campaign

August 30, 2024

[66]:
```python
#Import Important Libraries

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
warnings.filterwarnings('ignore')
```

[67]:
```python
#Downloading Dataset

!gdown 1uuBCtiihGxx85czcXc-R804_VxENPPtR
```

```
Downloading…
From: https://drive.google.com/uc?id=1uuBCtiihGxx85czcXc-R804_VxENPPtR
To: /content/campaign.csv
100% 220k/220k [00:00<00:00, 72.9MB/s]
```

[68]:
```python
#Assigning Dataset

df = pd.read_csv("campaign.csv")
```

#Analysing Dataset

[69]:
```python
df.head()
```

[69]:
```
      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]
```

[70]:

```
#Datatype Information

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
```

[71]:
```python
#Finding Null Percentage

df.isna().sum() / len(df) * 100
```

[71]:
```
ID                     0.0
Year_Birth             0.0
Education              0.0
Marital_Status         0.0
Income                 0.0
Kidhome                0.0
Teenhome               0.0
Dt_Customer            0.0
Recency                0.0
MntWines               0.0
MntFruits              0.0
MntMeatProducts        0.0
MntFishProducts        0.0
MntSweetProducts       0.0
MntGoldProds           0.0
NumDealsPurchases      0.0
NumWebPurchases        0.0
NumCatalogPurchases    0.0
NumStorePurchases      0.0
NumWebVisitsMonth      0.0
AcceptedCmp3           0.0
AcceptedCmp4           0.0
AcceptedCmp5           0.0
AcceptedCmp1           0.0
AcceptedCmp2           0.0
Complain               0.0
Country                0.0
dtype: float64
```

Insights : There is no null values in the dataset.

[72]:
```python
# Removing '$' from Income and converting it to float datatype
```

```
df["Income"] = df["Income"].str.replace('$', '').str.replace(',','').
↪astype(float)

#Filling null values with mean of Income

df["Income"] = df["Income"].fillna(df["Income"].mean())
```

Insights : There were 24 null values in income column, which we replaced with mean because the data was not sckewed.

[73]:
```
df["date"] = df["Dt_Customer"].str.split("/", expand = True)[1] # Extracting␣
↪date of purchase
df["month"] = df["Dt_Customer"].str.split("/", expand = True)[0] # Extracting␣
↪month of purchase
df["year"] = df["Dt_Customer"].str.split("/", expand = True)[2] # Extracting␣
↪year of purchase
```

#Statistical Analysis

[74]:
```
#Statistical Analysis of Numerical Column

df.describe().T
```

[74]:
```
                      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  51969.861400  21410.586353  1730.0  35533.5
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
```

```
                         50%      75%       max
ID                    5455.0   8423.5   11191.0
Year_Birth            1970.0   1977.0    1996.0
Income               51717.0  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
```

Insights :

1. Demographics:

- Average Birth Year: Most customers were born around 1968, with a majority falling between 1959 and 1977.
- Average Income: The average income is approximately $51,970, with a wide range from $1,730 to $162,397.
- Household Composition: On average, households have 0.44 children and 0.51 teenagers, indicating that many customers likely have small families or no children at home.

2. Purchase Behavior:

- Wine Purchases: Customers spend the most on wine, with an average of $304, significantly higher than other product categories.
- Meat Products: After wine, meat products are the second most purchased category, with an average spending of $167.
- Deals and Promotions: On average, customers participate in 2.32 deals purchases, indicating moderate engagement with promotions.

3. Shopping Channels:

- Store Purchases: Customers make the most purchases in physical stores, with an average of 5.79 purchases.
- Web Purchases: Web purchases average 4.08, showing that online shopping is also popular among these customers.
- Catalog Purchases: Catalog purchases are less frequent, with an average of 2.66 purchases.

4. Campaign Acceptance: Campaigns generally have low acceptance rates, with less than 7.5% of customers accepting any campaign. The AcceptedCmp2 campaign had the lowest acceptance rate at 1.3%. Complaints:
5. Complaints are rare, with only 0.9% of customers having lodged a complaint, indicating overall customer satisfaction.

[75]:
```
#Statistical Analysis of Categorical Column

df.describe(include = 'object')
```

[75]:

	Education	Marital_Status	Dt_Customer	Country	date	month	year
count	2239	2239	2239	2239	2239	2239	2239
unique	5	8	663	8	31	12	3
top	Graduation	Married	8/31/12	SP	12	8	13
freq	1126	864	12	1095	103	222	1188

Insights :

1. Education: The majority of customers (50.3%) have a Graduation level of education.
2. Marital Status: Married customers make up the largest group, with 864 individuals, indicating that married individuals are a significant portion of the customer base.
3. Customer Acquisition: The most common customer acquisition date is August 31, 2012, with 12 customers joining on that date. Geographic Distribution:
4. The most frequent country listed is SP (likely Spain), with 1,095 customers, suggesting a strong customer base in that region. Date Analysis:
5. December is the most common month for the data records, with 103 occurrences.
6. The most frequent day is the 8th, with 222 records.
7. The year 2013 dominates the dataset, with 1,188 records, indicating that a significant amount of customer data is from this year.

[76]:
```
#create total spending column

df["Total_spending"] = df["MntWines"] + df["MntFruits"] + df["MntMeatProducts"]␣
↪+ df["MntFishProducts"] + df["MntSweetProducts"] + df["MntGoldProds"]
```

#Basic EDA

[77]:
```
df.columns
```

[77]:
```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Complain', 'Country', 'date', 'month', 'year',
       'Total_spending'],
      dtype='object')
```

[78]:
```python
df["date"].value_counts()
```

[78]:
```
date
12    103
17     91
22     89
23     89
11     83
7      83
29     82
10     79
18     78
2      77
5      75
3      75
1      74
28     74
25     73
20     73
4      71
8      71
16     71
19     69
13     69
6      65
21     62
26     61
15     60
24     60
30     59
9      59
14     58
27     56
31     50
Name: count, dtype: int64
```

Insights : Most customers enrolled in the 12th.

