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Customer Segmentation Analysis

Clustering the data and performing classification algorithms

Import Libraries

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

```
from google.colab import drive
drive.mount('/content/drive')
```

```
Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.m
```

2. Load the dataset into the tool.

```
ig=pd.read_csv("/content/drive/MyDrive/Mall_Customers.csv")
ig
```

	CustomerID	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39

```
ig.shape
```

```
(200, 5)
```

```
ig = ig.drop(columns=["CustomerID"],axis=1)
ig.head()
```

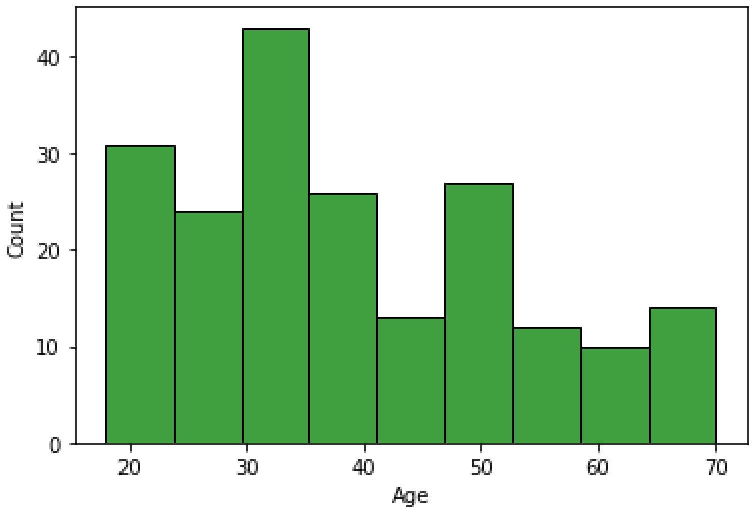
	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	Male	19	15	39
1	Male	21	15	81
2	Female	20	16	6
3	Female	23	16	77
4	Female	31	17	40

3. Perform Below Visualizations.

• Univariate Analysis

```
sns.histplot(x=ig.Age,color='Green')
```

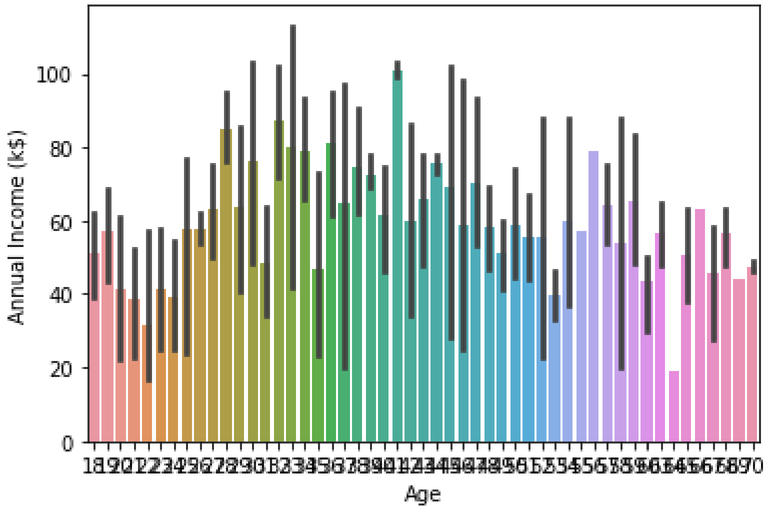
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f949067f8d0>
```



•Bi-Variate Analysis

```
sns.barplot(x=ig.Age,y=ig['Annual Income (k$)'])
```

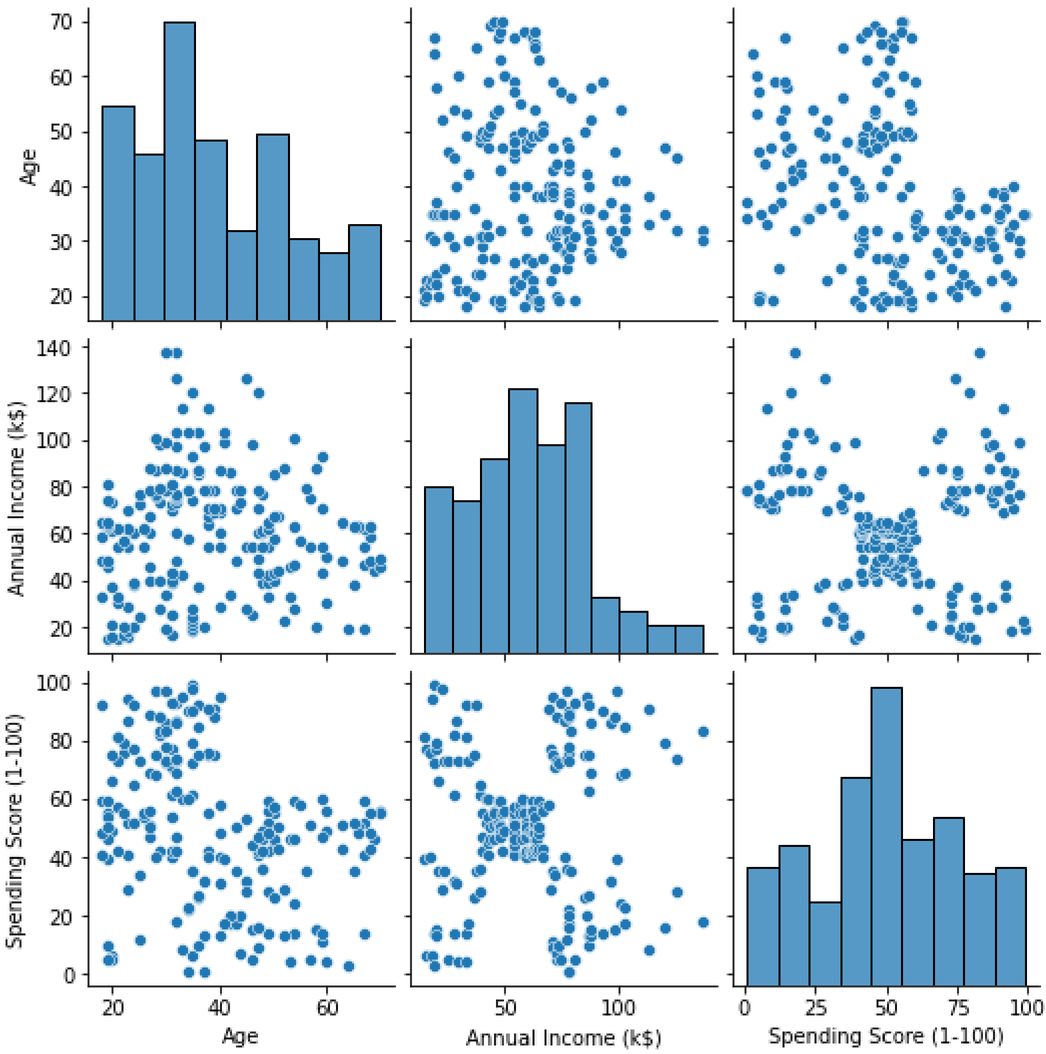
```
<matplotlib.axes._subplots.AxesSubplot at 0x7f948eddb250>
```



• Multi-Variate Analysis

```
sns.pairplot(ig)
```

```
<seaborn.axisgrid.PairGrid at 0x7f948ebf3210>
```



4. Perform descriptive statistics on the dataset.

```
ig.describe()
```

	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000
mean	38.850000	60.560000	50.200000
std	13.969007	26.264721	25.823522
min	18.000000	15.000000	1.000000
25%	28.750000	41.500000	34.750000
50%	36.000000	61.500000	50.000000
75%	49.000000	78.000000	73.000000
max	70.000000	137.000000	99.000000

5. Check for Missing values and deal with them.

```
ig.isnull().any()
```

```
Gender                    False
Age                       False
Annual Income (k$)        False
Spending Score (1-100)    False
dtype: bool
```

```
ig.isnull().sum()
```

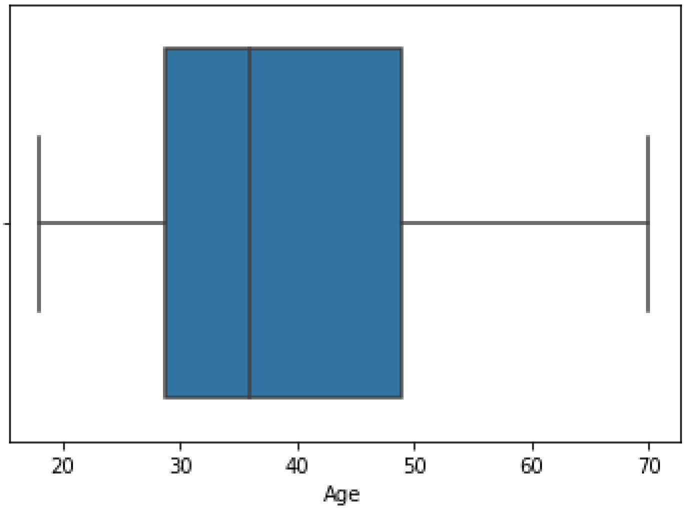
```
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

> There is no missing values so we go for next step.....

