

# Last lecture

Functions of a random variable (Ch 3.8)

- General form of increasing function  $g$
- Create uniform distribution using CDF as a function

Generating a customized RV (Ch 3.8.2)

- Intuition  $g = F_X^{-1}$
- Examples
  - Uniform to Exponential
  - Uniform to D6 outcome
- Area rule – Compute  $E[X]$  using  $F_X$  (Ch 3.8.3)

# Agenda

Binary Hypothesis Testing with continuous distribution ([Ch 3.10](#))

- Example

Jointly Distributed RV/ Joint CDF ([Ch 4.1](#))

- Motivation
- Definition
- Properties

Joint PMF ([Ch 4.2](#))

- Definition
- Example

# **Binary Hypothesis Testing on Continuous Distribution**

# Overview

Similar to discrete, but with some changes

- $P\{X = u|H_1\} \rightarrow f_1(u)$

→ Likelihood Ratio  $\Lambda(u) = \frac{f_1(u)}{f_0(u)}$

- LRT rule  $\Lambda(X) \begin{cases} > \tau & H_1 \\ < \tau & H_0 \end{cases}$

$p_{\text{false alarm}}, p_{\text{miss}}, p_e$  remain the same

↳  $P\{\text{Claim } H_1 | H_0\}, P\{\text{Claim } H_0 | H_1\}$   
 $P\{\text{Claim } H_1, H_0\} + P\{\text{Claim } H_0, H_1\}$

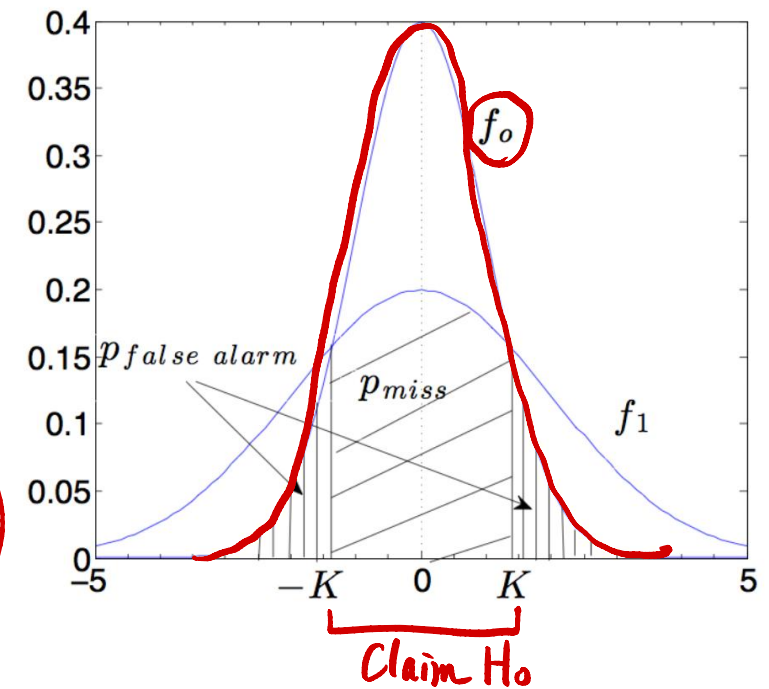
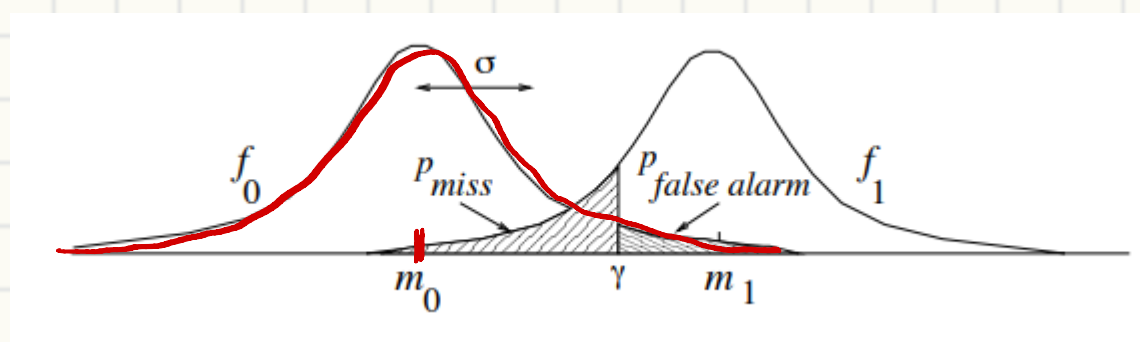


Figure 3.27:  $N(0, 1)$  and  $N(0, 4)$  pdfs and ML threshold  $K$ .

# Example



$X$  under  $H_i$  follows  $N(m_i, \sigma^2)$ . Given  $m_i, \sigma, \pi_i$ , Find ML and MAP rule

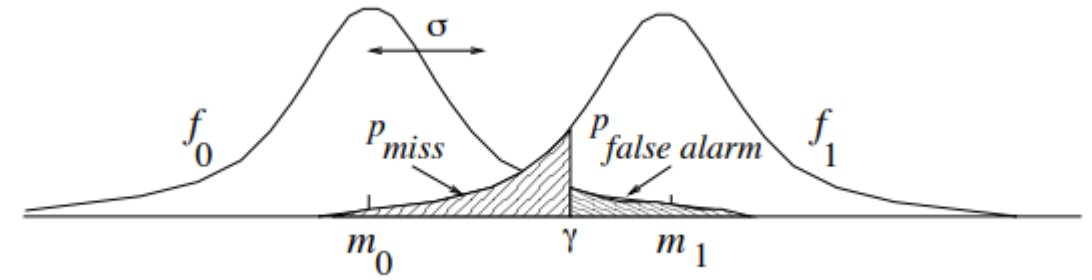
- $f_i(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(u-m_i)^2}{2\sigma^2}\right\}$
- $\Lambda(u) = \exp\left\{\left(u - \frac{m_0+m_1}{2}\right)\left(\frac{m_1-m_0}{\sigma^2}\right)\right\}$
- ML rule –

$\Rightarrow$  Asking  $\tau_{ML} = 1$

$\tau_{MAP}$

ML  $\left\{ \begin{array}{l} \underline{\Lambda(u)} > 1 \quad H_1 \\ \text{otherwise} \end{array} \right. \rightarrow \gamma_{ML} \triangleq \text{"decision boundary"}$   
 $u > \frac{m_0+m_1}{2}$  Claim  $H_1$  (Not always exist)  
 $\text{otherwise}$  Claim  $H_0$   $\Rightarrow$  Threshold on X-axis

# Example



$X$  under  $H_i$  follows  $N(m_i, \sigma^2)$ . Given  $m_i, \sigma, \pi_i$ , Find ML and MAP rule

- $f_i(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(u-m_i)^2}{2\sigma^2}\right\}$
- $\Lambda(u) = \exp\left\{\left(u - \frac{m_0+m_1}{2}\right)\left(\frac{m_1-m_0}{\sigma^2}\right)\right\}$
- MAP rule –

Recall MAP  $\begin{cases} \Lambda > \frac{\pi_0}{\pi_1} & H_1 \\ \Lambda < \frac{\pi_0}{\pi_1} & H_0 \end{cases}$   $\tau_{MAP}$

$\downarrow \ln$

$\begin{cases} \ln \Lambda > \ln \tau_{MAP} \\ \ln \Lambda < \ln \tau_{MAP} \end{cases}$

$$\left(\mu - \frac{m_0 + m_1}{2}\right) \left(\frac{m_1 - m_0}{\sigma^2}\right) \geq \ln \zeta_{\text{MAP}}$$

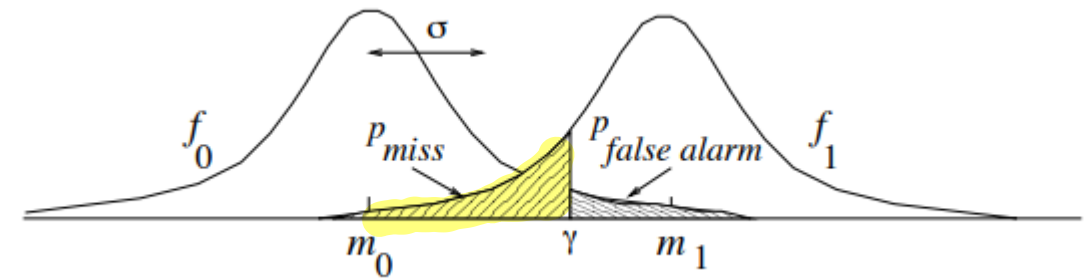
$$\Rightarrow \mu \geq \left(\frac{\sigma^2}{m_1 - m_0}\right) \ln \left(\frac{\pi_0}{\pi_1}\right) + \frac{m_1 + m_0}{2}$$

$\zeta_{\text{MAP}}$

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$\gamma_{\text{MAP}}$

# Example



$X$  under  $H_i$  follows  $N(m_i, \sigma^2)$ . Given  $m_i, \sigma, \pi_i$ , Find ML and MAP rule

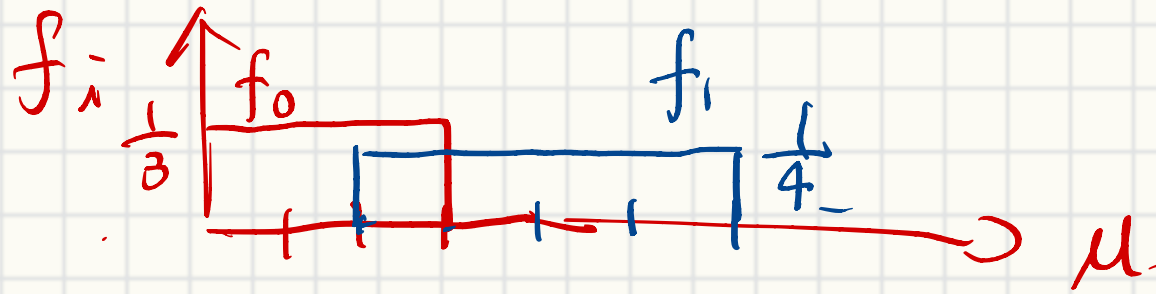
- $f_i(u) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp\left\{-\frac{(u-m_i)^2}{2\sigma^2}\right\}$
- $\Lambda(u) = \exp\left\{\left(u - \frac{m_0+m_1}{2}\right)\left(\frac{m_1-m_0}{\sigma^2}\right)\right\}$

- $P_{miss} = P(X < \gamma | H_1) = P\left(\frac{X-m_1}{\sigma} < \frac{\gamma-m_1}{\sigma} | H_1\right)$

- $P_{false\ alarm} = Q\left(\frac{m_1-\gamma}{\sigma}\right) = \Phi\left(\frac{\gamma-m_1}{\sigma}\right)$

$$Q\left(\frac{\gamma-m_0}{\sigma}\right)$$

# Slido



$f_1 = \text{Unif}([2,6])$ ,  $f_0 = \text{Unif}([0,3])$ . Assume  $\frac{\pi_1}{\pi_0} = \frac{3}{4}$

- Using MAP rule, the region we claim  $H_1$



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~~(a) None~~

~~(b) [2,3]~~

(c) [2,6]

~~(d) [3,6]~~

$$\Lambda(u) = \frac{f_1}{f_0} = \begin{cases} 0 & u \in [0, 2] \\ \frac{3}{4} & u \in [2, 3] \\ \infty & u \in [3, 6] \end{cases}$$

$$\Lambda > \frac{\pi_0}{\pi_1} = \frac{4}{3}$$

**Exam II until here**

# **Jointly Distributed Random Variables**

# Motivation

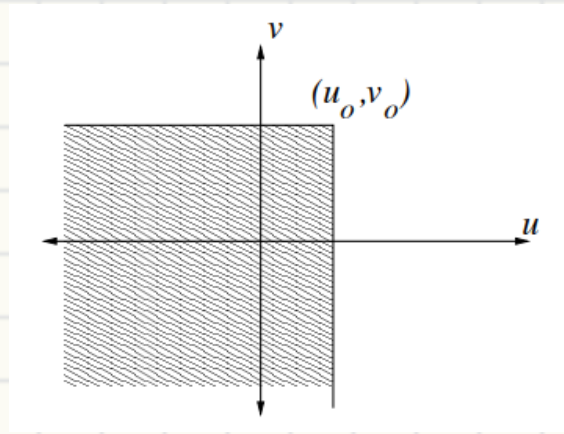
Given  $X$  and  $Y$ , we have learnt

- Independence
- Function & Scaling (e.g.  $X=3Y-2$ )

But real-world cases are more complex

- How to show the “ ” between  $X$  and  $Y$
- “Jointly distributed” RVs
- $F_X(u) \rightarrow F_{X,Y}(u, v)$
- $P_X(u) \rightarrow P_{X,Y}(u, v)$

# Joint CDF

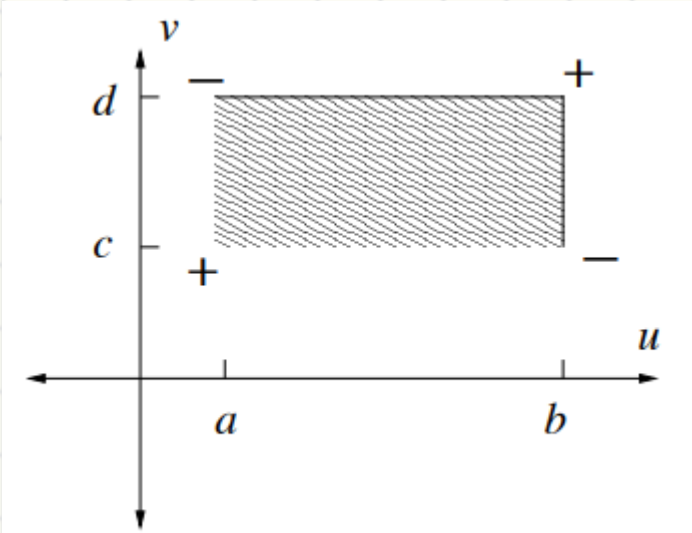


AND  
↓

Joint CDF of  $X$  and  $Y$

- $F_{X,Y}(u, v) = P\{X \leq u, Y \leq v\}$  for any  $(u, v) \in \mathbb{R}^2$
- Completely defines all events concerning  $X$  and  $Y$
- For a 2D rectangle region  $R = (a, b] \times (c, d]$ 
  - $P\{(X, Y) \in R\} = F_{X,Y}(b, d) - F_{X,Y}(a, d) - F_{X,Y}(b, c) + F_{X,Y}(a, c)$
- $F_X(u) = F_{X,Y}(u, \infty)$

$$F_Y(v) = F_{X,Y}(\infty, v)$$

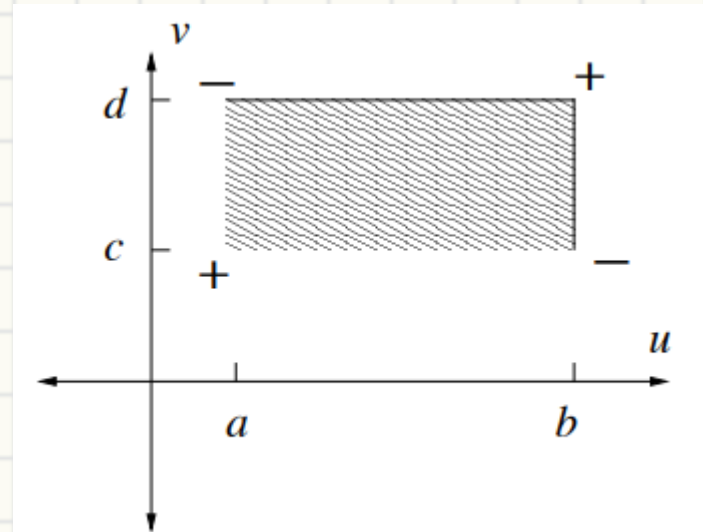
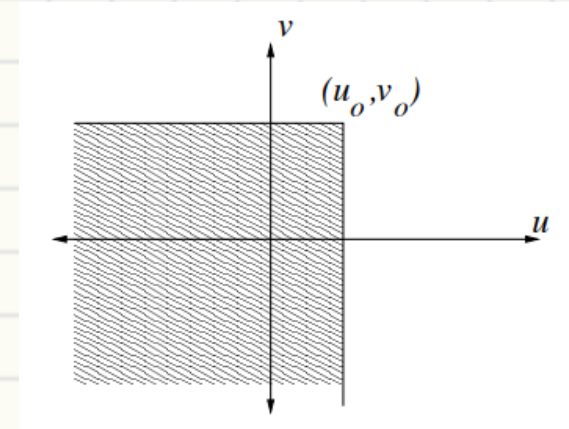


# Joint CDF Properties

Denote  $F_{X,Y}$  as  $F$

- $0 \leq F(u, v) \leq 1$  for all  $(u, v) \in \mathbb{R}^2$
- along  $u$  and along  $v$  respectively
  - $F$  is non-decreasing
  - $F$  is right-continuous
- $\lim_{u \rightarrow -\infty} F(u, v) = 0$
- $\lim_{u \rightarrow \infty} \lim_{v \rightarrow \infty} F(u, v) = 1$

$$\lim_{u \rightarrow \infty} F(u, v) = F_{X,Y}(\infty, v) = F_Y(v)$$



# Joint PMF

Roll 2 D6  $\begin{cases} X \\ Y \end{cases}$

$$P_{X,Y}(3,4) = \frac{1}{36}$$

If  $X$  and  $Y$  are discrete, joint PMF  $p_{X,Y}(u, v) = P\{X = u, Y = v\}$

## Marginalization

- Getting single RV PMF/ PDF from joint PMF/ PDF
- $p_X(u) = \sum_{v_j} p_{X,Y}(u, v_j)$  called "marginal PMF"

$Y = v_j$  are partitions

## Conditional PMF

- $p_{Y|X}(v|u_0) = \frac{p_{X,Y}(u_0, v)}{p_X(u_0)}$

# Example

Given joint PMF  $p_{X,Y}$  as the table, find

		$0.2$		
$0.2$	$Y=3$	0.1	0.1	
$0.4$	$Y=2$		0.2	$0.2$
$0.4$	$Y=1$		0.3	$0.1$
		$X=1$	$X=2$	$X=3$
		$0.1$	$0.6$	$0.3$

- $p_X$   $P_X(u) = \sum_{v} P_{X,Y}(u,v)$

$$P_X(u) = [0.1, 0.6, 0.3]$$

- $p_Y$

$$P_Y(v) = [0.4, 0.4, 0.2]$$

- $P\{X = Y\}$

$$= \sum_u P_{X,Y}(u,u) = 0.2$$

- $P\{X > Y\}$

$$= \sum_u \sum_{v < u} P_{X,Y}(u,v) = 0.3 + 0.1 + 0.2 = 0.6$$

- $p_{Y|X}(v|2)$

$$= P\{Y=v | X=2\} = \frac{P_{X,Y}(v,2)}{P_X(2)} = \frac{[0.3, 0.2, 0.1]}{0.6}$$

$$P_{Y|X}(v|2) = \left[ \frac{1}{2}, \frac{1}{3}, \frac{1}{6} \right]$$

**Joint PDF**