=1}^3 \frac{1}{2} \log \left( 1 + \frac{P_i}{\lambda^2 N} \right) + \lambda \sum_{i=1}^3 P_i = 0$$

$\frac{dJ}{d\lambda} = 0$

$$\frac{1}{1 + \frac{P_i}{\lambda^2 N}} \cdot \frac{1}{\lambda^2 N} - \lambda = 0$$

$$\lambda = \frac{1}{\sqrt{P_i + N}}$$



$$i^2 N + P_1 = \lambda$$

$$i^2 N + P_2 = \gamma$$

$$P_i = \gamma - i^2 N$$

$$u=2$$

$$i^2 N + P_1 = \gamma \quad + \quad 2i^2 N + P_2 = \gamma$$

$$N + P_1 = 4N + P_2$$

$$P_1 + P_2 = 2\gamma$$

$$N + 2\gamma - P_2 = 4N + P_2$$

$$2\gamma - P_2 = 3N + 2P_2$$

$$P_1 = 2\gamma - P_2$$

$$P = \frac{2\gamma + P_2}{2}$$

$$P_2 = \gamma - \frac{3N}{2}$$

$$P_1 = 2\gamma - \gamma + \frac{3N}{2} = \gamma + \frac{3N}{2}$$

$$P_1 = \gamma + \frac{3N}{2}$$

$$I(x_1^2, x_2^2) = \frac{1}{2} \ln \left( 1 + \frac{\gamma + \frac{3N}{2}}{N} \right) + \frac{1}{2} \ln \left( 1 + \frac{\gamma - \frac{3N}{2}}{N} \right)$$

$$= \frac{1}{2} \ln \left( \frac{N + \gamma + \frac{3N}{2}}{N} \right) \left( \frac{N + \gamma - \frac{3N}{2}}{N} \right)$$

$$= \frac{1}{2} \ln \left( \frac{\frac{5N}{2} + \gamma^2 - \frac{5N^2}{4} - \frac{N\gamma}{2}}{N} \right)$$

$$= \frac{1}{2} \ln \left( \frac{4\gamma + \gamma^2 - \frac{5N}{4}}{4} \right)$$

$$I(x_1^2, x_2^2) = \sum_i h(x_i) - \sum_i h(\gamma + i^2 N) \geq \sum_i h(x_i) - \sum_i (1 - p_i) \ln R$$

$$h(x_i | \gamma) \leq h(\gamma) - p_i \ln R \leq 1 - p_i \ln R$$

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$$E[x_i^2] = \frac{1}{i^2} E[x_i^2] + E[x_i^0] = \frac{P_i}{i^2} + N$$

$$h(x_i) \leq \frac{1}{2} \ln \left( \frac{P_i}{i^2} + N \right)$$

$$E[h(x_i)] \leq f(E[x_i])$$

$$R \leq \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \ln \left( 1 + \frac{P_i}{i^2 N} \right) \leq$$

Jensen's inequality

$$\leq \frac{1}{2} \ln \left( 1 + \frac{1}{4} \sum_{i=1}^4 \frac{P_i}{i^2 N} \right)$$

$$A = \frac{P_i}{i^2}$$

$P_i = A i^2$   
KONINA  
METROSTOVKA!

$$\frac{1}{4} \sum_{i=1}^4 \frac{A i^2}{i^2 N} = \frac{A}{4N} \cdot 4 = \frac{A}{N}$$

$$\frac{1}{4} \sum_{i=1}^4 P_i \leq P$$

$$\sum_{i=1}^4 i^2 = 4(24+1)(4+1)$$

$$\frac{1}{4} \sum_{i=1}^4 (24+1)(4+1) \leq P$$

$$A \leq \frac{6P}{(24+1)(4+1)}$$

$$R \leq \frac{1}{2} \ln \left( 1 + \frac{6P}{N(24+1)(4+1)} \right) + \dots$$

$N \rightarrow \infty \quad R \rightarrow 0$

167 **PROBLEM 9.17** FEEDBACK CAPACITY. LET  $(Z_1, Z_2)$

$N(0, K)$   $K = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$

FIND MAXIMUM OF  $\frac{1}{2} \log \frac{|K_{X+Z}|}{|K_Z|}$  WITH AND WITHOUT FEEDBACK GIVEN A TRACE (POWER) CONSTRAINT  $\text{tr}(K_X) \leq 2P$ .

**GAUSSIAN CHANNEL WITH FEEDBACK (RECALL)**

$Z_i = X_i + Z_i$   $Z_i \sim N(0, K_Z^{(i)})$   
 $X_i(w, \tau^{i-1})$   $w \in \{1, 2, \dots, 2^{nR}\}$

$E \left[ \frac{1}{4} \sum_{i=1}^n X_i^2(w, \tau^{i-1}) \right] \leq P$ ,  $w \in \{1, 2, \dots, 2^{nR}\}$

$C_{n,FB} = \max_{\tau} \frac{1}{2n} \log \frac{|K_{X+Z}^{(n)}|}{|K_Z^{(n)}|}$  \*4

$X_i = \sum_{j=1}^4 b_{ij} Z_j + V_i$   $i = 1, 2, \dots, 4$

$X = BZ + V$   $Z = X + Z$

$C_{n,FB} = \max_{\tau} \frac{1}{2n} \log \frac{|(B+I)K_Z^{(n)}(B+I)^T + K_V|}{|K_Z^{(n)}|}$

$\text{tr}(BK_Z^{(n)}B^T + K_V) \leq 4P$

B=0 IF FEEDBACK IS NOT ALLOWED

- WITHOUT FEEDBACK

$C_n = \max_{\tau} \frac{1}{2n} \log \frac{|K_X^{(n)} + K_Z^{(n)}|}{|K_Z^{(n)}|}$

$C_n = \frac{1}{2n} \sum_{\lambda=1}^n \log \left( 1 + \frac{(\lambda - \lambda_i^{(n)})^+}{\lambda_i^{(n)}} \right)$  (7)† = max(0, 0)

$\sum_{\lambda=1}^n (\lambda - \lambda_i^{(n)})^+ = 4 \cdot P$

**THEOREM 9.6.1** FOR A GAUSSIAN CHANNEL WITH FEEDBACK, THE RATE  $R_n$  FOR ANY SEQUENCE OF  $(P_n, n)$  CODES WITH  $P_n \rightarrow P$  SATISFIES

$R_n \leq C_{n,FB} + \epsilon_n$   $\epsilon_n \rightarrow 0$  AS  $n \rightarrow \infty$

WHERE  $C_{n,FB}$  IS DEFINED WITH \*4

$h(w|\hat{w}) \leq 1 + 4P_n \cdot \epsilon_n = 4 \epsilon_n$   
 $4P_n = h(w) = I(w; \hat{w}) + h(w|\hat{w}) \leq I(w; \hat{w}) + 4 \epsilon_n$

$$\begin{aligned} & I(w; z^y) + y \epsilon_y = \sum_{i=1}^y I(w_i; z_i | z_1^{i-1}) + y \epsilon_y \\ & \sum_{i=1}^y (h(z_i | z_1^{i-1}) - h(z_i | w, z_1^{i-1})) + y \epsilon_y = \\ & \sum_{i=1}^y (h(z_i | z_1^{i-1}) - h(z_i | w, z_1^{i-1}, x_i, z_1^{i-1})) + y \epsilon_y \end{aligned}$$

$$w = f(x_i, z_1^{i-1}) \quad z^{i-1} = z_1^{i-1}, x^{i-1}$$

$$\begin{aligned} & \sum_{i=1}^y (h(z_i | z_1^{i-1}) - h(z_i | z_1^{i-1})) + y \epsilon_y = \\ & = h(z^y) - \sum_{i=1}^y h(z_i | z^{i-1}) + y \epsilon_y = \frac{h(z^y) - h(z^1)}{y} + y \epsilon_y \end{aligned}$$

$$y R_y \leq h(z^y) - h(z^1) + y \epsilon_y \quad R_y \leq \frac{1}{y} h(z^y) - \frac{1}{y} h(z^1) + \epsilon_y$$

$$R_y \leq \frac{1}{2y} \left[ \frac{|K_z^{(y)}|}{|K_z^{(1)}|} + \epsilon_y \right] \leq C_{y,FD} + \epsilon_y$$

**Lemma 9.6.1**

$$K_{x+z} + K_{x-z} = 2K_x + 2K_z$$

$$\begin{aligned} K_{x+z} &= E[(x+z)(x+z)^T] = E[(x+z)(x^T+z^T)] = \\ &= E[x x^T + z z^T + z x^T + x z^T] = K_x + K_z + K_{zx} + K_{xz} \end{aligned}$$

$$\begin{aligned} K_{x-z} &= E[(x-z)(x-z)^T] = E[x^T - z^T - z x^T + x z^T] = \\ &= K_x - K_z - K_{zx} + K_{xz} \end{aligned}$$

$$K_{x+z} + K_{x-z} = 2K_x + 2K_z$$

**Lemma 9.6.2**

$A=B$  nonnegative definite  
 $|A| \geq |B|$

$$C = A - B$$

$$x = x_1 + x_2$$

$$\begin{aligned} x_1 &\sim N(0, A) \quad x_2 \sim N(0, C) \\ h(x) &= h(x_1 + x_2) = h(x_1 | x_2) = h(x_1) \\ \frac{1}{2} \log \det(A) &\geq \frac{1}{2} \log \det(C) \end{aligned}$$

$$A \geq B + C$$

$$\Rightarrow |A| \geq |B|$$

**Lemma 9.6.3**

$$|K_{x+z}| \leq 2^y |K_x + K_z|$$

$$2K_x + 2K_z - K_{x+z} = K_{x-z} \geq 0$$

$$|2K_x + 2K_z| \geq |K_{x-z}| \quad |2(K_x + K_z)| = 2^y |K_x + K_z|$$

**Lemma 9.6.4**

$$\begin{aligned} A, B \geq 0 \quad 0 \leq \lambda \leq 1 \\ |\lambda A + (1-\lambda)B| &\geq |\lambda|^y |A|^{1-\lambda} |B|^{1-\lambda} \end{aligned}$$

PROOF:  $X \sim N(0, A)$

$Y \sim N(0, B)$

$$Z = \begin{cases} X & \theta=1 \\ Y & \theta=2 \end{cases}$$

$$\theta = \begin{cases} 1 & Y = \lambda \\ 2 & Y = 1 - \lambda \end{cases}$$

$$K_Z = \lambda A + (1 - \lambda) B$$

$$K_Z = E[Z^2]$$

$$H(Z, \theta) = H(Z) + H(\theta|Z) = H(\theta) + H(Z|\theta)$$

$$H(Z|\theta) = \underbrace{\gamma(\theta=1)}_{\lambda} H(Z|\theta=1) + \underbrace{\gamma(\theta=2)}_{(1-\lambda)} H(Z|\theta=2)$$

$$E[Z] = \int \gamma(z) \cdot z \, dz$$

$$E_Z[E_\theta[Z|\theta]] = \int \gamma(\theta) \int f(z|\theta) \cdot z \, dz =$$

$$= \sum_{\theta=1}^2 \gamma(\theta) \int f(z|\theta) \cdot z \, dz = \underbrace{\gamma(\theta=1)}_{\lambda} E[X] + \underbrace{\gamma(\theta=2)}_{(1-\lambda)} E[Y]$$

$$E_Z[Z] = \lambda E[X] + (1 - \lambda) E[Y]$$

ANALOGOUSLY:

$$E_Z[Z^2] = \lambda E[X^2] + (1 - \lambda) E[Y^2]$$

$$K_Z = \lambda K_X + (1 - \lambda) K_Y$$

$$K_Z = \lambda A + (1 - \lambda) B$$

$$\begin{aligned} \frac{1}{2} \ln((2\pi e)^n |\lambda A + (1 - \lambda) B|) &\geq h(Z) \geq h(Z|\theta) = \\ &= \lambda h(X) + (1 - \lambda) h(Y) = \frac{\lambda}{2} \ln((2\pi e)^n |K_X|) + \frac{(1 - \lambda)}{2} \ln((2\pi e)^n |K_Y|) \\ &= \frac{1}{2} \ln((2\pi e)^n |K_X|^\lambda |K_Y|^{1 - \lambda}) = \frac{1}{2} \ln((2\pi e)^n |A|^\lambda |B|^{1 - \lambda}) \end{aligned}$$

$$|\lambda A + (1 - \lambda) B| \geq |A|^\lambda |B|^{1 - \lambda}$$

**LEMMA 9.6.5**

IF  $X^n$  AND  $Z^n$  ARE GAUSSIAN CORRELATED  
THEN:

$$h(X^n - Z^n) \geq h(Z^n)$$

$$(|K_{X-Z}| \geq |K_Z|)$$

PROOF:  $h(X^n - Z^n) = \sum_{i=1}^n h(x_i - z_i | x^{i-1} - z^{i-1})$

$$\begin{aligned} &\stackrel{(b)}{\geq} \sum_{i=1}^n h(x_i - z_i | x^{i-1} - z^{i-1}, x_i) \stackrel{(d)}{=} \sum_{i=1}^n h(z_i | z^{i-1}) = \\ &= h(Z^n) \end{aligned}$$

$$h(X^n - Z^n) \geq h(Z^n)$$

$$\begin{aligned} \frac{1}{2} \ln((2\pi e)^n |K_{X-Z}|) &= h(\tilde{X}^n - \tilde{Z}^n) \geq h(\tilde{Z}^n) = \\ &= \frac{1}{2} \ln((2\pi e)^n |K_Z|) \end{aligned} \quad |K_{X-Z}| \geq |K_Z|$$

THEOREM 9.6.2

$$C_{1,FD} \leq C_1 + \frac{1}{2}$$

$$C_{1,FD} \leq \max_{tr(K_x) \leq 1} \frac{1}{2n} \log \frac{|K_x|}{|K_z|} \leq \max_{tr(K_x) \leq 1} \frac{1}{2n} \log \frac{2^n |K_x + K_z|}{|K_z|} = \max_{tr(K_x) \leq 1} \frac{1}{2n} \log \frac{|K_x + K_z|}{|K_z|} + \frac{1}{2} \leq C_1 + \frac{1}{2}$$

THEOREM 9.6.3

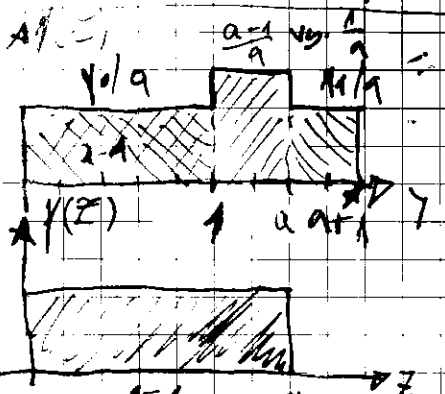
$$C_{1,FD} \leq 2C_1$$

$$\frac{1}{2} \frac{1}{2n} \log \frac{|K_{x+z}|}{|K_z|} \leq \frac{1}{2n} \log \frac{|K_x + K_z|}{|K_z|}$$

$$\left[ \frac{1}{2n} \log \frac{|K_x + K_z|}{|K_z|} \right] \stackrel{(a)}{=} \frac{1}{2n} \log \left( \frac{1}{2} |K_{x+z}| + \frac{1}{2} |K_{x-z}| \right) \geq \frac{1}{2n} \log \frac{|K_{x+z}|^{1/2} |K_{x-z}|^{1/2}}{|K_z|} = \frac{1}{2n} \log \frac{|K_{x+z}|}{|K_z|}$$

$$2C_1 \geq C_{1,FD}$$

we FROM NIKK JOVAN STOSIC



$$f(0 \leq x \leq 1) = f(x=0) \cdot f(x=a) = 1 \cdot \frac{1}{a} = \frac{1}{a}$$

$$f(1 < x \leq a) = f(x=1) \cdot f(x=a) = \frac{1}{a} \cdot \frac{1}{a} = \frac{1}{a^2}$$

$$f(a \leq x \leq a+1) = f(x=a) \cdot f(x=a+1) = \frac{1}{a} \cdot \frac{1}{a} = \frac{1}{a^2}$$

$$\int_{-1}^a \frac{1}{a} dz = \frac{1}{a} (a - (-1)) = \frac{1}{a} (a+1)$$

$$\int_0^a \frac{1}{a} dx = \frac{1}{a} (a - 0) = \frac{1}{a} a = 1$$

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$$\frac{f_0}{a} + \frac{f_1}{a} + \frac{f_2}{a} = \frac{f_0}{a} + 1 - \frac{f_1}{a} + \frac{f_2}{a} = \frac{f_0}{a} + 1 - \frac{f_1}{a} + \frac{f_1}{a} = 1$$

$$\frac{f_0}{a} + \frac{1}{a} + \frac{1}{a} = \frac{f_0}{a} + \frac{2}{a} = \frac{2}{a}$$

$$\text{INTEGRAL: } \frac{f_0}{a} + \frac{a-1}{a} (a-1) + \frac{f_0}{a} \text{ vs } \frac{f_0}{a} + \frac{1}{a} (a-1) + \frac{1}{a} = 1$$

PROBLEM 8.8 RECALL:

$$\frac{1}{2}q_{-2} + \frac{1}{2}q_{-2} + \frac{1}{2}q_{-1} + \frac{1}{2}q_{-1} + \frac{1}{2}q_0 + \frac{1}{2}q_0 + \frac{1}{2}q_1 + \frac{1}{2}q_1 + \frac{1}{2}q_2 + \frac{1}{2}q_2 = q_{-2} + q_{-1} + q_0 + q_1 + q_2 = 1$$

$$I(x; \tau) = H(x) - H(x|\tau) \quad H(x) = H(\tau)$$

$$P(x, \tau) = P(x|\tau) \cdot P(\tau|x) = P(\tau) \cdot P(x|\tau)$$

$$P(x|\tau) = \frac{P(x=1) \cdot P(\tau|x=1)}{P(x=1)} = \frac{P(x=1) \cdot P(\tau|x=1)}{P(x=1) \cdot P(\tau|x=0) + P(x=1) \cdot P(\tau|x=1)}$$

$$P(x=1|\tau) = \frac{P \cdot \frac{1}{a}}{(1-P) \cdot \frac{1}{a} + P \cdot \frac{1}{a}} = P \quad \boxed{MMV}$$

$$H(x|\tau) = P(1 \leq \tau \leq a) H(\tau) = \frac{a-1}{a} H(\tau)$$

$$H(x|\tau) = P(0 \leq \tau \leq 1) \cdot H(x|0 \leq \tau \leq 1) + P(1 \leq \tau \leq a) \cdot H(x|1 \leq \tau \leq a) + P(a \leq \tau \leq a+1) \cdot H(x|a \leq \tau \leq a+1)$$

$x=0$  SIGURNO!!  
 $x=1$  SIGURNO!!!

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$$H(x|1 \leq \tau \leq a+1) = H(\tau)$$

$$H(x|\tau) = P(1 \leq \tau \leq a) \cdot H(x|1 \leq \tau \leq a) = \frac{a-1}{a} \cdot H(\tau)$$

$$I(x; \tau) = H(\tau) - \frac{a-1}{a} H(\tau) = H(\tau) - \frac{a-1}{a} H(\tau) = \frac{1}{a} H(\tau)$$

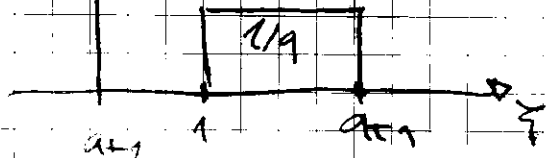
$$I(x; \tau) = \frac{H(\tau)}{a}$$

$$f(\tau) = \begin{cases} (1-\tau)^{\frac{1}{a}} & 0 \leq \tau \leq 1 \\ \frac{1}{a} & 1 \leq \tau \leq a \\ \frac{1}{a} & a \leq \tau \leq a+1 \end{cases}$$

$$h(\tau) = - \int_0^1 (1-y)^{\frac{1}{a}} dy + \int_1^a \frac{1}{a} dy + \int_a^{a+1} \frac{1}{a} dy = - \frac{1}{\frac{1}{a}+1} (1-y)^{\frac{1}{a}+1} \Big|_0^1 + \frac{1}{a} (a-1) + \frac{1}{a} (a+1-a) = - \frac{1}{\frac{1}{a}+1} (1-1)^{\frac{1}{a}+1} + \frac{1}{\frac{1}{a}+1} (1-0)^{\frac{1}{a}+1} + \frac{1}{a} (a-1) + \frac{1}{a} (a+1-a) = - \frac{1}{\frac{1}{a}+1} (1-1)^{\frac{1}{a}+1} + \frac{1}{\frac{1}{a}+1} (1-0)^{\frac{1}{a}+1} + \frac{1}{a} (a-1) + \frac{1}{a} (a+1-a) = - \frac{1}{\frac{1}{a}+1} (1-1)^{\frac{1}{a}+1} + \frac{1}{\frac{1}{a}+1} (1-0)^{\frac{1}{a}+1} + \frac{1}{a} (a-1) + \frac{1}{a} (a+1-a) = - \frac{1}{\frac{1}{a}+1} (1-1)^{\frac{1}{a}+1} + \frac{1}{\frac{1}{a}+1} (1-0)^{\frac{1}{a}+1} + \frac{1}{a} (a-1) + \frac{1}{a} (a+1-a) = \frac{1}{a} \ln(a) + \ln(a) - \frac{1}{a} \ln(a) = \frac{1}{a} + \ln(a)$$

$f(z|x=0) \sim U(0, a)$      $g(z|x=0) = \frac{1}{a}$

$f(z|x=1) \sim U(1, a+1)$      $g(z|x=1) = \frac{1}{a}$



$g(z|x=1) = \int_{a_1}^{a_2} \frac{1}{a} dz = \frac{1}{a} (a+1 - a) = \frac{1}{a}$

$g(z) = P(x=0) \cdot g(z|x=0) + P(x=1) \cdot g(z|x=1) = (1-p) \frac{1}{a} + p \frac{1}{a} = \frac{1}{a}$

$I(x; z) = g(z) - g(z|x) = \frac{1}{a} - \frac{1}{a} = 0$

(d) THE MUTUAL INFORMATION IS MAXIMIZED FOR  $p = \frac{1}{2}$  (UNIFORM DISTRIBUTION, MAXIMIZE ENTROPY)

$C = \frac{1}{a} H\left(\frac{1}{2}\right) = \frac{1}{a} \rightarrow \text{UNIT TO EQ}$

**PROBLEM 9.16**

GAUSSIAN MUTUAL INFORMATION

PROVE THAT  $(X, Z, Z)$  ARE JOINTLY GAUSSIAN. LET  $X$  AND  $Z$  HAVE COVARIANCE COEFFICIENT  $\rho_1$  AND LET  $Z$  AND  $Z$  HAVE COVARIANCE COEFFICIENT  $\rho_2$ . FIND  $I(X; Z)$

$I(X, Z; Z) = I(X; Z) + I(Z; Z|X) = I(Z; Z) + I(X; Z|Z)$

$I(Z; Z|X) = H(Z|X) - H(Z|X, Z) = H(Z|X) - H(Z|X, Z) = 0$

$I(X; Z|Z) = H(X|Z) - H(X|Z, Z) = H(X|Z) - H(X|Z, Z) = 0$

$I(X; Z) = H(X, Z) - H(X, Z|Z) = H(X, Z) - H(X, Z) = 0$

$I(X; Z|Z) = H(X|Z) - H(X|Z, Z) = H(X|Z) - H(X|Z, Z) = 0$

$I(X, Z; Z) = H(X, Z) - H(X, Z|Z) = \frac{1}{2} \log \frac{2\pi e}{\sigma_x^2 \sigma_z^2 (1 - \rho_1^2)} - \frac{1}{2} \log \frac{2\pi e}{\sigma_x^2 \sigma_z^2 (1 - \rho_2^2)}$

$E[(X - \bar{X})(Z - \bar{Z})] = \rho_1 \sigma_x \sigma_z$

$\begin{bmatrix} \sigma_x^2 & \rho_1 \sigma_x \sigma_z \\ \rho_1 \sigma_x \sigma_z & \sigma_z^2 \end{bmatrix}$   
 $\begin{bmatrix} \sigma_x^2 & \rho_2 \sigma_x \sigma_z \\ \rho_2 \sigma_x \sigma_z & \sigma_z^2 \end{bmatrix}$

$I(X; Z) = H(X) - H(X|Z) = H(X) - H(X, Z) + H(Z)$

$= H(X) + H(Z) - H(X, Z)$

$= \frac{1}{2} \log \frac{2\pi e}{\sigma_x^2} + \frac{1}{2} \log \frac{2\pi e}{\sigma_z^2} - \frac{1}{2} \log \frac{2\pi e}{\sigma_x^2 \sigma_z^2 (1 - \rho_1^2)}$

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$$\textcircled{A} \quad I(x, z) = \frac{1}{2} \ln \frac{1}{(x+z)} \frac{1}{(1-z^2)}$$

$$\begin{bmatrix} \sigma_x^2 & \rho \sigma_x \sigma_z \\ \rho \sigma_x \sigma_z & \sigma_z^2 \end{bmatrix} \quad \begin{bmatrix} \sigma_1^2 & \sigma_2^2 \\ \sigma_1 \sigma_2 \rho & \sigma_2^2 \end{bmatrix}$$

$$f(x, z|\gamma) = f(x|z) \cdot f(z|\gamma)$$

$$f(x, z|\gamma) = \frac{f(x|z) \cdot f(z|\gamma)}{f(z)} = \frac{f(x|z) \cdot f(z|\gamma)}{f(z)}$$

$$f(x, z|\gamma) = f(x|\gamma) \cdot f(z|\gamma) \rightarrow$$

$$E_{xz}[x, z] = \sigma_\gamma [E_{xz}[x, z|\gamma]] = \sigma_\gamma [E_x[x|\gamma] \cdot E_z[z|\gamma]] = \sigma_\gamma \int \int x \cdot z \cdot f(x|\gamma) \cdot f(z|\gamma) dx dz$$

$$\int x \cdot \gamma(x|\gamma) dx \quad E_z[z|\gamma] = \int z \cdot \gamma(z|\gamma) dz$$

$$E[R] = P(E) \cdot E_r[R|E] + P(\bar{E}) \cdot E_r[R|\bar{E}] = \sum_{i=0}^6 P(i) E_r[R|i]$$

$$E_r[R|E] = \sum_R R \cdot \gamma(R|E) = 1 \cdot \gamma(1|E) + 2 \cdot \gamma(2|E) + 3 \cdot \gamma(3|E) + 4 \cdot \gamma(4|E) + 5 \cdot \gamma(5|E) + 6 \cdot \gamma(6|E)$$

$$E_r[R|E] = 2 \cdot \frac{1}{3} + 4 \cdot \frac{1}{3} + 6 \cdot \frac{1}{3} = \frac{12}{3} = 4$$

$$E_r[R|\bar{E}] = 1 \cdot \frac{1}{3} + 3 \cdot \frac{1}{3} + 5 \cdot \frac{1}{3} = \frac{9}{3} = 3$$

$$E[R] = \frac{1}{2} \cdot 4 + \frac{1}{2} \cdot 3 = \frac{7}{2} = \sum_{i=1}^6 \frac{i}{6} = \frac{1+2+3+4+5+6}{6} = \frac{21}{6} = \frac{7}{2}$$

$$E_{xz}[x|z] = \int x \cdot \gamma(x|z) dx = E[x|z]$$

$$E_{xz}[z] = \int z \cdot \gamma(z) dz = E[z]$$

$$\int \int x \cdot \gamma(x|z) \cdot \gamma(z) dz = \int \int x \cdot \gamma(x) \cdot \gamma(z) dz dx = \int x \cdot \gamma(x) dx \int \gamma(z) dz = E[x] \cdot E[z]$$

$$\int \int x \cdot z \cdot \gamma(x, z) dx dz = E[xz]$$



$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x z^{-1} \gamma(x|z) \cdot \gamma(z|\gamma) \gamma(\gamma) dx dz d\gamma = \textcircled{a}$$

$$\gamma(x|z) = \frac{\gamma(xz)}{\gamma(z)} \quad E_x[x|z] = \int x \gamma(x|z) dx = \sqrt{x} \cdot z \cdot \rho_1 / \sigma_1$$

$$E_z[x|z] = \int z \cdot \gamma(z|\gamma) dz = \sqrt{z} \cdot \tau \cdot \rho_2 / \sigma_2$$

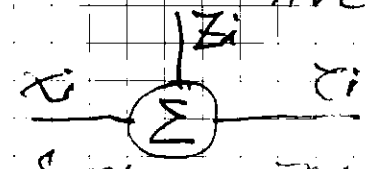
$$\gamma(z|\gamma) = \frac{\gamma(z\tau)}{\gamma(\tau)}$$

$$\textcircled{a} = \frac{\sigma_x \sigma_z \rho_1 \rho_2}{\sigma_y^2} \int_{-\infty}^{\infty} z^2 \gamma(z) dz = \sigma_x \sigma_z \cdot \rho_1 \rho_2$$

$$\sigma_z = \sigma_1 \sigma_2 \quad \text{9.169 (a)} \Rightarrow I(x; z) = -\frac{1}{2} \log(\sigma_z) (1 - \rho_1^2)$$

**PROBLEM 9.17**

IMPULSE POWER. CONSIDER THE ADDITIVE WHITE GAUSSIAN CHANNEL  $Z \sim N(0, N)$  WITH THE INPUT SIGNAL HAS AVERAGE CONSTRAINT  $P$ .



(a) SUPPOSE THAT WE USE ALL AVAILABLE POWER AT TIME 1 (I.E.  $E x_1^2 = 4P$   $E z_1^2 = N$  FOR  $\lambda = 2, 3, \dots, 4$ ). FIND

$$\max_{\{x_i\}} \frac{I(x^4; z^4)}{4}$$

WHERE THE OPTIMIZATION SUBJECT TO PART (a)

ALL DISCRETE CONSTRAINT:  $E x_i^2 = 4P$   
 $E z_i^2 = N$   
 $\lambda = 2, 3, \dots, 4$

(b) FIND:

$$\max_{\{x_i\}} \frac{1}{4} I(x^4; z^4)$$

AND COMPARE TO PART (a).

$$c: E \left[ \frac{1}{4} \sum_{i=1}^4 x_i^2 \right] \leq P$$

$$I(x^4; z^4) = H(z^4) - H(z^4|x^4) = H(z^4) - H(z^4) = 0$$

$$= H(z^4) - \frac{1}{2} \log(\sigma_z^4) |K| = H(z^4) - \frac{1}{2} \log(\sigma_z^4) N_4$$

$$\leq \sum_{i=1}^4 \frac{1}{2} \log(P_i + N_i) - \sum_{i=1}^4 \frac{1}{2} \log(\sigma_z^4) \cdot N_i$$

$$= \sum_{i=1}^4 \frac{1}{2} \log \frac{P_i + N_i}{N_i} = \sum_{i=1}^4 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right)$$

$$\sum_{i=1}^4 P_i \leq 4P \quad \frac{1}{1 + \frac{P_i}{N_i}} = \frac{1}{N_i} \Rightarrow \lambda = 0$$

$$\frac{1}{N_i + P_i} - \lambda = 0 \quad N_i + P_i = \frac{1}{\lambda} \quad \therefore P = N_1 + P_1 = N_2 + P_2 = \dots = N_4$$

111 Jensen's Inequality:  $E[f(X)] \geq f(E[X])$  if  $f$  is convex  $\checkmark$   
 $E[f(X)] \leq f(E[X])$  if  $f$  is concave

$$\textcircled{a} \frac{1}{N} \sum_{i=1}^N \ln\left(1 + \frac{P_i}{N}\right) \leq \frac{1}{N} \ln\left(1 + \frac{\sum_{i=1}^N P_i}{N}\right) \leq \frac{1}{2} \ln\left(1 + \frac{P}{N}\right)$$

$$\textcircled{a} \frac{1}{N} \sum_{i=1}^N \frac{1}{2} \ln\left(1 + \frac{P_i}{N}\right) = \frac{1}{N} \ln\left(1 + \frac{NP}{N}\right)$$

$P_i = NP$     $P_i = 0$     $i = 1, 2, \dots, N$   
 $f(x) = \frac{1}{\sqrt{2\pi} |K|} e^{-\frac{1}{2} x^T K^{-1} x}$

$$K = \begin{bmatrix} NP & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$f(x) = \frac{1}{NP \sqrt{2\pi}} e^{-\frac{x^2}{2NP}}$$

$$\frac{1}{2} \ln\left(1 + \frac{P}{N}\right) \text{ vs. } \frac{1}{N} \ln\left(1 + \frac{NP}{N}\right)$$

" = " FOL "N=1"

→ PROOF AND GRAPHICALLY IN MATHE (FOR DIFFERENT N)

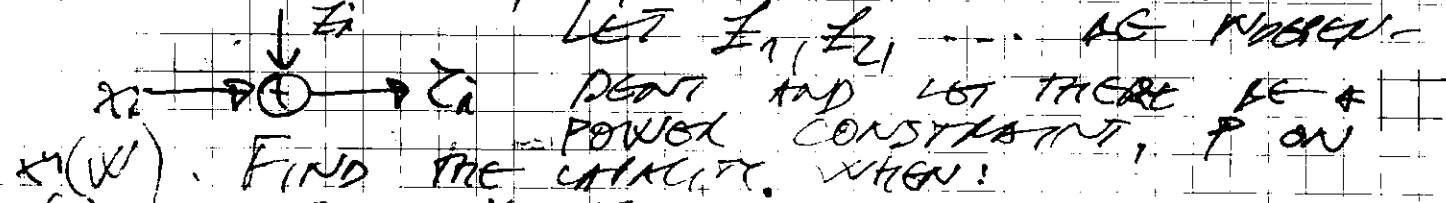
$$\ln(1+x) = 1 + \frac{f(x)}{1} x + \frac{f''(x)}{2!} x^2$$

$f''(1/x) = \left(\frac{1}{x}\right)' = -\frac{1}{x^2}$

$$O(1) = \frac{1}{1+x} x \quad \ln(1+x) \geq \ln x$$

$$\ln(1+x) = 1 + \frac{1}{x} x - \frac{1}{2x^2} x^2 \leq 1+x \quad \text{US } x \leq 0$$

**Problem 3.18** GAUSSIAN CHANNELS WITH TIME-VARYING MEAN. FIND THE CAPACITY OF THE FOLLOWING GAUSSIAN CHANNELS:



- (a)  $M_i = 0$  FOL REL 1
- (b)  $M_i = e^{i-1}$   $i = 1, 2, \dots$  ASSUME THAT  $P_i$  IS KNOWN TO TRANSMITTER AND RECEIVER

$\mu_i$  UNKNOWN, BUT  $\mu_i \text{ i.i.d } N(0, N_i)$   
 FOR ALL  $i$ .

$$C = \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log \left( 1 + \frac{P_i}{N_i} \right) \leq \frac{1}{2} \log \left( 1 + \sum_{i=1}^4 \frac{P_i}{N_i} \right)$$

$$N_i = \sigma^2 [z_i^2] - \mu_i^2 \quad \textcircled{1} = \sigma^2 \left[ \frac{P_i}{N_i} \right]$$

$$C = \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log \left( 1 + \frac{P_i}{\sigma^2 [z_i^2]} \right)$$

$$C = \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log \left( 1 + \frac{P_i}{\sigma^2 [z_i^2] - \mu_i^2} \right) =$$

$$\frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log \left( \frac{P_i}{\sigma^2 [z_i^2] - \mu_i^2} \right) = \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log P_i - \frac{1}{4} \sum_{i=1}^4 \frac{1}{2} \log [\sigma^2 [z_i^2] - \mu_i^2]$$

$$= \frac{1}{2} \sum_{i=1}^4 \log \left( 1 + \frac{P_i}{\sigma^2 [z_i^2] - \mu_i^2} \right)$$

$$E[\mu_i] = 0$$

8) (REVISED)

$$Y = P_i + N_i$$

$$P_i = Y - N_i$$

$$P_1 + N_1 = P_2 + N_2 = \dots = P_M + N_M$$

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a) When  $\mu_i = 0$   $C = 0.5 \log \left( 1 + \frac{P}{N} \right)$

b) When  $\mu_i = e^i$  SINCE IT IS KNOWN TRANSMITTER AND THE RECEIVER THE RECEIVER WILL BE ABLE TO SUBSTRACT IT WHILE TRANSMITTING AND THEN WE WILL GO BACK TO THE ZERO CASE:  $C = 0.5 \log \left( 1 + \frac{P}{N} \right)$

c) When  $\mu_i \sim N(0, N_i)$   $\Sigma = \Sigma +$

$$\sigma_{z_i}^2 = \sigma_c^2 + \sigma_{\mu_i}^2 = N + N_i$$

$$C = 0.5 \log \left( 1 + \frac{P}{N + N_i} \right)$$

Problem 9.19

PARAMETRIC FORM FOR CHANNEL CAPACITY  
 CONSIDER  $n$  INDEPENDENT GAUSSIAN CHANNELS  $T_i = \alpha + \beta_i$  WHERE  $\beta_i \sim N(0, N_i)$  AND  $\alpha_i$  ARE INDEPENDENT RANDOM VARIABLES.  
 $C = \sum_{i=1}^n \frac{1}{2} \log \left( 1 + \frac{(\alpha - \lambda_i)^2}{N_i} \right)$  WHERE  $\sum_{i=1}^n (\lambda_i - \alpha)^2 = 1$

197 SHOW THAT THIS CAN BE REWRITTEN AS:

$$P(\lambda) = \sum_{i: \lambda_i < \lambda} (\lambda - \lambda_i) \quad C(\lambda) = \sum_{i: \lambda_i < \lambda} \frac{1}{2} \log \frac{\lambda}{\lambda_i}$$

WHERE  $P(\lambda)$  IS PIECEWISE LINEAR AND  $C(\lambda)$  IS PIECEWISE LOGARITHMIC IN  $\lambda$ .

$$C = \sum_{i=1}^M \frac{1}{2} \log \left( 1 + \frac{(\lambda - \lambda_i)^+}{\lambda_i} \right) \quad \sum_{i=1}^M (\lambda - \lambda_i)^+ \rightarrow$$

$$\begin{aligned} C(\lambda) &= \sum_{i: \lambda_i < \lambda} \frac{1}{2} \log \left( 1 + \left( \frac{\lambda}{\lambda_i} - 1 \right)^+ \right) = \sum_{i: \lambda_i < \lambda} \frac{1}{2} \log \left( \lambda + \frac{\lambda}{\lambda_i} - \lambda \right) \\ &= \sum_{i: \lambda_i < \lambda} \frac{1}{2} \log \left( \frac{\lambda}{\lambda_i} \right) \end{aligned}$$

$$P(\lambda) = \sum_{i: \lambda_i < \lambda} (\lambda - \lambda_i)^+ = \sum_{i: \lambda_i < \lambda} (\lambda - \lambda_i)$$

**PROBLEM 9.20** (STAEGER PAGE 14) ROBUST DECODING CONSIDER AN ADDITIVE NOISE CHANNEL WHOSE OUTPUT  $Y$  IS GIVEN WITH

$$Y = X + Z \quad \text{WHERE THE CHANNEL INPUT } X \text{ IS AVERAGE POWER LIMITED: } E[X^2] \leq P \text{ AND THE NOISE PROCESS } \{Z_k\}_{k=1}^n \text{ IS I.I.D. WITH}$$

MARGINAL DISTRIBUTION  $f_Z(z)$  (NON-NECESSARILY GAUSSIAN) OF POWER "N",  $E[Z^2] = N$ .

(A) SHOW THAT THE CHANNEL CAPACITY,  $C = \max_{E[X^2] \leq P} I(X; Y)$  IS LOWER BOUNDED BY  $C_G$  WHERE

$$C_G = \frac{1}{2} \log \left( 1 + \frac{P}{N} \right)$$

(I.E. THE CAPACITY  $C_G$  CORRESPONDING TO WHITE GAUSSIAN NOISE.)

(B) DECODING THE RECEIVED VECTOR TO THE CODEWORD THAT IS CLOSEST TO IT IN EUCLIDEAN DISTANCE IS IN GENERAL SUBOPTIMAL IF THE NOISE IS NON-GAUSSIAN. SHOW, HOWEVER, THAT THE RATE  $C_G$  IS ACHIEVABLE EVEN IF ONE INSIST ON PERFORMING NEAREST-NEIGHBOR DECODING (MINIMUM EUCLIDEAN DISTANCE DECODING) RATHER THAN THE OPTIMAL MAXIMUM-LIKELIHOOD OR JOINT TYPICAL DECODING (WITH RESPECT TO THE TRUE NOISE DISTRIBUTION).

(C) EXTEND THE RESULT TO THE CASE WHERE NOISE IS NOT I.I.D BUT IS STATIONARY ERGODIC WITH POWER N.

HINT FOR (B) AND (C) CONSIDER A SIZE  $2^{nR}$  RANDOM CODEBOOK WHOSE CODEWORDS ARE DRAWN INDEPENDENTLY OF EACH OTHER ACCORDING TO A UNIFORM DISTRIBUTION OVER THE  $n$ -DIMENSIONAL SPHERE OF

### RADIUS (M.P.)

(a) USING A SYMMETRIC ARGUMENT, SHOW THAT CONDITIONAL ON THE NOISE VECTOR THE UNBIASED AVERAGE PROBABILITY OF ERROR DEPENDS ON THE NOISE VECTOR ONLY VIA ITS EUCLIDEAN NORM  $\|z\|$ .

(b) USE A GEOMETRIC ARGUMENT TO SHOW THAT THIS DEPENDENCE IS MONOTONIC.

(c) GIVEN A RATE  $R < C_0$ , CHOOSE SOME  $\epsilon > 0$  SUCH THAT

$$\epsilon < \frac{1}{2} \log \left( 1 + \frac{P}{N} \right)$$

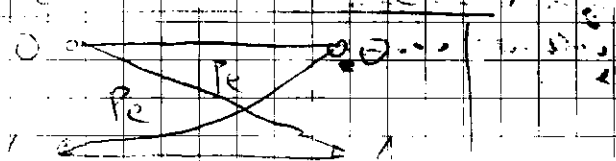
CONSIDER THE CASE WHERE NOISE IS I.I.D  $N(0, N)$  WITH  $n$  DIMENSIONS AT HAND.

INCLUDE THE PROOF USING THE FACT THAT THE DENSITY OF PERPENDICULARS CAN BE TREATED AS GAUSSIAN (NEED TO TAKE)

$$\frac{1}{n} \sum_{i=1}^n x_i^2 \leq P$$

$$P_e = \frac{1}{2} P(z > 0 | x = -\sqrt{P}) + \frac{1}{2} P(z < 0 | x = \sqrt{P}) = \frac{1}{2} P(z \geq \sqrt{P} | x = -\sqrt{P}) + \frac{1}{2} P(z \leq -\sqrt{P} | x = \sqrt{P}) = P(z \geq \sqrt{P}) = 1 - \Phi(\sqrt{P})$$

$$\Phi = \int_{-\infty}^x \frac{1}{\sqrt{2\pi}} e^{-\frac{t^2}{2}} dt$$



### 1) GENERATION OF THE CODEBOOK.

$$\frac{1}{n} \sum_{i=1}^n x_i^2 \leq P - \epsilon \quad x_i(w), i=1,2,\dots,n, w=1,2,\dots,2^{nR}$$

$$x^y(1), x^y(2), \dots, x^y(2^{nR}) \in \mathbb{R}^n$$

$$r^y = x^y(1) + \dots + x^y(n), \quad \epsilon_0 = \left\{ \frac{1}{n} \sum_{i=1}^n x_i^2(1) > P \right\}$$

$$E_1 = \left\{ (x^y(1), r^y) \in A_\epsilon^{(n)} \right\}$$

$$P_1(\epsilon | W=1) = P(\epsilon) = P(\epsilon_0 \cup E_1^c \cup E_2 \cup \dots \cup E_{2^{nR}})$$

$$\leq P(\epsilon_0) + P(E_1^c) + \sum_{i=2}^{2^{nR}} P(E_i) \quad P(E_i) \leq \epsilon \quad n \uparrow$$

$$P_2(\epsilon) = \frac{1}{2^{nR}} \sum_{i=1}^{2^{nR}} P_i = P(\epsilon) / P_e^{(n)} \quad P_e^{(n)} = P_1(\epsilon) = P(\epsilon_0) + P(E_1^c) + \sum_{i=2}^{2^{nR}} P(E_i)$$

$$\leq \epsilon + \epsilon + \sum_{i=2}^{2^{nR}} \epsilon = 2\epsilon + (2^{nR} - 1) \epsilon = 2\epsilon + (2^{nR} - 1) \frac{1}{2^{nR}} \sum_{i=1}^{2^{nR}} \epsilon$$

BETTER SOLUTIONS

(a) THE PROOF DEPENDS ON THE ENTROPY POWER INEQUALITY

$$2^{2h(x+z)} \geq 2^{2h(x)} + 2^{2h(z)} \quad / \quad 2^{2h(z)}$$

$$2^{2(h(x+z) - h(z))} \geq 2^{2h(x) - 2h(z)} + 1$$

$$E[Z^2] = N \quad h(z) \leq \frac{1}{2} \log(2\pi e) N \quad h(x) = \frac{1}{2} \log(2\pi e) P$$

$$2^{2(h(x+z) - h(z))} \geq 1 + \frac{2^{\log(2\pi e) P}}{2^{\log(2\pi e) N}} = \frac{2\pi e P}{2\pi e N} + 1$$

$$2^{2(h(x+z) - h(z))} \geq \frac{P}{N} + 1 \quad 2^{(h(x+z) - h(z))} \geq \sqrt{\frac{P}{N} + 1}$$

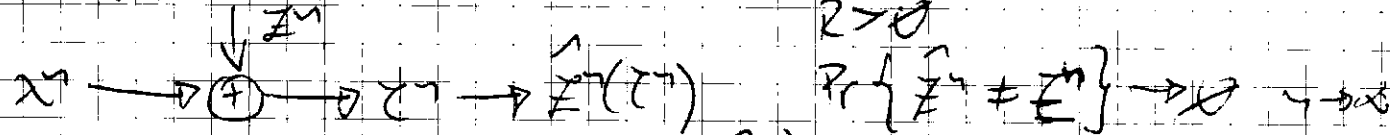
$$h(x+z) - h(z) \geq \frac{1}{2} \log\left(1 + \frac{P}{N}\right) \quad I(x; z) \geq \frac{1}{2} \log\left(1 + \frac{P}{N}\right)$$

THUS WE HAVE FOUND A SPECIFIC INPUT DISTRIBUTION (THE GAUSSIAN DISTRIBUTION WITH MEAN 0 AND VARIANCE P) FOR WHICH  $I(x; z)$  IS AT LEAST AS BIG AS  $\frac{1}{2} \log\left(1 + \frac{P}{N}\right)$ . THIS PROVES THAT CAPACITY OF THE CHANNEL IS BOUNDED ABOVE BY  $\frac{1}{2} \log\left(1 + \frac{P}{N}\right)$

**PROBLEM 9.22** (CONTINUE FROM N164)

$X_i \sim N(0, N) \quad i = 1, 2, \dots, n$   
 $X = (X_1, X_2, \dots, X_n)^T$

$$Z = \sum_{i=1}^n \lambda_i X_i \quad \sum_{i=1}^n \lambda_i^2 \leq P$$



$$R = H(W) = I(W; Z) + H(W|Z) \leq I(X; Z) + H(E_n) =$$

$$= H(Z) - H(E_n) = \sum_{i=1}^n \frac{1}{2} \log(2\pi e) \left(1 + \frac{P_i}{N}\right) + H(E_n)$$

$$R \leq \frac{1}{n} \sum_{i=1}^n \frac{1}{2} \log(2\pi e) \left(1 + \frac{P_i}{N}\right) + H(E_n) \leq \frac{1}{2} \log(2\pi e) \left(1 + \frac{P}{N}\right) + H(E_n)$$

$$R \leq \frac{1}{n} \left[ \frac{1}{2} \log(2\pi e)^n \left(1 + \frac{P_1}{N}\right) \right] \quad P_2, P_3, \dots, P_n = 0$$

$$R \leq \frac{1}{2n} \log(2\pi e)^n + \frac{1}{2n} \log\left(1 + \frac{P_1}{N}\right) = \log \sqrt{2\pi e} + \log\left(1 + \frac{P_1}{N}\right)^{\frac{1}{n}}$$

$$n \rightarrow \infty \quad R \leq \log \sqrt{2\pi e} + 0 = \log \sqrt{2\pi e}$$

WIKI SOLUTION

We have that:  $\log R = C = C(P/N)$

If  $R < C$  FROM THE ACHIEVABILITY PROOF OF THE CHANNEL CODING THEOREM 2<sup>nd</sup> DIFFERENT  $2^N$  SEQUENCES CAN BE RECOVERED EXACTLY WITH ARBITRARY SMALL ERROR FOR  $n$  LARGE ENOUGH. ONCE  $2^N$  IS DETERMINED,  $2^n$  CAN BE EASILY COMPUTED AS  $2^N \rightarrow 2^n$ .

WE SHOW THAT THIS IS ~~PROVE~~ OPTIMAL BY USING PROOF BY CONTRADICTION. ASSUME THAT THERE IS SOME  $R > C$  SUCH THAT  $2^n$  CAN BE RECOVERED WITH  $\epsilon$   $2^n \neq 2^N$  AS  $n \rightarrow \infty$ . BUT THIS IMPLIES THAT  $2^N = 2^n 2^{-n}$  CAN BE DETERMINED WITH ARBITRARY PRECISION THAT IS, THERE IS SOME  $\delta > 0$  SUCH THAT  $2^N = 2^n \pm \delta$  WITH  $R > C$  AND  $2^N = 2^n \pm \delta$  AS  $n \rightarrow \infty$  AS WE STAY IN THE CHANNEL CAPACITY OF THE CHANNEL CODING THEOREM, THIS IS IMPOSSIBLE. HENCE WE HAVE CONTRADICTION AND  $R$  CANNOT BE GREATER THAN  $C$ .

$$x(t) = x(t) + z(t) * g(t)$$

STAND UNLIMITED CHANNEL

$$X(f) = \int_{-\infty}^{\infty} x(t) e^{-j2\pi ft} dt$$

$$Z(f) = \int_{-\infty}^{\infty} z(t) e^{-j2\pi ft} dt$$

$$G\left(\frac{1}{2W}\right) = \frac{1}{T} \int_{-\infty}^{\infty} g(t) e^{-j2\pi \frac{1}{2W} t} dt$$

$$x_{ENC}(t) = \frac{\sum_{k=-\infty}^{\infty} X(f_k) e^{j2\pi f_k t}}{\sum_{k=-\infty}^{\infty} G\left(\frac{1}{2W}\right)}$$

$$y(t) = \sum_{k=-\infty}^{\infty} f\left(\frac{1}{2W}\right) \text{sinc}\left(t - \frac{k}{2W}\right)$$

IF THE NOISE HAS POWER SPECTRAL DENSITY  $N_0/2$  W/Hz AND BANDWIDTH  $W$  HERTZ THE NOISE HAS POWER  $\frac{N_0 2W}{2} = N_0 W$  AND EACH OF THE  $2W T$  NOISE SAMPLES IN TIME  $T$  HAS VARIANCE  $N_0 W T / (2W T) = N_0/2$

$$C = \frac{1}{2} \log\left(1 + \frac{P}{N}\right) \text{ BITS/TRANSMISSION}$$

THIS ENERGY PER SAMPLE OVER THE TIME INTERVAL  $[0, T]$

IN THIS CASE, THE ENERGY PER SAMPLE IS:  $\frac{P T}{2W T} = \frac{P}{2W}$

THE NOISE VARIANCE PER SAMPLE IS:  $\frac{N_0 2W T}{2} \frac{1}{2W T} = \frac{N_0 T}{2}$

$$= N_0/2$$

$$C = \frac{1}{2} \log\left(1 + \frac{\frac{P}{2W}}{\frac{N_0 T}{2}}\right) = \frac{1}{2} \log\left(1 + \frac{P}{W N_0}\right) \text{ BITS/TRANSMISSION}$$

(177)

$$C = W \log\left(1 + \frac{P}{N_0 W}\right) = 2W \cdot \frac{1}{2} \log\left(1 + \frac{P}{N_0 W}\right)$$

SINCE THERE ARE  $2W$  SAMPLES PER SECOND

THIS EQUATION IS ONE OF THE MOST FAMOUS FORMULAS OF INFORMATION THEORY. IT GIVES THE CAPACITY OF BANDLIMITED GAUSSIAN CHANNEL WITH NOISE SPECTRAL DENSITY  $N_0/2$  WATTS/Hz AND POWER  $P$  WATTS.

$$W \rightarrow \infty \Rightarrow C = \lim_{W \rightarrow \infty} \frac{1}{2} \log\left(1 + \frac{P}{N_0 W}\right)$$

$$\begin{aligned} &= \lim_{W \rightarrow \infty} \frac{1}{2} \frac{1}{1 + \frac{P}{N_0 W}} \cdot \frac{P}{N_0 W} \cdot \frac{1}{2W} \\ &= \lim_{W \rightarrow \infty} \frac{P}{W N_0} \cdot \frac{1}{2} = \frac{P}{N_0} \cdot \frac{1}{2} = \frac{P}{N_0} \cdot \ln e \end{aligned}$$

$$\log e = \ln e = \frac{\ln e}{\ln 2} \Rightarrow C = \frac{P}{N_0} \cdot \ln e$$

FOR CHANNEL WITH INFINITE BANDWIDTH THE CAPACITY GROWS LINEARLY WITH THE POWER

$$W \log\left(1 + \frac{P}{W N_0}\right) = 3200 \cdot \log\left(1 + \frac{P}{2000}\right) = 36200 \text{ kbps}$$

EIGENVALUES AND EIGENVECTORS (WIKIPEDIA)

$$A \cdot \vec{v} = \lambda \cdot \vec{v}$$

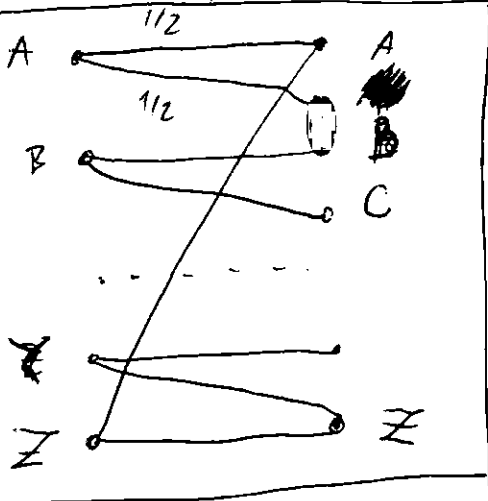
$\lambda$  - EIGENVALUE  
 $\vec{v}$  - EIGENVECTOR

IN THREE DIMENSIONAL SPACE EIGENVECTOR  $\vec{v}$  IS AN ARROW WHOSE DIRECTION IS EITHER PRESERVED OR EXACTLY REVERSED AFTER MULTIPLICATION BY  $A$ .



**7.6** NOISY TYPEWRITER. CONSIDER 26-KEY TYPEWRITER.

- (a) IF PUSHTING THE KEY RESULTS IN PRINTING THE ASSOCIATED LETTER, WHAT IS THE CAPACITY  $C$  IN BITS?
- (b) NOW SUPPOSE THAT PUSHTING A KEY RESULTS IN PRINTING THE LETTER OF NEXT (WITH EQUAL PROBABILITY) THUS  $A \rightarrow A$  OR  $B, \dots, Z \rightarrow Z$  OR  $A$ . WHAT IS THE CAPACITY?
- (c) WHAT IS THE HIGHEST RATE CODE WITH BLOCK LENGTH ONE THAT YOU CAN FIND THAT ACHIEVES ZERO PROBABILITY OF ERROR FOR THE CHANNEL IN PART (b)?



(b)  $I(X; Z) = H(Z) - H(Z|X) =$   
 $= H(Z) - H(Z|Z)$   
 $H(Z) = 26 \cdot \frac{1}{26} \cdot \log 26 = \log 26$   
 $H(Z|X) = \sum P(X) \cdot H(Z|X=X)$   
 $P(A) \cdot H(Z|X=A) = \frac{1}{26} \cdot \left[ \frac{P(Z=A|X=A)}{P(Z=A|X=A)} \right]$   
 $\log \frac{1}{P(Z=A|X=A)} + P(Z=A|X=A) \cdot \log \frac{1}{P(Z=A|X=A)} = \frac{1}{26} \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right]$   
 $H(Z|X) = \sum P(X) \cdot 1 = 1$   
 $C = \max_{P(X)} [H(Z) - 1] = \log 26 - 1 = \log 26 - \log 2 = \log 13$

(a)  $I(X; Z) = H(Z) - H(Z|X) = \log 26 - \sum_x P(x) \left[ \frac{1}{26} \log 1 \right] = \log 26$

(c)  $R = \frac{\log 4}{\log 2} = \log_2 4$   $W \in \{1, 2, \dots, 2^{4R}\}$   
 $H(W) = 2^{4R} \cdot \frac{1}{2^{4R}} \log 2^{4R} = 4R = H(W|W) + I(W; W) \leq$   
 $\leq 1 + P_e \cdot \log 2^{4R} + I(W; W) \leq 1 + P_e \cdot 4R + I(W; W)$   
 $I(W; W) = H(W) - H(W|W) = H(W) - \sum_{i=1}^4 H(W_i|W_{1:i-1})$

$$\begin{aligned}
 I(x^y; \gamma^y) &= H(\gamma^y) - \sum_{i=1}^y H(\tau_i | x^{i-1}, \gamma^y) = H(\gamma^y) - \sum_{i=1}^y H(\tau_i | \tau_i) \\
 &= \sum_{i=1}^y H(\tau_i | \gamma^i) - \sum_{i=1}^y H(\tau_i | x_i) \leq \sum_{i=1}^y H(\tau_i) - H(\gamma^y | x^y) = \\
 &= \sum_{i=1}^y I(x_i; \tau_i) \leq \underline{u \cdot C}
 \end{aligned}$$

$$u \cdot R \leq 1 + P_e \cdot uR + uC \quad R \leq \frac{1}{u} + P_e \cdot R + C$$

$$u \rightarrow \infty \Rightarrow \boxed{R \leq C}$$

$$\boxed{u=1} \quad R \leq 1 + P_e \cdot R + C \quad P_e = 0$$

$$R \leq 1 + C$$

$$\max(R) = C + 1$$

$$\boxed{R - C - 1 \leq P_e R}$$

$$1 - \frac{C}{R} - \frac{1}{R} \leq 0$$

$$\frac{R - C - 1}{R} \leq 0$$

$$\boxed{R \leq C + 1}$$

$$P_e = \frac{1}{2^{uR}} \sum_{i=1}^u \lambda_i$$

$$\lambda_i = P(\hat{w} \neq w | w) = P(g(\gamma^y) \neq i | x^y = x^y(i)) = \sum_{\gamma^y: \hat{I}(g(\gamma^y) \neq i)} P(\gamma^y | x^y(i))$$

• ZERO ERROR CODES:

$$u \cdot R = H(w | \hat{w}) + I(w; \hat{w}) \leq I(x^y, \gamma^y) \leq u \cdot C$$

$$\boxed{R \leq C}$$

$$\boxed{R \leq \text{rd } 13}$$

$$\boxed{R_{\max} = \text{rd } 13}$$

• EDITION 1 SOLUTION

SIMPLE ZERO ERROR BLOCK LENGTH ONE CODE IS ONE THAT USES GREAT ALPHABETIC LETTERS:

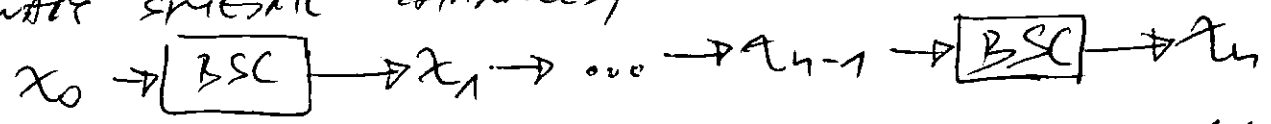
A C E ... IN THIS CASE NONE OF THE 'CORE-WORDS' WILL BE CONFUSED. 'A' WILL PRODUCE EITHER 'A' OR 'B', 'C' WILL PRODUCE 'C' OR 'D' AND SO ON.

$$R = \frac{\log(\# \text{ CODEWORDS})}{\text{BLOCK LENGTH}} = \frac{\log 13}{1} = \log 13$$

IN THIS CASE WE CAN ACHIEVE THE CAPACITY WITH SIMPLE CODE WITH ZERO ERRORS.

**PROBLEM 7.7** CASCADE OF BINARY SYMMETRIC CHANNELS.

SHOW THAT A CASCADE OF  $n$  IDENTICAL INDEPENDENT BINARY SYMMETRIC CHANNELS,



EACH WITH PAW ERROR PROBABILITY  $\gamma$  IS EQUIVALENT TO A SINGLE BSC WITH ERROR PROBABILITY

$$\frac{1}{2} (1 - (1 - 2\gamma)^n)$$

AND HENCE THAT  $\lim_{n \rightarrow \infty} I(x_0; x_n) = 0$  IF  $\gamma \neq 0, 1$ . NO ENCODING OR DECODING TAKES PLACE AT THE INTERMEDIATE TERMINALS  $x_1, \dots, x_{n-1}$ . THUS, THE CAPACITY OF CASCADE TENDS TO ZERO.

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix}^T \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} (1-\gamma)x_1 + \gamma x_2 \\ \gamma x_1 + (1-\gamma)x_2 \end{bmatrix}$$

$$\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} (1-\gamma)x_1 + \gamma x_2 \\ \gamma x_1 + (1-\gamma)x_2 \end{bmatrix} = \begin{bmatrix} (1-\gamma)^2 x_1 + (1-\gamma)\gamma x_2 + \gamma^2 x_1 + \gamma(1-\gamma)x_2 \\ \gamma(1-\gamma)x_1 + (1-\gamma)^2 x_2 + \gamma^2 x_1 + \gamma(1-\gamma)x_2 \end{bmatrix}$$

$$= \begin{bmatrix} [(1-\gamma)^2 + \gamma^2] x_1 + 2(1-\gamma)\gamma x_2 \\ 2(1-\gamma)\gamma x_1 + [(1-\gamma)^2 + \gamma^2] x_2 \end{bmatrix}$$

$$C = 1 - H(\gamma) = H(2) - H(2|x) = 1 - H(\gamma)$$

$$H(2|x) = \sum_x \gamma(x) \cdot H(2|x=x) = \frac{1}{2} H(\gamma) + \frac{1}{2} H(\gamma) = H(\gamma)$$

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$$\begin{bmatrix} \gamma_1^{(2)} \\ \gamma_2^{(2)} \end{bmatrix} = \begin{bmatrix} [(1-\gamma)^2 + \gamma^2]x_1 + 2(1-\gamma)\gamma x_2 \\ 2(1-\gamma)\gamma x_1 + [(1-\gamma)^2 + \gamma^2]x_2 \end{bmatrix}$$

$$I(x^{(1)}; \gamma^{(2)}) = H(\gamma^{(2)}) - H(\gamma^{(2)}|X) = \log 2 - H(\gamma^{(2)}|X)$$

$$H(\gamma^{(2)}|X) = \sum_x p(x) H(\gamma^{(2)}|x) = \frac{1}{2} [(1-\gamma)^2 + \gamma^2] \log \frac{1}{(1-\gamma)^2 + \gamma^2} +$$

$$+ \frac{1}{2} 2(1-\gamma)\gamma \log \frac{1}{2(1-\gamma)\gamma} =$$

$$= \frac{1}{2} \log \frac{1}{(1-\gamma)^2 + \gamma^2} = \frac{1 - 2\gamma + \gamma^2 + \gamma^2}{2(1-\gamma)\gamma} = \frac{1 - 2\gamma + 2\gamma^2}{2(1-\gamma)\gamma} =$$

$$= \frac{1}{2} \log \frac{1}{(1-\gamma)^2 + \gamma^2} - 2\gamma \log \frac{1}{(1-\gamma)^2 + \gamma^2} + 2\gamma^2 \log \frac{1}{(1-\gamma)^2 + \gamma^2} +$$

$$\gamma \log \frac{1}{2(1-\gamma)\gamma} - \gamma^2 \log \frac{1}{2(1-\gamma)\gamma}$$

$$= \frac{1}{2} \log \frac{1}{(1-\gamma)^2 + \gamma^2} + \gamma \log \frac{(1-\gamma)^2 + \gamma^2}{2(1-\gamma)\gamma} + \gamma^2 \log \frac{2(1-\gamma)\gamma}{(1-\gamma)^2 + \gamma^2}$$

$$\frac{1}{2} (1 - (1-2\gamma)^2) = \frac{1}{2} (1 - 1 + 4\gamma - 4\gamma^2) = \frac{2}{2} (\gamma - \gamma^2)$$

$$= 2\gamma(1-\gamma)$$

$$P_e = \frac{1}{2} \sum_i \lambda(i) = \frac{1}{2} [Pr(g(\gamma^{(2)}) = X_2 | X = X_1) + Pr(g(\gamma^{(2)}) = X_1 | X = X_2)] = \frac{1}{2} [2(1-\gamma)\gamma + 2(1-\gamma)\gamma] = 2(1-\gamma)\gamma$$

$$\begin{bmatrix} \gamma_1^{(2)} \\ \gamma_2^{(2)} \end{bmatrix} = \begin{bmatrix} \sim & \gamma_{12} \\ \gamma_{21} & \sim \end{bmatrix} \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$\frac{1}{2} (1 - (1-2\gamma)^2) =$$

$$\frac{1}{2} (1 - 1 + 4\gamma - 4\gamma^2) =$$

$$= \frac{1}{2} \cdot 4(\gamma - \gamma^2) =$$

$$= 2\gamma(1-\gamma)$$

$$\begin{bmatrix} (1-\gamma) & \gamma \\ \gamma & (1-\gamma) \end{bmatrix} \begin{bmatrix} [(1-\gamma)^2 + \gamma^2]x_1 + 2(1-\gamma)\gamma x_2 \\ 2(1-\gamma)\gamma x_1 + [(1-\gamma)^2 + \gamma^2]x_2 \end{bmatrix}$$

$$\gamma_{12}^{(2)} = 2(1-\gamma)^2\gamma + [(1-\gamma)^2 + \gamma^2]\gamma = 3(1-\gamma)^2\gamma + \cancel{\gamma^3}$$

$$\frac{1}{2}(1 - (1-2\gamma)^3) = \frac{1}{2}(1 - (1 - 6\gamma + 12\gamma^2 - 8\gamma^3))$$

$$= \frac{1}{2}(1 - 1 + 6\gamma - 12\gamma^2 + 8\gamma^3) = \frac{6\gamma - 12\gamma^2 + 8\gamma^3}{2} = (3 - 6\gamma + 4\gamma^2)\gamma$$

$$\textcircled{*} = 3(1 - 2\gamma + \gamma^2)\gamma + \gamma^3 = 3\gamma - 6\gamma^2 + 3\gamma^3 + \gamma^3 =$$

$$= 3\gamma - 6\gamma^2 + 4\gamma^3 = (3 - 6\gamma + 4\gamma^2)\gamma$$

$$\gamma_{11}^{(3)} = (1-\gamma)^3 + \gamma^2(1-\gamma) + 2(1-\gamma)\gamma^2 = (1-\gamma)^3 + 3\gamma^2(1-\gamma)$$

$$= (1-\gamma)[(1-\gamma)^2 + 3\gamma^2] = (1-\gamma)[1 - 2\gamma + \gamma^2 + 3\gamma^2] =$$

$$= (1-\gamma)[1 - 2\gamma + 4\gamma^2] = \cancel{1 - 2\gamma + 4\gamma^2} - \gamma + 2\gamma^2 - 4\gamma^3$$

$$= 1 - 3\gamma + \frac{1}{6}\gamma^2 - \frac{1}{4}\gamma^3 = \cancel{\dots}$$

$$\gamma_{12} = 1 - \gamma_{11} = 1 - (1 - 2\gamma)^3$$

$$\Pi^{(2)} = \begin{bmatrix} (1-\gamma)^2 + \gamma^2 & 2(1-\gamma)\gamma \\ 2(1-\gamma)\gamma & (1-\gamma)^2 + \gamma^2 \end{bmatrix}$$

$$1 - \frac{1}{2}(1 - (1-2\gamma)^2) =$$

$$= 1 - \frac{1}{2} + \frac{1}{2}(1-2\gamma)^2 =$$

$$= \frac{1}{2} + \frac{1}{2}(1-2\gamma)^2 = \frac{1}{2}(1 + (1-2\gamma)^2)$$

$$\gamma_{11}^{(2)} = (1-\gamma)^2 + \gamma^2 = 1 - 2\gamma + \gamma^2 + \gamma^2 = (1 - 2\gamma + 2\gamma^2) = \frac{1}{2}(1 + (1-2\gamma)^2)$$

$$\frac{1}{2}[1 + (1-2\gamma)^2] = \frac{1}{2}[1 + 1 - 4\gamma + 4\gamma^2] \frac{1}{2} = 1 - 2\gamma + 2\gamma^2$$

$$\begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix}$$

$$\begin{bmatrix} (1-\gamma)^2 + \gamma^2 & 2(1-\gamma)\gamma \\ 2(1-\gamma)\gamma & (1-\gamma)^2 + \gamma^2 \end{bmatrix} \begin{bmatrix} (1-\gamma)^2 + \gamma^2 & 2(1-\gamma)\gamma \\ 2(1-\gamma)\gamma & (1-\gamma)^2 + \gamma^2 \end{bmatrix}$$

$$\begin{bmatrix} 1-\gamma & \gamma \\ \gamma & 1-\gamma \end{bmatrix} \begin{bmatrix} (1-\gamma)^2 + \gamma^2 & 2(1-\gamma)\gamma \\ 2(1-\gamma)\gamma & (1-\gamma)^2 + \gamma^2 \end{bmatrix} =$$

$$= \begin{bmatrix} (1-\gamma)^3 + \gamma^2(1-\gamma) + 2\gamma^2(1-\gamma) & 2(1-\gamma)^2\gamma + \gamma(1-\gamma)^2 + \gamma^3 \\ 2(1-\gamma)^2\gamma + \gamma(1-\gamma)^2 + \gamma^3 & (1-\gamma)^3 + \gamma^2(1-\gamma) + 2\gamma^2(1-\gamma) \end{bmatrix}$$

$$(1-\gamma-\gamma)^2 = (1-\gamma)^2 + 2\gamma(1-\gamma) + \gamma^2$$

$$(1-\gamma-\gamma)^3 = (1-\gamma)^3 + \binom{3}{1}(1-\gamma)\gamma^2 + \binom{3}{2}(1-\gamma)^2\gamma - \gamma^3$$

$$= (1-\gamma)^3 - 3(1-\gamma)\gamma^2 + 3(1-\gamma)^2\gamma - \gamma^3$$

$$1 - (1-\gamma-\gamma)^3 = 1 - (1-\gamma)^3 + 3(1-\gamma)\gamma^2 - 3(1-\gamma)^2\gamma + \gamma^3$$

$$= 3(1-\gamma)\gamma^2 - 3(1-\gamma)^2\gamma + 2\gamma^3 =$$

$$= 3(1-\gamma)\gamma^2 - 3(1-\gamma)^2\gamma + 2\gamma^3 =$$

$$\textcircled{+} = 3\gamma^2 - 3\gamma^2 - 5\gamma(1-2\gamma+\gamma^2) = 3\gamma^2 - 3\gamma^2 - 5\gamma + 10\gamma^2 - 5\gamma^3$$

CONTINUE FROM N. 62. 74  $P_e^{(n)} = \frac{1}{2^{nr}} \sum_{i=1}^n \binom{n}{i} 2^{-i}$

$$P_e^{(4)} = \frac{1}{2^{4r}} \left( \left(\frac{3}{2}\right)^4 - 1 \right)$$

$$\left(\frac{3}{2}\right)^4 = 1 \Rightarrow \ln \left( \frac{3}{2} \right) = 0$$

$$P_{min} = 0.6$$

$$\lim_{n \rightarrow \infty} \frac{1}{2^{nr}} \left( \left(\frac{3}{2}\right)^n - 1 \right) = 0 \Rightarrow P_e = 0 \text{ FOR } r \in [0.6, 1]$$

14.09.13

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ΣΥΝΤΗΡΙΑ ΝΑ ΣΑΡΑΧΑΝΑ 7-Ε ΝΑ ΜΟΣΤΟ ΡΕΣΕΝΤΕ Ε ΟΕΝΑ :

$$\lambda_i = P_r \{j(k^y) \neq i | x^y = x^y(i)\} = \sum_{j^y} P(x^y | x^y = x^y(i)) \cdot I(j(x^y) \neq i)$$

$P(x^y | x^y = x^y(i))$  ~~ΕΙΝΑΙ~~ ΕΙΝΑΙ Ε ΜΠΟΡΕΙ ΝΑ ΣΕ ΝΑ ΠΕ  
- ΠΡΟΕΤΗΘΗΚΕ ΝΑ ΕΙΝΑΙ ΕΙΝΑΙ ΜΕΣΟΝ :

$i=1$

$$\lambda_i = \binom{4}{1} \cdot P(x^y | x^y(i=1)) = \binom{4}{1} \frac{1}{2}$$

ΣΑΜΟ ΕΙΝΑΙ  
ΕΙΝΑΙ ΜΑ  
ΝΑ ΣΕ ΝΑ

$i=2$

$$\lambda_i = \binom{4}{2} \left(\frac{1}{2^2}\right)$$

ΝΕΡΟΝΤΙΝΟΣΤ ΔΥΕ  
ΕΙΝΑΙ ΜΑ ΔΙΔΑΤ  
ΕΙΝΑΙ

ΜΑ ΜΑ ΣΕ ΝΑ ΕΙΝΑΙ ΕΙΝΑΙ

ΑΝΑ ΜΕ ΜΟΝΑ 2 ΕΙΝΑΙ ΜΑ ΔΙΔΑΤ ΕΙΝΑΙ  
ΜΟΡΕ ΕΙΝΑΙ ΜΑ ΔΙΔΑΤ ΕΙΝΑΙ ΜΑ 2<sup>Ε</sup> ΜΑ ΣΕ  
ΕΙΝΑΙ ΜΑ ΕΙΝΑΙ :

$$\lambda_i = \binom{4}{2} \left(\frac{1}{2} + \frac{1}{2^2}\right)$$

- ΝΟ ΓΕΝΕΡΑΙΟΝ ΣΕ ΝΑ

$i=k$

$$\lambda_k = \binom{4}{k} \left(\frac{1}{2} + \frac{1}{2^2} + \dots + \frac{1}{2^k}\right) = \binom{4}{k} \frac{1}{2} \left(1 + \frac{1}{2} + \dots + \frac{1}{2^{k-1}}\right)$$

$$S = \frac{1 - \frac{1}{2^k}}{1 - \frac{1}{2}} = 2 \left(1 - \frac{1}{2^k}\right) ; \lambda_k = \binom{4}{k} \left(1 - \frac{1}{2^k}\right)$$

$$P_e^{(4)} = \frac{1}{2^{4R}} \sum_{i=1}^4 \binom{4}{i} \left(1 - \frac{1}{2^i}\right) = \frac{1}{2^{4R}} \left[ \sum_{i=1}^4 \binom{4}{i} - \sum_{i=1}^4 \binom{4}{i} \frac{1}{2^i} \right]$$

$$= \frac{1}{2^{4R}} \left[ 2^4 - \binom{3}{2} \right] = \frac{2^4}{2^{4R}} - \frac{3^4}{2^{4R+4}} = \frac{2^{24} - 3^4}{2^{4R+4}}$$

$$= \frac{1}{2^{4R-4}} - \frac{3^4}{2^{4R+4}}$$

$$\lim_{n \rightarrow \infty} \frac{2^{24} - 3^4}{2^{4R+4}} = 0 \Rightarrow R = 1.000 \cdot 1 = 1 + \epsilon$$

$$n \cdot R \leq 1 + P_e \cdot nR + nC$$

$$R \leq \frac{1 + P_e \cdot R + C}{n}$$

$$n \rightarrow \infty \quad R \leq C$$

EXERCISE 1 SOLUTION

$x \in [0, 1]$

$$\begin{bmatrix} Y(t_1) \\ Y(t_2) \end{bmatrix} = \begin{bmatrix} 1 & 1/2 \\ 0 & 1/2 \end{bmatrix} \begin{bmatrix} X(t_1) \\ X(t_2) \end{bmatrix} = P(X) = \left\{ \begin{matrix} 1 \\ 1/2 \end{matrix} \right\}$$

$$H(\tau) = - \left[ Y(\tau=t_1) \cdot \log Y(\tau=t_1) + Y(\tau=t_2) \cdot \log Y(\tau=t_2) \right]$$

$$H(\tau|X) = \sum_x P(x) \cdot H(\tau|X=x)$$

$$Y(\tau=t_1) = Y(x_1) + \frac{1}{2} Y(x_2) = \frac{1}{2} + \frac{1}{4} = \frac{3}{4}$$

$$Y(\tau=t_2) = \frac{1}{2} \cdot Y(x_2) = \frac{1}{4}$$

$$H(\tau) = - \left[ \left( \frac{3}{4} \log \frac{3}{4} + \frac{1}{4} \log \frac{1}{4} \right) \right] = - \left[ \frac{3}{4} \log 4 - \frac{3}{4} \log 3 + \frac{1}{2} \right] = 2 - \frac{3}{4} \log 3$$

$$H(\tau|X) = \frac{1}{2} \cdot \left[ 1 \cdot \log 1 \right] + \frac{1}{2} \cdot \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right] = \frac{1}{2} \left[ \frac{1}{2} + \frac{1}{2} \right] = 1/2$$

$$I(X; \tau) = H(\tau) - H(\tau|X) = 2 - \frac{3}{4} \log 3 - \frac{1}{2} = \frac{3}{2} - \frac{3}{4} \log 3$$

$$= 0.31128 \leq 0.322$$

RATE                      CAPACITY

$R = \frac{2^R}{n}$	PRESENTO VO PROBLEMA 8 PODN DEVA ZA $Y(x_2) = \frac{2}{5}$ , $Y(x_1) = \frac{3}{5}$ SE POSTAVI- CAPACITY NA KANALU. SEGA $Y(A_1) = Y(A_2)$
UMA $= \frac{1}{2}$	IT ZATOA NE SE POSTAVI VAHACITET NA KANALU. !!! MMV

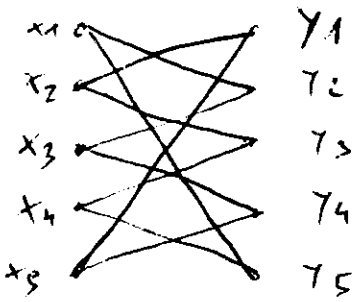
FROM THE PROOF OF THE CHANNEL CODING THEOREM, IT FOLLOWS THAT USING A RANDOM CODE WITH CODEWORDS GENERATED ACCORDING TO PROBABILITY  $q(x)$  WE CAN SEND INFORMATION AT RATE  $I(X; \tau)$  CORRESPONDING TO THAT  $q(x)$  WITH AN ARBITRARY PROBABILITY OF ERROR.

JAS ZA PRAVNU ZADACUVA VANO DA NE ZA ZNAMY CHANNEL CODING THEOREMA.



CONTINUE FROM (80a)

$$X^4 = \{14, 20, 31, 42, 03\}$$



$$(x_2 x_3) \rightarrow Z_4 = (Y_1 \vee Y_2, Y_1 \vee Y_3) = Y_1 Y_1, Y_1 Y_3, Y_2 Y_1, Y_2 Y_3$$

$$(x_4 x_5) \rightarrow Z_4 = (Y_2 \vee Y_3, Y_1 \vee Y_4) = Y_2 Y_1, Y_2 Y_4, Y_3 Y_1, Y_3 Y_4$$

POKOLJU BI SI MAJOL IDEALNITE KODIRAN-  
CII NA  $x_i x_j$  TAQA ŠTO NE SE DAVI  
GRESKA :

$$H(Z^4 | X^4) = \sum P(x_i x_j) H(Z^4 | x_i x_j) = 5 \cdot \frac{1}{5} \cdot \frac{1}{4} \cdot \log 4 = \frac{1}{2}$$

$$C = \max_{Y^4} I(X^4, Z^4) = H(Z^4) - H(Z^4 | X^4) = \log 5 - \frac{1}{2} = 1.82$$

$$(x_3 x_5) \rightarrow (Y_2 \vee Y_4, Y_1 \vee Y_4) = Y_2 Y_1, Y_2 Y_4, Y_4 Y_1, Y_4 Y_4$$

$$(x_1 x_3) \rightarrow (Y_2 \vee Y_5, Y_2 \vee Y_4) = Y_2 Y_2, Y_2 Y_4, Y_5 Y_2, Y_5 Y_4$$

$$(x_2 x_5) \rightarrow (Y_1 \vee Y_3, Y_1 \vee Y_4) = Y_1 Y_1, Y_1 Y_4, Y_3 Y_1, Y_3 Y_4$$

$$(x_4 x_2) \rightarrow (Y_3 \vee Y_5, Y_1 \vee Y_3) = Y_3 Y_1, Y_3 Y_3, Y_5 Y_1, Y_5 Y_3$$

$$(x_1 x_4) \rightarrow (Y_2 \vee Y_5, Y_3 \vee Y_5) = Y_2 Y_3, Y_2 Y_5, Y_5 Y_3, Y_5 Y_5$$

$$(x_2 x_4) \rightarrow (Y_1 \vee Y_3, Y_3 \vee Y_5) = Y_1 Y_3, Y_1 Y_5, Y_3 Y_3, Y_3 Y_5$$

$$(x_5 x_3) \rightarrow (Y_1 \vee Y_4, Y_2 \vee Y_4) = Y_1 Y_2, Y_1 Y_4, Y_4 Y_2, Y_4 Y_4$$

$$(x_5 x_2) \rightarrow (Y_1 \vee Y_4, Y_1 \vee Y_3) = Y_1 Y_1, Y_1 Y_3, Y_4 Y_1, Y_4 Y_3$$

$$(x_4 x_2) \rightarrow (Y_2 \vee Y_5, Y_1 \vee Y_3) = Y_3 Y_1, Y_3 Y_3, Y_5 Y_1, Y_5 Y_3$$

$$(x_4 x_1) \rightarrow (Y_3 \vee Y_5, Y_2 \vee Y_5) = Y_3 Y_2, Y_3 Y_5, Y_5 Y_2, Y_5 Y_5$$

$$(x_3 x_1) \rightarrow (Y_2 \vee Y_4, Y_2 \vee Y_5) = Y_2 Y_2, Y_2 Y_5, Y_4 Y_2, Y_4 Y_5$$

$$= \frac{4!}{(4-k)! k!} = \frac{24}{1 \cdot 1} = 24$$

$$P = \frac{4!}{(4-k)!} = \frac{6}{1} = 6$$

12	13	23
21	31	32

- $(x_2 x_5) \rightarrow (Y_1 \vee Y_3, Y_1 \vee Y_4) = Y_1 Y_1, Y_1 Y_4, Y_3 Y_1, Y_3 Y_4$
- $(x_2 x_1) \rightarrow (Y_2 \vee Y_4, Y_2 \vee Y_5) = Y_2 Y_2, Y_2 Y_5, Y_4 Y_2, Y_4 Y_5$
- $(x_1 x_2) \rightarrow (Y_1 \vee Y_5, Y_1 \vee Y_3) = Y_1 Y_1, Y_1 Y_3, Y_4 Y_1, Y_4 Y_3$
- $(x_5 x_3) \rightarrow (Y_1 \vee Y_4, Y_2 \vee Y_4) = Y_1 Y_2, Y_1 Y_4, Y_4 Y_2, Y_4 Y_4$
- $(x_1 x_4) \rightarrow (Y_2 \vee Y_5, Y_3 \vee Y_5) = Y_2 Y_3, Y_2 Y_5, Y_5 Y_3, Y_5 Y_5$

$$X^4 = \{11, 20, 31, 42, 03\}$$

ČAMPŠTOŽAC DOPOV DO OVE KODI ZADOKVI. ① SI POTROV  
 ZA DA NEVAM 2X "0" TE "1" NA PAVIOT DIT DO KODIOT  
 ZADOK. SEVNE VAKVIDO KOD NE DEZPREJEN ZATO ITO VO  
 KODITE ZADOKVI.

$$(x_3 x_1) \rightarrow (z_2 z_4, z_2 z_5) = (z_2 z_2, z_2 z_5, z_4 z_2, z_4 z_5)$$

$$(x_1 x_4) \rightarrow (z_2 z_5, z_3 z_5) = (z_2 z_3, z_2 z_5, z_5 z_3, z_5 z_5)$$

IMA PO EDRA MOZA KOMBINACIJA VDA MOZE DA  
 VODI KON GREŠKA 7-0

$$H(z^4 | X^4) = ? \quad H(z^4) = \sum_{x^4} p(x^4) H(z^4 | x^4 = x^4)$$

ČIENOVITE ZA:  $x^4 = (x_2 x_5, x_4 x_2, x_5 x_3)$  VODI KON  
 UNIKATNI  $z^4$  TE. NE SE ŽIVVA GREŠKA.

$$\hat{W} = (0, 1, 2, 3, 4) \quad z^4(w=0) = (z_1 z_1, z_1 z_4, z_1 z_1, z_1 z_4)$$

$$z^4 = (z_1^4, z_2^4, z_3^4, z_4^4, z_5^4)$$

DLO VDA KOMBINACIJA ①

OVE IZČER I VODI ŽRACI ISKLUVIVO POPREDEK DOK  
 DIL ISTATEN  $(x_2 x_5) = x_1^4 = x^4(w=0)$

$$\text{ISTOTO VARI, ZA: } x^4(w=2) = (x_4 x_2)$$

$$\hat{W}=2 = g(z^4) \quad z^4(w=2) = (z_3 z_1, z_3 z_3, z_5 z_1, z_5 z_3)$$

SIO VODI OVE KOMBINTE DO KODI ŽVITCI DA SE ŽAVI-  
 NA ŽELE KTE SE DEKODIJA  $\hat{W}=2$

$$H(z^4 | x^4) = \sum_{x^4 = x_1 x_4, x_2 x_5} p(z^4) H(z^4 | x^4 = x^4) = \frac{1}{3} H(z^4 | x^4 = x_1 x_4) +$$

MMV

$$+ \frac{1}{3} H(z^4 | x^4 = x_2 x_5) = ②$$

AVO KODI  $(x_2 x_5): g(z^4) = 1$  Ili  $g(z^4) = 4$   
 AVO KODI  $(x_1 x_4): g(z^4) = 4$  Ili  $g(z^4) = 1$

$$\textcircled{2} = \frac{1}{3} \left[ \frac{3}{4} \log \frac{4}{3} + \frac{1}{4} \log \frac{4}{4} \right] + \frac{1}{3} \left[ \frac{3}{4} \log \frac{4}{3} + \frac{1}{4} \log \frac{4}{4} \right] =$$

$$= \frac{2}{3} \left[ \frac{3}{4} \log \frac{4}{3} + \frac{1}{4} \log 2 \right] = \frac{2}{3} \left[ \frac{3}{4} \cdot 2 - \frac{3}{4} \log 3 + \frac{1}{2} \right] =$$

$$= \frac{2}{3} \left[ 2 - \frac{3}{4} \log 3 \right] = 0.32, \quad C_2 = H(z^4) - H(z^4 | x^4) = \log 5 - 0.32 = 1.97742; C_1 = \frac{C_2}{2} = 0.98871$$

CONTINUE FROM 87a

CHANNEL WITH DEPENDANCE BETWEEN LETTERS.

00 → 01    01 → 10    10 → 11    11 → 00

$$(a) I(x_1 x_2; z_1 z_2) = H(z_1 z_2) - \underbrace{H(z_1 z_2 | x_1 x_2)}_{\emptyset}$$

$$P(x_1 x_2) = \{ p_1, p_2, p_3, p_4 \}$$

$$H(y_1 y_2 | x_1 x_2) = \sum_{x_1 x_2} P(x_1 x_2) \underbrace{H(z_1 z_2 | x_1 x_2 = x_1 x_2)}_{\emptyset} = \emptyset$$

$$H(z_1 z_2) = ? \quad P(z_1 z_2 = \gamma_1 \gamma_2) = \underbrace{P(x_1 x_2)}_1 - \underbrace{P(z_1 z_2 = \gamma_1 \gamma_2 | x_1 x_2)}_{\emptyset}$$

$$P(\gamma_1 \gamma_2) = P(x_1 x_2) = \{ p_1, p_2, p_3, p_4 \}$$

$$H(z_1 z_2) = H(x_1 x_2) = H(p_1, p_2, p_3, p_4)$$

e.g. IF  $p_1 = p_2 = p_3 = p_4 = \frac{1}{4}$

$$H(z_1 z_2) = 4 \cdot \frac{1}{4} \log_2 4 = 4 \cdot \frac{1}{2} = 2$$

$$(b) C = \max_{P(x_1 x_2)} I(x_1 x_2; z_1 z_2) =$$

$$\max_{\substack{P(x_1 x_2) \\ \text{uniform}}} [H(z_1 z_2)] = \left(\frac{1}{4} \log_2 4\right) 4 = \log_2 4 = 2 \text{ bits}$$

$$(c) I(x_1; z_1) = \emptyset$$

$$P(x_1 x_2) = \left\{ \frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right\}$$

$x_1 \backslash x_2$	0	1	$P(x_1 x_2)$
0	1/4	1/4	1/2
1	1/4	1/4	1/2
$P(x_2)$	1/2	1/2	

$$P(x_1) = \sum_{x_2} P(x_1 x_2 \neq x_2)$$

$$P(\gamma_1 \gamma_2) = \left\{ \frac{1}{4}, \frac{1}{4}, \frac{1}{4}, \frac{1}{4} \right\}$$

$$\gamma_1 \gamma_2 = \{ 01, 10, 11, 00 \}$$

$$P(\gamma_1) = \left\{ \frac{1}{2}, \frac{1}{2} \right\} \quad P(\gamma_2) = \left\{ \frac{1}{2}, \frac{1}{2} \right\}$$

$$I(x_1; z_1) = H(z_1) - \underbrace{H(z_1 | x_1)}_{\emptyset} = 2 \cdot \frac{1}{2} \log_2 2 - \emptyset = H(z_1 | x_1)$$

$$= 1 - H(z_1 | x_1) ; \quad H(z_1 | x_1) = ?$$

$$H(z_1 | x_1) = \sum P(x_1) \cdot H(z_1 | x_1 = x_1) = \frac{1}{2} H(z_1 | x_1 = 0) +$$

$$+ \frac{1}{2} H(z_1 | x_1 = 1) = -\frac{1}{2} \left[ P(z_1 = 0 | x_1 = 0) \cdot \log_2 P(z_1 = 0 | x_1 = 0) \right.$$

$$+ P(z_1 = 1 | x_1 = 0) \cdot \log_2 P(z_1 = 1 | x_1 = 0) \left. \right] - \frac{1}{2} \left[ P(z_1 = 0 | x_1 = 1) \cdot \log_2 P(z_1 = 0 | x_1 = 1) \right.$$

$$H(\tau_1 | x_1) = + \frac{1}{2} \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right] + \frac{1}{2} \left[ \frac{1}{2} \log 2 + \frac{1}{2} \log 2 \right] =$$

$$= \frac{1}{2} \left[ \frac{1}{2} + \frac{1}{2} \right] = 1$$

$$I(x_1; \tau_1) = H(\tau_1) - H(\tau_1 | x_1) = 1 - 1 = 0$$

$$\max I(x_1, x_2; \tau_1, \tau_2) = 2$$

CONTINUE FROM 9.19

$$(a) H(X) = \left( \frac{1}{2} \log 2 \right) \cdot 2 = 1 \quad H(\tau) = \left( \frac{1}{2} \log 2 \right) \cdot 2 = 1$$

$$H(X, \tau) = -2(0.45 \log 0.45) - 2(0.05 \log 0.05) = 1.469$$

$$I(X; \tau) = H(X) - H(\tau | X) \quad H(\tau | X) = ?$$

X \ \tau	0	1
0	0.9	0.1
1	0.1	0.9
$\tau   X$		

$$P(\tau | X) = \frac{P(X, \tau)}{P(X)}$$

$$H(\tau | X) = -2(0.9 \log 0.9) - 2(0.1 \log 0.1)$$

$$= 0.94 - 0.73799 \quad (7)$$

$$I(X; \tau) = 1 - 0.94 = 0.06 \quad ?$$

$$H(X, \tau) = H(X) + H(\tau | X) = 1 + 0.937 \quad ?$$

$$H(\tau | X) = \sum_{x, \tau} P(x, \tau) \log \frac{1}{P(\tau | X)}$$

$$= (0.45 \log 0.9) \cdot 2 + 2(0.05 \log 0.1) = 0.469$$

$$H(X, \tau) = H(X) + H(\tau | X) = 1 + 0.469 = 1.469$$

$$I(X; \tau) = 1 - 0.469 = 0.531$$

(b)  $X \sim \text{Bernoulli}(\frac{1}{2})$

$$\left| \frac{1}{2} - P(X) \right| \leq \frac{1}{2} \Rightarrow P(X) \leq 2^{-\frac{1}{2}(\frac{1}{2} - \epsilon)}$$

$$\left| 1 - H(X) - \frac{1}{n} \log P(X^n) \right| \leq \epsilon$$

$$H(X) = \left( \frac{1}{2} \log 2 \right) \cdot 2 = 1 \quad H - \epsilon \leq -\frac{1}{n} \log P(X^n) \leq H + \epsilon$$

$$1 - 0.2 \leq \frac{1}{n} \log P(X^n) \leq 1.2 \quad 0.8 \leq \frac{1}{n} \log P(X^n) \leq 1.2$$

$$0.8 \leq \frac{1}{4} \log p(x_1^4) \leq 1.2$$

$$p(x_1^4) = p(x_1) p(x_2) \dots p(x_4)$$

$$\frac{1}{4} \log p(x_1^4) = \frac{1}{4} \sum_{i=1}^4 \log p(x_i)$$

$\left. \begin{aligned} k=1 \\ \binom{4}{k} p^k \cdot (1-p)^{4-k} \end{aligned} \right\}$

VEROJATNOS DA SE DANI SEKVENCA OD 4<sup>ta</sup> MITA VADE 1 BIT E 1<sup>ta</sup> 1-p-1 SE 4<sup>ta</sup> 2<sup>ta</sup>

$$P(A_{\epsilon}^4) = \sum_{k=1}^2 \binom{4}{k} p^k (1-p)^{4-k} \geq 1 - \epsilon = 1 - 0.2 = 0.8$$

$$p = \frac{1}{2} \Rightarrow \sum_{k=1}^2 \binom{4}{k} \frac{1}{2^k} \frac{1}{2^{4-k}} = \frac{1}{2^4} \sum_{k=1}^2 \binom{4}{k}$$

EXAMPLE: n=10

$$\frac{1}{2^{10}} = 0.00098$$

$$-\frac{1}{4} \log \frac{1}{2^4} = + \frac{1}{4} \log 2^4 = + \frac{1}{4} \cdot 4 = 1$$

$p(x_1^4) = \frac{1}{2^4}$  } ZA NILO VOJA SEKVENCA  
 $x_1, x_2, \dots, x_n$   
 BATA CTO  $p(x_i=0) = p(x_i=1) = \frac{1}{2}$

ZAVOA ZA NILO VOJA SEKVENCA  $x_1^4$

$$0.8 \leq -\frac{1}{4} \log p(x_1^4) = -\frac{1}{4} \cdot (-4) = 1 \leq 1.2 \quad \forall x_1, x_2, \dots$$

ZNASI SITE 2<sup>n</sup> MOGI SEKVENCI SE TRAZNI !!!

$$p(z_1^4) = p(z_1) \cdot p(z_2) \dots p(z_4)$$

$$p(z_i) = \begin{cases} 1/2 & z_i=0 \\ 1/2 & z_i=1 \end{cases} \quad 0.8 \leq -\frac{1}{4} \log p(z_1^4) \leq 1.2$$

$$P(z_1^4 = z_1, z_2, \dots, z_4) = \frac{1}{2^4} \quad 0.8 \leq -\frac{1}{4} \cdot (-4) \leq 1.2$$

$0.8 \leq 1 \leq 1.2$  } ~~ALL~~ All 2<sup>n</sup> z<sub>1</sub><sup>n</sup> SEQUENCES  
 ALL MEMBERS OF THE TUPLE SET.

**JOINT AEP**

1.)  $P_r((x^n, z^n) \in A_\epsilon^n) \rightarrow 1$  as  $n \rightarrow \infty$

2.)  $|A_\epsilon^n| \leq 2^{n(H(x,z) + \epsilon)}$

3.)  $(\tilde{x}^n, \tilde{z}^n) \sim p(x^n) \cdot p(z^n)$

$P_r[(\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n] \leq 2^{-n(I(x,z) - 3\epsilon)}$

$P_r[(\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n] \geq (1-\epsilon) 2^{-n(H(x,z) + \epsilon)}$

$1 = \sum_{(x^n, z^n)} p(x^n, z^n) \geq \sum_{(x^n, z^n) \in A_\epsilon^n} p(x^n, z^n) \geq |A_\epsilon^n| \cdot 2^{-n(H(x,z) + \epsilon)}$

$|A_\epsilon^n| \leq 2^{n(H(x,z) + \epsilon)}$

$(\tilde{x}^n, \tilde{z}^n) \cdot P_r((\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n) = \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n} p(\tilde{x}^n) p(\tilde{z}^n)$

$\leq |A_\epsilon^n| \cdot 2^{-n(H(x,z) - \epsilon)} \leq 2^{n(H(x,z) + \epsilon)} \cdot 2^{-n(H(x,z) - \epsilon)}$

$= 2^{n(H(x,z) + \epsilon - H(x,z) + \epsilon)} = 2^{n(2\epsilon)} \Rightarrow P_r[(\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n] \leq 2^{-n(I - 3\epsilon)}$

$(1-\epsilon) \leq \sum_{(x^n, z^n) \in A_\epsilon^n} p(x^n, z^n) \leq |A_\epsilon^n| \cdot 2^{-n(H(x,z) - \epsilon)}$

$|A_\epsilon^n| \geq (1-\epsilon) 2^{n(H(x,z) - \epsilon)}$

$P_r((\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n) = \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_\epsilon^n} p(\tilde{x}^n) \cdot p(\tilde{z}^n) \geq |A_\epsilon^n| \cdot 2^{-n(H(x,z) + \epsilon)}$

$\geq (1-\epsilon) 2^{n(H(x,z) - \epsilon) - n(H(x,z) + \epsilon)} = (1-\epsilon) 2^{-n(I + 3\epsilon)}$

$$(1-\epsilon)^2 \leq \Pr[(\tilde{x}^n, \tilde{\tau}^n) \in A_\epsilon] \leq 2^{-n(I(x, \tau) - 2\epsilon)}$$

(c)  $p(x^n, \tau^n) = \sum_{z=1}^n p(x_i, \tau_i) = (0.45)^{n-k} \cdot (0.05)^k = \left(\frac{1}{2}\right)^n (1-p)^{n-k} p^k$

$k$  - NUMBER OF PLACES IN WHICH  $x^n$  DIFFERS FROM  $\tau^n$ .  
 $z = \tau \oplus x$

$$p(x^n, \tau^n) = p(x^n) \cdot p(\tau^n | x^n) = p(x^n) \cdot p(z^n | x^n) = p(x^n) p(z^n) = \left(\frac{1}{2}\right)^n (1-p)^{n-k} p^k$$

SOFT OR HARD: NOT STO  $z=1$  TAMU  $\tau \neq x$   $\tau = e$   
 HARD STO  $z=0$   $\tau = x$

$$z = x \oplus \tau$$

$$z = (x - \tau) \bmod 2$$

$$x = (\tau - z) \bmod 2$$

$$I(x, \tau) = ?$$

$$I(x, \tau) = H(x) - H(x | \tau) = H(x) - \sum_{z \in \mathcal{Z}} p(z) \cdot H(x | \tau, z)$$

$$= H(x) - \sum_{z \in \mathcal{Z}} p(z) H(x + z | x) = H(x) - H(z)$$

$$p(x + z | x) = p(z)$$

$$H(x, \tau) = H(x) + H(\tau | x) = H(x) + H(z)$$

x	z	$\tau$	$(x - \tau) \bmod 2$
0	0	0	0
0	1	1	1
1	0	1	0
1	1	0	1

$$2^{-n(H(x, \tau) + \epsilon)} \leq p(x^n, \tau^n) \leq 2^{-n(H(x, \tau) - \epsilon)}$$

$$p(x^n, \tau^n) = p(x^n) \cdot p(\tau^n) \leq 2^{-n(H(x) + \epsilon)} \leq 2^{-n(H(x, \tau) - \epsilon)}$$

$$2^{-n(H(z) + \epsilon)} \leq p(z^n) \leq 2^{-n(H(z) - \epsilon)}$$

$$2^{-n(H(x) + H(z) + 2\epsilon)} \leq p(x^n) \cdot p(z^n) \leq 2^{-n(H(x, \tau) - 2\epsilon)}$$

$$2^{-n(H(x, \tau) + 2\epsilon)} \leq p(x^n, \tau^n) \leq 2^{-n(H(x, \tau) - 2\epsilon)}$$

$$(d) \binom{4}{k} p^k (1-p)^{4-k} = \left|_{k=0} \right| = 1 \cdot 1 \cdot (1-p)^{25} = 0.071790$$

$$(1-p) = \sqrt[25]{0.071790} = 0.9$$

$$(p = 1 - 0.9 = 0.1)$$

$$p = P(Y=0|X=1) + P(Y=1|X=0)$$

$$Pr(Z=1) = p = 0.1 = P(Y=1|X=0) + P(Y=0|X=1) \quad \text{MMV}$$

$$-\frac{1}{4} \log_2 p(Z^4) = -\frac{1}{25} \log_2 \left( \frac{1}{2^{25}} \right) = 1$$

$$Pr(Z) = \{0.1, 0.9\}$$

$$p(Z=1) = 0.1$$

$$p(Z=0) = 0.9$$

NA RESTO-  
DVA STRANA  
GO DOVAJAV  
MATEMATIKI!!!

$$H(Z) = -[0.1 \log_2(0.1) + 0.9 \log_2(0.9)] = H(Z|X) = 0.469$$

NEZVEKOSTA ZA GREŠKA E EDNAVA NA NEZVEKOSTI  
H(Z|X) !!! MMV

$$2^{-n(H(Z)+\epsilon)} \leq p(Z) \leq 2^{-n(H(Z)-\epsilon)}$$

$$1 - \frac{1}{n} \log_2 p(Z) - H(Z) \leq \epsilon = 0.2$$

OVA E UPOCORO  
SAMO ZA:

$$|A_\epsilon^{(n)}| = \sum_{k=1}^4 \binom{25}{k} = \binom{25}{1} + \binom{25}{2} + \binom{25}{3} + \binom{25}{4} = 15275$$

(e)  $[X^4(Y)]$  ARE JOINTLY TYPICAL IF  
 $Z^4$  IS TYPICAL (SINCE  $Z^4$  IS ALWAYS TYPICAL)

$$Pr(Z^4 \in A_\epsilon^4) = \sum_{k=1}^4 \binom{4}{k} p^k (1-p)^k = 0.83022$$

CONTINUE FROM 116

**Problem 7.26** CONSIDER THE CHANNEL WITH  $X \in \{0,1,2,3\}$   
AND TRANSITION PROBABILITIES  $p(Z|X)$  GIVEN BY:

$$\begin{bmatrix} \frac{1}{2} & \frac{1}{2} & 0 & 0 \\ 0 & \frac{1}{2} & \frac{1}{2} & 0 \\ 0 & 0 & \frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & 0 & 0 & \frac{1}{2} \end{bmatrix}$$

(a) FIND THE CAPACITY OF THIS CHANNEL

(b) DEFINE THE RANDOM VARIABLE

$Z = g(Y)$  WHERE

$$g(Y) = \begin{cases} A & \text{IF } Y \in \{0,1\} \\ B & \text{IF } Y \in \{2,3\} \end{cases}$$



FOR THE TWO PMFS FOR  $X =$  COMPUTE  $I(X; Z)$ :

(i)  $f(x) = \begin{cases} 1/2 & \text{if } x \in \{1, 2\} \\ 0 & \text{if } x \in \{0, 3\} \end{cases}$

(ii)  $f(x) = \begin{cases} 0 & \text{if } x \in \{1, 2\} \\ 1/2 & \text{if } x \in \{0, 3\} \end{cases}$

(c) FIND THE CAPACITY OF THE CHANNEL BETWEEN  $X$  &  $Z$  SPECIFYING WHERE  $x \in \{0, 1, 2, 3\}$ ,  $z \in \{A, B\}$  AND THE TRANSITION PROBABILITIES  $P(Z|x)$  ARE GIVEN AS:

$$P(Z=z | X=x) = \sum_{g(z)=z} P(Z=g | X=x)$$

(d) FOR THE  $X$  DISTRIBUTION OF PART (i) OF (c), DOES  $X \rightarrow Z \rightarrow Y$  FORM MARKOV CHAIN?

(a)  $C = \log_2 4 - 1 = \log_2 2 = 1$

$I(X; Z) = H(Z) - H(Z|X)$        $H(Z) = \log_2 4 = 2$

$H(Z|X) = \sum_x P(X=x) H(Z|X=x) = \sum_x P(X=x) \cdot 1 = 1$

$H(Z|X=1) = H(Z|X=0) = 1$   
 $H(Z|X=1) = H(Z|X=0) = \frac{1}{2} \log_2 2 = 1$

$I(X; Z) = H(Z) - H(Z|X) = 2 - 1 = 1$

(b)  $Z = g(X)$        $I(X; Z) = ?$       (i)  $f(x) = \begin{cases} 1/2 & x \in \{1, 3\} \\ 0 & x \in \{0, 2\} \end{cases}$   
 $g(x) = \begin{cases} A & x \in \{0, 1\} \\ B & x \in \{2, 3\} \end{cases}$

$I(X; Z) = H(X) - H(X|Z) = H(Z) - H(Z|X) = (\frac{1}{2} \log_2 2) - H(Z|X)$

$Z \backslash X$	0	1	2	3
A	$p_1$	$p_2$	0	0
B			$p_3$	$p_4$

$P(Z=A) = P(Z=A|Z=0) + P(Z=A|Z=1)$   
 $P(Z=B) = P(Z=B|Z=2) + P(Z=B|Z=3)$

$Z \backslash X$	0	1	2	3	$P(X)$
0	0	0	0	0	0
1	$1/4$	$1/4$	0	0	$1/2$
2	0	0	0	0	0
3	0	0	$1/4$	$1/4$	$1/2$
$P(Z)$	$1/4$	$1/4$	$1/4$	$1/4$	

$X \backslash Z$	0	1	2	3
0	$1/2$	0	0	$1/2$
1	$1/2$	$1/2$	0	0
2	0	$1/2$	$1/2$	0
3	0	0	$1/2$	$1/2$

$P(X) \cdot P(Z|X) = P(X, Z)$

$P(Z=A) = P(X=0) + P(X=1) = 1/2$   
 $P(Z=B) = P(X=2) + P(X=3) = 1/2$

$P(Z|X)$  I.E. TRANSITION MATRIX

$P(x, z)$

$X \setminus Z$	A	B	$P(x)$
0	0	0	0
1	1/2	0	1/2
2	0	0	0
3	0	1/2	1/2
$P(z)$	1/2	1/2	

$P(x=1, z=A) = 1/2$      $P(x=3, z=B) = 1/2$   
 $P(x=0, z=A) = 0$      $P(x=2, z=B) = 0$

$X \setminus Z$	A	B	$P(z x)$
0	0	0	
1	1	0	
2	0	0	
3	0	1	

$H(z|x) = - \sum_{z \in Z} P(x, z) \cdot \log P(z|x) = - \left[ \frac{1}{2} \log 1 + \frac{1}{2} \log 1 \right] = 0$

$I(x; z) = H(z) - H(z|x) = 1 - 0 = 1$

$I(x; z) = H(x, z) - H(x) - H(z|x) = H(x) + H(z|x) = H(x) + H(z|x)$

$H(x) \geq H(z)$

(ii)

$X \setminus Z$	0	1	2	3	$P(x)$
0	1/4	1/4	0	0	1/2
1	0	0	0	0	0
2	0	0	1/4	1/4	1/2
3	0	0	0	0	0
$P(z)$	1/4	1/4	1/4	1/4	

$X \setminus Z$	A	B	$P(x)$
0	1/2	0	1/2
1	0	0	0
2	0	1/2	1/2
3	0	0	0
$P(z)$	1/2	1/2	

$X \setminus Z$	A	B
0	1	0
1	0	0
2	0	1
3	0	0
$P(z x)$		

$H(z|x) = - \sum_{z \in Z} P(x, z) \cdot \log P(z|x) = - \left[ \frac{1}{2} \log 1 + \frac{1}{2} \log 1 \right] = 0$   
 $I(x; z) = H(z) - H(z|x) = \log 2 - 0 = 1$

**PROBLEM 3.6**

VARIATION INEQUALITY VERIFY FOR POSITIVE

RANDOM VARIABLES  $X$  THAT

$\log E P(X) = \sup_Q \left[ E_Q \log(X) - D(Q||P) \right]$

WHERE  $E P(X) = \sum_X X P(X)$

AND  $D(Q||P) = \sum_Q Q \log \frac{Q(X)}{P(X)}$

AND THE SUPPLEMENT IS OVER ALL  $Q(X) \geq 0, \sum Q(X) = 1$ .  
 IT IS ENOUGH TO EXTREMIZE  $J(Q) = E_Q[\log X] - D(Q||P)$   
 $+\lambda (\sum Q(X) - 1)$

LAGRANGE MULTIPLIERS

$$J(\lambda) = E_g [L_n X] - D(Q|P) + \lambda (\sum Q(x) - 1)$$

$$f(\lambda) = \lambda J(x, \gamma, z)$$

$$f(\lambda, \gamma, z) = \lambda J(x, \gamma, z) \quad \frac{\partial J(Q(x))}{\partial Q(x_1)}, \quad \frac{\partial J(Q(x_2))}{\partial Q(x_2)}, \quad \dots \quad \frac{\partial J(Q(x_n))}{\partial Q(x_n)}$$

$$\frac{\partial J(Q)}{\partial Q(x)} = \frac{d}{dQ(x)} [E_g [L_n X]] - \frac{d}{dQ(x)} D(Q|P) + \lambda \frac{d}{dQ(x)} [\sum Q(x) - 1]$$

$$E_g [L_n X] = \frac{\sum Q(x) Q(x)}{x} \quad \frac{d}{dQ_i} [E_g (L_n X)] = \frac{\sum Q(x)}{x} \frac{dQ_i}{dQ_i} = \frac{1}{x} \ln \frac{1}{P(x_i)}$$

$$D(Q|P) = \sum \frac{Q(x)}{x} \ln \frac{Q(x)}{P(x)} \quad \frac{\partial D(Q|P)}{\partial Q(x_i)} = \frac{\partial}{\partial Q(x_i)} \left[ \sum \frac{Q(x)}{x} \ln \frac{Q(x)}{P(x)} \right] = \frac{1}{x} \ln \frac{Q(x)}{P(x)} + \frac{1}{x} = \frac{1}{x} \ln \frac{Q(x)}{P(x)} + \frac{1}{x}$$

$$= \ln \left[ \frac{Q(x_i)}{P(x_i)} \right] + \frac{1}{x} = \ln \left[ \frac{Q(x_i)}{P(x_i)} \right] + \frac{1}{x}$$

$$\frac{\partial J(Q(x))}{\partial Q(x_i)} = \ln \left( \frac{Q(x_i)}{P(x_i)} \right) + \frac{1}{x} + \lambda = 0$$

DEFINITION: The mutual information between two random variables X and Y is given by:

$$I(X; Y) = \sum_{P, Q} I([X]_P, [X]_Q)$$

$$I(X; Y) = \sum_{x, y} P(x, y) \ln \frac{P(x, y)}{P(x)P(y)} = D(P(x, y) || P(x)P(y))$$

$$\ln E_p(x) = \ln \left[ \sum_x P(x) \right]$$

JENSEN INEQUALITY:  $E[f(x)] \geq f(E[x])$   $f$  - convex

$f$  - concave function  $\ln E_p(x) \geq E_p[\ln(x)] = \ln P(x)$

$$\ln \left[ \frac{Q(x_i)}{P(x_i)} \right] = \ln (\ln(x_i) + \frac{1}{x}) = \ln [\ln(x_i) + \ln e^{\frac{1}{x}}]$$

$$\ln \left[ \frac{Q(x_i)}{P(x_i)} \right] = \ln(x_i e^{\frac{1}{x}}) = \ln(x_i) + \frac{1}{x} = \ln(x_i) + \frac{1}{x}$$

$$\ln[\mathcal{L}(\theta)] = \sup_{\theta} [\mathbb{E}_{\theta} \ln(X) - D(\theta \| P)]$$

$$\mathcal{L}(\theta) = \mathbb{E}_{\theta}[\ln X] - D(\theta \| P) + \lambda (\sum \theta(x) - 1)$$

$$\ln \left[ e \frac{q(x_i)}{p(x_i)} \right] = \ln x_i e^{\lambda} = \ln 2 \cdot \ln(x_i e^{\lambda})$$

$$\ln \left[ e \frac{q(x_i)}{p(x_i)} \right] = \ln x_i e^{\lambda} e^{\lambda \ln 2}; \quad \left[ e \frac{q(x_i)}{p(x_i)} = x_i e^{\lambda} e^{\lambda \ln 2} \right]$$

$$\left[ f(x_i) = \frac{e^{q(x_i)}}{x_i e^{\lambda} e^{\lambda \ln 2}} \right] \quad \equiv \quad p(x_i) = \sum \frac{q(x_i)}{x_i e^{\lambda} e^{\lambda \ln 2 - 1}}$$

$$\sum_x p(x_i) = \frac{1}{e^{\lambda \ln 2 - 1}} \sum_x \frac{q(x_i)}{x_i e^{\lambda}} = 1$$

$$\frac{q(x_i)}{x_i e^{\lambda} e^{\lambda \ln 2 - 1}} = e^{\lambda \ln 2 - 1}$$

$$\text{if } \boxed{D(\theta \| P) = \sum \theta \ln \frac{\theta}{P}}$$

$$\frac{d \mathcal{L}(\theta)}{d \theta_i} = \ln x_i - \ln \frac{q(x_i)}{p(x_i)} - 1 + \lambda = 0$$

$$\ln x_i + \lambda = \ln \frac{q}{p} \cdot e$$

$$\ln(x_i e^{\lambda}) = \ln \frac{q(x_i) \cdot e}{p(x_i)}$$

$$x_i e^{\lambda} = \frac{q(x_i)}{p(x_i)} \cdot e$$

$$\frac{q(x_i)}{p(x_i)} = x_i e^{\lambda - 1}$$

$$\left[ p(x_i) = \frac{q(x_i)}{x_i e^{\lambda - 1}} \right]$$

$$\sum p(x_i) = \sum \frac{q(x_i)}{x_i e^{\lambda - 1}} = e^{1 - \lambda} \sum \frac{q(x_i)}{x_i}$$

$$\frac{q(x_i)}{x_i} = e^{1 - \lambda}$$

$$q(x_i) = p(x_i) x_i e^{\lambda - 1} \quad \sum q(x_i) = 1$$

$$\sum x_i e^{\lambda - 1} p(x_i) = e^{\lambda - 1} \sum x_i p(x_i) = e^{\lambda - 1} \mathbb{E}_p(X) = 1$$

$$\mathbb{E}_p(X) = \frac{1}{e^{\lambda - 1}} = e^{1 - \lambda}$$

MMV

$$D(Q||P) = \sum_{x_i} g_i \ln \frac{g_i}{p} = \sum_{x_i} g_i \ln(x_i e^{\lambda-1}) = \sum_{x_i} g_i(x_i) \ln x_i + \sum_{x_i} g_i(x_i) (\lambda-1) = E_g[\ln X] + (\lambda-1)$$

$$\begin{aligned} \ln[E_g(\eta)] &= \sup_{\lambda} [E_g[\ln(X)] - D(Q||P)] \\ \ln[E_g(\lambda)] &= (1-\lambda) \sup [E_g[\ln(\eta)] - D(Q||P)] = E_g[\ln(\eta)] - (1-\lambda) \\ \sup [E_g[\ln X] - D(Q||P)] &= 1-\lambda = \ln[E_g(\lambda)] \end{aligned}$$

**EXPLICIT SOLUTIONS**

$$\ln x_i - \ln \frac{g_i}{p} - 1 + \lambda = 0$$

$$\ln \frac{g_i}{p} + 1 = \lambda + \ln x_i \quad \Rightarrow \quad \ln \frac{g_i}{p} = (\lambda-1) + \ln x_i$$

$$\ln \frac{g_i}{p} = \ln(e^{\lambda-1} x_i) \quad \left[ \frac{g_i}{p} = k \cdot x_i \right] \quad (g_i(x) = k \cdot x \cdot P(x))$$

$$\sum_{x_i} g_i(x_i) = k \sum_{x_i} x_i P(x_i) = k \cdot E_P(X) = 1 \quad \left[ k = \frac{1}{E_P(X)} \right]$$

$$\left[ g_i(x_i) = \frac{x_i P(x_i)}{E_P(X)} \right] \Rightarrow \sum_{x_i} g_i(x_i) \ln(x_i) - \sum_{x_i} g_i(x_i) \ln \frac{g_i(x_i)}{P(x_i)} + \lambda (\sum_{x_i} g_i(x_i) - 1)$$

$$\begin{aligned} &= \sum_{x_i} g_i(x_i) \ln(x_i) - \sum_{x_i} g_i(x_i) \ln \frac{x_i}{g_i(x_i)} + \lambda (\sum_{x_i} g_i(x_i) - 1) = \\ &= \sum_{x_i} g_i(x_i) \ln(x_i) - \sum_{x_i} g_i(x_i) \ln x_i + \sum_{x_i} g_i(x_i) \ln g_i(x_i) + \lambda [\sum_{x_i} g_i(x_i) - 1] = \\ &= E_g[\ln(X)] - E_g[\ln X] + \ln E_P(X) + \lambda [\sum_{x_i} g_i(x_i) - 1] = 0 \end{aligned}$$

$$\ln[E_g(\lambda)] = \sup [E_g[\ln(\eta)] - D(Q||P)]$$

$$\ln[E_g(\lambda)] = \ln[E_g(\lambda)]$$

$$\ln[E_g(\lambda)] \geq E_g[\ln(\eta) - D(Q||P)]$$

**PROBLEM 8.1** DIFFERENTIATE ENTROPY BOUND ON DISCRETE ENTROPY. LET  $X$  BE A DISCRETE RANDOM VARIABLE ON THE SET  $X = \{x_1, x_2, \dots\}$  WITH  $P(X=x_i) = p_i$ . SHOW THAT:

$$H(p_1, p_2, \dots) \leq \frac{1}{2} \ln(2\pi e) \left( \sum_{i=1}^{\infty} p_i^2 - \left( \sum_{i=1}^{\infty} p_i \right)^2 + \frac{1}{12} \right)$$

Moreover for every permutation  $\sigma$ ,

$$H(\gamma_1, \gamma_2, \dots) \leq \frac{1}{2} \log(2\pi e) \left( \sum_{i=1}^n \gamma_i^2 - \left( \sum_{i=1}^n \gamma_i \right)^2 + \frac{1}{12} \right)$$

HINT: CONSTRUCT A RANDOM VARIABLE  $X'$  SUCH THAT  
 $\Pr(X'=i) = p_i$ . LET  $U$  BE A UNIFORM  $(0,1)$  RANDOM VARIABLE AND LET  $Z = X' + U$ , WHERE  $X'$  AND  $U$  ARE INDEPENDENT. USE THE MAXIMUM ENTROPY BOUND ON  $Z$  TO OBTAIN BOUNDS IN THE PROBLEM.

$$H(\gamma_1, \gamma_2, \dots) \leq \frac{1}{2} \log(2\pi e) \left( \sum_{i=1}^{\infty} \gamma_i^2 - \left( \sum_{i=1}^{\infty} \gamma_i \right)^2 + \frac{1}{12} \right)$$

~~Let~~  $Z = X' + U$   $h(z) \leq \frac{1}{2} \log(2\pi e) \sigma^2$  ~~scribble~~

$$f(u) = \begin{cases} 1 & u \in [0,1] \\ 0 & \text{OTHERWISE} \end{cases}$$

$$I(x'; z) = h(x') - h(x'|z) = \underline{h(z)} - h(z|x')$$

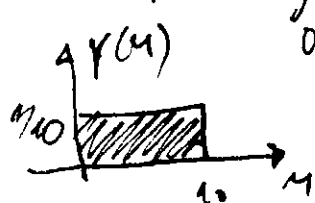
$$h(z|x') = \int p(x) h(z|x'=x) dx = \int p(x) h(x+u) dx$$

$$= \int p(x) h(x+u) dx = \underline{h(u)}$$

$I(x'; z) = h(z) - h(u)$

$$h(x') = h(x) - \log 4 = h(u) - h$$

$$h(u) = \int_0^1 1 \log 1 du = 0 = \underline{\log 1}$$



$$h(u) = \int_0^1 \frac{1}{10} \log 10 du = \frac{1}{10} \cdot 10 \cdot \log 10 = \log 10$$

$$I(x'; z) = h(z) = h(x') - h(x'|z)$$

$$h(x'|z) = \sum p(x=i) h(z-u|i) = \underline{h(u)}$$

$$\Pr(X'=i) = p_i \quad \Pr(X'=1) = p_1 \quad \Pr(X'=2) = p_2, \quad \Pr(X'=i) = p_i$$

$$E[X'] = \sum_{i=1}^{\infty} i p_i \quad E[X'^2] = \sum_{i=1}^{\infty} i^2 p_i$$

$$\sigma^2 = \sum_{i=1}^{\infty} (x_i - \bar{x})^2 p_i = \sum_{i=1}^{\infty} \left( i - \sum_{j=1}^{\infty} j p_j \right)^2 p_i$$

$$\sum_{i=1}^n i = \frac{n(n+1)}{2}$$

$$\begin{array}{r} 1 + 2 + 3 + \dots + n \\ n + (n-1) + (n-2) + \dots + 1 \\ \hline (n+1) + (n+1) + (n+1) + \dots + (n+1) \end{array} \quad | \quad \times$$

$$\left( i - \sum_{j=1}^{\infty} j p_j \right)^2 = i^2 - 2i \sum_{j=1}^{\infty} j p_j + \left( \sum_{j=1}^{\infty} j p_j \right)^2$$

$$\sum_{i=0}^{\infty} i \frac{1}{2^i} = \frac{\frac{1}{2}}{\left(1 - \frac{1}{2}\right)^2} = 2$$

$$\sum_{i=0}^{\infty} \frac{1}{2^i} = \frac{1}{1 - \frac{1}{2}}$$

$$\begin{aligned} S &= 1 + \frac{1}{2} + \frac{1}{2^2} + \dots + \frac{1}{2^n} \\ \frac{S}{2} &= \frac{1}{2} + \frac{1}{2^2} + \dots + \frac{1}{2^{n+1}} \end{aligned}$$

$$S \left(1 - \frac{1}{2}\right) = 1 - \frac{1}{2^{n+1}}$$

$$S = \frac{1 - \frac{1}{2^{n+1}}}{1 - \frac{1}{2}} \xrightarrow{n \rightarrow \infty} = \frac{1}{1 - \frac{1}{2}}$$

$$S = \sum_{n=0}^{\infty} x^n$$

$$S = \frac{1}{1-x}$$

$$dS/dx = \sum_{n=0}^{\infty} n x^{n-1}$$

$$\left(\frac{1}{1-x}\right)' = \sum_{n=0}^{\infty} n x^{n-1}$$

$$\frac{1}{(1-x)^2} = \sum_{n=0}^{\infty} (n+1) x^n$$

$$\left(\frac{1}{1-x}\right)' = \left[(1-x)^{-1}\right]' = -1 \cdot (1-x)^{-2} \cdot (-1) = \frac{1}{(1-x)^2}$$

$$\frac{1}{(1-x)} = \sum_{n=0}^{\infty} x^n$$

$$\sum_{n=0}^{\infty} (n+1) x^n = \frac{x}{(1-x)^2}$$

$$p(\tau) = \gamma(x, v)$$

$$K = \begin{bmatrix} \sigma^2 & 0 \\ 0 & 1 \end{bmatrix}$$

$$f(\tau) \leq \frac{1}{2} \ln(2\pi e) |K| = \frac{1}{2} \ln(2\pi e) \sigma^2$$

$$H(W) = nR = H(W, \bar{W}) = H(W) + H(\bar{W}|W) = H(\bar{W}) + H(W|\bar{W})$$

$$H(\bar{W}) = 1 + p_e \ln 2^{1/p_e}$$

$$W \rightarrow X^n \rightarrow \bar{W}$$

$$\begin{aligned} I(W, \bar{W}) &\leq I(W, X^n) \\ I(W, \bar{W}) &\leq I(X^n, \bar{W}) \end{aligned}$$

$$H(W) = H(R) = \frac{I(W; \bar{W}) + H(W|\bar{W})}{H(W) - H(W|\bar{W})} \leq 1 + P_e \log R + I(W; \bar{W})$$

$$\leq 1 + P_e \log R + I(X; Y)$$

$$W.R \leq 1 + P_e \log R + \log C$$

$$R \leq \frac{1}{P_e} + P_e \log C$$

$R \leq C$

CONTINUOUS FROM N.16K

8.8 CHANNEL WITH UNIFORMELY DISTRIBUTED NOISE

CONSIDER A ADDITIVE CHANNEL WHOSE INPUT ALPHABET  $X = \{0, \pm 1, \pm 2\}$  AND WHOSE OUTPUT  $Z = X + Z$ , WHERE  $Z$  IS DISTRIBUTED UNIFORMLY OVER THE INTERVAL  $[-1, 1]$ . THUS THE INPUT OF THE CHANNEL IS A DISCRETE RANDOM VARIABLE, WHEREAS THE OUTPUT IS CONTINUOUS. CALCULATE  $C = \max_{P(X)} I(X; Z)$  OF THIS CHANNEL.

$$I(X; Z) = H(X) - H(X|Z) = H(Z) - H(Z|X)$$

From 8.7

$$H(X) = - \sum_{i=1}^{\infty} p_i \log p_i = - \sum_{i=1}^{\infty} \left( \int_{i-1}^{i+1} p(\gamma) d\gamma \right) \left( \log \int_{i-1}^{i+1} p(\gamma) d\gamma \right)$$

$$= \sum_{i=1}^{\infty} \int_{i-1}^{i+1} p(\gamma) \log p(\gamma) d\gamma = \underline{H(\gamma)}$$

$$X = \{-2, -1, 0, 1, 2\}$$

$$P(X) = \{p_1, p_2, p_3, p_4, p_5\}$$

$$f(x_i) \cdot \Delta = \int_{x_i}^{(i+1)\Delta} f(x) dx$$

$$H(X) = - \sum_{i=1}^5 p_i \log p_i = - \sum_{i=1}^5 \left( \int_{i-1}^{i+1} p(\gamma) d\gamma \right) \left( \log \int_{i-1}^{i+1} p(\gamma) d\gamma \right)$$

$$= - \sum_{i=1}^5 \int_{i-1}^{i+1} p(\gamma) \log p(\gamma) d\gamma = - \left[ \int_0^2 p(\gamma) \log p(\gamma) d\gamma + \int_1^2 p(\gamma) \log p(\gamma) d\gamma + \dots + \int_4^6 p(\gamma) \log p(\gamma) d\gamma \right]$$

$$= - \left[ \int_0^1 p(\gamma) \log p(\gamma) d\gamma + \int_1^2 p(\gamma) \log p(\gamma) d\gamma + \dots + \int_4^5 p(\gamma) \log p(\gamma) d\gamma + \int_5^6 p(\gamma) \log p(\gamma) d\gamma \right]$$



$$= -\int^x \gamma(\tau) \mathcal{L}d\gamma(\tau) - \int^x \gamma(\tau) \mathcal{L}d\gamma(\tau) d\tau$$

$$x \in [-2, -1, 0, 1, 2] \quad \gamma(x) = \{ \gamma_{-2}, \gamma_{-1}, \gamma_0, \gamma_1, \gamma_2 \}$$

$$\tau \in [(-3, -1), (-2, 0), (-1, 1), (0, 2), (1, 3)]$$

$x \setminus \gamma$	-3	-2	-1	0	1	2	3	$\gamma(x)$
-2								$\gamma_{-2}$
-1								$\gamma_{-1}$
0								$\gamma_0$
1								$\gamma_1$
2								$\gamma_2$
$\gamma(\tau)$								

$$H(x) = -\sum_{i=-2}^2 \gamma_i \mathcal{L}d\gamma_i =$$

$$= -\sum_{i=-2}^2 \int_{\gamma_{i-1}}^{\gamma_{i+1}} \gamma(\tau) \mathcal{L}d\gamma(\tau) d\gamma =$$

$$= \int^x \gamma(\tau) \mathcal{L}d\gamma(\tau) d\gamma = \underline{\underline{G(x)}}$$

$$\int_{-3}^{-1} \gamma \mathcal{L}d\gamma + \int_{-2}^0 \gamma \mathcal{L}d\gamma + \int_{-1}^1 \gamma \mathcal{L}d\gamma + \int_0^2 \gamma \mathcal{L}d\gamma + \int_1^3 \gamma \mathcal{L}d\gamma$$

$$\int_{-2}^{-1} \gamma \mathcal{L}d\gamma + \int_{-1}^0 \gamma \mathcal{L}d\gamma + \int_0^1 \gamma \mathcal{L}d\gamma + \int_1^2 \gamma \mathcal{L}d\gamma + \int_2^3 \gamma \mathcal{L}d\gamma$$

$$H(x) = -\left[ \int_{-3}^x \gamma(\tau) \mathcal{L}d\gamma(\tau) d\gamma + \int_{-2}^x \gamma(\tau) \mathcal{L}d\gamma(\tau) d\gamma \right]$$

$$H(x) = -\sum_{i=-2}^2 \gamma_i \mathcal{L}d\gamma_i \quad H(x|z) \quad x = z - z$$

$$H(x|z) = \int \gamma(\tau) H(x-z|\tau) d\gamma = G(z)$$

$$I(x, \tau) = H(x) - G(z) \quad G(z) = \int \frac{1}{2} dz = \frac{1}{2} \cdot 2 = 1$$

$$I(x, \tau) = H(x) - 1$$

$$P(x) = \left\{ \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5}, \frac{1}{5} \right\}$$

$$I(x, \tau) = 6.5 - 1 = \mathcal{L}d \frac{5}{2} = \mathcal{L}d(2.5)$$

$$f_{\tau}(\tau) = \begin{cases} \frac{1}{2} P_{-2} & \gamma \in (-3, -2) \\ \frac{1}{2} (P_{-2} + P_{-1}) & \gamma \in (-2, -1) \\ \frac{1}{2} (P_{-1} + P_0) & \gamma \in (-1, 0) \\ \frac{1}{2} (P_0 + P_1) & \gamma \in (0, 1) \\ \frac{1}{2} (P_1 + P_2) & \gamma \in (1, 2) \\ \frac{1}{2} P_2 & \gamma \in (2, 3) \end{cases}$$

SIRNOV VO  
SOLUCIONA NA  
PUBLIC PROBLETA

$$\begin{aligned}
 h(\tau) &= - \int_{-3}^{-2} \frac{1}{2} P_{-2} \ln \frac{P_{-2}}{2} d\tau + \int_{-2}^{-1} \frac{P_{-2} + P_{-1}}{2} \ln \frac{P_{-2} + P_{-1}}{2} d\tau + \int_{-1}^0 \frac{P_{-1} + P_0}{2} \ln \frac{P_{-1} + P_0}{2} d\tau \\
 &+ \left[ \int_0^1 \frac{P_0 + P_1}{2} \ln \frac{P_0 + P_1}{2} d\tau + \int_1^2 \frac{P_1 + P_2}{2} \ln \frac{P_1 + P_2}{2} d\tau + \int_2^3 \frac{P_2}{2} \ln \frac{P_2}{2} d\tau \right] = \\
 &= \left[ \frac{P_{-2}}{2} \ln \frac{P_{-2}}{2} + \frac{P_{-2} + P_{-1}}{2} \ln \frac{P_{-2} + P_{-1}}{2} + \frac{P_{-1} + P_0}{2} \ln \frac{P_{-1} + P_0}{2} + \frac{P_0 + P_1}{2} \ln \frac{P_0 + P_1}{2} \right] \\
 &+ \frac{P_1 + P_2}{2} \ln \frac{P_1 + P_2}{2} + \frac{P_2}{2} \ln \frac{P_2}{2}
 \end{aligned}$$

Prilozheniya iz sledstviya kakoy skladnoy zashchity mozhno vyvesti !!!

$$\begin{aligned}
 &= \left[ \frac{P_{-2}}{2} \ln \frac{P_{-2}}{2} \cdot \frac{P_{-2} + P_{-1}}{2} + \frac{P_{-1}}{2} \ln \left( \frac{P_{-2} + P_{-1}}{2} \right) + \frac{P_0}{2} \ln \frac{P_{-1} + P_0}{2} \cdot \frac{P_0 + P_1}{2} + \right. \\
 &\left. + \frac{P_1}{2} \ln \left( \frac{P_0 + P_1}{2} \cdot \frac{P_1 + P_2}{2} \right) + \frac{P_2}{2} \ln \frac{P_2}{2} \right] + I_2 + I_1 + I_0 + I_{-1} + I_{-2}
 \end{aligned}$$

$$h(x|\tau) = f(\tau) \cdot h(x|\tau) d\tau = \int_{-3}^{-2} \frac{P_{-2}}{2} \cdot h(x|\tau \in (-2:-1)) d\tau$$

$$\Rightarrow I_2 = \int_{-2}^{-1} \frac{P_{-2} + P_{-1}}{2} \cdot h(x|\tau \in (-2:-1)) d\tau = \frac{P_{-2} + P_{-1}}{2}$$

$$\begin{aligned}
 h(x|\tau \in (-2:-1)) &= P(x=-2|\tau \in (-2:-1)) \ln P(x=-2|\tau \in (-2:-1)) + \\
 &+ P(x=-1|\tau \in (-2:-1)) \ln P(x=-1|\tau \in (-2:-1)) = \left( \frac{1}{2} \ln \frac{1}{2} \right) \cdot 2 = 1
 \end{aligned}$$

$$\begin{aligned}
 I_{-1} &= \frac{P_{-1} + P_0}{2} & I_0 &= \frac{P_0 + P_1}{2} & I_1 &= \frac{P_1 + P_2}{2} & I_2 &= \frac{P_2}{2} \\
 h(x|\tau) &= \frac{P_{-2} + P_{-1} + P_{-1} + P_0 + P_0 + P_1 + P_1 + P_2}{2} = \frac{P_{-2} + 2P_{-1} + 2P_0 + 2P_1 + P_2}{2}
 \end{aligned}$$

$$h(x|\tau) = \sum_{i=-1}^1 \frac{P_i + P_{i+1}}{2} = \frac{P_{-1} + P_0}{2} + \frac{P_0 + P_1}{2} + \frac{P_1 + P_2}{2}$$

$$\begin{aligned}
 h(\tau) &= \sum_{i=-2}^3 \frac{P_{i-1} + P_i}{2} \ln \frac{P_{i-1} + P_i}{2} = \frac{P_{-2}}{2} \ln \frac{P_{-2}}{2} + \frac{P_{-2} + P_{-1}}{2} \ln \frac{P_{-2} + P_{-1}}{2} + \\
 &+ \dots + \frac{P_1 + P_2}{2} \ln \frac{P_1 + P_2}{2} + \frac{P_2}{2} \ln \frac{P_2}{2} \\
 I(x|\tau) &= - \sum_{i=-2}^3 \frac{P_{i-1} + P_i}{2} \ln \frac{P_{i-1} + P_i}{2} + \sum_{i=-1}^1 \frac{P_i + P_{i+1}}{2}
 \end{aligned}$$

$$f(R) = - \sum_{i=2}^{\infty} \frac{P_{i-1} + P_i}{2} \ln \frac{P_{i-1} + P_i}{2} + \sum_{i=-1}^1 \frac{P_i + P_{i+1}}{2} + \lambda \left( \sum_{i=-2}^2 P_i - 1 \right)$$

$$\frac{d f(R)}{d P_i} = - \frac{1}{2} \ln \frac{P_{i-1} + P_i}{2} + \frac{P_{i-1} + P_i}{2} \cdot \frac{1}{P_{i-1} + P_i} + \frac{1}{2} + \lambda = 0$$

$$\lambda = \frac{1}{2} \ln \frac{P_{i-1} + P_i}{2} \quad \lambda = \frac{1}{2} \left( 1 + \ln \frac{P_{i-1} + P_i}{2} \right)$$

$$\lambda = \frac{1}{2} \ln \left( \frac{P_{i-1} + P_i}{2} \right) \quad 2 \cdot 2^{2\lambda} = (P_{i-1} + P_i) \quad P_i = 2^{2\lambda+1} - P_{i-1}$$

$$\sum_{i=2}^{\infty} P_i = 1 \quad \sum_{i=-2}^2 (2^{2\lambda+1} - P_{i-1}) = 1 \quad 5 \cdot 2^{2\lambda} - \sum_{i=-2}^2 P_{i-1} = 1$$

$$5 \cdot 2^{2\lambda+1} - \sum_{i=-1}^2 P_{i+1} = 1$$

$$5 \cdot 2^{2\lambda+1} = \sum_{i=-2}^1 P_i = 1$$

$$i = \lambda - 1; i = -1; i = -2; i = 2; i = 1$$

$$\sum_{j=-2}^1 P_j = 1 - P_2$$

$$5 \cdot 2^{2\lambda+1} - 1 + P_2 = 1 \quad P_2 = 2 - 5 \cdot 2^{2\lambda+1}$$

$$5 \cdot 2^{2\lambda+1} = 2 - P_2$$

$$2^{2\lambda+1} = \frac{2 - P_2}{5} \quad 2^{2\lambda+1} = \ln \frac{2 - P_2}{5}$$

$$\lambda = - \frac{1}{2} + \frac{1}{2} \ln \frac{2 - P_2}{5} = \frac{1}{2} \ln \frac{2 - P_2}{10}$$

$$\frac{1}{2} \ln \frac{2 - P_2}{10} = \frac{1}{2} \ln (P_{i-1} + P_i)$$

$$P_i + P_{i-1} = (2 - P_2) / 10$$

$$\left\{ \frac{1}{2}, \frac{1}{4}, \frac{1}{8}, \frac{1}{16}, \frac{1}{16} \right\}$$

$$\frac{1}{2} + \frac{1}{4} = \frac{3}{4} \quad \left( 2 - \frac{1}{16} \right) \frac{1}{10} = \frac{32-1}{16} = \frac{31}{16} \cdot \frac{1}{10} = \frac{31}{160}$$

$$\left\{ \frac{1}{16}, \frac{1}{16}, \frac{1}{8}, \frac{1}{4}, \frac{1}{2} \right\} \quad \frac{1}{8} \quad \left( 2 - \frac{1}{2} \right) \frac{1}{10} = \frac{1}{10} \cdot \frac{4-1}{2} = \frac{3}{20}$$

$$L = \sum_{i=-2}^2 \frac{2 - P_2}{20} \ln \frac{2 - P_2}{20} + \sum_{i=-1}^1 \frac{2 - P_2}{20}$$

$$L = 6 \cdot \frac{2 - P_2}{20} \ln \frac{2 - P_2}{20} + 3 \cdot \frac{2 - P_2}{20} = \frac{6 P_2}{10} \ln \frac{2 - P_2}{20} + 3 \frac{2 - P_2}{20}$$

$$L \nearrow \text{as } P_2 \searrow \quad \text{FOR } P_2 = 0 \quad L = 0.3$$

• Bayesian Solution  $f(x) = \left\{ \frac{P_2}{2}, \frac{P_2 + P_1}{2}, \frac{P_1 + P_0}{2}, \frac{P_0 + P_{-1}}{2}, \frac{P_{-1} + P_{-2}}{2}, \frac{P_{-2}}{2} \right\}$

$$\textcircled{A} \quad (11.26) \Rightarrow \pi(x) = \ln 6$$

$$\frac{P_{-2}}{2} = \frac{P_2}{2} = \frac{1}{6} \quad \frac{P_{-2} + P_{-1}}{2} = \frac{1}{6} \quad \frac{P_{-1} + P_0}{2} = \frac{1}{6} \quad \frac{P_0}{2} = \frac{1}{6} \quad P_0 = \frac{1}{3}$$

$P_{-2} = P_2 = P_0 = \frac{1}{3}$      $P_{-1} = P_1 = 0$

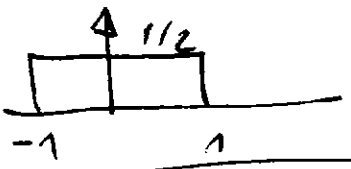
$Z = X + \epsilon$

$I(X; Z) = H(Z) - H(Z|X)$

$H(Z|X) = \sum_x p(x) \cdot H(Z|X=x) = \sum_x p(x) \cdot H(X+Z|x)$

$H(Z|X) = H(Z)$

$H(Z) = \int_{-1}^1 \frac{1}{2} \ln 2 \, dz = \frac{1}{2} (1+1) = 1$



$H(Z|X) = P_{-2} H(Z|X=-2) + P_{-1} H(Z|X=-1) + P_0 H(Z|X=0) + P_1 H(Z|X=1) + P_2 H(Z|X=2)$

$P_{-2} H(Z|X=-2) = -P_{-2} \int_{-1}^1 f(\gamma) \cdot \ln f(\gamma) \, d\gamma = -P_{-2} \int_{-1}^1 \frac{P_{-2}}{2} \ln \frac{P_{-2}}{2} \, d\gamma$

$= -P_{-2} \left[ \frac{P_{-2}}{2} \ln \frac{P_{-2}}{2} + \frac{P_{-2} + P_{-1}}{2} \ln \frac{P_{-2} + P_{-1}}{2} \right] = -\frac{1}{6} \cdot \frac{1}{3} \ln \frac{1}{6} = \frac{1}{24} \ln 6$

$P_{-1} H(Z|X=-1) = \frac{1}{24} \ln 6$

$H(Z|X) = \frac{1}{6} \ln 6$      $H(Z) = \frac{1}{6} \ln 6$

$C = \ln 6 - H(Z) = \ln 6 - 1 = \ln 6 - \ln 2 = \ln 3$

ПОДРОБНО РЕШАТЬ И ДАВАТЬ ПОДСКАЗКИ

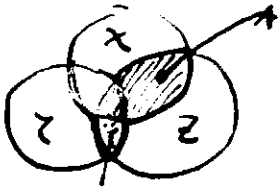
**PROBLEM 8.9**

GAUSSIAN MUTUAL INFORMATION

SUPPOSE THAT  $(X, Z, \epsilon)$  ARE JOINTLY GAUSSIAN AND THAT  $X \rightarrow Z \rightarrow \epsilon$  FORMS A MARKOV CHAIN. LET  $X$  AND  $Z$  HAVE CORRELATION COEFFICIENT  $\rho_1$  AND LET  $Z$  AND  $\epsilon$  HAVE CORRELATION COEFFICIENT  $\rho_2$ . FIND  $I(X; Z)$ .

$I(X, Z; \epsilon) = I(X; Z) + I(Z; \epsilon|X) = I(X; Z) + I(Z; \epsilon|X)$

$= I(Z; \epsilon) + I(X; Z|Y)$



$$I(x, y, z) = I(x; z) + I(y; z|x)$$

$$I(x; z|y) = h(z|y) - h(z|x, y) \\ = h(z|y) - h(z|y) = 0$$

$$K_1 = \begin{bmatrix} \sigma_x^2 & \rho_{12} \\ \rho_{12} & \sigma_y^2 \end{bmatrix}$$

$$K_2 = \begin{bmatrix} \sigma_y^2 & \rho_{23} \\ \rho_{23} & \sigma_z^2 \end{bmatrix}$$

$$K = \begin{bmatrix} \sigma_x^2 & \rho_{12} & 0 \\ \rho_{12} & \sigma_y^2 & \rho_{23} \\ 0 & \rho_{23} & \sigma_z^2 \end{bmatrix}$$

$$-\begin{bmatrix} x \\ y \\ z \end{bmatrix} K^{-1} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$

$$p(x, y) = \frac{1}{(\sqrt{2\pi})^2 |K_1|^{1/2}} e^{-\frac{1}{2} \begin{bmatrix} x \\ y \end{bmatrix} K_1^{-1} \begin{bmatrix} x \\ y \end{bmatrix}}; \quad p(x, y, z) = \frac{1}{(\sqrt{2\pi})^3 |K|} e^{-\frac{1}{2} \begin{bmatrix} x \\ y \\ z \end{bmatrix} K^{-1} \begin{bmatrix} x \\ y \\ z \end{bmatrix}}$$

$$I(x; z) = h(x) - h(x|z)$$

$$h(x, y, z) = h(x, y) + h(z|x, y) = h(x, y) + \cancel{h(z|y)}$$

$$h(x, y, z) = \frac{1}{2} \ln \left( \frac{1}{(2\pi e)^3 |K|} \right); \quad h(x, y) = \frac{1}{2} \ln \left( \frac{1}{(2\pi e)^2 |K_1|} \right)$$

$$p(x) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} \frac{1}{(\sqrt{2\pi})^2 |K_1|^{1/2}} e^{-\frac{1}{2} \begin{bmatrix} x \\ y \end{bmatrix} K_1^{-1} \begin{bmatrix} x \\ y \end{bmatrix}} dy$$

$$p(x) = \frac{1}{2\pi |K_1|} \int_{-\infty}^{\infty} e^{-\frac{1}{2} \frac{x^2 \sigma_y^2 + 2xy \rho_{12} + y^2 \sigma_x^2}{\sigma_x^2 \sigma_y^2 - \rho_{12}^2}} dy$$

$$p(x) = \frac{1}{2\pi \sqrt{(\sigma_x^2 \sigma_y^2 - \rho_{12}^2)}} \cdot e^{-\frac{x^2 (\sigma_y^2 - \rho_{12}^2)}{(\sigma_x^2 \sigma_y^2 - \rho_{12}^2) \sigma_x^2}}$$

$$p(x) = \frac{1}{2\pi \sigma_x} e^{-\frac{x^2 (\sigma_y^2 - \rho_{12}^2)}{(\sigma_x^2 \sigma_y^2 - \rho_{12}^2) \sigma_x^2}}$$

**PROBLEM 8.11 CONTINUE FROM N16K**

(e) Even though the process is not ergodic, it is stationary, and it does have an AEP, because

$$-\frac{1}{N} \ln p(X^N) = -\frac{1}{N} \ln \frac{1}{(\sqrt{2\pi})^N |K_{X^N}|} e^{-x^T K^{-1} x/2} = \\ = \frac{1}{N} \ln (2\pi)^{N/2} + \frac{1}{N} \ln \sqrt{|K_{X^N}|} + \frac{1}{2N} x^T K^{-1} x =$$

$$\begin{aligned}
 &= \frac{1}{2n} \ln(2\pi)^n + \frac{1}{2n} \ln |K_{X^n}| + \frac{1}{2n} x^t K^{-1} x = \\
 &= \frac{1}{2n} \ln(2\pi)^n \cdot |K_{X^n}| + \frac{1}{2n} x^t K^{-1} x + \frac{1}{2n} \ln e^n - \frac{1}{2n} \ln e^x \\
 &= \frac{1}{2n} \ln(2\pi e)^n |K_{X^n}| + \frac{1}{2n} x^t K^{-1} x - \frac{1}{2} = \frac{1}{n} \ln \left( \frac{x^t x}{2n} \right) - \frac{1}{2} + \frac{1}{2n} x^t x
 \end{aligned}$$

SINCE:  $x \sim N(0, K)$  we can write  $x = K^{1/2} W$   
 WHERE  $W = N(0, I)$  THEN:  
 $x^t K^{-1} x = W^T K^{1/2 T} \cdot K^{-1} \cdot K^{1/2} W = W^T \underbrace{K^{1/2} K^{-1} K^{1/2}}_{K \text{ is symmetric}} W = W^T W$

$x^t K^{-1} x = W^T W = \sum W_i^2$  THEREFORE  $x^t K^{-1} x$  has

$\chi^2$  (chi-squared) DISTRIBUTION WITH  $n^2$  DEGREES OF FREEDOM. THE DENSITY OF CHI-SQUARED DISTRIBUTION

$$f(x) = \frac{x^{\frac{n}{2}-1} e^{-\frac{x}{2}}}{\Gamma(\frac{n}{2}) 2^{n/2}}$$

$$M(s) = \int_{-\infty}^{\infty} f(x) e^{sx} dx$$

$$M(s) = \frac{1}{\sqrt{(1-2t)^n}}$$

BY CHEBYSHEV BOUND:

$$Pr \left\{ \frac{1}{n} \sum W_i^2 > 1 + \epsilon \right\} \leq \min_s e^{-s(1+\epsilon)} (1-2s)^{-\frac{n}{2}} \leq e^{-\frac{n}{2}(\epsilon - \ln(1+\epsilon))}$$

$$\begin{aligned}
 s &= \frac{\epsilon}{2(1+\epsilon)} \quad e^{-\frac{\epsilon}{2(1+\epsilon)} \cdot (1+\epsilon)} \left( 1 - \frac{\epsilon}{2(1+\epsilon)} \right)^{-\frac{n}{2}} = \\
 &= e^{-\frac{\epsilon}{2}} \left( \frac{2+2\epsilon-\epsilon}{2(1+\epsilon)} \right)^{-\frac{n}{2}} = e^{-\frac{\epsilon}{2}} \left( \frac{2+\epsilon}{2(1+\epsilon)} \right)^{-\frac{n}{2}} = e^{-\frac{\epsilon}{2}} (1+\epsilon)^{\frac{n}{2}} \\
 &= e^{-\frac{\epsilon}{2}} e^{\frac{n}{2} \ln(1+\epsilon)} = e^{-\frac{1}{2}[\epsilon - n \ln(1+\epsilon)]}
 \end{aligned}$$

$$-\frac{1}{n} \ln[f(x^n)] - \frac{1}{n} \ln(x^n) = -\frac{1}{2} + \frac{1}{2n} \sum W_i^2$$

$$Pr \left\{ \left| -\frac{1}{n} \ln[f(x^n)] - \frac{1}{n} \ln(x^n) \right| > \epsilon \right\} = Pr \left\{ \left| \frac{1}{2n} \sum W_i^2 - \frac{1}{2} \right| > \epsilon \right\} \leq e^{-\frac{n}{2}(\epsilon - \ln(1+\epsilon))}$$

THE BOUND GOES TO 0 AS  $n \rightarrow \infty$  AND THEREFORE BY BOOLEZ CANTELLI LEMMA:  $-\frac{1}{n} \ln f(x^n) - \ln(x^n) \rightarrow 0$  WITH PROBABILITY 1.

So  $X_i$  satisfies AEP even though it is not IID.

**LEMMA 11.9.1 (CHEBYSHEV LEMMA)** Let  $X$  be any random variable and let  $\psi(s)$  be the moment generating function of  $X$ .

$$\psi(s) = E[e^{sX}]$$

Then for all  $s > 0$ :  $Pr(X \geq a) \leq e^{-sa} \psi(s)$

and thus:  $Pr(X \geq a) \leq \min_{s > 0} e^{-sa} \psi(s)$

MARKOV INEQUALITY:

$$Pr\{X(x) \leq a\} \leq \frac{1}{a} E[X]$$

$$Pr\{X \geq a\} \leq \frac{E[X]}{a}$$

$$X_i = V + Z_i$$

$$i=1 \dots n \quad X_i = V$$

$$f(V|X^n) \sim N\left(\frac{s}{s+N} \sum X_i, \frac{sN}{N(s+N)}\right)$$

$$f(V|X^n) = \frac{f(V, X^n)}{f(X^n)}$$

$$\frac{f(X|\tau)}{f(\tau)} = f(X|\tau)$$

$$\int x \cdot f(x|\tau) dx = E[X|\tau]$$

$$E[X] = \sum_{\tau} P(\tau) E[X|\tau] = \sum_{\tau} P(\tau) \int x \cdot P(x|\tau)$$

$$f(V|X^n) = \frac{f(V, X^n)}{f(X^n)}$$

$$K_{(V, X^n)} = \begin{bmatrix} sN & s & s \\ s & sN & s \\ s & s & s \end{bmatrix}$$

MAV

MAPLE:

$$f(V|X^n) = \frac{1}{\sqrt{2\pi} \cdot \left(\frac{sN}{s+N}\right)^{1/2}} e^{-\frac{1}{2} \frac{1}{sN/(s+N)} (V - \frac{s}{s+N} \sum_{i=1}^n X_i)^2}$$

$$\begin{aligned} &= -\frac{1}{2} \frac{N^2}{sN/(s+N)} \left[ V - \frac{s}{N} \sum_{i=1}^n X_i + V \cdot \frac{s}{N} \right]^2 \\ &= -\frac{1}{2} \frac{NK}{sN/(s+N)} \left[ V \left( \frac{N+2s}{N} \right) - \frac{s}{N} \sum_{i=1}^n X_i \right]^2 = -\frac{N}{s(2s+N)} \left[ V \left( \frac{N+2s}{N} \right) - \frac{s}{N} \sum_{i=1}^n X_i \right]^2 \\ &= -\frac{N}{s(2s+N)} \left( \frac{N+2s}{N} \right)^2 \left[ V - \frac{N}{N+2s} \cdot \frac{s}{N} \sum_{i=1}^n X_i \right]^2 = -\frac{N+2s}{N \cdot s} \left[ V - \frac{s}{N+2s} \sum_{i=1}^n X_i \right]^2 \end{aligned}$$

$$\mu = \frac{s}{N+2s} \sum_{i=1}^n X_i \quad \sigma^2 = \frac{Ns}{N+2s}$$

$$\frac{q(x)}{p(x)} = k \cdot x$$

$$\sum_x q(x) = 1$$

$$q(x) = k \cdot x \cdot p(x)$$

$$\sum k \cdot x \cdot p(x) = 1$$

$$k = \frac{1}{\sum x p(x)} = \frac{1}{E(x)}$$

$$q(x) = \frac{x p(x)}{E(x)}$$

$$\log q(x) = \log \frac{x p(x)}{E(x)}$$

$$\sum_x q(x) \log(x) - \sum_x q(x) \log \frac{x p(x)}{E(x)} = 0$$

$$\sum_x q(x) \log(x) - \sum_x q(x) \log x - \sum_x q(x) \log \frac{1}{E(x)} = 0$$

$$\sum_x q(x) \log(x) - E_q[\log x] = \log \frac{1}{E(x)}$$

$$E_q[\log x] - \sum_x q(x) \log x$$

$$J(q, \lambda) = \sum_x q(x) \ln(x) - \sum_x q(x) \ln \frac{q(x)}{p(x)} - \lambda \left( \sum_x q(x) - 1 \right)$$

$$\frac{dJ(q, \lambda)}{dq} = \ln x - \ln \frac{q(x)}{p(x)} - 1 + \lambda = 0$$

$$\ln \frac{q(x)}{p(x)} = \ln x - 1 + \lambda \quad e^{\ln x - 1 + \lambda} = \frac{q(x)}{p(x)}$$

$$q(x) = p(x) \cdot e^{\ln x - 1 + \lambda} = p(x) \cdot \frac{e^{\lambda-1}}{k} \cdot x = k \cdot p(x) \cdot x$$

$$\sum_x q(x) = 1 \quad k \cdot \sum_x x p(x) = 1 \quad k = \frac{1}{E(x)}$$

$$e^{\lambda-1} = \frac{1}{E(x)} \quad G(x) = e^{1-\lambda} \quad 1-\lambda = \ln G(x)$$

$$\lambda = 1 - \ln G(x)$$

$$q(x) = \frac{p(x) \cdot x}{G(x)}$$

$$J(q, \lambda) /_{\max} = G(\ln x) - \sum_x q(x) \ln \frac{p(x) \cdot x}{p(x) G(x)} - 0 =$$

$$= G(\ln x) - \sum_x q(x) \ln x - \sum_x q(x) \ln \frac{1}{G(x)} = \ln G(x)$$

$$J(q, \lambda) \leq J(q, \lambda) /_{\max} = \ln G(x) = \lambda \left( \sum_x q(x) \right)$$

$$\sum_x q(x) \ln(x) - \sum_x q(x) \ln \frac{q(x)}{p(x)} - 0 \leq \ln G(x)$$



$$E[X|Y] = \frac{7.96_1}{\sqrt{0.1^2(1-0.4)}} \cdot \sqrt{\frac{1}{0.1^2(1-0.4)}} = \frac{7.96_1}{0.1} \quad \checkmark$$

**CHAPTER 9.1 GAUSSIAN CHANNEL: DEFINITIONS**

WE NOW DEFINE THE (INFORMATION) CAPACITY OF THE CHANNEL AS THE MAXIMUM OF THE MUTUAL INFORMATION BETWEEN THE INPUT AND OUTPUT OVER ALL DISTRIBUTIONS ON THE INPUT THAT SATISFY THE POWER CONSTRAINT

DEFINITION THE INFORMATION CAPACITY OF GAUSSIAN CHANNEL AS MAXIMUM OF THE MUTUAL INFORMATION BETWEEN THE INPUT AND OUTPUT OVER ALL DISTRIBUTIONS ON THE INPUT THAT SATISFY THE POWER CONSTRAINT IS:

$$C = \max_{f(x): E[X^2] \leq P} I(X; Z)$$

$$I(X; Z) = h(Z) - h(Z|X) = h(Z) - h(X+Z|X) = h(Z) - h(Z)$$

$$h(Z) - h(Z) ; \quad h(Z) = \frac{1}{2} \log 2\pi e N$$

$$E[Z^2] = E[(X+Z)^2] = E[X^2 + 2XZ + Z^2] = E[X^2] + \underbrace{2E[XZ]}_0 + E[Z^2]$$

$$E[Z^2] = E[X^2] + E[Z^2] = P + N$$

$$h(Z) \leq \frac{1}{2} \log(2\pi e) \cdot (P+N)$$

$$I(X; Z) = h(Z) - h(Z) \leq \frac{1}{2} \log(2\pi e) (P+N) - \frac{1}{2} \log(2\pi e N)$$

$$I(X; Z) \leq \frac{1}{2} \log(2\pi e) \left(1 + \frac{P}{N}\right)$$

HENCE THE INFORMATION CAPACITY OF GAUSSIAN CHANNEL IS:

$$C = \max_{E[X^2] \leq P} I(X; Z) = \frac{1}{2} \log(2\pi e) \left(1 + \frac{P}{N}\right)$$

THE MAXIMUM IS ATTAINED WHEN  $X \sim N(0, P)$ .  
 - WE WILL NOW SHOW THAT THIS CAPACITY IS ALSO THE SUM-RATE OF THE FASTEST RATE FOR THE CHANNEL.

DEFINITION: AN  $(M, \gamma)$  CODE FOR THE GAUSSIAN CHANNEL WITH POWER CONSTRAINT  $P$  CONSISTS OF THE FOLLOWING:

1. AN INDEX SET  $\{1, 2, \dots, M\}$
2. AN ENCODING FUNCTION  $x: \{1, 2, \dots, M\} \rightarrow \mathbb{R}^n$

YIELDING CODEWORDS:  $x^N(1), x^N(2), \dots, x^N(M)$ , SATISFYING THE POWER CONSTRAINT  $P$ ; THAT IS, FOR EVERY CODEWORD:

$$\sum_{i=1}^N x_i^2(w) \leq 4P$$

$$w = 1, 2, \dots, M$$

3. A DECODING FUNCTION

$$g: \mathcal{Y}^N \rightarrow \{1, 2, \dots, M\}$$

• THE ARITHMETIC AVERAGE OF PROBABILITY OF ERROR IS DEFINED AS:

$$P_e^{(N)} = \frac{1}{2^{NR}} \sum \lambda_i$$

$$\lambda_i = P_r(g(z^N) \neq i | x^N = x^N(i)) = \sum_{y^N} P(y^N | x^N(i)) \cdot I(g(z^N) \neq i)$$

i.e.  $I(g(y^N) \neq i)$

$$\lambda_i = P_v(g(z^N) \neq i | x^N = x^N(i)) = \sum_{y^N} P(y^N | x^N(i)) \cdot I(g(z^N) \neq i)$$

$$\lambda^{(N)} = \max_{i \in \{1, \dots, M\}} \lambda_i$$

$$P_e^{(N)} = \frac{1}{2^{NR}} \sum_{i=1}^M \lambda_i$$

DEFINITION A RATE "R" IS SAID TO BE ACHIEVABLE FOR GAUSSIAN CHANNEL WITH POWER CONSTRAINT P IF THERE EXISTS A SEQUENCE OF  $(2^{NR}, N)$  CODES WITH CODEWORDS SATISFYING THE POWER CONSTRAINT SUCH THAT THE MAXIMUM PROBABILITY OF ERROR  $P_e^{(N)}$  TENDS TO ZERO AS N GOES TO INFINITY. THE CAPACITY OF THE CHANNEL IS THE SUPERIOR OF THE ACHIEVABLE RATES.

THEOREM 9.1.1 THE CAPACITY OF A GAUSSIAN CHANNEL WITH POWER CONSTRAINT P AND NOISE VARIANCE N IS:

$$C = \frac{1}{2} \log \left( 1 + \frac{P}{N} \right)$$

BITS PER TRANSMISSION

PROOF (ACHIEVABILITY)

1. GENERATION OF THE CODEBOOK. WE WISH TO GENERATE CODEBOOK IN WHICH ALL THE CODEWORDS SATISFY THE POWER CONSTRAINT. TO ENSURE THIS, WE GENERATE THE CODEWORDS WITH EACH ELEMENT i.i.d. ACCORDING TO

A NORMAL DISTRIBUTION WITH VARIANCE  $P-E$ . SINCE FOR LARGE  $n = \frac{1}{4} \sum x_i^2 \rightarrow P-E$  THE PROBABILITY THAT CODEWORD DOESN'T SATISFY THE POWER CONSTRAINT IS VERY SMALL.

LET  $x_i(w)$   $i=1,2, \dots, n$   $w=1,2, \dots, 2^{4R}$  BE I.I.D  $N(0, P-E)$ , FORMING CODEWORDS  $x^1(1), x^1(2), \dots, x^1(2^{4R}) \in \mathbb{R}^n$ .

(2) ENCODING. AFTER GENERATION OF THE CODEBOOK THE CODEBOOK IS REVEALED TO BOTH SENDER AND RECEIVER. TO SEND THE MESSAGE INDEX  $w$ , THE TRANSMITTER SENDS THE  $w$ TH CODEWORD  $x^1(w)$  IN THE CODEBOOK.

(3) DECODING. THE RECEIVER LOOKS DOWN THE LIST OF CODEWORDS  $\{x^1(w)\}$  AND SEARCHES FOR ONE THAT IS JOINTLY TYPICAL WITH RECEIVED VECTOR. IF THERE IS ONE AND ONLY ONE SUCH CODEWORD  $x^1(w)$ , THE RECEIVER DECLARES  $\hat{w} = w$  TO BE THE TRANSMITTED CODEWORD. OTHERWISE THE RECEIVER DECLARES AN ERROR. THE RECEIVER ALSO DECLARES AN ERROR IF THE CHOSEN CODEWORD DOESN'T SATISFY THE POWER CONSTRAINT.

(4) WITHOUT LOSS OF GENERALITY ASSUME THAT CODEWORD  $1$  WAS SENT. THUS  $z^n = x^1(1) + z^n$ . DEFINE THE FOLLOWING EVENTS:

$$E_0 = \left\{ \frac{1}{4} \sum_{i=1}^n x_i^2 > P \right\} \quad \text{AND}$$

$$E_1 = \left\{ (x^1(1), z^n) \text{ IS IN } A_{\epsilon}^n \right\}$$

THEN AN ERROR OCCURS IF  $E_0$  OCCURS (THE POWER CONSTRAINT IS VIOLATED) OR  $E_1^c$  OCCURS (THE TRANSMITTED CODEWORD AND THE RECEIVED SEQUENCE ARE NOT JOINTLY TYPICAL) OR  $E_2 \cup E_3 \cup \dots \cup E_{2^{4R}}$  OCCURS (SOME WRONG CODEWORD IS JOINTLY TYPICAL WITH RECEIVED SEQUENCE). LET  $E^c$  DENOTE THE EVENT  $\hat{w} \neq w$  AND LET  $P$  DENOTE THE CONDITIONAL PROBABILITY GIVEN THAT  $w=1$ . HENCE,

$$P(E|w=1) = P(E) = P(E_0 \cup E_1^c \cup E_2 \cup E_3 \cup \dots \cup E_{2^{4R}}) \leq P(E_0) + P(E_1^c) + \sum_{i=2}^{2^{4R}} P(E_i)$$

- BY THE LAW OF LARGE NUMBERS

$$P(E_0) \rightarrow 0 \quad \text{AS } n \rightarrow \infty$$

-  $P(E_1^c) \rightarrow 0$  HENCE  $P(E) \leq \epsilon$  FOR SUFFICIENTLY LARGE  $n$

PROBABILITY THAT  $Z^*(i)$  AND  $Z^*$  ARE BOTH TYPICAL IS  $\leq 2^{-4(I(x;Z) - 3\epsilon)}$

- LET  $W$  BE UNIFORMELY DISTRIBUTED  $\{1, 2, \dots, 2^{4R}\}$

$$P_V(\mathcal{E}) = \frac{1}{2^{4R}} \sum_{i=1}^4 \mathcal{E}_i = P_{\mathcal{E}}^{(4)}$$

$$P_{\mathcal{E}}^{(4)} = P_V(\mathcal{E}) = P_V(\mathcal{E} | W=1) \leq P(\mathcal{E}_0) + P(\mathcal{E}_1^c) + \sum_{i=2}^{2^{4R}} P(\mathcal{E}_i) \leq \epsilon + \epsilon + \sum_{i=2}^{2^{4R}} 2^{-4(I(x_i; Z) - 3\epsilon)} = 2\epsilon + \left(2^{4R} - 1\right) 2^{-4(I(x; Z) - 3\epsilon)}$$

$$\begin{aligned} &= 2\epsilon + 2^{4R-4} 2^{-4(I(x; Z) - 3\epsilon)} - 2^{-4(I(x; Z) - 3\epsilon)} \\ &= 2\epsilon + 2^{-4(I(x; Z) - 3\epsilon - 4R)} \\ &\leq 2\epsilon + 2^{4R} \cdot 2^{-4(I(x; Z) - 3\epsilon)} = 2\epsilon + 2^{34R - 4(I(x; Z) - R)} \leq 3\epsilon \end{aligned}$$

**PROOF**  $P_V((\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}) = \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} P(\tilde{x}^n, \tilde{z}^n) = \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} P(\tilde{x}^n) \cdot P(\tilde{z}^n) \geq \textcircled{A}$

$$\geq \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} 2^{-n(H(x) + \epsilon)} \cdot 2^{-n(H(z) + \epsilon)} \geq (\epsilon) 2^{-2n(H(x) + \epsilon) - 2n(H(z) + \epsilon)}$$

$$(|A_{\epsilon}^{(4)}| \geq (\epsilon) 2^{2n(H(x) + \epsilon) + 2n(H(z) + \epsilon)}) \implies |A_{\epsilon}^{(4)}| \leq 2^{2n(H(x) + \epsilon) + 2n(H(z) + \epsilon)}$$

$$\begin{aligned} & 2^{2n(H(x) + \epsilon) + 2n(H(z) + \epsilon)} = 2^{2n(H(x) + H(z) + 2\epsilon)} \\ & = 2^{2n(H(x; Z) - H(x) - H(z) + 2\epsilon)} = 2^{-4n(I(x; Z) - 3\epsilon)} \end{aligned}$$

$$1 = \sum_{(\tilde{x}^n, \tilde{z}^n)} P(\tilde{x}^n, \tilde{z}^n) \geq \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} P(\tilde{x}^n, \tilde{z}^n) \geq |A_{\epsilon}^{(4)}| \cdot 2^{-4n(I(x; Z) - 3\epsilon)}$$

$$|A_{\epsilon}^{(4)}| \leq 2^{4n(I(x; Z) - 3\epsilon)} \implies \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} P(\tilde{x}^n) \cdot P(\tilde{z}^n) \leq |A_{\epsilon}^{(4)}| 2^{-4n(I(x; Z) - 3\epsilon)} \leq \textcircled{B}$$

$$(1 - \epsilon) \leq \sum_{(\tilde{x}^n, \tilde{z}^n) \in A_{\epsilon}^{(4)}} P(\tilde{x}^n, \tilde{z}^n) \leq |A_{\epsilon}^{(4)}| \cdot 2^{-4n(I(x; Z) - 3\epsilon)} \implies |A_{\epsilon}^{(4)}| \geq (1 - \epsilon) 2^{4n(I(x; Z) - 3\epsilon)}$$

$$P_1((\tilde{x}_i, \tilde{z}_i) \in A_\epsilon^{(n)}) \leq 2^{-n(I(x; z) - 3\epsilon)} \leq 2^{-n(I(x; z) - 3\epsilon)}$$

$$(1-\epsilon) 2^{-n(I+3\epsilon)} \leq P_1((\tilde{x}_i, \tilde{z}_i) \in A_\epsilon^{(n)}) \leq 2^{-n(I(x; z) - 3\epsilon)}$$

$$2^{-n[3\epsilon - I(x; z) + R]} \leq 2^{-n[I(x; z) - 3\epsilon + R]}$$

$-I+3\epsilon+R \leq 0$   
 $I(x; z) - 3\epsilon \geq R$

**9.2 CONVERSE TO THE CODING THEOREM FOR GAUSSIAN CHANNELS**

IN THIS SECTION WE COMPLETE THE PROOF THAT CAPACITY OF A GAUSSIAN CHANNEL IS:  $C = \frac{1}{2} \log(1 + \frac{P}{N})$  BY PROVING THAT RATES  $R > C$  ARE NOT ACHIEVABLE. THE PROOF PARALLELS THE PROOF FOR DISCRETE CHANNELS. THE MAIN NEW INGREDIENT IS THE POWER CONSTRAINT.

$$R \leq C = \frac{1}{2} \log(1 + \frac{P}{N})$$

CONSIDER  $(2^{nR}, n)$  CODE THAT SATISFIES THE POWER CONSTRAINT:  $\frac{1}{n} \sum_{i=1}^n x_i^2(w) \leq P$   $w=1, 2, \dots, 2^{nR}$

$$x_i \rightarrow x_i^2(w) \rightarrow \sum_{i=1}^n x_i^2(w)$$

$$h(R) = 1 + P e^{nR} \cdot nR = n \cdot \epsilon_n$$

$$nR = h(w) = h(w|\tilde{w}) + I(w; \tilde{w}) \leq 1 + P e^{nR} \cdot nR + I(x_i; z_i)$$

$$= 1 + P e^{nR} \cdot nR + h(z_i) - h(z_i|x_i) \leq n \cdot \epsilon_n + \sum_{i=1}^n h(z_i) - h(z_i)$$

$$= n \cdot \epsilon_n + \sum_{i=1}^n h(z_i) - \sum_{i=1}^n h(z_i) = n \cdot \epsilon_n + \sum_{i=1}^n I(x_i; z_i)$$

NOW LET  $P_i$  BE THE AVERAGE POWER OF THE  $i$ -TH COLUMN OF THE CODEBOOK, THAT IS:

$$P_i = \frac{1}{2^{nR}} \sum_{w=1}^{2^{nR}} x_i^2(w)$$

$z_i = x_i + z_i$   
 $x_i$  &  $z_i$  ARE INDEPENDENT

$$E[y_i^2] = E[x_i^2] + E[z_i^2] = P_i + N$$

ENTROPY IS MAXIMIZED BY THE NOISEY PSEUDO.  
 DUTTON:  $\frac{1}{2} \log(2\pi e) \cdot (P_i + N)$

$$R \leq \sum (\log(x_i) - \log(z_i)) + \eta \epsilon_n \leq \sum \left( \frac{1}{2} \log(2\pi e(P_i + N)) - \frac{1}{2} \log(2\pi e N) \right) + \eta \epsilon_n = \sum \frac{1}{2} \log\left(1 + \frac{P_i}{N}\right) + \eta \epsilon_n \quad (*)$$

SINCE EACH OF THE CODEWORDS SATISFIES THE POWER CONSTRAINT, SO DOES THEIR AVERAGE, AND HENCE:

$$\frac{1}{2} \sum P_i \leq P$$

SINCE  $\frac{1}{2} \log(1+x)$  IS CONCAVE FUNCTION OF  $x$ , WE CAN APPLY JENSEN'S INEQUALITY TO OBTAIN:

$$\frac{1}{2} \sum \frac{1}{2} \log\left(1 + \frac{P_i}{N}\right) \leq \frac{1}{2} \log\left(1 + \frac{1}{2} \sum \frac{P_i}{N}\right) \leq f[E[x]]$$

$$\leq \frac{1}{2} \log\left(1 + \frac{P}{N}\right)$$

$$NR \leq \eta \cdot \frac{1}{2} \sum \frac{1}{2} \log\left(1 + \frac{P_i}{N}\right) + \eta \epsilon_n \quad R \leq \frac{1}{2} \sum \frac{1}{2} \log\left(1 + \frac{P_i}{N}\right) + \epsilon_n$$

$$R \leq \frac{1}{2} \log\left(1 + \frac{P}{N}\right) + \epsilon_n \quad \epsilon_n \rightarrow 0$$

**3.3 BANDLIMITED CHANNELS**

A COMMON MODEL FOR COMMUNICATION OVER A AUDIO NETWORK OR A TELEPHONE LINE IS A BANDLIMITED CHANNEL WITH WHITE NOISE.

$$x(t) = (x(t) + z(t)) * h(t)$$

- $x(t)$  - signal waveform
- $z(t)$  - is the waveform of white gaussian noise
- $h(t)$  - impulse response of ideal bandpass filter which cuts all frequencies greater than  $W$ .

**Theorem 3.3.1** SUPPOSE THAT A FUNCTION  $f(t)$  IS BANDLIMITED TO  $W$  HERTZ, THE SPECTRUM OF THIS FUNCTION IS 0 FOR ALL FREQUENCIES GREATER THAN  $W$ .

THEN THE FUNCTION IS COMPLETELY DETERMINED BY SAMPLES OF THE FUNCTION SPACED  $1/2W$  SECONDS APART.

PROOF:  $F(\omega) = \mathcal{F}\{f(t)\}$

$$f(t) = \frac{1}{2\pi} \int_{-\infty}^{\infty} F(\omega) e^{j\omega t} d\omega = \frac{1}{2\pi} \int_{-2W}^{2W} F(\omega) e^{j\omega t} d\omega$$

VALUES OF THE SIGNAL AT THE SAMPLE POINTS IS:

$$f\left(\frac{t}{2W}\right) = \frac{1}{2\pi} \int_{-2W}^{2W} F(\omega) e^{j\omega \frac{t}{2W}} d\omega$$

$$\text{sinc}(t) = \frac{\sin(2Wt)}{2Wt}$$

THE SPECTRUM OF THIS FUNCTION IS CONSTANT IN THE BAND  $(-W, W)$  AND 0 OUTSIDE.

$$g(t) = \sum_{n=-\infty}^{\infty} f\left(\frac{t}{2W}\right) \text{sinc}\left(t - \frac{t}{2W}\right) \quad g(t) = f(t)$$

$g(t)$  REPRESENTS  $f(t)$  IN TERMS OF ITS SAMPLES.

A GENERAL FUNCTION HAS AN INFINITE NUMBER OF DEGREES OF FREEDOM - THE VALUE OF THE FUNCTION AT EVERY POINT CAN BE CHOSEN INDEPENDENTLY.

THE NYQUIST-SHANNON SAMPLING THEORY SHOWS THAT BANDLIMITED FUNCTION HAS ONLY  $2W$  DEGREES OF FREEDOM PER SECOND.

$$f(t) = \sum_{n=-\infty}^{\infty} C_n e^{+jn\omega_0 t} \quad C_n = \int f(t) e^{-jn\omega_0 t} dt$$

$$f(t) = \sum_{n=-\infty}^{\infty} a_n \cos(\omega_0 n t) + b_n \sin(\omega_0 n t)$$

THERE ARE ABOUT  $2W$  ORTHONORMAL BASIS FUNCTIONS FOR THE SET OF ALMOST TIME-LIMITED, ALMOST BANDLIMITED FUNCTIONS, AND WE CAN DESCRIBE ANY FUNCTION WITHIN THE SET BY ITS COORDINATES IN THIS BASIS.

MOOREOVER THE PROJECTION OF WHITE NOISE ON THIS BASIS VECTORS FORMS AN I.I.D. GAUSSIAN PROCESS. THE ABOVE ARGUMENTS ENABLE US TO VIEW THE BANDLIMITED TIME LIMITED FUNCTIONS AS VECTORS IN VECTOR SPACE OF  $2W$  DIMENSIONS.

ASSUMING THAT CHANNEL HAS BANDWIDTH  $W$ , WE CAN REPRESENT BOTH THE INPUT AND THE OUTPUT BY SAMPLES TAKEN  $1/2W$  SECONDS APART. EACH OF THE INPUT SAMPLES

IS CORRELATED BY NOISE TO PRODUCE THE CORRESPONDING OUTPUT SAMPLE. SINCE THE NOISE IS WHITE AND GAUSSIAN, IT CAN BE SHOWN THAT EACH NOISE SAMPLE IS AN INDEPENDENT, IDENTICALLY DISTRIBUTED GAUSSIAN RANDOM VARIABLE.

IF THE NOISE HAS POWER SPECTRAL DENSITY  $\frac{N_0}{2}$  W/Hz AND THE BANDWIDTH OF  $W$  Hz, THE NOISE HAS POWER

$$\frac{N_0}{2} \cdot 2W = N_0 \cdot W$$

✓ SOME OF THESE POWER SHOULD BE USED TO SAMPLE THE VALUE OF SIGNAL (NO SIGNAL SHOULD BE USED)

EACH OF THE  $2W$  NOISE SAMPLES IN TIME  $T$  HAS VARIANCE  $\frac{N_0 W T}{2 W T} = \frac{N_0}{2}$

LOOKING AT THE INPUT AS A VECTOR IN THE  $2W$ -DIMENSIONAL SPACE WE SEE THAT THE RECEIVED SIGNAL IS SPHERICALLY NORMALLY DISTRIBUTED ABOUT THIS POINT WITH COVARIANCE  $\frac{N_0}{2} \mathbf{I}$ .

- CAPACITY OF DISCRETE GAUSSIAN CHANNEL IS:

$$C = \frac{1}{2} \log_2 \left( 1 + \frac{P}{N} \right)$$

- LET THE CHANNEL BE USED OVER THE INTERVAL:  $[0, T]$

THE ENERGY PER SAMPLE IS  $\frac{P T}{2 W T} = \frac{P}{2 W}$

- NOISE VARIANCE PER SAMPLE IS:

$$\frac{N_0}{2} \cdot 2W \cdot \frac{T}{2 W T} = \frac{N_0}{2}$$

HENCE THE CAPACITY PER SAMPLE IS:

$$C = \frac{1}{2} \log_2 \left( 1 + \frac{\frac{P}{2W}}{\frac{N_0}{2}} \right) = \frac{1}{2} \log_2 \left( 1 + \frac{P}{N_0 \cdot W} \right)$$

Bits per sample

SINCE THERE ARE  $2W$  SAMPLES EACH SECOND THE CAPACITY OF THE CHANNEL IS:

$$C = W \log_2 \left( 1 + \frac{P}{N_0 \cdot W} \right) \text{ BITS PER SECOND}$$

MMV

CAPACITY OF A BANDLIMITED GAUSSIAN CHANNEL WITH NOISE SPECTRAL DENSITY  $N_0/2$  WATTS/Hz AND POWER  $P$  WATTS.

$$C \approx \lim_{W \rightarrow \infty} \frac{\log_2 \left( 1 + \frac{P}{N_0 \cdot W} \right)}{\frac{1}{W}} = \lim_{W \rightarrow \infty} \frac{1}{\ln 2} \cdot \frac{1}{1 + \frac{P}{N_0 \cdot W}} \cdot \frac{P}{N_0 \cdot W^2} = \frac{P}{N_0} \cdot \frac{1}{\ln 2}$$

$$C = \frac{P}{N_0} \cdot \frac{\ln e}{\ln 2}$$

$$C = \frac{P}{N_0} \cdot \ln e$$

ОТКАЗ БА КАНАЛИ СО БЕШКОДЕЧЕН ОПСЕГ, КАКОВОТО ЛАЗЕ ЧИСТАТО СО МОЃНОСТА НА КАНАЛОТ.



**EXAMPLE 9.3.1** (TELEPHONE LINE) TO ALLOW MULTIPLEXING OF MANY CHANNELS, TELEPHONE SIGNALS ARE BANDLIMITED TO 3300 Hz. USING A BANDWIDTH OF 3300 Hz AND SNR OF 33 dB (i.e.  $P/N_{0W} = 2000$ )

$$10 \log \frac{P}{N_{0W}} = 33 \quad \left[ \frac{P}{N_{0W}} = 10^{3.3} = 1995 \right]$$

$$N_0(\text{Hz}) = \frac{W_{\text{Hz}}}{\text{Hz}}$$

WE FIND THE CAPACITY OF THE CHANNEL TO BE:

$$C = 3300 \log(1 + 1995) = 36,178,00 \text{ bits/sec}$$

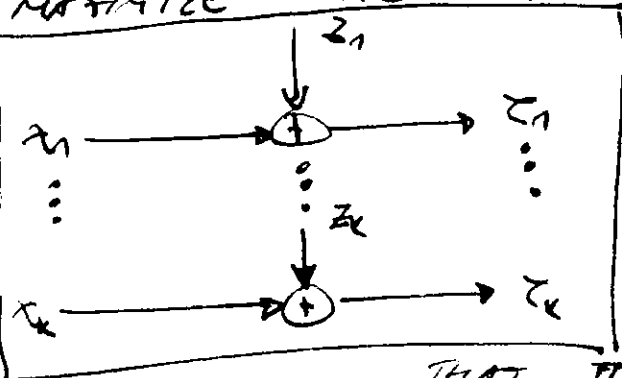
IN REAL TELEPHONE CHANNELS, THERE ARE OTHER FACTORS, SUCH AS CROSSTALK, INTERFERENCE, ECHOES AND NOISE CHANNELS WHICH MUST BE COMPENSATED FOR TO ACHIEVE THIS CAPACITY.

V90 MODEMS ACHIEVE 56 kbps (> 36 kbps) OVER TELEPHONE CHANNEL, ACHIEVE THIS RATE IN ONE DIRECTION TAKING ADVANTAGE OF PURELY DIGITAL CHANNEL FROM THE SERVER TO THE TELEPHONE SWITCH IN THE NETWORK.

$$\frac{15}{12} = \frac{24}{27}$$

**9.4 PARALLEL GAUSSIAN CHANNELS**

IN THIS SECTION WE CONSIDER  $k$  INDEPENDENT GAUSSIAN CHANNELS IN PARALLEL WITH A COMMON POWER CONSTRAINT. THE OBJECTIVE IS TO DISTRIBUTE THE TOTAL POWER AMONG THE CHANNELS SO AS TO MAXIMIZE THE CAPACITY.



THE OUTPUT OF EACH IS SUM OF THE INPUT AND THE GAUSSIAN NOISE. FOR CHANNEL  $j = 1, 2, \dots, k$ :

$$y_j = x_j + z_j \quad j = 1, 2, \dots, k$$

$$z_j \sim \mathcal{N}(0, N_j)$$

AND THE NOISE IS ASSUMED TO BE INDEPENDENT FROM CHANNEL TO CHANNEL.

WE ASSUME THAT THERE IS A COMMON POWER CONSTRAINT USED I.E.:

$$E \left[ \sum_{j=1}^k x_j^2 \right] \leq P$$

WE WISH TO DISTRIBUTE THE POWER AMONG THE VARIOUS CHANNELS SO AS TO MAXIMIZE THE TOTAL CAPACITY.

$$C = \max_{\{x_1, x_2, \dots, x_k\} : \sum E[x_j^2] \leq P} I(x_1, x_2, \dots, x_k; y_1, y_2, \dots, y_k)$$

$$I(x_1^n; y_1^n) = h(y_1^n) - h(y_1^n | x_1^n) \leq \sum_{i=1}^n h(y_i) - h(z_i)$$

$$= \sum_{i=1}^k \ell(\tau_i) - \sum_{i=1}^k \ell(\bar{z}_i) = \sum_{i=1}^k I(x_i; \tau_i) \leq \sum_{i=1}^k \frac{1}{2} \ell\left(1 + \frac{P_i}{N_i}\right)$$

$$P_i = E[x_i^2] \quad P = \sum_{i=1}^k P_i$$

$$(x_i^n) \sim N\left(0, \begin{bmatrix} P_1 & 0 & 0 & \dots & 0 \\ 0 & P_2 & 0 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & P_k \end{bmatrix}\right)$$

$$\sum_{i=1}^k \frac{1}{2} \ell\left(1 + \frac{P_i}{N_i}\right)$$

SO THE PROBLEM IS REDUCED TO FINDING THE POWER ALLOCATION THAT MAXIMIZES THE CAPACITY SUBJECT TO CONSTRAINT THAT  $\sum P_i = P$ .

$$J(p_1, p_2, \dots, p_k) = \sum_{i=1}^k \frac{1}{2} \ell\left(1 + \frac{P_i}{N_i}\right) + \lambda \left(\sum_{i=1}^k P_i - P\right)$$

$$\frac{\partial J}{\partial P_i} = 0 \quad \left(\frac{1}{\ln 2}\right) \cdot \frac{1}{2} \cdot \frac{1}{1 + \frac{P_i}{N_i}} \cdot \frac{1}{N_i} + \lambda = 0$$

$$\frac{1}{2} \cdot \frac{1}{N_i + P_i} + \lambda = 0 \quad (KKT)$$

$$2(N_i + P_i) = -\frac{1}{\lambda}$$

$$\boxed{P_i = -\frac{1}{2\lambda} - N_i = \nu - N_i}$$

$P_i$  MUST BE POSITIVE (NONNEGATIVE)  $\rightarrow$  KKT-TUCKER CONDITIONS  $\Rightarrow$

$$\sum (\nu - N_i)^+ = P$$

$$(x)^+ = \begin{cases} x & \text{if } x \geq 0 \\ 0 & \text{if } x < 0 \end{cases}$$

$\nu \in \text{CONSTANT}$   $\rightarrow$   $\nu$  Ε ΚΩΝΣΤΑΝΤΗ  $\rightarrow$  ΣΥΝΕΠΙΣΤΑΣΗ ΚΑΙ ΕΙΣΑΓΩΓΗ ΤΗΣ ΚΑΤΑΝΟΜΗΣ ΤΗΣ ΙΣΧΥΟΣ ΣΤΑ ΚΑΝΑΛΙΑ. ΟΤΑ  $\nu - N_i \geq 0$  Τ.Ε. ΑΝΟ  $N_i \downarrow P_i \uparrow$  Ι ΟΥΣΙΑΣΤΕΡΗ ΑΠΟΡΟΠΙΑ.

**9.5 CHANNELS WITH COLORED GAUSSIAN NOISE**

IN 9.4. WE CONSIDERED A SET OF PARALLEL INDEPENDENT GAUSSIAN CHANNELS IN WHICH THE NOISE SAMPLES FROM DIFFERENT CHANNEL WERE INDEPENDENT. NOW WE WILL CONSIDER THE CASE WHERE THE NOISE IS DEPENDENT. FOR CHANNELS WITH MEMORY WE CAN CONSIDER A BLOCK OF  $n$  CONSECUTIVE USES OF THE CHANNEL AS  $n$  CHANNELS IN PARALLEL WITH DEPENDENT NOISE.

LET  $K_z$  BE THE COVARIANCE MATRIX OF THE NOISE, AND LET  $K_x$  BE THE INPUT COVARIANCE MATRIX.

TRACE =  
(SUM OF  
THE DIAGONALS)

THE POWER CONSTRAINT ON THE INPUT CAN THEN BE WRITTEN AS:

$$\frac{1}{4} \sum_i s x_i^2 \leq P \quad \text{OR EQUIVALENTLY: } \frac{1}{4} \text{tr}(K_x) \leq P$$

UNLIKE SECTION 9.4 THE POWER CONSTRAINT HERE DEPENDS ON "M"; THE CAPACITY WILL HAVE TO BE CALCULATED FOR EACH "M".

$$I(x_1^n; z_1^n) = h(z_1^n) - h(z_1^n)$$

$h(z_1^n)$  IS DETERMINED ONLY BY THE DISTRIBUTION OF THE NOISE AND IS NOT DEPENDENT ON THE CHOICE OF THE INPUT DISTRIBUTION. SO FINDING CAPACITY AMOUNTS TO

MAXIMIZING  $h(z_1, z_2, \dots, z_n)$ . THE ENTROPY OF THE OUTPUT IS MAXIMIZED WHEN  $z$  IS NORMAL, WHICH IS ACHIEVED WHEN INPUT IS NORMAL. SINCE THE INPUT AND NOISE ARE INDEPENDENT THE COVARIANCE OF THE OUTPUT IS:  $K_z = K_x + K_z$  AND:

$$h(z_1^n) = \frac{1}{2} \log \left( (2\pi e)^n |K_x + K_z| \right)$$

NOW THE PROBLEM IS REDUCED TO CHOOSING  $K_x$  SO AS TO MAXIMIZE  $|K_x + K_z|$ , SUBJECT TO A TRACE CONSTRAINT ON  $K_x$ . TO DO THIS, WE DECOMPOSE  $K_z$  INTO DIAGONAL FORM,

$$K_z = Q \Lambda Q^T \quad \text{WHERE } Q Q^T = I$$

$$\begin{aligned} |K_x + K_z| &= |K_x + Q \Lambda Q^T| = |Q (Q^T K_x Q + \Lambda) Q^T| = \\ &= |Q| \cdot |Q^T K_x Q + \Lambda| \cdot |Q^T| = |A + \Lambda| \end{aligned}$$

(MMV)

• DISTRIBUTIVEN COMMON WHEN EA DETERMINANTS

$$|AB| = |A| \cdot |B| \quad |I| = |A A^{-1}| = |A| \cdot |A^{-1}| = 1$$

$$A = Q^T K_x Q$$

• THE MATRICES IN THE TRACE OF THE PRODUCT CAN BE SWITCHED:  $\text{tr}(BC) = \text{tr}(CB)$

$$\text{tr}(A) = \text{tr} \left( \underbrace{Q^T}_{b} K_x \underbrace{Q}_c \right) = \text{tr} \left( \underbrace{Q Q^T}_{b} K_x \right) = \text{tr}(K_x)$$

NOW THE PROBLEM IS REDUCED TO MAXIMIZING  $|A|$  SUBJECT TO TRACE CONSTRAINT:  $\text{tr}(A) \leq 4P$ .

HADAMARD'S INEQUALITY STATES THAT THE DETERMINANT OF ANY POSITIVE DEFINITIVE MATRIX  $K$  IS LESS THAN THE PRODUCT OF ITS DIAGONAL ELEMENTS, THAT IS:

$$|K| \leq \prod_i K_{ii}$$

WITH EQUALITY IF THE MATRIX IS DIAGONAL.

$$|A + \Lambda| \leq \prod_i (A_{ii} + \lambda_i) \quad \frac{1}{n} \sum_i A_{ii} \leq \eta$$

MAXIMUM VALUE OF  $\prod_i (A_{ii} + \lambda_i)$  IS ATTAINED WHEN

$$A_{ii} + \lambda_i = \nu$$

• KNOWN-TUCKER CONDITIONS

$$A_{ii} = (\nu - \lambda_i)^+$$

WHERE WATER LEVEL  $\nu$  IS CHOSEN SO THAT  $\sum_i A_{ii} = nP$

- FOR CHANNELS IN WHICH NOISE FOLLOWS A STATIONARY STOCHASTIC PROCESS, THE INPUT SIGNAL SHOULD BE CHOSEN TO BE GAUSSIAN PROCESS WITH SPECTRUM THAT IS LARGE AT FREQUENCIES WHERE THE NOISE SPECTRUM IS SMALL.

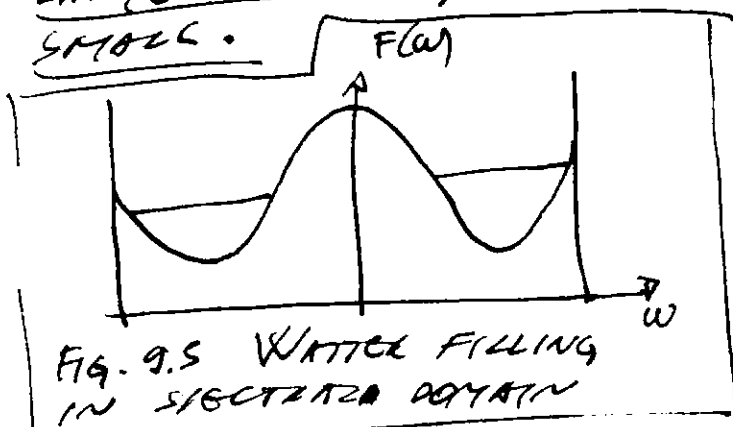


FIG. 9.5 WATER FILLING IN SPECTRAL DOMAIN

THE CAPACITY OF AN ADDITIVE GAUSSIAN NOISE CHANNEL WITH POWER SPECTRUM  $N(f)$  IS:

$$C = \int_{-\pi}^{\pi} \frac{1}{2} \log \left( 1 + \frac{(\nu - N(f))^+}{N(f)} \right) df$$

WHERE  $\nu$  IS CHOSEN SO THAT:  $\int (\nu - N(f))^+ df = P$

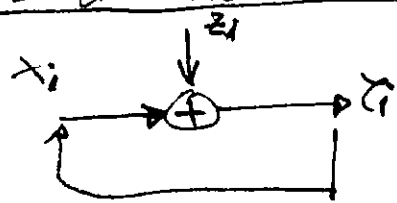
### 9.6 GAUSSIAN CHANNELS WITH FEEDBACKS

FOR CHANNELS WITH MEMORY, WHERE THE NOISE IS COLLECTED FROM TIME INSTANT TO TIME INSTANT, FEEDBACK DOES INCREASE CAPACITY.

$$H(f(x), x) = H(x) + \underbrace{H(f(x)|x)}_0 = H(x) = H(x|f(x))$$

$$H(x) \geq H(f(x))$$

IN THIS SECTION WE DESCRIBE AN EXPRESSION FOR THE CAPACITY OF THE CHANNEL WITH FEEDBACK IN TERMS OF THE COVARIANCE MATRIX OF THE NOISE  $Z_i$ . WE PROVE A CONVERSE FOR THIS EXPRESSION FOR CAPACITY. WE THEN DERIVE A SIMPLE FORM ON THE INCREASE IN CAPACITY DUE TO FEEDBACK.



THE OUTPUT OF THE CHANNEL  $Z_i$  IS:

$$Z_i = \lambda x_i + Z_i \quad Z_i \sim N(0, K_z^{(i)})$$

THE FEEDBACK ALLOWS THE INPUT OF THE CHANNEL TO DEPEND ON THE PAST VALUES OF THE OUTPUT.

A  $(2^M, M)$  CODE FOR GAUSSIAN CHANNEL WITH FEEDBACK CONSIST OF A SEQUENCE OF MAPPINGS  $x_i(w, z^{i-1})$  WHERE  $w \in \{1, 2, \dots, 2^M\}$  IS THE INPUT MESSAGE AND  $z^{i-1}$  IS SEQUENCE OF PAST VALUES OF THE OUTPUT. THUS  $x_i(w, \cdot)$  IS A CODE FUNCTION RATHER THAN A CODEWORD. IN ADDITION:

$$E \left[ \frac{1}{M} \sum_{i=1}^M x_i^2(w, z^{i-1}) \right] \leq P \quad w \in \{1, 2, \dots, 2^M\}$$

EXPECTATION IS OVER ALL POSSIBLE NOISE SEQUENCES. BECAUSE OF THE FEEDBACK  $z^i$  AND  $z^{i+1}$  ARE NOT INDEPENDENT.  $x_i$  DEPENDS CAUSALLY ON THE PAST VALUES OF  $Z$ .

1.) WITH FEEDBACK. THE CAPACITY  $C_{M, FB}$  IN BITS PER TRANSMISSION OF THE TIME-VARYING GAUSSIAN CHANNEL WITH FEEDBACK IS:

$$C_{M, FB} = \max_{\substack{K_x^{(M)} \\ K_z^{(M)} \leq P}} \frac{1}{2M} \log \frac{|K_{x+z}^{(M)}|}{|K_z^{(M)}|} \quad (1)$$

WHERE MAXIMIZATION IS TAKEN OVER ALL DC  $z^M$  OF THE FORM

$$x_i = \sum_{j=1}^{i-1} b_{ij} z_j + v_i \quad i=1, 2, \dots, M \quad (2)$$

AND  $v_M$  IS INDEPENDENT OF  $z_M$ . RECASTING (1) & (2) USING  $\underline{x} = BZ + V$  AND  $z = z + z$  WE CAN WRITE:

$$C_{M, FB} = \max \frac{1}{2M} \log \frac{|(B+I)K_z^{(M)}(B+I)^t + K_v|}{|K_z^{(M)}|} \quad (3)$$

WHERE MAXIMUM IS TAKEN OVER ALL NONNEGATIVE DEFINITE  $K_v$  AND STRICTLY TRIANGULAR  $B$  SUCH THAT:

$$\text{tr}(BK_z^{(M)}B^t + K_v) \leq M P \quad (4)$$

NOTE THAT  $B=0$  IF FEEDBACK IS NOT ALLOWED.

(2) WITHOUT FEEDBACK. THE CAPACITY  $C_M$  OF THE TIME-VARYING GAUSSIAN CHANNEL WITHOUT FEEDBACK IS GIVEN BY:

$$C_M = \max_{\substack{K_x^{(M)} \\ K_z^{(M)} \leq P}} \frac{1}{2M} \log \frac{|K_x^{(M)} + K_z^{(M)}|}{|K_z^{(M)}|} \quad (5)$$

THIS REDUCES TO WATER-FILLING ON THE EIGENVALUES:

$\{\lambda_i^{(M)}\}$  OF  $K_z^{(M)}$ :  $C_M = \frac{1}{2M} \sum_{i=1}^M \log \left( 1 + \frac{(\lambda - \lambda_i^{(M)})^+}{\lambda_i^{(M)}} \right) \quad (6)$

where  $(\gamma)^+ = \max\{\gamma, 0\}$  AND WHERE  $\lambda$  IS CHOSEN:

$$\sum_{i=1}^n (\lambda - \lambda_i(\gamma))^+ = nP$$

• WE NOW HAVE AN UPPER BOUND FOR THE CAPACITY OF THE GAUSSIAN CHANNEL WITH FEEDBACK.

**THEOREM 9.6.1** FOR A GAUSSIAN CHANNEL WITH FEEDBACK, THE RATE  $R_n$  FOR ANY SEQUENCE  $(2^{nR_n}, n)$  CODES WITH  $P_e^{(n)} \rightarrow 0$  SATISFIES:  $R_n \leq C_{n,FB} + \epsilon_n$

WITH  $\epsilon_n \rightarrow 0$  AS  $n \rightarrow \infty$ , WHERE  $C_{n,FB}$  IS (1).

PROOF: LET  $W$  BE UNIFORM OVER  $\mathbb{Z}^{nR}$  AND THEREFORE THE PROBABILITY OF ERROR  $P_e^{(n)}$  IS BOUNDED BY FANO'S INEQUALITY

$$H(W|\hat{W}) \leq 1 + nR_n P_e^{(n)} = n\epsilon_n \quad \forall n$$

$\epsilon_n \rightarrow 0$  AS  $P_e^{(n)} \rightarrow 0$

WE CAN THEN BOUND THE RATE AS FOLLOWS:

$$\begin{aligned} P(x_1, x_2, \dots, x_n) &= P(x_1) \cdot P(x_2|x_1) \cdot P(x_3|x_1, x_2) \dots P(x_n|x_1, \dots, x_{n-1}) \\ nR_n = H(W) &= I(W; \hat{W}) + H(W|\hat{W}) \leq I(W; \hat{W}) + n\epsilon_n \leq \\ &\leq I(W; Z^n) + n\epsilon_n = \sum I(W; Z_i | Z_1^{i-1}) + n\epsilon_n = \\ &= \sum h(Z_i | Z_1^{i-1}) - h(Z_i | Z_1^{i-1}, W) + n\epsilon_n = \\ &= \sum h(Z_i | Z_1^{i-1}) - h(Z_i | Z_1^{i-1}, W, x_1, \dots, x_{i-1}, Z_1^{i-1}) + n\epsilon_n \\ & \quad |x_i = f(Z_1^{i-1}, W) \quad Z_i^{i-1} = Z_1^{i-1} - x_1^{i-1} \\ &= \sum [h(Z_i | Z_1^{i-1}) - h(Z_i | Z_1^{i-1})] + n\epsilon_n = h(Z) - h(Z) + n\epsilon_n \\ R_n &\leq \frac{1}{n} [h(Z) - h(Z)] + \epsilon_n \leq \frac{1}{2n} \left[ \log \frac{|K_Z|}{|K_Z|} - \log \frac{|K_Z|}{|K_Z|} \right] \end{aligned}$$

$$R_n \leq \frac{1}{2n} \log \frac{|K_Z|}{|K_Z|} + \epsilon_n$$

$$R_n \leq C_{n,FB} + \epsilon_n$$

WE HAVE PROVED AN UPPER BOUND ON THE CAPACITY OF THE GAUSSIAN CHANNEL WITH FEEDBACK IN TERMS OF COVARIANCE MATRIX:  $K_{X+Z}$ . WE NOW DERIVE BOUNDS ON THE CAPACITY WITH FEEDBACK IN TERMS OF  $K_X^{(n)}$  AND  $K_Z^{(n)}$ , WHICH WILL THEN BE USED TO DERIVE BOUNDS IN TERMS OF THE CAPACITY WITHOUT FEEDBACK.

**LEMMA 9.6.1** Let  $X$  and  $Z$  be 4-DIMENSIONAL RANDOM VECTORS. THEN:

$$\boxed{K_{X+Z} + K_{X-Z} = 2K_X + 2K_Z} \quad \star$$

**PROOF:**  $K_{X+Z} = E[(X+Z)(X+Z)^T] = E[X \cdot X^T + XZ^T + ZX^T + ZZ^T]$   
 $= K_X + K_{XZ} + K_{ZX} + K_Z$

$$K_{X-Z} = E[(X-Z)(X-Z)^T] = E[X \cdot X^T] - E[XZ^T] - E[ZX^T] + E[ZZ^T]$$

$$= K_X - K_{XZ} - K_{ZX} + K_Z$$

$$K_{X+Z} + K_{X-Z} = K_X + K_{XZ} + K_{ZX} + K_Z + K_X - K_{XZ} - K_{ZX} + K_Z$$

$$= 2K_X + 2K_Z$$

**LEMMA 9.6.2** For two  $n \times n$  NONNEGATIVE DEFINITE MATRICES  $A$  &  $B$ , IF  $A-B$  IS NONNEGATIVE DEFINITE, THEN:  $|A| \geq |B|$

**PROOF:**  $C = A - B$   $B, C$  - NONNEGATIVE DEFINITE HENCE WE CAN CONSIDER THEM AS COVARIANCE MATRICES.

$$x_1 \sim N(0, B) \quad ; \quad x_2 \sim N(0, C) \quad \text{LET } z = x_1 + x_2$$

$$f(z) = f(z|x_2) = f(x_1|x_2) = f(x_1) \quad \text{SINCE } x_1 \text{ \& } x_2 \text{ ARE INDEPENDENT}$$

$$\frac{1}{2} \text{Vol}(2\pi e)^{-n} |K_z| \geq \frac{1}{2} \text{Vol}(2\pi e)^{-n} |K_{x_1}| \quad \text{Vol}(2\pi e)^{-n} |A| \geq \text{Vol}(2\pi e)^{-n} |B|$$

$$\Rightarrow |A| \geq |B|$$

**LEMMA 9.6.3** For two  $n$ -DIMENSIONAL VECTORS  $X$  &  $Z$ ,

$$\boxed{|K_{X+Z}| \leq 2^n |K_X + K_Z|}$$

**PROOF:**  $2(K_X + K_Z) - K_{X+Z} = K_{X-Z} \geq 0$

$$\} \quad \boxed{A - B \geq 0}$$

WHERE " $\geq$ " MEANS  $A \geq 0$   $A$  IS NONNEGATIVE DEFINITE  
 HENCE" APPLYING LEMMA 9.6.2! WE HAVE:

$$|K_{X+Z}| \leq |2(K_X + K_Z)| = 2^n |K_X + K_Z|$$

FROM PROPERTIES OF DETERMINANTS

$$|C \cdot A| = |C \cdot I \cdot A| = |C \cdot I| \cdot |A| = C^n \cdot |A| \quad \} \quad \text{IF } A \text{ IS } n \times n \text{ MATRIX}$$

**LEMMA 9.6.4** For  $A, B$  NONNEGATIVE DEFINITE MATRICES AND  $\lambda \in [0, 1]$

$$\boxed{|\lambda A + (1-\lambda)B| \geq |A|^\lambda |B|^{1-\lambda}}$$

PROOF: LET  $X \sim N(0, A)$  AND  $Y \sim N(0, B)$ . LET  $Z$  BE THE MIXTURE RANDOM VECTOR:

$$Z = \begin{cases} X & \text{if } \theta = 1 \\ Y & \text{if } \theta = 2 \end{cases} \quad \text{WHERE } \theta = \begin{cases} 1 & \text{with } P = \lambda \\ 2 & \text{with } P = 1 - \lambda \end{cases}$$

LET  $X, Y$  AND  $\theta$  BE INDEPENDENT

$$K_Z = \lambda A + (1 - \lambda) B$$

$$h(z|\theta) = P(\theta=1) \cdot h(z|\theta=1) + P(\theta=2) \cdot h(z|\theta=2) = \lambda \cdot h(x) + (1 - \lambda) h(y)$$

$$|K_Z| \geq |A|^\lambda \cdot |B|^{1-\lambda}$$

~~$$h(z) = h(\lambda) + \lambda h(x) + (1 - \lambda) h(y)$$~~

$$h(z, \theta) = h(\theta) + h(z|\theta) = h(\theta) + h(z|\theta)$$

$$h(z) = h(\lambda) + \lambda h(x) + (1 - \lambda) h(y) \quad | \quad h(z) \geq h(z|\theta)$$

$$E[Z] = E[E[Z|\theta]] = \sum_{\theta} P(\theta) E[Z|\theta] = \lambda \cdot E[Z|\theta=1] + (1 - \lambda) E[Z|\theta=2] = \lambda \cdot E[X] + (1 - \lambda) E[Y]$$

ANALOGOUS FOR VARIANCES MOMENTS:

$$K_Z = E[Z^2] = E[E[Z^2|\theta]] = \sum_{\theta} P(\theta) E[Z^2|\theta] = \lambda E[X^2] + (1 - \lambda) E[Y^2] = \lambda K_X + (1 - \lambda) K_Y$$

$$K_Z = \lambda K_X + (1 - \lambda) K_Y \quad \text{---} \quad |K_Z| \geq |A|^\lambda |B|^{1-\lambda} \Rightarrow$$

$$|\lambda K_X + (1 - \lambda) K_Y| \geq |A|^\lambda |B|^{1-\lambda} \quad |\lambda A + (1 - \lambda) B| \geq |A|^\lambda |B|^{1-\lambda}$$

- case 1:  $\frac{1}{2} \int \dots$

$$\frac{1}{2} \int \dots \geq \frac{1}{2} \int \dots = \lambda h(x) + (1 - \lambda) h(y) = \lambda \int \dots + (1 - \lambda) \int \dots = \int \dots = \frac{1}{2} \int \dots \Rightarrow |\lambda A + (1 - \lambda) B| \geq |A|^\lambda |B|^{1-\lambda}$$



DEFINITION: We say that a random vector  $Z^n$  is CAUSALY RELATED TO  $X^n$  IF:

$$f(x^n, z^n) = f(z^n) \prod_{i=1}^n f(x_i | x^{i-1}, z^{i-1}) \quad (1)$$

$$f(x^2, z^2) = f(z_1^2) \cdot f(x_1) \cdot f(x_2 | x_1, z_1) = f(z_1, z_2) f(x_1) f(x_2 | z_1, x_1)$$

$$f(x_1, x_2 | z_1) (?) \quad f(x_1, x_2 | z_1) = f(x_1 | z_1) f(x_2 | x_1, z_1)$$

$$f(x^3, z^3) = f(z_1^3) f(x_1) f(x_2 | x_1, z_1) \cdot f(x_3 | x_1^2, z_1^2)$$

LEMMA 9.6.5 IF  $Z^n$  AND  $X^n$  ARE CAUSALLY RELATED THEN:

$$h(X^n - Z^n) \geq h(Z^n)$$

$$|K_{X-Z}| \geq |K_Z|$$

WHERE  $K_{X-Z}$  AND  $K_Z$  ARE COVARIANCE MATRICES OF  $X^n - Z^n$  AND  $Z^n$  RESPECTIVELY.

PROOF:  $h(X^n - Z^n) \stackrel{(a)}{=} \sum_{i=1}^n h(x_i - z_i | x^{i-1} - z^{i-1}) \geq$

$$\stackrel{(b)}{\geq} \sum_{i=1}^n h(x_i - z_i | x^{i-1} - z^{i-1}, x_i) \stackrel{(c)}{=} \sum_{i=1}^n h(z_i | x^{i-1}, z^{i-1}, x_i) \stackrel{(d)}{=} \sum_{i=1}^n h(z_i | z^{i-1})$$

$$\stackrel{(e)}{=} h(Z^n)$$

$$f(x^{i-1}, z^{i-1}) = f(z^{i-1}) \cdot \prod_{j=1}^{i-1} f(x_j | x^{j-1}, z^{j-1})$$

$$f(x^{i-1}, x_i, z^{i-1}) = f(x_i, z^{i-1}) = f(z^{i-1}) \cdot \prod_{j=1}^{i-1} f(x_j | x^{j-1}, z^{j-1})$$

~~(\*)~~  $\Rightarrow$  KAUZALNA FOLKAZDIKA X ZAVISI OD Z NO NE Z OD X (TAKA GO FOLKOVANJE (1))

$$\frac{1}{2} \log(2\pi e) |K_{X-Z}| \geq h(\tilde{Z}^n) = \frac{1}{2} \log(2\pi e) |K_Z| \Rightarrow$$

$$|K_{X-Z}| \geq |K_Z|$$

$$= h(\tilde{X}^n - \tilde{Z}^n)$$

$\tilde{X}^n, \tilde{Z}^n$  } MULTIVARIATE NORMAL (CAUSALLY RELATED)

WE ARE NOW IN POSITION TO PROVE THAT FEEDBACK INCREASES THE CAPACITY OF NONWHITE GAUSSIAN ADDITIVE NOISE CHANNEL BY AT MOST HALF A BIT.

**THEOREM 9.6.2**

$$C_{n,FB} \leq \max_{\text{tr}(K_x) \leq \gamma P} \frac{1}{2\pi} \log \frac{|K_x + K_z|}{|K_z|} \leq \max_{\text{tr}(K_x) \leq \gamma P} \left[ \frac{1}{2} + \frac{1}{2\pi} \log \frac{|K_x + K_z|}{|K_z|} \right] = \max_{\text{tr}(K_x) \leq \gamma P} \frac{1}{2\pi} \log \left( \frac{|K_x + K_z|}{|K_z|} + \frac{1}{2} \right)$$

$$= C_n + \frac{1}{2} \quad \boxed{C_{n,FB} \leq C_n + \frac{1}{2}} \quad \text{MLB 4.5 (5)}$$

- WE NOW MAKE PINSKER'S STATEMENT THAT FEEDBACK CAN AT MOST DOUBLE THE CAPACITY OF COLORED NOISE CHANNELS.

**THEOREM 9.6.3**

$C_{n,FB} \leq 2C_n$

IT IS ENOUGH TO SHOW THAT:

$$\frac{1}{2} \leq \frac{1}{2\pi} \log \frac{|K_x + K_z|}{|K_z|} \leq \frac{1}{2\pi} \log \frac{|K_x + K_z|}{|K_z|}$$

$$\Rightarrow \frac{1}{2} C_{n,FB} \leq C \quad \Rightarrow \quad \boxed{C_{n,FB} \leq 2C}$$

$$\frac{1}{2\pi} \log \frac{|K_x + K_z|}{|K_z|} \stackrel{(a)}{=} \frac{1}{2\pi} \log \left| \frac{\frac{1}{2} K_x + z + \frac{1}{2} K_x - z}{|K_z|} \right| \stackrel{(b)}{\geq} \frac{1}{2\pi} \log \left( \frac{|K_x + z|^{1/2} |K_x - z|^{1/2}}{|K_z|} \right) \stackrel{(c)}{\geq} \frac{1}{2\pi} \log \left( \frac{|K_x + z|^{1/2} |K_x - z|^{1/2}}{|K_z|^{1/2}} \right) = \frac{1}{2} \frac{1}{2\pi} \log \frac{|K_x + z|}{|K_z|}$$

PROVED

THUS, WE HAVE SHOWN THAT GAUSSIAN CHANNEL CAPACITY IS NOT INCREASED BY MORE THAN A HALF BIT OR BY MORE THAN A FACTOR 2 WHEN WE HAVE FEEDBACK. FEEDBACK HELPS BUT NOT MUCH.

**SUMMARY**

■ MAXIMUM ENTROPY

$$\max_{E\{X^2\} = \gamma} h(X) = \frac{1}{2} \log \left( \frac{2\pi\gamma}{e} \right)$$

■ GAUSSIAN CHANNEL

$Z_i = X_i + N_i$   $Z_i \sim N(0, N)$  POWER  
 CONSTRAINT:  $\frac{1}{\gamma} \sum_{i=1}^{\gamma} x_i^2 \leq P$   $C = \frac{1}{2} \log \left( 1 + \frac{P}{N} \right)$  bits/sec TRANSMISSION

- BANDLIMITED ADDITIVE WHITE GAUSSIAN NOISE CHANNEL  
BANDWIDTH  $W$ ; TWO-SIDED POWER SPECTRAL DENSITY  $N_0/2$ ; SIGNAL POWER  $P$ ; AND:

$$C = W \log \left( 1 + \frac{P}{N_0 W} \right) \quad \text{BITS PER SECOND}$$

- WATER-FILLING (K PARALLEL GAUSSIAN CHANNELS).

$$z_j = x_j + z_j, \quad j = 1, 2, \dots, k; \quad z_j \sim N(0, N_j); \quad \sum_{j=1}^k x_j^2 \leq P$$

$$C = \sum_{i=1}^k \frac{1}{2} \log \left( 1 + \frac{(\nu - N_i)^+}{N_i} \right)$$

WHERE  $\nu$  IS CHOSEN SO THAT:  $\sum (\nu - N_i)^+ = P$ .

- ADDITIVE NONWHITE GAUSSIAN NOISE CHANNEL.

$$z_i = x_i + z_i, \quad [z_i \sim N(0, K_z)]_i \quad \text{AND}$$

$$C = \frac{1}{n} \sum_{i=1}^n \frac{1}{2} \log \left( 1 + \frac{(\nu - \lambda_i)^+}{\lambda_i} \right)$$

WHERE  $\lambda_1, \lambda_2, \dots, \lambda_n$  ARE THE EIGENVALUES OF  $K_z$  AND  $\nu$  IS CHOSEN SO THAT  $\sum_i (\nu - \lambda_i)^+ = nP$

- CAPACITY WITHOUT FEEDBACK

$$C_n = \max_{\text{tr}(K_x) \leq nP} \frac{1}{2n} \log \frac{|K_x + K_z|}{|K_z|}$$

- CAPACITY WITH FEEDBACK

$$C_{n,FB} = \max_{\text{tr}(K_x) \leq nP} \frac{1}{2n} \log \frac{|K_x + z|}{|K_z|}$$

- FEEDBACK BOUNDS:

$$C_{n,FB} \leq C_n + \frac{1}{2} \quad C_{n,FB} \leq 2C_n$$

## PROBLEMS

### PROBLEM 9.1 CHANNEL WITH TWO INDEPENDENT LOOKS AT $\tau$ .

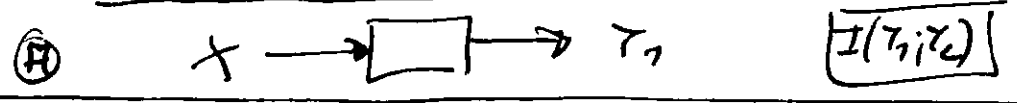
LET  $\zeta_1$  AND  $\zeta_2$  BE CONDITIONALLY INDEPENDENT AND CONDITIONALLY IDENTICALLY DISTRIBUTED GIVEN  $X$ .

(a) SHOW:  $I(X; \zeta_1, \zeta_2) = 2I(X; \zeta_1) - I(\zeta_1; \zeta_2)$

(e) CONCLUDE THAT CAPACITY OF THE CHANNEL:



↳ LESS THAN TWICE THE CAPACITY OF THE CHANNEL



(a)  $I(x, z_1, z_2) = I(x; z_1) + I(x; z_2 | z_1)$

$I(x; z_2 | z_1) = H(z_2 | z_1) - H(z_2 | z_1, x) = H(z_2 | z_1) - H(z_2 | x) =$   
 $= -H(z_2) + H(z_2 | z_1) + H(z_2) - H(z_2 | x) = I(x; z_2) - I(z_1; z_2)$   
 $- I(z_1; z_2)$

$I(x; z_1) = I(x; z_2)$

$z_1$  &  $z_2$  ARE IDENTICALLY DISTRIBUTED!

$H(z_1|x) = H(z_2|x)$   
 CONDITIONAL INVT. DIST.

(b)  $I(x, z_1, z_2) = I(x; z_1) + I(x; z_2) - I(z_1; z_2) = \underline{2I(x; z_1) - I(z_1; z_2)}$

③  $C_{\square} = \max_{p(x)} I(x; z_1)$

④  $C_{\Delta} = \max_{p(x)} I(x; z_1, z_2) = \max_{p(x)} [2I(x; z_1) - I(z_1; z_2)]$

$= \max_{p(x)} [2I(x; z_1)] - I(z_1; z_2) = 2 \max_{p(x)} I(x; z_1) - I(z_1; z_2)$

$C_{\Delta} = 2 C_{\square} - I(z_1; z_2)$        $2 C_{\square} = C_{\Delta} + I(z_1; z_2)$

$C_{\Delta} = \frac{1}{2} [C_{\Delta} + I(z_1; z_2)]$        $\Rightarrow 2 C_{\Delta} \geq C_{\Delta}$

PROVED  $C_{\Delta}$  IS LESS THAN TWICE THE CAPACITY OF  $C_{\square}$

• REVISITED (CONDITIONAL INDEPENDENT  $z_1$  &  $z_2$ )

$I(x; z_1, z_2) = H(z_1, z_2) - H(z_1, z_2 | x) = H(z_1) + H(z_2 | z_1) -$   
 $- H(z_1 | x) - H(z_2 | x, z_1) = H(z_1) + H(z_2) - H(z_1 | x) - H(z_2 | x) =$   
 $= I(x; z_1) + I(x; z_2)$  (no terms  $H(z_2 | z_1) = H(z_2)$ )

$= | \text{no shared} | = H(z_1) - H(z_1 | x) + H(z_2 | z_1) - H(z_2 | x) =$   
 $I(x; z_1) = I(x; z_1) + H(z_2) - H(z_2 | x) - H(z_2) + H(z_2 | z_1)$   
 $= I(x; z_1) + I(z_1; z_2)$

$$I(x; z_1 z_2) = I(x; z_1) + I(x; z_2) - I(z_1; z_2)$$

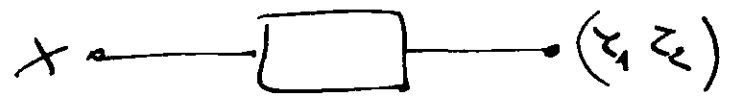
$$\left. \begin{aligned} I(x; z_1) &= h(x_1) - h(z_1|x) \\ I(x; z_2) &= h(z_2) - h(z_2|x) \end{aligned} \right\} \begin{aligned} h(z_1|x) &= h(z_2|x) \\ \text{CONDITIONALLY IDENTICAL} \\ \text{DISTRIBUTED GIVEN } x \end{aligned}$$

$h(z_1) = h(z_2) \Rightarrow$  SINCE  $z_1$  &  $z_2$  ARE IDENTICALLY DISTRIBUTED

$$I(x; z_1 z_2) = 2I(x; z_1) - I(z_1; z_2)$$

**PROBLEM 9.2**

TWO LOOK GAUSSIAN CHANNEL



CONSIDER THE ORDINARY GAUSSIAN CHANNEL WITH TWO COLLECTOR LOOKS AT  $x$ , THAT IS:  $z = (z_1, z_2)$  WHERE:

$$z_1 = x + z_1 \quad z_2 = x + z_2$$

WITH POWER CONSTRAINT  $P$  ON  $x$ , AND  $(z_1, z_2) \sim \mathcal{N}_2(0, K)$

$$K = \begin{bmatrix} N & N\rho \\ N\rho & N \end{bmatrix}$$

FIND CAPACITY FOR:

- (a)  $\rho = 1$
- (b)  $\rho = 0$
- (c)  $\rho = -1$

$$y = z + z_0$$

$$\theta = \begin{cases} 1 & z = z_1 \\ 2 & z = z_2 \end{cases}$$

$$I(x; z_1 z_2) = 2I(x; z_1) - I(z_1; z_2)$$

$$I(z_1; z_2) = h(z_1) - h(z_2|z_1)$$

$$z = \begin{cases} z_1 & \theta = 1 \\ z_2 & \theta = 2 \end{cases}$$

$$h(z, \theta) = h(z) + \underbrace{h(\theta|z)}_{\theta} = h(\theta) + h(z|\theta) = h(\theta) + P(\theta=1) \cdot h(z_1) - \frac{z \cdot K^{-1} \cdot z^T}{2}$$

$$(b) \quad K = \begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$$

$$p(z_1, z_2) = \frac{1}{(2\pi)^2 |K|^{1/2}} e^{-\frac{z_1^2}{2N} - \frac{z_2^2}{2N}}$$

$$p(z_1, z_2) = p(z_1) \cdot p(z_2) = \frac{1}{\sqrt{2\pi N_1}} e^{-\frac{z_1^2}{2N_1}} \cdot \frac{1}{\sqrt{2\pi N_2}} e^{-\frac{z_2^2}{2N_2}}$$

$$I(x; z_1, z_2) = 2I(x; z_1) - I(z_1; z_2)$$

$$C = \max_{\gamma(x)} \left[ I(x; z_1) \right] - \underline{I(z_1; z_2)}$$

$$\begin{aligned} I(x; z_1) &= H(z_1) - H(z_1|x) = H(z_1) - H(x+z_1|x) \\ &= H(z_1) - H(z_1) \leq \frac{1}{2} \log \det(\Sigma + N) - \frac{1}{2} \log \det(\Sigma) = \\ &= \frac{1}{2} \log \left( 1 + \frac{N}{P} \right) \end{aligned}$$

$$C = \frac{1}{2} \log \left( 1 + \frac{N}{P} \right) - I(z_1; z_2)$$

$$\begin{aligned} I(z_1; z_2) &= H(z_1) - H(z_1|z_2) = H(z_1) - H(x+z_1|x+z_2) \\ &= H(z_1) - \underline{H(z_1|z_2)} \end{aligned}$$

$$H(x+z_1|x+z_2) = \sum_{x, z_1, z_2} p(x, z_1, z_2) \cdot \log \frac{1}{p(x+z_1|x+z_2)} =$$

$$= \sum_x p(x) \sum_{z_1, z_2} p(z_1, z_2) \log \frac{1}{p(x+z_1|z_2, x)} = H(z_1|z_2)$$

ALTERNATIVELY:

$$\begin{aligned} H(z_1|z_2) &= \sum_x p(x) H(z_1|Y_2 = x+z_2) = \\ &= \sum_x p(x) \cdot H(x+z_1|x+z_2) = H(z_1|z_2) \end{aligned}$$

(b)  $\begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$   $z_1$  INDEPENDENT  $z_2$   
 $H(z_1|z_2) = H(z_1)$

$$\begin{aligned} I(z_1; z_2) &= H(z_1) - H(z_1) = \\ C &= \frac{1}{2} \log \left( 1 + \frac{N}{P} \right) - [H(z_1) - H(z_1)] \end{aligned}$$

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$$\begin{aligned} I(x; z_1, z_2) &= H(z_1, z_2) - H(z_1, z_2|x) = H(z_1, z_2) - \\ &- \sum_x p(x) H(x+z_1, x+z_2|x=x) = H(z_1, z_2) - H(z_1, z_2) \end{aligned}$$

$$I(x; z_1 z_2) \leq \sum_{i=1}^2 h(y_i) - \sum_{i=1}^2 h(z_i) \leq \sum_{i=1}^2 \left\{ \frac{1}{2} \log(e^c) (P+N_i) - \frac{1}{2} \log(e^c) N_i \right\} = \sum_{i=1}^2 \frac{1}{2} \log \left( \frac{P+N_i}{N_i} \right) = \frac{1}{2} \sum_{i=1}^2 \log \left( 1 + \frac{P}{N_i} \right)$$

$$J(P_1, P_2) = \sum_{i=1}^2 \frac{1}{2} \log \left( \frac{P_i}{N_i} \right) + \lambda \left( \sum P_i \right)$$

$$\frac{\partial J}{\partial P_i} = \frac{1}{2} \cdot \frac{1}{1 + \frac{P_i}{N_i}} \cdot \frac{1}{N_i} + \lambda = 0 \quad \frac{1}{2} \frac{1}{P_i + N_i} + \lambda = 0$$

$$\frac{1}{2(P_i + N_i)} = -\lambda \quad \frac{1}{P_i + N_i} = -2\lambda \quad P_i + N_i = -\frac{1}{2\lambda}$$

$$P_i = -N_i - \frac{1}{2\lambda} = \underline{\underline{V - N_i}}$$

(6)  $P_1 = P_2 = P \quad N_1 = N_2 = N$

$K_Z = \begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$

$$C = \frac{1}{2} \sum_{i=1}^2 \log \left( 1 + \frac{V-N}{N} \right) \quad \sum (V - N_i) = \sqrt{P}$$

$$f(z_1 | z_2) = \frac{f(z_1 z_2)}{f(z_2)} = \frac{\frac{1}{2\pi |K|} e^{-\frac{z^T K^{-1} z}{2}}}{\frac{1}{\sqrt{N}} e^{-\frac{z_1^2}{2N}}}$$

MY SOLUTION BASED ON 8.11

(6)  $E[z_1 z_2] = E[(x+z_i)(x+z_j)] = E[x^2] + E[z_i z_j] =$

$$= \begin{cases} P & i \neq j \\ P+N & i=j \end{cases} \quad K = \begin{bmatrix} P+N & P \\ P & P+N \end{bmatrix} \quad K_Z = \begin{bmatrix} N & 0 \\ 0 & N \end{bmatrix}$$

$$I(x; z_1 z_2) = H(z_1 z_2) - H(z_1 z_2 | x) = \frac{1}{2} \log \frac{|K_Z|}{|K|}$$

$$\leq \frac{1}{2} \log(e^c) |K_Z| - \frac{1}{2} \log(e^c) |K| = \frac{1}{2} \log \frac{|K_Z|}{|K|}$$

GAUSSIAN DISTRIBUTION MATRICES ENTROPY

$$C = \frac{1}{2} \log \frac{(P+N)^2 - P^2}{N^2} = \frac{1}{2} \log \frac{P^2 + 2PN + N^2 - P^2}{N^2} = \frac{1}{2} \log \frac{N(N+2P)}{N^2}$$

$$= \frac{1}{2} \log \left( 1 + \frac{2P}{N} \right)$$

$$(a) E[z_1 z_2] = E[x^2] + E[z_1 z_2] = \begin{cases} p+n & i=j \\ p+n & i \neq j \end{cases}$$

$$K_z = \begin{bmatrix} N & N \\ N & N \end{bmatrix} \quad K_r = \begin{bmatrix} p+n & p+n \\ p+n & p+n \end{bmatrix}$$

$$I(x; z_1 z_2) = h(\gamma_1 \gamma_2) - \cancel{h(z_1 z_2)} = \frac{1}{2} \log \frac{|K_r|}{|K_z|} = \frac{1}{2} \log \frac{(p+n)^2}{N^2 - N^2} = \infty$$

$$C = \frac{1}{2} \log \frac{|K_r|}{|K_z|} = \frac{1}{2} \log \frac{(p+n)^2 - (p+n)^2}{N^2 - N^2} = 0$$

$$(c) K_z = \begin{bmatrix} N & -N \\ -N & N \end{bmatrix} \quad K_r = \begin{bmatrix} p+n & p-n \\ p-n & p+n \end{bmatrix}$$

$$C = \frac{1}{2} \log \frac{(p+n)^2 - (p-n)^2}{N^2 - N^2} = \frac{1}{2} \log \frac{p^2 + 2pn + n^2 - p^2 + 2pn - n^2}{0} = \infty$$

$$= \frac{1}{2} \log \frac{4pn}{0} = \infty$$

SOLUÇÃO DE SUBD.  
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CORRELACIONAL MATEMÁTICA BA N°

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$$K_r = \begin{bmatrix} p & p \\ p & p \end{bmatrix} + K_z \quad ; \quad K_z = \begin{bmatrix} N & \rho N \\ \rho N & N \end{bmatrix}$$

$$|K_z| = N^2 - \rho^2 N^2 = N^2(1 - \rho^2)$$

$$K_r = \begin{bmatrix} p+n & p+\rho n \\ p+\rho n & p+n \end{bmatrix}$$

$$|K_r| = (p+n)^2 - (p+\rho n)^2$$

$$|K_r| = \underline{p^2 + 2pn + n^2} - \underline{p^2 + 2\rho pn + \rho^2 n^2} = \underline{N^2(1 - \rho^2) + 2n(1 - \rho)}$$

$$C = \frac{1}{2} \log \frac{N^2(1 - \rho^2) + 2n(1 - \rho)}{N^2(1 - \rho^2)} = \frac{1}{2} \log \left( 1 + \frac{2\rho}{N(1 + \rho)} \right)$$

$$(a) \boxed{\rho = 1} \quad C = \frac{1}{2} \log \left( 1 + \frac{2\rho}{N(1 + \rho)} \right) = \frac{1}{2} \log \left( 1 + \frac{2\rho}{2N} \right)$$

$$C = \frac{1}{2} \log \left( 1 + \frac{\rho}{N} \right)$$

$$(b) \boxed{\rho = 0} \quad C = \frac{1}{2} \log \left( 1 + \frac{2\rho}{N} \right)$$

$$(c) \boxed{\rho = -1} \quad C = \infty$$



**Problem 9.3** OUTPUT POWER CONSTRAINT. CONSIDER AN ADDITIVE GAUSSIAN CHANNEL WITH AN EXPECTED OUTPUT POWER CONSTRAINT  $P$ . Thus,  $Y = X + Z$ ,  $Z \sim N(0, \sigma^2)$ ,  $Z$  IS INDEPENDENT OF  $X$ , AND  $E[X^2] = P$ . FIND THE CAPACITY.

$C = \max_{p(x)} I(X; Y)$        $I(X; Y) = \underline{h(Y)} - \underline{h(Z)}$

$J = \underline{h(Y)} + \lambda \sum P_i$        $\sum_{i=1}^n P_i = P$   
 $P_i = \gamma_i^2$

$J = -\sum_{i=1}^n p(i) \ln p(i) + \lambda \sum_{i=1}^n p(i) \cdot \frac{\gamma_i^2}{P}$

$\frac{dJ}{dP_i} = -\left( \ln p(i) + p(i) \cdot \frac{1}{p(i)} + \lambda \gamma_i^2 \right) = 0$

$\ln p(i) + \lambda \cdot P_i = 0$

$\ln p(i) = -\lambda P_i$

$p(i) = 2^{-\lambda P_i}$

$\sum_{i=1}^n p(i) = 1$

$\sum_{i=1}^n \frac{1}{2^{\lambda P_i}} = 1$

$\sum_{i=1}^n \frac{1}{2^{\lambda P_i}} = \sum_{i=0}^n 2^{-\lambda P_i} = \frac{1 - 2^{-\lambda(n+1)}}{1 - 2^{-\lambda}} - 1 = \frac{1 - 2^{-\lambda(n+1)} - 1 + 2^{-\lambda}}{1 - 2^{-\lambda}}$

$= \frac{(-2^{-\lambda(n+1)} + 2^{-\lambda})}{1 - 2^{-\lambda}} = 1 \implies 2^{-\lambda(n+1)} = 1 - 2^{-\lambda}$

$2 \cdot 2^{-\lambda(n+1)} = 1$

$2(2 - 2^{-\lambda}) = 1$

(?)

$2^{\lambda P_i} = 2^{i \cdot \lambda P_i} \implies \lambda P_i = i$

$P_i = \frac{1}{\lambda}$

$I(X; Y) = \underline{h(Y)} - \underline{h(Z)} \leq \frac{1}{2} \ln \frac{P_Y}{N}$

$J = \frac{1}{2} \ln \left( \frac{P_Y}{N} \right) + \lambda \sum_{i=1}^n P_i$        $E(Y^2) = P_Y$

$J = \frac{1}{2} \ln \left( \frac{\sum_{i=1}^n P_i \cdot P_i}{N} \right) + \lambda \sum_{i=1}^n P_i$  ;  $\frac{dJ}{dP_i} = 0$


$$J = \frac{1}{2} \ln \left( \frac{\sum_{i=1}^n p_i \cdot p_i}{N} \right) + \lambda \sum_{i=1}^n p_i$$

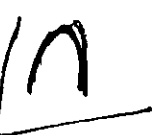
$$\frac{\delta J}{\delta p_i} = -\frac{1}{2} \ln N + \left[ \frac{1}{2} \ln \sum_{i=1}^n p_i \cdot p_i \right]' + \frac{d}{dp_i} \left[ \lambda \sum_{i=1}^n p_i \right]$$

Jensen's Inequality:

$$E[f(x)] \geq f(E[x])$$

$$E[f(x)] \leq f(E[x])$$

$f(x) \Rightarrow$  CONVEX 

$f(x) \Rightarrow$  CONCAVE 

$$\frac{1}{2} \ln \left( \frac{\sum_{i=1}^n p_i \cdot p_i}{N} \right) \geq \frac{1}{2} \sum_{i=1}^n p_i \ln p_i$$

$$J \geq -\frac{1}{2} \ln N + \frac{1}{2} \sum_{i=1}^n p_i \ln p_i + \lambda \sum_{i=1}^n p_i$$

$$\frac{dJ}{dp_i} = 0 \quad \frac{p_i}{p_i} \cdot \frac{1}{2} \Rightarrow \lambda \cdot 1 = 0 \quad \lambda = + \frac{p_i}{p_i} \cdot \frac{1}{2}$$

$$p_i = \frac{p_i}{\lambda} \cdot \ln e$$

$$p_i = \frac{p_i \cdot \lambda}{\ln e}$$

$$\sum_{i=1}^n p_i = 1$$

$$\sum_{i=1}^n \frac{p_i \cdot \lambda}{\ln e} = 1$$

$$\frac{\lambda}{\ln e} \sum_{i=1}^n p_i = 1$$

$$\lambda = \frac{\ln e}{P}$$

$$p_i = \frac{p_i}{\frac{\ln e}{P}} \cdot \ln e = P \cdot p_i$$

$$P_C = \sum_{i=1}^n P_i \cdot p_i = \sum_{i=1}^n P p_i^2 = P \sum_{i=1}^n p_i^2$$

$$C = \frac{1}{2} \ln \frac{P_C}{N} = \frac{1}{2} \ln \frac{P}{N}$$

$$N = 62$$

- solns - 5 - 229A - 1987. ydf (Berkeley)

(if  $P \leq 62$  it is infeasible to meet the power constraint, so capacity in this case is 0 bits.

$$C = \left( \frac{1}{2} \ln \frac{P}{62} \right) +$$

$$(M) = \max(M, 0)$$

This bound can be achieved when  $\gamma(x)$  is Gaussian

WITH:  $\sigma_x^2 = P - N = P - \sigma_z^2$        $\sigma^2 = \sigma_z^2$   
 $\sigma_y^2 = P = \sigma_x^2 + \sigma_z^2 = P - \sigma_z^2 + \sigma_z^2 = P$

**PROBLEM 3.9** VECTOR GAUSSIAN CHANNEL. CONSIDER THE

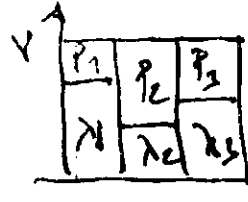
VECTOR GAUSSIAN NOISE CHANNEL:  $r = x + z$   
 WHERE  $x = (x_1, x_2, x_3)$ ,  $z = (z_1, z_2, z_3)$ ,  $r = (r_1, r_2, r_3)$ ,  
 $\in [iAR] \leq P$  AND

$z \sim \mathcal{N}(0, \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 2 \end{bmatrix})$

FIND THE CAPACITY. THE ANSWER MAY BE SURPRISING

$K_z = V \Lambda V$        $\Lambda = \begin{bmatrix} \lambda_1 & 0 & 0 \\ 0 & \lambda_2 & 0 \\ 0 & 0 & \lambda_3 \end{bmatrix}$        $\lambda_1 = 0$   
 $\lambda_2 = 3$   
 $\lambda_3 = 1$

$C = \frac{1}{2} \sum_{i=1}^n \frac{1}{2} \log \left( 1 + \frac{(P - \lambda_i)^+}{\lambda_i} \right)$        $\sum \lambda_i \leq P$



$P_1 + \lambda_1 = P_2 + \lambda_2 = P_3 + \lambda_3$   
 $P_1 + P_2 + P_3 = P$   
 $P_1 + 0 = P_2 \Rightarrow P_2 = P_1$   
 $P_2 + \lambda_2 = P_1$   
 $P_3 + \lambda_3 = P_1$

$P_1 - P_2 = 0$        $P_2 = (P_1 - 3)^+$   
 $P_1 - P_3 = 1$        $P_3 = P_1 - 1$   
 $P_1 + P_2 + P_3 = P$        $P_1 + P_1 - 3 + P_1 - 1 = P$   
 $3P_1 = P + 4$        $P_1 = \frac{P+4}{3}$   
 $P_2 = \frac{P+4}{3} - 3 = \frac{P+4-9}{3} = \frac{P-5}{3}$        $P_3 = \frac{P+4}{3} - 1 = \frac{P+4-3}{3} = \frac{P+1}{3}$   
 NO  $P < 5 \Rightarrow P_2 = 0$

$P_1 + P_2 + P_3 = \frac{P+4}{3} + \frac{P-5}{3} + \frac{P+1}{3} = \frac{3P + P - 5}{3} = P$   
 $C = \frac{1}{2} \log \left( 1 + \frac{P+4}{3 \cdot 0} \right) + \frac{1}{2} \log \left( 1 + \frac{P-5}{3 \cdot 3} \right) + \frac{1}{2} \log \left( 1 + \frac{P+1}{3 \cdot 1} \right)$

$C \rightarrow \infty$

$\frac{1}{2} \sum \log \left( 1 + \frac{P}{\lambda_i} \right) \leq P$        $\frac{1}{2} \text{tr}(K_x) \leq P$   
 $I(x^n; r^n) = \log |K_r| - \log |K_z|$        $K_r = K_x + K_z$   
 $\log |K_r| = \frac{1}{2} \log |K_x + K_z|$   
 $K_z = Q \cdot 1 \cdot Q^T$        $|K_r| = |Q \cdot Q^T + 1| = |Q \cdot Q^T + 1| \cdot |Q^T| = |1 + 1|$

$$A = Q^T \cdot K_x \cdot Q$$

$$\text{tr}(BC) = \text{tr}(CB)$$

$$\text{tr}(A) = \text{tr}(Q^T \cdot K_x \cdot Q) = \text{tr}(Q \cdot Q^T \cdot K_x) = \text{tr}(K_x)$$

$$\text{max: } |A + \lambda I| \quad \text{s.t.} \quad \text{tr}(A) \leq \text{tr}(I)$$

$$|K| \leq \prod_i K_{ii}$$

$$|A + \lambda I| \leq \prod_i (A_{ii} + \lambda_i)$$

$$\frac{1}{4} \sum_i A_{ii} \leq P$$

$$K_2 = \begin{bmatrix} 1 & 0 & 1 \\ 0 & 1 & 1 \\ 1 & 1 & 2 \end{bmatrix}$$

MAXIMUM VALUE OF  $\prod_i (A_{ii} + \lambda_i)$  IS ATTAINED WHEN

$$A_{ii} \lambda_i = (P - \lambda_i)^2 \quad \text{i.e.} \quad A_{ii} + \lambda_i = P$$

$$\sum_i A_{ii} \lambda_i = \text{tr}(I)$$

$$C = \int_{-\infty}^{\infty} \frac{1}{2} K(f) \left( 1 + \frac{(P - N(f))^2}{N(f)} \right) df$$

$$\int (P - N(f))^2 df = P$$

PROBLEM 9.9 (VIC SOLUTIONS)

CALCULATION OF EIGEN VALUES:

$$|K_2 - xI| = \begin{vmatrix} 1-x & 0 & 1 \\ 0 & 1-x & 1 \\ 1 & 1 & 2-x \end{vmatrix} = (1-x) [(1-x)(2-x) - 1] + (x-1) = (1-x) [(1-x)(2-x) - 1 - 1]$$

$$= (1-x) [2-x - 2x + x^2 - 2] = (1-x)x [x-3] \quad \lambda_i [1, 0, 3]$$

$|K_2| = 0$  THIS MEANS THAT COLUMNS (OR ROWS SINCE  $K_2$  IS SYMMETRIC) ARE LINEARLY DEPENDENT. IN PARTICULAR WE CAN SEE THAT LAST COLUMN (ROW) CAN BE COMPUTED AS THE SUMMATION OF THE FIRST TWO COLUMNS (ROWS).

SINCE  $K_2$  IS COVARIANCE MATRIX, THIS IMPLIES THAT  $Z_3$  CAN BE REWRITTEN AS A FUNCTION OF  $Z_1$  AND  $Z_2$ :  $Z_3 = Z_1 + Z_2$ . THIS FACT CAN BE UTILIZED TO VERIFY THE EFFECT OF NOISE. IN PARTICULAR IF THE SAME SIGNAL IS SENT OVER THE THREE CHANNELS ITS VALUE CAN PERFECTLY BE RECOVERED BY SUBTRACTING  $Z_3$  TO THE SUMMATION OF  $Z_1$  AND  $Z_2$ :

$$Z_1 + Z_2 - Z_3 = x + z_1 + x + z_2 - x - z_3 = x + z_1 + z_2 - z_1 - z_2 = x$$

THUS, AS IN EXERCISE 9.2, CAPACITY OF THE CHANNEL CAN BE CONSIDERED TO BE INFINITE. (NO FLOORING OF  $C$ )

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$$C = \frac{1}{2} \log(2\pi e) \quad \frac{|K_1 + K_2|}{|K_2|} \quad |K_2| = 0 \Rightarrow C \rightarrow \infty$$

$$P(u, \lambda) = \frac{\lambda^u e^{-\lambda}}{u!}$$

POISSON

THE OPTIMAL CODING SCHEME IS TO SET  $x_1 = z_1 = 0$  FROM WHICH RECEIVER DETECTS VALUES OF  $E_1$  AND  $E_2$  THEN USES THEM TO CANCEL THE NOISE IN  $z_2$ , THUS PROVIDING NOISE FREE CHANNEL FROM  $x_2$  TO  $z_2$ , WHICH CLEARLY PERMITS AN INFINITE RATE OF ERROR FREE COMMUNICATION FOR ANY  $P > 0$ .

**PROBLEM 9.10 CAPACITY OF PHOTOGRAPHIC FILM.** HERE IS A PROBLEM WITH A NICE ANSWER THAT TAKES A LITTLE TIME. WE'RE INTERESTED IN THE CAPACITY OF PHOTOGRAPHIC FILM. THE FILM CONSIST OF SILVER IODIDE CRYSTALS POISSON DISTRIBUTED, WITH A DENSITY OF  $\lambda$  PARTICLES PER SQUARE INCH. THE FILM IS ILLUMINATED WITHOUT KNOWLEDGE OF THE POSITION OF THE SILVER IODIDE PARTICLES. IT IS THEN DEVELOPED AND THE RECEIVER SEES ONLY THE SILVER IODIDE PARTICLES THAT WERE ILLUMINATED. IT IS ASSUMED THAT LIGHT INCIDENT ON THE CELL EXPOSES THE GRAIN IF IT IS THERE AND OTHERWISE RESULTS IN A BLANK RESPONSE. SILVER IODIDE PARTICLES THAT ARE NOT ILLUMINATED AND VACANT PORTIONS OF THE FILM REMAIN BLANK. WHAT IS THE CAPACITY OF THIS FILM?

WE MAKE FOLLOWING ASSUMPTIONS. WE GRID THE FILM VERY FINELY INTO CELLS OF AREA  $\Delta A$ . IT IS ASSUMED THAT THERE IS AT MOST ONE SILVER IODIDE PARTICLE PER CELL AND NO SILVER IODIDE PARTICLE IS INTERSECTED BY CELL BOUNDARIES. THUS THE FILM CAN BE CONSIDERED TO BE LARGE NUMBER OF BINARY ASYMMETRIC CHANNELS WITH CROSSTALK PROBABILITY  $1 - \lambda \Delta A$ . BY CALCULATING THE CAPACITY OF THIS BINARY CHANNEL (ASYMMETRIC CH.) TO FIRST ORDER IN  $\Delta A$  (MAKING THE NECESSARY APPROXIMATIONS) ONE CAN CALCULATE THE CAPACITY OF THE FILM IN BITS PER SQUARE INCH. IT IS OF COURSE PROPORTIONAL TO  $\lambda$ . WHAT IS THE MULTIPLICATIVE CONSTANT. THE ANSWER WILL BE  $\lambda$  BITS PER UNIT AREA IF BOTH THE ILLUMINATOR AND THE RECEIVER KNEW THE POSITIONS OF THE CRYSTALS.

$$K = \sum_{k=0}^{\infty} k \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{(k-1)!} = e^{-\lambda} \left( \lambda \frac{\lambda^0}{0!} + \frac{\lambda^2}{1!} + \dots \right)$$

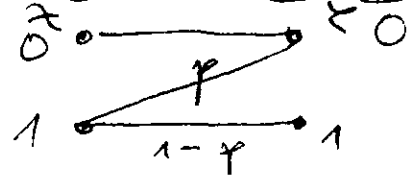
$$= e^{-\lambda} \lambda \left( 1 + \frac{\lambda}{1!} + \frac{\lambda^2}{2!} + \dots \right) = \lambda e^{-\lambda} e^{\lambda} = \lambda$$

$\bar{K} = \lambda$

$$\sum_{k=0}^{\infty} P(k, \lambda) = \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = e^{-\lambda} \left( 1 + \frac{\lambda}{1} + \frac{\lambda^2}{2!} + \dots \right) = e^{-\lambda} e^{\lambda} = 1$$

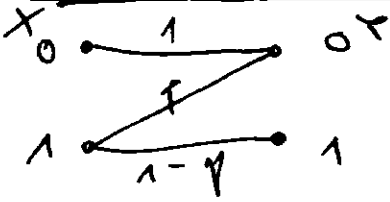
$E[X] = \lambda$

$X \sim P(k, \lambda)$



$p = 1 - \lambda \Delta A$

**BINARY ARITHMETIC CHANNEL**



$$I(x; y) = H(y) - H(y|x) = H(x) - H(x|y)$$

$$H(y|x) = P(x=0) \cdot H(y|x=0) + P(x=1) \cdot H(y|x=1)$$

$$H(y|x=0) = - [P(y=0|x=0) \cdot \log_2 P(y=0|x=0) + P(y=1|x=0) \cdot \log_2 P(y=1|x=0)]$$

$$H(y|x=0) = 0 \quad \text{because reversibility.}$$

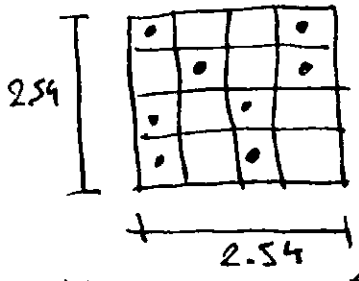
$$H(y|x=1) = - [P(y=0|x=1) \cdot \log_2 P(y=0|x=1) + P(y=1|x=1) \cdot \log_2 P(y=1|x=1)]$$

$$H(y|x=1) = H(y)$$

$$H(x|y) = P(x=1) \cdot H(y) \quad \text{--- (A)}$$

$$p = 1 - \lambda \cdot dA$$

$$(1-p) = \lambda \cdot dA$$



$$\lambda = 8 \text{ particles/mch}^2$$

$$\lambda = \frac{8}{16} = 50\% \quad \star$$

SAMA DA KAZI DEKA NA EDEN KVADRATEN INCH IMAS VO POKR λ IODIDE KMITANJ DESIČKI. BLOD NA KMITANJ DESIČKI IO KVADRATEN INCH E KRESKOVAN IO POKROVANJA ESTRE

INCH E DEKA

- VARIANCA NA POKROVANJE:

$$E[k^2] = \sum_{k=0}^{\infty} k^2 \frac{\lambda^k e^{-\lambda}}{k!}$$

$$E[k^2] = \sum_{k=0}^{\infty} k \frac{\lambda^k e^{-\lambda}}{(k-1)!} = \sum_{k=1}^{\infty} (k-1) \frac{\lambda^k e^{-\lambda}}{(k-1)!} + \sum_{k=1}^{\infty} \frac{\lambda^k e^{-\lambda}}{(k-1)!}$$

$$\text{--- (B)} \quad \sum_{k=1}^{\infty} \frac{\lambda^{k-1} e^{-\lambda}}{(k-1)!} = \lambda \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = \lambda$$

$$\text{--- (C)} \quad \sum_{k=1}^{\infty} \frac{\lambda^{k-1} e^{-\lambda}}{(k-1)!} = \lambda \sum_{k=0}^{\infty} \frac{\lambda^k e^{-\lambda}}{k!} = \lambda$$

$$E[(k-1)^2] = E[k^2] - G^2[k] = \lambda^2 + \lambda - \lambda^2 = \lambda$$

$$P_x(k, A) = \frac{(\lambda \cdot A)^k}{k!} \cdot e^{-\lambda \cdot A}$$

$$P(x=1) = \lambda \cdot dA$$

$$P(x=0) = 1 - \lambda \cdot dA$$

⊛ ⇒ 33% OF CELLS ARE VO 1 ΚΥΒΙΚΑΤΕΝ ΙΝΤΗ ΙΜΑΤ 100ΠΕ ΚΑΤΑΡΓΙΑ ΔΕΣΠΙΣΚΑ.

ΖΗΤΩ, ΠΩΣ ΝΕΚΡΟΤΑΤΟΤΑ ΕΦΙΑ ΚΕΛΥΑ ΔΑ ΕΥΑ ΚΑΤΑΡΓΙΑ ΔΕΣΠΙΣΚΑ Ε:

$$P(X=1) = \lambda(e) \frac{1}{2} = 0.5 \quad (\text{ΚΑΤΟ ΚΑ ΕΛΥΕΣ ΕΑ ΣΥΝΑΡΤΗΣΗ})$$

- ΖΗΤΩΙ ΟΔ ⓐ ΣΥΝΟΙ:

$$H(Z|X) = \lambda \cdot dA \cdot H(P) = \lambda \cdot H(P) = \lambda \cdot H(\lambda)$$

$$I(x; z) = H(z) - \lambda \cdot \left[ (1-\lambda) \log \frac{1}{1-\lambda} + \lambda \log \frac{1}{\lambda} \right]$$

GAUSSIAN DISTRIBUTION MAXIMIZES ENTROPY ⇒

$$H(\tau) / \text{max} = \frac{1}{2} \log(2\pi e) \cdot \lambda$$

$$C = \frac{1}{2} \log(2\pi e) \lambda - \lambda \cdot H(\lambda)$$

$$\begin{aligned} C &= \frac{1}{2} \log(2\pi e) \cdot \lambda - \lambda \left[ (1-\lambda) \log \frac{1}{1-\lambda} + \lambda \log \frac{1}{\lambda} \right] = \\ &= \frac{1}{2} \log(2\pi e) + \frac{1}{2} \log \lambda - \lambda \log \frac{1}{1-\lambda} + \lambda^2 \log \frac{1}{1-\lambda} = \frac{1}{2} \log \frac{1}{\lambda} \\ &= \frac{1}{2} \log(2\pi e) + \frac{1}{2} \log \lambda - \lambda \log \frac{1}{1-\lambda} + \lambda^2 \log \frac{1}{1-\lambda} \\ &= \frac{1}{2} \log(2\pi e) + \log \sqrt{\lambda} + \lambda \log(1-\lambda) + \lambda^2 \log \frac{1}{1-\lambda} = \\ &= \frac{1}{2} \log(2\pi e) + \log \sqrt{\lambda} \cdot (1-\lambda)^{\lambda} + \lambda^2 \log \frac{1}{1-\lambda} = \frac{1}{2} \log(2\pi e) + \frac{1}{2} \log \lambda \cdot (1-\lambda)^{2\lambda} + \lambda^2 \log \frac{1}{1-\lambda} \\ &= \frac{1}{2} \log(2\pi e) \lambda (1-\lambda)^{2\lambda} + \lambda^2 \log \left( \frac{\lambda}{1-\lambda} \right) = \frac{1}{2} \log(2\pi e) \lambda (1-\lambda)^{2\lambda} + \frac{1}{2} \log \left( \frac{\lambda}{1-\lambda} \right)^{\lambda^2 \cdot 2} \\ &= \frac{1}{2} \log(2\pi e) \lambda \cdot (1-\lambda)^{2\lambda} \cdot \left( \frac{\lambda}{1-\lambda} \right)^{2\lambda^2} = \frac{1}{2} \log(2\pi e) \lambda^{2\lambda^2+1} (1-\lambda)^{\lambda^2(1-\lambda)} \end{aligned}$$

$$\frac{d}{d\lambda} = \lambda \cdot (1-\lambda)^{2\lambda} \cdot \frac{\lambda^{2\lambda^2+1}}{(1-\lambda)^{2\lambda \cdot \lambda - 2\lambda}} = \frac{\lambda^{2\lambda^2+1}}{(1-\lambda)^{2\lambda(\lambda-1)}} = \frac{\lambda^{2\lambda^2+1}}{(1-\lambda)^{-2\lambda(1-\lambda)}}$$

$$C = \frac{1}{2} \log(2\pi e) \lambda (1-\lambda)^{2\lambda} \left( \frac{\lambda}{1-\lambda} \right)^{2\lambda^2} \quad \frac{\text{BITS}}{\text{CELL}}$$

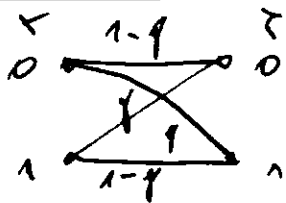
- FOR DISCRETE VARIABLES UNIFORM DISTRIBUTION MAXIMIZES ENTROPY HENCE: ⊛ ⇒

$$C = 1 - \lambda \cdot H(\lambda) = 1 - \lambda \left( (1-\lambda) \log \frac{1}{1-\lambda} + \lambda \log \frac{1}{\lambda} \right) \quad \frac{\text{BITS}}{\text{CELL}}$$

$$1 \text{ INCH} = 25,4 + 25,4 \text{ mm} = 645,16 \text{ mm}^2$$

$$\rightarrow \frac{1 \text{ CELL} = 1 \text{ mm}^2}{1 \text{ CELL} = 1 \text{ mm}^2}$$

$$C_{\text{INCH}} = C \cdot 645,16 = C(0.8) \cdot 645,16 = 272,55 \text{ BITS/INCH}$$



$$I(x; z) = H(z) - H(z|x) = 1 - H(z|x)$$

$$H(z|x) = P(x=0) \cdot \frac{H(z|x=0)}{H(z)} + P(x=1) \cdot \frac{H(z|x=1)}{H(z)}$$

$$= H(z)$$

$$I(x; z) = 1 - H(z)$$

$$C = \lambda d \left( \frac{A}{\lambda d A} - \lambda \cdot d A H(\lambda \cdot d A) \right)$$

A - SIZE OF THE FILM IN SQ INCH

e.g.  $\lambda = 1000 / \text{SQ INCH}$        $A = 0.64 \text{ INCH}^2$

APS-C  $25.1 \times 16.7 \text{ mm} = \frac{419.17 \text{ cm}^2}{645.16} = \frac{419.17}{645.16} = 0.64 \text{ INCH}^2$

$$C = \lambda d A \left( \frac{A}{\lambda d A} - \lambda \cdot d A H(\lambda \cdot d A) \right)$$

$$\lambda = \frac{1000}{645.16} \frac{\text{KIRSTARS}}{\text{cm}^2}$$

$$\lambda = 1.55 \frac{\text{KIRSTARS}}{\text{cm}^2}$$

$$1 \text{ KIRSTAR} = 0.5 \text{ cm}^2 = 1 \text{ UNIT} = dA$$

$$\lambda = \frac{1.55}{2} \frac{\text{KIRSTARS}}{\text{UNIT}} = 0.725 \frac{\text{KIRSTARS}}{\text{UNIT}}$$

$$dA = A = \frac{645 \text{ cm}^2}{0.5 \text{ cm}^2} = 2 \cdot 645 = 1290$$

$$C = \lambda d 1290 - 0.725 H(0.725) =$$

$\frac{A}{\lambda \cdot dA} \Rightarrow$  NUMBER OF KIRSTARS

$$C = \lambda d \frac{A}{\lambda d A} - \lambda \cdot d A H(\lambda \cdot d A)$$

$$\lambda = \frac{N}{645.16} = 0.0155 \cdot N \text{ KIRSTARS/cm}^2$$

$\lambda (=) \frac{\text{KIRSTARS}}{\text{cm}^2}$

$$dA = (\text{UNIT AREA}) \text{ cm}^2 \quad A - \text{TOTAL AREA OF FILM (SOURCE)}$$

$$C(A; \lambda; dA) = \lambda d \left( \frac{A}{\lambda d A} - \lambda \cdot d A H(\lambda \cdot d A) \right)$$

$$C = \lambda \frac{A}{dA} (1 - \lambda \cdot d A H(\lambda \cdot d A))$$

BITS/(INCH AREA)

0.5 x 1 CELL  
 $\lambda$  - PARTICLES FOR CELL  
 $A$  - AREA IN  $\text{cm}^2$   
 $dA$  - CELL (UNIT AREA)

**PROBLEM 9.11** SUPPOSE THAT  $(x, z, z)$  ARE JOINTLY GAUSSIAN AND THAT  $x \rightarrow z \rightarrow z$  FORMS MARKOV CHAIN. LET  $x$  AND  $z$  HAVE COVARIATION COEFFICIENT  $\rho_1$  AND LET  $z$  AND  $z$  HAVE COVARIATION COEFFICIENT  $\rho_2$ . FIND  $I(x; z)$ .

$$I(x, z; z) = I(x; z) + I(z; z|x) = I(z; z) + I(x; z|z)$$

$$I(x; z|z) = H(z|z) - H(z|x, z) = H(z|z) - H(z|z) = 0$$



$$I(x; z) = I(z; x) - \frac{I(z; x|x)}$$

$$I(x; z|x) = h(z|x) - h(z|x, x) = \underline{h(z|x)} - \underline{h(z|x)}$$

$$I(z; x) = h(x) - h(x|z)$$

$$I(z; x) = h(x) - \underline{h(x|z)} = \frac{1}{2} \log \frac{p(x)}{p(x|z)} G_z^2$$

$$h(z|x) = \int_{-\infty}^{\infty} p(\gamma) \cdot h(z|x, \gamma) d\gamma - \frac{I(z; x) \cdot K_{xx}^{-1} \cdot [z, z]^T}{2}$$

$$p(\gamma, z) = \frac{1}{\sqrt{2\pi} |K_{zz}|} e^{-\frac{1}{2} [z, z] K_{zz}^{-1} [z, z]^T}$$

$$= \int_{-\infty}^{\infty} p(\gamma) \int_{-\infty}^{\infty} p(z|\gamma) \log \frac{1}{p(z|\gamma)} dz$$

$$h(z|x) = \int_{-\infty}^{\infty} p(z, z) \log \frac{1}{p(z|x)}$$

$$p(z|\gamma) = \frac{p(\gamma, z)}{p(\gamma)}$$

$$p(\gamma) = \int_{-\infty}^{\infty} p(\gamma, z) dz$$

$$I(x, z; z) = h(x, z) - h(x, z|z) = h(x, z) - h(z|x) \times \infty$$

$$G_{xz}^2 = E[z^2] \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z^2 \cdot p(z|\gamma) dz = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} z^2 p(x, \gamma) dx d\gamma$$

$$E[z^2] = E_z [E[z^2|x]]$$

**PROBLEM 7.13** (CONTINUE FROM N16K)

$$K = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

(a)  $C_{2, FB} = \frac{1}{2\pi} \max_{\text{tr}[K] \leq 2P} \log \frac{|K_{x+z}|}{|K_x|}$

$(z_1, z_2) \sim \mathcal{N}(0, K)$   
 $|K| = 1 - \rho^2$

(b)  $C_{2, MB} = C_2 = \frac{1}{2\pi} \max_{\text{tr}[K] \leq 2P} \log \frac{|K_x + K_z|}{|K_x|}$

(a)  $K_{x+z} + K_{x-z} = 2K_x + 2K_z$   
 $= E[x^2] + E[z^2] + E[2xz] + E[2z^2]$

$K_{x+z} = E[(x+z)(x+z)] \rightarrow$   
 $|A-B| > 0 \Rightarrow |A| > |B|$   
 $\Rightarrow 2K_x + 2K_z - K_{x+z} = K_{x-z} \succ 0$   
 $\Rightarrow |2(K_x + K_z)| \geq |K_{x+z}|$

$|K_{x+z}| \leq |A+B| \leq |A| + |B|$   
 $\frac{1}{2} \log \frac{p(x)}{p(x|z)} |K_{x+z}| \leq \frac{1}{2} \log \frac{p(x)}{p(x|z)} (2\pi |K_x + K_z|)$

~~$C_{2, MB} = \frac{1}{2\pi} \max_{\text{tr}[K] \leq 2P} \log \frac{|K_x + K_z|}{|K_x|} \leq \frac{1}{2\pi} \max_{\text{tr}[K] \leq 2P} \log \frac{2\pi |K_x + K_z|}{|K_x|}$~~

~~$\frac{1}{2^n} \max_{\text{tr}[K_x] \leq 2P} \frac{1}{2} \log \frac{|K_x + K_z|}{|K_z|} \leq \frac{1}{8} \log \frac{P^2}{(1-\rho^2)}$~~

(b)  $C_2 = \frac{1}{2^n} \max_{\text{tr}[K_x] \leq 2P} \sum_{i=1}^2 \log \left( 1 + \frac{(\lambda - \lambda_i)^+}{\lambda_i} \right)$

$\lambda_1 = 1 + \rho \quad \lambda_2 = 1 - \rho$

$\rho_2 = \lambda - \lambda_i \quad \lambda = \rho_i + \rho_i$

$\rho_1 + \lambda_1 = \rho_2 + \lambda_2 \quad \rho_1 + \rho + \rho = \rho_2 + 1 - \rho \quad \rho_1 = \rho_2 - 2\rho$

$\rho_1 + \rho_2 = 2\rho \quad \rho_2 = 2\rho + \rho_2 = 2\rho \quad 2\rho_2 - 2\rho = 2\rho$

$\rho_2 = \rho + \rho \quad \rho_1 = \rho + \rho - 2\rho = \rho - \rho$

$C_2 = \frac{1}{4} \left[ \log \left( 1 + \frac{1-\rho}{1+\rho} \right) + \log \left( 1 + \frac{\rho+\rho}{1-\rho} \right) \right] = \frac{1}{4} \log \frac{(1+\rho)^2}{(1-\rho^2)} = \frac{1}{4} \log \frac{1+2\rho+\rho^2}{1-\rho^2}$

(a)  $C_{FB, \gamma} = \max_{\text{tr}[K_x] \leq 2P} \frac{1}{2^n} \log \frac{|K_x + K_z|}{|K_z|} \leq \frac{1}{2^n} \log 2^n + \frac{1}{2^n} \log \frac{|K_x + K_z|}{|K_z|}$

$\frac{|K_x + K_z|}{|K_z|} \leq \frac{|2(K_x + K_z)|}{|K_z|} \leq 2^n \frac{|K_x + K_z|}{|K_z|} \leq \frac{1}{2} + \frac{1}{2^n} \log \frac{|K_x|^{1/2} |K_z|^{1/2}}{|K_z|^{1/2}} = \frac{1}{2} + \frac{1}{2^n} \log \frac{|K_x|}{|K_z|}$

$= \frac{1}{2} + \frac{1}{8} \log \frac{P^2}{(1-\rho^2)} = \frac{1}{8} \log 16 + \frac{1}{8} \log \frac{P^2}{(1-\rho^2)}$

$= \frac{1}{8} \log \frac{16 P^2}{(1-\rho^2)}$

- (1)  $K_x + K_z + K_x + K_z = 2K_x + 2K_z$
- (2)  $|a+b| \geq 0 \Rightarrow |a| \geq |b|$
- (3)  $|K_x + K_z| \leq 2^n |K_x + K_z|$
- (4)  $\frac{1}{2^n} |K_x + K_z| \geq |K_x|^{1/2} |K_z|^{1/2}$

$C_{FB, \gamma} - C_2 = \frac{1}{8} \log \frac{16 P^2}{(1-\rho^2)} - \frac{1}{4} \log \frac{(1+2\rho+\rho^2)^2}{(1-\rho^2)^2}$

$|\lambda K_x + (1-\lambda) K_z| \leq |K_x|^\lambda |K_z|^{1-\lambda}$

$|\frac{1}{2} K_x + \frac{1}{2} K_z| \leq |K_x|^{1/2} |K_z|^{1/2} \quad \frac{1}{2^n} |K_x + K_z| \leq |K_x|^{1/2} |K_z|^{1/2}$

$\frac{1}{2} + \frac{1}{4} \log \frac{|K_x + K_z|}{(1-\rho^2)} \leq \frac{1}{2} + \frac{1}{4} \log \frac{4 |K_x|^{1/2} |K_z|^{1/2}}{(1-\rho^2)}$

$\leq \frac{1}{2} + \frac{1}{4} \log 4 + \frac{1}{4} \log \frac{|K_x|^{1/2} |K_z|^{1/2}}{|K_z|^{1/2}}$

$= \frac{1}{2} + \frac{1}{2} + \frac{1}{8} \log \frac{|K_x|}{|K_z|} = \frac{1}{8} \log 256 + \frac{1}{8} \log \frac{P^2}{1-\rho^2} = \frac{1}{8} \log \frac{256 P^2}{1-\rho^2}$

$$\frac{1}{2} \rho_d \frac{|k_{x+z}|}{|k_z|} = \left( \text{WITHOUT FEED} \right) \frac{1}{2} \rho_d \frac{|k_x| + |k_z|}{|k_z|} =$$

$$= \frac{1}{2} \rho_d \left( 1 + \frac{|k_x|}{|k_z|} \right) = \frac{1}{2} \rho_d \left( 1 + \frac{\rho^2}{1-\rho^2} \right) = \frac{1}{2} \rho_d \frac{1+\rho^2}{1-\rho^2}$$

SOLUTION

$$(b) \left| \begin{bmatrix} \rho & 0 \\ 0 & 1 \end{bmatrix} \right| + \left| \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix} \right| = \left| \begin{bmatrix} \rho+1 & \rho \\ \rho & \rho+1 \end{bmatrix} \right| = \frac{(\rho+1)^2 - \rho^2}{}$$

$$|k_{x+z}| \leq 2^{\gamma} |k_x + k_z| = 2^{\gamma} \left[ (\rho+1)^{\rho} - \rho^{\rho} \right]$$

$$C_2 = \frac{1}{2} \rho_d \frac{|k_x + k_z|}{|k_z|} = \frac{1}{2} \rho_d \frac{(\rho+1)^2 - \rho^2}{1-\rho^2}$$

$$(a) C_{\rho,2} = \frac{1}{2} \rho_d \frac{|k_{x+z}|}{|k_z|} \leq \frac{1}{2} \rho_d \frac{2^{\gamma} |k_x + k_z|}{|k_z|} = \frac{1}{2} \rho_d 2^{\gamma} + \frac{1}{2} \rho_d \frac{|k_x + k_z|}{|k_z|}$$

$$= 1 + \frac{1}{2} \rho_d \frac{(\rho+1)^2 - \rho^2}{1-\rho^2} = \frac{1}{2} \rho_d 4 + \frac{1}{2} \rho_d \frac{(\rho+1)^2 - \rho^2}{1-\rho^2} =$$

$$= \frac{1}{2} \rho_d \frac{4[(\rho+1)^2 - \rho^2]}{1-\rho^2}$$

$$C_{\rho,2} - C_2 = \frac{1}{2} \rho_d \frac{4[(\rho+1)^2 - \rho^2]}{1-\rho^2} \cdot \frac{1-\rho^2}{(\rho+1)^2 - \rho^2} = 1 \text{ bit/sec}$$

NE & MORE 0 SO CASE 0 THEOREM 9.6.2

$$C_{\rho,2} \leq C_2 + \frac{1}{2} \quad C_{\rho,2} /_{\max} = C_2 + \frac{1}{2} = \frac{1}{2} + \frac{1}{2} \rho_d \frac{(\rho+1)^2 - \rho^2}{1-\rho^2}$$

$$C_{\rho,2} = C_2 + \frac{1}{2}$$

**PROBLEM 9.14** ADDITIVE NOISE CHANNEL. CONSIDER THE CHANNEL  $Z = X + Z$  WHERE  $X$  IS THE TRANSMITTED SIGNAL WITH POWER CONSTRAINT  $P$  &  $Z$  IS INDEPENDENT ADDITIVE NOISE, AND  $Z$  IS RECEIVED SIGNAL. LET

$Z = \begin{cases} 0 & \text{WITH PROBABILITY } 1/10 \\ Z^* & \text{WITH PROBABILITY } 9/10 \end{cases}$  WHERE  $Z^* \sim \mathcal{N}(0, N)$ . THUS  $Z$  HAS MIXTURE DISTRIBUTION THAT IS THE MIXTURE OF GAUSSIAN DISTRIBUTION AND A DEGENERATE DISTRIBUTION WITH MASS 1 AT 0.

- (a) WHAT IS THE CAPACITY OF THIS CHANNEL? THIS SHOULD BE A PLEASANT SURPRISE.  
 (b) HOW WOULD YOU SIGNAL TO ACHIEVE CAPACITY?

(a)  $Z = X + Z^*$        $Z = \begin{cases} 0 & r = 1/10 \\ Z^* & r = 9/10 \end{cases}$        $Z^* \sim N(0, N)$

$I(X; Z) = H(Z) - H(Z|X) = H(Z) - H(X+Z|X) = H(Z) - H(Z)$

$H(Z, Z^*) = H(Z^*) + H(Z|Z^*) = H(Z^*) + H(Z^*|Z)$   
 $Z = f(Z^*)$

$X = X_1 + X_2$        $X_1 \sim p_1$        $X_2 \sim p_2$   
 $\theta = \begin{cases} 1 & X = X_1 \\ 2 & X = X_2 \end{cases}$        $\theta = f(X)$   
 $H(\theta, X) = H(\theta) + H(X|\theta) = H(X) + H(\theta|X) = H(X) + H(\theta)$   
 $H(X|\theta) = P(\theta=1) \cdot H(X|\theta=1) + P(\theta=2) \cdot H(X|\theta=2) = \alpha H(X_1) + (1-\alpha) H(X_2)$   
 $H(X) = H(\alpha) + \alpha H(X_1) + (1-\alpha) H(X_2)$

$H(Z) = H(Z) + H(Z^*/Z) = H(1/10) + H(Z^*|Z)$

$H(Z^*|Z) = P(Z=0) \cdot H(Z^*|Z=0) + P(Z=Z^*) \cdot H(Z^*|Z^*)$

$H(Z^*) = H(1/10) + \frac{9}{10} H(Z^*)$        $\frac{9}{10} H(Z^*) = H(1/10)$

$H(Z^*) = \frac{10}{9} H(1/10)$        $f(X, \theta) = \begin{cases} 1 & Z=0 \\ 0 & Z \neq 0 \end{cases}$

$Z = \begin{cases} Z^+ & f(Z^+, 0) \\ Z^* & N(0, N) \end{cases}$        $\theta = \begin{cases} 1 & Z = Z^+; p = 1/10 \\ 2 & Z = Z^*; p = 9/10 \end{cases}$   
 $\theta = f(Z)$

$H(Z, \theta) = H(Z) + H(\theta|Z) = H(\theta) + H(Z|\theta) = H(1/10) + H(Z|\theta)$

$H(Z|\theta) = P(\theta=1) H(Z|\theta=1) + P(\theta=2) H(Z|\theta=2) = \frac{1}{10} H(Z^+) + \frac{9}{10} H(Z^*) = \frac{9}{10} \cdot \frac{1}{2} \log(2\pi e \cdot N)$   
 $Z^+ \in \{0, 1\}$        $P(Z^+) = \{1, 0\}$        $H(Z^+) = 1 \cdot \log 1 = 0$

$H(Z) = H(1/10) + H(Z|\theta) = H(1/10) + \frac{9}{20} \log(2\pi e \cdot N) = \frac{1}{10} \log 10 + \frac{9}{10} \log \frac{10}{9}$   
 $+ \frac{9}{20} \log(2\pi e \cdot N) = \frac{1}{10} \log 10 + \frac{9}{10} \left[ \log \frac{10}{9} + \log \sqrt{2\pi e \cdot N} \right] = \frac{1}{10} \log 10 + \frac{9}{10} \log \frac{10 \sqrt{2\pi e \cdot N}}{9}$

$$H(z) = \frac{1}{10} \left[ \log 10 + \log \left( \frac{10}{j} \right)^9 \cdot \sqrt{(2\pi e N)^2} \right] = \frac{1}{10} \log \frac{10^{10}}{j^9} \sqrt{(2\pi e N)^2}$$

$$I(x; z) = H(z) - H(z) \quad C = \frac{1}{2} \log(2\pi e) P_x - \frac{1}{10} \log \frac{10^{10}}{j^9} \sqrt{(2\pi e N)^2}$$

$$P_z = E[x^2] + E[z^2] = P + \frac{E[z^2]}{2}$$

$$E_z[z^2] = E_\theta [E[z^2 | \theta]] = \sum_{\theta=1}^9 P(\theta) E_z[z^2 | \theta] = \frac{1}{10} \frac{E[z^2]}{\theta} \frac{1}{10}$$

$$E_z[z^2] = \frac{9}{10} E[z^2] = \frac{9}{10} N$$

$$C = \frac{1}{2} \log(2\pi e) \left( P + \frac{9}{10} N \right) - \frac{1}{2} \log \frac{10^{10}}{j^9} \cdot (2\pi e)^{\frac{9}{10}} N^{\frac{9}{10}}$$

$$C \approx \frac{1}{2} \log \frac{(2\pi e)}{(2\pi e)^{9/10}} \frac{P + \frac{9}{10} N}{N^{9/10}} = \frac{1}{2} \log \sqrt[10]{2\pi e} \left( \frac{9}{10} \sqrt[10]{N} + \frac{P}{\sqrt[10]{N^9}} \right)$$

VLC SOLUTION (HW 9.2, 9.2P)

CAPACITY OF THIS CHANNEL IS INFINITE, SINCE AT THE TIMES THE NOISE IS 0 THE OUTPUT IS EXACTLY EQUAL TO THE INPUT, AND WE CAN SEND INFINITE NUMBER OF BITS. TO SEND INFORMATION THROUGH THIS CHANNEL JUST REPEAT SAME MESSAGE NUMBER OF THE OUTPUT. WHEN WE HAVE THREE OR FOUR OUTPUTS THAT AGREE, THAT SHOULD CORRESPOND TO THE POINTS WHERE THE NOISE IS 0, AND WE CAN DECODE INFINITE NUMBER OF BITS.

**PROBLEM 9.15**

DISCREET INPUT, CONTINUOUS OUTPUT CHANN.

Let  $Pr\{x=1\} = \gamma$ ,  $Pr\{x=0\} = 1-\gamma$ , AND LET  $z = x + Z$  WHERE  $Z$  IS UNIFOLY OVER THE INTERVAL  $[0, a]$   $a > 1$ , AND  $Z$  IS INDEPENDENT OF  $x$ .

- (a) CALCULATE:  $I(x; z) = H(x) - H(x|z)$
- (b) NOW CALCULATE  $I(x; z)$  THE OTHER WAY BT:  $I(x; z) = h(z) - h(z|x)$
- (c) CALCULATE CAPACITY OF THE CHANNEL MAXIMIZING OVER  $\gamma$ .

RECALL: (PROBLEM 8.7)  $z = x' + Z$   $Z \sim U[0, 1]$   
 $x' \in [a_1, a_2, \dots]$   
 $P(x') = \{p_1, p_2, \dots\}$   
 $h(z) = H(x')$   
 $h(z) \leq \frac{1}{2} \log(2\pi e) \sigma_z^2 = \frac{1}{2} \log(2\pi e) [\sigma_{x'}^2 + \sigma_z^2] =$   
 $= \frac{1}{2} \log(2\pi e) \left[ \sum_{i=1}^n i^2 p(i) - \left( \sum_{i=1}^n i p(i) \right)^2 + \sigma_z^2 \right]$

$Z \sim U[0,1]$



$E[Z] = \int_0^1 z \cdot 1 dz = \frac{z^2}{2} \Big|_0^1 = \frac{1}{2}$

$E[Z^2] = \int_0^1 z^2 dz = \frac{z^3}{3} \Big|_0^1 = \frac{1}{3}$

$\sigma_z^2 = E[Z^2] - E[Z]^2 = \frac{1}{3} - \frac{1}{4} = \frac{4-3}{12} = \frac{1}{12}$

$g(z) = \frac{1}{2} \log(2\pi e) \left[ \sum_{i=1}^{\infty} i^2 \eta_i + \sum_{i=1}^{\infty} i \eta_i + \frac{1}{12} \right]$

(a)  $I(x; z) = H(x) - H(z|x)$

$Z = X + Z$

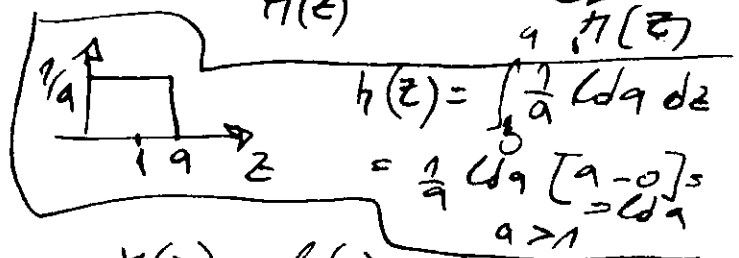
$H(x) = q \log \frac{1}{q} + (1-q) \log \frac{1}{1-q} = H(q)$

$x \in \{0, 1\}$

$q \in \{p, 1-p\}$

$H(z|x) = \sum q_i H(z|x) = (1-q) H(z|x=0) + q H(z|x=1)$

$H(z|x) = H(z)$



$I(x; z) = H(z) - H(z)$

$I(x; z) = H(q) - \log q$

(b)  $I(x; z) = H(z) - H(x|z)$

$H(z) = H(x) = ?$

$H(x) = \sum_{i=0}^1 q_i \log \frac{1}{q_i} = - \sum_{i=0}^1 q_i \log q_i$

$Z = X + Z \in [x+0, x+q] \in [0, 1+q]$

$\begin{matrix} 0+0 & 0+q \\ 1+0 & 1+q \end{matrix}$

$x_1 \in \{0, 1\}$

$x_2 \in [q, q+1]$

~~...~~  $H(z=0) = q$

Recall from 8.7

$z = \{a_1, a_2\}$

$y = \{x = q_i\} = p_i$

$Z = X + Z, U \sim U[0,1]$

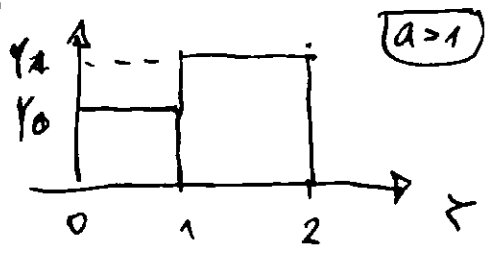
$H(x) = - \sum_{i=0}^1 q_i \log q_i = - [q_0 \log q_0 + q_1 \log q_1] =$

$= - \sum_{i=0}^1 \int_{x_{i-1}}^{x_i} f_z(\gamma) d\gamma \log \int_{x_{i-1}}^{x_i} f_z(\gamma) d\gamma = - \left( \int_0^1 f_z(\gamma) d\gamma \right) \log \int_0^1 f_z(\gamma) d\gamma -$

$- \left( \int_1^2 f_z(\gamma) d\gamma \right) \log \left( \int_1^2 f_z(\gamma) d\gamma \right)$

$$\ln \left[ \int_0^1 x dx \right] = \ln \left( \frac{x^2}{2} \Big|_0^1 \right) = \ln \frac{1}{2}$$

$$\int_0^1 \ln x dx = \frac{1}{x} \Big|_0^1 = (1 - \infty)$$



$a > 1$

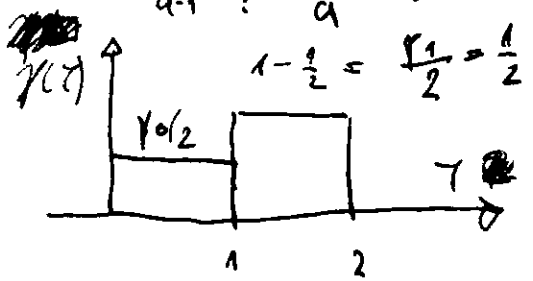
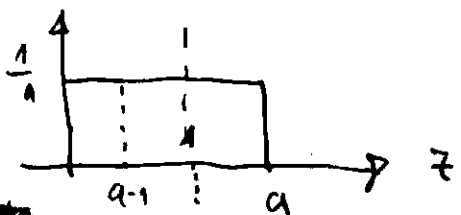
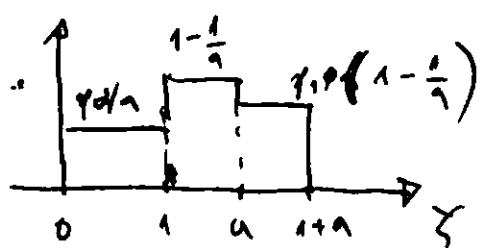
$$y_0 + y_1 = 1$$

$$y_0 = 1 - y_1$$

$$y_1 = y$$

$$h(z) = \int_0^z y(x) dx =$$

$$= \int_0^1 y_0 dx + \int_1^z y_1 dx = \sum_{i=0}^{z-1} \int_{x_i}^{x_{i+1}} y_i dx_i$$



$$y(x \in [0..1]) = y(x=0) \cdot y(z \le 1) = y_0 \cdot \frac{1}{a}$$

$$y(z \le 1) = \int_0^1 \frac{1}{a} dz = \frac{1}{a} \cdot 1 = \frac{1}{a}$$

$$y(z \ge 1) = \int_1^a \frac{1}{a} dz = \frac{1}{a} \cdot (a-1) = 1 - \frac{1}{a}$$

$$y(x \in [1..a]) = y(x=1) \cdot y(z \ge 1) + y(x=1) \cdot y(z \le a-1)$$

$$= y_0 \left(1 - \frac{1}{a}\right) + y_1 \left(1 - \frac{1}{a}\right) = \left(1 - \frac{1}{a}\right) y_1$$

$$y(z \le a-1) = \int_0^{a-1} \frac{1}{a} dz = \frac{1}{a} (a-1) = 1 - \frac{1}{a}$$

$$y(x \in [a..a+1]) = y(x=1) \cdot y(z \le a-1) = y_0 \cdot \frac{1}{a} = y_1/a$$

$$\int_0^1 y(x) dx = \int_0^1 \frac{y_0}{a} dx + \int_1^a \left(1 - \frac{1}{a}\right) dx + \int_a^{a+1} \frac{y_1}{a} dx$$

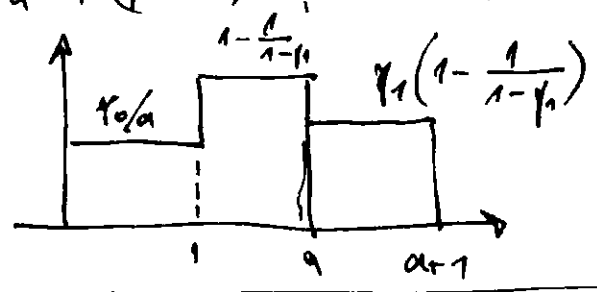
$$= \frac{y_0}{a} + \left(\frac{a-1}{a}\right) (a-1) + \frac{y_1}{a} (a+1 - a) = \frac{y_0}{a} + \frac{(a-1)^2}{a} + \frac{y_1}{a}$$

$$= \frac{y_0 + (a-1)^2 + y_1}{a} = \frac{1 + a^2 - 2a + 1 + y_1}{a} = \frac{a^2 - 2a + 2 + y_1}{a}$$

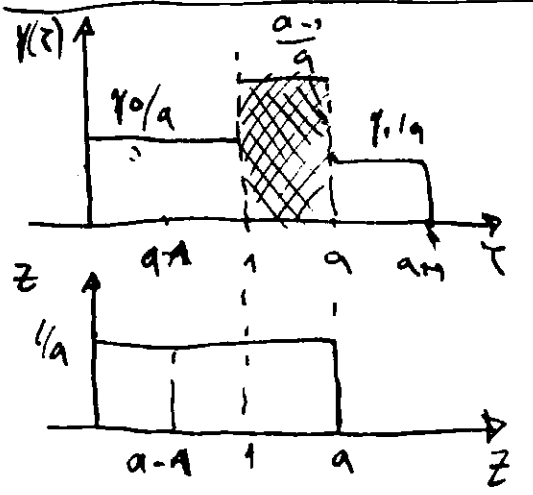
$$\int_0^{1+a} f(\gamma) d\gamma = \frac{f_0}{a} + \frac{(a-1)}{a}(a-1) + \gamma_1 \frac{a-1}{a} = \frac{f_0 + a^2 - 2a + 1 + \gamma_1 a - \gamma_1}{a}$$

$$\begin{aligned} f_0 + a^2 - 2a + 1 + \gamma_1 a - \gamma_1 &= a \\ 1 - \gamma_1 + a^2 - 3a + 1 + \gamma_1 a - \gamma_1 &= 0 \\ a^2 + (\gamma_1 - 3)a + 2(1 - \gamma_1) &= 0 \end{aligned}$$

$$\begin{aligned} \gamma_0 &= 1 - \gamma_1 \\ a^2 - 3a + 2 + \gamma_1 a - 2\gamma_1 &= 0 \\ \Rightarrow \boxed{a = 1 - \gamma_1} \end{aligned}$$



$$\gamma_1 \left( \frac{1 - \gamma_1 - 1}{1 - \gamma_1} \right) = - \frac{\gamma_1^2}{1 - \gamma_1}$$



- $\gamma(x \leq 1) = f(x=0) \cdot \gamma(0 \leq z \leq 1) = f_0 \cdot 1/a$
- $\gamma(z \leq 1) = \int_0^1 \frac{1}{a} dz = \frac{1}{a}$
- $\gamma(1 \leq \gamma \leq a) = f(x=1) \cdot \gamma(0 \leq z \leq a-1) + f(x=0) \cdot \gamma(1 \leq z \leq a) = f_0 \frac{a-1}{a} + f_0 \frac{a-1}{a}$
- $\int_0^{a-1} \frac{1}{a} dz = \frac{1}{a}(a-1) \quad \int_1^a \frac{1}{a} dz = \frac{1}{a}(a-1)$
- $\boxed{\gamma(1 \leq \gamma \leq a) = \frac{a-1}{a}}$

- $\gamma(a \leq \gamma \leq a+1) = \gamma(x=1) \cdot \gamma(z > a-1) = \gamma_1 \cdot 1/a$

$$\gamma(z \geq a-1) = \int_{a-1}^a \frac{1}{a} dz = \frac{1}{a}(a - a + 1) = \frac{1}{a}$$

$$\frac{f_0}{a} + \frac{a-1}{a}(a-1) + \frac{1}{a} = \frac{1}{a} + (1 - \frac{1}{a})(a-1) = \frac{1}{a} + a - 1 - 1 + \frac{1}{a}$$

$$\begin{aligned} -H(\tau) &= \int_0^1 \frac{f_0}{a} \ln \frac{f_0}{a} d\gamma + \int_1^a \frac{a-1}{a} \ln \frac{a-1}{a} d\gamma + \int_a^{a+1} \frac{1}{a} \ln \frac{1}{a} d\gamma \\ &= \frac{f_0}{a} \ln \frac{f_0}{a} + \left( \frac{a-1}{a} \ln \frac{a-1}{a} \right) (a-1) + \frac{1}{a} \ln \frac{1}{a} \cdot 1 \\ &= \frac{f_0}{a} \ln f_0 - \frac{f_0}{a} \ln a + \frac{1}{a} \ln \gamma_1 - \frac{\gamma_1}{a} \ln a + \frac{(a-1) \ln \frac{a-1}{a}}{a} \\ &= \frac{1}{a} [-H(f)] + \frac{\ln a}{a} (\gamma_0 + \gamma_1) + \frac{(a-1) \ln(a-1)}{a} - \frac{(a-1) \ln a}{a} \end{aligned}$$



$$\begin{aligned}
 -H(\gamma) &= -\frac{H(\gamma)}{a} - \frac{1}{a} \log a + \frac{(a-1)^k}{a} \log(a-1) - \frac{a^k - 2a - 1}{a} \log a = \\
 &= -\frac{H(\gamma)}{a} - \frac{(a-1)^2}{a} \log(a-1) + \frac{2a - a^k}{a} \log a = -\frac{H(\gamma)}{a} - \frac{a^2 - 2a + 1}{a} \log(a-1) \\
 &= -\frac{H(\gamma)}{a} - \frac{(a-1)^2}{a} \log(a-1) + \frac{(2-a)a}{a} \log a = \\
 &= -\frac{H(\gamma)}{a} - \frac{a^2 - 2a + 1}{a} \log(a-1) + 2 \log a - a \log a = \\
 &= -\frac{H(\gamma)}{a} + \frac{2a - a^2 - 1}{a} \log(a-1) + 2 \log a - a \log a = \\
 &= -\frac{H(\gamma)}{a} + (2-a) \log(a-1) - \frac{1}{a} \log(a-1) + (2-a) \log a = \\
 &= -\frac{H(\gamma)}{a} + (2-a) \log a(a-1) - \frac{1}{a} \log(a-1) \quad \boxed{H(\gamma) = \frac{H(\gamma)}{a} - \frac{(2a-1) \log a(a-1)}{a} + \frac{1}{a} \log(a-1)}
 \end{aligned}$$

$$\begin{aligned}
 H(\gamma|\underline{x}) &=? \quad I(x;\gamma) = H(\gamma) - \log a = H(\gamma) - H(\gamma|\underline{x}) \\
 H(\underline{x}|\gamma) &= -H(\gamma) + \log a + \frac{H(\gamma)}{a} - (2-a) \log(a-1) + \frac{1}{a} \log(a-1) = \\
 &= H(\gamma) \left( \frac{1}{a} - 1 \right) + \log a - (2-a) \log a - (2-a) \log(a-1) + \frac{1}{a} \log(a-1) \\
 &= H(\gamma) \left( \frac{1}{a} - 1 \right) + \log a - 2 \log a + a \log a + \left( \frac{1}{a} - 2 + a \right) \log(a-1) = \\
 &= H(\gamma) \frac{1-a}{a} + (a-1) \log a + \frac{(1-2a+a^2)}{a} \log(a-1) = \\
 &= H(\gamma) \frac{1-a}{a} + (a-1) \log a + \frac{(a-1)^2}{a} \log(a-1) = \\
 &= H(\gamma) \frac{1-a}{a} + (a-1) \left[ \log a + \frac{a-1}{a} \log(a-1) \right] = \\
 &= H(\gamma) \frac{1-a}{a} + (a-1) \left[ \log a + \log(a-1) - \frac{1}{a} \log(a-1) \right] = \\
 &= H(\gamma) \frac{1-a}{a} + (a-1) \left[ \log a(a-1) - \frac{1}{a} \log(a-1) \right]
 \end{aligned}$$

(a)  $I(x;\gamma) = H(\gamma) - H(\gamma|\underline{x})$        $\boxed{\gamma = x+z}$        $x = \gamma - z$   
 $H(\underline{x}) = H(\gamma)$        $H(\underline{x}|\gamma) = H(\gamma - z|\gamma) = H(z) = \log a$

$I(x;\gamma) = H(\gamma) - \log a$

(b)  $I(x;\gamma) = H(\gamma) - H(\gamma|\underline{x}) = H(\gamma) - \log a$

**PROBLEM 8.8 REVISITED**       $x \in \{0, \pm 1, \pm 2\}$        $z \in [-1, 1]$        $\gamma = x+z$   
 $\gamma(\underline{x}) = [\gamma_2, \gamma_1, \gamma_0, \gamma_{-1}, \gamma_{-2}]$        $\gamma \in \{-3, -2, -1, 0, 1, 2, 3\}$

$$\gamma(\tau) = \begin{cases} \gamma_2/2 \\ (\gamma_2 + \gamma_1)/2 \\ (\gamma_1 + \gamma_0)/2 \\ (\gamma_0 + \gamma_{-1})/2 \\ (\gamma_{-1} + \gamma_{-2})/2 \end{cases}$$

$x \in [0, 1]$       $\gamma(x) \in \{\gamma_0, \gamma_1\}$       $Z \sim U[0..a]$

~~...~~      $Z \in [0..1, 1..a, a..(a+1)]$

$\gamma(z) = \left[ \frac{\gamma_0}{a}, 1 - \frac{1}{a}, \frac{\gamma_1}{a} \right]$       $1 - \frac{\gamma_0 + \gamma_1}{a} = 1 - \frac{1}{a}$

$h(z)_{max} = 1/3$       $\frac{\gamma_0}{a} = \frac{1}{3} = \frac{\gamma_1}{a}$       $\gamma_0 = \frac{a}{3} = \gamma_1$

$\gamma_0 + \gamma_1 = \frac{a}{3} + \frac{a}{3} = \frac{2a}{3} = 1$       $a = \frac{3}{2}$       $\gamma_0 = \frac{1}{2} = \gamma_1$

$\gamma(z) = \left[ \frac{1}{3}, 1 - \frac{2}{3}, \frac{1}{3} \right] = \left[ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$

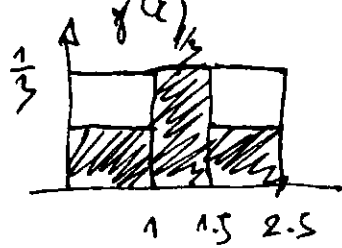
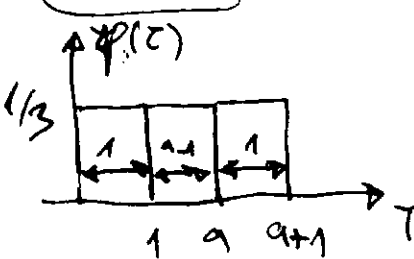
$h(z) = - \left[ \frac{\gamma_0}{a} \ln \frac{\gamma_0}{a} + \left[ \left(1 - \frac{1}{a}\right) \ln \left(1 - \frac{1}{a}\right) \right] \frac{(a-1)}{\int_{(z)} dz} + \frac{\gamma_1}{a} \ln \frac{\gamma_1}{a} \right]$

(c)  $C = \max_{\gamma} I(x; z)$       $I(x; z) = h(z) - \frac{h(z|x)}{h(z)_{max}}$

$h(z)_{max} = 1/3$      FOR UNIFORM DISTRIBUTION      $\gamma(z) = \left[ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$

$\Rightarrow \frac{\gamma_0}{a} = \frac{1}{3}$       $\gamma_0 = \frac{a}{3} = \gamma_1$       $\frac{a}{3} + \frac{a}{3} = 1$       $\frac{2a}{3} = 1$

$a = \frac{3}{2}$       $\gamma_0 = \frac{1}{2} = \gamma_1$       $\Rightarrow \gamma(z) = \left[ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right]$



$\frac{1}{3} + \frac{1}{3} \cdot \frac{1}{2} + \frac{1}{3}$

$\frac{\gamma_0}{a} = \left(1 - \frac{1}{a}\right)(a-1) = \frac{\gamma_1}{a} = \frac{1}{3}$       $\gamma_0 = a - \left(\frac{a-1}{a}\right)(a-1) = (a-1)^2$

$\gamma_1 = 1 - (a-1)^2$       $(a-1)^2 = \frac{a}{3}$       $a^2 - 2a + 1 = \frac{a}{3}$

$a^2 - 2a - \frac{a}{3} + 1 = 0$       $a^2 - \frac{6a + a}{3} + 1 = 0$       $a^2 - \frac{7a}{3} + 1 = 0$

$a = \frac{7 \pm \sqrt{13}}{6}$

$a = 1.76759$

$C = 1/3 - 1/a = 0.76318$

~~...~~      $\gamma_0 = (a-1)^2 =$

THE ENTROPY POWER INEQUALITY

$$2^{2h(x+z)} \geq 2^{2h(x)} \cdot 2^{2h(z)} \quad \left| \cdot 2^{-2h(z)} \right.$$

$$2^{2h(x+z) - 2h(z)} \geq 2^{2h(x) - 2h(z)} \quad \left| \cdot 2^{2h(z)} \right.$$

$$2^{2[h(x+z) - h(z)]} \geq 2^{2h(x) - 2h(z)} \Rightarrow \frac{2^{2[h(x+z) - h(z)]}}{2^{2h(x) - 2h(z)}} \geq 1$$

$$\frac{2^{2[h(x+z) - h(z)]}}{2^{2h(x) - 2h(z)}} = \frac{2^{2h(x+z) - 2h(x)}}{2^{2h(z) - 2h(x)}} = \frac{2^{2h(x+z)}}{2^{2h(x)}} \cdot \frac{2^{2h(x)}}{2^{2h(z)}} = \frac{2^{2h(x+z)}}{2^{2h(x)}} \cdot \frac{1}{2^{2h(z) - 2h(x)}}$$

$$\frac{2^{2[h(x+z) - h(z)]}}{2^{2h(x) - 2h(z)}} \geq \frac{1}{2^{2h(z) - 2h(x)}} \Rightarrow 2^{2[h(x+z) - h(z)]} \geq 2^{2h(z) - 2h(x)}$$

$$2[h(x+z) - h(z)] \geq 2h(z) - 2h(x) \Rightarrow 2[h(x+z) - h(z)] \geq 2h(z) - 2h(x)$$

$$2[h(x+z) - h(z)] \geq \frac{2}{N} + 1 \quad 2[h(x+z) - h(z)] \geq \log\left(\frac{P}{N} + 1\right)$$

$$h(x) = \frac{1}{2} \log(e) P$$

$$h(z) = \frac{1}{2} \log(e) N$$

$I(x; x) = I(x; z) \geq \frac{1}{2} \log\left(1 + \frac{P}{N}\right)$

Since since  $I(x; z) \in [0, \log(P)]$  and  $I(x; z) \in [0, \log(P)]$  then

$C = \max_{P(x)} I(x; z) \in [0, \log(P)]$  is the capacity.

- Recall (using two channels in series) Problem 7.5

$$C \leq C_1 + C_2$$

$$I(x; z) \leq I(x_1; z_1) + I(x_2; z_2)$$

- ENTROPY OF DISJOINT MIXTURE PROBLEM 9.10

$$h(x) = h(x) + \alpha h(x_1) + (1-\alpha) h(x_2) \quad \left| \cdot 2^x \right.$$

$$2^{h(x)} = 2^{h(x)} \cdot 2^{\alpha h(x_1)} \cdot 2^{(1-\alpha) h(x_2)}$$

$$= 2 + 2^{\frac{h(x_1)}{2}} \cdot 2^{\alpha h(x_1)} \cdot 2^{(1-\alpha) h(x_2)} \leq 2 + 2^{\frac{h(x_1)}{2}} + 2^{\alpha h(x_1)}$$

$$\frac{dh(x)}{d\alpha} = -\left[ \log \frac{1}{\alpha} + (1-\alpha) \log(1-\alpha) \right] + h(x_1) - h(x_2) = 0$$

$$-\left[ \log \alpha + \alpha \cdot \frac{1}{\alpha} \cdot \frac{1}{\alpha} + \left[ -1 \cdot \log(1-\alpha) \right] + \frac{(1-\alpha)^{-1}}{\alpha} \right] + h(x_1) - h(x_2) = 0$$

$$-\left[ \log \alpha + \frac{1}{\alpha} - \log(1-\alpha) - \frac{1}{\alpha} \right] + h(x_1) - h(x_2) = 0$$

$$-\log \frac{\alpha}{1-\alpha} = h(x_2) - h(x_1) \quad \frac{\alpha}{1-\alpha} = 2$$

$$\alpha = 2 \frac{1-\alpha}{1 + 2^{h_2+h_1}} \Rightarrow \alpha (1 + 2^{h_2+h_1}) = 2^{h_2+h_1}$$

$$\alpha = \frac{2^{h_2}}{2^{h_1} + 2^{h_2}} \quad h(x)_{max} = h(x) \Big|_{\alpha} = h(x) \Big|_{\alpha} = \frac{2^{h_2}}{2^{h_1} + 2^{h_2}}$$

$$2^{h_{max}} = 2^{h_1} + 2^{h_2} \quad 2^h \leq 2^{h_{max}} \leq 2^{h_1} + 2^{h_2}$$

(6) The random codebook can be listed as an array with  $2^m$  rows and  $n$  columns, the entry  $x_i(m)$  in row  $i$  and column  $m$  being the  $i$ -th coordinate of the  $m$ -th codeword. Each  $x_i(m)$  is Gaussian with mean zero and variance  $\sigma^2$  and all these random variables are mutually independent. Let  $W$  denote the message transmitted, this is uniformly distributed on  $\{1, 2, \dots, 2^m\}$  and is independent of the random codebook.

The received vector  $(z_1, \dots, z_n)$  then has coordinates given with  $z_i = x_i(W) + z_i$  where  $(z_1, \dots, z_n)$  are i.i.d with marginal distribution  $f_z(z)$  and these are independent of  $W$  and the random codebook. Let  $\hat{W}$  denote the decoded message. This is determined by the rule

$$\hat{W} = \underset{i}{\operatorname{arg\,min}} \sum_{i=1}^n (z_i - x_i(m))^2$$

and since ties occur with probability of zero, we can speak of the event that tie-breaking is needed. The probability of error is:  $P(\hat{W} \neq W)$ . Note that this is automatically being averaged over the transmitted message and the random codebook.

(i) The probability of error conditioned on noise realization being  $z$  can be written as  $P(\hat{W} \neq W | Z=z)$  where  $Z$  denotes  $(z_1, \dots, z_n)$ . The suggested geometric argument works as follows. Let  $U$  be any orthogonal  $n \times n$  real matrix. Given random codebook, we can consider another one with the same number of codewords but with  $m$ -th row being given by:  $(\tilde{x}_1(m), \dots, \tilde{x}_n(m))$  where

$$\begin{bmatrix} \tilde{x}_1(m) \\ \vdots \\ \tilde{x}_n(m) \end{bmatrix} = U \begin{bmatrix} x_1(m) \\ \vdots \\ x_n(m) \end{bmatrix} \quad \begin{matrix} U^T = U^{-1} \\ U^T \cdot U = I \end{matrix}$$

By invariance under rotation, for the new codebook the probability of error conditioned on the noise realization being  $(Uz)^T$  is identical to the probability of error under the old codebook conditioned on the noise realization being  $z$ . However, the new codebook is statistically indistinguishable from old codebook, hence probability of error conditioned on the noise vector being  $z$  depends only on the Euclidean norm  $\|z\|$ .

(ii) Error occurs if the vector  $x(W)^T + z^T$  is closer to  $x(m)^T$  than to  $x(W)^T$  for some  $m \neq W$ . The closest such  $m$  is  $\hat{W}$ . Let  $\lambda > 1$ . By considering the triangle defined by three points  $x(W)^T$ ,  $x(\hat{W})^T$  and  $x(W)^T + z^T$  in the two dimensional plane that they span, simple geometric argument show that this implies that, in Euclidean norm,  $x(W)^T + \lambda z^T$  is closer to  $x(W)^T$  than it is to  $x(\hat{W})^T$ . This

IMPLIES THAT PROBABILITY OF ERROR CONDITIONED ON EUCLIDEAN NORM OF THE NOISE VECTOR IS MONOTONICALLY INCREASING IN THIS EUCLIDEAN NORM.

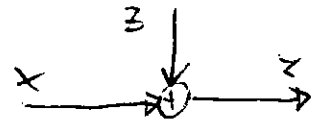
(III) BY THE WEAK LAW OF LARGE NUMBERS THE PROBABILITY THAT THE NORM OF THE NOISE VECTOR  $Z$  EXCEEDS THAT OF GAUSSIAN NOISE VECTOR  $(Z'_1, \dots, Z'_N)$  EACH OF WHOSE COORDINATES TAKE MEAN ZERO AND VARIANCE  $N'$ , WHERE  $N' > N$ , GOES TO 0 BY THE GEOMETRIC ARGUMENT OF THE PRECEDING PART IT FOLLOWS THAT THE PROBABILITY OF ERROR IN THE ORIGIN CASE IS ASYMPTOTICALLY NO BIGGER THAN THAT IN THE GAUSSIAN NOISE CASE (WHERE THE VARIANCE OF THE GAUSSIAN NOISE IS STRICTLY BIGGER THAN  $N$ )

(IV) SINCE THE PROBABILITY OF ERROR IN THE GAUSSIAN CASE (WITH NOISE VARIANCE  $N'$  STRICTLY BIGGER THAN  $N$ ) BUT SUCH AS  $D < \frac{1}{2} \log(1 + \frac{P}{N'})$  ASYMPTOTICALLY GOES TO ZERO IT DOES SO IN THE ORIGIN CASE WE ARE CONSIDERING.

(c) EVERY STEP IN THE DISCUSSION ABOVE GOES THROUGH EVEN IF WE ONLY ASSUME THAT THE NOISE PROCESS IS STATIONARY AND ERGODIC THE ONLY THING THAT NEEDS TO CHANGE IS THAT INSTEAD OF WEAK LAW OF LARGE NUMBERS FOR I.I.D NOISE VARIABLES  $Z_i$ , WE NEED TO UTIL AN ERGODIC THEOREM.

**PROBLEM 3.2A** MUTUAL INFORMATION GAME. CONSIDER THE

FOLLOWING CHANNEL:



THROUGHOUT THIS PROBLEM WE SHALL CONSIDER THE SIGNAL POWER  $E[X^2] = P$  AND THE NOISE POWER  $E[Z^2] = N$

AND ASSUME THAT  $X$  AND  $Z$  ARE INDEPENDENT. THE CHANNEL CAPACITY IS GIVEN BY  $I(X; X+Z)$ . NOW FOR THE GAME, THE NOISE PLAYER CHOOSES A DISTRIBUTION ON  $Z$  TO MINIMIZE  $I(X; X+Z)$ , WHILE THE SIGNAL PLAYER CHOOSES A DISTRIBUTION ON  $X$  TO MAXIMIZE  $I(X; X+Z)$ . LETTING  $X^* \sim N(0, P)$ ;  $Z^* \sim N(0, N)$ , SHOW THAT GAUSSIAN  $X^*$  AND  $Z^*$  SATISFY THE SADDLEPOINT CONDITIONS

$$I(X; X+Z^*) \leq I(X^*; X^*+Z) \leq I(X^*; X^*+Z^*)$$

THIS:  $\min_Z \max_X I(X; X+Z) = \max_X \min_Z I(X; X+Z) = \frac{1}{2} \log(1 + \frac{P}{N})$

AND THE GAME HAS A VALUE IN PARTICULAR DEVIATION FROM NORMALITY FOR EITHER PLAYER WORSENS THE ~~PERFORMED~~ MUTUAL INFORMATION FROM THAT PLAYER'S STANDPOINT CAN YOU DISCUSS THE INDICATIONS OF THIS?

NOTE: PART OF THE PROOF HINGES ON ENTROPY POWER INEQUALITY FROM SECTION 17.2, WHICH STATES THAT IF  $X$  AND  $Z$  ARE INDEPENDENT RANDOM VECTORS WITH DENSITIES, THEN:

$$\frac{1}{2} \log h(x+z) \geq \frac{1}{2} \log h(x) + \frac{1}{2} \log h(z)$$

$$2^{\frac{1}{2}} h(x+z) \geq 2^{\frac{1}{2}} h(x) + 2^{\frac{1}{2}} h(z)$$

$$I(x; x+z) = H(x+z) - H(x+z|x) = H(x+z) - H(z)$$

$$x = x^* \sim \mathcal{N}(0, P) \quad z = z^* \sim \mathcal{N}(0, N)$$

$$I(x^*; x^*+z^*) = \frac{1}{2} \log \det(P+N) - \frac{1}{2} \log \det(N) = \frac{1}{2} \log \det \left( I + \frac{P}{N} \right)$$

$$I(x^*; x^*+z) = \frac{1}{2} H(x^*+z) - H(z); \quad I(x; x+z^*) = \frac{1}{2} H(x+z^*) - H(z^*)$$

$$I(x; x+z^*) = \frac{1}{2} H(x+z^*) - \frac{1}{2} \log \det(N) \leq \frac{1}{2} H(x^*+z^*) - \frac{1}{2} \log \det(N) = I(x^*+z^*; z^*)$$

(F) GAUSSIAN DISTRIBUTION MAXIMIZES ENTROPY! <sup>(E)</sup> HENCE FIRST PART IS PROVEN

$$I(x^*; x^*+z) = \frac{1}{2} H(x^*+z) - H(z)$$

$$2^{\frac{1}{2}} h(x^*+z) \geq 2^{\frac{1}{2}} h(x^*) + 2^{\frac{1}{2}} h(z) = 2^{\frac{1}{2}} \log \det(P) + 2^{\frac{1}{2}} h(z)$$

$$2^{\frac{1}{2}} h(x^*+z) \geq \log \det(P) + 2^{\frac{1}{2}} h(z) \quad \left| \frac{h(z) = \frac{1}{2} \log \det(N)}{2^{\frac{1}{2}} h(z)} \right.$$

$$2^{\frac{1}{2}} [h(x^*+z) - h(z)] \geq \frac{\log \det(P)}{2^{\frac{1}{2}} h(z)} + 1 \geq \left| \begin{array}{l} \text{GAUSSIAN} \\ \text{MAXIMIZES} \\ \text{ENTROPY} \end{array} \right. \geq \frac{\log \det(P)}{\log \det(N)} + 1$$

$$h(x^*+z) - h(z) = I(x^*+z; z) \geq \frac{1}{2} \log \det \left( I + \frac{P}{N} \right) = I(x^*+z^*; z^*)$$

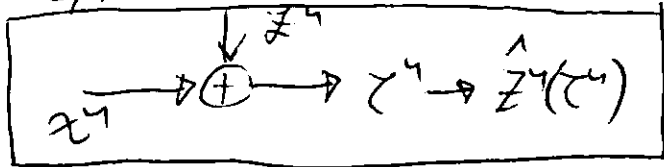
HENCE:  $I(x^*+z; z) \geq I(x^*+z^*; z^*) \geq I(x; x+z^*)$  i.e.  
 $I(x; x+z^*) \leq I(x^*+z^*; z^*) \leq I(x^*+z; z)$  PROVED !!!

(F)

- REGARDING \$ THE STATEMENT IN FEKETE SOLUTIONS  
 sol 5-229 AS PROOF PPT: \$ WAS PROVED IN 9.20, WHILE  
 WE ASSUMED THAT THE NOISELESS ADDITIVE NOISE CHANNEL  
 WITH NOISE VARIANCE N, WHEN THE INPUT DISTRIBUTION  
 IS CHOSEN TO BE GAUSSIAN WITH MEAN ZERO AND VARIANCE  
 P, THE MUTUAL INFORMATION BETWEEN THE INPUT AND  
 THE OUTPUT IS AT LEAST AS LARGE AS IN THE CASE OF  
 GAUSSIAN NOISE OF VARIANCE N.

**PROBLEM 9.22** RECOVERING THE NOISE. CONSIDER A STATIONARY  
 GAUSSIAN CHANNEL  $y^N = x^N + z^N$  WHERE  $z^N$   
 IS I.I.D.  $\mathcal{N}(0, N)$   $i = 1, 2, \dots, N$  AND  $\frac{1}{N} \sum_{i=1}^N x_i^2 \leq P$   
 HERE WE ARE INTERESTED IN RECOVERING THE NOISE  $z^N$   
 AND WE DON'T CARE ABOUT THE SIGNAL  $x^N$ . BY SENDING

$x^n = (0, 0, \dots, 0)$ , THE RECEIVER GETS  $z^n = Z^n$  AND CAN FULLY DETERMINE THE VALUE OF  $Z^n$ . WE WONDER HOW MUCH VARIABILITY THERE CAN BE IN  $x^n$  AND STILL RECOVER GAUSSIAN NOISE  $Z^n$ . USE OF THE CHANNEL LOOKS LIKE:



ALIVE THAT FOR SOME  $R > 0$  THE TRANSMITTER CAN ARBITRARILY SEND ONE OF  $2^{nR}$  DIFFERENT SEQUENCES OF  $x^n$  WITHOUT AFFECTING THE RECOVERY OF THE

NOISE IN THE SENSE THAT:

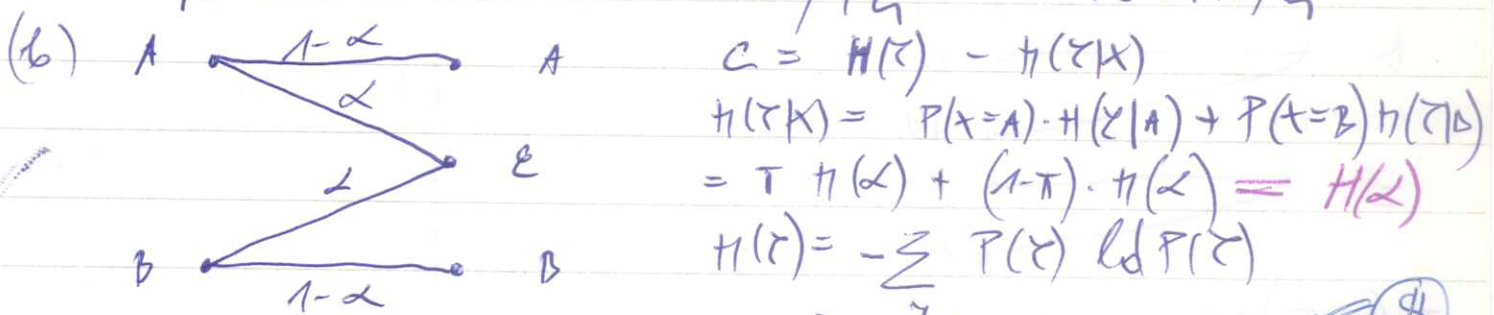
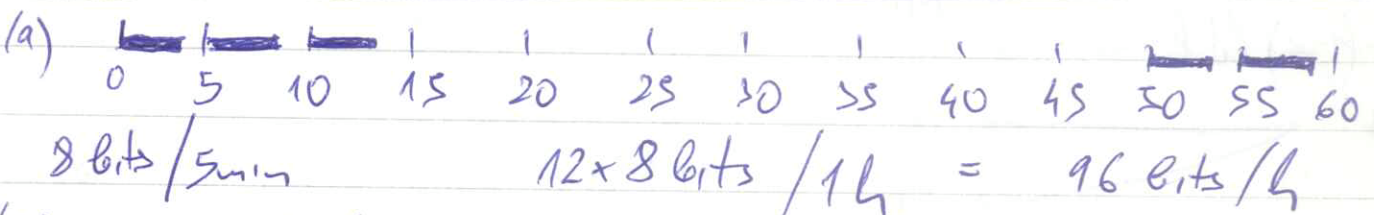
$\Pr\{\hat{Z}^n \neq Z^n\} \rightarrow 0$  AS  $n \rightarrow \infty$   
FOR WHAT  $R$  IS THIS POSSIBLE?

$$\begin{aligned}
 nR &= H(W) = I(W; \hat{W}) + H(W|\hat{W}) \leq I(x^n; z^n) + n \cdot \epsilon_n = \\
 &= H(z^n) - H(z^n|x^n) \stackrel{n \epsilon_n}{=} H(z^n) - H(Z^n) \leq \sum_{i=1}^n H(z_i) - \sum_{i=1}^n \underbrace{H(z_i)}_{\text{GAUSS}} \\
 &\leq \sum_{i=1}^n \frac{1}{2} \log_2(P_i + N_i) - \sum_{i=1}^n \frac{1}{2} \log_2(2\pi e) N_i = \sum_{i=1}^n \frac{1}{2} \log_2\left(1 + \frac{P_i}{N_i}\right)
 \end{aligned}$$

**PROBLEM 7.19** CAPACITY OF CARRIER PIGEON CHANNEL

CONSIDER A COMMANDER OF AN ARMY BESIEGED IN A FORT FOR WHOM THE ONLY MEANS OF COMMUNICATION TO HIS ALLIES IS A SET OF CARRIER PIGEONS. ASSUME THAT EACH CARRIER PIGEON CAN CARRY ONE LETTER (8 BITS), THAT PIGEONS ARE RELEASED ONCE EVERY 5 MIN, AND THAT EACH PIGEON TAKES EXACTLY 3 MINUTES TO REACH ITS DESTINATION.

- (a) ASSUMING THAT ALL THE PIGEONS REACH SAFELY, WHAT IS THE CAPACITY OF THIS LINK IN BITS/HOUR
  - (b) NOW ASSUME THAT THE ENEMIES TRY TO SHOOT DOWN THE PIGEONS AND THAT THEY MANAGE TO HIT FRACTION  $\alpha$  OF THEM. SINCE THE PIGEONS ARE SENT AT CONSTANT RATE THE RECEIVER KNOWS WHEN THE PIGEONS ARE MISSING. WHAT IS THE CAPACITY OF THIS LINK?
  - (c) NOW ASSUME THAT THE ENEMY IS MORE CUNNING AND THAT EVERY TIME THEY SHOT DOWN THE PIGEON, THEY SEND OUT A DUMMY PIGEON CARRYING A RANDOM LETTER (CHOSEN UNIFORMLY FROM ALL 8-BIT LETTERS). WHAT IS THE CAPACITY OF THIS LINK IN BITS/HOUR?
- SET UP AN APPROXIMATE MODEL FOR THE CHANNEL IN EACH OF THE ABOVE CASES, AND INDICATE HOW TO GO ABOUT FINDING THE CAPACITY.



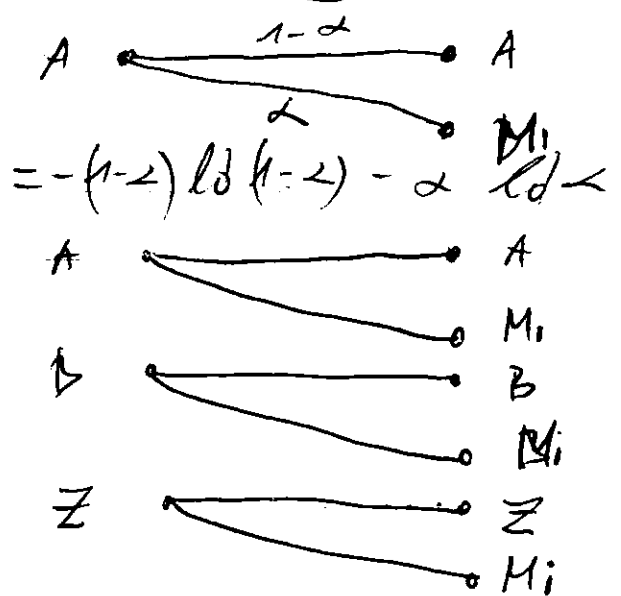
$P(Z) = \{ P(Z=A), P(Z=E), P(Z=B) \} = \{ P(X=A) \cdot (1-\alpha), P(X=A) \cdot \alpha + P(X=B) \cdot \alpha, P(X=B) \cdot (1-\alpha) \}$   
 $= \{ \pi(1-\alpha), \alpha, (1-\pi)(1-\alpha) \}$

$H(Z) = -\pi(1-\alpha) \log \pi(1-\alpha) - \alpha \log \alpha - (1-\pi)(1-\alpha) \log (1-\pi)(1-\alpha)$   
 $= -\pi(1-\alpha) \log \pi - \pi(1-\alpha) \log(1-\alpha) - \alpha \log \alpha - (1-\pi)(1-\alpha) \log(1-\pi) - (1-\pi)(1-\alpha) \log(1-\alpha)$   
 $= -\alpha \log \alpha - (1-\alpha) \log(1-\alpha) - (1-\alpha) \log(\pi) + \pi(1-\alpha) \log(1-\pi) - \pi(1-\alpha) \log \pi$



$$\begin{aligned}
 H(\tau) &= H(\alpha) - (1-\alpha) \log(1-\alpha) + \alpha \log \frac{1-\alpha}{\alpha} = \\
 &= H(\alpha) - \log(1-\alpha) + \alpha \log(1-\alpha) + \alpha \log \frac{1-\alpha}{\alpha} - \alpha \log \frac{1-\alpha}{\alpha} \\
 &= H(\alpha) - \log(1-\alpha) + \alpha \log(1-\alpha) + \alpha \log \frac{1}{\alpha} + \alpha \log(1-\alpha) - \alpha \log(1-\alpha) - \\
 &\quad - \alpha \log \frac{1}{\alpha} \\
 &= H(\alpha) - \underbrace{(1-\alpha) \log(1-\alpha) + \alpha \log(1-\alpha)} + \alpha \log \frac{1}{\alpha} = \\
 &= H(\alpha) - (1-\alpha)(1-\alpha) \log(1-\alpha) + \alpha \log \frac{1}{\alpha} = \\
 &= H(\alpha) + (1-\alpha) \left[ - (1-\alpha) \log(1-\alpha) + \alpha \log \frac{1}{\alpha} \right] = H(\alpha) + (1-\alpha) H(\alpha) \\
 C &= \left[ H(\tau) - H(\tau|x) \right]_{\max} = H(\alpha) + (1-\alpha) H(\alpha) - H(\alpha)
 \end{aligned}$$

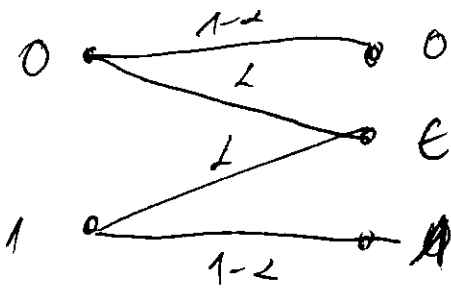
$$\begin{aligned}
 I(x; \tau) &= (1-\alpha) H(\alpha) \quad \text{if: } \tau = \left\{ \frac{1}{2}, \frac{1}{2} \right\} \Rightarrow \\
 \boxed{I(x; \tau) = 1-\alpha}
 \end{aligned}$$



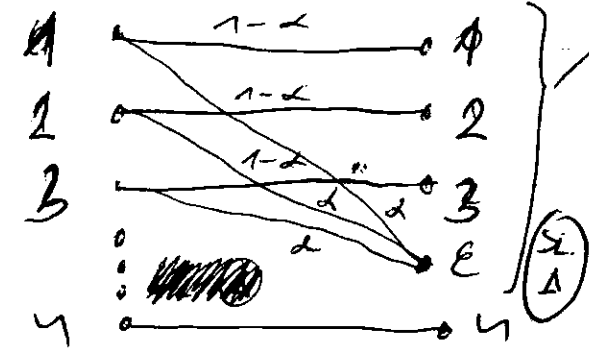
" $M_i$ " - MISSING PIGEON

$$\begin{aligned}
 I(x; \tau) &= H(\tau) - H(\tau|x) = \\
 &= H(\alpha) - H(\alpha) = 0 \\
 x &\in \{A, M_i, \dots, Z\} \\
 H(\alpha) &= \left( \frac{1}{26} \log 26 \right) \cdot 26 = \log 26 \\
 H(\tau|x) &= P(A) \cdot H(\tau=A|A) + \\
 &\quad + P(A=B) \cdot H(\tau=A|B) + \dots + P(x=Z) \cdot H = \\
 &= \left[ \sum_x P(x) \right] \cdot H(\alpha) = H(\alpha)
 \end{aligned}$$

$$\begin{aligned}
 I(x; \tau) &= H(\tau) - H(\alpha) \\
 H(\tau) &= H(A, B, \dots, Z, M_i) = \left[ (1-\alpha) \sum p(x) \cdot \log p(x) + \alpha \log \alpha \right] \\
 &= (1-\alpha) \cdot H(\alpha) + \alpha \log \alpha \\
 H(\tau) &= (1-\alpha) H(\alpha) - \alpha \log \alpha \\
 \max [H(\tau)] &= (1-\alpha) \log \frac{1}{1-\alpha} - \alpha \log \alpha \\
 C &= (1-\alpha) \log \frac{1}{1-\alpha} - \alpha \log \alpha - H(\alpha)
 \end{aligned}$$

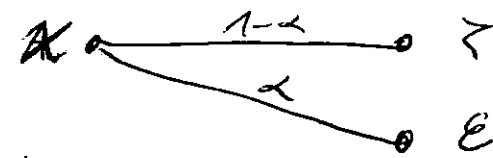


$$P(\tau) = \{ \pi(1-\alpha), \pi\alpha + (1-\pi)\alpha, (1-\pi)(1-\alpha) \} = \{ \pi(1-\alpha), \alpha, (1-\pi)(1-\alpha) \}$$



NE E VANA ZOŠTO,  $\alpha$  E PROCENT OD VUŠNO ISKAZENIOT DLOV NA GULATI !!! MOLE SEJAK E !!

DEFINITIVNO VARIJANT E:



$\alpha$  E PROCENT OD ANO SI SOŠTIRAJI PUKVI I E MAI

VUŠNIOT DLOV NA NA GULATI ITO MOŠT PARIČI

$$N_1 G(1); N_2 G(2); N_3 G(3); \dots; N_n G(n);$$

$$N = N_1 + N_2 + \dots + N_n$$

$$\alpha \cdot N = \alpha N_1 + \alpha N_2 + \dots + \alpha N_n$$

OLUO GULADI MOŠI NA POLONA ~~u1~~ I E ŠTIGAT NA REŠTINAGATA.

BUO NA GULADI MOŠI NA IŠTAKATA ~~u2~~ ITO CE ŠTIGAT NA OBŠTINAGATA.

ZNAJI ŠBAK VARIJANT E VANO NA SZ. 1

$$P(\tau) = \{ p_1(1-\alpha), p_2(1-\alpha), \dots, (1-\alpha)p_n, p_1\alpha + p_2\alpha + \dots + p_n\alpha \} = \{ p_1(1-\alpha), p_2(1-\alpha), \dots, (1-\alpha)p_n, \alpha \}$$

$$H(\tau) = - \left[ \sum_{i=1}^n p_i(1-\alpha) \ln p_i(1-\alpha) + \alpha \ln \alpha \right]$$

NA IST VIKOV MAŠN MOŠEN VA ŠO DOŠEŠI NA ABC. 1

$$H(\tau) = \sum_{i=1}^n p_i(1-\alpha) \ln \frac{1}{p_i(1-\alpha)} + \alpha \ln \frac{1}{\alpha} =$$

$$= \sum_{i=1}^n p_i(1-\alpha) \left[ \ln \frac{1}{p_i} + \ln \frac{1}{(1-\alpha)} \right] + \alpha \ln \frac{1}{\alpha} =$$

$$= (1-\alpha) \sum_{i=1}^n p_i \ln \frac{1}{p_i} + (1-\alpha) \sum_{i=1}^n p_i \ln \frac{1}{(1-\alpha)} + \alpha \ln \frac{1}{\alpha}$$

$$H(\tau) = (1-\alpha)H(x) + \alpha H(z)$$

$$I(x; \tau) = H(\tau) - H(\tau|x) = (1-\alpha)H(x) + \alpha H(z) - H(z)$$

$$I(x; \tau) = (1-\alpha)H(x)$$

$$C_B = \max_{\gamma(\tau)} I(x; \tau) = (1-\alpha) \log_2 m \text{ BITES}$$

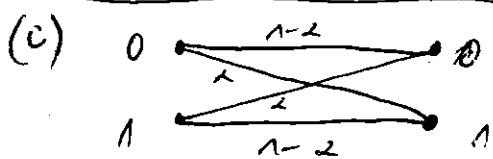
IF  $m = 2^8 = 256$

$$C_B = (1-\alpha) \cdot 8$$

$$C_B = C_B / 8 = (1-\alpha) \log_2 m$$

КАНАЛИТЕТОТ ВО БИТЕ:

$$C_B = (1-\alpha) \log_2 m$$



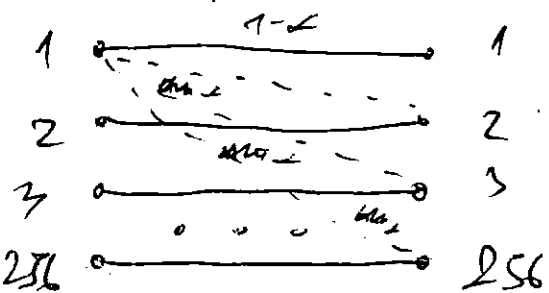
$$I(x; \tau) = H(\tau) - H(\tau|x)$$

$$H(\tau|x) = P(x=0) \cdot H(z) + P(x=1) \cdot H(z)$$

$$H(z) = H(\alpha)$$

$$I(x; \tau) = H(\tau) - H(\alpha)$$

$$C = \max_{\gamma(\tau)} I(x; \tau) = 1 - H(\alpha)$$



$$I(x; \tau) = H(\tau) - H(\tau|x)$$

$$H(\tau|x) = \sum_x \gamma(x) H(\tau|x=x)$$

$$H(\tau|x=1) = -[P(\tau=1) \cdot \log_2 P(\tau=1) + P(\tau=0) \cdot \log_2 P(\tau=0)] = -[(1-\alpha) \cdot \log_2(1-\alpha) + \alpha \cdot \log_2 \alpha] = H(\alpha)$$

$$H(\tau|x) = \sum_x \gamma(x) \cdot H(\tau|x=x) = \gamma(x=0) \cdot H(\alpha) + \dots + \gamma(x=1) \cdot H(\alpha)$$

$$H(\tau|x) = H(\alpha) \cdot \sum_x \gamma(x) = H(\alpha)$$

$$C = \max I(x; \tau)$$

$$C = \log_2 m - H(\alpha)$$

$$C = \log_2 256 - H(\alpha) = \log_2 2^8 - H(\alpha) = 8 - H(\alpha)$$

JOHN HOPKINGS SOLUTIONS

$$(b) \max [(1-\alpha)H(x)] = (1-\alpha) \log_2 256$$

$$C = (1-\alpha) \cdot 96 \frac{\text{bits}}{\text{hour}}$$

8 USES OF THE CHANNEL  
 96 bits/hour !!!  
 ЗАДАЧА 1 ИЛИ 90 СРЕДСТВ ВО БИТ 1 ГОДА 90 МНОЖИТЬ 96 БИТ/ЧАС !!!

$$H(\tau|x_i) = H\left(1 - \frac{L}{256} + \frac{L}{256}, \frac{L}{256}, \frac{L}{256}, \dots, \frac{L}{256}\right)$$

14 ie stigne deza sa pozitia 14 ie stigne sa pozitia no pozitia uota lucidro ce sa izstat ie sa pozitia da mpe ista 40 ishataata locata.

$$H(\tau|x_i) = -\left(1 - \frac{L}{256} + \frac{L}{256}\right) \log\left(1 - \frac{L}{256}\right) - \frac{L}{256} \log\frac{L}{256}$$

$$\begin{aligned} H(\tau|x_i) &= -\left(1 - \frac{255L}{256}\right) \log\left(1 - \frac{255L}{256}\right) - \frac{255L}{256} \log\frac{L}{256} = \\ &= -\left(1 - \frac{255L}{256}\right) \log\left(1 - \frac{255L}{256}\right) - \frac{255L}{256} \log\frac{255L}{256} + \frac{255L}{256} \log 255 = \\ &= H\left(\frac{255L}{256}\right) + \frac{255L}{256} \log 255 \end{aligned}$$

$$\begin{aligned} \max_{\tau} I(x_i, \tau) &= \log 256 - H\left(\frac{255L}{256}\right) - \frac{255L}{256} \log 255 = \log 256 \\ &= \log 256 - \left( H\left(\frac{255L}{256}\right) - \frac{255L}{256} \log 255 \right) = 8 \left( 1 - \frac{1}{8} H\left(\frac{255L}{256}\right) - \frac{255L}{2048} \right) \end{aligned}$$

BITES

VO BITI 40 DEZIS KARACT SA 8 ZATOA SA MAS 8 UNOTENI SA ISTOT SA ZATOA

$$C = \left( 1 - \frac{1}{8} H\left(\frac{255L}{256}\right) - \frac{255L}{2048} \right) \log 256$$

• KAPACITETOT VO bits/look 40 DOAIVA ANO 40 GO 10MROZIS SA 96 bits/look T.E:

$$C = 96 \left( 1 - \frac{1}{8} H\left(\frac{255L}{256}\right) - \frac{255L}{2048} \right) \log 256$$

$IF L=1$

$$C = 96 \left( 1 - \frac{1}{8} H\left(\frac{255}{256}\right) - \frac{255}{2048} \right) \log 256$$

$$C = 96 \left( 1 + \frac{1}{8} \log\frac{1}{256} + \frac{255}{256} \log 255 - \frac{255}{2048} \log 255 \right) = 96 \frac{\log 256}{8}$$

$-H = \frac{255}{256} \log\frac{255}{256} + \frac{1}{256} \log\frac{1}{256} = \frac{255}{256} \log\frac{1}{256} + \frac{255}{256} \log\frac{255}{256}$

$C(L=0) = 96 \frac{\log 256}{8}$

60

**PROBLEM 7.25**

[CONTINUE FROM (A)] BOTTLENECK CHANNEL

$X \rightarrow V \rightarrow Z$

$X = \{1, 2, \dots, m\}$   $Z = \{1, 2, \dots, n\}$   
 $U = \{1, 2, \dots, k\}$

$I(X; Z) = \sum_U I(X; Z|U)$  [  $C \leq C_d(k)$  ]

$I(X; V) = I(V) - H(V|X)$   
 $I(X; V; Z) = I(X; Z) + I(V; Z|X)$

DATA PROCESSING:  $X \rightarrow Z \rightarrow Y$

$I(Z; Y) \geq I(X; Z)$

$I(X; Z; Y) = I(X; Z) + I(Z; Y|X) = I(Z; Y) + I(X; Z|Y)$

$I(Z; Y|X) = H(Z|X) - H(Z|X, Y) = H(Z|X) - H(Z|Y)$

$I(X; Z|Y) = H(Z|Y) - H(Z|Y, X) = H(Z|Y) - H(Z|X) = -I(Z; Y|X)$

$I(Z; Y) \geq I(X; Z)$

$I(X; Z; Y) = I(X; Z) + I(Z; Y|X) = I(X; Z) + I(Z; Y) - I(Z; Y|X)$

MMV

$C = \max [I(X; Z)]$

$I(X; Z) \leq I(V; Z) \leq I(V; Y) \leq I(V; X)$

$C = \max [I(X; Z)] \leq \max [I(V; X)] = \max [H(X) - H(X|V)]$

$C = \max [I(X; Z)] \leq \max [I(X; V)] = \max [H(X) - H(X|V)] = \max [H(V) - H(V|X)] \leq \max [H(V)] = C_d(k)$

$C \leq C_d(k)$

$P(X, Z|Y) = \frac{P(X, Z, Y)}{P(Y)} = \frac{P(X, Y) \cdot P(Z|X, Y)}{P(Y)} = \frac{P(X) \cdot P(Y|X) \cdot P(Z|X, Y)}{P(Y)}$

$P(X, Z|Y) = P(X|Y) \cdot P(Z|X, Y) = \frac{P(X, Z, Y)}{P(Y)} = \frac{P(X, Y) \cdot P(Z|X, Y)}{P(Y)}$

$= \frac{P(Z) \cdot P(X|Z) \cdot P(Z|X)}{P(Z)} = P(X|Z) \cdot P(Z|X)$

DATA & ENTROPY AND LOG-LIKE!!!

V0 GENERAZIONE ALTA (DUE METROSTAVKA ZA HARRON CH.)  
 $\epsilon = \min_{\mu_1} [I(x; z)] ; I(x; z) = \underline{H(x)} - \underline{H(z|x)}$

$H(z|x) = \sum_x p(x) \cdot \underline{H(z|x)}$

$\begin{bmatrix} p(z_1) \\ p(z_2) \end{bmatrix} = \begin{bmatrix} p(z_1|x_1); p(z_1|x_2) \\ p(z_2|x_1); p(z_2|x_2) \end{bmatrix} ; \begin{bmatrix} p(x_1) \\ p(x_2) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} \\ p_{21} & p_{22} \end{bmatrix} \begin{bmatrix} p(z_1) \\ p(z_2) \end{bmatrix}$

$\begin{bmatrix} p(z_1) \\ p(z_2) \\ p(z_3) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \\ p_{13} & p_{23} \end{bmatrix} \begin{bmatrix} p(x_1) \\ p(x_2) \end{bmatrix} ; \begin{bmatrix} p(x_1) \\ p(x_2) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \end{bmatrix} \begin{bmatrix} p(z_1) \\ p(z_2) \\ p(z_3) \end{bmatrix}$

$\begin{bmatrix} p(x_1) \\ p(x_2) \\ p(x_3) \end{bmatrix} = \begin{bmatrix} p_{11} & p_{21} \\ p_{12} & p_{22} \\ p_{13} & p_{23} \end{bmatrix} \underbrace{\begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \end{bmatrix}}_{= p(z_1|x_2)} \underbrace{\begin{bmatrix} p(x_1) \\ p(x_2) \\ p(x_3) \end{bmatrix}}_{p(z_1|x_2)}$

VIOLI 3C

$\begin{bmatrix} p(z_1) \\ p(z_2) \\ p(z_3) \end{bmatrix} = \begin{bmatrix} p_{11} p_{11} + p_{21} p_{12} & p_{11} p_{12} + p_{21} p_{13} & p_{11} p_{13} + p_{21} p_{23} \\ p_{12} p_{11} + p_{22} p_{12} & p_{12} p_{12} + p_{22} p_{13} & p_{12} p_{13} + p_{22} p_{23} \\ p_{13} p_{11} + p_{23} p_{12} & p_{13} p_{12} + p_{23} p_{13} & p_{13} p_{13} + p_{23} p_{23} \end{bmatrix} \begin{bmatrix} p(x_1) \\ p(x_2) \\ p(x_3) \end{bmatrix}$

$I(x; z) = H(z) - H(z|x) \leq H(z)$

$H(z) = - \sum p(z) \log p(z)$

$p(z_1) = \left[ \sum_{\sigma} p(z_1|\sigma) \cdot p(\sigma|x_1) \right] \cdot p(x_1) + \left[ \sum_{\sigma} p(z_1|\sigma) \cdot p(\sigma|x_2) \right] \cdot p(x_2) + \dots$

⊙  $p_{11} p_{11} + p_{21} p_{12} = p(z_1|\sigma_1) \cdot p(\sigma_1|x_1) + p(z_1|\sigma_2) \cdot p(\sigma_2|x_1)$

⊕  $p_{11} p_{21} + p_{21} p_{22} = p(z_1|\sigma_1) \cdot p(\sigma_1|x_2) + p(z_1|\sigma_2) \cdot p(\sigma_2|x_2)$

⊗  $p_{13} p_{12} + p_{23} p_{13} = p(z_1|\sigma_1) \cdot p(\sigma_1|x_3) + p(z_1|\sigma_2) \cdot p(\sigma_2|x_3)$

$p(z_1) = \sum_{x=1}^n p(x) \cdot \sum_{\sigma} p(z_1|\sigma) \cdot p(\sigma|x) = \sum_x \sum_{\sigma} p(x) p(z_1|\sigma) p(\sigma|x)$

$$\gamma(z_1) = \sum_{\sigma} \gamma(z_1|\sigma) \underbrace{\sum_x \gamma(x) \cdot \gamma(\sigma|x)}_{\gamma(\sigma)} = \sum_{\sigma} \gamma(z_1|\sigma) \underbrace{\left[ \sum_x \gamma(x|\sigma) \right]}_{\gamma(\sigma)}$$

$$\textcircled{1} \textcircled{2} \left[ \gamma(z_1|\sigma_1) \cdot \gamma(\sigma_1|x_1) + \gamma(z_1|\sigma_2) \cdot \gamma(\sigma_2|x_1) \right] \cdot \gamma(x_1) = \gamma(z_1|\sigma_1) \cdot \gamma(x_1|\sigma_1) + \gamma(z_1|\sigma_2) \cdot \gamma(x_1|\sigma_2)$$

$$\gamma(z_1) = \sum_{\tau, \sigma} \gamma(\tau, \sigma) \cdot \gamma(z_1|\sigma) \quad \gamma(z_2) = \sum_{\tau, \sigma} \gamma(\tau, \sigma) \cdot \gamma(z_2|\sigma)$$

$$H(\tau) = \sum_{\gamma} \left[ \sum_{\sigma} \gamma(\sigma, \sigma) \cdot \gamma(\gamma, \sigma) \right] \text{ and } \left[ \sum_{\sigma} \gamma(\tau, \sigma) \cdot \gamma(\gamma|\sigma) \right]$$

$$\textcircled{1} \textcircled{1} = \gamma(z_1|\sigma_1) \cdot \gamma(\sigma_1|x_2) + \gamma(z_1|\sigma_2) \cdot \gamma(\sigma_2|x_2)$$

$$\textcircled{1} \textcircled{2} = \gamma(z_1|\sigma_1) \cdot \gamma(\sigma_1|x_2) + \gamma(z_1|\sigma_2) \cdot \gamma(\sigma_2|x_2)$$

$$\gamma(z_1) = \gamma(z_1|\sigma_1) \underbrace{\sum_{x_i} \gamma(\sigma_1|x_i)}_{\gamma(\sigma_1)} + \gamma(z_1|\sigma_2) \underbrace{\sum_{x_i} \gamma(\sigma_2|x_i)}_{\gamma(\sigma_2)}$$

$$\gamma(x) = \int_{-\infty}^{\infty} \gamma(x, \tau) d\tau$$

$$\textcircled{1} \Rightarrow \gamma(z_1) = \sum_{\sigma} \gamma(z_1|\sigma) \cdot \underbrace{\sum_x \gamma(x, \sigma)}_{\gamma(\sigma)} = \sum_{\sigma} \gamma(z_1|\sigma) \cdot \gamma(\sigma) = \gamma(z_1)$$

$$H(z|x) = \sum_{\tau} \gamma(x) H(\tau|x=\tau) = ?$$

$$- H(\tau|x_1) = \left( \gamma_{11} \gamma_{11} + \gamma_{21} \gamma_{12} \right) \text{ and } \left( \gamma_{11} \gamma_{11} + \gamma_{21} \gamma_{12} \right) + \left( \gamma_{12} \gamma_{11} + \gamma_{22} \gamma_{12} \right) \text{ and } \left( \gamma_{12} \gamma_{11} + \gamma_{22} \gamma_{12} \right) + \left( \gamma_{12} \gamma_{11} + \gamma_{22} \gamma_{12} \right) \cdot \text{and } \left( \gamma_{12} \gamma_{11} + \gamma_{22} \gamma_{12} \right) = \left[ \gamma(z_1|\sigma_1) \cdot \gamma(\sigma_1|x_1) + \gamma(z_1|\sigma_2) \cdot \gamma(\sigma_2|x_1) \right] \cdot \text{and } \left[ \gamma(z_1|\sigma_1) \cdot \gamma(\sigma_1|x_1) + \gamma(z_1|\sigma_2) \cdot \gamma(\sigma_2|x_1) \right] + \left[ \gamma(z_2|\sigma_1) \cdot \gamma(\sigma_1|x_1) + \gamma(z_2|\sigma_2) \cdot \gamma(\sigma_2|x_1) \right] \cdot \text{and } \left[ \gamma(z_2|\sigma_1) \cdot \gamma(\sigma_1|x_1) + \gamma(z_2|\sigma_2) \cdot \gamma(\sigma_2|x_1) \right]$$

8c

$$-H(\tau|x_1) = P(\sigma_1|x_1) [Y(\tau_1|\sigma_1) / d(A) + Y(\tau_2|\sigma_1) / d(B) + Y(\tau_3|\sigma_1) / d(C)]$$

$$IF: Y(\tau_1|\sigma_1) \cdot P(\sigma_1|x_1) = Y(\tau_1|x_1) \quad Y(\tau_2|\sigma_2) \cdot P(\sigma_2|x_2) = Y(\tau_2|x_2)$$

$$Y(\tau_1|x_2) = \underbrace{Y(\tau_1|\sigma_1)}_{P(\sigma_1)} \cdot Y(\sigma_1|x_2) + Y(\tau_1|\sigma_2) \cdot Y(\sigma_2|x_2) \quad \boxed{MMV}$$

~~USE KOLMOGOROV'S ...~~  
~~(OBTAIN ...)~~

$$-H(\tau|x_1) = [Y(\tau_1|\sigma_1)P(\sigma_1|x_1) + Y(\tau_2|\sigma_2)P(\sigma_2|x_1)] \cdot d \cdot Y(\tau_1|x_1) +$$

$$+ [Y(\tau_2|\sigma_1) \cdot P(\sigma_1|x_1) + Y(\tau_2|\sigma_2) \cdot P(\sigma_2|x_1)] \cdot d \cdot Y(\tau_2|x_1) +$$

$$+ [Y(\tau_3|\sigma_1) \cdot P(\sigma_1|x_1) + Y(\tau_3|\sigma_2) \cdot P(\sigma_2|x_1)] \cdot d \cdot [Y(\tau_3|x_1)]$$

$$\Rightarrow Y(\sigma_1|x_1) [Y(\tau_1|\sigma_1) \cdot d \cdot Y(\tau_1|x_1) + Y(\tau_2|\sigma_1) \cdot d \cdot Y(\tau_2|x_1) +$$

$$+ Y(\tau_3|\sigma_1) \cdot d \cdot Y(\tau_3|x_1)] \Rightarrow P(\sigma_1|x_1) [Y(\tau_1|\sigma_1) \cdot d \cdot [Y(\tau_1|\sigma_1) \cdot P(\sigma_1|x_1)] + \dots$$

$$Y(\tau_1|x_1) = Y(\tau_1|\sigma_1) P(\sigma_1|x_1) + Y(\tau_1|\sigma_2) \cdot Y(\sigma_2|x_1)$$

$$Y(\tau_1|x_1) \geq Y(\tau_1|\sigma_1) \cdot P(\sigma_1|x_1) \quad \text{KLEINER RELATIVES}$$

$$\dots + Y(\tau_1|\sigma_n) \cdot d \cdot [Y(\tau_2|\sigma_n) \cdot P(\sigma_n|x_1)] + Y(\tau_2|\sigma_n) \cdot d \cdot [Y(\tau_3|\sigma_n) \cdot P(\sigma_n|x_1)]$$

$$\Rightarrow P(\sigma_1|x_1) [-H(\tau|V=\sigma_1)] = P(\sigma_1|x_1) [Y(\tau_1|\sigma_1) \cdot d \cdot \frac{1}{P(\sigma_1|x_1)} +$$

$$+ Y(\tau_2|\sigma_1) \cdot d \cdot \frac{1}{P(\sigma_1|x_1)} + Y(\tau_3|\sigma_1) \cdot d \cdot \frac{1}{P(\sigma_1|x_1)}] =$$

$$= -Y(\sigma_1|x_1) H(\tau|V=\sigma_1) - Y(\sigma_1|x_1) \cdot [d \cdot \frac{1}{P(\sigma_1|x_1)}] \cdot \sum Y(\tau_i|\sigma_1)$$

$$H(\tau|x_1) \geq P(\sigma_1|x_1) \cdot H(\tau|V=\sigma_1) + P(\sigma_2|x_1) \cdot H(\tau|V=\sigma_2) + \dots + P(\sigma_n|x_1) \cdot H(\tau|V=\sigma_n)$$

$$\Rightarrow Y(\sigma_2|x_1) [Y(\tau_1|\sigma_2) \cdot d \cdot Y(\tau_1|x_1) + Y(\tau_2|\sigma_2) \cdot d \cdot Y(\tau_2|x_1) +$$

$$+ Y(\tau_3|\sigma_2) \cdot d \cdot Y(\tau_3|x_1)] \geq Y(\sigma_2|x_1) [Y(\tau_1|\sigma_2) \cdot d \cdot P(\tau_1|\sigma_2) +$$

$$+ Y(\tau_2|\sigma_2) \cdot d \cdot P(\tau_2|\sigma_2) + Y(\tau_3|\sigma_2) \cdot d \cdot P(\tau_3|\sigma_2)] +$$

$$+ Y(\sigma_2|x_1) [Y(\tau_1|\sigma_2) \cdot d \cdot Y(\sigma_2|x_1) + Y(\tau_2|\sigma_2) \cdot d \cdot Y(\sigma_2|x_1) + Y(\tau_3|\sigma_2) \cdot d \cdot Y(\sigma_2|x_1)]$$

$$= Y(\sigma_2|x_1) [-H(\tau|V=\sigma_2)] + Y(\sigma_2|x_1) \cdot [d \cdot Y(\sigma_2|x_1)] \cdot P(\tau|V=\sigma_2)$$



(100)

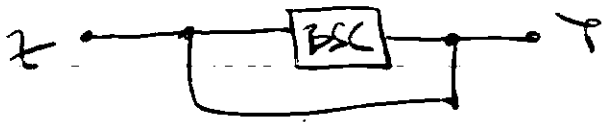
$$\begin{aligned}
 H(Z|X) &\leq P(\sigma_1|X) \cdot H(Z|V=\sigma_1) + P(\sigma_2|X) \cdot H(Z|V=\sigma_2) \cdot \left( \frac{1}{P(\sigma_1|X)} \right) \\
 &+ P(\sigma_2|X) \cdot H(Z|V=\sigma_2) + P(\sigma_2|X) \cdot H(Z|V=\sigma_2) \cdot \left( \frac{1}{P(\sigma_2|X)} \right) \\
 \cdot H(Z|X) &= \sum_x H(Z|x) \cdot P(x) = \sum_x P(x) \cdot [P(\sigma_1|x) \cdot H(Z|V=\sigma_1) \\
 &+ P(\sigma_2|x) \cdot H(Z|V=\sigma_2)] + \sum_x P(x) \cdot [P(\sigma_1|x) \cdot H(Z|V=\sigma_1) \\
 &\cdot \left( \frac{1}{P(\sigma_1|x)} \right) + P(\sigma_2|x) \cdot H(Z|V=\sigma_2) \cdot \left( \frac{1}{P(\sigma_2|x)} \right)] \\
 &\leq \underbrace{\sum_x P(x, \sigma_1) H(Z|V=\sigma_1)}_{P(\sigma_1) \cdot H(Z|V=\sigma_1)} + \underbrace{\sum_x P(x, \sigma_2) H(Z|V=\sigma_2)}_{P(\sigma_2) \cdot H(Z|V=\sigma_2)} + \\
 &+ \underbrace{\sum_x P(x, \sigma_1) P(Z|\sigma_1) \cdot \left( \frac{1}{P(\sigma_1|x)} \right)}_{P(Z|\sigma_1) \cdot H(\sigma_1|X)} + \underbrace{\sum_x P(x, \sigma_2) P(Z|\sigma_2) \cdot \left( \frac{1}{P(\sigma_2|x)} \right)}_{P(Z|\sigma_2) \cdot H(\sigma_2|X)} \\
 &= P(\sigma_1) \cdot H(Z|V=\sigma_1) + P(\sigma_2) \cdot H(Z|V=\sigma_2) + P(Z|\sigma_1) \cdot H(\sigma_1|X) + \\
 &+ P(Z|\sigma_2) \cdot H(\sigma_2|X) = \underline{H(Z|V)} + \sum_{\sigma} P(Z|\sigma) \cdot H(\sigma|X) \\
 I(X; Z) &= H(Z) - H(Z|X) \geq H(Z) - H(Z|V) - \epsilon \\
 \Rightarrow \max_{P(X)} I(X; Z) &\geq \max_{P(X)} (H(Z) - H(Z|V) - \epsilon) \\
 & \qquad \qquad \qquad H(V; X) = H(V) - H(V|X)
 \end{aligned}$$

**PROBLEM 7.3** BSC WITH FEEDBACK. SUPPOSE THAT FEED-

BACK IS USED ON BINARY SYMMETRIC CHANNEL WITH PARAMETER  $p$ . EACH TIME  $Y$  IS RECEIVED, IT BECOMES THE NEXT TRANSMISSION. THUS  $X_1$  IS  $\text{Bern}\left(\frac{1}{2}\right)$ ,  $X_2 = Y_1$ ,  $X_3 = Y_2, \dots, X_n = Y_{n-1}$ .

- (a) FIND  $\lim_{n \rightarrow \infty} \frac{1}{n} I(X^n; Z^n)$
- (b) SHOW THAT FOR SOME VALUES OF  $p$  THIS CAN EXCEED THE CAPACITY
- (c) USING THIS FEEDBACK TRANSMISSION SCHEME  $X^n(V^n)$   $\rightarrow (X_1(V_1), Z_1, Z_2, \dots, Z_{n-1})$ , WHAT IS ASYMPTOTIC COMMUNICATION RATE ACHIEVED; THAT IS, WHAT IS  $\lim_{n \rightarrow \infty} \frac{1}{n} I(X^n; Z^n)$

(1/2)



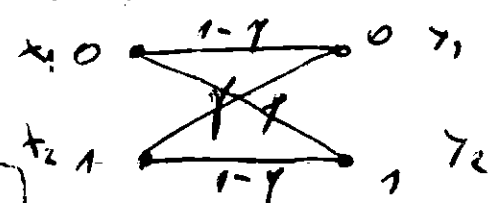
$$x_1 = \text{Bern}\left(\frac{1}{2}\right)$$

$$x_2 = x_1 ; x_3 = x_2 \dots$$

$$x_n = x_{n-1}$$

$$(a) \lim_{n \rightarrow \infty} \frac{I(x^n; z^n)}{n} = \lim_{n \rightarrow \infty} \left[ \frac{H(x^n) - H(x^n | z^n)}{n} \right]$$

$$H(x^n) = H(x_1, x_2, \dots, x_n)$$



$$\begin{bmatrix} p(x_1) \\ p(x_2) \end{bmatrix} = \begin{bmatrix} 1-p & p \\ p & 1-p \end{bmatrix} \begin{bmatrix} p(x_1) \\ p(x_2) \end{bmatrix}$$

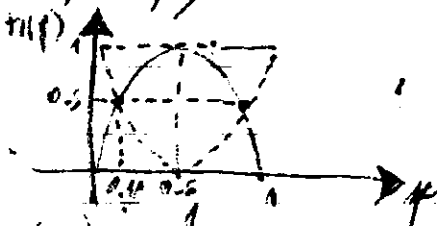
$$p(x_1) = \begin{bmatrix} \frac{1}{2} & \frac{1}{2} \end{bmatrix} \quad x_1 = \begin{cases} 0 & \text{with } p = \frac{1}{2} \\ 1 & \text{with } p = \frac{1}{2} \end{cases}$$

$$H(x^n) = \underbrace{H(x_1)}_{H(\frac{1}{2})=1} + \underbrace{H(x_2 | x_1)}_{H(p)} + \underbrace{H(x_3 | x_1, x_2)}_{= H(x_2 | x_1)} + \underbrace{H(x_4 | x_1, x_2, x_3)}_{= H(x_3 | x_2)} + \dots + \underbrace{H(x_{n-1} | x_{n-2})}_{H(p)} = 1 + (n-1)H(p)$$

$$H(x^n | z^n) = H(x_1 | z_1) + H(x_2 | x_1, z_1) + H(x_3 | x_1, x_2, z_1, z_2) + \dots + H(x_n | x_1, \dots, x_{n-1}, z_1, \dots, z_{n-1}) = H(x_1) + H(x_2 | x_1, z_1) + H(x_3 | x_1, x_2, z_1, z_2) + \dots + H(x_n | x_1, \dots, x_{n-1}) = H(x_1) = 1$$

$$I(x^n; z^n) = n(1 - H(p)) = (n-1)H(p)$$

$$\lim_{n \rightarrow \infty} \left[ \frac{(n-1)H(p)}{n} \right] = H(p)$$



$$(b) C_{BSC} = 1 - H(p)$$

$$H(p) = 1 - H(p) \quad \text{if } H(p) = 1 \quad H(p) = \frac{1}{2}$$

$$-p \log p - (1-p) \log (1-p) = \frac{1}{2} \rightarrow \boxed{p = 0.11}$$

(c)  $X^n(W, Z^n) = (X_1(W), Z_1, Z_2, \dots, Z_{n-1})$  (12c)

$\lim_{n \rightarrow \infty} \frac{1}{n} I(W; X^n)$

$W \rightarrow X^n \rightarrow Z^n \rightarrow \hat{W}$   $W \in \{1, 2, \dots, 2^{4R}\}$

$$n \cdot R = H(W) = H(W|\hat{W}) + I(W; \hat{W}) \leq 1 + 2^{4R} \cdot n \cdot R + I(X^n; Z^n)$$

$$I(X^n; Z^n) = H(X^n) - H(Z^n|X^n) = \sum_{i=1}^n H(X_i|X_1^{i-1}) - \sum_{i=1}^n H(Z_i|X_1^{i-1}) \leq \sum_{i=1}^n H(X_i) - \sum_{i=1}^n H(Z_i|X_i) = \sum_{i=1}^n I(X_i; Z_i) \leq 4n \cdot C$$

$$I(W; Z^n) = H(W) - H(W|Z^n)$$

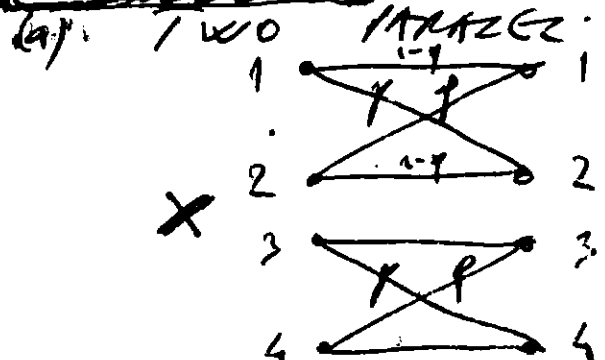
$$I(W; X^n; Z^n) = I(X^n; Z^n) + I(W; Z^n|X^n) = I(W; Z^n) + I(X^n; Z^n|W)$$

$$I(X^n; Z^n) \leq I(W; Z^n)$$

$$\lim_{n \rightarrow \infty} \frac{I(W; Z^n)}{n} \leq \lim_{n \rightarrow \infty} \frac{I(X^n; Z^n)}{n} \lim_{n \rightarrow \infty} \frac{n-1}{n} H(Z) = H(Z)$$

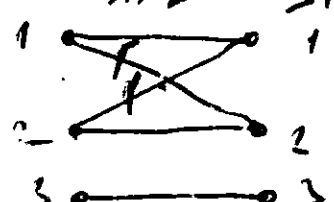
**PROBLEM 7.34**

FIND THE CAPACITY OF BSC:

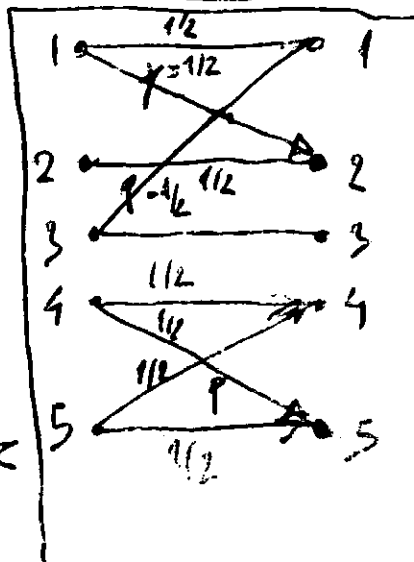


$$2^C = 2^{C_1} + 2^{C_2}$$

(b) BSC AND SINGLE STREAM



(c) BSC AND TERMINAL ARRANGEMENT



(b) TOLUANE CHAINING

13c

$$\gamma(\tau|x) = \begin{bmatrix} \frac{2}{3} & \frac{1}{3} & 0 \\ 0 & \frac{1}{3} & \frac{2}{3} \end{bmatrix}$$

$$(a) \quad 2^L = 2^{1-\pi(\gamma)} + 2^{1-\pi(\gamma)} = 2 \cdot 2^{1-\pi(\gamma)} = 2^{2-\pi(\gamma)}$$

$$\boxed{L = 2 - \pi(\gamma)} \quad \textcircled{a}$$

RECALL:  $\pi(\tau_1|x_1) = \pi(\gamma) \quad \pi(\tau_2|x_2) = \pi(\gamma)$

$$I(x;\tau) = I(x_1, x_2; \tau_1, \tau_2) = \underline{H(\tau_1, \tau_2)} - H(\tau_1, \tau_2 | x_1, x_2)$$

$$H(\tau_1, \tau_2) = H(\tau_1) + H(\tau_2)$$

$$H(\tau_1, \tau_2 | x_1, x_2) = H(\tau_1 | x_1, x_2) + H(\tau_2 | \tau_1, x_1, x_2) = H(\tau_1 | x_1) + H(\tau_2 | x_2)$$

$$I(x;\tau) = H(\tau_1) - H(\tau_1 | x_1) + H(\tau_2) - H(\tau_2 | x_2)$$

$$I(x;\tau) = I(x_1; \tau_1) + I(x_2; \tau_2)$$

$$H(\tau_1 | x_1) = \cancel{H(\tau_1)} \cdot H(\tau_1 | x_1=1) + \cancel{p(x_1=2)} \cdot H(\tau_1 | x_1=2)$$

$$= H(\gamma) [ \gamma(x_1=1) + \gamma(x_1=2) ] = \alpha \cdot H(\gamma)$$

$$H(\tau_2 | x_2) = \gamma(x_2=2) \cdot H(\tau_2 | x_2=2) + \gamma(x_2=1) \cdot H(\tau_2 | x_2=1)$$

$$\boxed{H(\tau_2 | x_2) = (1-\alpha) \cdot H(\gamma)}$$

$$\gamma(\tau_1=1) = \gamma(x_1=1) \cdot (1-\gamma) + \gamma(x_1=2) \cdot \gamma = \frac{\alpha}{2} (1-\gamma) + \frac{1-\alpha}{2} \gamma = \frac{\alpha}{2}$$

$$H(\tau_1) = \gamma \cdot \frac{\alpha}{2} \log \frac{\alpha}{2} = \alpha \log \frac{\alpha}{2}$$

$$I(x;\tau) = \alpha \log \frac{\alpha}{2} - \alpha H(\gamma) + (1-\alpha) \log \frac{1-\alpha}{2} - (1-\alpha) H(\gamma)$$

$$I(x;\tau) = H(\alpha) + \alpha \log 2 + (1-\alpha) \log 2 + H(\gamma)$$

$$I(x;\tau) = H(\alpha) + (\log 2 - H(\gamma)) = \underline{H(\alpha) + 1 - H(\gamma)}$$

$$\frac{dI(x;\tau)}{d\alpha} = 0$$

$$\frac{d}{d\alpha} [ \alpha \log \alpha + (1-\alpha) \log(1-\alpha) ] = \log \alpha + \frac{1}{\alpha} - \log(1-\alpha) - \frac{1}{1-\alpha}$$

$$= \log \frac{\alpha}{1-\alpha} - \frac{1}{\alpha(1-\alpha)}$$

$$I(x;\tau) = \log \frac{\alpha}{1-\alpha} + (1 - H(\gamma)) = \frac{1}{1-\alpha} \log \left( \frac{\alpha}{1-\alpha} \right) = 0$$

$$\frac{\alpha}{1-\alpha} = 1 \quad \alpha = 1-\alpha \quad 2\alpha = 1 \quad \boxed{\alpha = \frac{1}{2}}$$

$$\boxed{L = H\left(\frac{1}{2}\right) + 1 - H(\gamma) = 2 - H(\gamma)}$$

1ST REQUEST 1000

• Two period BSC se l'equilibrio ad utroque:

$$I(x; z) = \alpha \log \frac{2}{1-\alpha} + (1-\alpha) \log \frac{2}{1-\alpha} - 2H(y) - (1-\alpha)H(z)$$

$$= H(\alpha) + \alpha \log 2 + (1-\alpha) \log 2 - 2H_1 - (1-\alpha)H_2$$

$$\frac{dI(x; z)}{d\alpha} = \log \left( \frac{1-\alpha}{\alpha} \right) + H_1 + H_2 = 0$$

$$\log \left( \frac{1-\alpha}{\alpha} \right) = H_2 - H_1 \quad \frac{1-\alpha}{\alpha} = 2^{H_2 - H_1}$$

$$1-\alpha = \alpha 2^{H_2 - H_1} \quad \alpha = \frac{1}{1 + 2^{H_2 - H_1}} \quad \alpha = \frac{1}{1 + 2^{H_1 - H_2}}$$

$$\alpha_{opt} = \frac{2^{H_2}}{2^{H_1} + 2^{H_2}}$$

$$C = I(x; z) \Big|_{\alpha = \alpha_{opt}} = \log \left( 2^{1-H_1} \cdot 2^{1-H_2} \right)$$

WMM -  $2^C = 2^{C_1} + 2^{C_2}$

(b)  $2^C = 2^{1-H(y)} + 2^0 = 1 + 2^{1-H(y)}$

$$C = \log \left( 1 + 2^{1-H(y)} \right)$$

(d) 
$$y(z|x) = \begin{bmatrix} \frac{2}{3} & \frac{1}{3} & 0 \\ 0 & \frac{2}{3} & \frac{1}{3} \end{bmatrix}$$

$$y(z_1) = \frac{2}{3} y(x_1) + \frac{1}{3} y(x_2)$$

$$y(z_2) = \frac{1}{3} y(x_1) + \frac{2}{3} y(x_2)$$

$$I(x; z) = H(z) - H(z|x)$$

$$H(z|x) = p(x_1) \cdot H(z|x_1) + p(x_2) \cdot H(z|x_2)$$

$$H(z|x_1) = p(z_1|x_1) \log \frac{1}{p(z_1|x_1)} + p(z_2|x_1) \log \frac{1}{p(z_2|x_1)}$$

$$= \frac{2}{3} \log \frac{3}{2} + \frac{1}{3} \log 3$$

$$H(z|x_2) = p(z_1|x_2) \log \frac{1}{p(z_1|x_2)} + p(z_2|x_2) \log \frac{1}{p(z_2|x_2)}$$

$$= \frac{1}{3} \log 3 + \frac{2}{3} \log \frac{3}{2}$$

$$H(z|x) = \frac{2}{3} \left( \frac{2}{3} \log \frac{3}{2} + \frac{1}{3} \log 3 \right) + \frac{1}{3} \left( \frac{1}{3} \log 3 + \frac{2}{3} \log \frac{3}{2} \right)$$

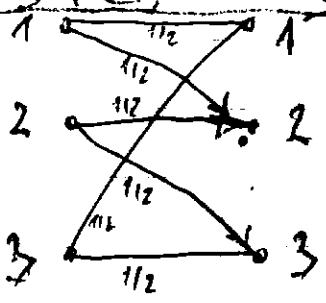
$$= \frac{2}{3} \log \frac{3}{2}$$

$$H(z|x) = p(x=x_2) \cdot \left[ \frac{1}{3} \log 2 + \frac{1}{3} \log 3 \right]$$

~~WMM~~ 
$$y(x) = 1 - y(x_1) - y(x_2)$$

$$y(x_2) = \frac{1}{3} y(x_2) + \frac{2}{3} (1 - y(x_1) - y(x_2)) = ?$$

$$= \frac{1}{3} y(x_2) + \frac{2}{3} - \frac{2}{3} y(x_1) - \frac{2}{3} y(x_2) = \frac{2}{3} - \frac{2}{3} y(x_1) - \frac{1}{3} y(x_2)$$



ovos ni acina, NOISEY TIME - WRITE CHANGE!!!

$$I(x; z) = H(y) - H(z|x) = H(z) - H\left(\frac{1}{2}\right)$$

$$I(x; z) = H(z) - 1 \quad \text{CS unq } I(x; z) = \log 3 - 1 = \log \frac{3}{2}$$

$$I(x; z) = 1 + H(x) - x H(y) - (1-x) H(z|x_2)$$

$$H(z|x_2) = p(x=x_1) \cdot H(z|x=x_1) + p(x=x_2) \cdot H(z|x=x_2) + p(x=x_3) \cdot H(z|x=x_3) = \left( \sum p(x_i) \right) H\left(\frac{1}{2}\right) = 1$$

$$I(x; z) = 1 + H(x) - x H(y) - (1-x) H_2$$

$$2^C = 2^{C_1} + 2^{C_2} = 2^{1-H(y)} + 2^{C_2} \cdot \frac{1}{2}$$

$$C = \log \left[ \frac{2^{1-H(y)}}{2} + 2^{C_2} \right] \quad \left[ y = \frac{1}{2} \right] \quad H(y) = 1$$

$$C = \log \left[ 1 + 2^{C_2} \right] = \log \left( 1 + \frac{3}{2} \right) = \log \frac{5}{2}$$

(d) RECAPITULAZIONE:  $C = \max_{p(x)} [H(z) - H(x|z)] = \max_{p(x)} [H(z) - p(x) \cdot \frac{2}{3} \log 3] =$

$p(x) = \left[ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right] \rightarrow p(x_1) = \frac{2}{3} \cdot \frac{1}{3} + \frac{1}{3} \cdot \frac{1}{3} = \frac{2}{9} + \frac{1}{9} = \frac{3}{9} = \frac{1}{3}$   
 $p(x_2) = \frac{1}{3} \cdot \frac{1}{3} + \frac{2}{3} \cdot \frac{1}{3} = \frac{1}{9} + \frac{2}{9} = \frac{3}{9} = \frac{1}{3}$

MAXIMUM SE RICHIEDE:  $p(x) = \left[ \frac{1}{2}, \frac{1}{2} \right]$

$$\frac{1}{2} = \frac{2}{3} p(x_1) + \frac{1}{3} p(x_2) \Rightarrow p(x_2) = \left[ \frac{1}{2} - \frac{2}{3} p(x_1) \right] \cdot \frac{1}{3}$$

$$\frac{1}{2} = \frac{1}{3} p(x_2) + \frac{2}{3} (1 - p(x_1) - p(x_2)) = \frac{1}{3} p(x_2) + \frac{2}{3} - \frac{2}{3} p(x_1) - \frac{2}{3} p(x_2)$$

$$= \frac{2}{3} - \frac{2}{3} p(x_1) - \frac{1}{3} p(x_2) \quad \frac{2}{3} p(x_1) + \frac{1}{3} p(x_2) = \frac{2}{3} - \frac{1}{2}$$

$$2 p(x_1) + p(x_2) = 2 - \frac{1}{2} = \frac{3}{2} \quad p(x_1) = \left[ \frac{1}{2} - p(x_2) \right] \cdot \frac{1}{2}$$

$$p(x_1) = \frac{1}{4} - \frac{p(x_2)}{2} \quad p(x_2) = \frac{1}{2} - \frac{2}{3} \left( \frac{1}{4} - \frac{p(x_2)}{2} \right) + \frac{2}{3} p(x_2) = \frac{1}{2} - \frac{1}{6} + \frac{p(x_2)}{3}$$

$$p(x_2) = \frac{1}{6} + \frac{p(x_2)}{3} = \frac{1}{3} + \frac{p(x_2)}{3}$$

$$2 p(x_2) = 1 \quad \boxed{p(x_2) = \frac{1}{2}}$$

$$3 p(x_2) - p(x_1) = 1$$

$$\boxed{p(x_1) = \frac{1}{4} - \frac{1}{4} = 0}$$

$$\boxed{p(x_3) = 1 - p(x_1) - p(x_2) = 1/2}$$

THE MAXIMIZING DISTRIBUTION OF INPUT SYMBOLS IS:  $p(x) = \left[ 0, \frac{1}{2}, \frac{1}{2} \right]$  FOR THIS DISTRIB. THE CAPACITY OF THE CHANNEL IS:

$$C = \log 2 - \frac{1}{2} \cdot \frac{2}{3} \log 3 = \log 2 - \frac{1}{3} \log 3 = 1 - \frac{1}{3} \log 3 = 0.472$$

**Problem 7.25** Suppose that channel  $\mathcal{P}$  has capacity  $C$  and its channel matrix is  $\mathbf{P}$ , where  $\mathcal{P}$  is an  $n \times n$  channel matrix.

(a) What is the capacity of

$$\hat{\mathcal{P}} = \begin{bmatrix} \mathcal{P} & \mathbf{0} \\ \mathbf{0} & \mathbf{1} \end{bmatrix}$$

(b) What about the capacity of

$$\hat{\mathcal{P}} = \begin{bmatrix} \mathcal{P} & \mathbf{0} \\ \mathbf{0} & \mathbf{I}_k \end{bmatrix}$$

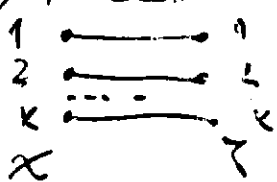
where  $\mathbf{I}_k$  is the  $k \times k$  identity matrix.

(a)  $2^C = 2^{C_1} + 2^{C_2}$       $C_1 = \log_2 \left( \frac{1}{\mathcal{P}} \right) = C$   
 $C_2 = \log_2 \left( \frac{1}{\mathbf{1}} \right) + 2^0 = \log_2 \left( \frac{1}{1} \right) + 1 = 2^0 + 1 = 2^0 + 1$

(b)  $2^C = 2^{C_1} + \sum_{i=1}^k 2^{C_i} = 2^{C_1} + k \cdot 1$   
 $2^C = 2^{\log_2 \left( \frac{1}{\mathcal{P}} \right)} + k$   
 $C = \log_2 \left[ \frac{1}{\mathcal{P}} + k \right]$

$C = \log_2 [2^C + k]$

→ DVA to solus. pdf of Toronto Univ. solutions go to that link with NOISELESS K-AR CHANNEL.



$$I(x, y) = H(y) - H(y|x) = H(y)$$

$$C = \max_{p(x)} H(y) = \log_2 k$$

$$2^{C_{eff}} = 2^C + 2^{\log_2 k}$$

$C_{eff} = \log_2 [2^C + k]$

• Chicago Midterm 1 - 2009 Solutions (Doroluvand & KA Problem 7.25) CHANNELS WITH MEMORY

(a) A DISCRETE CHANNEL IS MEMORYLESS IF

$$p(y_n | x_1, x_2, \dots, x_n, y_1, y_2, \dots, y_{n-1}) = p(y_n | x_n)$$

THAT IS THE OUTPUT AT CHANNEL USE  $n$  DEPENDS ONLY ON THE INPUT AT CHANNEL USE  $n$  AND NOT ON ANY OTHER INPUTS AND OUTPUTS.

EMBC

(b) DO YOU EXPECT THE CAPACITY OF A CHANNEL WITH MEMORY TO BE LARGER OR SMALLER THAN MEMORYLESS VERSION?

$$I(X^4; Z^4) = H(Z^4) - H(Z^4 | X^4) = H(Z^4) - \sum_{i=1}^4 H(Z_i | X^4)$$

$$= H(Z^4) - \underbrace{\sum_{i=1}^4 H(Z_i | X_i)}_{\text{MEMORYLESS CHANNEL}} \leq \sum_{i=1}^4 H(Z_i) - \sum_{i=1}^4 H(Z_i | X_i) = \sum_{i=1}^4 I(X_i; Z_i)$$

$$H(Z^4) = \sum_{i=1}^4 H(Z_i | X_i^{i-1}) = H(X_1) + H(Z_1 | X_1) + \dots + H(Z_4 | X_4)$$

$$\leq \sum_{i=1}^4 H(X_i) \rightarrow \text{CONDITIONING REDUCES ENTROPY.}$$

FOR MEMORYLESS:  $H(Z^4) = \sum_{i=1}^4 H(Z_i)$

FOR CHANNEL WITH MEMORY:  $H(Z^4) \leq \sum_{i=1}^4 H(Z_i)$

FOR MEMORYLESS:  $H(Z^4 | X^4) = \sum_{i=1}^4 H(Z_i | X_i)$

FOR CHAN WITH MEMO:  $H(Z^4 | X^4) \leq \sum_{i=1}^4 H(Z_i | X_i)$

IF:  $H(Z^4) = \sum_{i=1}^4 H(Z_i)$  } FOR BOTH MEMORYLESS AND CHAN. WITH MEMORY.

$$I(X^4; Z^4) = \sum_{i=1}^4 H(Z_i) - \sum_{i=1}^4 H(Z_i | X^4) \geq \sum_{i=1}^4 H(Z_i) - \sum_{i=1}^4 H(Z_i | X_i)$$

$$I_H(X^4; Z^4) \geq I_{ML}(X^4; Z^4) \quad I_{ML}(X^4; Z^4)$$

(c) "Z" VARIES FOR EACH CHANNEL USE

(d)  $Z_i = (X_i + Z_i) \bmod 2$   $X_i, Z_i, Z_i \in \{0, 1\}$

$$P(Z_i = 1) = \gamma = 1 - P(Z_i = 0)$$

$X_i \backslash Z_i$	0	1	$P(X_i)$
0	$(1-\gamma)/2$	0	$(1-\gamma)/2$
0	0	$\gamma/2$	$\gamma/2$
1	0	$(1-\gamma)/2$	$(1-\gamma)/2$
1	$\gamma/2$	0	$\gamma/2$
$P(Z_i)$	$\gamma/2$	$(1-\gamma)/2$	

$$I(X; Z) = H(Z) - H(Z | X) = H(Z) - H(Z | X)$$

$$H(Z | X) = P(X=0) \left[ \frac{\gamma}{2} \log \frac{\gamma}{\gamma} + \frac{1-\gamma}{2} \log \frac{1-\gamma}{1-\gamma} \right]$$

$$+ P(X=1) \left[ \frac{\gamma}{2} \log \frac{\gamma}{\gamma} + \frac{1-\gamma}{2} \log \frac{1-\gamma}{1-\gamma} \right] = 0$$

$$= \frac{\gamma}{2} \log \frac{\gamma}{\gamma} + \frac{(1-\gamma)}{2} \log \frac{1-\gamma}{1-\gamma} = \frac{1}{2} \left[ \gamma \log \frac{\gamma}{\gamma} + (1-\gamma) \log \frac{1-\gamma}{1-\gamma} \right] = 0$$

$$+ (1-\gamma) \log \frac{1-\gamma}{1-\gamma} = \frac{1}{2} \left[ \gamma \log \frac{\gamma}{\gamma} + (1-\gamma) \log \frac{1-\gamma}{1-\gamma} \right] = 0$$

$$= \frac{1}{2} [1 + H(\gamma)]$$

$$C = \max_{P(X)} I(X; Z) = 1 - \frac{1}{2} H(\gamma) = \frac{1}{2} [1 + H(\gamma)]$$



(e) Suppose now that channel has memory of length  $K$  = which we define to mean that  $K=1$  consecutive instances of noise  $Z_i$  are equal, i.e.  $Z_1 = Z_2 = \dots = Z_K$  then the next  $K=1$  are independent of the first  $K=1$  and are again equal:

$Z_{K+1} = Z_{K+2} = \dots = Z_{2K}$  and so forth  
 We still have that  $P(Z_1=1) = \gamma = 1 - P(Z_1=0)$

$$C^{(K)} = \max_{\gamma(x_1 \dots x_K)} \left[ \frac{1}{K} I(x_1^k; z_1^k) \right]$$

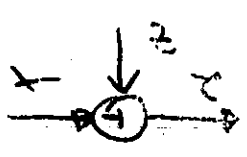
$$I(x^k; z^k) = H(z^k) - H(z^k | x^k)$$

$$z = (z + x) \bmod 2$$

$$I(x^k; z^k) = H(z^k) - \sum_{i=1}^k H(z_i | x_1^i z_1^{i-1}) - \sum_{i=k+1}^{2k} H(z_i | x_1^{2k})$$

$$C^{(K)} = \max_{\gamma(x^k)} I(x_1^k; z_1^k) = \max_{\gamma(x^k)} I(x_1^k; z_1^k) + \max_{\gamma(x_{k+1}^{2k})} I(x_{k+1}^{2k}; z_{k+1}^{2k})$$

$$\begin{aligned} &= H(z^k) - \underbrace{H(z_1 | x_1)}_{\frac{1}{2}(1+H(\gamma))} - \underbrace{H(z_2 | x_2)}_{=0} - \dots - \underbrace{H(z_{k+1} | x_{k+1})}_{\frac{1}{2}(1+H(\gamma))} - \dots - \underbrace{H(z_{2k} | x_{2k})}_{=0} - \dots \\ &= 4k - \frac{1}{k} \cdot \frac{1}{2} (1+H(\gamma)) \\ I(x^k; z^k) &\leq 4C \quad C \geq \frac{I(x^k; z^k)}{4} \\ &= 1 - \frac{1}{2k} (1+H(\gamma)) \end{aligned}$$



$$\begin{aligned} I(x; z) &= H(z) - H(z|x) \\ &= H(z) - \sum_x \gamma(x) \cdot H(z_{x+1} | z_x) \\ &= 1 - H(\gamma) \end{aligned}$$



$$\int_{-\infty}^{\infty} x^2 e^{-x^2} dx = \frac{\sqrt{\pi}}{2} \quad \left| \begin{array}{l} u = x^2 \quad du = 2x dx \\ v = \int e^{-x^2} dx \end{array} \right.$$

$$\int_{-\infty}^{\infty} x e^{-x^2} dx = \left| \begin{array}{l} u = x^2 \quad du = 2x dx \\ v = \int e^{-x^2} dx = \frac{e^{-x^2}}{2} \end{array} \right.$$

$$= -\frac{x}{2} e^{-x^2} \Big|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} \frac{e^{-x^2}}{2} dx = -\lim_{x \rightarrow \infty} \frac{x}{e^{x^2}} +$$

$$+ \lim_{x \rightarrow \infty} \frac{x}{e^{x^2}} + \frac{1}{2} \sqrt{\pi} = -0 + 0 + \frac{\sqrt{\pi}}{2} \quad \text{PROOF}$$

~~$$h(x) = \frac{1}{2\sigma^2 \sqrt{2\pi}} \ln(5\sqrt{2\sigma}) \int_{-\infty}^{\infty} x^2 e^{-\frac{x^2}{2\sigma^2}} dx =$$

$$= \frac{1}{2\sigma^2 \sqrt{2\pi}} \ln(5\sqrt{2\sigma}) \cdot \frac{\sqrt{\pi}}{2} = \frac{1}{2} \ln 5\sqrt{2\sigma}$$~~

$$h(x) = \frac{1}{\sigma \sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{x^2}{2\sigma^2}} \left[ \ln(5\sqrt{2\sigma}) + \frac{x^2}{2\sigma^2} \right] dx$$

$$= \frac{1}{\sigma \sqrt{2\pi}} \left[ \ln(5\sqrt{2\sigma}) \int_{-\infty}^{\infty} e^{-\frac{x^2}{2\sigma^2}} d\left(\frac{x}{\sigma\sqrt{2}}\right) - \int_{-\infty}^{\infty} \frac{x^2}{2\sigma^2} e^{-\frac{x^2}{2\sigma^2}} d\left(\frac{x}{\sigma\sqrt{2}}\right) \right]$$

$$= \frac{1}{\sqrt{2\pi}} \left[ \ln(5\sqrt{2\sigma}) \cdot \sqrt{\pi} - \frac{\sqrt{\pi}}{2} \right] = \left[ \ln 5\sqrt{2\sigma} - \frac{1}{2} \right]$$

s  $\ln 5\sqrt{2\sigma} - \frac{1}{2} \ln e = \ln 5\sqrt{2\sigma} \text{ bits}$

$$h(x) = \ln(5\sqrt{2\sigma}) \text{ bits}$$

$$h(x) = \frac{1}{2} \ln(2\pi e \sigma^2) \text{ bits}$$

## 8.2 AEP FOR CONTINUOUS RANDOM VARIABLES

- FOR THE SEQUENCE OF I.I.D RANDOM VARIABLES  $(x_1, x_2, \dots, x_n)$  IS CLOSE TO  $2^{-nH(X)}$  WITH HIGH PROBABILITY !!! (FOR DISCRETE RANDOM VARIABLES)

**THEOREM 8.2.1** LET  $x_1, x_2, \dots, x_n$  BE A SEQUENCE OF RANDOM VARIABLES PERIOD I.I.D HAVING PD DENSITY  $f(x)$ . THEN

$$-\frac{1}{n} \log f(x_1, x_2, \dots, x_n) \rightarrow E[-\log f(X)] = H(X) \quad \text{IN PROBABILITY}$$

**DEFINITION:** FOR  $\epsilon > 0$  AND ANY  $n \in \mathbb{N}$  WE DEFINE THE TYPICAL SET  $A_\epsilon^{(n)}$  WITH RESPECT TO  $f(x)$

$$A_\epsilon^{(n)} = \left\{ (x_1, x_2, \dots, x_n) \in S^n : \left| -\frac{1}{n} \log f(x_1, x_2, \dots, x_n) - H(X) \right| \leq \epsilon \right\}$$

$$f(x_1, x_2, \dots, x_n) = \prod_{i=1}^n f(x_i)$$

THE ANALOG OF CARDINALITY OF THE TYPICAL SET FOR THE DISCRETE CASE IS THE VOLUME OF THE TYPICAL SET FOR CONTINUOUS RANDOM VARIABLES.

**DEFINITION** THE VOL(A) OF A SET  $A \subset \mathbb{R}^n$  IS DEFINED AS

$$\text{Vol}(A) = \int_A dx_1 dx_2 \dots dx_n$$

**THEOREM 8.2.2** THE TYPICAL SET  $A_\epsilon^{(n)}$  HAS THE FOLLOWING PROPERTIES:

1.  $P((x_1, x_2, \dots, x_n) \in A_\epsilon^{(n)}) \geq 1 - \epsilon$  FOR  $n$  SUFFICIENTLY LARGE
2.  $\text{Vol}(A_\epsilon^{(n)}) \leq 2^{n(H(X) + \epsilon)}$  FOR  $n$  SUFFICIENTLY LARGE
3.  $\text{Vol}(A_\epsilon^{(n)}) \geq (1 - \epsilon) 2^{n(H(X) - \epsilon)}$  FOR  $n$  SUFFICIENTLY LARGE

$$P = \int_{S^n} f(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n \geq \int_{A_\epsilon^{(n)}} f(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n$$

$$P \geq \int_{A_\epsilon^{(n)}} f(x_1, x_2, \dots, x_n) dx_1 dx_2 \dots dx_n \geq \int_{A_\epsilon^{(n)}} 2^{-n(H(X) + \epsilon)} dx_1 dx_2 \dots dx_n = 2^{-n(H(X) + \epsilon)} \text{Vol}(A_\epsilon^{(n)})$$

$$\text{Vol}(A_\epsilon^{(n)}) \leq 2^{n(H(X) + \epsilon)}$$

$$(1-\epsilon) \leq \int_{A_\epsilon} f(x) dx \leq \int_{A_\epsilon} 2^{-n(L(x)-\epsilon)} dx$$

$$2^{-n(L(x)-\epsilon)} \cdot \text{Vol}(A)$$

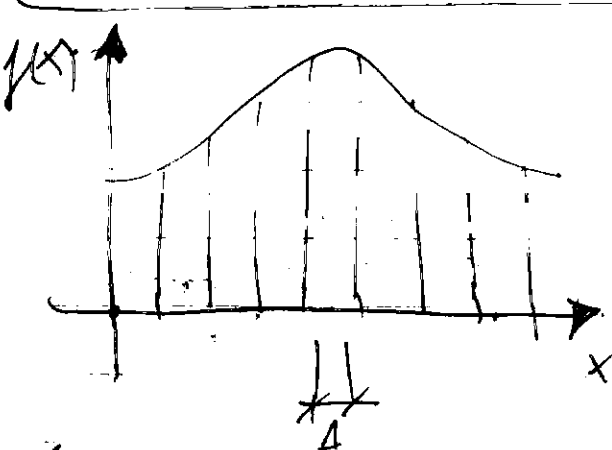
$$\text{Vol}(A) \geq (1-\epsilon) 2^{n(L(x)-\epsilon)}$$

$$(1-\epsilon) 2^{n(L(x)-\epsilon)} \leq \text{Vol}(A) \leq 2^{n(L(x)+\epsilon)}$$

**THEOREM 8.23** The set  $A_\epsilon^{(n)}$  is the smallest volume set with probability  $\geq 1-\epsilon$ , to first order  $n$  existent.

Small entropy implies that random variable is confined to a small effective volume and high entropy indicates that the random variable is widely dispersed. MMV

8.3 Relation of differential entropy to discrete entropy



$$f(x_i) \cdot \Delta = \int_{i\Delta}^{(i+1)\Delta} f(x) dx$$

BY MEAN VALUE THEOREM

Consider a quantized random variable  $X^A$   
 $X^A = x_i$  if  $i \cdot \Delta \leq X < (i+1) \cdot \Delta$

The probability that  $X^A = x_i$  is:

$$p_i = \int_{i\Delta}^{(i+1)\Delta} f(x) dx = f(x_i) \Delta$$

$$H(X^A) = - \sum_i f(x_i) \Delta \log(f(x_i) \Delta) = - \sum_i f(x_i) \Delta \cdot \log f(x_i)$$

$$- \sum_i f(x_i) \Delta \cdot \log \Delta = - \sum_i f(x_i) \Delta \cdot \log f(x_i) - \log \Delta =$$

$$H(X^A) + \log \Delta \rightarrow h(f) = h(x)$$

$$\sum_i \int_{i\Delta}^{(i+1)\Delta} f(x) dx = 1$$

Theorem 8.3.1 If the density  $f(x)$  of the random variable  $X$  is Riemann integrable

$$H(x^\Delta) + \log \Delta \rightarrow h(f) = H(x), \text{ as } \Delta \rightarrow 0$$

Thus the entropy of an  $n$ -bit quantization of a continuous random variable  $X$  is approximately  $h(X) + n$ .

Example 8.3.1 If  $X$  has uniform distribution on  $[0, 1]$  and we let  $\Delta = 2^{-n}$

$$h(X) = - \int_0^1 \log \Delta dx = 0 \quad H(x^\Delta) + \log \Delta \rightarrow 0$$

$$H(x^\Delta) \approx \log \frac{1}{2^n} \rightarrow 0 \quad H(x^\Delta) \rightarrow \log 2^n = n$$

$H(x^\Delta) \rightarrow n$   $n$ -bits suffice to describe  $X$  to  $n$ -bit accuracy

2.  $X \sim [0, \frac{1}{8}]$   $h(X) = \int_0^{\frac{1}{8}} \log 8 \cdot dx =$

$$= -8 \cdot 3 \left[ \frac{1}{8} - 0 \right] = -8 \cdot 3 \cdot \frac{1}{8} = -3$$

$H(x^\Delta) \rightarrow n-3$  TO DESCRIBE  $X$  WITH  $n$  BIT ACCURACY REQUIRE  $n-3$  BITS

3. If  $X \sim N(0, \sigma^2)$  with  $\sigma^2 = 100$ , DESCRIBING  $X$  TO  $n$  BIT ACCURACY WOULD REQUIRE:

$$n + h(X) = n + \frac{1}{2} \log 2\pi e \sigma^2 = n + \frac{1}{2} \log 2\pi e \cdot 100$$

$n + h(X) = n + 5.37$  bits

IN GENERAL,  $h(X) + n$  IS THE NUMBER OF BITS ON AVERAGE REQUIRED TO DESCRIBE  $X$  TO  $n$ -BIT ACCURACY.

THE DIFFERENTIAL ENTROPY OF DISCRETE RANDOM VARIABLE CAN BE CONSIDERED TO BE  $-\infty$ . NOTE THAT  $2^{-\infty} = 0$  AGREEING WITH THE IDEA THAT SUPPORT SET OF DISCRETE RANDOM VARIABLE IS  $\emptyset$ .

### 8.4 JOINT AND DIFFERENTIAL ENTROPY

DEFINITION: THE DIFFERENTIAL ENTROPY OF A SET  $X_1, X_2, \dots, X_n$  OF RANDOM VARIABLES WITH DENSITY  $f(x_1, x_2, \dots, x_n)$  IS DEFINED AS:

$$h(x_1, x_2, \dots, x_n) = - \int f(x) \ln f(x) dx$$

DEFINITION: If  $x, y$  have joint density function  $f(x, y)$  we can define the conditional differential entropy  $h(x|y)$  as:

$$h(x|y) = - \int f(x, y) \ln f(x|y) dx dy$$

$$f(x|y) = \frac{f(x, y)}{f(y)}$$

$$h(x|y) = h(x, y) - h(y)$$

**THEOREM 8.4.1** (ENTROPY OF MULTIVARIATE NORMAL DISTRIBUTION)

Let  $x_1, x_2, \dots, x_n$  have a multivariate normal distribution

with mean  $\mu$  and covariance matrix  $K$ . Then

$$h(x_1, x_2, \dots, x_n) = h(N_n(\mu, K)) = \frac{1}{2} \ln(2\pi e)^n |K| \text{ bits}$$

- |K| DETERMINANT OF  $K$ .

PROOF: The probability density function of

$$f(x) = \frac{1}{(2\pi)^n |K|^{1/2}} e^{-\frac{1}{2}(x-\mu)^T K^{-1}(x-\mu)}$$

$$\begin{aligned} h(f) &= - \int f(x) \left[ -\frac{1}{2}(x-\mu)^T K^{-1}(x-\mu) - \ln \frac{1}{(2\pi)^n |K|^{1/2}} \right] dx = \\ &= \frac{1}{2} E \left[ \sum_{ij} (x_i - \mu) (K^{-1})_{ij} (x_j - \mu) \right] + \frac{1}{2} \ln (2\pi)^n |K| = \\ &= \frac{1}{2} E \left[ \sum_{ij} (x_i - \mu) (x_j - \mu) (K^{-1})_{ij} \right] + \frac{1}{2} \ln (2\pi)^n |K| = \\ &= \frac{1}{2} \sum_{ij} E \left[ (x_i - \mu) (x_j - \mu) (K^{-1})_{ij} \right] + \frac{1}{2} \ln (2\pi)^n |K| = \\ &= \frac{1}{2} \sum_i \sum_j K_{ij} (K^{-1})_{ij} + \frac{1}{2} \ln (2\pi)^n |K| = \\ &= \frac{1}{2} \sum_i (K K^{-1})_{ii} + \frac{1}{2} \ln (2\pi)^n |K| = \frac{1}{2} \sum_i I_{ii} + \frac{1}{2} \ln (2\pi)^n |K| \\ &= \frac{n}{2} + \frac{1}{2} \ln (2\pi)^n |K| = \frac{1}{2} \ln e^n + \frac{1}{2} \ln (2\pi)^n |K| = \frac{1}{2} \ln (2\pi e)^n |K| \end{aligned}$$

**MMV**  $h(f) = h(x) = \frac{1}{2} \ln (2\pi e)^n |K| \text{ bits}$

## 8.5 RELATIVE ENTROPY AND MUTUAL INFORMATION

DEFINITION: THE RELATIVE ENTROPY (KULLBACK-LEIBLER DISTANCE)  $D(f||g)$  BETWEEN TWO DENSITIES  $f, g$  IS DEFINED AS:

$$D(f||g) = \int f \ln \frac{f}{g}$$

$D(f||g)$  IS FINITE ONLY IF SUPPORT SET OF  $f$  IS CONTAINED IN THE SUPPORT SET OF  $g$ .

DEFINITION: THE MUTUAL INFORMATION  $I(X; Z)$  BETWEEN TWO RANDOM VARIABLES WITH JOINT DENSITY  $f(x, y)$  IS DEFINED AS:

$$I(X; Z) = \int f(x, y) \ln \frac{f(x, y)}{f(x)f(y)} dx dy$$

$$I(X; Z) = h(X) - h(X|Z) = h(Z) - h(Z|X) = h(X) - h(X, Z) + h(Z)$$

$$I(X; Z) = D[f(x, y) || f(x)f(y)]$$

$$I(X^A; Z^A) = h(X^A) - h(X^A|Z^A) \approx h(X) - h(A) - h(Z|X) + h(A) = h(X) - h(Z|X) = \underline{I(X; Z)}$$

MORE GENERALLY WE CAN DEFINE MUTUAL INFORMATION IN TERMS OF FINITE PARTITIONS OF THE RANGE OF RANDOM VARIABLES. LET  $\mathcal{X}$  BE RANGE OF A RANDOM VARIABLE  $X$ . A PARTITION  $\mathcal{P}$  OF  $\mathcal{X}$  IS FINITE COLLECTION OF DISJOINT SETS  $P_i$  SUCH AS  $\cup P_i = \mathcal{X}$ . THE QUANTIZATION OF  $X$  AT  $\mathcal{P}$  (DENOTED  $[X]_{\mathcal{P}}$ ) IS DISCRETE RANDOM VARIABLE DEFINED AS:

$$\Pr([X]_{\mathcal{P}} = i) = \Pr(X \in P_i) = \int \mathbb{1}_{P_i} f(x)$$

$$I(X; Z) = \sup_{\mathcal{P}, \mathcal{Q}} I([X]_{\mathcal{P}}; [Z]_{\mathcal{Q}})$$

WHERE SUPREMUM IS OVER ALL FINITE PARTITIONS  $\mathcal{P}$  AND  $\mathcal{Q}$ .

THIS IS MOST GENERAL DEFINITION OF MUTUAL INFORMATION THAT ALWAYS APPLIES.



**EXAMPLE 8.51** (MUTUAL INFORMATION BETWEEN CORRELATED GAUSSIAN RANDOM VARIABLES WITH CORRELATION  $\rho$ ). Let  $(X, Z) \sim N(\mu, K)$

$$K = \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix} \quad |K| = \sigma^4 - \rho^2\sigma^4 = \sigma^4(1-\rho^2)$$

$$h(X) = \frac{1}{2} \log(2\pi e) \sigma^2 = h(Z) \quad h(X, Z) = \frac{1}{2} \log(2\pi e)^2 |K|$$

$$= \frac{1}{2} \log(2\pi e)^2 \sigma^2 (1-\rho^2) = \frac{1}{2} \log(2\pi e)^2 \sigma^4 (1-\rho^2)$$

$$I(X; Z) = h(X) + h(Z) - h(X, Z) = \log(2\pi e) \sigma^2 - \frac{1}{2} \log(2\pi e)^2 \sigma^4 (1-\rho^2)$$

$$= \log(2\pi e) \sigma^2 - \frac{1}{2} \log(2\pi e)^2 \sigma^4 (1-\rho^2)$$

**MMV**  

$$h(X) = -\frac{1}{2} \log(1-\rho^2)$$

BIVARIATE GAUSSIAN DISTRIBUTION (DENSITY FUNCTION)

$$f(x_1, x_2) = \frac{1}{2\pi\sigma_1\sigma_2\sqrt{1-\rho^2}} \exp\left[-\frac{z}{2(1-\rho^2)}\right]$$

$$z = \frac{(x_1-\mu_1)^2}{\sigma_1^2} - \frac{2\rho(x_1-\mu_1)(x_2-\mu_2)}{\sigma_1\sigma_2} + \frac{(x_2-\mu_2)^2}{\sigma_2^2}$$

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$$f(x_1) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_2 = \frac{1}{\sigma_1\sqrt{2\pi}} e^{-\frac{(x_1-\mu_1)^2}{2\sigma_1^2}}$$

$$f(x_2) = \int_{-\infty}^{\infty} f(x_1, x_2) dx_1 = \frac{1}{\sigma_2\sqrt{2\pi}} e^{-\frac{(x_2-\mu_2)^2}{2\sigma_2^2}}$$

$$\mu_1 = \mu_2 = 0 \quad z = \frac{x_1^2}{\sigma_1^2} - \frac{2\rho x_1 x_2}{\sigma_1\sigma_2} + \frac{x_2^2}{\sigma_2^2}$$

$$f(x, z) = \frac{1}{(\sqrt{2\pi})^2 |K|^{1/2}} e^{-\frac{1}{2} [ \begin{matrix} x \\ z \end{matrix} ]^T K^{-1} [ \begin{matrix} x \\ z \end{matrix} ]}$$

MMV

$$f(x, z) = \frac{1}{2\pi |K|^{1/2}} e^{-\frac{1}{2} [ \begin{matrix} x \\ z \end{matrix} ]^T K^{-1} [ \begin{matrix} x \\ z \end{matrix} ]}$$

$$\begin{bmatrix} x & z \end{bmatrix} \begin{bmatrix} \sigma^2 & \rho\sigma^2 \\ \rho\sigma^2 & \sigma^2 \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix} = \begin{bmatrix} x & z \end{bmatrix} \begin{bmatrix} \sigma^2 x + \rho\sigma^2 z \\ \rho\sigma^2 x + \sigma^2 z \end{bmatrix} =$$

$$= \sigma^2 x^2 + \rho\sigma^2 xz + \rho\sigma^2 xz + \sigma^2 z^2 = \sigma^2 x^2 + 2\rho\sigma^2 xz + \sigma^2 z^2$$

$$f(x, z) = \frac{1}{2\pi\sigma^2\sqrt{1-\rho^2}} \exp\left[-\frac{\sigma^2 x^2 + 2\rho\sigma^2 xz + \sigma^2 z^2}{2}\right]$$

$$K^{-1} = \frac{1}{|K|} \begin{bmatrix} \sigma^2 & -\rho\sigma^2 \\ -\rho\sigma^2 & \sigma^2 \end{bmatrix} = \frac{1}{\sigma^2(1-\rho^2)} \begin{bmatrix} \sigma^2 & -\rho\sigma^2 \\ -\rho\sigma^2 & \sigma^2 \end{bmatrix} =$$

$$= \frac{1}{\sigma^2(1-\rho^2)} \begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix}$$

$$\frac{1}{2} \frac{[x \ z]}{\sigma^2(1-\rho^2)} \begin{bmatrix} 1 & -\rho \\ -\rho & 1 \end{bmatrix} \begin{bmatrix} x \\ z \end{bmatrix} = \frac{1}{2\sigma^2(1-\rho^2)} [x \ z] \begin{bmatrix} 1-\rho z \\ -\rho x + z \end{bmatrix} =$$

$$= \frac{1}{2\sigma^2(1-\rho^2)} \begin{pmatrix} x^2 - \rho x z + z^2 \\ -\rho x z + z^2 \end{pmatrix} = \frac{x^2 - 2\rho x z + z^2}{2\sigma^2(1-\rho^2)}$$

$$z = \frac{x^2 - 2\rho x z + z^2}{\sigma^2} \quad \leftarrow \quad \varphi(x, z) = \frac{1}{2\sigma^2 \sqrt{1-\rho^2}} e^{-\frac{z}{2(1-\rho^2)}}$$

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$$\varphi(x, z) = \frac{1}{2\sigma^2 \sqrt{1-\rho^2}} e^{-\frac{x^2 - 2\rho x z + z^2}{2\sigma^2(1-\rho^2)}}$$

$$\int \varphi(x, z) dx = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{z^2}{2\sigma^2}} \quad \left. \vphantom{\int} \right\} \begin{matrix} \text{GAUSSIAN} \\ N(0, \sigma^2) \end{matrix}$$

⊙ ⇒ If  $\rho = 0$ ,  $x$  AND  $z$  ARE INDEPENDENT AND THE MUTUAL INFORMATION IS 0. If  $\rho = \pm 1$ ,  $x$  AND  $z$  ARE PERFECTLY CORRELATED AND THE MUTUAL INFORMATION IS INFINITE!!!

8.6 PROPERTIES OF DIFFERENTIAL ENTROPY, RELATIVE ENTROPY, AND MUTUAL INFORMATION +

THEOREM 8.6.1  $D(f||g) \geq 0$  WITH EQUALITY IF  $f=g$  ALMOST EVERYWHERE (A.E.)

PROOF:  $S$  = SUPPORT SET OF  $f$

$$-D(f||g) = \int_S f \ln \frac{g}{f} \leq \ln \int_S f \frac{g}{f} = \ln \int_S g \leq \ln 1 = 0$$

$e[f(x)] \leq f(e[x])$  Jensen Inequality ⇒ CONCAVE FUNCTION  $D(f||g) \geq 0$

EQUAZITY is FOR:  $f=g$

~~COROLLARY~~  $I(x; \tau) \geq 0$  WITH EQUAZITY IF  $(\tilde{x}, \tilde{\tau})$

$$I(x; \tau) = \int_{x, \tau} f(x, \tau) \log \frac{f(x, \tau)}{f(x) \cdot f(\tau)} dx d\tau = D(f(x, \tau) \| f(x) f(\tau))$$

$$I(x; \tau) = \sum_{x, \tau} p(x, \tau) \log \frac{p(x, \tau)}{p(x) \cdot p(\tau)} = - \sum_{x, \tau} p(x, \tau) \log \frac{1}{p(x, \tau)} +$$

$$+ \sum_{x, \tau} p(x, \tau) \log p(x) + \sum_{x, \tau} p(x, \tau) \log p(\tau) =$$

$$= -H(x, \tau) - \sum_x \log p(x) \sum_{\tau} p(x, \tau) - \sum_{\tau} \log p(\tau) \sum_x p(x, \tau)$$

$$= -H(x, \tau) + H(x) + H(\tau) = \cancel{H(x)} + \cancel{H(\tau)} - \underbrace{H(p(x, \tau))}_{H(x, \tau)}$$

$$- \cancel{H(x)} - H(\tau|x) = H(\tau) - H(\tau|x)$$

~~COROLLARY~~  $h(x; \tau) \leq h(x)$  WITH EQUAZITY  $(\tilde{x}, \tilde{\tau})$

THEOREM 8.6.2 CHAIN RULE FOR DIFFERENTIAL ENTROPY.

$$h(x_1, x_2, \dots, x_n) = \sum_{i=1}^n h(x_i | x_1^{i-1})$$

~~COROLLARY~~:  $h(x_1, x_2, \dots, x_n) \leq \sum_{i=1}^n h(x_i)$

WITH EQUAZITY IF  $(x_1, x_2, \dots, x_n)$  ARE INDEPENDENT.

APPLICATION (HADAMARD'S INEQUALITY) IF WE LET

$X \sim \mathcal{N}(0, K)$  BE A MULTIVARIATE NORMAL RANDOM VARIABLE, CALCULATING THE ENTROPY IN THE ABOVE INEQUALITY GIVES:

$$|K| \leq \prod_{i=1}^n K_i$$

**THEOREM 8.6.3**  $h(x+c) = h(x)$

TRANSLATION DOESN'T CHANGE THE DIFFERENTIAL ENTROPY.

**THEOREM 8.6.4**  $h(aX) = h(X) + \log |a|$

PROOF: Let  $\tau = aX$   $p(\tau) = \frac{p(x)}{\frac{d\tau}{dx}} \Big|_{x=f(\tau)} =$

$$\frac{p(\frac{\tau}{a})}{|a|} \quad \left| \frac{p(\tau)}{p(\frac{\tau}{a})} = \frac{1}{|a|} \right|$$

$$h(ax) = - \int f(x) \ln f(x) dx = \int \frac{1}{|a|} f\left(\frac{x}{a}\right) \ln \frac{1}{|a|} f\left(\frac{x}{a}\right) dx$$

$$= \int \frac{1}{|a|} f\left(\frac{x}{a}\right) \ln f\left(\frac{x}{a}\right) dx + \int f\left(\frac{x}{a}\right) \ln |a| dx =$$

$$= - \int f\left(\frac{x}{a}\right) \ln f\left(\frac{x}{a}\right) dx + \ln |a| = h\left(\frac{x}{a}\right) + \ln |a|$$

**COVARIANCE**

$$h(AX) = h(X) + \ln |\det(A)|$$

**THEOREM 8.6.4 FOR VECTOR-VALUED RANDOM VAR.**

• WE NOW SHOW THAT MULTIVARIATE NORMAL DISTRIBUTION MAXIMIZES THE ENTROPY OVER ALL DISTRIBUTIONS WITH SAME COVARIANCE.

**THEOREM 8.6.5** LET THE RANDOM VECTOR  $X \in \mathbb{R}^n$  HAVE ZERO MEAN AND COVARIANCE  $K = E[XX^T]$  (I.E.  $K_{ij} = E[X_i X_j]$ ,  $1 \leq i, j \leq n$ ). THEN  $h(X) \leq \frac{1}{2} \ln (2\pi e)^n |K|$  WITH EQUALITY IF:  $X \sim N(0, K)$

**PROOF:** LET  $g(x)$  BE ANY DENSITY SATISFYING  $\int g(x) x_i x_j dx = K_{ij}$  FOR ALL  $i, j$ . LET  $\phi_K$  BE DENSITY OF  $N(0, K)$  VECTOR AS GIVEN IN (8.35) WHERE WE SET  $\mu=0$ . NOTE THAT  $\ln \phi_K(x)$  IS QUADRATIC FORM AND  $\int x_i x_j \phi_K(x) dx = K_{ij}$ . THEN

$$0 \leq D(g || \phi_K) = \int g \ln \frac{g}{\phi_K} = -h(g) - \int g \ln \phi_K =$$

$$-h(g) - \int \phi_K \ln \phi_K = -h(g) + h(\phi_K)$$

$$h(\phi_K) \geq h(g)$$

WHERE THE SUBSTITUTION  $\int g \ln \phi_K = \int \phi_K \ln \phi_K$  FOLLOWS FROM THE FACT THAT  $g$  AND  $\phi_K$  YIELD THE SAME MOMENTS OF QUADRATIC FORM  $\ln \phi_K(x)$

$$h(g) \leq h(\phi_K) = \frac{1}{2} \ln (2\pi e)^n |K|$$

**PROBLEMS** (CONTINUE FROM N169)

**8.1** Differential entropy. Evaluate differential entropy:  $h(X) = - \int f \ln f$  FOR THE FOLLOWING:

- (a) THE EXPONENTIAL DENSITY  $f(x) = \lambda e^{-\lambda x}$   $x \geq 0$
- (b) LAPLACE DENSITY  $f(x) = \frac{1}{2} \lambda e^{-\lambda |x|}$
- (c) THE SUM OF  $X_1$  AND  $X_2$  WHERE  $X_1$  AND  $X_2$  ARE INDEPENDENT RANDOM VARIABLES (NORMAL)

WITH MEANS  $\mu_i$  AND VARIANCES  $\sigma_i^2$ ,  $i=1, 2$ .

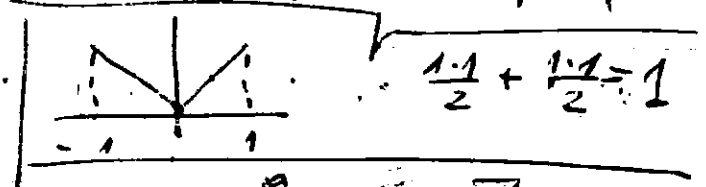
(a)  $f(x) = \lambda e^{-\lambda x}$        $h(x) = -\int f(x) \ln f(x) dx =$   
 $= -\int_0^{\infty} \lambda e^{-\lambda x} \ln(\lambda \cdot e^{-\lambda x}) dx = -\lambda \left[ \int_0^{\infty} e^{-\lambda x} \ln \lambda dx + \int_0^{\infty} e^{-\lambda x} \ln e^{-\lambda x} dx \right]$   
 $= -\lambda \left[ \ln(\lambda) \int_0^{\infty} e^{-\lambda x} dx + \int_0^{\infty} \lambda x e^{-\lambda x} dx \right] =$   
 $= -\lambda \left[ \ln(\lambda) \frac{1}{\lambda} \int_0^{\infty} e^{-\lambda x} d(\lambda x) - \lambda \int_0^{\infty} \frac{x}{\lambda} \frac{1}{\lambda} e^{-\lambda x} d(\lambda x) \right] =$   
 $= -\lambda \left[ \ln(\lambda) \frac{(-1)}{\lambda} \cdot e^{-\lambda x} \Big|_0^{\infty} - \lambda \left( x \cdot \frac{-1}{\lambda} \Big|_0^{\infty} + \int_0^{\infty} \frac{e^{-\lambda x}}{\lambda} dx \right) \right]$   
 $\int_0^{\infty} e^{-\lambda x} dx = \frac{1}{\lambda} \int_0^{\infty} e^{-\lambda x} d(\lambda x) = \frac{(-1)}{\lambda} e^{-\lambda x} \Big|_0^{\infty}$   
 $= -\lambda \left[ \frac{\ln(\lambda)}{\lambda} \left[ e^{-\infty} - e^0 \right] - \lambda \left( \frac{x}{\lambda} e^{-\lambda x} \Big|_0^{\infty} + \frac{-e^{-\lambda x}}{\lambda^2} \Big|_0^{\infty} \right) \right] =$   
 $= -\lambda \left[ + \frac{\ln(\lambda)}{\lambda} - \lambda \left( 0 - \frac{0}{\lambda} + \frac{1}{\lambda^2} (0 - 1) \right) \right]$   
 $= -\ln(\lambda) + \lambda^2 \left( + \frac{1}{\lambda^2} \right) = \underline{1 - \ln(\lambda)}$

(b)  $f(x) = \frac{1}{2} \lambda e^{-\lambda |x|}$        $-\int f(x) \ln f(x) dx = 1 + \ln 2 - \ln(\lambda)$

$h(x) = 1 + \ln \frac{2}{\lambda}$        $h(x) = -\frac{\lambda}{2} \int_{-\infty}^{\infty} e^{-\lambda |x|} \left[ \ln e^{-\lambda |x|} + \ln \frac{\lambda}{2} \right] dx =$   
 $= \frac{\lambda}{2} \left[ \int_{-\infty}^{\infty} -\lambda |x| e^{-\lambda |x|} dx + \int_{-\infty}^{\infty} e^{-\lambda |x|} \ln \frac{\lambda}{2} dx \right] =$   
 $= \frac{\lambda}{2} \left[ -\lambda \int_0^{\infty} x e^{-\lambda x} dx - \lambda \int_{-\infty}^0 (-x) e^{-\lambda (-x)} dx + \ln \frac{\lambda}{2} \int_{-\infty}^{\infty} e^{-\lambda |x|} dx \right]$   
 $+ \ln \frac{\lambda}{2} \int_{-\infty}^{\infty} e^{-\lambda |x|} dx = \text{⊗}$

$|x| = \begin{cases} x & x \geq 0 \\ -x & x < 0 \end{cases}$

$$\int_{-1}^1 |x| dx = \int_0^1 x dx + \int_{-1}^0 -x dx = \frac{x^2}{2} \Big|_0^1 - \frac{x^2}{2} \Big|_{-1}^0 = \frac{1}{2} - \left(0 - \frac{1}{2}\right) = 1$$



$$\begin{aligned} (*) &= -\frac{\Delta}{2} \left[ \underbrace{-\lambda \cdot 2 \int_0^{\infty} x e^{-\lambda x} dx}_{\text{GAMMA FUNKTION}} + 2 \ln \frac{\lambda}{2} \int_0^{\infty} e^{-\lambda x} dx \right] = \\ &= -\frac{\Delta}{2} \left[ -2 \cdot \lambda \cdot \frac{1}{\lambda^2} + 2 \ln \frac{\lambda}{2} \cdot \frac{(-1)}{\lambda} e^{-\lambda x} \Big|_0^{\infty} \right] = \\ &= -\frac{\Delta}{2} \left[ -\frac{2}{\lambda} - \frac{2}{\lambda} \left( \ln \frac{\lambda}{2} \right) \cdot (0 - 1) \right] = 1 + \left( \ln \frac{\lambda}{2} \right) \cdot (-1) \\ &= 1 - \ln \frac{\lambda}{2} = 1 + \ln \frac{2}{\lambda} \end{aligned}$$

(c)  $x_1 \sim \mathcal{N}(\mu_1, \sigma_1^2)$      $x_2 \sim \mathcal{N}(\mu_2, \sigma_2^2)$

$\boxed{x = x_1 + x_2}$      $\boxed{f(x) = ?}$

$M_f(s) = \int f(x) \cdot e^{-sx} dx$      $M(s) = \int f(x) \cdot e^{sx} dx$

$M(s) = M_1(s) \cdot M_2(s)$   
MGF

$W(s) = W_1(s) \cdot W_2(s)$   
STATISTISCHE F.

$$W(s) = \int e^{-\frac{(x-\mu)^2}{2\sigma^2} - sx} dx$$

$$W(s) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2} - sx} dx$$

$$W_1(s) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{s(4\mu-s)}{8\sigma^2}}$$

$$W = (W_1(s))^2 = \frac{1}{2\sigma\sqrt{2\pi}} e^{-\frac{s(4\mu-s)}{4\sigma^2} + sx}$$

$$f(x) = \int_{-\infty}^{\infty} \frac{1}{2\sigma\sqrt{2\pi}} e^{-\frac{s(4\mu-s)}{4\sigma^2} + sx} ds =$$

CONTINUE FROM N16a | CONCAVITY OF DETERMINANTS.

$$|\lambda K_1 + \bar{\lambda} K_2| \geq |\lambda|^\lambda |\bar{\lambda}|^{\bar{\lambda}} |K_1|^\lambda |K_2|^{\bar{\lambda}} \quad \begin{matrix} 0 \leq \lambda \leq 1 \\ \bar{\lambda} = 1 - \lambda \end{matrix}$$

$z = x_\theta \quad x_1 \sim N(0, K_1) \quad x_2 \sim N(0, K_2) \quad \theta \sim \text{Bernoulli}(\lambda)$

$h(z|\theta) \leq h(z)$

$h(z|\theta) = \gamma(\theta=1) \cdot h_1(z|\theta=1) + \gamma(\theta=2) h_2(z|\theta=2) =$   
 $= \lambda h_1(x_1) + \bar{\lambda} h_2(x_2)$

$h_1(x_1) = \frac{1}{2} \ln(2\pi e)^{-1} |K_1|^{-1/2} \quad h_2(x_2) = \frac{1}{2} \ln(2\pi e)^{-1} |K_2|^{-1/2}$

$h(z|\theta) = \frac{\lambda}{2} \ln(2\pi e)^{-1} |K_1|^{-1/2} + \frac{\bar{\lambda}}{2} \ln(2\pi e)^{-1} |K_2|^{-1/2} =$   
 $= \frac{\lambda}{2} \ln(2\pi e)^{-1} + \frac{\lambda}{2} \ln |K_1|^{-1/2} + \frac{\bar{\lambda}}{2} \ln(2\pi e)^{-1} + \frac{\bar{\lambda}}{2} \ln |K_2|^{-1/2} -$   
 $- \frac{\lambda}{2} \ln(2\pi e)^{-1} - \frac{\bar{\lambda}}{2} \ln |K_2|^{-1/2} = \frac{\lambda}{2} \ln(2\pi e)^{-1} + \frac{\bar{\lambda}}{2} \ln |K_1|^{-1/2} +$   
 $+ \frac{\bar{\lambda}}{2} \ln |K_2|^{-1/2} = \frac{1}{2} \ln(2\pi e)^{-1} + \frac{1}{2} \ln(|K_1|^\lambda \cdot |K_2|^{\bar{\lambda}}) =$   
 $= \frac{1}{2} \ln(2\pi e)^{-1} \cdot |K_1|^\lambda \cdot |K_2|^{\bar{\lambda}}$

$h(z, \theta) = h(z) + h(\theta|z) = h(z) + \lambda h(\theta|z=x_1) +$   
 $+ \bar{\lambda} h(\theta|z=x_2) = h(z) = \underbrace{h(\theta)}_{\pi(\theta)} + \underbrace{h(z|\theta)}_{f(z|\theta)}$

$h(z) \geq h(z|\theta)$

$\frac{1+2+3+5+6}{6} = \frac{17}{6} = \frac{7}{2}$

$E[zz^T] = E[E[zz^T|\theta]]$

ESTIMATION AND TOTAL ESTIMATION

$E[zz^T] = P(\theta=1) \cdot E[zz^T|\theta=1] + P(\theta=2) E[zz^T|\theta=2] =$

$= \lambda E[x_1 x_1^T] + \bar{\lambda} E[x_2 x_2^T]$

$\sigma[zz^T] = P(\theta=1) \cdot \sigma[zz^T|\theta=1] + P(\theta=2) \sigma[zz^T|\theta=2] =$

$= \lambda \underbrace{\sigma[x_1 x_1^T]}_{|K_1|} + \bar{\lambda} \underbrace{\sigma[x_2 x_2^T]}_{|K_2|}$

$\sigma^2 = \int (x - \bar{x})^2 \gamma(x) dx = \int x^2 \gamma(x) dx = |K|$

$E[zz^T] = E[\lambda E[x_1] + \bar{\lambda} E[x_2]] = \lambda |K_1| + \bar{\lambda} |K_2|$

Among JOINT DENSITIES WITH GIVEN COVARIANCE MATRIX A MULTIVARIATE GAUSSIAN DENSITY WITH THAT COVARIANCE MATRIX IS MAXIMIZING THE ENTROPY

$$G(z) \leq \frac{1}{2} G(2\pi e)^{\frac{1}{2}} |\lambda|k_1 + \bar{\lambda}|k_2|$$

$$G(z) \geq G(z\theta) \Rightarrow \frac{1}{2} G(2\pi e)^{\frac{1}{2}} |\lambda|k_1 + \bar{\lambda}|k_2| \geq$$

$$\frac{1}{2} G(2\pi e)^{\frac{1}{2}} |k_1|^{\lambda} \cdot |k_2|^{\bar{\lambda}}$$

FOURZANO!!!

**PROBLEM 8.2** UNIFORMLY DISTRIBUTED NOISE. LET THE INPUT

RANDOM VARIABLE  $X$  TO A CHANNEL BE UNIFORMLY DISTRIBUTED OVER THE INTERVAL  $-1/2 \leq X \leq 1/2$ . LET THE OUTPUT OF THE CHANNEL BE  $Z = X + \Xi$  WHERE THE NOISE-RANDOM VARIABLE  $\Xi$  IS UNIFORMLY DISTRIBUTED OVER THE INTERVAL  $-a/2 \leq \Xi \leq a/2$

(a) FIND  $I(x; z)$  AS A FUNCTION OF  $a$ .

(b) FOR  $a=1$  FIND THE CAPACITY OF THE CHANNEL WHEN THE INPUT  $X$  IS PEAK-LIMITED; THAT IS THE RANGE OF  $X$  IS LIMITED TO  $-1/2 \leq X \leq 1/2$ .

WHAT PROBABILITY DISTRIBUTION ON  $X$  MAXIMIZES THE MUTUAL INFORMATION  $I(x; z)$ ?

(c) (ORIGINAL) FIND CAPACITY OF THE CHANNEL FOR ALL VALUES OF  $a$  ASSUMING THAT RANGE OF  $X$  IS LIMITED TO  $-1/2 \leq X \leq 1/2$ .

$$(a) I(x; z) = h(x) - h(x|z) = h(x) - h(z) = h(x) - h(z)$$

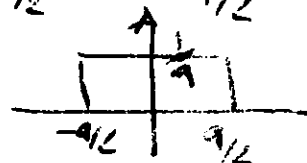
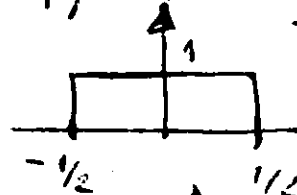
$$h(x|z) = \int_{-1/2}^{1/2} p(x=y) h(y-z|x=y) dy = h(z)$$

$$-h(x) = \int_{-1/2}^{1/2} p(x) \log p(x) dx$$

$$-h(x) = \int_{-1/2}^{1/2} 1 \log 1 dx = 0$$

$$+ h(z) = \int_{-a/2}^{a/2} \frac{1}{a} \log \frac{1}{a} dx = \frac{1}{a} \log a \left( \frac{a}{2} + \frac{a}{2} \right) = \log a$$

$$I(x; z) = \log a$$



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$$a \cdot \frac{1}{a} = 1$$

(c)  $C = \max_{p(x)} I(x; z) = h(x) - h(z) = h(x) - \log a$

$= (a=1) = \log 2$

GAUSSIAN DENSITY FUNCTION MAXIMIZES THE ENTROPY.



$$f(x) = \int_{-\infty}^x f(t) dt \quad \left| \frac{d f(x)}{dx} = f(x) \right| \quad \text{FTC 1.}$$

$$h(x) \leq \frac{1}{2} \ln 2\pi e b^2$$

$$-h(x) = \int_{-\infty}^{-1/2} \gamma(t) \ln \gamma(t) dt + \int_{-1/2}^{\infty} \gamma(t) \ln \gamma(t) dt$$

$$\int_{-\infty}^{\infty} \gamma(t) \ln \gamma(t) dt = \int_{-\infty}^{-1/2} \gamma(t) \ln \gamma(t) dt + \int_{-1/2}^{\infty} \gamma(t) \ln \gamma(t) dt$$

if  $\gamma(x) = \gamma(-x)$

$$\frac{d(-h(x))}{dx} = \gamma\left(\frac{1}{2}\right) \ln \gamma\left(\frac{1}{2}\right) - \gamma\left(-\frac{1}{2}\right) \ln \gamma\left(-\frac{1}{2}\right) = 0$$

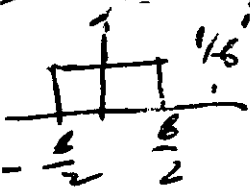
$$\gamma\left(\frac{1}{2}\right) \ln \gamma\left(\frac{1}{2}\right) = \gamma\left(-\frac{1}{2}\right) \ln \gamma\left(-\frac{1}{2}\right) \Rightarrow$$

$$\gamma\left(\frac{1}{2}\right) = \gamma\left(-\frac{1}{2}\right)$$

$$h(x) = \int_{-\infty}^{\infty} \frac{e^{-\frac{(x-t)^2}{2b^2}}}{\sqrt{2\pi}} \ln \frac{e^{-\frac{(x-t)^2}{2b^2}}}{\sqrt{2\pi}} dt$$

$\mu=0, \sigma=1$        $h(x) = 1.32832$

$$\frac{1}{2} \ln(2\pi e b^2) = \frac{1}{2} \ln(2\pi e) = \underline{4.09419}$$



$$C = h(x) = \int_{-b/2}^{b/2} \frac{1}{b} \ln b dx = \ln b$$

$$\frac{dC}{db} = \frac{d}{db} (\ln b) = \frac{1}{\ln 2} \frac{d}{db} \ln b = \frac{1}{\ln 2}$$

$$b \rightarrow 0 \Rightarrow C \rightarrow \infty$$

$$(c) C = 1.32832 - \ln a$$

$a \rightarrow \infty$

$$\frac{dC}{da} = 0 \cdot 0 = \frac{1}{a \cdot \ln 2} = 0$$

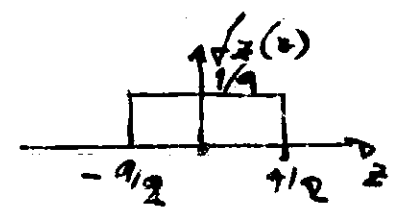
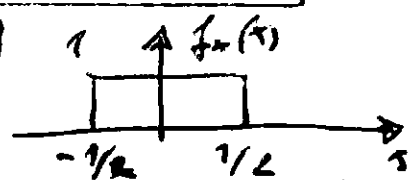
$I(x; z) = h(x) * h(z) = g(z) - g(x)$   
 $z = x + z \quad g(z) = \int \frac{1}{a} \mathbb{1}_{[a, \infty)} dt = \mathbb{1}_{[a, \infty)}$

DISTRIBUTION OF THE SUM OF TWO RANDOM VARIABLES IS CONVOLUTION OF THEIR PDFs

$M(s) = \int_{-\infty}^{\infty} p(x) e^{+sx} dx \quad M(-s) = \int_{-\infty}^{\infty} \gamma(t) e^{-st} dt$

$P(s) = \int_{-\infty}^{\infty} \gamma(t) e^{+js\omega} dt$  — CHARACTERISTIC FUNCTION

For  $a < 1$



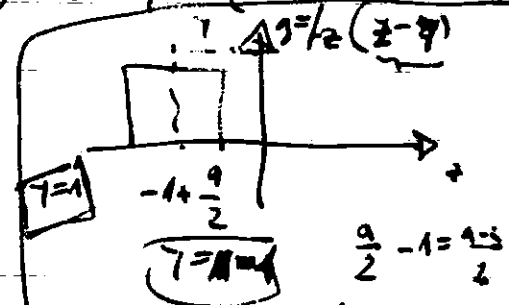
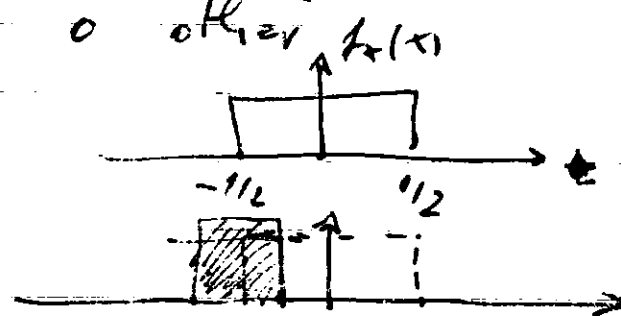
$f_1(z) = \int_{-\infty}^{\infty} f_x(t) f_z(z-t) dt$

$f_z(z) = \begin{cases} \frac{1}{a} & -\frac{a}{2} \leq z \leq \frac{a}{2} \\ 0 & \text{otherwise} \end{cases}$

$f_x(t) = \begin{cases} 1 & -\frac{1}{2} \leq t \leq \frac{1}{2} \\ 0 & \text{otherwise} \end{cases}$

$f_z(-t) = \begin{cases} \frac{1}{a} & -\frac{a}{2} \leq -t \leq \frac{a}{2} \\ 0 & \text{otherwise} \end{cases}$

$f_z(-t) = \begin{cases} \frac{1}{a} & -\frac{1}{2} \leq t \leq \frac{1}{2} \\ 0 & \text{otherwise} \end{cases}$

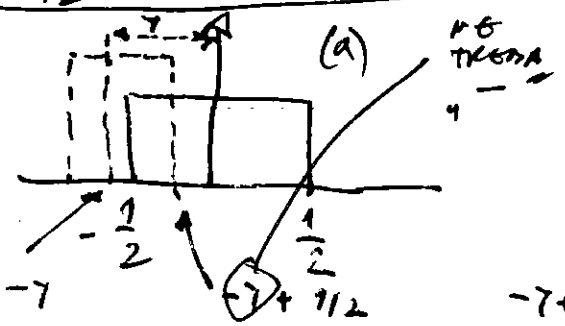


$g(\frac{a}{2}) = f_z(\frac{1}{2} + \frac{a}{2}) = f_z(\frac{1}{2})$

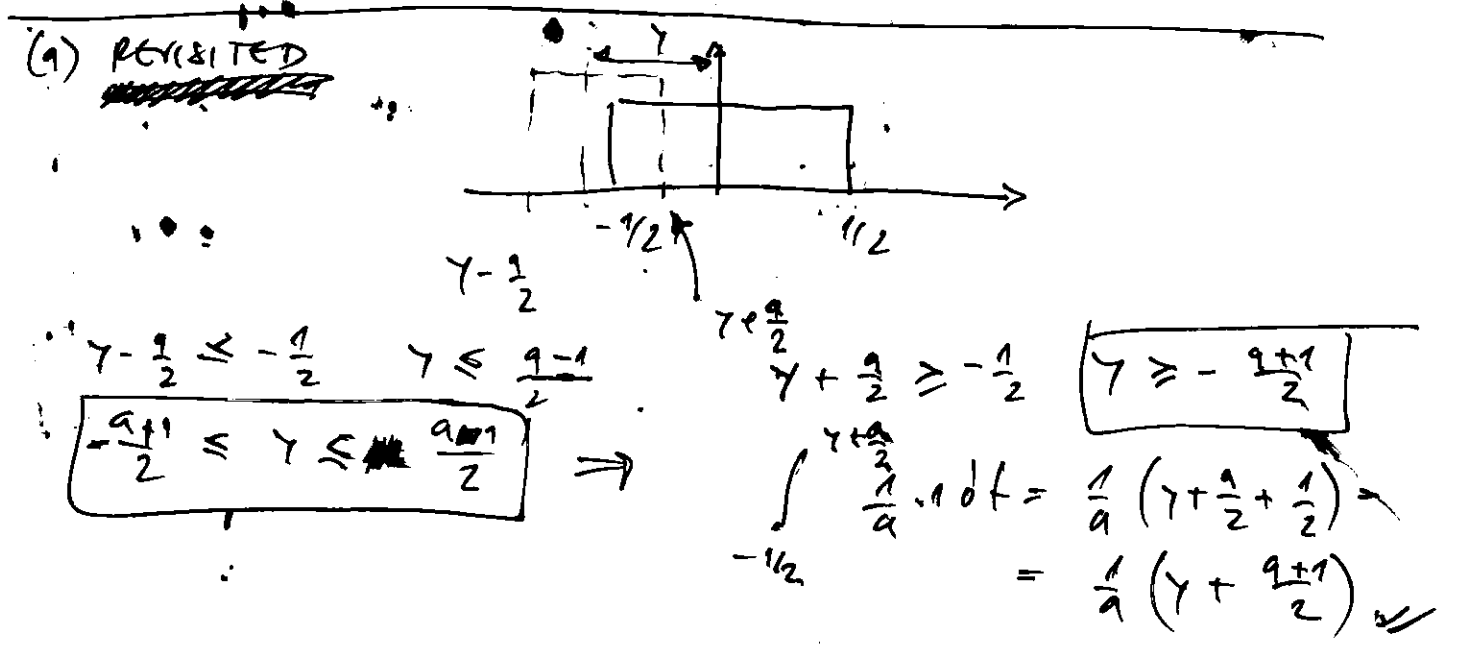
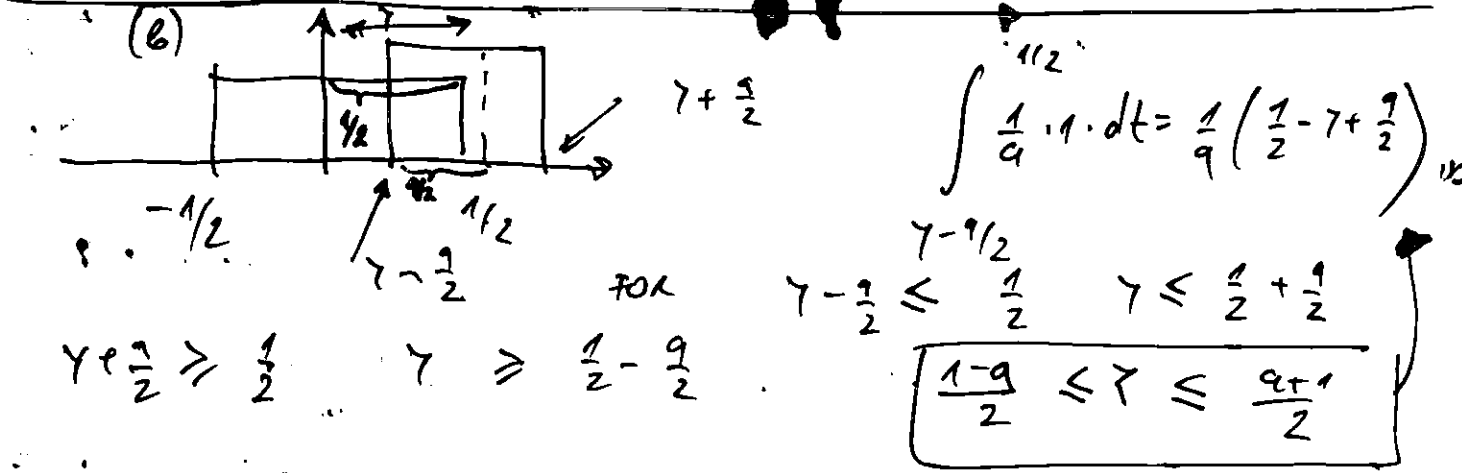
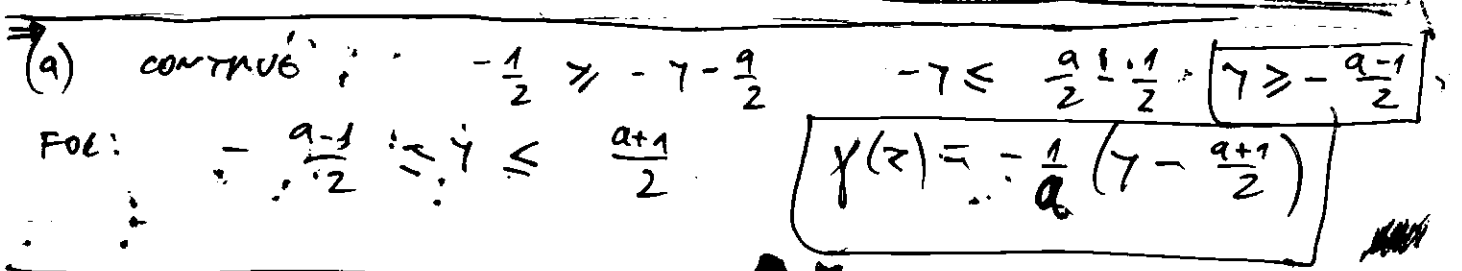
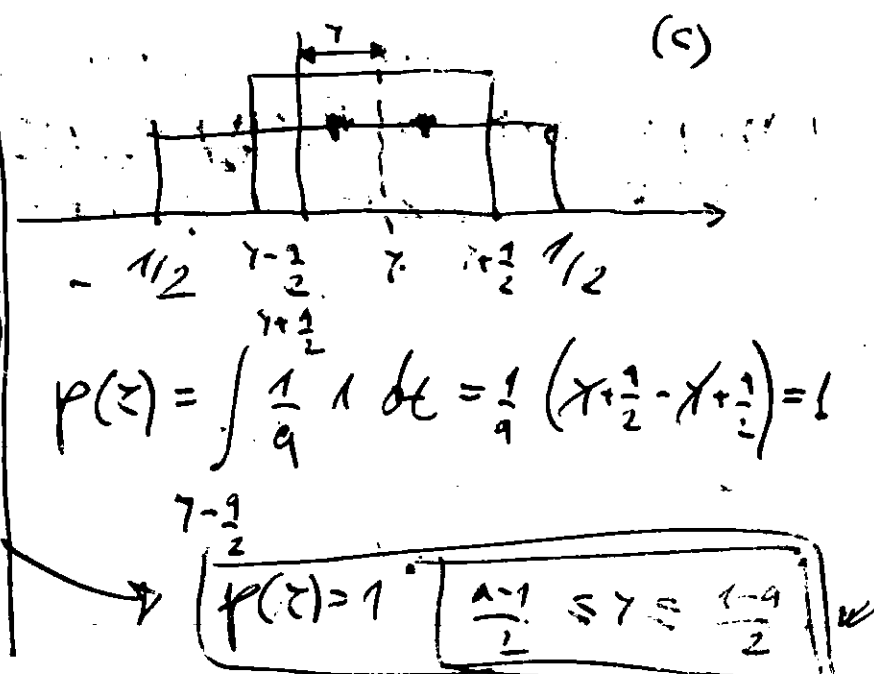
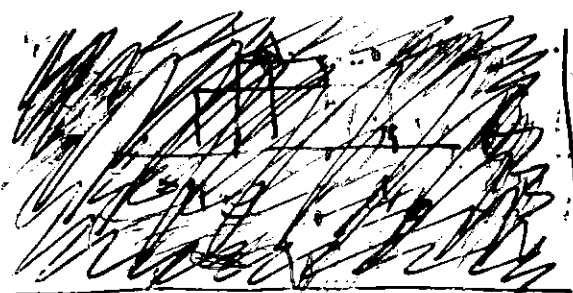
$g(z) = f_z(z + \gamma)$

$g(-1 - \frac{a}{2}) = f_z(-1 - \frac{a}{2} + \gamma) = f_z(-\frac{1}{2})$

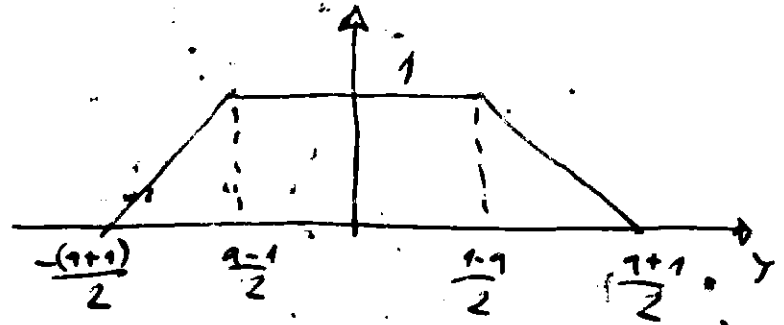
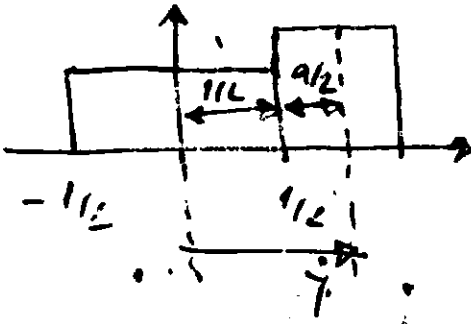
$\int_{-1/2}^{\gamma} 1 \cdot \frac{1}{a} dt = \frac{1}{a} (\gamma + \frac{1}{2}) = \frac{2\gamma + 1}{2a}$



$\int_{-1/2}^{-\gamma + 1/2} \frac{1}{a} \cdot 1 dt = \frac{1}{a} (-\gamma + \frac{1}{2} + \frac{1}{2}) = -\frac{1}{a} (\gamma - \frac{a+1}{2})$   
 $-\gamma + \frac{1}{2} \geq -\frac{1}{2} \Rightarrow -\gamma \geq -\frac{1}{2} - \frac{1}{2} \Rightarrow \gamma \leq \frac{a+1}{2}$



$$f(\tau) = \begin{cases} \frac{1}{a} \left( \tau + \frac{a+1}{2} \right) & -\frac{a+1}{2} \leq \tau \leq \frac{a-1}{2} & (a) \\ 1 & \frac{a-1}{2} \leq \tau \leq \frac{1-a}{2} & (c) \\ -\frac{1}{a} \left( \tau - \frac{a+1}{2} \right) & \frac{1-a}{2} \leq \tau \leq \frac{a+1}{2} & (b) \end{cases}$$



NO OVERLAP BETWEEN  
SUPPORTS IN (a):

We can see  $\tau$  as two disjoint variables  $\tau_1$  and  $\tau_2$  which happen to be  $\tau$  depending on section.  $\tau_1$  can be assigned to the uniform part and  $\tau_2$  to the triangular part of the total distribution.

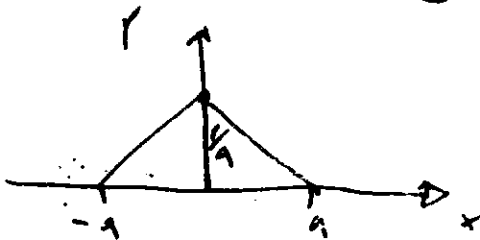
$$\tau = \begin{cases} \tau_1 & \text{with probability } \lambda \\ \tau_2 & \text{with probability } 1-\lambda \end{cases}$$

$$\theta = f(\tau) = \begin{cases} 1 & \tau = \tau_1 \\ 2 & \tau = \tau_2 \end{cases}$$

$$h(\tau, \theta) = h(\tau) + \frac{h(\theta|\tau)}{\theta} = h(\theta) + h(\tau|\theta) = h(\tau) + \lambda \cdot h(\tau_1) + (1-\lambda) \cdot h(\tau_2)$$

$$\lambda = \int_{-\frac{a-1}{2}}^{\frac{1-a}{2}} 1 \cdot d\tau = \left[ \frac{\tau-a}{2} - \frac{a-1}{2} \right] = \frac{1-a-a+1}{2} = \underline{1-a}$$

This means that  $\tau$  has uniform distribution with probability  $1-a$

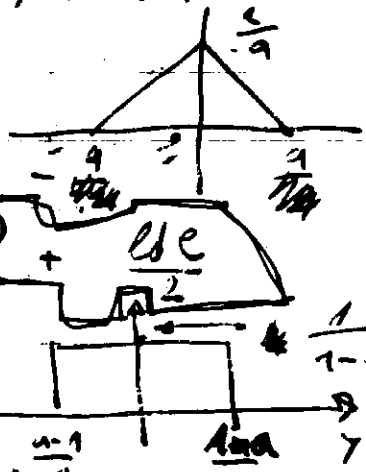


$$\begin{aligned} \tau = \frac{1}{a} \cdot (x+a) &= \frac{1}{a} \cdot (x+a) \\ x = a & \Rightarrow \tau = \frac{1}{a} \cdot (a+a) = 2 \\ x = -a & \Rightarrow \tau = \frac{1}{a} \cdot (-a+a) = 0 \end{aligned}$$

$$\begin{aligned} h(x) &= \int_{-a}^a f(\tau) \ln \frac{1}{f(\tau)} d\tau \\ &= \int_{-a}^0 \frac{1}{a^2} (\tau+a) \ln \frac{a^2}{(\tau+a)} d\tau + \\ &+ \int_0^a \frac{-\tau+a}{a^2} \ln \frac{a^2}{(-\tau+a)} d\tau = \frac{2 \ln a + 1}{4 \ln 2} \\ &+ \frac{1}{4} \frac{2 \ln a + 1}{\ln 2} = \frac{2 \ln a + 1}{2 \ln 2} = \ln \frac{4e}{2} \end{aligned}$$

$$I(x; z) = H(z) - H(z) = H(\lambda) + \lambda \cdot H(z_1) + (1-\lambda) H(z_2) = H(z)$$

•  $H(z_2) = ?$



$$H(z_2) = \ln\left(\frac{a}{1-a}\right) + \frac{1/a \cdot 1/a}{2}$$

•  $H(z_1) = ?$

$$\frac{a+1}{2} - \frac{1-a}{2} = a$$

$$\frac{a+1 - 1+a}{2} = \frac{2a}{2} = a$$

~~$$\frac{1-a}{2} - \frac{1-a}{2} = \frac{1-a-1+a}{2} = \frac{0}{2} = 0$$~~

$$h(z_1) = \int_{\frac{1-a}{2}}^{\frac{a+1}{2}} \frac{1}{(1-a)} dy = -\ln\left[\frac{1-a}{2} - \frac{1-a}{2}\right] = \ln(1-a)$$

$$h(z_1) = \ln(1-a) \cdot (1-a) = \ln(1-a) = H(z)$$

$$I(x; z) = \lambda \ln \frac{1}{\lambda} + (1-\lambda) \ln(1-\lambda) + \lambda \ln(1-a) + (1-\lambda) \left[ \ln\left(\frac{a}{1-a}\right) + \frac{1/a}{2} \right]$$

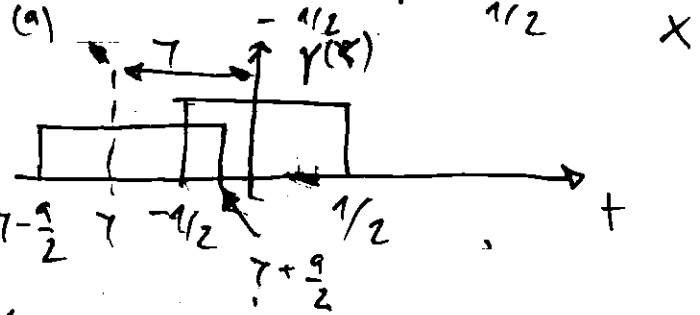
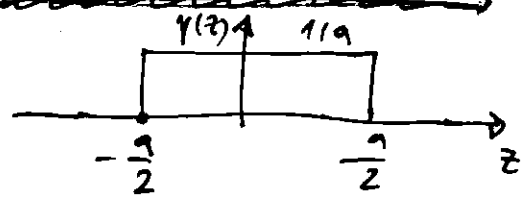
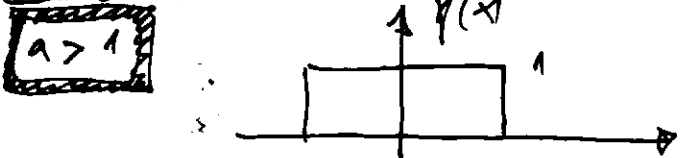
2nd case  $a < 1$   $h_2(x)$ :

$$I(x; z) = \lambda \ln \frac{1}{\lambda} + (1-\lambda) \ln(1-\lambda) + \lambda \ln(1-a) + (1-\lambda) \left[ \ln\left(\frac{a}{1-a}\right) + \frac{1}{2} \right]$$

$$I(x; z) = (1-a) \ln \frac{1}{1-a} + a \ln \frac{1}{a} + (1-a) \ln(1-a) + a \ln a$$

$$I(x; z) = \frac{a}{2} - \ln a$$

$$I(x; z) = \frac{a \ln a}{2} - \ln a$$



$$y + \frac{a}{2} \geq -\frac{1}{2} \quad y \geq -\frac{a+1}{2}$$

$$y + \frac{a}{2} \leq \frac{1}{2} \quad y \leq \frac{1-a}{2}$$

$$y(z) = \int_{\frac{1-a}{2}}^{\frac{a+1}{2}} \frac{1}{a} dy = \frac{1}{a} \left( \frac{a+1}{2} + \frac{1}{2} \right)$$

$$(b) \quad y + \frac{a}{2} \geq \frac{1}{2} \quad y \geq \frac{1-a}{2}$$

$$y - \frac{1}{2} \leq -\frac{1}{2} \quad y \leq \frac{a-1}{2}$$

$$y \leq \frac{a-1}{2}$$

$$y(x) = \int_{\frac{1-a}{2}}^{\frac{a+1}{2}} 1 \cdot dy = 1/a$$

$$\frac{1-a}{2} \leq y \leq \frac{a+1}{2}$$

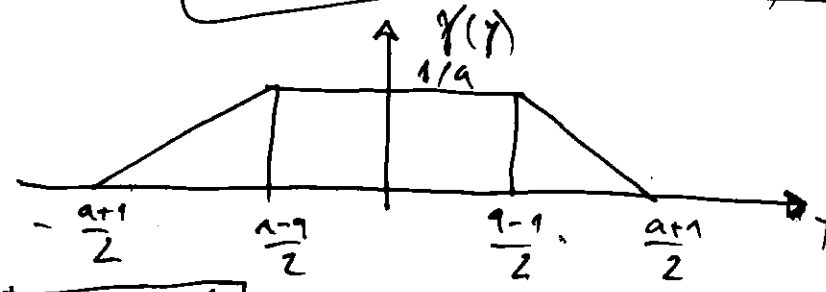
(c)  $\gamma - \frac{a-1}{2} \geq -\frac{1}{2} \quad \gamma \geq \frac{a-1}{2}$   $\frac{a-1}{2} \leq \gamma \leq \frac{a+1}{2}$

$\gamma - \frac{a-1}{2} \leq \frac{1}{2} \quad \gamma \leq \frac{1+a}{2}$

$\int \frac{1}{a} \cdot 1 d\gamma = \frac{1}{a} \left( -\gamma + \frac{a+1}{2} \right) = \frac{1}{a} \left( -\gamma + \frac{a+1}{2} \right)$

$\gamma - \frac{a-1}{2}$  ~~um~~

$f(\gamma) = \begin{cases} \frac{1}{a} \left( \gamma + \frac{a+1}{2} \right) & -\frac{a+1}{2} \leq \gamma \leq \frac{1-a}{2} \quad (a) \\ \frac{1}{a} & \frac{1-a}{2} \leq \gamma \leq \frac{a-1}{2} \quad (b) \\ \frac{1}{a} \left( -\gamma + \frac{a+1}{2} \right) & \frac{a-1}{2} \leq \gamma \leq \frac{a+1}{2} \quad (c) \end{cases}$

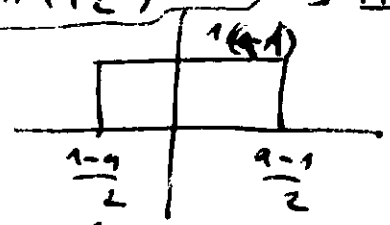


$\lambda = \int_{\frac{1-a}{2}}^{\frac{a-1}{2}} \frac{1}{a} d\gamma = \frac{1}{a} \left( \frac{a-1}{2} - \frac{1-a}{2} \right) = \frac{a-1-1+a}{2a} = \frac{2a-2}{2a} = \frac{a-1}{a}$

$\lambda = 1 - \frac{1}{a} \quad 1 - \lambda = 1 - \frac{a-1}{a} = \frac{1}{a}$

$H(x) = H(\lambda) + \lambda H(\tau_1) + (1-\lambda) \cdot H(\tau_2) - H(x)$   $\frac{1-a}{2} + \frac{a-1}{2} = \frac{1-a+a-1}{2} = \frac{-2}{2} = -1$

$H(\tau_1) = \int_{-\frac{a+1}{2}}^{\frac{1-a}{2}} \frac{1}{a-1} \ln(a-\gamma) d\gamma$

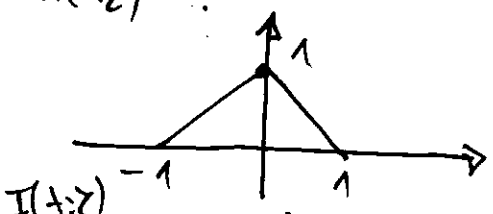


$H(\tau_1) = \frac{1}{a-1} \ln(a-1) \left[ \frac{a-1}{2} - \frac{1-a}{2} \right] = \ln(a-1)$

$H(\tau_2) = ?$

$\frac{a+1}{2} - \frac{a-1}{2} = \frac{a+1-a+1}{2} = 1$

$\frac{1-a}{2} + \frac{a+1}{2} = 1$



$H(\tau_2) = \ln a + \frac{1}{2} = \ln \left( a + \frac{1}{2} \right) = \frac{1}{2}$

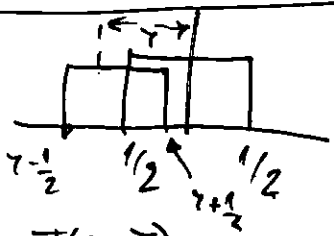
$I(x; \tau) = \left( 1 - \frac{1}{a} \right) \ln \frac{1}{1-\frac{1}{a}} + \frac{1}{a} \ln a + \left( 1 - \frac{1}{a} \right) \ln(a-1) + \frac{1}{a} \frac{1}{2} - \ln a =$

$= \frac{a-1}{a} \ln \frac{a}{a-1} + \frac{1}{a} \ln a + \frac{a-1}{a} \ln(a-1) + \frac{1}{2a} - \ln a =$

$= \left( 1 - \frac{1}{a} \right) \ln a + \frac{1}{a} \ln a + \frac{1}{2a} - \ln a = \frac{1}{2a}$

$I(x; \tau) = 1/2a$

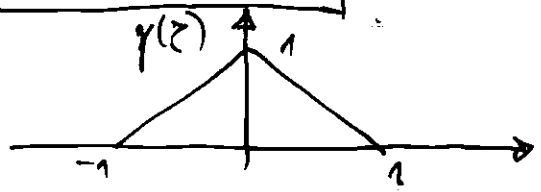
$a=1$



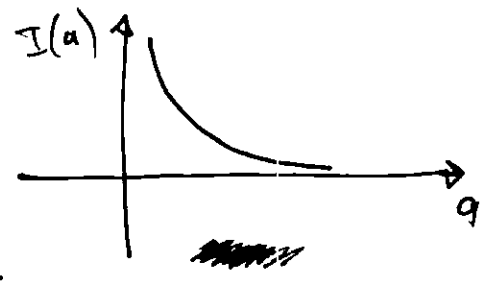
$f(\gamma) = \begin{cases} \gamma+1 & -1 \leq \gamma \leq 0 \\ -\gamma+1 & 0 \leq \gamma \leq 1 \end{cases}$

$H(\tau_1) = 0 \quad H(\tau_2) = 1/2$

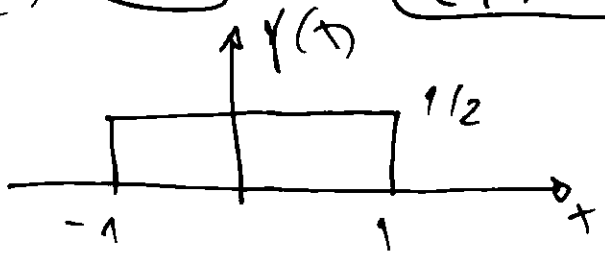
$I(x; \tau) = 0 + 0 + 1 \cdot \frac{1}{2} - \ln a = \frac{1}{2}$  (39)



$$I(x; \tau) = \begin{cases} \frac{a}{2} - \ln a & a < 1 \\ \frac{1}{2a} & a > 1 \\ \frac{1}{2} & a = 1 \end{cases}$$



(c)  $a=1$   $I(x; \tau) = \frac{1}{2}$   $\Rightarrow$  FOR ANY  $q(x)$



$$h(x) = \int \frac{1}{2} \ln 2 \, dx = \frac{1}{2} (1+1) = \frac{1}{2} \cdot 2 = 1$$

**PROBLEM 8.4** ~~Quantized~~ QUANTIZED RANDOM VARIABLES.

ROUGHLY HOW MANY BITS ARE REQUIRED ON AVERAGE TO RESOLVE TO THREE DIGIT ACCURACY THE DEATH TIME (IN YEARS) OF A RADIONUCLIDE IF THE HALF TIME OF RADIONUCLIDE IS 80 YEARS? NOTE THAT HALF TIME IS MEDIAN OF THE DISTRIBUTION.

$$I(x; \Delta) = \int_{(i-1)\Delta}^{i\Delta} f(x) \, dx \quad x_i^{\Delta} = x_i \quad i\Delta \leq x \leq (i+1)\Delta$$

$$h(x_i^{\Delta}) + \ln \Delta = h(x)$$

$h(x_i^{\Delta}) \rightarrow h(x) + \text{bit accuracy}$   $\Rightarrow$  NUMBER OF BITS ON THE AVERAGE REQUIRED TO RESOLVE  $x$  TO  $n$ -BIT ACCURACY

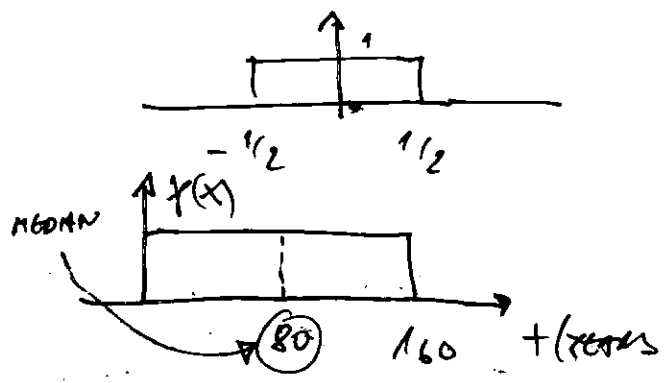
$\mu = 80 \text{ years}$   
~~160~~

bit accuracy  
MEDIAN OF DISTRIBUTION

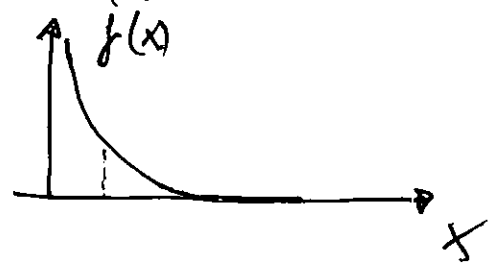
$$h(x) = \int_0^{160} \frac{1}{160} \cdot dt = \frac{1}{160} (160-0) = 1$$

$$h(x) = \int_{-1/2}^{1/2} 1 \cdot dx = 1 \cdot \left(\frac{1}{2} - \left(-\frac{1}{2}\right)\right) = 1$$

$$h(x^{\Delta}) = 1 + 3 = 4 \text{ bits}$$



$$f(x; \lambda) = \begin{cases} \lambda e^{-\lambda x} & x \geq 0 \\ 0 & x < 0 \end{cases}$$



$$\bar{x} = \int_0^{\infty} x \lambda e^{-\lambda x} dx = \left( \frac{1}{\lambda} \right)$$

MEAN LIFETIME

$$\frac{1}{\bar{x}} = \lambda \Rightarrow$$

INVERSE OF THE MEAN LIFETIME

WIKIPEDIA FORMULA

$$t_{112} = \frac{h_1(2)}{\lambda} = 80 \text{ years} \quad (*)$$

$$\lambda = \frac{h_1(2)}{80} = \underline{\underline{0.00866}}$$

$$h_1(x) = - \int_0^x \lambda(x) \ln \lambda(x) dx = - \int_0^x \lambda \cdot e^{-\lambda x} \ln(\lambda e^{-\lambda x}) dx$$

$$= - \int_0^x \lambda e^{-\lambda x} (\ln \lambda + \lambda x) \ln(\lambda e^{-\lambda x}) dx = - \lambda \int_0^x (\lambda x + 1) e^{-\lambda x} dx$$

$$h_1(x) = \ln\left(\frac{e}{\lambda}\right)$$

$$h_1(x) = -\lambda \cdot \ln(\lambda e) \cdot \frac{1}{\lambda} = \ln(\lambda e) = \frac{h_1(\lambda e)}{h_1 2} = \frac{h_1(\lambda)}{h_1 2} + \frac{h_1 e}{h_1 2}$$

$$h_1(x) = \ln\left(\left[\frac{h_1(2)}{80}\right]^{-1} \cdot e\right) = \underline{\underline{8.29}}$$

$$H(x^*) = h_1(x) + 4 = 8.29 + 3 = 11.29 \sim \underline{\underline{12 \text{ bits}}}$$

• CONCORDIA UNIVERSITY SOLUTIONS

$$\int_0^{80} \lambda e^{-\lambda x} dx = \frac{1}{2}$$

~~Handwritten scribbles and crossed-out equations.~~

$$\int_0^{80} e^{-\lambda x} d(\lambda x) = -e^{-\lambda x} \Big|_0^{80} = \frac{1}{2}$$

$$[e^{-\lambda 80} - e^0] = \frac{1}{2} \quad e^{-\lambda 80} = 1 - \frac{1}{2} = \frac{1}{2}$$

$$e^{-\lambda 80} = \frac{1}{2} \quad \lambda 80 = \ln 2$$

$$\lambda = \frac{\ln(2)}{80}$$

WIKIPEDIA FORMULA DO KONCORDIA UNIVERZITETA

TRABA DA SE ZADATI DOKA KVA JE IZREK METODA MEDIANA

MMV

MEDIAN

$$\int_0^x \lambda(x) dx = \frac{1}{2}$$

3 DIGITS ~ 10 BITS  $2^{10} = 1024$

$$H(x^*) = 8.29 + 10 = 18.3 \text{ BITS}$$



**PROBLEM 8.5** Substitution. Let  $h(x) = - \int f(x) \ln f(x) dx$   
 SHOW  $h(Ax) = \ln |\det(A)| + h(x)$ .

$$A = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix}$$

$$x = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix}$$

$$Ax = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 \\ a_{21}x_1 + a_{22}x_2 \end{bmatrix}$$

$$h(Ax) = - \int f(Ax) \ln f(Ax) dx$$

$$f(Ax) = \frac{f(x)}{|J|} \Big|_{x = \frac{y}{A}}$$

$$J = \begin{bmatrix} \frac{\partial y_1}{\partial x_1} & \frac{\partial y_1}{\partial x_2} \\ \frac{\partial y_2}{\partial x_1} & \frac{\partial y_2}{\partial x_2} \end{bmatrix}$$

$$y = A \cdot \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} y_1 \\ y_2 \end{bmatrix} = \begin{bmatrix} a_{11}x_1 + a_{12}x_2 \\ a_{21}x_1 + a_{22}x_2 \end{bmatrix} \begin{cases} y_1 = a_{11}x_1 + a_{12}x_2 \\ y_2 = a_{21}x_1 + a_{22}x_2 \end{cases} \quad \boxed{dy = J dx = A^2 dx}$$

$$|J| = \begin{bmatrix} a_{11} & a_{12} \\ a_{21} & a_{22} \end{bmatrix} = \det(A) \quad f(y) = \frac{f(x)}{|\det(A)|} = \frac{f(x)}{|\det(J)|}$$

$$\begin{aligned} h(y) &= - \int f(y) \ln f(y) dy = - \int \frac{f(x)}{|\det(A)|} \ln \left( \frac{f(x)}{|\det(A)|} \right) \frac{dy}{dx} dx \\ &= - \int f(x) \ln \left( \frac{f(x)}{|\det(A)|} \right) dx = - \int f(x) \ln f(x) dx + \int f(x) dx \\ &= h(x) + \ln |\det(A)| \int f(x) dx = h(x) + \ln |\det(A)| \end{aligned}$$

SHOW FOR THE CASE  $n > 2$ :  $x = [x_1, x_2, \dots, x_n]$

~~Substitution  $y = Ax$  and  $dy = A dx$~~

$$y = Ax \quad \boxed{x = A^{-1}y} \quad g(y) = \frac{f(A^{-1}y)}{|\det(A)|}$$

$$\begin{aligned} h(y) &= - \int g(y) \ln g(y) dy = - \int \frac{f(A^{-1}y)}{|\det(A)|} \ln \left( \frac{f(A^{-1}y)}{|\det(A)|} \right) |\det(A)| dy \\ &= \int f(x) \ln f(x) dx + \int f(x) \ln |\det(A)| dx = \\ &= h(x) + \ln |\det(A)| \end{aligned}$$

# 8.7 DIFFERENTIAL ENTROPY & BOUND ON DISCRETE ENTROPY (CONTINUED FROM 166)

THEOREM 8.6.6. ESTIMATION ERROR AND DIFFERENTIAL ENTROPY

$$E(x - \hat{x})^2 \geq \frac{1}{2\pi e} e^{2h(x)}$$

WITH EQUALITY IF  $X \sim$  GAUSSIAN AND  $\hat{x}$  IS THE MEAN OF  $X$ .

PROOF  $E(x - \hat{x})^2 \geq \min_{\hat{x}} E(x - \hat{x})^2 = E(x - E(x))^2$   
 $= \text{VAR}(X) \geq \frac{e^{2h(x)}}{2\pi e}$

$$h(x) \leq \frac{1}{2} \ln(2\pi e \sigma^2)$$

$E(x)$  IS BEST ESTIMATOR FOR  $X$

$$E(x - \hat{x}(z))^2 \geq \frac{e^{2h(x)}}{2\pi e} \geq \frac{e^{2h(x|z)}}{2\pi e} \implies h(x) \geq h(x|z)$$

$$x = \{a_1, a_2, \dots\} \quad P_r(x = a_i) = p_i$$

$$H(p_1, p_2, \dots) \leq \frac{1}{2} \ln(2\pi e) \left( \sum_{i=1}^{\infty} p_i i^2 - \left( \sum_{i=1}^{\infty} i p_i \right)^2 + \frac{1}{12} \right)$$

$$H(x^4) = h(x) = \ln 4 = \left| \ln 2^2 \right| = h(x) = 4$$

$$x' \sim P_r(x' = i) = p_i \quad \sigma \sim [0, 1]$$

$$z = x' + \sigma$$

$$I(x'; z) = H(x) - H(z|x) = H(x) - \sum p(x) H(x' + \sigma | x')$$

$$= H(x) - H(\sigma) \quad H(\sigma) = 0$$

$$h(\sigma) = \int_0^1 1 \, d_1 \, d_1 = 1 \quad I(x'; z) = h(z)$$

$$E(x') = \sum_{i=1}^{\infty} i p_i \quad \left| p_i = \frac{1}{2^i} \right| = \sum_{i=1}^{\infty} i \frac{1}{2^i} = \sum_{i=0}^{\infty} i \frac{1}{2^i} = \frac{2}{(2-1)^2}$$

$$= \frac{1}{\frac{1}{4}} = 2 \quad E(x'^2) = \sum_{i=1}^{\infty} i^2 p_i = \sum_{i=1}^{\infty} i^2 \frac{1}{2^i} = 6$$

$$\sigma^2 = E[(x' - \bar{x})^2] = E[x'^2] - 2E[x'] \bar{x} + \bar{x}^2 = E[x'^2] - \bar{x}^2$$

$$x \in \{a_1, a_2, \dots\}$$

$$x' \in \{1, 2, \dots\}$$

remains:

$$x_1 \in \{1, 2, \dots, m\}$$

$$x_2 \in \{m, \dots, n\}$$

$$H(x) = H(x')$$

$$z = x' + v$$

$$\Theta = \begin{cases} 1 & x = x_1 & p \\ 2 & x = x_2 & 1-p \end{cases}$$

$$H(x, \Theta) = H(x) + H(\Theta|x) = H(x) = H(\Theta) + H(x|\Theta)$$

$$H(x|\Theta) = H(\Theta=1) \cdot H(x|\Theta=1) + H(\Theta=2) \cdot H(x|\Theta=2)$$

$$= p H(x_1) + (1-p) H(x_2)$$

$$H(z) = H(y) + p [H(x_1)] + (1-p) H(x_2)$$

$$z \in \{z_1, z_2, \dots\}$$

$$z \in \{i, i+1\}$$

$$I(x'; z) = H(x') - H(x'|z) = H(z) - H(x|z)$$

$$H(z) = H(x) - H(x'|z) = H(x) - H(x|z) = I(x; z)$$

$$H(x) = H(z) + H(x|z) = H(x, z)$$

$$H(x) \leq \frac{1}{2} \ln 2\pi e \sigma^2$$

$$H(z) = \lim_{n \rightarrow \infty} \frac{1}{n} H(z_1, z_2, \dots, z_n) =$$

$$= \frac{1}{n} H(z_i) = \text{UNIFORM EZ} \quad \left| \begin{array}{l} 0 \div 0.5 \Rightarrow 0 \\ 0.5 \div 1 \Rightarrow 1 \end{array} \right. = H\left(\frac{1}{2}\right) = 1$$

$$H(x) = 1 + H(x|z) = 1 + p(z=i) H(x|z=i)$$

$$= 1 + p(z=i) [p(x=i|z=i) \ln p(x=i|z=i) + p(x=i-1|z=i) \ln p(x=i-1|z=i)] = 1 + \sum_i p(z=i) \cdot 1$$

**PROBLEM 8.9**

(CONTINUE FROM 164)

$$\gamma(x, z) = \frac{1}{(2\pi) \sqrt{|K_{11}|}} e^{-\frac{1}{2}(x-z)^T K_{11}^{-1} \begin{bmatrix} x \\ z \end{bmatrix}}$$

$$K_{11} = \begin{bmatrix} \sigma_x^2 & \rho_1 \\ \rho_1 & \sigma_y^2 \end{bmatrix}$$

$$K_{11} = \begin{bmatrix} \sigma_x^2 & \rho_1 \sigma_x \sigma_y \\ \rho_1 \sigma_x \sigma_y & \sigma_y^2 \end{bmatrix} \quad |K_{11}| = \sigma_x^2 \sigma_y^2 - \rho_1^2$$

$$K_{11}^{-1} = \frac{1}{\sigma_x^2 \sigma_y^2 - \rho_1^2} \begin{bmatrix} \sigma_y^2 & -\rho_1 \\ \rho_1 & \sigma_x^2 \end{bmatrix}$$

$$\gamma(x) = \frac{1}{\sqrt{2\pi} \sigma_x} e^{-\frac{x^2}{2\sigma_x^2}}$$

$$\gamma(x) = \frac{1}{2\sqrt{\pi} \sigma_x} e^{-\frac{x^2}{(\sigma_x^2 - \rho_1^2) \sigma_x^2}} = \frac{1}{2\sqrt{\pi}} e^{-\frac{x^2}{(\sigma_x^2 - \rho_1^2) \sigma_x^2}}$$

$$h(x) = h(z) = \frac{1}{2} \ln(2\pi e) \sigma^2$$

$$h(x, z) = \frac{1}{2} \ln(2\pi e)^2 |K| = \frac{1}{2} \ln(2\pi e)^2 (\sigma_x^2 - \rho_1^2 \sigma_y^2)$$

$$I(x, z) = h(x) - h(x, z) = h(x) - h(x, z) + h(z)$$

$$h(x, z) = h(x) + h(z) \quad \underline{h(x, z) = h(x) - h(z)}$$

$$I(x, z) = \frac{1}{2} \ln(2\pi e) \sigma_x^2 - \frac{1}{2} \ln(2\pi e)^2 \sigma_x^2 (\sigma_y^2 - \rho_1^2)$$

$$= \frac{1}{2} \ln(2\pi e) \sigma_x^2 - \frac{1}{2} \ln(2\pi e)^2 \sigma_x^2 (1 - \rho_1^2)$$

$$I(x, z) = -\frac{1}{2} \ln(1 - \rho_1^2)$$

$$I(z, z) = -\frac{1}{2} \ln(1 - \rho_2^2)$$

$$I(x, z) = I(x, z) + I(z, z|x) = I(z, z) + I(x, z|z)$$

$$I(x, z|z) = h(x|z) - h(x, z) = h(z|x) - h(z|x, z)$$

$$I(x, z) = I(x, z) + I(z, z|x) = I(z, z)$$

$$I(x, z) = I(z, z) - I(z, z|x) = -\frac{1}{2} \ln(1 - \rho_2^2) - I(z, z|x)$$

$$I(z, z|x) = h(z|x) - h(z|x, z) = h(x|z) - h(x|z, z) =$$

$$= h(x) - h(z|x) = h(xz) - h(x) - h(xz) + h(z)$$

$$h(xz) = h(x, z) - h(z|x, z) = h(x, z) - h(z|x)$$

$$K = \begin{bmatrix} \sigma^2 & \rho_1 \sigma^2 & 0 \\ \rho_1 \sigma^2 & \sigma^2 & \rho_2 \sigma^2 \\ 0 & \rho_2 \sigma^2 & \sigma^2 \end{bmatrix}$$

$$h(x, y, z) = \frac{1}{2} \ln \left( (2\pi e)^3 |K| \right)$$

$$K = \sigma^2 \begin{vmatrix} \sigma^2 & \rho_2 \sigma^2 \\ \rho_2 \sigma^2 & \sigma^2 \end{vmatrix} - \rho_1 \sigma^2 \begin{vmatrix} \rho_1 \sigma^2 & \rho_2 \sigma^2 \\ 0 & \sigma^2 \end{vmatrix} = \sigma^2 (\sigma^4 - \rho_2^2 \sigma^4) - \rho_1 \sigma^2 \cdot \rho_1 \sigma^4$$

$$K = \sigma^6 (1 - \rho_2^2) - \rho_1^2 \sigma^6 = \sigma^6 (1 - \rho_1^2 - \rho_2^2)$$

$$h(x, y, z) = \frac{1}{2} \ln \left( (2\pi e)^3 \sigma^6 (1 - \rho_1^2 - \rho_2^2) \right)$$

$$\begin{aligned} I(x, y, z) &= h(x, z) - h(x, y) - h(y, z) + h(x, y, z) \\ &= h(x, z) - h(y, z) = h(x, y, z) - h(y, x, z) - h(x, z) = \\ &= h(x, y, z) - h(y, x, z) - h(x, z) = h(x, y, z) - (h(x, y) - h(x)) - \\ &\quad - h(y, z) = h(x, y, z) - h(x, y) + h(x) - h(y, z) \\ &= \frac{1}{2} \ln \left( (2\pi e)^3 \sigma^6 (1 - \rho_1^2 - \rho_2^2) \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_1^2) \right) + \\ &\quad + \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_2^2) \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_2^2) \right) \end{aligned}$$

$$\begin{aligned} I(x, y, z) &= \frac{1}{2} \ln \left( (2\pi e)^3 \sigma^6 (1 - \rho_1^2 - \rho_2^2) \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_1^2) \right) - \\ &\quad - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_2^2) \right) + \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_2^2) \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_1^2) \right) \\ &= \frac{1}{2} \ln \left( (2\pi e)^3 \sigma^6 (1 - \rho_1^2 - \rho_2^2) \right) - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_1^2) \right) \\ &\quad - \frac{1}{2} \ln \left( (2\pi e)^2 \sigma^4 (1 - \rho_2^2) \right) \end{aligned}$$

CONTINUE FROM N.16R:

$$h(x|y) = \sum_x \sum_y p(y) \cdot \ln \frac{1}{p(x|y)} = \sum_y p(y) h(x|y)$$

$$E(x|y) = \sum_x x p(x|y) \quad E(x) = \sum_y p(y) E(x|y)$$

$$E(x|y) = \sum_x x p(x|y)$$

$$E[x|y] = \int x p(x|y) dx$$

$$E[x|y] = \int p(y) \int x p(x|y) dx dy$$

$$E[x|Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x \gamma(x|y) dx dy = \int_{-\infty}^{\infty} x \gamma(x|y) dx$$

$$E[xz|Y] = ? \quad \gamma(xz|Y) = \frac{f(x,y,z)}{f(y)} = \frac{f(x,y) \cdot f(z|y)}{f(y)} = \frac{f(x,y) \cdot f(z|y)}{f(y)}$$

$$E[xz|Y] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xz \cdot \gamma(xz|Y) dx dz = \int_{-\infty}^{\infty} x \gamma(x|Y) dx + \int_{-\infty}^{\infty} z \gamma(z|Y) dz$$

THEOREM FOR TOTAL EXPECTATION

$$E[xz] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xz \gamma(xz|Y) dx dz \int_{-\infty}^{\infty} f(y) dy = E_x[E(x|Y)] E_z[E(z|Y)]$$

MMV

$$f(x,y) = \frac{1}{2\pi \sqrt{|K|}} e^{-\frac{1}{2} [x \ y] K^{-1} \begin{bmatrix} x \\ y \end{bmatrix}}$$

$$= \frac{1}{2\pi \sqrt{b_1 b_2 (1-\rho_{12}^2)}} e^{-\frac{x^2 - 2xy\rho_{12} + y^2}{2b_1 b_2 (1-\rho_{12}^2)}}$$

$$\gamma(x|z) = \frac{\gamma(x,y)}{f(y)} = \frac{1}{\sigma \sqrt{2\pi}} e^{-x^2/2\sigma^2}$$

MARLE

$$E[x] = \int_{-\infty}^{\infty} x \gamma(x|z) dx = \dots \gamma \cdot \rho_{12}$$

$$E[z|Y] = \int_{-\infty}^{\infty} z \gamma(z|Y) dz = \gamma \cdot \rho_{21}$$

$$E_x \left[ \frac{y^2}{2\sigma_1^2 \sigma_2^2} \right] = \dots = \frac{\sigma^2 \rho_{12} \rho_{21}}{2\sigma_1^2 \sigma_2^2}$$

~~Handwritten scribbles and crossed-out equations~~

$$\rho_{x+z} = \frac{E[xz]}{\sigma_x \sigma_z} = \frac{E_x[E(xz|Y)]}{\sigma_x \sigma_z} = \frac{E_x[E_x[x|Y] \cdot E_z[z|Y]]}{\sigma_x \sigma_z} = \frac{\rho_{12} \rho_{21} E_z[Y]}{\sigma_x \sigma_z}$$

$$\rho_{x+z} = \rho_{12} \rho_{21}$$

TOTAL EXPECTATION

$$E[X+Z] = \int p(\gamma) E[X+Z|\gamma] d\gamma$$

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ARTICLE:  
Conditional Expectation  
AND TOTAL EXPECTATION

**PROBLEM 8.11**

NON-ERGODIC GAUSSIAN PROCESS CONSIDER A

CONSTANT SIGNAL  $V$  IN THE PRESENCE OF IID OBSERVATION-  
NOISE  $\{Z_i\}$ . THUS  $X_i = V + Z_i$  WHERE:  
 $V \sim \mathcal{N}(0, S)$  AND  $Z_i$  ARE IID  $\sim \mathcal{N}(0, N)$ . ASSUME  
THAT  $V$  AND  $\{Z_i\}$  ARE INDEPENDENT.

- (a) IS  $\{X_i\}$  STATIONARY?
- (b) FIND  $\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i$ . IS THE LIMIT RANDOM?
- (c) WHAT IS THE ENTROPY RATE  $h$  OF  $\{X_i\}$ ?
- (d) FIND THE LEAST-MEAN-SQUARED ERROR PREDICTOR  $\hat{X}_n(x^n)$  AND FIND  $\sigma_{\infty}^2 = \lim_{n \rightarrow \infty} E[\hat{X}_n - X_n]^2$ .
- (e) DOES  $\{X_i\}$  HAVE AEP? THAT IS DOES  $-\frac{1}{n} \log f(x^n) \rightarrow h$ ?

(a) NISLAM DENA E STACIONAREN  $\{X_i\}$  ZARBA ETO  
SUMA OD DVE GAUSSOV SUCIATNI MOMENTUM E  
POVTOARO GAUSSOVA NAMA SO SLEBA VLEA OST KOP  
E SUMA OD DVE SLEBY VLEA OTI VOTPANE  
KOP E SUMA OD DVE VLEA OTI VOTPANE

$$X_i \sim \mathcal{N}(0, S+N)$$

ZA DVO UBE, I?  $X_i$   
E ISTO DISTRIBUCIJA NA  
ZARBA PROCES E STACIONAREN.

(b) SO OULED NA TOA ISTO PROCES E STACIONAREN  
STABILIZI KOP VLEA OST  
SLEBA E ETO NA SLE-  
DVA VLEA OTI TO VLEA.

$$\lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = E[X_i] = 0$$

$$\frac{1}{n} \log \frac{1}{p(x^n)} \xrightarrow[n \rightarrow \infty]{\text{STRONG LAW}} E \left[ \log \frac{1}{p(x^n)} \right] = h(x)$$

$$(c) \lim_{n \rightarrow \infty} \frac{h(x^n)}{n} = h(x) = \frac{1}{2} \log 2\pi e(S+N)$$

(d) MEAN SQUARE PREDICTOR

$$E[(X - \hat{X})^2] \geq \min_{\hat{X}} E(X - \hat{X})^2 = E(X - \bar{X})^2 = \text{var}(X)$$

$$h(x) \leq \frac{1}{2} \log(2\pi e \sigma^2)$$

$$\sigma^2 \geq \frac{2^{24(n)}}{27e} \quad \cdot \quad \boxed{E[(X-\bar{X})^2] \geq \frac{e^{24(n)}}{27e}}$$

$$E[(X-\bar{X}(X))^2] \geq \frac{e^{24(X|X)}}{27e} \quad \hookrightarrow \quad \hookrightarrow 27e(S+N)$$

$$E[(X-\bar{X}(X))^2] \xrightarrow{n \rightarrow \infty} \frac{e^{24(X|X)}}{27e} = \frac{e}{27e}$$

$$h(x_{min}|X^n) = h(x_{min}) = h(x_i) = \frac{1}{2} \ln 27e(S+N)$$

$$E[(X-\bar{X}(X))^2] = \frac{27e(S+N)}{27e} = S+N$$

$$(e) \quad f(x^n) = f(x_1) \cdot f(x_2) \cdot \dots \cdot f(x_n)$$

$$\frac{1}{n} \ln f(x^n) = \frac{1}{n} \sum_{i=1}^n \ln f(x_i) \xrightarrow{n \rightarrow \infty} E[\ln f(x_i)] = h(x)$$

$$h(x) = \frac{1}{2} \ln 27e(S+N) \quad (DA)$$

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$$(a) \quad \text{Yes!} \quad E[X_i] = E[V] + E[Z_i] = 0$$

$$E[X_i X_j] = E[(V+Z_i)(V+Z_j)] = \begin{cases} S & i=j \\ S+N & i \neq j \end{cases}$$

SINCE  $X_i$  IS GAUSSIAN DISTRIBUTED IT IS COMPLETELY CHARACTERIZED BY ITS FIRST AND SECOND MOMENTS. SINCE THE MOMENTS ARE STATIONARY  $X_i$  IS WIDE SENSE STATIONARY WHICH FOR GAUSSIAN DISTRIBUTION IMPLIES THAT  $X_i$  IS STATIONARY.

$$E[(V+Z_i)^2] = E[V^2 + \underline{2VZ_i} + Z_i^2] = \underbrace{E[V^2]}_S + \underbrace{2E[VZ_i]}_0 + \underbrace{E[Z_i^2]}_N$$

$$E[(V+Z_i)(V+Z_j)] = E[V^2 + VZ_j + VZ_i + Z_i Z_j] = E[V^2] + E[VZ_j] + E[VZ_i] + E[Z_i Z_j] = S + 0 + 0 + 0$$

$$(b) \quad \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n X_i = \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n (V+Z_i) = V + \lim_{n \rightarrow \infty} \frac{1}{n} \sum_{i=1}^n Z_i$$

$$= V + \underbrace{E[Z_i]}_0 = V$$

↑ STRONG LAW OF LARGE NUMBERS

THE LIMIT IS RANDOM - VARIANCE  $N(0, S)$



(c)  $x_1 \sim N(0, K_{x1})$  where  $K_{x1}$  has diagonal values  $SN$  and off diagonal values of  $S$ .

$$K = \begin{bmatrix} SN & S & S \\ S & SN & S \\ S & S & SN \end{bmatrix}$$

$$|K| = 3SN^2 + N^3 = \left(\frac{3S}{N} + 1\right) N^3$$

$$|K| = \left(\frac{4S}{N} + 1\right) \cdot N^4$$

$h=3$   $|K_3| = \left(\frac{3S}{N} + 1\right) N^3$

$h=k$   $|K_k| = \left(\frac{kS}{N} + 1\right) N^k$

$h=k+1$   $|K_{k+1}| = \left(\frac{(k+1)S}{N} + 1\right) N^{k+1}$

$$|K_{k+1}| = \begin{vmatrix} K_k & S \\ S & N+S \end{vmatrix} = |K_k| \cdot (N+S) + S^2 = \left(\frac{kS}{N} + 1\right) N^k (N+S) + S^2 =$$

$$= \left(\frac{kS}{N} \cdot N + N + \frac{kS^2}{N} + S\right) N^k = kS N^k + N^{k+1} + S N^k + S$$

$$h(x) = \lim_{n \rightarrow \infty} \frac{P(x_1^n)}{2^n} = \lim_{n \rightarrow \infty} \frac{1}{2^n} \ln(2\pi e)^n \cdot |K| =$$

$$= \lim_{n \rightarrow \infty} \frac{1}{2n} \ln \left[ (2\pi e)^n \cdot \left(\frac{4S}{N} + 1\right) \cdot N^n \right] =$$

$$= \lim_{n \rightarrow \infty} \frac{1}{2} \ln(2\pi e) + \frac{1}{2n} \lim_{n \rightarrow \infty} \ln \left(\frac{4S}{N} + 1\right) N^n =$$

$$= \frac{1}{2} \ln(2\pi e) + \frac{1}{2} \lim_{n \rightarrow \infty} \ln \left(\frac{4S}{N} + 1\right) N^n =$$

$$= \frac{1}{2} \ln(2\pi e) + \frac{1}{2} \lim_{n \rightarrow \infty} \ln \left(\frac{4S}{N} + 1\right) N^n =$$

$$= \frac{1}{2} \ln(2\pi e) + \frac{1}{2} \lim_{n \rightarrow \infty} \ln \left(\frac{4S}{N} + 1\right) N^n =$$

$$= \lim_{n \rightarrow \infty} \frac{1}{2n} \ln(2\pi e)^n + \lim_{n \rightarrow \infty} \frac{1}{2n} \ln \left(\frac{4S}{N} + 1\right) N^n$$

$$= \frac{1}{2} \ln(2\pi e)$$

$$\begin{aligned}
 (d) \quad E[(x_{n+1} - \hat{x}_{n+1}(x^n))^2] &= E_{x^n} \left\{ E[(x_{n+1} - \hat{x}_{n+1}(x^n))^2 | x^n] \right\} = \\
 &= E \left\{ E[x_{n+1}^2 - 2x_{n+1} \hat{x}_{n+1}(x^n) + \hat{x}_{n+1}^2(x^n)] \right\} \\
 \frac{\partial E[(x_{n+1} - \hat{x}_{n+1}(x^n))^2]}{\partial x_{n+1}} &= E[2x_{n+1} - 2\hat{x}_{n+1}(x^n)] = 0
 \end{aligned}$$

$$E[2x_{n+1}] - 2\hat{x}_{n+1} = 0$$

$$\boxed{\hat{x}_{n+1}(x^n) = E[x_{n+1}]} \quad \text{25}$$

$$f(V|x^n) = \frac{f(x^n, V)}{f(x^n)}$$

$$f(x^n, V) = \frac{1}{(2\pi)^{n+1} \cdot |K|} e^{-\frac{[x^n, V] \cdot K^{-1} \cdot [x^n, V]}{2}}$$

$n - n - 1 + 1$

$$f(x^n) = \frac{1}{(2\pi)^n \cdot |K_x|} e^{-\frac{[x^n] K^{-1} [x^n]}{2}}$$

$$f(V|x^n) \sim N\left(\frac{s}{s+N} \sum_{i=1}^n x_i, \frac{SN}{4s+N}\right)$$

$$\begin{aligned}
 \hat{x}_{n+1}(x^n) &= E[x_{n+1} | x^n] = E[V | x^n] + E[z_{n+1} | x^n] \\
 &= \frac{s}{s+N} \sum_{i=1}^n x_i + 0
 \end{aligned}$$

THEREFORE THE LIMITING SQUARE ERROR IS:

$$\begin{aligned}
 e^2 &= \lim_{n \rightarrow \infty} E[(\hat{x}_n - x_n)^2] = \lim_{n \rightarrow \infty} E\left[\left(\frac{s}{(n-1)s+N} \sum_{i=1}^{n-1} x_i - x_n\right)^2\right] \\
 &= \lim_{n \rightarrow \infty} E\left[\left(\frac{s}{(n-1)s+N} \sum_{i=1}^{n-1} (V + z_i) - z_n - V\right)^2\right] = 0
 \end{aligned}$$

$$\begin{aligned}
 \frac{s}{(n-1)s+N} \cdot (n-1)V - V &= \frac{s(n-1)V - (n-1)SV - NV}{(n-1)s+N} = \frac{s(n-1)V - (n-1)SV - NV}{(n-1)s+N} \\
 &= \frac{s(n-1)V - (n-1)SV - NV}{(n-1)s+N} = -\frac{NV}{(n-1)s+N}
 \end{aligned}$$

$$\begin{aligned}
 e^2 &= \lim_{n \rightarrow \infty} E\left[\left(\frac{s}{(n-1)s+N} \sum_{i=1}^{n-1} z_i - z_n - \frac{NV}{(n-1)s+N}\right)^2\right] = \\
 &= \lim_{n \rightarrow \infty} E\left[\left(\frac{s}{(n-1)s+N} \sum_{i=1}^{n-1} z_i - z_n\right)^2\right] - E[z_n^2] - \left(\frac{NV}{(n-1)s+N}\right)^2 E[V^2]
 \end{aligned}$$

$$= \lim_{n \rightarrow \infty} \left[ \left( \frac{s}{(n-1)s + N} \right)^2 (n-1)N + N + \left( \frac{n}{(n-1)s + N} \right)^2 s \right]$$

$$= N \quad \left[ e^2 = \lim_{n \rightarrow \infty} E[\hat{x}_n - x_n]^2 = N \right]$$

**PROBLEM 9.4** (CONTINUE FROM 16R)

$$M_x(s) = \frac{M_Y(-s)}{M_Z(-s)} \quad Y_X(x) = \mathcal{L}^{-1}[M_X(-s)]$$

$$M_Y(-s) = e^{s(s\sigma^2 - 2\mu)/2} \quad M_Z(-s) = \frac{\lambda}{s + \lambda}$$

$$M_X(-s) = \left(1 + \frac{s}{\lambda}\right) e^{s(s\sigma^2 - 2\mu)/2}$$

$$Y_X(x) = Y_Y(x) + \frac{1}{\lambda} \mathcal{L}^{-1} \left[ s e^{s(s\sigma^2 - 2\mu)/2} \right] + \frac{1}{\lambda} Y_Y(0)$$

$$\mathcal{L} \left[ \frac{df(t)}{dt} \right] = sF(s) - f(0) \quad sF(s) = \mathcal{L} \left[ \frac{df(t)}{dt} \right] + f(0)$$

$$\mathcal{L} \left[ \frac{1}{\lambda} \frac{df(t)}{dt} \right] = \frac{sF(s)}{\lambda} - \frac{f(0)}{\lambda} \quad \frac{sF(s)}{\lambda} = \frac{1}{\lambda} \mathcal{L} \left[ \frac{df(t)}{dt} \right] + \frac{f(0)}{\lambda}$$

$$Y_X(x) = -\frac{1}{\sqrt{2}} \frac{(x - \mu - \lambda\sigma^2) e^{-\frac{\lambda(x - \mu - \lambda\sigma^2)^2 - \mu^2}{2\sigma^2}}}{\sqrt{\pi} \lambda \sigma^3} + \frac{1}{\sigma \sqrt{2\pi} \lambda} e^{-\frac{\mu^2}{2\sigma^2}}$$

$$= -\frac{x e^{-\frac{(x - \mu)^2}{2\sigma^2}}}{\lambda \sigma^3 \sqrt{2\pi}} + \frac{(\mu + \lambda\sigma^2)}{\lambda \sigma^3 \sqrt{2\pi}} e^{-\frac{(x - \mu)^2}{2\sigma^2}} + \frac{e^{-\frac{\mu^2}{2\sigma^2}}}{\lambda \sigma \sqrt{2\pi}}$$

**PROBLEM 9.5** FADING CHANNEL (CONTINUE FROM 16R)

$$Z = XV + Z$$

KNOWLEDGE OF THE FADING FACTOR  $V$  IMPROVES CAPACITY

$$I(x; Z|N) \geq I(x; Y)$$

$$I(x; Z|N) = h(Y|N) - h(Z|XV) = h(Z|V) - h(Z) \leq h(Z) + h(Z)$$

$$I(x; Y) = h(Y) - h(XV + Z|X) = h(Y) - h(V + Z)$$

$$h(f(x)) \leq h(x) \Rightarrow h(V + Z) = h(f(V, Z)) \leq h(V, Z)$$

$$I(x; Z) = h(Y) - h(V + Z) \geq h(Y) - h(V, Z) = h(Z) -$$

$$\textcircled{2} - [h(Z) + h(V|Z)] = h(Z) - h(Z) - h(V)$$

INDEPENDENT

$$I(x; z|V) = I(x, V; z) - I(V; z)$$

$$I(x, V; z) = \underline{I(x; z)} + I(V; z|x) = I(V; z) + \underline{I(x; z|V)}$$

$$I(V; z|x) = h(y|x) - h(z|x, V) = h(z|x) - h(z)$$

$$h(z|x) = h(V+z) \leq h(V, z) = h(z) + h(z|V) = 2 \cdot h(z)$$

$$\boxed{I(V; z|x) \leq 2h(z) - h(z) = h(z)}$$

$$I(V; z) = h(y) - h(z|V) = h(z) - h(x+z)$$

$$I(V; z) = h(V) - h(V|z)$$

$$I(x; z) = I(V; z) - I(V; z|x) + I(x; z|V)$$

$$I(V; z) - I(V; z|x) = h(y) - h(z|V) - (h(z|x) - h(z|x, V))$$

$$= \underbrace{h(z) - h(z|x)}_{> 0} - \underbrace{(h(z|V) - h(z|x, V))}_{> 0}$$

$$= h(z) - h(x+z) - h(V+z) + h(z) = \textcircled{*}$$

$$= h(z) + h(z) - h(x+z) - h(V+z) \geq h(z) + h(z) - h(x, z) - h(V, z)$$

$$/ h(x+z) < h(x, z) / \geq h(z) + h(z) - h(x) - h(z|x) - h(V) - h(z|V)$$

$$= h(z) + h(z) - h(x) - h(z|x) - h(V) - h(z)$$

$$\boxed{h(z) \leq h(x, V, z) \leq h(x, V, z) = h(x, V) + h(z|x, V) = h(x) + h(V|x) + h(z) = h(x) + h(V) + h(z)}$$

$$\textcircled{*} \leq h(x) + h(V) + h(z) - h(x+z) - h(V+z) + h(z) =$$

$$= h(x) + h(V) + h(z) - h(z|V) - h(z|x) + h(z) \leq \text{KONDITIONIERUNG / ERDICHTUNG / ENTWICKELUNG}$$

$$\leq h(x) + h(V) + h(z) - \underbrace{h(z|V, x)}_{h(z)} - \underbrace{h(z|x, V)}_{h(z)} + h(z) = \textcircled{*}$$

$$= h(x) + h(V) + 2h(z) - 2h(z) = h(x) + h(V)$$

$$I(x; z) = I(V; z) - I(V; z|x) + I(x; z|V) \leq h(x) + h(V) + I(x; z|V)$$

$$\textcircled{*} \leq h(x) + h(V) + h(z) - \underbrace{h(z|V, x)}_{h(z)} - \underbrace{h(z|x, V)}_{h(z)} + h(z) = h(x) + h(z)$$

$$I(x; z|V) = h(z|V) - h(z|x, V) = h(z|V) - h(z)$$

$$I(x; z) = h(z) - h(z|x) \leq h(z) - h(z|x, V) = h(z) - h(z)$$

$$I(x, z|V) = H(z|V) - H(z|x, V) = H(z|V) - H(z)$$

$$I(x, z) = H(z) - H(z|x) \leq H(z) - H(z|x, V) = \underline{H(z) - H(z)}$$

$$z = a \cdot x \quad \gamma(\gamma) = \frac{\gamma(x)}{\frac{d\gamma(x)}{dx}} \Big|_{x=f(\gamma)} = \frac{\gamma(x)}{a} \Big|_{x=\frac{z}{a}}$$

$$H(z) = - \sum_{\gamma} \gamma(\gamma) \cdot \log \gamma(\gamma) = - \sum_{\gamma} \frac{\gamma(x)}{a} \log \frac{\gamma(x)}{a} =$$

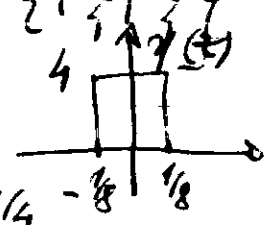
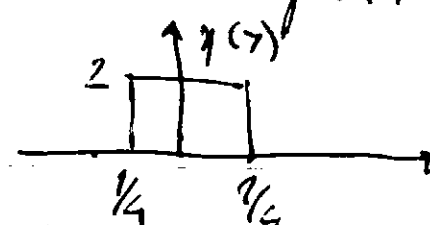
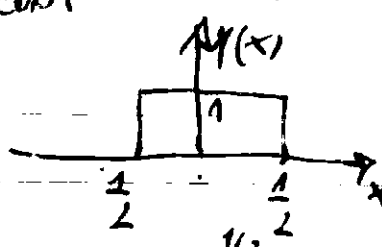
$$= -a^{-1} \sum_x \gamma(x) [\log \gamma(x) - \log a] = \frac{1}{a} \sum_x \gamma(x) \log \gamma(x) + \frac{\log a}{a}$$

NONA LEZIONE SU DISCRETE E CONTINUE

2. DISCRETE E CONTINUE MISCELE PER  $H(x) = H(y)$

ESEMPLO:  $x \in \{1, 2, 3\}$   
 $\gamma \in \{2, 4, 6\}$

$\gamma(\gamma) = \left\{ \frac{1}{2}, \frac{1}{4}, \frac{1}{4} \right\}$   
 $\gamma(z) = \left\{ \frac{1}{2}, \frac{1}{4}, \frac{1}{4} \right\}$

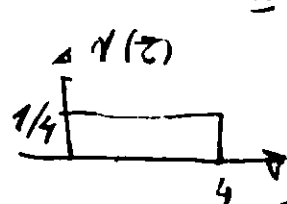
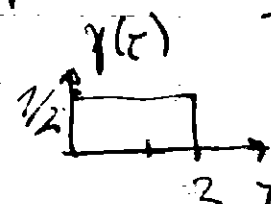
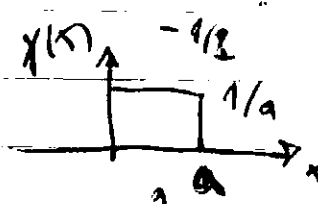


$$h(x) = \int p(x) \log p(x) dx = 0$$

$$h(\gamma) = - \int 2 \cdot \log 2 d\gamma$$

$$h(\gamma) = -2\gamma \Big|_{-1/4}^{1/4} = -2 \left( \frac{1}{4} + \frac{1}{4} \right) = -2 \cdot \frac{1}{2} = -1 \quad ?$$

$$h(z) = \int p(z) \log \frac{1}{p(z)} dz = \int_{-1/8}^{1/8} 4 \log \frac{1}{4} dz = 4 \cdot 2 \left( \frac{1}{8} + \frac{1}{8} \right) = -8 \cdot \frac{1}{4} = -2$$



$$h(x) = - \int p(x) \cdot \log p(x) dx = \int_0^1 \frac{1}{a} \log a dx = \frac{1}{a} \log a \cdot x \Big|_0^1 = \log a$$

$$h(\gamma) = \log a = 2 \log 2 = 1$$

$$h(z) = \log 4 = 2$$

$$z = 2 \cdot \gamma = b \cdot \gamma$$

$$\gamma(z) = \frac{\gamma(z)}{b} = \frac{1/2}{2} = \frac{1}{4}$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{x^2}{2\sigma^2}} \quad \gamma = 2x \quad f(\gamma) = \frac{f(x)}{\frac{d\gamma}{dx}} \Big|_{x=\frac{\gamma}{2}}$$

$$f(\gamma) = \frac{1}{2 \cdot \sigma\sqrt{2\pi}} e^{-\frac{\gamma^2}{2 \cdot 4\sigma^2}} = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{\gamma^2}{2\sigma^2}} \quad \sigma_\gamma = 2\sigma$$

$$h(x) = \frac{1}{2} \log(2\pi e) \sigma^2 \quad h(\gamma) = \frac{1}{2} \log(2\pi e) \sigma_\gamma^2$$

$$h(\gamma) = \frac{1}{2} \log(2\pi e) 4 \cdot \sigma^2 = \frac{1}{2} \log(2\pi e) \sigma_\gamma^2 + \frac{1}{2} \log(2\pi e) \cdot 4$$

$$h(\gamma) \geq h(x)$$

$$I(x; z|v) = h(z|v) - h(z|xv) = h(z|v) - h(z)$$

$$I(x; z) = h(z) - h(z|x) = h(z) - h(z|v)$$

$$I(x; z) - I(x; z|v) = \underbrace{h(z) - h(z|x)}_{> 0} - \underbrace{[h(z|v) - h(z|xv)]}_{> 0} = I(v; z) - I(v; z|x)$$

NONNEGATIVITY OF MUTUAL ENTROPY

$$h(z|v) = h(v \cdot x + z|v) \leq h(v, x, z)$$

$$I(v; z|x) = h(v|x) - h(v|x, z) = \dots$$

$$z = vx + z$$

$$z - z = vx$$

$vx \rightarrow$  *gleđna 40 kada edita momenta.*  
*DA SE ODREDE DA JE TOČNO!!!*  
 (9) CONDITIONING REDUCES ENTROPY

$$h(z|x) - h(z|v) \geq h(z) - h(z|v) \geq h(z|x) - h(z|v)$$

$$h(z) \leq h(z|v) = h(xv + z|v) \leq h(x, v, z) = h(x) + h(v) + h(z)$$

$$(6) h(f(x)) \leq h(x)$$

$$h(z) \leq h(x) + h(v) + h(z)$$

$$h(x) + h(v) \geq 0$$

SO OVA DOKAZUJE DA JE:  
 $I(x; z) - I(x; z|v) \leq 0$  i.e

$$I(x; z) \leq I(x; z|v)$$

OVA VEĆI DOKAZUJE DA JE:  
 $h(v) \leq 0$  (more precisely  $h(v) \geq 0$ )

$$I(x; z) - I(x; z|v) = h(z) - h(z|x) - h(z|v) + h(z|xv) = h(z) - h(z|x) - h(z|v) + h(z) \leq h(z) - h(z|x) - h(z|v) + h(z) \leq h(z) - h(z|v)$$

REVERSE:  $I(x; z|v) - I(x; z) = h(z|v) - h(z|xv) - h(z) + h(z|x) = h(z|x) - h(z) + h(z|v) - h(z) \leq h(z|x) - h(z)$

(?)  $h(z|v) - h(z) = h(xv + z|v) - h(z) \leq h(x, v, z|v) - h(z) \leq h(x, v, z) - h(z) \leq h(x) + h(v) + h(z) - h(z) \Rightarrow I(x; z|v) = I(x; z) + h(x) + h(v)$  PROVA 55

REVISITED (THIRD TIME) PROOF:  $\stackrel{H(x)}{=} \stackrel{H(z|x)}{=} \quad ?$

$$I(x; z|V) - I(x; z) = H(x|V) - H(z|V) - H(z|x) + H(z|xV) \leq$$

$$\leq H(z|V) - H(z) - H(z|x) + H(z|xV) = H(xV+z|V) - H(z)$$

$$\leq H(x, V, z|V) - H(z) = H(x) + H(z) - H(z) = H(x)$$

$$H(xV+z|V) = H(x|V) + H(V|xV) + H(z|xV) = H(x|V) + H(z|xV)$$

$$H(x_1, x_2, x_3) = \sum_{i=1}^3 H(x_i | x_{i-1}) = H(x_1) + H(x_2 | x_1) + H(x_3 | x_1, x_2)$$

$$I(x; z|V) - I(x; z) = H(z|V) - H(z|xV) - H(z) + H(z|x)$$

$$= H(z|V) - H(z) + H(z|x) - H(z|xV) = \underbrace{H(z|x) - H(z|xV)}_{\geq 0} - \underbrace{(H(z) - H(z|V))}_{\geq 0}$$

So we have  $I(x; z|V) \geq I(x; z)$

$$H(z|x) - H(z|xV) \geq H(z) - H(z|V) \geq H(z|x) - H(z|V)$$

$$H(z) \leq H(z|V) = H(xV+z|V) \leq H(xVz|V) =$$

$$H(x|V) + H(V|xV) + H(z|xV) = H(x) + 0 + H(z)$$

$$H(z) \leq H(x) + H(z) \quad \checkmark \quad \boxed{H(x) \geq 0} \quad \underline{\text{TRUE!!}}$$

HENCE:  $I(x; z|V) - I(x; z) \geq 0 \quad I(x; z|V) \geq I(x; z)$

PERKINS SOLUTIONS (soln 5.229A & 207.100)

$$I(x; VZ) = I(x; V) + I(x; Z|V) = I(x; Z|V)$$

$$I(x; V) = H(V) - H(V|x) = H(V) - H(V) = 0$$

$$I(x; VZ) = I(x; Z) + I(x; V|Z) \geq I(x; Z)$$

$$I(x; Z|V) = I(x; Z) + I(x; V|Z) \geq I(x; Z)$$

$$\boxed{I(x; Z|V) \geq I(x; Z)}$$

**Problem 9.6** PARALLEL CHANNELS AND WATER-FILLING.  
CONSIDER A PAIR OF PARALLEL GAUSSIAN CHANNELS:

$$\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} = \begin{bmatrix} x_1 \\ x_2 \end{bmatrix} + \begin{bmatrix} z_1 \\ z_2 \end{bmatrix}$$

WHERE:  $\begin{bmatrix} z_1 \\ z_2 \end{bmatrix} \sim N(0, \begin{bmatrix} \sigma_1^2 & 0 \\ 0 & \sigma_2^2 \end{bmatrix})$

AND THERE IS A POWER CONSTRAINT  $E[x_1^2 + x_2^2] \leq 2P$

ASSUME THAT  $\sigma_1^2 > \sigma_2^2$ . AT WHAT POWER DOES THE CHANNEL STOP BEHAVING LIKE A SINGLE CHANNEL WITH NOISE VARIANCE  $\sigma_2^2$  AND BEGIN BEHAVING LIKE A PAIR OF CHANNELS?

(1)  $I(x_1^n, z_1^n) = h(x_1^n) - h(z_1^n | x_1^n) = h(z_1^n) - h(z_1^n)$   
 $= h(z_1^n) - \sum_{i=1}^n h(z_i) \leq \sum_i h(z_i) - h(z_i) \leq P_i$   
 $\leq \sum_i \frac{1}{2} \log\left(\frac{\sigma_{z_i}^2 + \sigma_{x_i}^2}{\sigma_{z_i}^2}\right) = \sum_i \frac{1}{2} \log\left(1 + \frac{P_i}{N_i}\right)$

$P_i = E[x_i^2]$        $\sum P_i = P$

$z_1^n \sim N\left(0, \begin{bmatrix} P_1 & 0 & \dots & 0 \\ 0 & P_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & P_n \end{bmatrix}\right)$

$J(P_i) = \sum_i \frac{1}{2} \ln\left(1 + \frac{P_i}{N_i}\right) + \lambda \sum_i P_i$

$\frac{dJ(P_i)}{dP_i} = 0 \implies \frac{1}{2} \frac{1}{1 + \frac{P_i}{N_i}} \cdot \left(\frac{1}{N_i}\right) + \lambda = 0$

$\frac{1}{2} \frac{1}{N_i + P_i} + \lambda = 0 \implies -\lambda = \frac{1}{2(N_i + P_i)} \implies N_i + P_i = -\frac{1}{2\lambda}$

$P_i = -\frac{1}{2\lambda} - N_i = V - N_i$

$P_i = (V - N_i)^+$

$\sum_i (V - N_i)^+ = n \cdot P$

$(x)^+ = \begin{cases} x & x \geq 0 \\ 0 & x < 0 \end{cases}$

$(V - \sigma_1^2)^+ + (V - \sigma_2^2)^+ = 2P$

$2V - (\sigma_1^2 + \sigma_2^2) = 2P$

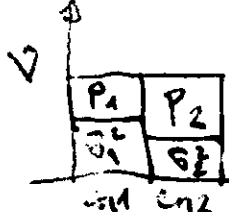
$\sigma_1^2 > \sigma_2^2$

$2(V - P) = \sigma_1^2 + \sigma_2^2$

$2V = 2P + \sigma_1^2 + \sigma_2^2$

$V = \frac{2P + \sigma_1^2 + \sigma_2^2}{2}$

$(V - \sigma_1^2)^+ = 0$



$\sigma_1^2 > V \implies V = 2P + \sigma_2^2$

SINGLE CHANNEL WITH NOISE  $\sigma_2^2$  AND POWER  $2P$  ST

WITH NOISE VARIANCE  $\sigma_2^2$  AND POWER  $2P$  ST



$$(Y - \sigma_1^2)^+ + (Y - \sigma_2^2)^+ = 2P \quad \left. \begin{array}{l} (Y - \sigma_1^2)^+ = Y - \sigma_1^2 \\ \text{IF } Y \geq \sigma_2^2 \end{array} \right\}$$

$$\text{IF } \sigma_1^2 \leq Y \text{ AND } \sigma_2^2 \leq Y \Rightarrow 2Y = 2P + \sigma_1^2 + \sigma_2^2$$

$$Y = \frac{2P + \sigma_1^2 + \sigma_2^2}{2}$$

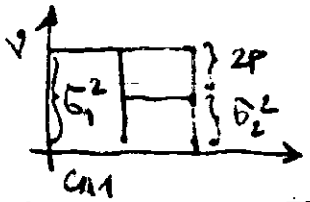
USUALLY MOST POWER:  $\sigma_1^2 \leq Y$  TOGETHER:  $(Y - \sigma_2^2)^+ = 2P - Y + \sigma_2^2$

- OP  $\star$  BE CLONED POWER  $\rightarrow 2P = \sigma_1^2 - \sigma_2^2$  } OUT MEAN TOTAL ACC OR PROBABLY SOLVABLE.

NA ORA SAKA & GRAMICATA!!!

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WE WILL PUT ALL THE POWER INTO CHANNEL WITH LESS NOISE UNTIL THE TOTAL POWER OF NOISE + SIGNAL IN THE CHANNEL EQUALS THE NOISE POWER IN OTHER CHANNEL. AFTER THAT WE WILL SPLIT THE ADDITIONAL POWER EQUALLY BETWEEN THE TWO CHANNELS.



SO THE ORDERED CHANNELS BEGINS TO RECEIVE HERE A PAIR OF PARALLEL CHANNELS WHEN SIGNAL POWER:  $2P = \sigma_1^2 - \sigma_2^2$

**Problem 9.13 Feedback Capacity (CONTINUE FROM 9.12)**

$$(Z_1, Z_2) \sim N(0, K) \quad K = \begin{bmatrix} 1 & \rho \\ \rho & 1 \end{bmatrix}$$

$$\max_{\text{tr}(Kx) \leq 2P} \frac{1}{2} \log \frac{|K + xI|}{|K|} = C_{\text{MFB}}$$

$$C_{\text{MFB}} = \max_{\text{tr}(Kx) \leq 2P} \frac{1}{2} \log \frac{|K + xI|}{|K|} = \frac{1}{2n} \sum_{\lambda=1}^n \left( 1 + \frac{(x - \lambda_i^{(K)})^+}{\lambda_i^{(K)}} \right)$$

$$K = V \Lambda V^T \quad \Lambda = \begin{bmatrix} 1+\rho & 0 \\ 0 & 1-\rho \end{bmatrix} \quad \begin{array}{l} \lambda_1 = 1+\rho \\ \lambda_2 = 1-\rho \end{array}$$

**WITHOUT FEEDBACK**

$$(\lambda - \lambda_1)^+ = P_1 \quad (\lambda - \lambda_2)^+ = P_2$$

$$P_1 - \lambda_1 = P_2 - \lambda_2$$

$$2P - \lambda_2 - \lambda_1 = \lambda_2 - \lambda_2$$

$$2P - 2\lambda_2 - \lambda_1 + \lambda_2 = 0$$

$$P_1 = 2P - \lambda_2 = 2P - \frac{2P - \lambda_1 + \lambda_2}{2} = \frac{4P - 2P + \lambda_1 - \lambda_2}{2}$$

$$P_1 = \frac{2P + \lambda_1 - \lambda_2}{2}$$

$$P_2 = \frac{2P - \lambda_1 + \lambda_2}{2} = \frac{2P - 2P + \lambda_1 - \lambda_2}{2} = \frac{\lambda_1 - \lambda_2}{2} = P - \rho$$

$$P_1 + P_2 = P + P - P = 2P$$

$$P_1 = P + P \quad P_2 = P - P$$

$$C_2 = \frac{1}{4} \left\{ \ln \left( 1 + \frac{P_1}{\lambda_1} \right) + \ln \left( 1 + \frac{P_2}{\lambda_2} \right) \right\} = \frac{1}{4} \ln \left( 1 + \frac{P + P}{P + P} \right) + \frac{1}{4} \ln \left( 1 + \frac{P - P}{P - P} \right)$$

$$= \frac{1}{4} \ln \left( 1 + \frac{P - P}{P - P} \right) = \frac{1}{4} \ln \left( 1 + \frac{P - P}{P - P} \right) \left( 1 + \frac{P + P}{P + P} \right) =$$

$$= \frac{1}{4} \ln \frac{(1 + P - P)(1 + P + P)}{1 - P^2} = \frac{1}{4} \ln \frac{(1 + P)^2 - (P - P)^2}{1 - P^2}$$

$$C_2 = \frac{1}{4} \ln \frac{1 + 2P + P^2 - 0}{1 - P^2}$$

$$\begin{array}{r} 52550 \\ 44000 \\ \hline 8550 \end{array}$$

**WITH FEEDBACK**

$$C_{1,FB} = \max_{\text{tr}(K_1) \leq 2P} \frac{1}{2} \ln \frac{|K_1 + z|}{|K_2|} \leq \max_{\text{tr}(K_1) \leq 2P} \frac{1}{2} \ln \frac{|K_1 + K_2|}{|K_2|} + \frac{1}{2} \ln \frac{|K_2|}{|K_2|}$$

$$\leq \frac{1}{2} \ln \frac{|K_1 + z|}{|K_2|} = \frac{1}{2} \ln \frac{|K_1|}{|K_2|} + \frac{1}{2} \ln \frac{|K_1 + z|}{|K_1|}$$

$$C_{2,FB} \leq \frac{1}{4} \ln \frac{|K_1|}{(1 - P^2)} + \frac{1}{2} = \frac{1}{4} \ln \frac{1}{(1 - P^2)} + \frac{1}{2}$$

we need:  $|K_1| = P_1^2 + P_2^2 = (P + P)^2 + (P - P)^2 =$   
 $= P + 2P + P + P^2 + P^2 - 2P + P^2 = 2P^2 + 2P^2$

$$C_{2,FB} = \frac{1}{4} \ln \frac{2P^2 + 2P^2}{(1 - P^2)} + \frac{1}{2}$$

$$C_{2,FB} - C_2 = \frac{1}{4} \ln \frac{2P^2 + 2P^2}{1 + 2P + P^2 - 4P^2} + \frac{1}{2} > 0 \Rightarrow$$

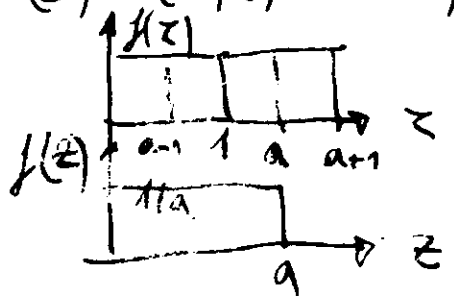
$$C_{2,FB} \geq C_2$$

**Problem 9.15 (CONTINUE FROM N164) / DISCRETE INPUT**

continuous output  $R_X(x=1) = \gamma$  ;  $R_X(x=0) = 1 - P$  ;  $z = z + z \quad z \sim U[0, a]$

(a)  $I(x; z) = h(x) - h(x|z) = h(\gamma) - h(z - z|z) = h(\gamma) - \ln a$

(b)  $F(x; z) = h(z) - h(z|x) = h(z) - h(z) = h(z) - \ln a$



$$\gamma(0 \leq z \leq 1) = \gamma(x=0) \cdot \gamma(z \leq 1) = \frac{\gamma}{a}$$

$$\gamma(1 \leq z \leq a) = \gamma(x=1) \cdot \gamma(0 \leq z \leq a-1) + \gamma(x=0) \cdot \gamma(1 \leq z \leq a) = (\gamma + \gamma) \cdot \frac{a-1}{a}$$

$$\int_0^{a-1} \frac{1}{a} dz = \frac{1}{a} z \Big|_0^{a-1} = \frac{a-1}{a} \quad \int_1^a \frac{1}{a} dz = \frac{1}{a} (a-1)$$

$$P(a \leq T \leq a+1) = P(T=1) \cdot P(Z \geq a-1) = P_1 \cdot \int_a^{a+1} \frac{1}{z} dz = P_1 \cdot \frac{a+1}{a} = P_1 \cdot \frac{a+1}{a}$$

$$f(z) = \begin{cases} \frac{P_0}{a} & 0 \leq z < a-1 \\ \frac{a-1}{a} & a-1 \leq z < a \\ \frac{P_1}{a} & a \leq z < a+1 \end{cases}$$

$$P(Z=1) = 1 - \frac{P_0}{a} - \frac{P_1}{a} = 1 - \frac{1}{a} = \frac{a-1}{a}$$

$$G(z) = \int_0^z \frac{P_0}{a} dt + \int_{a-1}^z \frac{a-1}{a} dt + \int_a^z \frac{P_1}{a} dt$$

$$= \frac{P_0}{a} (z - 0) + \frac{a-1}{a} (z - (a-1)) + \frac{P_1}{a} (z - a)$$

$$= \frac{1}{a} (P_0 z + (a-1)z - (a-1)^2) + \frac{P_1}{a} (z - a)$$

$$= \frac{P_0 z}{a} + \frac{1}{a} z + \frac{(a-1)^2}{a} - \frac{P_1 z}{a}$$

$$G(z) = \frac{P_0 z}{a} + \frac{1}{a} z + \frac{(a-1)^2}{a} - \frac{P_1 z}{a}$$

$I(x; z) = G(z) - G(x)$

$$I(x; z) = \frac{P_0 z}{a} + \frac{1}{a} z + \frac{a^2 - 2a + 1}{a} (z - x) - \frac{P_1 z}{a}$$

$$= \frac{P_0 z}{a} + \frac{1}{a} z + z - \frac{2z}{a} + \frac{1}{a} z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + \frac{2}{a} z - \frac{2z}{a} + \frac{(a-1)^2}{a} (z - x) + z = \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$= \frac{P_0 z}{a} + z + \frac{(a-1)^2}{a} (z - x)$$

$$H(a) = \frac{1}{a} \ln a + \left(1 - \frac{1}{a}\right) \ln \frac{1}{1 - \frac{1}{a}} - (a-1) \ln \frac{1}{1 - \frac{1}{a}} + \left(1 - \frac{1}{a}\right) \ln \frac{1}{1 - \frac{1}{a}}$$

$$\ln \frac{1}{a} - \frac{1}{a} \ln \frac{1}{a} = (1-a) \ln \frac{1}{1 - \frac{1}{a}} = 1 + \frac{1}{a} \ln \frac{1}{1 - \frac{1}{a}}$$

$$= \ln \frac{1}{a} + \frac{1}{a} \left( \ln \frac{a}{a-1} \right) - (a-1) \ln \frac{a}{a-1}$$

$$\begin{aligned}
 \boxed{y = \frac{1}{a}} \quad I(x; \gamma) &= + \pi(y_0) \cdot \gamma + \ln \gamma - \int \ln \gamma + \left(\frac{1}{\gamma} - 2 + \gamma\right) \ln \frac{1}{1-\gamma} \\
 &= + \pi(y_0) \cdot \gamma + \ln \gamma + \gamma \ln \frac{1}{\gamma} + \left(\frac{1}{\gamma} - 1\right) \ln \frac{1}{1-\gamma} - (1-\gamma) \ln \frac{1}{1-\gamma} \\
 &= + \pi(y_0) \cdot \gamma - \ln \left(\frac{1}{\gamma}\right) + \gamma \ln \frac{1}{\gamma} + \frac{1-\gamma}{\gamma} \ln \frac{1}{(1-\gamma)} - (1-\gamma) \ln \frac{1}{1-\gamma} = \\
 &= + \pi(y_0) \cdot \gamma - (1-\gamma) \ln \frac{1}{\gamma} + (1-\gamma) \left(\ln \frac{1}{1-\gamma}\right) \left(\frac{1}{\gamma} - 1\right) = \\
 &= + \pi(y_0) \cdot \gamma + \underbrace{(1-\gamma) \left[ \ln \left(\frac{1}{\gamma}\right) - \left(\frac{1}{\gamma} - 1\right) \ln \frac{1}{1-\gamma} \right]}_{\pi\left(\frac{1}{a}\right)} = \\
 &= \pi(y_0) \cdot \gamma + \left(\frac{1-\gamma}{1}\right) \left[ \pi\left(\frac{1}{\gamma}\right) + (1-\gamma) \ln \frac{1}{1-\gamma} \right] - 2 \left(\frac{1-\gamma}{\gamma}\right) \gamma \ln \frac{1}{\gamma} \\
 &= \frac{\pi(y_0)}{a} + \left(\frac{1}{1} - 1\right) \cdot \pi\left(\frac{1}{a}\right) - 2 \left(\frac{1-1}{1}\right) \ln \frac{1}{1}
 \end{aligned}$$

$$\boxed{I(x; \gamma) = \frac{\pi(y_0)}{a} + (a-1) \pi\left(\frac{1}{a}\right) - 2\left(1 - \frac{1}{a}\right) \ln a}$$

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(c)  $\left(\frac{y_0}{a} = \frac{a-1}{a} \cdot (a-1) = \frac{y_1}{a} = \frac{1}{3}\right)$   $a^2 - 2a + 1 = 0$   $a^2 - 2a + 1 = \left(\frac{1}{3}\right)$

$$a^2 - 2a + 1 = \frac{1}{3} \quad a^2 - 2a + 1 = 0 \Rightarrow a = \frac{7}{6} + \frac{\sqrt{13}}{6}$$

$C = \log_2(3) - \ln a = 0.7632$   $y_0 = (a-1)^2 = 0.5892$

$y_1 = 1 - y_0 = 1 - (a-1)^2 = 0.4108$

$h(\gamma) = \frac{\pi(y_0)}{a} + \frac{1}{\gamma} \ln a + \frac{(a-1)^2}{\gamma} \ln \frac{1}{a-1}$

GI EDNACIJS TOVAŠKITE; ZA DA  $h(\gamma) = \left\{ \frac{1}{3}, \frac{1}{3}, \frac{1}{3} \right\}$   
 TOČNI POSIATIVI  
 DA  $\Rightarrow$  DAKA MOJA  $y_0 = y_1$  NO NE  
 VEZUVA TAKA

~~.....~~  
 $a^2 - 2a + \frac{1}{2} = 0 \Rightarrow a = 1 + \frac{\sqrt{2}}{2} \quad a \approx 1.7071$

za vrniti  $y_0 = \left(1 + \frac{\sqrt{2}}{2} - 1\right)^2 = \frac{1}{2}$

$y_1 = 1 - y_0 = \frac{1}{2}$   $\Rightarrow$  Maximiziraj kapacitet le  
 pozitivna za optimizirati kapaciteta  
 na vrniti simetri.

$C = I(x; \gamma) \Big|_{\gamma = \frac{1}{2}} = \frac{1}{a} + (a-1) \pi\left(\frac{1}{a}\right) - 2\left(1 - \frac{1}{a}\right) \ln a = 0.6386$

$$\int_0^1 \frac{1}{a} + (a-1) + 2(1-\frac{1}{a}) dy = \frac{1}{a} + (a-1) - 2 \frac{a-1}{a} = \frac{1}{a} + \frac{(a-1)^2}{a} = 0.8787$$

$$\int_0^1 \gamma(\tau) dy = \frac{1}{a} \cdot 1 + \frac{a-1}{a} (a-1) + \frac{1}{a} = \frac{1}{a} + \frac{(a-1)^2}{a} = 0.8787$$

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**CONCORDIA SOLUTION**

(a)  $f(\tau | x=0) = \begin{cases} \frac{1}{a} & 0 \leq \tau \leq a \\ 0 & \text{otherwise} \end{cases}$

$f(\tau | x=1) = \begin{cases} (1-\tau) \frac{1}{a} & 0 \leq \tau \leq 1 \\ \frac{1}{a} & 1 \leq \tau \leq a \\ \frac{1}{a} \tau & a \leq \tau \leq a+1 \end{cases}$

$f(\tau) = \begin{cases} (1-\tau) \frac{1}{a} & 0 \leq \tau \leq 1 \\ \frac{1}{a} & 1 \leq \tau \leq a \\ \frac{1}{a} \tau & a \leq \tau \leq a+1 \end{cases}$

(b)  $H(x) = H(y)$   $P(x=1 | \tau=y)$  is NONZERO ONLY FOR  $1 \leq \tau \leq a$ , AND AT THESE VALUES, CONDITIONED ON  $\tau$ , THE PROBABILITY THAT  $x=1$  IS:

$$P(x=1 | \tau=y) = \frac{P(x=1) f(\tau | x=1)}{P(x=1) f(\tau | x=1) + P(x=0) f(\tau | x=0)} = y$$

**BAYES' THEOREM**

$$P(W|L) = \frac{P(L|W)P(W)}{P(L)}$$

$$P(W,L) = P(W,L)$$

$$P(L) \cdot P(W|L) = P(L|W) \cdot P(W)$$

$$P(W|L) = \frac{P(L|W)P(W)}{P(L)}$$

$$P(x=1, \tau) = P(x=1, Y)$$

$$P(x=1 | \tau) \cdot \gamma(\tau) = P(x=1) \cdot P(\tau | x=1)$$

$$P(x=1 | \tau) = \frac{P(x=1) P(\tau | x=1)}{\gamma(\tau)} = \frac{P(x=1) P(\tau | x=1)}{P(x=0) \cdot P(\tau | x=0) + P(x=1) P(\tau | x=1)}$$

$$P(x=1 | \tau) = \frac{P \cdot \frac{1}{a}}{(1-\tau) \frac{1}{a} + P \frac{1}{a}} = \frac{P \cdot \frac{1}{a}}{\frac{1}{a}} = P$$