Assignment Date	
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Student Roll Number	111519104007
Maximum Marks	2 Marks

#**Problem Statement: Customer Segmentation Analysis**

###**Description:** You own the mall and want to understand the customers who can quickly converge [Target Customers] so that the insight can be given to the marketing team and planthe strategy accordingly.

Download and load Dataset

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

```
df=pd.read_csv('Mall_Customers.csv') #No Target Column - UnsupervisedMachine Learning
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)':
'Spending_Score'})df.head()
```

```
   CustomerID  Gender  Age  Annual_Income  Spending_Score0        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([19,54,
29, 21, 20, 23, 31, 22, 35, 64, 30, 67, 58, 24, 37, 52, 25, 46,
51,
69, 45, 40, 60, 53, 18, 49, 42, 36, 65, 48, 50, 27, 33, 59, 47,
41])
70, 63, 43, 68, 32, 26, 57, 38, 55, 34, 66, 39, 44, 28, 56,

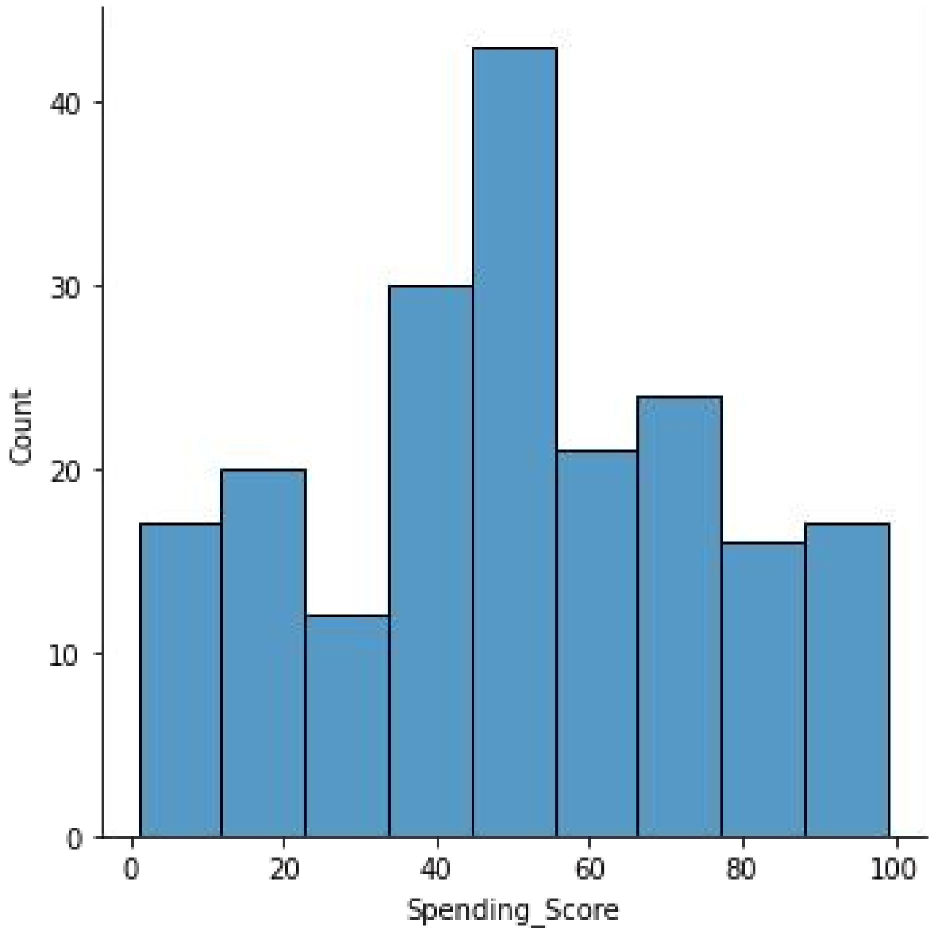
df.Gender.value_counts()Female
112
Male 88
Name: Gender, dtype: int64

Visualizations

Univariate Analysis

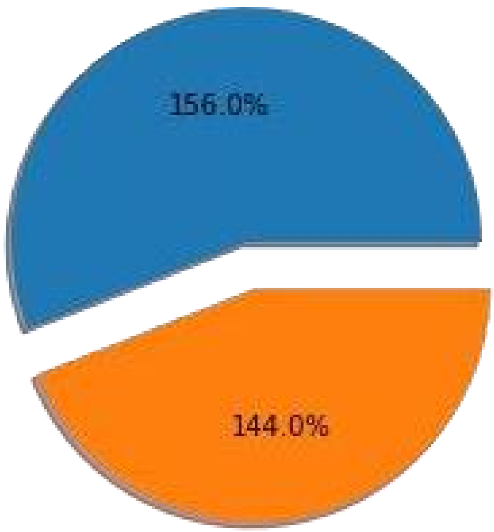
sns.displot(df.Spending_Score)

<seaborn.axisgrid.FacetGrid at 0x7f700626b950>



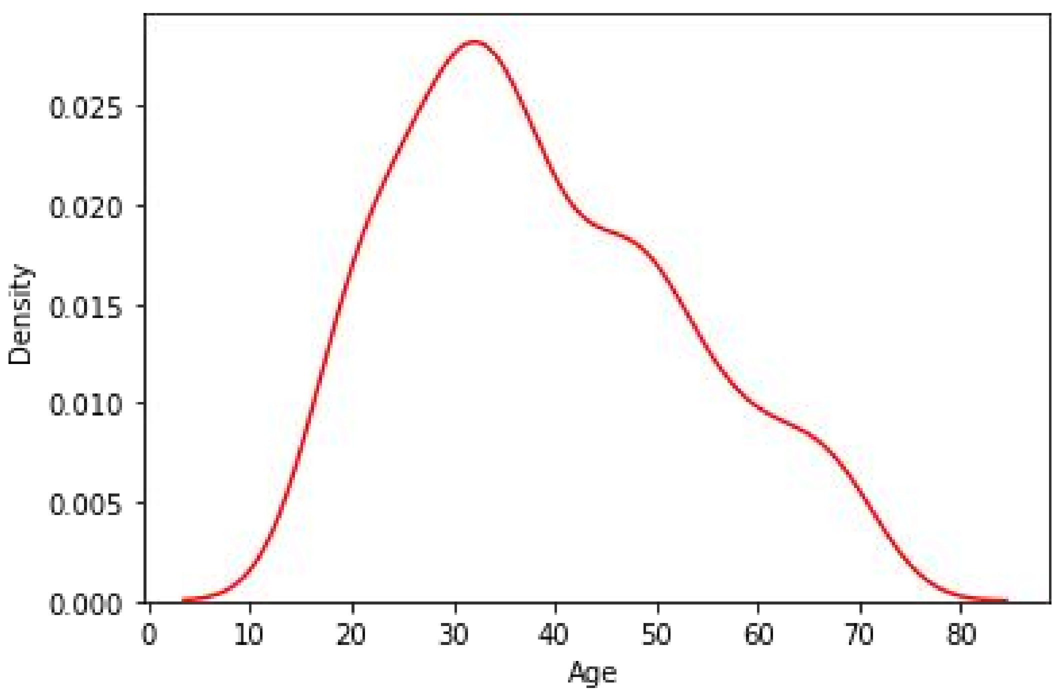

