Importing Libraries and Data

```
import pandas as pd
import numpy as np

# Exploratory Data Analysis (EDA)
import plotly.express as px
import seaborn as sns
import matplotlib.pyplot as plt

# Modelling
import scipy.cluster.hierarchy as sch
from sklearn.cluster import KMeans
from sklearn.cluster import DBSCAN
from sklearn.cluster import AgglomerativeClustering
from sklearn.metrics import silhouette_score
from sklearn.metrics import davies_bouldin_score
```

```
df_segmentation = pd.read_csv("segmentation data.csv")
```

Project Objectives

The primary objective of this project is to perform a customer segmentation analysis using machine learning techniques. By clustering customers based on their demographic and behavioral characteristics, we aim to uncover distinct groups within the customer base. This segmentation will enable us to:

- Understand Customer Profiles: Identify and understand the different types of customers, including their purchasing behaviors and preferences.
- Personalize Marketing Strategies: Develop targeted marketing campaigns and personalized strategies for each customer segment to improve customer engagement and satisfaction.
- Enhance Business Decision-Making: Provide valuable insights for data-driven decision-making in areas such as product development, pricing strategies, and customer service enhancements.
- Improve Resource Allocation: Allocate resources more effectively by focusing on high-value customer segments and optimizing marketing and operational efforts.
- Increase Revenue and Profitability: Ultimately, drive business growth by increasing customer retention, enhancing customer lifetime value, and acquiring new customers through more effective segmentation strategies.

By achieving these objectives, the project will contribute to a deeper understanding of our customer base, leading to more informed business strategies and improved overall performance.

Exploratory Data Analysis (EDA)

- Data Understanding: check the data types of each column to ensure they are appropriate for the analysis and calculate basic statistics (mean, median, standard deviation, etc.) to get an overview of the data distribution.
- Data Cleaning: identify and handle missing values through imputation or removal, depending on the context, and detect and address outliers that might skew the analysis.
- Data Transformation: convert categorical variables (Gender) into numerical format.
- Data Visualization: use scatter plots, and histograms to explore relationships between pairs of variables.

```
df_segmentation.head()
```

	CustomerID	Gender	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_segmentation.dtypes
```

```
CustomerID                 int64
Gender                    object
Age                        int64
Annual Income (k$)         int64
Spending Score (1-100)     int64
dtype: object
```

```
df_segmentation.describe()
```

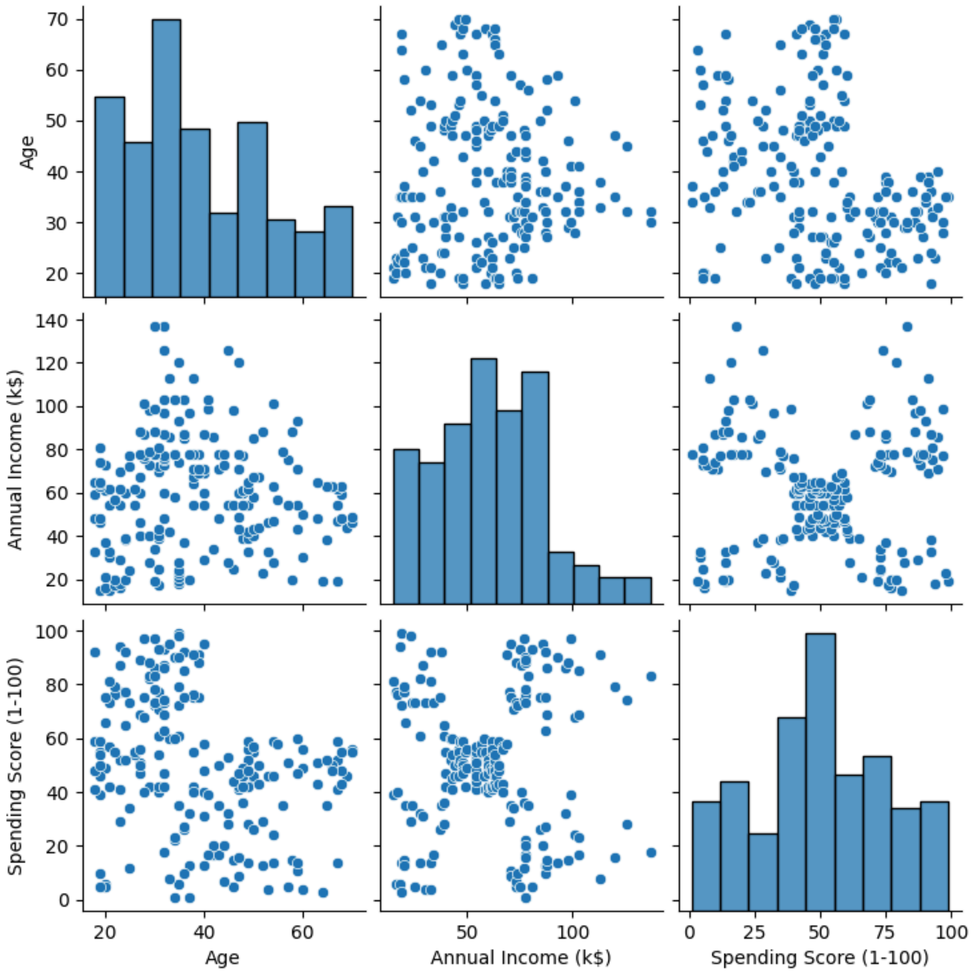
	CustomerID	Age	Annual Income (k$)	Spending Score (1-100)
count	200.000000	200.000000	200.000000	200.000000
mean	100.500000	38.850000	60.560000	50.200000
std	57.879185	13.969007	26.264721	25.823522
min	1.000000	18.000000	15.000000	1.000000
25%	50.750000	28.750000	41.500000	34.750000
50%	100.500000	36.000000	61.500000	50.000000
75%	150.250000	49.000000	78.000000	73.000000
max	200.000000	70.000000	137.000000	99.000000

