Marketing Campaigns

Problem scenario:

Marketing mix stands as a widely utilized concept in the execution of marketing strategies. It encompasses various facets within a comprehensive marketing plan, with a central focus on the four Ps of marketing: product, price, place, and promotion.

Problem objective:

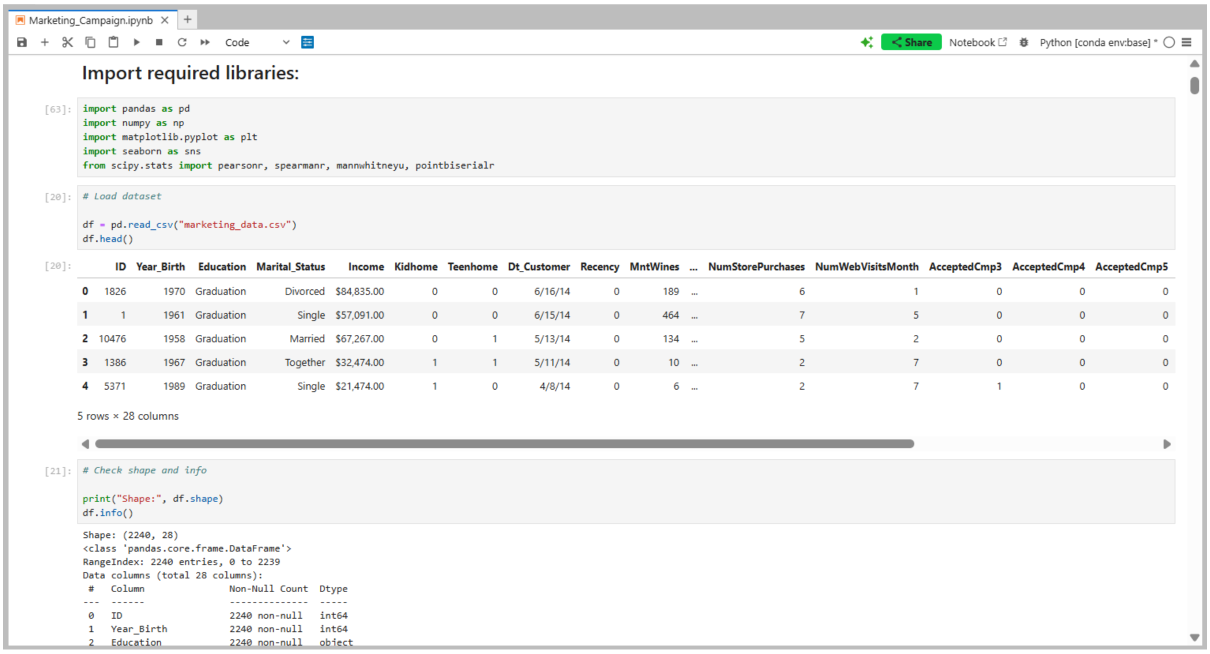
As a data scientist, you must conduct exploratory data analysis and hypothesis testing to enhance your comprehension of the diverse factors influencing customer acquisition.

Data description:

The variables such as birth year, education, income, and others pertain to the first 'P' or 'People' in the tabular data presented to the user. The expenditures on items like wine, fruits, and gold, are associated with ‘Product’. Information relevant to sales channels, such as websites and stores, is connected to ‘Place’, and the fields discussing promotions and the outcomes of various campaigns are linked to ‘Promotion’.

Step 1: Import Libraries & Load the Dataset

* Imported essential libraries for data manipulation and visualization
* Loaded the dataset (marketing_data.csv)
* Displayed the first few rows to verify successful loading
* Checked the dataset shape and structure



Marketing_Campaign.ipynb

Import required libraries:

[63]:
```python
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from scipy.stats import pearsonr, spearmanr, mannwhitneyu, pointbiserialr
```

[20]:
```python
# Load dataset

df = pd.read_csv("marketing_data.csv")
df.head()
```

[20]:

