# Advanced_D_A_in_Action

February 9, 2025

## 1 Import the libraries

The first step is importing the libraries which will be used in this assignment such as pandas numpy or seaborn.

[1]:
```
#import the libraries which will be used
import pandas as pd
import numpy as np
import seaborn as sns
from scipy import stats
from flask import Flask, request, jsonify
import traceback
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import OneHotEncoder, MinMaxScaler, LabelEncoder
from sklearn.metrics import classification_report, confusion_matrix,␣
↪precision_score, recall_score, auc,roc_curve, roc_auc_score, f1_score
from urllib.request import urlopen
from sklearn.inspection import permutation_importance
from sklearn.linear_model import LogisticRegression
from sklearn.ensemble import RandomForestClassifier,␣
↪HistGradientBoostingClassifier
from sklearn.model_selection import GridSearchCV,ParameterGrid, RepeatedKFold
import plotly.express as px
import multiprocessing
import joblib
```

### 1.1 Download the dataset and Inspect the dataset

How i have the libraries now i need the dataset which will be study. I will upload it and show a few of its rows.

[6]:
```
#dowload the dataset
dir = 'online+shoppers+purchasing+intention+dataset/online_shoppers_intention.
↪csv'
rev = pd.read_csv(dir, sep = ',')
pd.options.display.max_columns = None #show all the columns
print(rev.head())#show the dataset first rows
```

```
   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
```

These are the different varriables:

- Administrative: Number of pages visited under the "administrative" category.
- Administrative_Duration: Total time spent on administrative pages.
- Informational: Number of pages visited under the "informational" category.
- Informational_Duration: Total time spent on informational pages.
- ProductRelated: Number of pages visited under the "product-related" category.
- ProductRelated_Duration: Total time spent on product-related pages.
- BounceRates: Percentage of visitors who leave the site after viewing only one page.
- ExitRates: Percentage of visitors who leave the site after viewing multiple pages.
- PageValues: Average value per page view.
- SpecialDay: A numerical value representing how close the visit is to a special day (e.g., holidays).
- Month: The month in which the visit occurred.
- OperatingSystems: The operating system used by the visitor.

- Browser: The browser used by the visitor.
- Region: The geographic region of the visitor.
- TrafficType: The source of the visitor's traffic (e.g., search engine, direct access).
- VisitorType: Whether the visitor is a new or returning visitor.
- Weekend: Whether the visit occurred on a weekend (binary: 1 for yes, 0 for no).
- Revenue: Whether the visitor made a purchase (binary: 1 for purchase, 0 for no purchase).

In this exercise i will predict if a client make purchase (Revenue) depending of the rest of variables.

# 2 Data Preprocessing

## 2.1 Handle missing values

Following i will the see the type of the columns and if there are missing values.

[7]:
```
rev.info()#show the structure of the data
```

```
<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
```

It is not possible to see missing values but if we study the values of the categorical columns the variable VisitorType has three categories so other is a missing value.

[8]:
```
# show the number of elements from each non ordinal variable which can be␣
↪cualitative
non_ord = ['OperatingSystems', 'Browser', 'Region',
           'TrafficType', 'VisitorType', 'Weekend']# columns of type distinct to␣
↪ordinal
low_num = []
high_num = []
for col in non_ord:
    print(col, rev[col].unique())# print the variable and its elements
# put variables with 10 or more distict elements in a vector and the rest on␣
↪other
    if len(rev[col].unique()) <10:
        low_num.append(col)
    else:
        high_num.append(col)
print(low_num)
print(high_num)
```

```
OperatingSystems [1 2 4 3 7 6 8 5]
Browser [ 1  2  3  4  5  6  7 10  8  9 12 13 11]
Region [1 9 2 3 4 5 6 7 8]
TrafficType [ 1  2  3  4  5  6  7  8  9 10 11 12 13 14 15 18 19 16 17 20]
VisitorType ['Returning_Visitor' 'New_Visitor' 'Other']
Weekend [False  True]
['OperatingSystems', 'Region', 'VisitorType', 'Weekend']
['Browser', 'TrafficType']
```

It is neccesary to change Other for NaN in the column VisitorType using the function "replace".

[9]:
```
# change Other in VisitorType to NaN
rev = rev.replace("Other", np.nan)
rev
```

[10]:
```
rev.isnull().sum() # show the number of NaN of each column
```

[10]:
```
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              85
Weekend                   0
Revenue                   0
dtype: int64
```

Now there are missing values only in VisitorType.

To fill the new missing values i will sustitute them by the mode of VisitorType.

[11]:
```
# fill NaN using the mode
moda = rev['VisitorType'].mode()[0]#create the mode

rev['VisitorType'].fillna(moda, inplace = True) # fill the Na with the mode of␣
↪the variable
```

## 2.2 Encode categorical variables

The next step is data and create new variables so i will make a copy of the dataset.

[13]:
```
rev_fin = rev.copy() # copy the dataset
rev_fin
```

To begin i will use a label encoding to convert the categorical columns with an order or few diffrent categories in numerical.

[14]:
```
# use a label encoding for the categorical columns with an order
ordinal = ['Month']# columns of type ordinal

label_encoder = LabelEncoder()# create the label encoder

rev_fin['Month'] = label_encoder.fit_transform(rev_fin['Month']) #transform the␣
↪columns
rev_fin
```

[15]:
```
# use a label encoding for the categorical columns with few distinct elements

label_encoder = LabelEncoder()# create the label encoder

for k in low_num:

    rev_fin[k] = label_encoder.fit_transform(rev_fin[k]) #transform the columns

rev_fin
```

[15]:

```
       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
...               ...                      ...            ...
12325               3                    145.0              0
12326               0                      0.0              0
12327               0                      0.0              0
12328               4                     75.0              0
12329               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
...                       ...             ...                      ...
12325                     0.0              53              1783.791667
12326                     0.0               5               465.750000
12327                     0.0               6               184.250000
12328                     0.0              15               346.000000
12329                     0.0               3                21.250000

       BounceRates  ExitRates  PageValues  SpecialDay  Month  \
0         0.200000   0.200000    0.000000         0.0      2
1         0.000000   0.100000    0.000000         0.0      2
2         0.200000   0.200000    0.000000         0.0      2
3         0.050000   0.140000    0.000000         0.0      2
4         0.020000   0.050000    0.000000         0.0      2
...            ...        ...         ...         ...    ...
12325     0.007143   0.029031   12.241717         0.0      1
12326     0.000000   0.021333    0.000000         0.0      7
12327     0.083333   0.086667    0.000000         0.0      7
12328     0.000000   0.021053    0.000000         0.0      7
12329     0.000000   0.066667    0.000000         0.0      7

       OperatingSystems  Browser  Region  TrafficType  VisitorType  Weekend  \
0                     0        1       0            1            1        0
1                     1        2       0            2            1        0
2                     3        1       8            3            1        0
3                     2        2       1            4            1        0
4                     2        3       0            4            1        1
...                 ...      ...     ...          ...          ...      ...
12325                 3        6       0            1            1        1
```

```
12326                    2         2        0           8             1         1
12327                    2         2        0          13             1         1
12328                    1         2        2          11             1         0
12329                    2         2        0           2             0         1

       Revenue
0        False
1        False
2        False
3        False
4        False
...        ...
12325    False
12326    False
12327    False
12328    False
12329    False

[12330 rows x 18 columns]
```

The rest of categorical features will be transform into numerical using a one-hot encoding by which each distinct category of a variable will be represented in a new column.

[16]:
```
# convert the rest of categorical features using one-hot encodering
for k in high_num: # run the vector of categorical variable names
#inicialize the encoderer
    encoder = OneHotEncoder(sparse = False)

# Fit and transform the categorical columns
    encoded = encoder.fit_transform(rev_fin[[k]]) # convert the categorical␣
 ↪features
    if hasattr(encoder, 'get_feature_names_out'):# see if the encoderer has the␣
 ↪atribute get_feature_names_out
        feature_names = encoder.get_feature_names_out([k]) # add the name of the␣
 ↪feature in a list
    else:
        feature_names = [f'{k}_{cat}' for cat in encoder.categories_[0]] #␣
 ↪create and add the name of the feature
    encoderdata = pd.DataFrame(encoded, columns=feature_names)# add to the new␣
 ↪features to the dataset

    rev_fin = rev_fin.join(encoderdata) # put the new features to the dataset␣
 ↪rev_fin
rev_fin = rev_fin.drop(non_ord, axis=1) # delete old features
rev_fin
```

```
[16]:        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
      ...               ...                      ...            ...
      12325               3                    145.0              0
      12326               0                      0.0              0
      12327               0                      0.0              0
      12328               4                     75.0              0
      12329               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
      ...                       ...             ...                      ...
      12325                     0.0              53              1783.791667
      12326                     0.0               5               465.750000
      12327                     0.0               6               184.250000
      12328                     0.0              15               346.000000
      12329                     0.0               3                21.250000

             BounceRates  ExitRates  PageValues  SpecialDay  Month  Revenue  \
      0         0.200000   0.200000    0.000000         0.0      2    False
      1         0.000000   0.100000    0.000000         0.0      2    False
      2         0.200000   0.200000    0.000000         0.0      2    False
      3         0.050000   0.140000    0.000000         0.0      2    False
      4         0.020000   0.050000    0.000000         0.0      2    False
      ...            ...        ...         ...         ...    ...      ...
      12325     0.007143   0.029031   12.241717         0.0      1    False
      12326     0.000000   0.021333    0.000000         0.0      7    False
      12327     0.083333   0.086667    0.000000         0.0      7    False
      12328     0.000000   0.021053    0.000000         0.0      7    False
      12329     0.000000   0.066667    0.000000         0.0      7    False

             Browser_1  Browser_2  Browser_3  Browser_4  Browser_5  Browser_6  \
      0            1.0        0.0        0.0        0.0        0.0        0.0
      1            0.0        1.0        0.0        0.0        0.0        0.0
      2            1.0        0.0        0.0        0.0        0.0        0.0
      3            0.0        1.0        0.0        0.0        0.0        0.0
      4            0.0        0.0        1.0        0.0        0.0        0.0
      ...          ...        ...        ...        ...        ...        ...
      12325        0.0        0.0        0.0        0.0        0.0        1.0
```

```
12326        0.0        1.0        0.0        0.0        0.0        0.0
12327        0.0        1.0        0.0        0.0        0.0        0.0
12328        0.0        1.0        0.0        0.0        0.0        0.0
12329        0.0        1.0        0.0        0.0        0.0        0.0

       Browser_7  Browser_8  Browser_9  Browser_10  Browser_11  Browser_12  \
0            0.0        0.0        0.0         0.0         0.0         0.0
1            0.0        0.0        0.0         0.0         0.0         0.0
2            0.0        0.0        0.0         0.0         0.0         0.0
3            0.0        0.0        0.0         0.0         0.0         0.0
4            0.0        0.0        0.0         0.0         0.0         0.0
...          ...        ...        ...         ...         ...         ...
12325        0.0        0.0        0.0         0.0         0.0         0.0
12326        0.0        0.0        0.0         0.0         0.0         0.0
12327        0.0        0.0        0.0         0.0         0.0         0.0
12328        0.0        0.0        0.0         0.0         0.0         0.0
12329        0.0        0.0        0.0         0.0         0.0         0.0

       Browser_13  TrafficType_1  TrafficType_2  TrafficType_3  TrafficType_4  \
0             0.0            1.0            0.0            0.0            0.0
1             0.0            0.0            1.0            0.0            0.0
2             0.0            0.0            0.0            1.0            0.0
3             0.0            0.0            0.0            0.0            1.0
4             0.0            0.0            0.0            0.0            1.0
...           ...            ...            ...            ...            ...
12325         0.0            1.0            0.0            0.0            0.0
12326         0.0            0.0            0.0            0.0            0.0
12327         0.0            0.0            0.0            0.0            0.0
12328         0.0            0.0            0.0            0.0            0.0
12329         0.0            0.0            1.0            0.0            0.0

       TrafficType_5  TrafficType_6  TrafficType_7  TrafficType_8  \
0                0.0            0.0            0.0            0.0
1                0.0            0.0            0.0            0.0
2                0.0            0.0            0.0            0.0
3                0.0            0.0            0.0            0.0
4                0.0            0.0            0.0            0.0
...              ...            ...            ...            ...
12325            0.0            0.0            0.0            0.0
12326            0.0            0.0            0.0            1.0
12327            0.0            0.0            0.0            0.0
12328            0.0            0.0            0.0            0.0
12329            0.0            0.0            0.0            0.0

       TrafficType_9  TrafficType_10  TrafficType_11  TrafficType_12  \
0                0.0             0.0             0.0             0.0
1                0.0             0.0             0.0             0.0
```

```
2                 0.0           0.0           0.0           0.0
3                 0.0           0.0           0.0           0.0
4                 0.0           0.0           0.0           0.0
...               ...           ...           ...           ...
12325             0.0           0.0           0.0           0.0
12326             0.0           0.0           0.0           0.0
12327             0.0           0.0           0.0           0.0
12328             0.0           0.0           1.0           0.0
12329             0.0           0.0           0.0           0.0

       TrafficType_13  TrafficType_14  TrafficType_15  TrafficType_16  \
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
...               ...             ...             ...             ...
12325             0.0             0.0             0.0             0.0
12326             0.0             0.0             0.0             0.0
12327             1.0             0.0             0.0             0.0
12328             0.0             0.0             0.0             0.0
12329             0.0             0.0             0.0             0.0

       TrafficType_17  TrafficType_18  TrafficType_19  TrafficType_20
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
...               ...             ...             ...             ...
12325             0.0             0.0             0.0             0.0
12326             0.0             0.0             0.0             0.0
12327             0.0             0.0             0.0             0.0
12328             0.0             0.0             0.0             0.0
12329             0.0             0.0             0.0             0.0

[12330 rows x 45 columns]
```

### 2.3 Feature creation

Now i will create two new variable using the (number of pages visited under the category)/(total time spent on pages of type) “administrative”, “informational” and “product-related”.

[17]:
```
rev_fin['Number pages'] = rev_fin['Administrative'] + rev_fin['Informational'] +␣
 ↪rev_fin['ProductRelated']
rev_fin['Total time'] = rev_fin['Administrative_Duration'] +␣
 ↪rev_fin['Informational_Duration'] + rev_fin['ProductRelated_Duration']
```

```
rev_fin
```

## 2.4 Normalization

To end this section i will normalize the numerical variables of the original dataset using a MixMaxScaler.

[18]:
```
# standarization of the numerical variables using a min max scaler

for k in rev.columns.to_list()[0:10]: # find and run the vector of numerical␣
↪variable names
    scaler = MinMaxScaler()
    rev_fin[k] = scaler.fit_transform(rev_fin[[k]]) # standarize the numeral␣
↪features and add to the dataset

rev_fin
```

[18]:
```
       Administrative  Administrative_Duration  Informational  \
0            0.000000                 0.000000            0.0
1            0.000000                 0.000000            0.0
2            0.000000                 0.000000            0.0
3            0.000000                 0.000000            0.0
4            0.000000                 0.000000            0.0
...               ...                      ...            ...
12325        0.111111                 0.042663            0.0
12326        0.000000                 0.000000            0.0
12327        0.000000                 0.000000            0.0
12328        0.148148                 0.022067            0.0
12329        0.000000                 0.000000            0.0

       Informational_Duration  ProductRelated  ProductRelated_Duration  \
0                         0.0        0.001418                 0.000000
1                         0.0        0.002837                 0.001000
2                         0.0        0.001418                 0.000000
3                         0.0        0.002837                 0.000042
4                         0.0        0.014184                 0.009809
...                       ...             ...                      ...
12325                     0.0        0.075177                 0.027883
12326                     0.0        0.007092                 0.007280
12327                     0.0        0.008511                 0.002880
12328                     0.0        0.021277                 0.005408
12329                     0.0        0.004255                 0.000332

       BounceRates  ExitRates  PageValues  SpecialDay  Month  Revenue  \
0         1.000000   1.000000    0.000000         0.0      2    False
1         0.000000   0.500000    0.000000         0.0      2    False
2         1.000000   1.000000    0.000000         0.0      2    False
```

```
3      0.250000  0.700000   0.000000        0.0     2   False
4      0.100000  0.250000   0.000000        0.0     2   False
...         ...       ...        ...        ...   ...     ...
12325  0.035714  0.145153   0.033839        0.0     1   False
12326  0.000000  0.106667   0.000000        0.0     7   False
12327  0.416667  0.433333   0.000000        0.0     7   False
12328  0.000000  0.105263   0.000000        0.0     7   False
12329  0.000000  0.333333   0.000000        0.0     7   False

       Browser_1  Browser_2  Browser_3  Browser_4  Browser_5  Browser_6  \
0            1.0        0.0        0.0        0.0        0.0        0.0
1            0.0        1.0        0.0        0.0        0.0        0.0
2            1.0        0.0        0.0        0.0        0.0        0.0
3            0.0        1.0        0.0        0.0        0.0        0.0
4            0.0        0.0        1.0        0.0        0.0        0.0
...          ...        ...        ...        ...        ...        ...
12325        0.0        0.0        0.0        0.0        0.0        1.0
12326        0.0        1.0        0.0        0.0        0.0        0.0
12327        0.0        1.0        0.0        0.0        0.0        0.0
12328        0.0        1.0        0.0        0.0        0.0        0.0
12329        0.0        1.0        0.0        0.0        0.0        0.0

       Browser_7  Browser_8  Browser_9  Browser_10  Browser_11  Browser_12  \
0            0.0        0.0        0.0         0.0         0.0         0.0
1            0.0        0.0        0.0         0.0         0.0         0.0
2            0.0        0.0        0.0         0.0         0.0         0.0
3            0.0        0.0        0.0         0.0         0.0         0.0
4            0.0        0.0        0.0         0.0         0.0         0.0
...          ...        ...        ...         ...         ...         ...
12325        0.0        0.0        0.0         0.0         0.0         0.0
12326        0.0        0.0        0.0         0.0         0.0         0.0
12327        0.0        0.0        0.0         0.0         0.0         0.0
12328        0.0        0.0        0.0         0.0         0.0         0.0
12329        0.0        0.0        0.0         0.0         0.0         0.0

       Browser_13  TrafficType_1  TrafficType_2  TrafficType_3  TrafficType_4  \
0             0.0            1.0            0.0            0.0            0.0
1             0.0            0.0            1.0            0.0            0.0
2             0.0            0.0            0.0            1.0            0.0
3             0.0            0.0            0.0            0.0            1.0
4             0.0            0.0            0.0            0.0            1.0
...           ...            ...            ...            ...            ...
12325         0.0            1.0            0.0            0.0            0.0
12326         0.0            0.0            0.0            0.0            0.0
12327         0.0            0.0            0.0            0.0            0.0
12328         0.0            0.0            0.0            0.0            0.0
12329         0.0            0.0            1.0            0.0            0.0
```

```
       TrafficType_5  TrafficType_6  TrafficType_7  TrafficType_8  \
0                0.0            0.0            0.0            0.0
1                0.0            0.0            0.0            0.0
2                0.0            0.0            0.0            0.0
3                0.0            0.0            0.0            0.0
4                0.0            0.0            0.0            0.0
...              ...            ...            ...            ...
12325            0.0            0.0            0.0            0.0
12326            0.0            0.0            0.0            1.0
12327            0.0            0.0            0.0            0.0
12328            0.0            0.0            0.0            0.0
12329            0.0            0.0            0.0            0.0

       TrafficType_9  TrafficType_10  TrafficType_11  TrafficType_12  \
0                0.0             0.0             0.0             0.0
1                0.0             0.0             0.0             0.0
2                0.0             0.0             0.0             0.0
3                0.0             0.0             0.0             0.0
4                0.0             0.0             0.0             0.0
...              ...             ...             ...             ...
12325            0.0             0.0             0.0             0.0
12326            0.0             0.0             0.0             0.0
12327            0.0             0.0             0.0             0.0
12328            0.0             0.0             1.0             0.0
12329            0.0             0.0             0.0             0.0

       TrafficType_13  TrafficType_14  TrafficType_15  TrafficType_16  \
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
...               ...             ...             ...             ...
12325             0.0             0.0             0.0             0.0
12326             0.0             0.0             0.0             0.0
12327             1.0             0.0             0.0             0.0
12328             0.0             0.0             0.0             0.0
12329             0.0             0.0             0.0             0.0

       TrafficType_17  TrafficType_18  TrafficType_19  TrafficType_20  \
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
...               ...             ...             ...             ...
```

```
12325              0.0              0.0              0.0              0.0
12326              0.0              0.0              0.0              0.0
12327              0.0              0.0              0.0              0.0
12328              0.0              0.0              0.0              0.0
12329              0.0              0.0              0.0              0.0

       Number pages   Total time
0                 1     0.000000
1                 2    64.000000
2                 1     0.000000
3                 2     2.666667
4                10   627.500000
...             ...          ...
12325            56  1928.791667
12326             5   465.750000
12327             6   184.250000
12328            19   421.000000
12329             3    21.250000

[12330 rows x 47 columns]
```

