Appendix B

March 19, 2020

1 Twitter Disaster Classification: Natural Language Processing

In [2]:
```
# Importing Libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
from collections import defaultdict
from sklearn.pipeline import Pipeline
from sklearn.compose import ColumnTransformer
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
from sklearn.feature_extraction.text import CountVectorizer
```

In [3]:
```
#Importing data
df = pd.read_csv('data/train.csv')
```

In [4]:
```
# Feature Selection
X = df['text']
y = df['target']

#vectorizer = CountVectorizer(ngram_range=(2,2))
#X = vectorizer.fit_transform(X)
#X = pd.DataFrame(X.toarray(), columns=vectorizer.get_feature_names())
```

In [5]:
```
# Let's split the data for training, cross-validation, and testing
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size = 0.2,
                                                    random_state = 72);
X_train, X_val, y_train, y_val = train_test_split(X_train, y_train,
                                                  test_size = 0.2,
                                                  random_state = 72);
```

In [7]:
```
# Plotting:
acc = []
pre = []
rec=[]
fs=[]
```

```
def evaluation(y_val, predictions):
    """ Prints out evaluation information.

        y_val: true value of the targets
        predictions: predicted value of the targets"""
    # Let's look at the evaluation metrics:
    ## 1. Accuracy
    accuracy = accuracy_score(y_val, predictions)
    acc.append(accuracy)

    ## 2. Precision
    precision = precision_score(y_val, predictions)
    pre.append(precision)

    ## 3. Recall
    recall = recall_score(y_val, predictions)
    rec.append(recall)

    ## 4. F1 score
    f1 = f1_score(y_val, predictions)
    fs.append(f1)
    print("Accuracy: ",accuracy, "\nPrecision:",
          precision, "\nRecall:   ",recall, "\nF1:       ",f1)
    return f1
```

In [8]:
```
# Algorithm 1: Naive Bayes

from sklearn.naive_bayes import MultinomialNB
classifier = MultinomialNB()
vectorizer = CountVectorizer(ngram_range=(1,2))

# Make a pipeline
stepsNB = [("count", vectorizer),("classifier", classifier)]
pipeNB = Pipeline(steps = stepsNB)

# Fit the pipe:
pipeNB.fit(X_train, y_train)
predictionsNB = pipeNB.predict(X_val)

# Evaluation
evaluation(y_val, predictionsNB)
```

```
Accuracy:  0.7996715927750411
Precision: 0.8171806167400881
Recall:    0.6973684210526315
F1:        0.7525354969574035
```

Out[8]: 0.7525354969574035

In [8]:
```python
# Algorithm 2: AdaBoost
from sklearn.ensemble import AdaBoostClassifier
modelAB = AdaBoostClassifier(n_estimators = 150, random_state = 1)
stepsAB = [("count", vectorizer),("adaboost", modelAB)]
pipeAB = Pipeline(steps = stepsAB)
pipeAB.fit(X_train, y_train)
predictionsAB = pipeAB.predict(X_val)
evaluation(y_val, predictionsAB)
```

```
Accuracy:  0.7750410509031199
Precision: 0.776824034334764
Recall:    0.6804511278195489
F1:        0.7254509018036073
```

Out[8]: 0.7254509018036073

In [9]:
```python
# Algorithm 3: Logistic Regression
from sklearn.linear_model import LogisticRegression
modelLR = LogisticRegression(random_state = 1, max_iter = 100000)
stepsLR = [("counts",vectorizer), ("LR", modelLR)]
pipeLR = Pipeline(steps = stepsLR)
pipeLR.fit(X_train, y_train)
predictionsLR = pipeLR.predict(X_val)
evaluation(y_val, predictionsLR)
```

```
Accuracy:  0.7947454844006568
Precision: 0.827906976744186
Recall:    0.6691729323308271
F1:        0.74012474012474
```

Out[9]: 0.74012474012474

In [10]:
```python
# Algorithm 4: Support Vector Classifier
from sklearn.svm import SVC
modelSVC = SVC(C = 2, degree = 1)
stepsSVC = [("counts",vectorizer), ("SVC", modelSVC)]
pipeSVC = Pipeline(steps = stepsSVC)
pipeSVC.fit(X_train, y_train)
predictionsSVC = pipeSVC.predict(X_val)
evaluation(y_val, predictionsSVC)
```

```
Accuracy:  0.7848932676518884
Precision: 0.8609625668449198
Recall:    0.6052631578947368
F1:        0.7108167770419427
```

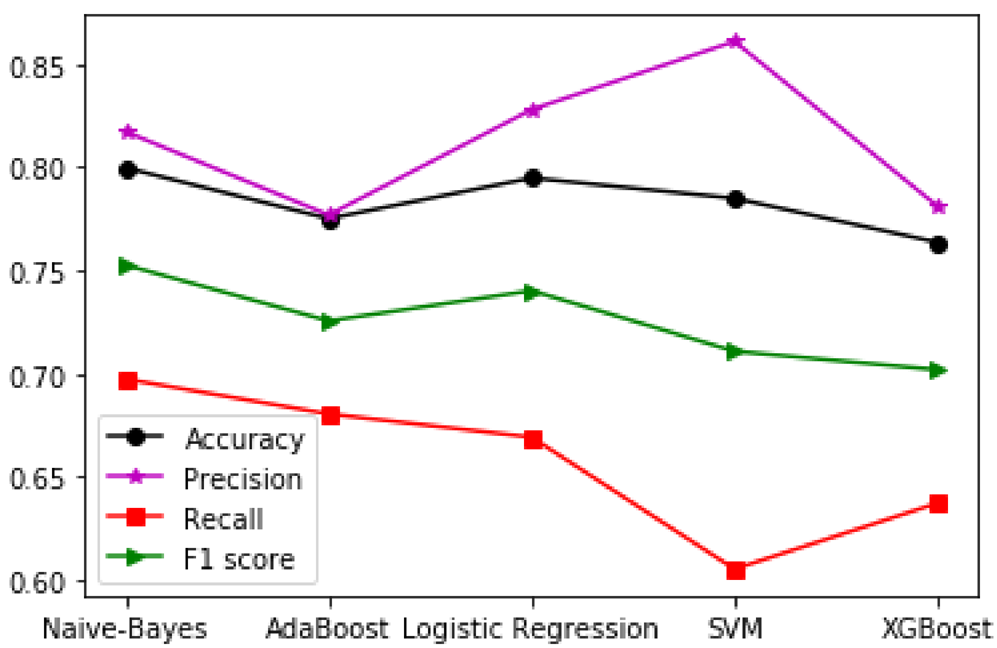
Out[10]: 0.7108167770419427

```
In [11]: # Algorithm 5: XGBoost
         from xgboost import XGBClassifier
         modelXGB = XGBClassifier(max_depth = 100, learning_rate = .1)
         stepsXGB = [("counts",vectorizer), ("XGB", modelXGB)]
         pipeXGB = Pipeline(steps = stepsXGB)
         pipeXGB.fit(X_train, y_train)
         predictionsXGB = pipeXGB.predict(X_val)
         evaluation(y_val, predictionsXGB)
```

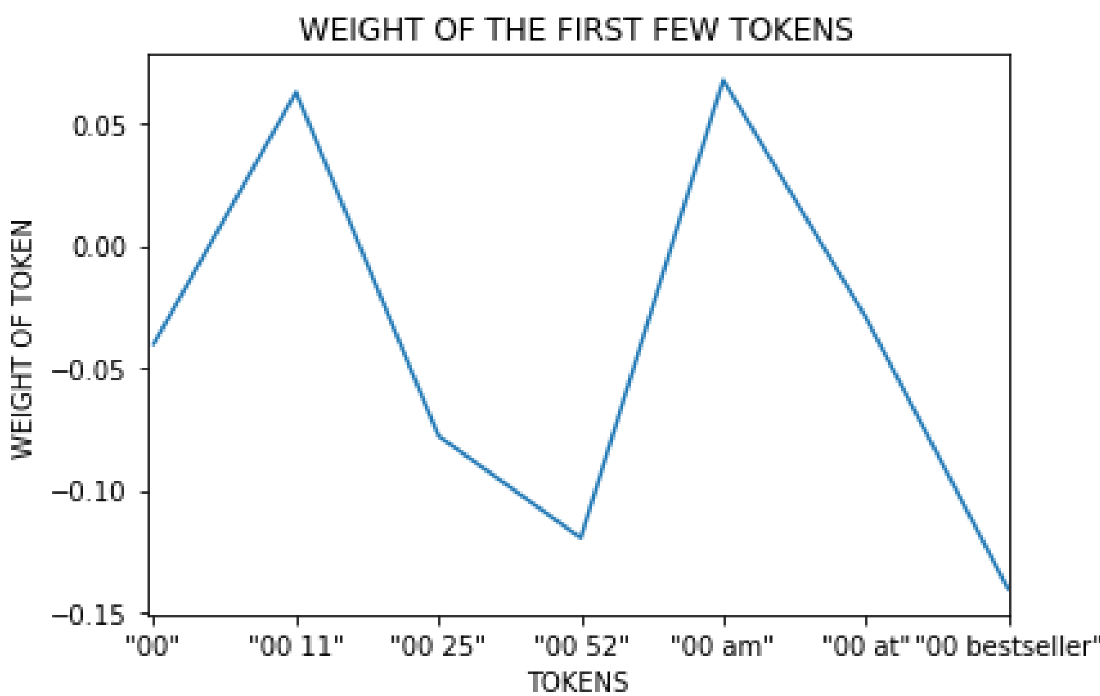
```
Accuracy:  0.7635467980295566
Precision: 0.7811059907834101
Recall:    0.6372180451127819
F1:        0.7018633540372671
```

```
Out[11]: 0.7018633540372671
```

```
In [65]: #Plot 1

         fig = plt.figure();
         plt.plot([0, 10, 20, 30, 40],acc,'ko-')
         plt.xticks([0, 10, 20, 30, 40], ["Naive-Bayes", "AdaBoost",
                                          "Logistic Regression", "SVM", "XGBoost"])
         plt.plot([0, 10, 20, 30, 40],pre,'m*-')
         plt.plot([0, 10, 20, 30, 40],rec,'rs-')
         plt.plot([0, 10, 20, 30, 40],fs, 'g>-')
         plt.legend(["Accuracy","Precision","Recall","F1 score"])
         plt.savefig(fname = "comparison.png")
```



In [63]:
```
#Plot 2

# We can take a look at the importance of tokens with
# the help of Logistic Regression Model
coeffs = modelLR.coef_
df = pd.read_csv('data/train.csv')
X = df['text']
y = df['target']
vectorizer = CountVectorizer(ngram_range=(1,2))
Xa = vectorizer.fit_transform(X)
X = pd.DataFrame(Xa.toarray(), columns=vectorizer.get_feature_names())
# Since this is a very high dimensional space, we will look at the first few tokens

x_axis = np.linspace(2,500, 7)
plt.plot(x_axis, coeffs[0][0:7])
plt.xticks(x_axis, ["\"00\"", "\"00 11\"", "\"00 25\"", "\"00 52\"",
                    "\"00 am\"", "\"00 at\"", "\"00 bestseller\""])
plt.xlabel("TOKENS")
plt.xlim([-2, 500])
plt.ylabel("WEIGHT OF TOKEN")
plt.title("WEIGHT OF THE FIRST FEW TOKENS")
plt.savefig(fname = "weight.png")
```



In [10]:
```
# Final Results
# Test Set evaluation

testPredictions = pipeNB.predict(X_test)
evaluation(y_test, testPredictions)
```

```
Accuracy:  0.799080761654629
Precision: 0.823943661971831
Recall:    0.6943620178041543
F1:        0.7536231884057971
```

Out[10]:
```
0.7536231884057971
```