

PRACTICAL-1

AIM: Study about Python learn following Data Structure : List, Dictionary, Dataframe, Numpy/scipy package in Python.

DESCRIPTION:

Python:

Python is an interpreted high-level general-purpose programming language. Its design philosophy emphasizes code readability with its use of significant indentation. Its language constructs as well as its object-oriented approach aim to help programmers write clear, logical code for small and large-scale projects.

Python is dynamically-typed and garbage-collected. It supports multiple programming paradigms, including structured (particularly, procedural), object-oriented and functional programming. It is often described as a "batteries included" language due to its comprehensive standard library.

Guido van Rossum began working on Python in the late 1980s, as a successor to the ABC programming language, and first released it in 1991 as Python 0.9.0. It supports functional and structured programming methods as well as OOP. It can be used as a scripting language or can be compiled to byte-code for building large applications. It provides very high-level dynamic data types and supports dynamic type checking. It supports automatic garbage collection. It can be easily integrated with C, C++, COM, ActiveX, CORBA, and Java.

List in Python :

Lists are just like dynamically sized arrays, declared in other languages (vector in C++ and ArrayList in Java). Lists need not be homogeneous always which makes it the most powerful tool in Python. A single list may contain DataTypes like Integers, Strings, as well as Objects. Lists are mutable, and hence, they can be altered even after their creation.

List in Python are ordered and have a definite count. The elements in a list are indexed according to a definite sequence and the indexing of a list is done with 0 being the first index. Each element in the list has its definite place in the list, which allows duplicating of elements in the list, with each element having its own distinct place and credibility.

Dictionary in Python :

Dictionary in Python is an unordered collection of data values, used to store data values like a map, which, unlike other Data Types that hold only a single value as an element, Dictionary holds key:value pair. Key-value is provided in the dictionary to make it more optimized.

In Python, a Dictionary can be created by placing a sequence of elements within curly {} braces, separated by ‘comma’. Dictionary holds pairs of values, one being the Key and the other corresponding pair element being its Key:value. Values in a dictionary can be of any data type and can be duplicated, whereas keys can't be repeated and must be immutable.

DataFrame:

Pandas DataFrame is two-dimensional size-mutable, potentially heterogeneous tabular data structure with labeled axes (rows and columns). A Data frame is a two-dimensional data structure, i.e., data is aligned in a tabular fashion in rows and columns. Pandas DataFrame consists of three principal components, the data, rows, and columns.

Numpy:

NumPy is the fundamental package for scientific computing in Python. It is a Python library that provides a multidimensional array object, various derived objects (such as masked arrays and matrices), and an assortment of routines for fast operations on arrays, including mathematical, logical, shape manipulation, sorting, selecting, I/O, discrete Fourier transforms, basic linear algebra, basic statistical operations, random simulation and much more.

NumPy is a Python library used for working with arrays. It also has functions for working in domain of linear algebra, fourier transform, and matrices. NumPy was created in 2005 by Travis Oliphant. It is an open source project and you can use it freely. NumPy stands for Numerical Python.

Scipy:

SciPy is a free and open-source Python library used for scientific computing and technical computing. SciPy contains modules for optimization, linear algebra, integration, interpolation, special functions, FFT, signal and image processing, ODE solvers and other tasks common in science and engineering.

SciPy is a scientific computation library that uses NumPy underneath. SciPy stands for Scientific Python. It provides more utility functions for optimization, stats and signal processing. Like NumPy, SciPy is open source so we can use it freely. SciPy was created by NumPy's creator Travis Olliphant.

CODE:

```
import numpy as np
from scipy import constants
import pandas as pd

"""List"""

list=["Hello",15,1562.452,'a'] #Creating a List
list[0]
print(list)
```

"""Dictionary"""

```
dictionary={ 1:"A",2:"B",3:"C" } # Creating a Dictionary
print(dictionary[1])
print(dictionary)
```

"""DataFrame"""

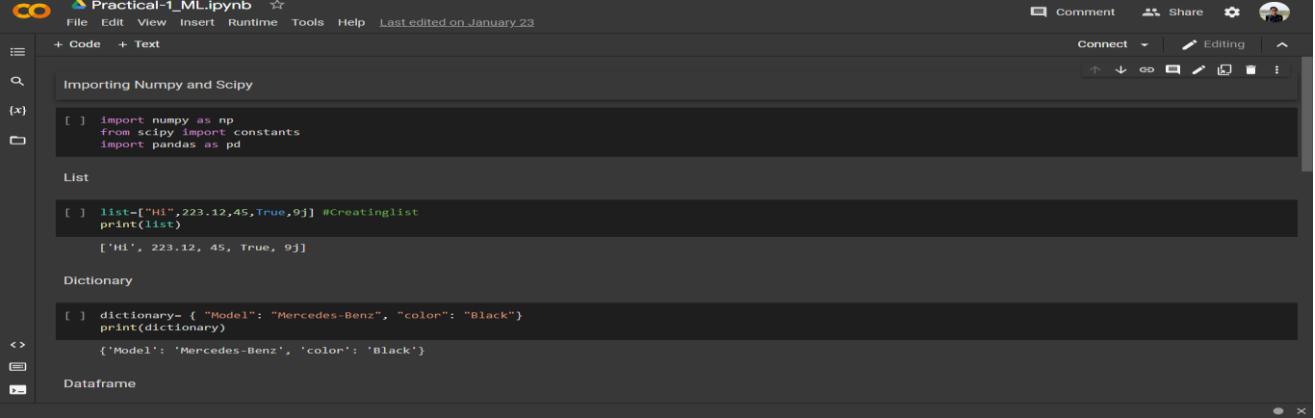
```
list=["Hello",15,1562.452,'a']
df=pd.DataFrame(list)
print(df)
```

"""Numpy Use"""

```
data=np.array([1,2,3,4,5])
for a in data:
    print(a)
```

"""Scipy Use"""

```
pi=constants.pi
radius=10
area=pi*radius*radius
print(" Area of Circle is : ",area)
```

OUTPUT:


```

Practical-1_ML.ipynb
File Edit View Insert Runtime Tools Help Last edited on January 23
Comment Share Editing
+ Code + Text
Importing Numpy and Scipy
{x}
[ ] import numpy as np
from scipy import constants
import pandas as pd
List
[ ] list=[["H1",223.12,45,True,9j] #Creating list
print(list)
['H1', 223.12, 45, True, 9j]
Dictionary
[ ] dictionary= { "Model": "Mercedes-Benz", "color": "Black"}
print(dictionary)
{'Model': 'Mercedes-Benz', 'color': 'Black'}
Dataframe

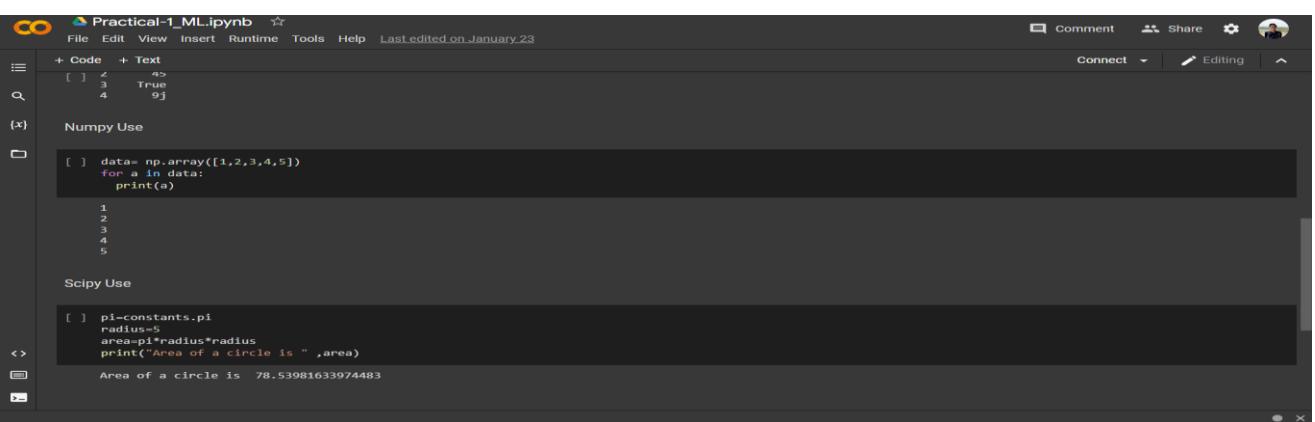
```




```

Practical-1_ML.ipynb
File Edit View Insert Runtime Tools Help Last edited on January 23
Comment Share Editing
+ Code + Text
Dictionary
{x}
[ ] dictionary= { "Model": "Mercedes-Benz", "color": "Black"}
print(dictionary)
{'Model': 'Mercedes-Benz', 'color': 'Black'}
Dataframe
[ ] list=[["H1",223.12,45,True,9j]
df=pd.DataFrame(list)
print(df)
   0
0  H1
1  223.12
2  45
3  True
4  9j
Numpy Use

```

```

Practical-1_ML.ipynb
File Edit View Insert Runtime Tools Help Last edited on January 23
Comment Share Editing
+ Code + Text
{x}
[ ] 
Numpy Use
[ ] data= np.array([1,2,3,4,5])
for a in data:
    print(a)
1
2
3
4
5
Scipy Use
[ ] pi=constants.pi
radius=5
area=pi*radius*radius
print("Area of a circle is ",area)
Area of a circle is  78.53981633974483

