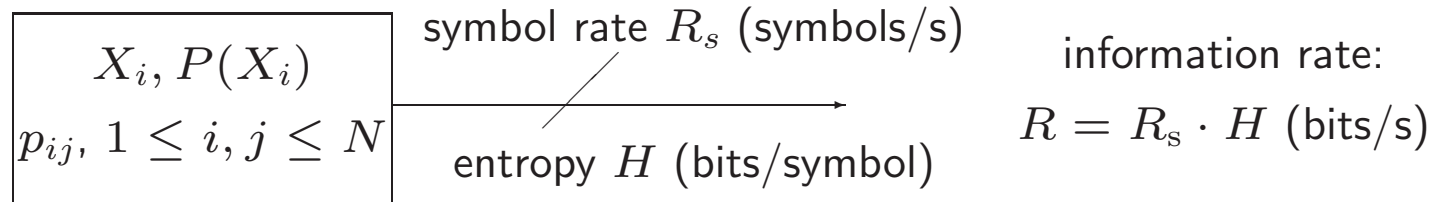


Revision of Lecture 3



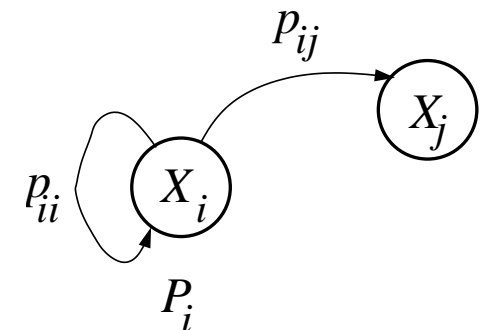
- 1st-order Markov process

- Prior probability $P_i = P(X_i)$ and conditional probability p_{ij}
- Symbol (state) entropy $H_i = - \sum_{j=1}^N p_{ij} \cdot \log_2 p_{ij}$ (bits/symbol)
- Source entropy $H = \sum_{i=1}^N P_i H_i$ (bits/symbol)

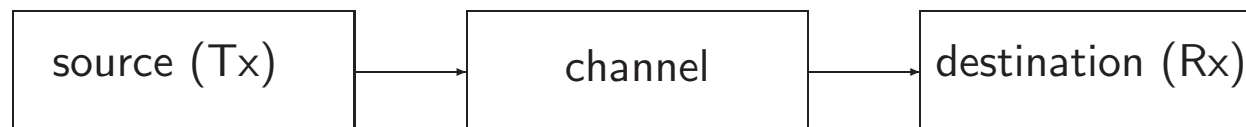
- AR model

$$y(n) = \sum_{k=1}^M a_k y(n-k) + \epsilon(n)$$

- Run length encoding

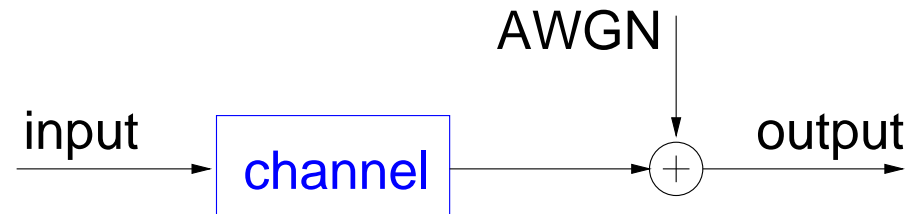


What happens to **information** transmitted through **channel**?



