KJ’S Educational Institutes

TRINITY ACADEMY OF ENGINEEIRNG, PUNE

(Accredited with ‘A’ grade by NAAC)

Department of MCA

LABORATORY MANUAL

Machine Learning Laboratory

(Subject Code: 410904B)

For the Academic Year 2022 - 2023

SYMCA- Semester I

Teaching Scheme:
PR: 04Hours/Week

Credit 02

Examination Scheme:
TW:25Marks
PR: 50 Marks

PROGRAM OUTCOMES	
PO No.	**Program Outcome Description**
PO 1	Apply knowledge of mathematics, computer science, computing specializations appropriate for real world applications.
PO 2	Identify, formulate, analyze and solve *complex* computing problems using relevant domain disciplines.
PO 3	Design and evaluate solutions for *complex* computing problems that meet specified needs with appropriate considerations for real world problems.
PO 4	Find solutions of complex computing problems using design of experiments, analysis and interpretation of data.
PO 5	Apply appropriate techniques and modern computing tools for development of complex computing activities.
PO 6	Apply professional ethics, cyber regulations and norms of professional computing practices.
PO 7	Recognize the need to have ability to engage in independent and life-long learning in the broadest context of technological change.
PO 8	Demonstrate knowledge and understanding of the computing and management principles and apply these to one's own work, as a member and leader in a team, to manage projects and in multidisciplinary environments.
PO 9	Communicate effectively with the computing community and with society at large, such as, being able to comprehend and write effective reports and design documentation, make effective presentations, and give and receive clear instructions.
PO 10	Assess societal, environmental, health, safety, legal and cultural issues within local and global contexts, and the consequent responsibilities relevant to the professional computing practices.
PO 11	Function effectively as an individual, and as a member or leader in diverse teams, and in multidisciplinary environments.
PO 12	Identify a timely opportunity and use innovation, to pursue opportunity, as a successful Entrepreneur /professional.

OBJECTIVE:

- To introduce machine learning techniques.
- Understanding Human learning aspects.
- Understanding primitives and methods in learning process by computer.
- Understanding nature of problems solved with Machine Learning.
- To become aware of various logic based and algebraic models in machine learning.
- To learn state-of-art dimensionality trends in machine learning.

Course Outcomes	
CO 1	Model the learning primitives.
CO 2	Build the learning model.
CO 3	Tackle real world problems in the domain of Data Mining and Big Data Analytics, Information retrieval, Computer vision, Linguistics and Bioinformatics.
CO 4	Devise/develop machine learning model for real time applications.
CO 5	Evaluate a given problem and apply appropriate machine learning technique to gain knowledge from the problem.
CO 6	Develop skills of using recent machine learning techniques and solve practical problems.

Guidelines for Student Journal:

- The laboratory assignments are to be submitted by student in the form of journal.
- Journal consists of prologue, Certificate, table of contents, and **handwritten write-up** of each assignment (Title, Objectives, Problem Statement, Outcomes, software & Hardware requirements, Date of Completion, Assessment grade/marks and assessor's sign, Theory-Concept in brief conclusion/analysis.
- Program codes with sample output of all Performed assignments are to be submitted as softcopy. As a conscious effort and little contribution towards Green IT and environment awareness, attaching printed papers as part of write-ups and program listing to journal may be avoided. Use of DVD containing students' programs maintained by lab In-charge is highly encouraged. For reference one or two journals may be maintained with program prints at Laboratory.

Sample Programs:

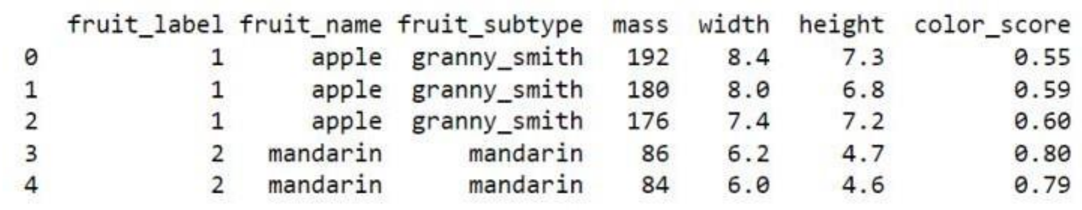
Practical No:01

Aim : On the fruit dataset, compare the performance of Logistic Regression, SVM, KNN on the basis of their accuracy.

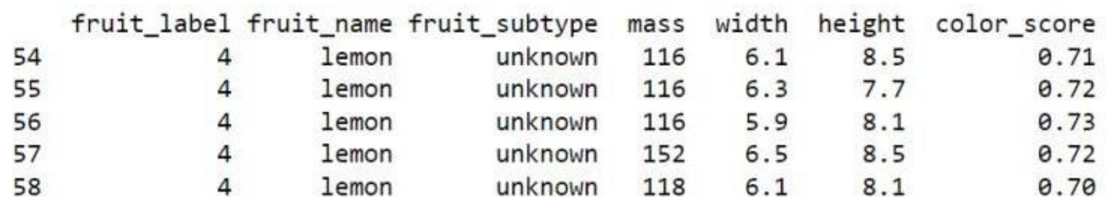
Code :

```
import numpy as np import pandas as pd
import matplotlib.pyplot as plt from sklearn.metrics import classification_report from
sklearn.model_selection import train_test_split from sklearn.preprocessing
import MinMaxScaler from sklearn.linear_model import LogisticRegression from sklearn.tree
import DecisionTreeClassifier from sklearn.neighbors
import KNeighborsClassifier from sklearn.discriminant_analysis import LinearDiscriminantAnalysis
from sklearn.svm
import SVC import os os.chdir("C:\\Users\PramodJ\Desktop\Python")
fruits = pd.read_table('fruit.txt')
print(fruits.head()) print(fruits.tail())
print (fruits.describe()) feature_names=['mass','width','height','color_score']
X = fruits[feature_names] Y = fruits['fruit_label'] X_train,
X_test,y_train,y_test=train_test_split(X,Y,random_state=0)
scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train) X_test= scaler.transform(X_test)
knn = KNeighborsClassifier() knn.fit(X_train, y_train)
print('Accuracy of K-NN classifier on training set:{:.2f}'.format(knn.score(X_train,y_train)))
print('Accuracy of K-NN classifier on test set:{:.2f}'.format(knn.score(X_test,y_test)))
svm = SVC() svm.fit(X_train,y_train)
print('Accuracy of SVM classifier on trainning set:{:.2f}'.format(svm.score(X_train,y_train)))
print('Accuracy of SVM classifier on test set:{:.2f}'.format(svm.score(X_test,y_test)))

# Logistic Regression
from sklearn.linear_model import LogisticRegression model = LogisticRegression()
model.fit(X_train, y_train) predictions = model.predict(X_test)
print('Accuracy of Logistic Regression on training set: {:.2f}'.format(model.score(X_train, y_train)))
print('Accuracy of Logistic Regressionr on test set: {:.2f}'.format(model.score(X_test, y_test)))
classification_report(y_test, predictions)
```