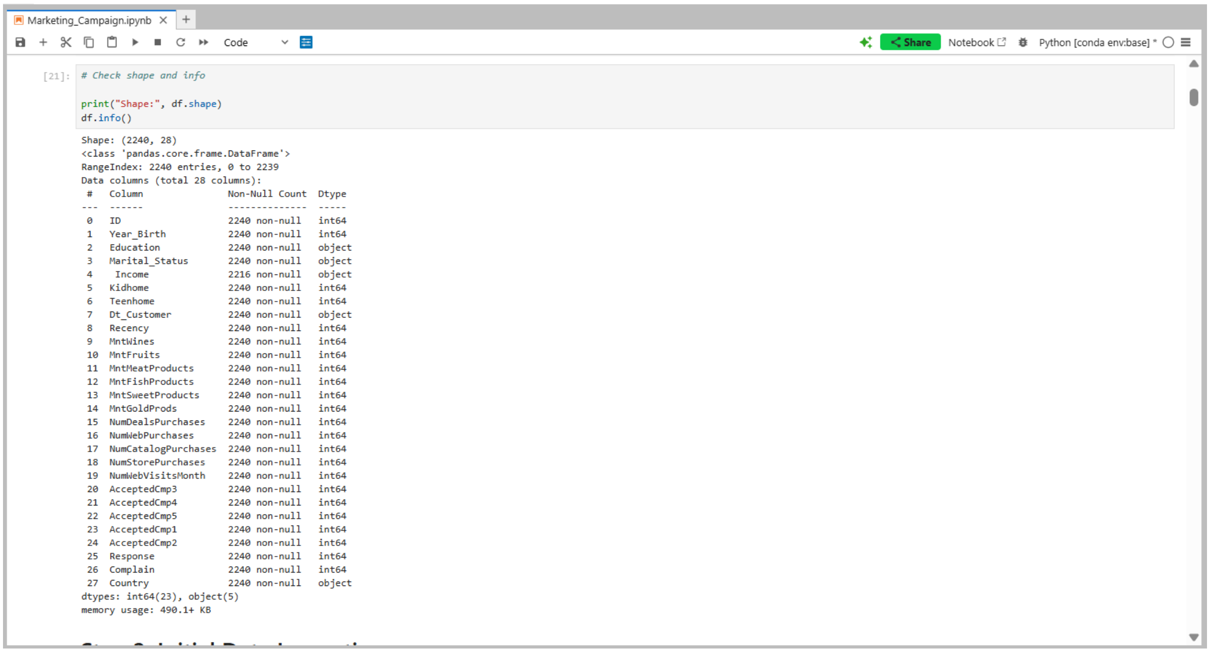
	ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	NumStorePurchases	NumWebVisitsMonth	AcceptedCmp3	AcceptedCmp4	AcceptedCmp5
0	1826	1970	Graduation	Divorced	$84,835.00	0	0	6/16/14	0	189	...	6	1	0	0	0
1	1	1961	Graduation	Single	$57,091.00	0	0	6/15/14	0	464	...	7	5	0	0	0
2	10476	1958	Graduation	Married	$67,267.00	0	1	5/13/14	0	134	...	5	2	0	0	0
3	1386	1967	Graduation	Together	$32,474.00	1	1	5/11/14	0	10	...	2	7	0	0	0
4	5371	1989	Graduation	Single	$21,474.00	1	0	4/8/14	0	6	...	2	7	1	0	0

5 rows × 28 columns

[21]:
```python
# Check shape and info

print("Shape:", df.shape)
df.info()
```

```
Shape: (2240, 28)
<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
```



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[21]:
```python
# Check shape and info

print("Shape:", df.shape)
df.info()
```

```
Shape: (2240, 28)
<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
```

Step 2: Initial Data Inspection

* Checked column names and identified any irregular formatting
* Reviewed summary statistics for numerical variables
* Inspected missing values across all columns
* Verified that key variables (Income, Dt_Customer) require cleaning

Marketing_Campaign.ipynb

Code   Share   Notebook   Python [conda env:base] *

[22]:
```
# View column names

df.columns.tolist()
```

[22]:
```
['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']
```


[23]:
```
# Summary statistics for numeric columns

df.describe()
```

[23]:

	ID	Year_Birth	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	...	NumCatalogPurchases	NumStorePurchases	NumWe
count	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	...	2240.000000	2240.000000	
mean	5592.159821	1968.805804	0.444196	0.506250	49.109375	303.935714	26.302232	166.950000	37.525446	27.062946	...	2.662054	5.790179	

Marketing_Campaign.ipynb

Code   Share   Notebook   Python [conda env:base] *

[23]:
```
# Summary statistics for numeric columns

df.describe()
```

[23]:

	ID	Year_Birth	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	MntSweetProducts	...	NumCatalogPurchases	NumStorePurchases	NumWe
count	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	2240.000000	...	2240.000000	2240.000000	
mean	5592.159821	1968.805804	0.444196	0.506250	49.109375	303.935714	26.302232	166.950000	37.525446	27.062946	...	2.662054	5.790179	
std	3246.662198	11.984069	0.538398	0.544538	28.962453	336.597393	39.773434	225.715373	54.628979	41.280498	...	2.923101	3.250958	
min	0.000000	1893.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	0.000000	...	0.000000	0.000000	
25%	2828.250000	1959.000000	0.000000	0.000000	24.000000	23.750000	1.000000	16.000000	3.000000	1.000000	...	0.000000	3.000000	
50%	5458.500000	1970.000000	0.000000	0.000000	49.000000	173.500000	8.000000	67.000000	12.000000	8.000000	...	2.000000	5.000000	
75%	8427.750000	1977.000000	1.000000	1.000000	74.000000	504.250000	33.000000	232.000000	50.000000	33.000000	...	4.000000	8.000000	
max	11191.000000	1996.000000	2.000000	2.000000	99.000000	1493.000000	199.000000	1725.000000	259.000000	263.000000	...	28.000000	13.000000	

8 rows × 23 columns

[24]:
```
# Check missing values in each column

df.isna().sum().sort_values(ascending=False)
```

[24]:
```
 Income                24
ID                      0
NumDealsPurchases       0
Complain                0
Response                0
AcceptedCmp2            0
AcceptedCmp1            0
AcceptedCmp5            0
AcceptedCmp4            0
AcceptedCmp3            0
NumWebVisitsMonth       0
NumStorePurchases       0
NumCatalogPurchases     0
NumWebPurchases         0
MntGoldProds            0
```

