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1. Find the correlation matrix.

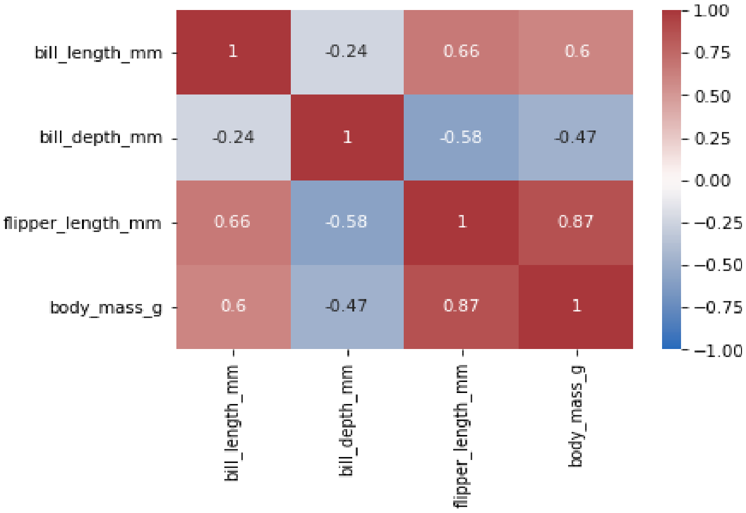
```
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import numpy as np

# load the dataset
df=sns.load_dataset('penguins')

matrix=df.corr().round(2)
matrix
```

	bill_length_mm	bill_depth_mm	flipper_length_mm	body_mass_g
bill_length_mm	1.00	-0.24	0.66	0.60
bill_depth_mm	-0.24	1.00	-0.58	-0.47
flipper_length_mm	0.66	-0.58	1.00	0.87
body_mass_g	0.60	-0.47	0.87	1.00

```
sns.heatmap(matrix,annot=True,cmap='vlag',vmax=1,vmin=-1)
<AxesSubplot:>
```



plt.show()

plt.savefig('heatmap.png')

<Figure size 432x288 with 0 Axes>

2. Plot the correlation plot on dataset and visualize giving an overview of Relationships among data on iris data.

```
import pandas as pd

from sklearn import datasets

iris=datasets.load_iris()

iris df=pd.DataFrame(data=iris.data,columns=iris.feature_names)

df
```

sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	
0	5.1	3.5	1.4	0.2
1	4.9	3.0	1.4	0.2
2	4.7	3.2	1.3	0.2
3	4.6	3.1	1.5	0.2
4	5.0	3.6	1.4	0.2
...	...	...	...	...
145	6.7	3.0	5.2	2.3
146	6.3	2.5	5.0	1.9
147	6.5	3.0	5.2	2.0
148	6.2	3.4	5.4	2.3
149	5.9	3.0	5.1	1.8

150 rows × 4 columns

```
df['target']=iris.target

df.head()
```

	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

r=df["sepal length (cm)"].corr(df["petal length (cm)"]) r

0.8717537758865831

corr=df.corr()

corr

	sepal length (cm)	sepal width (cm)	petal length (cm)	petal width (cm)	target
sepal length (cm)	1.000000	-0.117570	0.871754	0.817941	0.782561
sepal width (cm)	-0.117570	1.000000	-0.428440	-0.366126	-0.426658
petal length (cm)	0.871754	-0.428440	1.000000	0.962865	0.949035
petal width (cm)	0.817941	-0.366126	0.962865	1.000000	0.956547
target	0.782561	-0.426658	0.949035	0.956547	1.000000

import seaborn as sns

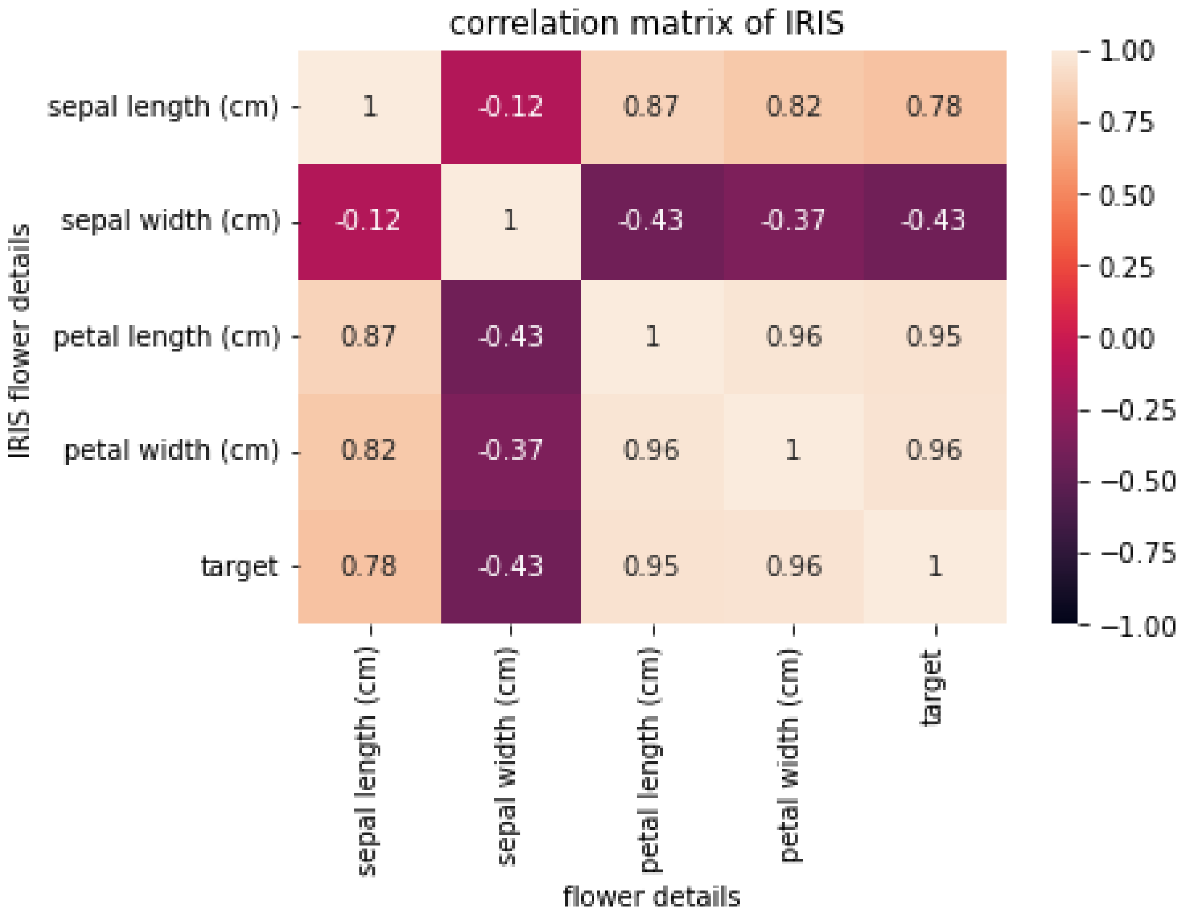
import matplotlib.pyplot as plt

hm=sns.heatmap(df.corr(),annot=True,vmax=1,vmin=-1)

hm.set(xlabel="flower details",ylabel="IRIS flower details",title="correlation matrix of IRIS ")

plt.show()

plt.savefig("plotting correlation.jpg")

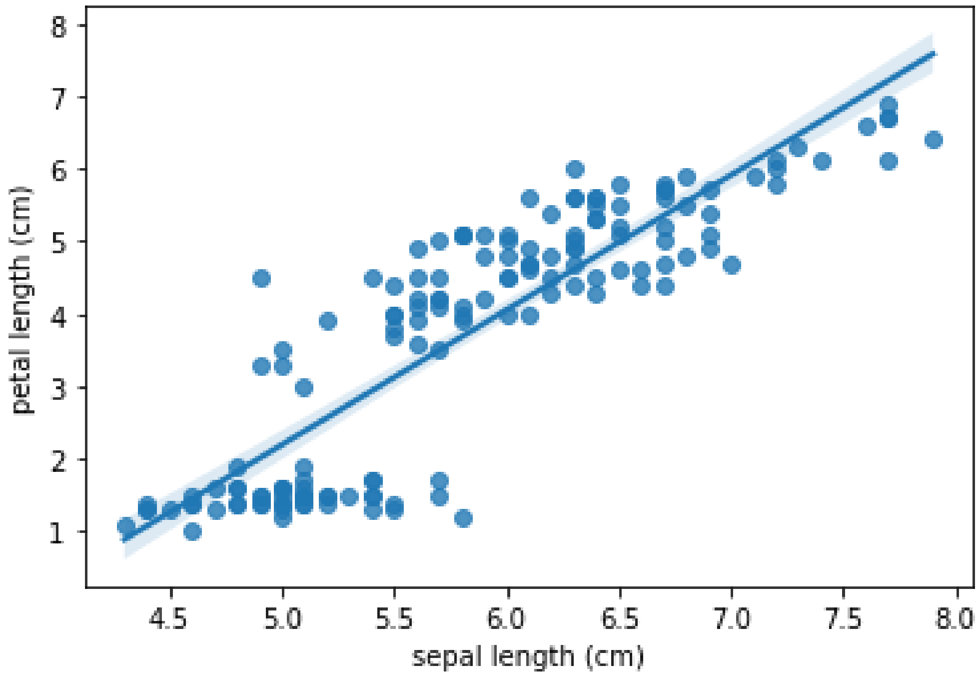


<Figure size 432x288 with 0 Axes>

#use the function regplotto make a scatterplot

sns.regplot(x=df["sepal length (cm)"],y=df["petal length (cm)"])

