Marketing-Compaign-EDA-Hypothesis-And-Feature-engineering

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1 Project: Marketing Campaign - Applied Data Science With Python

1.1 Developed by: Ravi Ranjan Lal

1.1.1 Project Overview :

This project covers the following processes: 1. #### **Data Cleaning**: Ensuring data quality by handling missing, inconsistent, or incorrect values. 2. #### **Exploratory Data Analysis (EDA)**: Deriving insights and identifying patterns through data visualization. 3. #### **Hypothesis Testing**: Conducting statistical tests to validate assumptions. 4. #### **Feature Engineering**: Transforming and encoding data to optimize it for machine learning models.

2 Data Cleaning

[1]:
```
# importing the required packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from datetime import datetime
import warnings
```

[2]:
```
df_main = pd.read_csv("marketing_data.csv")
df_main.head()
```

[2]:
```
      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  …  NumStorePurchases  \
0         0     6/16/14        0       189  …                  6
1         0     6/15/14        0       464  …                  7
2         1     5/13/14        0       134  …                  5
3         1     5/11/14        0        10  …                  2
```

```
4         0      4/8/14        0         6  …                  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  Response  Complain  Country
0             0         1         0       SP
1             1         1         0       CA
2             0         0         0       US
3             0         0         0      AUS
4             0         1         0       SP

[5 rows x 28 columns]
```

[3]:
```python
#check the shape of the dataset , number of rows and columns
df_main.shape
```

[3]: (2240, 28)

[4]:
```python
# check info of the datset like datatypes in int, object
df_main.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 28 columns):
 #   Column               Non-Null Count  Dtype
---  ------               --------------  -----
 0   ID                   2240 non-null   int64
 1   Year_Birth           2240 non-null   int64
 2   Education            2240 non-null   object
 3   Marital_Status       2240 non-null   object
 4    Income              2216 non-null   object
 5   Kidhome              2240 non-null   int64
 6   Teenhome             2240 non-null   int64
 7   Dt_Customer          2240 non-null   object
 8   Recency              2240 non-null   int64
 9   MntWines             2240 non-null   int64
 10  MntFruits            2240 non-null   int64
 11  MntMeatProducts      2240 non-null   int64
 12  MntFishProducts      2240 non-null   int64
 13  MntSweetProducts     2240 non-null   int64
 14  MntGoldProds         2240 non-null   int64
 15  NumDealsPurchases    2240 non-null   int64
```

```
 16  NumWebPurchases      2240 non-null   int64
 17  NumCatalogPurchases  2240 non-null   int64
 18  NumStorePurchases    2240 non-null   int64
 19  NumWebVisitsMonth    2240 non-null   int64
 20  AcceptedCmp3         2240 non-null   int64
 21  AcceptedCmp4         2240 non-null   int64
 22  AcceptedCmp5         2240 non-null   int64
 23  AcceptedCmp1         2240 non-null   int64
 24  AcceptedCmp2         2240 non-null   int64
 25  Response             2240 non-null   int64
 26  Complain             2240 non-null   int64
 27  Country              2240 non-null   object
dtypes: int64(23), object(5)
memory usage: 490.1+ KB
```

[5]:
```
# using describe method to check the stats of the datset like, mean, standard␣
 ↪deviation , percentile
df_main.describe()
```

[5]:
```
                 ID   Year_Birth      Kidhome     Teenhome      Recency  \
count   2240.000000  2240.000000  2240.000000  2240.000000  2240.000000
mean    5592.159821  1968.805804     0.444196     0.506250    49.109375
std     3246.662198    11.984069     0.538398     0.544538    28.962453
min        0.000000  1893.000000     0.000000     0.000000     0.000000
25%     2828.250000  1959.000000     0.000000     0.000000    24.000000
50%     5458.500000  1970.000000     0.000000     0.000000    49.000000
75%     8427.750000  1977.000000     1.000000     1.000000    74.000000
max    11191.000000  1996.000000     2.000000     2.000000    99.000000

          MntWines    MntFruits  MntMeatProducts  MntFishProducts  \
count  2240.000000  2240.000000      2240.000000      2240.000000
mean    303.935714    26.302232       166.950000        37.525446
std     336.597393    39.773434       225.715373        54.628979
min       0.000000     0.000000         0.000000         0.000000
25%      23.750000     1.000000        16.000000         3.000000
50%     173.500000     8.000000        67.000000        12.000000
75%     504.250000    33.000000       232.000000        50.000000
max    1493.000000   199.000000      1725.000000       259.000000

       MntSweetProducts  …  NumCatalogPurchases  NumStorePurchases  \
count       2240.000000  …          2240.000000        2240.000000
mean          27.062946  …             2.662054           5.790179
std           41.280498  …             2.923101           3.250958
min            0.000000  …             0.000000           0.000000
25%            1.000000  …             0.000000           3.000000
50%            8.000000  …             2.000000           5.000000
75%           33.000000  …             4.000000           8.000000
```

```
max          263.000000  ...          28.000000          13.000000

       NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  \
count        2240.000000   2240.000000   2240.000000   2240.000000
mean            5.316518      0.072768      0.074554      0.072768
std             2.426645      0.259813      0.262728      0.259813
min             0.000000      0.000000      0.000000      0.000000
25%             3.000000      0.000000      0.000000      0.000000
50%             6.000000      0.000000      0.000000      0.000000
75%             7.000000      0.000000      0.000000      0.000000
max            20.000000      1.000000      1.000000      1.000000

       AcceptedCmp1  AcceptedCmp2     Response     Complain
count   2240.000000   2240.000000  2240.000000  2240.000000
mean       0.064286      0.013393     0.149107     0.009375
std        0.245316      0.114976     0.356274     0.096391
min        0.000000      0.000000     0.000000     0.000000
25%        0.000000      0.000000     0.000000     0.000000
50%        0.000000      0.000000     0.000000     0.000000
75%        0.000000      0.000000     0.000000     0.000000
max        1.000000      1.000000     1.000000     1.000000

[8 rows x 23 columns]
```

[6]:
```
# check how many features have total null values
df_main.isnull().sum()
```

[6]:
```
ID                      0
Year_Birth              0
Education               0
Marital_Status          0
 Income                24
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
Response               0
Complain               0
Country                0
dtype: int64
```

[7]:
```
# creating a copy of the dataframe, to avoid direct modification on the main␣
↪datset.
df = df_main.copy()
```

[8]:
```
# drop duplicates if any and check using shape to verify the shape
df.drop_duplicates(subset='ID', inplace=True)
df.shape
```

[8]:
```
(2240, 28)
```

[9]:
```
# check columns for extra spaces
df.columns
```

[9]:
```
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', 'Response', 'Complain', 'Country'],
      dtype='object')
```

[10]:
```
#There is extra space in column name ex- Income column has space before and␣
↪after the Income column name.
df.columns = df.columns.str.strip()
df.columns
```

[10]:
```
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', 'Response', 'Complain', 'Country'],
      dtype='object')
```

[11]:
```python
df['Income'].isnull().sum()
# so there are 24 null values in the Income feature.
```

[11]:
```
np.int64(24)
```

[12]:
```python
df['Income'].unique()
```

[12]:
```
array(['$84,835.00 ', '$57,091.00 ', '$67,267.00 ', …, '$46,310.00 ',
       '$65,819.00 ', '$94,871.00 '], shape=(1975,), dtype=object)
```

[13]:
```python
# Remove all the $ and comma from the Income feature so that we have all the␣
↪values converted to float type
df['Income'] = df['Income'].str.strip()
chars_to_remove = ["$", ","]
for item in chars_to_remove:
    df['Income'] = df['Income'].str.replace(item, '')
```

[14]:
```python
# Transform the income to numeric from string type
df['Income'] = pd.to_numeric(df['Income'], errors="coerce")
```

[15]:
```python
df.head(2) #verify Income column cleaned with $ and , and converted to float
```

[15]:
```
     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

  Dt_Customer  Recency  MntWines  …  NumStorePurchases  NumWebVisitsMonth  \
0     6/16/14        0       189  …                  6                  1
1     6/15/14        0       464  …                  7                  5

   AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  \
0             0             0             0             0             0
1             0             0             0             0             1

   Response  Complain  Country
0         1         0       SP
1         1         0       CA

[2 rows x 28 columns]
```

[16]:
```python
df['Income'].info() #verify Income feature values converted to float
```

```
<class 'pandas.core.series.Series'>
RangeIndex: 2240 entries, 0 to 2239
Series name: Income
Non-Null Count  Dtype
--------------  -----
```

```
2216 non-null   float64
dtypes: float64(1)
memory usage: 17.6 KB
```

2.0.1 Problem Statement: Income values for a few customers are missing. Perform missing value imputation. Assume that the customers with similar education and marital status make the same yearly income, on average.

Mean Imputation of Income using Average income of group by Education and Marital_Status.

[17]:
```python
df['Education'].unique()
```

[17]:
```
array(['Graduation', 'PhD', '2n Cycle', 'Master', 'Basic'], dtype=object)
```

[18]:
```python
df['Marital_Status'].unique()
```

[18]:
```
array(['Divorced', 'Single', 'Married', 'Together', 'Widow', 'YOLO',
       'Alone', 'Absurd'], dtype=object)
```

[19]:
```python
#Group by Education and Marital_Status to get the average of their income.
mean_income_grp_by = df.groupby(['Education', 'Marital_Status'])['Income'].
 ↪mean()
print(mean_income_grp_by)
```

```
Education   Marital_Status
2n Cycle    Divorced          49395.130435
            Married           46201.100000
            Single            53673.944444
            Together          44736.410714
            Widow             51392.200000
Basic       Divorced           9548.000000
            Married           21960.500000
            Single            18238.666667
            Together          21240.071429
            Widow             22123.000000
Graduation  Absurd            79244.000000
            Alone             34176.000000
            Divorced          54526.042017
            Married           50800.258741
            Single            51322.182927
            Together          55758.480702
            Widow             54976.657143
Master      Absurd            65487.000000
            Alone             61331.000000
            Divorced          50331.945946
            Married           53286.028986
            Single            53530.560000
            Together          52109.009804
```

```
              Widow            58401.545455
PhD           Alone            35860.000000
              Divorced         53096.615385
              Married          58138.031579
              Single           53314.614583
              Together         56041.422414
              Widow            60288.083333
              YOLO             48432.000000
Name: Income, dtype: float64
```

[20]:
```
# Apply row wise update using lambda to get the mean from group by, for␣
↪replacing nan values
df['Income'] = df.apply(
    lambda row: mean_income_grp_by.get((row['Education'],␣
↪row['Marital_Status']), row['Income'])
    if pd.isna(row['Income']) else row['Income'], axis=1
)
df['Income'].isnull().sum() #no null values present after the imputation
```

[20]: np.int64(0)

Converting date feature to seperate features with day, month and year into numerical, later can be used for model training

[21]:
```
df['Dt_Customer'].unique()
```

[21]:
```
array(['6/16/14', '6/15/14', '5/13/14', '5/11/14', '4/8/14', '3/17/14',
       '1/29/14', '1/18/14', '1/11/14', '12/27/13', '12/9/13', '12/7/13',
       '10/16/13', '10/5/13', '9/11/13', '8/1/13', '7/23/13', '7/1/13',
       '5/28/13', '3/26/13', '3/15/13', '2/12/13', '11/23/12', '10/13/12',
       '9/14/12', '6/29/14', '5/31/14', '5/30/14', '4/27/14', '4/11/14',
       '10/29/13', '10/9/13', '5/10/13', '5/9/13', '4/25/13', '4/20/13',
       '3/30/13', '3/1/13', '2/14/13', '1/11/13', '1/3/13', '12/19/12',
       '12/15/12', '12/2/12', '9/17/12', '9/11/12', '5/12/14', '4/28/14',
       '3/29/14', '3/6/14', '3/4/14', '2/4/14', '2/3/14', '1/1/14',
       '12/12/13', '11/15/13', '9/20/13', '9/5/13', '8/31/13', '7/30/13',
       '7/27/13', '6/22/13', '1/5/13', '11/21/12', '11/11/12', '9/28/12',
       '9/27/12', '9/7/12', '8/13/12', '8/11/12', '8/2/12', '6/25/14',
       '5/28/14', '4/14/14', '3/10/14', '2/27/14', '2/7/14', '1/28/14',
       '11/17/13', '11/7/13', '10/17/13', '10/13/13', '10/12/13',
       '9/30/13', '7/3/13', '6/10/13', '5/29/13', '4/29/13', '3/10/13',
       '1/2/13', '11/2/12', '10/18/12', '10/1/12', '9/3/12', '8/26/12',
       '5/23/14', '5/17/14', '4/21/14', '3/23/14', '12/16/13', '11/26/13',
       '11/14/13', '11/6/13', '10/6/13', '9/27/13', '9/18/13', '9/9/13',
       '7/18/13', '7/8/13', '5/27/13', '3/5/13', '2/20/13', '1/12/13',
       '12/24/12', '11/19/12', '3/28/14', '2/24/14', '9/2/13', '8/20/13',
       '6/23/13', '5/5/13', '4/5/13', '1/4/13', '12/27/12', '11/10/12',
```

'10/29/12', '9/22/12', '3/31/14', '3/21/14', '2/9/14', '9/23/13',
'6/27/13', '3/28/13', '3/12/13', '1/16/13', '1/8/13', '12/29/12',
'12/12/12', '11/25/12', '9/21/12', '9/9/12', '9/5/12', '8/17/12',
'6/22/14', '5/1/14', '1/3/14', '10/11/13', '8/13/13', '6/9/13',
'5/7/13', '10/2/12', '9/12/12', '3/19/14', '3/3/14', '2/22/14',
'1/24/14', '12/4/13', '11/28/13', '11/5/13', '10/3/13', '8/9/13',
'8/7/13', '7/17/13', '7/9/13', '6/11/13', '5/17/13', '3/23/13',
'2/19/13', '1/19/13', '1/10/13', '1/1/13', '11/12/12', '5/18/14',
'3/30/14', '1/30/14', '1/26/14', '1/22/14', '1/15/14', '12/13/13',
'8/4/13', '5/1/13', '4/24/13', '4/3/13', '2/3/13', '11/16/12',
'8/3/12', '4/18/14', '4/1/14', '3/18/14', '2/10/14', '11/23/13',
'11/21/13', '10/2/13', '7/21/13', '6/18/13', '3/24/13', '12/6/12',
'11/9/12', '2/14/14', '10/22/13', '10/4/13', '9/21/13', '8/5/13',
'7/14/13', '7/4/13', '4/12/13', '4/10/13', '4/8/13', '3/31/13',
'3/17/13', '1/21/13', '12/10/12', '9/24/12', '8/6/12', '6/18/14',
'4/5/14', '12/21/13', '10/27/13', '10/21/13', '9/19/13', '9/4/13',
'6/25/13', '4/27/13', '4/18/13', '12/30/12', '8/22/12', '8/8/12',
'6/19/14', '4/20/14', '2/28/14', '12/17/13', '11/25/13',
'10/28/13', '8/15/13', '7/5/13', '6/19/13', '6/16/13', '4/22/13',
'3/19/13', '2/23/13', '2/15/13', '10/31/12', '10/7/12', '8/9/12',
'5/6/14', '4/15/14', '3/5/14', '2/19/14', '9/7/13', '8/6/13',
'7/25/13', '4/30/13', '9/10/12', '3/20/14', '9/28/13', '9/24/13',
'2/16/13', '11/22/12', '9/18/12', '8/16/12', '6/5/14', '4/13/14',
'4/10/14', '4/3/14', '2/12/14', '12/15/13', '10/30/13', '8/26/13',
'2/2/13', '1/25/13', '11/17/12', '11/13/12', '11/7/12', '11/1/12',
'10/16/12', '5/8/14', '3/2/14', '6/24/13', '6/13/13', '4/23/13',
'4/15/13', '1/29/13', '10/30/12', '10/23/12', '4/17/14', '2/25/14',
'12/11/13', '10/10/13', '5/20/13', '5/18/13', '4/7/13', '3/3/13',
'12/7/12', '11/28/12', '10/27/12', '9/15/12', '6/17/14', '5/29/14',
'3/1/14', '2/15/14', '12/23/13', '11/29/13', '10/25/13', '8/17/13',
'6/6/13', '3/29/13', '9/23/12', '8/30/12', '8/1/12', '2/8/14',
'1/25/14', '11/27/13', '10/19/13', '3/7/13', '2/28/13', '1/17/13',
'11/20/12', '11/5/12', '11/3/12', '8/31/12', '8/12/12', '5/15/14',
'4/12/14', '4/6/14', '2/6/14', '7/29/13', '6/29/13', '6/17/13',
'6/8/13', '5/26/13', '11/8/12', '8/4/12', '4/30/14', '4/7/14',
'3/12/14', '4/13/13', '2/13/13', '6/3/14', '3/25/14', '2/17/14',
'2/5/14', '1/27/14', '1/14/14', '7/11/13', '6/2/13', '6/1/13',
'5/4/13', '3/18/13', '12/3/12', '11/24/12', '10/26/12', '6/20/14',
'1/19/14', '1/9/14', '12/29/13', '12/26/13', '12/8/13', '11/20/13',
'8/23/13', '8/19/13', '7/24/13', '10/6/12', '8/18/12', '5/7/14',
'11/9/13', '8/25/13', '5/16/13', '4/1/13', '3/27/13', '2/8/13',
'9/20/12', '5/22/14', '12/30/13', '11/2/13', '8/21/13', '7/12/13',
'6/28/13', '6/4/13', '5/31/13', '3/6/13', '2/18/13', '9/26/12',
'8/19/12', '5/2/14', '4/29/14', '2/2/14', '1/5/14', '12/5/13',
'11/18/13', '9/10/13', '8/3/13', '2/21/13', '2/10/13', '1/31/13',
'12/9/12', '9/29/12', '6/9/14', '4/2/14', '3/24/14', '1/23/14',
'9/16/13', '9/12/13', '7/15/13', '3/9/13', '2/9/13', '12/14/12',

```
'10/17/12', '6/23/14', '6/12/14', '6/7/14', '4/9/14', '2/13/14',
'12/6/13', '10/20/13', '6/20/13', '5/8/13', '3/11/13', '9/6/12',
'3/9/14', '2/11/14', '10/8/13', '8/28/13', '7/6/13', '5/30/13',
'5/22/13', '4/2/13', '3/20/13', '3/14/13', '1/22/13', '9/8/12',
'8/25/12', '8/14/12', '11/19/13', '6/3/13', '12/21/12', '10/10/12',
'8/7/12', '12/24/13', '12/14/13', '5/15/13', '5/6/13', '1/7/13',
'11/29/12', '4/24/14', '3/8/14', '7/16/13', '2/22/13', '1/20/13',
'1/13/13', '12/25/12', '12/11/12', '6/27/14', '3/16/14', '11/3/13',
'9/25/13', '9/15/13', '9/1/13', '8/2/13', '8/27/12', '4/4/14',
'9/22/13', '12/22/12', '12/16/12', '8/20/12', '1/7/14', '12/1/13',
'9/26/13', '2/25/13', '10/24/12', '10/22/12', '7/31/12', '5/19/14',
'5/3/14', '4/16/14', '12/31/13', '12/2/13', '7/22/13', '4/21/13',
'4/11/13', '3/22/14', '2/6/13', '12/4/12', '11/6/12', '8/28/12',
'7/2/13', '10/12/12', '5/16/14', '4/25/14', '11/13/13', '9/6/13',
'11/18/12', '10/15/12', '6/14/14', '1/17/14', '2/7/13', '12/20/13',
'9/13/13', '1/6/13', '5/26/14', '1/13/14', '8/8/13', '4/6/13',
'2/26/14', '5/14/13', '8/24/12', '5/27/14', '2/23/14', '1/10/14',
'7/19/13', '3/25/13', '2/11/13', '1/15/13', '12/5/12', '6/13/14',
'6/2/14', '11/1/13', '8/16/13', '2/17/13', '2/4/13', '10/19/12',
'6/26/14', '10/23/13', '4/14/13', '10/28/12', '10/1/13', '3/8/13',
'11/14/12', '1/12/14', '11/4/13', '8/22/13', '6/21/13', '1/23/13',
'10/21/12', '10/4/12', '1/31/14', '1/21/14', '12/28/13', '8/11/13',
'5/13/13', '9/2/12', '6/24/14', '6/8/14', '5/24/14', '10/18/13',
'9/17/13', '8/14/13', '7/20/13', '6/30/13', '5/11/13', '4/16/13',
'5/25/14', '5/10/14', '5/4/14', '8/29/13', '3/22/13', '6/4/14',
'5/23/13', '2/1/13', '2/16/14', '10/24/13', '3/2/13', '12/18/12',
'11/4/12', '6/11/14', '6/14/13', '6/10/14', '5/5/14', '4/19/14',
'8/18/13', '2/26/13', '8/30/13', '6/12/13', '5/12/13', '10/9/12',
'11/10/13', '8/24/13', '9/4/12', '2/27/13', '1/6/14', '7/7/13',
'11/26/12', '8/29/12', '5/2/13', '3/4/13', '1/27/13', '8/23/12',
'10/14/13', '12/23/12', '12/1/12', '8/5/12', '8/27/13', '12/17/12',
'6/21/14', '3/26/14', '11/22/13', '8/21/12', '4/22/14', '10/26/13',
'5/9/14', '4/17/13', '3/21/13', '1/24/13', '12/28/12', '3/13/14',
'2/1/14', '10/15/13', '1/14/13', '10/5/12', '7/13/13', '4/23/14',
'2/18/14', '11/12/13', '8/12/13', '12/31/12', '6/28/14', '12/3/13',
'12/26/12', '7/30/12', '1/2/14', '4/19/13', '1/26/13', '10/14/12',
'9/30/12', '3/11/14', '9/14/13', '7/28/13', '5/19/13', '4/28/13',
'1/9/13', '10/20/12', '7/31/13', '5/21/13', '9/25/12', '5/3/13',
'12/8/12', '3/27/14', '12/18/13', '11/30/13', '8/10/13', '3/16/13',
'11/30/12', '3/7/14', '12/19/13', '10/25/12', '12/25/13', '1/4/14',
'11/8/13', '11/27/12', '7/26/13', '12/20/12', '10/11/12',
'4/26/14', '12/22/13', '6/26/13', '5/24/13', '8/15/12', '12/10/13',
'9/19/12', '8/10/12', '6/6/14', '5/25/13', '4/9/13', '9/1/12'],
dtype=object)
```

[22]:
```
#Feature engineering : new feature Day Month Year from the feature, Date of
↪Customer Enrolment
```

```
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%m/%d/%y')
df['Day_Customer_Enroll'] = df['Dt_Customer'].dt.day
df['Month_Customer_Enroll'] = df['Dt_Customer'].dt.month
df['Year_Customer_Enroll'] = df['Dt_Customer'].dt.year
df.drop('Dt_Customer', axis=1, inplace=True)
```

[23]:
```
df.head(2) # verify the 3 new date features updated in the data frame
```

[23]:
```
     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

   Recency  MntWines  MntFruits  …  AcceptedCmp4  AcceptedCmp5  \
0        0       189        104  …             0             0
1        0       464          5  …             0             0

   AcceptedCmp1  AcceptedCmp2  Response  Complain  Country  \
0             0             0         1         0       SP
1             0             1         1         0       CA

   Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll
0                   16                      6                  2014
1                   15                      6                  2014

[2 rows x 30 columns]
```

3 EDA - Visualization

3.0.1 Problem Statement : Create variables to populate the total number of children, age, and total spending.

[24]:
```
# create feature, total number of children
df['Total_Children'] = df['Kidhome'] + df['Teenhome']
```

[25]:
```
# create feature, age of the customer
current_year = datetime.now().year
df['Age'] = current_year - df['Year_Birth']
```

[26]:
```
# create feature, total spending from the amount features (sum of all the␣
↪amount columns) : row wise sum
df['Total_Spending'] = df[['MntWines', 'MntFruits', 'MntMeatProducts',␣
↪'MntFishProducts',
                           'MntSweetProducts', 'MntGoldProds']].sum(axis=1)
```

[27]:
```
df.head()
```

[27]:
```
      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  …  AcceptedCmp2  Response  Complain  \
0        0       189        104  …             0         1         0
1        0       464          5  …             1         1         0
2        0       134         11  …             0         0         0
3        0        10          0  …             0         0         0
4        0         6         16  …             0         1         0

   Country  Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0       SP                   16                      6                  2014
1       CA                   15                      6                  2014
2       US                   13                      5                  2014
3      AUS                   11                      5                  2014
4       SP                    8                      4                  2014

   Total_Children  Age  Total_Spending
0               0   55            1190
1               0   64             577
2               1   67             251
3               2   58              11
4               1   36              91

[5 rows x 33 columns]
```

