

# EECS 126: Probability & Random Processes

## Fall 2021

Digital Link

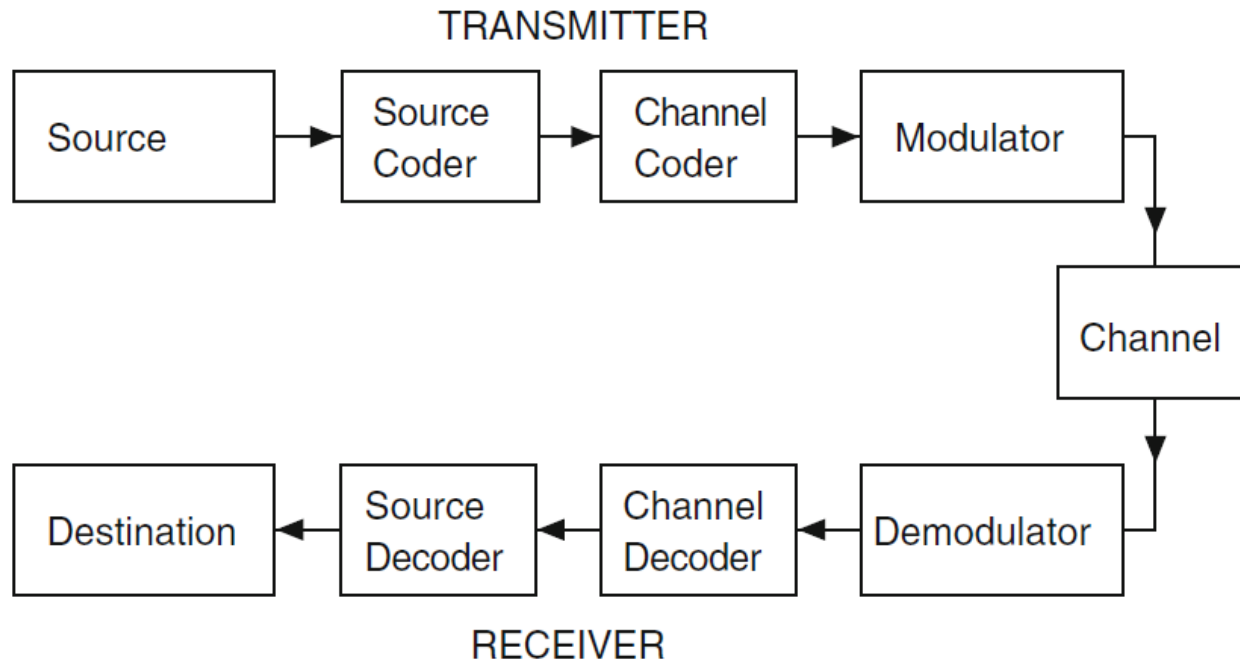
Shyam Parekh

## Topics Covered in Lectures on Digital Link

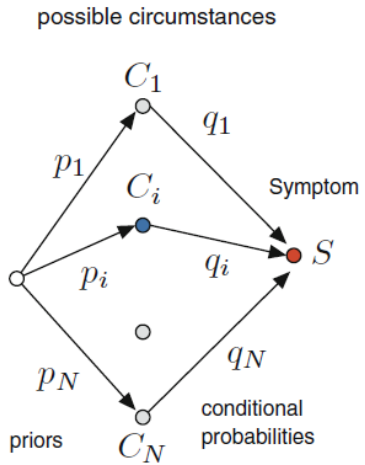
- Digital Link (Section 7.1)
- Detection and Bayes' Rule (Section 7.2)
- Huffman Codes (Section 7.3)
- Capacity of BSC (Section 15.7)
- Gaussian Channel (Section 7.4 excluding Section 7.4.1)
- Hypothesis Testing (Section 7.6)
- Proof of Neyman-Pearson Theorem (Section 8.2)
- Jointly Gaussian Random Variables (Sections 8.3)

## Components

- Transfer information reliably (i.e., meeting performance requirements) using minimum resources (computation, bandwidth, storage, energy, ...)
- Physical medium: phone line, cable, fiber, wireless (cellular or Wi-Fi), ...