[79]:
```python
df["month"].value_counts()
```

[79]:
```
month
8     222
5     216
10    212
3     211
1     197
9     193
11    187
4     182
2     178
12    175
6     165
7     101
Name: count, dtype: int64
```

Insights : Most customers enrolled in the month of August.

[80]:
```python
df["year"].value_counts()
```

[80]:
```
year
13    1188
14     557
12     494
Name: count, dtype: int64
```

Insights : This dataset containes data of 3 years, i.e. 12, 13, 14 and most enrollment is done in 13 only.

[81]:
```python
df["Income"].value_counts()
```

[81]:
```
Income
51969.8614    24
7500.0000     12
35860.0000     4
80134.0000     3
63841.0000     3
              ..
46086.0000     1
42243.0000     1
35788.0000     1
36026.0000     1
94871.0000     1
Name: count, Length: 1974, dtype: int64
```

Insights : There are 24 nan values present in the Dataset. Lets replace them with

[82]:
```
df.Education.value_counts()
```

[82]:
```
Education
Graduation    1126
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: count, dtype: int64
```

Insights : Most of the people are done Graduation, following PhD, then masters, 2ns Cycle and then Basic.

[83]:
```
df.Marital_Status.value_counts()
```

[83]:
```
Marital_Status
Married     864
Together    579
Single      480
Divorced    232
Widow        77
Alone         3
YOLO          2
Absurd        2
Name: count, dtype: int64
```

Insights : count of Married people is most with 864 and YOLO and Absurd with 2.

[84]:
```
df.Kidhome.value_counts()
```

[84]:
```
Kidhome
0    1293
1     898
2      48
Name: count, dtype: int64
```

Insights : There are 1293 customers who doesn't have any kid. 898 have 1 kid and 48 have 2 kids. We can say very few people have 2 kids.

[85]:
```
df.Teenhome.value_counts()
```

[85]:
```
Teenhome
0    1157
1    1030
2      52
Name: count, dtype: int64
```

Insights : There are 1157 customers who doesn't have teen at their home, 1030 have 1 teen and 52 have 2 teens. So we can say that very few people ave 2 teens at their home.

[86]:
```
df.AcceptedCmp1.value_counts()
```

[86]:
```
AcceptedCmp1
0    2095
1     144
Name: count, dtype: int64
```

Insights : Only 144 customers accepted the first offer and 2095 rejected first offer.

[87]:
```
df.AcceptedCmp2.value_counts()
```

[87]:
```
AcceptedCmp2
0    2209
1      30
Name: count, dtype: int64
```

Insights : Only 30 customers accepted the second offer and 2209 rejected second offer.

[88]:
```
df.AcceptedCmp3.value_counts()
```

[88]:
```
AcceptedCmp3
0    2076
1     163
Name: count, dtype: int64
```

Insights : Only 163 customers accepted the third offer and 2076 rejected third offer.

[89]:
```
df.AcceptedCmp4.value_counts()
```

[89]:
```
AcceptedCmp4
0    2072
1     167
Name: count, dtype: int64
```

Insights : Only 167 customers accepted the forth offer and 2072 rejected forth offer.

[90]:
```
df.AcceptedCmp5.value_counts()
```

[90]:
```
AcceptedCmp5
0    2076
1     163
Name: count, dtype: int64
```

Insights : Only 163 customers accepted the fifth offer and 2076 rejected fifth offer. Count of customers who accepted and rejected the third and fifth order is same.

[91]:
```
df.Complain.value_counts()
```

[91]:
```
Complain
0    2218
1      21
Name: count, dtype: int64
```

Insights : 2218 customers are not having any complaint and only 21 have complaint.

[92]:
```
df.Country.value_counts()
```

[92]:
```
Country
SP     1095
SA      336
CA      268
AUS     160
IND     148
GER     120
US      109
ME        3
Name: count, dtype: int64
```

Insights : There are total 8 unique countries in this dataset and SP is toping with 1095 customers and only 3 customers are from ME.

[93]:
```
df.duplicated().sum()
```

[93]:
```
0
```

Insights : There is not a single duplicate value present in our dataset.

[94]:
```
#Unique values in all the columns

df.nunique()
```

[94]:
```
ID                       2239
Year_Birth                 59
Education                   5
Marital_Status              8
Income                   1974
Kidhome                     3
Teenhome                    3
Dt_Customer               663
Recency                   100
MntWines                  776
MntFruits                 158
MntMeatProducts           558
MntFishProducts           182
MntSweetProducts          177
MntGoldProds              213
```

```
NumDealsPurchases        15
NumWebPurchases          15
NumCatalogPurchases      14
NumStorePurchases        14
NumWebVisitsMonth        16
AcceptedCmp3              2
AcceptedCmp4              2
AcceptedCmp5              2
AcceptedCmp1              2
AcceptedCmp2              2
Complain                  2
Country                   8
date                     31
month                    12
year                      3
Total_spending         1054
dtype: int64
```

[95]:
```
df["Income"].value_counts()
```

[95]:
```
Income
51969.8614    24
7500.0000     12
35860.0000     4
80134.0000     3
63841.0000     3
              ..
46086.0000     1
42243.0000     1
35788.0000     1
36026.0000     1
94871.0000     1
Name: count, Length: 1974, dtype: int64
```

#Univariate and Bivariate Analysis

[96]:
```
df.dtypes
```

[96]:
```
ID                        int64
Year_Birth                int64
Education                object
Marital_Status           object
Income                  float64
Kidhome                   int64
Teenhome                  int64
Dt_Customer              object
Recency                   int64
```

```
MntWines                 int64
MntFruits                int64
MntMeatProducts          int64
MntFishProducts          int64
MntSweetProducts         int64
MntGoldProds             int64
NumDealsPurchases        int64
NumWebPurchases          int64
NumCatalogPurchases      int64
NumStorePurchases        int64
NumWebVisitsMonth        int64
AcceptedCmp3             int64
AcceptedCmp4             int64
AcceptedCmp5             int64
AcceptedCmp1             int64
AcceptedCmp2             int64
Complain                 int64
Country                 object
date                    object
month                   object
year                    object
Total_spending           int64
dtype: object
```

[97]:

```
corr_columns = df[['Income', 'Kidhome', 'Teenhome', 'Recency',␣
 ↪'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',␣
 ↪'NumStorePurchases', 'NumWebVisitsMonth']]
```

[98]:

```
corr_columns.corr()
```

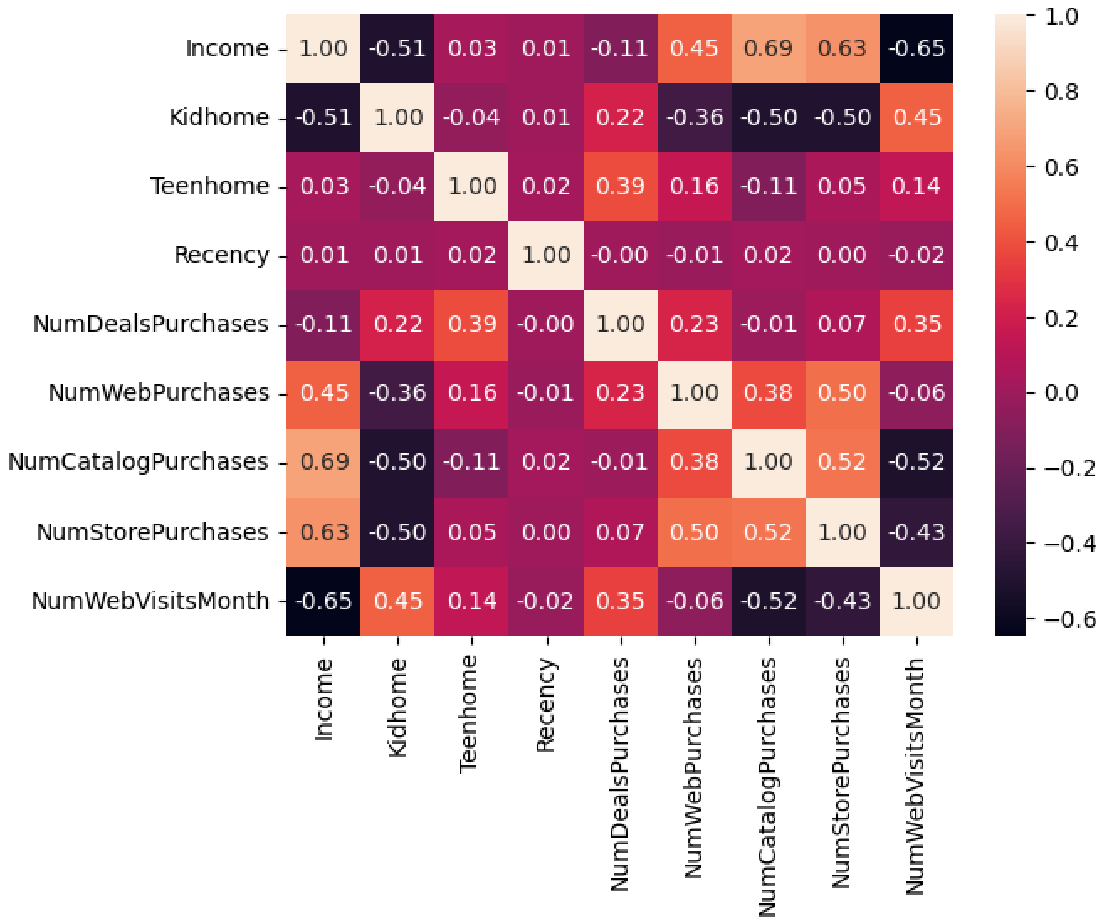
[98]:

```
                       Income   Kidhome  Teenhome   Recency  \
Income               1.000000 -0.510736  0.034156  0.006904
Kidhome             -0.510736  1.000000 -0.035720  0.009246
Teenhome             0.034156 -0.035720  1.000000  0.015829
Recency              0.006904  0.009246  0.015829  1.000000
NumDealsPurchases   -0.107398  0.221488  0.388241 -0.000749
NumWebPurchases      0.450144 -0.361566  0.155373 -0.010886
NumCatalogPurchases  0.693658 -0.502131 -0.111034  0.024888
NumStorePurchases    0.626974 -0.499488  0.050357  0.000453
NumWebVisitsMonth   -0.646725  0.447831  0.135029 -0.021335

                     NumDealsPurchases  NumWebPurchases  NumCatalogPurchases  \
Income                       -0.107398         0.450144             0.693658
Kidhome                       0.221488        -0.361566            -0.502131
Teenhome                      0.388241         0.155373            -0.111034
Recency                      -0.000749        -0.010886             0.024888
NumDealsPurchases             1.000000         0.234383            -0.008399
```

```
NumWebPurchases              0.234383        1.000000               0.378317
NumCatalogPurchases         -0.008399        0.378317               1.000000
NumStorePurchases            0.069234        0.502664               0.518643
NumWebVisitsMonth            0.347589       -0.055800              -0.520339

                     NumStorePurchases  NumWebVisitsMonth
Income                        0.626974          -0.646725
Kidhome                      -0.499488           0.447831
Teenhome                      0.050357           0.135029
Recency                       0.000453          -0.021335
NumDealsPurchases             0.069234           0.347589
NumWebPurchases               0.502664          -0.055800
NumCatalogPurchases           0.518643          -0.520339
NumStorePurchases             1.000000          -0.428443
NumWebVisitsMonth            -0.428443           1.000000
```

[99]:
```python
sns.heatmap(corr_columns.corr(), annot = True, fmt='.2f')
```

[99]: <Axes: >



Insights :

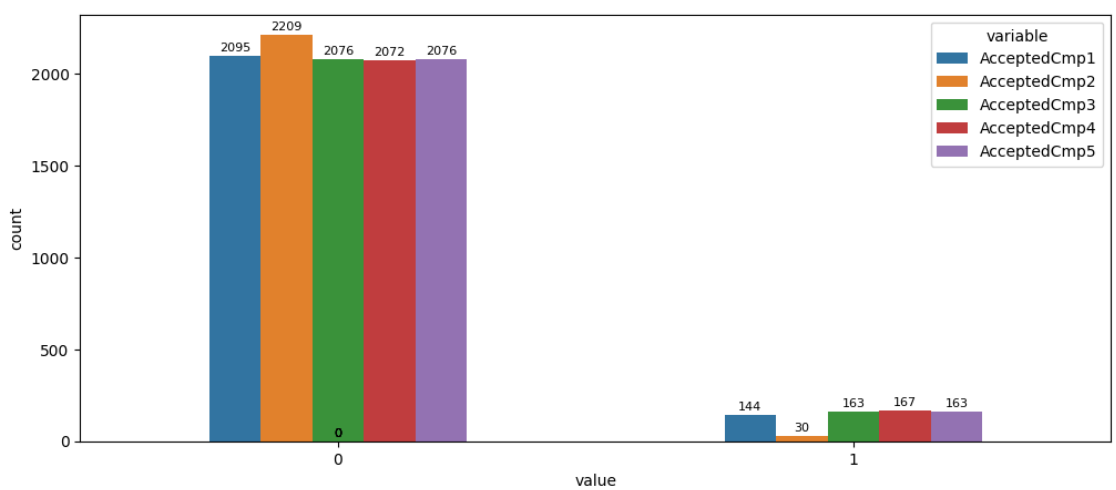
1. Income and Num Catalogue Purchase & Income and Num Store Purchase are highly coupled. It means if Income is inceasing then Catalogue and store purchase are also increasing. Also, Kidhome and Income is negatively coupled, it means people who have higher income are not having kids at home or rarely be 1,2 kids at home. Also, higher income leads to less web visit to store.

2. People who have kids at home are preferring deals purchase instead of store, catalogue and web purchase. More kids at home leads for more web visits.

3. People who have teen at home are also preferring deals purchasing.

#Univariate, Bivariate & Multivariate Analysis

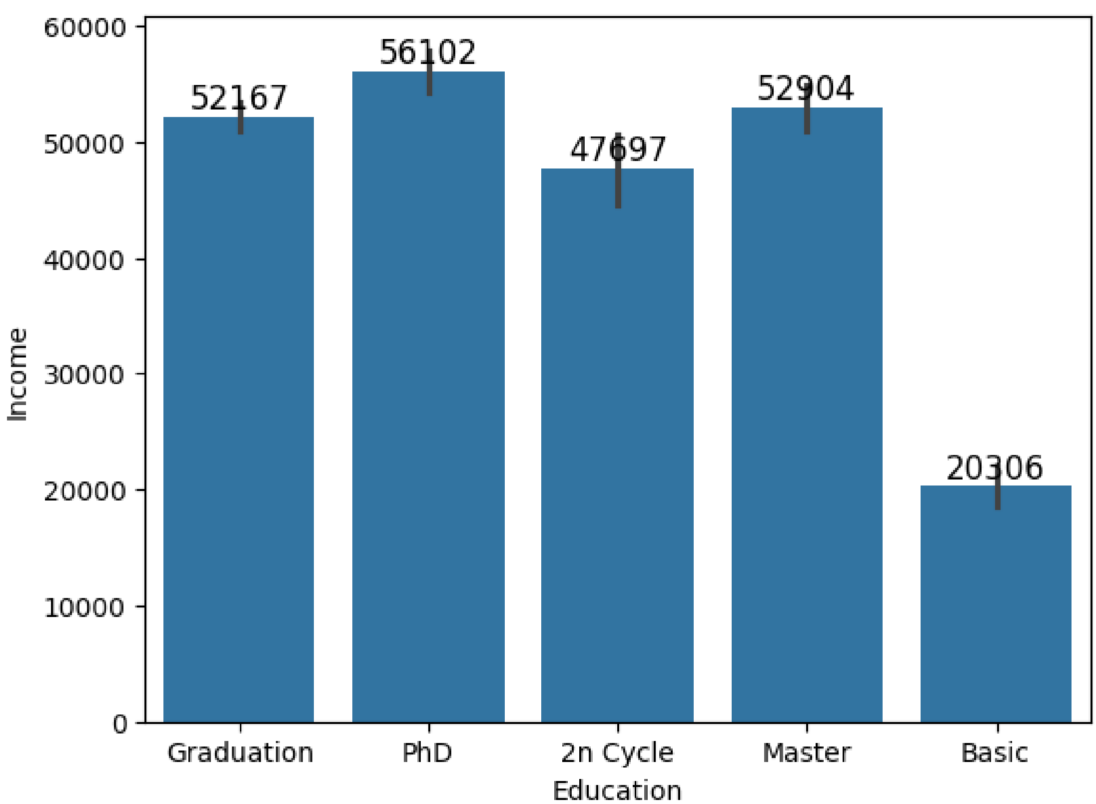
[100]:
```
df_melted = df[["AcceptedCmp1", "AcceptedCmp2", "AcceptedCmp3", "AcceptedCmp4",␣
↪"AcceptedCmp5"]].melt()

plt.figure(figsize=(12, 5))
ax = sns.countplot(x="value", data=df_melted, hue="variable", width=0.5)

# Add count values on the bars
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=8, color='black',␣
↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```



Insights :

1. Most Successful Compaign is Campaign 4 : Customer Accepted Offer - 167, Customer Rejected Offer - 2072
2. Second Most Successful Campaign is Campaign 3 & 5 Both : Customer Accepted Offer - 163, Customer Rejected Offer - 2076
3. Third Most Successful Campaign is Campaign 4 : Customer Accepted Offer - 144, Customer Rejected Offer - 2095.
4. Least Successful Offer is Campaign 2 : Customer Accepted Offer - 30 only, Customer Rejected Offer - 2209.

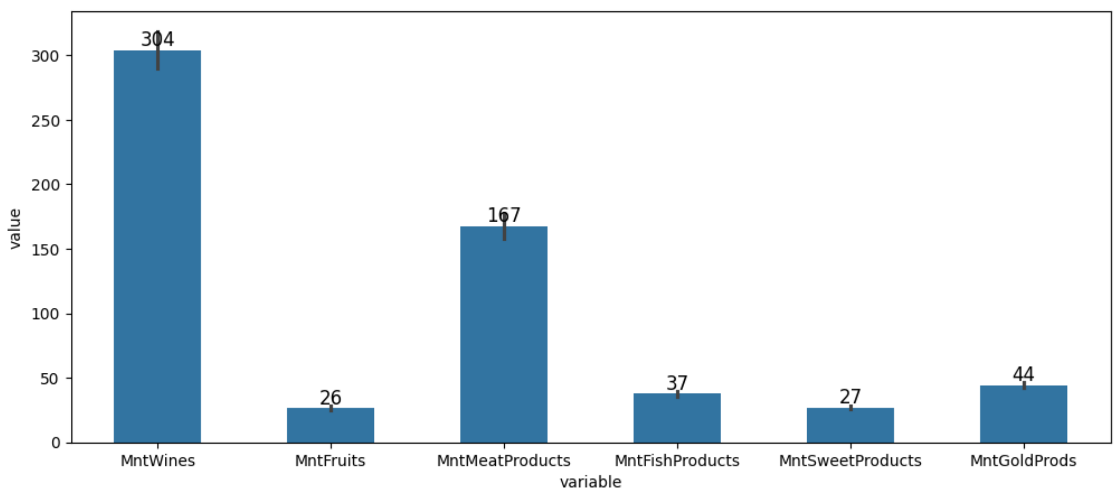
[101]:
```
ax = sns.barplot(x = "Education", y = "Income", data = df)

