22P-9252

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0.2.1 LAB TASK -8

0.3 Problem: 1 - Customer Segmentation using K-means Clustering.

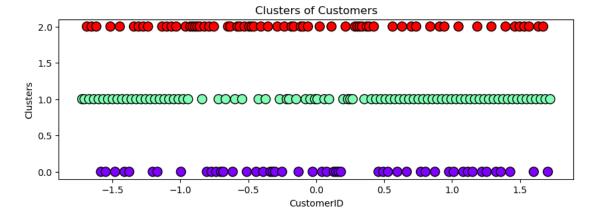
```
[1]: import pandas as pd
df = pd.read_csv('Mall_Customers.csv')
print(df.head())
```

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

```
[2]: from sklearn.impute import SimpleImputer
     from sklearn.preprocessing import StandardScaler
     from sklearn.cluster import KMeans
     from sklearn.preprocessing import LabelEncoder
     # Drop duplicates
     df.drop_duplicates(inplace=True)
     #Encoding
     encoder = LabelEncoder()
     gender_encoded = encoder.fit_transform(df['Gender'])
     df['Gender'] = gender_encoded
     # Replace missing values with the mean of the column
     imputer = SimpleImputer(strategy='mean')
     df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
     print(df.head())
     # Normalization
     print("After Normalization :")
     scaler = StandardScaler()
     df = pd.DataFrame(scaler.fit_transform(df), columns=df.columns)
```

```
# Select the relevant features
           X = df[['Gender','Age','Annual Income (k$)','Spending Score (1-100)']]
           X.head()
                CustomerID Gender
                                                                 Age Annual Income (k$)
                                                                                                                           Spending Score (1-100)
                                                    1.0 19.0
          0
                                 1.0
                                                                                                              15.0
                                                                                                                                                                     39.0
                                 2.0
                                                   1.0 21.0
                                                                                                             15.0
                                                                                                                                                                     81.0
          1
          2
                                 3.0
                                                   0.0 20.0
                                                                                                             16.0
                                                                                                                                                                        6.0
          3
                                 4.0
                                                   0.0 23.0
                                                                                                             16.0
                                                                                                                                                                     77.0
                                 5.0
                                                   0.0 31.0
                                                                                                             17.0
                                                                                                                                                                     40.0
          4
          After Normalization :
[2]:
                      Gender
                                                    Age Annual Income (k$)
                                                                                                              Spending Score (1-100)
           0 1.128152 -1.424569
                                                                                     -1.738999
                                                                                                                                             -0.434801
           1 1.128152 -1.281035
                                                                                     -1.738999
                                                                                                                                               1.195704
           2 -0.886405 -1.352802
                                                                                     -1.700830
                                                                                                                                             -1.715913
           3 -0.886405 -1.137502
                                                                                     -1.700830
                                                                                                                                              1.040418
           4 -0.886405 -0.563369
                                                                                     -1.662660
                                                                                                                                             -0.395980
[3]: #Model
           kmeans = KMeans(n_clusters=3, random_state=0,n_init=10)
           kmeans.fit(X)
           centroids = kmeans.cluster centers
           print("Centroids:")
           print(centroids)
           labels = kmeans.labels_
           print("\nLabels:")
           print(labels)
          Centroids:
          [[ 1.12815215  0.74307816  0.06431159  -0.79449512]
            [ 0.03792108 -0.77529133  0.04688104  0.88056434]
            [-0.88640526  0.44680201  -0.10812358  -0.5442077 ]]
          Labels:
          [1 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 0 \ 1 \ 0 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \ 1 \ 2 \
            \begin{smallmatrix} 0 & 1 & 2 & 0 & 1 & 2 & 0 & 0 & 0 & 2 & 1 & 0 & 2 & 1 & 1 & 2 & 2 & 1 & 0 & 2 & 2 & 1 & 2 & 1 & 0 & 1 & 1 & 2 & 0 & 1 & 0 & 1 & 2 & 0 & 0 & 0 & 0 \\ \end{smallmatrix}
            1 2 1 2 1 2 1 0 1 2 1 2 1 0 1]
[4]: identified_clusters = kmeans.fit_predict(X)
           identified_clusters
```

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

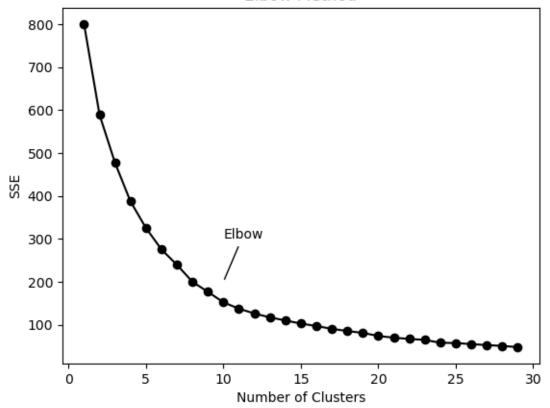


0.4 Problem: 2 - Optimal number of clusters

```
[6]: sse = []
for k in range(1, 30):
    kmeans = KMeans(n_clusters=k, random_state=0, n_init=10, max_iter=1000)
    kmeans.fit(X)
    sse.append(kmeans.inertia_)

number_clusters = range(1,30)
plt.plot(number_clusters, sse, marker='o', color='black')
plt.annotate('Elbow', xy=(10, 200), xytext=(10, 300), arrowprops={'arrowstyle':u'-'})
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()
```

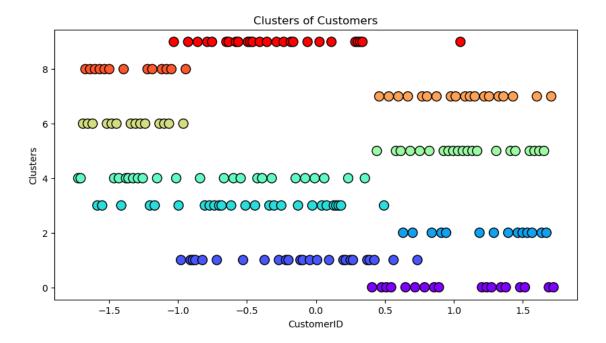
Elbow Method



```
[7]: kmeans = KMeans(n_clusters=10, random_state=0, n_init=10)
kmeans.fit(X)
```

```
centroids = kmeans.cluster_centers_
     print("Centroids:")
     print(centroids)
     labels = kmeans.labels_
     print("\nLabels:")
     print(labels)
    Centroids:
     [[ 1.12815215 -0.39989994 1.01344075 1.26040667]
     [-0.88640526 -0.78153925 -0.12214217 -0.11957041]
     [-0.88640526  0.35421988  1.24912183  -1.14745442]
     [ 1.12815215 -0.97602698 -0.73705168  0.41603773]
      [-0.88640526 -0.47793198 0.97284787 1.22158511]
      [ 1.12815215 -0.02700694  0.96701244 -1.39716754]
      [-0.88640526 -0.96084556 -1.33087991 1.17778643]
     [-0.88640526 1.09830638 -0.24158313 -0.04807901]]
    Labels:
     [4\ 4\ 6\ 8\ 6\ 8\ 6\ 8\ 3\ 8\ 3\ 8\ 6\ 8\ 6\ 4\ 6\ 4\ 3\ 8\ 4\ 4\ 6\ 4\ 6\ 4\ 6\ 4\ 6\ 8\ 3\ 8\ 3\ 4\ 6\ 8\ 6
      \begin{smallmatrix} 8 & 6 & 8 & 9 & 4 & 3 & 1 & 6 & 8 & 9 & 1 & 1 & 1 & 9 & 4 & 1 & 3 & 9 & 3 & 9 & 3 & 1 & 3 & 3 & 4 & 9 & 9 & 3 & 4 & 9 & 9 & 4 & 1 & 3 & 9 & 9 \\ \end{smallmatrix} 
     3\ 4\ 9\ 4\ 1\ 9\ 3\ 4\ 3\ 9\ 1\ 3\ 9\ 1\ 1\ 9\ 9\ 4\ 3\ 1\ 1\ 4\ 9\ 1\ 3\ 4\ 1\ 9\ 3\ 4\ 3\ 1\ 9\ 3\ 3\ 3\ 3
     1\; 1\; 4\; 1\; 1\; 9\; 9\; 9\; 9\; 4\; 1\; 1\; 0\; 1\; 5\; 7\; 0\; 3\; 0\; 7\; 0\; 1\; 5\; 7\; 5\; 2\; 0\; 7\; 5\; 2\; 0\; 1\; 5\; 7\; 0\; 7\; 5
     2 0 7 0 2 5 2 5 7 5 7 5 9 5 7 5 7 5 7 5 2 0 7 0 7 0 2 5 7 0 7 0 2 5 7 5 2
     0 2 0 2 5 2 5 7 5 2 5 2 0 7 0]
[8]: identified clusters = kmeans.fit predict(X)
     data with clusters = df.copy()
     data with_clusters['Clusters'] = identified_clusters
     fig = plt.figure(figsize=(10,5))
     plt.subplots_adjust(left=0.125, right=0.9, bottom=0.1, top=0.9)
     data_with_clusters = df.copy()
     data_with_clusters['Clusters'] = identified_clusters
     plt.scatter(data_with_clusters['CustomerID'], labels,__
      oc=data_with_clusters['Clusters'], cmap='rainbow', s=100,edgecolors='black')
     plt.title('Clusters of Customers')
     plt.xlabel('CustomerID')
     plt.ylabel('Clusters')
```

plt.show()



[]: