

PREFIX CODE (OR) :- Instantaneous Code

- Prefix Code is a type of source code which is not only decodable but also offers the possibility of realising an average code word length ~~to~~ made close to the source entropy.
- For the code to be uniquely decodable, we ensure that for each finite sequence of symbols the corresponding sequence of code words is different from the sequence of code words corresponding to any other source.
- Any sequence made up of the initial part of the code word is the prefix of any other code word.
- The Prefix Code are distinguished from other uniquely decodable codes by the fact that the end of code word is always recognisable. Thus the decoding of prefix.

Can be accomplished as soon as the source
signal symbol,

That's why prefix code is called
instantaneous code.

PROPERTIES OF PREFIX CODE

* not property
* Kraft-McMillan
Inequality :-

⇒ * of a prefix code is, constructed from a
discrete memoryless source, the code
word length should satisfy certain
inequality called Kraft-McMillan Inequality.

⇒ It states that :-

$$\sum_{k=0}^{K-1} 2^{-l_k} \leq 1$$

length of code is given
by Kraft McMillan
inequality,

Where,

l_k = Codeword length of k^{th} symbol,

K = Total no. of symbols

Properties:-

(1) The prefix code satisfy that Kraft Mc-Millan inequality.

Source Symbol	Probability of occurrence	Prefix Code
s_0	0.5	0 $l_0=1$
s_1	0.25	10 $l_1=2$
s_2	0.125	110 $l_2=3$
s_3	0.125	111 $l_3=3$

$$\sum_{k=0}^{K-1} 2^{-l_k} \leq 1$$

here, $K=4$

$$\begin{aligned} \Rightarrow \sum_{k=0}^3 2^{-l_k} &= 2^{-l(s_0)} + 2^{-l(s_1)} + 2^{-l(s_2)} + 2^{-l(s_3)} \\ &= 2^{-1} + 2^{-2} + 2^{-3} + 2^{-3} \\ &= \frac{1}{2} + \frac{1}{4} + \frac{1}{8} + \frac{1}{8} = 1 \end{aligned}$$

Thus Kraft's Mc-Millan inequality is satisfied.

ii) The probability of k^{th} is related to 2^{-l_k} is given by:-

$$P_k = 2^{-l_k}$$

$$P_0 = 2^{-l_0} = 2^{-1} = \frac{1}{2}$$

$$P_1 = 2^{-l_1} = 2^{-2} = \frac{1}{4}$$

$$P_2 = 2^{-l_2} = 2^{-3} = \frac{1}{8}$$

$$P_3 = 2^{-l_3} = 2^{-3} = \frac{1}{8}$$

iii) The average code word length of a prefix code is bounded by

$$H(S) \leq \bar{N} \leq H(S) + 1$$

where, $\bar{N} \rightarrow$ Average code word length

$$\bar{N} = \sum_{k=0}^{K-1} P_k l_k$$

$$\therefore \bar{N} = \sum_{k=0}^{K-1} 2^{-l_k} l_k$$

$$[\because P_k = 2^{-l_k}]$$

$$\bar{N} = \sum_{k=0}^{K-1} \frac{1}{2^{l_k}} \cdot l_k$$

Entropy of the source,

$$H(S) = \sum_{k=0}^{K-1} P_k \log_2 \left(\frac{1}{P_k} \right)$$

$$\because P_k = 2^{-lk}$$

$$\frac{1}{P_k} = 2^{lk}$$

$$= \sum_{k=0}^{K-1} \frac{1}{2^{lk}} \log_2 \left(\frac{1}{2^{-lk}} \right)$$

$$= \sum_{k=0}^{K-1} \frac{1}{2^{lk}} \cdot lk \log_2 2$$

$$= \sum_{k=0}^{K-1} \frac{1}{2^{lk}} \cdot lk \quad (\log_2 2 = 1)$$

$$= \sum_{k=0}^{K-1} \frac{lk}{2^{lk}}$$

$$\Rightarrow H(S) = \sum_{k=0}^{K-1} \frac{lk}{2^{lk}}$$

$$\& \text{ also } \bar{N} = \sum_{k=0}^{K-1} \frac{lk}{2^{lk}}$$

Prop 3
 \Rightarrow Thus the avg code word length of a prefix Code is equal to the entropy of the source.

