classification

May 12, 2017

1 Part 3 -- Classification

The libraries that we are going to use:

```
In [1]: import pandas as pd
        import numpy as np
        import csv
        import random
        import math
        import matplotlib.pyplot as plt1
        import matplotlib.pyplot as plt2
        import operator
        from operator import itemgetter
        from collections import Counter
        from wordcloud import STOPWORDS
        from sklearn.feature_extraction.text import ENGLISH_STOP_WORDS
        from sklearn.naive_bayes import MultinomialNB, BernoulliNB
        from sklearn.feature_extraction.text import TfidfTransformer
        from sklearn.feature_extraction.text import CountVectorizer
        from sklearn import svm
        from sklearn.ensemble import RandomForestClassifier, ExtraTreesClassifier
        from sklearn.metrics import classification_report, accuracy_score, auc
        from sklearn.model_selection import KFold
        from sklearn.decomposition import TruncatedSVD
        from sklearn.linear_model import SGDClassifier
        from sklearn import metrics
```

1.1 Setting up

We are using a dictionary to map our Evaluation Metrics for each classifier in a way in which we can print the neatly in a "board" style when we are done.

```
In [2]: EvaluationMetric = {
            'Statistic Measure':['Accuracy', 'Precision', 'Recall', 'F-Measure', 'AUC'],
            'Naive Bayes':[] ,
            'Random Forest':[],
            'SVM':[],
            'KNN':[] }
```

```
In [3]: testSet = {'ID':[], 'Predicted_Category':[]}
        testSet_index = 0
```

```
In [4]: mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
```

We load our data and we define a list and a dictionary to help us with our following operations. Then we define our stopwords and our vectorizer, which is a *count vectorizer*. Following the project's specifiction suggestions, we are going to use the 'Title' field as a classification criterion.

```
In [5]: # load our data
        test_data = pd.read_csv('test_set.csv', sep='\t')
        train_data = pd.read_csv('train_set.csv', sep='\t')

        # a list of our categories (taken as facts)
        categories = ['Politics','Football','Business','Technology','Film']

        # we will use a number to represent each of our categories
        category_dict = {'Politics':0, 'Football':1, 'Business':2, 'Technology':3, 'Film':4}

        # for our text data, we use a count vectorizer
        stopwords = set(STOPWORDS) | set(ENGLISH_STOP_WORDS)
        # some additional stopwords based on our own observations
        stopwords.add('said')
        stopwords.add('say')
        stopwords.add('says')
        stopwords.add('set')

        # our count vectorizer
        count_vect = CountVectorizer(stop_words=stopwords)

        # we will classify using the 'Title' as a criterion
        category_criteria = 'Title'
```

```
In [6]: train_data.head()
```

```
Out[6]:    RowNum     Id                                              Title  \
        0    9560   9561  Sam Adams founder: Beer is more than just 'col...
        1   10801  10802  Slump in oil prices could mean fall in investm...
        2    6726   6727  British Gas owner Centrica warns of higher gas...
        3   12365  12366  Ole Gunnar Solskjaer appointed manager of Card...
        4   11782  11783  Sunderland target loan signings of Kurt Zouma ...

                                                     Content  Category
        0  The craft beer boom, which and been attributed...  Business
        1  The International Energy Agency has warned tha...  Business
        2  Senior executives at British have been accused...  Business
        3   is confident he will have complete control of...  Football
        4  Kurt Zouma and Jack Rodwell are on Sunderland...  Football
```

1.2 Data Preprocessing

```
In [7]: # for training
        X_train_counts = count_vect.fit_transform(train_data[category_criteria])
        tfidf_transformer = TfidfTransformer(use_idf=False).fit(X_train_counts)
        X_train_tfidf = tfidf_transformer.fit_transform(X_train_counts)
        print(X_train_counts.shape)
        print(X_train_counts.shape)

        # for testing
        X_test_counts = count_vect.transform(test_data[category_criteria])
        X_test_tfidf = tfidf_transformer.transform(X_test_counts)
        print(X_test_counts.shape)
        print(X_test_tfidf.shape)

        # we create a 'target' array where we will the category of each of our training data
        target = []
        for x in train_data['Category']:
            target.append(category_dict[x])

        target = np.array(target)
        print("target[] sample:")
        print(target[:40])
```

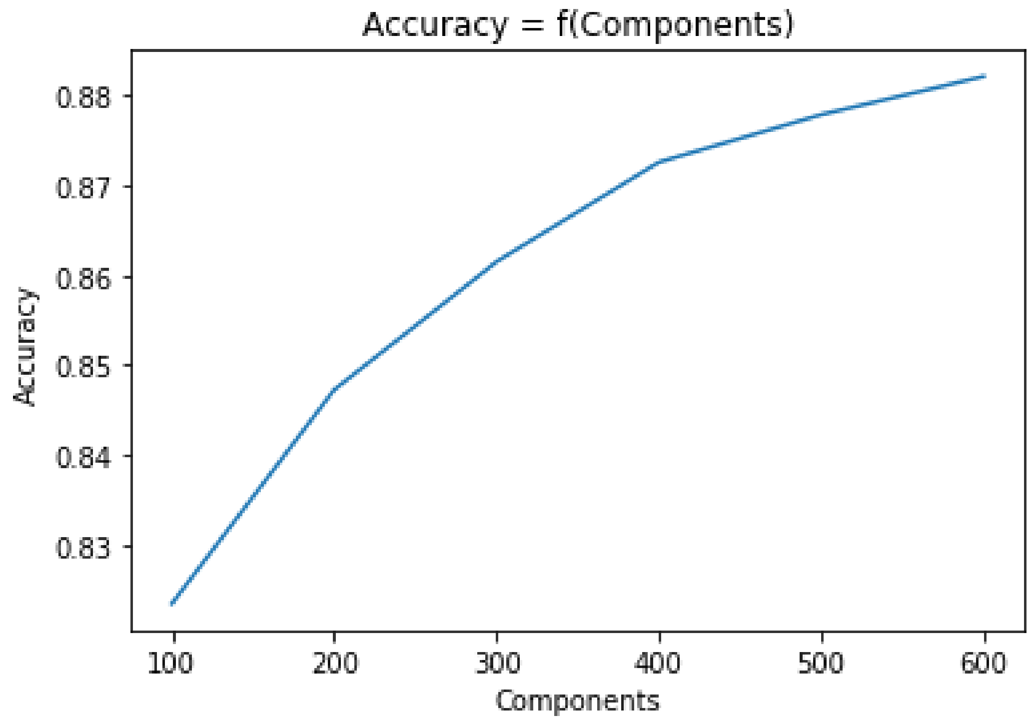
```
(12266, 13712)
(12266, 13712)
(3067, 13712)
(3067, 13712)
target[] sample:
[2 2 2 1 1 2 0 1 2 4 2 4 4 4 2 4 0 2 0 0 1 3 0 2 4 1 0 4 2 3 1 0 0 2 1 3 2
 0 3 3]
```

