Classification: Spambase Data Set

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Data Repository: https://archive.ics.uci.edu/ml/datasets/Spambase (https://archive.ics.uci.edu/ml/datasets/Spambase)

In [147]:
```
%matplotlib inline

# import necessary libraries

import numpy as np

import matplotlib.pyplot as plt
plt.rcParams['figure.figsize'] = (20.0, 10.0)
```

Data Preprocessing

Normalization

In [156]:
```
spam = np.genfromtxt('/Users/ruiqiliu/Desktop/MSBA/Fall/MSBA 6420 Pred
ictive Analytics/Hw/spambase.csv',
                     delimiter=',')
spam.shape
```

Out[156]: (4601, 58)

In [157]:
```
#Shuffle and Split the data
from sklearn.cross_validation import KFold,train_test_split

spam = spam[np.random.permutation(len(spam))]
X_train,X_test,y_train,y_test = train_test_split(spam[:,0:56],
                                                 spam[:,57],
                                                 test_size = .2,random
_state = 0)
```

Since all of the variables are in different range and are quite sketwed. To ensure classifiers like KNN to work, I first applied min-max scaler to fix the range.

In [158]:
```
from sklearn.preprocessing import MinMaxScaler

min_max_scaler = MinMaxScaler()
X_train= min_max_scaler.fit_transform(X_train)
X_test = min_max_scaler.transform(X_test)
```

Feature Selection

In [164]:
```
from sklearn.ensemble import ExtraTreesClassifier

# Build a forest and compute the feature importances
forest = ExtraTreesClassifier(n_estimators=250,
                              random_state=0)

forest.fit(X_train, y_train)
importances = forest.feature_importances_
std = np.std([tree.feature_importances_ for tree in forest.estimators_
],
             axis=0)
indices = np.argsort(importances)[::-1]

# Print the feature ranking
print("Feature ranking:")

for f in range(X_train.shape[1]):
    print("%d. feature %d (%f)" % (f + 1, indices[f], importances[indi
ces[f]]))
```

```
Feature ranking:
1. feature 20 (0.068191)
2. feature 6 (0.058892)
3. feature 51 (0.056283)
4. feature 52 (0.051711)
5. feature 15 (0.045461)
6. feature 18 (0.042078)
7. feature 22 (0.041256)
8. feature 55 (0.039322)
9. feature 24 (0.038424)
10. feature 54 (0.036101)
11. feature 26 (0.030038)
12. feature 4 (0.029378)
13. feature 23 (0.026741)
14. feature 10 (0.025024)
15. feature 16 (0.022078)
16. feature 7 (0.021033)
17. feature 25 (0.020109)
18. feature 45 (0.019867)
```

```
19. feature 2 (0.018367)
20. feature 17 (0.017649)
21. feature 36 (0.017172)
22. feature 19 (0.016479)
23. feature 44 (0.016343)
24. feature 8 (0.016249)
25. feature 5 (0.015513)
26. feature 11 (0.015380)
27. feature 49 (0.015345)
28. feature 9 (0.014144)
29. feature 1 (0.012352)
30. feature 41 (0.011765)
31. feature 14 (0.010033)
32. feature 0 (0.009473)
33. feature 29 (0.009197)
34. feature 27 (0.008830)
35. feature 48 (0.008809)
36. feature 21 (0.007283)
37. feature 12 (0.007202)
38. feature 38 (0.006196)
39. feature 28 (0.006136)
40. feature 34 (0.005906)
41. feature 32 (0.005900)
42. feature 53 (0.005880)
43. feature 35 (0.005551)
44. feature 43 (0.005481)
45. feature 13 (0.004909)
46. feature 42 (0.004751)
47. feature 50 (0.004716)
48. feature 30 (0.004518)
49. feature 40 (0.003971)
50. feature 39 (0.003386)
51. feature 3 (0.003060)
52. feature 47 (0.002614)
53. feature 33 (0.002522)
54. feature 31 (0.002301)
55. feature 37 (0.001729)
56. feature 46 (0.000905)
```

All Features except for feature 46 are somewhat important. So I decided to temporarely keep all features and apply feature selection in a pipeline afterward.

Uniform Weighted Class

I performed 10 fold cross validation and used GridSearchCV to select the best parameters for the following models:

In [203]:
```
#Create classifier
from sklearn.linear_model import LogisticRegression
from sklearn.naive_bayes import GaussianNB
from sklearn.ensemble import RandomForestClassifier
from sklearn.svm import SVC
from sklearn.neighbors import KNeighborsClassifier
from sklearn.metrics import (accuracy_score,precision_score, recall_sc
ore,f1_score,roc_curve, auc)

classifiers = {'Logistic':LogisticRegression(),
               'Naive Bayes':GaussianNB(),
               'Support Vector Classification':SVC(),
               'Random Forest':RandomForestClassifier(),
               'KNN':KNeighborsClassifier(),
               }
```

In [206]:
```
#Set Parameters
svm_params = [{'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],'C': [1, 10, 1
00]},
             {'kernel': ['linear'], 'C': [1, 10, 100]}]

knn_params = {'n_neighbors':[5,10,30,50,100]}

log_params = {'penalty':['l1','l2']}

forest_params = {'max_depth': [5,10,30],
                'n_estimators':[10,20],
                'min_samples_split': [2,5,10]}
bayes_params = {}


params = {'Logistic': log_params,
          'Naive Bayes':bayes_params,
          'Support Vector Classification':svm_params,
          'Random Forest':forest_params,
          'KNN':knn_params,}
```

In [207]:
```
#Parameter selection + Cross Validation
from sklearn.cross_validation import KFold,train_test_split
from sklearn.grid_search import GridSearchCV

for (name, model), (name2,param) in zip(classifiers.items(),params.ite
ms()):
    print "%s:" % name
    clf = GridSearchCV(model, param, cv=10)

    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print clf.best_params_
    print
```

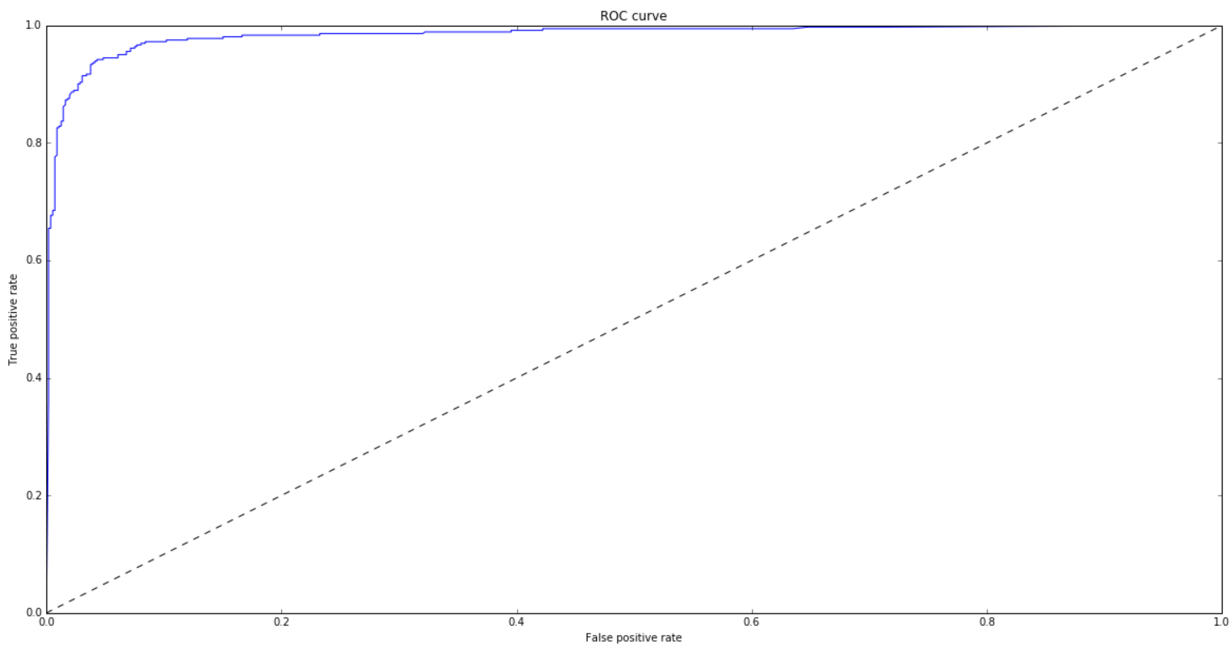
```
KNN:
{'n_neighbors': 5}

Support Vector Classification:
{'kernel': 'linear', 'C': 100}

Naive Bayes:
{}

Random Forest:
{'min_samples_split': 5, 'n_estimators': 20, 'max_depth': 30}

Logistic:
{'penalty': 'l1'}
```

In [208]:
```
#Evaluate Performance across all models

classifiers = {'Logistic':LogisticRegression(penalty = 'l1'),
               'Naive Bayes':GaussianNB(),
               'Support Vector Classification':SVC( kernel ='linear',
C = 100),
               'Random Forest':RandomForestClassifier(min_samples_spli
t = 5, n_estimators= 20, max_depth = 30),
               'KNN':KNeighborsClassifier(n_neighbors =5),
               }

for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print "%s:" % name

    # Model performance is evaluated with accuracy, precision, recall
and f-score
    print "\tAccuracy: %1.3f" % accuracy_score(y_test, y_pred)
    print "\tPrecision: %1.3f" % precision_score(y_test, y_pred)
    print "\tRecall: %1.3f" % recall_score(y_test, y_pred)
    print "\tF1: %1.3f\n" % f1_score(y_test, y_pred)
```

```
KNN:
        Accuracy: 0.907
        Precision: 0.894
        Recall: 0.865
        F1: 0.879

Support Vector Classification:
        Accuracy: 0.934
        Precision: 0.910
        Recall: 0.923
        F1: 0.916

Naive Bayes:
        Accuracy: 0.818
        Precision: 0.695
        Recall: 0.956
        F1: 0.805

Random Forest:
        Accuracy: 0.949
        Precision: 0.941
        Recall: 0.928
        F1: 0.935

Logistic:
        Accuracy: 0.914
        Precision: 0.901
        Recall: 0.878
        F1: 0.890
```

Considering that we don't want normal emails be classified as spam, I decided to reduce false positive rate. Therefore, I chose Random forest as my final model, which has both high accuracy and precision.

In [214]:
```
#The best model
best = RandomForestClassifier(min_samples_split = 5, n_estimators= 20,
max_depth = 30)

#ROC
y_pred_rf = best.fit(X_train,y_train).predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_rf)

plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.show()
```



Cost Sensitive

I applied the same procedure for cost sensitvie model.

In [226]:
```
#Create classifier

cs_classifiers = {'Logistic':LogisticRegression(class_weight={0: 10,1:
1}),
               'Support Vector Classification':SVC(class_weight={0:10,
1:1}),
               'Random Forest':RandomForestClassifier(class_weight={0:
10,1:1}),
               }
```

In [227]:
```
#Set Parameters
svm_params = [{'kernel': ['rbf'], 'gamma': [1e-3, 1e-4],'C': [1, 10, 1
00]},
             {'kernel': ['linear'], 'C': [1, 10, 100]}]


log_params = {'penalty':['l1','l2']}

forest_params = {'max_depth': [5,10,30],
                'n_estimators':[10,20],
                'min_samples_split': [2,5,10]}


params = {'Logistic': log_params,
          'Support Vector Classification':svm_params,
          'Random Forest':forest_params}
```

In [231]:
```
#Parameter selection + Cross Validation
from sklearn.cross_validation import KFold,train_test_split
from sklearn.grid_search import GridSearchCV

for (name, model), (name2,param) in zip(cs_classifiers.items(),params.
items()):
    print "%s:" % name
    clf = GridSearchCV(model, param, scoring = 'precision', cv=10)

    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print clf.best_params_
    print
```

```
Support Vector Classification:
{'kernel': 'linear', 'C': 100}

Random Forest:
{'min_samples_split': 2, 'n_estimators': 20, 'max_depth': 30}

Logistic:
{'penalty': 'l1'}
```

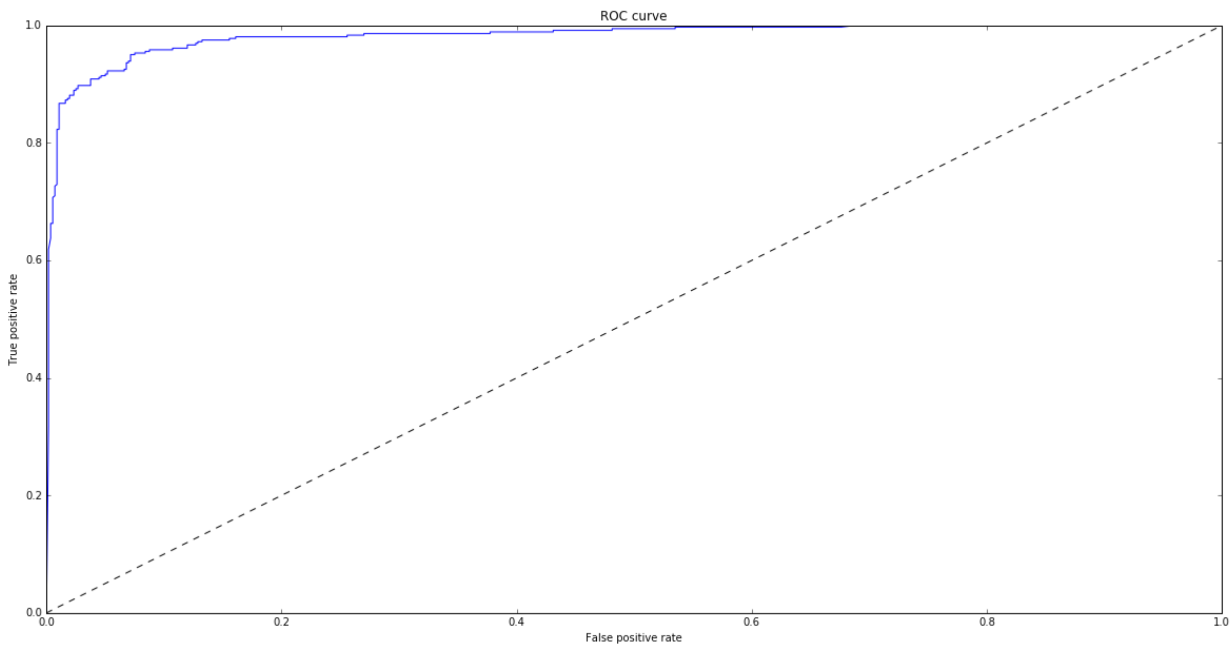
In [237]:

```
#Evaluate Performance across all models

classifiers = {'Logistic':LogisticRegression(penalty = 'l1',class_weig
ht= {0: 10,1:1}),
               'Support Vector Classification':SVC( kernel ='linear',
C = 100,class_weight= {0: 10,1:1}),
               'Random Forest':RandomForestClassifier(min_samples_spli
t = 5, n_estimators= 20,
                                                       max_depth = 30,c
lass_weight= {0: 10,1:1}),
               }

for name, clf in classifiers.items():
    clf.fit(X_train, y_train)
    y_pred = clf.predict(X_test)
    print "%s:" % name

    # Model performance is evaluated with accuracy, precision, recall
and f-score
    print "\tAccuracy: %1.3f" % accuracy_score(y_test, y_pred)
    print "\tPrecision: %1.3f" % precision_score(y_test, y_pred)
    print "\tRecall: %1.3f" % recall_score(y_test, y_pred)
    print "\tF1: %1.3f\n" % f1_score(y_test, y_pred)
```

```
Support Vector Classification:
        Accuracy: 0.835
        Precision: 0.969
        Recall: 0.599
        F1: 0.741

Random Forest:
        Accuracy: 0.940
        Precision: 0.948
        Recall: 0.898
        F1: 0.922

Logistic:
        Accuracy: 0.814
        Precision: 0.975
        Recall: 0.541
        F1: 0.696
```

Although Logistic regression and SVM generates high precisions, their accuracies are worse than random forest. I chose random forest as the final model since it's well-balanced.

In [238]:
```
#The best model
cs_best = RandomForestClassifier(min_samples_split = 5, n_estimators=
20, max_depth = 30,class_weight= {0: 10,1:1})

#ROC
y_pred_rf = cs_best.fit(X_train,y_train).predict_proba(X_test)[:, 1]
fpr, tpr, _ = roc_curve(y_test, y_pred_rf)

plt.figure(1)
plt.plot([0, 1], [0, 1], 'k--')
plt.plot(fpr, tpr)
plt.xlabel('False positive rate')
plt.ylabel('True positive rate')
plt.title('ROC curve')
plt.show()
```



Conclusion

Random forest perferms great for general model and cost-sensitive classification model.

The performance for senario 1 is: Accuracy: 0.949 Precision: 0.941 Recall: 0.928 F1: 0.935

The performance for senario 2 is:

```
Accuracy: 0.940
Precision: 0.948
Recall: 0.898
F1: 0.922
```