## Bayes' Rule, MAP & MLE

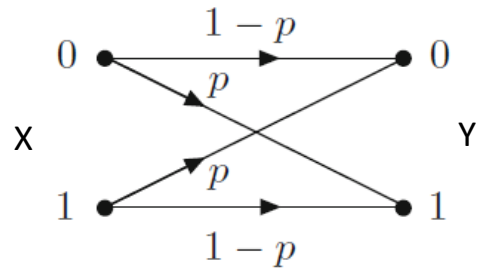


Priors:  $p_i = P(C_i)$

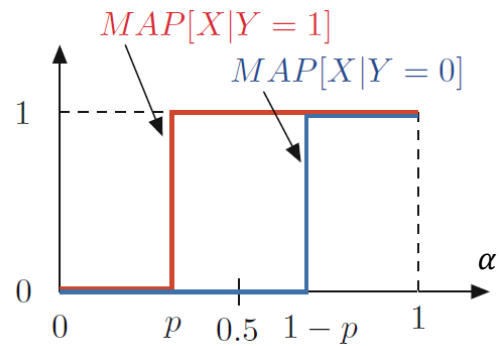
Conditionals:  $q_i = P[S|C_i]$

- Theorem: Let  $\pi_i = P[C_i|S]$ . Then,  $\pi_i = \frac{p_i q_i}{\sum_{j=1}^N p_j q_j}$ .
- Maximum A Posteriori estimate:  $MAP = \arg \max_i P[C_i | S] = \arg \max_i p_i q_i$ .
- Maximum Likelihood Estimate:  $MLE = \arg \max_i P[S | C_i] = \arg \max_i q_i$ .
- Example: Ice Cream & Sunburn.
- General Definition: Let  $X$  &  $Y$  be discrete RVs.
  - $MAP[X | Y = y] = \arg \max_x P(X = x, Y = y)$ .
  - $MLE[X | Y = y] = \arg \max_x P[Y = y | X = x]$ .

## Binary Symmetric Channel (BSC)

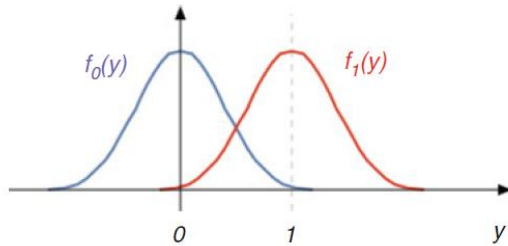


- Theorem: For BSC,
  - $MAP[X | Y = 0] = 1\{\alpha > (1-p)\}$ ,  $MAP[X | Y = 1] = 1\{\alpha > p\}$ .
  - $MLE[X | Y] = Y$ , if  $p < 0.5$ .



## Gaussian Channel

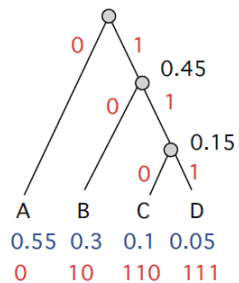
- Additive Gaussian Noise Channel:  $Y = X + Z$ , where  $Z \equiv_D \mathcal{N}(0, \sigma^2)$  is independent of  $X$ .
  - Suppose  $X \in \{0, 1\}$ .
  - Let  $f_0 = f_{Y|\{X=0\}}$  and  $f_1 = f_{Y|\{X=1\}}$ .



- Theorem: For Gaussian channel,
  - $MAP[X | Y = y] = 1 \{y \geq \frac{1}{2} + \sigma^2 \log_e \left(\frac{p_0}{p_1}\right)\}$ .
  - $MLE[X | Y = y] = 1\{y \geq 0.5\}$ .
  - Corollary: For MLE, probability of error  $p = P\left(\mathcal{N}(0, 1) > \frac{0.5}{\sigma}\right)$  is same as that for a BSC.