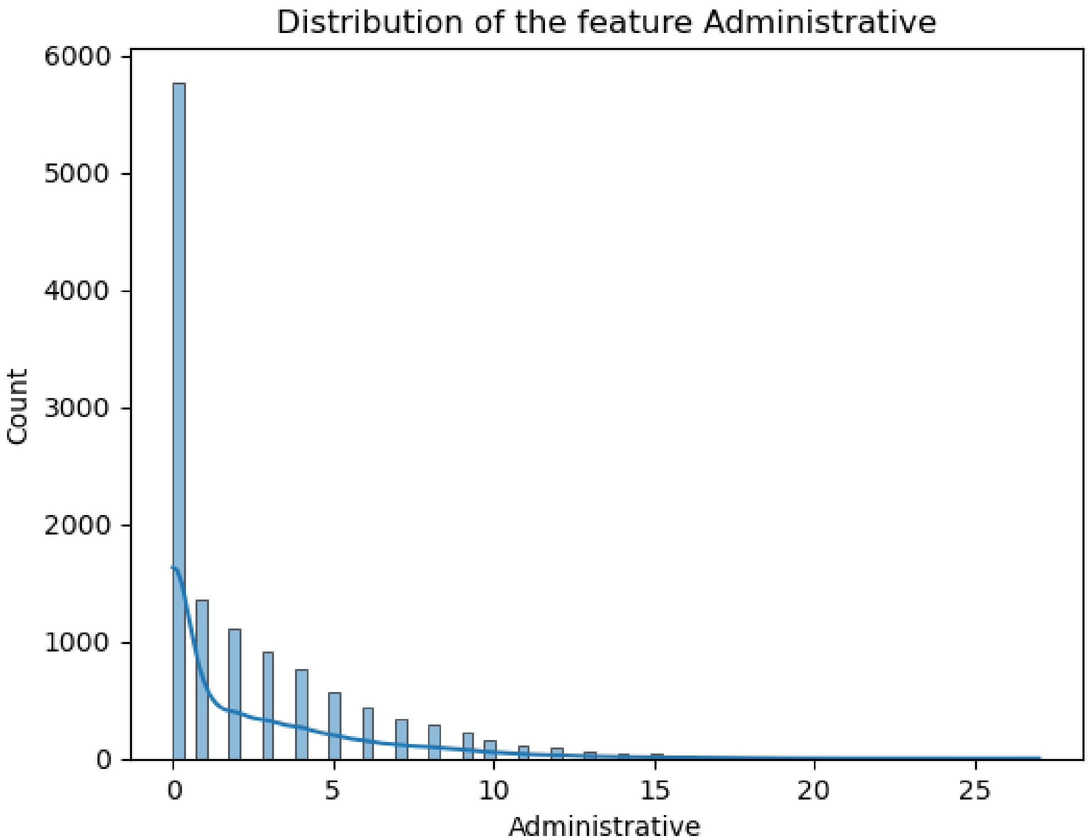
# 3 Exploratory Data Analysis

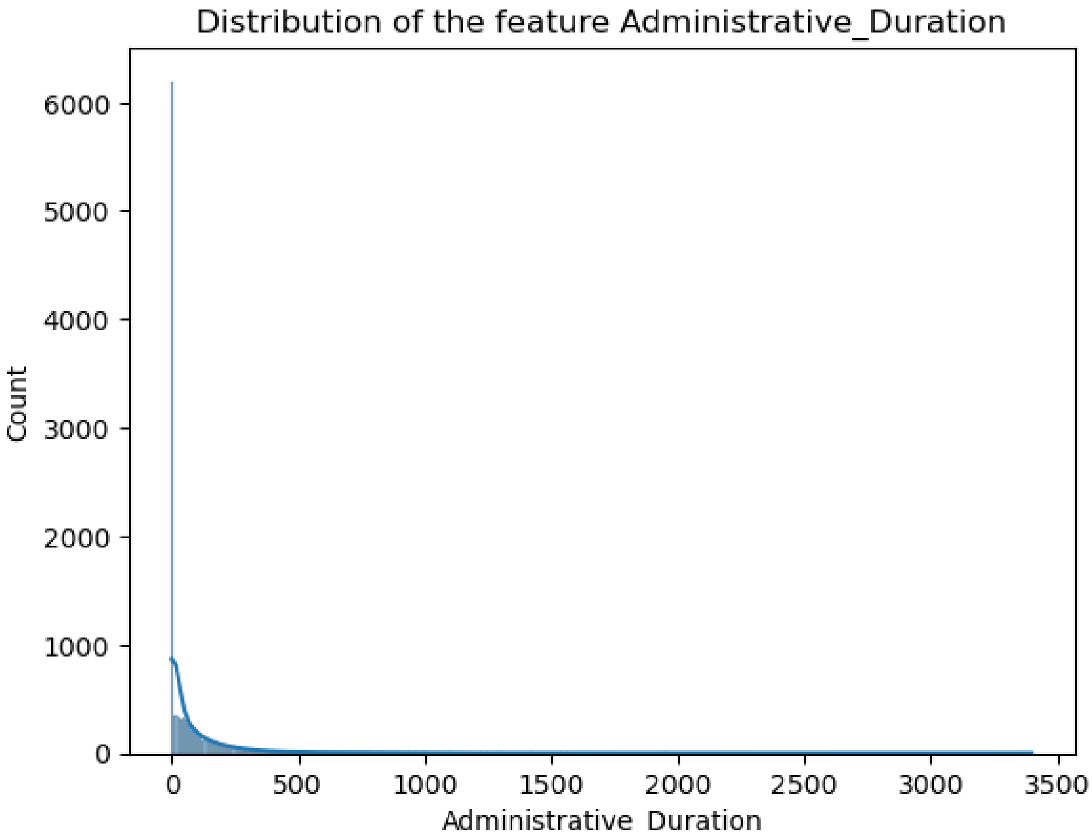
In this section i will to explore the dataset.

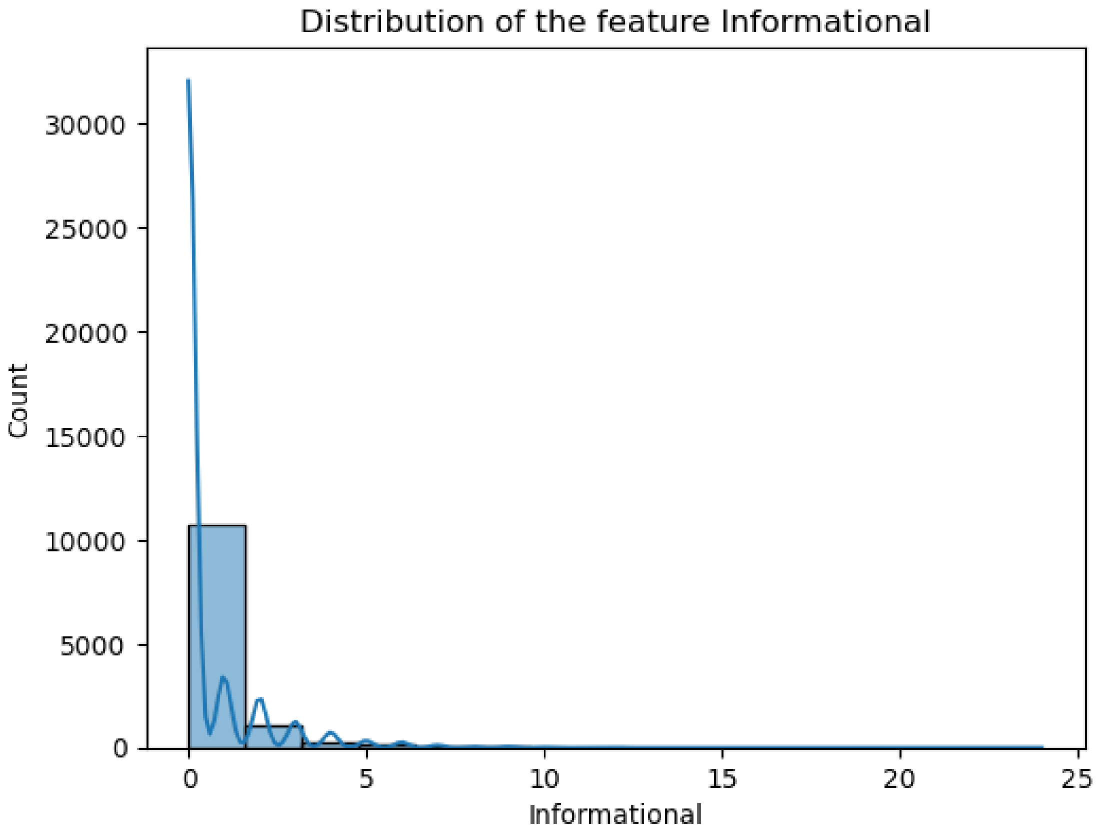
## 3.1 Visualize numerical variables

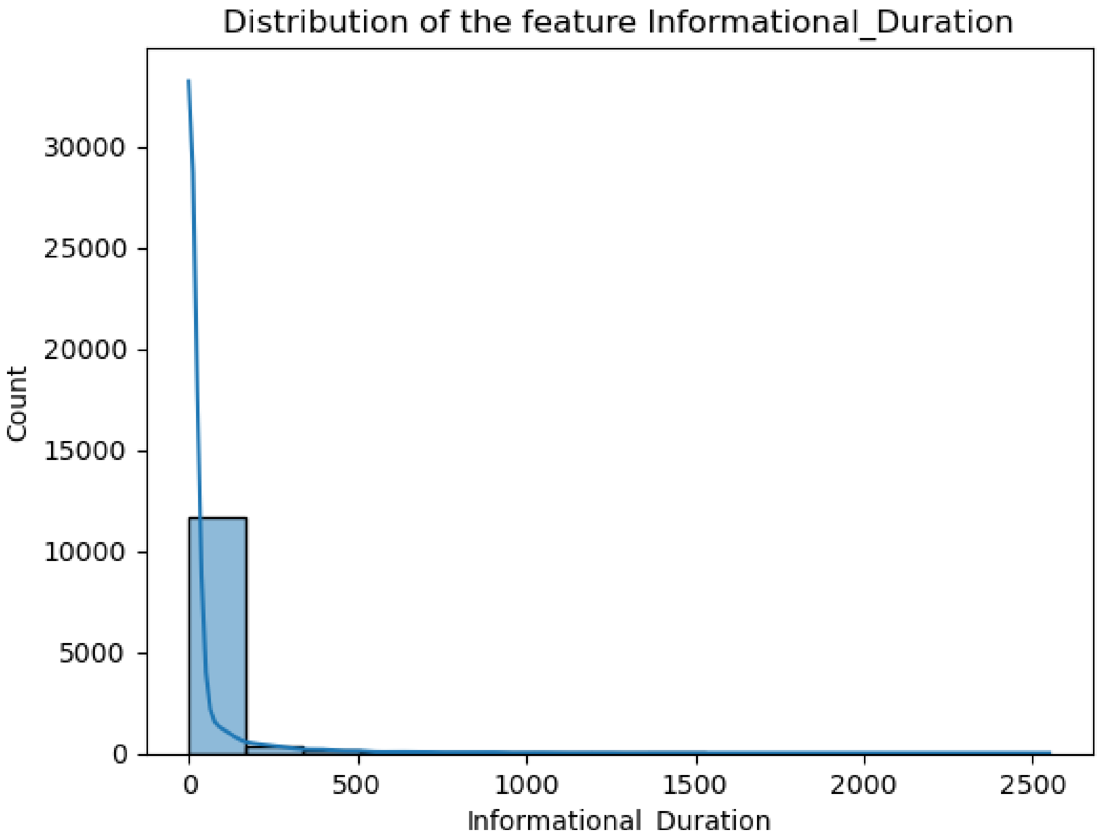
First of all i will use histograms, box plots, and pair plots to examine the distribution of numerical variables.

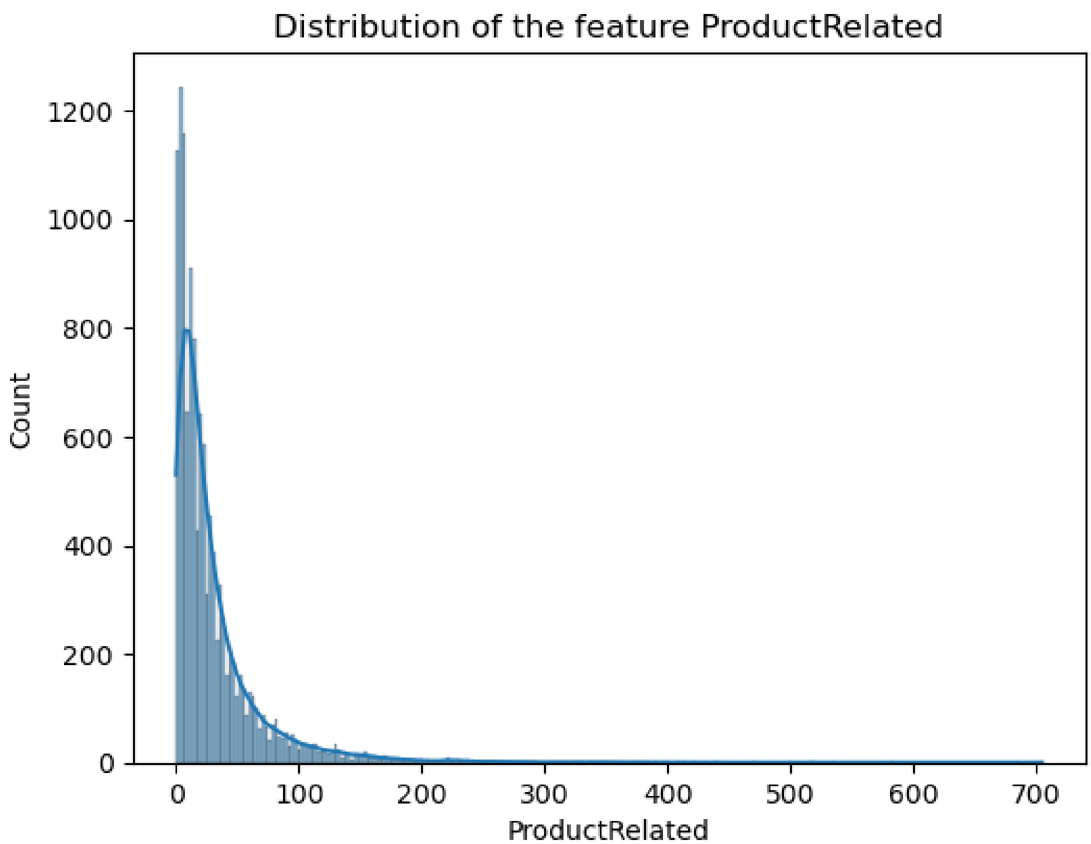
[20]:
```
#plot the histogram of the numerical variables to study their distribution
for k in numerical:
    sns.histplot(rev[k], kde=True) # create the histogram
    plt.title('Distribution of the feature ' + k) # change the title
    plt.show() # plot the histogram
```

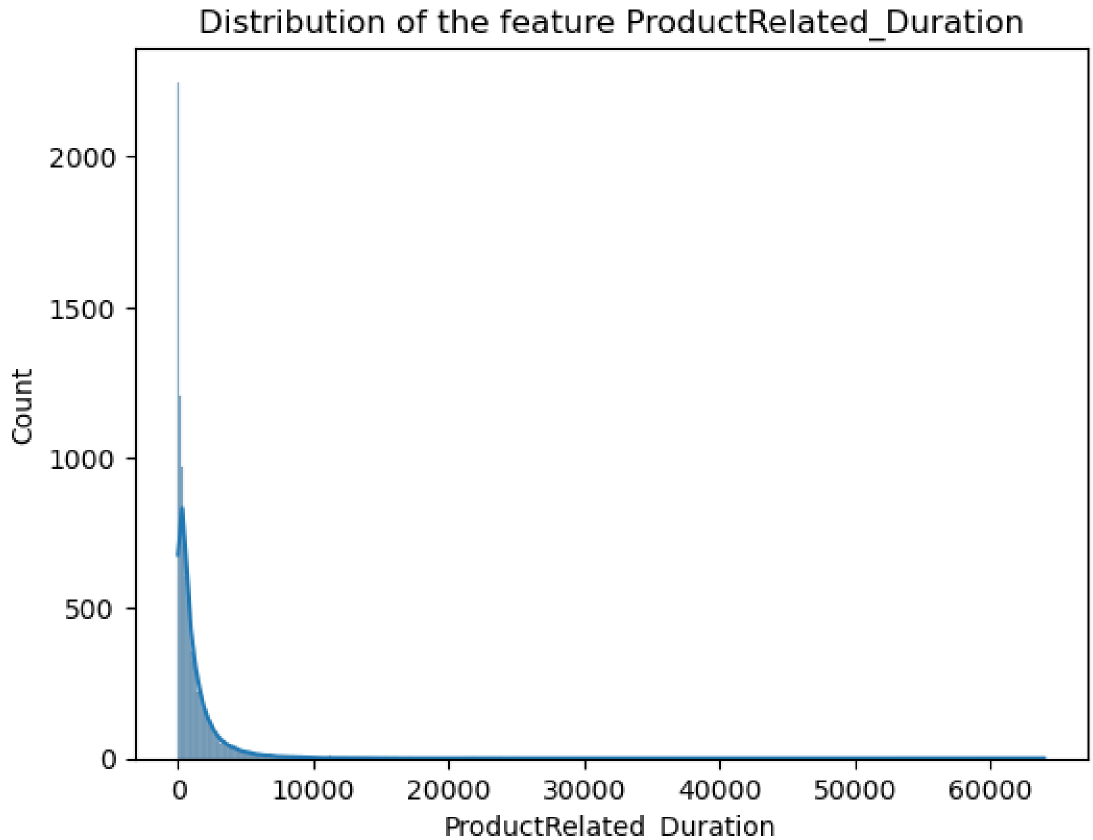

Distribution of the feature Administrative
Count
Administrative
0
1000
2000
3000
4000
5000
6000
0
5
10
15
20
25

