E-commerce-Campaign dataset@DhanunjayaReddy

October 11, 2024

1 Campaign Dataset

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

Downloading and reading the shopping csv file

[ ]:
```
df = pd.read_csv("campaign.csv")
df
```

[ ]:
```
         ID  Year_Birth   Education Marital_Status      Income  Kidhome  \
0      1826        1970  Graduation       Divorced  $84,835.00        0
1         1        1961  Graduation         Single  $57,091.00        0
2     10476        1958  Graduation        Married  $67,267.00        0
3      1386        1967  Graduation       Together  $32,474.00        1
4      5371        1989  Graduation         Single  $21,474.00        1
…       …           …           …              …           …        …
2234  10142        1976         PhD       Divorced  $66,476.00        0
2235   5263        1977    2n Cycle        Married  $31,056.00        1
2236     22        1976  Graduation       Divorced  $46,310.00        1
2237    528        1978  Graduation        Married  $65,819.00        0
2238   4070        1969         PhD        Married  $94,871.00        0

      Teenhome Dt_Customer  Recency  MntWines  …  NumCatalogPurchases  \
0            0     6/16/14        0       189  …                    4
1            0     6/15/14        0       464  …                    3
2            1     5/13/14        0       134  …                    2
3            1     5/11/14        0        10  …                    0
4            0      4/8/14        0         6  …                    1
…          …           …        …         …  …                  …
2234         1      3/7/13       99       372  …                    2
2235         0     1/22/13       99         5  …                    0
2236         0     12/3/12       99       185  …                    1
2237         0    11/29/12       99       267  …                    4
2238         2      9/1/12       99       169  …                    5
```

```
      NumStorePurchases  NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  \
0                     6                  1             0             0
1                     7                  5             0             0
2                     5                  2             0             0
3                     2                  7             0             0
4                     2                  7             1             0
…                   …                 …            …            …
2234                 11                  4             0             0
2235                  3                  8             0             0
2236                  5                  8             0             0
2237                 10                  3             0             0
2238                  4                  7             0             1

      AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  Country
0                0             0             0         0       SP
1                0             0             1         0       CA
2                0             0             0         0       US
3                0             0             0         0      AUS
4                0             0             0         0       SP
…              …            …            …         …       …
2234             0             0             0         0       US
2235             0             0             0         0       SP
2236             0             0             0         0       SP
2237             0             0             0         0      IND
2238             1             0             0         0       CA

[2239 rows x 27 columns]
```

[ ]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2239 entries, 0 to 2238
Data columns (total 27 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2239 non-null   int64
 1   Year_Birth           2239 non-null   int64
 2   Education            2239 non-null   object
 3   Marital_Status       2239 non-null   object
 4   Income               2239 non-null   object
 5   Kidhome              2239 non-null   int64
 6   Teenhome             2239 non-null   int64
 7   Dt_Customer          2239 non-null   object
 8   Recency              2239 non-null   int64
 9   MntWines             2239 non-null   int64
 10  MntFruits            2239 non-null   int64
 11  MntMeatProducts      2239 non-null   int64
```

```
 12  MntFishProducts      2239 non-null   int64
 13  MntSweetProducts     2239 non-null   int64
 14  MntGoldProds         2239 non-null   int64
 15  NumDealsPurchases    2239 non-null   int64
 16  NumWebPurchases      2239 non-null   int64
 17  NumCatalogPurchases  2239 non-null   int64
 18  NumStorePurchases    2239 non-null   int64
 19  NumWebVisitsMonth    2239 non-null   int64
 20  AcceptedCmp3         2239 non-null   int64
 21  AcceptedCmp4         2239 non-null   int64
 22  AcceptedCmp5         2239 non-null   int64
 23  AcceptedCmp1         2239 non-null   int64
 24  AcceptedCmp2         2239 non-null   int64
 25  Complain             2239 non-null   int64
 26  Country              2239 non-null   object
dtypes: int64(22), object(5)
memory usage: 472.4+ KB
```

Unique number of values for specific categorical columns

[ ]:
```
columns_list = df[['ID', 'Education', 'Marital_Status', 'Country']]

for columns in columns_list.columns:
  unique_count = columns_list[columns].nunique()
  print(columns, "-", unique_count)
```

```
ID - 2239
Education - 5
Marital_Status - 8
Country - 8
```

Checking for the presence of null values in dataset.

[ ]:
```
df.isna().sum()
```

[ ]:
```
ID                     0
Year_Birth             0
Education              0
Marital_Status         0
Income                 0
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
Country                0
dtype: int64
```

shape of the dataset

[ ]:
```
df.shape
```

[ ]:
```
(2239, 27)
```

summary statistics of the dataset

[ ]:
```
df['Income'] = df['Income'].replace({'\$': '', ',': ''}, regex=True).
 ↪astype(float)
df['Income'] = df['Income'].fillna(0).astype(int)
```

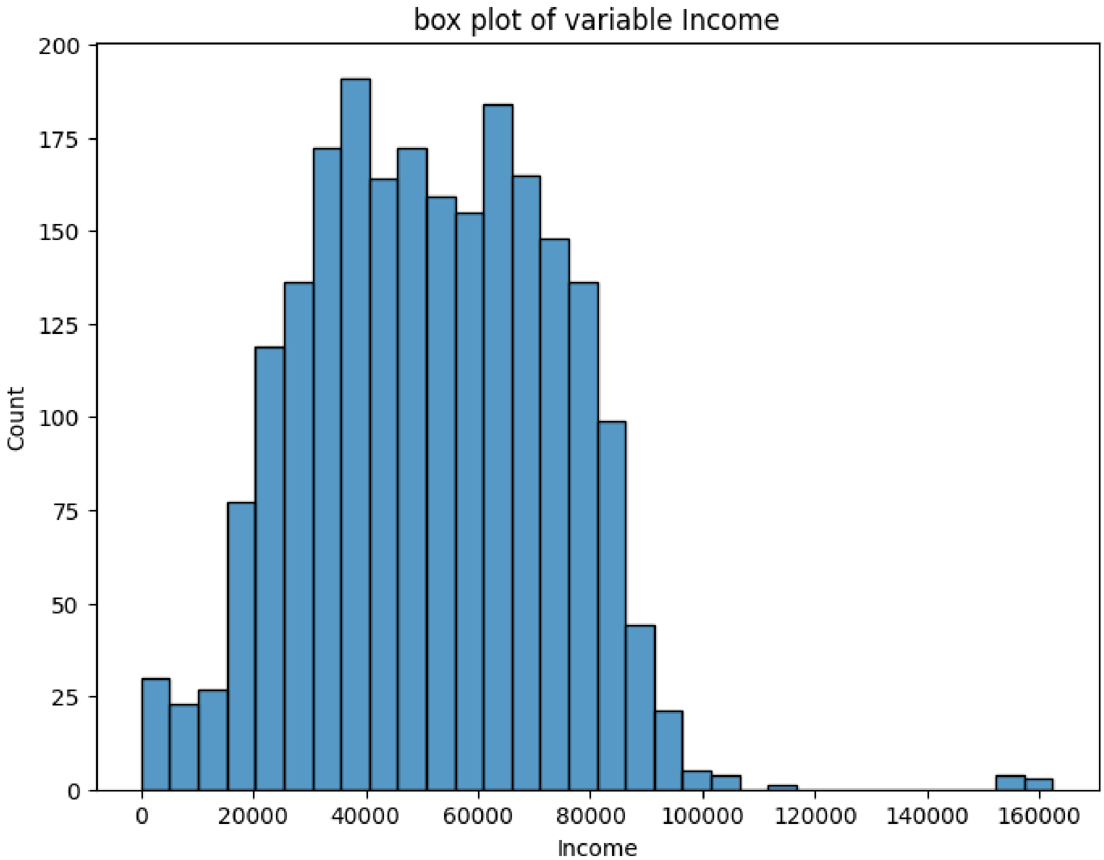
[ ]:
```
selected_variables = df[['Income', 'Kidhome',
       'Teenhome', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth']]

summary_df = selected_variables.describe()
summary_df
```

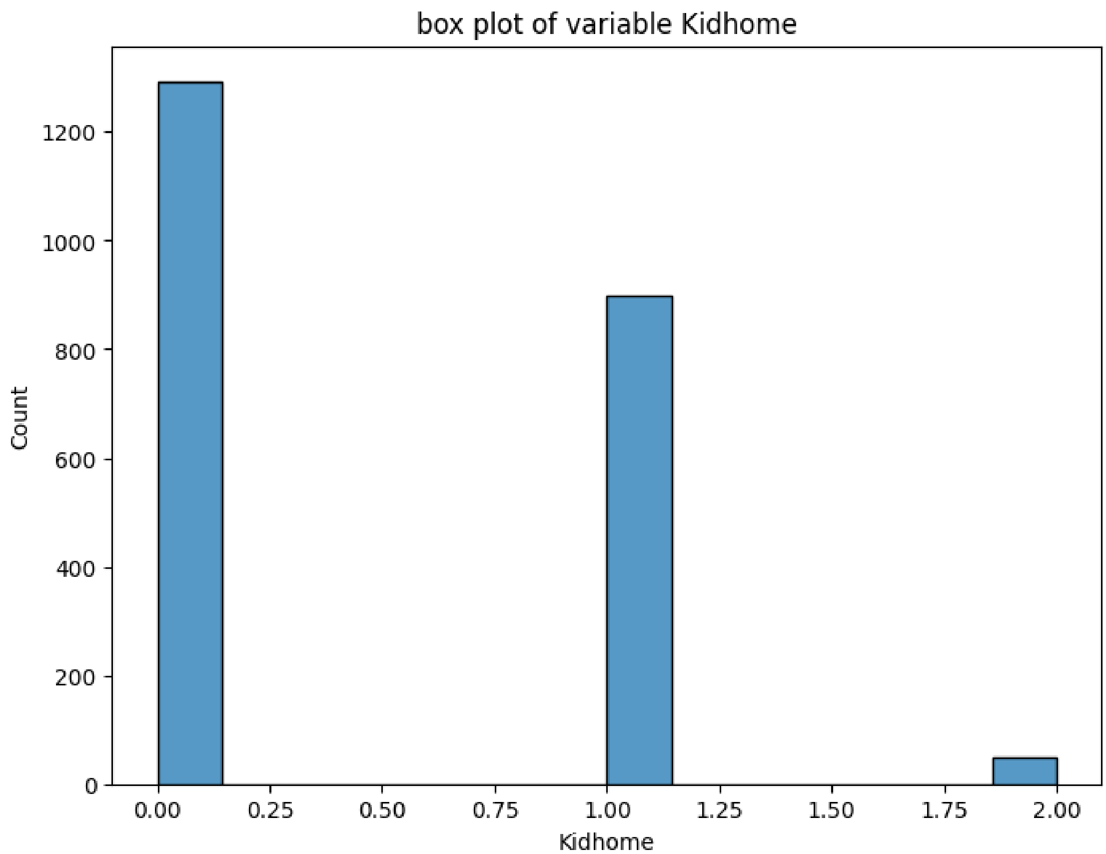
[ ]:
```
              Income      Kidhome     Teenhome      Recency     MntWines  \
count    2239.000000  2239.000000  2239.000000  2239.000000  2239.000000
mean    51412.792765     0.443948     0.506476    49.121036   304.067441
std     22069.582225     0.538390     0.544555    28.963662   336.614830
min         0.000000     0.000000     0.000000     0.000000     0.000000
25%     34716.000000     0.000000     0.000000    24.000000    24.000000
50%     51039.000000     0.000000     0.000000    49.000000   174.000000
75%     68277.500000     1.000000     1.000000    74.000000   504.500000
max    162397.000000     2.000000     2.000000    99.000000  1493.000000

         MntFruits  MntMeatProducts  MntFishProducts  MntSweetProducts  \
count  2239.000000      2239.000000      2239.000000       2239.000000
```

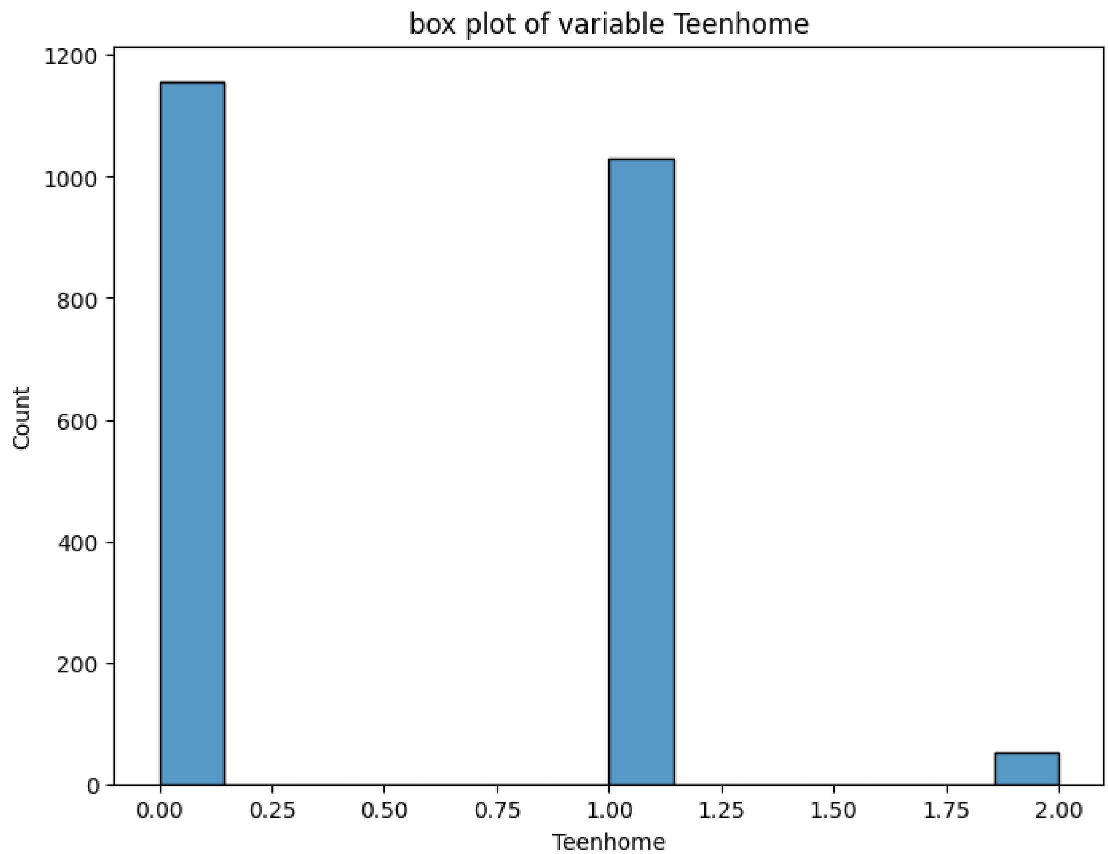
```
mean     26.307727    167.016525    37.538633    27.074587
std      39.781468    225.743829    54.637617    41.286043
min       0.000000      0.000000     0.000000     0.000000
25%       1.000000     16.000000     3.000000     1.000000
50%       8.000000     67.000000    12.000000     8.000000
75%      33.000000    232.000000    50.000000    33.000000
max     199.000000   1725.000000   259.000000   263.000000

       MntGoldProds  NumDealsPurchases  NumWebPurchases  NumCatalogPurchases  \
count   2239.000000        2239.000000      2239.000000          2239.000000
mean      44.036177           2.324252         4.085306             2.662796
std       52.174700           1.932345         2.779240             2.923542
min        0.000000           0.000000         0.000000             0.000000
25%        9.000000           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      362.000000          15.000000        27.000000            28.000000

       NumStorePurchases  NumWebVisitsMonth
count        2239.000000        2239.000000
mean            5.791425           5.316213
std             3.251149           2.427144
min             0.000000           0.000000
25%             3.000000           3.000000
50%             5.000000           6.000000
75%             8.000000           7.000000
max            13.000000          20.000000
```

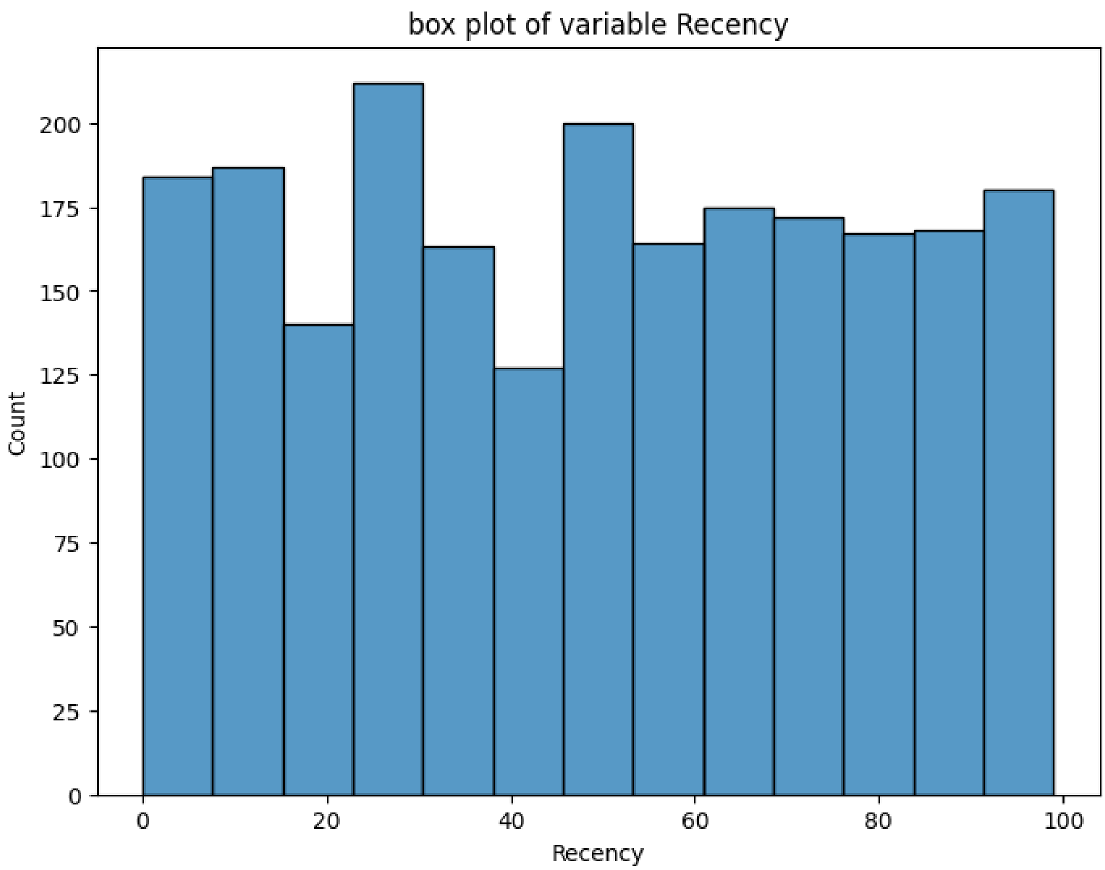
Distribution of the numerical features in the dataset

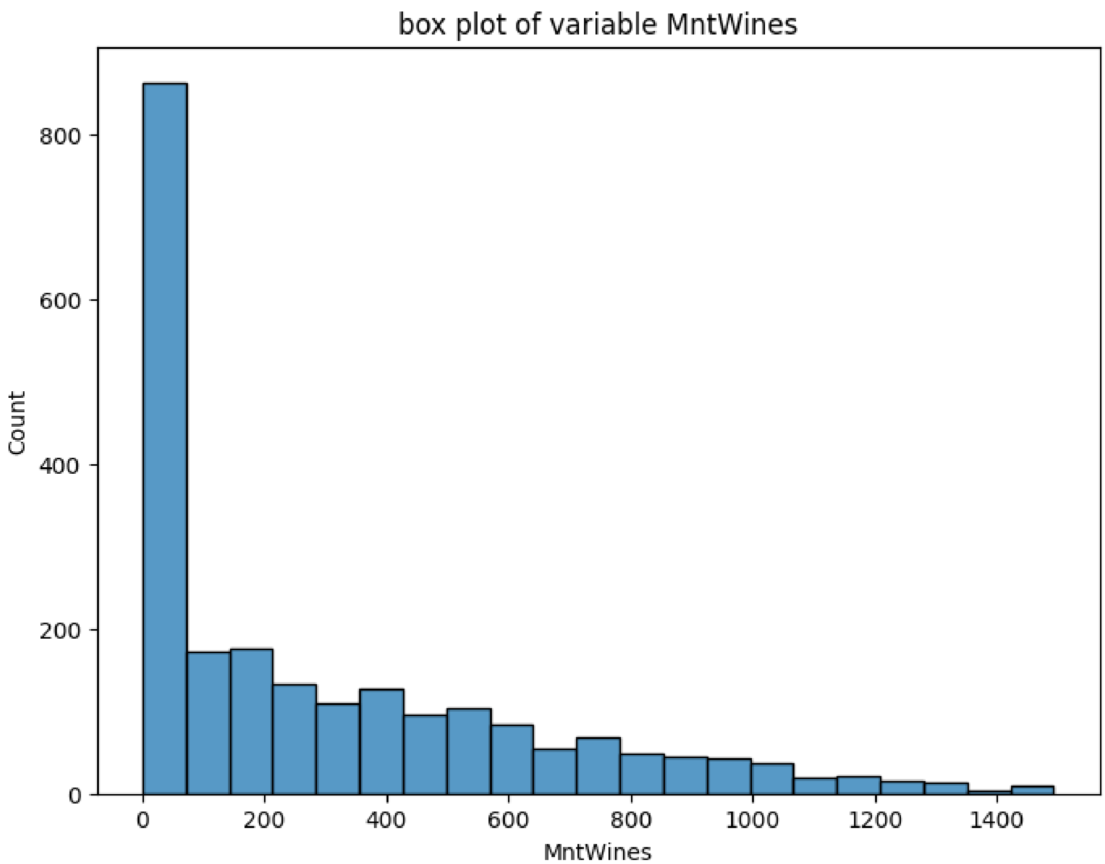
[ ]:
```python
for variable in selected_variables:
  plt.figure(figsize = (8, 6))
  sns.histplot(data = selected_variables[variable])
  plt.title(f"box plot of variable {variable}")
```

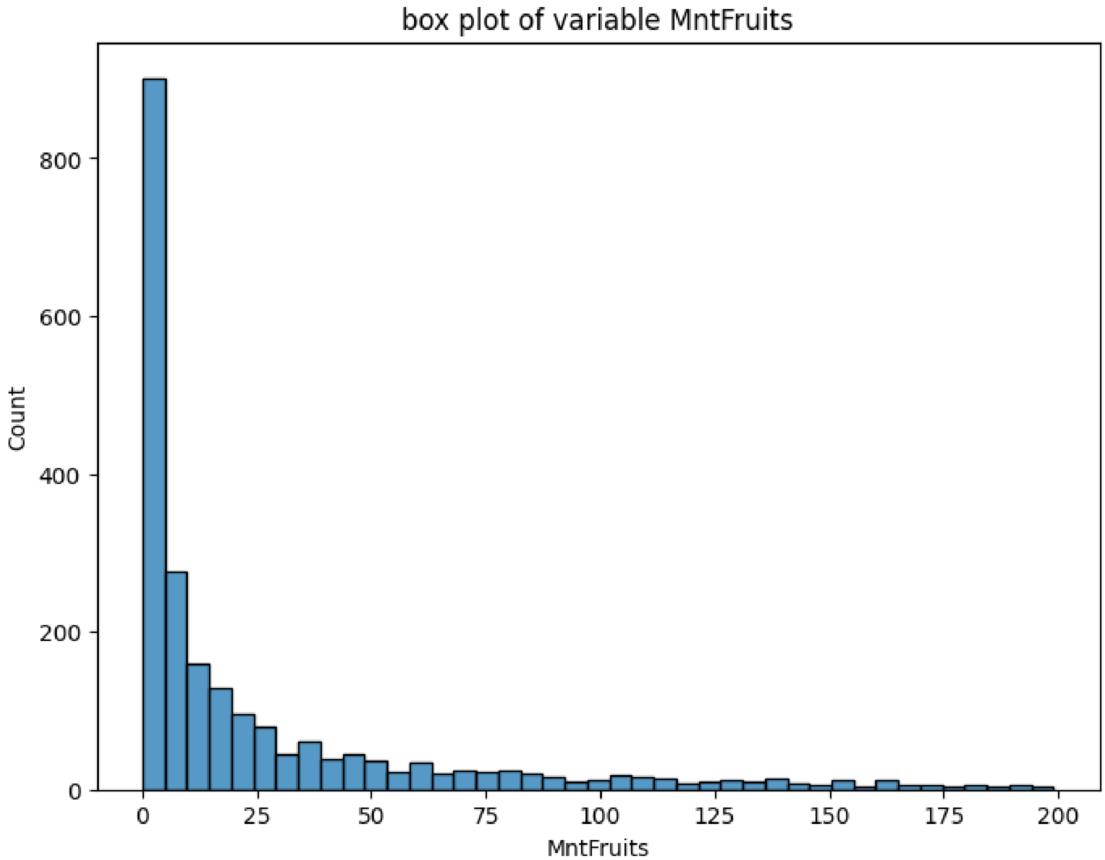

box plot of variable Income
Count
Income
200
175
150
125
100
75
50
25
0
0
20000
40000
60000
80000
100000
120000
140000
160000

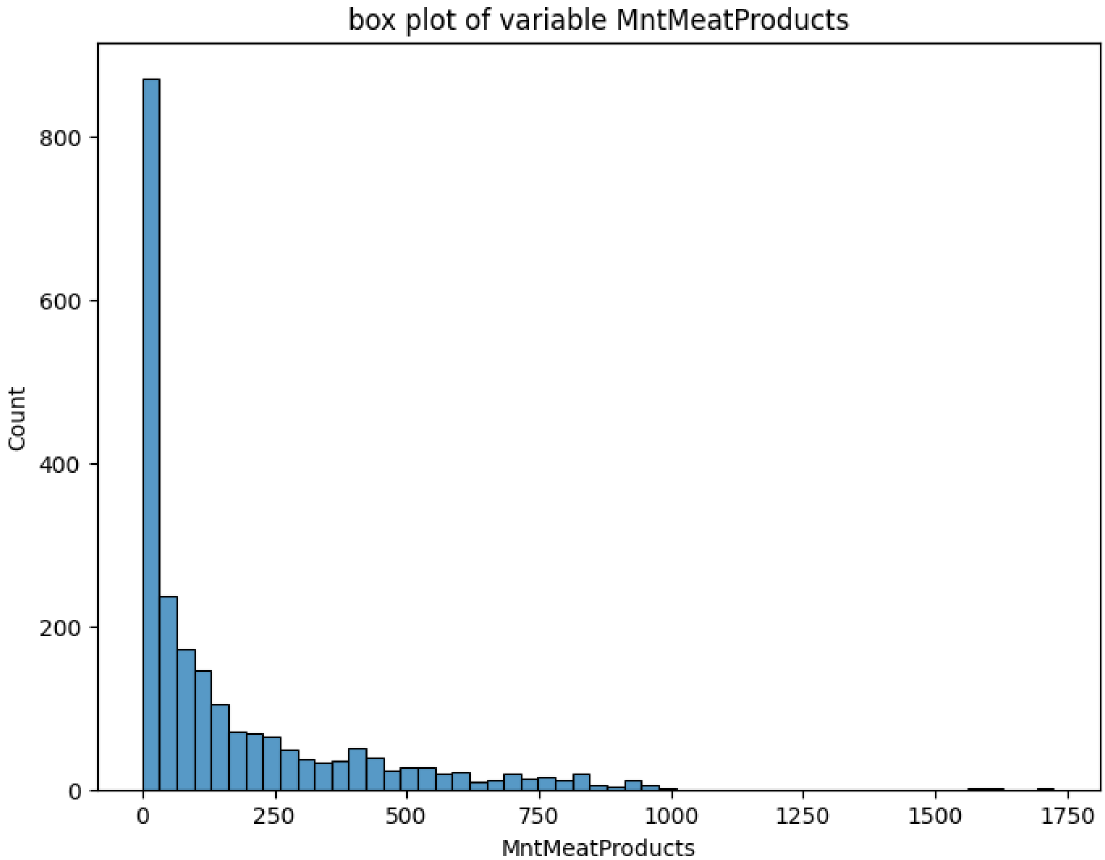

box plot of variable Kidhome
Count
1200
1000
800
600
400
200
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Kidhome

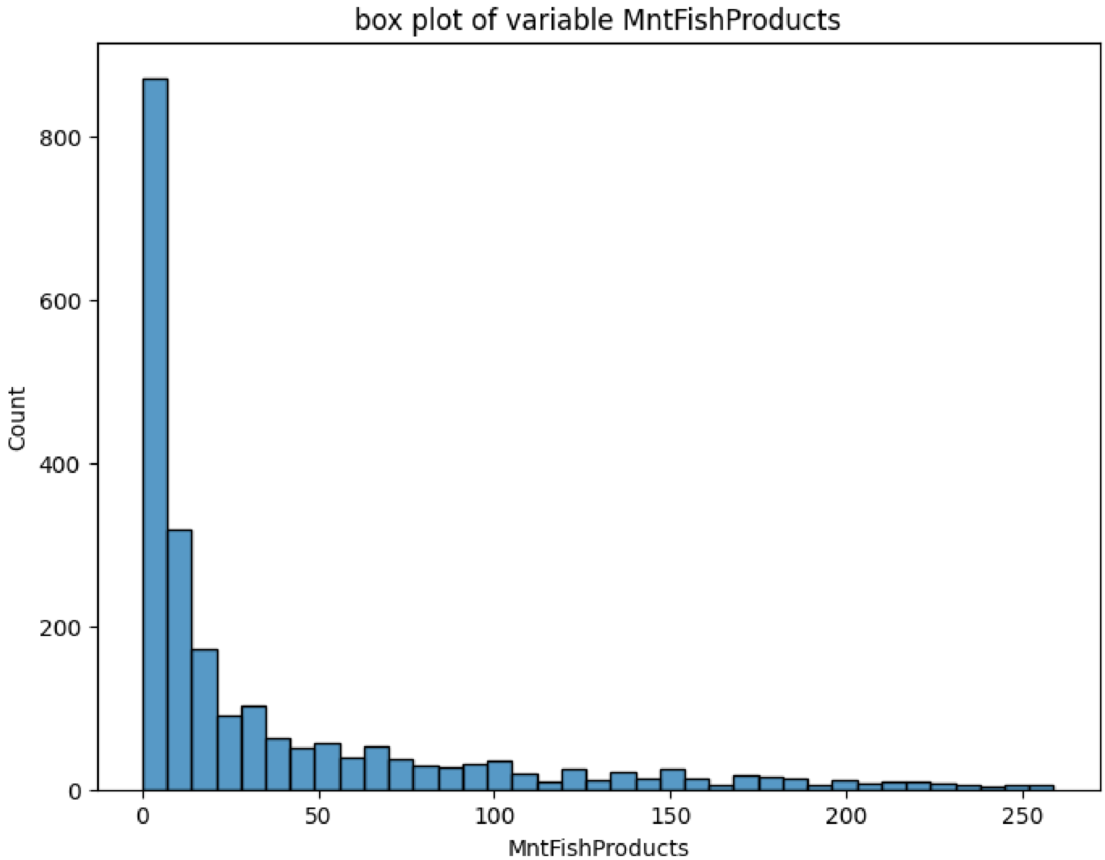

box plot of variable Teenhome
Count
1200
1000
800
600
400
200
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Teenhome

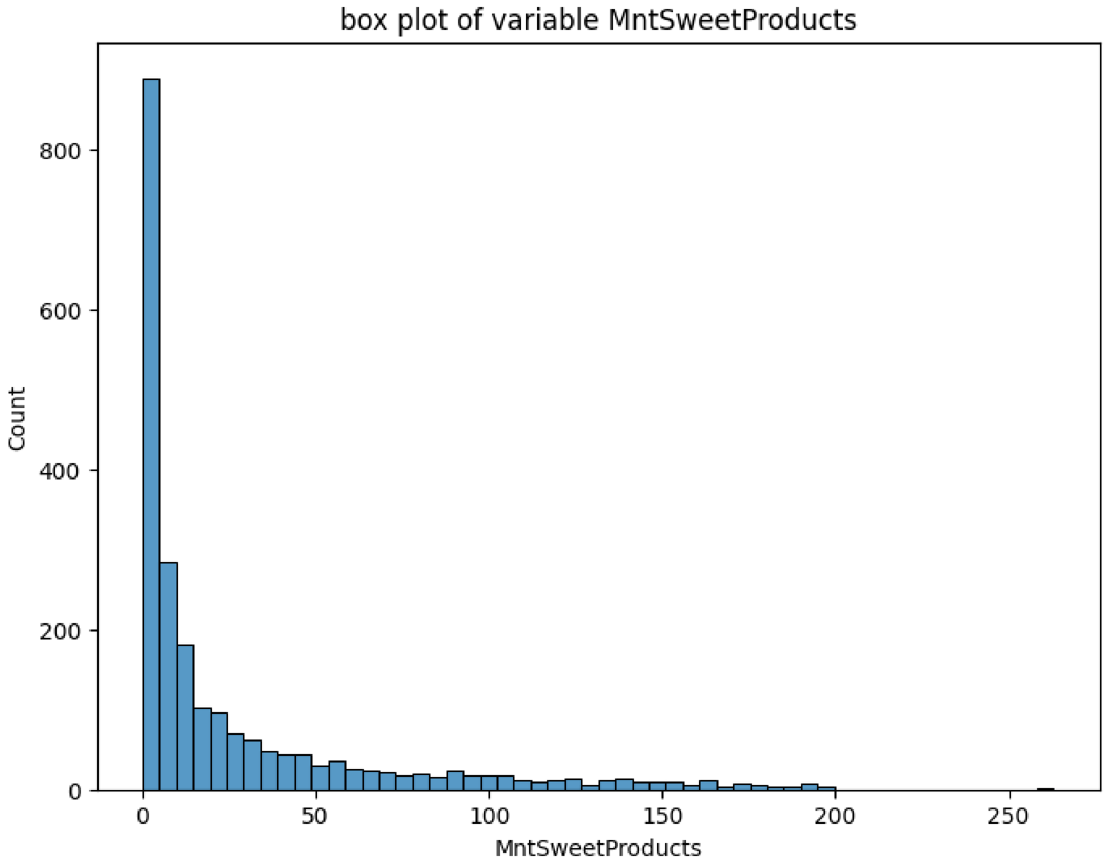

box plot of variable Recency
Count
0
25
50
75
100
125
150
175
200
0
20
40
60
80
100
Recency

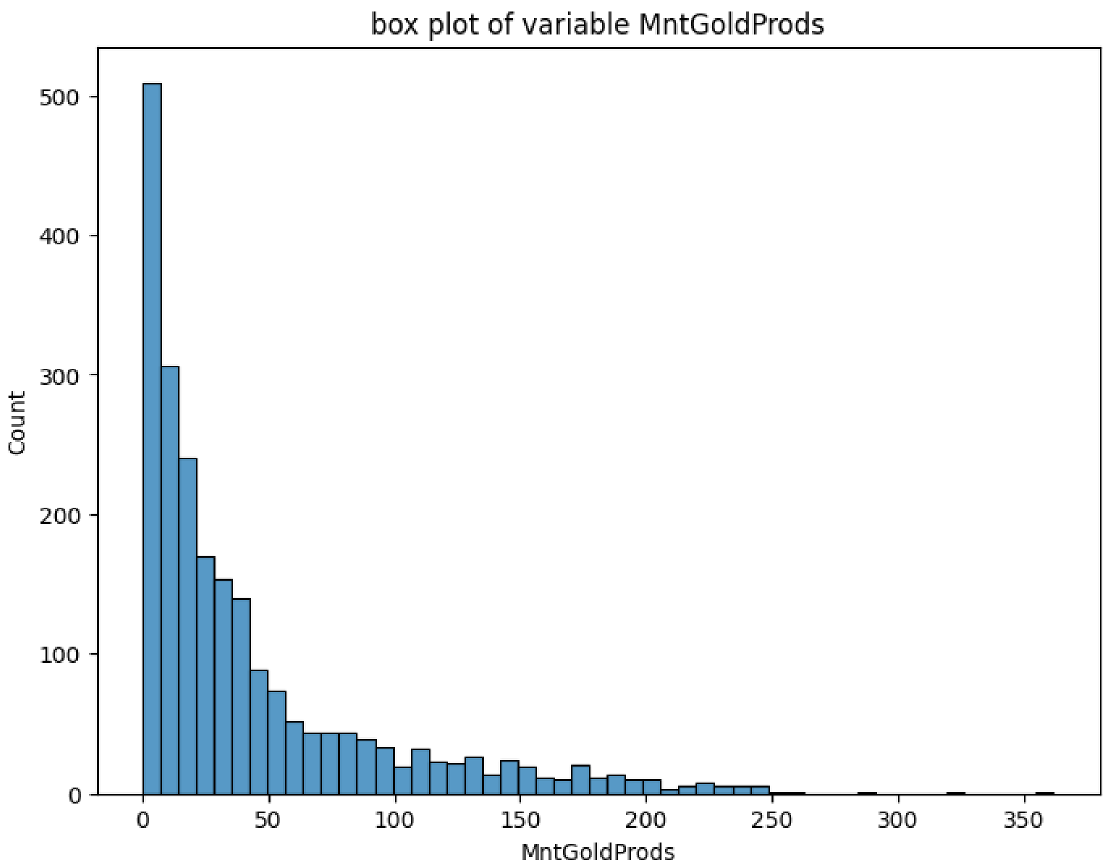

box plot of variable MntWines
Count
800
600
400
200
0
0
200
400
600
800
1000
1200
1400
MntWines

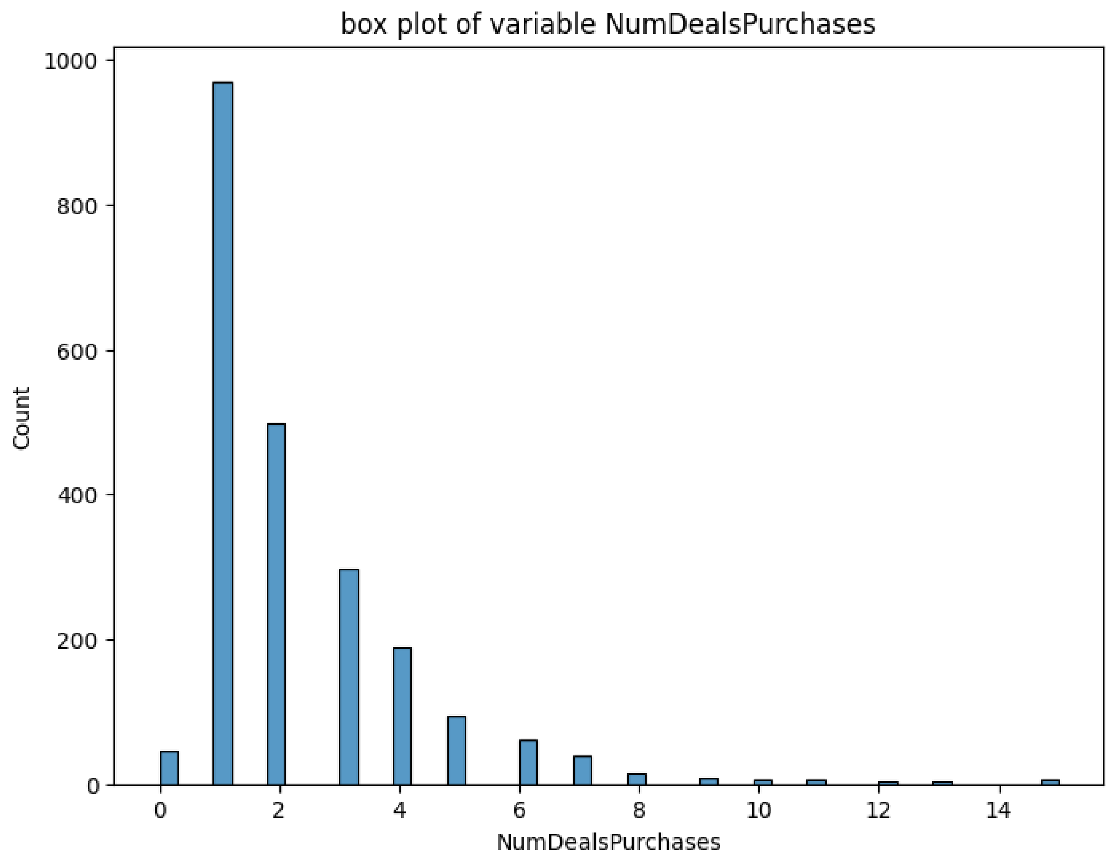

box plot of variable MntFruits
Count
MntFruits
0
200
400
600
800
0
25
50
75
100
125
150
175
200

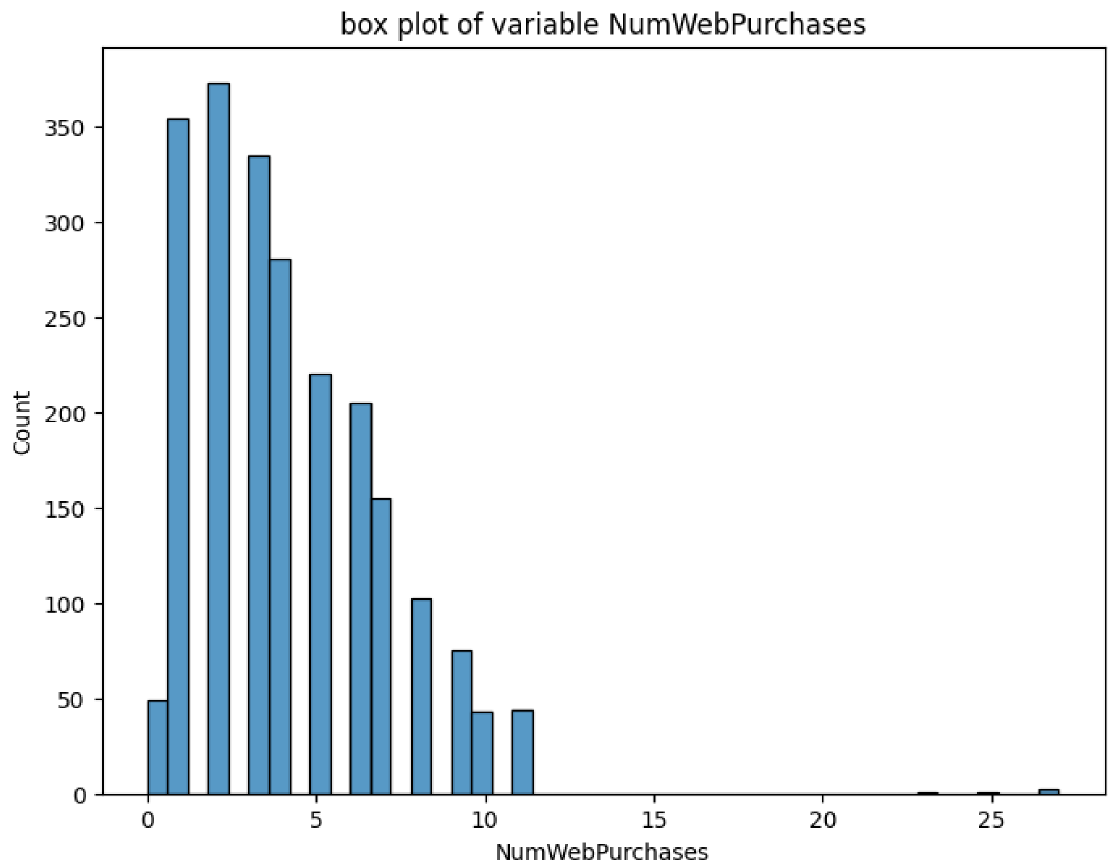

box plot of variable MntMeatProducts
Count
0
200
400
600
800
0
250
500
750
1000
1250
1500
1750
MntMeatProducts

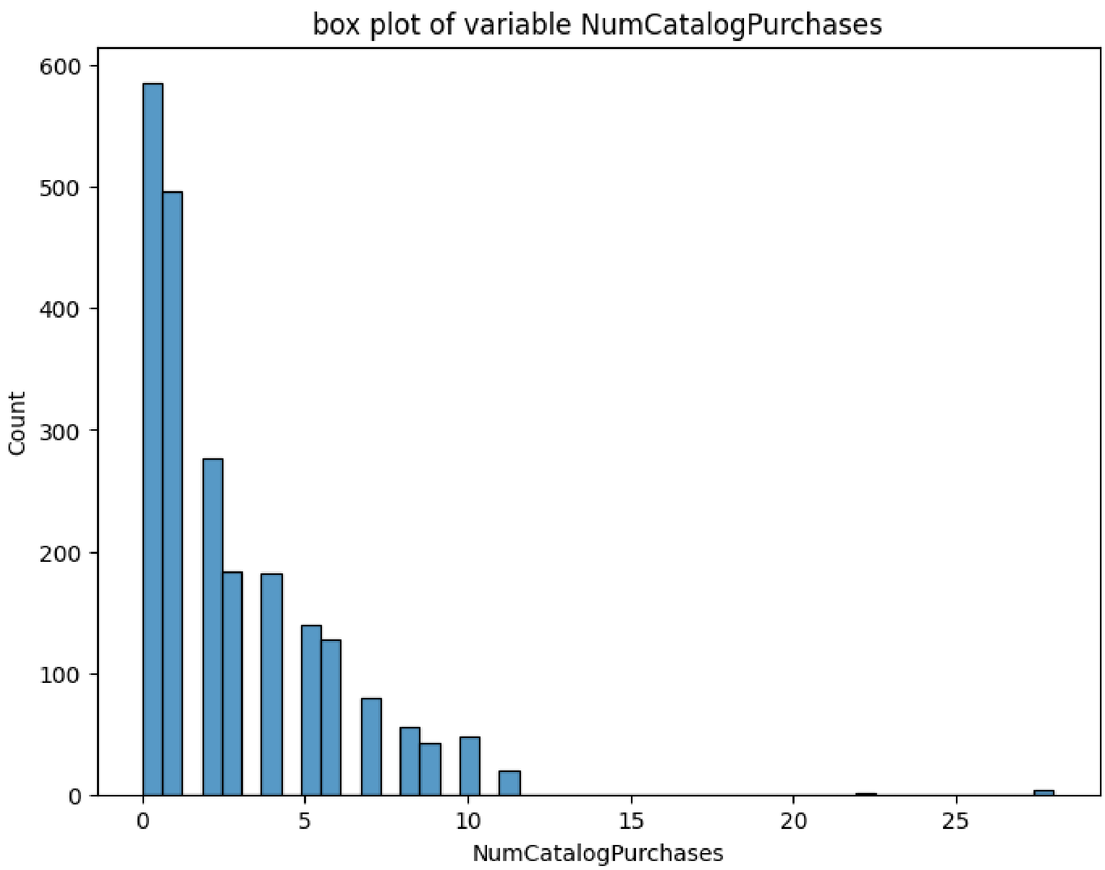

box plot of variable MntFishProducts
Count
MntFishProducts
0
200
400
600
800
0
50
100
150
200
250

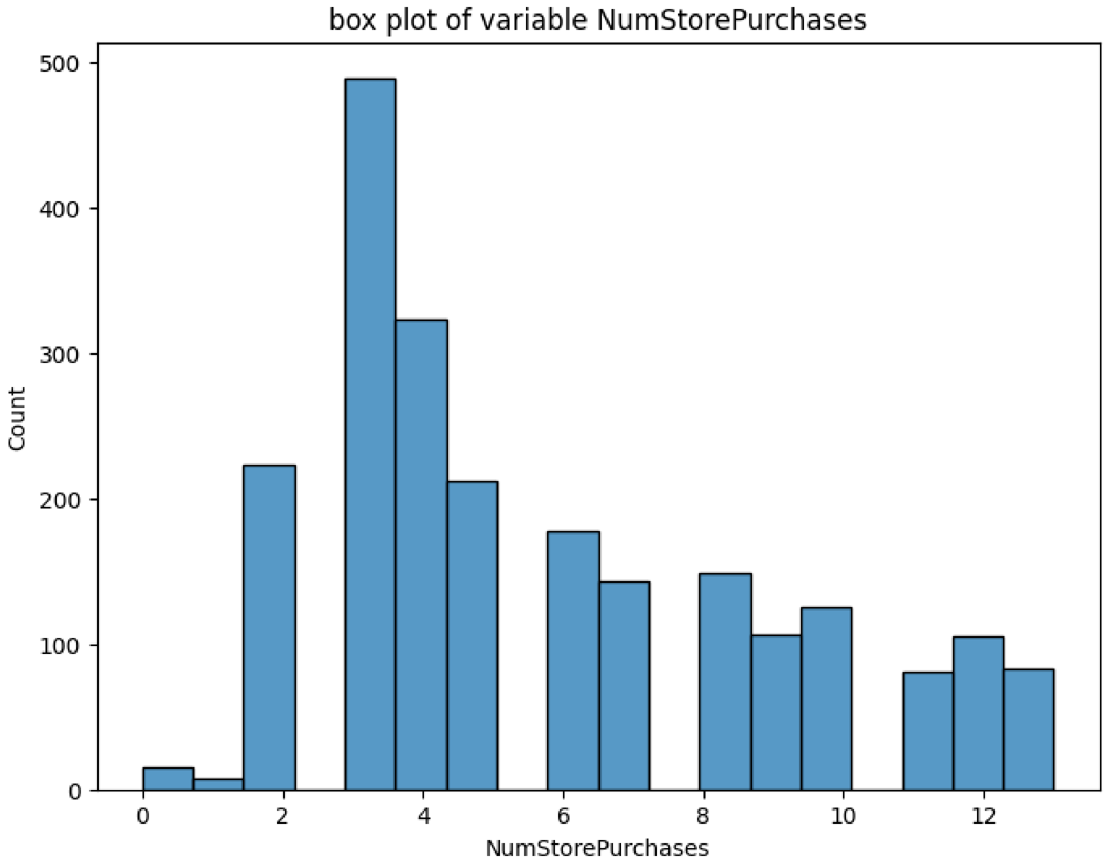

box plot of variable MntSweetProducts
Count
800
600
400
200
0
0
50
100
150
200
250
MntSweetProducts

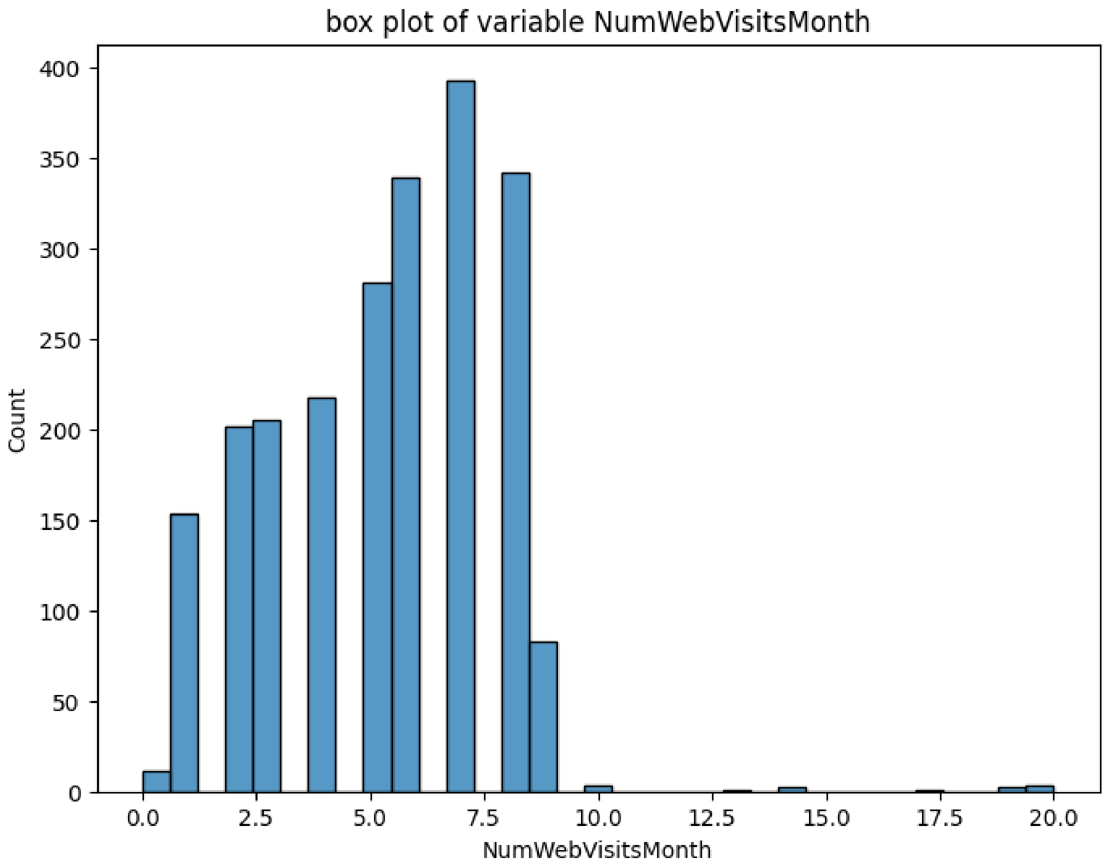

box plot of variable MntGoldProds
Count
500
400
300
200
100
0
0
50
100
150
200
250
300
350
MntGoldProds


box plot of variable NumDealsPurchases
Count
NumDealsPurchases
0
200
400
600
800
1000
0
2
4
6
8
10
12
14


box plot of variable NumWebPurchases
Count
NumWebPurchases
0
50
100
150
200
250
300
350
0
5
10
15
20
25

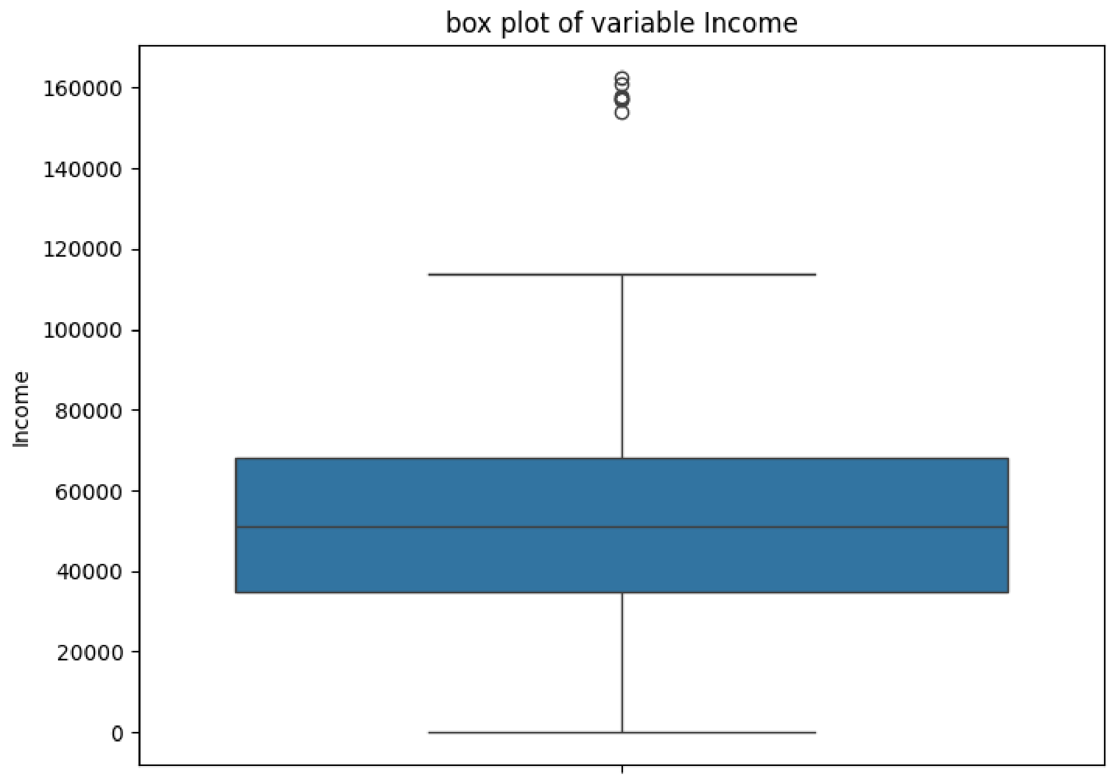

box plot of variable NumCatalogPurchases
600
500
400
300
200
100
0
Count
0
5
10
15
20
25
NumCatalogPurchases

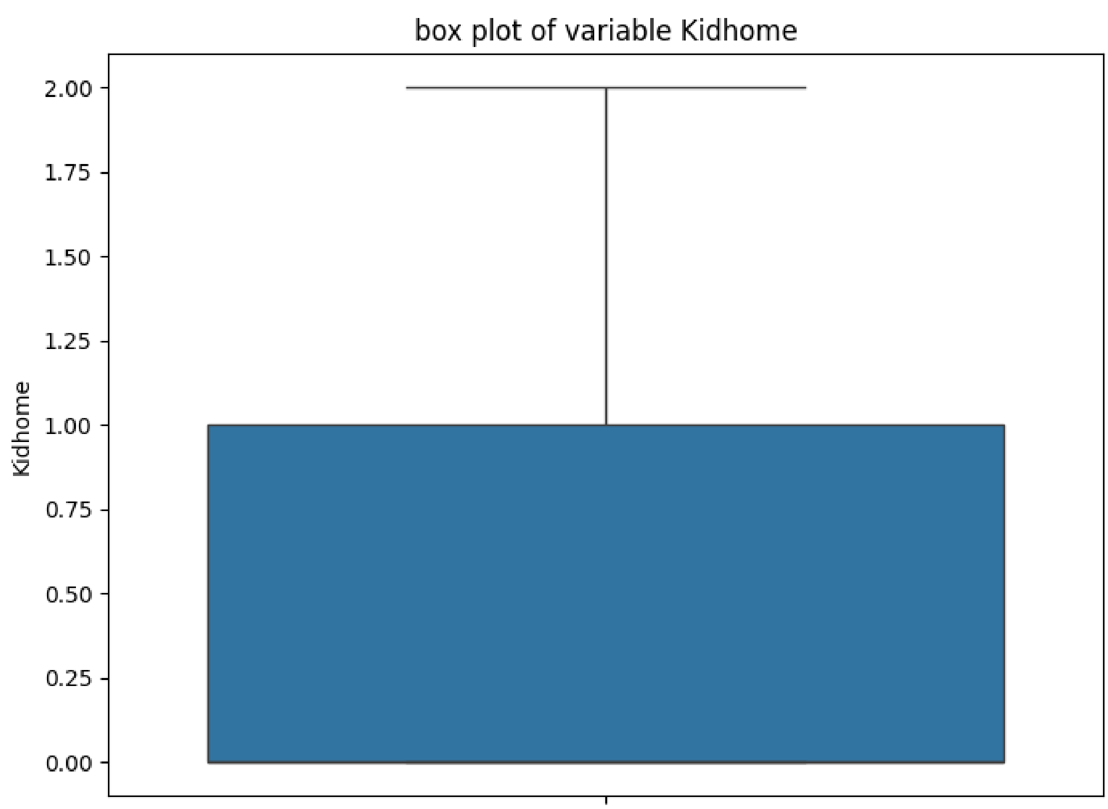

box plot of variable NumStorePurchases
Count
NumStorePurchases
0
100
200
300
400
500
0
2
4
6
8
10
12

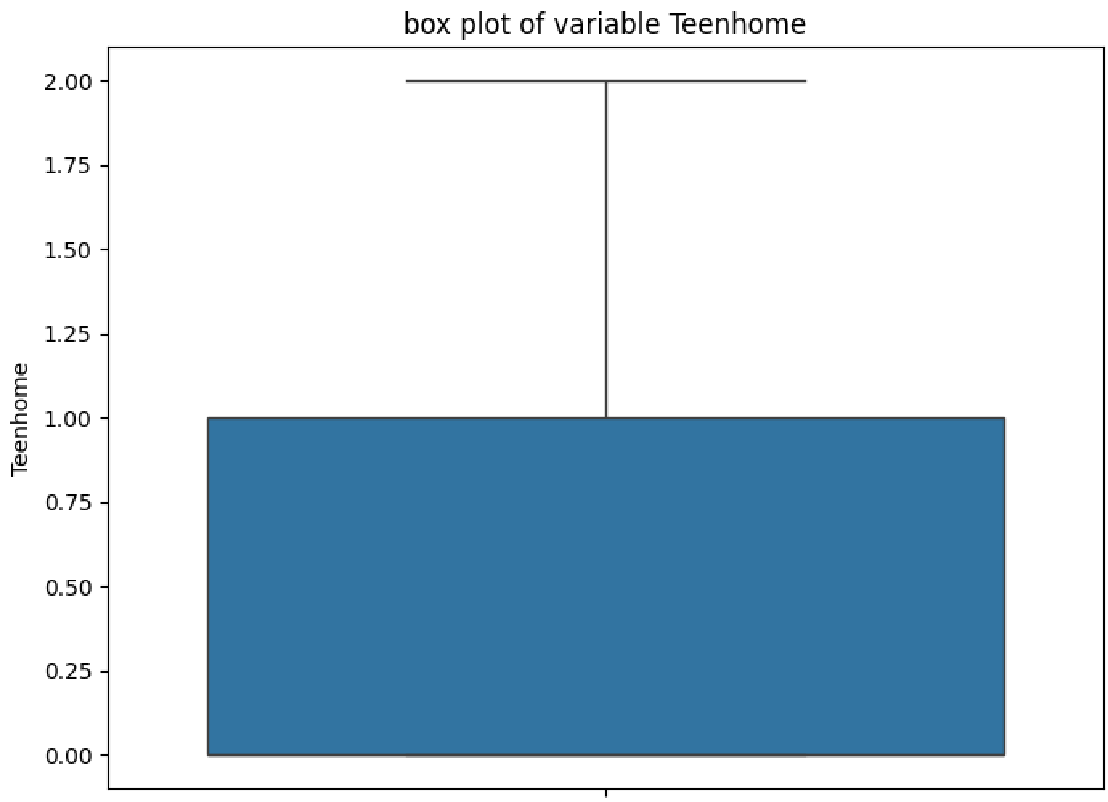


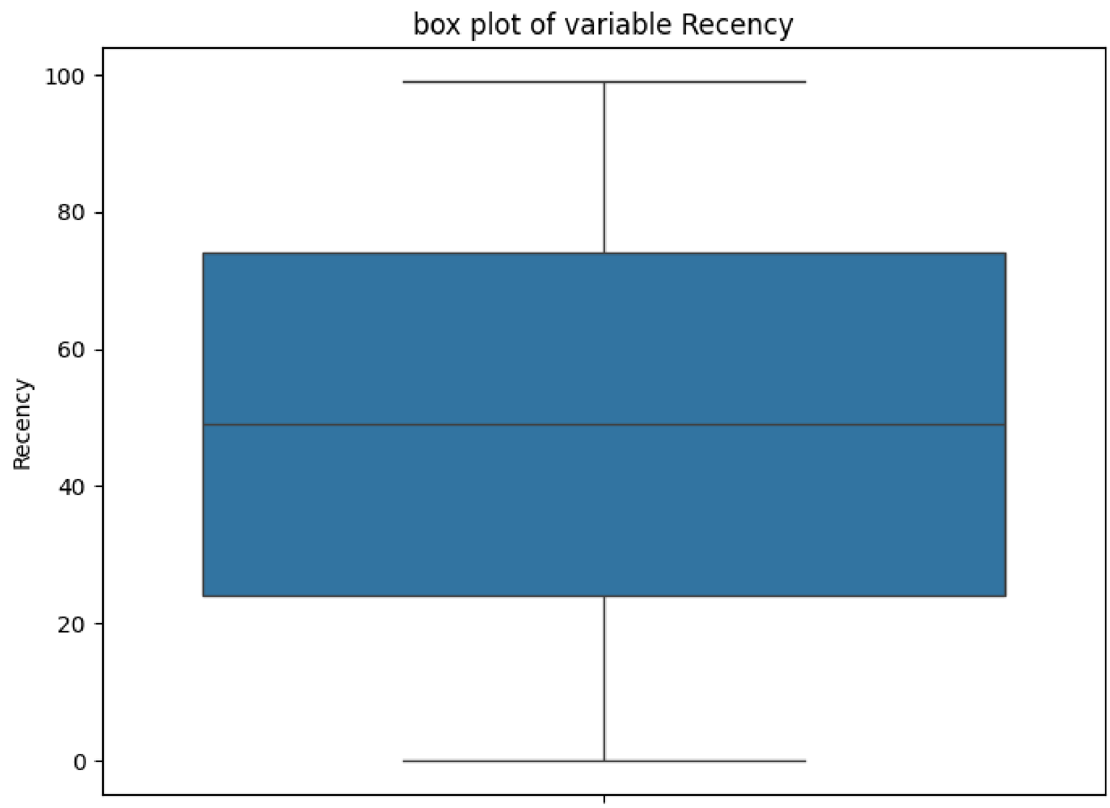
Checking for the presence of outliers in the dataset

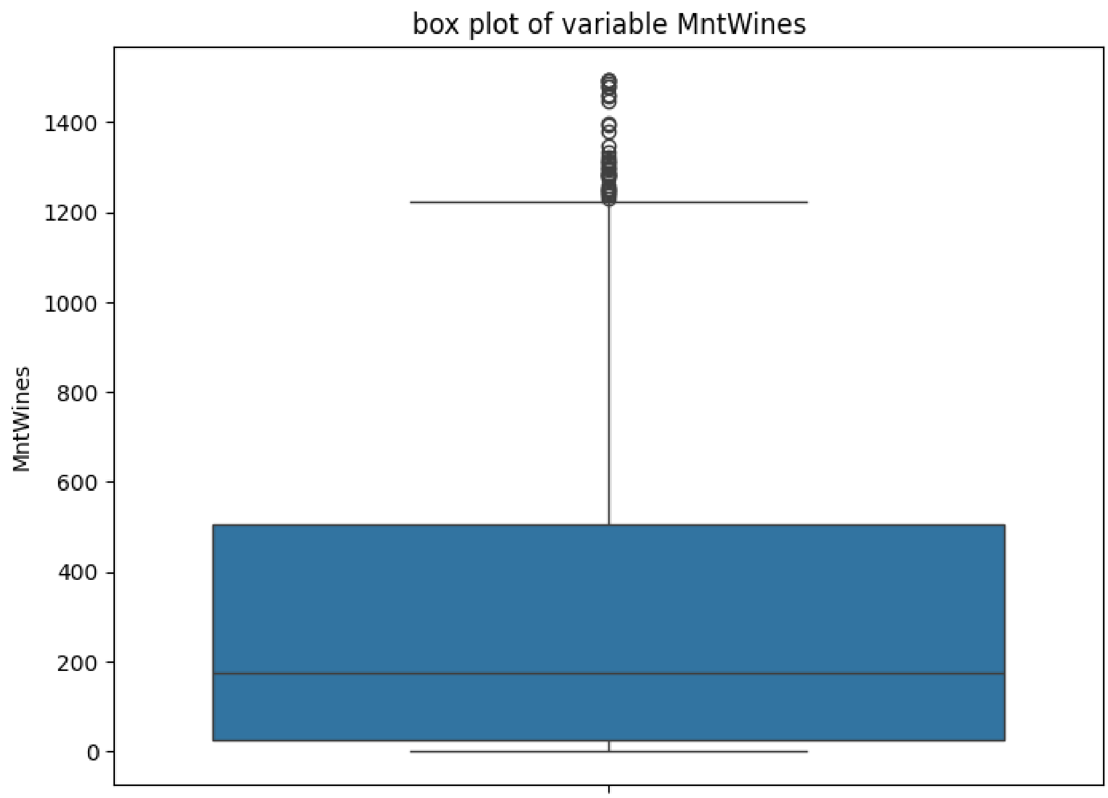
```
[ ]: for variable in selected_variables:
       plt.figure(figsize = (8, 6))
       sns.boxplot(data = selected_variables[variable])
       plt.title(f"box plot of variable {variable}")
```

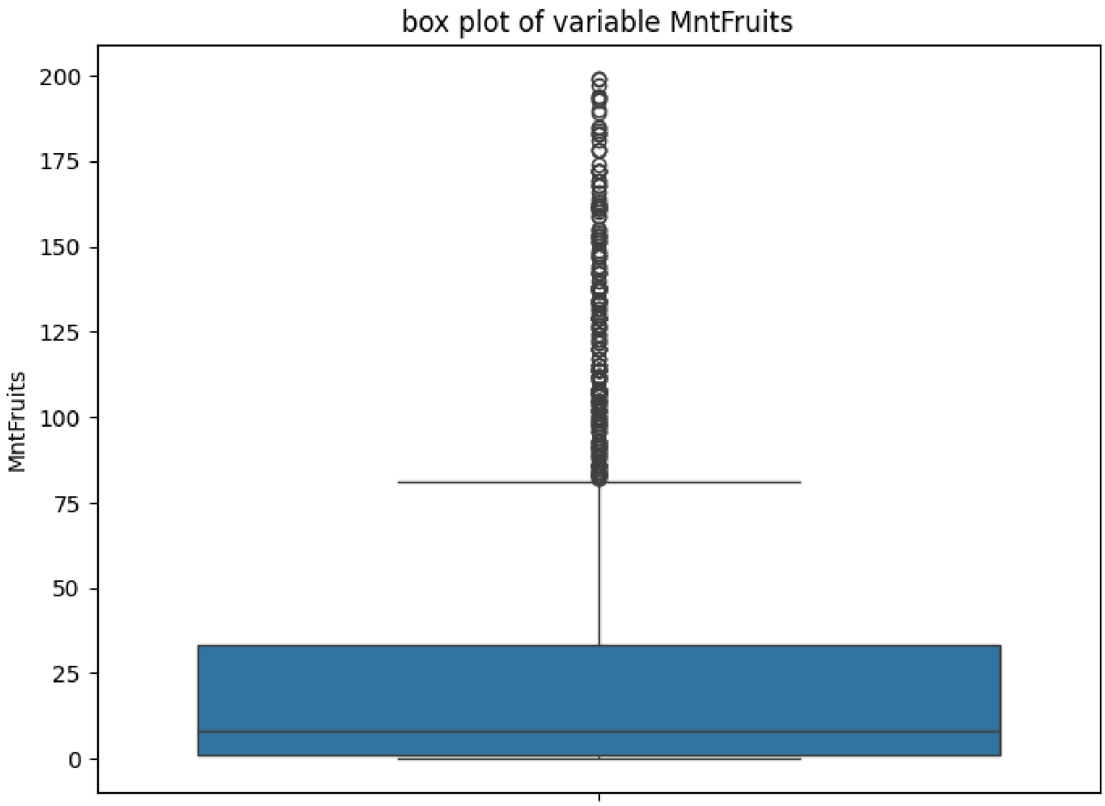

box plot of variable Income
Income
160000
140000
120000
100000
80000
60000
40000
20000
0

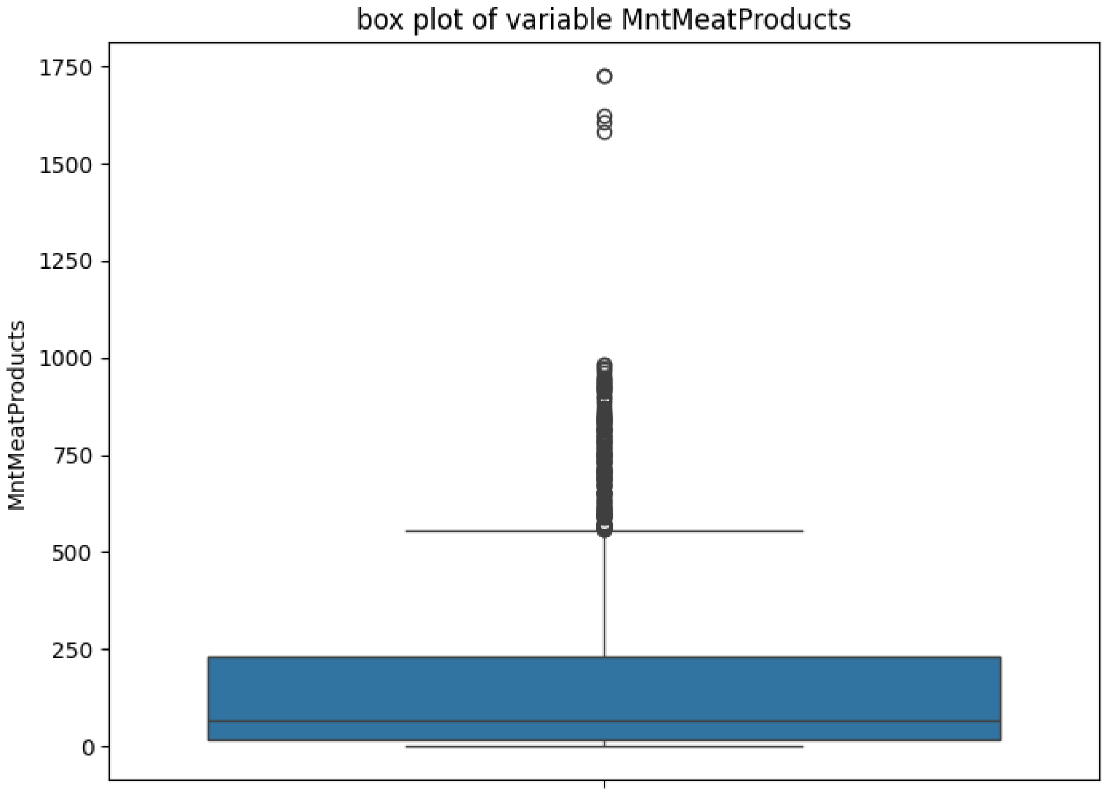

box plot of variable Kidhome
Kidhome
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

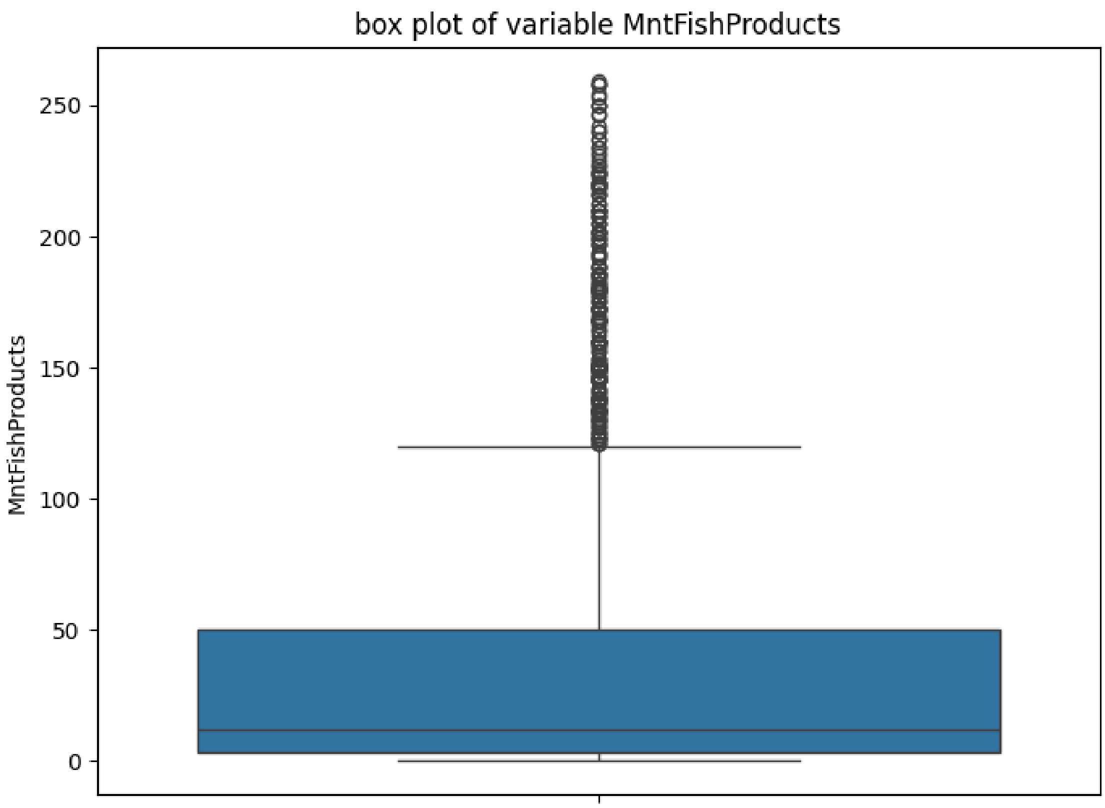

box plot of variable Teenhome
Teenhome
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

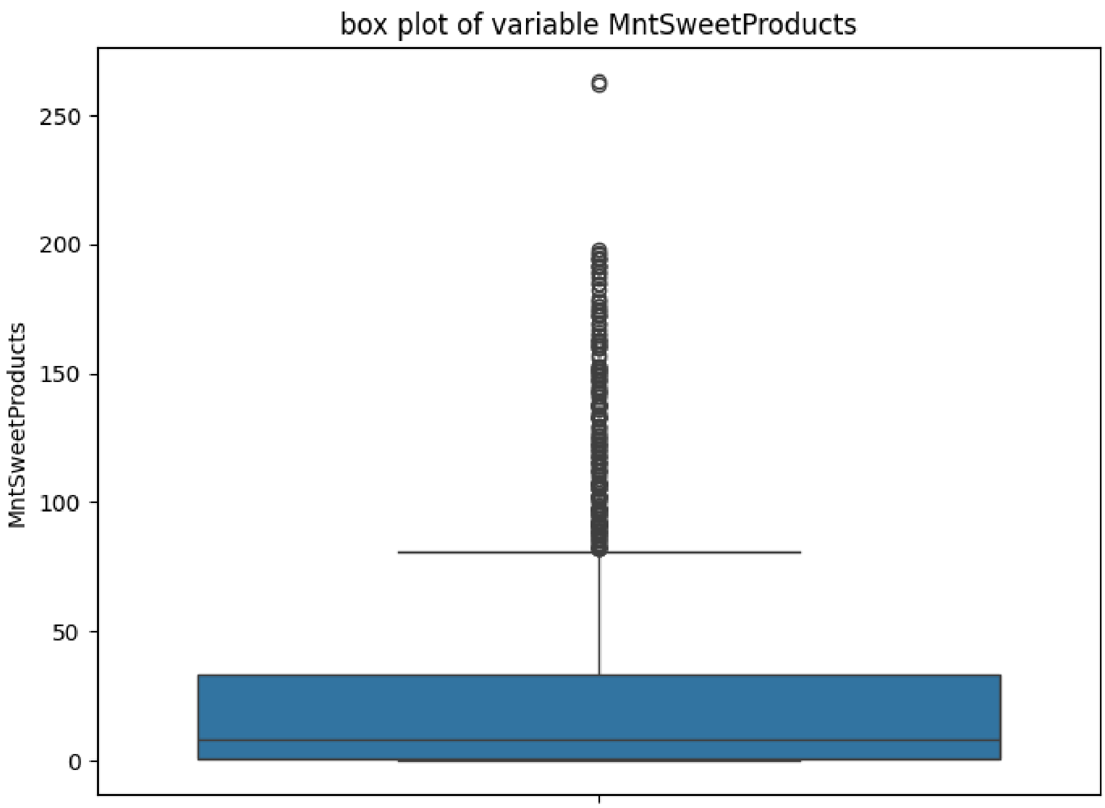

box plot of variable Recency
Recency
100
80
60
40
20
0

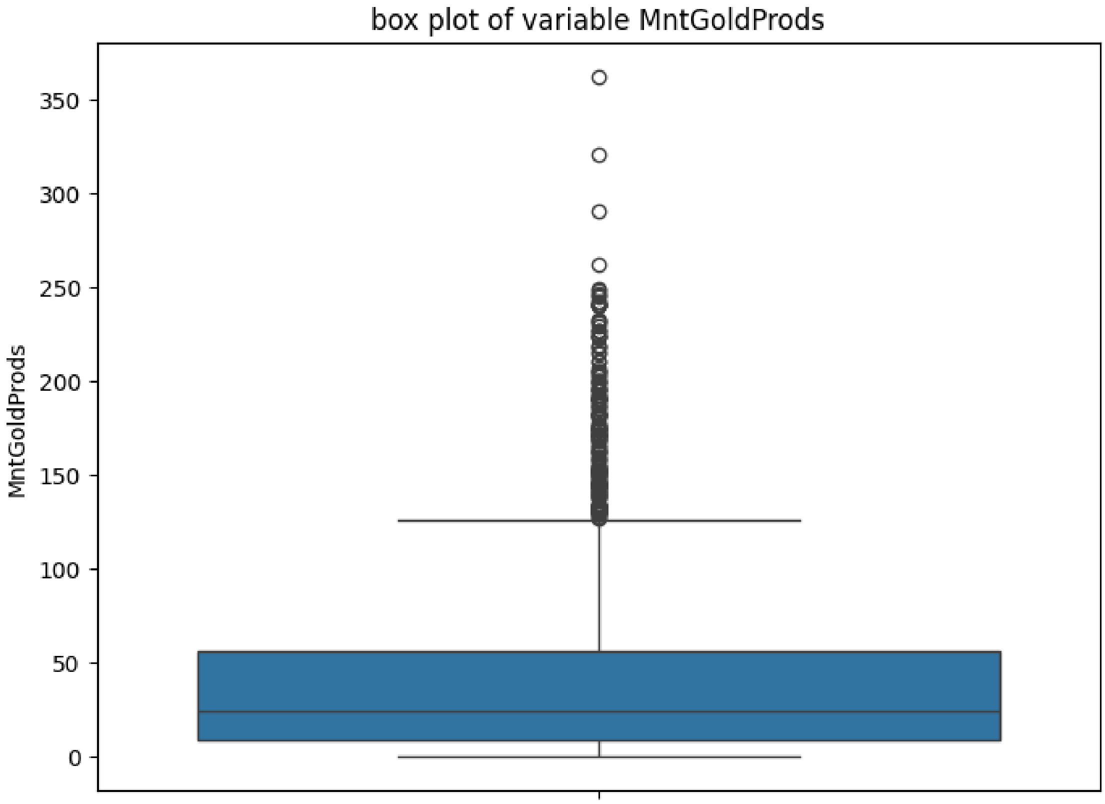

box plot of variable MntWines
MntWines
1400
1200
1000
800
600
400
200
0

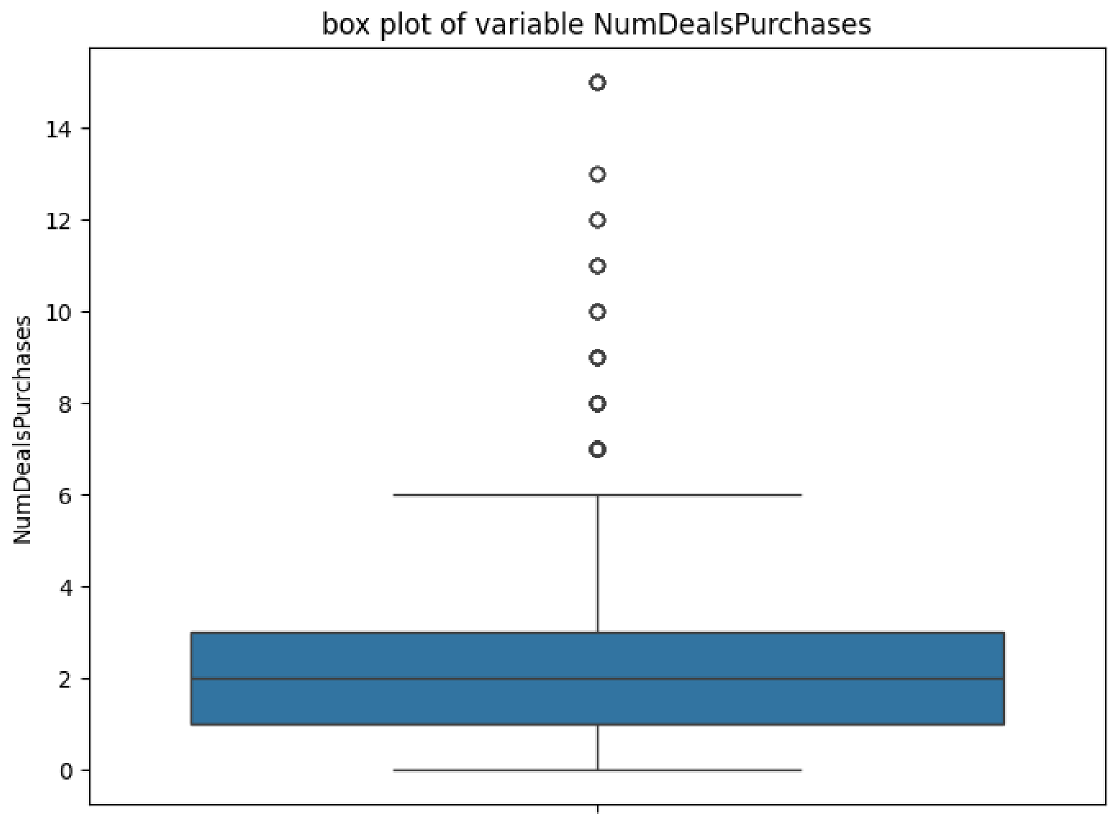

box plot of variable MntFruits
MntFruits
200
175
150
125
100
75
50
25
0

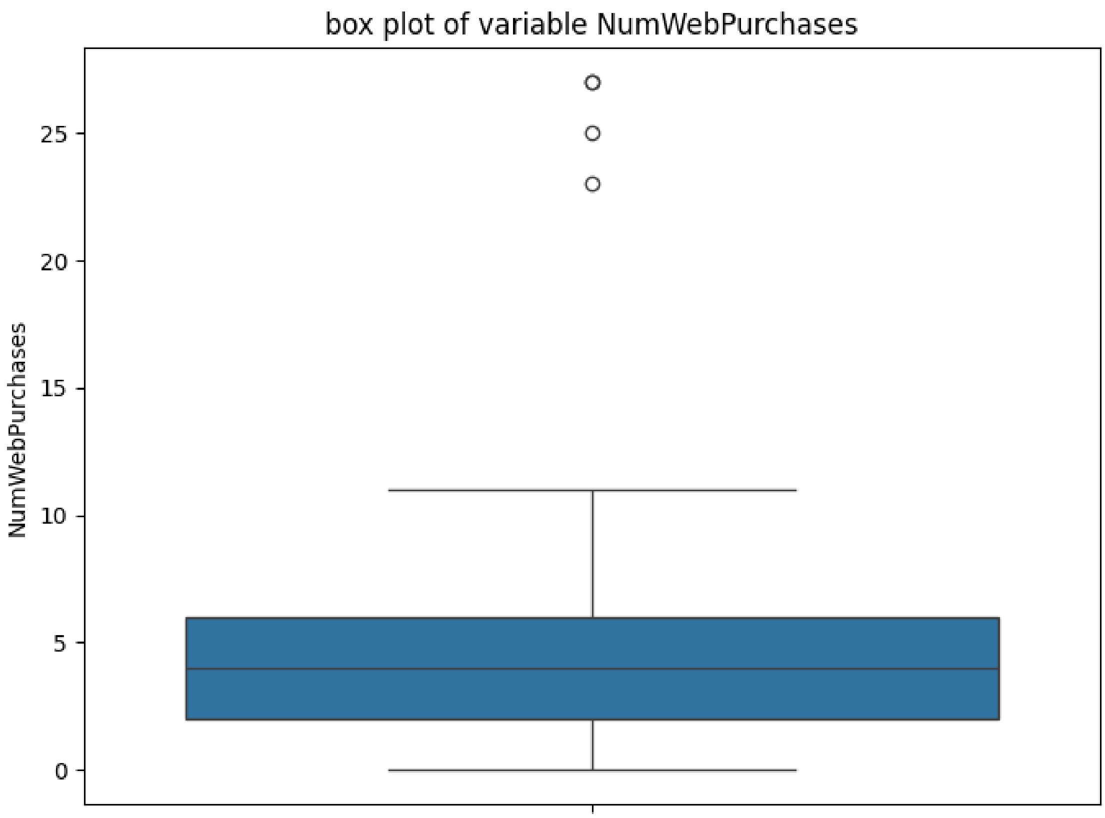

box plot of variable MntMeatProducts
MntMeatProducts
1750
1500
1250
1000
750
500
250
0

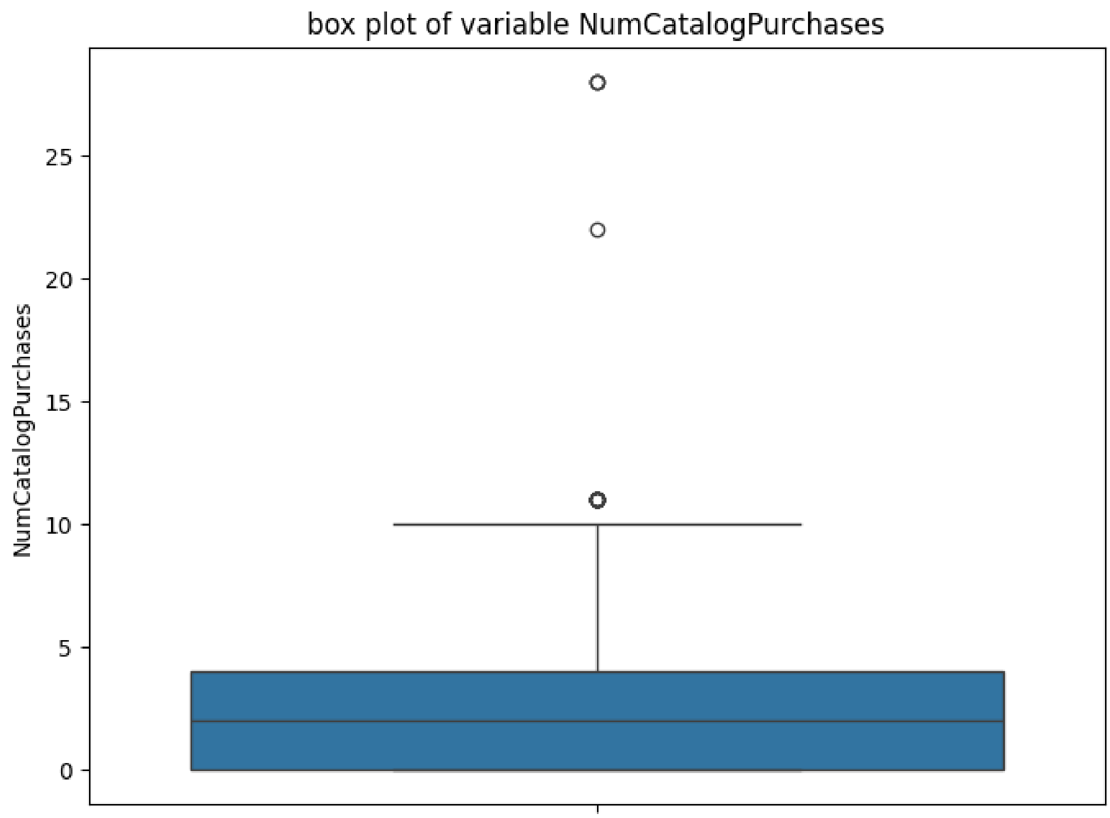

box plot of variable MntFishProducts
MntFishProducts
250
200
150
100
50
0

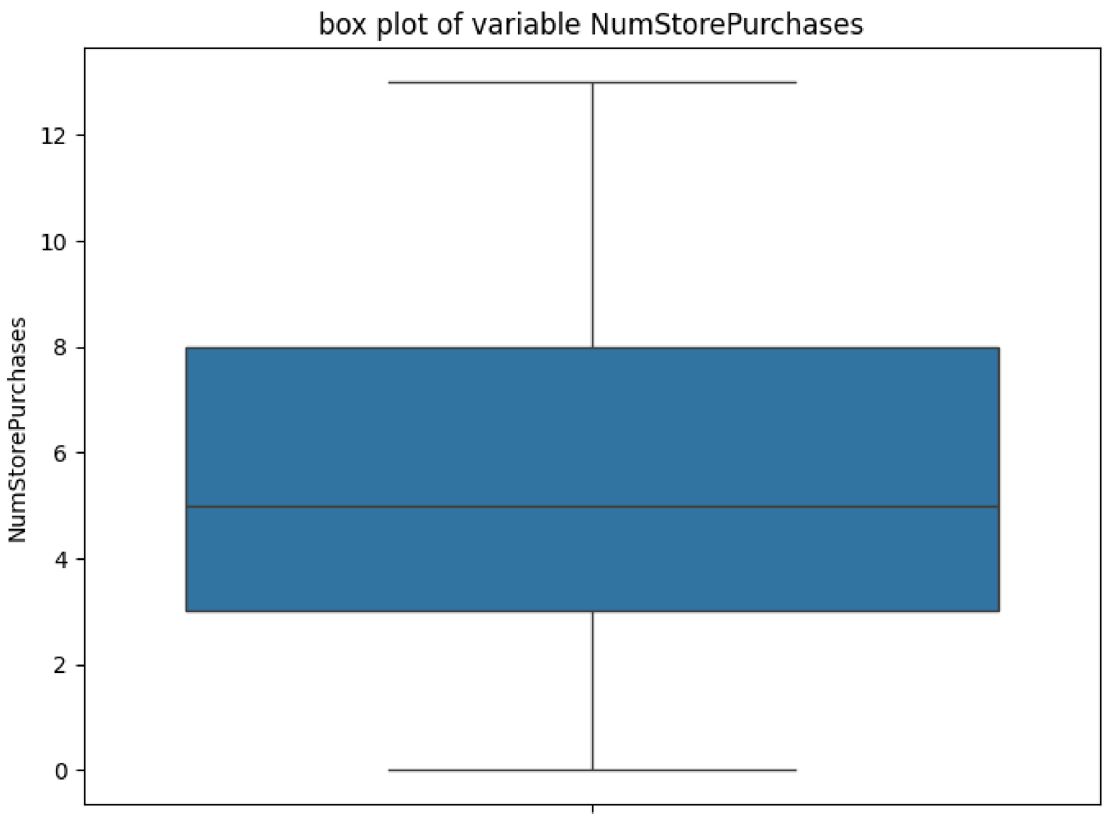

box plot of variable MntSweetProducts
MntSweetProducts
250
200
150
100
50
0

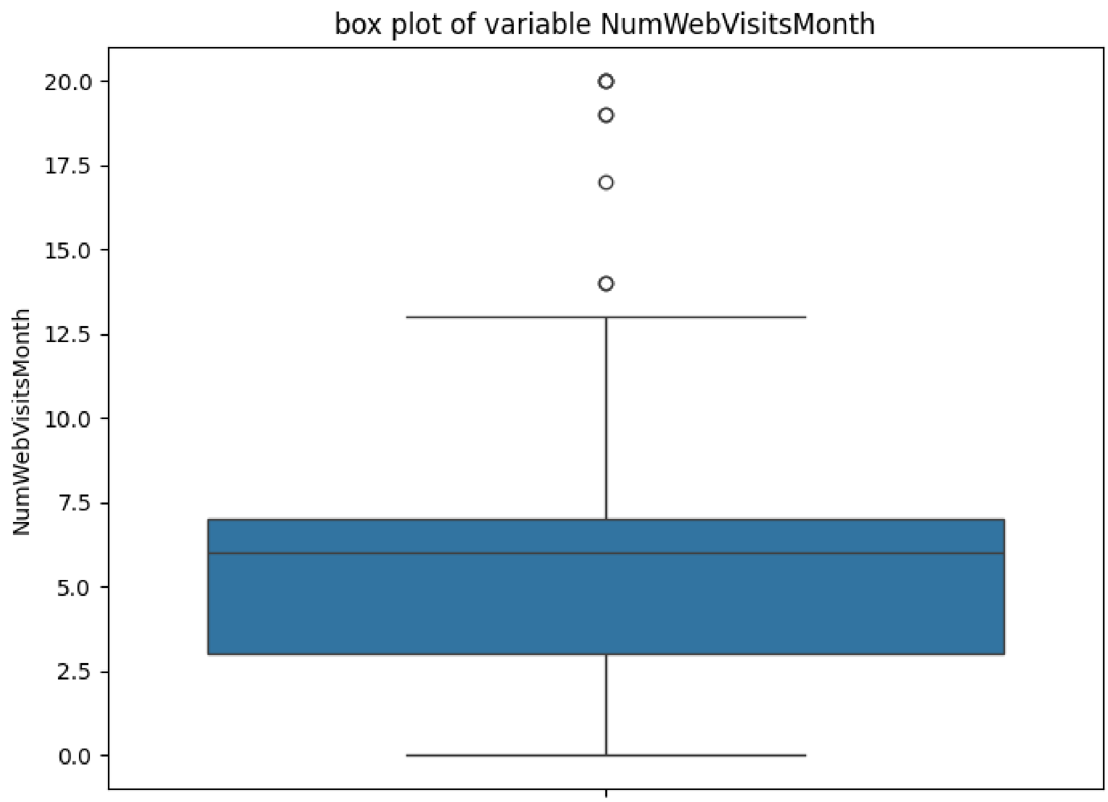

box plot of variable MntGoldProds
MntGoldProds
350
300
250
200
150
100
50
0


box plot of variable NumDealsPurchases
NumDealsPurchases
0
2
4
6
8
10
12
14


box plot of variable NumWebPurchases
NumWebPurchases
0
5
10
15
20
25


box plot of variable NumCatalogPurchases
NumCatalogPurchases
25
20
15
10
5
0


box plot of variable NumStorePurchases
NumStorePurchases
0
2
4
6
8
10
12



Calculating Total number of outliers

```
[ ]: Q1 = summary_df.loc["25%"]
     Q3 = summary_df.loc["75%"]

     IQR = Q3- Q1
     print(IQR)
```

```
Income                  33561.5
Kidhome                     1.0
Teenhome                    1.0
Recency                    50.0
MntWines                  480.5
MntFruits                  32.0
MntMeatProducts           216.0
MntFishProducts            47.0
MntSweetProducts           32.0
MntGoldProds               47.0
NumDealsPurchases           2.0
NumWebPurchases             4.0
NumCatalogPurchases         4.0
NumStorePurchases           5.0
```

```
NumWebVisitsMonth          4.0
dtype: float64
```

[ ]:
```
lower_bound = Q1- 1.5*IQR
upper_bound = Q3 + 1.5*IQR

bounds_df = pd.DataFrame({"LowerBound" : lower_bound, "UpperBound":␣
 ↪upper_bound})
print(bounds_df)
```

```
                     LowerBound  UpperBound
Income                -15626.25   118619.75
Kidhome                   -1.50        2.50
Teenhome                  -1.50        2.50
Recency                  -51.00      149.00
MntWines                -696.75     1225.25
MntFruits                -47.00       81.00
MntMeatProducts         -308.00      556.00
MntFishProducts          -67.50      120.50
MntSweetProducts         -47.00       81.00
MntGoldProds             -61.50      126.50
NumDealsPurchases         -2.00        6.00
NumWebPurchases           -4.00       12.00
NumCatalogPurchases       -6.00       10.00
NumStorePurchases         -4.50       15.50
NumWebVisitsMonth         -3.00       13.00
```

[ ]:
```
outliers_lower = (summary_df < lower_bound).sum()
outliers_upper = (summary_df > upper_bound).sum()
total_outliers = outliers_lower  + outliers_upper

ouliers_count_df = pd.DataFrame({"LowerBound_outliers" :outliers_lower,␣
 ↪"UpperBound_outliers" :outliers_upper, "Total" : total_outliers})
print(ouliers_count_df)
```

```
                     LowerBound_outliers  UpperBound_outliers  Total
Income                                 0                    1      1
Kidhome                                0                    1      1
Teenhome                               0                    1      1
Recency                                0                    1      1
MntWines                               0                    2      2
MntFruits                              0                    2      2
MntMeatProducts                        0                    2      2
MntFishProducts                        0                    2      2
MntSweetProducts                       0                    2      2
MntGoldProds                           0                    2      2
NumDealsPurchases                      0                    2      2
NumWebPurchases                        0                    2      2
```

```
NumCatalogPurchases                     0                    2       2
NumStorePurchases                       0                    1       1
NumWebVisitsMonth                       0                    2       2
```

Feature engineering

```
[ ]: bins = [0, 5000, 25000, 45000, 65000, 85000, 105000, 125000, 145000, 165000]

     labels = ['<=5k', '>5k-25k', '>25k-45k', '>45k-65k', '>65k-85k', '>85k-105k',␣
      ↪'>105k-125k', '>125k-145k', '>145-165k']

     df['Income_lables'] = pd.cut(df['Income'], bins = bins, labels = labels)
```

```
[ ]: import datetime
     df['Age'] = datetime.datetime.now().year - df['Year_Birth']
```

```
[ ]: bins = [25, 45, 65, 85, 105, 125, 135]

     labels = ['25-45', '>45-65', '>65-85', '>85-105', '>105-125', '>125+']

     df['age_labels'] = pd.cut(df['Age'], bins = bins, labels = labels)
```

```
[ ]: df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'])
     df['Customer_period'] =  (datetime.datetime.now().year - df['Dt_Customer'].dt.
      ↪year) * 12 + (datetime.datetime.now().month - df['Dt_Customer'].dt.month)
```

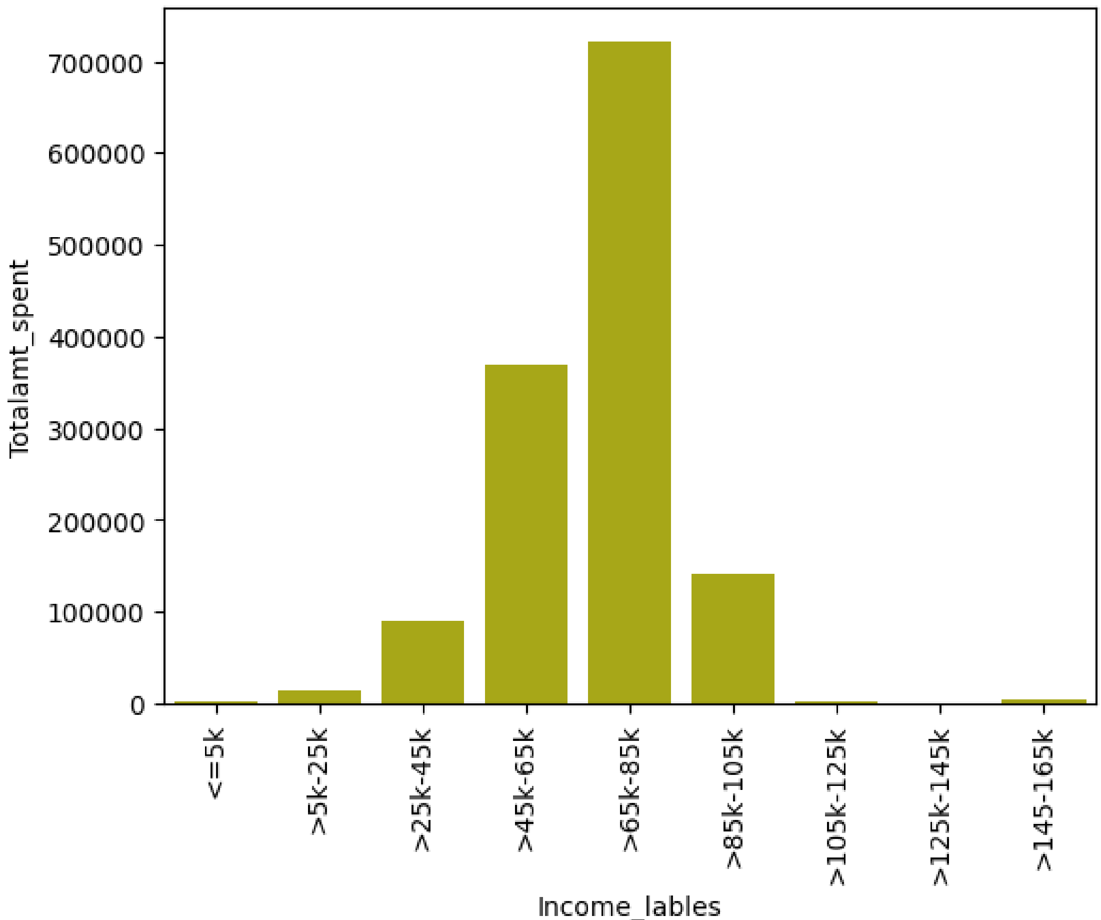
```
[ ]: df['Totalamt_spent'] = df['MntWines'] + df['MntFruits'] + df['MntMeatProducts']␣
      ↪+ df['MntFishProducts'] + df['MntSweetProducts'] + df['MntGoldProds']

     df['Total_purchases'] = df['NumDealsPurchases'] + df['NumWebPurchases'] +␣
      ↪df['NumCatalogPurchases'] + df['NumStorePurchases']
```

Total amt spent on different products categorized under income labels.

```
[ ]: import warnings

     warnings.filterwarnings('ignore', category=FutureWarning)
     warnings.filterwarnings('ignore')

     Income_label_amt_spent = df.groupby('Income_lables')[['MntWines', 'MntFruits',␣
      ↪'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',␣
      ↪'Totalamt_spent']].sum()
     Income_label_amt_spent = Income_label_amt_spent.sort_values(by =␣
      ↪['Totalamt_spent'], ascending = False).reset_index()
     print(Income_label_amt_spent)

     sns.barplot(data = Income_label_amt_spent, x = 'Income_lables', y =␣
      ↪'Totalamt_spent', color = 'y')
```

```python
plt.xticks(rotation = 90)
plt.show()
```

```
  Income_lables  MntWines  MntFruits  MntMeatProducts  MntFishProducts  \
0      >65k-85k    350199      32641           215341            47866
1      >45k-65k    215973      14038            73676            18969
2     >85k-105k     66082       5841            49390             7832
3      >25k-45k     39914       4191            21323             6591
4       >5k-25k      2661       1467             3508             1904
5     >145-165k       203         22             4957               26
6          <=5k        27          8             1743                6
7    >105k-125k      1015        183              107              203
8    >125k-145k         0          0                0                0

   MntSweetProducts  MntGoldProds  Totalamt_spent
0             33792         41565          721404
1             13547         32050          368253
2              6624          5705          141474
3              4109         13304           89432
4              1524          4237           15301
5                 9            18            5235
6                 7           326            2117
7               283           210            2001
8                 0             0               0
```



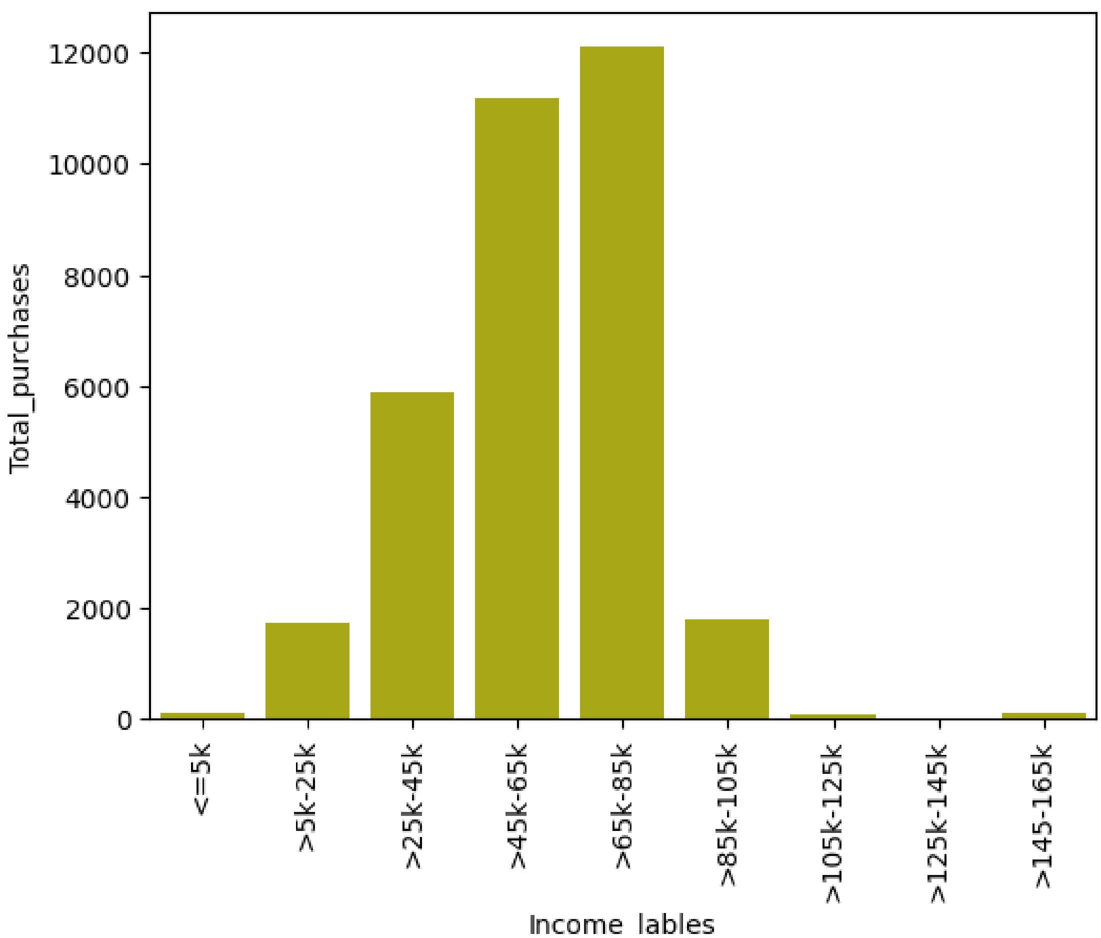
Type of purchases categorized under income labels.

[ ]:
```
Income_label_purchases = df.groupby('Income_lables')[['NumDealsPurchases',␣
↪'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',␣
↪'Total_purchases']].sum()
Income_label_purchases = Income_label_purchases.sort_values(by =␣
↪['Total_purchases'], ascending = False).reset_index()
print(Income_label_purchases)

sns.barplot(data = Income_label_purchases, x = 'Income_lables', y =␣
↪'Total_purchases', color = 'y')
plt.xticks(rotation = 90)
plt.show()
```

```
  Income_lables  NumDealsPurchases  NumWebPurchases  NumCatalogPurchases  \
0      >65k-85k                970             3122                 3072
1      >45k-65k               2024             3271                 1646
2      >25k-45k               1510             1660                  439
```

3	>85k-105k	75	467	548
4	>5k-25k	491	468	99
5	>145-165k	30	1	78
6	<=5k	45	25	28
7	>105k-125k	0	36	8
8	>125k-145k	0	0	0

	NumStorePurchases	Total_purchases
0	4945	12109
1	4229	11170
2	2292	5901
3	708	1798
4	662	1720
5	3	112
6	0	98
7	13	57
8	0	0



Purchases categorized for number of teenagers and kids in each household

[ ]:
```
df.groupby('Teenhome')[['Totalamt_spent', 'Total_purchases']].sum().
↪reset_index()
```

[ ]:
```
   Teenhome  Totalamt_spent  Total_purchases
0         0          802199            16061
1         1          524091            16338
2         2           30636              881
```

[ ]:
```
df.groupby('Kidhome')[['Totalamt_spent', 'Total_purchases']].sum().reset_index()
```

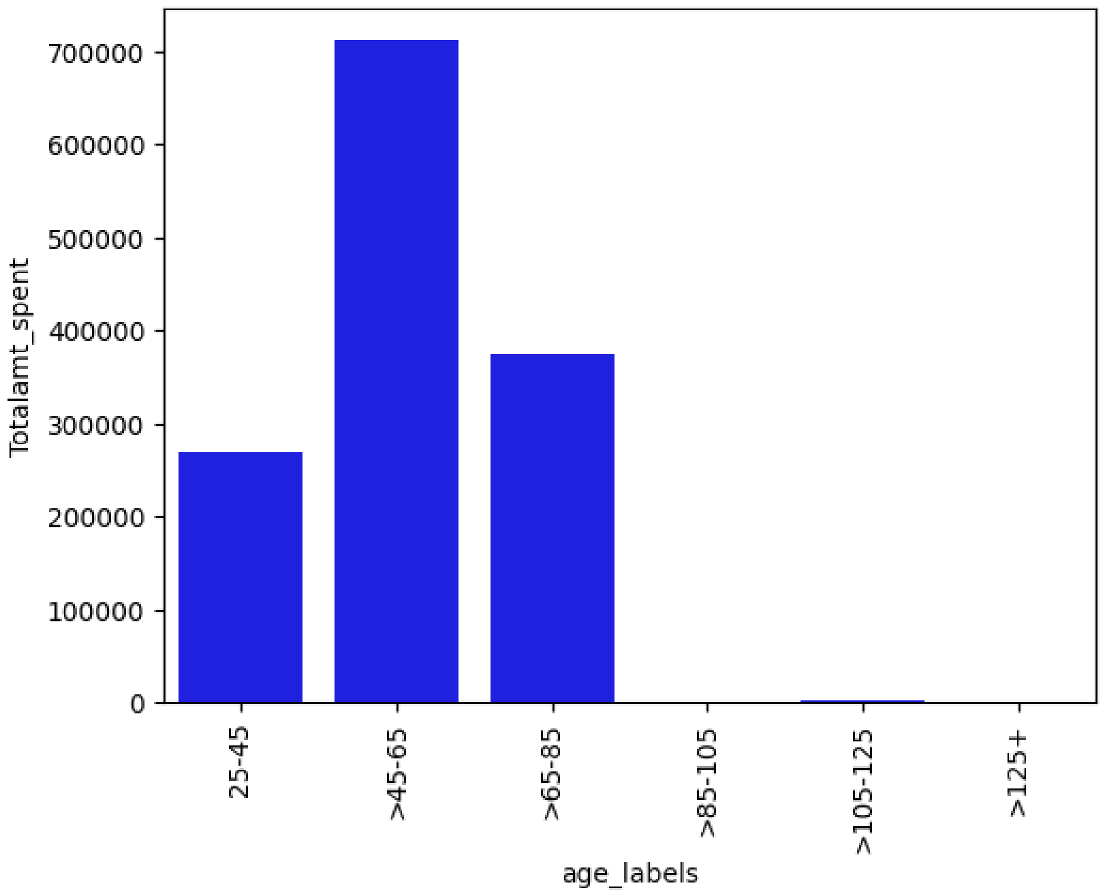
[ ]:
```
   Kidhome  Totalamt_spent  Total_purchases
0        0         1165330            23395
1        1          184624             9416
2        2            6972              469
```

Total amt spent on different products categorized under Age labels.

[ ]:
```
import warnings

warnings.filterwarnings('ignore', category=FutureWarning)
warnings.filterwarnings('ignore')

Age_label_amt_spent = df.groupby('age_labels')[['MntWines', 'MntFruits',␣
↪'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',␣
↪'Totalamt_spent']].sum()
Age_label_amt_spent = Age_label_amt_spent.sort_values(by = ['Totalamt_spent'],␣
↪ascending = False).reset_index()
print(Age_label_amt_spent)

sns.barplot(data = Age_label_amt_spent, x = 'age_labels', y = 'Totalamt_spent',␣
↪color = 'b')
plt.xticks(rotation = 90)
plt.show()
```

```
  age_labels  MntWines  MntFruits  MntMeatProducts  MntFishProducts  \
0     >45-65    367850      30701           187090            42260
1     >65-85    196310      14039           100228            22594
2      25-45    115869      14013            86057            19077
3   >105-125       770        150              570              111
4      >125+         8          0                5                7
5    >85-105         0          0                0                0

   MntSweetProducts  MntGoldProds  Totalamt_spent
0             31383         51898          711182
1             15432         26147          374750
2             13737         20301          269054
```

```
3                   68            249           1918
4                    0              2             22
5                    0              0              0
```



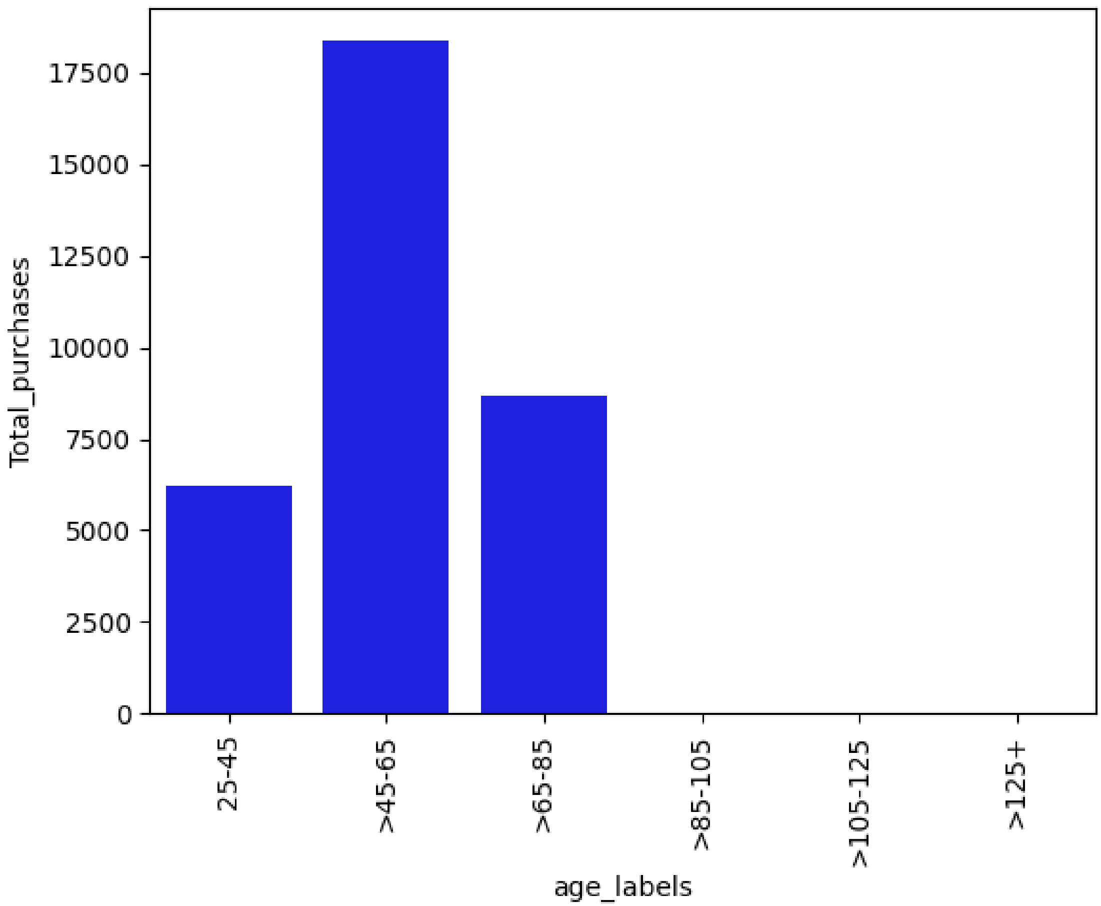
Type of purchases categorized under Age labels.

```
[ ]: Age_label_purchases = df.groupby('age_labels')[['NumDealsPurchases',
      'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',
      'Total_purchases']].sum()
     Age_label_purchases = Age_label_purchases.sort_values(by = ['Total_purchases'],
      ascending = False).reset_index()
     print(Age_label_purchases)

     sns.barplot(data = Age_label_purchases, x = 'age_labels', y =
      'Total_purchases', color = 'b')
     plt.xticks(rotation = 90)
     plt.show()
```

```
  age_labels  NumDealsPurchases  NumWebPurchases  NumCatalogPurchases  \
```

0	>45-65	3097	5068	3101
1	>65-85	1213	2395	1713
2	25-45	891	1677	1141
3	>105-125	2	6	7
4	>125+	1	1	0
5	>85-105	0	0	0

	NumStorePurchases	Total_purchases
0	7089	18355
1	3331	8652
2	2539	6248
3	6	21
4	2	4
5	0	0

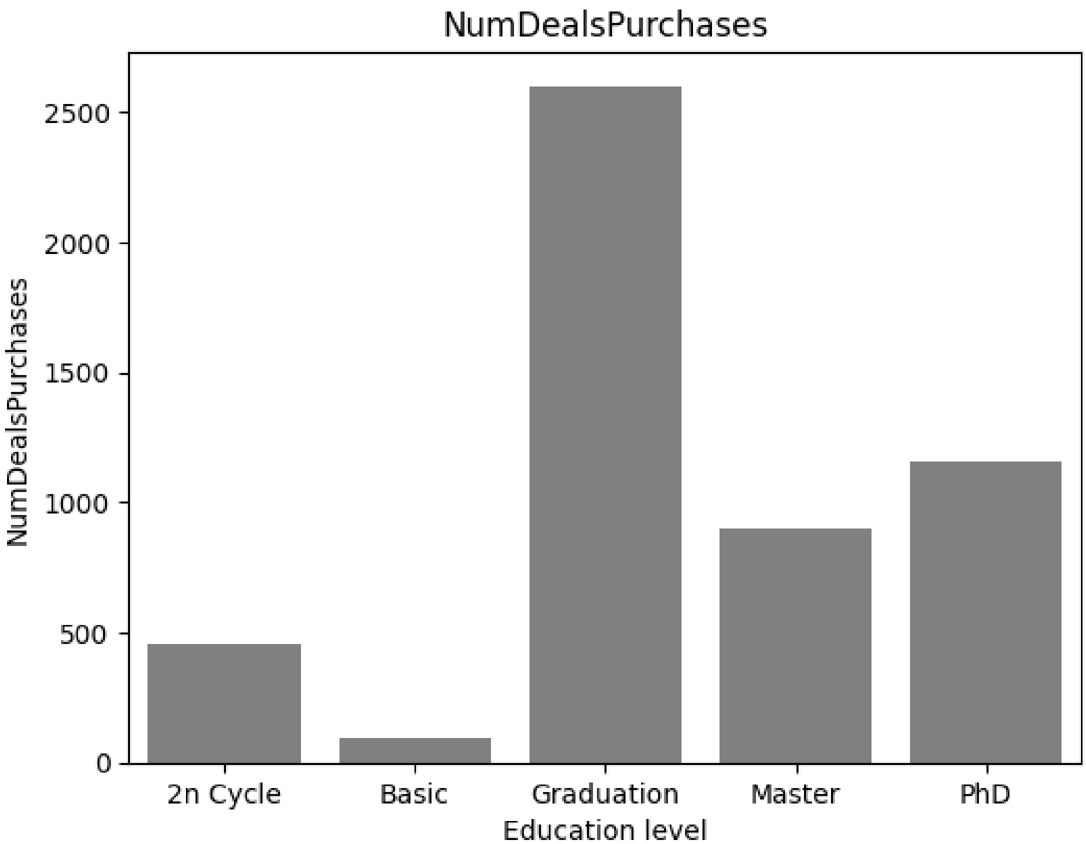


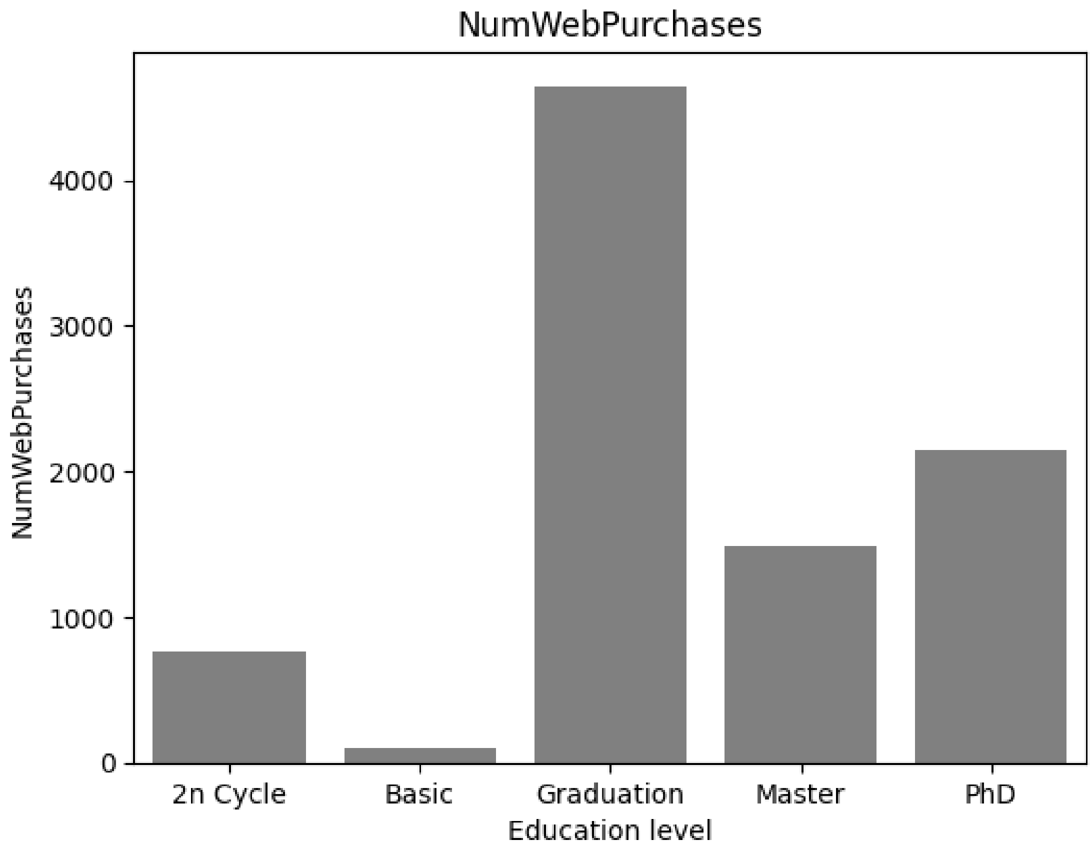
Type of purchases categorized under different Education levels.

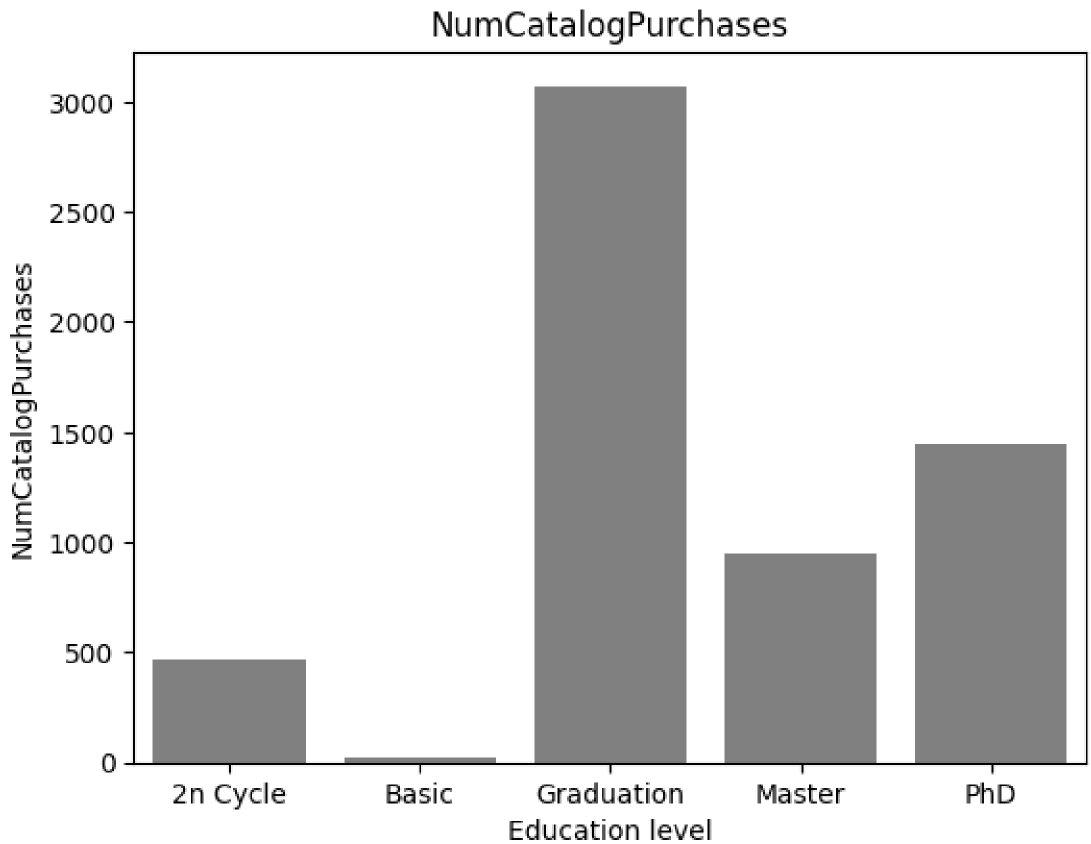
```
[ ]:
```

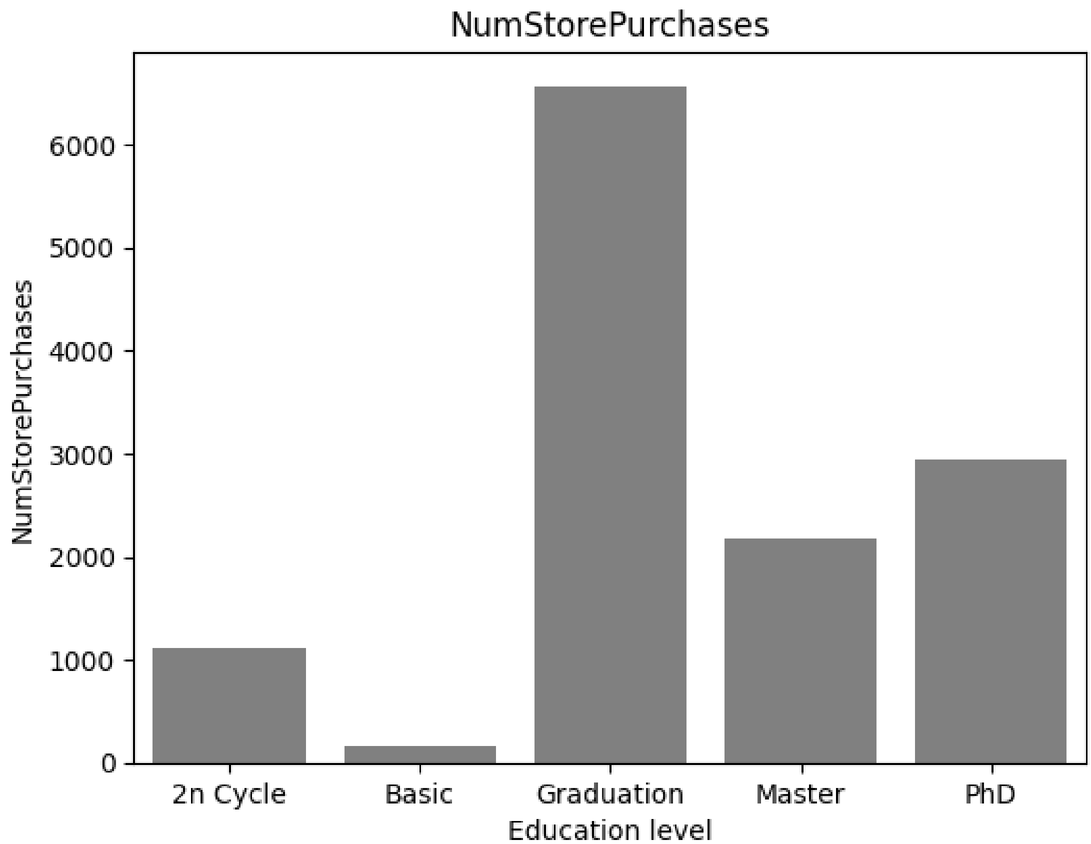
```
Purchases_by_Education_level = df.groupby('Education')[['NumDealsPurchases',␣
 ↪'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',␣
 ↪'NumWebVisitsMonth']].sum()
Purchases_by_Education_level = Purchases_by_Education_level.reset_index()
print(Purchases_by_Education_level)

purchase_types = ['NumDealsPurchases', 'NumWebPurchases',␣
 ↪'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth']

for purchase_type in purchase_types:
  sns.barplot(data = Purchases_by_Education_level, x = 'Education', y =␣
 ↪purchase_type, color = 'grey')
  plt.title(purchase_type)
  plt.xlabel('Education level')
  plt.show()
```