[25]:
```
# Preview unique values for key categorical columns

print("Education:", df['Education'].unique())
print("Marital_Status:", df['Marital_Status'].unique())
print("Country:", df['Country'].unique())
```

```
Education: ['Graduation' 'PhD' '2n Cycle' 'Master' 'Basic']
Marital_Status: ['Divorced' 'Single' 'Married' 'Together' 'Widow' 'YOLO' 'Alone' 'Absurd']
Country: ['SP' 'CA' 'US' 'AUS' 'GER' 'IND' 'SA' 'ME']
```

Step 3: Data Cleaning

3.1 - Clean Column Names

* Cleaned column names by removing leading/trailing whitespace
* Standardized column names by replacing spaces with underscores
* Ensured consistent naming for later processing

```
[26]: # Clean Column Names

      df.columns = df.columns.str.strip().str.replace(' ', '_')
      df.columns.tolist()

[26]: ['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']
```

3.2 - Fix Income Formatting

* Remove $, ,, and whitespace
* Convert Income to numeric
* Confirm missing-value count

```
[28]: # Fix Income formatting

      df['Income'] = (
          df['Income']
          .astype(str)
          .str.replace(r'[\$,]', '', regex=True)
          .str.strip()
      )

      df['Income'] = pd.to_numeric(df['Income'], errors='coerce')

      df['Income'].isna().sum()

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

3.3 - Clean Marital_Status Categories

* Standardize inconsistent categories (Alone, YOLO, Absurd, etc.)
* Map them into consistent groups: Married, Single, Previously_Married
* Ensure categories match the business logic

```
[29]: # Clean Marital_Status categories

      marital_map = {
          'Married': 'Married',
          'Together': 'Married',
          'Single': 'Single',
          'Alone': 'Single',
          'YOLO': 'Single',
          'Absurd': 'Single',
          'Divorced': 'Previously_Married',
          'Widow': 'Previously_Married'
      }

      df['Marital_Status'] = df['Marital_Status'].map(marital_map)

      df['Marital_Status'].value_counts()

[29]: Marital_Status
      Married               1444
      Single                 487
      Previously_Married     309
      Name: count, dtype: int64
```

3.4 - Clean Education Categories

The dataset sometimes contains inconsistent education labels.
This step will:

* Standardize education categories
* Ensure categories match the expected five groups
* Verify final unique values

```
[32]: # Clean Education categories

edu_map = {
    'Graduation': 'Graduation',
    'PhD': 'PhD',
    '2n Cycle': '2n Cycle',
    'Master': 'Master',
    'Basic': 'Basic'
}

df['Education'] = df['Education'].map(edu_map)

df['Education'].value_counts()
```

```
[32]: Education
Graduation    1127
PhD            486
Master         370
2n Cycle       203
Basic           54
Name: count, dtype: int64
```

3.5 - Convert Dt_Customer to Datetime Format

* Convert the Dt_Customer field from string to datetime
* Ensure proper recognition of month/day/year format
* Verify successful conversion

```
[33]: df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%m/%d/%y')

df['Dt_Customer'].head()
```

```
[33]: 0   2014-06-16
1   2014-06-15
2   2014-05-13
3   2014-05-11
4   2014-04-08
Name: Dt_Customer, dtype: datetime64[ns]
```

3.6 - Impute Missing Income Values

According to the problem statement:
` Customers with similar education and marital status tend to have similar yearly incomes on average.`

So we will:

* Group by Education + Marital_Status
* Compute median income for each group
* Fill missing Income values accordingly
* Verify no missing values remain

```
[35]: # compute median income by Education + Marital_Status
group_medians = df.groupby(['Education', 'Marital_Status'])['Income'].median()

# fill missing income
df['Income'] = df.apply(
    lambda row: group_medians[row['Education'], row['Marital_Status']]
    if pd.isna(row['Income']) else row['Income'],
    axis=1
)

df['Income'].isna().sum()
```

```
[35]: np.int64(0)
```

Step 4: Feature Engineering

Create feature columns

* Derived TotalChildren
* Calculated Age
* Created TotalSpending
* Derived TotalPurchases for all channels

[36]:
```python
# total children
df['TotalChildren'] = df['Kidhome'] + df['Teenhome']

# age (using 2025 as reference year)
df['Age'] = 2025 - df['Year_Birth']

# total spending across product categories
spending_cols = [
    'MntWines', 'MntFruits', 'MntMeatProducts',
    'MntFishProducts', 'MntSweetProducts', 'MntGoldProds'
]
df['TotalSpending'] = df[spending_cols].sum(axis=1)

# total purchases across all channels
purchase_cols = ['NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases']
df['TotalPurchases'] = df[purchase_cols].sum(axis=1)

df[['TotalChildren', 'Age', 'TotalSpending', 'TotalPurchases']].head()
```

[36]:

	TotalChildren	Age	TotalSpending	TotalPurchases
0	0	55	1190	14
1	0	64	577	17
2	1	67	251	10
3	2	58	11	3
4	1	36	91	6

Step 5: Outlier Treatment for Income

* Calculated 1st and 99th percentiles
* Capped values outside this range
* Replaced original Income with capped values
* Verified updated distribution

[37]:
```python
# compute percentiles
Q1 = df['Income'].quantile(0.01)
Q99 = df['Income'].quantile(0.99)

# cap outliers
df['Income_capped'] = df['Income'].clip(lower=Q1, upper=Q99)

# replace original column
df['Income'] = df['Income_capped']
df.drop(columns=['Income_capped'], inplace=True)

df['Income'].describe()
```

[37]:
```
count     2240.000000
mean     51762.999464
std      20616.153112
min       7705.920000
25%      35538.750000
50%      51342.000000
75%      68289.750000
max      94437.680000
Name: Income, dtype: float64
```

Step 6: Remove Unrealistic Age Values

* Checked for customers with Age > 100
* Removed those rows from the dataset
* Verified that no unrealistic ages remain

[40]:
```python
# inspect rows with unrealistic ages
df[df['Age'] > 100][['ID', 'Year_Birth', 'Age']]

# remove ages > 100
df = df[df['Age'] <= 100].copy()

df[df['Age'] > 100]
```

[40]:

ID	Year_Birth	Education	Marital_Status	Income	Kidhome	Teenhome	Dt_Customer	Recency	MntWines	...	AcceptedCmp5	AcceptedCmp1	AcceptedCmp2	Response	Complain	Country	TotalChildren	Age

0 rows × 32 columns

Step 7: Encoding Categorical Variables

* Applied ordinal encoding to Education
* Created one-hot encoded variables for Marital_Status
* Created one-hot encoded variables for Country
* Joined encoded columns back to the main DataFrame

[42]:
```python
# Ordinal encoding for Education:

edu_order = {
    'Basic': 1,
    '2n_Cycle': 2,
    'Graduation': 3,
    'Master': 4,
    'PhD': 5
}

# fix column name
df['Education'] = df['Education'].str.replace('2n Cycle', '2n_Cycle')

df['Education_ord'] = df['Education'].map(edu_order)

df[['Education', 'Education_ord']].head()
```

[42]:

	Education	Education_ord
0	Graduation	3
1	Graduation	3
2	Graduation	3
3	Graduation	3
4	Graduation	3

[43]:
```python
# One-hot encoding for Marital_Status:

marital_dummies = pd.get_dummies(df['Marital_Status'], prefix='Marital')
df = pd.concat([df, marital_dummies], axis=1)

marital_dummies.head()
```

[43]:

	Marital_Married	Marital_Previously_Married	Marital_Single
0	False	True	False
1	False	False	True
2	True	False	False
3	True	False	False
4	False	False	True

[44]:
```python
# One-hot encoding for Country:

country_dummies = pd.get_dummies(df['Country'], prefix='Country')
df = pd.concat([df, country_dummies], axis=1)

country_dummies.head()
```

[44]:

	Country_AUS	Country_CA	Country_GER	Country_IND	Country_ME	Country_SA	Country_SP	Country_US
0	False	False	False	False	False	False	True	False
1	False	True	False	False	False	False	False	False
2	False	False	False	False	False	False	False	True
3	True	False	False	False	False	False	False	False
4	False	False	False	False	False	False	True	False

Step 8: Correlation Heatmap

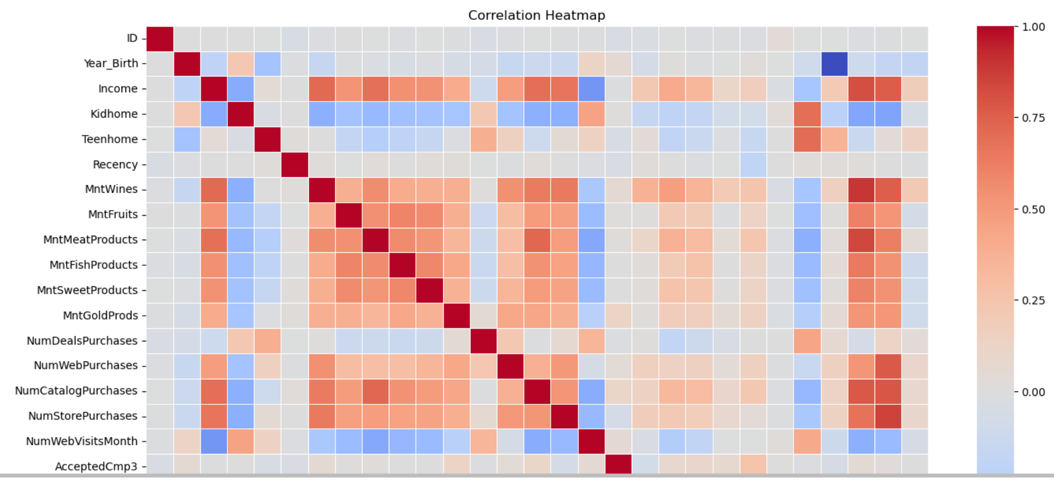
* Select only numeric columns
* Compute the correlation matrix
* Plot a heatmap for visual interpretation

[45]:
```python
# Select numeric columns and compute correlation:

numeric_df = df.select_dtypes(include=['int64', 'float64'])
corr_matrix = numeric_df.corr()
corr_matrix
```

[45]:

	ID	Year_Birth	Income	Kidhome	Teenhome	Recency	MntWines	MntFruits	MntMeatProducts	MntFishProducts	...	AcceptedCmp5	AcceptedCmp1	AcceptedCmp2	Response
ID	1.000000	0.003024	0.002879	0.002202	-0.003543	-0.046755	-0.021181	0.007080	-0.002622	-0.023181	...	-0.005062	-0.021524	-0.015027	-0.021810
Year_Birth	0.003024	1.000000	-0.208115	0.234133	-0.363350	-0.019670	-0.163035	-0.013751	-0.030927	-0.042519	...	0.015322	-0.008227	-0.007657	0.018424
Income	0.002879	-0.208115	1.000000	-0.524802	0.040044	0.006729	0.717841	0.528080	0.685489	0.542402	...	0.408476	0.336654	0.107633	0.168745
Kidhome	0.002202	0.234133	-0.524802	1.000000	-0.035753	0.007544	-0.496367	-0.372488	-0.437059	-0.387536	...	-0.204994	-0.172512	-0.081794	-0.080176
Teenhome	-0.003543	-0.363350	0.040044	-0.035753	1.000000	0.017115	0.005409	-0.175951	-0.260820	-0.203900	...	-0.190227	-0.140288	-0.015664	-0.154730
Recency	-0.046755	-0.019670	0.006729	0.007544	0.017115	1.000000	0.016668	-0.003592	0.023705	0.001532	...	0.000956	-0.019258	-0.001764	-0.198568
MntWines	-0.021181	-0.163035	0.717841	-0.496367	0.005409	0.016668	1.000000	0.388518	0.561993	0.399073	...	0.471969	0.354365	0.206040	0.247392
MntFruits	0.007080	-0.013751	0.528080	-0.372488	-0.175951	-0.003592	0.388518	1.000000	0.542057	0.594438	...	0.212027	0.195380	-0.009701	0.125904
MntMeatProducts	-0.002622	-0.030927	0.685489	-0.437059	-0.260820	0.023705	0.561993	0.542057	1.000000	0.567880	...	0.372212	0.310096	0.043090	0.236640
MntFishProducts	-0.023181	-0.042519	0.542402	-0.387536	-0.203900	0.001532	0.399073	0.594438	0.567880	1.000000	...	0.198163	0.260908	0.002583	0.111415
MntSweetProducts	-0.006444	-0.019571	0.538464	-0.370656	-0.162218	0.023045	0.385992	0.567054	0.523418	0.579553	...	0.258848	0.241875	0.009972	0.117366
MntGoldProds	-0.010661	-0.057599	0.404110	-0.349633	-0.020186	0.017412	0.386376	0.390042	0.348845	0.422103	...	0.176382	0.167145	0.050252	0.140693
NumDealsPurchases	-0.036917	-0.067999	-0.116465	0.221799	0.387792	-0.000987	0.010829	-0.131886	-0.122465	-0.139440	...	-0.182910	-0.123530	-0.037814	0.001854
NumWebPurchases	-0.017913	-0.153973	0.476716	-0.362063	0.155776	-0.010616	0.542177	0.297024	0.293579	0.293489	...	0.138958	0.154991	0.034103	0.148453
NumCatalogPurchases	-0.001893	-0.125439	0.690528	-0.502438	-0.110285	0.025449	0.634784	0.487307	0.723519	0.534033	...	0.321419	0.308240	0.099891	0.220894
NumStorePurchases	-0.014062	-0.139465	0.665315	-0.500387	0.050517	0.001117	0.642433	0.463168	0.480110	0.460099	...	0.216147	0.183043	0.085098	0.038855
NumWebVisitsMonth	-0.008104	0.117570	-0.646763	0.447641	0.134491	-0.021959	-0.320337	-0.417427	-0.539203	-0.445760	...	-0.276371	-0.192948	-0.007330	-0.004449
AcceptedCmp3	-0.035959	0.061013	-0.012898	0.014606	-0.042823	-0.032976	0.062201	0.014983	0.018331	0.000370	...	0.080930	0.094661	0.071981	0.254144
AcceptedCmp4	-0.025292	-0.064341	0.225366	-0.161775	0.038790	0.018890	0.373532	0.010402	0.103053	0.016864	...	0.307812	0.251225	0.292184	0.176890
AcceptedCmp5	-0.005062	0.015322	0.408476	-0.204994	-0.190227	0.000956	0.471969	0.212027	0.372212	0.198163	...	1.000000	0.404616	0.222333	0.328182

[46]:
```python
# Plot heatmap:

plt.figure(figsize=(16, 12))
sns.heatmap(corr_matrix, cmap='coolwarm', linewidths=0.5)
plt.title("Correlation Heatmap")
plt.show()
```



Step 9: Hypothesis Testing

9.1 - Hypothesis A - Age vs Store Purchases

* Compared Age with number of in-store purchases
* Visualized relationship using a scatter plot
* Calculated Pearson correlation coefficient
* Evaluated statistical significance

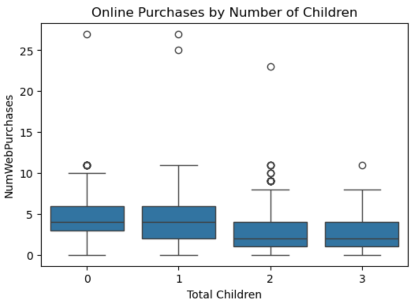
```
[48]: # Scatter plot:

plt.figure(figsize=(6,4))
plt.scatter(df['Age'], df['NumStorePurchases'], alpha=0.4)
plt.xlabel('Age')
plt.ylabel('NumStorePurchases')
plt.title('Age vs Store Purchases')
plt.show()
```


