

Lectures

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Claude Shannon

- C. E. Shannon, "A mathematical theory of communication," Bell System Technical Journal, 1948.
- Two fundamental questions in communication theory:
- Ultimate limit on data compression
 - entropy
- Ultimate transmission rate of communication
 - channel capacity
- Almost all important topics in information theory were initiated by Shannon

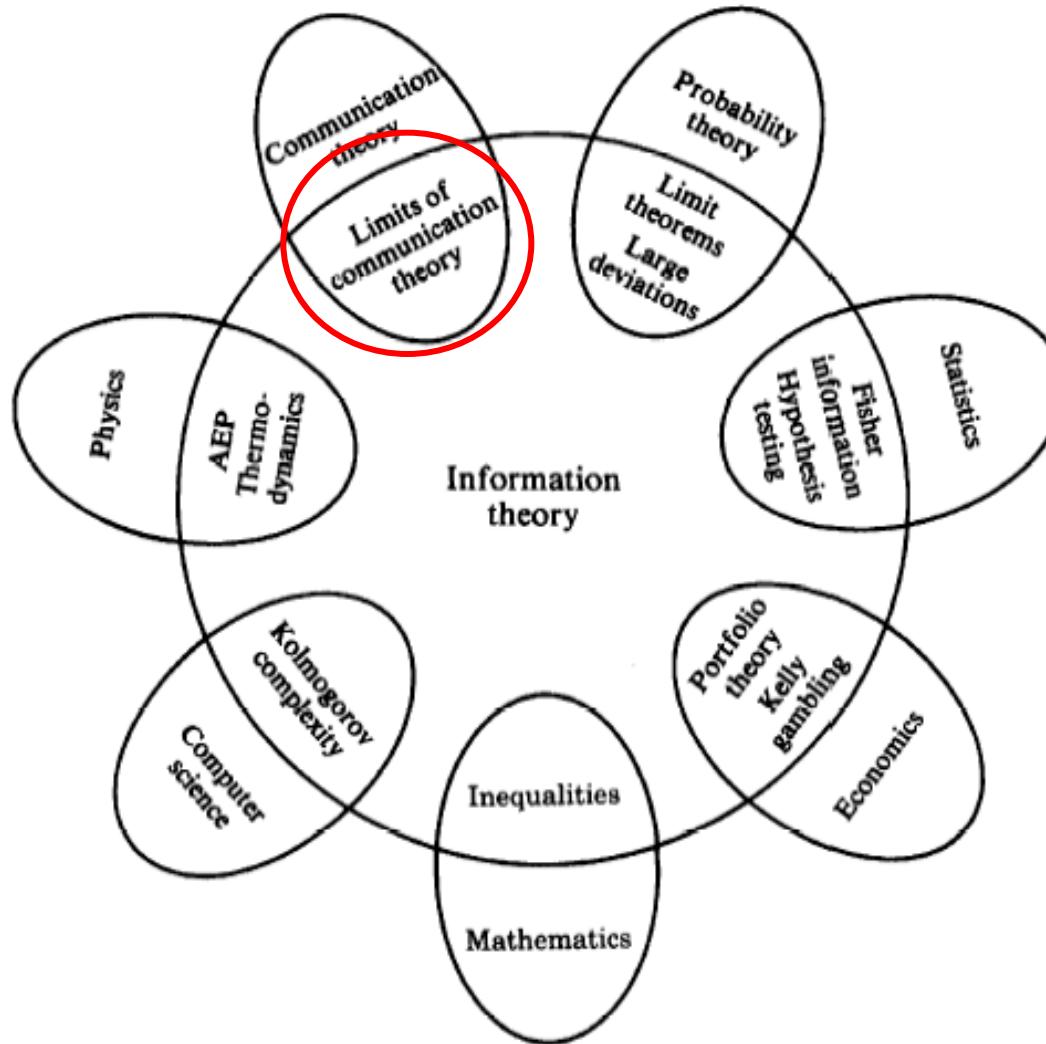


1916 - 2001

Origin of Information Theory

- Common wisdom in 1940s:
 - It is impossible to send information error-free at a positive rate
 - Error control by using retransmission: rate $\rightarrow 0$ if error-free
- Still in use today
 - ARQ (automatic repeat request) in TCP/IP computer networking
- Shannon showed reliable communication is possible for all rates below channel capacity
- As long as source entropy is less than channel capacity, asymptotically error-free communication can be achieved
- And anything can be represented in bits
 - Rise of digital information technology

Relationship to Other Fields



Course Objectives

- In this course we will (focus on communication theory):
 - Define what we mean by information.
 - Show how we can compress the information in a source to its theoretically minimum value and show the tradeoff between data compression and distortion.
 - Prove the channel coding theorem and derive the information capacity of different channels.
 - Generalize from point-to-point to network information theory.

Relevance to Practice

- Information theory suggests means of achieving ultimate limits of communication
 - Unfortunately, these theoretically optimum schemes are computationally impractical
 - So some say “little info, much theory” (wrong)
- Today, information theory offers useful guidelines to design of communication systems
 - Polar code (achieves channel capacity)
 - CDMA (has a higher capacity than FDMA/TDMA)
 - Channel-coding approach to source coding (duality)
 - Network coding (goes beyond routing)

Books/Reading

Book of the course:

- *Elements of Information Theory* by T M Cover & J A Thomas, Wiley, £39 for 2nd ed. 2006, or £14 for 1st ed. 1991 (Amazon)

Free references

- *Information Theory and Network Coding* by R. W. Yeung, Springer
<http://iest2.ie.cuhk.edu.hk/~whyeung/book2/>
- *Information Theory, Inference, and Learning Algorithms* by D MacKay, Cambridge University Press
<http://www.inference.phy.cam.ac.uk/mackay/itila/>
- *Lecture Notes on Network Information Theory* by A. E. Gamal and Y.-H. Kim, (Book is published by Cambridge University Press)
<http://arxiv.org/abs/1001.3404>
- C. E. Shannon, "A mathematical theory of communication," *Bell System Technical Journal*, Vol. 27, pp. 379–423, 623–656, July, October, 1948.

Other Information

- Course webpage:
<http://www.commsp.ee.ic.ac.uk/~ cling>
- Assessment: Exam only – no coursework.
- Students are encouraged to do the problems in problem sheets.
- Background knowledge
 - Mathematics
 - Elementary probability
- Needs intellectual maturity
 - Doing problems is not enough; spend some time thinking

Notation

- Vectors and matrices
 - \mathbf{v} =vector, \mathbf{V} =matrix
- Scalar random variables
 - $x = R.V$, x = specific value, X = alphabet
- Random column vector of length N
 - $\mathbf{x} = R.V$, \mathbf{x} = specific value, X^N = alphabet
 - x_i and x_i are particular vector elements
- Ranges
 - $a:b$ denotes the range $a, a+1, \dots, b$
- Cardinality
 - $|X|$ = the number of elements in set X

Discrete Random Variables

- A random variable x takes a value x from the alphabet X with probability $p_x(x)$. The vector of probabilities is \mathbf{p}_x .

Examples:



$$X = [1; 2; 3; 4; 5; 6], \mathbf{p}_x = [\frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}]$$

\mathbf{p}_x is a “probability mass vector”

“english text”

$$X = [a; b; \dots, y; z; \text{<space>}]$$

$$\mathbf{p}_x = [0.058; 0.013; \dots; 0.016; 0.0007; 0.193]$$

Note: we normally drop the subscript from p_x if unambiguous

Expected Values

- If $g(x)$ is a function defined on X then

$$E_x g(X) = \sum_{x \in X} p(x)g(x) \quad \text{often write } E \text{ for } E_X$$

Examples:



$$X = [1; 2; 3; 4; 5; 6], \mathbf{p}_X = [\frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}; \frac{1}{6}]$$

$$E X = 3.5 = \mu \quad \sigma^2 = E(X^2) - (E(X))^2 = 15.17 - 12.25 = 2.92$$

$$E X^2 = 15.17 = \sigma^2 + \mu^2$$

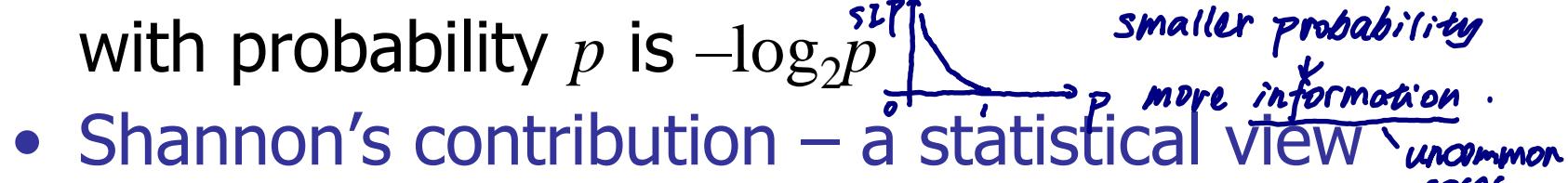
$$E \sin(0.1X) = 0.338$$

$$E - \log_2(p(X)) = 2.58 \quad \text{This is the "entropy" of } X$$

Shannon Information Content

SIP: the amount of info. associated with an event with probability P .

- The Shannon Information Content of an outcome with probability p is $-\log_2 p$
- Shannon's contribution – a statistical view
 - Messages, noisy channels are random
 - Pre-Shannon era: deterministic approach (Fourier...)
- Example 1: Coin tossing
 - $X = [\text{Head}; \text{Tail}], p = [1/2; 1/2], \text{SIC} = [1; 1] \text{ bits}$
- Example 2: Is it my birthday ?
 - $X = [\text{No}; \text{Yes}], p = [364/365; 1/365], \text{SIC} = [0.004; 8.512] \text{ bits}$

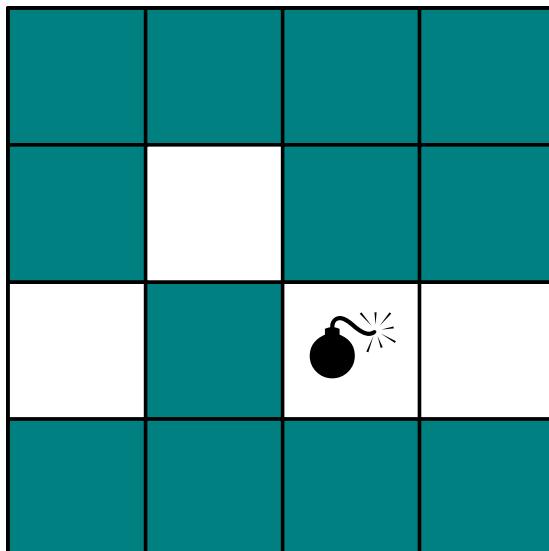


Unlikely outcomes give more information

Minesweeper

- Where is the bomb ?
- 16 possibilities – needs 4 bits to specify

$$4 \geq \log_2 16$$



Guess	Prob	SIC
1. No	$15/16$	0.093 bits
2. No	$14/15$	0.100 bits
3. No	$13/14$	0.107 bits
4. Yes	$1/13$	3.700 bits
Total		4.000 bits

$SIC = -\log_2 p$

$$H'(X) = \log_2 |X| \geq H(X)$$

\therefore apply at uniform distribution.

Entropy

entropy

- a measurement of uncertainty 16
- bits numbers required to describe a r.v..
- expectation of information

$$H(X) = E - \log_2(p_x(x)) = - \sum_{x \in X} p_x(x) \log_2 p_x(x)$$

"transmission cost or verification"

- $H(x)$ = the average Shannon Information Content of x
- $H(x)$ = the average information gained by knowing its value
- the average number of "yes-no" questions needed to find x is in the range $[H(x), H(x)+1]$
- $H(x)$ = the amount of uncertainty before we know its value

We use $\log(x) \equiv \log_2(x)$ and measure $H(x)$ in bits

- if you use \log_e it is measured in nats
- 1 nat = $\log_2(e)$ bits = 1.44 bits

- $\log_2(x) = \frac{\ln(x)}{\ln(2)}$

$$\frac{d \log_2 x}{dx} = \frac{\log_2 e}{x}$$

$H(X)$ depends only on the probability vector p_x not on the alphabet X , so we can write $H(p_x)$

$$H(x) = -(1-p)\log(1-p) - p\log p$$

$$H'(x) = \log(1-p) + 1 - \log p - 1 = \log(1-p) - \log p$$

$$H'(x) = 0 \Rightarrow p = \frac{1}{2}$$

$$H(x) = -\frac{1}{2}\log\frac{1}{2} - \frac{1}{2}\log\frac{1}{2} = 1$$

Entropy Examples

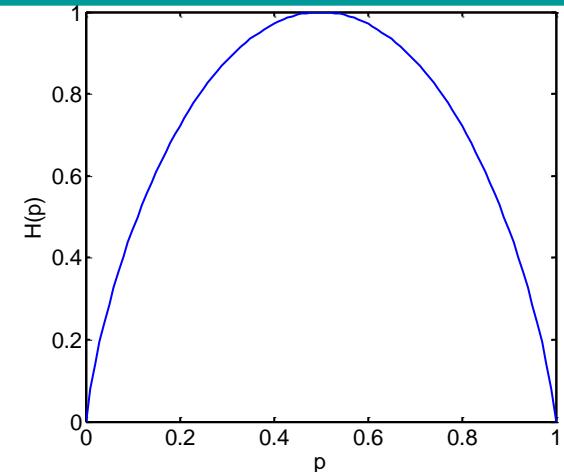
(1) Bernoulli Random Variable

$$X = [0;1], \mathbf{p}_x = [1-p; p]$$

$$H(x) = -(1-p)\log(1-p) - p\log p$$

Very common – we write $H(p)$ to mean $H([1-p; p]).$

Maximum is when $p=1/2$



$$H(p) = -(1-p)\log(1-p) - p\log p$$

$$H'(p) = \log(1-p) - \log p$$

$$H''(p) = -p^{-1}(1-p)^{-1}\log e$$

(2) Four Coloured Shapes

$$X = [\text{Red circle}; \text{Green square}; \text{Blue diamond}; \text{Black asterisk}], \mathbf{p}_x = [\frac{1}{2}; \frac{1}{4}; \frac{1}{8}; \frac{1}{8}]$$

$$\begin{aligned} H(x) &= H(\mathbf{p}_x) = \sum -\log(p(x))p(x) \\ &= 1 \times \frac{1}{2} + 2 \times \frac{1}{4} + 3 \times \frac{1}{8} + 3 \times \frac{1}{8} = 1.75 \text{ bits} \end{aligned}$$

entropy {
 monotonic non-decreasing
 additive
 non-negative
 $\Rightarrow H(X) := -c \sum_{x \in X} P(x) \log P(x) \quad (c > 0 \rightarrow c = 1)$

Comments on Entropy

- Entropy plays a central role in information theory
- Origin in thermodynamics
 - $S = k \ln \Omega$, k : Boltzmann's constant, Ω : number of microstates
 - The second law: entropy of an isolated system is non-decreasing
- Shannon entropy
 - Agrees with intuition: additive, monotonic, continuous
 - Logarithmic measure could be derived from an axiomatic approach (Shannon 1948)

Lecture 2

- Joint and Conditional Entropy
 - Chain rule
- Mutual Information
 - If x and y are correlated, their mutual information is the average information that y gives about x
 - E.g. Communication Channel: x transmitted but y received
 - It is the amount of information transmitted through the channel
- Jensen's Inequality

Joint and Conditional Entropy

Joint Entropy: $H(X, Y)$

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

$$= -\sum_{x,y} P(x, y) \log P(x, y)$$

$$= \frac{1}{2} \times 1 + \frac{1}{4} \times 2 + \frac{1}{4} \times 2 = 1.5 \text{ bits}$$

$$\underline{H(X, Y) = E - \log p(X, Y)}$$

$$= -\frac{1}{2} \log \frac{1}{2} - \frac{1}{4} \log \frac{1}{4} - 0 \log 0 - \frac{1}{4} \log \frac{1}{4} = 1.5 \text{ bits}$$

$p(X, Y)$	$y=0$	$y=1$
$x=0$	$\frac{1}{2}$	$\frac{1}{4}$
$x=1$	0	$\frac{1}{4}$

Note: $0 \log 0 = 0$

$$0 \log 0 = \lim_{x \rightarrow 0} x \log x$$

$$= \lim_{x \rightarrow 0} \frac{\log x}{\frac{1}{x}} = \lim_{x \rightarrow 0} \frac{-\frac{1}{x}}{-\frac{1}{x^2}} = \lim_{x \rightarrow 0} 1 = 0$$

Conditional Entropy: $H(Y|X)$

$$H(Y|X) = E - \log P(Y|X)$$

$$\underline{H(Y|X) = E - \log p(Y|X)}$$

$$= -\sum_{x,y} P(x, y) \log P(Y|X)$$

$$= -\sum_{x,y} p(x, y) \log p(y|x)$$

$$= -\frac{1}{2} \times \log \frac{2}{3} - \frac{1}{4} \times \log \frac{1}{3} - \frac{1}{4} \times \log 1$$

$$= 0.689 \text{ bits}$$

$$= -\frac{1}{2} \log \frac{2}{3} - \frac{1}{4} \log \frac{1}{3} - 0 \log 0 - \frac{1}{4} \log 1 = 0.689 \text{ bits}$$

$p(Y X)$	$y=0$	$y=1$
$x=0$	$\frac{2}{3}$	$\frac{1}{3}$
$x=1$	0	1

Note: rows sum to 1

Conditional Entropy – View 1

Additional Entropy:

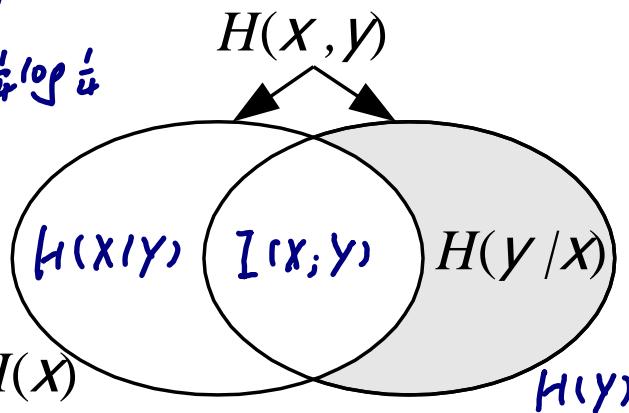
$$H(Y|X) = E \left\{ -\log p(Y|X) \right\} = E \left\{ -\sum_{x,y} P(x,y) \log P(y|x) \right\}$$

$H(Y|X)$ is the average remaining uncertainty in Y when you know X

$$\begin{aligned}
 H(X,Y) &= -\sum_{x,y} P(x,y) \log P(x,y) \\
 &= -\frac{1}{2} \left(\log \frac{1}{2} - \frac{1}{4} \log \frac{1}{4} - \frac{1}{4} \log \frac{1}{4} \right) \\
 &= \frac{1}{2} + \frac{1}{2} + \frac{1}{2} = 1.5 \text{ bits}
 \end{aligned}$$

$$\begin{aligned}
 H(X) &= - \sum_{\pi} P(\pi) \log P(\pi) \\
 &= - \frac{3}{4} \log \frac{3}{4} - \frac{1}{4} \log \frac{1}{4} \\
 &= 0.311 + 0.5 = 0.811
 \end{aligned}$$

$$H(y|x) = H(x,y) - H(x) = 0.689 \text{ bits}$$



Conditional Entropy – View 2

Average Row Entropy:

$$H(y|x) = - \sum_{x,y} p(x,y) \log p(y|x)$$

$$= - \sum_{x,y} p(y|x)p(x) \log p(y|x)$$

$$= - \sum_x p(x) \sum_y p(y|x) \log p(y|x) = \sum_x p(x) H(y|x=x)$$

$$H(y|x) = E - \log p(y|x) = \sum_{x,y} -p(x,y) \log p(y|x) \stackrel{\text{conditional entropy } H(y|x)}{\text{remaining uncertainty of } y \text{ known } x} \stackrel{\text{weighted average row entropy}}{=} \sum_{x,y} -p(x,y) \log p(y|x)$$

$$= \sum_{x,y} -p(x)p(y|x) \log p(y|x) = \sum_{x \in X} p(x) \sum_{y \in Y} -p(y|x) \log p(y|x)$$

$$= \sum_{x \in X} p(x) H(y|x=x) = \frac{3}{4} \times H\left(\frac{1}{3}\right) + \frac{1}{4} \times H(0) = 0.689 \text{ bits}$$

$$H(y|x=0) = - \sum_y p(y|x=0) \log p(y|x=0) = -\frac{2}{3} \log \frac{2}{3} - \frac{1}{3} \log \frac{1}{3} = 0.918 \text{ bits}$$

$$H(y|x=1) = - \sum_y p(y|x=1) \log p(y|x=1) = -1 \log 1 = 0 \text{ bits}$$

Take a weighted average of the entropy of each row using $p(x)$ as weight

$$\therefore H(y|x) = \sum_x p(x) H(y|x=x) = \frac{3}{4} \times 0.918 + \frac{1}{4} \times 0 = 0.689 \text{ bits}$$

$p(x, y)$	$y=0$	$y=1$	$H(y x=x)$	$p(x)$
$x=0$	$\frac{1}{2}$	$\frac{1}{4}$	$H(1/3)$	$\frac{3}{4}$
$x=1$	0	$\frac{1}{4}$	$H(1)$	$\frac{1}{4}$

Conditional entropy $H(y|x)$
 remaining uncertainty of y known x
 $H(y|x) = H(x,y) - H(x)$
 $H(y|x) = \sum_x p(x) H(y|x=x)$

$$\begin{aligned}
 H(x, y, z) &= -\sum_{x,y,z} P(x, y, z) \log P(x, y, z) = -\sum_{x,y,z} P(x, y, z) (\log P(z|x, y) P(y|x) P(x)) \\
 &= -\sum_{x,y,z} P(x, y, z) (\log P(z|x, y) - \sum_{x,y,z} P(x, y, z) (\log P(y|x) - \sum_{x,y,z} P(x, y, z) (\log P(x))) \\
 &= -\sum_z P(z) (\log P(z|x, y) - \sum_y P(y) \log P(y|x) - \sum_x P(x) \log P(x)) \\
 &= H(z|x, y) + H(y|x) + H(x)
 \end{aligned}$$

Chain Rules

- Probabilities

$$p(x, y, z) = p(z | x, y) p(y | x) p(x)$$

- Entropy

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

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

The log in the definition of entropy converts products of probability into sums of entropy

Mutual information: the reduction of uncertainty in x given y .



Conditional entropy: the remaining uncertainty of x given y .

Mutual Information

Mutual information is the average amount of information that you get about x from observing the value of y

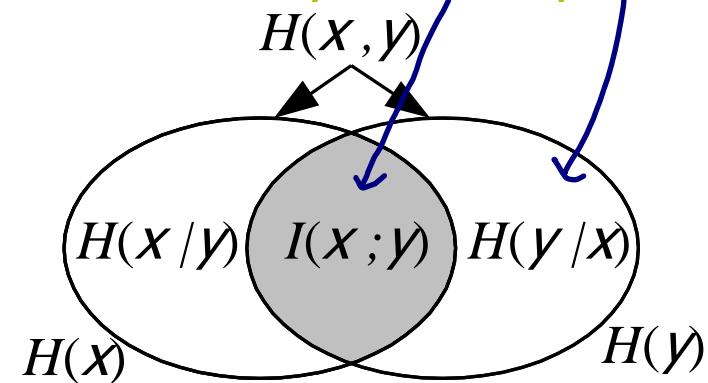
- Or the reduction in the uncertainty of x due to knowledge of y

$$I(x; y) = H(x) - H(x | y) = H(x) + H(y) - H(x, y)$$

Information in x Information in x when you already know y

Mutual information is symmetrical

$$I(x; y) = I(y; x)$$



Use ";" to avoid ambiguities between $I(x;y,z)$ and $I(x,y;z)$

$$H(x) = - \sum_x P(x) \log P(x) = - \frac{3}{4} \log \frac{3}{4} - \frac{1}{4} \log \frac{1}{4} = 0.811 \text{ bits}$$

$$H(y) = - \sum_y P(y) \log P(y) = - \frac{1}{2} \log \frac{1}{2} - \frac{1}{2} \log \frac{1}{2} = 1 \text{ bit}$$

$$H(x,y) = - \sum_{x,y} P(x,y) \log P(x,y)$$

$$= - \frac{1}{2} \log \frac{1}{2} - \frac{1}{4} \log \frac{1}{4} - \frac{1}{4} \log \frac{1}{4} = 1.5 \text{ bits}$$

Mutual Information Example

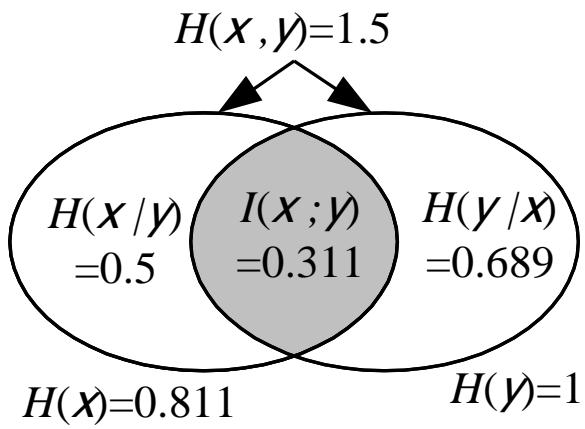
		$H(X Y)$	$H(Y X)$
		$H(X)$	$H(Y)$
		$y=0$	$y=1$
$x=0$		$\frac{1}{2}$	$\frac{1}{4}$
$x=1$		0	$\frac{1}{4}$

$$H(X|Y) = H(X.Y) - H(Y) = 0.5 \text{ bits}$$

$$H(Y|X) = H(X.Y) - H(X) = 0.689 \text{ bits}$$

$$I(X;Y) = H(X) + H(Y) - H(X,Y) = 0.311 \text{ bits}$$

- If you try to guess y you have a 50% chance of being correct.
- However, what if you know x ?
 - Best guess: choose $y = x$
 - If $x=0$ ($p=0.75$) then 66% correct prob
 - If $x=1$ ($p=0.25$) then 100% correct prob
 - Overall 75% correct probability



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

$$= H(X) + H(Y) - H(X,Y)$$

$$H(X) = 0.811, \quad H(Y) = 1, \quad H(X,Y) = 1.5$$

$$I(X;Y) = 0.311$$

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

$$I(X_1, X_2, \dots, X_n; Y) = H(X_1, X_2, \dots, X_n) - H(X_1, X_2, \dots, X_n|Y)$$

Conditional Mutual Information

$$\begin{aligned} &= \sum_{i=1}^n H(X_i | X_{1:i-1}) - \sum_{i=1}^n H(X_i | X_{1:i-1}, Y) \\ &= \sum_{i=1}^n I(X_i; Y | X_{1:i-1}) \end{aligned}$$

$$\begin{aligned} I(X_1, X_2; Y) &= I(X_1; Y) + I(X_2; Y | X_1) \\ &= H(X_1) - H(X_1|Y) + \\ &\quad H(X_2|X_1) - H(X_2|X_1, Y) \\ &= H(X_1, X_2) - H(X_1, X_2|Y) \end{aligned}$$

Conditional Mutual Information

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

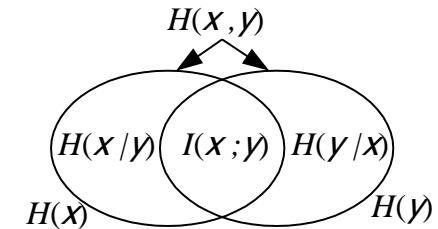
Note: Z conditioning applies to both X and Y

Chain Rule for Mutual Information

► $I(X_1, X_2, X_3; Y) = I(X_1; Y) + I(X_2; Y | X_1) + I(X_3; Y | X_1, X_2)$

$$I(X_{1:n}; Y) = \sum_{i=1}^n I(X_i; Y | X_{1:i-1})$$

Review/Preview



- **Entropy:** $H(x) = \sum_{x \in X} -\log_2(p(x)) p(x) = E - \log_2(p_x(x))$
 - Positive and bounded $0 \leq H(x) \leq \log |X|$
fixed pattern *uniform distribution*
- **Chain Rule:** $H(x, y) = H(x) + H(y | x) \leq H(x) + H(y)$
 - Conditioning reduces entropy $H(y | x) \leq H(y)$
- **Mutual Information:**

$$I(y; x) = H(y) - H(y | x) = H(x) + H(y) - H(x, y)$$

– Positive and Symmetrical $I(x; y) = I(y; x) \geq 0$

– x and y independent $\Leftrightarrow H(x, y) = H(y) + H(x)$

$$\Leftrightarrow I(x; y) = 0$$

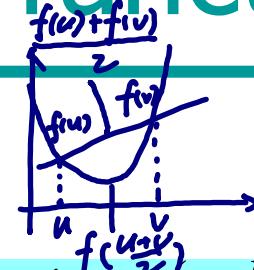
◆ = inequalities not yet proved

Convex & Concave functions

$f(x)$ is strictly convex over (a, b) if

$$f(\lambda u + (1 - \lambda)v) < \lambda f(u) + (1 - \lambda)f(v) \quad \forall u \neq v \in (a, b), 0 < \lambda < 1$$

definition



- every chord of $f(x)$ lies above $f(x)$
- $f(x)$ is **concave** $\Leftrightarrow -f(x)$ is **convex**

- Examples

- Strictly Convex: $x^2, x^4, e^x, x \log x [x \geq 0]$
- Strictly Concave: $\log x, \sqrt{x} [x \geq 0]$
- Convex and Concave: x

Concave is like this



- **Test:** $\frac{d^2 f}{dx^2} > 0 \quad \forall x \in (a, b) \Rightarrow f(x) \text{ is strictly convex}$

“convex” (not strictly) uses “ \leq ” in definition and “ \geq ” in test

Jensen's Inequality

Jensen's Inequality: (a) $f(x)$ convex $\Rightarrow Ef(x) \geq f(Ex)$

(b) $f(x)$ strictly convex $\Rightarrow Ef(x) > f(Ex)$ unless x constant

Proof by induction on $|X|$

– $|X|=1$: $E f(x) = f(E x) = f(x_1)$

– $|X|=k$: $E f(x) = \sum_{i=1}^k p_i f(x_i) = p_k f(x_k) + (1 - p_k) \sum_{i=1}^{k-1} \frac{p_i}{1 - p_k} f(x_i)$

convex: $E f(x) \geq f(Ex)$

$$\geq p_k f(x_k) + (1 - p_k) f\left(\sum_{i=1}^{k-1} \frac{p_i}{1 - p_k} x_i \right)$$

definition: $f(\lambda u + (1-\lambda)v) \leq \lambda f(u) + (1-\lambda)f(v)$

$$\geq f\left(p_k x_k + (1 - p_k) \sum_{i=1}^{k-1} \frac{p_i}{1 - p_k} x_i \right) = f(E x)$$

These sum to 1

Assume JI is true
for $|X|=k-1$

Follows from the definition of convexity for two-mass-point distribution

Jensen's Inequality Example

Mnemonic example:

$f(x) = x^2$: strictly convex

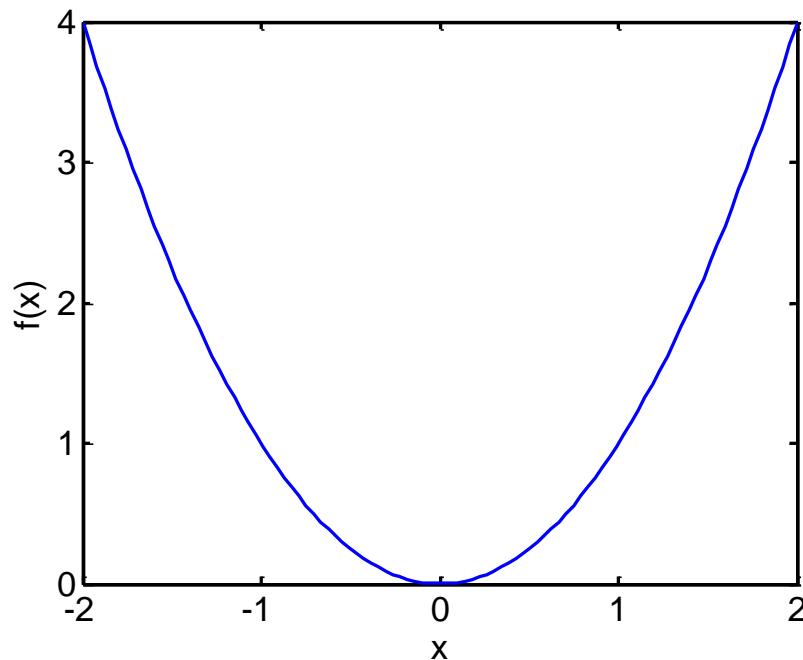
$X = [-1; +1]$

$p = [1/2; 1/2]$

$E X = 0$

$f(E X) = 0$

$E f(X) = 1 > f(E X)$



Summary

- Chain Rule:

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

- Conditional Entropy:

$$H(y | x) = H(x, y) - H(x) = \sum_{x \in X} p(x)H(y | x)$$

- Conditioning reduces entropy

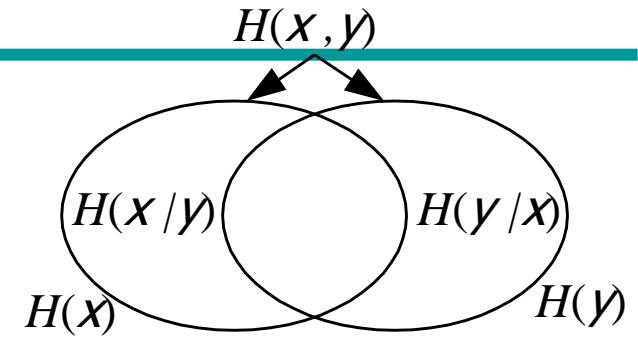
$$H(y | x) \leq H(y)$$

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

- In communications, mutual information is the amount of information transmitted through a noisy channel

- Jensen's Inequality $f(x)$ convex $\Rightarrow E f(x) \geq f(E x)$

◆ = inequalities not yet proved



Lecture 3

- Relative Entropy
 - A measure of how different two probability mass vectors are
- Information Inequality and its consequences
 - Relative Entropy is always positive
 - Mutual information is positive
 - Uniform bound
 - Conditioning and correlation reduce entropy
- Stochastic Processes
 - Entropy Rate
 - Markov Processes

entropy $H(X) = - \sum_x P(x) \log_2 P(x) = \sum_x P(x) \log_2 \frac{1}{P(x)}$: a measurement of uncertainty

cross entropy $H(P, Q) = - \sum_x P(x) \log_2 Q(x) = \sum_x P(x) \log_2 \frac{1}{Q(x)}$: the cost of selected scheme to eliminate the system uncertainty.

relative entropy $D(P||Q) = \sum_x P(x) \log_2 \frac{P(x)}{Q(x)}$: the cost difference of schemes corresponding to different distributions.

Relative Entropy or Kullback-Leibler Divergence between two probability mass vectors p and q

$$D(p \parallel q) = \sum_{x \in X} p(x) \log \frac{p(x)}{q(x)} = E_p \log \frac{p(x)}{q(x)} = E_p (-\log q(x)) - H(x)$$

where E_p denotes an expectation performed using probabilities p
 $D(p \parallel q) \geq 0$: the assumed distribution $q(x)$ cannot be more accurate than the real case.
 $D(p \parallel q)$ measures the "distance" between the probability mass functions p and q .

We must have $p_i=0$ whenever $q_i=0$ else $D(p \parallel q)=\infty$

Beware: $D(p \parallel q)$ is not a true distance because:

- (1) it is asymmetric between p , q and
- (2) it does not satisfy the triangle inequality.

Relative Entropy Example

$$D(P \parallel Q) = E_p \left(\log_2 \frac{P(x)}{Q(x)} \right) = E_p \left(\log_2 \frac{P(x)}{q'_m} - H(P(x)) \right)$$



$$X = [1 \ 2 \ 3 \ 4 \ 5 \ 6]^T$$

$$H(P) = - \sum_x P(x) \log_2 P(x) = 2.585 \quad H(Q) = - \sum_x Q(x) \log_2 Q(x) = 2.161$$

$$D(P \parallel Q) = E_p \left(\log_2 \frac{P(x)}{q'_m} - H(P(x)) \right) = 2.935 - 2.585 = 0.35$$

$$p = \left[\begin{array}{cccccc} 1 & 1 & 1 & 1 & 1 & 1 \\ \cancel{6} & \cancel{6} & \cancel{6} & \cancel{6} & \cancel{6} & \cancel{6} \end{array} \right] \Rightarrow H(p) = 2.585$$

$$D(Q \parallel P) = E_q \left(\log_2 \frac{q(x)}{P(x)} - H(Q(x)) \right) = 2.585 - 2.161 = 0.424$$

$$q = \left[\begin{array}{cccccc} 1 & 1 & 1 & 1 & 1 & 1 \\ \cancel{10} & \cancel{10} & \cancel{10} & \cancel{10} & \cancel{10} & \cancel{2} \end{array} \right] \Rightarrow H(q) = 2.161$$

$$D(p \parallel q) = E_p \left(-\log q_x \right) - H(p) = 2.935 - 2.585 = 0.35$$

$$D(q \parallel p) = E_q \left(-\log p_x \right) - H(q) = 2.585 - 2.161 = 0.424$$

Information Inequality

The assumed distribution $q(x)$ cannot be more accurate than the real case.

Information (Gibbs') Inequality: $\underline{D(p \parallel q) \geq 0}$

- Define $A = \{x : p(x) > 0\} \subseteq X$

• Proof

(log: concave function $E f(x) \leq f(E x)$)

$$D(p \parallel q) = - \sum_{x \in A} p(x) \log \frac{p(x)}{q(x)} = \sum_{x \in A} p(x) \log \frac{q(x)}{p(x)}$$

Jensen's inequality $\leq \log \left(\sum_{x \in A} p(x) \frac{q(x)}{p(x)} \right) = \log \left(\sum_{x \in A} q(x) \right) \leq \log \left(\sum_{x \in X} q(x) \right) = \log 1 = 0$

If $D(p \parallel q) = 0$: Since $\log(\cdot)$ is strictly concave we have equality in the proof only if $q(x)/p(x)$, the argument of \log , equals a constant.

But $\sum_{x \in X} p(x) = \sum_{x \in X} q(x) = 1$ so the constant must be 1 and $p \equiv q$

Information Inequality Corollaries

- Uniform distribution has highest entropy
 - Set $\mathbf{q} = [|\mathcal{X}|^{-1}, \dots, |\mathcal{X}|^{-1}]^T$ giving $H(\mathbf{q}) = \log |\mathcal{X}|$ bits
$$D(\mathbf{p} \parallel \mathbf{q}) = E_{\mathbf{p}} \left\{ -\log q(x) \right\} - H(\mathbf{p}) = \log |\mathcal{X}| - H(\mathbf{p}) \geq 0$$

- Mutual Information is non-negative

$$\begin{aligned}
 D(p \parallel q) &= E_p \log_2 \frac{p(x)}{q(x)} \\
 I(X;Y) &= E \log_2 \frac{p(x,y)}{p(x)p(y)} = D(p(x,y) \parallel p(x)p(y)) = \\
 &\quad \boxed{E \log \frac{p(x,y)}{p(x)p(y)}} \\
 &= D(p(x,y) \parallel p(x)p(y)) \geq 0
 \end{aligned}$$

with equality only if $p(x,y) \equiv p(x)p(y) \Leftrightarrow x$ and y are independent.

More Corollaries

- Conditioning reduces entropy

$$0 \leq I(x; y) = H(y) - H(y | x) \Rightarrow H(y | x) \leq H(y)$$

with equality only if x and y are independent.

- Independence Bound

$$H(x_{1:n}) = \sum_{i=1}^n H(x_i | x_{1:i-1}) \leq \sum_{i=1}^n H(x_i)$$

with equality only if all x_i are independent.

E.g.: If all x_i are identical $H(x_{1:n}) = H(x_1)$

independence bound $H(X_{1:n}) = \sum_{i=1}^n H(X_i | X_{1:i-1}) \leq \sum_{i=1}^n H(X_i)$
 conditional independence bound $H(X_{1:n}|Y_{1:n}) = \sum_{i=1}^n H(X_i | X_{1:i-1}, Y_{1:n}) \leq \sum_{i=1}^n H(X_i | Y_i)$
 mutual information independence bound $I(X_{1:n}; Y_{1:n}) = H(X_{1:n}) - H(X_{1:n}|Y_{1:n}) \geq \sum_{i=1}^n H(X_i) - \sum_{i=1}^n H(X_i | Y_i) = \sum_{i=1}^n I(X_i; Y_i)$

Conditional Independence Bound

- Conditional Independence Bound

$$H(X_{1:n} | Y_{1:n}) = \underbrace{\sum_{i=1}^n H(X_i | X_{1:i-1}, Y_{1:n})}_{\text{Conditional Independence Bound}} \leq \sum_{i=1}^n H(X_i | Y_i)$$

- Mutual Information Independence Bound

If all x_i are independent or, by symmetry, if all y_i are independent:

$$\begin{aligned} I(X_{1:n}; Y_{1:n}) &= H(X_{1:n}) - H(X_{1:n} | Y_{1:n}) \\ &\geq \sum_{i=1}^n H(X_i) - \sum_{i=1}^n H(X_i | Y_i) = \sum_{i=1}^n I(X_i; Y_i) \end{aligned}$$

E.g.: If $n=2$ with x_i i.i.d. Bernoulli ($p=0.5$) and $y_1=x_2$ and $y_2=x_1$, then $I(X_i; Y_i)=0$ but $I(X_{1:2}; Y_{1:2}) = 2$ bits.

Stochastic Process

Stochastic Process $\{X_i\} = X_1, X_2, \dots$

Entropy: $H(\{X_i\}) = H(X_1) + H(X_2 | X_1) + \dots = \infty$ often

Entropy Rate: $H(X) = \lim_{n \rightarrow \infty} \frac{1}{n} H(X_{1:n})$ if limit exists

*the increasing rate of entropy
w.r.t. n.*

- Entropy rate estimates the additional entropy per new sample.
- Gives a lower bound on number of code bits per sample.

Examples:

- Typewriter with m equally likely letters each time: $H(X) = \log m$
- X_i i.i.d. random variables: $H(X) = H(X_i)$

Stationary Process

Stochastic Process $\{x_i\}$ is **stationary** iff

$$p(\mathbf{X}_{1:n} = \mathbf{a}_{1:n}) = p(\mathbf{X}_{k+(1:n)} = \mathbf{a}_{1:n}) \quad \forall k, n, \mathbf{a}_i \in \mathbf{X}$$

If $\{x_i\}$ is stationary then $H(X)$ exists and

Proof: $0 \leq H(x_n | x_{1:n-1}) \leq H(x_n | x_{2:n-1}) = H(x_{n-1} | x_{1:n-2})$

(a) conditioning reduces entropy, (b) stationarity

Hence $H(x_n | x_{1:n-1})$ is positive, decreasing \Rightarrow tends to a limit, say b

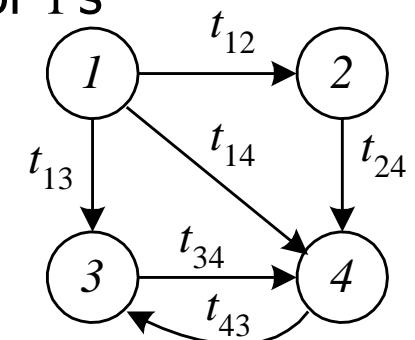
Hence

$$H(\mathbf{X}_k \mid \mathbf{X}_{1:k-1}) \rightarrow b \quad \Rightarrow \quad \frac{1}{n} H(\mathbf{X}_{1:n}) = \frac{1}{n} \sum_{k=1}^n H(\mathbf{X}_k \mid \mathbf{X}_{1:k-1}) \rightarrow b = H(\mathbf{X})$$

Markov Process (Chain)

Discrete-valued stochastic process $\{x_i\}$ is

- Independent iff $p(x_n|x_{0:n-1})=p(x_n)$
- Markov iff $p(x_n|x_{0:n-1})=p(x_n|x_{n-1})$
 - time-invariant iff $p(x_n=b|x_{n-1}=a) = p_{ab}$ indep of n
 - States
 - Transition matrix: $\mathbf{T} = \{t_{ab}\}$
 - Rows sum to 1: $\mathbf{T}\mathbf{1} = \mathbf{1}$ where $\mathbf{1}$ is a vector of 1's
 - $\mathbf{p}_n = \mathbf{T}^T \mathbf{p}_{n-1}$
 - Stationary distribution: $\mathbf{p}_\$ = \mathbf{T}^T \mathbf{p}_\$$



Independent Stochastic Process is easiest to deal with, Markov is next easiest

Stationary Markov Process

If a Markov process is

- a) **irreducible**: you can go from any state a to any b in a finite number of steps
- b) **aperiodic**: \forall state a , the possible times to go from a to a have highest common factor = 1

then it has exactly one stationary distribution, $\mathbf{p}_\$$.