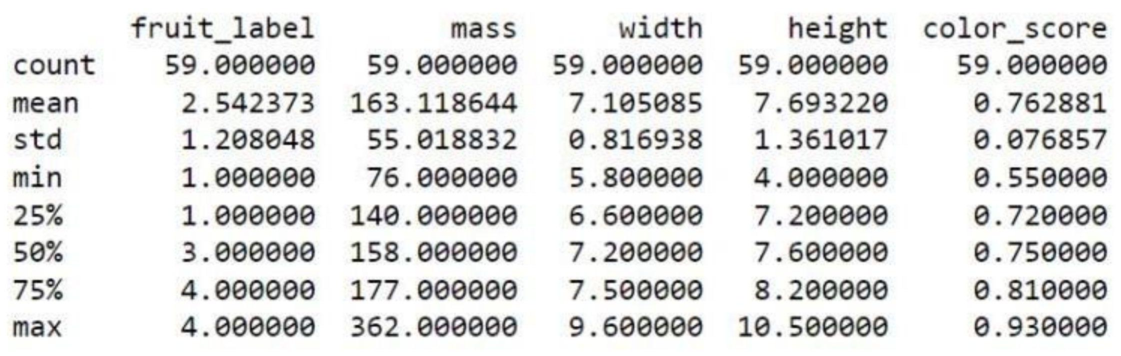
Output :



```
   fruit_label fruit_name fruit_subtype  mass  width  height  color_score
0            1      apple  granny_smith   192    8.4     7.3         0.55
1            1      apple  granny_smith   180    8.0     6.8         0.59
2            1      apple  granny_smith   176    7.4     7.2         0.60
3            2   mandarin      mandarin    86    6.2     4.7         0.80
4            2   mandarin      mandarin    84    6.0     4.6         0.79
```

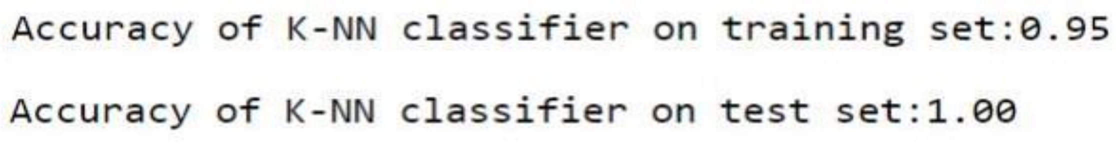


```
    fruit_label fruit_name fruit_subtype  mass  width  height  color_score
54            4      lemon       unknown   116    6.1     8.5         0.71
55            4      lemon       unknown   116    6.3     7.7         0.72
56            4      lemon       unknown   116    5.9     8.1         0.73
57            4      lemon       unknown   152    6.5     8.5         0.72
58            4      lemon       unknown   118    6.1     8.1         0.70
```



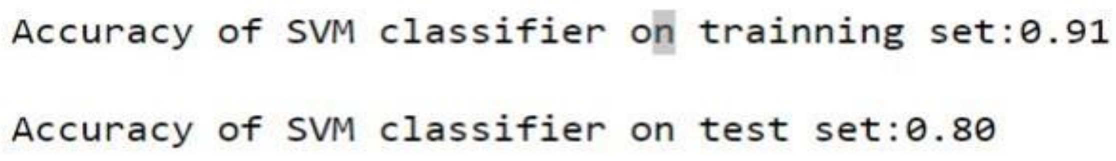
```
       fruit_label        mass      width     height  color_score
count    59.000000   59.000000  59.000000  59.000000    59.000000
mean      2.542373  163.118644   7.105085   7.693220     0.762881
std       1.208048   55.018832   0.816938   1.361017     0.076857
min       1.000000   76.000000   5.800000   4.000000     0.550000
25%       1.000000  140.000000   6.600000   7.200000     0.720000
50%       3.000000  158.000000   7.200000   7.600000     0.750000
75%       4.000000  177.000000   7.500000   8.200000     0.810000
max       4.000000  362.000000   9.600000  10.500000     0.930000
```

K-NN classifier:



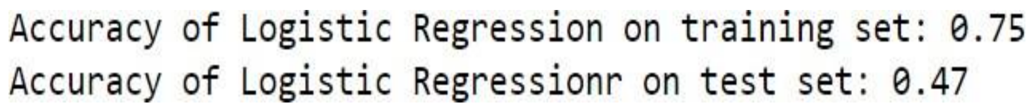
```
Accuracy of K-NN classifier on training set:0.95

Accuracy of K-NN classifier on test set:1.00
```

SVM classifier:

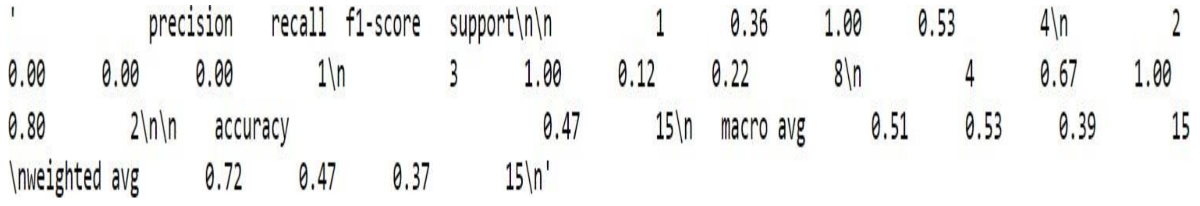


```
Accuracy of SVM classifier on trainning set:0.91

Accuracy of SVM classifier on test set:0.80
```

