ommerce-marketing-and-shopping-eda

August 29, 2024

[1]:
```
import pandas as pd
import numpy as np
from scipy import stats
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.preprocessing import StandardScaler
import scipy.stats as stats
from scipy.stats import kruskal
from datetime import datetime
```

[2]:
```
shop_df = pd.read_csv('/content/shopping.csv')
```

[3]:
```
shop_df.head()
```

[3]:
```
   Administrative  Administrative_Duration  Informational  \
0               0                      0.0              0
1               0                      0.0              0
2               0                      0.0              0
3               0                      0.0              0
4               0                      0.0              0

   Informational_Duration  ProductRelated  ProductRelated_Duration  \
0                     0.0               1                 0.000000
1                     0.0               2                64.000000
2                     0.0               1                 0.000000
3                     0.0               2                 2.666667
4                     0.0              10               627.500000

   BounceRates  ExitRates  PageValues  SpecialDay Month  OperatingSystems  \
0         0.20       0.20         0.0         0.0   Feb                 1
1         0.00       0.10         0.0         0.0   Feb                 2
2         0.20       0.20         0.0         0.0   Feb                 4
3         0.05       0.14         0.0         0.0   Feb                 3
4         0.02       0.05         0.0         0.0   Feb                 3

   Browser  Region  TrafficType        VisitorType  Weekend  Revenue
0        1       1            1  Returning_Visitor    False    False
```

```
1         2        1            2  Returning_Visitor    False    False
2         1        9            3  Returning_Visitor    False    False
3         2        2            4  Returning_Visitor    False    False
4         3        1            4  Returning_Visitor     True    False
```

[3]:

```

```

1 Data Preprocessing

2 1. Shopping dataframe

[4]:

```
shop_df.shape
```

[4]:

```
(12330, 18)
```

In the shopping dataset we have 12330 rows and 18 columns

[5]:

```
shop_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 12330 entries, 0 to 12329
Data columns (total 18 columns):
 #   Column                   Non-Null Count  Dtype
---  ------                   --------------  -----
 0   Administrative           12330 non-null  int64
 1   Administrative_Duration  12330 non-null  float64
 2   Informational            12330 non-null  int64
 3   Informational_Duration   12330 non-null  float64
 4   ProductRelated           12330 non-null  int64
 5   ProductRelated_Duration  12330 non-null  float64
 6   BounceRates              12330 non-null  float64
 7   ExitRates                12330 non-null  float64
 8   PageValues               12330 non-null  float64
 9   SpecialDay               12330 non-null  float64
 10  Month                    12330 non-null  object
 11  OperatingSystems         12330 non-null  int64
 12  Browser                  12330 non-null  int64
 13  Region                   12330 non-null  int64
 14  TrafficType              12330 non-null  int64
 15  VisitorType              12330 non-null  object
 16  Weekend                  12330 non-null  bool
 17  Revenue                  12330 non-null  bool
dtypes: bool(2), float64(7), int64(7), object(2)
memory usage: 1.5+ MB
```

[6]:

```
shop_df.isnull().sum()
```

[6]:
```
Administrative             0
Administrative_Duration    0
Informational              0
Informational_Duration     0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
PageValues                 0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
TrafficType                0
VisitorType                0
Weekend                    0
Revenue                    0
dtype: int64
```

We don't have any null values in the shopping dataset

[7]:
```
shop_df[shop_df.duplicated()]
```

[7]:
```
       Administrative  Administrative_Duration  Informational  \
158                 0                      0.0              0
159                 0                      0.0              0
178                 0                      0.0              0
418                 0                      0.0              0
456                 0                      0.0              0
…                 …                      …             …
11934               0                      0.0              0
11938               0                      0.0              0
12159               0                      0.0              0
12180               0                      0.0              0
12185               0                      0.0              0

       Informational_Duration  ProductRelated  ProductRelated_Duration  \
158                       0.0               1                      0.0
159                       0.0               1                      0.0
178                       0.0               1                      0.0
418                       0.0               1                      0.0
456                       0.0               1                      0.0
…                       …             …                      …
11934                     0.0               1                      0.0
11938                     0.0               1                      0.0
12159                     0.0               1                      0.0
```

```
12180                  0.0               1                      0.0
12185                  0.0               1                      0.0

       BounceRates  ExitRates  PageValues  SpecialDay Month  OperatingSystems  \
158            0.2        0.2         0.0         0.0   Feb                 1
159            0.2        0.2         0.0         0.0   Feb                 3
178            0.2        0.2         0.0         0.0   Feb                 3
418            0.2        0.2         0.0         0.0   Mar                 1
456            0.2        0.2         0.0         0.0   Mar                 2
…              …          …           …           …     …                 …
11934          0.2        0.2         0.0         0.0   Dec                 1
11938          0.2        0.2         0.0         0.0   Dec                 1
12159          0.2        0.2         0.0         0.0   Dec                 1
12180          0.2        0.2         0.0         0.0   Dec                 1
12185          0.2        0.2         0.0         0.0   Dec                 8

       Browser  Region  TrafficType        VisitorType  Weekend  Revenue
158          1       1            3  Returning_Visitor    False    False
159          2       3            3  Returning_Visitor    False    False
178          2       3            3  Returning_Visitor    False    False
418          1       1            1  Returning_Visitor     True    False
456          2       4            1  Returning_Visitor    False    False
…            …       …            …                  …        …        …
11934        1       1            2        New_Visitor    False    False
11938        1       4            1  Returning_Visitor     True    False
12159        1       1            3  Returning_Visitor    False    False
12180       13       9           20  Returning_Visitor    False    False
12185       13       9           20              Other    False    False

[125 rows x 18 columns]
```

[8]:
```
shop_df.drop_duplicates(inplace=True)
```

[9]:
```
shop_df.duplicated().sum()
```

[9]: 0

These are duplicated values in the shopping dataset. Removed it for clear analysis.

2.0.1 - outliers

[10]:
```
numerical_col = shop_df.select_dtypes(include=np.number).columns
```

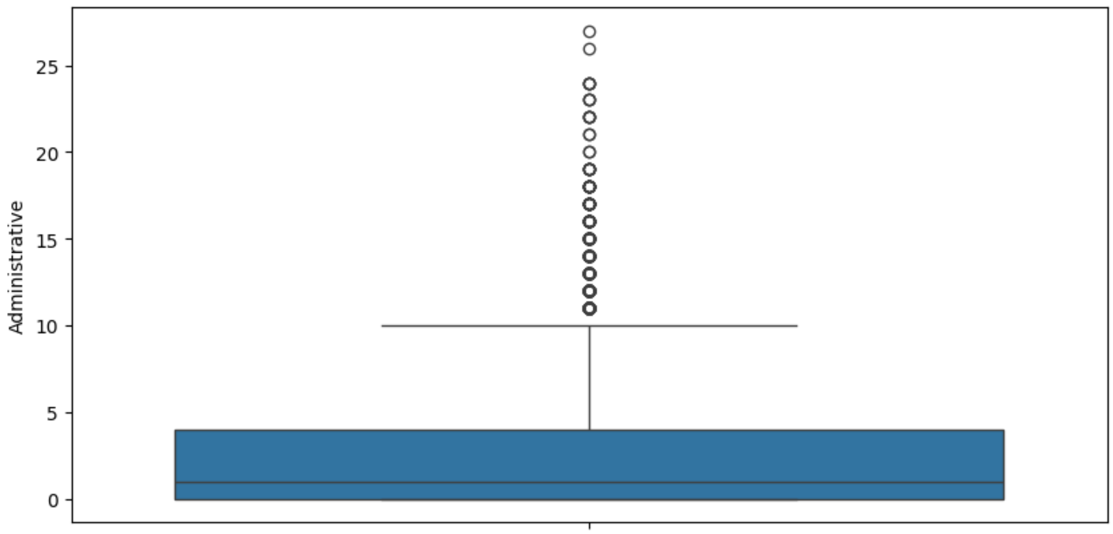
[11]:
```
numerical_col
```

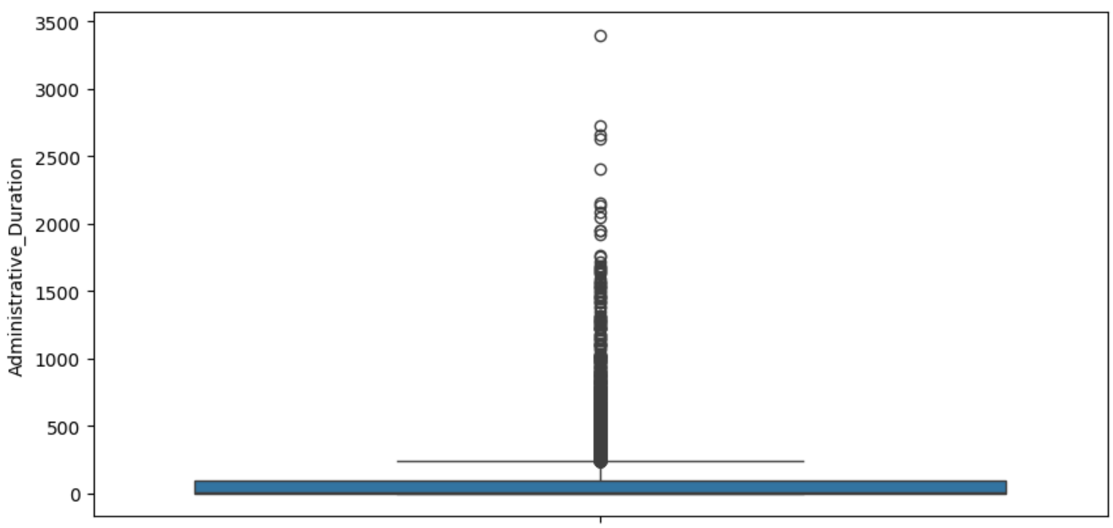
[11]:
```
Index(['Administrative', 'Administrative_Duration', 'Informational',
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
```

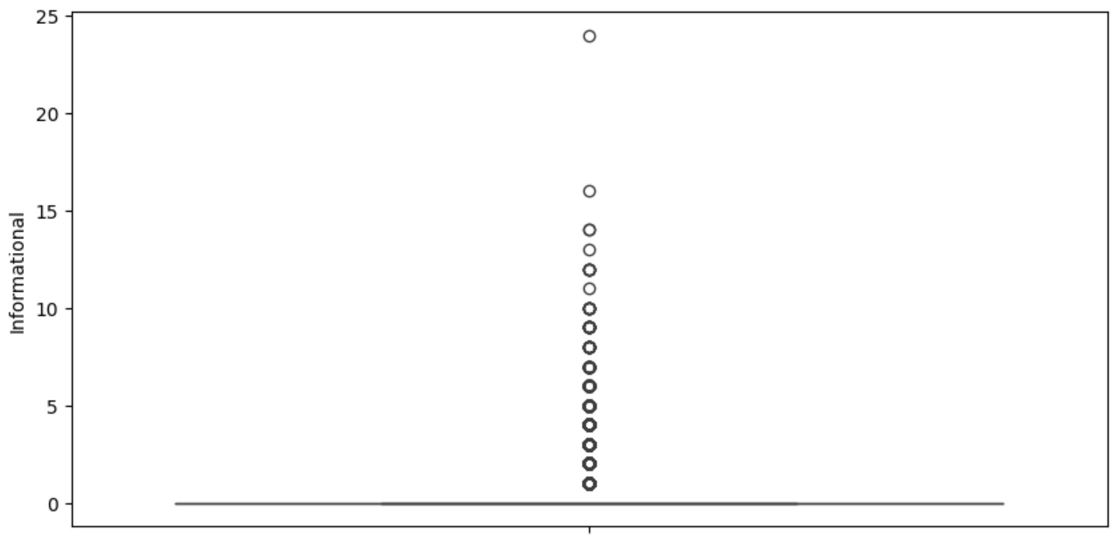
```
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType'],
      dtype='object')
```

Visulizing Outliers

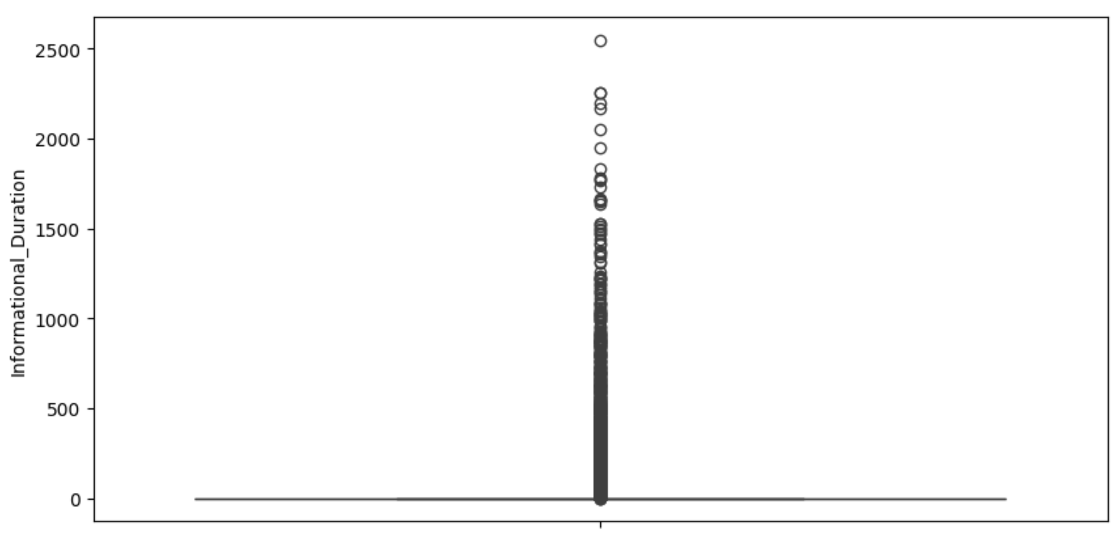
```
[12]: for col in numerical_col:
        plt.figure(figsize=(10,5))
        sns.boxplot(shop_df[col])
        plt.show()
```



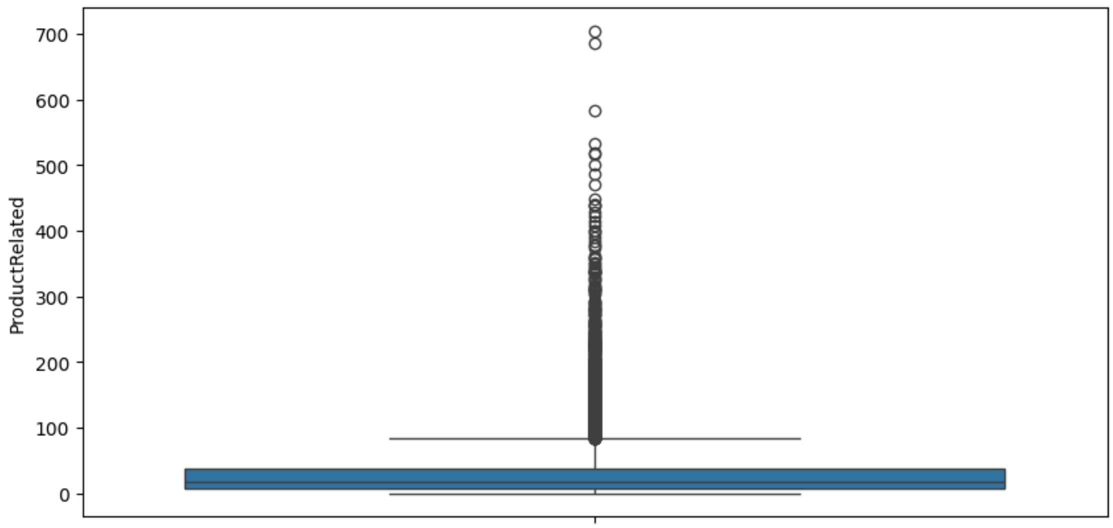


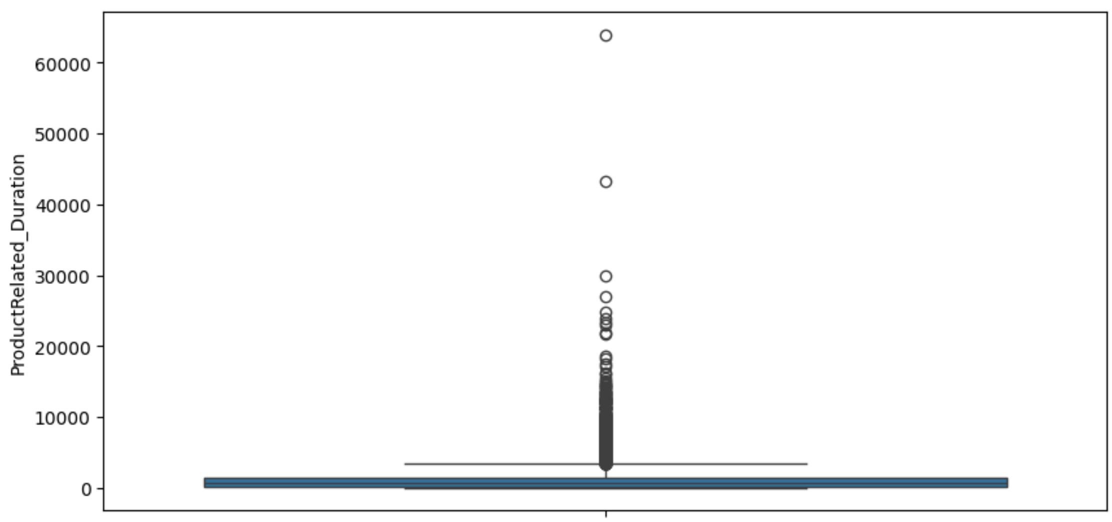


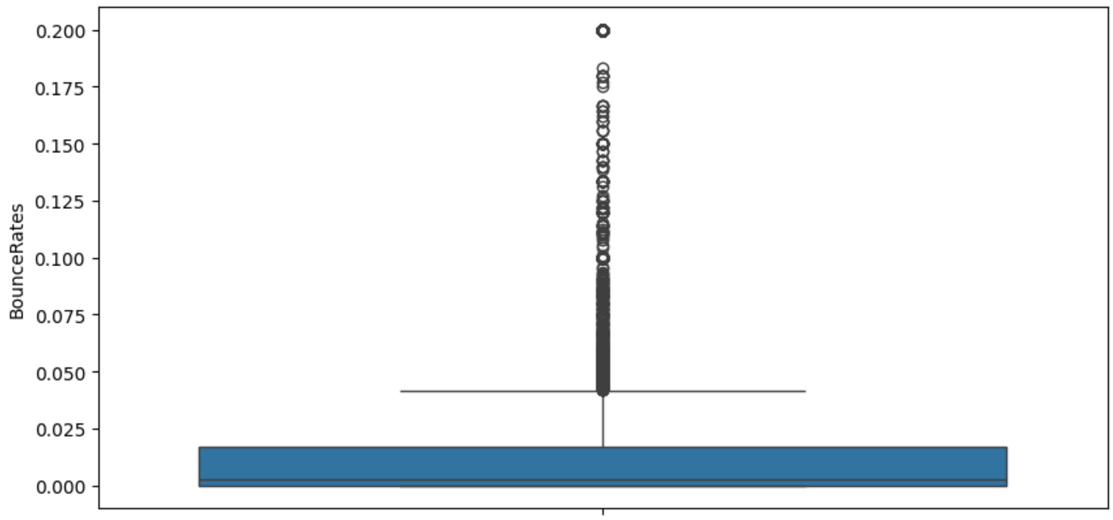
Informational
0
5
10
15
20
25

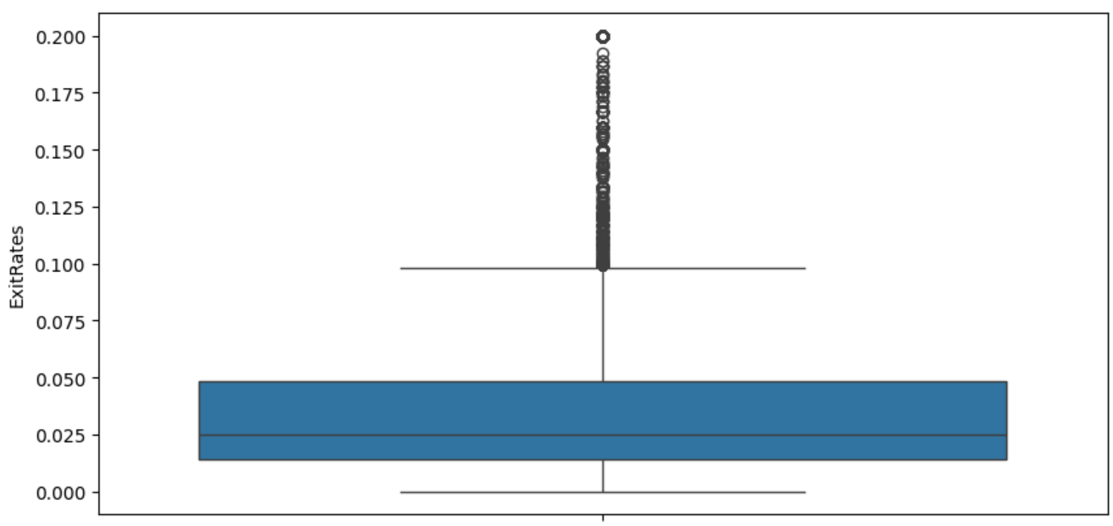


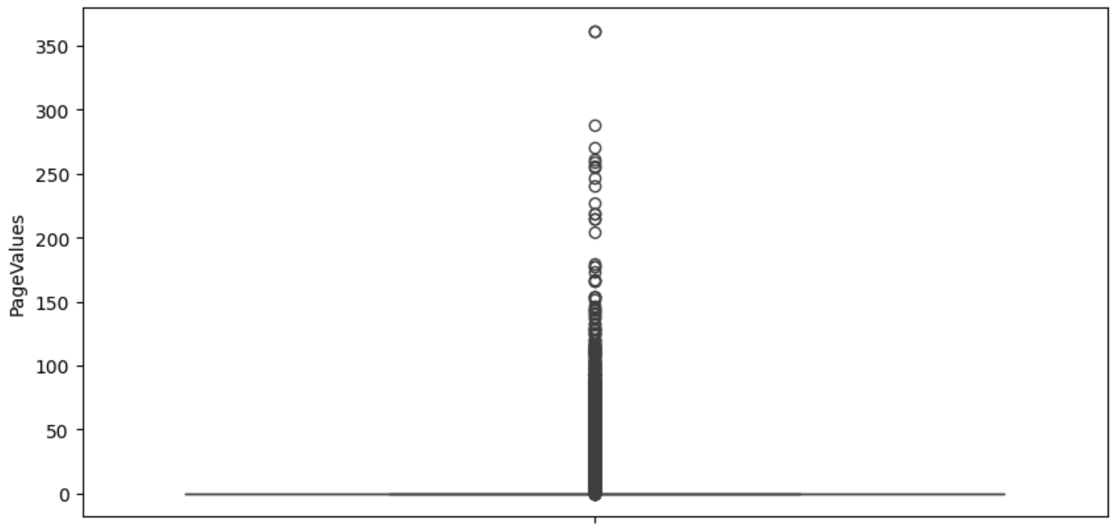
Informational_Duration
0
500
1000
1500
2000
2500

