Customer Personality Analysis

Customer Personality Analysis is a detailed analysis of a company's ideal customers. It helps a business to better understand its customers and makes it easier for them to modify products according to the specific needs, behaviors and concerns of different types of customers.

Customer personality analysis helps a business to modify its product based on its target customers from different types of customer segments. For example, instead of spending money to market a new product to every customer in the company's database, a company can analyze which customer segment is most likely to buy the product and then market the product only on that particular segment.

References

- Customer Personality Kaggle

```
# load libraries
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
import pandas as pd

from sklearn.preprocessing import StandardScaler
from sklearn.decomposition import PCA
from sklearn.cluster import KMeans
from sklearn.metrics import silhouette_score

import warnings
warnings.filterwarnings("ignore", category=FutureWarning,
message=".*use_inf_as_na option is deprecated.*")
```

1. Exploratory Data Analysis

```
# Load the data
df =
pd.read_csv('/kaggle/input/customer-personality-analysis/marketing_cam
paign.csv', sep='\t')

# Display basic information
print('Dataframe info: \n',df.info())
print('Dataframe summary statistics: \n',df.describe())

# Check for missing values
print('Dataframe null values: \n',df.isnull().sum())

# Display the first few rows
df.head()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 29 columns):
 #   Column               Non-Null Count  Dtype  
---  ------               --------------  -----  
 0   ID                   2240 non-null   int64  
 1   Year_Birth           2240 non-null   int64  
 2   Education            2240 non-null   object 
 3   Marital_Status       2240 non-null   object 
 4   Income               2216 non-null   float64
 5   Kidhome              2240 non-null   int64  
 6   Teenhome             2240 non-null   int64  
 7   Dt_Customer          2240 non-null   object 
 8   Recency              2240 non-null   int64  
 9   MntWines             2240 non-null   int64  
 10  MntFruits            2240 non-null   int64  
 11  MntMeatProducts      2240 non-null   int64  
 12  MntFishProducts      2240 non-null   int64  
 13  MntSweetProducts     2240 non-null   int64  
 14  MntGoldProds         2240 non-null   int64  
 15  NumDealsPurchases    2240 non-null   int64  
 16  NumWebPurchases      2240 non-null   int64  
 17  NumCatalogPurchases  2240 non-null   int64  
 18  NumStorePurchases    2240 non-null   int64  
 19  NumWebVisitsMonth    2240 non-null   int64  
 20  AcceptedCmp3         2240 non-null   int64  
 21  AcceptedCmp4         2240 non-null   int64  
 22  AcceptedCmp5         2240 non-null   int64  
 23  AcceptedCmp1         2240 non-null   int64  
 24  AcceptedCmp2         2240 non-null   int64  
 25  Complain             2240 non-null   int64  
 26  Z_CostContact        2240 non-null   int64  
 27  Z_Revenue            2240 non-null   int64  
 28  Response             2240 non-null   int64  
dtypes: float64(1), int64(25), object(3)
memory usage: 507.6+ KB
Dataframe info:
 None
Dataframe summary statistics:
                  ID   Year_Birth         Income      Kidhome
Teenhome  \
count   2240.000000  2240.000000    2216.000000  2240.000000
2240.000000
mean    5592.159821  1968.805804   52247.251354     0.444196
0.506250
std     3246.662198    11.984069   25173.076661     0.538398
0.544538
min        0.000000  1893.000000    1730.000000     0.000000
0.000000
25%     2828.250000  1959.000000   35303.000000     0.000000
```

```
0.000000
50%     5458.500000  1970.000000   51381.500000     0.000000
0.000000
75%     8427.750000  1977.000000   68522.000000     1.000000
1.000000
max    11191.000000  1996.000000  666666.000000     2.000000
2.000000

           Recency     MntWines    MntFruits  MntMeatProducts  \
count  2240.000000  2240.000000  2240.000000      2240.000000
mean     49.109375   303.935714    26.302232       166.950000
std      28.962453   336.597393    39.773434       225.715373
min       0.000000     0.000000     0.000000         0.000000
25%      24.000000    23.750000     1.000000        16.000000
50%      49.000000   173.500000     8.000000        67.000000
75%      74.000000   504.250000    33.000000       232.000000
max      99.000000  1493.000000   199.000000      1725.000000

       MntFishProducts  ...  NumWebVisitsMonth  AcceptedCmp3
AcceptedCmp4  \
count      2240.000000  ...        2240.000000   2240.000000
2240.000000
mean         37.525446  ...           5.316518      0.072768
0.074554
std          54.628979  ...           2.426645      0.259813
0.262728
min           0.000000  ...           0.000000      0.000000
0.000000
25%           3.000000  ...           3.000000      0.000000
0.000000
50%          12.000000  ...           6.000000      0.000000
0.000000
75%          50.000000  ...           7.000000      0.000000
0.000000
max         259.000000  ...          20.000000      1.000000
1.000000

       AcceptedCmp5  AcceptedCmp1  AcceptedCmp2     Complain
Z_CostContact  \
count   2240.000000   2240.000000   2240.000000  2240.000000
2240.0
mean       0.072768      0.064286      0.013393     0.009375
3.0
std        0.259813      0.245316      0.114976     0.096391
0.0
min        0.000000      0.000000      0.000000     0.000000
3.0
25%        0.000000      0.000000      0.000000     0.000000
3.0
50%        0.000000      0.000000      0.000000     0.000000
```

```
3.0
75%        0.000000      0.000000      0.000000     0.000000
3.0
max        1.000000      1.000000      1.000000     1.000000
3.0

       Z_Revenue     Response
count     2240.0  2240.000000
mean        11.0     0.149107
std          0.0     0.356274
min         11.0     0.000000
25%         11.0     0.000000
50%         11.0     0.000000
75%         11.0     0.000000
max         11.0     1.000000

[8 rows x 26 columns]
Dataframe null values:
 ID                        0
Year_Birth               0
Education                0
Marital_Status           0
Income                  24
Kidhome                  0
Teenhome                 0
Dt_Customer              0
Recency                  0
MntWines                 0
MntFruits                0
MntMeatProducts          0
MntFishProducts          0
MntSweetProducts         0
MntGoldProds             0
NumDealsPurchases        0
NumWebPurchases          0
NumCatalogPurchases      0
NumStorePurchases        0
NumWebVisitsMonth        0
AcceptedCmp3             0
AcceptedCmp4             0
AcceptedCmp5             0
AcceptedCmp1             0
AcceptedCmp2             0
Complain                 0
Z_CostContact            0
Z_Revenue                0
Response                 0
dtype: int64
```

```
     ID  Year_Birth   Education Marital_Status   Income  Kidhome
Teenhome  \
0  5524        1957  Graduation         Single  58138.0        0
0
1  2174        1954  Graduation         Single  46344.0        1
1
2  4141        1965  Graduation       Together  71613.0        0
0
3  6182        1984  Graduation       Together  26646.0        1
0
4  5324        1981         PhD        Married  58293.0        1
0

  Dt_Customer  Recency  MntWines  ...  NumWebVisitsMonth  AcceptedCmp3
\
0  04-09-2012       58       635  ...                  7             0

1  08-03-2014       38        11  ...                  5             0

2  21-08-2013       26       426  ...                  4             0

3  10-02-2014       26        11  ...                  6             0

4  19-01-2014       94       173  ...                  5             0


   AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  \
0             0             0             0             0         0
1             0             0             0             0         0
2             0             0             0             0         0
3             0             0             0             0         0
4             0             0             0             0         0

   Z_CostContact  Z_Revenue  Response
0              3         11         1
1              3         11         0
2              3         11         0
3              3         11         0
4              3         11         0

[5 rows x 29 columns]
```

Column Description

- People
  - ID: Customer's unique identifier
  - Year_Birth: Customer's birth year
  - Education: Customer's education level
  - Marital_Status: Customer's marital status
  - Income: Customer's yearly household income