Logistic Regression :



```
Accuracy of Logistic Regression on training set: 0.75
Accuracy of Logistic Regressionr on test set: 0.47
```



```
'           precision    recall  f1-score   support\n\n           1       0.36      1.00      0.53         4\n           2
0.00      0.00      0.00         1\n           3       1.00      0.12      0.22         8\n           4       0.67      1.00
0.80         2\n\n    accuracy                           0.47        15\n   macro avg       0.51      0.53      0.39        15
\nweighted avg       0.72      0.47      0.37        15\n'
```

Practical No:02

Aim : On the iris dataset, perform KNN algorithm and discuss result

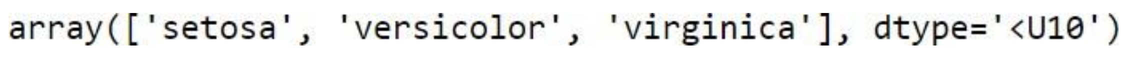
Code :

```
import pandas as pd
from sklearn.datasets import load_iris iris=load_iris()
iris.feature_names iris.target_names
df= pd.DataFrame(iris.data,columns=iris.feature_names) df.head()
df['target']=iris.target df.head() df[df.target==1].head() df.shape
df['flower_name'] =df.target.apply(lambda x: iris.target_names[x] ) df.head()
df0 =df[:50] df1=df[50:100]
df2=df[100:]
from sklearn.model_selection import train_test_split x=df.drop(['target','flower_name'],axis='columns')
y=df.target
x_train,x_test,y_train,y_test =train_test_split(x,y,test_size=0.2,random_state=1) len(x_train)
from sklearn.neighbors import KNeighborsClassifier # create knn classifier knn
=KNeighborsClassifier(n_neighbors=10)
knn.fit(x_train, y_train) knn.score(x_test,y_test)
from sklearn.metrics import confusion_matrix y_pred=knn.predict(x_test)
cm = confusion_matrix(y_test,y_pred) cm
```

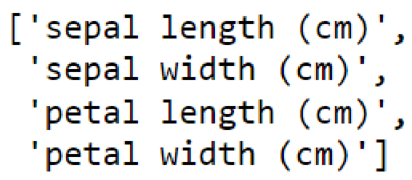
%matplotlib inline
import matplotlib.pyplot as plt import seaborn as sn plt.figure(figsize=(7,5)) sn.heatmap(cm, annot=True) plt.xlabel('predicted') plt.ylabel('True')
from sklearn.metrics import classification_report print(classification_report(y_test,y_pred)

Output : feature names :

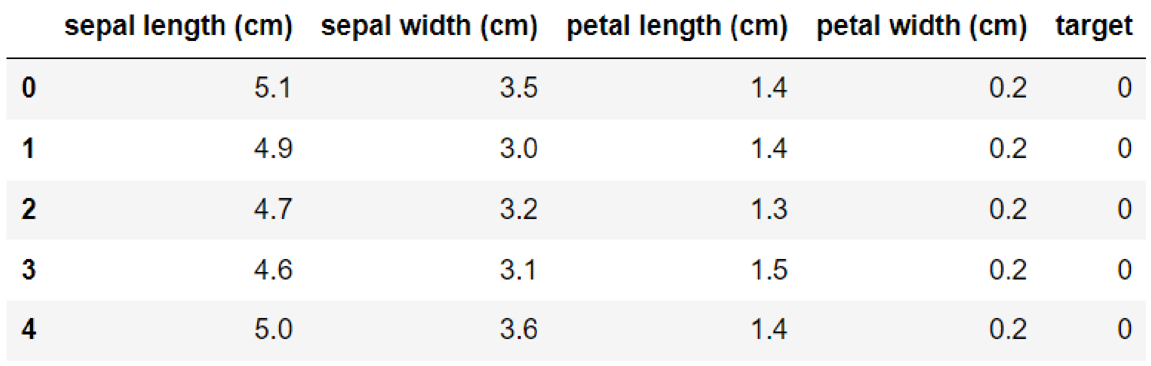
Target names :



```
array(['setosa', 'versicolor', 'virginica'], dtype='<U10')
```

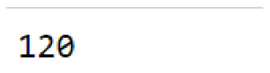


```
['sepal length (cm)',
 'sepal width (cm)',
 'petal length (cm)',
 'petal width (cm)']
```



	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
0	5.1	3.5	1.4	0.2	0
1	4.9	3.0	1.4	0.2	0
2	4.7	3.2	1.3	0.2	0
3	4.6	3.1	1.5	0.2	0
4	5.0	3.6	1.4	0.2	0

