E-commerce Marketing EDA & Hypothesis testing

October 24, 2024

1 E-commerce Marketing EDA & Hypothesis testing

1.1 Marketing Campaign Dataset Description

- **ID:** Customer's Unique Identifier
- **Year_Birth:** Customer's Birth Year
- **Education:** Customer's education level (Graduation, Master, PhD, 2n Cycle(Diploma), Basic)
- **Marital_Status:** Customer's marital status
- **Income:** Customer's yearly household income
- **Kidhome:** Number of children in customer's household
- **Teenhome:** Number of teenagers in customer's household
- **Dt_Customer:** Date of customer's enrollment with the company
- **Recency:** Number of days since customer's last purchase
- **MntWines:** Amount spent on wine in the last 2 years
- **MntFruits:** Amount spent on fruits in the last 2 years
- **MntMeatProducts:** Amount spent on meat in the last 2 years
- **MntFishProducts:** Amount spent on fish in the last 2 years
- **MntSweetProducts:** Amount spent on sweets in the last 2 years
- **MntGoldProds:** Amount spent on gold in the last 2 years
- **NumDealsPurchases:** Number of purchases made with a discount
- **NumWebPurchases:** Number of purchases made through the company's web site
- **NumCatalogPurchases:** Number of purchases made using a catalogue
- **NumStorePurchases:** Number of purchases made directly in stores
- **NumWebVisitsMonth:** Number of visits to company's web site in the last month
- **AcceptedCmp1:** 1 if customer accepted the offer in the 1st campaign, 0 otherwise (Target variable)

- **AcceptedCmp2:** 1 if customer accepted the offer in the 2nd campaign, 0 otherwise (Target variable)
- **AcceptedCmp3:** 1 if customer accepted the offer in the 3rd campaign, 0 otherwise (Target variable)
- **AcceptedCmp4:** 1 if customer accepted the offer in the 4th campaign, 0 otherwise (Target variable)
- **AcceptedCmp5:** 1 if customer accepted the offer in the 5th campaign, 0 otherwise (Target variable)
- **Complain:** 1 if customer complained in the last 2 years, 0 otherwise
- **Country:** Customer's location

1.2 Importing Libraries and Loading Datasets

[89]:
```
# importing required modules
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import scipy.stats as stats
import warnings
warnings.filterwarnings('ignore')

# Loading dataset
!gdown 1E-llv0qvRujhRIng_A46-yHTJErHBb2R

df = pd.read_csv('/content/campaign - campaign.csv')
```

```
Downloading…
From: https://drive.google.com/uc?id=1E-llv0qvRujhRIng_A46-yHTJErHBb2R
To: /content/campaign - campaign.csv
100% 220k/220k [00:00<00:00, 5.56MB/s]
```

1.3 Basic Metrics

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

[ ]:
```
      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

   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

   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

   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

[5 rows x 27 columns]
```

[ ]:
```python
# shape
df.shape
```

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

[ ]:
```python
# information of the dataset
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
```

[ ]:
```python
# checking duplicates
df.duplicated().sum()
```

[ ]:
```
0
```

[ ]:
```python
# Checking Nulls
df.isna().sum().sum()
```

[ ]:
```
0
```

1.4 Data Processing and Adding Features

[90]:
```python
df['Income'] = df['Income'].str.replace('$','')
df['Income'] = df['Income'].str.replace(',','')
df['Income'] = df['Income'].str.replace('nan','0')
df['Income'] = pd.to_numeric(df['Income'])
df.head()
```

[90]:
```
      ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0   1826        1970  Graduation       Divorced  84835.0        0         0
1      1        1961  Graduation         Single  57091.0        0         0
2  10476        1958  Graduation        Married  67267.0        0         1
3   1386        1967  Graduation       Together  32474.0        1         1
4   5371        1989  Graduation         Single  21474.0        1         0

  Dt_Customer  Recency  MntWines  …  NumCatalogPurchases  NumStorePurchases  \
0     6/16/14        0       189  …                    4                  6
1     6/15/14        0       464  …                    3                  7
2     5/13/14        0       134  …                    2                  5
3     5/11/14        0        10  …                    0                  2
```

```
4      4/8/14         0          6  …                    1                  2

   NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  \
0                  1             0             0             0             0
1                  5             0             0             0             0
2                  2             0             0             0             0
3                  7             0             0             0             0
4                  7             1             0             0             0

   AcceptedCmp2  Complain  Country
0             0         0       SP
1             1         0       CA
2             0         0       US
3             0         0      AUS
4             0         0       SP

[5 rows x 27 columns]
```

[91]:
```python
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%m/%d/%y')
df['Age'] = df['Dt_Customer'].dt.year - df['Year_Birth']

df['Enrolled_month'] = df['Dt_Customer'].dt.month_name()
df['Enrolled_year'] = df['Dt_Customer'].dt.year
df['Enrolled_day'] = df['Dt_Customer'].dt.day

df.drop('Dt_Customer', axis=1, inplace=True)
df.head()
```

[91]:
```
      ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0   1826        1970  Graduation       Divorced  84835.0        0         0
1      1        1961  Graduation         Single  57091.0        0         0
2  10476        1958  Graduation        Married  67267.0        0         1
3   1386        1967  Graduation       Together  32474.0        1         1
4   5371        1989  Graduation         Single  21474.0        1         0

   Recency  MntWines  MntFruits  …  AcceptedCmp4  AcceptedCmp5  \
0        0       189        104  …             0             0
1        0       464          5  …             0             0
2        0       134         11  …             0             0
3        0        10          0  …             0             0
4        0         6         16  …             0             0

   AcceptedCmp1  AcceptedCmp2  Complain  Country  Age  Enrolled_month  \
0             0             0         0       SP   44            June
1             0             1         0       CA   53            June
2             0             0         0       US   56             May
3             0             0         0      AUS   47             May
```

```
4              0              0          0       SP    25            April

   Enrolled_year  Enrolled_day
0           2014            16
1           2014            15
2           2014            13
3           2014            11
4           2014             8

[5 rows x 30 columns]
```

