

# Last lecture

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](#))

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

- Overview

# 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  $\Lambda(u) = \frac{f_1(u)}{f_2(u)}$
- LRT rule  $\Lambda(X) \begin{cases} > \tau & H_1 \\ < \tau & H_0 \end{cases}$

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

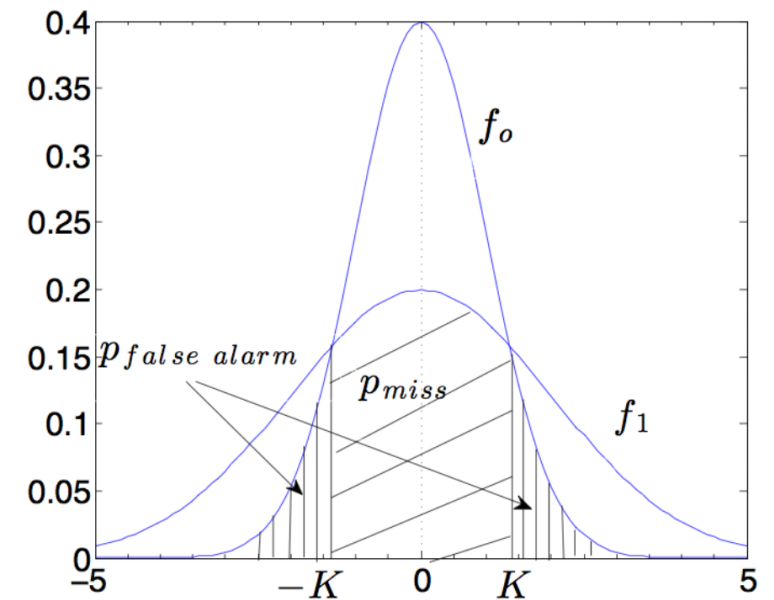
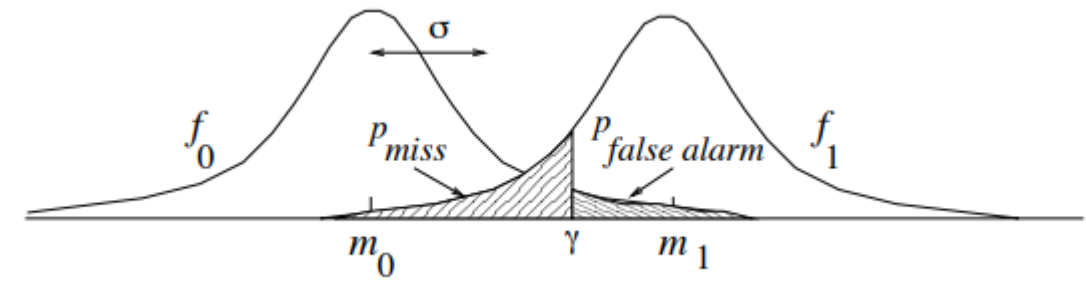


Figure 3.27:  $N(0, 1)$  and  $N(0, 4)$  pdfs and ML threshold  $K$ .

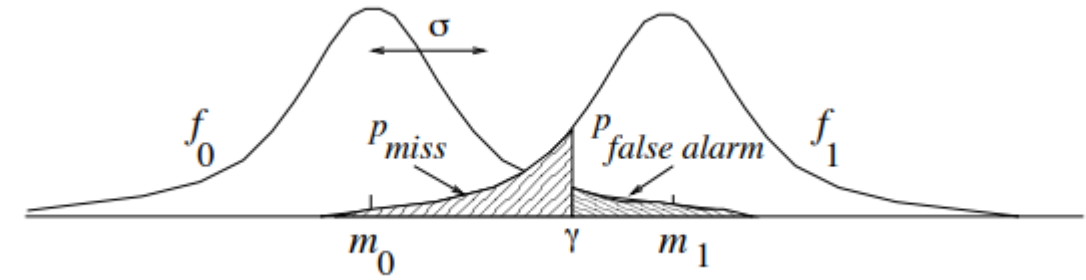
# Example



$X$  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 –

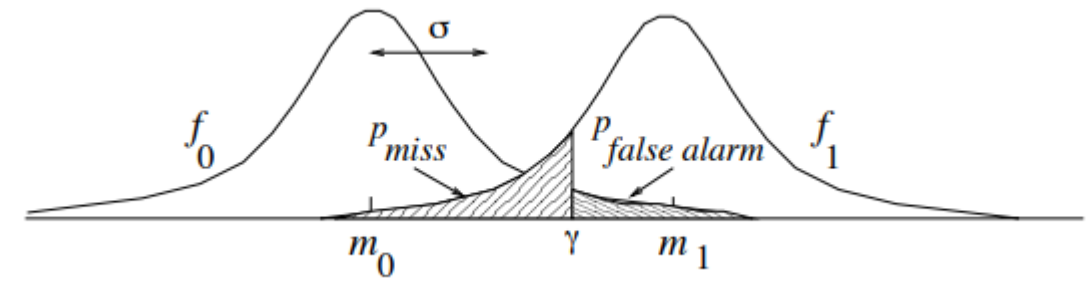
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- $P_{miss} =$
  
- $P_{false\ alarm} =$

# **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

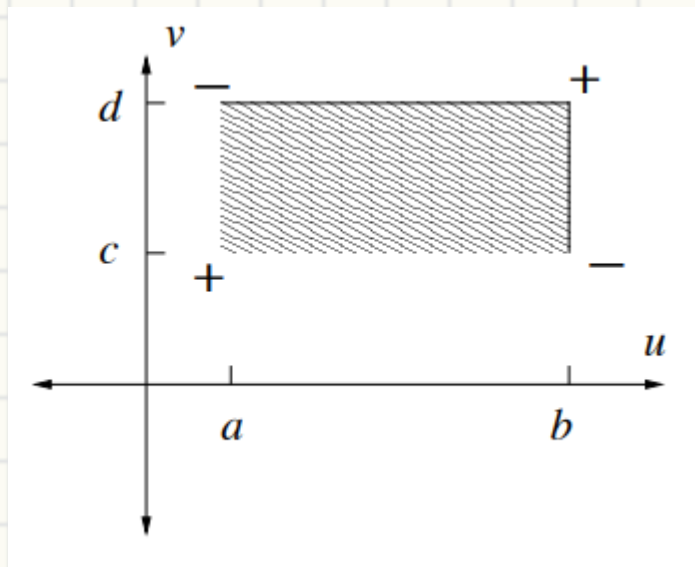
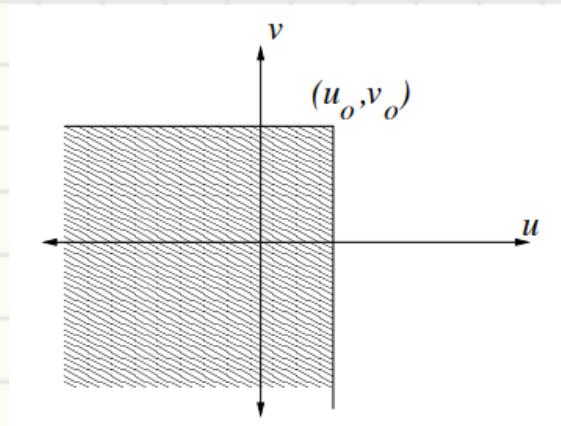
- How to show the “ ” between  $X$  and  $Y$
- “Jointly distributed” RVs
- $F_X(u) \rightarrow F_{X,Y}(u, v)$
- $P_X(u) \rightarrow P_{X,Y}(u, v)$

# Joint CDF

Joint CDF of  $X$  and  $Y$

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

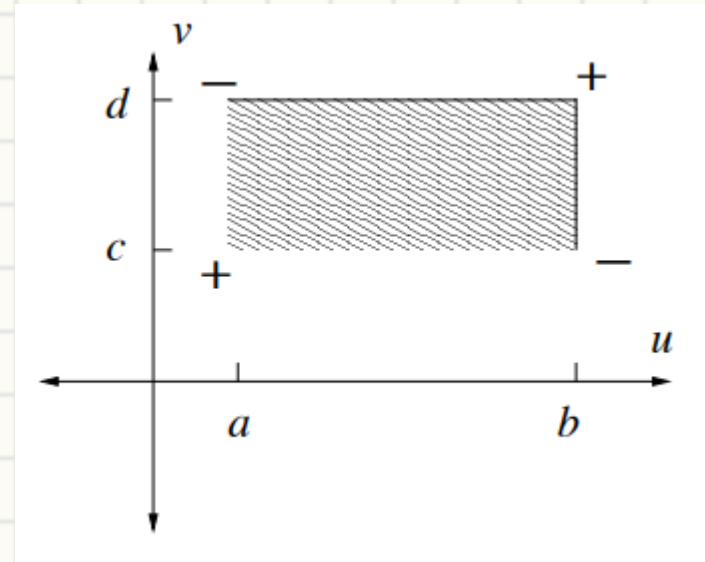
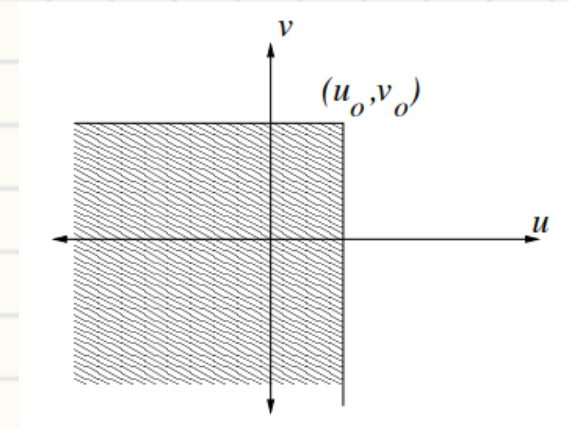
- $F_X(u) = F_{X,Y}(u, \infty)$



# 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
- $\lim_{u \rightarrow -\infty} F(u, v) = 0$
- $\lim_{u \rightarrow \infty} \lim_{v \rightarrow \infty} F(u, v) = 1$



# Joint PMF

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”

## 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

- $p_X$
- $p_Y$
- $P\{X = Y\}$
- $P\{X > Y\}$
- $p_{Y|X}(v|2)$

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