len(x_train) :



```
120
```

len(x_test) :

```
30
```

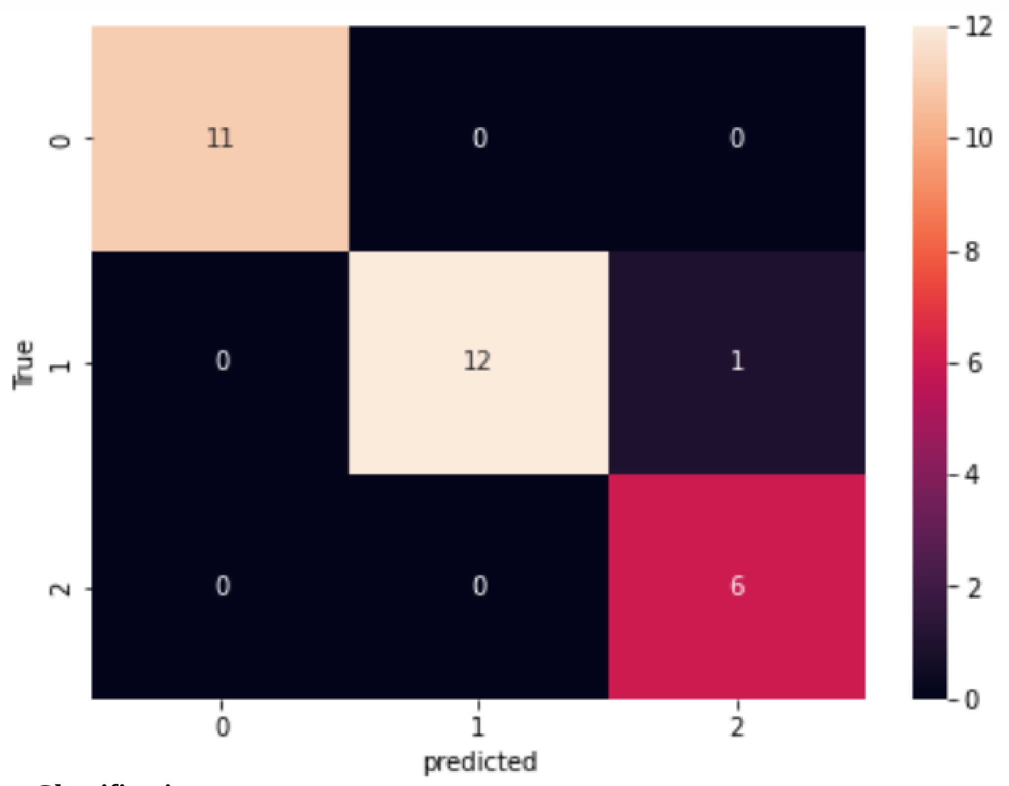
Knn score :

```
0.9666666666666667
```

Confusion matrix:

```
array([[11,  0,  0],
       [ 0, 12,  1],
       [ 0,  0,  6]], dtype=int64)
```

Heatmap:



Classification report :

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        11
           1       1.00      0.92      0.96        13
           2       0.86      1.00      0.92         6

    accuracy                           0.97        30
   macro avg       0.95      0.97      0.96        30
weighted avg       0.97      0.97      0.97        30
```

Practical No:03

Aim : Implement apriori algorithm on Online retail dataset and discuss results.

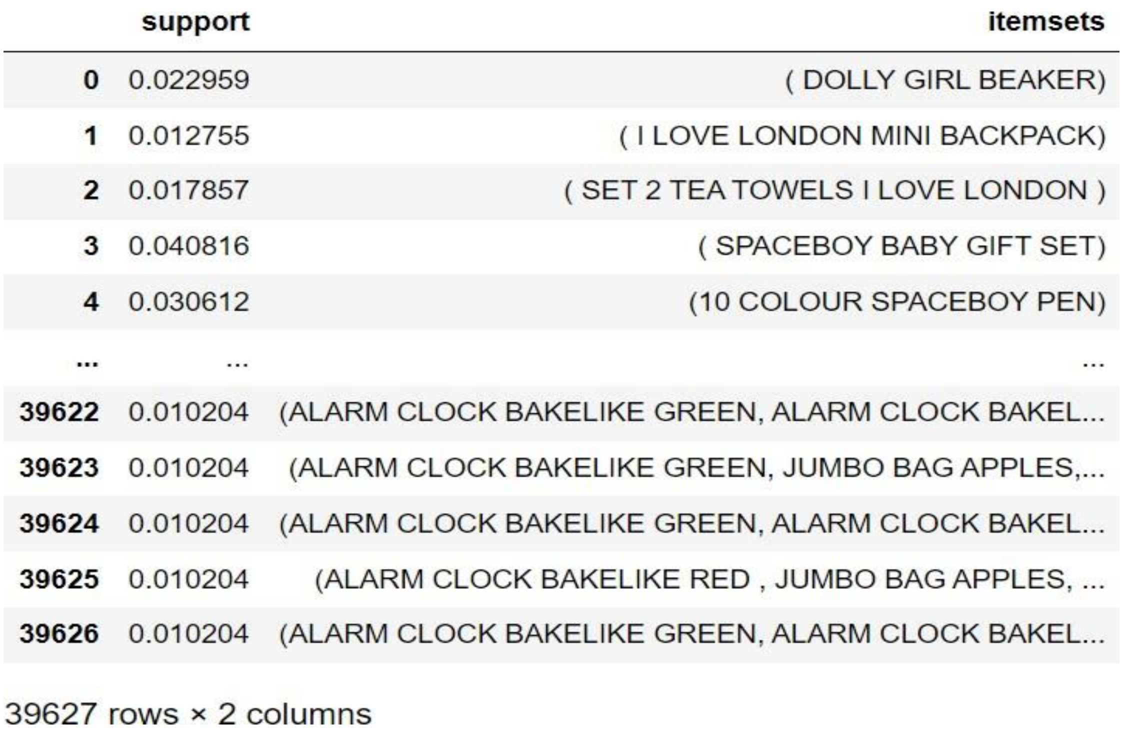
Code :