Information Across Channels

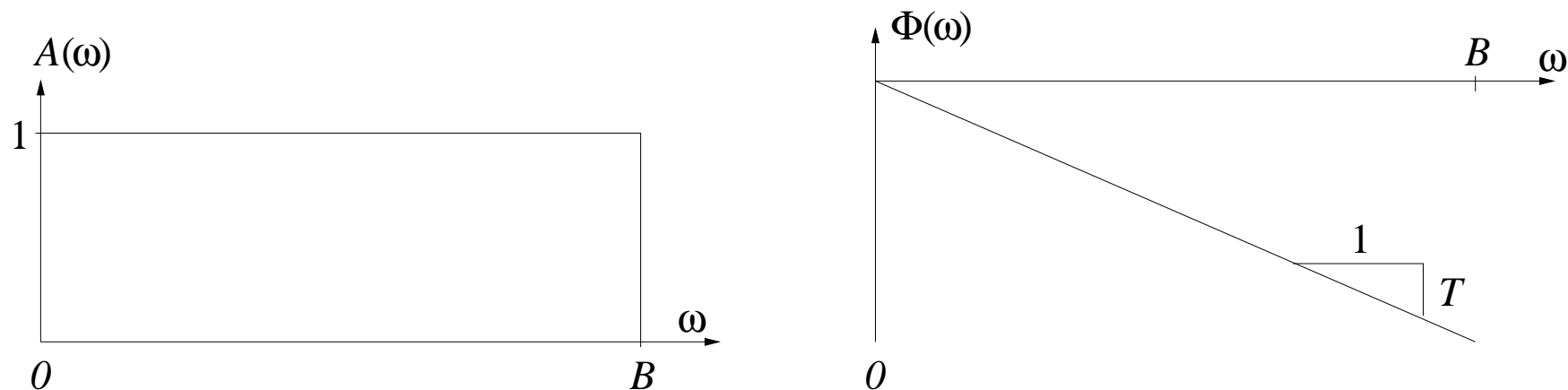
- For conveying information across a transmission channel, a suitable model is:



- The **channel** itself introduces amplitude and phase **distortion**, is potentially time-varying, and has a **limited bandwidth** B
- Error-free reception of symbols is additionally impeded by additive white Gaussian noise (AWGN); its severeness is described by the **signal-to-noise ratio** (SNR)
- Therefore, dependent on the above parameters, we are interested in determining the maximum possible error-free information transmission (**channel capacity** C)
- We will see that C depends on B and SNR

Characteristics of Channel

- The channel can be described by its **impulse response** $h(t)$ or equivalently its **frequency response** $H(j\omega) = A(\omega) \cdot e^{j\Phi(\omega)}$ with amplitude response $A(\omega)$ and phase response $\Phi(\omega)$; $h(t)$ and $H(j\omega)$ are Fourier pair
- Ideal channel** (pure delay): $h(t) = \delta(t - T) \rightarrow A(\omega) = 1, \Phi(\omega) = -\omega T$



- Flat magnitude and linear phase (= constant group delay $G(\omega) = -\partial\Phi(\omega)/\partial\omega$)
- The only impairment caused by an ideal channel is AWGN

