Mall Customers Dataset

This dataset contains information about people visiting the mall. The dataset has gender, customer id, age, annual income, and spending score

Customer Segmentation is the process of division of customer base into several groups of individuals that share a similarity in different ways that are relevant to marketing such as gender, age, interests, and miscellaneous spending habits.

The technique of customer segmentation is dependent on several key differentiators that divide customers into groups to be targeted. Data related to demographics, geography, economic status as well as behavioral patterns play a crucial role in determining the company direction towards addressing the various segments.

Customer Segmentation is one the most important applications of unsupervised learning. Using clustering techniques, companies can identify the several segments of customers allowing them to target the potential user base. In this machine learning project, we will make use of K-means clustering which is the essential algorithm for clustering unlabeled dataset.

The dataset is from https://www.kaggle.com/shwetabh123/mall-customers

IMPORTING THE LIBRARIES

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

```
/usr/local/lib/python3.6/dist-packages/statsmodels/tools/_testing.py:1
9: FutureWarning: pandas.util.testing is deprecated. Use the functions
in the public API at pandas.testing instead.
  import pandas.util.testing as tm
```

UPLOADING THE DATA TO GOOGLE DRIVE

In [2]:

```
from google.colab import files
uploaded=files.upload()
```

Choose Files No file chosen

Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving mall.csv to mall.csv
```

LOADING THE DATA

In [3]:

```
import io
data = pd.read_csv(io.BytesIO(uploaded['mall.csv']))
```

EDA

View top few rows

In [6]:

```
data.head()
```

Out[6]:

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
0	1	Male	19	15	39
1	2	Male	21	15	81

	CustomerID	Genre	Age	Annual Income (k$)	Spending Score (1-100)
2	3	Female	20	16	6
3	4	Female	23	16	77
4	5	Female	31	17	40

Columns of the dataset

In [7]:
```
data.columns
```

Out[7]:
```
Index(['CustomerID', 'Genre', 'Age', 'Annual Income (k$)',
       'Spending Score (1-100)'],
      dtype='object')
```

Statistical info about the data

In [8]:
```
data.describe()
```

Out[8]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
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

Datatype of the features

In [9]:
```
data.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   Genre                   200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

Size of the data set

In [11]:
```
data.shape
```

Out[11]:
```
(200, 5)
```

Check for null values

In [12]:
```
data.isnull().sum()
```

Out[12]:
```
CustomerID                0
Genre                     0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

No missing data

Number of male and female

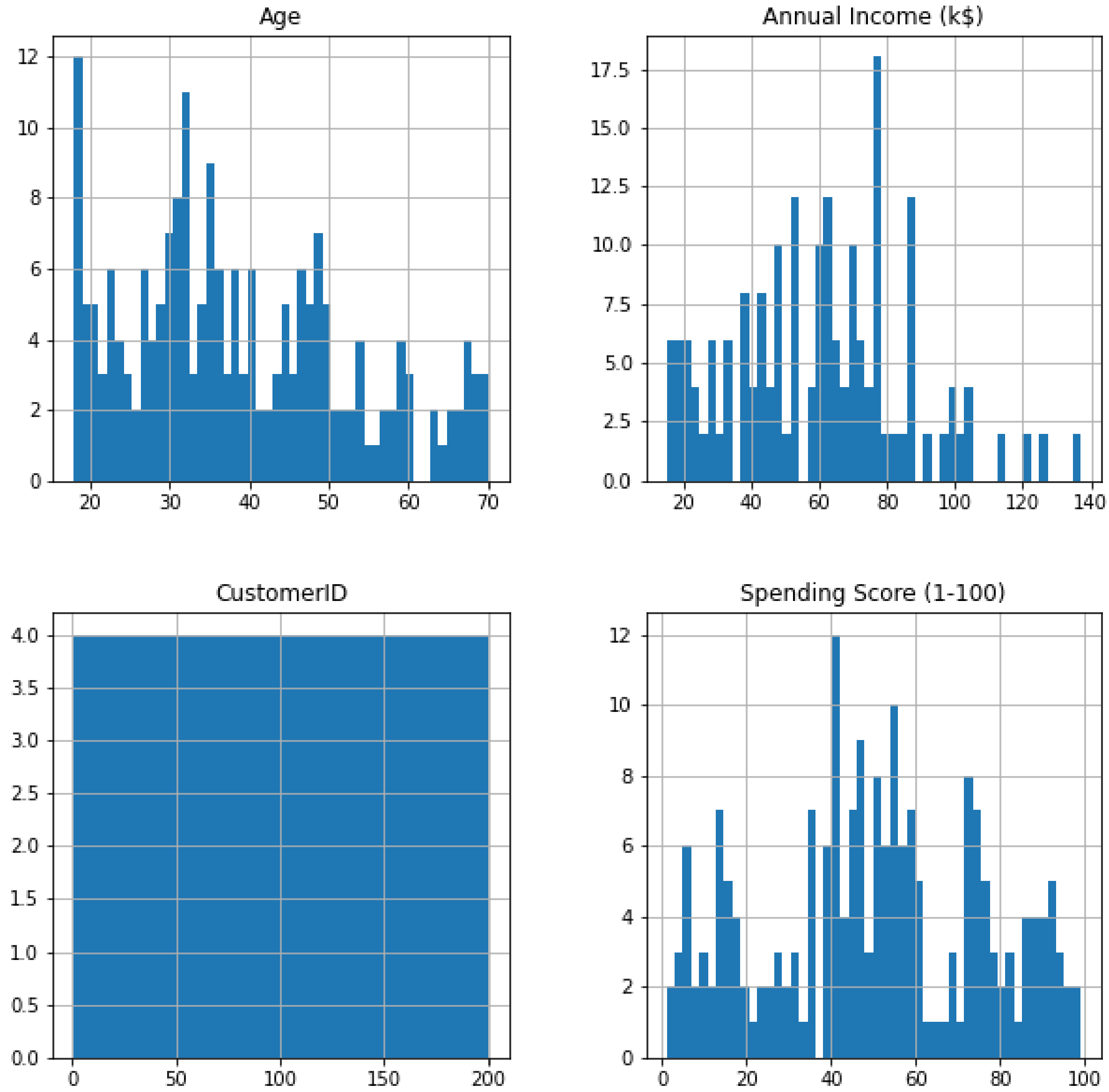
In [13]:
```
data['Genre'].value_counts()
```

Out[13]:
```
Female    112
Male       88
Name: Genre, dtype: int64
```

PLOTTING FEW GRAPHS

In [14]:
```
data.hist(bins=50,figsize=(10,10))
```

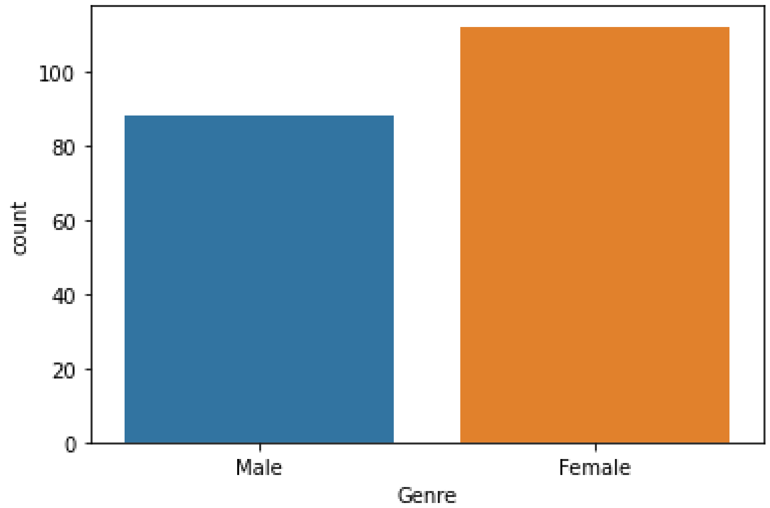
Out[14]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7ff523562b38
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7ff523532e80
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7ff523478128
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7ff5234aa390
>]],
      dtype=object)
```


