E-commerce_Python EDA: Campaign

Step-1: Importing Python Libraries

In [249…
```
# importing libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy import stats
from sklearn.preprocessing import LabelEncoder, StandardScaler
from sklearn.impute import SimpleImputer

# warnings
import warnings
warnings.filterwarnings('ignore')

#Hypothesis Testing
from scipy.stats import shapiro, ttest_ind, mannwhitneyu, f_oneway, chi2_contingenc
```

Step-2: Reading the Dataset

1. Loading the data
2. Analyzing the data
3. Checking for duplicates
4. Missing Value Calculation

In [250…
```
df = pd.read_csv('/content/campaign - campaign - campaign - campaign.csv')
```

In [251…
```
df.shape
```

Out[251]:
```
(2239, 27)
```

In [252…
```
df.head()
```

Out[252]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	R
0	1826	1970	Graduation	Divorced	$84,835.00	0	0	6/16/14	
1	1	1961	Graduation	Single	$57,091.00	0	0	6/15/14	
2	10476	1958	Graduation	Married	$67,267.00	0	1	5/13/14	
3	1386	1967	Graduation	Together	$32,474.00	1	1	5/11/14	
4	5371	1989	Graduation	Single	$21,474.00	1	0	4/8/14	

5 rows × 27 columns

In [253…
```
df.tail()
```

Out[253]:

	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer
2234	10142	1976	PhD	Divorced	$66,476.00	0	1	3/7/13
2235	5263	1977	2n Cycle	Married	$31,056.00	1	0	1/22/13
2236	22	1976	Graduation	Divorced	$46,310.00	1	0	12/3/12
2237	528	1978	Graduation	Married	$65,819.00	0	0	11/29/12
2238	4070	1969	PhD	Married	$94,871.00	0	2	9/1/12

5 rows × 27 columns

In [254…

```
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
```

In [255…

```
df.nunique()
```

Out[255]:

	0
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

dtype: int64

In [256…
```
df.duplicated().sum()
```

Out[256]:
```
0
```

In [257…
```
df.isna().sum()
```

Out[257]:

	0
ID	0
Year_Birth	0
Education	0
Marital_Status	0
Income	0
Kidhome	0
Teenhome	0
Dt_Customer	0
Recency	0
MntWines	0
MntFruits	0
MntMeatProducts	0
MntFishProducts	0
MntSweetProducts	0
MntGoldProds	0
NumDealsPurchases	0
NumWebPurchases	0
NumCatalogPurchases	0
NumStorePurchases	0
NumWebVisitsMonth	0
AcceptedCmp3	0
AcceptedCmp4	0
AcceptedCmp5	0
AcceptedCmp1	0
AcceptedCmp2	0
Complain	0
Country	0

dtype: int64

Observations:

- Shape: Data has 2239 rows and 27 columns.
- Duplicates: No Duplicates found
- Missing values: No Missing values

Step-3: Data Reduction

In [258...
```
# Dropping the primary key column 'ID' since it's not useful for analysis
df = df.drop(['ID'], axis=1)
```

Observations:

- Removed the ID column since it's not necessary for analysis.

Step-4: Feature Engineering

In [259...
```
# Remove '$' and ',' from 'Income' and convert to numeric
df['Income'] = pd.to_numeric(df['Income'].str.replace('[\$,]', '', regex=True), err
```

In [260...
```
# Convert 'Dt_Customer' to datetime format and create a 'Customer_Year' feature
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'])
df['Customer_Year'] = pd.DatetimeIndex(df['Dt_Customer']).year
```

Observation:

- Transformed Income and Dt_Customer columns into usable formats.

Step-5: Creating Features

In [261...
```
df['Total_Spending'] = df[['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProd
```

In [262...
```
df['Couple_Status'] = df['Marital_Status'].replace({
    'Married': 'In couple', 'Together': 'In couple',
    'Single': 'Alone', 'Divorced': 'Alone', 'Widow': 'Alone',
    'Absurd': 'Alone', 'YOLO': 'Alone'
})
```

In [263...
```
df['Accepted_Any_Campaign'] = df[['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', '
```

In [264...
```
df['Age'] = 2024 - df['Year_Birth']
```

Observation:

- Created new features to capture total spending, couple status, age and campaign acceptance.

Step-6 Data Cleaning

In [265...
```
# Correct any obvious data entry errors (example for 'Year_Birth')
df = df[df['Year_Birth'] > 1900]  # Removing erroneous birth years
```

Step-7: EDA - Statistical Summary

In [266...
```
df.describe().T
```

Out[266]:

	count	mean	min	25%	50%	75%	max
Year_Birth	2236.0	1968.898032	1940.0	1959.0	1970.0	1977.0	1996.0
Income	2212.0	51958.810579	1730.0	35233.5	51371.0	68487.0	162397.0
Kidhome	2236.0	0.444097	0.0	0.0	0.0	1.0	2.0
Teenhome	2236.0	0.506708	0.0	0.0	0.0	1.0	2.0
Dt_Customer	2236	2013-07-10 05:26:30.697674496	2012-07-30 00:00:00	2013-01-16 00:00:00	2013-07-08 00:00:00	2013-12-30 06:00:00	2014-06-29 00:00:00
Recency	2236.0	49.116279	0.0	24.0	49.0	74.0	99.0
MntWines	2236.0	304.12746	0.0	24.0	174.0	504.25	1493.0
MntFruits	2236.0	26.275939	0.0	1.0	8.0	33.0	199.0
MntMeatProducts	2236.0	166.983453	0.0	16.0	67.0	232.0	1725.0
MntFishProducts	2236.0	37.536225	0.0	3.0	12.0	50.0	259.0
MntSweetProducts	2236.0	27.080501	0.0	1.0	8.0	33.0	263.0
MntGoldProds	2236.0	43.983005	0.0	9.0	24.0	56.0	362.0
NumDealsPurchases	2236.0	2.326029	0.0	1.0	2.0	3.0	15.0
NumWebPurchases	2236.0	4.087657	0.0	2.0	4.0	6.0	27.0
NumCatalogPurchases	2236.0	2.663238	0.0	0.0	2.0	4.0	28.0
NumStorePurchases	2236.0	5.795617	0.0	3.0	5.0	8.0	13.0
NumWebVisitsMonth	2236.0	5.318873	0.0	3.0	6.0	7.0	20.0
AcceptedCmp3	2236.0	0.072898	0.0	0.0	0.0	0.0	1.0
AcceptedCmp4	2236.0	0.074687	0.0	0.0	0.0	0.0	1.0
AcceptedCmp5	2236.0	0.072451	0.0	0.0	0.0	0.0	1.0
AcceptedCmp1	2236.0	0.064401	0.0	0.0	0.0	0.0	1.0
AcceptedCmp2	2236.0	0.013417	0.0	0.0	0.0	0.0	1.0
Complain	2236.0	0.008945	0.0	0.0	0.0	0.0	1.0
Customer_Year	2236.0	2013.027728	2012.0	2013.0	2013.0	2013.0	2014.0
Total_Spending	2236.0	605.986583	5.0	69.0	396.5	1045.5	2525.0
Age	2236.0	55.101968	28.0	47.0	54.0	65.0	84.0

In [267…

```
df.describe(include=['object']).T
```

Out[267]:

	count	unique	top	freq
Education	2236	5	Graduation	1126
Marital_Status	2236	8	Married	864
Country	2236	8	SP	1094
Couple_Status	2236	2	In couple	1442

Step-9: Separate Numerical, Categorical, and Target Columns

In [268…
```
# Identify numerical and categorical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

# Target Columns (based on your project needs)
target_cols = ['Accepted_Any_Campaign']

df.drop(columns=['AcceptedCmp1', 'AcceptedCmp2', 'AcceptedCmp3', 'AcceptedCmp4', 'A
```

Step-10 EDA - Non-Graphical Analysis

Helper Functions

In [269…
```
# Function to print basic useful details for a given column
def get_column_details(df,column):
    print("Details of",column,"column")

    #DataType of column
    print("\nDataType: ",df[column].dtype)

    #Check if null values are present
    count_null = df[column].isnull().sum()
    if count_null==0:
        print("\nThere are no null values")
    elif count_null>0:
        print("\nThere are ",count_null," null values")

    #Get Number of Unique Values
    print("\nNumber of Unique Values: ",df[column].nunique())

    #Get Distribution of Column
    print("\nDistribution of column:\n")
    print(df[column].value_counts())
```

In [270…
```
for col in df.columns:
    get_column_details(df,col)
```

```
Details of Year_Birth column

DataType:  int64

There are no null values

Number of Unique Values:  56

Distribution of column:

Year_Birth
1976    89
1971    87
1975    83
1972    79
1970    77
1978    77
1965    74
1973    74
1969    71
1974    69
1956    55
1958    53
1979    53
1952    52
1959    51
1977    51
1968    51
1954    50
1966    50
1960    49
1955    49
1963    45
1982    45
1967    44
1962    44
1957    43
1951    43
1964    42
1983    42
1986    42
1980    39
1981    39
1984    38
1961    36
1953    35
1985    32
1989    30
1949    30
1950    29
1988    29
1987    27
1948    21
1990    18
1946    16
1947    16
1991    15
1992    13
1945     8
1944     7
1943     7
1993     5
1995     5
1994     3
```

```
1996     2
1941     1
1940     1
Name: count, dtype: int64
Details of Education column

DataType:  object

There are no null values

Number of Unique Values:  5

Distribution of column:

Education
Graduation    1126
PhD            485
Master         370
2n Cycle       201
Basic           54
Name: count, dtype: int64
Details of Marital_Status column

DataType:  object

There are no null values

Number of Unique Values:  8

Distribution of column:

Marital_Status
Married     864
Together    578
Single      479
Divorced    231
Widow        77
Alone         3
YOLO          2
Absurd        2
Name: count, dtype: int64
Details of Income column

DataType:  float64

There are  24  null values

Number of Unique Values:  1970

Distribution of column:

Income
7500.0     12
35860.0     4
83844.0     3
34176.0     3
18929.0     3
           ..
61346.0     1
46086.0     1
42243.0     1
35788.0     1
94871.0     1
Name: count, Length: 1970, dtype: int64
```

```
Details of Kidhome column

DataType:  int64

There are no null values

Number of Unique Values:  3

Distribution of column:

Kidhome
0    1291
1     897
2      48
Name: count, dtype: int64
Details of Teenhome column

DataType:  int64

There are no null values

Number of Unique Values:  3

Distribution of column:

Teenhome
0    1155
1    1029
2      52
Name: count, dtype: int64
Details of Dt_Customer column

DataType:  datetime64[ns]

There are no null values

Number of Unique Values:  663

Distribution of column:

Dt_Customer
2012-08-31    12
2012-09-12    11
2013-02-14    11
2014-05-12    11
2013-08-20    10
              ..
2014-06-04     1
2012-12-21     1
2014-04-10     1
2013-07-20     1
2012-09-01     1
Name: count, Length: 663, dtype: int64
Details of Recency column

DataType:  int64

There are no null values

Number of Unique Values:  100

Distribution of column:

Recency
```

```
56    37
54    32
30    32
46    31
92    30
      ..
5     15
59    14
22    13
7     12
44    11
Name: count, Length: 100, dtype: int64
Details of MntWines column

DataType:  int64

There are no null values

Number of Unique Values:  775

Distribution of column:

MntWines
2      42
5      40
6      37
1      37
4      33
       ..
281     1
731     1
913     1
294     1
169     1
Name: count, Length: 775, dtype: int64
Details of MntFruits column

DataType:  int64

There are no null values

Number of Unique Values:  158

Distribution of column:

MntFruits
0      399
1      162
2      120
3      116
4      104
      ...
184      1
140      1
160      1
143      1
189      1
Name: count, Length: 158, dtype: int64
Details of MntMeatProducts column

DataType:  int64

There are no null values
```

```
Number of Unique Values:  557

Distribution of column:

MntMeatProducts
7      53
11     49
5      49
8      45
6      43
       ..
569     1
174     1
185     1
274     1
701     1
Name: count, Length: 557, dtype: int64
Details of MntFishProducts column

DataType:  int64

There are no null values

Number of Unique Values:  182

Distribution of column:

MntFishProducts
0      384
2      156
3      130
4      108
6       82
      ...
231      1
167      1
229      1
232      1
242      1
Name: count, Length: 182, dtype: int64
Details of MntSweetProducts column

DataType:  int64

There are no null values

Number of Unique Values:  177

Distribution of column:

MntSweetProducts
0      418
1      160
2      128
3      101
4       81
      ...
187      1
132      1
191      1
196      1
113      1
Name: count, Length: 177, dtype: int64
Details of MntGoldProds column
```

```
DataType:  int64

There are no null values

Number of Unique Values:  213

Distribution of column:

MntGoldProds
1      73
4      70
3      69
5      63
12     62
       ..
137     1
157     1
247     1
103     1
123     1
Name: count, Length: 213, dtype: int64
Details of NumDealsPurchases column

DataType:  int64

There are no null values

Number of Unique Values:  15

Distribution of column:

NumDealsPurchases
1     967
2     497
3     297
4     188
5      94
6      61
0      46
7      40
8      14
9       8
15      7
11      5
10      5
12      4
13      3
Name: count, dtype: int64
Details of NumWebPurchases column

DataType:  int64

There are no null values

Number of Unique Values:  15

Distribution of column:

NumWebPurchases
2     372
1     353
3     335
4     279
```

```
5     220
6     205
7     155
8     102
9      75
0      49
11     44
10     43
27      2
25      1
23      1
Name: count, dtype: int64
Details of NumCatalogPurchases column

DataType:  int64

There are no null values

Number of Unique Values:  14

Distribution of column:

NumCatalogPurchases
0     585
1     495
2     276
3     184
4     182
5     140
6     127
7      79
8      55
10     48
9      42
11     19
28      3
22      1
Name: count, dtype: int64
Details of NumStorePurchases column

DataType:  int64

There are no null values

Number of Unique Values:  14

Distribution of column:

NumStorePurchases
3     489
4     322
2     221
5     212
6     178
8     149
7     143
10    125
9     106
12    105
13     83
11     81
0      15
1       7
Name: count, dtype: int64
```

```
Details of NumWebVisitsMonth column

DataType:  int64

There are no null values

Number of Unique Values:  16

Distribution of column:

NumWebVisitsMonth
7     393
8     342
6     339
5     280
4     217
3     205
2     202
1     152
9      83
0      11
10      3
20      3
14      2
19      2
17      1
13      1
Name: count, dtype: int64
Details of Complain column

DataType:  int64

There are no null values

Number of Unique Values:  2

Distribution of column:

Complain
0    2216
1      20
Name: count, dtype: int64
Details of Country column

DataType:  object

There are no null values

Number of Unique Values:  8

Distribution of column:

Country
SP     1094
SA      335
CA      268
AUS     160
IND     147
GER     120
US      109
ME        3
Name: count, dtype: int64
Details of Customer_Year column
```

```
DataType:  int32

There are no null values

Number of Unique Values:  3

Distribution of column:

Customer_Year
2013    1186
2014     556
2012     494
Name: count, dtype: int64
Details of Total_Spending column

DataType:  int64

There are no null values

Number of Unique Values:  1054

Distribution of column:

Total_Spending
46      19
22      17
57      16
55      15
44      15
        ..
590      1
1890     1
1456     1
292      1
1078     1
Name: count, Length: 1054, dtype: int64
Details of Couple_Status column

DataType:  object

There are no null values

Number of Unique Values:  2

Distribution of column:

Couple_Status
In couple    1442
Alone         794
Name: count, dtype: int64
Details of Accepted_Any_Campaign column

DataType:  bool

There are no null values

Number of Unique Values:  2

Distribution of column:

Accepted_Any_Campaign
False    1774
True      462
Name: count, dtype: int64
```

