1 Data Science Career Change Likelihood ¶

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Data Science Career Change Likelihood

1.1 Overview

Client: RADS - Recruiting Awesome Data Scientists Incorporation. Data Scientist recruiting firm looking for potential future Data Scientists

Data, Methodology, and Analysis:
HR Analytics https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists (https://www.kaggle.com/arashnic/hr-analytics-job-change-of-data-scientists)

Data context: the data source is from a company that is active in Big Data and Data Science and ran a training program with the intention to hire data scientists among people who successfully passed some courses they conducted.

This dataset includes current credentials, demographics, experience, education, which will help us build model for RADs about candidates that are likely to be looking for a job change.

Models Built:

1. Baseline Logical Regression Classifier

2. Decision Tree Classifier
3. Random Forest Classifier
4. Gradient Booster Classifier

2 Data Exploration, Cleansing, Visualization, and Preparation

Data Exploration
Explore HR Analytics data

Data Cleansing
Check for duplicates (none); drop NaN values and unnecessary columns; continuously clean data as necessary

Data Visualization
Use visualizations to explore the data and determine how to further refine the dataset in order to prepare for modeling

Data Preparation

2.1 Data Exploration and Cleansing

Import data and all packages needed for data exploration and modeling

In [1]:
```
import pandas as pd
import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.impute import SimpleImputer
import sklearn.preprocessing as preprocessing
from sklearn.preprocessing import OneHotEncoder, StandardScaler, MinMaxScal
from sklearn.metrics import classification_report, accuracy_score
from sklearn.tree import DecisionTreeClassifier
from sklearn.linear_model import LogisticRegression
from sklearn import svm, datasets
from sklearn.model_selection import GridSearchCV


import matplotlib.pyplot as plt
%matplotlib inline

import seaborn as sns

import os
import warnings
```
executed in 940ms, finished 11:14:48 2021-12-20

Explore: columns, shape, info

In [2]:
```
# Import data

df = pd.read_csv('aug_train.csv',index_col=0)
```
executed in 33ms, finished 11:14:48 2021-12-20

In [3]:
```
# Look at DataFrame

df
```
executed in 19ms, finished 11:14:48 2021-12-20

Out[3]:

	city	city_development_index	gender	relevent_experience	enrolled_university	educa
enrollee_id						
8949	city_103	0.920	Male	Has relevent experience	no_enrollment	
29725	city_40	0.776	Male	No relevent experience	no_enrollment	
11561	city_21	0.624	NaN	No relevent experience	Full time course	
33241	city_115	0.789	NaN	No relevent experience	NaN	
666	city_162	0.767	Male	Has relevent experience	no_enrollment	
...	...	...	...	...	...	
7386	city_173	0.878	Male	No relevent experience	no_enrollment	
31398	city_103	0.920	Male	Has relevent experience	no_enrollment	
24576	city_103	0.920	Male	Has relevent experience	no_enrollment	
5756	city_65	0.802	Male	Has relevent experience	no_enrollment	Hi
23834	city_67	0.855	NaN	No relevent experience	no_enrollment	Prim

19158 rows × 13 columns

In [4]:
```
# Explore columns and values

df.info()
```

executed in 13ms, finished 11:14:48 2021-12-20

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19158 entries, 8949 to 23834
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype  
---  ------                  --------------  -----  
 0   city                    19158 non-null  object 
 1   city_development_index  19158 non-null  float64
 2   gender                  14650 non-null  object 
 3   relevent_experience     19158 non-null  object 
 4   enrolled_university     18772 non-null  object 
 5   education_level         18698 non-null  object 
 6   major_discipline        16345 non-null  object 
 7   experience              19093 non-null  object 
 8   company_size            13220 non-null  object 
 9   company_type            13018 non-null  object 
 10  last_new_job            18735 non-null  object 
 11  training_hours          19158 non-null  int64  
 12  target                  19158 non-null  float64
dtypes: float64(2), int64(1), object(10)
memory usage: 2.0+ MB
```

2.2 Feature Descriptions

Features

enrollee_id: Unique ID for candidate

city: City code

city_development_index: Development index of the city (scaled)

gender: Gender of candidate

relevant_experience: Relevant experience of candidate

enrolled_university: Type of University course enrolled if any

education_level: Education level of candidate

major_discipline: Education major discipline of candidate

experience: Candidate total experience in years

company_size: No of employees in current employer's company

company_type : Type of current employer

lastnewjob: Difference in years between previous job and current job

training_hours: data science course training hours completed target: 0 – Not looking for job change, 1 – Looking for a job change

In [5]:
```python
# Check for duplicates
# (keep='first').sum()

df.duplicated().sum()
```
executed in 15ms, finished 11:14:48 2021-12-20

Out[5]:
```
49
```

In [6]:
```python
# Drop duplicates
# (subset=None, keep='first', inplace=False)

df = df.drop_duplicates()
```
executed in 15ms, finished 11:14:48 2021-12-20

In [7]:
```python
# Check there are no duplicates remaining

df.duplicated().sum()
```
executed in 15ms, finished 11:14:48 2021-12-20

Out[7]:
```
0
```

In [8]:
```python
# Check sum of Missing (NaN) values

df.isna().sum()
```
executed in 10ms, finished 11:14:48 2021-12-20

Out[8]:
```
city                         0
city_development_index       0
gender                    4508
relevent_experience          0
enrolled_university        386
education_level            460
major_discipline          2809
experience                  65
company_size              5920
company_type              6122
last_new_job               423
training_hours               0
target                       0
dtype: int64
```

In [9]:
```
# Create formula to observe percentages of the values missing

df_missing = df.isna().sum()
df_missing/len(df)
```
executed in 12ms, finished 11:14:48 2021-12-20

Out[9]:
```
city                      0.000000
city_development_index    0.000000
gender                    0.235910
relevent_experience       0.000000
enrolled_university       0.020200
education_level           0.024072
major_discipline          0.146999
experience                0.003402
company_size              0.309802
company_type              0.320373
last_new_job              0.022136
training_hours            0.000000
target                    0.000000
dtype: float64
```

In [10]:
```
# Check data types

df.info()
```
executed in 11ms, finished 11:14:48 2021-12-20

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 19109 entries, 8949 to 23834
Data columns (total 13 columns):
 #   Column                  Non-Null Count  Dtype
---  ------                  --------------  -----
 0   city                    19109 non-null  object
 1   city_development_index  19109 non-null  float64
 2   gender                  14601 non-null  object
 3   relevent_experience     19109 non-null  object
 4   enrolled_university     18723 non-null  object
 5   education_level         18649 non-null  object
 6   major_discipline        16300 non-null  object
 7   experience              19044 non-null  object
 8   company_size            13189 non-null  object
 9   company_type            12987 non-null  object
 10  last_new_job            18686 non-null  object
 11  training_hours          19109 non-null  int64
 12  target                  19109 non-null  float64
dtypes: float64(2), int64(1), object(10)
memory usage: 2.0+ MB
```

In [11]:
```
# would df.descibe() or df.correlation() at this point cause data leakage?
```
executed in 2ms, finished 11:14:48 2021-12-20