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PROPERTIES OF ENTROPY

(i) To Prove:- Entropy $H=0$, when $P_k=0$,
& $P_k=1$.

$$H = \sum_{n=1}^M P_k \log_2 \left(\frac{1}{P_k} \right)$$

Case (i) when $P_k=1$

$$H = \sum_{n=1}^M 1 \log_2(1)$$

[$\because \log_2 1=0$]

$$= 0$$

$$\boxed{H=0} \text{ when } P_k=1.$$

Case (ii) when $P_k=0$,

$$H = \sum_{k=1}^M 0 \log_2 \left(\frac{1}{P_k} \right)$$

$$H = \sum_{k=1}^M P_k \log_2 \left(\frac{1}{P_k} \right)$$

$$= \sum_{k=1}^M \lim_{P_k \rightarrow 0} P_k \log_2 \left(\frac{1}{P_k} \right)$$

$$= 0$$

$$\boxed{H=0}, P_k=0$$

Flaw

Thus Entropy is 0 for both certain and rare message.

ii) To Prove: $H = \log_2 M$

for 'M' equally likely messages.

$$P = \frac{1}{M}$$

$$\Rightarrow P_1 = P_2 = P_3 = \dots = P_m = \frac{1}{M}$$

$$\text{Entropy, } H = \sum_{k=1}^M P_k \log_2 \left(\frac{1}{P_k} \right)$$

$$= \cancel{P_1} \log_2 \left(\frac{1}{P_1} \right) + P_2 \log_2 \left(\frac{1}{P_2} \right) \\ + P_3 \log_2 \left(\frac{1}{P_3} \right) + \dots \\ \dots + P_m \log_2 \left(\frac{1}{P_m} \right)$$

$$= \frac{1}{M} \log_2 (M) + \frac{1}{M} \log_2 M + \dots + \frac{1}{M} \log_2 M$$

$$\boxed{H = \log_2 M}$$

iii) To prove:- $H_{\max} \leq \log_2 M$

Using the property of natural log,
 $\ln x \leq x-1$, for $x > 0$ — (1)

$$\boxed{\log_e x = \ln x}$$

Let us consider two probability distribution
 $\{p_1, p_2, \dots, p_M\}$ & $\{q_1, q_2, \dots, q_n\}$ on
the alphabet $X = \{x_1, x_2, \dots, x_m\}$ of
discrete memoryless source.

Consider the term,

$$\begin{aligned} & \sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) \\ &= \sum_{k=1}^M p_k \frac{\log_{10} \left(\frac{q_k}{p_k} \right)}{\log_{10}(2)} \end{aligned} \quad \because \log_2 x = \frac{\log_{10} x}{\log_{10} 2}$$

Multiplying & div by R.H.S by $\log_{10} e$

$$\begin{aligned} \sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) &= \frac{\log_{10} e}{\log_{10}(2)} \frac{\log_{10} \left(\frac{q_k}{p_k} \right)}{\log_{10} e} \\ &= \log_2 e \cdot \log_e \left(\frac{q_k}{p_k} \right) \end{aligned}$$

$$\text{But } \log_e \left(\frac{q_k}{p_k} \right) = \ln \left(\frac{q_k}{p_k} \right)$$

$$\sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) = \log_2 e \sum_{k=1}^M p_k \ln \left(\frac{q_k}{p_k} \right)$$

from (1),

$$\ln \left(\frac{q_k}{p_k} \right) \leq \frac{q_k}{p_k} - 1$$

$$\sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) \leq \log_2 e \sum_{k=1}^M p_k \left(\frac{q_k}{p_k} - 1 \right)$$

$$\leq \log_2 e \sum_{k=1}^M (q_k - p_k)$$

$$\Rightarrow \sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) \leq \log_2 e \left[\sum_{k=1}^M q_k - \sum_{k=1}^M p_k \right]$$

$$\therefore \sum_{k=1}^M q_k = 1$$

$$\sum_{k=1}^M p_k = 1$$

$$\Rightarrow \sum_{k=1}^M p_k \log_2 \left(\frac{q_k}{p_k} \right) \leq 0$$

Consider $q_k = \frac{1}{p_k}$, for all 'k'

$$\begin{aligned} \log \frac{m}{n} &= \log m - \log n \\ &= \log m + \log \frac{1}{n} \end{aligned}$$

$$\Rightarrow \sum_{k=1}^M p_k \left[\log_2 q_k + \log_2 \left(\frac{1}{p_k} \right) \right] \leq 0$$

$$= \sum_{k=1}^M p_k \left[\log_2 \left(\frac{1}{p_k} \right) + \log_2 \left(\frac{1}{p_k} \right) \right] \leq 0$$

$$= \sum_{k=1}^M p_k \log_2 \frac{1}{p_k} + \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq 0$$

$$= \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq - \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right)$$

$$\leq - \sum_{k=1}^M p_k \log_2 (q_k)$$

$$= \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq \sum_{k=1}^M p_k \log_2 \left(\frac{1}{q_k} \right)$$

$$\text{sub } q_k = \frac{1}{M}$$

$$\Rightarrow \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq \sum_{k=1}^M p_k \log_2 M$$

$$\Rightarrow \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq \log_2 M \sum_{k=1}^M p_k$$

$$\therefore \sum_{k=1}^M p_k = 1$$

$$\Rightarrow \sum_{k=1}^M p_k \log_2 \left(\frac{1}{p_k} \right) \leq \log_2 M$$

$$\Rightarrow \boxed{H_{\max} \leq \log_2 M}$$

PROPERTIES OF MUTUAL INFORMATION

(1) To prove: $I(X;Y) = I(Y;X)$

From Probability theory, formula's:-

$$(1) P(x_i, y_j) = P(x_i | y_j) P(y_j) \quad \text{--- (1)}$$

$$P(x_i, y_j) = P(y_j | x_i) P(x_i) \quad \text{--- (2)}$$

where,

$P(x_i, y_j)$ \rightarrow joint probability that x_i is transmitted & y_j is received

$P(x_i | y_j)$ \rightarrow Conditional probability that x_i is transmitted & y_j is received,

$P(y_j | x_i)$ \rightarrow Conditional probability that y_j is received & x_i is transmitted,

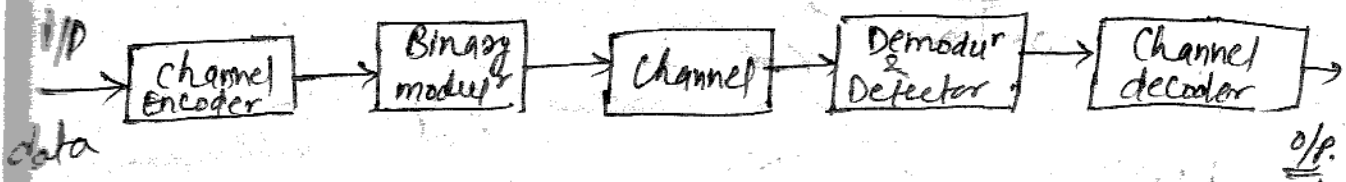
$P(x_i)$ \rightarrow Probability of symbol x_i for transm.

$P(y_j)$ \rightarrow Probability of symbol y_j for reception.

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NOISY CODING :-Types of Channels :-

- (i) Binary Symmetric channel or (BSC)
- (ii) Discrete Memoryless channel
- (iii) Waveform channel.

Binary Symmetric Channel (BSC)Block Diagram :-HARD DECISION :-

If the modulation is binary, the detector decides whether the transmitted bit is bit (0 or 1), this is hard decision.

SOFT DECISION :- If the transmission is

M-ary and 'Q' is greater than or equal to M, then detector detects any 1 level out of Q possible levels.

This is similar to quantizing many signal to the nearest Q -level. when $Q \rightarrow \infty$, there is no quantization, this is soft decision.