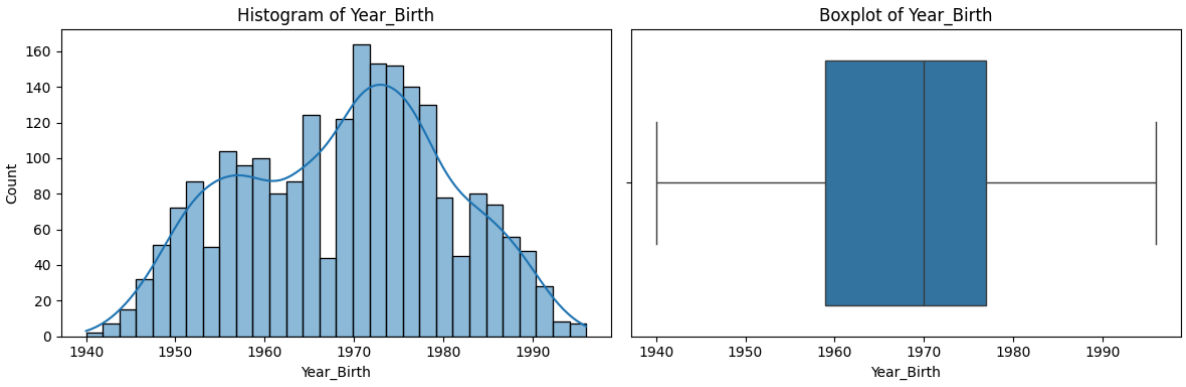
```
Details of Age column

DataType:  int64

There are no null values

Number of Unique Values:  56

Distribution of column:

Age
48    89
53    87
49    83
52    79
54    77
46    77
59    74
51    74
55    71
50    69
68    55
66    53
45    53
72    52
65    51
47    51
56    51
70    50
58    50
64    49
69    49
61    45
42    45
57    44
62    44
67    43
73    43
60    42
41    42
38    42
44    39
43    39
40    38
63    36
71    35
39    32
35    30
75    30
74    29
36    29
37    27
76    21
34    18
78    16
77    16
33    15
32    13
79     8
80     7
81     7
31     5
29     5
30     3
```

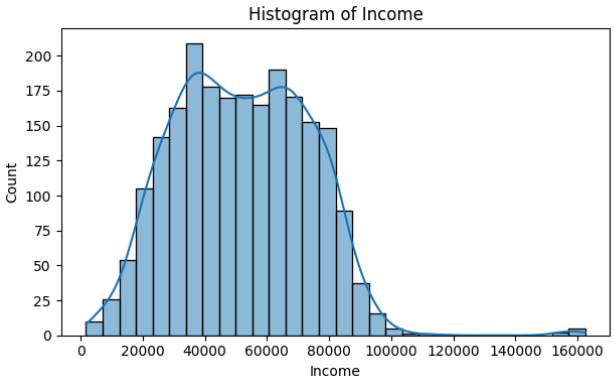
```
28     2
83     1
84     1
Name: count, dtype: int64
```

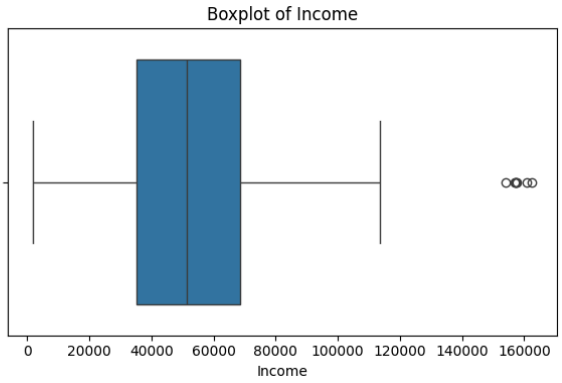
Step-10: Univariate Analysis

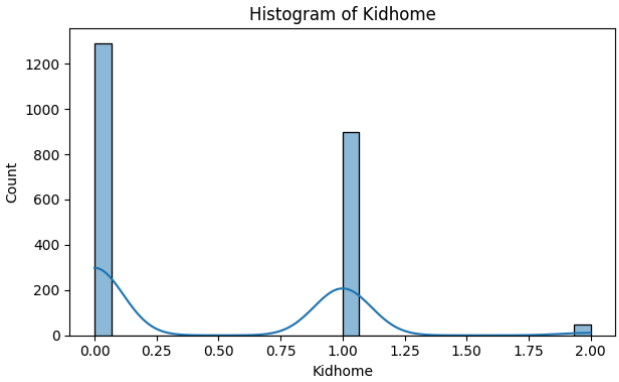
In [271…

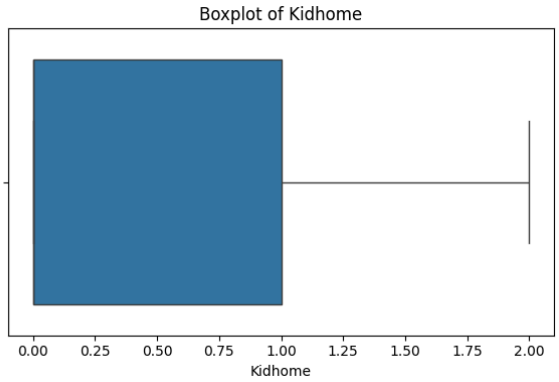
```python
# Function to plot histograms and boxplots for numerical columns
def plot_numerical(df, numerical_cols):
    for col in numerical_cols:
        fig, axes = plt.subplots(1, 2, figsize=(12, 4))  # 1 row, 2 columns: histog
        sns.histplot(df[col], kde=True, bins=30, ax=axes[0])
        axes[0].set_title(f'Histogram of {col}')
        sns.boxplot(data=df, x=col, ax=axes[1])
        axes[1].set_title(f'Boxplot of {col}')
        plt.tight_layout()
        plt.show()

# Function to plot count plots for categorical columns
def plot_categorical(df, categorical_cols):
    n_cols = 3  # Set number of columns per row
    n_rows = int(np.ceil(len(categorical_cols) / n_cols))  # Dynamic number of rows
    fig, axes = plt.subplots(n_rows, n_cols, figsize=(16, n_rows * 4))  # Adjust he
    axes = axes.flatten()  # Flatten axes to iterate easily

    for idx, col in enumerate(categorical_cols):
        sns.countplot(data=df, x=col, ax=axes[idx])
        axes[idx].set_title(f'Countplot of {col}')
        axes[idx].tick_params(axis='x', rotation=45)  # Rotate x-axis labels for be

    # Hide any empty subplots (in case columns are not perfectly divisible by n_col
    for ax in axes[len(categorical_cols):]:
        ax.set_visible(False)

    plt.tight_layout()
    plt.show()

# List of numerical and categorical columns
numerical_cols = df.select_dtypes(include=['int64', 'float64']).columns.tolist()
categorical_cols = df.select_dtypes(include=['object']).columns.tolist()

# Perform univariate analysis
plot_numerical(df, numerical_cols)
plot_categorical(df, categorical_cols)
```

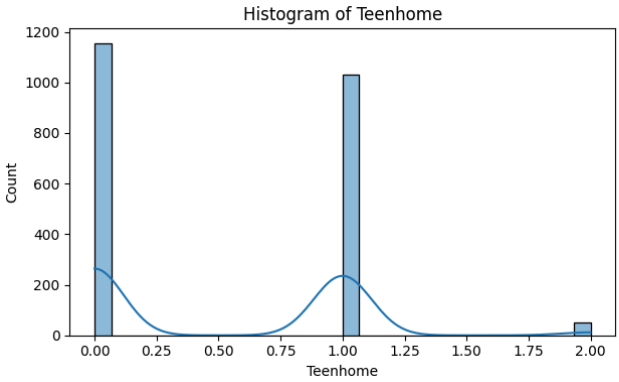


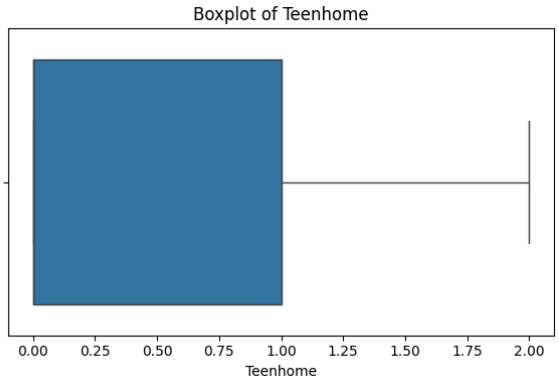

Histogram of Income
Count
Income

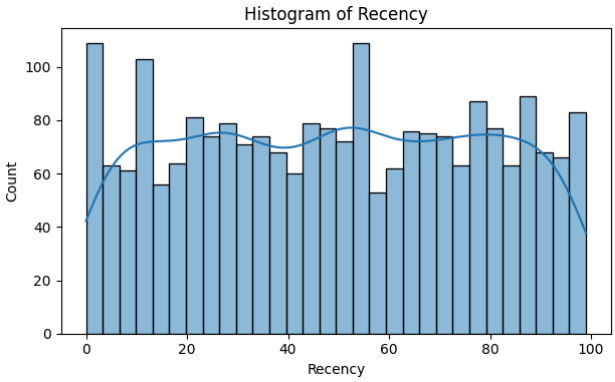

Boxplot of Income
Income

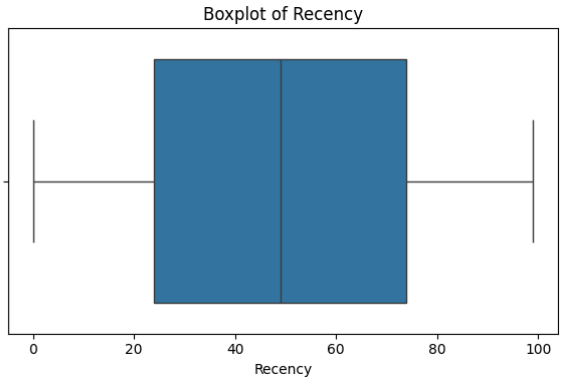

Histogram of Kidhome
Count
Kidhome

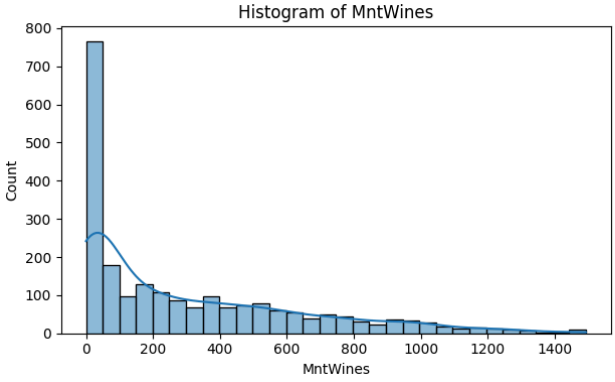

Boxplot of Kidhome
Kidhome

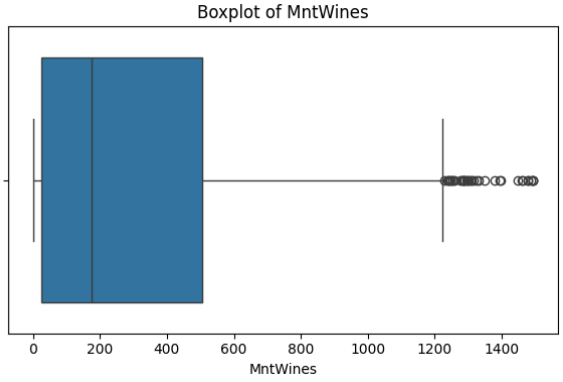

Histogram of Teenhome
Count
Teenhome

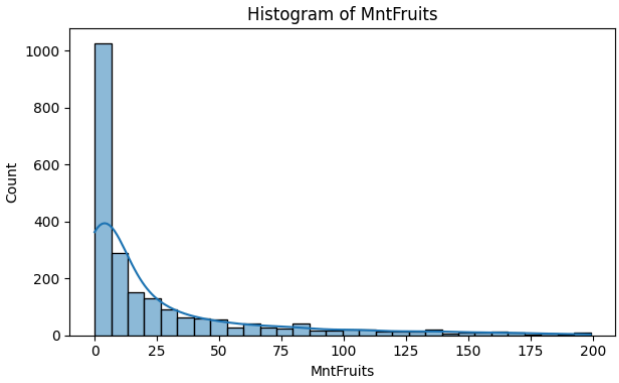

Boxplot of Teenhome
Teenhome

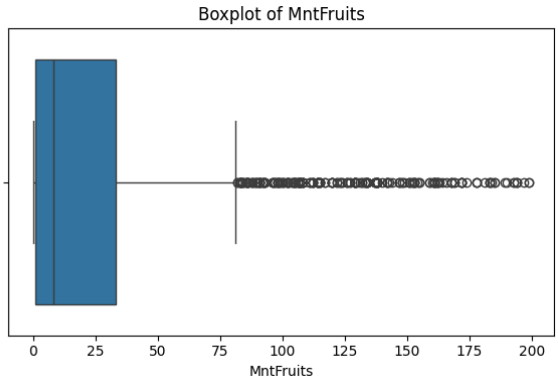

Histogram of Recency
Count
Recency

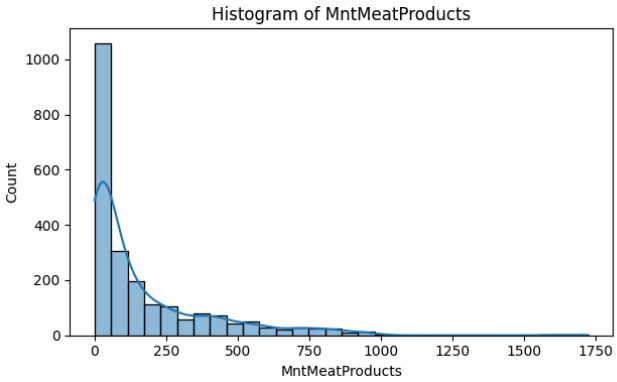

Boxplot of Recency
Recency

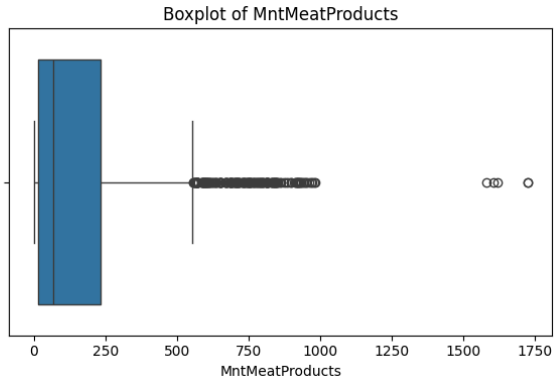

Histogram of MntWines
Count
MntWines

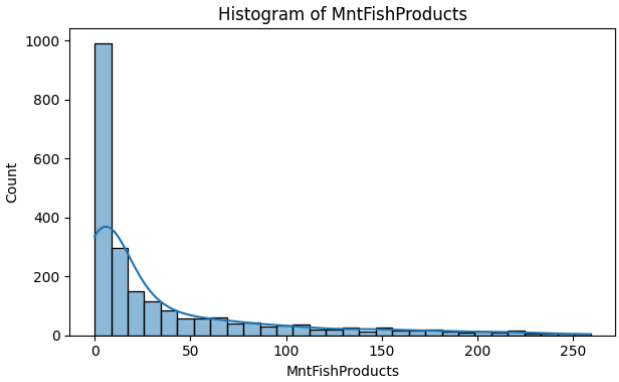

Boxplot of MntWines
MntWines

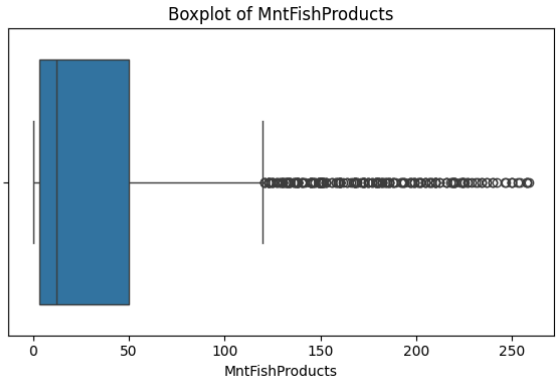

Histogram of MntFruits
Count
MntFruits

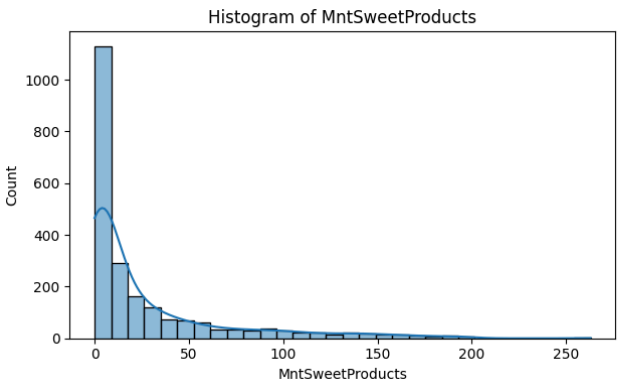

Boxplot of MntFruits
MntFruits

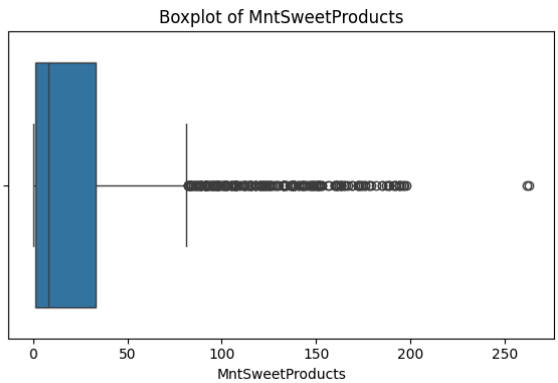

Histogram of MntMeatProducts
Count
MntMeatProducts

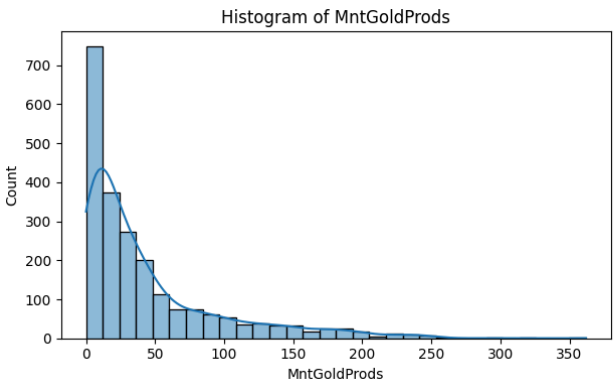

Boxplot of MntMeatProducts
MntMeatProducts

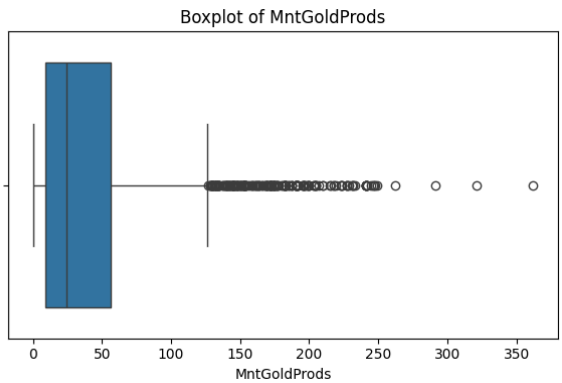

Histogram of MntFishProducts
Count
MntFishProducts

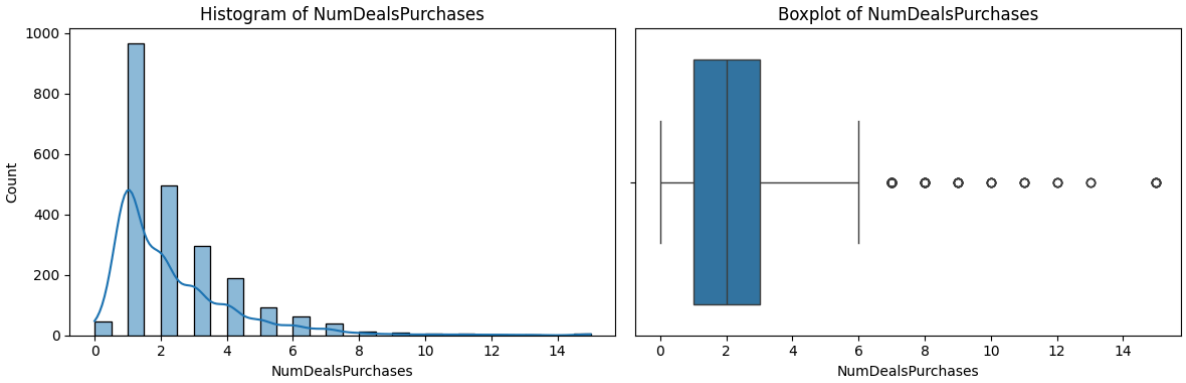

Boxplot of MntFishProducts
MntFishProducts


Histogram of MntSweetProducts
Count
MntSweetProducts

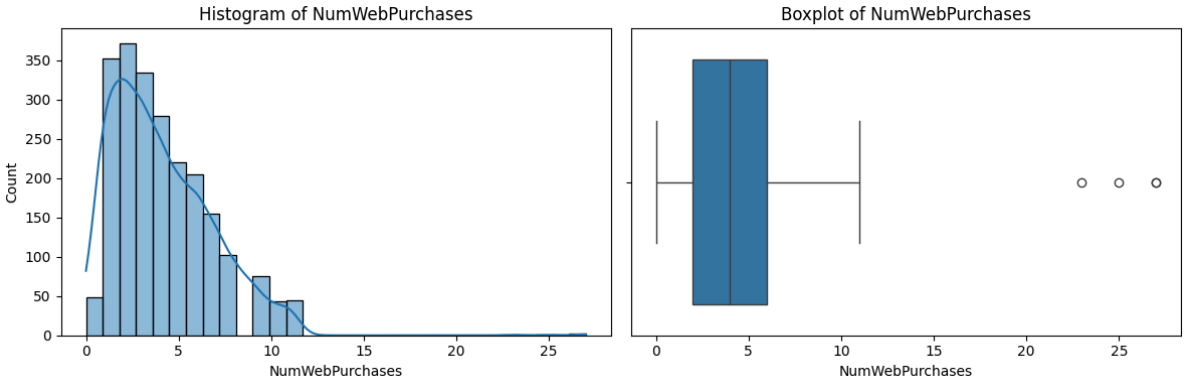

Boxplot of MntSweetProducts
MntSweetProducts


Histogram of MntGoldProds
Count
MntGoldProds

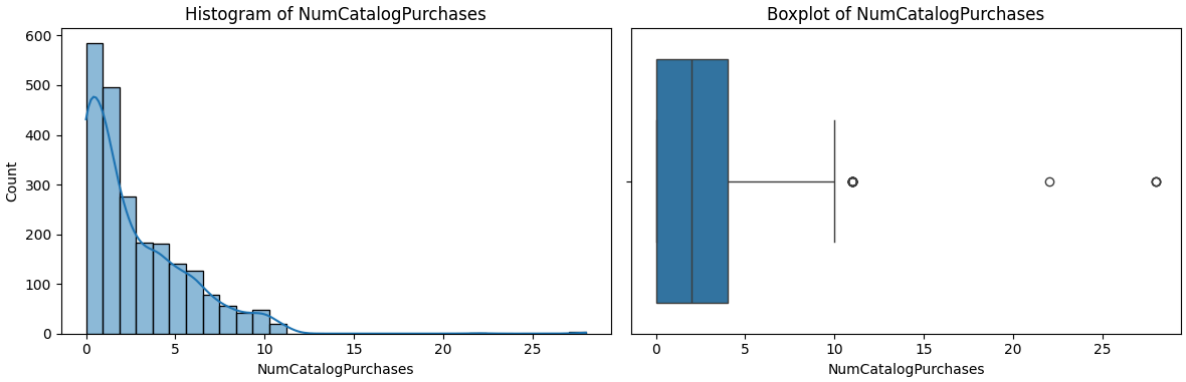

Boxplot of MntGoldProds
MntGoldProds


Histogram of NumDealsPurchases
Count
NumDealsPurchases

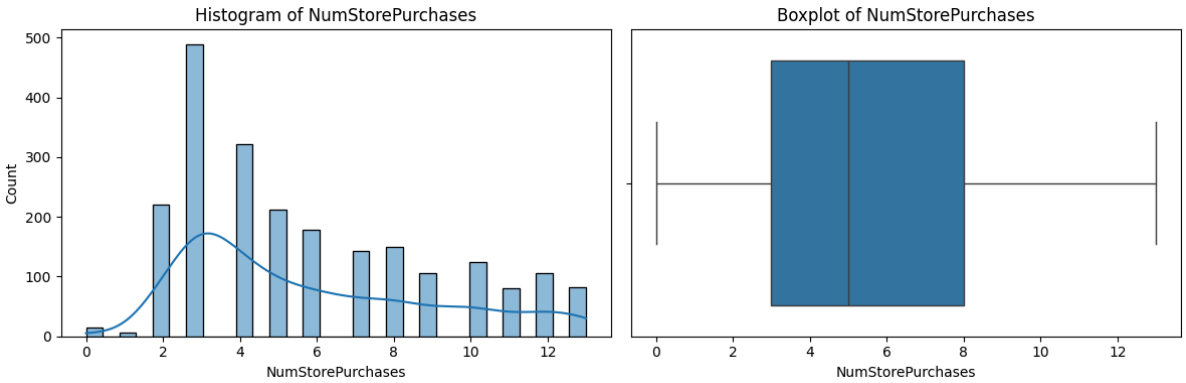
Boxplot of NumDealsPurchases
NumDealsPurchases


Histogram of NumWebPurchases
Count
NumWebPurchases

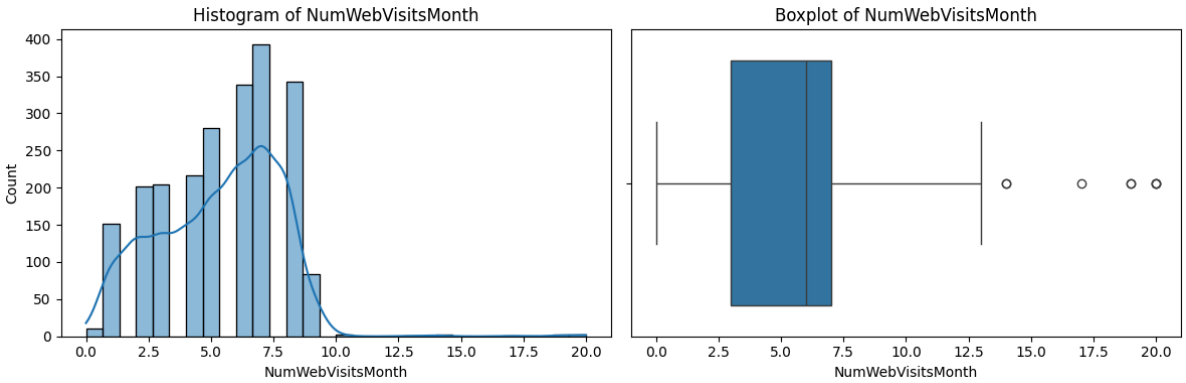
Boxplot of NumWebPurchases
NumWebPurchases


Histogram of NumCatalogPurchases
Count
NumCatalogPurchases

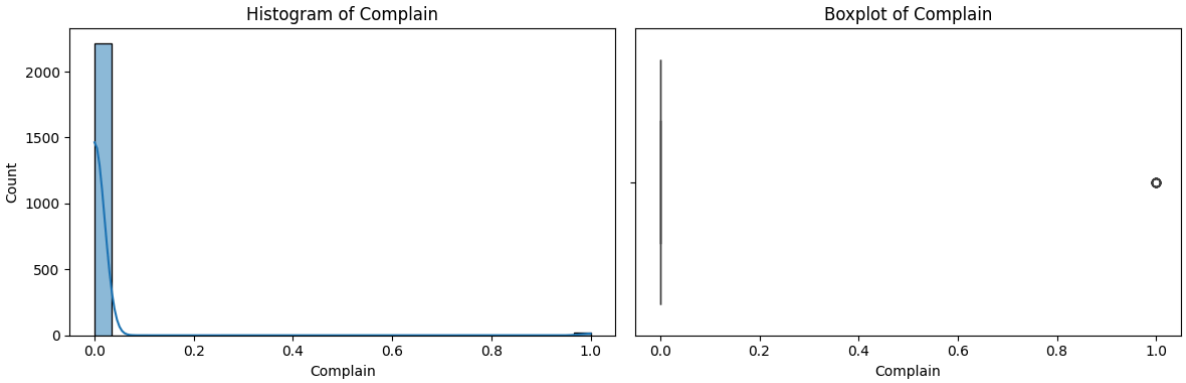
Boxplot of NumCatalogPurchases
NumCatalogPurchases

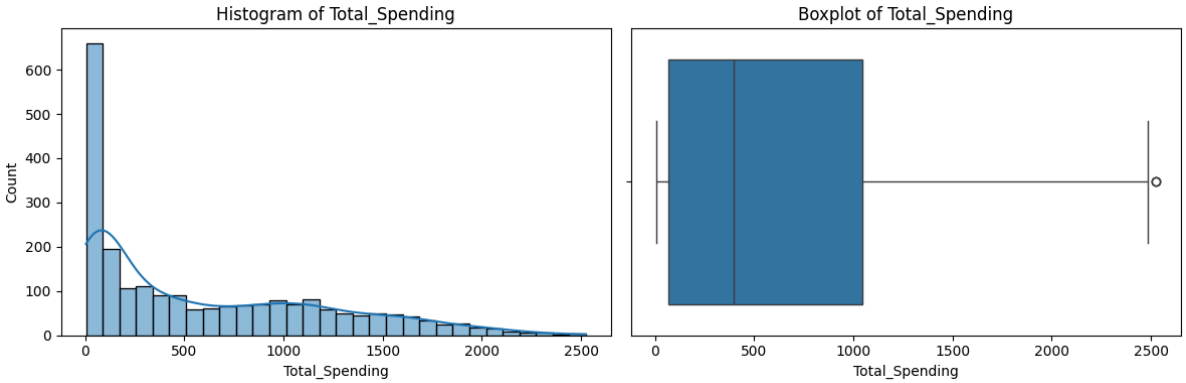

Histogram of NumStorePurchases
Count
NumStorePurchases

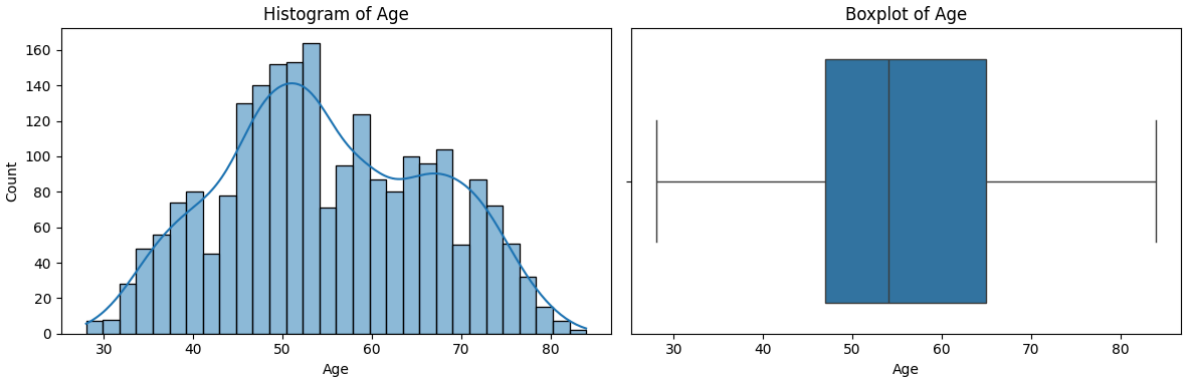
Boxplot of NumStorePurchases
NumStorePurchases

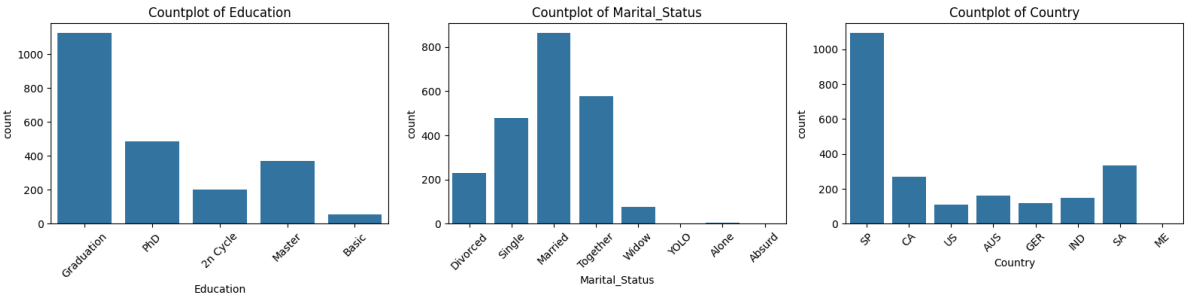

Histogram of NumWebVisitsMonth
Count
NumWebVisitsMonth

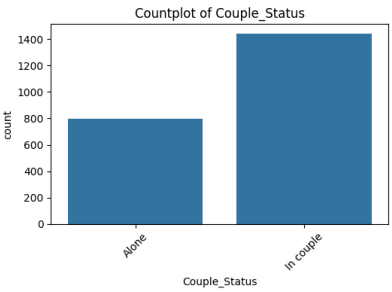
Boxplot of NumWebVisitsMonth
NumWebVisitsMonth









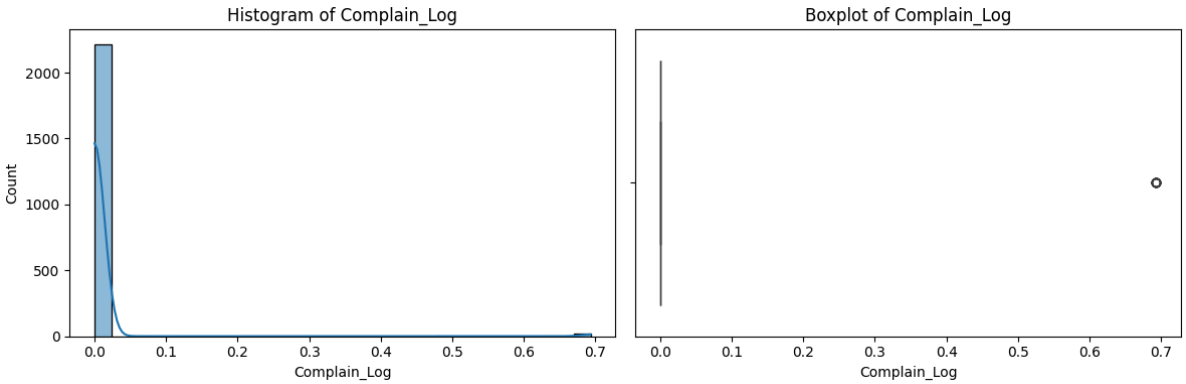


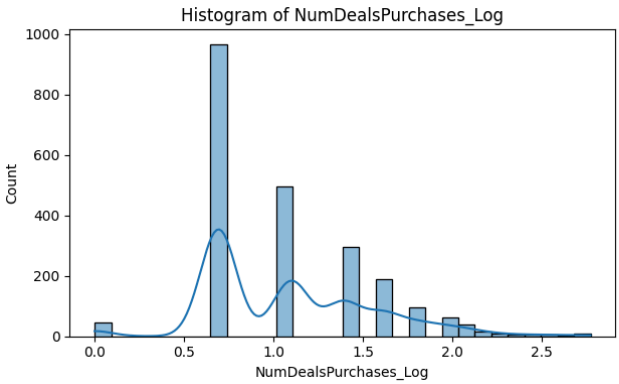
Step-11: Data Transformation (for skewed data)

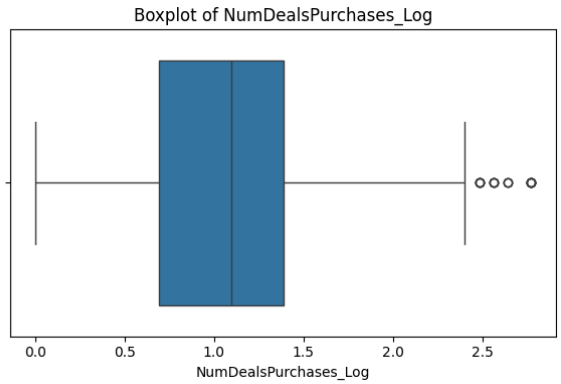
In [272…

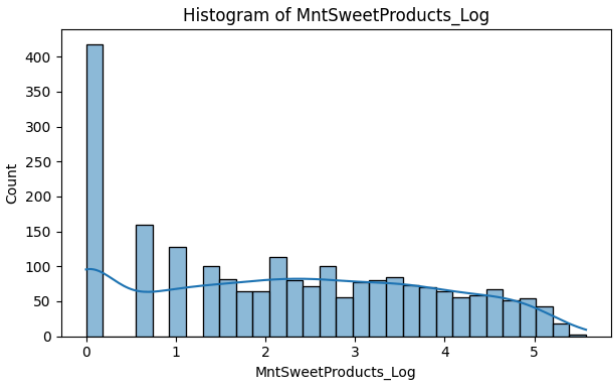
```
from scipy.stats import skew

# Identify skewed columns and apply log transformation
skewed_cols = df[numerical_cols].apply(lambda x: skew(x.dropna())).sort_values(asce
```

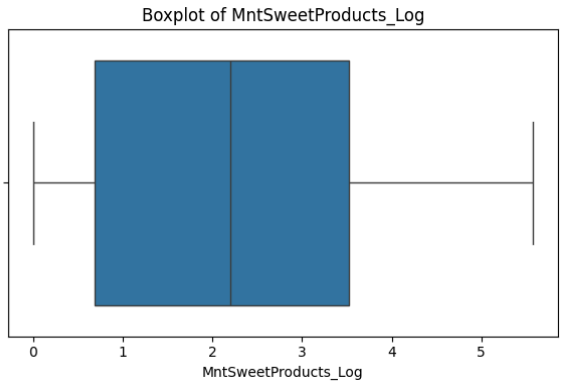
```
high_skew = skewed_cols[abs(skewed_cols) > 0.75]  # Threshold of 0.75 for high skew

# Apply log transformation for highly skewed columns
for col in high_skew.index:
    df[col + '_Log'] = np.log1p(df[col])  # log1p to handle zeros in data

# Plot the transformed columns
plot_numerical(df, [col + '_Log' for col in high_skew.index])
```