In [12]:

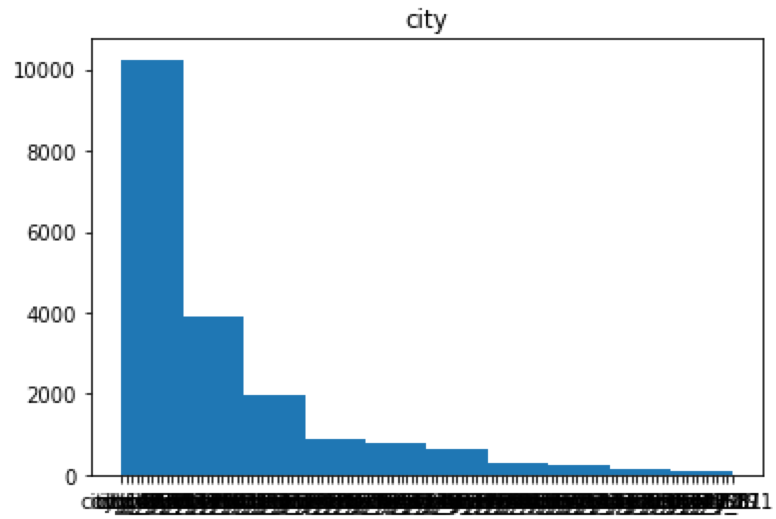
```
# Explore the value counts of each feature

for col in df.columns:
    print(df[col].value_counts())
```

executed in 28ms, finished 11:14:48 2021-12-20

```
city_103    4318
city_21     2697
city_16     1530
city_114    1336
city_160     842
            ...
city_129       3
city_121       3
city_111       3
city_171       1
city_140       1
Name: city, Length: 123, dtype: int64
0.920    5160
0.624    2697
0.910    1530
0.926    1336
0.698     683
         ...
0.649       4
```

2.3 Data Visualization

In [13]:
```python
# Visualize the data

for col in df.columns:
    plt.hist(df[col])
    plt.title(col)
    plt.show()
```
executed in 3.41s, finished 11:14:52 2021-12-20



In [14]:
```python
# Follow-up: scatterplot

# for col in df.columns:
#    plt.figure(figsize=(12,8))
#    sns.scatterplot((df[col].value_counts()))
#    plt.title(col)
#    plt.show();
```
executed in 1ms, finished 11:14:52 2021-12-20

2.4 Check for Class Imbalance

In [15]:
```python
# Check for class imbalance

y = df['target']
X = df.drop(columns=['target'])
y.value_counts(normalize=True)
```
executed in 7ms, finished 11:14:52 2021-12-20

Out[15]:
```
0.0    0.750641
1.0    0.249359
Name: target, dtype: float64
```

The data is imbalanced

2.5 Train Test Split the Data

In [16]:
```
# Create Train and Test data subsets using train_test_split
# Check shape of each data set

X_train, X_test, y_train, y_test = train_test_split(
    X, y, random_state=100, stratify=y)

X_train.shape, X_test.shape, y_train.shape, y_test.shape
```
executed in 12ms, finished 11:14:52 2021-12-20

Out[16]:
```
((14331, 12), (4778, 12), (14331,), (4778,))
```

In [17]:
```
14331+4778
```
executed in 2ms, finished 11:14:52 2021-12-20

Out[17]:
```
19109
```

2.6 Impute, Fit, and Transform the Data

We believe the missing values in the dataset will be useful to our modeling
Impute NaN values to "Missing"

In [18]:
```
# Impute NaN values to "Missing"
# Fit the data

imputer = SimpleImputer(strategy='constant', fill_value='Missing')
imputer.fit(X_train)

# Transform the data

X_train_processed = pd.DataFrame(
    imputer.transform(X_train),columns=X_train.columns)

X_test_processed = pd.DataFrame(
    imputer.transform(X_test), columns=X_test.columns)
```
executed in 27ms, finished 11:14:52 2021-12-20

In [19]:
```
# Look the the transformed data and datatypes

X_train_processed.info()
```
executed in 13ms, finished 11:14:52 2021-12-20

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 14331 entries, 0 to 14330
Data columns (total 12 columns):
 #   Column                  Non-Null Count  Dtype 
---  ------                  --------------  ----- 
 0   city                    14331 non-null  object
 1   city_development_index  14331 non-null  object
 2   gender                  14331 non-null  object
 3   relevent_experience     14331 non-null  object
 4   enrolled_university     14331 non-null  object
 5   education_level         14331 non-null  object
 6   major_discipline        14331 non-null  object
 7   experience              14331 non-null  object
 8   company_size            14331 non-null  object
 9   company_type            14331 non-null  object
 10  last_new_job            14331 non-null  object
 11  training_hours          14331 non-null  object
dtypes: object(12)
memory usage: 1.3+ MB
```

In [20]:
```
X_train_processed
```
executed in 14ms, finished 11:14:52 2021-12-20

Out[20]:

	city	city_development_index	gender	relevent_experience	enrolled_university	educatior
0	city_162	0.767	Male	No relevent experience	Full time course	High !
1	city_103	0.92	Male	Has relevent experience	no_enrollment	M
2	city_7	0.647	Male	No relevent experience	no_enrollment	Gr
3	city_24	0.698	Missing	No relevent experience	no_enrollment	M
4	city_105	0.794	Male	Has relevent experience	no_enrollment	M
...	...	...	...	...	...	
14326	city_46	0.762	Missing	No relevent experience	Full time course	M

In [21]:
```
# Explore the Train data using .describe()

X_train_processed.describe()
```
executed in 45ms, finished 11:14:52 2021-12-20

Out[21]:

	city	city_development_index	gender	relevent_experience	enrolled_university	education
count	14331	14331.00	14331	14331	14331	
unique	123	93.00	4	2	4	
top	city_103	0.92	Male	Has relevent experience	no_enrollment	Gra
freq	3260	3899.00	9879	10339	10348	

In [22]:
```
# Explore the Test data using .describe()

X_test_processed.describe()
```
executed in 49ms, finished 11:14:52 2021-12-20

Out[22]:

	city	city_development_index	gender	relevent_experience	enrolled_university	education
count	4778	4778.00	4778	4778	4778	
unique	116	88.00	4	2	4	
top	city_103	0.92	Male	Has relevent experience	no_enrollment	Gra
freq	1058	1261.00	3294	3410	3424	

In [23]:
```
# Create variable for "Number" columns (integers, floats)
# Create variable for "Category" columns (objects, strings)
# Check Category Columns

# NUMBER_COLUMNS = X_train_processed.select_dtypes('number').columns

CATEGORY_COLUMNS = X_train_processed.select_dtypes('object').columns
CATEGORY_COLUMNS
```
executed in 5ms, finished 11:14:52 2021-12-20

Out[23]:
```
Index(['city', 'city_development_index', 'gender', 'relevent_experience',
       'enrolled_university', 'education_level', 'major_discipline',
       'experience', 'company_size', 'company_type', 'last_new_job',
       'training_hours'],
      dtype='object')
```

In [24]:
```
# ONE HOT ENCODE

ohe = OneHotEncoder(handle_unknown='ignore',sparse=False)
X_train_ohe = ohe.fit_transform(X_train_processed[CATEGORY_COLUMNS])
X_test_ohe = ohe.transform(X_test_processed[CATEGORY_COLUMNS])