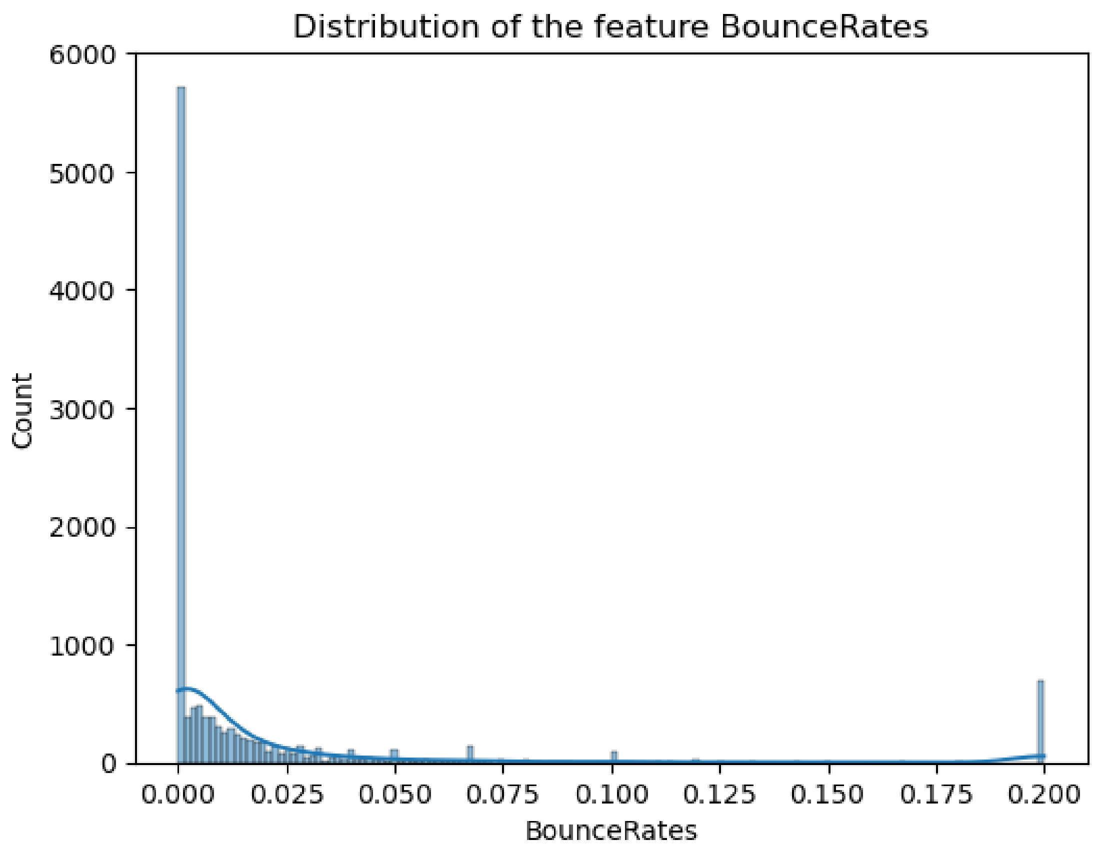

Distribution of the feature Administrative_Duration
Count
0
1000
2000
3000
4000
5000
6000
0
500
1000
1500
2000
2500
3000
3500
Administrative_Duration

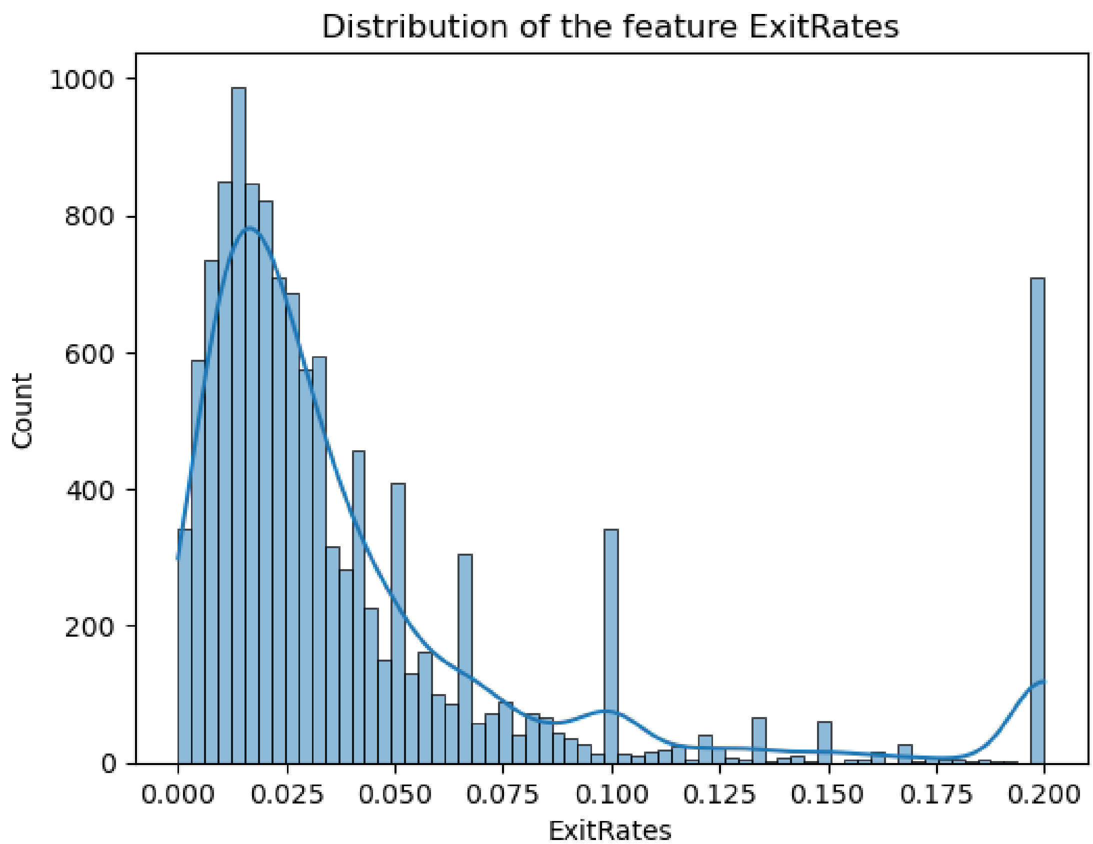

Distribution of the feature Informational
Count
30000
25000
20000
15000
10000
5000
0
0
5
10
15
20
25
Informational

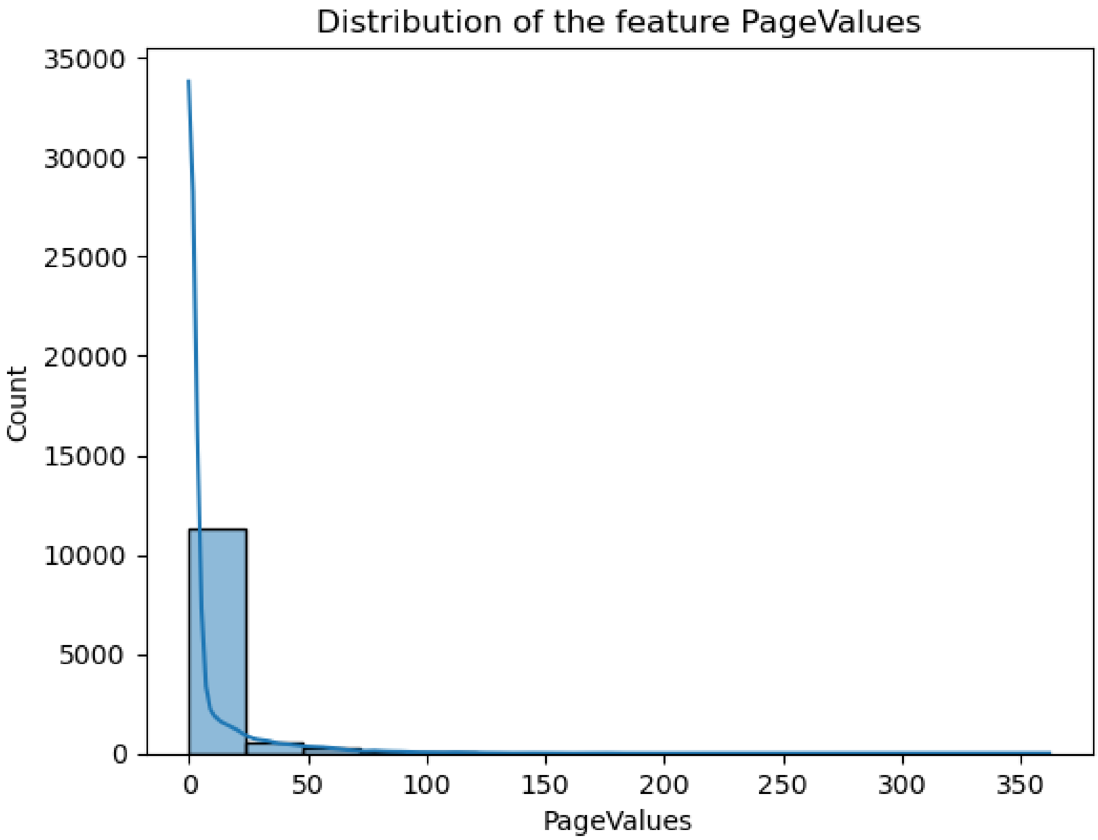

Distribution of the feature Informational_Duration
Count
30000
25000
20000
15000
10000
5000
0
0
500
1000
1500
2000
2500
Informational_Duration

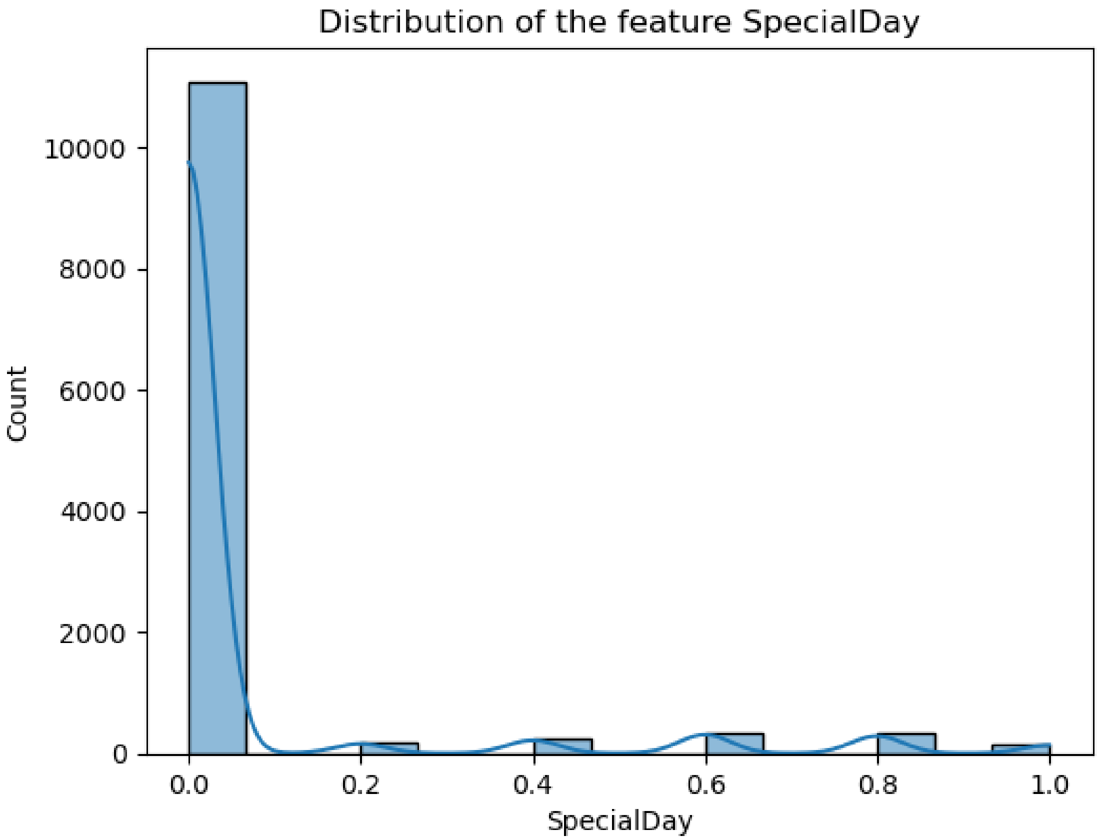

Distribution of the feature ProductRelated
Count
ProductRelated
0
200
400
600
800
1000
1200
0
100
200
300
400
500
600
700


Distribution of the feature ProductRelated_Duration
Count
2000
1500
1000
500
0
0
10000
20000
30000
40000
50000
60000
ProductRelated_Duration


Distribution of the feature BounceRates
Count
BounceRates
6000
5000
4000
3000
2000
1000
0
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200

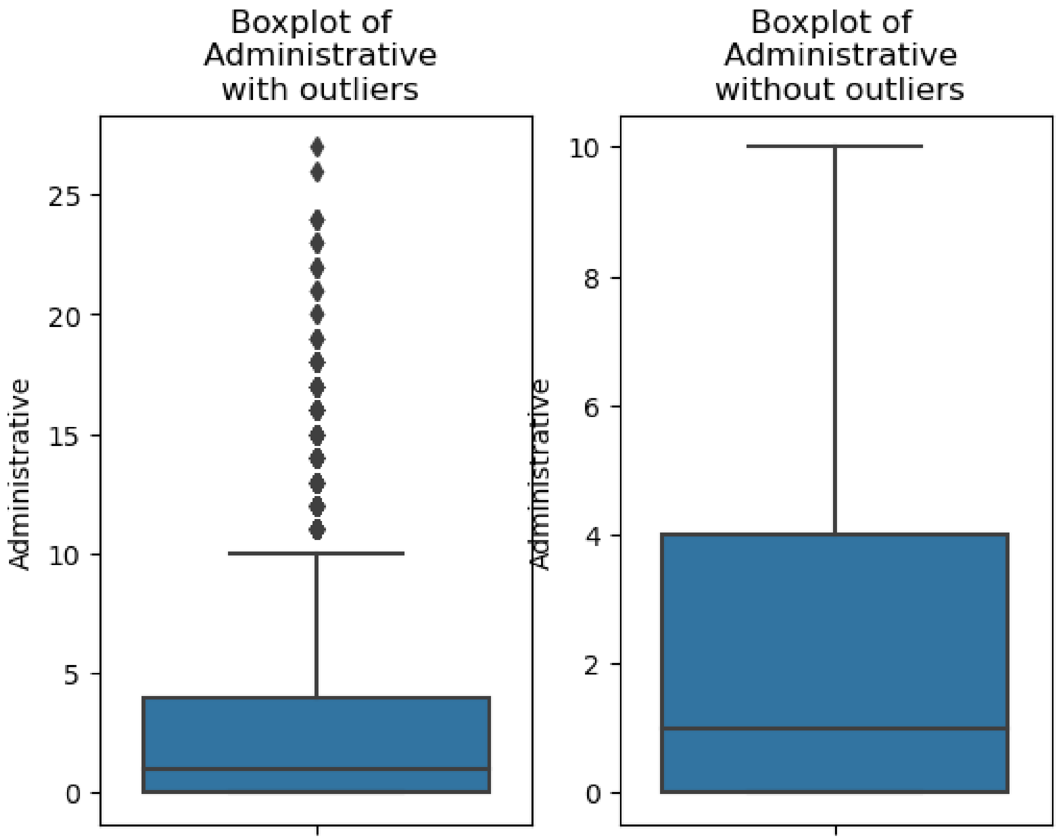

Distribution of the feature ExitRates
Count
ExitRates
0
200
400
600
800
1000
0.000
0.025
0.050
0.075
0.100
0.125
0.150
0.175
0.200

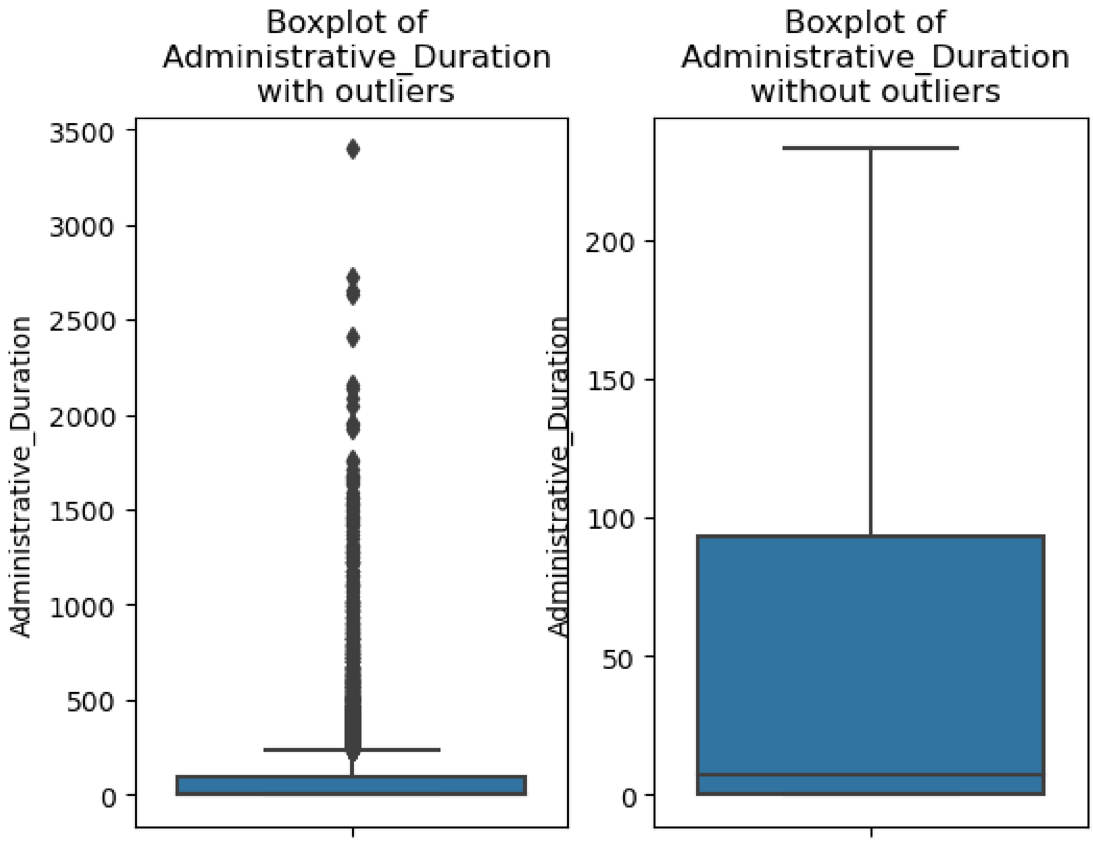

Distribution of the feature PageValues
35000
30000
25000
20000
15000
10000
5000
0
Count
0
50
100
150
200
250
300
350
PageValues

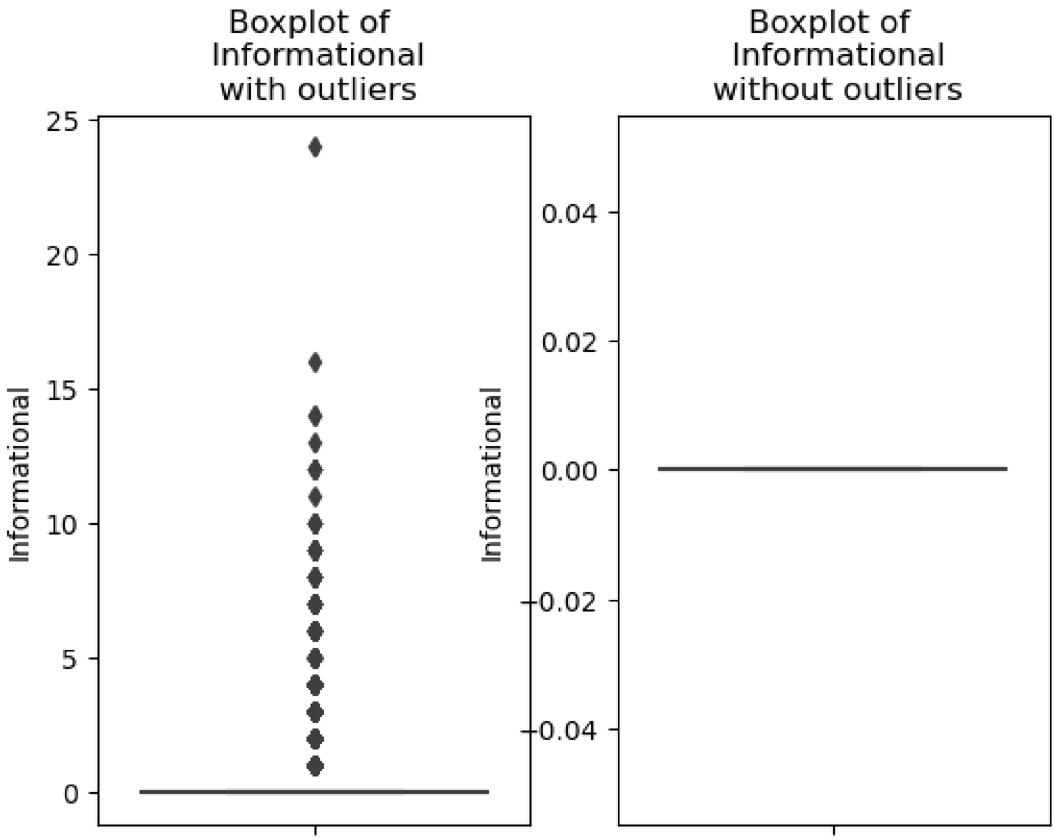


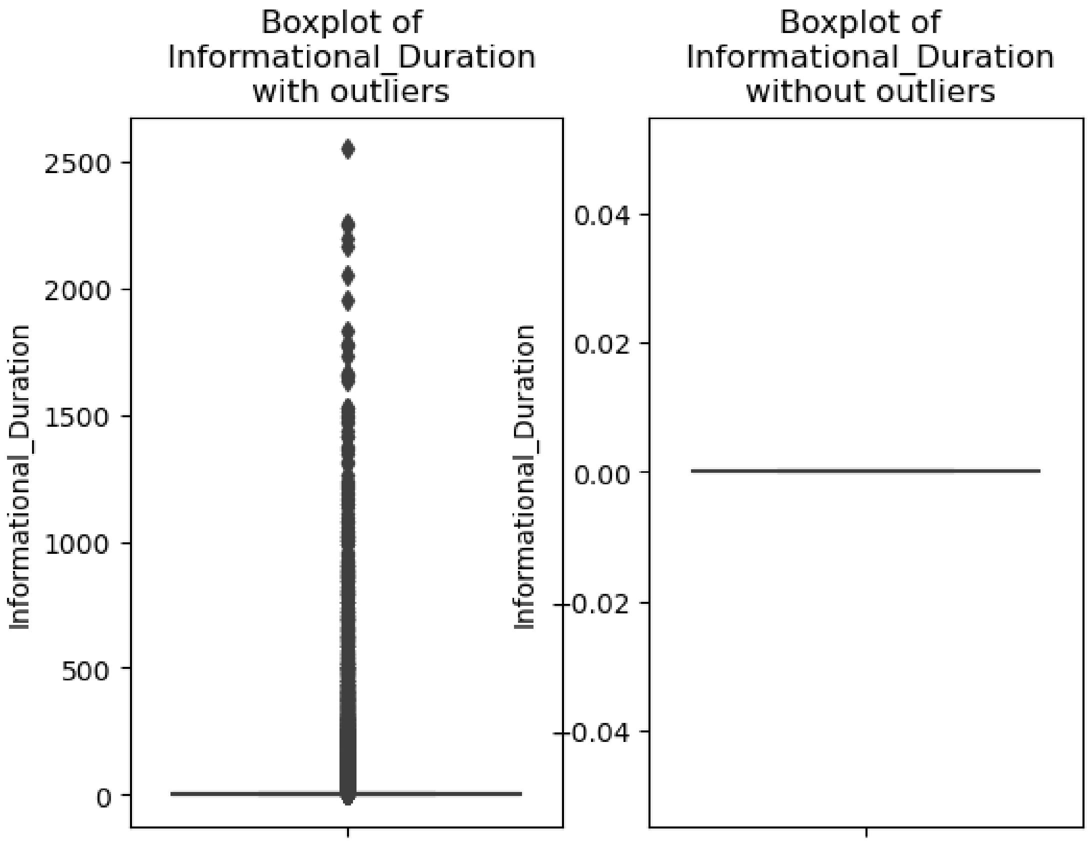

[21]:

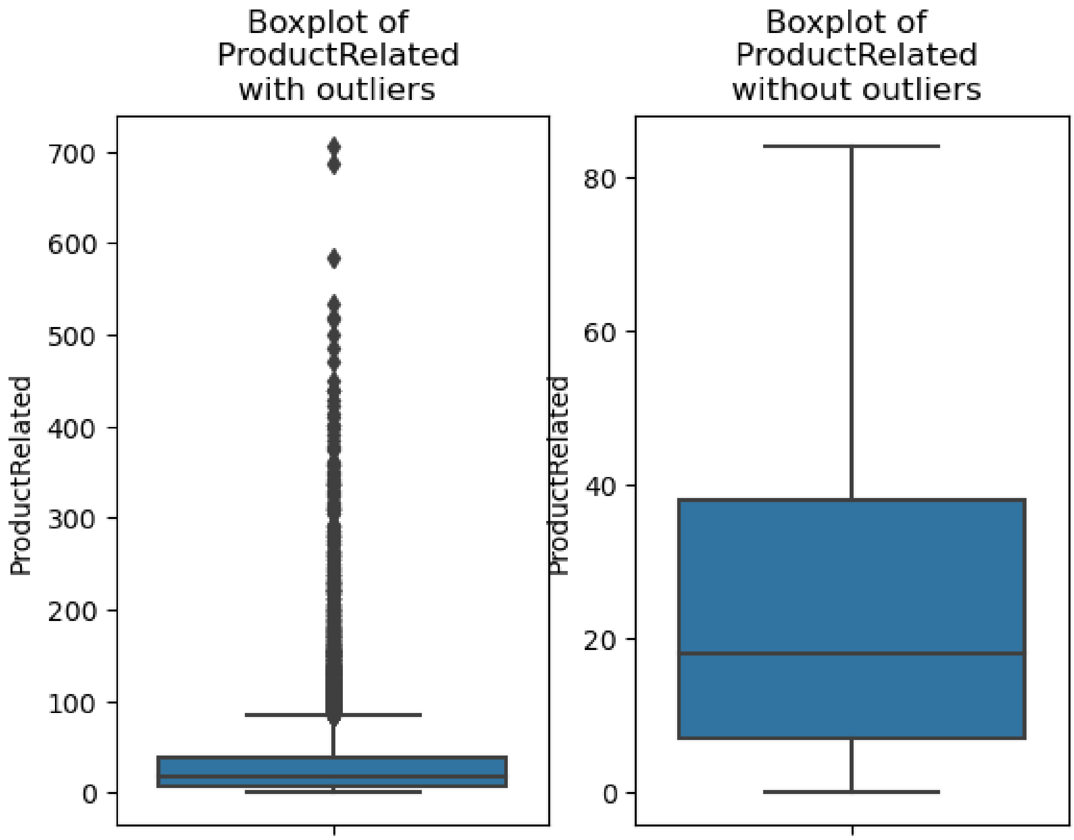
```
#plot the boxplot of the numerical variables to study their distribution
for k in numerical:
    plt.subplot(1, 2, 1)
    sns.boxplot(y=rev[k], orient = 'v' ) # create the boxplot
    plt.title('Boxplot of \n ' + k + '\n with outliers') # change the title
    plt.subplot(1, 2, 2)
    sns.boxplot(y=rev[k], showfliers=False, orient = 'v') # create the boxplot
    plt.title('Boxplot of \n ' + k + '\n without outliers') # change the title
    plt.show() # plot the histogram
```

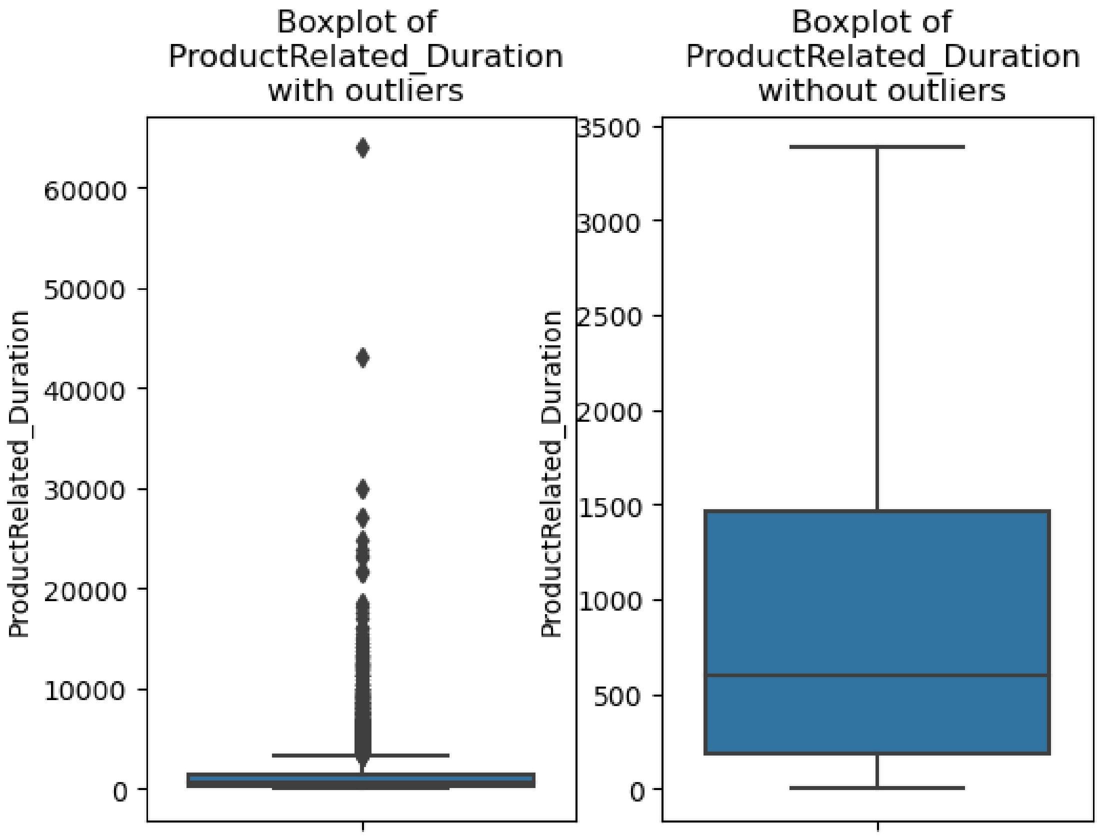

Boxplot of Administrative with outliers
Administrative
0
5
10
15
20
25
Boxplot of Administrative without outliers
Administrative
0
2
4
6
8
10

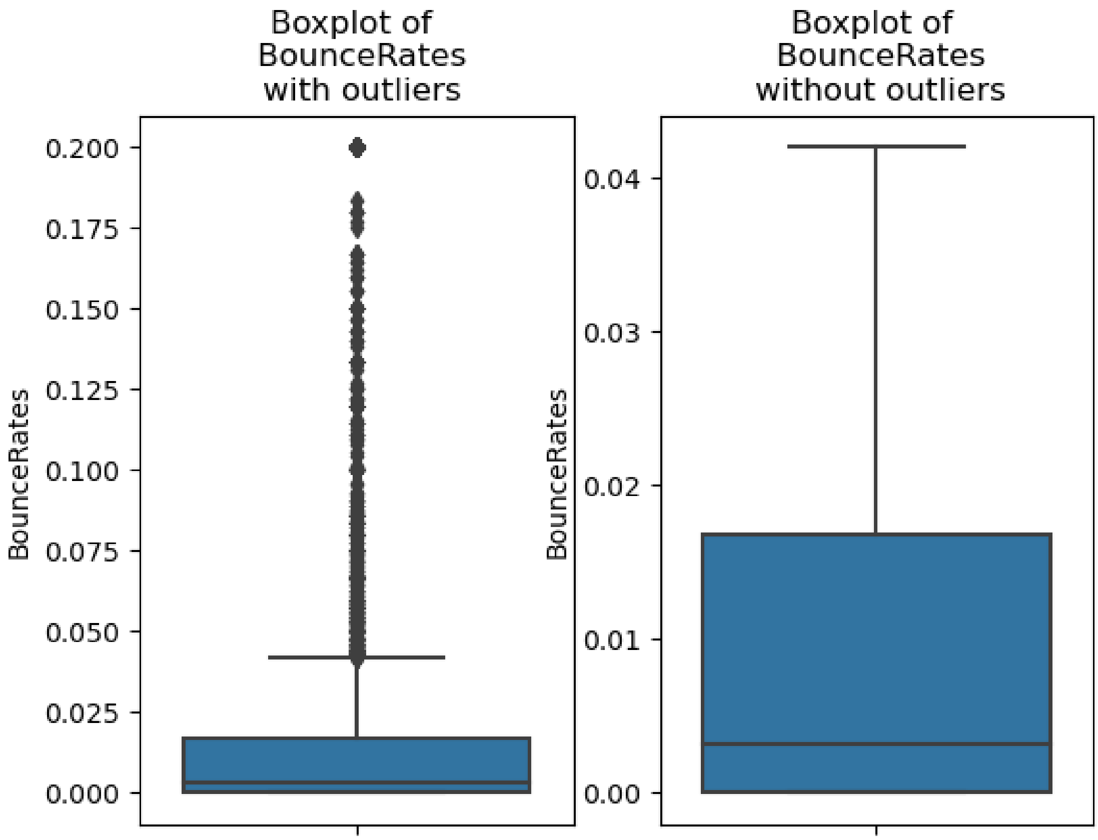

Boxplot of
Administrative_Duration
with outliers
Administrative_Duration
3500
3000
2500
2000
1500
1000
500
0
Boxplot of
Administrative_Duration
without outliers
Administrative_Duration
200
150
100
50
0

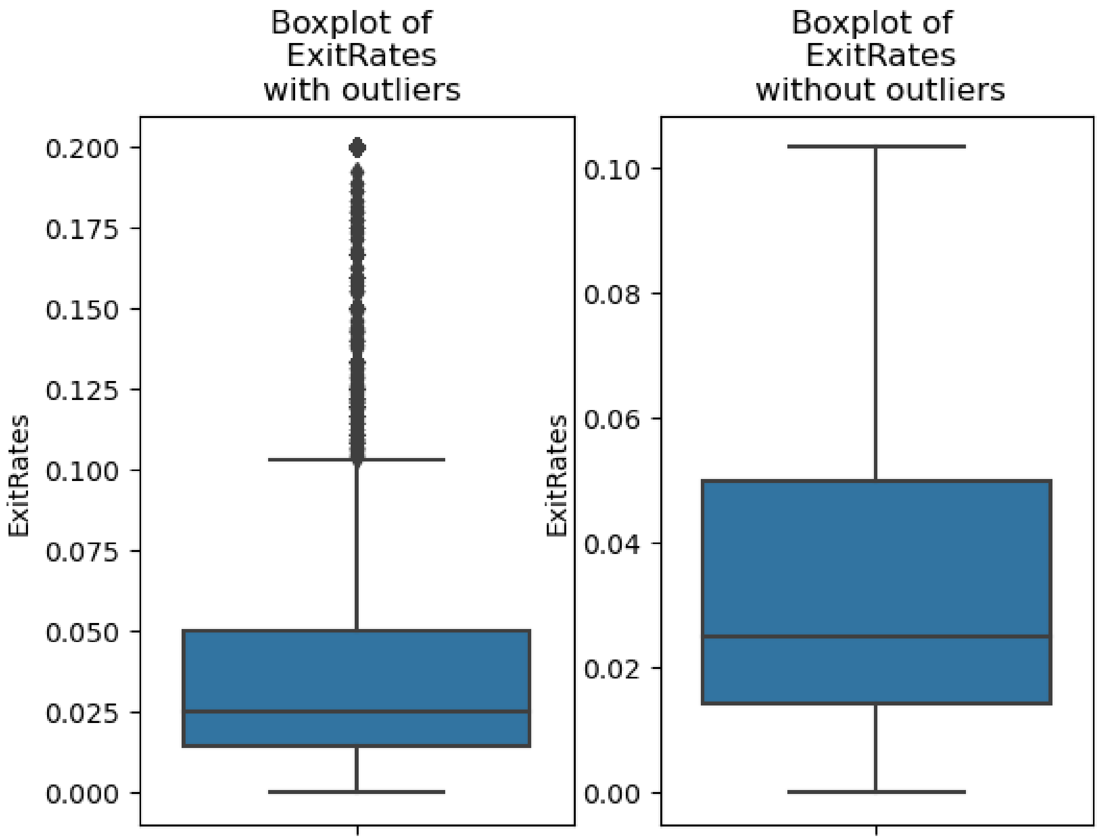

Boxplot of Informational with outliers
Boxplot of Informational without outliers
Informational
Informational
25
20
15
10
5
0
0.04
0.02
0.00
−0.02
−0.04