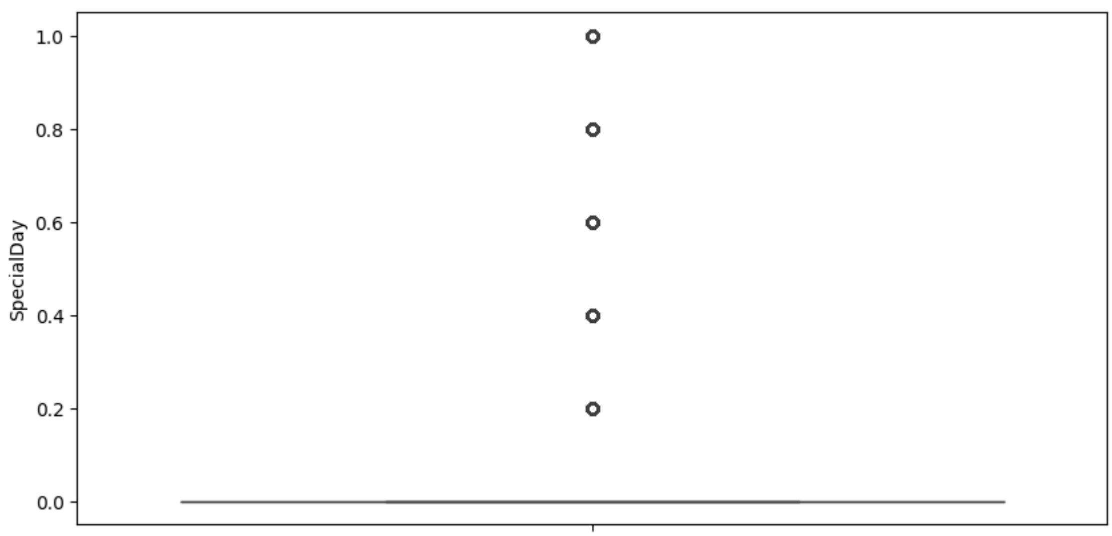

ProductRelated
0
100
200
300
400
500
600
700

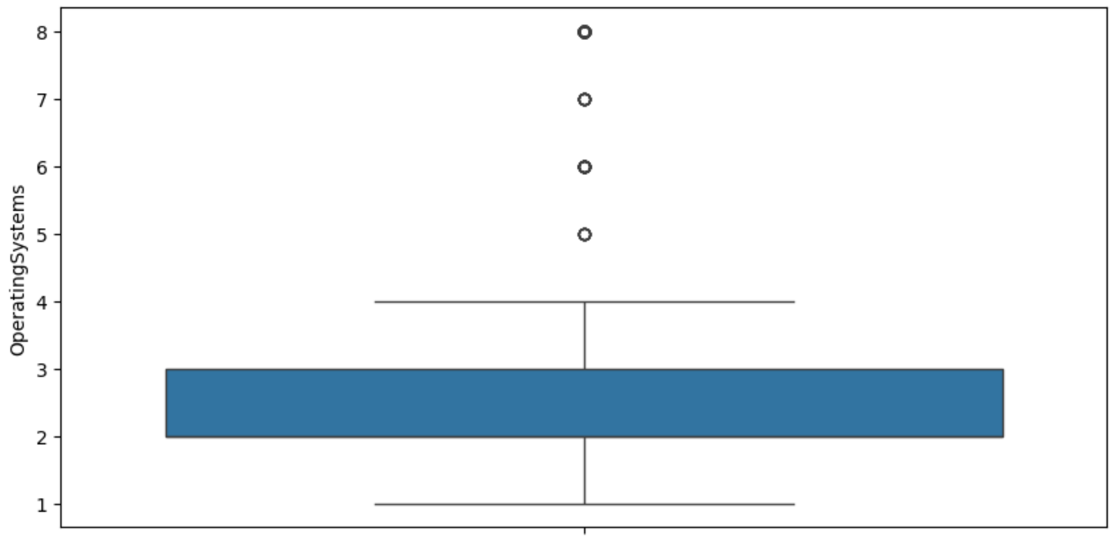

ProductRelated_Duration
0
10000
20000
30000
40000
50000
60000

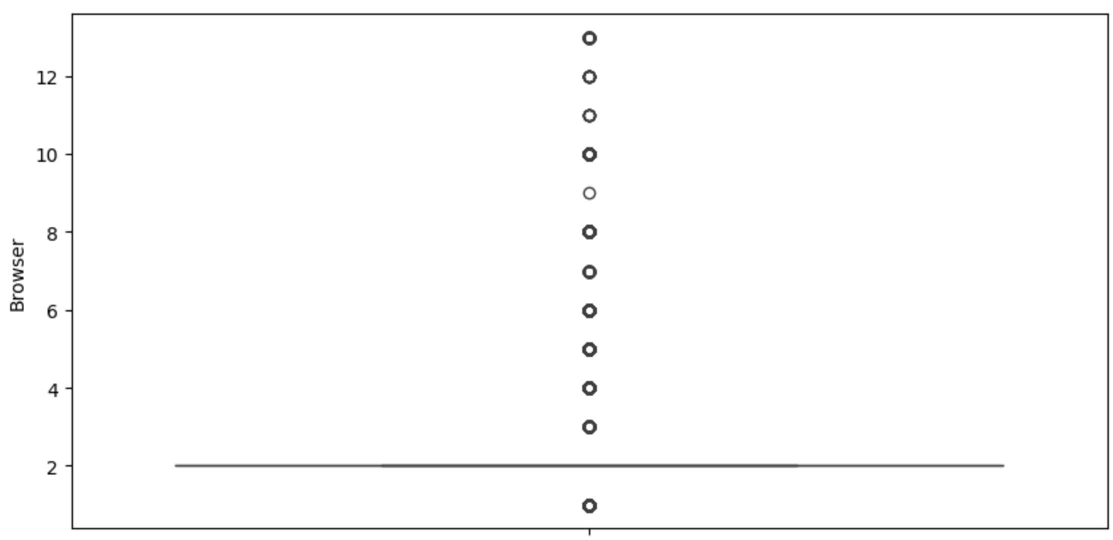

0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
BounceRates

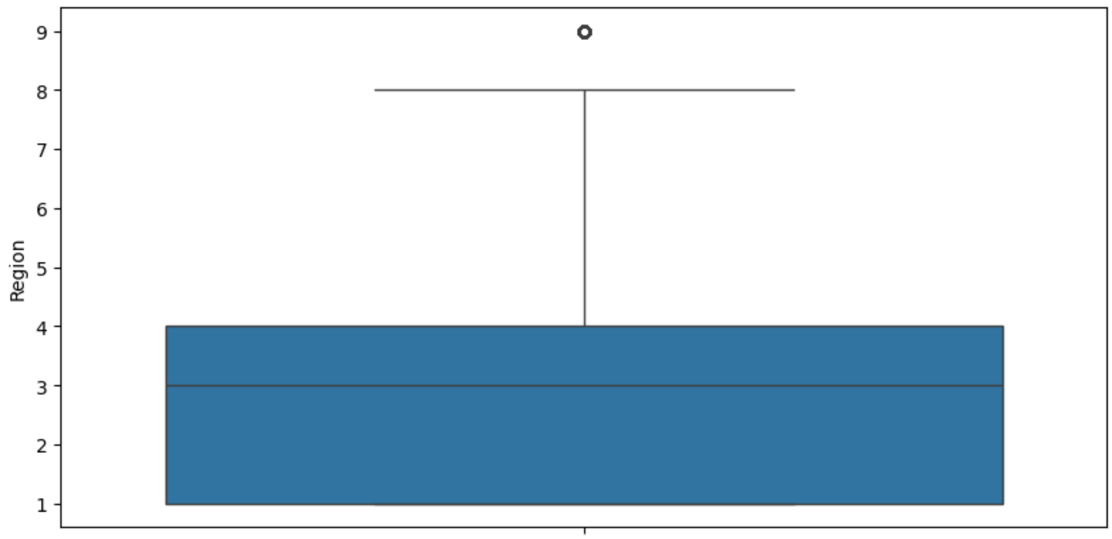

0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
ExitRates

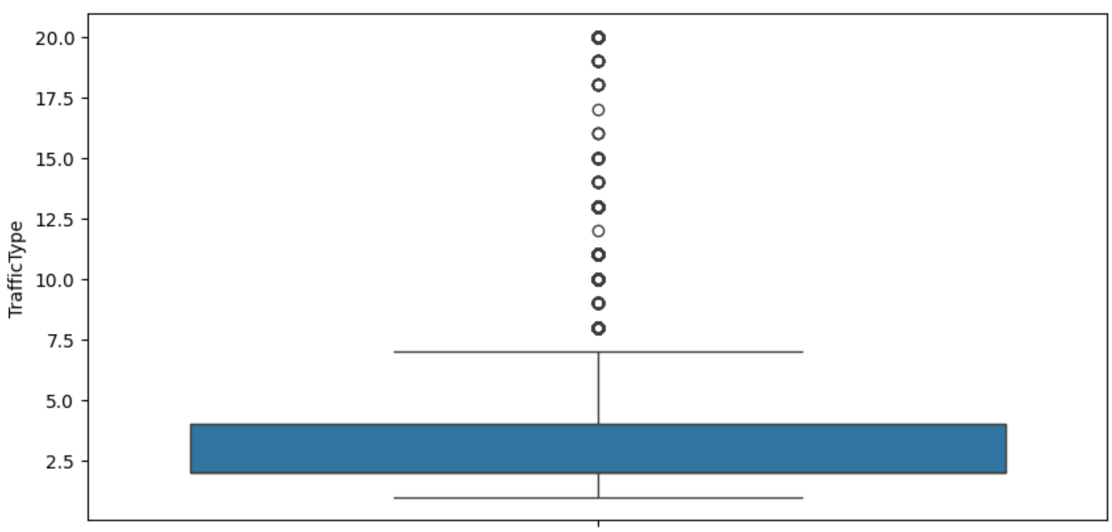

PageValues
350
300
250
200
150
100
50
0


SpecialDay
1.0
0.8
0.6
0.4
0.2
0.0


OperatingSystems
1
2
3
4
5
6
7
8


Browser
2
4
6
8
10
12

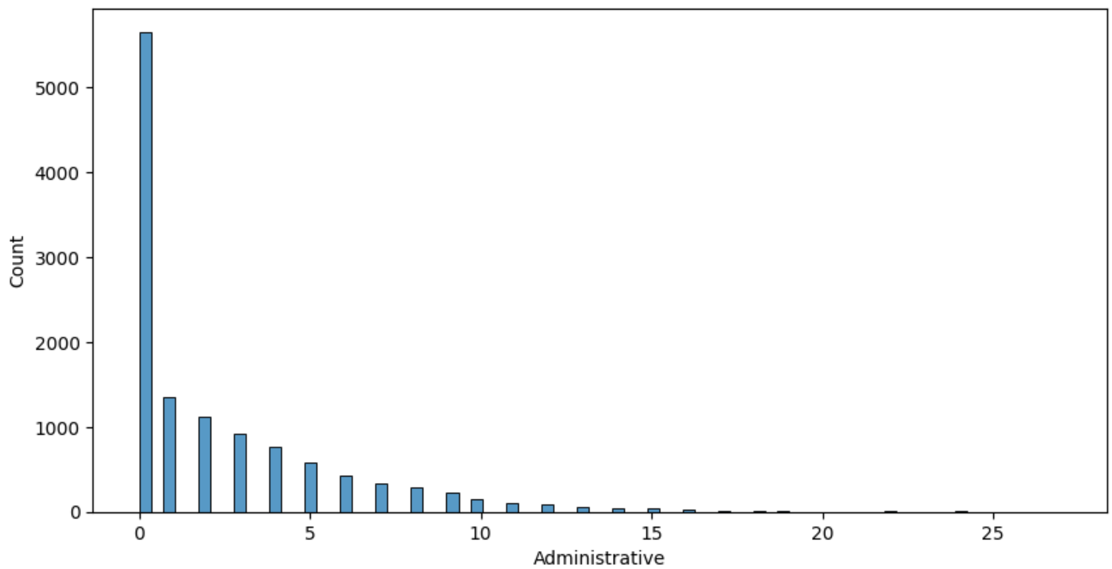




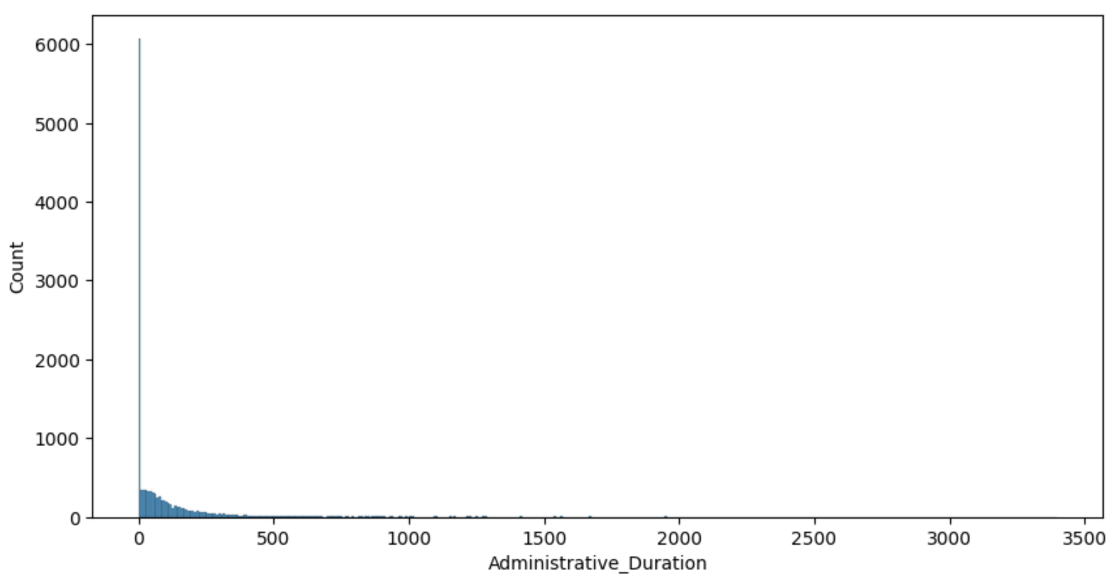
Univeriant Analysis

---

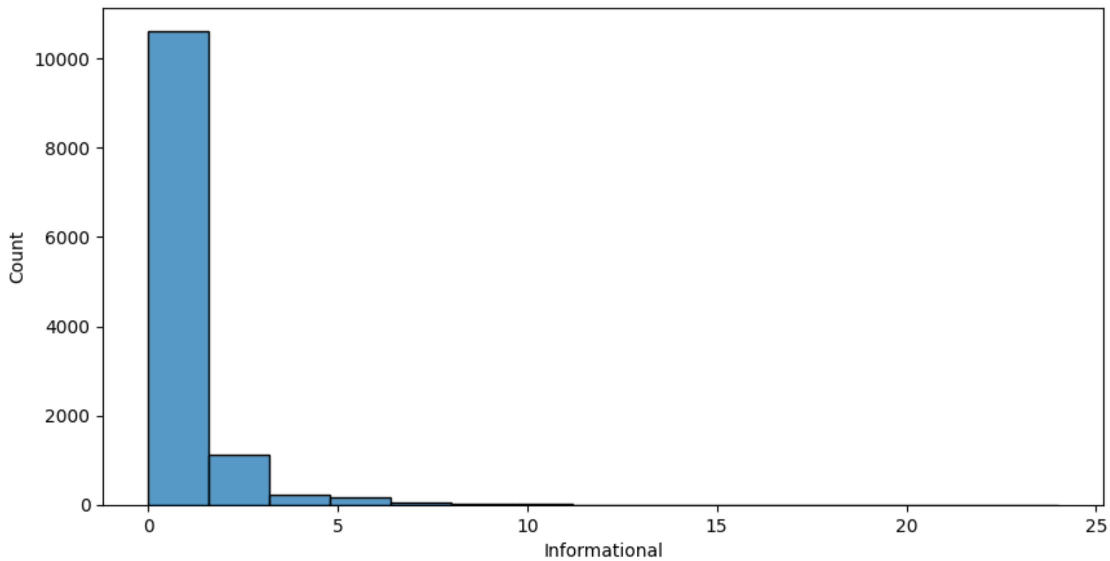
[13]:
```
for col in numerical_col:
  plt.figure(figsize=(10,5))
  sns.histplot(shop_df[col])
  plt.show()
```

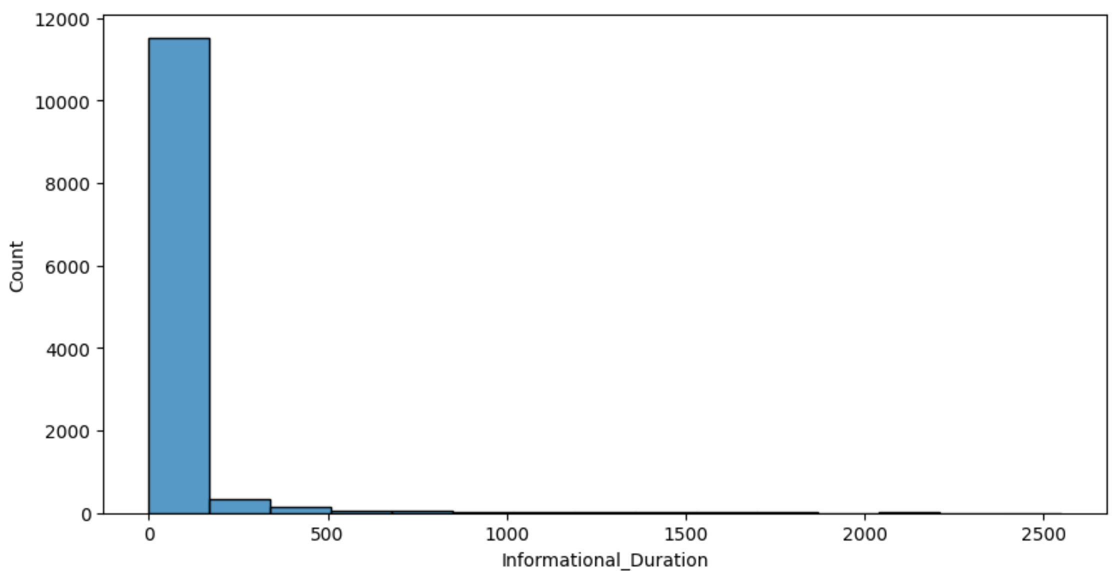


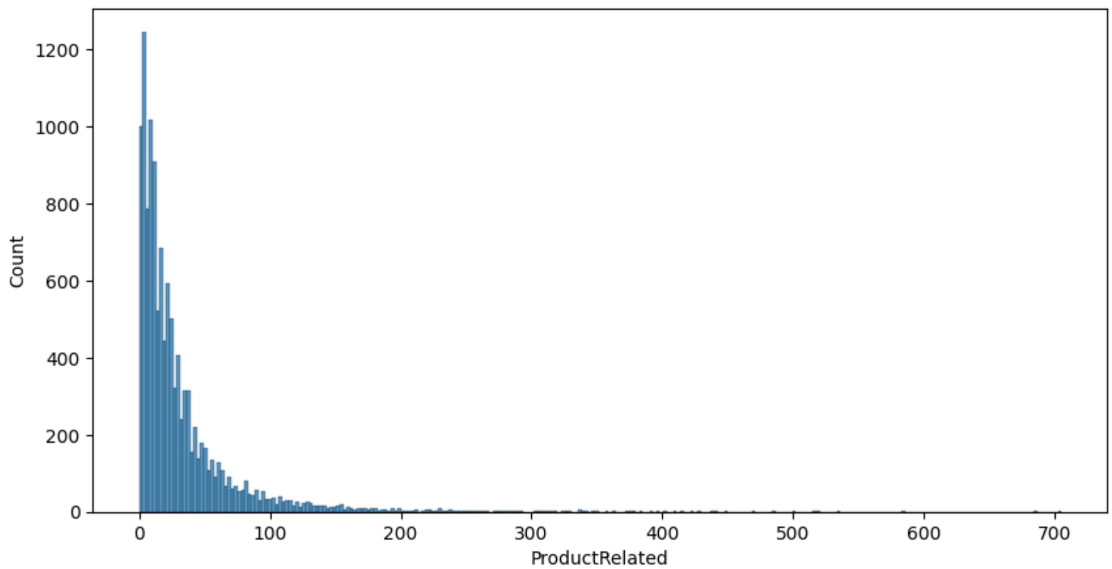
Count
5000
4000
3000
2000
1000
0
0
5
10
15
20
25
Administrative



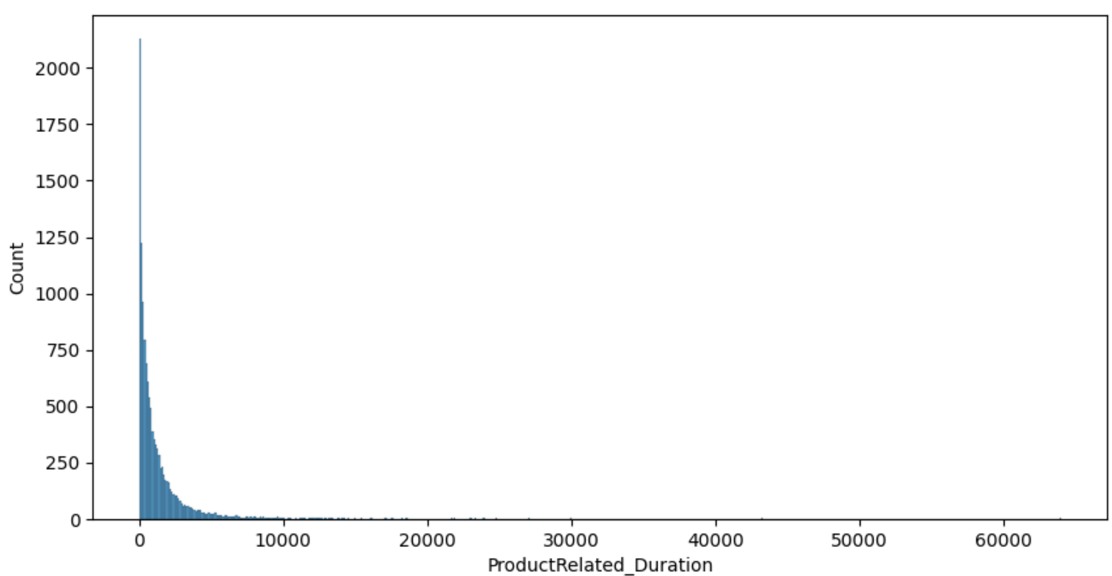
Count
6000
5000
4000
3000
2000
1000
0
0
500
1000
1500
2000
2500
3000
3500
Administrative_Duration


