# Lecture - 5

Probabilistic classifier

$c|x$

$h(x)$ → discriminative function

$x \in \omega_1$

$\varphi(x) > 0.5$

$x \in \omega_2$

$\varphi(x) < 0.5$

$x$ → $C_1$ 0.75 → 1

$C_2$ → 0.25

Sigmoid function

logistic regression → Activation function

[0 - 1]

$\frac{1}{1+e^{-z}}$ → (0, 1)

# Conceptual Notion

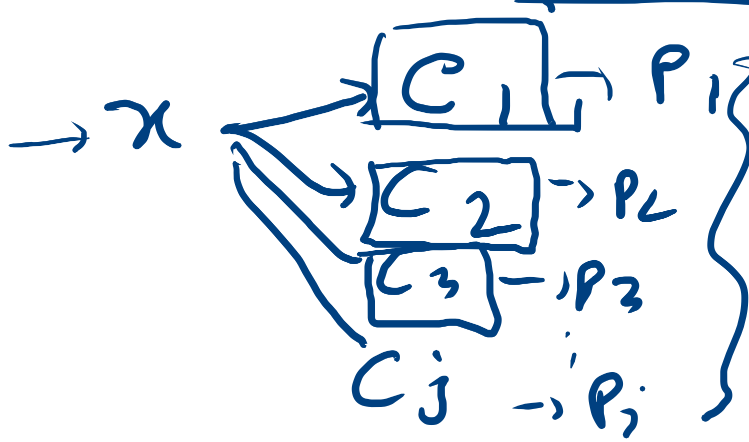
→ The model used for classification is a probabilistic model

Input: $S_{train} = \{(x_i, y_i)\}_{i=1}^{N}$ $\quad y_i \in \{c_1, c_2 \cdots c_J\}$

Goal: $h : X \to Y$,

for each class, estimate

$$\boxed{P(y = c_j \mid x, S_{train})}$$




$\hat{y} = h(x)$

$= \underset{c}{\arg\max}\; P(y = c \mid x, S_{train})$

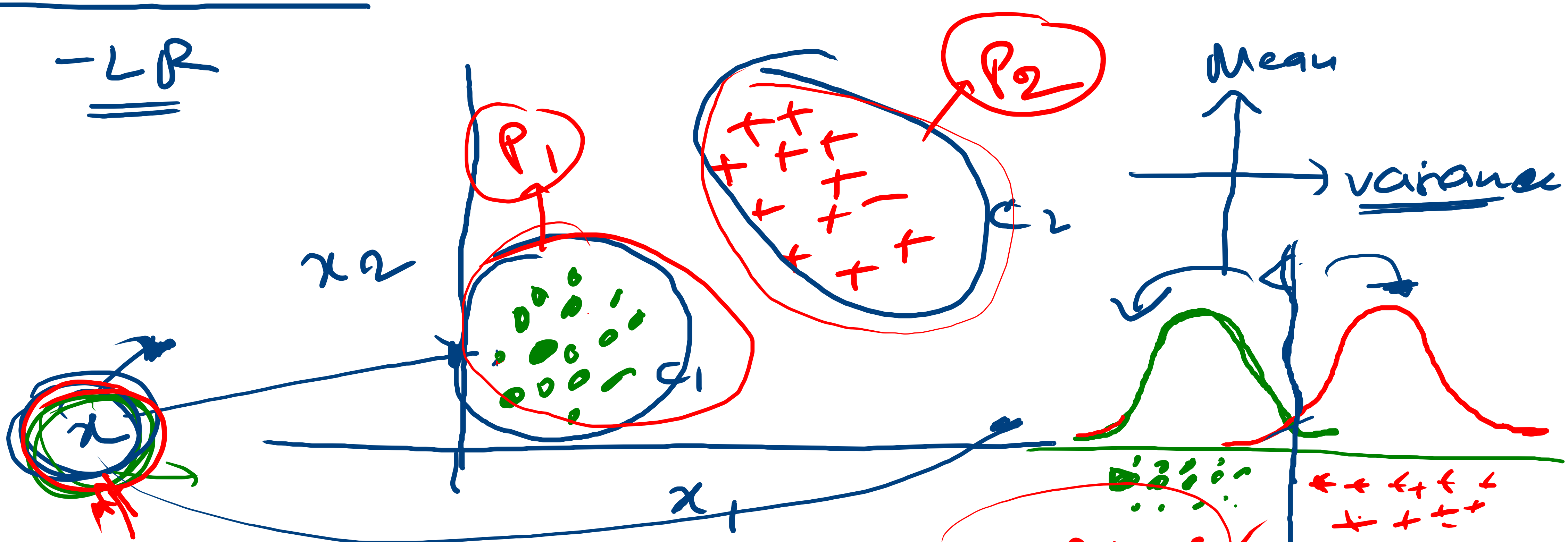
# Probabilistic Models

two forms

**Discriminative**

- LR

**Generative**




Naive Bayes

HMM

GAN

Encoder Decoder

Suppose, $P(x|y)$, $P(y)$

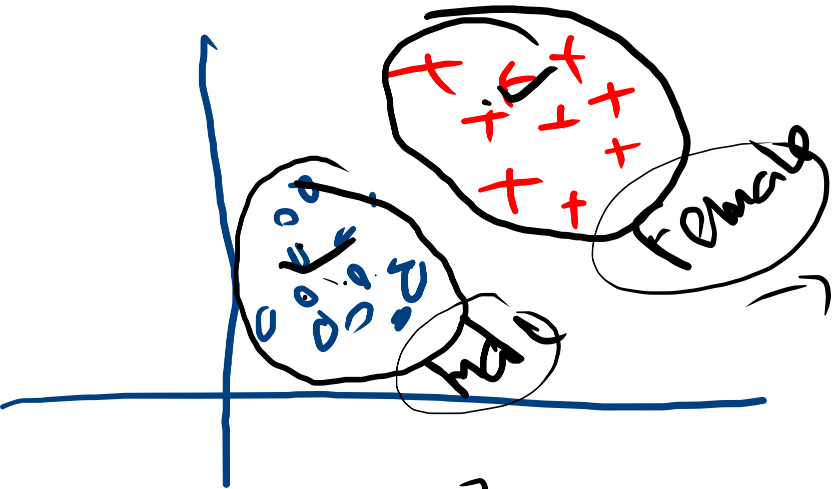
$y = 1$
$y = 0$

$$P(A|B) = \frac{P(B|A) \cdot P(A)}{P(B)}$$

prior

bays rule

Given new $x$:




$$\underbrace{P(y=1|x)}_{\text{posterior probability}} = \frac{\underbrace{P(x|y=1)}_{\text{likelihood}}\ \underbrace{P(y=1)}_{\text{prior}}}{\underbrace{P(x)}_{\text{evidence}}}$$

$$P(y=0|x) = \frac{P(x|y=0)\,P(y=0)}{P(x)}$$

P

where $P(x) = \sum_y P(x,y) = P(x|y=1)P(y=1) + P(x|y=0)P(y=0)$