Logistic Regression and AdaBoost

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The code below steps through loading the data, splitting it into test/train datasets, tuning parameters and

First we import libraries.

In [124]:

```
import pandas as pd
import numpy as np
import sklearn
from sklearn.model_selection import cross_val_score, train_test_split
from sklearn.utils import resample
from sklearn.tree import DecisionTreeClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.ensemble import AdaBoostClassifier
from sklearn.metrics import accuracy_score
import matplotlib.pyplot as plt
from time import time
from sklearn.linear_model import LogisticRegression
from sklearn.linear_model import LogisticRegressionCV

%matplotlib inline

import seaborn as sns
sns.set(style='whitegrid')
pd.set_option('display.width', 1500)
pd.set_option('display.max_columns', 100)

import warnings
warnings.filterwarnings('ignore')
```

Next, we load the data.

In [159]:

```
#import data
tweets1 = pd.read_csv('tweets_nlp_1_2.csv')
tweets2 = pd.read_csv('tweets_nlp_2_2.csv')
tweets3 = pd.read_csv('tweets_nlp_3_2.csv')
all_tweets = pd.concat([tweets1, tweets2, tweets3], sort=False)
```

Next we filter down to only the features we want to keep. Since we are going to compare the accuracy of our models between a base set of features and an extended set with nlp features, we can filter first for the extended set

In [201]:

```
all_tweets_df_nlp2 = all_tweets[['retweet_count', 'favorite_count', 'num_hashtag
s', 'num_urls', 'num_mentions',\
                                 'user_type', 'sentiment_negative', 'sentiment_n
eutral', 'sentiment_positive',\
                                 'token_count', 'url_token_ratio', 'ratio_neg',
\
                                 'ant', 'fear', 'joy', 'trust','jaccard']]
```

Now we standardize columns in our dataset

In [202]:

```
def standardize(df, col_list):
    for column in col_list:
        min_x = df[column].min()
        max_x = df[column].max()
        rangex = max_x - min_x
        df.loc[:, column]= df.loc[:,column].apply(lambda x: (x-min_x)/rangex)
    return(df)

col_list = ['retweet_count', 'favorite_count', 'num_hashtags', 'num_urls', 'num_
mentions','url_token_ratio', 'jaccard', 'token_count']
all_tweets_df_nlp = standardize(all_tweets_df_nlp2, col_list)
all_tweets_df = all_tweets_df_nlp[['retweet_count', 'favorite_count', 'num_hasht
ags', 'num_urls', 'num_mentions','user_type']]
```

In [204]:

```
all_tweets_df_nlp.describe()
```

Out[204]:

	retweet_count	favorite_count	num_hashtags	num_urls	num_mentions	user_
count	120260.000000	120260.000000	120260.000000	120260.000000	120260.000000	120260.00
mean	0.000096	0.002141	0.007242	0.122886	0.027090	0.40
std	0.005292	0.013521	0.022699	0.129295	0.051426	0.49
min	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
25%	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
50%	0.000000	0.000000	0.000000	0.000000	0.000000	0.00
75%	0.000000	0.000000	0.000000	0.250000	0.058824	1.00
max	1.000000	1.000000	1.000000	1.000000	1.000000	1.00

Split our data into train/test for the base and extended feature dataset.

In [208]:

```
def train_test_split_nlp(basedf, nlpdf):
    splits = {}
    i=0
    for df in [basedf, nlpdf]:
        train_df, test_df = train_test_split(df, test_size=0.33, random_state=42
, stratify=df['user_type'])
        ytrain_df = train_df['user_type']
        xtrain_df = train_df.drop('user_type', axis = 1)
        ytest_df = test_df['user_type']
        xtest_df = test_df.drop('user_type', axis = 1)
        if i == 0:
            splits['base'] = (xtrain_df, ytrain_df, xtest_df, ytest_df)
            i+=1
        else:
            splits['nlp'] = (xtrain_df, ytrain_df, xtest_df, ytest_df)
    return splits


splits = train_test_split_nlp(all_tweets_df, all_tweets_df_nlp)

xtrain_base, ytrain_base, xtest_base, ytest_base = splits['base'][0], splits['ba
se'][1], splits['base'][2],splits['base'][3]
xtrain_nlp, ytrain_nlp, xtest_nlp, ytest_nlp = splits['nlp'][0], splits['nlp'][1
], splits['nlp'][2], splits['nlp'][3]
```

Next we compared accuracy of a Logistic Regression Classifier (LR) when using the base vs extended features. The accuracy of the LR improved by 6% when NLP features were used in addition to the base features. LR with base features achieved a test accuracy of 74% while the LR with NLP features scored 82%.

In [206]:

```
model_log_cv_base = LogisticRegressionCV(cv = 5).fit(xtrain_base, ytrain_base)

train_score_logcv_base = model_log_cv_base.score(xtrain_base, ytrain_base)
test_score_logcv_base = model_log_cv_base.score(xtest_base, ytest_base)
print("Log Regression Model Accuracy with Base Features (Train) is ",train_score
_logcv_base)
print("Log Regression Model Accuracy with Base Features (Test) is ",test_score_l
ogcv_base)
```

```
Log Regression Model Accuracy with Base Features (Train) is  0.76626
45518405441
Log Regression Model Accuracy with Base Features (Test) is  0.764022
5772312654
```

In [207]:

```
model_log_cv = LogisticRegressionCV(cv = 5).fit(xtrain_nlp, ytrain_nlp)

train_score_logcv_nlp = model_log_cv.score(xtrain_nlp, ytrain_nlp)
test_score_logcv_nlp = model_log_cv.score(xtest_nlp, ytest_nlp)
print("Log Regression Model Accuracy with NLP (Train) is ",train_score_logcv_nlp
)
print("Log Regression Model Accuracy with NLP (Test) is ",test_score_logcv_nlp)
```

```
Log Regression Model Accuracy with NLP (Train) is  0.825017995879564
1
Log Regression Model Accuracy with NLP (Test) is  0.8247492818626215
```

ADABOOST

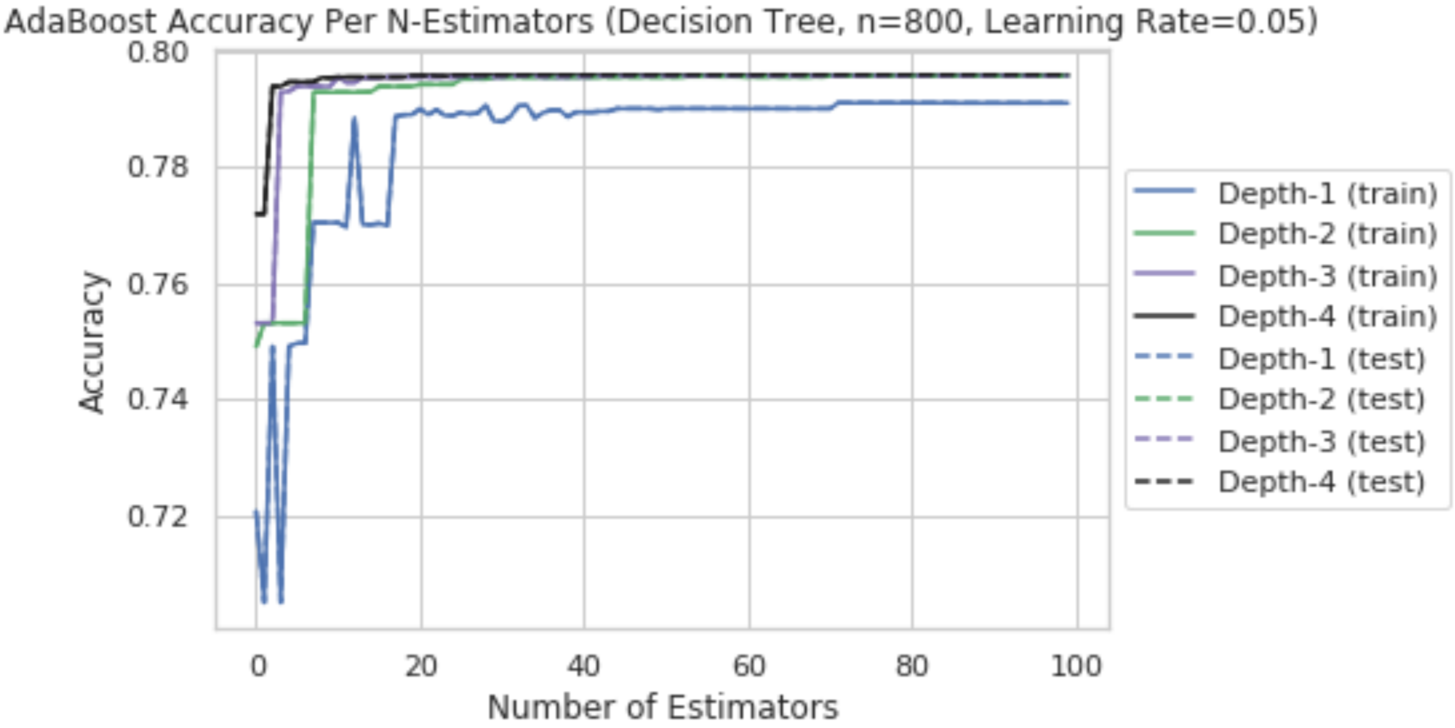
Moving on to AdaBoost, we chose model parameters by performing model tuning. The plot below shows accuracy as a function of max depth and estimators. We found that for 100 estimators and a fast learning rate of 0.2, using a max depth of 2 could achieve the same performance if the max depth was 4. We chose the lower cost features for our AdaBoost model: 0.2 learning rate, 100 estimators, max depth 2.

In [210]:

```
def fitSkAdaBoost(max_depth_list, data_tuple):
    #fits an AdaBoost model for each depth in the max_depth_list
    #returns a list of staged_score generators for each model
    X_train = data_tuple[0]
    y_train = data_tuple[1]
    X_test = data_tuple[0]
    y_test = data_tuple[1]
    score_list_train = []
    score_list_test = []
    #iterate through
    for depth in max_depth_list:
        skadaboost = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(ma
x_depth=depth),\
                                        n_estimators=100, learning_rate=0.20)
        skadaboost.fit(X_train, y_train)

        #hacky way of saving off stages scores.
        #if I didn't use this way, the variables would only hold the values temp
orarily
        score_test = skadaboost.staged_score(X_test, y_test)
        scores_test=[]
        for stagesc in score_test:
            scores_test=np.append(scores_test,stagesc)
        score_list_test.append(scores_test)

        score_train = skadaboost.staged_score(X_train, y_train)
        scores_train=[]
        for stagesc in score_train:
            scores_train=np.append(scores_train,stagesc)
        score_list_train.append(scores_train)


    return score_list_train, score_list_test


ss_train, ss_test = fitSkAdaBoost([1,2,3,4], splits['base'])

colors = ['b','g','m','k']
plt.figure()
for i in range(0,4):
    label = 'Depth-'+str(i+1)+' (train)'
    plt.plot(np.arange(0,100),list(ss_train[i]), color=colors[i], label=label)
for i in range(0,4):
    label = 'Depth-'+str(i+1)+' (test)'
    plt.plot(np.arange(0,100),list(ss_test[i]), color=colors[i], linestyle='dash
ed',label=label)
plt.title('AdaBoost Accuracy Per N-Estimators (Decision Tree, n=800, Learning Ra
te=0.05)')
plt.xlabel('Number of Estimators')
plt.ylabel('Accuracy')
plt.legend(loc="center left", bbox_to_anchor=(1, 0.5))
```

Out[210]:

```
<matplotlib.legend.Legend at 0xa1a7cfd30>
```



We saw a major improvement in accuracy of the AdaBoost models when the NLP features were included. Without NLP features, the model only reached an accuracy of 79%. The model achieved an accuracy of 98% when the NLP features were included.

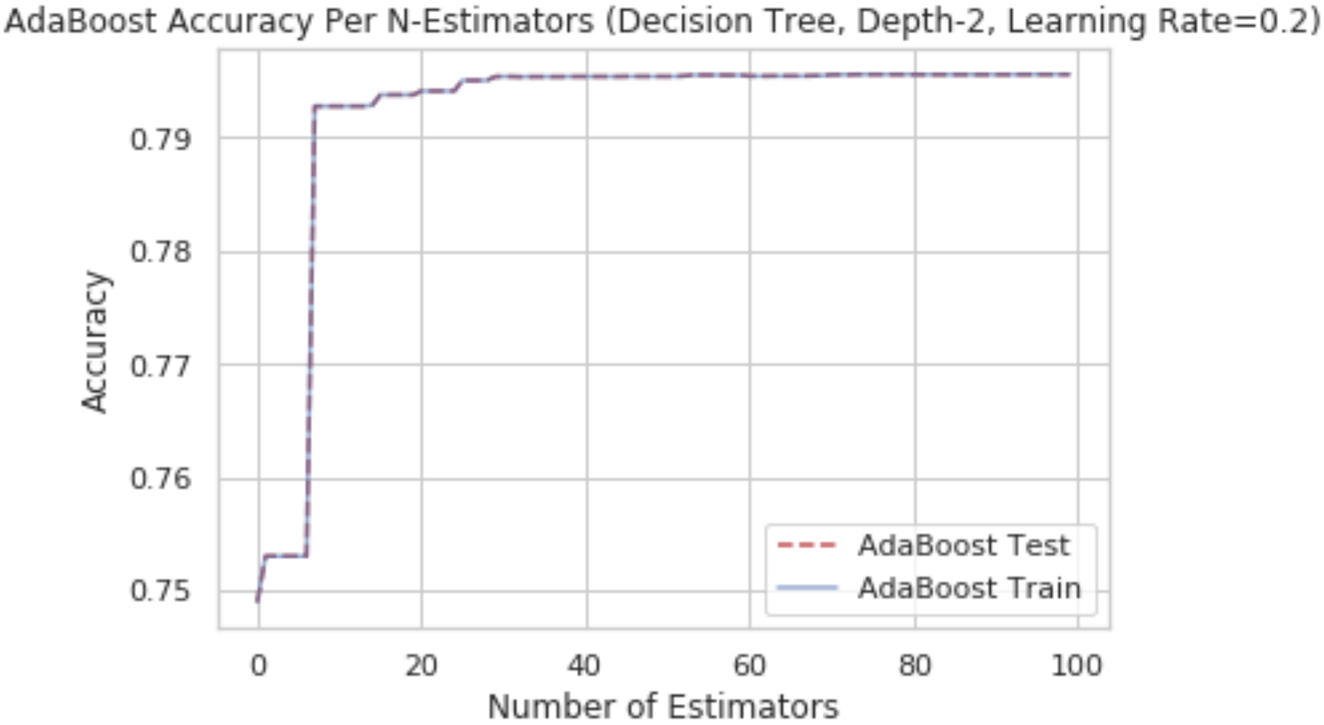
In [194]:

```
#modified from lab 9 notes
def adaboost_build_and_plot(data_tuple, max_depth, n_estimators, learning_rate,
makeplot=False):
    X_train = data_tuple[0]
    y_train = data_tuple[1]
    X_test = data_tuple[0]
    y_test = data_tuple[1]

    skadaboost = AdaBoostClassifier(base_estimator=DecisionTreeClassifier(max_de
pth=max_depth),
                              n_estimators=n_estimators, learning_rate=learning_
rate)
    skadaboost.fit(X_train, y_train)
    print('AdaBoost Accuracy (train)', skadaboost.score(X_train, y_train))
    print('AdaBoost Accuracy (test)', skadaboost.score(X_test, y_test))

    if makeplot == True:
        title = 'AdaBoost Accuracy Per N-Estimators (Decision Tree, Depth-' + st
r(max_depth) + ', Learning Rate=' + \
                str(learning_rate) + ')'
        staged_scores_test = skadaboost.staged_score(X_test, y_test)
        staged_scores_train = skadaboost.staged_score(X_train, y_train)
        plt.figure()
        plt.plot(np.arange(0,n_estimators),list(staged_scores_test), label='AdaB
oost Test', linestyle='dashed', color='r')
        plt.plot(np.arange(0,n_estimators),list(staged_scores_train), label='Ada
Boost Train', color='b', alpha = 0.6)
        plt.title(title)
        plt.xlabel('Number of Estimators')
        plt.ylabel('Accuracy')
        plt.legend()
```

In [195]:

```
t0 = time()
adaboost_build_and_plot(splits['base'], 2, 100, 0.2, makeplot=True)
print("done in %0.3fs." % (time() - t0))
```

```
AdaBoost Accuracy (train) 0.7955792191029364
AdaBoost Accuracy (test) 0.7955792191029364
done in 6.109s.
```



In [211]:

```
#adaboost_build_and_plot(data_tuple, max_depth, n_estimators, makeplot=False, it
erate=False)
t0 = time()
adaboost_build_and_plot(splits['nlp'],2,100,0.2, makeplot=True)
print("done in %0.3fs." % (time() - t0))
```

```
AdaBoost Accuracy (train) 0.9893017598729119
AdaBoost Accuracy (test) 0.9893017598729119
done in 9.379s.
```