Count
Informational
0
2000
4000
6000
8000
10000
5
10
15
20
25

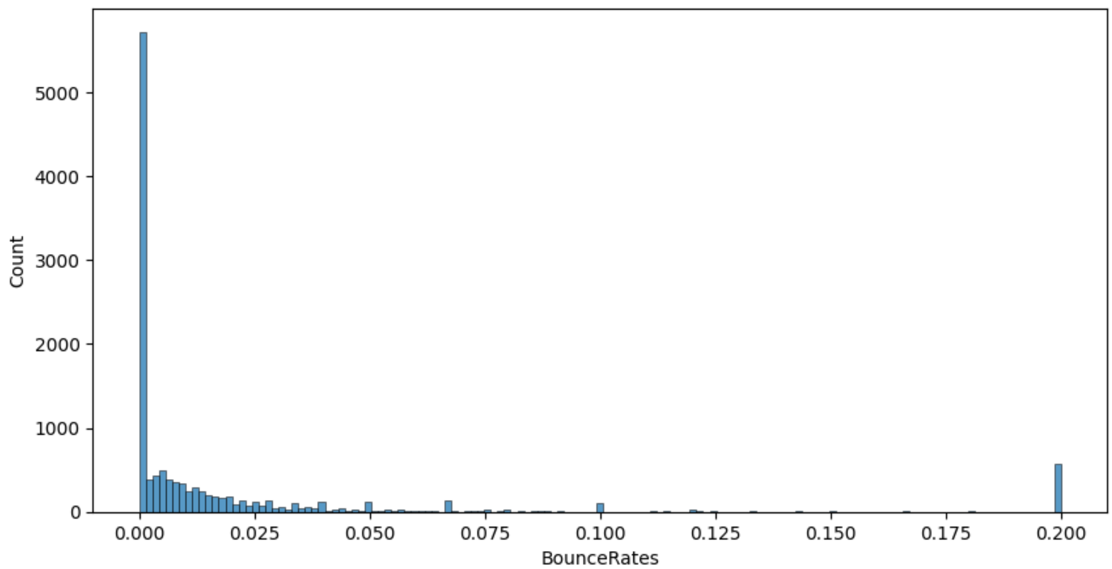

Count
Informational_Duration
0
2000
4000
6000
8000
10000
12000
500
1000
1500
2000
2500



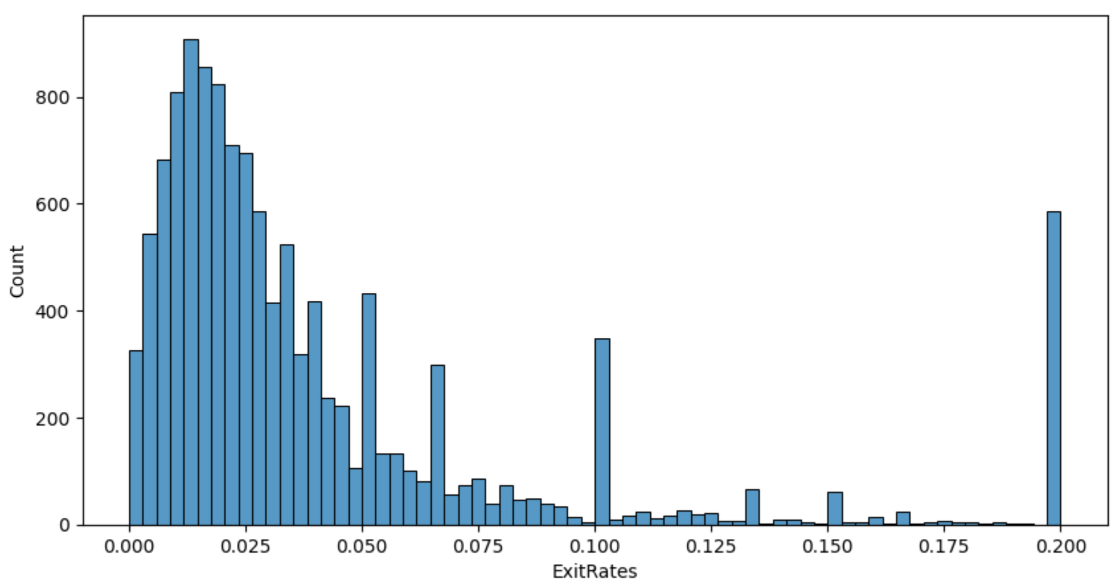
1200
1000
800
600
400
200
0
Count
0
100
200
300
400
500
600
700
ProductRelated



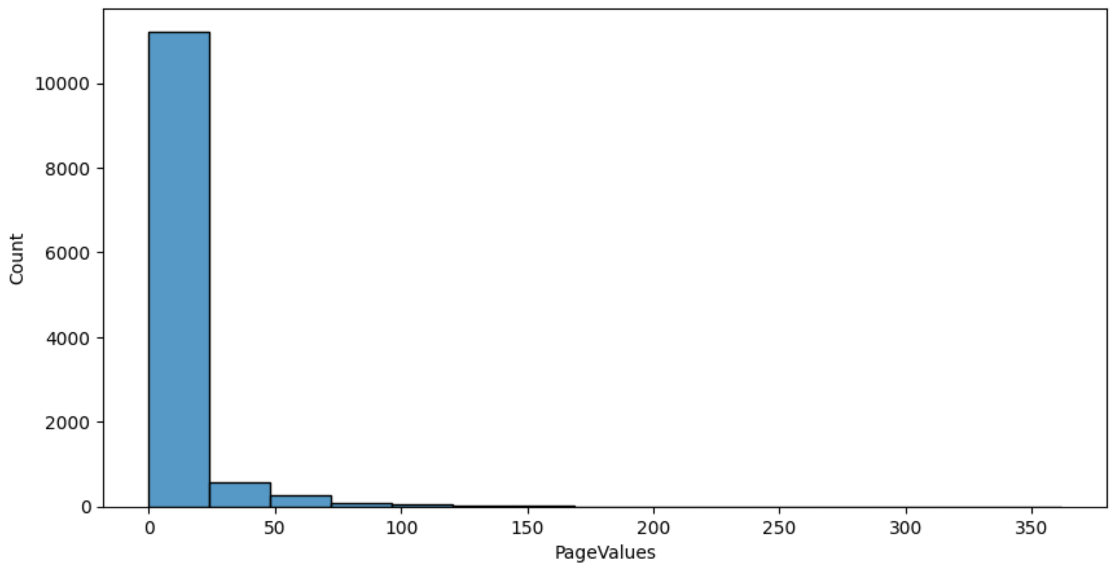
2000
1750
1500
1250
1000
750
500
250
0
Count
0
10000
20000
30000
40000
50000
60000
ProductRelated_Duration



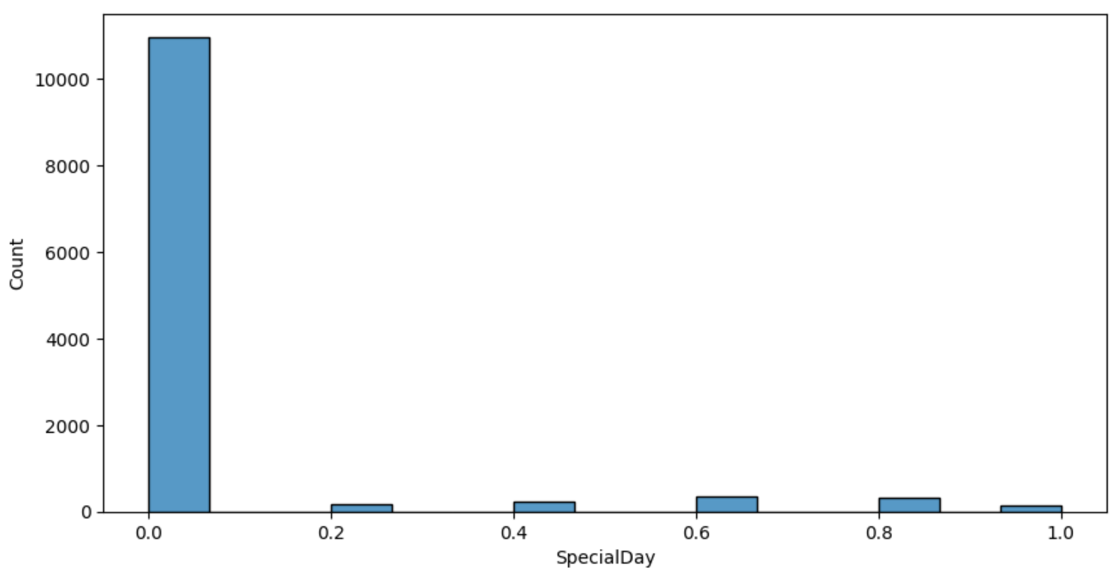
Count
5000
4000
3000
2000
1000
0
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
BounceRates



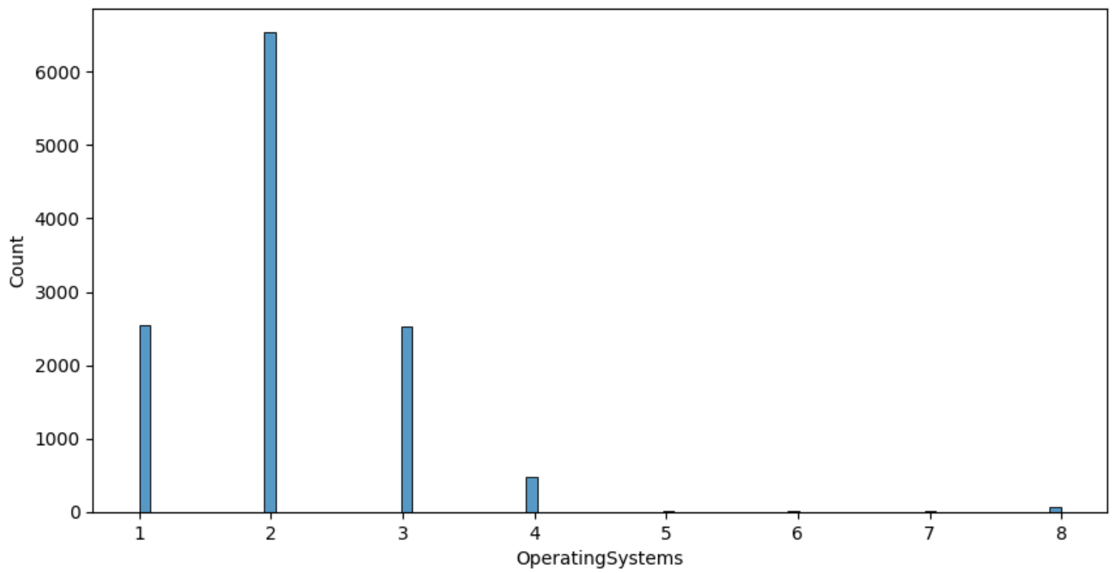
Count
800
600
400
200
0
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200
ExitRates

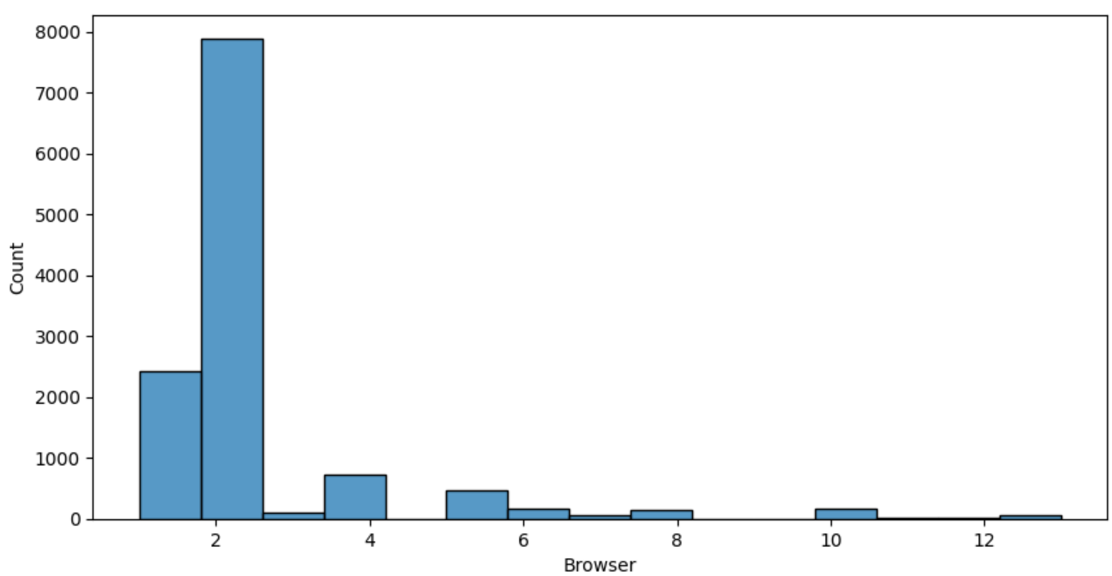


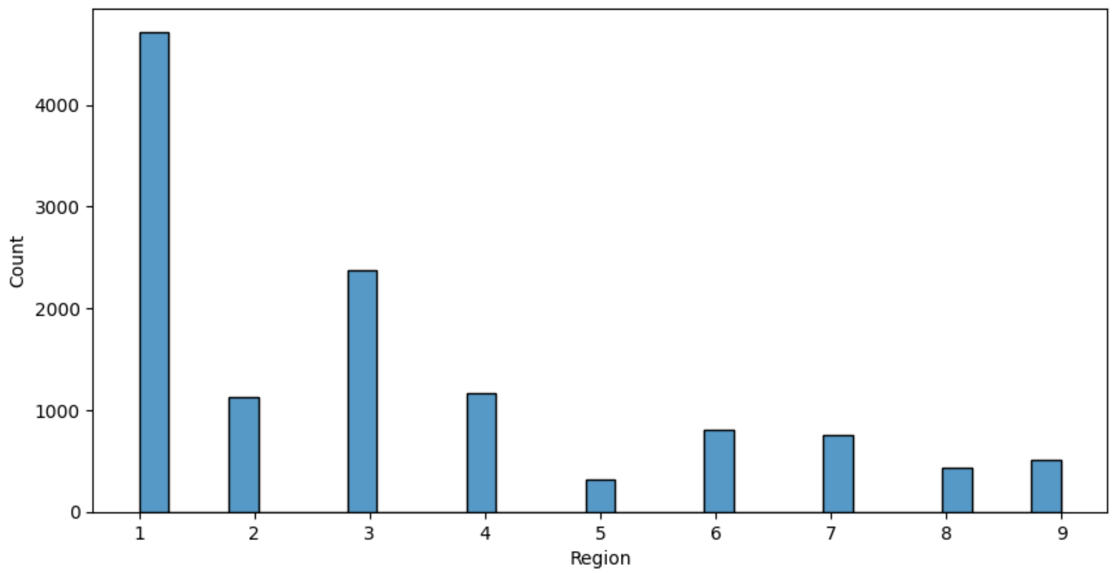
10000
8000
6000
4000
2000
0
Count
0
50
100
150
200
250
300
350
PageValues

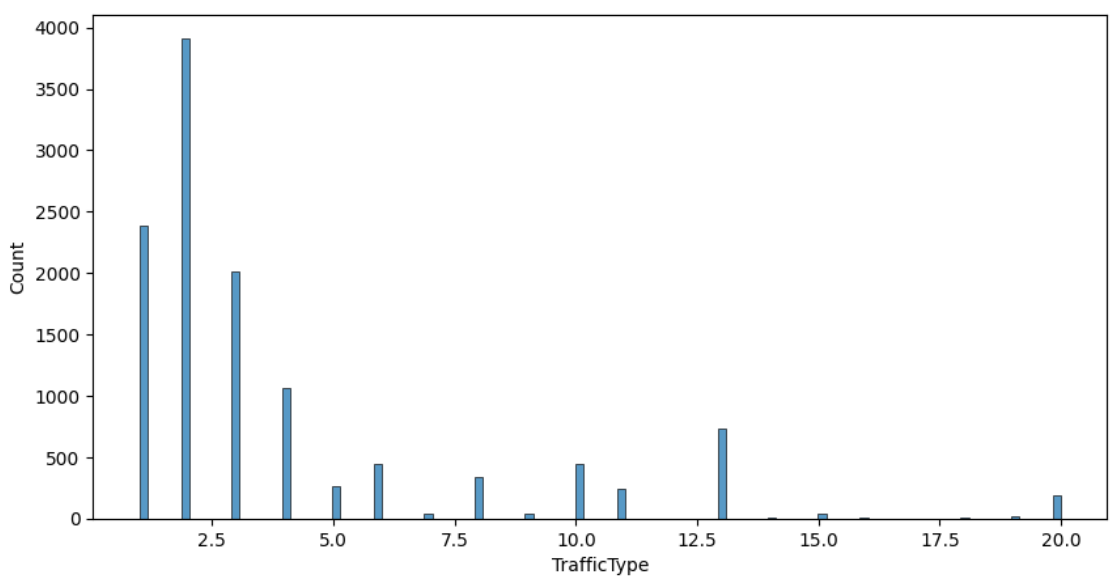


10000
8000
6000
4000
2000
0
Count
0.0
0.2
0.4
0.6
0.8
1.0
SpecialDay


Count
OperatingSystems
0
1000
2000
3000
4000
5000
6000
1
2
3
4
5
6
7
8


Count
Browser
0
1000
2000
3000
4000
5000
6000
7000
8000
2
4
6
8
10
12

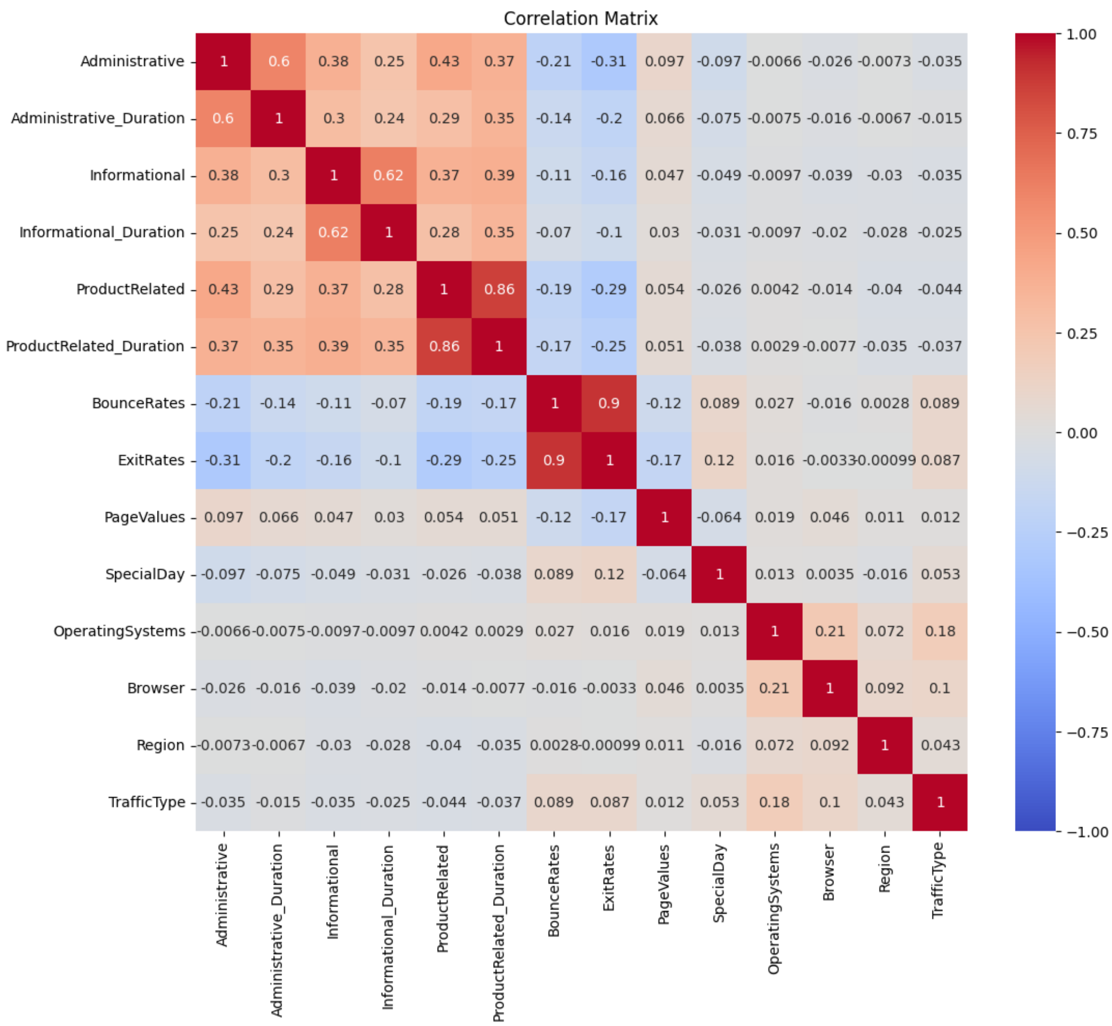




- Correlation Analysis

---

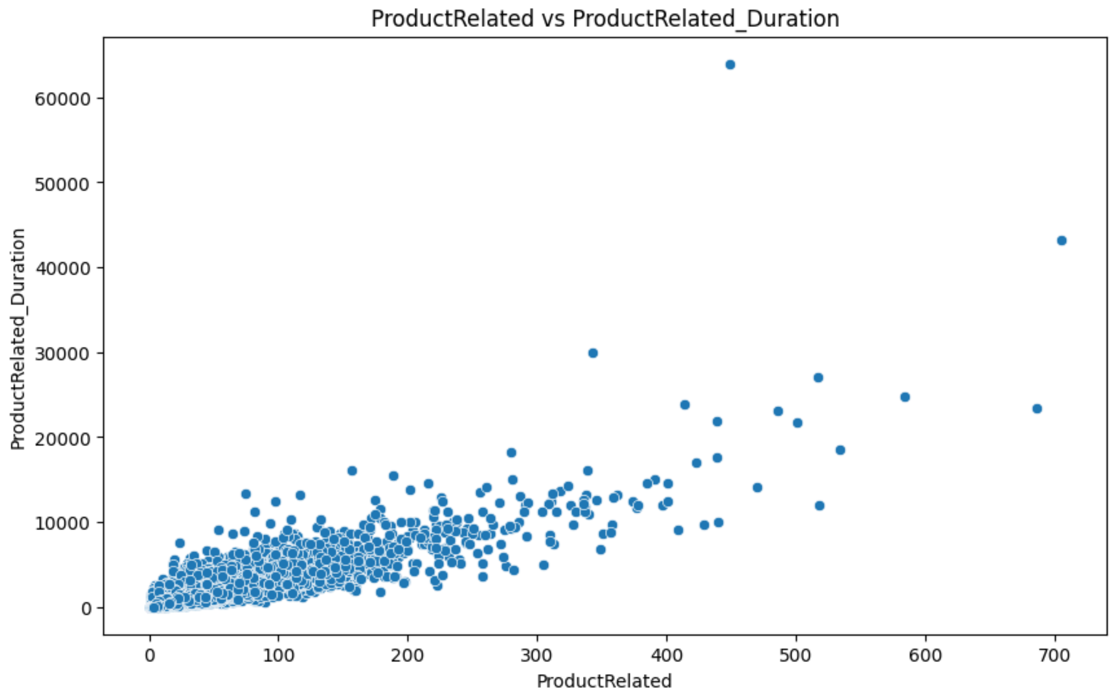
[14]:
```
correlation_matrix = shop_df[numerical_col].corr()
plt.figure(figsize=(12, 10))
sns.heatmap(correlation_matrix, annot=True, cmap='coolwarm', vmin=-1, vmax=1)
plt.title('Correlation Matrix')
plt.show()
```



- Visualizations

---

[15]:
```
plt.figure(figsize=(10, 6))
sns.scatterplot(x='ProductRelated', y='ProductRelated_Duration', data=shop_df)
plt.title('ProductRelated vs ProductRelated_Duration')
plt.xlabel('ProductRelated')
plt.ylabel('ProductRelated_Duration')
plt.show()
```



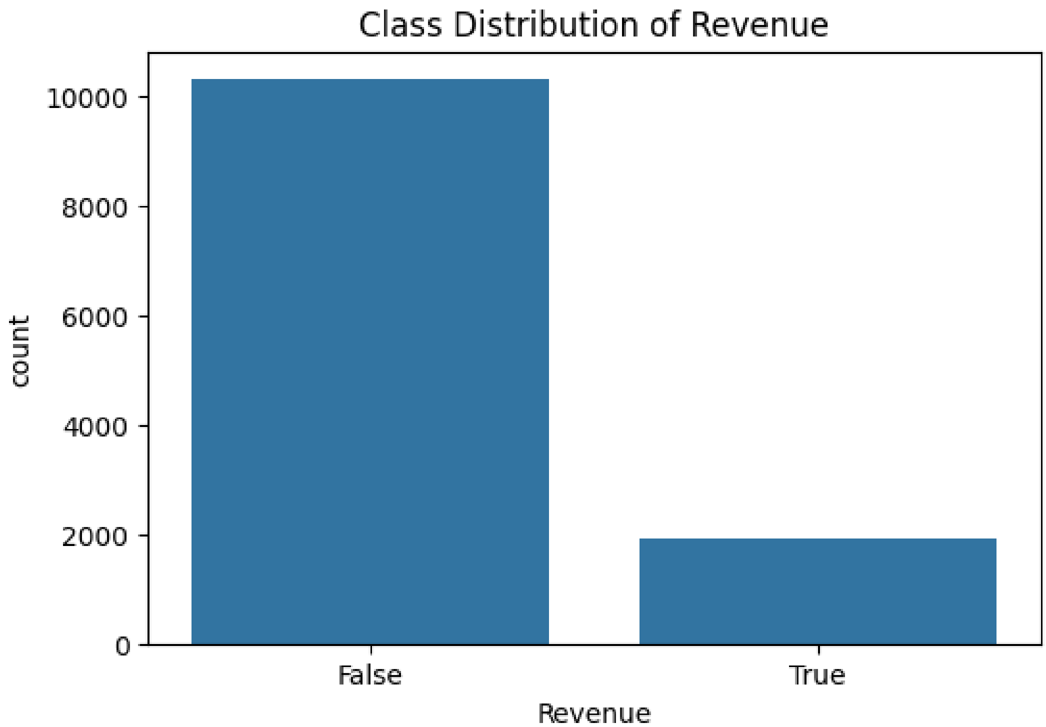
Users spending more time on product-related pages could be more likely to convert into customers. This suggests a need to optimize these pages to encourage further engagement and eventually drive conversions.

Class Distribution

[16]:
```
revenue_distribution = shop_df['Revenue'].value_counts(normalize = True)
revenue_distribution
```

[16]:
```
Revenue
False    0.843671
True     0.156329
Name: proportion, dtype: float64
```

[17]:
```
plt.figure(figsize=(6, 4))
sns.countplot(x='Revenue', data=shop_df)
plt.title('Class Distribution of Revenue')
plt.show()
```



Summarize page views, durations, and bounce/exit rates for each page category.

---

[18]:
```
shop_df.columns
```

[18]:
```
Index(['Administrative', 'Administrative_Duration', 'Informational',
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay', 'Month',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType', 'VisitorType',
       'Weekend', 'Revenue'],
      dtype='object')
```

[19]:
```
page_summary = shop_df.groupby('ProductRelated').agg({
    'Administrative': 'sum',
    'Administrative_Duration': 'sum',
    'Informational': 'sum',
    'Informational_Duration': 'sum',
    'BounceRates': 'mean',
    'ExitRates': 'mean'
})
print(page_summary)
```

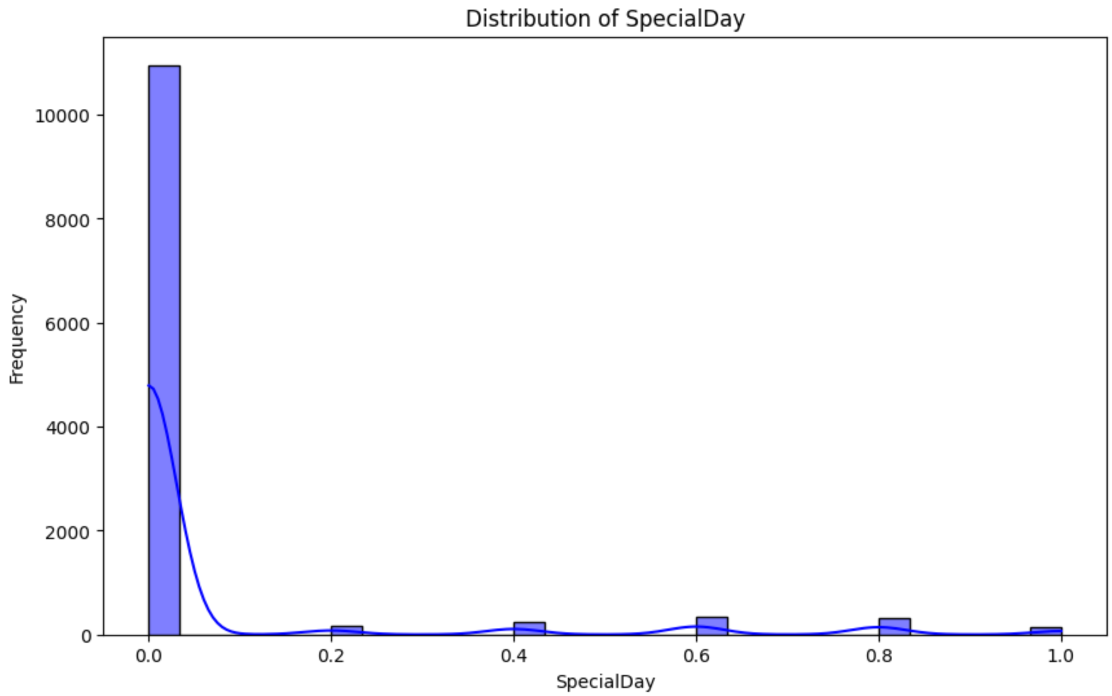
```
                Administrative  Administrative_Duration  Informational  \
```

```
ProductRelated
0                          35         847.400000           12
1                          67        2867.450000           31
2                         232        8854.512500           30
3                         379       13080.666667           23
4                         332       12124.116349           64
…                        …                 …             …
518                         8         161.668571            0
534                         9         444.284722            0
584                        27         853.735949            2
686                        20         199.456273            7
705                        17        2629.253968           24

                Informational_Duration  BounceRates  ExitRates
ProductRelated
0                            89.000000     0.098158   0.127446
1                          1751.650000     0.166177   0.179688
2                          1064.750000     0.046546   0.103480
3                           643.400000     0.033990   0.077767
4                          3723.666667     0.027736   0.064376
…                                  …           …          …
518                           0.000000     0.000038   0.003837
534                           0.000000     0.010857   0.023309
584                         126.500000     0.002099   0.009347
686                         299.033333     0.009853   0.022771
705                        2050.433333     0.004851   0.015431

[311 rows x 6 columns]
```

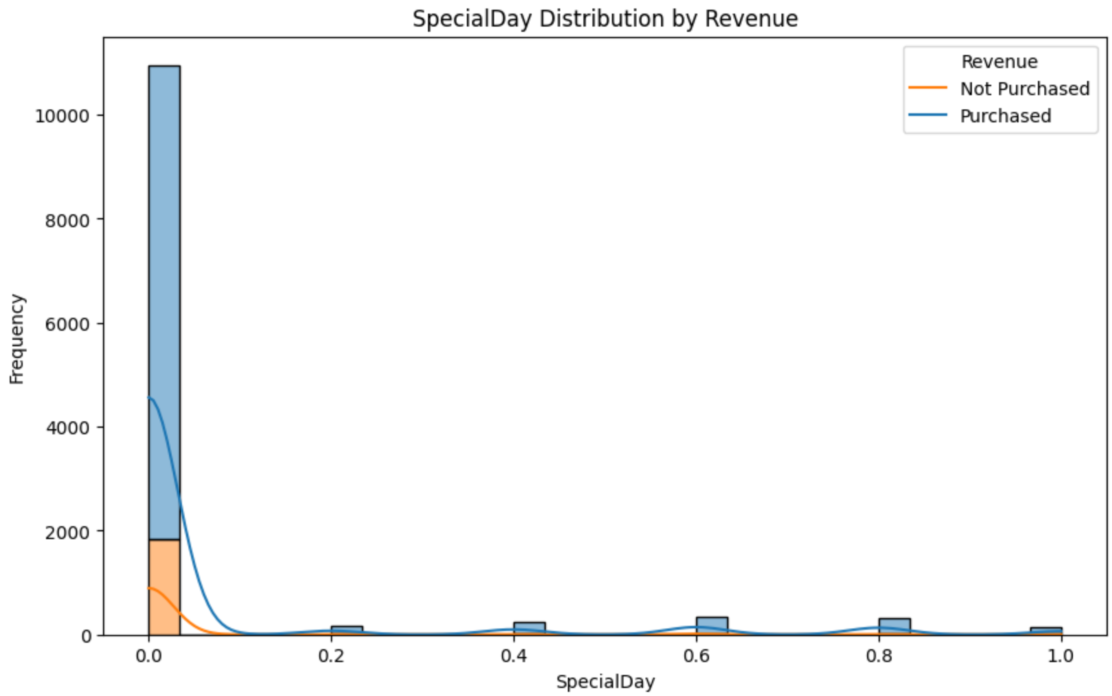
Analyze SpecialDay Distribution and Its Correlation with Revenue

---

[20]:
```
plt.figure(figsize=(10, 6))
sns.histplot(shop_df['SpecialDay'], bins=30, kde=True, color='blue')
plt.title('Distribution of SpecialDay')
plt.xlabel('SpecialDay')
plt.ylabel('Frequency')
plt.show()
```



[21]:
```
plt.figure(figsize=(10, 6))
sns.histplot(data=shop_df, x='SpecialDay', hue='Revenue', multiple='stack',␣
↪bins=30, kde=True)
plt.title('SpecialDay Distribution by Revenue')
plt.xlabel('SpecialDay')
plt.ylabel('Frequency')
plt.legend(title='Revenue', labels=['Not Purchased', 'Purchased'])
plt.show()
```



Generate a binary feature indicating whether the user visited all three page categories.

---

[22]:
```
shop_df.columns
```

[22]:
```
Index(['Administrative', 'Administrative_Duration', 'Informational',
       'Informational_Duration', 'ProductRelated', 'ProductRelated_Duration',
       'BounceRates', 'ExitRates', 'PageValues', 'SpecialDay', 'Month',
       'OperatingSystems', 'Browser', 'Region', 'TrafficType', 'VisitorType',
       'Weekend', 'Revenue'],
      dtype='object')
```

[23]:
```
shop_df['All_Pages_Visited'] = ((shop_df['Administrative'] > 0) &
                                (shop_df['Informational'] > 0) &
                                (shop_df['ProductRelated'] > 0)).astype(int)
```

[24]:
```
shop_df['All_Pages_Visited'].value_counts()
```

[24]:
```
All_Pages_Visited
0    10038
1     2167
Name: count, dtype: int64
```

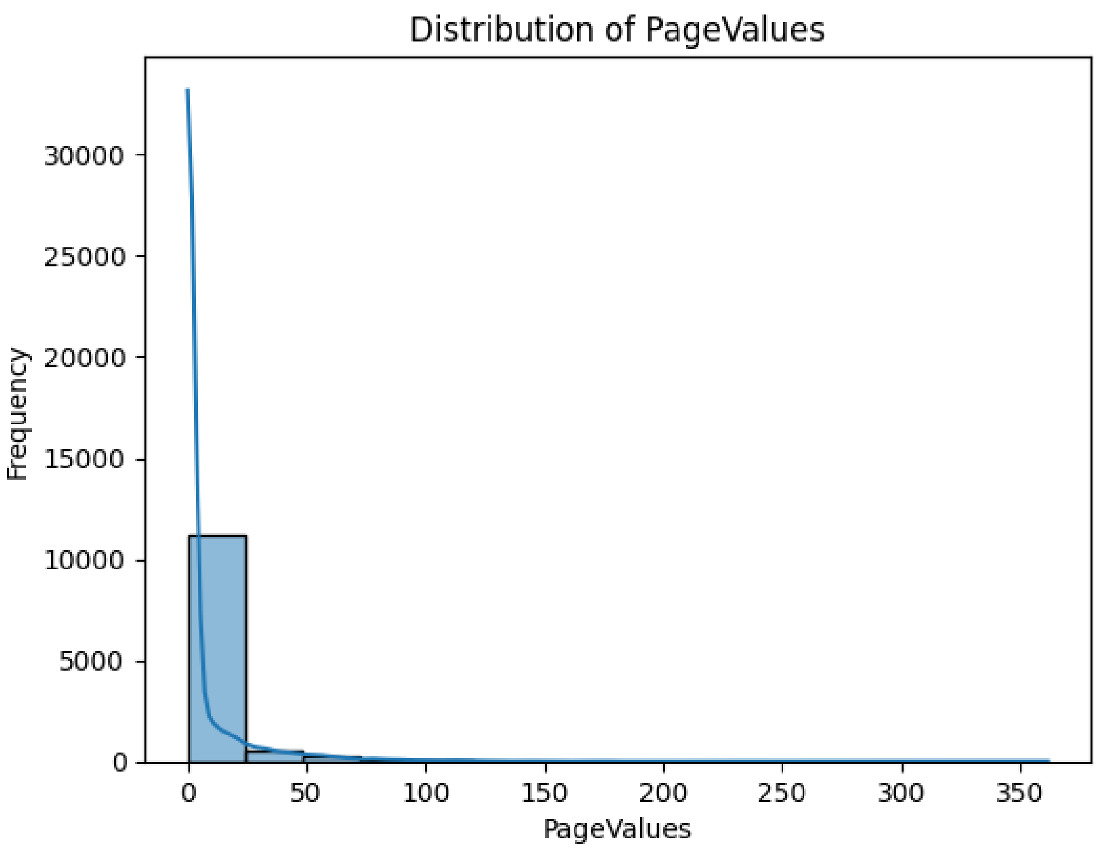
users are not exploring all content types, possibly missing critical information.

Recommendation: Improve Cross-Linking: Ensure that there are clear and intuitive links between different types of content. For instance, product pages could link to related informational content or FAQs.

Explore PageValues distribution and its relationship with TrafficType, VisitorType, and Region

---

[25]:
```
sns.histplot(shop_df['PageValues'], kde=True)
plt.title('Distribution of PageValues')
plt.xlabel('PageValues')
plt.ylabel('Frequency')
plt.show()
```



- relationship between traffic and pagevalue

[26]:
```
corr = shop_df[['PageValues', 'TrafficType']].corr()
corr
```

[26]:

	PageValues	TrafficType
PageValues	1.000000	0.012286

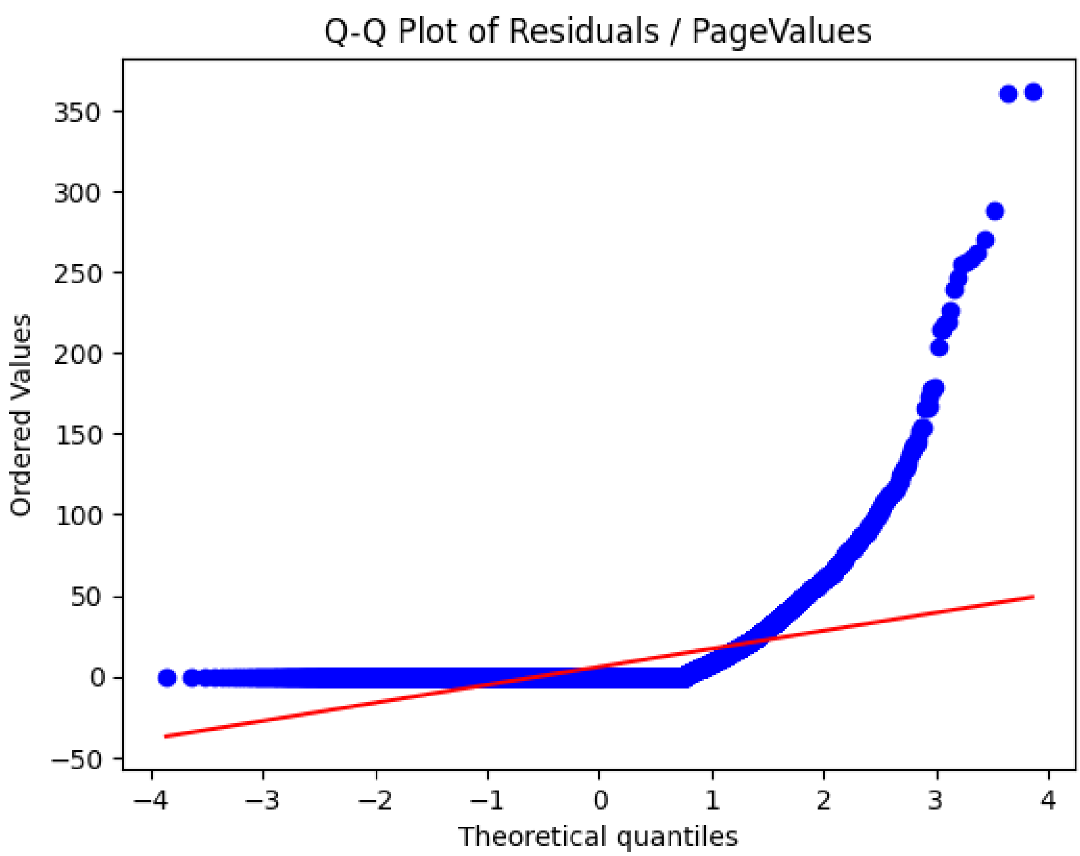
```
TrafficType     0.012286     1.000000
```

- relationship between vistitorType and pagevalue

[27]:
```
visitor_stats = shop_df.groupby('VisitorType')['PageValues'].agg(['mean',␣
↪'median', 'std', 'count'])
print(visitor_stats)
```

```
                        mean  median        std  count
VisitorType
New_Visitor        10.778550     0.0  29.197231   1693
Other              19.090173     0.0  54.328142     81
Returning_Visitor   5.063768     0.0  15.501615  10431
```

[28]:
```
residuals = shop_df['PageValues']
stats.probplot(residuals, dist="norm", plot=plt)
plt.title('Q-Q Plot of Residuals / PageValues')
plt.show()
```

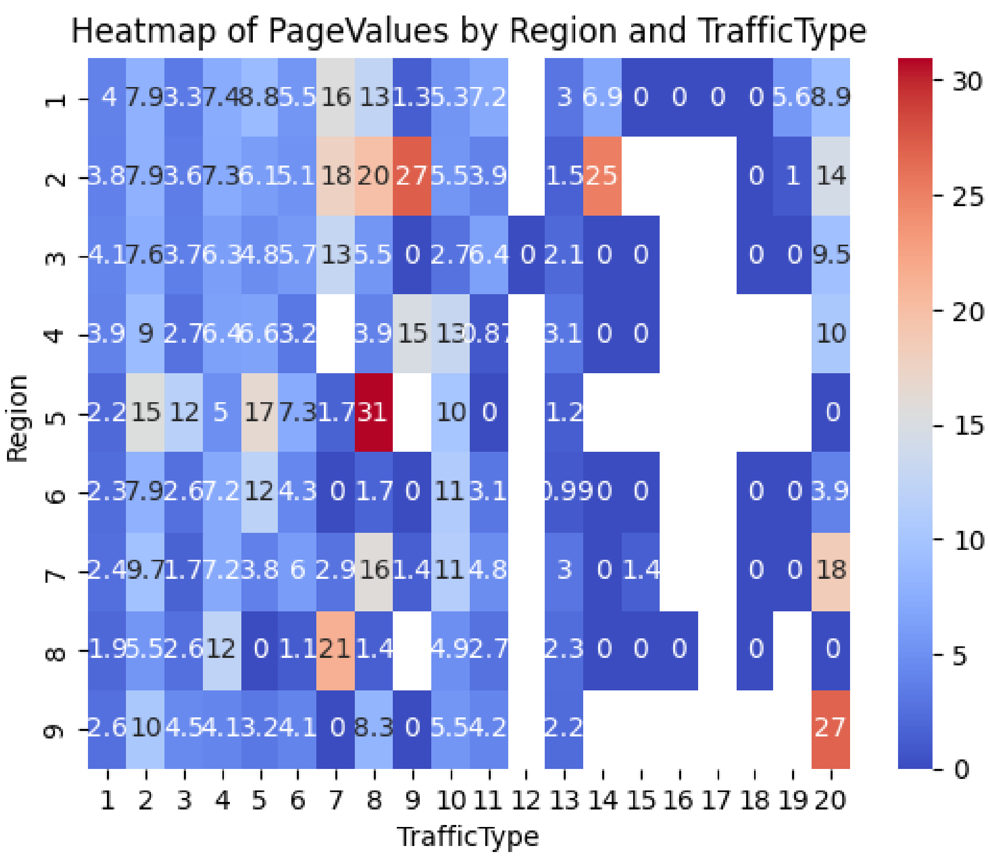


```
[29]: kruskal_test = kruskal(*[group['PageValues'].values for name, group in shop_df.
      ↪groupby('VisitorType')])
      print("Kruskal-Wallis Test:", kruskal_test)
```

```
Kruskal-Wallis Test: KruskalResult(statistic=6.207841451955822,
pvalue=0.04487292261362119)
```

- Realtionship between pagevalues and region

```
[30]: pivot_table = shop_df.pivot_table(values='PageValues', index='Region',␣
      ↪columns='TrafficType', aggfunc='mean')
      sns.heatmap(pivot_table, annot=True, cmap='coolwarm')
      plt.title('Heatmap of PageValues by Region and TrafficType')
      plt.show()
```



- Investigate user session lengths and their impact on conversion rates.

```
[31]: shop_df['sessionlength'] = shop_df['Administrative'] + shop_df['Informational']␣
      ↪+ shop_df['ProductRelated']
```

```
[32]: shop_df['sessionlength'].max()
```

[32]: 746

[33]:
```
shop_df['Session_category'] = pd.cut(shop_df['sessionlength'] ,␣
↪bins=[0,250,500,750,np.inf] , labels = [ 'Short', 'Medium', 'Long', 'Very␣
↪Long'])
```

[34]:
```
shop_df['Session_category'].value_counts()
```

[34]:
```
Session_category
Short        12106
Medium          86
Long             7
Very Long        0
Name: count, dtype: int64
```

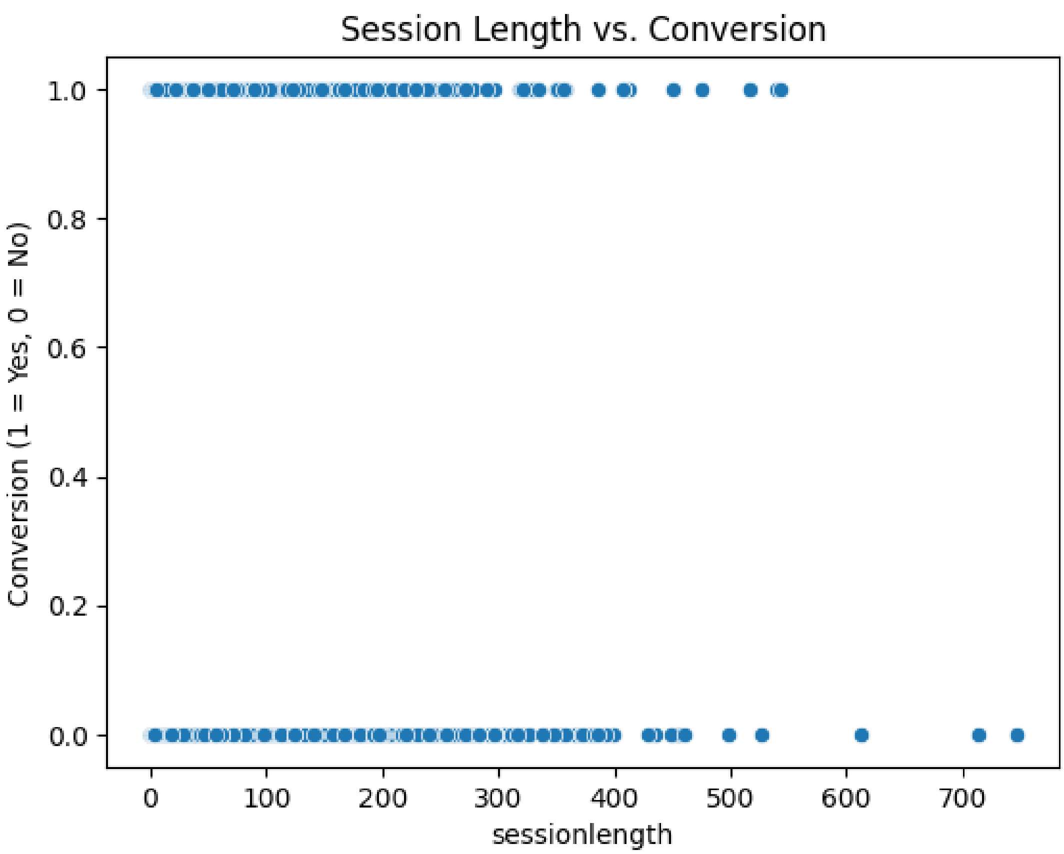
Insight : Longer session lengths generally lead to higher conversion rates, with "Long" sessions having a conversion rate of 42.86%. However, "Very Long" sessions didn't result in conversions.

Recommendation: Focus on optimizing the user experience to maintain engagement during "Long" sessions without overstaying, as this might lead to frustration or indecision. Tools like personalized recommendations or limited-time offers could help convert these sessions.

[35]:
```
conversion_rate = shop_df.groupby('Session_category' , observed =␣
↪False)['Revenue'].mean() * 100
print(conversion_rate)
```

```
Session_category
Short        15.488188
Medium       34.883721
Long         42.857143
Very Long          NaN
Name: Revenue, dtype: float64
```

[36]:
```
sns.scatterplot(x='sessionlength', y='Revenue', data=shop_df)
plt.title('Session Length vs. Conversion')
plt.xlabel('sessionlength')
plt.ylabel('Conversion (1 = Yes, 0 = No)')
plt.show()
```



Group users based on VisitorType, OperatingSystems, and Region to identify potential differences in behavior and conversion rates.

---

[37]:
```python
grouped = shop_df.groupby(['VisitorType', 'OperatingSystems', 'Region'])
```

[38]:
```python
conversion_rate = grouped['Revenue'].mean() * 100
conversion_rate.reset_index(name='ConversionRate')
```

[38]:

	VisitorType	OperatingSystems	Region	ConversionRate
0	New_Visitor	1	1	26.744186
1	New_Visitor	1	2	34.146341
2	New_Visitor	1	3	14.942529
3	New_Visitor	1	4	29.729730
4	New_Visitor	1	5	33.333333
..	…	…	…	…
110	Returning_Visitor	8	4	0.000000
111	Returning_Visitor	8	5	0.000000
112	Returning_Visitor	8	6	0.000000
113	Returning_Visitor	8	7	0.000000

```
114  Returning_Visitor                 8       9        0.000000

[115 rows x 4 columns]
```

Segment users based on TrafficType and analyze their engagement patterns and purchase probability.

---

[39]:
```python
grouped = shop_df.groupby('TrafficType')
```

[40]:
```python
engagement_metrics = grouped[['PageValues', 'sessionlength']].mean()
print(engagement_metrics)
```

```
             PageValues  sessionlength
TrafficType
1              3.546226      35.078308
2              8.308613      41.774994
3              3.339503      28.428217
4              7.062934      31.458724
5              7.712489      21.842308
6              5.087703      32.164786
7             13.567345      32.600000
8             10.302436      29.498542
9              3.911694      17.414634
10             6.208230      35.751111
11             5.068642      27.344130
12             0.000000       3.000000
13             2.386929      35.571429
14             4.936097      85.076923
15             0.037454      18.378378
16             0.000000      18.333333
17             0.000000       4.000000
18             0.000000      16.300000
19             3.497520      41.352941
20            15.520252      23.036269
```

[41]:
```python
conversion_rate = grouped['Revenue'].mean() * 100
print(conversion_rate)
```

```
TrafficType
1      10.971524
2      21.656865
3       8.941878
4      15.478424
5      21.538462
6      11.963883
7      30.000000
```

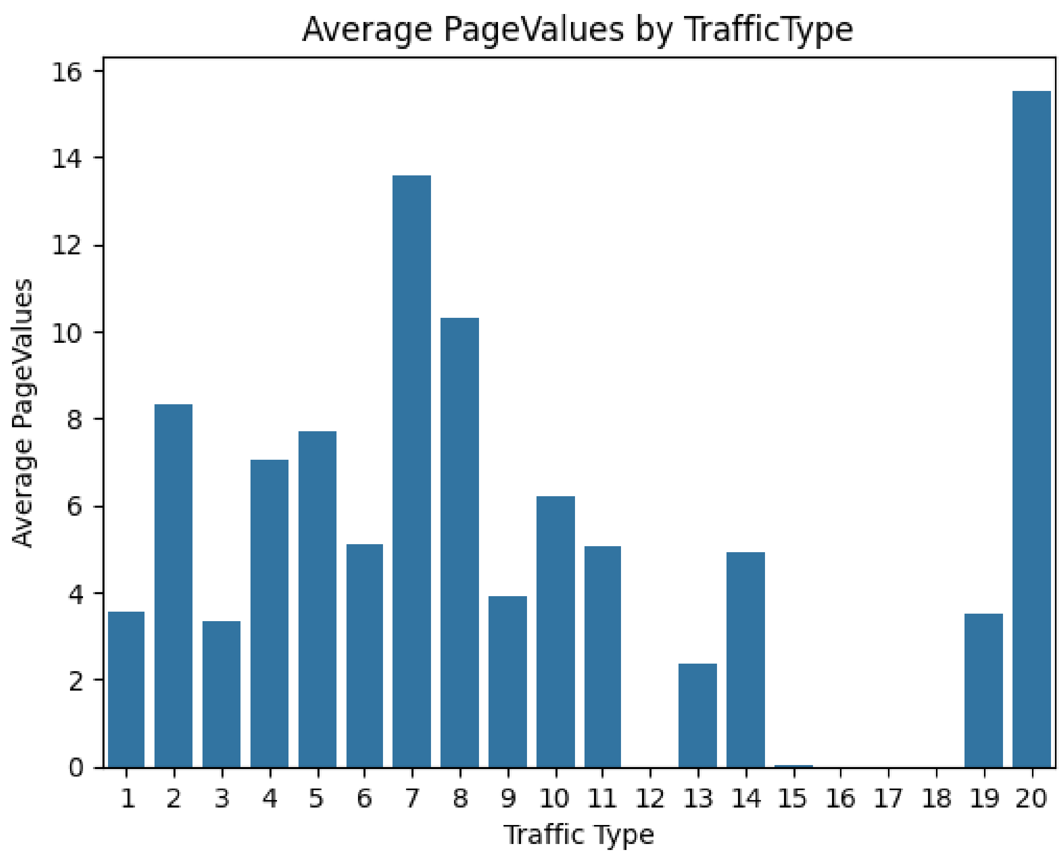
```
8     27.696793
9      9.756098
10    20.000000
11    19.028340
12     0.000000
13     5.906593
14    15.384615
15     0.000000
16    33.333333
17     0.000000
18     0.000000
19     5.882353
20    25.906736
Name: Revenue, dtype: float64
```

[42]:

```
engagement_metrics = grouped[['PageValues', 'sessionlength']].agg(['mean',␣
↪'median'])
```

[43]:

```
sns.barplot(x=engagement_metrics.index,␣
↪y=engagement_metrics['PageValues']['mean'])
plt.title('Average PageValues by TrafficType')
plt.xlabel('Traffic Type')
plt.ylabel('Average PageValues')
plt.show()
```



[43]:

[43]:

#Campaign Dataset

EDA on various features and columns.

---

[44]:
```
camp_df= pd.read_csv('/content/campaign - campaign.csv')
```

[45]:
```
camp_df.head()
```

[45]:
```
      ID  Year_Birth   Education Marital_Status      Income  Kidhome  \
0   1826        1970  Graduation       Divorced  $84,835.00        0
1      1        1961  Graduation         Single  $57,091.00        0
2  10476        1958  Graduation        Married  $67,267.00        0
3   1386        1967  Graduation       Together  $32,474.00        1
4   5371        1989  Graduation         Single  $21,474.00        1
```

```
   Teenhome Dt_Customer  Recency  MntWines  …  NumCatalogPurchases  \
0         0     6/16/14        0       189  …                    4
1         0     6/15/14        0       464  …                    3
2         1     5/13/14        0       134  …                    2
3         1     5/11/14        0        10  …                    0
4         0      4/8/14        0         6  …                    1

   NumStorePurchases  NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  \
0                  6                  1             0             0
1                  7                  5             0             0
2                  5                  2             0             0
3                  2                  7             0             0
4                  2                  7             1             0

   AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  Country
0             0             0             0         0       SP
1             0             0             1         0       CA
2             0             0             0         0       US
3             0             0             0         0      AUS
4             0             0             0         0       SP

[5 rows x 27 columns]
```

[46]:
```
camp_df.shape
```

[46]:
```
(2239, 27)
```

[47]:
```
camp_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
```

[48]:
```
camp_df['Dt_Customer'] =  pd.to_datetime(camp_df['Dt_Customer'], format='%m/%d/
↪%y')
```

[49]:
```
camp_df['Income'] = camp_df['Income'].replace({'\$' : '' , ',' : ''} , regex=␣
↪True ).astype(float)
```

[50]:
```
camp_df.isnull().sum()
```

[50]:
```
ID                      0
Year_Birth              0
Education               0
Marital_Status          0
Income                 24
Kidhome                 0
Teenhome                0
Dt_Customer             0
Recency                 0
MntWines                0
MntFruits               0
MntMeatProducts         0
MntFishProducts         0
MntSweetProducts        0
MntGoldProds            0
NumDealsPurchases       0
NumWebPurchases         0
NumCatalogPurchases     0
NumStorePurchases       0
NumWebVisitsMonth       0
AcceptedCmp3            0
AcceptedCmp4            0
```

```
AcceptedCmp5           0
AcceptedCmp1           0
AcceptedCmp2           0
Complain               0
Country                0
dtype: int64
```

[51]:
```
camp_df[camp_df['Income'].isnull()]
```

[51]:
```
         ID  Year_Birth   Education Marital_Status  Income  Kidhome  Teenhome  \
134    8996        1957         PhD        Married     NaN        2         1
262    1994        1983  Graduation        Married     NaN        1         0
394    3769        1972         PhD       Together     NaN        1         0
449    5255        1986  Graduation         Single     NaN        1         0
525    8268        1961         PhD        Married     NaN        0         1
589   10629        1973    2n Cycle        Married     NaN        1         0
898   10475        1970      Master       Together     NaN        0         1
996    9235        1957  Graduation         Single     NaN        1         1
1095   4345        1964    2n Cycle         Single     NaN        1         1
1184   7187        1969      Master       Together     NaN        1         1
1212   8720        1978    2n Cycle       Together     NaN        0         0
1311   8557        1982  Graduation         Single     NaN        1         0
1514   2863        1970  Graduation         Single     NaN        1         2
1557   2437        1989  Graduation        Married     NaN        0         0
1692   5250        1943      Master          Widow     NaN        0         0
1803   7281        1959         PhD         Single     NaN        0         0
1857   1612        1981         PhD         Single     NaN        1         0
1862   5079        1971  Graduation        Married     NaN        1         1
1879  10339        1954      Master       Together     NaN        0         1
1966   5798        1973      Master       Together     NaN        0         0
1982   2902        1958  Graduation       Together     NaN        1         1
2138   3117        1955  Graduation         Single     NaN        0         1
2164   7244        1951  Graduation         Single     NaN        2         1
2169   1295        1963  Graduation        Married     NaN        0         1

     Dt_Customer  Recency  MntWines  …  NumCatalogPurchases  \
134   2012-11-19        4       230  …                    2
262   2013-11-15       11         5  …                    0
394   2014-03-02       17        25  …                    0
449   2013-02-20       19         5  …                    0
525   2013-07-11       23       352  …                    1
589   2012-09-14       25        25  …                    0
898   2013-04-01       39       187  …                    2
996   2014-05-27       45         7  …                    0
1095  2014-01-12       49         5  …                    0
1184  2013-05-18       52       375  …                   10
1212  2012-08-12       53        32  …                    0
```

```
1311  2013-06-17       57         11  …                    0
1514  2013-08-23       67        738  …                    3
1557  2013-06-03       69        861  …                    5
1692  2013-10-30       75        532  …                    5
1803  2013-11-05       80         81  …                    3
1857  2013-05-31       82         23  …                    0
1862  2013-03-03       82         71  …                    1
1879  2013-06-23       83        161  …                    1
1966  2013-11-23       87        445  …                    4
1982  2012-09-03       87         19  …                    0
2138  2013-10-18       95        264  …                    1
2164  2014-01-01       96         48  …                    1
2169  2013-08-11       96        231  …                    5

      NumStorePurchases  NumWebVisitsMonth  AcceptedCmp3  AcceptedCmp4  \
134                   8                  9             0             0
262                   2                  7             0             0
394                   3                  7             0             0
449                   0                  1             0             0
525                   7                  6             0             0
589                   3                  8             0             0
898                   6                  5             0             0
996                   2                  7             0             0
1095                  2                  7             0             0
1184                  4                  3             0             0
1212                  1                  0             0             1
1311                  3                  6             0             0
1514                 10                  7             0             1
1557                 12                  3             0             1
1692                 11                  1             0             0
1803                  4                  2             0             0
1857                  3                  6             0             0
1862                  3                  8             0             0
1879                  4                  6             0             0
1966                  8                  1             0             0
1982                  3                  5             0             0
2138                  5                  7             0             0
2164                  4                  6             0             0
2169                  7                  4             0             0

      AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  Complain  Country
134              0             0             0         0      GER
262              0             0             0         0       US
394              0             0             0         0      AUS
449              0             0             0         0      AUS
525              0             0             0         0       CA
589              0             0             0         0      GER
```

```
898                  0                0                0            0         US
996                  0                0                0            0        GER
1095                 0                0                0            0        AUS
1184                 0                0                0            0        AUS
1212                 0                0                0            0        IND
1311                 0                0                0            0        AUS
1514                 0                1                0            0         SP
1557                 0                1                0            0         SP
1692                 1                0                0            0        AUS
1803                 0                0                0            0        AUS
1857                 0                0                0            0        AUS
1862                 0                0                0            0        AUS
1879                 0                0                0            0        AUS
1966                 0                0                0            0        GER
1982                 0                0                0            0        AUS
2138                 0                0                0            0        AUS
2164                 0                0                0            0        AUS
2169                 0                0                0            0         CA

[24 rows x 27 columns]
```

[52]:
```
camp_df['Income'] = camp_df['Income'].fillna(0)
```

[53]:
```
camp_df['Income'].isnull().sum()
```

[53]:
```
0
```

Feature Engineering

---

[54]:
```
camp_df['Customer_Lifetime'] = (pd.to_datetime('today') -
 ↪camp_df['Dt_Customer']).dt.days
```

- Binning

[55]:
```
camp_df['Recency_Binned'] = pd.cut(camp_df['Recency'], bins=[0, 30, 60, 90,
 ↪120, 180], labels=['Very Recent', 'Recent', 'Moderate', 'Old', 'Very Old'])
```

[56]:
```
camp_df['Recency_Binned'].value_counts()
```

[56]:
```
Recency_Binned
Very Recent    695
Moderate       664
Recent         654
Old            198
Very Old         0
Name: count, dtype: int64
```

Remove extreme values if required.

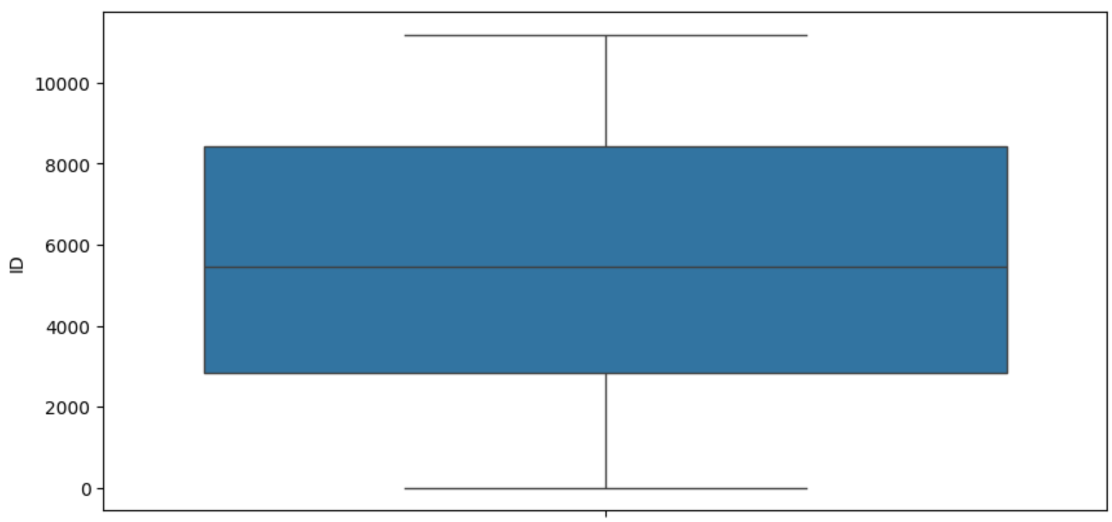
---

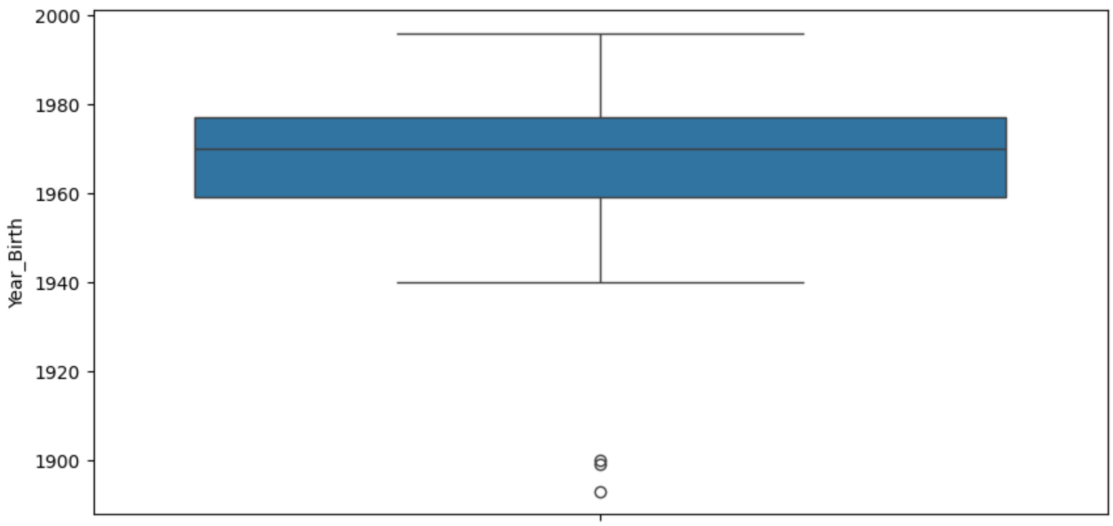
[57]:
```python
numerical_cols = camp_df.select_dtypes(include=np.number).columns
```

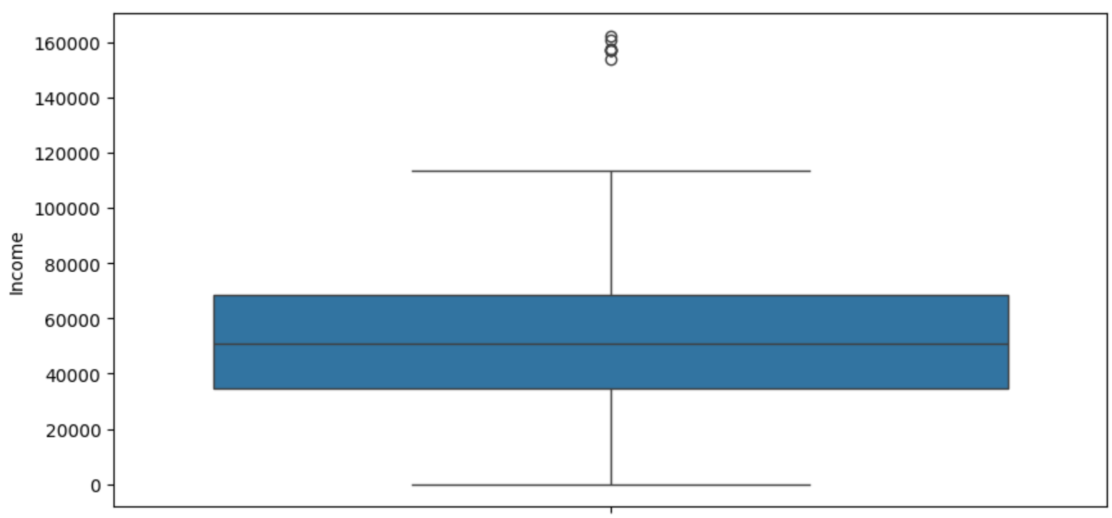
[58]:
```python
numerical_cols
```

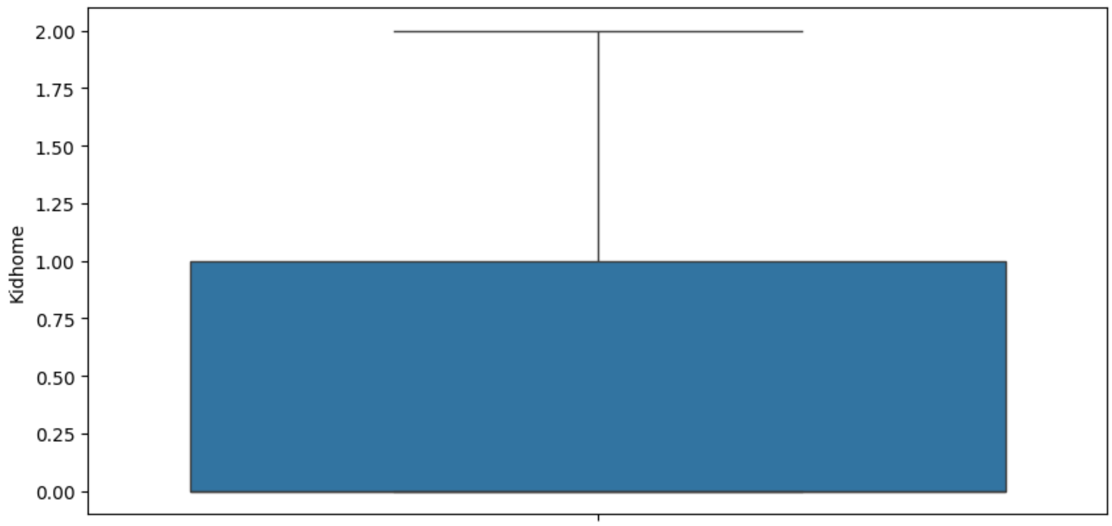
[58]:
```
Index(['ID', 'Year_Birth', 'Income', 'Kidhome', 'Teenhome', 'Recency',
       'MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',
       'MntSweetProducts', 'MntGoldProds', 'NumDealsPurchases',
       'NumWebPurchases', 'NumCatalogPurchases', 'NumStorePurchases',
       'NumWebVisitsMonth', 'AcceptedCmp3', 'AcceptedCmp4', 'AcceptedCmp5',
       'AcceptedCmp1', 'AcceptedCmp2', 'Complain', 'Customer_Lifetime'],
      dtype='object')
```

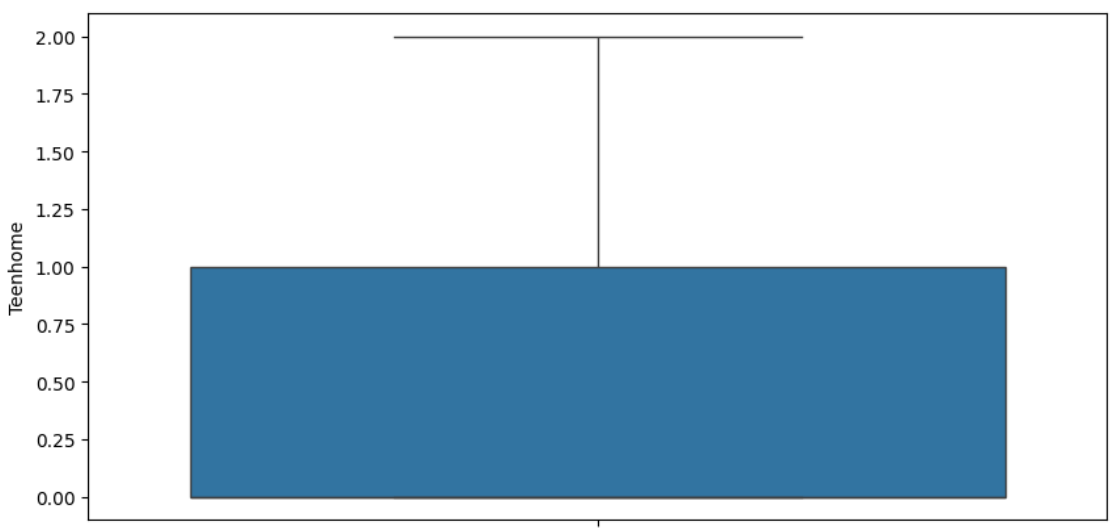
[59]:
```python
for col in numerical_cols:
  plt.figure(figsize=(10,5))
  sns.boxplot(camp_df[col])
  plt.show()
```

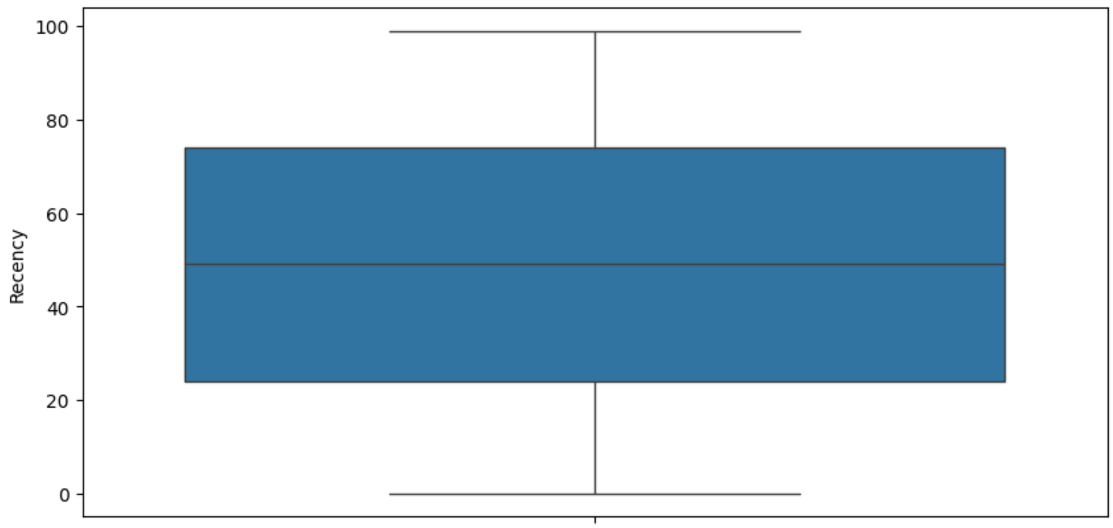


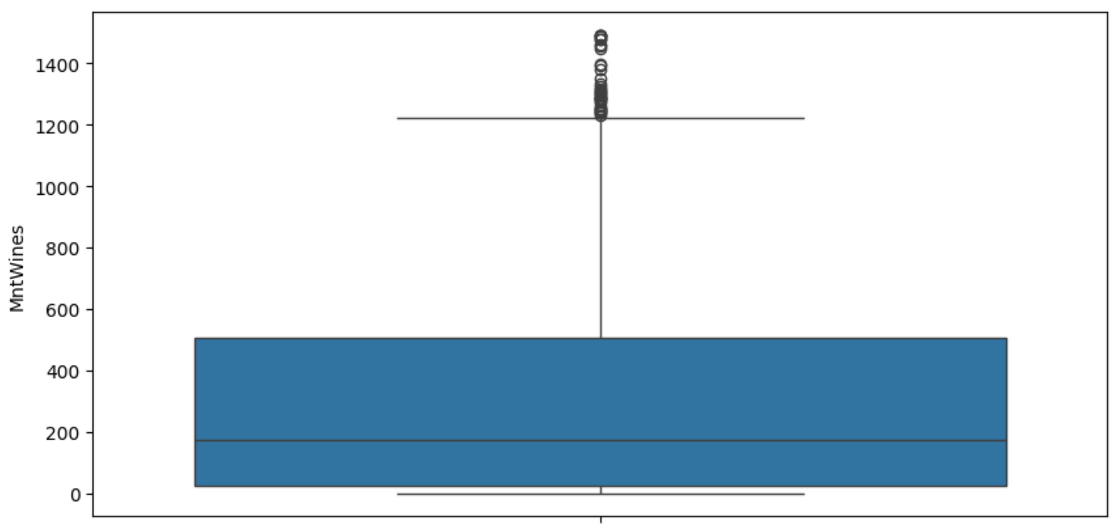

2000
1980
1960
1940
1920
1900
Year_Birth

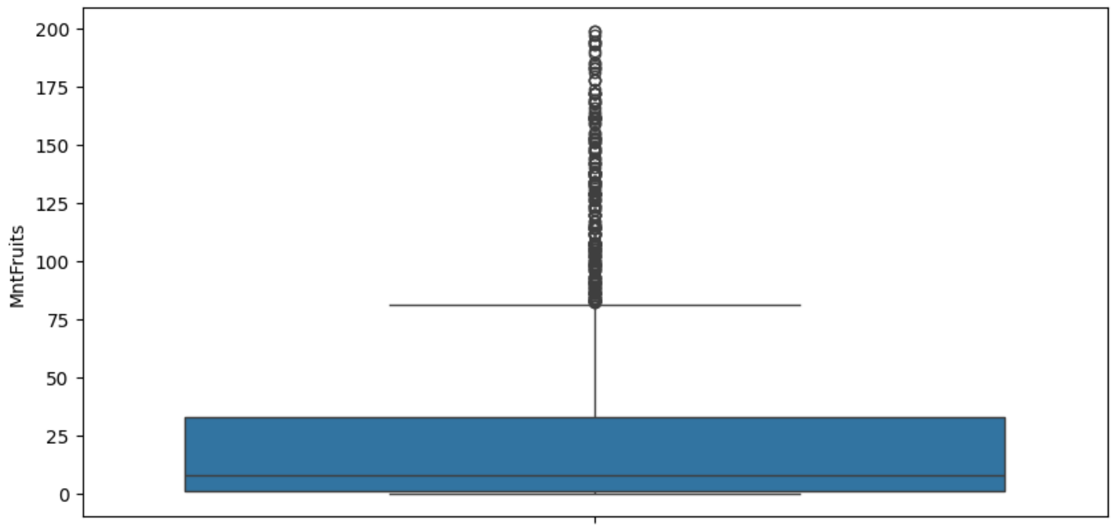

160000
140000
120000
100000
80000
60000
40000
20000
0
Income


2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Kidhome

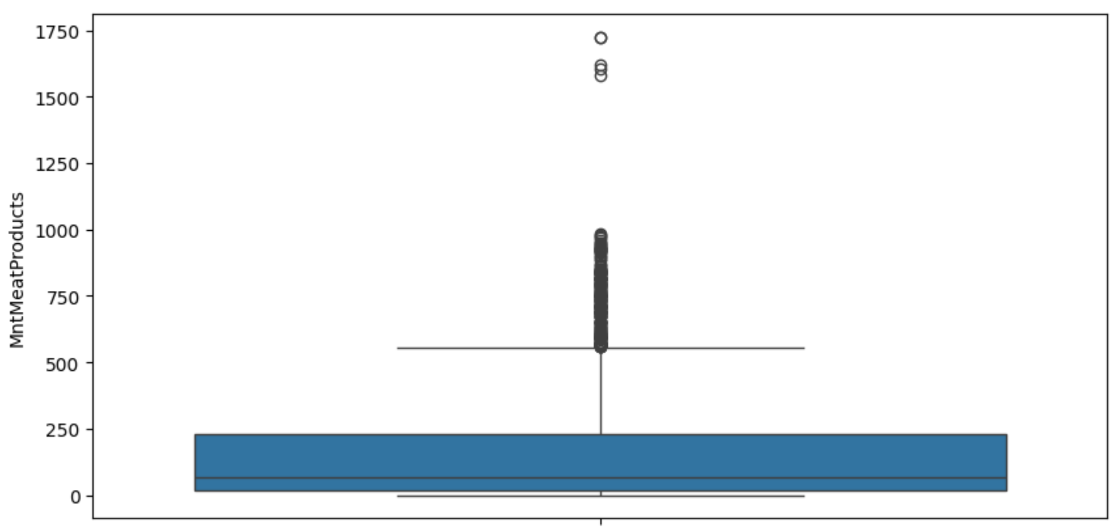

2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Teenhome


100
80
60
40
20
0
Recency

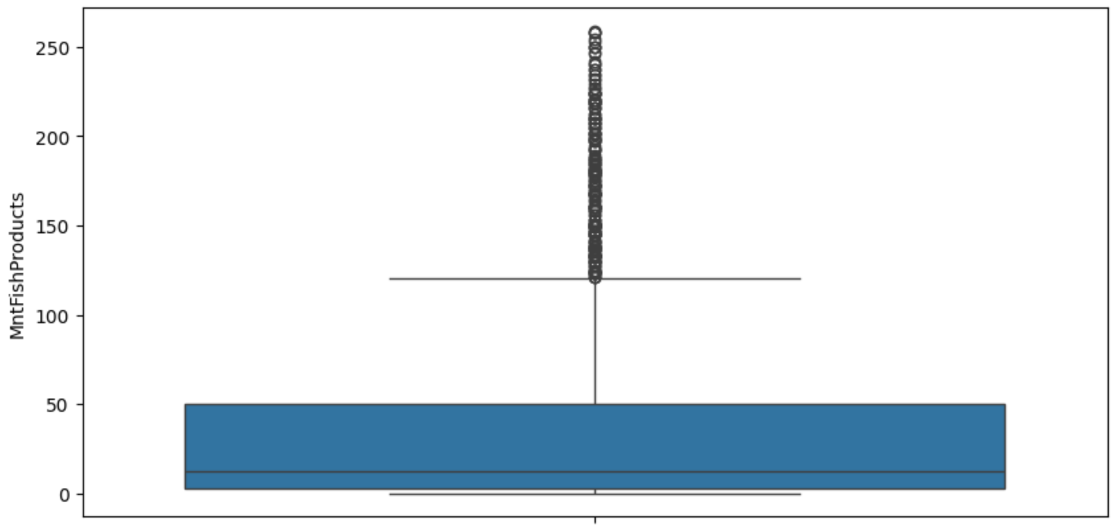

1400
1200
1000
800
600
400
200
0
MntWines

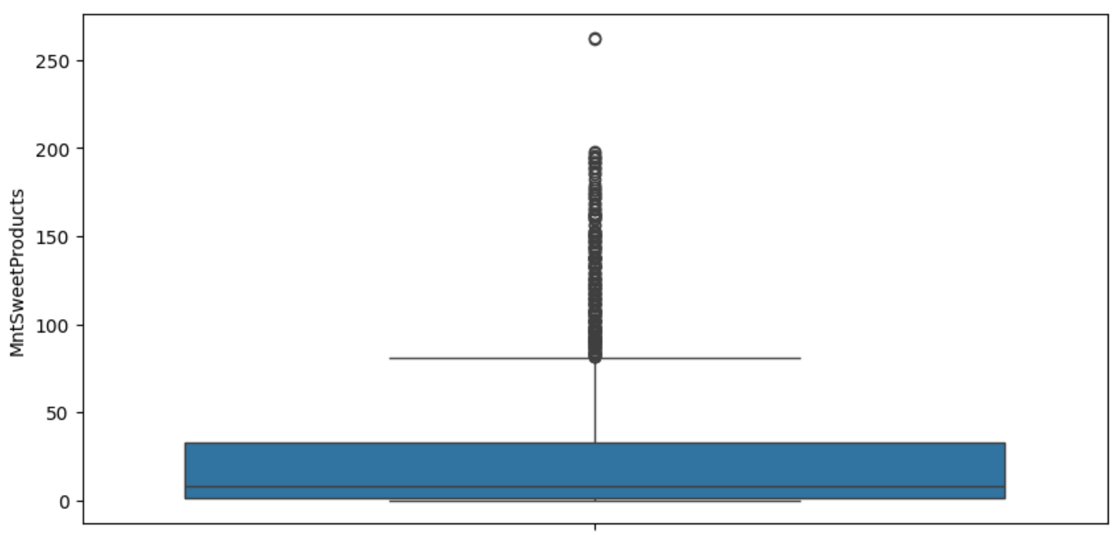


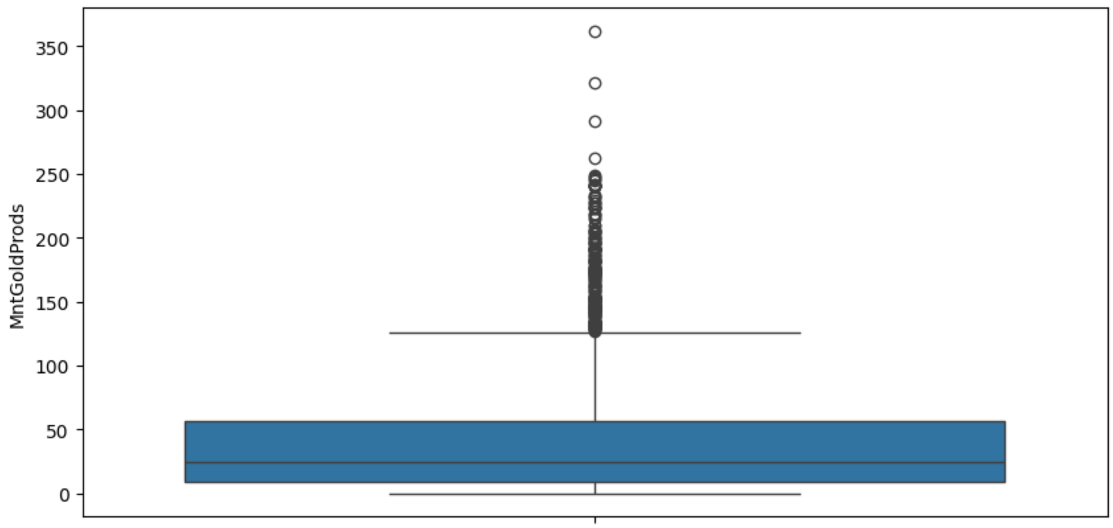
MntFruits
200
175
150
125
100
75
50
25
0

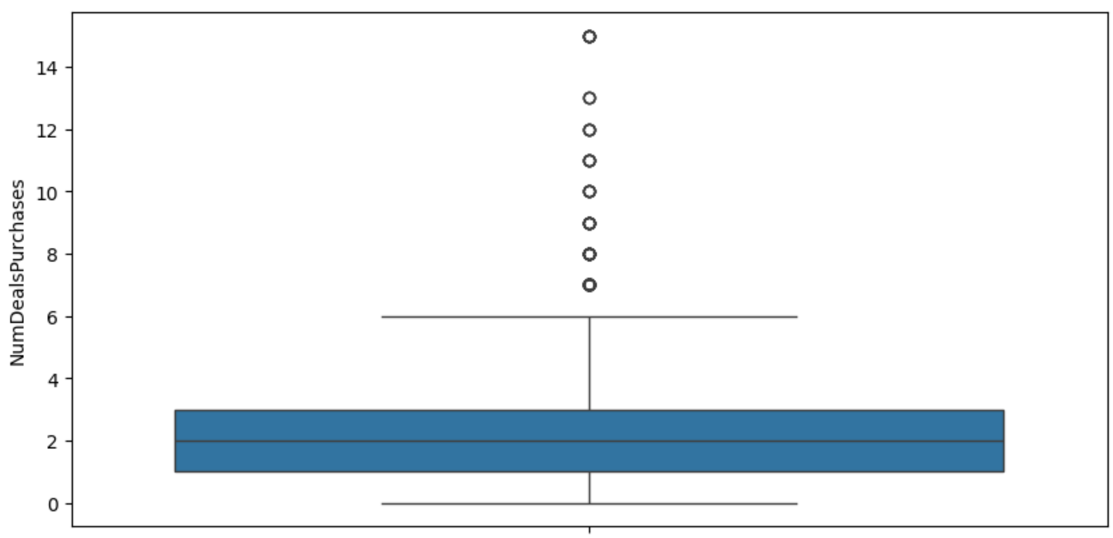


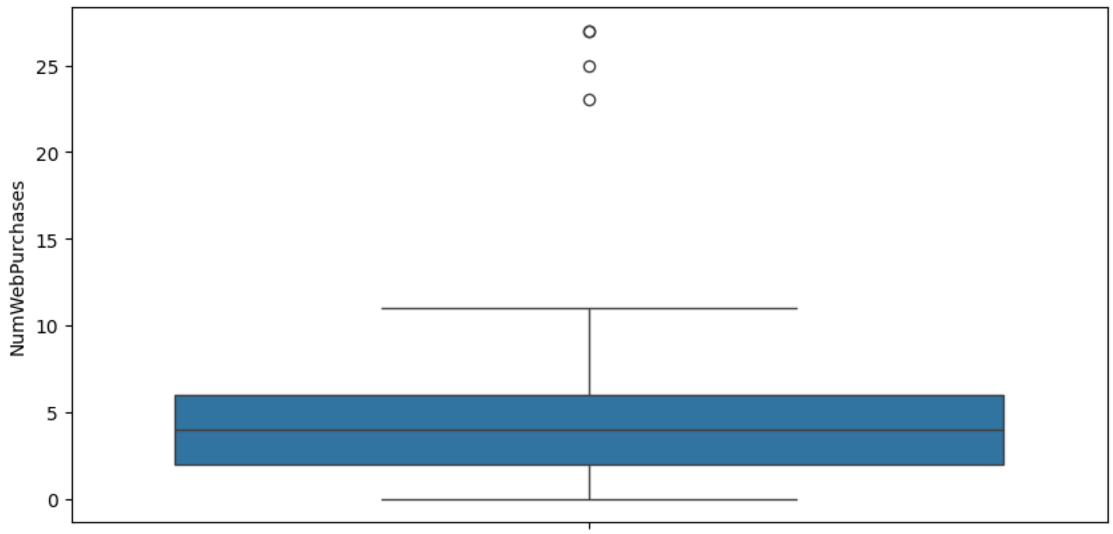
MntMeatProducts
1750
1500
1250
1000
750
500
250
0

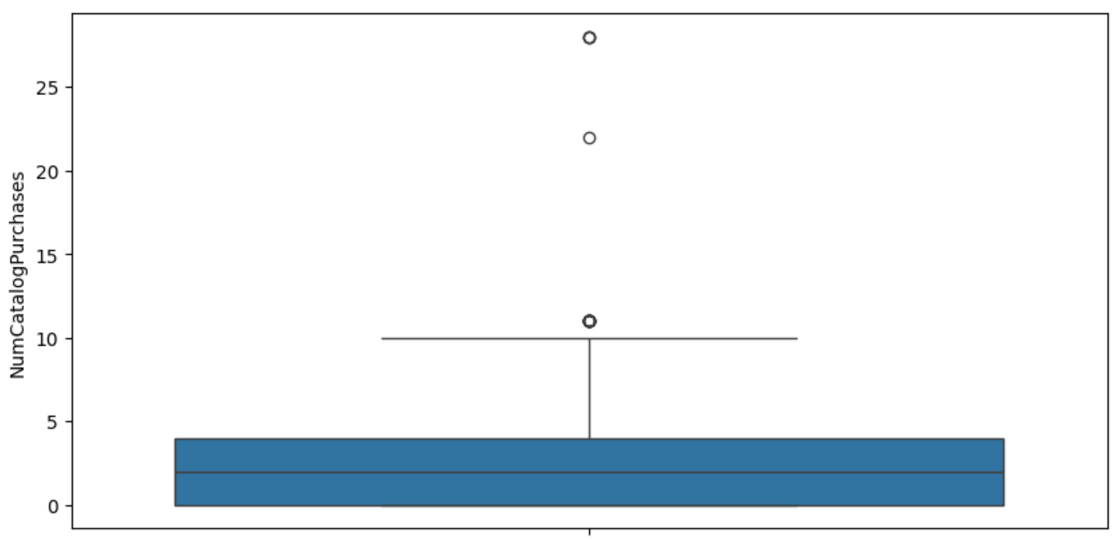

MntFishProducts
250
200
150
100
50
0

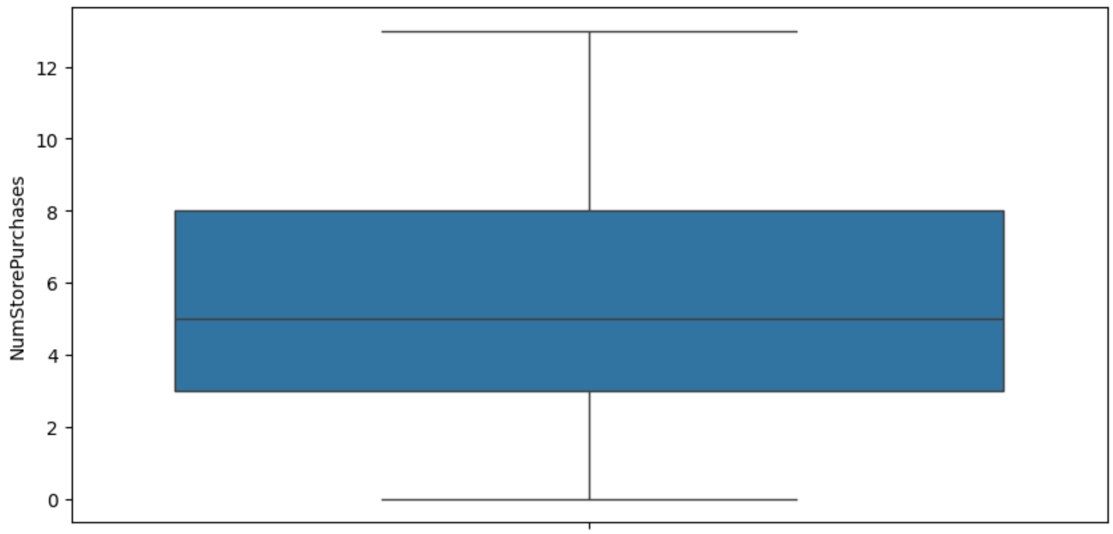

MntSweetProducts
250
200
150
100
50
0


MntGoldProds
350
300
250
200
150
100
50
0

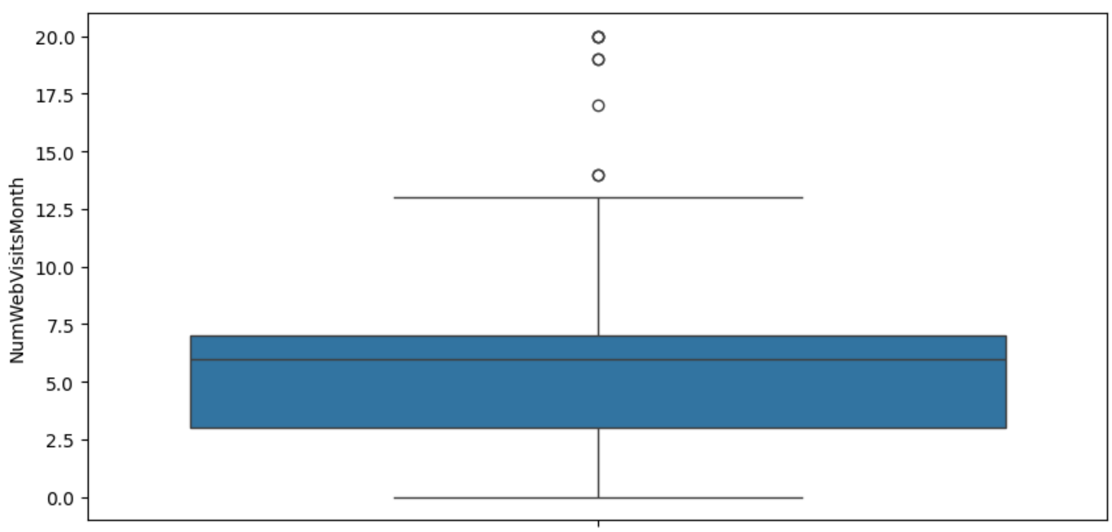

NumDealsPurchases
14
12
10
8
6
4
2
0


NumWebPurchases
0
5
10
15
20
25

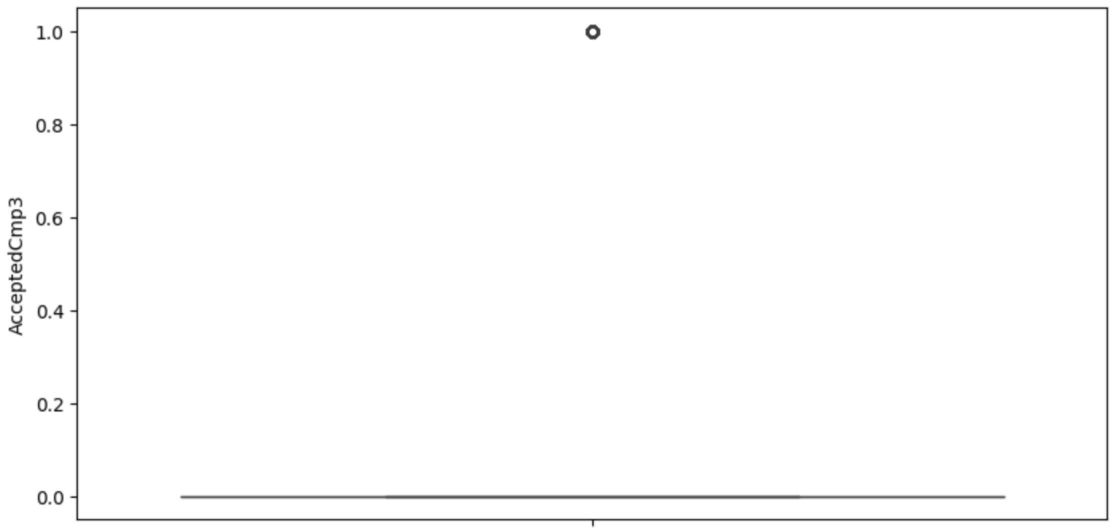

NumCatalogPurchases
0
5
10
15
20
25

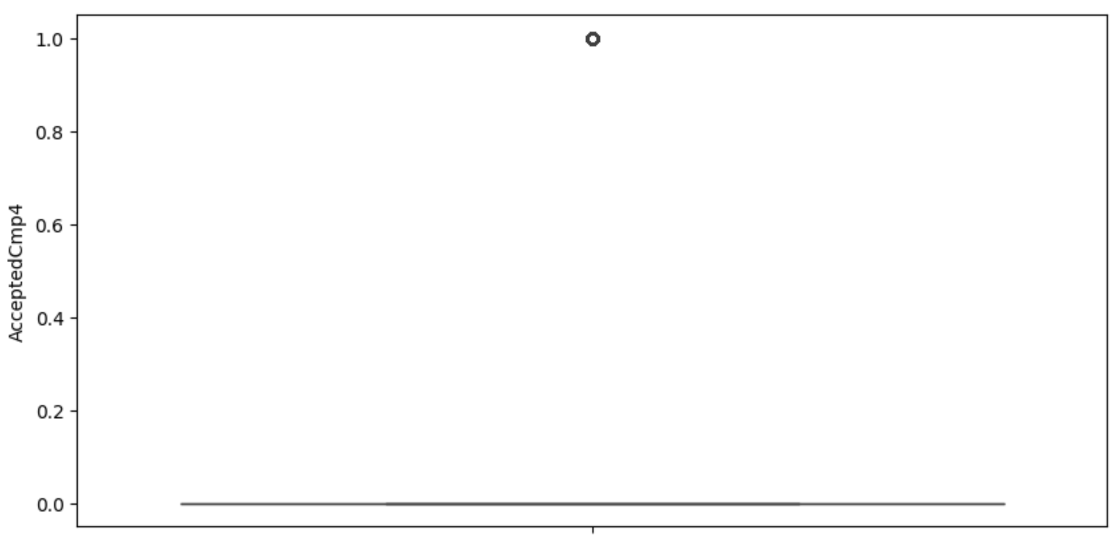


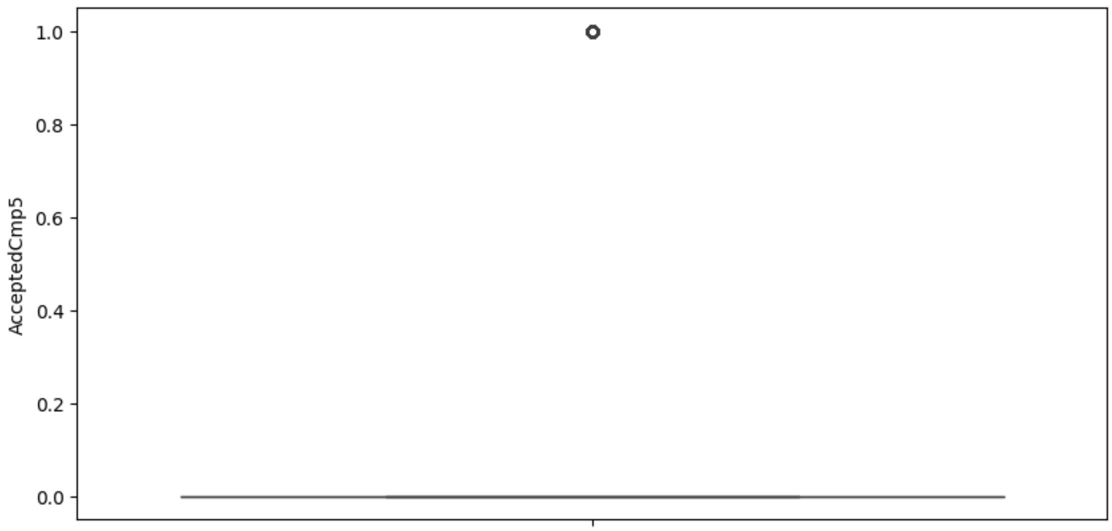
NumStorePurchases
0
2
4
6
8
10
12

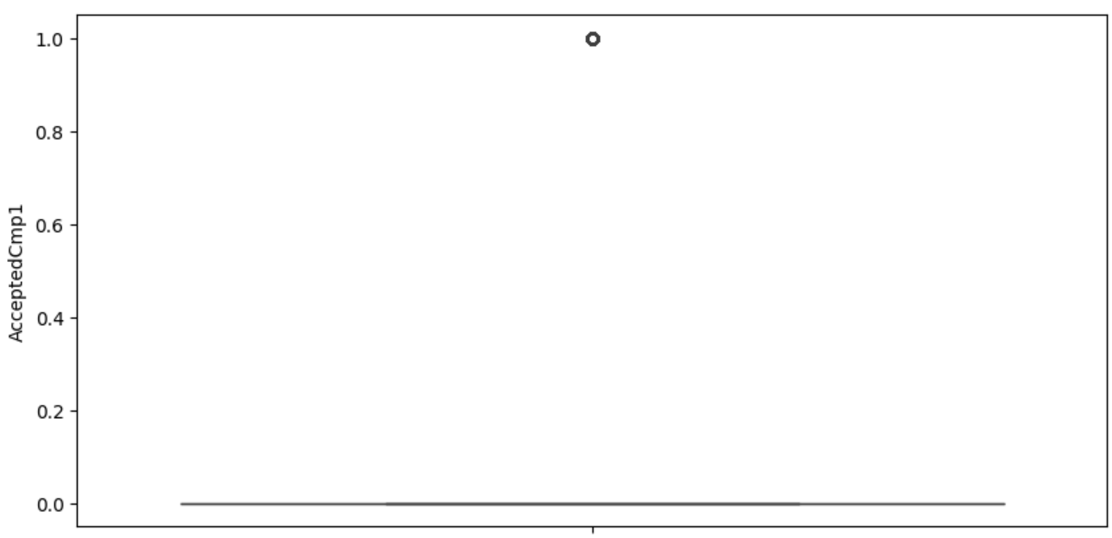


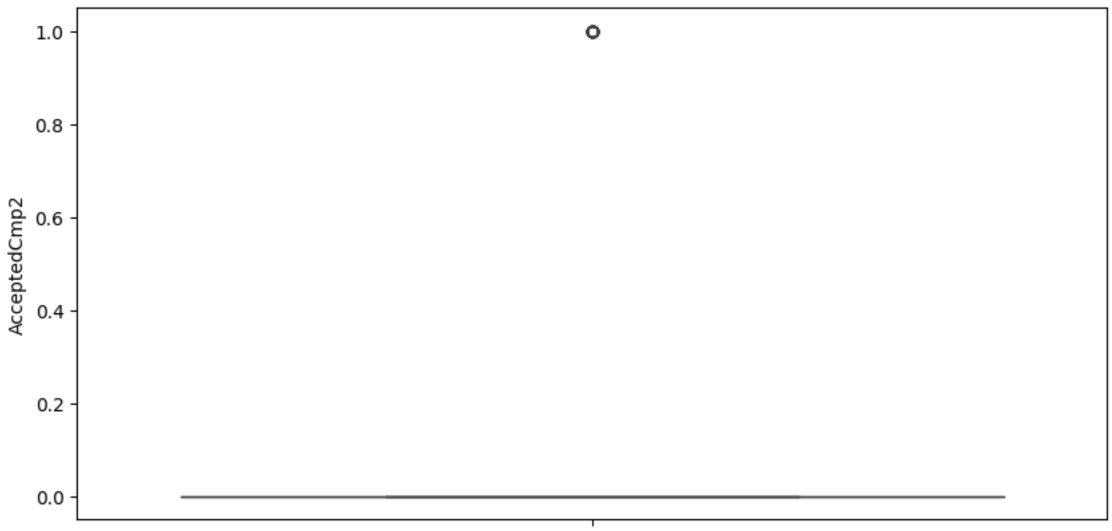
NumWebVisitsMonth
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0

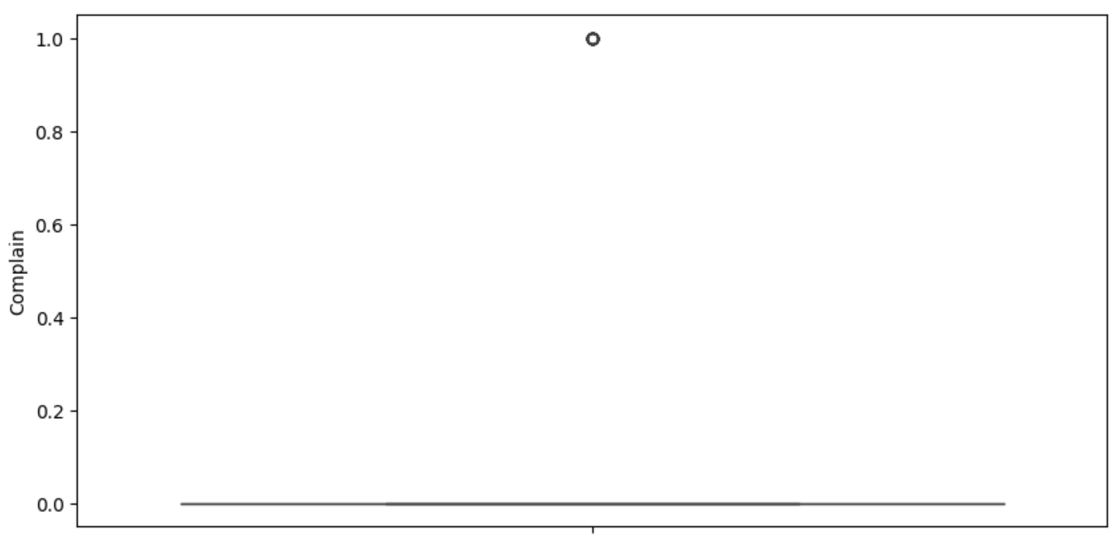

1.0
0.8
0.6
0.4
0.2
0.0
AcceptedCmp3

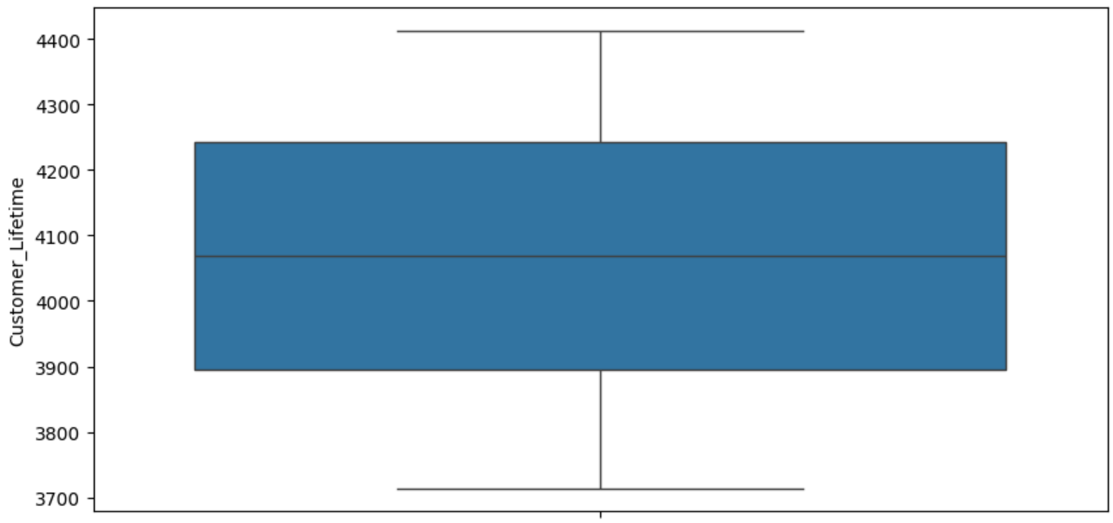

1.0
0.8
0.6
0.4
0.2
0.0
AcceptedCmp4


1.0
0.8
0.6
0.4
0.2
0.0
AcceptedCmp5


1.0
0.8
0.6
0.4
0.2
0.0
AcceptedCmp1


1.0
0.8
0.6
0.4
0.2
0.0
AcceptedCmp2


1.0
0.8
0.6
0.4
0.2
0.0
Complain



[60]:
```
key_columns = [
    'Income', 'MntWines', 'MntFruits', 'MntMeatProducts', 'MntFishProducts',
    'MntSweetProducts', 'MntGoldProds'
]
```

[61]:
```
Q1 = camp_df[key_columns].quantile(0.25)
Q3 = camp_df[key_columns].quantile(0.75)
IQR = Q3 - Q1


lower_bound = Q1 - 1.5 * IQR
upper_bound = Q3 + 1.5 * IQR


outliers = ((camp_df[key_columns] < lower_bound) | (camp_df[key_columns] >␣
 ↪upper_bound)).any(axis=1)


camp_df[outliers]
```

[61]:
```
          ID  Year_Birth   Education Marital_Status   Income  Kidhome  \
0       1826        1970  Graduation       Divorced  84835.0        0
5       7348        1958         PhD         Single  71691.0        0
10      2079        1947    2n Cycle        Married  81044.0        0
12     10530        1959         PhD          Widow  67786.0        0
14     10311        1969  Graduation        Married   4428.0        0
…      …          …           …             …        …      …
2218    5687        1980  Graduation       Divorced  81702.0        0
2222    2831        1976  Graduation       Together  78416.0        0
```

```
2225   1743         1974  Graduation         Single  69719.0        0
2237    528         1978  Graduation        Married  65819.0        0
2238   4070         1969         PhD        Married  94871.0        0

      Teenhome Dt_Customer  Recency  MntWines  …  NumWebVisitsMonth  \
0            0  2014-06-16        0       189  …                  1
5            0  2014-03-17        0       336  …                  2
10           0  2013-12-27        0       450  …                  1
12           0  2013-12-07        0       431  …                  1
14           1  2013-10-05        0        16  …                  1
…          …         …       …        …  …                …
2218         0  2012-09-23       98       563  …                  3
2222         1  2014-06-27       99       453  …                  3
2225         0  2014-05-26       99       273  …                  1
2237         0  2012-11-29       99       267  …                  3
2238         2  2012-09-01       99       169  …                  7

      AcceptedCmp3  AcceptedCmp4  AcceptedCmp5  AcceptedCmp1  AcceptedCmp2  \
0                0             0             0             0             0
5                0             0             0             0             0
10               0             0             0             0             0
12               0             0             0             0             0
14               0             0             0             0             0
…              …           …           …           …           …
2218             0             0             0             0             0
2222             0             0             0             0             0
2225             0             0             0             0             0
2237             0             0             0             0             0
2238             0             1             1             0             0

      Complain  Country  Customer_Lifetime Recency_Binned
0            0       SP               3727            NaN
5            0       SP               3818            NaN
10           0       US               3898            NaN
12           0      IND               3918            NaN
14           0       SP               3981            NaN
…          …      …                …            …
2218         0       CA               4358            Old
2222         0       SP               3716            Old
2225         0       SP               3748            Old
2237         0      IND               4291            Old
2238         0       CA               4380            Old

[630 rows x 29 columns]
```

[62]:
```python
for col in key_columns:
    median = camp_df[col].median()
```

```
    camp_df.loc[outliers, col] = median
```

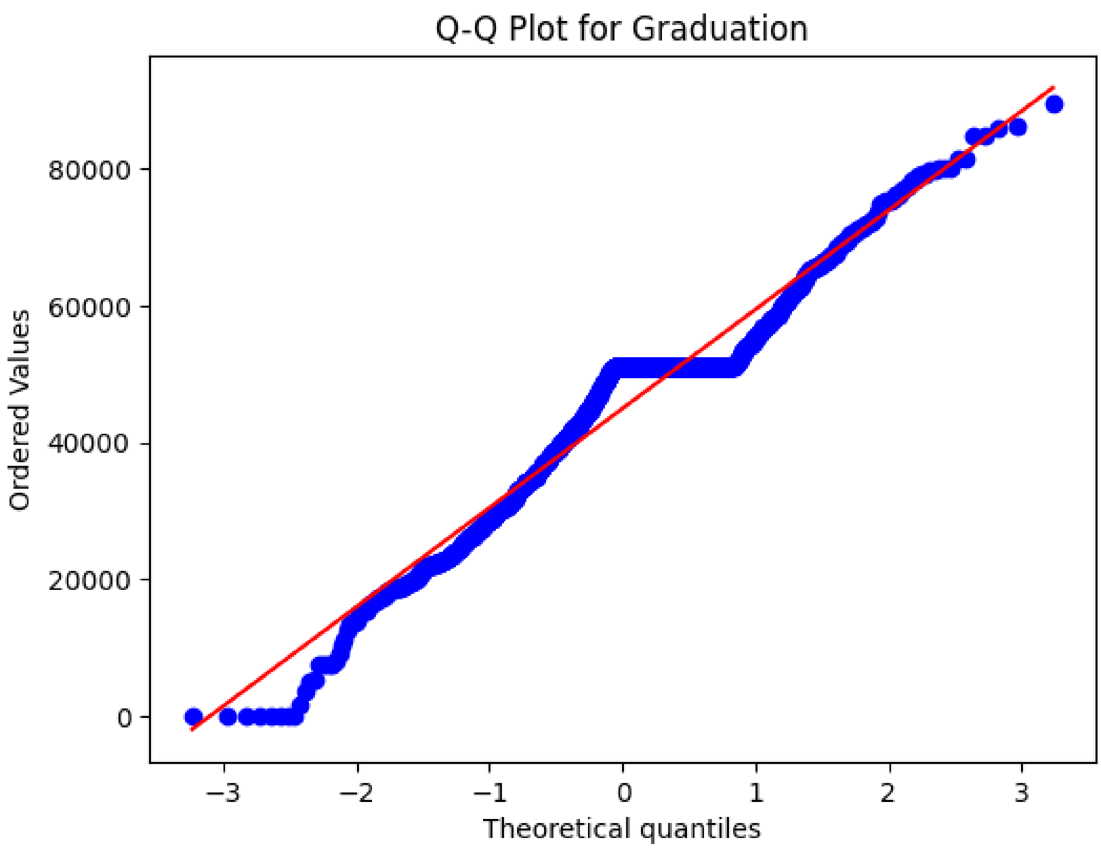
Hypothesis testing:

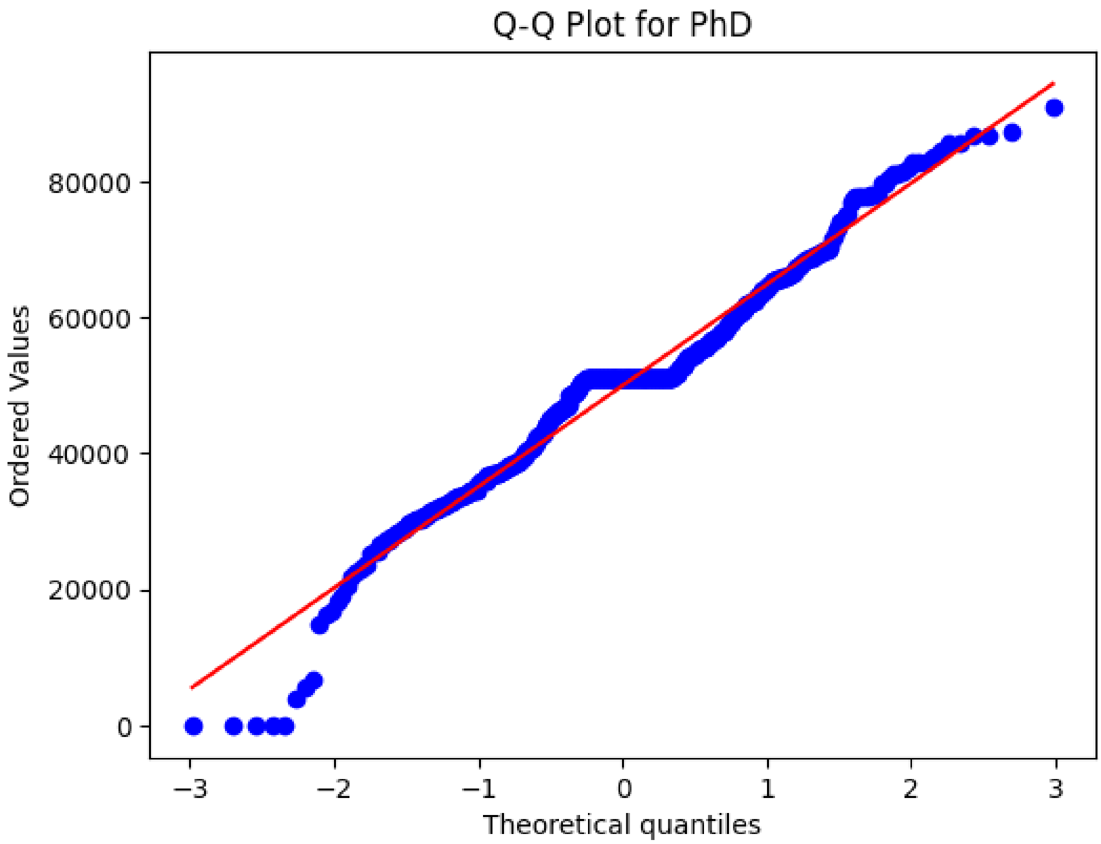
- Is income of customers dependent on their education

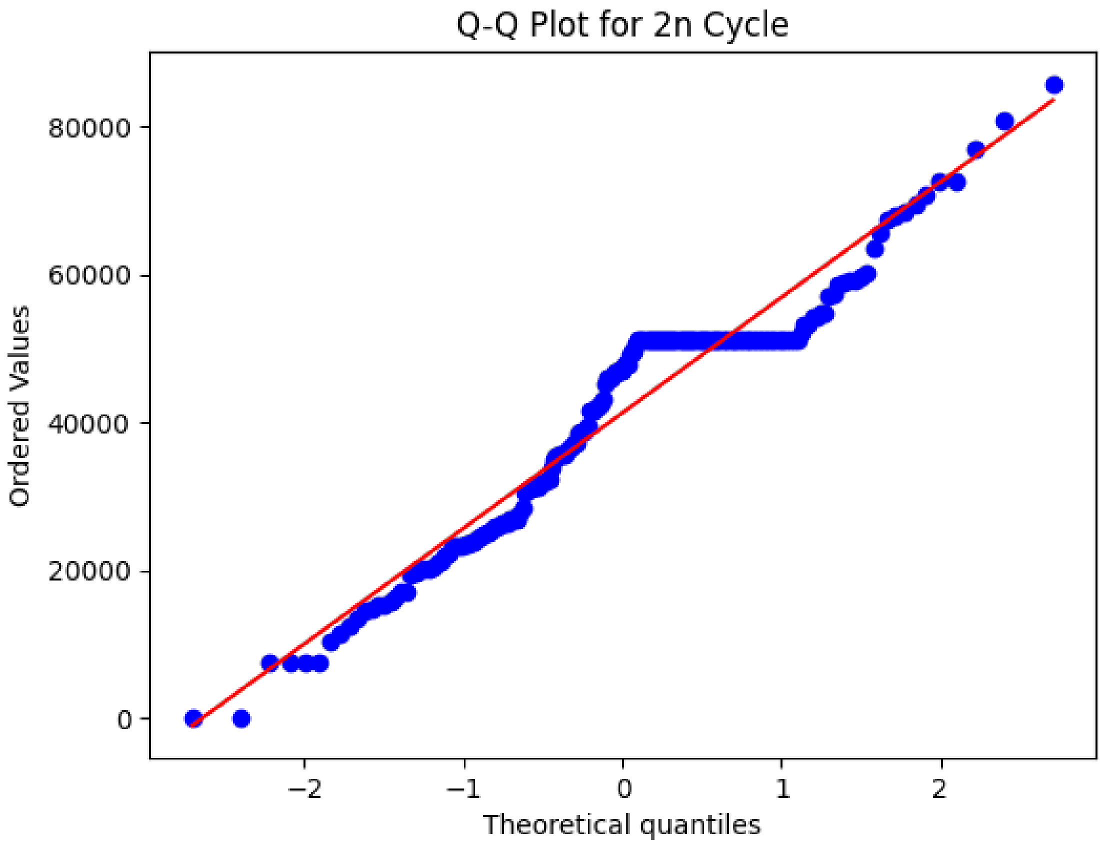
One-way Anova

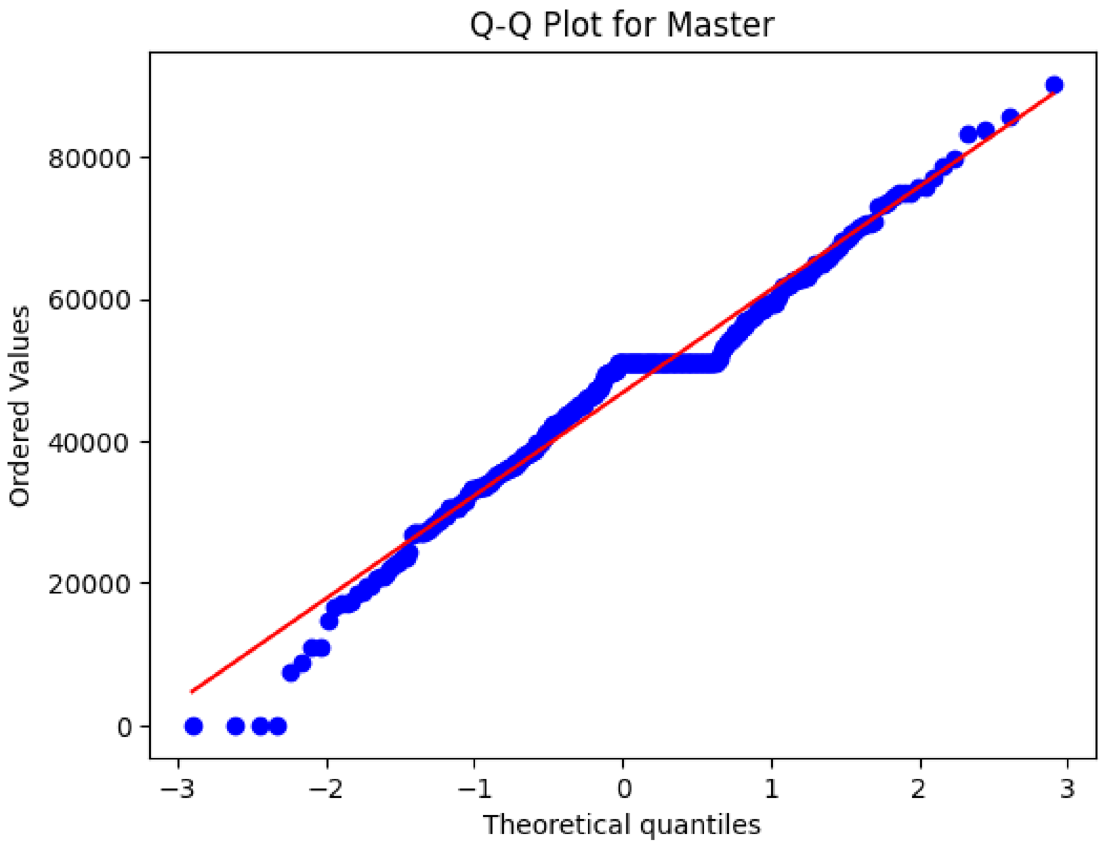
Assumptions

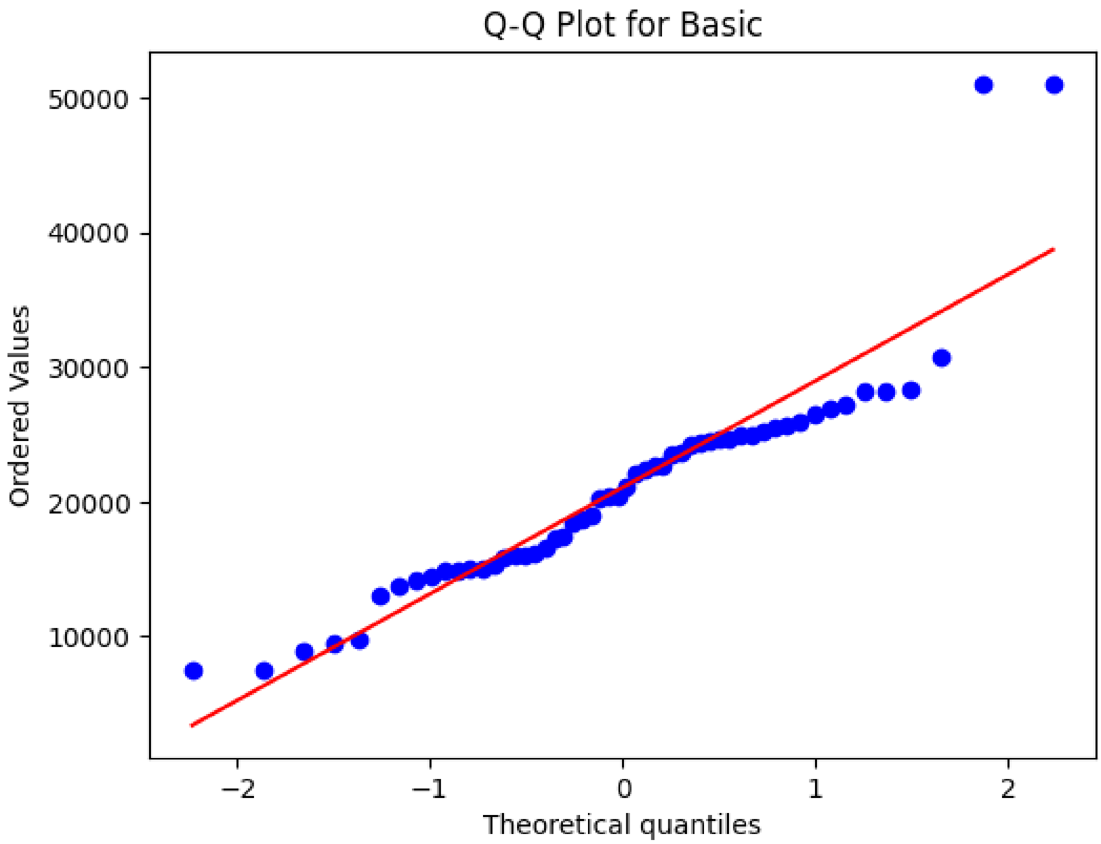
[63]:
```
for level in camp_df['Education'].unique():
    income_data = camp_df[camp_df['Education'] == level]['Income']
    stats.probplot(income_data, dist="norm", plot=plt)
    plt.title(f'Q-Q Plot for {level}')
    plt.show()
```



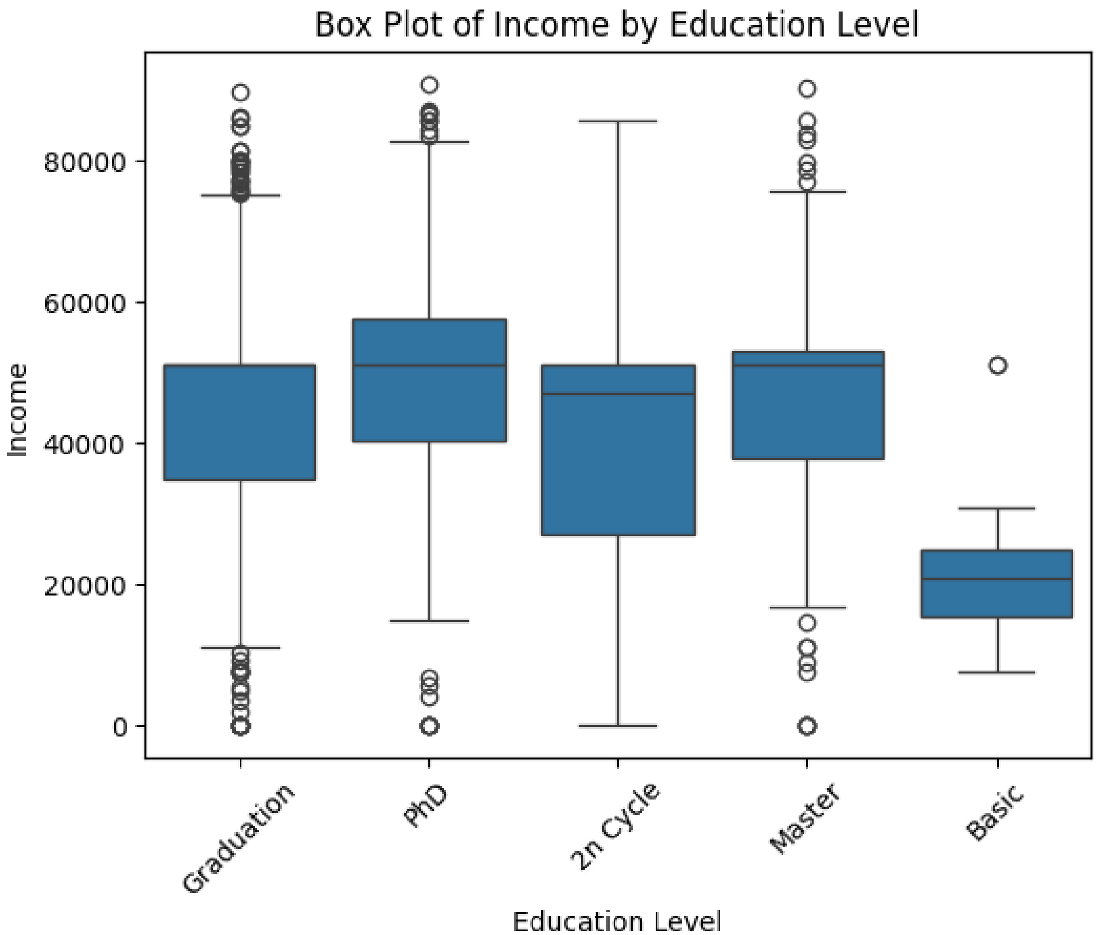

Q-Q Plot for PhD
Ordered Values
Theoretical quantiles
0
20000
40000
60000
80000
−3
−2
−1
0
1
2
3


Q-Q Plot for 2n Cycle
Ordered Values
80000
60000
40000
20000
0
−2
−1
0
1
2
Theoretical quantiles


Q-Q Plot for Master
Ordered Values
Theoretical quantiles
0
20000
40000
60000
80000
−3
−2
−1
0
1
2
3



[64]:
```
sns.boxplot(x='Education', y='Income', data=camp_df)
plt.title('Box Plot of Income by Education Level')
plt.xlabel('Education Level')
plt.ylabel('Income')
plt.xticks(rotation=45)
plt.show()
```



[65]:
```
grouped  = camp_df.groupby('Education')['Income']
```

[66]:
```
Graduation = grouped.get_group('Graduation')
PhD = grouped.get_group('PhD')
Master = grouped.get_group('Master')
Basic = grouped.get_group('Basic')
twon_Year = grouped.get_group('2n Cycle')
```

[67]:
```
anova_result = stats.f_oneway(Graduation, PhD, Master, Basic, twon_Year)
anova_result
```

[67]:
```
F_onewayResult(statistic=52.71479834410078, pvalue=1.7164204702604772e-42)
```

[68]:
```
alpha = 0.05
if anova_result.pvalue < alpha:
    print("Reject the null hypothesis. There is a significant difference in␣
↪income between education levels.")
```

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

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

Do higher income people spend more (take in account spending in all categories together)

```
[69]: camp_df['Total_Spending'] = camp_df['MntWines'] + camp_df['MntFruits'] +␣
 ↪camp_df['MntMeatProducts'] + camp_df['MntFishProducts'] +␣
 ↪camp_df['MntSweetProducts']
```

```
[70]: corr , p_value = stats.pearsonr(camp_df['Income'], camp_df['Total_Spending'])
```

```
[71]: corr, p_value
```

```
[71]: (0.7091856965640443, 0.0)
```

```
[72]: alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis. There is a significant correlation␣
 ↪between income and total spending.")
else:
    print("Fail to reject the null hypothesis. There is no significant␣
 ↪correlation between income and total spending.")
```

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

Do couples spend more or less money on wine than people living alone (set 'Married','Together':'In couple' and 'Divorced','Single','Absurd','Widow','YOLO':'Alone')

```
[73]: camp_df['Living_Status'] = camp_df['Marital_Status'].apply(lambda x: 'Couple'␣
 ↪if x in ['Married', 'Together'] else 'Alone')
```

```
[74]: camp_df['Living_Status'].value_counts()
```

```
[74]: Living_Status
Couple    1443
Alone      796
Name: count, dtype: int64
```

```
[75]: wine_spending_couple = camp_df[camp_df['Living_Status'] == 'Couple']['MntWines']
wine_spending_alone = camp_df[camp_df['Living_Status'] == 'Alone']['MntWines']
```

[76]:
```python
h_stat, p_value = stats.kruskal(wine_spending_couple, wine_spending_alone)
```

[77]:
```python
h_stat, p_value
```

[77]:
```
(0.5516579031462469, 0.45764106602403265)
```

[78]:
```python
alpha = 0.05
if p_value < alpha:
    print("Reject the null hypothesis. There is a significant difference in␣
 ↪wine spending between couples and people living alone.")
else:
    print("Fail to reject the null hypothesis. There is no significant␣
 ↪difference in wine spending between couples and people living alone.")
```

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

Are people with lower income are more attracted towards campaign or simply put accept more campaigns. (create two income brackets one below median , other above median income and create a column which tells if they have ever accepted any campaign)

---

[79]:
```python
medium_income = camp_df['Income'].median()
```

[80]:
```python
camp_df['Income_Category'] = camp_df['Income'].apply(lambda x: 'Low Income' if␣
 ↪x < medium_income else 'High Income')
```

[83]:
```python
camp_df['Total_Acceptency'] = camp_df['AcceptedCmp1'] + camp_df['AcceptedCmp2']␣
 ↪+ camp_df['AcceptedCmp3'] + camp_df['AcceptedCmp4'] + camp_df['AcceptedCmp5']
```

[84]:
```python
camp_df['Accepted_any_campaign'] =camp_df.groupby('ID')['Total_Acceptency'].
 ↪transform(lambda x: 1 if x.sum() > 0  else  0 )
```

[85]:
```python
acceptance_rate = camp_df.groupby('Income_Category')['Accepted_any_campaign'].
 ↪mean() * 100
```

[86]:
```python
acceptance_rate
```

[86]:
```
Income_Category
High Income    30.901288
Low Income      9.590317
Name: Accepted_any_campaign, dtype: float64
```

Approximately 31% of high-income individuals have accapted at least one campaign.

This suggests that individuals with higher income are more likely to accept campaigns. This could be because they have more disposable income, feel more targeted by the campaigns, or simply because the campaigns are better tailored to their preferences.

```
[ ]:
```