```

PRACTICAL-2

AIM: Implement Linear Regression in Python

CODE:

```
import numpy as np

from sklearn.linear_model import LinearRegression
import matplotlib.pyplot as plt

x=np.array([5,15,25,35,45,55]).reshape(-1,1)
y=np.array([5,20,14,32,22,38])

model=LinearRegression().fit(x,y)

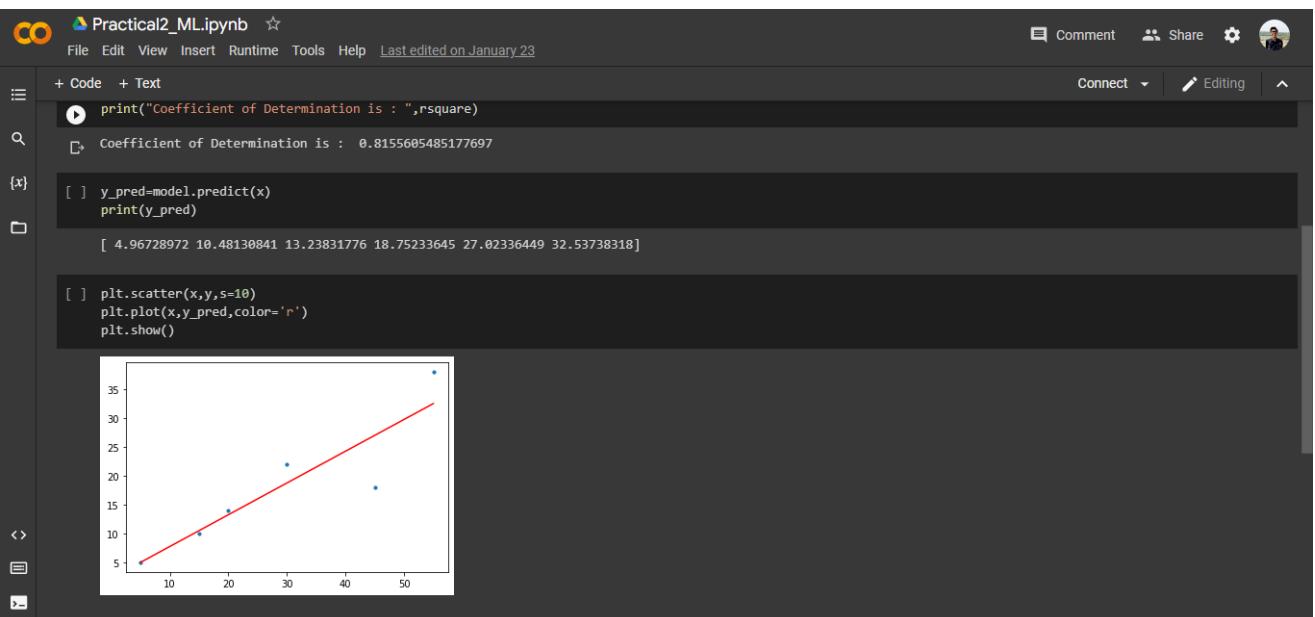
rsquare=model.score(x,y)

print("Coefficient of Determination is : ",rsquare)

y_pred=model.predict(x)
print(y_pred)

plt.scatter(x,y,s=10)
plt.plot(x,y_pred,color='r')
plt.show()
```

OUTPUT:



```
+ Code + Text
File Edit View Insert Runtime Tools Help Last edited on January 23
Comment Share ⚙️ 🧑
+ Code + Text
print("Coefficient of Determination is : ",rsquare)
Coefficient of Determination is :  0.8155605485177697
{x}
[ ] y_pred=model.predict(x)
print(y_pred)
[ 4.96728972 10.48130841 13.23831776 18.75233645 27.02336449 32.53738318]

[ ] plt.scatter(x,y,s=10)
plt.plot(x,y_pred,color='r')
plt.show()
```

The figure shows a scatter plot of data points (x, y) with a linear regression line fitted to them. The x-axis ranges from approximately 5 to 55, and the y-axis ranges from approximately 5 to 35. The data points are approximately at (5, 5), (15, 14), (25, 20), (35, 32), (45, 22), and (55, 38). The regression line passes through the general trend of the data.

PRACTICAL-3

AIM: Implement Logistic Regression in Python

CODE:

Implement Logistic Regression in Python

```
import numpy as np

from sklearn.linear_model import LinearRegression

import matplotlib.pyplot as plt

import pandas as pd

from sklearn import datasets

from sklearn.linear_model import LogisticRegression

iris= datasets.load_iris()

X = iris.data[:, :2]

y = iris.target

model=LogisticRegression()

model.fit(X,y)

model.predict(X[:2,:])

model.predict_proba(X[:2,:])

model.score(X,y)

t=X[:,0]

plt.scatter(t,y,s=10)

plt.show()
```

Logistic Regression using Insurance Dataset

```
data=pd.read_csv("/content/drive/MyDrive/ML/insurance.csv")

data.rename({'tbought_insurance':'brought_insurance'}) 

data.shape

data.head()

plt.title(" Insurance vs Age ")

plt.scatter(data['age'],data['bought_insurance'],marker='+',color='red')
```

```

plt.xlabel(" Age ")
plt.ylabel(" Insurance ")

from sklearn.model_selection import train_test_split

Xtrain,Xtest,ytrain,ytest=train_test_split( data[['age']],data[['bought_insurance']],test_size=0.2)
model.fit(Xtrain,ytrain)

y_pred=model.predict(Xtest)

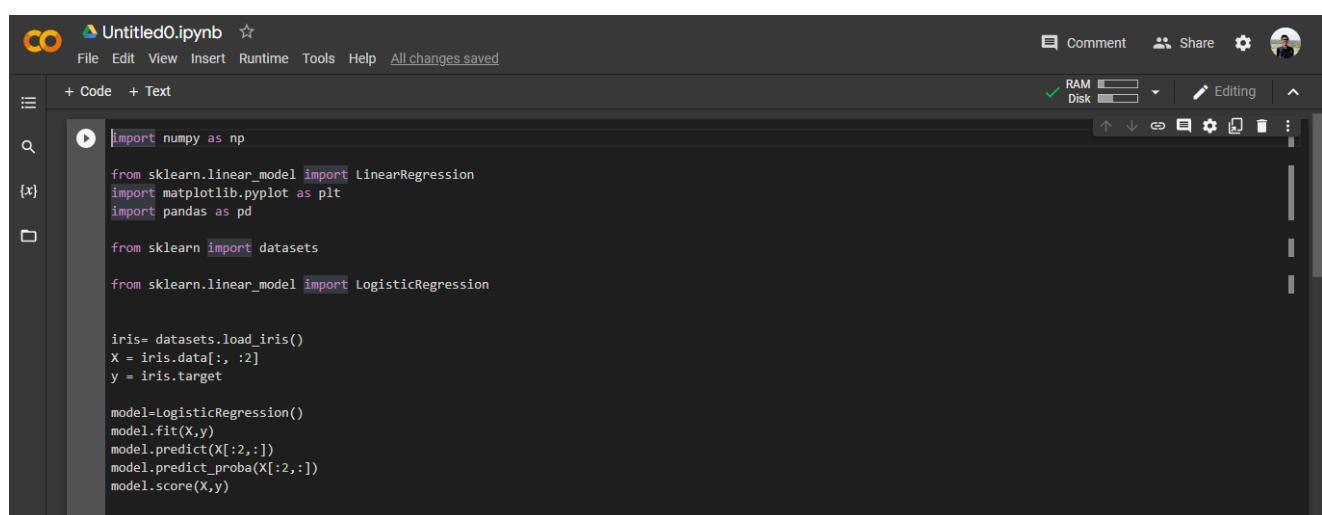
score=model.score(Xtest,ytest)

print(" Accuracy Score is : ",score)

model.coef_
model.intercept_

```

OUTPUT:



A screenshot of a Jupyter Notebook interface titled "Untitled0.ipynb". The code cell contains Python code for loading the Iris dataset, creating a logistic regression model, and fitting it to the data. The code includes imports for numpy, matplotlib.pyplot, pandas, and various sklearn modules. It shows the creation of a model, its fit to the data, and the calculation of accuracy.

```

import numpy as np
from sklearn.linear_model import LogisticRegression
import matplotlib.pyplot as plt
import pandas as pd

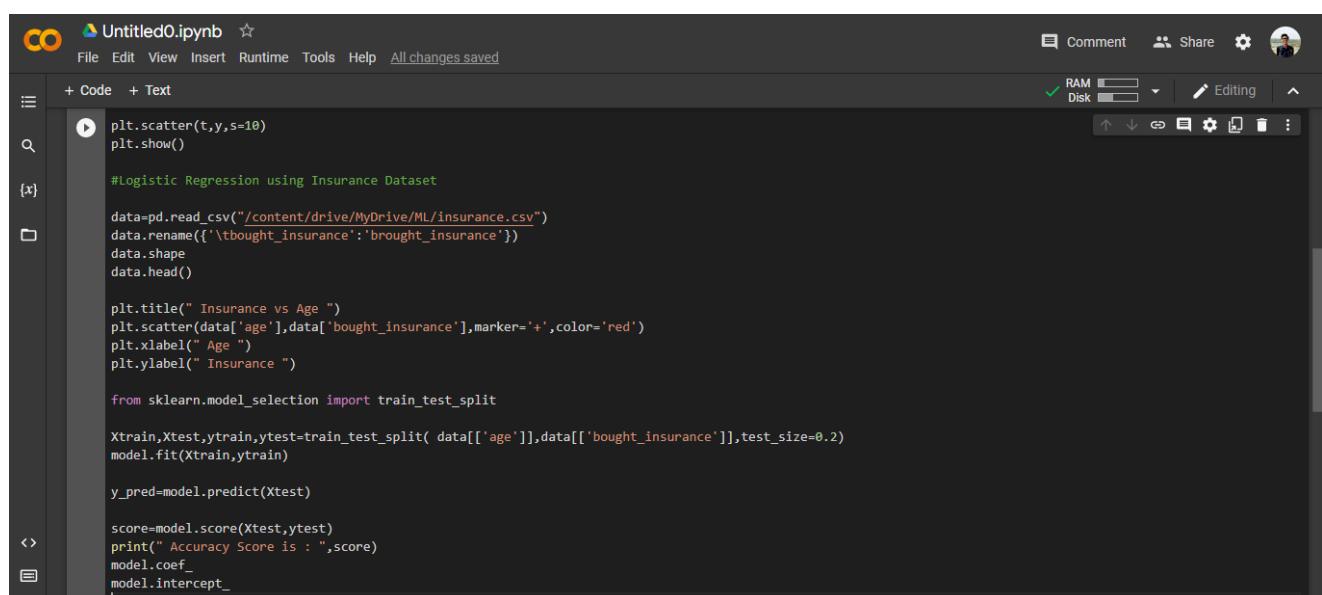
from sklearn import datasets

from sklearn.linear_model import LogisticRegression

iris= datasets.load_iris()
X = iris.data[:, :2]
y = iris.target

model=LogisticRegression()
model.fit(X,y)
model.predict(X[:2,:])
model.predict_proba(X[:2,:])
model.score(X,y)

