marketing_mix

March 29, 2025

[1]:
```python
import pandas as pd

df = pd.read_csv('marketing_data.csv')
df.isnull().sum()
df.info()
# df.columns
df.head()
```

```
<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
```

[1]:
```
      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]
```

[2]:
```
print(df[' Income '].head(10))
# probably will delete this cell
```

```
0     $84,835.00
1     $57,091.00
2     $67,267.00
3     $32,474.00
4     $21,474.00
5     $71,691.00
6     $63,564.00
7     $44,931.00
8     $65,324.00
```

```
9    $65,324.00
Name:  Income , dtype: object
```

[3]:
```
# 1. After importing the data, examine variables such as Dt_Customer and Income
↪to verify their accurate importation.
```

[4]:
```
print(df.columns.tolist())
```

```
['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']
```

[5]:
```
## I notice there is a space in income
df.columns = df.columns.str.strip()
print(df.columns.tolist()) # print to check and see if it's corrected.

# the list of columns is small enough to visually check the rest of them for
↪similar issues.  If it was a really large dataset, I would proactively strip
↪them all.  If there were any special characters in the column names I would
↪get rid of those too but I don't see any here.
```

```
['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']
```

[6]:
```
print(df['Dt_Customer'])
```

```
0        6/16/14
1        6/15/14
2        5/13/14
3        5/11/14
4         4/8/14
          …
2235      3/7/13
2236     1/22/13
2237     12/3/12
2238    11/29/12
2239      9/1/12
Name: Dt_Customer, Length: 2240, dtype: object
```

[7]:
```
# this data is not in the correct datetime format (as also we learn from .info␣
↪the datatype is an object) so I need to convert it.
```

[8]:
```
print(df['Dt_Customer'].head())
```

```
0    6/16/14
1    6/15/14
2    5/13/14
3    5/11/14
4     4/8/14
Name: Dt_Customer, dtype: object
```

[9]:
```
df['Dt_Customer'] = pd.to_datetime(df['Dt_Customer'], format='%m/%d/%y')
print(df['Dt_Customer'].head()) # to see if it works
```

```
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]
```

[10]:
```
## 2. There are missing income values for some customers. Conduct missing value␣
↪imputation, considering that customers with similar education and marital␣
↪status tend to have comparable yearly incomes, on average. It may be␣
↪necessary to cleanse the data before proceeding. Specifically, scrutinize␣
↪the categories of education and marital status for data cleaning.
print(df['Income'].head(10)) # first see what the data looks like
```

```
0    $84,835.00
1    $57,091.00
2    $67,267.00
3    $32,474.00
4    $21,474.00
5    $71,691.00
6    $63,564.00
7    $44,931.00
8    $65,324.00
9    $65,324.00
Name: Income, dtype: object
```

[11]:
```
# convert income to numeric
df['Income'] = df['Income'].replace({'\$': '', ',': ''}, regex=True).
↪astype(float)
# check to see if it worked
print(df['Income'].head())
```

```
0    84835.0
1    57091.0
2    67267.0
3    32474.0
4    21474.0
Name: Income, dtype: float64
```

[12]:
```
print("Missing Income values:", df['Income'].isnull().sum())
```

```
Missing Income values: 24
```

[13]:
```
# so if I want to fill in the missing income values with the mean of what would␣
↪be similar education and marital status, I want to take a look at that data␣
↪first and see if anything needs to be cleaned up before I start working with␣
↪it.
print(df['Education'].unique())
print(df['Marital_Status'].unique())
```

```
['Graduation' 'PhD' '2n Cycle' 'Master' 'Basic']
['Divorced' 'Single' 'Married' 'Together' 'Widow' 'YOLO' 'Alone' 'Absurd']
```

[14]:
```
# some of the smartass answers for marital status could be a problem so␣
↪checking to see how frequent they are and if I need to do anything with them
print(df['Marital_Status'].value_counts())
```

```
Marital_Status
Married     864
Together    580
Single      480
Divorced    232
Widow        77
Alone         3
YOLO          2
Absurd        2
Name: count, dtype: int64
```

[15]:
```
# decided to group the marital status oddball entries in with "single"
df['Marital_Status'] = df['Marital_Status'].replace({'Alone': 'Single', 'YOLO':␣
↪'Single', 'Absurd': 'Single'})
# see if it worked
print(df['Marital_Status'].value_counts())
```

```
Marital_Status
Married     864
Together    580
Single      487
Divorced    232
Widow        77
Name: count, dtype: int64
```

[16]:
```
group_means = df.groupby(['Education', 'Marital_Status'])['Income'].mean().
    ↪round(2)
print(group_means)
```

```
Education   Marital_Status
2n Cycle    Divorced          49395.13
            Married           46201.10
            Single            53673.94
            Together          44736.41
            Widow             51392.20
Basic       Divorced           9548.00
            Married           21960.50
            Single            18238.67
            Together          21240.07
            Widow             22123.00
Graduation  Divorced          54526.04
            Married           50800.26
            Single            51365.63
            Together          55758.48
            Widow             54976.66
Master      Divorced          50331.95
            Married           53286.03
            Single            53787.14
            Together          52109.01
            Widow             58401.55
PhD         Divorced          53096.62
            Married           58138.03
            Single            53039.67
            Together          56041.42
            Widow             60288.08
Name: Income, dtype: float64
```

[17]:
```
# defining the function to fill lin missing income values based on the mean␣
    ↪values corresponding to similar groups
def impute_income(row):
    if pd.isnull(row['Income']):
        try:
            return group_means.loc[(row['Education'], row['Marital_Status'])]
        except KeyError:
            return df['Income'].mean()  # Fallback option
    return row['Income']

df['Income'] = df.apply(impute_income, axis=1)
# confirm this worked
print("Remaining missing Income values:", df['Income'].isnull().sum())
```

```
Remaining missing Income values: 0
```

[19]:
```
# 3. Create variables to represent the total number of children, age, and total␣
↪spending.  Derive the total purchases from the number of transactions across␣
↪the three channels.
## make new column for all children
df['Total_Children'] = df['Kidhome'] + df['Teenhome']
## get the age of the children (using 2014 because that's what the Dt_customer␣
↪dates are from
df['Age'] = 2014 - df['Year_Birth']
df.columns # check if it worked
```

