CSDS 340 Case Study 1

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In [ ]:
```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pylab as pl
import matplotlib.pyplot as plt
from sklearn.metrics import auc, roc_auc_score
import numpy as np
from classifySpam import aucCV, predictTest
from sklearn.model_selection import cross_val_score, GridSearchCV, train_test_s
from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import StandardScaler
import multiprocessing
from sklearn.svm import SVC
import xgboost as xgb
```

In [ ]:
```
df = pd.read_csv('spamTrain1.csv')
df.columns = np.arange(0,31)
df.rename(columns={30:'Target'})
```

Out[ ]:

	0	1	2	3	4	5	6	7	8	9	...	21
0	0.0074	0.0000	0.000	0.0000	0.0000	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0000
1	0.0000	0.0000	0.000	0.0000	0.0000	0.0	0.0000	0.0040	0.0000	0.0000	...	0.0000
2	0.0000	0.0202	0.000	0.0000	0.0000	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0000
3	0.0000	0.0000	0.000	0.0019	0.0000	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0009
4	0.0000	0.0000	0.000	0.0000	0.0000	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0000
...	...	...	...	...	...	...	...	...	...	...	...	...
1494	0.0000	0.0000	0.000	0.0014	0.0044	0.0	0.0000	0.0067	0.0003	0.0044	...	0.0000
1495	0.0000	0.0000	0.000	0.0000	0.0000	0.0	0.0057	0.0000	0.0000	0.0000	...	0.0000
1496	0.0036	0.0000	0.000	0.0036	0.0036	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0000
1497	0.0000	0.0000	0.002	0.0031	0.0020	0.0	0.0000	0.0052	0.0020	0.0020	...	0.0000
1498	0.0000	0.0000	0.000	0.0000	0.0000	0.0	0.0000	0.0000	0.0000	0.0000	...	0.0000

1499 rows × 31 columns

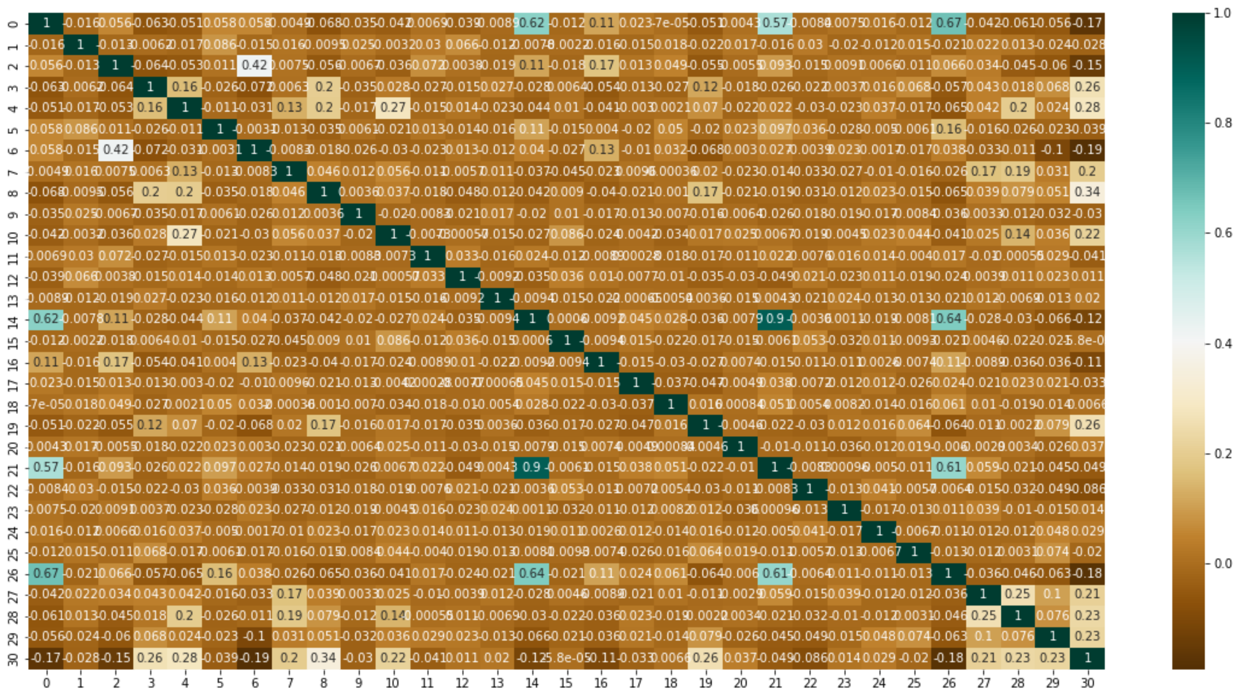
Let us do some basic exploratory data analysis first