Experimenting with Latent Semantic Indexing (LSI) for various number of components:

```
In [8]: print("Latent Semantic Indexing (LSI) for various number of components: ")

        accuracy = []
        components = []
        for i in range(6):
            components.append(i*100+100)
            print("For ", components[i], " components:")
            svd = TruncatedSVD(n_components=components[i])
            X_lsi = svd.fit_transform(X_train_tfidf)
            clfSVD = SGDClassifier(loss='hinge', penalty='l2', alpha=1e-3, n_iter=5, random_stat
            X_test_lsi = svd.transform(X_train_counts)
            predictedSVD = clfSVD.predict(X_test_lsi)
            print("Accuracy:")
            acc = accuracy_score(target, predictedSVD)
```

```
            accuracy.append(acc)
            print("acc == ",acc)
            print(accuracy[i])

        plt1.title('Accuracy = f(Components)')
        plt1.plot(components, accuracy)
        plt1.legend(loc = 'lower right')
        plt1.ylabel('Accuracy')
        plt1.xlabel('Components')
        plt1.show()
        cross_val_instance = 0
```

```
Latent Semantic Indexing (LSI) for various number of components:
For  100  components:
Accuracy:
acc ==  0.823414315995
0.823414315995
For  200  components:
Accuracy:
acc ==  0.847219957606
0.847219957606
For  300  components:
Accuracy:
acc ==  0.861487037339
0.861487037339
For  400  components:
Accuracy:
acc ==  0.872574596445
0.872574596445
For  500  components:
Accuracy:
acc ==  0.877873797489
0.877873797489
For  600  components:
Accuracy:
acc ==  0.882113158324
0.882113158324


/home/marinos/.local/lib/python3.5/site-packages/matplotlib/axes/_axes.py:545: UserWarning: No l
  warnings.warn("No labelled objects found. "
```



Our 10-fold cross validation function

```
In [9]: # 10-FOLD CROSS VALIDATION FOR THE ARGUMENT'S CLASSIFIER
        # global variable to keep track of how many times we have called the following function
        cross_val_instance = 0

        def cross_validate(clf):
            global cross_val_instance    # Needed to modify global copy of a global variable

            kf = KFold(n_splits=10)

            fold = 0
            for train_index, test_index in kf.split(train_data[category_criteria]):
                cross_val_instance += 1

                X_train_counts = count_vect.transform(train_data[category_criteria][train_index]
                X_test_counts = count_vect.transform(train_data[category_criteria][test_index].v

                clf_cv = clf.fit(X_train_counts, target[train_index])
                yPred = clf_cv.predict(X_test_counts)
                fold += 1
                print ("Fold " + str(fold))
```

```
        accuracy = accuracy_score(target[test_index], yPred)
        mylist['Accuracy'].append(accuracy)
        print("Accuracy: ", accuracy)

        #A = auc(target[test_index], yPred, reorder=True)
        #mylist['AUC'].append(A)
        #print("AUC: ", A)

        p = metrics.precision_score(target[test_index], yPred, average='macro')
        mylist['Precision'].append(p)
        print("PRESICION: ", p)

        recall = metrics.recall_score(target[test_index], yPred, average='macro')
        mylist['Recall'].append(recall)
        print("Recall: ", recall)
        f_1 = metrics.f1_score(target[test_index], yPred, average='micro')
        mylist['F-Measure'].append(f_1)
        print("F-1: ", f_1)

        fpr, tpr, thresholds = metrics.roc_curve(target[test_index], yPred, pos_label=2)
        A = metrics.auc(fpr, tpr)
        print("AUC: ",A)
        mylist['AUC'].append(A)


        # construct ROC's plot
        plt2.subplot(6, 10, cross_val_instance)
        plt2.plot(fpr, tpr, 'b')
        plt2.plot([0,1], [0, 1],'r--')
        plt2.xlim([0,1])
        plt2.ylim([0, 1])
```