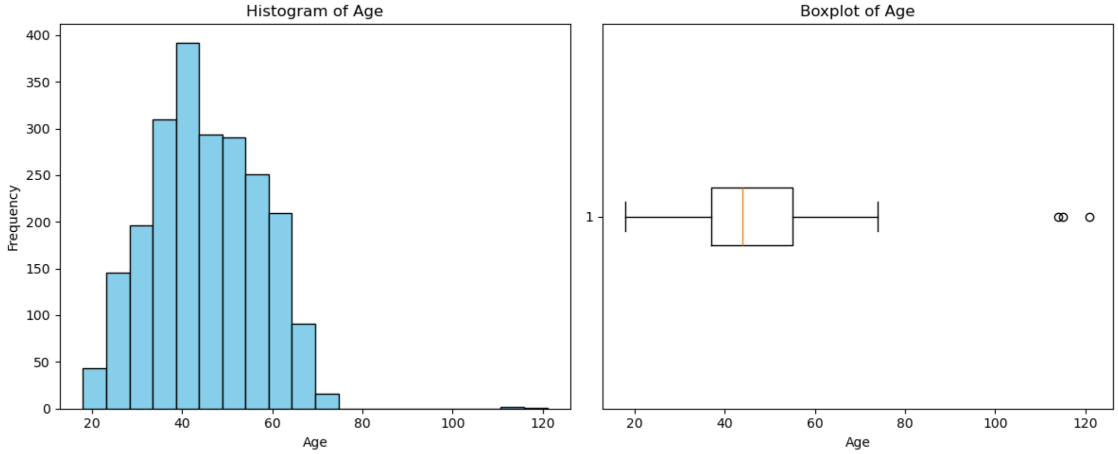
[19]:
```
Index(['ID', 'Year_Birth', 'Education', 'Marital_Status', 'Income', 'Kidhome',
       'Teenhome', 'Dt_Customer', 'Recency', 'MntWines', 'MntFruits',
       'MntMeatProducts', 'MntFishProducts', 'MntSweetProducts',
       'MntGoldProds', 'NumDealsPurchases', 'NumWebPurchases',
       'NumCatalogPurchases', 'NumStorePurchases', 'NumWebVisitsMonth',
       'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5', 'AcceptedCmp1',
       'AcceptedCmp2', 'Response', 'Complain', 'Country', 'Total_Children',
       'Age'],
      dtype='object')
```

[21]:
```
# add a column for total spending
df['Total_Spending'] = (df['MntWines'] + df['MntFruits'] +␣
↪df['MntMeatProducts'] +
                        df['MntFishProducts'] + df['MntSweetProducts'] +␣
↪df['MntGoldProds'])
# for the number of transactions accross the three chanels
df['Total_Purchases'] = (df['NumWebPurchases'] + df['NumCatalogPurchases'] +␣
↪df['NumStorePurchases'])
# check if it makes sense
print(df[['Total_Children', 'Age', 'Total_Spending', 'Total_Purchases']].
↪head(30))
```

```
    Total_Children  Age  Total_Spending  Total_Purchases
0                0   44            1190               14
1                0   53             577               17
2                1   56             251               10
3                2   47              11                3
4                1   25              91                6
5                0   56            1192               16
6                0   60            1215               27
7                1   47              96                6
8                1   60             544               17
9                1   60             544               17
10               0   67            1208               21
11               1   35             222               10
12               0   55            1156               15
13               0   33              72                4
```

14	1	45	359	25
15	2	37	174	8
16	2	37	174	8
17	1	56	22	4
18	1	54	72	5
19	3	56	13	3
20	1	60	335	12
21	1	48	393	14
22	1	35	92	6
23	1	38	404	14
24	1	45	704	22
25	1	49	122	7
26	2	58	684	19
27	2	58	684	19
28	2	58	45	5
29	0	39	726	15

[22]:
```
# 4. Generate box plots and histograms to gain insights into the distributions␣
↪and identify outliers. Implement outlier treatment as needed.

import matplotlib.pyplot as plt

# Histogram and Boxplot for Age
plt.figure(figsize=(12, 5))

# Histogram
plt.subplot(1, 2, 1)
plt.hist(df['Age'], bins=20, color='skyblue', edgecolor='black')
plt.title("Histogram of Age")
plt.xlabel("Age")
plt.ylabel("Frequency")

# Box Plot
plt.subplot(1, 2, 2)
plt.boxplot(df['Age'], vert=False)
plt.title("Boxplot of Age")
plt.xlabel("Age")

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

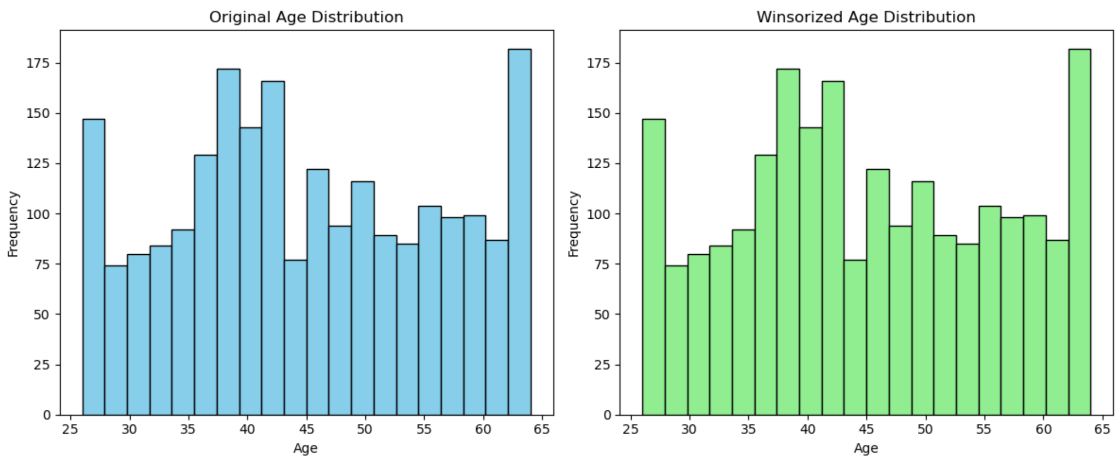


[27]:
```
## the outliers in age are really skewing the data.  will try the winsorize to␣
↪fix the distribution
from scipy.stats.mstats import winsorize
df['winsorized_age'] = winsorize(df['Age'], limits=[0.05, 0.05])

# check if it worked
print(df['winsorized_age'].head())
```

```
0    44
1    53
2    56
3    47
4    26
Name: winsorized_age, dtype: int64
```

[28]:
```
## visually see how this looks now
import matplotlib.pyplot as plt

plt.figure(figsize=(12, 5))

# Histogram for original Age
plt.subplot(1, 2, 1)
plt.hist(df['Age'], bins=20, color='skyblue', edgecolor='black')
plt.title("Original Age Distribution")
plt.xlabel("Age")
plt.ylabel("Frequency")

# Histogram for winsorized Age
plt.subplot(1, 2, 2)
plt.hist(df['winsorized_age'], bins=20, color='lightgreen', edgecolor='black')
plt.title("Winsorized Age Distribution")
```

```
plt.xlabel("Age")
plt.ylabel("Frequency")

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



[35]:

```
# 5. Apply ordinal and one-hot encoding based on the various types of␣
↪categorical variables.
## define the order for education
education_order = ['Basic', '2n Cycle', 'Graduation', 'Master', 'PhD']
education_mapping = {level: i for i, level in enumerate(education_order)}
## create an ordinal column for Education
df['education_ordinal'] = df['Education'].map(education_mapping)
print(df[['Education', 'education_ordinal']].head(20)) # had to print out more␣
↪because the first .head() was all the same in the first 5
```

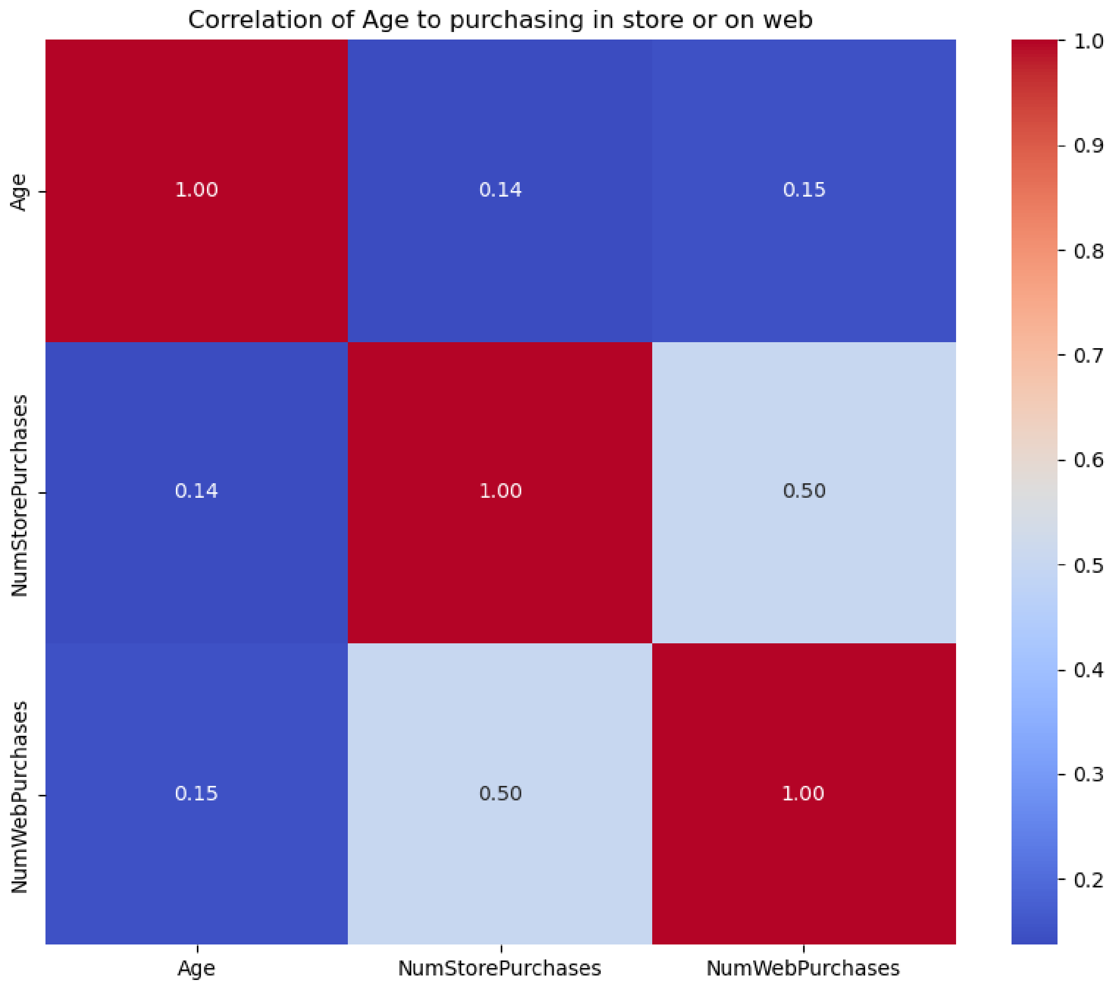
```
     Education  education_ordinal
0   Graduation                  2
1   Graduation                  2
2   Graduation                  2
3   Graduation                  2
4   Graduation                  2
5          PhD                  4
6     2n Cycle                  1
7   Graduation                  2
8          PhD                  4
9          PhD                  4
10    2n Cycle                  1
11      Master                  3
12         PhD                  4
13  Graduation                  2
```

```
14  Graduation                 2
15  Graduation                 2
16  Graduation                 2
17         PhD                 4
18    2n Cycle                 1
19      Master                 3
```

