

| | |
|-------------------|------------------------|
| AssignmentDate | |
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| StudentRollNumber | 111519104017 |
| MaximumMarks | 2 Marks |

#ProblemStatement:CustomerSegmentationAnalysis

###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 plan the strategy accordingly.

Download and load Dataset

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

```
df = pd.read_csv('Mall_Customers.csv') #No Target Column - Unsupervised Machine Learning
df.head()
```

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

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

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

```
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                200non-null      int64
3   Annual_Income      200non-null      int64
4   Spending_Score     200non-null      int64
dtypes: int64(4),
object(1)memoryusage: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

```

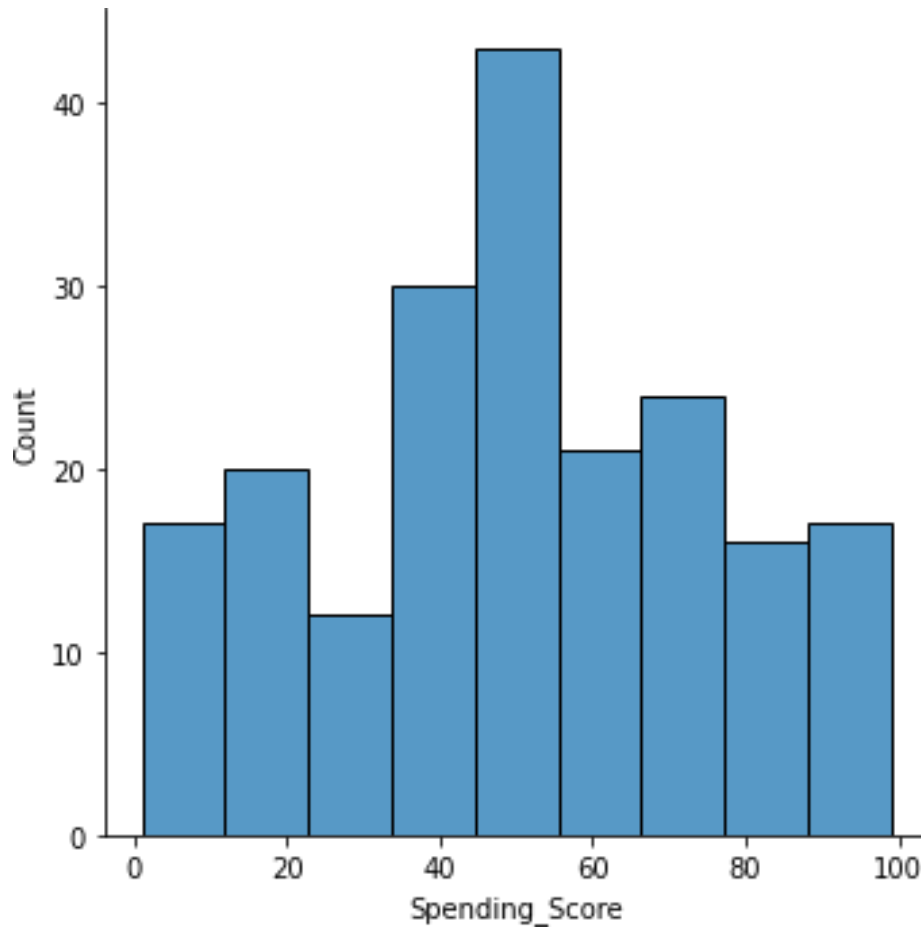
Visualizations

UnivariateAnalysis

```

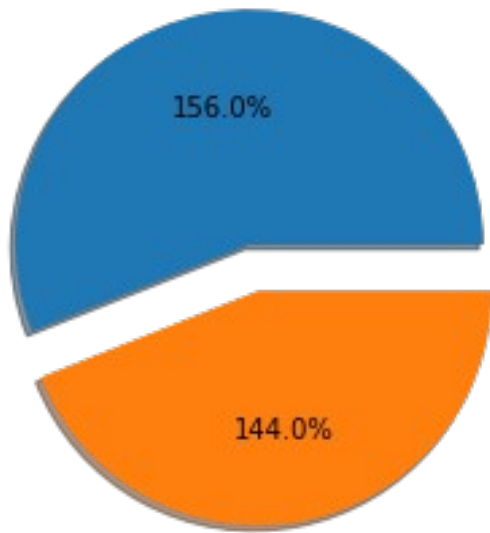
sns.displot(df.Spending_Score)
<seaborn.axisgrid.FacetGridat0x7f700626b950>

