

CSC 5521 – Intro to Machine Learning

HW1

Saksham Goel

goelx029 | 5138568

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CSC7 5521
Homework 1

①

Name - Saksham Goel

ID - goelx029 / 5138568

Q1 Let - D = Event that a person has the disease
 $+$ = Event that the checkup comes '+' for disease
 $-$ = " " " " " '-' for disease

Given:

$$P(D) = 1/10000$$

$$P(+|D) = 0.983 \quad \left. \begin{array}{l} \text{know} \\ P(+|D) + P(-|D) = 1 \end{array} \right\}$$

$$P(\bar{D}) = 9999/10000$$

$$P(-|D) = 0.017$$

$$P(+|\bar{D}) = 0.055 \quad \left. \begin{array}{l} \text{know} \\ P(+|\bar{D}) + P(-|\bar{D}) = 1 \end{array} \right\}$$

$$P(-|\bar{D}) = 0.945$$

Need to find

$$\begin{aligned} a) P(D|+) &= \frac{P(+|D) P(D)}{P(+|D) P(D) + P(+|\bar{D}) P(\bar{D})} = \frac{0.983 \times 10^{-4}}{0.983 \times 10^{-4} + 0.055 \times 9999 \times 10^{-4}} \\ &= \frac{0.983}{0.983 + 549.945} = \frac{0.983}{550.928} \approx 0.00178 \\ &\quad \boxed{0.178\%} \text{ chances.} \end{aligned}$$

$$\begin{aligned} b) C(T|\bar{D}) &= 1000 \\ C(\bar{T}|D) &= 1000000 \\ C(T|D) &= 0 \\ C(\bar{T}|\bar{D}) &= 0 \end{aligned} \quad \left. \begin{array}{l} \text{Expected Cost of Treatment} \\ \text{(when you test first)} \end{array} \right\} \begin{aligned} &= C(T|\bar{D}) P(\bar{D}) + C(\bar{T}|D) P(D) \\ &= 1000 \times 0.9999 + 0 \times 0.0001 \\ &= \boxed{999.9} \\ E(C(\bar{T})) &= C(\bar{T}|\bar{D}) P(\bar{D}) + C(\bar{T}|D) P(D) = 1000000 \times \frac{1}{10000} = 100 \end{aligned}$$

$$c) \frac{E(T|+)}{\downarrow}$$

Expected cost given + test

$$\begin{aligned} E(T|+) &= E(T|D) P(D|+) + E(T|\bar{D}) P(\bar{D}|+) \\ &= 0 \times 0.00178 + 1000 \times 0.99822 \\ &= \boxed{\$998.22} \end{aligned}$$

d) We know

$$E(T) = \$999.9$$

$$E(T|+) = \$998.22$$

finding

$$\begin{aligned} E(\bar{T}|+) &= E(\bar{T}|D) P(D|+) + E(\bar{T}|\bar{D}) P(\bar{D}|+) \\ &= 1000000 \times 0.00178 + 0 \times 0.99822 \\ &= \$1780 \end{aligned}$$

So as $E(T|+)$ is the least = \$998.22, we can say going for a treatment when tested +ve for the disease is the least risky option.

$$e) E(\bar{T}|-) = E(\bar{T}|D) P(D|-) + E(\bar{T}|\bar{D}) P(\bar{D}|-)$$

using Bayes theorem to find

$$\begin{aligned} P(D|-) &= \frac{P(-|D)P(D)}{P(-|D)P(D) + P(-|\bar{D})P(\bar{D})} = \frac{0.017 \times 10^{-4}}{0.017 \times 10^{-4} + 0.945 \times 9999 \times 10^{-4}} = \frac{0.017}{9449.072} \\ &= 1.8 \times 10^{-6} \end{aligned}$$

$$\Rightarrow E(\bar{T}|-) = 1000000 \times 1.8 \times 10^{-6} + 0 \times (1 - 1.8 \times 10^{-6})$$

