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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",force_remount=True)
```

```
Mounted at /content/drive
```

## 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 |
| **1** | 2 | Male | 21 | 15 | 81 |
| **2** | 3 | Female | 20 | 16 | 6 |
| **3** | 4 | Female | 23 | 16 | 77 |
| **4** | 5 | Female | 31 | 17 | 40 |
| **...** | ... | ... | ... | ... | ... |
| **195** | 196 | Female | 35 | 120 | 79 |
| **196** | 197 | Female | 45 | 126 | 28 |
| **197** | 198 | Male | 32 | 126 | 74 |
| **198** | 199 | Male | 32 | 137 | 18 |
| **199** | 200 | Male | 30 | 137 | 83 |

200 rows × 5 columns

```
ig.shape
```

```
(200, 5)
```

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

```
ig.head()
```

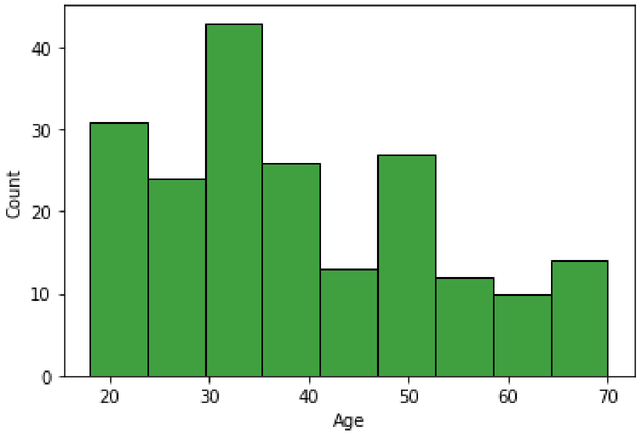
| | Gender | Age | Annual Income (k$) | Spending Score (1-100) |
|---|---|---|---|---|
| **0** | Male | 19 | 15 | 39 |
| **1** | Male | 21 | 15 | 81 |
| **2** | Female | 20 | 16 | 6 |
| **3** | Female | 23 | 16 | 77 |
| **4** | Female | 31 | 17 | 40 |

## 3. Perform Below Visualizations.

### • Univariate Analysis

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

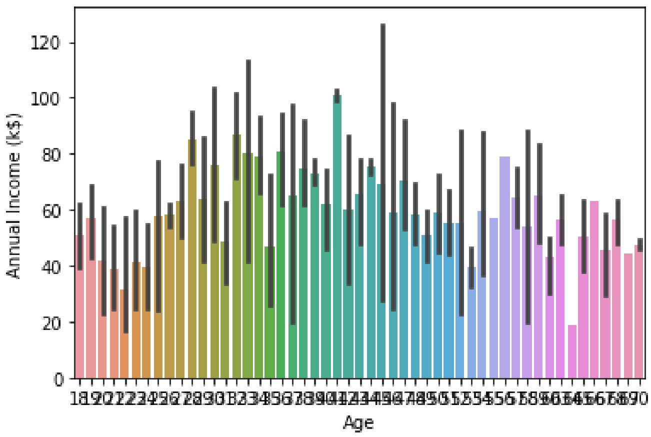
<matplotlib.axes._subplots.AxesSubplot at 0x7f5469316990>




### •Bi-Variate Analysis

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

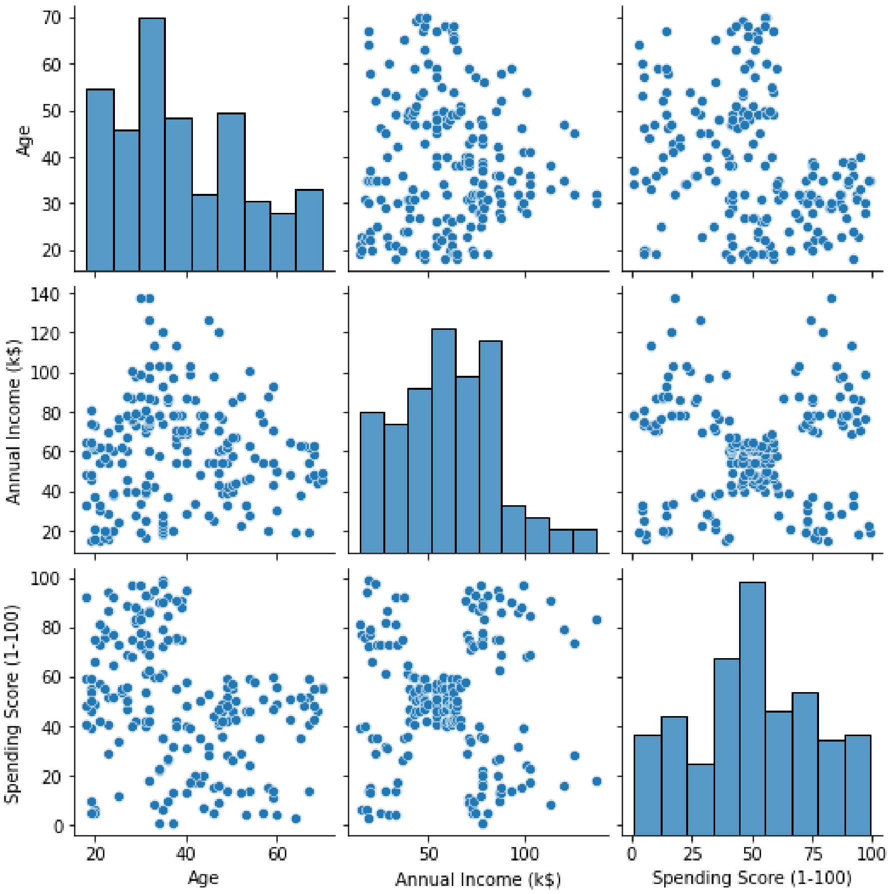
<matplotlib.axes._subplots.AxesSubplot at 0x7f5468d744d0>




### • Multi-Variate Analysis

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

```
<seaborn.axisgrid.PairGrid at 0x7f5468d63a50>
```




## 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()
```

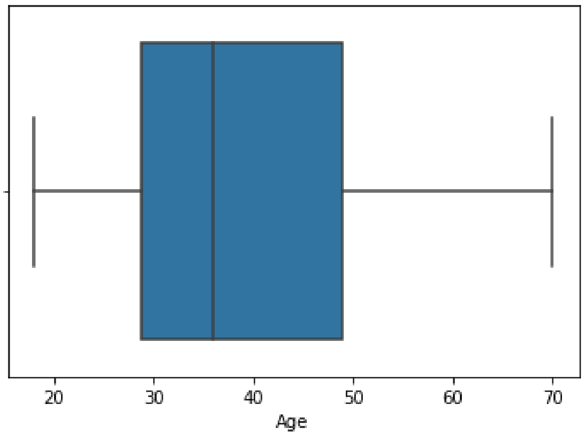
```
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

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

## 6. Find the outliers and replace them outliers

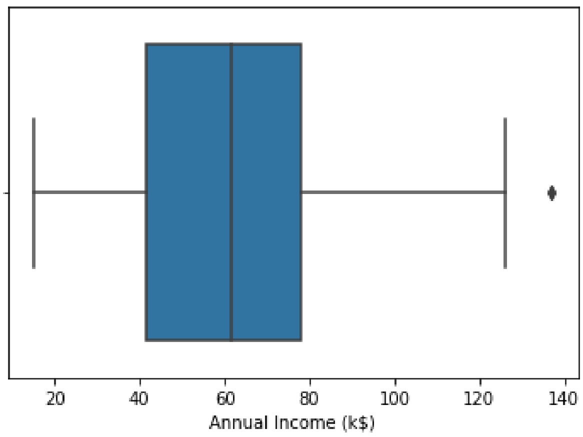
```
sns.boxplot(ig.Age)
```

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following v
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f54687453d0>
```




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following v
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f5468748690>
```

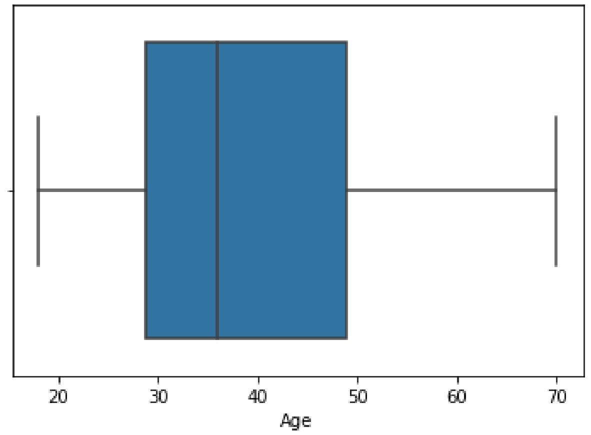



```
ig['Annual Income (k$)'].median()
```

```
61.5
```

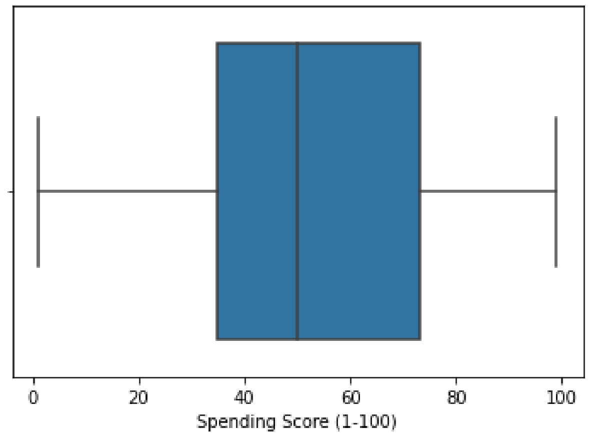
```
q1=ig['Annual Income (k$)'].quantile(0.25)
q3=ig['Annual Income (k$)'].quantile(0.75)

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 Income (k$)'])
sns.boxplot(x=ig.Age,showfliers=False)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x7f5468623f10>
```




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

```
/usr/local/lib/python3.7/dist-packages/seaborn/_decorators.py:43: FutureWarning: Pass the following v
  FutureWarning
<matplotlib.axes._subplots.AxesSubplot at 0x7f54685f6250>
```




# 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 |
| **4** | 0 | 31 | 17 | 40 |

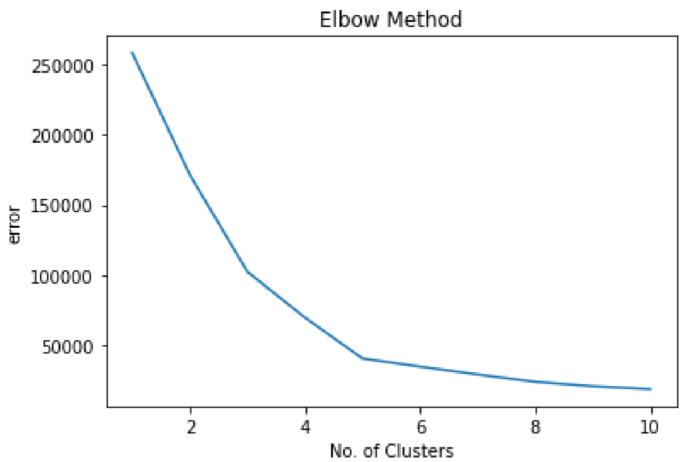
## 8. Scaling the data

```
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_state = 0)
    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_state = 0)
```

```
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, 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:  1.0
```

## 15. Test the Model

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

```
Testing accuracy:  0.975
```

## 16. Measure the performance using Metrics

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

| col_0 | 0 | 1 | 2 | 3 | 4 |
|---|---|---|---|---|---|
| Outcome | | | | | |
| 0 | 11 | 1 | 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      0.92      0.96        12
           1       0.94      1.00      0.97        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                           0.97        40
   macro avg       0.99      0.98      0.99        40
weighted avg       0.98      0.97      0.97        40
```