[91]:

```

```

1.5 Descriptive Statistics

[92]:

```
df.describe().T
```

[92]:

```
                      count          mean           std     min      25%  \
ID                   2239.0   5590.444841   3246.372471     0.0   2827.5
Year_Birth           2239.0   1968.802144     11.985494  1893.0   1959.0
Income               2239.0  51412.792765  22069.582225     0.0  34716.0
Kidhome              2239.0      0.443948      0.538390     0.0      0.0
Teenhome             2239.0      0.506476      0.544555     0.0      0.0
Recency              2239.0     49.121036     28.963662     0.0     24.0
MntWines             2239.0    304.067441    336.614830     0.0     24.0
MntFruits            2239.0     26.307727     39.781468     0.0      1.0
MntMeatProducts      2239.0    167.016525    225.743829     0.0     16.0
MntFishProducts      2239.0     37.538633     54.637617     0.0      3.0
MntSweetProducts     2239.0     27.074587     41.286043     0.0      1.0
MntGoldProds         2239.0     44.036177     52.174700     0.0      9.0
NumDealsPurchases    2239.0      2.324252      1.932345     0.0      1.0
NumWebPurchases      2239.0      4.085306      2.779240     0.0      2.0
NumCatalogPurchases  2239.0      2.662796      2.923542     0.0      0.0
NumStorePurchases    2239.0      5.791425      3.251149     0.0      3.0
NumWebVisitsMonth    2239.0      5.316213      2.427144     0.0      3.0
AcceptedCmp3         2239.0      0.072800      0.259867     0.0      0.0
AcceptedCmp4         2239.0      0.074587      0.262782     0.0      0.0
AcceptedCmp5         2239.0      0.072800      0.259867     0.0      0.0
AcceptedCmp1         2239.0      0.064314      0.245367     0.0      0.0
AcceptedCmp2         2239.0      0.013399      0.115001     0.0      0.0
Complain             2239.0      0.009379      0.096412     0.0      0.0
Age                  2239.0     44.225994     12.024284    16.0     36.0
Enrolled_year        2239.0   2013.028138      0.684707  2012.0   2013.0
Enrolled_day         2239.0     15.644484      8.787914     1.0      8.0

                        50%      75%      max
ID                   5455.0   8423.5  11191.0
```

```
Year_Birth             1970.0   1977.0    1996.0
Income                51039.0  68277.5  162397.0
Kidhome                   0.0      1.0       2.0
Teenhome                  0.0      1.0       2.0
Recency                  49.0     74.0      99.0
MntWines                174.0    504.5    1493.0
MntFruits                 8.0     33.0     199.0
MntMeatProducts          67.0    232.0    1725.0
MntFishProducts          12.0     50.0     259.0
MntSweetProducts          8.0     33.0     263.0
MntGoldProds             24.0     56.0     362.0
NumDealsPurchases         2.0      3.0      15.0
NumWebPurchases           4.0      6.0      27.0
NumCatalogPurchases       2.0      4.0      28.0
NumStorePurchases         5.0      8.0      13.0
NumWebVisitsMonth         6.0      7.0      20.0
AcceptedCmp3              0.0      0.0       1.0
AcceptedCmp4              0.0      0.0       1.0
AcceptedCmp5              0.0      0.0       1.0
AcceptedCmp1              0.0      0.0       1.0
AcceptedCmp2              0.0      0.0       1.0
Complain                  0.0      0.0       1.0
Age                      43.0     54.0     121.0
Enrolled_year          2013.0   2013.0    2014.0
Enrolled_day             16.0     23.0      31.0
```

- This is the data of enrolled customers for an ecommerce comany from July 10, 2012 to June 29, 2014 i.e., over a period of 2 years.
- Age of the enrolled customers ranges from 16 to 121 with a mean of 44.
- Yearly income of enrolled customers ranges from 0 to 1.6M USD with a mean of 51K USD.
- Average Recency of the customers is 49 days.

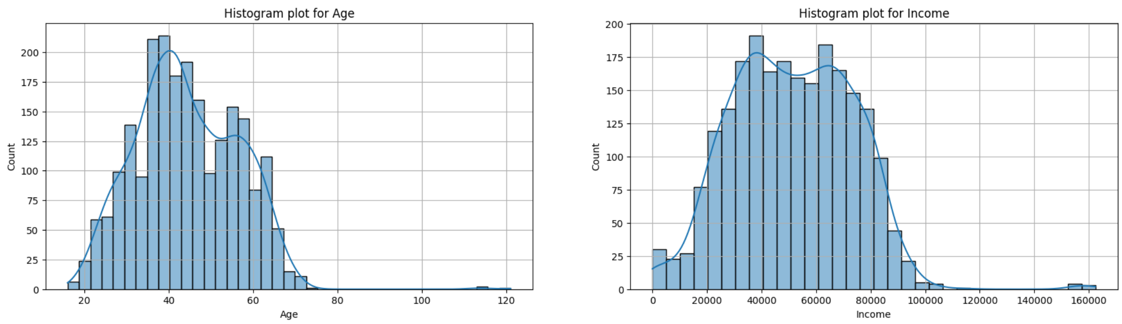
[93]:
```
df.describe(include='object')
```

[93]:
```
         Education Marital_Status Country Enrolled_month
count         2239           2239    2239           2239
unique           5              8       8             12
top     Graduation        Married      SP         August
freq          1126            864    1095            222
```

- Most of the Enrolled customers have done graduation.
- Most of the Enrolled customers are Married.
- Most of the Enrolled customers are from Country Spain.
- Most of the Enrollments happened in August month.