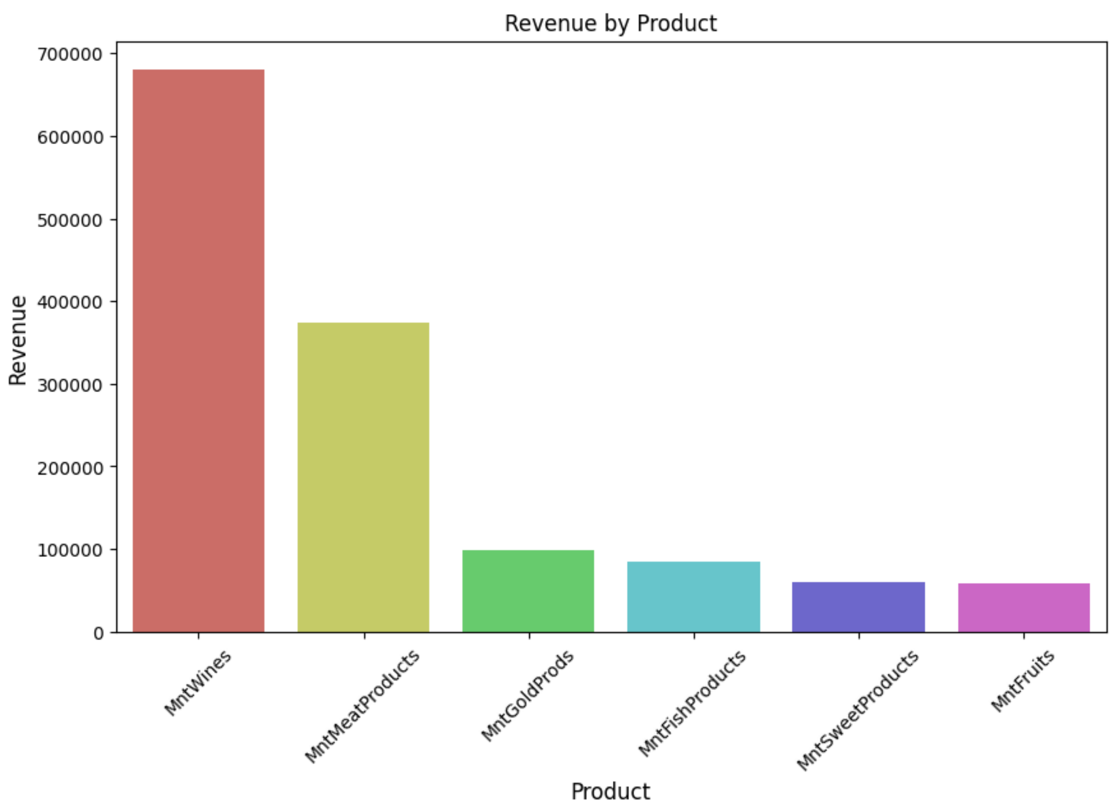
3.0.2 Which products are performing the best, and which are performing the least in terms of revenue?

[28]:
```python
product_columns = ['MntWines', 'MntFruits', 'MntMeatProducts',␣
 ↪'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']
product_revenue = df[product_columns].sum()
product_revenue_df = product_revenue.reset_index()
product_revenue_df.columns = ['Product', 'Revenue']
product_revenue_df = product_revenue_df.sort_values(by="Revenue",␣
 ↪ascending=False)
product_revenue_df
```

[28]:
```
           Product  Revenue
0         MntWines   680816
2  MntMeatProducts   373968
5     MntGoldProds    98609
3  MntFishProducts    84057
```

```
4  MntSweetProducts    60621
1         MntFruits    58917
```

[29]:
```python
plt.figure(figsize=(10,6))
sns.barplot(x="Product",
            y="Revenue",
            data=product_revenue_df,
            palette='hls',
            hue="Product"
           )
plt.title("Revenue by Product")
plt.xlabel('Product', fontsize=12)
plt.ylabel('Revenue', fontsize=12)
plt.xticks(rotation=45)
plt.show()
```



3.0.3 Insights

Best performing Product is: `Wine` **with Reveneu of -** `$680816`

Least performing Product is: `Fruits` **with Reveneu of -** `$58917`

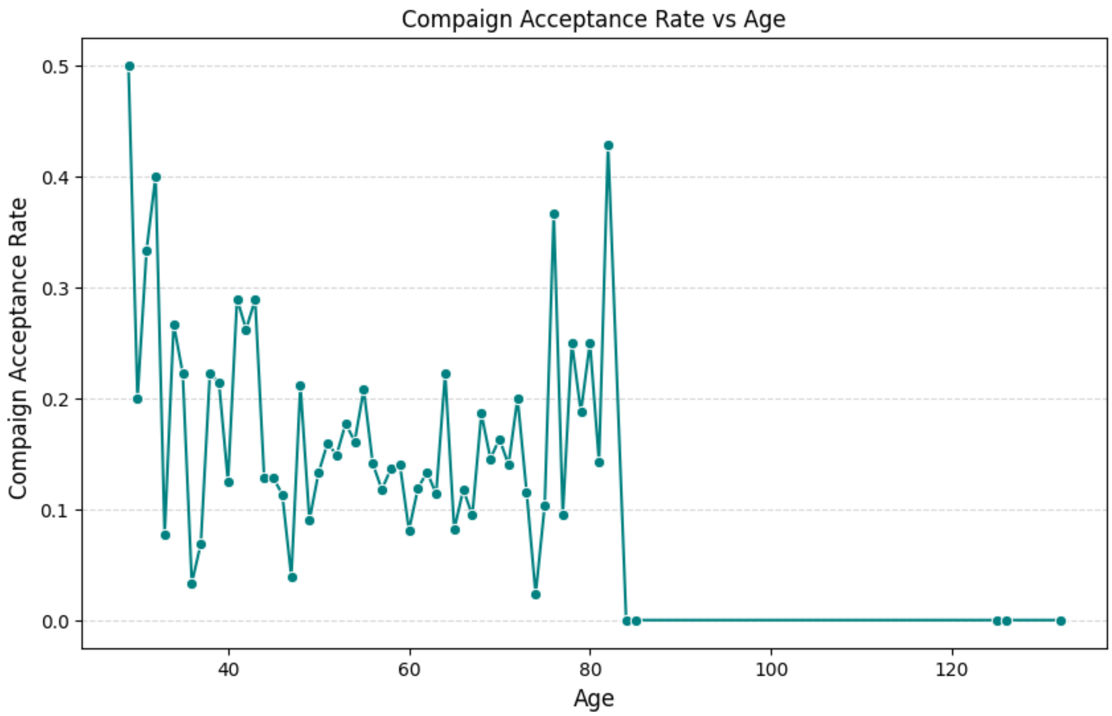
3.0.4 Is there any pattern between the age of customers and the last campaign acceptance rate?

[30]:
```
# createing a df Compaign Acceptance Rate, with the mean of Response grouped by␣
↪Age
df_age_acceptance_rate = df.groupby('Age')['Response'].mean().reset_index()
df_age_acceptance_rate.columns = ['Age', 'Compaign Acceptance Rate']
df_age_acceptance_rate.head()
```

[30]:

	Age	Compaign Acceptance Rate
0	29	0.500000
1	30	0.200000
2	31	0.333333
3	32	0.400000
4	33	0.076923

[31]:
```
# plotting Compaign Acceptance Rate vs Age
plt.figure(figsize=(10,6))
sns.lineplot(
    x='Age',
    y='Compaign Acceptance Rate',
    data=df_age_acceptance_rate,
    marker="o",
    color="teal",
)
plt.title("Compaign Acceptance Rate vs Age")
plt.xlabel("Age", fontsize=12)
plt.ylabel("Compaign Acceptance Rate ", fontsize=12)
plt.grid(axis='y', linestyle="--", alpha=0.5)
plt.show()
```



3.0.5 Insights

People under the age group below 30 accepted more offer. People in the age group (15 to 30), mostly children and younger accepted more offer almost 50% on an average.

There is decrease in acceptance of offer in the age group from (40 to 70)

There is significant rise in the acceptance of offer from (70 to 80) age group.

For the age group above 80, there seems to be no acceptance of offer almost 0%.

3.0.6 Which Country has the greatest number of customers who accepted the last campaign?

[32]:
```
df['Country'].unique()
```

[32]:
```
array(['SP', 'CA', 'US', 'AUS', 'GER', 'IND', 'SA', 'ME'], dtype=object)
```

[33]:
```
# creating a df Last Campaign Acceptance, sum of Response grouped by Country
df_country_by_offer_acceptance = df.groupby("Country")['Response'].sum().
 ↪reset_index()
df_country_by_offer_acceptance.columns = ['Country', "Last Campaign Acceptance"]
df_country_by_offer_acceptance = df_country_by_offer_acceptance.
 ↪sort_values("Last Campaign Acceptance", ascending=False)
```

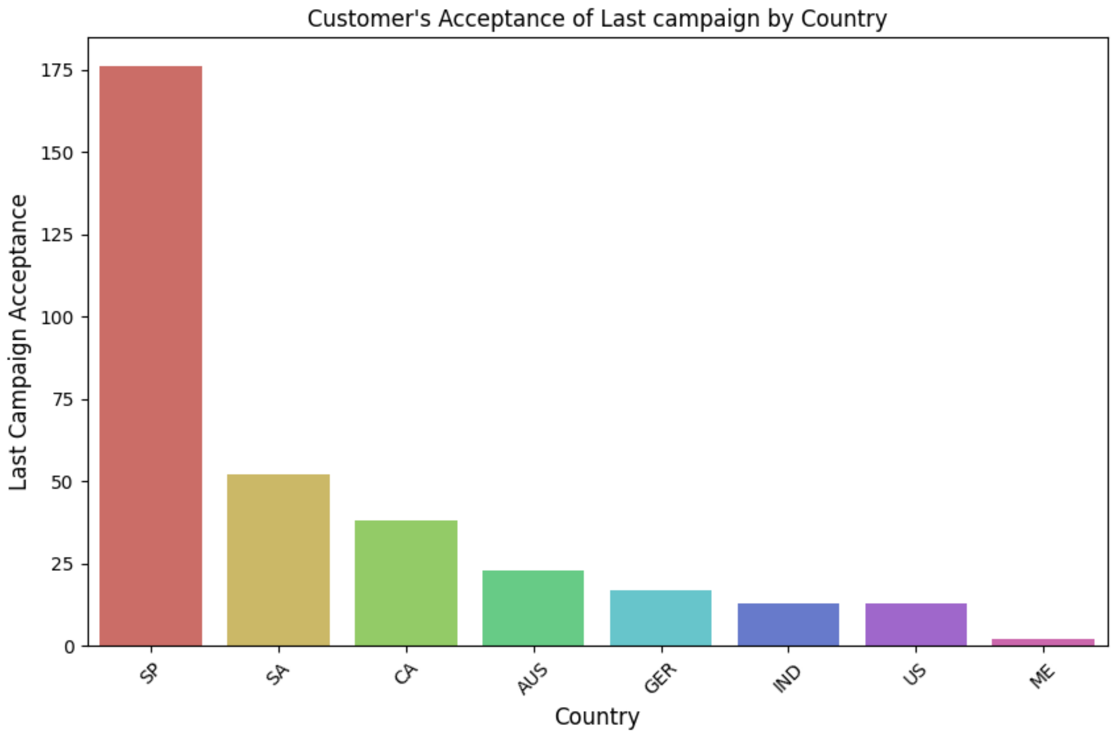
```
df_country_by_offer_acceptance
```

[33]:

	Country	Last Campaign Acceptance
6	SP	176
5	SA	52
1	CA	38
0	AUS	23
2	GER	17
3	IND	13
7	US	13
4	ME	2

[34]:

```
# Plotting Customer's Acceptance of Last campaign by Country
plt.figure(figsize=(10,6))
sns.barplot(
    x="Country",
    y="Last Campaign Acceptance",
    data=df_country_by_offer_acceptance,
    palette="hls",
    hue="Country"
)
plt.title("Customer's Acceptance of Last campaign by Country")
plt.xlabel("Country", fontsize=12)
plt.ylabel("Last Campaign Acceptance", fontsize=12)
plt.xticks(rotation=45)
plt.show()
```



3.0.7 Insight

The country, Spain has highest number of customers who accepted the last campaign.