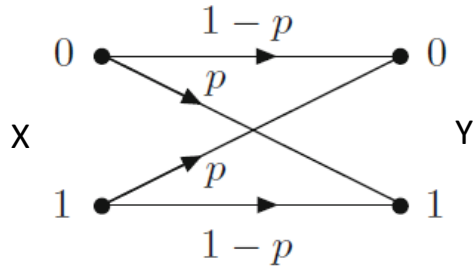
## Huffman Codes

- Consider coding of 4 symbols A, B, C, D.
  - One option: Assign 00, 01, 10, 11 to A, B, C, D, respectively.
  - We can decode a received string (without any errors) unambiguously: 0100110001 → BADAB
  - 2 bits per symbol.
- Suppose, we know probability of occurrence of each symbol: 0.55, 0.3, 0.1, 0.05, respectively.
  - Let's assign 0, 10, 110, 111 to A, B, C, D, respectively.
    - Observe we are assigning shorter codes to more frequent symbols.
  - Here also we can unambiguously decode in one pass since the codes are prefix-free: 110100111 → CBAD.
  - Average # of bits per symbol = 1.6 (20% saving in transmission).
  - These are called Huffman Codes.
- Construction:

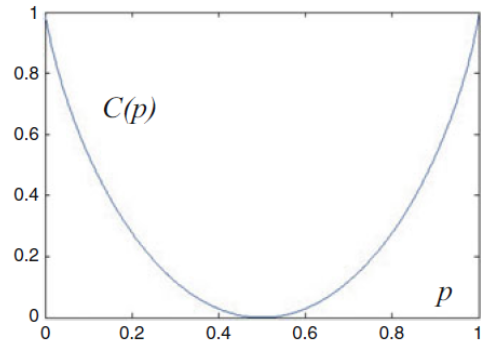


- Theorem: The Huffman Code has the smallest average number of bits per symbol among all prefix-free codes.

## Capacity of Binary Symmetric Channel (BSC)



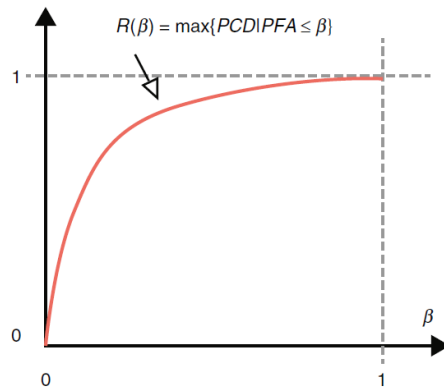
- Theorem: Capacity of BSC :=  $C(p) = 1 - H(p)$ ,  
where entropy  $H(p) = -p \log p - (1-p) \log(1-p)$ .





## Hypothesis Testing

- Formulation:  $X \in \{0, 1\}$  and  $P[Y | X]$  is known. Let  $\hat{X}$  be the estimate of  $X$ .  
Maximize Probability of Correct Detection (PCD)  $:= P[\hat{X} = 1 | X = 1]$   
Subject to Probability of False Alarm (PFA)  $:= P[\hat{X} = 1 | X = 0] \leq \beta$ .
- Receiver Operating Characteristic (ROC): PCD for the solution of the above problem as a function  $R(\beta)$ .



- Solution is provided by the following theorem.
- Neyman-Pearson Theorem:

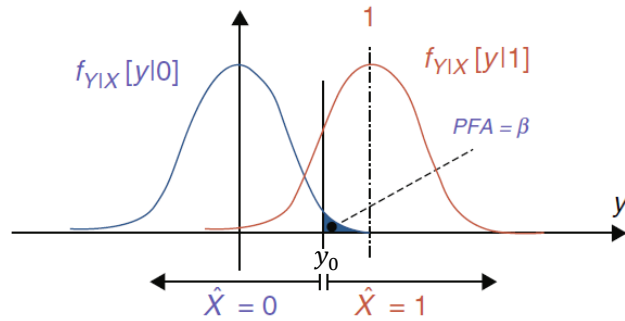
$$\hat{X} = \begin{cases} 1, & \text{if } L(Y) > \lambda \\ 1 \text{ w. p. } \gamma, & \text{if } L(Y) = \lambda \\ 0, & \text{if } L(Y) < \lambda \end{cases}$$

where the likelihood ratio  $L(y) = \frac{f_{Y|X}[y | 1]}{f_{Y|X}[y | 0]}$  and  $\lambda, \gamma$  are chosen s. t.

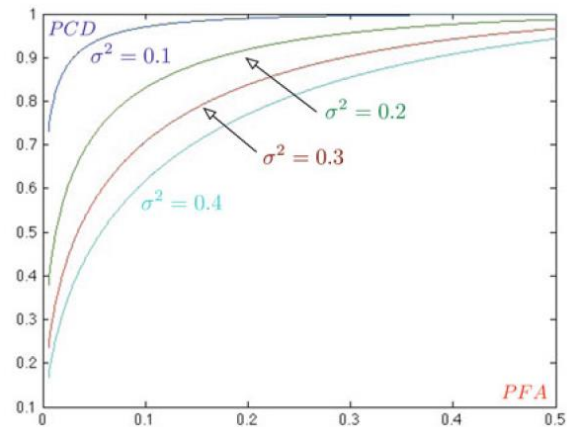
$$P[\hat{X} = 1 | X = 0] = \beta.$$

## Hypothesis Testing – Example (1)

- Gaussian Channel:  $Y = X + Z$ , where  $Z \equiv_D \mathcal{N}(0, \sigma^2)$  is independent of  $X$ .
  - Receiver wants to guess  $X$  from the received signal  $Y$  with  $PFA \leq \beta$ .
- Solution of the hypothesis problem:



- ROC:



## Hypothesis Testing – Example (2)

- Mean of Exponential RVs: A machine produces lightbulbs with IID  $Exp(\lambda_x)$  lifespans, where  $x \in \{0, 1\}$ ,  $\lambda_0 < \lambda_1$ , and  $x = 1$  indicates a defective machine.
  - By observing the lifespans of  $n$  lightbulb, we want to detect if the machine is defective with  $PFA \leq \beta$ .

## Hypothesis Testing – Example (3)

- Bias of a coin: A coin is  $B(p_x)$ , where  $x \in \{0, 1\}$  with  $p_1 > p_0 = 0.5$ 
  - By observing  $n$  coin flips, we want to detect if it's a biased coin with  $PFA \leq \beta$ .

## Hypothesis Testing – Example (4)

- Discrete observations:  $X \in \{0, 1\}$  and  $Y \in \{A, B, C\}$ .
  - Given  $P[Y | X]$ , guess  $X$ .
  - $P[Y | X]$ :

	Y=A	Y=B	Y=C
X=0	0.2	0.5	0.3
X=1	0.2	0.2	0.6

- $L(Y)$ :

1.0	0.4	2.0
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- Solution:

Y	B	A	C
$P[Y X=1]$	0.2	0.2	0.6
$P[Y X=0]$	0.5	0.2	0.3
$L(Y)$	0.4	1	2

$$\lambda = 2.1 \Rightarrow PCD = 0, PFA = 0$$

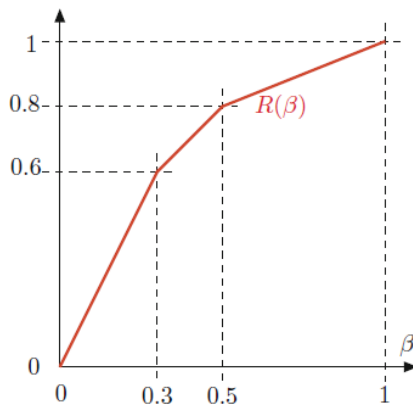
$$\lambda = 2 \Rightarrow PCD = 0.6\gamma, PFA = 0.3\gamma$$

$$\lambda = 1.4 \Rightarrow PCD = 0.6, PFA = 0.3$$

$$\lambda = 1 \Rightarrow PCD = 0.6 + 0.2\gamma, PFA = 0.3 + 0.2\gamma$$

$$\lambda = 0.4 \Rightarrow PCD = 0.8 + 0.2\gamma, PFA = 0.5 + 0.5\gamma$$

- ROC:



## Recall from Basic Probability, Section B.7

### Density of a Function of RVs

- Suppose a RV  $X$  has PDF  $f_X(x)$  and  $Y = aX + b$ . Then,

$$f_Y(y) = \frac{1}{|a|} f_X(x) \text{ where } ax + b = y.$$

- Suppose a random vector  $\mathbf{X}$  has JPDF  $f_X(\mathbf{x})$ , and  $\mathbf{Y} = A\mathbf{X} + \mathbf{b}$  where  $A$  is a nonsingular matrix. Then,

$$f_Y(\mathbf{y}) = \frac{1}{|A|} f_X(\mathbf{x}) \text{ where } A\mathbf{x} + \mathbf{b} = \mathbf{y}, \text{ and } |A| \text{ is the absolute value of the determinant of } A.$$

- Suppose  $\mathbf{Y} = g(\mathbf{X})$  where  $\mathbf{X}$  has density  $f_X(\mathbf{x})$ . Then,

$$f_Y(\mathbf{y}) = \sum_i \frac{1}{|J(\mathbf{x}_i)|} f_X(\mathbf{x}_i) \text{ where the sum is over all } \mathbf{x}_i \text{ such that } g(\mathbf{x}_i) = \mathbf{y} \text{ and } |J(\mathbf{x}_i)| \text{ is the absolute value of Jacobian evaluated at } \mathbf{x}_i.$$

- Recall  $J_{i,j}(\mathbf{x}) = \frac{\partial}{\partial x_j} g_i(\mathbf{x})$ .

## Jointly Gaussian (JG) RVs

- **Definition:**  $Y_1, \dots, Y_n$  are JG RVs if  $\mathbf{Y} := \begin{bmatrix} Y_1 \\ \vdots \\ Y_n \end{bmatrix} = \mathbf{A}\mathbf{Z} + \boldsymbol{\mu}_Y$ , where  $Z_i$ 's in  $\mathbf{Z} := \begin{bmatrix} Z_1 \\ \vdots \\ Z_k \end{bmatrix}$  are IID  $\mathcal{N}(0, 1)$ , and  $\mathbf{A}$  and  $\boldsymbol{\mu}_Y$  are  $n \times k$  and  $n \times 1$  constant matrices, respectively.
  - Mean and covariance of  $\mathbf{Y}$  are  $\boldsymbol{\mu}_Y$  and  $\boldsymbol{\Sigma}_Y := \mathbf{A}\mathbf{A}'$ .
  - We write  $Y \equiv_D \mathcal{N}(\boldsymbol{\mu}_Y, \boldsymbol{\Sigma}_Y)$ .
- **Theorem:** Assuming  $\boldsymbol{\Sigma}_Y$  is invertible,  
$$f_Y(\mathbf{y}) = \frac{1}{\sqrt{|\boldsymbol{\Sigma}_Y|}(2\pi)^{n/2}} \exp\left\{-\frac{1}{2}(\mathbf{y} - \boldsymbol{\mu}_Y)' \boldsymbol{\Sigma}_Y^{-1}(\mathbf{y} - \boldsymbol{\mu}_Y)\right\}.$$
- **Example:** IID  $\mathcal{N}(0, \sigma_i^2)$  RVs
- **Fact:** Level curves for the JG PDF are elliptical.
- **Example:** Marginals are Gaussian, but not JG.
- **Theorem:** JG RVs are independent if and only if they are uncorrelated.
- **Theorem:** If  $\mathbf{V}$  and  $\mathbf{W}$  are JG, their linear combinations  $\mathbf{A}\mathbf{V} + \mathbf{a}$  and  $\mathbf{B}\mathbf{W} + \mathbf{b}$  are also JG.
- **Example:** Given IID  $\mathcal{N}(0, 1)$   $X, Y$ ,  $X + Y$  and  $X - Y$  are JG.







