

# Last lecture

$$\operatorname{argmax}_{\theta} P_{\theta}(X)$$

## Maximum Likelihood Estimation (MLE) (Ch 2.8)

- Not focus

## Markov and Chebychev inequalities (Ch 2.9)

- Markov inequality
- Chebychev inequality
- Confidence interval

$$\rightarrow X \quad P\{X \geq c\} \leq \frac{E\{X\}}{c}$$

$$\rightarrow P\{|Y - \mu_Y| \geq a\sigma\}$$

$$\hookrightarrow P\left\{P \in \left[\hat{P} \pm \frac{a\sigma}{\sqrt{n}}\right]\right\} \geq 1 - \frac{1}{a^2}$$

$$\leq \frac{1}{a^2}$$

## Binary Hypothesis Testing (Ch 2.11)

- Definition
- Likelihood table
- Maximum likelihood decision rule

# Agenda

## Binary Hypothesis Testing (Ch 2.11)

- Likelihood Ratio Test (LRT)
- Maximum likelihood decision rule
- Maximum A Posteriori (MAP) decision rule
- Examples

## Union Bound/ Reliability (Ch 2.12)

# Hypothesis Testing

# Maximum Likelihood Table

- Table showing **likelihood** of two hypotheses  $P(X|H_i)$

patient cares.  $P(H|X)$

$P(X H)$	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	0.1	<u>0.3</u>	<u>0.6</u>
$H_0$	<u>0.4</u>	<u>0.3</u>	0.2	0.1

↓  
Claim  $H_0$  if  $X=0$ .

- Decision rule can be shown on the table by **underscore** each column

# False alarm and missing

	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	<u>0.1</u>	<u>0.3</u>	<u>0.6</u>
$H_0$	<u>0.4</u>	0.3	0.2	0.1

- $P_{false\ alarm} = P(\text{Claim } H_1 | H_0) = \sum_{C \in H_0, \text{ non underscored}} C = 0.6$
- $P_{miss} = P(\text{Claim } H_0 | H_1) = \sum_{C \in H_1, \text{ non underscored}} C = 0$

	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	0.1	<u>0.3</u>	<u>0.6</u>
$H_0$	<u>0.4</u>	<u>0.3</u>	0.2	0.1

# Maximum Likelihood (ML) decision rule

Pick whichever is higher per column!

$$P_i(k) = P(X=k | H_i)$$

	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	$p_1(0) = 0$	0.1	0.3	0.6
$H_0$	0.4	0.3	0.2	0.1

$$\wedge \quad \frac{0}{0.4} = 0 \quad \frac{0.1}{0.3} = \frac{1}{3} \quad \frac{0.3}{0.2} = 1.5 \quad \frac{0.6}{0.1} = 6$$

Likelihood Ratio Test (LRT)  $\Lambda(k) = \frac{p_1(k)}{p_0(k)}$

A LRT with threshold  $\tau$ :

$$\Lambda(k) \geq \tau \Rightarrow \text{Claim } H_1$$
$$< \quad \text{Claim } H_0$$

# Maximum Likelihood (ML) decision rule

Pick whichever is higher per column!

= LRT w/  $\gamma = 1$

	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	0.1	<u>0.3</u>	<u>0.6</u>
$H_0$	<u>0.4</u>	<u>0.3</u>	0.2	0.1

What's the problem?

Good balance of  $P_{\text{false alarm}}$  &  $P_{\text{miss}}$

But 1, If we want to care  $P_{\text{false alarm}}$  more?

2. Minimize total error counts?

# Slidos – Midterm Review and Early Feedback

## Midterm Review

- Next Thursday class time
- Vote for the contents!



# 5831917

## Early Feedback

- Suggest improvement
- Anonymous by default



# 1551303

# Maximum A Posteriori (MAP) decision rule

Let's pick joint probability  $P(H, X)$  instead of  $P(X|H)$

- Pick the higher  $P(H, X)$  per column
- Lowest total error rate  $p_e$

- But how do we get the joint probability?
- Recall conditional probability

$$P(A, B) = P(A|B)P(B)$$

$$P(H_1, X = k) = P\{X = k | H_1\} \times P(H_1)$$

$P(H, X)$	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	0.02	0.06	<u>0.12</u>
$H_0$	<u>0.32</u>	<u>0.24</u>	<u>0.16</u>	0.08

# Prior and Posterior

$$P(H_1, X = k) = P(X = k | H_1) P(H_1)$$

- $P(H_1) \triangleq \pi_1$ : “**Prior**”, probability assumed before observation
- $P(H_0) \triangleq \pi_0 = 1 - \pi_1$
- Bayes’ rule revisited (**Param/Hypothesis** vs. **Observation**)

$$P(H|X) = \frac{P(X|H)P(H)}{P(X)}$$

**Posterior**

**Evidence**

**Likelihood**

**Prior**

# Terminologies

Exam Safe

$$P(\theta|X) = \frac{P(X|\theta)P(\theta)}{P(X)}$$

Likelihood	$P(X \theta)$	Tractable, well defined	Toss $p = 0.3$ coin
Posterior	$P(\theta X)$	Typical goal	$x_{1:3} = \{H, T, T\}, p = ?$
Prior	$P(\theta)$	Domain knowledge	# coins $p = 0.3$ in world
Evidence	$P(X)$	Approx. with large data	# $H$ in world

# Likelihood table to joint probability

Assume  $\pi_1 = P(H_1) = 0.2$ ,  $\pi_0 = 1 - 0.2 = 0.8$ .

- Decide on joint probability is same as posterior probability

- MAP rule = LRT rule with  $\tau = \frac{\pi_0}{\pi_1}$  NOT  $\frac{\pi_1}{\pi_0}$

$\hookrightarrow P_1(k) \times \pi_1 \geq P_0(k) \times \pi_0$  Claim  $H_1$

$\Lambda(k) = \frac{P_1(k)}{P_0(k)} \geq \frac{\pi_0}{\pi_1}$  Claim  $H_1$   
 $\times P(H)$

<u><math>P(X H)</math></u>	$X = 0$	$X = 1$	$X = 2$	$X = 3$		<u><math>P(H, X)</math></u>	$X = 0$	$X = 1$	$X = 2$	$X = 3$
$H_1$	0	0.1	0.3	0.6	$\times 0.2$ $\rightarrow$	$H_1$	0	$0.1 \times 0.2$	0.06	<u>.12</u>
$H_0$	0.4	0.3	0.2	0.1	$\rightarrow$ $\times 0.8$	$H_0$	<u>.32</u>	<u>.24</u>	<u>.16</u>	<u>.08</u>

# Example

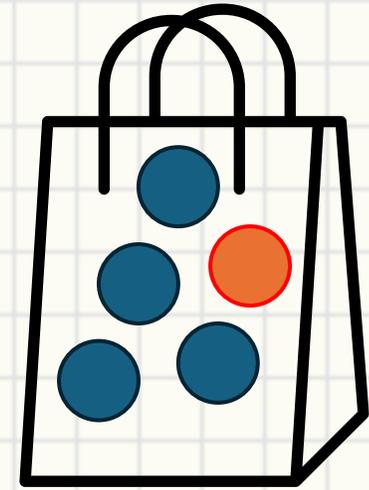
$X$ : Draw a coin from the bag and toss it 5 times # of Heads

- Likelihood table
- Joint probability table
- Describe ML and MAP rule, compute
  - $p_{\text{false\_alarm}}$
  - $p_{\text{miss}}$
  - $p_e$  error rate  $= \sum C_i$

$$\text{yellow square} \times \pi_0 + \text{green square} \times \pi_1$$

$C_i$  none underscore  
↑

joint prob. or  $P_{i-}(X) \pi_i$



  $H_1: p = \frac{2}{3}$  coin  
  $H_0: p = \frac{1}{2}$  coin

# Example

$$X \sim \text{Bin}(5, p)$$

$P(X|H)$

	0	1	2	3	4	5
$H_1$	$\left(\frac{2}{3}\right)^5$					
$H_0$						



- $H_1: p = \frac{2}{3}$  coin
- $H_0: p = \frac{1}{2}$  coin

$$P(X = k | H_1) = \binom{5}{k} \left(\frac{2}{3}\right)^k \left(\frac{1}{3}\right)^{5-k}$$

$$P(X = k | H_0) = \binom{5}{k} \left(\frac{1}{2}\right)^k \left(\frac{1}{2}\right)^{5-k}$$

$$\Lambda(p) = \left(\frac{\frac{2}{3}}{\frac{1}{2}}\right)^k \left(\frac{\frac{1}{3}}{\frac{1}{2}}\right)^{5-k} = \left(\frac{4}{3}\right)^k \left(\frac{2}{3}\right)^{5-k} \geq 1 \quad \text{ML} \quad k \geq 3$$

$$\geq \frac{4}{1} \quad \text{MAP}$$

# Example

Receive on-off keying (OOK) signal from a deep space Tx.

$X$ : # of photons observe from a telescope

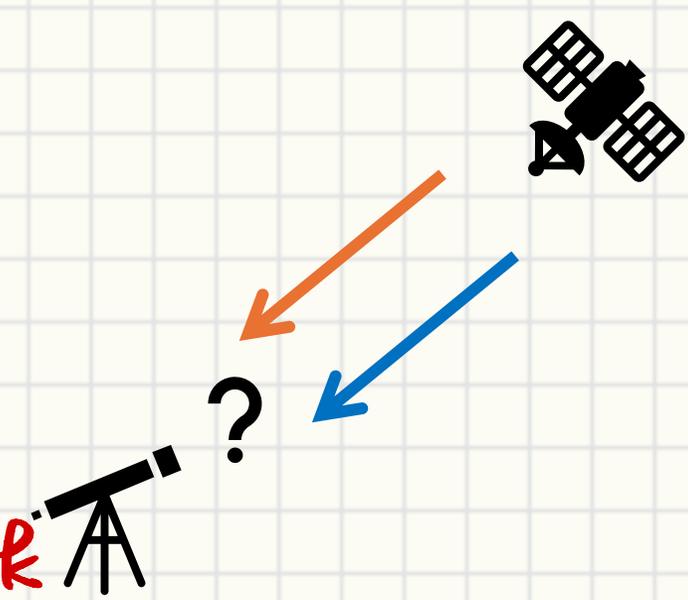
- $\lambda = 6$  If it's **ON**
- $\lambda = 2$  If it's **OFF**
- $\frac{\pi_0}{\pi_1} = 5$
- Describe ML and MAP rule, compute
  - $p_{false\_alarm}$
  - $p_{miss}$
  - $p_e$

$4^3$       $2^2$   
 $3^5$

$$Poi_{\lambda}(k) = \frac{e^{-\lambda} \lambda^k}{k!}$$

$$H_1: Pois(\lambda = 6)$$

$$H_0: Pois(\lambda = 2)$$

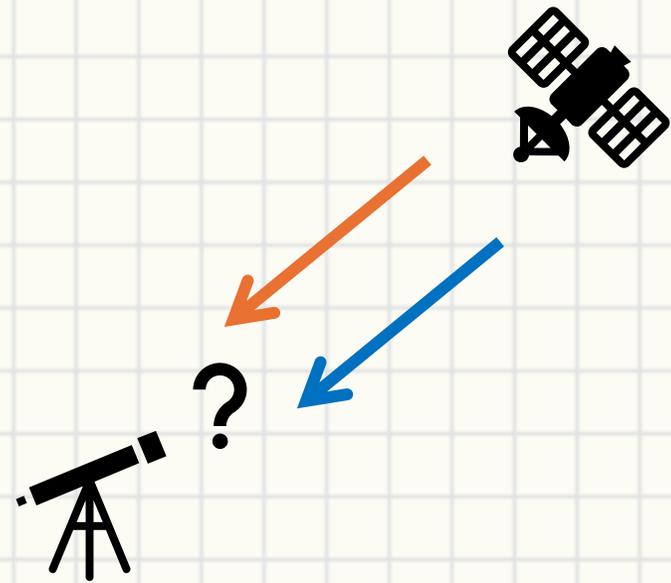


## Example

$$\Lambda(k) = \frac{P_1(k)}{P_0(k)} = \frac{e^{-6} 6^k}{\cancel{k!} \frac{e^{-2} 2^k}{\cancel{k!}}} = e^{-4} 3^k$$

ML.  $k \geq k^* \Rightarrow \Lambda(k) \geq 1$  Claim  $H_1$ .

MAP.  $\Lambda(k) \geq \frac{\pi_0}{\pi_1} = 5$ ,



$H_1: \text{Pois}(\lambda = 6)$

$H_0: \text{Pois}(\lambda = 2)$

## Union Bound/ Reliability

Skip, network flow.



# Motivation and Definition

## Reliability

- How likely a system will fail?
  - Each subsystem fail with *small* probability
  - If sub-systems fail in some pattern, the system fails

## Union Bound

- Bounds for *union* of small probability events
- $P(A \cup B) \leq P(A) + P(B)$
- $P(A_1 \cup A_2 \cup \dots \cup A_m) \leq \sum P(A_i)$
- Bound is at most *2x* far from the actual value

# Example – Array codes

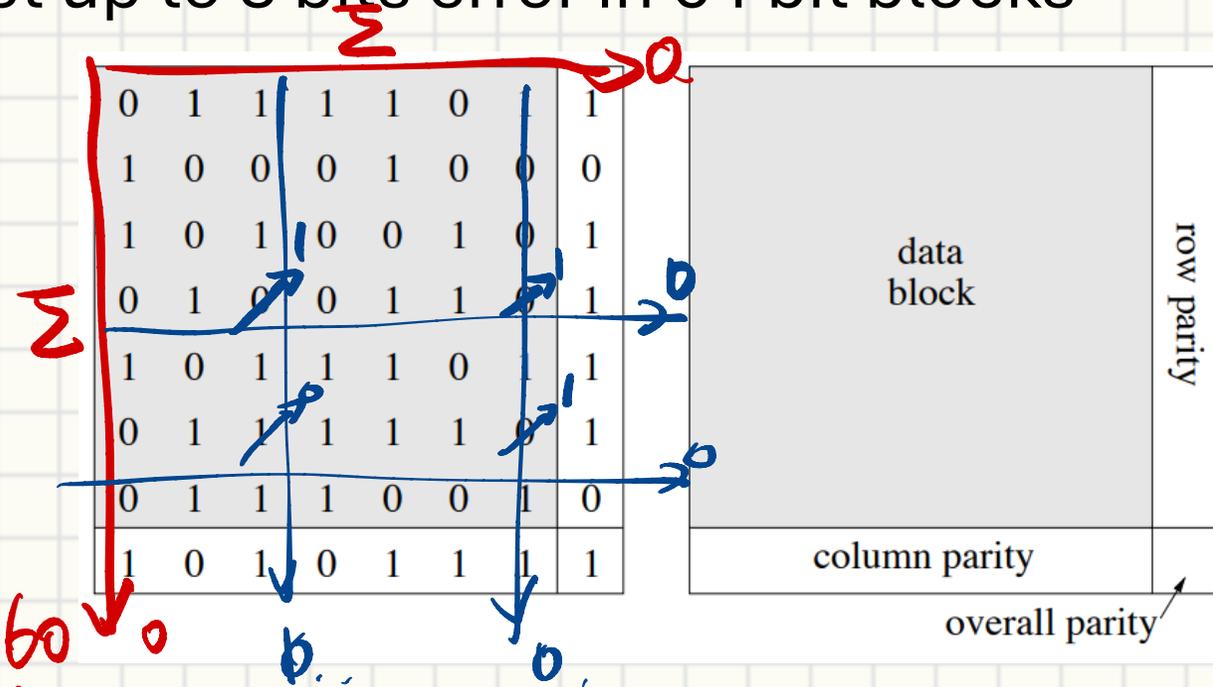
Consider a code that can detect up to 3 bits error in 64 bit blocks

- Let  $Y$  denotes # error bits
- Solve  $P\{Y = 4\}$

Denote BER as  $p$ .

$$Y \sim \text{Bin}(64, p)$$

$$P\{Y = 4\} = \binom{64}{4} p^4 (1-p)^{60}$$



# Example – Array codes

Consider a code that can detect up to 3 bits error in 64 bit blocks

- Let  $Y$  denotes # error bits
- Bound  $P\{Y \geq 4\}$

$X_i = \binom{64}{4}$  bits error.  
rest bits don't care

$$\begin{aligned} & P\{Y \geq 4\} \\ &= P\{\cup X_i\} \leq \sum P\{X_i\} \\ &= \binom{64}{4} p^4 \end{aligned}$$

**Midterm #1 Until Here!**