```



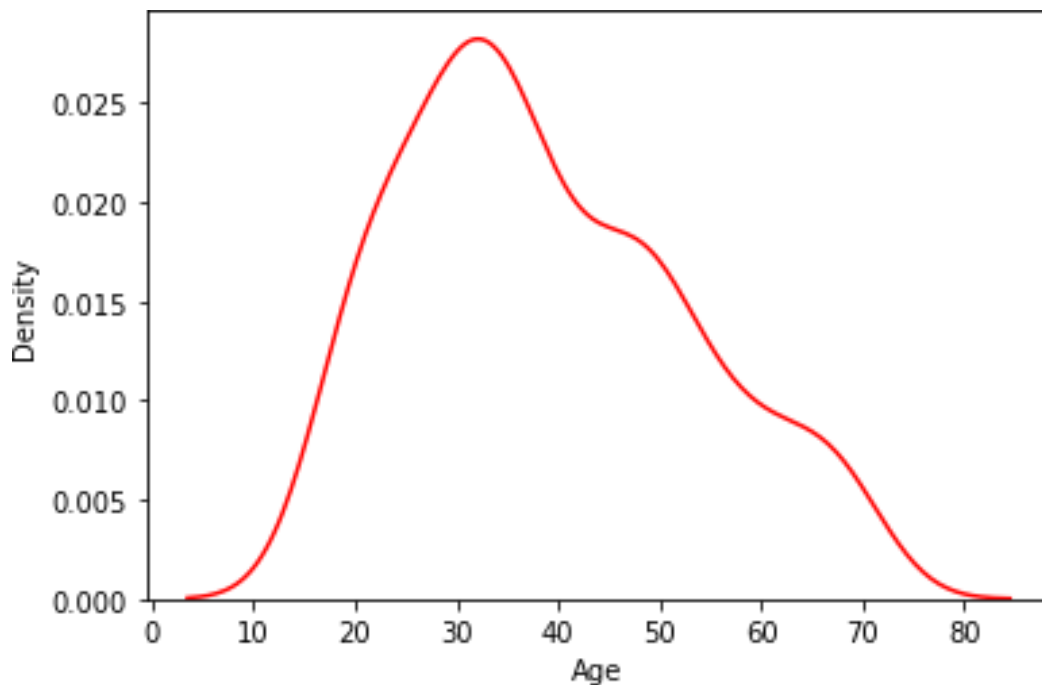
```
plt.pie(df.Gender.value_counts(),[0,0.2],shadow='True',autopct="1%.1f%
%)      #categoricalcolumn
```

```
([<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>
```



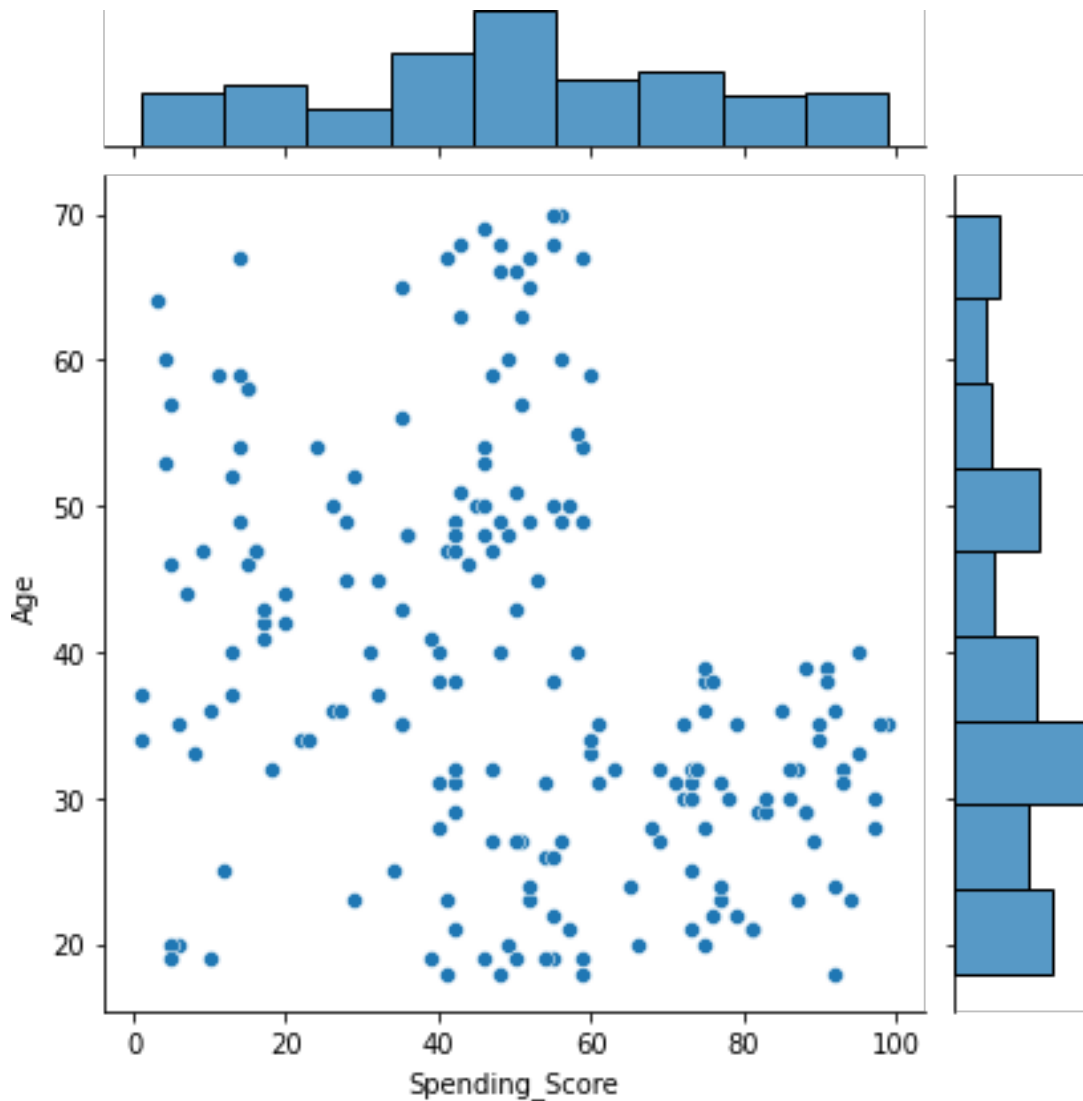
Bi-variateAnalysis

```
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 in an error or misinterpretation.
FutureWarning

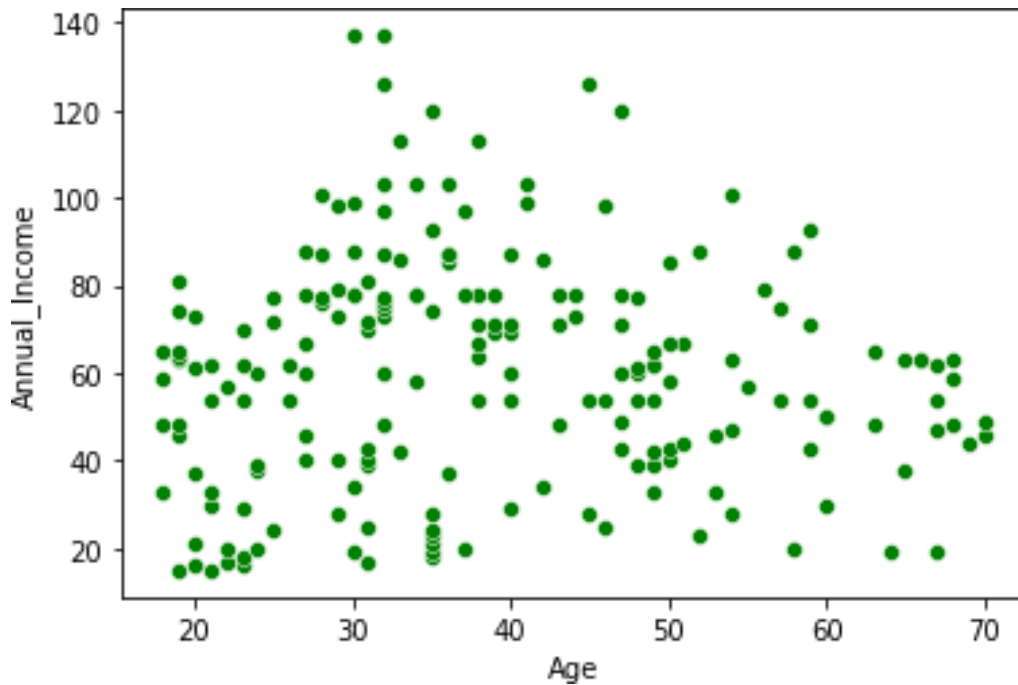
<seaborn.axisgrid.JointGrid at 0x7f7005459c50>



