

Information Theory and Coding
Forth Stage

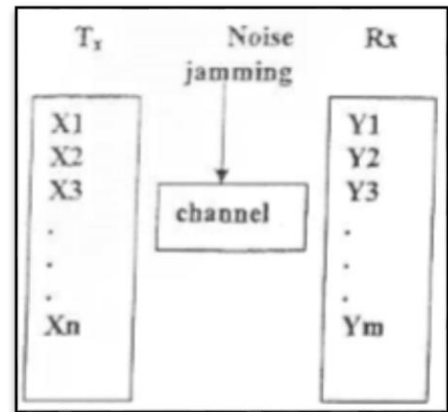
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Lecture Six

First Course

Mutual information for noisy channel:

Consider the set of symbols x_1, x_2, \dots, x_n , the transmitter T_x may produce. The receiver R_x may receive y_1, y_2, \dots, y_m . Theoretically, if the noise and jamming is neglected, then the set $X = \text{set } Y$. However and due to noise and jamming, there will be a conditional probability $P(y_j | x_i)$:



- 1- $P(x_i)$ to be what is so called the a priori probability of the symbol x_i , which is the prob of selecting x_i for transmission.
- 2- $P(y_j | x_i)$ to be what is called the aposteriori probability of the symbol x_i after the reception of y_j . The amount of information that y_j provides about x_i is called **the mutual information** between x_i and y_i . This is given by:

$$I(x_i, y_j) = \log_2 \left(\frac{\text{aposteriori prob}}{\text{apriori prob}} \right) = \log_2 \left(\frac{P(y_j | x_i)}{P(x_i)} \right)$$

Properties of $I(x_i, y_j)$:

- 1- It is symmetric, $I(x_i, y_j) = I(y_j, x_i)$.
- 2- $I(x_i, y_j) > 0$ if aposteriori probability $>$ a priori probability, y_j provides +ve information about x_i .
- 3- $I(x_i, y_j) = 0$ if aposteriori probability = a priori probability, which is the case of statistical independence when y_j provides no information about x_i .
- 4- $I(x_i, y_j) < 0$ if aposteriori probability $<$ a priori probability, y_j provides -ve information about x_i , or y_j adds ambiguity.



Example: Show that $I(X, Y)$ is zero for extremely noisy channel.

Solution: For extremely noisy channel, then y_j gives no information about x_i the receiver can't decide anything about x_i as if we transmit a deterministic signal x_i but the receiver receives noise like signal y_j that is completely has no correlation with x_i . Then x_i and y_j are statistically independent so that $P(x_i | y_j) = P(x_i)$ and $P(y_j | x_i) = P(y_j)$ for all i and j , then: $I(x_i, y_j) = \log_2 1 = 0$ for all i & j , then $I(X, Y) = 0$

1. Joint entropy:

In information theory, joint entropy is a measure of the uncertainty associated with a set of variables.

$$H(X, Y) = H(XY) = - \sum_{j=1}^m \sum_{i=1}^n P(x_i, y_j) \log_2 P(x_i, y_j) \quad \text{bits/symbol}$$

2. Conditional entropy:

In information theory, the conditional entropy quantifies the amount of information needed to describe the outcome of a random variable Y given that the value of another random variable X is known.

$$H(Y | X) = - \sum_{j=1}^m \sum_{i=1}^n P(x_i, y_j) \log_2 P(y_j | x_i) \quad \text{bits/symbol}$$

3. Marginal Entropies:

Marginal entropies is a term usually used to denote both source entropy $H(X)$ defined as before and the receiver entropy $H(Y)$ given by:

$$H(y) = - \sum_{j=1}^m P(y_j) \log_2 P(y_j) \quad \text{bit/symbol}$$

4. Relationship between joint, conditional and transinformation:

Noise entropy: $H(Y | X) = H(X, Y) - H(X)$

Loss entropy: $H(X | Y) = H(X, Y) - H(Y)$



Also we have transinformation (average mutual information):

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

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

Example: The joint probability of a system is given by:

$$P(X,Y) = \begin{matrix} x_1 & 0.5 & 0.25 \\ x_2 & 0 & 0.125 \\ x_3 & 0.0625 & 0.0625 \end{matrix}$$

Find:

- 1- Marginal entropies.
- 2- Joint entropy.
- 3- Conditional entropies.
- 4- The transinformation.

Solution:

$$\begin{matrix} x_1 & x_2 & x_3 & & y_1 & y_2 \\ P(x)=[0.75 & 0.125 & 0.125], & P(y)=[0.5625 & 0.4375] \end{matrix}$$

1-

$$H(x) = - \sum_{i=1}^n P(x_i) \log_2 P(x_i) = - \left[\frac{0.75 \ln 0.75 + 2 * 0.125 \ln 0.125}{\ln 2} \right]$$

$$= 1.06127 \text{ bit/symbol}$$

$$H(y) = - \sum_{j=1}^m P(y_j) \log_2 P(y_j) = - \left[\frac{0.5625 \ln 0.5625 + 0.4375 \ln 0.4375}{\ln 2} \right]$$

$$= 0.9887 \text{ bit/symbol}$$



2-

$$\begin{aligned} H(x, y) &= - \sum_{j=1}^m \sum_{i=1}^n P(x_i, y_j) \log_2 P(x_i, y_j) \\ &= - \left[\frac{0.5 \ln 0.5 + 0.25 \ln 0.25 + 0.125 \ln 0.125 + 2 * 0.0625 \ln 0.0625}{\ln 2} \right] \\ &= 1.875 \text{ bit/symbol} \end{aligned}$$

3-

$$\begin{aligned} H(y | x) &= H(x, y) - H(x) = 1.875 - 1.06127 = 0.813 \text{ bit/symbol} \\ H(x | y) &= H(x, y) - H(y) = 1.875 - 0.9887 = 0.886 \text{ bit/symbol} \end{aligned}$$

4-

$$I(x, y) = H(x) - H(x | y) = 1.06127 - 0.886 = 0.175 \text{ bit/symbol}$$