1.3 Random Forest (RF) Classification

Classifying:

```
In [10]: RANDOM_STATE = 123

         rndf = RandomForestClassifier(warm_start=True, oob_score=True, max_features="sqrt", ran
         rndf.set_params(n_estimators=30)
         rndf.fit(X_train_tfidf, target)

         predicted = rndf.predict(X_test_tfidf)

         for x in range(10):
             print(test_data['Title'][x] + "---->" + categories[predicted[x]])
```

```
Syria airstrikes: Jeremy Corbyn gives Labour MPs free vote ---->Politics
Apple faces damages bill after jury finds iPhone and iPad chip violates processor patent ---->Te
```

```
'I'm sitting next to a weirdo on the bus' and other true meanings of emoji ---->Technology
Black Friday 2015: UK retailers serve up alternative options ---->Business
A third of boardroom positions should be held by women, UK firms told ---->Business
Marks and Spencer customers hit by delays to online shopping orders ---->Business
Argos owner sees distorting effect of Black Friday on sales ---->Business
TalkTalk says hackers accessed fraction of data originally thought ---->Technology
Gameover Zeus returns: thieving malware rises a month after police action ---->Technology
TalkTalk boss says cybersecurity 'head and shoulders' above competitors ---->Business
```

```
In [11]: i = 0
         for x in predicted :
             testSet['ID'].append(train_data['Id'][i])
             testSet_index+=1
             i+=1
             testSet['Predicted_Category'].append(str(categories[x]))
```

Cross Validating:

```
In [12]: # 10-FOLD CROSS VALIDATION FOR RF CLASSIFICATION
         mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
         cross_validate(rndf)
```

```
/home/marinos/.local/lib/python3.5/site-packages/sklearn/ensemble/forest.py:303: UserWarning: Wa
  warn("Warm-start fitting without increasing n_estimators does not "
```

```
Fold 1
Accuracy:  0.991035044825
PRESICION:  0.989384749981
Recall:  0.990774165485
F-1:  0.991035044825
AUC:  0.608916764577
Fold 2
Accuracy:  0.989405052975
PRESICION:  0.988332842019
Recall:  0.98783237197
F-1:  0.989405052975
AUC:  0.605693472927
Fold 3
Accuracy:  0.9902200489
PRESICION:  0.989042750174
Recall:  0.989098698168
F-1:  0.9902200489
AUC:  0.610897706836
Fold 4
Accuracy:  0.9934800326
PRESICION:  0.992187953556
Recall:  0.992900596293
```

```
F-1:  0.9934800326
AUC:  0.578441318449
Fold 5
Accuracy:  0.99185004075
PRESICION:  0.991220047171
Recall:  0.991245588691
F-1:  0.99185004075
AUC:  0.613842585609
Fold 6
Accuracy:  0.9869600652
PRESICION:  0.985666839531
Recall:  0.985452629565
F-1:  0.9869600652
AUC:  0.597410890514
Fold 7
Accuracy:  0.987765089723
PRESICION:  0.988093186277
Recall:  0.987187864585
F-1:  0.987765089723
AUC:  0.615101675588
Fold 8
Accuracy:  0.995921696574
PRESICION:  0.995205997415
Recall:  0.995662410167
F-1:  0.995921696574
AUC:  0.605170787277
Fold 9
Accuracy:  0.988580750408
PRESICION:  0.987348677484
Recall:  0.987790501106
F-1:  0.988580750408
AUC:  0.5955377115
Fold 10
Accuracy:  0.989396411093
PRESICION:  0.989729307879
Recall:  0.988548134965
F-1:  0.989396411093
AUC:  0.618477939114
```

Store RF's Evaluation Metrics in our dictionary:

```
In [13]: EvaluationMetric['Random Forest']=[]
         EvaluationMetric['Random Forest'].append(np.mean(mylist['Precision']))
         EvaluationMetric['Random Forest'].append(np.mean(mylist['Recall']))
         EvaluationMetric['Random Forest'].append(np.mean(mylist['F-Measure']))
         EvaluationMetric['Random Forest'].append(np.mean(mylist['AUC']))
         EvaluationMetric['Random Forest'].append(np.mean(mylist['Accuracy']))
         EvaluationMetric
```

```
Out[13]: {'KNN': [],
          'Naive Bayes': [],
          'Random Forest': [0.9896212351486593,
           0.98964929609941843,
           0.99046142330462883,
           0.60494908523923507,
           0.99046142330462883],
          'SVM': [],
          'Statistic Measure': ['Accuracy', 'Precision', 'Recall', 'F-Measure', 'AUC']}
```

1.4 Support Vector Machines Classification

1.4.1 Part I -- with linear kernel and c=0.2

Classifying:

```
In [14]: lnr = svm.SVC(C=0.2, kernel='linear')
         lnr.fit(X_train_tfidf, target)

         predicted = lnr.predict(X_test_tfidf)

         print("SVM with linear kernel and c=0.2:")
         for x in range(10):
             print(test_data['Title'][x] + "---->" + categories[predicted[x]])

         print(predicted)
```

```
SVM with linear kernel and c=0.2:
Syria airstrikes: Jeremy Corbyn gives Labour MPs free vote ---->Politics
Apple faces damages bill after jury finds iPhone and iPad chip violates processor patent ---->Te
'I'm sitting next to a weirdo on the bus' and other true meanings of emoji ---->Film
Black Friday 2015: UK retailers serve up alternative options ---->Business
A third of boardroom positions should be held by women, UK firms told ---->Business
Marks and Spencer customers hit by delays to online shopping orders ---->Business
Argos owner sees distorting effect of Black Friday on sales ---->Business
TalkTalk says hackers accessed fraction of data originally thought ---->Technology
Gameover Zeus returns: thieving malware rises a month after police action ---->Politics
TalkTalk boss says cybersecurity 'head and shoulders' above competitors ---->Business
[0 3 4 ..., 3 1 1]
```

```
In [15]: i = 0
         for x in predicted :
             testSet['ID'].append(train_data['Id'][i])
             testSet_index+=1
             i+=1
             testSet['Predicted_Category'].append(str(categories[x]))
         print(len(testSet['ID']),len(testSet['Predicted_Category']))
```

```
6134 6134
```

