```
In [1]:
import pandas as pd
pd.set option('display.max rows', 1000)
import numpy as np
from numpy import mean
import matplotlib.pyplot as plt
#turn off warnings for final run
import warnings
warnings.filterwarnings('ignore')
                                                                           In [2]:
from sklearn import metrics
from sklearn.preprocessing import StandardScaler
from sklearn.model selection import train test split
from sklearn.model selection import KFold
from sklearn.model selection import cross val score
from sklearn.model selection import StratifiedKFold
from sklearn.model_selection import GridSearchCV
from sklearn.model selection import RandomizedSearchCV
from sklearn.feature selection import RFE
from sklearn.feature selection import RFECV
from sklearn.linear model import LogisticRegression
from sklearn.ensemble import BaggingClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.ensemble import RandomForestClassifier
```

 $from \ statsmodels.stats.outliers_influence \ import \ variance_inflation_factor$

Data Load and Preparation

Out[5]:

| | Duration | Start Time | Keywords | Campaign | Page | Device Type | Browser | Referrer | sale | State |
|------|----------|---------------------|------------------------------|----------------------------------|-------------------------------|----------------|---------|----------------|------|-------|
| 0 | 167 | 12/22/2021 12:45 | NaN | NaN | main/estate- planning-ppc/ | mobile | Chrome | www.google.com | 0 | PA |
| 1 | 115 | 12/22/2021 12:36 | NaN | Medicaid - Elder Law - 001 | NaN | NaN | NaN | NaN | 0 | IA |
| 2 | 106 | 12/22/2021 12:23 | NaN | NaN | main/ | desktop | Chrome | direct | 0 | PA |
| 3 | 33 | 12/22/2021 12:01 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA |
| 4 | 112 | 12/22/2021 11:47 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | CA |
| | | | | | | | | | | |
| 1780 | 18 | 1/5/2021 8:47 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA |
| 1781 | 44 | 1/5/2021 8:23 | power of attorney will | Estate Planning 005 | main/estate- planning-ppc/ | desktop | Chrome | www.google.com | 0 | NY |
| 1782 | 188 | 1/4/2021 14:28 | NaN | NaN | NaN | NaN | NaN | NaN | 1 | PA |
| 1783 | 91 | 1/4/2021 13:12 | NaN | NaN | main/contact/ | desktop | Chrome | www.google.com | 0 | МО |
| 1784 | 26 | 1/4/2021 8:45 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA |

1785 rows × 10 columns

```
In [6]:
#convert start time to month and hour variables
calls_subset['Month'] = calls_subset['Start Time'].apply(lambda x: x.split('
')[0].split('/')[0])
calls_subset['Hour'] = calls_subset['Start Time'].apply(lambda x: x.split('
')[1].split(':')[0])
calls_subset = calls_subset.drop('Start Time', axis=1)
calls_subset
```

Out[6]:

| | Duration | Keywords | Campaign | Page | Device Type | Browser | Referrer | sale | State | Month | Hour |
|---|----------|----------|----------------------------------|-------------------------------|----------------|---------|----------------|------|-------|-------|------|
| 0 | 167 | NaN | | main/estate- planning-ppc/ | mobile | Chrome | www.google.com | 0 | PA | 12 | 12 |
| 1 | 115 | | Medicaid - Elder Law - 001 | NaN | NaN | NaN | NaN | 0 | IA | 12 | 12 |
| 2 | 106 | NaN | NaN | main/ | desktop | Chrome | direct | 0 | PA | 12 | 12 |

| | Duration | Keywords | Campaign | Page | Device Type | Browser | Referrer | sale | State | Month | Hour |
|------|----------|------------------------------|----------|-------------------------------|----------------|---------|----------------|------|-------|-------|------|
| 3 | 33 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA | 12 | 12 |
| 4 | 112 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | CA | 12 | 11 |
| | | | | | | | | | | | |
| 1780 | 18 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA | 1 | 8 |
| 1781 | 44 | power of attorney will | Pinning | main/estate- planning-ppc/ | desktop | Chrome | www.google.com | 0 | NY | 1 | 8 |
| 1782 | 188 | NaN | NaN | NaN | NaN | NaN | NaN | 1 | PA | 1 | 14 |
| 1783 | 91 | NaN | NaN | main/contact/ | desktop | Chrome | www.google.com | 0 | MO | 1 | 13 |
| 1784 | 26 | NaN | NaN | NaN | NaN | NaN | NaN | 0 | PA | 1 | 8 |