```
[49]: # Pearson correlation test:

r, p = pearsonr(df['Age'], df['NumStorePurchases'])

print("Correlation coefficient (r):", r)
print("p-value:", p)

Correlation coefficient (r): 0.13946510380279412
p-value: 3.472816546739386e-11
```

9.2 - Hypothesis B - Children vs Online Purchases

* Compared TotalChildren with number of online purchases
* Visualized distributions using a boxplot
* Performed the Spearman rank correlation test
* Checked if online purchases increase with more children

```
[50]: # Boxplot:

plt.figure(figsize=(6,4))
sns.boxplot(x=df['TotalChildren'], y=df['NumWebPurchases'])
plt.xlabel('Total Children')
plt.ylabel('NumWebPurchases')
plt.title('Online Purchases by Number of Children')
plt.show()
```

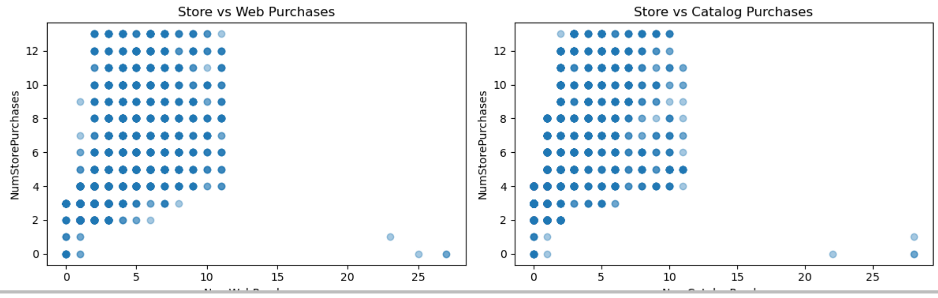


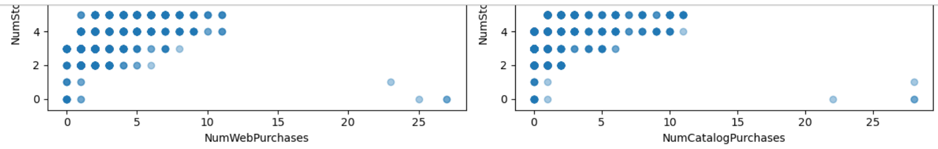

```
[52]: # Spearman correlation test:

rho, p = spearmanr(df['TotalChildren'], df['NumWebPurchases'])

print("Spearman rho:", rho)
print("p-value:", p)

Spearman rho: -0.1853333569053294
p-value: 9.791403824731e-19
```

9.3 - Hypothesis C — Store vs Web & Catalog Purchases

* Visualized relationships using scatterplots
* Performed Pearson correlation tests
* Checked if online/catalog sales negatively impact store sales

[53]:
```python
# Scatterplots:

plt.figure(figsize=(12,4))

# Store vs Web
plt.subplot(1,2,1)
plt.scatter(df['NumWebPurchases'], df['NumStorePurchases'], alpha=0.4)
plt.xlabel('NumWebPurchases')
plt.ylabel('NumStorePurchases')
plt.title('Store vs Web Purchases')

# Store vs Catalog
plt.subplot(1,2,2)
plt.scatter(df['NumCatalogPurchases'], df['NumStorePurchases'], alpha=0.4)
plt.xlabel('NumCatalogPurchases')
plt.ylabel('NumStorePurchases')
plt.title('Store vs Catalog Purchases')

plt.tight_layout()
plt.show()
```





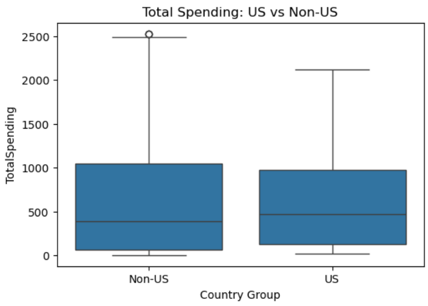
[54]:
```python
# Correlation tests:

# Store vs Web
r_web, p_web = pearsonr(df['NumStorePurchases'], df['NumWebPurchases'])

# Store vs Catalog
r_cat, p_cat = pearsonr(df['NumStorePurchases'], df['NumCatalogPurchases'])

print("Store vs Web: r =", r_web, ", p-value =", p_web)
print("Store vs Catalog: r =", r_cat, ", p-value =", p_cat)
```

