Implement hierarchical clustering on customer dataset. Determine the number of clusters using the elbow method. Dataset link : https://www.kaggle.com/code/heeraldedhia/kmeans-clustering-for-customer-data/input

In [3]:

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.cluster import AgglomerativeClustering
from sklearn.decomposition import PCA
from sklearn.metrics import silhouette_score
from scipy.cluster.hierarchy import dendrogram, linkage
```

In [4]:

```
data = pd.read_csv("C:/Users/Atharva/OneDrive/Desktop/LP3 code/Mall_Customers.csv")
print(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
```

In [5]:

```
# Preprocess the data
# Encode the 'Gender' column as numeric values (Male = 0, Female = 1)
label_encoder = LabelEncoder()
data['Gender'] = label_encoder.fit_transform(data['Gender'])
```

In [6]:

```
# Select the relevant columns for clustering (ignoring 'CustomerID' as it's not needed for clustering)
X = data[['Gender', 'Age', 'Annual Income (k$)', 'Spending Score (1-100)']]
```

In [7]:

```
# Normalize the data for better clustering
scaler = StandardScaler()
X_scaled = scaler.fit_transform(X)
```

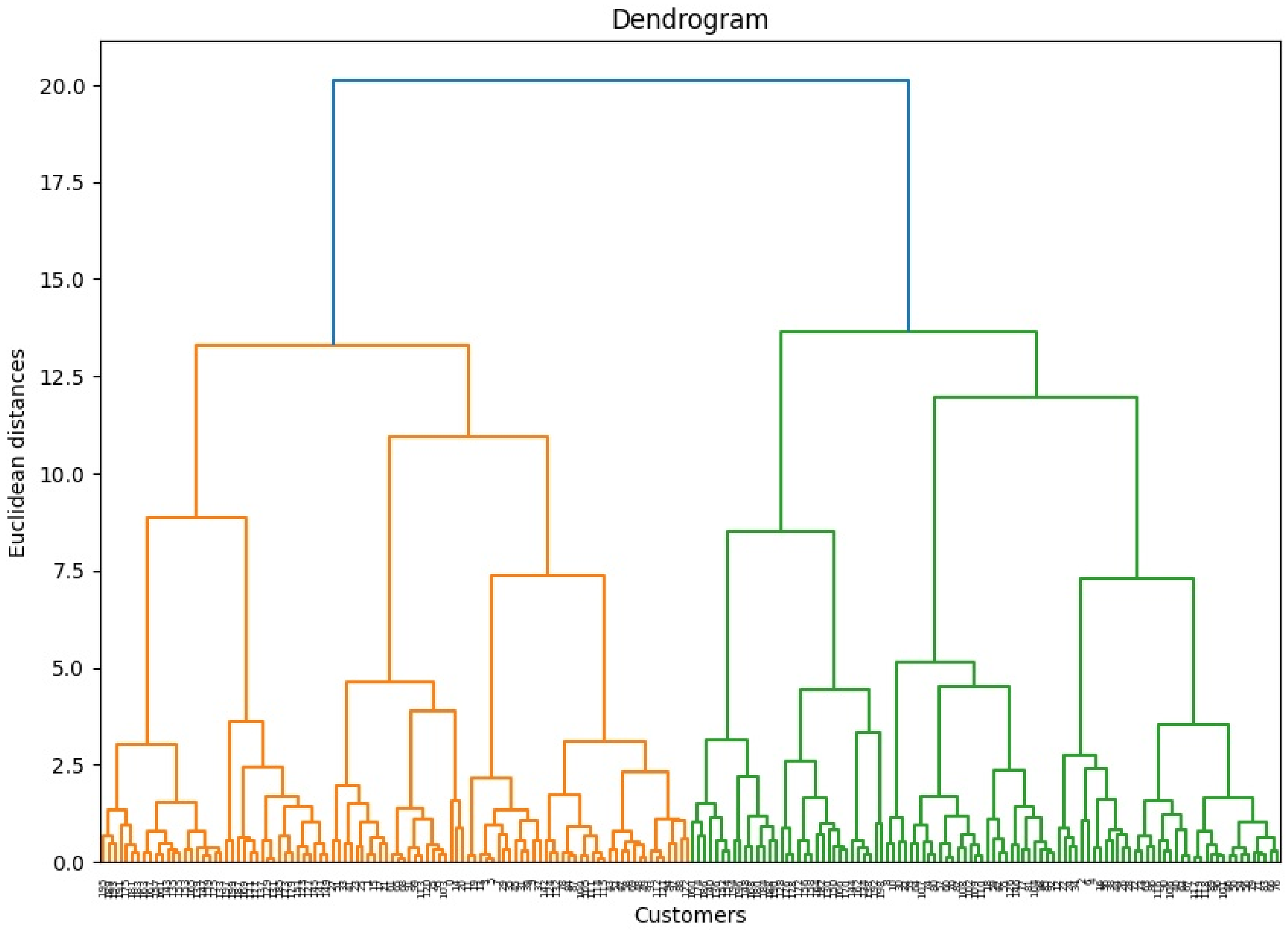
In [8]:

```
# Step 1: Perform Hierarchical Clustering and Visualize the Dendrogram

# Perform hierarchical/agglomerative clustering
linked = linkage(X_scaled, method='ward')
```

In [9]:

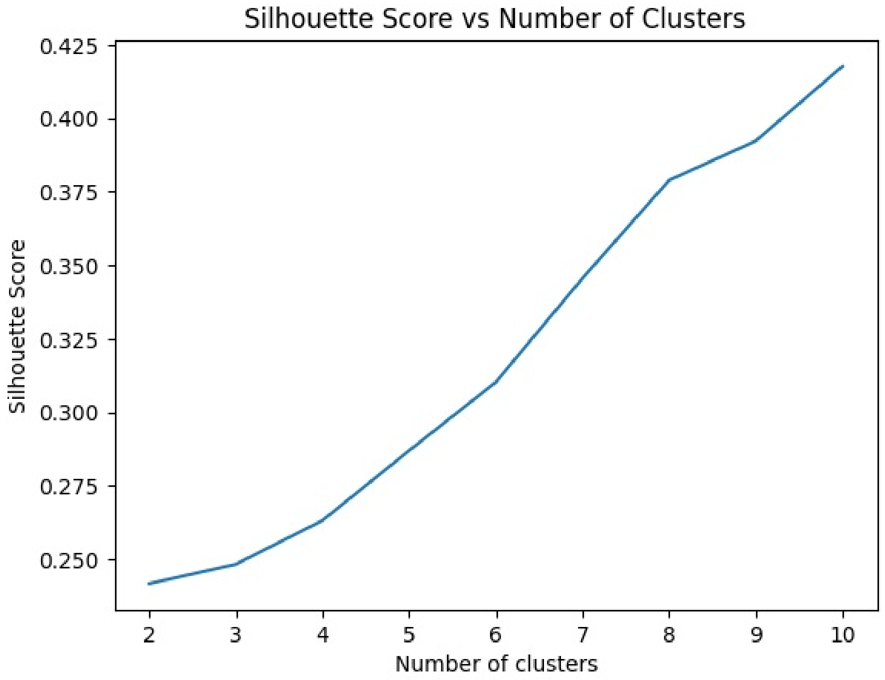
```
# Plot the dendrogram to visualize the hierarchical structure
plt.figure(figsize=(10, 7))
dendrogram(linked)
plt.title('Dendrogram')
plt.xlabel('Customers')
plt.ylabel('Euclidean distances')
plt.show()
```



In [10]:
```
# Step 2: Determine the number of clusters using Silhouette Score

# Calculate the silhouette score for different numbers of clusters
sil_scores = []
for n_clusters in range(2, 11):  # Trying different numbers of clusters
    model = AgglomerativeClustering(n_clusters=n_clusters, linkage='ward')
    cluster_labels = model.fit_predict(X_scaled)
    sil_score = silhouette_score(X_scaled, cluster_labels)
    sil_scores.append(sil_score)
```

In [11]:
```
# Plot the silhouette scores to find the optimal number of clusters
plt.plot(range(2, 11), sil_scores)
plt.title('Silhouette Score vs Number of Clusters')
plt.xlabel('Number of clusters')
plt.ylabel('Silhouette Score')
plt.show()
```

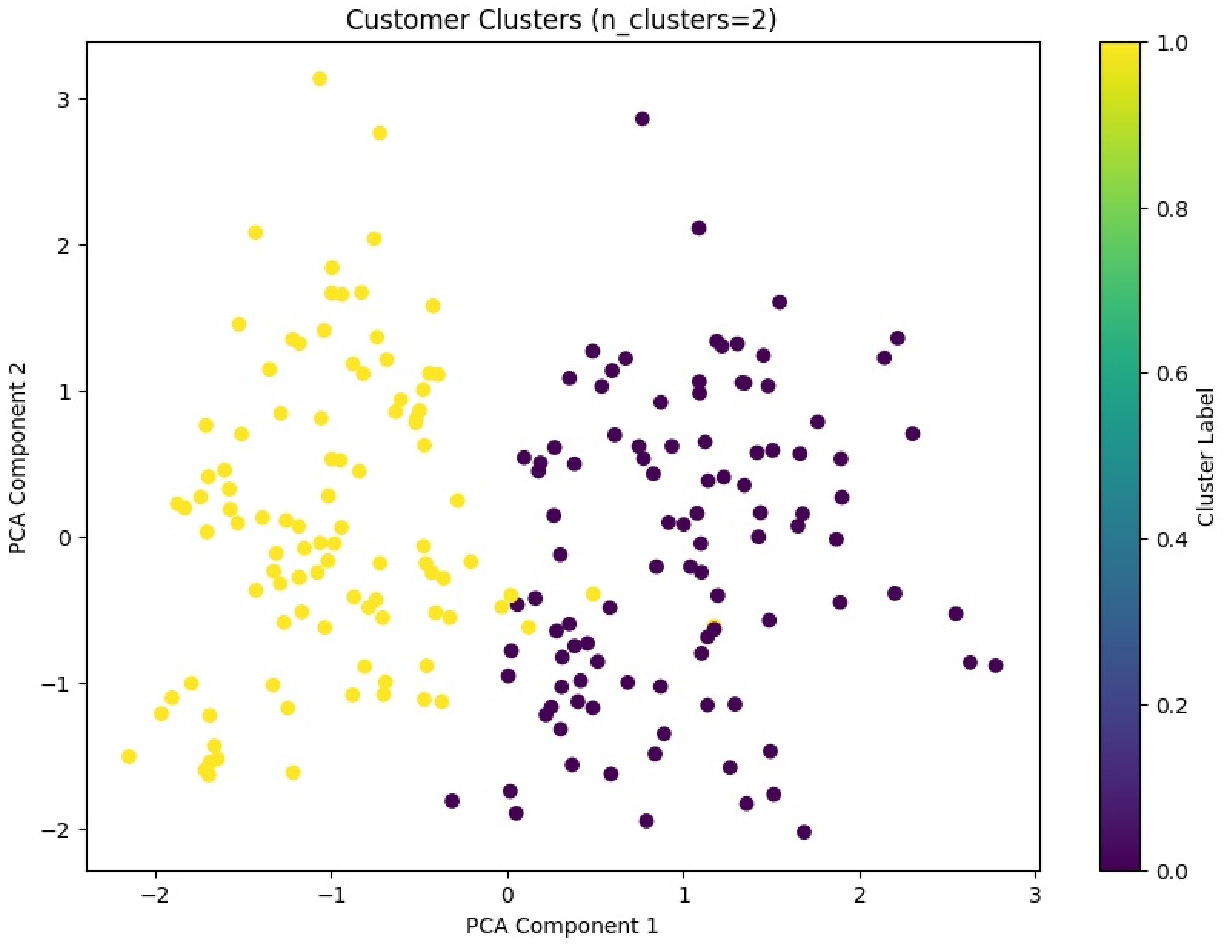


In [12]:
```
# Step 3: Perform Agglomerative Clustering with the chosen number of clusters
# Assuming the best number of clusters is determined by either the dendrogram or silhouette score (e.g., 5)
best_n_clusters = 2
final_model = AgglomerativeClustering(n_clusters=best_n_clusters, linkage='ward')
final_cluster_labels = final_model.fit_predict(X_scaled)
```

In [13]:

```
# Step 4: Dimensionality Reduction for Visualization
pca = PCA(n_components=2)
X_pca = pca.fit_transform(X_scaled)

# Plot the clusters
plt.figure(figsize=(10, 7))
plt.scatter(X_pca[:, 0], X_pca[:, 1], c=final_cluster_labels, cmap='viridis', marker='o')
plt.title(f'Customer Clusters (n_clusters={best_n_clusters})')
plt.xlabel('PCA Component 1')
plt.ylabel('PCA Component 2')
plt.colorbar(label='Cluster Label')
plt.show()
```



In [ ]:

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