- Non-ideal channel:** channel is *dispersive*, causing intersymbol interference

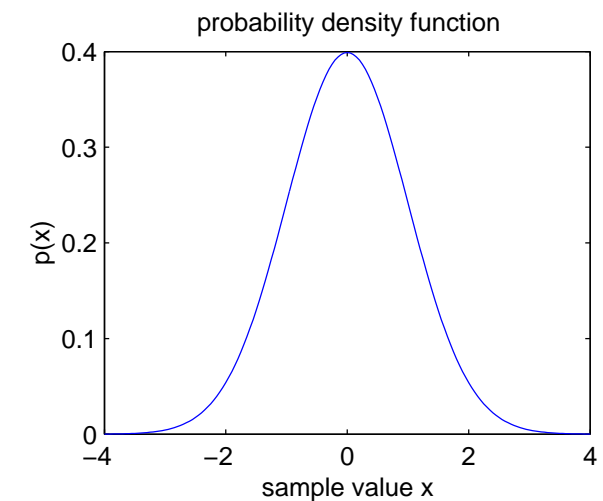
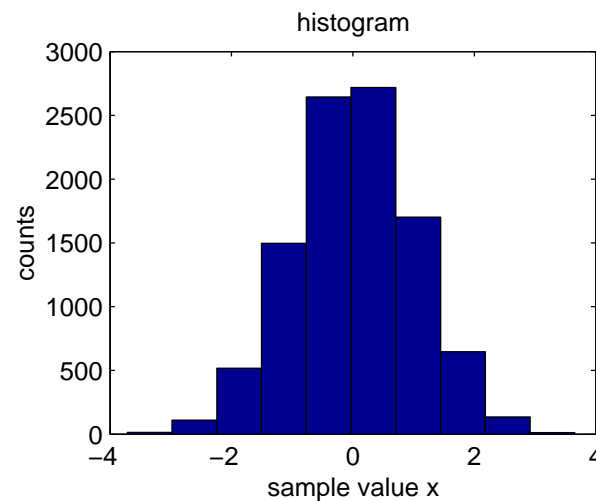
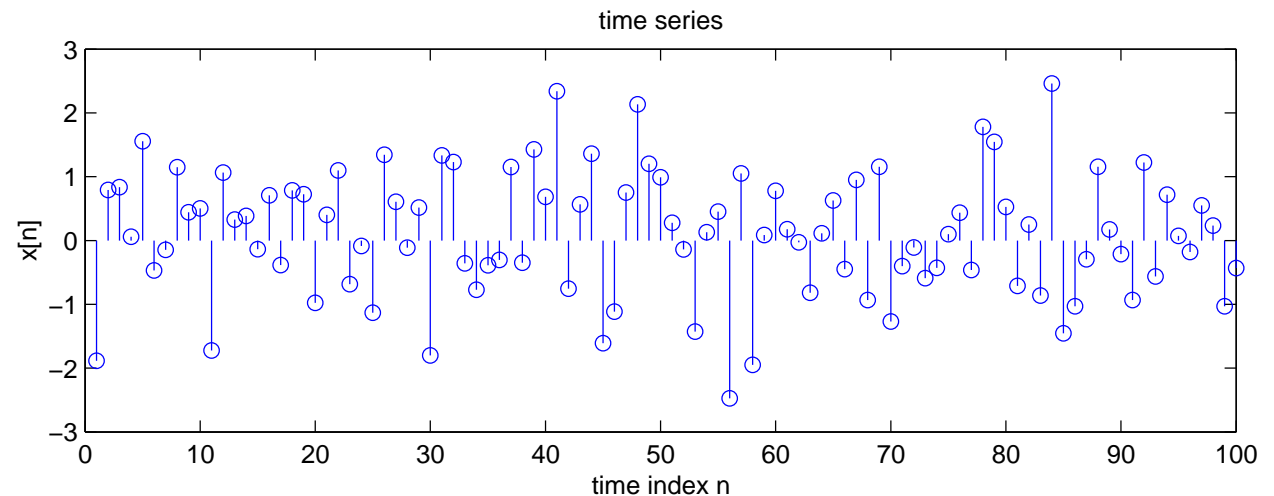
Additive White Gaussian Noise

- Noise is uncorrelated with the signal
- **Gaussian** noise has a bell shaped probability density function (normally distributed)