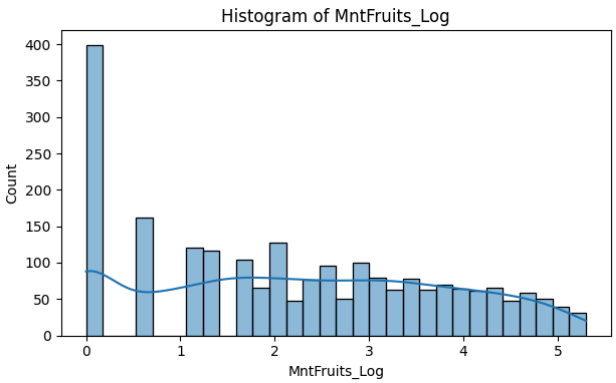


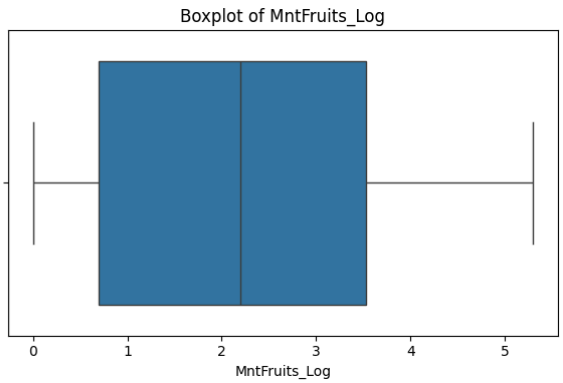


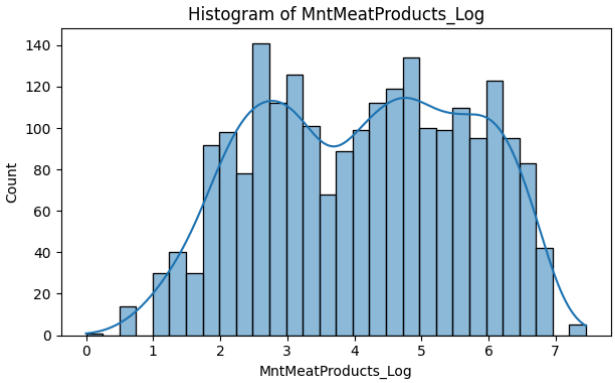


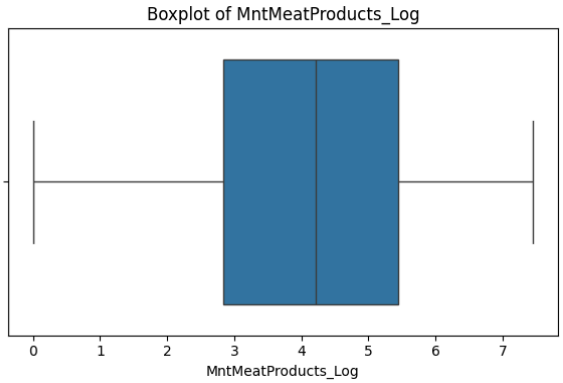


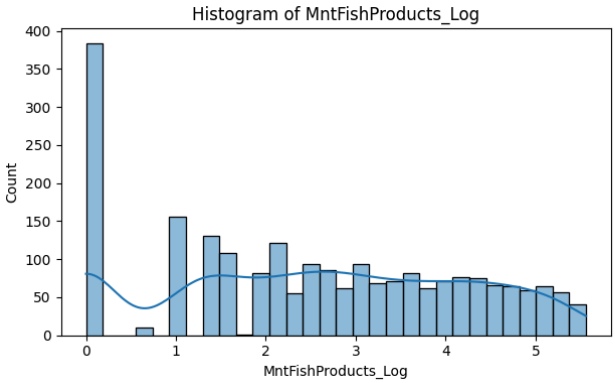


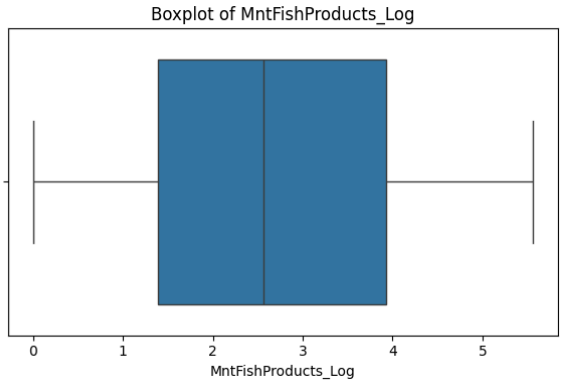


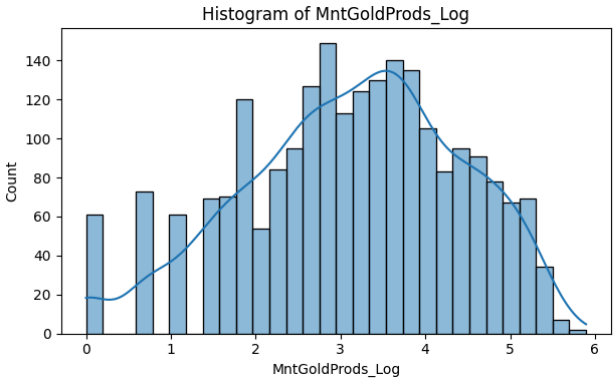


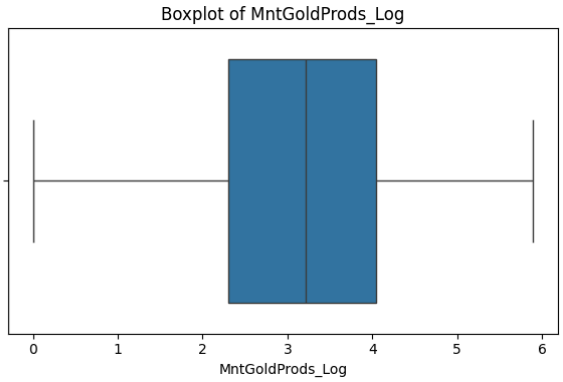

Histogram of MntMeatProducts_Log
Count
MntMeatProducts_Log

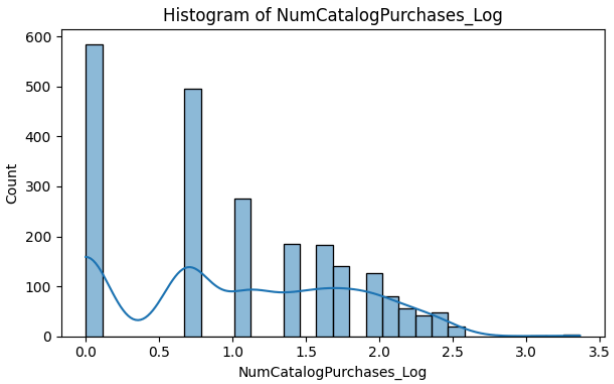

Boxplot of MntMeatProducts_Log
MntMeatProducts_Log

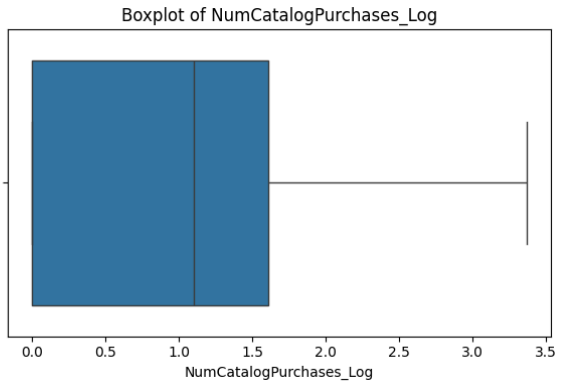

Histogram of MntFishProducts_Log
Count
MntFishProducts_Log

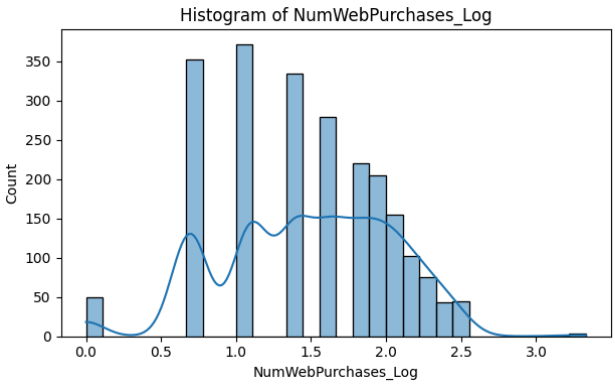

Boxplot of MntFishProducts_Log
MntFishProducts_Log

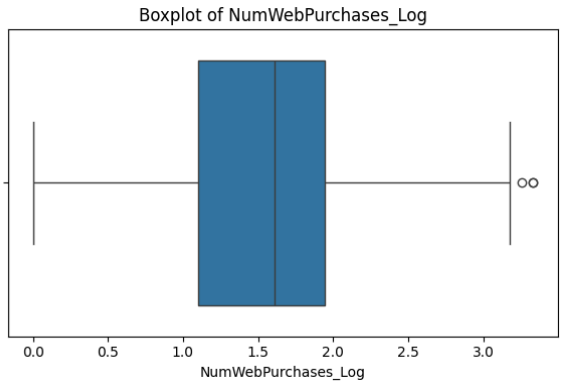

Histogram of MntGoldProds_Log
Count
MntGoldProds_Log

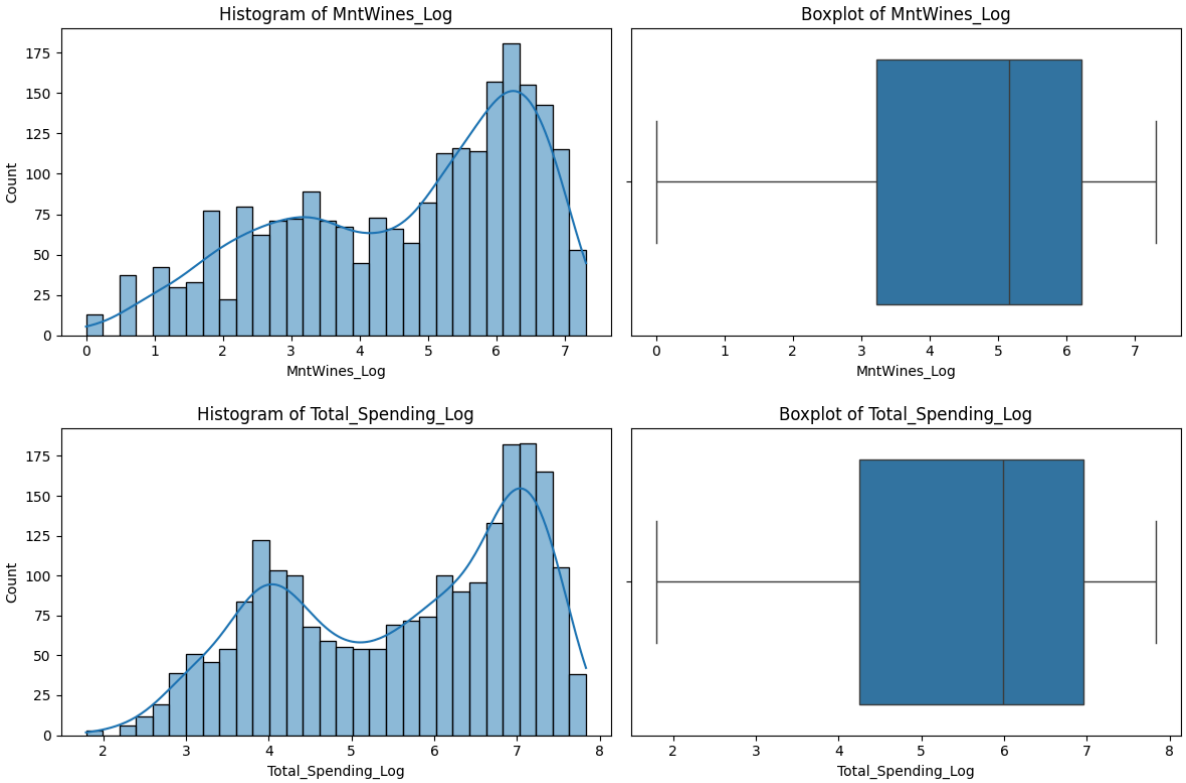

Boxplot of MntGoldProds_Log
MntGoldProds_Log


Histogram of NumCatalogPurchases_Log
Count
NumCatalogPurchases_Log


Boxplot of NumCatalogPurchases_Log
NumCatalogPurchases_Log


Histogram of NumWebPurchases_Log
Count
NumWebPurchases_Log


Boxplot of NumWebPurchases_Log
NumWebPurchases_Log



In [273…

```
df.isna().sum()
```

Out[273]:

	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
Complain	0
Country	0
Customer_Year	0
Total_Spending	0
Couple_Status	0
Accepted_Any_Campaign	0
Age	0
Complain_Log	0
NumDealsPurchases_Log	0
MntSweetProducts_Log	0
MntFruits_Log	0
MntMeatProducts_Log	0
MntFishProducts_Log	0
MntGoldProds_Log	0
NumCatalogPurchases_Log	0
NumWebPurchases_Log	0
MntWines_Log	0

	0
Total_Spending_Log	0

dtype: int64

In [274…
```
df.dropna(inplace=True)
```

Step-12: Bi-Variate Analysis

In [291…
```
df.head().T
```

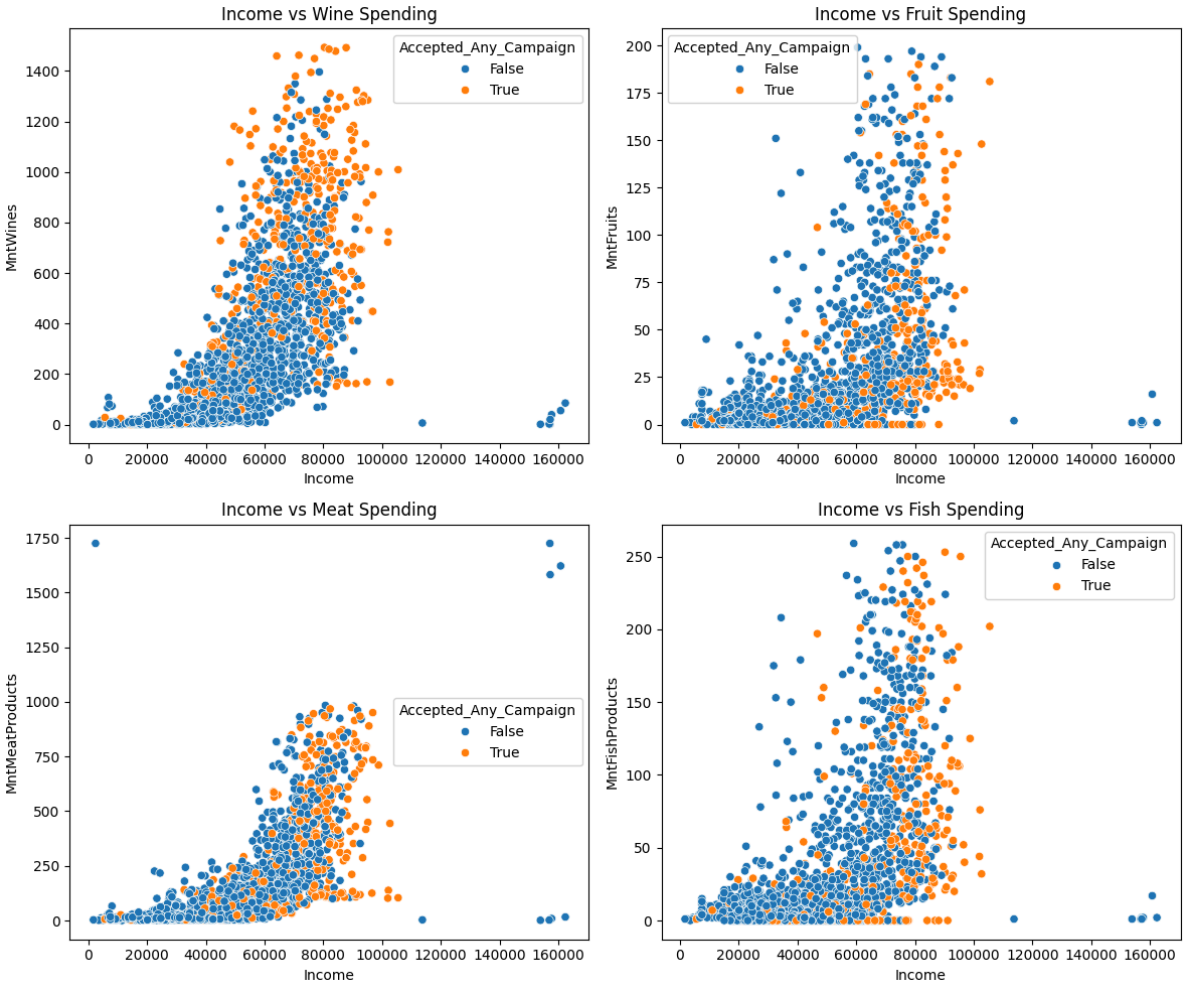
Out[291]:

	0	1	2	3	4
Year_Birth	1970	1961	1958	1967	1989
Education	Graduation	Graduation	Graduation	Graduation	Graduation
Marital_Status	Divorced	Single	Married	Together	Single
Income	84835.0	57091.0	67267.0	32474.0	21474.0
Kidhome	0	0	0	1	1
Teenhome	0	0	1	1	0
Dt_Customer	2014-06-16 00:00:00	2014-06-15 00:00:00	2014-05-13 00:00:00	2014-05-11 00:00:00	2014-04-08 00:00:00
Recency	0	0	0	0	0
MntWines	189	464	134	10	6
MntFruits	104	5	11	0	16
MntMeatProducts	379	64	59	1	24
MntFishProducts	111	7	15	0	11
MntSweetProducts	189	0	2	0	0
MntGoldProds	218	37	30	0	34
NumDealsPurchases	1	1	1	1	2
NumWebPurchases	4	7	3	1	3
NumCatalogPurchases	4	3	2	0	1
NumStorePurchases	6	7	5	2	2
NumWebVisitsMonth	1	5	2	7	7
Complain	0	0	0	0	0
Country	SP	CA	US	AUS	SP
Customer_Year	2014	2014	2014	2014	2014
Total_Spending	1190	577	251	11	91
Couple_Status	Alone	Alone	In couple	In couple	Alone
Accepted_Any_Campaign	False	True	False	False	True
Age	54	63	66	57	35
Complain_Log	0.0	0.0	0.0	0.0	0.0
NumDealsPurchases_Log	0.693147	0.693147	0.693147	0.693147	1.098612
MntSweetProducts_Log	5.247024	0.0	1.098612	0.0	0.0
MntFruits_Log	4.65396	1.791759	2.484907	0.0	2.833213
MntMeatProducts_Log	5.940171	4.174387	4.094345	0.693147	3.218876
MntFishProducts_Log	4.718499	2.079442	2.772589	0.0	2.484907
MntGoldProds_Log	5.389072	3.637586	3.433987	0.0	3.555348
NumCatalogPurchases_Log	1.609438	1.386294	1.098612	0.0	0.693147
NumWebPurchases_Log	1.609438	2.079442	1.386294	0.693147	1.386294

	0	1	2	3	4
MntWines_Log	5.247024	6.142037	4.905275	2.397895	1.94591
Total_Spending_Log	7.082549	6.359574	5.529429	2.484907	4.521789
IncomeBracket	High	High	High	Low	Low

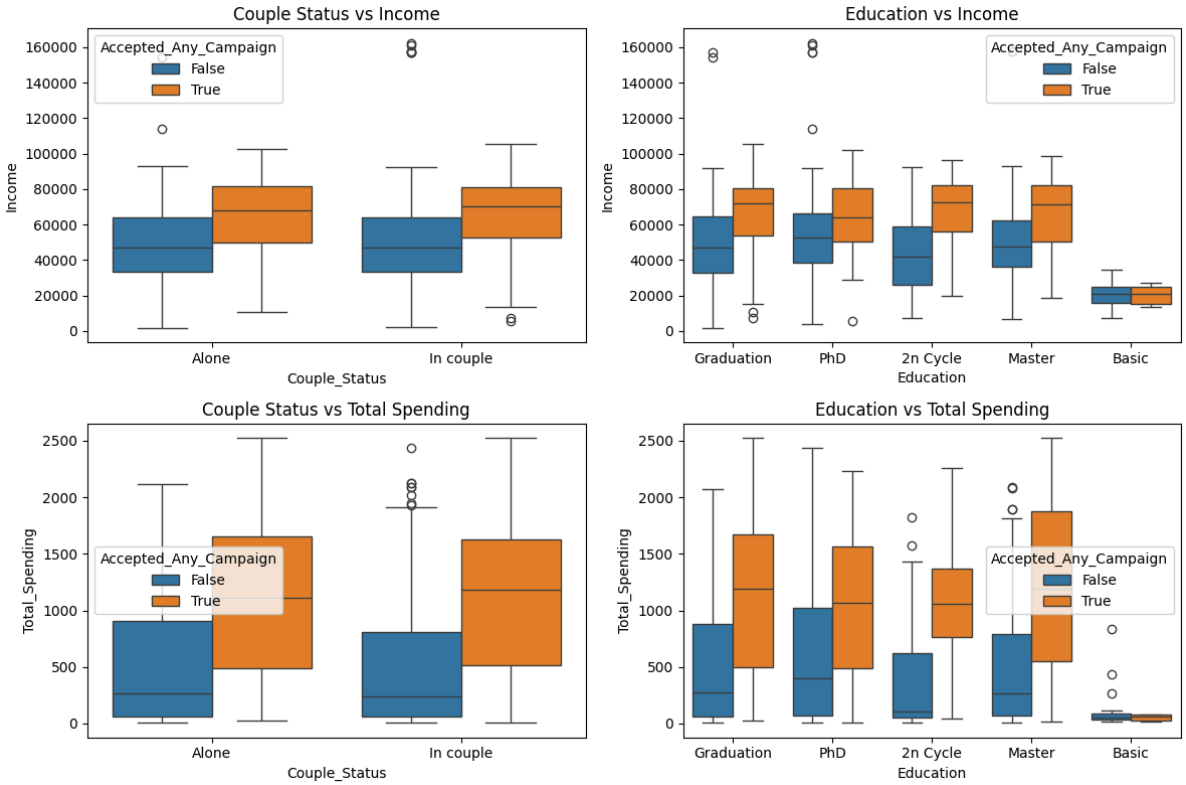
In [294…

```
def scatter_plots(df, numerical_cols):
    """
    This function creates scatter plots between relevant numerical columns.
    """
    plt.figure(figsize=(12, 10))

    # Scatter: Income vs various spending categories
    plt.subplot(2, 2, 1)
    sns.scatterplot(x=df['Income'], y=df['MntWines'], hue=df['Accepted_Any_Campaign
    plt.title('Income vs Wine Spending')

    plt.subplot(2, 2, 2)
    sns.scatterplot(x=df['Income'], y=df['MntFruits'], hue=df['Accepted_Any_Campaig
    plt.title('Income vs Fruit Spending')

    plt.subplot(2, 2, 3)
    sns.scatterplot(x=df['Income'], y=df['MntMeatProducts'], hue=df['Accepted_Any_C
    plt.title('Income vs Meat Spending')

    plt.subplot(2, 2, 4)
    sns.scatterplot(x=df['Income'], y=df['MntFishProducts'], hue=df['Accepted_Any_C
    plt.title('Income vs Fish Spending')

    plt.tight_layout()
    plt.show()

scatter_plots(df, numerical_cols)
```



