

Telecommunications – Section 2 (Lecture 1)

12/11/09

Information Theory: Channel Capacity

Goal: Answer the question: “What is the capacity of a communications channel to carry information?”

Recall from 2nd Year:

The information content of a symbol:

$$\begin{aligned} I(x_i) &= \log_2 \left[\frac{1}{P(x_i)} \right] \\ &= -\log_2 [P(x_i)] \\ \therefore I(x_i) &= 0 \text{ for } P(x_i) = 1 \\ I(x_i) &\geq 0 \end{aligned}$$

The information content I of a symbol i from source x is greater than that of a symbol j if the probability of occurrence of i is less than that of j , i.e.:

$$I(x_i) > I(x_j) \text{ when } P(x_i) < P(x_j)$$

The combined information content of two symbols i and j is equal to the sum of the information content of each element, i.e.:

$$I(x_i x_j) = I(x_i) + I(x_j), \text{ provided } i \text{ and } j \text{ are independent.}$$

Average Information or Entropy:

The entropy of a data source x is equal to the expected value of the information content of x , and is measured in bits/symbol. (In this case, ‘bits’ refers to Shannon units of information rather than digital bits.) i.e.:

Number of
symbols in source x

$$\begin{aligned} H(x) &= E[I(x_i)] \\ &= \sum_{i=1}^m P(x_i) I(x_i) \end{aligned}$$

$$H(x) = \sum_{i=1}^m P(x_i) \log_2 [P(x_i)]$$

It can be shown that $H(x)$, the entropy of source x , satisfies:-

$$0 \leq H(x) \leq \log_2 [m]$$

Occurs in the equiprobable

case: $P(x_i) = 1/m$

Information Rate:

If the source emits r symbols/s then the information rate R of the source is given by:

$$R = rH(x) \text{ b / s}$$

Discrete Memoryless Channels

Channel Representation:

A communications channel is the path or medium through which the symbols flow to the receiver. A discrete memoryless channel (DMC) is a statistical model with an input X and an output Y . During each signalling interval the channel accepts an input signal from X and, in response, generates an output signal from Y . The channel is discrete when the alphabets of X and Y are finite. It is memoryless when the current output depends only on the current input and not on any previous inputs.

$$\left. \begin{matrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{matrix} \right\} P(y_j | x_i) \left\{ \begin{matrix} y_1 \\ y_2 \\ \vdots \\ y_m \end{matrix} \right.$$

Where $P(y_j | x_i)$ represents the conditional probability of receiving y_j having sent x_i .

We assume the “a-priori” probabilities of x_i are available to us. Each possible input-output path is indicated with a conditional probability $P(y_j | x_i)$, also known as the “channel transmission probability”, given x_i .

Channel Matrix:

For our purposes, a channel is completely specified by the complete set of transition probabilities. Accordingly, a matrix representation is often used, denoted $[P(Y/X)]$, given by:

$$[P(Y/X)] = \begin{bmatrix} P(y_1 | x_1) & \cdots & P(y_n | x_1) \\ \vdots & \ddots & \vdots \\ P(y_1 | x_m) & \cdots & P(y_n | x_m) \end{bmatrix}$$

Channel Matrix (continued...)

$[P(Y|X)]$ is called the “Channel Matrix”. Since each input to the channel results in some output. If that is the case, each row of the channel matrix must sum to unity, i.e.

$$\sum_{j=1}^n P(y_j | x_i) = 1 \text{ for all } i$$

Now, if the input probabilities $P(x)$ are represented by the row matrix:

$$[P(x)] = [P(x_1) \ P(x_2) \ \dots \ P(x_m)]$$

and the output probabilities $P(y)$ represented by the row matrix:

$$[P(y)] = [P(y_1) \ P(y_2) \ \dots \ P(y_n)]$$

then:-

$$[P(y)] = [P(x)][P(Y|X)]$$

Alternatively, if $P(x)$ is represented as a diagonal matrix:-

$$[P(x)]_d = \begin{bmatrix} P(x_1) & 0 & \dots & 0 \\ 0 & P(x_2) & \dots & 0 \\ \vdots & & & \\ 0 & 0 & \dots & P(x_m) \end{bmatrix}$$