$$p(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)/2\sigma^2}$$

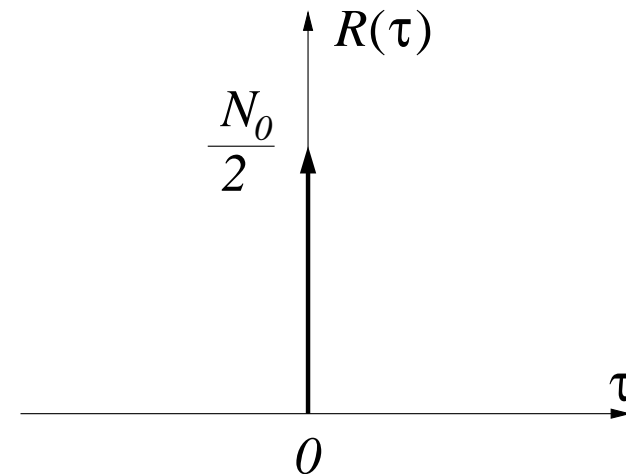
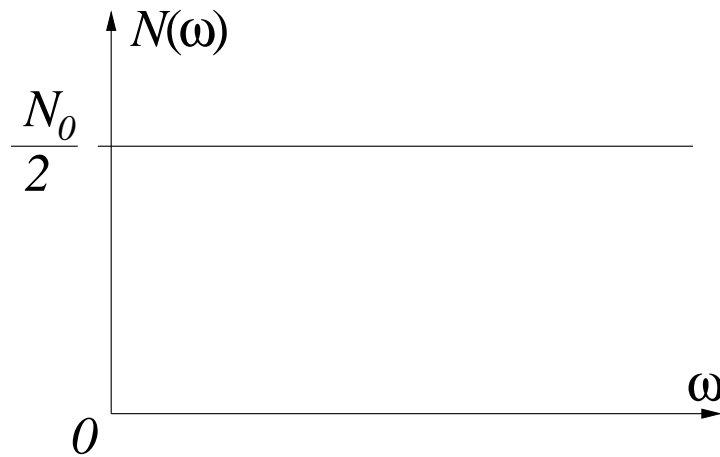
with mean μ and variance σ^2

- **White** noise has zero mean, and channel noise is usually modelled as an AWGN



White Noise

- **White noise** is characterised by a **flat power spectral density function**, $N(\omega)$, or equivalently, its **impulse-shaped auto-correlation function**, $R(\tau)$



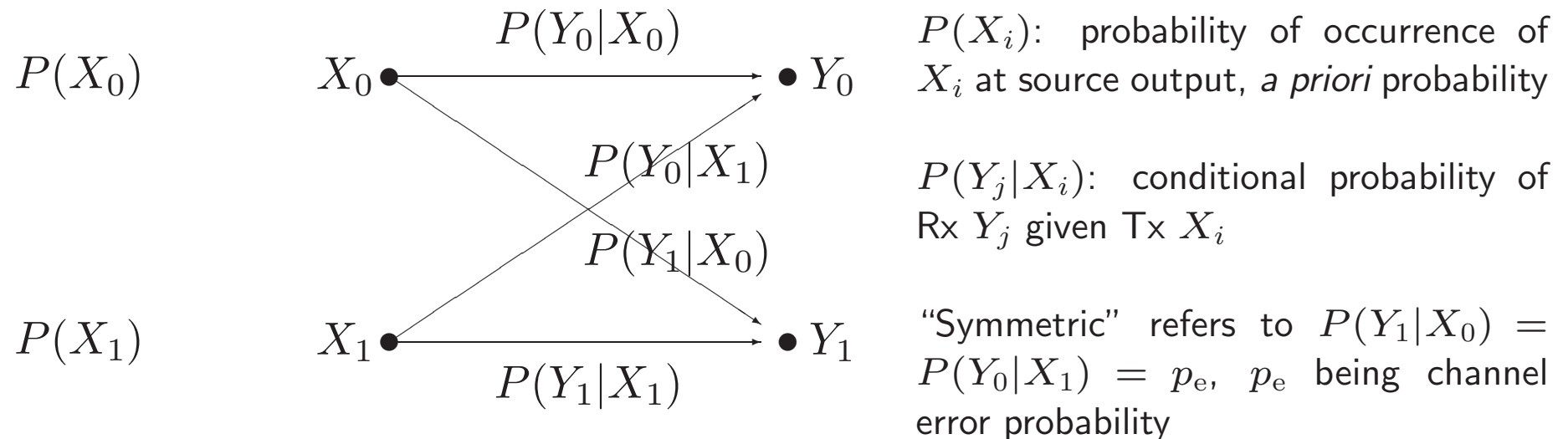
- $N(\omega)$ and $R(\tau)$ are a Fourier pair:

$$R(\tau) = \frac{1}{2\pi} \int_{-\infty}^{\infty} N(\omega) e^{j\omega\tau} d\omega \quad N(\omega) = \int_{-\infty}^{\infty} R(\tau) e^{-j\omega\tau} d\tau$$

- **Two-side** spectrum is usually used for convenience, and N_0 is the noise power

Binary Symmetric Channel (BSC)

- **BSC** is the simplest model for information transmission via a discrete channel (channel is ideal, no amplitude and phase distortion, only distortion is due to AWGN):

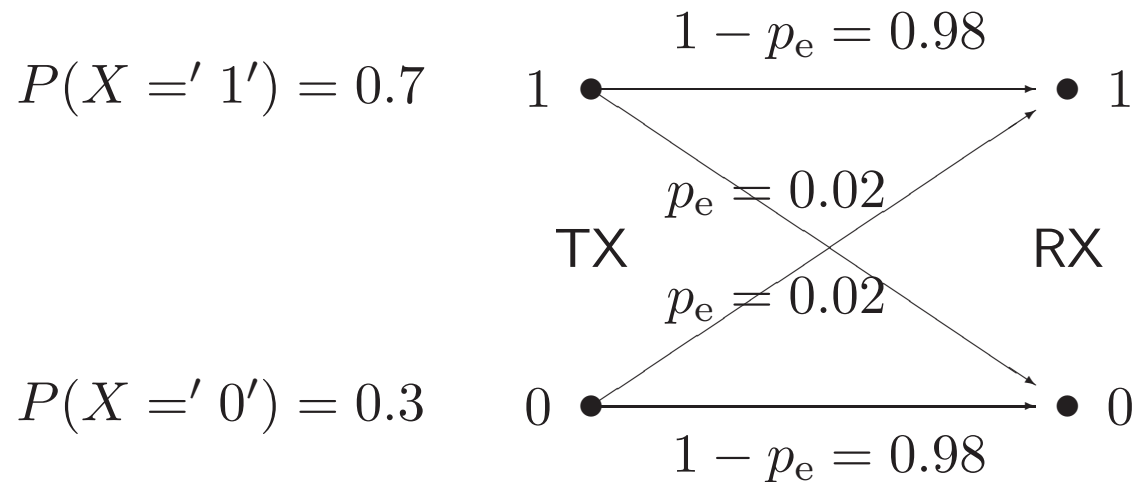


- The joint probability $P(Y_j, X_i)$ (Tx X_i and Rx Y_j) is linked with the conditional probabilities $P(Y_j|X_i)$ by Bayes' rule:

$$\begin{aligned}
 P(Y_j, X_i) &= P(X_i) \cdot P(Y_j|X_i) = P(Y_j) \cdot P(X_i|Y_j) \\
 &= P(X_i, Y_j)
 \end{aligned}$$

Binary Symmetric Channel – Example

- Consider a BSC:



- This has a non-equiprobable source with $P(X = '1') = 0.7$ and $P(X = '0') = 0.3$: on average, 70% of transmitted bits are '1' and 30% are '0'
- Channel's error probability $p_e = 0.02$: on average, bit error rate is 2%

Binary Symmetric Channel – Example (continue)

- Probability of correct reception: $P_{\text{correct}} = P(Y = '1', X = '1') + P(Y = '0', X = '0') = 0.98$, as

$$P(Y = '1', X = '1') = P(X = '1') \cdot P(Y = '1'|X = '1') = 0.7 \cdot 0.98 = 0.686$$

$$P(Y = '0', X = '0') = P(X = '0') \cdot P(Y = '0'|X = '0') = 0.3 \cdot 0.98 = 0.294$$

- Probability of erroneous reception: $P_{\text{error}} = P(Y = '1', X = '0') + P(Y = '0', X = '1') = 0.02$, as

$$P(Y = '1', X = '0') = P(X = '0') \cdot P(Y = '1'|X = '0') = 0.3 \cdot 0.02 = 0.006$$

$$P(Y = '0', X = '1') = P(X = '1') \cdot P(Y = '0'|X = '1') = 0.7 \cdot 0.02 = 0.014$$

- Total probability of receiving a '1' (or a '0'):

$$\begin{aligned} P(Y = '1') &= P(X = '1') \cdot P(Y = '1'|X = '1') + P(X = '0') \cdot P(Y = '1'|X = '0') \\ &= 0.7 \cdot 0.98 + 0.3 \cdot 0.02 = 0.692 \end{aligned}$$

$$\begin{aligned} P(Y = '0') &= P(X = '0') \cdot P(Y = '0'|X = '0') + P(X = '1') \cdot P(Y = '0'|X = '1') \\ &= 0.3 \cdot 0.98 + 0.7 \cdot 0.02 = 0.308 \end{aligned}$$

Mutual Information

- Definition of **mutual information** of X_i and Y_j :

$$I(X_i, Y_j) = \log_2 \frac{P(X_i|Y_j)}{P(X_i)} \quad (\text{bits})$$

- **Perfect, noiseless** channel: $Y_i = X_i$, i.e. $P(X_i|Y_i) = 1$ and

$$I(X_i, Y_i) = \log_2 \frac{1}{P(X_i)}$$

This is the information of X_i , hence no information is lost in the channel

- **Extremely noisy** channel with error probability 0.5 $\rightarrow Y_i$ is independent of X_i , hence

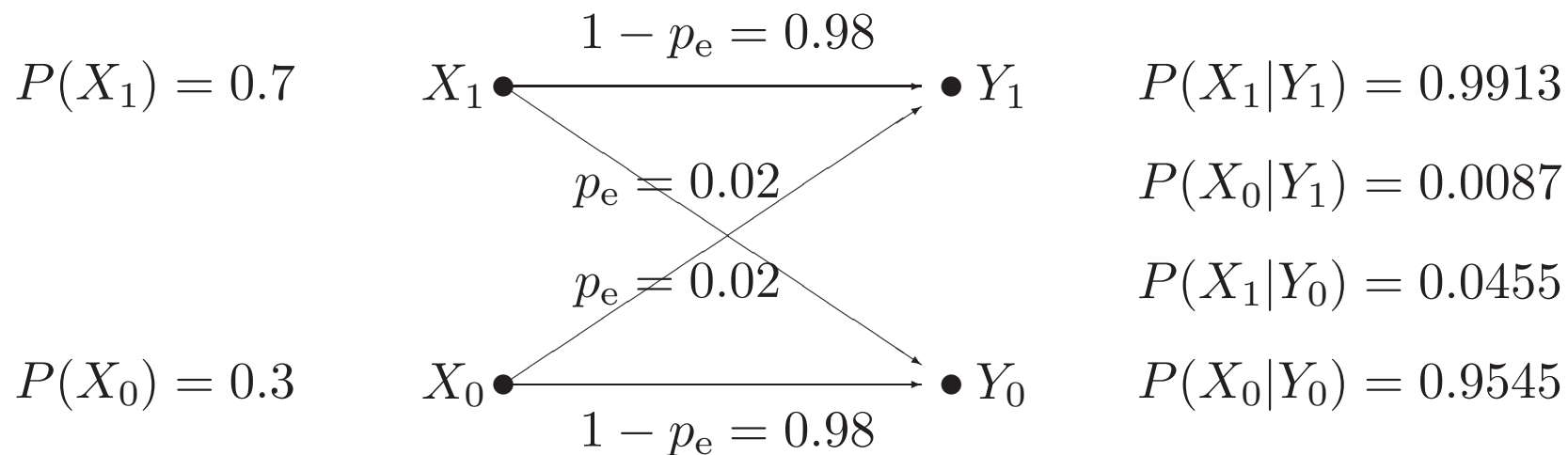
$$P(X_i|Y_i) = \frac{P(X_i, Y_i)}{P(Y_i)} = \frac{P(X_i) \cdot P(Y_i)}{P(Y_i)}$$

Therefore $I(X_i, Y_i) = \log_2 1 = 0$, meaning all information is lost in the channel



Mutual Information – Example

- Consider the earlier BSC example:



- Here, the mutual information results in:

	$I(X_1, Y_1) = 0.502$ bits	$I(X_0, Y_0) = 1.670$ bits
(source info:	$I(X_1) = 0.515$ bits	$I(X_0) = 1.737$ bits)
	$I(X_0, Y_1) = -5.113$ bits	$I(X_1, Y_0) = -3.945$ bits

The negative quantities represent “mis-information”!

Average Mutual Information

- Based on received symbols Y_j given transmitted symbols X_i through a BSC, **average mutual information** is defined as:

$$\begin{aligned}
 I(X, Y) &= \sum_i \sum_j P(X_i, Y_j) \cdot I(X_i, Y_j) \\
 &= \sum_i \sum_j P(X_i, Y_j) \cdot \log_2 \frac{P(X_i|Y_j)}{P(X_i)} \quad (\text{bits/symbol})
 \end{aligned}$$

- This gives the average amount of **source information acquired per received symbol** by the receiver, and should be distinguished from the average source information (entropy $H(X)$)
- Note that due to Bayes:

$$\frac{P(X_i|Y_j)}{P(X_i)} = \frac{P(X_i, Y_j)}{P(X_i) \cdot P(Y_j)} = \frac{P(Y_j|X_i)}{P(Y_j)}$$

Imperfect Channel: Information Loss

- Consider re-arranging the mutual information between transmitted symbol X_i and received symbol Y_j :

$$\begin{aligned} I(X_i, Y_j) &= \log_2 \frac{P(X_i|Y_j)}{P(X_i)} = \log_2 \frac{1}{P(X_i)} - \log_2 \frac{1}{P(X_i|Y_j)} \\ &= I(X_i) - I(X_i|Y_j) \end{aligned}$$

$I(X_i, Y_j)$ is the amount of information conveyed to receiver when transmitting X_i and receiving Y_j , $I(X_i)$ is the source information of X_i , and $I(X_i|Y_j)$ can be regarded as the information loss due to the channel

- Therefore,

$$\underbrace{I(X_i)}_{\text{Source Inf.}} - \underbrace{I(X_i, Y_j)}_{\text{Inf. conveyed to rec.}} = \underbrace{I(X_i|Y_j)}_{\text{Inf. loss}}$$

- $0 \leq I(X_i|Y_j) \leq I(X_i)$, see for example the previous cases of $p_e = 0$ and $p_e = 0.5$

Imperfect Channel: Average Mutual Information

- Average mutual information is given by:

$$I(X, Y) = \sum_i \sum_j P(X_i, Y_j) \cdot \log_2 \frac{P(X_i|Y_j)}{P(X_i)} \quad (\text{bits/symbol})$$

- But this average conveyed information $I(X, Y)$

$$\begin{aligned} &= \sum_i \sum_j P(X_i, Y_j) \cdot \log_2 \frac{1}{P(X_i)} - \sum_i \sum_j P(X_i, Y_j) \cdot \log_2 \frac{1}{P(X_i|Y_j)} \\ &= \sum_i \left(\sum_j P(X_i, Y_j) \right) \cdot \log_2 \frac{1}{P(X_i)} - \sum_j P(Y_j) \cdot \left(\sum_i P(X_i|Y_j) \cdot \log_2 \frac{1}{P(X_i|Y_j)} \right) \\ &= \sum_i P(X_i) \cdot \log_2 \frac{1}{P(X_i)} - \sum_j P(Y_j) \cdot I(X|Y_j) = \underbrace{H(X)}_{\text{av. source info}} - \underbrace{H(X|Y)}_{\text{av. info lost}} \end{aligned}$$

- A similar re-arrangement leads to:

$$\underbrace{H(Y)}_{\text{destination entropy}} - \underbrace{I(Y, X)}_{\text{av. conveyed info}} = \underbrace{H(Y|X)}_{\text{error entropy}}$$

Summary

- General consideration for transferring information across channels
- Channel characteristics
- Binary symmetric channel
- Mutual information and average mutual information