- $\mathbf{p}_\$$ is the eigenvector of \mathbf{T}^T with $\lambda = 1$: $\mathbf{T}^T \mathbf{p}_\$ = \mathbf{p}_\$$
 $\mathbf{T}^n \xrightarrow[n \rightarrow \infty]{} \mathbf{1} \mathbf{p}_\T where $\mathbf{1} = [1 \quad 1 \quad \dots \quad 1]^T$
- Initial distribution becomes irrelevant (**asymptotically stationary**) $(\mathbf{T}^T)^n \mathbf{p}_0 = \mathbf{p}_\$ \mathbf{1}^T \mathbf{p}_0 = \mathbf{p}_\$, \quad \forall \mathbf{p}_0$

Chess Board

$$H(X) = \lim_{n \rightarrow \infty} H(X_n | X_{n-1})$$

$$= \lim_{n \rightarrow \infty} - \sum P(X_n, X_{n-1}) \log_2 P(X_n | X_{n-1})$$

$$\text{Random Walk} = - \sum P(X_{n-1}) P(X_n | X_{n-1}) \log_2 P(X_n | X_{n-1})$$

- Move $\leftrightarrow \uparrow \downarrow \leftarrow \rightarrow$ equal prob
- $$P(X_n | X_{n-1}) = \frac{P(X_n, X_{n-1})}{P(X_{n-1})}$$

- $p_1 = [1 \ 0 \dots \ 0]^T$

- $- H(p_1) = 0$

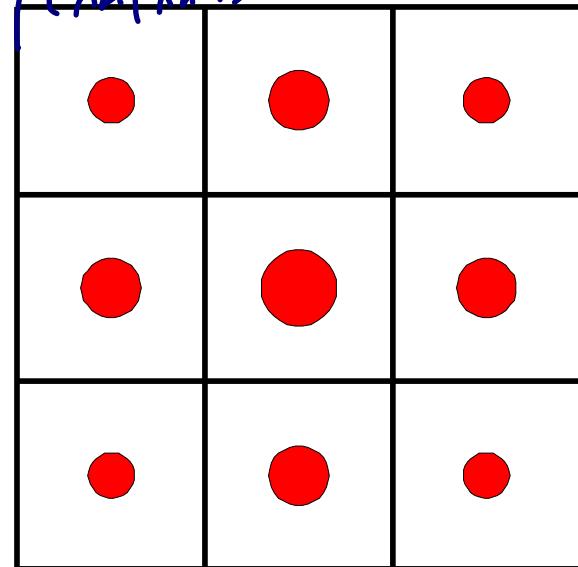
- $p_{\$} = \frac{1}{40} \times [3 \ 5 \ 3 \ 5 \ 8 \ 5 \ 3 \ 5 \ 3]^T$

- $- H(p_{\$}) = 3.0855$

- $H(X) = \lim_{n \rightarrow \infty} H(X_n | X_{n-1})$

$$= \lim_{n \rightarrow \infty} - \sum p(x_n, x_{n-1}) \log p(x_n | x_{n-1}) = \sum_{i,j} - p_{\$,i} t_{i,j} \log(t_{i,j}) = 2.2365$$

$H(p_8) = 3.0827, \quad H(p_8 | p_7) = 2.23038$



Summary

- **Relative Entropy:** $D(\mathbf{p} \parallel \mathbf{q}) = E_{\mathbf{p}} \log \frac{p(x)}{q(x)} \geq 0$
 - $D(\mathbf{p} \parallel \mathbf{q}) = 0$ iff $\mathbf{p} \equiv \mathbf{q}$
- **Corollaries**
 - Uniform Bound: Uniform \mathbf{p} maximizes $H(\mathbf{p})$
 - $I(X; Y) \geq 0 \Rightarrow$ Conditioning reduces entropy
 - Indep bounds: $H(X_{1:n}) \leq \sum_{i=1}^n H(X_i)$ $H(X_{1:n} | Y_{1:n}) \leq \sum_{i=1}^n H(X_i | Y_i)$
 $I(X_{1:n}; Y_{1:n}) \geq \sum_{i=1}^n I(X_i; Y_i)$ if X_i or Y_i are indep
- **Entropy Rate of stochastic process:**
 - $\{X_i\}$ stationary: $H(X) = \lim_{n \rightarrow \infty} H(X_n | X_{1:n-1})$
 - $\{X_i\}$ stationary Markov:

$$H(X) = H(X_n | X_{n-1}) = \sum_{i,j} -p_{\$,i} t_{i,j} \log(t_{i,j})$$


Lecture 4

- Source Coding Theorem
 - n i.i.d. random variables each with entropy $H(X)$ can be compressed into more than $nH(X)$ bits as n tends to infinity
- Instantaneous Codes
 - Symbol-by-symbol coding
 - Uniquely decodable
- Kraft Inequality
 - Constraint on the code length
- Optimal Symbol Code lengths
 - Entropy Bound

Source Coding

- **Source Code:** C is a mapping $X \rightarrow D^+$
 - X a random variable of the message
 - $D^+ =$ set of all finite length strings from D
 - D is often binary
 - e.g. $\{E, F, G\} \rightarrow \{0,1\}^+$: $C(E)=0, C(F)=10, C(G)=11$
an extension contains all codewords derived from the basis set.
- **Extension:** C^+ is mapping $X^+ \rightarrow D^+$ formed by concatenating $C(x_i)$ without punctuation
 - e.g. $C^+(EFEEGE) = 01000110$

Desired Properties

- **Non-singular:** $x_1 \neq x_2 \Rightarrow C(x_1) \neq C(x_2)$
 - Unambiguous description of a single letter of X
- **Uniquely Decable:** C^+ is non-singular
 - The sequence $C^+(x^+)$ is unambiguous
 - A stronger condition
 - Any encoded string has only one possible source string producing it
 - However, one may have to examine the entire encoded string to determine even the first source symbol
 - One could use punctuation between two codewords but inefficient

Instantaneous Codes

- Instantaneous (or Prefix) Code
 - No codeword is a prefix of another
 - Can be decoded **instantaneously** without reference to future codewords
- Instantaneous \Rightarrow Uniquely Decodable \Rightarrow Non-singular

Examples:

- $C(E, F, G, H) = (0, 1, 00, 11)$ $uv \ 1x \bar{IU}$
- $C(E, F) = (0, 101)$ $uv \ 1v \ IU$
- $C(E, F) = (1, 101)$ $uv \ 1x \bar{IU}$
- $C(E, F, G, H) = (00, 01, 10, 11)$ $uv \ 1v \ IU$
- $C(E, F, G, H) = (0, 01, 011, 111)$ $uv \ 1x \bar{IU}$

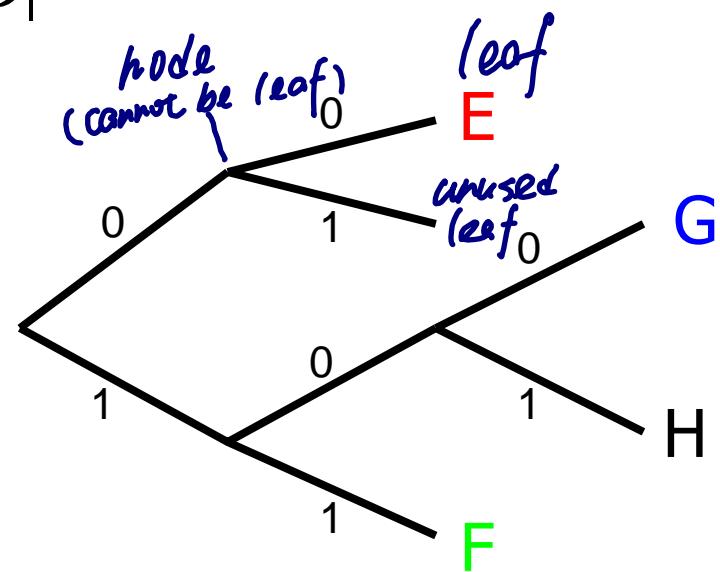


Code Tree

Instantaneous code: $C(E,F,G,H) = (00, 11, 100, 101)$

Form a D -ary tree where $D = |D|$

- D branches at each node
- Each codeword is a leaf
- Each node along the path to a leaf is a prefix of the leaf
⇒ can't be a leaf itself
- Some leaves may be unused



$111011000000 \rightarrow \text{FHGEE}$

kraft inequality (for instantaneous codes)

$$\sum_{i=1}^{|X|} 2^{-l_i} \leq (\text{budget})$$

Kraft Inequality (instantaneous codes)

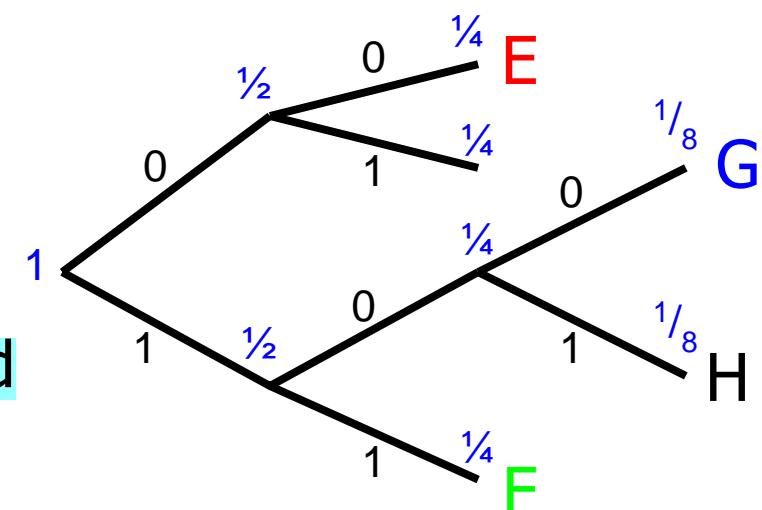
code cost $\propto \frac{1}{\text{code length}}$

- Limit on codeword lengths of instantaneous codes
 - Not all codewords can be too short
- Codeword lengths $l_1, l_2, \dots, l_{|X|} \Rightarrow$
- Label each node at depth l with 2^{-l}
- Each node equals the sum of all its leaves
- Equality iff all leaves are utilised
- Total code budget = 1

Code 00 uses up $\frac{1}{4}$ of the budget

Code 100 uses up $\frac{1}{8}$ of the budget

$$\boxed{\sum_{i=1}^{|X|} 2^{-l_i} \leq 1}$$



Same argument works with D-ary tree

McMillan inequality (for uniquely decodable codewords)

$$\sum_{i=1}^{|X|} D^{-l_i} \leq 1 \quad (\text{same with Kraft ineq.})$$

McMillan Inequality (uniquely decodable codes)

$$S^N = \left(\sum_{i=1}^{|X|} D^{-l_i} \right)^N = \sum_{i_1=1}^{|X|} \sum_{i_2=1}^{|X|} \dots \sum_{i_N=1}^{|X|} D^{-\sum_{i=1}^N l_{i,i_1+i_2+\dots+i_N}} = \sum_{x \in X^N} D^{-\text{length}\{C^+(x)\}}$$

If uniquely decodable C has codeword lengths

$$l_1, l_2, \dots, l_{|X|}, \text{ then } \sum_{i=1}^{|X|} D^{-l_i} \leq 1$$

every codebook length D_{sum}

The same

Proof: Let $S = \sum_{i=1}^{|X|} D^{-l_i}$ and $M = \max_i l_i$ then for any N ,

$$S^N \leq NM \quad \text{for } N \geq 1 \Rightarrow S \leq 1.$$

exp linear $\sum_{i=1}^{|X|} D^{-l_i}$

$$S^N = \left(\sum_{i=1}^{|X|} D^{-l_i} \right)^N = \sum_{i_1=1}^{|X|} \sum_{i_2=1}^{|X|} \dots \sum_{i_N=1}^{|X|} D^{-\sum_{i=1}^N l_{i,i_1+i_2+\dots+i_N}} = \sum_{x \in X^N} D^{-\text{length}\{C^+(x)\}}$$

Sum over all possible codeword length

$$N=1 \sum_{l=1}^{NM} D^{-l} | x : l = \text{length}\{C^+(x)\}| \leq \sum_{l=1}^{NM} D^{-l} \stackrel{\text{re-order sum by total length}}{=} \sum_{l=1}^{NM} 1 = NM$$

Sum over all sequences of length N

If $S > 1$ then $S^N > NM$ for some N . Hence $S \leq 1$.

max number of distinct sequences of length l

Implication: uniquely decodable codes doesn't offer further reduction of codeword lengths than instantaneous codes

McMillan Inequality (uniquely decodable codes)

If uniquely decodable C has codeword lengths

$$l_1, l_2, \dots, l_{|X|}, \text{ then } \sum_{i=1}^{|X|} D^{-l_i} \leq 1 \quad \text{The same}$$

Proof: Let $S = \sum_{i=1}^{|X|} D^{-l_i}$ and $M = \max l_i$ then for any N ,

$$S^N = \left(\sum_{i=1}^{|X|} D^{-l_i} \right)^N = \sum_{i_1=1}^{|X|} \sum_{i_2=1}^{|X|} \dots \sum_{i_N=1}^{|X|} D^{-\left(l_{i_1} + l_{i_2} + \dots + l_{i_N}\right)} = \sum_{\mathbf{x} \in X^N} D^{-\text{length}\{C^+(\mathbf{x})\}}$$

$$= \sum_{l=1}^{NM} D^{-l} | \{\mathbf{x} : l = \text{length}\{C^+(\mathbf{x})\}\}| \leq \sum_{l=1}^{NM} D^{-l} D^l = \sum_{l=1}^{NM} 1 = NM$$

If $S > 1$ then $S^N > NM$ for some N . Hence $S \leq 1$.

Implication: uniquely decodable codes doesn't offer further reduction of codeword lengths than instantaneous codes

How Short are Optimal Codes?

If $l(x) = \text{length}(C(x))$ then C is optimal if $L=E l(x)$ is as small as possible.

We want to minimize $\sum_{x \in X} p(x)l(x)$ subject to

1. $\sum_{x \in X} D^{-l(x)} \leq 1$
2. all the $l(x)$ are integers

Simplified version:

Ignore condition 2 and assume condition 1 is satisfied with equality.

optimistic mistakes

less restrictive so lengths may be shorter than actually possible \Rightarrow lower bound

Optimal Codes (non-integer l_i)

- Minimize $\sum_{i=1}^{|X|} p(x_i)l_i$ subject to $\sum_{i=1}^{|X|} D^{-l_i} = 1$

Use Lagrange multiplier:

Define $J = \sum_{i=1}^{|X|} p(x_i)l_i + \lambda \sum_{i=1}^{|X|} D^{-l_i}$ and set $\frac{\partial J}{\partial l_i} = 0$

$$\frac{\partial J}{\partial l_i} = p(x_i) - \lambda \ln(D) D^{-l_i} = 0 \Rightarrow D^{-l_i} = p(x_i) / \lambda \ln(D)$$

also $\sum_{i=1}^{|X|} D^{-l_i} = 1 \Rightarrow \lambda = 1 / \ln(D) \Rightarrow l_i = -\log_D(p(x_i))$

$$E[l(X)] = E - \log_D(p(X)) = \frac{E - \log_2(p(X))}{\log_2 D} = \frac{H(X)}{\log_2 D} = H_D(X)$$

no uniquely decodable code can do better than this D .

Bounds on Optimal Code Length

Round up optimal code lengths:

- l_i are bound to satisfy the Kraft Inequality (since the optimum lengths do) $\sum D^{-l_i} \leq 1$?
 $\begin{array}{c} \text{True: } \checkmark \\ \text{False: } \times \end{array}$
- For this choice, $-\log_D(p(x_i)) \leq l_i \leq -\log_D(p(x_i)) + 1$
- Average shortest length:



$$H_D(X) \leq L^* < H_D(X) + 1$$

(since we added <1 to optimum values)

- We can do better by encoding blocks of n symbols

$$n^{-1} H_D(X_{1:n}) \leq n^{-1} E l(X_{1:n}) \stackrel{\text{normalise the length}}{\leq} n^{-1} H_D(X_{1:n}) + n^{-1}$$

- If entropy rate $\overset{n \rightarrow \infty}{\Rightarrow}$ tighter bound \Rightarrow avg. symbol length \rightarrow entropy. of x_i exists ($\Leftarrow x_i$ is stationary process)

$$n^{-1} H_D(X_{1:n}) \rightarrow H_D(X) \Rightarrow n^{-1} E l(X_{1:n}) \rightarrow H_D(X)$$

Also known as source coding theorem

Block Coding Example

$$X = [A; B], p_x = [0.9; 0.1]$$

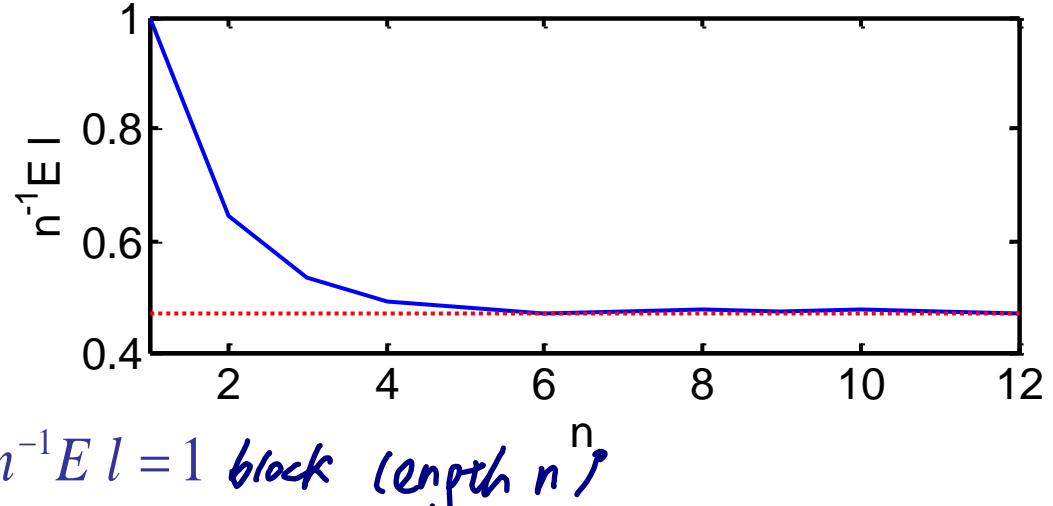
$$H(x_i) = 0.469$$

Huffman coding:

- $n=1$
- | sym | A | B |
|------|-----|-----|
| prob | 0.9 | 0.1 |
| code | 0 | 1 |
- $$n^{-1}E_l = \frac{0.9 \times 1 + 0.1 \times 1}{1} = 1$$

- $n=2$
- | sym | AA | AB | BA | BB |
|------|------|------|------|------|
| prob | 0.81 | 0.09 | 0.09 | 0.01 |
| code | 0 | 11 | 100 | 101 |
- $$n^{-1}E_l = \frac{0.81 \times 1 + 0.09 \times 2 + 0.09 \times 3}{2} = 0.645$$

- $n=3$
- | sym | AAA | AAB | ... | BBA | BBB |
|------|-------|-------|-----|-------|-------|
| prob | 0.729 | 0.081 | ... | 0.009 | 0.001 |
| code | 0 | 101 | ... | 10010 | 10011 |



\Rightarrow avg. symbol length \rightarrow entropy
 $n^{-1}E_l$ (longer block, less uncertainty)
 $n^{-1}E_l = 0.645$

$$n^{-1}E_l = 0.583$$

The extra 1 bit inefficiency becomes insignificant for large blocks

Summary

- McMillan Inequality for D-ary codes:
 - any uniquely decodable C has $\sum_{i=1}^{|X|} D^{-l_i} \leq 1$
 - Any uniquely decodable code:

$$E l(x) \geq H_D(x)$$

- Source coding theorem
 - Symbol-by-symbol encoding

$$H_D(x) \leq E l(x) \leq H_D(x) + 1$$

- Block encoding $n^{-1} E l(x_{1:n}) \rightarrow H_D(X)$

Lecture 5

- Source Coding Algorithms
- Huffman Coding
- Lempel-Ziv Coding

Huffman Code

An optimal binary instantaneous code must satisfy:

1. $p(x_i) > p(x_j) \Rightarrow l_i \leq l_j$ (else swap codewords)
 2. The two longest codewords have the same length
(else chop a bit off the longer codeword)
 3. \exists two longest codewords differing only in the last bit
(else chop a bit off all of them)
- 

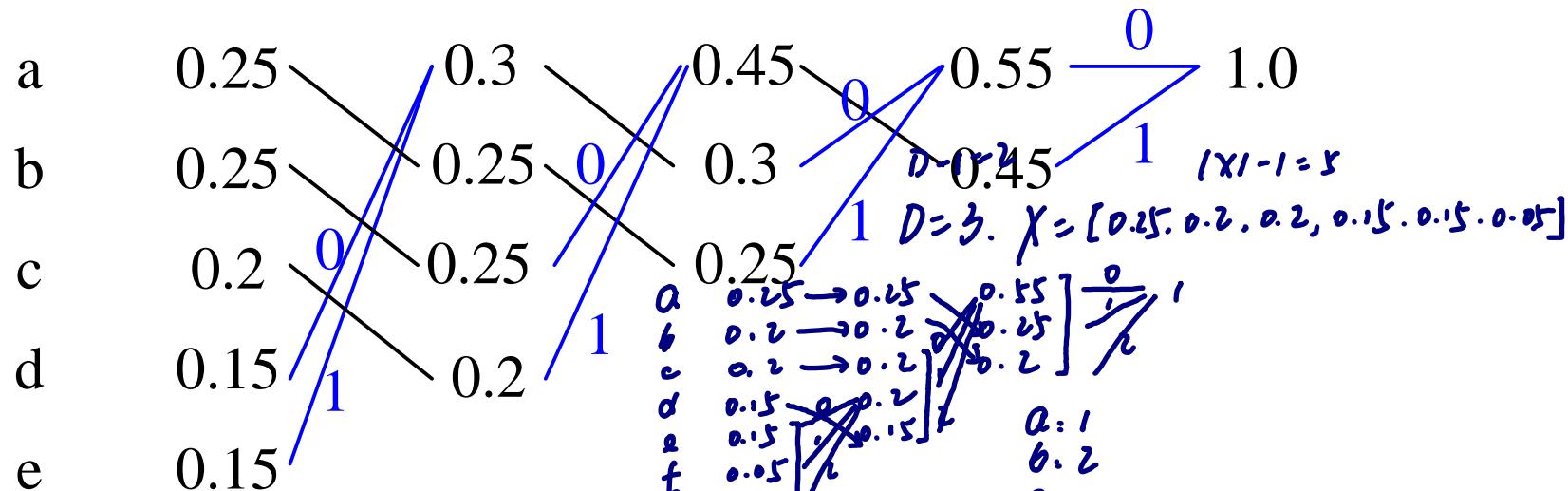
Huffman Code construction

1. Take the two smallest $p(x_i)$ and assign each a different last bit. Then merge into a single symbol.
2. Repeat step 1 until only one symbol remains

Used in JPEG, MP3...

Huffman Code Example

$$X = [a, b, c, d, e], p_X = [0.25 \ 0.25 \ 0.2 \ 0.15 \ 0.15]$$



① go from symbol to the end ② read backwards

Read diagram backwards for codewords:

$$C(X) = [01 \ 10 \ 11 \ 000 \ 001], L = 2.3, H(X) = 2.286$$

For D-ary code, first add extra zero-probability symbols until $|X|-1$ is a multiple of $D-1$ and then group D symbols at a time

Huffman Code is Optimal Instantaneous Code

Huffman traceback gives codes for progressively larger alphabets:
 $\begin{array}{c} a: 0.55 \\ b: 0.45 \end{array}$, $L_2 = 0.55 + 0.45 = 1$

$$\mathbf{p}_2 = [0.55 \ 0.45],$$

$$\mathbf{c}_2 = [0 \ 1], L_2 = 1$$

a: 0.45	b: 0.3	c: 0.25	0.55 0	0.45 1
a: 1	b: 00	c: 01	0.55 0	0.45 1

$$L_3 = 0.45 \times 1 + 0.55 \times 2 = 1.55$$

$$\mathbf{p}_3 = [0.45 \ 0.3 \ 0.25],$$

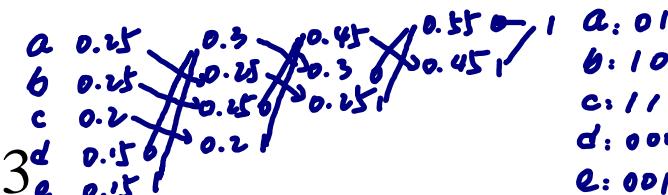
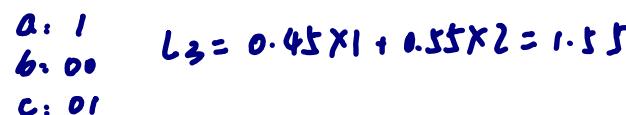
$$\mathbf{c}_3 = [1 \ 00 \ 01], L_3 = 1.55$$

$$\mathbf{p}_4 = [0.3 \ 0.25 \ 0.25 \ 0.2],$$

$$\mathbf{c}_4 = [00 \ 01 \ 10 \ 11], L_4 = 2$$

$$\mathbf{p}_5 = [0.25 \ 0.25 \ 0.2 \ 0.15 \ 0.15],$$

$$\mathbf{c}_5 = [01 \ 10 \ 11 \ 000 \ 001], L_5 = 2.3$$



$$L_5 = 2 \times 0.7 + 3 \times 0.3 = 2.3$$

We want to show that all these codes are optimal including C_5

Huffman Code is Optimal Instantaneous Code

Huffman traceback gives codes for progressively larger alphabets:

$$\mathbf{p}_2 = [0.55 \ 0.45],$$

$$\mathbf{c}_2 = [0 \ 1], L_2 = 1$$

$$\mathbf{p}_3 = [0.45 \ 0.3 \ 0.25],$$

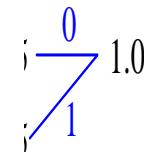
$$\mathbf{c}_3 = [1 \ 00 \ 01], L_3 = 1.55$$

$$\mathbf{p}_4 = [0.3 \ 0.25 \ 0.25 \ 0.2],$$

$$\mathbf{c}_4 = [00 \ 01 \ 10 \ 11], L_4 = 2$$

$$\mathbf{p}_5 = [0.25 \ 0.25 \ 0.2 \ 0.15 \ 0.15],$$

$$\mathbf{c}_5 = [01 \ 10 \ 11 \ 000 \ 001], L_5 = 2.3$$



We want to show that all these codes are optimal including C_5

Huffman Optimality Proof

Suppose one of these codes is sub-optimal:

- $\exists m > 2$ with c_m the first sub-optimal code (note c_2 is definitely optimal)
- An optimal c'_m must have $L_{C'm} < L_{Cm}$
- Rearrange the symbols with longest codes in c'_m so the two lowest probs p_i and p_j differ only in the last digit (doesn't change optimality)
- Merge x_i and x_j to create a new code c'_{m-1} as in Huffman procedure
- ~~$L_{C'm-1} = L_{Cm} - p_i - p_j$ since identical except 1 bit shorter with prob $p_i + p_j$~~
- But also $L_{C'm-1} = L_{Cm} - p_i - p_j$ hence $L_{C'm-1} < L_{Cm-1}$ which contradicts assumption that c_m is the first sub-optimal code

Hence, Huffman coding satisfies $H_D(x) \leq L < H_D(x) + 1$

Note: Huffman is just one out of many possible optimal codes

Shannon-Fano Code

Fano code Fano: split

1. Put probabilities in decreasing order
2. Split as close to 50-50 as possible; repeat with each half

source of information loss

a	0.20	<u>largest probability: shortest. all zeros</u>	00	$I(X) = 2.81 \text{ bits}$
b	0.19	0	010	
c	0.17	1	011	$L_{SF} = 2.89 \text{ bits}$
d	0.15	1	100	
e	0.14	0	101	
f	0.06	1	110	Not necessarily optimal: the
g	0.05	1	1110	best code for this p actually
h	0.04	0	1111	has $L = 2.85 \text{ bits}$
<i>smallest probability. longest. all ones.</i>				

Shannon versus Huffman

Shannon

$$F_i = \sum_{k=1}^{i-1} p(x_k), \quad p(x_1) \geq p(x_2) \geq \dots \geq p(x_m)$$

Shannon: $\lceil -\log_2 p(x_i) \rceil$

encoding: round the number $F_i \in [0,1]$ to $\lceil -\log p(x_i) \rceil$ bits

$$H_D(x) \leq L_{SF} \leq H_D(x) + 1 \quad (\text{excercise})$$

$$\mathbf{p}_x = [0.36 \quad 0.34 \quad 0.25 \quad 0.05] \Rightarrow H(x) = 1.78 \text{ bits}$$

$$-\log_2 \mathbf{p}_x = [1.47 \quad 1.56 \quad 2 \quad 4.32]$$

$$\mathbf{l}_S = \lceil -\log_2 \mathbf{p}_x \rceil = [2 \quad 2 \quad 2 \quad 5]$$

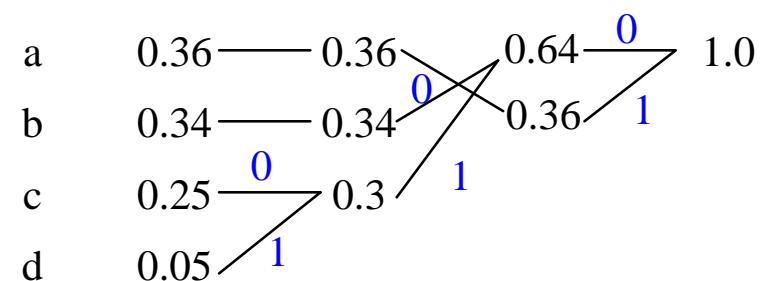
$$L_S = 2.15 \text{ bits}$$

Huffman

$$\mathbf{l}_H = [1 \quad 2 \quad 3 \quad 3]$$

$$L_H = 1.94 \text{ bits}$$

Individual codewords may be longer in Huffman than Shannon but not the average



Issues with Huffman Coding

- Requires the probability distribution of the source
 - Must recompute entire code if any symbol probability changes
 - A block of N symbols needs $|X|^N$ pre-calculated probabilities
- For many practical applications, however, the underlying probability distribution is unknown
 - Estimate the distribution
 - Arithmetic coding: extension of Shannon-Fano coding; can deal with large block lengths
 - Without the distribution
 - Universal coding: Lempel-Ziv coding

Universal Coding

- Does not depend on the distribution of the source
- Compression of an individual sequence
- Run length coding
 - Runs of data are stored (e.g., in fax machines)
Example:
The sequence is: WWWWBWWWWWWBWWWWWWB
Annotations: 'white' under the first four 'W's, 'black' under the 'B', and '9W2B7W6B2W' below.

white black
9W2B7W6B2W
- Lempel-Ziv coding *encode strings into phrases*
 - Generalization that takes advantage of runs of strings of characters (such as WWWWWWWWWB)
 - Adaptive dictionary compression algorithms
 - Asymptotically optimum: achieves the entropy rate for any stationary ergodic source

Lempel-Ziv Coding (LZ78)

Memorize previously occurring substrings in the input data

- parse input into the shortest possible distinct 'phrases', i.e., each phrase is the shortest phrase not seen earlier

phrases	#	codewords (<u>head location + tail</u>)
A	1	0A
B	2	0B
AA	3	1A
BA	4	2A
BAB	5	4B
BB	6	2B
AB	7	HB

number the phrases starting from 1 (0 is the empty string)

ABAABABABBBAB... *new phrase = old phrase (head) + tail*

Look up a dictionary

- each phrase consists of a previously occurring phrase (head) followed by an additional A or B (tail)

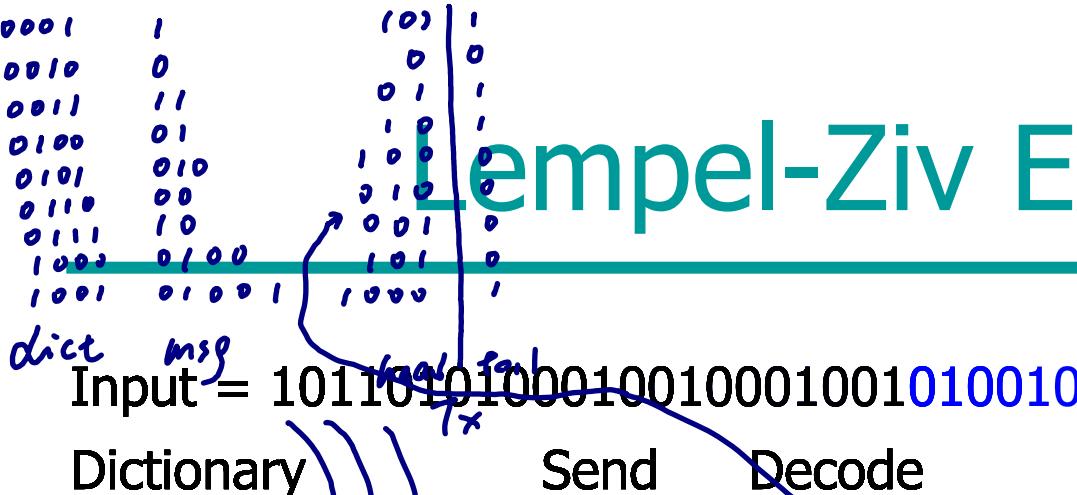
- encoding: give location of head followed by the additional symbol for tail

0A0B1A2A4B2B1B...

- decoder uses an identical dictionary

locations are underlined

Lempel-Ziv Example



Dictionary

		Send	Decode
0000	φ	(0)1	1
0001	1	00	0
0010	0	011	11
0011	11	101	01
0100	01	1000	010
0101	010	0100	00
0110	00	0010	10
0111	10	1010	0100
1000	0100	10001	01001
1001	01001	10010	010010

↑
location

No need to always
send 4 bits

Remark:

- No need to send the dictionary (imagine zip and unzip!)
- Can be reconstructed
- Need to send 0's in 01, 010 and 001 to avoid ambiguity (i.e., instantaneous code)

Lempel-Ziv Comments

Dictionary D contains K entries $D(0), \dots, D(K-1)$. We need to send $M=\text{ceil}(\log K)$ bits to specify a dictionary entry. Initially $K=1$, $D(0)=\phi$ = null string and $M=\text{ceil}(\log K) = 0$ bits.

Input	Action
1	"1" $\notin D$ so send "1" and set $D(1)="1"$. Now $K=2 \Rightarrow M=1$.
0	"0" $\notin D$ so split it up as " ϕ "+"0" and send location "0" (since $D(0)=\phi$) followed by "0". Then set $D(2)="0"$ making $K=3 \Rightarrow M=2$.
1	"1" $\in D$ so don't send anything yet – just read the next input bit.
1	"11" $\notin D$ so split it up as "1" + "1" and send location "01" (since $D(1)="1"$ and $M=2$) followed by "1". Then set $D(3)="11"$ making $K=4 \Rightarrow M=2$.
0	"0" $\in D$ so don't send anything yet – just read the next input bit.
1	"01" $\notin D$ so split it up as "0" + "1" and send location "10" (since $D(2)="0"$ and $M=2$) followed by "1". Then set $D(4)="01"$ making $K=5 \Rightarrow M=3$.
0	"0" $\in D$ so don't send anything yet – just read the next input bit.
1	"01" $\in D$ so don't send anything yet – just read the next input bit.
0	"010" $\notin D$ so split it up as "01" + "0" and send location "100" (since $D(4)="01"$ and $M=3$) followed by "0". Then set $D(5)="010"$ making $K=6 \Rightarrow M=3$.

So far we have sent **1000111011000** where dictionary entry numbers are in **red**.

Lempel-Ziv Properties

- Simple to implement
- Widely used because of its speed and efficiency
 - applications: compress, gzip, GIF, TIFF, modem ...
 - variations: LZW (considering last character of the current phrase as part of the next phrase, used in Adobe Acrobat), LZ77 (sliding window)
 - different dictionary handling, etc
- Excellent compression in practice
 - many files contain repetitive sequences
 - worse than arithmetic coding for text files

Asymptotic Optimality

- Asymptotically optimum for stationary ergodic source (i.e. achieves entropy rate)
- Let $c(n)$ denote the number of phrases for a sequence of length n
- Compressed sequence consists of $c(n)$ pairs (location, last bit)
- Needs $\boxed{c(n)[\log c(n)+1]}$ bits in total
- $\{X_i\}$ stationary ergodic \Rightarrow

$$\limsup_{n \rightarrow \infty} n^{-1} l(X_{1:n}) = \limsup_{n \rightarrow \infty} \frac{c(n)[\log c(n)+1]}{n} \leq H(X) \text{ with probability } 1$$

-
- Proof: C&T chapter 12.10
 - may only approach this for an enormous file

Summary

- **Huffman Coding:** $H_D(x) \leq E l(x) \leq H_D(x) + 1$
 - Bottom-up design
 - Optimal \Rightarrow shortest average length
- **Shannon-Fano Coding:** $H_D(x) \leq E l(x) \leq H_D(x) + 1$
 - Intuitively natural top-down design
- **Lempel-Ziv Coding**
 - Does not require probability distribution
 - Asymptotically optimum for stationary ergodic source (i.e. achieves entropy rate)

Lecture 6

- Markov Chains
 - Have a special meaning
 - Not to be confused with the standard definition of Markov chains (which are sequences of discrete random variables)
- Data Processing Theorem
 - You can't create information from nothing
- Fano's Inequality
 - Lower bound for error in estimating X from Y

Markov Chains

If we have three random variables: x, y, z

$$p(x, y, z) = p(z | x, y) p(y | x) p(x)$$

they form a **Markov chain** $x \rightarrow y \rightarrow z$ if

$$p(z | x, y) = p(z | y) \Leftrightarrow p(x, y, z) = p(z | y) p(y | x) p(x)$$

A Markov chain $x \rightarrow y \rightarrow z$ means that

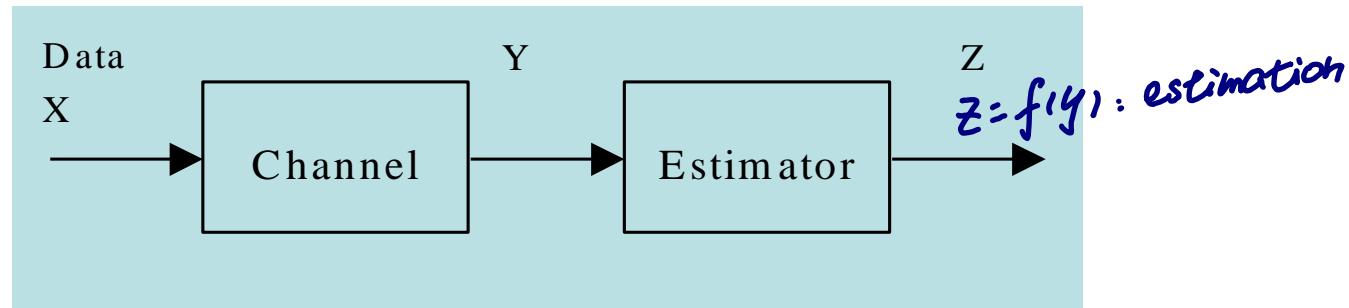
- the only way that x affects z is through the value of y
- if you already know y , then observing x gives you no additional information about z , i.e. $I(x; z | y) = 0 \Leftrightarrow H(z | y) = H(z | x, y)$
- if you know y , then observing z gives you no additional information about x .

$$I(x; z | y) = H(z | y) - H(z | x, y)$$

$$H(x | y) = H(x | y, z)$$

Data Processing

- Estimate $z = f(y)$, where f is a function
- A special case of a Markov chain $x \rightarrow y \rightarrow f(y)$



- Does processing of y increase the information that y contains about x ? *No. even less!*

Markov Chain Symmetry

If $x \rightarrow y \rightarrow z$ $\xrightarrow{MC} x \rightarrow y \rightarrow z$

$$p(x, z | y) = \frac{p(x, y, z)}{p(y)} \stackrel{(a)}{=} \frac{p(x, y)p(z | y)}{p(y)} = p(x | y)p(z | y)$$

given y. x, z are independent.

$$(a) \quad p(z | x, y) = p(z | y)$$

Hence x and z are conditionally independent given y

Also $x \rightarrow y \rightarrow z$ iff $z \rightarrow y \rightarrow x$ since $p(x|y)p(z|y) = p(x,z|y)$

$$p(x | y) = p(x | y) \frac{p(z | y)p(y)}{p(y, z)} \stackrel{(a)}{=} \frac{p(x, z | y)p(y)}{p(y, z)} = \frac{p(x, y, z)}{p(y, z)}$$

$$= p(x | y, z) \quad (a) \quad p(x, z | y) = p(x | y)p(z | y)$$

given y, & does not provide additional information Conditionally indep.
Markov chain property is symmetrical

Data Processing Theorem

If $x \rightarrow y \rightarrow z$ then $I(x; y) \geq I(x; z)$ *(even decrease)* *extract useful info
do not lose mutual info*

- processing y cannot add new information about x

If $x \rightarrow y \rightarrow z$ then $I(x; y) \geq I(x; y | z)$ *(even less)*

- Knowing z does not increase the amount y tells you about x

Proof:

Apply chain rule in different ways

$$I(x; y, z) = I(x; y) + \underbrace{I(x; z | y)}_{(a)} = I(x; z) + I(x; y | z)$$

$x \rightarrow y$: observation

$y \rightarrow z$: data processing but $I(x; z | y) = 0$

hence $I(x; y) = I(x; z) + I(x; y | z)$

so $I(x; y) \geq I(x; z)$ and $I(x; y) \geq I(x; y | z)$

(a) $I(x; z) = 0$ iff x and z are independent; Markov $\Rightarrow p(x, z | y) = p(x | y)p(z | y)$

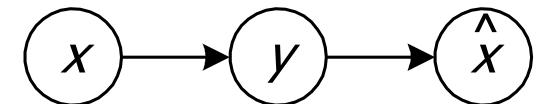
So Why Processing?

- One can not create information by manipulating the data
- But no information is lost if equality holds
- Sufficient statistic
 - z contains all the information in y about x
 - Preserves mutual information $I(x; y) = I(x; z)$
- The estimator should be designed in a way such that it outputs sufficient statistics
- Can the estimation be arbitrarily accurate?

Fano's Inequality

If we estimate x from y , what is $p_e = p(\hat{x} \neq x)$?

$$H(x|y) \leq H(p_e) + p_e \log |X|$$



$$\Rightarrow p_e \geq \frac{(H(x|y) - H(p_e))}{\log |X|} \stackrel{(a)}{\geq} \frac{(H(x|y) - 1)}{\log |X|}$$

(a) the second form is weaker but easier to use

Proof: Define a random variable $e = \begin{cases} 1 & \hat{x} \neq x \\ 0 & \hat{x} = x \end{cases}$

$$H(e, x | \hat{x}) = H(x | \hat{x}) + H(e | x, \hat{x}) = H(e | \hat{x}) + H(x | e, \hat{x}) \quad \text{chain rule}$$

$$\begin{aligned} \Rightarrow H(x | \hat{x}) + 0 &\leq H(e) + H(x | e, \hat{x}) && H \geq 0; H(e | y) \leq H(e) \\ &= H(e) + H(x | \hat{x}, e = 0)(1 - p_e) + H(x | \hat{x}, e = 1)p_e \\ &\leq H(p_e) + 0 \times (1 - p_e) + p_e \log |X| && H(e) = H(p_e) \end{aligned}$$

$$H(x | y) \leq H(x | \hat{x}) \text{ since } I(x; \hat{x}) \leq I(x; y) \quad \text{Markov chain}$$

Implications

- Zero probability of error $p_e = 0 \Rightarrow H(x|y) = 0$
- Low probability of error if $H(x|y)$ is small
- If $H(x|y)$ is large then the probability of error is high
- Could be slightly strengthened to

$$H(x|y) \leq H(p_e) + p_e \log(|X|-1)$$

- Fano's inequality is used whenever you need to show that errors are inevitable
 - E.g., Converse to channel coding theorem

Fano Example

$$X = \{1:5\}, p_x = [0.35, 0.35, 0.1, 0.1, 0.1]^T$$

$Y = \{1:2\}$ if $x \leq 2$ then $y = x$ with probability $6/7$
while if $x > 2$ then $y = 1$ or 2 with equal prob.

