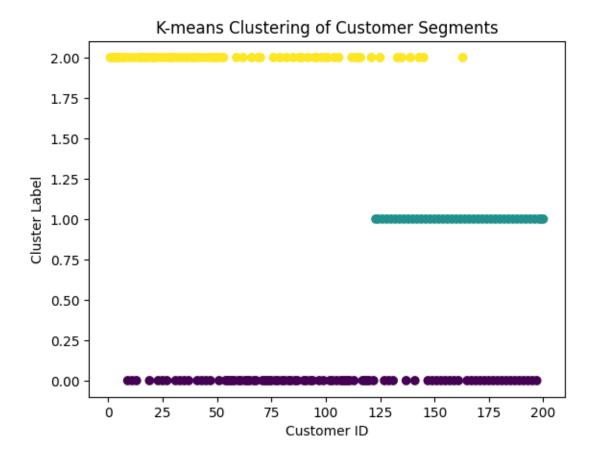
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March 29, 2024

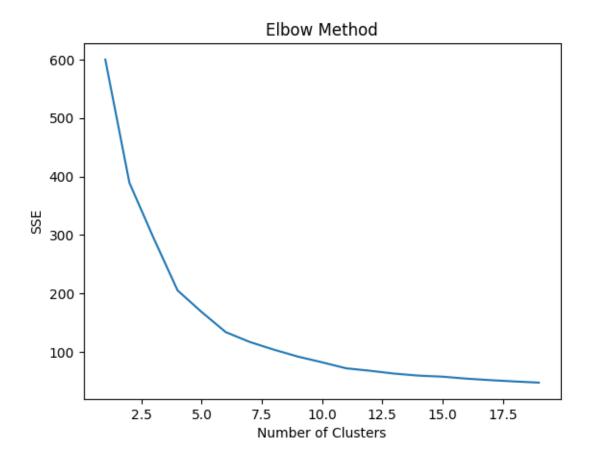
```
[39]: from sklearn.impute import SimpleImputer
      from sklearn.preprocessing import StandardScaler, LabelEncoder
      from sklearn.cluster import KMeans
      import matplotlib.pyplot as plt
      import pandas as pd
      # Load the dataset
      df = pd.read_csv('Mall_Customers.csv')
[40]: # Drop duplicates
      df.drop_duplicates(inplace=True)
[41]: # Encode the categorical column 'Gender'
      encoder = LabelEncoder()
      gender_encoded = encoder.fit_transform(df['Gender'])
      df['Gender'] = gender_encoded
[42]: # Replace missing values with the mean of the column
      imputer = SimpleImputer(strategy='mean')
      df = pd.DataFrame(imputer.fit_transform(df), columns=df.columns)
[43]: # Normalize the data
      scaler = StandardScaler()
      df_normalized = pd.DataFrame(scaler.fit_transform(df[['Age', 'Annual Income_
       ⇔(k$)', 'Spending Score (1-100)']]), columns=['Age', 'Annual Income (k$)', □

¬'Spending Score (1-100)'])
[44]: # Select the relevant features
      X = df_normalized[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
[45]: # K-means clustering
      kmeans = KMeans(n_clusters=3, n_init=10, max_iter=300, random_state=0)
      kmeans.fit(X)
      identified_clusters = kmeans.predict(X)
[46]: # Centroids
      centroids = kmeans.cluster centers
```

```
print("Centroids:")
                  print(centroids)
                Centroids:
                 [-0.43033758 1.02223317 1.15593564]
                   [-0.93381128 -0.67979753 0.1338202 ]]
[47]: # Getting the labels assigned to each data point
                  labels = kmeans.labels_
                  print("\nLabels:")
                  print(labels)
                Labels:
                \begin{smallmatrix} 2 & 0 & 2 & 2 & 2 & 0 & 0 & 0 & 0 & 2 & 0 & 1 & 1 & 2 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 2 & 1 & 2 & 1 & 0 & 1 & 2 & 1 & 2 & 1 & 0 & 1 \\ \end{smallmatrix}
                   \begin{smallmatrix} 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 0 & 1 & 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 & 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 & 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 & 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 & 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 & 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 & 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 0 1 0 1 1 1]
[48]: # Visualize the resulting clusters
                 plt.scatter(df['CustomerID'], labels, c=labels, cmap='viridis')
                  plt.xlabel('Customer ID')
                  plt.ylabel('Cluster Label')
                  plt.title('K-means Clustering of Customer Segments')
                  plt.show()
```



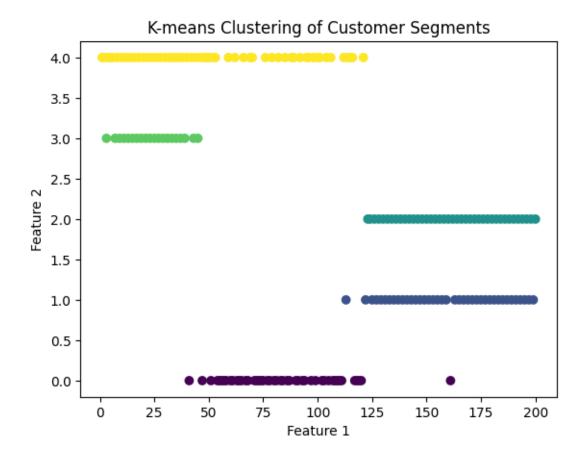
```
[49]: # Elbow Method to determine the optimal number of clusters
sse = []
for k in range(1, 20):
    kmeans = KMeans(n_clusters=k,n_init=10, max_iter=300, random_state=0)
    kmeans.fit(X)
    sse.append(kmeans.inertia_)
number_clusters = range(1,20)
plt.plot(number_clusters, sse)
plt.title('Elbow Method')
plt.xlabel('Number of Clusters')
plt.ylabel('SSE')
plt.show()
```



Question 2

```
[50]: new_data = X
kmeans = KMeans(n_clusters=5, max_iter=300, n_init=10, random_state=0)
kmeans.fit(X)
labels = kmeans.predict(new_data)
# print(labels)

# Visualize the resulting clusters
plt.scatter(df['CustomerID'], labels, c=labels, label='centroids',u
cmap='viridis')
plt.xlabel('Feature 1')
plt.ylabel('Feature 2')
plt.title('K-means Clustering of Customer Segments')
plt.show()
```



 $\label{lambda} \begin{array}{lll} data_with_clusters &=& data.copy() & data_with_clusters[`Clusters'] &=& identified_clusters \\ plt.scatter(data_with_clusters[`Longitude'], data_with_clusters[`Latitude'], c=data_with_clusters[`Clusters'], c=data_with_clu$