# CHECK
X_train = pd.DataFrame(X_train_ohe, columns=ohe.get_feature_names(CATEGORY_
X_test = pd.DataFrame(X_test_ohe, columns=ohe.get_feature_names(CATEGORY_CO

#X_train_ohe.columns = [c.lower() for c in X_train_ohe]
#X_test_ohe.columns = [c.lower() for c in X_test_ohe]
```

executed in 82ms, finished 11:14:52 2021-12-20

In [25]:
```
X_train
```

executed in 27ms, finished 11:14:52 2021-12-20

Out[25]:

	city_city_1	city_city_10	city_city_100	city_city_101	city_city_102	city_city_103	city_city_104
0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1	0.0	0.0	0.0	0.0	0.0	1.0	0.0
2	0.0	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	0.0
4	0.0	0.0	0.0	0.0	0.0	0.0	0.0
...	...	...	...	...	...	...	...
14326	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14327	0.0	0.0	0.0	0.0	0.0	1.0	0.0
14328	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14329	0.0	0.0	0.0	0.0	0.0	0.0	0.0
14330	0.0	0.0	0.0	0.0	0.0	0.0	0.0

14331 rows × 526 columns

3 CLASSIFICATION MODELS

3.1 Baseline Logistic Regression Model

In [26]:
```
logreg = LogisticRegression(solver='liblinear')
log_reg_model = logreg.fit(X_train, y_train)
log_reg_model
```

executed in 106ms, finished 11:14:52 2021-12-20

Out[26]:
```
LogisticRegression(solver='liblinear')
```

In [27]:
```
y_pred_test = logreg.predict(X_test)
y_pred_train = logreg.predict(X_train)
```
executed in 18ms, finished 11:14:52 2021-12-20

In [28]:
```
# Training data performance

residuals = np.abs(y_train - y_pred_train)
print(pd.Series(residuals).value_counts())
print(pd.Series(residuals).value_counts(normalize=True))
```
executed in 7ms, finished 11:14:52 2021-12-20

```
0.0    11324
1.0     3007
Name: target, dtype: int64
0.0    0.790175
1.0    0.209825
Name: target, dtype: float64
```

Classifier was about 79% correct on the training data

In [29]:
```
# Test data performance

residuals = np.abs(y_test - y_pred_test)
print(pd.Series(residuals).value_counts())
print(pd.Series(residuals).value_counts(normalize=True))
```
executed in 6ms, finished 11:14:52 2021-12-20

```
0.0    3745
1.0    1033
Name: target, dtype: int64
0.0    0.783801
1.0    0.216199
Name: target, dtype: float64
```

Classifier was about 78% correct on the test data

3.1.1 Confusion Matrix

Understanding the Confusion Matrix

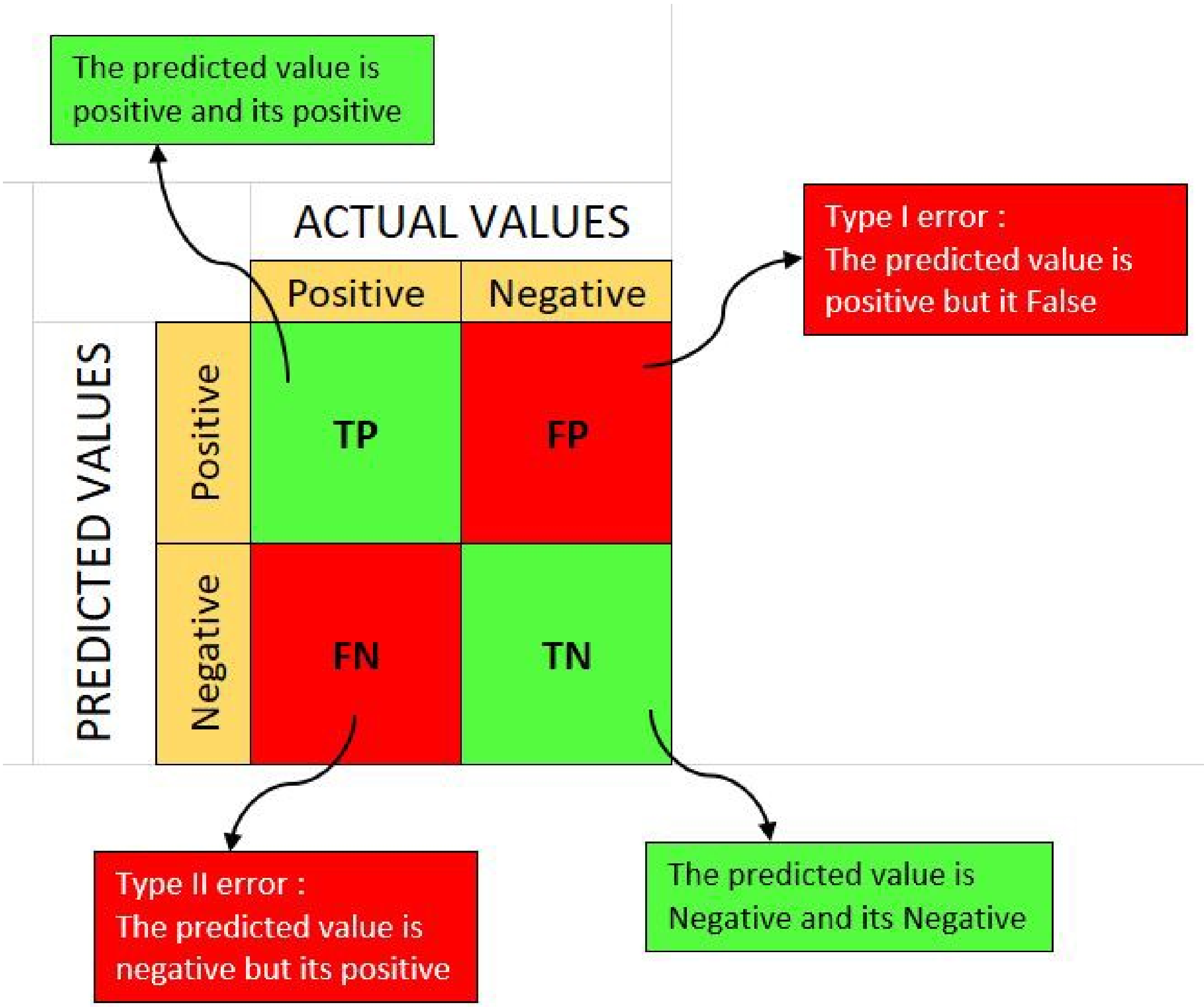
Every item in a Binary Classification dataset has a ground-truth value of 1 or 0. The Confusion Matrix helps us understand:

True Positives (TP): The number of observations where the model predicted the instance to be true (1), and it is actually true (1). In our case, where our model predicts a candidate is looking for a new job, and they are actually looking for a new job.

True Negatives (TN): The number of observations where the model predicted the instance to be not true (0), and the instance is actually not true (0). In our case, where our model predicts a candidate is not looking for a new job, and they are actually not looking for a new job.

False Positives (FP): The number of observations where the model predicted the instance to be true (1), but the instance is actually not true (0). In our case, where our model predicts a candidate is looking for a new job, and they are actually not looking for a new job.

False Negatives (FN): The number of observations where the model predicted the instance to be not true (0), but the instance is actually true (1). In our case, where our model predicts a candidate is not looking for a new job, and they are actually looking for a new job.



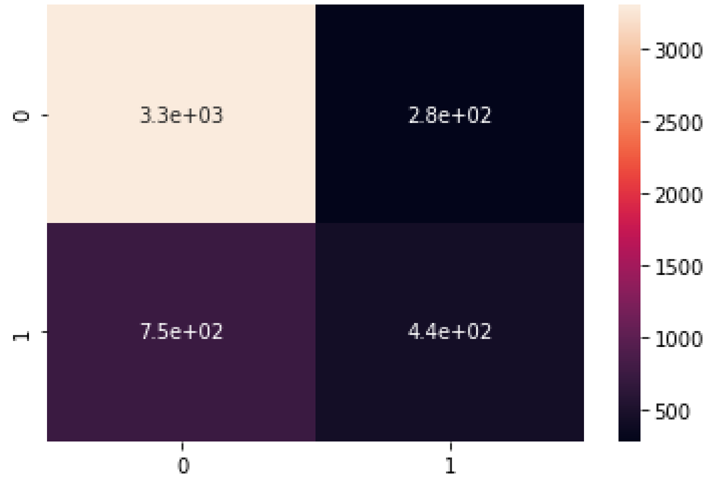
In [30]:
```
# Create a Confusion Matrix

from sklearn.metrics import confusion_matrix

#print(confusion_matrix(y_train, y_pred_train))
confusion_matrix = confusion_matrix(y_test, y_pred_test)
print(confusion_matrix)
```

executed in 8ms, finished 11:14:52 2021-12-20

```
[[3303  284]
 [ 749  442]]
```

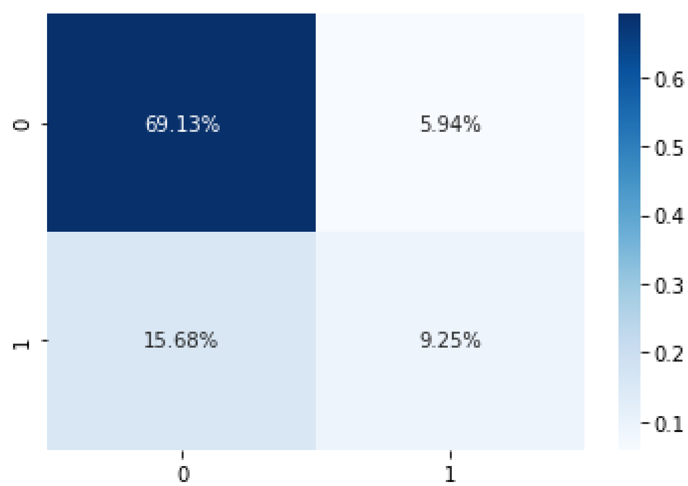
In [31]:
```
sns.heatmap(confusion_matrix, annot=True)
```
executed in 137ms, finished 11:14:52 2021-12-20

Out[31]: <AxesSubplot:>



In [32]:
```
sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 183ms, finished 11:14:53 2021-12-20

Out[32]: <AxesSubplot:>



3.1.2 Classification Report

In [33]:
```
print(classification_report(y_train, y_pred_train))
print(classification_report(y_test, y_pred_test))
```
executed in 33ms, finished 11:14:53 2021-12-20

```
              precision    recall  f1-score   support

         0.0       0.82      0.92      0.87     10757
         1.0       0.62      0.40      0.49      3574

    accuracy                           0.79     14331
   macro avg       0.72      0.66      0.68     14331
weighted avg       0.77      0.79      0.77     14331

              precision    recall  f1-score   support

         0.0       0.82      0.92      0.86      3587
         1.0       0.61      0.37      0.46      1191

    accuracy                           0.78      4778
   macro avg       0.71      0.65      0.66      4778
weighted avg       0.76      0.78      0.76      4778
```

In [34]:
```
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Scikit-learn's built in roc_curve method returns the fpr, tpr, and thresh
# for various decision boundaries given the case member probabilites

# First calculate the probability scores of each of the datapoints:
y_score = logreg.fit(X_train, y_train).decision_function(X_test)

fpr, tpr, thresholds = roc_curve(y_test, y_score)
```
executed in 107ms, finished 11:14:53 2021-12-20

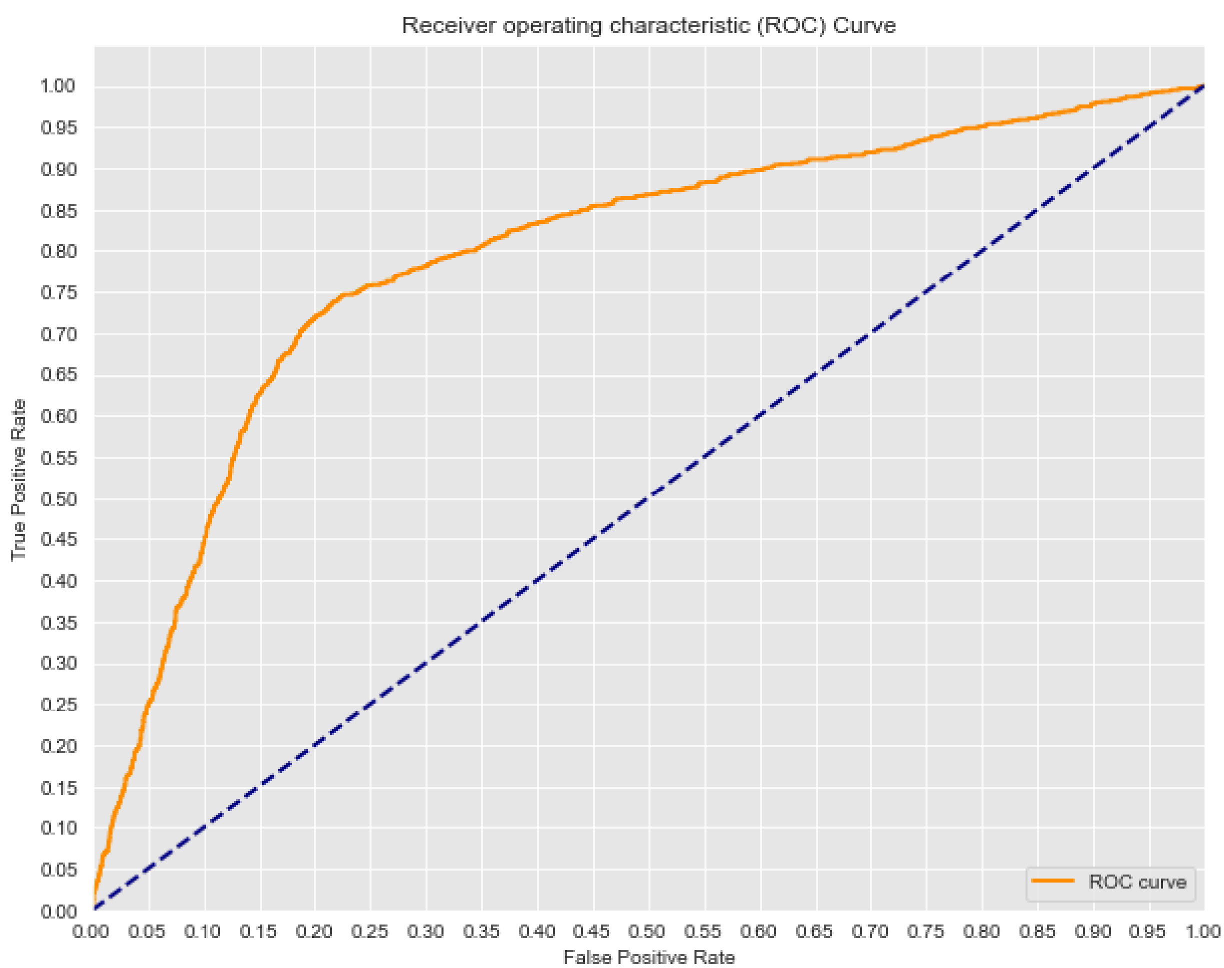
In [35]:
```
print('AUC: {}'.format(auc(fpr, tpr)))
```
executed in 2ms, finished 11:14:53 2021-12-20

```
AUC: 0.7939938208621159
```

