Final Project - Team Number 2

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Dataset: Online Shopper Intention (Dataset 3)

Origin: UCI Machine Learning Repository

Data Importing and Pre-processing

Import libraries and dataset from Github repository

In [1]:

```
# Import libraries for future work
import numpy as np
import pandas as pd
from sklearn import preprocessing
from sklearn.preprocessing import StandardScaler
import matplotlib.pyplot as plt
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import train_test_split
import seaborn as sns
from imblearn.over_sampling import SMOTE
import statsmodels.api as sm
import warnings
from statsmodels.stats.outliers_influence import variance_inflation_factor
from pandas.api.types import is_numeric_dtype
from sklearn.feature_selection import RFE
from sklearn.metrics import confusion_matrix
from sklearn.metrics import confusion_matrix as confusion_matrix2
from sklearn.metrics import classification_report
from sklearn.metrics import roc_auc_score
from sklearn.metrics import roc_curve
from sklearn.feature_selection import RFECV


sns.set(style="white")
sns.set(style="whitegrid", color_codes=True)
warnings.filterwarnings('ignore')
```

In [2]:

```
# Import data from Github (online_shoppers_intention.csv)
url = 'https://raw.githubusercontent.com/rcancel3/Online-Shopper-Dataset/main/online_sh
df = pd.read_csv(url, header=0, index_col=None)
df.head()
```

Out[2]:

	Administrative	Administrative_Duration	Informational	Informational_Duration	ProductRelated	Produ
0	0	0.0	0.0	0.0	1	
1	0	0.0	0.0	0.0	2	
2	0	0.0	0.0	0.0	1	
3	0	0.0	0.0	0.0	2	
4	0	0.0	0.0	0.0	10	

As seen in the code above, we first call the df.head() function to ensure that our data has imported into Pyhon correctly. We used the Panda's function: pd.read_csv(), to read our CSV file from our Github repository.

Now that we have confirmed that the data imported properly, we will check the dimensions of our DataFrame to look at it's size and shape (number of rows, number of columns)

Describe characteristics such as dimensions

In [3]:
```
# dataframe.size
size = df.size

# dataframe.shape
shape = df.shape

# printing size and shape
print("Size:", size,"Shape:", shape)
```

```
Size: 221940 Shape: (12330, 18)
```

Addressing Missing Data

Step 1: Identify Missing Data:

While the reason for the missing data in our dataset is unclear, we must identify and address it to avoid inaccurate statistical results and possible bias in our model.

First, we will use the isnull().sum() function to counts how many rows of missing data exist for each column.

In [4]:
```
# Count missing data per variable
df.isnull().sum()
```

Out[4]:
```
Administrative               0
Administrative_Duration      0
Informational              128
Informational_Duration       0
ProductRelated               0
ProductRelated_Duration      0
BounceRates                  0
ExitRates                    0
PageValues                 135
SpecialDay                   0
Month                        0
OperatingSystems           123
Browser                      0
Region                       0
TrafficType                  0
VisitorType                  0
Weekend                      0
Revenue                      0
dtype: int64
```

Step 2: Subset Missing Data

In [5]:
```
# Pull the subset with all missing data
df_null = df.loc[df.isnull().any(axis=1)]
# Verify all Null data was pulled
df_null.isnull().sum()
```

Out[5]:
```
Administrative              0
Administrative_Duration     0
Informational             128
Informational_Duration      0
ProductRelated              0
ProductRelated_Duration     0
BounceRates                 0
ExitRates                   0
PageValues                135
SpecialDay                  0
Month                       0
OperatingSystems          123
Browser                     0
Region                      0
TrafficType                 0
VisitorType                 0
Weekend                     0
Revenue                     0
dtype: int64
```

Step 3: Determine Extent/Proportion of Missing Data

In [6]:
```
# Confirm the number of True Revenue's with missing data is not large
df_null['Revenue'].value_counts().div(df['Revenue'].value_counts())
```

Out[6]:
```
False    0.031184
True     0.029874
Name: Revenue, dtype: float64
```

Since missing data is evenly distributed across revenue types, we decided that dropping the observations with NULLs was the most efficient method for handling our missing values.

Step 4: Drop observations with missing data

We used the drop.na() function to drop all missing data from each variable. To ensure all missing data was dropped, we ran print df.shape to count the rows and columns and summed missing data using the .isna().sum() functions.

In [7]:
```
# Clean up data by dropping Nulls
df = df.dropna()
```

In [8]:
```
# Set to display all cols and rows
# Print new Shape and Confirm dropped Null's
print (df.shape)
print(df.isna().sum())
```

```
(11948, 18)
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
```

After ensuring that we dropped all of the missing data, we created a new variable, totalPageViews, which summed views across view across all page types. We used totalPageViews to remove all rows with zero total views and no revenue. We also ran print(df.shape) to see if the data frame added totalPageValues and count the rows removed.

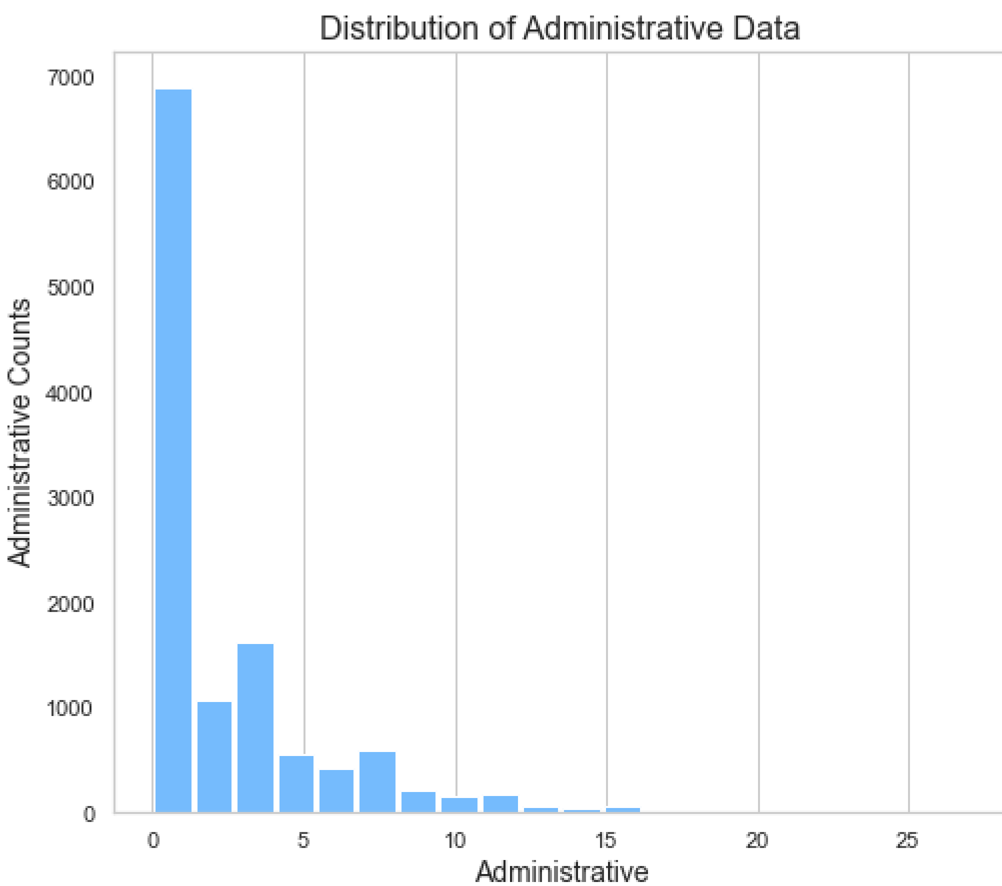
In [9]:

```
# Create new column, to look for 0,0,0, 0
df['totalPageViews'] = df['Administrative'] + df['Informational'] + df['ProductRelated'
df = df.loc[(df['totalPageViews'] != 0)]
```

We must identify and remove outliers in our data set. To do this, we will first create histograms to evaluate the distribution (specifically skewness) of each feature to decide whether to replace outliers with the feature mean (if normally distributed) or median (if skewed distribution).

In [10]:

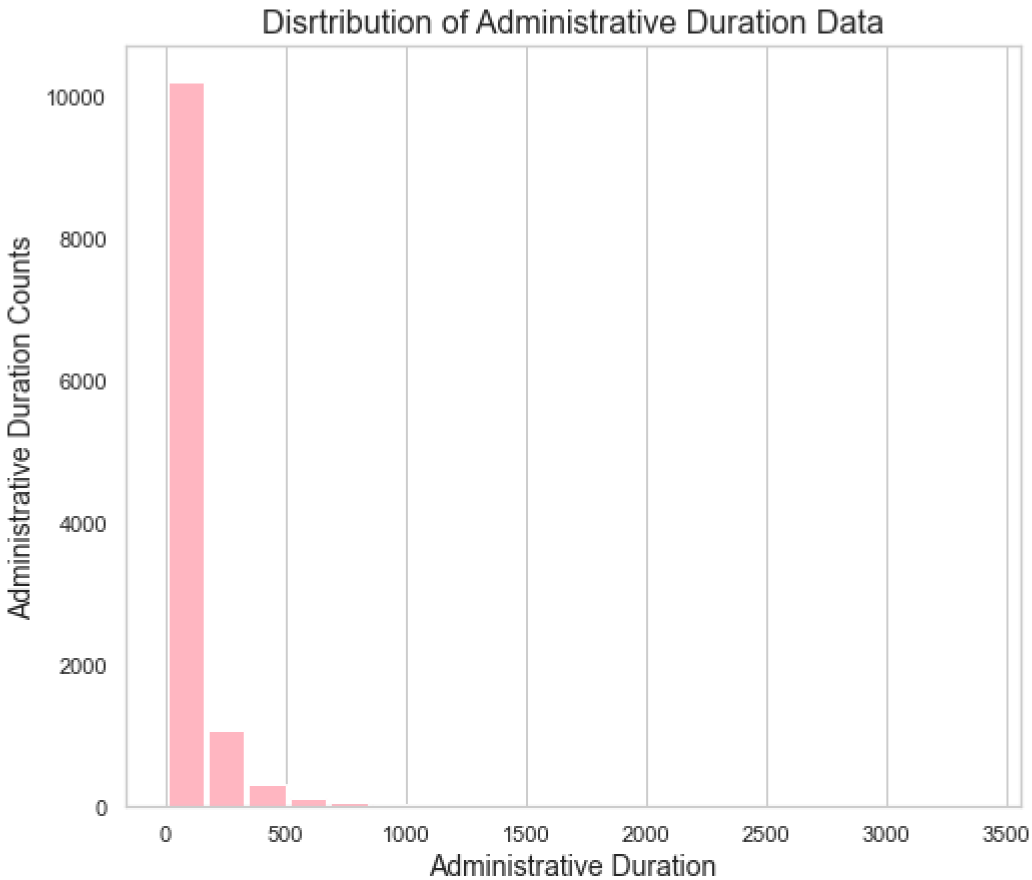
```
df['Administrative'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9,
                   color='xkcd:sky blue')
plt.title('Distribution of Administrative Data', fontsize = 16)
plt.xlabel('Administrative', fontsize = 14)
plt.ylabel('Administrative Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



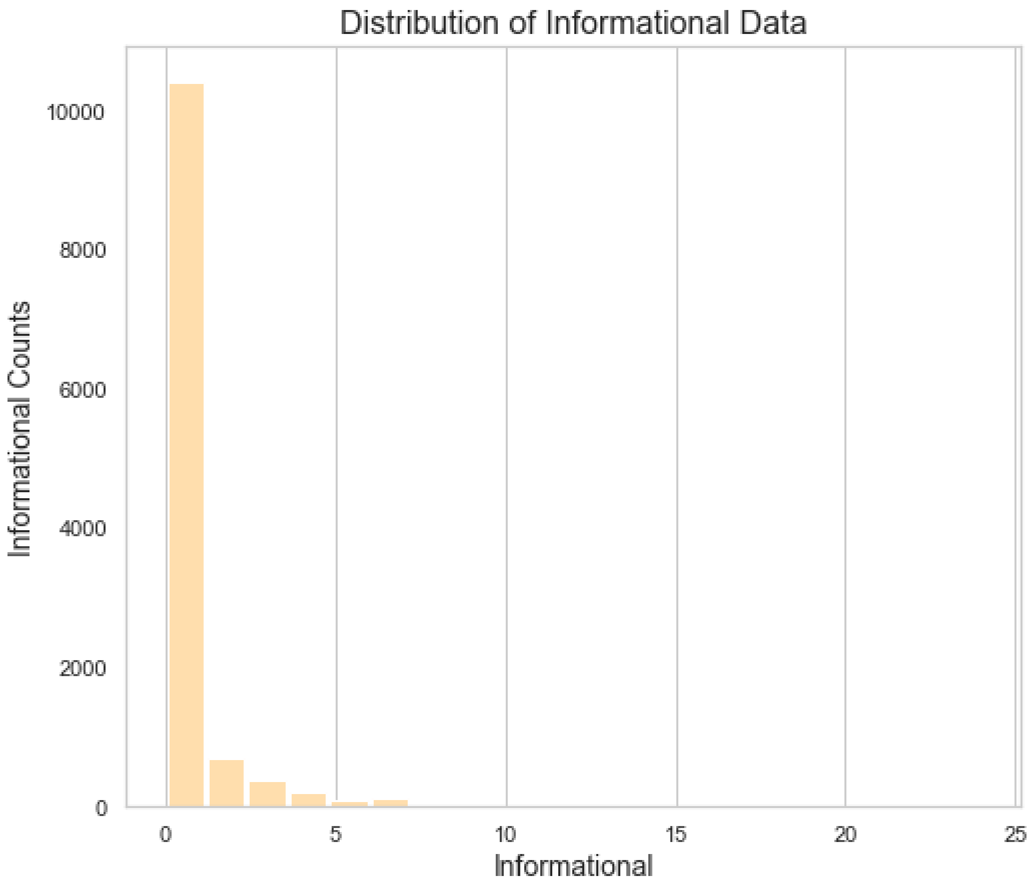
In [11]:

```
df['Administrative_Duration'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9
                   color='LightPink')
plt.title('Disrtribution of Administrative Duration Data', fontsize = 16)
plt.xlabel('Administrative Duration', fontsize = 14)
```

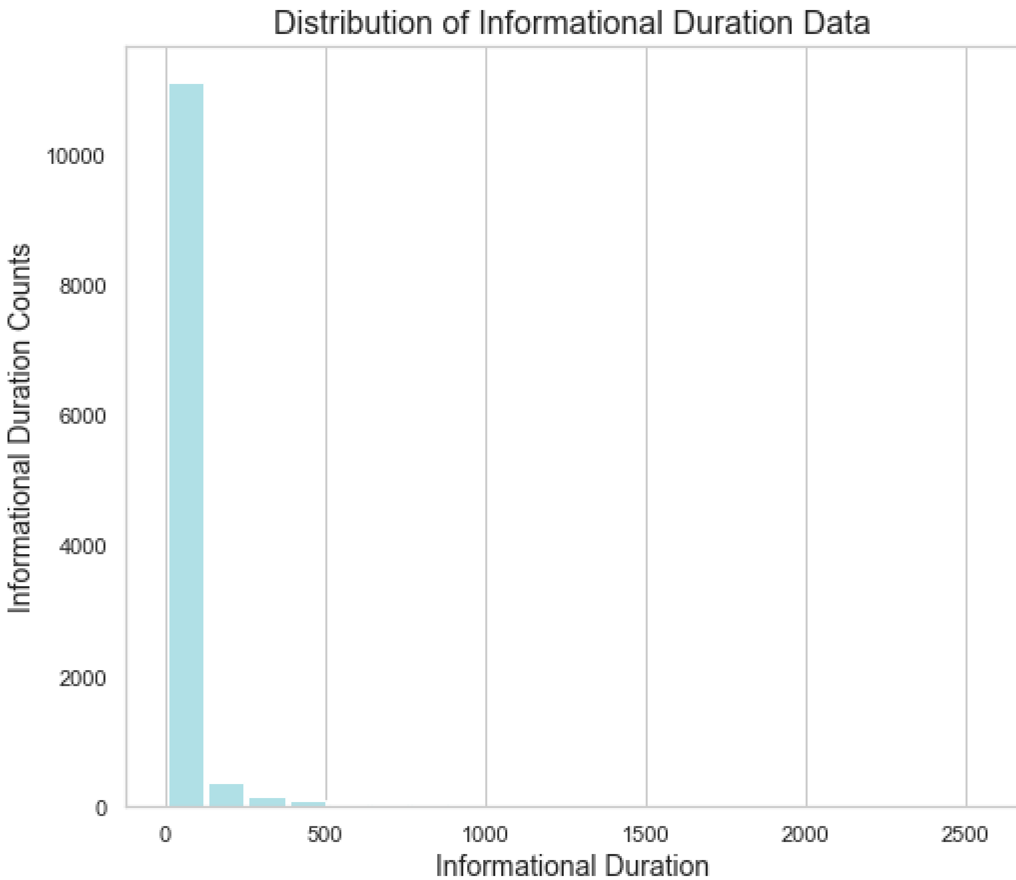
```
plt.ylabel('Administrative Duration Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



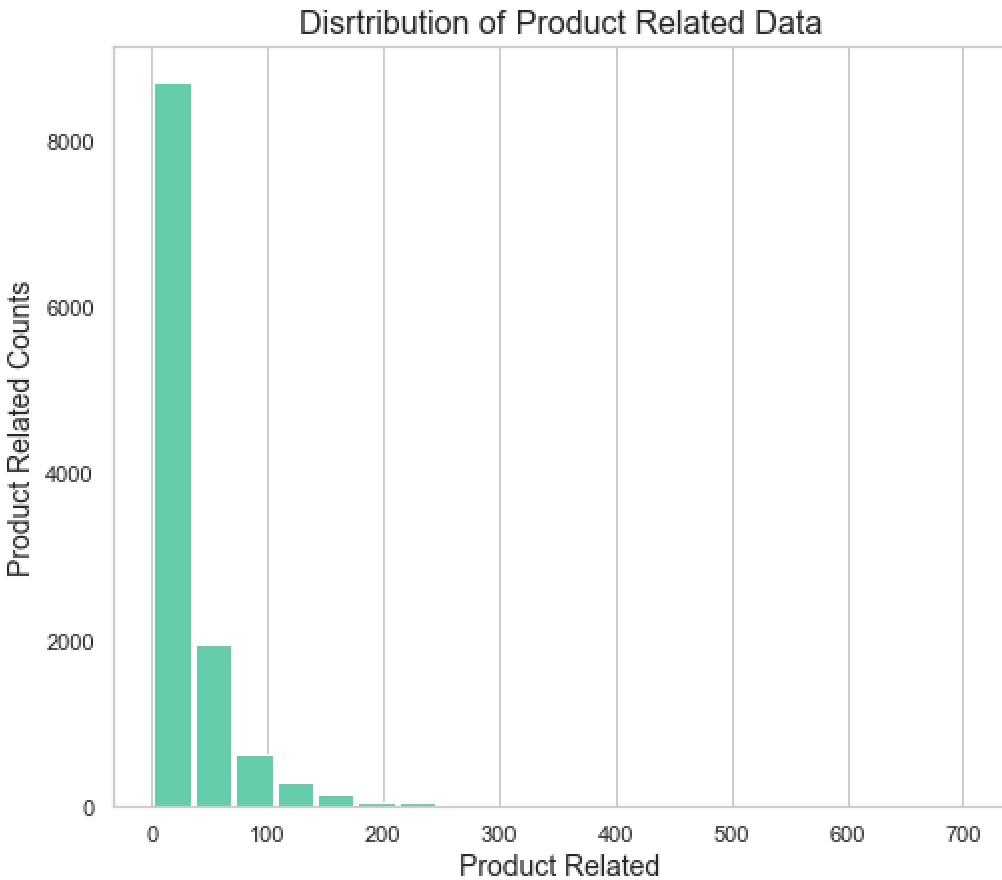
In [12]:
```
df['Informational'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9,
                   color='navajowhite')
plt.title('Distribution of Informational Data', fontsize = 16)
plt.xlabel('Informational', fontsize = 14)
plt.ylabel('Informational Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



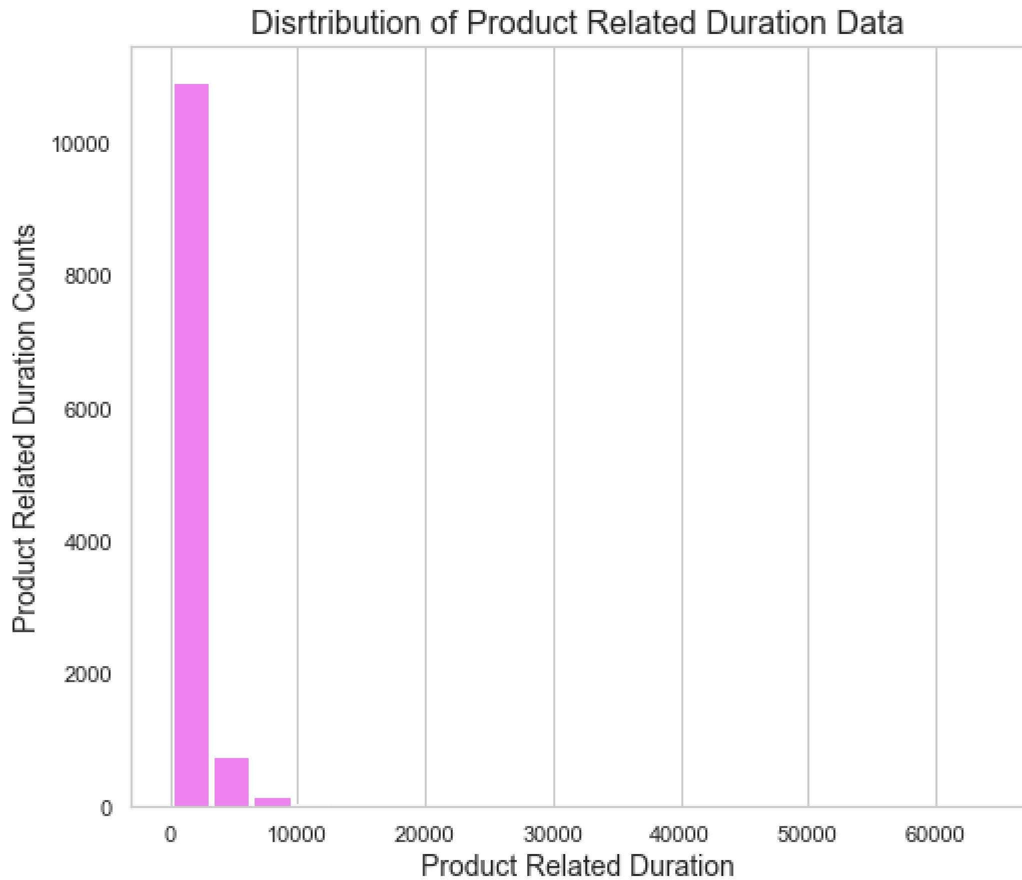
In [13]:
```
df['Informational_Duration'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9,
                    color='powderblue')
plt.title('Distribution of Informational Duration Data', fontsize = 16)
plt.xlabel('Informational Duration', fontsize = 14)
plt.ylabel('Informational Duration Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



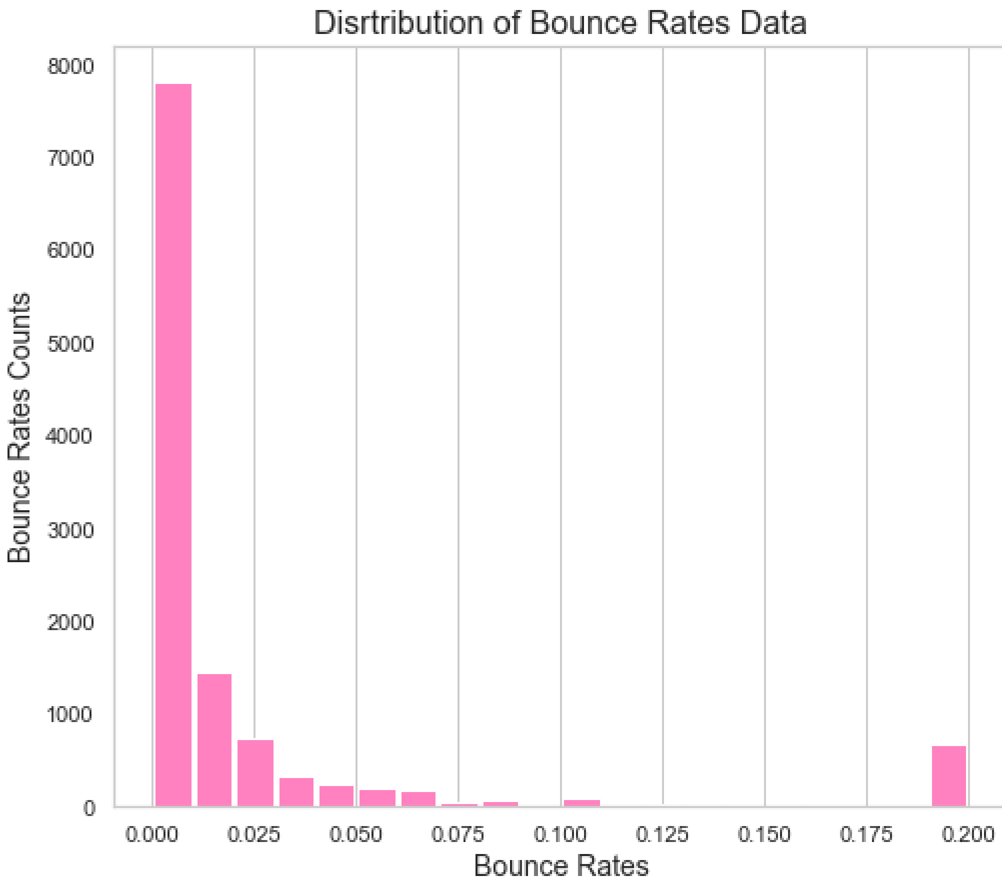
In [14]:
```
df['ProductRelated'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9,
                   color='mediumaquamarine')
plt.title('Disrtribution of Product Related Data', fontsize = 16)
plt.xlabel('Product Related', fontsize = 14)
plt.ylabel('Product Related Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



In [15]:
```
df['ProductRelated_Duration'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9
                    color='violet')
plt.title('Disrtribution of Product Related Duration Data', fontsize = 16)
plt.xlabel('Product Related Duration', fontsize = 14)
plt.ylabel('Product Related Duration Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```