Then:-

$$[P(y)] = [P(x)]_d [P(Y|X)]$$

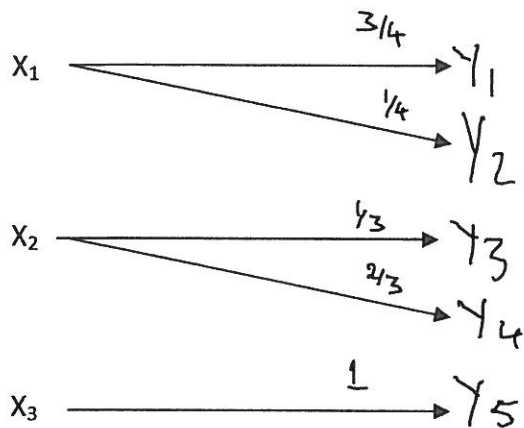
where the (i,j) element of $[P(X,Y)]$ has the form $P(x_i, y_j)$. (i.e. probability of sending x_i and subsequently receiving y_j . The matrix $[P(X,Y)]$ is known as the “**Joint Probability Matrix**”.

Special Channels

Lossless Channels

Lossless channels have only one non-zero element in each column. For example: -

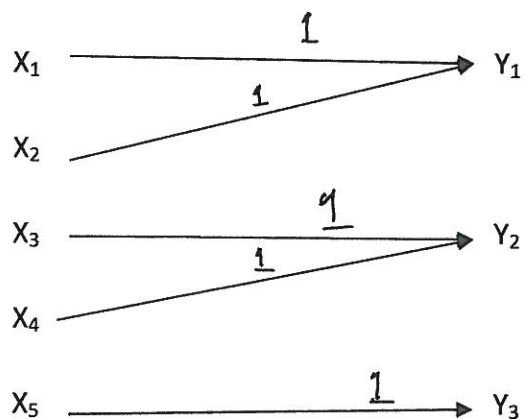
$$[P(X|Y)] = \begin{bmatrix} \frac{3}{4} & \frac{1}{4} & 0 & 0 & 0 \\ 0 & 0 & \frac{1}{3} & \frac{2}{3} & 0 \\ 0 & 0 & 0 & 0 & 1 \end{bmatrix}$$



Deterministic Channels

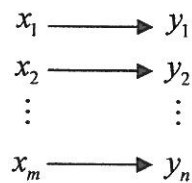
A channel whose channel matrix has only one non-zero element in each row is called a **"Deterministic Channel"**. For example, consider:

$$[P(X|Y)] = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



Noiseless Channel

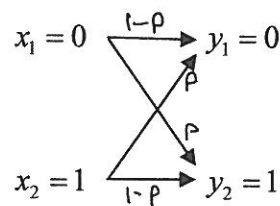
This channel is both lossless and deterministic. For example,



Binary Symmetric Channel

The binary symmetric channel is defined by: -

$$[P(Y|X)] = \begin{bmatrix} 1-p & p \\ p & 1-p \end{bmatrix}$$



The transition probability p denotes the probability of error, given a particular input symbol. Note that the channel is symmetric since p applies in both error types (i.e. send 0, receive 1 and send 1, receive 0).

Mutual Information

Conditional and Joint Entropies

Using the input probabilities $P(x_i)$, the transition probabilities $P(y_j|x_i)$ and joint probabilities $P(x_i, y_j)$ we can define the following entropy functions for a channel with m inputs and n outputs: -

$$H(X) = -\sum_{i=1}^m P(x_i) \log_2 [P(x_i)]$$

$$H(Y) = -\sum_{j=1}^n P(y_j) \log_2 [P(y_j)]$$

$$H(X|Y) = -\sum_{j=1}^n \sum_{i=1}^m P(x_i, y_j) \log_2 [P(x_i | y_j)]$$

Equivocation of x w.r.t. y .

$$H(Y|X) = -\sum_{j=1}^n \sum_{i=1}^m P(x_i, y_j) \log_2 [P(y_j | x_i)]$$

Preverification of y w.r.t. x.

$$H(X, Y) = -\sum_{j=1}^n \sum_{i=1}^m P(x_i, y_j) \log_2 [P(x_i, y_j)]$$

(Generally easiest to use)

$H(x)$ is the average uncertainty of the channel input. $H(y)$ is the average uncertainty of the channel output. $H(X/Y)$ is a measure of the average uncertainty about the channel input after the channel output has been observed (*Equivocation*). $H(Y/X)$ is the measure of the average uncertainty about the channel output given the channel input (*Preverification – relates to average uncertainty from the transmitter's viewpoint*).