In [36]:
```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

sns.set_style('darkgrid', {'axes.facecolor': '0.9'})

print('AUC: {}'.format(auc(fpr, tpr)))
plt.figure(figsize=(10, 8))
lw = 2
plt.plot(fpr, tpr, color='darkorange',
         lw=lw, label='ROC curve')
plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])
plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

executed in 266ms, finished 11:14:53 2021-12-20

```
AUC: 0.7939938208621159
```



3.2 Decision Tree Classifier

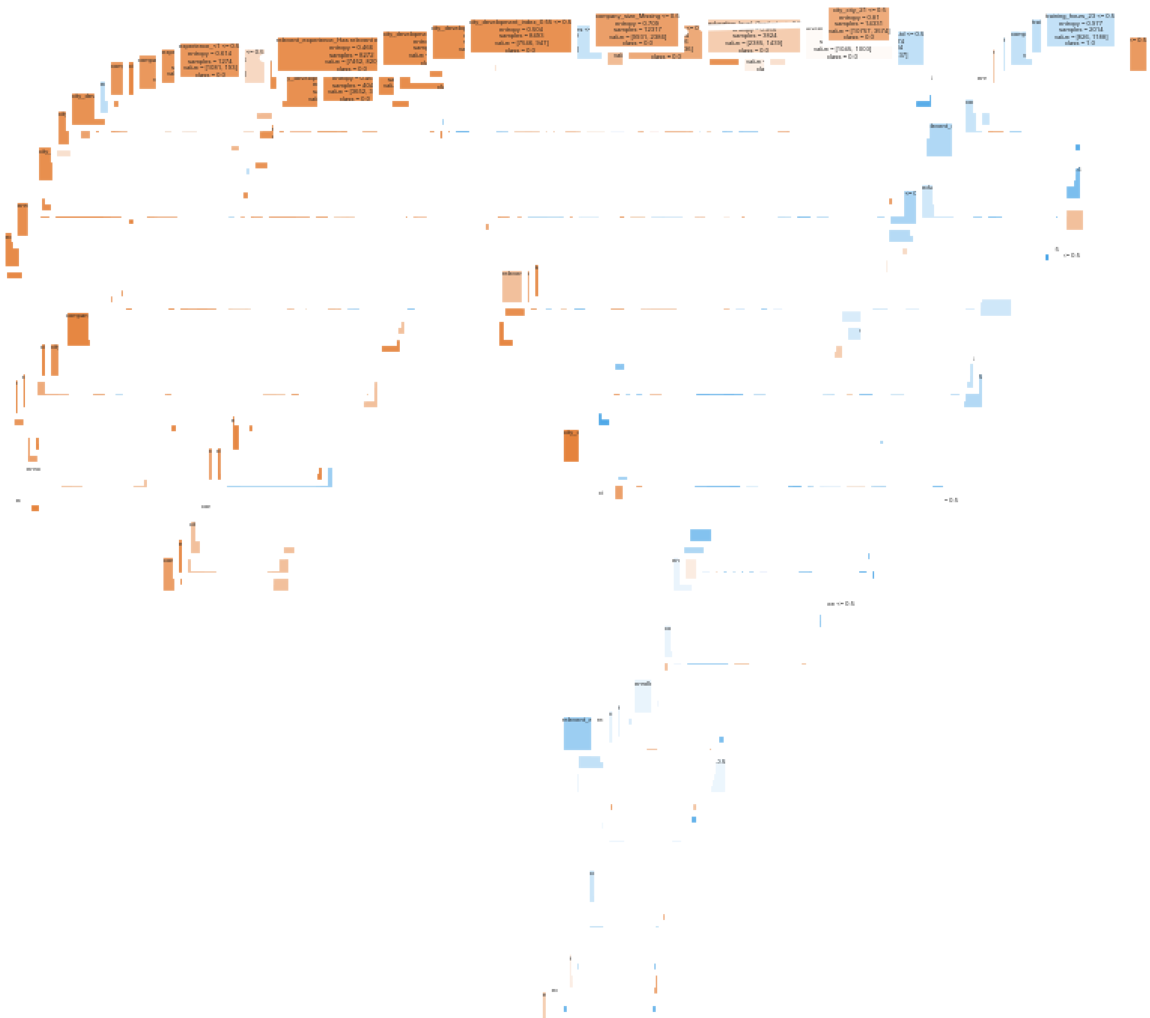
In [37]:
```
from sklearn import tree

