PIRENS Institute of Business Management and Administration, Loni BK.		
Seat Number:10097	**Sign:**	**Date: / /**
Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q1. Find the correlation matrix.		

Program:

import numpy as np

ModuleNotFoundError Traceback (most recent call last)Input In [2], in <cell line: 1>()
----> 1 import numpy as np

ModuleNotFoundError: No module

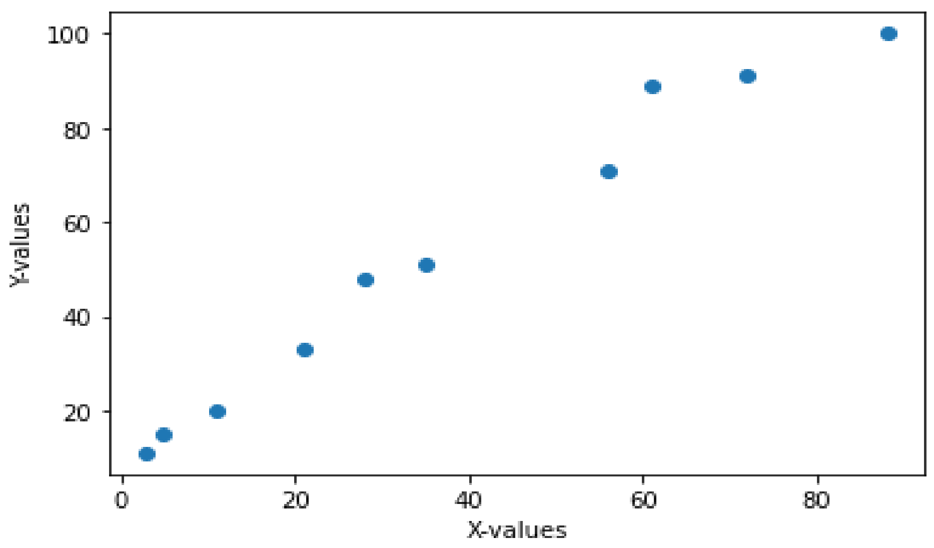
named 'numpy' x =

np.array([3,5,11,21,28,35,56,61,72,88]

)
y = np.array([11,15,20,33,48,51,71,89,91,100])
z = np.array([104,100,89,81,76,66,69,43,17,11])

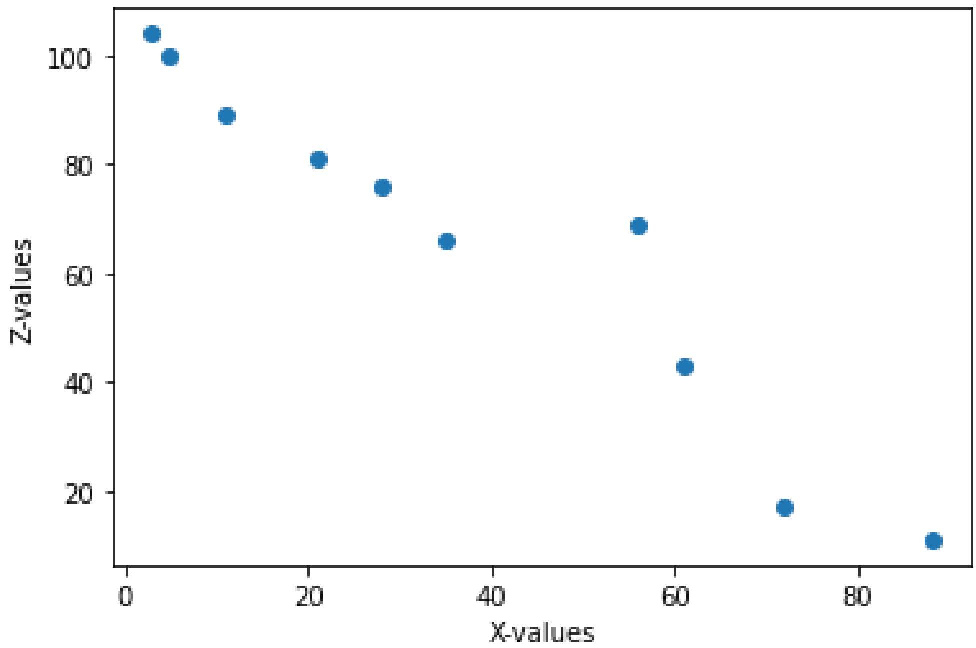
type(x) numpy.ndarr ay
import matplotlib.pyplot as plt
plt.xlabel('X-values') plt.ylabel('Y-values') plt.scatter(x, y)

<matplotlib.collections.PathCollection at 0x7f153834ffa0>



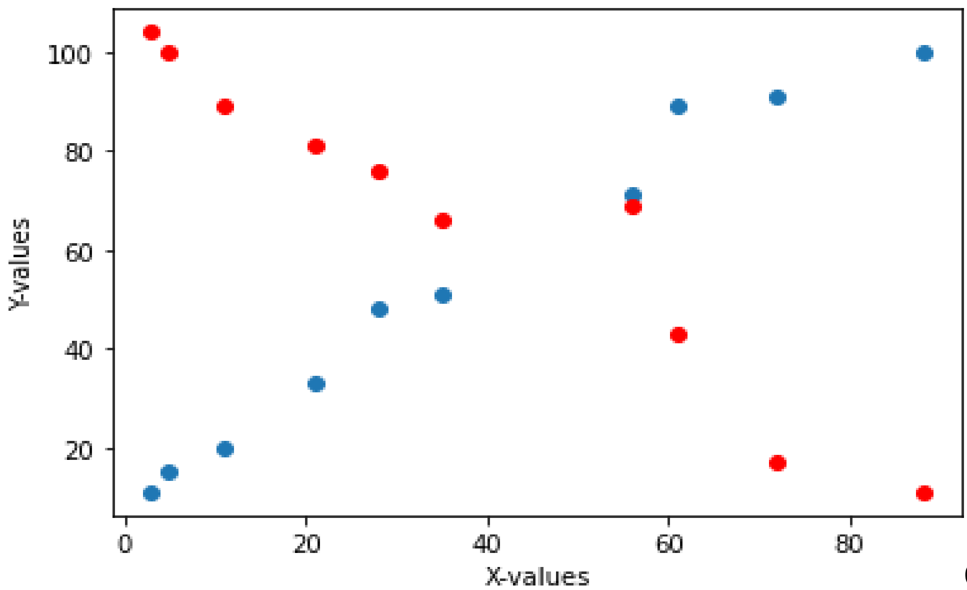
plt.xlabel('X-values')
plt.ylabel('Z-values')
plt.scatter(x, z)

<matplotlib.collections.PathCollection at 0x7f15362423d0>



plt.xlabel('X-values')
plt.ylabel('Y-values') plt.scatter(x,
y) plt.scatter(x, z, color = 'r')

<matplotlib.collections.PathCollection at 0x7f153



61aa130

```
np.corrcoef(x, y)

array([[1.        , 0.98757408],
       [0.98757408, 1.        ]])

np.corrcoef(x, z)

array([[ 1.        , -0.96149075],
       [-0.96149075,  1.        ]])

np.corrcoef(z, y)

array([[ 1.        , -0.95002927],
       [-0.95002927,  1.        ]])

import scipy.stats as st

st.pearsonr(x, y)[0]

0.9875740814243562

st.pearsonr(x, z)[0]

-0.9614907503686154

st.pearsonr(z, y)[0]

-0.9500292724815624

import pandas as pd

x1 = pd.Series([3,5,11,21,28,35,56,61,72,88])
y1 = pd.Series([11,15,20,33,48,51,71,89,91,100]) z1 =
pd.Series([104,100,89,81,76,66,69,43,17,11])

x1.corr(y1)

0.98757408142435

62

y1.corr(z1)

-0.9500292724815624

df=
     pd.DataFrame(
     {'x': x,
     'y': y,
     'z': z
 })
```

df

	x	y	z
0	3	11	104
1	5	15	100
2	11	20	89
3	21	33	81
4	28	48	76
5	35	51	66
6	56	71	69
7	61	89	43
8	72	91	17
9	88	100	11

df.corr()

	x	y	z
x	1.000000	0.987574	-0.961491
y	0.987574	1.000000	-0.950029
z	-0.961491	-0.950029	1.000000

df.corrwith(x1)
x
1.00000
0
y 0.987574
z -0.961491
dtype: float64
st.spearmanr(x, y)[0]
0.9999999999999999
st.spearmanr(x, z)[0]

-0.9878787878787878

st.spearmanr(z, y)[0]

-0.9878787878787878

df.corr(method='spearman')

	x	y	z
x	1.000000	1.000000	-0.987879
y	1.000000	1.000000	-0.987879
z	-0.987879	-0.987879	1.000000

st.kendalltau(x, y)[0]

0.9999999999999999

st.kendalltau(x, z)[0]

-0.9555555555555554

```
st.kendalltau(z, y)[0]
```

```
-0.9555555555555554
```

```
df.corr(method='kendall')
```

	x	y	z
x	1.000000	1.000000	-0.955556
y	1.000000	1.000000	-0.955556
z	-0.955556	-0.955556	1.000000

```
df.corrwith(x1, method='kendall')x
```

```
     1.000000
y    1.000000
z   -0.955556
dtype: float64
```

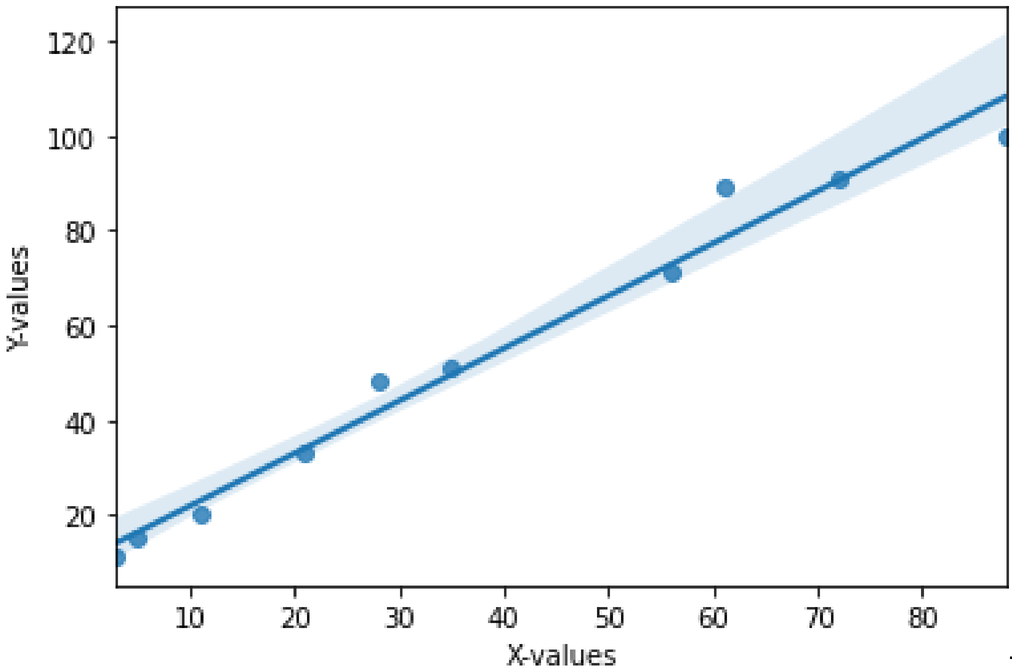
```
cor = df.corr
(method='kendall')cor.values
```

```
array([[ 1.        ,  1.        , -0.95555556],
       [ 1.        ,  1.        , -0.95555556],
       [-0.95555556, -0.95555556,  1.        ]])
```

```
import seaborn as sns
```

```
plt.xlabel('X-values')
plt.ylabel('Y-values')
sns.regplot(x=x, y=y, data=df)
```

```
<AxesSubplot:xlabel='X-values', ylabel='Y
```




```
-values'>
```

PIRENS Institute of Business Management and Administration, Loni BK.		
Roll Number: 10097	Sign:	Date: / /
Student Name:Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q.2 Plot the correlation plot on dataset and visualize giving an overview ofrelationships among data on iris data.		

Program:

```
# Data Import
import pandas as pd

x = ['slength','swidth','plength','pwidth','species']
df = pd.read_csv('https://archive.ics.uci.edu/ml/machine-learning-databases/iris/iris.data',
names=x)

df
```

	slength	swidth	plength	pwidth	species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa
..	...	...	...	...	...
145	6.7	3.0	5.2	2.3	Iris-virginica
146	6.3	2.5	5.0	1.9	Iris-virginica
147	6.5	3.0	5.2	2.0	Iris-virginica
148	6.2	3.4	5.4	2.3	Iris-virginica
149	5.9	3.0	5.1	1.8	Iris-virginica

[150 rows x 5 columns]

```
df = pd.read_csv('iris.csv') # Local data import

df
```

	sepal_length	sepal_width	petal_length	petal_width	species
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
..	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

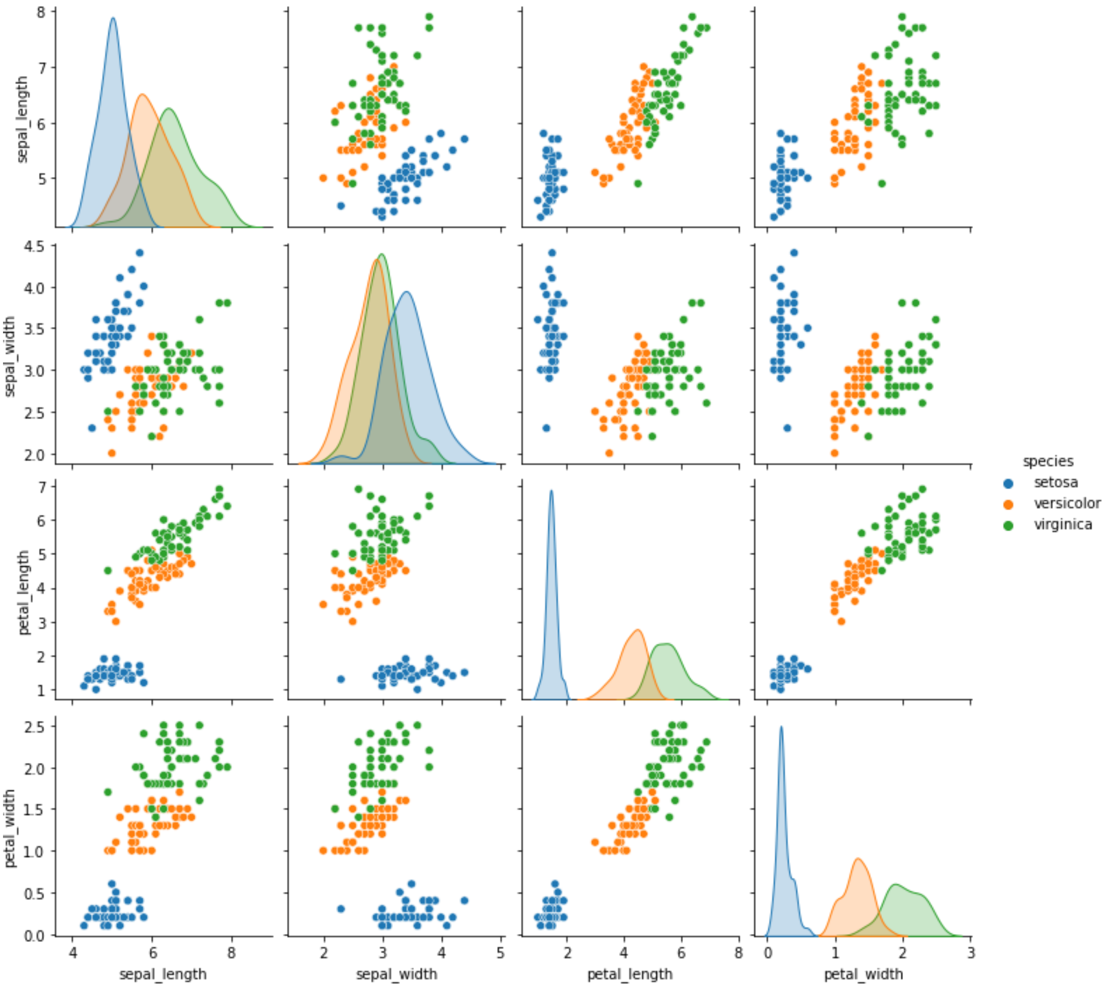
[150 rows x 5 columns]

```
import seaborn as sns
```

```
sns.get_dataset_names()

['anagrams',
 'anscombe',
 'attention',
 'brain_networks',
 'car_crashes',
 'diamonds', 'dots',
 'exercise',
 'flights', 'fmri',
 'gammas',
 'geyser',
 'iris',
 'mpg',
 'penguins',
 'planets',
 'taxis',
 'tips',
 'titanic']

iris = sns.load_dataset('iris')

iris
```

	sepal_length	sepal_width	petal_length	petal_width	species
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
..	...	...	...	...	...
145	6.7	3.0	5.2	2.3	virginica
146	6.3	2.5	5.0	1.9	virginica
147	6.5	3.0	5.2	2.0	virginica
148	6.2	3.4	5.4	2.3	virginica
149	5.9	3.0	5.1	1.8	virginica

```
[150 rows x 5 columns]

sns.pairplot(df, hue='species')

<seaborn.axisgrid.PairGrid at 0x7fbe5dfb5df0>
```



import matplotlib.pyplot as plt

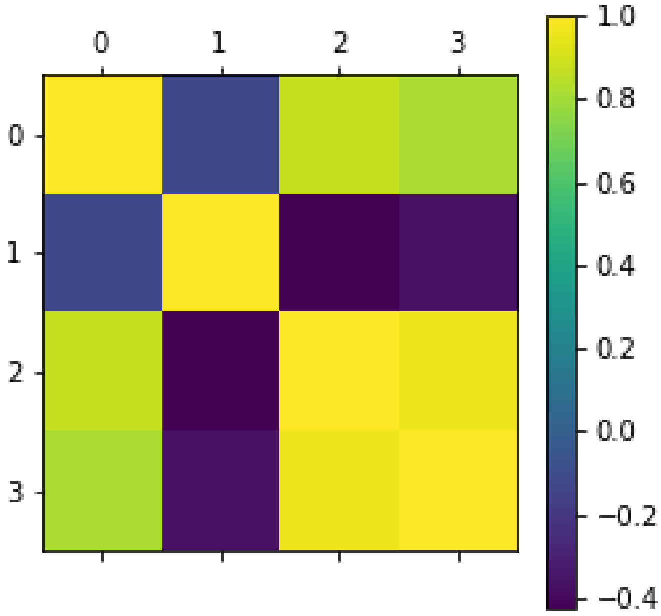
df.corr()

	sepal_length	sepal_width	petal_length	petal_width
sepal_length	1.000000	-0.117570	0.871754	0.817941
sepal_width	-0.117570	1.000000	-0.428440	-0.366126
petal_length	0.871754	-0.428440	1.000000	0.962865
petal_width	0.817941	-0.366126	0.962865	1.000000

```
plt.figure(figsize=(16,9))
plt.matshow(df.corr()) plt.colorbar()
```

<matplotlib.colorbar.Colorbar at 0x7fbe556e8a30>

<Figure size 1152x648 with 0 Axes>



sns.heatmap(df.corr(), annot=True)

<AxesSubplot:>

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Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		

Program Title: Q.3 Analysis of covariance: variance (ANOVA), if data have ategorical variables on iris data.

```
import pandas as pd
df = pd.read_csv("data.txt",sep='\t')
df.head()
```

	id	gender	bdate	educ	jobcat	salary	salbegin	jobtime	prevexp	\0	1
	m	2/3/1952		15	3	57000	27000	98	144		
1	2	m	5/23/1958	16	1	40200	18750	98	36		
2	3	f	7/26/1929	12	1	21450	12000	98	381		
3	4	f	4/15/1947	8	1	21900	13200	98	190		
4	5	m	2/9/1955	15	1	45000	21000	98	138		

	minority	jobcat_name
0	0	Manager
1	0	Clerical
2	0	Clerical
3	0	Clerical
4	0	Clerical

```
df[['jobcat_name','prevexp']].groupby('jobcat_name').mean()
```

	prevexp
jobcat_name	
Clerical	85.038567
Custodial	298.111111
Manager	77.619048

```
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))
```

F_Statistic: 69.19167101209159, P-Value: 4.515360685161322e-27

```
from statsmodels.formula.api import ols
model_name = ols('prevexp ~ C(jobcat_name)', data=df).fit()
model_name.summary()
```

```
 <class 'statsmodels.iolib.summary.Summary'>"""
                              OLS Regression Results
==============================================================
==========
=
```

Dep. Variable: prevexp R-
squared:0.227
Model: OLS Adj. R-squared:
0.224
Method: Least Squares F-statistic:
69.19
Date: Fri, 11 Mar 2022 Prob (F-statistic): 4.52e-
27
Time: 13:16:41 Log-Likelihood: -
2815.1
No. Observations: 474 AIC:
5636.
Df Residuals: 471 BIC:
5649.
Df Model: 2
Covariance Type: nonrobust

==
==========
==================

coef std err t P>|t|
[0.025 0.975]

-

Intercept 85.0386 4.836 17.584 0.000
75.535 94.542
C(jobcat_name)[T.Custodial] 213.0725 18.380 11.592 0.000
176.955 249.190
C(jobcat_name)[T.Manager] -7.4195 11.156 -0.665 0.506 -
29.342 14.503
==
========
=
Omnibus: 133.381 Durbin-Watson:
1.817
Prob(Omnibus): 0.000 Jarque-Bera (JB):
277.084
Skew: 1.525 Prob(JB): 6.79e-
61
Kurtosis: 5.175 Cond. No.
4.46
==
========
=

Notes:
[1] Standard Errors assume that the covariance matrix of the errors iscorrectly specified.
""""

PIRENS Institute of Business Management and Administration, Loni BK.		
Roll Number: 10097	Sign:	Date: / /
Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q.4 Apply linear regression Model techniques to predict the data on anydataset.		

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

# Import pandas package
import pandas as pd

# Find the current working directory
import  os
os.getcwd
()
'/home/mitu'

# Import dataset
df = pd.read_csv('Salary_Data.csv')

df
```

	YearsExperience	Salary
0	1.1	39343
1	1.3	46205
2	1.5	37731
3	2.0	43525
4	2.2	39891
5	2.9	56642
6	3.0	60150
7	3.2	54445
8	3.2	64445
9	3.7	57189
10	3.9	63218
11	4.0	55794
12	4.0	56957
13	4.1	57081
14	4.5	61111
15	4.9	67938
16	5.1	66029
17	5.3	83088
18	5.9	81363
19	6.0	93940
20	6.8	91738
21	7.1	98273
22	7.9	101302
23	8.2	113812
24	8.7	109431
25	9.0	105582
26	9.5	116969
27	9.6	112635
28	10.3	122391
29	10.5	121872

df.sha

pe(30,

2)

df.columns

Index(['YearsExperience', 'Salary'], dtype='object')

```
# Input
x = df['YearsExperience'].values
```

```
# Output
y = df['Salary'].values
```

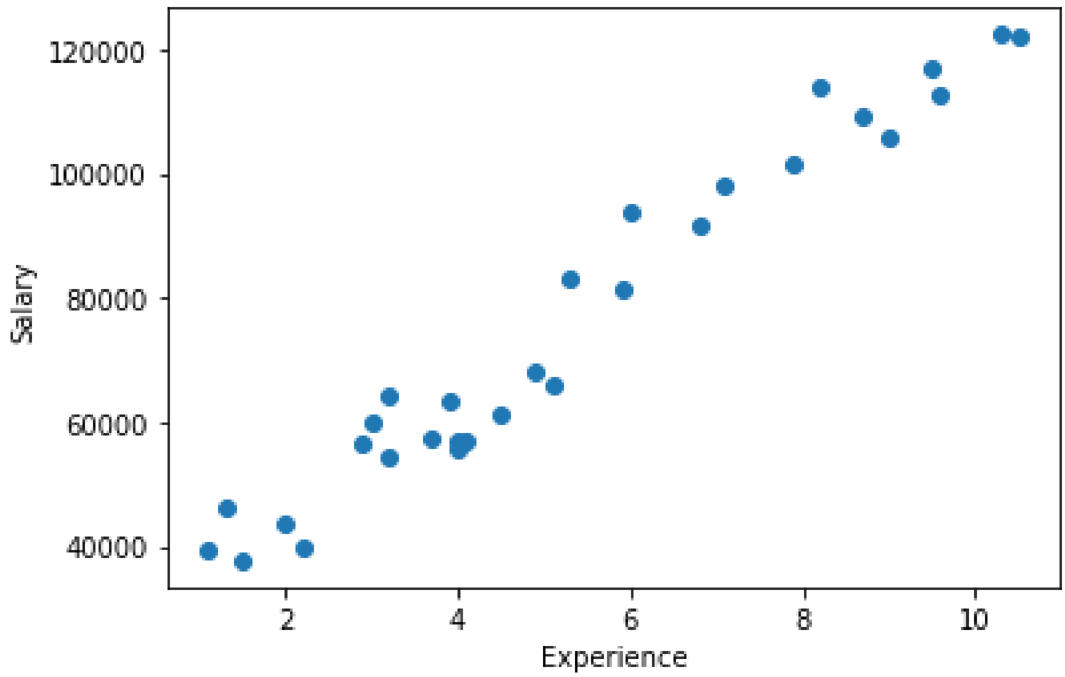
df.corr()

	YearsExperience	Salary
YearsExperience	1.000000	0.978242
Salary	0.978242	1.000000

import matplotlib.pyplot as plt

```
plt.xlabel('Experience')
plt.ylabel('Salary') plt.scatter(x, y)
```

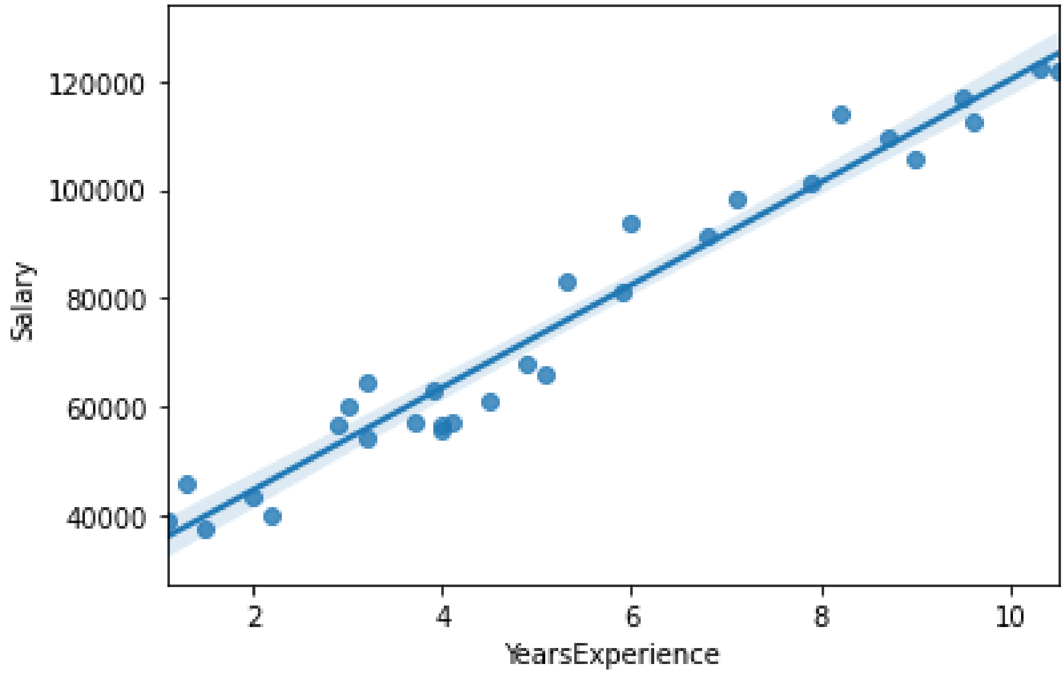
<matplotlib.collections.PathCollection at 0x7f97a5137310>




```
# Import LR class
from sklearn.linear_model import LinearRegression
```

```
# Create the object
regressor = LinearRegression()

x = x.reshape(-1,1)x

    array([[  1.1],
           [  1.3],
           [  1.5],
           [  2. ],
           [  2.2],
           [  2.9],
           [  3. ],
           [  3.2],
           [  3.2],
           [  3.7],
           [  3.9],
           [  4. ],
           [  4. ],
           [  4.1],
           [  4.5],
           [  4.9],
           [  5.1],
           [  5.3],
           [  5.9],
           [  6. ],
           [  6.8],
           [  7.1],
           [  7.9],
           [  8.2],
           [  8.7],
           [  9. ],
           [  9.5],
           [  9.6],
           [10.3],
           [10.5]])

# Train the algorithm with data
regressor.fit(x, y)

LinearRegression()

# Prediction
regressor.predict([[5]])

array([73042.01180594])

y_pred = regressor.predict(x)

import seaborn as sns sns.regplot(x='YearsExperience',
y='Salary', data=df)
```

<AxesSubplot:xlabel='YearsExperience', ylabel='Salary'>



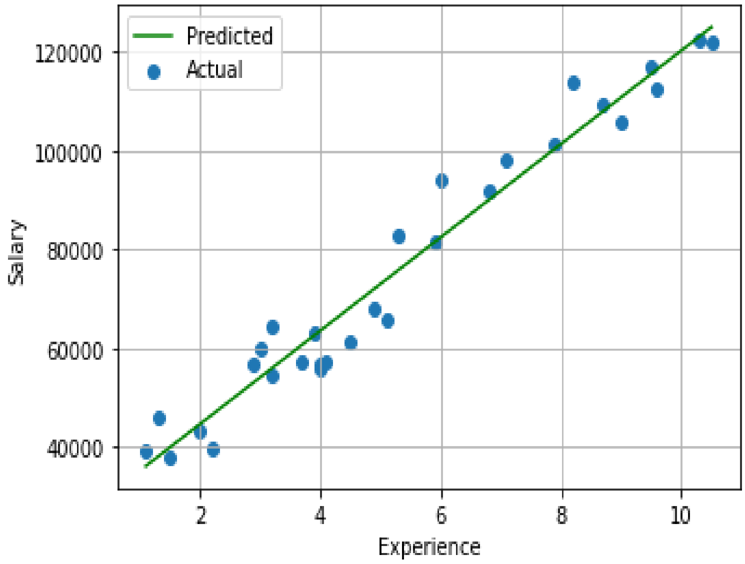

```
result = pd.DataFrame({
        'Actual': y,
        'Predicted': y_pred
})

result
```

```
                 Actual
        Predicted0      39343
                36187.158752
                   1        46205
                38077.151217
                   2        37731
                39967.143681
                   3        43525
                44692.124842
                   4        39891
                46582.117306
                   5        56642
                53197.090931
                   6        60150
                54142.087163
                   7        54445
                56032.079627
                   8        64445
                56032.079627
                   9        57189
                60757.060788
                   10       63218
                62647.053252
```

```
11      55794
63592.049484
12      56957
63592.049484
13      57081
64537.045717
14      61111
68317.030645
15      67938
72097.015574
16      66029
73987.008038
17      83088
75877.000502
18      81363
81546.977895

19      93940      82491.974127
20      91738      90051.943985
21      98273      92886.932681
22  101302   100446.902538
23  113812   103281.891235
24  109431   108006.872395
25  105582   110841.861092
26  116969   115566.842252
27  112635   116511.838485
28  122391   123126.812110
29  121872   125016.804574
```

```
plt.xlabel('Experience')
plt.ylabel('Salary')
plt.grid()
plt.scatter(x, y, label = 'Actual')
plt.plot(x, y_pred, label = 'Predicted', color='g')plt.legend()
```

```
<matplotlib.legend.Legend at 0x7f97a618dd30>
```



regressor.coef_ *# Slope of line*

array([9449.96232146])

regressor.intercept_ *# y-intercept of line*

25792.200198668696

5 * 9449.96232146 + 25792.200198668696

73042.0118059687

 # r2 score
regressor.score(x, y)

0.9569566610097508 6

from sklearn.metrics import r2_score, mean_absolute_error,mean_absolute_percentage_error

r2_score(y, y_pred)

0.956956661009750

86

mean_absolute_error(y, y_pred)

4644.2012894435375

mean_absolute_percentage_error(y, y_pred)

0.07048034398306606

df = pd.read_csv('mtcars.csv')

```
df.shape
```

(32, 11)

```
# input
x = df[['disp','hp','wt']]

# Output
y = df['mpg']
```

```
x
```

	disp	hp	wt
0	160.0	110	2.620
1	160.0	110	2.875
2	108.0	93	2.320
3	258.0	110	3.215
4	360.0	175	3.440

```
5       225.0   105     3.460
6       360.0   245     3.570
7       146.7    62     3.190
8       140.8    95     3.150
9       167.6   123     3.440
10      167.6   123     3.440
11      275.8   180     4.070
12      275.8   180     3.730
13      275.8   180     3.780
14      472.0   205     5.250
15      460.0   215     5.424
16  440.0   230  5.345
17     78.7      66  2.200
18     75.7      52  1.615
19     71.1      65  1.835
20  120.1        97  2.465
21  318.0   150  3.520
22  304.0   150  3.435
23  350.0   245  3.840
24  400.0   175  3.845
25     79.0      66  1.935
26  120.3        91  2.140
27     95.1   113  1.513
28  351.0   264  3.170
29  145.0   175  2.770
30  301.0   335  3.570
31  121.0   109  2.780
```

```
regressor = LinearRegression()

regressor.fit(x, y)

LinearRegression()

regressor.intercept_

37.10550526903182

regressor.coef_

array([-9.37009081e-04, -3.11565508e-02, -3.80089058e+00])

# r2 Score
regressor.score(x, y)

0.8268361424946447

# prediction
new = [[221, 102, 3.81]]
regressor.predict(new)

array([19.23906496])

new = [[211, 134, 2.81]]
```

regressor.predict(new)

array([22.052316])

x.corrwith(y)

disp	-0.847551
hp	-0.776168
wt	-0.867659
dtype:	float64

y_pred = regressor.predict(x)

mean_absolute_error(y, y_pred)

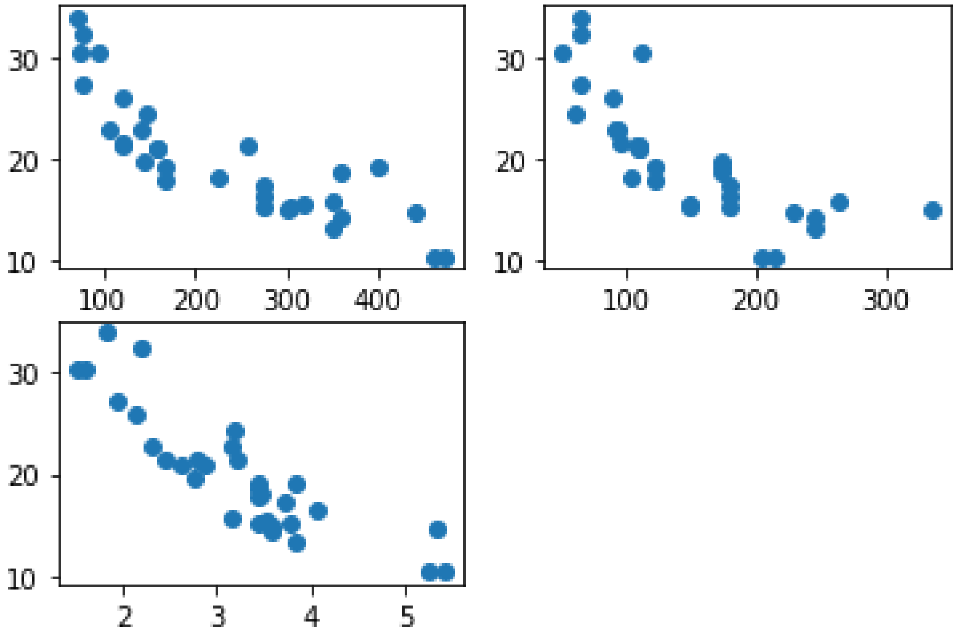
1.9070264019715124

r2_score(y, y_pred)

0.82683614249464

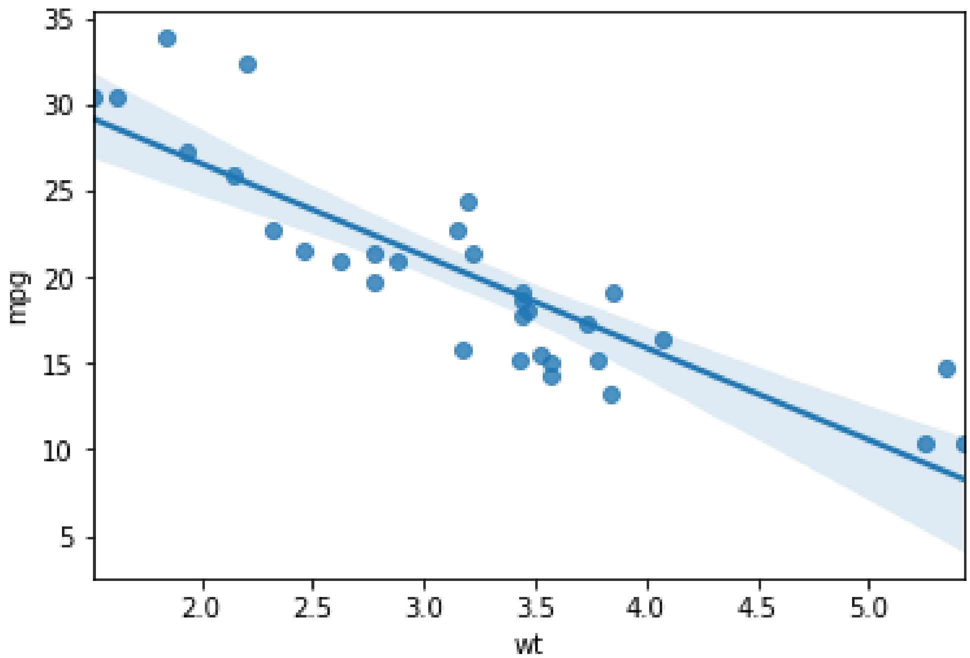
47