```



A screenshot of a Jupyter Notebook interface titled "Untitled0.ipynb". The code cell contains Python code for reading an insurance dataset, plotting a scatter plot of 'Age' vs 'bought_insurance', and printing the accuracy score of the logistic regression model. The code also prints the coefficients and intercept of the model.

```

plt.scatter(t,y,s=10)
plt.show()

#Logistic Regression using Insurance Dataset

data=pd.read_csv("/content/drive/MyDrive/ML/insurance.csv")
data.rename({'tbought_insurance':'brought_insurance'}) 
data.shape
data.head()

plt.title(" Insurance vs Age ")
plt.scatter(data['age'],data['bought_insurance'],marker='+',color='red')
plt.xlabel(" Age ")
plt.ylabel(" Insurance ")

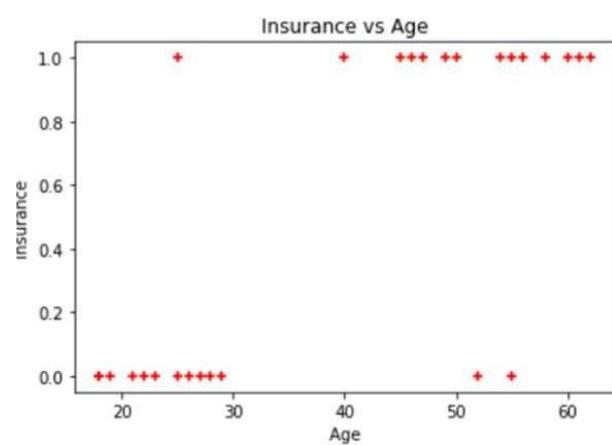
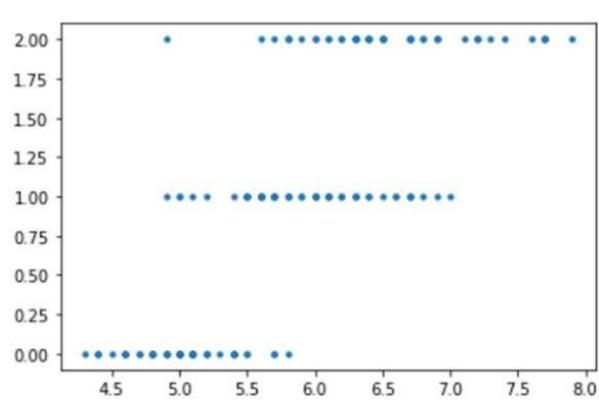
from sklearn.model_selection import train_test_split

Xtrain,Xtest,ytrain,ytest=train_test_split( data[['age']],data[['bought_insurance']],test_size=0.2)
model.fit(Xtrain,ytrain)

y_pred=model.predict(Xtest)

score=model.score(Xtest,ytest)
print(" Accuracy Score is : ",score)
model.coef_
model.intercept_

```



PRACTICAL-4

AIM: Implement SVM Classifier in python

CODE:

Implement SVM Classifier in python

```
import numpy as np
```

```
import pandas as pd
```

```
from sklearn.datasets import load_iris
```

```
import matplotlib.pyplot as plt
```

```
%matplotlib inline
```

```
from sklearn.model_selection import train_test_split
```

```
from sklearn.svm import SVC
```

```
dataset=load_iris()
```

```
dataset.feature_names
```

```
dataset.target_names
```

```
dataframe=pd.DataFrame(dataset.data,columns=dataset.feature_names)
```

```
dataframe
```

```
dataframe['target']=dataset.target
```

```
dataframe
```

```
dataframe['flower_name']=dataframe.target.apply(lambda x: dataset.target_names[x])
```

```
dataframe.head(5) dataframe[55:60]
```

```
dataframe[105:110]
```

```
dataframe_setosa=dataframe[0:50]
```

```
dataframe_setosa.head(5) datafram
```

```
e_versicolor=dataframe[50:100]
```

```
dataframe_versicolor.head(5)
```

```
dataframe_virginica=dataframe[100:150]
```

```
dataframe_virginica.head(5)
```

```
plt.title('Setosa Vs Versicolor ')
```

```
plt.xlabel('Sepal Length')
```

```
plt.ylabel('Sepal Width')
```

```
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'], color="green", marker='+')
```

```
plt.scatter(dataframe_versicolor['sepal length (cm)'], dataframe_versicolor['sepal width (cm)'], color="blue", marker='.)
```

```
plt.title('Setosa Vs Virginica ')
```

```
plt.xlabel('Sepal Length')
```

```
plt.ylabel('Sepal Width')
```

```
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'], color="green", marker='+')
```

```
plt.scatter(dataframe_virginica['sepal length (cm)'], dataframe_virginica['sepal width (cm)'], color="red", marker='*')
```

```
X = dataframe.drop(['target', 'flower_name'], axis='columns')
```

```
y = dataframe['target']
```

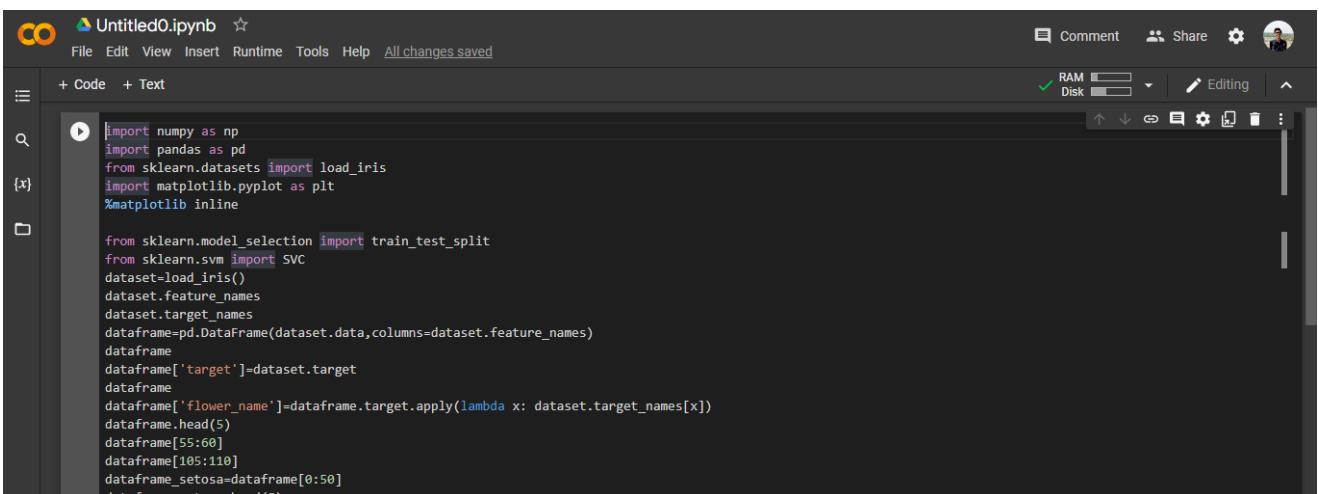
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

```
svmModel=SVC()
```

```
svmModel.fit(X_train,y_train)
```

```
svmModel.score(X_test,y_test)
```

OUTPUT:



The screenshot shows a Jupyter Notebook interface with the following details:

- File Bar:** File, Edit, View, Insert, Runtime, Tools, Help, All changes saved.
- Toolbar:** Comment, Share, RAM, Disk, Editing.
- Code Cell:** The cell contains Python code for loading the Iris dataset, splitting it into training and testing sets, and creating an SVC model. The code includes imports for numpy, pandas, sklearn, and matplotlib, along with specific code for handling the dataset and applying a lambda function to map target values to their names.

Untitled0.ipynb

```
File Edit View Insert Runtime Tools Help All changes saved
```

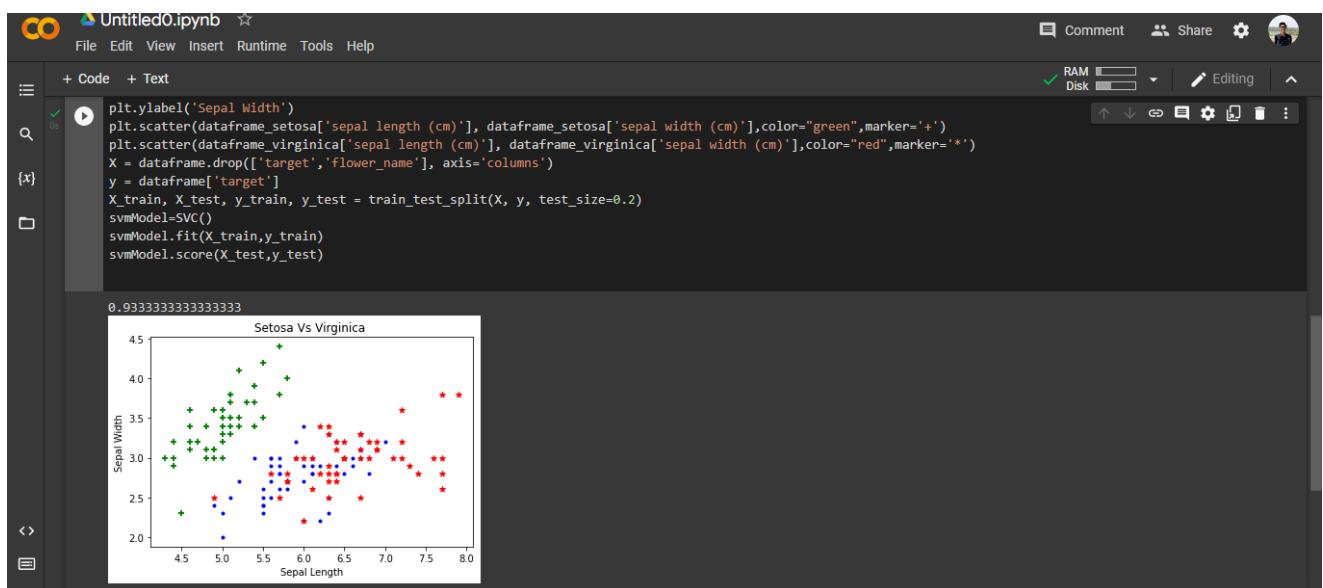
+ Code + Text

{x}

```
dataframe = pd.read_csv('iris.csv')
dataframe.head(5)
dataframe[55:60]
dataframe[105:110]
dataframe_setosa=dataframe[0:50]
dataframe_setosa.head(5)
dataframe_versicolor=dataframe[50:100]
dataframe_versicolor.head(5)

dataframe_virginica=dataframe[100:150]
dataframe_virginica.head(5)
plt.title('Setosa Vs Versicolor ')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'], color="green", marker='+')
plt.scatter(dataframe_versicolor['sepal length (cm)'], dataframe_versicolor['sepal width (cm)'], color="blue", marker='.')

plt.title('Setosa Vs Virginica ')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
```