  - Kidhome: Number of children in customer's household
  - Teenhome: Number of teenagers in customer's household
  - Dt_Customer: Date of customer's enrollment with the company
  - Recency: Number of days since customer's last purchase
  - Complain: 1 if the customer complained in the last 2 years, 0 otherwise
- Products
  - MntWines: Amount spent on wine in last 2 years
  - MntFruits: Amount spent on fruits in last 2 years
  - MntMeatProducts: Amount spent on meat in last 2 years
  - MntFishProducts: Amount spent on fish in last 2 years
  - MntSweetProducts: Amount spent on sweets in last 2 years
  - MntGoldProds: Amount spent on gold in last 2 years
- Promotion
  - NumDealsPurchases: Number of purchases made with a discount
  - AcceptedCmp1: 1 if customer accepted the offer in the 1st campaign, 0 otherwise
  - AcceptedCmp2: 1 if customer accepted the offer in the 2nd campaign, 0 otherwise
  - AcceptedCmp3: 1 if customer accepted the offer in the 3rd campaign, 0 otherwise
  - AcceptedCmp4: 1 if customer accepted the offer in the 4th campaign, 0 otherwise
  - AcceptedCmp5: 1 if customer accepted the offer in the 5th campaign, 0 otherwise
  - Response: 1 if customer accepted the offer in the last campaign, 0 otherwise
- Place
  - NumWebPurchases: Number of purchases made through the company’s website
  - NumCatalogPurchases: Number of purchases made using a catalogue
  - NumStorePurchases: Number of purchases made directly in stores
  - NumWebVisitsMonth: Number of visits to company’s website in the last month

Clean Data

Outliers and missing data

- There is one Income with a value of 666666 and it's greater than the mean(52247).
- There is one Year_Birth with a value of 1893 and it's greater than the mean(1968).

```
# Drop rows with missing values
df = df.dropna()

# remove outliers
df = df[df['Income'] < 666666]
df = df[df['Year_Birth'] > 1900]
```

Feature Selection

- The following features are not necessary for our analysis:
  - 'ID'
  - 'Dt_Customer'

- 'Z_CostContact'
- 'Z_Revenue'
- 'Complain'
- 'Response'
- 'Recency'

- Map Marital_Status column
- Map Education column
- Map Children column
- Create a new column TotalAcceptedCmp

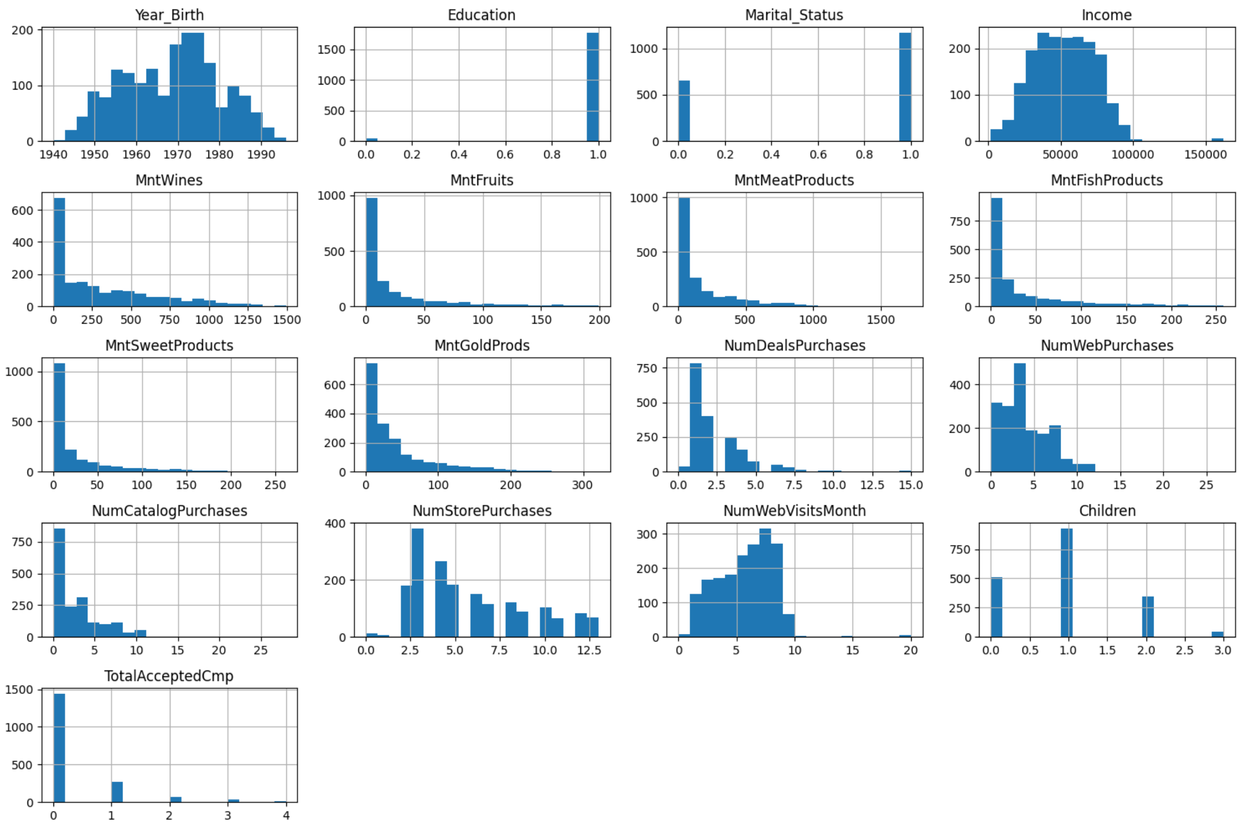
```
# Drop irrelevant columns
# ID -> random value
# Z_CostContact, Z_Revenue -> constant value
# Dt_Customer -> not relevant to problem
df =
df.drop(['ID','Dt_Customer','Z_CostContact','Z_Revenue','Complain','Re
sponse','Recency'], axis=1)

# Map the numerical values to categorical labels
df['Marital_Status'] =
df['Marital_Status'].map({'Alone':0,'Divorced':0,'Single':0,'Widow':0,
'YOLO':0, 'Married':1,'Together':1})

# Map education levels to binary values
df['Education'] = df['Education'].map({'Basic': 0, 'Graduation': 1,
'Master': 1, 'PhD': 1})

df['Children'] = df[['Kidhome', 'Teenhome']].sum(axis=1)
df = df.drop(['Kidhome','Teenhome'], axis=1)

# Create a new column 'TotalAcceptedCmp' by summing up the individual
campaign columns
df['TotalAcceptedCmp'] = df[['AcceptedCmp1', 'AcceptedCmp2',
'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']].sum(axis=1)

# Drop the original campaign columns if no longer needed
df = df.drop(['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',
'AcceptedCmp4', 'AcceptedCmp5'], axis=1)

# Drop rows with missing values
df = df.dropna()

# Convert categorical columns to numerical (e.g., Education,
Marital_Status)
df = pd.get_dummies(df, drop_first=True)

# Check for duplicates
df = df.drop_duplicates()

df.reset_index(inplace=True, drop=True)
```

```
print('Dataframe summary statistics: \n',df.describe())

Dataframe summary statistics:
         Year_Birth    Education  Marital_Status         Income
MntWines  \
count  1825.000000  1825.000000     1825.000000    1825.000000
1825.000000
mean   1968.429589     0.973151        0.640548   52513.021918
315.092603
std      11.625252     0.161687        0.479971   21513.422145
341.367109
min    1940.000000     0.000000        0.000000    1730.000000
0.000000
25%    1959.000000     1.000000        0.000000   36065.000000
27.000000
50%    1970.000000     1.000000        1.000000   52190.000000
185.000000
75%    1977.000000     1.000000        1.000000   69084.000000
517.000000
max    1996.000000     1.000000        1.000000  162397.000000
1493.000000

         MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts
\
count  1825.000000      1825.000000      1825.000000       1825.000000

mean     26.070685       171.418082        36.628493         26.462466

std      39.873621       229.394882        54.033920         40.650020

min       0.000000         1.000000         0.000000          0.000000

25%       1.000000        16.000000         2.000000          1.000000

50%       8.000000        69.000000        11.000000          8.000000

75%      33.000000       238.000000        49.000000         33.000000

max     199.000000      1725.000000       258.000000        262.000000


       MntGoldProds  NumDealsPurchases  NumWebPurchases
NumCatalogPurchases  \
count   1825.000000        1825.000000      1825.000000
1825.000000
mean      43.264658           2.329315         4.135890
2.703014
std       51.215485           1.922153         2.760576
2.956653
min        0.000000           0.000000         0.000000
```

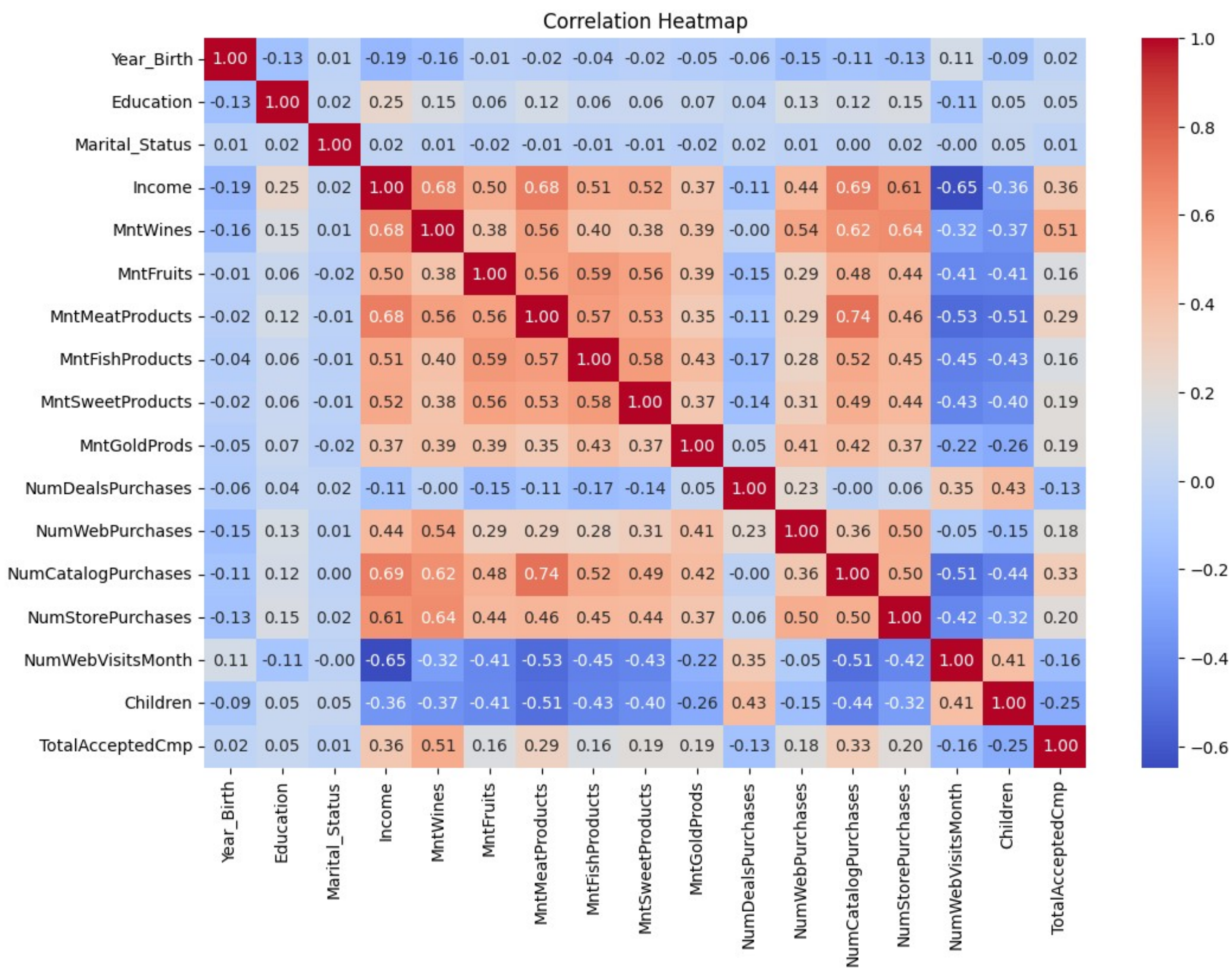
```
0.000000
25%         8.000000           1.000000          2.000000
0.000000
50%        24.000000           2.000000          4.000000
2.000000
75%        56.000000           3.000000          6.000000
4.000000
max       321.000000          15.000000         27.000000
28.000000

       NumStorePurchases  NumWebVisitsMonth     Children
TotalAcceptedCmp
count        1825.000000        1825.000000  1825.000000
1825.000000
mean            5.813151           5.296438     0.955616
0.304110
std             3.244368           2.455372     0.749051
0.687538
min             0.000000           0.000000     0.000000
0.000000
25%             3.000000           3.000000     0.000000
0.000000
50%             5.000000           6.000000     1.000000
0.000000
75%             8.000000           7.000000     1.000000
0.000000
max            13.000000          20.000000     3.000000
4.000000
```

Distribution and correlations

```
# Plot distributions of numerical features
df.hist(bins=20, figsize=(15, 10))
plt.tight_layout()
plt.show()
```




```python
# Correlation heatmap
plt.figure(figsize=(12, 8))
sns.heatmap(df.corr(), annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



Unsuppervised Modeling

```
# Standardize the data
scaler = StandardScaler()
scaled_data = scaler.fit_transform(df)

# Convert back to a DataFrame for easier interpretation
scaled_df = pd.DataFrame(scaled_data, columns=df.columns)
```

Apply PCA to scaled data

```
# Apply PCA with all components
pca = PCA()
pca_data = pca.fit_transform(scaled_data)

# Explained variance ratio
explained_variance_ratio = pca.explained_variance_ratio_
cumulative_variance = np.cumsum(explained_variance_ratio)
```

```python
# Display explained variance and cumulative variance
for i, (evr, cv) in enumerate(zip(explained_variance_ratio,
cumulative_variance), 1):
    print(f"Principal Component {i}: Explained Variance = {evr:.4f},
Cumulative Variance = {cv:.4f}")
```

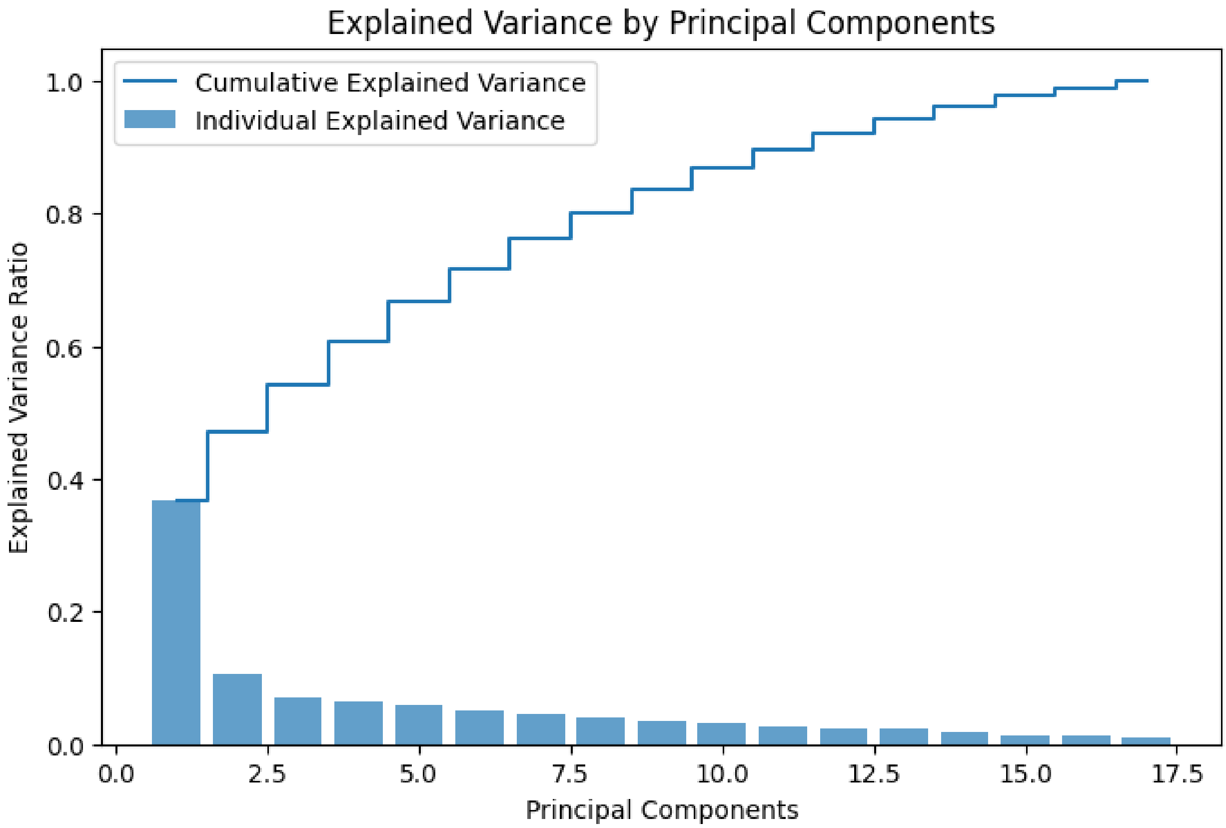
```
Principal Component 1: Explained Variance = 0.3677, Cumulative
Variance = 0.3677
Principal Component 2: Explained Variance = 0.1045, Cumulative
Variance = 0.4723
Principal Component 3: Explained Variance = 0.0696, Cumulative
Variance = 0.5419
Principal Component 4: Explained Variance = 0.0655, Cumulative
Variance = 0.6075
Principal Component 5: Explained Variance = 0.0590, Cumulative
Variance = 0.6664
Principal Component 6: Explained Variance = 0.0513, Cumulative
Variance = 0.7178
Principal Component 7: Explained Variance = 0.0448, Cumulative
Variance = 0.7626
Principal Component 8: Explained Variance = 0.0393, Cumulative
Variance = 0.8018
Principal Component 9: Explained Variance = 0.0352, Cumulative
Variance = 0.8370
Principal Component 10: Explained Variance = 0.0327, Cumulative
Variance = 0.8697
Principal Component 11: Explained Variance = 0.0266, Cumulative
Variance = 0.8964
Principal Component 12: Explained Variance = 0.0245, Cumulative
Variance = 0.9208
Principal Component 13: Explained Variance = 0.0229, Cumulative
Variance = 0.9438
Principal Component 14: Explained Variance = 0.0190, Cumulative
Variance = 0.9628
Principal Component 15: Explained Variance = 0.0142, Cumulative
Variance = 0.9770
Principal Component 16: Explained Variance = 0.0129, Cumulative
Variance = 0.9899
Principal Component 17: Explained Variance = 0.0101, Cumulative
Variance = 1.0000
```

```python
# Find the number of components to explain 90% of the variance
n_components = np.argmax(cumulative_variance >= 0.90) + 1
print(f"Number of components to retain for 95% variance:
{n_components}")

# Apply PCA with the selected number of components
pca = PCA(n_components=n_components)
pca_data = pca.fit_transform(scaled_data)
```

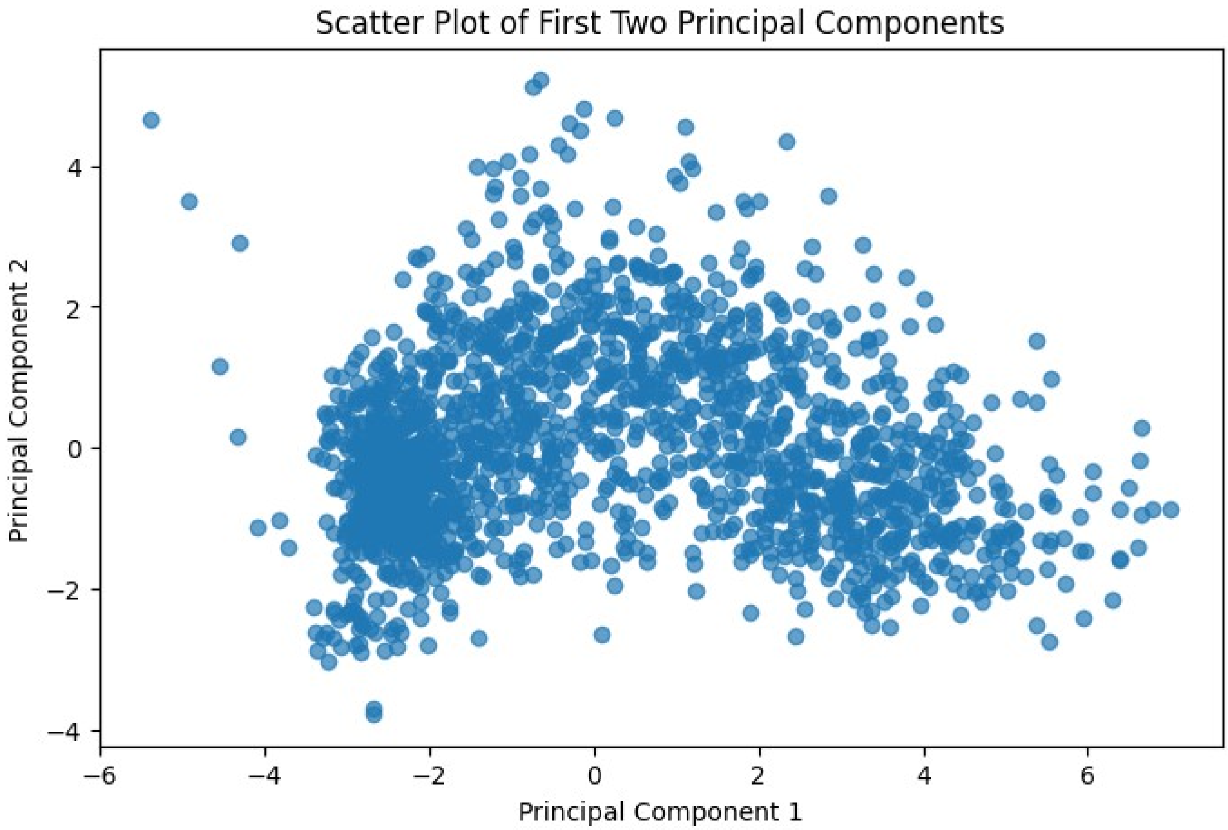
```python
# Create a DataFrame for the reduced data
pca_df = pd.DataFrame(pca_data, columns=[f'PC{i+1}' for i in
range(n_components)])

# Display the reduced data
print(pca_df.head())
```

```
Number of components to retain for 95% variance: 12
        PC1       PC2       PC3       PC4       PC5       PC6
PC7  \
0  3.711080  0.266227  1.329842 -1.353038  1.314457  0.170927 -
0.144921
1 -2.348474 -0.143627 -1.410541 -0.742371  1.482729  0.372218
0.386792
2  1.875066 -0.070527 -0.139948 -0.520546 -0.634604  0.468504 -
1.126120
3 -2.350207 -0.915921  0.253994  0.169082 -0.955281 -0.884539 -
0.056691
4 -0.139387  0.504651  0.648843 -0.471870 -1.088177 -0.843610
0.893717

        PC8       PC9      PC10      PC11      PC12
0  1.207069 -0.610492  2.498160  0.355056  0.191594
1  0.828966 -0.283474 -0.440060  0.060105  0.295269
2 -1.628047  0.132591  0.193654 -0.492643 -0.116726
3 -0.430931  0.128278  0.002937 -0.088045 -0.258504
4 -0.415090 -0.221385  0.048104 -0.127011  0.064756
```

```python
# Plot explained variance ratio
plt.figure(figsize=(8, 5))
plt.bar(range(1, len(explained_variance_ratio) + 1),
explained_variance_ratio, alpha=0.7, align='center', label='Individual
Explained Variance')
plt.step(range(1, len(cumulative_variance) + 1), cumulative_variance,
where='mid', label='Cumulative Explained Variance')
plt.xlabel('Principal Components')
plt.ylabel('Explained Variance Ratio')
plt.title('Explained Variance by Principal Components')
plt.legend(loc='best')
plt.show()
```



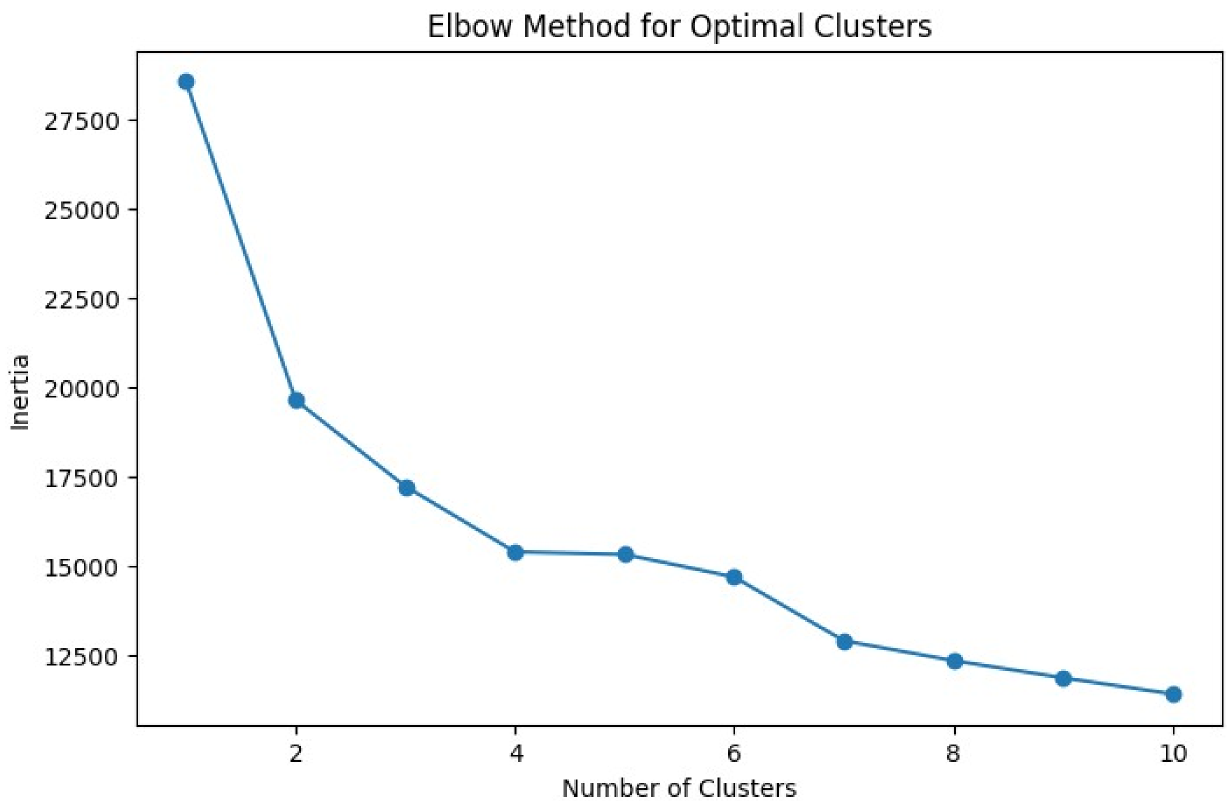

```python
# Scatter plot of the first two principal components
plt.figure(figsize=(8, 5))
plt.scatter(pca_df['PC1'], pca_df['PC2'], alpha=0.7)
plt.xlabel('Principal Component 1')
plt.ylabel('Principal Component 2')
plt.title('Scatter Plot of First Two Principal Components')
plt.show()
```

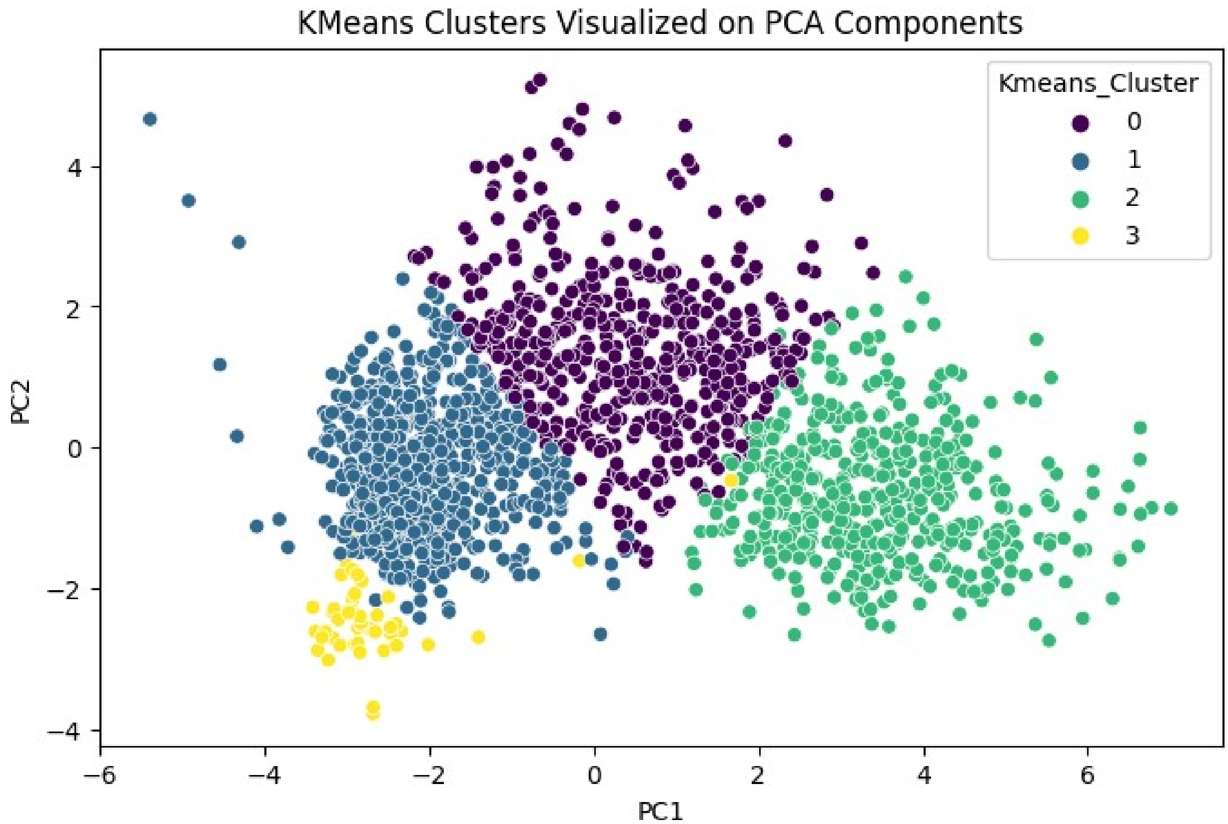


Kmeans

```
# Determine the optimal number of clusters using the Elbow Method
inertia = []
for k in range(1, 11):
    kmeans = KMeans(n_clusters=k, n_init=3,random_state=42)
    kmeans.fit(pca_data)
    inertia.append(kmeans.inertia_)

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

# Apply K-Means with the optimal number of clusters (e.g., k=3)
kmeans = KMeans(n_clusters=4, n_init=3, random_state=42)
clusters = kmeans.fit_predict(pca_data)

# Add cluster labels to the PCA DataFrame
pca_df['Kmeans_Cluster'] = clusters

#visualize clusters
```

```python
# Scatter plot of clusters
plt.figure(figsize=(8, 5))
sns.scatterplot(x='PC1', y='PC2', hue='Kmeans_Cluster', data=pca_df,
palette='viridis')
plt.title('KMeans Clusters Visualized on PCA Components')
plt.show()

# Calculate silhouette score
silhouette_avg = silhouette_score(pca_data, clusters)
print(f'Kmeans Silhouette Score: {silhouette_avg}')
```

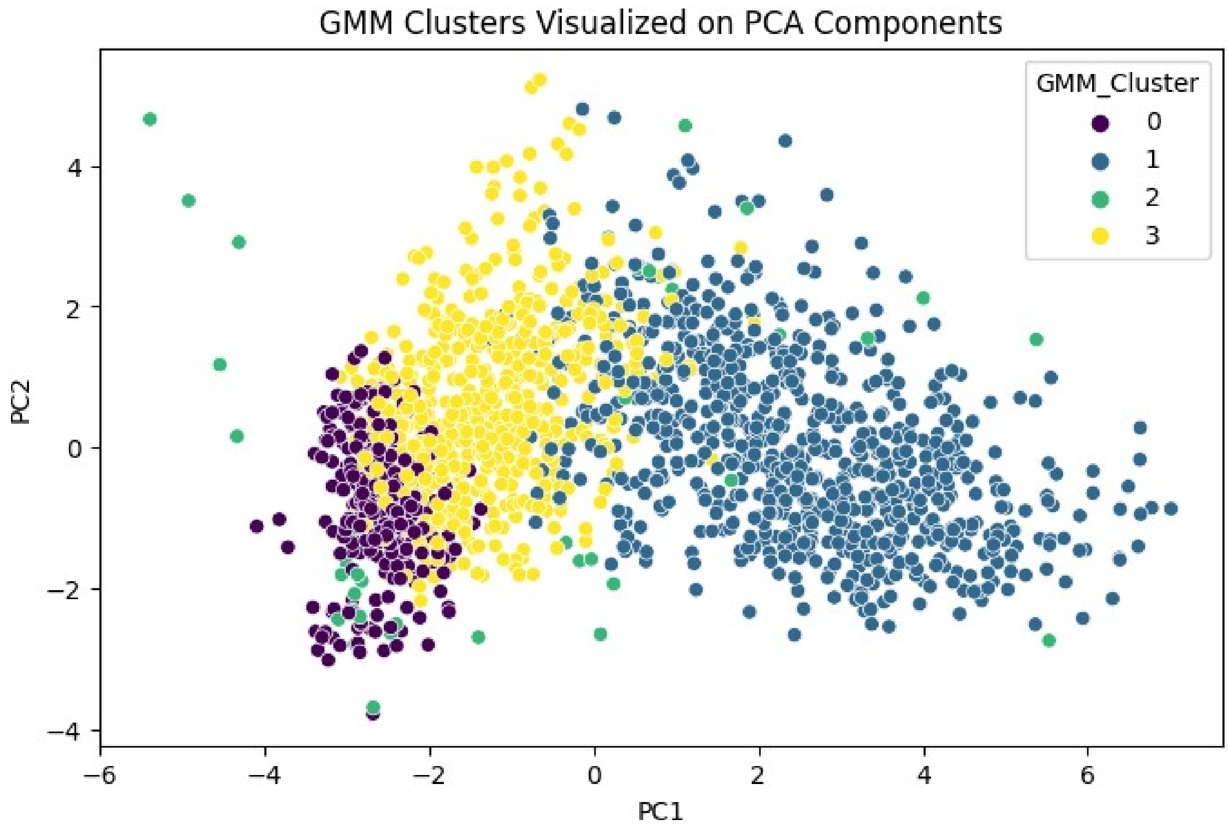





```
Kmeans Silhouette Score: 0.2489910132172435
```

GaussianMixture

```python
from sklearn.mixture import GaussianMixture

# Apply Gaussian Mixture Model
gmm = GaussianMixture(n_components=4, random_state=42)
gmm_clusters = gmm.fit_predict(pca_data)

# Add cluster labels to the PCA DataFrame
pca_df['GMM_Cluster'] = gmm_clusters

# Visualize GMM clusters
plt.figure(figsize=(8, 5))
sns.scatterplot(x='PC1', y='PC2', hue='GMM_Cluster', data=pca_df,
palette='viridis')
plt.title('GMM Clusters Visualized on PCA Components')
plt.show()

silhouette_avg = silhouette_score(pca_data, gmm_clusters)
print(f'GaussianMixture Silhouette Score: {silhouette_avg}')
```

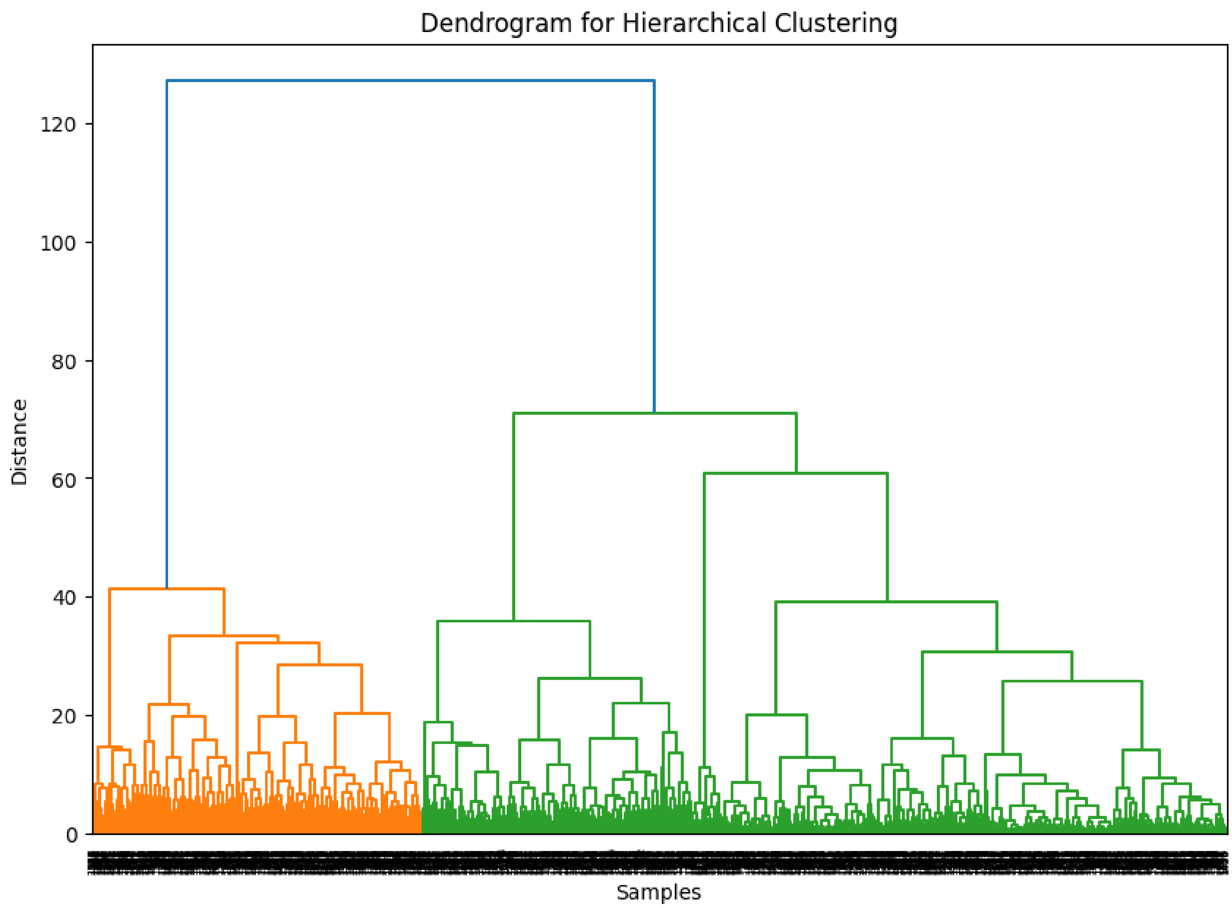


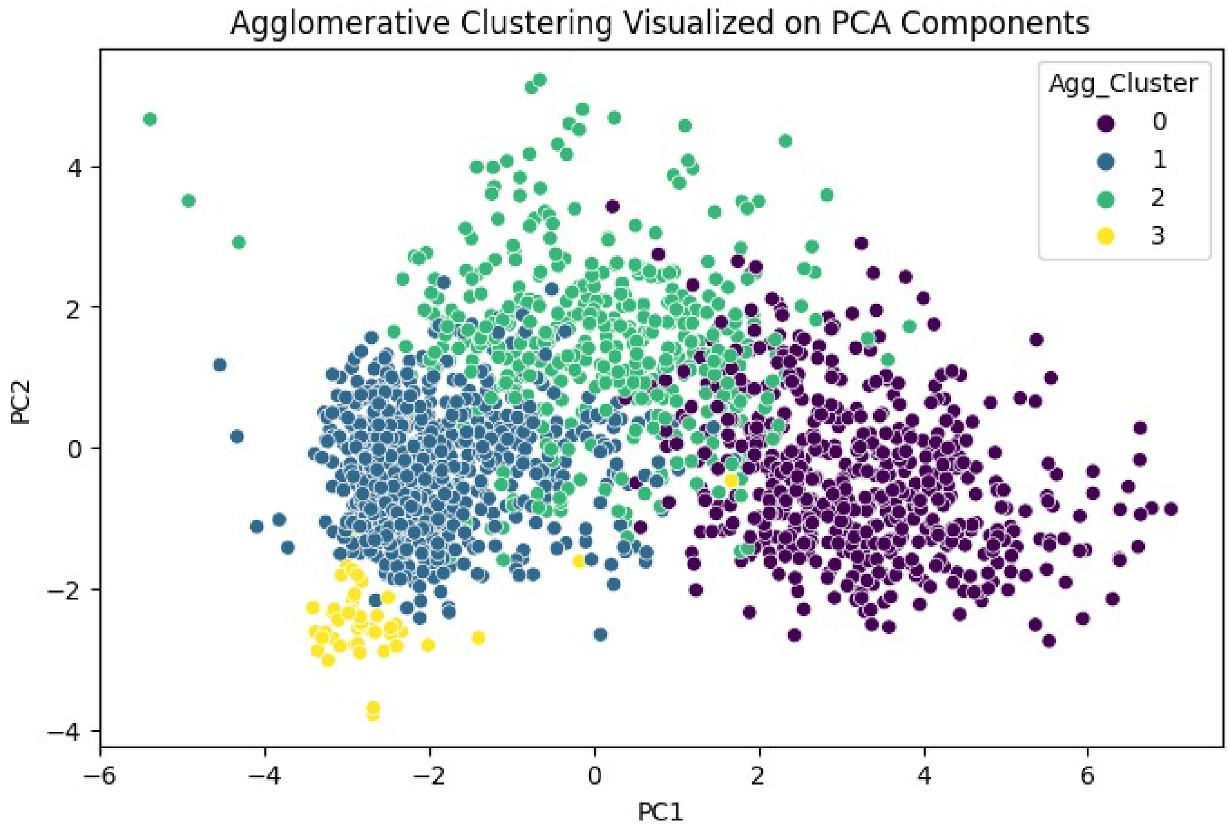

```
GaussianMixture Silhouette Score: 0.08408710473896387
```

AgglomerativeClustering

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

# Perform hierarchical clustering
linkage_matrix = linkage(pca_data, method='ward')

# Plot dendrogram
plt.figure(figsize=(10, 7))
dendrogram(linkage_matrix)
plt.title('Dendrogram for Hierarchical Clustering')
plt.xlabel('Samples')
plt.ylabel('Distance')
plt.show()

# Apply Agglomerative Clustering
agg_clustering = AgglomerativeClustering(n_clusters=4)
agg_clusters = agg_clustering.fit_predict(pca_data)

# Add cluster labels to the PCA DataFrame
pca_df['Agg_Cluster'] = agg_clusters
```

```python
# Visualize Agglomerative Clustering results
plt.figure(figsize=(8, 5))
sns.scatterplot(x='PC1', y='PC2', hue='Agg_Cluster', data=pca_df,
palette='viridis')
plt.title('Agglomerative Clustering Visualized on PCA Components')
plt.show()

silhouette_avg = silhouette_score(pca_data, agg_clusters)
print(f'AgglomerativeClustering Silhouette Score: {silhouette_avg}')
```






```
AgglomerativeClustering Silhouette Score: 0.22266569233751274
```

Model Analysis

We run 3 unsuppervised models and we get the following results:

- Based on the elbow method, 3 clusters or grups are identified.
- Scores:
  - Kmeans Silhouette Score: 0.2489
  - GaussianMixture Silhouette Score: 0.0840
  - AgglomerativeClustering Silhouette Score: 0.2226
- KMeans achieves the highest silhouette score, indicating the best cluster separation and cohesion among the three models. Optimizes for compact, spherical clusters, which often matches the structure of data after PCA or when clusters are well-separated.
- Agglomerative Clustering comes second, showing reasonable but slightly less distinct clusters compared to KMeans. Can capture more complex cluster shapes, but may be more sensitive to noise or outliers

- Gaussian Mixture yields the lowest score, suggesting that the clusters it found are less well-defined or that the data may not fit the Gaussian assumptions well. Assume clusters are Gaussian-distributed, which may not fit your data's true distribution, especially after PCA or with non-Gaussian clusters

- Silhouette Scores: All scores are positive (which is good), but below 0.3, indicating moderate clustering structure. This suggests some overlap between clusters or that the data is not strongly clustered.

Group analysis

```
df_with_groups = df.merge(pca_df[['Kmeans_Cluster']],
right_index=True,left_index=True)

df_with_groups[df_with_groups['Kmeans_Cluster'] == 0].describe()
```

```
        Year_Birth  Education  Marital_Status        Income
MntWines  \
count    509.000000      509.0      509.000000    509.000000
509.000000
mean    1965.011788        1.0        0.654224  58496.123772
484.119843
std       10.052806        0.0        0.476089  10876.074724
292.428051
min     1943.000000        1.0        0.000000   4428.000000
16.000000
25%     1956.000000        1.0        0.000000  52034.000000
262.000000
50%     1965.000000        1.0        1.000000  58512.000000
415.000000
75%     1973.000000        1.0        1.000000  65526.000000
642.000000
max     1992.000000        1.0        1.000000  93404.000000
1462.000000

        MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts
\
count  509.000000       509.000000       509.000000        509.000000

mean    21.630648       143.538310        28.396857         22.245580

std     25.408108        97.612468        31.571686         27.372694

min      0.000000        12.000000         0.000000          0.000000

25%      5.000000        72.000000         6.000000          4.000000

50%     12.000000       123.000000        16.000000         13.000000

75%     30.000000       186.000000        42.000000         30.000000
```

```
max    142.000000       650.000000       175.000000        157.000000


       MntGoldProds  NumDealsPurchases  NumWebPurchases
NumCatalogPurchases  \
count    509.000000         509.000000       509.000000
509.000000
mean      59.707269           3.732809         6.453831
3.151277
std       54.033006           2.251711         2.491784
1.942759
min        0.000000           0.000000         2.000000
0.000000
25%       21.000000           2.000000         5.000000
2.000000
50%       42.000000           3.000000         6.000000
3.000000
75%       82.000000           5.000000         8.000000
4.000000
max      321.000000          13.000000        25.000000
11.000000

       NumStorePurchases  NumWebVisitsMonth    Children
TotalAcceptedCmp  \
count         509.000000         509.000000  509.000000
509.000000
mean            7.842829           5.724951    1.151277
0.290766
std             2.656676           1.839790    0.597488
0.590220
min             0.000000           0.000000    0.000000
0.000000
25%             6.000000           4.000000    1.000000
0.000000
50%             8.000000           6.000000    1.000000
0.000000
75%            10.000000           7.000000    1.000000
0.000000
max            13.000000           9.000000    3.000000
4.000000

       Kmeans_Cluster
count           509.0
mean              0.0
std               0.0
min               0.0
25%               0.0
50%               0.0
75%               0.0
max               0.0
```

```python
df_with_groups[df_with_groups['Kmeans_Cluster'] == 1].describe()
```

```
        Year_Birth  Education  Marital_Status         Income  
MntWines  \
count   800.000000      800.0      800.000000     800.000000   
800.000000   
mean   1970.275000        1.0        0.645000   36636.521250   
50.367500   
std      10.963216        0.0        0.478813   14621.543238   
57.806461   
min    1940.000000        1.0        0.000000    1730.000000   
0.000000   
25%    1963.000000        1.0        0.000000   28329.000000   
10.000000   
50%    1971.000000        1.0        1.000000   36140.500000   
26.000000   
75%    1978.000000        1.0        1.000000   44172.500000   
69.000000   
max    1995.000000        1.0        1.000000  162397.000000  
308.000000   

        MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts
\
count  800.000000       800.000000        800.00000        800.000000   

mean     4.320000        24.265000          6.31500          4.377500   

std      6.940664        23.831538         10.78813          6.512719   

min      0.000000         1.000000          0.00000          0.000000   

25%      0.000000         8.000000          0.00000          0.000000   

50%      2.000000        16.000000          3.00000          2.000000   

75%      5.000000        31.000000          8.00000          5.250000   

max     65.000000       137.000000        150.00000         48.000000   


       MntGoldProds  NumDealsPurchases  NumWebPurchases  
NumCatalogPurchases  \
count    800.000000         800.000000       800.000000   
800.000000   
mean      14.835000           2.072500         2.201250   
0.582500   
std       19.846729           1.456845         1.352973   
0.764149   
min        0.000000           0.000000         0.000000   
0.000000   
```

```
25%        3.000000          1.000000          1.000000
0.000000
50%        9.000000          2.000000          2.000000
0.000000
75%       20.000000          3.000000          3.000000
1.000000
max      262.000000         15.000000          9.000000
5.000000

       NumStorePurchases  NumWebVisitsMonth    Children
TotalAcceptedCmp  \
count         800.000000         800.000000  800.000000
800.000000
mean            3.281250           6.396250    1.277500
0.088750
std             1.165696           2.130707    0.691803
0.293225
min             0.000000           0.000000    0.000000
0.000000
25%             3.000000           5.000000    1.000000
0.000000
50%             3.000000           7.000000    1.000000
0.000000
75%             4.000000           8.000000    2.000000
0.000000
max             9.000000          20.000000    3.000000
2.000000

       Kmeans_Cluster
count           800.0
mean              1.0
std               0.0
min               1.0
25%               1.0
50%               1.0
75%               1.0
max               1.0
```

```
df_with_groups[df_with_groups['Kmeans_Cluster'] == 2].describe()
```

```
        Year_Birth  Education  Marital_Status         Income
MntWines  \
count   467.000000      467.0      467.000000     467.000000
467.000000
mean   1968.008565        1.0        0.623126   76609.779443
616.597430
std      13.061095        0.0        0.485123   12100.468585
323.297018
min    1941.000000        1.0        0.000000    2447.000000
1.000000
```

```
25%    1957.000000        1.0        0.000000   70144.000000
367.000000
50%    1969.000000        1.0        1.000000   76542.000000
562.000000
75%    1978.000000        1.0        1.000000   82197.000000
835.500000
max    1995.000000        1.0        1.000000  160803.000000
1493.000000

        MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts
\
count  467.000000       467.000000       467.000000        467.000000

mean    69.730193       470.633833        99.511777         70.344754

std     51.325896       253.271379        66.116633         52.228359

min      0.000000         3.000000         0.000000          0.000000

25%     27.500000       276.000000        43.000000         29.500000

50%     57.000000       431.000000        89.000000         56.000000

75%    105.500000       619.500000       150.000000        104.000000

max    199.000000      1725.000000       258.000000        262.000000


       MntGoldProds  NumDealsPurchases  NumWebPurchases
NumCatalogPurchases  \
count    467.000000         467.000000       467.000000
467.000000
mean      76.197002           1.289079         5.156317
6.079229
std       59.404518           1.334564         2.410452
3.029210
min        0.000000           0.000000         0.000000
0.000000
25%       30.000000           1.000000         4.000000
4.000000
50%       56.000000           1.000000         5.000000
6.000000
75%      111.000000           1.000000         6.000000
8.000000
max      249.000000          15.000000        27.000000
28.000000

       NumStorePurchases  NumWebVisitsMonth    Children
TotalAcceptedCmp  \
count         467.000000         467.000000  467.000000
```

```
467.000000
mean            8.246253           2.775161    0.214133
0.708779
std             2.954839           1.724223    0.426048
1.032096
min             0.000000           0.000000    0.000000
0.000000
25%             6.000000           1.000000    0.000000
0.000000
50%             8.000000           2.000000    0.000000
0.000000
75%            11.000000           4.000000    0.000000
1.000000
max            13.000000           9.000000    2.000000
4.000000

       Kmeans_Cluster
count           467.0
mean              2.0
std               0.0
min               2.0
25%               2.0
50%               2.0
75%               2.0
max               2.0
```

```
df_with_groups[df_with_groups['Kmeans_Cluster'] == 3].describe()
```

```
        Year_Birth  Education  Marital_Status        Income
MntWines  \
count    49.000000       49.0       49.000000     49.000000
49.000000
mean   1977.816327        0.0        0.591837  19913.346939
7.795918
std      11.698777        0.0        0.496587   6365.638062
32.270975
min    1947.000000        0.0        0.000000   7500.000000
0.000000
25%    1973.000000        0.0        0.000000  15056.000000
1.000000
50%    1979.000000        0.0        1.000000  20194.000000
2.000000
75%    1987.000000        0.0        1.000000  24882.000000
5.000000
max    1996.000000        0.0        1.000000  34445.000000
228.000000

        MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts
\
count   49.000000        49.000000        49.000000         49.000000
```

```
mean    11.204082         11.816327         17.734694          12.612245
std     18.501103         19.716399         33.933621          20.626456
min      0.000000          1.000000          0.000000           0.000000
25%      3.000000          3.000000          4.000000           3.000000
50%      7.000000          7.000000         10.000000           7.000000
75%     11.000000         12.000000         16.000000          14.000000
max    122.000000        122.000000        208.000000         129.000000

       MntGoldProds  NumDealsPurchases  NumWebPurchases
NumCatalogPurchases  \
count     49.000000          49.000000        49.000000
49.000000
mean      22.755102           1.857143         1.918367
0.489796
std       25.320060           1.172604         1.578986
0.680761
min        2.000000           1.000000         0.000000
0.000000
25%        9.000000           1.000000         1.000000
0.000000
50%       15.000000           1.000000         2.000000
0.000000
75%       27.000000           2.000000         2.000000
1.000000
max      144.000000           6.000000        11.000000
2.000000

       NumStorePurchases  NumWebVisitsMonth   Children
TotalAcceptedCmp  \
count          49.000000          49.000000  49.000000
49.000000
mean            2.877551           6.918367   0.734694
0.102041
std             0.992317           1.483756   0.531331
0.305839
min             2.000000           3.000000   0.000000
0.000000
25%             2.000000           6.000000   0.000000
0.000000
50%             3.000000           7.000000   1.000000
0.000000
75%             3.000000           8.000000   1.000000
```

```
0.000000
max               8.000000           9.000000   2.000000
1.000000

       Kmeans_Cluster
count            49.0
mean              3.0
std               0.0
min               3.0
25%               3.0
50%               3.0
75%               3.0
max               3.0
```

