

# Naive Bayes

Recap: MLE: model  $P(x, y)$  with  $\theta \in \Theta$

$$\theta_{MLE} = \operatorname{argmax}_{\theta \in \Theta} P_{\theta}(D)$$

model  $\theta$  that maximizes likelihood of data

MAP: 
$$\theta_{MAP} = \operatorname{argmax}_{\theta \in \Theta} P(\theta | D) = P(D | \theta) P(\theta)$$

$\downarrow$  likelihood       $\downarrow$  Prior

Eg

$Y$	$X = \text{Favorite dish}$	$X = \{\text{Soup, Mac N cheese, Tacos}\}$
Adult	Soup	
child	Mac N Cheese	Estimate $P(Y = \text{"child"}   X = \text{"Mac or cheese"})? = 3/4$
child	Mac N Cheese	
Adult	Tacos	
Adult	Soup	
Child	Tacos	
Adult	Soup	
Adult	Mac N Cheese	
child	Mac N Cheese	

Estimate  $P(Y = y | X = x)$ ?

$$\frac{\sum_{i=1}^n \mathbb{1}\{x_i = x\} \mathbb{1}\{y_i = y\}}{\sum_{i=1}^n \mathbb{1}\{x_i = x\}}$$

What is the issue with this?

Exact matches are rare with many features

Eg

$Y$	$X(1) = \text{Favorite dish}$	$X(2) = \text{\# words known}$	$X(3) = \text{Favorite Movie}$	$X(4) = \text{Hours of sleep}$
Adult	Soup	20000	Godfather	8
child	Mac N Cheese	200	Frozen	11
child	Mac N Cheese	400	Frozen	12
Adult	Tacos	17000	La la land	6
Adult	Soup	15000	Godfather	5
Child	Tacos	1000	Eternals	10
Adult	Soup	21000	Avengers	10
Adult	Mac N Cheese	11000	Avengers	8
child	Mac N Cheese	700	Avengers	11

$$\hat{P}(Y = \text{"Adult"} | X = (\text{"soup"}, 20000, \text{"Avengers"}, 8)) ?$$

## Naive Bayes Model

Assumption:  $P(X = \vec{x} | Y = y) = \prod_{\alpha=1}^d P(X^{(\alpha)} = x^{(\alpha)} | Y = y)$

"Given it's a child, favorite dish, # words known, hours of sleep. are all independent"

why is this useful?

$$\begin{aligned} P(Y=y | X=x) &= \frac{P(X=x | Y=y) P(Y=y)}{P(X=x)} \\ &= \frac{\prod_{\alpha=1}^d P(X^{(\alpha)} = x^{(\alpha)} | Y=y) P(Y=y)}{P(X=x)} \\ &= \frac{\prod_{\alpha=1}^d P(X^{(\alpha)} = x^{(\alpha)} | Y=y) P(Y=y)}{\sum_{c \in \mathcal{Y}} \prod_{\alpha=1}^d P(X^{(\alpha)} = x^{(\alpha)} | Y=c) P(Y=c)} \end{aligned}$$

$P(Y=y)$  and  $\forall \alpha, P(X^{(\alpha)} = x^{(\alpha)} | Y=y)$  are easy to estimate

Eg. estimate

$$\hat{P}(Y = \text{"Adult"} | X = (\text{"soup"}, 20000, \text{"Avengers"}, 8)) ?$$

$$\begin{aligned} h(x) &= \operatorname{argmax}_{y \in \mathcal{Y}} \hat{P}(Y=y | X=x) \\ &= \operatorname{argmax}_{y \in \mathcal{Y}} \prod_{\alpha} P(X^{(\alpha)} = x^{(\alpha)} | Y=y) P(Y=y) \\ &= \operatorname{argmax}_{y \in \mathcal{Y}} \sum_{\alpha} \log(P(X^{(\alpha)} = x^{(\alpha)} | Y=y)) + \log P(Y=y) \end{aligned}$$

when  $X_i(d)$  are counts

Eg  $X_i(d) = j$  means  $i^{\text{th}}$  word in the dictionary occurs  $j$  times in the document  $i$

$x$  is an  $m$  word document:  $X(d) \in \{0, 1, \dots, m\}$   $\sum_{\alpha=1}^d X(d) = m$

Multinomial Distribution

$$P(X=x | m, Y=y) = \frac{m!}{X(d)! X(d)! \dots X(d)!} \prod_{i=1}^d (\theta_{d,y})^{X(d)}$$

MLE estimate: 
$$\hat{\theta}_{d,y} = \frac{\sum_{i=1}^d \mathbb{1}\{y_i=y\} X_i(d)}{\sum_{i=1}^d \mathbb{1}\{y_i=y\} m_i}$$

$m_i = \#$  words in document  $i$

$$h(x) = \operatorname{argmax}_{y \in Y} P(Y=y) \prod_{\alpha=1}^d \hat{\theta}_{\alpha,y}^{X(d)}$$

$X(d)$ 's are continuous variables.: Gaussian distribution conditioned on  $Y$

$$p(X(d)=x | Y=y) = \frac{1}{\sqrt{2\pi}\sigma_y} \exp\left(-\frac{(x-\mu_y)^2}{2\sigma_y^2}\right)$$

Parameter estimation:

$$\hat{\mu}_{y,d} = \frac{\sum_{i=1}^d \mathbb{1}\{y_i=y\} X_i(d)}{\sum_{i=1}^d \mathbb{1}\{y_i=y\}} \quad \hat{\sigma}_y^2 = \frac{\sum_{i=1}^d \mathbb{1}\{y_i=y\} (X_i(d) - \hat{\mu}_{y,d})^2}{\sum_{i=1}^d \mathbb{1}\{y_i=y\}}$$

1. For both multinomial case and Gaussian case (with variance between class per feature fixed) classification boundary is linear.

2. For Gaussian case

$$P(Y=y | x) = \frac{1}{1 + \exp(-y(w^T x + b))}$$

logistic link function.

$Y$	$X(1) =$ Favorite dish	$X(2) =$ # words known	$X(3) =$ Favorite Movie	$X(4) =$ Hours of sleep
• Adult	Soup •	20000 •	Godfather	8 •
child	Mac N Cheese	200	Frozen	11
child	Mac N Cheese	400	Frozen	12
• Adult	Tacos	17000	La la land	6
• Adult	Soup •	15000	Godfather	5
child	Tacos	1000	Eternals	10
• Adult	Soup •	21000	Avengers •	10
• Adult	Mac N Cheese	11000	Avengers •	8 •
child	Mac N Cheese	700	Avengers •	11

$$P(Y = \text{"Adult"} \mid X = (\text{"soup"}, 20000, \text{"Avengers"}, 8)) ?$$

$$= \frac{\prod_{d=1}^d P(X(d) = x(d) \mid Y = y) P(Y = y)}{\sum_{c \in Y} \prod_{d=1}^d P(X(d) = x(d) \mid Y = c) P(Y = c)}$$

$$P(Y = \text{"Adult"}) = \frac{5}{9} \quad \begin{array}{l} 5 \text{ adults} \\ 9 \text{ people} \end{array} \quad P(Y = \text{child})$$

$$P(X(1) = \text{"soup"} \mid Y = \text{Adult}) = \frac{3}{5} \quad \frac{3 \text{ soups for adults}}{5 \text{ adults}}$$

$$P(X(2) = 20000 \mid Y = \text{Adult}) = \frac{1}{5}$$

$$P(X(3) = \text{"Avengers"} \mid Y = \text{Adult}) = \frac{2}{5}$$

$$P(X(4) = 8 \mid Y = \text{Adult}) = \frac{2}{5}$$

$$\hat{p}(x_{(1)} = \text{"soup"} \mid Y = \text{child}) = 0/4$$

$$\hat{p}(Y = \text{"Adult"} \mid X = (\text{"soup"}, 20000, \text{"Avengers"}, 8))$$

$$= \frac{\prod_{d=1}^d P(X_{(d)} = x_{(d)} \mid Y = y) P(Y = y)}{\sum_{c \in \mathcal{Y}} \prod_{d=1}^d P(X_{(d)} = x_{(d)} \mid Y = c) P(Y = c)}$$

$$= \frac{\left( \frac{3}{5} \times \frac{1}{5} \times \frac{2}{5} \times \frac{2}{5} \right) \times \frac{5}{9}}{\left( \frac{3}{5} \times \frac{1}{5} \times \frac{2}{5} \times \frac{2}{5} \right) \times \frac{5}{9} + 0 \times \frac{4}{9}}$$

$$= 1$$