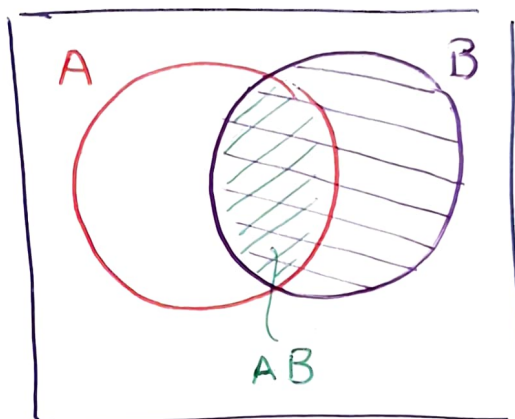


- Conditional Probability, ...
- Bayes' Rule ↔ classification metrics
- Naïve Bayes' classifier

$$P(AB) \equiv P(A \cap B)$$

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

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



→ if A, B are independent

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

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

$$P(AB) = P(A)P(B)$$

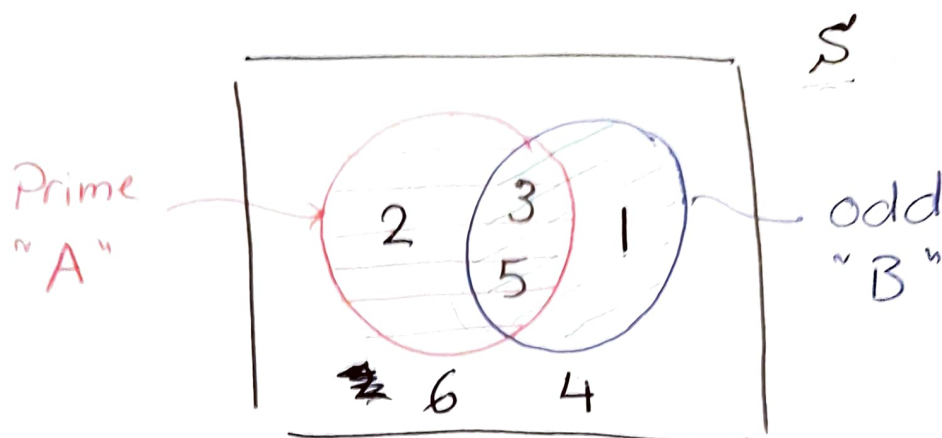
$$P(AB) = P(B|A)P(A) = P(A|B)P(B)$$

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

Posterior ←  $P(A|B)$       Likelihood ←  $P(B|A)$       evidence ←  $P(B)$       Prior Bayes' Rule \* ←  $P(A)$

ex.

(2)



$$\rightarrow P(A, B) = \frac{2}{6} \leftarrow P(\text{odd and Prime})$$

$$\rightarrow P(A|B) = \frac{2}{3} \quad P(\text{Prime} | \text{odd})$$

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

$$P(A|B) = \frac{P(A, B)}{P(B)} = \frac{2/6}{3/6} = 2/3$$

$$P(B|A) = \frac{P(A, B)}{P(A)} = \frac{2/6}{3/6} = 2/3$$

$$P(A|B) = P(A, B) / P(B) \quad \leftarrow \text{events } A, B$$

$$\underbrace{P_{X/Y}(x/y)}_{\text{Conditional Prob.}} = \underbrace{P_{X,Y}(x,y)}_{\text{Joint Prob.}} / \underbrace{P_Y(y)}_{\text{Marginal Prob.}} \quad \leftarrow \text{R.V.'s } \underline{x, y}$$

$$\underbrace{f_{X/Y}(x/y)}_{\text{Conditional PDF}} = \underbrace{f_{X,Y}(x,y)}_{\text{Joint PDF}} / \underbrace{f_Y(y)}_{\text{Marginal PDF}}$$

also can be written in terms of CDF!

ex. two jointly Gaussian R.V.'s  $x, y$  (3)

$$f_{x,y}(x,y) = \frac{1}{2\pi \sigma_x \sigma_y \sqrt{1-\rho_{xy}^2}} e^{-\left[ \frac{1}{1-\rho_{xy}^2} \left[ \frac{(x-\mu_x)^2}{2\sigma_x^2} + \frac{(y-\mu_y)^2}{2\sigma_y^2} - \rho_{xy} \left( \frac{x-\mu_x}{\sigma_x} \right) \left( \frac{y-\mu_y}{\sigma_y} \right) \right] \right]}$$

$$f_x(x) = \frac{1}{\sqrt{2\pi}\sigma_x} e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2}}$$

$$f_y(y) = \frac{1}{\sqrt{2\pi}\sigma_y} e^{-\frac{(y-\mu_y)^2}{2\sigma_y^2}}$$

Joint PDF

if  $x, y$  are uncorrelated

$$\Rightarrow \rho_{xy} = 0$$

$$\begin{aligned} \Rightarrow f_{x,y}(x,y) &= \frac{1}{2\pi \sigma_x \sigma_y} e^{-\left[ \frac{(x-\mu_x)^2}{2\sigma_x^2} + \frac{(y-\mu_y)^2}{2\sigma_y^2} \right]} \\ &= \underbrace{\frac{1}{\sqrt{2\pi}\sigma_x}}_{f_x(x)} \times \underbrace{\frac{1}{\sqrt{2\pi}\sigma_y}}_{f_y(y)} \times e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2}} \times e^{-\frac{(y-\mu_y)^2}{2\sigma_y^2}} \end{aligned}$$

given  $f_{x,y}(x,y) \Rightarrow$  we can find  $f_x(x)$  &  $f_y(y)$

$$\text{then we can find } f_{x/y}(x/y) = \frac{f_{x,y}(x,y)}{f_y(y)}$$

$$f_{y/x}(y/x) = \frac{f_{x,y}(x,y)}{f_x(x)}$$

## Multiplication Rule . "Chain Rule"

(4)

$$P(A B C D) = P(A) P(B/A) P(C/AB) P(D/ABC)$$

~~$P(A) P(B/A) P(C/AB) P(D/ABC)$~~

→ Drawing cards without Replacement

$$\begin{aligned} P(A^1 A^2 A^3 A^4) &= P(A^1) P(A^2/A^1) P(A^3/A^1 A^2) P(A^4/A^1 A^2 A^3) \\ &= \frac{4}{52} \times \frac{3}{51} \times \frac{2}{50} \times \frac{1}{49} \\ &= 0.000 \dots \end{aligned}$$

Birthday Paradox

n persons       $P(\text{two persons at least share the same birthday})$

$$= 1 - P(\text{no two persons share the same birthday}),$$

$$= 1 - P(\text{each person was born on a different day})$$

$$= 1 - \left( \frac{365}{365} \right) \left( \frac{364}{365} \right) \dots$$



Monty Hall problem



# Bayes' Rule

(and total Probability theorem)

5

ex.

→ 1 % of Population suffer certain allergy.

→ test → 98% accurate in detecting Allergy.

recall

$\frac{TN}{N}$

→ 97% accurate in detecting no Allergy.

→ if a person took the test, and tested +ve,

what is the probability that this person actually has allergy.

A: has allergy

A': does not have allergy.

$$P(A) = 0.01 \quad \checkmark$$

$$P(A') = 0.99$$

B: test +ve

B': test -ve

$$P(\underline{A/B}) = \frac{0.01 \times 0.98 \quad \checkmark \quad P(A) P(B/A)}{P(B)} = \underline{0.248}$$

? 0.0395 ?

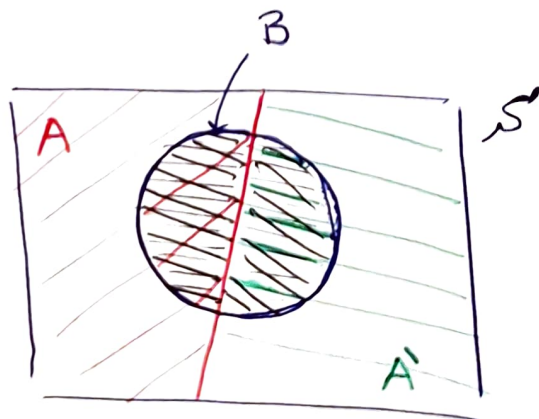
belief updating

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

$\xrightarrow{P(B/A)P(A)}$   $\xrightarrow{P(B/A')P(A')}$

$\xrightarrow{0.98 \quad 0.01}$   $\xrightarrow{0.03 \quad 0.99}$

$$P(B) = 0.98 \times 0.01 + 0.03 \times 0.99$$
$$= 0.0395$$



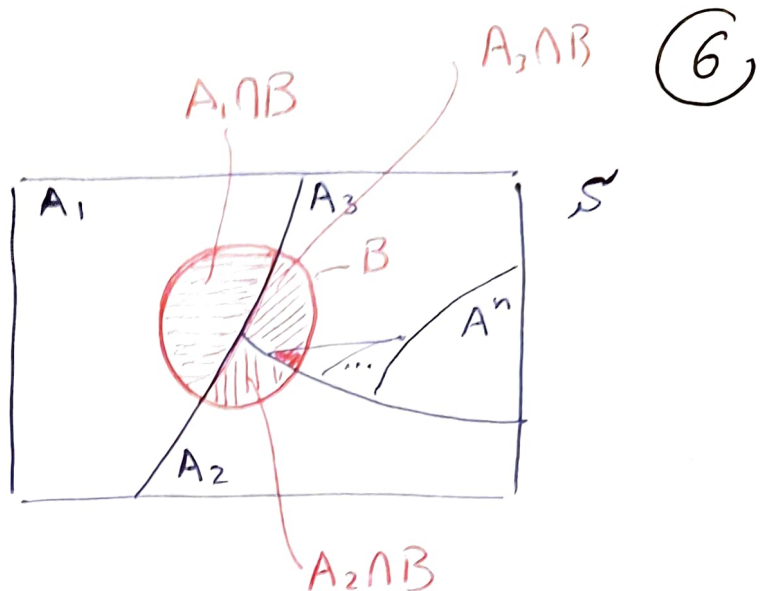
total Probability

if

$$S = A_1 \cup A_2 \cup \dots \cup A_n$$

$A_i$  are disjoint events  
 $i = 1 \rightarrow n$

$$\bigcup_{i=1}^n A_i = S$$



$$B = (A_1 \cap B) \cup (A_2 \cap B) \cup \dots \cup (A_n \cap B)$$

$$P(B) = \sum_{i=1}^n P(A_i \cap B)$$

		Predictions		Confusion Matrix
		P	N	
ground truth	✓	TP ✓	FN	( Binary Classifiers )
	✗	FP	TN ✓	

nesbet el homa  
 3ndhom w elmodel tl3  
 eno 3ndhom 3la kol ely  
 el model tl3 enhom  
 3ndhom

$$\text{Precision} = \frac{TP}{\text{all Pos.}} = \frac{TP}{TP + FP}$$

nesbet el homa 3ndhom w elmodel tl3 eno  
 3ndhom 3la kol ely bgd 3ndhom

$$\text{Recall} = \frac{TP}{\text{real } \checkmark} = \frac{TP}{TP + FN}$$

$$\frac{\text{Prec.} \times \text{Recall}}{\text{Prec.} + \text{Recall}} \times 2$$

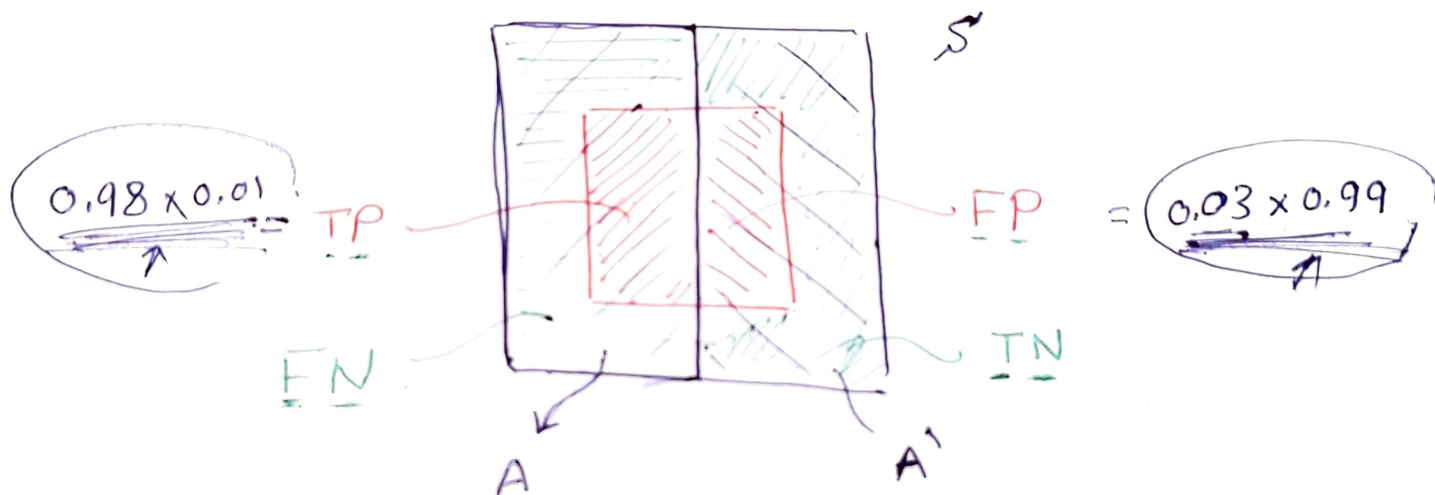
$$\text{F1-score} = \text{harmonic mean of Pr. \& Recall} = \frac{2}{1/\text{Prec.} + 1/\text{Recall.}}$$

$$\text{Accuracy} = \frac{\text{Correct classifications}}{\text{all classifications}} = \frac{TP + TN}{TP + TN + FP + FN}$$

$P(A) = 0.01$   
 FP:  $0.03 \times 0.99$   
 TP:  $.98 \times 0.01$   
 FN  
 TN  
 2% of 1%  
 0.01      0.99

$$0.03 \times 0.99 + 0.98 \times 0.01$$

positive test



# Naive Bayes Classifier

(7)

$$P(A/B) = \frac{P(A) P(B/A)}{P(B)}$$

Binary classification

$x \rightarrow$  male or female

$y \rightarrow$  cat or not cat

~~P(x)~~  $P(\text{male} / \text{features}) = ?$  a

$a > b \Rightarrow$  male

$P(\text{female} / \text{features}) = ?$  b

$b > a \Rightarrow$  female

$P(\text{cat} / \text{features}) = 0.35$

$P(\text{not cat} / \text{features}) = 0.65$

$\Rightarrow$  not cat

training  $\rightarrow$

$$f(h/m) = \frac{1}{\sqrt{2\pi}\sigma_{hm}} e^{-\frac{(h - \mu_{hm})^2}{2\sigma_{hm}^2}}$$

$f(w/m) = \checkmark$

$f(ss/m) = \checkmark$

$f(h/f) = \checkmark$

$f(w/f) = \checkmark$

$f(ss/f) = \checkmark$

gender	height	weight	shoe size
male	170	x	-
male	175	x	-
male	165	x	-
male	173	x	-
<u><math>\mu = \sqrt{\sigma^2}</math></u>			
female	160	x	-
"	175	x	-
"	155	x	-
"	165	<	-



$$P(\text{male} / \vec{f}) = \frac{P(\text{male}) \cdot P(\vec{f} / \text{male})}{P(\vec{f})} \quad P(B)$$

$$P(\text{female} / \vec{f}) = \frac{P(\text{female}) \cdot P(\vec{f} / \text{female})}{P(\vec{f})} \quad P(B)$$

Naïve assumption → assume independence!

$$P(\vec{f} / \text{male})$$

$$= P(\text{weight, height, shoesize} / \text{male})$$

joint probability

features are dependent (not indep.)

assuming independence

$$P(\vec{f} / \text{male}) = P(\text{height} / \text{male}) \cdot P(\text{w} / \text{male}) \cdot P(\text{s.s.} / \text{male})$$

$$P(\vec{f} / \text{female}) =$$

$$\frac{1}{\sqrt{2\pi} \cdot \sigma_{h/m}} e^{-\frac{(\hat{h} - \mu_{h/m})^2}{2 \sigma_{h/m}^2}}$$

$h = 6$