The joint entropy $H(X,Y)$ is the average uncertainty of the communications channel as a whole. Two useful relationships amongst the various entropies are:-

$$\text{Chain Rules for Entropy} \begin{cases} H(x,y) = H(x|y) + H(y) \\ H(x,y) = H(y|x) + H(x) \end{cases}$$

Aside:

Prove the equivocation formula:

$$H(X|Y) = - \sum_{j=1}^n \sum_{i=1}^m P(x_i, y_j) \log_2 [P(x_i | y_j)]$$

Solution :

$$H(X|Y = y_j) = \sum_{i=1}^m P(x_i | y_j) \log_2 (P(x_i | y_j))$$

Now we average with respect to Y

$$\begin{aligned} \Rightarrow H(X|Y) &= \sum_{j=1}^n P(y_j) H(x|y = y_j) \\ &= - \sum_{j=1}^n \sum_{i=1}^m \underbrace{P(y_j) P(x_i | y_j)}_{P(x_i, y_j)} \log_2 (P(x_i | y_j)) \end{aligned}$$

Mutual Information

The guiding principle is "Information is always a measure of the decrease of uncertainty at a receiver". With this in mind, the mutual information $I(x;y)$ of a channel is defined by:-

$$I(x;y) = H(X) - H(X|Y) \text{ (bits/sym)}$$

Since $H(x)$ represents the average uncertainty about the channel input before the channel output is observed and $H(x|y)$ (equivocation) represents the average uncertainty about the channel input after the output has been observed, $I(x;y)$ represents the uncertainty about the channel input that is resolved by observing the channel output.

Properties of $I(x;y)$

$$\text{Symmetric :} \quad I(x;y) = I(y;x)$$

$$I(x;y) \geq 0$$

$$\text{Normally, we use these} \begin{cases} I(x;y) = H(Y) - H(Y|X) \\ I(x;y) = H(X) - H(X|Y) \end{cases}$$

Channel Capacity

Channel capacity per symbol C_s :

The channel capacity per symbol of a discrete memoryless channel is defined by:

$$C_s = \underset{\{P(x_i)\}}{\text{Max}} [I(x;y)]$$

Where the maximisation is over all possible input probability distributions $\{P(x_i)\}$ on X . Note that C_s is a function only of the channel transition probabilities.

Channel Capacity per Second (=C)

If r symbols per second are being transmitted (on average), then the channel capacity per second is:-

$$C = rC_s \quad (\text{bits / s})$$

This is the max rate of transmission of information per second.

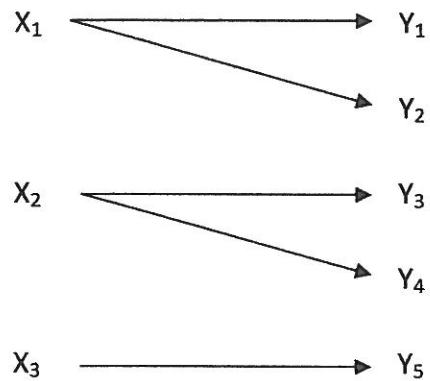
Channel Coding Theorem

Given a discrete memoryless source with entropy $H(X)$ bits/symbol and a discrete memoryless channel with capacity C_s bits/symbol, **"if $H(X) \leq C_s$, there exists a coding scheme for which the source output can be transmitted over the channel with an arbitrarily small probability of error"**. Conversely, if $H(X) > C_s$, it is impossible to transmit information over the channel with an arbitrarily small probability of error \rightarrow unrecoverable errors are guaranteed.

Capacities of Typical Channels

Lossless Channel

E.g. recall:



It is clear which x was sent for a given y .

What is the capacity of a lossless channel?

When we observe output Y_i in a lossless channel, it is clear which x was transmitted.

Therefore:

$$P(x_i | y_j) = 0 \text{ or } 1$$

Now,

$$\begin{aligned}
H(x|y) &= -\sum_{j=1}^n \sum_{i=1}^m P(x_i|y_j) \log_2 [P(x_i|y_j)] \\
&= -\sum_{j=1}^n \sum_{i=1}^m P(y_j) P(x_i|y_j) \log_2 P(x_i|y_j) \\
&= -\sum_{j=1}^n P(y_j) \sum_{i=1}^m \underbrace{P(x_i|y_j) \log_2 P(x_i|y_j)}_{0 \cdot \log_2(0) \text{ or } 1 \cdot \log_2(1)} \\
&= 0
\end{aligned}$$