1785 rows × 11 columns

```
In [7]:
#remove rows without full data
calls_noNa = calls_subset.dropna().reset_index(drop=True)
print('Number of records: ' + str(calls_noNa.shape[0]))
print('Number of records with sale: ' + str(calls_noNa[calls_noNa['sale'] ==
1].reset_index().shape[0]))
Number of records: 401
Number of records with sale: 48
```

Get Dummies

```
In [8]:
#get raw value counts for variables
#for i in ['Keywords', 'Campaign', 'Page', 'Device Type', 'Browser',
'Referrer']:
    print(calls noNa[i].value counts())
                                                                           In [9]:
#update keyword categories to include at least 15 per category
keyword categories = ['probate and estate administration lawyers',
'medicaid planning attorney',
'pittsburgh probate lawyers',
'elder law attorney',
'estate administration lawyer near me',
'pennsylvania lawyers']
calls noNa['Keywords Categories'] = calls noNa['Keywords']
calls_noNa.loc[~calls_noNa['Keywords'].isin(keyword_categories), 'Keywords
Categories'] = 'Other Keywords'
calls noNa = calls noNa.drop('Keywords', axis=1)
calls noNa['Keywords Categories'].value counts()
                                                                          Out[9]:
                                              288
Other Keywords
```

```
probate and estate administration lawyers
                                               25
medicaid planning attorney
                                               22
pittsburgh probate lawyers
                                               20
elder law attorney
                                               16
estate administration lawyer near me
                                               15
pennsylvania lawyers
                                               15
Name: Keywords Categories, dtype: int64
                                                                          In [10]:
#update page categories to include at least 15 per category
page categories = ['elder-law-ppc/',
'estate-planning-ppc/',
'estate-admin-ppc/',
'main/',
'main/pittsburgh-estate-planning-lawyer/power-of-attorney-pittsburgh-pa/',
'main/firstname-redacted/',
'main/contact/'l
calls noNa['Page Categories'] = calls noNa['Page']
calls noNa.loc[~calls noNa['Page'].isin(page categories), 'Page Categories']
= 'Other Page'
calls noNa = calls noNa.drop('Page', axis=1)
calls noNa['Page Categories'].value counts()
                                                                          Out[10]:
Other Page
322
main/
main/pittsburgh-estate-planning-lawyer/power-of-attorney-pittsburgh-pa/
19
main/contact/
16
main/firstname-redacted/
Name: Page Categories, dtype: int64
                                                                          In [11]:
#update browser categories to include at least 10 per category
browser categories = ['Chrome', 'Safari']
calls noNa['Browser Categories'] = calls noNa['Browser']
calls_noNa.loc[~calls_noNa['Browser'].isin(browser_categories), 'Browser
Categories'] = 'Firefox or Opera'
calls noNa = calls noNa.drop('Browser', axis=1)
calls noNa['Browser Categories'].value counts()
                                                                          Out[11]:
Chrome
                    214
Safari
                    176
Firefox or Opera
                     11
```

```
Name: Browser Categories, dtype: int64
                                                                          In [12]:
#reduce state categories to PA or not PA
calls noNa['State Categories'] = calls noNa['State']
calls noNa.loc[calls noNa['State'] != 'PA', 'State Categories'] = 'Not PA'
calls noNa = calls noNa.drop('State', axis=1)
calls noNa['State Categories'].value counts()
                                                                         Out[12]:
PΑ
          312
Not PA
          89
Name: State Categories, dtype: int64
                                                                          In [13]:
#lump all google values
calls noNa.loc[calls noNa['Referrer'] == 'cse.google.com', 'Referrer'] =
'www.google.com'
                                                                          In [14]:
categorical = ['Keywords Categories', 'Campaign', 'Page Categories', 'Device
Type', 'Browser Categories', 'Referrer', 'State Categories']
for i in categorical:
    dummies = pd.get dummies(calls noNa[i], drop first=True)
pd.concat([calls noNa,dummies],axis=1).dropna().reset index(drop=True)
    calls noNa = calls noNa.drop(i, axis=1)
calls noNa = calls_noNa.astype(int)
                                                                          In [15]:
#check for and fix multicollinearity
vif df = pd.DataFrame()
vif df["feature"] = calls noNa.columns
vif df["VIF"] = [variance inflation factor(calls noNa.values, i)
                          for i in range(len(calls noNa.columns))]
print(vif df)
print('\n')
calls noNa = calls noNa.drop('Hour', axis=1)
calls noNa = calls noNa.drop('www.google.com', axis=1)
vif df = pd.DataFrame()
vif df["feature"] = calls noNa.columns
vif df["VIF"] = [variance inflation factor(calls noNa.values, i)
                          for i in range(len(calls noNa.columns))]
print(vif df)
                                               feature VIF
                                              Duration 1.795709
```

