Lab 5

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import packages

```
In [34]: import datascience as ds
         from datascience import *
         import numpy as np
         from graphviz import Source
         import pandas as pd
         import re
         import string
         from copy import copy
         import nltk
         from datetime import datetime

         from sklearn.feature_extraction.text import CountVectorizer, TfidfVectorizer
         from sklearn.model_selection import train_test_split
         from sklearn.tree import DecisionTreeClassifier
         from sklearn.linear_model import LogisticRegression
         from sklearn.ensemble import RandomForestClassifier
         from xgboost import XGBClassifier as XGBoostClassifier
         from sklearn import tree
         from sklearn import metrics
         from sklearn.metrics import confusion_matrix
         import matplotlib.pyplot as plt
         from sklearn.model_selection import cross_val_score
         import seaborn as sns
         from imblearn.over_sampling import SMOTE

         %matplotlib inline
```

```
In [35]: tagged = pd.read_csv('cleaned_tagged.csv', sep=',')
         Relevant = np.array([0]*tagged.size)
         Relevant[tagged[tagged.sentiment!=-1].index.tolist()] = 1
         tagged['Relevant'] = pd.Series(Relevant, name='Relevant')
         tagged = tagged.drop(tagged.columns[0], axis=1).reset_index(drop=True)
         tagged.to_csv('relevant_binary_tagged.csv')
```

1) tweets data loaded into Jupyter Notebook as Table object

```
In [36]: df = ds.Table.read_table('relevant_binary_tagged.csv', sep=',')
         df
```

```
Out[36]: Unnamed: 0 | user_id             | user_name                    | tweet_time
         0          | 802657195661742080  | Christine Warren             | Wed Sep 12 01:38:14
         1          | 1039245812230893570 | Trumpservative               | Wed Sep 12 01:38:16
         2          | 282084840           | Darrel Sheldon #MAGAVETERAN  | Wed Sep 12 01:38:18
         3          | 62315639            | Queer Liberal Voting Snowflake | Wed Sep 12 01:38:18
         4          | 823307049266245633  | don jones #veteran (K)       | Wed Sep 12 01:38:19
         5          | 340428574           | DelcoGal                     | Wed Sep 12 01:38:21
         6          | 1603928228          | Julz                         | Wed Sep 12 01:38:22
         7          | 1865678516          | Barbara Kuczinski            | Wed Sep 12 01:38:22
         8          | 59288409            | Josh Steed PhD               | Wed Sep 12 01:38:25
         9          | 325172419           | Mrs. Linz                    | Wed Sep 12 01:38:25
         ... (1286 rows omitted)
```

data preprocessing

```
In [37]: relevant_tweet = df.where('Relevant', are.equal_to(1))
         irrelevant_tweet = df.where('Relevant', are.equal_to(0))
```

```
In [38]: relevant_tweet_cnt = relevant_tweet.num_rows
         irrelevant_tweet_cnt = irrelevant_tweet.num_rows
```

```
In [39]: relevant_tweet_cnt, irrelevant_tweet_cnt
```

```
Out[39]: (1133, 163)
```

```
In [40]: relevant_training_size = round(relevant_tweet_cnt*0.8)
         irrelevant_training_size = round(irrelevant_tweet_cnt*0.8)
```

```
In [41]: relevant_training_size, irrelevant_training_size
```

```
Out[41]: (906, 130)
```

```
In [42]: relevant_train_idx = list(range(relevant_training_size))
         irrelevant_train_idx = list(range(irrelevant_training_size))
         relevant_test_idx = list(range(relevant_tweet_cnt))[int(relevant_training_size):]
         irrelevant_test_idx = list(range(irrelevant_tweet_cnt))[irrelevant_training_size:]


         relevant_training_text = list(relevant_tweet.take(relevant_train_idx)['text'])
         irrelevant_training_text = list(irrelevant_tweet.take(irrelevant_train_idx)['text'])
         relevant_training_relevant = list(relevant_tweet.take(relevant_train_idx)['Relevant'])
         irrelevant_training_relevant = list(irrelevant_tweet.take(irrelevant_train_idx)['Releva

         relevant_testing_text = list(relevant_tweet.take(relevant_test_idx)['text'])
         irrelevant_testing_text = list(irrelevant_tweet.take(irrelevant_test_idx)['text'])
```

```
relevant_testing_relevant = list(relevant_tweet.take(relevant_test_idx)['Relevant'])
irrelevant_testing_relevant = list(irrelevant_tweet.take(irrelevant_test_idx)['Relevant

X_train = relevant_training_text + irrelevant_training_text
y_train = relevant_training_relevant + irrelevant_training_relevant
X_test = relevant_testing_text + irrelevant_testing_text
y_test = relevant_testing_relevant + irrelevant_testing_relevant
```