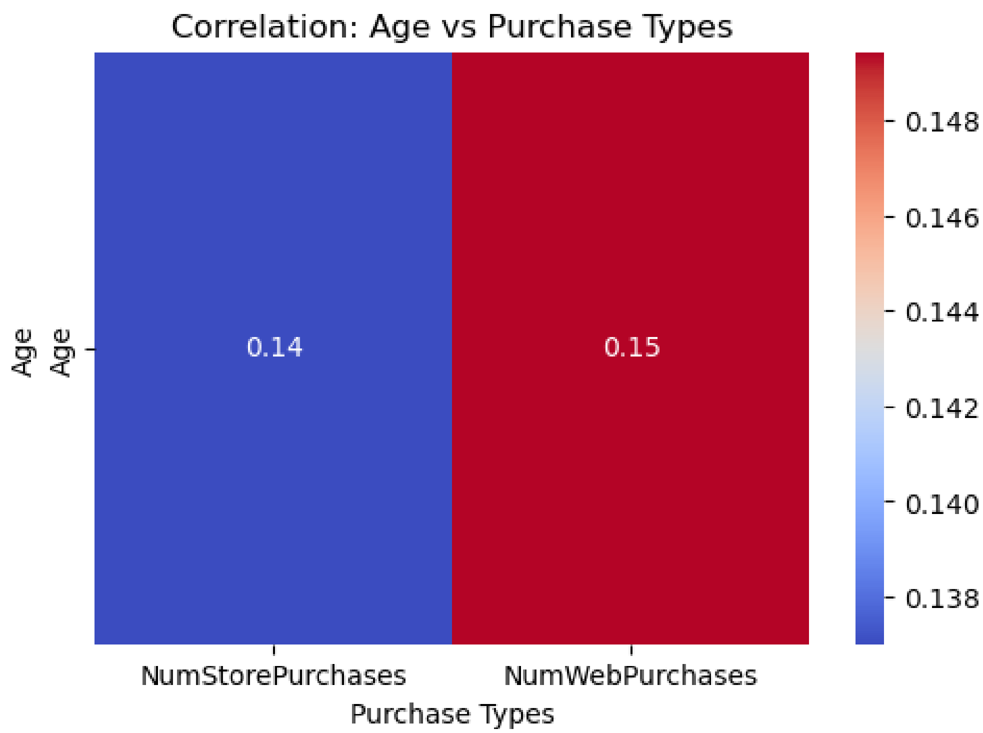
[38]:
```
## use one hot encoding for marital status
df = pd.get_dummies(df, columns=['Marital_Status'], prefix='Marital')
print(df.columns) # check if it worked
```

```
Index(['ID', 'Year_Birth', 'Education', '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', 'Total_Children', 'Age',
       'Total_Spending', 'Total_Purchases', 'winsorized_age',
       'education_ordinal', 'Marital_Divorced', 'Marital_Married',
       'Marital_Single', 'Marital_Together', 'Marital_Widow'],
      dtype='object')
```

[44]:
```
# 6. Generate a heatmap to illustrate the correlation between different pairs␣
 ↪of variables.
## considering the upcoming steps in the assignment, I will look at the␣
 ↪correlation between age and store purchases vs. web purchases
import seaborn as sns
import matplotlib.pyplot as plt
## define which columns I want to look at for correlation
cols_to_correlate = ['Age', 'NumStorePurchases', 'NumWebPurchases']
## compute the correlation
corr_subset = df[cols_to_correlate].corr()
## set up matplotlib figure
plt.figure(figsize=(10, 8))
## use seaborn for the heatmap using parameters I picked out on the seaborn␣
 ↪documentation
sns.heatmap(corr_subset, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation of Age to purchasing in store or on web")
plt.xlabel(
plt.show()
```



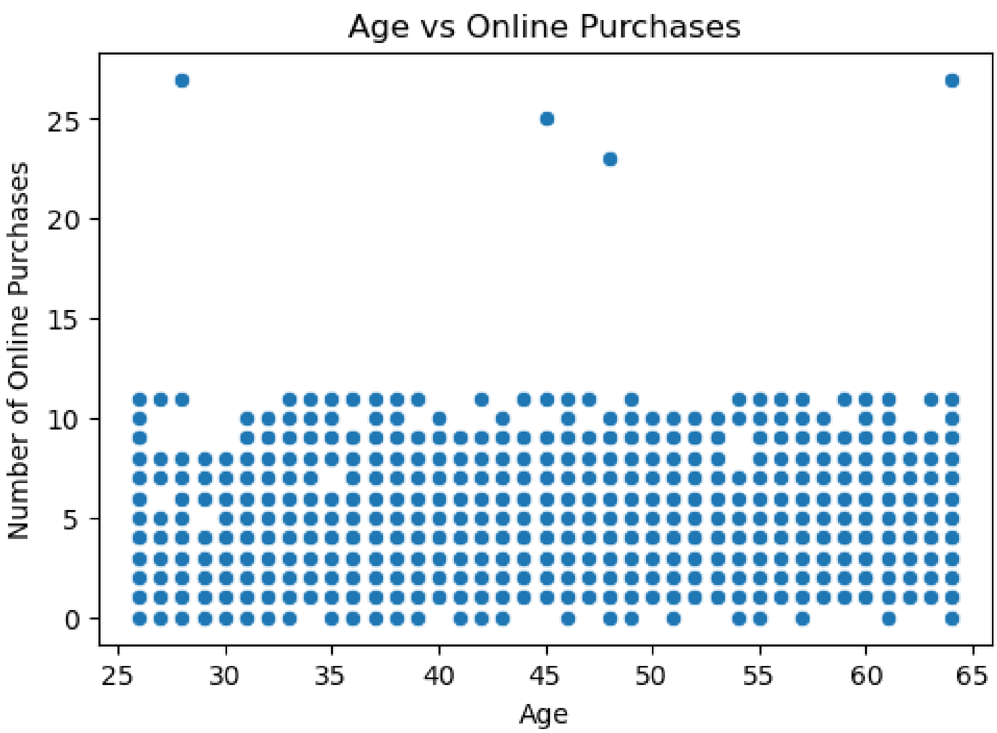
[45]:
```
## restructuring the heatmap to show age and purhase type on different axes
# Create a custom DataFrame with correlations between Age and purchase␣
↪variables because the heatmap above doesn't appear to show a correlation␣
↪between age and whether purchase are made in the store or on the web.
custom_corr = df[['Age']].join(df[['NumStorePurchases', 'NumWebPurchases']])
custom_corr = custom_corr.corr().loc[['Age'], ['NumStorePurchases',␣
↪'NumWebPurchases']]
plt.figure(figsize=(6, 4))
sns.heatmap(custom_corr, annot=True, cmap='coolwarm', fmt=".2f")
plt.title("Correlation: Age vs Purchase Types")
plt.xlabel("Purchase Types")
plt.ylabel("Age")
plt.show()
```



[ ]:
```
# 7. Test the following hypotheses:
   ## Older individuals may not possess the same level of technological
 ↪proficiency and may, therefore, lean toward traditional in-store shopping
 ↪preferences.
   ## Customers with children likely experience time constraints, making online
 ↪shopping a more convenient option.
   ## Sales at physical stores may face the risk of cannibalization by
 ↪alternative distribution channels.
   ## Does the United States significantly outperform the rest of the world in
 ↪total purchase volumes?
```

[46]:
```
## 7A Hypothesis: Older individuals lean toward traditional in-store shopping
 ↪preferences.  (Spoiler alert, the heatmap says not true, but I will do a
 ↪scatter graph to look at the data better.)
import seaborn as sns
import matplotlib.pyplot as plt

# Scatter plot: Age vs In-Store Purchases
plt.figure(figsize=(6, 4))
sns.scatterplot(data=df, x='Age', y='NumStorePurchases')
plt.title("Age vs In-Store Purchases")
plt.xlabel("Age")
plt.ylabel("Number of In-Store Purchases")
```

```
plt.show()

# Scatter plot: Age vs Online Purchases
plt.figure(figsize=(6, 4))
sns.scatterplot(data=df, x='Age', y='NumWebPurchases')
plt.title("Age vs Online Purchases")
plt.xlabel("Age")
plt.ylabel("Number of Online Purchases")
plt.show()

# Print correlation coefficients
corr_instore = df['Age'].corr(df['NumStorePurchases'])
corr_web = df['Age'].corr(df['NumWebPurchases'])
print("Correlation (Age vs In-Store Purchases):", round(corr_instore, 2))
print("Correlation (Age vs Online Purchases):", round(corr_web, 2))
```




```
Correlation (Age vs In-Store Purchases): 0.14
Correlation (Age vs Online Purchases): 0.15
```

[47]:

```
## for the official hypothesis test for age and store vs. web purchases, the 2␣
↪sample T-test is used comparing the mean values of the separated samples for␣
↪two different age groups.

from scipy.stats import ttest_ind

# Define arbitrary age threshold (e.g., 50) to create two groups:
older = df[df['Age'] >= 50]['NumStorePurchases']
younger = df[df['Age'] < 50]['NumStorePurchases']

# Perform independent two-sample t-test:
t_stat, p_value = ttest_ind(older, younger, equal_var=False)  # equal_var=False␣
↪for Welch's t-test (so not assuming that the two age groups hav equal␣
↪variances)
print("t-statistic:", t_stat)
print("p-value:", p_value)
```

```
t-statistic: 6.470077671069668
p-value: 1.2944790125372907e-10
```

[48]:
```
## Output shows that the p-value is significanly lower that the t-stat so the␣
↪hypothesis is rejected.  It is not true that older people will purhase in␣
↪the store more often than they will purchase online.
```

[49]:
```
## 7B Hypothesis: Customers with children likely experience time constraints,␣
↪making online shopping a more convenient option.
## This will also be a two sample T test because we can separate the two groups␣
↪(with and without kids) to have independent mean values for shopping online␣
↪or instore.
# Define groups based on Total_Children
with_children = df[df['Total_Children'] > 0]['NumWebPurchases']
without_children = df[df['Total_Children'] == 0]['NumWebPurchases']

# Perform independent two-sample t-test (Welch's t-test)
t_stat, p_value = ttest_ind(with_children, without_children, equal_var=False)
print("t-statistic:", t_stat)
print("p-value:", p_value)
```

```
t-statistic: -3.541893836382714
p-value: 0.0004108102700005601
```

[50]:
```
## output shows the p-value significantly lower than .05 and the negative␣
↪t-stat indicates that the opposite might be true, so we reject the␣
↪hypothesis that people with children are more likely to purchase online than␣
↪in the store.
```

[51]:
```
## 7C Hypothesis:  Sales at physical stores may face the risk of␣
↪cannibalization by alternative distribution channels.
## Check if there a negative relationship between in store sales and online␣
↪sales using Pearson correlation from scipy
from scipy.stats import pearsonr

corr_coef, p_value = pearsonr(df['NumStorePurchases'], df['NumWebPurchases'])
print("Pearson correlation coefficient:", corr_coef)
print("p-value:", p_value)
```

```
Pearson correlation coefficient: 0.502713413299732
p-value: 8.962802398081327e-144
```

[52]:
```
## output shows a p-value near zero with the perason correlation coefficient of␣
↪.50 so there is a statistically significant relationship between in store␣
↪and onlines sales.
## but it is not what the hypothesis posits.  It is the opposite; as online␣
↪sales increase, so does in store sales.  Hypothesis is rejected.
```

[60]:
```
## 7D Hypothesis: Does the United States significantly outperform the rest of␣
↪the world in total purchase volumes?
```

```
## Because the data can be grouped in two groups with independent mean values,␣
↪the two sample t-test

# For US customers (Country code "US")
us_purchases = df[df['Country'] == 'US']['Total_Purchases']

# For non-US customers
non_us_purchases = df[df['Country'] != 'US']['Total_Purchases']

print("US customers:", len(us_purchases))
print("Non-US customers:", len(non_us_purchases))
```

```
US customers: 109
Non-US customers: 2131
```

[61]:
```
from scipy.stats import ttest_ind

# Create groups based on Country code 'US'
us_purchases = df[df['Country'] == 'US']['Total_Purchases'] # hypothesis
non_us_purchases = df[df['Country'] != 'US']['Total_Purchases'] #null hypothesis

# Perform the t-test (Welch's t-test)
t_stat, p_value = ttest_ind(us_purchases, non_us_purchases, equal_var=False)
print("t-statistic:", t_stat)
print("p-value:", p_value)
```

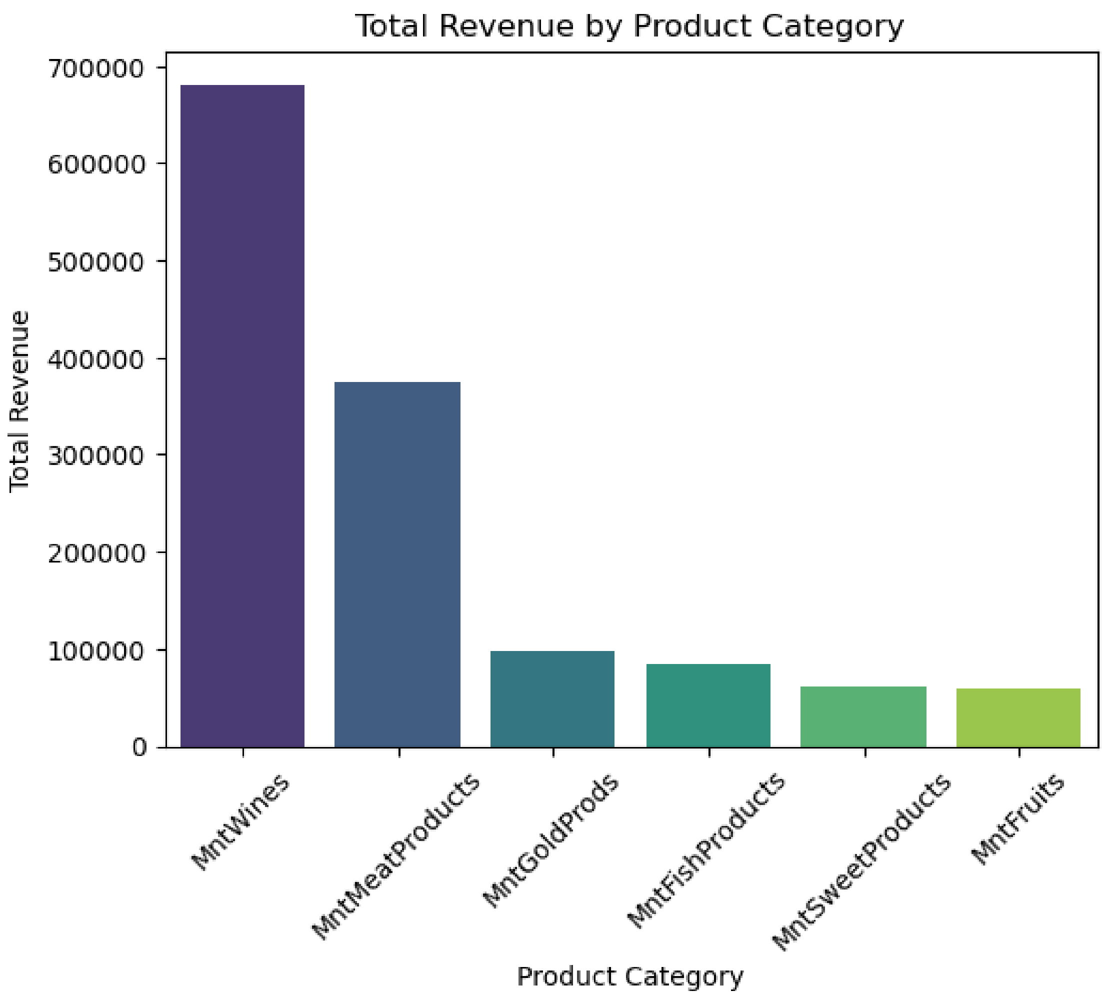
```
t-statistic: 1.4681953545474953
p-value: 0.1446759042957516
```