```
# Searching for null values

null_counts = df_segmentation.isnull().sum()
total_rows = len(df_segmentation)
null_percentage = (null_counts / total_rows) * 100

null_summary_df = pd.DataFrame({
    'Column': null_counts.index,
    'Total Values': total_rows,
    'Null Values': null_counts.values,
    'Percentage': null_percentage.values
})
print(null_summary_df)
```

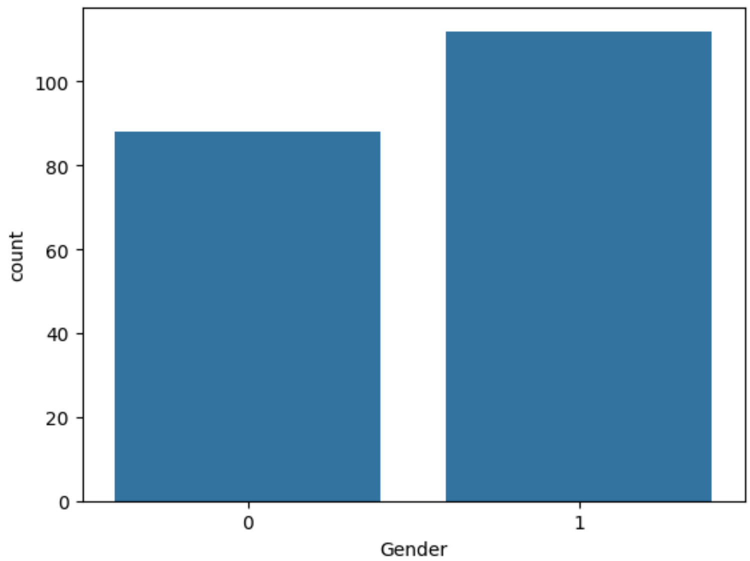
```
                   Column  Total Values  Null Values  Percentage
0              CustomerID           200            0         0.0
1                  Gender           200            0         0.0
2                     Age           200            0         0.0
3      Annual Income (k$)           200            0         0.0
4  Spending Score (1-100)           200            0         0.0
```

```
# Format Gender to binary

df_segmentation['Gender'] = df_segmentation['Gender'].map({'Male': 0, 'Female': 1})
```

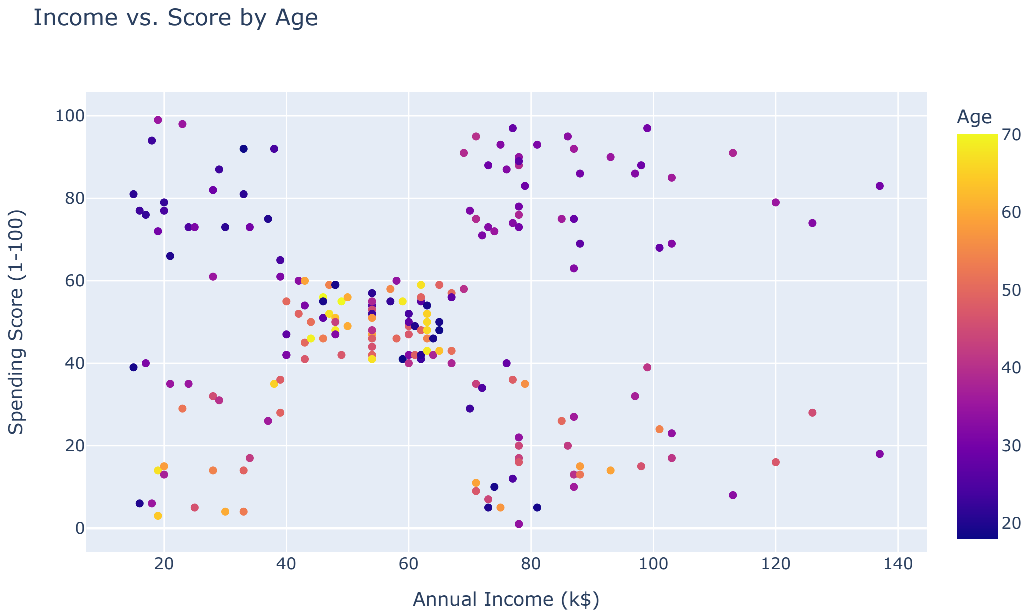
```
# Distribution of numerical variables

sns.pairplot(df_segmentation[['Age', 'Annual Income (k$)', 'Spending Score (1-100)']])
plt.show()
```




```
# Gender distribution ====> Male = 0 and Female = 1

sns.countplot(x='Gender', data=df_segmentation)
plt.show()
```




```
fig  = px.scatter(df_segmentation, x = 'Annual Income (k$)', y = 'Spending Score (1-100)', width = 800, color = "Age",title = 'Income vs
fig.show()
```



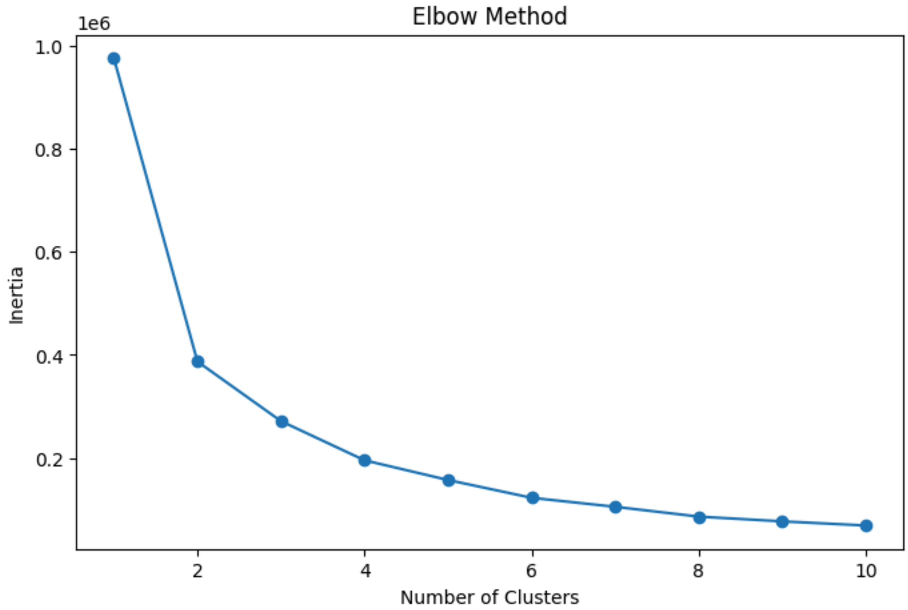