```
import pandas as pd import numpy as np import seaborn as sns import matplotlib as mlp
import matplotlib.pyplot as plt
from mlxtend.frequent_patterns import apriori
from mlxtend.frequent_patterns import association_rules import os
os.getcwd() os.chdir("C:\\Users\\PramodJ\\Desktop ") transaction_df=pd.read_csv('OnlineRetail.csv')
transaction_df.head()
transaction_df = transaction_df[transaction_df.Country=='France'] transaction_filtered =
transaction_df[['InvoiceNo','Description','Quantity']].copy() transaction_filtered
transaction_filtered = transaction_filtered[transaction_filtered.Quantity > 0 ]
transaction_filtered.sort_values(by='Quantity', ascending=True) transaction_filtered['Quantity']=
[1]*len(transaction_filtered)
[2]*5
invoice = list(transaction_filtered.InvoiceNo)
index_no = [invoice[index] for index in np.arange(len(invoice)) if not invoice[index].isnumeric()]
transaction_filtered[transaction_filtered['InvoiceNo'].isin(index_no)]
temp_df = transaction_filtered[transaction_filtered.Description != transaction_filtered.Description]
temp_df
for invoice in list(temp_df.InvoiceNo):
if len(transaction_filtered[transaction_filtered.Invoice == invoice]) > 1: print((str)(invoice))
```

temp = transaction_filtered[transaction_filtered.Invoice ==
invoice].groupby(['Invoice']).agg({'Description':lambda x: list(x)})
if len(list(set(temp)))>0 :
print(temp) transaction_filtered.dropna(axis=0, inplace=True) transaction_filtered
def return_one(x): return 1
table = pd.pivot_table(transaction_filtered, values='Quantity', index=['InvoiceNo'],
columns=['Description'], aggfunc=return_one, fill_value=0)
table
frequent_itemsets = apriori(table, min_support=0.01, use_colnames=True) frequent_itemsets
rules = association_rules(frequent_itemsets, metric="lift", min_threshold=1) rules
rules.sort_values(by=['support','confidence'], ascending=False)

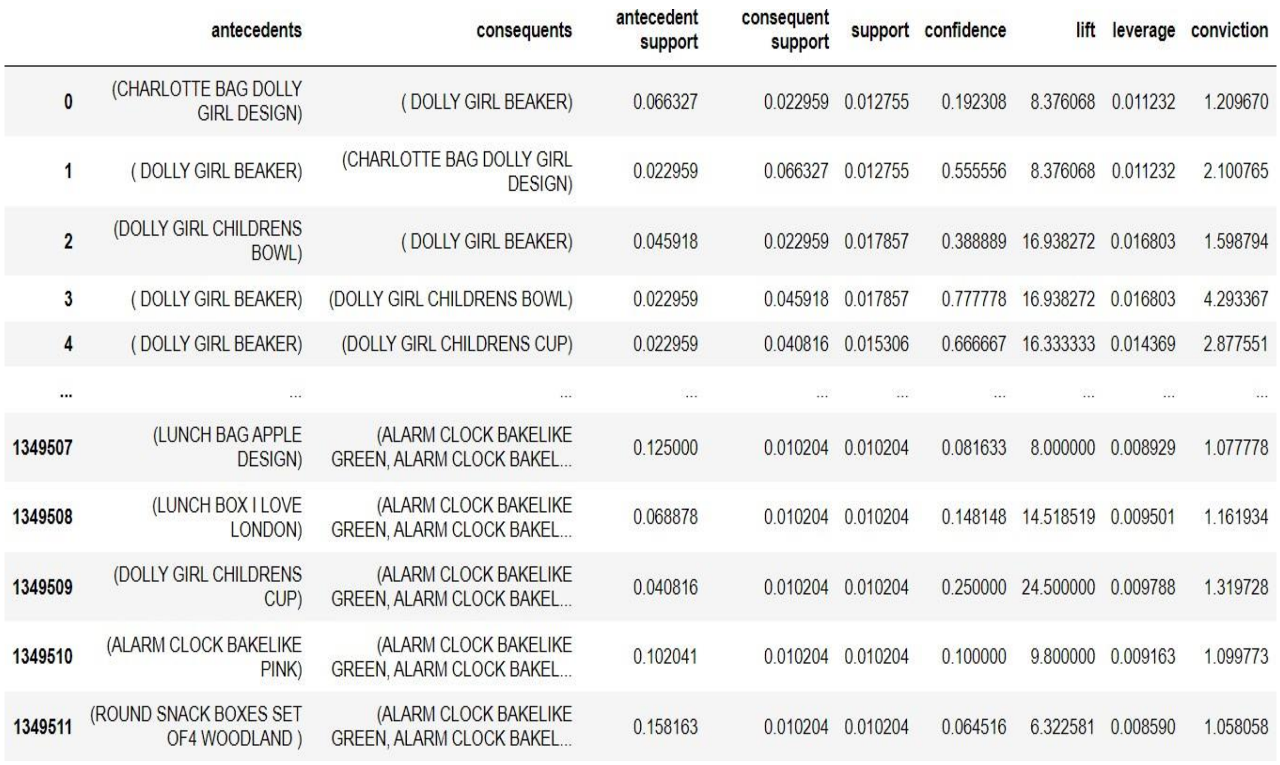
Output :

Apriori :



	support	itemsets
0	0.022959	(DOLLY GIRL BEAKER)
1	0.012755	(I LOVE LONDON MINI BACKPACK)
2	0.017857	(SET 2 TEA TOWELS I LOVE LONDON)
3	0.040816	(SPACEBOY BABY GIFT SET)
4	0.030612	(10 COLOUR SPACEBOY PEN)
...	...	...
39622	0.010204	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...
39623	0.010204	(ALARM CLOCK BAKELIKE GREEN, JUMBO BAG APPLES,...
39624	0.010204	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...
39625	0.010204	(ALARM CLOCK BAKELIKE RED , JUMBO BAG APPLES, ...
39626	0.010204	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...

39627 rows × 2 columns



	antecedents	consequents	antecedent support	consequent support	support	confidence	lift	leverage	conviction
0	(CHARLOTTE BAG DOLLY GIRL DESIGN)	(DOLLY GIRL BEAKER)	0.066327	0.022959	0.012755	0.192308	8.376068	0.011232	1.209670
1	(DOLLY GIRL BEAKER)	(CHARLOTTE BAG DOLLY GIRL DESIGN)	0.022959	0.066327	0.012755	0.555556	8.376068	0.011232	2.100765
2	(DOLLY GIRL CHILDRENS BOWL)	(DOLLY GIRL BEAKER)	0.045918	0.022959	0.017857	0.388889	16.938272	0.016803	1.598794
3	(DOLLY GIRL BEAKER)	(DOLLY GIRL CHILDRENS BOWL)	0.022959	0.045918	0.017857	0.777778	16.938272	0.016803	4.293367
4	(DOLLY GIRL BEAKER)	(DOLLY GIRL CHILDRENS CUP)	0.022959	0.040816	0.015306	0.666667	16.333333	0.014369	2.877551
...	...	...	...	...	...	...	...	...	...
1349507	(LUNCH BAG APPLE DESIGN)	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	0.125000	0.010204	0.010204	0.081633	8.000000	0.008929	1.077778
1349508	(LUNCH BOX I LOVE LONDON)	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	0.068878	0.010204	0.010204	0.148148	14.518519	0.009501	1.161934
1349509	(DOLLY GIRL CHILDRENS CUP)	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	0.040816	0.010204	0.010204	0.250000	24.500000	0.009788	1.319728
1349510	(ALARM CLOCK BAKELIKE PINK)	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	0.102041	0.010204	0.010204	0.100000	9.800000	0.009163	1.099773
1349511	(ROUND SNACK BOXES SET OF4 WOODLAND)	(ALARM CLOCK BAKELIKE GREEN, ALARM CLOCK BAKEL...	0.158163	0.010204	0.010204	0.064516	6.322581	0.008590	1.058058

Practical No:04

Aim : Implement Naïve Bayes Classifier and K-Nearest Neighbor Classifier on Data set of your choice. Test and Compare for Accuracy and Precision.

Code :

KNN

```
import numpy as np import pandas as pd
import matplotlib.pyplot as plt

from sklearn.metrics import classification_report from sklearn.model_selection import train_test_split from
sklearn.preprocessing import MinMaxScaler from sklearn.linear_model import LogisticRegression from
sklearn.tree import DecisionTreeClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis from sklearn.svm
import SVC import os
os.chdir("C:\\Users\PramodJ\Desktop\Python") fruits = pd.read_table('fruit.txt') print(fruits.head())
print(fruits.tail())
print (fruits.describe()) feature_names=['mass','width','height','color_score'] X = fruits[feature_names]
Y = fruits['fruit_label']
X_train, X_test,y_train,y_test=train_test_split(X,Y,random_state=0) scaler = MinMaxScaler()
X_train = scaler.fit_transform(X_train) X_test= scaler.transform(X_test)
knn = KNeighborsClassifier() knn.fit(X_train, y_train) print('Accuracy of K-NN classifier on training
set:{:.2f}'.format(knn.score(X_train,y_train))) print('Accuracy of K-NN classifier on test
set:{:.2f}'.format(knn.score(X_test,y_test)))
```

naïve bayes

```
import numpy as np
import matplotlib.pyplot as plt import pandas as pd
os.chdir("C:\\Users\\PramodJ\\Desktop\\Python") dataset = pd.read_csv('iris.csv')
X = dataset.iloc[:,:4].values y = dataset['variety'].values dataset.head(5)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2) from sklearn.preprocessing import
StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train) X_test = sc.transform(X_test)
from sklearn.naive_bayes import GaussianNB classifier = GaussianNB()
classifier.fit(X_train, y_train) y_pred = classifier.predict(X_test) y_pred
from sklearn.metrics import confusion_matrix cm = confusion_matrix(y_test, y_pred)
from sklearn.metrics import accuracy_score
print ("Accuracy : ", accuracy_score(y_test, y_pred)) cm
```

Output : KNN

```
   fruit_label fruit_name fruit_subtype  mass  width  height  color_score
0            1      apple  granny_smith   192    8.4     7.3         0.55
1            1      apple  granny_smith   180    8.0     6.8         0.59
2            1      apple  granny_smith   176    7.4     7.2         0.60
3            2   mandarin      mandarin    86    6.2     4.7         0.80
4            2   mandarin      mandarin    84    6.0     4.6         0.79
5            2   mandarin      mandarin    80    5.8     4.3         0.77
6            2   mandarin      mandarin    80    5.9     4.3         0.81
7            2   mandarin      mandarin    76    5.8     4.0         0.81
8            1      apple      braeburn   178    7.1     7.8         0.92
9            1      apple      braeburn   172    7.4     7.0         0.89
```

```
       fruit_label        mass      width     height  color_score
count    59.000000   59.000000  59.000000  59.000000    59.000000
mean      2.542373  163.118644   7.105085   7.693220     0.762881
std       1.208048   55.018832   0.816938   1.361017     0.076857
min       1.000000   76.000000   5.800000   4.000000     0.550000
25%       1.000000  140.000000   6.600000   7.200000     0.720000
50%       3.000000  158.000000   7.200000   7.600000     0.750000
75%       4.000000  177.000000   7.500000   8.200000     0.810000
max       4.000000  362.000000   9.600000  10.500000     0.930000
```

```
 Accuracy of K-NN classifier on training set:0.95

Accuracy of K-NN classifier on training set:1.00
```

naïve bayes :

	sepal.length	sepal.width	petal.length	petal.width	variety
0	5.1	3.5	1.4	0.2	Setosa
1	4.9	3.0	1.4	0.2	Setosa
2	4.7	3.2	1.3	0.2	Setosa
3	4.6	3.1	1.5	0.2	Setosa
4	5.0	3.6	1.4	0.2	Setosa

```
Accuracy :  0.9333333333333333
```

Confusion matrix :

```
array([[10,  0,  0],
       [ 0,  8,  1],
       [ 0,  1, 10]], dtype=int64)
```

Practical No:05

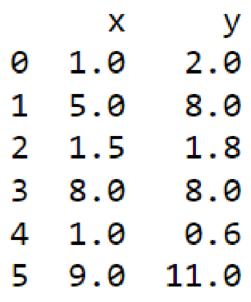
Aim : Implement K-Means Clustering on the proper data set of your choice.

Code :

