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Download and load Dataset

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

```
df=pd.read_csv('Mall_Customers.csv')
df.head()
```

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

```
df = df.rename(columns = {'Annual Income (k$)': 'Annual_Income','Spending Score (1-100)':
df.head()
```

	CustomerID	Gender	Age	Annual_Income	Spending_Score
0	1	Male	19	15	39
1	2	Male	21	15	81
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

```
df.shape
```

```
(200, 5)
```

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
```

```
---  ------          --------------  -----
 0   CustomerID      200 non-null    int64
 1   Gender          200 non-null    object
 2   Age             200 non-null    int64
 3   Annual_Income   200 non-null    int64
 4   Spending_Score  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
df.Gender.unique()
```

```
array(['Male', 'Female'], dtype=object)
```

```
df.Age.unique()
```

```
array([19, 21, 20, 23, 31, 22, 35, 64, 30, 67, 58, 24, 37, 52, 25, 46, 54,
       29, 45, 40, 60, 53, 18, 49, 42, 36, 65, 48, 50, 27, 33, 59, 47, 51,
       69, 70, 63, 43, 68, 32, 26, 57, 38, 55, 34, 66, 39, 44, 28, 56, 41])
```

```
df.Gender.value_counts()
```

```
Female    112
Male       88
Name: Gender, dtype: int64
```

Visualizations

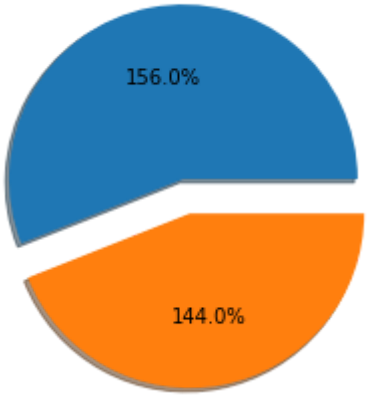
Univariate Analysis

```
sns.displot(df.Spending_Score)
```

```
<seaborn.axisgrid.FacetGrid at 0x7f0cc0852d90>
```

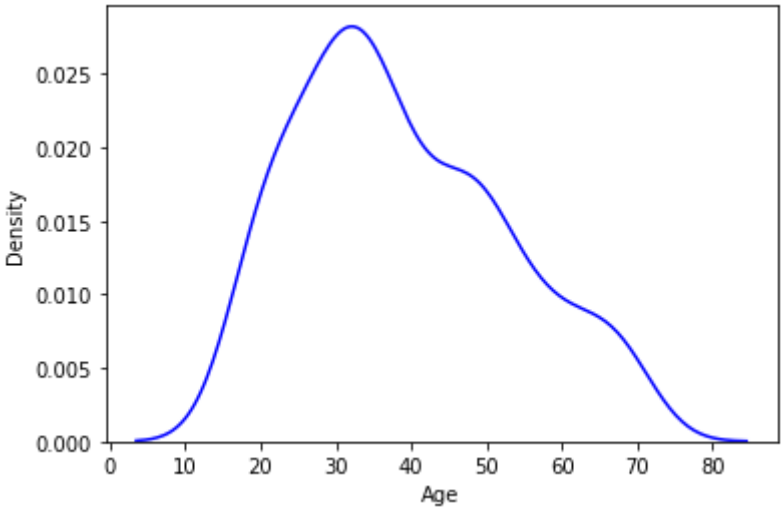
```
plt.pie(df.Gender.value_counts(),[0,0.2],shadow='True',autopct="1%.1f%%")
```

```
([<matplotlib.patches.Wedge at 0x7f0cb70dbad0>,
  <matplotlib.patches.Wedge at 0x7f0cb70e8510>],
 [Text(-0.20611945413751356, 1.080515974257694, ''),
  Text(0.24359571852615253, -1.2769734241227293, '')],
 [Text(-0.11242879316591647, 0.5893723495951058, '156.0%'),
  Text(0.14990505755455538, -0.7858297994601411, '144.0%')])
```