```
plt.pie(df.Gender.value_counts(),[0,0.2],shadow='True',autopct="1%.1f%
%")        #categorial column
```

```
([<matplotlib.patches.Wedge at 0x7f7005485ed0>,
  <matplotlib.patches.Wedge at 0x7f7005492950>], [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="red")

<matplotlib.axes._subplots.AxesSubplot at 0x7f700549a450>



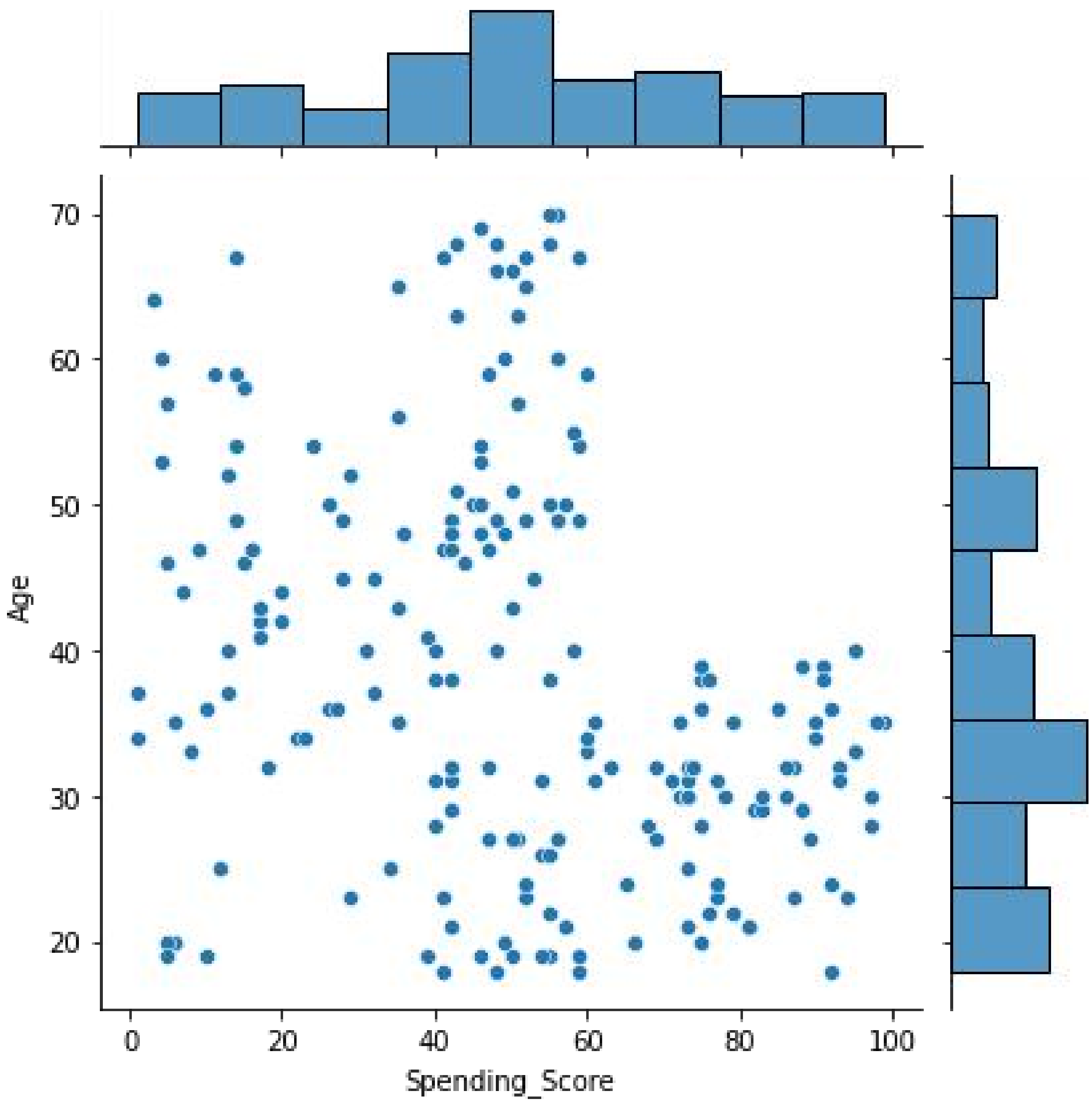
Bi-variate Analysis

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

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`,

and passing other arguments without an explicit keyword will result inan error or misinterpretation.
  FutureWarning

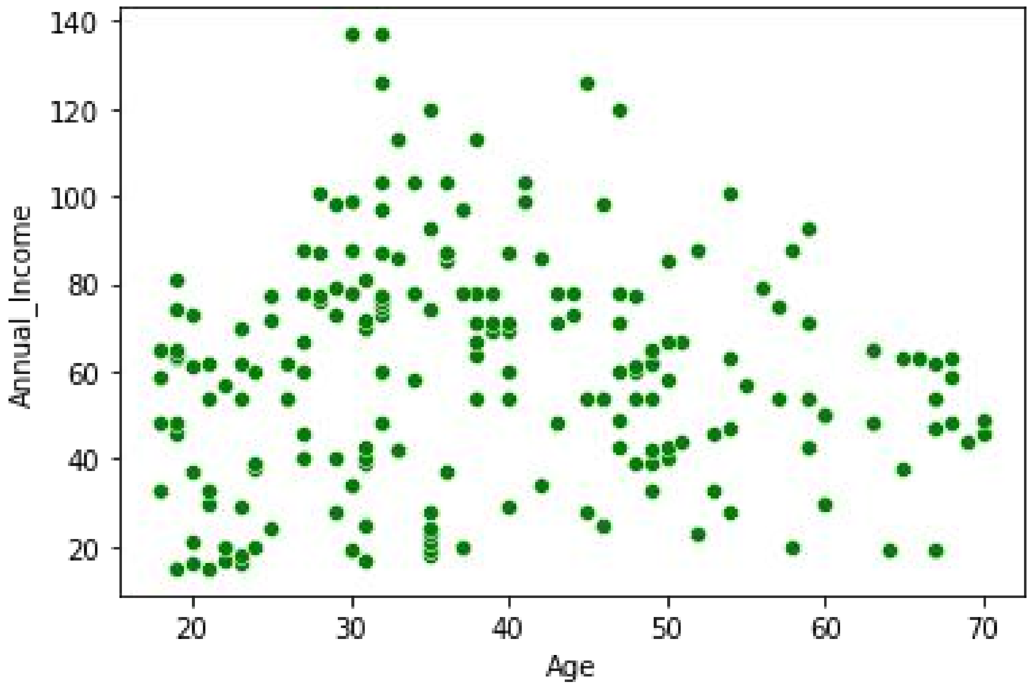
<seaborn.axisgrid.JointGrid at 0x7f7005459c50>




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:
FutureWarning: Pass the following variables as keyword args: x, y.
From version 0.12, the only valid positional argument will be `data`,
and passing other arguments without an explicit keyword will result in
an error or misinterpretation.
  FutureWarning
```

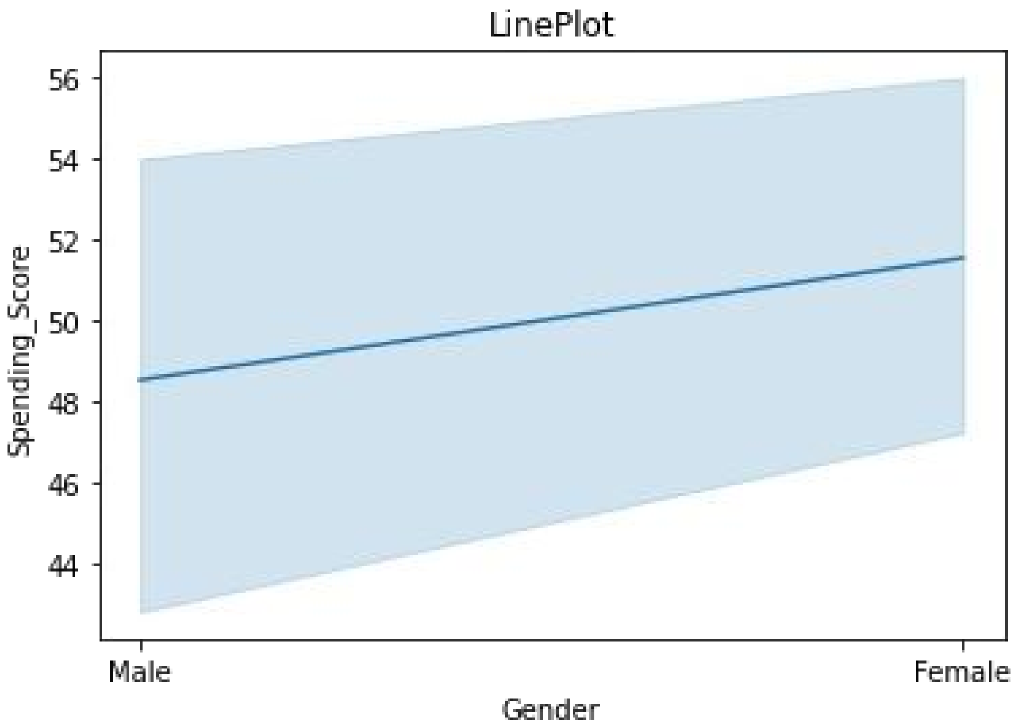
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f7005268410>
```




```
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: Pass the following variables as keyword args: x, y. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result inan error or misinterpretation.
  FutureWarning
```

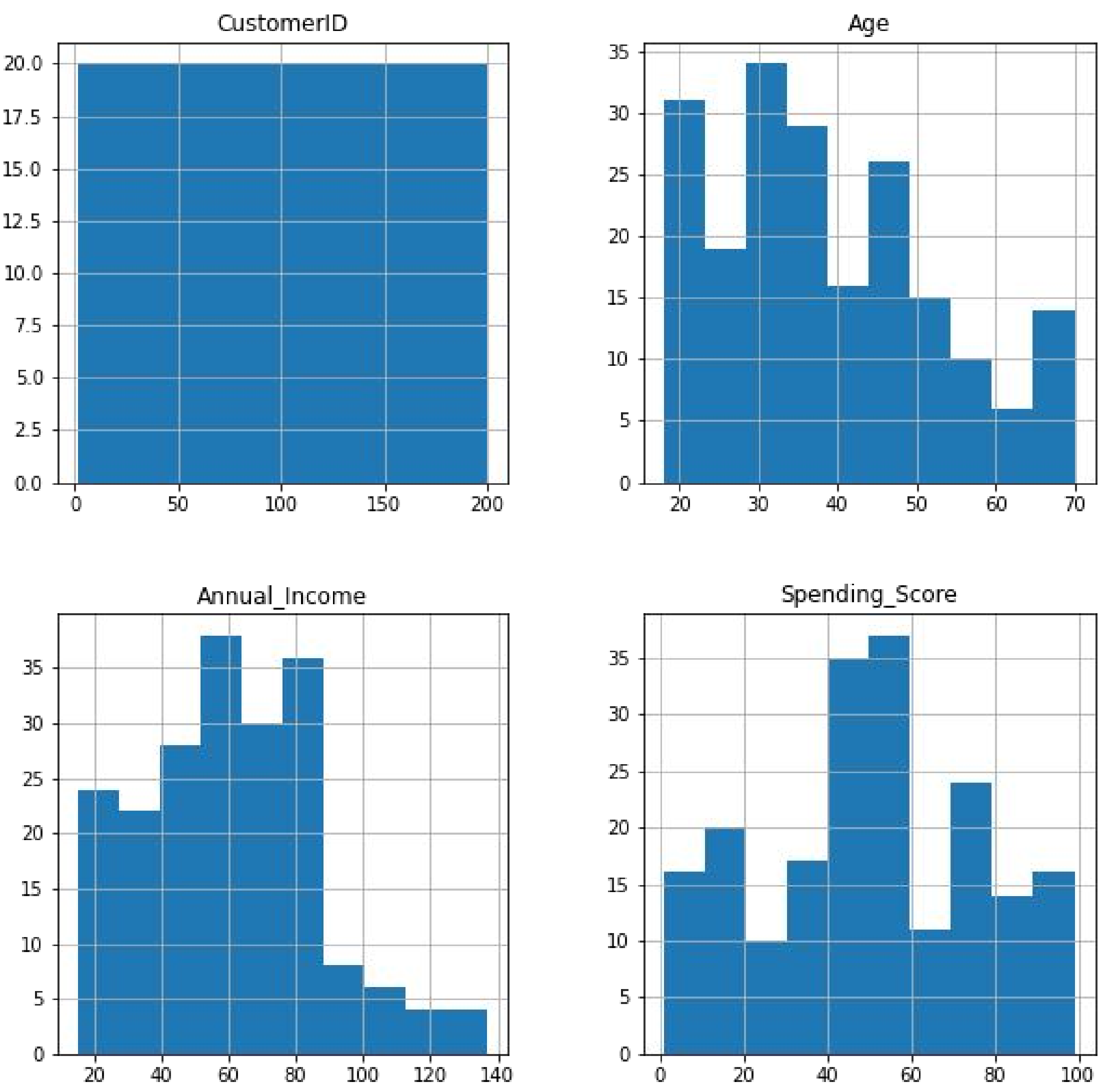
```
Text(0.5, 1.0, 'LinePlot')
```



Multi-variate Analysis

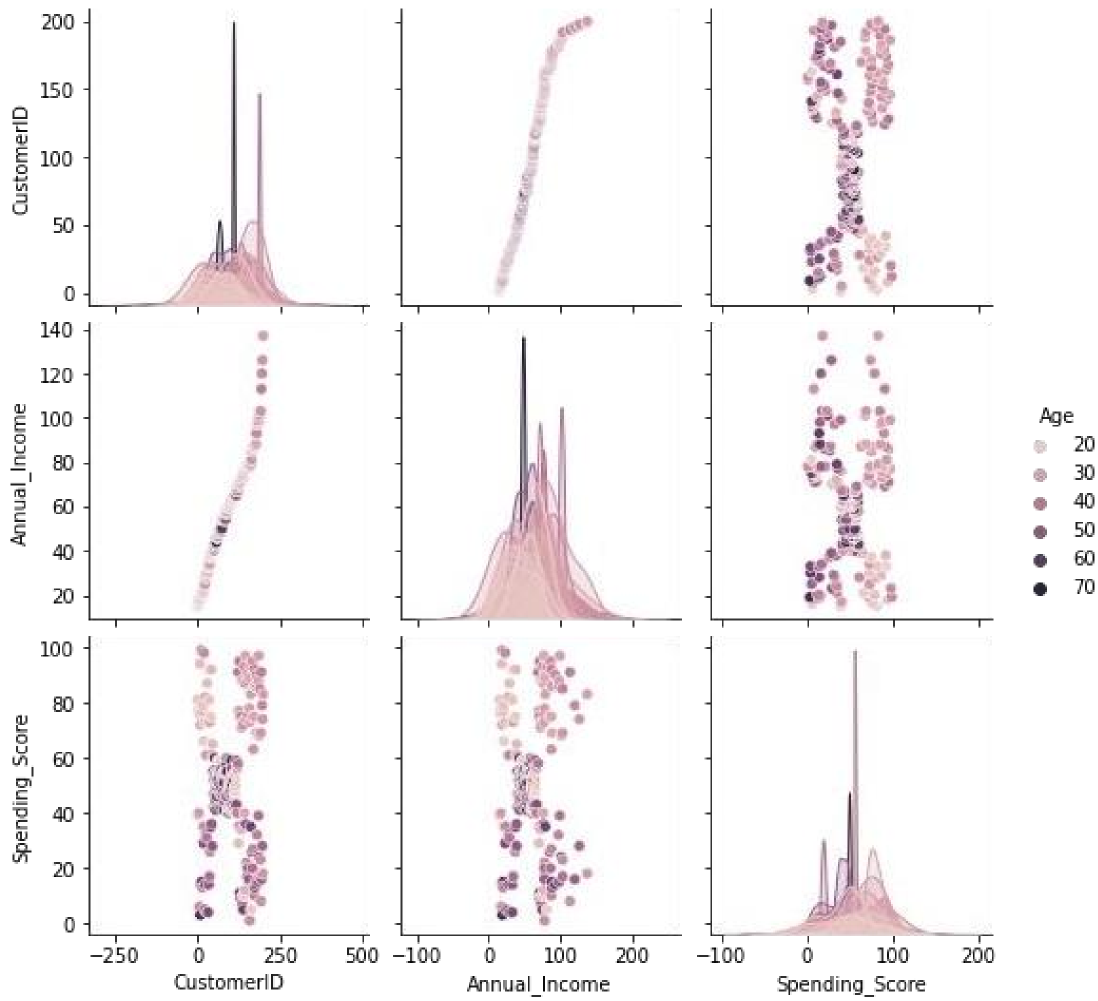
```
df.hist(figsize=(10,10))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at0x7f7005203910>,
        <matplotlib.axes._subplots.AxesSubplot object at0x7f70051db810>],
       [<matplotlib.axes._subplots.AxesSubplot object at0x7f7005191c90>,
        <matplotlib.axes._subplots.AxesSubplot object at0x7f70051541d0>]],
      dtype=object)
```



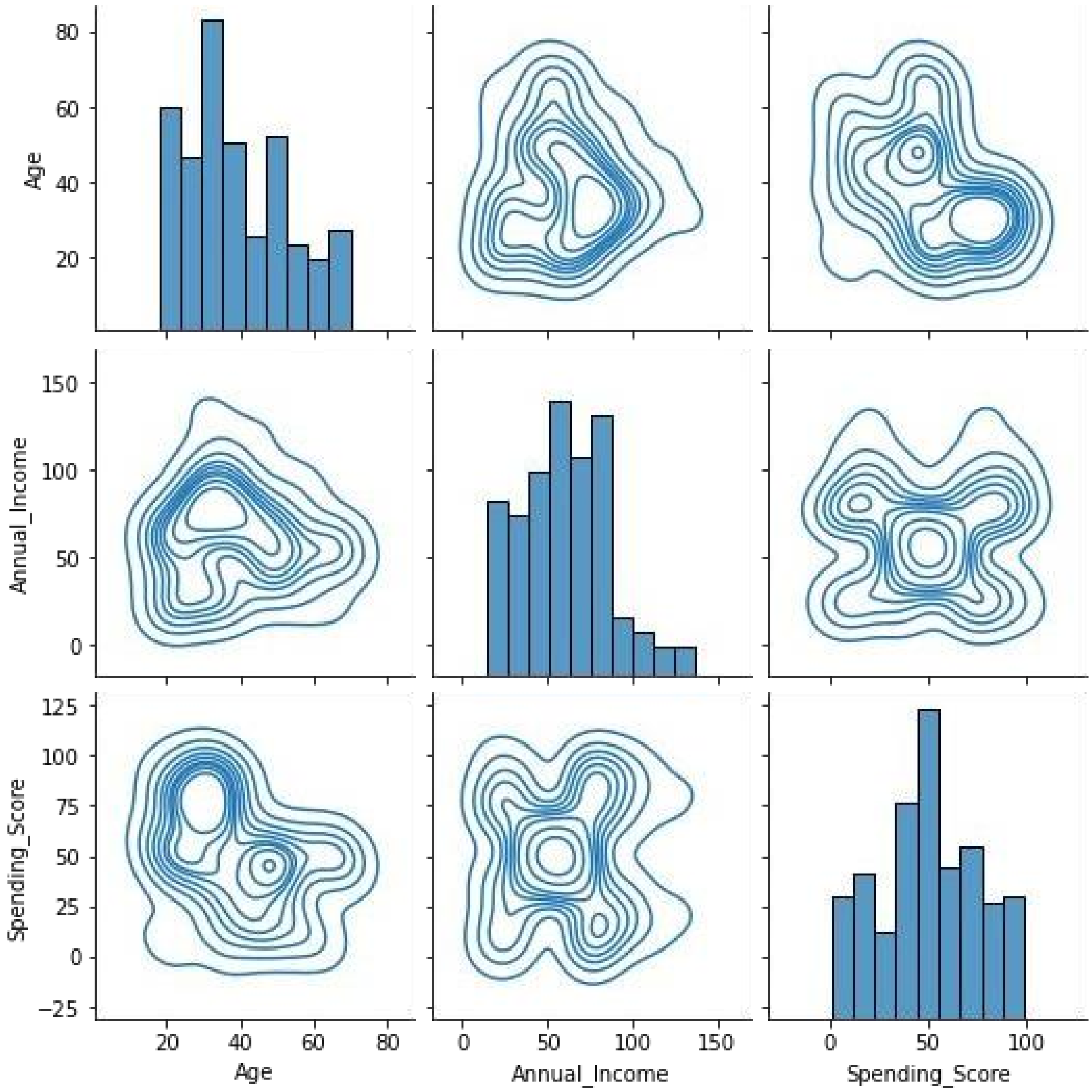

```
sns.pairplot(df,kind='scatter',hue='Age')
```

<seaborn.axisgrid.PairGrid at 0x7f700510cd90>



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

<seaborn.axisgrid.PairGrid at 0x7f7004bd3cd0>



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() #no missing data
```

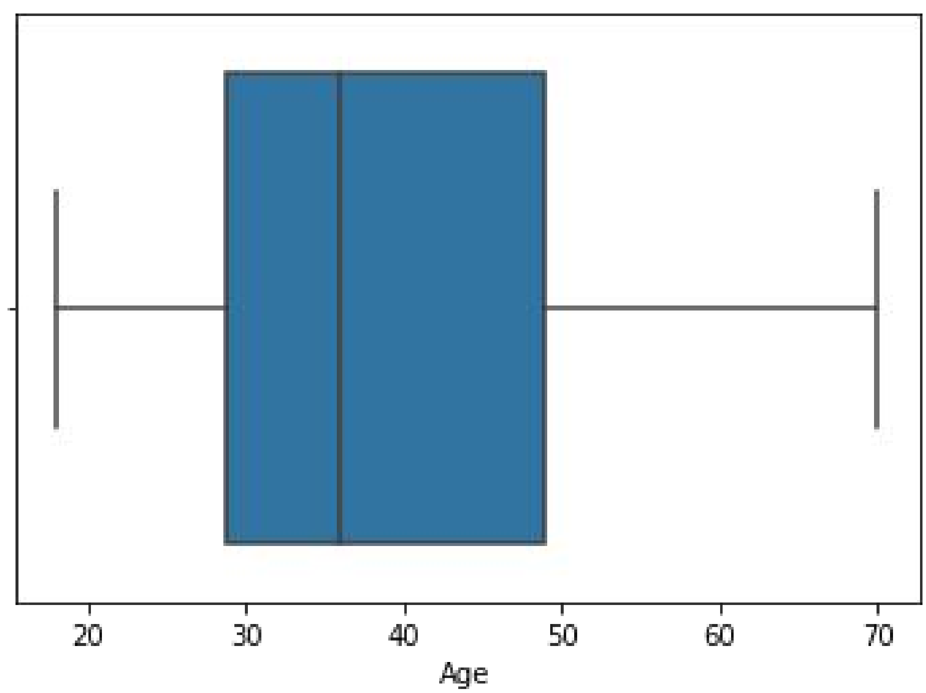
```
CustomerID        False
Gender            False
Age               False
Annual_Income     False
Spending_Score    False
dtype: bool
```

#**Outliers Replacement**

sns.boxplot(df.Age) *#no outliers*

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following variable as a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments without an explicit keyword will result in anerror or misinterpretation.
 FutureWarning

<matplotlib.axes._subplots.AxesSubplot at 0x7f7004604090>



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
```

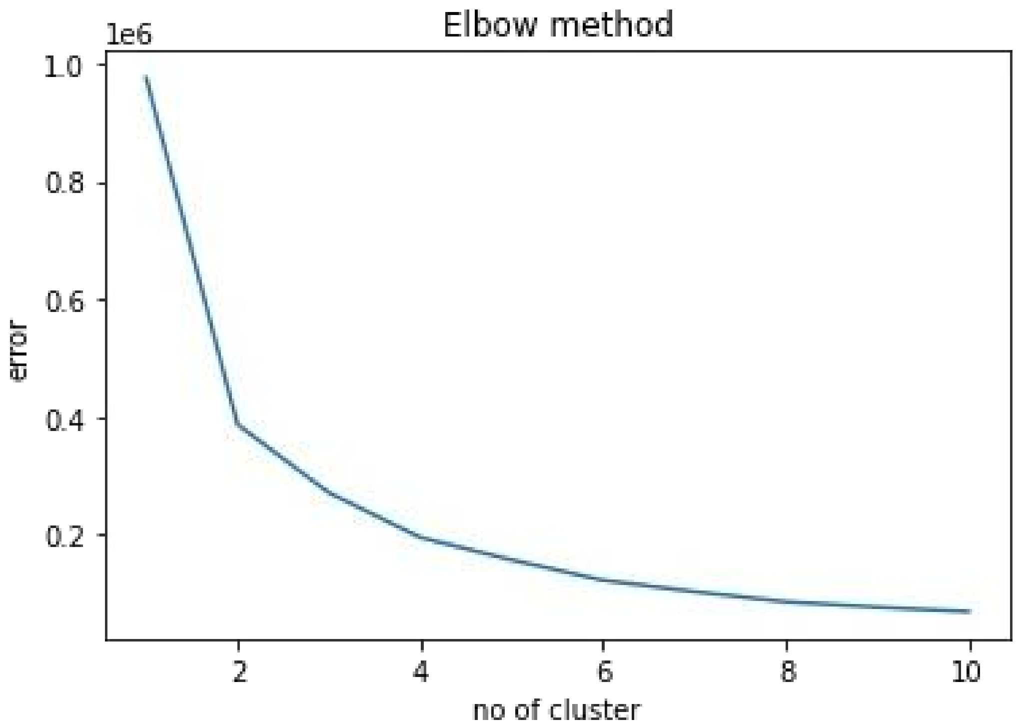
Perform clustering algorithm

```
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                          #y - target columns
```

```
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()                                              #X - predicting columns
```

	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,ra
ndom_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
```

```
58     0
40     0
34     0
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_t
est})
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))
```

```
Training accuracy:  0.9214285714285714
Testing accuracy:  0.9166666666666666
```

```
#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
```