```
fig  = px.scatter(df_segmentation, x = 'Annual Income (k$)', y = 'Age', width = 800, color = "Gender",title = 'Income vs. Age by Gender
fig.show()
```

Modelling

- Model Selection: choose appropriate clustering algorithms based on the data characteristics and analysis goals (K-means, DBSCAN, Agglomerative Clustering) experimenting with different parameters (number of clusters in K-means and AC, eps in DBSCAN) to find the optimal configuration.
- Model Training: apply the algorithm to the data to create the model.
- Model Evaluation: evaluate the quality of clusters using metrics like silhouette score and Davies-Bouldin index. After visualize the resulting clusters using scatter plots to understand their structure and distribution.

K-Means

```
# Determine inertia for different numbers of clusters

inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, random_state=42, n_init = 10)
    kmeans.fit(df_segmentation)
    inertia.append(kmeans.inertia_)

# Plot the elbow graph
plt.figure(figsize=(8, 5))
plt.plot(range(1, 11), inertia, marker='o')
plt.xlabel('Number of Clusters')
plt.ylabel('Inertia')
plt.title('Elbow Method')
plt.show()
```

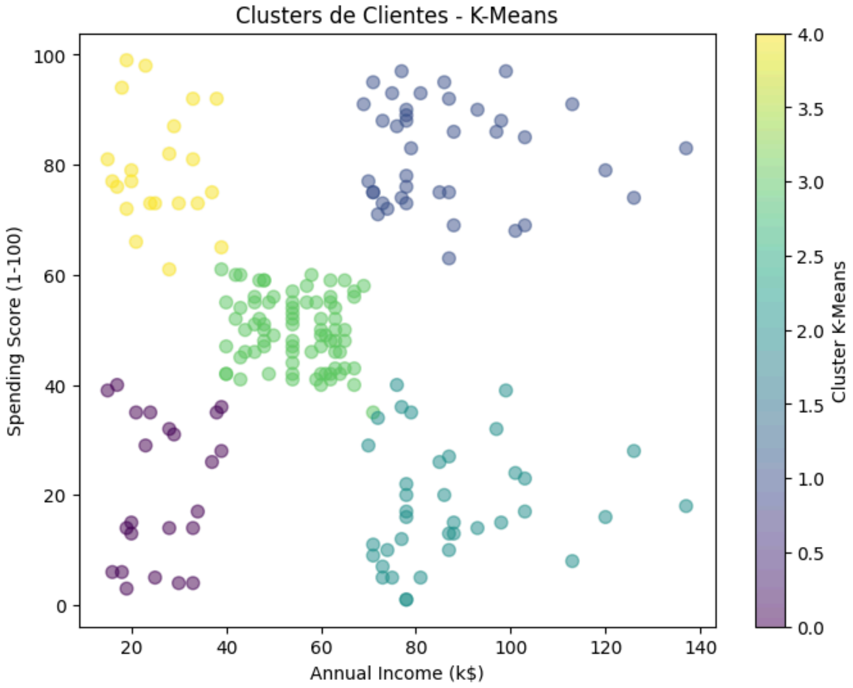



```
# Setting K-Means

features_kmeans = df_segmentation.iloc[:, 1:] # Remove Id
k = 5
kmeans = KMeans(n_clusters=k, init='k-means++', random_state=42,n_init = 10)
Clusters_KMeans = kmeans.fit_predict(features_kmeans)
features_kmeans.loc[:, 'Cluster'] = Clusters_KMeans
```

```
# Analyze cluster characteristics

cluster_analysis = features_kmeans.groupby('Cluster').mean()
print(cluster_analysis)
```

```
           Gender        Age  Annual Income (k$)  Spending Score (1-100)
Cluster
0        0.608696  45.217391           26.304348               20.913043
1        0.538462  32.692308           86.538462               82.128205
2        0.486486  40.324324           87.432432               18.189189
3        0.582278  43.126582           54.822785               49.835443
4        0.590909  25.272727           25.727273               79.363636
```