Cross Validating:

```
In [16]: # 10-FOLD CROSS VALIDATION FOR SVM CLASSIFICATION (I)
         # with linear kernel and c=0.2
         mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
         cross_validate(lnr)
```

```
Fold 1
Accuracy:  0.918500407498
PRESICION:  0.91757075151
Recall:  0.912208434671
F-1:  0.918500407498
AUC:  0.579489867226
Fold 2
Accuracy:  0.923390383048
PRESICION:  0.921925378451
Recall:  0.912066023875
F-1:  0.923390383048
AUC:  0.569844481019
Fold 3
Accuracy:  0.908720456398
PRESICION:  0.90273893386
Recall:  0.901835584143
F-1:  0.908720456398
AUC:  0.586424587487
Fold 4
Accuracy:  0.910350448248
PRESICION:  0.913037106346
Recall:  0.906168113688
F-1:  0.910350448248
AUC:  0.55192148137
Fold 5
Accuracy:  0.918500407498
PRESICION:  0.912397008362
Recall:  0.911178841417
F-1:  0.918500407498
AUC:  0.594595715794
Fold 6
Accuracy:  0.896495517522
PRESICION:  0.896217842102
Recall:  0.886978375802
F-1:  0.896495517522
AUC:  0.58331204768
Fold 7
Accuracy:  0.903752039152
```

```
PRESICION:  0.904609740542
Recall:  0.897569501622
F-1:  0.903752039152
AUC:  0.586655870894
Fold 8
Accuracy:  0.909461663948
PRESICION:  0.907808527014
Recall:  0.903905038073
F-1:  0.909461663948
AUC:  0.570005873872
Fold 9
Accuracy:  0.92088091354
PRESICION:  0.918452002286
Recall:  0.911395855922
F-1:  0.92088091354
AUC:  0.570501864067
Fold 10
Accuracy:  0.911092985318
PRESICION:  0.906778484195
Recall:  0.896837544515
F-1:  0.911092985318
AUC:  0.590438335463
```

Store SVM's Evaluation Metrics in our dictionary:

```
In [17]: EvaluationMetric['SVM']=[]
         EvaluationMetric['SVM'].append(np.mean(mylist['Accuracy']))
         EvaluationMetric['SVM'].append(np.mean(mylist['Precision']))
         EvaluationMetric['SVM'].append(np.mean(mylist['Recall']))
         EvaluationMetric['SVM'].append(np.mean(mylist['F-Measure']))
         EvaluationMetric['SVM'].append(np.mean(mylist['AUC']))
         EvaluationMetric
```

```
Out[17]: {'KNN': [],
          'Naive Bayes': [],
          'Random Forest': [0.9896212351486593,
           0.98964929609941843,
           0.99046142330462883,
           0.60494908523923507,
           0.99046142330462883],
          'SVM': [0.91211452221694844,
           0.91015357746674508,
           0.90401433137283504,
           0.91211452221694844,
           0.57831901248714579],
          'Statistic Measure': ['Accuracy', 'Precision', 'Recall', 'F-Measure', 'AUC']}
```

1.4.2 Part II -- with rbf kernel, c=5000000.0 and gamma=100000

Classifying:

```
In [18]: rbf = svm.SVC(C=5000000.0, kernel='rbf', gamma=100000)
         rbf.fit(X_train_tfidf, target)

         predicted = rbf.predict(X_test_tfidf)

         print("SVM with rbf kernel, c=5000000.0 and gamma=100000:")
         for x in range(10):
             print(test_data['Title'][x] + "---->" + categories[predicted[x]])
```

```
SVM with rbf kernel, c=5000000.0 and gamma=100000:
Syria airstrikes: Jeremy Corbyn gives Labour MPs free vote ---->Football
Apple faces damages bill after jury finds iPhone and iPad chip violates processor patent ---->Fo
'I'm sitting next to a weirdo on the bus' and other true meanings of emoji ---->Football
Black Friday 2015: UK retailers serve up alternative options ---->Football
A third of boardroom positions should be held by women, UK firms told ---->Football
Marks and Spencer customers hit by delays to online shopping orders ---->Football
Argos owner sees distorting effect of Black Friday on sales ---->Football
TalkTalk says hackers accessed fraction of data originally thought ---->Football
Gameover Zeus returns: thieving malware rises a month after police action ---->Football
TalkTalk boss says cybersecurity 'head and shoulders' above competitors ---->Football
```

```
In [19]: i = 0
         for x in predicted :
             testSet['ID'].append(train_data['Id'][i])
             testSet_index+=1
             i+=1
             testSet['Predicted_Category'].append(str(categories[x]))
         print(len(testSet['ID']),len(testSet['Predicted_Category']))
```

```
9201 9201
```

