Clustering Implementation - Mall Customers Segmentation

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In [1]:

```
import pandas as pd
import numpy as np

import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

from sklearn.cluster import KMeans,AgglomerativeClustering,DBSCAN
from sklearn.metrics import silhouette_score,davies_bouldin_score

from scipy.cluster.hierarchy import dendrogram

import warnings
warnings.filterwarnings('ignore')

%matplotlib inline
```

Data Ingestion

In [2]:

```
raw_df = pd.read_csv("https://raw.githubusercontent.com/NelakurthiSudheer/Mall-Customers-Segmentation/main/Dataset/Mall_Cust
```

In [3]:

```
print(f"This dataset contains {raw_df.shape[0]} rows and {raw_df.shape[1]} columns")
```

```
This dataset contains 200 rows and 5 columns
```

In [4]:

```
df=raw_df.copy()
```

Profile of the Data

In [6]:

```
df.duplicated().sum()
```

Out[6]:

```
0
```

In [7]:

```
df.isnull().sum()
```

Out[7]:

```
CustomerID                0
Gender                    0
Age                       0
Annual Income (k$)        0
Spending Score (1-100)    0
dtype: int64
```

In [8]:

```
df.describe().T
```

Out[8]:

	count	mean	std	min	25%	50%	75%	max
CustomerID	200.0	100.50	57.879185	1.0	50.75	100.5	150.25	200.0
Age	200.0	38.85	13.969007	18.0	28.75	36.0	49.00	70.0
Annual Income (k$)	200.0	60.56	26.264721	15.0	41.50	61.5	78.00	137.0
Spending Score (1-100)	200.0	50.20	25.823522	1.0	34.75	50.0	73.00	99.0

In [9]:

```
df.describe(include='object').T
```

Out[9]:

	count	unique	top	freq
Gender	200	2	Female	112

Exploratory Data Analysis

In [5]:
```
from pandas_profiling import ProfileReport

# EDA using pandas-profiling
profile = ProfileReport(df, explorative=True)

# Displaying report in notebook cell.
profile.to_notebook_iframe()
```

Summarize dataset: 100% 35/35 [00:18<00:00, 2.28it/s, Completed]

Generate report structure: 100% 1/1 [00:07<00:00, 7.12s/it]

Render HTML: 100% 1/1 [00:02<00:00, 2.27s/it]

Overview

Dataset statistics

Number of variables	5
Number of observations	200
Missing cells	0
Missing cells (%)	0.0%
Duplicate rows	0
Duplicate rows (%)	0.0%
Total size in memory	18.5 KiB
Average record size in memory	94.8 B