```
# Cluster Plot

plt.figure(figsize=(8, 6))
plt.scatter('Annual Income (k$)', 'Spending Score (1-100)', data=features_kmeans, c='Cluster',cmap='viridis', s=50, alpha=0.5)
plt.title('Clusters de Clientes - K-Means')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.colorbar(label='Cluster K-Means')
plt.show()
```

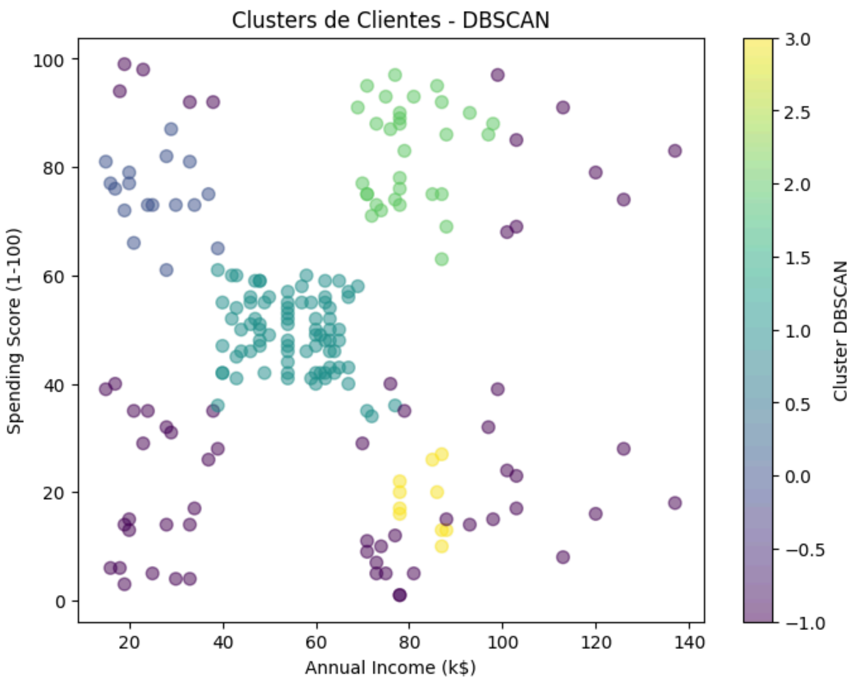


DBSCAN

```
# Setting DBSCAN

features_DBSCAN = df_segmentation.iloc[:, 1:] # Remove Id
dbscan = DBSCAN(eps=13, min_samples=10)
Clusters_DBSCAN = dbscan.fit_predict(features_DBSCAN)
features_DBSCAN.loc[:, 'Cluster'] = Clusters_DBSCAN


# Analyze cluster characteristics

cluster_analysis = features_DBSCAN.groupby('Cluster').mean()
print(cluster_analysis)
```

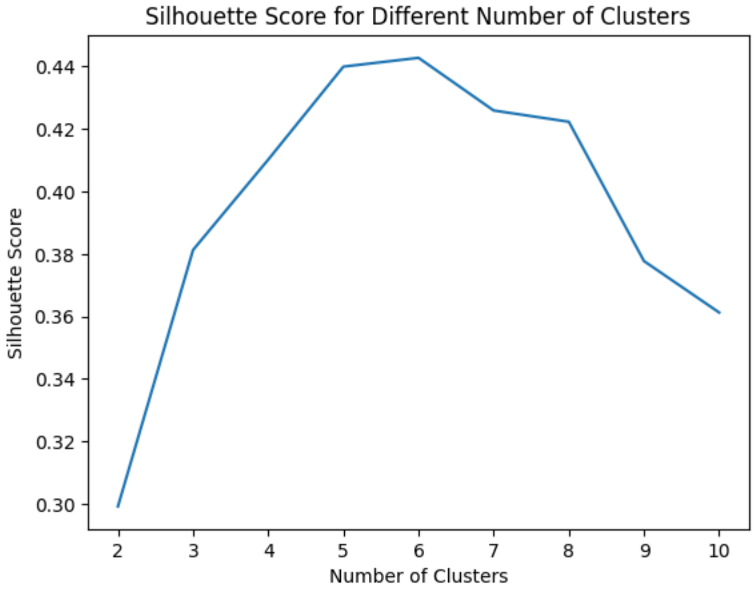
```
           Gender        Age  Annual Income (k$)  Spending Score (1-100)
Cluster
-1       0.550000  39.716667           64.216667               33.083333
 0       0.588235  24.764706           25.588235               74.764706
 1       0.573171  43.024390           55.109756               49.304878
 2       0.548387  32.709677           79.774194               82.483871
 3       0.500000  42.400000           83.200000               18.400000
```

```
# Cluster Plot

plt.figure(figsize=(8, 6))
plt.scatter('Annual Income (k$)', 'Spending Score (1-100)', data=features_DBSCAN, c='Cluster',cmap='viridis', s=50, alpha=0.5)
plt.title('Clusters de Clientes - DBSCAN')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.colorbar(label='Cluster DBSCAN')
plt.show()
```



Agglomerative Clustering