```
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>

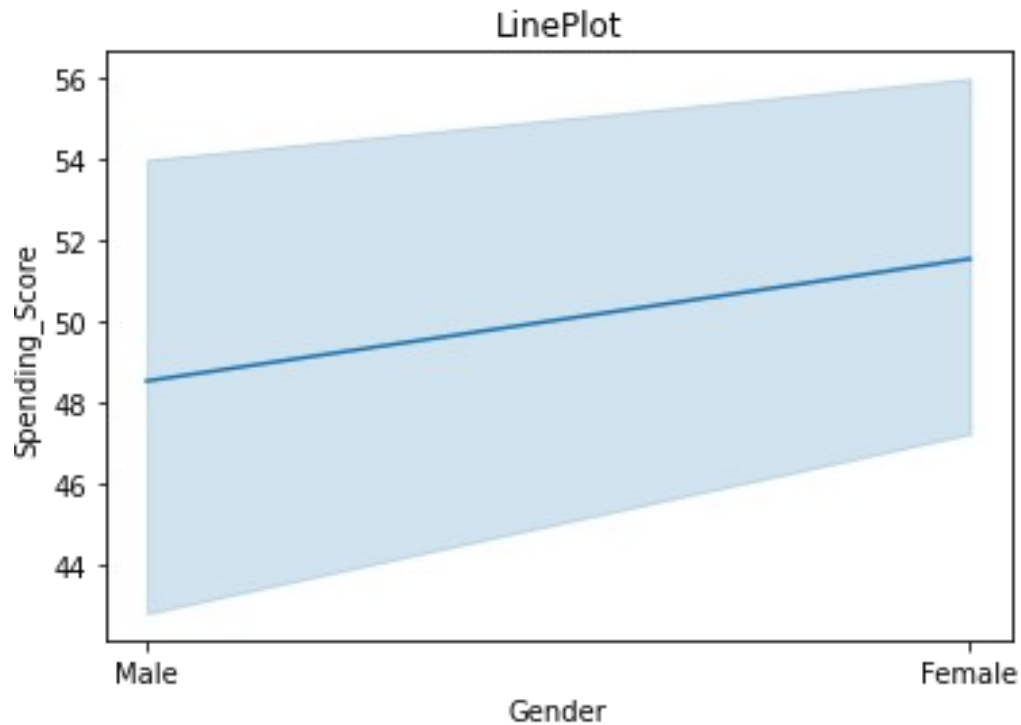


```
sns.lineplot(df.Gender,df.Spending_Score)plt.xlabel('Gender')plt.ylabel('Spending_Score')plt.title('LinePlot')
```

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:FutureWarning:Passthefollowingvariablesaskeywordargs: x,y.Fromversion0.12,theonlyvalidpositionalargumentwillbe`data`,andpassing otherargumentswithout an explicitkeyword willresult inan errorormisinterpretation.

FutureWarning

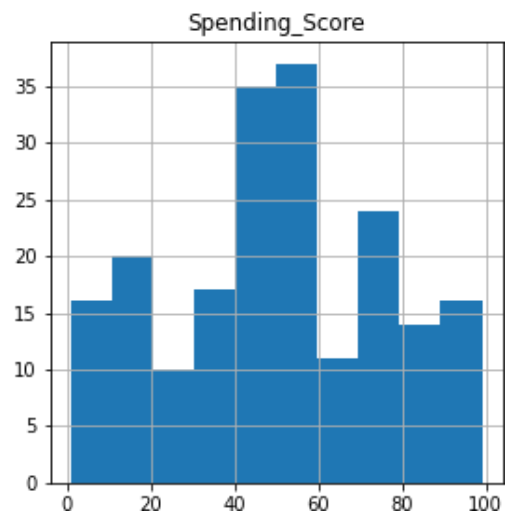
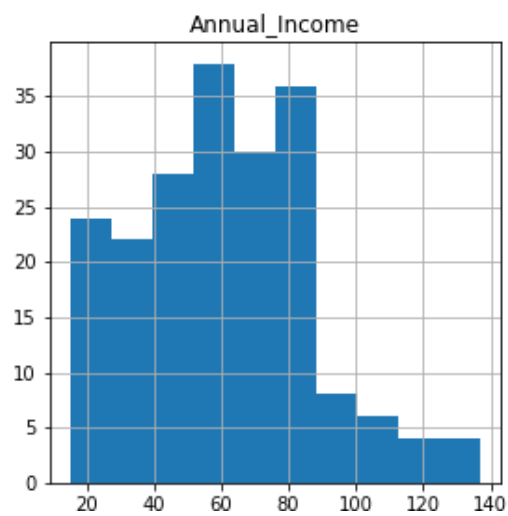
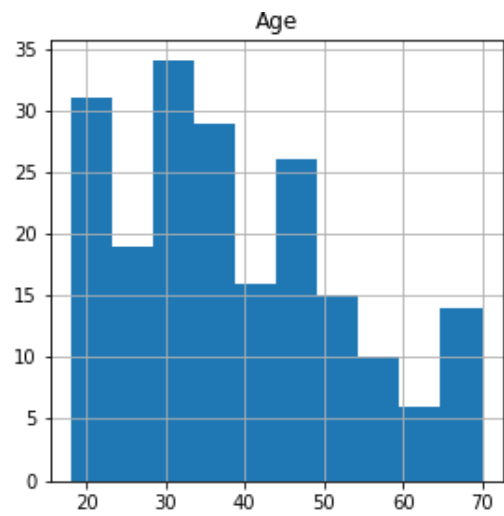
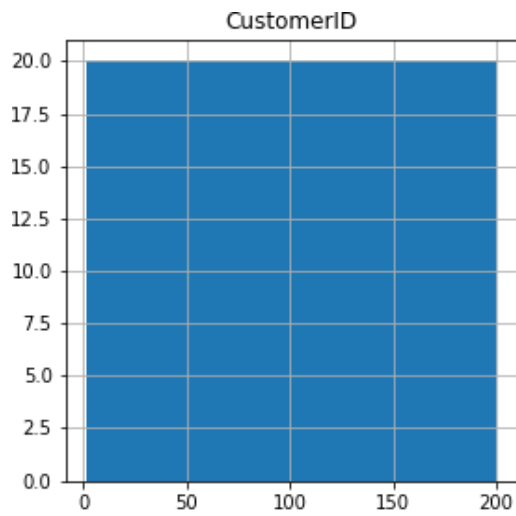
Text(0.5, 1.0,'LinePlot')