<AxesSubplot:xlabel='sepal length (cm)', ylabel='petal length (cm)'>

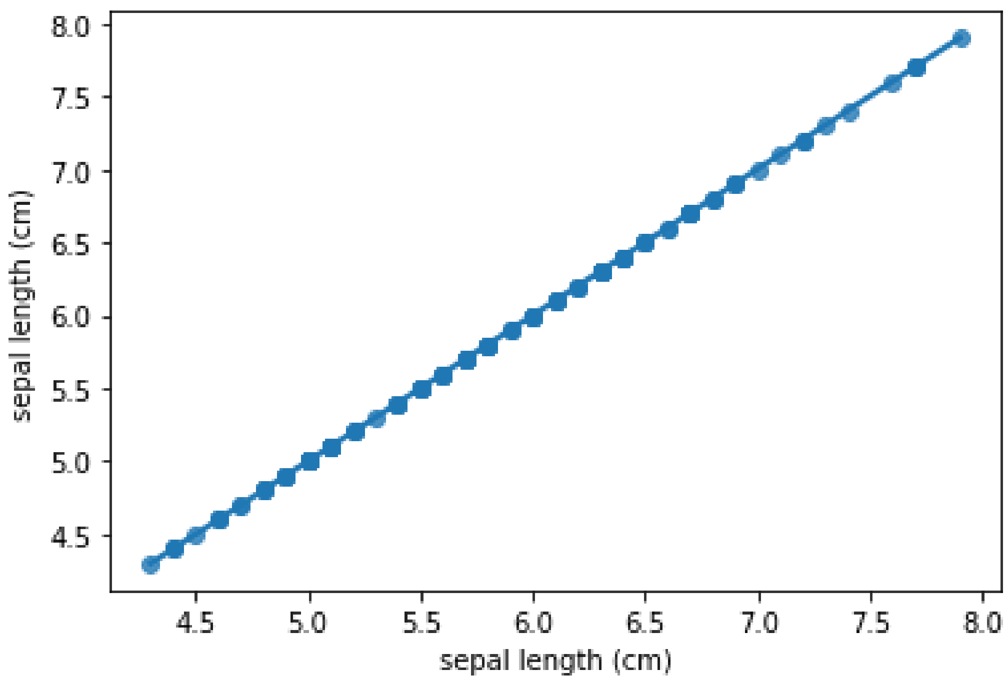


r=df["sepal length (cm)"].corr(df["sepal length (cm)"]) r

1.0

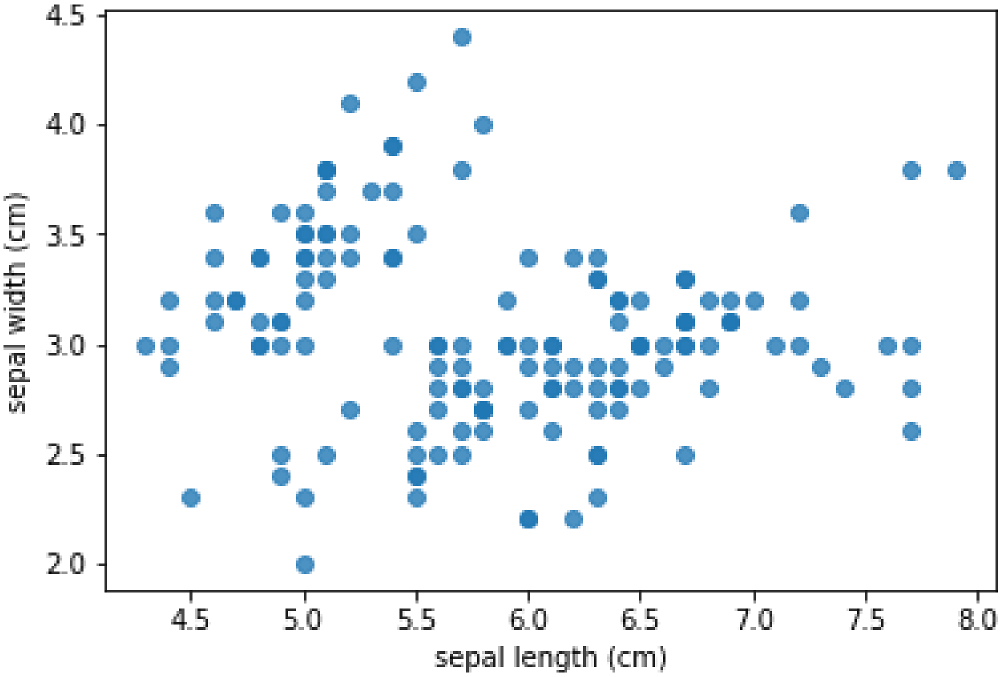
sns.regplot(x=df["sepal length (cm)"],y=df["sepal length (cm)"])

<AxesSubplot:xlabel='sepal length (cm)', ylabel='sepal length (cm)'>



```
sns.regplot(x=df["sepal length (cm)"],y=df["sepal width (cm)"], fit_reg=False)
```

<AxesSubplot:xlabel='sepal length (cm)', ylabel='sepal width (cm)'>



3. Analysis of covariance: variance (ANOVA), if data have categorical variables on iris data.

```
Import pandas as pd
df = pd.read_csv(“./data.txt”,sep=’\t’) df.head()
df[[‘jobcat_name’,’prevexp’]].groupby(‘jobcat_name’).mean() mgr
= df[df.jobcat_name==’Manager’][‘prevexp’]
cle = df[df.jobcat_name==’Clerical’][‘prevexp’]
cust = df[df.jobcat_name==’Custodial’][‘prevexp’]
from scipy import stats
f_statistic, p_value = stats.f_oneway(mgr, cle, cust) print(“F_Statistic:
{0}, P-Value: {1}”.format(f_statistic,p_value)) from
statsmodels.formula.api import ols
model_name = ols(‘prevexp ~ C(jobcat_name)’, data=df).fit()
model_name.summary()
```

4. Apply linear regression Model techniques to predict the data on any dataset.

```
import pandas as pd
from sklearn.datasets import load_iris
iris=load_iris()
df=pd.DataFrame(data=iris.data,columns=iris.feature_names) df["target"]=iris.target
df.head()
```

	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

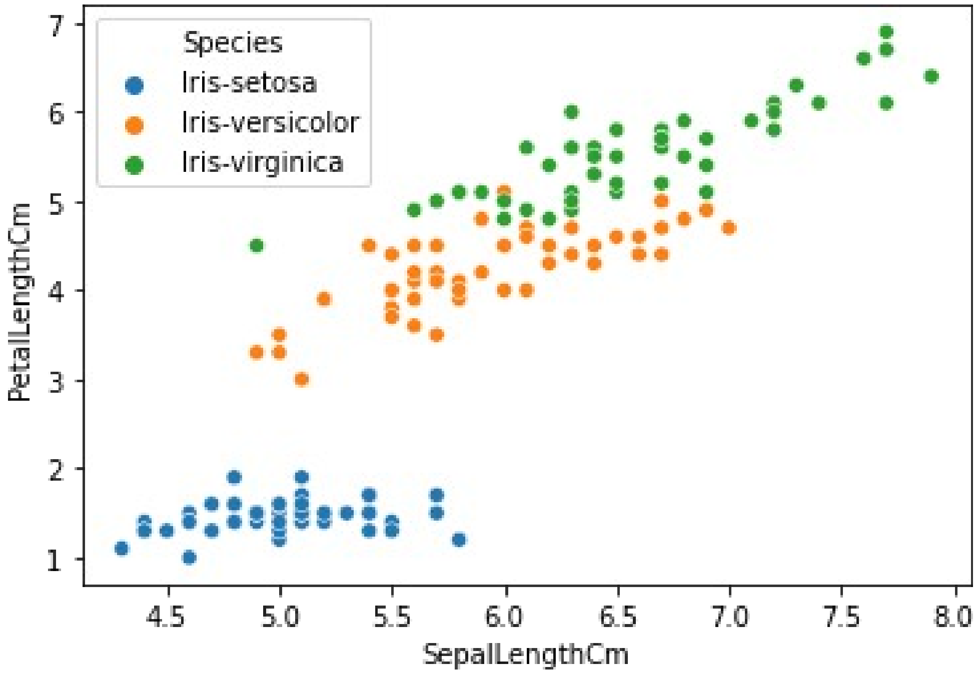
```
df=pd.read_csv('Iris.csv')
df
```

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa
...	...	...	...	...	...	...
145	146	6.7	3.0	5.2	2.3	Iris-virginica
146	147	6.3	2.5	5.0	1.9	Iris-virginica
147	148	6.5	3.0	5.2	2.0	Iris-virginica
148	149	6.2	3.4	5.4	2.3	Iris-virginica
149	150	5.9	3.0	5.1	1.8	Iris-virginica