```
# Finding the best Cluster Number

features_AC = df_segmentation.iloc[:, 1:] # Remove Id
def find_optimal_clusters(features_DBSCAN, max_clusters=10):
    silhouette_scores = []

    for n_clusters in range(2, max_clusters+1):
        model = AgglomerativeClustering(n_clusters=n_clusters)
        labels = model.fit_predict(features_AC)
        silhouette_avg = silhouette_score(features_AC, labels)
        silhouette_scores.append(silhouette_avg)

    # Plot the silhouette scores

    plt.plot(range(2, max_clusters+1), silhouette_scores)
    plt.xlabel('Number of Clusters')
    plt.ylabel('Silhouette Score')
    plt.title('Silhouette Score for Different Number of Clusters')
    plt.show()

    optimal_clusters = np.argmax(silhouette_scores) + 2  # +2 because the range starts at 2

    return optimal_clusters


optimal_clusters = find_optimal_clusters(features_DBSCAN, max_clusters=10)
print("Best Cluster Number:", optimal_clusters)
```




```
Best Cluster Number: 6
```

```
# Setting Agglomerative Clustering

model = AgglomerativeClustering(n_clusters=5) # I will use the cluster number 5 due to the silhouette score plot
Clusters_AC = model.fit_predict(features_kmeans)
features_AC.loc[:, 'Cluster'] = Clusters_AC


# Analyze cluster characteristics

cluster_analysis = features_AC.groupby('Cluster').mean()
print(cluster_analysis)
```

```
           Gender        Age  Annual Income (k$)  Spending Score (1-100)
Cluster
0        0.602410  42.156627           54.759036               49.771084
1        0.428571  41.685714           88.228571               17.285714
2        0.538462  32.692308           86.538462               82.128205
3        0.600000  24.850000           24.950000               81.000000
4        0.608696  45.217391           26.304348               20.913043
```

```
# Cluster Plot

plt.figure(figsize=(8, 6))
plt.scatter('Annual Income (k$)', 'Spending Score (1-100)', data=features_AC, c='Cluster',cmap='viridis', s=50, alpha=0.5)
plt.title('Clusters de Clientes - Agglomerative Clustering')
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.colorbar(label='Cluster Agglomerative Clustering')
plt.show()
```

Model Evaluation

```
# Setting Models

n_clusters = 5

models = {
    'KMeans': KMeans(n_clusters=n_clusters, random_state=42,n_init = 10),
    'DBSCAN': DBSCAN(eps=13, min_samples=10), # same parameters from previous model
    'AgglomerativeClustering': AgglomerativeClustering(n_clusters=n_clusters)
}
```

```
# Clustering Evaluation with Silhouette Score and  Davies Bouldin Index

silhouette_scores = {}
davies_bouldin_indices = {}
labels_dict = {}
features = df_segmentation.iloc[:, 1:]

for name, model in models.items():
    # Train
    labels = model.fit_predict(features)
    labels_dict[name] = labels

    # Performance
    silhouette_avg = silhouette_score(features, labels)
    db_index = davies_bouldin_score(features, labels)

    silhouette_scores[name] = silhouette_avg
    davies_bouldin_indices[name] = db_index

    print(f'{name} - Silhouette Score: {silhouette_avg}, Davies-Bouldin Index: {db_index}')
```

```
KMeans - Silhouette Score: 0.44424291275274114, Davies-Bouldin Index: 0.8196433344356222
DBSCAN - Silhouette Score: 0.18699358696080978, Davies-Bouldin Index: 2.28192907500783
AgglomerativeClustering - Silhouette Score: 0.43997527212476695, Davies-Bouldin Index: 0.8220436090843712
```

```
# Plot

fig, axes = plt.subplots(1, 3, figsize=(18, 5))

for ax, (name, labels) in zip(axes, labels_dict.items()):
    ax.scatter('Annual Income (k$)', 'Spending Score (1-100)', data=features, c=labels, cmap='viridis', marker='o')
    ax.set_title(f'{name} Clustering')
    ax.set_xlabel('Annual Income (k$)')
    ax.set_ylabel('Spending Score (1-100)')

plt.show()
```