#### → ASSIGNMENT 5

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```
Assignment 5:

Take all the columns in mall_customers.csv
gender age annual income spending score
perform label encoding on gender
train your data
```

#### ▼ 1. import necessary libraries.

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

## → 2. import dataset.

```
df = pd.read_csv("Mall_Customers.csv")
df.head()
```

	CustomerID	Genre	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.info()

```
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
                          Non-Null Count Dtype
# Column
0 CustomerID
                           200 non-null
                                           int64
                           200 non-null
                                          obiect
   Genre
1
   Age
                           200 non-null
                                           int64
    Annual Income (k$)
                                           int64
                           200 non-null
4 Spending Score (1-100) 200 non-null
                                           int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

<class 'pandas.core.frame.DataFrame'>

## 

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

df["Genre"] = le.fit_transform(df["Genre"])
```

#### → 3. Select the feature to cluster.

# Selecting annual income and spending as features for clustering.

```
X = df.iloc[:, 1:].values
x
```

```
28,
          76,
    32,
          76,
               87],
              12],
1,
     25,
          77,
 1,
    28,
          77,
          77,
1,
     48,
               36],
     32,
          77,
               74],
 0,
     34,
          78,
               22],
 1,
     34,
          78,
     43,
     39,
 1,
          78,
     44,
          78,
 0,
               201,
 0,
     38,
          78,
               76],
 0,
          78,
               16],
     27,
               89],
0,
          78.
 1,
     37,
          78,
                1],
 0,
     30,
          78,
               78],
 1,
     34,
          78,
 0,
     30,
          78, 73],
     56,
          79,
               35],
               83],
 1,
     19,
          81,
                5],
               931.
 0.
     31.
          81.
     50,
          85,
               26],
 1,
               75],
 0,
    36,
          85,
          86,
 1,
     42,
               20],
          86,
 0.
     33,
               951.
 0.
     36,
          87,
               27],
 1,
    32,
          87,
               63],
     40,
          87,
               13],
 1,
     28,
          87,
     36,
 1,
     36,
               92],
          88, 13],
 0,
    52,
 0,
     30,
          88,
               861,
 1.
     58.
          88.
               151.
 1.
     27,
          88.
               69]
 1.
     59.
          93.
               141.
1,
    35,
          93,
               90],
 0,
     37,
          97,
               32],
    32,
          97,
               86],
     46,
          98.
               15],
 0, 29,
          98,
          99,
 0,
     41,
 1,
    30,
          99,
     54, 101,
 0.
               241.
    28, 101,
 1.
               681.
0.
    41, 103,
               17],
 0,
     36, 103,
0,
     34, 103,
               23],
 0,
     32, 103,
     33, 113,
     38, 113,
               91],
    47, 120, 16],
 0,
    35, 120,
    45, 126,
               28],
 0,
    32, 126,
               74],
 1,
    32, 137,
1,
               18],
1, 30, 137, 83]])
```

type(X)

numpy.ndarray

# ▼ 5. Find the optimal number of clusters -- elbow method.

```
from sklearn.cluster import KMeans

# Trying different values of k and calculating WCSS for each value of k
wcss = []
for k in range(1,11):
    kmeans = KMeans(n_clusters = k, init="k-means++", random_state=0)
    kmeans.fit(X)
    wcss.append(kmeans.inertia_) #savind wcss value in a list

    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
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    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr
    warnings.warn(
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change fr warnings.warn(
```

wcss

```
[308862.06000000006,

212889.44245524303,

143391.59236035676,

104414.67534220168,

75399.61541401484,

58348.641363315044,

51132.703212576904,

44392.11566567935,

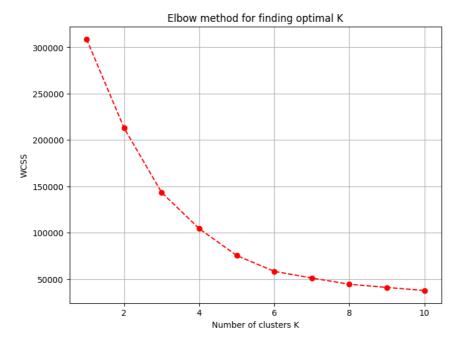
41000.8742213207,

37649.69225429742]

# PLOTTING ELBOW METHOD GRAPH

plt.figure(figsize = (8,6))
```

```
plt.figure(figsize = (8,6))
plt.plot(range(1,11), wcss, "o--", color="red")
plt.title("Elbow method for finding optimal K")
plt.xlabel("Number of clusters K")
plt.ylabel("WCSS")
plt.grid()
plt.show()
```



 $\mbox{\tt\#}$  Taking K=4 instead of K=3 coz WCSS value is low

4

#### 6. Train the model on dataset using optimal cluster value k.