```
from sklearn.cluster import KMeans import pandas as pd
import matplotlib.pyplot as plt from matplotlib import style style.use("ggplot")
%matplotlib inline
data = pd.DataFrame([[1, 2], [5, 8],
[1.5, 1.8],
[8, 8],
[1, 0.6],
[9, 11]], columns=['x','y']) print( data )
kmeans = KMeans(n_clusters=2).fit(data) centroids = kmeans.cluster_centers_ labels = kmeans.labels_
print(centroids) print(labels) Output :
```

Centroids :

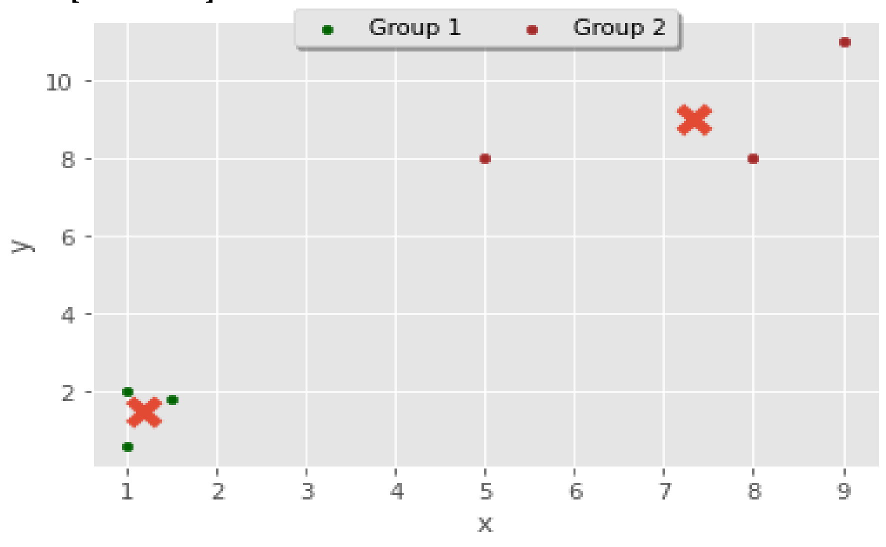
```
[[1.16666667 1.46666667 1.        ]
[7.33333333 9.  0.         ]]
```



```
     x     y
0  1.0   2.0
1  5.0   8.0
2  1.5   1.8
3  8.0   8.0
4  1.0   0.6
5  9.0  11.0
```

Labels

[1 0 1 0 1 0]



Practical No:06

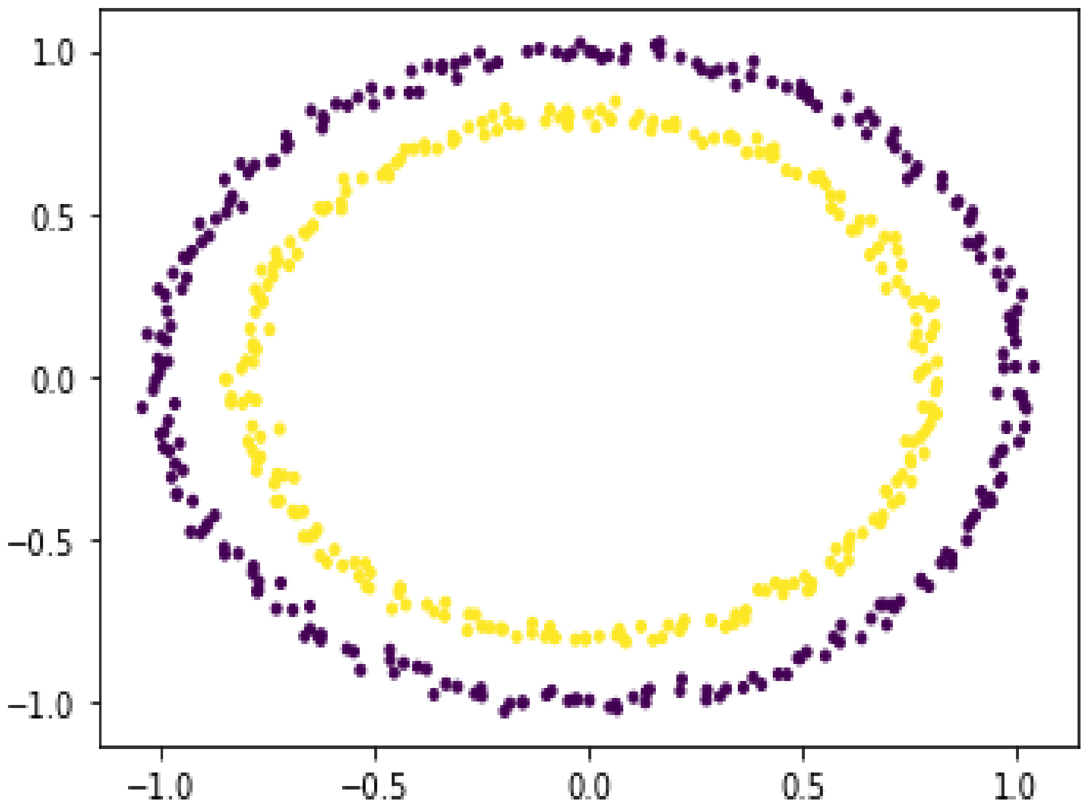
Aim : Design and implement SVM for classification with the proper data set of your choice. Comment on Design and Implementation for Linearly non separable Dataset.

Code :

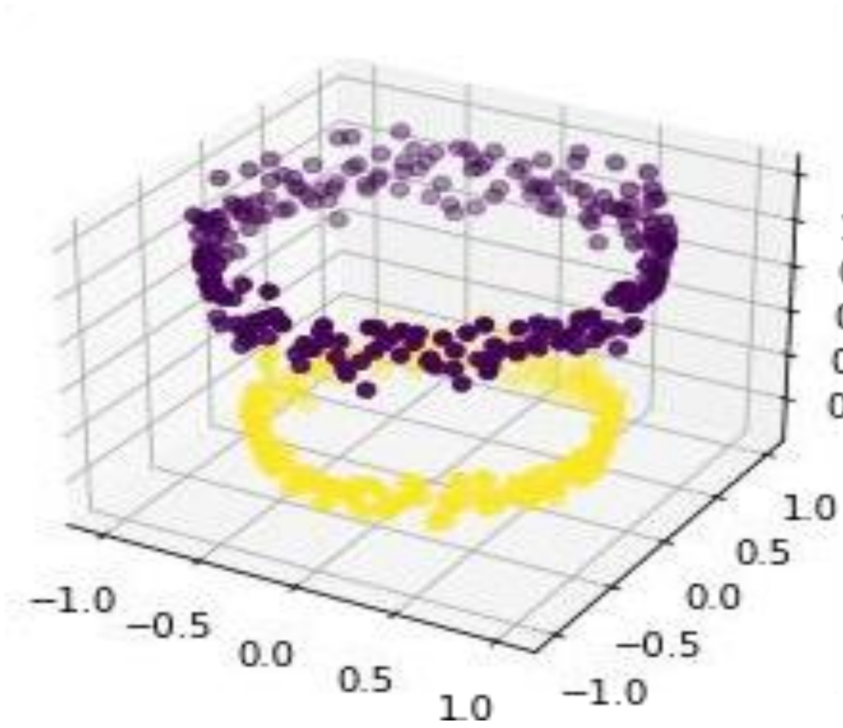
```
import numpy as np
import matplotlib.pyplot as plt
from sklearn.datasets import make_circles from mpl_toolkits.mplot3d import Axes3D