2) showing the sizes of your training and testing sets (number of relevant training + irrelevant training, number of relevant testing + irrelevant testing)

```
In [43]: len(X_train), len(X_test), len(y_train), len(y_test)
```

```
Out[43]: (1036, 260, 1036, 260)
```

Model (Bag of Words + DTree)

```
In [44]: vect = CountVectorizer(
              analyzer="word", ngram_range=([1,2]), tokenizer=nltk.word_tokenize,
            preprocessor=None, stop_words='english', max_features=3000)
         # vect = TfidfVectorizer(sublinear_tf=True, min_df=10, norm='l1', encoding='latin-1',
         #                          ngram_range=(1,2), stop_words='english')
         X_train_vect = vect.fit_transform(X_train).todense()
         X_test_vect = vect.transform(X_test)
         X_train_vect.shape, X_test_vect.shape
```

```
Out[44]: ((1036, 3000), (260, 3000))
```

```
In [45]: clf = DecisionTreeClassifier(criterion = 'entropy',
                                      random_state = 100,
                                      max_depth = 5,
                                      min_samples_leaf = 2)
         # clf = RandomForestClassifier(random_state=100,
         #                              n_estimators=60,
         #                              criterion='entropy',
         #                              n_jobs=4)
         # clf = XGBoostClassifier(max_depth=5, n_estimators=5)
         # clf = LogisticRegression()
         clf.fit(X_train_vect, y_train)
```

```
Out[45]: DecisionTreeClassifier(class_weight=None, criterion='entropy', max_depth=5,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=2, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=100,
                     splitter='best')
```

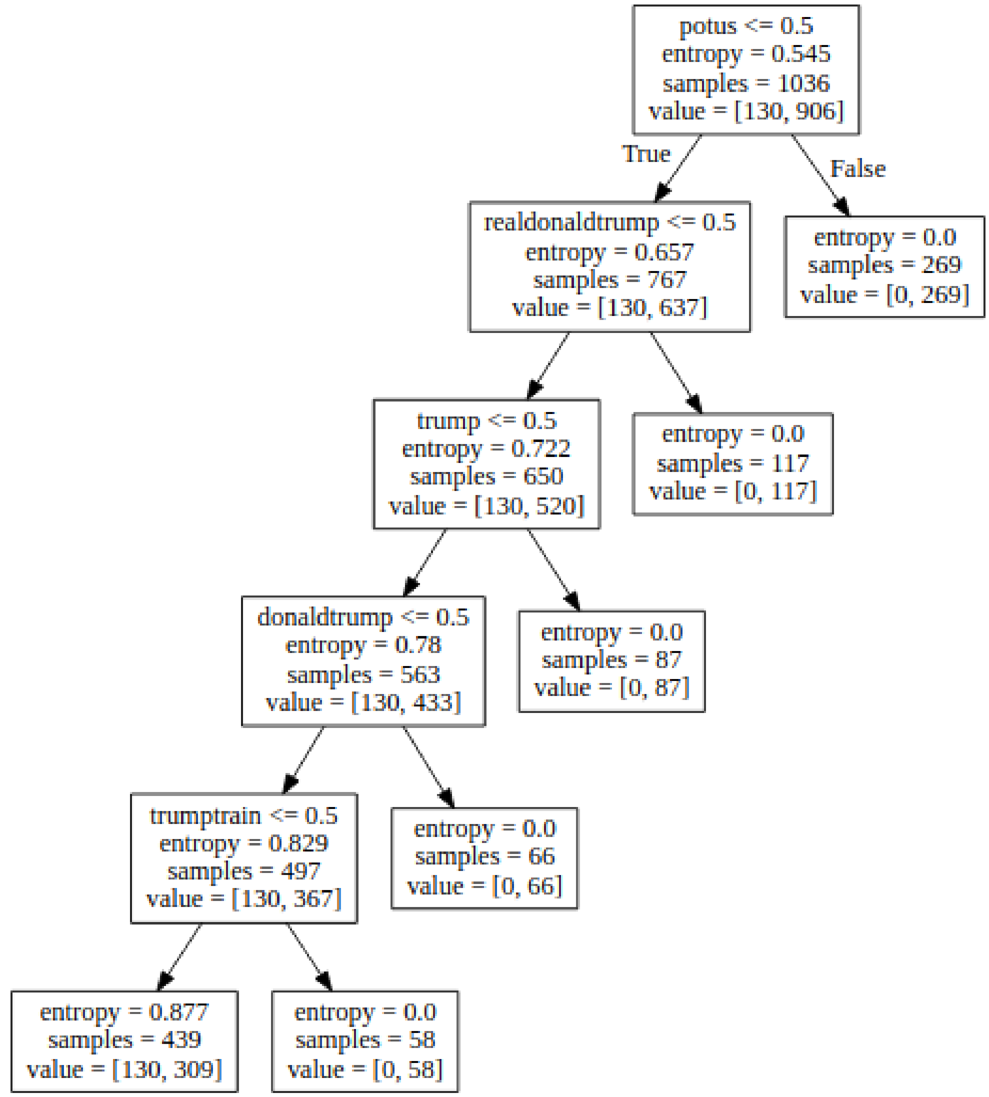
```
In [33]: y_pred = clf.predict(X_test_vect)
         np.mean([cross_val_score(clf, X_train_vect, y_train, cv=8)])
```

```
Out[33]: 0.8745339960944435
```