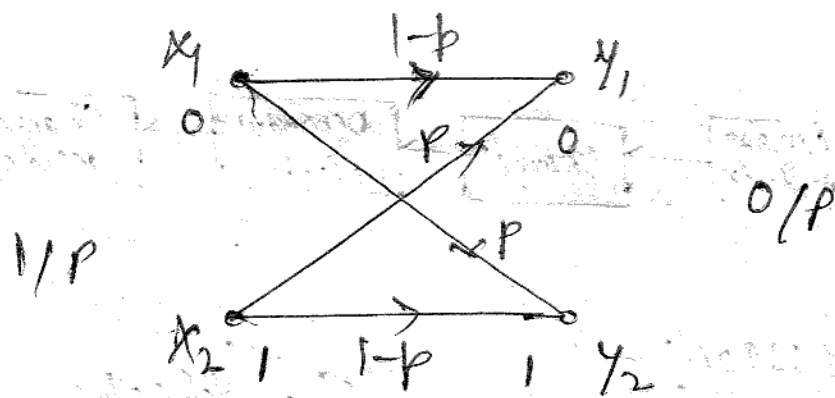
$X = \{0, 1\}$

$Y = \{0, 1\}$

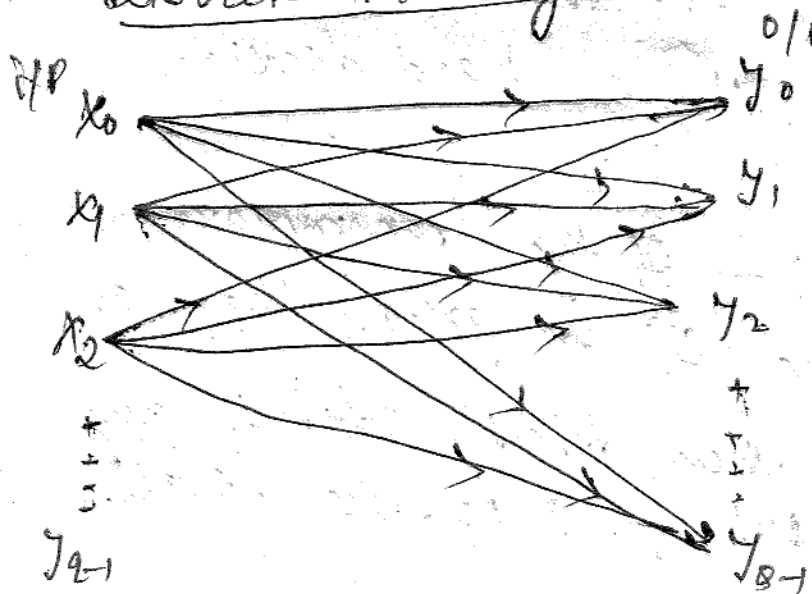
$P(Y=0/X=1) = P(Y=1/X=0) = p.$

then,

$P(Y=1/X=1) = P(Y=0/X=0) = 1-p.$



Discrete Memoryless Channel



note Here each i/p is connected with all o/p ie X_0 is connected with Y_0, Y_1, \dots, Y_{B-1}

Here we have 2-1 I/P's & 8-1 O/P's.

When the I/P to the discrete memoryless channel is sequence of n^{th} symbols.

& u_1, u_2, \dots, u_n selected from X

then the o/p will be v_1, v_2, \dots, v_n .

from Y .

For the discrete memoryless channel the sets of o/p ~~the~~ symbols is characterised by Joint Conditional probability.

$$\prod_{k=1}^n P(Y = y_k / X = u_k)$$

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*Classification of channels:-

- (i) Lossless Channel
- (ii) Deterministic Channel
- (iii) Noiseless Channel.
- (iv) Useless Channel.
- (v) Symmetric Channel.

~~Ass~~
Let us consider a discrete memoryless channel with input alphabets x_1, x_2, \dots, x_m and o/p alphabets y_1, y_2, \dots, y_n .

The channel matrix $[a_{ij}]$, where

$$a_{ij} = P(y_j/x_i), \quad \text{where } i=1, 2, \dots, M \text{ \& } j=1, 2, \dots, N$$

The joint distribution of X and Y is given by

$$P[X=x_i, Y=y_j] \\ = P(x_i) \cdot P(y_j/x_i)$$

⇒ The distribution of Y is given by

$$P[Y=y_j] = \sum_{i=1}^M P(x_i) P(y_j/x_i) \quad \text{--- (1) eqn}$$

⇒ The information processed by the channel is given by

$$I(X; Y) = H(X) - H(X/Y) \quad \text{--- (2) eqn}$$

But we have,

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

$$= H(X) + H(Y) - H(X, Y) \quad \text{--- (3) eqn}$$

→ The Channel Capacity is given by :-

$$C = \max_{P(x_i)} I(X; Y) \quad \text{--- (4) eqn}$$

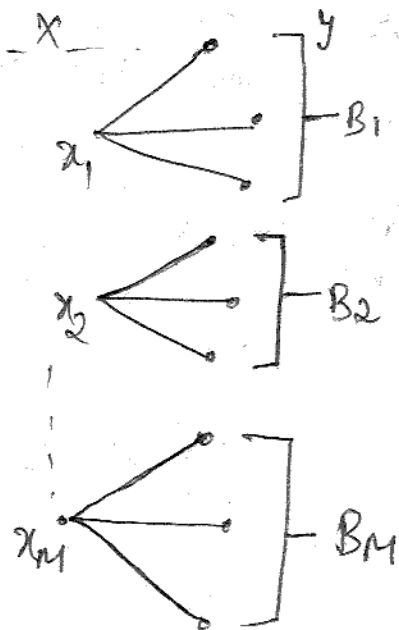
Probability of max. informatⁿ transmitted