Variable types

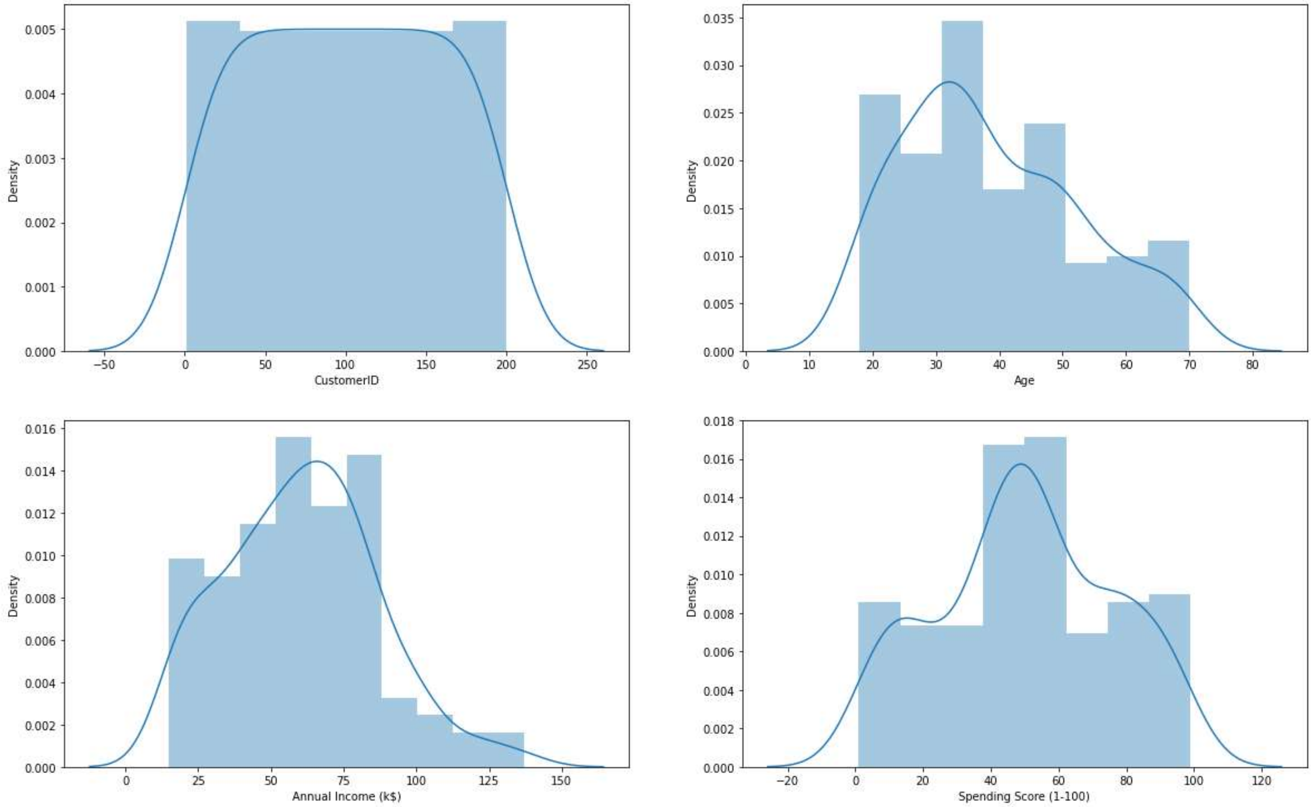
Numeric	4
Categorical	1

Alerts

`CustomerID` is highly correlated with `Age` and 2 other fields (Age, Annual Income (k$), Spending Score (1-100))	High correlation
`Annual Income (k$)` is highly correlated with `CustomerID` and 1 other fields (CustomerID, Spending Score (1-100))	High correlation
`Age` is highly correlated with `CustomerID` and 1 other fields (CustomerID, Spending Score (1-100))	High correlation
`Spending Score (1-100)` is highly correlated with `CustomerID` and 2 other fields (CustomerID, Age, Annual Income (k$))	High correlation
`CustomerID` is uniformly distributed	Uniform

In [7]:

```
cols = ['CustomerID','Age', 'Annual Income (k$)', 'Spending Score (1-100)']
plt.figure(figsize=(20,40), facecolor='white')

for i in range(0, len(cols)):
    plt.subplot(6, 2, i+1)
    sns.distplot(x=df[cols[i]],kde=True)
    plt.xlabel(cols[i])
```



In [10]:

```
df.Gender.value_counts()
```

Out[10]:

```
Female    112
Male       88
Name: Gender, dtype: int64
```

In [11]:

```
df.Gender.replace(('Male', 'Female'),(0,1), inplace=True)
```

In [12]:

```
k_df=df.iloc[:,-2:]
```

In [13]:

```
k_df.head()
```

Out[13]:

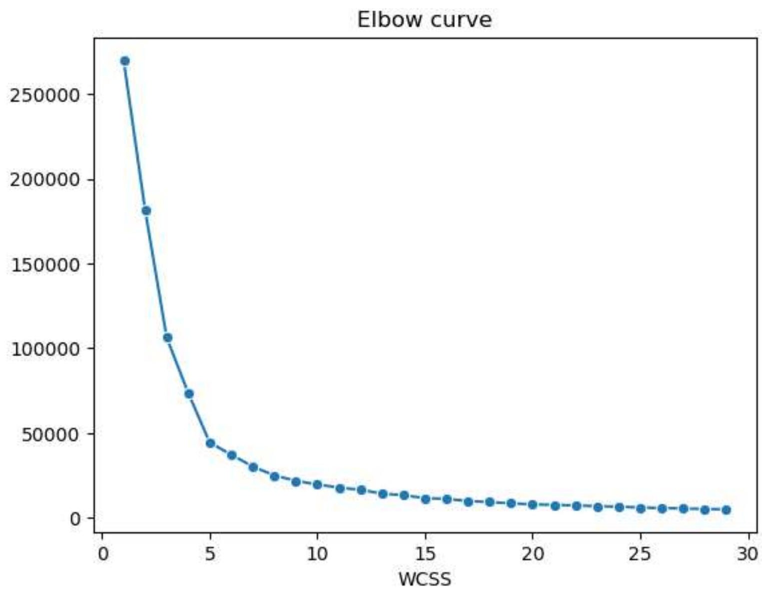
	Annual Income (k$)	Spending Score (1-100)
0	15	39
1	15	81
2	16	6
3	16	77
4	17	40