| 1 | 2212 | 2 022027 |
|---|--|--|
| 1 | sale | 2.022827 |
| 2 | | 5.896868 |
| 3 | Hour | 13.241278 |
| 4 | 1 | 1.213769 |
| 5 | estate administration lawyer near me | 1.554053 |
| 6 | medicaid planning attorney | 2.514512 |
| 7 | pennsylvania lawyers | 1.176284 |
| 8 | pittsburgh probate lawyers | 1.332965 |
| 9 | probate and estate administration lawyers | 1.351594 |
| 10 | Estate Admin - Overall | 1.555531 |
| 11 | Estate Planning 005 | 3.392152 |
| 12 | Medicaid - Elder Law - 001 | 3.481524 |
| 13 | main/ | 2.136406 |
| 14 | | 1.128137 |
| 15 | | 1.110253 |
| 16 | main/pittsburgh-estate-planning-lawyer/power-o | 1.133315 |
| 17 | | 4.683881 |
| 18 | Firefox or Opera | 1.175070 |
| 19 | Safari | 2.183395 |
| 20 | www.google.com | 11.865052 |
| 21 | PA | 4.678496 |
| | | |
| | | |
| | faatuma | 7.7 T. |
| 0 | feature | VIF |
| 0 | Duration | 1.734367 |
| 1 | Duration | 1.734367 2.019141 |
| 1 2 | Duration sale Month | 1.734367 2.019141 4.904542 |
| 1 2 3 | Duration sale Month elder law attorney | 1.734367 2.019141 4.904542 1.213154 |
| 1 2 3 4 | Duration sale Month elder law attorney estate administration lawyer near me | 1.734367 2.019141 4.904542 1.213154 1.506437 |
| 1 2 3 4 5 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 |
| 1 2 3 4 5 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 |
| 1 2 3 4 5 6 7 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 |
| 1 2 3 4 5 6 7 8 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 |
| 1 2 3 4 5 6 7 8 9 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 |
| 1 2 3 4 5 6 7 8 9 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 |
| 1 2 3 4 5 6 7 8 9 10 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 |
| 1 2 3 4 5 6 7 8 9 10 11 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ main/firstname-redacted/ | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 1.106895 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ main/firstname-redacted/ main/pittsburgh-estate-planning-lawyer/power-o | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 1.106895 1.124290 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ main/firstname-redacted/ main/pittsburgh-estate-planning-lawyer/power-o mobile | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 1.106895 1.124290 4.275562 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ main/firstname-redacted/ main/pittsburgh-estate-planning-lawyer/power-o mobile Firefox or Opera | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 1.106895 1.124290 4.275562 1.132177 |
| 1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 | Duration sale Month elder law attorney estate administration lawyer near me medicaid planning attorney pennsylvania lawyers pittsburgh probate lawyers pittsburgh probate lawyers probate and estate administration lawyers Estate Admin - Overall Estate Planning 005 Medicaid - Elder Law - 001 main/ main/contact/ main/firstname-redacted/ main/pittsburgh-estate-planning-lawyer/power-o mobile | 1.734367 2.019141 4.904542 1.213154 1.506437 2.483177 1.171927 1.291661 1.295143 1.554796 2.825811 3.062890 2.127636 1.119803 1.106895 1.124290 4.275562 1.132177 |