```
Store vs Web: r = 0.5022771005445519 , p-value = 2.676589141084666e-143
Store vs Catalog: r = 0.5188838960472143 , p-value = 1.9038335885192102e-154
```

9.4 - Hypothesis D - US vs Non-US Spending

* Created two groups (US vs Non-US)
* Visualized spending distributions
* Performed Mann–Whitney U test
* Checked if the difference is statistically significant

[55]:
```
# Boxplot:

plt.figure(figsize=(6,4))

sns.boxplot(
    x = df['Country'].apply(lambda x: 'US' if x=='US' else 'Non-US'),
    y = df['TotalSpending']
)

plt.xlabel('Country Group')
plt.ylabel('TotalSpending')
plt.title('Total Spending: US vs Non-US')
plt.show()
```



[56]:
```
# Median spending:

df.groupby(df['Country'].apply(lambda x: 'US' if x=='US' else 'Non-US'))['TotalSpending'].median()
```

[56]:
```
Country
Non-US    393.0
US        467.0
Name: TotalSpending, dtype: float64
```

[58]:
```
# Mann-Whitney U test:

us_spend = df[df['Country']=='US']['TotalSpending']
nonus_spend = df[df['Country']!='US']['TotalSpending']

stat, p = mannwhitneyu(us_spend, nonus_spend, alternative='two-sided')

print("Mann-Whitney U statistic:", stat)
print("p-value:", p)
print("\nUS median:", us_spend.median())
print("Non-US median:", nonus_spend.median())
```

```
Mann-Whitney U statistic: 123822.5
p-value: 0.23290054549364958

US median: 467.0
Non-US median: 393.0
```

Step 10: Visual Analysis

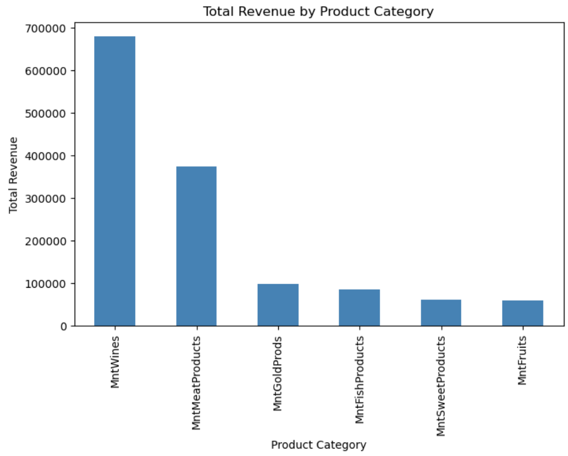
10.1 - Product Revenue Analysis

* Calculated revenue across all product categories
* Identified top and bottom performers
* Visualized using a bar chart

[59]:
```python
# Calculate product revenues:

product_cols = [
    'MntWines', 'MntFruits', 'MntMeatProducts',
    'MntFishProducts', 'MntSweetProducts', 'MntGoldProds'
]

product_revenue = df[product_cols].sum().sort_values(ascending=False)
product_revenue
```

[59]:
```
MntWines            680038
MntMeatProducts     373393
MntGoldProds         98358
MntFishProducts      83939
MntSweetProducts     60553
MntFruits            58767
dtype: int64
```

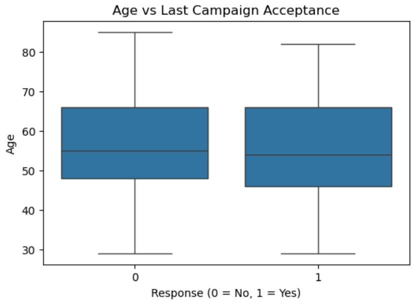
[60]:
```python
# Plot revenue by product category:

plt.figure(figsize=(8,5))
product_revenue.plot(kind='bar', color='steelblue')
plt.title("Total Revenue by Product Category")
plt.ylabel("Total Revenue")
plt.xlabel("Product Category")
plt.show()
```



10.2 - Age vs Campaign Acceptance

* Compared Age distribution between responders and non-responders
* Visualized using a boxplot
* Calculated point-biserial correlation to measure association

```
[61]: # Boxplot of Age vs Response:

plt.figure(figsize=(6,4))
sns.boxplot(x=df['Response'], y=df['Age'])
plt.xlabel("Response (0 = No, 1 = Yes)")
plt.ylabel("Age")
plt.title("Age vs Last Campaign Acceptance")
plt.show()
```




```
[62]: # Median Age by Response:

df.groupby('Response')['Age'].median()
```

```
[62]: Response
0    55.0
1    54.0
Name: Age, dtype: float64
```

```
[64]: # Point-Biserial correlation:

r, p = pointbiserialr(df['Response'], df['Age'])
print("Point-biserial correlation (r):", r)
print("p-value:", p)
```

```
Point-biserial correlation (r): -0.018424292565464954
p-value: 0.38375446666786445
```

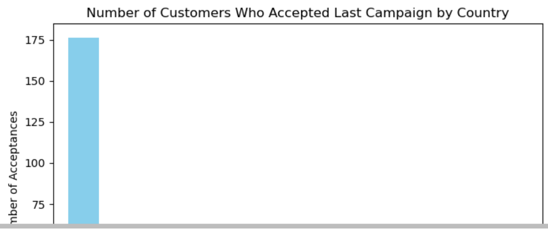
10.3 - Campaign Acceptance by Country

* Grouped customers by country
* Counted total number of acceptances
* Visualized acceptance distribution by country

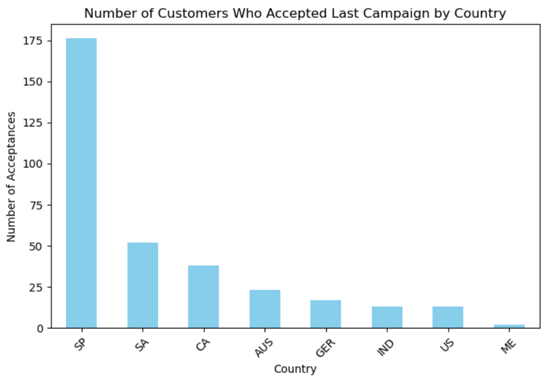
[65]:
```python
# Calculate acceptances by country:

acceptance_by_country = df.groupby('Country')['Response'].sum().sort_values(ascending=False)
acceptance_by_country
```

[65]:
```
Country
SP     176
SA      52
CA      38
AUS     23
GER     17
IND     13
US      13
ME       2
Name: Response, dtype: int64
```

[66]:
```python
# Plot acceptances by country:

plt.figure(figsize=(8,5))
acceptance_by_country.plot(kind='bar', color='skyblue')
plt.title("Number of Customers Who Accepted Last Campaign by Country")
plt.ylabel("Number of Acceptances")
plt.xlabel("Country")
plt.xticks(rotation=45)
plt.show()
```



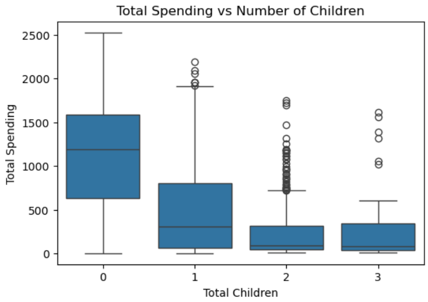
[66]:
```python
# Plot acceptances by country:

plt.figure(figsize=(8,5))
acceptance_by_country.plot(kind='bar', color='skyblue')
plt.title("Number of Customers Who Accepted Last Campaign by Country")
plt.ylabel("Number of Acceptances")
plt.xlabel("Country")
plt.xticks(rotation=45)
plt.show()
```



10.4 - Total Children vs Total Spending

* Visualized spending for customers with different numbers of children
* Calculated median spending across groups
* Measured correlation strength using Spearman rank correlation

```
[70]: # Boxplot:

plt.figure(figsize=(6,4))
sns.boxplot(x=df['TotalChildren'], y=df['TotalSpending'])
plt.xlabel('Total Children')
plt.ylabel('Total Spending')
plt.title('Total Spending vs Number of Children')
plt.show()
```




```
[71]: # Median spending by children group:

df.groupby('TotalChildren')['TotalSpending'].median()
```

```
[71]: TotalChildren
0    1189.0
1     306.0
2      93.0
3      88.0
Name: TotalSpending, dtype: float64
```

```
[72]: # Spearman correlation test:

rho, p = spearmanr(df['TotalChildren'], df['TotalSpending'])
print("Spearman rho:", rho)
print("p-value:", p)
```

```
Spearman rho: -0.4835857068087243
p-value: 1.817901317197658e-131
```

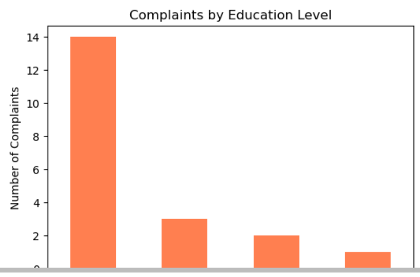
10.5 - Complaints by Education Level

* Filtered only customers who complained
* Counted complaints by education category
* Visualized distribution using a bar chart

```
[73]: # Count complaints by education:

complaints_by_edu = df[df['Complain'] == 1]['Education'].value_counts()
complaints_by_edu
```

```
[73]: Education
Graduation    14
2n_Cycle       3
Master         2
PhD            1
Name: count, dtype: int64
```

```
[74]: # Plot complaints by education:

plt.figure(figsize=(6,4))
complaints_by_edu.plot(kind='bar', color='coral')
plt.title("Complaints by Education Level")
plt.xlabel("Education Level")
plt.ylabel("Number of Complaints")
plt.xticks(rotation=45)
plt.show()
```



Step 11: Final Project Summary

Final Summary — Marketing Campaign Analysis

* Completed full data cleaning and preprocessing
* Engineered new features for deeper insights
* Performed exploratory data analysis
* Conducted outlier treatment and encoding
* Executed four hypothesis tests as required
* Generated key visual insights for business interpretation

Key data preparation steps:

* Cleaned Income, Education, and Marital_Status categories
* Converted Dt_Customer to datetime format
* Imputed missing income values using Education + Marital_Status groups
* Removed unrealistic Age values
* Created TotalChildren, Age, TotalSpending, and TotalPurchases

Key EDA findings:

* Income and spending variables are right-skewed
* Wines and Meat are the highest revenue products
* TotalSpending strongly correlates with premium product categories
* Multi-channel shoppers tend to spend more

Hypothesis testing results:

* Older customers show very weak preference for in-store shopping
* Customers with more children do not prefer online shopping; they shop less
* No evidence of channel cannibalization — store, web, and catalog purchases rise together
* US customers do not significantly outperform non-US customers in spending

Key visual insights:

* Spain has the highest campaign acceptance
* Campaign acceptance is not influenced by Age
* Families with more children spend significantly less
* Most complaints come from Graduation-level customers

Business insights:

* Spain is highly responsive — stronger marketing focus recommended
* High-value customers tend to have no children
* Multi-channel engagement drives higher spending
* Graduation-level customers may need better support or communication