```
# Data Visualization
plt.subplot(2,2,1)
plt.scatter(x['disp'], y)
plt.subplot(2,2,2)
plt.scatter(x['hp'], y)
plt.subplot(2,2,3)
plt.scatter(x['wt'], y)
<matplotlib.collections.PathCollection at 0x7f97a6219970>
```



sns.regplot(x='wt', y='mpg', data=pd.read_csv('mtcars.csv'))

<AxesSubplot:xlabel='wt', ylabel='mpg'>

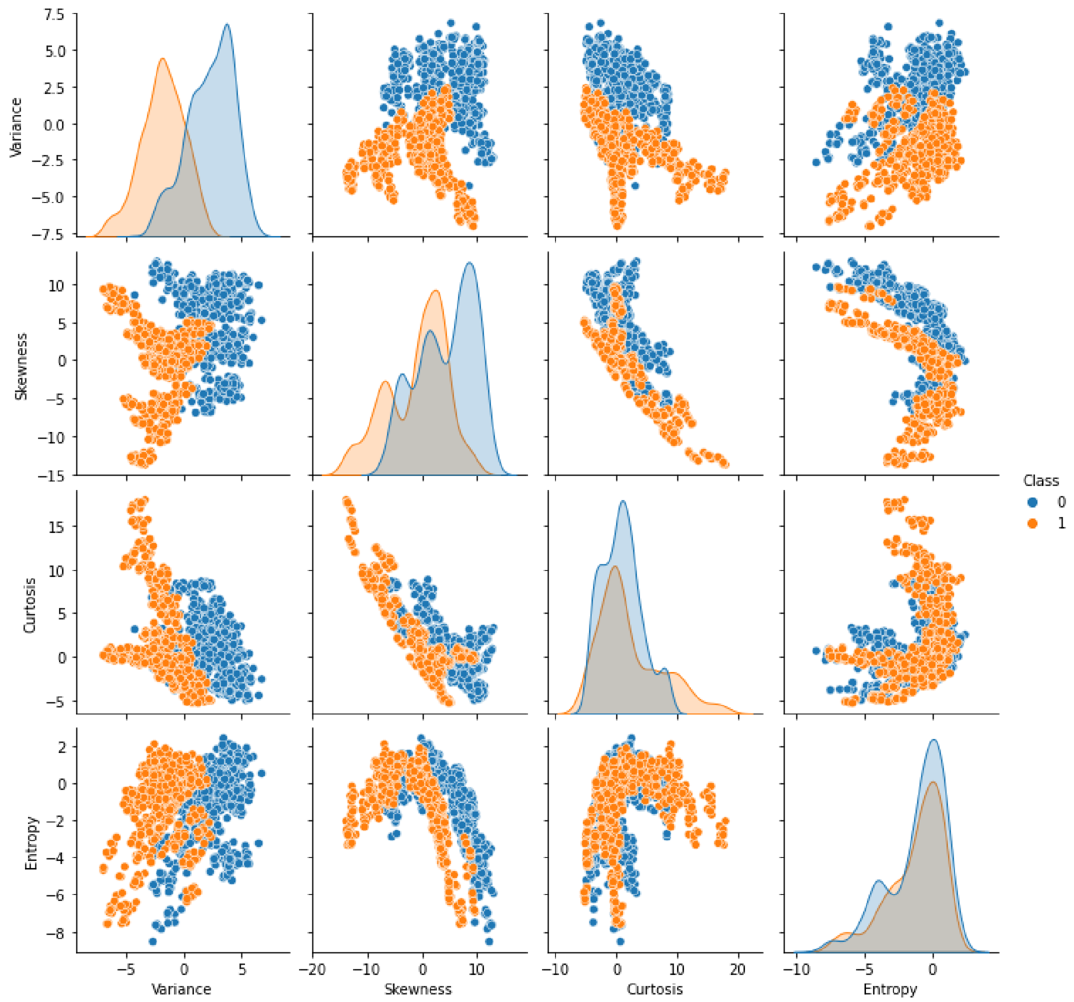

35
30
25
20
15
10
5
mpg
2.0
2.5
3.0
3.5
4.0
4.5
5.0
wt

PIRENS Institute of Business Management and Administration, Loni BK.		
Roll Number: 10097	**Sign: :**	**Date: / /**
Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q.5 Apply logical regression Model techniques to predict the data on any dataset.		

Program:

```
import pandas as pd

# Data import
df = pd.read_csv('banknotes.csv')

import seaborn as sns
sns.pairplot(df, hue='Class')
```

<seaborn.axisgrid.PairGrid at 0x7f42a29c9310>



```
# output
y = df['Class']

x.shape

(1372, 4)

# Cross validation
from sklearn.model_selection import train_test_splitx_train, x_test,
y_train, y_test = train_test_split(
        x, y, random_state=0, test_size=0.25)

x_train.head()
```

	Variance	Skewness	Curtosis	Entropy
662	2.9736	8.7944	-3.6359	-1.375400
512	2.6648	10.7540	-3.3994	-4.168500
1193	-3.7573	-8.2916	10.3032	0.380590
682	3.7321	-3.8840	3.3577	-0.006049
1313	-1.5078	-7.3191	7.8981	1.228900

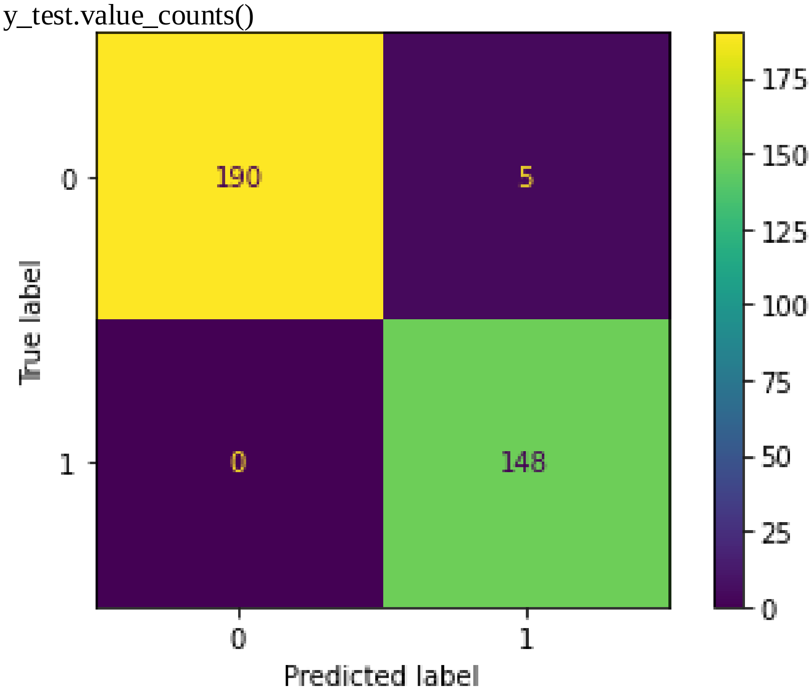
```
x_train.shape

(1029, 4)

# Import the class
from sklearn.linear_model import LogisticRegression

# Create the object
classifier = LogisticRegression()

# Train the algorithm
classifier.fit(x_train, y_train)

LogisticRegression() x_test.shape

(343, 4)

# Predict on the test data
y_pred = classifier.predict(x_test)set(y)

{0, 1}

y.value_counts()0

        762
1       610
Name: Class, dtype: int64
```

```
result = pd.DataFrame({
        'Actual': y_test,
        'Predicted': y_pred
})
```

```
result
      Actual   Predicted
1023       1           1
642        0           0
1196       1           1
31         0           0
253        0           0
...      ...         ...
866        1           1
361        0           0
703        0           0
328        0           0
530        0           0

[343 rows x 2 columns]
```

fromsklearn.metricsimport plot_confusion_matrix, accuracy_score plot_confusion_matrix(classifier, x_test, y_test);

y_test.value_counts()



0 195
1 148
Name: Class, dtype: int64 accuracy_score(y_test, y_pred)0.9854227405247813 new1 = [[0.7057,-5.4981,8.3368,-2.8715]]
new2 = [[-0.4665,2.3383,-2.9812,-1.0431]]

classifier.predict(new1) array([0]) classifier.predict_proba(new1) array([[0.99724553, 0.00275447]]) classifier.predict(new2) array([1]) classifier.predict_proba(new2) array([[6.24842128e-04, 9.99375158e-01]])

PIRENS Institute of Business Management and Administration, Loni BK.	
RollNumber:10097 **Date: / /**	**Sign:**
StudentName:Yash Bora	
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL	
Program Title: Q.6 Clustering algorithms for unsupervised classification.	

Program:

```
import pandas as pd
    df = pd.read_csv('/home/mitu/Mall_Customers.csv')df.shape (200, 5)

list(df.columns)

['CustomerID', 'Genre', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']

# Input data
x = df.iloc[:,3:]

x
```

	Annual Income (k$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40
..	...	...
195	120	79
196	126	28
197	126	74
198	137	18
199	137	83

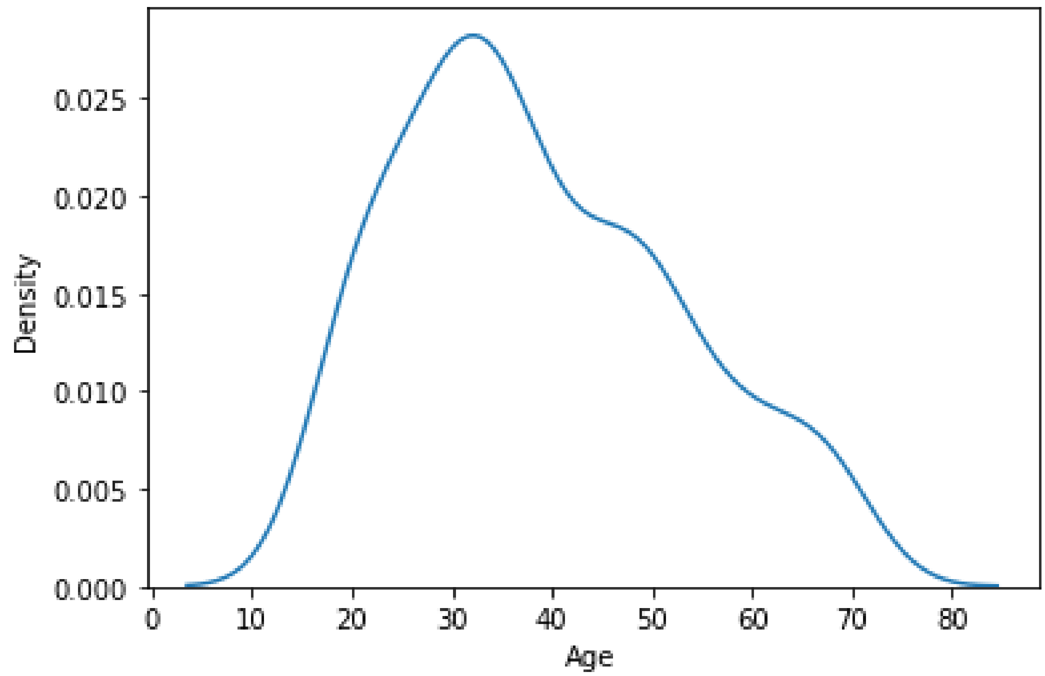
[200 rows x 2 columns]

```
# Summerize
df.describe()
```

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000

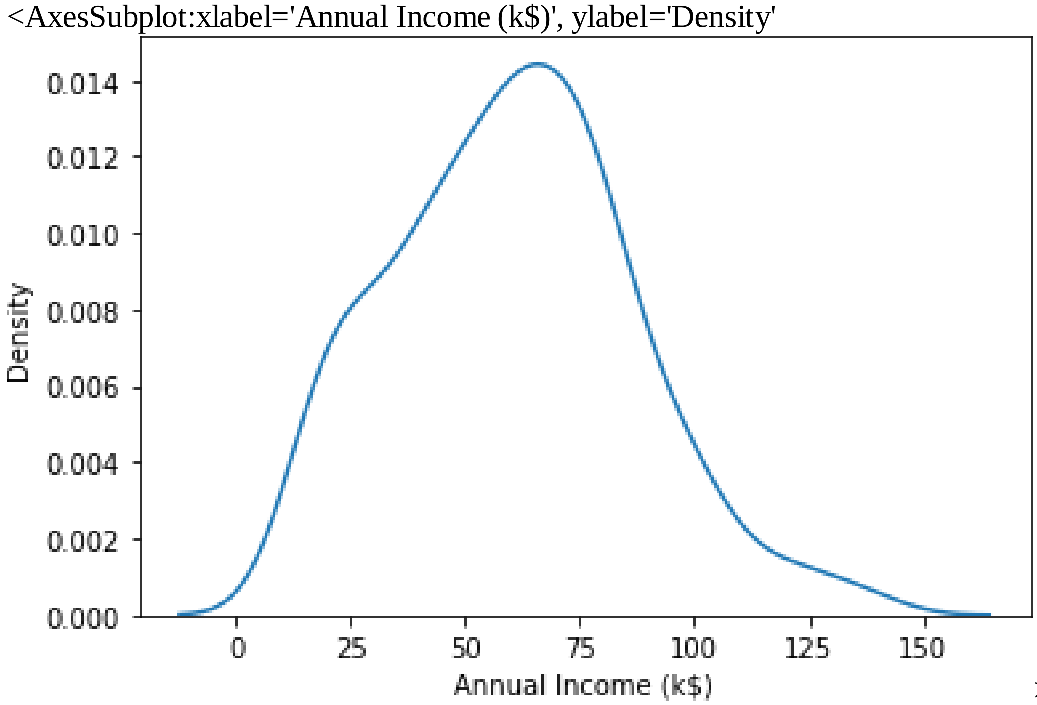
```
# import seaborn package
import seaborn as sns

sns.kdeplot(df['Age'])
```

```
<AxesSubplot:xlabel='Age', ylabel='Density'>
```




```
sns.kdeplot(df['Annual Income (k$)'])
```

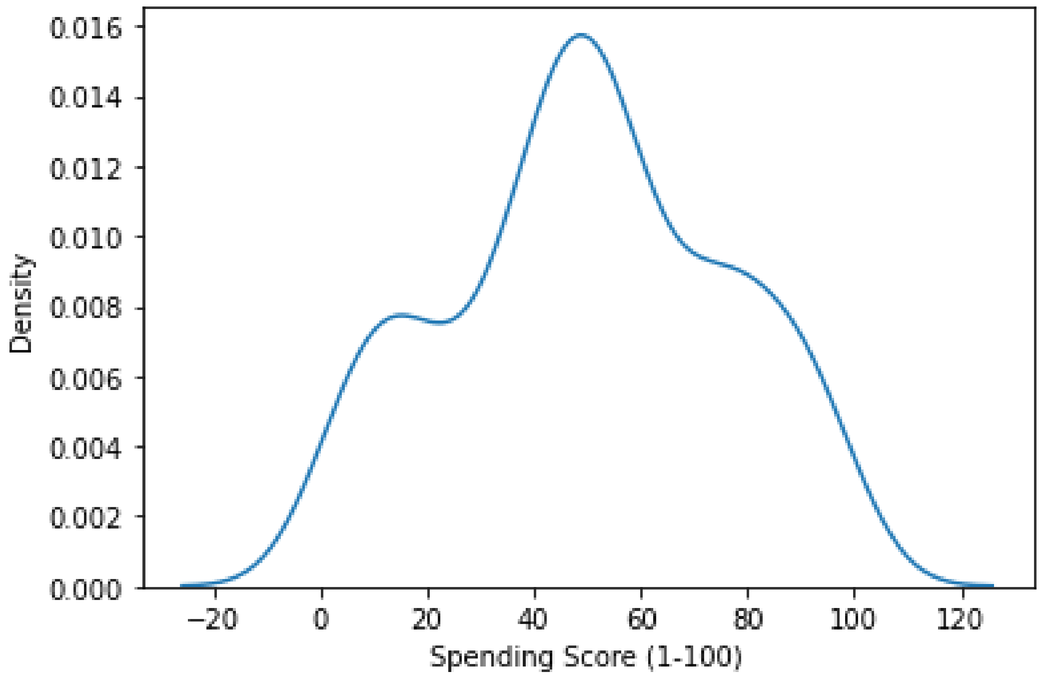
```
<AxesSubplot:xlabel='Annual Income (k$)', ylabel='Density'
```



>

```
sns.kdeplot(df['Spending Score (1-100)'])
```

<AxesSubplot:xlabel='Spending Score (1-100)', ylabel='Density'>



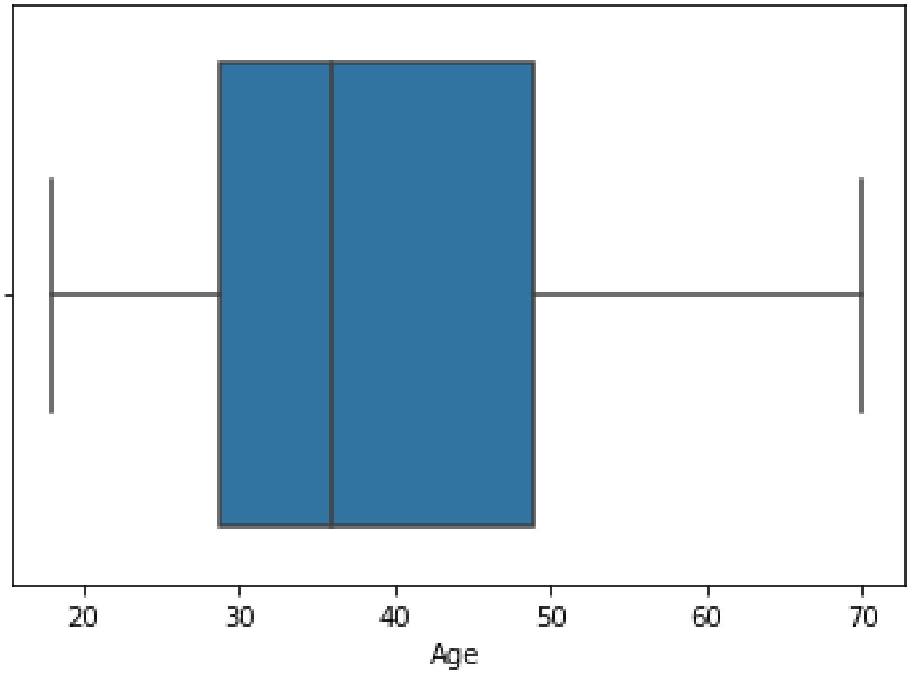

```
sns.boxplot(df['Age'])
```

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version

0.12, the only valid positional argument will be `data`, and passing otherarguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

(

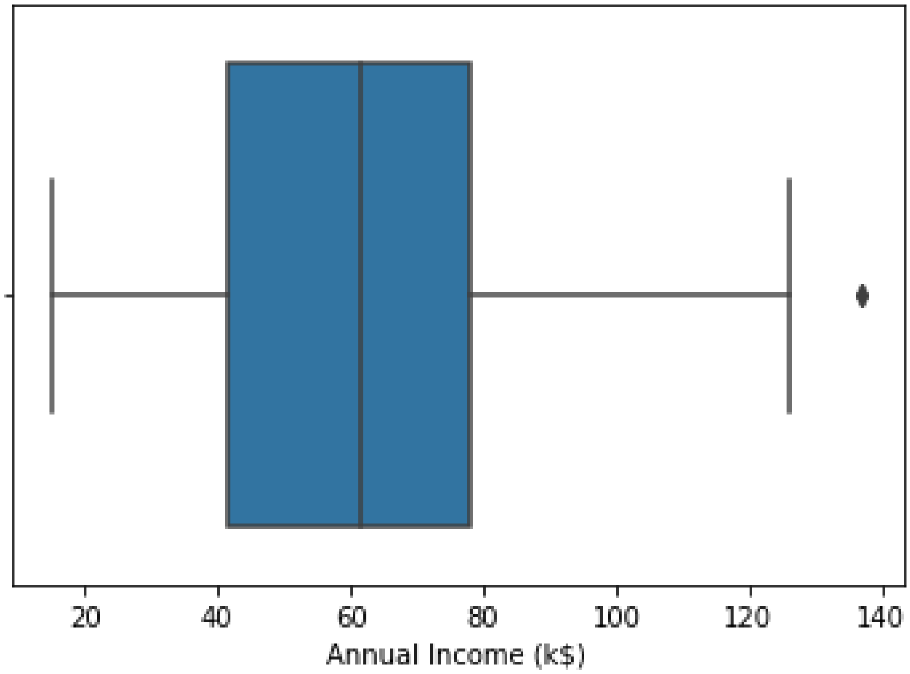
<AxesSubplot:xlabel='Age'>



sns.boxplot(df['Annual Income (k$)'])

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
warnings.warn(

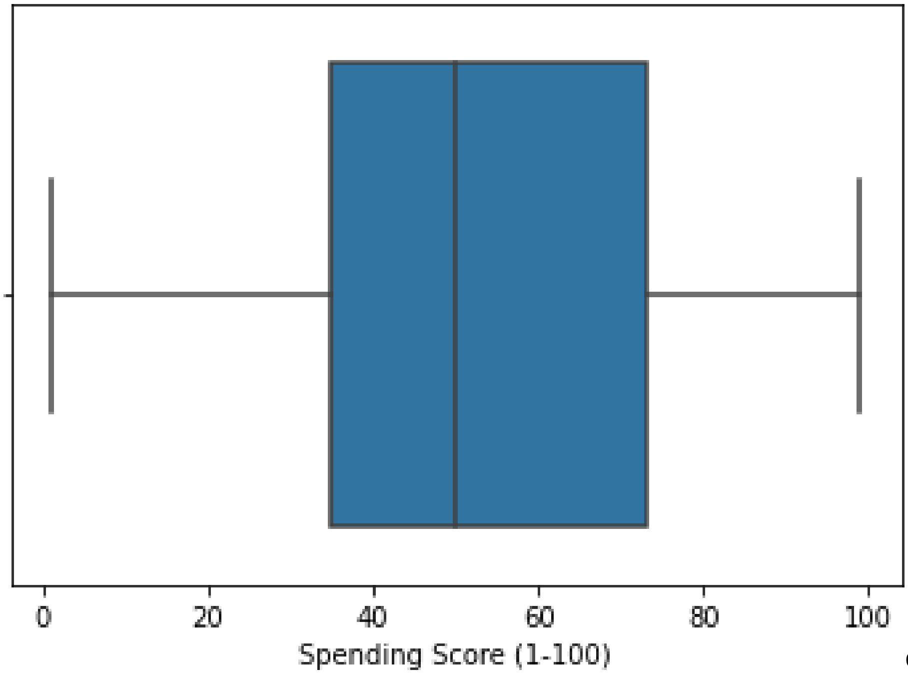
<AxesSubplot:xlabel='Annual Income (k$)'>



sns.boxplot(df['Spending Score (1-100)'])

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

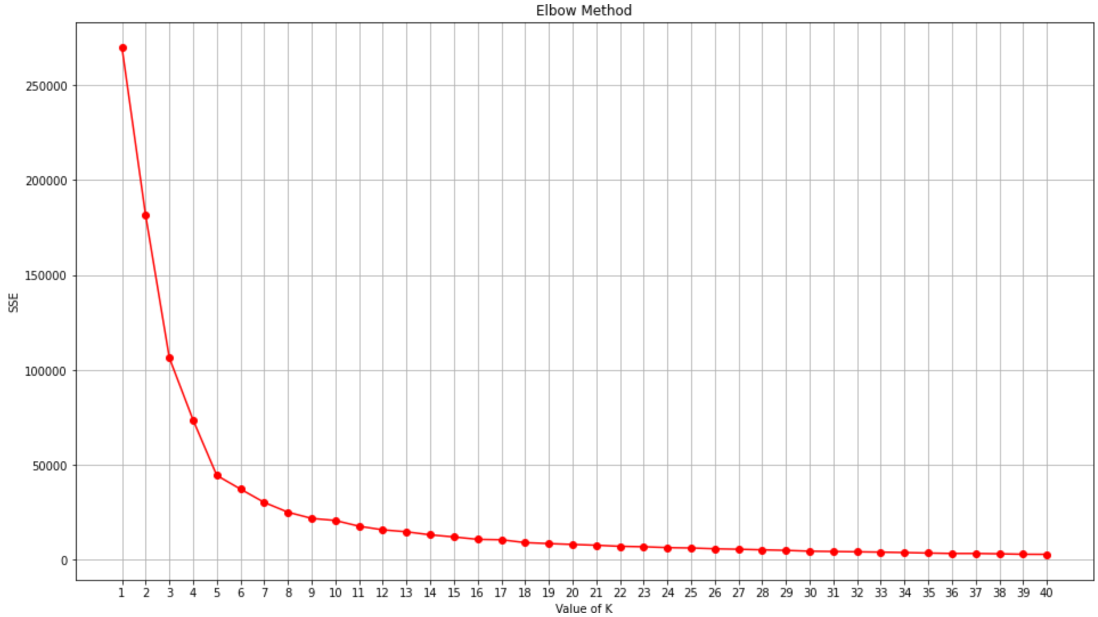
<AxesSubplot:xlabel='Spending Sc



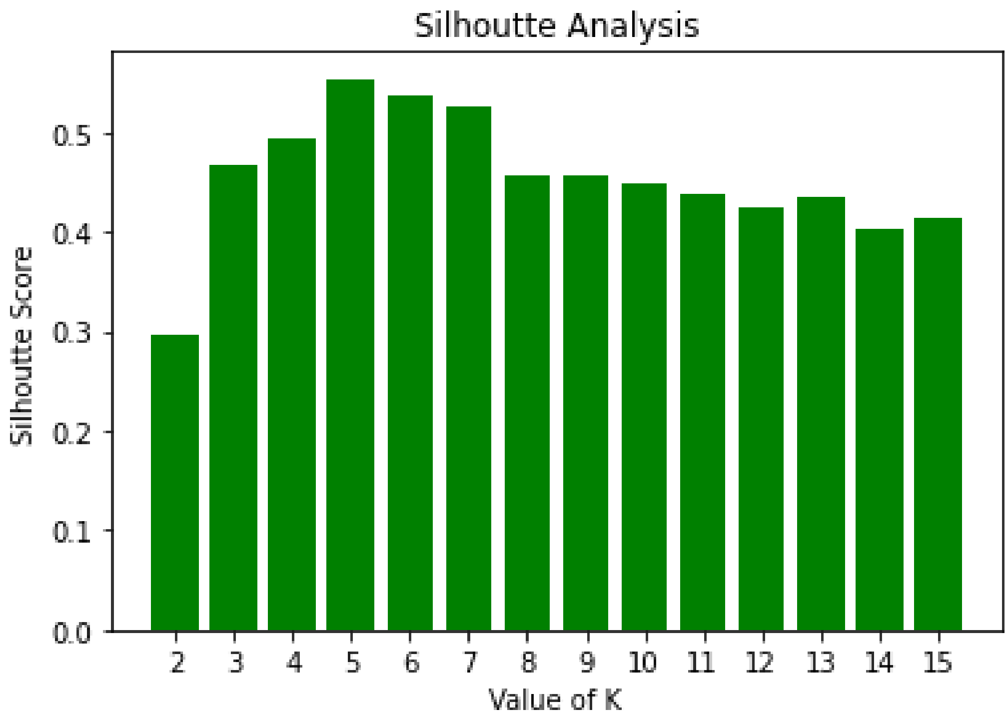
ore (1-100)

```
# 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_

15810.838613705504

# 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')
```

```
[<matplotlib.lines.Line2D at 0x7f9dac6b3070>]
```




```
# 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')

<BarContainer object of 14 ar tists>
```




```
# Create the object
km = KMeans(n_clusters=5, random_state=0)

# Train the algorithm
labels = km.fit_predict(x)

labels
```

```
array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2,
       1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
      0, 2], dtype=int32)
```

```
# Cluster labels
km.labels_
```

```
array([4 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
      ,
      4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
      4, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
      1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2,
```

1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,

0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
0, 2, 0,
0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
0, 2, 0,
0, 2], dtype=int32)

0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,

0, 2], dtype=int32)

```
# SSE
km.inertia_
```

44448.45544793369

```
# Centroids
km.cluster_centers_
```

```
array([[88.2        , 17.11428571],
       [55.2962963 , 49.51851852],
       [86.53846154, 82.12820513],
       [25.72727273, 79.36363636],
       [26.30434783, 20.91304348]])
```

```
# Extract the clusters
df[labels==2] # Boolean filtering
```

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)123
	124	Male	39	69	91
125	126	Female	31	70	77
127	128	Male	40	71	95
129	130	Male	38	71	75
131	132	Male	39	71	75
133	134	Female	31	72	71
135	136	Female	29	73	88
137	138	Male	32	73	73
139	140	Female	35	74	72
141	142	Male	32	75	93
143	144	Female	32	76	87
145	146	Male	28	77	97
147	148	Female	32	77	74
149	150	Male	34	78	90
151	152	Male	39	78	88
153	154	Female	38	78	76
155	156	Female	27	78	89
157	158	Female	30	78	78
159	160	Female	30	78	73
161	162	Female	29	79	83
163	164	Female	31	81	93
165	166	Female	36	85	75
167	168	Female	33	86	95
169	170	Male	32	87	63
171	172	Male	28	87	75
173	174	Male	36	87	92
175	176	Female	30	88	86
177	178	Male	27	88	69
179	180	Male	35	93	90

181	182	Female	32	97	86
183	184	Female	29	98	88
185	186	Male	30	99	97
187	188	Male	28	101	68
189	190	Female	36	103	85
191	192	Female	32	103	69
193	194	Female	38	113	91
195	196	Female	35	120	79
197	198	Male	32	126	74
199	200	Male	30	137	83

```
one = df[labels==1]
```

```
one.shape
```

(81, 5)

```
# 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]))
```

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

```
# Prediction
new = [[45, 76]]
km.predict(new)[0]3
```

```
# Prediction
new = [[25, 36]]
km.predict(new)[0]4
```

```
# Prediction
new = [[85, 76]]
km.predict(new)[0]2
```

```
# Prediction
new = [[45, 47]]
km.predict(new)[0]1
```

from sklearn.preprocessing import LabelEncoderle =
LabelEncoder()
df['Genre'] = le.fit_transform(df['Genre'])import

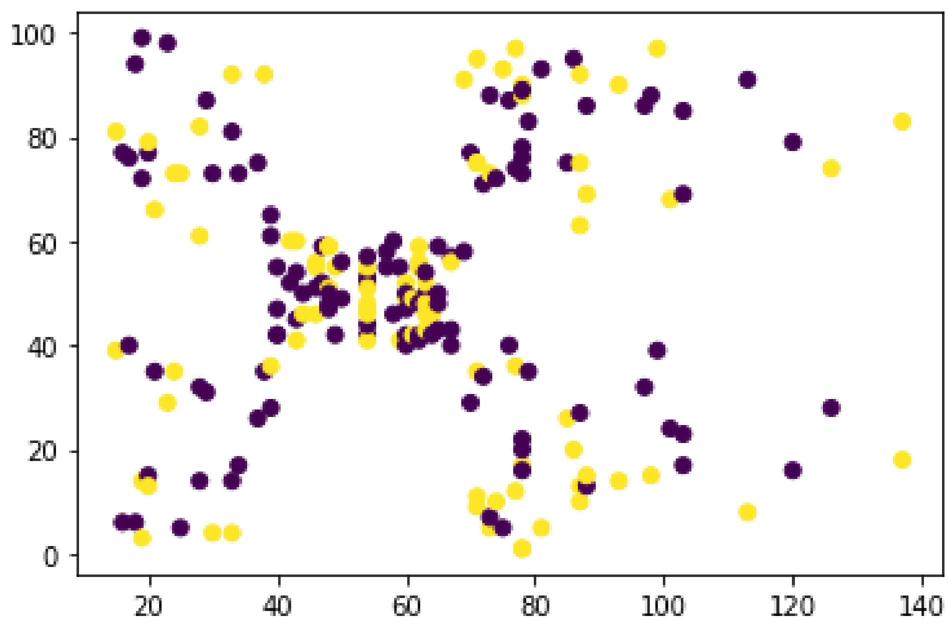
matplotlib.pyplot as plt

df['Genre']

```
0      1
1      1
2      0
3      0
4      0
       ..
195    0
196    0
197    1
198    1
199    1
Name:  Genre, Length: 200, dtype: int64
```

plt.scatter(df['Annual Income (k$)'], df['Spending Score (1-100)'],c=df['Genre'])

<matplotlib.collections.PathCollection at 0x7f9dac6e2fd0>



PIRENS Institute of Business Management and Administration, Loni BK.
Roll Number:10097 **Sign:** **Date: / /**
Student Name: Yash Bora
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL
Program Title: Q.7 Association algorithms for supervised classification on any dataset.

Program:

```
dataset = [['Apple', 'Beer', 'Rice', 'Chicken'],
           ['Apple', 'Beer', 'Rice'],
           ['Apple', 'Beer'],
           ['Apple', 'Pear'],
           ['Milk', 'Beer', 'Rice', 'Chicken'],
           ['Milk', 'Beer', 'Rice'],
           ['Milk', 'Beer'],
           ['Apple', 'Pear']]

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)df_t

array([[ True, True, True, False, False, True],[ True, True, False,
        False, False, True],[ True, True, False, False, False,
        False],[ True, False, False, False, True, False], [False,
        True, True, True, False, True], [False, True,False,
        True, False, True],[False, True, False, True, False,
        False],[ True, False, False, False, True, False]])

trans.columns_

['Apple', 'Beer', 'Chicken', 'Milk', 'Pear', 'Rice']import pandas as pd
```

```
df
```

	Apple	Beer	Chicken	Milk	Pear	Rice
0	True	True	True	False	False	True
1	True	True	False	False	False	True
2	True	True	False	False	False	False
3	True	False	False	False	True	False
4	False	True	True	True	False	True
5	False	True	False	True	False	True
6	False	True	False	True	False	False
7	True	False	False	False	True	False

```
# Support count
sum(df['Rice']) / len(df)0.5

# Generate frequent itemsets
from mlxtend.frequent_patterns import apriori

freq_itemset = apriori(df, min_support=0.25, use_colnames=True)freq_itemset
```

	support	itemsets
0	0.625	(Apple)
1	0.750	(Beer)
2	0.250	(Chicken)
3	0.375	(Milk)
4	0.250	(Pear)
5	0.500	(Rice)
6	0.375	(Beer, Apple)
7	0.250	(Pear, Apple)
8	0.250	(Rice, Apple)
9	0.250	(Beer, Chicken)
10	0.375	(Beer, Milk)
11	0.500	(Beer, Rice)
12	0.250	(Rice, Chicken)
13	0.250	(Rice, Milk)
14	0.250	(Beer, Rice, Apple)
15	0.250	(Beer, Rice, Chicken)
16	0.250	(Beer, Rice, Milk)

```
# Generate strong association rules
from mlxtend.frequent_patterns import association_rules

rules = association_rules(freq_itemset,
                          metric='confidence',
                          min_threshold=0.5)

rules
```

	antecedents	consequents	...	leverage	conviction0
	(Beer)	(Apple)	...	-0.09375	0.750
1	(Apple)	(Beer)	...	-0.09375	0.625
2	(Pear)	(Apple)	...	0.09375	inf
3	(Rice)	(Apple)	...	-0.06250	0.750
4	(Chicken)	(Beer)	...	0.06250	inf
5	(Beer)	(Milk)	...	0.09375	1.250
6	(Milk)	(Beer)	...	0.09375	inf
7	(Beer)	(Rice)	...	0.12500	1.500
8	(Rice)	(Beer)	...	0.12500	inf
9	(Rice)	(Chicken)	...	0.12500	1.500
10	(Chicken)	(Rice)	...	0.12500	inf
11	(Rice)	(Milk)	...	0.06250	1.250
12	(Milk)	(Rice)	...	0.06250	1.500
13	(Beer, Rice)	(Apple)	...	-0.06250	0.750
14	(Beer, Apple)	(Rice)	...	0.06250	1.500
15	(Rice, Apple)	(Beer)	...	0.06250	inf
16	(Rice)	(Beer, Apple)	..	0.06250	1.250
17	(Beer, Rice)	(Chicken)	...	0.12500	1.500
18	(Beer, Chicken)	(Rice)	...	0.12500	inf
19	(Rice, Chicken)	(Beer)	...	0.06250	inf
20	(Rice)	(Beer, Chicken)	...	0.12500	1.500
21	(Chicken)	(Beer, Rice)	...	0.12500	inf
22	(Beer, Rice)	(Milk)	...	0.06250	1.250
23	(Beer, Milk)	(Rice)	...	0.06250	1.500
24	(Rice, Milk)	(Beer)	...	0.06250	inf
25	(Rice)	(Beer, Milk)	...	0.06250	1.250
26	(Milk)	(Beer, Rice)	...	0.06250	1.500

[27 rows x 9 columns]

```
rules = rules[['antecedents','consequents','support','confidence']]
```

```
rules
```

	antecedents	consequents	support	confidence
0	(Beer)	(Apple)	0.375	0.500000
1	(Apple)	(Beer)	0.375	0.600000
2	(Pear)	(Apple)	0.250	1.000000
3	(Rice)	(Apple)	0.250	0.500000
4	(Chicken)	(Beer)	0.250	1.000000
5	(Beer)	(Milk)	0.375	0.500000
6	(Milk)	(Beer)	0.375	1.000000
7	(Beer)	(Rice)	0.500	0.666667
8	(Rice)	(Beer)	0.500	1.000000
9	(Rice)	(Chicken)	0.250	0.500000
10	(Chicken)	(Rice)	0.250	1.000000
11	(Rice)	(Milk)	0.250	0.500000
12	(Milk)	(Rice)	0.250	0.666667
13	(Beer, Rice)	(Apple)	0.250	0.500000

14	(Beer, Apple)	(Rice)	0.250	0.666667
15	(Rice, Apple)	(Beer)	0.250	1.000000
16	(Rice)	(Beer, Apple)	0.250	0.500000
17	(Beer, Rice)	(Chicken)	0.250	0.500000
18	(Beer, Chicken)	(Rice)	0.250	1.000000
19	(Rice, Chicken)	(Beer)	0.250	1.000000
20	(Rice)	(Beer, Chicken)	0.250	0.500000
21	(Chicken)	(Beer, Rice)	0.250	1.000000
22	(Beer, Rice)	(Milk)	0.250	0.500000
23	(Beer, Milk)	(Rice)	0.250	0.666667
24	(Rice, Milk)	(Beer)	0.250	1.000000
25	(Rice)	(Beer, Milk)	0.250	0.500000
26	(Milk)	(Beer, Rice)	0.250	0.666667

```
rules['antecedent_len'] = rules['antecedents'].apply(lambda x: len(x))
```

<ipython-input-24-514ef6b1bde9>:1: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/indexing.html#returning-a-view-versus-a-copy
rules['antecedent_len'] = rules['antecedents'].apply(lambda x: len(x))

```
rules
```

	antecedents	consequents	support	confidence	antecedent_len
0	(Beer)	(Apple)	0.375	0.500000	1
1	(Apple)	(Beer)	0.375	0.600000	1
2	(Pear)	(Apple)	0.250	1.000000	1
3	(Rice)	(Apple)	0.250	0.500000	1
4	(Chicken)	(Beer)	0.250	1.000000	1
5	(Beer)	(Milk)	0.375	0.500000	1
6	(Milk)	(Beer)	0.375	1.000000	1
7	(Beer)	(Rice)	0.500	0.666667	1
8	(Rice)	(Beer)	0.500	1.000000	1
9	(Rice)	(Chicken)	0.250	0.500000	1
10	(Chicken)	(Rice)	0.250	1.000000	1
11	(Rice)	(Milk)	0.250	0.500000	1
12	(Milk)	(Rice)	0.250	0.666667	1
13	(Beer, Rice)	(Apple)	0.250	0.500000	2
14	(Beer, Apple)	(Rice)	0.250	0.666667	2
15	(Rice, Apple)	(Beer)	0.250	1.000000	2
16	(Rice)	(Beer, Apple)	0.250	0.500000	1
17	(Beer, Rice)	(Chicken)	0.250	0.500000	2
18	(Beer, Chicken)	(Rice)	0.250	1.000000	2
19	(Rice, Chicken)	(Beer)	0.250	1.000000	2
20	(Rice)	(Beer, Chicken)	0.250	0.500000	1
21	(Chicken)	(Beer, Rice)	0.250	1.000000	1

24	(Rice, Milk)	(Beer)	0.250	1.000000	2
25	(Rice)	(Beer, Milk)	0.250	0.500000	1
26	(Milk)	(Beer, Rice)	0.250	0.666667	1

```
nrules = rules[(rules['antecedent_len'] == 1) &
               (rules['support'] > 0.30)]

nrules
```

	antecedents	consequents	support	confidence	antecedent_len
0	(Beer)	(Apple)	0.375	0.500000	1
1	(Apple)	(Beer)	0.375	0.600000	1
5	(Beer)	(Milk)	0.375	0.500000	1
6	(Milk)	(Beer)	0.375	1.000000	1
7	(Beer)	(Rice)	0.500	0.666667	1
8	(Rice)	(Beer)	0.500	1.000000	1

```
# Prediction / Suggestion / Recommendation
nrules[nrules['antecedents'] == {'Apple'}]['consequents'][1]
```

frozenset({'Beer'})

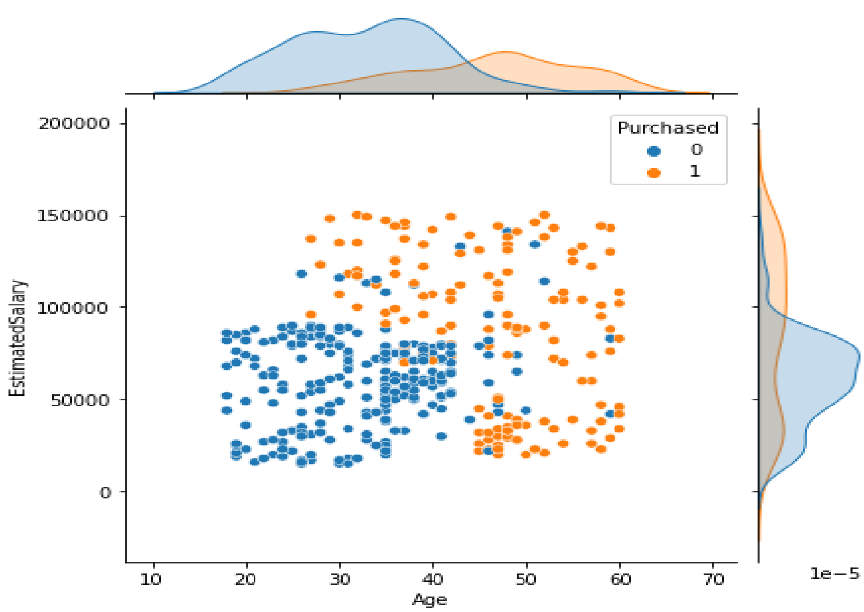
```
rules.sort_values(by='confidence', ascending=False)
```

	antecedents	consequents	support	confidence	antecedent_len
18	(Beer, Chicken)	(Rice)	0.250	1.000000	2
2	(Pear)	(Apple)	0.250	1.000000	1
21	(Chicken)	(Beer, Rice)	0.250	1.000000	1
4	(Chicken)	(Beer)	0.250	1.000000	1
24	(Rice, Milk)	(Beer)	0.250	1.000000	2
6	(Milk)	(Beer)	0.375	1.000000	1
15	(Rice, Apple)	(Beer)	0.250	1.000000	2
8	(Rice)	(Beer)	0.500	1.000000	1
19	(Rice, Chicken)	(Beer)	0.250	1.000000	2
10	(Chicken)	(Rice)	0.250	1.000000	1
12	(Milk)	(Rice)	0.250	0.666667	1
14	(Beer, Apple)	(Rice)	0.250	0.666667	2
26	(Milk)	(Beer, Rice)	0.250	0.666667	1
7	(Beer)	(Rice)	0.500	0.666667	1
23	(Beer, Milk)	(Rice)	0.250	0.666667	2
1	(Apple)	(Beer)	0.375	0.600000	1
22	(Beer, Rice)	(Milk)	0.250	0.500000	2
25	(Rice)	(Beer, Milk)	0.250	0.500000	1
20	(Rice)	(Beer, Chicken)	0.250	0.500000	1
0	(Beer)	(Apple)	0.375	0.500000	1
17	(Beer, Rice)	(Chicken)	0.250	0.500000	2
16	(Rice)	(Beer, Apple)	0.250	0.500000	1
11	(Rice)	(Milk)	0.250	0.500000	1
9	(Rice)	(Chicken)	0.250	0.500000	1
5	(Beer)	(Milk)	0.375	0.500000	1

PIRENS Institute of Business Management and Administration, Loni BK.		
Roll Number: 10097	**Sign:**	**Date: / /**
Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q.8 Developing and implementing Decision Tree model on the dataset		

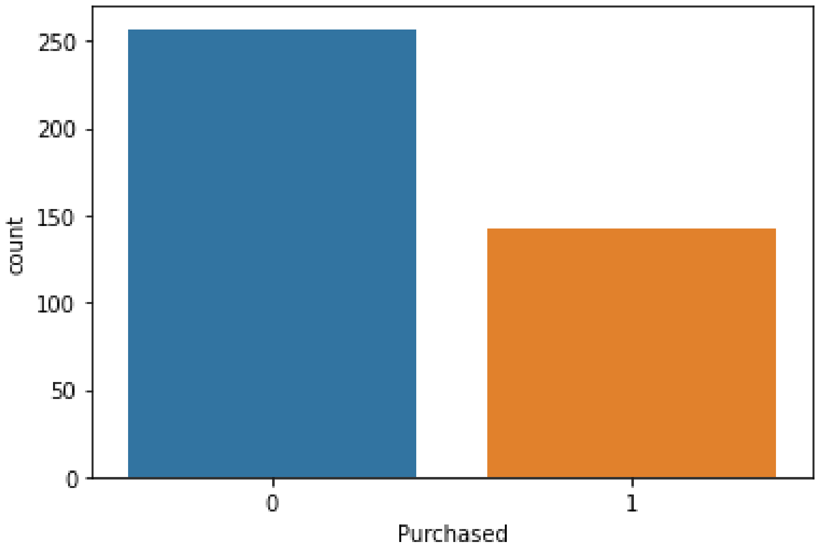
Program:

```
import pandas as pd

# Data import
df = pd.read_csv('Social_Network_Ads.csv')

df.shape

(400, 5)

# input
x = df[['Age','EstimatedSalary']]

# output

y = df['Purchased']
import seaborn as sns
sns.jointplot(x='Age', y='EstimatedSalary', hue='Purchased', data=df)

<seaborn.axisgrid.JointGrid at 0x7fb1b1c5e9a0>
```



```
sns.countplot(x=y)
```

<AxesSubplot:xlabel='Purchased', ylabel='count'




```
y.value_counts()
```

```
0       257
1       143
Name: Purchased, dtype: int64
```

```
# Cross-validation
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)

x_train.shape
```

```
(300, 2)
```

```
x_test.shape
```

```
(100, 2)
```

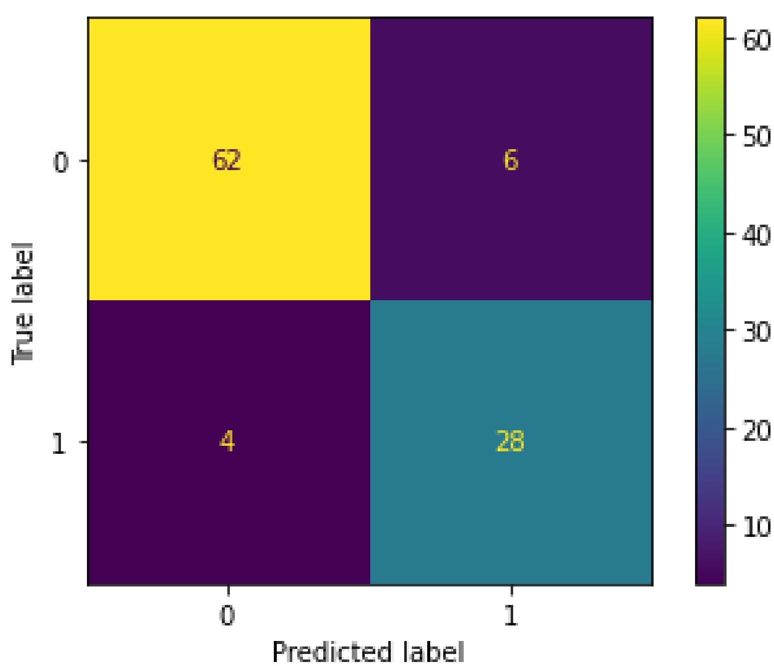
```
# Import the class
from sklearn.tree import DecisionTreeClassifier

# Create the object
classifier = DecisionTreeClassifier(random_state=0)

# Train the algorithm with data
```

```
# Predictions
y_pred = classifier.predict(x_test)

# Combine the data
result = pd.DataFrame({
        'Actual': y_test,
        'Predicted': y_pred
})

result
```

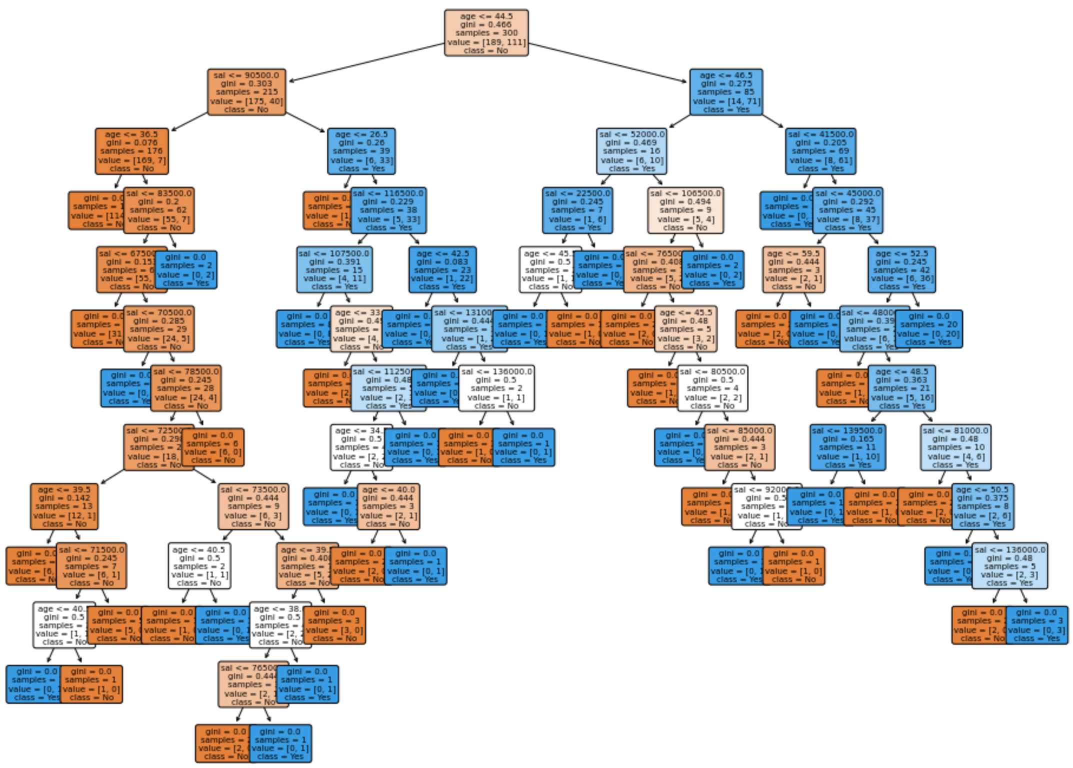
	Actual	Predicted
132	0	0
309	0	0
341	0	0
196	0	0
246	0	0
..	...	...
146	1	1
135	0	0
390	1	1
264	1	1
364	1	1

[100 rows x 2 columns]

```
from sklearn.metrics import plot_confusion_matrix, accuracy_score

plot_confusion_matrix(classifier, x_test, y_test);
```



```
accuracy_score(y_test, y_pred)0.9

# Single prediction
new1 = [[34, 123000]]
new2 = [[25, 48900]]

classifier.predict(new1)array([1])

classifier.predict(new2)array([0])

from sklearn.tree import plot_treeimport
matplotlib.pyplot as plt

plt.figure(figsize=(16,12))
plot_tree(classifier, fontsize=7, feature_names=['age','sal'],class_names=['No','Yes'],
            filled=True, rounded=True);
```



Program Title: Q.9 Bayesian classification on any dataset.

Program:

```
# Import packages import
pandas as pd import
seaborn as sns

# Data import
df = pd.read_csv('iris.csv')

# The data shape
df.shape
```

(150, 5)

```
# The columns names
list(df.columns)
```

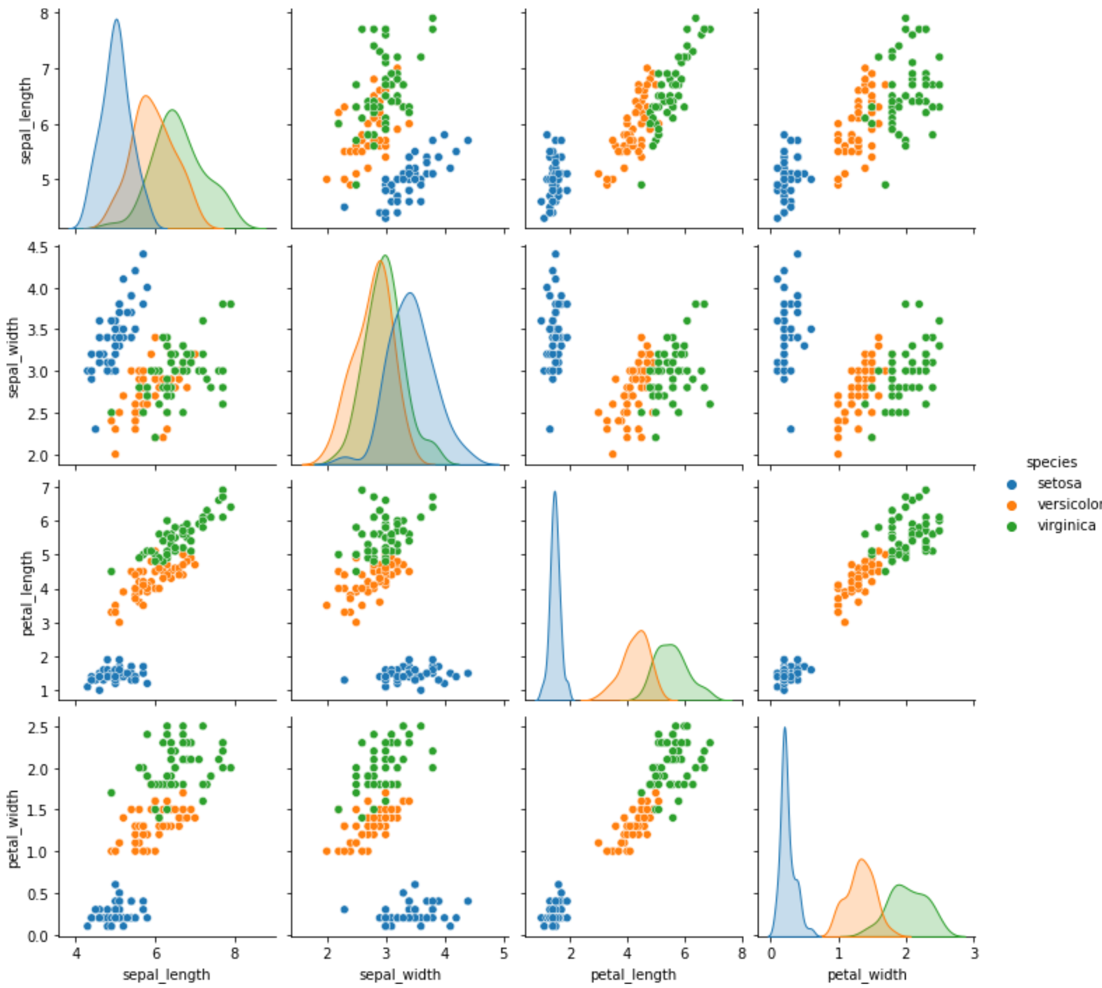
['sepal_length', 'sepal_width', 'petal_length', 'petal_width', 'species']

```
# Let's describe
df.describe()
```

	sepal_length	sepal_width	petal_length	petal_width
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.057333	3.758000	1.199333
std	0.828066	0.435866	1.765298	0.762238
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

```
# Check the clusters
sns.pairplot(df, hue='species')
```

<seaborn.axisgrid.PairGrid at 0x7fa2f1e0df40>

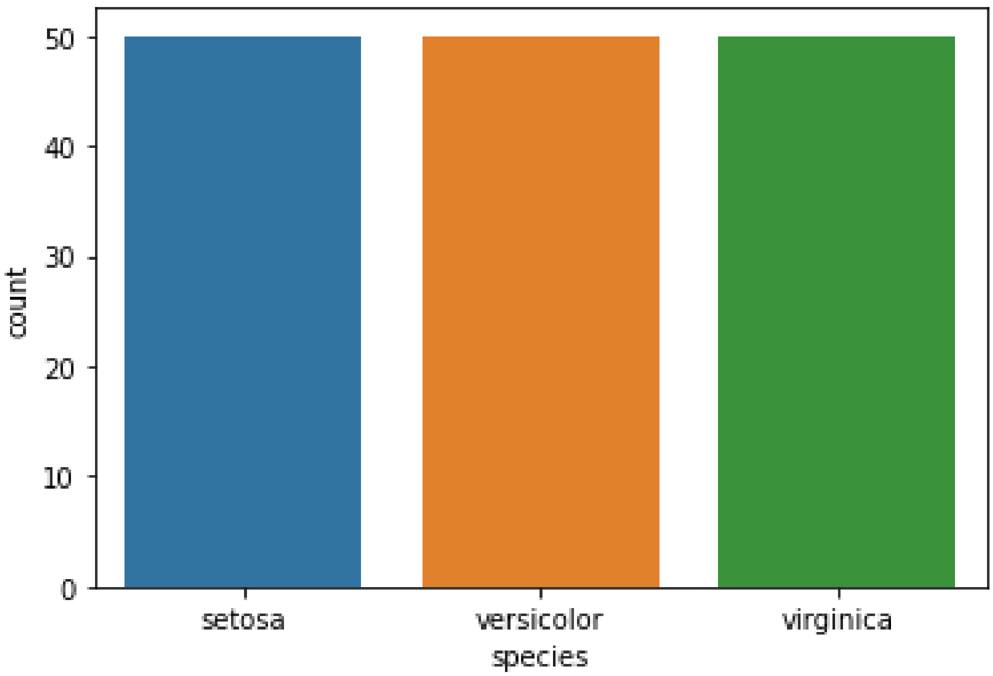



```
# input data
x = df.drop('species', axis = 1)

# output data
y = df['species']

x.shape
```

(150, 4)

```
sns.countplot(x = y)
```

<AxesSubplot:xlabel='species', ylabel='count'>




```
y.value_counts()
```

```
setosa        50
virginica     50
versicolor    50
Name: species, dtype: int64
```

```
# 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)

x_train.shape
```

```
(112, 4)
```

```
x_test.shape
```

```
(38, 4)
```

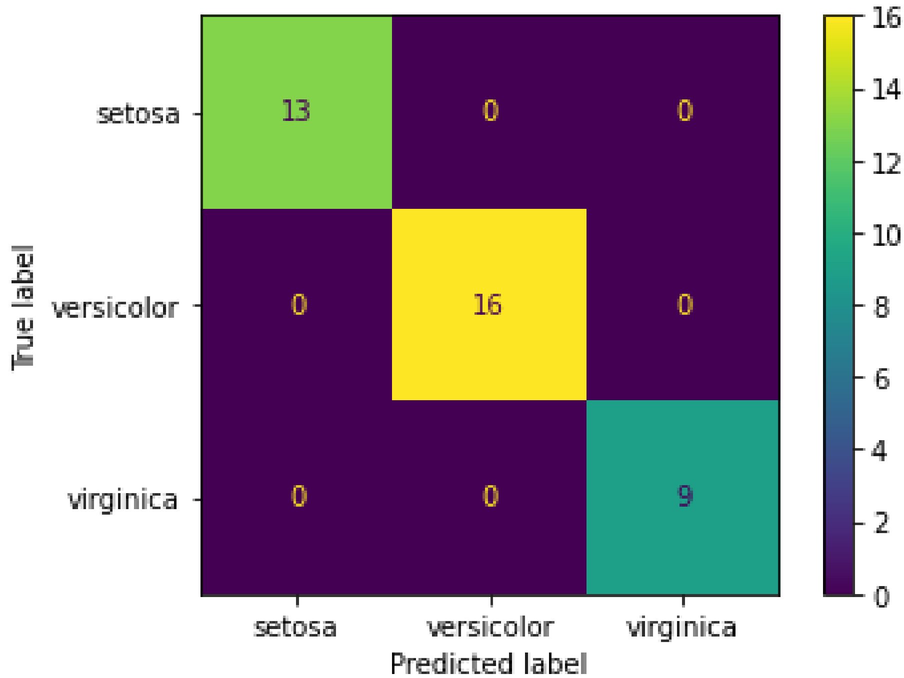
```
# Import the class
from sklearn.naive_bayes import GaussianNB

# Create the object
classifier = GaussianNB()

# Train the algorithm with data
```

 # Predictions
y_pred = classifier.predict(x_test)

 # Import all functions
from sklearn.metrics import plot_confusion_matrix, accuracy_scorefrom sklearn.metrics import classification_report

 # Plot the confusion matrix
plot_confusion_matrix(classifier, x_test, y_test)

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at0x7fa2e177e6d0>



 # Accuracy
accuracy_score(y_test, y_pred)1.0

 # Classification report
print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support
setosa	1.00	1.00	1.00	13
versicolor	1.00	1.00	1.00	16
virginica	1.00	1.00	1.00	9
accuracy			1.00	38
macro avg	1.00	1.00	1.00	38

weighted avg 1.00 1.00 1.00 38

```
# Print the probabilities
classifier.predict_proba(x_test)
```

```
array([[2.05841140e-233, 1.23816844e-006, 9.99998762e-001],
       [1.76139943e-084, 9.99998414e-001, 1.58647449e-006],
       [1.00000000e+000, 1.48308613e-018, 1.73234612e-027],
       [6.96767669e-312, 5.33743814e-007, 9.99999466e-001],
       [1.00000000e+000, 9.33944060e-017, 1.22124682e-026],
       [4.94065646e-324, 6.57075840e-011, 1.00000000e+000],
       [1.00000000e+000, 1.05531886e-016, 1.55777574e-026],
       [2.45560284e-149, 7.80950359e-001, 2.19049641e-001],
       [4.01160627e-153, 9.10103555e-001, 8.98964447e-002],
       [1.46667004e-094, 9.99887821e-001, 1.12179234e-004],
       [5.29999917e-215, 4.59787449e-001, 5.40212551e-001],
       [4.93479766e-134, 9.46482991e-001, 5.35170089e-002],
       [5.23735688e-135, 9.98906155e-001, 1.09384481e-003],
       [4.97057521e-142, 9.50340361e-001, 4.96596389e-002],
       [9.11315109e-143, 9.87982897e-001, 1.20171030e-002],
       [1.00000000e+000, 7.81797826e-019, 1.29694954e-028],
       [3.86310964e-133, 9.87665084e-001, 1.23349155e-002],
       [2.27343573e-113, 9.99940331e-001, 5.96690955e-005],
       [1.00000000e+000, 1.80007196e-015, 9.14666201e-026],
       [1.00000000e+000, 1.30351394e-015, 8.42776899e-025],
       [4.66537803e-188, 1.18626155e-002, 9.88137385e-001],
       [1.02677291e-131, 9.92205279e-001, 7.79472050e-003],
       [1.00000000e+000, 6.61341173e-013, 1.42044069e-022],
       [1.00000000e+000, 9.98321355e-017, 3.50690661e-027],
       [2.27898063e-170, 1.61227371e-001, 8.38772629e-001],
       [1.00000000e+000, 2.29415652e-018, 2.54202512e-028],
       [1.00000000e+000, 5.99780345e-011, 5.24260178e-020],
       [1.62676386e-112, 9.99340062e-001, 6.59938068e-004],
       [2.23238199e-047, 9.99999965e-001, 3.47984452e-008],
       [1.00000000e+000, 1.95773682e-013, 4.10256723e-023],
       [3.52965800e-228, 1.15450262e-003, 9.98845497e-001],
       [3.20480410e-131, 9.93956330e-001, 6.04366979e-003],
       [1.00000000e+000, 1.14714843e-016, 2.17310302e-026],
       [3.34423817e-177, 8.43422262e-002, 9.15657774e-001],
       [5.60348582e-264, 1.03689515e-006, 9.99998963e-001],
       [7.48035097e-091, 9.99950155e-001, 4.98452400e-005],
       [1.00000000e+000, 1.80571225e-013, 1.83435499e-022],

       [8.97496247e-182, 5.65567226e-001, 4.34432774e-001]])
```

```
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]
```

'setosa' classifier.predict(new2)[0]

'versicolor' classifier.predict(new3)[0]

'virginica'

PIRENS Institute of Business Management and Administration, Loni BK.		
Roll Number: 10097	**Sign:**	**Date: / /**
Student Name: Yash Bora		
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL		
Program Title: Q.10 SVM classification on any dataset		

Program:

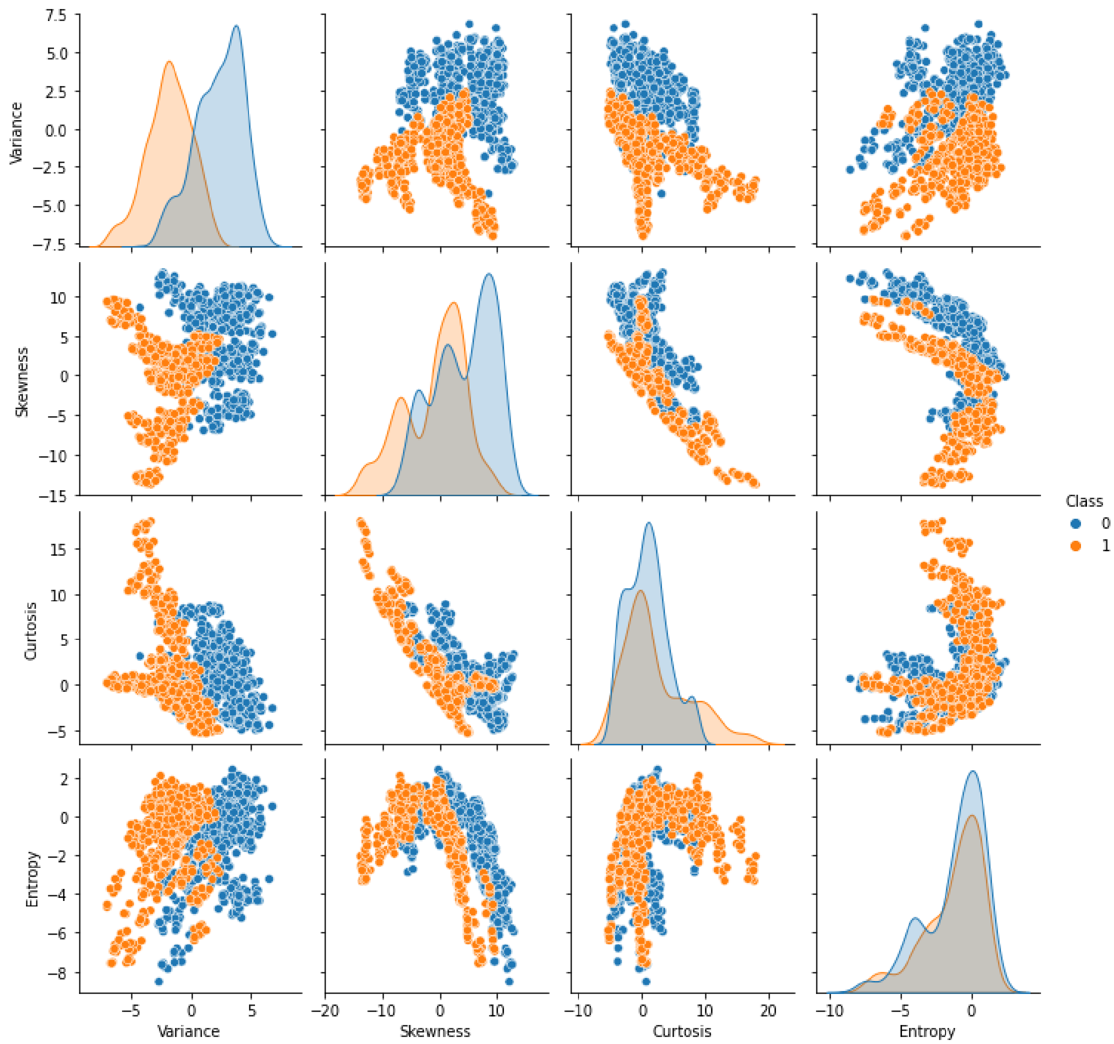
import pandas as pd

 # Data import
df = pd.read_csv('banknotes.csv')import

seaborn as sns sns.pairplot(df,

hue='Class')

<seaborn.axisgrid.PairGrid at 0x7f03ccecc490>



 # Input data

```
x.shape
```

(1372, 4)

```
# 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, test_size=0.25)

x_train.shape
```

(1029, 4)

```
x_test.shape
```

(343, 4)

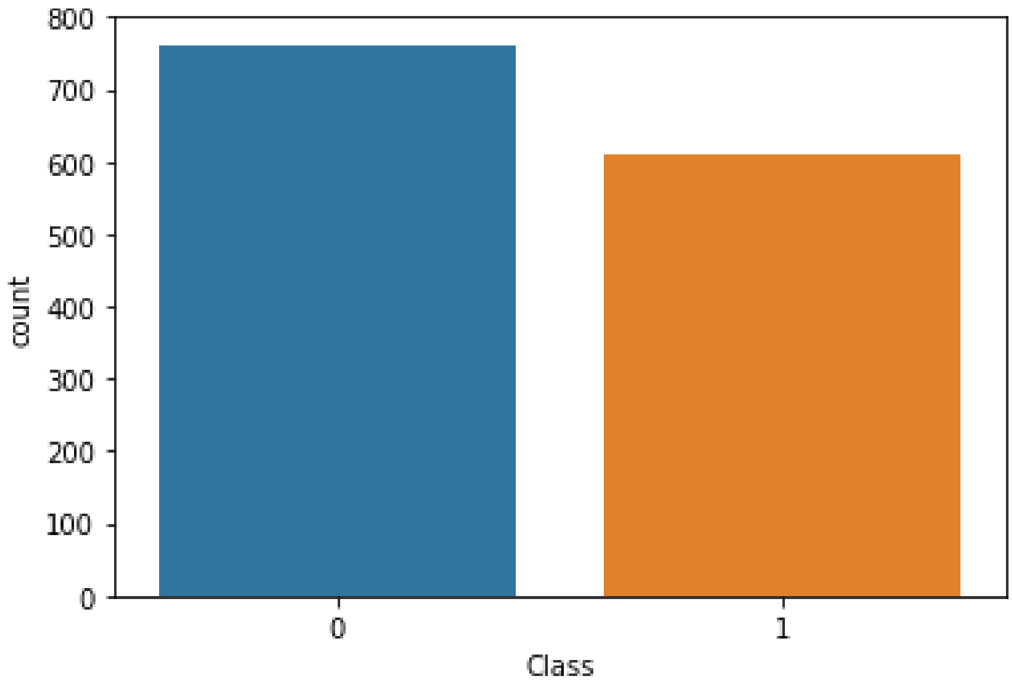
```
x_train
```

	Variance	Skewness	Curtosis	Entropy
662	2.97360	8.794400	-3.635900	-1.375400
512	2.66480	10.754000	-3.399400	-4.168500
1193	-3.75730	-8.291600	10.303200	0.380590
682	3.73210	-3.884000	3.357700	-0.006049
1313	-1.50780	-7.319100	7.898100	1.228900
...	...	...	...	...
763	0.39012	-0.142790	-0.031994	0.350840
835	-0.94255	0.039307	-0.241920	0.315930
1216	0.60050	0.999450	-2.212600	0.097399
559	2.01650	-0.252460	5.170700	1.076300
684	-2.07590	10.822300	2.643900	-4.837000

[1029 rows x 4 columns]

```
sns.countplot(x=y)
```

<AxesSubplot:xlabel='Class', ylabel='count'>



y.value_counts()

```
0       762
1       610
Name: Class, dtype: int64
```

```
y_train.value_counts()
```

```
0       567
1       462
Name: Class, dtype: int64
```

```
y_test.value_counts()
```

```
0       195
1       148
Name: Class, dtype: int64
```

```
# Import the SVM class
from sklearn.svm import SVC

# Create the object of SVC
classifier = SVC(random_state=0, kernel='sigmoid')

# Train the algorithm
classifier.fit(x_train, y_train)
```

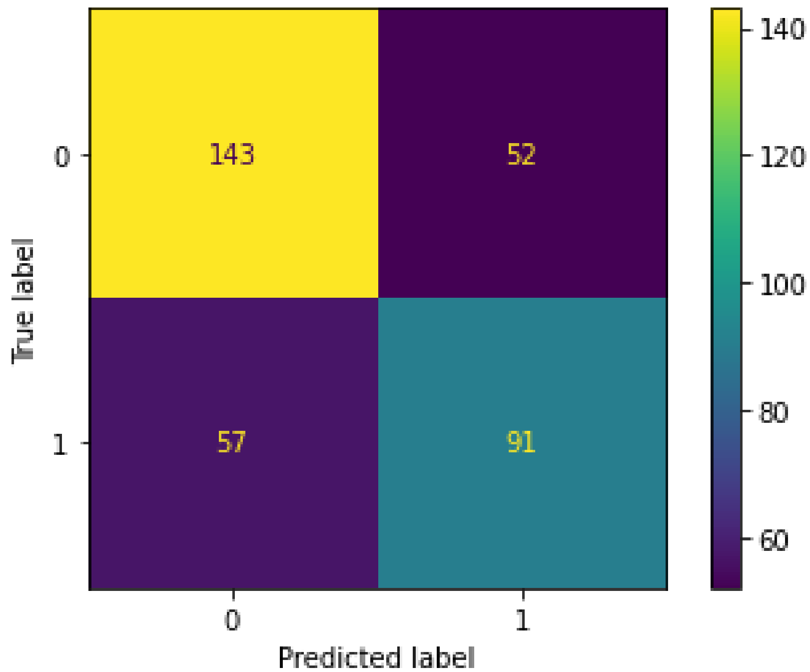
```
SVC(kernel='sigmoid', random_state=0)
```

```
# Predictions
y_pred = classifier.predict(x_test)
```

from sklearn.metrics import plot_confusion_matrix, classification_reportfrom

sklearn.metrics import accuracy_score plot_confusion_matrix(classifier, x_test, y_test)

<sklearn.metrics._plot.confusion_matrix.ConfusionMatrixDisplay at0x7f03a41518e0>



print(classification_report(y_test, y_pred))

	precision	recall	f1-score	support
0	0.71	0.73	0.72	195
1	0.64	0.61	0.63	148
accuracy			0.68	343
macro avg	0.68	0.67	0.67	343
weighted avg	0.68	0.68	0.68	343

accuracy_score(y_test, y_pred)

0.6822157434402333

new1 = [[3.73210,-3.884000,3.357700,-0.006049]]
classifier.predict(new1)array([1])

 # Linear - 0.9854227405247813
 # Polynomial - 0.967930029154519#
RBF - 0.9970845481049563
 # Sigmoid - 0.6822157434402333

PIRENS Institute of Business Management and Administration, Loni BK.
Roll Number: 10097 Sign: Date: / /
Student Name: Yash Bora
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL
Program Title: Q.11 Text Mining algorithms on unstructured dataset

Program:

```
import pandas as pd

df = pd.read_csv('SMSSpamCollection',
sep='\t',
names = ['class','body_text'])

df

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

[5572 rows x 2 columns]

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)

17.07

# Add feature of punctuation percentages
df['punct%'] = df['body_text'].apply(lambda x: count_punct(x))
```

df

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

```
# Add the column body length to it
df['body_len'] = df['body_text'].apply(lambda x: len(x) - x.count(" "))

df

      class                                          body_text  punct% \
0       ham  Go until jurong point, crazy.. Available only ...    9.78
1       ham                      Ok lar... Joking wif u oni...   25.00
2      spam  Free entry in 2 a wkly comp to win FA Cup fina...    4.69
3       ham  U dun say so early hor... U c already then say...   15.38
4       ham  Nah I don't think he goes to usf, he lives aro...    4.08
...     ...                                                ...     ...

5567   spam  This is the 2nd time we have tried 2 contact u...    6.11
5568    ham               Will ü b going to esplanade fr home?    3.45
5569    ham  Pity, * was in mood for that. So...any other s...   14.58
5570    ham  The guy did some bitching but I acted like i'd...    1.00
5571    ham                         Rofl. Its true to its name    4.76

      body_len
0           92
1           24
2          128
3           39
4           49
...        ...
5567       131
5568        29
5569        48
5570       100
5571        21

[5572 rows x 4 columns]

from nltk.corpus import stopwords s_words

= stopwords.words('english')s_words;
```

```
from nltk.stem import PorterStemmerps =
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)

['hello', 'friend', 'how', 'welcom', 'pune']

# Seperate the input and output
X = df.drop('class', axis = 1)
y = df['class']

X
```

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

```
[5572 rows x 3 columns]
# Import tfidf vectorizer
from sklearn.feature_extraction.text import TfidfVectorizertfidf =

TfidfVectorizer(analyzer=clean_text)

X_trans = tfidf.fit_transform(X['body_text'])
X_trans.shape

(5572, 8277)

X_vect = pd.concat([X[['body_len', 'punct%']]
                                        .reset_index(drop=True),
                                        pd.DataFrame(X_trans.toarray())], axis=1)
X_vect.shape

(5572, 8279)
```

```
y.value_counts()

ham      4825
spam      747
Name: class, dtype: int64

X_vect.info()

<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5572 entries, 0 to 5571
Columns: 8279 entries, body_len to 8276dtypes:
float64(8278), int64(1)
memory usage: 351.9 MB

# Cross validation
from sklearn.model_selection import train_test_splitX_train, X_test,
y_train, y_test = train_test_split(
    X_vect, y, stratify=y, random_state=0)

X_train.shape

(4179, 8279)

from sklearn.ensemble import RandomForestClassifierclf =

RandomForestClassifier(random_state=0) clf.fit(X_train,

y_train) RandomForestClassifier(random_state=0)

y_pred = clf.predict(X_test)

from sklearn.metrics import accuracy_score, classification_reportaccuracy_score(y_test, y_pred)

0.9662598707824839

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


new = pd.read_csv("sample.csv",
                  names=['body_text'], sep='\t')
```

new

	body_text
0	Ok lar i double check wif da hair dresser alre...
1	As a valued customer, I am pleased to advise y...
2	Today is "song dedicated day.." Which song wil...

```
new['body_len'] = new['body_text'].apply(lambda x: len(x) - x.count(" "))new['punct%'] = new['body_text'].apply(lambda x: count_punct(x))
```

```
new_vect = tfidf.transform(new['body_text'])
```

```
sample_vect = new
sample_vect = pd.concat([new[['body_len', 'punct%']].reset_index(drop=True),
                        pd.DataFrame(new_vect.toarray())], axis=1)
```

sample_vect.shape(3,

8279)

sample_vect

\	body_len	punct %	0	1	2	3	4	5	6	7	...	8267	8268
0	89	4.49	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
1	125	2.40	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0
2	102	9.80	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	...	0.0	0.0

	8269	8270	8271	8272	8273	8274	8275	8276
0	0.0	0.0	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	0.0	0.0
2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0

[3 rows x 8279 columns]

clf.predict(sample_vect)

array(['ham', 'spam', 'ham'], dtype=object)

PIRENS Institute of Business Management and Administration, Loni BK.
Roll Number: 10097 **Sign:** **Date: / /**
Student Name: Yash Bora
Subject Name: Knowledge Representation and Artificial Intelligence, ML, DL
Program Title: Q.12 Plot the cluster data using python visualizations.

Program:

```
# Import packages
import pandas as pd

# Import the dataset
df = pd.read_csv('Mall_Customers.csv')

df.shape

(200, 5)

list(df.columns)

['CustomerID', 'Genre', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']

# Input data
x = df.iloc[:,3:]

x
     Annual  Income  (k$)   Spending  Score  (1-100)
0                      15                        39
1                      15                        81
2                      16                         6
3                      16                        77
4                      17                        40
..                    ...                       ...
195                   120                        79
196                   126                        28
197                   126                        74
198                   137                        18
199                   137                        83

[200 rows x 2 columns]
# Summerize
df.describe()

        CustomerID         Age  Annual  Income (k$)  Spending   Score (1-100)
count   200.000000  200.000000          200.000000             200.000000
mean    100.500000   38.850000           60.560000              50.200000
std      57.879185   13.969007           26.264721              25.823522
min       1.000000   18.000000           15.000000               1.000000
25%      50.750000   28.750000           41.500000              34.750000
```

import seaborn package

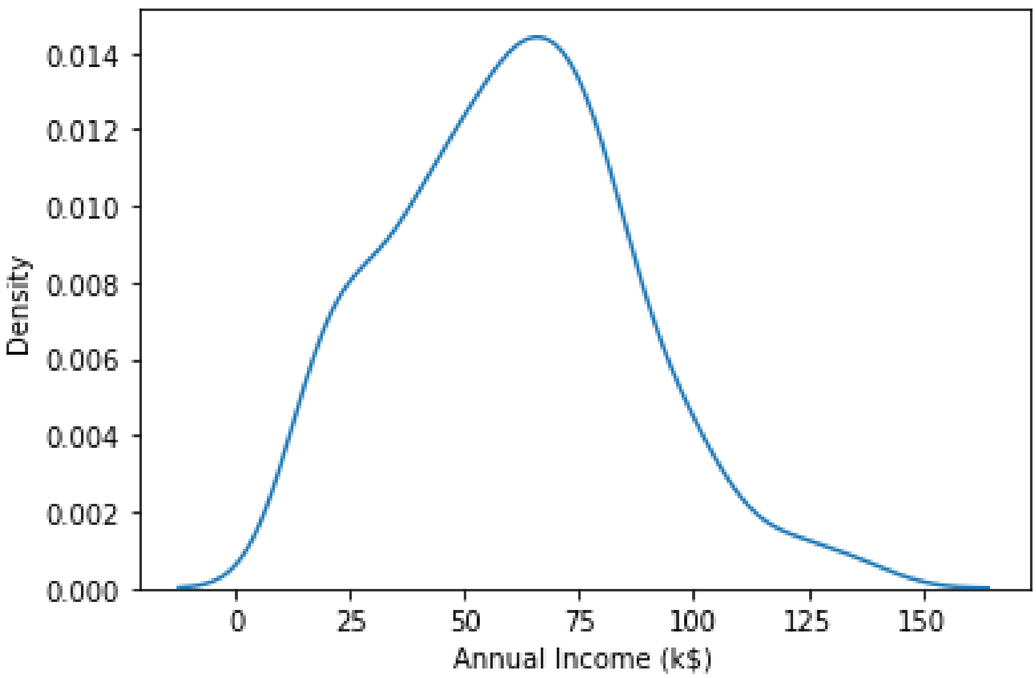
import seaborn as sns

sns.kdeplot(df['Age'])

<AxesSubplot:xlabel='Age', ylabel='Density'>

sns.kdeplot(df['Annual Income (k$)'])

<AxesSubplot:xlabel='Annual Income

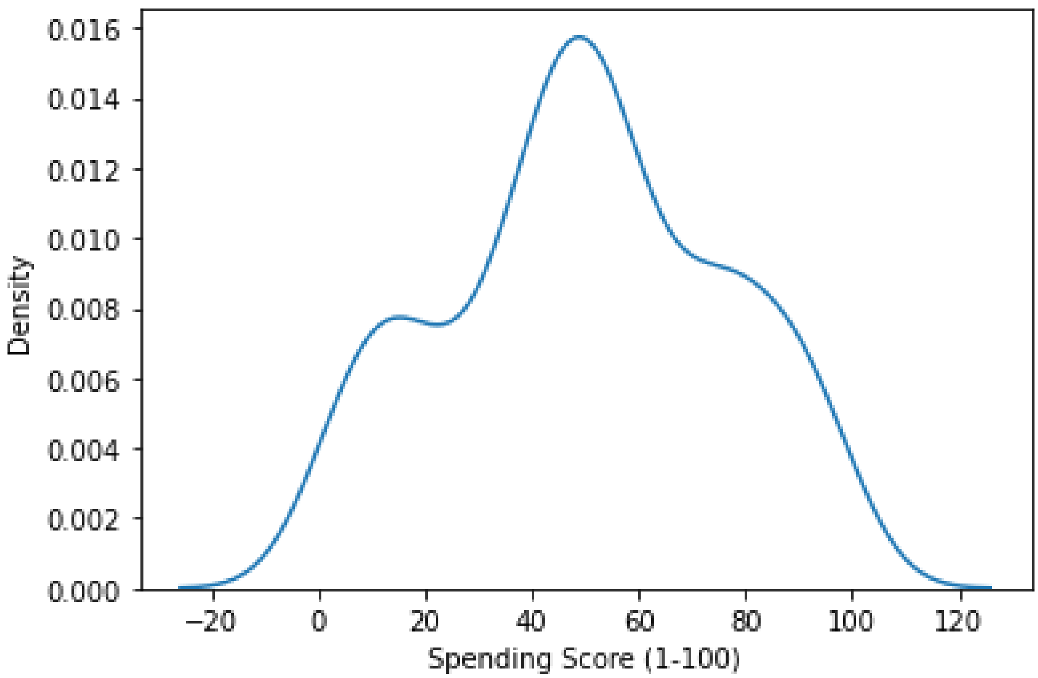


(k$)',

ylabel='Density'>

```
sns.kdeplot(df['Spending Score (1-100)'])
```

<AxesSubplot:xlabel='Spending Score (1-100)', ylabel='Density'>

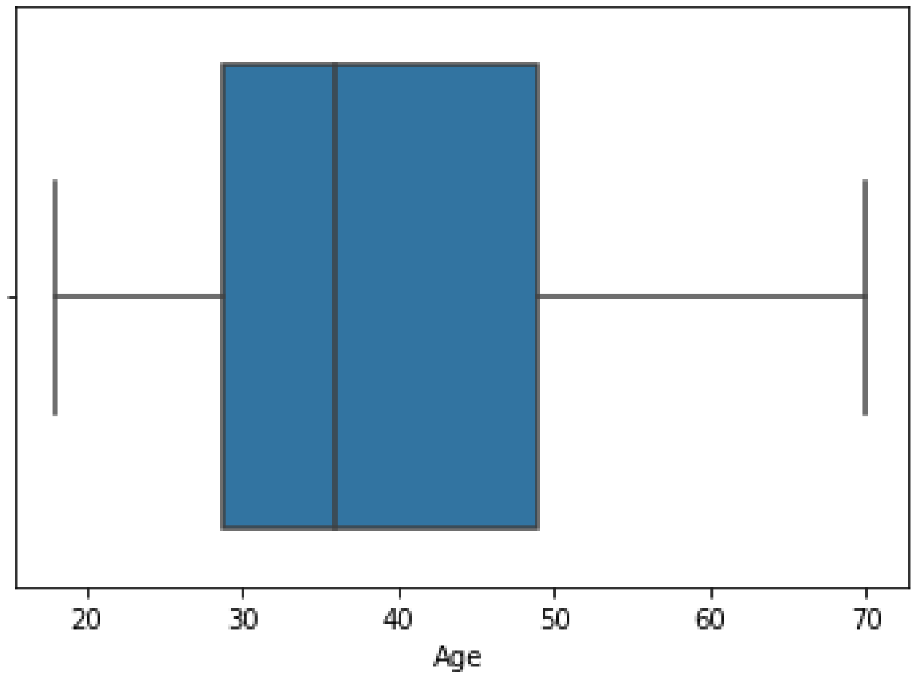



```
sns.boxplot(df['Age'])
```

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version

0.12, the only valid positional argument will be `data`, and passing otherarguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

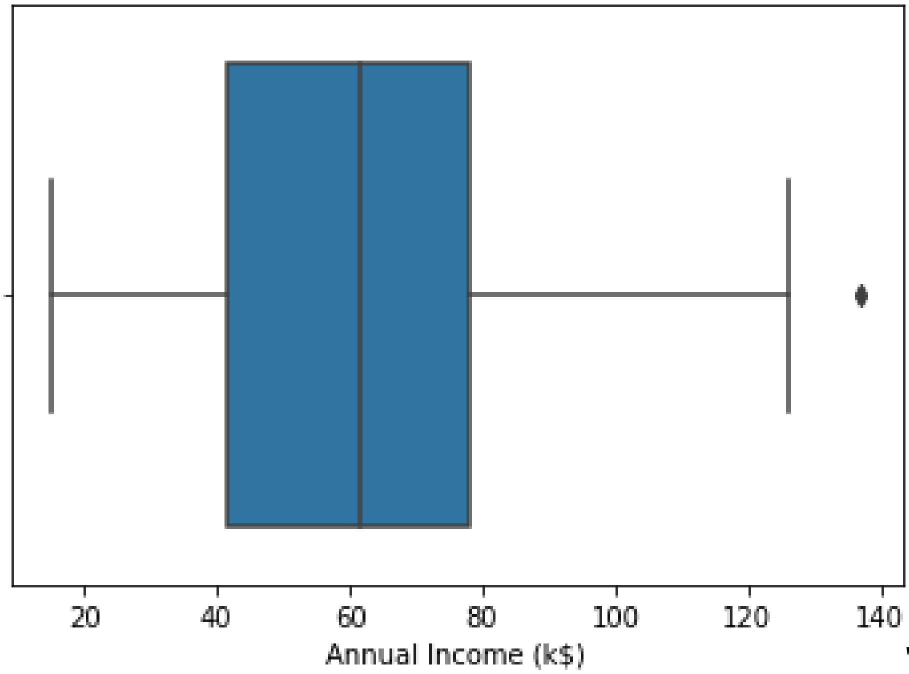
<AxesSubplot:xlabel='Age'>




```
sns.boxplot(df['Annual Income (k$)'])
```

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.
  warnings.warn(

<AxesSubplot:xlabel='Annual Income (k


20
40
60
80
100
120
140
Annual Income (k$)

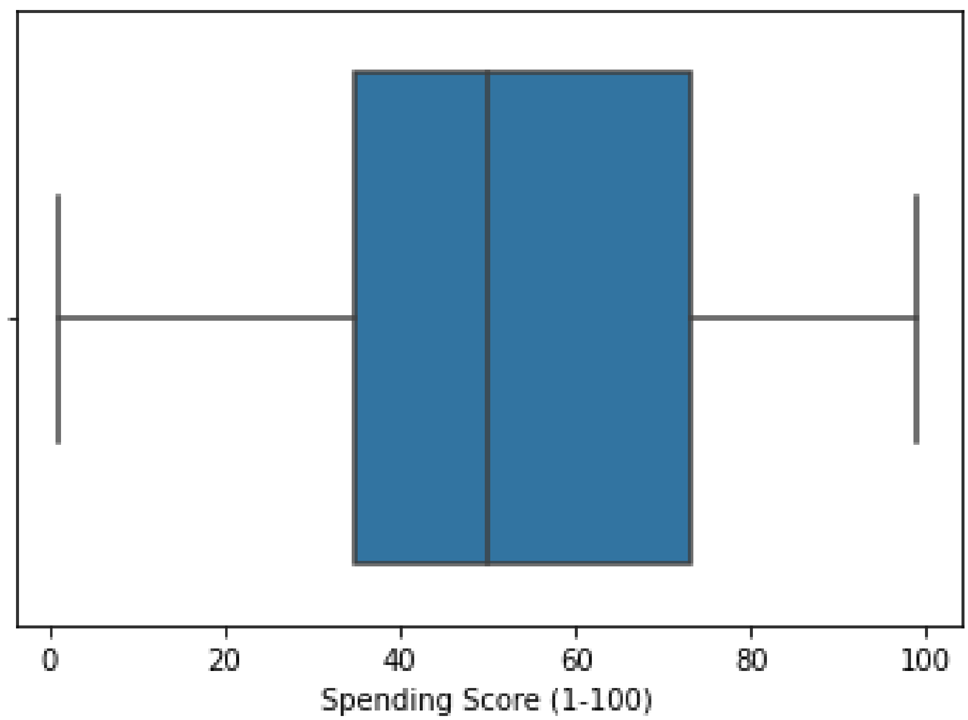
'>

```
sns.boxplot(df['Spending Score (1-100)'])
```

/home/mitu/.local/lib/python3.8/site-packages/seaborn/_decorators.py:36: FutureWarning: Pass the following variable as a keyword arg: x. From version0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in an error or misinterpretation.

warnings.warn(

<AxesSubplot:xlabel='Spending Score (1-100)'>

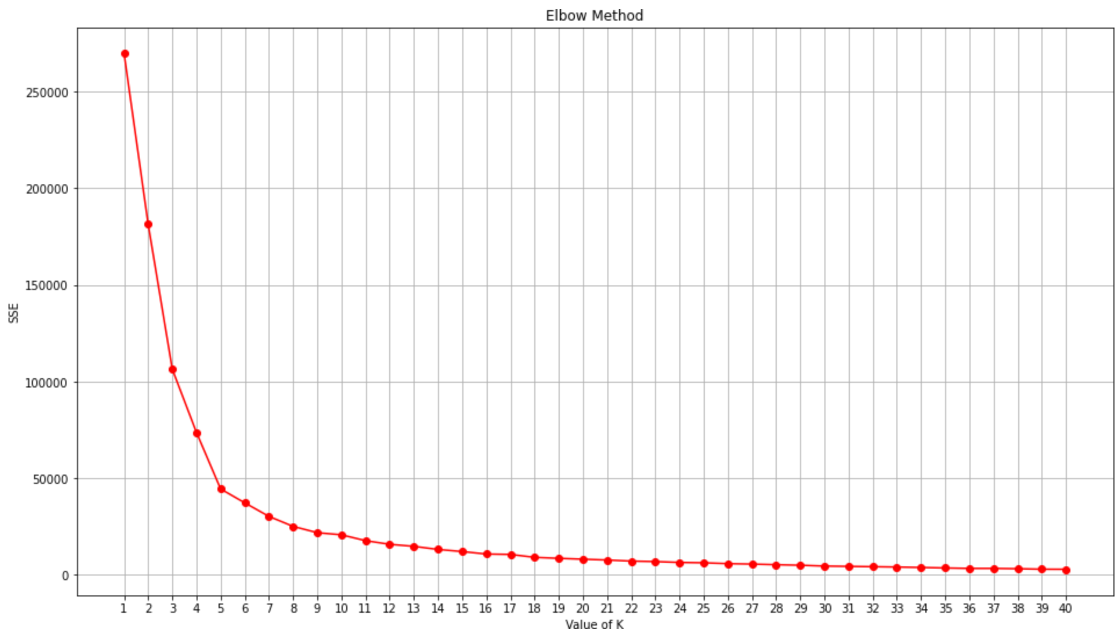


```python
# Import the class
from sklearn.cluster import KMeans

# 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_
```

15810.838613705504

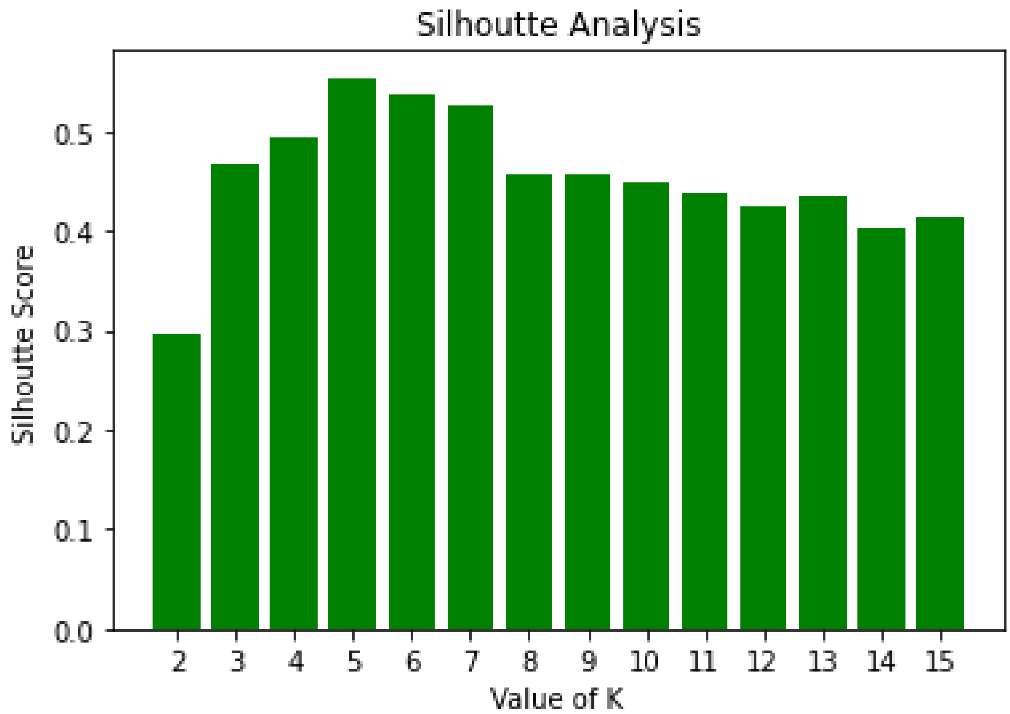
```python
# elbow method
sse = []
for k in range(1,41):
    km = KMeans(n_clusters=k, random_state=0)

    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')
```

[<matplotlib.lines.Line2D at 0x7fb5f259fa60>]




```
# 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')
```

<BarContainer object of 14 artists>




```
# Create the object
km = KMeans(n_clusters=5, random_state=0)

# Train the algorithm
labels = km.fit_predict(x)

labels

array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 0, 2, 1, 2, 0, 2, 0, 2,
       1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 1, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
       0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2, 0, 2,
      0, 2], dtype=int32)

# Cluster labels
km.labels_

array([4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3,
       4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 3, 4, 1,
       4, 3, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
```

```
1,  1,   1,  1,   1,  1,   1,  1,   1,  1,   1,  1,   1, 2,    0,   2,  1,   2,  0,   2,  0,   2,
1,  2,   0,  2,   0,  2,   0,  2,   0,  2,   1,  2,   0, 2,    0,   2,  0,   2,  0,   2,  0,   2,
0,  2, 0, 2, 0, 2, 0, 2, 0, 2,                      0, 2, 0, 2,              0, 2, 0, 2, 0, 2, 0, 2,
0,  2, 0, 2, 0, 2, 0, 2, 0, 2,                      0, 2, 0, 2,              0, 2, 0, 2, 0, 2, 0, 2,
0,  2], dtype=int32)
```

```
# SSE
km.inertia_
```

```
44448.45544793369
```

```
# Centroids
km.cluster_centers_
```

```
array([[88.2        , 17.11428571],
       [55.2962963 ,  49.51851852],
       [86.53846154,  82.12820513],
       [25.72727273,  79.36363636],
       [26.30434783,  20.91304348]])
```

```
# Extract the clusters
df[labels==2]  # Boolean filtering
```

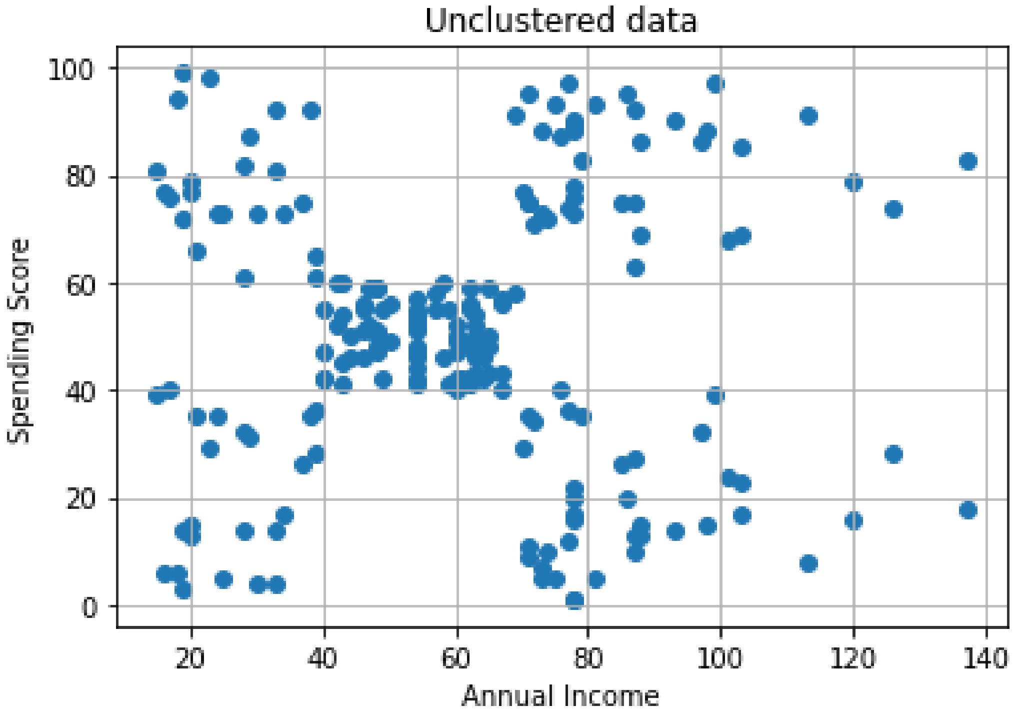
	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
123	124	Male	39	69	91
125	126	Female	31	70	77
127	128	Male	40	71	95
129	130	Male	38	71	75
131	132	Male	39	71	75
133	134	Female	31	72	71
135	136	Female	29	73	88
137	138	Male	32	73	73
139	140	Female	35	74	72
141	142	Male	32	75	93
143	144	Female	32	76	87
145	146	Male	28	77	97
147	148	Female	32	77	74
149	150	Male	34	78	90
151	152	Male	39	78	88
153	154	Female	38	78	76
155	156	Female	27	78	89
157	158	Female	30	78	78
159	160	Female	30	78	73
161	162	Female	29	79	83
163	164	Female	31	81	93
165	166	Female	36	85	75
167	168	Female	33	86	95
169	170	Male	32	87	63
171	172	Male	28	87	75
173	174	Male	36	87	92

175	176	Female	30	88	86
177	178	Male	27	88	69
179	180	Male	35	93	90
181	182	Female	32	97	86
183	184	Female	29	98	88
185	186	Male	30	99	97
187	188	Male	28	101	68
189	190	Female	36	103	85
191	192	Female	32	103	69
193	194	Female	38	113	91
195	196	Female	35	120	79
197	198	Male	32	126	74
199	200	Male	30	137	83

```
one = df[labels==1]

one.shape

(81, 5)
# 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]))

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

# Prediction
new = [[45, 76]]
km.predict(new)[0]3

# Prediction
new = [[25, 36]]
km.predict(new)[0]4

# Prediction
new = [[85, 76]]
km.predict(new)[0]2

# Prediction
new = [[45, 47]]
km.predict(new)[0]1
```

```
# 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)'])
```

```
<matplotlib.collections.PathCollection at 0x7fb5f14582e0>
```



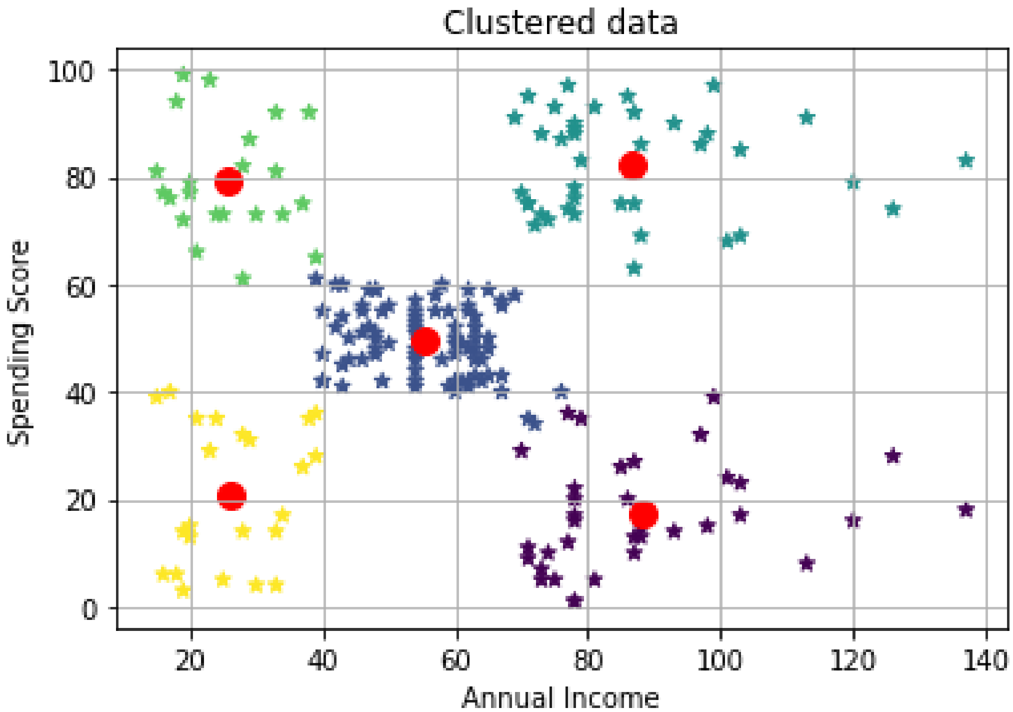

```
# Save the centroids
cent = km.cluster_centers_cent
```

```
array([[88.2        , 17.11428571],
       [55.2962963 ,  49.51851852],
       [86.53846154,  82.12820513],
       [25.72727273,  79.36363636],
       [26.30434783,  20.91304348]])
```

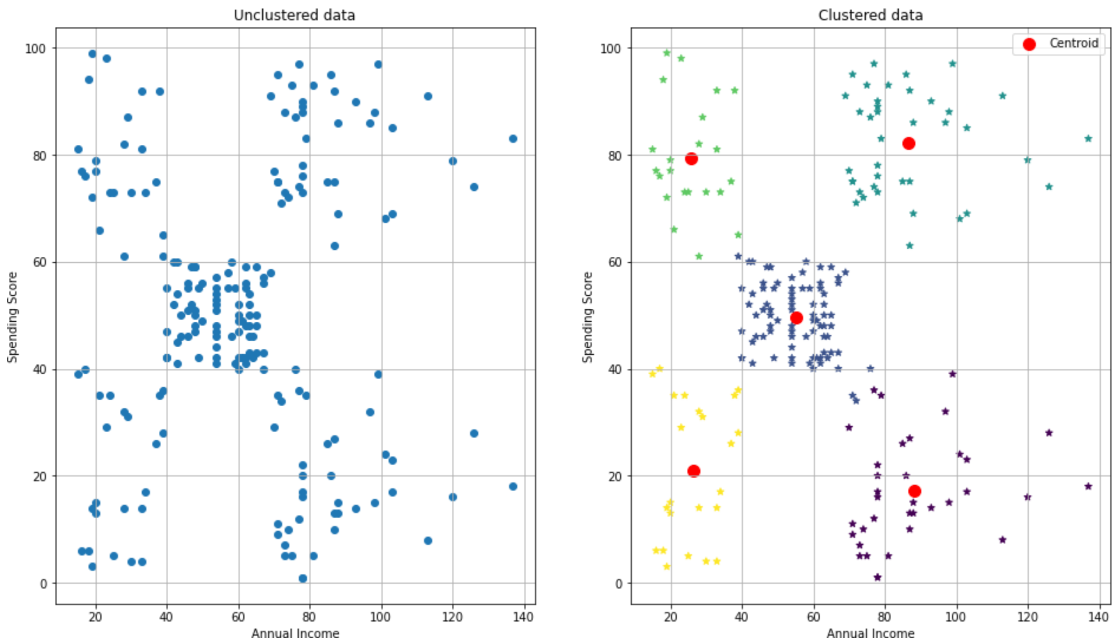
```
# Visualization of clusters
plt.title('Clustered data')
plt.xlabel('Annual Income')
plt.ylabel('Spending Score')
plt.grid()
plt.scatter(x['Annual Income (k$)'], x['Spending Score (1-100)'],
```

```
                c = labels, marker='*')
plt.scatter(cent[:,0], cent[:,1], s=100, marker='o', color='r')
```

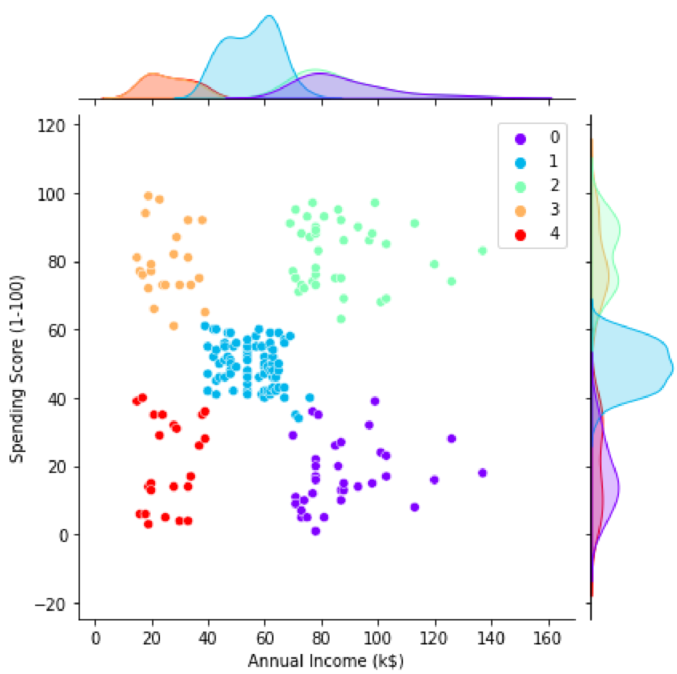
<matplotlib.collections.PathCollection at 0x7fb5f0ed0b80>




```
# 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')
```



131 [D loss: 0.038602, acc.: 100.00%] [G loss: 4.238760]
132 [D loss: 0.066584, acc.: 98.44%] [G loss: 4.631004]
133 [D loss: 0.064235, acc.: 98.44%] [G loss: 4.729104]
134 [D loss: 0.057679, acc.: 100.00%] [G loss: 4.399063]
135 [D loss: 0.038678, acc.: 100.00%] [G loss: 3.980439]
136 [D loss: 0.070430, acc.: 96.88%] [G loss: 4.184968]
137 [D loss: 0.269052, acc.: 85.94%] [G loss: 3.930685]
138 [D loss: 0.071771, acc.: 98.44%] [G loss: 4.210067]
139 [D loss: 0.175595, acc.: 92.19%] [G loss: 3.578120]
140 [D loss: 0.057856, acc.: 96.88%] [G loss: 4.090517]
141 [D loss: 0.091329, acc.: 98.44%] [G loss: 3.495711]
142 [D loss: 0.074046, acc.: 98.44%] [G loss: 3.672240]
143 [D loss: 0.067564, acc.: 100.00%] [G loss: 3.488506]
144 [D loss: 0.097541, acc.: 96.88%] [G loss: 3.927138]
145 [D loss: 0.189200, acc.: 92.19%] [G loss: 3.607136]
146 [D loss: 0.069164, acc.: 100.00%] [G loss: 4.224221]
147 [D loss: 0.577445, acc.: 79.69%] [G loss: 2.658618]
148 [D loss: 0.192502, acc.: 92.19%] [G loss: 3.820522]
149 [D loss: 0.084979, acc.: 98.44%] [G loss: 4.757998]
150 [D loss: 0.261661, acc.: 92.19%] [G loss: 2.996725]
151 [D loss: 0.188527, acc.: 89.06%] [G loss: 4.621965]
152 [D loss: 0.151155, acc.: 93.75%] [G loss: 3.851809]
153 [D loss: 0.136393, acc.: 93.75%] [G loss: 4.189128]
154 [D loss: 0.083352, acc.: 100.00%] [G loss: 4.461646]
155 [D loss: 0.206723, acc.: 89.06%] [G loss: 4.497554]
156 [D loss: 0.241861, acc.: 89.06%] [G loss: 4.464531]
157 [D loss: 0.319591, acc.: 82.81%] [G loss: 3.933166]
158 [D loss: 0.078051, acc.: 100.00%] [G loss: 3.995445]
159 [D loss: 0.258115, acc.: 89.06%] [G loss: 3.682753]
160 [D loss: 0.068538, acc.: 98.44%] [G loss: 3.920011]
161 [D loss: 0.137065, acc.: 95.31%] [G loss: 2.958877]
162 [D loss: 0.092553, acc.: 95.31%] [G loss: 3.897508]
163 [D loss: 0.243603, acc.: 89.06%] [G loss: 3.506659]
164 [D loss: 0.044570, acc.: 100.00%] [G loss: 4.298730]
165 [D loss: 0.274047, acc.: 89.06%] [G loss: 3.803701]
166 [D loss: 0.216394, acc.: 90.62%] [G loss: 4.244328]
167 [D loss: 0.938720, acc.: 57.81%] [G loss: 1.454402]
168 [D loss: 0.281417, acc.: 85.94%] [G loss: 3.043864]
169 [D loss: 0.071866, acc.: 100.00%] [G loss: 4.173522]
170 [D loss: 0.167514, acc.: 95.31%] [G loss: 3.013133]
171 [D loss: 0.095101, acc.: 96.88%] [G loss: 3.071562]
172 [D loss: 0.062486, acc.: 98.44%] [G loss: 3.801221]
173 [D loss: 0.169537, acc.: 96.88%] [G loss: 3.312897]
174 [D loss: 0.098783, acc.: 96.88%] [G loss: 4.142616]
175 [D loss: 0.244112, acc.: 92.19%] [G loss: 3.173460]
176 [D loss: 0.129209, acc.: 96.88%] [G loss: 5.158587]
177 [D loss: 0.785221, acc.: 67.19%] [G loss: 2.247335]
178 [D loss: 0.319861, acc.: 81.25%] [G loss: 3.888173]

179 [D loss: 0.074654, acc.: 96.88%] [G loss: 5.345549]
180 [D loss: 0.378398, acc.: 84.38%] [G loss: 2.330404]
181 [D loss: 0.144777, acc.: 90.62%] [G loss: 3.041365]
182 [D loss: 0.095836, acc.: 95.31%] [G loss: 4.223273]
183 [D loss: 0.157615, acc.: 96.88%] [G loss: 3.565648]
184 [D loss: 0.109397, acc.: 98.44%] [G loss: 4.065246]
185 [D loss: 0.226231, acc.: 92.19%] [G loss: 3.359378]
186 [D loss: 0.151613, acc.: 95.31%] [G loss: 4.360668]
187 [D loss: 0.582917, acc.: 70.31%] [G loss: 2.666638]
188 [D loss: 0.080962, acc.: 100.00%] [G loss: 4.300864]
189 [D loss: 0.176439, acc.: 95.31%] [G loss: 3.181917]
190 [D loss: 0.107121, acc.: 98.44%] [G loss: 3.637481]
191 [D loss: 0.209021, acc.: 92.19%] [G loss: 4.648886]
192 [D loss: 0.334682, acc.: 85.94%] [G loss: 2.255054]
193 [D loss: 0.154234, acc.: 95.31%] [G loss: 4.317871]
194 [D loss: 0.288475, acc.: 90.62%] [G loss: 2.890252]
195 [D loss: 0.113874, acc.: 98.44%] [G loss: 3.731670]
196 [D loss: 0.272280, acc.: 90.62%] [G loss: 3.698488]
197 [D loss: 0.375167, acc.: 81.25%] [G loss: 5.970434]
198 [D loss: 1.642656, acc.: 42.19%] [G loss: 1.831249]
199 [D loss: 0.910615, acc.: 62.50%] [G loss: 1.924973]