150 rows × 6 columns

```
from matplotlib import pyplot as plt
import seaborn as sns
sns.scatterplot(data=df,x='SepalLengthCm',y='PetalLengthCm',hue
='Species')
```

<AxesSubplot:xlabel='SepalLengthCm', ylabel='PetalLengthCm'>




```
y=df[['SepalWidthCm']]
y
```

	SepalWidthCm
0	3.5
1	3.0
2	3.2
3	3.1
4	3.6
...	...
145	3.0
146	2.5
147	3.0
148	3.4

	SepalWidthCm
149	3.0

150 rows × 1 columns

```
x=df[['SepalLengthCm']]
x
```

	SepalLengthCm
0	5.1
1	4.9
2	4.7
3	4.6
4	5.0
...	...
145	6.7
146	6.3
147	6.5
148	6.2
149	5.9

150 rows × 1 columns

```
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.3)
x_train
```

	SepalLengthCm
64	5.6
30	4.8
141	6.9
59	5.2
74	6.4

SepalLengthCm	
...	...
31	5.4
46	5.1
115	6.4
104	6.5
40	5.0

105 rows × 1 columns

x_test.head()

	SepalLengthCm
47	4.6
68	6.2
2	4.7
18	5.7
16	5.4

y_test.head()

	SepalWidthCm
47	3.2
68	2.2
2	3.2
18	3.8
16	3.9

y_train.head()

	SepalWidthCm
64	2.9
30	3.1
141	3.1

	SepalWidthCm
59	2.7
74	2.9

from sklearn.linear_model import LinearRegression

LR=LinearRegression()

LR.fit(x_train,y_train)

LinearRegression()
y_pred=LR.predict(x_test)

y_pred[0:5]

```
array([[3.0786979 ],
       [3.02951804],
       [3.07562416],
       [3.04488674],
 [3.05410797]])
```

y_test.head()

	SepalWidthCm
47	3.2
68	2.2
2	3.2
18	3.8
16	3.9

from sklearn.metrics import mean_squared_error

mean_squared_error(y_test,y_pred) 0.2327396540269164

5. Apply logical regression Model techniques to predict the data on any dataset.

```
import pandas as pd
df=pd.read_csv("diabetes.csv")
df
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1
...	...	...	...	...	...	...	...	...	...
763	10	101	76	48	180	32.9	0.171	63	0
764	2	122	70	27	0	36.8	0.340	27	0
765	5	121	72	23	112	26.2	0.245	30	0
766	1	126	60	0	0	30.1	0.349	47	1
767	1	93	70	31	0	30.4	0.315	23	0

768 rows × 9 columns

```
feature_cols=['Pregnancies','Glucose','BloodPressure','SkinThickness','Insulin','BMI','DiabetesPedigreeFunction','Age']
x=df[feature_cols]
y=df.Outcome
from sklearn.model_selection import train_test_split
x_train,x_test,y_train,y_test=train_test_split(x,y,test_size=0.25)
```

x_test

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age
581	6	109	60	27	0	25.0	0.206	27
323	13	152	90	33	29	26.8	0.731	43
333	12	106	80	0	0	23.6	0.137	44
513	2	91	62	0	0	27.3	0.525	22
123	5	132	80	0	0	26.8	0.186	69
...	...	...	...	...	...	...	...	...
330	8	118	72	19	0	23.1	1.476	46
609	1	111	62	13	182	24.0	0.138	23
263	3	142	80	15	0	32.4	0.200	63
626	0	125	68	0	0	24.7	0.206	21
728	2	175	88	0	0	22.9	0.326	22

192 rows × 8 columns

```
from sklearn.linear_model import LogisticRegression
logreg=LogisticRegression()
logreg.fit(x_train,y_train)
logreg
y_pred=logreg.predict(x_test)
y_pred
```

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

```
df.head()
```

	Pregnancies	Glucose	BloodPressure	SkinThickness	Insulin	BMI	DiabetesPedigreeFunction	Age	Outcome
0	6	148	72	35	0	33.6	0.627	50	1
1	1	85	66	29	0	26.6	0.351	31	0
2	8	183	64	0	0	23.3	0.672	32	1
3	1	89	66	23	94	28.1	0.167	21	0
4	0	137	40	35	168	43.1	2.288	33	1

```
from sklearn import metrics
cnf_matrix=metrics.confusion_matrix(y_test,y_pred)
cnf_matrix
```

```
array([[116,   11],
       [ 31,   34]], dtype=int64)
```

```
print("Accuracy:",metrics.accuracy_score(y_test,y_pred))
```

```
Accuracy: 0.78125
```

```
print("Precision:",metrics.precision_score(y_test,y_pred))
```

```
Precision: 0.7555555555555555
```

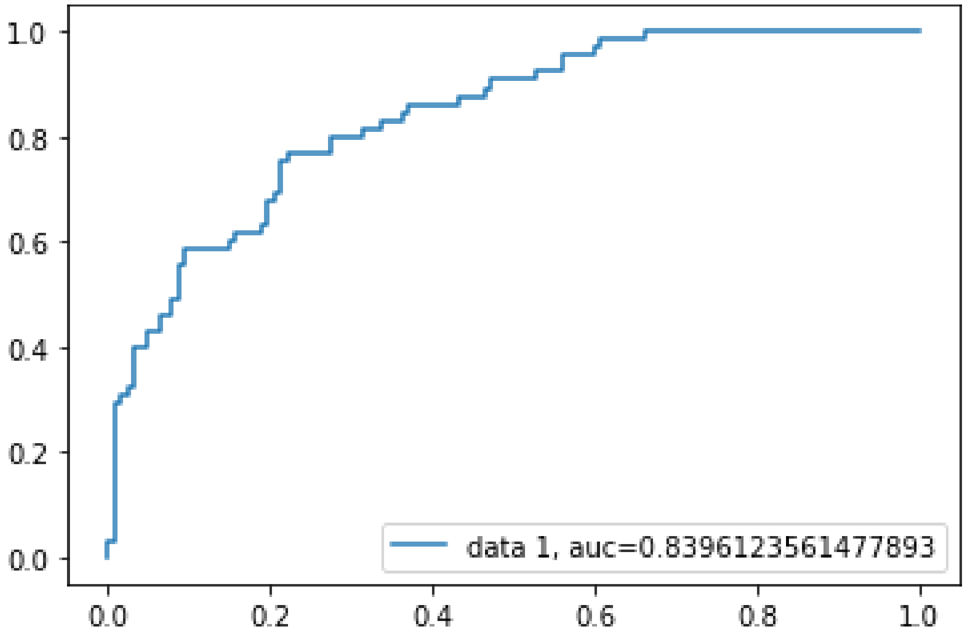
```
print("Recall:",metrics.recall_score(y_test,y_pred))
```

```
Recall: 0.5230769230769231
```

```
y_pred_proba=logreg.predict_proba(x_test)[::,1]
```

```
import matplotlib.pyplot as plt
fpr,tpr,_=metrics.roc_curve(y_test,y_pred_proba)
auc=metrics.roc_auc_score(y_test,y_pred_proba)
plt.plot(fpr,tpr,label="data 1, auc="+str(auc))
```

```
plt.legend(loc=4)
plt.show()
```

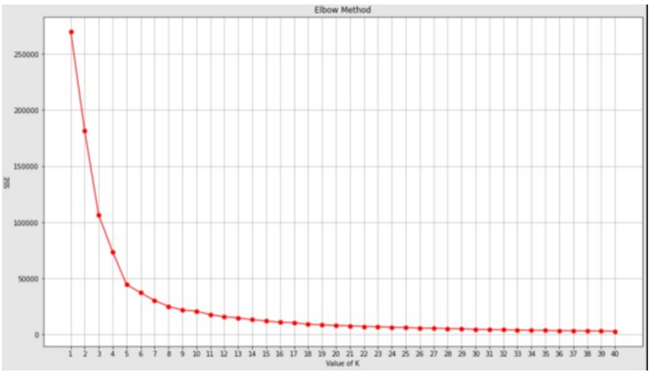


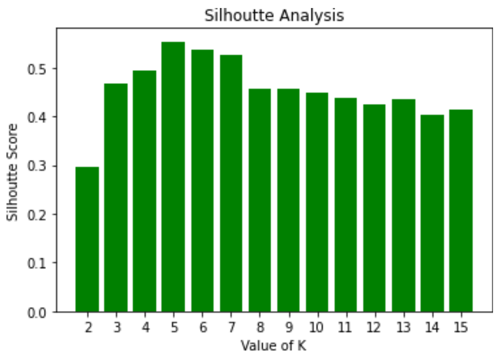
6. Clustering algorithms for unsupervised classification.