PRACTICAL-5

AIM: To implement KNN classifier in Python

CODE:

Practical5_ML.ipynb

Implement KNN Classifier in python

```
import numpy as np
import pandas as pd
from sklearn.datasets import load_iris
import matplotlib.pyplot as plt
%matplotlib inline
from sklearn.model_selection import train_test_split
from sklearn.neighbors import KNeighborsClassifier

dataset=load_iris()
dataset.feature_names
dataset.target_names
dataframe=pd.DataFrame(dataset.data,columns=dataset.feature_names)
dataframe
dataframe['target']=dataset.target
dataframe
dataframe['flower_name']=dataframe.target.apply(lambda x: dataset.target_names[x])
```

```
dataframe.head(5)
```

```
dataframe_setosa=dataframe[0:50]
```

```
dataframe_versicolor=dataframe[50:100]
```

```
dataframe_virginica=dataframe[100:150]
```

```
plt.title('Setosa Vs Versicolor ')
```

```
plt.xlabel('Sepal Length')
```

```
plt.ylabel('Sepal Width')
```

```
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'], color="green", marker='+')
```

```
plt.scatter(dataframe_versicolor['sepal length (cm)'], dataframe_versicolor['sepal width (cm)'], color="blue", marker='.')
```

```
plt.title('Setosa Vs Virginica ')
```

```
plt.xlabel('Sepal Length')
```

```
plt.ylabel('Sepal Width')
```

```
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'], color="green", marker='+')
```

```
plt.scatter(dataframe_virginica['sepal length (cm)'], dataframe_virginica['sepal width (cm)'], color="red", marker='*')
```

```
X = dataframe.drop(['target','flower_name'], axis='columns')
```

```
y = dataframe['target']
```

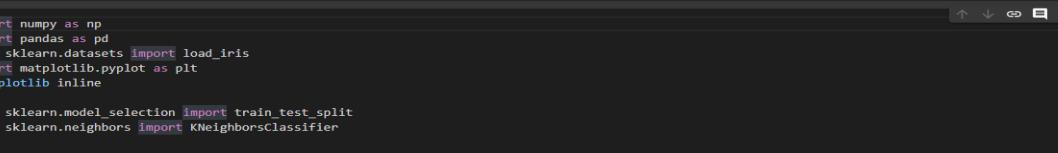
```
X_train, X_test, y_train, y_test=train_test_split(X, y, test_size=0.2)
```

```
knn_model = KNeighborsClassifier(n_neighbors=5)
```

```
knn_model.fit(X_train,y_train)
```

```
knn_model.score(X_test,y_test)
```

OUTPUT:



The screenshot shows a Jupyter Notebook interface with the following details:

- Title Bar:** Untitled0.ipynb
- Menu Bar:** File, Edit, View, Insert, Runtime, Tools, Help
- Toolbar:** Comment, Share, Settings, User icon
- Code Cell:** Contains Python code for loading the Iris dataset, creating a DataFrame, applying target names, and displaying the first 5 rows.
- Output Cell:** Shows the first 5 rows of the DataFrame.
- Bottom Status Bar:** RAM usage (4.7 GB), Disk usage (100%), Editing mode, and other icons.

The screenshot shows a Jupyter Notebook interface with the following details:

- Title:** Untitled0.ipynb
- Header:** File, Edit, View, Insert, Runtime, Tools, Help
- Toolbar:** Comment, Share, Settings, RAM Disk, Editing
- Code Cell:**

```
dataframe_virginica=dataframe[100:150]
plt.title('Setosa Vs Versicolor ')
plt.xlabel('Sepal Length')
plt.ylabel('Sepal Width')
plt.scatter(dataframe_setosa['sepal length (cm)'], dataframe_setosa['sepal width (cm)'],color="green",marker='+')
def scatter(x, y, s=None, c=None, marker=None, cmap=None, norm=None, vmin=None, vmax=None, alpha=None,
           linewidths=None, verts=cbook.deprecation._deprecated_parameter, edgecolors=None, *, plotnonfinite=False,
           data=None, **kwargs):
    ...
Open in tab View source
A scatter plot of "y" vs. "x" with varying marker size and/or color.
```
- Parameter Documentation:**
 - x, y : scalar or array-like, shape (n,) The data positions.
 - s : scalar or array-like, shape (n,), optional The marker size in points**2. Default is $\text{np.pi} * \text{linins}^2$.
 - marker : {None, '+', 'x', 'o', 'v', 's', '^', 'd', 'D', 'p', 'P', 'h', 'H', 'x', 'X', 'd', 'D', 's', 'S', 'p', 'P', 'h', 'H', 't', 'T', 'l', 'L', 'r', 'R', 'd', 'D', 's', 'S', 'p', 'P', 'h', 'H', 't', 'T', 'l', 'L', 'r', 'R'}
- Code Below Cell:**

```
X = dataframe.drop(['target'], axis='columns')
y = dataframe['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train, y_train)
```

```
X = dataframe.drop(['target', 'flower_name'], axis='columns')
y = dataframe['target']
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
knn_model = KNeighborsClassifier(n_neighbors=5)
knn_model.fit(X_train,y_train)
knn_model.score(X_test,y_test)

0.9333333333333333
```

Setosa Vs Virginica

Sepal Width

Sepal Length

PRACTICAL-6

AIM: Study and Implement K-Fold cross validation and ROC

CODE:

ML_P6.ipynb

Implement K-Fold cross validation and ROC

```
import matplotlib.pyplot as plt
from scipy import interp
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import StratifiedKFold
import matplotlib.patches as patches
import numpy as np
import pandas as pd

data = pd.read_csv('/content/drive/MyDrive/ML/voice.csv')
print(data.columns)
label_value_count = data.label.value_counts()
print(label_value_count)
print(data.info())

dict = {'label':{'male':1,'female':0}}
data.replace(dict,inplace = True)
x = data.loc[:, data.columns != 'label']
```

```
y = data.loc[:, 'label']

random_state = np.random.RandomState(0)
clf = RandomForestClassifier(random_state=random_state)
cv = StratifiedKFold(n_splits=5, shuffle=False)

fig1 = plt.figure(figsize=[12,12])
ax1 = fig1.add_subplot(111, aspect='equal')

tprs = []
aucs = []
mean_fpr = np.linspace(0, 1, 100)
i = 1

for train, test in cv.split(x, y):
    prediction = clf.fit(x.iloc[train], y.iloc[train]).predict_proba(x.iloc[test])

    fpr, tpr, _ = roc_curve(y[test], prediction[:, 1])
    tprs.append(interp(mean_fpr, fpr, tpr))
    roc_auc = auc(fpr, tpr)
    aucs.append(roc_auc)

    plt.plot(fpr, tpr, lw=2, alpha=0.3, label='ROC fold %d (AUC = %0.2f)' % (i, roc_auc))

    i += 1

plt.plot([0, 1], [0, 1], linestyle='--', lw=2, color='black')
mean_tpr = np.mean(tprs, axis=0)
mean_auc = auc(mean_fpr, mean_tpr)
plt.plot(mean_fpr, mean_tpr, color='blue',
```

```

label=r'Mean ROC (AUC = %0.2f )' % (mean_auc),lw=2, alpha=1)

plt.xlabel('False Positive Rate')

plt.ylabel('True Positive Rate')

plt.title('ROC')

plt.legend(loc="lower right")

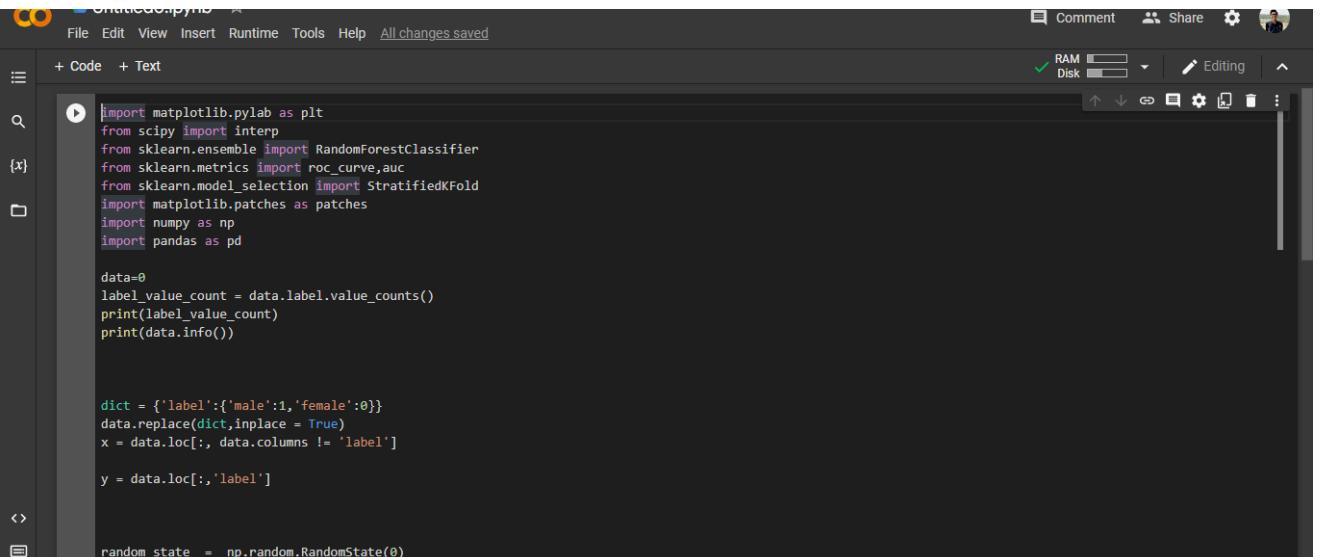
plt.text(0.32,0.7,'More accurate area',fontsize = 12)

plt.text(0.63,0.4,'Less accurate area',fontsize = 12)

plt.show()

