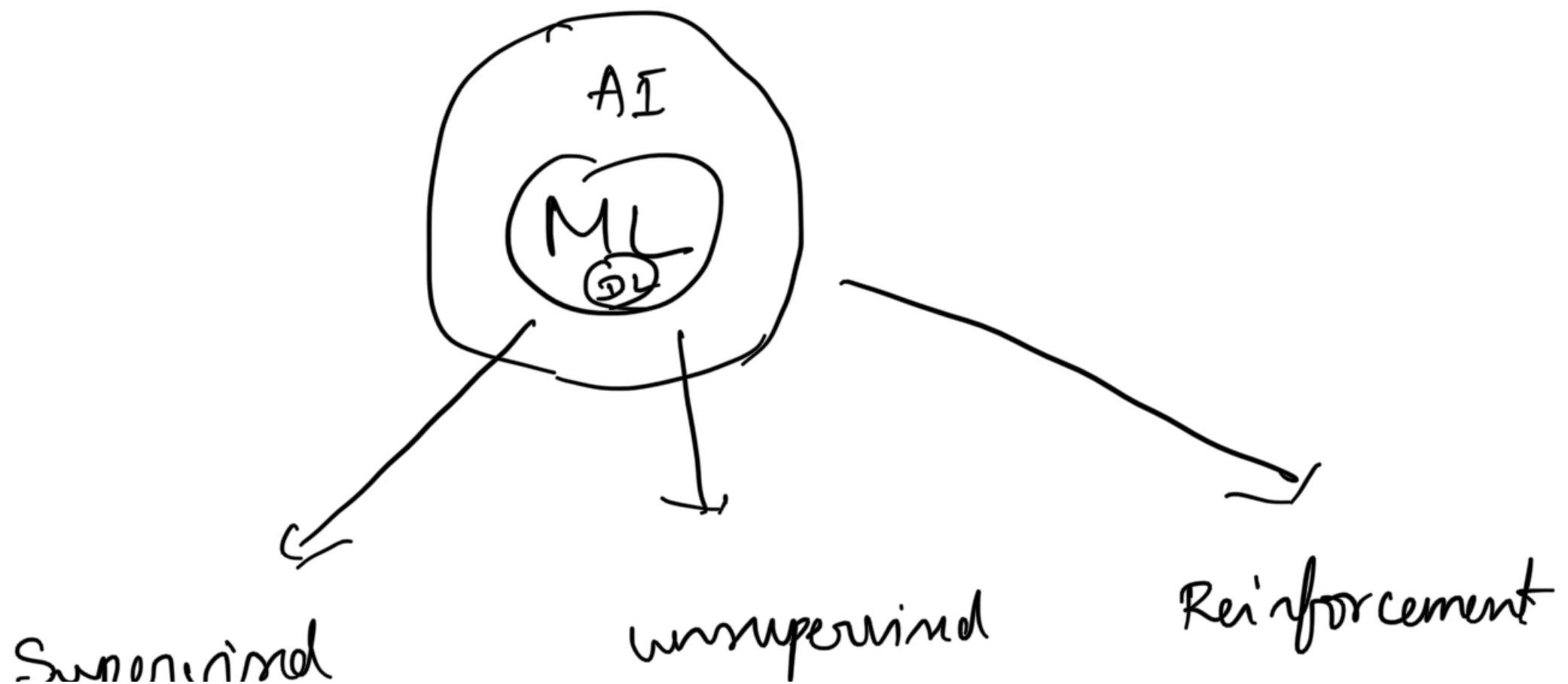


## Outline

1. Overview of ML
2. Bayes classifier
3. Nearest neighbour classifier.



Supervised



Data with Labels.

Supervised Learning:

$$(x_i, y_i)_{i=1}^n$$

Data with labels.

→  $n$  examples.