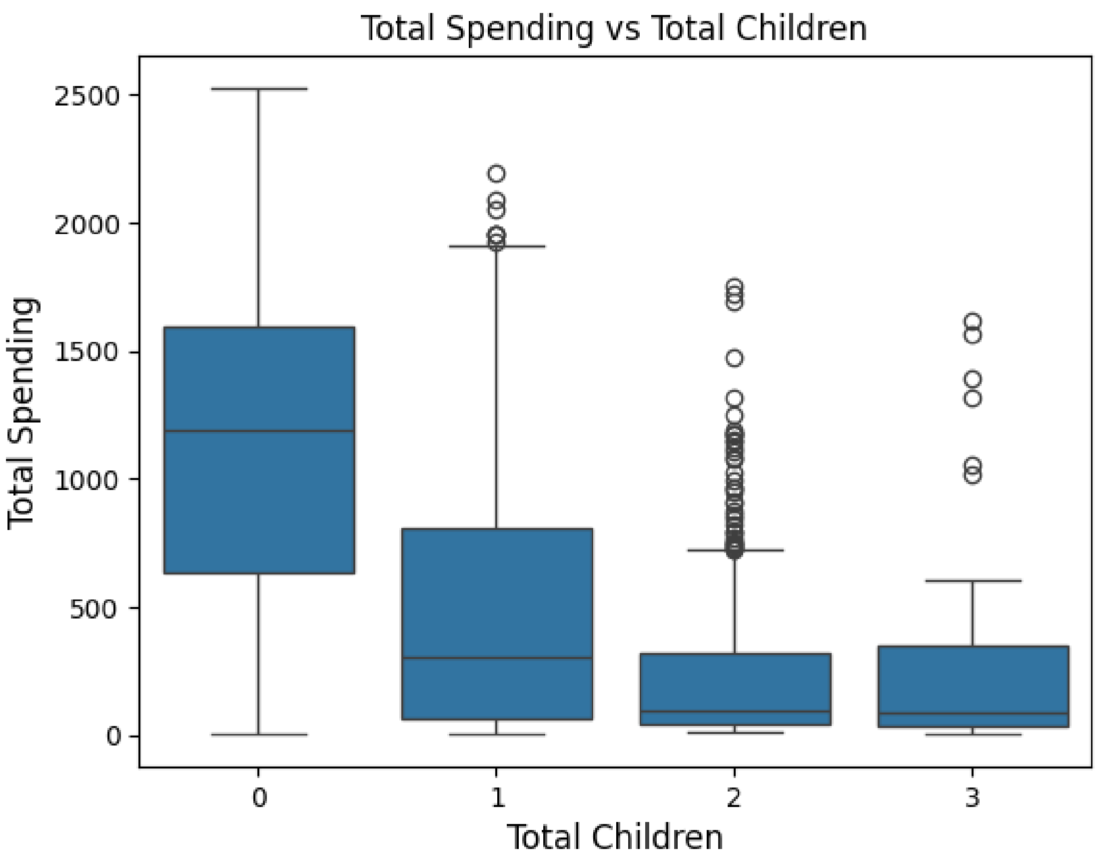
3.0.8 Do you see any pattern in the no. of children at home and total spend?

[35]:
```
df.head()
```

[35]:
```
      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  …  AcceptedCmp2  Response  Complain  \
0        0       189        104  …             0         1         0
1        0       464          5  …             1         1         0
2        0       134         11  …             0         0         0
3        0        10          0  …             0         0         0
4        0         6         16  …             0         1         0

   Country  Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0       SP                   16                      6                  2014
1       CA                   15                      6                  2014
2       US                   13                      5                  2014
3      AUS                   11                      5                  2014
4       SP                    8                      4                  2014

   Total_Children  Age  Total_Spending
0               0   55            1190
1               0   64             577
2               1   67             251
3               2   58              11
4               1   36              91

[5 rows x 33 columns]
```

[36]:
```
# Plotting Total Spending vs Total Children
plt.title("Total Spending vs Total Children")
sns.boxplot(
    x="Total_Children",
    y="Total_Spending",
    data=df
)
```

```
plt.xlabel('Total Children', fontsize=12)
plt.ylabel('Total Spending', fontsize=12)
plt.show()
```



[37]:
```
# calculate IQR and finding outliers
q1 = df['Total_Spending'].quantile(0.25)
q3 = df['Total_Spending'].quantile(0.5)
IQR = q3 - q1

lower_bound = q1 - 1.5* IQR
upper_bound = q3 + 1.5 * IQR

outliers = df[(df['Total_Spending'] < lower_bound) | (df['Total_Spending'] >␣
↪upper_bound)]
print(f"Number of Outliers: {len(outliers)}")
outliers.shape
```

```
Number of Outliers: 708
```

[37]:
```
(708, 33)
```

3.0.9 Insights

Customers with 0 children : Spending more. The higher IQR shows, that there are significant number of customers spending more.

Customers with 1 Child : Spending drops as compared to the customers with 0 children. The IQR shows that significant number of customers spends less than the median spending .

Customer with more than 1 children(2,3) : Spending is very less. The IQR shows that there are significantly more customers who tends to spends less with more than 1 children.

For Customers with 1,2 and 3 children, there are some outliers with count 708, which suggest that, there are few customers with higher spending having 1 or more kids.

3.0.10 Education background of the customers who complained in the last 2 years.

[38]:
```
df['Education'].unique()
```

[38]:
```
array(['Graduation', 'PhD', '2n Cycle', 'Master', 'Basic'], dtype=object)
```

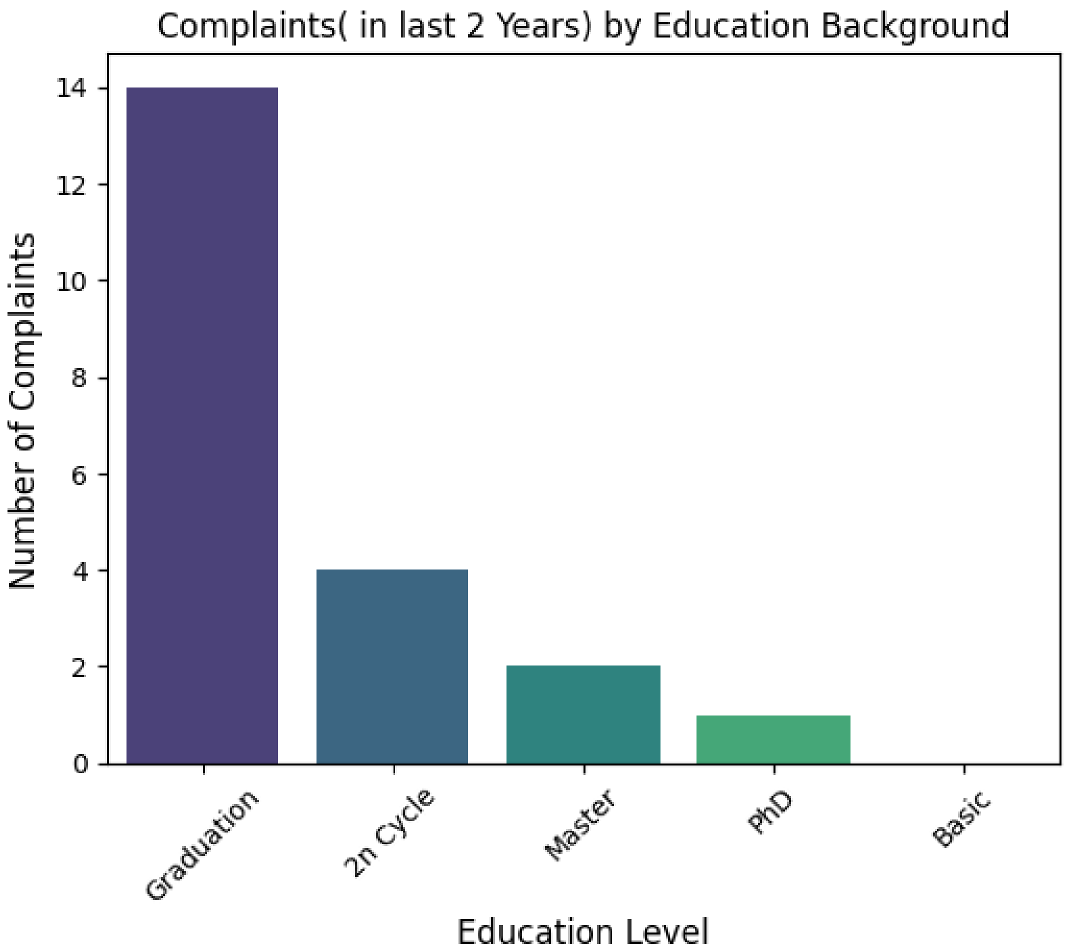
[39]:
```
# education_with_complain df, Sum of complain grouped by Education
df_education_with_complain = df.groupby('Education')['Complain'].sum().
↪reset_index()
df_education_with_complain = df_education_with_complain.sort_values("Complain",␣
↪ascending=False)
df_education_with_complain
```

[39]:

	Education	Complain
2	Graduation	14
0	2n Cycle	4
3	Master	2
4	PhD	1
1	Basic	0

[40]:
```
#Plotting Complaints( in last 2 Years) by Education Background
plt.title("Complaints( in last 2 Years) by Education Background")
sns.barplot(
    x='Education',
    y='Complain',
    data=df_education_with_complain,
    palette='viridis',
    hue='Education'
)
plt.xlabel('Education Level', fontsize=12)
plt.ylabel('Number of Complaints', fontsize=12)
```

```
plt.xticks(rotation=45)
plt.show()
```



3.0.11 Insight

Customer who are Graduated have more number of Complaints in last 2 years.

This indicates that there are high customer service and support required for people who are Graduated.

4 Hypothesis Testing

4.1 1. Problem Statement: Older people are not as tech-savvy and probably prefer shopping in-store.

`Null Hypothesis(H0)` : There is no significant difference in number of store shopping between Younger and Older People

Alternate Hypothesis(H1) : There is significant difference in number of store shopping between Younger and Older People

[41]:
```
df.head(2)
```

[41]:
```
     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

   Recency  MntWines  MntFruits  …  AcceptedCmp2  Response  Complain  \
0        0       189        104  …             0         1         0
1        0       464          5  …             1         1         0

   Country  Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0       SP                   16                      6                  2014
1       CA                   15                      6                  2014

   Total_Children  Age  Total_Spending
0               0   55            1190
1               0   64             577

[2 rows x 33 columns]
```

[42]:
```
df.columns
```

[42]:
```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'AcceptedCmp3',
       'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1', 'AcceptedCmp2',
       'Response', 'Complain', 'Country', 'Day_Customer_Enroll',
       'Month_Customer_Enroll', 'Year_Customer_Enroll', 'Total_Children',
       'Age', 'Total_Spending'],
      dtype='object')
```

[43]:
```
# Creating a Categorical variable of Age Group with two categories Younger(<45)␣
↪and Older(>=45)
df['Age_Group'] = df['Age'].apply(lambda x: 'Younger' if x < 45 else 'Older')
df[['Age_Group', 'NumStorePurchases']].head()
```

[43]:

	Age_Group	NumStorePurchases
0	Older	6
1	Older	7
2	Older	5
3	Older	2
4	Younger	2

[44]:
```
plt.figure(figsize=(10, 6))
sns.boxplot(data=df, x='Age_Group', y='NumStorePurchases', palette='Set2',␣
↪hue='Age_Group')
plt.title("Comparison of Store Purchases by Age Group")
plt.xlabel("Age Group (Younger < 45) (Older>=45)")
plt.ylabel("Number of Store Purchases")
plt.show()
```

4.1.1 Insights

The median in Store purchasing for Older group of customers (>=45) are slightly higher compared to Younger groups. Older customers tends to prefer more In Store Shopping compared to Younger Customers.

4.1.2 T-test to Interpret Number of Web Purchases based on Age Group :

[45]:
```
from scipy.stats import ttest_ind
```

[46]:
```
# creating two groups with Younger and Older with number of store purchases
younger_grp_df = df[df['Age_Group'] == 'Younger'][['NumStorePurchases']].
↪reset_index(drop=True)
older_grp_df = df[df['Age_Group'] == 'Older'][['NumStorePurchases']].
↪reset_index(drop=True)
```

```
print(younger_grp_df.head())
print(older_grp_df.head())
```

```
   NumStorePurchases
0                  2
1                  2
2                  9
3                  3
4                  4
   NumStorePurchases
0                  6
1                  7
2                  5
3                  2
4                  5
```

[47]:

```
#independent t-test
t_stat, p_value = ttest_ind(younger_grp_df, older_grp_df)

print(f"T-statistic: {t_stat[0]:.4f}")
print(f"P-Value: {p_value[0]:.4f}")

#set alpha
alpha = 0.05
if(p_value < alpha):
    print("Rejecting Null Hypothesis : There is significant difference in␣
 ↪number of store shopping between Younger and Older People.")
else :
    print("Failed to Reject Null Hypothesis: There is no significant difference␣
 ↪in number of store shopping between Younger and Older People.")
```

```
T-statistic: -3.4229
P-Value: 0.0006
Rejecting Null Hypothesis : There is significant difference in number of store
shopping between Younger and Older People.
```

4.1.3 Conclusion / Observation

T-Test result indicates significant difference in number of store shopping by age group.

Based on both visual and statistical analysis, older people tends to shop more in store and is not more tech savy.

4.2 2. Problem Statement : Customers with kids probably have less time to visit a store and would prefer to shop online.

`Null Hypothesis(H0)` : There is no significant difference in number of web purchases between Customer with kids and those without kids.

`Alternate Hypothesis(H1)` : There is significant difference in number of web purchases between Customer with kids and those without kids.

[48]:
```
df.head()
```

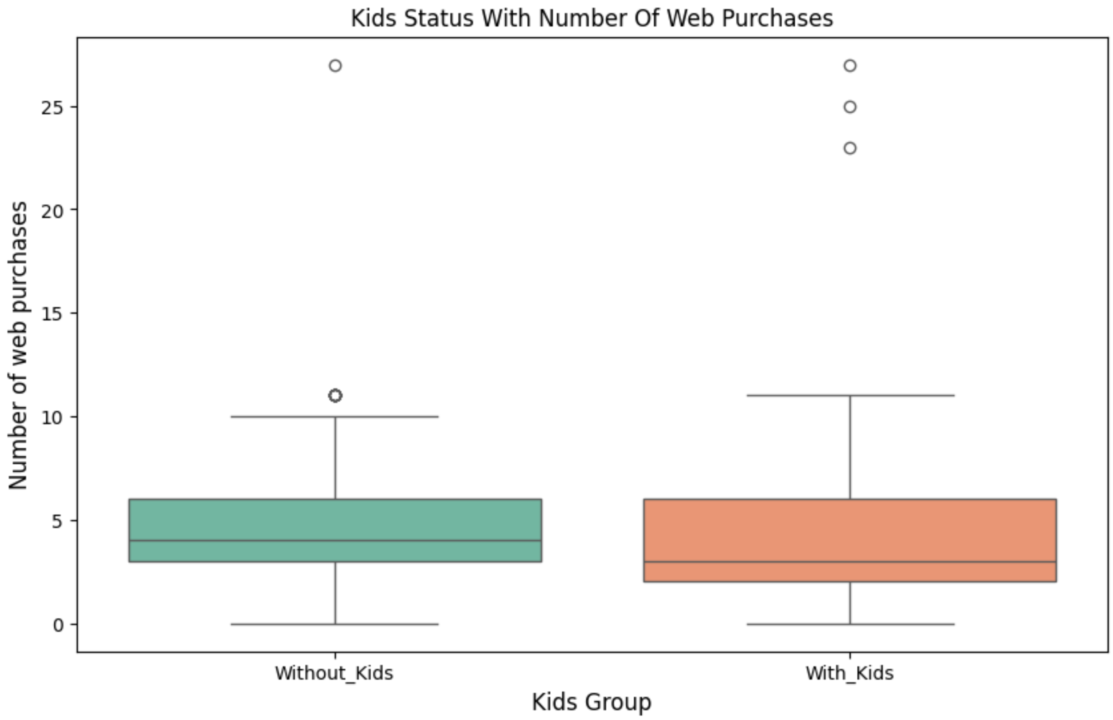
[48]:
```
      ID  Year_Birth   Education Marital_Status   Income  Kidhome  Teenhome  \
0   1826        1970  Graduation       Divorced  84835.0        0         0
1      1        1961  Graduation         Single  57091.0        0         0
2  10476        1958  Graduation        Married  67267.0        0         1
3   1386        1967  Graduation       Together  32474.0        1         1
4   5371        1989  Graduation         Single  21474.0        1         0

   Recency  MntWines  MntFruits  …  Response  Complain  Country  \
0        0       189        104  …         1         0       SP
1        0       464          5  …         1         0       CA
2        0       134         11  …         0         0       US
3        0        10          0  …         0         0      AUS
4        0         6         16  …         1         0       SP

   Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0                   16                      6                  2014
1                   15                      6                  2014
2                   13                      5                  2014
3                   11                      5                  2014
4                    8                      4                  2014

   Total_Children  Age  Total_Spending Age_Group
0               0   55            1190     Older
1               0   64             577     Older
2               1   67             251     Older
3               2   58              11     Older
4               1   36              91   Younger

[5 rows x 34 columns]
```

[49]:
```
df.columns
```

[49]:
```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Recency', 'MntWines', 'MntFruits', 'MntMeatProducts',
       'MntFishProducts', 'MntSweetProducts', 'MntGoldProds',
       'NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
       'NumStorePurchases', 'NumWebVisitsMonth', 'AcceptedCmp3',
       'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1', 'AcceptedCmp2',
       'Response', 'Complain', 'Country', 'Day_Customer_Enroll',
       'Month_Customer_Enroll', 'Year_Customer_Enroll', 'Total_Children',
       'Age', 'Total_Spending', 'Age_Group'],
      dtype='object')
```

[50]:
```
#create a df with Kids_Group with two variables
df['Kids_Group'] = df['Total_Children'].apply(lambda x: 'With_Kids' if x > 0␣
↪else 'Without_Kids')
```

[51]:
```
#Plotting Kids Status With Number Of Web Purchases
plt.figure(figsize=(10,6))
sns.boxplot(x='Kids_Group', y='NumWebPurchases', data=df, palette='Set2',␣
↪hue="Kids_Group")
plt.xlabel("Kids Group", fontsize=12)
plt.ylabel("Number of web purchases", fontsize=12)
plt.title("Kids Status With Number Of Web Purchases")
plt.show()
```



4.2.1 Insights

The median number of purchases for Customer without kids seems bit higher as compared to customers with kids but there is no significant difference in the median of both the groups.

The IQR shows high variablity for Customers with kids as compared to without kids demontrating more prefrence for online purchase.

There are few outliers which suggest extreme number of online shopping for few customers having kids.

4.2.2 T-Test to interpret Number of Web Purchases based on Kids Group

[52]:
```
from scipy.stats import ttest_ind
```

[53]:
```
#Creating two groups with and without kids based on number of web purchases
number_web_purchase_with_kids = df[df['Total_Children'] >␣
↪0][['NumWebPurchases']].reset_index(drop=True)
number_web_purchase_without_kids = df[df['Total_Children'] ==␣
↪0][['NumWebPurchases']].reset_index(drop=True)
```

[54]:
```
# t-test stats for hypothesis
t_stat, p_value = ttest_ind(number_web_purchase_with_kids,␣
↪number_web_purchase_without_kids, equal_var=False)

print(f"T-statistic: {t_stat[0]:.4f}")
print(f"P-Value: {p_value[0]:.4f}")

alpha = 0.5
if(p_value < alpha):
    print("Rejecting Null Hypothesis : There is significant difference in␣
↪number of web purchases for customers having kids with those not having kids.
↪")
else :
    print("Failed to Reject Null Hypothesis: There is no significant difference␣
↪in number of web purchases for customers having kids with those not having␣
↪kids.")
```

```
T-statistic: -3.5419
P-Value: 0.0004
Rejecting Null Hypothesis : There is significant difference in number of web
purchases for customers having kids with those not having kids.
```

4.2.3 Conclusion / Observation

T-Test result indicates significant difference in number of web purchases for Customer with and without kids.

Based on both visual and statistical analysis, customers with kids have probably less time visiting store and prefer more online shopping.

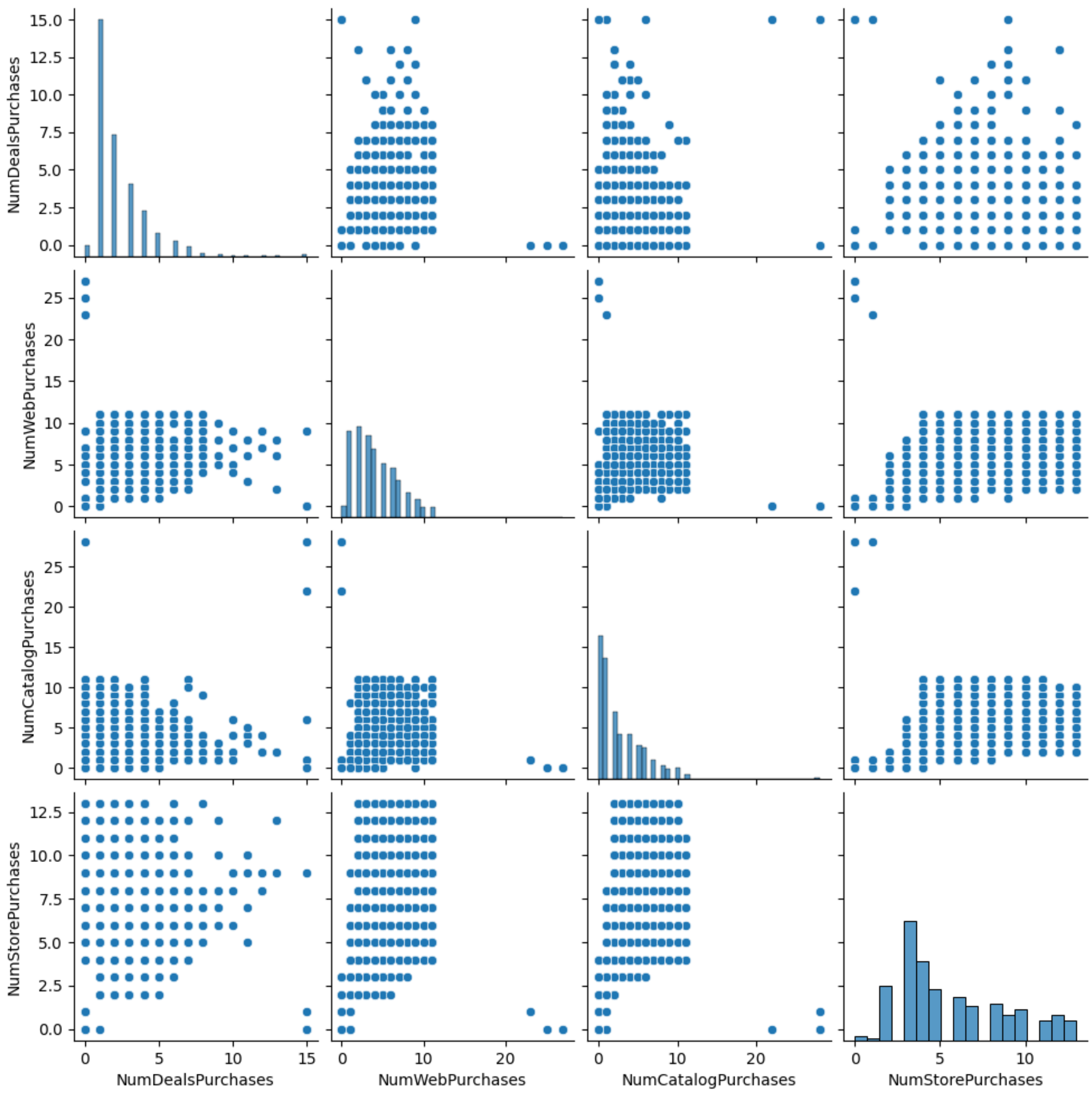
The median number of web purchases for Customer without kids are slightly high, but the customers with kids demonstrate online shoppping behaviour.

4.3 3. Problem Statement : Other distribution channels may cannibalize sales at the store.

`Null Hypothesis(H0)` : The avergae purchases of all the channels are similar.

`Alternate Hypothesis(H1) :` The average purchases of one of the channel is different.

[55]:
```
# Visualization: "Pair plot for all the distribution channel"
sns.pairplot(df[['NumDealsPurchases', 'NumWebPurchases', 'NumCatalogPurchases',
    'NumStorePurchases']])
plt.show()
```



4.3.1 Insights

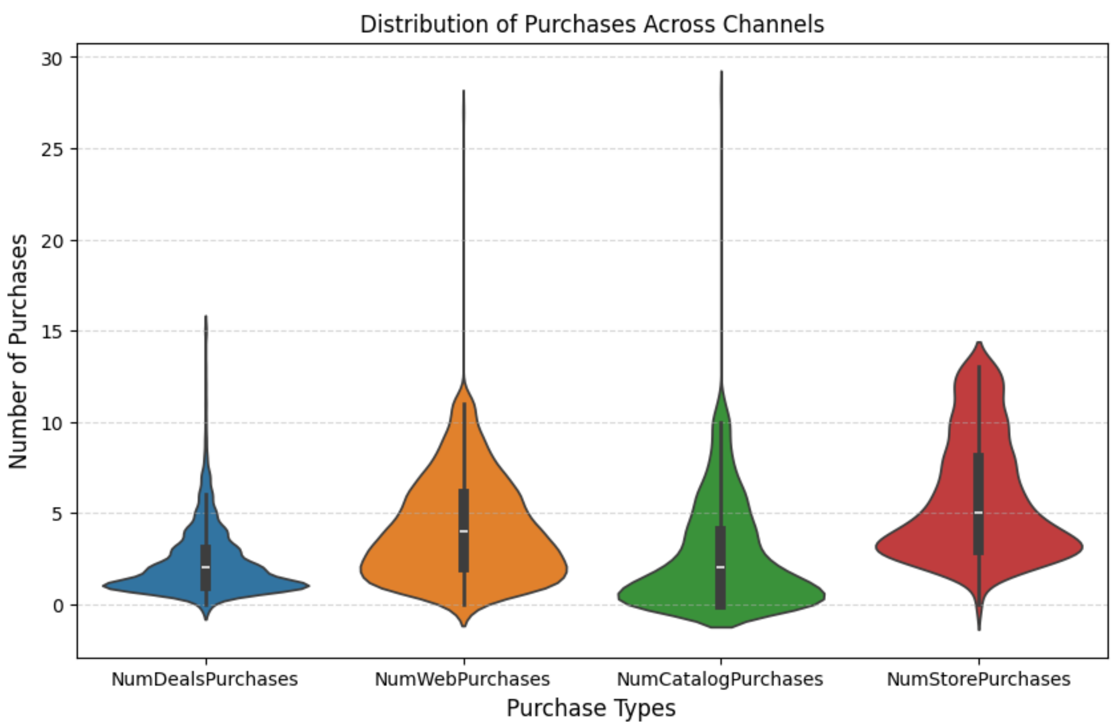
The Historgram along the diagonal, for Number of Store purchases suggest, there are more number of purchases clusterd around 2 to 5 purchases. While there is some skewness when the there are more than 10 purchases, indicating fewer people making large number of purchases in store.

The Scatterplot , Number of Store vs Number of Deals Purchases indicates that there are more number of store purchases when there are more deals.

Number of Store vs Number of Web purchases does not show any correlation between them. This suggests that in store purchase and web purchases customers are different.

Number of Store vs Number of Catelogue purchases does not show any correlation between them. This suggests there are completely different customers preferring on or the other

[56]:
```
# Visualization: "Pair plot for all the distribution channel"
plt.figure(figsize=(10,6))
plt.title("Distribution of Purchases Across Channels")
sns.violinplot(df[['NumDealsPurchases', 'NumWebPurchases',␣
 ↪'NumCatalogPurchases', 'NumStorePurchases']])
plt.grid(axis='y', linestyle="--", alpha=0.5)
plt.xlabel("Purchase Types", fontsize=12)
plt.ylabel("Number of Purchases", fontsize=12)
plt.show()
```



4.3.2 Insights

The Number of Store purchases from the Violin plot seems more consistent and preferred mode of purchases.

The median for Number of Store purchase suggest, there are more pople prefrring byuing in store compared to other channels.

The distrubution suggest most number of purchases (2 to 5) are in store as compared to other channels.

4.3.3 One-Way Anova Test to interpret Variability in Distrubution Channels

[57]:
```
import pandas as pd
from scipy.stats import f_oneway

deals_purchases = df['NumDealsPurchases']
web_purchases = df['NumWebPurchases']
catalog_purchases = df['NumCatalogPurchases']
store_purchases = df['NumStorePurchases']

# one way anova test for all the ditribution channels
anova_result = f_oneway(deals_purchases, web_purchases, catalog_purchases,␣
 ↪store_purchases)

print("ANOVA F-statistic:", anova_result.statistic)
print("ANOVA p-value:", anova_result.pvalue)

# Hypothesis Test
if anova_result.pvalue < 0.05:
    print("The p-value is less than 0.05. We reject the null hypothesis.")
    print("There is a significant difference in the means of at least one␣
 ↪distribution channel.")
else:
    print("The p-value is greater than 0.05. We fail to reject the null␣
 ↪hypothesis.")
    print("There is no significant difference in the means of the distribution␣
 ↪channels.")
```

```
ANOVA F-statistic: 731.2212807584392
ANOVA p-value: 0.0
The p-value is less than 0.05. We reject the null hypothesis.
There is a significant difference in the means of at least one distribution
channel.
```

[58]:
```
from scipy.stats import f_oneway
```

[59]:
```
anova_f_stats, p_value = f_oneway(df['NumDealsPurchases'],
                                  df['NumWebPurchases'],
                                  df['NumCatalogPurchases'],
                                  df['NumStorePurchases'])
print(f"ANOVA F Stats: {anova_f_stats}")
```

```
print(f"ANOVA P value: {p_value}")

alpha = 0.5
if p_value < alpha:
    print("Rejecting Null Hypothesis : The average purchase of all the␣
↪distribution channels are not similar.")
else :
    print("Failed to Reject Null Hypothesis: The average purchase of all the␣
↪distribution channels are similar.")
```

```
ANOVA F Stats: 731.2212807584392
ANOVA P value: 0.0
Rejecting Null Hypothesis : The average purchase of all the distribution
channels are not similar.
```

4.3.4 Conclusion / Observation

One-Way Anova result indicates significant difference in means of distribution channels. There may be chances of one or more distribution channels significantly being high.

The Visualization analysis indicates that In Store Purchase are higher as compared to other channels.

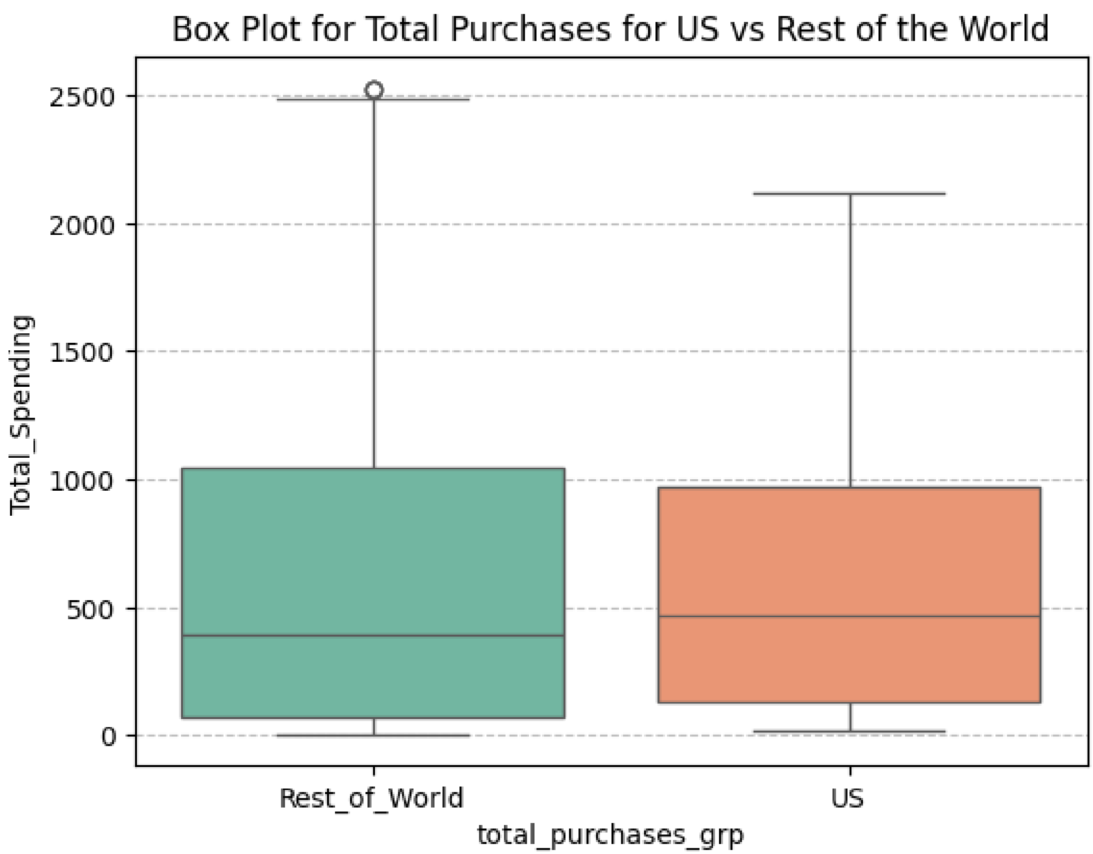
While visualization indicates higher Store purchases, Anova stats indicates variablity in purchases accross channels. Further investigation is needed to confirm the role of other channels cannabalizing the In Store Purchases

4.4 4. Problem Statement : Does the US fare significantly better than the rest of the world in terms of total purchases?.

`Null Hypothesis(H0)` : The mean total purchases of US is equal to the mean of rest of the countries.

`Alternate Hypothesis(H1)` : The mean total purchases of US is not equal to the mean spending of rest of the countries.

[60]:
```
# creating a column for total purchase grouped by US and Rest of the world
df['total_purchases_grp'] = df['Country'].apply(lambda x : 'US' if x == 'US'␣
↪else 'Rest_of_World').reset_index(drop=True)

# bos plot for Total Purchases for US vs Rest of the World
plt.title("Box Plot for Total Purchases for US vs Rest of the World")
sns.boxplot(x='total_purchases_grp', y='Total_Spending', data=df,␣
↪palette='Set2', hue='total_purchases_grp')
plt.grid(axis='y', linestyle="--", alpha=0.8)
plt.show()
```



4.4.1 Insights

Median Spending : The median purchases for US is slightly higher around $500 as compared to Rest of the World.

Spending Variability : The variablity in the Rest of the world suggest, spending behaviour varies slight widely in Rest of the world as compared to US.

The spending of US has lower variablity as compared to the Rest of the World but the overall spending pattern is similar.

There are outliers in Rest of the world that suggest , the some regions contribute to higher spendings around $2500.

4.4.2 Independent T-Stat Test to interpret Total Purchases for US and Rest of World

[61]:
```
US_total_spending = df[df['Country'] == 'US']['Total_Spending']
rest_of_world_spending = df[df['Country'] != 'US']['Total_Spending']
```

[62]:
```python
from scipy.stats import ttest_ind
```

[63]:
```python
# t stat for Hypothesis Test for US vs rest of the world
t_stats, p_value = ttest_ind(US_total_spending, rest_of_world_spending)

print(f"T-statistics: {t_stat[0]:.4f}")
print(f"P Value: {p_value:.4f}")

alpha = 0.05
if(p_value < alpha):
    print("Rejecting Null Hypothesis : The mean of US vs Rest of the world are␣
 ↪significantly different.")
else :
    print("Failed to Reject Null Hypothesis: There is no significant difference␣
 ↪in mean of US vs Rest of the world")
```

```
T-statistics: -3.5419
P Value: 0.7630
Failed to Reject Null Hypothesis: There is no significant difference in mean of
US vs Rest of the world
```

4.4.3 Obeservations / Conclusions

The T-statistics and Visual analysis suggest there is no significant difference in the mean spending of US as compared to Rest of the world.

While the US spending variablity is slightly lower , the overall spending pattern is similar.

5 Feature Engineering : (Data Encoding, Normalization/Standardization)

5.1 Encoding

Encoding is performed after visualization and hypothesis testing to ensure that the categorical variables remain intact and relevant for Visualization and Hypothesis.

Encoding ensures that the categorcial features are transfomed to numeric for machine learning as, machines can only process numerical data for training.

Encoding to be perfomed for Categorical variables : `Education` , `Marital_Status`, `Country`

`NOTE` **: We will drop the features `Age_Group`, `Kids_Group`, and `total_purchases_grp` as these were created for the purpose of analysis from the raw data and the relevant information alread exist in the raw features.**

[64]:
```python
# Dropping Age_Group, Kids_Group, and total_purchases_grp
columns_to_drop = ['Age_Group', 'Kids_Group', 'total_purchases_grp']
```

```
df.drop(columns=columns_to_drop, axis=1, inplace=True)
df.head(2)
```

[64]:
```
     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

   Recency  MntWines  MntFruits  …  AcceptedCmp2  Response  Complain  \
0        0       189        104  …             0         1         0
1        0       464          5  …             1         1         0

   Country  Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0       SP                   16                      6                  2014
1       CA                   15                      6                  2014

   Total_Children  Age  Total_Spending
0               0   55            1190
1               0   64             577

[2 rows x 33 columns]
```

Ordinal Encoding for Education Feature

[65]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 33 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   ID                      2240 non-null   int64
 1   Year_Birth              2240 non-null   int64
 2   Education               2240 non-null   object
 3   Marital_Status          2240 non-null   object
 4   Income                  2240 non-null   float64
 5   Kidhome                 2240 non-null   int64
 6   Teenhome                2240 non-null   int64
 7   Recency                 2240 non-null   int64
 8   MntWines                2240 non-null   int64
 9   MntFruits               2240 non-null   int64
 10  MntMeatProducts         2240 non-null   int64
 11  MntFishProducts         2240 non-null   int64
 12  MntSweetProducts        2240 non-null   int64
 13  MntGoldProds            2240 non-null   int64
 14  NumDealsPurchases       2240 non-null   int64
 15  NumWebPurchases         2240 non-null   int64
 16  NumCatalogPurchases     2240 non-null   int64
 17  NumStorePurchases       2240 non-null   int64
```

```
 18  NumWebVisitsMonth      2240 non-null   int64
 19  AcceptedCmp3           2240 non-null   int64
 20  AcceptedCmp4           2240 non-null   int64
 21  AcceptedCmp5           2240 non-null   int64
 22  AcceptedCmp1           2240 non-null   int64
 23  AcceptedCmp2           2240 non-null   int64
 24  Response               2240 non-null   int64
 25  Complain               2240 non-null   int64
 26  Country                2240 non-null   object
 27  Day_Customer_Enroll    2240 non-null   int32
 28  Month_Customer_Enroll  2240 non-null   int32
 29  Year_Customer_Enroll   2240 non-null   int32
 30  Total_Children         2240 non-null   int64
 31  Age                    2240 non-null   int64
 32  Total_Spending         2240 non-null   int64
dtypes: float64(1), int32(3), int64(26), object(3)
memory usage: 551.4+ KB
```

[66]:
```
df['Education'].unique()
```

[66]:
```
array(['Graduation', 'PhD', '2n Cycle', 'Master', 'Basic'], dtype=object)
```

[67]:
```
from sklearn.preprocessing import OrdinalEncoder
```

[68]:
```
categories = ['Basic', '2n Cycle', 'Graduation', 'Master', 'PhD']
# create an instance of OrdinalEncoder and
ordinal_encoder_education = OrdinalEncoder(categories=[categories])

# applying fit_transform
df['Education_Encoded'] = ordinal_encoder_education.
  ↪fit_transform(df[['Education']])

#drop the education categorical feature
df.drop('Education', axis=1, inplace=True)

# encoded unique values
df['Education_Encoded'].unique()
```

[68]:
```
array([2., 4., 1., 3., 0.])
```

[69]:
```
# Education_encoded feature added to dataset
df.head()
```

[69]:
```
      ID  Year_Birth Marital_Status   Income  Kidhome  Teenhome  Recency  \
0   1826        1970       Divorced  84835.0        0         0        0
1      1        1961         Single  57091.0        0         0        0
2  10476        1958        Married  67267.0        0         1        0
```

```
3   1386          1967       Together  32474.0          1           1          0
4   5371          1989         Single  21474.0          1           0          0

   MntWines  MntFruits  MntMeatProducts  …  Response  Complain  Country  \
0       189        104              379  …         1         0       SP
1       464          5               64  …         1         0       CA
2       134         11               59  …         0         0       US
3        10          0                1  …         0         0      AUS
4         6         16               24  …         1         0       SP

   Day_Customer_Enroll  Month_Customer_Enroll  Year_Customer_Enroll  \
0                   16                      6                  2014
1                   15                      6                  2014
2                   13                      5                  2014
3                   11                      5                  2014
4                    8                      4                  2014

   Total_Children  Age  Total_Spending  Education_Encoded
0               0   55            1190                2.0
1               0   64             577                2.0
2               1   67             251                2.0
3               2   58              11                2.0
4               1   36              91                2.0

[5 rows x 33 columns]
```

[70]:
```
# verify the uniue transformed data for each categories
# suppressing the warning. The below code is just for demonstrating the encoded␣
↪value we got for each education category
warnings.filterwarnings("ignore", category=UserWarning)

for categ in categories:
    encoded_value = ordinal_encoder_education.transform([[categ]])
    print(f"{categ}: {encoded_value[0][0]}")
```

```
Basic: 0.0
2n Cycle: 1.0
Graduation: 2.0
Master: 3.0
PhD: 4.0
```

One Hot Encoding for Country

[71]:
```
df['Country'].unique()
```

[71]:
```
array(['SP', 'CA', 'US', 'AUS', 'GER', 'IND', 'SA', 'ME'], dtype=object)
```

[72]:
```
from sklearn.preprocessing import OneHotEncoder
```

[73]:
```
#create an instance of One Hot Encoder
encoder = OneHotEncoder()
# fit and transform 'Country' column into one-hot encoded array
country_encoded = encoder.fit_transform(df[['Country']]).toarray()
country_encoded
```

[73]:
```
array([[0., 0., 0., …, 0., 1., 0.],
       [0., 1., 0., …, 0., 0., 0.],
       [0., 0., 0., …, 0., 0., 1.],
       …,
       [0., 0., 0., …, 0., 1., 0.],
       [0., 0., 0., …, 0., 0., 0.],
       [0., 1., 0., …, 0., 0., 0.]], shape=(2240, 8))
```

[74]:
```
#convert each encoded columns into data frame with each country features
encoded_country_df = pd.DataFrame(country_encoded, columns=encoder.
 ↪get_feature_names_out())
encoded_country_df.head(5)
```

[74]:
```
   Country_AUS  Country_CA  Country_GER  Country_IND  Country_ME  Country_SA  \
0          0.0         0.0          0.0          0.0         0.0         0.0
1          0.0         1.0          0.0          0.0         0.0         0.0
2          0.0         0.0          0.0          0.0         0.0         0.0
3          1.0         0.0          0.0          0.0         0.0         0.0
4          0.0         0.0          0.0          0.0         0.0         0.0

   Country_SP  Country_US
0         1.0         0.0
1         0.0         0.0
2         0.0         1.0
3         0.0         0.0
4         1.0         0.0
```

[75]:
```
#merge the original data with the enocded columns
df = pd.concat([df, encoded_country_df], axis=1)
#drop the categorical feature 'Country' after the encoded country features␣
 ↪merged
df.drop('Country', axis=1, inplace=True)
df.head()
```

[75]:
```
      ID  Year_Birth Marital_Status   Income  Kidhome  Teenhome  Recency  \
0   1826        1970       Divorced  84835.0        0         0        0
1      1        1961         Single  57091.0        0         0        0
2  10476        1958        Married  67267.0        0         1        0
3   1386        1967       Together  32474.0        1         1        0
4   5371        1989         Single  21474.0        1         0        0
```

```
   MntWines  MntFruits  MntMeatProducts  …  Total_Spending  \
0       189        104              379  …            1190
1       464          5               64  …             577
2       134         11               59  …             251
3        10          0                1  …              11
4         6         16               24  …              91

   Education_Encoded  Country_AUS  Country_CA  Country_GER  Country_IND  \
0                2.0          0.0         0.0          0.0          0.0
1                2.0          0.0         1.0          0.0          0.0
2                2.0          0.0         0.0          0.0          0.0
3                2.0          1.0         0.0          0.0          0.0
4                2.0          0.0         0.0          0.0          0.0

   Country_ME  Country_SA  Country_SP  Country_US
0         0.0         0.0         1.0         0.0
1         0.0         0.0         0.0         0.0
2         0.0         0.0         0.0         1.0
3         0.0         0.0         0.0         0.0
4         0.0         0.0         1.0         0.0

[5 rows x 40 columns]
```

Target Guided Ordinal encoding for Marital Status

Target Guided Ordinal encoding is a technique used to encode categorical variables based on their relationship with the target variable.

In Target Guided Ordinal Encoding, we replace each category in the categorical variable with a numerical value based on the mean or median of the target variable for that category. This creates a monotonic relationship between the categorical variable and the target variable, which can improve our model's predication.

Here in the dataset we will perform the Target Guided Ordinal Encoding with the categorical Variable 'Marital Status' and Target Variable 'Total_Spending'. We will get the mean of the 'Total Spending' for the group of 'Marital Status'. This will ensure a better model predication where the relationship of this 'Marital Status' category and Total Spending is retained.

[76]:
```python
df['Marital_Status'].unique()
```

[76]:
```
array(['Divorced', 'Single', 'Married', 'Together', 'Widow', 'YOLO',
       'Alone', 'Absurd'], dtype=object)
```

[77]:
```python
# mean of total spending grouped by marital status
mean_spending = df.groupby('Marital_Status')['Total_Spending'].mean().round(4)
```

```
mean_spending
```

[77]:
```
Marital_Status
Absurd      1192.5000
Alone        256.6667
Divorced     610.6293
Married      590.8021
Single       606.4833
Together     608.3879
Widow        738.8182
YOLO         424.0000
Name: Total_Spending, dtype: float64
```

[78]:
```
# Marital Status encoded feature with mean of each group
df['Marital_Status_Encoded'] = df['Marital_Status'].map(mean_spending)

#dropping categorical feature Marital_Status after encoding
df.drop('Marital_Status', axis=1, inplace=True)
df.head()
```

[78]:
```
      ID  Year_Birth   Income  Kidhome  Teenhome  Recency  MntWines  \
0   1826        1970  84835.0        0         0        0       189
1      1        1961  57091.0        0         0        0       464
2  10476        1958  67267.0        0         1        0       134
3   1386        1967  32474.0        1         1        0        10
4   5371        1989  21474.0        1         0        0         6

   MntFruits  MntMeatProducts  MntFishProducts  …  Education_Encoded  \
0        104              379              111  …                2.0
1          5               64                7  …                2.0
2         11               59               15  …                2.0
3          0                1                0  …                2.0
4         16               24               11  …                2.0

   Country_AUS  Country_CA  Country_GER  Country_IND  Country_ME  Country_SA  \
0          0.0         0.0          0.0          0.0         0.0         0.0
1          0.0         1.0          0.0          0.0         0.0         0.0
2          0.0         0.0          0.0          0.0         0.0         0.0
3          1.0         0.0          0.0          0.0         0.0         0.0
4          0.0         0.0          0.0          0.0         0.0         0.0

   Country_SP  Country_US  Marital_Status_Encoded
0         1.0         0.0                610.6293
1         0.0         0.0                606.4833
2         0.0         1.0                590.8021
3         0.0         0.0                608.3879
4         1.0         0.0                606.4833
```

```
[5 rows x 40 columns]
```

[79]:
```
# All the categorical features encoded into numerical
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 40 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   ID                      2240 non-null   int64
 1   Year_Birth              2240 non-null   int64
 2   Income                  2240 non-null   float64
 3   Kidhome                 2240 non-null   int64
 4   Teenhome                2240 non-null   int64
 5   Recency                 2240 non-null   int64
 6   MntWines                2240 non-null   int64
 7   MntFruits               2240 non-null   int64
 8   MntMeatProducts         2240 non-null   int64
 9   MntFishProducts         2240 non-null   int64
 10  MntSweetProducts        2240 non-null   int64
 11  MntGoldProds            2240 non-null   int64
 12  NumDealsPurchases       2240 non-null   int64
 13  NumWebPurchases         2240 non-null   int64
 14  NumCatalogPurchases     2240 non-null   int64
 15  NumStorePurchases       2240 non-null   int64
 16  NumWebVisitsMonth       2240 non-null   int64
 17  AcceptedCmp3            2240 non-null   int64
 18  AcceptedCmp4            2240 non-null   int64
 19  AcceptedCmp5            2240 non-null   int64
 20  AcceptedCmp1            2240 non-null   int64
 21  AcceptedCmp2            2240 non-null   int64
 22  Response                2240 non-null   int64
 23  Complain                2240 non-null   int64
 24  Day_Customer_Enroll     2240 non-null   int32
 25  Month_Customer_Enroll   2240 non-null   int32
 26  Year_Customer_Enroll    2240 non-null   int32
 27  Total_Children          2240 non-null   int64
 28  Age                     2240 non-null   int64
 29  Total_Spending          2240 non-null   int64
 30  Education_Encoded       2240 non-null   float64
 31  Country_AUS             2240 non-null   float64
 32  Country_CA              2240 non-null   float64
 33  Country_GER             2240 non-null   float64
 34  Country_IND             2240 non-null   float64
 35  Country_ME              2240 non-null   float64
```