→ A discrete memory channel can be defined by channel matrix 'D' where,

$$D = P(Y_j/X_i) = \begin{bmatrix} P(y_1/x_1) & P(y_2/x_1) & \dots & P(y_M/x_1) \\ P(y_1/x_2) & P(y_2/x_2) & \dots & P(y_M/x_2) \\ \vdots & \vdots & \ddots & \vdots \\ P(y_1/x_M) & P(y_2/x_M) & \dots & P(y_M/x_M) \end{bmatrix}$$

* Classificatⁿ of Channel

(1) Lossless Channel :-



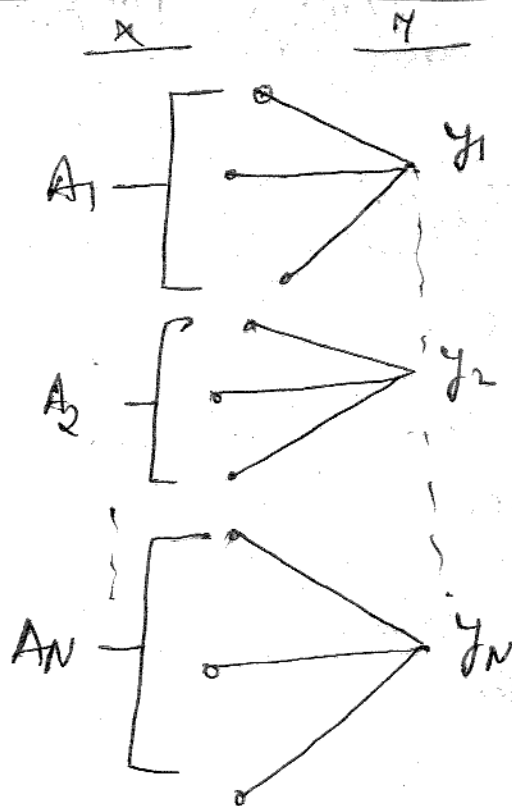
A channel is lossless if $H(X/Y)$ is equal to zero for all i/p distributions.

The lossless channel is one in which the i/p is determined by o/p, and hence no transmission error occurs

i.e. no information is lost but ideally it is not possible.

The amount of infoⁿ transmitted = amount of v received

Deterministic Channel :-



A Channel is deterministic if $P(y_j/x_i) = 1 \text{ or } 0$

for all values of $i, + j$

⇒ The Conditional probability $P(y_j/x_i)$

can be defined as,

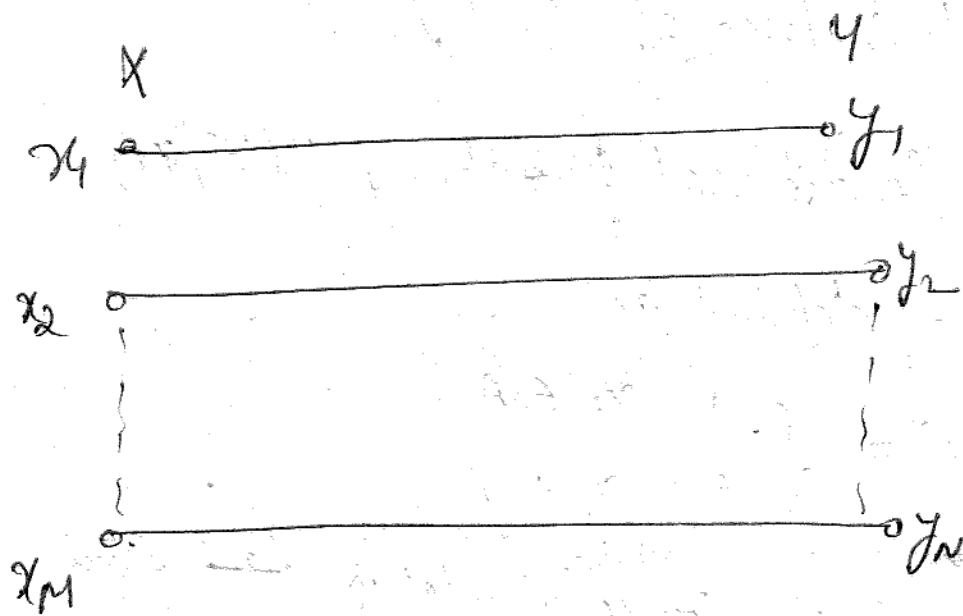
$$P(y_j/x_i) = \begin{cases} 1, & x_i \in A \\ 0, & x_i \notin A \end{cases}$$

⇒ ^{when} ~~in~~ a given source symbol is ~~said~~ sent through a deterministic channel, ~~with~~ it is clear that which destination symbol will be received.

⇒ For Deterministic Channel, the Channel matrix has only one non-zero element in each row and this element is unity (1).

ex: $A = \begin{bmatrix} 0 & 0 & 1 \\ 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix} \leftarrow \text{Deterministic channel}$

Noisy Noiseless Channel:

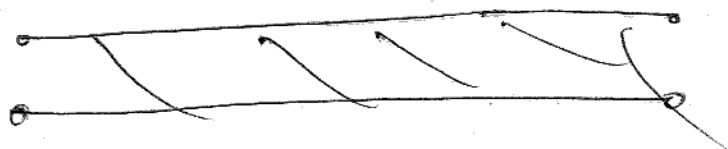


A channel is said to be noiseless, if it is both lossless and deterministic.

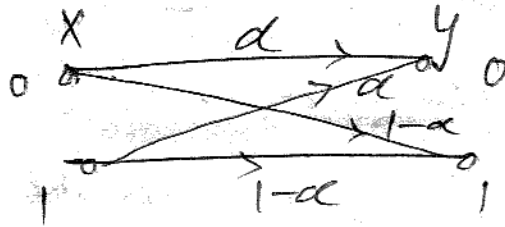
$$I(X; Y) = H(X) = H(Y)$$

⇒ The channel matrix has only one non zero element in each row and in each column, and this element is unit

USELESS CHANNEL



USELESS CHANNEL



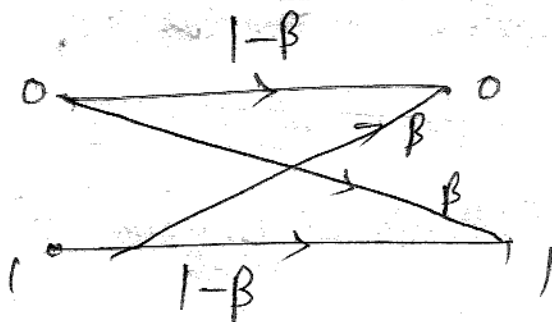
A channel is useless or zero capacity if

$$\boxed{I(X; Y) = 0} \text{ for all i/p distribution}$$

\Rightarrow No information can be transmitted

\Rightarrow A channel is useless if & only if, its channel matrix has identical rows.

Symmetric Channel



A channel is symmetric if each row of the channel matrix and each column of the channel matrix contains the same set of numbers. i.e. rows and columns are identical.

⇒ For Symmetric Channel

$H(Y|X)$ is independent of $P(x_i)$,
and it depends only on the channel
probability $P(y_j|x_i)$.

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Calculation of Channel Capacity :-

(i) Lossless Channel :-

The channel capacity is obtained when
the source entropy is \max^m . i.e

$$C = \max_{P(x_i)} H(X) = \log_2 M$$

$P(x_i) =$ uniform distribution

This \max^m is obtained when all x_i
are equally likely or when $P(x_i)$
is a uniform distribution.

(ii) Deterministic Channel :-

Channel Capacity is obtained when the destination Entropy is \max^m , i.e.

$$C = \max_{P(y_j)} H(x) = \log_2 N$$

This \max^m is obtained when all y_j are equally likely, or $P(y_j)$ is a uniform distribution.

(iii) Noiseless Channel

Channel Capacity is given by :-

$$C = \log_2 M = \log_2 N$$

\Rightarrow It has both lossless & deterministic.

(iv) Symmetric Channel :-

For symbol x_i with marginal probability, a_i , we have

$$P(y_j/x_i) = \alpha_{ij} \quad \text{--- (1)}$$

$$P(x_i/y_j) = \beta_{ij} \quad \text{--- (2)}$$

The max^m of $H(Y)$ occurs when all the received symbols have same probability, i.e

$$C = \log m - h \quad \text{--- (3)}$$

$m = \text{no. of symbols}$

$h = \text{Constant}$

For symmetric channel,

$$P(x_i) \alpha_{ij} = P(y_j) \beta_{ij}$$

Channel Capacity,

$$C = \max [H(X) - H(X/Y)]$$

$$= \max [H(X)] - h'$$

$$C = \log X - h'$$

where $h' = \text{Conditional entropy}$

$$= H(X/Y)$$

(v) Unsymmetric Channel

⇒ Channel capacity is given by:-

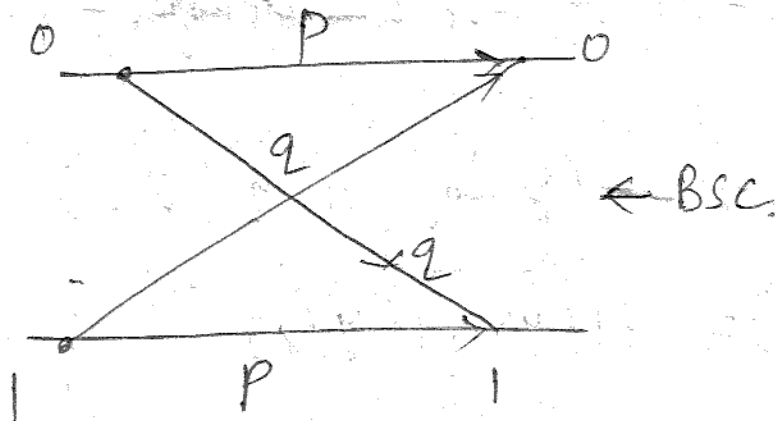
$$C = \frac{\ln [e^{a_1} + e^{a_2}]}{\log_2 [2^{a_1} + 2^{a_2}]}$$

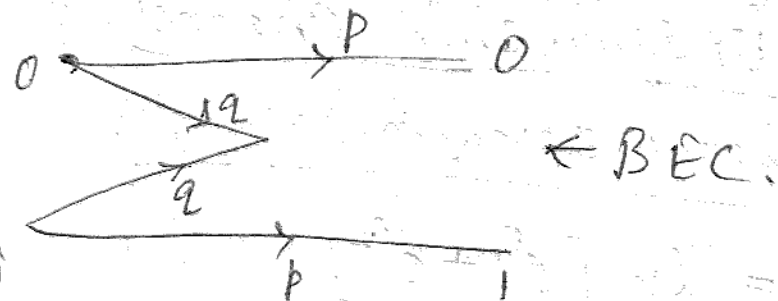
When a_1 & a_2 = variables.

(vi) Useless Channel:-

Binary Symmetric Channel (BSC):-

and Binary Erasure Channel (BEC):-





We assume that $0/1$ of binary source is transmitted through BSC or BEC

For BSC, Let

$$P(0) = \alpha, \quad P(1) = 1 - \alpha,$$

$$P(0/0) = P(1/1) = p$$

$$P(0/1) = P(1/0) = q$$

$$H(X) = H(\alpha, 1 - \alpha) = -\alpha \log \alpha - (1 - \alpha) \log (1 - \alpha)$$

$$H(Y/X) = -(p \log p + q \log q)$$

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

$$= H(Y) + (p \log p + q \log q)$$

But

$$C = \max_{P(x)} [I(X; Y)]$$

$$C = 1 + p \log p + q \log q$$

For BEC

There are 2 i/p symbols $\{0, 1\}$, and
three o/p symbols $\{0, y, 1\}$.

The letter y indicates the fact that
o/p is erased and no deterministic decision
can be made as together the transmitted
symbol of for 0 & 1.

$$\text{Let } P(0) = \alpha, \quad P(1) = 1 - \alpha$$

$$P(0/0) = P(1/1) = p$$

$$P(0/1) = P(1/0) = q$$

$$H(x) = H(\alpha, 1 - \alpha) =$$

$$H(x/y) = (1 - p)H(x)$$

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

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

$$= H(x) - H(x) + p H(x)$$

$$= p H(x)$$

$$C = \left[\max I[x; y] = p \right]$$