Our best strategy is to guess $\hat{x} = y$ ($x \rightarrow y \rightarrow \hat{x}$)

- $p_{x|y=1} = [0.6, 0.1, 0.1, 0.1, 0.1]^T$
- actual error prob: $p_e = 0.4$

Fano bound: $p_e \geq \frac{H(x|y) - 1}{\log(|X|-1)} = \frac{1.771 - 1}{\log(4)} = 0.3855$ **(exercise)**

Main use: to show when error free transmission is impossible since $p_e > 0$

Summary

- **Markov:** $x \rightarrow y \rightarrow z \Leftrightarrow p(z | x, y) = p(z | y) \Leftrightarrow I(x; z | y) = 0$
- **Data Processing Theorem:** if $x \rightarrow y \rightarrow z$ then
 - $I(x; y) \geq I(x; z), I(y; z) \geq I(x; z)$
 - $I(x; y) \geq I(x; y | z)$ can be false if not Markov
 - Long Markov chains: If $x_1 \rightarrow x_2 \rightarrow x_3 \rightarrow x_4 \rightarrow x_5 \rightarrow x_6$, then Mutual Information increases as you get closer together:
 - e.g. $I(x_3, x_4) \geq I(x_2, x_4) \geq I(x_1, x_5) \geq I(x_1, x_6)$
- **Fano's Inequality:** if $x \rightarrow y \rightarrow \hat{x}$ then

$$p_e \geq \frac{H(x | y) - H(p_e)}{\log(|X| - 1)} \geq \frac{H(x | y) - 1}{\log(|X| - 1)} \geq \frac{H(x | y) - 1}{\log |X|}$$

weaker but easier to use since independent of p_e

Lecture 7

- Law of Large Numbers
 - Sample mean is close to expected value
- Asymptotic Equipartition Principle (AEP)
 - $-\log P(x_1, x_2, \dots, x_n)/n$ is close to entropy H
- The Typical Set
 - Probability of each sequence close to 2^{-nH}
 - Size ($\sim 2^{nH}$) and total probability (~ 1)
- The Atypical Set
 - Unimportant and could be ignored

Typicality: Example

$$X = \{a, b, c, d\}, p = [0.5 \ 0.25 \ 0.125 \ 0.125]$$

$$-\log p = [1 \ 2 \ 3 \ 3] \Rightarrow H(p) = 1.75 \text{ bits}$$

Sample eight i.i.d. values

- typical \Rightarrow correct proportions

$$\text{adbabaac} \quad -\log p(\mathbf{x}) = 14 = 8 \times 1.75 = nH(\mathbf{x})$$

- not typical $\Rightarrow \log p(\mathbf{x}) \neq nH(\mathbf{x})$

$$\text{dddddddd} \quad -\log p(\mathbf{x}) = 24$$

Convergence of Random Variables

- Convergence

$$x_n \xrightarrow[n \rightarrow \infty]{} y \Rightarrow \forall \varepsilon > 0, \exists m \text{ such that } \forall n > m, |x_n - y| < \varepsilon$$

Example: $x_n = \pm 2^{-n}, \quad y = 0$

choose $m = -\log \varepsilon$

- Convergence in probability (weaker than convergence)

$$x_n \xrightarrow{\text{prob}} y \Rightarrow \forall \varepsilon > 0, \quad P(|x_n - y| > \varepsilon) \rightarrow 0$$

Example: $x_n \in \{0; 1\}, \quad p = [1 - n^{-1}; n^{-1}]$

for any small ε , $p(|x_n| > \varepsilon) = n^{-1} \xrightarrow{n \rightarrow \infty} 0$

so $x_n \xrightarrow{\text{prob}} 0$ (but $x_n \not\rightarrow 0$)

Note: y can be a constant or another random variable

Law of Large Numbers

Given i.i.d. $\{x_i\}$, sample mean $s_n = \frac{1}{n} \sum_{i=1}^n x_i$

$$- E s_n = E x = \mu \quad \text{Var } s_n = n^{-1} \text{Var } x = n^{-1} \sigma^2$$

As n increases, $\text{Var } s_n$ gets smaller and the values become clustered around the mean

LLN: $s_n \xrightarrow{\text{prob}} \mu$

$$\Leftrightarrow \forall \varepsilon > 0, \quad P(|s_n - \mu| > \varepsilon) \xrightarrow{n \rightarrow \infty} 0$$

The expected value of a random variable is equal to the long-term average when sampling repeatedly.

Asymptotic Equipartition Principle

- \mathbf{x} is the i.i.d. sequence $\{x_i\}$ for $1 \leq i \leq n$
 - Prob of a particular sequence is $p(\mathbf{x}) = \prod_{i=1}^n p(x_i)$
 - Average $E - \log p(\mathbf{x}) = n E - \log p(x_i) = nH(X)$

- AEP:

$$-\frac{1}{n} \log p(\mathbf{x}) \xrightarrow{\text{prob}} H(X)$$

- Proof:

$$-\frac{1}{n} \log p(\mathbf{x}) = -\frac{1}{n} \sum_{i=1}^n \log p(x_i)$$

law of large numbers

$$\xrightarrow{\text{prob}} E - \log p(x_i) = H(X)$$

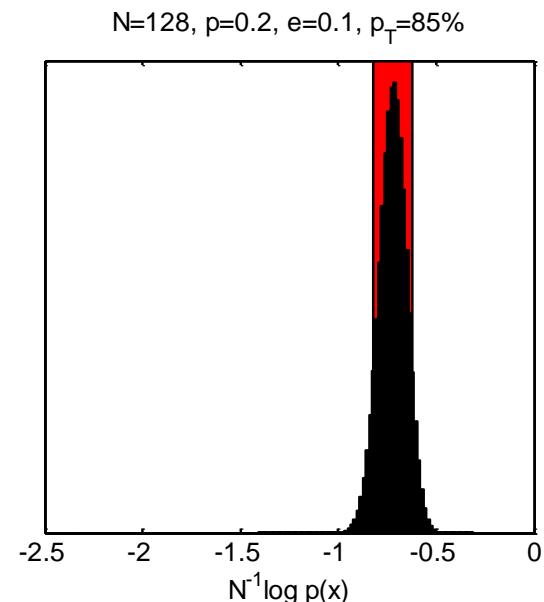
Typical Set

Typical set (for finite n)

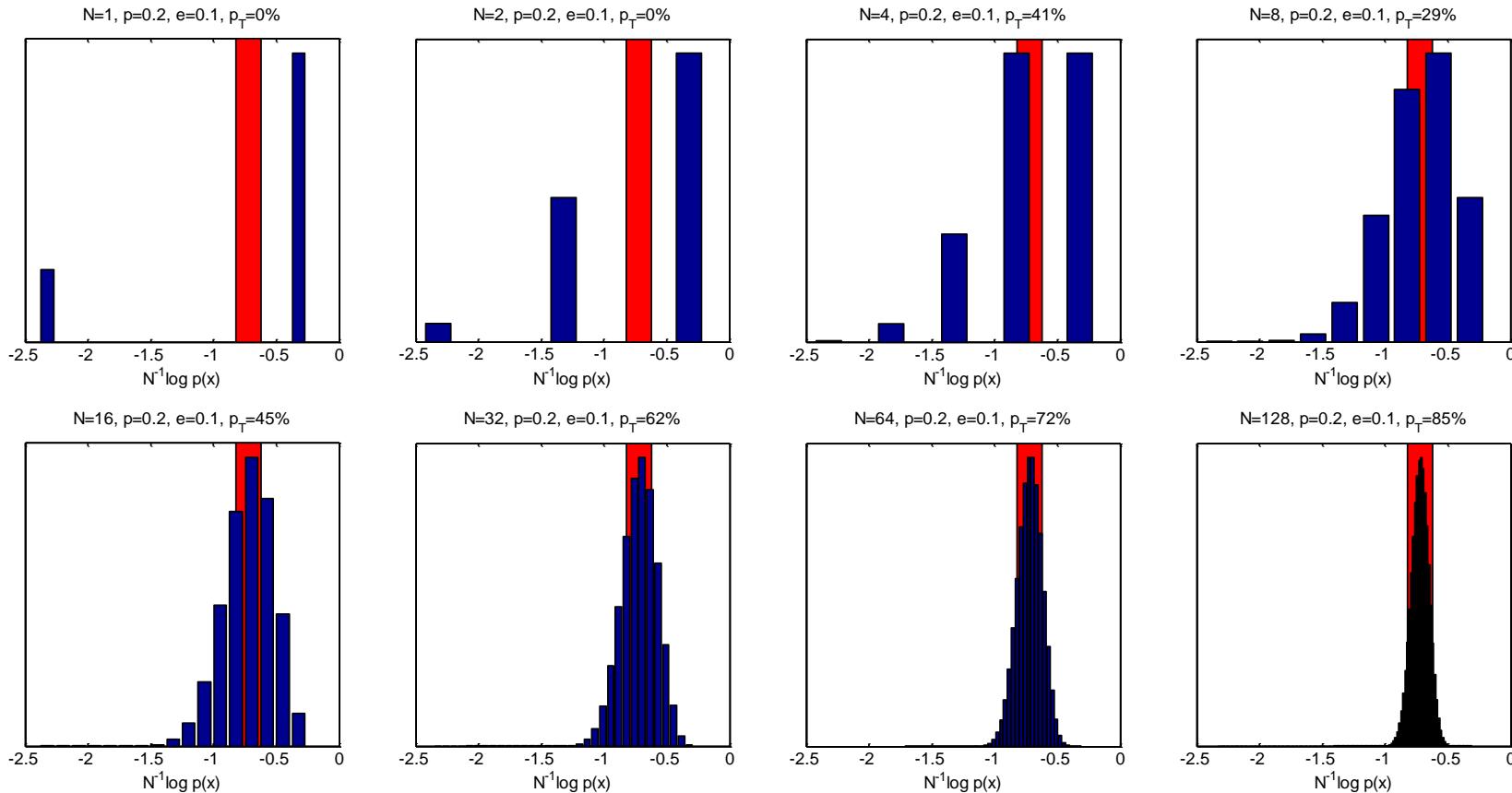
$$T_{\varepsilon}^{(n)} = \left\{ \mathbf{x} \in X^n : \left| -n^{-1} \log p(\mathbf{x}) - H(X) \right| < \varepsilon \right\}$$

Example:

- x_i Bernoulli with $p(x_i=1)=p$
- e.g. $p([0 \ 1 \ 1 \ 0 \ 0 \ 0])=p^2(1-p)^4$
- For $p=0.2$, $H(X)=0.72$ bits
- Red bar shows $T_{0.1}^{(n)}$



Typical Set Frames



Typical Set: Properties

$$\mathbf{x} \in T_{\varepsilon}^{(n)} \Rightarrow \log p(\mathbf{x}) = -nH(X) \pm n\varepsilon$$

$$p(\mathbf{x} \in T_{\varepsilon}^{(n)}) > 1 - \varepsilon \text{ for } n > N_{\varepsilon}$$

$$(1 - \varepsilon)2^{n(H(X) - \varepsilon)} < |T_{\varepsilon}^{(n)}| \leq 2^{n(H(X) + \varepsilon)}$$

Proof 2:

$$-n^{-1} \log p(\mathbf{x}) = n^{-1} \sum_{i=1}^n -\log p(x_i) \xrightarrow{\text{prob}} E - \log p(x_i) = H(X)$$

$$\text{Hence } \forall \varepsilon > 0 \exists N_{\varepsilon} \text{ s.t. } \forall n > N_{\varepsilon} \quad p(|-n^{-1} \log p(\mathbf{x}) - H(X)| > \varepsilon) < \varepsilon$$

Proof 3a:

$$\text{f.l.e. } n, \quad 1 - \varepsilon < p(\mathbf{x} \in T_{\varepsilon}^{(n)}) \leq \sum_{\mathbf{x} \in T_{\varepsilon}^{(n)}} 2^{-n(H(X) - \varepsilon)} = 2^{-n(H(X) - \varepsilon)} |T_{\varepsilon}^{(n)}|$$

Proof 3b:

$$1 = \sum_{\mathbf{x}} p(\mathbf{x}) \geq \sum_{\mathbf{x} \in T_{\varepsilon}^{(n)}} p(\mathbf{x}) \geq \sum_{\mathbf{x} \in T_{\varepsilon}^{(n)}} 2^{-n(H(X) + \varepsilon)} = 2^{-n(H(X) + \varepsilon)} |T_{\varepsilon}^{(n)}|$$

Consequence

- for any ε and for $n > N_\varepsilon$
 “Almost all events are almost equally surprising”

- $p(\mathbf{x} \in T_\varepsilon^{(n)}) > 1 - \varepsilon \quad \text{and} \quad \log p(\mathbf{x}) = -nH(x) \pm n\varepsilon$

Coding consequence

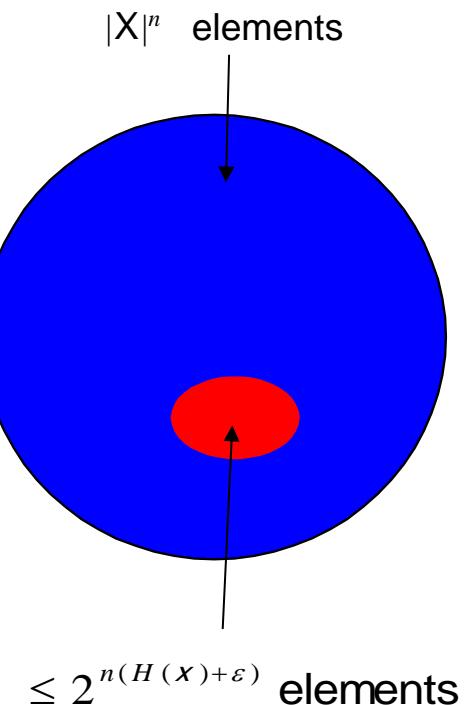
- $\mathbf{x} \in T_\varepsilon^{(n)}$: ‘0’ + at most $1+n(H+\varepsilon)$ bits
- $\mathbf{x} \notin T_\varepsilon^{(n)}$: ‘1’ + at most $1+n\log|\mathcal{X}|$ bits
- $L = \text{Average code length}$

$$\leq p(\mathbf{x} \in T_\varepsilon^{(n)})[2 + n(H + \varepsilon)]$$

$$+ p(\mathbf{x} \notin T_\varepsilon^{(n)})[2 + n \log |\mathcal{X}|]$$

$$\leq n(H + \varepsilon) + \varepsilon(n \log |\mathcal{X}|) + 2\varepsilon + 2$$

$$= n(H + \varepsilon + \varepsilon \log |\mathcal{X}| + 2(\varepsilon + 2)n^{-1}) = n(H + \varepsilon')$$



Source Coding & Data Compression

For any choice of $\varepsilon > 0$, we can, by choosing block size, n , large enough, do the following:

- make a lossless code using only $H(x) + \varepsilon$ bits per symbol on average:

$$\frac{L}{n} \leq H + \varepsilon$$

- The coding is one-to-one and decodable
 - However impractical due to exponential complexity
- Typical sequences have short descriptions of length $\approx nH$
 - Another proof of source coding theorem (Shannon's original proof)
- However, encoding/decoding complexity is exponential in n

Smallest high-probability Set

$T_\varepsilon^{(n)}$ is a small subset of X^n containing most of the probability mass. Can you get even smaller ?

For any $0 < \varepsilon < 1$, choose $N_0 = -\varepsilon^{-1} \log \varepsilon$, then for any $n > \max(N_0, N_\varepsilon)$ and any subset $S^{(n)}$ satisfying $|S^{(n)}| < 2^{n(H(x) - 2\varepsilon)}$

$$\begin{aligned}
 p(\mathbf{x} \in S^{(n)}) &= p(\mathbf{x} \in S^{(n)} \cap T_\varepsilon^{(n)}) + p(\mathbf{x} \in S^{(n)} \cap \overline{T_\varepsilon^{(n)}}) \\
 &< |S^{(n)}| \max_{\mathbf{x} \in T_\varepsilon^{(n)}} p(\mathbf{x}) + p(\mathbf{x} \in \overline{T_\varepsilon^{(n)}}) \\
 &< 2^{n(H - 2\varepsilon)} 2^{-n(H - \varepsilon)} + \varepsilon \quad \text{for } n > N_\varepsilon \\
 &= 2^{-n\varepsilon} + \varepsilon < 2\varepsilon \quad \text{for } n > N_0, \quad 2^{-n\varepsilon} < 2^{\log \varepsilon} = \varepsilon
 \end{aligned}$$

Answer: No

Summary

- Typical Set
 - Individual Prob $\mathbf{x} \in T_\varepsilon^{(n)} \Rightarrow \log p(\mathbf{x}) = -nH(x) \pm n\varepsilon$
 - Total Prob $p(\mathbf{x} \in T_\varepsilon^{(n)}) > 1 - \varepsilon \text{ for } n > N_\varepsilon$
 - Size $(1 - \varepsilon)2^{n(H(x) - \varepsilon)} < |T_\varepsilon^{(n)}| \leq 2^{n(H(x) + \varepsilon)}$
- No other high probability set can be much smaller than $T_\varepsilon^{(n)}$
- Asymptotic Equipartition Principle
 - Almost all event sequences are equally surprising
- Can be used to prove source coding theorem

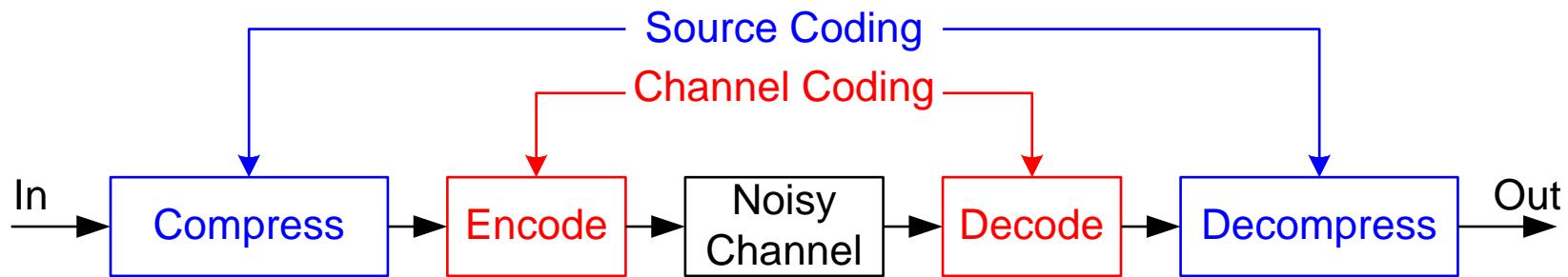
Lecture 8

- Channel Coding
- Channel Capacity
 - The highest rate in bits per channel use that can be transmitted reliably
 - The maximum mutual information
- Discrete Memoryless Channels
 - Symmetric Channels
 - Channel capacity
 - Binary Symmetric Channel
 - Binary Erasure Channel
 - Asymmetric Channel



◆ = proved in channel coding theorem

Model of Digital Communication



- **Source Coding**
 - Compresses the data to remove redundancy
- **Channel Coding**
 - Adds redundancy/structure to protect against channel errors

Discrete Memoryless Channel

- Input: $x \in X$, Output $y \in Y$



- Time-Invariant Transition-Probability Matrix

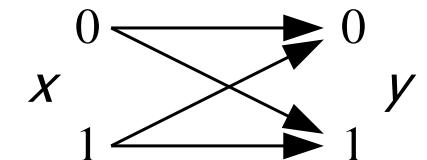
$$(\mathbf{Q}_{y|x})_{i,j} = p(y = y_j | x = x_i)$$

- Hence $\mathbf{p}_y = \mathbf{Q}_{y|x}^T \mathbf{p}_x$
- \mathbf{Q} : each row sum = 1, average column sum = $|X||Y|^{-1}$
- **Memoryless**: $p(y_n | x_{1:n}, y_{1:n-1}) = p(y_n | x_n)$
- **DMC** = Discrete Memoryless Channel

Binary Channels

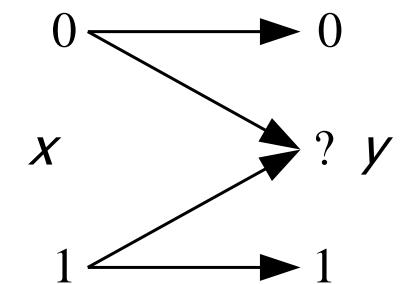
- Binary Symmetric Channel
 - $X = [0 \ 1]$, $Y = [0 \ 1]$

$$\begin{pmatrix} 1-f & f \\ f & 1-f \end{pmatrix}$$



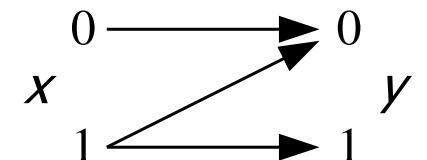
- Binary Erasure Channel
 - $X = [0 \ 1]$, $Y = [0 \ ? \ 1]$

$$\begin{pmatrix} 1-f & f & 0 \\ 0 & f & 1-f \end{pmatrix}$$



- Z Channel
 - $X = [0 \ 1]$, $Y = [0 \ 1]$

$$\begin{pmatrix} 1 & 0 \\ f & 1-f \end{pmatrix}$$



Symmetric: rows are permutations of each other; columns are permutations of each other
 Weakly Symmetric: rows are permutations of each other; columns have the same sum

Weakly Symmetric Channels

Weakly Symmetric:

1. All columns of \mathbf{Q} have the same sum = $|X||Y|^{-1}$

- If x is uniform (i.e. $p(x) = |X|^{-1}$) then y is uniform

$$p(y) = \sum_{x \in X} p(y|x)p(x) = |X|^{-1} \sum_{x \in X} p(y|x) = |X|^{-1} \times |X||Y|^{-1} = |Y|^{-1}$$

2. All rows are permutations of each other

- Each row of \mathbf{Q} has the same entropy so

$$H(Y|X) = \sum_{x \in X} p(x)H(Y|X=x) = H(\mathbf{Q}_{1,:})\sum_{x \in X} p(x) = H(\mathbf{Q}_{1,:})$$

where $\mathbf{Q}_{1,:}$ is the entropy of the first (or any other) row of the \mathbf{Q} matrix

Symmetric:

1. All rows are permutations of each other
2. All columns are permutations of each other

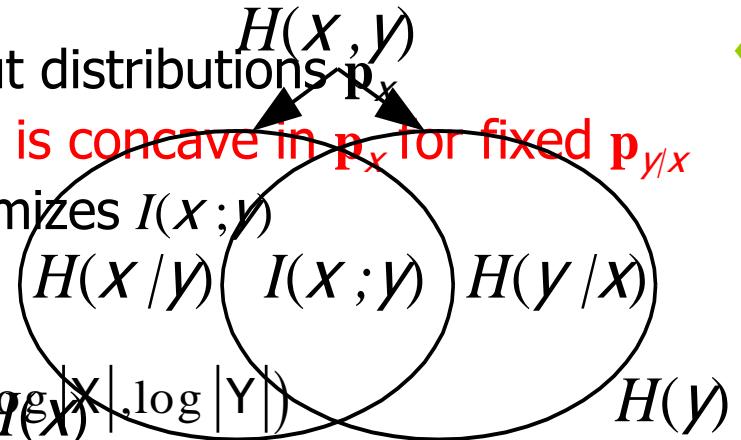
Symmetric \Rightarrow weakly symmetric

Channel Capacity

- Capacity of a DMC channel: $C = \max_{\mathbf{p}_x} I(x; y)$

- Mutual information (not entropy itself) is what could be transmitted through the channel
- Maximum is over all possible input distributions \mathbf{p}_x
- \exists only one maximum since $I(x; y)$ is concave in \mathbf{p}_x for fixed $\mathbf{p}_{y/x}$
- We want to find the \mathbf{p}_x that maximizes $I(x; y)$
- Limits on C :

$$0 \leq C \leq \min(H(X), H(Y)) \leq \min(H(X) + \log |Y|)$$

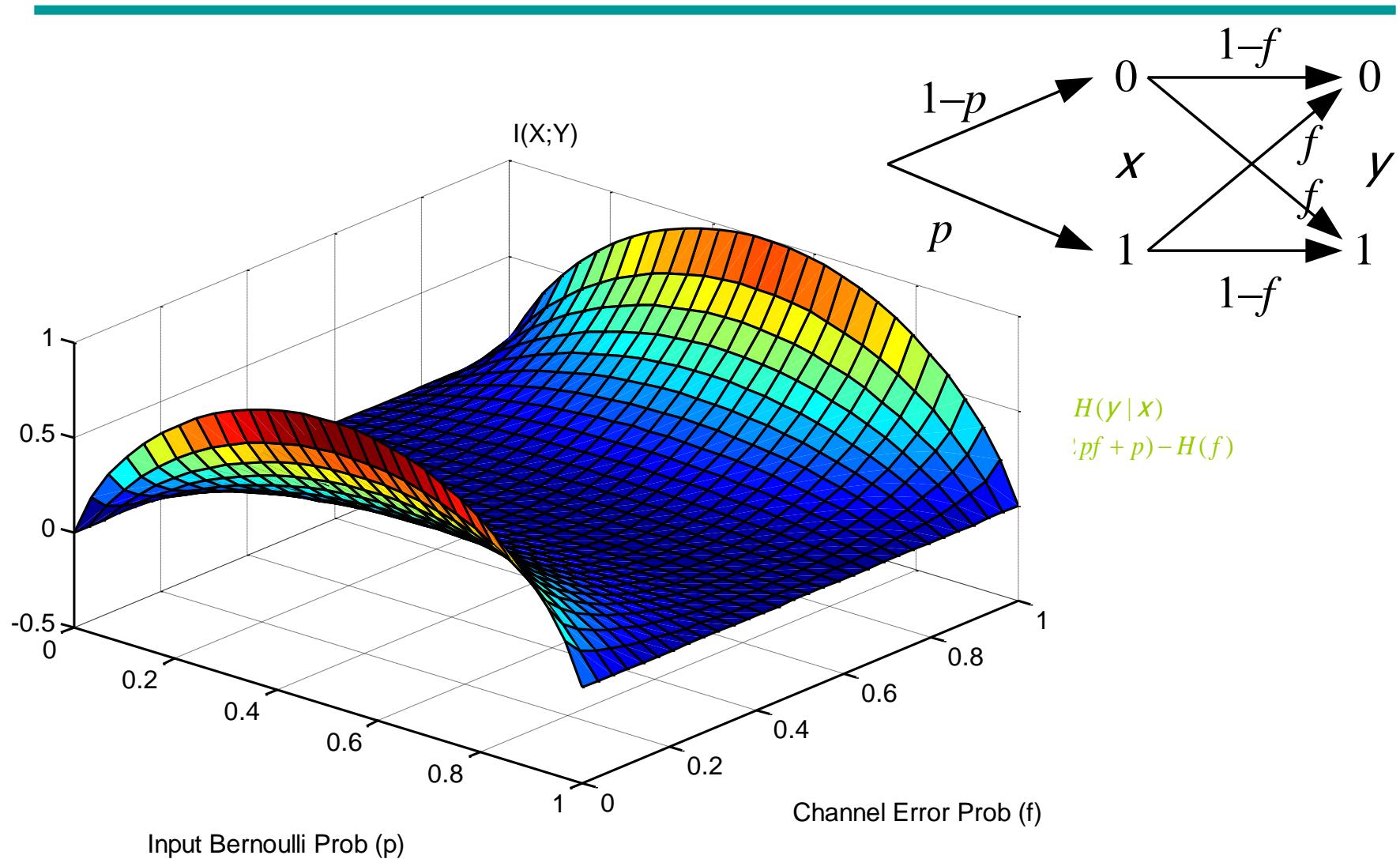


- Capacity for n uses of channel:

$$C^{(n)} = \frac{1}{n} \max_{\mathbf{p}_{x_{1:n}}} I(x_{1:n}; y_{1:n})$$

◆ = proved in two pages time

Mutual Information Plot



Mutual Information Concave in p_X

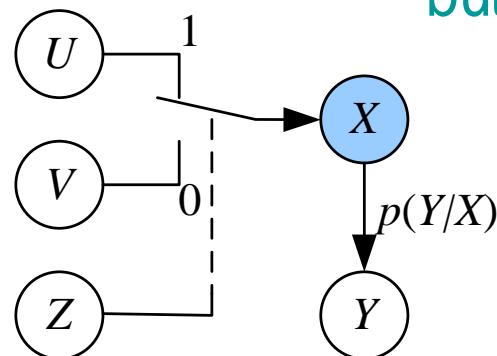
Mutual Information $I(x; y)$ is **concave** in p_X for fixed $p_{y/x}$

Proof: Let u and v have prob mass vectors p_u and p_v

- Define z : bernoulli random variable with $p(1) = \lambda$
- Let $x = u$ if $z=1$ and $x=v$ if $z=0 \Rightarrow p_x = \lambda p_u + (1-\lambda) p_v$

$$I(x, z; y) = I(x; y) + I(z; y | x) = I(z; y) + I(x; y | z)$$

but $I(z; y | x) = H(y | x) - H(y | x, z) = 0$ so



$$\begin{aligned} I(x; y) &\geq I(x; y | z) \\ &= \lambda I(x; y | z=1) + (1-\lambda) I(x; y | z=0) \\ &= \lambda I(u; y) + (1-\lambda) I(v; y) \end{aligned}$$

Special Case: $y=x \Rightarrow I(X; X)=H(X)$ is concave in p_X

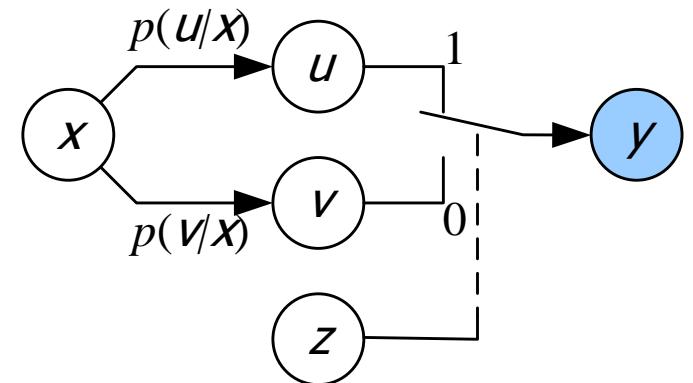
Mutual Information Convex in $p_{Y|X}$

Mutual Information $I(X;Y)$ is **convex** in $p_{Y|X}$ for fixed p_X

Proof: define u, v, x etc:

- $\mathbf{p}_{Y|X} = \lambda \mathbf{p}_{u|X} + (1 - \lambda) \mathbf{p}_{v|X}$

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



but $I(X;Z)=0$ and $I(X;Z|Y)\geq 0$ so

$$\begin{aligned} I(X;Y) &\leq I(X;Y|Z) \\ &= \lambda I(X;Y|Z=1) + (1 - \lambda) I(X;Y|Z=0) \\ &= \lambda I(X;U) + (1 - \lambda) I(X;V) \end{aligned}$$

n -use Channel Capacity

For Discrete Memoryless Channel:

$$\begin{aligned}
 I(\mathbf{x}_{1:n}; \mathbf{y}_{1:n}) &= H(\mathbf{y}_{1:n}) - H(\mathbf{y}_{1:n} | \mathbf{x}_{1:n}) \\
 &= \sum_{i=1}^n H(\mathbf{y}_i | \mathbf{y}_{1:i-1}) - \sum_{i=1}^n H(\mathbf{y}_i | \mathbf{x}_i) && \text{Chain; Memoryless} \\
 &\leq \sum_{i=1}^n H(\mathbf{y}_i) - \sum_{i=1}^n H(\mathbf{y}_i | \mathbf{x}_i) = \sum_{i=1}^n I(\mathbf{x}_i; \mathbf{y}_i) && \text{Conditioning Reduces Entropy}
 \end{aligned}$$

with equality if y_i are independent $\Rightarrow x_i$ are independent

We can maximize $I(\mathbf{x}; \mathbf{y})$ by maximizing each $I(\mathbf{x}_i; \mathbf{y}_i)$ independently and taking x_i to be i.i.d.

- We will concentrate on maximizing $I(x; y)$ for a single channel use
- The elements of X_i are not necessarily i.i.d.

Capacity of Symmetric Channel

If channel is **weakly symmetric**:

$$I(X;Y) = H(Y) - H(Y|X) = H(Y) - H(Q_{1,:}) \leq \log |Y| - H(Q_{1,:})$$

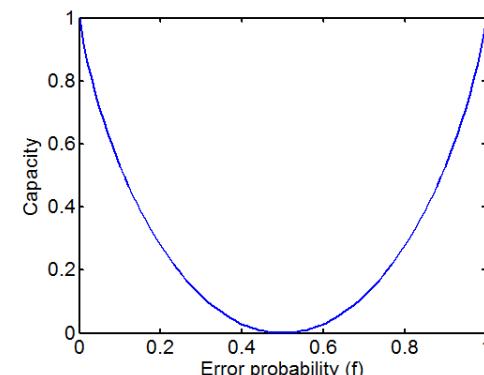
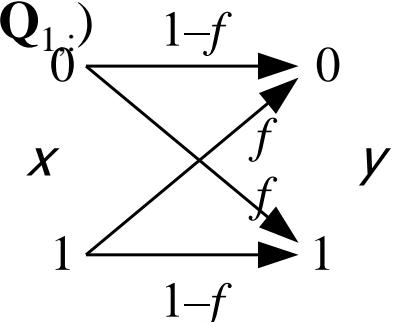
with equality iff input distribution is uniform

\therefore Information Capacity of a WS channel is $C = \log |Y| - H(Q_{1,:})$

For a **binary symmetric channel (BSC)**:

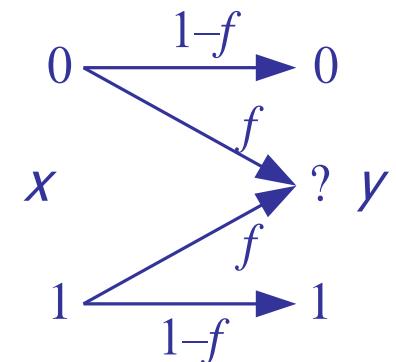
- $|Y| = 2$
- $H(Q_{1,:}) = H(f)$
- $I(X;Y) \leq 1 - H(f)$

\therefore Information Capacity of a BSC is $1 - H(f)$



Binary Erasure Channel (BEC)

$$\begin{pmatrix} 1-f & f & 0 \\ 0 & f & 1-f \end{pmatrix}$$



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

$$= H(x) - p(y = 0) \times 0 - p(y = ?) H(x) - p(y = 1) \times 0$$

$$= H(x) - H(x)f$$

$H(x|y) = 0$ when $y=0$ or $y=1$

$$= (1 - f)H(x)$$

$$\leq 1 - f$$

since max value of $H(x) = 1$

with equality when x is uniform

$$C = 1 - f$$

since a fraction f of the bits are lost, the capacity is only $1-f$ and this is achieved when x is uniform

Asymmetric Channel Capacity

Let $\mathbf{p}_x = [a \ a \ 1-2a]^T \Rightarrow \mathbf{p}_y = \mathbf{Q}^T \mathbf{p}_x = \mathbf{p}_x$

$$H(y) = -2a \log a - (1-2a) \log (1-2a)$$

$$H(y|x) = 2aH(f) + (1-2a)H(1) = 2aH(f)$$

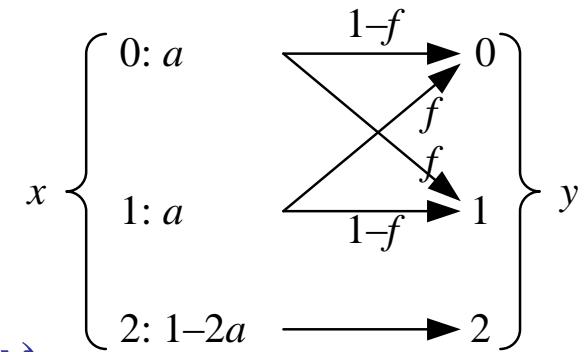
To find C , maximize $I(x;y) = H(y) - H(y|x)$

$$I = -2a \log a - (1-2a) \log (1-2a) - 2aH(f)$$

$$\frac{dI}{da} = -2 \log e - 2 \log a + 2 \log e + 2 \log(1-2a) - 2H(f) = 0$$

$$\log \frac{1-2a}{a} = \log(a^{-1} - 2) = H(f) \Rightarrow a = (2 + 2^{H(f)})^{-1}$$

$$\Rightarrow C = -2a \log(a 2^{H(f)}) - (1-2a) \log(1-2a) = -\log(1-2a)$$



Note:

$$d(\log x) = x^{-1} \log e$$

Examples: $f=0 \Rightarrow H(f)=0 \Rightarrow a=1/3 \Rightarrow C=\log 3 = 1.585$ bits/use
 $f=1/2 \Rightarrow H(f)=1 \Rightarrow a=1/4 \Rightarrow C=\log 2 = 1$ bits/use

Summary

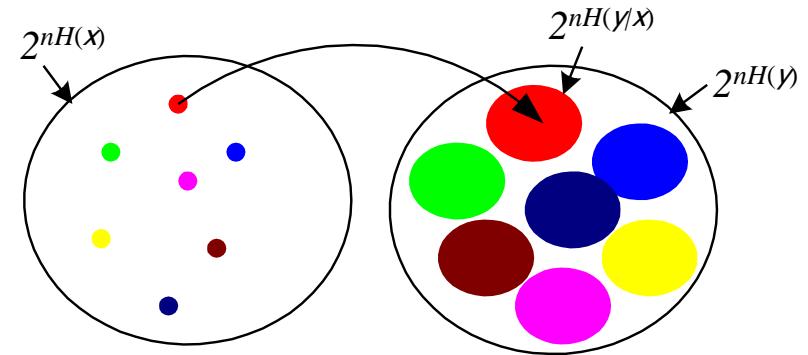
- Given the channel, mutual information is concave in input distribution
- Channel capacity $C = \max_{\mathbf{p}_x} I(x; y)$
 - The maximum exists and is unique
- DMC capacity
 - Weakly symmetric channel: $\log|\mathbf{Y}| - H(\mathbf{Q}_{1,:})$
 - BSC: $1 - H(f)$
 - BEC: $1 - f$
 - In general it very hard to obtain closed-form;
numerical method using convex optimization instead

Lecture 9

- Jointly Typical Sets
- Joint AEP
- Channel Coding Theorem
 - Ultimate limit on information transmission is channel capacity
 - The central and most successful story of information theory
 - Random Coding
 - Jointly typical decoding

Intuition on the Ultimate Limit

- Consider blocks of n symbols:



- For large n , an average input sequence $x_{1:n}$ corresponds to about $2^{nH(y|x)}$ typical output sequences
- There are a total of $2^{nH(y)}$ typical output sequences
- For nearly error free transmission, we select a number of input sequences whose corresponding sets of output sequences hardly overlap
- The maximum number of distinct **sets** of output sequences is $2^{n(H(y)-H(y|x))} = 2^{nI(y;x)}$
- One can send $I(y;x)$ bits per channel use
for large n can transmit at any rate $< C$ with negligible errors

Jointly Typical Set

\mathbf{x}, \mathbf{y} is the i.i.d. sequence $\{x_i, y_i\}$ for $1 \leq i \leq n$

- Prob of a particular sequence is $p(\mathbf{x}, \mathbf{y}) = \prod_{i=1}^N p(x_i, y_i)$
- $E - \log p(\mathbf{x}, \mathbf{y}) = n E - \log p(x_i, y_i) = nH(x, y)$
- Jointly Typical set:

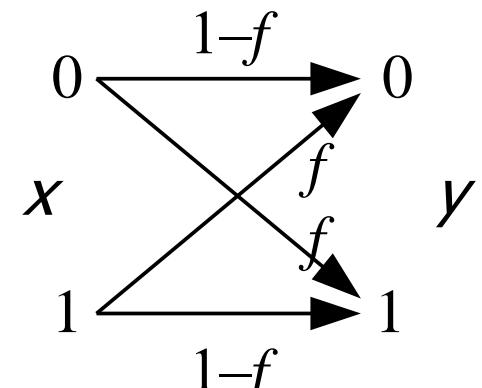
$$\begin{aligned} J_{\varepsilon}^{(n)} = \left\{ \mathbf{x}, \mathbf{y} \in \mathcal{X} \mathcal{Y}^n : \right. & \left| -n^{-1} \log p(\mathbf{x}) - H(x) \right| < \varepsilon, \\ & \left| -n^{-1} \log p(\mathbf{y}) - H(y) \right| < \varepsilon, \\ & \left. \left| -n^{-1} \log p(\mathbf{x}, \mathbf{y}) - H(x, y) \right| < \varepsilon \right\} \end{aligned}$$

Jointly Typical Example

Binary Symmetric Channel

$$f = 0.2, \quad \mathbf{p}_x = \begin{pmatrix} 0.75 & 0.25 \end{pmatrix}^T$$

$$\mathbf{p}_y = \begin{pmatrix} 0.65 & 0.35 \end{pmatrix}^T, \quad \mathbf{P}_{xy} = \begin{pmatrix} 0.6 & 0.15 \\ 0.05 & 0.2 \end{pmatrix}$$



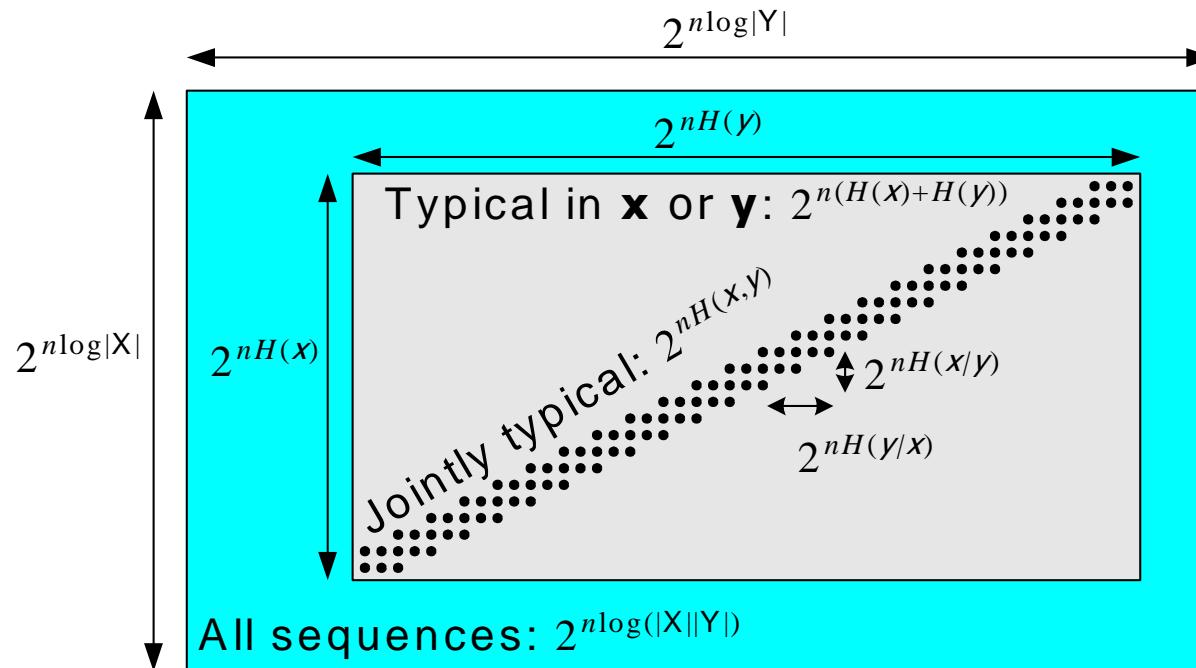
Jointly typical example (for any ε):

x = 1 1 1 1 1 0 0 0 0 0 0 0 0 0 0 0 0 0 0 0

all combinations of x and y have exactly the right frequencies

Jointly Typical Diagram

Each point defines both an **x** sequence and a **y** sequence



Dots represent
jointly typical
pairs (\mathbf{x}, \mathbf{y})

Inner rectangle
represents pairs
that are typical
in **x** or **y** but not
necessarily
jointly typical

- There are about $2^{nH(x)}$ typical \mathbf{x} 's in all
- Each typical \mathbf{y} is jointly typical with about $2^{nH(x,y)}$ of these typical \mathbf{x} 's
- The jointly typical pairs are a fraction $2^{-nI(x;y)}$ of the inner rectangle
- Channel Code: choose \mathbf{x} 's whose J.T. \mathbf{y} 's don't overlap; use J.T. for decoding
- There are $2^{nI(x;y)}$ such codewords \mathbf{x} 's

Joint Typical Set Properties

1. Indiv Prob: $\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)} \Rightarrow \log p(\mathbf{x}, \mathbf{y}) = -nH(x, y) \pm n\varepsilon$
2. Total Prob: $p(\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}) > 1 - \varepsilon \quad \text{for } n > N_{\varepsilon}$
3. Size: $(1 - \varepsilon)2^{n(H(x, y) - \varepsilon)} < |J_{\varepsilon}^{(n)}| \leq 2^{n(H(x, y) + \varepsilon)}$

Proof 2: (use weak law of large numbers)

Choose N_1 such that $\forall n > N_1, \quad p\left(\left| -n^{-1} \log p(\mathbf{x}) - H(x) \right| > \varepsilon \right) < \frac{\varepsilon}{3}$

Similarly choose N_2, N_3 for other conditions and set $N_{\varepsilon} = \max(N_1, N_2, N_3)$

Proof 3: $1 - \varepsilon < \sum_{\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}} p(\mathbf{x}, \mathbf{y}) \leq |J_{\varepsilon}^{(n)}| \max_{\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}} p(\mathbf{x}, \mathbf{y}) = |J_{\varepsilon}^{(n)}| 2^{-n(H(x, y) - \varepsilon)} \quad n > N_{\varepsilon}$

$$1 \geq \sum_{\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}} p(\mathbf{x}, \mathbf{y}) \geq |J_{\varepsilon}^{(n)}| \min_{\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}} p(\mathbf{x}, \mathbf{y}) = |J_{\varepsilon}^{(n)}| 2^{-n(H(x, y) + \varepsilon)} \quad \forall n$$

Properties

4. If $p_x = p_{x'}$ and $p_y = p_{y'}$ with x' and y' independent:

$$(1 - \varepsilon)2^{-n(I(x,y)+3\varepsilon)} \leq p(\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}) \leq 2^{-n(I(x,y)-3\varepsilon)} \text{ for } n > N_\varepsilon$$

Proof: $|J| \times (\text{Min Prob}) \leq \text{Total Prob} \leq |J| \times (\text{Max Prob})$

$$p(\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}) = \sum_{\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}} p(\mathbf{x}', \mathbf{y}') = \sum_{\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}} p(\mathbf{x}') p(\mathbf{y}')$$

$$\begin{aligned} p(\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}) &\leq |J_\varepsilon^{(n)}| \max_{\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}} p(\mathbf{x}') p(\mathbf{y}') \\ &\leq 2^{n(H(x,y)+\varepsilon)} 2^{-n(H(x)-\varepsilon)} 2^{-n(H(y)-\varepsilon)} = 2^{-n(I(x,y)-3\varepsilon)} \end{aligned}$$

$$\begin{aligned} p(\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}) &\geq |J_\varepsilon^{(n)}| \min_{\mathbf{x}', \mathbf{y}' \in J_\varepsilon^{(n)}} p(\mathbf{x}') p(\mathbf{y}') \\ &\geq (1 - \varepsilon) 2^{-n(I(x,y)+3\varepsilon)} \text{ for } n > N_\varepsilon \end{aligned}$$

Channel Coding



- Assume Discrete Memoryless Channel with known $\mathbf{Q}_{y|x}$
 - An (M, n) code is
 - A fixed set of M codewords $\mathbf{x}(w) \in \mathcal{X}^n$ for $w=1:M$
 - A deterministic decoder $g(\mathbf{y}) \in 1:M$
 - The rate of an (M,n) code: $R=(\log M)/n$ bits/transmission
 - Error probability $\lambda_w = p(g(\mathbf{y}(w)) \neq w) = \sum_{\mathbf{y} \in \mathcal{Y}^n} p(\mathbf{y} | \mathbf{x}(w)) \delta_{g(\mathbf{y}) \neq w}$
 - Maximum Error Probability $\lambda^{(n)} = \max_{1 \leq w \leq M} \lambda_w$
 - Average Error probability $P_e^{(n)} = \frac{1}{M} \sum_{w=1}^M \lambda_w$
- $\delta_C = 1$ if C is true or 0 if it is false

Shannon's ideas

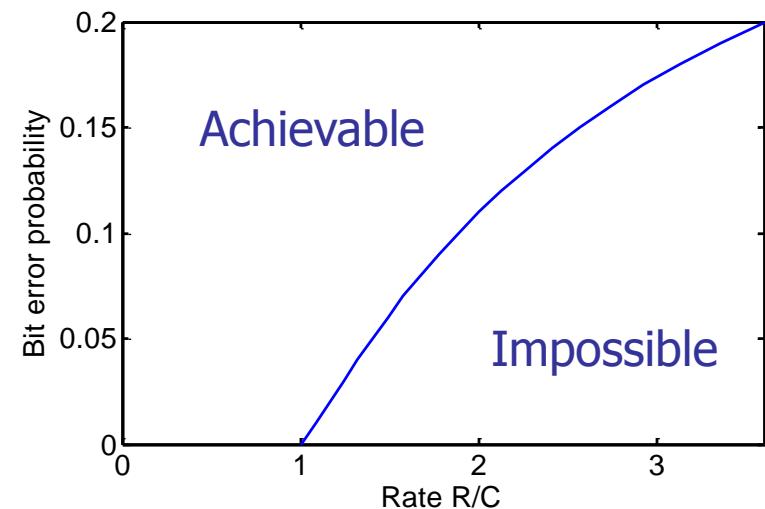
- Channel coding theorem: the basic theorem of information theory
 - Proved in his original 1948 paper
- How do you correct all errors?
- Shannon's ideas
 - Allowing arbitrarily small but nonzero error probability
 - Using the channel many times in succession so that AEP holds
 - Consider a **randomly** chosen code and show the expected **average** error probability is small
 - Use the idea of typical sequences
 - Show this means \exists at least one code with small max error prob
 - Sadly it doesn't tell you how to construct the code

Channel Coding Theorem

- A rate R is achievable if $R < C$ and not achievable if $R > C$
 - If $R < C$, \exists a sequence of $(2^{nR}, n)$ codes with max prob of error $\lambda^{(n)} \rightarrow 0$ as $n \rightarrow \infty$
 - Any sequence of $(2^{nR}, n)$ codes with max prob of error $\lambda^{(n)} \rightarrow 0$ as $n \rightarrow \infty$ must have $R \leq C$

A very counterintuitive result:

Despite channel errors you can get arbitrarily low bit error rates provided that $R < C$



Summary

- Jointly typical set

$$-\log p(\mathbf{x}, \mathbf{y}) = nH(X, Y) \pm n\varepsilon$$

$$p\left(\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}\right) > 1 - \varepsilon$$

$$\left|J_{\varepsilon}^{(n)}\right| \leq 2^{n(H(X, Y) + \varepsilon)}$$

$$(1 - \varepsilon)2^{-n(I(X, Y) + 3\varepsilon)} \leq p\left(\mathbf{x}', \mathbf{y}' \in J_{\varepsilon}^{(n)}\right) \leq 2^{-n(I(X, Y) - 3\varepsilon)}$$

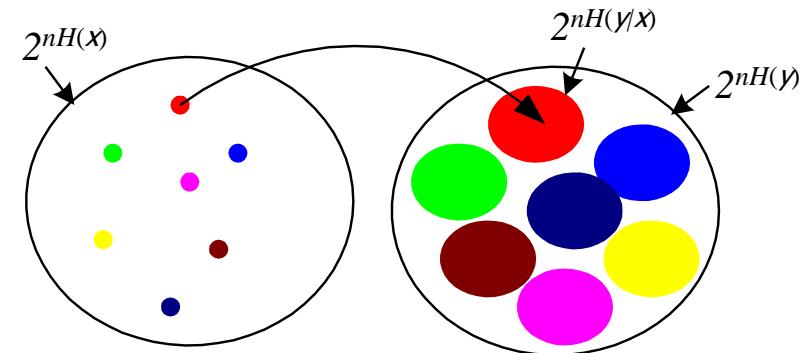
- Machinery to prove channel coding theorem

Lecture 10

- Channel Coding Theorem
 - Proof
 - Using joint typicality
 - Arguably the simplest one among many possible ways
 - Limitation: does not reveal $P_e \sim e^{-nE(R)}$
 - Converse (next lecture)

Channel Coding Principle

- Consider blocks of n symbols:



- An average input sequence $x_{1:n}$ corresponds to about $2^{nH(y|x)}$ typical output sequences
- Random Codes:** Choose $M = 2^{nR}$ ($R \leq I(x,y)$) random codewords $\mathbf{x}(w)$
 - their typical output sequences are unlikely to overlap much.
- Joint Typical Decoding:** A received vector \mathbf{y} is very likely to be in the typical output set of the transmitted $\mathbf{x}(w)$ and no others. Decode as this w .

Channel Coding Theorem: for large n , can transmit at any rate $R < C$ with negligible errors

Random $(2^{nR}, n)$ Code

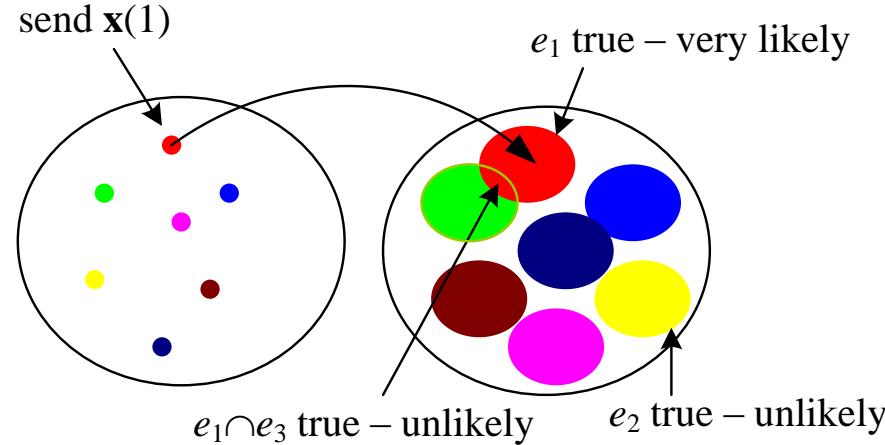
- Choose $\varepsilon \approx$ error prob, joint typicality $\Rightarrow N_\varepsilon$, choose $n > N_\varepsilon$
- Choose \mathbf{p}_x so that $I(x; y) = C$, the information capacity
- Use \mathbf{p}_x to choose a code \mathbf{C} with random $\mathbf{x}(w) \in \mathcal{X}^n$, $w=1:2^{nR}$
 - the receiver knows this code and also the transition matrix \mathbf{Q}
- Assume the message $W \in 1:2^{nR}$ is uniformly distributed
- If received value is y ; decode the message by seeing how many $\mathbf{x}(w)$'s are jointly typical with y
 - if $\mathbf{x}(k)$ is the only one then k is the decoded message
 - if there are 0 or ≥ 2 possible k 's then declare an error message 0
 - we calculate error probability averaged over all \mathbf{C} and all W

$$p(E) = \sum_C p(C) 2^{-nR} \sum_{w=1}^{2^{nR}} \lambda_w(C) = 2^{-nR} \sum_{w=1}^{2^{nR}} \sum_C p(C) \lambda_w(C) \stackrel{(a)}{=} \sum_C p(C) \lambda_1(C) = p(E | w=1)$$

(a) since error averaged over all possible codes is independent of w

Decoding Errors

- Assume we transmit $\mathbf{x}(1)$ and receive \mathbf{y}
- Define the J.T. events $e_w = \{(\mathbf{x}(w), \mathbf{y}) \in J_\varepsilon^{(n)}\}$ for $w \in 1 : 2^{nR}$



- Decode using joint typicality
- We have an error if either e_1 false or e_w true for $w \geq 2$
- The $\mathbf{x}(w)$ for $w \neq 1$ are independent of $\mathbf{x}(1)$ and hence also independent of \mathbf{y} . So $p(e_w \text{ true}) < 2^{-n(I(x,y)-3\varepsilon)}$ for any $w \neq 1$

Joint AEP

Error Probability for Random Code

- Upper bound

$$p(A \cup B) \leq p(A) + p(B)$$

$$\begin{aligned}
 p(E) &= p(E | W = 1) = p(\overline{e_1} \cup e_2 \cup e_3 \cup \dots \cup e_{2^{nR}}) \leq p(\overline{e_1}) + \sum_{w=2}^{2^{nR}} p(e_w) \\
 &\leq \varepsilon + \sum_{i=2}^{2^{nR}} 2^{-n(I(x;Y)-3\varepsilon)} < \varepsilon + 2^{nR} 2^{-n(I(x;Y)-3\varepsilon)} \quad (1) \text{ Joint typicality} \\
 &\leq \varepsilon + 2^{-n(C-R-3\varepsilon)} \leq 2\varepsilon \quad \text{for } R < C - 3\varepsilon \text{ and } n > -\frac{\log \varepsilon}{C - R - 3\varepsilon} \quad (2) \text{ Joint AEP}
 \end{aligned}$$

we have chosen $p(x)$ such that $I(x; Y) = C$

- Since average of $P(E)$ over all codes is $\leq 2\varepsilon$ there must be at least one code for which this is true: this code has $2^{-nR} \sum_w \lambda_w \leq 2\varepsilon$
- Now throw away the worst half of the codewords; the remaining ones must all have $\lambda_w \leq 4\varepsilon$. The resultant code has rate $R - n^{-1} \cong R$.

◆ = proved on next page

Code Selection & Expurgation

- Since average of $P(E)$ over all codes is $\leq 2\epsilon$ there must be at least one code for which this is true.

Proof:

$$2\epsilon \geq K^{-1} \sum_{i=1}^K P_{e,i}^{(n)} \geq K^{-1} \sum_{i=1}^K \min_i \left(P_{e,i}^{(n)} \right) = \min_i \left(P_{e,i}^{(n)} \right)$$

K = num of codes

- Expurgation: Throw away the worst half of the codewords; the remaining ones must all have $\lambda_w \leq 4\epsilon$.

Proof: Assume λ_w are in descending order

$$\begin{aligned} 2\epsilon &\geq M^{-1} \sum_{w=1}^M \lambda_w \geq M^{-1} \sum_{w=1}^{\frac{1}{2}M} \lambda_w \geq M^{-1} \sum_{w=1}^{\frac{1}{2}M} \lambda_{\frac{1}{2}M} \geq \frac{1}{2} \lambda_{\frac{1}{2}M} \\ \Rightarrow \quad \lambda_{\frac{1}{2}M} &\leq 4\epsilon \quad \Rightarrow \quad \lambda_w \leq 4\epsilon \quad \forall w > \frac{1}{2}M \end{aligned}$$

$$M' = \frac{1}{2} \times 2^{nR} \text{ messages in } n \text{ channel uses} \Rightarrow R' = n^{-1} \log M' = R - n^{-1}$$

Summary of Procedure

- For any $R < C - 3\epsilon$ set $n = \max \left\{ N_\epsilon, -(\log \epsilon) / (C - R - 3\epsilon), \epsilon^{-1} \right\}$
see (a),(b),(c) below
- Find the optimum p_X so that $I(X; Y) = C$
- Choosing codewords randomly (using p_X) to construct codes with 2^{nR} (a) codewords and using joint typicality as the decoder
- Since average of $P(E)$ over all codes is $\leq 2\epsilon$ there must be at least (b) one code for which this is true.
- Throw away the worst half of the codewords. Now the worst (c) codeword has an error prob $\leq 4\epsilon$ with rate $= R - n^{-1} > R - \epsilon$
- The resultant code transmits at a rate as close to C as desired with an error probability that can be made as small as desired (but n unnecessarily large).

Note: ϵ determines both error probability and closeness to capacity

Remarks

- Random coding is a powerful method of proof, not a method of signaling
- Picking randomly will give a good code
- But n has to be large (AEP)
- Without a structure, it is difficult to encode/decode
 - Table lookup requires exponential size
- Channel coding theorem does not provide a practical coding scheme
- Folk theorem (but outdated now):
 - Almost all codes are good, except those we can think of

Lecture 11

- Converse of Channel Coding Theorem
 - Cannot achieve $R > C$
- Capacity with feedback
 - No gain for DMC but simpler encoding/decoding
- Joint Source-Channel Coding
 - No point for a DMC



Converse of Coding Theorem

- Fano's Inequality: if $P_e^{(n)}$ is error prob when estimating w from \mathbf{y} ,

$$H(w | \mathbf{y}) \leq 1 + P_e^{(n)} \log |W| = 1 + nR P_e^{(n)}$$

- Hence $nR = H(w) = H(w | \mathbf{y}) + I(w; \mathbf{y})$

Definition of I

$$\leq H(w | \mathbf{y}) + I(\mathbf{x}(w); \mathbf{y})$$

Markov : $w \rightarrow \mathbf{x} \rightarrow \mathbf{y} \rightarrow \hat{w}$

$$\leq 1 + nR P_e^{(n)} + I(\mathbf{x}; \mathbf{y})$$

Fano

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

n -use DMC capacity

$$\Rightarrow P_e^{(n)} \geq \frac{R - C - n^{-1}}{R} \xrightarrow[n \rightarrow \infty]{} 1 - \frac{C}{R} > 0 \text{ if } R > C$$

- For large (hence for all) n , $P_e^{(n)}$ has a lower bound of $(R-C)/R$ if w equiprobable

- If achievable for small n , it could be achieved also for large n by concatenation.



Minimum Bit-Error Rate



Suppose

- $w_{1:nR}$ is i.i.d. bits with $H(w_i) = 1$
- The bit-error rate is $P_b = E_i \left\{ p(w_i \neq \hat{w}_i) \right\} \stackrel{\Delta}{=} E_i \left\{ p(e_i) \right\}$

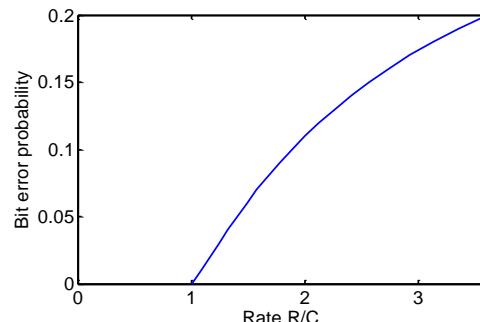
Then

$$\begin{aligned}
 nC &\stackrel{(a)}{\geq} I(X_{1:n}; Y_{1:n}) \stackrel{(b)}{\geq} I(w_{1:nR}; \hat{w}_{1:nR}) = H(w_{1:nR}) - H(w_{1:nR} | \hat{w}_{1:nR}) \\
 &= nR - \sum_{i=1}^{nR} H(w_i | \hat{w}_{1:nR}, w_{1:i-1}) \stackrel{(c)}{\geq} nR - \sum_{i=1}^{nR} H(w_i | \hat{w}_i) = nR \left(1 - E_i \left\{ H(w_i | \hat{w}_i) \right\} \right) \\
 &\stackrel{(d)}{=} nR \left(1 - E_i \left\{ H(e_i | \hat{w}_i) \right\} \right) \stackrel{(e)}{\geq} nR \left(1 - E_i \left\{ H(e_i) \right\} \right) \geq nR \left(1 - H(E_i P(e_i)) \right) = nR (1 - H(P_b))
 \end{aligned}$$

Hence

$$R \leq C(1 - H(P_b))^{-1}$$

$$P_b \geq H^{-1}(1 - C/R)$$

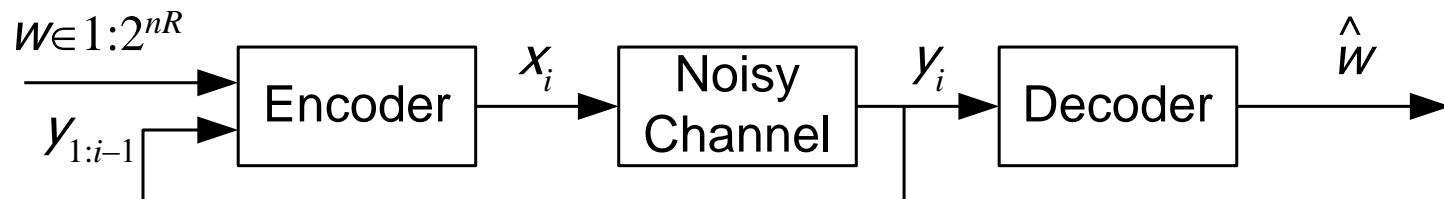


- (a) n-use capacity
- (b) Data processing theorem
- (c) Conditioning reduces entropy
- (d) $e_i = w_i \oplus \hat{w}_i$
- (e) Jensen: $E H(x) \leq H(E x)$

Coding Theory and Practice

- Construction for good codes
 - Ever since Shannon founded information theory
 - **Practical**: Computation & memory $\propto n^k$ for some k
- Repetition code: rate $\rightarrow 0$
- Block codes: encode a block at a time
 - Hamming code: correct one error
 - Reed-Solomon code, BCH code: multiple errors (1950s)
- Convolutional code: convolve bit stream with a filter
- Concatenated code: RS + convolutional
- Capacity-approaching codes:
 - Turbo code: combination of two interleaved convolutional codes (1993)
 - Low-density parity-check (LDPC) code (1960)
 - **Dream has come true for some channels today**

Channel with Feedback



- Assume error-free feedback: does it increase capacity ?
- A $(2^{nR}, n)$ feedback code is
 - A sequence of mappings $x_i = x_i(w, y_{1:i-1})$ for $i=1:n$
 - A decoding function $\hat{w} = g(y_{1:n})$
- A rate R is **achievable** if \exists a sequence of $(2^{nR}, n)$ feedback codes such that $P_e^{(n)} = P(\hat{w} \neq w) \xrightarrow{n \rightarrow \infty} 0$
- Feedback capacity, $C_{FB} \geq C$, is the sup of achievable rates

Feedback Doesn't Increase Capacity

$$\begin{aligned}
 I(W; \mathbf{y}) &= H(\mathbf{y}) - H(\mathbf{y} | W) \\
 &= H(\mathbf{y}) - \sum_{i=1}^n H(y_i | y_{1:i-1}, W) \\
 &= H(\mathbf{y}) - \sum_{i=1}^n H(y_i | y_{1:i-1}, W, x_i) \\
 &= H(\mathbf{y}) - \sum_{i=1}^n H(y_i | x_i) \\
 &\leq \sum_{i=1}^n H(y_i) - \sum_{i=1}^n H(y_i | x_i) = \sum_{i=1}^n I(x_i; y_i) \leq nC
 \end{aligned}$$



since $x_i = x_i(w, y_{1:i-1})$

since y_i only directly depends on x_i

cond reduces ent
DMC

Hence

$$nR = H(W) = H(W | \mathbf{y}) + I(W; \mathbf{y}) \leq 1 + nRP_e^{(n)} + nC \quad \text{Fano}$$

$$\Rightarrow P_e^{(n)} \geq \frac{R - C - n^{-1}}{R} \quad \rightarrow \text{Any rate } > C \text{ is unachievable}$$

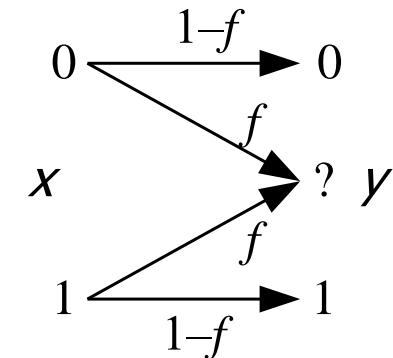
The DMC does not benefit from feedback: $C_{FB} = C$

Example: BEC with feedback

- Capacity is $1 - f$
- Encode algorithm
 - If $y_i = ?$, tell the sender to retransmit bit i
 - Average number of transmissions per bit:

$$1 + f + f^2 + \dots = \frac{1}{1 - f}$$

- Average number of successfully recovered bits per transmission = $1 - f$
 - Capacity is achieved!
- Capacity unchanged but encoding/decoding algorithm much simpler.



Joint Source-Channel Coding



- Assume w_i satisfies AEP and $|W| < \infty$
 - Examples: i.i.d.; Markov; stationary ergodic
- Capacity of DMC channel is C
 - if time-varying: $C = \lim_{n \rightarrow \infty} n^{-1} I(\mathbf{x}; \mathbf{y})$
- Joint Source-Channel Coding Theorem:

$$\exists \text{ codes with } P_e^{(n)} = P(\hat{w}_{1:n} \neq w_{1:n}) \xrightarrow[n \rightarrow \infty]{} 0 \quad \text{iff } H(W) < C$$
 - errors arise from two reasons
 - Incorrect encoding of \mathbf{w}
 - Incorrect decoding of \mathbf{y}

◆ = proved on next page

Source-Channel Proof (\Leftarrow)

- Achievability is proved by using two-stage encoding
 - Source coding
 - Channel coding
- For $n > N_\varepsilon$ there are only $2^{n(H(W)+\varepsilon)}$ **w's** in the typical set: encode using $n(H(W)+\varepsilon)$ bits
 - encoder error $< \varepsilon$
- Transmit with error prob less than ε so long as $H(W)+\varepsilon < C$
- Total error prob $< 2\varepsilon$

Source-Channel Proof (\Rightarrow)



Fano's Inequality: $H(\mathbf{w} | \hat{\mathbf{w}}) \leq 1 + P_e^{(n)} n \log |\mathcal{W}|$

$$\begin{aligned}
 H(W) &\leq n^{-1} H(W_{1:n}) && \text{entropy rate of stationary process} \\
 &= n^{-1} H(W_{1:n} | \hat{W}_{1:n}) + n^{-1} I(W_{1:n}; \hat{W}_{1:n}) && \text{definition of } I \\
 &\leq n^{-1} (1 + P_e^{(n)} n \log |\mathcal{W}|) + n^{-1} I(X_{1:n}; Y_{1:n}) && \text{Fano + Data Proc Inequ} \\
 &\leq n^{-1} + P_e^{(n)} \log |\mathcal{W}| + C && \text{Memoryless channel}
 \end{aligned}$$

Let $n \rightarrow \infty \Rightarrow P_e^{(n)} \rightarrow 0 \Rightarrow H(W) \leq C$

Separation Theorem

- **Important result:** source coding and channel coding might as well be done separately since same capacity
 - Joint design is more difficult
- Practical implication: for a **DMC** we can design the source encoder and the channel coder separately
 - Source coding: efficient compression
 - Channel coding: powerful error-correction codes
- Not necessarily true for
 - Correlated channels
 - Multiuser channels
- Joint source-channel coding: still an area of research
 - Redundancy in human languages helps in a noisy environment

Summary

- Converse to channel coding theorem
 - Proved using Fano's inequality
 - Capacity is a clear dividing point:
 - If $R < C$, error prob. $\rightarrow 0$
 - Otherwise, error prob. $\rightarrow 1$
- Feedback doesn't increase the capacity of DMC
 - May increase the capacity of memory channels (e.g., ARQ in TCP/IP)
- Source-channel separation theorem for DMC and stationary sources

Lecture 12

- Polar codes
 - Channel polarization
 - How to construct polar codes
 - Encoding and decoding
- Polar source coding
- Extension

About Polar Codes

- Provably capacity-achieving
- Encoding complexity $O(N \log N)$
- Successive decoding complexity
 $O(N \log N)$
- Probability of error $\approx 2^{-\sqrt{N}}$
- Main idea: channel polarization

What Is Channel Polarization?

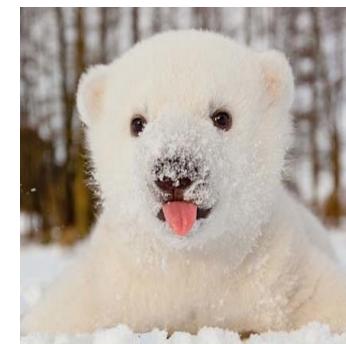
- Normal channel
- Extreme channel



sometimes cute,
sometimes lazy,
hard to manage



Useless
channel



Perfect
channel

Channel Polarization

- Among all channels, there are two classes which are easy to communicate optimally
 - The perfect channels
the output Y determines the input X
 - The useless channels
 Y is independent of X
- Polarization is a technique to convert noisy channels to a mixture of **extreme** channels
 - The process is **information-conserving**

Generator Matrix

- Generator Matrix

$$\mathbf{F}_N = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}^{\otimes n}, N = 2^n$$

$\otimes n$ denotes the n -fold Kronecker product.

- Example

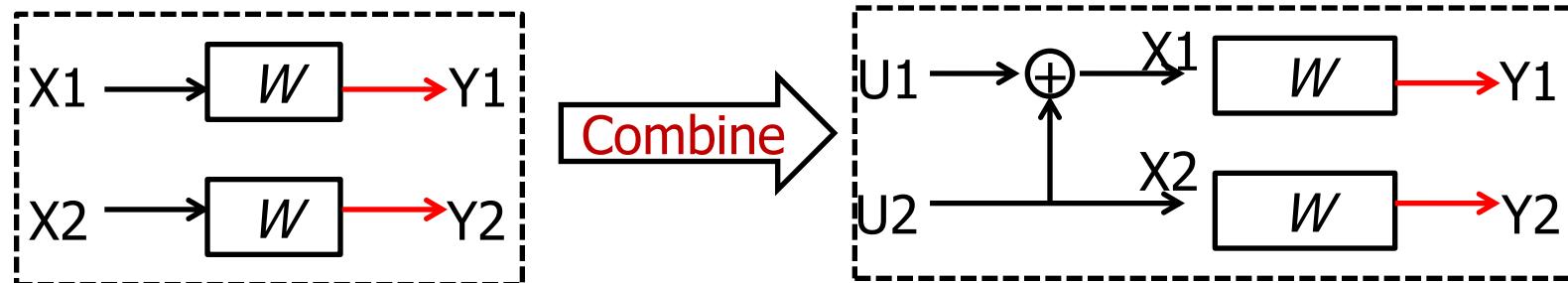
$$\mathbf{F}_2 = \begin{bmatrix} 1 & 0 \\ 1 & 1 \end{bmatrix}, \mathbf{F}_4 = \begin{bmatrix} \mathbf{F}_2 & 0 \\ \mathbf{F}_2 & \mathbf{F}_2 \end{bmatrix} \text{ and so on.}$$

- Encoding

Let \mathbf{u} be the length- N input to the encoder, then $\mathbf{x} = \mathbf{u}\mathbf{F}_N$ is the codeword.

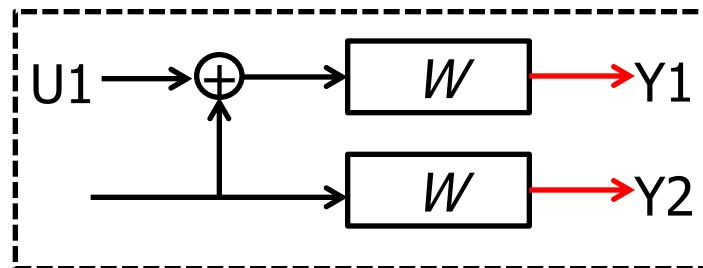
Channel Combining and Splitting

- Basic operation ($N = 2$)

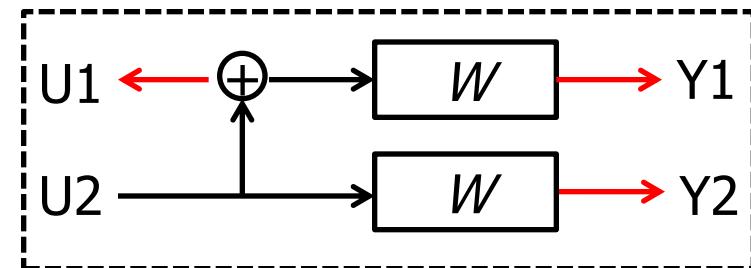


Channel splitting

$$(X_1, X_2) = (U_1, U_2) F_2$$



$$W^-: U_1 \rightarrow (Y_1, Y_2)$$



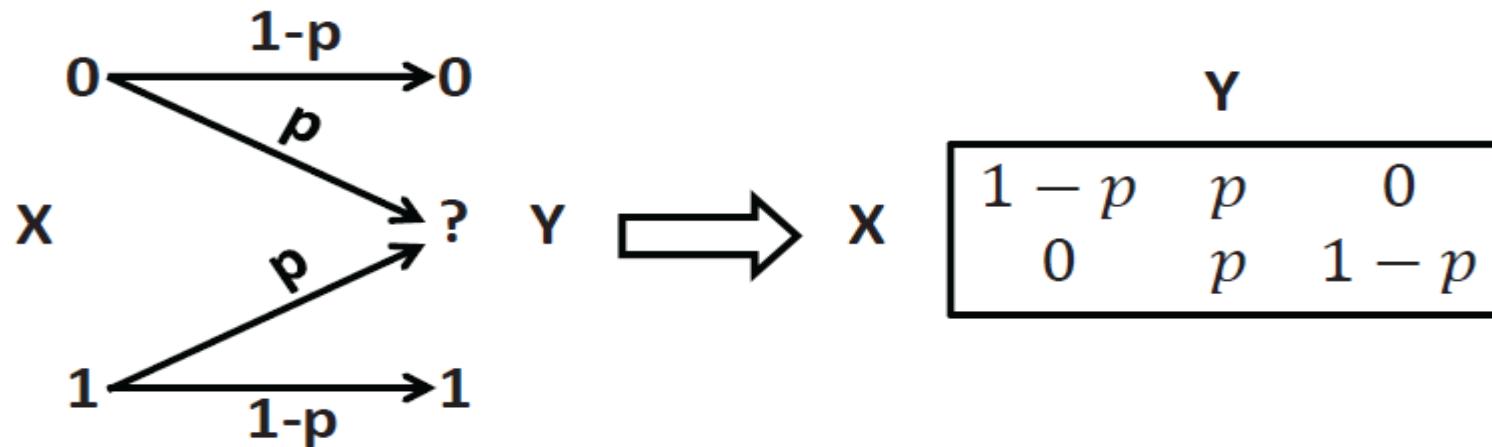
$$W^+: U_2 \rightarrow (Y_1, Y_2, U_1)$$

What Happens?

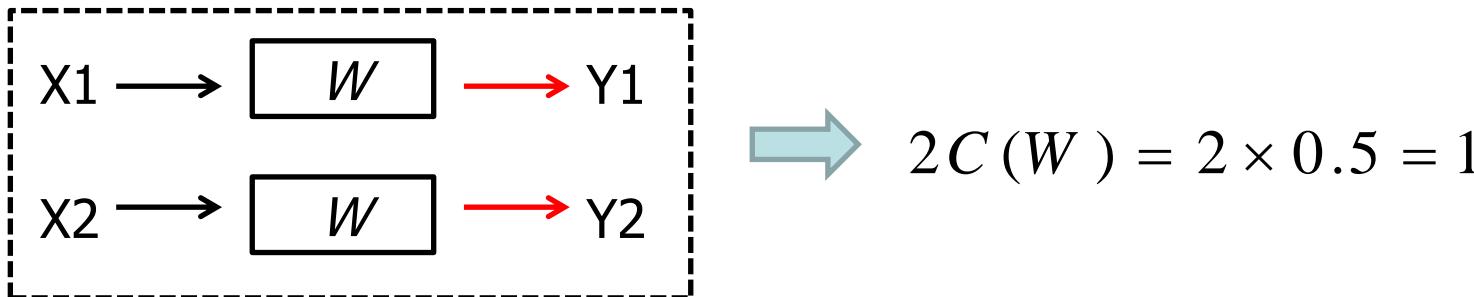
- Suppose W is a BEC(p), i.e., $Y=X$ with probability $1-p$, and $Y=?$ (erasure) with probability p .
 - W^- has input U_1 and output $(Y_1, Y_2)=(U_1+U_2, U_2)$ or $(?, U_2)$ or $(U_1+U_2, ?)$ or $(?, ?)$.
 - W^- is a BEC($2p - p^2$)
 - W^+ has input U_2 and output $(Y_1, Y_2, U_1)=(U_1+U_2, U_2, U_1)$ or $(?, U_2, U_1)$ or $(U_1+U_2, ?, U_1)$ or $(?, ?, U_1)$.
 - W^+ is a BEC(p^2)
- W^- is **worse** than W , and W^+ is **better** (recall capacity $C(W)=1-p$).
 - $C(W^-) + C(W^+) = 2C(W)$
 - $C(W^-) \leq C(W) \leq C(W^+)$

Example: BEC(0.5)

- W is a BEC with erasure probability $p = 0.5$.

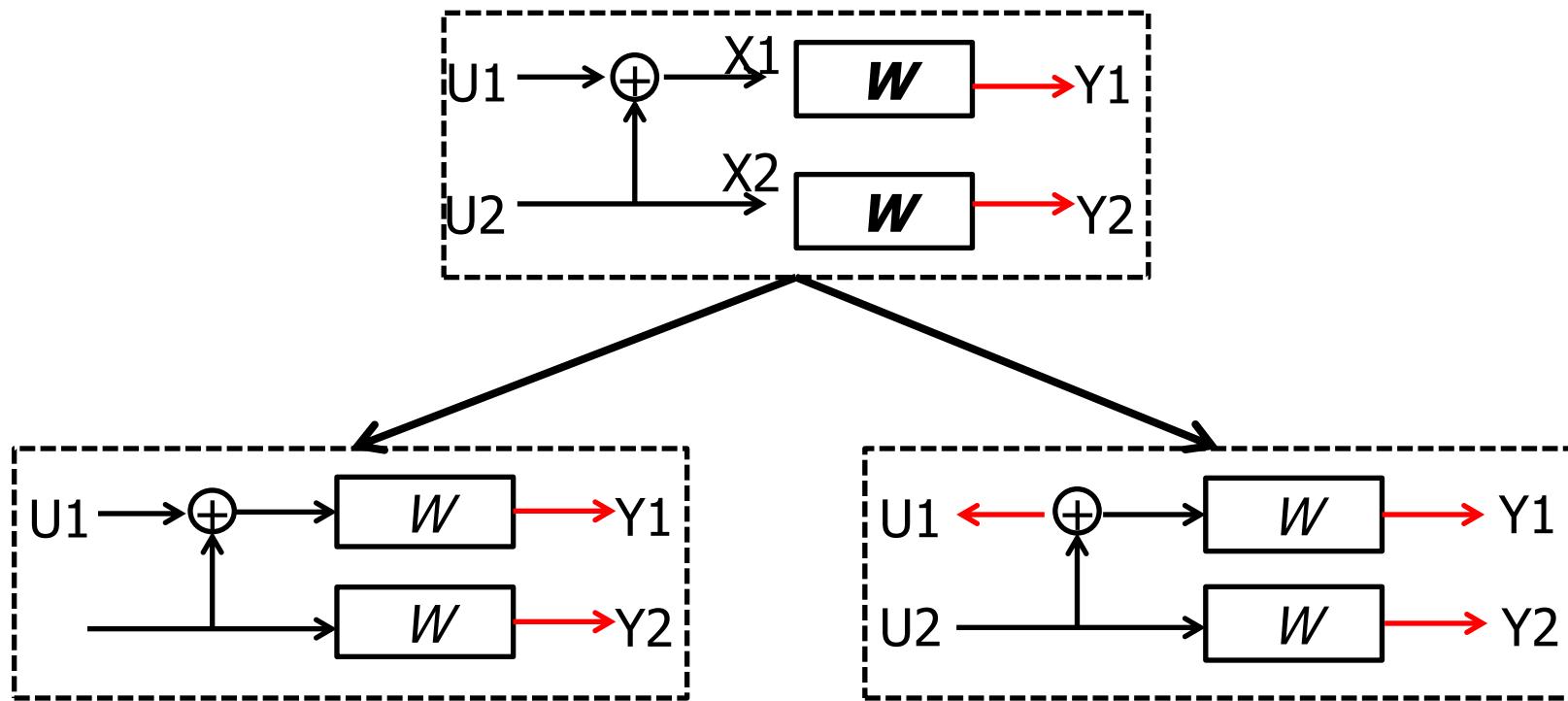


- If we use two copies of W separately



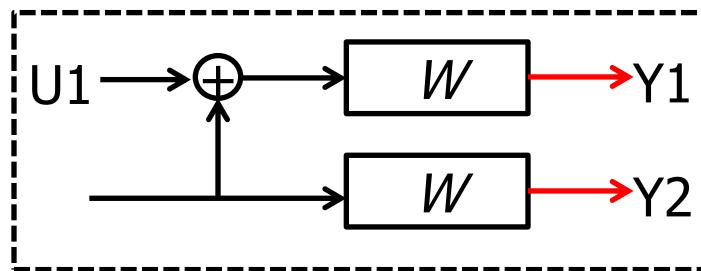
Example: BEC(0.5)

- Channel combining and splitting



Example: BEC(0.5)

- Channel W^-



$$C(W^-) = 4 \times \frac{1}{16} \log 2 = 0.25$$

(Y1,Y2)

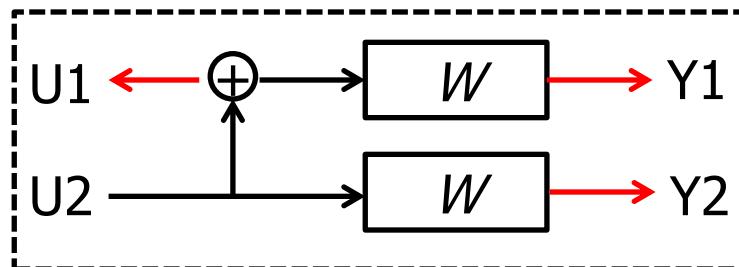
Transitional probabilities

	00	0?	01	?0	??	?1	10	1?	11	
U1	0	1/8	1/8	0	1/8	1/4	1/8	0	1/8	1/8
	1	0	1/8	1/8	1/8	1/4	1/8	1/8	1/8	0



Example: BEC(0.5)

- Channel W^+



$$C(W^+) = 12 \times \frac{1}{16} \log 2 = 0.75$$

$$C(W^-) + C(W^+) = 2C(W)$$

$$C(W^-) < C(W) < C(W^+)$$

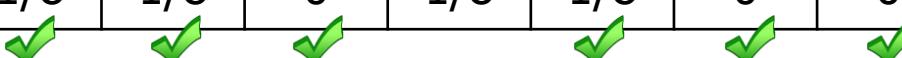
(Y_1, Y_2, U_1)

Transitional probabilities

	000	0?0	010	?00	?0?	?10	100	1?0	110
0	1/8	1/8	0	1/8	1/8	0	0	0	0
1	0	0	0	0	1/8	1/8	0	1/8	1/8

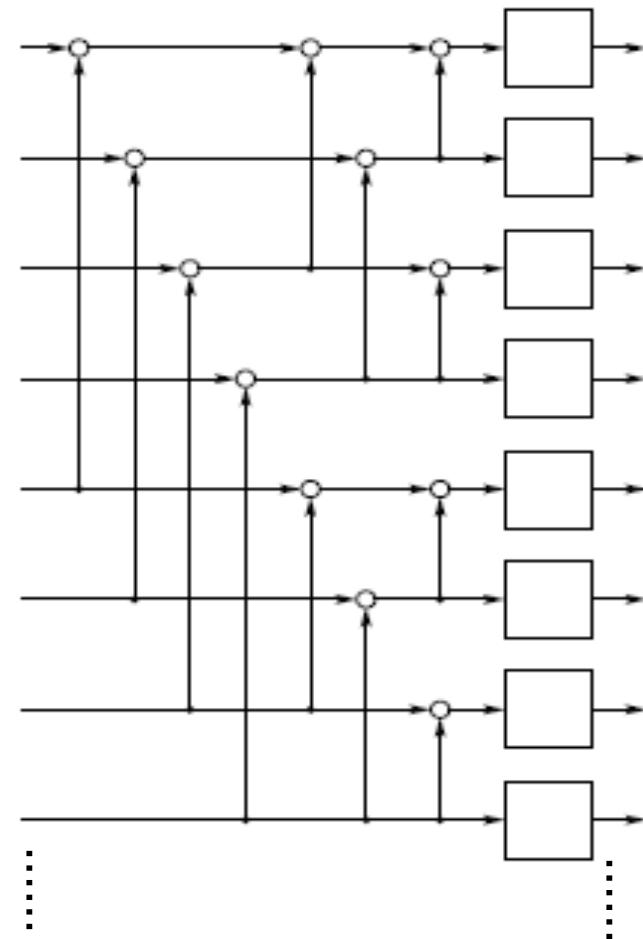
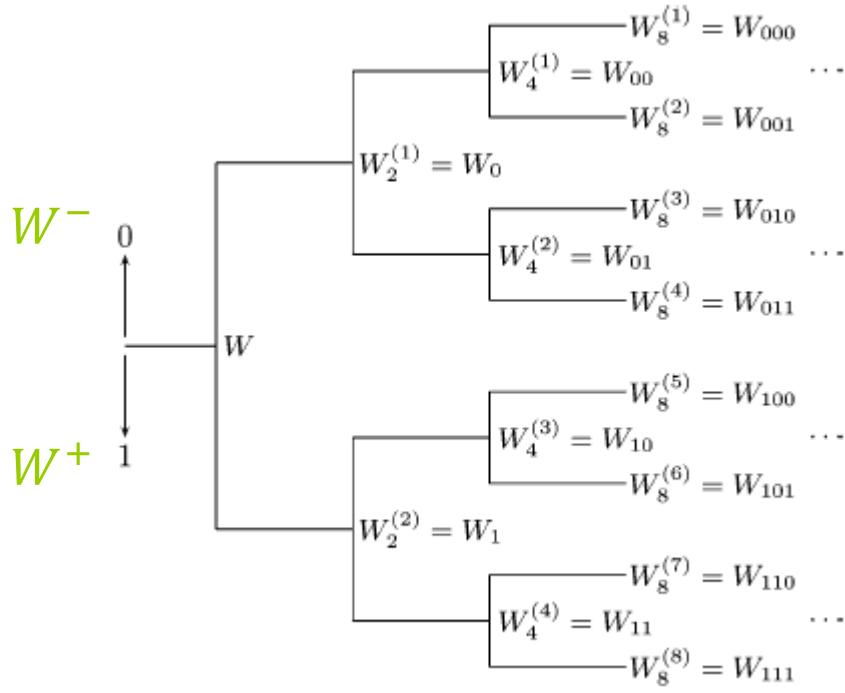
U_2

	001	0?1	011	?01	?11	?11	101	1?1	111
0	0	0	0	1/8	1/8	0	1/8	1/8	0
1	0	1/8	1/8	0	1/8	1/8	0	0	0



More Polarization

- Repeating this, we obtain N 'bit channels' at the n -th step.
- More conveniently, this process can be described as a binary tree.
–Note how the 'bit channels' $W_{b_1 b_2 \dots b_n}$ are labelled in the tree.



Martingale

- Now pick a ‘bit channel’ uniformly at random on the n -th level of the tree, which is equivalent to a random traverse on the tree, namely, at each step the r.v b_i takes the value of 0 or 1 with equal probability.
- We claim capacity C_n at the n -th step is a **martingale**.
- **Proof:** By information-preserving

$$\begin{aligned} E[C_{n+1}|b_1, \dots, b_n] &= \frac{1}{2} C(W_{b_1 b_2 \dots b_n 0}) + \frac{1}{2} C(W_{b_1 b_2 \dots b_n 1}) \\ &= C(W_{b_1 b_2 \dots b_n}) = C_n \end{aligned}$$

- By the martingale convergence theorem, C_n converges to a random variable C_∞ such that $E[C_\infty] = E[C_0] = C_0 = C(W)$.
- In fact, the limit $C_\infty = 0$ or 1 is a binary random variable (these are the fixed points of the polar transform).

Review of Martingales

- Let $\{X_n, n \geq 0\}$ be a random process. If
$$E[X_{n+1}|X_n, \dots, X_1, X_0] = X_n$$
then $\{X_n\}$ is referred to as a **martingale**.
- **Martingale convergence theorem:** Let $\{X_n, n \geq 0\}$ be a martingale with finite means. Then there exists a random variable X_∞ such that
$$X_n \rightarrow X_\infty \text{ almost surely}$$
as $n \rightarrow \infty$.

How to construct polar codes

- To achieve $C(W)$, we need to identify the indices of those bit channels (branches in tree) with capacity ≈ 1 .
- For BEC, this can be computed recursively
$$C(W_{b_1 b_2 \dots b_n 0}) = C(W_{b_1 b_2 \dots b_n})^2$$
$$C(W_{b_1 b_2 \dots b_n 1}) = 2C(W_{b_1 b_2 \dots b_n}) - C(W_{b_1 b_2 \dots b_n})^2$$
- For other types of channels, it is difficult to obtain closed-form formulas. So numerical computation is often used.

Polarization Speed

- For any positive real number $\beta < 0.5$,

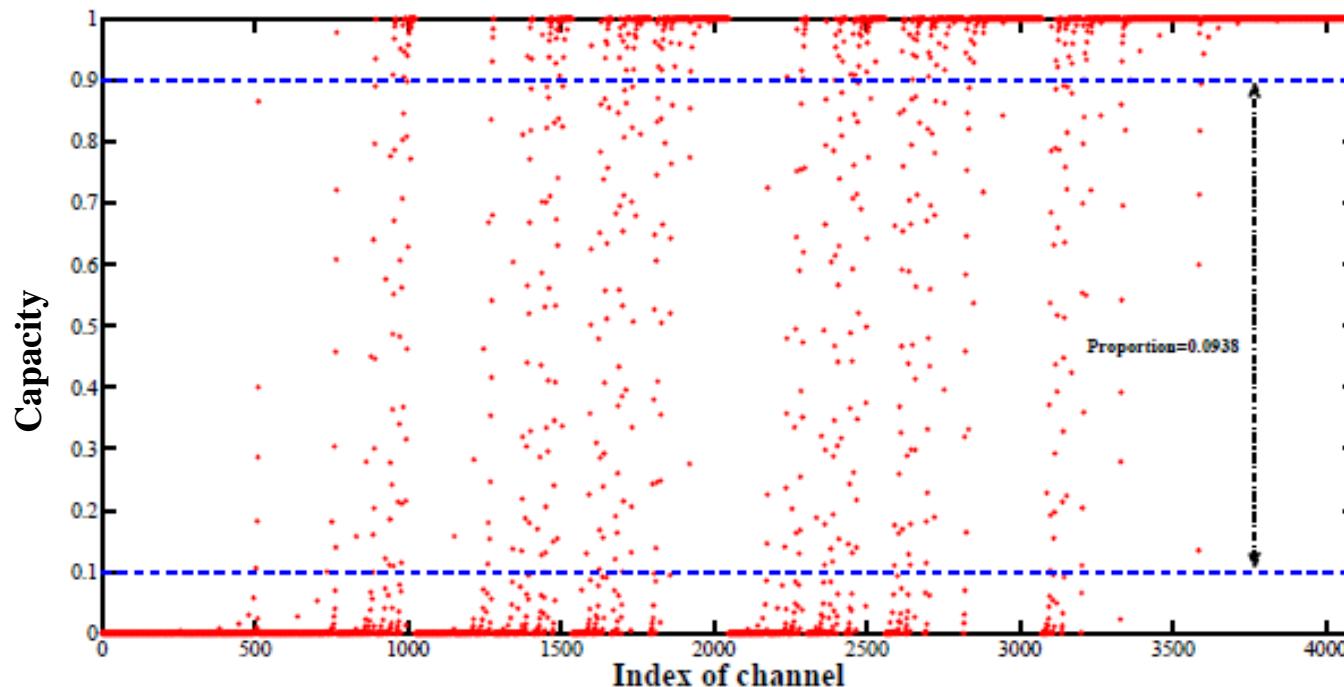
$$\lim_{n \rightarrow \infty} \frac{1}{N} \# \left\{ (b_1 \cdots b_n) : C(W_{b_1 b_2 \dots b_n}) \geq 1 - 2^{-N^\beta} \right\} = C(W).$$

$$\lim_{n \rightarrow \infty} \frac{1}{N} \# \left\{ (b_1 \cdots b_n) : C(W_{b_1 b_2 \dots b_n}) < 1 - 2^{-N^\beta} \right\} = 1 - C(W).$$

- The above statements do not hold for $\beta > 0.5$.
- Thus, the polarization speed is roughly $2^{-\sqrt{N}}$.

Convergence

- The portion of almost perfect bit channels is $C(W)$, meaning that the capacity is achieved.
- Example: capacities for $N = 2^{12}$ for BEC(0.5)

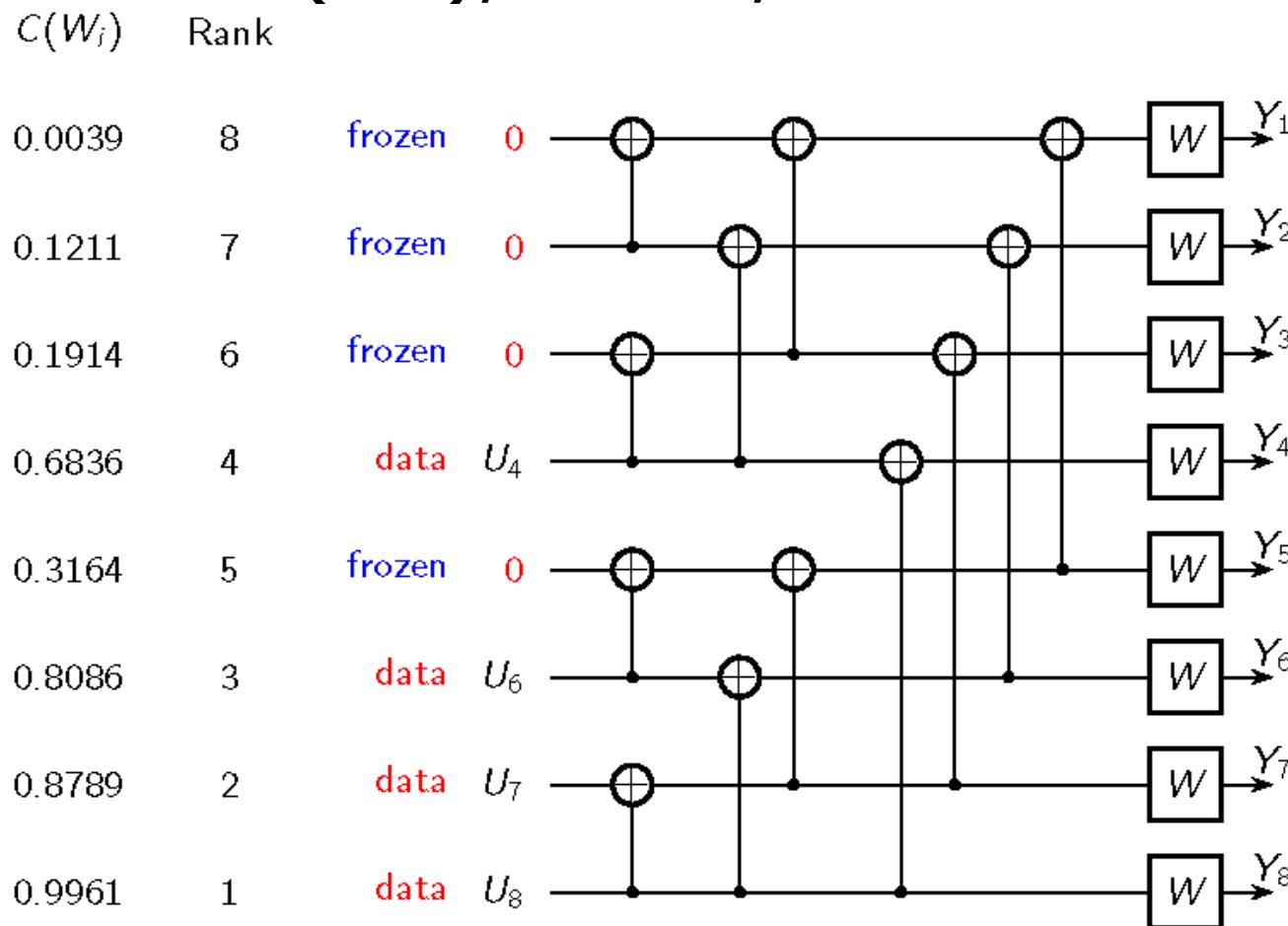


Encoding

- Given $N = 2^n$, calculate $C(W_{b_1 b_2 \dots b_n})$ for all synthetic bit channels.
- Given rate $R < 1$ and $K = NR$, sort $C(W_{b_1 b_2 \dots b_n})$ in descending order and define the union of the indices of the first K elements as the information set Ω .
- Choose the information bits u^Ω and freeze u^{Ω^c} to be all-zero. Obtain the codeword $\mathbf{x} = (u^\Omega, u^{\Omega^c}) \cdot \mathbf{F}_N$.

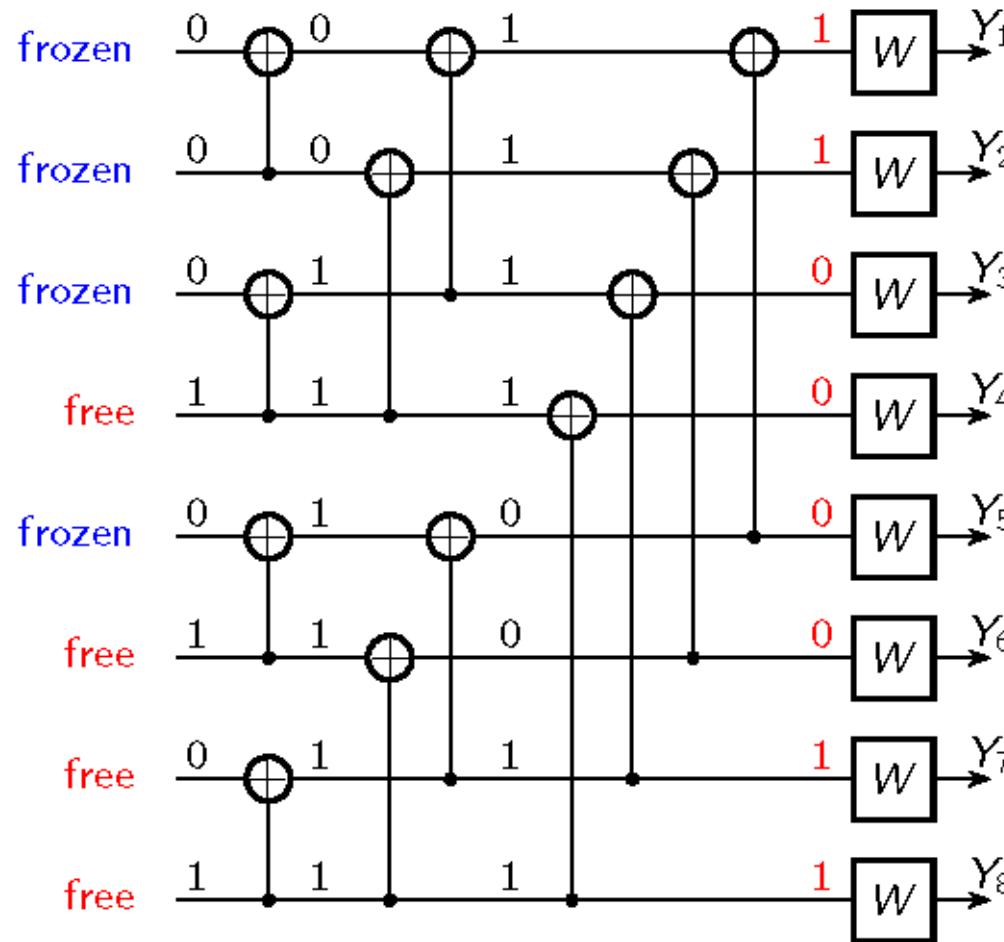
Construction Example

- W is a BEC(0.5), $N = 8, R=0.5$.



Construction Example

- W is a BEC(0.5), $N = 8$, $R=0.5$.



Encoding
complexity
 $O(N \log N)$

Successive decoding

- For the decoding we need to compute the likelihood ratio for $u_i, i = (b_1 \cdots b_n)$

$$LR(u_i) = \frac{W_{b_1 b_2 \dots b_n}(\cdot | 1)}{W_{b_1 b_2 \dots b_n}(\cdot | 0)}$$

If $i \in \Omega$, $\hat{u}_i = 1$ if $LR(u_i) > 1$; otherwise, $\hat{u}_i = 0$.

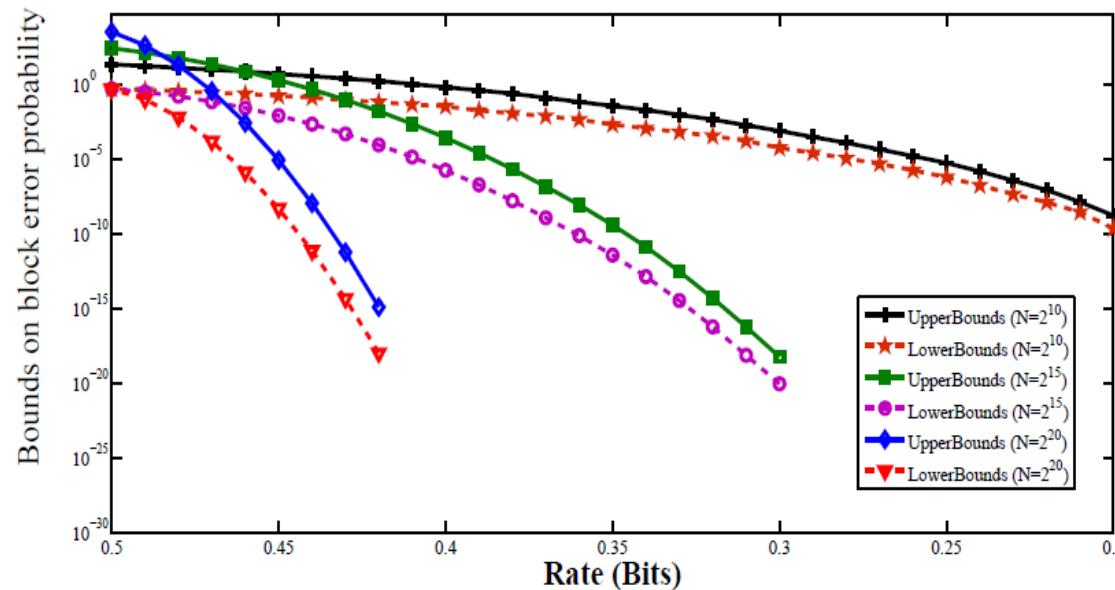
- Similar to $C(W_{b_1 b_2 \dots b_n})$, $LR(u_i)$ can also be calculated recursively.
- For more details of the decoding, see

E. Arikan, "Channel polarization: A method for constructing capacity-achieving codes for symmetric binary-input memoryless channels," *IEEE Trans. on Information Theory*, vol. 55, no. 7, pp. 3051–3073, 2009.

Probability of Error

- For a polar code with block length N and rate $R < C(W)$, the error probability under the successive cancellation decoding is given by

$$P_e \leq O(2^{-N^\beta}) \quad \beta < 0.5$$



Error Bound of the SC decoding for BEC(0.5)

Polar Source Coding

- Let x be a random variable generated by a Bernoulli source $\text{Ber}(p)$, i.e.,

$$\Pr(x=0)=p \text{ and } \Pr(x=1)=1-p.$$

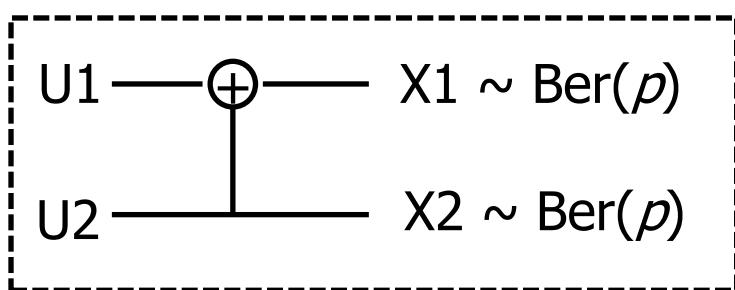
- The entropy (in bits) of x is

$$H(x) = -p \log_2 p - (1-p) \log_2 (1-p)$$

- If $H(x) = 0$, i.e., $p = 0$ or 1 , x is a **constant**, no need for compression.
- If $H(x) = 1$, i.e., $p = 0.5$, x is **totally random**, we cannot do any compression.
- In other cases, can the polarization technique be used to achieve rate $H(x)$?

Source Polarization

- Similar idea applies to source coding:
general sources $\xrightarrow{\text{polarization}}$ extreme sources
- Basic source polarization



$$\begin{aligned}
 (U_1, U_2) &= (X_1, X_2)\mathbf{F}_2 \\
 H(U_1) + H(U_2|U_1) &= H(U_1, U_2) \\
 &= H(X_1, X_2) = 2H(x) \\
 H(U_1) &\geq H(x) \geq H(U_2|U_1)
 \end{aligned}$$

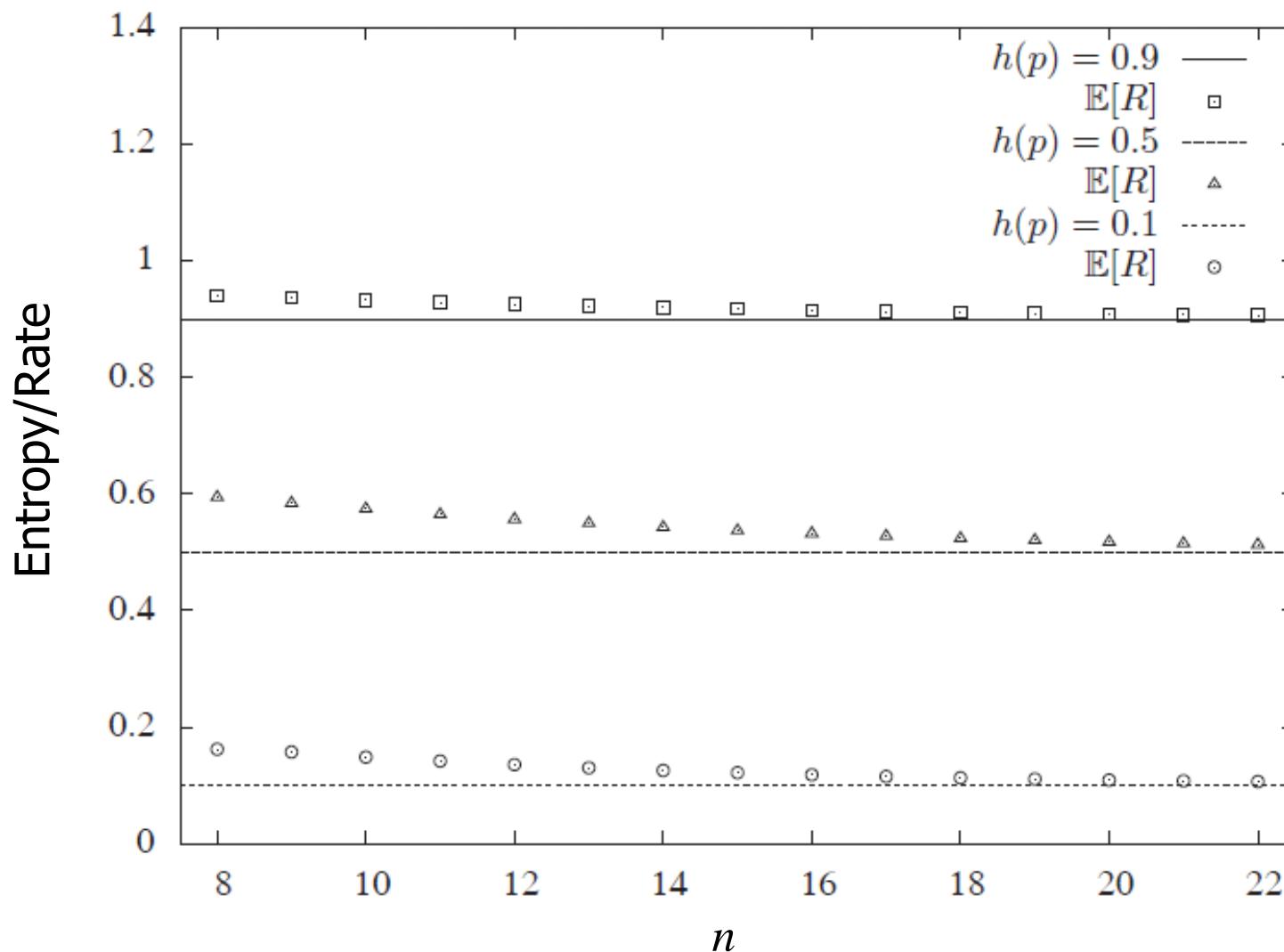
The process is **entropy-conserving**, but we obtain two new sources with **higher** and **lower** entropy than the original one.

- Example: when $p = 0.11$, $H(x) = 0.5$, $H(U_1) = 0.713$, $H(U_2|U_1) = 0.287$.

Source Coding

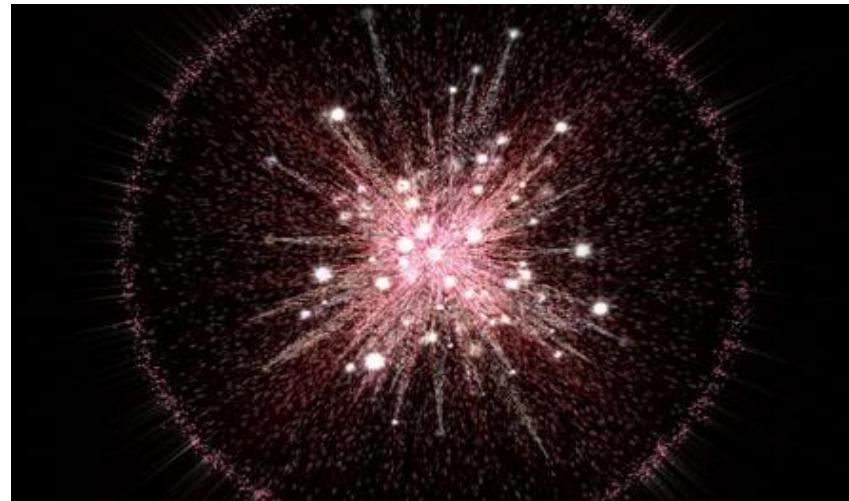
- Keep polarizing by increasing N , the entropy of the synthetic sources tends to 0 or 1.
- Again, by the property of the **martingale**, the proportion of those sources with **entropy close to 1 is close to $H(x)$** .
- Source coding is realized by recording the indexes with **entropy close to 1**, while the rest bits can be recovered with high probability because their associated entropy is **almost 0**.
- For me details, see
E. Arikan, "Source polarization," *IEEE ISIT* 2010, pp. 899-903.

Performance



Extensions

- Polar codes also achieve capacity of other types of channels (discrete or continuous).
- Achieve entropy bound of other types of sources (lossless or lossy).
- Quantum polar codes, network information theory...



Big bang in information theory

Lecture 13

- Continuous Random Variables
- Differential Entropy
 - can be negative
 - not really a measure of the information in x
 - coordinate-dependent
- Maximum entropy distributions
 - Uniform over a finite range
 - Gaussian if a constant variance

Continuous Random Variables

Changing Variables

- pdf: $f_x(x)$ CDF: $F_x(x) = \int_{-\infty}^x f_x(t)dt$
- For $g(x)$ monotonic: $y = g(x) \Leftrightarrow x = g^{-1}(y)$

$$F_y(y) = F_x(g^{-1}(y)) \quad \text{or} \quad 1 - F_x(g^{-1}(y)) \quad \text{according to slope of } g(x)$$

$$f_y(y) = \frac{dF_y(y)}{dy} = f_x(g^{-1}(y)) \left| \frac{dg^{-1}(y)}{dy} \right| = f_x(x) \left| \frac{dx}{dy} \right| \quad \text{where} \quad x = g^{-1}(y)$$
- Examples:

Suppose $f_x(x) = 0.5$ for $x \in (0,2)$ $\Rightarrow F_x(x) = 0.5x$

(a) $y = 4x \Rightarrow x = 0.25y \Rightarrow f_y(y) = 0.5 \times 0.25 = 0.125$ for $y \in (0,8)$

(b) $z = x^4 \Rightarrow x = z^{1/4} \Rightarrow f_z(z) = 0.5 \times \frac{1}{4} z^{-3/4} = 0.125 z^{-3/4}$ for $z \in (0,16)$

Joint Distributions

Joint pdf: $f_{x,y}(x, y)$

Marginal pdf: $f_x(x) = \int_{-\infty}^{\infty} f_{x,y}(x, y) dy$

Independence: $\Leftrightarrow f_{x,y}(x, y) = f_x(x) f_y(y)$

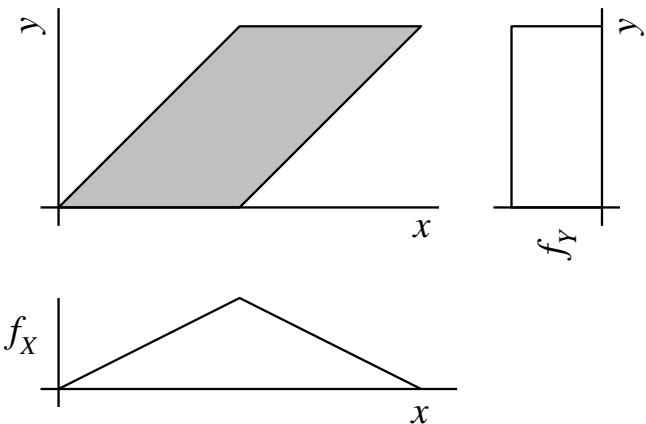
Conditional pdf: $f_{x|y}(x) = \frac{f_{x,y}(x, y)}{f_y(y)}$

Example:

$f_{x,y} = 1$ for $y \in (0,1), x \in (y, y+1)$

$f_{x|y} = 1$ for $x \in (y, y+1)$

$f_{y|x} = \frac{1}{\min(x, 1-x)}$ for $y \in (\max(0, x-1), \min(x, 1))$



Entropy of Continuous R.V.

- Given a continuous pdf $f(x)$, we divide the range of x into bins of width Δ
 - For each i , $\exists x_i$ with $f(x_i)\Delta = \int_{i\Delta}^{(i+1)\Delta} f(x)dx$ mean value theorem
- Define a discrete random variable Y
 - $Y = \{x_i\}$ and $p_Y = \{f(x_i)\Delta\}$
 - Scaled, quantised version of $f(x)$ with slightly unevenly spaced x_i
- $$\begin{aligned} H(Y) &= -\sum f(x_i)\Delta \log(f(x_i)\Delta) \\ &= -\log \Delta - \sum f(x_i) \log(f(x_i))\Delta \\ &\xrightarrow[\Delta \rightarrow 0]{} -\log \Delta - \int_{-\infty}^{\infty} f(x) \log f(x) dx = -\log \Delta + h(x) \end{aligned}$$
- Differential entropy: $h(x) = -\int_{-\infty}^{\infty} f_x(x) \log f_x(x) dx$
 - Similar to entropy of discrete r.v. but there are differences

Differential Entropy

Differential Entropy:
$$h(x) \stackrel{\Delta}{=} - \int_{-\infty}^{\infty} f_x(x) \log f_x(x) dx = E - \log f_x(x)$$

Bad News:

- $h(x)$ does not give the amount of information in x
- $h(x)$ is not necessarily positive
- $h(x)$ changes with a change of coordinate system

Good News:

- $h_1(x) - h_2(x)$ does compare the uncertainty of two continuous random variables **provided they are quantised to the same precision**
- Relative Entropy and Mutual Information still work fine
- If the range of x is normalized to 1 and then x is quantised to n bits, the entropy of the resultant discrete random variable is approximately $h(x) + n$

Differential Entropy Examples

- Uniform Distribution: $x \sim U(a, b)$
 - $f(x) = (b - a)^{-1}$ for $x \in (a, b)$ and $f(x) = 0$ elsewhere
 - $h(X) = -\int_a^b (b - a)^{-1} \log(b - a)^{-1} dx = \log(b - a)$
 - Note that $h(x) < 0$ if $(b-a) < 1$

- Gaussian Distribution: $x \sim N(\mu, \sigma^2)$
 - $f(x) = (2\pi\sigma^2)^{-1/2} \exp\left(-\frac{1}{2}(x - \mu)^2 \sigma^{-2}\right)$
 - $$\begin{aligned} h(X) &= -(\log e) \int_{-\infty}^{\infty} f(x) \ln f(x) dx \\ &= -\frac{1}{2}(\log e) \int_{-\infty}^{\infty} f(x) \left(-\ln(2\pi\sigma^2) - (x - \mu)^2 \sigma^{-2} \right) dx \\ &= \frac{1}{2}(\log e) \left(\ln(2\pi\sigma^2) + \sigma^{-2} E((x - \mu)^2) \right) \\ &= \frac{1}{2}(\log e) \left(\ln(2\pi\sigma^2) + 1 \right) = \frac{1}{2} \log(2\pi e \sigma^2) \approx \log(4.1\sigma) \text{ bits} \end{aligned}$$

$$\log_x y = \frac{\log_e y}{\log_e x}$$

Multivariate Gaussian

Given mean, \mathbf{m} , and symmetric positive definite covariance matrix \mathbf{K} ,

$$\begin{aligned}
 \mathbf{x}_{1:n} \sim \mathbf{N}(\mathbf{m}, \mathbf{K}) &\iff f(\mathbf{x}) = |2\pi\mathbf{K}|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(\mathbf{x} - \mathbf{m})^T \mathbf{K}^{-1}(\mathbf{x} - \mathbf{m})\right) \\
 h(f) &= -(\log e) \int f(\mathbf{x}) \times \left(-\frac{1}{2}(\mathbf{x} - \mathbf{m})^T \mathbf{K}^{-1}(\mathbf{x} - \mathbf{m}) - \frac{1}{2} \ln |2\pi\mathbf{K}| \right) d\mathbf{x} \\
 &= \frac{1}{2} \log(e) \times \left(\ln |2\pi\mathbf{K}| + E((\mathbf{x} - \mathbf{m})^T \mathbf{K}^{-1}(\mathbf{x} - \mathbf{m})) \right) \\
 &= \frac{1}{2} \log(e) \times \left(\ln |2\pi\mathbf{K}| + E \operatorname{tr}((\mathbf{x} - \mathbf{m})(\mathbf{x} - \mathbf{m})^T \mathbf{K}^{-1}) \right) \quad \text{tr}(\mathbf{AB}) = \text{tr}(\mathbf{BA}) \\
 &= \frac{1}{2} \log(e) \times \left(\ln |2\pi\mathbf{K}| + \operatorname{tr}(E(\mathbf{x} - \mathbf{m})(\mathbf{x} - \mathbf{m})^T \mathbf{K}^{-1}) \right) \quad E_f \mathbf{xx}^T = \mathbf{K} \\
 &= \frac{1}{2} \log(e) \times \left(\ln |2\pi\mathbf{K}| + \operatorname{tr}(\mathbf{KK}^{-1}) \right) \quad = \frac{1}{2} \log(e) \times (\ln |2\pi\mathbf{K}| + n) \\
 &= \frac{1}{2} \log(e^n) + \frac{1}{2} \log(|2\pi\mathbf{K}|) \quad \operatorname{tr}(\mathbf{I}) = n = \ln(e^n) \\
 &= \frac{1}{2} \log(|2\pi e \mathbf{K}|) = \frac{1}{2} \log((2\pi e)^n |\mathbf{K}|) \quad \text{bits}
 \end{aligned}$$

Other Differential Quantities

Joint Differential Entropy

$$h(x, y) = - \iint_{x, y} f_{x,y}(x, y) \log f_{x,y}(x, y) dx dy = E - \log f_{x,y}(x, y)$$

Conditional Differential Entropy

$$h(x | y) = - \iint_{x, y} f_{x,y}(x, y) \log f_{x,y}(x | y) dx dy = h(x, y) - h(y)$$

Mutual Information

$$I(x; y) = \iint_{x, y} f_{x,y}(x, y) \log \frac{f_{x,y}(x, y)}{f_x(x) f_y(y)} dx dy = h(x) + h(y) - h(x, y)$$

Relative Differential Entropy of two pdf's:

$$\begin{aligned} D(f \| g) &= \int f(x) \log \frac{f(x)}{g(x)} dx \\ &= -h_f(x) - E_f \log g(x) \end{aligned}$$

(a) must have $f(x)=0 \Rightarrow g(x)=0$

(b) continuity $\Rightarrow 0 \log(0/0) = 0$

Differential Entropy Properties

Chain Rules

$$h(x, y) = h(x) + h(y | x) = h(y) + h(x | y)$$

$$I(x, y; z) = I(x; z) + I(y; z | x)$$

Information Inequality: $D(f \parallel g) \geq 0$

Proof: Define $S = \{\mathbf{x} : f(\mathbf{x}) > 0\}$

$$-D(f \parallel g) = \int_{\mathbf{x} \in S} f(\mathbf{x}) \log \frac{g(\mathbf{x})}{f(\mathbf{x})} d\mathbf{x} = E_f \left(\log \frac{g(\mathbf{x})}{f(\mathbf{x})} \right)$$

$$\leq \log \left(E \frac{g(\mathbf{x})}{f(\mathbf{x})} \right) = \log \left(\int_S f(\mathbf{x}) \frac{g(\mathbf{x})}{f(\mathbf{x})} d\mathbf{x} \right) \quad \text{Jensen + log() is concave}$$

$$= \log \left(\int_S g(\mathbf{x}) d\mathbf{x} \right) \leq \log 1 = 0$$

all the same as for discrete r.v. $H()$

Information Inequality Corollaries

Mutual Information ≥ 0

$$I(x; y) = D(f_{x,y} \parallel f_x f_y) \geq 0$$

Conditioning reduces Entropy

$$h(x) - h(x | y) = I(x; y) \geq 0$$

Independence Bound

$$h(\mathbf{x}_{1:n}) = \sum_{i=1}^n h(\mathbf{x}_i | \mathbf{x}_{1:i-1}) \leq \sum_{i=1}^n h(\mathbf{x}_i)$$

all the same as for $H()$

Change of Variable

Change Variable: $y = g(x)$

from earlier

$$f_y(y) = f_x(g^{-1}(y)) \left| \frac{dg^{-1}(y)}{dy} \right|$$

$$h(y) = -E \log(f_y(y)) = -E \log(f_x(g^{-1}(y))) - E \log \left| \frac{dx}{dy} \right|$$

$$= -E \log(f_x(x)) - E \log \left| \frac{dx}{dy} \right| = h(x) + E \log \left| \frac{dy}{dx} \right|$$

Examples:

- Translation: $y = x + a \Rightarrow dy/dx = 1 \Rightarrow h(y) = h(x)$
- Scaling: $y = cx \Rightarrow dy/dx = c \Rightarrow h(y) = h(x) + \log |c|$
- Vector version: $y_{1:n} = \mathbf{A}x_{1:n} \Rightarrow h(\mathbf{y}) = h(\mathbf{x}) + \log |\det(\mathbf{A})|$

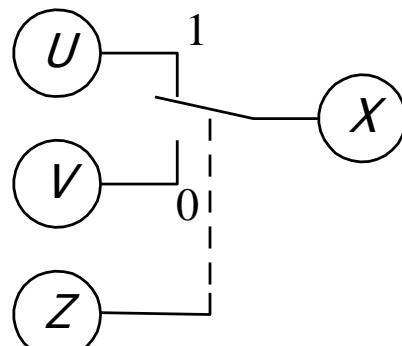
not the same as for $H()$

Concavity & Convexity

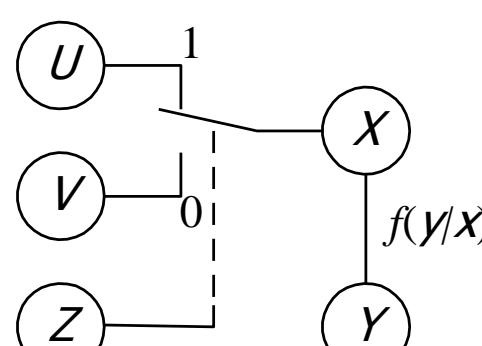
- Differential Entropy:
 - $h(x)$ is a **concave** function of $f_x(x) \Rightarrow \exists$ a maximum
- Mutual Information:
 - $I(x; y)$ is a **concave** function of $f_x(x)$ for fixed $f_{y|x}(y)$
 - $I(x; y)$ is a **convex** function of $f_{y|x}(y)$ for fixed $f_x(x)$

Proofs:

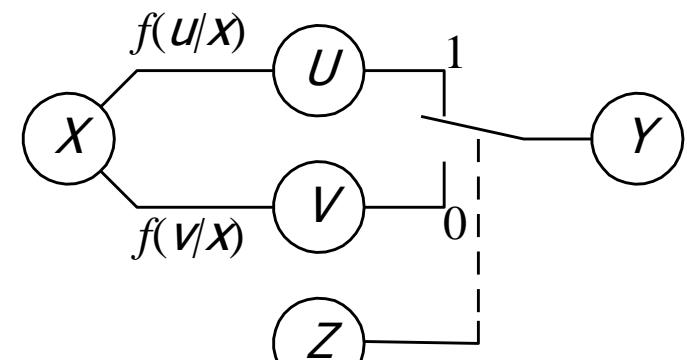
Exactly the same as for the discrete case: $\mathbf{p}_z = [1-\lambda, \lambda]^T$



$$H(X) \geq H(X | Z)$$



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



$$I(X; Y) \leq I(X; Y | Z)$$

Uniform Distribution Entropy

What distribution over the finite range (a,b) maximizes the entropy ?

Answer: A uniform distribution $u(x)=(b-a)^{-1}$

Proof:

Suppose $f(x)$ is a distribution for $x \in (a,b)$

$$\begin{aligned} 0 \leq D(f \parallel u) &= -h_f(x) - E_f \log u(x) \\ &= -h_f(x) + \log(b-a) \end{aligned}$$

$$\Rightarrow h_f(x) \leq \log(b-a)$$

Maximum Entropy Distribution

What zero-mean distribution maximizes the entropy on $(-\infty, \infty)^n$ for a given covariance matrix \mathbf{K} ?

Answer: A multivariate Gaussian $\phi(\mathbf{x}) = |2\pi\mathbf{K}|^{-\frac{1}{2}} \exp(-\frac{1}{2}\mathbf{x}^T \mathbf{K}^{-1} \mathbf{x})$

Proof: $0 \leq D(f \parallel \phi) = -h_f(\mathbf{x}) - E_f \log \phi(\mathbf{x})$

$$\begin{aligned} \Rightarrow h_f(\mathbf{x}) &\leq -(\log e)E_f \left(-\frac{1}{2} \ln (|2\pi\mathbf{K}|) - \frac{1}{2}\mathbf{x}^T \mathbf{K}^{-1} \mathbf{x} \right) \\ &= \frac{1}{2}(\log e) \left(\ln (|2\pi\mathbf{K}|) + \text{tr}(E_f \mathbf{x} \mathbf{x}^T \mathbf{K}^{-1}) \right) \\ &= \frac{1}{2}(\log e) \left(\ln (|2\pi\mathbf{K}|) + \text{tr}(\mathbf{I}) \right) \quad E_f \mathbf{x} \mathbf{x}^T = \mathbf{K} \\ &= \frac{1}{2} \log (|2\pi e \mathbf{K}|) = h_\phi(\mathbf{x}) \quad \text{tr}(\mathbf{I}) = n = \ln(e^n) \end{aligned}$$

Since translation doesn't affect $h(X)$, we can assume zero-mean w.l.o.g.

Summary

- Differential Entropy: $h(x) = - \int_{-\infty}^{\infty} f_x(x) \log f_x(x) dx$
 - Not necessarily positive
 - $h(x+a) = h(x)$, $h(ax) = h(x) + \log|a|$
- Many properties are formally the same
 - $h(x|y) \leq h(x)$
 - $I(x; y) = h(x) + h(y) - h(x, y) \geq 0$, $D(f||g) = E \log(f/g) \geq 0$
 - $h(x)$ concave in $f_x(x)$; $I(x; y)$ concave in $f_x(x)$
- Bounds:
 - Finite range: Uniform distribution has max: $h(x) = \log(b-a)$
 - Fixed Covariance: Gaussian has max: $h(x) = \frac{1}{2}\log((2\pi e)^n |\mathbf{K}|)$

Lecture 14

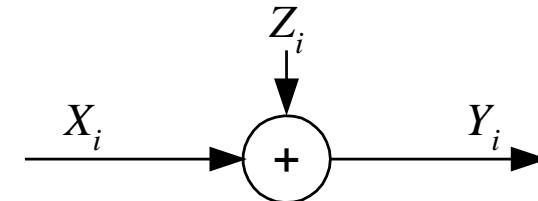
- Discrete-Time Gaussian Channel Capacity
- Continuous Typical Set and AEP
- Gaussian Channel Coding Theorem
- Bandlimited Gaussian Channel
 - Shannon Capacity

Capacity of Gaussian Channel

Discrete-time channel: $y_i = x_i + z_i$

- Zero-mean Gaussian i.i.d. $z_i \sim N(0, N)$
- Average power constraint $n^{-1} \sum_{i=1}^n x_i^2 \leq P$

$$EY^2 = E(x + z)^2 = Ex^2 + 2E(x)E(z) + Ez^2 \leq P + N$$



X, Z indep and $EZ=0$

Information Capacity

- Define information capacity: $C = \max_{Ex^2 \leq P} I(x; y)$

$$\begin{aligned} I(x; y) &= h(y) - h(y | x) = h(y) - h(x + z | x) \\ &\stackrel{(a)}{=} h(y) - h(z | x) = h(y) - h(z) \end{aligned}$$

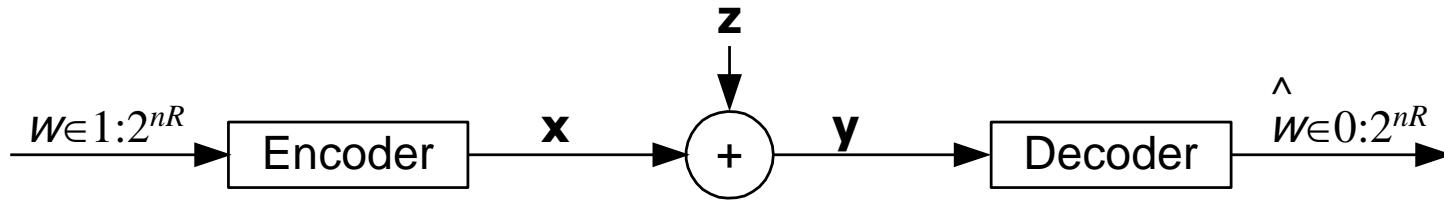
(a) Translation independence

$$\begin{aligned} &\leq \frac{1}{2} \log 2\pi e(P + N) - \frac{1}{2} \log 2\pi e N \\ &= \frac{1}{2} \log \left(1 + \frac{P}{N} \right) \end{aligned}$$

Gaussian Limit with equality when $x \sim N(0, P)$

The optimal input is Gaussian

Achievability



- An (M,n) code for a Gaussian Channel with power constraint is
 - A set of M codewords $\mathbf{x}(w) \in \mathcal{X}^n$ for $w=1:M$ with $\mathbf{x}(w)^T \mathbf{x}(w) \leq nP \quad \forall w$
 - A deterministic decoder $g(\mathbf{y}) \in 0:M$ where 0 denotes failure
 - Errors: codeword : λ_i $\max_i : \lambda^{(n)}$ average : $P_e^{(n)}$
- Rate R is achievable if \exists seq of $(2^{nR},n)$ codes with $\lambda^{(n)} \xrightarrow[n \rightarrow \infty]{} 0$
- Theorem: R achievable iff $R < C = \frac{1}{2} \log (1 + PN^{-1})$ ◆

◆ = proved on next pages

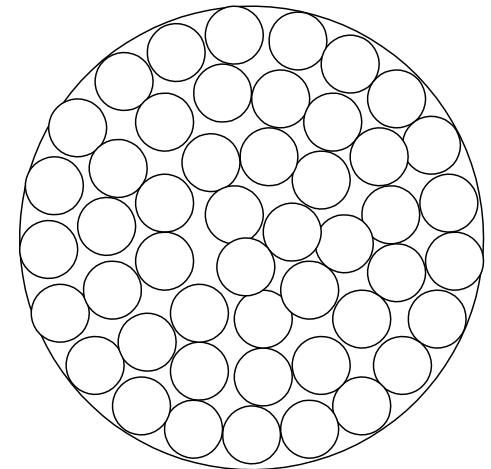
Argument by Sphere Packing

- Each transmitted \mathbf{x}_i is received as a probabilistic cloud \mathbf{y}_i
 - cloud ‘radius’ = $\sqrt{\text{Var}(\mathbf{y} \mid \mathbf{x})} = \sqrt{nN}$
- Energy of \mathbf{y}_i constrained to $n(P+N)$ so clouds must fit into a hypersphere of radius $\sqrt{n(P+N)}$
- Volume of hypersphere $\propto r^n$
- Max number of non-overlapping clouds:

$$\frac{(nP + nN)^{\frac{1}{2}n}}{(nN)^{\frac{1}{2}n}} = 2^{\frac{1}{2}n \log(1+PN^{-1})}$$

- Max achievable rate is $\frac{1}{2}\log(1+P/N)$

Law of large numbers



Continuous AEP

Typical Set: Continuous distribution, discrete time i.i.d.