K-Means

In [14]:
```
# Experimenting with different k values

wcss=[]
l1 = list(np.arange(1,30))

for i in l1:
    kmeans=KMeans(n_clusters=i,init='k-means++',random_state=40)
    kmeans.fit(k_df)
    wcss.append(kmeans.inertia_)
```

In [15]:
```
sns.lineplot(x=l1, y=wcss,marker='o')
plt.xlabel('number of clusters')
plt.xlabel('WCSS')
plt.title("Elbow curve")
```

Out[15]:
```
Text(0.5, 1.0, 'Elbow curve')
```



In [16]:
```
kmeans=KMeans(n_clusters=5,init='k-means++',random_state=40)
```

In [17]:
```
kmeans.fit(k_df)
```

Out[17]:
```
KMeans
KMeans(n_clusters=5, random_state=40)
```

In [18]:
```
kmeans.predict(k_df)
```

Out[18]:
```
array([0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4,
       0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 4, 0, 1,
       0, 4, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
       1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 3, 2, 1, 2, 3, 2, 3, 2,
       1, 2, 3, 2, 3, 2, 3, 2, 3, 2, 1, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2,
       3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2,
       3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2, 3, 2,
       3, 2], dtype=int32)
```

In [19]:
```
labels=kmeans.labels_
```

In [20]:
```
kmeans.cluster_centers_
```

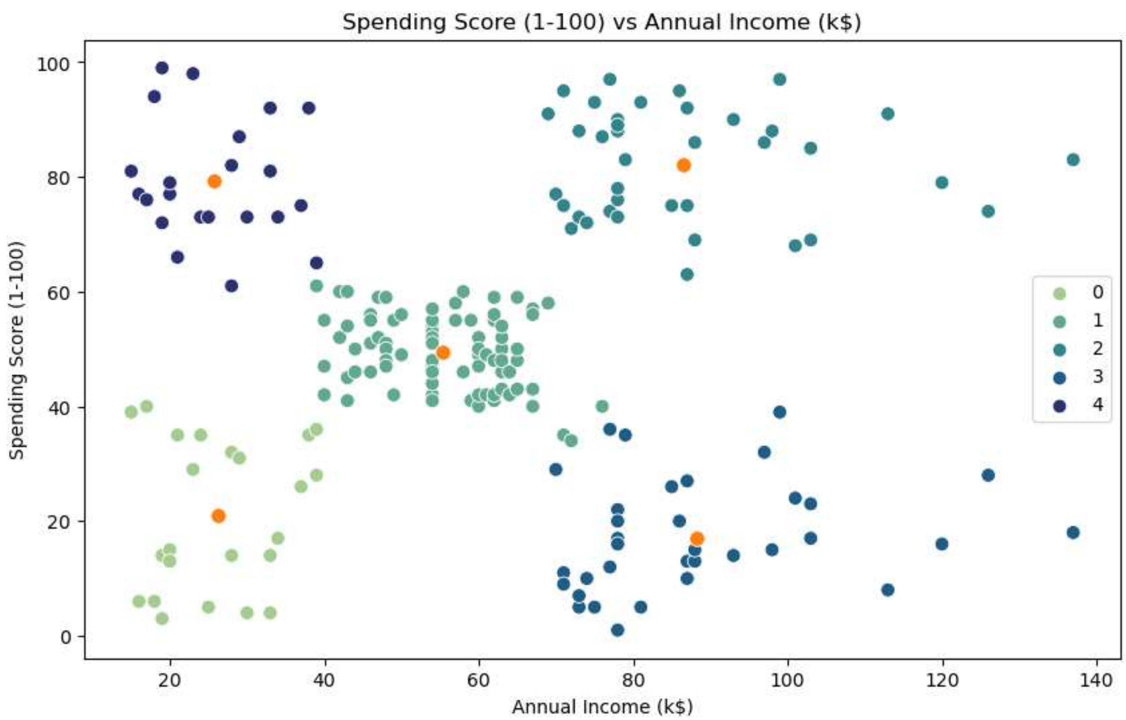
Out[20]:
```
array([[26.30434783, 20.91304348],
       [55.2962963 , 49.51851852],
       [86.53846154, 82.12820513],
       [88.2       , 17.11428571],
       [25.72727273, 79.36363636]])
```

In [21]:
```
kmeans.inertia_
```
Out[21]: 44448.455447933724

In [22]:
```
print(f"Silhouette score is {silhouette_score(k_df,labels)}")
print(f"Davies Bouldin score {davies_bouldin_score(k_df,labels)}")
```
```
Silhouette score is 0.553931997444648
Davies Bouldin score 0.5725628995597081
```

In [23]:
```
k_df["KMeans_label"] = labels
```

In [24]:
```
#Scatterplot of the clusters
plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',hue="KMeans_label",
                palette='crest', legend='full',data = k_df  ,s = 60 )
sns.scatterplot(x = kmeans.cluster_centers_[:,0],y = kmeans.cluster_centers_[:,1], s=70 )
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```



Agglomerative clustering

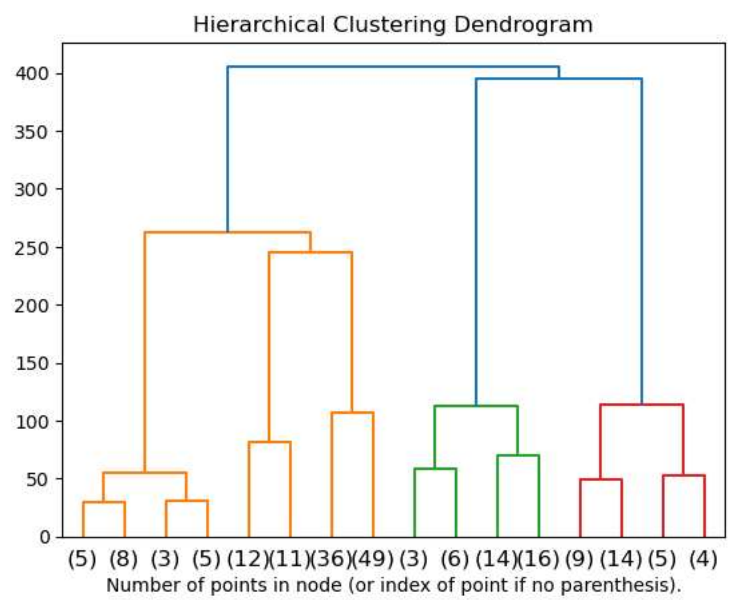
In [25]:
```
def plot_dendrogram(model, **kwargs):
    # Create linkage matrix and then plot the dendrogram

    # create the counts of samples under each node
    counts = np.zeros(model.children_.shape[0])
    n_samples = len(model.labels_)
    for i, merge in enumerate(model.children_):
        current_count = 0
        for child_idx in merge:
            if child_idx < n_samples:
                current_count += 1  # leaf node
            else:
                current_count += counts[child_idx - n_samples]
        counts[i] = current_count

    linkage_matrix = np.column_stack(
        [model.children_, model.distances_, counts]
    ).astype(float)

    # Plot the corresponding dendrogram
    dendrogram(linkage_matrix, **kwargs)
```

In [26]:
```
agc_df = df.iloc[:,-2:]
```

In [27]:
```
# setting distance_threshold=0 ensures we compute the full tree.
Agglomerative_Clustering_model = AgglomerativeClustering(distance_threshold=0, n_clusters=None)
```

In [28]:
```
model = Agglomerative_Clustering_model.fit(agc_df)
```

In [29]:
```
plt.title("Hierarchical Clustering Dendrogram")
# plot the top three levels of the dendrogram
plot_dendrogram(Agglomerative_Clustering_model, truncate_mode="level", p=3)
plt.xlabel("Number of points in node (or index of point if no parenthesis).")
plt.show()
```



DBSCAN

In [30]:
```
dbscan_df = df.iloc[:,-2:]
```

In [31]:
```
DBSCAN_clustering_models = DBSCAN(eps=9, min_samples=2).fit(dbscan_df)
```

In [32]:
```
print(f"Silhouette score is {silhouette_score(dbscan_df,DBSCAN_clustering_models.labels_)}")
print(f"Davies Bouldin score {davies_bouldin_score(dbscan_df,DBSCAN_clustering_models.labels_)}")
```

```
Silhouette score is 0.4437895954843984
Davies Bouldin score 0.941762705322535
```

In [33]:
```
dbscan_df["DBSCAN_label"] = DBSCAN_clustering_models.labels_
```

In [34]:
```
#Scatterplot of the clusters
plt.figure(figsize=(10,6))
sns.scatterplot(x = 'Annual Income (k$)',y = 'Spending Score (1-100)',hue="DBSCAN_label",
                palette='crest', legend='full',data = dbscan_df  ,s = 60 )
sns.scatterplot(x = kmeans.cluster_centers_[:,0],y = kmeans.cluster_centers_[:,1], s=70 )
plt.xlabel('Annual Income (k$)')
plt.ylabel('Spending Score (1-100)')
plt.title('Spending Score (1-100) vs Annual Income (k$)')
plt.show()
```

Thank You!