BlueOwl

February 4, 2020

Last name: ILORI Date: 04-February-2020 Approach:Upsampled the minority class since the dataset had imbalanced classes and then modeled on the upsampled dataset and predicted on the original test set. Target AUC: 0.825 Achieved AUC: 0.974

[1]:

```
#import packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
```

[2]:

```
#load the datasets
train_data = pd.read_csv('train.csv')
test_data = pd.read_csv('test.csv')
```

[3]:

```
#display first five observations of both data
train_data.head(5)
test_data.head(5)
```

[3]:

```
   age  cost_of_ad device_type gender  in_initial_launch_location  income  \
0   34    0.005134     Android      F                           1   40376
1   53    0.005223     desktop      F                           1   84511
2   46    0.004939      laptop      F                           0   79322
3   36    0.004924     Android      F                           0   63295
4   28    0.005146       other      F                           1   36170

   n_drivers  n_vehicles  prior_ins_tenure
0          1           3                 7
1          1           1                11
2          1           1                 4
3          1           2                 0
4          1           3                 3
```

[4]:

```
#display info of the data
train_data.info()
test_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 10 columns):
age                           10000 non-null int64
```

```
cost_of_ad                    10000 non-null float64
device_type                   10000 non-null object
gender                        9731 non-null object
in_initial_launch_location    10000 non-null int64
income                        10000 non-null int64
n_drivers                     10000 non-null int64
n_vehicles                    10000 non-null int64
prior_ins_tenure              10000 non-null int64
outcome                       10000 non-null int64
dtypes: float64(1), int64(7), object(2)
memory usage: 781.3+ KB
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 9 columns):
age                           10000 non-null int64
cost_of_ad                    10000 non-null float64
device_type                   10000 non-null object
gender                        9751 non-null object
in_initial_launch_location    10000 non-null int64
income                        10000 non-null int64
n_drivers                     10000 non-null int64
n_vehicles                    10000 non-null int64
prior_ins_tenure              10000 non-null int64
dtypes: float64(1), int64(6), object(2)
memory usage: 703.2+ KB
```

[5]:

```python
#view description of the data
train_data.describe()
test_data.describe()
```

[5]:

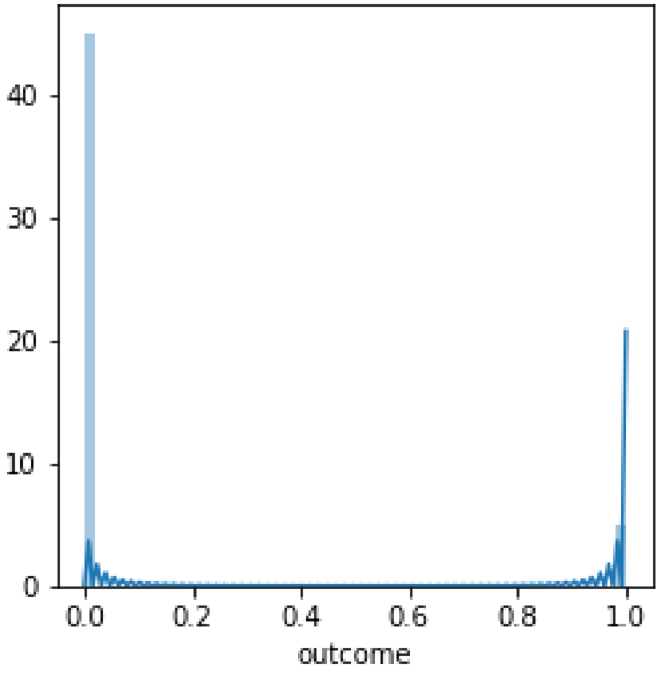
```
                age    cost_of_ad  in_initial_launch_location        income  \
count  10000.000000  10000.000000                10000.000000  10000.000000
mean      38.029200      0.004668                    0.500900  58232.104800
std       12.896921      0.000836                    0.500024  17318.192722
min       16.000000      0.003173                    0.000000  16124.000000
25%       27.000000      0.004000                    0.000000  45575.250000
50%       38.000000      0.004609                    1.000000  58271.000000
75%       49.000000      0.005175                    1.000000  70438.750000
max       60.000000      0.007049                    1.000000  99916.000000

          n_drivers    n_vehicles  prior_ins_tenure
count  10000.000000  10000.000000      10000.000000
mean       1.486300      2.009100          5.319800
std        0.499837      0.817242          5.019487
min        1.000000      1.000000          0.000000
25%        1.000000      1.000000          1.000000
50%        1.000000      2.000000          4.000000
75%        2.000000      3.000000          8.000000
```

```
max         2.000000       3.000000          22.000000
```

[6]:
```
#display distribution plot for the outcome feature
fig, ax = plt.subplots(figsize=(4, 4))
sns.distplot(train_data.outcome, ax=ax)
```

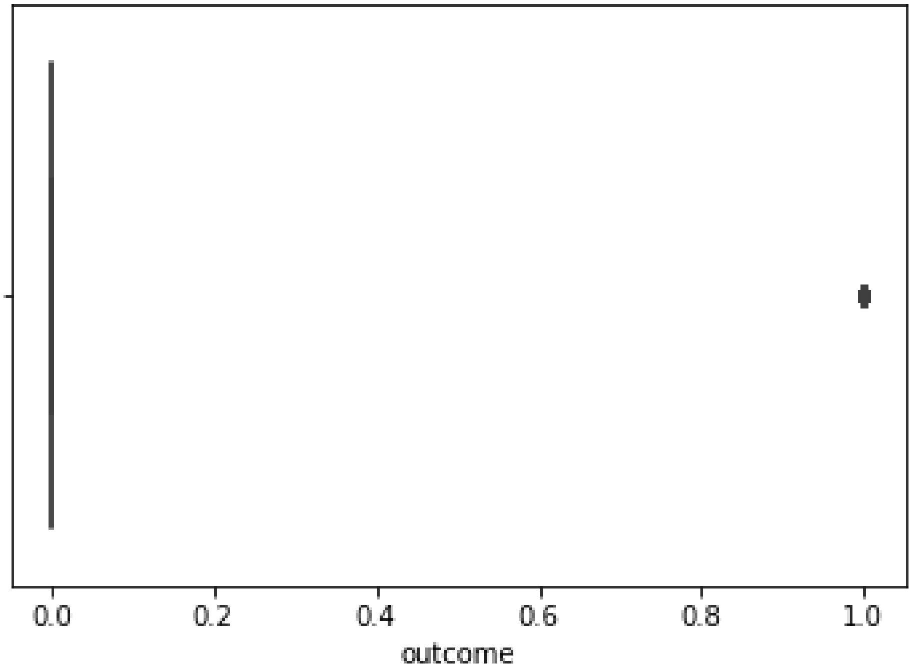
```
C:\Users\Israel Ilori\Anaconda3\lib\site-packages\scipy\stats\stats.py:1713:
FutureWarning: Using a non-tuple sequence for multidimensional indexing is
deprecated; use `arr[tuple(seq)]` instead of `arr[seq]`. In the future this will
be interpreted as an array index, `arr[np.array(seq)]`, which will result either
in an error or a different result.
  return np.add.reduce(sorted[indexer] * weights, axis=axis) / sumval
```

[6]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x21828161a20>
```



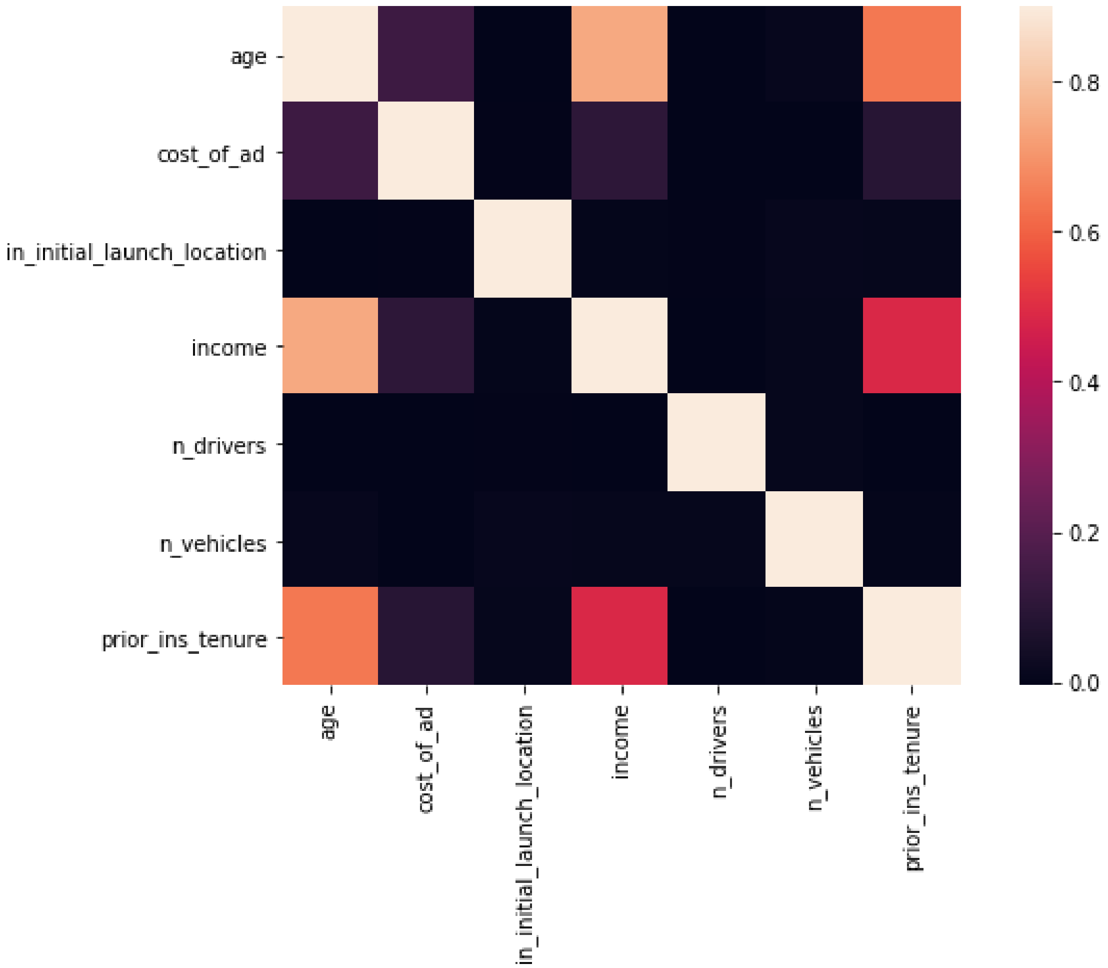
[7]:
```
#using boxplot check for outliers
import seaborn as sns
sns.boxplot(x='outcome', data = train_data)
```

[7]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2182a361a20>
```



