#### → 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	11.
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()

```
<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
                           200 non-null
                                          object
    Genre
    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
```

# 

```
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,
0,
    32,
          76,
               87],
          77,
               12],
    25,
1,
1.
    28.
          77,
               97],
1,
    48,
          77,
               36],
0,
    32,
          77,
               74],
0,
    34,
          78,
               22],
1,
    34,
          78,
               90],
    43,
1,
          78,
          78,
               201,
    38,
          78,
               761,
0,
          78,
               16],
    27,
          78.
0.
               89],
1,
    37,
          78,
0,
    30,
          78,
               78],
1,
    34.
          78,
    30,
          78,
               73],
               35],
0,
    56,
          79,
               83],
1,
    19,
          81,
                 5],
               931.
0.
    31.
          81.
          85,
    50,
               26],
               75],
0,
    36,
          85,
1,
    42,
          86,
               20],
               95],
0.
    33.
          86,
0.
    36,
          87,
               27],
1,
    32,
          87,
               63],
    40,
          87,
               13],
1,
    28,
          87,
               75],
          88,
0,
    52,
               13],
    30,
          88,
0,
               861,
               15],
    58.
1.
          88.
1.
    27,
          88,
               69]
1.
    59.
          93.
               141.
1,
    35,
          93,
               90],
0,
    37,
          97,
               32],
    32,
          97,
1,
    46,
          98,
               15],
0, 29,
          98,
0,
    41,
1,
    30,
          99,
    54, 101,
0.
               241,
    28, 101,
               681.
1.
0.
    41, 103,
               17],
0,
    36, 103,
    34, 103,
               23],
0,
    32, 103,
               69],
    33, 113,
    38, 113,
    47, 120, 16],
0,
    35, 120,
               79],
    45, 126,
0,
               28],
    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(1,16):
    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 frc
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change frc
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change frc
    warnings.warn(
    /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change frc
    warnings.warn(
```

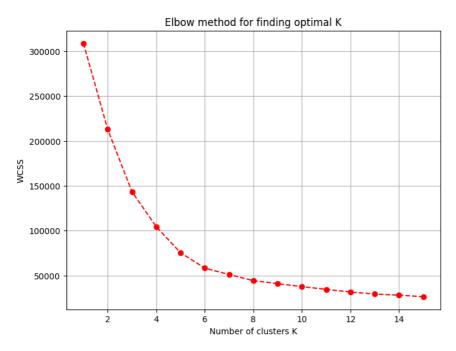
```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                    warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                      warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                      warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
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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 from the control of the con
                    warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                    warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                      warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from
                    warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                      warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                    warnings.warn(
  /usr/local/lib/python3.10/dist-packages/sklearn/cluster/ kmeans.py:870: FutureWarning: The default value of `n init` will change fro
                    warnings.warn(
```

wcss

```
[308862.06000000006,
212889.44245524303,
143391.59236035676,
104414.67534220168,
75399.61541401484,
58348.641363315044,
51132.703212576904,
44392.11566567935,
41000.8742213207,
37649.69225429742,
34665.087277598795,
31659.187454375693,
29388.61288883975,
28170.631036266237,
26470.47953378321]
```

#### # PLOTTING ELBOW METHOD GRAPH

```
plt.figure(figsize = (8,6))
plt.plot(range(1,16), 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()
```



<sup>#</sup> Taking K=6 instead of becausa WCSS value is low

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

```
kmeans = KMeans(n_clusters = 6, init="k-means++", random_state=0) #"k-means++" means initializing the random clusters
#return a label for data based on their cluster.
Y_kmeans = kmeans.fit_predict(X)
              /usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870: FutureWarning: The default value of `n_init` will change from the control of the con
                   warnings.warn(
            4
Y kmeans
 \Rightarrow array([5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 
                                  5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 5, 4, 1, 4, 1, 0,
                                  5, 4, 1, 0, 0, 0, 1, 0, 0, 1, 1, 1, 1, 1, 0, 1, 1, 0, 1, 1, 1, 0,
                                  1, 1, 0, 0, 1, 1, 1, 1, 0, 1, 0, 0, 1, 1, 0, 1, 1, 0, 1, 1, 0,
                                  0, 1, 1, 0, 1, 0, 0, 0, 1, 0, 1, 0, 0, 1, 1, 0, 1, 0, 1, 1, 1, 1,
                                  1, 0, 0, 0, 0, 0, 1, 1, 1, 1, 0, 0, 0, 3, 0, 3, 2, 3, 2, 3, 2,
                                  0, 3, 2, 3, 2, 3, 2, 3, 2, 3, 0, 3, 2, 3, 2, 3, 2, 3, 2, 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, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3,
                                  2, 3], dtype=int32)
                                                                                                                                                                      + Code — + Text
# Age that belongs to cluster 0
X[Y_kmeans == 0,1]
              array([31, 27, 29, 31, 33, 31, 27, 19, 18, 19, 32, 26, 40, 23, 38, 21, 22,
                                  34, 18, 40, 32, 24, 27, 20, 23, 26, 21, 19, 38, 19, 18, 19, 27, 38,
                                  40, 23, 25, 28])
# Age that belongs to cluster 1
X[Y_kmeans == 1,1]
              array([65, 48, 50, 49, 59, 50, 47, 51, 69, 53, 70, 67, 54, 63, 43, 68, 70,
                                  47, 60, 60, 59, 45, 49, 57, 67, 46, 48, 55, 50, 68, 48, 47, 48, 49,
                                  67, 49, 66, 54, 68, 66, 65, 63, 49, 51, 50])
# Age that belongs to cluster 2
X[Y_kmeans == 2,1]
              array([43, 59, 47, 20, 44, 19, 57, 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,
                                  321)
# Data points that belong to cluster 0
X[Y_kmeans == 0]
              array([[ 0, 31, 39, 61],
                                       0, 27, 40, 47],
                                       0, 29, 40, 42],
                                  [ 0, 31, 40, 42],
                                  [ 1, 33, 42, 60],
                                  [ 0, 31, 43, 54],
                                  [ 0, 27, 46, 51],
                                  [ 1, 19, 46, 55],
                                  [ 1, 18, 48, 59],
                                  [ 1, 19, 48, 59],
                                  [ 0, 32, 48, 47],
                                   [ 1, 26, 54, 54],
                                  [ 1, 40, 54, 48],
                                  [ 0, 23, 54, 52],
                                  [ 1, 38, 54, 55],
                                  [ 0, 21, 54, 57],
                                  [ 0, 22, 57, 55],
                                  [ 0, 34, 58, 60],
                                  [ 1, 18, 59, 41],
                                  [ 0, 40, 60, 40],
                                  [ 0, 32, 60, 42],
                                  [ 1, 24, 60, 52],
                                  [ 0, 27, 60, 50],
                                  [ 1, 20, 61, 49],
                                  [ 0, 23, 62, 41],
                                      1, 26, 62, 55],
                                  [ 0, 21, 62, 42],
                                  [ 0, 19, 63, 54],
                                  [ 0, 38, 64, 42],
                                  [ 1, 19, 64, 46],
                                  [ 0, 18, 65, 48],
                                  [ 0, 19, 65, 50],
[ 1, 27, 67, 56],
                                  [ 0, 38, 67, 40],
```

```
[ 0, 40, 69, 58],
[ 0, 23, 70, 29],
[ 0, 25, 72, 34],
[ 0, 28, 76, 40]])
```