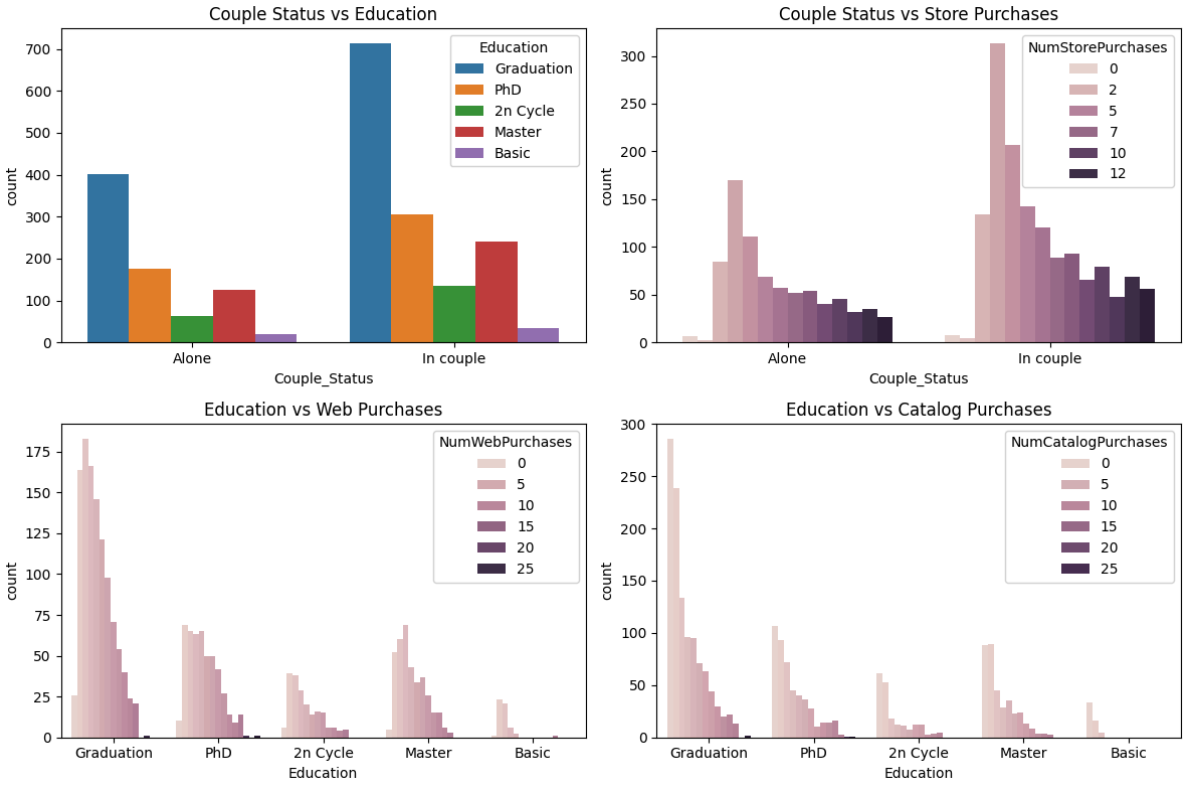
In [296…

```
def box_plots(df, categorical_cols, numerical_cols):
    """
    This function creates box plots between categorical and numerical columns.
    """
    plt.figure(figsize=(12, 8))

    # Boxplot: Categorical vs Income and Spending
    plt.subplot(2, 2, 1)
    sns.boxplot(x='Couple_Status', y='Income', data=df, hue=df['Accepted_Any_Campai
    plt.title('Couple Status vs Income')

    plt.subplot(2, 2, 2)
    sns.boxplot(x='Education', y='Income', data=df, hue=df['Accepted_Any_Campaign']
    plt.title('Education vs Income')

    plt.subplot(2, 2, 3)
    sns.boxplot(x='Couple_Status', y='Total_Spending', data=df, hue=df['Accepted_Ar
    plt.title('Couple Status vs Total Spending')

    plt.subplot(2, 2, 4)
    sns.boxplot(x='Education', y='Total_Spending', data=df, hue=df['Accepted_Any_Ca
    plt.title('Education vs Total Spending')

    plt.tight_layout()
    plt.show()

box_plots(df, categorical_cols, numerical_cols)
```



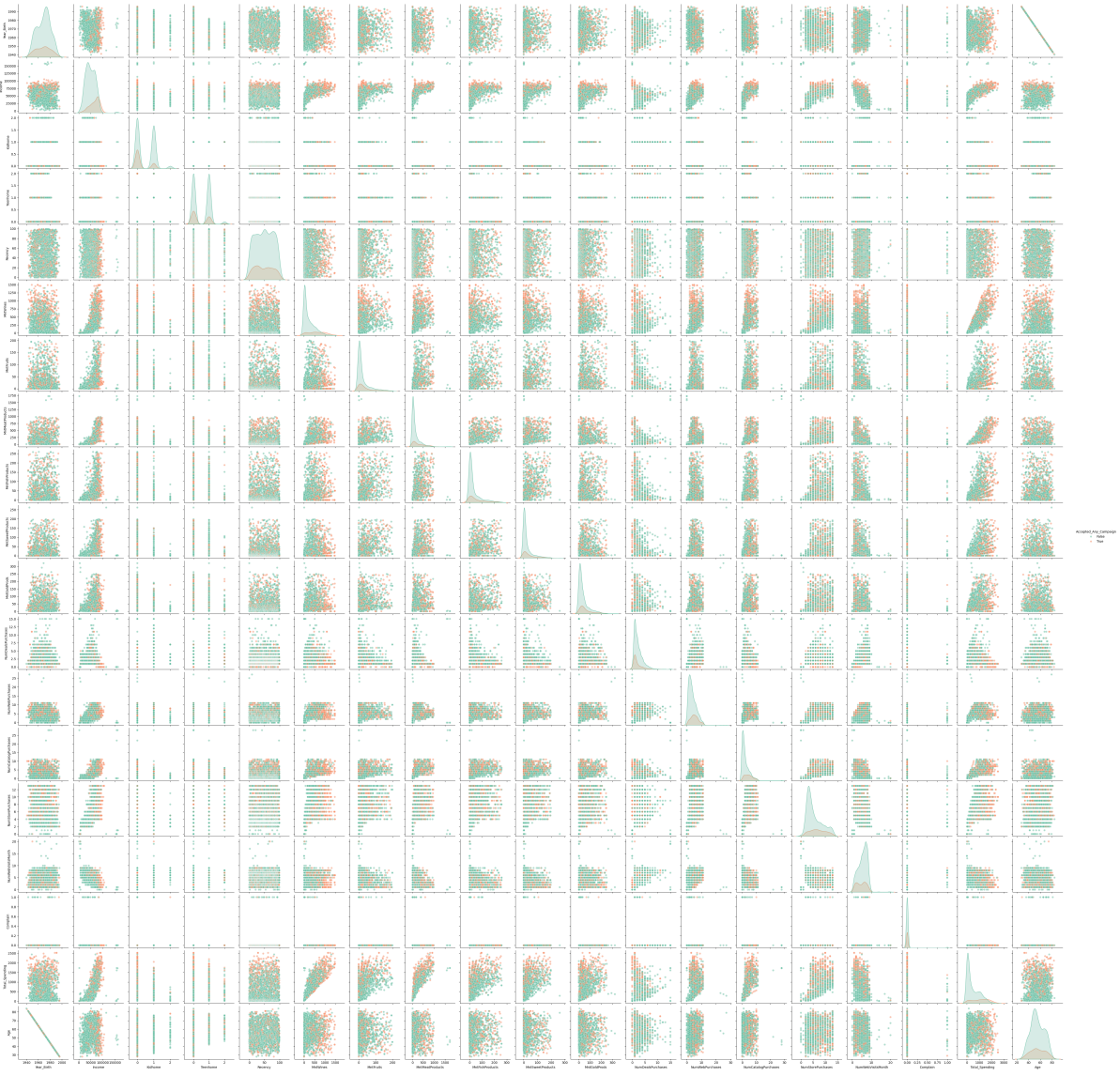
In [298…

```
def bar_plots(df, categorical_cols):
    """
    This function creates bar plots between categorical columns.
    """
    plt.figure(figsize=(12, 8))

    # Barplot: Categorical vs Categorical
    plt.subplot(2, 2, 1)
    sns.countplot(x='Couple_Status', hue='Education', data=df)
    plt.title('Couple Status vs Education')

    plt.subplot(2, 2, 2)
    sns.countplot(x='Couple_Status', hue='NumStorePurchases', data=df)
    plt.title('Couple Status vs Store Purchases')

    plt.subplot(2, 2, 3)
    sns.countplot(x='Education', hue='NumWebPurchases', data=df)
    plt.title('Education vs Web Purchases')

    plt.subplot(2, 2, 4)
    sns.countplot(x='Education', hue='NumCatalogPurchases', data=df)
    plt.title('Education vs Catalog Purchases')

    plt.tight_layout()
    plt.show()

bar_plots(df, categorical_cols)
```



In [278…

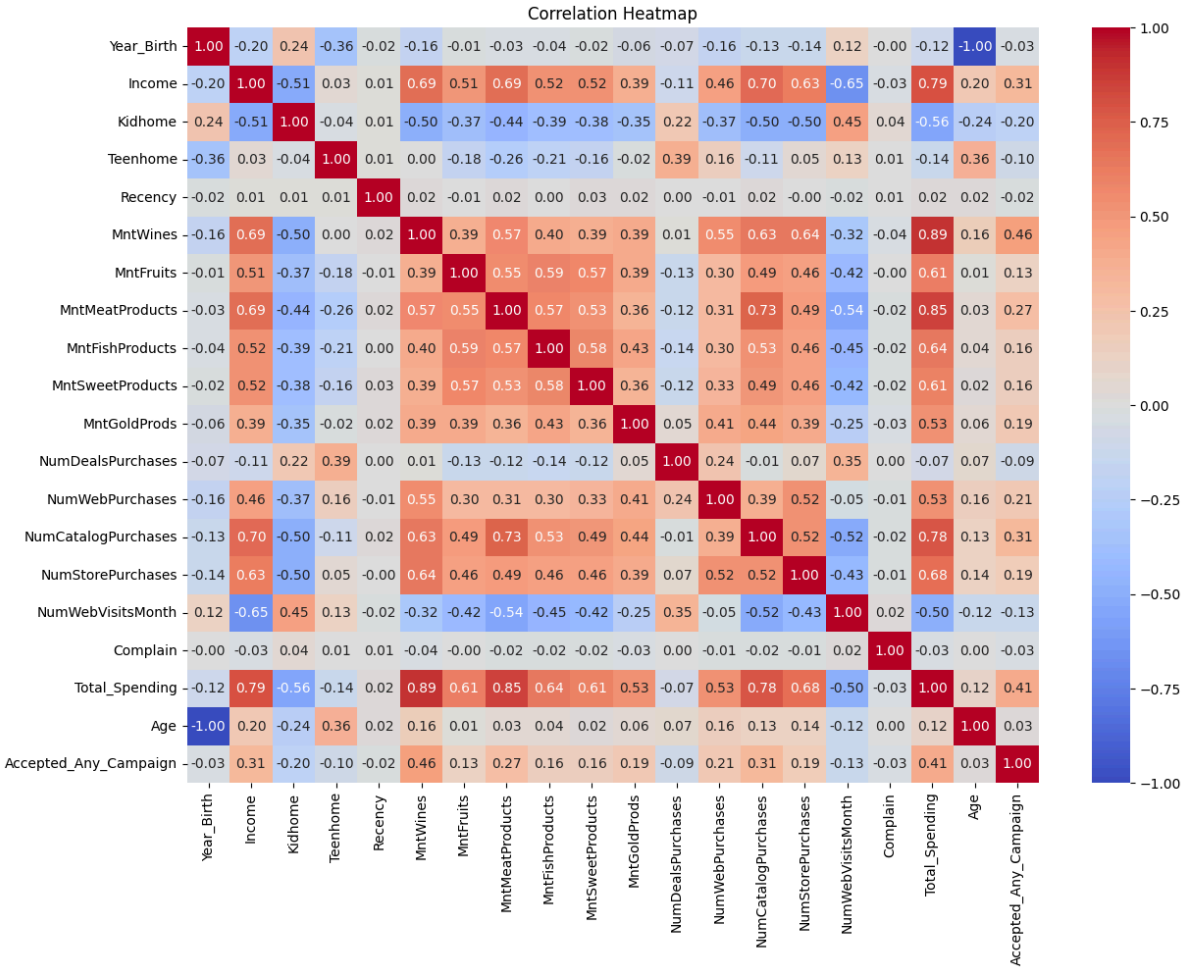
```
def pairplot_with_hue(df, numerical_cols, target_col):
    """
    This function creates pairplots for all numerical combinations with hue based c
    """
    # Select relevant numerical columns along with the target column for the pairpl
    plot_data = df[numerical_cols + [target_col]]

    # Create pairplot
    sns.pairplot(plot_data, hue=target_col, diag_kind='kde', palette='Set2', plot_k

    # Display the plot
    plt.show()

pairplot_with_hue(df, numerical_cols, 'Accepted_Any_Campaign')
```