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=12, color='black',␣
↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```



Insights :

Customer who have done PhD has the highest income following the customers who have done Masters. Then Customer who have done Graduation earning best, following the 2n Cycle Education. Customers with only Basic are earning the least.

[102]:
```
plt.figure(figsize = (12,5))
sales_data = df[['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',␣
↪'MntSweetProducts', 'MntGoldProds']].melt()

ax = sns.barplot(x="variable", y="value", data=sales_data, width = 0.5)

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=12, color='black',␣
↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```

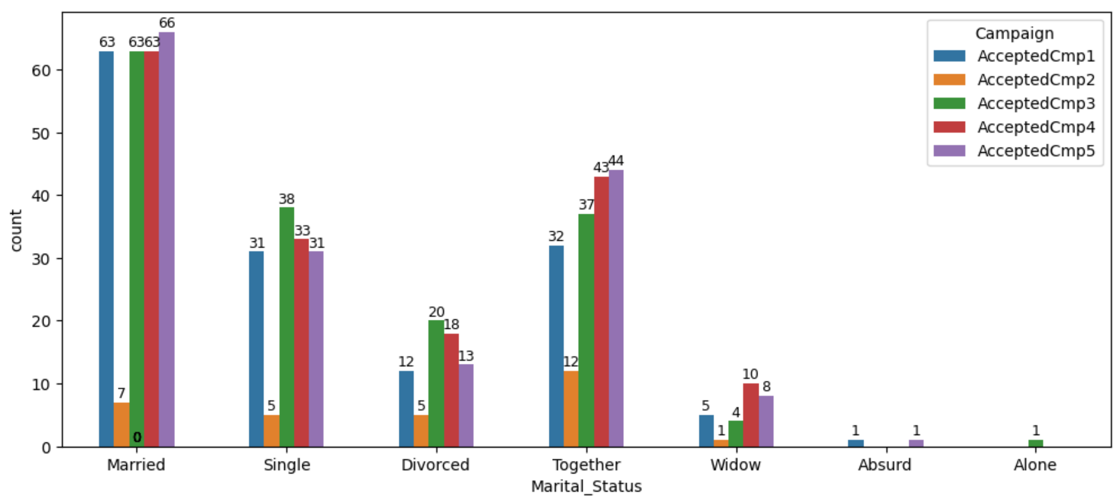


Insights :

Company is spending most on Wines, which is followed by Meat and then Gold Products, Fist Products. Spending on sweet and fruits is almost same.

[103]:
```
#Visualizing count of accepted offers for each marital_status

# Melt the DataFrame correctly
df_melted_marital = df.melt(id_vars="Marital_Status",
                            value_vars=["AcceptedCmp1", "AcceptedCmp2",␣
↪"AcceptedCmp3", "AcceptedCmp4", "AcceptedCmp5"],
```

```
                            var_name="Campaign", value_name="Accepted")

# Filter out rows where 'Accepted' is not 1 (if necessary)
df_melted_marital = df_melted_marital[df_melted_marital["Accepted"] == 1]

# Plot the data
plt.figure(figsize=(12, 5))
ax = sns.countplot(x="Marital_Status", hue="Campaign", data=df_melted_marital,␣
 ↪width=0.5)

# Annotate the bars with counts
for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black',␣
 ↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```

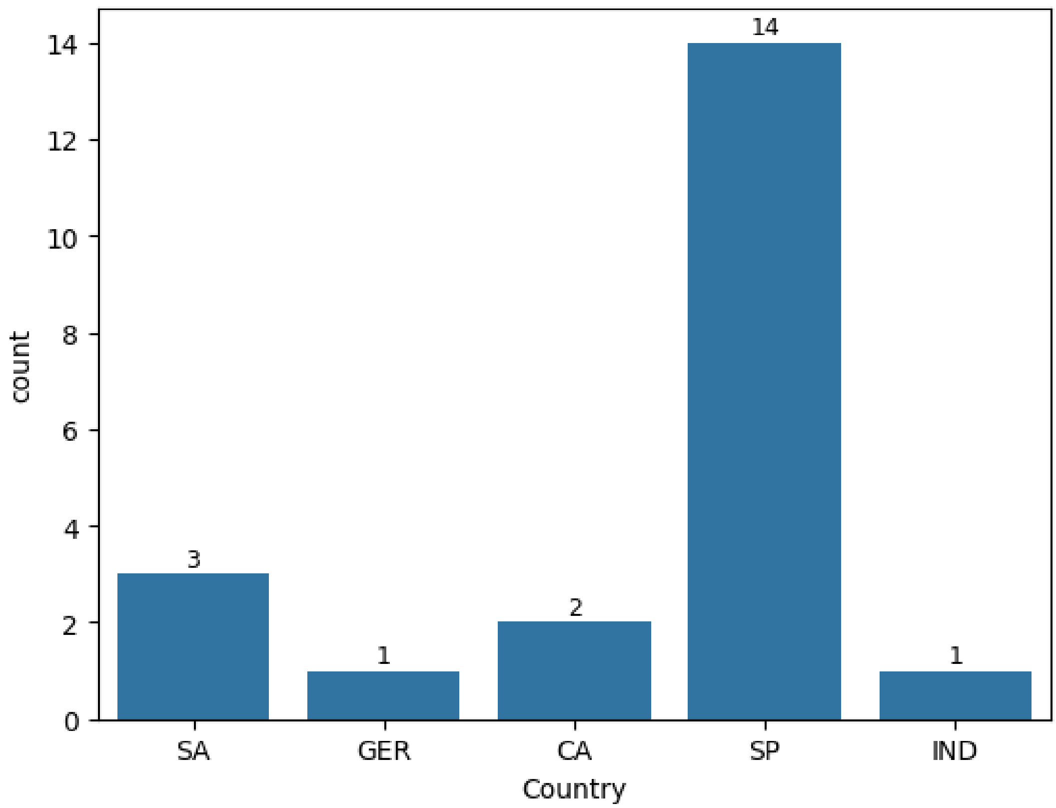


Insights :

1. Married Customers are accepting campaigns most rather than others.
2. Together customers are also getting benefits from the campaigns and availing it at second posiiting.
3. At third positing we are seeing that single customers are attacted towards campaign.
4. Seems like divorced and window customers are not accepting campaign offers mostly.
5. Absurd and alone are not interested in campaign offers.
6. Amongest all the campaigns, campaign-2 didn't brought much benifit to the company.

Insights :

[104]:
```
complain_data = df[df["Complain"]==1]
ax = sns.countplot(x = complain_data["Country"])

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black',␣
 ↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```

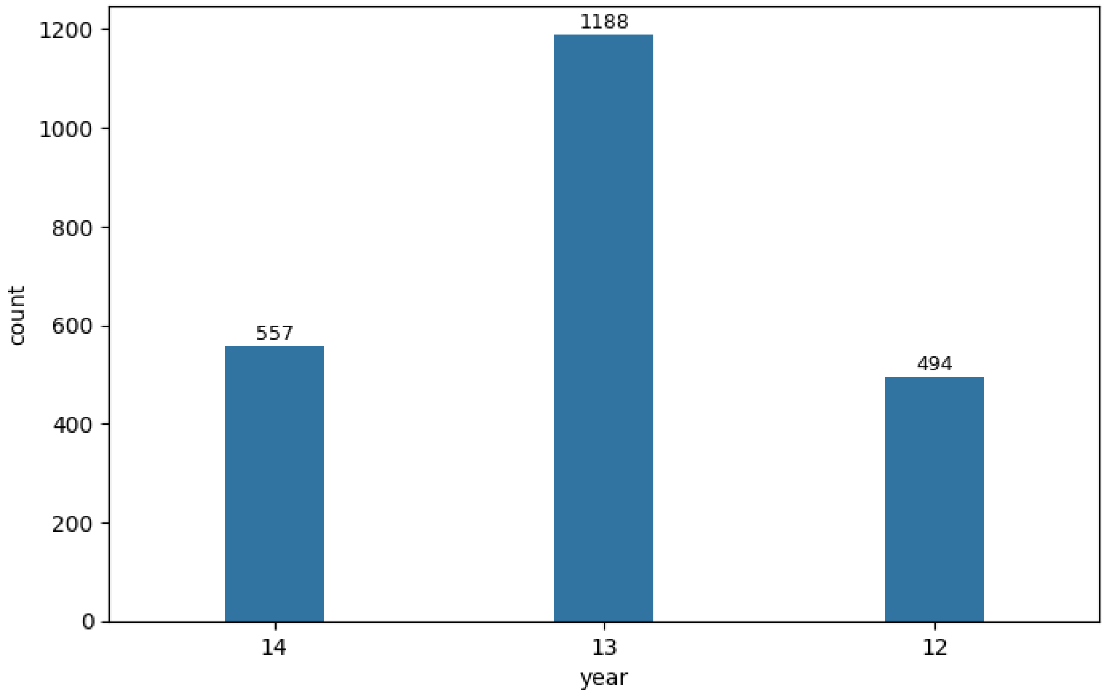


Insights :

Spain is having the most complain with the count of 14 and India is having the least complain count.

[105]:
```
plt.figure(figsize = (8,5))
ax = sns.countplot(x = df["year"], width = 0.3)

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
```

```
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black',␣
↪xytext=(0, 3),
                textcoords='offset points')

plt.show()
```

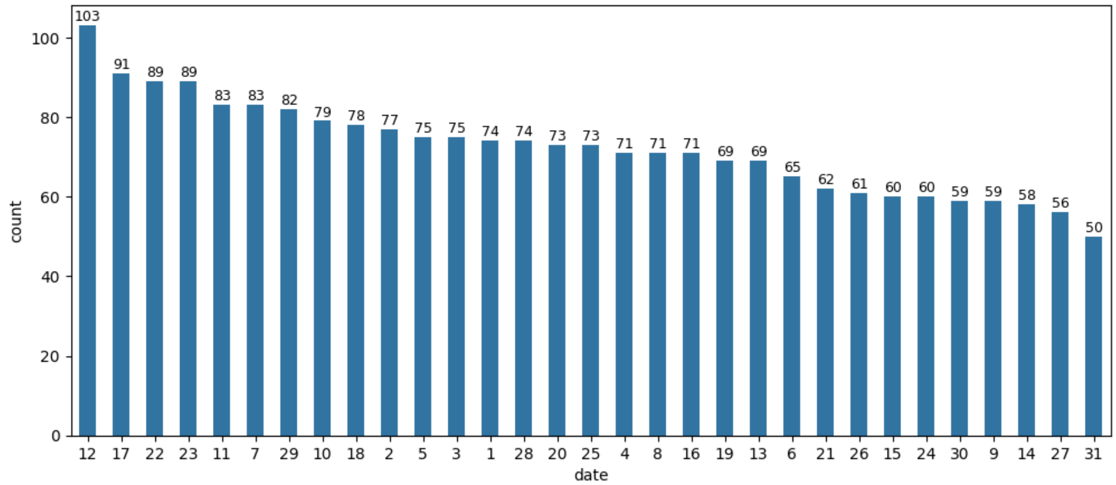


Insights :

In 13, customers enrollment was highest. while in 12, it is lowest.

[106]:
```
date_order = df["date"].value_counts().sort_values(ascending = False).index

df["date"] = pd.Categorical(df["date"], categories = date_order, ordered = True)

plt.figure(figsize = (12,5))
ax = sns.countplot(x = df["date"], width = 0.5)

for p in ax.patches:
    ax.annotate(f'{int(p.get_height())}',
                (p.get_x() + p.get_width() / 2., p.get_height()),
                ha='center', va='baseline', fontsize=9, color='black',␣
↪xytext=(0, 3),
                textcoords='offset points')
```

```
plt.show()
```



Insights :

Most of the customers enrolled on 12th of every month and least enrollment is in 31st of every month. Overall, what we can observe from this dataset is customers are enrolling through out the month.

#Hypothesis Testing:

0.1 Question - Is income of customers dependent on their education?

Null Hypothesis (H0): The income of customers is independent of their education level. (All means are equal across education levels.)

Alternative Hypothesis (H1): The income of customers depends on their education level. (At least one mean is different.)

[107]:
```
# one_way_ANOVA Test
# alpha = 0.05

import scipy.stats as stats

alpha = 0.05

educational_groups = [df["Income"][df["Education"] == level] for level in␣
↪df["Education"].unique()]

f_stats, p_value = stats.f_oneway(*educational_groups) #perfrom ANOVA Test

if p_value < alpha:
```

```
    print("Reject the null hypothesis. There is a significant difference in␣
↪income between education levels.")
else:
    print("Fail to reject the null hypothesis. There is no significant␣
↪difference in income between education levels.")
```

```
Reject the null hypothesis. There is a significant difference in income between
education levels.
```

##Question - Do higher income people spend more (take in account spending in all categories together)?

Null Hypothesis (H0): "Income and Total_spending are independent"

Alternate Hypothesis (H1): "Income and Total_spending are dependent"

[108]:
```
# pearsonr
# alpha = 0.05

from scipy.stats import pearsonr

corr, p_value = pearsonr(df["Income"], df["Total_spending"])

if p_value < alpha:
    print("Reject the null hypothesis. There is a significant correlation␣
↪between income and total spending.")
else:
    print("Fail to reject the null hypothesis. There is no significant␣
↪correlation between income and total spending.")
```

```
Reject the null hypothesis. There is a significant correlation between income
and total spending.
```

0.2 Question - 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')

Null Hypothesis (H0) = There is no significant difference in average wine spending between couples and alone.

Alternate Hypothesis (H1) = There is a significant difference in average wine spending between couples and alone.

[109]:
```
in_couple_df = df[df["Marital_Status"].isin(["Married", "Together"])]
```

[110]:
```
alone_df = df[df["Marital_Status"].isin(["Single", "Divorced", "Widow",␣
↪"Alone", "YOLO", "Absurd"])]
```

```
[111]: # ttest_ind
# alpha = 0.05

import scipy.stats as stats

t_stat, p_value = stats.ttest_ind(in_couple_df["MntWines"],␣
↪alone_df["MntWines"])
t_stat, p_value
```

```
[111]: (-0.2712259990062464, 0.7862422428083654)
```

```
[112]: # z-test (2 tail test)
# alpha = 0.05

mean_diff = in_couple_df["MntWines"].mean() - alone_df["MntWines"].mean()
std_in_couple_df = np.std(in_couple_df["MntWines"], ddof=1)
std_alone_df = np.std(alone_df["MntWines"], ddof=1)
std_error_diff = np.sqrt((std_in_couple_df**2 / len(in_couple_df)) +␣
↪(std_alone_df**2 / len(alone_df)))
z_stat = mean_diff / std_error_diff
p_value = 2*(1-stats.norm.cdf(np.abs(z_stat)))
z_stat, p_value

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

```
Fail to reject the null hypothesis. There is no significant difference in
average wine spending between couples and alone.
```

0.3 Question - 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)

Null Hypothesis (H0) = There is no significant difference in Income and accepted campaign.