X, Y = make_circles(n_samples = 500, noise = 0.02)



plt.scatter(X[:, 0], X[:, 1], c = Y, marker = '.') plt.show()
X1 = X[:, 0].reshape((-1, 1))
X2 = X[:, 1].reshape((-1, 1)) X3 = (X1**2 + X2**2)
X = np.hstack((X, X3))



# visualizing data in higher dimension fig = plt.figure()
axes = fig.add_subplot(111, projection = '3d') axes.scatter(X1, X2, X1**2 + X2**2, c = Y, depthshade =
True) plt.show()
from sklearn import svm



svc = svm.SVC(kernel = 'linear') svc.fit(X, Y)
w = svc.coef_
b = svc.intercept_



x1 = X[:, 0].reshape((-1, 1))
x2 = X[:, 1].reshape((-1, 1))
```

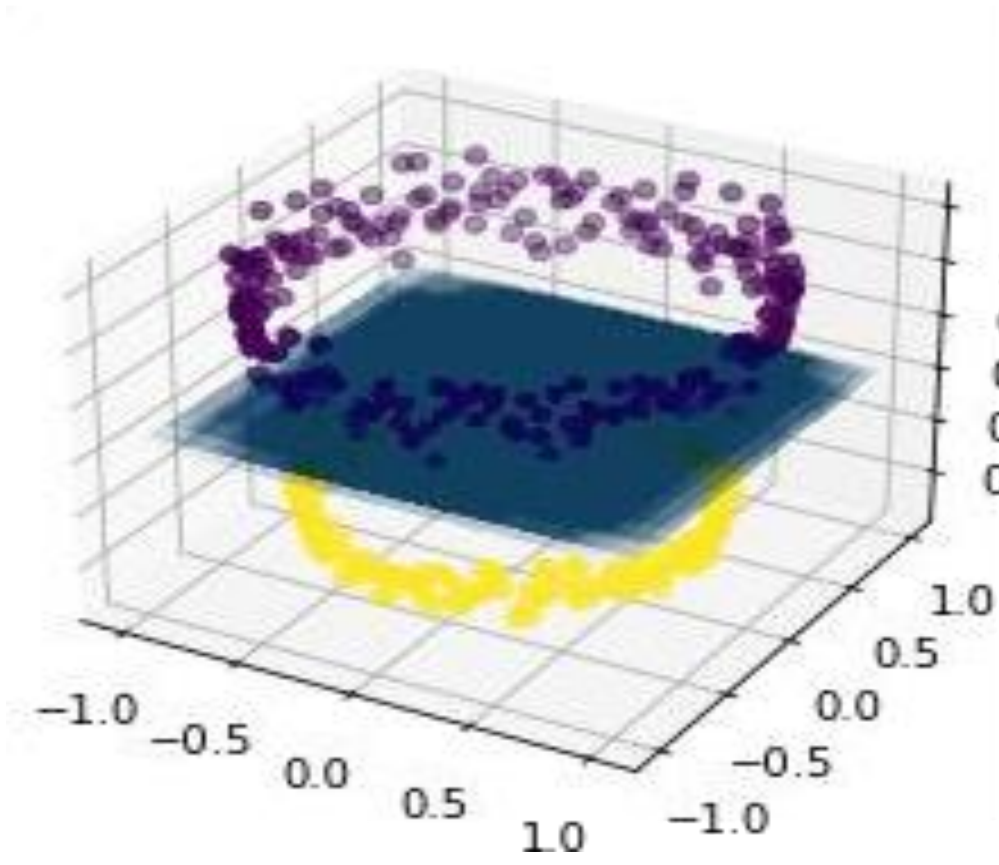
```
x1, x2 = np.meshgrid(x1, x2)
x3 = -(w[0][0]*x1 + w[0][1]*x2 + b) / w[0][2]

fig = plt.figure()
axes2 = fig.add_subplot(111, projection = '3d') axes2.scatter(X1, X2, X1**2 + X2**2, c = Y, depthshade =
True) axes1 = fig.gca(projection = '3d')
axes1.plot_surface(x1, x2, x3, alpha = 0.01) plt.show()
```

Output:



support vector classifier using a linear kernel





Practical No:07

Aim : Implement a basic not gate using perceptron.

Code :

```
# importing Python library
import numpy as np

# define Unit Step Function
def unitStep(v):
	if v >= 0:
		return 1
	else:
		return 0

# design Perceptron Model
def perceptronModel(x, w, b):
	v = np.dot(w, x) + b
	y = unitStep(v)
	return y

# NOT Logic Function
# w = -1, b = 0.5
def NOT_logicFunction(x):
	w = -1
	b = 0.5
	return perceptronModel(x, w, b)

# testing the Perceptron Model
test1 = np.array(1)
test2 = np.array(0)

print("NOT({}) = {}".format(1, NOT_logicFunction(test1)))
print("NOT({}) = {}".format(0, NOT_logicFunction(test2)))
```

Output :

```
NOT(1) = 0
NOT(0) = 1
```

Content of Lab Experiments for Journal

S.No.	Title of Program
1	On the fruit dataset, compare the performance of Logistic Regression, SVM, KNN on the basis of their accuracy.
2	On the iris dataset, perform knn algorithm and discuss result.
3	Implement apriori algorithm on Online retail dataset and discuss results.
4	Implement Naïve Bayes Classifier and K-Nearest Neighbor Classifier on Data set of your choice. Test and Compare for Accuracy and Precision.
5	Implement K-Means Clustering on the proper data set of your choice.
6	Design and implement SVM for classification with the proper data set of your choice. Comment on Design and Implementation for Linearly non separable Dataset.
7	Implement a basic not gate using perceptron.