customer-segmentation-analysis

February 22, 2024

[1]:
```python
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
import seaborn as sns
```

[2]:
```python
data = pd.read_csv("/content/ifood_df.csv")
data.head()
```

[2]:
```
    Income  Kidhome  Teenhome  Recency  MntWines  MntFruits  MntMeatProducts  \
0  58138.0        0         0       58       635         88              546
1  46344.0        1         1       38        11          1                6
2  71613.0        0         0       26       426         49              127
3  26646.0        1         0       26        11          4               20
4  58293.0        1         0       94       173         43              118

   MntFishProducts  MntSweetProducts  MntGoldProds  …  marital_Together  \
0              172                88            88  …                 0
1                2                 1             6  …                 0
2              111                21            42  …                 1
3               10                 3             5  …                 1
4               46                27            15  …                 0

   marital_Widow  education_2n Cycle  education_Basic  education_Graduation  \
0              0                   0                0                     1
1              0                   0                0                     1
2              0                   0                0                     1
3              0                   0                0                     1
4              0                   0                0                     0

   education_Master  education_PhD  MntTotal  MntRegularProds  \
0                 0              0      1529             1441
1                 0              0        21               15
2                 0              0       734              692
3                 0              0        48               43
4                 0              1       407              392

   AcceptedCmpOverall
```

```
0                    0
1                    0
2                    0
3                    0
4                    0

[5 rows x 39 columns]
```

Data Exploration and Cleaning:

[3]:
```
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2205 entries, 0 to 2204
Data columns (total 39 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   Income                2205 non-null   float64
 1   Kidhome               2205 non-null   int64
 2   Teenhome              2205 non-null   int64
 3   Recency               2205 non-null   int64
 4   MntWines              2205 non-null   int64
 5   MntFruits             2205 non-null   int64
 6   MntMeatProducts       2205 non-null   int64
 7   MntFishProducts       2205 non-null   int64
 8   MntSweetProducts      2205 non-null   int64
 9   MntGoldProds          2205 non-null   int64
 10  NumDealsPurchases     2205 non-null   int64
 11  NumWebPurchases       2205 non-null   int64
 12  NumCatalogPurchases   2205 non-null   int64
 13  NumStorePurchases     2205 non-null   int64
 14  NumWebVisitsMonth     2205 non-null   int64
 15  AcceptedCmp3          2205 non-null   int64
 16  AcceptedCmp4          2205 non-null   int64
 17  AcceptedCmp5          2205 non-null   int64
 18  AcceptedCmp1          2205 non-null   int64
 19  AcceptedCmp2          2205 non-null   int64
 20  Complain              2205 non-null   int64
 21  Z_CostContact         2205 non-null   int64
 22  Z_Revenue             2205 non-null   int64
 23  Response              2205 non-null   int64
 24  Age                   2205 non-null   int64
 25  Customer_Days         2205 non-null   int64
 26  marital_Divorced      2205 non-null   int64
 27  marital_Married       2205 non-null   int64
 28  marital_Single        2205 non-null   int64
 29  marital_Together      2205 non-null   int64
 30  marital_Widow         2205 non-null   int64
```

```
 31  education_2n Cycle    2205 non-null   int64
 32  education_Basic       2205 non-null   int64
 33  education_Graduation  2205 non-null   int64
 34  education_Master      2205 non-null   int64
 35  education_PhD         2205 non-null   int64
 36  MntTotal              2205 non-null   int64
 37  MntRegularProds       2205 non-null   int64
 38  AcceptedCmpOverall    2205 non-null   int64
dtypes: float64(1), int64(38)
memory usage: 672.0 KB
```

[4]:
```
# Check the dimensions of the dataset (number of rows and columns)
print("\033[1mDimensions of the dataset:\033[0m", data.shape)
```

```
Dimensions of the dataset: (2205, 39)
```

[5]:
```
# Check for missing values in each column
print("\033[1mMissing values in each column:\033[0m")
print(data.isnull().sum())
```

```
Missing values in each column:
Income                  0
Kidhome                 0
Teenhome                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
Age                     0
Customer_Days           0
marital_Divorced        0
```

```
marital_Married          0
marital_Single           0
marital_Together         0
marital_Widow            0
education_2n Cycle       0
education_Basic          0
education_Graduation     0
education_Master         0
education_PhD            0
MntTotal                 0
MntRegularProds          0
AcceptedCmpOverall       0
dtype: int64
```

[6]:

```
# Check for duplicate rows
print("\033[1mNumber of duplicate rows:\033[0m", data.duplicated().sum())
```

Number of duplicate rows: 184

Descriptive Statistics:

[7]:

```
data.describe()
```

[7]:

	Income	Kidhome	Teenhome	Recency	MntWines	\
count	2205.000000	2205.000000	2205.000000	2205.000000	2205.000000	
mean	51622.094785	0.442177	0.506576	49.009070	306.164626	
std	20713.063826	0.537132	0.544380	28.932111	337.493839	
min	1730.000000	0.000000	0.000000	0.000000	0.000000	
25%	35196.000000	0.000000	0.000000	24.000000	24.000000	
50%	51287.000000	0.000000	0.000000	49.000000	178.000000	
75%	68281.000000	1.000000	1.000000	74.000000	507.000000	
max	113734.000000	2.000000	2.000000	99.000000	1493.000000	

	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	\
count	2205.000000	2205.000000	2205.000000	2205.000000	
mean	26.403175	165.312018	37.756463	27.128345	
std	39.784484	217.784507	54.824635	41.130468	
min	0.000000	0.000000	0.000000	0.000000	
25%	2.000000	16.000000	3.000000	1.000000	
50%	8.000000	68.000000	12.000000	8.000000	
75%	33.000000	232.000000	50.000000	34.000000	
max	199.000000	1725.000000	259.000000	262.000000	

	MntGoldProds	…	marital_Together	marital_Widow	education_2n Cycle	\
count	2205.000000	…	2205.000000	2205.000000	2205.000000	
mean	44.057143	…	0.257596	0.034467	0.089796	
std	51.736211	…	0.437410	0.182467	0.285954	
min	0.000000	…	0.000000	0.000000	0.000000	

```
25%       9.000000  …          0.000000        0.000000            0.000000
50%      25.000000  …          0.000000        0.000000            0.000000
75%      56.000000  …          1.000000        0.000000            0.000000
max     321.000000  …          1.000000        1.000000            1.000000

       education_Basic  education_Graduation  education_Master  education_PhD  \
count      2205.000000           2205.000000       2205.000000    2205.000000
mean          0.024490              0.504762          0.165079       0.215873
std           0.154599              0.500091          0.371336       0.411520
min           0.000000              0.000000          0.000000       0.000000
25%           0.000000              0.000000          0.000000       0.000000
50%           0.000000              1.000000          0.000000       0.000000
75%           0.000000              1.000000          0.000000       0.000000
max           1.000000              1.000000          1.000000       1.000000

          MntTotal  MntRegularProds  AcceptedCmpOverall
count  2205.000000      2205.000000          2205.00000
mean    562.764626       518.707483             0.29932
std     575.936911       553.847248             0.68044
min       4.000000      -283.000000             0.00000
25%      56.000000        42.000000             0.00000
50%     343.000000       288.000000             0.00000
75%     964.000000       884.000000             0.00000
max    2491.000000      2458.000000             4.00000

[8 rows x 39 columns]
```

[8]:
```python
#Median
print("\033[1mMedian of each numerical column:\033[0m")
print(data.median())
```

```
Median of each numerical column:
Income                  51287.0
Kidhome                     0.0
Teenhome                    0.0
Recency                    49.0
MntWines                  178.0
MntFruits                   8.0
MntMeatProducts            68.0
MntFishProducts            12.0
MntSweetProducts            8.0
MntGoldProds               25.0
NumDealsPurchases           2.0
NumWebPurchases             4.0
NumCatalogPurchases         2.0
NumStorePurchases           5.0
NumWebVisitsMonth           6.0
```

```
AcceptedCmp3                 0.0
AcceptedCmp4                 0.0
AcceptedCmp5                 0.0
AcceptedCmp1                 0.0
AcceptedCmp2                 0.0
Complain                     0.0
Z_CostContact                3.0
Z_Revenue                   11.0
Response                     0.0
Age                         50.0
Customer_Days             2515.0
marital_Divorced             0.0
marital_Married              0.0
marital_Single               0.0
marital_Together             0.0
marital_Widow                0.0
education_2n Cycle           0.0
education_Basic              0.0
education_Graduation         1.0
education_Master             0.0
education_PhD                0.0
MntTotal                   343.0
MntRegularProds            288.0
AcceptedCmpOverall           0.0
dtype: float64
```

[9]:

```
#Standard deviation
print("\033[1mStandard deviation of each numerical column:\033[0m")
print(data.std())
```

```
Standard deviation of each numerical column:
Income                  20713.063826
Kidhome                     0.537132
Teenhome                    0.544380
Recency                    28.932111
MntWines                  337.493839
MntFruits                  39.784484
MntMeatProducts           217.784507
MntFishProducts            54.824635
MntSweetProducts           41.130468
MntGoldProds               51.736211
NumDealsPurchases           1.886107
NumWebPurchases             2.737424
NumCatalogPurchases         2.798647
NumStorePurchases           3.241796
NumWebVisitsMonth           2.413535
AcceptedCmp3                0.261705
AcceptedCmp4                0.262442
```

```
AcceptedCmp5                0.260222
AcceptedCmp1                0.245518
AcceptedCmp2                0.115872
Complain                    0.094827
Z_CostContact               0.000000
Z_Revenue                   0.000000
Response                    0.358150
Age                        11.705801
Customer_Days             202.563647
marital_Divorced            0.305730
marital_Married             0.487244
marital_Single              0.411833
marital_Together            0.437410
marital_Widow               0.182467
education_2n Cycle          0.285954
education_Basic             0.154599
education_Graduation        0.500091
education_Master            0.371336
education_PhD               0.411520
MntTotal                  575.936911
MntRegularProds           553.847248
AcceptedCmpOverall          0.680440
dtype: float64
```

[10]:

```python
#Variance
print("\033[1mVariance of each numerical column:\033[0m")
print(data.var())
```

Variance of each numerical column:

```
Income                  4.290310e+08
Kidhome                 2.885107e-01
Teenhome                2.963497e-01
Recency                 8.370671e+02
MntWines                1.139021e+05
MntFruits               1.582805e+03
MntMeatProducts         4.743009e+04
MntFishProducts         3.005741e+03
MntSweetProducts        1.691715e+03
MntGoldProds            2.676636e+03
NumDealsPurchases       3.557398e+00
NumWebPurchases         7.493489e+00
NumCatalogPurchases     7.832425e+00
NumStorePurchases       1.050924e+01
NumWebVisitsMonth       5.825153e+00
AcceptedCmp3            6.848937e-02
AcceptedCmp4            6.887580e-02
AcceptedCmp5            6.771527e-02
AcceptedCmp1            6.027919e-02
```

```
AcceptedCmp2            1.342642e-02
Complain                8.992103e-03
Z_CostContact           0.000000e+00
Z_Revenue               0.000000e+00
Response                1.282714e-01
Age                     1.370258e+02
Customer_Days           4.103203e+04
marital_Divorced        9.347054e-02
marital_Married         2.374067e-01
marital_Single          1.696063e-01
marital_Together        1.913273e-01
marital_Widow           3.329424e-02
education_2n Cycle      8.176970e-02
education_Basic         2.390089e-02
education_Graduation    2.500907e-01
education_Master        1.378907e-01
education_PhD           1.693487e-01
MntTotal                3.317033e+05
MntRegularProds         3.067468e+05
AcceptedCmpOverall      4.629986e-01
dtype: float64
```

[11]:

```python
#Skewness
print("\033[1mSkewness of each numerical column:\033[0m")
print(data.skew())
```