Perform Analysis

Feature Selection

```
def feature_selection(X,y,model,cv,score):
    features_names=pd.DataFrame(X.columns)

#perform RFECV and fit model to get rankings
    rfecv = RFECV(model, step=1, cv=cv, scoring=score)
    fitted_values=rfecv.fit(X,y)
    ranks=pd.DataFrame(fitted_values.ranking_)

rank=pd.concat([features_names,ranks], axis=1)
    rank.columns = ["Feature", "Rank"]

#Select rank 1's
    most_important = rank.loc[rank['Rank'] ==1]
    most_important = most_important['Feature']

print('Most important features ('+str(len(most_important))+')')
    print(str(most_important))

return most important
```

Analysis

```
In [17]:

def run_lr_model_split(df, n=5, score='f1', random_state=56):

    cv = StratifiedKFold(n_splits=n)

#split dataset into dependent and independent variables
    features = list(df.columns) #all columns but sale
    features.remove('sale')

X = df[features].astype('category') # Features
y = df['sale'] # independent var

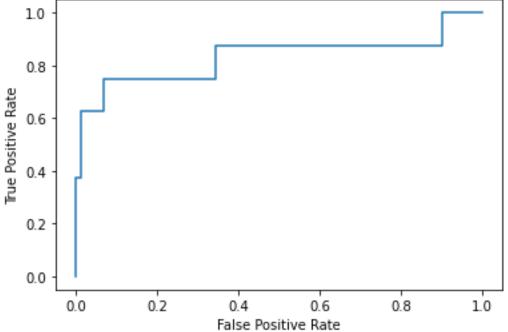
# split X and y into test and train
    X_train,X_test,y_train,y_test=train_test_split(X,y,test_size=0.2,
random_state=random_state)

# instantiate the model
```

```
model = LogisticRegression(max iter=10000)
    # fit the model
    model.fit(X train,y train)
    #predict
    y pred=model.predict(X test)
    #create confusion matrix
    cMat = metrics.confusion matrix(y test, y pred)
    print(cMat)
    print('Accuracy score with train/test: %.3f' %
metrics.accuracy score(y test, model.predict(X test))) #model accuracy
    print('Balanced Accuracy score with train/test: %.3f' %
metrics.balanced accuracy score(y test, model.predict(X test))) #balanced
model accuracy
    print('F1 score with train/test: %.3f' % metrics.f1 score(y test,
model.predict(X test))) #model accuracy
    print('ROC AUC with train/test: %.3f' % metrics.accuracy score(y test,
model.predict(X test))) #model accuracy
    #metrics
    y pred prb = model.predict proba(X test)[::,1]
    fpr, tpr, = metrics.roc curve(y test, y pred prb)
    #ROC curve plot
    plt.plot(fpr,tpr)
    plt.ylabel('True Positive Rate')
    plt.xlabel('False Positive Rate')
    plt.show()
                                                                         In [18]:
def run lr model cv(df, n=5, score='f1', random state=56):
    cv = StratifiedKFold(n splits=n)
    #split dataset into dependent and independent variables
    features = list(df.columns) #all columns but sale
    features.remove('sale')
    X = df[features].astype('category') # Features
    y = df['sale'] # independent var