```
kmeans = KMeans(n_{clusters} = 4, init="k-means++", random_state=0) #"k-means++" means initializing the random clusters #return a label for data based on their cluster.

Y_{clusters} = x_{clusters} = x_{clusters}
```

/usr/local/lib/python3.10/dist-packages/sklearn/cluster/\_kmeans.py:870: FutureWarning: The default value of `n\_init` will change fr warnings.warn(

Y\_kmeans

```
array([3, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
                       2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
                       2, 3, 2, 2, 2, 2, 3, 2, 2, 2, 2, 2, 2, 2, 2, 2, 3, 2, 2, 3,
                       2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 2, 1, 0, 1, 0, 1, 0, 1, 0, 1,
                       0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
                       0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,\ 0,\ 1,
                       0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1, 0, 1,
                       0, 1], dtype=int32)
# Age that belongs to cluster 0
X[Y \text{ kmeans} == 0,1]
          array([23, 43, 59, 47, 25, 20, 44, 19, 57, 28, 25, 48, 34, 43, 44, 47, 37,
                       34, 56, 19, 50, 42, 36, 40, 36, 52, 58, 59, 37, 46, 41, 54, 41, 34,
                       33, 47, 45, 32])
# Age that belongs to cluster 1
X[Y_kmeans == 1,1]
          array([39, 31, 40, 38, 39, 31, 29, 32, 35, 32, 32, 28, 32, 34, 39, 38, 27,
                       30, 30, 29, 31, 36, 33, 32, 28, 36, 30, 27, 35, 32, 29, 30, 28, 36, 32, 38, 35, 32, 30])
# Age that belongs to cluster 2
X[Y \text{ kmeans} == 2,1]
          array([20, 31, 35, 64, 67, 58, 37, 35, 52, 35, 46, 54, 45, 40, 60, 53, 49, 42, 36, 65, 48, 49, 50, 27, 29, 31, 49, 31, 59, 50, 47, 51, 69, 27,
                       53, 70, 67, 54, 63, 43, 68, 32, 70, 47, 60, 60, 59, 26, 45, 40, 23,
                       49, 57, 38, 67, 46, 21, 48, 55, 22, 34, 50, 68, 18, 48, 40, 32, 24,
                       47, 27, 48, 20, 23, 49, 67, 26, 49, 21, 66, 54, 68, 66, 65, 19, 38,
                       19, 18, 19, 63, 49, 51, 50, 27, 38, 40])
# Data points that belong to cluster 0
X[Y_kmeans == 0]
          array([[ 0, 23,
                                             70,
                                                       29],
                            1,
                                   43,
                                             71,
                                                       35],
                           1, 59,
                                             71, 11],
                            1, 47,
                                             71,
                                                       9],
                           0, 25,
                                             72, 34],
                                                        5],
                            1, 20,
                                             73.
                           0, 44,
                                                         7],
                                             73.
                            1, 19,
                                             74, 10],
                            0, 57,
                                             75,
                                                       5],
                            0,
                                   28,
                                             76,
                                                       40],
                            1,
                                   25,
                                             77,
                                                       12],
                                   48,
                                             77,
                                                       36],
                            0,
                                   34,
                                             78,
                                                       22],
                            1, 43,
                                             78, 17],
                            0,
                                   44,
                                             78,
                                                       20],
                            0, 47,
                                             78, 16],
                                   37,
                                             78.
                            1,
                                                        1],
                                   34,
                                             78,
                            1,
                                                         1],
                                   56,
                            0,
                                             79, 35],
                            1,
                                  19,
                                             81,
                                                        5],
                            1,
                                   50,
                                             85,
                                                       26],
                            1,
                                   42,
                                             86,
                                                       20],
                            0, 36,
                                             87,
                                                       27],
                            1,
                                   40,
                                             87,
                                                       13],
                            1, 36,
                                             87, 10],
                            0,
                                   52,
                                             88, 13],
                            1,
                                   58,
                                             88, 15],
                                   59,
                                             93, 14],
                            1,
                            0, 37,
                                             97, 32],
                                  46,
                                             98, 15],
                            1,
                            0,
                                   41,
                                             99,
                                                       39],
                                   54, 101,
                            0,
                                                       24],
                            0,
                                   41, 103, 17],
                            0, 34, 103, 23],
                                   33, 113,
                            1,
                            0, 47, 120, 16],
                                   45, 126, 28],
                            0,
                       [ 1, 32, 137, 18]])
```