Problem of Classifying some one as

child or Adult

$$x_i = (\text{Height}_i, \text{weight}_i).$$

$$y_i \in \{\text{Adult}, \text{child}\}.$$

<u>Features</u>	<u>Labels</u>
(5.1 ft, 60 Kg)	Adult
(5.0 ft, 50 Kg)	child

---

Data

(7.0 ft, 60 Kg)	Predict $\longrightarrow$	child or Adult
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Supervised Learning

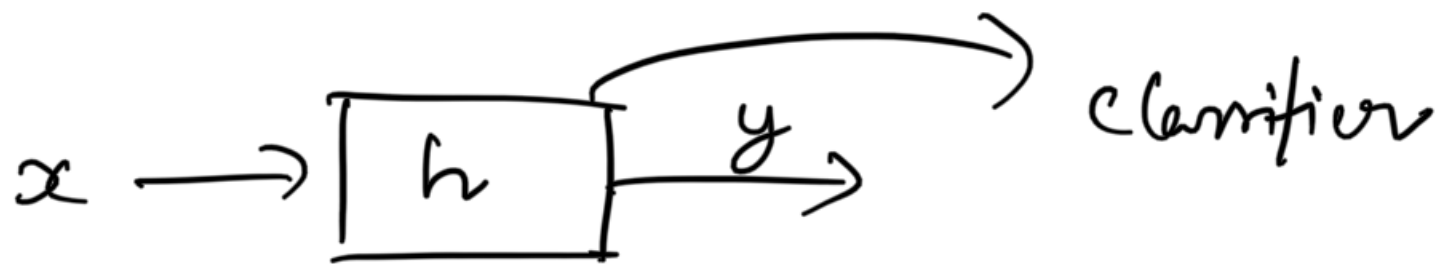


Classification

Task:

$(x_i \in \mathbb{R}^d, y_i \in \{0, 1\})_{i=1}^n$

Features. Labels.



$y = h(x)$  Build  $h$ .

## Random variable vs variable

Random variable is a variable.

because you have a distribution associated with values the variable can take.

$$X = \begin{matrix} \text{Head} & , & \text{Tail} \\ \downarrow & & \downarrow \\ 0 & & 1 \end{matrix}$$

$$\left[ P(X=0) = \frac{1}{2} \quad P(X=1) = \frac{1}{2} \right]$$

# Distribution or frequency with values

1. Support of a random variable
2. Distribution / Density associated with a random variable.

## Examples of Random variables

1. Throw of a die

$X \in \{1, 2, 3, 4, 5, 6\}$ .  $\rightarrow$  Support of a RV

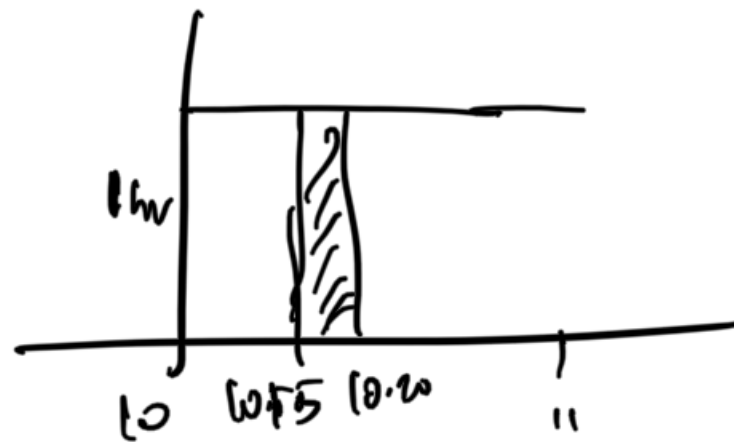
Prob.  $P(X=i) = \frac{1}{6}$   $i = 1, 2, \dots, 6$ .

$$f(x) = 1 / - \frac{1}{6}$$

Discrete Random variable.

2. Class session - (10 - 11.)

The arrival of a student to the  
class is a continuous random variable



mass density

$m/\text{length}$

$m/\text{Area}$

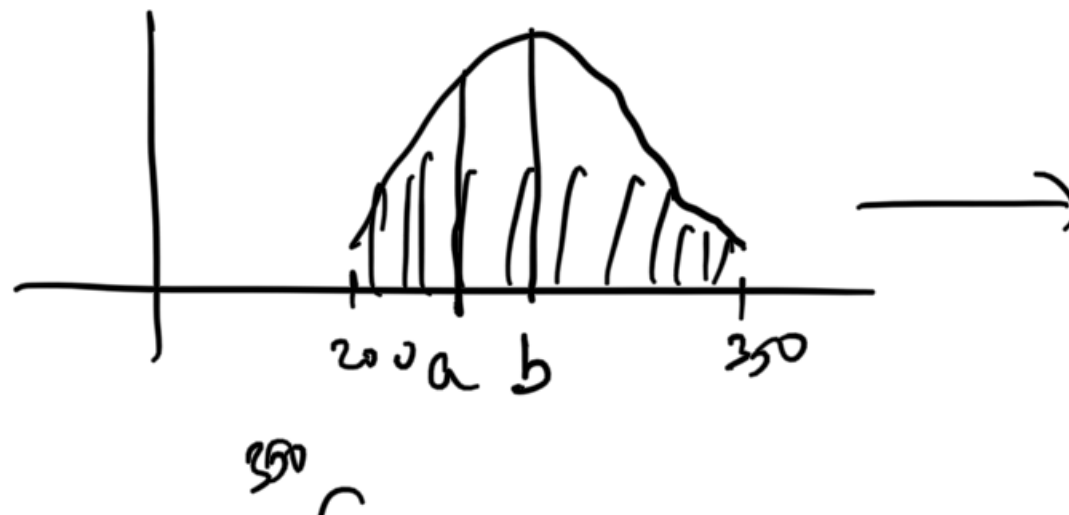




Continuous random variable.

1. Time of arrival to class which is  
Scheduled between 10 to 11 AM.

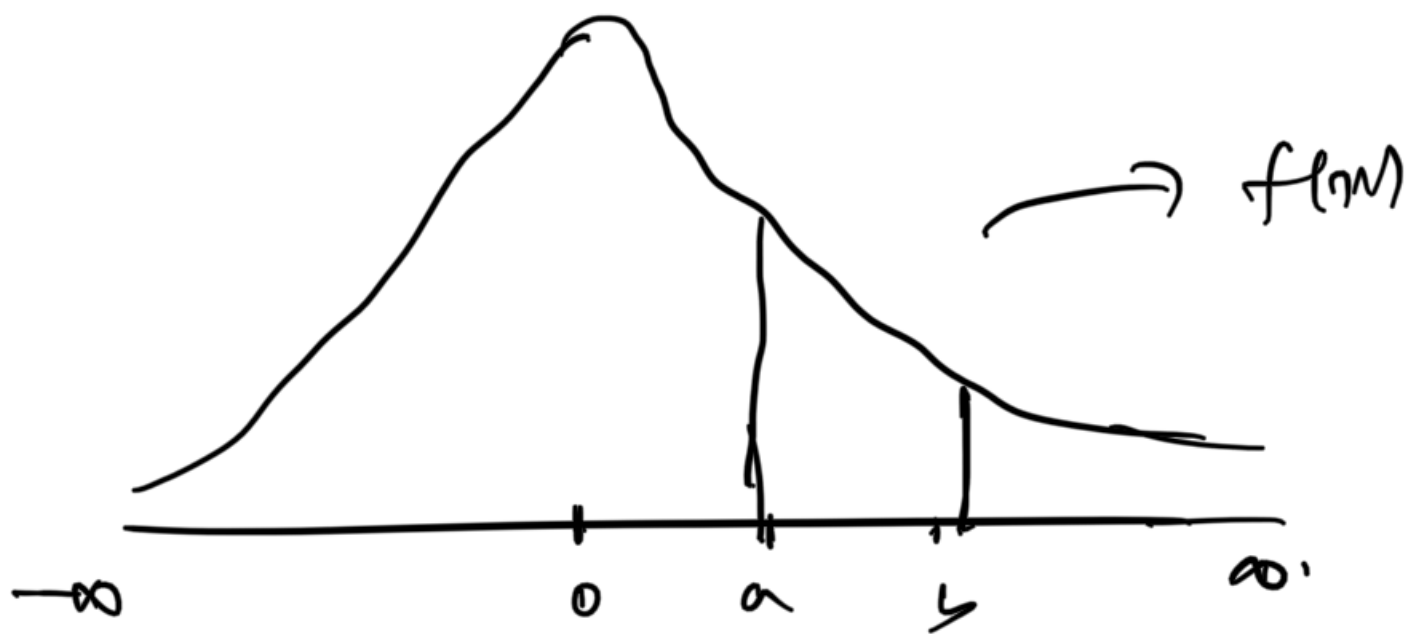
2. Temperature of a boiler.  
200 — 350





$$\int_{-\infty}^{\infty} f(x) dx = 1.$$

$$P(a \leq x \leq b) = \int_a^b f(x) dx$$



$$\int_a^b f(x) dx = P[a \leq x \leq b].$$

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right)$$

↓  
Normal density.

Random variable (RV)

1. Discrete RV  $\rightarrow$  Probability mass function
2. Continuous RV  $\rightarrow$  Probability density function
3. Mixed RV

# Bayes Rule: (Counting in two ways)

$A, B \rightarrow \text{Events}$

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

Experiment	<u>A</u>	<u>B</u>	
1. out 1	1	0	
2. out 2	1	1	$P(A \cap B) = \frac{2}{7}$
3. out 3	0	1	$P(A) = \frac{3}{7}$
4. out 4	0	0	$P(B) = \frac{4}{7}$
5. out 5	0	1	

5. out 5

0 0

$$P(A|B) = \frac{2}{4}$$

6. out 6

0 0

$$P(B|A) = \frac{2}{3}$$

7. out 7

1 1

$$P(A) P(B|A) = \frac{3}{7} \times \frac{2}{3} = \frac{2}{7}$$

$$P(B) P(A|B) = \frac{4}{7} \times \frac{2}{4} = \frac{2}{7}$$

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

$$= P(A \cap B)$$

## Bayes Classifier.

$$P(D) = 0.2$$

$$P(R) = 0.8$$

Prediction strategies:

1. Predict he will default (always)
2. Predict he will Return (always)
3. ... with him P A coming

5. Coin with bias  $p$

heads.

$P \rightarrow \text{Return}$

$1-P \rightarrow \text{Default.}$

Strategy 1:

Predict always he will default

$$P(\text{error}) = 0.8$$

Strategy 2:

$$P(\text{error}) = 0.7$$

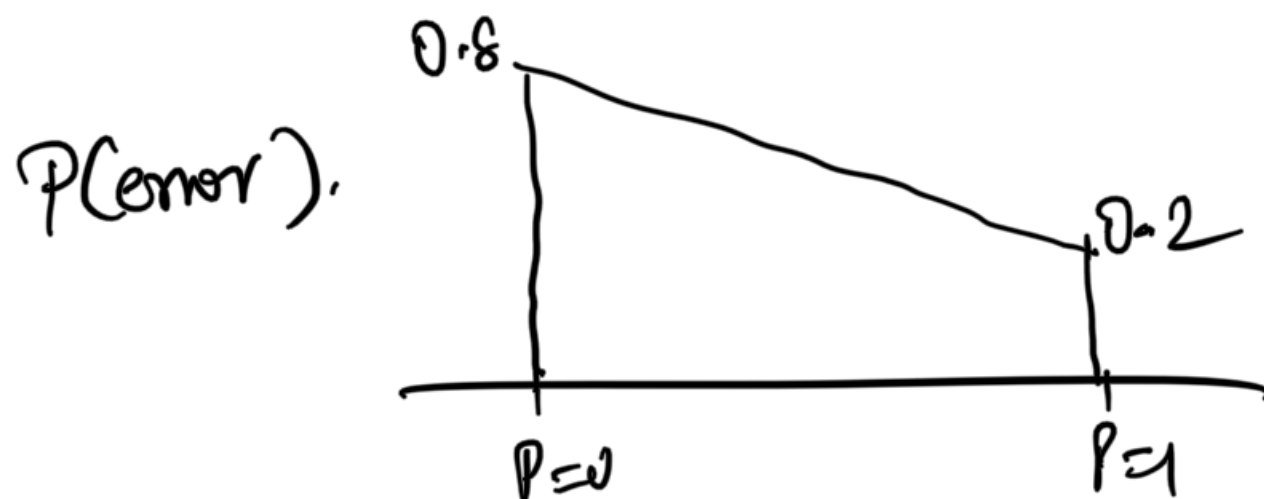
Strategy 3:

H       $P \rightarrow$  Return

T       $1-P \rightarrow$  Default

$$P(\text{error}) = P \cdot 0.2 + (1-P) \cdot 0.8$$

$$= 0.8 - 0.6P$$



$P = 1 \Rightarrow$  Predict always Return,

$H \rightarrow$  <sup>more than</sup> 10 times his salary

$L \rightarrow$  less than 10 times his salary

$$\boxed{P(H | D) = \frac{2}{3}} \rightarrow \text{Given}$$

$$P(L | D) = \frac{1}{3}$$

$$\boxed{P(H | R) = \frac{1}{10}} \rightarrow \text{Given}$$



$$P(L|R) = \frac{9}{10}$$

$$P(D|H), P(R|H)$$

$$P(D|L), P(R|L).$$

Suppose,

$$P(D|H) > P(R|H)$$

$$H \longrightarrow D$$

$$P(D|H) > P(R|H)$$

$$P(D|L) < P(R|L)$$

$$L \rightarrow R$$

H	L
$P:D$	$P:R$

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

$$P(H) = P(H \cap D) + P(H \cap R).$$

$$= P(H|D) P(D) + P(H|R) P(R)$$

$$P(D|H) = 0.625$$

$$P(R|H) = 0.375$$

$$P(D|L) = 0.08$$

$$P(R|L) = 0.92$$

$$P(\text{error}) = P(\text{High Loaner returns money}) \\ + P(\text{low Loaner defaulting money})$$