```
import pandas as pd
df = pd.read_csv('/content/Mall_Customers.csv') list(df.columns)
x = df.iloc[:,3:]
df.describe()
from sklearn.cluster import KMeans
km = KMeans(n_clusters=12, random_state=0)
labels = km.fit_predict(x)
km.inertia_
sse = []
for k in range(1,41):
 km = KMeans(n_clusters=k, random_state=0)
 labels = km.fit_predict(x)
 sse.append(km.inertia_)
from sklearn.metrics import silhouette_score silh
= []
for k in range(2,16):
 km = KMeans(n_clusters=k, random_state=0)
 labels = km.fit_predict(x)
 score = silhouette_score(x, labels)
 silh.append(score)
km = KMeans(n_clusters=5, random_state=0)
labels = km.fit_predict(x)
km.labels_ km.cluster_centers_
df[labels==2] # Boolean filter
one = df[labels==1]
```

```
one.to_csv('one.csv')
print('Cluster-0:',       len(df[labels==0]))
print('Cluster-1:',       len(df[labels==1]))
print('Cluster-2:',       len(df[labels==2]))
print('Cluster-3:',       len(df[labels==3]))
print('Cluster-4:',       len(df[labels==4]))
new = [[45, 76]]
km.predict(new)[0] new
= [[25, 36]]
km.predict(new)[0] new
= [[85, 76]]
km.predict(new)[0] new
= [[45, 47]]
km.predict(new)[0]
```

Output:





```
[33] # Export the cluster
     one.to_csv('one.csv')
```

```
[34] print('Cluster-0:', len(df[labels==0]))
     print('Cluster-1:', len(df[labels==1]))
     print('Cluster-2:', len(df[labels==2]))
     print('Cluster-3:', len(df[labels==3]))
     print('Cluster-4:', len(df[labels==4]))
```

```
Cluster-0: 35
Cluster-1: 81
Cluster-2: 39
Cluster-3: 22
Cluster-4: 23
```

7. Association algorithms for supervised classification on any dataset.

```
Dataset = [['Apple', 'Beer', 'Rice', 'Chicken'],
 ['Apple', 'Beer', 'Rice'],
 ['Apple',  'Beer'],
 ['Apple', 'Pear'],
 ['Milk', 'Beer', 'Rice', 'Chicken'],
 ['Milk', 'Beer', 'Rice'],
 ['Milk', 'Beer'],
 ['Apple', 'Pear']]
# Import the transaction encoder
from mlxtend.preprocessing import  TransactionEncoder #
Create the object
trans = TransactionEncoder() #
Apply the operation
df_t = trans.fit_transform(dataset)
trans.columns_
import pandas as pd
# Create a structured dataframe
df = pd.DataFrame(df_t, columns=trans.columns_) #
Support count
sum(df['Rice']) / len(df)
# Generate frequent itemsets
from mlxtend.frequent_patterns import apriori
freq_itemset = apriori(df, min_support=0.25, use_colnames=True)
freq_itemset
# Generate strong association rules
from mlxtend.frequent_patterns import association_rules
rules = association_rules(freq_itemset,
```

```
 metric='confidence',
min_threshold=0.5)
rules
rules = rules[['antecedents','consequents','support','confidence']]
rules['antecedent_len'] = rules['antecedents'].apply(lambda x: len(x)) nrules
= rules[(rules['antecedent_len'] == 1) &
 (rules['support'] > 0.30)]
nrules
# Prediction / Suggestion / Recommendation
nrules[nrules['antecedents'] == {'Apple'}]['consequents'][1]
rules.sort_values(by='confidence', ascending=False)
# Export the rules
rules.to_csv('rules.csv', index=False)
```

Output:

```
rules.sort_values(by='confidence', ascending=False)
```

	antecedents	consequents	support	confidence	antecedent_len
14	(Apple, Rice)	(Beer)	0.250	1.000000	2
2	(Pear)	(Apple)	0.250	1.000000	1
24	(Rice, Milk)	(Beer)	0.250	1.000000	2
4	(Chicken)	(Beer)	0.250	1.000000	1
6	(Milk)	(Beer)	0.375	1.000000	1
20	(Chicken)	(Beer, Rice)	0.250	1.000000	1
8	(Rice)	(Beer)	0.500	1.000000	1
9	(Chicken)	(Rice)	0.250	1.000000	1
18	(Chicken, Rice)	(Beer)	0.250	1.000000	2
17	(Chicken, Beer)	(Rice)	0.250	1.000000	2
13	(Apple, Beer)	(Rice)	0.250	0.666667	2
23	(Beer, Milk)	(Rice)	0.250	0.666667	2
26	(Milk)	(Beer, Rice)	0.250	0.666667	1

8. Developing and implementing Decision Tree model on the dataset.

```
import pandas as pd #
Data import
df = pd.read_csv('/content/sample_data/Social_Network_Ads.csv')
df.shape
# input
x = df[['Age','EstimatedSalary']]
# output
y = df['Purchased']
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(
 x, y, random_state=0, test_size=0.25)
# Import the class
from sklearn.ensemble import RandomForestClassifier #
Create the object
classifier =  RandomForestClassifier(random_state=0,  n_estimators=10) #
n_estimators -> number of trees in the forest
# Train the algorithm with data
classifier.fit(x_train, y_train)
# Predictions
y_pred = classifier.predict(x_test)
# Combine the data
result = pd.DataFrame({
 'Actual': y_test,
 'Predicted': y_pred
})
Result
from sklearn.tree import plot_tree
```

import matplotlib.pyplot as plt

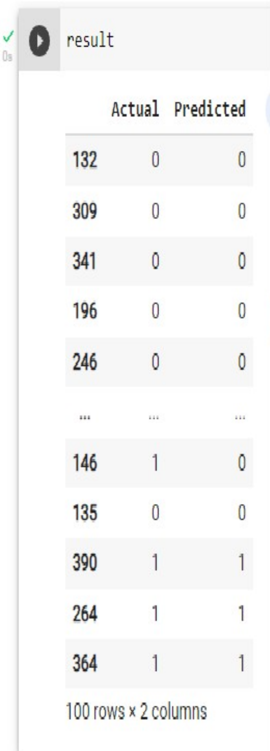
classifier.estimators_[0]

plt.figure(figsize=(16,12))

plot_tree(classifier.estimators_[8], fontsize=7, feature_names=['age','sal'],

class_names=['No','Yes'], filled=True, rounded=True);

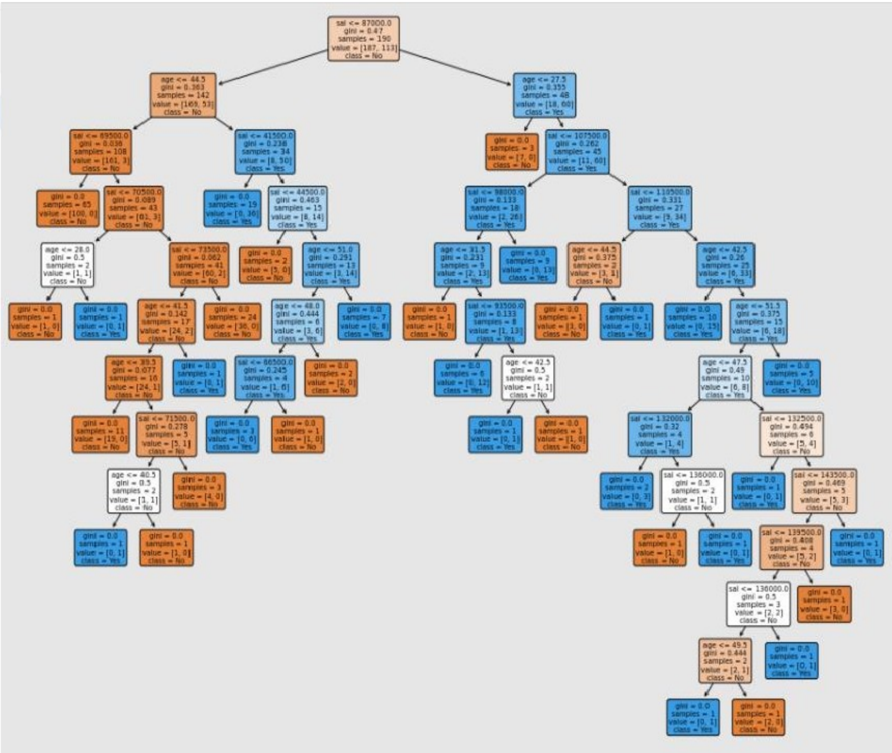
Output:



result

	Actual	Predicted
132	0	0
309	0	0
341	0	0
196	0	0
246	0	0
...	...	...
146	1	0
135	0	0
390	1	1
264	1	1
364	1	1

100 rows × 2 columns

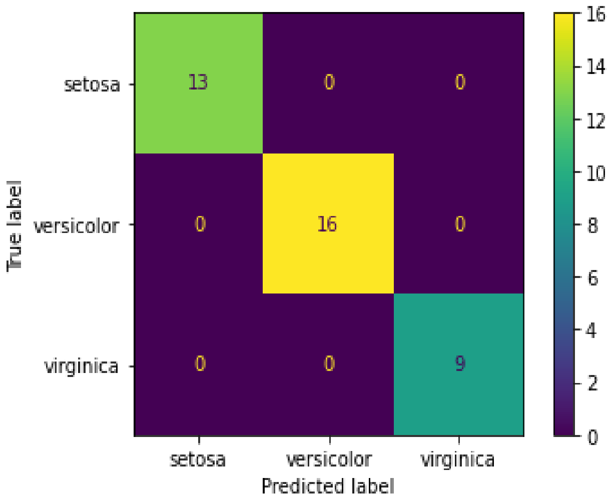


9. Bayesian classification on any dataset.