    # instantiate the model
    model = LogisticRegression(max iter=10000)
```

```
#Setting the range for class weights
    weights = np.linspace(0.0, 0.99, 100)
    #Creating a dictionary grid for grid search
    param grid = {'class weight': [\{0:x, 1:1.0-x\} \text{ for } x \text{ in weights}]\}
    #Fitting grid search to the train data with cv to find class weights
    gridsearch = GridSearchCV(estimator= model,
                          param grid= param grid,
                          cv=cv,
                          n jobs=-1,
                          scoring=score,
                          verbose=2).fit(X, y)
    weight df = pd.DataFrame({ 'score':
gridsearch.cv results ['mean test score'], 'weight': (1- weights)})
    optimum weight = max(weight df[weight df['score'] ==
max(weight df['score'])]['weight'])
    # re-instantiate the model
    model = LogisticRegression(max iter=10000, random state=random state,
                                        class weight={0: 1-optimum weight, 1:
optimum weight})
    #perform feature selection
    Best X Columns = feature selection(X,y,model,n,score)
    X = X[Best X Columns]
    # fit the model
    #model.fit(X train,y train)
    #predict
    #y_pred=model.predict(X_test)
    # evaluate model with k-fold validation
    scores = cross val score(model, X, y, scoring='accuracy', cv=cv, n jobs=-
1)
    bal scores = cross val score(model, X, y, scoring='balanced accuracy',
cv=cv, n jobs=-1)
    f1_scores = cross_val_score(model, X, y, scoring='f1', cv=cv, n_jobs=-1)
    w f1 scores = cross val score(model, X, y, scoring='f1 weighted', cv=cv,
n jobs=-1)
    auc scores = cross val score(model, X, y, scoring='roc auc', cv=cv,
n jobs=-1)
    # k-fold validiation acuracy
```

```
print('Accuracy with K-Fold validation: %.3f' % (mean(scores)))
    print('Balanced Accuracy with K-Fold validation: %.3f' %
(mean(bal scores)))
    print('F1-Score with K-Fold validation: %.3f' % (mean(f1_scores)))
    print('ROC AUC with K-Fold validation: %.3f' % (mean(auc scores)))
    return model
                                                                          In [19]:
seed = np.random.randint(1000)
seed
                                                                          Out[19]:
204
                                                                          In [20]:
#linear regression, F1, CV = 5
run lr model split(calls noNa)
[[72 1]
[ 5 3]]
Accuracy score with train/test: 0.926
Balanced Accuracy score with train/test: 0.681
F1 score with train/test: 0.500
ROC AUC with train/test: 0.926
   1.0
   0.8
```