```
    Education  NumDealsPurchases  NumWebPurchases  NumCatalogPurchases  \
0    2n Cycle                456              757                  471
1       Basic                 97              102                   26
2  Graduation               2599             4646                 3071
3      Master                898             1492                  951
4         PhD               1154             2150                 1443

   NumStorePurchases  NumWebVisitsMonth
0               1118               1107
1                154                371
2               6567               5953
3               2182               1916
4               2946               2556
```

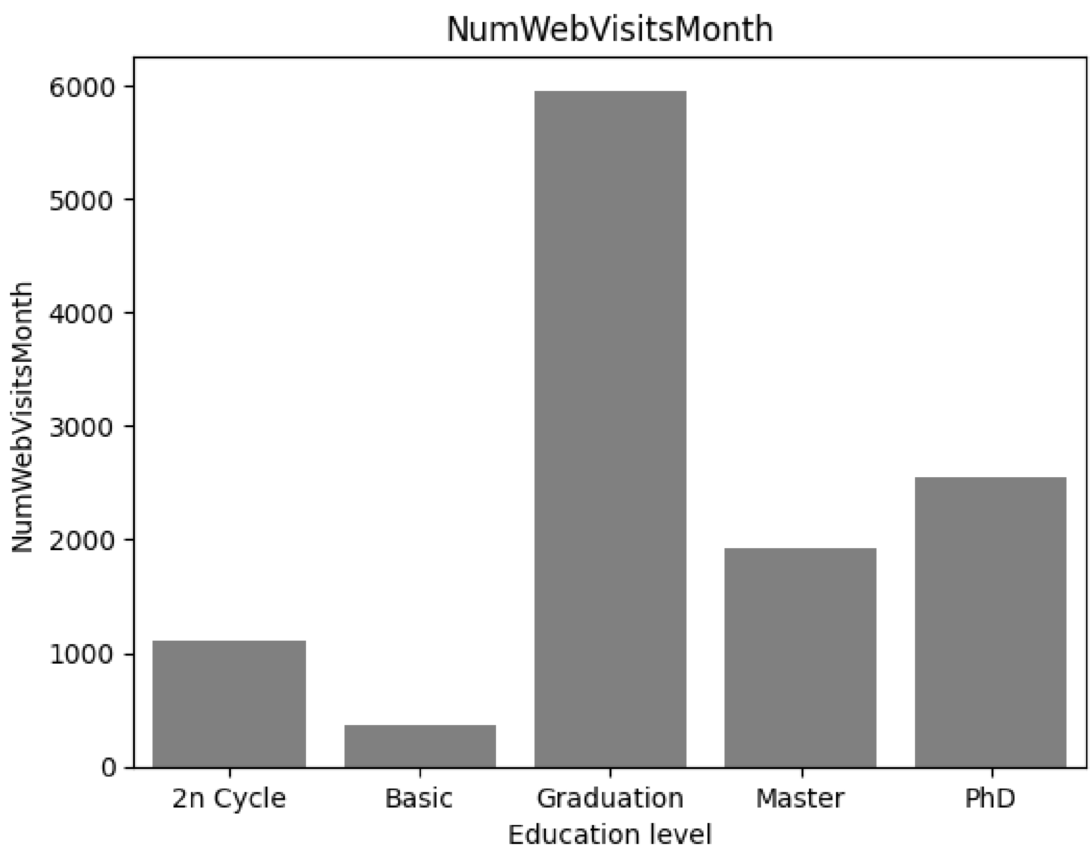

NumDealsPurchases
NumDealsPurchases
2500
2000
1500
1000
500
0
2n Cycle
Basic
Graduation
Master
PhD
Education level


NumWebPurchases
4000
3000
2000
1000
0
NumWebPurchases
2n Cycle
Basic
Graduation
Master
PhD
Education level


NumCatalogPurchases
3000
2500
2000
1500
1000
500
0
NumCatalogPurchases
2n Cycle
Basic
Graduation
Master
PhD
Education level



NumStorePurchases
6000
5000
4000
3000
2000
1000
0
NumStorePurchases
2n Cycle
Basic
Graduation
Master
PhD
Education level



Number of customers attracted for each Different campaign

[ ]:
```
count_of_offers = df[['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3',␣
 ↪'AcceptedCmp4', 'AcceptedCmp5']].sum()
count_of_offers = count_of_offers.reset_index()
count_of_offers.columns = ['Campaign', 'count']
count_of_offers
```

[ ]:

	Campaign	count
0	AcceptedCmp1	144
1	AcceptedCmp2	30
2	AcceptedCmp3	163
3	AcceptedCmp4	167
4	AcceptedCmp5	163

Total number of Complaints

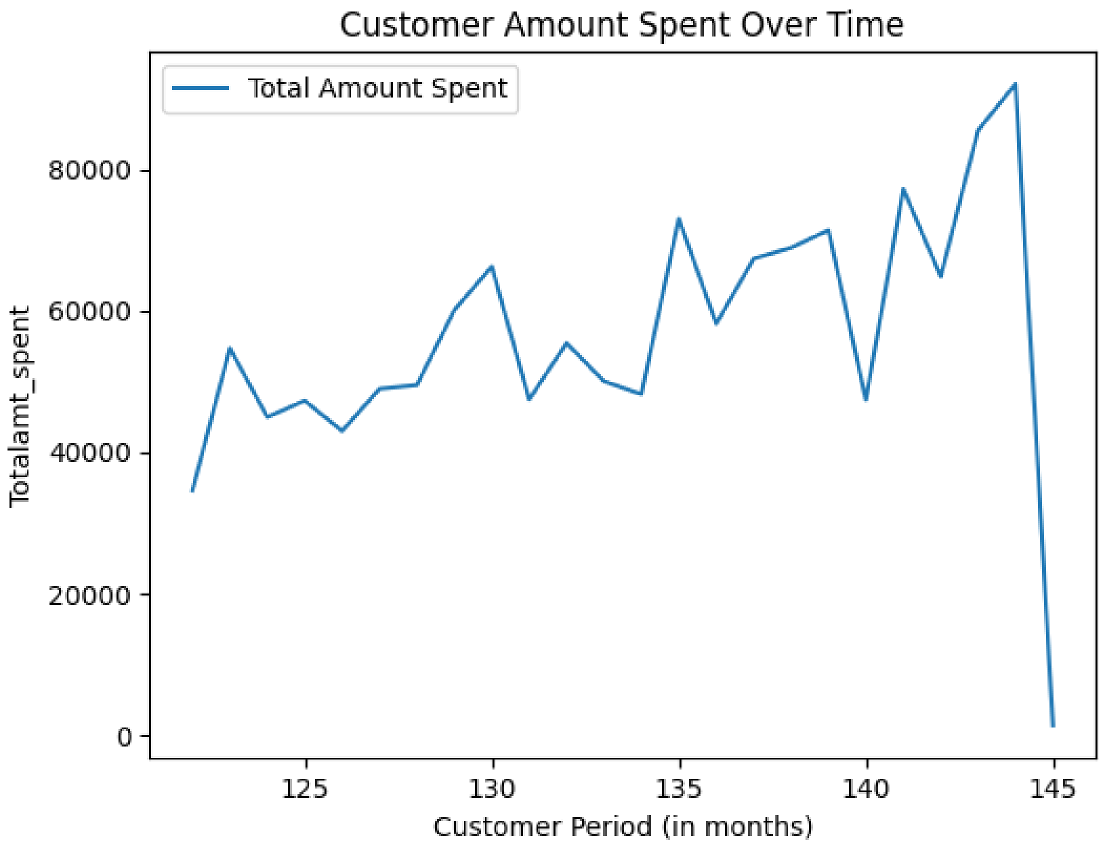
[ ]:
```
Total_complaints = df['Complain'].sum()
Total_complaints
```

[ ]: 21

Total amt spent withrespect to customer period. (in months)

```
[ ]: customer_purchases_wtr_period = df.
      ↪groupby('Customer_period')[['Totalamt_spent', 'Total_purchases']].sum()
     customer_purchases_wtr_period = customer_purchases_wtr_period.sort_values(by =␣
      ↪['Totalamt_spent'], ascending = False).reset_index()
     print(customer_purchases_wtr_period)

     sns.lineplot(data=customer_purchases_wtr_period, x='Customer_period',␣
      ↪y='Totalamt_spent', label='Total Amount Spent')
     plt.title('Customer Amount Spent Over Time')
     plt.xlabel('Customer Period (in months)')
     plt.show()
```

```
    Customer_period  Totalamt_spent  Total_purchases
0               144           92046             2026
1               143           85492             1812
2               141           77190             1722
3               135           72954             1593
4               139           71351             1789
5               138           68879             1671
6               137           67322             1667
7               130           66221             1704
8               142           64802             1598
9               129           60064             1394
10              136           58135             1369
11              132           55393             1478
12              123           54648             1475
13              133           49986             1358
14              128           49455             1243
15              127           48932             1306
16              134           48171             1335
17              131           47432             1236
18              140           47382             1116
19              125           47247             1306
20              124           44938             1154
21              126           42970              972
22              122           34559              911
23              145            1357               45
```



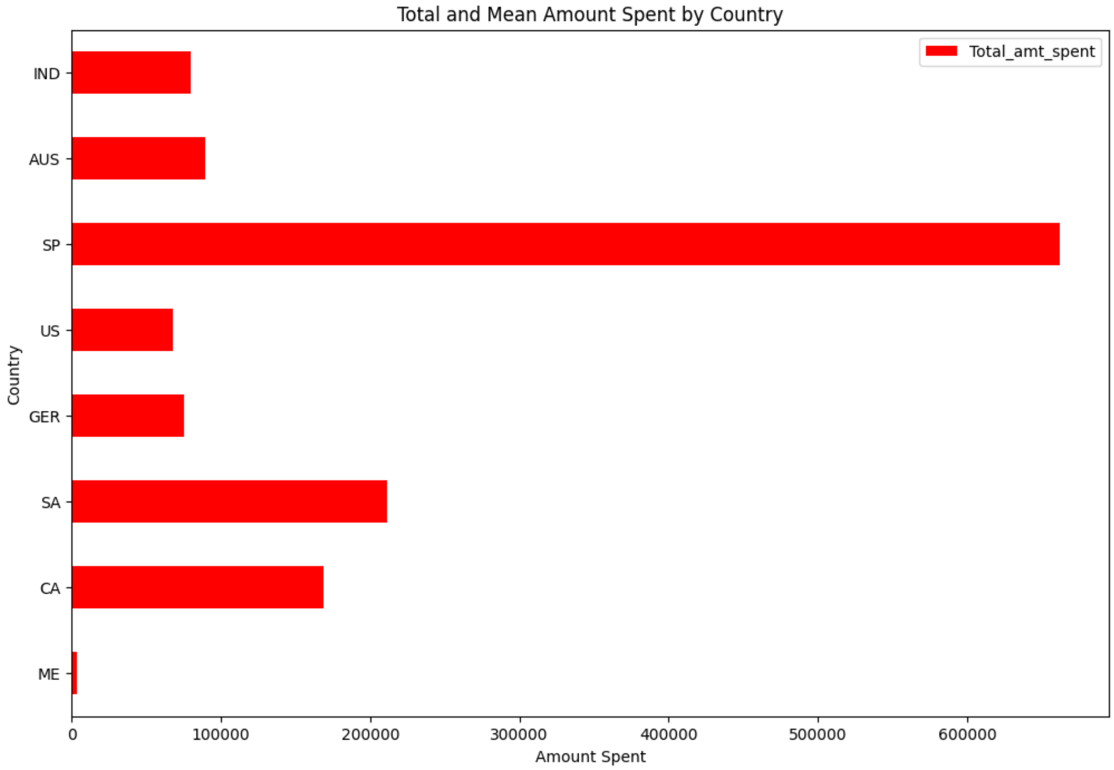
Total amt spent and mean amt spent for each country

[ ]:
```python
Country_purchases = df.groupby('Country')['Totalamt_spent'].aggregate({'sum',
    'mean'})
Country_purchases = Country_purchases.sort_values(by = ['mean'], ascending =
    False).reset_index()
Country_purchases.columns = ['country', 'Total_amt_spent', 'mean_amt_spent']
print(Country_purchases)

Country_purchases.plot(kind='barh', x='country', y='Total_amt_spent',
    figsize=(12, 8), color = 'r')
plt.title('Total and Mean Amount Spent by Country')
plt.xlabel('Amount Spent')
plt.ylabel('Country')
plt.show()
```

```
  country  Total_amt_spent  mean_amt_spent
0      ME             3122     1040.666667
1      CA           168532      628.850746
2      SA           211009      628.002976
```

```
3      GER          74913      624.275000
4       US          67882      622.770642
5       SP         662220      604.767123
6      AUS          89763      561.018750
7      IND          79485      537.060811
```



Hypothesis testing

Is income of customers dependent on their education

[ ]:
```
from scipy.stats import f_oneway

alpha = 0.05
 # H0: The means of Incomes between different education levels would be equal
 # H1: The means of Incomes between different education levels would be not␣
 ↪equal

education_groups = [group['Income'].values for name, group in df.
 ↪groupby('Education')]

f_statistic, p_value = f_oneway(*education_groups)
print(f_statistic, p_value)
print("<------------------->")
```

```
if p_value < 0.05:
    print("Reject the null hypothesis. Income depends on education level.")
else:
    print("Fail to reject null hypothesis : Income doesn't depend on Education␣
↪levels.")
```

```
35.42763066856272 9.87796950058819e-29
<------------------->
Reject the null hypothesis. Income depends on education level.
```

Do higher income people spend more (take in account spending in all categories together)

```
[ ]: import scipy.stats as stats

corr_coefficient, p_value = stats.pearsonr(df['Income'], df['Totalamt_spent'])

print(f"Pearson correlation coefficient: {corr_coefficient}")
print(f"P-value: {p_value}")

print("<---------------->")

if p_value < 0.05:
    print("Reject the null hypothesis. There is a significant linear␣
↪relationship between income and purchases.")
else:
    print("Fail to reject the null hypothesis. No significant linear␣
↪relationship exists between income and purchases.")
```

```
Pearson correlation coefficient: 0.7706290398754154
P-value: 0.0
<---------------->
Reject the null hypothesis. There is a significant linear relationship between
income and purchases.
```

Do couples spend more or less money on wine than people living alone (set 'Married','Together':'In couple' and 'Divorced','Single','Absurd','Widow','YOLO':'Alone')

```
[ ]: df['Living_Status'] = df['Marital_Status'].apply(lambda x: 'Couple' if x in␣
↪['Married', 'Together'] else 'Alone')

wine_spending_couples = df[df['Living_Status'] == 'Couple']['MntWines']
wine_spending_alone = df[df['Living_Status'] == 'Alone']['MntWines']

import scipy.stats as stats

# Perform the t-test
```

```
t_statistic, p_value = stats.ttest_ind(wine_spending_couples,␣
↪wine_spending_alone, equal_var=False)  # Use equal_var=False if variances␣
↪are unequal

print(f"T-statistic: {t_statistic}")
print(f"P-value: {p_value}")

print("<-------------------->")

if p_value < 0.05:
    print("Reject the null hypothesis. There is a significant difference in␣
↪wine spending between couples and people living alone.")
else:
    print("Fail to reject the null hypothesis. No significant difference in␣
↪wine spending exists between couples and people living alone.")
```

```
T-statistic: -0.2711337908368919
P-value: 0.7863223090103292
<-------------------->
Fail to reject the null hypothesis. No significant difference in wine spending
exists between couples and people living alone.
```

Are people with lower income are more attracted towards campaign or simply put accept more campaigns. (create two income brackets one below median , other above median income and create a column which tells if they have ever accepted any campaign)

[ ]:
```
median_income = df['Income'].median()

df['Income_Bracket'] = df['Income'].apply(lambda x: 'Below_Median' if x <␣
↪median_income else 'Above_Median')

df['Accepted_Any_Campaign'] = df[['AcceptedCmp1', 'AcceptedCmp2',␣
↪'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']].sum(axis=1).apply(lambda x:␣
↪1 if x > 0 else 0)



import scipy.stats as stats

# Create a contingency table
contingency_table = pd.crosstab(df['Income_Bracket'],␣
↪df['Accepted_Any_Campaign'])

# Perform the Chi-Square test
chi2, p, dof, expected = stats.chi2_contingency(contingency_table)

print(f"Chi-Square statistic: {chi2}")
print(f"P-value: {p}")
```

```
print("<----------------->")

if p < 0.05:
    print("Reject the null hypothesis. There is a significant association␣
 ↪between income level and campaign acceptance.")
else:
    print("Fail to reject the null hypothesis. No significant association␣
 ↪between income level and campaign acceptance.")
```

```
Chi-Square statistic: 138.8199834041559
P-value: 4.8224046007539564e-32
<----------------->
Reject the null hypothesis. There is a significant association between income
level and campaign acceptance.
```

[ ]:
```
!jupyter nbconvert --to pdf "/content/drive/MyDrive/Colab Notebooks/Campaign␣
 ↪dataset@DhanunjayaReddy.ipynb"
```

```
[NbConvertApp] Converting notebook /content/drive/MyDrive/Colab
Notebooks/Campaign dataset@DhanunjayaReddy.ipynb to pdf
[NbConvertApp] Support files will be in Campaign dataset@DhanunjayaReddy_files/
[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
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[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
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[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
[NbConvertApp] Making directory ./Campaign dataset@DhanunjayaReddy_files
[NbConvertApp] Writing 127053 bytes to notebook.tex
[NbConvertApp] Building PDF
[NbConvertApp] Running xelatex 3 times: ['xelatex', 'notebook.tex', '-quiet']
[NbConvertApp] Running bibtex 1 time: ['bibtex', 'notebook']
[NbConvertApp] WARNING | bibtex had problems, most likely because there were no
citations
[NbConvertApp] PDF successfully created
[NbConvertApp] Writing 826069 bytes to /content/drive/MyDrive/Colab
Notebooks/Campaign dataset@DhanunjayaReddy.pdf
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