6. Find the outliers and replace them outliers

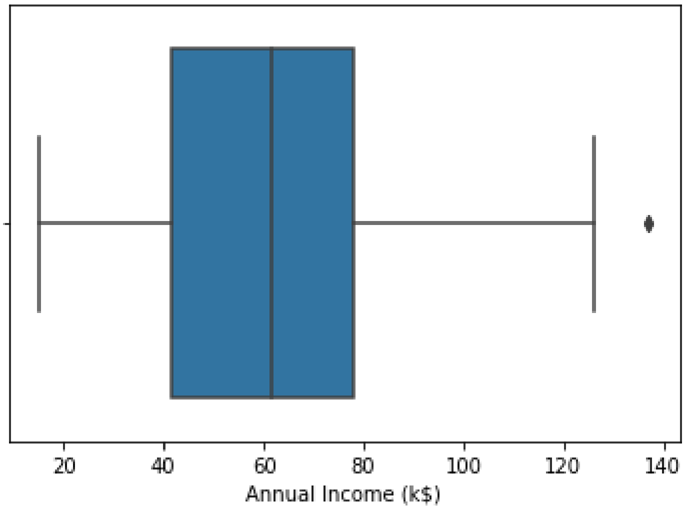
```
sns.boxplot(ig.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f948ec23990>
```




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas:
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f948bf18550>
```

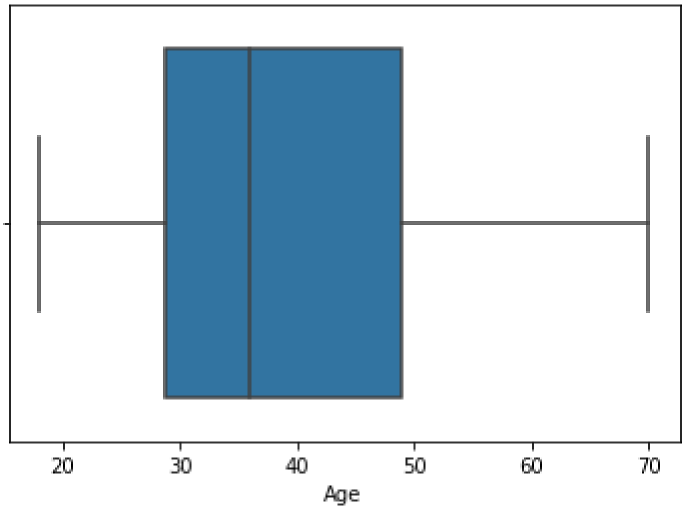



```
ig['Annual Income (k$)'].median()
```

```
61.5
```

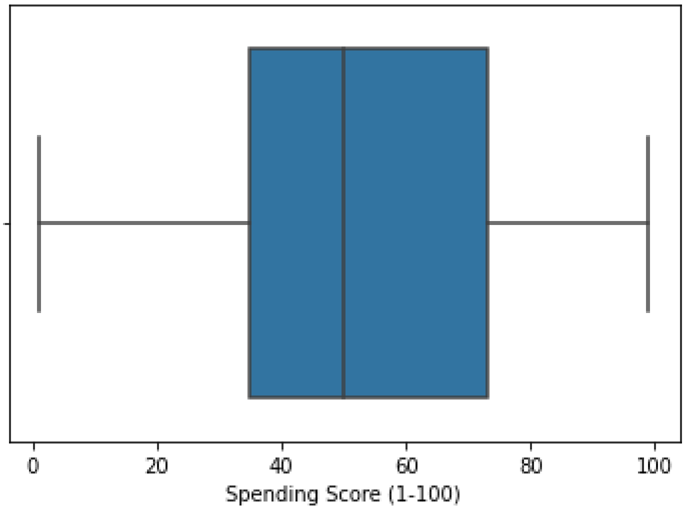
```
q1=ig['Annual Income (k$)'].quantile(0.25)
q3=ig['Annual Income (k$)'].quantile(0.75)

IQR=q3-q1

upper_limit= q3 + 1.5*IQR
lower_limit= q1 - 1.5*IQR

ig['Annual Income (k$)']= np.where(ig['Annual Income (k$)']>upper_limit,61,ig['Annual Inco
sns.boxplot(x=ig.Age,showfliers=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f948a607a50>
```




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pas
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f948a5cee90>
```



7. Check for Categorical columns and perform encoding

• Label encoding

```
from sklearn.preprocessing import LabelEncoder
le=LabelEncoder()

ig.Gender=le.fit_transform(ig.Gender)

ig.head()
```

	Gender	Age	Annual Income (k$)	Spending Score (1-100)
0	1	19	15	39
1	1	21	15	81
2	0	20	16	6
3	0	23	16	77

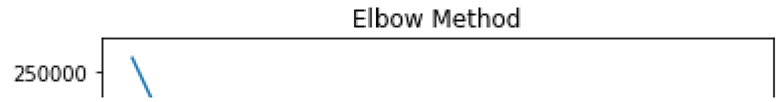
8. Scaling the data

```
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
data_scaled = scaler.fit_transform(ig)
data_scaled[0:5]
```

```
array([[1.        , 0.01923077, 0.        , 0.3877551 ],
       [1.        , 0.05769231, 0.        , 0.81632653],
       [0.        , 0.03846154, 0.00900901, 0.05102041],
       [0.        , 0.09615385, 0.00900901, 0.7755102 ],
       [0.        , 0.25      , 0.01801802, 0.39795918]])
```

9. Perform any of the clustering algorithms

```
target = ig[['Annual Income (k$)' , 'Spending Score (1-100)']].iloc[: , :].values
from sklearn.cluster import KMeans

error = []
for i in range(1, 11):
    km = KMeans(n_clusters = i, init = 'k-means++', max_iter = 300, n_init = 10, random_st
    km.fit(target)
    error.append(km.inertia_)

plt.plot(range(1, 11), error)
plt.title('Elbow Method')
plt.xlabel('No. of Clusters')
plt.ylabel('error')
plt.show()
```




```
k_means = KMeans(n_clusters = 5, init = 'k-means++', max_iter = 300, n_init = 10, random_s
y_means = k_means.fit_predict(target)
```

```
k_means
```

```
KMeans(n_clusters=5, random_state=0)
```

```
y_means
```

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

10. Add the cluster data with the primary dataset

```
ig['Outcome'] = pd.Series(y_means)
```

```
ig.head()
```

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

11. Split the data into dependent and independent variables.

(i) Independent variable

```
x=ig.drop(columns=['Outcome'],axis = 1)
x.head()
```

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

(ii) Dependent variable

```
y = ig.Outcome
y.head()
```

```
0    3
1    4
2    3
3    4
4    3
Name: Outcome, dtype: int32
```

12. 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(x,y, test_size=0.2, random_state=42)
```

```
x_train.shape
```

```
(160, 4)
```

```
x_test.shape
```

```
(40, 4)
```

```
y_train.shape
```

```
(160,)
```

```
y_test.shape
```

```
(40,)
```

13. Build the Model

```
from sklearn.ensemble import RandomForestClassifier
model = RandomForestClassifier(n_estimators=10,criterion='entropy')
```

```
model.fit(x_train,y_train)
```

```
RandomForestClassifier(criterion='entropy', n_estimators=10)
```

```
y_predict = model.predict(x_test)
```

```
y_predict_train = model.predict(x_train)
```

14. Train the Model

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

```
print('Training accuracy: ',accuracy_score(y_train,y_predict_train))
```

```
Training accuracy:  0.99375
```

15. Test the Model

```
print('Testing accuracy: ',accuracy_score(y_test,y_predict))
```

```
Testing accuracy:  1.0
```

16. Measure the performance using Metrics

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

col_0	0	1	2	3	4
Outcome					
0	12	0	0	0	0
1	0	17	0	0	0
2	0	0	5	0	0
3	0	0	0	3	0
4	0	0	0	0	3

```
print(classification_report(y_test,y_predict))
```

```
              precision    recall  f1-score   support

           0       1.00      1.00      1.00        12
           1       1.00      1.00      1.00        17
           2       1.00      1.00      1.00         5
           3       1.00      1.00      1.00         3
           4       1.00      1.00      1.00         3

    accuracy                           1.00        40
   macro avg       1.00      1.00      1.00        40
weighted avg       1.00      1.00      1.00        40
```