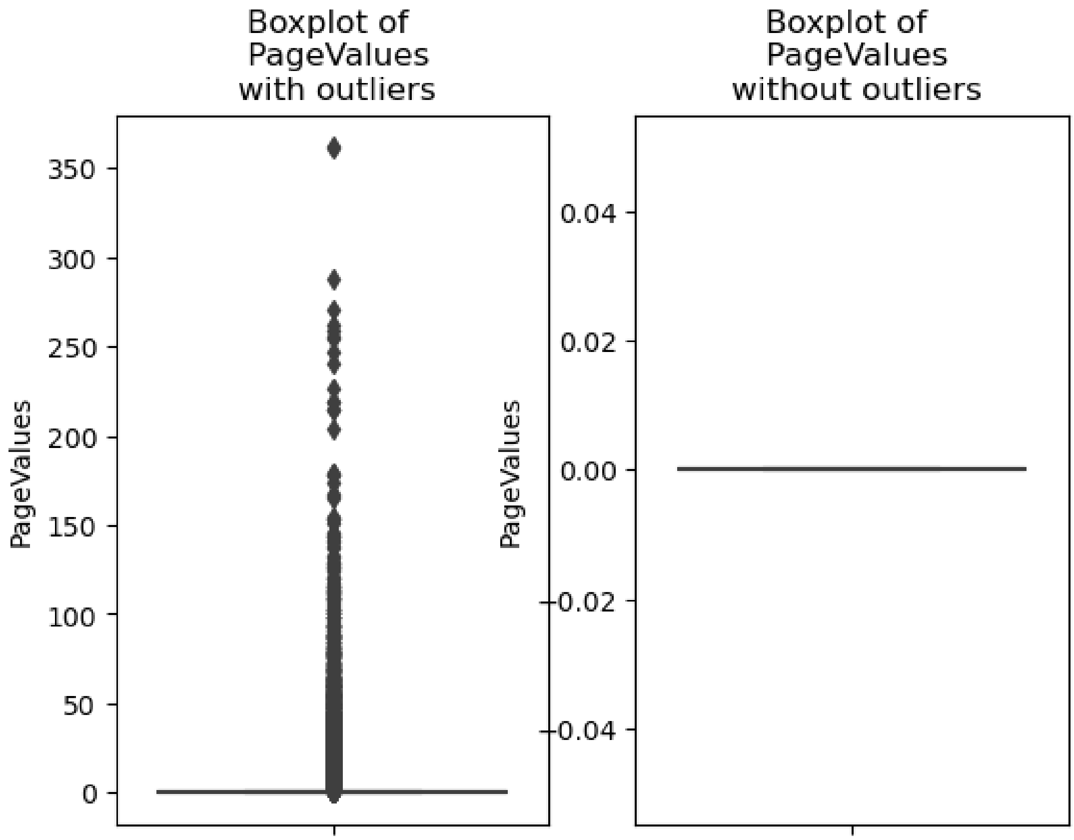

Boxplot of Informational_Duration with outliers
2500
2000
1500
1000
500
0
Informational_Duration
Boxplot of Informational_Duration without outliers
0.04
0.02
0.00
−0.02
−0.04
Informational_Duration

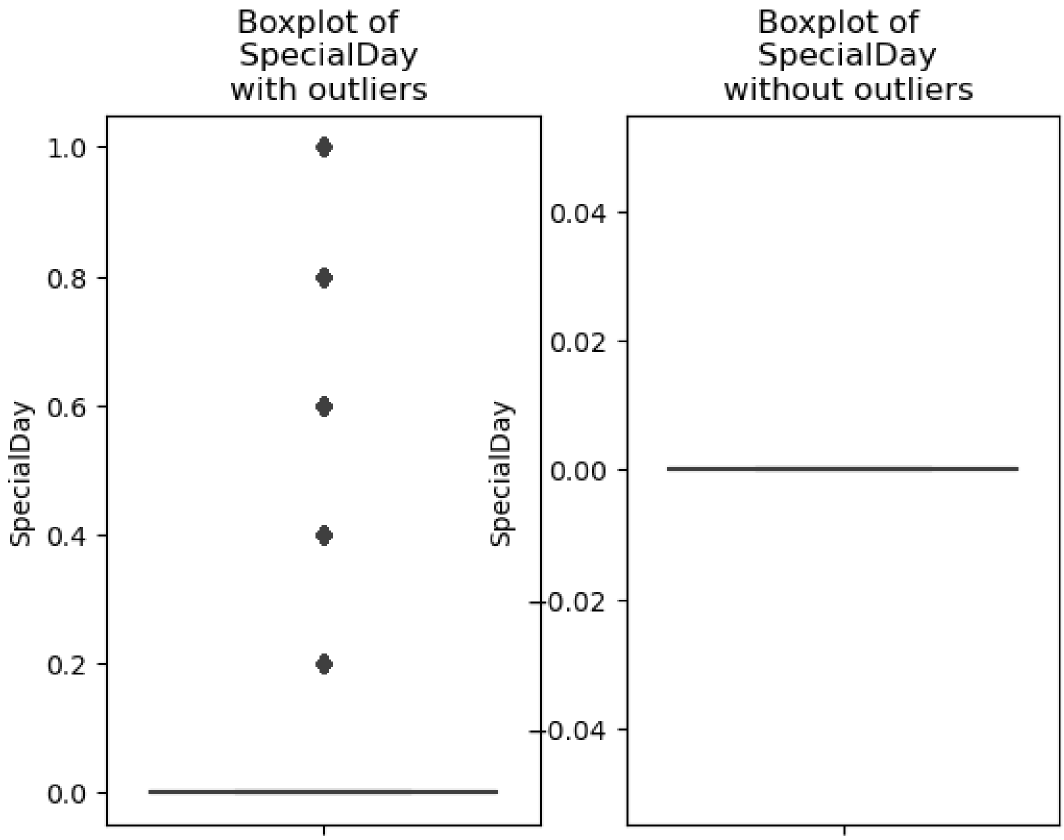

Boxplot of
ProductRelated
with outliers
Boxplot of
ProductRelated
without outliers
ProductRelated
ProductRelated
0
100
200
300
400
500
600
700
0
20
40
60
80


Boxplot of
ProductRelated_Duration
with outliers
ProductRelated_Duration
60000
50000
40000
30000
20000
10000
0
Boxplot of
ProductRelated_Duration
without outliers
ProductRelated_Duration
3500
3000
2500
2000
1500
1000
500
0

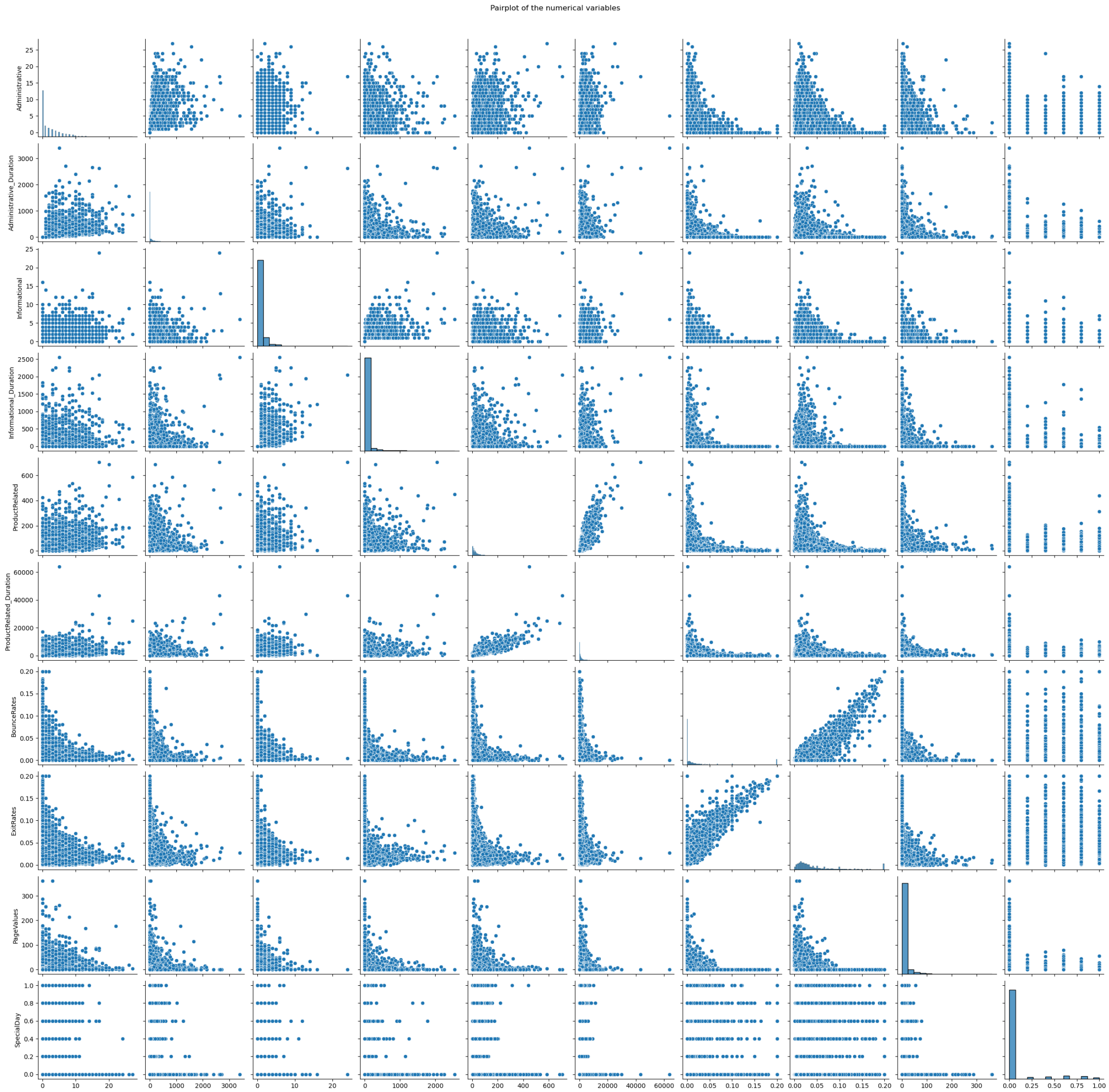

Boxplot of
BounceRates
with outliers
Boxplot of
BounceRates
without outliers
BounceRates
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
BounceRates
0.04
0.03
0.02
0.01
0.00


Boxplot of
ExitRates
with outliers
Boxplot of
ExitRates
without outliers
ExitRates
ExitRates
0.200
0.175
0.150
0.125
0.100
0.075
0.050
0.025
0.000
0.10
0.08
0.06
0.04
0.02
0.00


Boxplot of
PageValues
with outliers
350
300
250
200
150
100
50
0
PageValues
Boxplot of
PageValues
without outliers
0.04
0.02
0.00
−0.02
−0.04
PageValues




[22]:
```
pair = sns.pairplot(rev[numerical])
pair. fig . subplots_adjust (top= .95 )
pair.fig.suptitle('Pairplot of the numerical variables')
plt.show()
```



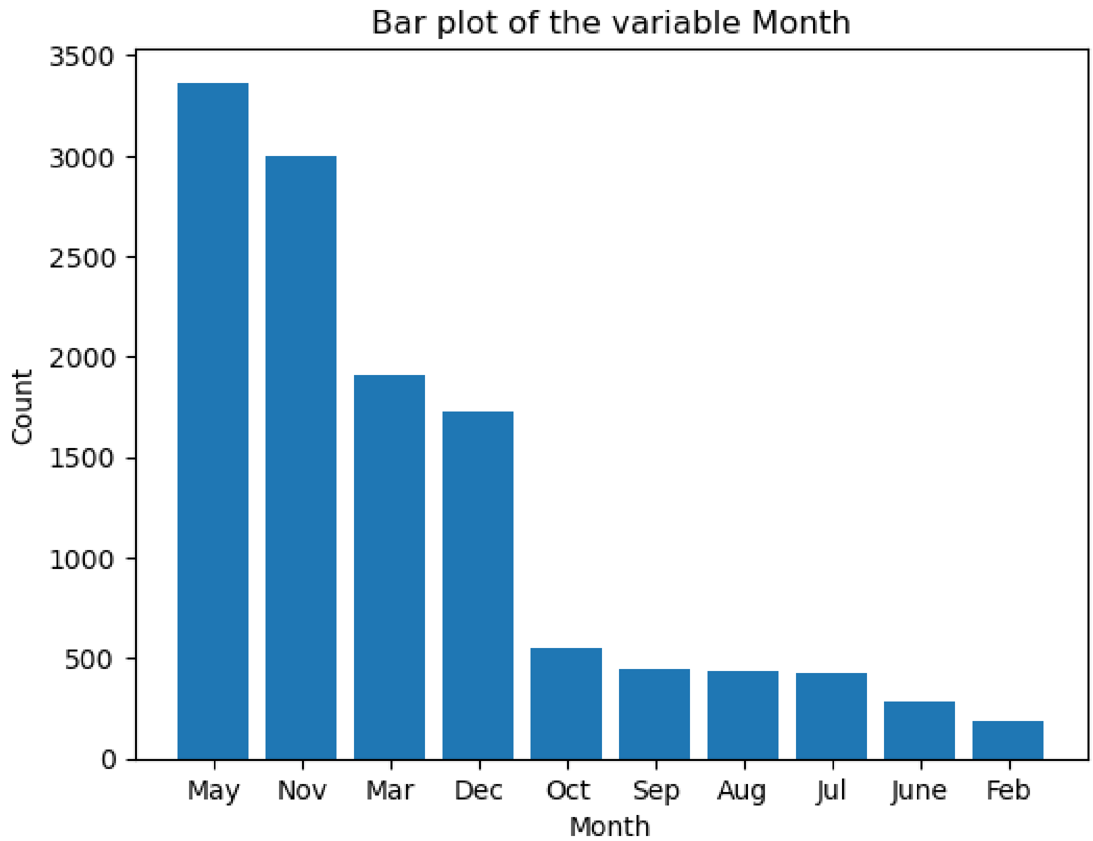

No-one of the numerical variables have a gaussian distribution.

## 3.2 Analyze categorical variables

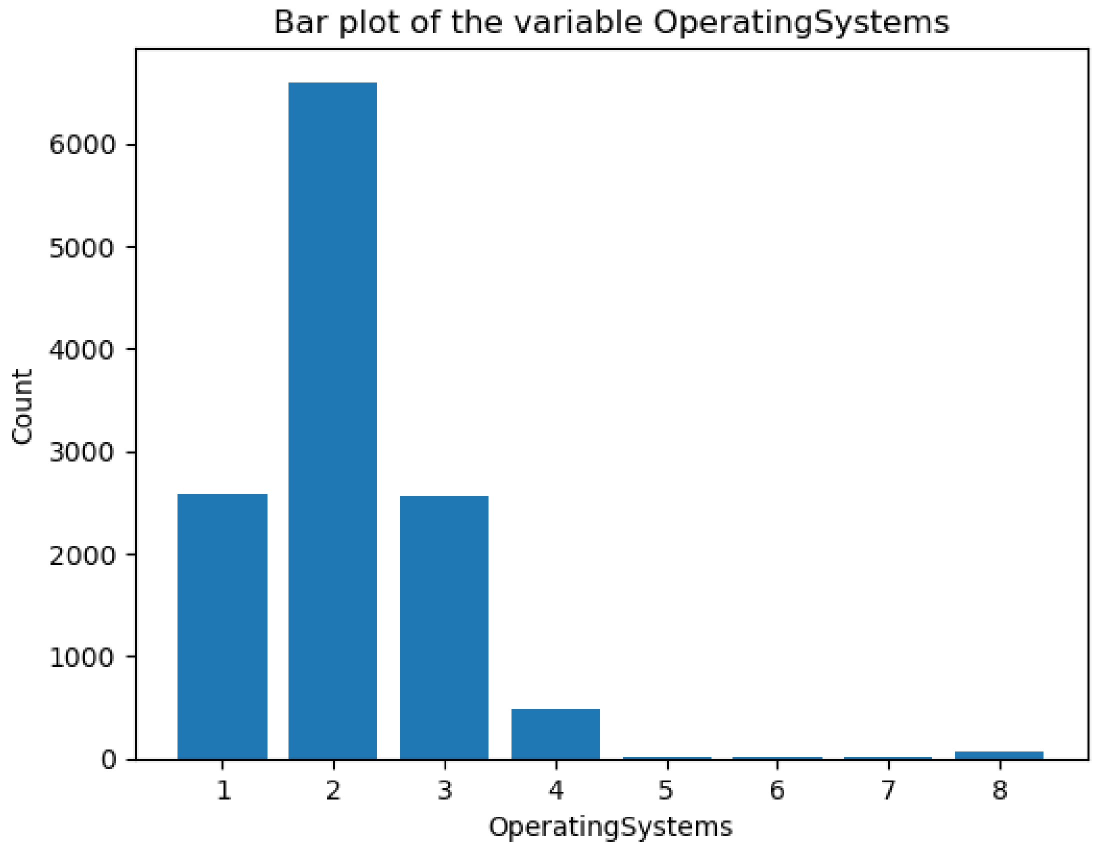
Next categorical variables will be represented by using plot bar charts and pie charts.

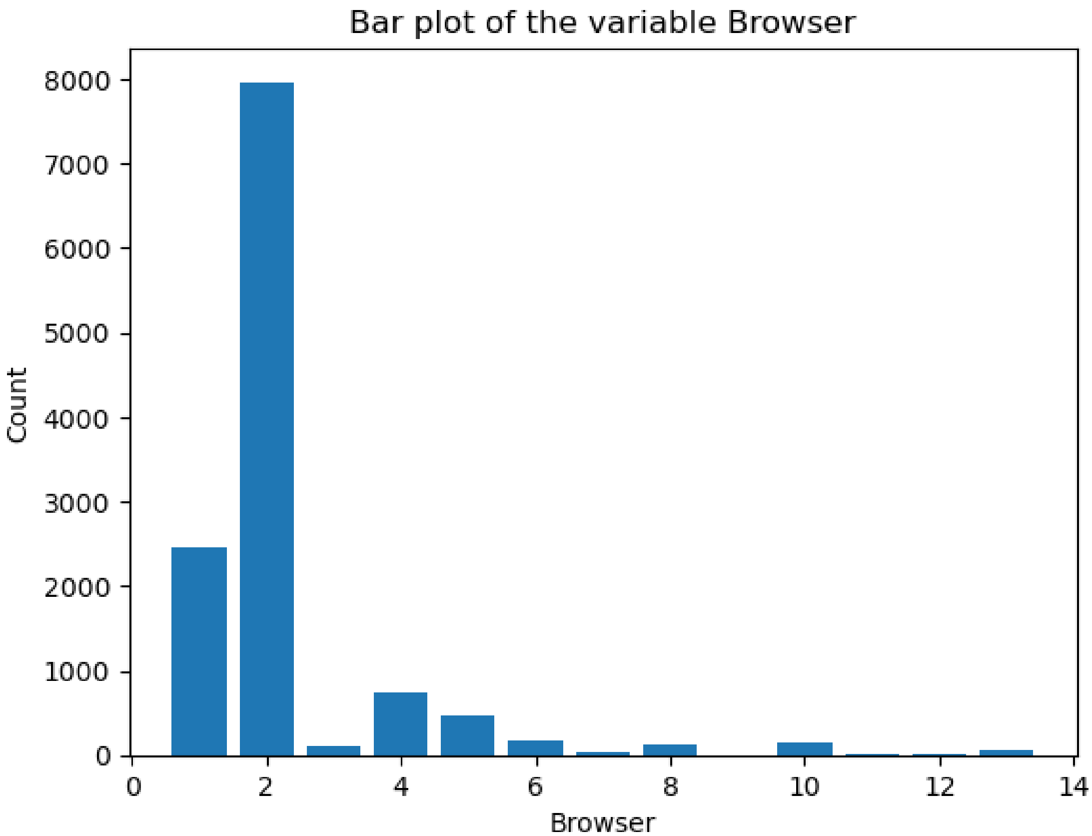
[23]:
```
#now use the barplot to show the distribution of categorical variables

for k in categorical:
    cut_counts = rev[k].value_counts()# count the repetitions of each class
    fig = plt.bar(x = cut_counts.index, height=cut_counts.values)
    plt.title( 'Bar plot of the variable ' + k )
    plt.xlabel(k)
    plt.ylabel('Count')
```

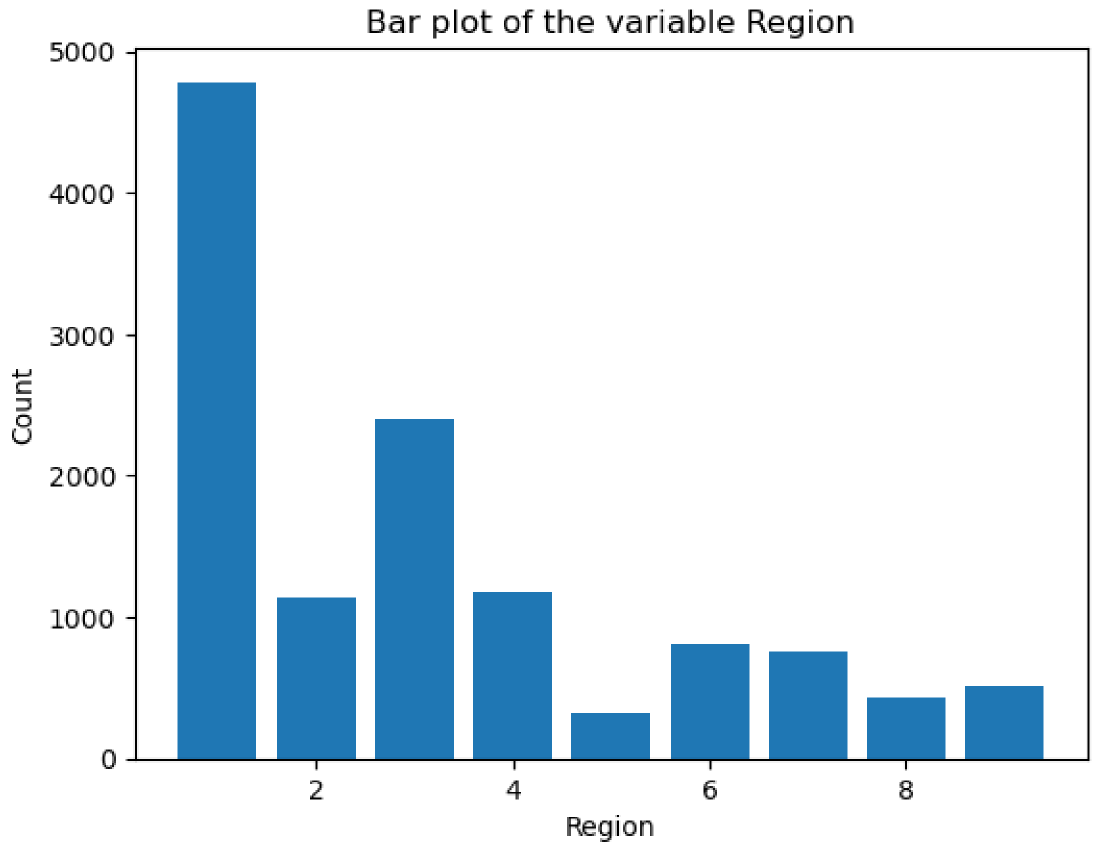
```
plt.show()
```

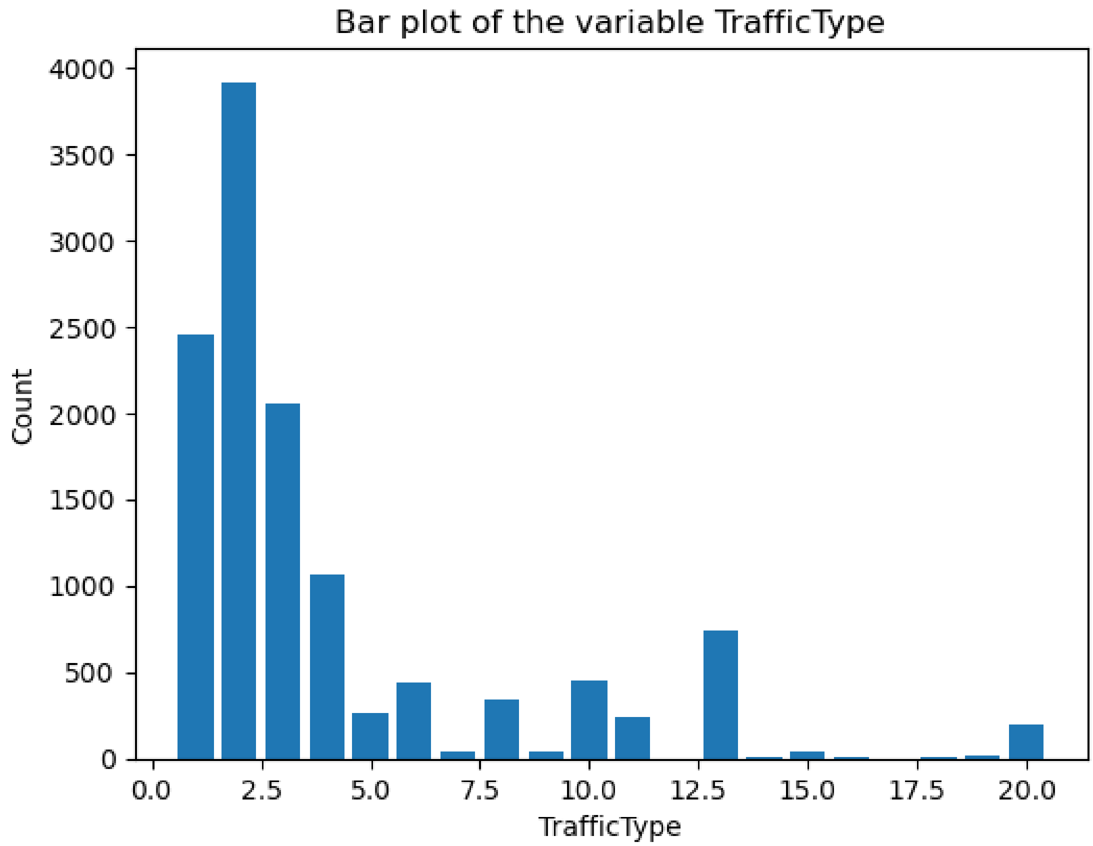


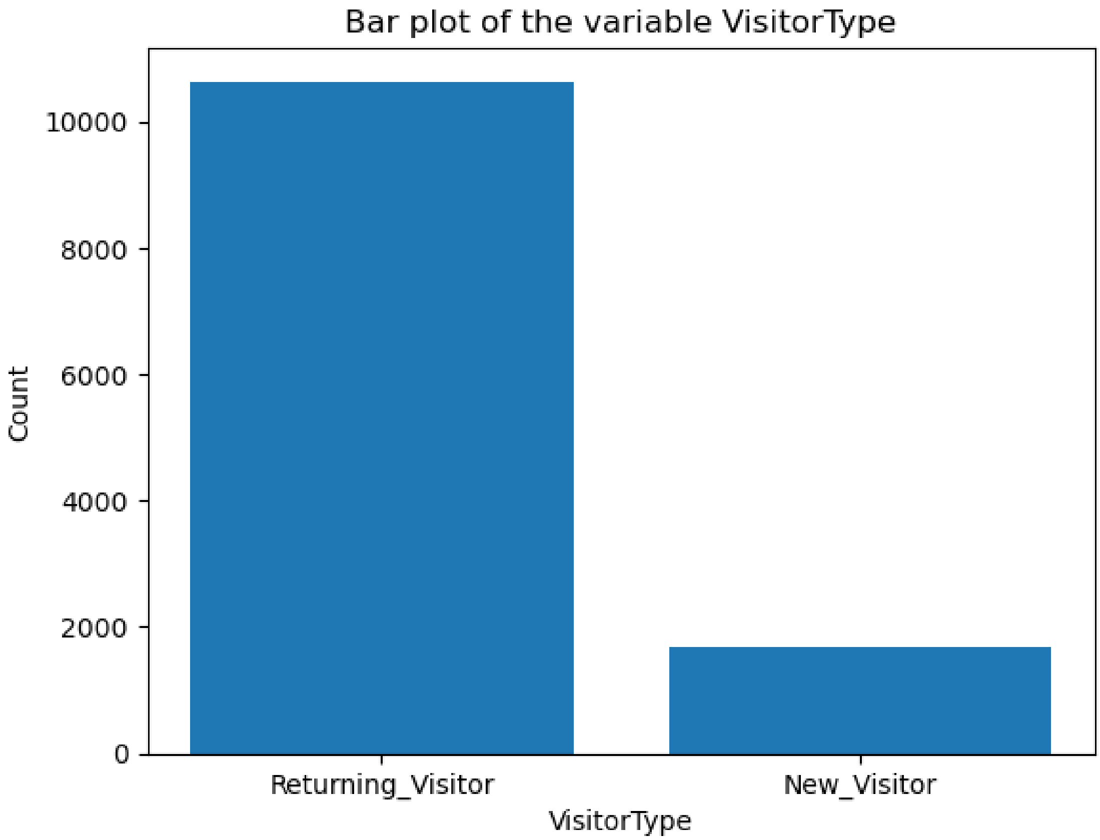
Bar plot of the variable Month
Count
3500
3000
2500
2000
1500
1000
500
0
May
Nov
Mar
Dec
Oct
Sep
Aug
Jul
June
Feb
Month

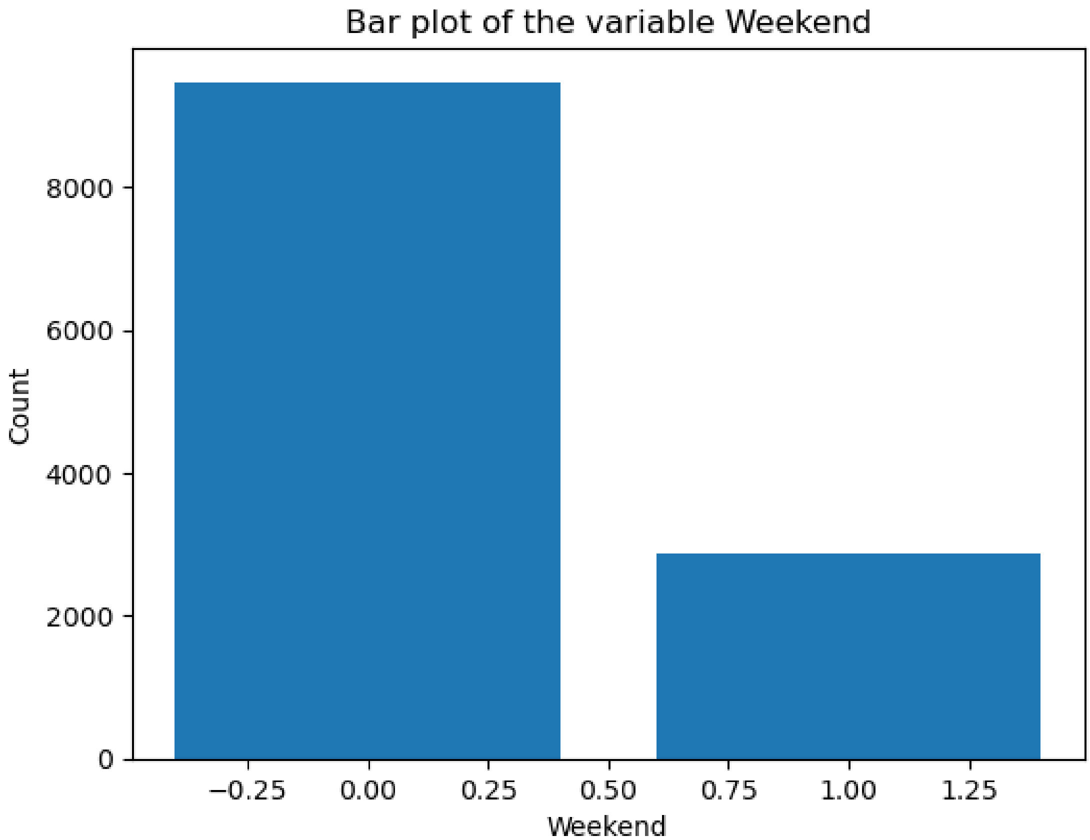

Bar plot of the variable OperatingSystems
Count
6000
5000
4000
3000
2000
1000
0
1
2
3
4
5
6
7
8
OperatingSystems


Bar plot of the variable Browser
Count
8000
7000
6000
5000
4000
3000
2000
1000
0
0
2
4
6
8
10
12
14
Browser

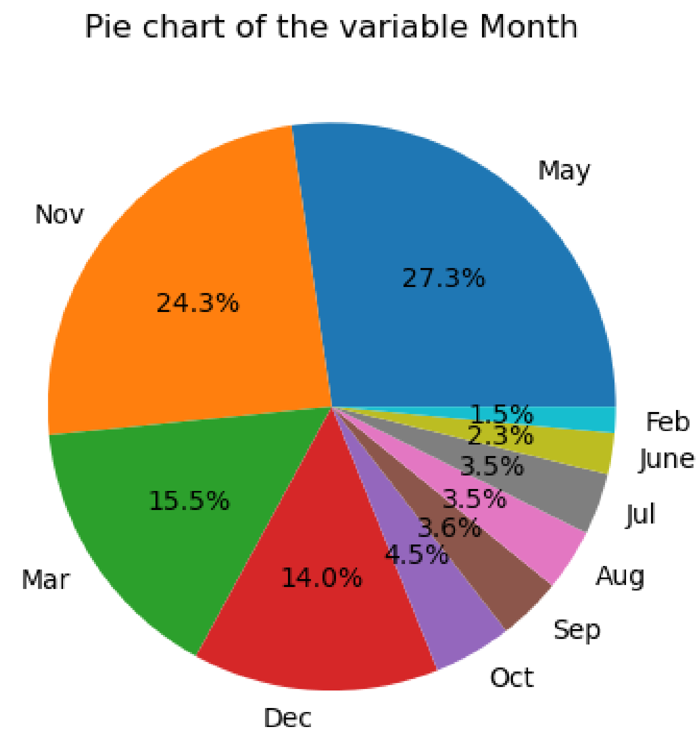

Bar plot of the variable Region
5000
4000
3000
2000
1000
0
Count
2
4
6
8
Region

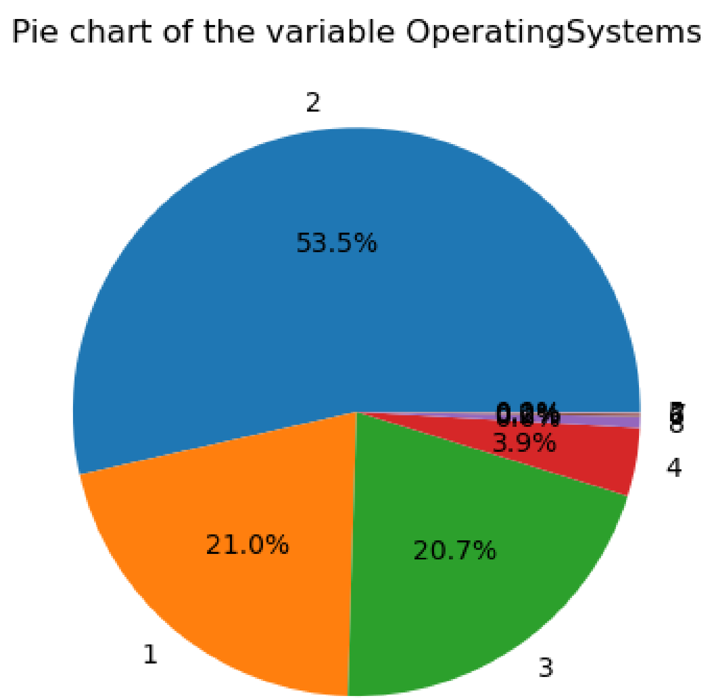

Bar plot of the variable TrafficType
Count
4000
3500
3000
2500
2000
1500
1000
500
0
0.0
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
TrafficType

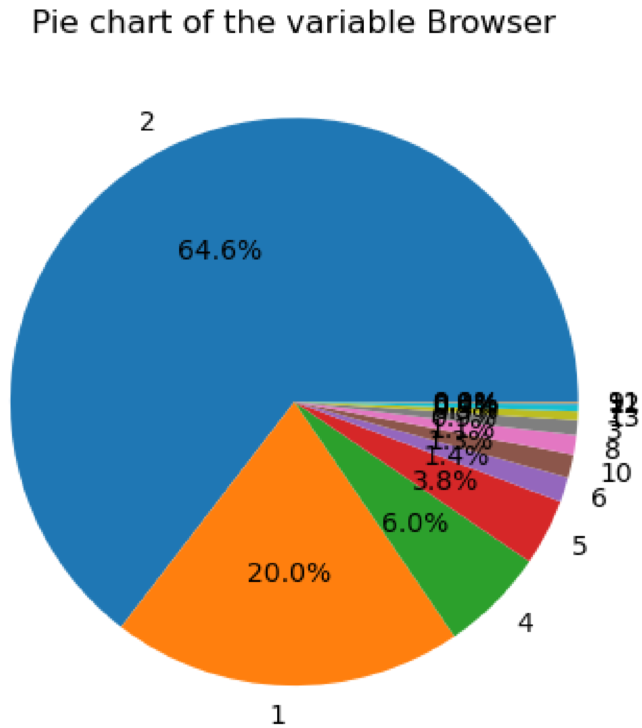

Bar plot of the variable VisitorType
10000
8000
6000
4000
2000
0
Count
Returning_Visitor
New_Visitor
VisitorType



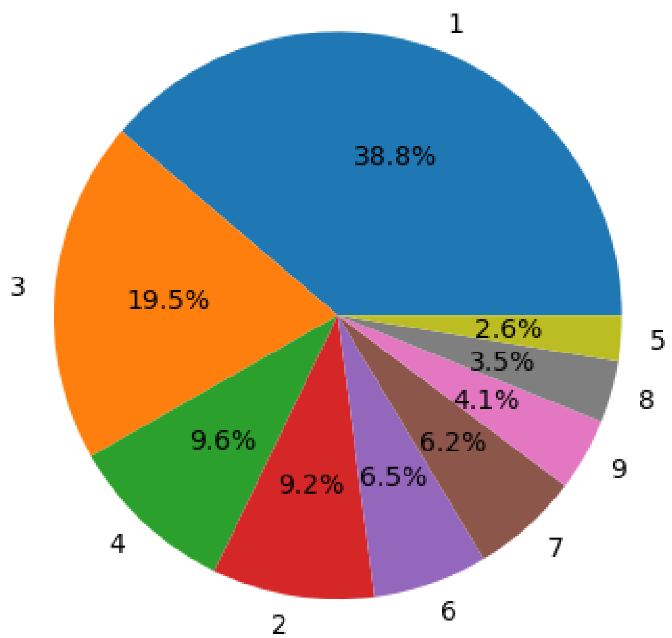

[24]:
```
#now use the pie charts to show the distribution of categorical variables

for k in categorical:
    cut_counts = rev[k].value_counts()# count the repetitions of each class

    plt.pie( cut_counts.values, labels = cut_counts.index, autopct='%1.1f%%')#␣
 ↪plot the pie charts to indicate the number of repetitiones of each class
    plt.title( 'Pie chart of the variable ' + k )
    plt.show()
```


Pie chart of the variable Month
May
27.3%
Nov
24.3%
Mar
15.5%
Dec
14.0%
Oct
4.5%
Sep
3.6%
Aug
3.5%
Jul
3.5%
June
2.3%
Feb
1.5%

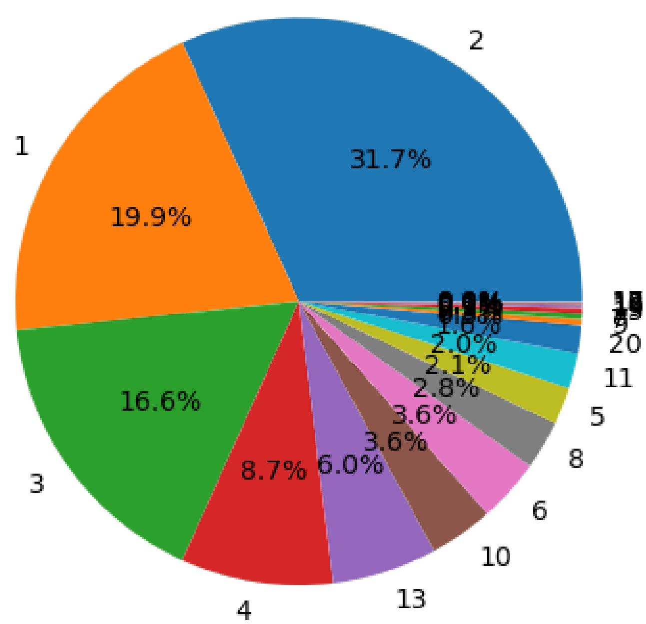

Pie chart of the variable OperatingSystems
2
53.5%
1
21.0%
3
20.7%
4
3.9%

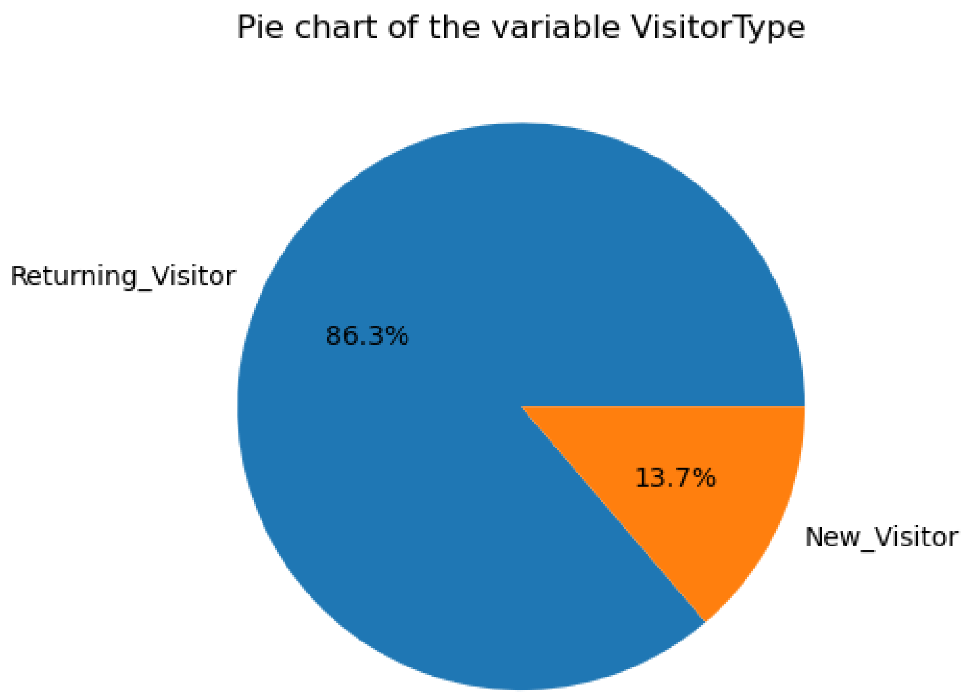

Pie chart of the variable Browser
2
64.6%
1
20.0%
4
6.0%
5
3.8%
6
1.4%
10
8
3
13

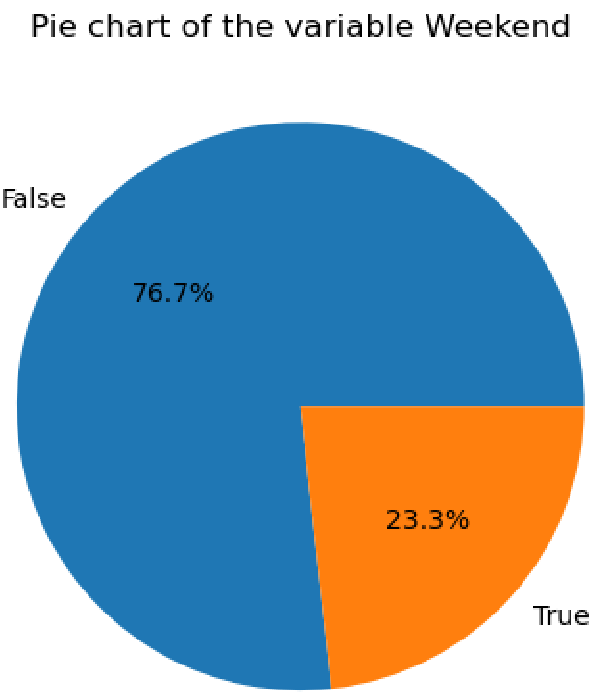
Pie chart of the variable Region




Pie chart of the variable TrafficType



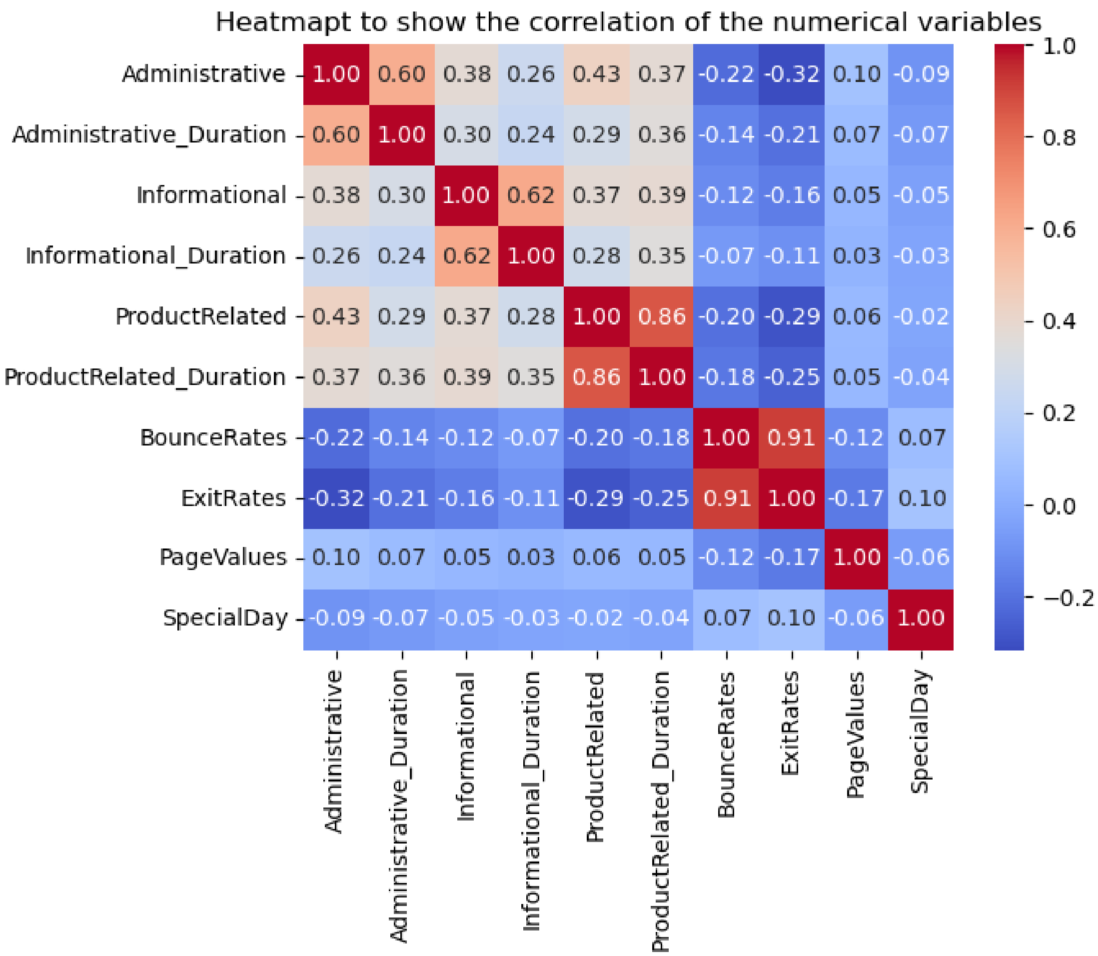

Pie chart of the variable VisitorType
Returning_Visitor
86.3%
13.7%
New_Visitor




### 3.3 Correlation analysis

Finally, i will study the correlation between the numerical variables using a a heatmap of the correlation matrix.

[25]:
```
# I am going to see the correlation matrix between the variables

corrmat_new = rev[numerical].corr()# create the correlation matrix
#print the headmap of the group which have been made

ax = plt.axes()
heat = sns.heatmap(corrmat_new, annot=True, cmap='coolwarm', fmt='.2f', ax = ax)
ax.set_title('Heatmapt to show the correlation of the numerical variables')
plt.show()
```




Due to the heatmap we can say that:

1. The time spent onadministrative/informational pages and the number of pages visited of type administrative/informational have a correlation near to 0,6.
2. The time spent on product related pages and the number of pages visited of type product related have a correlation of 0,86.
3. The correlation between BounceRates and ExitRates is of 0,91.
4. The rest of correlation is not up to 0,5.

# 4 Feature Engineering

## 4.1 Create new features

Now i will create a new variable in which the variable VisitorType will be transform into binary.

[26]:
```
# create a new variable VisitorType_New which convert VisitorType in a binary␣
↪variable
rev_fin["VisitorType_New"] = rev["VisitorType"].replace({'Returning_Visitor': 1,␣
↪'New_Visitor': 0}, regex=True)
rev_fin
```

## 4.2 Tarjet variable creation

Also i will transform Revenue in a categorical variable.

[27]:
```
# convert Revenue in a binary variable
label_encoder = LabelEncoder()# create the label encoder

rev_fin["Revenue"] = label_encoder.fit_transform(rev_fin["Revenue"]) #transform␣
↪Revenue

rev_fin
```

[27]:
```
       Administrative  Administrative_Duration  Informational  \
0            0.000000                 0.000000            0.0
1            0.000000                 0.000000            0.0
2            0.000000                 0.000000            0.0
3            0.000000                 0.000000            0.0
4            0.000000                 0.000000            0.0
...               ...                      ...            ...
12325        0.111111                 0.042663            0.0
12326        0.000000                 0.000000            0.0
12327        0.000000                 0.000000            0.0
12328        0.148148                 0.022067            0.0
12329        0.000000                 0.000000            0.0

       Informational_Duration  ProductRelated  ProductRelated_Duration  \
0                         0.0        0.001418                 0.000000
1                         0.0        0.002837                 0.001000
2                         0.0        0.001418                 0.000000
3                         0.0        0.002837                 0.000042
4                         0.0        0.014184                 0.009809
...                       ...             ...                      ...
12325                     0.0        0.075177                 0.027883
12326                     0.0        0.007092                 0.007280
12327                     0.0        0.008511                 0.002880
12328                     0.0        0.021277                 0.005408
12329                     0.0        0.004255                 0.000332

       BounceRates  ExitRates  PageValues  SpecialDay  Month  Revenue  \
0         1.000000   1.000000    0.000000         0.0      2        0
1         0.000000   0.500000    0.000000         0.0      2        0
```

```
2        1.000000  1.000000   0.000000        0.0      2        0
3        0.250000  0.700000   0.000000        0.0      2        0
4        0.100000  0.250000   0.000000        0.0      2        0
...           ...       ...        ...        ...    ...      ...
12325    0.035714  0.145153   0.033839        0.0      1        0
12326    0.000000  0.106667   0.000000        0.0      7        0
12327    0.416667  0.433333   0.000000        0.0      7        0
12328    0.000000  0.105263   0.000000        0.0      7        0
12329    0.000000  0.333333   0.000000        0.0      7        0

       Browser_1  Browser_2  Browser_3  Browser_4  Browser_5  Browser_6  \
0            1.0        0.0        0.0        0.0        0.0        0.0
1            0.0        1.0        0.0        0.0        0.0        0.0
2            1.0        0.0        0.0        0.0        0.0        0.0
3            0.0        1.0        0.0        0.0        0.0        0.0
4            0.0        0.0        1.0        0.0        0.0        0.0
...          ...        ...        ...        ...        ...        ...
12325        0.0        0.0        0.0        0.0        0.0        1.0
12326        0.0        1.0        0.0        0.0        0.0        0.0
12327        0.0        1.0        0.0        0.0        0.0        0.0
12328        0.0        1.0        0.0        0.0        0.0        0.0
12329        0.0        1.0        0.0        0.0        0.0        0.0

       Browser_7  Browser_8  Browser_9  Browser_10  Browser_11  Browser_12  \
0            0.0        0.0        0.0         0.0         0.0         0.0
1            0.0        0.0        0.0         0.0         0.0         0.0
2            0.0        0.0        0.0         0.0         0.0         0.0
3            0.0        0.0        0.0         0.0         0.0         0.0
4            0.0        0.0        0.0         0.0         0.0         0.0
...          ...        ...        ...         ...         ...         ...
12325        0.0        0.0        0.0         0.0         0.0         0.0
12326        0.0        0.0        0.0         0.0         0.0         0.0
12327        0.0        0.0        0.0         0.0         0.0         0.0
12328        0.0        0.0        0.0         0.0         0.0         0.0
12329        0.0        0.0        0.0         0.0         0.0         0.0

       Browser_13  TrafficType_1  TrafficType_2  TrafficType_3  TrafficType_4  \
0             0.0            1.0            0.0            0.0            0.0
1             0.0            0.0            1.0            0.0            0.0
2             0.0            0.0            0.0            1.0            0.0
3             0.0            0.0            0.0            0.0            1.0
4             0.0            0.0            0.0            0.0            1.0
...           ...            ...            ...            ...            ...
12325         0.0            1.0            0.0            0.0            0.0
12326         0.0            0.0            0.0            0.0            0.0
12327         0.0            0.0            0.0            0.0            0.0
12328         0.0            0.0            0.0            0.0            0.0
```

```
12329          0.0            0.0            1.0            0.0            0.0

       TrafficType_5  TrafficType_6  TrafficType_7  TrafficType_8  \
0                0.0            0.0            0.0            0.0
1                0.0            0.0            0.0            0.0
2                0.0            0.0            0.0            0.0
3                0.0            0.0            0.0            0.0
4                0.0            0.0            0.0            0.0
...              ...            ...            ...            ...
12325            0.0            0.0            0.0            0.0
12326            0.0            0.0            0.0            1.0
12327            0.0            0.0            1.0            0.0
12328            0.0            0.0            0.0            0.0
12329            0.0            0.0            0.0            0.0

       TrafficType_9  TrafficType_10  TrafficType_11  TrafficType_12  \
0                0.0             0.0             0.0             0.0
1                0.0             0.0             0.0             0.0
2                0.0             0.0             0.0             0.0
3                0.0             0.0             0.0             0.0
4                0.0             0.0             0.0             0.0
...              ...             ...             ...             ...
12325            0.0             0.0             0.0             0.0
12326            0.0             0.0             0.0             0.0
12327            0.0             0.0             0.0             0.0
12328            0.0             0.0             1.0             0.0
12329            0.0             0.0             0.0             0.0

       TrafficType_13  TrafficType_14  TrafficType_15  TrafficType_16  \
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
...               ...             ...             ...             ...
12325             0.0             0.0             0.0             0.0
12326             0.0             0.0             0.0             0.0
12327             1.0             0.0             0.0             0.0
12328             0.0             0.0             0.0             0.0
12329             0.0             0.0             0.0             0.0

       TrafficType_17  TrafficType_18  TrafficType_19  TrafficType_20  \
0                 0.0             0.0             0.0             0.0
1                 0.0             0.0             0.0             0.0
2                 0.0             0.0             0.0             0.0
3                 0.0             0.0             0.0             0.0
4                 0.0             0.0             0.0             0.0
```

```
...                 ...          ...          ...          ...
12325               0.0          0.0          0.0          0.0
12326               0.0          0.0          0.0          0.0
12327               0.0          0.0          0.0          0.0
12328               0.0          0.0          0.0          0.0
12329               0.0          0.0          0.0          0.0

       Number pages   Total time  VisitorType_New
0                 1     0.000000                1
1                 2    64.000000                1
2                 1     0.000000                1
3                 2     2.666667                1
4                10   627.500000                1
...             ...          ...              ...
12325            56  1928.791667                1
12326             5   465.750000                1
12327             6   184.250000                1
12328            19   421.000000                1
12329             3    21.250000                0

[12330 rows x 48 columns]
```

# 5 Train-Test Split

In this section i will split the data into training and testing sets.

[28]:
```
# I am going to split the dataset into training and testing sets
# first i separate the predictive variable Y and the predictors variables X
y= rev_fin['Revenue']
x = rev_fin.drop(['Revenue'], axis=1)
#create the training and testing sets using to create de testing set the 20% of␣
↪data
# use the parameter stratify = y to get stratified samples
x_train, x_test,y_train,y_test = train_test_split(x,y, test_size=0.2, stratify =␣
↪y, random_state=23)
```

Finally i have to see if both groups have a balance of both categories of Revenue.

[25]:
```
count_train = y_train.value_counts()
count_test = y_test.value_counts()
#calculate the percentage of purchase or non purchase in the test and train sets
print(count_train/sum(count_train.values))
print(count_test/sum(count_test.values))
```

```
0    0.845296
1    0.154704
Name: Revenue, dtype: float64
0    0.845093
```

```
1    0.154907
Name: Revenue, dtype: float64
```

Both groups are balanced so are good.

Stratified samples will not be used because there are many variables so it will mean many strates with few elements.

# 6 Model Development

In this section i will develop a example of the following models:

- Logistic Regression
- Random Forest
- Gradient Boosting

Secondly in each model i will use a Grid Search CV of the models to find the best hiperparameters of the corresponding model.

## 6.1 Logistic Regression

In the Logistic Regression i will find the hiperparameters penalty, C, solver and maximun of iterations.

[ ]:
```
# Grid of evaluated hiperparmeters
# ==============================================================================
param_grid_lr = [
    {'penalty':['l1','l2','elasticnet','none'],
    'C' : np.logspace(-4,4,9),
    'solver': ['lbfgs','newton-cg','liblinear','sag','saga'],
    'max_iter'  : [50, 100, 500, 1000]
}
]

# CV to grid search
# ==============================================================================
grid_lr = GridSearchCV(
        estimator  = LogisticRegression(random_state=123),
        param_grid = param_grid_lr,
        scoring    = 'accuracy',
        n_jobs     = multiprocessing.cpu_count() - 1,
        cv         = RepeatedKFold(n_splits=3, n_repeats=1, random_state=123),
        refit      = True,
        verbose    = True,
        return_train_score = True
       )

grid_lr.fit(X = x_train, y = y_train)
```

```
# Results
# ==============================================================================
result_lr = pd.DataFrame(grid_lr.cv_results_)
result_lr.filter(regex = '(param*|mean_t|std_t)') \
    .drop(columns = 'params') \
    .sort_values('mean_test_score', ascending = False) \
    .head(4)
```

Here the best hiperparameters of the Logistic Regression model can be seen.

[ ]:
```
#Best parameters
# ==============================================================================
print("----------------------------------------")
print("Best parameters found (cv)")
print("----------------------------------------")
print(grid_lr.best_params_, ":", grid_lr.best_score_, grid_lr.scoring)
```

I make the model with the best hiperparameters and save it using a joblib.

[ ]:
```
mod_lr_fin = grid_lr.best_estimator_
mod_lr_fin
```

[26]:
```
joblib.dump(mod_lr_fin, 'my_model_lr.pkl.pkl')
```

[2]:
```
lr_load = joblib.load('my_model_lr.pkl.pkl')
lr_load
```

[2]:
```
LogisticRegression(C=10.0, max_iter=50, penalty='l1', random_state=123,
                   solver='liblinear')
```

### 6.2 Random Forest

In the Random Forest i will find the hiperparameters bootstrap, maximun depth, maximun features, minimun of samples of each leaf, minimun of samples of each split and number of estimators.

[ ]:
```
# Grid of  evaluated parameters
# ==============================================================================
param_grid_rf = {
    'bootstrap': [True],
    'max_depth': [80, 90, 100, 110],
    'max_features': [2, 3],
    'min_samples_leaf': [3, 4, 5],
    'min_samples_split': [8, 10, 12],
    'n_estimators': [50, 100, 500, 1000]
}
#

# CV to grid search
```

```
# ==============================================================================
grid_rf = GridSearchCV(
        estimator  = RandomForestClassifier(random_state=123),
        param_grid = param_grid_rf,
        scoring    = 'accuracy',
        n_jobs     = multiprocessing.cpu_count() - 1,
        cv         = RepeatedKFold(n_splits=3, n_repeats=1, random_state=123),
        refit      = True,
        verbose    = 0,
        return_train_score = True
       )

grid_rf.fit(X = x_train, y = y_train)

# Results
# ==============================================================================
resultados = pd.DataFrame(grid_rf.cv_results_)
resultados.filter(regex = '(param*|mean_t|std_t)') \
    .drop(columns = 'params') \
    .sort_values('mean_test_score', ascending = False) \
    .head(4)
```

As in the Logistic model i will show the hiperparameters, create the best model and save it.

[ ]:
```
# Best parameters
# ==============================================================================
print("----------------------------------------")
print("Best parameters found (cv)")
print("----------------------------------------")
print(grid_rf.best_params_, ":", grid_rf.best_score_, grid_rf.scoring)
```

[ ]:
```
mod_rf_fin = grid_rf.best_estimator_
mod_rf_fin
```

[ ]:
```
joblib.dump(mod_rf_fin, 'my_model_rf.pkl.pkl')
```

[3]:
```
rf_load = joblib.load('my_model_rf.pkl.pkl')
rf_load
```

[3]:
```
RandomForestClassifier(max_depth=80, max_features=3, min_samples_leaf=3,
                       min_samples_split=8, n_estimators=1000,
                       random_state=123)
```

### 6.3 Gradient Boosting

The hiperparameters which will be studied in the Gradient Boosting model are maximun number of iterations, maximun depth and learning rate.

```
[ ]: # Grid of evaluated parameters
# ==============================================================================
param_grid_gbc = {
    'max_iter'      : [50, 100, 500, 1000],
    'max_depth'     : [3, 5, 10, 20],
    'learning_rate' : [0.001, 0.01, 0.1]
}

# CV to grid search
# ==============================================================================
grid_gbc = GridSearchCV(
        estimator  = HistGradientBoostingClassifier(random_state=123),
        param_grid = param_grid_gbc,
        scoring    = 'accuracy',
        n_jobs     = multiprocessing.cpu_count() - 1,
        cv         = RepeatedKFold(n_splits=3, n_repeats=1, random_state=123),
        refit      = True,
        verbose    = 0,
        return_train_score = True
       )

grid_gbc.fit(X = x_train, y = y_train)

# Results
# ==============================================================================
result_gbc = pd.DataFrame(grid_gbc.cv_results_)
result_gbc.filter(regex = '(param*|mean_t|std_t)') \
    .drop(columns = 'params') \
    .sort_values('mean_test_score', ascending = False) \
    .head(4)
```

Once i have made the GridSearchCV, i print the best hiperparameters, make the best model and save it.

```
[ ]: # Best parameters
# ==============================================================================
print("----------------------------------------")
print("Best parameters found(cv)")
print("----------------------------------------")
print(grid_gbc.best_params_, ":", grid_gbc.best_score_, grid_gbc.scoring)
```

```
----------------------------------------
Mejores hiperparámetros encontrados (cv)
----------------------------------------
<bound method BaseEstimator.get_params of
HistGradientBoostingClassifier(learning_rate=0.01, max_depth=3, max_iter=1000,
                               random_state=123)> : grid_gbc.best_score_,
grid_gbc.scoring
```

[ ]:
```
mod_ran_fin = grid_gbc.best_estimator_
mod_ran_fin
```

[ ]:
```
joblib.dump(mod_ran_fin, 'my_model_ran.pkl.pkl')
```

[2]:
```
ran_load = joblib.load('my_model_ran.pkl.pkl')
ran_load
```

[2]:
```
HistGradientBoostingClassifier(learning_rate=0.01, max_depth=3, max_iter=1000,
                               random_state=123)
```

# 7 Model Evaluation

Now i have the models which will be compare. To do it i will predict the values of Revenue using test set of predictive data.

[30]:
```
#now i am going to make predictions using the models
y_pred_lr = lr_load.predict(x_test)

y_pred_rf = rf_load.predict(x_test)

y_pred_gbc = ran_load.predict(x_test)
```

To compare the different models i will use the predicted data and Revenue data of the test set. The metrics which will be used in the comparison are:

- Train Accuracy
- Test Accuracy
- Preccision
- Recall
- AUC
- F1-score

[31]:
```
clf =  [lr_load, rf_load, ran_load]

ind = ['Logistic Regression', 'Random Forest', 'LightGBM']
clf_columns = []
clf_compare = pd.DataFrame(columns = clf_columns)
row_index = 0

for alg in clf:
    predicted = alg.predict(x_test)
    fp, tp, th = roc_curve(y_test, predicted)
    clf_name = alg.__class__.__name__
    clf_compare.loc[ind[row_index], 'Train Accuracy'] = round(alg.score(x_train,␣
 ↪y_train), 5)
```

```
    clf_compare.loc[ind[row_index], 'Test Accuracy'] = round(alg.score(x_test,␣
↪y_test), 5)
    clf_compare.loc[ind[row_index], 'Precission'] =␣
↪round(precision_score(y_test, predicted),5)
    clf_compare.loc[ind[row_index], 'Recall'] = round(recall_score(y_test,␣
↪predicted),5)
    clf_compare.loc[ind[row_index], 'AUC'] = round(roc_auc_score(y_test, alg.
↪predict_proba(x_test)[:,1]),5)
    clf_compare.loc[ind[row_index], 'F1-Score'] = round(f1_score(y_test,␣
↪predicted),5)
    row_index+=1


clf_compare
```

[31]:

```
                    Train Accuracy  Test Accuracy  Precission   Recall  \
Logistic Regression         0.88696        0.88118     0.73057  0.36911
Random Forest               0.92954        0.88848     0.87413  0.32723
LightGBM                    0.91809        0.90268     0.71386  0.62042

                         AUC  F1-Score
Logistic Regression  0.88667   0.49043
Random Forest        0.92783   0.47619
LightGBM             0.93544   0.66387
```

Also to compare the models i will print the classification reports and confussion matrics of the models.

[32]:

```
# i will print the classification report of the models
index = 0
for alg in clf:
    predicted = alg.predict(x_test)
    print(ind[index] + ' Classification Report\n', classification_report(y_test,␣
↪predicted, zero_division = 0.0))
    index += 1
```

```
Logistic Regression Classification Report
               precision    recall  f1-score   support

           0       0.89      0.98      0.93      2084
           1       0.73      0.37      0.49       382

    accuracy                           0.88      2466
   macro avg       0.81      0.67      0.71      2466
weighted avg       0.87      0.88      0.86      2466

Random Forest Classification Report
               precision    recall  f1-score   support
```

```
           0       0.89      0.99      0.94      2084
           1       0.87      0.33      0.48       382

    accuracy                           0.89      2466
   macro avg       0.88      0.66      0.71      2466
weighted avg       0.89      0.89      0.87      2466

LightGBM Classification Report
              precision    recall  f1-score   support

           0       0.93      0.95      0.94      2084
           1       0.71      0.62      0.66       382

    accuracy                           0.90      2466
   macro avg       0.82      0.79      0.80      2466
weighted avg       0.90      0.90      0.90      2466
```

```
[ ]: # i will print the confusion matrix of the models
index = 0
for alg in clf:
    predicted = alg.predict(x_test)
    print(ind[index] + ' Classification Matrix\n',  confusion_matrix(y_test,␣
 ↪predicted))
    index += 1
```

```
Logistic Regression Classification Matrix
 [[2032   52]
 [ 241  141]]
Random Forest Classification Matrix
 [[2066   18]
 [ 257  125]]
LightGBM Classification Matrix
 [[1989   95]
 [ 145  237]]
```

I have seen that there are data in different category of the dataset which appear more than others so i will use the F1-Score to choose the best model. By this reason the best model is the Gradient Boosting model.

# 8 Insights and Variable Importance

In this final section i will use the permutation importances to see which variables are more important to predict if someone will do a purchase. The importances of the features will be shown in a table and in a graphic.

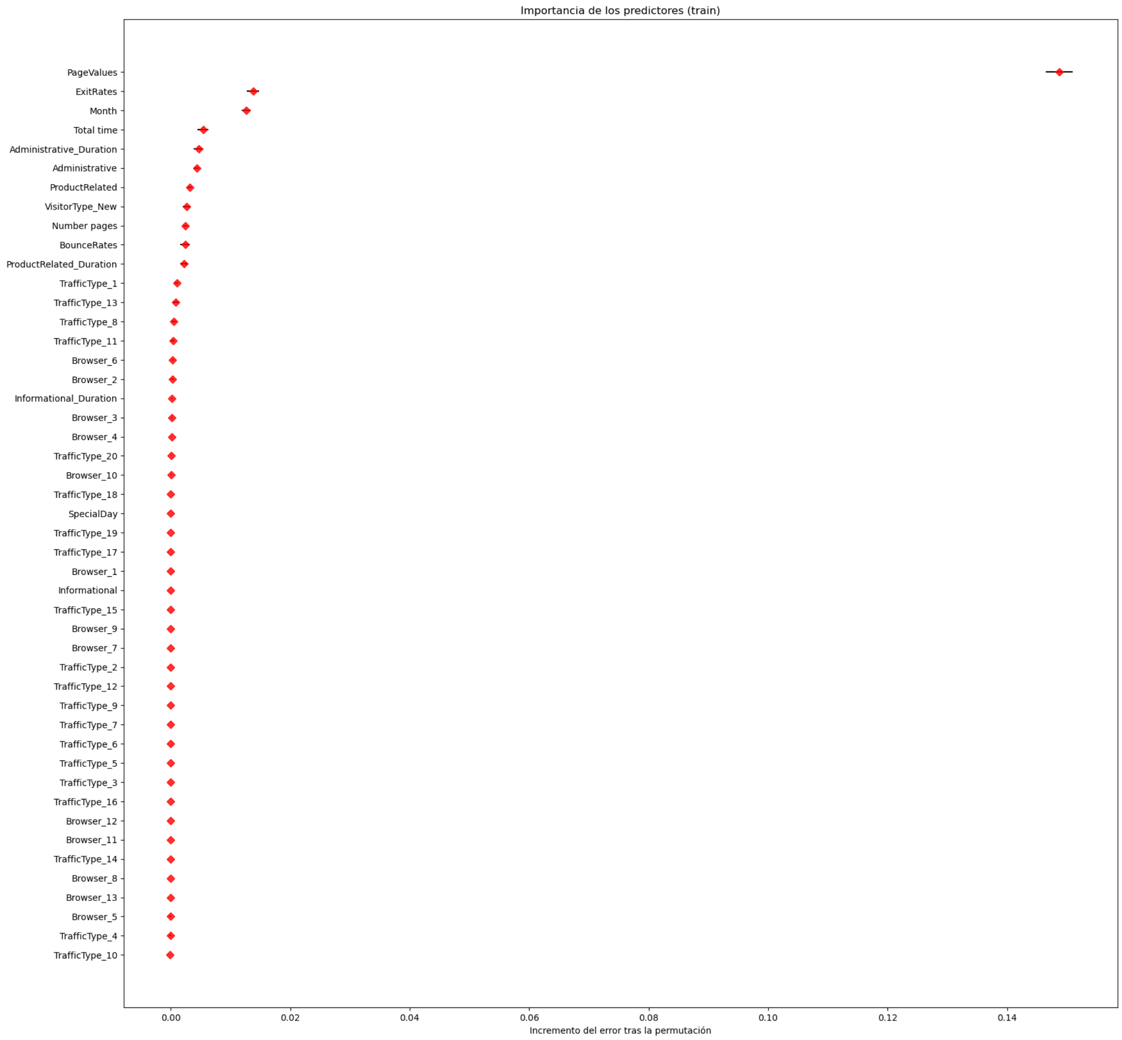
[ ]:
```python
# now study the permutation importance to predict Sales
importancia = permutation_importance(best_mod, x_train, y_train)
# store mean y desviation in a dataframe
sales_importancia = pd.DataFrame(
                    {k: importancia[k] for k in ['importances_mean',␣
 ↪'importances_std']}
                 )
sales_importancia['feature'] =  x_train.columns.values
sales_importancia
```

[ ]:

| | importances_mean | importances_std | feature |
|---|---|---|---|
| 0 | 0.004339 | 0.000392 | Administrative |
| 1 | 0.004663 | 0.000811 | Administrative_Duration |
| 2 | 0.000000 | 0.000000 | Informational |
| 3 | 0.000223 | 0.000118 | Informational_Duration |
| 4 | 0.003183 | 0.000291 | ProductRelated |
| 5 | 0.002230 | 0.000638 | ProductRelated_Duration |
| 6 | 0.002413 | 0.000830 | BounceRates |
| 7 | 0.013788 | 0.001044 | ExitRates |
| 8 | 0.148702 | 0.002241 | PageValues |
| 9 | 0.000000 | 0.000000 | SpecialDay |
| 10 | 0.012652 | 0.000778 | Month |
| 11 | 0.000000 | 0.000000 | Browser_1 |
| 12 | 0.000264 | 0.000236 | Browser_2 |
| 13 | 0.000162 | 0.000081 | Browser_3 |
| 14 | 0.000142 | 0.000081 | Browser_4 |
| 15 | -0.000081 | 0.000118 | Browser_5 |
| 16 | 0.000345 | 0.000165 | Browser_6 |
| 17 | 0.000000 | 0.000000 | Browser_7 |
| 18 | 0.000000 | 0.000000 | Browser_8 |
| 19 | 0.000000 | 0.000000 | Browser_9 |
| 20 | 0.000061 | 0.000103 | Browser_10 |
| 21 | 0.000000 | 0.000000 | Browser_11 |
| 22 | 0.000000 | 0.000000 | Browser_12 |
| 23 | 0.000000 | 0.000000 | Browser_13 |
| 24 | 0.000994 | 0.000297 | TrafficType_1 |
| 25 | 0.000000 | 0.000000 | TrafficType_2 |
| 26 | 0.000000 | 0.000000 | TrafficType_3 |
| 27 | -0.000081 | 0.000197 | TrafficType_4 |
| 28 | 0.000000 | 0.000000 | TrafficType_5 |
| 29 | 0.000000 | 0.000000 | TrafficType_6 |
| 30 | 0.000000 | 0.000000 | TrafficType_7 |
| 31 | 0.000547 | 0.000331 | TrafficType_8 |
| 32 | 0.000000 | 0.000000 | TrafficType_9 |
| 33 | -0.000182 | 0.000076 | TrafficType_10 |
| 34 | 0.000365 | 0.000284 | TrafficType_11 |
| 35 | 0.000000 | 0.000000 | TrafficType_12 |

```
36         0.000831       0.000446       TrafficType_13
37         0.000000       0.000000       TrafficType_14
38         0.000000       0.000000       TrafficType_15
39         0.000000       0.000000       TrafficType_16
40         0.000000       0.000000       TrafficType_17
41         0.000000       0.000000       TrafficType_18
42         0.000000       0.000000       TrafficType_19
43         0.000101       0.000064       TrafficType_20
44         0.002453       0.000297         Number pages
45         0.005414       0.000901           Total time
46         0.002636       0.000631     VisitorType_New
```

[ ]:
```
# plot the importance of each variable in the permutation
fig, ax = plt.subplots(figsize=(20, 20))
sales_importancia = sales_importancia.sort_values('importances_mean',␣
 ↪ascending=True)
ax.barh(
    sales_importancia['feature'],
    sales_importancia['importances_mean'],
    xerr=sales_importancia['importances_std'],
    align='center',
    alpha=0
)
ax.plot(
    sales_importancia['importances_mean'],
    sales_importancia['feature'],
    marker="D",
    linestyle="",
    alpha=0.8,
    color="r"
)
ax.set_title('Importancia de los predictores (train)')
ax.set_xlabel('Incremento del error tras la permutación');
```




Due to the table and the graphics we know that the more important variables are

1. PageValues
2. ExitRates
3. Month
4. TotalTime
5. Administrative_Duration
6. Administrative
7. NumberPages
8. ProductRelated
9. VisitorType_New
10. ProductRelated_Duration

11. BounceRates

# 9 Suggestions

To end the report i will give some advices:

1. During the months in which less people buy it could be good idea add and promote new products
2. Increase the page value offering a better experience in a the pages.For example it should be easy to see feature of products and it should have a interative and well choosen colours.
3. Increasing the marketing efforts in social media could be useful to get new visitors.