marketing-analytics-customer-segmentation (1)

August 26, 2024

[ ]:
```
Hi This is Sameer Mohammad an Data Analytic intern.
```

Introduction Customer segmentation is a powerful marketing technique that involves dividing a customer base into distinct segments based on shared characteristics, behaviours, or demographics. The primary purpose of customer segmentation is to better understand and serve customers in a more personalized and targeted way. Marketing segmentation helps to understand customer needs better and reach the right customer with right messaging.
Exploratory Data Analysis (EDA) is a necessary preliminary step before using a segmentation algorithm.

Data The data contains 2,205 observations and 39 columns. The dataset description on the card does not match the actual columns in the dataset. The below list contains actual columns from the dataset and the assumed descriptions from the column's names.

Feature	Description	Comment
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	
AcceptedCmpOverall	overall number of accepted campaigns	This column was added from the list of actual columns
Response	1 if customer accepted the offer in the last campaign, 0 otherwise	
Complain	1 if customer complained in the last 2 years	
DtCustomer	date of customer's enrolment with the company	There is no such column in the dataset
Customer_Days	number of days since registration as a customer	
Education	customer's level of education	There is no such column in the actual dataset

Feature	Description	Comment
education_2n Cycle	customer has secondary education	This column was added from the list of actual columns
education_Basic	customer has basic education	This column was added from the list of actual columns
education_Graduation	Customer has a bachelor degree	This column was added from the list of actual columns
education_Master	Customer has a masters degree	This column was added from the list of actual columns
education_PhD	Customer has a PhD	This column was added from the list of actual columns
Marital	customer's marital status.	There is no such column in the actual dataset
marital_Divorced	1 if customer is divorced, 0 otherwise.	This column was added from the list of actual columns
marital_Married	1 if customer is married, 0 otherwise.	This column was added from the list of actual columns
marital_Single	1 if customer is single, 0 otherwise.	This column was added from the list of actual columns
marital_Together	1 if customer is in relationship, 0 otherwise.	This column was added from the list of actual columns
marital_Widow	1 if customer is a widow / widower, 0 otherwise	
Kidhome	number of small children in customer's household	
Teenhome	number of teenagers in customer's household	
Income	customer's yearly household income	
MntFishProducts	amount spent on fish products in the last 2 years	
MntMeatProducts	amount spent on meat products in the last 2 years	
MntFruits	amount spent on fruits products in the last 2 years	
MntSweetProducts	amount spent on sweet products in the last 2 years	
MntWines	amount spent on wine products in the last 2 years	

Feature	Description	Comment
MntGoldProds	amount spent on gold products in the last 2 years	
NumDealsPurchases	number of purchases made with discount	
NumCatalogPurchases	number of purchases made using catalogue	
NumStorePurchases	number of purchases made directly in stores	
NumWebPurchases	number of purchases made through company's web site	
NumWebVisitsMonth	number of visits to company's web site in the last month	
Recency	number of days since the last purchase	
Z_CostContact		This column was added from the list of actual columns
Z_Revenue		This column was added from the list of actual columns
Age	Age of customer	This column was added from the list of actual columns
MntTotal	Total amount spent on all the products	This column was added from the list of actual columns
MntRegularProds		This column was added from the list of actual columns

Data Preparation and Cleaning In this section: - Reviewing data columns and comparing them to the dataset description - Looking for missing values - Checking column types - Assessing unique values

[1]:
```
#Importing necessary libraries
import numpy as np # linear algebra
import pandas as pd # data processing, CSV file I/O (e.g. pd.read_csv)
import warnings
warnings.filterwarnings("ignore")
import seaborn as sns
import matplotlib.pyplot as plt
from scipy.stats import pointbiserialr
```

[2]:
```
#Reading the data
data = pd.read_csv('/kaggle/input/marketing-data/ifood_df.csv')
```

```
#Taking a look at the top 5 rows of the data
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]
```

There is some data in the dataframe. Let's dig into the data.

0.1 Reviewing data columns and comparing them to the dataset description

Retrieving the list of actual columns to compare with the column's description in the dictionary.png. The list of columns has been updated and the data description contains actual columns.

[3]:
```
data.columns
```

[3]:
```
Index(['Income', 'Kidhome', 'Teenhome', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Z_CostContact', 'Z_Revenue', 'Response',
       'Age', 'Customer_Days', 'marital_Divorced', 'marital_Married',
       'marital_Single', 'marital_Together', 'marital_Widow',
       'education_2n Cycle', 'education_Basic', 'education_Graduation',
       'education_Master', 'education_PhD', 'MntTotal', 'MntRegularProds',
       'AcceptedCmpOverall'],
      dtype='object')
```

0.2 Looking for missing values

Surprisingly, there is no missing values in the data and there are 2,205 observations in the data frame.

[4]:
```
data.isna().sum()
```

[4]:
```
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
```

0.3 Checking column types

All column types look good. There is no need to change any data types.

[5]:
```
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
```

0.4 Assessing unique values

Let's check the unique values in each column. If a column has the same values then we cannot use this column in our analysis and can remove it from the data frame.

[6]:
```python
data.nunique()
```

[6]:
```
Income                 1963
Kidhome                   3
Teenhome                  3
Recency                 100
MntWines                775
MntFruits               158
MntMeatProducts         551
MntFishProducts         182
MntSweetProducts        176
MntGoldProds            212
NumDealsPurchases        15
NumWebPurchases          15
NumCatalogPurchases      13
NumStorePurchases        14
NumWebVisitsMonth        16
AcceptedCmp3              2
AcceptedCmp4              2
AcceptedCmp5              2
AcceptedCmp1              2
AcceptedCmp2              2
```

```
Complain                    2
Z_CostContact               1
Z_Revenue                   1
Response                    2
Age                        56
Customer_Days             662
marital_Divorced            2
marital_Married             2
marital_Single              2
marital_Together            2
marital_Widow               2
education_2n Cycle          2
education_Basic             2
education_Graduation        2
education_Master            2
education_PhD               2
MntTotal                  897
MntRegularProds           974
AcceptedCmpOverall          5
dtype: int64
```

Columns Z_CostContact and Z_Revenue have all the same values. These columns will not help us to understand our customers better. We can drop these columns from the data frame.

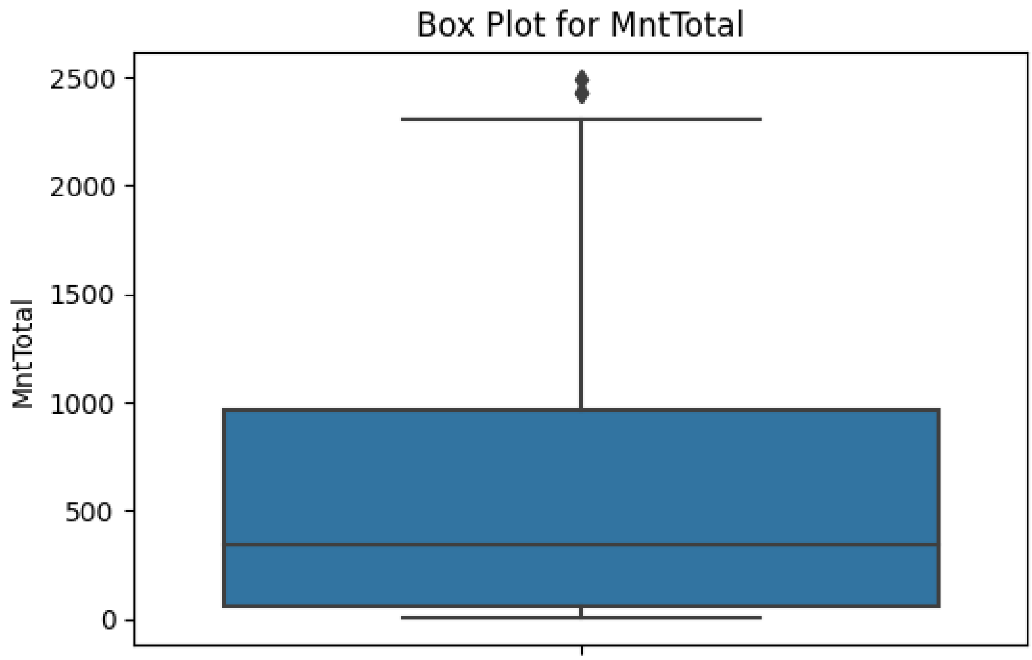
[7]:
```
data.drop(columns=['Z_CostContact','Z_Revenue'],inplace=True)
```

Data Exploration In this section: - Box plot for the total amount spent on all products (MntTotal) - Outliers - Box plot and histogram for income - Histogram for age - Correlation matrix - Point-Biserial correlations for binary variables

0.5 Box plot for the total amount spent on all products (MntTotal)

Our analysis will be focused on total amount spent on all products (MntTotal). Boxplot will help us to find outliers if any.

[8]:
```
plt.figure(figsize=(6, 4))
sns.boxplot(data=data, y='MntTotal')
plt.title('Box Plot for MntTotal')
plt.ylabel('MntTotal')
plt.show()
```



0.6 Outliers

The box plot spotted a few outliers in the MntTotal. Let's take a closer look at the outliers.

[9]:
```
Q1 = data['MntTotal'].quantile(0.25)
Q3 = data['MntTotal'].quantile(0.75)
IQR = Q3 - Q1
lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR
outliers = data[(data['MntTotal'] < lower_bound) | (data['MntTotal'] >
 ↪upper_bound)]
outliers.head()
```

[9]:
```
       Income  Kidhome  Teenhome  Recency  MntWines  MntFruits  \
1159  90638.0        0         0       29      1156        120
1467  87679.0        0         0       62      1259        172
1547  90638.0        0         0       29      1156        120

      MntMeatProducts  MntFishProducts  MntSweetProducts  MntGoldProds  …  \
1159              915               94               144            96  …
1467              815               97               148            33  …
1547              915               94               144            96  …

      marital_Together  marital_Widow  education_2n Cycle  education_Basic  \
1159                 0              0                   0                0
```

```
1467                 1              0                   0                 0
1547                 0              0                   0                 0

      education_Graduation  education_Master  education_PhD  MntTotal  \
1159                     0                 1              0      2429
1467                     1                 0              0      2491
1547                     0                 1              0      2429

      MntRegularProds  AcceptedCmpOverall
1159             2333                   1
1467             2458                   3
1547             2333                   1

[3 rows x 37 columns]
```

0.6.1 Outliers removal

[10]:
```python
data = data[(data['MntTotal'] > lower_bound) & (data['MntTotal'] < upper_bound)]
data.describe()
```

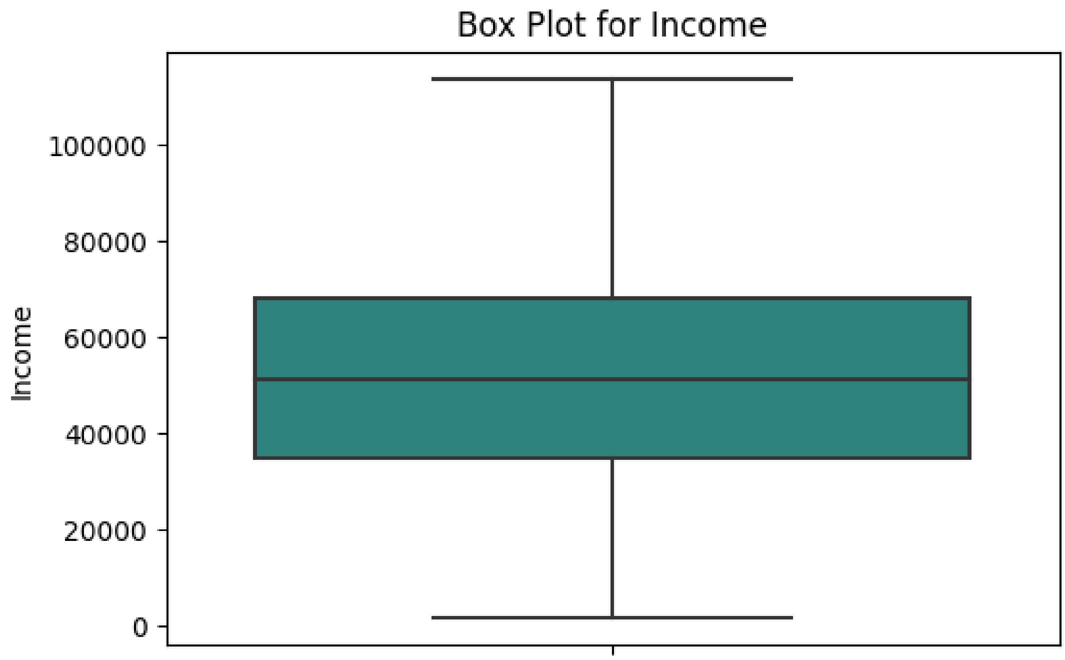
[10]:
```
              Income      Kidhome     Teenhome      Recency     MntWines  \
count    2202.000000  2202.000000  2202.000000  2202.000000  2202.000000
mean    51570.283379     0.442779     0.507266    49.021344   304.960036
std     20679.438848     0.537250     0.544429    28.944211   336.135586
min      1730.000000     0.000000     0.000000     0.000000     0.000000
25%     35182.500000     0.000000     0.000000    24.000000    24.000000
50%     51258.500000     0.000000     0.000000    49.000000   176.500000
75%     68146.500000     1.000000     1.000000    74.000000   505.000000
max    113734.000000     2.000000     2.000000    99.000000  1493.000000

         MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts  \
count  2202.000000      2202.000000      2202.000000       2202.000000
mean     26.252044       164.336058        37.678474         26.967302
std      39.589747       216.312982        54.821185         40.926101
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       230.750000        50.000000         33.000000
max     199.000000      1725.000000       259.000000        262.000000

       MntGoldProds  …  marital_Together  marital_Widow  education_2n Cycle  \
count   2202.000000  …       2202.000000    2202.000000         2202.000000
mean      44.014986  …          0.257493       0.034514            0.089918
std       51.747221  …          0.437353       0.182587            0.286130
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      2202.000000           2202.000000       2202.000000    2202.000000
mean          0.024523              0.504995          0.164396       0.216167
std           0.154702              0.500089          0.370719       0.411723
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  2202.000000      2202.000000         2202.000000
mean    560.193915       516.178928            0.297457
std     572.096830       549.962471            0.678134
min       4.000000      -283.000000            0.000000
25%      56.000000        42.000000            0.000000
50%     342.500000       288.000000            0.000000
75%     962.000000       883.000000            0.000000
max    2304.000000      2259.000000            4.000000

[8 rows x 37 columns]
```

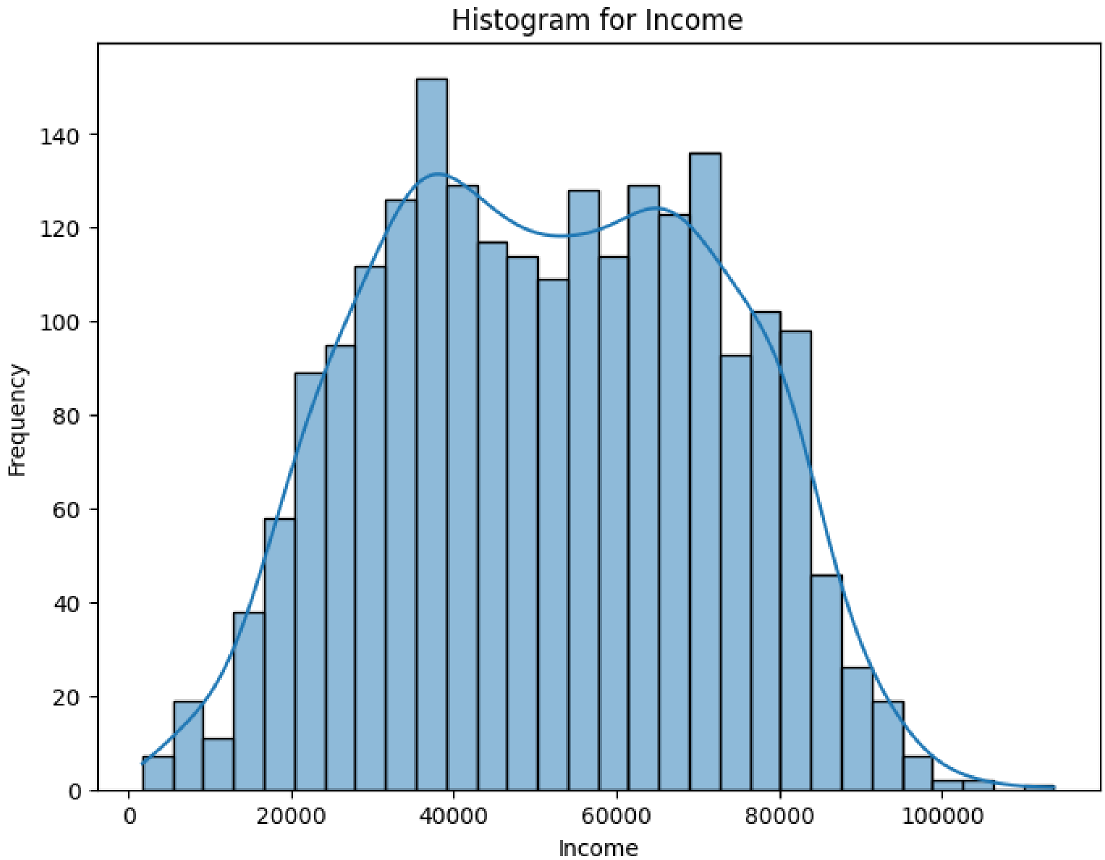
0.7 Box plot and histogram for income

[11]:

```
plt.figure(figsize=(6, 4))
sns.boxplot(data=data, y='Income', palette='viridis')
plt.title('Box Plot for Income')
plt.ylabel('Income')
plt.show()
```



[12]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Income', bins=30, kde=True)
plt.title('Histogram for Income')
plt.xlabel('Income')
plt.ylabel('Frequency')
plt.show()
```



Income distribution is close to normal distribution with no outliers.

0.8 Histogram for age

[13]:
```
plt.figure(figsize=(8, 6))
sns.histplot(data=data, x='Age', bins=30, kde=True)
plt.title('Histogram for Age')
plt.xlabel('Age')
plt.ylabel('Frequency')
plt.show()
```

[14]:
```
print("Skewness: %f" % data['Age'].skew())
print("Kurtosis: %f" % data['Age'].kurt())
```

```
Skewness: 0.091227
Kurtosis: -0.796125
```

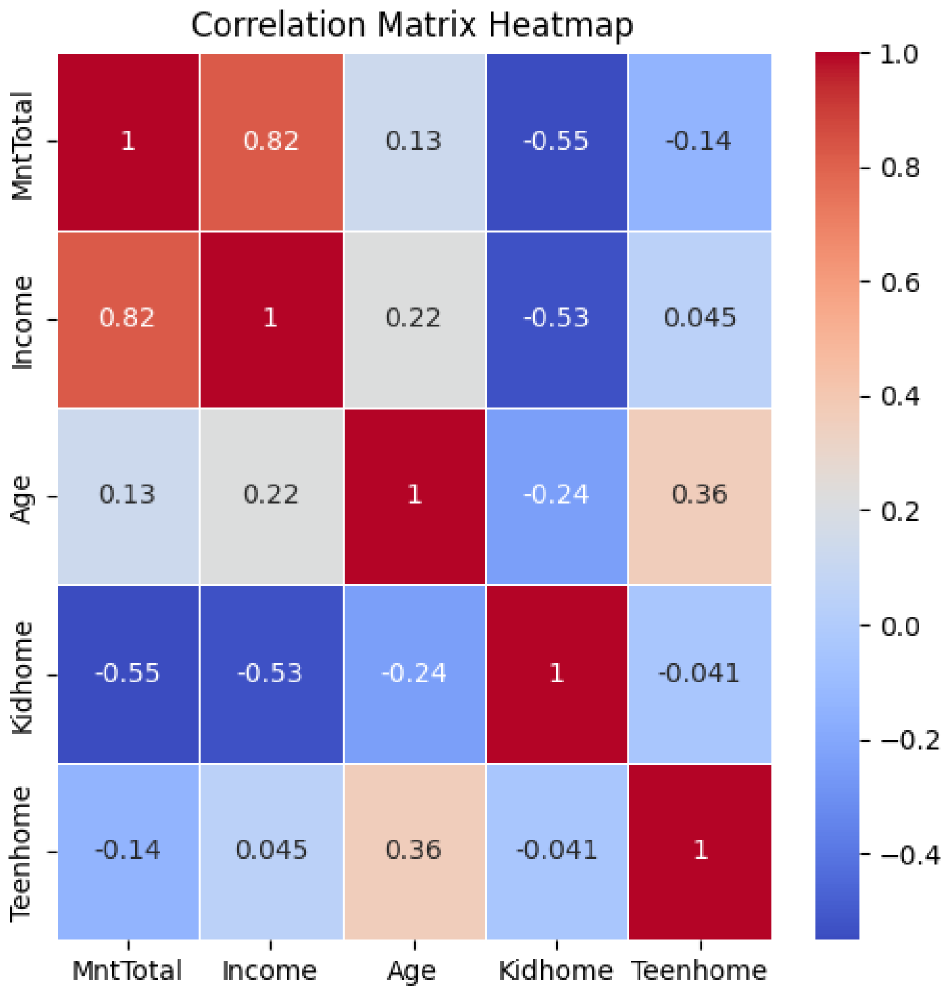
The age distribution looks approximately symmetrical and the left and right sides of distribution are roughly equal. Skewness of 0.09 (close to zero) supports the visual observation of the distribution. Kurtosis of -0.8 suggests that the distribution is close to normal with lighter tails and less peaked than a normal distribution.

0.9 Correlation matrix

There are many columns in the data. The correlation matrix will be very crowded if we use all columns of the data frame. We will group the columns and explore correlation between columns in each group and the column ‘MntTotal’. We will focus on the column ‘MntTotal’ to understand how we can segment the customers who buy the most in overall. We can run similar analysis for every type of product.

[15]:
```python
cols_demographics = ['Income','Age']
cols_children = ['Kidhome', 'Teenhome']
cols_marital = ['marital_Divorced', 'marital_Married','marital_Single',␣
↪'marital_Together', 'marital_Widow']
cols_mnt = ['MntTotal', 'MntRegularProds','MntWines', 'MntFruits',␣
↪'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']
cols_communication = ['Complain', 'Response', 'Customer_Days']
cols_campaigns = ['AcceptedCmpOverall', 'AcceptedCmp1', 'AcceptedCmp2',␣
↪'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']
cols_source_of_purchase = ['NumDealsPurchases',␣
↪'NumWebPurchases','NumCatalogPurchases', 'NumStorePurchases',␣
↪'NumWebVisitsMonth']
cols_education = ['education_2n Cycle', 'education_Basic',␣
↪'education_Graduation', 'education_Master', 'education_PhD']
```

[16]:
```python
corr_matrix = data[['MntTotal']+cols_demographics+cols_children].corr()
plt.figure(figsize=(6,6))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', linewidths=0.5)
plt.title('Correlation Matrix Heatmap')
plt.show()
```



MntTotal has strong positive correlation with income and intermediate negative correlation with Kidhome. Income feature has nearly the same negative correlation with Kidhome and MntTotal.

0.10 Point-Biserial correlations for binary variables

Pearson correlation measures the strength and direction of a linear relationship between two continuous variables. We used Pearson correlation for MntTotal, Age and Income. When we try to understand the relationship between a continuous variable MntTotal and binary variables like marital status then we should use Point-Biserial Correlation Point-Biserial Correlation is used to measure the strength and direction of the linear relationship between a binary variable and a continuous variable.

[17]:
```
for col in cols_marital:
    correlation, p_value = pointbiserialr(data[col], data['MntTotal'])
    print(f'{correlation:.4f}: Point-Biserial Correlation for {col} with␣
 ↪p-value {p_value:.4f}')
```

```
0.0053: Point-Biserial Correlation for marital_Divorced with p-value 0.8041
-0.0188: Point-Biserial Correlation for marital_Married with p-value 0.3767
0.0011: Point-Biserial Correlation for marital_Single with p-value 0.9571
0.0008: Point-Biserial Correlation for marital_Together with p-value 0.9708
0.0370: Point-Biserial Correlation for marital_Widow with p-value 0.0826
```

There is no strong Point-Biserial correlation between MntTotal and different marital statuses. Some feature engineering may be required during the modelling process.

```
[18]: for col in cols_education:
          correlation, p_value = pointbiserialr(data[col], data['MntTotal'])
          print(f'{correlation:.4f}: Point-Biserial Correlation for {col} with␣
       ↪p-value {p_value:.4f}')
```

```
-0.0593: Point-Biserial Correlation for education_2n Cycle with p-value 0.0054
-0.1389: Point-Biserial Correlation for education_Basic with p-value 0.0000
0.0159: Point-Biserial Correlation for education_Graduation with p-value 0.4551
0.0004: Point-Biserial Correlation for education_Master with p-value 0.9842
0.0737: Point-Biserial Correlation for education_PhD with p-value 0.0005
```

There is no strong Point-Biserial correlation between MntTotal and various education levels.

Feature Engineering In this section: - New feature: Marital - New feature: In_relationship

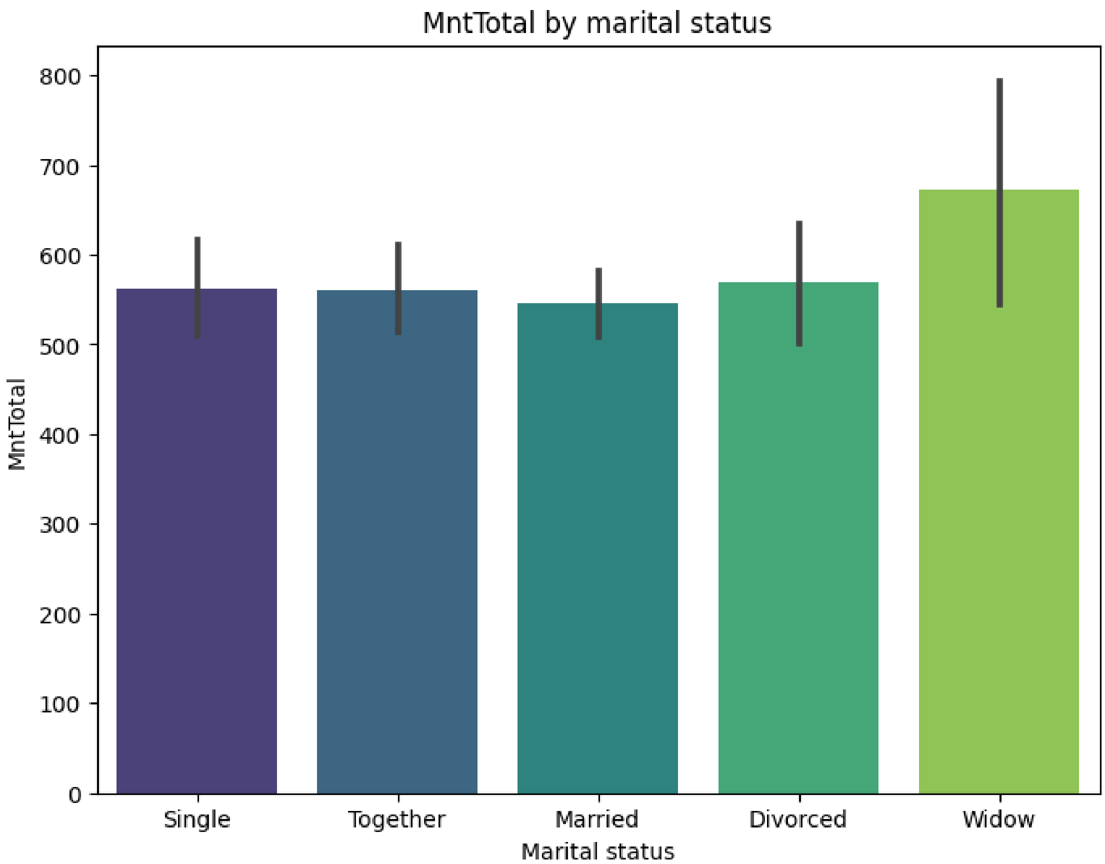
0.11 New feature: Marital

The data frame contains 5 columns to reflect marital status. We are going to create a new column 'marital' with values: Divorced, Married, Single, Together, Widow. This column will allow us to draw some additional plots.

```
[19]: def get_marital_status(row):
          if row['marital_Divorced'] == 1:
              return 'Divorced'
          elif row['marital_Married'] == 1:
              return 'Married'
          elif row['marital_Single'] == 1:
              return 'Single'
          elif row['marital_Together'] == 1:
              return 'Together'
          elif row['marital_Widow'] == 1:
              return 'Widow'
          else:
              return 'Unknown'
      data['Marital'] = data.apply(get_marital_status, axis=1)
```

```
[20]: plt.figure(figsize=(8, 6))
      sns.barplot(x='Marital', y='MntTotal', data=data, palette='viridis')
      plt.title('MntTotal by marital status')
      plt.xlabel('Marital status')
      plt.ylabel('MntTotal')
```

[20]: Text(0, 0.5, 'MntTotal')



0.12 New feature: In_relationship

There are 3 features that reflect if a person is single (Single, Divorced, Widow) and 2 features if a person is in relationship (Together, Married). We will add an additional feature 'In_relationship'. This feature will equal 1 if a customer's marital status is 'Married' or 'Together' and 0 in all other cases.

[21]:
```
def get_relationship(row):
    if row['marital_Married'] ==1:
        return 1
    elif row['marital_Together'] == 1:
        return 1
    else:
        return 0
data['In_relationship'] = data.apply(get_relationship, axis=1)
data.head()
```

```
[21]:     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  …  education_2n Cycle  \
0              172                88            88  …                   0
1                2                 1             6  …                   0
2              111                21            42  …                   0
3               10                 3             5  …                   0
4               46                27            15  …                   0

   education_Basic  education_Graduation  education_Master  education_PhD  \
0                0                     1                 0              0
1                0                     1                 0              0
2                0                     1                 0              0
3                0                     1                 0              0
4                0                     0                 0              1

   MntTotal  MntRegularProds  AcceptedCmpOverall   Marital  In_relationship
0      1529             1441                   0    Single                0
1        21               15                   0    Single                0
2       734              692                   0  Together                1
3        48               43                   0  Together                1
4       407              392                   0   Married                1

[5 rows x 39 columns]
```

K-Means Clustering K-means clustering is an unsupervised machine learning algorithm used to cluster data based on similarity. K-means clustering usually works well in practice and scales well to the large datasets.

In this section: - Standardising data - Principal Component Analysis (PCA) - Elbow method - Silhouette score analysis

[22]:
```python
from sklearn.cluster import KMeans
```

0.13 Standardising data

K-means clustering algorithm is based on the calculation of distances between data points to form clusters. When features have different scales, features with larger scales can disproportionately influence the distance calculation. There are various ways to standardise features, we will use standard scaling .

[23]:
```python
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
```

```
cols_for_clustering = ['Income', 'MntTotal', 'In_relationship']
data_scaled = data.copy()
data_scaled[cols_for_clustering] = scaler.
 ↪fit_transform(data[cols_for_clustering])
data_scaled[cols_for_clustering].describe()
```

[23]:

	Income	MntTotal	In_relationship
count	2.202000e+03	2.202000e+03	2.202000e+03
mean	2.742785e-17	-8.873717e-17	-4.678869e-17
std	1.000227e+00	1.000227e+00	1.000227e+00
min	-2.410685e+00	-9.724232e-01	-1.348874e+00
25%	-7.926475e-01	-8.815089e-01	-1.348874e+00
50%	-1.508040e-02	-3.806058e-01	7.413589e-01
75%	8.017617e-01	7.024988e-01	7.413589e-01
max	3.006747e+00	3.048788e+00	7.413589e-01

The mean value for all colums is almost zero and the standard deviation is almost 1. All the data points were replaced by their z-scores.

0.14 Principal Component Analysis (PCA)

PCA is a technique of dimensionality reduction. PCA takes the original features (dimensions) and create new features that capture the most variance of the data.

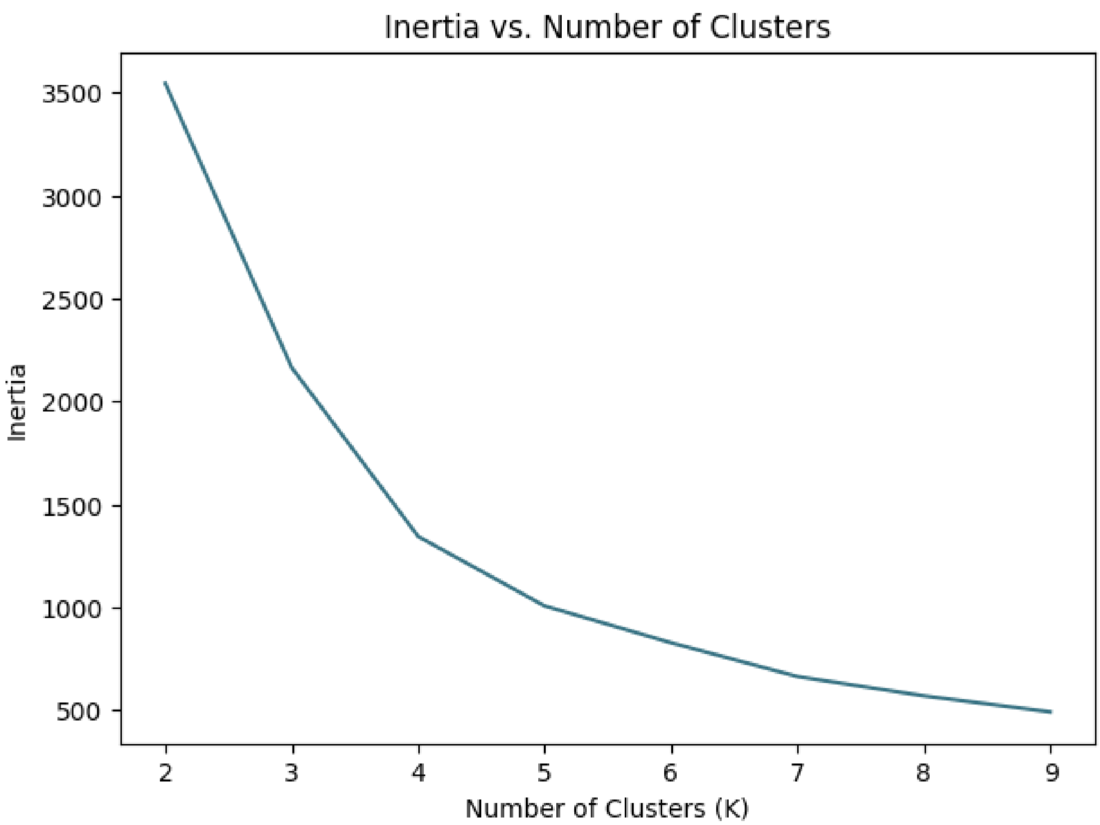
[24]:
```
from sklearn import decomposition
pca = decomposition.PCA(n_components = 2)
pca_res = pca.fit_transform(data_scaled[cols_for_clustering])
data_scaled['pc1'] = pca_res[:,0]
data_scaled['pc2'] = pca_res[:,1]
```

0.15 Elbow method

The elbow method is a technique used to determine the optimal number of clusters (K) for K-means clustering algorithm.

[25]:
```
X = data_scaled[cols_for_clustering]
inertia_list = []
for K in range(2,10):
    inertia = KMeans(n_clusters=K, random_state=7).fit(X).inertia_
    inertia_list.append(inertia)
```

[26]:
```
plt.figure(figsize=[7,5])
plt.plot(range(2,10), inertia_list, color=(54 / 255, 113 / 255, 130 / 255))
plt.title("Inertia vs. Number of Clusters")
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Inertia")
plt.show()
```



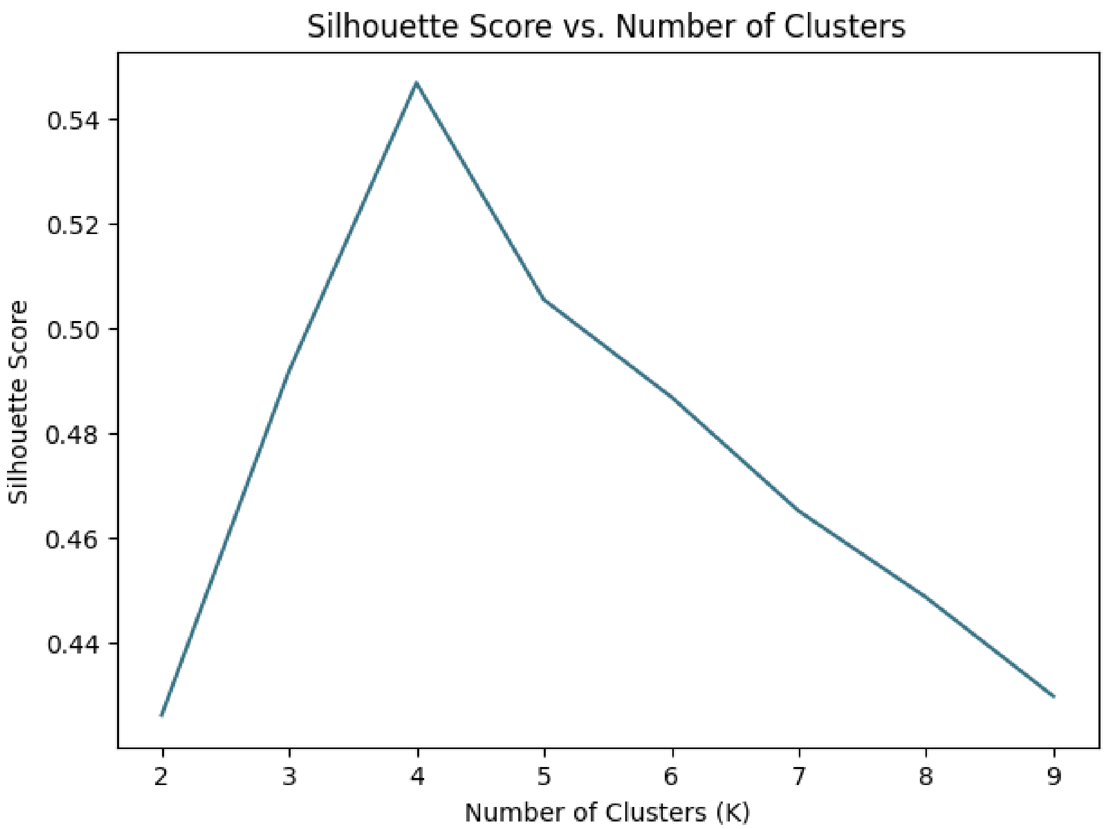
Elbow method suggests 4 or 5 clusters. Let's check silhouette score.

0.16 Silhouette score analysis

Silhouette score is a metric that used to assess the quality of clustering. A higher silhouette score indicates that the clusters are well-separated, while a lower score suggests that the clusters may overlap or are poorly defined.

[27]:
```
from sklearn.metrics import silhouette_score
silhouette_list = []
for K in range(2,10):
    model = KMeans(n_clusters = K, random_state=7)
    clusters = model.fit_predict(X)
    s_avg = silhouette_score(X, clusters)
    silhouette_list.append(s_avg)

plt.figure(figsize=[7,5])
plt.plot(range(2,10), silhouette_list, color=(54 / 255, 113 / 255, 130 / 255))
plt.title("Silhouette Score vs. Number of Clusters")
plt.xlabel("Number of Clusters (K)")
plt.ylabel("Silhouette Score")
```

```
plt.show()
```



The highest silhouette score is for 4 clusters.

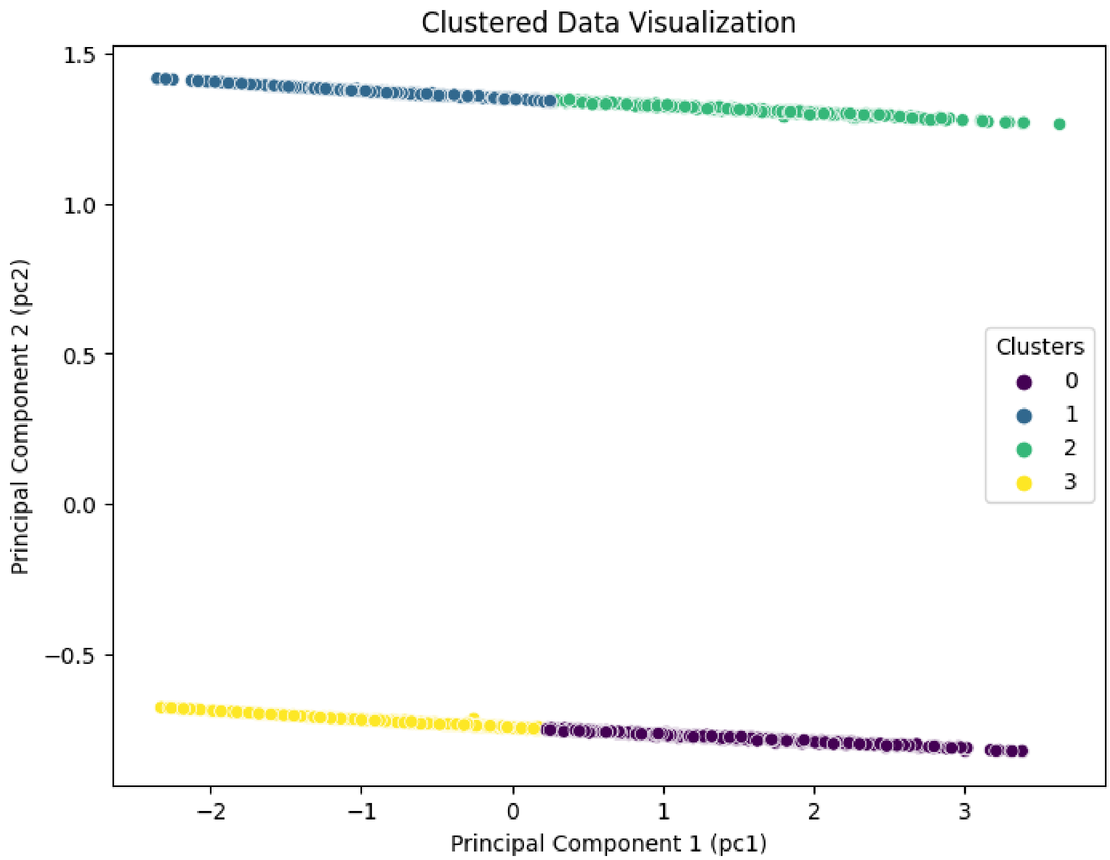
[28]:
```
model = KMeans(n_clusters=4, random_state = 7)
model.fit(data_scaled[cols_for_clustering])
data_scaled['Cluster'] = model.predict(data_scaled[cols_for_clustering])
```

Exploration of Clusters In this section: - Visualisation of clusters - Mean consumption of different product types by cluster - Cluster sizes - Income by cluster - In_relationship feature by cluster

0.17 Visualisation of clusters

[29]:
```
plt.figure(figsize=(8, 6))
sns.scatterplot(x='pc1', y='pc2', data=data_scaled, hue='Cluster',␣
 ↪palette='viridis')
plt.title('Clustered Data Visualization')
plt.xlabel('Principal Component 1 (pc1)')
plt.ylabel('Principal Component 2 (pc2)')
plt.legend(title='Clusters')
```

[29]: <matplotlib.legend.Legend at 0x79edb0f8b280>



[30]:
```
data['Cluster'] = data_scaled.Cluster
data.groupby('Cluster')[cols_for_clustering].mean()
```

[30]:

Cluster	Income	MntTotal	In_relationship
0	71818.929329	1147.372792	1.0
1	37332.339956	150.761589	0.0
2	71946.155488	1159.612805	0.0
3	37892.819883	158.463158	1.0

0.18 Mean consumption of different product types by cluster

[31]:
```
mnt_data = data.groupby('Cluster')[cols_mnt].mean().reset_index()
mnt_data.head()
```

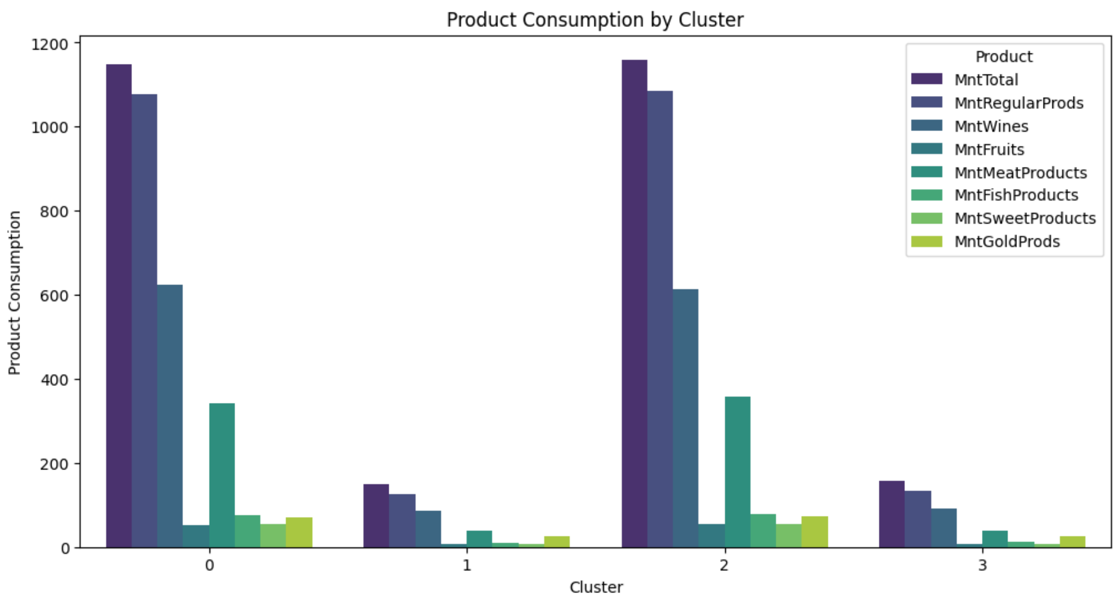
[31]:

	Cluster	MntTotal	MntRegularProds	MntWines	MntFruits \
0	0	1147.372792	1076.279152	623.261484	52.489399

1	1	150.761589	125.662252	85.450331	7.832230
2	2	1159.612805	1085.332317	613.862805	54.929878
3	3	158.463158	133.962573	92.046784	7.640936

	MntMeatProducts	MntFishProducts	MntSweetProducts	MntGoldProds
0	341.326855	75.577739	54.717314	71.093640
1	38.774834	10.971302	7.732892	25.099338
2	357.902439	77.603659	55.314024	74.280488
3	39.438596	11.423392	7.913450	24.500585

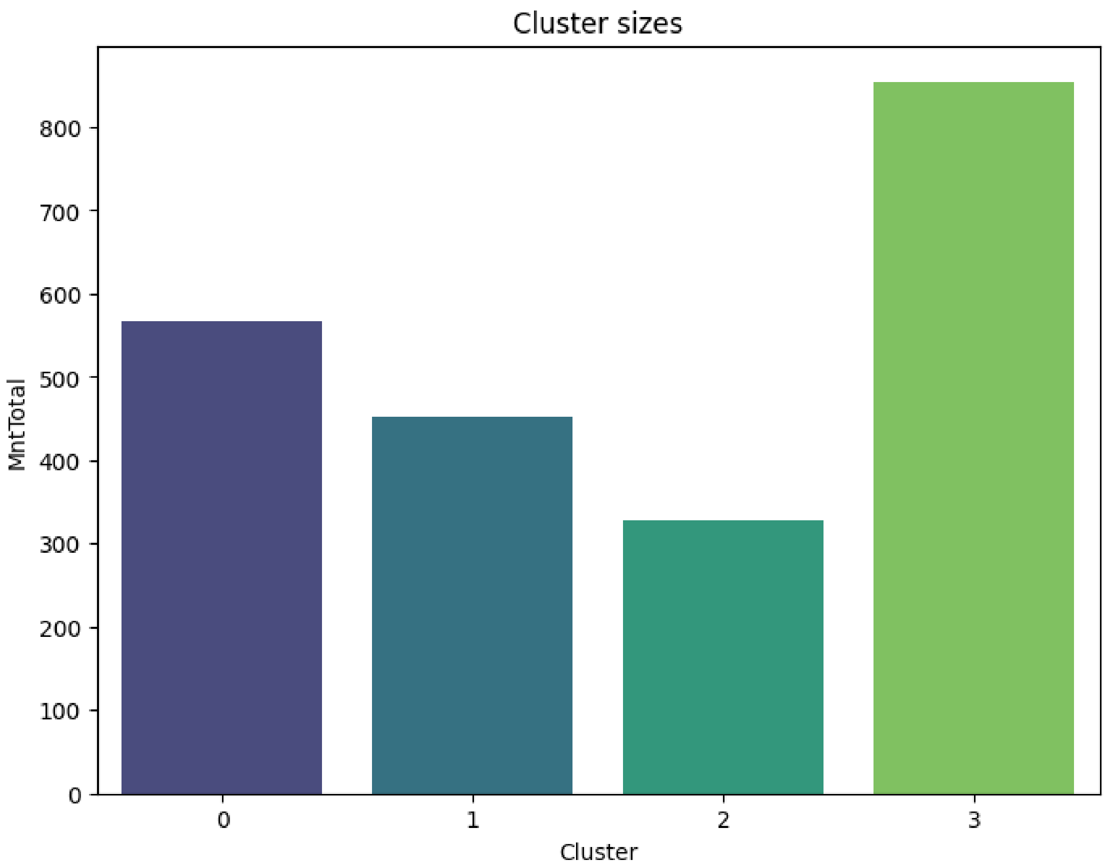
[32]:
```
melted_data = pd.melt(mnt_data, id_vars="Cluster", var_name="Product", value_name="Consumption")
plt.figure(figsize=(12, 6))
sns.barplot(x="Cluster", y="Consumption", hue="Product", data=melted_data, ci=None, palette="viridis")
plt.title("Product Consumption by Cluster")
plt.xlabel("Cluster")
plt.ylabel("Product Consumption")
plt.xticks(rotation=0)
plt.legend(title="Product", loc="upper right")

plt.show()
```



0.19 Cluster sizes

[33]:
```
cluster_sizes = data.groupby('Cluster')[['MntTotal']].count().reset_index()
plt.figure(figsize=(8,6))
sns.barplot(x='Cluster', y='MntTotal', data=cluster_sizes, palette = 'viridis')
plt.title('Cluster sizes')
plt.xlabel('Cluster')
plt.ylabel('MntTotal')
```

[33]:
```
Text(0, 0.5, 'MntTotal')
```



[34]:
```
total_rows = len(data)
cluster_sizes['Share%'] = round(cluster_sizes['MntTotal'] / total_rows*100,0)
cluster_sizes.head()
```

[34]:

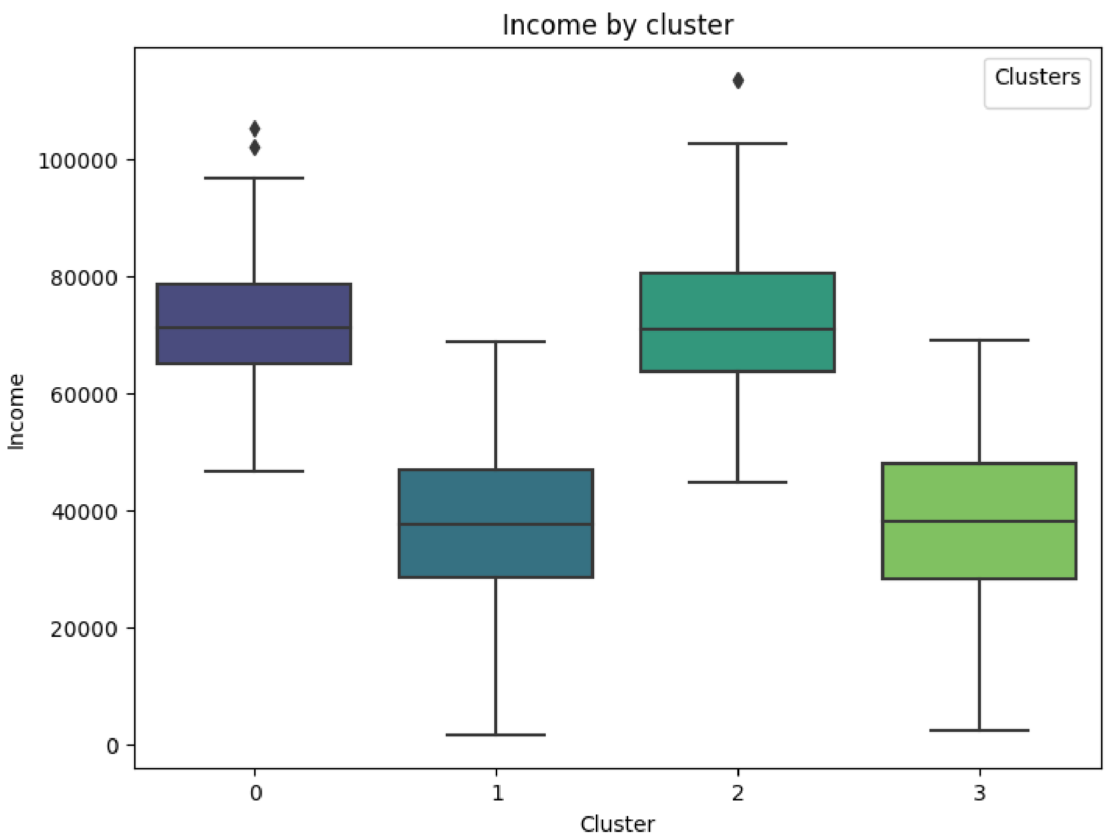
	Cluster	MntTotal	Share%
0	0	566	26.0
1	1	453	21.0
2	2	328	15.0
3	3	855	39.0

0.20 Income by cluster

0.20.1 Box plot

[35]:
```python
plt.figure(figsize=(8, 6))
sns.boxplot(x='Cluster', y='Income', data=data, palette='viridis')
plt.title('Income by cluster')
plt.xlabel('Cluster')
plt.ylabel('Income')
plt.legend(title='Clusters')
```

[35]:
```
<matplotlib.legend.Legend at 0x79edb0f5ab60>
```

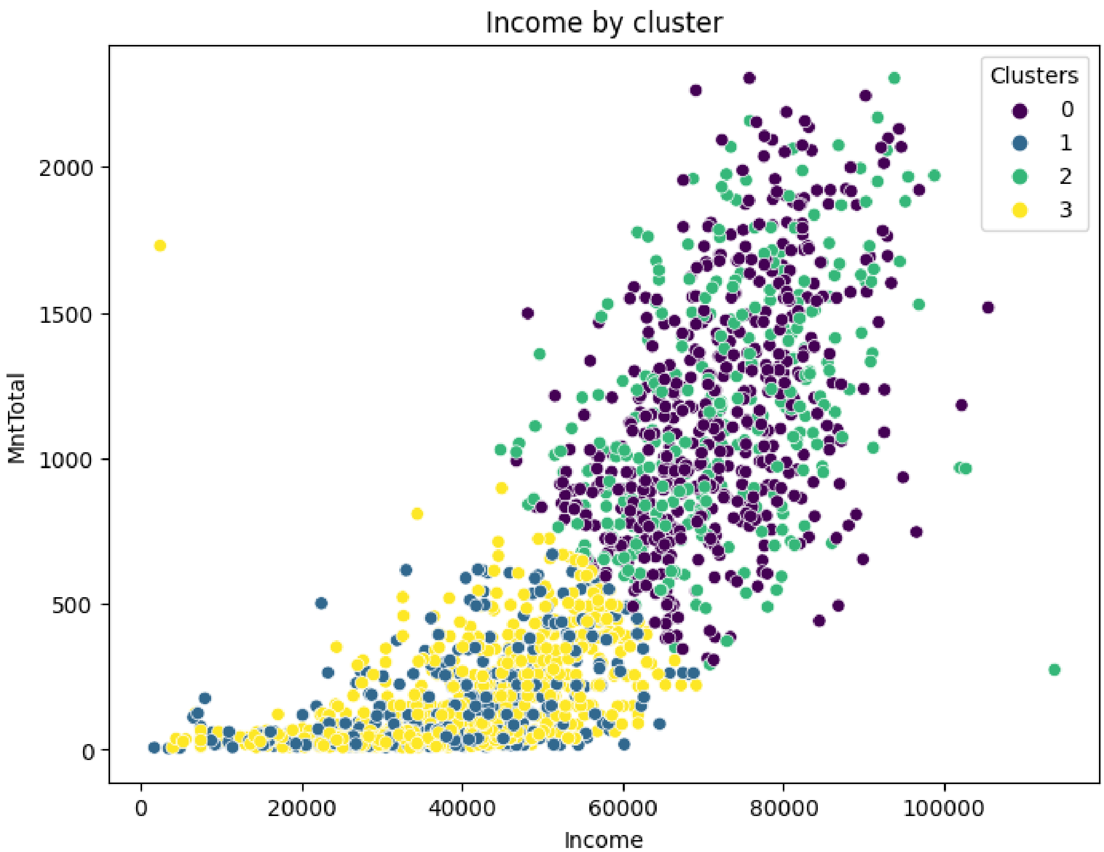


0.20.2 Scatter plot

[36]:
```python
plt.figure(figsize=(8, 6))
sns.scatterplot(x='Income', y='MntTotal', data=data, hue = 'Cluster',␣
↪palette='viridis')
plt.title('Income by cluster')
plt.xlabel('Income')
plt.ylabel('MntTotal')
```

```
plt.legend(title='Clusters')
```

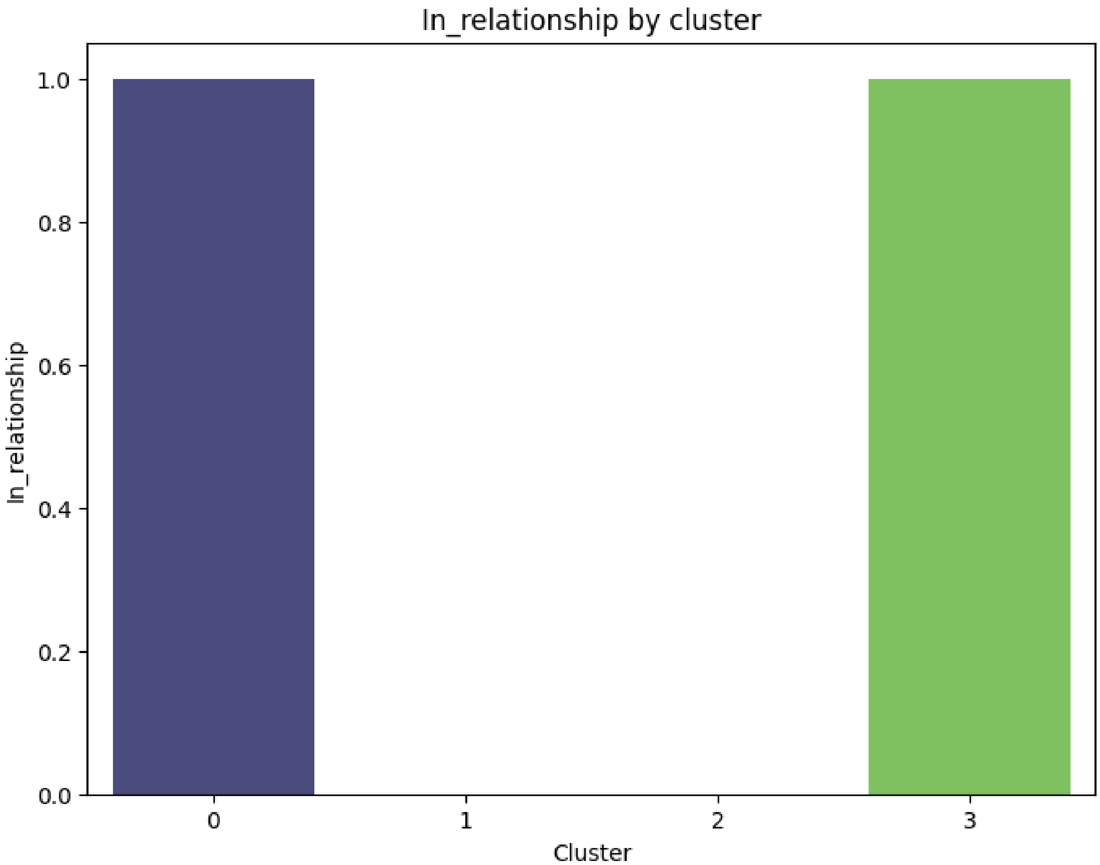
[36]: <matplotlib.legend.Legend at 0x79edac123b50>



0.21 In_relationship feature by cluster

[37]:
```
plt.figure(figsize=(8, 6))
sns.barplot(x='Cluster', y='In_relationship', data=data, palette='viridis')
plt.title('In_relationship by cluster')
plt.xlabel('Cluster')
plt.ylabel('In_relationship')
```

[37]: Text(0, 0.5, 'In_relationship')



Results This section contains the results of the K-means clustering analysis, which aimed to identify distinct customer segments based on the total amount of purchases they made (MntTotal). The analysis utilised 'Income' and 'In_relationship' features.

0.22 Optimal number of clusters = 4

The Elbow Method and Silhouette Analysis suggested 4 clusters (k=4). The elbow method highlighted the number of 4 or 5 clusters as a reasonable number of clusters. The silhouette score analysis revealed a peak silhouette score for k=4.

0.23 Cluster Characteristics

0.23.1 Cluster 0: High value customers in relationship (either married or together)

- This cluster represents 26% of the customer base
- These customers have high income and they are in a relationship

0.23.2 Cluster 1: Low value single customers

- This cluster represents 21% of the customer base
- These customers have low income and they are single

0.23.3 Cluster 2: High value single customers

- This cluster represents 15% of the customer base
- These customers have high income and they are single

0.23.4 Cluster 3: Low value customers in relationship

- This cluster represents 39% of the customer base
- These customers have low income and they are in a relationship