# random state

decision_tree_clf = DecisionTreeClassifier(criterion='entropy', random_stat
decision_tree_clf.fit(X_train, y_train)
```

executed in 1.27s, finished 11:14:54 2021-12-20

Out[37]:
```
DecisionTreeClassifier(criterion='entropy', random_state=100)
```

In [38]:
```
fig, axes = plt.subplots(nrows = 1,ncols = 1, figsize = (3,3), dpi=300)
tree.plot_tree(decision_tree_clf,
               feature_names = X_train.columns,
               class_names=np.unique(y).astype('str'),
               filled = True)
plt.show()
```

executed in 1m 41.7s, finished 11:16:36 2021-12-20



In [39]:
```
# tree.plot_tree(decision_tree_clf)
```
executed in 2ms, finished 11:16:36 2021-12-20

In [40]:
```
# Hyperparameter Tuning and Pruning
```
executed in 2ms, finished 11:16:36 2021-12-20

In [41]:
```
y_predict = decision_tree_clf.predict(X_test)
```
executed in 14ms, finished 11:16:36 2021-12-20

In [42]:
```
print(classification_report(y_test, y_predict))
```
executed in 12ms, finished 11:16:36 2021-12-20

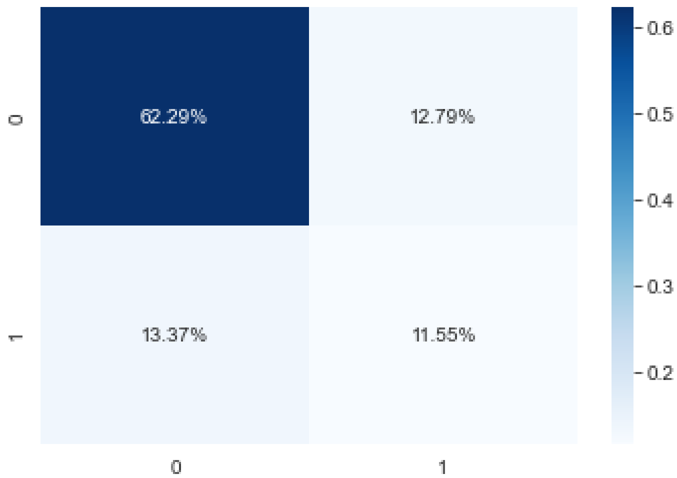
```
              precision    recall  f1-score   support

         0.0       0.82      0.83      0.83      3587
         1.0       0.47      0.46      0.47      1191

    accuracy                           0.74      4778
   macro avg       0.65      0.65      0.65      4778
weighted avg       0.74      0.74      0.74      4778
```

In [43]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_predict)
print(confusion_matrix)
```
executed in 7ms, finished 11:16:36 2021-12-20

```
[[2976  611]
 [ 639  552]]
```

In [44]:
```python
sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 135ms, finished 11:16:36 2021-12-20

Out[44]: <AxesSubplot:>



3.3 Random Forest Classifier

In [45]:
```python
from sklearn.ensemble import BaggingClassifier, RandomForestClassifier
```
executed in 9ms, finished 11:16:36 2021-12-20

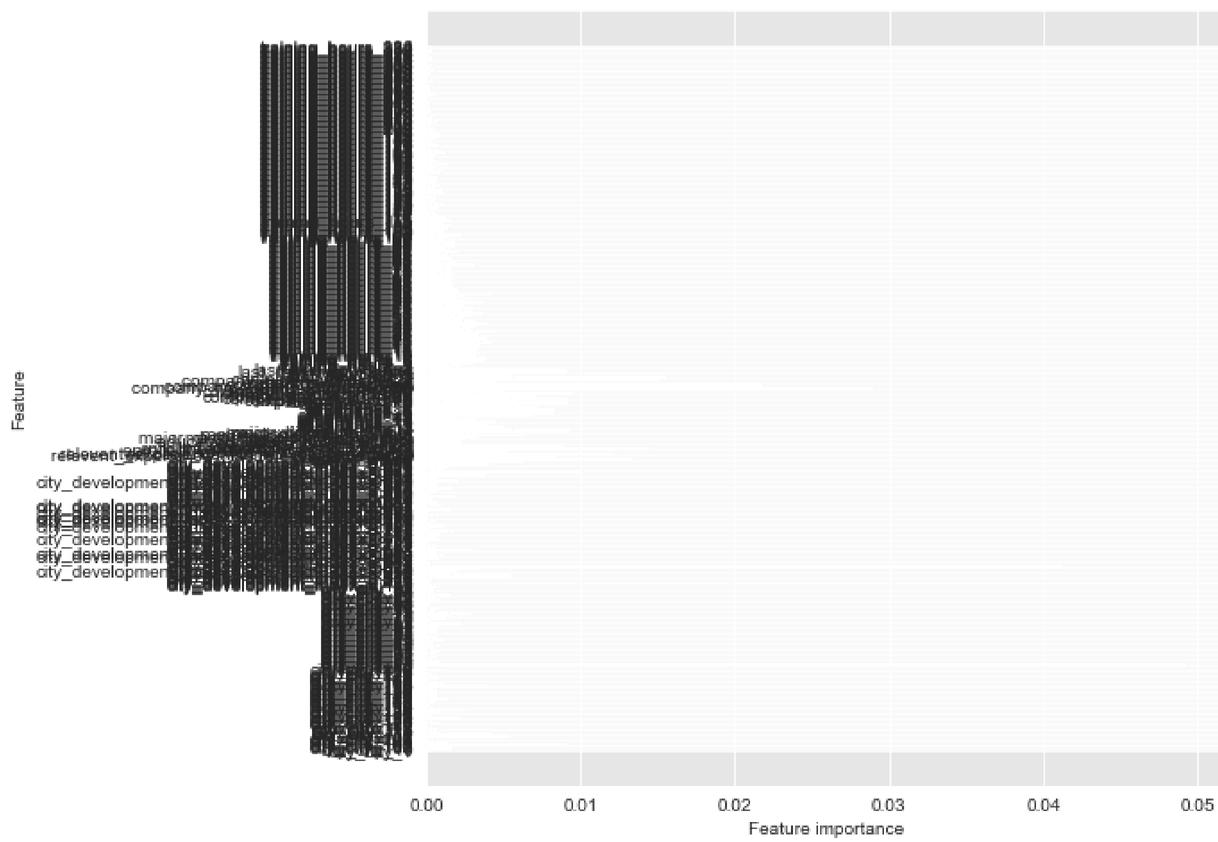
In [46]:
```python
from sklearn.ensemble import RandomForestClassifier
from sklearn.datasets import make_classification

random_forest_clf = RandomForestClassifier(random_state=100)
random_forest_clf.fit(X_train, y_train)
y_predict = random_forest_clf.predict(X_test)
```
executed in 4.49s, finished 11:16:41 2021-12-20

In [47]:
```python
# print('Accuracy: ', accuracy_score(y_test, y_predict))
```
executed in 1ms, finished 11:16:41 2021-12-20

In [48]:
```
print(classification_report(y_test, y_predict))
```
executed in 12ms, finished 11:16:41 2021-12-20

```
              precision    recall  f1-score   support

         0.0       0.83      0.89      0.86      3587
         1.0       0.59      0.46      0.52      1191

    accuracy                           0.79      4778
   macro avg       0.71      0.68      0.69      4778
weighted avg       0.77      0.79      0.78      4778
```

In [49]:
```
def plot_feature_importances(random_forest_clf):
    n_features = X_train.shape[1]
    plt.figure(figsize=(8,8))
    plt.barh(range(n_features), random_forest_clf.feature_importances_, ali
    plt.yticks(np.arange(n_features), X_train.columns.values)
    plt.xlabel('Feature importance')
    plt.ylabel('Feature')

plot_feature_importances(random_forest_clf)
```
executed in 5.76s, finished 11:16:46 2021-12-20

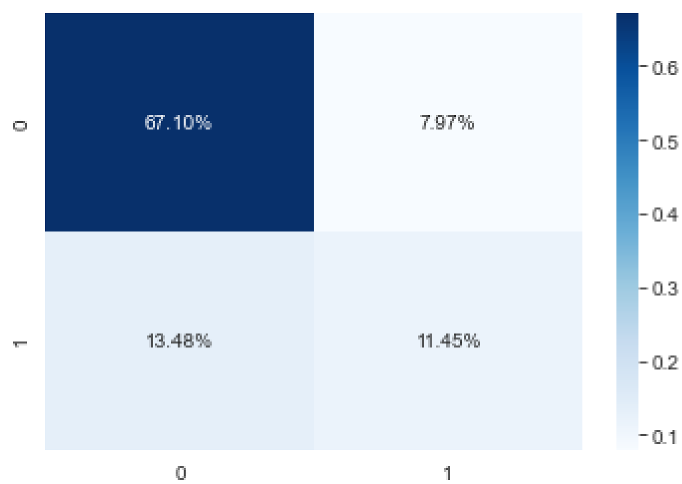


In [50]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_predict)
print(confusion_matrix)
```
executed in 7ms, finished 11:16:46 2021-12-20

```
[[3206  381]
 [ 644  547]]
```

In [51]:
```
sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 134ms, finished 11:16:47 2021-12-20

Out[51]: <AxesSubplot:>



3.3.1 Create a Pipeline with Grid Search integrated

In [52]:
```
from sklearn.pipeline import Pipeline

pipe = Pipeline([('mms', MinMaxScaler()),
                 ('tree', DecisionTreeClassifier(random_state=100))])
```
executed in 3ms, finished 11:16:47 2021-12-20

In [53]:
```
pipe.fit(X_train, y_train)
```
executed in 1.59s, finished 11:16:48 2021-12-20

Out[53]:
```
Pipeline(steps=[('mms', MinMaxScaler()),
                ('tree', DecisionTreeClassifier(random_state=100))])
```

In [54]:
```
pipe.score(X_test, y_test)
```
executed in 20ms, finished 11:16:48 2021-12-20

Out[54]: 0.7360820426956886

In [55]:
```
pipe = Pipeline([('mms', MinMaxScaler()),
                 ('tree', DecisionTreeClassifier(random_state=100))])

grid = [{'tree__max_depth': [None, 2, 6, 10],
         'tree__min_samples_split': [5, 10]}]


gridsearch = GridSearchCV(estimator=pipe,
                          param_grid=grid,
                          scoring='accuracy',
                          cv=5)

gridsearch.fit(X_train, y_train)

gridsearch.score(X_test, y_test)
```
executed in 23.1s, finished 11:17:11 2021-12-20

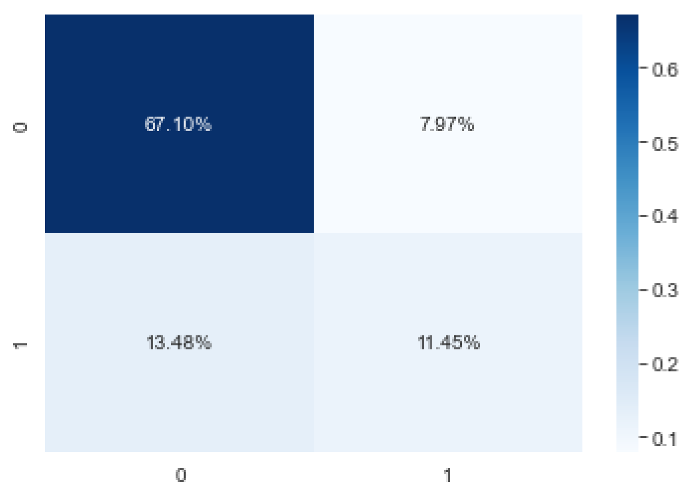
Out[55]:
```
0.7867308497279196
```

In [56]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_predict)
print(confusion_matrix)
```
executed in 7ms, finished 11:17:11 2021-12-20

```
[[3206  381]
 [ 644  547]]
```

In [57]:
```
sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 136ms, finished 11:17:11 2021-12-20

Out[57]:
```
<AxesSubplot:>
```



3.4 Gradient Boost

In [58]:
```
from sklearn.ensemble import GradientBoostingClassifier

gradient_boost_clf = GradientBoostingClassifier(random_state=100)
gradient_boost_clf.fit(X_train, y_train)
gradient_boost_clf.score(X_test, y_test)
```

executed in 27.1s, finished 11:17:39 2021-12-20

Out[58]:
```
0.7886144830473001
```

In [59]:
```
y_predict = gradient_boost_clf.predict(X_test)
```

executed in 22ms, finished 11:17:39 2021-12-20

In [60]:
```
print(classification_report(y_test, y_predict))
```

executed in 15ms, finished 11:17:39 2021-12-20

```
              precision    recall  f1-score   support

         0.0       0.84      0.89      0.86      3587
         1.0       0.59      0.48      0.53      1191

    accuracy                           0.79      4778
   macro avg       0.72      0.69      0.70      4778
weighted avg       0.78      0.79      0.78      4778
```

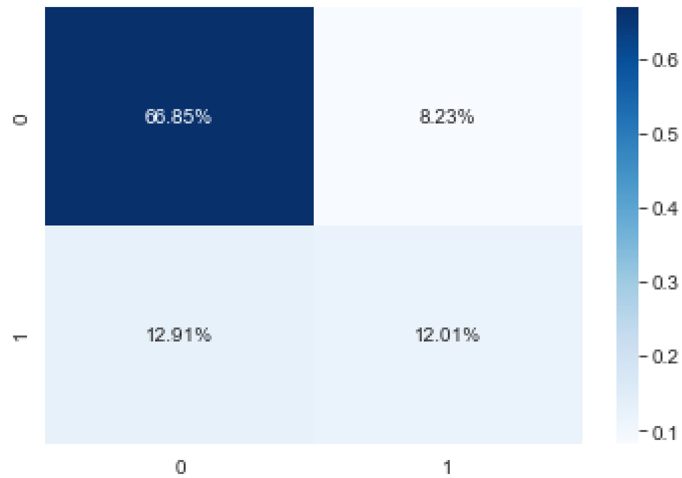
In [61]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_predict)
print(confusion_matrix)
```

executed in 7ms, finished 11:17:39 2021-12-20

```
[[3194  393]
 [ 617  574]]
```