3) the confusion matrix of evaluating your Decision Tree-based relevant classifier using TESTING data, and identify false positive and false negative in your evaluation result.

```
In [46]: cm = confusion_matrix(y_test, y_pred)
         cm

Out[46]: array([[  0,  33],
                [  0, 227]])

In [47]: FP = cm[0][1]
         FN = cm[1][0]
         TP = cm[1][1]
         TN = cm[0][0]
         print('The False Positive:', FP)
         print('The False Negative:', FN)
         print('The True Positive:', TP)
         print('The True Negative:', TN)

The False Positive: 33
The False Negative: 0
The True Positive: 227
The True Negative: 0

In [53]: dot_data = tree.export_graphviz(clf, out_file=None, feature_names=vect.get_feature_name
         graph = Source(dot_data)
         graph.render('RelevantClassifier')

Out[53]: 'RelevantClassifier.pdf'
```

4) A visualization of your decision tree.



5) A description of a rule based on the tree

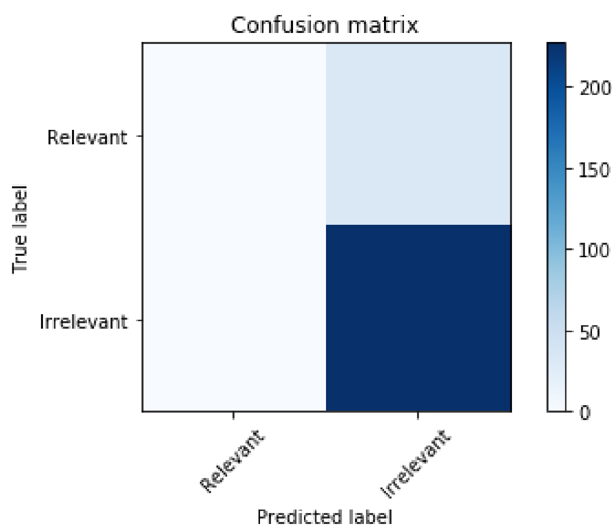
- If potus<=0.5:
  - If realdonaldtrump<=0.5:
    - If trump > 0.5:
      - then the tree reaches the leaf, value = $[0, 87]$, indicating that there are 87 tweets are categorized as `Relevant`

6) A short summary of your evaluation result using the confusion matrix

```
In [58]: def plot_cm(cm, title='Confusion matrix', cmap=plt.cm.Blues, classes=['Relevant', 'Irre
             print(cm)
```

```
            plt.imshow(cm, interpolation='nearest', cmap=cmap)
            plt.title(title)
            plt.colorbar()
            tick_marks = np.arange(len(classes))
            target_names = classes
            plt.xticks(tick_marks, target_names, rotation=45)
            plt.yticks(tick_marks, target_names)
            plt.tight_layout()
            plt.ylabel('True label')
            plt.xlabel('Predicted label')
        plot_cm(confusion_matrix(y_test, y_pred))
```

```
[[  0  33]
 [  0 227]]
```




```
In [56]: print("AUC(ROC): " + str(metrics.roc_auc_score(y_test, y_pred)))
         print("Precision: " + str(metrics.precision_score(y_test, y_pred)))
         print("Recall: " + str(metrics.recall_score(y_test, y_pred)))
         print("F1 score: " + str(metrics.f1_score(y_test, y_pred)))
```

```
AUC(ROC): 0.5
Precision: 0.8730769230769231
Recall: 1.0
F1 score: 0.5322381930184805
```

Here we can see from the confusion matrix that the `True Negative`=0, and `False Positive`=33, which means all 33 `Irrelevant` tweets are categorized as `Relevant`. Thus there appears to have a serious problem here: even with the accuracy is decent, it is actually inflated.