Multi-variateAnalysis

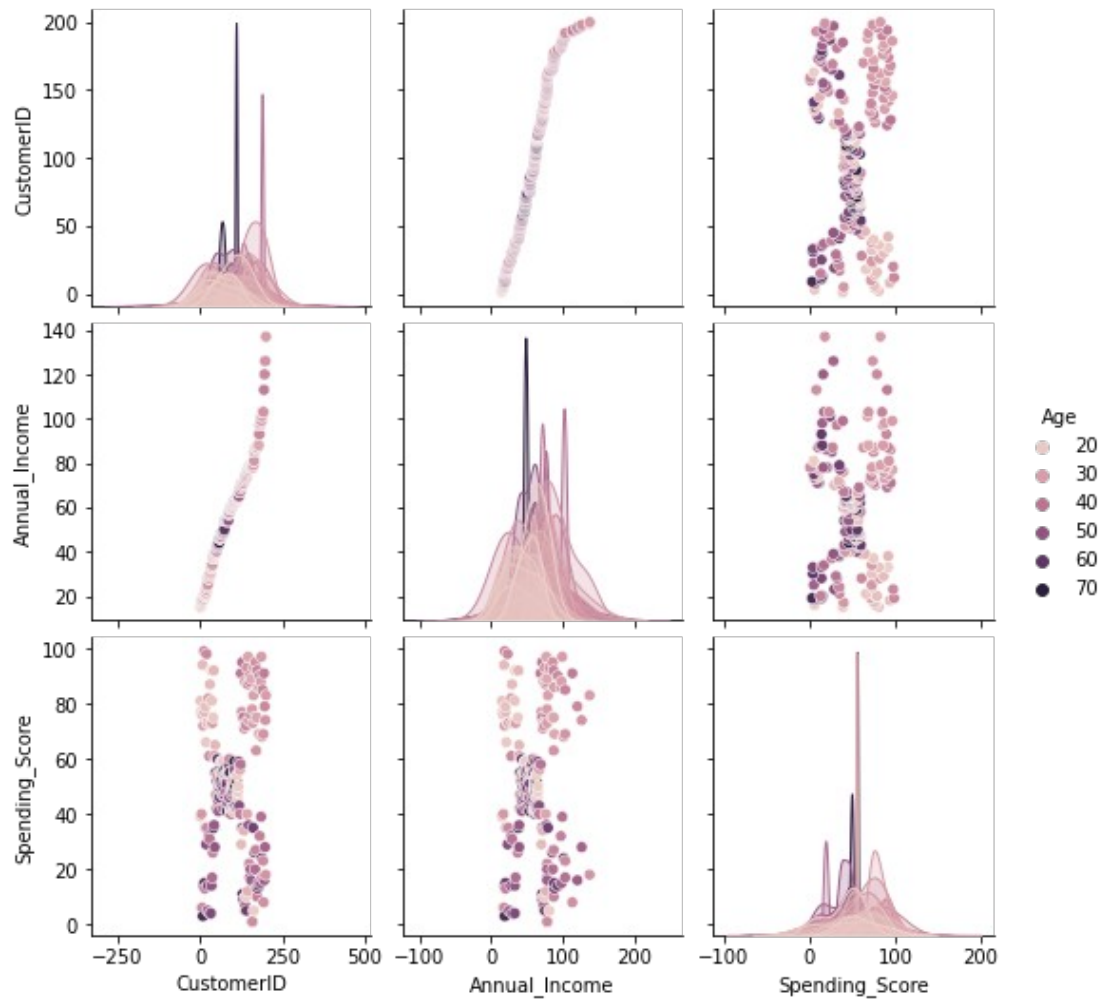
```
df.hist(figsize=(10,10))
```

```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f7005203910>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x7f70051db810>],  
      [<matplotlib.axes._subplots.AxesSubplot object at 0x7f7005191c90>,  
      <matplotlib.axes._subplots.AxesSubplot object at 0x7f70051541d0>]],  
      dtype=object)
```



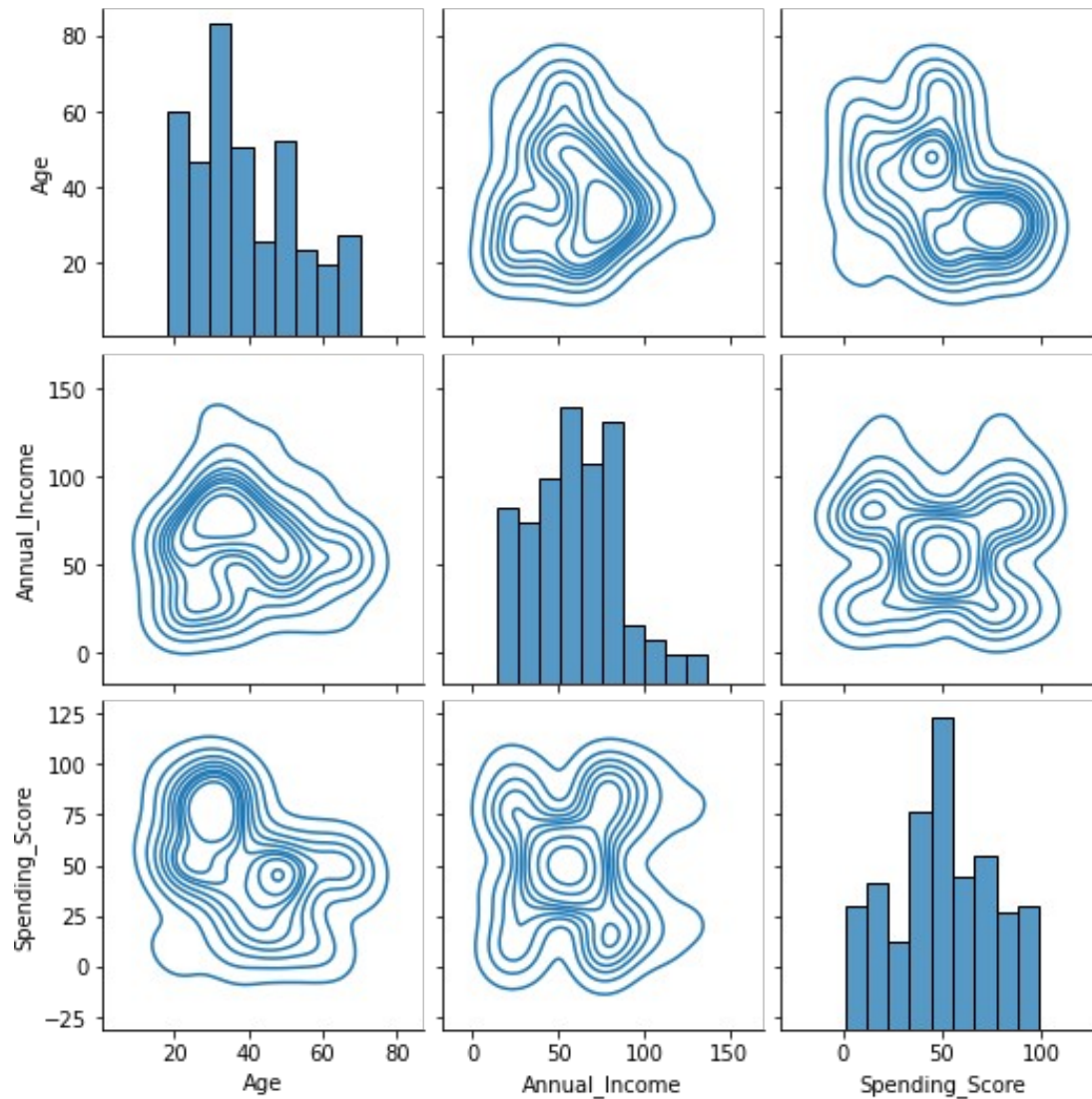
```
sns.pairplot(df,kind='scatter',hue='Age')
```

```
<seaborn.axisgrid.PairGrid at 0x7f700510cd90>
```

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

```
<seaborn.axisgrid.PairGrid at 0x7f7004bd3cd0>
```



Descriptivestatistics

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
```

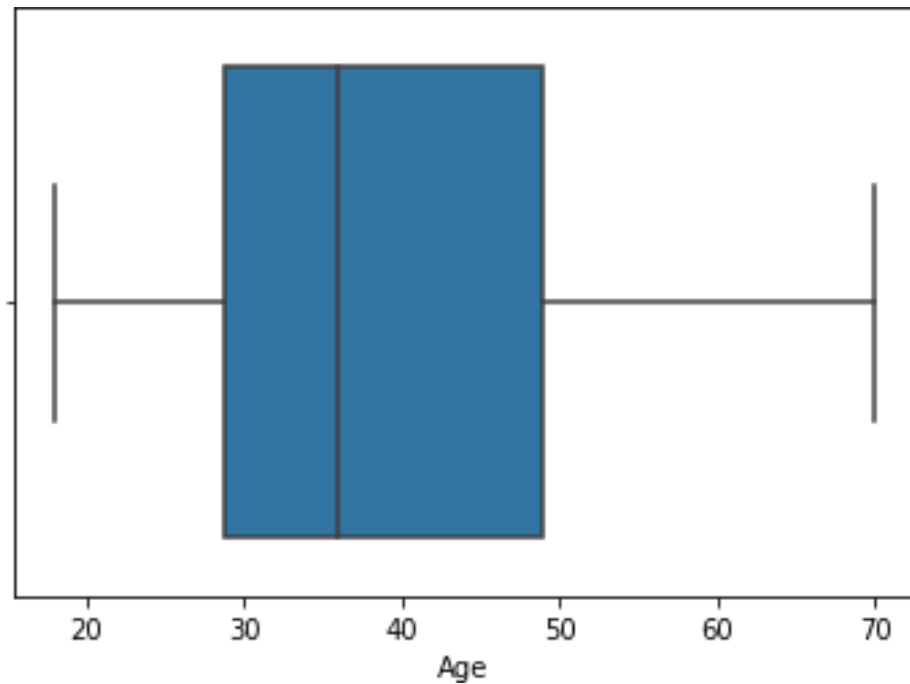
#Outliers Replacement

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

/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43:FutureWarning:Pass the following variables 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 an error 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 | |
|---|------------|--------|-----|---------------|----------------|----|
| | 1 | 1 | 19 | 15 | 39 | 1 |
| 1 | 2 | 1 | 21 | 15 | 15 | 81 |
| 2 | 3 | 0 | 20 | 16 | 16 | 6 |
| 3 | 4 | 0 | 23 | 16 | 16 | 77 |
| 4 | 5 | 0 | 31 | 17 | 17 | 40 |

Perform clustering algorithm

```
from sklearn import cluster
```

```
error=[]
```

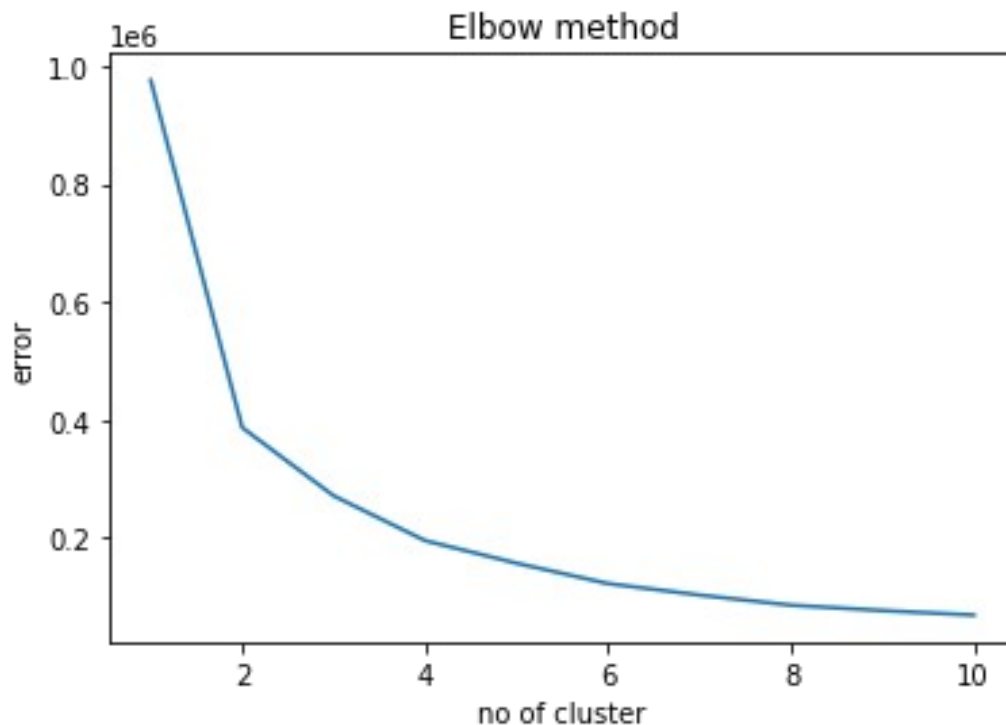
```
for i in range(1,11): kmeans=cluster.KMeans(n_clusters=i,init='k-means++',random_state=0) kmeans.fit(df) error.append(kmeans.inertia_)
```

```
error[9]75512.060000000
```

```
3,
```

```
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 | 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,),(6
0,))
```

Buildthemodel

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

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

KNeighborsClassifier()
```

Trainthemodel

```
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,
1,      0,  1,  1,  2,  0,  1,  0,  2,  1,  1,  1,  2,  1,  2,  0,  1,  1,  1,  2,  2,  2,
2,      2,  2,  2,  0,  0,  1,  2,  1,  2,  0,  2,  0,  2,  1,  2,  2,  1,  2,  1,  0,  0,
1,      1,  1,  0,  0,  1,  0,  0,  0,  2,  0,  2,  1,  2,  0,  1,  1,  2,  0,  1,  2,  0,
2,      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)
```

Testthedata

```
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([0,0, 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, 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))
```

Training accuracy:0.9214285714285714

Testing accuracy:0.9166666666666666

#Confusion Matrix

```
pd.crosstab(y_test,pred_test)
```

| col_0Clustered_dat | 0 | 1 | 2 |
|--------------------|----|----|----|
| a | | | |
| 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 |
| macroavg | 0.92 | 0.92 | 0.92 | 60 |

| | | | | |
|-------------|------|------|------|----|
| weightedavg | 0.92 | 0.92 | 0.92 | 60 |
|-------------|------|------|------|----|