```
# Import packages
import pandas as pd
import seaborn as sns #
Data import
df = pd.read_csv('/content/sample_data/iris.csv') #
Let's describe
df.describe()
# Check the clusters
sns.pairplot(df, hue='species') #
input data
x = df.drop('species', axis = 1)
# output data
y = df['species']
sns.countplot(x = y)
y.value_counts()
# Cross validation -> hold out method
from sklearn.model_selection import train_test_split
x_train, x_test, y_train, y_test = train_test_split(
 x, y, random_state=0, train_size=0.75)
# Import the class
from sklearn.naive_bayes import  GaussianNB #
Create the object
classifier = GaussianNB()
# Train the algorithm with dataset
classifier.fit(x_train, y_train)
# Predictions
y_pred = classifier.predict(x_test)
# Import all functions
```

```
from sklearn.metrics import plot_confusion_matrix, accuracy_score
from sklearn.metrics import classification_report
# Plot the confusion matrix
plot_confusion_matrix(classifier, x_test, y_test)
# Accuracy
accuracy_score(y_test, y_pred) #
Classification report
print(classification_report(y_test, y_pred)) #
Print the probabilities
classifier.predict_proba(x_test)
new1 = [[5.1,3.7,1.5,0.4]]
new2 = [[6.8,2.8,4.8,1.4]]
new3 = [[7.7,2.6,6.9,2.3]]
# Predictions
classifier.predict(new1)[0]
classifier.predict(new2)[0]
classifier.predict(new3)[0]
```

Output:



10. SVM classification on any dataset.

SVM

1) classification approach, it can easily handle multipe continuous and categorial variable

2) SVM construct a Hyperplanein multidimensial space to separate different classes.

3) SVM generate optimal hyperplane in a iterative manner which is used to minimize an error

4) the basic idea of svm is to find a Max Marginal Hyperplane(MMH) to divide the dataset into classes

#Support vectors

#are the data points which are closest to the hyperplane. These points will define the separating line better margins

```
from sklearn import datasets

cancer=datasets.load_breast_cancer()

print("features:",cancer.feature_names)
```

```
features: ['mean radius' 'mean texture' 'mean perimeter' 'mean area' 'mean smoothness' 'mean
  compactness' 'mean concavity'
  'mean concave points' 'mean symmetry' 'mean fractal dimension' 'radius error' 'texture error'
  'perimeter error' 'area error' 'smoothness error' 'compactness error' 'concavity error' 'concave
  points error' 'symmetry error' 'fractal dimension error' 'worst radius' 'worst texture' 'worst
  perimeter' 'worst area' 'worst smoothness' 'worst compactness' 'worst concavity'
  'worst concave points' 'worst symmetry' 'worst fractal dimension']
```

```
print("Labels:",cancer.target_names)
```

```
Labels: ['malignant' 'benign']
```

```
cancer.data.shape
```

```
(569, 30)
```

```
#spliting data

from sklearn.model_selection import train_test_split
```

```
x_train,x_test,y_train,y_test=train_test_split(cancer.data,cancer.target,test_si
ze=.3)

from sklearn import svm

clf=svm.SVC(kernel='linear')

clf.fit(x_train,y_train)

y_pred=clf.predict(x_test)

from sklearn import metrics

print("accuracy:",metrics.accuracy_score(y_test,y_pred))
```

```
accuracy: 0.9590643274853801
```

```
print("precision:",metrics.precision_score(y_test,y_pred))

print("recall:",metrics.recall_score(y_test,y_pred))
```

```
precision: 0.9478260869565217
recall: 0.990909090909091
```

11. Text Mining algorithms on unstructured dataset.

```
import pandas as pd
df = pd.read_csv('/content/sample_data/SMSSpamCollection', sep='\t', names
 = ['class','body_text'])
import string string.punctuation
# Function to count the punctuation symbols def
count_punct(text):
 count = sum([1 for x in text if x in string.punctuation])
 return(round(count/(len(text)-text.count(' '))*100,2))
s = 'Hello, friends! How are you? Welcome to Pune.!!!'
count_punct(s)
# Add feature of punctuation percentages
df['punct%'] = df['body_text'].apply(lambda x: count_punct(x)) #
Add the column body length to it
df['body_len'] = df['body_text'].apply(lambda x: len(x) - x.count(" ")) from
nltk.corpus import stopwords
s_words = stopwords.words('english')
s_words;
from nltk.stem import PorterStemmer ps
= PorterStemmer()
# analyzer function
def clean_text(text):
 data = [x for x in text if x not in string.punctuation]
 data = "".join(data)
 data = [ps.stem(x) for x in data.split() if x not in s_words] return
 data
clean_text(s)
# Seperate the input and output
```

```
X = df.drop('class', axis = 1)
y = df['class']
# Import tfidf vectorizer
from sklearn.feature_extraction.text import TfidfVectorizer tfidf
= TfidfVectorizer(analyzer=clean_text)
X_trans = tfidf.fit_transform(X['body_text'])
X_vect = pd.concat([X[['body_len', 'punct%']]
 .reset_index(drop=True),
 pd.DataFrame(X_trans.toarray())], axis=1)
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(
X_vect, y, stratify=y, random_state=0)
from sklearn.ensemble import RandomForestClassifier clf =
RandomForestClassifier(random_state=0) clf.fit(X_train,
y_train)
y_pred = clf.predict(X_test)
from sklearn.metrics import accuracy_score, classification_report
accuracy_score(y_test, y_pred)
```

Output:

```
df
```

	class	body_text	punct%	body_len
0	ham	Go until jurong point, crazy.. Available only ...	9.78	92
1	ham	Ok lar... Joking wif u oni...	25.00	24
2	spam	Free entry in 2 a wkly comp to win FA Cup fina...	4.69	128
3	ham	U dun say so early hor... U c already then say...	15.38	39
4	ham	Nah I don't think he goes to usf, he lives aro...	4.08	49
...	...	...	...	...
5567	spam	This is the 2nd time we have tried 2 contact u...	6.11	131
5568	ham	Will ü b going to esplanade fr home?	3.45	29
5569	ham	Pity, * was in mood for that. So...any other s...	14.58	48
5570	ham	The guy did some bitching but I acted like i'd...	1.00	100
5571	ham	Rofl. Its true to its name	4.76	21

5572 rows × 4 columns

```
[ ]  print(classification_report(y_test, y_pred))

              precision    recall  f1-score   support

         ham       0.96      1.00      0.98      1206
        spam       1.00      0.75      0.86       187

    accuracy                           0.97      1393
   macro avg       0.98      0.87      0.92      1393
weighted avg       0.97      0.97      0.96      1393
```

12. Plot the cluster data using python visualizations.

```
# Import packages
import pandas as pd #
Import the dataset
df = pd.read_csv('/content/sample_data/Mall_Customers.csv') #
Input data
x =
df.iloc[:,3:] x
# Summerize df.describe()
# import seaborn package
import seaborn as sns
sns.kdeplot(df['Age'])
sns.kdeplot(df['Annual Income (k$)'])
sns.kdeplot(df['Spending Score (1-100)'])
sns.boxplot(df['Age'])
sns.boxplot(df['Annual Income (k$)'])
sns.boxplot(df['Spending Score (1-100)']) #
Import the class
from sklearn.cluster import  KMeans #
Create the object
km = KMeans(n_clusters=12, random_state=0) #
Train the algorithm
labels = km.fit_predict(x) #
Sum   of   squared   errors
km.inertia_
#   elbow   method
sse = []
```

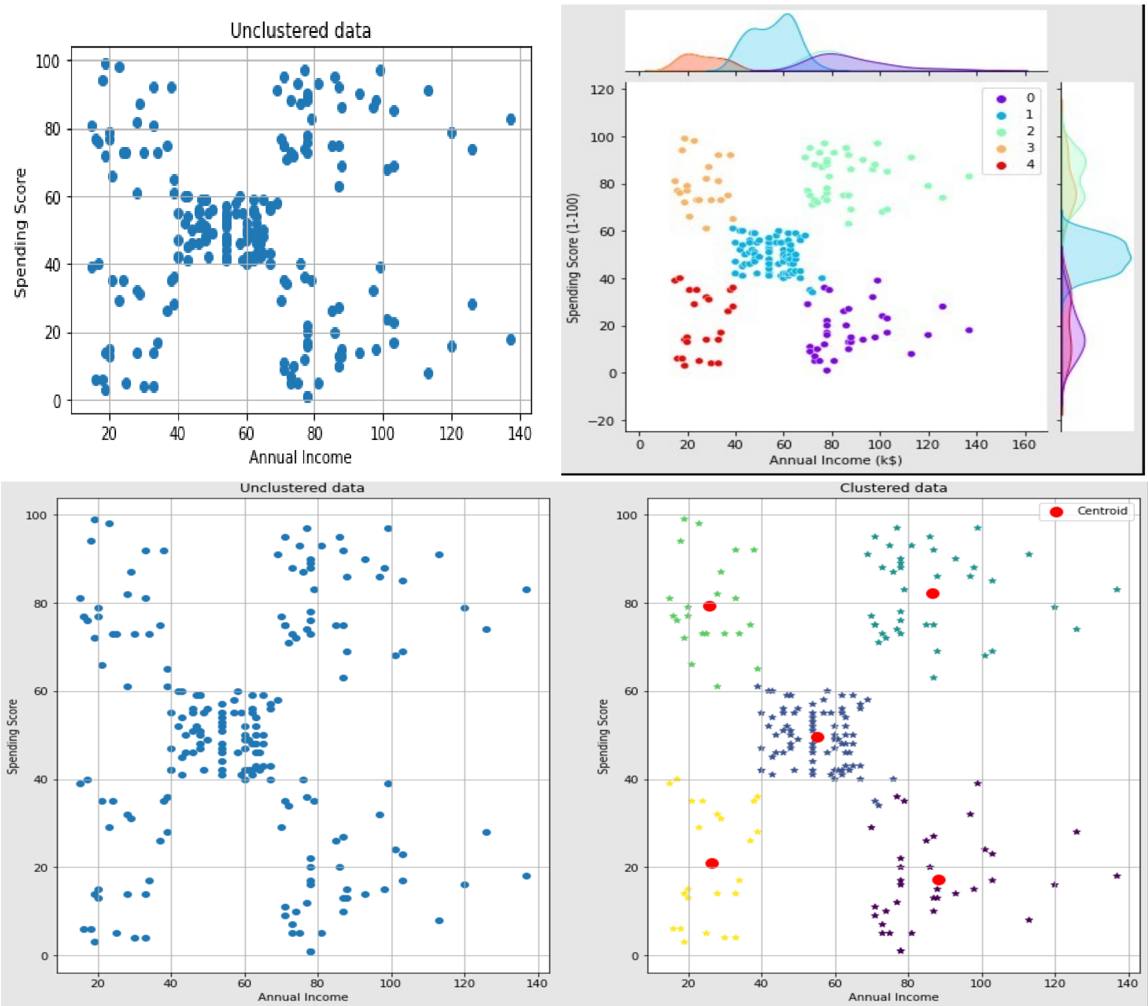
```
for k in range(1,41):
 km = KMeans(n_clusters=k, random_state=0)
 labels = km.fit_predict(x)
 sse.append(km.inertia_)
import matplotlib.pyplot as plt
plt.figure(figsize=(16,9))
plt.title('Elbow Method')
plt.xlabel('Value of K')
plt.ylabel('SSE')
plt.grid()
plt.xticks(range(1,41))
plt.plot(range(1,41), sse, marker='o', color='r') #
Silhoutte method
from sklearn.metrics import silhouette_score silh
= []
for k in range(2,16):
 km = KMeans(n_clusters=k, random_state=0)
 labels = km.fit_predict(x)
 score = silhouette_score(x, labels)
 silh.append(score)
# plot the silhoutte scores
plt.title('Silhoutte Analysis')
plt.xlabel('Value of K')
plt.ylabel('Silhoutte Score')
plt.xticks(range(2,16))
plt.bar(range(2,16), silh, color='g') #
Create the object
km = KMeans(n_clusters=5, random_state=0) #
Train the algorithm
labels = km.fit_predict(x)
```

```
# Cluster labels
km.labels_
# SSE
km.inertia_
# Extract the clusters
df[labels==2] # Boolean filtering
one = df[labels==1]
# Export the cluster
one.to_csv('one.csv')
print('Cluster-0:',     len(df[labels==0]))
print('Cluster-1:',     len(df[labels==1]))
print('Cluster-2:',     len(df[labels==2]))
print('Cluster-3:',     len(df[labels==3]))
print('Cluster-4:', len(df[labels==4])) #
Prediction
new = [[45, 76]]
km.predict(new)[0] #
Prediction
new = [[25, 36]]
km.predict(new)[0] #
Prediction
new = [[85, 76]]
km.predict(new)[0] #
Prediction
new = [[45, 47]]
km.predict(new)[0]
# Visualization of clusters
plt.title('Unclustered data')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
```

```
plt.grid()
plt.scatter(x['Annual Income (k$)'], x['Spending Score (1-100)']) #
Save the centroids
cent = km.cluster_centers_ #
Visualization of clusters
plt.title('Clustered data')
plt.xlabel('Annual Income')
plt.grid()
plt.scatter(x['Annual Income (k$)'], x['Spending Score (1-100)'], c =
 labels, marker='*')
plt.scatter(cent[:,0], cent[:,1], s=100, marker='o', color='r') #
Combined plot
plt.figure(figsize=(16,9))
plt.subplot(1,2,1)
plt.title('Unclustered data')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.grid()
plt.scatter(x['Annual Income (k$)'], x['Spending Score (1-100)']) plt.subplot(1,2,2)
plt.title('Clustered data')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.grid()
plt.scatter(x['Annual Income (k$)'], x['Spending Score (1-100)'], c =
 labels, marker='*')
plt.scatter(cent[:,0], cent[:,1], s=100, marker='o', color='r', label
 = 'Centroid')
plt.legend()
plt.savefig('Clusters.png')
```

```
import seaborn as sns
# Visualization using joint plot
p = sns.jointplot(x=x['Annual Income (k$)'],
 y=x['Spending Score (1-100)'],
 hue = labels,palette='rainbow', )
# sns.jointplot(x=cent[:,0], y=cent[:,1])
p.savefig('seaborn_clusters.png')
```

Output:



13. Creating & Visualizing Neural Network for the given data. (Use python)

```
from google.colab import drive
drive.mount('/content/drive') from
keras.layers import Dense
from keras.models import Sequential
import numpy as np
# fix random seed for reproducibility
seed = 7
np.random.seed(seed) #
load dataset
dataset = np.loadtxt('/content/sample_data/pima-new (1).csv', delimiter=',') dataset
# input data
X = dataset[:,:8]
# output data
Y = dataset[:,8]
Y
# create the model
model = Sequential()
model.add(Dense(12, input_dim=8, activation='relu')) # Input layer
model.add(Dense(8, activation='relu')) # Hiddel layer
model.add(Dense(1, activation='sigmoid')) # Output layer
# compile model
model.compile(loss='binary_crossentropy',
optimizer='adam',
 metrics=['accuracy'])
# train the model
model.fit(X, Y, epochs=200, batch_size=10)
```

Evaluate the model

scores = model.evaluate(X, Y)

scores

new = [[7,475,82,69,120,22.2,0.645,57]]

model.predict(new)

from keras.utils.vis_utils import plot_model

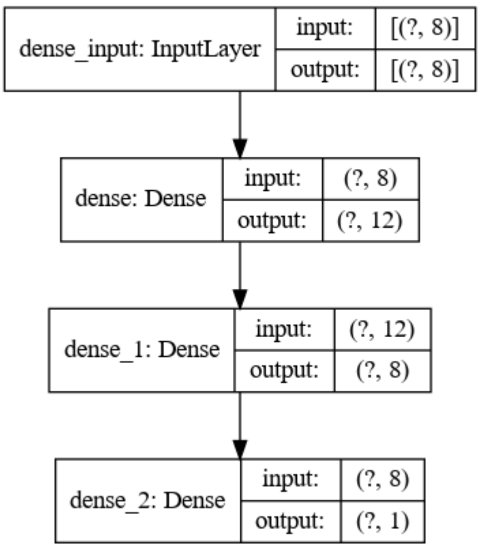
plot_model(model, show_shapes=True, show_layer_names=True,

to_file='neural_network.png')

Output:

```
# train the model
model.fit(X, Y, epochs=200, batch_size=10)
Epoch 172/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5381 - accuracy: 0.7344
Epoch 173/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5259 - accuracy: 0.7539
Epoch 174/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5361 - accuracy: 0.7240
Epoch 175/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5390 - accuracy: 0.7318
Epoch 176/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5213 - accuracy: 0.7539
Epoch 177/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5225 - accuracy: 0.7357
Epoch 178/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5297 - accuracy: 0.7435
Epoch 179/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5264 - accuracy: 0.7370
Epoch 180/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5247 - accuracy: 0.7422
Epoch 181/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5345 - accuracy: 0.7318
Epoch 182/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5303 - accuracy: 0.7487
Epoch 183/200
77/77 [==============================] - 0s 2ms/step - loss: 0.5304 - accuracy: 0.7383
Epoch 184/200
```

```
[ ] plot_model(model, show_shapes=True, show_layer_names=True,
               to_file='neural_network.png')
```

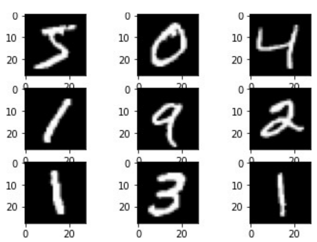


14. Recognize optical character using ANN.