Cross Validating:

```
In [20]: # 10-FOLD CROSS VALIDATION FOR SVM CLASSIFICATION (II)
         # with rbf kernel, c=5000000.0 and gamma=100000
         mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
         cross_validate(rbf)
```

```
Fold 1
Accuracy:  0.287693561532
PRESICION:  0.816177924217
Recall:  0.210933463303
F-1:  0.287693561532
```

```
AUC:  0.502292257009
Fold 2
Accuracy:  0.264058679707
PRESICION:  0.851112943116
Recall:  0.213320701982
F-1:  0.264058679707
AUC:  0.497054968835
Fold 3
Accuracy:  0.269763651182
PRESICION:  0.453594771242
Recall:  0.202545908479
F-1:  0.269763651182
AUC:  0.499490316004


/home/marinos/.local/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefin
  'precision', 'predicted', average, warn_for)


Fold 4
Accuracy:  0.237978810106
PRESICION:  0.247346938776
Recall:  0.201680672269
F-1:  0.237978810106
AUC:  0.498944033791
Fold 5
Accuracy:  0.259983700081
PRESICION:  0.251391162029
Recall:  0.20462962963
F-1:  0.259983700081
AUC:  0.497360084477
Fold 6
Accuracy:  0.257538712306
PRESICION:  0.450655737705
Recall:  0.207000028203
F-1:  0.257538712306
AUC:  0.496342737722
Fold 7
Accuracy:  0.261827079935
PRESICION:  0.850906095552
Recall:  0.211084844868
F-1:  0.261827079935
AUC:  0.5006651674
Fold 8
Accuracy:  0.245513866232
PRESICION:  0.448484848485
Recall:  0.204539232851
F-1:  0.245513866232
```

```
AUC:  0.499460671757
Fold 9
Accuracy:  0.26101141925
PRESICION:  0.651231527094
Recall:  0.206657639184
F-1:  0.26101141925
AUC:  0.50022751171
Fold 10
Accuracy:  0.26101141925
PRESICION:  0.451109285127
Recall:  0.207154692863
F-1:  0.26101141925
AUC:  0.498434237996
```

1.5 Naive Bayes Classification

1.5.1 Part I -- with Multinomial Naive Bayes

Classifying:

```
In [21]: mnb = MultinomialNB().fit(X_train_tfidf, target)

         predicted = mnb.predict(X_test_tfidf)

         print("Multinomial NB:")
         for x in range(10):
             print(test_data['Title'][x] + "---->" + categories[predicted[x]])
```

```
Multinomial NB:
Syria airstrikes: Jeremy Corbyn gives Labour MPs free vote ---->Politics
Apple faces damages bill after jury finds iPhone and iPad chip violates processor patent ---->Te
'I'm sitting next to a weirdo on the bus' and other true meanings of emoji ---->Politics
Black Friday 2015: UK retailers serve up alternative options ---->Business
A third of boardroom positions should be held by women, UK firms told ---->Business
Marks and Spencer customers hit by delays to online shopping orders ---->Business
Argos owner sees distorting effect of Black Friday on sales ---->Business
TalkTalk says hackers accessed fraction of data originally thought ---->Technology
Gameover Zeus returns: thieving malware rises a month after police action ---->Business
TalkTalk boss says cybersecurity 'head and shoulders' above competitors ---->Business
```

```
In [22]: i = 0
         for x in predicted :
             testSet['ID'].append(train_data['Id'][i])
             testSet_index+=1
             i+=1
             testSet['Predicted_Category'].append(str(categories[x]))
         print(len(testSet['ID']),len(testSet['Predicted_Category']))
```

```
12268 12268
```

Cross Validating:

```
In [23]: # 10-FOLD CROSS VALIDATION FOR NB CLASSIFICATION (I)
         # with Multinomial Naive Bayes
         mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
         cross_validate(mnb)
```

```
Fold 1
Accuracy:  0.925835370823
PRESICION:  0.923987190541
Recall:  0.917789562527
F-1:  0.925835370823
AUC:  0.592989993933
Fold 2
Accuracy:  0.926650366748
PRESICION:  0.929311760127
Recall:  0.915672904382
F-1:  0.926650366748
AUC:  0.59027682531
Fold 3
Accuracy:  0.911980440098
PRESICION:  0.906239387259
Recall:  0.903324389757
F-1:  0.911980440098
AUC:  0.609163538119
Fold 4
Accuracy:  0.913610431948
PRESICION:  0.913924365586
Recall:  0.911180868099
F-1:  0.913610431948
AUC:  0.559647005582
Fold 5
Accuracy:  0.920130399348
PRESICION:  0.918808367992
Recall:  0.914964289279
F-1:  0.920130399348
AUC:  0.613799215568
Fold 6
Accuracy:  0.902200488998
PRESICION:  0.899175374797
Recall:  0.89072561377
F-1:  0.902200488998
AUC:  0.601993111189
Fold 7
Accuracy:  0.899673735726
```

```
PRESICION:  0.896644827667
Recall:  0.889089629947
F-1:  0.899673735726
AUC:  0.597154033765
Fold 8
Accuracy:  0.924959216966
PRESICION:  0.92386627992
Recall:  0.91946875373
F-1:  0.924959216966
AUC:  0.585895587476
Fold 9
Accuracy:  0.916802610114
PRESICION:  0.913418324229
Recall:  0.908014455909
F-1:  0.916802610114
AUC:  0.585389542109
Fold 10
Accuracy:  0.915171288744
PRESICION:  0.908615821276
Recall:  0.901152869302
F-1:  0.915171288744
AUC:  0.598925388714
```

Store NB's Evaluation Metrics in our dictionary:

```
In [24]: EvaluationMetric['Naive Bayes']=[]
         EvaluationMetric['Naive Bayes'].append(np.mean(mylist['Accuracy']))
         EvaluationMetric['Naive Bayes'].append(np.mean(mylist['Precision']))
         EvaluationMetric['Naive Bayes'].append(np.mean(mylist['Recall']))
         EvaluationMetric['Naive Bayes'].append(np.mean(mylist['F-Measure']))
         EvaluationMetric['Naive Bayes'].append(np.mean(mylist['AUC']))
         EvaluationMetric
```

```
Out[24]: {'KNN': [],
          'Naive Bayes': [0.91570143495122669,
           0.91339916993948089,
           0.90713833367009133,
           0.91570143495122669,
           0.59352342417638937],
          'Random Forest': [0.9896212351486593,
           0.98964929609941843,
           0.99046142330462883,
           0.60494908523923507,
           0.99046142330462883],
          'SVM': [0.91211452221694844,
           0.91015357746674508,
           0.90401433137283504,
```

```
0.91211452221694844,
 0.57831901248714579],
'Statistic Measure': ['Accuracy', 'Precision', 'Recall', 'F-Measure', 'AUC']}
```

1.5.2 Part II -- with Bernoulli Naive Bayes

Classifying:

```
In [25]: bnb = BernoulliNB().fit(X_train_tfidf, target)

         predicted = bnb.predict(X_test_tfidf)

         print("Bernoulli NB:")
         for x in range(10):
             print(test_data['Title'][x] + "---->" + categories[predicted[x]])
```

```
Bernoulli NB:
Syria airstrikes: Jeremy Corbyn gives Labour MPs free vote ---->Politics
Apple faces damages bill after jury finds iPhone and iPad chip violates processor patent ---->Te
'I'm sitting next to a weirdo on the bus' and other true meanings of emoji ---->Film
Black Friday 2015: UK retailers serve up alternative options ---->Business
A third of boardroom positions should be held by women, UK firms told ---->Business
Marks and Spencer customers hit by delays to online shopping orders ---->Business
Argos owner sees distorting effect of Black Friday on sales ---->Business
TalkTalk says hackers accessed fraction of data originally thought ---->Technology
Gameover Zeus returns: thieving malware rises a month after police action ---->Business
TalkTalk boss says cybersecurity 'head and shoulders' above competitors ---->Business
```

```
In [26]: for x in predicted :
             testSet['ID'].append(testSet_index)
             testSet_index+=1
             testSet['Predicted_Category'].append(str(categories[x]))

         print(len(testSet['ID']),len(testSet['Predicted_Category']))
```

```
15335 15335
```

Cross Validating:

```
In [27]: # 10-FOLD CROSS VALIDATION FOR NB CLASSIFICATION (II)
         # with Bernoulli Naive Bayes
         cross_validate(bnb)
```

```
Fold 1
Accuracy:  0.903015484923
PRESICION:  0.914595832371
Recall:  0.877694811439
```

```
F-1:  0.903015484923
AUC:  0.612147810261
Fold 2
Accuracy:  0.898125509372
PRESICION:  0.907901236104
Recall:  0.869286032524
F-1:  0.898125509372
AUC:  0.618896584831
Fold 3
Accuracy:  0.883455582722
PRESICION:  0.889049697639
Recall:  0.854443218152
F-1:  0.883455582722
AUC:  0.633932937189
Fold 4
Accuracy:  0.876935615322
PRESICION:  0.890041322743
Recall:  0.852510308066
F-1:  0.876935615322
AUC:  0.593717001056
Fold 5
Accuracy:  0.899755501222
PRESICION:  0.909187880073
Recall:  0.877218402294
F-1:  0.899755501222
AUC:  0.633651380299
Fold 6
Accuracy:  0.872045639772
PRESICION:  0.885517187364
Recall:  0.843484833596
F-1:  0.872045639772
AUC:  0.619931111885
Fold 7
Accuracy:  0.880913539967
PRESICION:  0.891157594469
Recall:  0.853978371785
F-1:  0.880913539967
AUC:  0.621909743119
Fold 8
Accuracy:  0.89722675367
PRESICION:  0.907742229699
Recall:  0.874801531248
F-1:  0.89722675367
AUC:  0.60887844645
Fold 9
Accuracy:  0.894779771615
PRESICION:  0.906654524536
Recall:  0.871000101842
```

```
F-1:  0.894779771615
AUC:  0.602525571169
Fold 10
Accuracy:  0.896411092985
PRESICION:  0.899641070472
Recall:  0.861458315172
F-1:  0.896411092985
AUC:  0.622203440002
```

1.6 K-Nearest Neighbor Classification

Our assistant-funtions for the K-Nearest Neighbor Classification

In [28]:
```
train_array = svd.fit_transform(X_train_tfidf)
test_array = svd.fit_transform(X_test_tfidf)
```

In [29]:
```
# given two data points, calculate the euclidean distance between them
def get_distance(data1, data2):
    points = zip(data1, data2)
    diffs_squared_distance = [pow(a - b, 2) for (a, b) in points]
    return math.sqrt(sum(diffs_squared_distance))

# a function that returns sorted distances between a test case and all training cases
def get_neighbours(training_set, test_instance, k):
    distances = [_get_tuple_distance(training_instance, test_instance) for training_ins
    # index 1 is the calculated distance between training_instance and test_instance
    sorted_distances = sorted(distances, key=itemgetter(1))
    # extract only training instances
    sorted_training_instances = [tuple[0] for tuple in sorted_distances]
    # select first k elements
    return sorted_training_instances[:k]

def _get_tuple_distance(training_instance, test_instance):
    return (training_instance, get_distance(test_instance, training_instance))

# given an array of nearest neighbours for a test case, tally up their classes to vote
def get_majority_vote(neighbours):
    # index 1 is the class
    classes = [neighbour[1] for neighbour in neighbours]
    count = Counter(classes)
    return count.most_common()[0][0]
```

Our K-Nearest Neighbor Classification function

In [30]:
```
# generate predictions
def KNN(train_array,test_array): #synarthsh pou epistrefeei thn lista me ta predictions
    predictions = []
    # let's arbitrarily set k equal to 3
```

```
    k = 3

    # for each instance in the test set, get nearest neighbours and majority vote on pr
    for x in range(len(test_array)):#mono ta prwta 5
        #print('Classifying test instance number ' + str(x) + ":")
        neighbours = get_neighbours(training_set=train_array, test_instance=test_array[
        majority_vote = get_majority_vote(neighbours)
        predictions.append(majority_vote)
        #print ('Predicted label=' + str(majority_vote) + ', Actual label=' + str(test_
    for y in range(len(predictions)):
        predictions[y] = math.ceil(predictions[y])
    #print(predictions)
    return predictions
```

In [31]:
```
print(cross_val_instance)
```

```
50
```

Our K-Nearest Neighbor Cross Validation function

In [32]:
```
# 10-FOLD CROSS VALIDATION FOR THE ARGUMENT'S CLASSIFIER
# global variable to keep track of how many times we have called the following function
mylist = {'Accuracy':[], 'Precision':[], 'Recall':[], 'F-Measure':[], 'AUC':[]}
global cross_val_instance    # Needed to modify global copy of a global variable

kf = KFold(n_splits=10)

fold = 0
for train_index, test_index in kf.split(train_data[category_criteria]):
    cross_val_instance += 1

    X_train_counts = count_vect.transform(train_data[category_criteria][train_index])
    X_test_counts = count_vect.transform(train_data[category_criteria][test_index].valu

    #clf_cv = clf.fit(X_train_counts, target[train_index])
    #yPred = clf_cv.predict(X_test_counts)
    X_train_counts = svd.fit_transform(X_train_counts)
    X_test_counts = svd.fit_transform(X_test_counts)
    X_test_counts = X_test_counts[0:30]    # we take only the first 5
    test_index = test_index[0:30]
    yPred = KNN( X_train_counts ,  X_test_counts )
    fold += 1
    print ("Fold " + str(fold))

    accuracy = accuracy_score(target[test_index], yPred)
    mylist['Accuracy'].append(accuracy)
    print("Accuracy: ", accuracy)
```

```
#     A = auc(target[test_index], yPred, reorder=True)
#     mylist['AUC'].append(A)
#     print("AUC: ", A)

            p = metrics.precision_score(target[test_index], yPred, average='macro')
            mylist['Precision'].append(p)
            print("PRESICION: ", p)

            recall = metrics.recall_score(target[test_index], yPred, average='macro')
            mylist['Recall'].append(recall)
            print("Recall: ", recall)
            f_1 = metrics.f1_score(target[test_index], yPred, average='micro')
            mylist['F-Measure'].append(f_1)
            print("F-1: ", f_1)

            fpr, tpr, thresholds = metrics.roc_curve(target[test_index], yPred, pos_label=2)
            A = metrics.auc(fpr, tpr)
            print("AUC: ", A)
            mylist['AUC'].append(A)

            # construct ROC's plot
            plt2.subplot(6, 10, cross_val_instance)
            plt2.plot(fpr, tpr, 'b')
```

```
Fold 1
Accuracy:  0.133333333333
PRESICION:  0.0275862068966
Recall:  0.16
F-1:  0.133333333333
AUC:  0.525


/home/marinos/.local/lib/python3.5/site-packages/sklearn/metrics/classification.py:1113: Undefin
  'precision', 'predicted', average, warn_for)


Fold 2
Accuracy:  0.0666666666667
PRESICION:  0.0153846153846
Recall:  0.08
F-1:  0.0666666666667
AUC:  0.5
Fold 3
Accuracy:  0.133333333333
PRESICION:  0.0685714285714
Recall:  0.0945454545455
F-1:  0.133333333333
```

```
AUC:  0.520833333333
Fold 4
Accuracy:  0.133333333333
PRESICION:  0.0285714285714
Recall:  0.133333333333
F-1:  0.133333333333
AUC:  0.5
Fold 5
Accuracy:  0.3
PRESICION:  0.160256410256
Recall:  0.253472222222
F-1:  0.3
AUC:  0.536931818182
Fold 6
Accuracy:  0.1
PRESICION:  0.024
Recall:  0.075
F-1:  0.1
AUC:  0.521739130435
Fold 7
Accuracy:  0.233333333333
PRESICION:  0.0538461538462
Recall:  0.127272727273
F-1:  0.233333333333
AUC:  0.54
Fold 8
Accuracy:  0.133333333333
PRESICION:  0.0384615384615
Recall:  0.125
F-1:  0.133333333333
AUC:  0.590909090909
Fold 9
Accuracy:  0.233333333333
PRESICION:  0.048275862069
Recall:  0.175
F-1:  0.233333333333
AUC:  0.48
Fold 10
Accuracy:  0.2
PRESICION:  0.0444444444444
Recall:  0.133333333333
F-1:  0.2
AUC:  0.52
```

Store KNN's Evaluation Metrics in our dictionary:

```
In [33]: EvaluationMetric['KNN'] =[]
         EvaluationMetric['KNN'].append(np.mean(mylist['Accuracy']))
```

```
EvaluationMetric['KNN'].append(np.mean(mylist['Precision']))
EvaluationMetric['KNN'].append(np.mean(mylist['Recall']))
EvaluationMetric['KNN'].append(np.mean(mylist['F-Measure']))
EvaluationMetric['KNN'].append(np.mean(mylist['AUC']))
EvaluationMetric
```

```
Out[33]: {'KNN': [0.16666666666666669,
  0.05093980885015368,
  0.13569570707070705,
  0.16666666666666669,
  0.52354133728590246],
 'Naive Bayes': [0.91570143495122669,
  0.91339916993948089,
  0.90713833367009133,
  0.91570143495122669,
  0.59352342417638937],
 'Random Forest': [0.9896212351486593,
  0.98964929609941843,
  0.99046142330462883,
  0.60494908523923507,
  0.99046142330462883],
 'SVM': [0.91211452221694844,
  0.91015357746674508,
  0.90401433137283504,
  0.91211452221694844,
  0.57831901248714579],
 'Statistic Measure': ['Accuracy', 'Precision', 'Recall', 'F-Measure', 'AUC']}
```