In [21]:

```
1
                                                    Month
2
                                      elder law attorney
3
                   estate administration lawyer near me
4
                              medicaid planning attorney
5
                                    pennsylvania lawyers
6
                              pittsburgh probate lawyers
7
              probate and estate administration lawyers
8
                                  Estate Admin - Overall
                                     Estate Planning 005
10
                              Medicaid - Elder Law - 001
                                                    main/
11
12
                                           main/contact/
13
                                main/firstname-redacted/
14
      main/pittsburgh-estate-planning-lawyer/power-o...
15
                                                   mobile
16
                                        Firefox or Opera
17
                                                   Safari
18
                                                       PΑ
Name: Feature, dtype: object
Accuracy with K-Fold validation: 0.918
Balanced Accuracy with K-Fold validation: 0.719
F1-Score with K-Fold validation: 0.576
ROC AUC with K-Fold validation: 0.877
                                                                          Out[21]:
LogisticRegression(class weight={0: 0.4, 1: 0.6}, max iter=10000,
                    random state=56)
                                                                           In [22]:
#linear regression, F1, CV = 10
run lr model cv(calls noNa, n=10)
Fitting 10 folds for each of 100 candidates, totalling 1000 fits
Most important features (19)
                                                 Duration
1
                                                   Month
2
                                      elder law attorney
                   estate administration lawyer near me
4
                              medicaid planning attorney
5
                                    pennsylvania lawyers
6
                              pittsburgh probate lawyers
7
              probate and estate administration lawyers
8
                                  Estate Admin - Overall
9
                                     Estate Planning 005
                              Medicaid - Elder Law - 001
10
11
                                                   main/
12
                                           main/contact/
13
                                main/firstname-redacted/
14
      main/pittsburgh-estate-planning-lawyer/power-o...
```

```
15
                                                  mobile
16
                                        Firefox or Opera
17
                                                  Safari
18
                                                      PΑ
Name: Feature, dtype: object
Accuracy with K-Fold validation: 0.898
Balanced Accuracy with K-Fold validation: 0.788
F1-Score with K-Fold validation: 0.562
ROC AUC with K-Fold validation: 0.897
                                                                          Out[22]:
LogisticRegression(class weight={0: 0.19999999999999999, 1: 0.8},
                   max iter=10000, random state=56)
                                                                           In [23]:
def run rf model(df, n=5, score='f1', random state=56):
    cv = StratifiedKFold(n splits=n)
    #split dataset into dependent and independent variables
    features = list(df.columns) #all columns but sale
    features.remove('sale')
    X = df[features].astype('category') # Features
    y = df['sale'] # independent var
    # instantiate the model
    model = RandomForestClassifier(random state=random state)
    # Number of trees in random forest
    n estimators = [int(x) for x in np.linspace(50, 2000, num = 20)] # The
number of trees in the forest.
    max features = ['auto', 'sqrt'] # The number of features to consider when
looking for the best split
    \max depth = [int(x) \text{ for } x \text{ in np.linspace}(20, 120, num = 10)] # The
maximum depth of the tree.
    min samples split = [2, 4, 6, 8, 10] # The minimum number of samples
required to split an internal node
    min samples leaf = [1, 2, 3, 4, 5] # The minimum number of samples
required to be at a leaf node.
    bootstrap = [True, False] # Whether bootstrap samples are used when
building trees.
    random grid = {'n estimators': n estimators,
    'max_features': max_features,
    'max depth': max depth,
    'min samples split': min samples split,
    'min samples leaf': min samples leaf,
    'bootstrap': bootstrap}
```

```
# Create the random grid
   param grid = {'n estimators': n estimators,
               'max depth': max depth,
               'min samples split': min samples split,
               'min_samples_leaf': min_samples_leaf}
    model = RandomizedSearchCV(estimator = model, param distributions =
param grid, cv = 5,
                                   verbose=2, n jobs = -1, n iter = 250,
scoring='f1')
    # fit the model
    model.fit(X,y)
   print(model.best params )
    # evaluate model with k-fold validation
   scores = cross val score(model, X, y, scoring='accuracy', cv=cv, n jobs=-
1)
   bal scores = cross val score(model, X, y, scoring='balanced accuracy',
cv=cv, n jobs=-1)
    f1 scores = cross val score(model, X, y, scoring='f1', cv=cv, n jobs=-1)
    w f1 scores = cross val score(model, X, y, scoring='f1 weighted', cv=cv,
n_{jobs}=-1)
    auc scores = cross val score(model, X, y, scoring='roc auc', cv=cv,
n jobs=-1)
    # k-fold validiation acuracy
    print('Accuracy with K-Fold validation: %.3f' % (mean(scores)))
    print('Balanced Accuracy with K-Fold validation: %.3f' %
(mean(bal scores)))
    print('F1-Score with K-Fold validation: %.3f' % (mean(f1_scores)))
    print('ROC AUC with K-Fold validation: %.3f' % (mean(auc_scores)))
                                                                          In [69]:
\#random forest model, f1, CV = 5
run rf model(calls noNa, n=5, score='f1', random state=56)
Fitting 5 folds for each of 250 candidates, totalling 1250 fits
{'n estimators': 50, 'min samples split': 10, 'min samples leaf': 3,
'max depth': 97}
Accuracy with K-Fold validation: 0.895
Balanced Accuracy with K-Fold validation: 0.728
F1-Score with K-Fold validation: 0.510
ROC AUC with K-Fold validation: 0.843
                                                                           In []:
```

In []: