

Welcome to Week 2 of Online ML

Reminders: Gradience 5 - Due Tomorrow

PA2 - Due on April 13th

Probabilistic/Statistical Methods:

Categorical Random Variables

$$X = \{H, T\}$$

pmf.  $P(X=H)$

$$P(X=T)$$

$$P(X=T) = 1 - P(X=H)$$

$$X = \{1, 2, 3, 4, 5, 6\}$$

$$P(X=1)$$

$$P(X=2)$$

$\vdots$

$$P(X=6)$$

$$P(X=6) = 1 - \sum_{i=1}^5 P(X=i)$$

If a random variable takes  $K$  values

$$|X| = K$$

Then we need  $(K-1)$  probabilities to completely specify its pmf.

These are the parameters of  
the distribution

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How much data do you need?

e.g. a coin toss

$$D = \{H\} \quad \times$$

$$D = \{HHHTTHHTHH\} \quad \checkmark$$

If we have a roll of a dice  
would need more data.

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$$X = \{\text{roll of a dice, toss of a coin}\}$$

$$X = \begin{array}{c} 1, H \\ 1, T \\ 2, H \\ 2, T \\ \vdots \\ \vdots \end{array} \quad |X| = 12$$

$\# \text{ params} = 12 - 1 = 11$

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Tumor example:

Shape	Size	Color	Smoothness	Thickness
cir	large	dark	smooth	thick
ov.oid	small	light	irregular	thin

Target malignant (1) }  
benign (0) } y

$Y$  - random variable (Bernoulli)

$$P(Y = \text{benign} | X = x^*)$$

$$P(Y = \text{malignant} | X = x^*)$$

$$Y \sim \text{Ber}(\theta)$$

$$P(Y = \text{malignant}) = \theta$$

$$P(Y = \text{benign}) = 1 - \theta$$

Given just the labels on the training data.

I can estimate  $\theta$ :

$$\hat{\theta}_{MLE} = \frac{N_1}{N}$$

$$\hat{\theta}_{MAP} = \frac{N_1 + a - 1}{N + a + b - 2}$$

$$P(Y = \text{malignant}) = \theta$$

This is not  $P(Y = \text{malignant} | X = x^*)$

$$P(Y = \text{malignant} | X = x^*)$$

$$= \frac{P(X = x^* | Y = \text{malignant}) P(Y = \text{malignant})}{P(X = x^*)}$$

$$\left[ P(X=x^* | Y=\text{malignant}) P(Y=\text{mal.}) + P(X=x^* | Y=\text{benign}) P(Y=\text{benign}) \right]$$


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$$P(Y=\text{benign} | X=x^*) = 1 - P(Y=\text{mal.} | X=x^*)$$

$$\left[ \begin{array}{l} P(X=x^* | Y=\text{malignant}) \\ P(X=x^* | Y=\text{benign}) \end{array} \right] \rightarrow \text{Class-conditional probabilities}$$

$X$  is a random variable

multi-variate categorical r.v.

For a 5-D random variable where each feature is binary -

We can have  $2^5$  possible combinations

$$|X| = 2^5$$

We need to estimate  $2^5 - 1$  parameters

We need to estimate these parameters for both classes

$$P(X=x^* | Y=\text{mal.})$$

$$P(X=x^* | Y=\text{benign})$$

$\therefore (2^5 - 1)$  parameters to estimate

$x^* \in \mathcal{X}$

All features are independent of each other

Naive Bayes Classifier

$$P(\underbrace{x = x^*}_D | Y = \text{malignant}) \\ = \prod_{j=1}^D P(X_j = x_j^* | Y = \text{malignant})$$

Each  $P(X_j = x_j^* | Y = \text{malignant})$   
can be modeled as a Bernoulli r.v.

If each feature is binary, then we  
need  $2 \times D$  parameters

Training  $\begin{matrix} P(Y = \text{mal.}) \\ P(Y = \text{benign}) \end{matrix} \rightarrow \begin{matrix} \theta_{\text{mal.}} \theta_1 \\ \theta_{\text{benign}} \theta \end{matrix}$

$$\begin{cases} P(X_j = 1 | Y = \text{mal.}) & P(X_j = 1 | Y = \text{benign}) \\ P(X_j = 0 | Y = \text{mal.}) & P(X_j = 0 | Y = \text{benign}) \end{cases} \\ \rightarrow \forall j$$