Now,

$$\begin{aligned}
I(x; y) &= H(X) - H(X|Y) \\
&= H(X) \\
&\text{since } H(X|Y) = 0
\end{aligned}$$

Hence, our interpretation of $H(x)$ as the average information content of a source (ee2009) is valid. However, in general, entropy $H()$ measures average uncertainty. Since the mutual information ($I(x; y)$) is equal to the input source entropy, no source information is lost during transmission (hence the name). Hence, the channel capacity per symbol, C_s , is given by:-

$$C_s = \max_{\{P(x_i)\}} [H(X)] = \log_2 [m]$$

Number of symbols in x

Deterministic Channel

$$\begin{aligned}
H(X|Y) &= 0 \text{ for all input distributions } P(x_i) \\
\text{and } I(X; Y) &= H(Y) \\
\rightarrow C_s &= \max_{\{P(x_i)\}} [H(Y)] = \log_2 [n]
\end{aligned}$$

Noiseless Channel

Since this is both lossless and deterministic:

$$\begin{aligned}
I(x; y) &= H(x) = H(y) \\
\Rightarrow C_s &= \log_2 [m] = \log_2 [n] \\
&\text{since } n = m
\end{aligned}$$

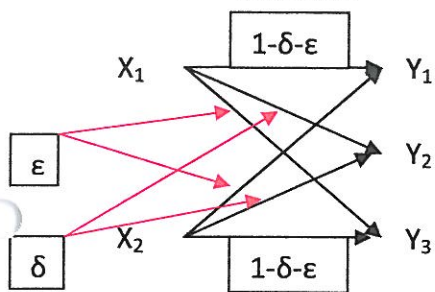
Summer 08 – Question 4

$$[P(Y|X)] = \begin{bmatrix} 1-\delta-\varepsilon & \delta & \varepsilon \\ \varepsilon & \delta & 1-\delta-\varepsilon \end{bmatrix}$$

Binary Symmetric Erasure Channel
(BSEC)

a) Show: $H(Y|X) = -(\delta \log_2[\delta] + \varepsilon \log_2[\varepsilon] + (1-\delta-\varepsilon) \log_2[1-\delta-\varepsilon])$

Solution:



$$\text{Let } P(x_1) = \alpha \Rightarrow P(x_2) = 1 - \alpha$$

$$H(Y|X) = - \sum_{j=1}^3 \sum_{i=1}^2 \underbrace{P(x_i, y_j)}_{P(x_i)P(y_j|x_i)} \log_2(P(y_j|x_i))$$

$$= (1-\delta-\varepsilon) \log_2[1-\delta-\varepsilon](1-\alpha + \alpha)$$

+

$$\log_2[\delta](\alpha + 1 - \alpha)$$

+

$$\log_2[\varepsilon](\alpha + 1 - \alpha)$$

as stated.

b) If the input symbols are equiprobable, show that:

$$C_{BSEC} = (\delta - 1) \log_2 \left[\frac{1 - \delta}{2} \right] + \varepsilon \log_2 [\varepsilon] + (1 - \delta - \varepsilon) \log_2 [1 - \delta - \varepsilon]$$

$$= \underset{\{P(x_i)\}}{\text{Max}} [H(Y) - H(Y|X)]$$

$$H(Y) = \sum_{j=1}^3 P(y_j) \log_2 [P(y_j)]$$

$$P(y_1) = \alpha(1 - \delta - \varepsilon) + (1 - \alpha)(\varepsilon)$$

$$= \alpha(1 - \delta) + \varepsilon(1 - 2\alpha) = \gamma \text{ say}$$

$$P(y_2) = \delta(\alpha + 1 - \alpha) = \delta$$

$$P(y_3) = 1 - (P(y_1) + P(y_2))$$

$$= 1 - (\delta + \gamma)$$

In the equiprobable case, $\alpha = 1/2$

$$\Rightarrow \gamma = (1 - \delta/2)$$

$$P(y_3) = 1 - (\delta + \gamma) = 1 - \left(\frac{1 + \delta}{2} \right) = \frac{1 - \delta}{2} = \gamma = P(y_1)$$

Now, substitute back in to yield:-

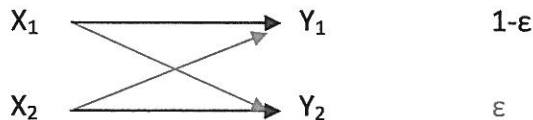
$$C_{BSEC} = (H(Y) - H(Y|X))|_{\alpha=1/2}$$

$$= - \sum_{j=1}^3 P(y_j) \log_2 (P(y_j))$$

and the answer emerges

- c) Consider the case $\delta \rightarrow 0$. Deduce the channel capacity of the resulting "binary symmetric channel".