Alternate Hypothesis (H1) = There is a significant difference in Income and accepted campaign.

```
[113]: df_below_median = df[df["Income"] < df["Income"].median()]
df['AcceptedAnyCampaign'] = df_below_median[["AcceptedCmp1", "AcceptedCmp2",␣
↪"AcceptedCmp3", "AcceptedCmp4", "AcceptedCmp5"]].any(axis=1).astype(int)
```

```
[114]: df_above_median = df[df["Income"] >= df["Income"].median()]
```

```
df['AcceptedAnyCampaign'] = df_below_median[["AcceptedCmp1", "AcceptedCmp2",␣
↪"AcceptedCmp3", "AcceptedCmp4", "AcceptedCmp5"]].any(axis=1).astype(int)
```

[115]:
```
# ttest_ind
# alpha = 0.05
t_stat, p_value = stats.ttest_ind(df["AcceptedAnyCampaign"],␣
↪df["AcceptedAnyCampaign"])

if p_value < alpha:
    print("Reject the null hypothesis. There is a significant difference in␣
↪Income and accepted campaign.")
else:
    print("Fail to reject the null hypothesis. There is no significant␣
↪difference in Income and accepted campaign.")
```

```
Fail to reject the null hypothesis. There is no significant difference in Income
and accepted campaign.
```

Insights and Recommendations :

1. High Variability in Income: With a standard deviation of 21,526 and income ranging from 1,730 to 162,397, there's a significant disparity between the low- and high-income segments. Half of the population earns between 35,284 and 68,487, with the mean (51,969) and median (51,373) close to each other, suggesting a fairly symmetrical distribution (All figures are in $).

- Recommendation: Segment Marketing: Given the large income disparity, create tiered marketing strategies targeting different income brackets. High-income individuals are more likely to respond to luxury products, while low-income individuals might prefer budget-conscious offers.

2. Household Size (Kidhome and Teenhome): Most Households Are Child-Free: Over half (57.75%) of households have no children at home, and 51.67% of households have no campaign teenagers. The maximum number of children or teenagers per household is 2, which is rare.

- Recommendation: Target Single Adults and Child-Free Couples: Focus campaigns and products on singles and couples without children, as they make up the majority of the customer base.

3. Recency (Days Since Last Purchase): Average Recency is 49 Days: While some customers purchased recently, others have not engaged in up to 99 days. The high standard deviation of 28.96 days shows varied shopping frequency.

- Recommendation:
  - Re-engagement Campaigns: Target customers who haven't purchased in 60+ days with personalized offers or reminders to drive retention.
  - Monetary Expenditure Across Categories:

4. Wine Spending: High-income individuals spend more on wines (mean: di h 304) ith , w somespen ngasmuc as 1,493. Low-income customers spend significantly less on wine (25th percentile: $24).

- Recommendation:
  - Luxury vs Budget Wine Marketing: High-income individuals could be targeted with premium wine selections, while budget-friendly wines should appeal to lowerincome customers.

5. Meat, Fish, Sweets, and Gold Product Spending: High-income individuals dominate these categories, while lower-income groups have limited spending power. Spending is more consistent across middle- and low-income groups, but lowerincome households tend to limit luxury expenditures.

- Recommendation:
  - Upsell Meat and Gold Products to High-Income Groups: Create tailored campaigns that emphasize premium quality for high-income individuals and offer value deals for lower-income segments.

5. Purchase Behavior: Store Purchases Dominate: On average, people make more in-store purchases (mean: 5.79) compared to web purchases (mean: 4).

- Outliers in Web and Catalog Purchases: There are some customers who purchase heavily online (maximum web purchases: 27; catalog: 28), though most customers make fewer web/catalog purchases.

- Recommendation:
  - Hybrid Shopping Strategy: Encourage online shopping for frequent in-store customers by offering online-exclusive deals. Focus on store-based promotions to maintain the engagement of in-store shoppers.

6. Campaign Acceptance: Low Campaign Acceptance: Only about 7% of customers accept any particular campaign. Despite this, there are no major complaints (complaint rate: 0.009).

- Recommendation:
  - Personalize Campaigns: Increase campaign acceptance by tailoring offers to individual preferences (e.g., wine offers for high-income customers or family discounts for customers with children).

7. Education Distribution: Highly Educated Population: Over 80% of the population has at least a graduate degree, with 21.71% holding PhDs.

- Recommendation:
  - Leverage Educational Targeting: Promote products or services that resonate with well-educated individuals, such as high-end, quality-driven goods or tech-oriented products.

8. Marital Status Distribution: Family-Oriented Population: The majority of the population (64.45%) is in a relationship or living with a partner. However, a sizable minority (35.55%) are living alone.

- Recommendation:
  - Custom Messaging for Couples vs Singles: Develop different marketing messages for couples (e.g., family-oriented promotions) and single individuals (e.g., convenience products).

9. Spending Patterns and Income Groups: Spending Increases with Income: High-income individuals consistently spend more across all categories. Low-income individuals, meanwhile, are constrained in luxury spending categories like wine, gold, and meat.

- Recommendation:
  - Targeted Promotions for Income Levels: Upsell premium products to high-income individuals and provide discount offers to lower-income groups to improve engagement across both brackets.

10. Hypothesis Testing Results: Wine Spending and Marital Status: The Mann-Whitney U test shows no significant difference in wine spending between couples and individuals living alone. Therefore, there is no need for differentiated pricing or campaigns based on marital status for wine products. Campaign Acceptance and Income:
11. The chi-square test indicates that lower-income individuals are more likely to accept campaigns, suggesting that price-sensitive segments respond better to offers. Income and Total Spending:
12. With a p-value of 0, which is less than the significance level (0.05), we reject the null hypothesis. This confirms that there is a significant difference in spending across income campaign groups, with higher-income individuals spending more across all categories. Income and Education:
13. The p-value for both the chi2_contingency and Kruskal-Wallis tests is very low, leading us to reject the null hypothesis. This means that education level has a significant impact on income—higher education levels are linked to higher incomes. Recommendations:
14. Price Sensitivity: Target lower-income groups with discounts, deals, and personalized promotions to increase campaign acceptance.
15. Spending Differences Across Income Groups: Focus premium products and services on higher-income segments, as they demonstrate significantly higher spending capacity across all categories.
16. Education-Linked Income: Use education data to segment customers and market high-end products to individuals with higher education levels, who tend to have higher incomes and greater spending potential.
17. Tailor premium products and services towards higher-income segments as they have a significantly higher spending capacity across all categories. Education-Linked Income:
18. Leverage education data to segment customers, focusing high-end product marketing on customers with higher education levels, who tend to have higher incomes and spending potential.