```
sns.kdeplot(df.Age,color="blue")
```

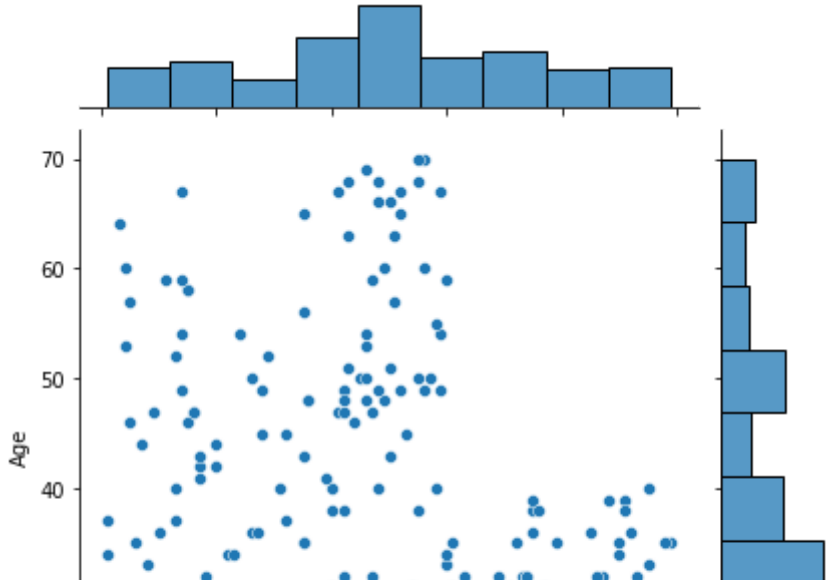
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f0cb7575ed0>
```



Bi-variate Analysis

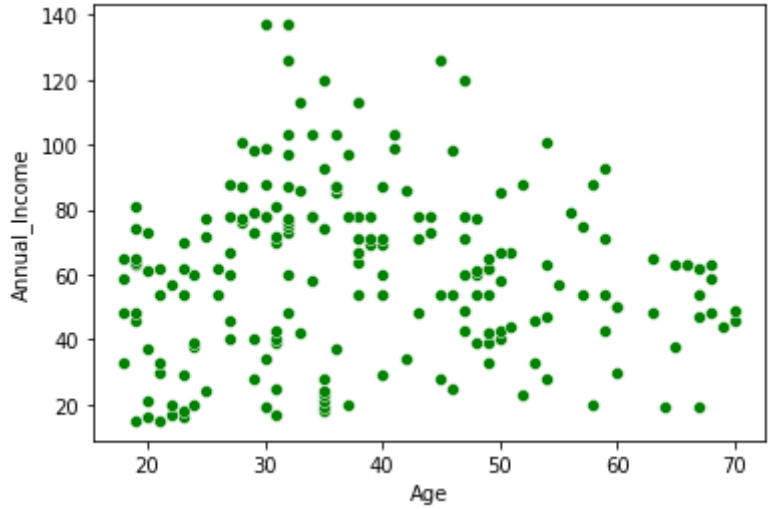
```
sns.jointplot(df.Spending_Score,df.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<seaborn.axisgrid.JointGrid at 0x7f0cb9dd2d50>
```



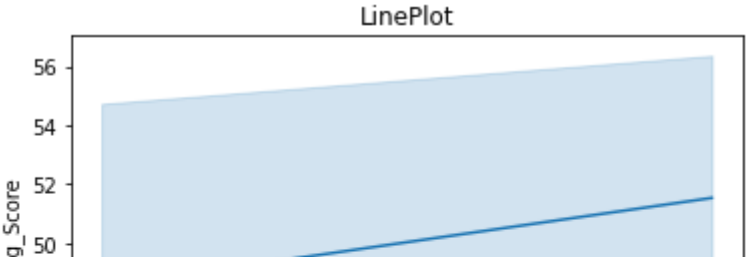

```
sns.scatterplot(df.Age,df.Annual_Income,color="green")
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f0cb6e75b50>
```




```
sns.lineplot(df.Gender,df.Spending_Score)
plt.xlabel('Gender')
plt.ylabel('Spending_Score')
plt.title('LinePlot')
```

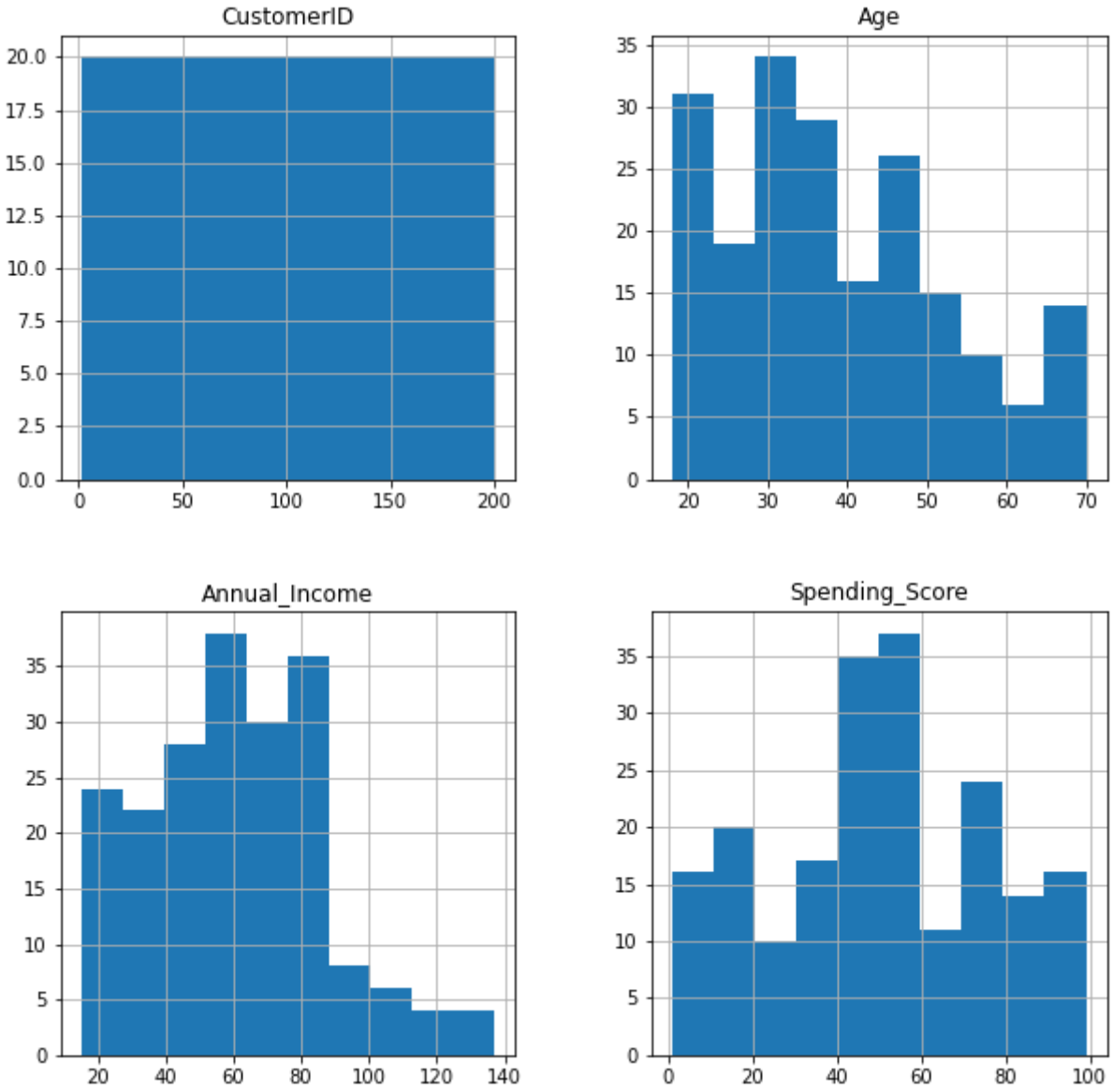
```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
Text(0.5, 1.0, 'LinePlot')
```



