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HOMEWORK 2.

1)
(a)

True Positive RATE = $\frac{\text{# True Positive Examples}}{\text{# of examples whose correctness is}}$

$$= \frac{\# TP}{\# TP + \# FN}$$

$$= \frac{0}{0 + 3}$$

$$= 0$$

(b)

False Positive Rate = $\frac{\# FP}{\# FP + \# TN}$

$$= \frac{1}{1 + 2} = \frac{1}{3}$$

(c)

accuracy = $\frac{\# TP + \# TN}{\# TP + \# TN + \# FP + \# FN}$

$$= \frac{86 + 41}{56 + 41 + 2 + 1} = \frac{97}{100} = 0.97$$

2)
Answer)

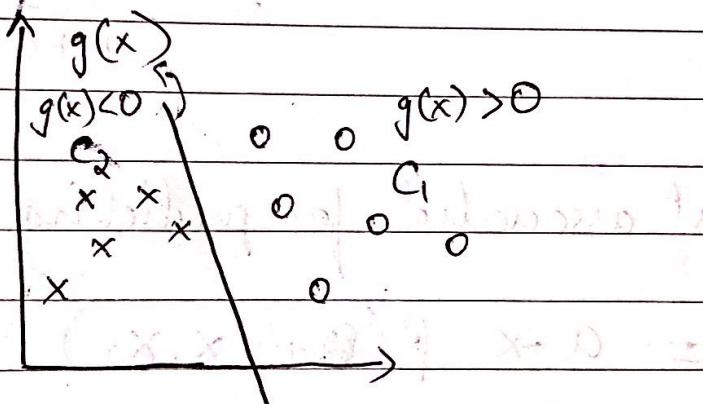
Now for the two classes we can take,

$$g_1(x) = 5x_2 + 3x_1 - 4 \text{ for class } C_1$$

$$g_2(x) = -3x_2 + 2x_1 - 6 \text{ for class } C_2$$

Now, we can generate $g(x)$ as:

$$g(x) = \begin{cases} C_1 & \text{if } g(x) > 0 \\ C_2 & \text{otherwise.} \end{cases}$$



since $g(x)$ will be line that separates
two classes.

$$\begin{aligned} g(x) &= g_1(x) - g_2(x) \\ &= (5x_2 + 3x_1 - 4) - (-3x_2 + 2x_1 - 6) \\ &= 5x_2 + 3x_1 - 4 + 3x_2 - 2x_1 + 6 \\ &= 8x_2 + x_1 + 2 \end{aligned}$$

$$w_2 = 8; w_1 = 1; w_0 = 2$$

$$A3) P(\text{Spam} | x_1, x_2) = \frac{1}{1 + e^{-(3x_2 - 2x_1 + 1)}}$$

given $x_2 = 2, x_1 = 3$

$$P(\text{Spam} | x_1, x_2) = \frac{1}{1 + e^{-(6 - 6 + 1)}} = \frac{e}{1 + e}$$

$$P(\text{Not Spam} | x_1, x_2) = 1 - P(\text{Spam})$$

$$= 1 - \frac{e}{1 + e}$$

$$= \frac{1}{1 + e}$$

Cost associated for predicting Not Spam

$$= a \times P(\text{Not Spam} | x_1, x_2)$$

$$= a \times \frac{e}{1 + e} = 5 \times \frac{e}{1 + e} = \frac{5e}{1 + e}$$

Cost associated for predicting Spam

$$= b \times P(\text{Spam} | x_1, x_2)$$

$$= 2 \times \frac{1}{1 + e} = \frac{2}{1 + e}$$

The Spam classification has lower risk:

$$\frac{2}{1 + e} < \frac{5e}{1 + e}$$

(a)

(b)

$$\text{Bias} = \text{Estimate} - \text{actual}$$

$$\text{Estimate} = \frac{\sum_{x \in X}^x}{N+1}$$

$$\text{Actual} = \frac{\sum_{x \in X}^x}{N}$$

$$\frac{\sum_{x \in X}^x}{N+1} - \frac{\sum_{x \in X}^x}{N} = \text{Bias}.$$

$$\frac{RI(\sum_{x \in X}^x) - [N(\sum_{x \in X}^x) + (\sum_{x \in X}^x)]}{(N+1)N} = \text{Bias}$$

$$- \frac{\sum_{x \in X}^x}{(N+1)N} = \text{Bias}.$$

(b) Even for β which is an exponential distribution the answer wouldn't change

Bias would still be estimate - actual

So bias would not change

MLE estimate with $\hat{\lambda} = \arg \min L(\lambda | \bar{x})$
 $\Rightarrow \hat{\lambda} = \bar{Y}_X$
where \bar{x} is mean.

Q5

For class +

$$\hat{p} = \frac{\sum_{t=1}^N x^+}{N}$$

$$\hat{p}_{x_1} = \frac{2.7 + 3.2 - 0.4}{3} = 1.833$$

$$\hat{p}_{x_2} = \frac{0.6 + 1.8 + 2.1}{3} = 1.5$$

For class -

$$\hat{p}_{x_1} = \frac{0.6 + 1.8 + 2.1}{3} = 1.5$$

$$\hat{p}_{x_2} = \frac{0.5 + 2.8 + 4.3}{3} = 2.53$$

$$\sum_{t=1}^N x^+ = \frac{1}{N} \begin{bmatrix} x_{11}^+ - m_{x_1}^+ & x_{12}^+ - m_{x_1}^+ & x_{13}^+ - m_{x_1}^+ \\ x_{21}^+ - m_{x_2}^+ & x_{22}^+ - m_{x_2}^+ & x_{23}^+ - m_{x_2}^+ \end{bmatrix} X$$

$$N = 3$$

$$\begin{bmatrix} x_{11}^+ - m_{x_1}^+ & m_{21}^+ - m_{x_2}^+ \\ x_{12}^+ - m_{x_1}^+ & m_{22}^+ - m_{x_2}^+ \\ x_{13}^+ - m_{x_1}^+ & x_{23}^+ - m_{x_1}^+ \end{bmatrix}$$

$$= \frac{1}{3} \begin{bmatrix} 27 - 21.833 & 8.2 - 1.833 & -(0.4) - 1.833 \\ 4.8 - 3.2 & 5.1 - 3.2 & -(6.3) - 3.2 \end{bmatrix}$$

$$\begin{bmatrix} 27 - 1.833 & 4.8 - 3.2 \\ 3.2 - 1.833 & 5.1 - 3.2 \\ -0.4 - 1.833 & -(0.3) - 3.2 \end{bmatrix}$$

$$= \frac{1}{3} \begin{bmatrix} 27 - 21.833 & 3.2 - 1.833 & -(0.4) - 1.833 \\ 4.8 - 3.2 & 5.1 - 3.2 & -(0.3) - 3.2 \end{bmatrix}$$

$$\begin{bmatrix} 0.867 & 1.6 \\ 1.367 & 1.9 \\ -2.233 & -3.5 \end{bmatrix}$$

$$= \begin{bmatrix} 2.533 & 3.933 \\ 3.933 & 6.14 \end{bmatrix}$$

$$\sum = \frac{1}{3} \begin{bmatrix} 0.6 - 1.5 & 1.8 - 1.5 & 2.1 - 1.5 \\ 0.5 - 2.533 & 2.8 - 2.533 & 4.3 - 2.533 \end{bmatrix} \begin{bmatrix} 0.6 - 2.5 & 0.5 - 2.533 \\ 1.8 - 1.5 & 2.8 - 2.533 \\ 2.1 - 1.5 & 4.3 - 2.533 \end{bmatrix}$$

$$= \begin{bmatrix} 0.42 & 0.91 \\ 0.91 & 2.4422 \end{bmatrix}$$

(56)
A)

$$\log p(x|+) = \log \left[\frac{1}{(2x)^{d/2} |\sum|^{1/2}} e^{\frac{1}{2} (x-p)^\top \sum^{-1} (x-p)} \right]$$

d=2

$$|\sum| = \begin{vmatrix} 2.535 & 3.933 \\ 3.933 & 6.14 \end{vmatrix} = 0.096411$$

$$\sum^{-1} = \begin{bmatrix} 63.6857 & -40.794 \\ -40.794 & 26.2937 \end{bmatrix}$$

$$y = \begin{bmatrix} 1.6 \\ 2.3 \end{bmatrix} \quad p_t = \begin{bmatrix} 1.833 \\ 3.2 \end{bmatrix}$$

$$\log p(x|+) = \log e^{-\frac{1}{2}} \begin{bmatrix} 1.6 - 1.833 & 2.3 - 3.2 \\ -40.794 & 26.2937 \end{bmatrix} \begin{bmatrix} 13.8817 - 40.794 \\ -40.794 26.2937 \end{bmatrix}$$

$$\begin{bmatrix} 1.6 - 1.83 \\ 2.3 - 3.2 \end{bmatrix}$$

$$\log ((2 \times 3.14)^{1/2} \times (0.096411)^{1/2})$$

$$= \log_e^{1/2} [7.646] - \cancel{10.581} - 1.95093$$

$$= \cancel{\log_e^{1/2} 7.646} - \cancel{10.581} \\ - 14.88111 = -5.77406$$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.42 & 0.99 \\ 0.99 & 2.4422 \end{bmatrix}$$

$$|\Sigma| = 0.046191$$

$$\begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} = \begin{bmatrix} 0.42 & 0.99 \\ 0.99 & 2.4422 \end{bmatrix} \quad -0.08572$$

$$\Sigma = \begin{bmatrix} 53.5287 & 21.679 \\ -21.699 & 9.205 \end{bmatrix}$$

$$x = \begin{bmatrix} 1.6 \\ 2.3 \end{bmatrix} \quad K = \begin{bmatrix} 1.5 \\ 2.533 \end{bmatrix}$$

$$\log P(x) = \log e^{-\frac{1}{2}} \left[\begin{bmatrix} 1.6 - 1.5 & 2.3 - 2.533 \end{bmatrix} \begin{bmatrix} 53.5287 - 21.699 & 9.205 \end{bmatrix} \right]$$

$$\begin{bmatrix} 1.6 - 1.5 \\ 2.3 - 2.533 \end{bmatrix}$$

$$= \log \left(\frac{1}{2} (0.046191) \right) - \log (1.34207)$$

$$= \frac{1}{2} (\log (0.046191) - \log (1.34207))$$

$$= -1.3$$

using ML hypothesis

we can conclude,

$$\operatorname{argmax}_{\Theta} [\log p(x|+), \log p(x|-)]$$

\Rightarrow -ve class is the predicted class.

(~~Σ~~) $\log p(x|-) = -1.3$

$$\log p(x|+) = -5.77406$$

$$|\Sigma_+| = 0.09641$$

$$|\Sigma_-| = 0.045624$$

$$\therefore \log p(x|-) > \log p(x|+)$$

if belongs to negative class

(c)

A(i) Under some circumstances, the attributes do

not have much relation with tokens.

Therefore distribution or variance may be very similar. we can consider them as one

for example: like ";" tokens in the reviews.

(ii) However, there are many other situations that covariance matrix differs a lot under different labels.

For example: Frequency of positive words in a single review may have more impact.

(b)
2) (a) In linear regression, we have a linear model

$$g(x^t | w_1, w_0) = w_1 x^t + w_0$$

and after taking the derivative of sum of squares error w.r.t w_1 and w_0 , we get,

$$\sum g_t^t = Nw_0 + w_1 \sum x^t$$

$$\sum g_t x^t = w_0 \sum x^t + w_1 \sum (x^t)^2.$$

which can be written in vector matrix form

as $\mathbf{w} = \mathbf{y}$ where

$$\mathbf{A} = \begin{bmatrix} N & \sum x^t \\ \sum x^t & \sum (x^t)^2 \end{bmatrix}, \mathbf{w} = \begin{bmatrix} w_0 \\ w_1 \end{bmatrix}, \mathbf{y} = \begin{bmatrix} \sum g_t^t \\ \sum g_t x^t \end{bmatrix}$$

can be solved as $\mathbf{w} = \mathbf{A}^{-1} \mathbf{y}$

$$N = 10$$

$$A = \begin{bmatrix} 10 & 7221 \\ 7221 & 6500115 \end{bmatrix} \quad Y = \begin{bmatrix} 527 \\ 477908 \end{bmatrix}$$

$$|A| = \boxed{12858309}$$

We know for 2×2 matrix,

$$\begin{bmatrix} a & b \\ c & d \end{bmatrix}^{-1} = \frac{1}{ad - bc} \begin{bmatrix} d & -b \\ -c & a \end{bmatrix}$$

↓ determinant

So for A we get

$$A^{-1} = \frac{1}{|A|} \times \begin{bmatrix} 6500115 & -7221 \\ -7221 & 10 \end{bmatrix}$$

$$A^{-1} = \begin{bmatrix} \frac{6500115}{12858309} & \frac{-7221}{12858309} \\ \frac{-7221}{12858309} & \frac{10}{12858309} \end{bmatrix}$$

~~$$A^{-1} = \begin{bmatrix} 0.00001 & -0.000562 \\ -0.000562 & 0.00001 \end{bmatrix}$$~~

$$W = \bar{A}^{-1} Y$$

$$= \begin{bmatrix} \frac{6500115}{12858309} & \frac{-7221}{12858309} \\ \frac{-7221}{12858309} & \frac{10}{12858309} \end{bmatrix} \begin{bmatrix} 527 \\ 477908 \end{bmatrix}$$

$$W = \begin{bmatrix} -8471021 \\ 4286103 \\ 973613 \\ 12858309 \end{bmatrix}$$

$$w_0 = \frac{-8471021}{4286103} = -1.9763$$

$$w_1 = \frac{973613}{12858309} = 0.075717$$

$$g(x) = (0.075717)x - 1.9763$$

$$(b) \quad x = 475$$

$$\begin{aligned} g(x) &= (0.075717)x475 - 1.9763 \\ &= 35.9665 - 1.9763 \\ &= 33.99 \end{aligned}$$

≈ 34 stems

7
a)

Original dataset

x_1	x_2	Label
2.5	42	+
3.8	51	+
-0.3	-1	+
0.7	3	-
1.6	26	-
2.3	41	-

Scaling formula: $x_i' = \frac{x_i - x_i^{\min}}{x_i^{\max} - x_i^{\min}}$

Scaled dataset

x_1	x_2	label
0.68	0.83	+
1.00	1.00	+
0.00	0	+
0.24	0.08	-
0.46	0.52	-
0.63	0.80	-

~~Exercises~~

$$x_{21}(\text{scaled}) = \frac{42 - (-1)}{51 - (-1)} = \frac{43}{52} = 0.83$$

$$x_{22} = \frac{51 - (-1)}{51 - (-1)} = \frac{52}{52} = 1$$

$$x_{23} = \frac{-1 - (-1)}{51 - (-1)} = \frac{0}{52} = 0$$

$$x_{24} = \frac{3 - (-1)}{51 - (-1)} = \frac{4}{52} = 0.08$$

$$x_{25} = \frac{26 - (-1)}{51 - (-1)} = \frac{27}{52} = 0.52$$

$$x_{26} = \frac{41 - (-1)}{51 - (-1)} = \frac{42}{52} = 0.80$$

x(b)

$$\text{Test data } x = \begin{bmatrix} 3.9 \\ 4 \end{bmatrix} \Rightarrow x_1 = 3.9, x_2 = 4.$$

$$\text{Scaling formula} : x_i = \frac{x_i - x_{i\min}}{x_{i\max} - x_{i\min}}$$

$$\text{Scaled Test data} : x = \begin{bmatrix} 1.02 \\ 0.096 \end{bmatrix}$$

$$x_1 = \frac{3.9 - (-0.3)}{3.8 - (-0.3)} = \frac{4.2}{4.1} = 1.02$$

$$x_2 = \frac{4 - (-1)}{51 - (-1)} = \frac{5}{52} = 0.096$$

Now we calculate the Euclidian distance
to all the scaled attributes to $(1.02, 0.096)$

for class = + ;

$$(x_1, x_2) = (0.68, 0.83) ; \text{class } +$$

$$\begin{aligned} E.D. &= \sqrt{(0.68 - 1.02)^2 + (0.096 - 0.83)^2} \\ &= 0.808 \end{aligned}$$

$$(x_1, x_2) = (1, 1) ; \text{class } +$$

$$E.D. = \sqrt{(1 - 1.02)^2 + (1 - 0.096)^2} = 0.904$$

$$(x_1, x_2) = (0, 0)$$

$$E.D. = \sqrt{(1.02)^2 + (0.096)^2} = 1.0245$$

~~(x_1, x_2)~~ For class = - ;

$$(x_1, x_2) = (0.24, 0.08)$$

$$\begin{aligned} ED &= \sqrt{(1.02 - 0.24)^2 + (0.096 - 0.08)^2} \\ &= 0.78 \end{aligned}$$

$$(x_1, x_2) = (0.46, 0.52)$$

$$ED = 0.702$$

$$(x_1, x_2) = (0.63, 0.80)$$

$$\begin{aligned} ED &= \sqrt{(0.63 - 1.02)^2 + (0.80 - 0.096)^2} \\ &= 0.804 \end{aligned}$$

From the above results, we can see that

ED is lowest when $(x_1, x_2) = (0.46, 0.52)$

So the predicted label is " "