Skewness of each numerical column:

```
Income                   0.013164
Kidhome                  0.635495
Teenhome                 0.404623
Recency                 -0.001874
MntWines                 1.166917
MntFruits                2.099281
MntMeatProducts          1.818916
MntFishProducts          1.912028
MntSweetProducts         2.098355
MntGoldProds             1.834468
NumDealsPurchases        2.312369
NumWebPurchases          1.201376
NumCatalogPurchases      1.368122
NumStorePurchases        0.706960
NumWebVisitsMonth        0.229994
AcceptedCmp3             3.259123
AcceptedCmp4             3.246508
AcceptedCmp5             3.284676
AcceptedCmp1             3.551642
AcceptedCmp2             8.402967
Complain                10.363651
```

```
Z_CostContact           0.000000
Z_Revenue               0.000000
Response                1.950559
Age                     0.089941
Customer_Days          -0.019176
marital_Divorced        2.590858
marital_Married         0.463015
marital_Single          1.378865
marital_Together        1.109366
marital_Widow           5.107283
education_2n Cycle      2.871626
education_Basic         6.157110
education_Graduation   -0.019061
education_Master        1.805504
education_PhD           1.382120
MntTotal                0.915811
MntRegularProds         0.984218
AcceptedCmpOverall      2.719448
dtype: float64
```

[12]:

```
#Kurtosis
print("\033[1mKurtosis of each numerical column:\033[0m")
print(data.kurtosis())
```

Kurtosis of each numerical column:

```
Income                  -0.847564
Kidhome                 -0.789442
Teenhome                -0.989633
Recency                 -1.198443
MntWines                 0.574909
MntFruits                4.050778
MntMeatProducts          3.248138
MntFishProducts          3.056338
MntSweetProducts         4.079829
MntGoldProds             3.143759
NumDealsPurchases        8.186671
NumWebPurchases          4.101823
NumCatalogPurchases      3.210414
NumStorePurchases       -0.635247
NumWebVisitsMonth        1.904398
AcceptedCmp3             8.629707
AcceptedCmp4             8.547565
AcceptedCmp5             8.797075
AcceptedCmp1            10.623796
AcceptedCmp2            68.672133
Complain               105.500953
Z_CostContact            0.000000
Z_Revenue                0.000000
```

```
Response                  1.806319
Age                      -0.797036
Customer_Days            -1.202857
marital_Divorced          4.716821
marital_Married          -1.787239
marital_Single           -0.098821
marital_Together         -0.770007
marital_Widow            24.106203
education_2n Cycle        6.251906
education_Basic          35.942609
education_Graduation     -2.001453
education_Master          1.260988
education_PhD            -0.089827
MntTotal                 -0.218527
MntRegularProds          -0.059651
AcceptedCmpOverall        7.974750
dtype: float64
```

Customer Segmentation:

[13]:
```
from sklearn.cluster import KMeans
from sklearn.preprocessing import StandardScaler
from sklearn.metrics import silhouette_score
```

[14]:
```
# Select relevant features for clustering
selected_features = ['Income', 'Recency', 'MntWines', 'MntFruits',␣
↪'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']

# Standardize the selected features
scaler = StandardScaler()
data_scaled = scaler.fit_transform(data[selected_features])
```

[15]:
```
# Determine the optimal number of clusters using silhouette score
silhouette_scores = []
for k in range(2, 11):
    kmeans = KMeans(n_clusters=k, random_state=42)
    kmeans.fit(data_scaled)
    silhouette_scores.append((k, silhouette_score(data_scaled, kmeans.labels_)))
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
```

```
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[16]:

```
# Choose the optimal number of clusters based on the highest silhouette score
optimal_num_clusters = max(silhouette_scores, key=lambda x: x[1])[0]

# Perform K-means clustering with the optimal number of clusters
kmeans = KMeans(n_clusters=optimal_num_clusters, random_state=42)
kmeans.fit(data_scaled)
```

```
/usr/local/lib/python3.10/dist-packages/sklearn/cluster/_kmeans.py:870:
FutureWarning: The default value of `n_init` will change from 10 to 'auto' in
1.4. Set the value of `n_init` explicitly to suppress the warning
  warnings.warn(
```

[16]:

```
KMeans(n_clusters=2, random_state=42)
```

[17]:

```
# Add cluster labels to the original dataset
data['Cluster'] = kmeans.labels_

# Display the cluster centers
cluster_centers = pd.DataFrame(scaler.inverse_transform(kmeans.
 ↪cluster_centers_), columns=selected_features)
```

```python
print("\033[1mCluster centers:\033[0m")
print(cluster_centers)
```

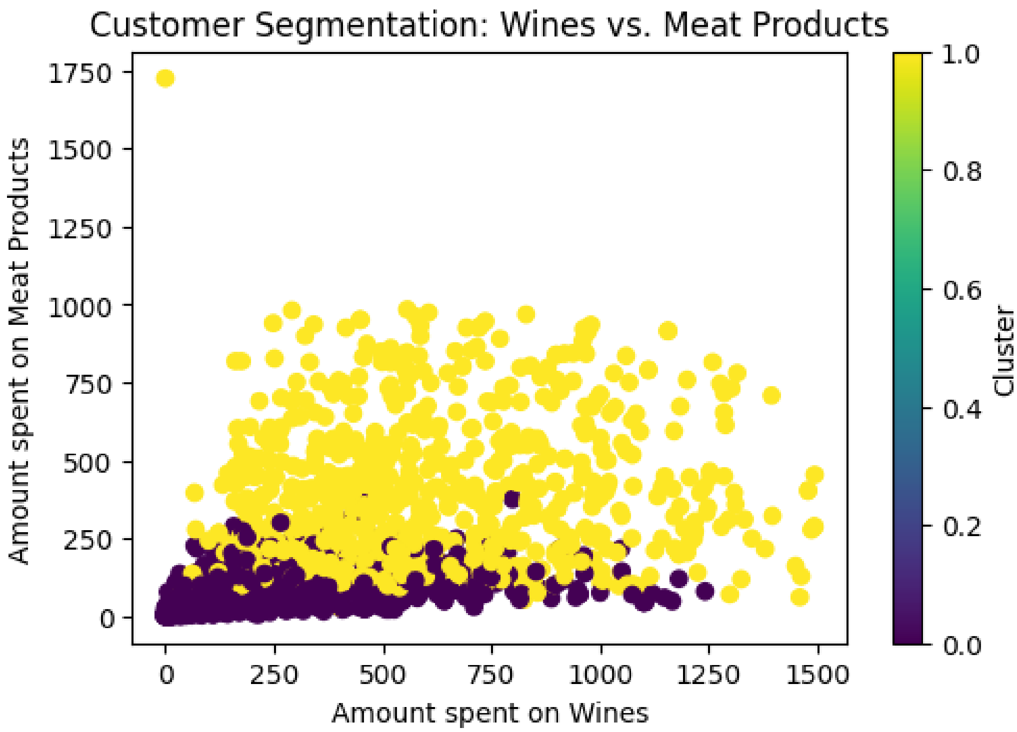
```
Cluster centers:
         Income    Recency    MntWines  MntFruits  MntMeatProducts  \
0  40509.257576  48.588154  146.756887   7.480716        46.162534
1  73050.832669  49.820717  613.548473  62.891102       395.066401