For any $\varepsilon > 0$ and any n , the **typical set** with respect to $f(\mathbf{x})$ is

$$T_{\varepsilon}^{(n)} = \left\{ \mathbf{x} \in S^n : \left| -n^{-1} \log f(\mathbf{x}) - h(\mathbf{x}) \right| \leq \varepsilon \right\}$$

where S is the **support** of $f \Leftrightarrow \{\mathbf{x} : f(\mathbf{x}) > 0\}$

$$f(\mathbf{x}) = \prod_{i=1}^n f(x_i) \text{ since } x_i \text{ are independent}$$

$$h(\mathbf{x}) = E - \log f(\mathbf{x}) = -n^{-1} E \log f(\mathbf{x})$$

Typical Set Properties

1. $p(\mathbf{x} \in T_{\varepsilon}^{(n)}) > 1 - \varepsilon$ for $n > N_{\varepsilon}$

Proof: LLN

2. $(1 - \varepsilon) 2^{n(h(\mathbf{x}) - \varepsilon)} \leq \text{Vol}(T_{\varepsilon}^{(n)}) \leq 2^{n(h(\mathbf{x}) + \varepsilon)}$

Proof: Integrate
max/min prob

where $\text{Vol}(A) = \int d\mathbf{x}$

Continuous AEP Proof

Proof 1: By law of large numbers

$$-n^{-1} \log f(\mathbf{x}_{1:n}) = -n^{-1} \sum_{i=1}^n \log f(\mathbf{x}_i) \xrightarrow{\text{prob}} E - \log f(\mathbf{x}) = h(\mathbf{x})$$

Reminder: $\mathbf{x}_n \xrightarrow{\text{prob}} \mathbf{y} \Rightarrow \forall \varepsilon > 0, \exists N_\varepsilon$ such that $\forall n > N_\varepsilon, P(|\mathbf{x}_n - \mathbf{y}| > \varepsilon) < \varepsilon$

Proof 2a: $1 - \varepsilon \leq \int_{T_\varepsilon^{(n)}} f(\mathbf{x}) d\mathbf{x}$ for $n > N_\varepsilon$ Property 1

$$\leq 2^{-n(h(\mathbf{x})-\varepsilon)} \int_{T_\varepsilon^{(n)}} d\mathbf{x} = 2^{-n(h(\mathbf{x})-\varepsilon)} \text{Vol}(T_\varepsilon^{(n)}) \quad \text{max } f(x) \text{ within } T$$

Proof 2b: $1 = \int_{S^n} f(\mathbf{x}) d\mathbf{x} \geq \int_{T_\varepsilon^{(n)}} f(\mathbf{x}) d\mathbf{x}$
 $\geq 2^{-n(h(\mathbf{x})+\varepsilon)} \int_{T_\varepsilon^{(n)}} d\mathbf{x} = 2^{-n(h(\mathbf{x})+\varepsilon)} \text{Vol}(T_\varepsilon^{(n)}) \quad \text{min } f(x) \text{ within } T$

Jointly Typical Set

Jointly Typical: x_i, y_i i.i.d from \Re^2 with $f_{X,Y}(x_i, y_i)$

$$\begin{aligned} J_{\varepsilon}^{(n)} = \left\{ \mathbf{x}, \mathbf{y} \in \Re^{2n} : \right. & \left| -n^{-1} \log f_X(\mathbf{x}) - h(X) \right| < \varepsilon, \\ & \left| -n^{-1} \log f_Y(\mathbf{y}) - h(Y) \right| < \varepsilon, \\ & \left. \left| -n^{-1} \log f_{X,Y}(\mathbf{x}, \mathbf{y}) - h(X, Y) \right| < \varepsilon \right\} \end{aligned}$$

Properties:

1. Indiv p.d.: $\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)} \Rightarrow \log f_{X,Y}(\mathbf{x}, \mathbf{y}) = -nh(X, Y) \pm n\varepsilon$
2. Total Prob: $p(\mathbf{x}, \mathbf{y} \in J_{\varepsilon}^{(n)}) > 1 - \varepsilon \quad \text{for } n > N_{\varepsilon}$
3. Size: $(1 - \varepsilon)2^{n(h(X, Y) - \varepsilon)} \stackrel{n > N_{\varepsilon}}{\leq} \text{Vol}(J_{\varepsilon}^{(n)}) \leq 2^{n(h(X, Y) + \varepsilon)}$
4. Indep \mathbf{x}', \mathbf{y}' : $(1 - \varepsilon)2^{-n(I(X;Y) + 3\varepsilon)} \stackrel{n > N_{\varepsilon}}{\leq} p(\mathbf{x}', \mathbf{y}' \in J_{\varepsilon}^{(n)}) \leq 2^{-n(I(X;Y) - 3\varepsilon)}$

Proof of 4.: Integrate max/min $f(\mathbf{x}', \mathbf{y}') = f(\mathbf{x}')f(\mathbf{y}')$, then use known bounds on $\text{Vol}(J)$

Gaussian Channel Coding Theorem

R is achievable iff $R < C = \frac{1}{2} \log (1 + P N^{-1})$

Proof (\Leftarrow):

Choose $\varepsilon > 0$

Random codebook: $\mathbf{x}_w \in \Re^n$ for $w = 1 : 2^{nR}$ where x_w are i.i.d. $\sim N(0, P - \varepsilon)$

Use Joint typicality decoding

- Errors:
1. Power too big $p(\mathbf{x}^T \mathbf{x} > nP) \rightarrow 0 \Rightarrow \leq \varepsilon$ for $n > M_\varepsilon$
 2. \mathbf{y} not J.T. with \mathbf{x} $p(\mathbf{x}, \mathbf{y} \notin J_\varepsilon^{(n)}) < \varepsilon$ for $n > N_\varepsilon$
 3. another \mathbf{x} J.T. with \mathbf{y} $\sum_{j=2}^{2^{nR}} p(\mathbf{x}_j, \mathbf{y}_i \in J_\varepsilon^{(n)}) \leq (2^{nR} - 1) \times 2^{-n(I(X;Y) - 3\varepsilon)}$

Total Err $P_\varepsilon^{(n)} \leq \varepsilon + \varepsilon + 2^{-n(I(X;Y) - R - 3\varepsilon)} \leq 3\varepsilon$ for large n if $R < I(X;Y) - 3\varepsilon$

Expurgation: Remove half of codebook*: $\lambda^{(n)} < 6\varepsilon$ now max error

We have constructed a code achieving rate $R - n^{-1}$

*:Worst codebook half includes \mathbf{x}_i : $\mathbf{x}_i^T \mathbf{x}_i > nP \Rightarrow \lambda_i = 1$

Gaussian Channel Coding Theorem

Proof (\Rightarrow): Assume $P_e^{(n)} \rightarrow 0$ and $n^{-1} \mathbf{x}^T \mathbf{x} < P$ for each $\mathbf{x}(w)$

$$\begin{aligned} nR &= H(\mathbf{W}) = I(\mathbf{W}; \mathbf{Y}_{1:n}) + H(\mathbf{W} | \mathbf{Y}_{1:n}) \xrightarrow{w \in 1:M} \text{Encoder} \xrightarrow{\mathbf{X}_{1:n}} \text{Noisy Channel} \xrightarrow{\mathbf{Y}_{1:n}} \text{Decoder } g(\mathbf{y}) \xrightarrow{\mathbf{W} \in 0:M} \\ &\leq I(\mathbf{X}_{1:n}; \mathbf{Y}_{1:n}) + H(\mathbf{W} | \mathbf{Y}_{1:n}) && \text{Data Proc Inequal} \\ &= h(\mathbf{Y}_{1:n}) - h(\mathbf{Y}_{1:n} | \mathbf{X}_{1:n}) + H(\mathbf{W} | \mathbf{Y}_{1:n}) \end{aligned}$$

$$\begin{aligned} &\leq \sum_{i=1}^n h(\mathbf{Y}_i) - h(\mathbf{Z}_{1:n}) + H(\mathbf{W} | \mathbf{Y}_{1:n}) && \text{Indep Bound + Translation} \end{aligned}$$

$$\begin{aligned} &\leq \sum_{i=1}^n I(\mathbf{X}_i; \mathbf{Y}_i) + 1 + nR P_e^{(n)} && Z \text{ i.i.d } + \text{Fano, } |\mathcal{W}| = 2^{nR} \end{aligned}$$

$$\begin{aligned} &\leq \sum_{i=1}^n \frac{1}{2} \log(1 + PN^{-1}) + 1 + nR P_e^{(n)} && \text{max Information Capacity} \end{aligned}$$

$$R \leq \frac{1}{2} \log(1 + PN^{-1}) + n^{-1} + RP_e^{(n)} \rightarrow \frac{1}{2} \log(1 + PN^{-1})$$

Bandlimited Channel

- Channel bandlimited to $f \in (-W, W)$ and signal duration T
 - Not exactly
 - Most energy in the bandwidth, most energy in the interval
- Nyquist: Signal is defined by $2WT$ samples
 - white noise with double-sided p.s.d. $\frac{1}{2}N_0$ becomes i.i.d gaussian $N(0, \frac{1}{2}N_0)$ added to each coefficient
 - Signal power constraint = $P \Rightarrow$ Signal energy $\leq PT$
 - Energy constraint per coefficient: $n^{-1}\mathbf{x}^T\mathbf{x} < PT/2WT = \frac{1}{2}W^{-1}P$
- Capacity:

$$C = \frac{1}{2} \log \left(1 + \frac{1/2 \cdot P / W}{N_0 / 2} \right) \times \frac{2WT}{T} = W \log \left(1 + \frac{P}{WN_0} \right) \text{ bits/second}$$
- More precisely, it can be represented in a vector space of about $n=2WT$ dimensions with prolate spheroidal functions as an orthonormal basis

Compare discrete time version: $\frac{1}{2}\log(1+PN^{-1})$ bits per channel use

Limit of Infinite Bandwidth

$$C = W \log \left(1 + \frac{P}{WN_0} \right) \text{ bits/second}$$

$$C \xrightarrow{W \rightarrow \infty} \frac{P}{N_0} \log e$$

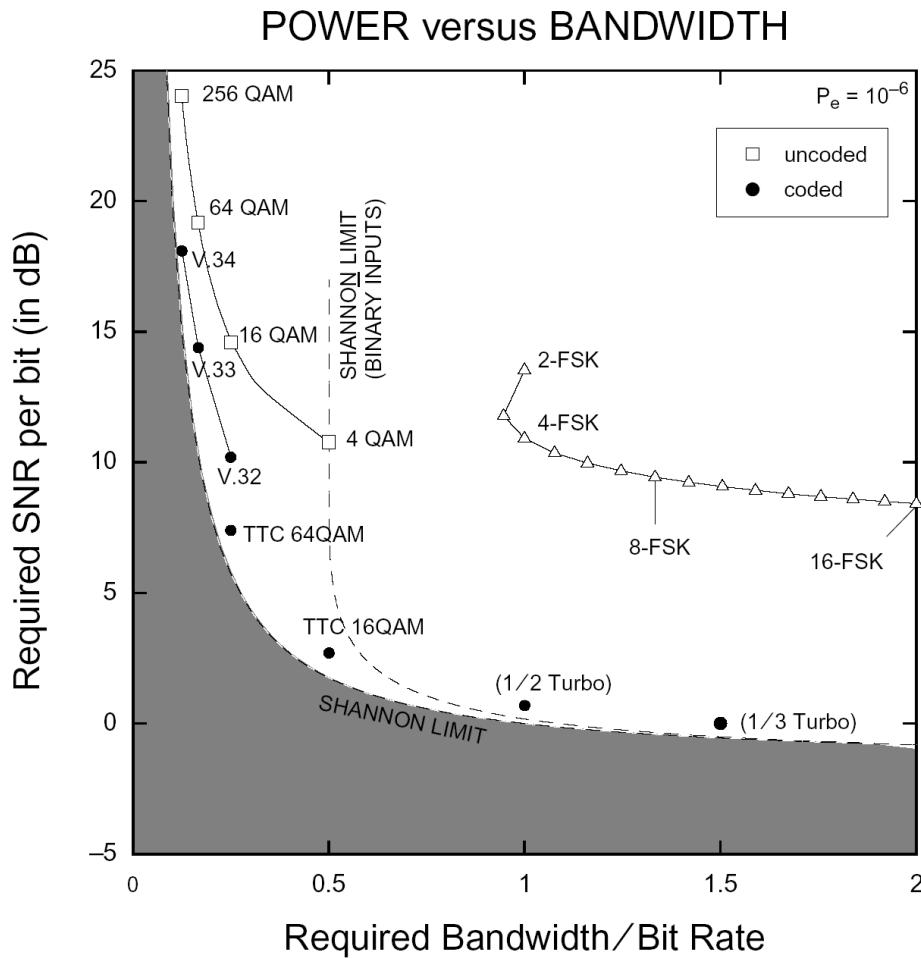
Minimum signal to noise ratio (SNR)

$$\frac{E_b}{N_0} = \frac{PT_b}{N_0} = \frac{P / C}{N_0} \xrightarrow{W \rightarrow \infty} \ln 2 = -1.6 \text{ dB}$$

Given capacity, trade-off between P and W

- Increase P , decrease W
- Increase W , decrease P
 - spread spectrum
 - ultra wideband

Channel Code Performance



- **Power Limited**
 - High bandwidth
 - Spacecraft, Pagers
 - Use QPSK/4-QAM
 - Block/Convolution Codes
- **Bandwidth Limited**
 - Modems, DVB, Mobile phones
 - 16-QAM to 256-QAM
 - Convolution Codes
- **Value of 1 dB for space**
 - Better range, lifetime, weight, bit rate
 - \$80 M (1999)

Summary

- Gaussian channel capacity

$$C = \frac{1}{2} \log \left(1 + \frac{P}{N} \right) \text{ bits/transmission}$$

- Proved by using continuous AEP
- Bandlimited channel

$$C = W \log \left(1 + \frac{P}{WN_0} \right) \text{ bits/second}$$

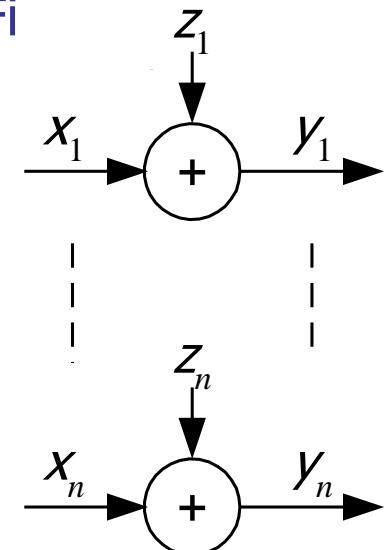
- Minimum SNR = -1.6 dB as $W \rightarrow \infty$

Lecture 15

- Parallel Gaussian Channels
 - Waterfilling
- Gaussian Channel with Feedback
 - Memoryless: no gain
 - Memory: at most $\frac{1}{2}$ bits/transmission

Parallel Gaussian Channels

- n independent Gaussian channels
 - A model for nonwhite noise wideband channel where each component represents a different frequency
 - e.g. digital audio, digital TV, Broadband ADSL, WiFi (multicarrier/OFDM)
- Noise is independent $z_i \sim N(0, N_i)$
- Average Power constraint $E\mathbf{x}^T\mathbf{x} \leq nP$
- Information Capacity: $C = \max_{f(\mathbf{x}): E_f \mathbf{x}^T \mathbf{x} \leq nP} I(\mathbf{x}; \mathbf{y})$
- $R < C \Leftrightarrow R$ achievable
 - proof as before
- What is the optimal $f(\mathbf{x})$?



Parallel Gaussian: Max Capacity

Need to find $f(\mathbf{x})$: $C = \max_{f(\mathbf{x}): E_f \mathbf{x}^T \mathbf{x} \leq nP} I(\mathbf{x}; \mathbf{y})$

$$I(\mathbf{x}; \mathbf{y}) = h(\mathbf{y}) - h(\mathbf{y} | \mathbf{x}) = h(\mathbf{y}) - h(\mathbf{z} | \mathbf{x})$$

Translation invariance

$$= h(\mathbf{y}) - h(\mathbf{z}) = h(\mathbf{y}) - \sum_{i=1}^n h(z_i)$$

\mathbf{x}, \mathbf{z} indep; Z_i indep

$$\stackrel{(a)}{\leq} \sum_{i=1}^n (h(y_i) - h(z_i)) \stackrel{(b)}{\leq} \sum_{i=1}^n \frac{1}{2} \log (1 + P_i N_i^{-1})$$

(a) indep bound;
(b) capacity limit

Equality when: (a) y_i indep $\Rightarrow x_i$ indep; (b) $x_i \sim N(0, P_i)$

We need to find the P_i that maximise $\sum_{i=1}^n \frac{1}{2} \log (1 + P_i N_i^{-1})$

Parallel Gaussian: Optimal Powers

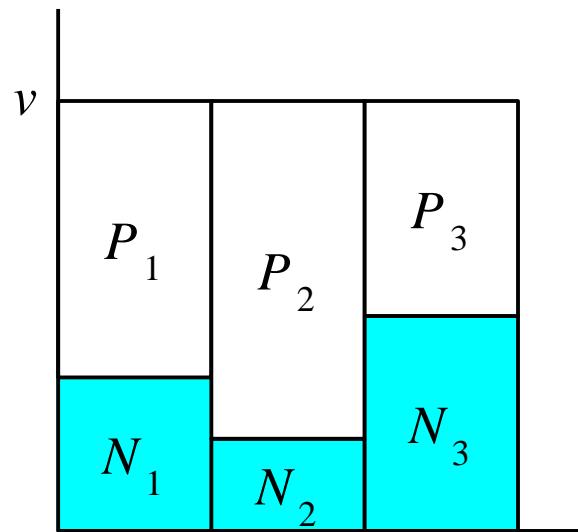
We need to find the P_i that maximise $\log(e) \sum_{i=1}^n \frac{1}{2} \ln(1 + P_i N_i^{-1})$

- subject to power constraint $\sum_{i=1}^n P_i = nP$
- use Lagrange multiplier

$$J = \sum_{i=1}^n \frac{1}{2} \ln(1 + P_i N_i^{-1}) - \lambda \sum_{i=1}^n P_i$$

$$\frac{\partial J}{\partial P_i} = \frac{1}{2} (P_i + N_i)^{-1} - \lambda = 0 \quad \Rightarrow \quad P_i + N_i = v$$

$$\text{Also } \sum_{i=1}^n P_i = nP \quad \Rightarrow \quad v = P + n^{-1} \sum_{i=1}^n N_i$$



Water Filling: put most power into least noisy channels to make equal power + noise in each channel

Very Noisy Channels

- What if water is not enough?
- Must have $P_i \geq 0 \forall i$
- If $v < N_i$ then set $P_i = 0$ and recalculate
 v (i.e., $P_i = \max(v - N_i, 0)$)

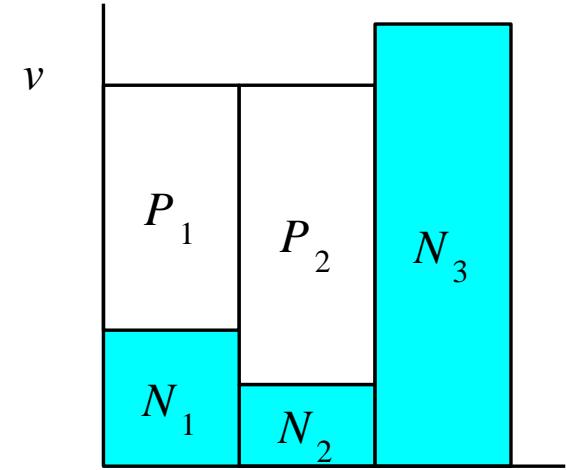
Kuhn-Tucker Conditions:

(not examinable)

- Max $f(\mathbf{x})$ subject to $\mathbf{Ax} + \mathbf{b} = \mathbf{0}$ and

$$g_i(\mathbf{x}) \geq 0 \quad \text{for } i \in 1 : M \quad \text{with } f, g_i \text{ concave}$$
- set $J(\mathbf{x}) = f(\mathbf{x}) - \sum_{i=1}^M \mu_i g_i(\mathbf{x}) - \boldsymbol{\lambda}^T \mathbf{Ax}$
- Solution $\mathbf{x}_0, \boldsymbol{\lambda}, \mu_i$ iff

$$\nabla J(\mathbf{x}_0) = \mathbf{0}, \quad \mathbf{Ax} + \mathbf{b} = \mathbf{0}, \quad g_i(\mathbf{x}_0) \geq 0, \quad \mu_i \geq 0, \quad \mu_i g_i(\mathbf{x}_0) = 0$$



Colored Gaussian Noise

- Suppose $\mathbf{y} = \mathbf{x} + \mathbf{z}$ where $E \mathbf{zz}^T = \mathbf{K}_z$ and $E \mathbf{xx}^T = \mathbf{K}_x$
- We want to find \mathbf{K}_x to maximize capacity subject to power constraint: $E \sum_{i=1}^n x_i^2 \leq nP \Leftrightarrow \text{tr}(\mathbf{K}_x) \leq nP$
 - Find noise eigenvectors: $\mathbf{K}_z = \mathbf{Q} \Lambda \mathbf{Q}^T$ with $\mathbf{QQ}^T = \mathbf{I}$
 - Now $\mathbf{Q}^T \mathbf{y} = \mathbf{Q}^T \mathbf{x} + \mathbf{Q}^T \mathbf{z} = \mathbf{Q}^T \mathbf{x} + \mathbf{w}$
where $E \mathbf{ww}^T = E \mathbf{Q}^T \mathbf{zz}^T \mathbf{Q} = E \mathbf{Q}^T \mathbf{K}_z \mathbf{Q} = \Lambda$ is diagonal
 - $\Rightarrow W_i$ are now independent (so previous result on P.G.C. applies)
 - Power constraint is unchanged $\text{tr}(\mathbf{Q}^T \mathbf{K}_x \mathbf{Q}) = \text{tr}(\mathbf{K}_x \mathbf{QQ}^T) = \text{tr}(\mathbf{K}_x)$
 - Use water-filling and indep. messages $\mathbf{Q}^T \mathbf{K}_x \mathbf{Q} + \Lambda = v\mathbf{I}$
 - Choose $\mathbf{Q}^T \mathbf{K}_x \mathbf{Q} = v\mathbf{I} - \Lambda$ where $v = P + n^{-1} \text{tr}(\Lambda)$

$$\Rightarrow \mathbf{K}_x = \mathbf{Q} (v\mathbf{I} - \Lambda) \mathbf{Q}^T$$

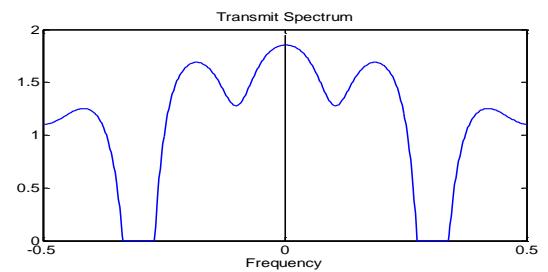
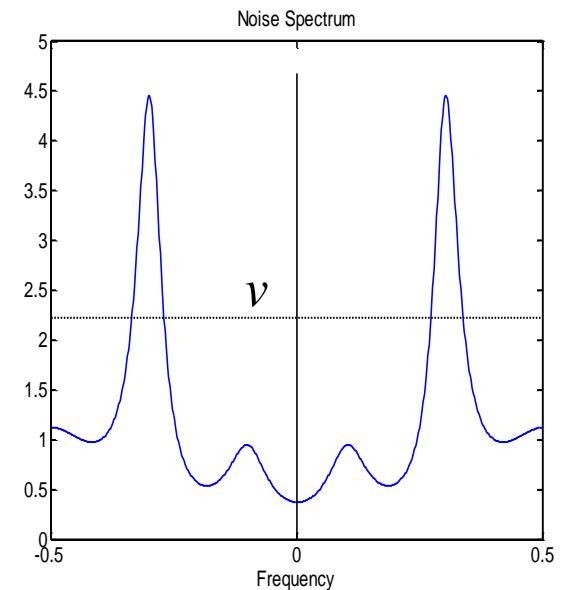
Power Spectrum Water Filling

- If \mathbf{z} is from a stationary process then $\text{diag}(\Lambda) \xrightarrow{n \rightarrow \infty} \text{power spectrum } N(f)$
 - To achieve capacity use waterfilling on noise power spectrum

$$P = \int_{-W}^W \max(v - N(f), 0) df$$

$$C = \int_{-W}^W \frac{1}{2} \log \left(1 + \frac{\max(v - N(f), 0)}{N(f)} \right) df$$

- Waterfilling on spectral domain

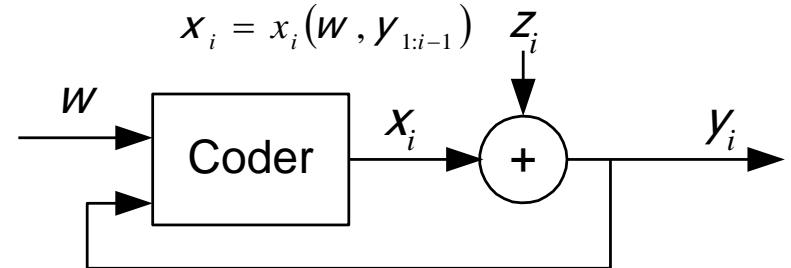


Gaussian Channel + Feedback

Does Feedback add capacity ?

- White noise (& DMC) – No
- Coloured noise – Not much

$$I(w; \mathbf{y}) = h(\mathbf{y}) - h(\mathbf{y} | w) = h(\mathbf{y}) - \sum_{i=1}^n h(y_i | w, y_{1:i-1})$$



Chain rule

$$= h(\mathbf{y}) - \sum_{i=1}^n h(y_i | w, y_{1:i-1}, x_{1:i}, z_{1:i-1})$$

$$\mathbf{x}_i = x_i(w, y_{1:i-1}), \mathbf{z} = \mathbf{y} - \mathbf{x}$$

$$= h(\mathbf{y}) - \sum_{i=1}^n h(z_i | w, y_{1:i-1}, x_{1:i}, z_{1:i-1})$$

$\mathbf{z} = \mathbf{y} - \mathbf{x}$ and translation invariance

$$= h(\mathbf{y}) - \sum_{i=1}^n h(z_i | z_{1:i-1})$$

\mathbf{z} may be colored; z_i depends only on $z_{1:i-1}$

Chain rule, $h(\mathbf{z}) = \frac{1}{2} \log(|2\pi e \mathbf{K}_{\mathbf{z}}|)$ bits

\Rightarrow maximize $I(w; \mathbf{y})$ by maximizing $h(\mathbf{y}) \Rightarrow \mathbf{y}$ gaussian

$$\leq \frac{1}{2} \log \frac{|\mathbf{K}_{\mathbf{y}}|}{|\mathbf{K}_{\mathbf{z}}|}$$

\Rightarrow we can take \mathbf{z} and $\mathbf{x} = \mathbf{y} - \mathbf{z}$ jointly gaussian

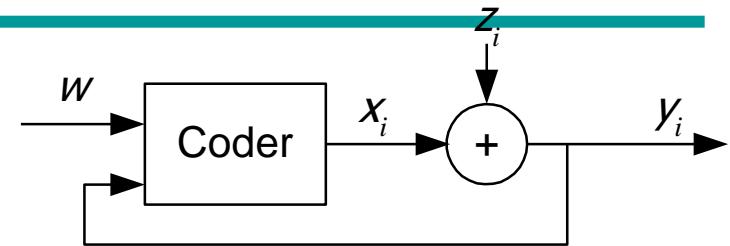
Maximum Benefit of Feedback

$$C_{n,FB} = \max_{\text{tr}(\mathbf{K}_x) \leq nP} \frac{1}{2} n^{-1} \log \frac{|\mathbf{K}_y|}{|\mathbf{K}_z|}$$

$$\leq \max_{\text{tr}(\mathbf{K}_x) \leq nP} \frac{1}{2} n^{-1} \log \frac{|2(\mathbf{K}_x + \mathbf{K}_z)|}{|\mathbf{K}_z|}$$

$$= \max_{\text{tr}(\mathbf{K}_x) \leq nP} \frac{1}{2} n^{-1} \log \frac{2^n |\mathbf{K}_x + \mathbf{K}_z|}{|\mathbf{K}_z|}$$

$$= \frac{1}{2} + \max_{\text{tr}(\mathbf{K}_x) \leq nP} \frac{1}{2} n^{-1} \log \frac{|\mathbf{K}_x + \mathbf{K}_z|}{|\mathbf{K}_z|} = \frac{1}{2} + C_n \text{ bits / transmission}$$



Lemmas 1 & 2:

$$|2(\mathbf{K}_x + \mathbf{K}_z)| \geq |\mathbf{K}_y|$$

$$|k\mathbf{A}| = k^n |\mathbf{A}|$$

$\mathbf{K}_y = \mathbf{K}_x + \mathbf{K}_z$ if no feedback

C_n : capacity without feedback

Having feedback adds at most $\frac{1}{2}$ bit per transmission for colored Gaussian noise channels

Max Benefit of Feedback: Lemmas

Lemma 1: $\mathbf{K}_{\mathbf{x}+\mathbf{z}} + \mathbf{K}_{\mathbf{x}-\mathbf{z}} = 2(\mathbf{K}_{\mathbf{x}} + \mathbf{K}_{\mathbf{z}})$

$$\begin{aligned}\mathbf{K}_{\mathbf{x}+\mathbf{z}} + \mathbf{K}_{\mathbf{x}-\mathbf{z}} &= E(\mathbf{x} + \mathbf{z})(\mathbf{x} + \mathbf{z})^T + E(\mathbf{x} - \mathbf{z})(\mathbf{x} - \mathbf{z})^T \\ &= E(\mathbf{xx}^T + \mathbf{xz}^T + \mathbf{zx}^T + \mathbf{zz}^T + \mathbf{xx}^T - \mathbf{xz}^T - \mathbf{zx}^T + \mathbf{zz}^T) \\ &= E(2\mathbf{xx}^T + 2\mathbf{zz}^T) = 2(\mathbf{K}_{\mathbf{x}} + \mathbf{K}_{\mathbf{z}})\end{aligned}$$

Lemma 2: If \mathbf{F}, \mathbf{G} are positive definite then $|\mathbf{F} + \mathbf{G}| \geq |\mathbf{F}|$

Consider two indep random vectors $\mathbf{f} \sim N(0, \mathbf{F}), \mathbf{g} \sim N(0, \mathbf{G})$

$$\begin{aligned}\tfrac{1}{2} \log \left((2\pi e)^n |\mathbf{F} + \mathbf{G}| \right) &= h(\mathbf{f} + \mathbf{g}) \\ &\geq h(\mathbf{f} + \mathbf{g} | \mathbf{g}) = h(\mathbf{f} | \mathbf{g}) \\ &= h(\mathbf{f}) = \tfrac{1}{2} \log \left((2\pi e)^n |\mathbf{F}| \right)\end{aligned}$$

Conditioning reduces $h()$
Translation invariance

\mathbf{f}, \mathbf{g} independent

Hence: $|2(\mathbf{K}_{\mathbf{x}} + \mathbf{K}_{\mathbf{z}})| = |\mathbf{K}_{\mathbf{x}+\mathbf{z}} + \mathbf{K}_{\mathbf{x}-\mathbf{z}}| \geq |\mathbf{K}_{\mathbf{x}+\mathbf{z}}| = |\mathbf{K}_{\mathbf{y}}|$

Gaussian Feedback Coder

\mathbf{x} and \mathbf{z} jointly gaussian \Rightarrow

$$\mathbf{x} = \mathbf{B}\mathbf{z} + \mathbf{v}(w)$$

where \mathbf{v} is indep of \mathbf{z} and

\mathbf{B} is strictly lower triangular since x_i indep of z_j for $j > i$.

$$\mathbf{y} = \mathbf{x} + \mathbf{z} = (\mathbf{B} + \mathbf{I})\mathbf{z} + \mathbf{v}$$

$$\mathbf{K}_y = E\mathbf{yy}^T = E((\mathbf{B} + \mathbf{I})\mathbf{zz}^T(\mathbf{B} + \mathbf{I})^T + \mathbf{vv}^T) = (\mathbf{B} + \mathbf{I})\mathbf{K}_z(\mathbf{B} + \mathbf{I})^T + \mathbf{K}_v$$

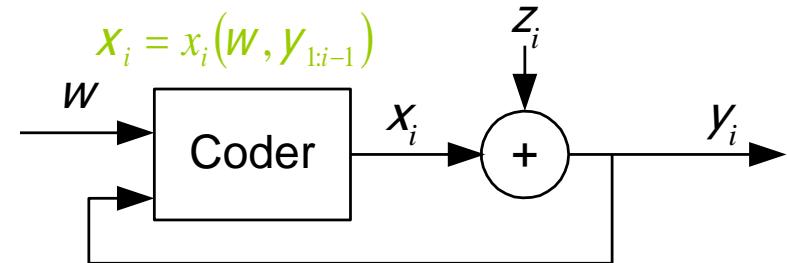
$$\mathbf{K}_x = E\mathbf{xx}^T = E(\mathbf{B}\mathbf{zz}^T\mathbf{B}^T + \mathbf{vv}^T) = \mathbf{BK}_z\mathbf{B}^T + \mathbf{K}_v$$

Capacity: $C_{n,FB} = \max_{\mathbf{K}_v, \mathbf{B}} \frac{1}{2} n^{-1} \frac{|\mathbf{K}_y|}{|\mathbf{K}_z|} = \max_{\mathbf{K}_v, \mathbf{B}} \frac{1}{2} n^{-1} \log \frac{|(\mathbf{B} + \mathbf{I})\mathbf{K}_z(\mathbf{B} + \mathbf{I})^T + \mathbf{K}_v|}{|\mathbf{K}_z|}$

subject to $\mathbf{K}_x = \text{tr}(\mathbf{BK}_z\mathbf{B}^T + \mathbf{K}_v) \leq nP$

hard to solve ☺

Optimization can be done numerically



Gaussian Feedback: Toy Example

$$n = 2, \quad P = 2, \quad \mathbf{K}_z = \begin{pmatrix} 2 & 1 \\ 1 & 2 \end{pmatrix}, \quad \mathbf{B} = \begin{pmatrix} 0 & 0 \\ b & 0 \end{pmatrix}$$

$$\mathbf{x} = \mathbf{B}\mathbf{z} + \mathbf{v} \Rightarrow x_1 = v_1, x_2 = bz_1 + v_2$$

Goal: Maximize (w.r.t. \mathbf{K}_v and b)

$$|\mathbf{K}_y| = |(\mathbf{B} + \mathbf{I})\mathbf{K}_z(\mathbf{B} + \mathbf{I})^T + \mathbf{K}_v|$$

Subject to:

\mathbf{K}_v must be positive definite

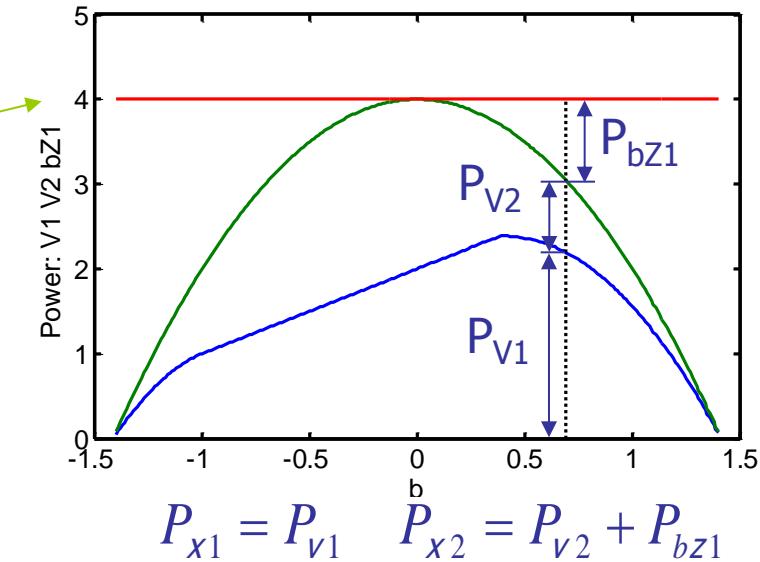
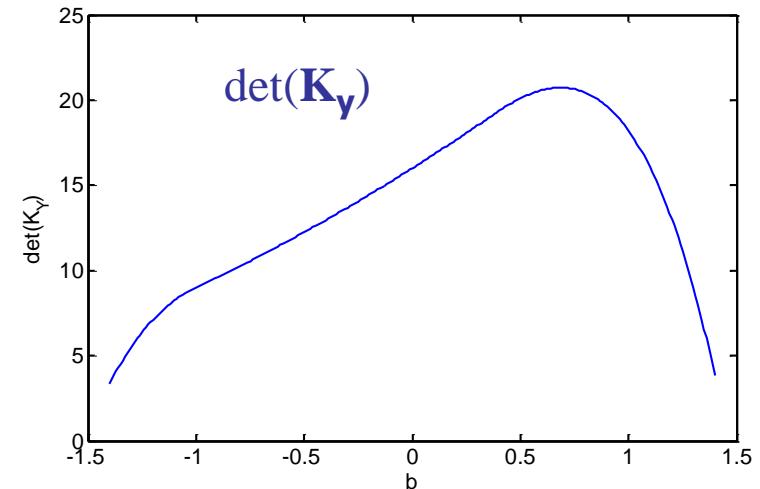
$$\text{Power constraint : } \text{tr}(\mathbf{B}\mathbf{K}_z\mathbf{B}^T + \mathbf{K}_v) \leq 4$$

Solution (via numerically search):

$$b=0: \quad |\mathbf{K}_y|=16 \quad C=0.604 \text{ bits}$$

$$b=0.69: \quad |\mathbf{K}_y|=20.7 \quad C=0.697 \text{ bits}$$

Feedback increases C by 16%



Summary

- Water-filling for parallel Gaussian channel

$$C = \sum_{i=1}^n \frac{1}{2} \log \left(1 + \frac{(v - N_i)^+}{N_i} \right) \quad x^+ = \max(x, 0)$$

$$\sum (v - N_i)^+ = nP$$

- Colored Gaussian noise

$$C = \sum_{i=1}^n \frac{1}{2} \log \left(1 + \frac{(v - \lambda_i)^+}{\lambda_i} \right) \quad \lambda_i \text{ eigenvalues of } \mathbf{K}_z$$

$$\sum (v - \lambda_i)^+ = nP$$

- Continuous Gaussian channel

$$C = \int_{-W}^W \frac{1}{2} \log \left(1 + \frac{(v - N(f))^+}{N(f)} \right) df$$

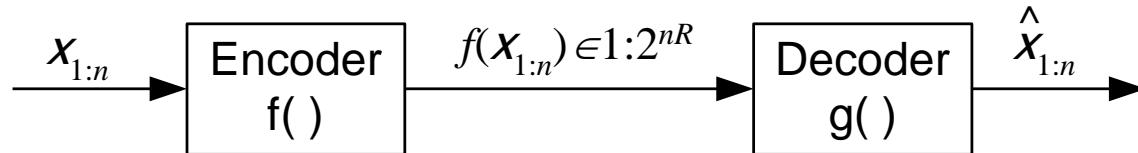
- Feedback bound

$$C_{n,FB} \leq C_n + \frac{1}{2}$$

Lecture 16

- Lossy Source Coding
 - For both discrete and continuous sources
 - Bernoulli Source, Gaussian Source
- Rate Distortion Theory
 - What is the minimum distortion achievable at a particular rate?
 - What is the minimum rate to achieve a particular distortion?
- Channel/Source Coding Duality

Lossy Source Coding



Distortion function: $d(x, \hat{x}) \geq 0$

- examples: (i) $d_s(x, \hat{x}) = (x - \hat{x})^2$ (ii) $d_H(x, \hat{x}) = \begin{cases} 0 & x = \hat{x} \\ 1 & x \neq \hat{x} \end{cases}$
- sequences: $d(\mathbf{x}, \hat{\mathbf{x}}) = n^{-1} \sum_{i=1}^n d(x_i, \hat{x}_i)$

Distortion of Code $f_n(), g_n()$: $D = E_{\mathbf{x} \in X^n} d(\mathbf{x}, \hat{\mathbf{x}}) = E d(\mathbf{x}, g(f(\mathbf{x})))$

Rate distortion pair (R,D) is achievable for source X if

\exists a sequence $f_n()$ and $g_n()$ such that $\lim_{n \rightarrow \infty} E_{\mathbf{x} \in X^n} d(\mathbf{x}, g_n(f_n(\mathbf{x}))) \leq D$

Rate Distortion Function

Rate Distortion function for $\{X_i\}$ with pdf $p(\mathbf{x})$ is defined as

$$R(D) = \min\{R\} \text{ such that } (R, D) \text{ is achievable}$$

Theorem: $R(D) = \min I(X; \hat{X})$ over all $p(x, \hat{x})$ such that :

- (a) $p(x)$ is correct
- (b) $E_{x, \hat{x}} d(x, \hat{x}) \leq D$



- this expression is the Rate Distortion function for X

Proof is not examinable

Lossless coding: If $D = 0$ then we have $R(D) = I(X; X) = H(X)$

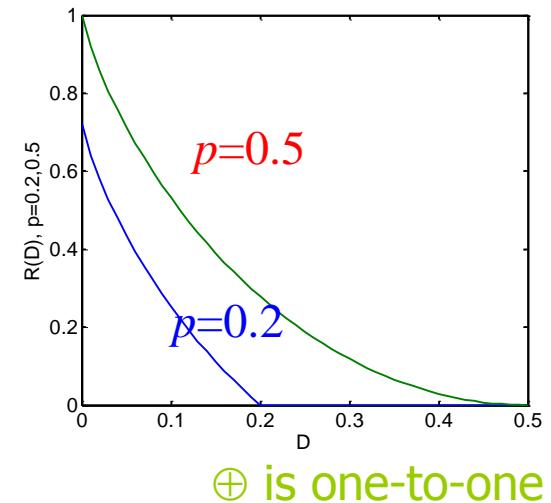
◆ $p(x, \hat{x}) = p(x)q(\hat{x} | x)$

$R(D)$ bound for Bernoulli Source

Bernoulli: $X = [0,1]$, $p_X = [1-p, p]$ assume $p \leq \frac{1}{2}$

- Hamming Distance: $d(x, \hat{x}) = x \oplus \hat{x}$
- If $D \geq p$, $R(D) = 0$ since we can set $g(\cdot) \equiv 0$
- For $D < p \leq \frac{1}{2}$, if $E d(x, \hat{x}) \leq D$ then

$$\begin{aligned} I(x; \hat{x}) &= H(x) - H(x | \hat{x}) \\ &= H(p) - H(x \oplus \hat{x} | \hat{x}) \\ &\geq H(p) - H(x \oplus \hat{x}) \\ &\geq H(p) - H(D) \end{aligned}$$



Conditioning reduces entropy

Prob.($x \oplus \hat{x} = 1$) $\leq D$ for $D \leq \frac{1}{2}$

$H(x \oplus \hat{x}) \leq H(D)$ as $H(p)$ monotonic

Hence $R(D) \geq H(p) - H(D)$

$R(D)$ for Bernoulli source

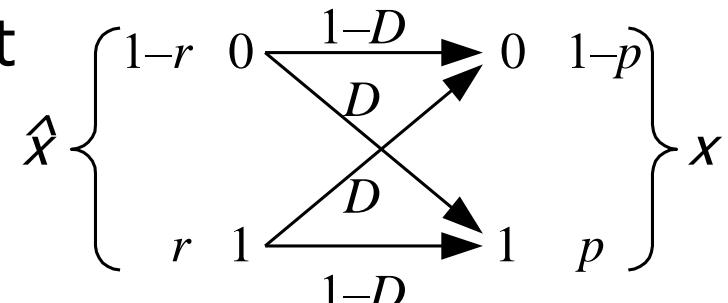
We know optimum satisfies $R(D) \geq H(p) - H(D)$

- We show we can find a $p(\hat{x}, x)$ that attains this.
- Peculiarly, we consider a **channel** with \hat{x} as the **input** and error probability D

Now choose r to give x the correct probabilities:

$$r(1 - D) + (1 - r)D = p$$

$$\Rightarrow r = (p - D)(1 - 2D)^{-1}, \quad D \leq p$$



$$\text{Now } I(x; \hat{x}) = H(x) - H(x | \hat{x}) = H(p) - H(D)$$

$$\text{and } p(x \neq \hat{x}) = D \Rightarrow \text{distortion} \leq D$$

$$\text{Hence } R(D) = H(p) - H(D)$$

If $D \geq p$ or $D \geq 1 - p$, we can achieve $R(D)=0$ trivially.