The reason for that is because the proportion of `Relevant` tweets(**1133/1296**) is way larger than that of `Irrelevant` tweets(**163/1296**), thus

$$accuracy = \frac{TP + TN}{TP + TN + FN + FP} = \frac{227}{260} = 87.3\%$$

In fact, with the task being to filter out the irrelevant tweets, this classifier basically fails the task because of the unbalanced data.

Possible fixes:

- Resampling
  - Downsampling on the `Relevant` tweets
  - Upsampling on the `Irrelevant` tweets

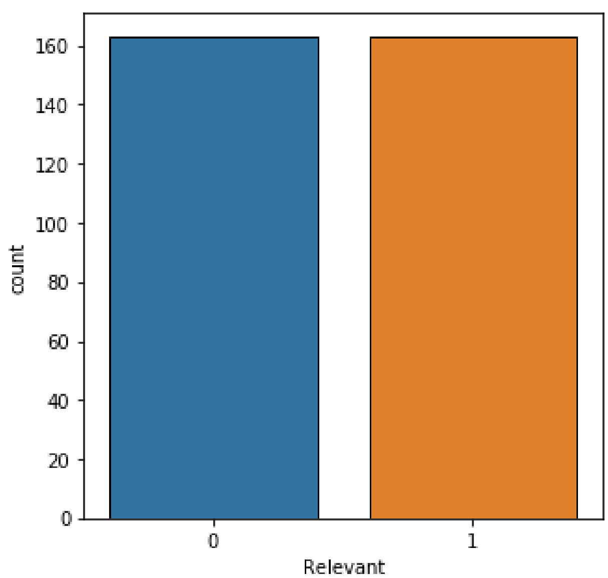
```
In [61]: def classify(X_train_vect, y_train, X_test_vect, y_test, model, vector):
             clf.fit(X_train_vect, y_train)
             y_pred = clf.predict(X_test_vect)
             cross_val_s = np.mean([cross_val_score(model, X_train_vect, y_train, cv=8)])
             print('Cross_val_score: {}'.format(cross_val_s))
             print("AUC(ROC): " + str(metrics.roc_auc_score(y_test, y_pred)))
             print("Precision: " + str(metrics.precision_score(y_test, y_pred)))
             print("Recall: " + str(metrics.recall_score(y_test, y_pred)))
             print("F1 score: " + str(metrics.f1_score(y_test, y_pred)))
             print(metrics.confusion_matrix(y_test, y_pred))
             plt.figure(figsize=(5,5))
             plot_cm(metrics.confusion_matrix(y_test, y_pred))
             plt.show()
             return cross_val_s
```

Experiment 1: Downsample the `Relevant` data

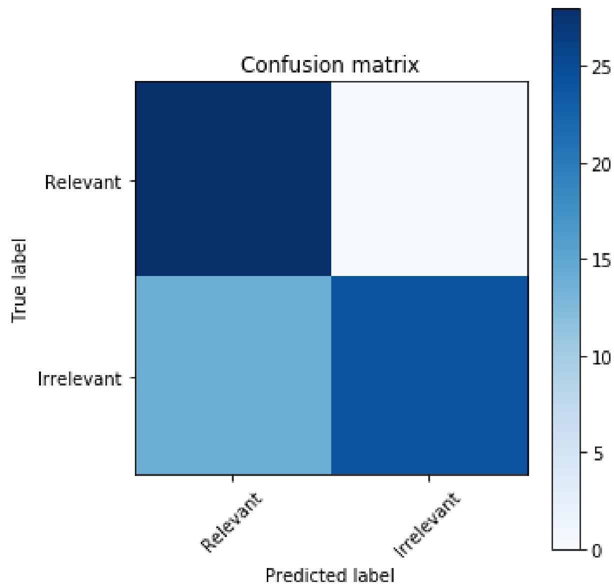
```
In [62]: def undersample(data, percentage, vector):
             relevant_idx = tagged[tagged.Relevant==1].index
             irrelevant_idx = tagged[tagged.Relevant==0].index
             undersample_relevant_idx = np.array(np.random.choice(relevant_idx,(int(percentage*l
             undersample_idx= np.concatenate([irrelevant_idx, undersample_relevant_idx])
             undersample_data = tagged.iloc[undersample_idx,:]
             print('There are {} relevant tweets.\n There are {} irrelevant tweets.'.format(len(
                                                                                           len(
             X_train, X_test, y_train, y_test = train_test_split(undersample_data.text, undersam
             X_train_vect = vector.fit_transform(X_train).todense()
             X_test_vect = vector.transform(X_test)
             plt.figure(figsize=(5,5))
             sns.countplot("Relevant",data=undersample_data)
             plt.show()
             return X_train_vect, X_test_vect, y_train, y_test
```

```
In [66]: cross_val_scores=[]
         for percentage in np.arange(1, 4, 0.5):
             X_train_vect, X_test_vect, y_train, y_test = undersample(tagged, percentage, vect)
             cross_val_s = classify(X_train_vect=X_train_vect,
                 X_test_vect=X_test_vect,
                 y_train =y_train,
                 y_test=y_test,
                 model=clf,
                 vector=vect)
             cross_val_scores.append(cross_val_s)
         plt.figure(figsize=(5,5))
         plt.plot(np.arange(1,4,0.5), cross_val_scores)
         plt.scatter(np.arange(1,4,0.5), cross_val_scores, c='r')
         plt.show()
```

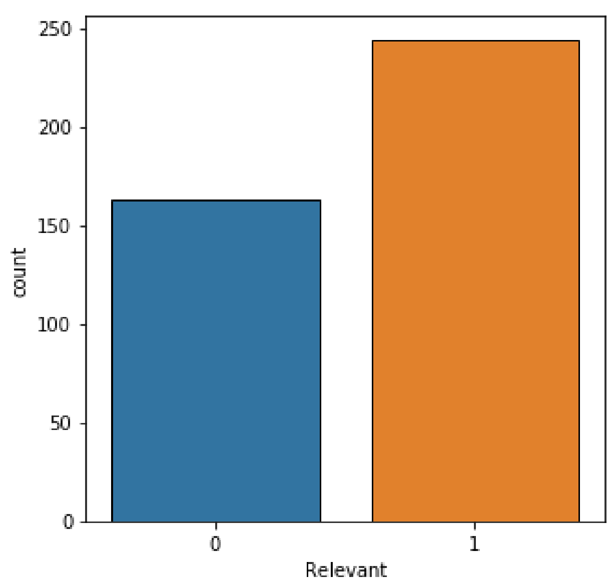
```
There are 163 relevant tweets.
 There are 163 irrelevant tweets.
```




```
Cross_val_score: 0.8041758308895406
AUC(ROC): 0.8157894736842105
Precision: 1.0
Recall: 0.631578947368421
F1 score: 0.7741935483870968
[[28  0]
 [14 24]]
[[28  0]
 [14 24]]
```

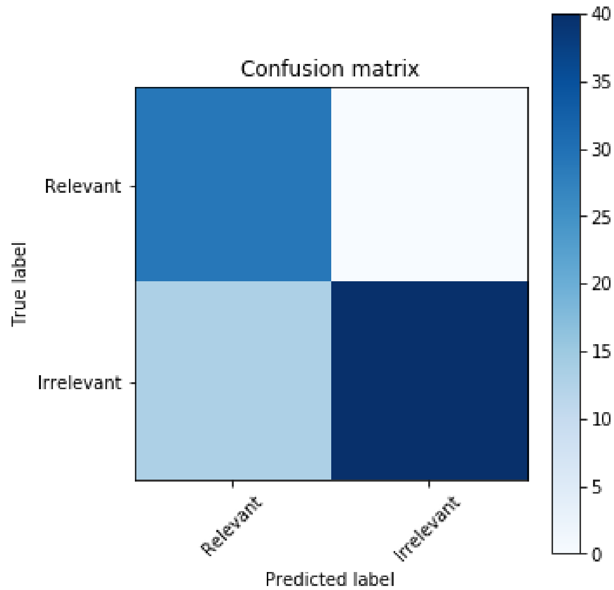



```
There are 244 relevant tweets.
 There are 163 irrelevant tweets.
```

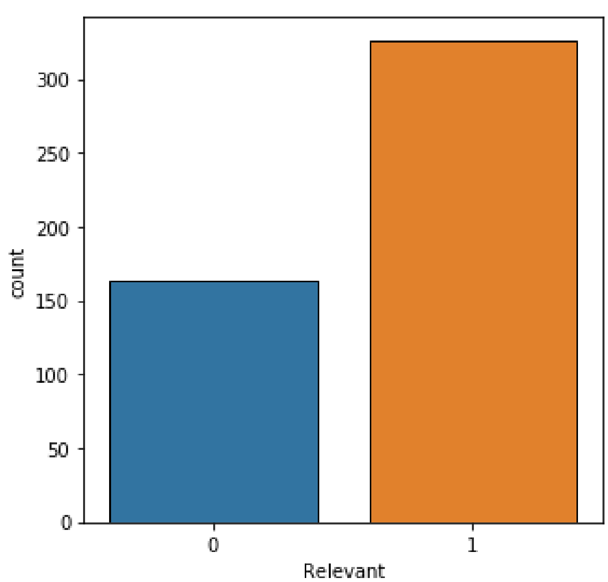



```
Cross_val_score: 0.824130315822389
AUC(ROC): 0.8773584905660378
Precision: 1.0
```

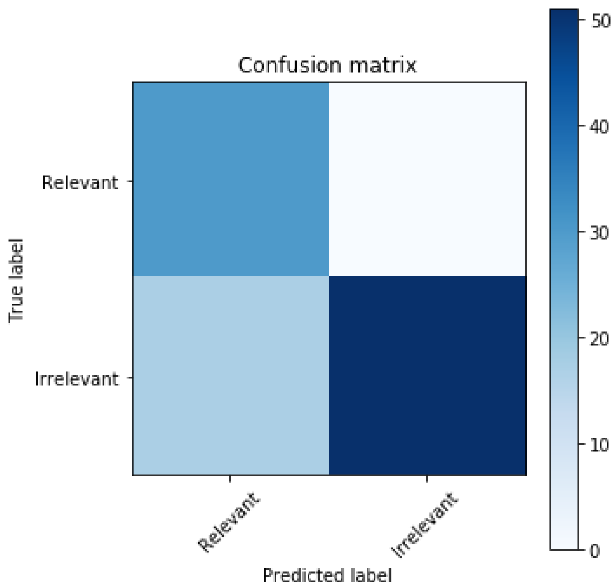
```
Recall: 0.7547169811320755
F1 score: 0.8602150537634409
[[29  0]
 [13 40]]
[[29  0]
 [13 40]]
```



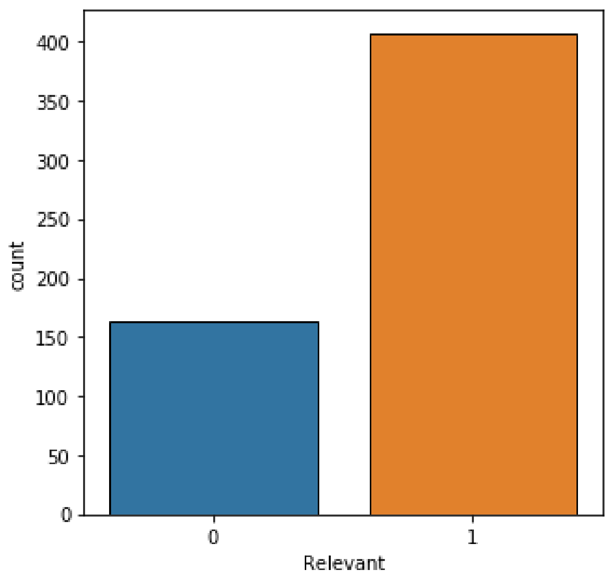

```
There are 326 relevant tweets.
 There are 163 irrelevant tweets.
```



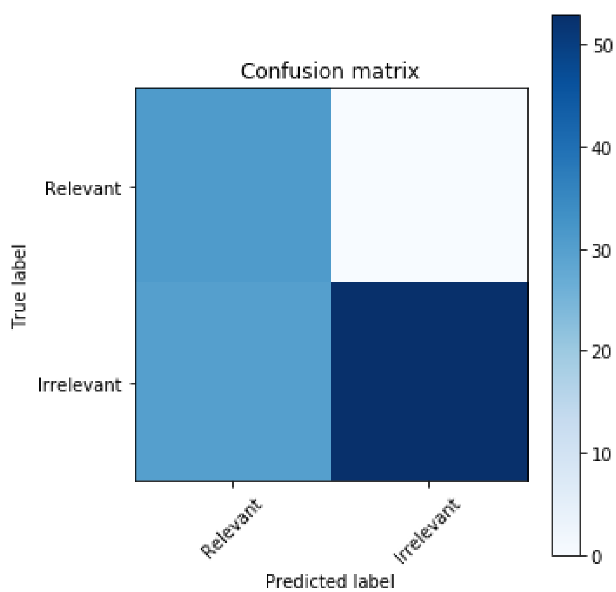
```
Cross_val_score: 0.7495153061224489
AUC(ROC): 0.875
Precision: 1.0
Recall: 0.75
F1 score: 0.8571428571428571
[[30  0]
 [17 51]]
[[30  0]
 [17 51]]
```