Multi-variate Analysis

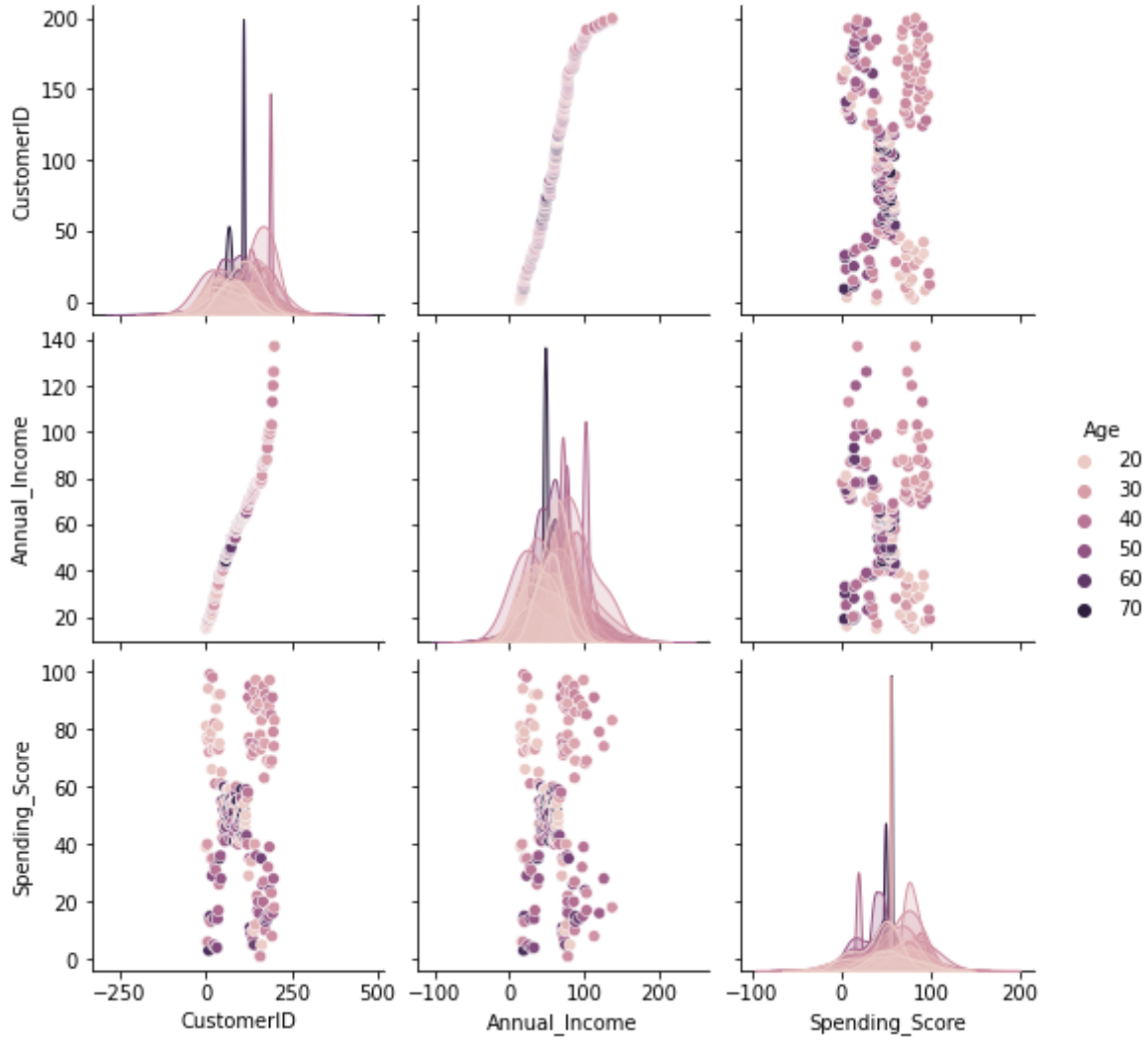

```
df.hist(figsize=(10,10))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f0cb6d52750>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f0cb6d05b90>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f0cb6cca1d0>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f0cb6c827d0>]],
      dtype=object)
```



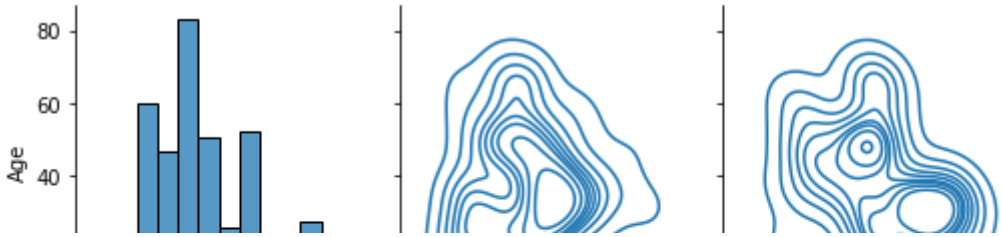

```
sns.pairplot(df,kind='scatter',hue='Age')
```

```
<seaborn.axisgrid.PairGrid at 0x7f0cb6b63a50>
```




```
sns.pairplot(data=df[['Age','Annual_Income','Spending_Score']],kind='kde',diag_kind='hist'
```

```
<seaborn.axisgrid.PairGrid at 0x7f0cb68a8990>
```