[8]:
```
#correlation between features in the data
a = train_data.iloc[:,:9]
corr_matrix = a.corr()
plt.subplots(figsize=(10,6))
sns.heatmap(corr_matrix, vmax=0.9, square=True)
```

[8]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x2182a3b3908>
```



[9]:

```
#Feature encoding for categorical values in the dataset
from sklearn.preprocessing import LabelEncoder

number = LabelEncoder()
train_data['gender'] = number.fit_transform(train_data['gender'].astype('str'))
test_data['gender'] = number.fit_transform(test_data['gender'].astype('str'))
train_data['device_type'] = number.fit_transform(train_data['device_type'].
 ↪astype('str'))
test_data['device_type'] = number.fit_transform(test_data['device_type'].
 ↪astype('str'))
```

[10]:

```
#display counts for both classes
train_data['outcome'].value_counts()
```

[10]:

```
0    9018
1     982
Name: outcome, dtype: int64
```

[11]:
```
from sklearn.utils import resample

#Separate majority and minority classes
train_majority = train_data[train_data.outcome==0]
train_minority = train_data[train_data.outcome==1]

#assign variable count of the majority class to be used in the method
majority_count = len(train_data[train_data.outcome==0])

#Upsample minority class
train_minority_upsampled = resample(train_minority,
                                    replace=True,     #sample with replacement
                                    n_samples=majority_count,    #to match␣
 ↪majority class
                                    random_state=123) # reproducible results

#Combine majority class with upsampled minority class
train_upsampled = pd.concat([train_majority, train_minority_upsampled])

#Display new counts for both classes
train_upsampled.outcome.value_counts()
```

[11]:
```
1    9018
0    9018
Name: outcome, dtype: int64
```

[12]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, f1_score, auc, roc_curve,␣
 ↪roc_auc_score
from sklearn.ensemble import RandomForestClassifier

#Separate input features (X) and target variable (y)
y = train_upsampled.outcome
X = train_upsampled.drop('outcome', axis=1)
test = test_data.iloc[:,:].values

from sklearn.model_selection import train_test_split

X_train, X_test, y_train, y_test = train_test_split (X, y, test_size = 0.3,␣
 ↪random_state = 42)
```

[13]:
```
#Train model
#Instantiate model and fit
log_reg = LogisticRegression().fit(X_train, y_train) #serves as base model
rand_forest = RandomForestClassifier().fit(X_train, y_train) #serves as second␣
 ↪model

#Predict on train set
```

```
y_pred = rand_forest.predict(X_test)

#display the classes for which model is predicting
print(np.unique(y_pred))


#display performance metrics
print('The Accuracy score is: ',accuracy_score(y_test, y_pred))
print('The F1_score score is: ',f1_score(y_test, y_pred))
print('The AUC score is: ',roc_auc_score(y_test, y_pred))
```

```
[0 1]
The Accuracy score is:  0.9732027351690999
The F1_score score is:  0.9740932642487047
The AUC score is:  0.9729981378026071
```

[14]:

```
#Run prediction on the test set
y_pred2 = rand_forest.predict(test)

#Display the first five predicted values
y_pred2[:5]
```

[14]:

```
array([0, 0, 0, 0, 0], dtype=int64)
```

[ ]: