

Your Data

①

a data point $\vec{x}_i = \begin{pmatrix} a_i \\ b_i \\ c_i \\ \vdots \end{pmatrix} \Rightarrow \{\vec{x}_i\}$

↑
index of
example

↑
random variables

$\{(\vec{x}_i, \vec{y}_i)\}$

↑
inputs

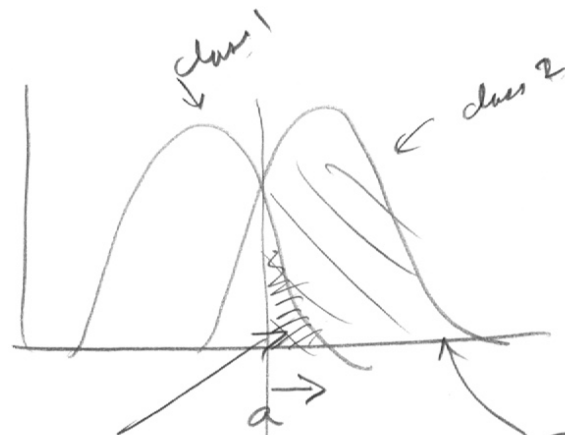
↑
outputs

Example index	a	b	c
1	a_1	b_1	c_1
2	a_2	b_2	c_2
3			

\Rightarrow Continuous variables
Discrete

$\vec{x} \rightarrow \vec{y} \leftarrow$ Discrete \Rightarrow classification
Continuous \Rightarrow regression

Variable



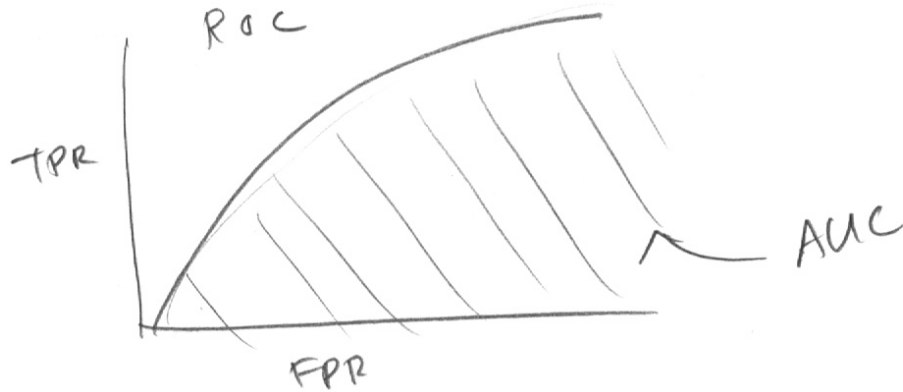
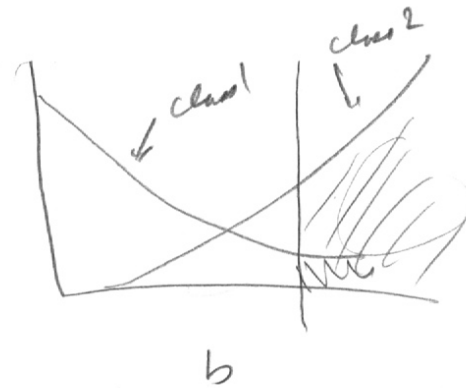
FPR

$$= \frac{\# \text{ class 1 selected}}{\text{total class 1}}$$

Roc

TPR

$$= \frac{\# \text{ class 2 selected}}{\text{total class 2}}$$



⇒ Hypothesis testing

Example

TPR

FPR

99%

1%

1 in 10^6 has measles...

test
⇒ 10^6 :

FP? $10^6 \cdot 10^{-2} = 10^4$

TP? 1

N # of Patient

\hat{n}

↑
of positive

\bar{b} = # of expected false pos.

\hat{s} = # of people w/ measles.

$$\bar{b} = \text{FPR} \cdot N \cdot r_i$$

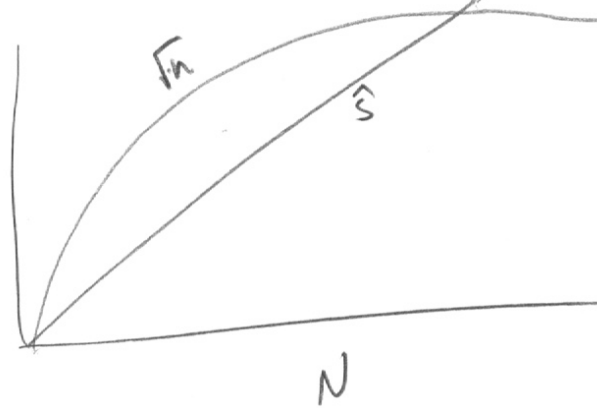
$$\bar{s} = \text{TPR} \cdot N \cdot r_s$$

$$\hat{s} = \hat{n} - \bar{b}$$

$$\sigma_{\hat{s}} \approx \sigma_{\hat{n}} = \sqrt{\hat{n}}$$

$$> 10 \pm 100$$

$$\left. \begin{array}{l} 5 \quad 100 \pm 100 \\ 5.0 \pm 100 \end{array} \right\}$$



$$\Rightarrow \max \frac{\bar{s}}{\sqrt{\bar{s} + \bar{b}}}$$

1) "cut" \rightarrow multi variate

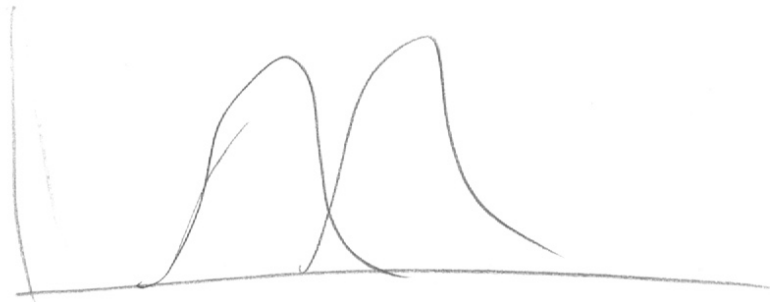
2) Prob Density Estimation (PDE)

$$P(\vec{x}_i | s)$$

$$P(\vec{x}_i | b)$$

$$\frac{P(\vec{x}_i | s)}{P(\vec{x}_i | b)} > c \quad \Leftarrow \quad \underline{\text{the best}}$$

Neymann Pearson Lemma

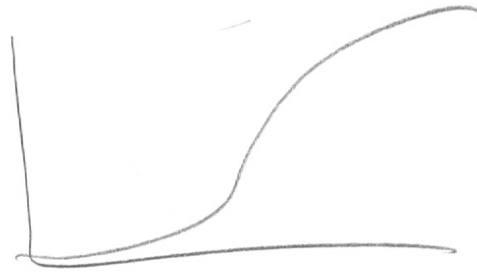


curse of dimensionality

3) Test statistic

$$\vec{x}_i \rightarrow t_i$$

$$t(\vec{x}_i) = t_i$$



a) $t(\vec{x}_i) = (w \vec{x}_i + b)$

Diagram illustrating the linear combination: $(\text{vector}) + (\text{scalar}) \rightarrow \text{Linear Comb.}$

The diagram shows a vector (---) and a scalar (---) being added together to form a linear combination, represented by a vector (---) .

Linear Discriminant Analysis
"Fisher Disc."

$$\vec{w} = (\Sigma_0 + \Sigma_1)^{-1} (\vec{m}_2 - \vec{m}_1) \quad F = \vec{w}^T \vec{x} = \vec{w} \cdot \vec{x}$$

$$S = \frac{\vec{w} \cdot \vec{m}_1 - \vec{w} \cdot \vec{m}_2}{\vec{w}^T \Sigma_1 \vec{w} - \vec{w}^T \Sigma_0 \vec{w}} \quad \vec{w}^T (\Sigma_1 - \Sigma_0) \vec{w}$$