Solution:

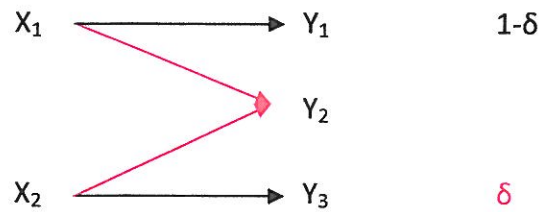


Let $\delta \rightarrow 0$ in part (b)

$$C_{bsc} = 1 + \varepsilon \log_2 [\varepsilon] + (1 - \varepsilon) \log_2 [1 - \varepsilon]$$

- d) Consider the case $\epsilon \rightarrow 0$. Deduce the channel capacity of the “binary erasure channel” (BEC).

Solution:



Let $\epsilon \rightarrow 0$

$$\therefore C_{BEC} = (1-\delta) \log_2 [1-\delta] + (\delta-1) \underbrace{\log_2 [1-\delta/2]}_{\log_2 [1-\delta] - \log_2 [2]}$$

Example: Summer 2007 Q.4

$$P(Y_1 | X) = \begin{bmatrix} 1-\rho & \alpha & \alpha \\ \alpha & 1-\rho & \alpha \\ \alpha & \alpha & 1-\rho \end{bmatrix}$$

$$= \underbrace{\begin{bmatrix} -1 & -1 & 1 \\ 0 & 1 & 1 \\ 1 & 0 & 1 \end{bmatrix}}_F \underbrace{\begin{bmatrix} 1-3\rho/2 & 0 & 0 \\ 0 & 1-3\rho/2 & 0 \\ 0 & 0 & 1 \end{bmatrix}}_D \underbrace{\begin{bmatrix} -1 & -1 & 2 \\ -1 & 2 & -1 \\ 1 & 1 & 1 \end{bmatrix}}_{F^{-1}} \frac{1}{3}$$

Also, $\alpha = \rho/2$ and the columns of F are eigenvectors of $P[Y_1|X]$. If n such that "3-ary uniform channels" are connected in series,

a) Show that the composite channel and matrix

$$[P(Y_n | X)] = \begin{bmatrix} 1+2q & 1-q & 1-q \\ 1-q & 1+2q & 1-q \\ 1-q & 1-q & 1+2q \end{bmatrix}$$

where $q = (1 - 3\rho/2)^n$

Solution:

Recall:

$$\begin{aligned} [P(Y)] &= [P(X)][P(Y|X)] \\ \Rightarrow [P(Y_1)] &= [P(X)][P(Y_1|X)] \\ \Rightarrow [P(Y_2)] &= [P(Y_1)][P(Y_2|X)] = [P(X)][P(Y_1|X)]^2 \\ &\vdots \\ [P(Y_n)] &= [P(X)] \underbrace{[P(Y_1|X)]^n}_{\text{Composite Channel}} \end{aligned}$$

①

14/01/10 Telecoms Q4 '07

c)

If p is sufficiently small so that its square and higher powers can be neglected show that.

$C_s^c \approx$ that of a single 3-ary uniform channel with probability of error-free transmission $= 1 - np$

note: $(x+y)^n = \sum_{i=0}^n \binom{n}{i} x^i y^{n-i}$ and $\binom{n}{i} = \frac{n!}{i!(n-i)!}$ [4]

Solution:

Let $n=1 \Rightarrow C_s^c = \log_2 \left[3(1-p)^1 \left(\frac{p}{2}\right)^1 \right]$

So, in our system with n channels in series, we have:-

$$q = \left(1 - \frac{3p}{2}\right)^n = \sum_{i=0}^n \binom{n}{i} x^i y^{n-i}$$

where $x=1$ and $y = -\frac{3p}{2}$

$$\Rightarrow q \approx n \left(-\frac{3p}{2}\right) + 1$$

$$= q \approx 1 - \frac{3(np)}{2}$$

now substitute this approximation into.

$$C_s^c \Rightarrow C_s^c \approx \log_2 \left[3(1-np)^1 \left(\frac{np}{2}\right)^1 \right]$$

Recall with $n=1$: $C_s^c = \log_2 \left[3(1-p)^1 \left(\frac{p}{2}\right)^1 \right]$