In [62]:
```
sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 136ms, finished 11:17:39 2021-12-20

Out[62]: <AxesSubplot:>



3.5 Support Vector Machines Classifier

- Good for imbalanced data like ours

In [63]:
```
import matplotlib.pyplot as plt
from sklearn.pipeline import make_pipeline
from sklearn.datasets import make_classification
from sklearn.metrics import plot_confusion_matrix
from sklearn.svm import SVC

svc_clf = SVC(random_state=100)
svc_clf.fit(X_train, y_train)
```
executed in 1m 30.4s, finished 11:19:09 2021-12-20

Out[63]: SVC(random_state=100)

In [64]:
```
y_predict = svc_clf.predict(X_test)
```
executed in 24.2s, finished 11:19:33 2021-12-20

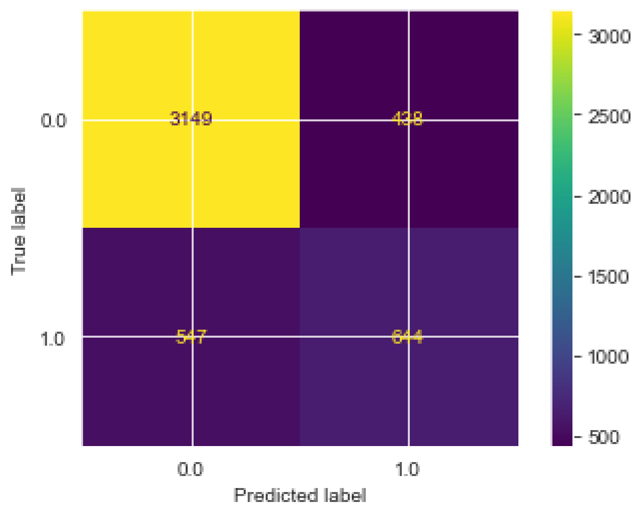
In [65]:
```
print(classification_report(y_test, y_predict))
```
executed in 14ms, finished 11:19:33 2021-12-20

```
              precision    recall  f1-score   support

         0.0       0.85      0.88      0.86      3587
         1.0       0.60      0.54      0.57      1191

    accuracy                           0.79      4778
   macro avg       0.72      0.71      0.72      4778
weighted avg       0.79      0.79      0.79      4778
```

In [66]:
```
from sklearn.metrics import confusion_matrix

confusion_matrix = confusion_matrix(y_test, y_predict)
print(confusion_matrix)
```
executed in 6ms, finished 11:19:33 2021-12-20

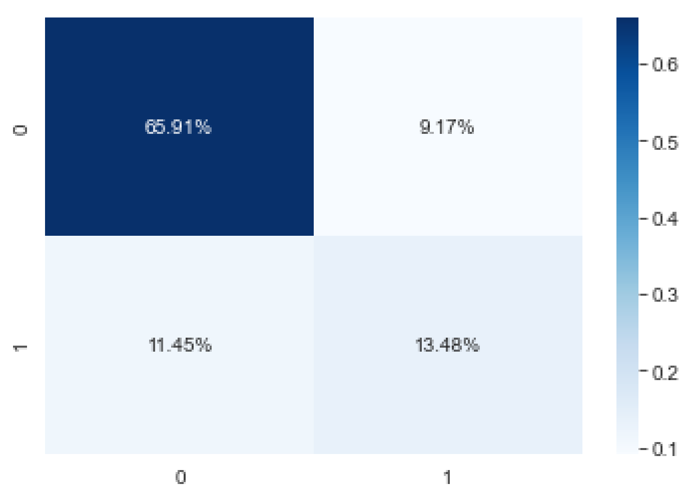
```
[[3149  438]
 [ 547  644]]
```

In [67]:
```
# See if visualizing the actuals will be interesting

plot_confusion_matrix(svc_clf, X_test, y_test)
plt.show()
```
executed in 24.3s, finished 11:19:58 2021-12-20



In [68]:
```
# Visualize in percentages

sns.heatmap(confusion_matrix/np.sum(confusion_matrix), annot=True,
            fmt='.2%', cmap='Blues')
```
executed in 134ms, finished 11:19:58 2021-12-20

Out[68]: <AxesSubplot:>



In [69]:
```
#Grid Search

#pipe = Pipeline([('mms', MinMaxScaler()),
#                  ('tree', DecisionTreeClassifier(random_state=123))])

#grid = [{'tree__max_depth': [None, 2, 6, 10],
#         'tree__min_samples_split': [5, 10]}]


#gridsearch = GridSearchCV(estimator=pipe,
#                          param_grid=grid,
#                          scoring='accuracy',
#                          cv=5)

#gridsearch.fit(X_train, y_train)

gridsearch.score(X_test, y_test)
```

executed in 19ms, finished 11:19:58 2021-12-20

Out[69]:
```
0.7867308497279196
```

4 Evaluation and Conclusions

After evaluating several classification models (baseline logistic regression, decision tree, random forest, gradient boost, and support vector machines), we've chosen Gradient Boost as the model to determine whether candidates are likely to change careers.

Conclusions

- With our data being imbalanced, we evaluated our models based on the F1 Score because the F1 score captures a poor balance between recall and precision
- The F1 score for our Gradient Boost model is 0.86
- Gradient Boost is a robust model that starts with a "weak learner" and continuously identifies examples that it got right or wrong. It then calculates the residuals to for each data point to determine how far off the predications were and combines these this with a loss function to calculate overall loss.
- In other words, the model continuously improves itself!
- Our confusion matrix shows the model predicted 67% of the True Positives (predicted a candidate is looking for a new job, and they are actually looking for a new job) and 12% True Positives (predicted a candidate is not looking for a new job, and they are actually not looking for a new job).

5 Future Work

Future work:

- Refine existing models
- Tune and prune hyperparameters
- AUC Roc Curve

In [70]:
```
from sklearn.metrics import roc_curve, auc, roc_auc_score

# Compare different regularization performances on the dataset:
weights = [None, 'balanced', {1:2, 0:1}, {1:10, 0:1}, {1:100, 0:1}, {1:1000
names = ['None', 'Balanced', '2 to 1', '10 to 1', '100 to 1', '1000 to 1']
colors = sns.color_palette('Set2')

plt.figure(figsize=(10,8))

for n, weight in enumerate(weights):
    # Fit a model
    logreg = LogisticRegression(fit_intercept=False, C=1e20, class_weight=w
    model_log = logreg.fit(X_train, y_train)
    print(model_log)

    # Predict
    y_hat_test = logreg.predict(X_test)

    y_score = logreg.fit(X_train, y_train).decision_function(X_test)

    fpr, tpr, thresholds = roc_curve(y_test, y_score)

    print('AUC for {}: {}'.format(names[n], auc(fpr, tpr)))
    print('-----------------------------------------------------------------
    lw = 2
    plt.plot(fpr, tpr, color=colors[n],
             lw=lw, label='ROC curve {}'.format(names[n]))

plt.plot([0, 1], [0, 1], color='navy', lw=lw, linestyle='--')
plt.xlim([0.0, 1.0])
plt.ylim([0.0, 1.05])

plt.yticks([i/20.0 for i in range(21)])
plt.xticks([i/20.0 for i in range(21)])
plt.xlabel('False Positive Rate')
plt.ylabel('True Positive Rate')
plt.title('Receiver operating characteristic (ROC) Curve')
plt.legend(loc='lower right')
plt.show()
```

executed in 8.64s, finished 11:20:06 2021-12-20

```
/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklea
rn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to c
onverge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown
in:
    https://scikit-learn.org/stable/modules/preprocessing.html (http
s://scikit-learn.org/stable/modules/preprocessing.html)
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression (https://scikit-learn.org/stable/modules/linear_model.html#l
ogistic-regression)
  n_iter_i = _check_optimize_result(
```

```
LogisticRegression(C=1e+20, fit_intercept=False)

/Users/v/opt/anaconda3/envs/learn-env/lib/python3.8/site-packages/sklea
rn/linear_model/_logistic.py:762: ConvergenceWarning: lbfgs failed to c
```