```
# IMPORTANT: RUN THIS CELL IN ORDER TO IMPORT YOUR KAGGLE DATA SOURCES,
# THEN FEEL FREE TO DELETE THIS CELL.
# NOTE: THIS NOTEBOOK ENVIRONMENT DIFFERS FROM KAGGLE'S PYTHON
# ENVIRONMENT SO THERE MAY BE MISSING LIBRARIES USED BY YOUR
# NOTEBOOK.
import kagglehub
vjchoudhary7_customer_segmentation_tutorial_in_python_path = kagglehub.dataset_download('vjchoudhary7/customer-segmentation-tutorial-in-python')

print('Data source import complete.')
```

```
# This Python 3 environment comes with many helpful analytics libraries installed
# It is defined by the kaggle/python Docker image: https://github.com/kaggle/docker-python
# For example, here's several helpful packages to load

import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)

import matplotlib.pyplot as plt
import seaborn as sns

# Input data files are available in the read-only "../input/" directory
# For example, running this (by clicking run or pressing Shift+Enter) will list all files under the input directory

import os
for dirname, _, filenames in os.walk('/kaggle/input'):
    for filename in filenames:
        print(os.path.join(dirname, filename))

# You can write up to 20GB to the current directory (/kaggle/working/) that gets preserved as output when you create a version using "Save & Run All"
# You can also write temporary files to /kaggle/temp/, but they won't be saved outside of the current session
```

```
/kaggle/input/customer-segmentation-tutorial-in-python/Mall_Customers.csv
```

Hour 4: Hierarchical Clustering Session: Mall Customer Segmentation

1. Data Loading and Exploration

Load the Mall Customer Segmentation Data from Kaggle. Explore the dataset's features and basic statistics. Visualize the data using scatter plots and histograms.

```
# Load the Mall Customer Segmentation Data
data = pd.read_csv("/kaggle/input/customer-segmentation-tutorial-in-python/Mall_Customers.csv")
```

```
# Basic exploration
data.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

```
data.info()
```

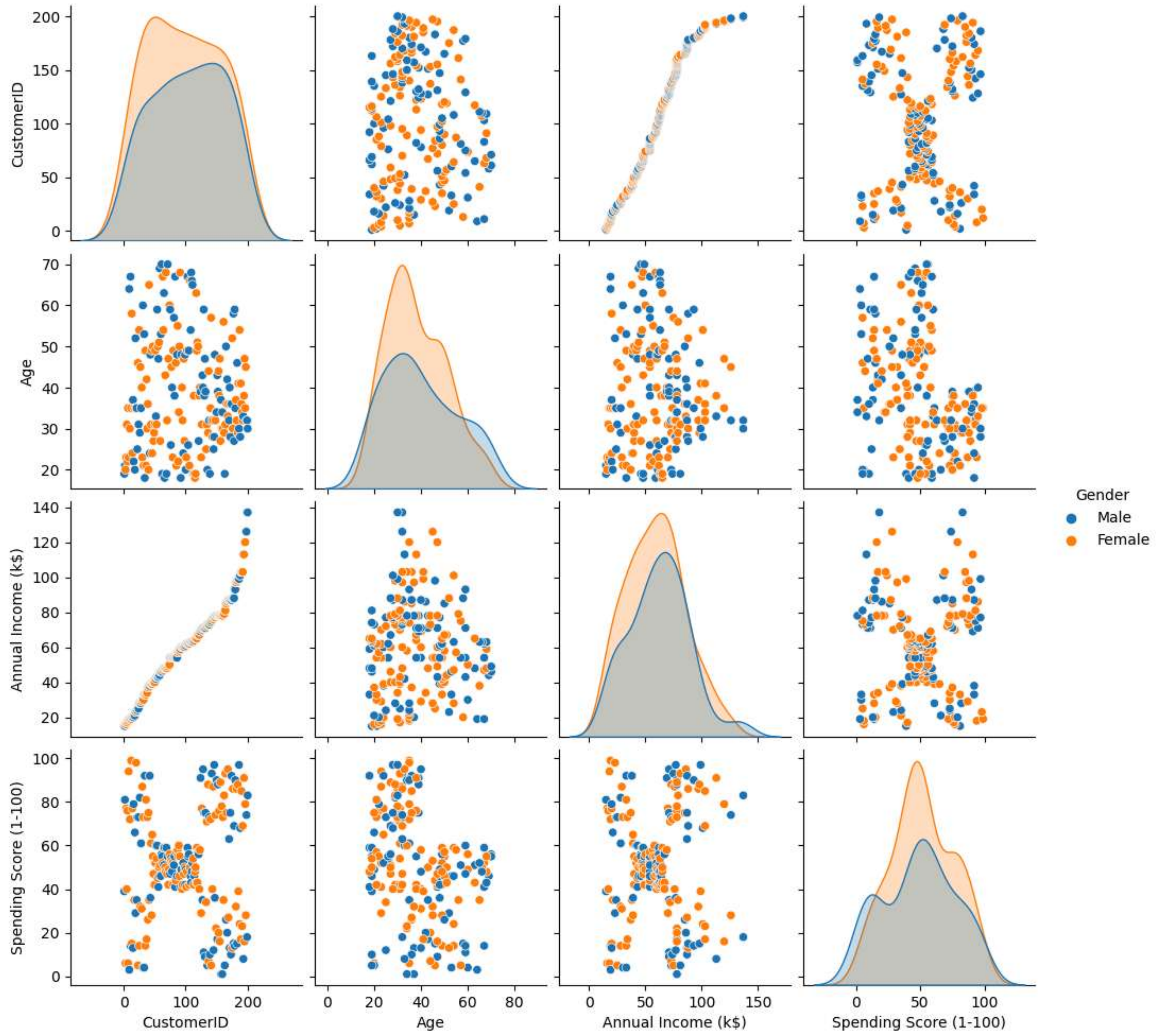
```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 200 entries, 0 to 199
Data columns (total 5 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   CustomerID              200 non-null    int64
 1   Gender                  200 non-null    object
 2   Age                     200 non-null    int64
 3   Annual Income (k$)      200 non-null    int64
 4   Spending Score (1-100)  200 non-null    int64
dtypes: int64(4), object(1)
memory usage: 7.9+ KB
```

```
data.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

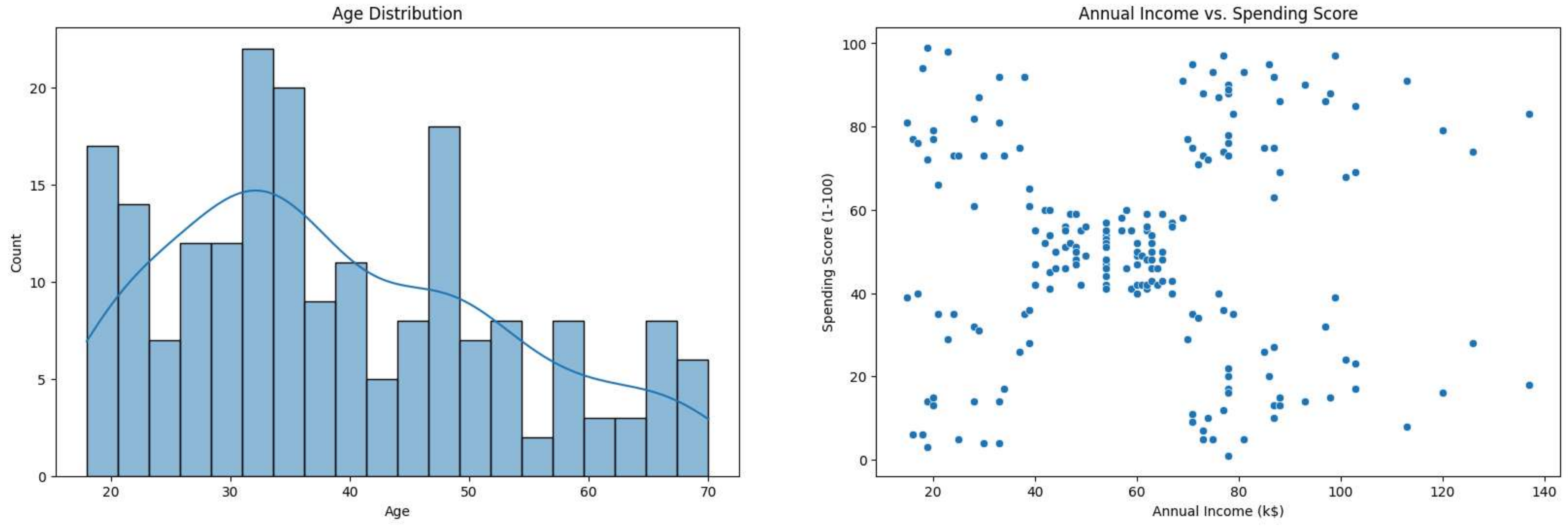
```
# Visualizations
sns.pairplot(data, hue='Gender')
plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf valu
  with pd.option_context('mode.use_inf_as_na', True):
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1075: FutureWarning: When grouping with a length-1 list-like, you will need to pass a length-1 tuple to get_group
  data_subset = grouped_data.get_group(pd_key)
```




```
fig, axes = plt.subplots(1, 2, figsize = (20, 6))

sns.histplot(data['Age'], bins=20, kde=True, ax=axes[0])
axes[0].set_title('Age Distribution')


sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)', data=data, ax=axes[1])
axes[1].set_title('Annual Income vs. Spending Score')

plt.show()
```

```
/usr/local/lib/python3.10/dist-packages/seaborn/_oldcore.py:1119: FutureWarning: use_inf_as_na option is deprecated and will be removed in a future version. Convert inf values
  with pd.option_context('mode.use_inf_as_na', True):
```



2. Data Preprocessing

Handle any missing values or outliers. Scale the data using StandardScaler.

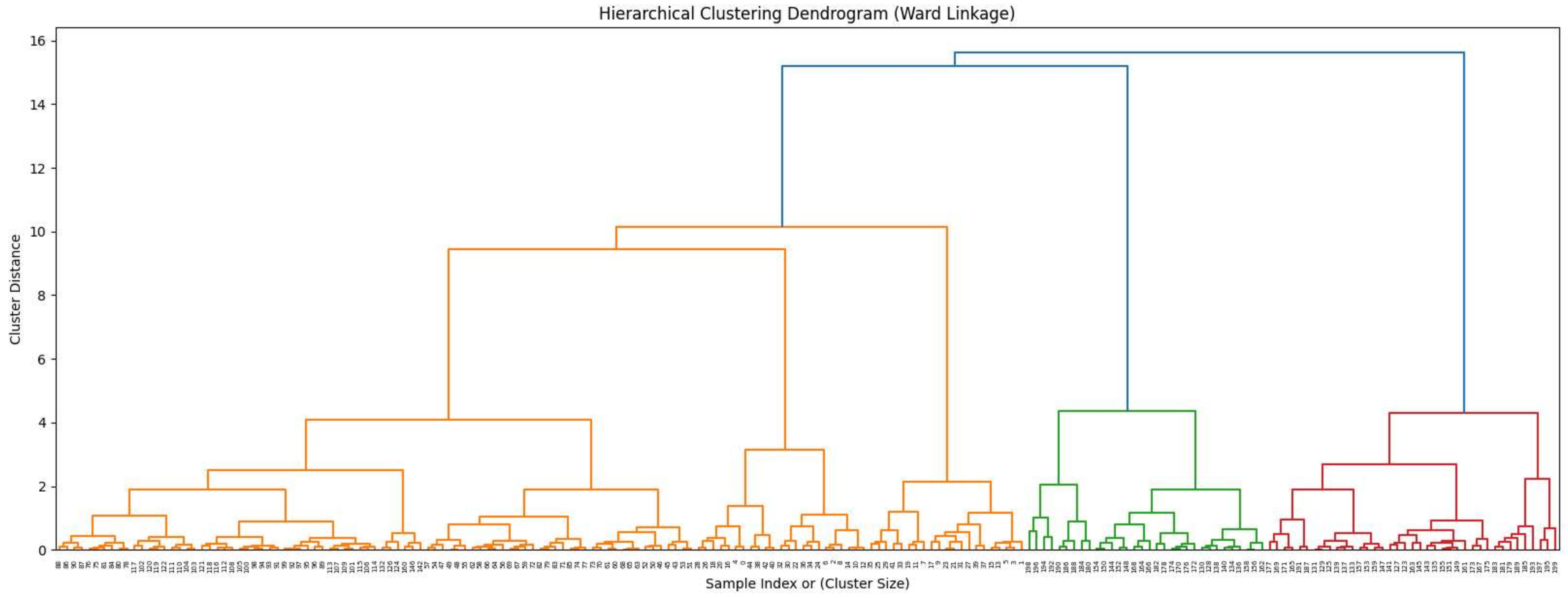
```
from sklearn.preprocessing import StandardScaler

# Check for missing values
print(data.isnull().sum())

# Select relevant features
X = data[['Annual Income (k$)', 'Spending Score (1-100)']]

# Scale the data
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