In [ ]:
```
df[30].value_counts()
```

Out[ ]:
```
0    878
1    621
Name: 30, dtype: int64
```

In [ ]:
```
pl.figure(figsize=(20,10));
c= df.corr();
sns.heatmap(c,cmap="BrBG",annot=True)
```

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



This heatmap helps us get a sense of the data and what variables may be correlated. Just looking at the data, it seems that perhaps a decision tree based model could work - perhaps in conjuction with an ensemble model

In [ ]:
```
data = np.loadtxt('spamTrain1.csv',delimiter=',')

# Randomly shuffle rows of data set then separate labels (last column)
np.random.seed(1)
shuffleIndex = np.arange(np.shape(data)[0])
np.random.shuffle(shuffleIndex)
data = data[shuffleIndex,:]
features = data[:,:-1]
labels = data[:,-1]


# Arbitrarily choose all odd samples as train set and all even as test set
# then compute test set AUC for model trained only on fixed train set
# Code from Kevin S. Xu
trainFeatures = features[0::2,:]
trainLabels = labels[0::2]
testFeatures = features[1::2,:]
testLabels = labels[1::2]
```

First, let's try an SVM model. We can use Grid Search to find the best parameters for the classifier

In [ ]:
```
# defining parameter range
param_grid = {'C': [0.1, 1, 10, 100, 1000],
              'gamma': [1, 0.1, 0.01, 0.001, 0.0001],
              'kernel': ['rbf']}

svm = GridSearchCV(SVC(), param_grid, refit = True, verbose = 1)
print("10-fold cross-validation mean AUC: ", np.mean(aucCV(trainFeatures,trainI
```

```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
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Fitting 5 folds for each of 25 candidates, totalling 125 fits
Fitting 5 folds for each of 25 candidates, totalling 125 fits
10-fold cross-validation mean AUC:  0.9081598089843969
```

In [ ]:
```
# fitting the model for grid search
svm.fit(trainFeatures, trainLabels)
print("Best parameters:{}".format(svm.best_params_))
```

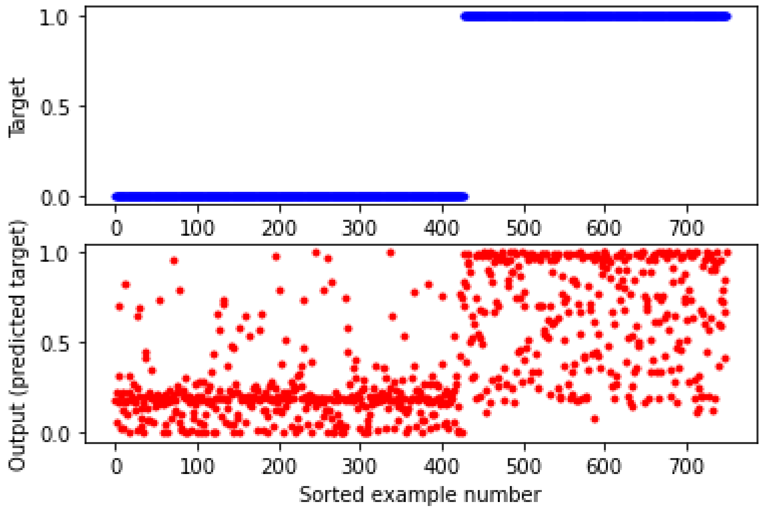
```
Fitting 5 folds for each of 25 candidates, totalling 125 fits
Best parameters:{'C': 1000, 'gamma': 1, 'kernel': 'rbf'}
```

In [ ]:
```
clf = SVC(C=1000, gamma=1, kernel='rbf', probability=True)
# Fit classifier to training data
clf.fit(trainFeatures, trainLabels)
# Test on testing set
testOutputs = predictTest(trainFeatures,trainLabels,testFeatures, model=clf)
print("Test set AUC: ", roc_auc_score(testLabels,testOutputs))
```

```
Test set AUC:  0.9012043126137427
```

Okay, not bad. The Naive Bayes' classifier had a test set accuracy of 0.83, so we're already seeing a significant improvement

In [ ]:
```
# Examine outputs compared to labels (code from Kevin S. Xu)
sortIndex = np.argsort(testLabels)
nTestExamples = testLabels.size
plt.subplot(2,1,1)
plt.plot(np.arange(nTestExamples),testLabels[sortIndex],'b.')
plt.xlabel('Sorted example number')
plt.ylabel('Target')
plt.subplot(2,1,2)
plt.plot(np.arange(nTestExamples),testOutputs[sortIndex],'r.')
plt.xlabel('Sorted example number')
plt.ylabel('Output (predicted target)')
plt.show()
```



Let's now try an XGBoost classifier (as defined by Chen, T., & Guestrin, C. (2016). XGBoost: A Scalable Tree Boosting System. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). New York, NY, USA: ACM. https://doi.org/10.1145/2939672.2939785)

In order to run this model, your python kernel will need the xgboost package, which is available through pip install xgboost

In [ ]:

```
# Define xgb classifier
xgb_model = xgb.XGBClassifier(objective='binary:logistic', n_jobs=multiprocessi
clf = GridSearchCV(xgb_model, {'max_depth': [2, 4, 6],'n_estimators': [50, 100,
# Evaluating classifier accuracy using 10-fold cross-validation
print("10-fold cross-validation mean AUC: ", np.mean(aucCV(trainFeatures,trainI
```

```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
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Fitting 5 folds for each of 72 candidates, totalling 360 fits
Fitting 5 folds for each of 72 candidates, totalling 360 fits
10-fold cross-validation mean AUC:  0.9267818868343607
```

In [ ]:

```
clf.fit(trainFeatures, trainLabels)
print("Best parameters:{}".format(clf.best_params_))
```

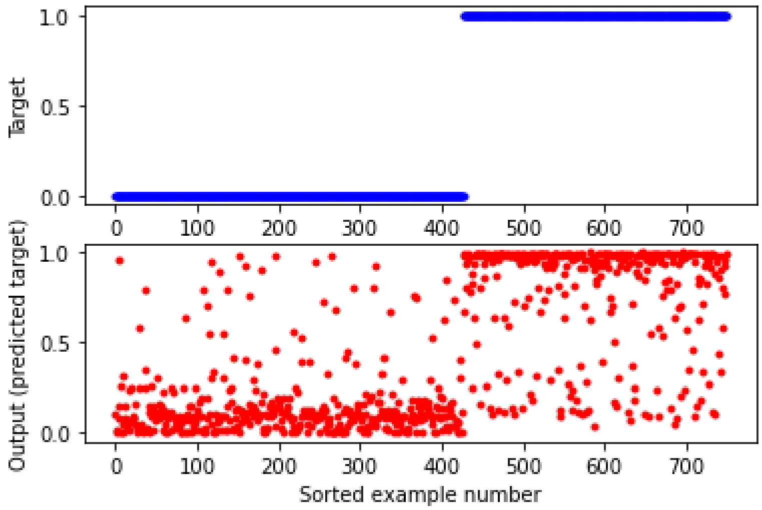
```
Fitting 5 folds for each of 72 candidates, totalling 360 fits
Best parameters:{'eta': 0.1, 'max_bin': 256, 'max_depth': 4, 'n_estimators': 1
00}
```

In [ ]:

```
clf = xgb.XGBClassifier(max_depth=4, eta=0.1, max_bin=256, n_estimators=100, ob
# Fit classifier to training data
clf.fit(trainFeatures, trainLabels)
# Test on testing set
testOutputs = predictTest(trainFeatures,trainLabels,testFeatures, model=clf)
print("Test set AUC: ", roc_auc_score(testLabels,testOutputs))
```

```
Test set AUC:  0.9377650974108367
```

In [ ]:
```
# Examine outputs compared to labels (code from Kevin S. Xu)
sortIndex = np.argsort(testLabels)
nTestExamples = testLabels.size
plt.subplot(2,1,1)
plt.plot(np.arange(nTestExamples),testLabels[sortIndex],'b.')
plt.xlabel('Sorted example number')
plt.ylabel('Target')
plt.subplot(2,1,2)
plt.plot(np.arange(nTestExamples),testOutputs[sortIndex],'r.')
plt.xlabel('Sorted example number')
plt.ylabel('Output (predicted target)')
plt.show()
```



A gradient boosted ensemble decision tree model appears to be the most effective (at least compared to SVM and Naive Bayes)