Age
Annual Income (k$)
CustomerID
Spending Score (1-100)

Plots male vs female

In [16]:
```
sns.countplot(x='Genre',data=data)
```

Out[16]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x7ff522ca8d68>
```



Correlation matrix

In [17]:
```
corr=data.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

Out[17]:

	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
CustomerID	1.00	-0.03	0.98	0.01
Age	-0.03	1.00	-0.01	-0.33
Annual Income (k$)	0.98	-0.01	1.00	0.01
Spending Score (1-100)	0.01	-0.33	0.01	1.00

For the anylsis the CustomerID is not an important feature so we would remove this from the dataset

In [18]:
```
data=data.drop('CustomerID',axis=1)
```

In [19]:
```
corr=data.corr()
corr.style.background_gradient(cmap='coolwarm').set_precision(2)
```

Out[19]:

	Age	Annual Income (k$)	Spending Score (1-100)
Age	1.00	-0.01	-0.33
Annual Income (k$)	-0.01	1.00	0.01
Spending Score (1-100)	-0.33	0.01	1.00

Rename the coulmns

In [24]:
```
data.columns=['gender','age','annual_income','spending_score']
```

In [25]:
```
data.head()
```

Out[25]:

	gender	age	annual_income	spending_score
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

LABEL ENCODING

In [27]:
```
from sklearn.preprocessing import LabelEncoder
```

```
label_encoder=LabelEncoder()

data['gender']=label_encoder.fit_transform(data['gender'])
```

In [28]:
```
data
```

Out[28]:

	gender	age	annual_income	spending_score
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
...	...	...	...	...
195	0	35	120	79
196	0	45	126	28
197	1	32	126	74
198	1	32	137	18
199	1	30	137	83

200 rows × 4 columns

K-Means Algorithm

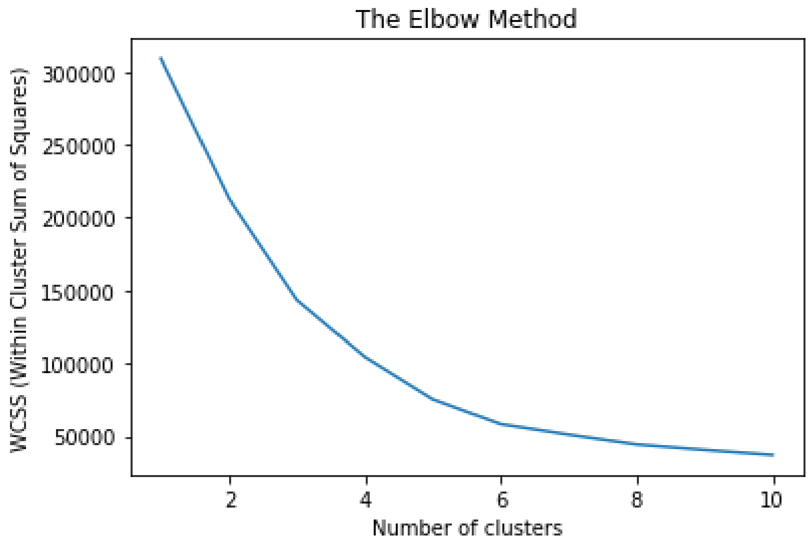
K-means clustering is one of the simplest and popular unsupervised machine learning algorithms.

Every data point is allocated to each of the clusters through reducing the in-cluster sum of squares. In other words, the K-means algorithm identifies k number of centroids, and then allocates every data point to the nearest cluster, while keeping the centroids as small as possible. In here we used elbow Method.

In [20]:
```
from sklearn.cluster import KMeans
```

FINDING THE OPTIMAL VALUE FOR NUMBER OF CLUSTERS

In [30]:
```
wcss=[]
for i in range (1,11):
  kmeans=KMeans(n_clusters=i,init='k-means++',random_state=42)
  kmeans.fit(data)
  wcss.append(kmeans.inertia_)
plt.plot(range(1,11),wcss)
plt.title("The Elbow Method")
plt.xlabel('Number of clusters')
plt.ylabel('WCSS (Within Cluster Sum of Squares)')
plt.show()
```



We find that a value of 5 would be optimal for the Clustering algorithm

Fittig the given data with 5 clusters and prediciting to which cluster they belong

In [52]:
```
X=data
```

In [67]:
```
kmeans=KMeans(n_clusters=5,init='k-means++',random_state=42)
y_kmeans = kmeans.fit_predict(data)
```

In [68]:
```
y_kmeans
```

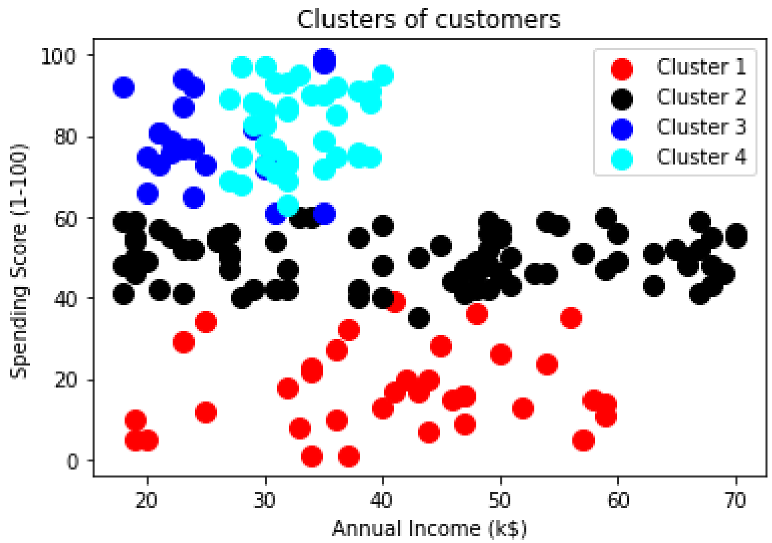
Out[68]:
```
array([4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4,
2,
       4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4, 2, 4,
2,
       4, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
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, 3, 0, 3, 1, 3, 0, 3, 0,
3,
       0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 1, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
3,
       0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
3,
       0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0, 3, 0,
3,
       0, 3], dtype=int32)
```

Plotting the prediction clusters

In [69]:
```
plt.scatter(X[y_kmeans ==0]['age'], X[y_kmeans ==0]['spending_score'],
s=100, c='red',label = 'Cluster 1')
plt.scatter(X[y_kmeans ==1]['age'], X[y_kmeans ==1]['spending_score'],
s=100, c='black',label = 'Cluster 2')
plt.scatter(X[y_kmeans ==2]['age'], X[y_kmeans ==2]['spending_score'],
```

```
s=100, c='blue',label = 'Cluster 3')
plt.scatter(X[y_kmeans ==3]['age'],X[y_kmeans ==3]['spending_score'], s
=100, c='cyan',label = 'Cluster 4')

plt.title('Clusters of customers')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.legend()
plt.show()
```



Plotting an dendogram

In [70]:
```
import scipy.cluster.hierarchy as sch
from sklearn.cluster import AgglomerativeClustering
```

In [71]:
```
# create dendrogram
dendrogram = sch.dendrogram(sch.linkage(X, method='ward'))
# create clusters
hc = AgglomerativeClustering(n_clusters=4, affinity = 'euclidean', link
age = 'ward')
```

```
# save clusters for chart
y_hc = hc.fit_predict(X)
```