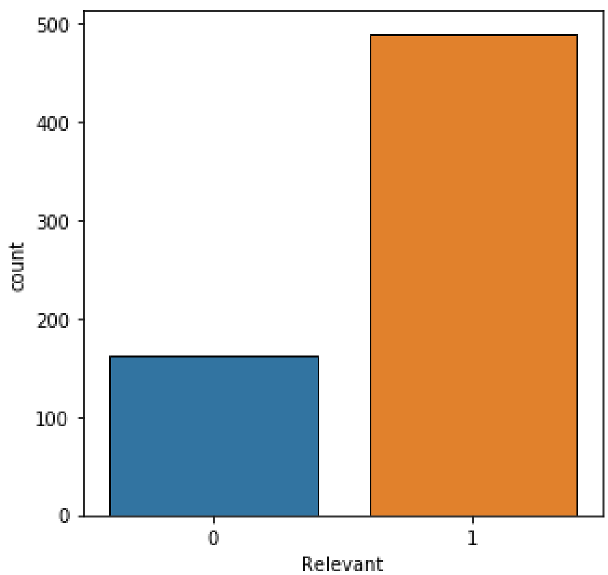

```
There are 407 relevant tweets.
 There are 163 irrelevant tweets.
```



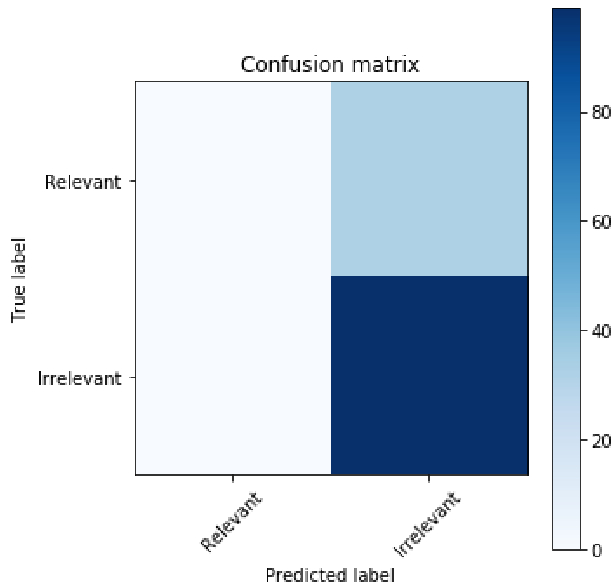

```
Cross_val_score: 0.7327586206896551
AUC(ROC): 0.8192771084337349
Precision: 1.0
Recall: 0.6385542168674698
F1 score: 0.7794117647058824
[[31  0]
 [30 53]]
[[31  0]
 [30 53]]
```



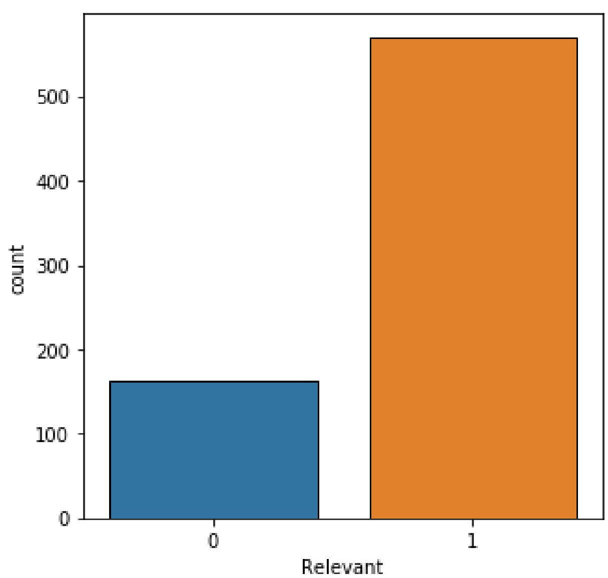
```
There are 489 relevant tweets.
 There are 163 irrelevant tweets.
```




```
Cross_val_score: 0.7214352054195804
AUC(ROC): 0.5
Precision: 0.7557251908396947
Recall: 1.0
F1 score: 0.8608695652173913
[[ 0 32]
 [ 0 99]]
[[ 0 32]
 [ 0 99]]
```