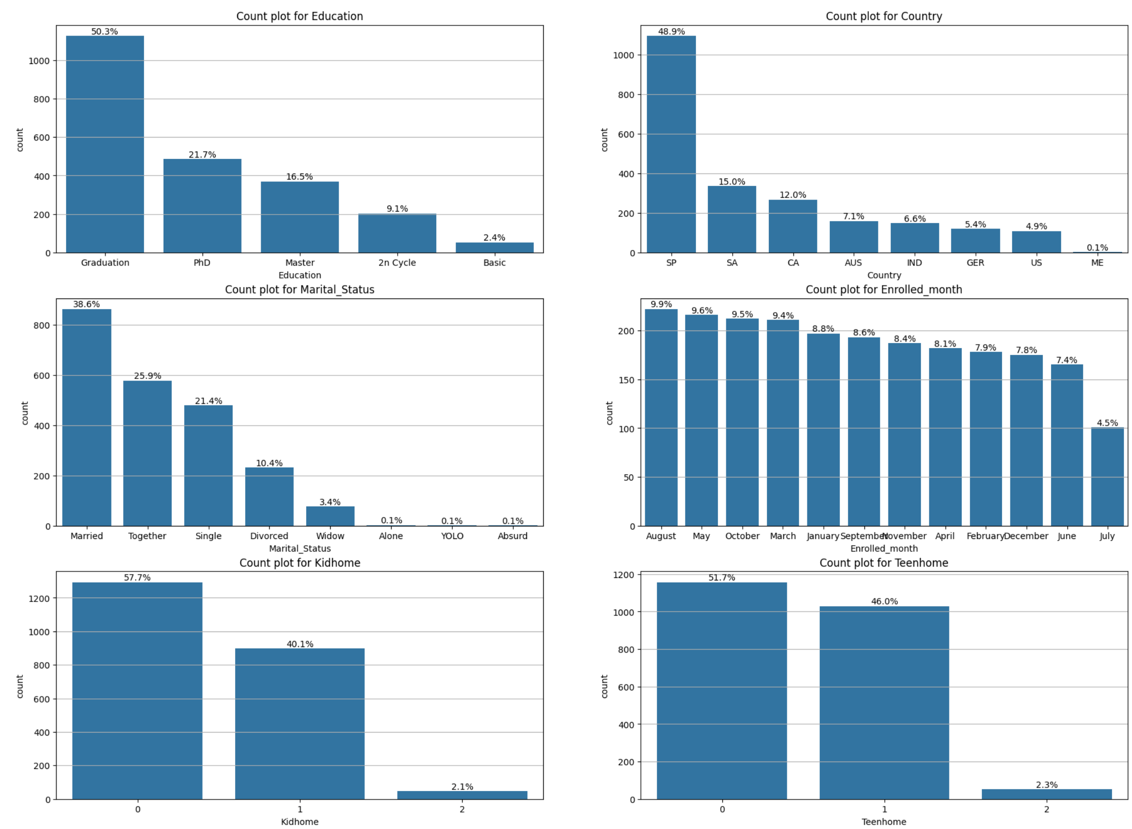
1.6 Univarient Analysis

[94]:
```
plt.figure(figsize=(20,5))

cols = ['Age', 'Income']

for i in cols:
  plt.subplot(1,2,cols.index(i)+1)
  plt.title('Histogram plot for '+ i)
  plt.grid(True)
  sns.histplot(data=df[i], kde=True)

plt.show()
```



- Most of the customers enrolled are in the age range of 20 to 70, while most of them are around 40.
- Most of the enrolled customer's yearly income is within 1M USD.

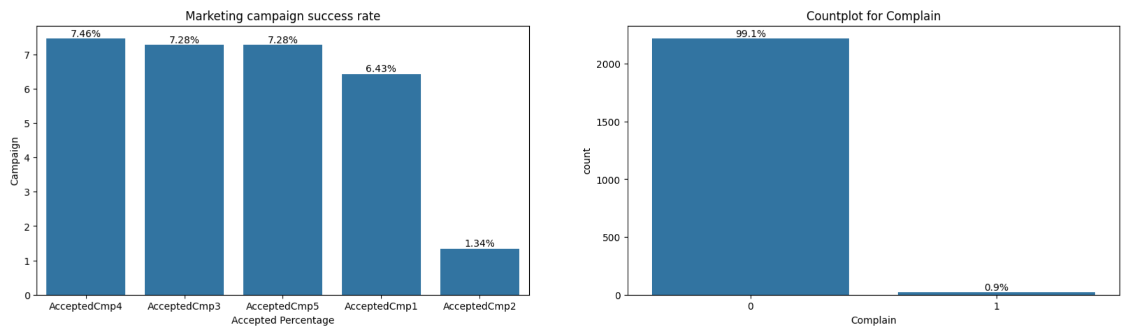
[95]:
```
plt.figure(figsize=(22,16))

cols = ['Education','Country', 'Marital_Status', 'Enrolled_month','Kidhome',␣
↪'Teenhome']

for i in cols:
  plt.subplot(3,2,cols.index(i)+1)
  plt.title('Count plot for '+ i)
  plt.grid(True)
  g = sns.countplot(df, x=i, order=df[i].value_counts().index)
  for j in g.patches:
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=str(round(((j.
↪get_height()/2239)*100),1)) + '%', ha='center', va='bottom')

plt.show()
```



- 50% of the customers has Graduation as higher qualification, followed by PhD with 22% and Masters with 16%.
- 49% of the customers are from country Spain, followed by South Africa with 15%.
- 39% of the customers are Married whereas 26% are living together and 21% are Singles.
- 10% of the enrollments happened in August, May, October and March with an average of 9.5% and rest below 9%.
- Around 55% of the customers don't have child and 43% has 1 child.

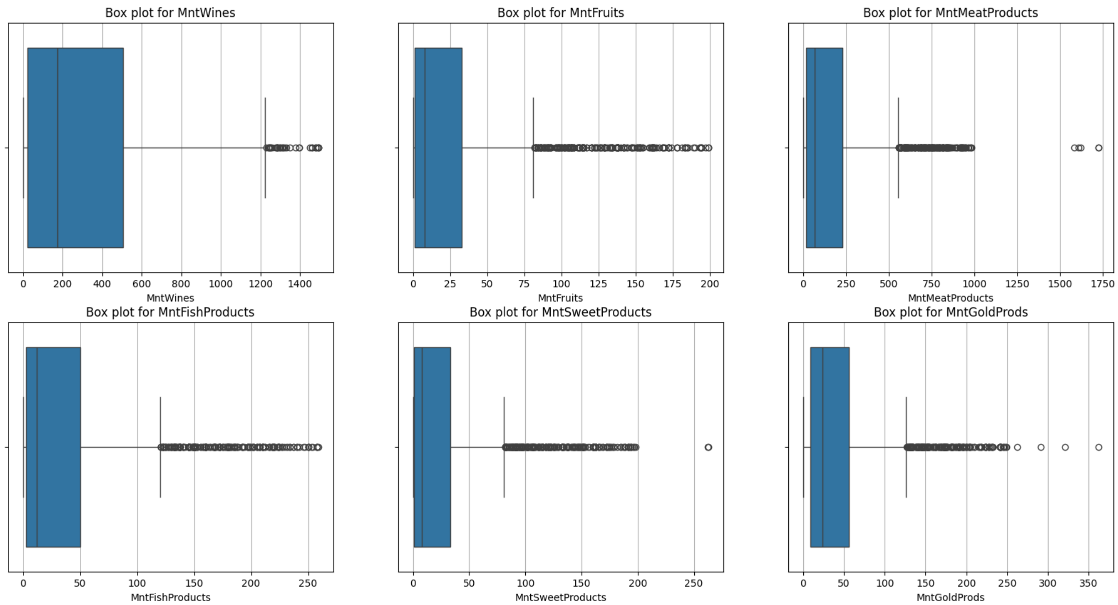
[96]:
```
camp_success = pd.DataFrame(df[['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5']].mean().round(4)*100,  columns=['Percent']).reset_index()

plt.figure(figsize=(20,5))

plt.subplot(1,2,1)
plt.title('Marketing campaign success rate')
g = sns.barplot(y='Percent', x='index', data=camp_success.sort_values('Percent',ascending=False))
for j in g.patches:
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=str(j.get_height()) + '%', ha='center', va='bottom')
```

```
plt.xlabel('Accepted Percentage')
plt.ylabel('Campaign')

plt.subplot(1,2,2)
plt.title('Countplot for Complain')
g = sns.countplot(df, x='Complain', order=df['Complain'].value_counts().index)
for j in g.patches:
    plt.text(x=j.get_x()+j.get_width()/2, y=j.get_height(), s=str(round(((j.
 ↪get_height()/2239)*100),1)) + '%', ha='center', va='bottom')

plt.show()
```



- 4th Campaign is the most successful campaign with 7.4% enrollments, followed by 3 and 5 with 7.2% and 1 with 6.4%
- 2nd Campaign is the least successful with 1.3% enrollments.
- Only 1% of the Customers made complaints.

[97]:
```
cols = ['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',␣
 ↪'MntSweetProducts', 'MntGoldProds']

plt.figure(figsize=(20,10))

for i in cols:
  plt.subplot(2,3,cols.index(i)+1)
  plt.title('Box plot for '+ i)
  plt.grid(True)
  sns.boxplot(df, x=i)

plt.show()

df[cols].sum()
```

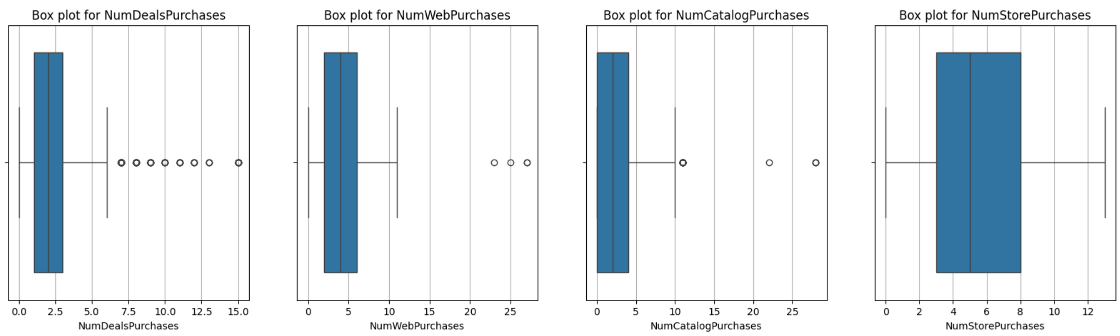


[97]:
```
MntWines            680807
MntFruits            58903
MntMeatProducts     373950
MntFishProducts      84049
MntSweetProducts     60620
MntGoldProds         98597
dtype: int64
```

- Total Wine sales in these 2 years is 6.8M USD where each customer usually spent upto 500 USD.
- Total Fruit sales in these 2 years is 58K USD where each customer usually spent upto 30 USD.
- Total Meat sales in these 2 years is 3.7M USD where each customer usually spent upto 250 USD.
- Total Fish sales in these 2 years is 84K USD where each customer usually spent upto 50 USD.
- Total Sweet sales in these 2 years is 60K USD where each customer usually spent upto 40 USD.
- Total Gold sales in these 2 years is 98K USD where each customer usually spent upto 60 USD.

[98]:
```
cols = ['NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',␣
 ↪'NumStorePurchases']

plt.figure(figsize=(20,5))

for i in cols:
  plt.subplot(1,4,cols.index(i)+1)
```

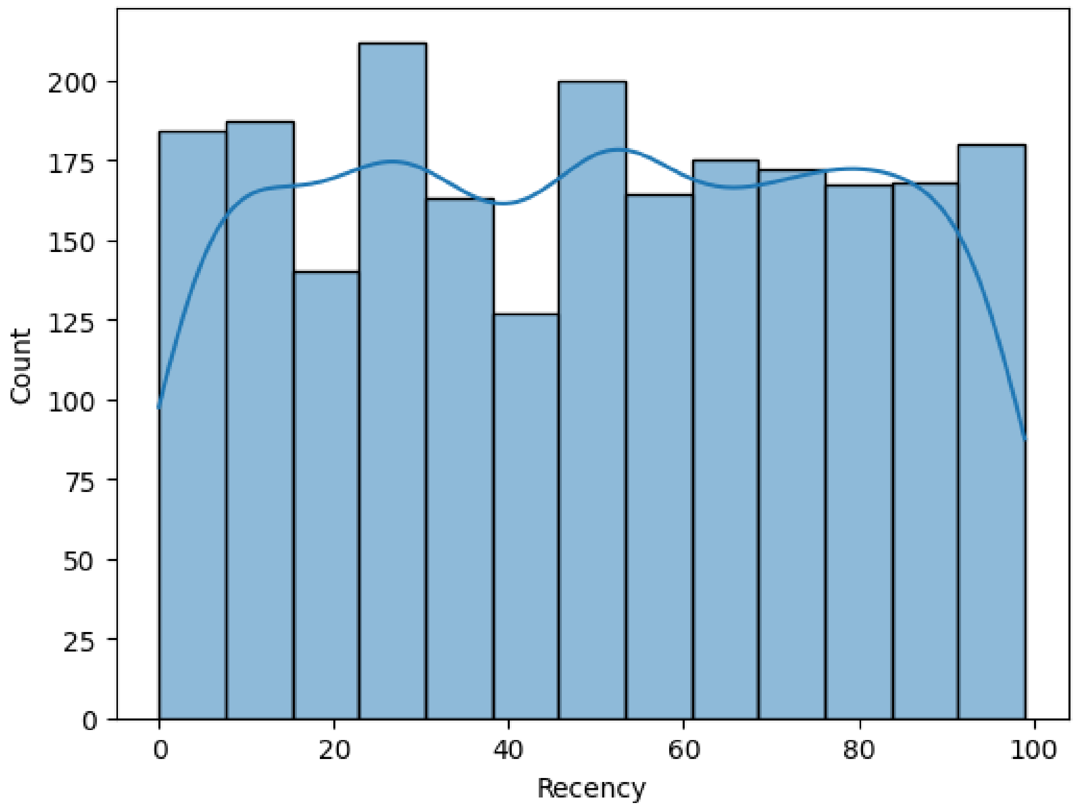
```
  plt.title('Box plot for '+ i)
  plt.grid(True)
  sns.boxplot(df, x=i)

plt.show()

df[cols].sum()
```



[98]:
```
NumDealsPurchases        5204
NumWebPurchases          9147
NumCatalogPurchases      5962
NumStorePurchases       12967
dtype: int64
```

- 5204 purchases are made with a discount in these 2 years where each customer usually make upto 3 purchases.
- 9147 purchases are made through the company's web site in these 2 years where each customer make upto 6 purchases.
- 5962 purchases are made made using a catalogue in these 2 years where each customer make upto 4 purchases.
- 12967 purchases are made directly in stores in these 2 years where each customer make upto 8 purchases.

[99]:
```
sns.histplot(df, x='Recency', kde=True)
plt.show()
```



- Recency of the customers is ranges from 0 to 100

1.7 Hypothesis Testing

1.7.1 Is income of customers dependent on their education?

[100]:
```
df.groupby('Education')['Income'].mean()
```

[100]:
```
Education
2n Cycle      46929.251232
Basic         20306.259259
Graduation    51660.098579
Master        52202.432432
PhD           55567.687243
Name: Income, dtype: float64
```

As this is the categorical vs numerical having more than 2 categorical variables, we have to use ANOVA (if satisfies assumptions of anova) or Kruskal Wallis test

Checking assumptions of ANOVA **Assumptions of ANOVA:**

1. Data should be normally distributed (QQ plot and shapiro test)

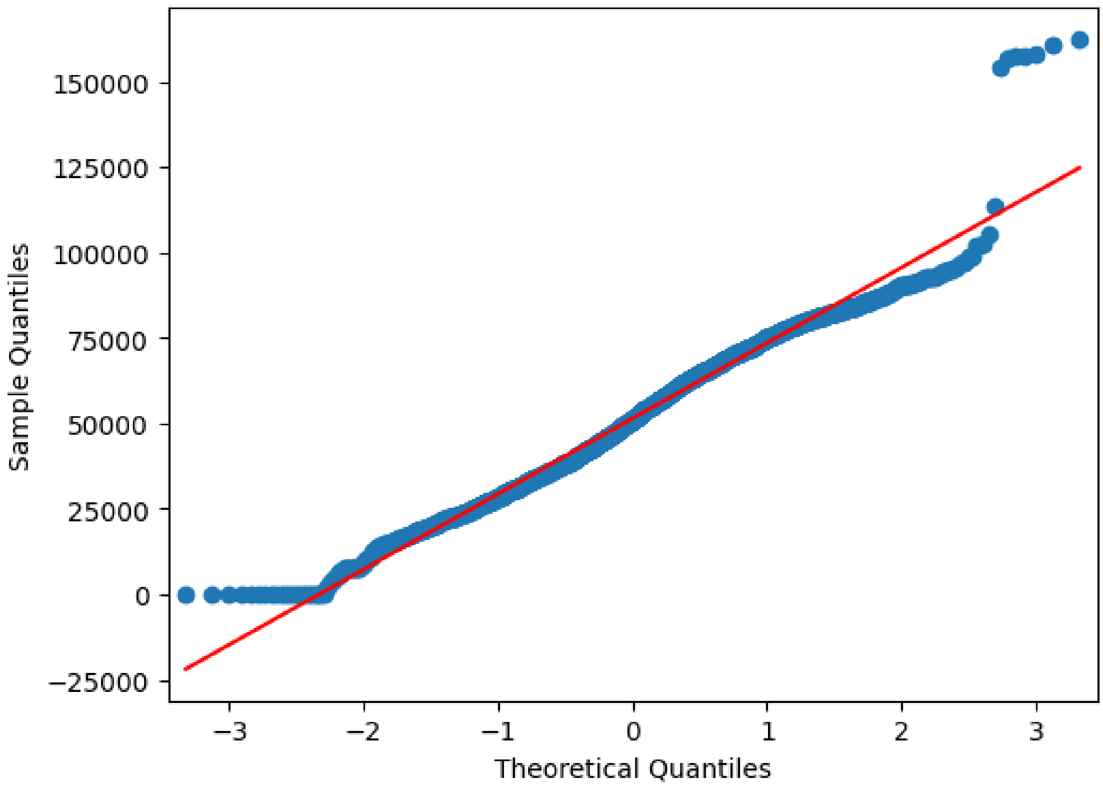
2. Data should be independent across each record
3. Equal variance in different groups (levene test)

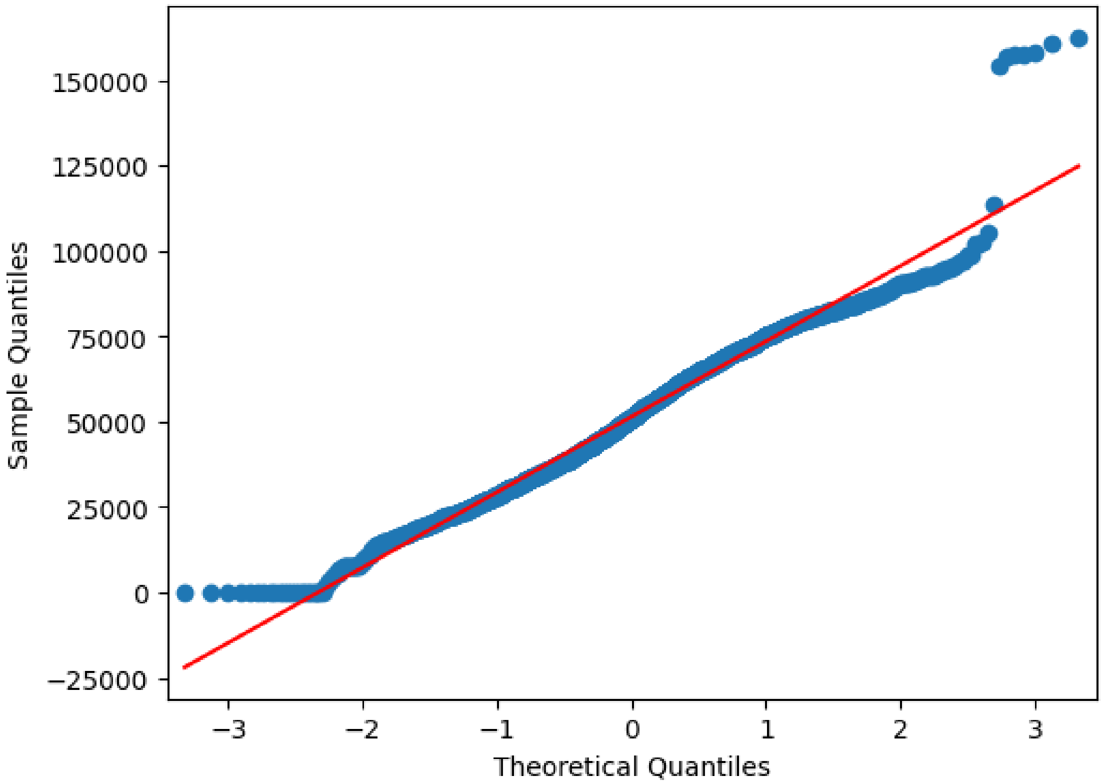
As data is independent, we can check for normality and equal variance

QQ Plot for checking Normality

[101]:
```python
import statsmodels.api as sm
sm.qqplot(df['Income'], line ='s')
```

[101]:





- As the data contains outliers we can say that the data is not normally distributed. Lets confirm this with Shapiro test.

Shapiro test for checking Normality

[102]:
```
test_stat, p_value = stats.shapiro(df['Income'].sample(200))
print('p-value', p_value)
if p_value < 0.05:
    print('The sample does not follow normal distribution')
else:
    print('The sample follows normal distribution')
```

```
p-value 0.005644794082171053
The sample does not follow normal distribution
```

We can say that data is not normally distributed. Let's check variance.

Levene's Test for checking Equal Variance

[103]:
```
income_by_education = [df[df['Education'] == edu]['Income'].dropna() for edu in␣
↪df['Education'].unique()]
```

[104]:
```python
test_stat, p_value = stats.levene(*income_by_education)
print('p-value', p_value)
if p_value < 0.5:
    print('The samples do not have Homogenous Variance')
else:
    print('The samples have Homogenous Variance ')
```

```
p-value 2.846067960002927e-14
The samples do not have Homogenous Variance
```

We can see that this Income date does not follows assumptions of ANOVA. So we have to use Kruskal Walli's Test

Kruskal Walli's Test **Null Hypothesis:** The mean income of customers is the same across all education levels (i.e., income is independent of education).

Alternate Hypothesis: The mean income of customers is different across at least one education level (i.e., income is dependent on education).

[105]:
```python
H0 = 'The mean income of customers is the same across all education levels (i.e.
 ↪, income is independent of education)'
Ha = 'The mean income of customers is different across at least one education␣
 ↪level (i.e., income is dependent on education)'
alpha = 0.05

# kruskal wallis test
h_stat, p_val = stats.kruskal(*income_by_education)

print(f'h_stat: {h_stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

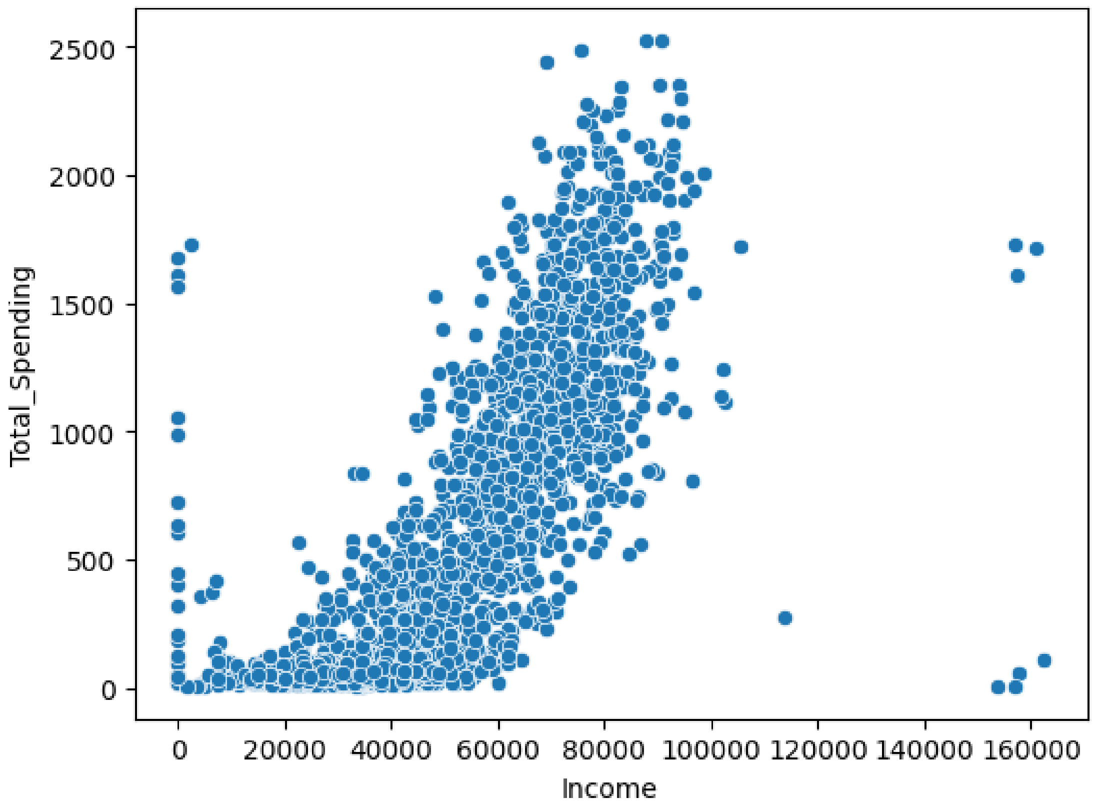
```
h_stat: 136.61469286229072
p-value: 1.4971856049770543e-28
alpha: 0.05

Result: Reject Null Hypothesis
The mean income of customers is different across at least one education level
(i.e., income is dependent on education)
```

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

[106]:
```
df['Total_Spending'] = df[['MntWines', 'MntFruits', 'MntMeatProducts',␣
↪'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']].sum(axis=1)
df.head()
```

[106]:
```
      ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0   1826        1970  Graduation       Divorced  84835.0        0         0
1      1        1961  Graduation         Single  57091.0        0         0
2  10476        1958  Graduation        Married  67267.0        0         1
3   1386        1967  Graduation       Together  32474.0        1         1
4   5371        1989  Graduation         Single  21474.0        1         0

   Recency  MntWines  MntFruits  …  AcceptedCmp5  AcceptedCmp1  \
0        0       189        104  …             0             0
1        0       464          5  …             0             0
2        0       134         11  …             0             0
3        0        10          0  …             0             0
4        0         6         16  …             0             0

   AcceptedCmp2  Complain  Country  Age  Enrolled_month  Enrolled_year  \
0             0         0       SP   44            June           2014
1             1         0       CA   53            June           2014
2             0         0       US   56             May           2014
3             0         0      AUS   47             May           2014
4             0         0       SP   25           April           2014

   Enrolled_day  Total_Spending
0            16            1190
1            15             577
2            13             251
3            11              11
4             8              91

[5 rows x 31 columns]
```

[107]:
```
sns.scatterplot(data = df, x = 'Income', y = 'Total_Spending')
plt.show()
```



As this is monotonic, we can use spearman correlation

Null Hypothesis: There is no relationship between income and total spending (spending in all categories combined).

Alternate Hypothesis: There is a positive relationship between income and total spending (i.e., higher income leads to higher spending).

[108]:
```
H0 = 'There is no relationship between income and total spending (spending in␣
↪all categories combined)'
Ha = 'There is a positive relationship between income and total spending (i.e.,␣
↪higher income leads to higher spending)'
alpha = 0.05

# spearman rank correlation test
spearman_corr, p_val = stats.spearmanr(df['Income'], df['Total_Spending'])

print(f'spearman_corr: {spearman_corr}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
```

```
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
spearman_corr: 0.8379782026407006
p-value: 0.0
alpha: 0.05

Result: Reject Null Hypothesis
There is a positive relationship between income and total spending (i.e., higher
income leads to higher spending)
```

1.7.3 Do couples spend more or less money on wine than people living alone?

[109]:
```
couples = ['Married', 'Together']
alone = ['Divorced', 'Single', 'Absurd', 'Widow', 'YOLO']

df['Living_Status'] = df['Marital_Status'].apply(lambda x: 'In couple' if x in␣
  ↪couples else 'Alone')

df.groupby('Living_Status')['MntWines'].mean()
```

[109]:
```
Living_Status
Alone        306.665829
In couple    302.634096
Name: MntWines, dtype: float64
```

As this is the categorical vs numerical having 2 categorical variables, we can use a two-sample t-test to compare the mean spending on wine (MntWines) between customers in a relationship and those living alone.

Null Hypothesis: There is no difference in wine spending between couples and people living alone.

Alternate Hypothesis: There is a difference in wine spending between couples and people living alone.

[110]:
```
H0 = 'There is no difference in wine spending between couples and people living␣
  ↪alone'
Ha = 'There is a difference in wine spending between couples and people living␣
  ↪alone'
alpha = 0.05

# 2 sample ttest
in_couple = df[df['Living_Status'] == 'In couple']['MntWines']
alone = df[df['Living_Status'] == 'Alone']['MntWines']
```

```
t_stat, p_value = stats.ttest_ind(in_couple, alone)

print(f't_stat: {t_stat}')
print(f'p-value: {p_val}')
print(f'alpha: {alpha}\n')
if p_val < alpha:
  print('Result: Reject Null Hypothesis')
  print(Ha)
else:
  print('Result: Failed to reject Null Hypothesis')
  print(H0)
```

```
t_stat: -0.2712259990062464
p-value: 0.0
alpha: 0.05

Result: Reject Null Hypothesis
There is a difference in wine spending between couples and people living alone
```

1.7.4 Are people with lower income more attracted towards campaigns (i.e., accept more campaigns)?

[111]:
```
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)

contingency_table = pd.crosstab(df['Income_Bracket'],
 ↪df['Accepted_Any_Campaign'])

contingency_table
```

[111]:

Accepted_Any_Campaign	0	1
Income_Bracket		
Above Median	775	345
Below Median	1001	118

As this is a categorical vs categorical, we can use chi-square test.

Null Hypothesis: There is no difference in campaign acceptance between customers with lower and higher income.

Alternate Hypothesis: People with lower income accept more campaigns than people with higher income.

```
[112]: H0 = 'There is no difference in campaign acceptance between customers with␣
        ↪lower and higher income'
       Ha = 'People with lower income accept more campaigns than people with higher␣
        ↪income'
       alpha = 0.05

       # chi square test
       chi2, p_value, dof, expected = stats.chi2_contingency(contingency_table)

       print(f'chi2: {spearman_corr}')
       print(f'p-value: {p_value}')
       print(f'alpha: {alpha}\n')
       if p_val < alpha:
         print('Result: Reject Null Hypothesis')
         print(Ha)
       else:
         print('Result Failed to reject Null Hypothesis')
         print(H0)
```

```
chi2: 0.8379782026407006
p-value: 4.8224046007539564e-32
alpha: 0.05

Result: Reject Null Hypothesis
People with lower income accept more campaigns than people with higher income
```

1.8 Feature Engineering

```
[113]: df.head()
```

```
[113]:       ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
        0   1826        1970  Graduation       Divorced  84835.0        0         0
        1      1        1961  Graduation         Single  57091.0        0         0
        2  10476        1958  Graduation        Married  67267.0        0         1
        3   1386        1967  Graduation       Together  32474.0        1         1
        4   5371        1989  Graduation         Single  21474.0        1         0

           Recency  MntWines  MntFruits  …  Complain  Country  Age  Enrolled_month  \
        0        0       189        104  …         0       SP   44            June
        1        0       464          5  …         0       CA   53            June
        2        0       134         11  …         0       US   56             May
        3        0        10          0  …         0      AUS   47             May
        4        0         6         16  …         0       SP   25           April

           Enrolled_year  Enrolled_day  Total_Spending  Living_Status  Income_Bracket  \
        0           2014            16            1190          Alone    Above Median
        1           2014            15             577          Alone    Above Median
```

```
2          2014          13            251      In couple     Above Median
3          2014          11             11      In couple     Below Median
4          2014           8             91          Alone     Below Median

   Accepted_Any_Campaign
0                      0
1                      1
2                      0
3                      0
4                      1

[5 rows x 34 columns]
```

[114]:
```
cols = ['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',␣
 ↪'MntSweetProducts', 'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',␣
 ↪'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',␣
 ↪'Year_Birth','Age','Enrolled_year','Enrolled_day','Total_Spending', 'Income']
from sklearn.preprocessing import MinMaxScaler
scaler = MinMaxScaler()
df[cols] = scaler.fit_transform(df[cols])
```

[115]:
```
df['Living_Status'] = df['Living_Status'].apply(lambda x: 1 if x == 'In couple'␣
 ↪else 0)
df['Income_Bracket'] = df['Income_Bracket'].apply(lambda x: 1 if x == 'Above␣
 ↪Median' else 0)
```

[116]:
```
months = ['January', 'February', 'March', 'April', 'May', 'June', 'July',␣
 ↪'August', 'September', 'October', 'November', 'December']
df['Enrolled_month'] = df['Enrolled_month'].apply(lambda x: months.index(x) + 1)
```

[117]:
```
cols = ['Education', 'Marital_Status','Country']

from sklearn.preprocessing import LabelEncoder
le = LabelEncoder()
for i in cols:
  df[i] = le.fit_transform(df[i])
```

[121]:
```
df.head().T
```

[121]:
```
                          0         1             2            3  \
ID              1826.000000  1.000000  10476.000000  1386.000000
Year_Birth         0.747573  0.660194      0.631068     0.718447
Education          2.000000  2.000000      2.000000     2.000000
Marital_Status     2.000000  4.000000      3.000000     5.000000
Income             0.522393  0.351552      0.414213     0.199967
Kidhome            0.000000  0.000000      0.000000     1.000000
Teenhome           0.000000  0.000000      1.000000     1.000000
```

Recency	0.000000	0.000000	0.000000	0.000000
MntWines	0.126591	0.310784	0.089752	0.006698
MntFruits	0.522613	0.025126	0.055276	0.000000
MntMeatProducts	0.219710	0.037101	0.034203	0.000580
MntFishProducts	0.428571	0.027027	0.057915	0.000000
MntSweetProducts	0.718631	0.000000	0.007605	0.000000
MntGoldProds	0.602210	0.102210	0.082873	0.000000
NumDealsPurchases	0.066667	0.066667	0.066667	0.066667
NumWebPurchases	0.148148	0.259259	0.111111	0.037037
NumCatalogPurchases	0.142857	0.107143	0.071429	0.000000
NumStorePurchases	0.461538	0.538462	0.384615	0.153846
NumWebVisitsMonth	0.050000	0.250000	0.100000	0.350000
AcceptedCmp3	0.000000	0.000000	0.000000	0.000000
AcceptedCmp4	0.000000	0.000000	0.000000	0.000000
AcceptedCmp5	0.000000	0.000000	0.000000	0.000000
AcceptedCmp1	0.000000	0.000000	0.000000	0.000000
AcceptedCmp2	0.000000	1.000000	0.000000	0.000000
Complain	0.000000	0.000000	0.000000	0.000000
Country	6.000000	1.000000	7.000000	0.000000
Age	0.266667	0.352381	0.380952	0.295238
Enrolled_month	6.000000	6.000000	5.000000	5.000000
Enrolled_year	1.000000	1.000000	1.000000	1.000000
Enrolled_day	0.500000	0.466667	0.400000	0.333333
Total_Spending	0.470238	0.226984	0.097619	0.002381
Living_Status	0.000000	0.000000	1.000000	1.000000
Income_Bracket	1.000000	1.000000	1.000000	0.000000
Accepted_Any_Campaign	0.000000	1.000000	0.000000	0.000000

	4
ID	5371.000000
Year_Birth	0.932039
Education	2.000000
Marital_Status	4.000000
Income	0.132232
Kidhome	1.000000
Teenhome	0.000000
Recency	0.000000
MntWines	0.004019
MntFruits	0.080402
MntMeatProducts	0.013913
MntFishProducts	0.042471
MntSweetProducts	0.000000
MntGoldProds	0.093923
NumDealsPurchases	0.133333
NumWebPurchases	0.111111
NumCatalogPurchases	0.035714
NumStorePurchases	0.153846

```
NumWebVisitsMonth         0.350000
AcceptedCmp3              1.000000
AcceptedCmp4              0.000000
AcceptedCmp5              0.000000
AcceptedCmp1              0.000000
AcceptedCmp2              0.000000
Complain                  0.000000
Country                   6.000000
Age                       0.085714
Enrolled_month            4.000000
Enrolled_year             1.000000
Enrolled_day              0.233333
Total_Spending            0.034127
Living_Status             0.000000
Income_Bracket            0.000000
Accepted_Any_Campaign     1.000000
```

2 Insights

1. **Customer Demographics**: The dataset includes customers aged 16 to 121 (mean: 44 years), with most customers aged between 20 and 70, and a large proportion around 40 years old.

2. **Income Distribution**: Yearly incomes range from 0 to $1.6M, with a mean of $51K. Most customers' incomes fall below $1M.

3. **Education**: Around 50% of customers have a graduate degree, followed by 22% with a PhD and 16% with a Master's.

4. **Marital Status**: Most customers are married (39%), followed by those living together (26%), and 21% are single. Living status is categorized as "In couple" or "Alone."

5. **Country Distribution**: 49% of the customers are from Spain, followed by 15% from South Africa.

6. **Campaign Success**: The 4th campaign was the most successful, with a 7.4% acceptance rate, while the 2nd campaign had the least success at 1.3%.

7. **Spending Patterns**: Total wine sales were $6.8M, meat sales were $3.7M, and each customer spent up to $500 on wine, $250 on meat, and smaller amounts on fruits, fish, sweets, and gold.

8. **Purchasing Channels**: Over 12.9K store purchases, 9.1K web purchases, and 5.9K catalog purchases were made in two years, with each customer making up to 8 store purchases.

9. **Recency**: The average recency (days since last purchase) is 49 days, with a range of 0 to 100 days.

10. **Income and Campaigns**: Customers with lower incomes accepted more campaigns, and a positive correlation exists between income and total spending. Income also varies significantly across different education levels.

3 Recommendations

1. **Target Younger and Middle-Aged Customers**: Since most customers are between 20 and 70 years old, focus marketing campaigns and promotions on this age group, particularly those around 40, to boost engagement.

2. **Segment by Income for Tailored Campaigns**: Create customized campaigns for higher-income customers to encourage increased spending, while offering more affordable, value-driven promotions for lower-income groups, who tend to accept more campaigns.

3. **Focus on Graduation-Level Education**: Since a significant portion of customers have a graduate degree, design campaigns that appeal to this demographic by promoting premium products or educational content that aligns with their interests.

4. **Leverage Successful Campaign Strategies**: Analyze what made the 4th campaign more successful and replicate those elements in future campaigns. Consider offering similar deals or refining messaging to increase effectiveness.

5. **Expand Presence in Spain and South Africa**: With nearly 50% of customers from Spain and 15% from South Africa, prioritize expanding the product offering, services, and marketing in these countries to tap into existing market strength.

6. **Optimize Wine and Meat Sales**: Since wine and meat are top-selling categories, create special bundles, loyalty programs, or discounts on these products to increase sales further. Offering wine and meat subscriptions or promotions could boost repeat purchases.

7. **Enhance Web and Catalog Shopping Experiences**: With significant purchases made via the web and catalogs, invest in improving the online user experience, streamlining the purchasing process, and offering personalized product recommendations based on browsing behavior.

8. **Reduce Customer Recency**: To address the average 49-day gap since the last purchase, implement automated email reminders, exclusive offers, or loyalty points for customers who haven't made a purchase recently to encourage more frequent buying.

9. **Utilize Predictive Analytics for Campaigns**: Use customer income, spending habits, and demographic data to predict which customers are most likely to accept campaigns, and tailor future marketing efforts to these segments for better targeting.

10. **Increase Focus on Store Purchases**: Since a large volume of purchases occurs in physical stores, explore ways to enhance the in-store experience, such as offering exclusive in-store promotions, events, or personalized consultations that can drive additional sales.