1.7 Presenting our Results

We present our 10-fold Cross Validation's Evaluation Metrics:

```
In [34]: # creating the dataframe
         EvaluationMetric_10fold = pd.DataFrame(data=EvaluationMetric)
         EvaluationMetric_10fold
```

Out[34]:

	KNN	Naive Bayes	Random Forest	SVM	Statistic Measure
0	0.166667	0.915701	0.989621	0.912115	Accuracy
1	0.050940	0.913399	0.989649	0.910154	Precision
2	0.135696	0.907138	0.990461	0.904014	Recall
3	0.166667	0.915701	0.604949	0.912115	F-Measure
4	0.523541	0.593523	0.990461	0.578319	AUC

```
In [35]: # making sure that the dataframe will be printed with the columns in the correct order
         EvaluationMetric_10fold = EvaluationMetric_10fold.ix[::, ['Statistic Measure', 'Naive B
         EvaluationMetric_10fold
```

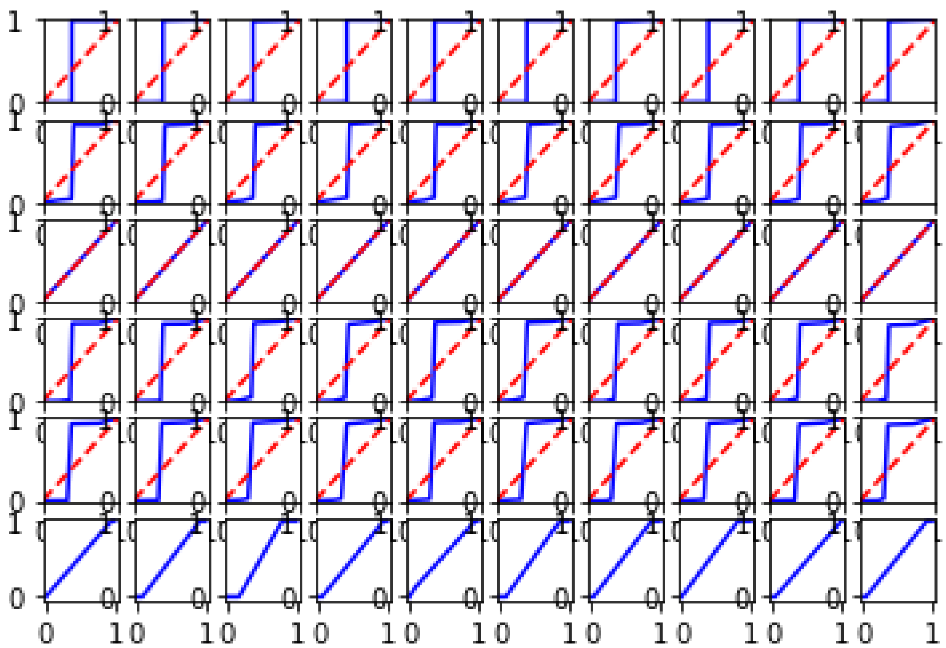
Out[35]:

	Statistic Measure	Naive Bayes	Random Forest	SVM	KNN
0	Accuracy	0.915701	0.989621	0.912115	0.166667

1	Precision	0.913399	0.989649	0.910154	0.050940
2	Recall	0.907138	0.990461	0.904014	0.135696
3	F-Measure	0.915701	0.604949	0.912115	0.166667
4	AUC	0.593523	0.990461	0.578319	0.523541

In [36]:
```
# creating the evaluation metrics' csv file
EvaluationMetric_10fold.to_csv(path_or_buf='EvaluationMetric_10fold.csv', sep='\t', ind
```

In [37]:
```
# save as .png and then show plot
plt2.savefig("roc_10fold.png")
plt2.show()
```



In [38]:
```
print(len(testSet['ID']),len(testSet['Predicted_Category']))
```

15335 15335

In [39]:
```
# printing our test set's data frame
testSetpd = pd.DataFrame(data=testSet)
testSetpd
```

Out[39]:

	ID	Predicted_Category
0	9561	Politics
1	10802	Technology
2	6727	Technology
3	12366	Business

4	11783	Business
5	14177	Business
6	308	Business
7	13636	Technology
8	1042	Technology
9	1227	Business
10	4042	Film
11	2578	Business
12	3615	Technology
13	1661	Business
14	3242	Business
15	10178	Business
16	3533	Business
17	8749	Technology
18	8127	Technology
19	3745	Technology
20	12163	Technology
21	10901	Business
22	7669	Business
23	569	Business
24	3053	Film
25	12288	Football
26	1320	Business
27	13094	Business
28	3426	Technology
29	4273	Politics
...	...	...
15305	15305	Football
15306	15306	Football
15307	15307	Football
15308	15308	Football
15309	15309	Football
15310	15310	Football
15311	15311	Football
15312	15312	Football
15313	15313	Football
15314	15314	Football
15315	15315	Football
15316	15316	Football
15317	15317	Football
15318	15318	Football
15319	15319	Technology
15320	15320	Business
15321	15321	Business
15322	15322	Football
15323	15323	Football
15324	15324	Film
15325	15325	Football

```
15326  15326          Football
15327  15327          Football
15328  15328          Football
15329  15329          Football
15330  15330              Film
15331  15331          Football
15332  15332          Business
15333  15333          Football
15334  15334          Football

[15335 rows x 2 columns]
```

```
In [40]: testSetcsv = testSetpd.ix[::, ['ID', 'Predicted_Category']]
```

```
In [41]: testSetcsv.to_csv(path_or_buf='testSet_categories.csv', sep = '\t')
```

```
In [ ]:
```