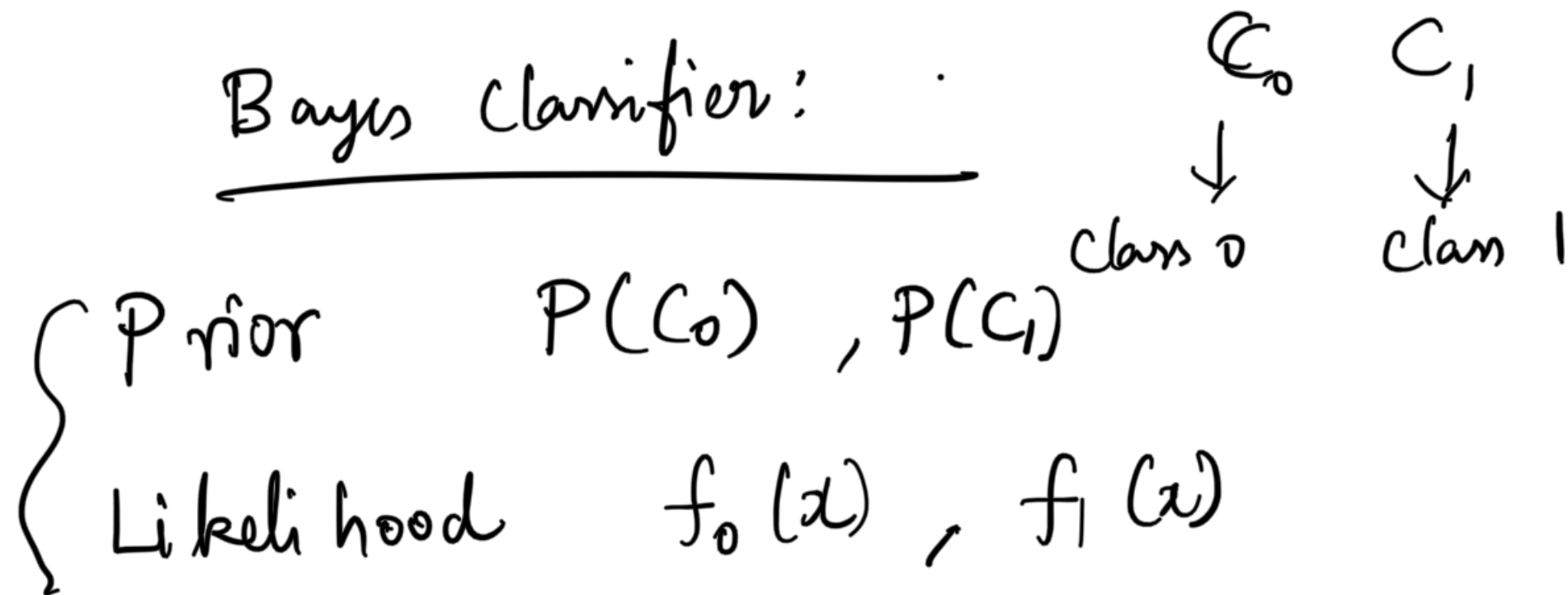
$$= P(H) P(R|H) + P(L) P(D|L)$$

$$= P(H|R)P(R) + P(L|R)P(R)$$

$$= P(R)P(H|R) + P(D)P(L|D)$$

$$\leq 0.2$$

Bayes Classifier:



$$f_0(x) = P(x=x | C_0)$$

$$f_1(x) = P(x=x | C_1)$$

$$f_1(x) = 1 - f_0(x)$$

Posterior  $\rightarrow P[C_0 | x=a]$

$$P[C_1 | x \neq a]$$

Bayes Classifier

$$P[C_0 | x=a] < P[C_1 | x=a]$$

$$x \rightarrow C_1$$

$$P[C_0 | x=a] > P[C_1 | x=a]$$

$$\lambda \rightarrow C_0$$