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

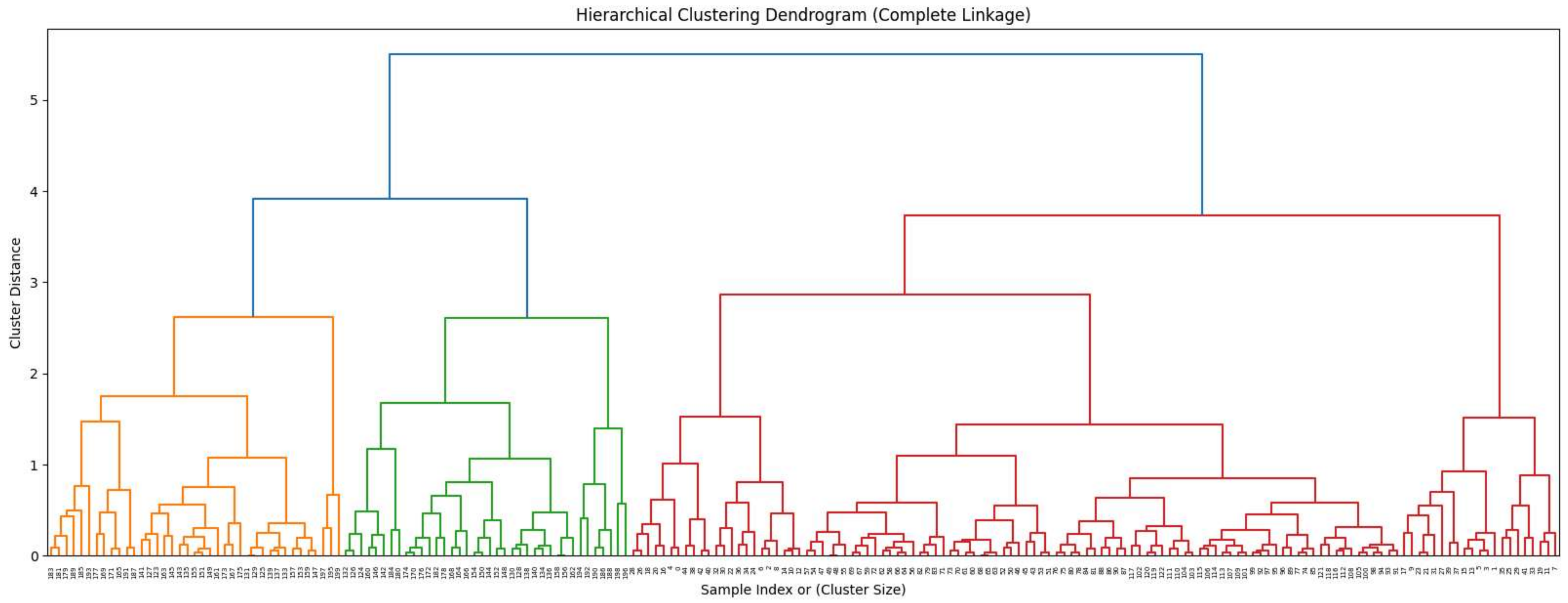
3. Hierarchical Clustering Implementation

Apply hierarchical clustering using different linkage methods (single, complete, ward). Experiment with different distance metrics (Euclidean, Manhattan). Visualize the resulting dendrograms.

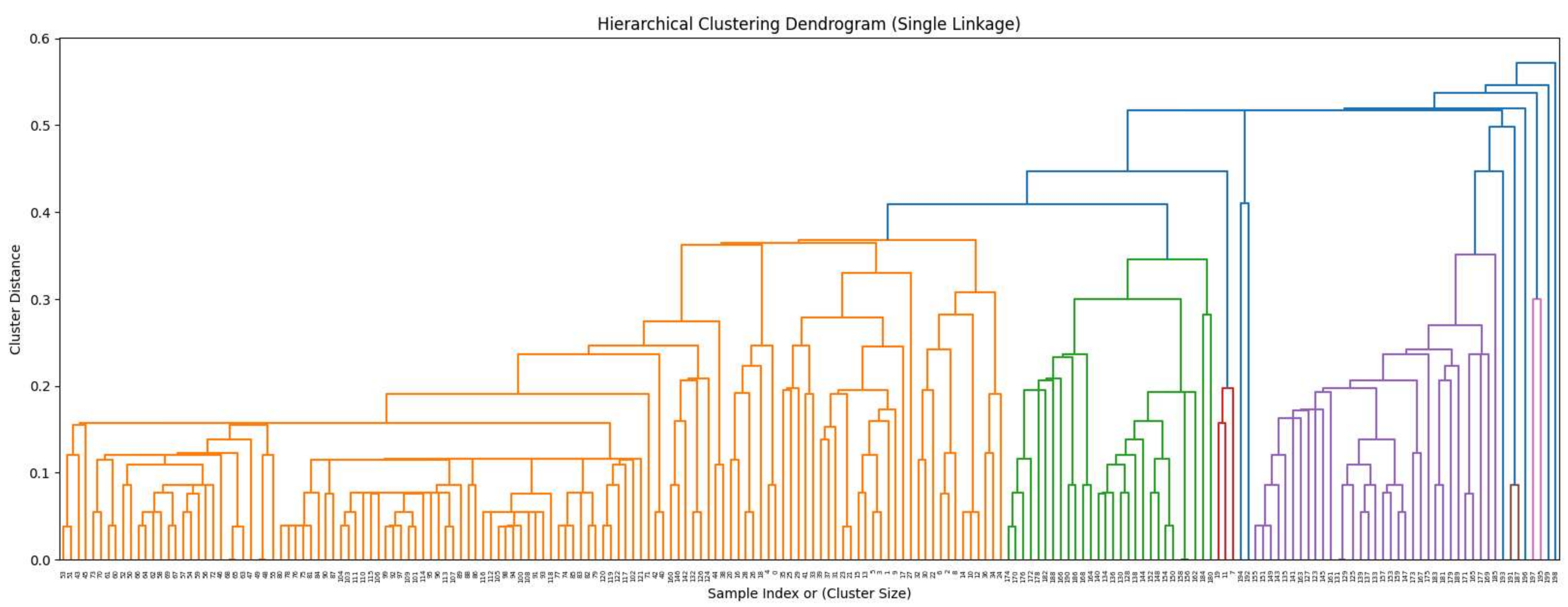
```
from scipy.cluster.hierarchy import dendrogram, linkage

# Ward linkage
linked_ward = linkage(X_scaled, 'ward')
plt.figure(figsize=(20, 7))
dendrogram(linked_ward, orientation='top', labels=data.index, distance_sort='descending', show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Ward Linkage)')
plt.xlabel('Sample Index or (Cluster Size)')
plt.ylabel('Cluster Distance')
plt.show()
```



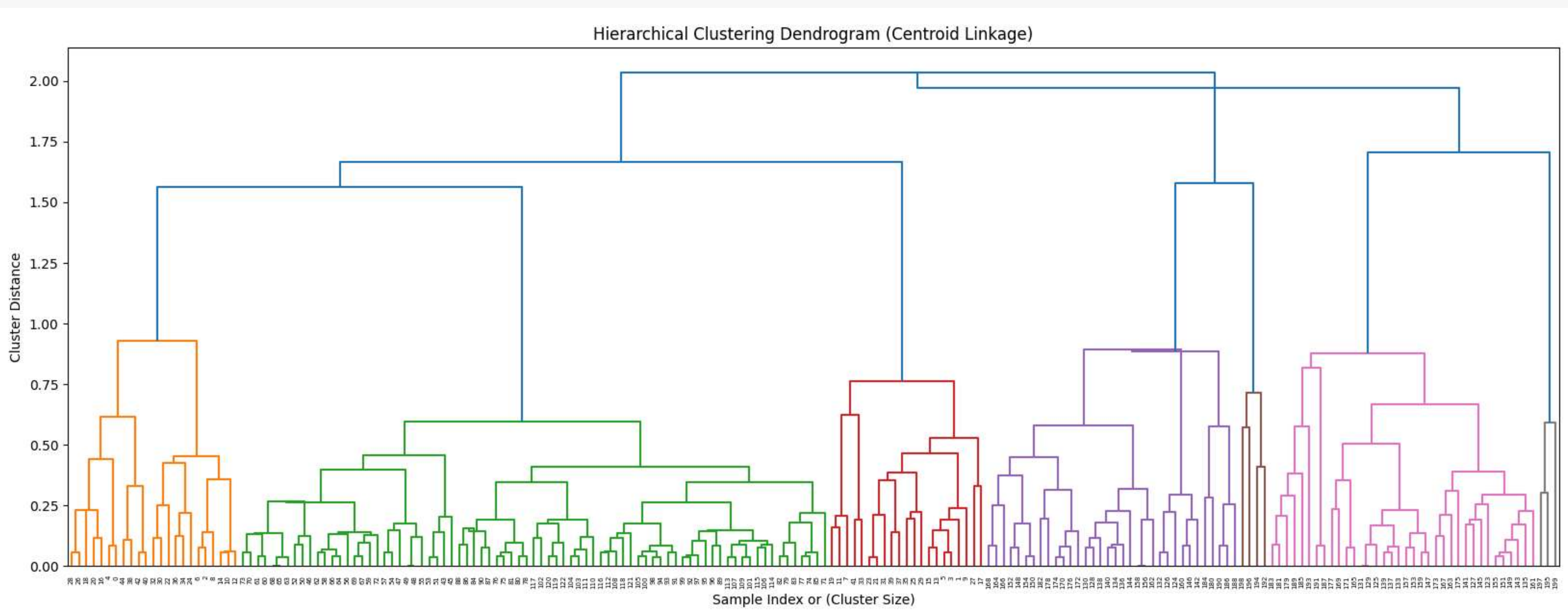

```
# Complete linkage
linked_complete = linkage(X_scaled, 'complete')
plt.figure(figsize=(20, 7))
dendrogram(linked_complete, orientation='top', labels=data.index, distance_sort='descending', show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Complete Linkage)')
plt.xlabel('Sample Index or (Cluster Size)')
plt.ylabel('Cluster Distance')
plt.show()
```



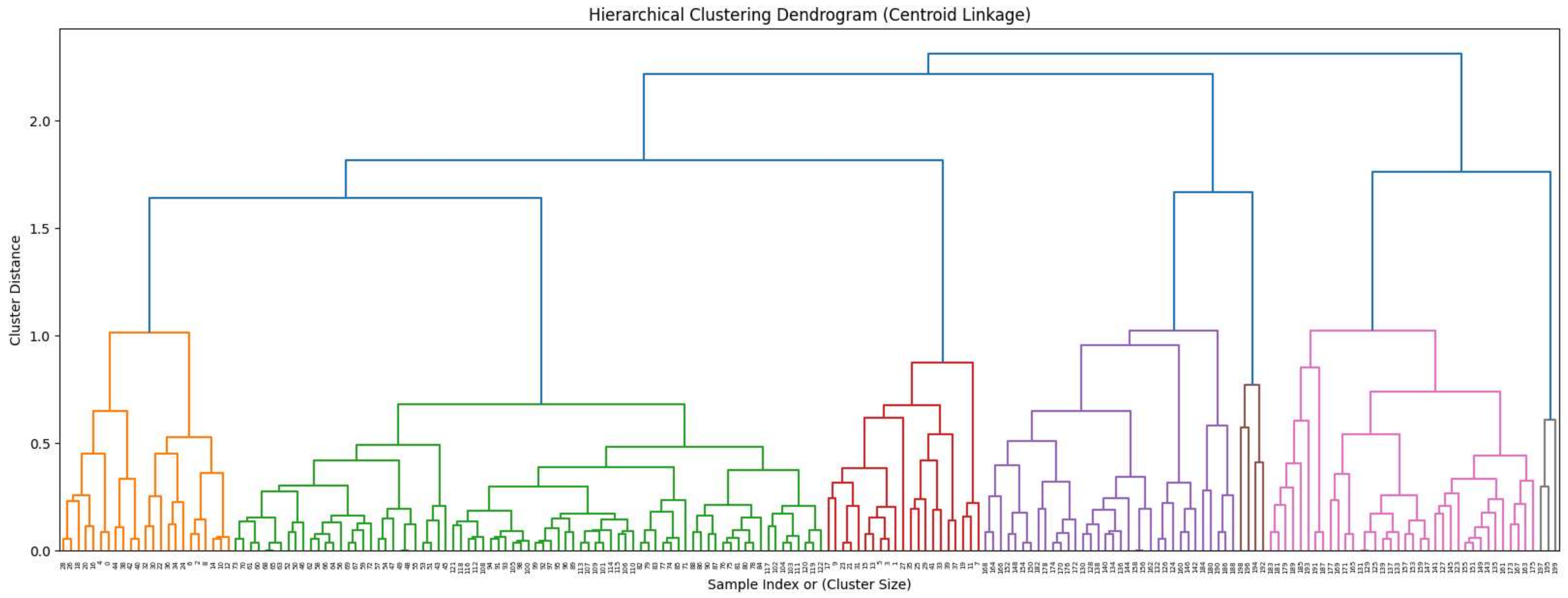

```
# Single linkage
linked_single = linkage(X_scaled, 'single')
plt.figure(figsize=(20, 7))
dendrogram(linked_single, orientation='top', labels=data.index, distance_sort='descending', show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Single Linkage)')
plt.xlabel('Sample Index or (Cluster Size)')
plt.ylabel('Cluster Distance')
plt.show()
```




```
# Single linkage
linked_single = linkage(X_scaled, 'centroid')
plt.figure(figsize=(20, 7))
dendrogram(linked_single, orientation='top', labels=data.index, distance_sort='descending', show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Centroid Linkage)')
plt.xlabel('Sample Index or (Cluster Size)')
plt.ylabel('Cluster Distance')
plt.show()
```




```
# Single linkage
linked_single = linkage(X_scaled, 'average')
plt.figure(figsize=(20, 7))
dendrogram(linked_single, orientation='top', labels=data.index, distance_sort='descending', show_leaf_counts=True)
plt.title('Hierarchical Clustering Dendrogram (Centroid Linkage)')
plt.xlabel('Sample Index or (Cluster Size)')
plt.ylabel('Cluster Distance')
plt.show()
```



4. Dendrogram Analysis and Cluster Selection

Analyze the dendrograms to identify potential clusters. Use dendrogram pruning and cutting techniques. Calculate the cophenetic correlation coefficient to evaluate the dendrograms.

```
from scipy.cluster.hierarchy import cophenet, cut_tree
from scipy.spatial.distance import pdist

# Cophenetic correlation
c_ward, coph_dist_ward = cophenet(linked_ward, pdist(X_scaled))
print(f"Cophenetic Correlation (Ward): {c_ward}")

c_complete, coph_dist_complete = cophenet(linked_complete, pdist(X_scaled))
print(f"Cophenetic Correlation (Complete): {c_complete}")

c_single, coph_dist_single = cophenet(linked_single, pdist(X_scaled))
print(f"Cophenetic Correlation (Single): {c_single}")

# Cut the dendrogram to get clusters
clusters = cut_tree(linked_ward, n_clusters=5).reshape(-1,)
print("Clusters:", clusters)
```

```
Cophenetic Correlation (Ward): 0.72091281930771
Cophenetic Correlation (Complete): 0.6669843292956471
Cophenetic Correlation (Single): 0.7173982395337909
Clusters: [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 2 0 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2 2
 2 2 2 2 2 2 2 2 2 2 2 2 3 2 3 2 3 4 3 4 3 2 3 4 3 4 3 4 3 4 3 2 3 4 3 2 3
 4 3 4 3 4 3 4 3 4 3 4 3 2 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3 4
 3 4 3 4 3 4 3 4 3 4 3 4 3 4 3]
```

5. Cluster Interpretation and Visualization

Interpret the characteristics of the identified clusters. Visualize the clusters using scatter plots and other appropriate techniques. Relate the clusters to customer segments.

```
import seaborn as sns

data['Cluster'] = clusters

plt.figure(figsize=(10, 8))
sns.scatterplot(x='Annual Income (k$)', y='Spending Score (1-100)', hue='Cluster', data=data, palette='viridis')
plt.title('Clusters (Ward Linkage)')
plt.show()

cluster_means = data.groupby('Cluster')[['Annual Income (k$)', 'Spending Score (1-100)']].mean()
print("Cluster Means:\n", cluster_means)
```