   MntFishProducts  MntSweetProducts  MntGoldProds
0        10.693526          7.440083     25.344353
1        89.941567         65.092961     80.140770
```

[18]:
```python
# Display the number of customers in each cluster
print("\033[1mNumber of customers in each cluster:\033[0m")
print(data['Cluster'].value_counts())
```

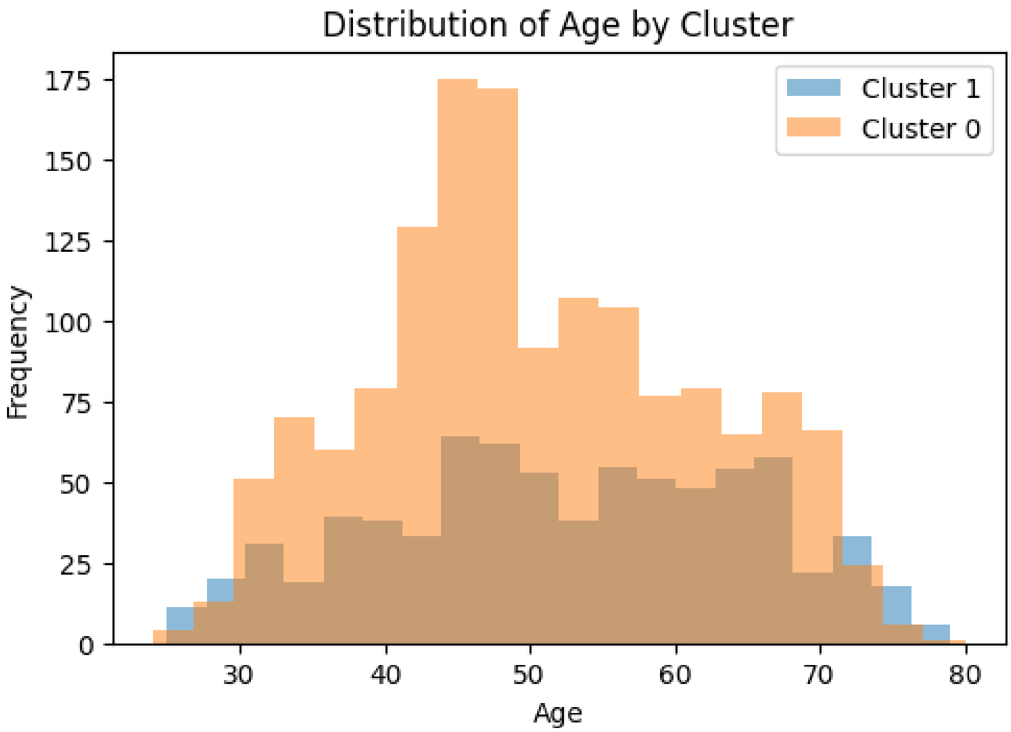
```
Number of customers in each cluster:
0    1452
1     753
Name: Cluster, dtype: int64
```

Visualization:

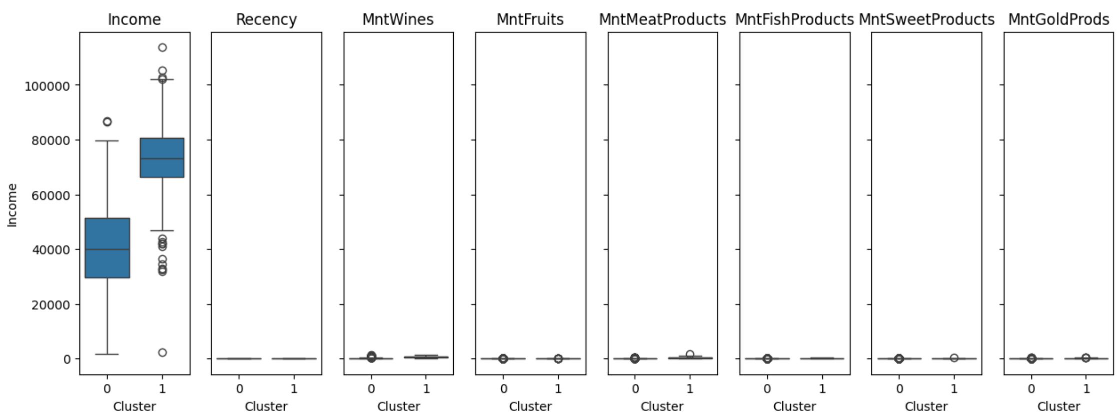
[19]:
```python
# Scatter plot of two features colored by cluster
plt.figure(figsize=(6, 4))
plt.scatter(data['MntWines'], data['MntMeatProducts'], c=data['Cluster'],␣
↪cmap='viridis')
plt.xlabel('Amount spent on Wines')
plt.ylabel('Amount spent on Meat Products')
plt.title('Customer Segmentation: Wines vs. Meat Products')
plt.colorbar(label='Cluster')
plt.show()
```



[20]:
```
# Create histograms of customer age for each cluster
plt.figure(figsize=(6, 4))
for cluster_label in data['Cluster'].unique():
    cluster_data = data[data['Cluster'] == cluster_label]
    plt.hist(cluster_data['Age'], bins=20, alpha=0.5, label=f'Cluster␣
    ↪{cluster_label}')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.title('Distribution of Age by Cluster')
plt.legend()
plt.show()
```



[21]:
```
# Create box plots of spending on different products for each cluster
fig, axes = plt.subplots(1, len(selected_features), figsize=(15, 5),␣
  ↪sharey=True)
for i, feature in enumerate(selected_features):
    sns.boxplot(x='Cluster', y=feature, data=data, ax=axes[i])
    axes[i].set_title(f'{feature}')
plt.show()
```



[22]:
```
# Create a pairplot colored by cluster
sns.pairplot(data, vars=['MntWines', 'MntMeatProducts', 'Income'],
    hue='Cluster', palette='viridis')
plt.show()
```