```
 36  Country_SA              2240 non-null   float64
 37  Country_SP              2240 non-null   float64
 38  Country_US              2240 non-null   float64
 39  Marital_Status_Encoded  2240 non-null   float64
dtypes: float64(11), int32(3), int64(26)
memory usage: 673.9 KB
```

5.1.1 Normalization / Standardization

`Normalization for Income :` Performing normalization for Income feature, as Income is expected to have bounded range and would follow normal ditribution with less variance. `Normalization will scale the values to range [0 to 1]`

`Standardization for Total Spending and Amount spent on items:` The features, MntWines, MntFruits, MntMeatProducts, MntFishProducts, MntSweetProducts, MntGoldProds and Total Spending may vary widely and would not follow a normal ditribution so Standardization here centers the ditribution around their mean(`mean of 0`) and scales them to unit variance(`standard deviation of 1`), ensuring consistency.

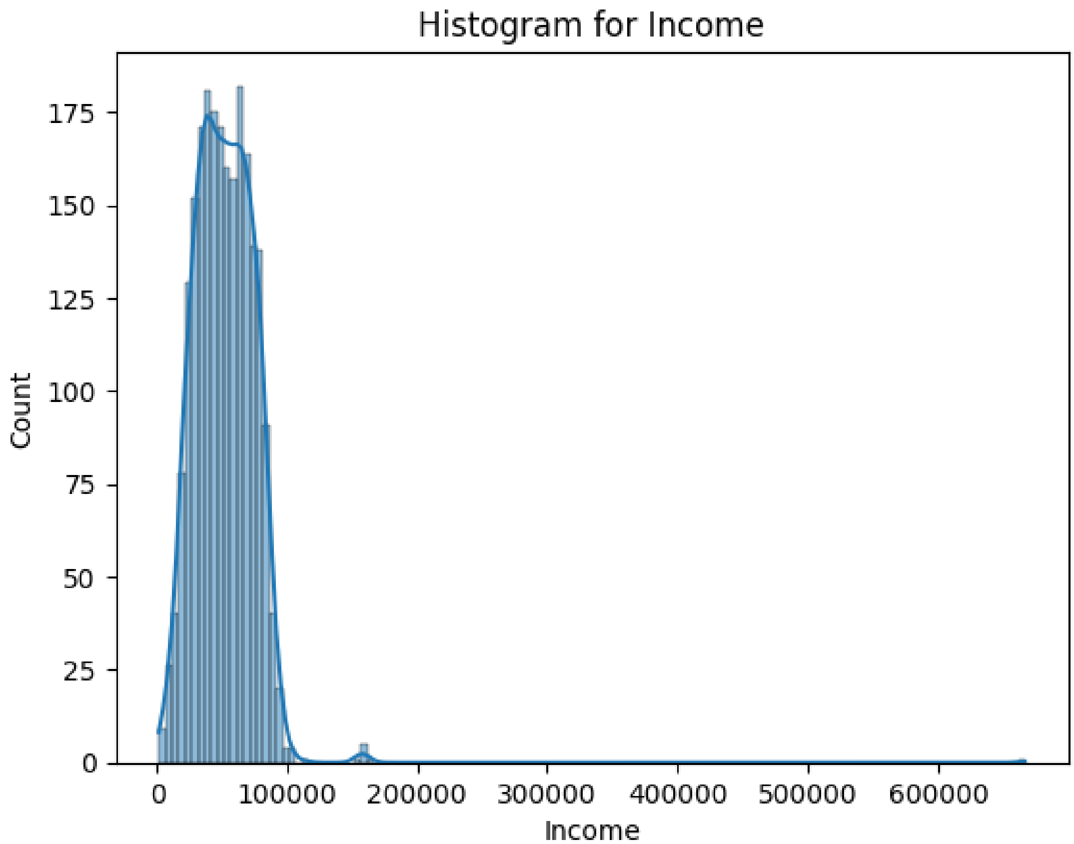
Normalization : Income Feature

[80]:
```
df[['Income']].head()
```

[80]:

	Income
0	84835.0
1	57091.0
2	67267.0
3	32474.0
4	21474.0

[81]:
```
# Plotting Histogram of Income shows bell curve with slightly postive skewed
plt.title("Histogram for Income")
sns.histplot(data=df, x='Income', kde=True)
plt.show()
```



[82]:
```
from sklearn.preprocessing import MinMaxScaler
```

[83]:
```
# initializae MinMaxScaler
scaler = MinMaxScaler()

#Normalize income fe and add it to the datframe
df['Income_Normalized'] = scaler.fit_transform(df[['Income']]).round(4)

#dropping original income feature
df.drop('Income', axis=1, inplace=True)
df.head()
```

[83]:
```
      ID  Year_Birth  Kidhome  Teenhome  Recency  MntWines  MntFruits  \
0   1826        1970        0         0        0       189        104
1      1        1961        0         0        0       464          5
2  10476        1958        0         1        0       134         11
3   1386        1967        1         1        0        10          0
4   5371        1989        1         0        0         6         16

   MntMeatProducts  MntFishProducts  MntSweetProducts  …  Country_AUS  \
```

```
0                379            111            189  ...          0.0
1                 64              7              0  ...          0.0
2                 59             15              2  ...          0.0
3                  1              0              0  ...          1.0
4                 24             11              0  ...          0.0

   Country_CA  Country_GER  Country_IND  Country_ME  Country_SA  Country_SP  \
0         0.0          0.0          0.0         0.0         0.0         1.0
1         1.0          0.0          0.0         0.0         0.0         0.0
2         0.0          0.0          0.0         0.0         0.0         0.0
3         0.0          0.0          0.0         0.0         0.0         0.0
4         0.0          0.0          0.0         0.0         0.0         1.0

   Country_US  Marital_Status_Encoded  Income_Normalized
0         0.0                610.6293             0.1250
1         0.0                606.4833             0.0833
2         1.0                590.8021             0.0986
3         0.0                608.3879             0.0462
4         0.0                606.4833             0.0297

[5 rows x 40 columns]
```

Standardization : Total Spending and Amount Spent on Items Features

[84]:
```python
from sklearn.preprocessing import StandardScaler
```

[85]:
```python
columns_to_standardize = ['Total_Spending', 'MntWines', 'MntFruits',␣
 ↪'MntMeatProducts',
                          'MntFishProducts', 'MntSweetProducts', 'MntGoldProds']

#initialize Standard scaler
scaler = StandardScaler()

#standardize columns
standardized_data = scaler.fit_transform(df[columns_to_standardize]).round(4)
standardized_df = pd.DataFrame(standardized_data,␣
 ↪columns=[f"{col}_Standardized" for col in columns_to_standardize])
standardized_df.head()
```

[85]:
```
   Total_Spending_Standardized  MntWines_Standardized  MntFruits_Standardized  \
0                       0.9702                -0.3415                  1.9539
1                      -0.0478                 0.4756                 -0.5357
2                      -0.5893                -0.5050                 -0.3848
3                      -0.9878                -0.8735                 -0.6614
4                      -0.8550                -0.8853                 -0.2591

   MntMeatProducts_Standardized  MntFishProducts_Standardized  \
```

```
0                      0.9397                         1.3453
1                     -0.4562                        -0.5589
2                     -0.4784                        -0.4124
3                     -0.7354                        -0.6871
4                     -0.6335                        -0.4857

   MntSweetProducts_Standardized  MntGoldProds_Standardized
0                         3.9237                     3.3357
1                        -0.6557                    -0.1346
2                        -0.6073                    -0.2688
3                        -0.6557                    -0.8440
4                        -0.6557                    -0.1922
```

[86]:
```
#add new standardized df to the original df
df = pd.concat([df, standardized_df], axis=1)
# drop original items spending features
df.drop(columns=columns_to_standardize, inplace=True)
df.head()
```

[86]:
```
      ID  Year_Birth  Kidhome  Teenhome  Recency  NumDealsPurchases  \
0   1826        1970        0         0        0                  1
1      1        1961        0         0        0                  1
2  10476        1958        0         1        0                  1
3   1386        1967        1         1        0                  1
4   5371        1989        1         0        0                  2

   NumWebPurchases  NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  \
0                4                    4                  6                  1
1                7                    3                  7                  5
2                3                    2                  5                  2
3                1                    0                  2                  7
4                3                    1                  2                  7

   …  Country_US  Marital_Status_Encoded  Income_Normalized  \
0  …         0.0                610.6293             0.1250
1  …         0.0                606.4833             0.0833
2  …         1.0                590.8021             0.0986
3  …         0.0                608.3879             0.0462
4  …         0.0                606.4833             0.0297

   Total_Spending_Standardized  MntWines_Standardized  MntFruits_Standardized  \
0                       0.9702                -0.3415                  1.9539
1                      -0.0478                 0.4756                 -0.5357
2                      -0.5893                -0.5050                 -0.3848
3                      -0.9878                -0.8735                 -0.6614
4                      -0.8550                -0.8853                 -0.2591
```

```
   MntMeatProducts_Standardized  MntFishProducts_Standardized  \
0                        0.9397                        1.3453
1                       -0.4562                       -0.5589
2                       -0.4784                       -0.4124
3                       -0.7354                       -0.6871
4                       -0.6335                       -0.4857

   MntSweetProducts_Standardized  MntGoldProds_Standardized
0                         3.9237                     3.3357
1                        -0.6557                    -0.1346
2                        -0.6073                    -0.2688
3                        -0.6557                    -0.8440
4                        -0.6557                    -0.1922

[5 rows x 40 columns]
```

Note: Perfoming `Standardization` on feature `Marital_Status_Encoded` as the Encoded mean value for Marital_Status is large and would affect the perormance during model training

[87]:
```python
scaler = StandardScaler()
df['Marital_Status_Standardized'] = scaler.
 ↪fit_transform(df[['Marital_Status_Encoded']]).round(4)
df.drop(columns=['Marital_Status_Encoded'], axis=1, inplace=True)
df.head()
```

[87]:
```
      ID  Year_Birth  Kidhome  Teenhome  Recency  NumDealsPurchases  \
0   1826        1970        0         0        0                  1
1      1        1961        0         0        0                  1
2  10476        1958        0         1        0                  1
3   1386        1967        1         1        0                  1
4   5371        1989        1         0        0                  2

   NumWebPurchases  NumCatalogPurchases  NumStorePurchases  NumWebVisitsMonth  \
0                4                    4                  6                  1
1                7                    3                  7                  5
2                3                    2                  5                  2
3                1                    0                  2                  7
4                3                    1                  2                  7

   …  Country_US  Income_Normalized  Total_Spending_Standardized  \
0  …         0.0             0.1250                       0.9702
1  …         0.0             0.0833                      -0.0478
2  …         1.0             0.0986                      -0.5893
3  …         0.0             0.0462                      -0.9878
4  …         0.0             0.0297                      -0.8550
```

```
   MntWines_Standardized  MntFruits_Standardized  \
0                -0.3415                  1.9539
1                 0.4756                 -0.5357
2                -0.5050                 -0.3848
3                -0.8735                 -0.6614
4                -0.8853                 -0.2591

   MntMeatProducts_Standardized  MntFishProducts_Standardized  \
0                        0.9397                        1.3453
1                       -0.4562                       -0.5589
2                       -0.4784                       -0.4124
3                       -0.7354                       -0.6871
4                       -0.6335                       -0.4857

   MntSweetProducts_Standardized  MntGoldProds_Standardized  \
0                         3.9237                     3.3357
1                        -0.6557                    -0.1346
2                        -0.6073                    -0.2688
3                        -0.6557                    -0.8440
4                        -0.6557                    -0.1922

   Marital_Status_Standardized
0                       0.1395
1                       0.0198
2                      -0.4330
3                       0.0748
4                       0.0198

[5 rows x 40 columns]
```

[88]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 2240 entries, 0 to 2239
Data columns (total 40 columns):
 #   Column                         Non-Null Count  Dtype
---  ------                         --------------  -----
 0   ID                             2240 non-null   int64
 1   Year_Birth                     2240 non-null   int64
 2   Kidhome                        2240 non-null   int64
 3   Teenhome                       2240 non-null   int64
 4   Recency                        2240 non-null   int64
 5   NumDealsPurchases              2240 non-null   int64
 6   NumWebPurchases                2240 non-null   int64
 7   NumCatalogPurchases            2240 non-null   int64
 8   NumStorePurchases              2240 non-null   int64
 9   NumWebVisitsMonth              2240 non-null   int64
```

```
 10  AcceptedCmp3                2240 non-null   int64
 11  AcceptedCmp4                2240 non-null   int64
 12  AcceptedCmp5                2240 non-null   int64
 13  AcceptedCmp1                2240 non-null   int64
 14  AcceptedCmp2                2240 non-null   int64
 15  Response                    2240 non-null   int64
 16  Complain                    2240 non-null   int64
 17  Day_Customer_Enroll         2240 non-null   int32
 18  Month_Customer_Enroll       2240 non-null   int32
 19  Year_Customer_Enroll        2240 non-null   int32
 20  Total_Children              2240 non-null   int64
 21  Age                         2240 non-null   int64
 22  Education_Encoded           2240 non-null   float64
 23  Country_AUS                 2240 non-null   float64
 24  Country_CA                  2240 non-null   float64
 25  Country_GER                 2240 non-null   float64
 26  Country_IND                 2240 non-null   float64
 27  Country_ME                  2240 non-null   float64
 28  Country_SA                  2240 non-null   float64
 29  Country_SP                  2240 non-null   float64
 30  Country_US                  2240 non-null   float64
 31  Income_Normalized           2240 non-null   float64
 32  Total_Spending_Standardized    2240 non-null   float64
 33  MntWines_Standardized       2240 non-null   float64
 34  MntFruits_Standardized      2240 non-null   float64
 35  MntMeatProducts_Standardized   2240 non-null   float64
 36  MntFishProducts_Standardized   2240 non-null   float64
 37  MntSweetProducts_Standardized  2240 non-null   float64
 38  MntGoldProds_Standardized   2240 non-null   float64
 39  Marital_Status_Standardized    2240 non-null   float64
dtypes: float64(18), int32(3), int64(19)
memory usage: 673.9 KB
```

[90]:

```
# Saving the final dataset after Cleaning, Feature Engineering(Encoding,
 ↪Normalizing and Standardizing)
# the relvant features for model training

#  Save file in csv
df.to_csv('marketing_data_final.csv', index=False)

# Save file in pickle(pkl) for faster loading in python for model training
df.to_pickle('marketing_data_final.pkl')

print("File saved successfully")
```

```
File saved successfully
```