Statistics

- Number of records:
  - Group 0: 509
  - Group 1: 800
  - Group 2: 467
  - Group 3: 49
- Education:
  - Group 0: With higher education (~22%)
  - Group 1: Without higher education (~100%)
  - Group 2: Without higher education (~100%)
  - Group 3: Without higher education (~100%)
- Marital Status:
  - Group 0: With a partner (~65%)
  - Group 1: With a partner (~64%)
  - Group 2: With a partner (~62%)
  - Group 3: With a partner (~59%)
- Income:
  - Group 0: Average 58496
  - Group 1: Average 36636
  - Group 2: Average 76609
  - Group 3: Average 19913
- Children
  - Group 0: Average 1.15
  - Group 1: Average 1.27
  - Group 2: Average 0.21
  - Group 3: Average 0.73
- Purchases:
  - Group 0: Average they do store purchases 7.84 times, web purchases 6.45 times and catalog purchases 3.15 times

  - Group 1: Average they do store purchases 3.28 times and catalog purchases 0.58 times
  - Group 2: Average they do store purchases 8.24 times and deals purchases 1.28 times
  - Group 3: Average they do store purchases 2.87 times and catalog purchases 0.48 times
- Amount spend in wine:
  - Group 0: Average 6.45
  - Group 1: Average 50.36
  - Group 2: Average 616.59
  - Group 3: Average 7.79
- Amount spend in fruits:
  - Group 0: Average 21.63
  - Group 1: Average 4.32
  - Group 2: Average 69.73
  - Group 3: Average 11.20
- Amount spend in meat:
  - Group 0: Average 143.53
  - Group 1: Average 24.26
  - Group 2: Average 470.63
  - Group 3: Average 11.81
- Amount spend in fish:
  - Group 0: Average 28.39
  - Group 1: Average 6.31
  - Group 2: Average 99.51
  - Group 3: Average 17.73
- Amount spend in sweet products:
  - Group 0: Average 22.24
  - Group 1: Average 4.37
  - Group 2: Average 70.34
  - Group 3: Average 12.61
- Amount spend in gold products:
  - Group 0: Average 59.70
  - Group 1: Average 14.83
  - Group 2: Average 76.19
  - Group 3: Average 22.75

Customer Profiles

- Group 0: **Moderate Earners with Higher Education Presence**
  - Largest group with moderate income (~$58k).
  - About 22% have higher education.
  - Majority have partners and around 1 child on average.
  - Active buyers across store, web, and catalog channels.

    - Moderate spending across all product categories, especially meat and gold products.
- Group 1: **Lower Income, Without Higher Education**
    - Largest group by count (800), but lowest average income (~$36k).
    - 100% without higher education.
    - Similar partner rate to group 0.
    - Lower purchase frequency, mainly store and catalog.
    - Spend heavily on wine compared to other groups, but low on other categories.
- Group 2: **High Income, Without Higher Education, Low Children**
    - High average income (~$76k), but no higher education.
    - Lowest average children count (0.21).
    - Highest store purchase frequency and deals purchases.
    - Extremely high spending on wine, meat, fruits, sweets, and gold products - the "premium buyers" group.
- Group 3: **Smallest Group, Low Income**
    - Smallest group (49 records), lowest income (~$20k).
    - No higher education.
    - Slightly fewer with partners.
    - Lowest purchase frequency and spending across all categories.
    - Possibly a low-engagement or budget-conscious segment.

Summary

- Group 2 stands out as high-income, premium buyers with heavy spending and purchase frequency.
- Group 1 and Group 3 are lower income, less engaged buyers with minimal education.
- Group 0 is a balanced middle segment with moderate income, some higher education, and diverse purchasing habits.

Marketing strategies should be tailored accordingly:

- Group 2: Premium product promotions and loyalty programs.
- Group 1 & 3: Value deals, discounts, and education-focused campaigns.
- Group 0: Mixed approach, highlighting variety and convenience.