Descriptive statistics

```
df.describe()
```

	CustomerID	Age	Annual_Income	Spending_Score
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
max	200.000000	70.000000	137.000000	99.000000

Handle missing data

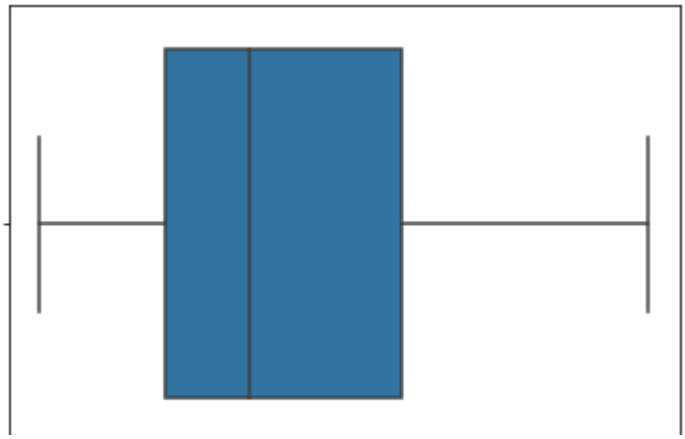
```
df.isnull().any()
```

```
CustomerID        False
Gender            False
Age               False
Annual_Income     False
Spending_Score    False
dtype: bool
```

Outliers Replacement

```
sns.boxplot(df.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f0cb456ec50>
```



Check for Categorical column and perform encoding

```
from sklearn.preprocessing import LabelEncoder

le = LabelEncoder()

df.Gender=le.fit_transform(df.Gender)

df.head()
```

	CustomerID	Gender	Age	Annual_Income	Spending_Score
0	1	1	19	15	39
1	2	1	21	15	81
2	3	0	20	16	6
3	4	0	23	16	77
4	5	0	31	17	40

Perform clustering algorithm

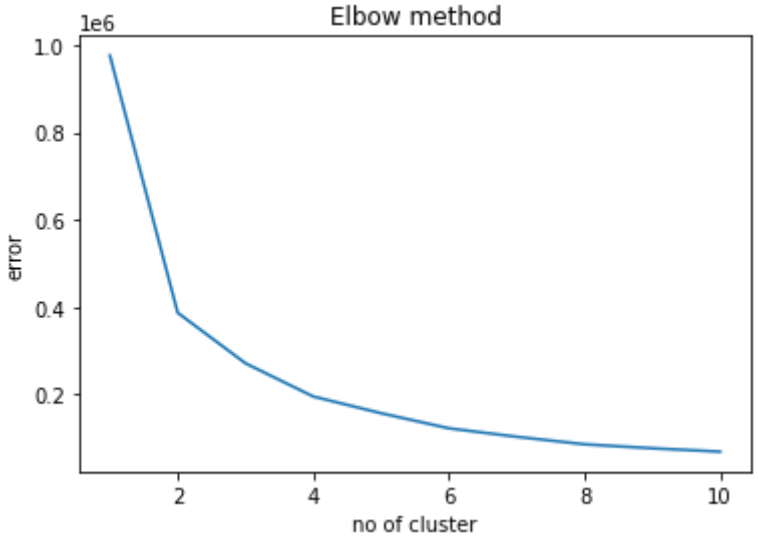
```
from sklearn import cluster

error =[]
for i in range(1,11):
    kmeans=cluster.KMeans(n_clusters=i,init='k-means++',random_state=0)
    kmeans.fit(df)
    error.append(kmeans.inertia_)
```

```
error
```

```
[975512.0600000003,
 387065.71377137717,
 271384.508782868,
 195401.19855991466,
 157157.7579059829,
 122625.19813553878,
 103233.01724386725,
 86053.67444777445,
 76938.97565600359,
 69231.33607611558]
```

```
import matplotlib.pyplot as plt
plt.plot(range(1,11),error)
plt.title('Elbow method')
plt.xlabel('no of cluster')
plt.ylabel('error')
plt.show()
```




```
k_means_model=cluster.KMeans(n_clusters=3,init='k-means++',random_state=0)
```

```
k_means_model.fit(df)
```

```
KMeans(n_clusters=3, random_state=0)
```

```
clustered_data =k_means_model.predict(df)
```

Add the cluster data with the primary dataset

```
df['Clustered_data'] = pd.Series(clustered_data)
df.head()
```

	CustomerID	Gender	Age	Annual_Income	Spending_Score	Clustered_data
0	1	1	19	15	39	0
1	2	1	21	15	81	0
2	3	0	20	16	6	0
3	4	0	23	16	77	0
4	5	0	31	17	40	0

Split the data into dependent and independent variables

```
y=df['Clustered_data']
y
```

```
0      0
1      0
2      0
3      0
4      0
      ..
195    2
196    2
197    2
198    2
199    2
Name: Clustered_data, Length: 200, dtype: int32
```

```
X=df.drop(columns=['Clustered_data'],axis=1)
X.head()
```

	CustomerID	Gender	Age	Annual_Income	Spending_Score
0	1	1	19	15	39
1	2	1	21	15	81
2	3	0	20	16	6
3	4	0	23	16	77
4	5	0	31	17	40

Scale the independent variables

```
from sklearn.preprocessing import scale
```

```
data=pd.DataFrame(scale(X),columns=X.columns)
data.head()
```

	CustomerID	Gender	Age	Annual_Income	Spending_Score
0	-1.723412	1.128152	-1.424569	-1.738999	-0.434801
1	-1.706091	1.128152	-1.281035	-1.738999	1.195704
2	-1.688771	-0.886405	-1.352802	-1.700830	-1.715913
3	-1.671450	-0.886405	-1.137502	-1.700830	1.040418
4	-1.654129	-0.886405	-0.563369	-1.662660	-0.395980

Split the data into training and testing

```
from sklearn.model_selection import train_test_split
X_train,X_test,y_train,y_test=train_test_split(data,y,test_size=0.3,random_state=1)
```

```
X_train.shape,X_test.shape
```

```
((140, 5), (60, 5))
```

```
y_train.shape,y_test.shape
```

```
((140,), (60,))
```

Build the model

```
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
```

```
model.fit(X_train,y_train)   # K - Nearest Neighbour model (KNN)
```

```
KNeighborsClassifier()
```

Train the model

```
pred_train = model.predict(X_train)
pred_train
```

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

Test the data

```
y_test
```

```
102    1
184    2
198    2
95     1
4      0
29     0
168    2
171    2
18     0
11     0
89     1
110    1
118    1
159    2
35     0
136    2
59     0
51     0
16     0
44     0
94     1
31     0
162    2
38     0
28     0
193    2
27     0
47     0
165    2
194    2
177    2
176    2
97     1
174    2
73     1
69     1
172    2
108    1
107    1
189    2
14     0
56     0
19     0
114    1
39     0
185    2
124    1
98     1
123    1
119    1
53     0
33     0
179    2
```

```
181    2
106    1
199    2
138    2
Name: Clustered_data, dtype: int32
```

```
pred_test=model.predict(X_test)
pred_test
```

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

```
pred = pd.DataFrame({'Actual_value':y_test,'Predicted_value_using_KNN':pred_test})
pred.head()
```

	Actual_value	Predicted_value_using_KNN
58	0	0
40	0	1
34	0	0
102	1	1
184	2	2

Measure the performance using metrics

```
from sklearn.metrics import accuracy_score,confusion_matrix,classification_report
```

```
#Accuracy Score
print('Training accuracy: ',accuracy_score(y_train,pred_train))
print('Testing accuracy: ',accuracy_score(y_test,pred_test))
```

```
#Confusion Matrix
pd.crosstab(y_test,pred_test)
```

col_0	0	1	2
Clustered_data			
0	19	4	0
1	1	16	0
2	0	0	20

```
#Classification Report
print(classification_report(y_test,pred_test))
```

	precision	recall	f1-score	support
0	0.95	0.83	0.88	23
1	0.80	0.94	0.86	17
2	1.00	1.00	1.00	20
accuracy			0.92	60
macro avg	0.92	0.92	0.92	60
weighted avg	0.92	0.92	0.92	60