```

OUTPUT:



The screenshot shows a Jupyter Notebook interface with a dark theme. The code cell contains Python code for generating an ROC curve. The code imports necessary libraries (matplotlib, scipy, sklearn), handles data loading and preprocessing, and plots the ROC curve with annotations.

```

import matplotlib.pyplot as plt
from scipy import interp
from sklearn.ensemble import RandomForestClassifier
from sklearn.metrics import roc_curve, auc
from sklearn.model_selection import StratifiedKFold
import matplotlib.patches as patches
import numpy as np
import pandas as pd

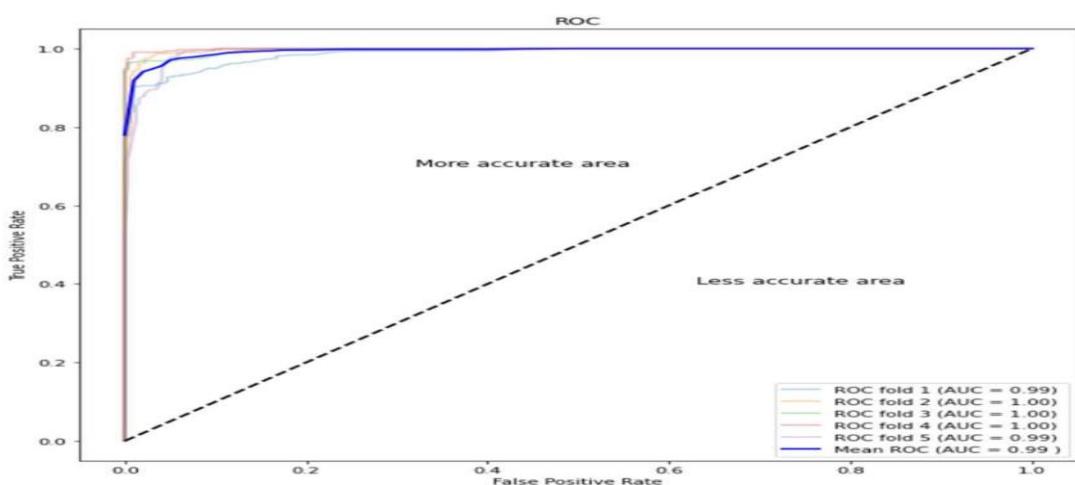
data=0
label_value_count = data.label.value_counts()
print(label_value_count)
print(data.info())

dict = {'label':{'male':1,'female':0}}
data.replace(dict,inplace = True)
x = data.loc[:, data.columns != 'label']

y = data.loc[:, 'label']

random_state = np.random.RandomState(0)

```



PRACTICAL-7

AIM: Implement BPNN Classifier in python

CODE:

```
import numpy as np

import pandas as pd

from sklearn.datasets import load_iris

from sklearn.model_selection import train_test_split

import matplotlib.pyplot as plt

data = load_iris()
X=data.data

y=data.target

y = pd.get_dummies(y).values

y[:3]

X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=20,random_state=4)

learning_rate = 0.1

iterations = 500

N=y_train.size

input_size = 4

hidden_size = 2
output_size = 3
results = pd.DataFrame(columns=["mse", "accuracy"])
np.random.seed(10)

W1 = np.random.normal(scale=0.5, size=(input_size, hidden_size))
W2 = np.random.normal(scale=0.5, size=(hidden_size , output_size))

def sigmoid(x):
    return 1 / (1 + np.exp(-x))

def mean_squared_error(y_pred, y_true):
    return ((y_pred - y_true)**2).sum() / (2*y_pred.size)

def accuracy(y_pred, y_true):
    acc = y_pred.argmax(axis=1) == y_true.argmax(axis=1)

    return acc.mean()
```

```
for itr in range(iterations):
    Z1 = np.dot(X_train, W1)
    A1 = sigmoid(Z1)
    Z2 = np.dot(A1, W2)
    A2 = sigmoid(Z2)

    mse = mean_squared_error(A2, y_train)
    acc = accuracy(A2, y_train)

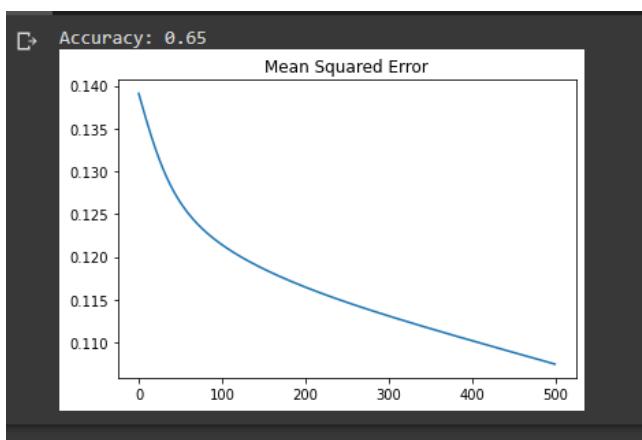
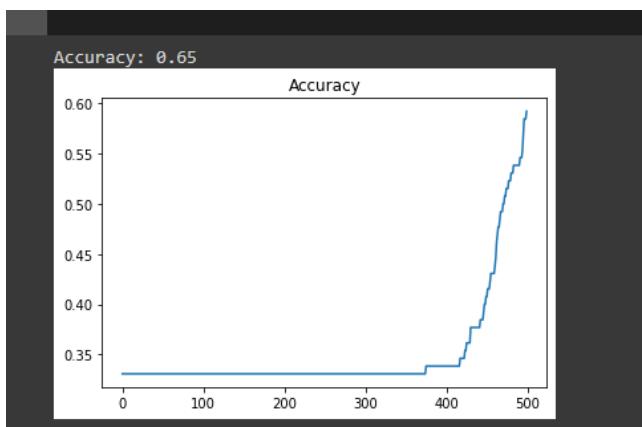
    results.append({"mse": mse, "accuracy": acc}, ignore_index=True)
    E1 = A2 - y_train
    dW1 = E1 * A2 * (1 - A2)
    E2 = np.dot(dW1, W2.T)
    dW2 = E2 * A1 * (1 - A1)

    W2_update = np.dot(A1.T, dW1) / N
    W1_update = np.dot(X_train.T, dW2) / N
    W2 = W2 - learning_rate * W2_update
    W1 = W1 - learning_rate * W1_update

results.mse.plot(title="Mean Squared Error")
results.accuracy.plot(title="Accuracy")

Z1 = np.dot(X_test, W1)
A1 = sigmoid(Z1)
Z2 = np.dot(A1, W2)
A2 = sigmoid(Z2)

acc = accuracy(A2, y_test)
print("Accuracy: {}".format(acc))
```

OUTPUT:

PRACTICAL-8

AIM: Study and Implement various Ensemble method of classifier : Bagging, Boosting and Stacking

CODE:

ML_P8.ipynb

Study and Implement various Ensemble method of classifier : Bagging, Boosting, Stacking

```
from numpy import mean  
from numpy import std  
from sklearn.datasets import make_classification  
from sklearn.model_selection import cross_val_score  
from sklearn.model_selection import RepeatedStratifiedKFold  
from sklearn.ensemble import BaggingClassifier  
from sklearn.linear_model import LogisticRegression  
from sklearn.neighbors import KNeighborsClassifier  
from sklearn.tree import DecisionTreeClassifier  
from sklearn.svm import SVC  
from sklearn.naive_bayes import GaussianNB  
from matplotlib import pyplot
```

#Bagging

```
X, y = make_classification(n_samples=1000, n_features=20, n_informative=15, n_redundant=5,  
random_state=5)
```

```
model = BaggingClassifier()
```

```
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

n_scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1, error_score='raise')

print('Accuracy: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
```

#Boosting

```
from sklearn.ensemble import GradientBoostingClassifier

X, y = make_classification(n_samples=1000, n_features=20, n_informative=15, n_redundant=5,
random_state=7)

model = GradientBoostingClassifier()
```

```
cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)
```

```
n_scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1)
```

```
print('Mean Accuracy: %.3f (%.3f)' % (mean(n_scores), std(n_scores)))
```

```
def evaluate_model(model, X, y):
```

```
    cv = RepeatedStratifiedKFold(n_splits=10, n_repeats=3, random_state=1)

    scores = cross_val_score(model, X, y, scoring='accuracy', cv=cv, n_jobs=-1, error_score='raise')

    return scores
```

#Stacking

```
X, y = make_classification(n_samples=1000, n_features=20, n_informative=15, n_redundant=5,
random_state=1)
```

```
models = dict()

models['lr'] = LogisticRegression()
models['knn'] = KNeighborsClassifier()
models['decisiontree'] = DecisionTreeClassifier()
models['svm'] = SVC()
models['bayes'] = GaussianNB()
```

```
results, names = list(), list()

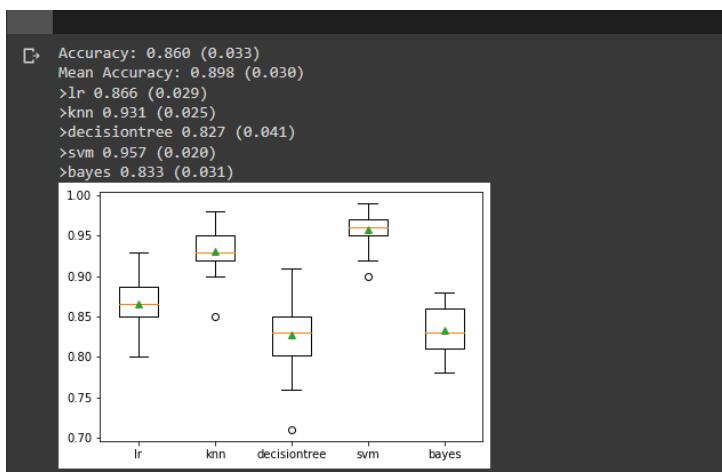
for name, model in models.items():
    scores=evaluate_model(model,X,y)
    results.append(scores)
    names.append(name)

print('>%s %.3f (%.3f)' % (name, mean(scores), std(scores)))
```

```
pyplot.boxplot(results, labels=names, showmeans=True)
```

```
pyplot.show()
```

OUTPUT:



PRACTICAL-9

AIM: Implement various Clustering algorithm in python.

CODE:

```
from numpy import where
from sklearn.datasets import make_classification
from matplotlib import pyplot
from numpy import unique

X, y = make_classification(n_samples=1000, n_features=2, n_informative=2, n_redundant=0,
n_clusters_per_class=1, random_state=4)

for class_value in range(2):
    row_ix = where(y == class_value)
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
    pyplot.show()

#KMeans
from sklearn.cluster import KMeans

model = KMeans(n_clusters=2)

model.fit(X)

ypredicted = model.predict(X)

clusters = unique(ypredicted)

for cluster in clusters:
    row_ix = where(ypredicted == cluster)
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
    pyplot.show()
```

#BIRCH

```
from sklearn.cluster import Birch

model = Birch(threshold=0.01, n_clusters=2)

model.fit(X)

ypredicted = model.predict(X)

clusters = unique(ypredicted)
```

```
for cluster in clusters:
```

```
    row_ix = where(ypredicted == cluster)
```

```
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
```

```
    pyplot.show()
```

```
#DBSCAN
```

```
from sklearn.cluster import DBSCAN
model = DBSCAN(eps=0.30, min_samples=9)
ypredicted = model.fit_predict(X)
```

```
clusters = unique(ypredicted)
```

```
for cluster in clusters:
```

```
    row_ix = where(ypredicted == cluster)
```

```
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
```

```
    pyplot.show()
```

```
#MiniBatchKMeans
```

```
from sklearn.cluster import MiniBatchKMeans
```

```
model = MiniBatchKMeans(n_clusters=2)
```

```
model.fit(X)
```

```
ypredicted = model.fit_predict(X)
```

```
clusters = unique(ypredicted)
```

```
for cluster in clusters:
```

```
    row_ix = where(ypredicted == cluster)
```

```
    pyplot.scatter(X[row_ix, 0], X[row_ix, 1])
```

```
    pyplot.show()
```

```
#MeanShift
```

```
from sklearn.cluster import MeanShift
```

```
model = MeanShift()
```

```
ypredicted = model.fit_predict(X)
```

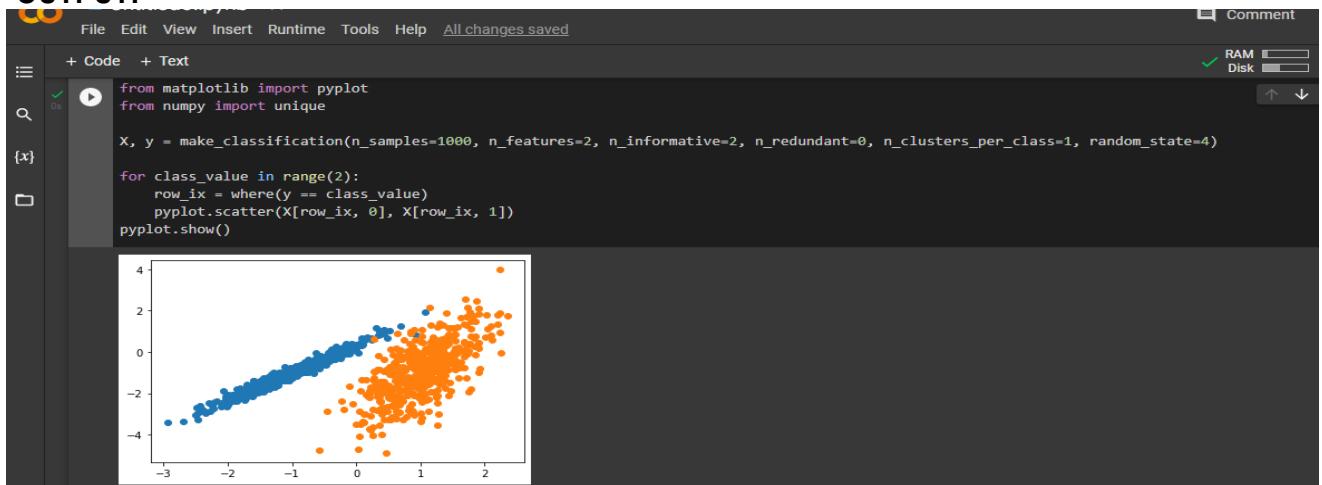
```
clusters = unique(ypredicted)
```

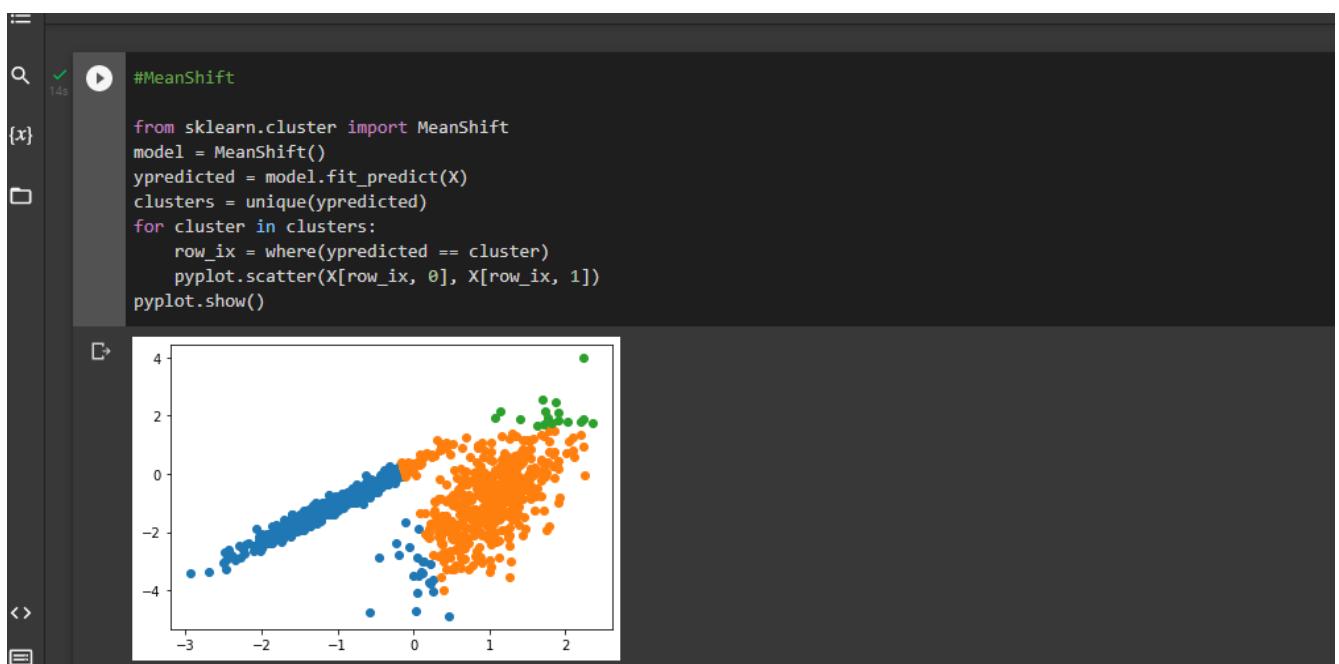
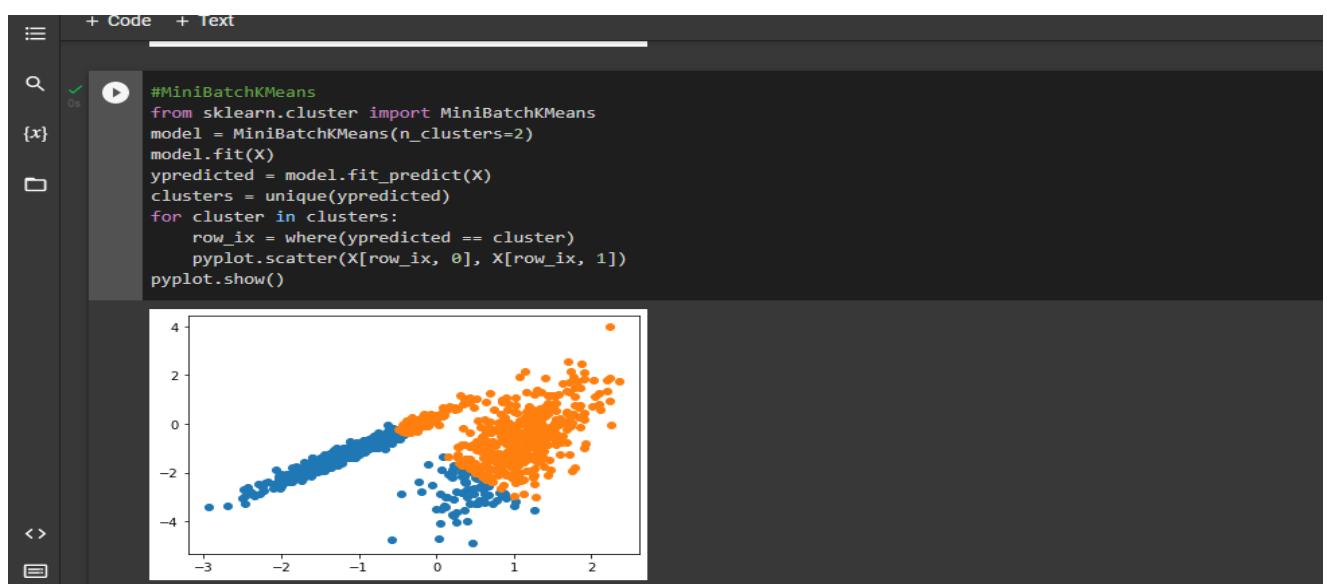
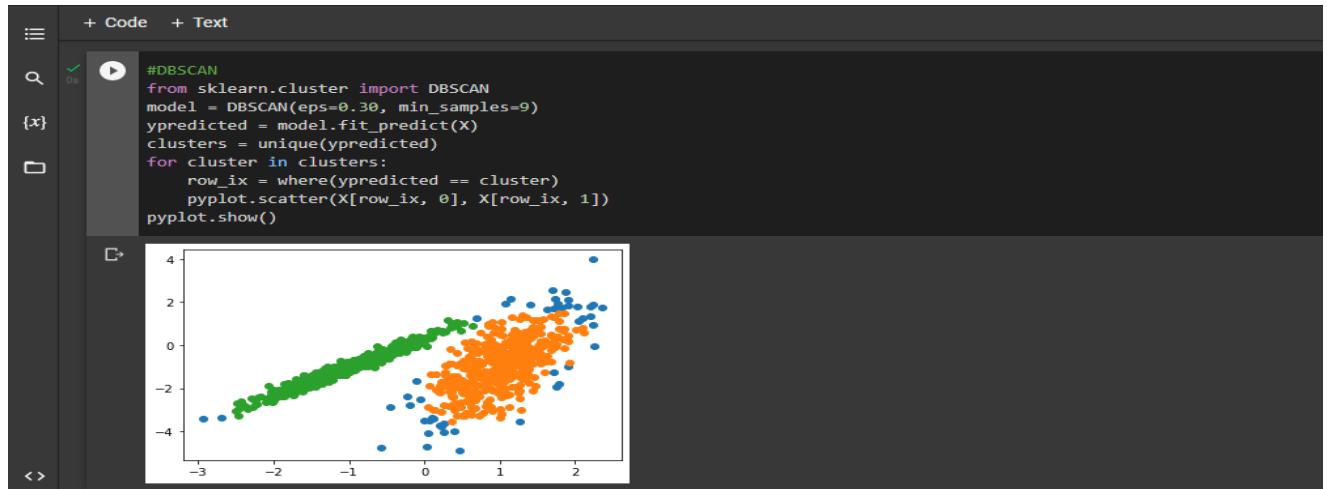
```
for cluster in clusters:
```

```
row_ix = where(ypredicted == cluster)

pyplot.scatter(X[row_ix, 0], X[row_ix, 1])

pyplot.show()
```