$$\boxed{E(\bar{T}|-) = \$1.8}$$

Q2 a) given $P(x|C_1) = \begin{cases} \frac{1}{4} & 0 \leq x < 4 \\ 0 & \text{otherwise} \end{cases}$

$$P(x|C_2) = \begin{cases} x-1 & 1 \leq x < 2 \\ 3-x & 2 \leq x < 3 \\ 0 & \text{otherwise} \end{cases}$$

$$P(C_1) = P(C_2) = 0.5$$

then

$$P(C_1|x=1.5) = \frac{P(x=1.5|C_1) \times P(C_1)}{P(x=1.5|C_1)P(C_1) + P(x=1.5|C_2)P(C_2)} = \frac{\frac{1}{4}}{\frac{1}{4} + \frac{1}{2}} = \boxed{\frac{1}{3}}$$

$$P(C_2|x=1.5) = \frac{P(x=1.5|C_2)P(C_2)}{P(x=1.5|C_1)P(C_1) + P(x=1.5|C_2)P(C_2)} = \frac{\frac{1}{2}}{\frac{1}{4} + \frac{1}{2}} = \boxed{\frac{2}{3}}$$

as $P(C_2|x=1.5) > P(C_1|x=1.5)$ [class = 2] or $\log\left(\frac{P(C_1|x)}{P(C_2|x)}\right) = \log\left(\frac{\frac{1}{3}}{\frac{2}{3}}\right) = \log\left(\frac{1}{2}\right) < 0$ hence $\boxed{C_2}$

$$b) P(C_1|x=1.5) = \frac{P(x=1.5|C_1)P(C_1)}{P(x=1.5|C_1)P(C_1) + P(x=1.5|C_2)P(C_2)} = \frac{\frac{1}{4} \times \frac{3}{4}}{\frac{1}{4} \times \frac{3}{4} + \frac{3}{4} \times \frac{1}{4}} = \boxed{\frac{3}{5}}$$

$$P(C_2|x=1.5) = \frac{P(x=1.5|C_2)P(C_2)}{P(x=1.5|C_1)P(C_1) + P(x=1.5|C_2)P(C_2)} = \frac{\frac{2}{4} \times \frac{1}{4}}{\frac{1}{4} \times \frac{3}{4} + \frac{3}{4} \times \frac{1}{4}} = \boxed{\frac{2}{5}}$$

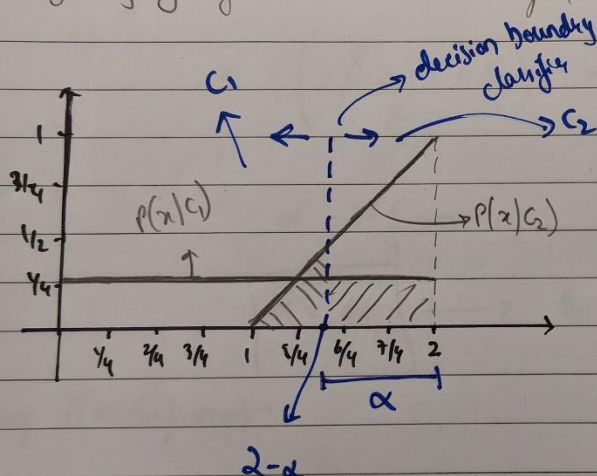
as $\log\left(\frac{P(C_1|x)}{P(C_2|x)}\right) = \log\left(\frac{\frac{3}{5}}{\frac{2}{5}}\right) = \log\left(\frac{3}{2}\right) > 0$ hence

C_1 is the class

c) Our new classifier is given by the following definition:

$$x \rightarrow \begin{cases} C_2 & \phi(x) < 0 \\ C_1 & \phi(x) \geq 0 \end{cases} \quad \text{where} \quad \phi(x) = |x-2| - \alpha$$

This leads to the following definition $\rightarrow C_2$ if $2-\alpha \leq x \leq 2+\alpha$ else C_1 ,
drawing this on graph using the
Symmetry of given distribution & classifier



Given this classifier the probability of misclassification can be given by \Rightarrow

Probability of an object of C_1 with $x > 2-\alpha$
+ Prob. " " " " C_2 with $x < 2+\alpha$

\rightarrow equivalent to finding the areas covered by the probability density function of each class in the region where misclassified.

$$P(\text{Misclassification}) = P(\text{Misclassifying } C_2 \text{ as } C_1) + P(\text{Misclassifying } C_1 \text{ as } C_2)$$

$$= \int_1^{2-\alpha} P(x|C_2) P(C_2) dx + \int_{2-\alpha}^2 P(x|C_1) P(C_1) dx \times 2 \quad (\text{account for symmetry})$$

$$= \left\{ \int_1^{2-\alpha} (x-1) dx + \int_{2-\alpha}^2 \frac{1}{4} dx \right\} \times \frac{2}{2} = \left\{ \left[\frac{x^2}{2} - x \right]_1^{2-\alpha} + \left[\frac{1}{4} x \right]_{2-\alpha}^2 \right\}$$

$$P(\text{misclassification}) = \left\{ \left\{ \frac{(2-\alpha)^2}{2} - (2-\alpha) + \frac{1}{2} + 1 \right\} + \left\{ \frac{1}{4} (2-2+\alpha)^2 \right\} \right\}$$

$$= \left(\frac{(2-\alpha)^2}{2} + \frac{5\alpha}{4} - \frac{3}{2} \right)$$

Now Minimizing $P(\text{misclassification}) \rightarrow \min_{\alpha} P(\text{misclassification})$

$$\frac{dP(\text{miscl})}{d\alpha} = \frac{d}{d\alpha} \left(\frac{(2-\alpha)^2}{2} + \frac{5\alpha}{4} - \frac{3}{2} \right) = 0$$

$$= \left(-\frac{2(2-\alpha)}{2} + \frac{5}{4} \right) = 0$$

$$= \alpha - 2 + \frac{5}{4} = 0$$

$\boxed{\alpha = 3/4} \rightarrow$ this gives us our optimal boundary.

Finding $P(\text{Misclassification}) \rightarrow$

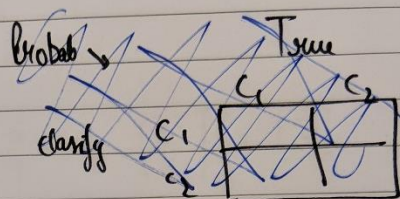
$$P(\text{Miscl}) = \left\{ \frac{(2-\alpha)^2}{2} + \frac{5\alpha}{4} - \frac{3}{2} \right\} = \left\{ \frac{(2-3/4)^2}{2} + \frac{5 \times 3}{4} - \frac{3}{2} \right\}$$

$$= \left(\frac{25}{32} + \frac{15}{16} - \frac{3}{2} \right) = \frac{25+30-48}{16}$$

$$= \frac{55-48}{16} = \boxed{\frac{7}{16}}$$

d) Cost \rightarrow

		True	
		G_1	G_2
classified	G_1	-5	+1
	G_2	+3	-5



Expected cost $\rightarrow -5 \times P(\text{correct classify } G_1) - 5 \times P(\text{correct classify } G_2)$
 $+ 3 \times P(\text{Wrong classify } G_1 \text{ as } G_2) + 1 \times P(\text{Wrong classify } G_2 \text{ as } G_1)$

$$E(\text{cost}) = \int_{2-\alpha}^{2-\alpha} -5x \int_0^{2-\alpha} P(x|G_1) P(G_1) dx - 5x \int_0^{2-\alpha} P(x|G_2) P(G_2) dx$$

$$+ 3x \int_{2-\alpha}^2 P(x|G_1) P(G_1) dx + 1x \int_1^{2-\alpha} P(x|G_2) P(G_2) dx \quad \text{symmetric}$$

$$= -5 \int_0^{2-\alpha} \frac{1}{4} dx - 5 \int_{2-\alpha}^2 (x-1) dx + 3 \int_{2-\alpha}^2 \frac{1}{4} dx + 1 \int_1^{2-\alpha} (x-1) dx$$

$$= \frac{-5(2-\alpha)}{4} - 5 \left(\frac{(2-\alpha) - (2-\alpha)^2}{2} \right) + \frac{3\alpha}{4} + \left(\frac{(2-\alpha)^2 - (2-\alpha) - \frac{1}{2} + 1}{2} \right)$$

$$= \frac{-5(2-\alpha)}{4} - 5(2-\alpha) + \frac{5(2-\alpha)^2}{2} + \frac{3\alpha}{4} + \frac{(2-\alpha)^2 - (2-\alpha) + \frac{1}{2}}{2}$$

$$= (2-\alpha) \left(\frac{-5}{4} - 5 - 1 \right) + (2-\alpha)^2 \left(\frac{5}{2} + \frac{1}{2} \right) + \frac{3\alpha}{4} + \frac{1}{2}$$

$$= \frac{3(2-\alpha)^2 - 29(2-\alpha) + \frac{3\alpha}{4} + \frac{1}{2}}{4} = \boxed{3(2-\alpha)^2 + 8\alpha - 14}$$

finds $\min_{\alpha} E(\text{cost}) \Rightarrow \frac{d}{d\alpha} E(\text{cost}) = 0$

$$\Rightarrow -6(2-\alpha) + 8 = 0$$

$$\Rightarrow -12 + 6\alpha + 8 = 0$$

$$\frac{d}{d\alpha} (3(2-\alpha)^2 + 8\alpha - 14) = 0$$

$$\boxed{\alpha = \frac{4}{6}} \quad \boxed{\alpha = \frac{2}{3}}$$

$$\begin{aligned}
 e) E(x|c_1) &= \int_0^4 x P(x|c_1) dx \\
 &= \int_0^4 x \frac{1}{4} dx = \int_0^4 \frac{x}{4} dx = \left[\frac{x^2}{8} \right]_0^4 = \boxed{2}
 \end{aligned}$$

$$\begin{aligned}
 E(x|c_2) &= \int_0^4 x P(x|c_2) dx \\
 &= \int_0^2 x P(x|c_2) dx + \int_2^3 x P(x|c_2) dx \\
 &= \int_0^2 (x^2 - x) dx + \int_2^3 (3x - x^2) dx \\
 &= \left[\frac{x^3}{3} - \frac{x^2}{2} \right]_0^2 + \left[\frac{3x^2}{2} - \frac{x^3}{3} \right]_2^3 \\
 &= \left[\frac{8}{3} - \frac{4}{2} - \frac{1}{3} + \frac{1}{2} \right] + \left[\frac{27}{2} - \frac{27}{3} - \frac{12}{2} + \frac{8}{3} \right] \\
 &= \left[\frac{7}{6} - \frac{3}{2} \right] + \left[\frac{15}{2} - \frac{11}{3} \right] = \frac{6}{2} - \frac{4}{3} = \boxed{2}
 \end{aligned}$$

for $\text{Var}(x|c_1)$ find $E(x|c_1)^2$ first

$$E(x|c_1)^2 = \int_0^4 x^2 \frac{1}{4} dx = \left[\frac{x^3}{12} \right]_0^4 = \frac{64}{12}$$

$$\text{Var}(x|c_1) = E(x|c_1)^2 - (E(x|c_1))^2 = \frac{64}{12} - 2^2 = \frac{64-48}{12} = \boxed{\frac{16}{12}}$$

for $\text{Var}(x|C_2)$ find $E((x|C_2)^2)$

$$E((x|C_2)^2) = \int_1^2 x^2(x-1)dx + \int_2^3 x^2(3-x)dx$$

$$= \int_1^2 (x^3 - x^2)dx + \int_2^3 (3x^2 - x^3)dx = \left[\frac{x^4}{4} - \frac{x^3}{3} \right]_1^2 + \left[x^3 - \frac{x^4}{4} \right]_2^3$$

$$= \left[\frac{16}{4} - \frac{8}{3} - \frac{1}{4} + \frac{1}{3} \right] + \left[27 - \frac{81}{4} - 8 + \frac{16}{4} \right]$$

$$= \frac{15}{4} - \frac{7}{3} + \frac{19}{4} - \frac{65}{4} = \frac{19}{3} - \frac{7}{3} - \frac{50}{4}$$

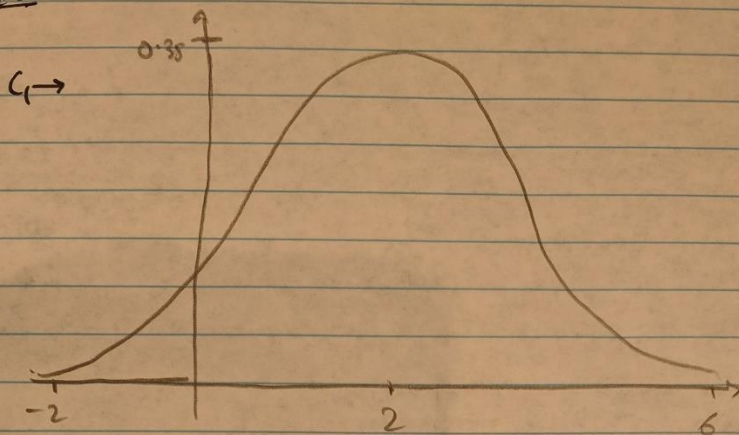
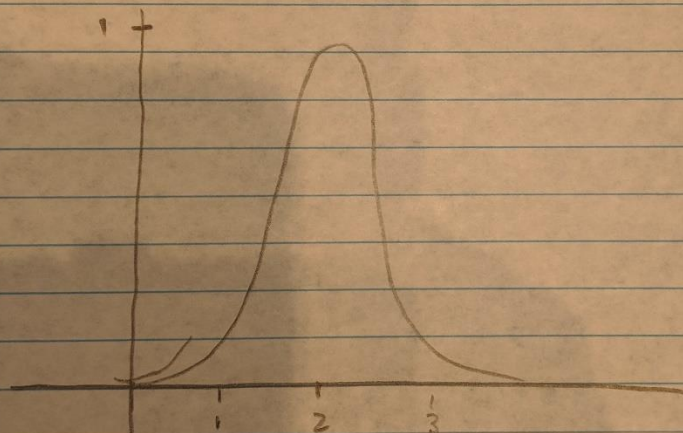
$$= \frac{228 - 28 - 150}{12} = \frac{50}{12}$$

$$\text{Var}(x|C_2) = E((x|C_2)^2) - (E(x|C_2))^2$$

$$= \frac{50}{12} - 4 = \frac{50 - 48}{12} = \frac{2}{12}$$

Standard Deviation $(x | C_1) = \sqrt{4/3} = 1.1547$

Standard Deviation $(x | C_2) = \sqrt{1/6} = 0.4082$

Q2 Plot $C_2 \rightarrow$ 

Q3 a) A classifier in this case is a function such that it takes in number x , and based on which bin it lies on, it gives the corresponding class. So a classifier can be supposed to have a mapping from bin no. to a class. Considering there are k total bins (sub-intervals) the map looks something like

Bin No	Class
1	1
2	2
3	2
⋮	⋮
k	1

mapping it as a binary no. when class 1 \rightarrow 0
class 2 \rightarrow 1

a classifier \rightarrow $\begin{array}{ccccccc} 1 & 0 & 0 & 1 & & & 1 \\ \hline & 1 & 2 & 3 & 4 & \dots & k \end{array}$

So the total no. of classifiers possible in hypothesis space H_k for given $k \rightarrow$

$$\boxed{|H_k| = 2^k} \rightarrow \text{total no. of binary no. possible.}$$

b) VC Dimension of H_k is equivalent $\rightarrow k$.

Reasoning:-

Consider k points, then ^{we} can put all k points in separate bins, then in H_k there always exist a classifier for each particular configuration of these k points which need to be classified.

Consider $k+1$ points, using pigeonhole principle we know that at least one bin (sub interval) would have at least two points. As soon as this happens no classifier would be able to exist or will exist in H_k such that it is able to correctly classify those two or more points if their original class is different from each other.

Hence H_k can shatter upto k points

94 formulas

$$\mu_1 = \frac{\sum_{i=1}^n X_{\text{train}}(i, :) \times I\{y_{\text{train}}(i) = 1\}}{\sum_{i=1}^n I\{y_{\text{train}}(i) = 1\}}$$

$$\mu_2 = \frac{\sum_{i=1}^n X_{\text{train}}(i, :) \times I\{y_{\text{train}}(i) = 2\}}{\sum_{i=1}^n I\{y_{\text{train}}(i) = 2\}}$$

$$S_1 = \frac{\sum_{i=1}^n (X_{\text{train}}(i, :) - \mu_1)^T (X_{\text{train}}(i, :) - \mu_1) \times I\{y_{\text{train}}(i) = 1\}}{\sum_{i=1}^n I\{y_{\text{train}}(i) = 1\}}$$

$$S_2 = \frac{\sum_{i=1}^n (X_{\text{train}}(i, :) - \mu_2)^T (X_{\text{train}}(i, :) - \mu_2) \times I\{y_{\text{train}}(i) = 2\}}{\sum_{i=1}^n I\{y_{\text{train}}(i) = 2\}}$$

here X_{train} = Dataset of the input features from training data \rightarrow Matrix

y_{train} = Dataset of the labels from training data, \rightarrow Column vector

$X_{\text{train}}(i, :)$ \rightarrow i^{th} Row \rightarrow row vector

$y_{\text{train}}(i)$ \rightarrow i^{th} element \rightarrow one element

$I\{\}$ \rightarrow Identity function, n = Total number of elements in training data
 m = # of elements in test data

$$\text{Error rate} = \frac{\sum_{i=1}^m I\{y_{\text{test}}(i) \neq y_{\text{pred}}(i)\}}{m}$$

```
[mu1, mu2, S1, S2, ConfusionMatrix, ErrorRate] = classify('./data/training_data.txt',  
'./data/test_data.txt')
```

mu1 =

```
1.0554  2.5181  3.2967 -1.8927 -1.3918  4.0635 -4.3540 -5.8705
```

mu2 =

```
3.8052  5.3740  5.7333  1.1596  1.1777  6.8000 -2.0286 -2.5044
```

S1 =

```
0.9729  0.7135  0.4570  0.8938  0.3096  0.1975  0.7362  1.6629  
0.7135  3.0658  2.5982  0.3878  1.2994  0.1442  0.9168  4.9388  
0.4570  2.5982  6.6612  0.9084  1.6397  0.8148  0.0779  5.4168  
0.8938  0.3878  0.9084  5.0754  0.0963  1.0611  2.3978  4.5946  
0.3096  1.2994  1.6397  0.0963  2.3973 -0.0191  0.2175  2.5378  
0.1975  0.1442  0.8148  1.0611 -0.0191  1.0412 -0.0531  1.8604  
0.7362  0.9168  0.0779  2.3978  0.2175 -0.0531  6.5154  3.8609  
1.6629  4.9388  5.4168  4.5946  2.5378  1.8604  3.8609 17.0931
```

S2 =

1.3486	0.8658	0.1559	0.5847	0.9473	0.2543	0.3705	0.9435
0.8658	2.8161	-0.1819	0.2152	0.7141	0.6797	-0.2383	2.4194
0.1559	-0.1819	6.6734	1.7716	1.0318	0.6526	1.6795	3.8992
0.5847	0.2152	1.7716	3.5433	0.3570	1.3665	2.1207	3.0899
0.9473	0.7141	1.0318	0.3570	2.7517	0.1225	1.4342	2.4651
0.2543	0.6797	0.6526	1.3665	0.1225	1.8107	0.3445	1.5113
0.3705	-0.2383	1.6795	2.1207	1.4342	0.3445	7.1134	2.6246
0.9435	2.4194	3.8992	3.0899	2.4651	1.5113	2.6246	13.9151

ConfusionMatrix =

24	11
6	59

ErrorRate =

0.1700