$R(D)$ bound for Gaussian Source

- Assume $X \sim N(0, \sigma^2)$ and $d(x, \hat{x}) = (x - \hat{x})^2$
- Want to minimize $I(X; \hat{X})$ subject to $E(X - \hat{X})^2 \leq D$

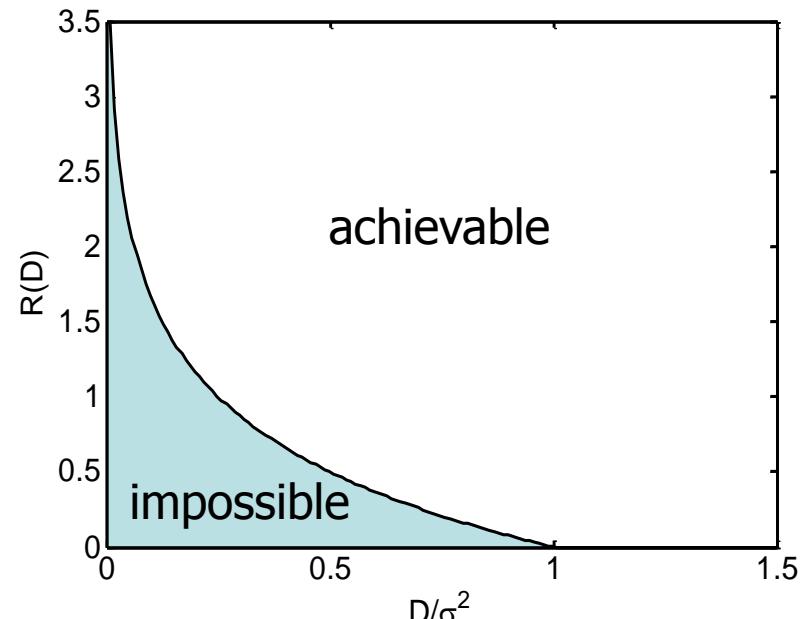
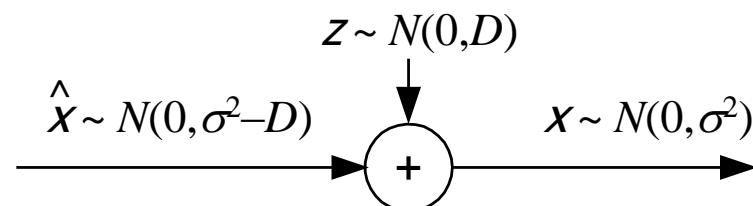
$$\begin{aligned}
 I(X; \hat{X}) &= h(X) - h(X | \hat{X}) \\
 &= \frac{1}{2} \log 2\pi e \sigma^2 - h(X - \hat{X} | \hat{X}) && \text{Translation Invariance} \\
 &\geq \frac{1}{2} \log 2\pi e \sigma^2 - h(X - \hat{X}) && \text{Conditioning reduces entropy} \\
 &\geq \frac{1}{2} \log 2\pi e \sigma^2 - \frac{1}{2} \log (2\pi e \operatorname{Var}(X - \hat{X})) && \text{Gauss maximizes entropy} \\
 &\geq \frac{1}{2} \log 2\pi e \sigma^2 - \frac{1}{2} \log 2\pi e D && \text{require } \operatorname{Var}(X - \hat{X}) \leq E(X - \hat{X})^2 \leq D \\
 I(X; \hat{X}) &\geq \max \left(\frac{1}{2} \log \frac{\sigma^2}{D}, 0 \right) && I(X; Y) \text{ always positive}
 \end{aligned}$$

$R(D)$ for Gaussian Source

To show that we can find a $p(\hat{x}, x)$ that achieves the bound, we construct a **test channel** that introduces distortion $D < \sigma^2$

$$\begin{aligned} I(X; \hat{X}) &= h(X) - h(X | \hat{X}) \\ &= \frac{1}{2} \log 2\pi e \sigma^2 - h(X - \hat{X} | \hat{X}) \\ &= \frac{1}{2} \log 2\pi e \sigma^2 - h(Z | \hat{X}) \\ &= \frac{1}{2} \log \frac{\sigma^2}{D} \\ \Rightarrow R(D) &= \max \left\{ \frac{1}{2} \log \frac{\sigma^2}{D}, 0 \right\} \end{aligned}$$

$$\Rightarrow D(R) = \frac{\sigma^2}{2^{2R}} \quad \text{cf. PCM} \quad D(R) = \frac{m_p^2 / 3}{2^{2R}} = \frac{16 / 3 \cdot \sigma^2}{2^{2R}}$$

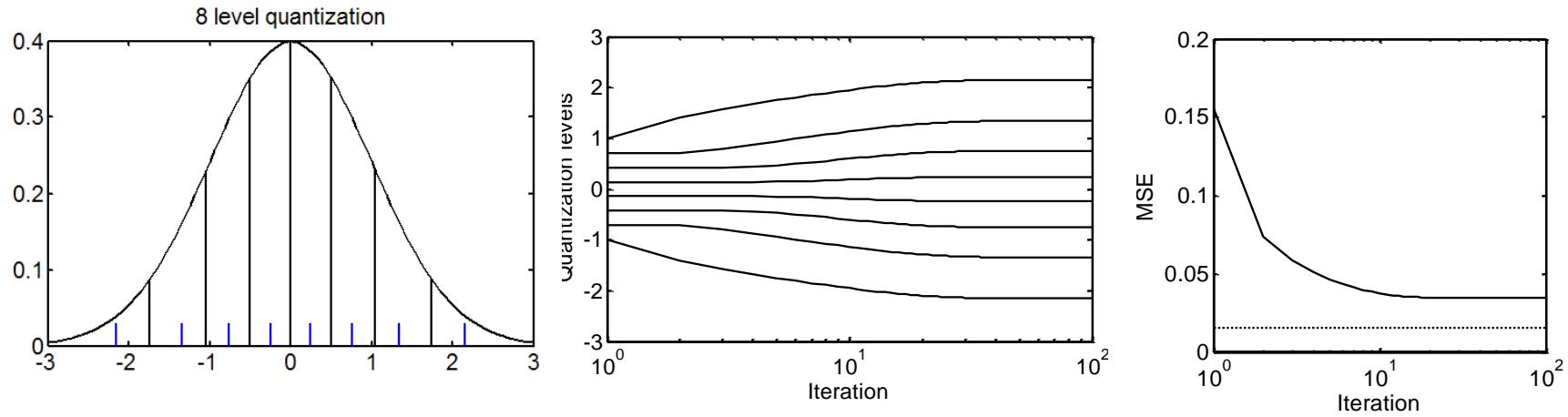


Lloyd Algorithm

Problem: Find optimum quantization levels for Gaussian pdf

- a. Bin boundaries are midway between quantization levels
- b. Each quantization level equals the mean value of its own bin

Lloyd algorithm: Pick random quantization levels then apply conditions (a) and (b) in turn until convergence.



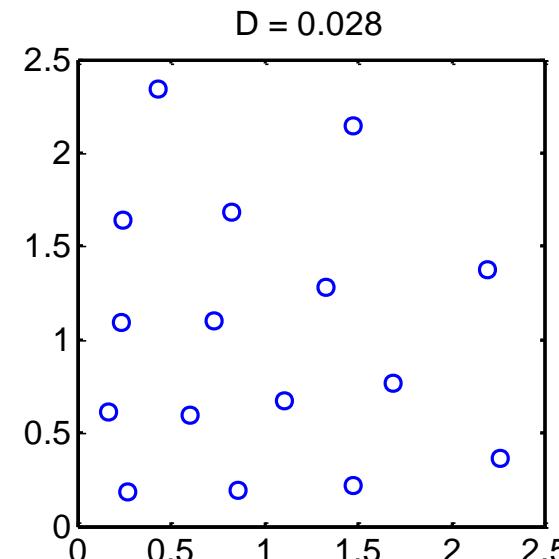
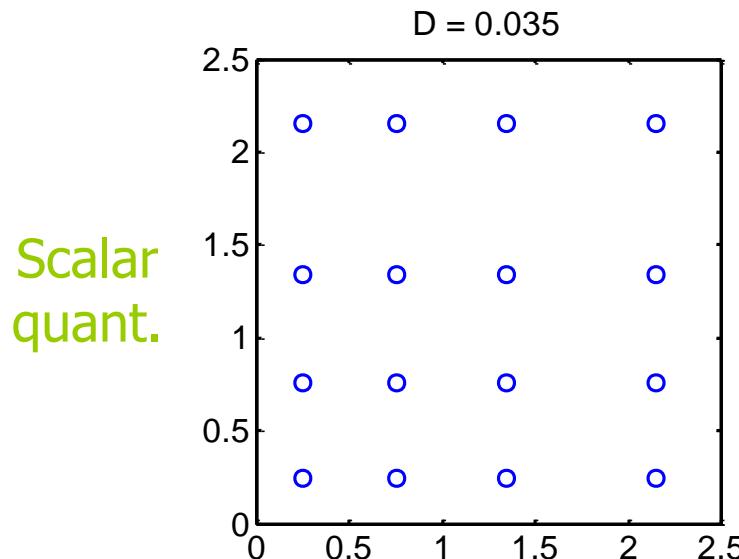
Solid lines are bin boundaries. Initial levels uniform in $[-1, +1]$.

Best mean sq error for 8 levels = $0.0345\sigma^2$. Predicted $D(R) = (\sigma/8)^2 = 0.0156\sigma^2$

Vector Quantization

To get $D(R)$, you have to quantize many values together

- True even if the values are independent



Two gaussian variables: one quadrant only shown

- Independent quantization puts dense levels in low prob areas
- Vector quantization is better (even more so if correlated)

Multiple Gaussian Variables

- Assume $x_{1:n}$ are independent gaussian sources with different variances. How should we apportion the available total distortion between the sources?
- Assume $x_i \sim N(0, \sigma_i^2)$ and $d(\mathbf{x}, \hat{\mathbf{x}}) = n^{-1}(\mathbf{x} - \hat{\mathbf{x}})^T(\mathbf{x} - \hat{\mathbf{x}}) \leq D$

$$I(x_{1:n}; \hat{x}_{1:n}) \geq \sum_{i=1}^n I(x_i; \hat{x}_i)$$

Mut Info Independence Bound
for independent x_i

$$\geq \sum_{i=1}^n R(D_i) = \sum_{i=1}^n \max\left(\frac{1}{2} \log \frac{\sigma_i^2}{D_i}, 0\right)$$

$R(D)$ for individual Gaussian

We must find the D_i that minimize

$$\sum_{i=1}^n \max\left(\frac{1}{2} \log \frac{\sigma_i^2}{D_i}, 0\right)$$

$$\Rightarrow D_i = \begin{cases} D_0 & \text{if } D_0 < \sigma_i^2 \\ \sigma_i^2 & \text{otherwise} \end{cases}$$

such that $n^{-1} \sum_{i=1}^n D_i = D$

Reverse Water-filling

Minimize $\sum_{i=1}^n \max\left(\frac{1}{2} \log \frac{\sigma_i^2}{D_i}, 0\right)$ subject to $\sum_{i=1}^n D_i \leq nD$

$$R_i = \frac{1}{2} \log \frac{\sigma_i^2}{D}$$

Use a Lagrange multiplier:

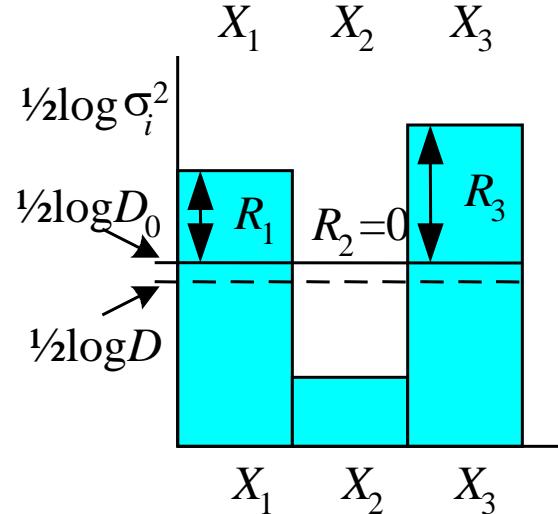
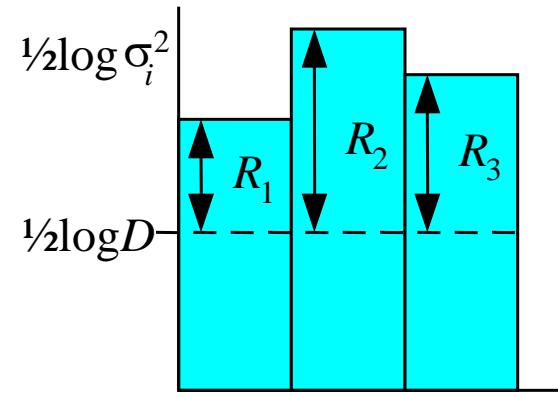
$$J = \sum_{i=1}^n \frac{1}{2} \log \frac{\sigma_i^2}{D_i} + \lambda \sum_{i=1}^n D_i$$

$$\frac{\partial J}{\partial D_i} = -\frac{1}{2} D_i^{-1} + \lambda = 0 \Rightarrow D_i = \frac{1}{2} \lambda^{-1} = D_0$$

$$\sum_{i=1}^n D_i = nD_0 = nD \Rightarrow D_0 = D$$

Choose R_i for equal distortion

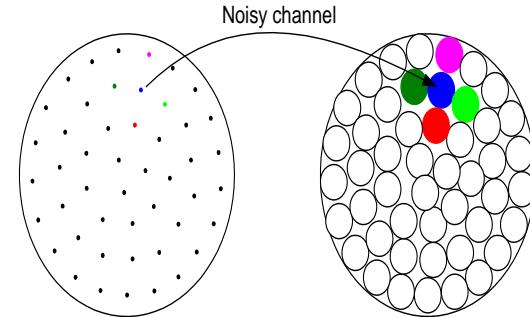
- If $\sigma_i^2 < D$ then set $R_i = 0$ (meaning $D_i = \sigma_i^2$) and increase D_0 to maintain the average distortion equal to D



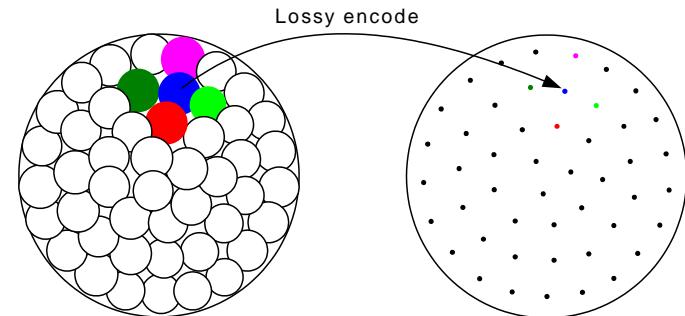
Channel/Source Coding Duality

- **Channel Coding**
 - Find codes separated enough to give non-overlapping output images.
 - Image size = channel noise
 - The maximum number (highest rate) is when the images just don't overlap (some gap).

- **Source Coding**
 - Find regions that cover the sphere
 - Region size = allowed distortion
 - The minimum number (lowest rate) is when they just fill the sphere (**with no gap**).



Sphere Packing

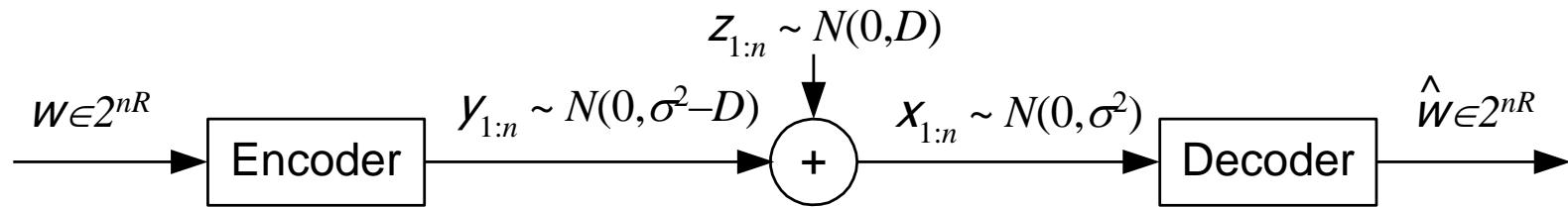


Sphere Covering

Gaussian Channel/Source

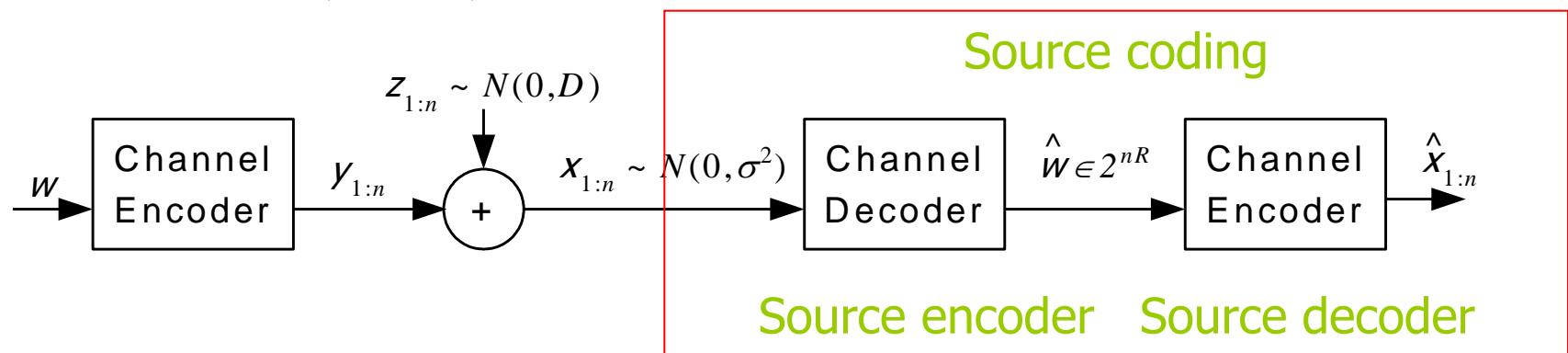
- Capacity of Gaussian channel (n : length)
 - Radius of big sphere $\sqrt{n(P + N)}$
 - Radius of small spheres \sqrt{nN}
 - Capacity $2^{nC} = \frac{\sqrt{n(P + N)}^n}{\sqrt{nN}^n} = \left(\frac{P + N}{N}\right)^{n/2}$ Maximum number of small spheres packed in the big sphere
- Rate distortion for Gaussian source
 - Variance $\sigma^2 \rightarrow$ radius of big sphere $\sqrt{n\sigma^2}$
 - Radius of small spheres \sqrt{nD} for distortion D
 - Rate $2^{nR(D)} = \left(\frac{\sigma^2}{D}\right)^{n/2}$ Minimum number of small spheres to cover the big sphere

Channel Decoder as Source Encoder



- For $R \cong C = \frac{1}{2} \log \left(1 + (\sigma^2 - D) D^{-1} \right)$, we can find a channel encoder/decoder so that $p(\hat{w} \neq w) < \varepsilon$ and $E(x_i - y_i)^2 = D$
- Now reverse the roles of encoder and decoder. Since

$$p(\hat{x} \neq y) = p(w \neq \hat{w}) < \varepsilon \text{ and } E(x_i - \hat{x}_i)^2 \cong E(x_i - y_i)^2 = D$$



We have encoded x at rate $R = \frac{1}{2} \log(\sigma^2 D^{-1})$ with distortion D !

Summary

- Lossy source coding: tradeoff between rate and distortion
- Rate distortion function

$$R(D) = \min_{\mathbf{p}_{\hat{x}|x} \text{ s.t. } Ed(x, \hat{x}) \leq D} I(x; \hat{x})$$

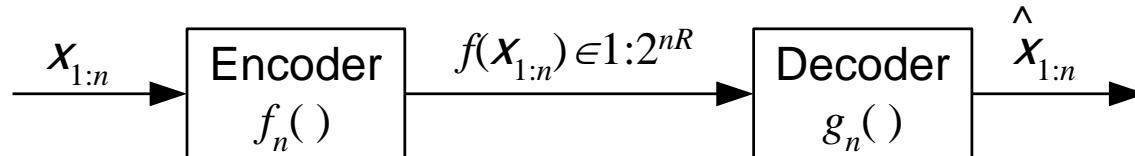
- Bernoulli source: $R(D) = (H(p) - H(D))^+$
- Gaussian source
(reverse waterfilling): $R(D) = \left(\frac{1}{2} \log \frac{\sigma^2}{D} \right)^+$
- Duality: channel decoding (encoding) \Leftrightarrow source encoding (decoding)

Nothing But Proof

- Proof of Rate Distortion Theorem
 - Converse: if the rate is less than $R(D)$, then distortion of any code is higher than D
 - Achievability: if the rate is higher than $R(D)$, then there exists a rate- R code which achieves distortion D

Quite technical!

Review



Rate Distortion function for x whose $p_x(\mathbf{x})$ is known is

$$R(D) = \inf R \text{ such that } \exists f_n, g_n \text{ with } \lim_{n \rightarrow \infty} E_{\mathbf{x} \in X^n} d(\mathbf{x}, \hat{\mathbf{x}}) \leq D$$

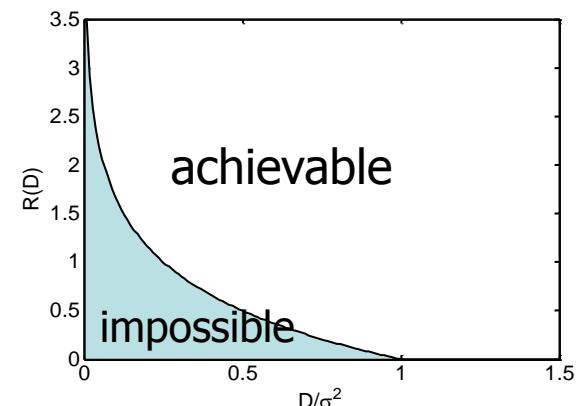
Rate Distortion Theorem:

$$R(D) = \min I(x; \hat{x}) \text{ over all } p(\hat{x} | x) \text{ such that } E_{x, \hat{x}} d(x, \hat{x}) \leq D$$

We will prove this theorem for discrete X and bounded $d(x, y) \leq d_{\max}$

$R(D)$ curve depends on your choice of $d(,)$

Decreasing and convex



Converse: Rate Distortion Bound

Suppose we have found an encoder and decoder at rate R_0 with expected distortion D for independent x_i (worst case)

We want to prove that $R_0 \geq R(D) = R(E d(\mathbf{x}; \hat{\mathbf{x}}))$

- We show first that $R_0 \geq n^{-1} \sum_i I(x_i; \hat{x}_i)$
- We know that $I(x_i; \hat{x}_i) \geq R(E d(x_i; \hat{x}_i))$ Defⁿ of $R(D)$
- and use convexity of $R(D)$ to show

$$n^{-1} \sum_i R(E d(x_i; \hat{x}_i)) \geq R\left(n^{-1} \sum_i E d(x_i; \hat{x}_i)\right) = R(E d(\mathbf{x}; \hat{\mathbf{x}})) = R(D)$$

We prove convexity first and then the rest

Convexity of $R(D)$

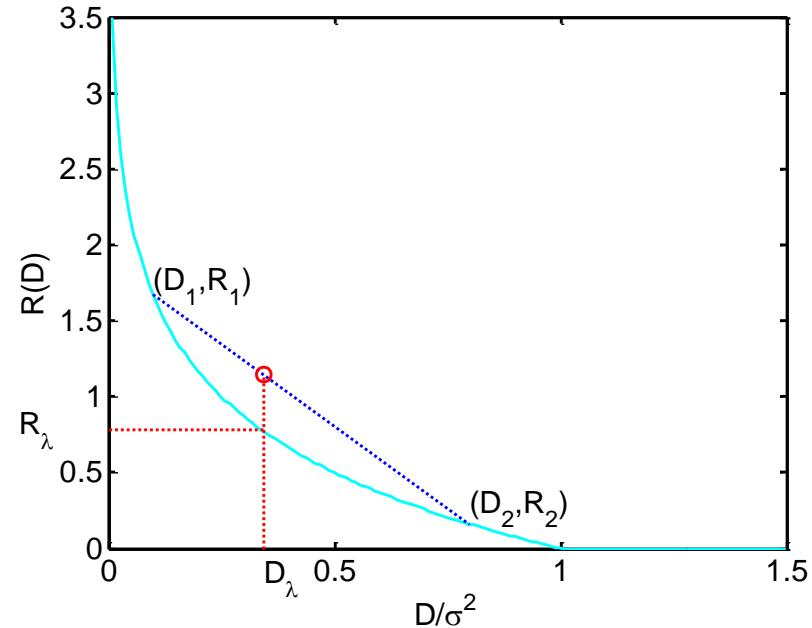
If $p_1(\hat{x} | x)$ and $p_2(\hat{x} | x)$ are associated with (D_1, R_1) and (D_2, R_2) on the $R(D)$ curve we define

$$p_\lambda(\hat{x} | x) = \lambda p_1(\hat{x} | x) + (1 - \lambda) p_2(\hat{x} | x)$$

Then

$$E_{p_\lambda} d(x, \hat{x}) = \lambda D_1 + (1 - \lambda) D_2 = D_\lambda$$

$$\begin{aligned} R(D_\lambda) &\leq I_{p_\lambda}(x; \hat{x}) \\ &\leq \lambda I_{p_1}(x; \hat{x}) + (1 - \lambda) I_{p_2}(x; \hat{x}) \\ &= \lambda R(D_1) + (1 - \lambda) R(D_2) \end{aligned}$$



$$R(D) = \min_{p(\hat{x}|x)} I(X; \hat{X})$$

$I(X; \hat{X})$ convex w.r.t. $p(\hat{x} | x)$

p_1 and p_2 lie on the $R(D)$ curve

Proof that $R \geq R(D)$

$$nR_0 \geq H(\hat{X}_{1:n}) \geq H(\hat{X}_{1:n}) - H(\hat{X}_{1:n} | X_{1:n}) \quad \text{Uniform bound; } H(\hat{X} | X) \geq 0$$

$$= I(\hat{X}_{1:n}; X_{1:n}) \quad \text{Definition of } I();$$

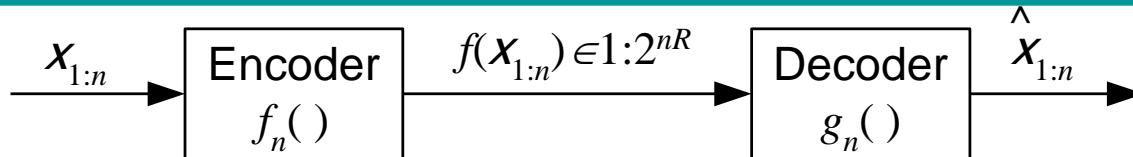
$$\geq \sum_{i=1}^n I(X_i; \hat{X}_i) \quad \begin{matrix} x_i \text{ indep: Mut Inf} \\ \text{Independence Bound} \end{matrix}$$

$$\geq \sum_{i=1}^n R(E d(X_i; \hat{X}_i)) = n \sum_{i=1}^n n^{-1} R(E d(X_i; \hat{X}_i)) \quad \text{definition of } R$$

$$\geq nR\left(n^{-1} \sum_{i=1}^n E d(X_i; \hat{X}_i)\right) = nR(E d(X_{1:n}; \hat{X}_{1:n})) \quad \begin{matrix} \text{convexity} \\ \text{defn of vector } d() \end{matrix}$$

$$\geq nR(D) \quad \begin{matrix} \text{original assumption that } E(d) \leq D \\ \text{and } R(D) \text{ monotonically decreasing} \end{matrix}$$

Rate Distortion Achievability



We want to show that for any D , we can find an encoder and decoder that compresses $x_{1:n}$ to $nR(D)$ bits.

- p_x is given
- Assume we know the $p(\hat{x} | x)$ that gives $I(x; \hat{x}) = R(D)$
- **Random codebook:** Choose 2^{nR} random $\hat{x}_i \sim p_{\hat{x}}$
 - There must be at least one code that is as good as the average
- **Encoder:** Use joint typicality to design
 - We show that there is almost always a suitable codeword

First define the typical set we will use, then prove two preliminary results.

Distortion Typical Set

Distortion Typical: $(x_i, \hat{x}_i) \in X \times \hat{X}$ drawn i.i.d. $\sim p(x, \hat{x})$

$$\begin{aligned}
 J_{d,\varepsilon}^{(n)} = \left\{ \mathbf{x}, \hat{\mathbf{x}} \in X^n \times \hat{X}^n : \right. & \left| -n^{-1} \log p(\mathbf{x}) - H(X) \right| < \varepsilon, \\
 & \left| -n^{-1} \log p(\hat{\mathbf{x}}) - H(\hat{X}) \right| < \varepsilon, \\
 & \left| -n^{-1} \log p(\mathbf{x}, \hat{\mathbf{x}}) - H(X, \hat{X}) \right| < \varepsilon \\
 & \left. \left| d(\mathbf{x}, \hat{\mathbf{x}}) - E d(X, \hat{X}) \right| < \varepsilon \right\} \quad \text{new condition}
 \end{aligned}$$

Properties of Typical Set:

1. Indiv p.d.: $\mathbf{x}, \hat{\mathbf{x}} \in J_{d,\varepsilon}^{(n)} \Rightarrow \log p(\mathbf{x}, \hat{\mathbf{x}}) = -nH(X, \hat{X}) \pm n\varepsilon$

2. Total Prob: $p(\mathbf{x}, \hat{\mathbf{x}} \in J_{d,\varepsilon}^{(n)}) > 1 - \varepsilon \quad \text{for } n > N_\varepsilon$

weak law of large numbers; $d(x_i, \hat{x}_i)$ are i.i.d.

Conditional Probability Bound

Lemma: $\mathbf{x}, \hat{\mathbf{x}} \in J_{d,\varepsilon}^{(n)} \Rightarrow p(\hat{\mathbf{x}}) \geq p(\hat{\mathbf{x}} | \mathbf{x}) 2^{-n(I(x; \hat{x}) + 3\varepsilon)}$

Proof:
$$p(\hat{\mathbf{x}} | \mathbf{x}) = \frac{p(\hat{\mathbf{x}}, \mathbf{x})}{p(\mathbf{x})}$$

$$= p(\hat{\mathbf{x}}) \frac{p(\hat{\mathbf{x}}, \mathbf{x})}{p(\hat{\mathbf{x}})p(\mathbf{x})}$$

take max of top and min of bottom

$$\leq p(\hat{\mathbf{x}}) \frac{2^{-n(H(x, \hat{x}) - \varepsilon)}}{2^{-n(H(x) + \varepsilon)} 2^{-n(H(\hat{x}) + \varepsilon)}}$$

bounds from defⁿ of J

$$= p(\hat{\mathbf{x}}) 2^{n(I(x; \hat{x}) + 3\varepsilon)}$$

defⁿ of I

Curious but Necessary Inequality

Lemma: $u, v \in [0,1], m > 0 \Rightarrow (1 - uv)^m \leq 1 - u + e^{-vm}$

Proof: $u=0$: $e^{-vm} \geq 0 \Rightarrow (1 - 0)^m \leq 1 - 0 + e^{-vm}$

$u=1$: Define $f(v) = e^{-v} - 1 + v \Rightarrow f'(v) = 1 - e^{-v}$

$f(0) = 0$ and $f'(v) > 0$ for $v > 0 \Rightarrow f(v) \geq 0$ for $v \in [0,1]$

Hence for $v \in [0,1]$, $0 \leq 1 - v \leq e^{-v} \Rightarrow (1 - v)^m \leq e^{-vm}$

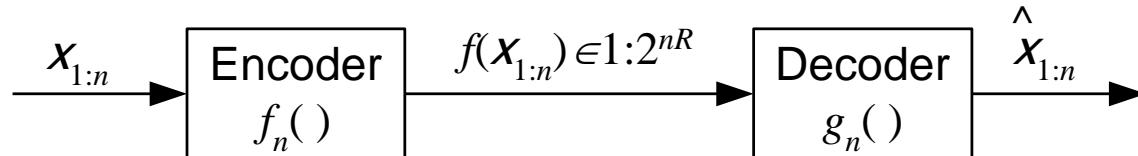
$0 < u < 1$: Define $g_v(u) = (1 - uv)^m$

$\Rightarrow g''_v(x) = m(m-1)v^2(1 - uv)^{n-2} \geq 0 \Rightarrow g_v(u)$ convex for $u, v \in [0,1]$

$(1 - uv)^m = g_v(u) \leq (1 - u)g_v(0) + ug_v(1)$ convexity for $u, v \in [0,1]$

$$= (1 - u)1 + u(1 - v)^m \leq 1 - u + ue^{-vm} \leq 1 - u + e^{-vm}$$

Achievability of $R(D)$: preliminaries



- Choose D and find a $p(\hat{x} | x)$ such that $I(x; \hat{x}) = R(D); E d(x, \hat{x}) \leq D$
Choose $\delta > 0$ and define $\mathbf{p}_{\hat{x}} = \{ p(\hat{x}) = \sum_x p(x) p(\hat{x} | x) \}$
- **Decoder:** For each $w \in 1 : 2^{nR}$ choose $g_n(w) = \hat{\mathbf{x}}_w$ drawn i.i.d. $\sim \mathbf{p}_{\hat{x}}^n$
- **Encoder:** $f_n(\mathbf{x}) = \min w$ such that $(\mathbf{x}, \hat{\mathbf{x}}_w) \in J_{d, \varepsilon}^{(n)}$ else 1 if no such w
- **Expected Distortion:** $\overline{D} = E_{\mathbf{x}, g} d(\mathbf{x}, \hat{\mathbf{x}})$
 - over all input vectors \mathbf{x} and all random decoding functions, g
 - for large n we show $\overline{D} = D + \delta$ so there must be one good code

Expected Distortion

We can divide the input vectors \mathbf{x} into two categories:

a) if $\exists w$ such that $(\mathbf{x}, \hat{\mathbf{x}}_w) \in J_{d, \varepsilon}^{(n)}$ then $d(\mathbf{x}, \hat{\mathbf{x}}_w) < D + \varepsilon$

since $E d(\mathbf{x}, \hat{\mathbf{x}}) \leq D$

b) if no such w exists we must have $d(\mathbf{x}, \hat{\mathbf{x}}_w) < d_{\max}$
 since we are assuming that $d()$ is bounded. Suppose
 the probability of this situation is P_e .

$$\begin{aligned}\text{Hence } \overline{D} &= E_{\mathbf{x}, g} d(\mathbf{x}, \hat{\mathbf{x}}) \\ &\leq (1 - P_e)(D + \varepsilon) + P_e d_{\max} \\ &\leq D + \varepsilon + P_e d_{\max}\end{aligned}$$

We need to show that the expected value of P_e is small

Error Probability

Define the set of valid inputs for (random) code g

$$V(g) = \left\{ \mathbf{x} : \exists w \text{ with } (\mathbf{x}, g(w)) \in J_{d,\varepsilon}^{(n)} \right\}$$

We have $P_e = \sum_g p(g) \sum_{\mathbf{x} \notin V(g)} p(\mathbf{x}) = \sum_{\mathbf{x}} p(\mathbf{x}) \sum_{g: \mathbf{x} \notin V(g)} p(g)$ Change the order

Define $K(\mathbf{x}, \hat{\mathbf{x}}) = 1$ if $(\mathbf{x}, \hat{\mathbf{x}}) \in J_{d,\varepsilon}^{(n)}$ else 0

Prob that a random $\hat{\mathbf{x}}$ does not match \mathbf{x} is $1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}}) K(\mathbf{x}, \hat{\mathbf{x}})$

Prob that an entire code does not match \mathbf{x} is $\left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}}) K(\mathbf{x}, \hat{\mathbf{x}}) \right)^{2^n R}$

Hence $P_e = \sum_{\mathbf{x}} p(\mathbf{x}) \left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}}) K(\mathbf{x}, \hat{\mathbf{x}}) \right)^{2^n R}$ Codewords are i.i.d.

Achievability for Average Code

Since $\mathbf{x}, \hat{\mathbf{x}} \in J_{d,\varepsilon}^{(n)} \Rightarrow p(\hat{\mathbf{x}}) \geq p(\hat{\mathbf{x}} | \mathbf{x}) 2^{-n(I(x;\hat{x})+3\varepsilon)}$

$$\begin{aligned} P_e &= \sum_{\mathbf{x}} p(\mathbf{x}) \left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}}) K(\mathbf{x}, \hat{\mathbf{x}}) \right)^{2^{nR}} \\ &\leq \sum_{\mathbf{x}} p(\mathbf{x}) \left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}} | \mathbf{x}) K(\mathbf{x}, \hat{\mathbf{x}}) \cdot 2^{-n(I(x;\hat{x})+3\varepsilon)} \right)^{2^{nR}} \end{aligned}$$

Using $(1 - uv)^m \leq 1 - u + e^{-vm}$

with $u = \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}} | \mathbf{x}) K(\mathbf{x}, \hat{\mathbf{x}}); \quad v = 2^{-nI(x;\hat{x})-3n\varepsilon}; \quad m = 2^{nR}$

$$\leq \sum_{\mathbf{x}} p(\mathbf{x}) \left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}} | \mathbf{x}) K(\mathbf{x}, \hat{\mathbf{x}}) + \exp \left(- 2^{-n(I(x;\hat{x})+3\varepsilon)} 2^{nR} \right) \right)$$

Note: $0 \leq u, v \leq 1$ as required

Achievability for Average Code

$$P_e \leq \sum_{\mathbf{x}} p(\mathbf{x}) \left(1 - \sum_{\hat{\mathbf{x}}} p(\hat{\mathbf{x}} | \mathbf{x}) K(\mathbf{x}, \hat{\mathbf{x}}) + \exp \left(- 2^{-n(I(X; \hat{X}) + 3\varepsilon)} 2^{nR} \right) \right)$$

$$= 1 - \sum_{\mathbf{x}, \hat{\mathbf{x}}} p(\mathbf{x}, \hat{\mathbf{x}}) K(\mathbf{x}, \hat{\mathbf{x}}) + \exp \left(- 2^{n(R - I(X; \hat{X}) - 3\varepsilon)} \right)$$

Mutual information does not involve particular \mathbf{x}

$$= P\left\{(\mathbf{x}, \hat{\mathbf{x}}) \notin J_{d, \varepsilon}^{(n)}\right\} + \exp \left(- 2^{n(R - I(X; \hat{X}) - 3\varepsilon)} \right)$$

$$\xrightarrow[n \rightarrow \infty]{} 0$$

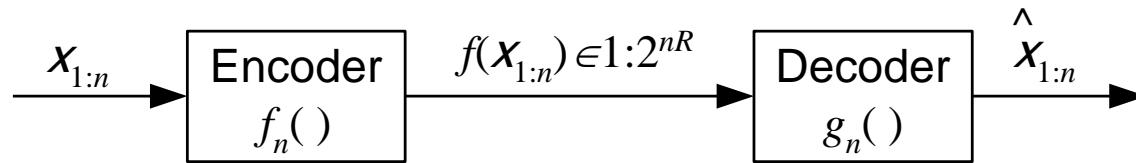
since both terms $\rightarrow 0$ as $n \rightarrow \infty$ provided $nR > I(X, \hat{X}) + 3\varepsilon$

Hence $\forall \delta > 0$, $\bar{D} = E_{\mathbf{x}, g} d(\mathbf{x}, \hat{\mathbf{x}})$ can be made $\leq D + \delta$

Achievability

Since $\forall \delta > 0$, $\bar{D} = E_{\mathbf{x},g} d(\mathbf{x}, \hat{\mathbf{x}})$ can be made $\leq D + \delta$
 there must be at least one g with $E_{\mathbf{x}} d(\mathbf{x}, \hat{\mathbf{x}}) \leq D + \delta$

Hence (R,D) is achievable for any $R > R(D)$



that is $\lim_{n \rightarrow \infty} E_{X_{1:n}} (\mathbf{x}, \hat{\mathbf{x}}) \leq D$

In fact a stronger result is true (proof in C&T 10.6):

$\forall \delta > 0, D$ and $R > R(D), \exists f_n, g_n$ with $p(d(\mathbf{x}, \hat{\mathbf{x}}) \leq D + \delta) \xrightarrow{n \rightarrow \infty} 1$

Lecture 17

- Introduction to network information theory
- Multiple access
- Distributed source coding

Network Information Theory

- System with **many senders and receivers**
- New elements: interference, cooperation, competition, relay, feedback...
- Problem: decide whether or not the sources can be transmitted over the channel
 - **Distributed source coding**
 - **Distributed communication**
 - The general problem has not yet been solved, so we consider various special cases
- Results are presented without proof (can be done using mutual information, joint AEP)

Implications to Network Design

- Examples of large information networks
 - Computer networks
 - Satellite networks
 - Telephone networks
- A complete theory of network communications would have **wide implications** for the design of communication and computer networks
- Examples
 - **CDMA** (code-division multiple access): mobile phone network
 - **Network coding**: significant capacity gain compared to routing-based networks

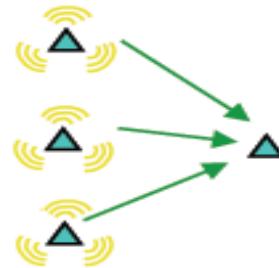
Network Models Considered

- Multi-access channel
- Broadcast channel
- Distributed source coding
- Relay channel
- Interference channel
- Two-way channel
- General communication network

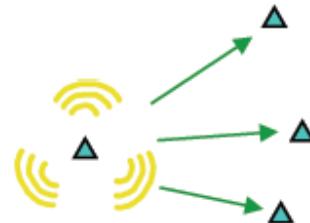
State of the Art

- **Triumphs**

- Multi-access channel



- Gaussian broadcast channel



- **Unknowns**

- The simplest relay channel



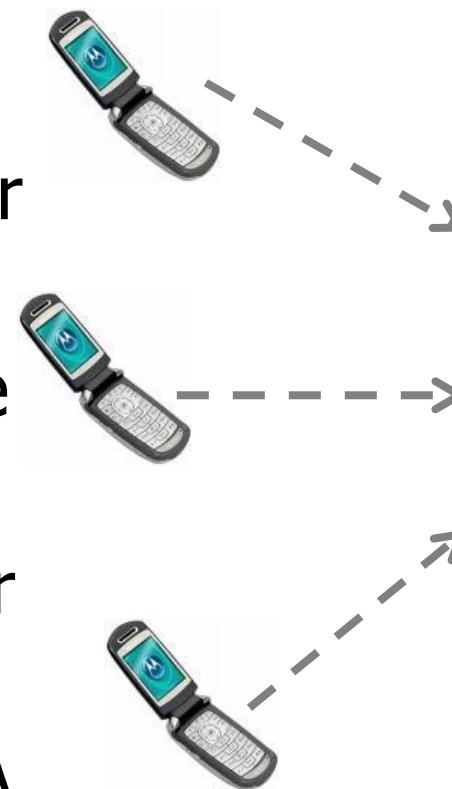
- The simplest interference channel



Reminder: Networks being built (ad hoc networks, sensor networks) are much more complicated

Multi-Access Channel

- Example: many users communicate with a common base station over a common channel
- What rates are achievable simultaneously?
- Best understood multiuser channel
- Very successful: 3G CDMA mobile phone networks



Capacity Region

- Capacity of single-user Gaussian channel

$$C = \frac{1}{2} \log \left(1 + \frac{P}{N} \right) = C\left(\frac{P}{N}\right)$$

- Gaussian multi-access channel with m users

$$Y = \sum_{i=1}^m X_i + Z$$

X_i has equal power P
noise Z has variance N

- Capacity region

$$R_i < C\left(\frac{P}{N}\right)$$

$$R_i + R_j < C\left(\frac{2P}{N}\right)$$

$$R_i + R_j + R_k < C\left(\frac{3P}{N}\right)$$

⋮

$$\sum_{i=1}^m R_i < C\left(\frac{mP}{N}\right)$$

R_i : rate for user i

Transmission: independent and simultaneous
(i.i.d. Gaussian codebooks)

Decoding: joint decoding, look for m
codewords whose sum is closest to Y

The last inequality dominates when all rates
are the same

The sum rate goes to ∞ with m

Two-User Channel

- Capacity region

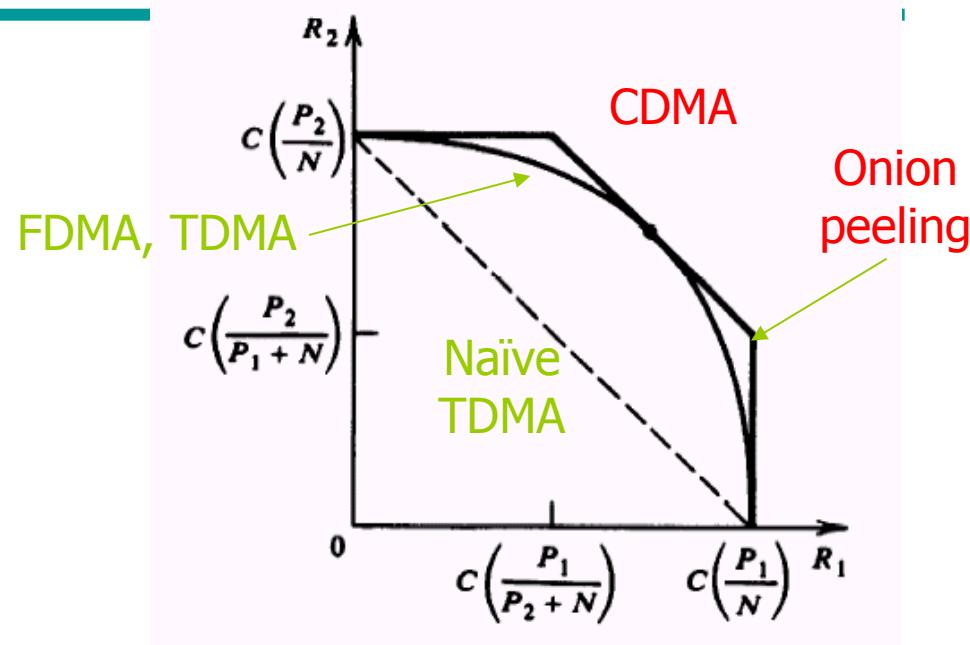
$$R_1 < C\left(\frac{P_1}{N}\right)$$

$$R_2 < C\left(\frac{P_2}{N}\right)$$

$$R_1 + R_2 < C\left(\frac{P_1 + P_2}{N}\right)$$

- Corresponds to CDMA
- Surprising fact: sum rate
= rate achieved by a single sender with power $P_1 + P_2$
- Achieves a higher sum rate than treating interference as noise, i.e.,

$$C\left(\frac{P_1}{P_2 + N}\right) + C\left(\frac{P_2}{P_1 + N}\right)$$



Onion Peeling

- Interpretation of corner point: **onion-peeling**
 - First stage: decoder user 2, considering user 1 as noise
 - Second stage: subtract out user 2, decoder user 1
- In fact, it can achieve the entire capacity region
 - Any rate-pairs between two corner points achievable by time-sharing
- Its technical term is successive interference cancelation (SIC)
 - Removes the need for joint decoding
 - Uses a sequence of single-user decoders
- SIC is implemented in the uplink of CDMA 2000 EV-DO (evolution-data optimized)
 - Increases throughput by about 65%