[62]:
```
## t-stat at 1.47 suggesting that the difference between the groups (US and all␣
↪the others) is 1.47 standard errors away from zerp.
## p-value at .145 the probability of the null hypothesis is 14.5% which is too␣
↪high to accept the hypothesis.
## The hypothesis is rejected that the US has significantly higher sales than␣
↪the rest of the countries as a whole.
```

[ ]:
```
# 8. Use appropriate visualization to help analyze the following:
   ## 8A Identify the top-performing products and those with the lowest revenue.
↪
   ## 8B Examine if there is a correlation between customers' age and the␣
↪acceptance rate of the last campaign.
   ## 8C Determine the country with the highest number of customers who␣
↪accepted the last campaign.
   ## 8D Investigate if there is a discernible pattern in the number of␣
↪children at home and the total expenditure.
   ## 8E Analyze the educational background of customers who lodged complaints␣
↪in the last two years.
```

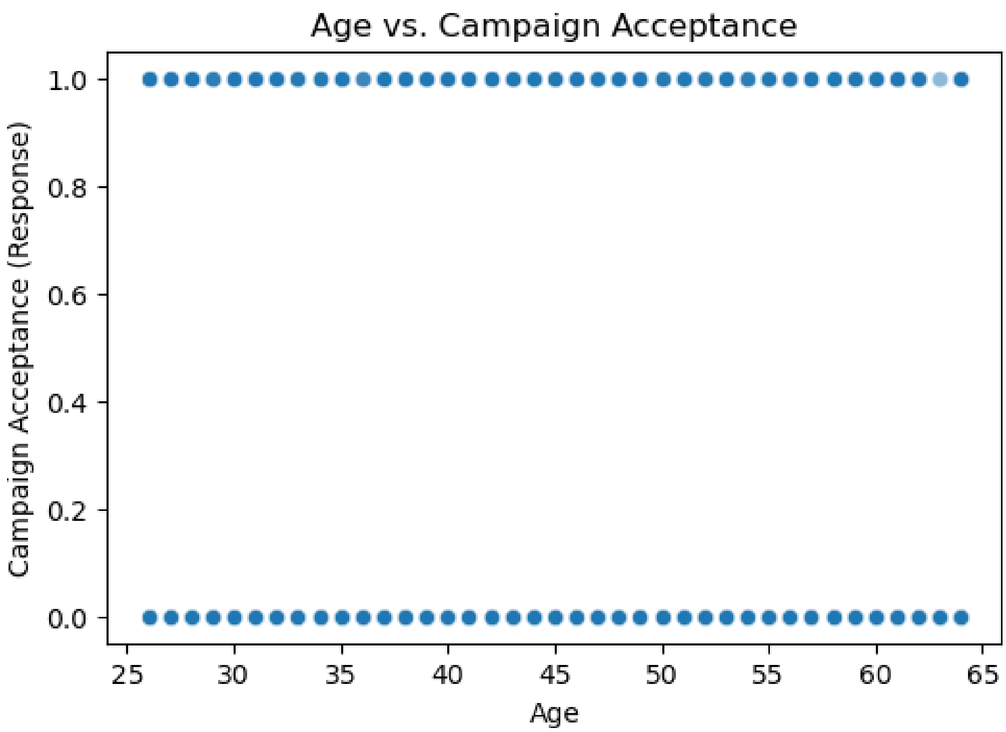
[64]:

```python
## 8A Identify the top-performing products and those with the lowest revenue.
import matplotlib.pyplot as plt
import pandas as pd
import seaborn as sns

# Sum total spending for each product category
product_cols = ['MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',␣
 ↪'MntSweetProducts', 'MntGoldProds']
total_revenue = df[product_cols].sum().sort_values(ascending=False)

# Plot a bar chart
sns.barplot(x=total_revenue.index, y=total_revenue.values,
            hue=total_revenue.index, palette='viridis', dodge=False)
plt.legend([], [], frameon=False)
plt.title("Total Revenue by Product Category")
plt.xlabel("Product Category")
plt.ylabel("Total Revenue")
plt.xticks(rotation=45)
plt.show()
```



[65]:
```
## 8B Examine if there is a correlation between customers' age and the␣
↪acceptance rate of the last campaign.
# Scatter plot of Age vs. Response
plt.figure(figsize=(6, 4))
sns.scatterplot(x='Age', y='Response', data=df, alpha=0.5)
plt.title("Age vs. Campaign Acceptance")
plt.xlabel("Age")
plt.ylabel("Campaign Acceptance (Response)")
plt.show()

# If Response is binary, you can also compute point-biserial correlation with␣
↪scipy
from scipy.stats import pointbiserialr
corr_coef, p_val = pointbiserialr(df['Age'], df['Response'])
print("Point-biserial correlation coefficient:", round(corr_coef, 2))
```

```
print("p-value:", p_val)
```




```
Point-biserial correlation coefficient: -0.02
p-value: 0.3186088501422738
```

[66]:
```
## point bisarial correlation coefficient at -0.02 wit a p-value of .32
↪indicates that there is no linear relationship between age and acceptance of
↪the last campaign.
## the correlation is essentially zero and the p-value > than .05 so no trend
↪with age and the ad campaign
```

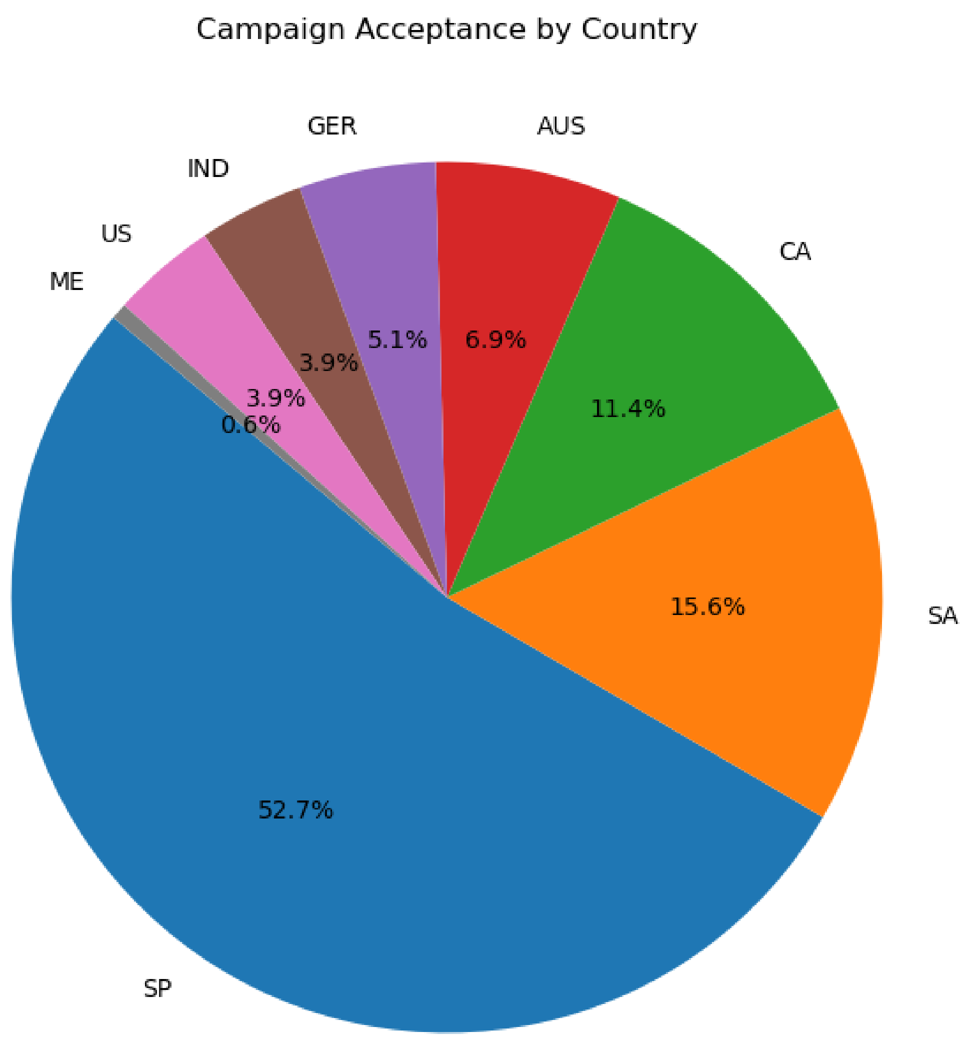
[67]:
```
## 8C Determine the country with the highest number of customers who accepted
↪the last campaign
## filter dataset to only include those who accepted the campaign
accepted_campaign_df = df[df['Response'] == 1]
## group by country and count
country_counts = accepted_campaign_df.groupby('Country').size().
↪reset_index(name='Count')
country_counts = country_counts.sort_values(by='Count', ascending=False)
print(country_counts)
```

```
  Country  Count
6      SP    176
5      SA     52
```

```
1      CA     38
0     AUS     23
2     GER     17
3     IND     13
7      US     13
4      ME      2
```

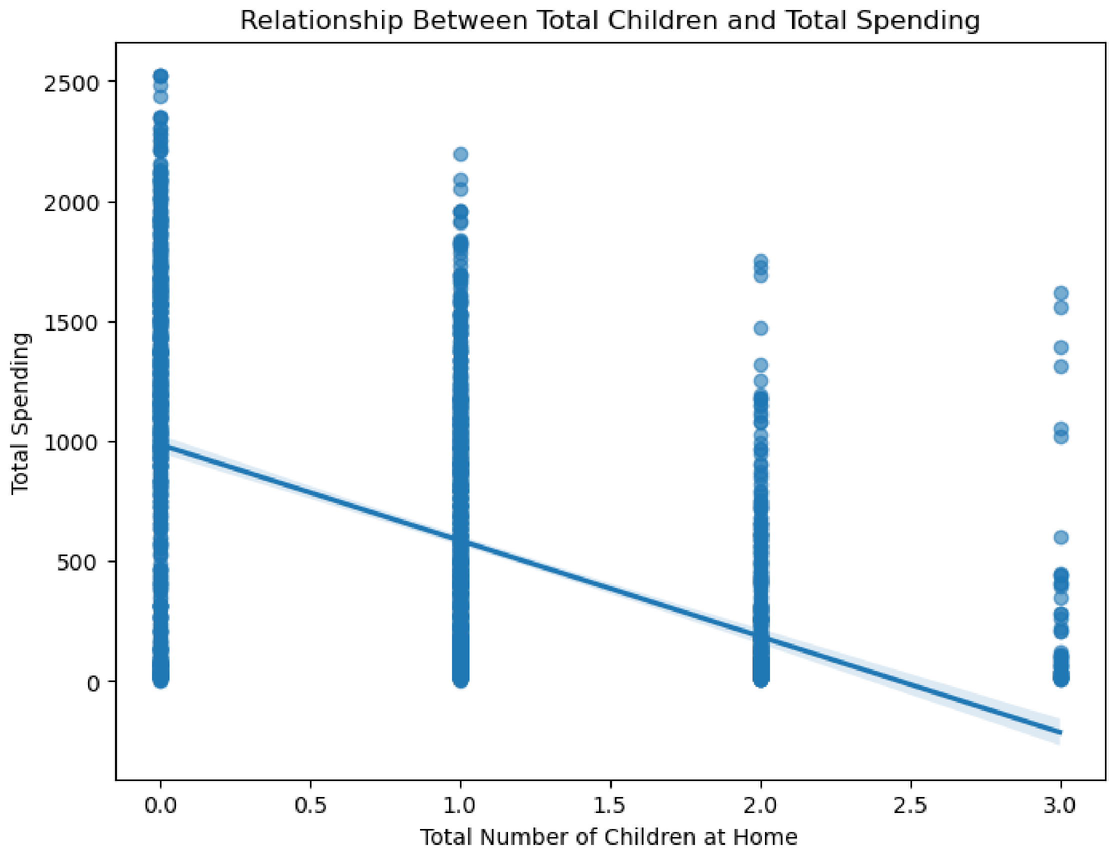
[68]:

```
## pie chart with matplotlib
import matplotlib.pyplot as plt

# Assuming country_counts is your DataFrame from groupby with columns 'Country'␣
↪and 'Count'
plt.figure(figsize=(8,8))
plt.pie(country_counts['Count'], labels=country_counts['Country'], autopct='%1.
↪1f%%', startangle=140)
plt.title("Campaign Acceptance by Country")
plt.show()
```



[69]:
```
## 8D Investigate if there is a discernible pattern in the number of children␣
↪at home and the total expenditure
import seaborn as sns
import matplotlib.pyplot as plt

plt.figure(figsize=(8, 6))
sns.regplot(x='Total_Children', y='Total_Spending', data=df,␣
↪scatter_kws={'alpha':0.6})
plt.title("Relationship Between Total Children and Total Spending")
plt.xlabel("Total Number of Children at Home")
plt.ylabel("Total Spending")
```

```
plt.show()
```

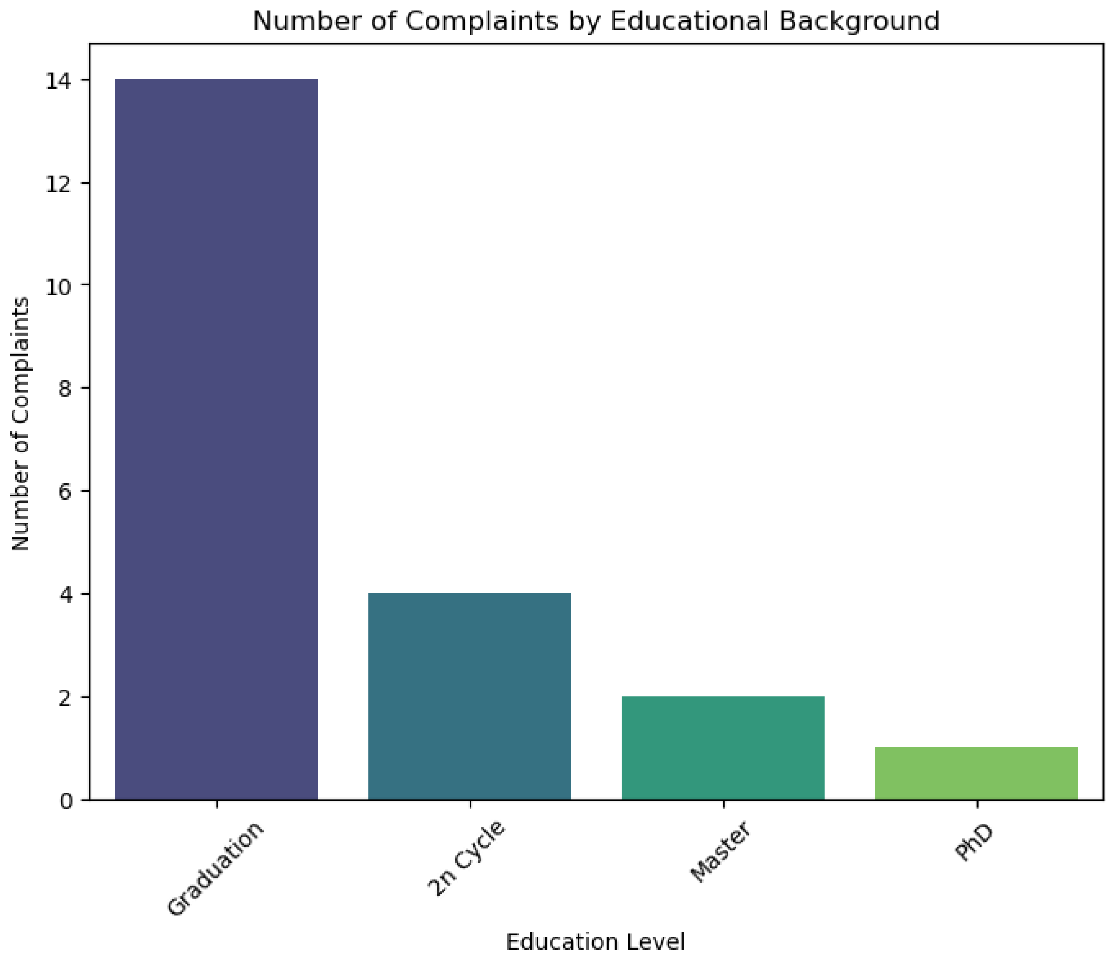


[70]:
```
## scatter graph shows a relationship between number of children and total␣
↪expenditures in that the higher the amount of children, the less the␣
↪expenditures
```

[73]:
```
## 8E Analyze the educational background of customers who lodged complaints in␣
↪the last two years
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt

# Filter for customers who lodged complaints
complainers = df[df['Complain'] == 1]

# Group by Education and count the number of complaints for each group
complaints_by_education = complainers['Education'].value_counts().reset_index()
complaints_by_education.columns = ['Education', 'Count']
```

```
print(complaints_by_education)

Plot the results using seaborn
plt.figure(figsize=(8, 6))
sns.barplot(x='Education', y='Count', data=complaints_by_education,␣
↪hue='Education', palette='viridis', dodge=False)
plt.legend([], [], frameon=False)
plt.title("Number of Complaints by Educational Background")
plt.xlabel("Education Level")
plt.ylabel("Number of Complaints")
plt.xticks(rotation=45)
plt.show()
```

```
    Education  Count
0  Graduation     14
1    2n Cycle      4
2      Master      2
3         PhD      1
```



```
[ ]: ## output shows that the higher the education level, the less likely a customer␣
     ↪is to complain
```