$$P(x = x^* | Y = y) = P(Y = y) \prod_{j=1}^D P(X_j = x_j^* | Y = y)$$

$$P(X \in \mathcal{X}, Y \in \mathcal{Y}) = \dots$$

For a training example  $x_i, y_i$

$x_1$	$y_1$
$x_2$	$y_2$
$\vdots$	$\vdots$

$$\frac{P(X=x_i, Y=y_i)}{= P(Y=y_i)P(X=x_i|Y=y_i)}$$

$$ll(D|\Theta) = \underline{N_1} \log \underline{\Theta} + \underline{N_2} \log \underline{(1-\Theta)}$$

all parameters  
in the model

$$+ \sum (N_{1,j} \log \Theta_{1,j} + (N_1 - N_{1,j}) \log (1 - \Theta_{1,j}))$$

$$+ \sum \dots$$

$$\Theta = \frac{N_1}{N}$$

$\leftarrow$  # examples with class 1

$\leftarrow$  # examples

$$\hat{\Theta}_c = \frac{N_c}{N} \quad \forall c$$

$$\hat{\Theta}_{c,j} = \frac{N_{c,j}}{N_c} \quad \forall j, c$$

These are MLE estimates

How to get a prediction for  $x^*$

$$P(Y = \text{mal} | x = x^*) = \underline{\hspace{2cm}}$$

↑  
refer to the ~~the~~ Bayes rule  
expression mentioned  
earlier.

$$\begin{aligned} \text{If } P(Y = \text{mal} | x = x^*) &\geq 0.5 & y^* = \text{mal.} \\ &< 0.5 & y^* = \text{ben} \end{aligned}$$

$$P(Y = \text{mal.} | x = \{x_1 = \text{cir}, x_2 = \text{sm}, x_3 = \text{li}\})$$

$$= \frac{P(x = \{x_1 = \text{cir}, x_2 = \text{sm}, x_3 = \text{li}\} | Y = \text{mal}) P(Y = \text{mal})}{P(x = \{x_1 = \text{cir}, x_2 = \text{sm}, x_3 = \text{li}\} | Y = \text{mal}) P(Y = \text{mal}) + P(x = \{x_1 = \text{cir}, x_2 = \text{sm}, x_3 = \text{li}\} | Y = \text{ben}) P(Y = \text{ben})}$$

$$= \frac{P(x_1 = \text{cir} | Y = \text{mal}) P(x_2 = \text{sm} | Y = \text{mal}) P(x_3 = \text{li} | Y = \text{mal})}{P(x_1 = \text{cir} | Y = \text{mal}) P(x_2 = \text{sm} | Y = \text{mal}) P(x_3 = \text{li} | Y = \text{mal}) + P(x_1 = \text{cir} | Y = \text{ben}) P(x_2 = \text{sm} | Y = \text{ben}) P(x_3 = \text{li} | Y = \text{ben})}$$

$$= \frac{P(x_1 = \text{cir} | Y = \text{mal}) P(x_2 = \text{sm} | Y = \text{mal}) P(x_3 = \text{li} | Y = \text{mal})}{P(x_1 = \text{cir} | Y = \text{mal}) P(x_2 = \text{sm} | Y = \text{mal}) P(x_3 = \text{li} | Y = \text{mal}) + P(x_1 = \text{cir} | Y = \text{ben}) P(x_2 = \text{sm} | Y = \text{ben}) P(x_3 = \text{li} | Y = \text{ben})}$$

$$P(Y = \text{mal}) = \frac{N_{\text{mal}}}{N} = 0.5$$

$$P(Y = \text{benign}) = \frac{N_{\text{ben}}}{N} = 0.5$$

$$P(X_1 = \text{cir} | Y = \text{mal}) = \frac{3}{5} \quad P(X_1 = \text{cir} | Y = \text{benign}) = \frac{2}{5}$$

$$P(X_2 = \text{sm} | Y = \text{mal}) = \frac{1}{5} \quad P(X_2 = \text{sm} | Y = \text{ben}) = \frac{3}{5}$$

$$P(X_3 = \text{li} | Y = \text{mal}) = \frac{2}{5} \quad P(X_3 = \text{li} | Y = \text{ben}) = \frac{3}{5}$$

$$P(Y = \text{mal} | X = \{\text{cir}, \text{sm}, \text{li}\})$$

$$= 0.5 * \frac{3}{5} * \frac{1}{5} * \frac{2}{5}$$

$$+ 0.5 * \frac{2}{5} * \frac{3}{5} * \frac{3}{5}$$

$$= \frac{6}{6 + 18} = \underline{\underline{0.25}}$$

Y is Benign

A continuous equivalent of NBC

Quadratic Discriminant Analysis

Linear Discriminant Analysis



QDA / LDA