Comparison with TDMA and FDMA

- FDMA (frequency-division multiple access)

$$R_1 = W_1 \log \left(1 + \frac{P_1}{N_0 W_1} \right)$$

Total bandwidth $W = W_1 + W_2$

$$R_2 = W_2 \log \left(1 + \frac{P_2}{N_0 W_2} \right)$$

Varying W_1 and W_2 tracing out the curve in the figure

- TDMA (time-division multiple access)

- Each user is allotted a time slot, transmits and other users remain silent
- Naïve TDMA: dashed line
- Can do better while still maintaining the same average power constraint; the same capacity region as FDMA

- CDMA capacity region is larger

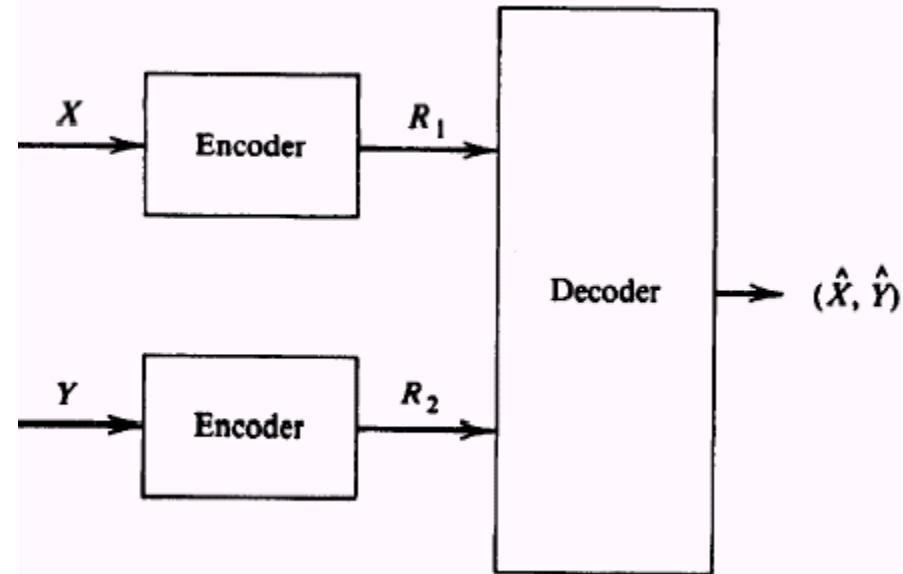
- But needs a **more complex decoder**

Distributed Source Coding

- Associate with nodes are sources that are generally dependent
- How do we take advantage of the dependence to reduce the amount of information transmitted?
- Consider the special case where channels are noiseless and without interference
- Finding the set of rates associate with each source such that all required sources can be decoded at destination
- Data compression dual to multi-access channel

Two-User Distributed Source Coding

- X and Y are correlated
- But **the encoders cannot communicate**; have to encode independently
- A single source: $R > H(X)$
- Two sources: $R > H(X, Y)$ if encoding together
- What if encoding separately?
 - Of course one can do $R > H(X) + H(Y)$
 - Surprisingly, $R = H(X, Y)$ is sufficient (**Slepian-Wolf coding, 1973**)
 - Sadly, the coding scheme was not practical (again)



Slepian-Wolf Coding

- Achievable rate region

$$R_1 \geq H(X | Y)$$

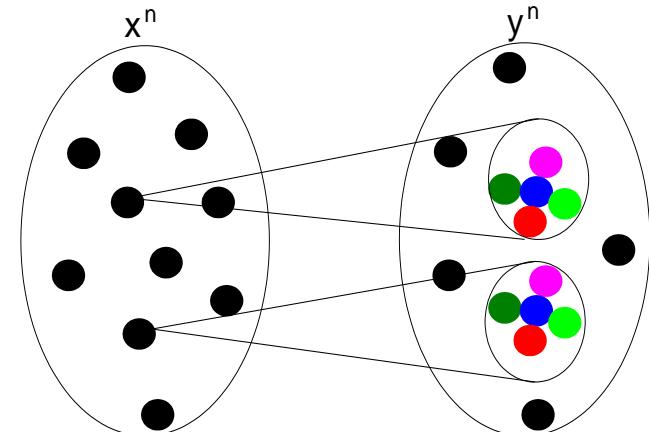
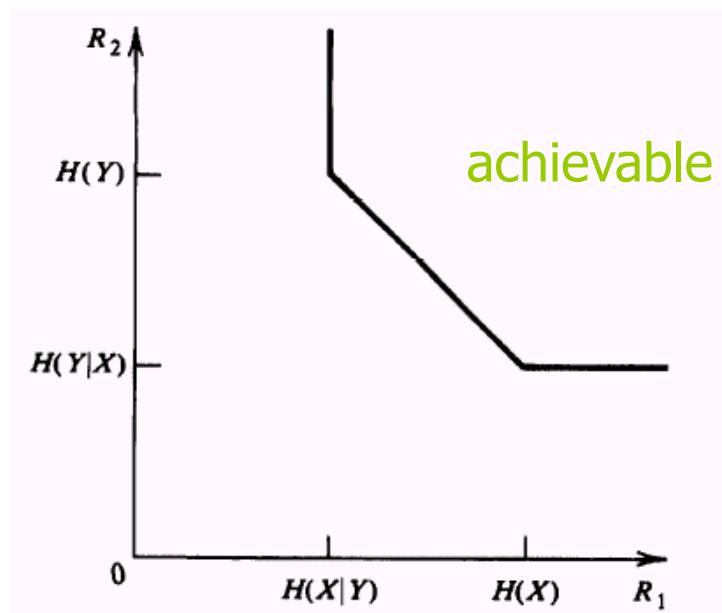
$$R_2 \geq H(Y | X)$$

$$R_1 + R_2 \geq H(X, Y)$$

- Core idea: joint typicality
- Interpretation of corner point $R_1 = H(X), R_2 = H(Y|X)$

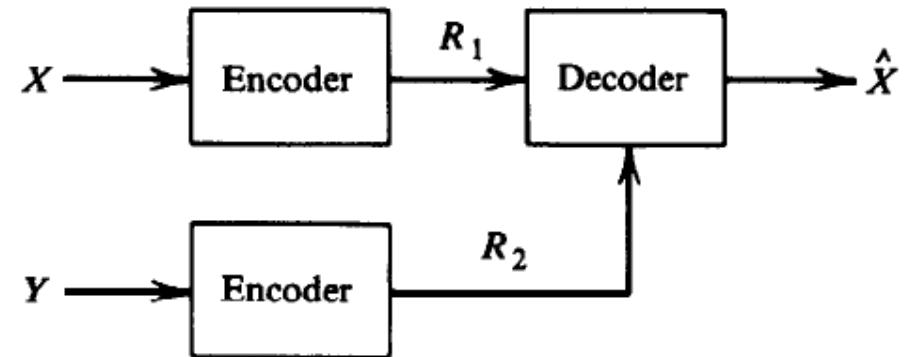
- X can encode as usual
- Associate with each x^n is a jointly typical fan (however Y doesn't know)
- **Y sends the color (thus compression)**
- Decoder uses the color to determine the point in jointly typical fan associated with x^n

- Straight line: achieved by time-sharing



Wyner-Ziv Coding

- Distributed source coding with **side information**
- Y is encoded at rate R_2
- Only X to be recovered
- How many bits R_1 are required?
- If $R_2 = H(Y)$, then $R_1 = H(X|Y)$ by Slepian-Wolf coding
- In general



$$R_1 \geq H(X | U)$$

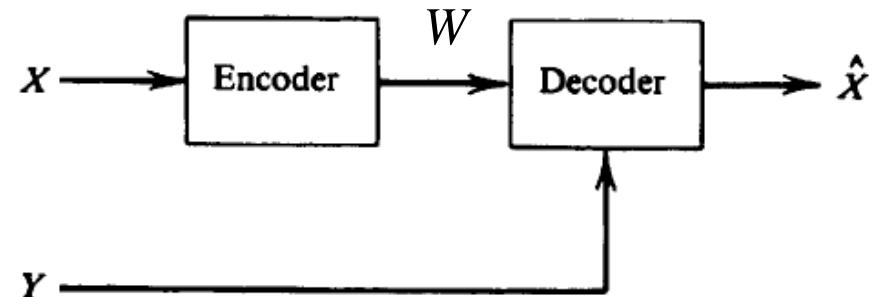
$$R_2 \geq I(Y; U)$$

where U is an auxiliary random variable (can be thought of as approximate version of Y)

Rate-Distortion

- Given Y , what is the rate-distortion to describe X ?

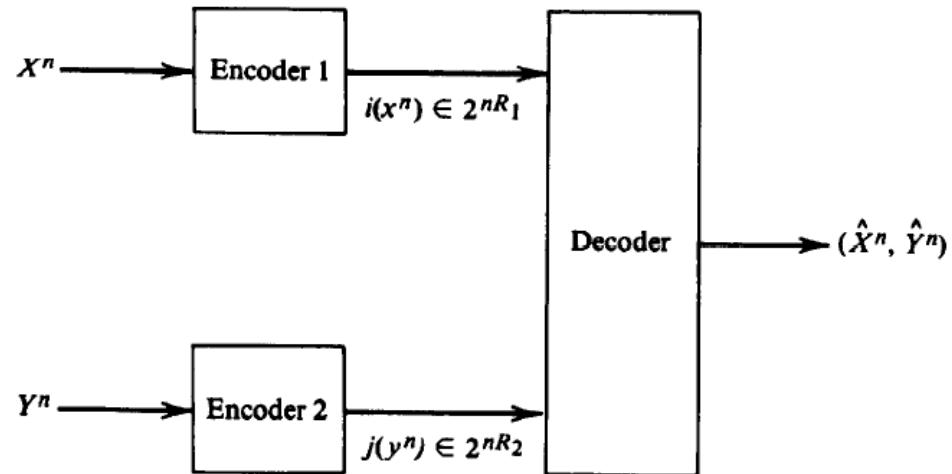
$$R_Y(D) = \min_{p(w|x)} \min_f \{I(X;W) - I(Y;W)\}$$



over all decoding functions $f : Y \times W \rightarrow \hat{X}$

and all $p(w|x)$ such that $E_{x,w,y} d(x, \hat{x}) \leq D$

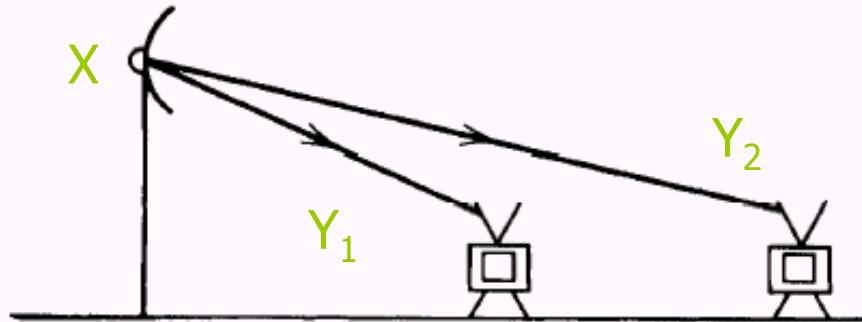
- The general problem of rate-distortion for correlated sources remains **unsolved**



Lecture 18

- Network information theory – II
 - Broadcast
 - Relay
 - Interference channel
 - Two-way channel
 - Comments on general communication networks

Broadcast Channel



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- One-to-many: HDTV station sending different information simultaneously to many TV receivers over a common channel; lecturer in classroom
- What are the achievable rates for all different receivers?
- How does the sender encode information meant for different signals in a common signal?
- Only partial answers are known.

Two-User Broadcast Channel

- Consider a memoryless broadcast channel with one encoder and two decoders
- Independent messages at rate R_1 and R_2
- Degraded broadcast channel: $p(y_1, y_2|x) = p(y_1|x)$
 $p(y_2|y_1)$
 - Meaning $X \rightarrow Y_1 \rightarrow Y_2$ (Markov chain)
 - Y_2 is a degraded version of Y_1 (receiver 1 is better)
- Capacity region of degraded broadcast channel

$$R_2 \leq I(U; Y_2)$$

$$R_1 \leq I(X; Y_1 | U)$$

U is an auxiliary
random variable

Scalar Gaussian Broadcast Channel

- All scalar Gaussian broadcast channels belong to the class of degraded channels

$$Y_1 = X + Z_1$$

Assume variance

$$Y_2 = X + Z_2$$

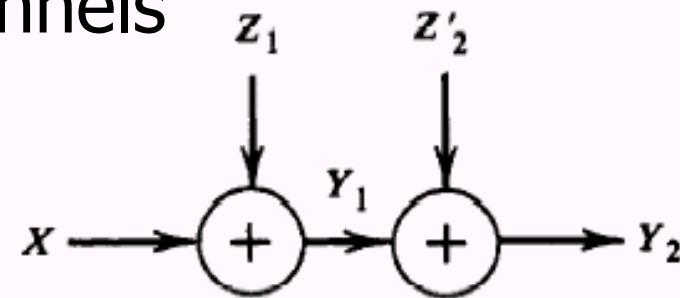
$$N_1 < N_2$$

- Capacity region

$$R_1 \leq C \left(\frac{\alpha P}{N_1} \right)$$

$$R_2 \leq C \left(\frac{(1-\alpha)P}{\alpha P + N_2} \right)$$

$$0 \leq \alpha \leq 1$$



Coding Strategy

Encoding: one codebook with power αP at rate R_1 , another with power $(1-\alpha)P$ at rate R_2 , send the sum of two codewords

Decoding: Bad receiver Y_2 treats Y_1 as noise; good receiver Y_1 first decode Y_2 , subtract it out, then decode his own message

Relay Channel

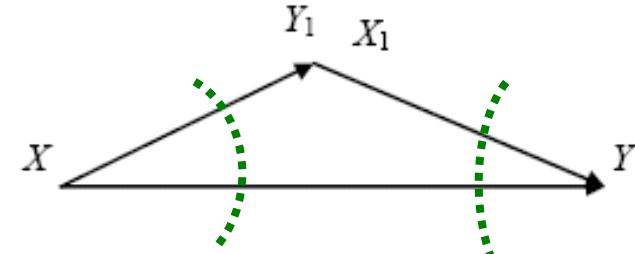
- One source, one destination, one or more intermediate relays

- Example: one relay

- A broadcast channel (X to Y and Y_1)
- A multi-access channel (X and X_1 to Y)
- Capacity is unknown! Upper bound:

$$C \leq \sup_{p(x,x_1)} \min\{ I(X, X_1; Y), I(X; Y, Y_1 | X_1) \}$$

- Max-flow min-cut interpretation
 - First term: maximum rate from X and X_1 to Y
 - Second term: maximum rate from X to Y and Y_1



Degraded Relay Channel

- In general, the max-flow min-cut bound cannot be achieved
- Reason
 - Interference
 - What for the relay to forward?
 - How to forward?
- Capacity is known for degraded relay channel (i.e., Y is a degradation of Y_1 , or relay is better than receiver), i.e., the upper bound is achieved

$$C = \sup_{p(x, x_1)} \min\{I(X, X_1; Y), I(X; Y, Y_1 | X_1)\}$$

Gaussian Relay Channel

- Channel model

$$Y_1 = X + Z_1 \quad \text{Variance}(Z_1) = N_1$$

$$Y = X + Z_1 + X_1 + Z_2 \quad \text{Variance}(Z_2) = N_2$$

- Encoding at relay: $X_{1i} = f_i(Y_{11}, Y_{12}, \dots, Y_{1i-1})$

- Capacity

$$C = \max_{0 \leq \alpha \leq 1} \min \left\{ C \left(\frac{P + P_1 + 2\sqrt{(1-\alpha)PP_1}}{N_1 + N_2} \right), C \left(\frac{\alpha P}{N_1} \right) \right\}$$

X has power P
X1 has power P1

- If

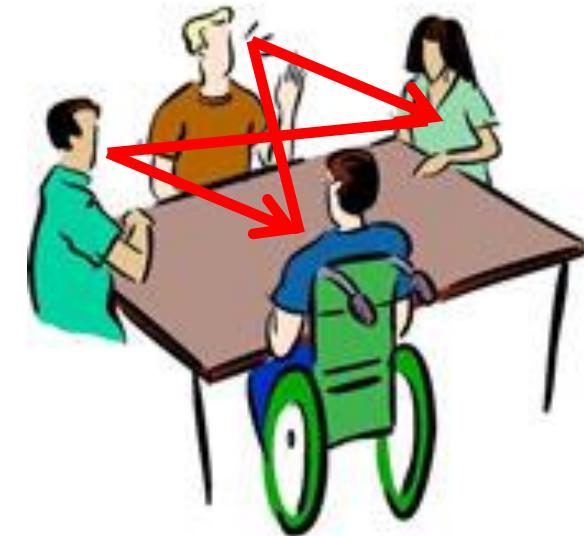
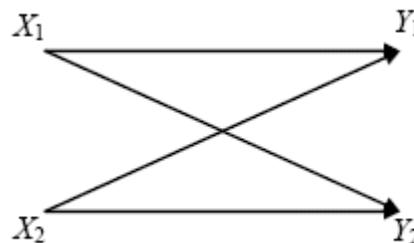
$$\text{relay - destination SNR} \quad \frac{P_1}{N_2} \geq \frac{P}{N_1} \quad \text{source - relay SNR}$$

then $C = C(P/N_1)$ (capacity from source to relay can be achieved; exercise)

- Rate $C = C(P/(N_1 + N_2))$ without relay is increased by the relay to $C = C(P/N_1)$

Interference Channel

- Two senders, two receivers, with crosstalk



- Y_1 listens to X_1 and doesn't care what X_2 speaks or what Y_2 hears
- Similarly with X_2 and Y_2
- Neither a broadcast channel nor a multiaccess channel
- This channel has not been solved
 - Capacity is known to within one bit (Etkin, Tse, Wang 2008)
 - A promising technique — **interference alignment** (Camdenbe, Jafar 2008)

Symmetric Interference Channel

- Model

$$Y_1 = X_1 + aX_2 + Z_1 \quad \text{equal power } P$$

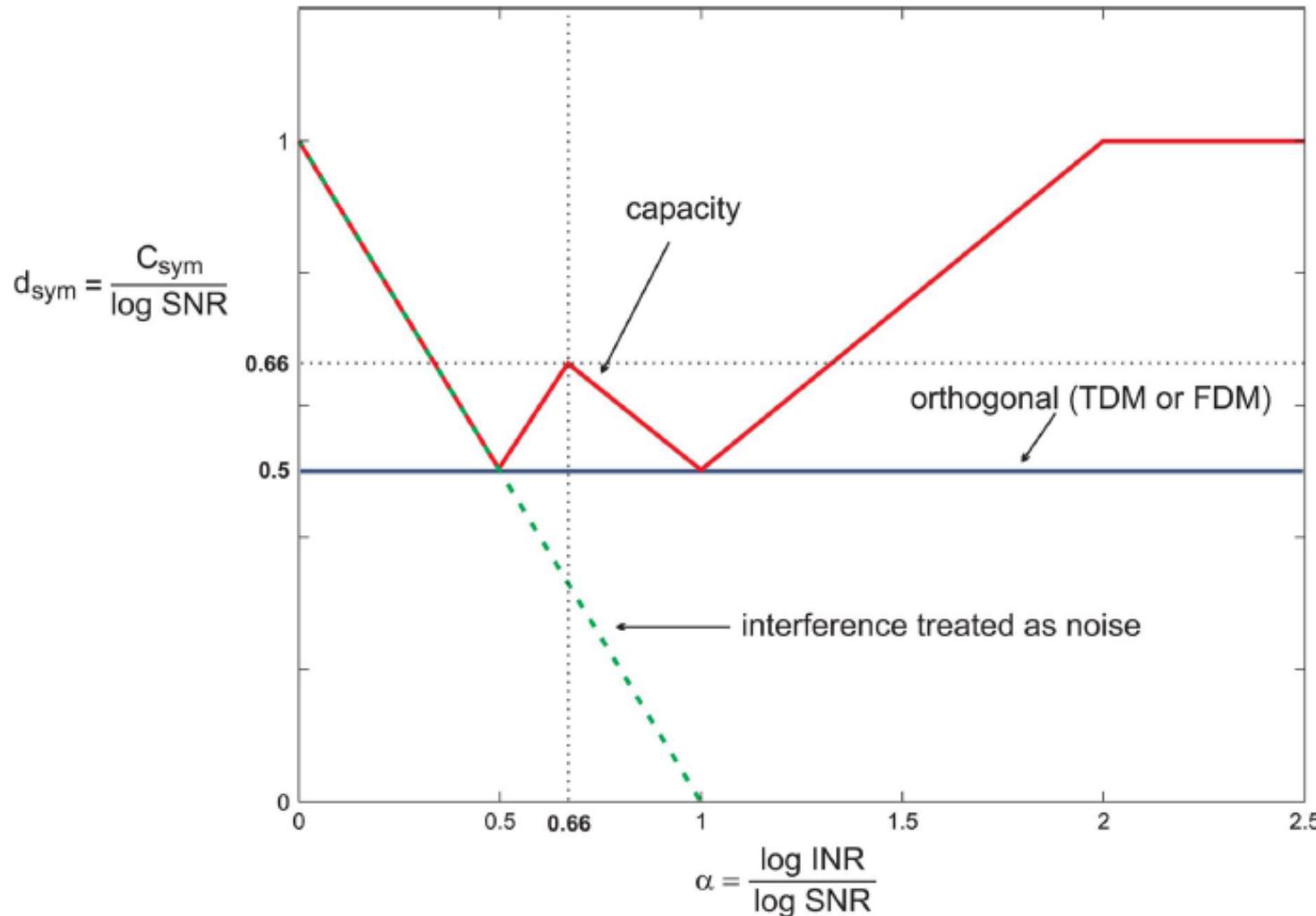
$$Y_2 = X_2 + aX_1 + Z_2 \quad \text{Var}(Z_1) = \text{Var}(Z_2) = N$$

- Capacity has been derived in the strong interference case ($a \geq 1$) (Han, Kobayashi, 1981)
 - Very strong interference ($a^2 \geq 1 + P/N$) is equivalent to no interference whatsoever
- Symmetric capacity (for each user $R_1 = R_2$)

$$d_{\text{sym}} = \begin{cases} 1 - \alpha, & 0 \leq \alpha < \frac{1}{2} \\ \alpha, & \frac{1}{2} \leq \alpha < \frac{2}{3} \\ 1 - \frac{\alpha}{2}, & \frac{2}{3} < \alpha \leq 1 \\ \frac{\alpha}{2}, & 1 \leq \alpha < 2 \\ 1, & \alpha \geq 2. \end{cases}$$

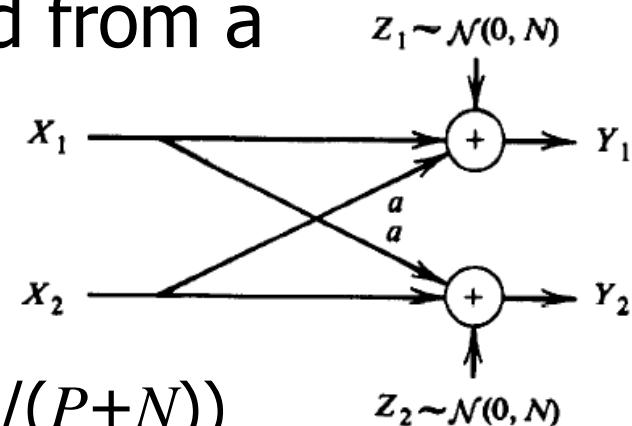
$d_{\text{sym}}(\alpha) := \lim_{\text{SNR, INR} \rightarrow \infty; \frac{\log \text{INR}}{\log \text{SNR}} = \alpha} \frac{C_{\text{sym}}(\text{INR, SNR})}{C_{\text{awgn}}(\text{SNR})}$
 SNR = P/N
 INR = $a^2 P/N$

Capacity

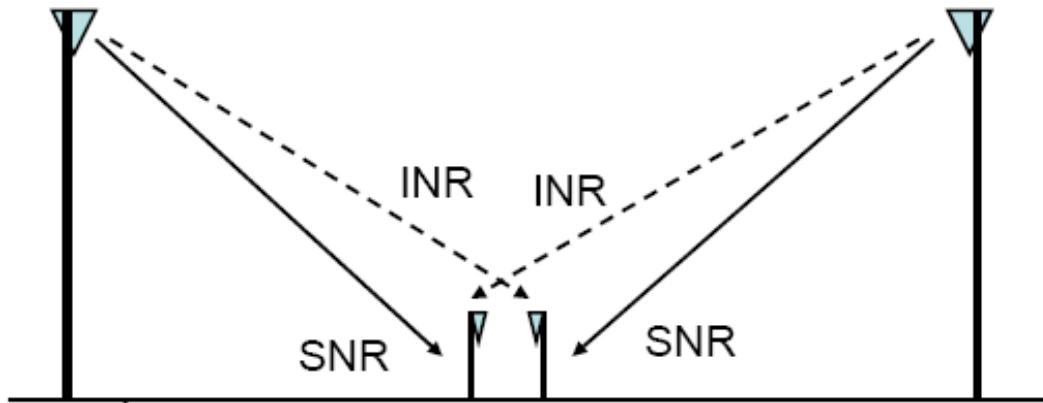


Very strong interference = no interference

- Each sender has power P and rate $C(P/N)$
- Independently sends a codeword from a Gaussian codebook
- Consider receiver 1
 - Treats sender 1 as interference
 - Can decode sender 2 at rate $C(a^2P/(P+N))$
 - If $C(a^2P/(P+N)) > C(P/N)$, i.e.,
 - rate 2 \rightarrow 1 $>$ rate 2 \rightarrow 2 (crosslink is better)
 - he can perfectly decode sender 2
 - Subtracting it from received signal, he sees a clean channel with capacity $C(P/N)$



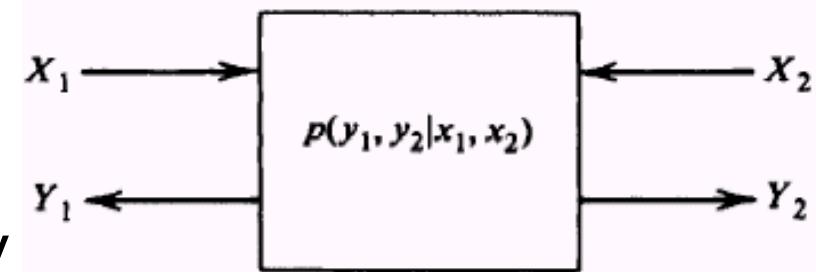
An Example



- Two cell-edge users (bottleneck of the cellular network)
- No exchange of data between the base stations or between the mobiles
- Traditional approaches
 - Orthogonalizing the two links (reuse $\frac{1}{2}$)
 - Universal frequency reuse and treating interference as noise
- Higher capacity can be achieved by advanced **interference management**

Two-Way Channel

- Similar to interference channel, but in both directions (Shannon 1961)
- Feedback
 - Sender 1 can use previously received symbols from sender 2, and vice versa
 - They can cooperate with each other
- Gaussian channel:
 - Capacity region is known (not the case in general)
 - Decompose into two independent channels



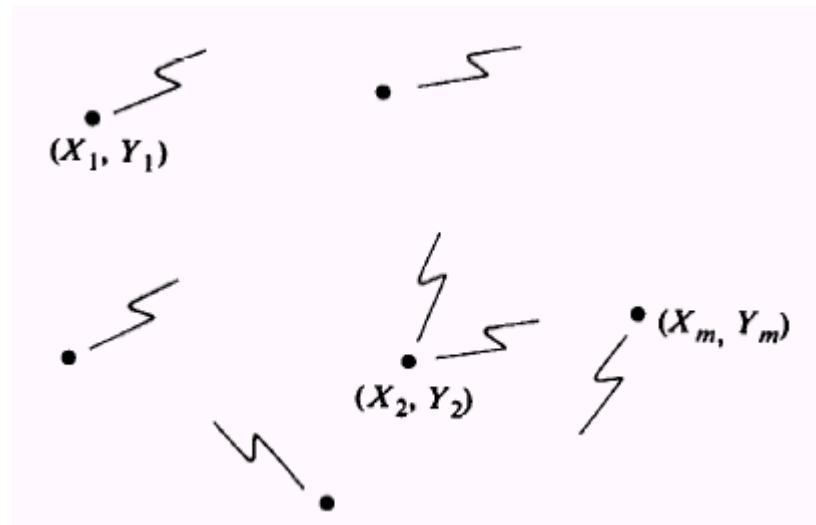
$$R_1 < C \left(\frac{P_1}{N_1} \right)$$

$$R_2 < C \left(\frac{P_2}{N_2} \right)$$

Coding strategy: Sender 1 sends a codeword; so does sender 2. Receiver 2 receives a sum but he can subtract out his own thus having an interference-free channel from sender 1.

General Communication Network

- Many nodes trying to communicate with each other
- Allows computation at each node using its own message and all past received symbols
- All the models we have considered are special cases
- A comprehensive theory of network information flow is yet to be found

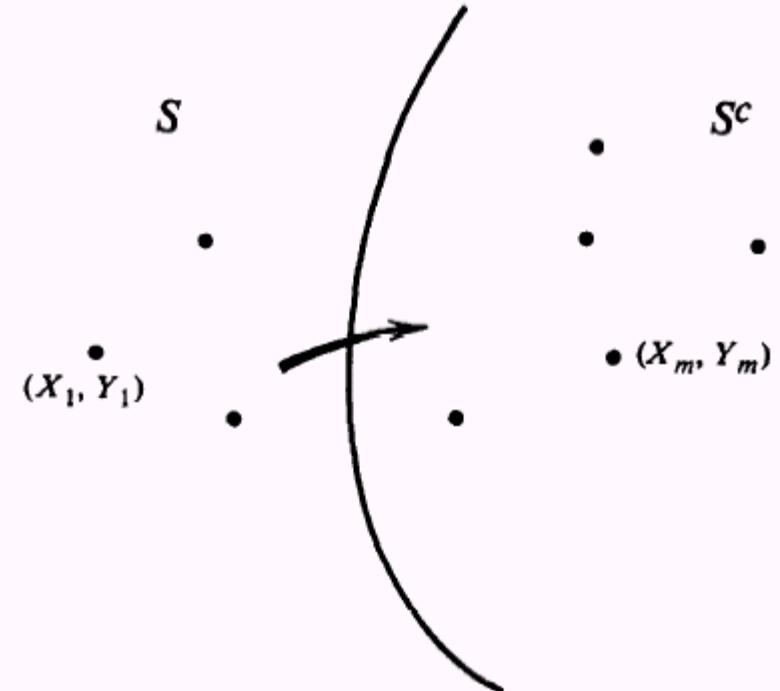
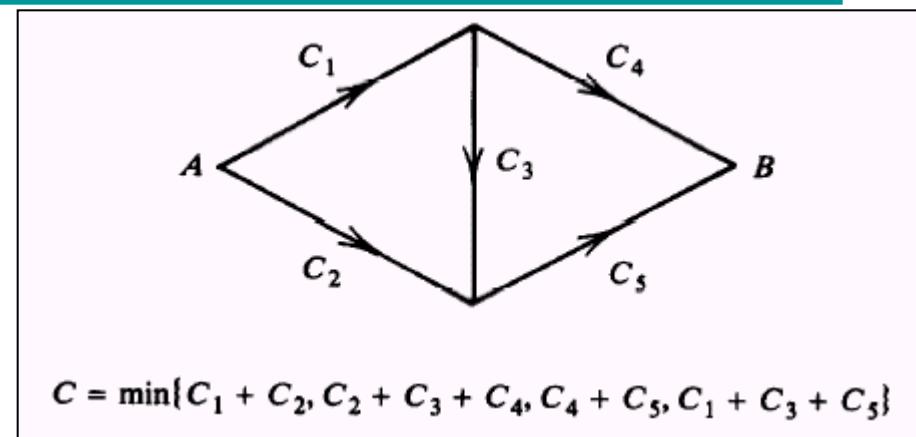


Capacity Bound for a Network

- **Max-flow min-cut**
 - Minimizing the maximum flow across cut sets yields an upper bound on the capacity of a network
- Outer bound on capacity region

$$\sum_{i \in S, j \in S^c} R^{(i,j)} \leq I(X^{(S)}; Y^{(S^c)} | X^{(S^c)})$$

- Not achievable in general



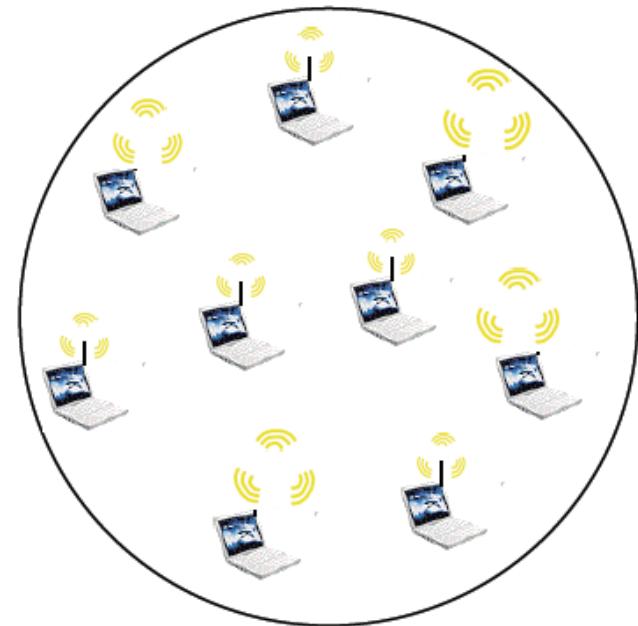
Questions to Answer

- Why multi-hop relay? Why decode and forward? Why treat interference as noise?
- Source-channel separation? Feedback?
- What is really the best way to operate wireless networks?
- What are the ultimate limits to information transfer over wireless networks?



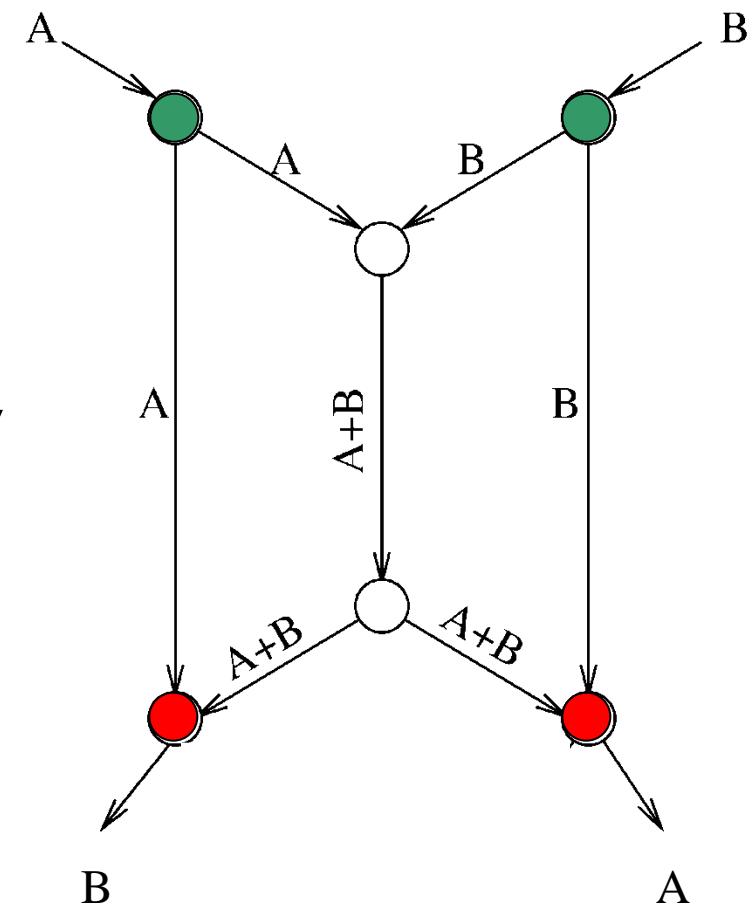
Scaling Law for Wireless Networks

- High signal attenuation:
(transport) capacity is $O(n)$
bit-meter/sec for a planar
network with n nodes (Xie-
Kumar'04)
- Low attenuation: capacity can
grow superlinearly
- Requires cooperation between
nodes
- Multi-hop relay is suboptimal
but order optimal



Network Coding

- Routing: store and forward (as in Internet)
- Network coding: recompute and redistribute
- Given the network topology, coding can increase capacity (Ahlswede, Cai, Li, Yeung, 2000)
 - Doubled capacity for butterfly network
- Active area of research



Butterfly Network

Lecture 19

- Revision Lecture

Summary (1)

- **Entropy:** $H(x) = \sum_{x \in X} p(x) \times -\log_2 p(x) = E - \log_2(p_X(x))$
 - Bounds: $0 \leq H(x) \leq \log |X|$
 - Conditioning reduces entropy: $H(y|x) \leq H(y)$
 - Chain Rule: $H(x_{1:n}) = \sum_{i=1}^n H(x_i | x_{1:i-1}) \leq \sum_{i=1}^n H(x_i)$
 $H(x_{1:n} | y_{1:n}) \leq \sum_{i=1}^n H(x_i | y_i)$
- **Relative Entropy:**

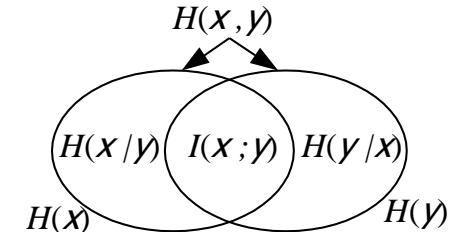
$$D(\mathbf{p} \parallel \mathbf{q}) = E_{\mathbf{p}} \log(p(x)/q(x)) \geq 0$$

Summary (2)

- Mutual Information:

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

$$= H(x) + H(y) - H(x, y) = D(\mathbf{p}_{x,y} \parallel \mathbf{p}_x \mathbf{p}_y)$$



– Positive and Symmetrical: $I(x; y) = I(y; x) \geq 0$

– x, y indep $\Leftrightarrow H(x, y) = H(y) + H(x) \Leftrightarrow I(x; y) = 0$

– Chain Rule: $I(x_{1:n}; y) = \sum_{i=1}^n I(x_i; y | x_{1:i-1})$
 x_i independent $\Rightarrow I(x_{1:n}; y_{1:n}) \geq \sum_{i=1}^n I(x_i; y_i)$

$p(y_i | x_{1:n}; y_{1:i-1}) = p(y_i | x_i) \Rightarrow I(x_{1:n}; y_{1:n}) \leq \sum_{i=1}^n I(x_i; y_i)$
n-use DMC capacity

Summary (3)

- **Convexity:** $f''(x) \geq 0 \Rightarrow f(x)$ convex $\Rightarrow Ef(x) \geq f(Ex)$
 - $H(p)$ concave in p
 - $I(X; Y)$ concave in p_x for fixed $p_{y|x}$
 - $I(X; Y)$ convex in $p_{y|x}$ for fixed p_x
- **Markov:** $x \rightarrow y \rightarrow z \Leftrightarrow p(z | x, y) = p(z | y) \Leftrightarrow I(X; Z | Y) = 0$
 $\Rightarrow I(X; Y) \geq I(X; Z)$ and $I(X; Y) \geq I(X; Y | Z)$
- **Fano:** $x \rightarrow y \rightarrow \hat{x} \Rightarrow p(\hat{x} \neq x) \geq \frac{H(X | Y) - 1}{\log(|X| - 1)}$
- **Entropy Rate:**
 - Stationary process $H(X) = \lim_{n \rightarrow \infty} n^{-1} H(X_{1:n})$
 - Markov Process: $H(X) = \lim_{n \rightarrow \infty} H(X_n | X_{1:n-1})$
 - $H(X) = \lim_{n \rightarrow \infty} H(X_n | X_{n-1})$ if stationary

Summary (4)

- **Kraft:** Uniquely Decodable $\Rightarrow \sum_{i=1}^{|X|} D^{-l_i} \leq 1 \Rightarrow \exists$ instant code
- **Average Length:** Uniquely Decodable $\Rightarrow L_C = E l(x) \geq H_D(x)$
- **Shannon-Fano:** Top-down 50% splits. $L_{SF} \leq H_D(x) + 1$
- **Huffman:** Bottom-up design. Optimal. $L_H \leq H_D(x) + 1$
 - Designing with wrong probabilities, $\mathbf{q} \Rightarrow$ penalty of $D(\mathbf{p}||\mathbf{q})$
 - Long blocks disperse the 1-bit overhead
- **Lempel-Ziv Coding:**
 - Does not depend on source distribution
 - Efficient algorithm widely used
 - Approaches entropy rate for stationary ergodic sources

Summary (5)

- Typical Set
 - Individual Prob $\mathbf{x} \in T_\varepsilon^{(n)} \Rightarrow \log p(\mathbf{x}) = -nH(\mathbf{x}) \pm n\varepsilon$
 - Total Prob $p(\mathbf{x} \in T_\varepsilon^{(n)}) > 1 - \varepsilon \text{ for } n > N_\varepsilon$
 - Size $(1 - \varepsilon)2^{n(H(\mathbf{x}) - \varepsilon)} < |T_\varepsilon^{(n)}| \leq 2^{n(H(\mathbf{x}) + \varepsilon)}$
 - No other high probability set can be much smaller
- Asymptotic Equipartition Principle
 - Almost all event sequences are equally surprising

Summary (6)

- DMC Channel Capacity: $C = \max_{\mathbf{p}_x} I(x; y)$
- Coding Theorem
 - Can achieve capacity: random codewords, joint typical decoding
 - Cannot beat capacity: Fano inequality
- Feedback doesn't increase capacity of DMC but could simplify coding/decoding
- Joint Source-Channel Coding doesn't increase capacity of DMC

Summary (7)

- Polar codes are low-complexity codes directly built from information theory.
- Their constructions are aided by the polarization phenomenon.
- For channel coding, polar codes achieve channel capacity.
- For source coding, polar codes achieve the entropy bound.
- And much more.

Summary (8)

- **Differential Entropy:** $h(x) = E - \log f_x(x)$
 - Not necessarily positive
 - $h(x+a) = h(x)$, $h(ax) = h(x) + \log|a|$, $h(x|y) \leq h(x)$
 - $I(x; y) = h(x) + h(y) - h(x, y) \geq 0$, $D(f||g) = E \log(f/g) \geq 0$
- **Bounds:**
 - **Finite range:** Uniform distribution has max: $h(x) = \log(b-a)$
 - Fixed Covariance: Gaussian has max: $h(x) = \frac{1}{2}\log((2\pi e)^n |K|)$
- **Gaussian Channel**
 - **Discrete Time:** $C = \frac{1}{2}\log(1+PN^{-1})$
 - **Bandlimited:** $C = W \log(1+PN_0^{-1}W^{-1})$
 - For constant C: $E_b N_0^{-1} = PC^{-1}N_0^{-1} = (W/C)(2^{(W/C)^{-1}} - 1) \xrightarrow[W \rightarrow \infty]{} \ln 2 = -1.6 \text{ dB}$
 - **Feedback:** Adds at most $\frac{1}{2}$ bit for coloured noise

Summary (9)

- **Parallel Gaussian Channels:** Total power constraint $\sum P_i = nP$
 - White noise: Waterfilling: $P_i = \max(v - N_i, 0)$
 - Correlated noise: Waterfill on noise eigenvectors
- **Rate Distortion:** $R(D) = \min_{\mathbf{p}_{\hat{x}|x} \text{ s.t. } Ed(x, \hat{x}) \leq D} I(x; \hat{x})$
 - Bernoulli Source with Hamming d : $R(D) = \max(H(\mathbf{p}_x) - H(D), 0)$
 - Gaussian Source with mean square d : $R(D) = \max(\frac{1}{2}\log(\sigma^2 D^{-1}), 0)$
 - Can encode at rate R : random decoder, joint typical encoder
 - Can't encode below rate R : independence bound

Summary (10)

- Gaussian multiple access channel $R_1 < C\left(\frac{P_1}{N}\right), \quad R_2 < C\left(\frac{P_2}{N}\right)$
 $R_1 + R_2 < C\left(\frac{P_1 + P_2}{N}\right), \quad C(x) = \frac{1}{2} \log(1 + x)$
- Distributed source coding
 - Slepian-Wolf coding $R_1 \geq H(X | Y), \quad R_2 \geq H(Y | X)$
 $R_1 + R_2 \geq H(X, Y)$
- Scalar Gaussian broadcast channel
 $R_1 \leq C\left(\frac{\alpha P}{N_1}\right), \quad R_2 \leq C\left(\frac{(1-\alpha)P}{\alpha P + N_2}\right), \quad 0 \leq \alpha \leq 1$
- Gaussian Relay channel

$$C = \max_{0 \leq \alpha \leq 1} \min \left\{ C\left(\frac{P + P_1 + 2\sqrt{(1-\alpha)PP_1}}{N_1 + N_2}\right), C\left(\frac{\alpha P}{N_1}\right) \right\}$$

Summary (11)

- Interference channel
 - Strong interference = no interference
- Gaussian two-way channel
 - Decompose into two independent channels
- General communication network
 - Max-flow min-cut theorem
 - Not achievable in general
 - But achievable for multiple access channel and Gaussian relay channel