OUTPUT:



PRACTICAL-10

AIM: Study and Implement various Dimensionality technique like PCA and LDA

CODE:

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

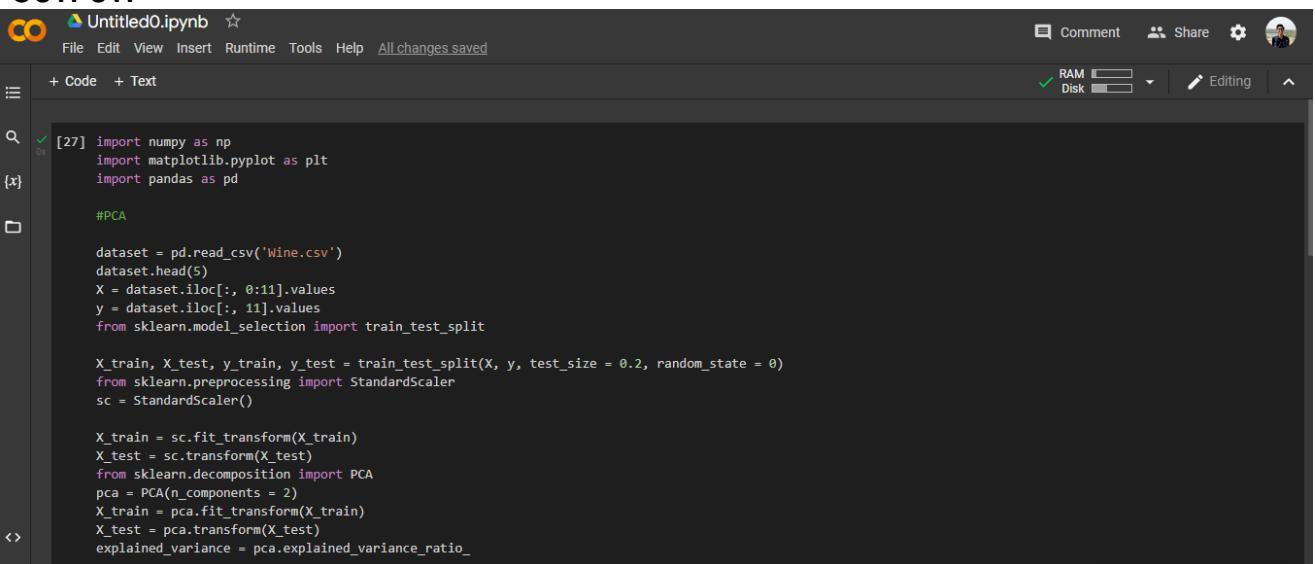
#PCA
dataset = pd.read_csv('/content/drive/MyDrive/ML/WineQT.csv')
dataset.head(5)
X=dataset.iloc[:, 0:11].values
y=dataset.iloc[:, 11].values
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2, random_state = 0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()
X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
from sklearn.decomposition import PCA
pca = PCA(n_components = 2)
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
explained_variance = pca.explained_variance_ratio_
```

```
from sklearn.linear_model import LogisticRegression  
classifier = LogisticRegression(random_state = 0)  
classifier.fit(X_train, y_train)
```

```
y_pred = classifier.predict(X_test)  
classifier.score(X_test,y_test)
```

#LDA:

```
dataset = pd.read_csv('/content/drive/MyDrive/ML/WineQT.csv')  
dataset.head(5)  
X=dataset.iloc[:, 0:11].values  
y=dataset.iloc[:, 11].values  
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, random_state = 0)  
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA  
lda = LDA(n_components = 2)  
X_train = lda.fit_transform(X_train, y_train)  
X_test = lda.transform(X_test)  
from sklearn.linear_model import LogisticRegression  
classifier = LogisticRegression(random_state = 0)  
classifier.fit(X_train, y_train)  
classifier = LogisticRegression(random_state = 0)  
classifier.fit(X_train, y_train)  
  
y_pred = classifier.predict(X_test)  
classifier.score(X_test,y_test)
```

OUTPUT:

A screenshot of a Jupyter Notebook interface. The title bar says "Untitled0.ipynb". The code cell contains Python code for performing PCA on a wine dataset. The code imports numpy, matplotlib.pyplot, and pandas, then reads the 'Wine.csv' file. It splits the data into X (features) and y (target), performs train-test split, scales the features, and applies PCA to reduce dimensions to 2. The output cell shows the explained variance ratio.

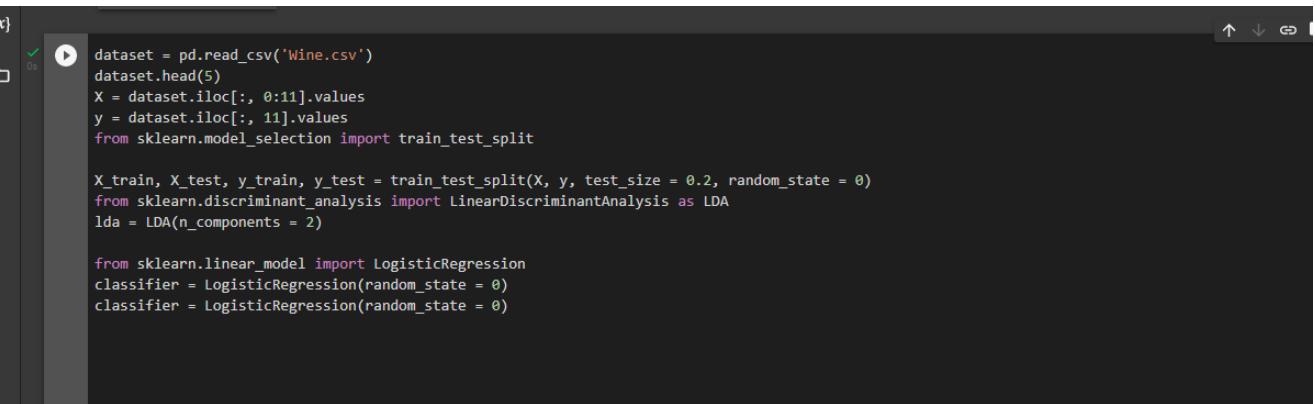
```
[27] import numpy as np
     import matplotlib.pyplot as plt
     import pandas as pd

#PCA

dataset = pd.read_csv('Wine.csv')
dataset.head(5)
X = dataset.iloc[:, 0:11].values
y = dataset.iloc[:, 11].values
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, random_state = 0)
from sklearn.preprocessing import StandardScaler
sc = StandardScaler()

X_train = sc.fit_transform(X_train)
X_test = sc.transform(X_test)
from sklearn.decomposition import PCA
pca = PCA(n_components = 2)
X_train = pca.fit_transform(X_train)
X_test = pca.transform(X_test)
explained_variance = pca.explained_variance_ratio_
```



A screenshot of a Jupyter Notebook interface. The code cell contains Python code for performing LDA and Logistic Regression on the same wine dataset. It loads the dataset, performs train-test split, applies PCA, and then uses LDA to further reduce dimensions. Finally, it trains a Logistic Regression classifier. The output cell shows the classifier's performance metrics.

```
dataset = pd.read_csv('Wine.csv')
dataset.head(5)
X = dataset.iloc[:, 0:11].values
y = dataset.iloc[:, 11].values
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, random_state = 0)
from sklearn.discriminant_analysis import LinearDiscriminantAnalysis as LDA
lda = LDA(n_components = 2)

from sklearn.linear_model import LogisticRegression
classifier = LogisticRegression(random_state = 0)
classifier = LogisticRegression(random_state = 0)
```

PRACTICAL-11

AIM: Course project on Recommender System, Sentiment Analysis, Image Captioning, Object detection

Recommendation engines are a subclass of machine learning which generally deal with ranking or rating products / users. Loosely defined, a recommender system is a system which predicts ratings a user might give to a specific item. These predictions will then be ranked and returned back to the user.

Sentiment analysis can help you determine the ratio of positive to negative engagements about a specific topic. You can analyze bodies of text, such as comments, tweets, and product reviews, to obtain insights from your audience.

Image Captioning is the process of generating textual description of an image. It uses both Natural Language Processing and Computer Vision to generate the captions. The dataset will be in the form [image → captions]. The dataset consists of input images and their corresponding output captions.

Object Recognition is a technology that lies under the broader domain of Computer Vision. This technology is capable of identifying objects that exist in images and videos and tracking them. Object Recognition also known as Object Detection, has various applications like face recognition, vehicle recognition, pedestrian counting, self-driving vehicles, security systems, and a lot more.

CODE:

ML_P11.ipynb

```
import pandas as pd  
from random import randint  
import numpy as np  
from scipy.sparse import csr_matrix
```

```

from scipy.sparse.linalg import svds

def generate_data(n_books=3000, n_genres=10, n_authors=450, n_publishers=50, n_readers=30000, dataset_size=100000):
    d = pd.DataFrame(
        {
            'book_id': [randint(1, n_books) for _ in range(dataset_size)],
            'author_id': [randint(1, n_authors) for _ in range(dataset_size)],
            'book_genre': [randint(1, n_genres) for _ in range(dataset_size)],
            'reader_id': [randint(1, n_readers) for _ in range(dataset_size)],
            'num_pages': [randint(75, 700) for _ in range(dataset_size)],
            'book_rating': [randint(1, 10) for _ in range(dataset_size)],
            'publisher_id': [randint(1, n_publishers) for _ in range(dataset_size)],
            'publish_year': [randint(2000, 2021) for _ in range(dataset_size)],
            'book_price': [randint(1, 200) for _ in range(dataset_size)],
            'text_lang': [randint(1, 7) for _ in range(dataset_size)]
        }
    ).drop_duplicates()
    return d

d = generate_data(dataset_size=1000)
d.to_csv('data.csv', index=False)

def normalize(pred_ratings):
    return (pred_ratings - pred_ratings.min()) / (pred_ratings.max() - pred_ratings.min())

def generate_prediction_df(mat, pt_df, n_factors):
    if not 1 <= n_factors < min(mat.shape):
        raise ValueError("Must be 1 <= n_factors < min(mat.shape)")

    u, s, v = svds(mat, k=n_factors)

```

```
s = np.diag(s)

pred_ratings = np.dot(np.dot(u, s), v)

pred_ratings = normalize(pred_ratings)

pred_df = pd.DataFrame(

    pred_ratings,

    columns = pt_df.columns,

    index = list(pt_df.index)

).transpose()

return pred_df

def recommend_items(pred_df, usr_id, n_recs):

    usr_pred = pred_df[usr_id].sort_values(ascending = False).reset_index().rename(columns = {usr_id : 'sim'})

    rec_df = usr_pred.sort_values(by = 'sim', ascending = False).head(n_recs)

    return rec_df

if __name__ == '__main__':

    PATH = '/content/data.csv'

    df = pd.read_csv(PATH)

    print(df.shape)

    pt_df = df.pivot_table(

        columns = 'book_id',

        index = 'reader_id',

        values = 'book_rating'

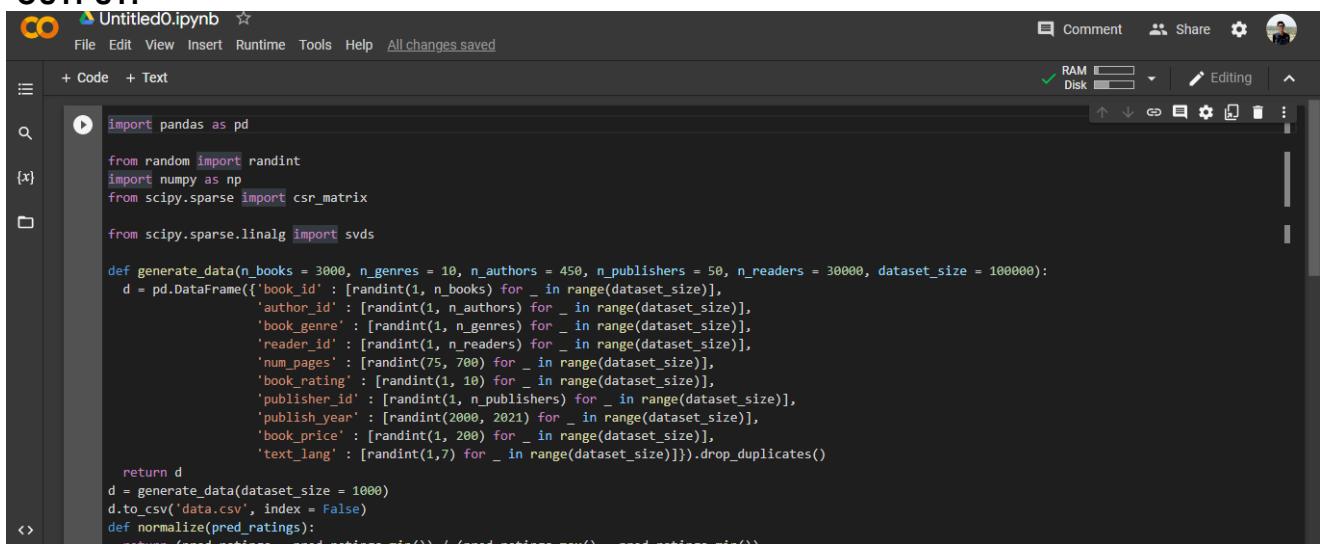
    ).fillna(0)

    mat = pt_df.values

    mat = csr_matrix(mat)

    pred_df = generate_prediction_df(mat, pt_df, 10)

    print(recommend_items(pred_df, 5, 5))
```

OUTPUT:


```

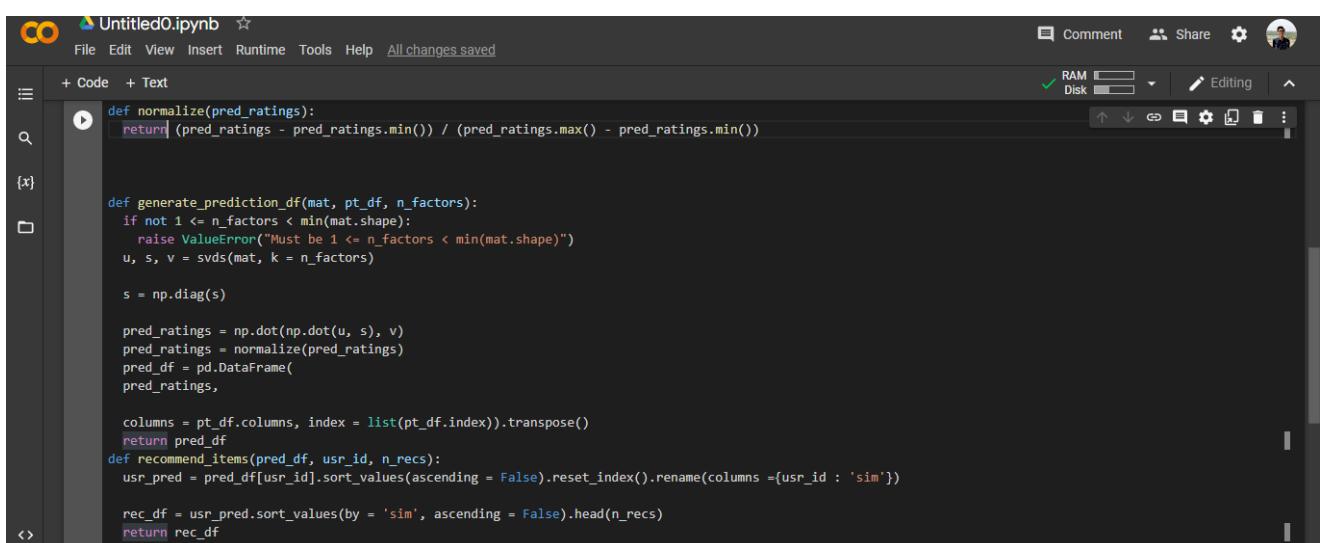
import pandas as pd

from random import randint
import numpy as np
from scipy.sparse import csr_matrix

from scipy.sparse.linalg import svds

def generate_data(n_books = 3000, n_genres = 10, n_authors = 450, n_publishers = 50, n_readers = 30000, dataset_size = 100000):
    d = pd.DataFrame({'book_id' : [randint(1, n_books) for _ in range(dataset_size)],
                      'author_id' : [randint(1, n_authors) for _ in range(dataset_size)],
                      'book_genre' : [randint(1, n_genres) for _ in range(dataset_size)],
                      'reader_id' : [randint(1, n_readers) for _ in range(dataset_size)],
                      'num_pages' : [randint(75, 700) for _ in range(dataset_size)],
                      'book_rating' : [randint(1, 10) for _ in range(dataset_size)],
                      'publisher_id' : [randint(1, n_publishers) for _ in range(dataset_size)],
                      'publish_year' : [randint(2000, 2021) for _ in range(dataset_size)],
                      'book_price' : [randint(1, 200) for _ in range(dataset_size)],
                      'text_lang' : [randint(1,7) for _ in range(dataset_size)]}).drop_duplicates()
    return d
d = generate_data(dataset_size = 1000)
d.to_csv('data.csv', index = False)
def normalize(pred_ratings):
    return (pred_ratings - pred_ratings.min()) / (pred_ratings.max() - pred_ratings.min())

```



```

def normalize(pred_ratings):
    return (pred_ratings - pred_ratings.min()) / (pred_ratings.max() - pred_ratings.min())

def generate_prediction_df(mat, pt_df, n_factors):
    if not 1 <= n_factors < min(mat.shape):
        raise ValueError("Must be 1 <= n_factors < min(mat.shape)")
    u, s, v = svds(mat, k = n_factors)

    s = np.diag(s)

    pred_ratings = np.dot(np.dot(u, s), v)
    pred_ratings = normalize(pred_ratings)
    pred_df = pd.DataFrame(
        pred_ratings,
        columns = pt_df.columns, index = list(pt_df.index)).transpose()
    return pred_df

def recommend_items(pred_df, usr_id, n_recs):
    usr_pred = pred_df[usr_id].sort_values(ascending = False).reset_index().rename(columns = {usr_id : 'sim'})

    rec_df = usr_pred.sort_values(by = 'sim', ascending = False).head(n_recs)
    return rec_df

```