

**ASSIGNMENT 3**  
**CLL788**

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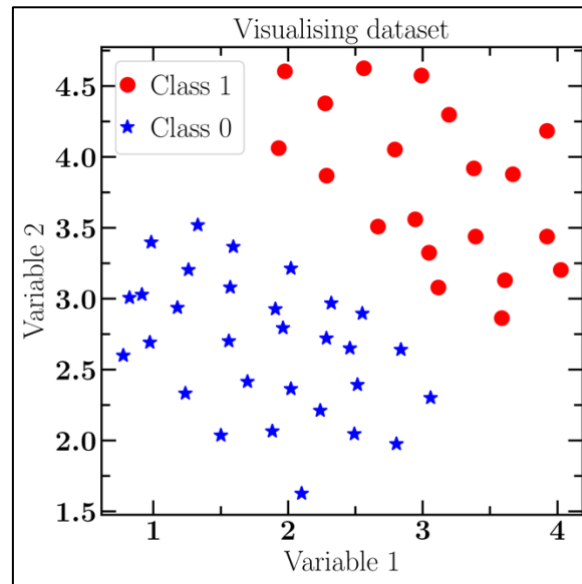
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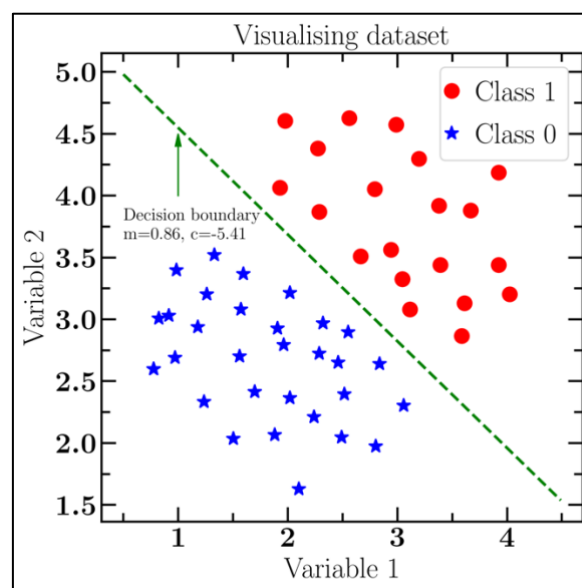
## Solution to Question 1

## 1) Visualizing training data (Data1.xlsx)

*Figure 1 – Visualizing training dataset*

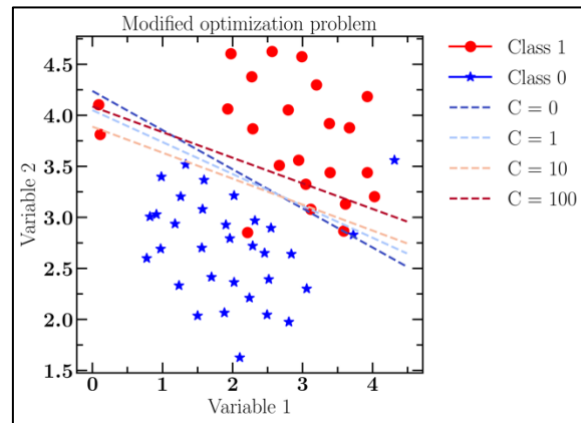
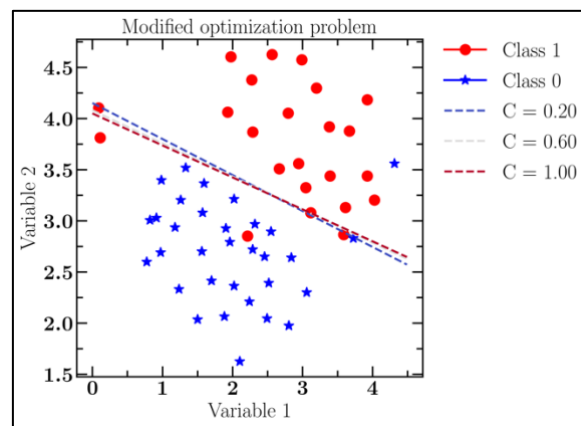
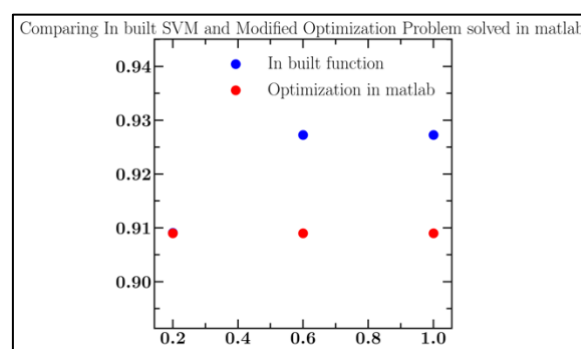
## Solution to Question 2

## 2.) Training data with decision boundary obtained by running vanilla version of SVM

*Figure 2 - SVM Result*

## Solution to Question 3

## 3.) Modified Optimization Problem

*Figure 3a – Comparing effect of  $C$* *Figure 4b – Comparing effect of  $C \leq 1$* *Figure 5c – Comparing effect of  $C \leq 1$* 

It has been observed from Figure 3a and 3b that number of misclassified points decreases when we enforce the optimization part strongly i.e. use **large C value**.

Also, we made an attempt in comparing our own optimization code and inbuilt SVM, the results hardly have a difference of 0.01 in accuracy which is equal to total correctly classified points/total number of points.

## Solution to Question 4

## 4.) Naïve Bayes Classification

Pre-requisites:

Probability	Value
<b>P(stolen = yes)</b>	0.5
<b>P(stolen = no)</b>	0.5
<b>P(red   stolen = yes)</b>	0.6
<b>P(red   stolen = no)</b>	0.4
<b>P(SUV   stolen = yes)</b>	0.2
<b>P(SUV   stolen = no)</b>	0.6
<b>P(domestic   stolen = yes)</b>	0.4
<b>P(domestic   stolen = no)</b>	0.6

Hence,

**P(stolen = yes | (Color = red, Type = SUV, Origin = Domestic))****= P(red | stolen=yes) x P(SUV | stolen=yes) x P(domestic | stolen=yes) x P(stolen=yes)**

$$= \frac{3}{5} \times \frac{1}{5} \times \frac{2}{5} \times \frac{1}{2}$$

$$= 0.6 \times 0.2 \times 0.4 \times 0.5$$

$$= 0.024$$

**P(stolen = no | (Color = red, Type = SUV, Origin = Domestic))****= P(red | stolen=no) x P(SUV | stolen=no) x P(domestic | stolen=no) x P(stolen=no)**

$$= \frac{2}{5} \times \frac{3}{5} \times \frac{3}{5} \times \frac{1}{2}$$

$$= 0.4 \times 0.6 \times 0.6 \times 0.5$$

$$= 0.072$$

By normalizing the above quantities to sum to one,

The conditional probability that the target value is no, given the observed attribute values =

$$\frac{0.072}{0.072 + 0.024} = 0.75$$

The conditional probability that the target value is yes, given the observed attribute values =

$$\frac{0.024}{0.072 + 0.024} = 0.25$$

Since, conditional probability of target value as No > conditional probability of target value as Yes

Thus, our example gets classified as 'NO' or

The STOLEN status for Red Domestic SUV will be highly YES.

## Solution to Question 5

## 5.) K-Means classification

## Iteration-1

Var1	Var2	Mean=x1	Mean=y1	Mean=x2	Mean=y2	D1	D2	CLASS
-1.54	2.29	0.5	1.5	-4.5	-5	2.19	7.87	1
-0.44	2.34	0.5	1.5	-4.5	-5	1.26	8.39	1
0.03	0.41	0.5	1.5	-4.5	-5	1.19	7.06	1
1.2	1.87	0.5	1.5	-4.5	-5	0.79	8.93	1
0.65	2.39	0.5	1.5	-4.5	-5	0.90	9.01	1
-4.67	-4.8	0.5	1.5	-4.5	-5	8.15	0.26	2
-3.37	-5.41	0.5	1.5	-4.5	-5	7.92	1.20	2
-3.93	-4.64	0.5	1.5	-4.5	-5	7.57	0.67	2
-4.78	-4.96	0.5	1.5	-4.5	-5	8.34	0.28	2
-4.12	-5.36	0.5	1.5	-4.5	-5	8.27	0.52	2

## Iteration-2

Var1	Var2	Mean=x1	Mean=y1	Mean=x2	Mean=y2	D1	D2	CLASS
-1.54	2.29	-0.02	1.86	-4.17	-5.03	1.58	7.78	1
-0.44	2.34	-0.02	1.86	-4.17	-5.03	0.64	8.27	1
0.03	0.41	-0.02	1.86	-4.17	-5.03	1.45	6.88	1
1.2	1.87	-0.02	1.86	-4.17	-5.03	1.22	8.75	1
0.65	2.39	-0.02	1.86	-4.17	-5.03	0.85	8.85	1
-4.67	-4.8	-0.02	1.86	-4.17	-5.03	8.12	0.55	2
-3.37	-5.41	-0.02	1.86	-4.17	-5.03	8.00	0.89	2
-3.93	-4.64	-0.02	1.86	-4.17	-5.03	7.59	0.46	2
-4.78	-4.96	-0.02	1.86	-4.17	-5.03	8.32	0.61	2
-4.12	-5.36	-0.02	1.86	-4.17	-5.03	8.30	0.33	2

## Iteration-3

Var1	Var2	Mean=x1	Mean=y1	Mean=x2	Mean=y2	D1	D2	CLASS
-1.54	2.29	-0.02	1.86	-4.17	-5.03	1.58	7.78	1
-0.44	2.34	-0.02	1.86	-4.17	-5.03	0.64	8.27	1
0.03	0.41	-0.02	1.86	-4.17	-5.03	1.45	6.88	1
1.2	1.87	-0.02	1.86	-4.17	-5.03	1.22	8.75	1
0.65	2.39	-0.02	1.86	-4.17	-5.03	0.85	8.85	1
-4.67	-4.8	-0.02	1.86	-4.17	-5.03	8.12	0.55	2
-3.37	-5.41	-0.02	1.86	-4.17	-5.03	8.00	0.89	2
-3.93	-4.64	-0.02	1.86	-4.17	-5.03	7.59	0.46	2
-4.78	-4.96	-0.02	1.86	-4.17	-5.03	8.32	0.61	2
-4.12	-5.36	-0.02	1.86	-4.17	-5.03	8.30	0.33	2

Center of Cluster 1 = (-0.02,1.86)

Center of Cluster 2 = (-4.17,-5.03)