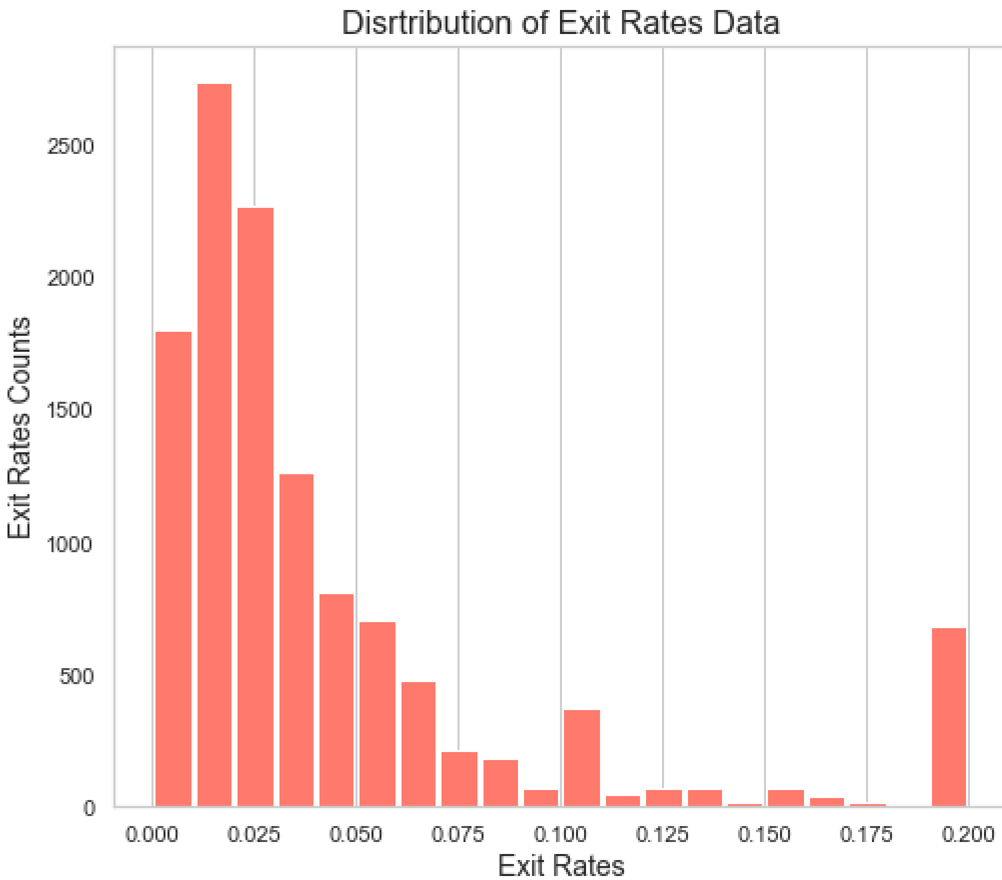


In [16]:
```
df['BounceRates'].plot.hist(figsize= (8,7), grid=True, bins=20, rwidth=0.9,
                   color='#FF81C0')
plt.title('Disrtribution of Bounce Rates Data', fontsize = 16)
plt.xlabel('Bounce Rates', fontsize = 14)
plt.ylabel('Bounce Rates Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```

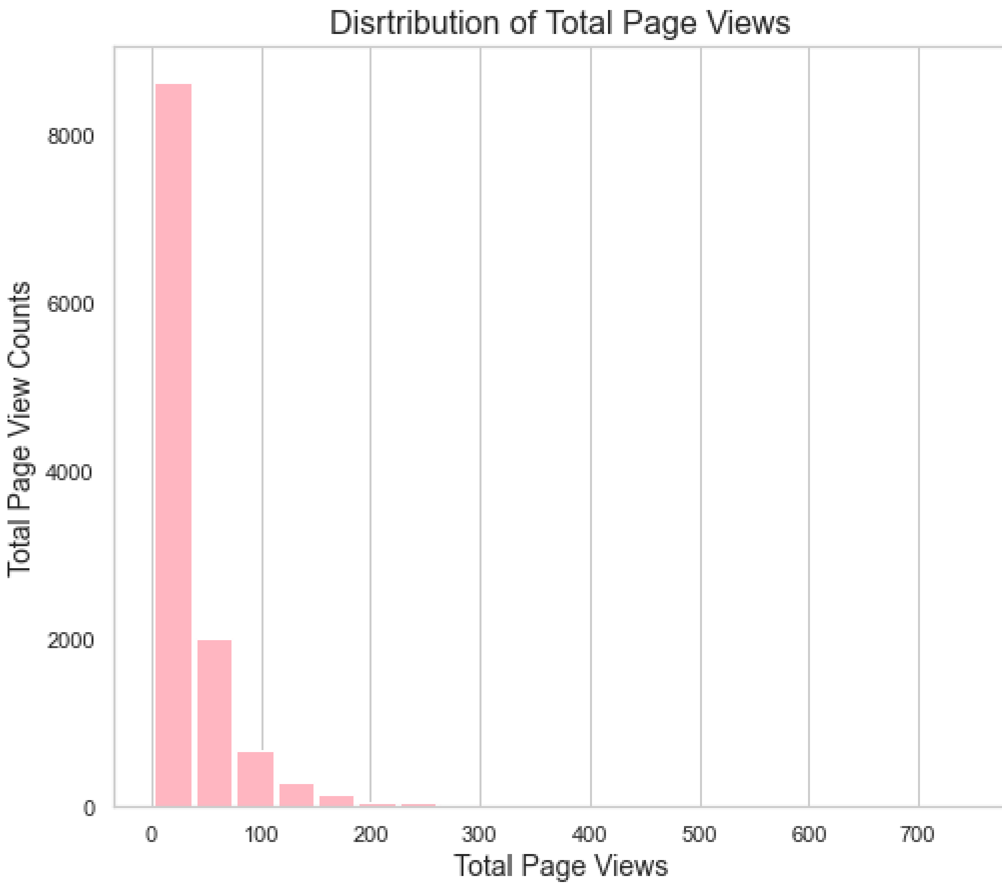


In [17]:

```
df['ExitRates'].plot.hist(figsize=(8,7), grid=True, bins=20, rwidth=0.9,
                          color='#FF796C')
plt.title('Disrtribution of Exit Rates Data', fontsize = 16)
plt.xlabel('Exit Rates', fontsize = 14)
plt.ylabel('Exit Rates Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```

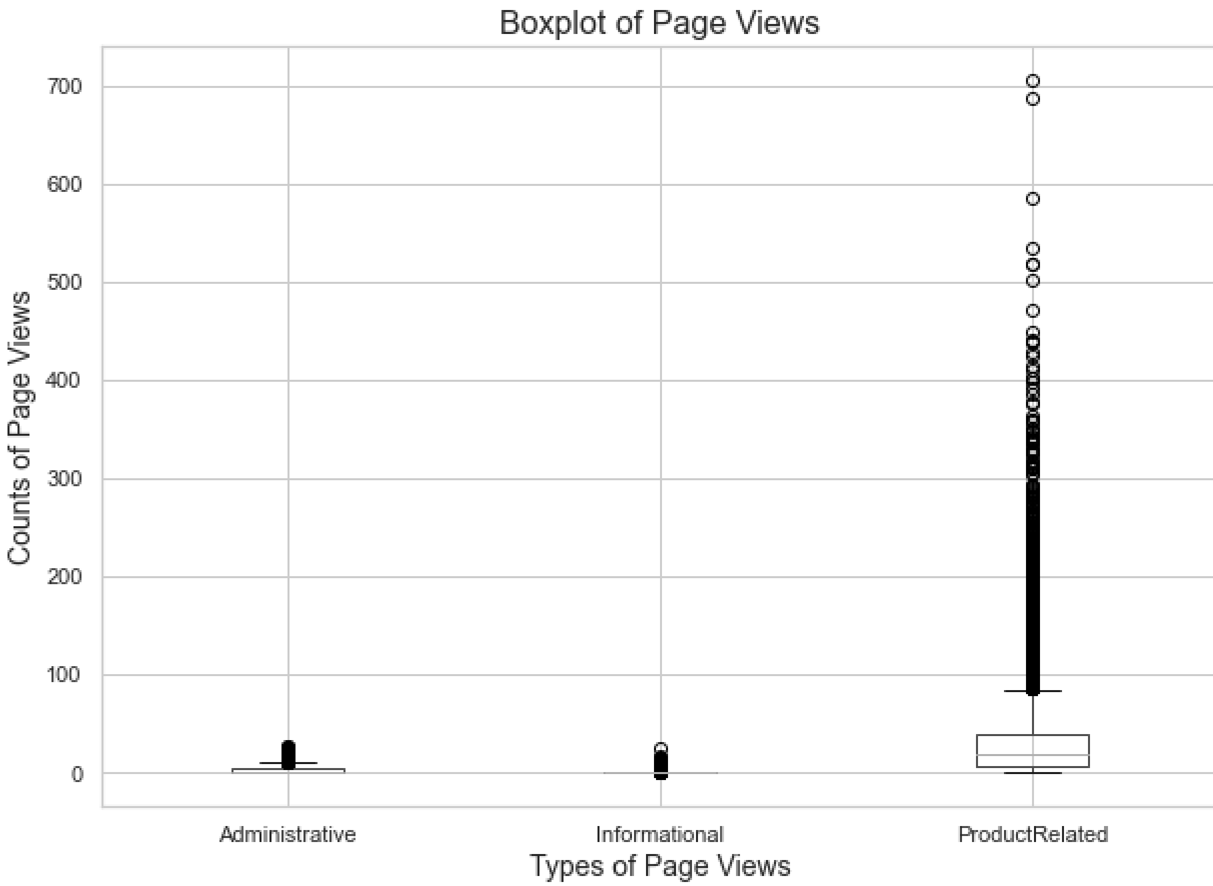


In [18]:
```
df['totalPageViews'].plot.hist(figsize = (8,7), grid=True, bins=20, rwidth=0.9,
                    color='LightPink')
plt.title('Disrtribution of Total Page Views', fontsize = 16)
plt.xlabel('Total Page Views', fontsize = 14)
plt.ylabel('Total Page View Counts', fontsize = 14)
plt.grid(axis='y', alpha=0.75)
```



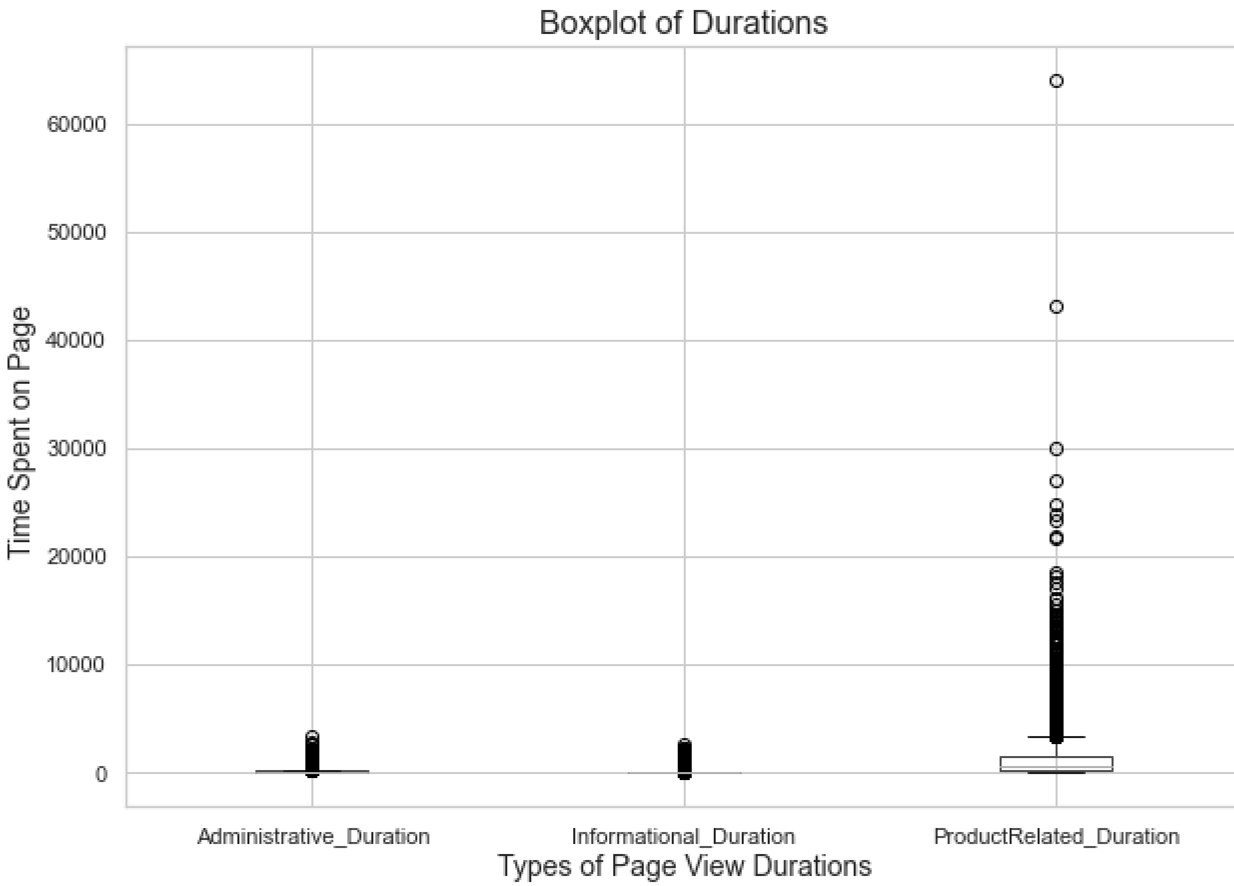
In [19]:
```
#checking non-categorical values for outliers
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['Administrative', 'Informational', 'ProductRelated'])
plt.title("Boxplot of Page Views", fontsize = 16)
plt.xlabel("Types of Page Views", fontsize = 14)
plt.ylabel("Counts of Page Views", fontsize= 14 )
```

Out[19]:
```
Text(0, 0.5, 'Counts of Page Views')
```



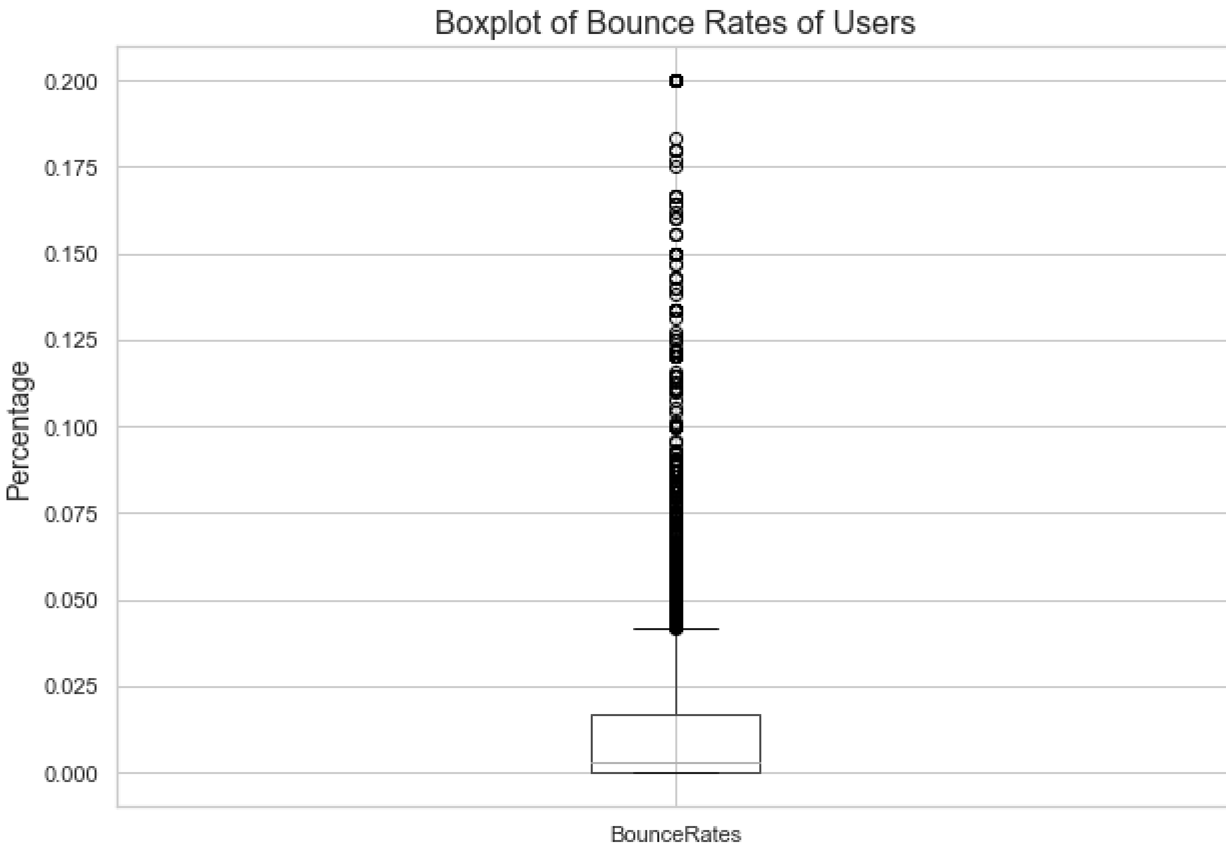
In [20]:
```
#checking non-categorical values for outliers
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['Administrative_Duration', 'Informational_Duration', 'Prod
plt.title("Boxplot of Durations", fontsize = 16)
plt.xlabel("Types of Page View Durations", fontsize = 14)
plt.ylabel("Time Spent on Page ", fontsize= 14 )
```