Step-13 Multi-Variate Analysis

In [279…

```
# Filter numerical columns and target variable for correlation analysis
corr_matrix = df[numerical_cols + target_cols].corr()

# Plot heatmap
plt.figure(figsize=(14, 10))
sns.heatmap(corr_matrix, annot=True, cmap='coolwarm', fmt='.2f')
plt.title('Correlation Heatmap')
plt.show()
```



Step-14 Performing Hypothesis Testing

Hypothesis Questions:

1. Does education level affect the income of customers?
    - Test: ANOVA (if education is categorical and income is continuous)
2. Do higher-income individuals spend more overall compared to lower-income individuals?
    - Test: T-test (comparing two income groups)
3. Do married couples spend more on wine than singles?
    - Test: T-test (comparing spending between two groups: married and singles)
4. Is there a significant difference in campaign acceptance between lower and higher-income brackets?
    - Test: Chi-square test (for categorical data: acceptance of campaigns)
5. Is there a relationship between the number of campaigns accepted and customer income?
    - Test: Spearman correlation (for ordinal data)
6. Do customers who accept campaigns have different spending habits compared to those who don't?
    - Test: T-test (comparing spending between two groups: accepted campaigns vs. not accepted)

In [299…

```
import numpy as np
import pandas as pd
```

```
from scipy import stats
from scipy.stats import shapiro, ttest_ind, mannwhitneyu, f_oneway, chi2_contingenc

def hypothesis_test(null_hypothesis, alt_hypothesis, data1, data2=None, test_type='
    alpha = 0.05  # Significance level
    print(f"\nNull Hypothesis: {null_hypothesis}")
    print(f"Alternative Hypothesis: {alt_hypothesis}")

    # Check if comparing two datasets
    if data2 is not None:
        assert len(data1) > 0 and len(data2) > 0, "Both data samples should have va

    # Step 2: Assumptions Check
    if test_type in ['t-test', 'anova']:
        # Check normality for parametric tests
        p_value_norm1 = shapiro(data1)[1]
        print(f"P-value for normality (group 1): {p_value_norm1}")
        if data2 is not None:
            p_value_norm2 = shapiro(data2)[1]
            print(f"P-value for normality (group 2): {p_value_norm2}")
        else:
            p_value_norm2 = None

        # If normality is violated, switch to non-parametric tests
        if p_value_norm1 < alpha or (p_value_norm2 is not None and p_value_norm2 <
            print("Normality assumption violated. Switching to non-parametric test.
            if test_type == 't-test':
                test_type = 'mann-whitney'
            elif test_type == 'anova':
                test_type = 'kruskal'

    # Variance check for t-tests
    if test_type == 't-test' and data2 is not None:
        _, p_value_var = levene(data1, data2)
        print(f"P-value for variance equality: {p_value_var}")
        if p_value_var < alpha:
            print("Variance assumption violated. Using Mann-Whitney U test.")
            test_type = 'mann-whitney'

    # Step 3: Perform the test
    if test_type == 't-test':
        # Independent t-test (parametric)
        t_stat, p_value = ttest_ind(data1, data2, equal_var=True)
        print(f"T-statistic: {t_stat}")
    elif test_type == 'mann-whitney':
        # Mann-Whitney U test (non-parametric)
        u_stat, p_value = mannwhitneyu(data1, data2)
        print(f"U-statistic: {u_stat}")
    elif test_type == 'anova':
        # ANOVA (parametric)
        f_stat, p_value = f_oneway(data1, data2)
        print(f"F-statistic: {f_stat}")
    elif test_type == 'kruskal':
        # Kruskal-Wallis (non-parametric ANOVA)
        h_stat, p_value = stats.kruskal(data1, data2)
        print(f"H-statistic: {h_stat}")
    elif test_type == 'chi-squared':
        # Chi-Square test for categorical data
        contingency_table = pd.crosstab(data1, data2)
        chi2_stat, p_value, _, _ = chi2_contingency(contingency_table)
        print(f"Chi-Squared statistic: {chi2_stat}")
    elif test_type == 'fisher':
        # Fisher Exact test for small sample categorical data
        contingency_table = pd.crosstab(data1, data2)
```

```
        odds_ratio, p_value = fisher_exact(contingency_table)
        print(f"Odds Ratio: {odds_ratio}")

    # Step 4: Decision-making
    print(f"P-value: {p_value}")
    if p_value < alpha:
        print("Reject the null hypothesis.")
    else:
        print("Fail to reject the null hypothesis.")
```

In [300…

```
def test_hypothesis_1(df):
    # 1. Null: Education level does not affect income
    #    Alternative: Education level affects income
    data1 = df[df['Education'] == 'Graduation']['Income']
    data2 = df[df['Education'] == 'Basic']['Income']
    hypothesis_test("Education level does not affect income",
                    "Education level affects income",
                    data1, data2, test_type='anova')

test_hypothesis_1(df)
```

```
Null Hypothesis: Education level does not affect income
Alternative Hypothesis: Education level affects income
P-value for normality (group 1): 2.609765154403154e-12
P-value for normality (group 2): 0.20598086530848786
Normality assumption violated. Switching to non-parametric test.
H-statistic: 113.02774256856688
P-value: 2.12776768762587e-26
Reject the null hypothesis.
```

In [301…

```
def test_hypothesis_2(df):
    # 1. Null: Higher-income individuals do not spend more
    #    Alternative: Higher-income individuals spend more
    high_income = df[df['Income'] > df['Income'].median()]['Total_Spending']
    low_income = df[df['Income'] <= df['Income'].median()]['Total_Spending']
    hypothesis_test("Higher-income individuals do not spend more",
                    "Higher-income individuals spend more",
                    high_income, low_income)

test_hypothesis_2(df)
```

```
Null Hypothesis: Higher-income individuals do not spend more
Alternative Hypothesis: Higher-income individuals spend more
P-value for normality (group 1): 4.970948716448737e-07
P-value for normality (group 2): 5.190214211682396e-41
Normality assumption violated. Switching to non-parametric test.
U-statistic: 1165242.0
P-value: 1.987227450784498e-297
Reject the null hypothesis.
```

In [302…

```
def test_hypothesis_3(df):
    # 1. Null: Married couples do not spend more on wine than singles
    #    Alternative: Married couples spend more on wine than singles
    married_spending = df[df['Marital_Status'] == 'Married']['MntWines']
    single_spending = df[df['Marital_Status'] == 'Single']['MntWines']
    hypothesis_test("Married couples do not spend more on wine than singles",
                    "Married couples spend more on wine than singles",
                    married_spending, single_spending)

test_hypothesis_3(df)
```

```
Null Hypothesis: Married couples do not spend more on wine than singles
Alternative Hypothesis: Married couples spend more on wine than singles
P-value for normality (group 1): 3.333615231124149e-29
P-value for normality (group 2): 2.0304534768700042e-22
Normality assumption violated. Switching to non-parametric test.
U-statistic: 205059.5
P-value: 0.5831388644016677
Fail to reject the null hypothesis.
```

In [303…

```
def test_hypothesis_4(df):
    # 1. Null: No significant difference in campaign acceptance between income brac
    #    Alternative: Significant difference in campaign acceptance between income
    df['IncomeBracket'] = np.where(df['Income'] > df['Income'].median(), 'High', 'L
    campaign_accepted = df['Accepted_Any_Campaign']
    hypothesis_test("No significant difference in campaign acceptance between incom
                    "Significant difference in campaign acceptance between income b
                    campaign_accepted, df['IncomeBracket'], test_type='chi-squared'

test_hypothesis_4(df)
```

```
Null Hypothesis: No significant difference in campaign acceptance between income b
rackets
Alternative Hypothesis: Significant difference in campaign acceptance between inco
me brackets
Chi-Squared statistic: 141.88672678294904
P-value: 1.0295542113515174e-32
Reject the null hypothesis.
```

In [304…

```
def test_hypothesis_5(df):
    # 1. Null: There is no relationship between campaigns accepted and income
    #    Alternative: There is a relationship between campaigns accepted and income
    correlation, p_value = stats.spearmanr(df['Accepted_Any_Campaign'], df['Income'
    print("\nHypothesis 6: Relationship between campaigns accepted and income")
    print(f"Spearman correlation: {correlation}, P-value: {p_value}")
    if p_value < 0.05:
        print("Reject the null hypothesis.")
    else:
        print("Fail to reject the null hypothesis.")

test_hypothesis_5(df)
```

```
Hypothesis 6: Relationship between campaigns accepted and income
Spearman correlation: 0.32421148702489455, P-value: 2.6364730873648996e-55
Reject the null hypothesis.
```

In [305…

```
def test_hypothesis_6(df):
    # 1. Null: Customers who accept campaigns do not have different spending habits
    #    Alternative: Customers who accept campaigns have different spending habits
    acceptors = df[df['Accepted_Any_Campaign'] == 1]['Total_Spending']
    non_acceptors = df[df['Accepted_Any_Campaign'] == 0]['Total_Spending']
    hypothesis_test("Customers who accept campaigns do not have different spending
                    "Customers who accept campaigns have different spending habits"
                    acceptors, non_acceptors)

test_hypothesis_6(df)
```

```
Null Hypothesis: Customers who accept campaigns do not have different spending hab
its
Alternative Hypothesis: Customers who accept campaigns have different spending hab
its
P-value for normality (group 1): 2.2396789117442009e-10
P-value for normality (group 2): 3.441381575741494e-39
Normality assumption violated. Switching to non-parametric test.
U-statistic: 611094.0
P-value: 2.381320679302262e-66
Reject the null hypothesis.
```

Insights

1. **Income and Campaign Acceptance**: People with lower incomes are more likely to accept promotional campaigns, showing they are sensitive to discounts.

2. **Spending by Education Level**: Customers with higher education tend to spend differently across product categories, suggesting targeted marketing could be effective.

3. **Marital Status Effects**: Couples spend differently than singles. Tailoring campaigns to target families or singles could improve results.

4. **Geographic Differences**: People in different countries respond differently to campaigns, so localized marketing strategies may boost acceptance rates.

5. **Importance of Recent Purchases**: Customers who have recently bought something are more likely to accept new campaign offers, indicating timely marketing is key.

Recommendations

1. **Focus Campaigns on Low-Income Individuals**: Create marketing campaigns specifically for lower-income groups, as they are more likely to respond to discounts.

2. **Personalized Offers**: Use spending data to create tailored offers that match individual preferences, improving customer engagement.

3. **Raise Campaign Awareness**: Implement strategies to make more customers aware of campaigns, especially those who haven't accepted past offers.

4. **Use Social Proof**: Share testimonials from satisfied customers in similar income brackets to encourage participation in campaigns.

5. **Optimize Communication Channels**: Determine which channels (like email, SMS, or social media) work best for campaign acceptance and focus marketing efforts there.