```
from keras.datasets import mnist
import matplotlib.pyplot as plt
(X_train, y_train), (X_test, y_test) = mnist.load_data()
plt.subplot(3,3,1)
plt.imshow(X_train[0], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,2)
plt.imshow(X_train[1], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,3)
plt.imshow(X_train[2], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,4)
plt.imshow(X_train[3], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,5)
plt.imshow(X_train[4], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,6)
plt.imshow(X_train[5], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,7)
plt.imshow(X_train[6], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,8)
plt.imshow(X_train[7], cmap=plt.get_cmap('gray'))
plt.subplot(3,3,9)
plt.imshow(X_train[8], cmap=plt.get_cmap('gray'))
from keras.layers import Dense
from keras.models import Sequential
import numpy as np
num_pixels = X_train[0].shape[0] * X_train[0].shape[1] #
Reshape
X_train = X_train.reshape(X_train.shape[0], num_pixels)
X_test = X_test.reshape(X_test.shape[0], num_pixels)
```

```
import pandas as pd
pd.DataFrame(X_train).describe()
# normalize inputs from 0-255 to 0-1
X_train = X_train / 255
X_test = X_test / 255
set(y_train)
from keras.utils import np_utils
y_train = np_utils.to_categorical(y_train)
y_test = np_utils.to_categorical(y_test)
y_train.shape
# Create the model
model = Sequential()
model.add(Dense(784, input_dim= 784, activation='relu')) model.add(Dense(10,
activation='softmax'))
# compile model model.compile(loss='categorical_crossentropy',
optimizer='adam', metrics=['accuracy'])
# Train the algorithm
model.fit(X_train, y_train, validation_data=(X_test, y_test),
 epochs=10, batch_size=200)
scores = model.evaluate(X_train, y_train)
scores
```

Output:



```
# Train the algorithm
model.fit(X_train, y_train, validation_data=(X_test, y_test),
          epochs=10, batch_size=200)

Epoch 1/10
300/300 [==============================] - 6s 17ms/step - loss: 0.2786 - accuracy: 0.9213 - val_loss: 0.1401 - val_accuracy
Epoch 2/10
300/300 [==============================] - 5s 16ms/step - loss: 0.1111 - accuracy: 0.9676 - val_loss: 0.1001 - val_accuracy
Epoch 3/10
300/300 [==============================] - 5s 16ms/step - loss: 0.0712 - accuracy: 0.9797 - val_loss: 0.0773 - val_accuracy
Epoch 4/10
300/300 [==============================] - 5s 16ms/step - loss: 0.0506 - accuracy: 0.9853 - val_loss: 0.0674 - val_accuracy
Epoch 5/10
300/300 [==============================] - 5s 16ms/step - loss: 0.0374 - accuracy: 0.9891 - val_loss: 0.0635 - val_accuracy
Epoch 6/10
300/300 [==============================] - 5s 16ms/step - loss: 0.0266 - accuracy: 0.9932 - val_loss: 0.0598 - val_accuracy
Epoch 7/10
261/300 [=========================>....] - ETA: 0s - loss: 0.0193 - accuracy: 0.9952
```

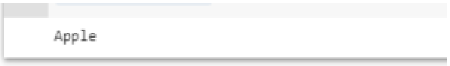
15. Write a program to implement CNN.

```
From keras.models import Sequential
from keras.layers import Dense
from keras.layers import Conv2D from
keras.layers import MaxPool2D from
keras.layers import Flatten
# Create the object of model
classifier = Sequential()
# Add first convolution layer
# Parameters – filters, kernel size, input shape, activation
classifier.add(Conv2D(32,(3,3), input_shape = (64, 64, 3),
activation = ‘relu’))
# Add first max pooling layer
classifier.add(MaxPool2D(pool_size = (2,2)))
# Add second convolution layer
classifier.add(Conv2D(32, (3,3), activation = ‘relu’)) #
Add max pooling layer
classifier.add(MaxPool2D(pool_size = (2,2)))
# Convert the 2D data to 1D format
classifier.add(Flatten())
#  Add the output  layer classifier.add(Dense(units=1,
activation=’sigmoid’)) # Compile the model
classifier.compile(optimizer=’adam’,
loss=’binary_crossentropy’,
 metrics=[‘accuracy’]) #
Image augmentation
from keras.preprocessing.image import ImageDataGenerator
train_datagen = ImageDataGenerator(rescale=1/255,
```

```
 shear_range=0.2,
 zoom_range=0.2,
 horizontal_flip=True,
 vertical_flip=True)
test_datagen = ImageDataGenerator(rescale = 1./255) #
Import the train images
train = train_datagen.flow_from_directory('/content/sample_data', target_size=(64,
 64),
batch_size=32,
class_mode='binary')
test = test_datagen.flow_from_directory('/content/sample_data', target_size=(64,
 64),
 batch_size=32,
class_mode='binary') #
Train the algorithm
classifier.fit(train, epochs=10, validation_data=test,
 validation_steps=10)
train.class_indices #
Prediction
import numpy as np
from keras.preprocessing.image  import  load_img from
keras.preprocessing.image  import img_to_array
test_image = load_img('/content/sample_data/sample1.jpg', target_size=(64, 64))
test_image  =  img_to_array(test_image)
test_image = np.expand_dims(test_image, axis = 0)
#test_image.shape
result  =  classifier.predict(test_image) if
result[0][0] == 1:
 print('Orange')
```

```
else:
 print('Apple')
```

Output:



16. Write a program to implement RNN.

```
import matplotlib.pyplot as plt
import pandas as pd
import numpy as np #
Data import
df = pd.read_csv('/content/sample_data/Google_Stock_Price_Train.csv') #
first 5 entries
df.head()
df.describe()
df.info()
training_set = df.iloc[:,[1,2]].values #
Visualize the trend
plt.plot(training_set)
# Feature scaling
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
training_set_scaled = scaler.fit_transform(training_set) #
The scaled data
training_set_scaled
# plot the scaled data
plt.plot(training_set_scaled)
X_train = []
y_train = []
for i in range(60, 1258):
 X_train.append(training_set_scaled[i-60:i, 0])
 y_train.append(training_set_scaled[i,     0])
X_train, y_train = np.array(X_train), np.array(y_train)
X_train = np.reshape(X_train, (X_train.shape[0], X_train.shape[1], 1)) #
Import the classes
```

```
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM from
keras.layers import Dropout #
Create the model
regressor = Sequential() #
add LSTM layer
regressor.add(LSTM(units = 50, return_sequences = True,
input_shape = (X_train.shape[1], 1)))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50, return_sequences = True))
regressor.add(Dropout(0.2))
regressor.add(LSTM(units = 50))
regressor.add(Dropout(0.2))
# Output layer
regressor.add(Dense(1)) #
Compile the model
regressor.compile(optimizer='adam', loss='mean_squared_error') #
Train the algorithm
regressor.fit(X_train, y_train, epochs=100, batch_size = 32)
testing_set = pd.read_csv('/content/sample_data/Google_Stock_Price_Test.csv')
testing_set.shape
testing_set
real_stock_price = testing_set.iloc[:,[1,2]].values
real_stock_price
dataset_total = pd.concat((df['Open'],
testing_set['Open']), axis = 0)
dataset_total
```

inputs = dataset_total[len(dataset_total) -

len(testing_set) - 60:].values inputs.shape

inputs = inputs.reshape(-1,2)

inputs.shape

Perform the scaling

inputs = scaler.transform(inputs) inputs

Output:

```
inputs

array([[0.9299055 , 0.93086447],
       [0.92750577, 0.9439371 ],
       [0.93876032, 0.9337778 ],
       [0.93483518, 0.93112593],
       [0.94636878, 0.96556296],
       [0.97510976, 0.9595122 ],
       [0.97808617, 1.        ],
       [0.98076494, 0.97071731],
       [0.98450406, 0.96038994],
       [0.9371419 , 0.9281379 ],
       [0.90804747, 0.87670644],
       [0.92153434, 0.93784899],
       [0.93165414, 0.95235961],
       [0.88812412, 0.88593198],
       [0.87032145, 0.88518498],
       [0.90743359, 0.91538275],
       [0.89941588, 0.91773582],
       [0.9089404 , 0.90210469],
       [0.89456061, 0.91568155],
       [0.9132934 , 0.88936822],
       [0.86589404, 0.88987245],
       [0.90335962, 0.89601658],
       [0.91777662, 0.93149943],
       [0.94114145, 0.95745793],
       [0.96413424, 0.9638822 ],
       [0.96971501, 0.95058547],
```

```
[29] testing_set
```

	Date	Open	High	Low	Close	Volume
0	1/3/2017	778.81	789.63	775.80	786.14	1,657,300
1	1/4/2017	788.36	791.34	783.16	786.90	1,073,000
2	1/5/2017	786.08	794.48	785.02	794.02	1,335,200
3	1/6/2017	795.26	807.90	792.20	806.15	1,640,200
4	1/9/2017	806.40	809.97	802.83	806.65	1,272,400
5	1/10/2017	807.86	809.13	803.51	804.79	1,176,800
6	1/11/2017	805.00	808.15	801.37	807.91	1,065,900
7	1/12/2017	807.14	807.39	799.17	806.36	1,353,100
8	1/13/2017	807.48	811.22	806.69	807.88	1,099,200
9	1/17/2017	807.08	807.14	800.37	804.61	1,362,100
10	1/18/2017	805.81	806.21	800.99	806.07	1,294,400
11	1/19/2017	805.12	809.48	801.80	802.17	919,300
12	1/20/2017	806.91	806.91	801.69	805.02	1,670,000
13	1/23/2017	807.25	820.87	803.74	819.31	1,963,600

17. Write a program to implement GAN.

```
From __future__import print_function, division
from keras.datasets import mnist
from keras.layers import Input, Dense, Reshape, Flatten, Dropout
from keras.layers import BatchNormalization, Activation, ZeroPadding2D
from keras.layers.advanced_activations import LeakyReLU
from keras.layers.convolutional import UpSampling2D, Conv2D
from keras.models import Sequential, Model
from tensorflow.keras.optimizers import Adam import
matplotlib.pyplot as plt
import sys
import numpy as np
class GAN():
 def __init__(self):
 self.img_rows = 28
 self.img_cols = 28
 self.channels = 1
 self.img_shape = (self.img_rows, self.img_cols, self.channels) self.latent_dim
 = 100
 optimizer = Adam(0.0002, 0.5)
 # Build and compile the discriminator self.discriminator =
 self.build_discriminator()
 self.discriminator.compile(loss='binary_crossentropy',
 optimizer=optimizer,
 metrics=['accuracy']) #
 Build the generator
 self.generator = self.build_generator()
 # The generator takes noise as input and generates imgs z =
 Input(shape=(self.latent_dim,))
```

```
img = self.generator(z)
# For the combined model we will only train the generator
self.discriminator.trainable = False
# The discriminator takes generated images as input and determines validity
validity = self.discriminator(img)
# The combined model (stacked generator and discriminator) #
Trains the generator to fool the discriminator
self.combined = Model(z, validity)
self.combined.compile(loss='binary_crossentropy',
optimizer=optimizer)
def build_generator(self):
model = Sequential()
model.add(Dense(256, input_dim=self.latent_dim))
model.add(LeakyReLU(alpha=0.2))
model.add(BatchNormalization(momentum=0.8))
model.add(Dense(512))
model.add(LeakyReLU(alpha=0.2))
model.add(BatchNormalization(momentum=0.8))
model.add(Dense(1024))
model.add(LeakyReLU(alpha=0.2))
model.add(BatchNormalization(momentum=0.8))
model.add(Dense(np.prod(self.img_shape), activation='tanh'))
model.add(Reshape(self.img_shape))
model.summary()
noise = Input(shape=(self.latent_dim,))
img = model(noise)
return Model(noise, img)
def build_discriminator(self):
model = Sequential()
```

```
model.add(Flatten(input_shape=self.img_shape))
model.add(Dense(512))
model.add(LeakyReLU(alpha=0.2))
model.add(Dense(256))
model.add(LeakyReLU(alpha=0.2))
model.add(Dense(1, activation='sigmoid'))
model.summary()
img = Input(shape=self.img_shape)
validity = model(img)
return Model(img, validity)
def train(self, epochs,  batch_size=128,  sample_interval=50): #
Load the dataset
(X_train, _), (_, _) =
mnist.load_data() # Rescale -1 to 1
X_train = X_train / 127.5 – 1.
X_train = np.expand_dims(X_train,  axis=3)
# Adversarial ground truths
valid  =  np.ones((batch_size,  1))
fake  =  np.zeros((batch_size,  1))
for epoch in range(epochs):
# ...........................................
# Train Discriminator
# ...........................................
# Select a random batch of images
idx = np.random.randint(0, X_train.shape[0], batch_size)
imgs = X_train[idx]
noise = np.random.normal(0, 1, (batch_size, self.latent_dim)) #
Generate a batch of new images
gen_imgs = self.generator.predict(noise) #
Train the discriminator
```

```
d_loss_real = self.discriminator.train_on_batch(imgs, valid)
d_loss_fake = self.discriminator.train_on_batch(gen_imgs, fake)
d_loss = 0.5 * np.add(d_loss_real, d_loss_fake)
#.............................................................
#   Train   Generator #
.............................................................
noise = np.random.normal(0, 1, (batch_size, self.latent_dim))
# Train the generator (to have the discriminator label samples as valid) g_loss
= self.combined.train_on_batch(noise, valid)
# Plot the progress
print ("%d [D loss: %f, acc.: %.2f%%] [G loss: %f]" % (epoch, d_loss[0],
100*d_loss[1], g_loss))
# If at save interval => save generated image samples if
epoch % sample_interval == 0: self.sample_images(epoch)
def sample_images(self, epoch):
r, c = 5, 5
noise = np.random.normal(0, 1, (r * c, self.latent_dim))
gen_imgs = self.generator.predict(noise)
# Rescale images 0 - 1
gen_imgs = 0.5 * gen_imgs + 0.5
fig, axs = plt.subplots(r, c)
cnt = 0
for I in rangeI:
for j in rangeI:
axs[I,j].imshow(gen_imgs[cnt, :,:,0], cmap='gray')
axs[I,j].axis('off')
cnt += 1
fig.savefig("/content/sample_data/d.jpg" % epoch)
plt.close()
```

gan = GAN()

gan.train(epochs=200, batch_size=32, sample_interval=200)

Output:

```
gan = GAN()
gan.train(epochs=200, batch_size=32, sample_interval=200)
```

```
Model: "sequential_2"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
=================================================================
 flatten_1 (Flatten)         (None, 784)               0

 dense_7 (Dense)             (None, 512)               401920

 leaky_re_lu_5 (LeakyReLU)   (None, 512)               0

 dense_8 (Dense)             (None, 256)               131328

 leaky_re_lu_6 (LeakyReLU)   (None, 256)               0

 dense_9 (Dense)             (None, 1)                 257

=================================================================
Total params: 533,505
Trainable params: 533,505
Non-trainable params: 0
_________________________________________________________________
Model: "sequential_3"
_________________________________________________________________
 Layer (type)                Output Shape              Param #
```

18. Web scraping experiments (by using tools).

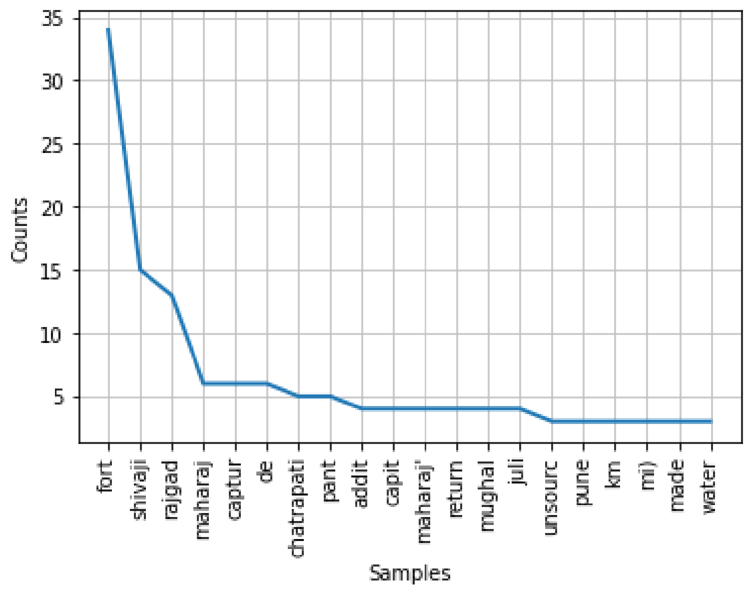
```
import urllib
import urllib.request
# create the reponse object
response =
urllib.request.urlopen('https://en.wikipedia.org/wiki/Rajgad_Fort') response
html = response.read()
print(html)
from bs4 import  BeautifulSoup soup
=  BeautifulSoup(html,  'html') data =
soup.get_text(strip=True) data
images = soup.find_all('img')
images[3]
images[3]['title']
images[3]['src']
soup.title
soup.title.string
text = [x for x in data.split()]
import nltk
frq  =  nltk.FreqDist(text) frq.plot(20,
cumulative=False) from nltk.corpus
import stopwords
swords = stopwords.words('english')
clean_tokens = []
for x in text:
 if x.lower() not in swords:
 clean_tokens.append(x.lower())
```

```
clean_tokens
frq = nltk.FreqDist(clean_tokens)
frq.plot(20, cumulative=False)
from nltk.stem import PorterStemmer ps
= PorterStemmer()
clean_tokens = [ps.stem(x) for x in clean_tokens] frq
= nltk.FreqDist(clean_tokens)
frq.plot(20, cumulative=False)
```

OUTPUT:

```
[ ]  clean_tokens

     ['rajgad',
      'fort',
      '-',
      'wikipediarajgad',
      'fortfrom',
      'wikipedia,',
      'free',
      'encyclopediajump',
      'navigationjump',
      'searchthis',
      'articleneeds',
      'additional',
      'citations',
      'forverification.please',
      'helpimprove',
      'articlebyadding',
      'citations',
      'reliable',
      'sources.',
      'unsourced',
      'material',
      'may',
      'challenged',
      'removed.find',
      'sources:"rajgad',
```




```
<AxesSubplot:xlabel='Samples', ylabel='Counts'>
```