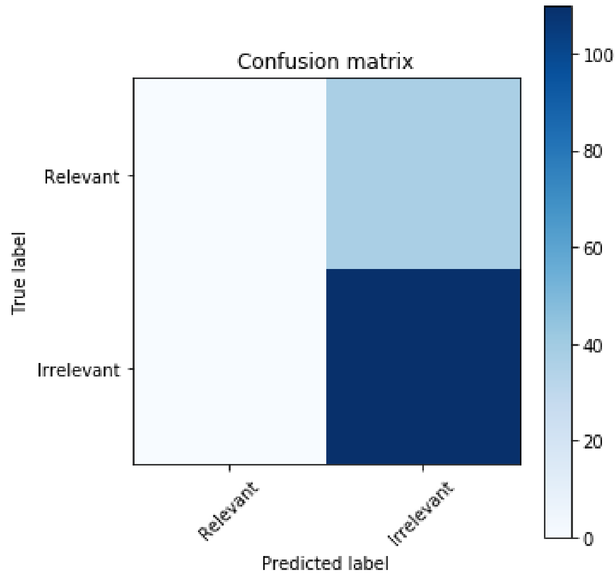


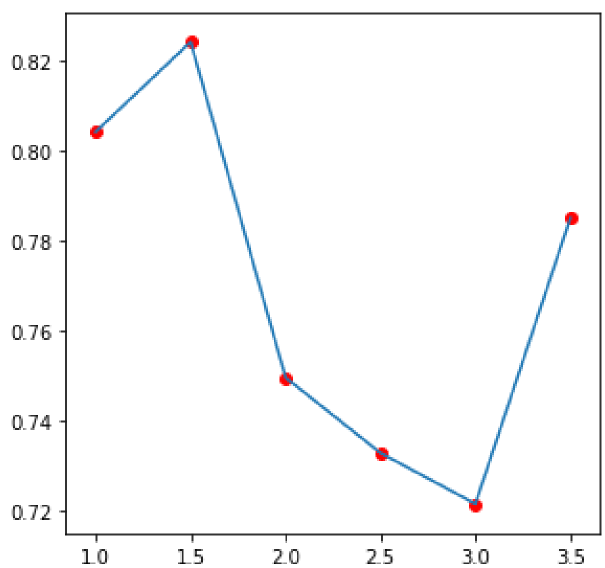

```
There are 570 relevant tweets.
 There are 163 irrelevant tweets.
```




```
Cross_val_score: 0.7850140380106133
AUC(ROC): 0.5
Precision: 0.7482993197278912
```

```
Recall: 1.0
F1 score: 0.8560311284046693
[[  0  37]
 [  0 110]]
[[  0  37]
 [  0 110]]
```



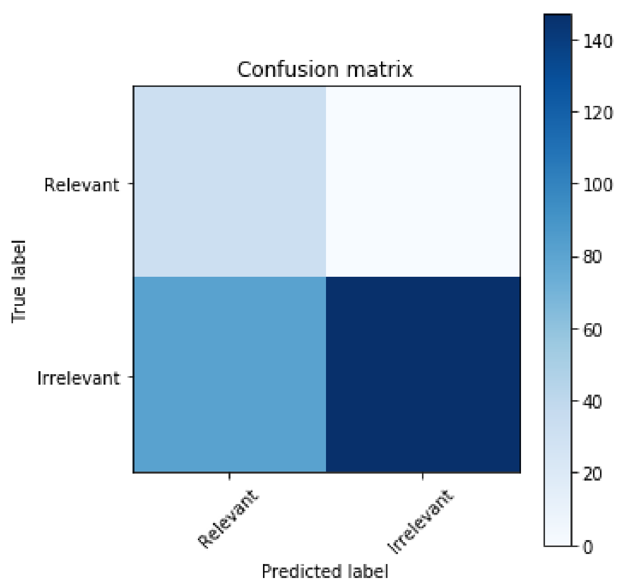


Experiment 2: Upsample the `Irrelevant` data

```
In [64]: def oversample(data, vector):
             os = SMOTE(random_state=0)
             X_train, X_test, y_train, y_test = train_test_split(data.text, data.Relevant, test_
             X_train_vect = vector.fit_transform(X_train).todense()
             X_test_vect = vector.transform(X_test)
             os_X_train, os_y_train = os.fit_sample(X_train_vect, y_train)
             return os_X_train, X_test_vect, os_y_train, y_test
```

```
In [65]: X_train_vect, X_test_vect, y_train, y_test = oversample(tagged, vect)
         classify(X_train_vect=X_train_vect,
                 X_test_vect=X_test_vect,
                 y_train =y_train,
                 y_test=y_test,
                 model=clf,
                 vector=vect)
```

```
Cross_val_score: 0.8281613879832324
AUC(ROC): 0.8223684210526316
Precision: 1.0
Recall: 0.6447368421052632
F1 score: 0.7839999999999999
[[ 32   0]
 [ 81 147]]
[[ 32   0]
 [ 81 147]]
```




```
Out[65]: 0.8281613879832324
```