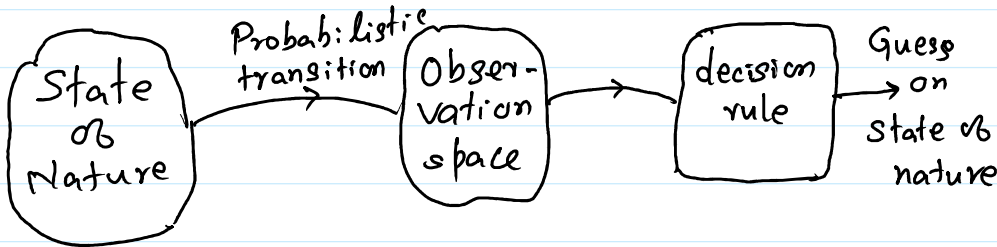


# Hypothesis Testing

A general framework for solving detection problems



⇓  
Finite number of states

(Wide Range of Applications)

- Communications
- Radar
- Medicine
- Finance
- Weather etc

To formulate hypothesis testing problem & solve

we need Conditional cdf/pdf  
Bayes' theorem  
Total Probability theorem.

## Conditional pdf/cdf.

Let  $X$  be a random variable

... .. (related to  $X$ )

Let  $X$  be a random variable

Let  $A$  be an event (related to  $X$ )  
with  $P(A) > 0$

Conditional cdf (definition)

$$F_X(x|A) = \frac{P\{X \leq x, A\}}{P(A)} = P\{X \leq x|A\}$$

Conditional pdf

$$f_X(x|A) = \frac{d}{dx} F_X(x|A)$$

Note:

$$\begin{aligned} \int_{-\infty}^{\infty} f_X(x|A) dx &= F_X(\infty|A) \\ &= \frac{P\{X \leq \infty, A\}}{P(A)} \\ &= \frac{P(A)}{P(A)} \\ &= 1 \end{aligned}$$

## Bayes Rule

$$\begin{aligned} P(A|X \leq x) &= \frac{P(A, X \leq x)}{P(X \leq x)} \\ &= \frac{P\{X \leq x|A\} P(A)}{P(X \leq x)} \end{aligned}$$

$$P_r \{X \leq x\}$$

$$P(A|X \leq x) = \frac{F_x(x|A) P(A)}{F_x(x)}$$

Now,

$$P(A | x < X \leq x + \Delta x)$$

$$= \frac{P(x < X \leq x + \Delta x | A) P(A)}{P(x < X \leq x + \Delta x)}$$

$$= \frac{[F_x(x + \Delta x | A) - F_x(x | A)] P(A)}{F_x(x + \Delta x) - F_x(x)}$$

Taking limit  
as  $\Delta x \rightarrow 0$

$$P(A | X = x) = \lim_{\Delta x \rightarrow 0} \frac{F_x(x + \Delta x | A) - F_x(x | A) P(A)}{\Delta x} \cdot \frac{1}{F_x(x + \Delta x) - F_x(x)}$$

$$P(A | X = x) = \frac{f_x(x | A) P(A)}{f_x(x)}$$

$$P(A|X=x) = \frac{f_X(x|A) P(A)}{f_X(x)}$$

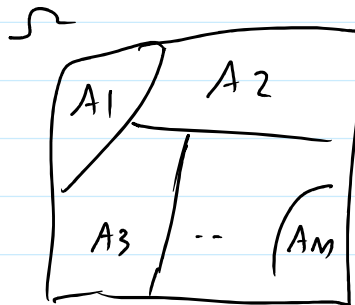
## Total Probability Theorem

Suppose  $A_1, A_2, \dots, A_M$  are

$M$  events such that

$$A_i \cap A_j = \phi \quad \text{if } i \neq j$$

$$\bigcup_{i=1}^M A_i = \Omega \quad (\text{sample space})$$



Now,

$$\begin{aligned} F_X(x) &= P\{X \leq x\} \\ &= P\{X \leq x, \Omega\} \end{aligned}$$

$$= P\left(X \leq x, \bigcup_{i=1}^M A_i\right)$$

union &  
intersection ↓  
distribute

$$= P\left(\bigcup_{i=1}^M (A_i, X \leq x)\right)$$

intersection ↓  
distribute =  $P\left(\bigcup_{i=1}^M (A_i, X \leq x)\right)$

Since  $A_i$ 's are disjoint →  $= \sum_{i=1}^M P(A_i, X \leq x)$

$$= \sum_{i=1}^M P(X \leq x | A_i) P(A_i)$$

$$F_X(x) = \sum_{i=1}^M F_X(x | A_i) P(A_i)$$

Similarly

$$f_X(x) = \sum_{i=1}^M f_X(x | A_i) P(A_i)$$

X ————— X

## Hypothesis testing

state of Nature

- say we have M states
- denote as  $H_1, H_2, \dots, H_M$
- Prior information

$$\begin{aligned} \Pr\{H_i \text{ is true state}\} \\ 1 \leq i \leq M &= P(H_i) \\ &= \pi_i \end{aligned}$$

$\Pi_i$ 's are known

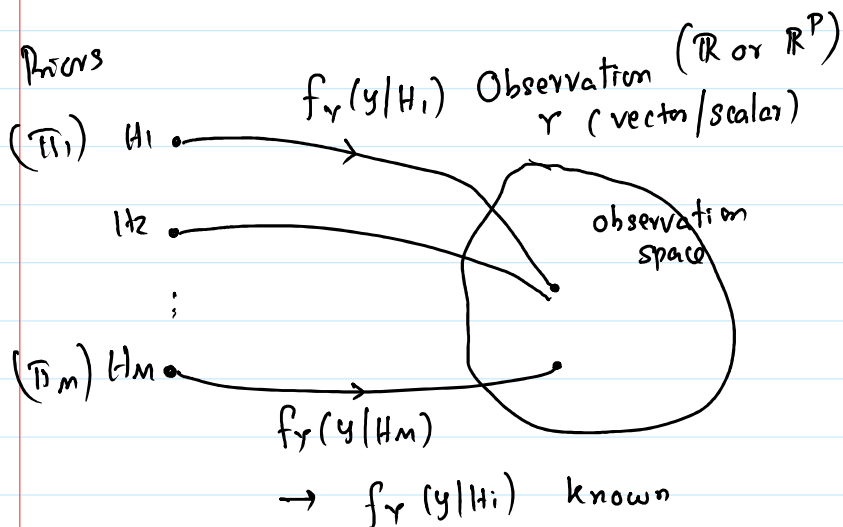
Observation space ( $\mathbb{R}$  or  $\mathbb{R}^P$ )

→ Measurements/observations  
are noisy

→ observation space contains  
all the possible

(y) measurements we can get

→ observations are related to  
state of nature  $H_i$   
thru conditional cdf  
 $f(y|H_i)$

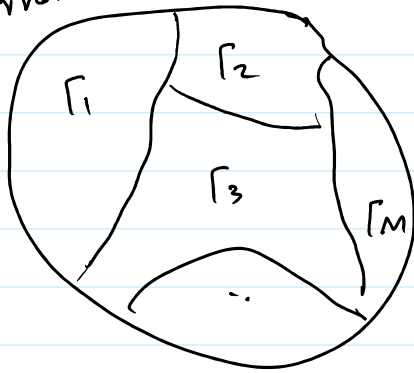


Decision Rule

- For each outcome  $y$  in observation space,  
pick a guess on the state of nature.

Observation space

Observation space



$$d(y) = \begin{cases} H_1 & \text{if } y \in \Gamma_1 \\ H_2 & \text{if } y \in \Gamma_2 \\ \vdots & \\ H_m & \text{if } y \in \Gamma_m \end{cases}$$

- Decision rule partitions the observation space into disjoint regions  $\Gamma_1, \Gamma_2, \dots, \Gamma_m$

Problem: Given  $\pi_i, f_Y(y|H_i)$ ,

choose the decision rule  $(\Gamma_1, \Gamma_2, \dots, \Gamma_m)$

in an optimal way

(for instance, minimize the chance of making an error)

∞ ————— ∞