Out[20]:
```
Text(0, 0.5, 'Time Spent on Page ')
```



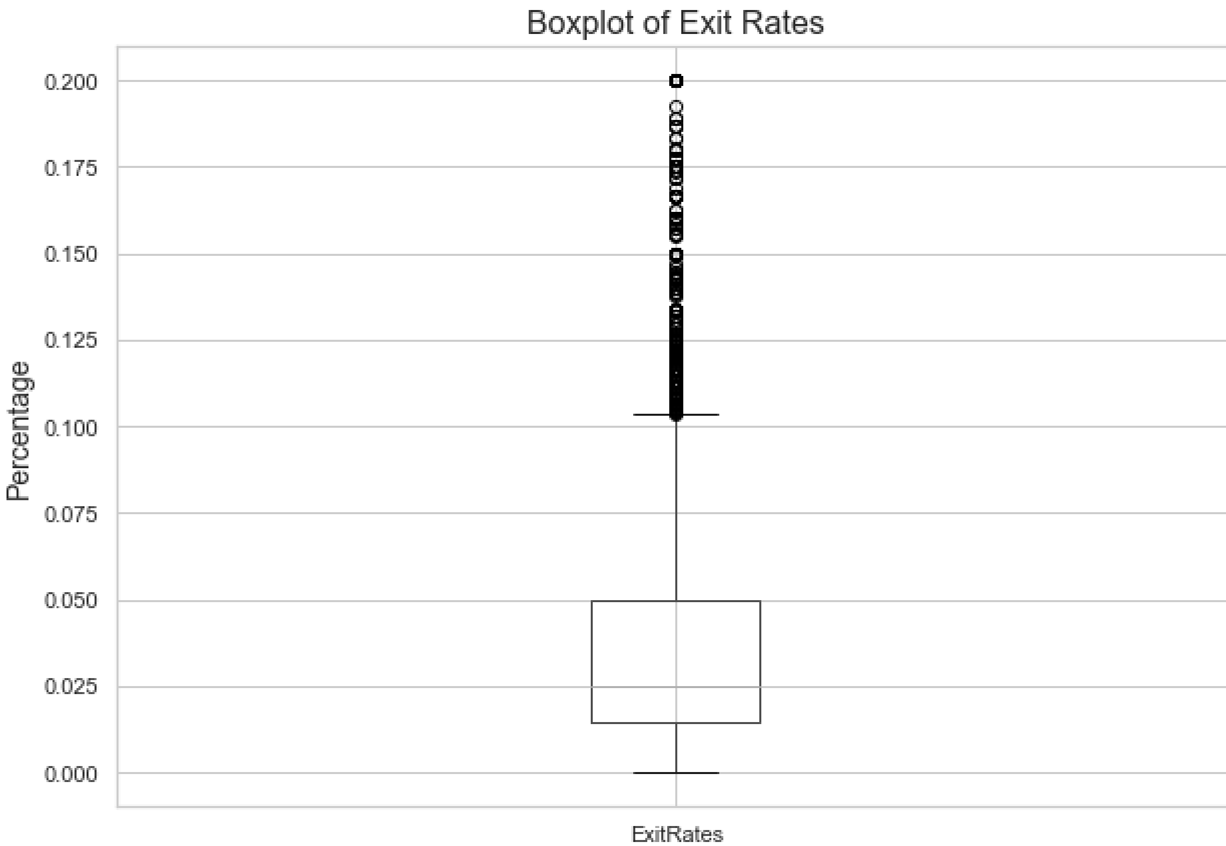
In [21]:
```
#checking non-categorical values for outliers
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['BounceRates'])
plt.title("Boxplot of Bounce Rates of Users", fontsize = 16)
plt.ylabel("Percentage", fontsize= 14 )
```

Out[21]:
```
Text(0, 0.5, 'Percentage')
```



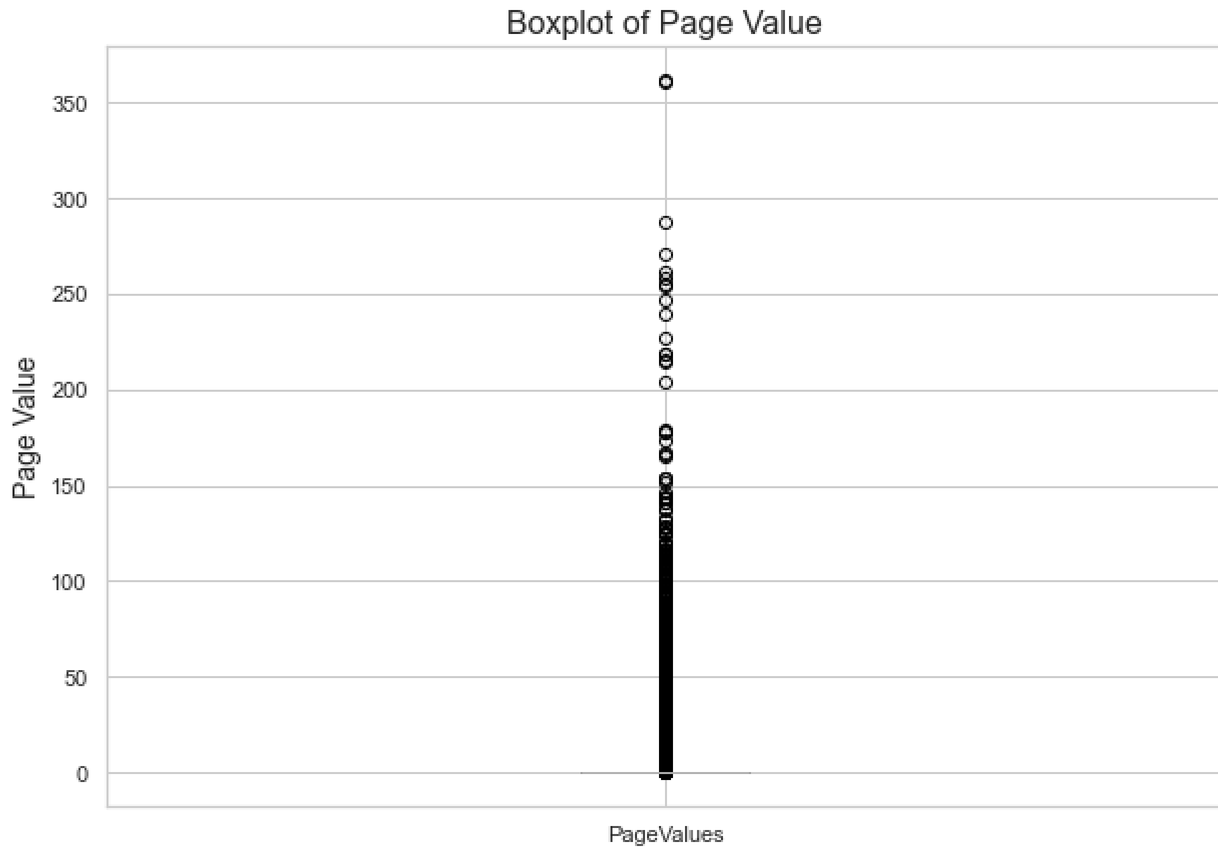
In [22]:
```
#Exit Rates
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['ExitRates'])
plt.title("Boxplot of Exit Rates", fontsize = 16)
plt.ylabel("Percentage", fontsize= 14 )
```

Out[22]:
```
Text(0, 0.5, 'Percentage')
```



In [23]:
```
#PageValues
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['PageValues'])
plt.title("Boxplot of Page Value", fontsize = 16)
plt.ylabel("Page Value", fontsize= 14 )
```

Out[23]:
```
Text(0, 0.5, 'Page Value')
```

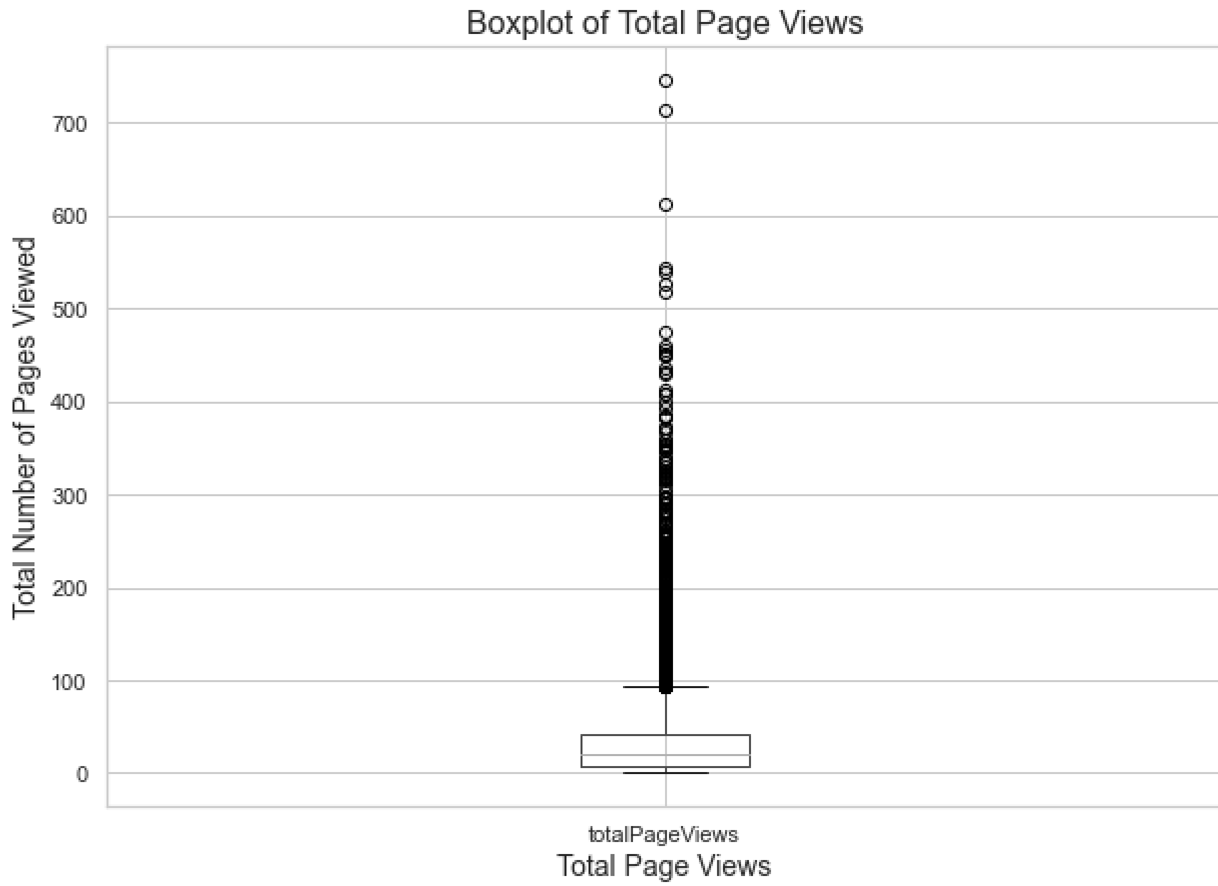


In [24]:

```
#Total Page Views
fig = plt.figure(figsize =(10, 7))
# Creating axes instance
boxplot = df.boxplot(column=['totalPageViews'])
plt.title("Boxplot of Total Page Views", fontsize = 16)
plt.xlabel("Total Page Views", fontsize = 14)
plt.ylabel("Total Number of Pages Viewed", fontsize= 14 )
```

Out[24]:

```
Text(0, 0.5, 'Total Number of Pages Viewed')
```



Our histograms of numerical variables indicated skewed distributions. Our boxplots showed numerous outliers; therefore, we subset our numerical variables in df1 and used a for loop to identify each feature’s outliers using IQR and impute with the median.

Identify Outliers & Impute with mean or median

In [25]:
```
df1 = df.select_dtypes(include=np.number)
df1 = df.drop(['TrafficType','SpecialDay', 'OperatingSystems', 'Browser', 'Region', 'Re
df1.reset_index(inplace=True, drop=True)

for col in df1:

    q3 = np.percentile(df1[col], 75)
    q1 = np.percentile(df1[col], 25)
    iqr = q3 - q1

    lower = q1 -(1.5 * iqr)
    upper = q3 +(1.5 * iqr)

    med = df1[col].median()

    df1[col] = np.where((df1[col] >= upper), med ,df1[col])

    df1[col] = np.where((df1[col] <= lower), med ,df1[col])
```

Afterward, we create df_toadd, a data frame that holds all of the variables not included in df1. Using concat, we joined the two data frames and ensured our updated df had no missing data.

In [26]:
```
# Pull missing variables from original df
df_toadd = df[['Informational','Informational_Duration','SpecialDay','Month','Operating
```

In [27]:
```
#Merge df_toadd and df1
frames = [df1, df_toadd]
df = pd.concat([df1, df_toadd], axis=1, join="inner")
df.isnull().sum()
```

Out[27]:
```
Administrative             0
Administrative_Duration    0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
totalPageViews             0
Informational              0
Informational_Duration     0
SpecialDay                 0
Month                      0
OperatingSystems           0
Browser                    0
Region                     0
VisitorType                0
PageValues                 0
TrafficType                0
Weekend                    0
Revenue                    0
dtype: int64
```

Transform Data Type

We then used the info() function to ensure our variables were the same dimension and identify each variable's data type.

In [28]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 11562 entries, 0 to 11941
Data columns (total 19 columns):
 #   Column                   Non-Null Count  Dtype  
---  ------                   --------------  -----  
 0   Administrative           11562 non-null  float64
 1   Administrative_Duration  11562 non-null  float64
 2   ProductRelated           11562 non-null  float64
 3   ProductRelated_Duration  11562 non-null  float64
 4   BounceRates              11562 non-null  float64
 5   ExitRates                11562 non-null  float64
 6   totalPageViews           11562 non-null  float64
 7   Informational            11562 non-null  float64
 8   Informational_Duration   11562 non-null  float64
 9   SpecialDay               11562 non-null  float64
 10  Month                    11562 non-null  object 
 11  OperatingSystems         11562 non-null  float64
 12  Browser                  11562 non-null  int64  
 13  Region                   11562 non-null  int64  
 14  VisitorType              11562 non-null  object 
 15  PageValues               11562 non-null  float64
 16  TrafficType              11562 non-null  int64  
 17  Weekend                  11562 non-null  bool   
 18  Revenue                  11562 non-null  bool   
dtypes: bool(2), float64(12), int64(3), object(2)
memory usage: 1.6+ MB
```

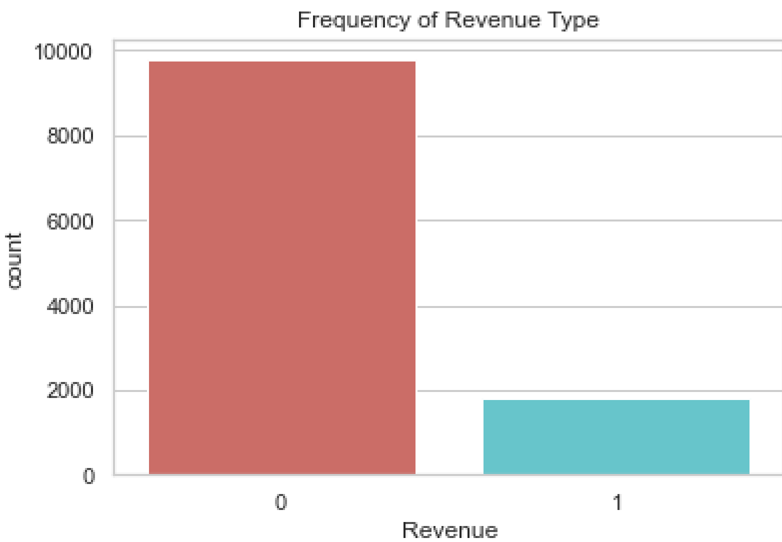
We converted our boolean variables to integers for model implementation.

In [29]:
```
# Convert Weekend to int
df.Weekend = df.Weekend.astype(int)
# Convert boolean to binary (int) and count for successful sale
df.Revenue = df.Revenue.astype(int)
```

After converting Revenue to an interger, we counted its classes and used a histrogram to visualize.

In [30]:
```
print(df.Revenue.value_counts())
sns.countplot(x=df['Revenue'],data=df,palette='hls').set_title("Frequency of Revenue Ty
plt.show()
```

```
0    9774
1    1788
Name: Revenue, dtype: int64
```



We created three new, more robust variables (Admin_Dur_View, Prod_Dur_View, and Info_Dur, View) using the three duration and three page variables. The new variables represent the time spent per click for each page type.

In [31]:
```
#Create Administrative Duration per view column
df['Admin_Dur_View'] = df['Administrative_Duration'].div(df['Administrative'])
#Create ProductRelated Duration per view column
df['Prod_Dur_View'] = df['ProductRelated_Duration'].div(df['ProductRelated'])
#Create Informational Duration per view column
df['Info_Dur_View'] = df['Informational_Duration'].div(df['Informational'])
```

To avoid the possibility of have (Page Duration)/O, we ran the fillna(0) to turn any NaN or inf values to 0. To check that no Nan or inf values remained, we utilized the isnull().sum()

In [32]:
```
#Replace division by zero results in NAN with 0
df=df.fillna(0)
#Check for any remaining na/nulls
df.isnull().sum()
```

Out[32]:
```
Administrative             0
Administrative_Duration    0
ProductRelated             0
ProductRelated_Duration    0
BounceRates                0
ExitRates                  0
```

```
totalPageViews           0
Informational            0
Informational_Duration   0
SpecialDay               0
Month                    0
OperatingSystems         0
Browser                  0
Region                   0
VisitorType              0
PageValues               0
TrafficType              0
Weekend                  0
Revenue                  0
Admin_Dur_View           0
Prod_Dur_View            0
Info_Dur_View            0
dtype: int64
```

Remove redudant features

After the creation of Admin_Dur_View, Info_Dur_View, and Prod_Dur_View, the following variables become redundant: Administrative, Administrative_Duration, Informational, Informational_Duration, ProductRelated, ProductRelated_Duration, and totalPageViews. For that reason, we drop them from the data frame.

In [33]:
```
df = df.drop(['Administrative','Administrative_Duration','Informational','Informational_
```

We rearranged our columns so that Admin_Dur_View, Infor_Dur_View, and Prod_Dur_View were the first three columns of our table. This is so that it was easier for the team to look for data when performing further analysis.

In [34]:
```
# Re-arrange the dataframe
cols_at_beg = ['Admin_Dur_View', 'Info_Dur_View', 'Prod_Dur_View']
df = df[[c for c in cols_at_beg if c in df]+ [c for c in df if c not in cols_at_beg]]
df.head()
```

Out[34]:

	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Month	Operat
0	0.0	0.0	0.000000	0.003094	0.025066	0.0	Feb	
1	0.0	0.0	32.000000	0.000000	0.100000	0.0	Feb	
2	0.0	0.0	0.000000	0.003094	0.025066	0.0	Feb	
3	0.0	0.0	1.333333	0.003094	0.025066	0.0	Feb	
4	0.0	0.0	62.750000	0.020000	0.050000	0.0	Feb	

Perform Need-based Discretization:

Removed Operating Systems because browsers can be dependent on operating systems (e.g.Safari only available on iOS) and browser optimization is actionable by client.

In [35]:
```
df = df.drop(['OperatingSystems'], axis = 1)
```

Data Analysis & Visualization

Identify Variable types within data

==========================Inputs(independent variables)===============================
'Admin_Dur_View': numerical
'Info_Dur_View': numerical
'Prod_Dur_view': numerical
'BounceRates': numerical
'ExitRates': numerical
'PageValues': numerical
'Special Day': categorical
'Month': categorical
'Browser': categorical
'Region': categorical
'TrafficType': categorical
'VisitorType': categorical
'Weekend': boolean converted to integer
=============================Predictor (desired target)==============================
'Revenue': boolean converted to integer

In [36]:
```
# Counts for sale/no sale in percentage
sale_count = len(df[df['Revenue']==1])
no_sale_count = len(df[df['Revenue']==0])
pct_sale_count = sale_count / (sale_count + no_sale_count)
print('Percentage of successful revenue is: ', round(pct_sale_count*100,2),'%')
pct_no_sale_count = no_sale_count / (sale_count + no_sale_count)
print('Percentage of no revenue is: ', round(pct_no_sale_count*100,2),'%')
```

```
Percentage of successful revenue is:  15.46 %
Percentage of no revenue is:  84.54 %
```

Note: The ratio of no revenue to succesful revenue instances is ~ 85:15. Let's further explore the dataset

Provide Measures of Centrality & distribution

In [37]:
```
df.mean()
```

Out[37]:
```
Admin_Dur_View    14.303725
Info_Dur_View     14.916307
Prod_Dur_View     38.420597
BounceRates        0.005990
ExitRates          0.029412
SpecialDay         0.063432
Browser            2.349075
Region             3.140893
PageValues         5.933794
TrafficType        4.056132
Weekend            0.231361
Revenue            0.154645
dtype: float64
```

Interpretation of means:

We see that, as expected for an ecommerce website, visitors, on average, spent the most time on Product Related pages, followed by informational pages, and the least amount of time on Administrative pages. On average, 23% of sessions were on the weekend and 15.4% resulted in a sale.

In [38]:
```
df.groupby('Revenue').mean()
```

Out[38]:

Revenue	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Browse
0	14.225289	13.398905	38.573522	0.006009	0.029453	0.070861	2.33476
1	14.732493	23.211100	37.584644	0.005889	0.029189	0.022819	2.42729

Analysis:

Successful Revenue have higher average values for: Info_Dur_View, PageValues; lower average values for Prod_Dur_View, SpecialDay; the rest of the variables have little difference.

In [39]:
```
df.groupby('Month').mean()
```

Out[39]:

Month	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Browser
Aug	21.232079	16.823422	40.294538	0.006486	0.027475	0.000000	2.355450
Dec	14.396003	15.229784	40.348774	0.005977	0.028192	0.000000	2.584381
Feb	2.020121	1.355556	37.351380	0.004169	0.034689	0.231111	2.166667
Jul	21.359726	18.434564	38.715820	0.006111	0.028368	0.000000	2.356295
June	17.555790	7.090725	40.519328	0.005225	0.025546	0.000000	2.328520
Mar	12.111063	15.033477	38.048085	0.004793	0.029643	0.000000	2.290270
May	12.622533	11.991647	37.469119	0.006598	0.031861	0.213453	2.367479
Nov	14.026237	18.332399	38.718799	0.006078	0.028415	0.000000	2.247400
Oct	19.513075	18.422626	39.035859	0.005977	0.026765	0.000000	2.231499
Sep	20.615059	15.068412	34.856938	0.006706	0.027010	0.000000	2.489796

Analysis:

As it relates to Revenue, certain months have a much higher revenue success rate than others, indicating that month is a determinant that should be considered.

In [40]:
```
df.groupby('Browser').mean()
```

Out[40]:

Browser	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Region
1	14.404301	12.022007	39.800192	0.006199	0.029358	0.053178	2.884998

Browser	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Region
2	14.336596	16.484068	38.248374	0.005949	0.029281	0.065935	3.172603
3	13.064464	11.741843	31.494910	0.006250	0.029660	0.097030	2.792079
4	12.349921	10.426278	37.227339	0.005886	0.028593	0.058686	3.286131
5	13.272753	12.407354	39.234802	0.006363	0.031689	0.068636	3.086364
6	18.271957	18.747087	36.965154	0.005867	0.032310	0.099401	2.904192
7	15.249180	14.914130	38.048085	0.006382	0.031424	0.043478	3.478261
8	14.148937	2.109756	37.809787	0.005612	0.030626	0.055285	3.373984
9	0.000000	0.000000	14.750000	0.000000	0.050000	0.000000	9.000000
10	18.088426	23.156490	34.323453	0.004886	0.028962	0.077419	3.129032
11	18.477619	2.600000	86.281240	0.008094	0.036412	0.000000	4.400000
12	10.489397	0.000000	23.858106	0.003796	0.032479	0.050000	4.000000
13	18.087988	1.733833	40.921275	0.004831	0.027622	0.000000	9.000000

Analysis:

As it relates to Revenue, Browser types range of values indicates that certain browsers are more likely to result in succesful revenue - indicating that Browser is a determinant that should be considered.

In [41]:

```python
df.groupby('TrafficType').mean()
```

Out[41]:

TrafficType	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Brow
1	14.816317	10.869426	38.452305	0.005665	0.029449	0.042419	2.506
2	13.326483	22.724776	39.026500	0.005956	0.028833	0.036585	2.192
3	14.350545	9.429246	38.071128	0.006011	0.030127	0.093244	2.254
4	14.015143	13.476790	36.644210	0.006930	0.031544	0.124615	2.295
5	19.420835	9.977134	36.517059	0.005796	0.027875	0.044980	2.477
6	14.189163	14.617152	38.072968	0.005582	0.028992	0.129665	2.569
7	12.893972	16.983020	33.873375	0.005621	0.026810	0.052632	2.315
8	11.308582	14.511467	39.188469	0.006358	0.028213	0.000000	2.123
9	18.879613	16.735000	41.507991	0.006685	0.028554	0.000000	1.675
10	14.809547	12.906380	36.187019	0.005677	0.027992	0.000000	2.007
11	12.410693	9.345651	46.273553	0.006008	0.030494	0.068722	3.325
12	54.000000	0.000000	35.083333	0.000000	0.020000	0.000000	4.000

TrafficType	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Brow
13	15.335552	8.924606	37.434039	0.006065	0.029498	0.138240	2.053
14	12.141346	25.629594	40.289603	0.013226	0.037513	0.092308	2.692
15	23.164146	3.827327	29.413736	0.007120	0.037109	0.075676	1.513
16	0.000000	0.000000	17.403241	0.002062	0.037522	0.000000	2.000
17	6.694444	0.000000	21.849593	0.003094	0.073413	1.000000	1.000
18	9.816931	29.555556	50.551744	0.003573	0.015277	0.088889	2.000
19	15.991468	130.892857	43.226256	0.007516	0.031235	0.200000	3.000
20	21.940148	11.647624	42.386861	0.005470	0.026142	0.027624	5.447

Analysis:

As it relates to Revenue, Traffictypes range of values indicates that certain traffic type are more likely to result in succesful revenue - indicating that Traffictypes is a determinant that should be considered.

In [42]:
```
df.groupby('VisitorType').mean()
```

Out[42]:

VisitorType	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay
New_Visitor	14.055067	8.955598	39.208115	0.006068	0.029388	0.019874
Other	17.692667	4.006134	40.708347	0.003779	0.025831	0.000000
Returning_Visitor	14.319015	15.952980	38.277479	0.005994	0.029442	0.070889

Analysis:

As it relates to Revenue, VisitorType range of values indicates that certain browsers are more likely to result in succesful revenue - indicating that VisitorType is a determinant that should be considered.

In [43]:
```
df.groupby('Weekend').mean()
```

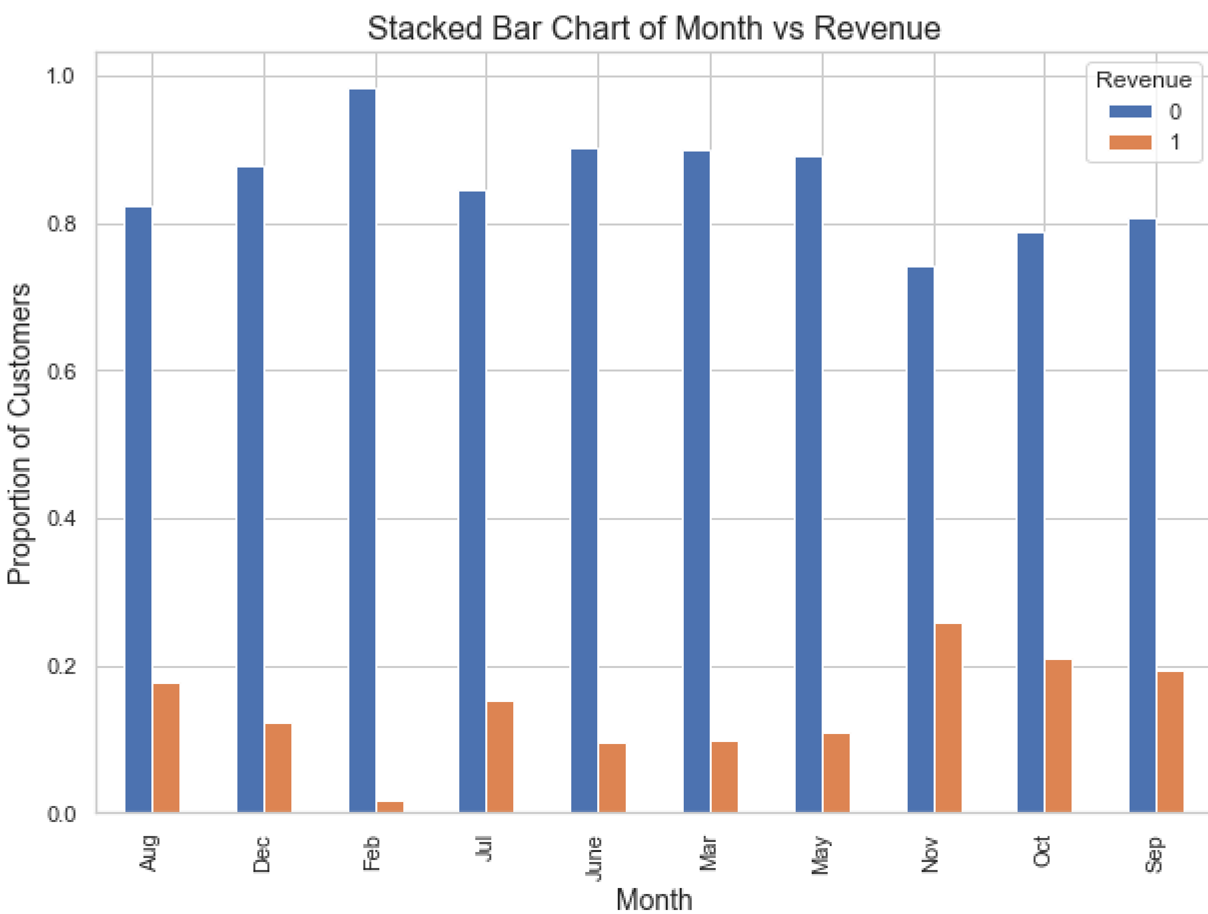
Out[43]:

Weekend	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay	Browse
0	14.264724	13.837685	38.237706	0.005960	0.029498	0.065331	2.38865
1	14.433297	18.499752	39.028206	0.006089	0.029128	0.057121	2.21757

Analysis:

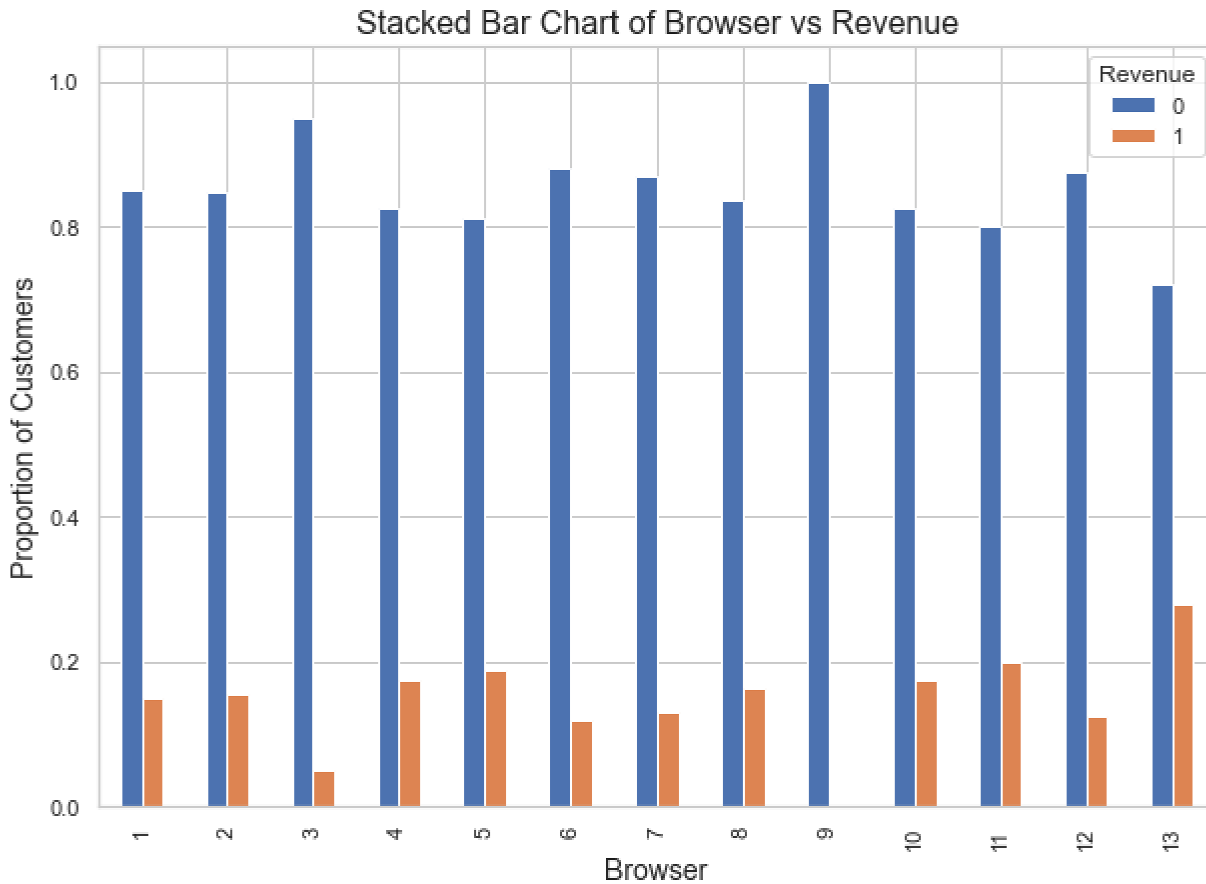
While Weekend shows a relatively small difference in Revenue success rates, it could be an indicator and we will allow RFE to determine it's impact.

In [44]:
```
# ============================== Month vs Revenue ==========================
table1=pd.crosstab(df.Month,df.Revenue)
table1.div(table1.sum(1).astype(float), axis=0).plot(kind='bar', figsize = (10,7))
plt.title('Stacked Bar Chart of Month vs Revenue', fontsize = 16)
plt.xlabel('Month', fontsize = 14)
plt.ylabel('Proportion of Customers', fontsize = 14)
plt.show()
```



Month appears to be a good predictor of Revenue.

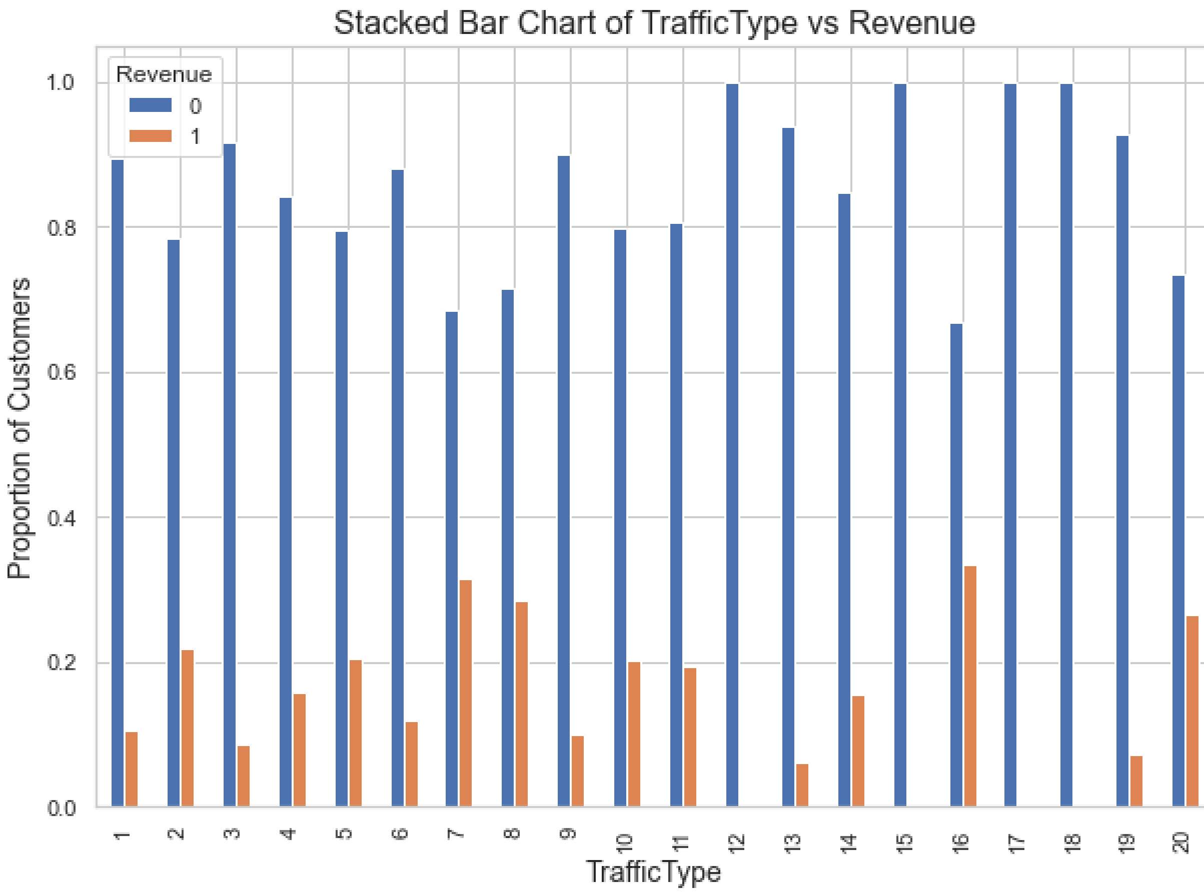
In [45]:
```
# ============================== Browser vs Revenue ==========================
table3=pd.crosstab(df.Browser,df.Revenue)
table3.div(table3.sum(1).astype(float), axis=0).plot(kind='bar', figsize = (10,7))
plt.title('Stacked Bar Chart of Browser vs Revenue', fontsize = 16)
plt.xlabel('Browser', fontsize = 14)
plt.ylabel('Proportion of Customers', fontsize = 14)
plt.show()
```



Browser appears to be a good predictor of Revenue.

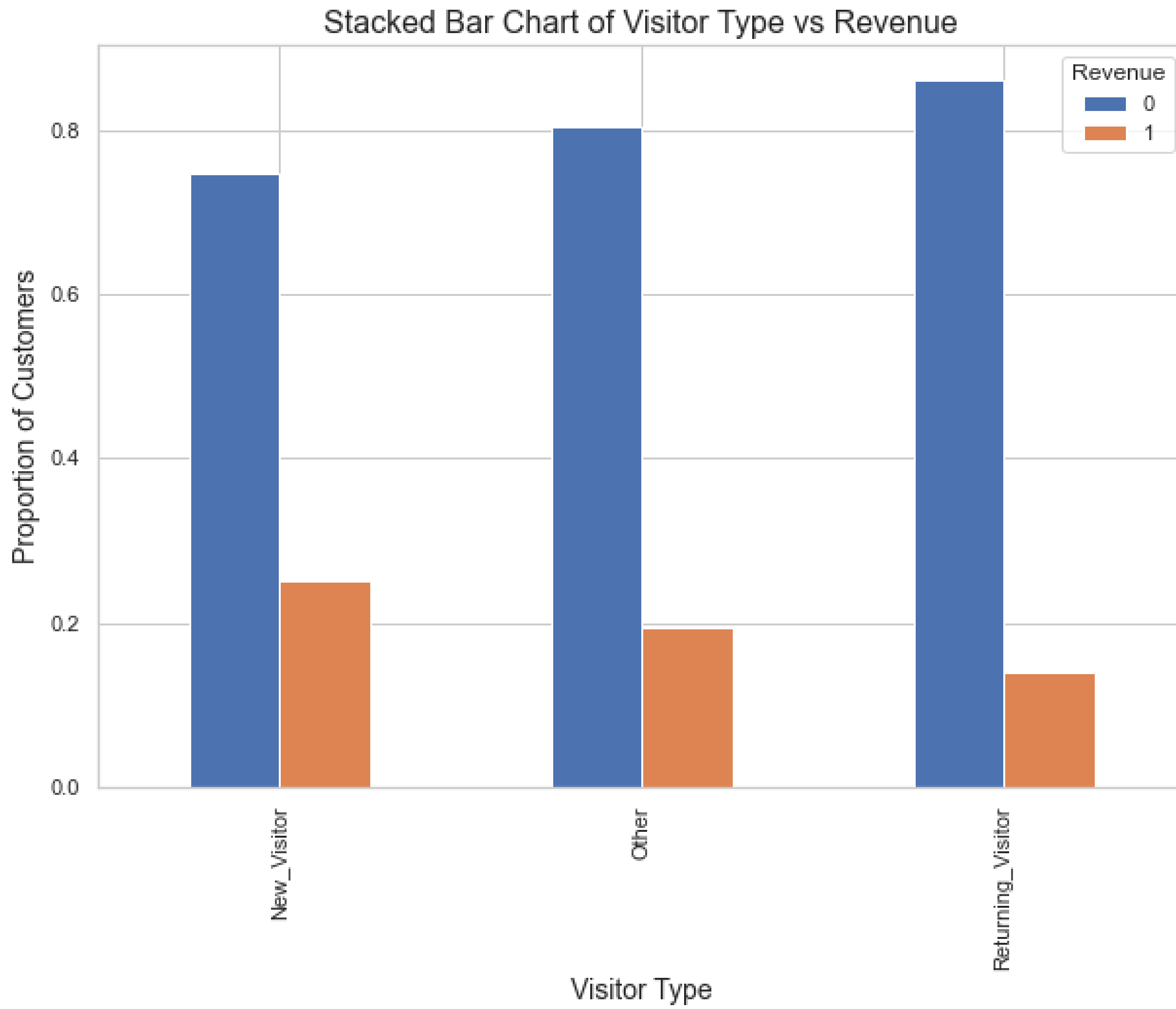
In [46]:

```
# ============================== TrafficType vs Revenue =========================
table4=pd.crosstab(df.TrafficType,df.Revenue)
table4.div(table4.sum(1).astype(float), axis=0).plot(kind='bar', figsize = (10,7))
plt.title('Stacked Bar Chart of TrafficType vs Revenue', fontsize = 16)
plt.xlabel('TrafficType', fontsize = 14)
plt.ylabel('Proportion of Customers', fontsize = 14)
plt.show()
```



TrafficType appears to be a good predictor of Revenue.

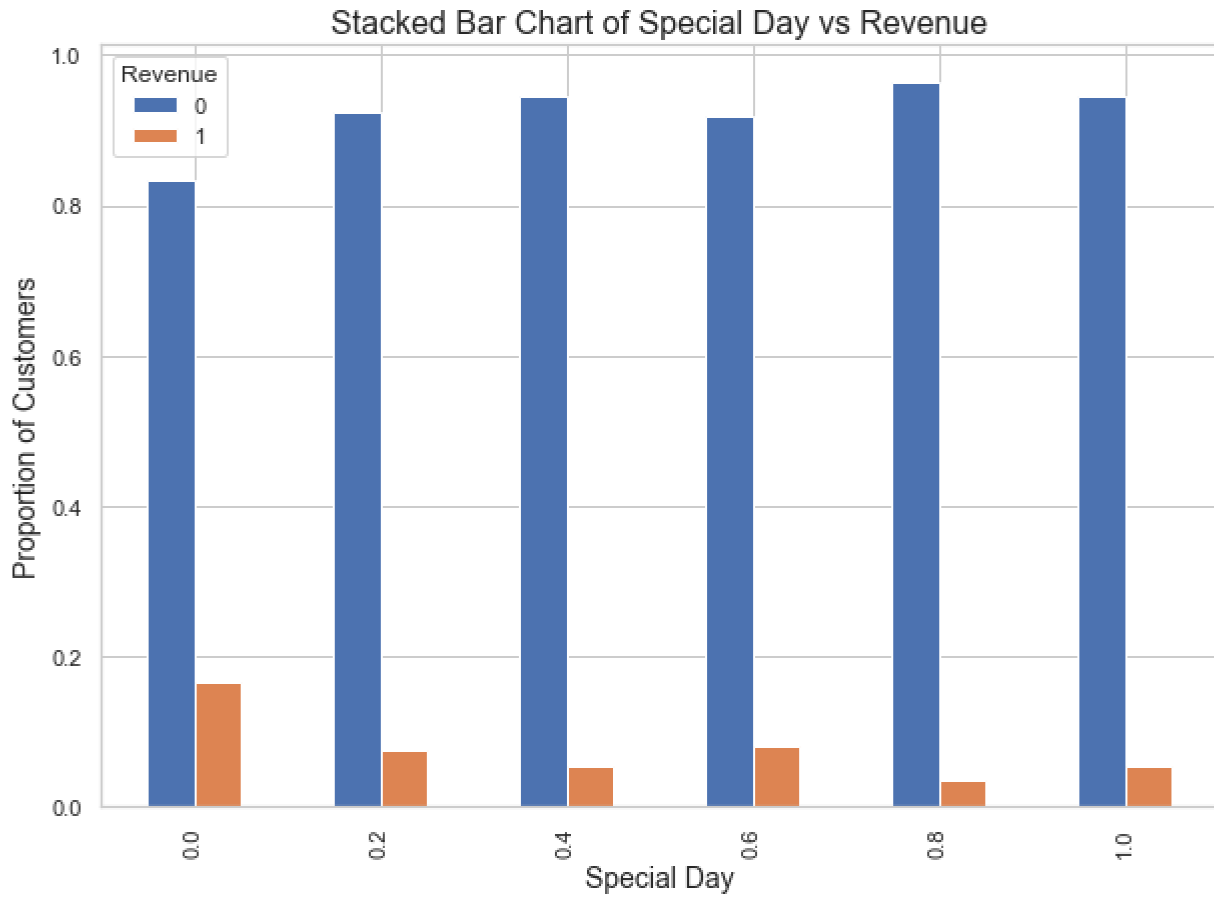
In [47]:
```
# ============================= VisitorType vs Revenue =========================
table5=pd.crosstab(df.VisitorType,df.Revenue)
table5.div(table5.sum(1).astype(float), axis=0).plot(kind='bar', figsize = (10,7))
plt.title('Stacked Bar Chart of Visitor Type vs Revenue', fontsize = 16)
plt.xlabel('Visitor Type', fontsize = 14)
plt.ylabel('Proportion of Customers', fontsize = 14)
plt.show()
```



VistorType appears to be a good predictor of Revenue.

In [48]:

```
# ============================== Special Day vs Revenue =========================
table5=pd.crosstab(df.SpecialDay,df.Revenue)
table5.div(table5.sum(1).astype(float), axis=0).plot(kind='bar', figsize = (10,7))
plt.title('Stacked Bar Chart of Special Day vs Revenue', fontsize = 16)
plt.xlabel('Special Day', fontsize = 14)
plt.ylabel('Proportion of Customers', fontsize = 14)
plt.show()
```



SpecialDay appears to be a good predictor of Revenue.

Ensure no multicollinearity within variables via correlation matrix

In [49]:
```
df.corr()
```

Out[49]:

	Admin_Dur_View	Info_Dur_View	Prod_Dur_View	BounceRates	ExitRates	SpecialDay
Admin_Dur_View	1.000000	0.000677	0.029819	-0.021784	-0.175418	-0.031402
Info_Dur_View	0.000677	1.000000	-0.017673	0.006272	0.004148	-0.031034
Prod_Dur_View	0.029819	-0.017673	1.000000	0.003928	0.012735	-0.000009
BounceRates	-0.021784	0.006272	0.003928	1.000000	0.334846	0.004994
ExitRates	-0.175418	0.004148	0.012735	0.334846	1.000000	0.030821
SpecialDay	-0.031402	-0.031034	-0.000009	0.004994	0.030821	1.000000
Browser	0.008712	-0.006824	-0.009523	-0.014064	0.010317	0.004807
Region	0.013285	-0.017644	0.014259	0.004029	-0.004951	-0.017220
PageValues	0.006093	0.027637	0.001511	-0.004983	-0.006821	-0.066766
TrafficType	0.023394	-0.018751	0.003103	0.004860	-0.007101	0.054067
Weekend	0.002468	0.029635	0.007033	0.005978	-0.007030	-0.017166
Revenue	0.006366	0.053478	-0.007543	-0.004769	-0.004305	-0.086126

In [50]:
```
# Look for linear relationships in Complete Dataset
corr = df.corr(method='pearson')
ax = sns.heatmap(
    corr,
    vmin=-1, vmax=1, center=0,
    cmap=sns.diverging_palette(20, 220, n=200),
    square=True
)
ax.set_xticklabels(
    ax.get_xticklabels(),
    rotation=45,
    horizontalalignment='right'
);
```

In [51]:
```
#Determine if Special Day values are dependent on Revenue (if Special Day =0, for all R
countSpecialDay = pd.crosstab(df['Revenue'],df['SpecialDay'])
countSpecialDay
```

Out[51]:

SpecialDay	0.0	0.2	0.4	0.6	0.8	1.0
Revenue						
0	8633	159	227	310	305	140
1	1716	13	13	27	11	8

Remove redundant or dependent variables

From the correlation matrix we can see that "BounceRates" and "ExitRates" are moderately linear to each. Removed Bounce Rate because it is a function of Exit Rate and Exit Rate matches page views.

From the correlation matrix we can see that PageValue is moderately correlated with Revenue, which means that it is not an independent variable. Removed PageValue since it is not independent.

After analyzing our variables, we can now procceed to the next step for our model building.

In [52]:
```
# Drop BounceRates & PageValues
df = df.drop(['BounceRates', 'PageValues'], axis = 1)
```

Data Analytics: Multi-Variable Logistic Regression (Supervised Learning)

Algorithm Selection Logic:

Since our goal is to predict the likelihood of Revenue, which is a boolean (binary) categorical variable, we determined the need for Supervised Learning and selected the Logistic Regression algorithm since it allows us to model a nonlinear association in a linear way with a boolean/binary target variable.

Create Dummy variables for the categorical variables using One-Hot key method selected as good predictors

In [53]:
```
#Define categorical variables to be encoded using dummy variables
cat_vars=['Month','Browser','TrafficType','VisitorType','Region','SpecialDay']
for var in cat_vars:
    cat_list='var'+'_'+var
    cat_list=pd.get_dummies(df[var], prefix=var)
    df1=df.join(cat_list)
    df=df1
```

In [54]:
```
cat_vars=['Month','Browser','TrafficType','VisitorType','Region','SpecialDay']
df_vars=df.columns.values.tolist()
to_keep=[i for i in df_vars if i not in cat_vars]
```

In [55]:
```
#Create the updated dataframe with dummy encoded categorical variables
df=df[to_keep]
#Display the updated dataframe columns
df.columns.values
```

Out[55]:
```
array(['Admin_Dur_View', 'Info_Dur_View', 'Prod_Dur_View', 'ExitRates',
       'Weekend', 'Revenue', 'Month_Aug', 'Month_Dec', 'Month_Feb',
       'Month_Jul', 'Month_June', 'Month_Mar', 'Month_May', 'Month_Nov',
       'Month_Oct', 'Month_Sep', 'Browser_1', 'Browser_2', 'Browser_3',
       'Browser_4', 'Browser_5', 'Browser_6', 'Browser_7', 'Browser_8',
       'Browser_9', 'Browser_10', 'Browser_11', 'Browser_12',
       'Browser_13', 'TrafficType_1', 'TrafficType_2', 'TrafficType_3',
       'TrafficType_4', 'TrafficType_5', 'TrafficType_6', 'TrafficType_7',
       'TrafficType_8', 'TrafficType_9', 'TrafficType_10',
       'TrafficType_11', 'TrafficType_12', 'TrafficType_13',
       'TrafficType_14', 'TrafficType_15', 'TrafficType_16',
       'TrafficType_17', 'TrafficType_18', 'TrafficType_19',
       'TrafficType_20', 'VisitorType_New_Visitor', 'VisitorType_Other',
       'VisitorType_Returning_Visitor', 'Region_1', 'Region_2',
       'Region_3', 'Region_4', 'Region_5', 'Region_6', 'Region_7',
       'Region_8', 'Region_9', 'SpecialDay_0.0', 'SpecialDay_0.2',
       'SpecialDay_0.4', 'SpecialDay_0.6', 'SpecialDay_0.8',
       'SpecialDay_1.0'], dtype=object)
```

Define X and y features and create train and test sets

In [56]:
```
# Define X and y features
X = df.loc[:, df.columns != 'Revenue']
y = df.loc[:, df.columns == 'Revenue']
```

```python
# breakdown train and test sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=5
columns = X_train.columns
```

Train and Test Ratio logic:

We then created Train and Test sets using Sklearn's train_test_split function and set our test size to 20% since we had 11,948 observations.

Scale the predictor variables for smoother machine learning*

In [57]:
```python
# Scaling helps the Logistic Regression better handle our mix of continuous and categor
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()

X_train2 = pd.DataFrame(scaler.fit_transform(X_train))
X_test2 = pd.DataFrame(scaler.transform(X_test))
X_train2.columns = X_train.columns.values
X_test2.columns = X_test.columns.values
X_train2.index = X_train.index.values
X_test2.index = X_test.index.values
X_train = X_train2
X_test = X_test2
```

Scaling Explanation:

Used the StandardScaler function to center (with_mean) and scale (with_std) all features to ensure magnitude of the features did not result in model bias.

Deploy SMOTE to balance our unbalanced Dataset

In [58]:
```python
# Deploy SMOTE (Syntheic Minority Oversampling Technique) to synthetically oversample t
os = SMOTE(random_state=500)
os_df_X,os_df_y=os.fit_resample(X_train, y_train)
os_df_X = pd.DataFrame(data=os_df_X,columns=columns )
os_df_y= pd.DataFrame(data=os_df_y,columns=['Revenue'])

# Let's ensure SMOTE corrected the disproportionately low number of succesful Revenue o
print("length of oversampled data is ",len(os_df_X))
print("Number of False Revenue in oversampled data",len(os_df_y[os_df_y['Revenue']==0])
print("Number of True Revenue",len(os_df_y[os_df_y['Revenue']==1]))
print("Proportion of Fale Revenue data in oversampled data is ",len(os_df_y[os_df_y['Re
print("Proportion of True Revenue data in oversampled data is ",len(os_df_y[os_df_y['Re
```

```
length of oversampled data is  15684
Number of False Revenue in oversampled data 7842
Number of True Revenue 7842
Proportion of Fale Revenue data in oversampled data is  0.5
Proportion of True Revenue data in oversampled data is  0.5
```

SMOTE Logic and Explanation:

Based on the disproportionately low number of succesful revenue observations and since there may not be sufficient patterns belonging to the minority class to adequately represent its distribution, we used the Synthetic Minority Oversampling Technique (SMOTE) algorithm, which aims to balance class

distribution by randomly increasing minority class examples through replication.

Eliminate less impactful variables by Recursive Feature Elimination

In [59]:
```
# LogisticRegression() parameters set to match Logit() parameters for easy rationalizat
# max_iter increased to reduce errors, ovr = binary classification, penalty=none since
# solver newton-cg to match Logit() fit_intercept to force convergence at y-axis,
logreg = LogisticRegression(max_iter=2000, multi_class='ovr', penalty='none', solver='n

# RFE to reduce features to avoid overfitting
rfe = RFE(estimator=logreg)
rfe = rfe.fit(os_df_X, os_df_y.values.ravel())
```

In [60]:
```
# Define rfeDf to pull features after RFE execution

rfesupport = rfe.support_
rfeRanking = rfe.ranking_
names = os_df_X.columns.values
rfeDf = pd.DataFrame()
rfeDf['rferanking'] = rfeRanking
rfeDf['names'] = names
rfeDf['rfesupport'] = rfesupport
rfeDf.sort_values(["rferanking"], axis=0,
                  ascending=True, inplace=True)
rfeDf = rfeDf.loc[rfeDf['rfesupport'] == True]
```

RFE Logic and Approach:

We deployed Recursive Feature Elimination (since we had 67 predictors going into the model) using the LogReg estimator.

1st Model Implementation

In [61]:
```
# Redefine X with RFE selected features
cols= rfeDf['names']
X=sm.add_constant(os_df_X[cols])
y=os_df_y['Revenue']
```

In [62]:
```
# Using Statsmodels.api Logit() for easy p-value rationalization
import statsmodels.api as sm
logit_model=sm.Logit(y,X)
result=logit_model.fit()

# Move result to dataframe for later rationalization
result = result.summary().tables[1].as_html()
result = pd.read_html(result, header=0)[0]

result = result.rename(columns={'Unnamed: 0': 'Names'})
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: inf
         Iterations: 35
```

In [63]:
```
# Only select features with p-values < 0.05 and any nans
result = result.dropna()
result = result.loc[(result['P>|z|'] <= 0.05)]
result
```

```
# Store selected features
cols= result['Names']

# Redefine X with selected features
X=sm.add_constant(os_df_X[cols])
y=os_df_y['Revenue']
```

Implementation Explanation:

We kept only statistically significant features with p-values greater than .05 which left us with 22 features that were used for our 1st model iteration and fit using the Logistic Regression algorithm.

Logistic Regression Model Fitting

In [64]:
```
# Resplit train and test sets with only features selected
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=5

# Fit LogisticRegression with selected features
#logreg = LogisticRegression(max_iter=2000, multi_class='ovr', penalty='none', solver='
logreg.fit(X_train, y_train)
```

Out[64]:
```
LogisticRegression(max_iter=2000, multi_class='ovr', penalty='none',
                   random_state=500, solver='newton-cg')
```

In [65]:
```
# Print features and coefficient in clean format
pd.DataFrame(zip(X_train.columns, np.transpose(logreg.coef_.tolist()[0])), columns=['fe
```

Out[65]:

	features	coef
0	const	-0.100619
1	SpecialDay_1.0	-0.072164
2	Browser_5	0.071130
3	Browser_13	0.073066
4	TrafficType_2	0.063836
5	TrafficType_3	-0.356256
6	TrafficType_13	-0.326239
7	SpecialDay_0.8	-0.162267
8	TrafficType_6	-0.096448
9	TrafficType_1	-0.298785
10	Browser_3	-0.111559
11	Region_9	-0.053990
12	ExitRates	-0.066419
13	SpecialDay_0.0	0.144198
14	Month_Dec	-0.095841
15	Month_Feb	-0.277841
16	Browser_2	0.049881

	features	coef
17	Prod_Dur_View	-0.073740
18	Month_June	-0.071636
19	Month_Nov	0.372507
20	Region_1	0.068503
21	Info_Dur_View	0.082104

Coefficient Evaluation:

The constant (slope of the Logistic Regression) is -0.100619 - indicating that the overall likelihood of a sale is leans more towards Revenue = False.

Features that positively impact the likelihood of a sale (push the outcome towards Revenue = True) in descending order are: Month_Nov, SpecialDay_0.0, Info_Dur_View, Browser_13, Browser_5, Region_1, TrafficType_2, and Browser_2.

Features that negatively impact the likelihood of a sale (push the outcome towards Revenue = False) in descending order are: Region_9, ExitRates, Month_June, SpecialDay_1.0, Prod_Dur_View, Month_Dec, TrafficType_6, Browser_3, SpecialDay_0.8, Month_Feb, TrafficType_1, TrafficType_13, and TrafficType_3.

Evaluate Variance Inflation Factor (VIF) to address multicollinearity concerns

In [66]:
```
def calc_vif(X):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = X.columns
    vif["VIF"] = [variance_inflation_factor(X.values, i) for i in range(X.shape[1])]

    return(vif)
```

In [67]:
```
num = X
calc_vif(num)
```

Out[67]:

	variables	VIF
0	const	1.064283
1	SpecialDay_1.0	1.183025
2	Browser_5	1.098066
3	Browser_13	1.226478
4	TrafficType_2	1.643059
5	TrafficType_3	1.372623
6	TrafficType_13	1.176496
7	SpecialDay_0.8	1.342604
8	TrafficType_6	1.107478

	variables	VIF
9	TrafficType_1	1.439835
10	Browser_3	1.016852
11	Region_9	1.193441
12	ExitRates	1.006652
13	SpecialDay_0.0	1.633906
14	Month_Dec	1.163066
15	Month_Feb	1.033678
16	Browser_2	1.161189
17	Prod_Dur_View	1.005160
18	Month_June	1.025273
19	Month_Nov	1.173743
20	Region_1	1.042915
21	Info_Dur_View	1.010983

Note: No Multicollinearity exists!

In [68]:
```
# Check model accuracy using predicted y and X_test
y_pred = logreg.predict(X_test)
print('Accuracy of logistic regression classifiers on test set: {:.2f}'.format(logreg.s
```

```
Accuracy of logistic regression classifiers on test set: 0.64
```

In [69]:
```
# Confusion matrix to evaluate model
confusion_matrix = confusion_matrix(y_test, y_pred)
print(confusion_matrix)
```

```
[[ 911  718]
 [ 407 1101]]
```

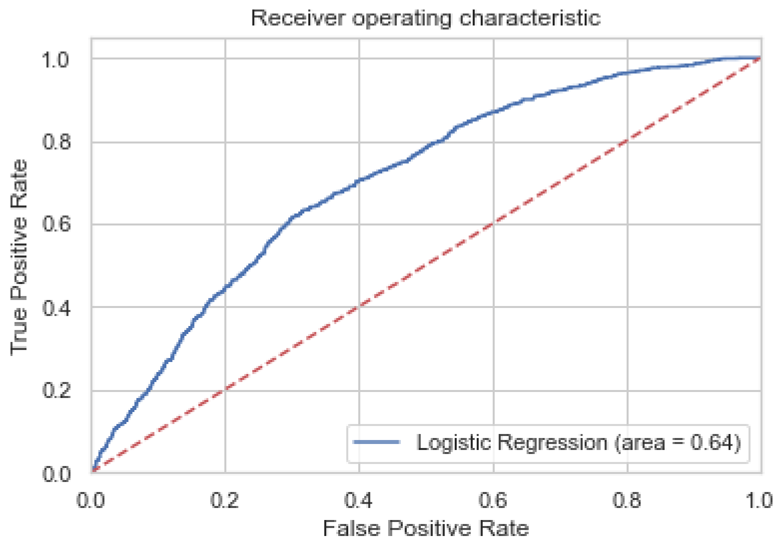
In [70]:
```
# Print Classification Report to review precision, recall, and f1-scores
print(classification_report(y_test, y_pred))
```

```
              precision    recall  f1-score   support

           0       0.69      0.56      0.62      1629
           1       0.61      0.73      0.66      1508

    accuracy                           0.64      3137
   macro avg       0.65      0.64      0.64      3137
weighted avg       0.65      0.64      0.64      3137
```

Model Evaluation Summary at the bottom of the notebook.

In [71]:
```
# Plot ROC Curve
logit_roc_auc = roc_auc_score(y_test, logreg.predict(X_test))
fpr, tpr, thresholds = roc_curve(y_test, logreg.predict_proba(X_test)[:,1])
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
```

```
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.savefig('Log_ROC')
plt.show()
```



2nd iteration of RFE and Cross-Validated Selection of the Best Number of Features

In [72]:
```
# Define Logreg2 using LogisticRegression for cross-validated feature selection and mat
logreg2 = LogisticRegression(max_iter=2000, multi_class='ovr', solver='newton-cg', fit_

# RFECV for cross-validated features selection using LogisticRegression
rfe2 = RFECV(estimator=logreg2)
rfe2 = rfe2.fit(os_df_X, os_df_y.values.ravel())
```

In [73]:
```
# Define rfeDf2 to pull features after RFECV execution

rfesupport2 = rfe2.support_
rfeRanking2 = rfe2.ranking_
names2 = os_df_X.columns.values
rfeDf2 = pd.DataFrame()
rfeDf2['rferanking2'] = rfeRanking2
rfeDf2['names2'] = names2
rfeDf2['rfesupport2'] = rfesupport2
rfeDf2.sort_values(["rferanking2"], axis=0,
                   ascending=True, inplace=True)
rfeDf2 = rfeDf2.loc[rfeDf2['rfesupport2'] == True]
```

RFECV Logic and Explanation:

We then decided to use cross-validation, which is backward selection that removes irrelevant features based on validation scores, to further reduce features to the most optimal result on the prepared data using the Logreg estimator. We kept only statistically significant features with p-values greater than .05 - leaving us with 17 features for our 2nd model iteration using the Logistic Regression algorithm.

2nd model iteration

In [74]:
```
# Redefine X2 with RFECV selected features
cols3= rfeDf2['names2']
X2=sm.add_constant(os_df_X[cols3])
y=os_df_y['Revenue']
```

In [75]:
```
# Using Statsmodels.api Logit() for easy p-value rationalization
import statsmodels.api as sm2
logit_model2=sm2.Logit(y,X2)
result2=logit_model2.fit()

# Move result to dataframe for later rationalization
result2 = result2.summary().tables[1].as_html()
result2 = pd.read_html(result2, header=0)[0]

result2 = result2.rename(columns={'Unnamed: 0': 'Names'})
```

```
Warning: Maximum number of iterations has been exceeded.
         Current function value: 0.619409
         Iterations: 35
```

In [76]:
```
# Only select features with p-values < 0.05 and any nans
result2 = result2.dropna()
result2 = result2.loc[(result2['P>|z|'] <= 0.05)]
result2

# Store selected features
cols4 = result2['Names']

# Redefine X2 with selected features
X2=sm2.add_constant(os_df_X[cols4])
y = os_df_y['Revenue']
```

2nd Model Iteration Explanation and Logic:

We kept only statistically significant features with p-values greater than .05 - leaving us with 17 features for our 2nd model iteration using the Logistic Regression algorithm.

2nd Logistic Regression Model Fitting

In [77]:
```
# Resplit train and test sets with only features selected
X2_train, X2_test, y2_train, y2_test = train_test_split(X2, y, test_size=0.2, random_st

#logreg2 = LogisticRegression(max_iter=2000, multi_class='ovr', penalty='none', solver=

# Fit LogisticRegression with selected features
logreg2.fit(X2, y)
```

Out[77]:
```
LogisticRegression(max_iter=2000, multi_class='ovr', random_state=500,
                   solver='newton-cg')
```

In [78]:
```
# Print features and coefficient in clean format
pd.DataFrame(zip(X2_train.columns, np.transpose(logreg2.coef_.tolist()[0])), columns=['
```

Out[78]:

	features	coef
0	const	-5.218389e-07
1	Month_Mar	-2.845743e-01
2	Browser_3	-1.344427e-01

	features	coef
3	Browser_13	5.482572e-02
4	TrafficType_1	-2.653096e-01
5	TrafficType_3	-3.588866e-01
6	Month_Nov	2.312914e-01
7	Month_May	-1.903996e-01
8	VisitorType_New_Visitor	1.634184e-01
9	Month_Feb	-3.074085e-01
10	Month_Dec	-2.303021e-01
11	SpecialDay_0.0	1.512664e-01
12	TrafficType_13	-3.207992e-01
13	SpecialDay_0.8	-1.394878e-01
14	TrafficType_6	-1.081073e-01
15	Info_Dur_View	1.053710e-01
16	Month_June	-1.122337e-01

Coefficient Evaluation:

The constant (slope of the Logistic Regression) is -0.0000005218389 - indicating that the overall likelihood of a sale is leans more towards Revenue = False.

Features that positively impact the likelihood of a sale (push the outcome towards Revenue = True) in descending order are: Month_Nov, VisitorType_New_Visitor, SpecialDay_0.0, Info_Dur_View, and Browser_13.

Features that negatively impact the likelihood of a sale (push the outcome towards Revenue = False) in descending order are: TrafficType_6, Month_June, Browser_3, SpecialDay_0.8, Month_May, Month_Dec, TrafficType_1, Month_Mar, Month_Feb, TrafficType_13, and TrafficType_3.

Evaluate Variance Inflation Factor (VIF) to address multicollinearity concerns

In [79]:
```
def calc_vif(X2):

    # Calculating VIF
    vif = pd.DataFrame()
    vif["variables"] = X2.columns
    vif["VIF"] = [variance_inflation_factor(X2.values, i) for i in range(X2.shape[1])]

    return(vif)
```

In [80]:
```
num = X2
calc_vif(num)
```

Out[80]:

	variables	VIF
0	const	1.067329

	variables	VIF
1	Month_Mar	1.538745
2	Browser_3	1.004137
3	Browser_13	1.041498
4	TrafficType_1	1.156913
5	TrafficType_3	1.112501
6	Month_Nov	1.942316
7	Month_May	2.193062
8	VisitorType_New_Visitor	1.111086
9	Month_Feb	1.093395
10	Month_Dec	1.524571
11	SpecialDay_0.0	1.638196
12	TrafficType_13	1.064941
13	SpecialDay_0.8	1.284234
14	TrafficType_6	1.043504
15	Info_Dur_View	1.014084
16	Month_June	1.094277

Note: No Multicollinearity exists!

In [81]:

```
# Check model accuracy using predicted y and X_test
y2_pred = logreg2.predict(X2_test)
print('Accuracy of logistic regression classifiers on test set: {:.2f}'.format(logreg2.
```

```
Accuracy of logistic regression classifiers on test set: 0.66
```

In [82]:

```
# Confusion Matrix to evaluate model performance
confusion_matrix2 = confusion_matrix2(y2_test, y2_pred)
print(confusion_matrix2)
```

```
[[1075  554]
 [ 513  995]]
```

In [83]:

```
# Classification Report to evaluate Precision, Recall, and f1-scores
print(classification_report(y2_test, y2_pred))
```

```
              precision    recall  f1-score   support

           0       0.68      0.66      0.67      1629
           1       0.64      0.66      0.65      1508

    accuracy                           0.66      3137
   macro avg       0.66      0.66      0.66      3137
weighted avg       0.66      0.66      0.66      3137
```

In [84]:

```
# ROC curve for model evaluation
logit_roc_auc = roc_auc_score(y2_test, logreg2.predict(X2_test))
fpr, tpr, thresholds = roc_curve(y2_test, logreg2.predict_proba(X2_test)[:,1])
```

```
plt.figure()
plt.plot(fpr, tpr, label='Logistic Regression (area = %0.2f)' % logit_roc_auc)
plt.plot([0, 1], [0, 1],'r--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic')
plt.legend(loc="lower right")
plt.show()
```

Decision Logic:

Since the cost of False Negatives (Sessions identified as not likely to purchase that are likely to purchase) is high (the client wouldn't deploy sales tactics to further entice the purchase or grow the basket) in our model, Recall is our primary model evaluation metric with overall accuracy (f1-score) as a secondary measure.

Final Model Selection:

Given the above results, Model 2 is determined as the best fit since it uses the fewest number of features, has the highest Recall (66% in Model 2 vs 64% in Model1), and the highest overall accuracy (66% in Model 2 vs 64% in Model1).

Final Logistic Regression Equation

ln[y/(1−y)]=-5.22e-07 + 0.231*Month_Nov + 0.163*VisitorType_New_Visitor + 0.151*SpecialDay_0.0 + 0.105*Info_Dur_View + 0.055*Browser13 - 0.108*TrafficType_6 - 0.359*TrafficType_3 - 0.321*TrafficType_13 - 0.307*Month_Feb - 0.285*Month_Mar - 0.265*TrafficType_1 - 0.230*Month_Dec - 0.19*Month_May -1.39*SpecialDay_0.8 - 0.134*Browser_3 - 0.122*Month_June + ε:

Using our Logistic Regression Equation for outcome predictions

In order to use this equation for further interpretation or predictions, input for our single numerical feature selected (Info_Dur_view) must be centered by its mean and scaled by its standard deviation. Outcome probabilities can be predicted by plugging in the appropriate values for each variable, summing the values and constant, and then calculating logistic transformation 1/(1+e) to determine the probability of a Revenue = True.