Titanic

June 11, 2018

```
In [1]: #Titanic
        %matplotlib inline
        import os
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.gridspec as gridspec
        import pandas as pd
        from sklearn import (datasets, decomposition, ensemble,
                             metrics, model_selection, preprocessing)

In [2]: os.chdir('D:\Titanic')

In [ ]: train_df = pd.read_csv('train.csv')
        train_df.head()

In [4]: #Explore types of data in the dataset
        train_df.dtypes

Out[4]: PassengerId      int64
        Survived         int64
        Pclass           int64
        Name            object
        Sex             object
        Age            float64
        SibSp            int64
        Parch            int64
        Ticket          object
        Fare           float64
        Cabin           object
        Embarked        object
        dtype: object

In [5]: train_df.describe()

Out[5]:        PassengerId    Survived      Pclass         Age       SibSp  \
        count   891.000000  891.000000  891.000000  714.000000  891.000000
        mean    446.000000    0.383838    2.308642   29.699118    0.523008
```

```
std     257.353842    0.486592    0.836071   14.526497    1.102743
min       1.000000    0.000000    1.000000    0.420000    0.000000
25%     223.500000    0.000000    2.000000   20.125000    0.000000
50%     446.000000    0.000000    3.000000   28.000000    0.000000
75%     668.500000    1.000000    3.000000   38.000000    1.000000
max     891.000000    1.000000    3.000000   80.000000    8.000000

            Parch        Fare
count  891.000000  891.000000
mean     0.381594   32.204208
std      0.806057   49.693429
min      0.000000    0.000000
25%      0.000000    7.910400
50%      0.000000   14.454200
75%      0.000000   31.000000
max      6.000000  512.329200
```

In [6]:
```
train_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
PassengerId    891 non-null int64
Survived       891 non-null int64
Pclass         891 non-null int64
Name           891 non-null object
Sex            891 non-null object
Age            714 non-null float64
SibSp          891 non-null int64
Parch          891 non-null int64
Ticket         891 non-null object
Fare           891 non-null float64
Cabin          204 non-null object
Embarked       889 non-null object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.6+ KB
```

In [7]:
```
#Check for NULL values
train_df.isnull().any()
```

Out[7]:
```
PassengerId    False
Survived       False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
```

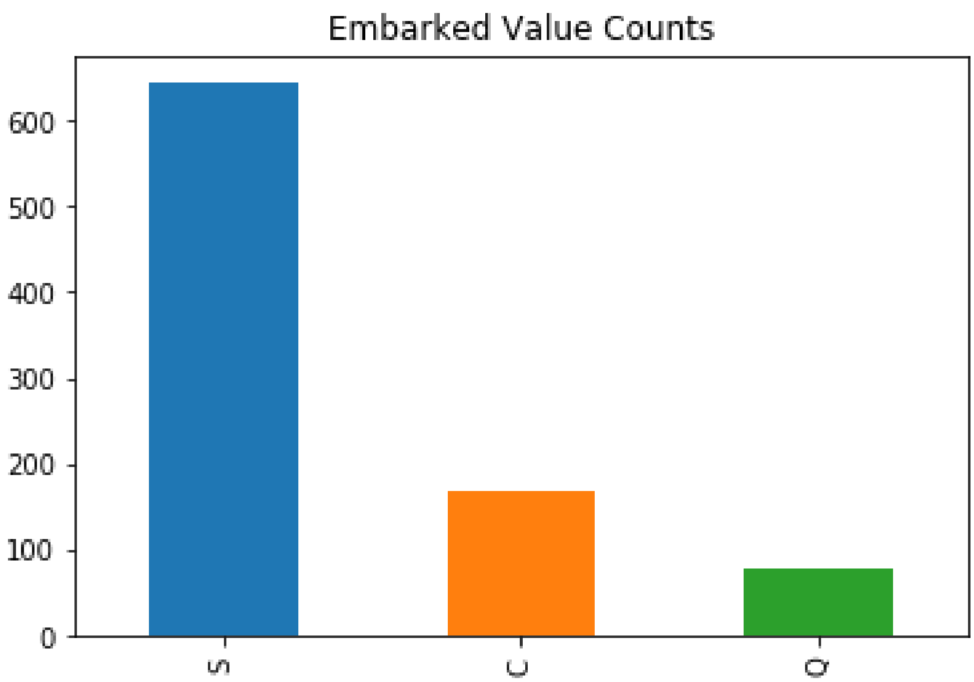
```
Ticket         False
Fare           False
Cabin           True
Embarked        True
dtype: bool
```

In [8]:
```
#Explore Embarked NULL values
train_df[train_df.Embarked.isnull()]
```

Out[8]:
```
     PassengerId  Survived  Pclass                                       Name  \
61            62         1       1                        Icard, Miss. Amelie
829          830         1       1  Stone, Mrs. George Nelson (Martha Evelyn)

        Sex   Age  SibSp  Parch  Ticket  Fare Cabin Embarked
61   female  38.0      0      0  113572  80.0   B28      NaN
829  female  62.0      0      0  113572  80.0   B28      NaN
```

In [9]:
```
#Visualize to determine how to handle categorical missing values
train_df.Embarked.value_counts().plot(kind='bar', title= 'Embarked Value Counts')
```

Out[9]: <matplotlib.axes._subplots.AxesSubplot at 0x1d5053c07f0>



In [10]:
```
#Since "S" is by far the most common,
#I will fill the only two missing values in train_df.Embarked with "S"
train_df.Embarked.fillna("S", inplace=True)
```

```
In [11]: #Look at the large number of Missing values for Cabinm
         train_df[train_df.Cabin.isnull()].head()
```

```
Out[11]:    PassengerId  Survived  Pclass                            Name     Sex  \
         0            1         0       3         Braund, Mr. Owen Harris    male
         2            3         1       3          Heikkinen, Miss. Laina  female
         4            5         0       3        Allen, Mr. William Henry    male
         5            6         0       3                Moran, Mr. James    male
         7            8         0       3  Palsson, Master. Gosta Leonard    male

             Age  SibSp  Parch            Ticket     Fare Cabin Embarked
         0  22.0      1      0         A/5 21171   7.2500   NaN        S
         2  26.0      0      0  STON/O2. 3101282   7.9250   NaN        S
         4  35.0      0      0            373450   8.0500   NaN        S
         5   NaN      0      0            330877   8.4583   NaN        Q
         7   2.0      3      1            349909  21.0750   NaN        S
```

```
In [12]: # In cabin == 1, not in cabin == 0
         train_df['InCabin'] = train_df['Cabin'].apply(lambda x: 0 if type(x) == float else 1)
         train_df.drop('Cabin', axis=1, inplace=True) #Drop original cabin column w/ NaNs
```

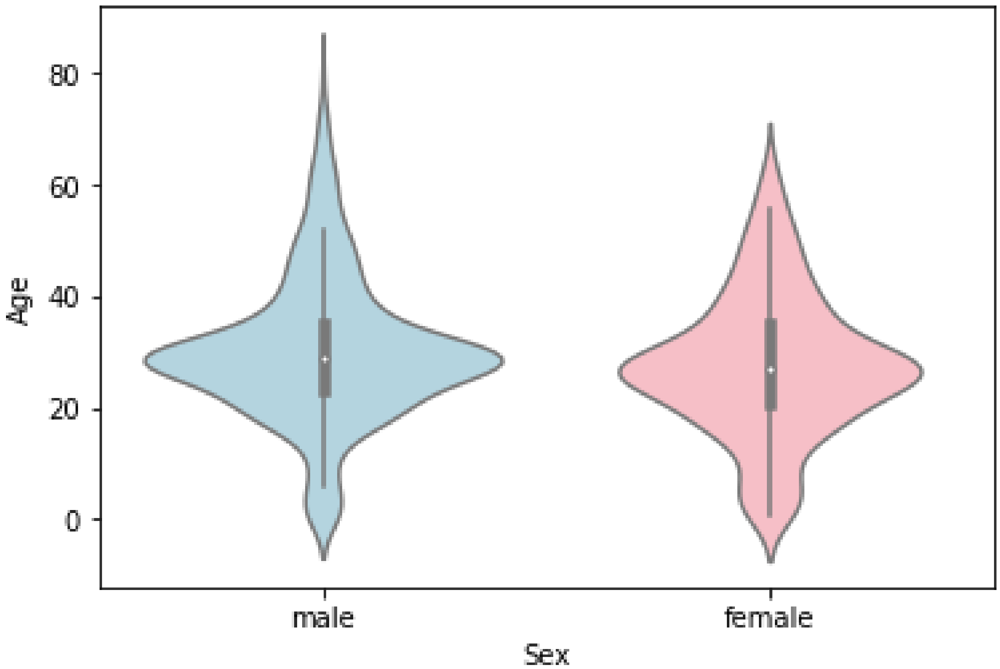
```
In [13]: #single out the missing values for age
         train_df[train_df.Age.isnull()].head()
```

```
Out[13]:     PassengerId  Survived  Pclass                            Name     Sex  Age  \
         5             6         0       3                Moran, Mr. James    male  NaN
         17           18         1       2    Williams, Mr. Charles Eugene    male  NaN
         19           20         1       3         Masselmani, Mrs. Fatima  female  NaN
         26           27         0       3         Emir, Mr. Farred Chehab    male  NaN
         28           29         1       3  O'Dwyer, Miss. Ellen "Nellie"  female  NaN

             SibSp  Parch  Ticket     Fare Embarked  InCabin
         5       0      0  330877   8.4583        Q        0
         17      0      0  244373  13.0000        S        0
         19      0      0    2649   7.2250        C        0
         26      0      0    2631   7.2250        C        0
         28      0      0  330959   7.8792        Q        0
```

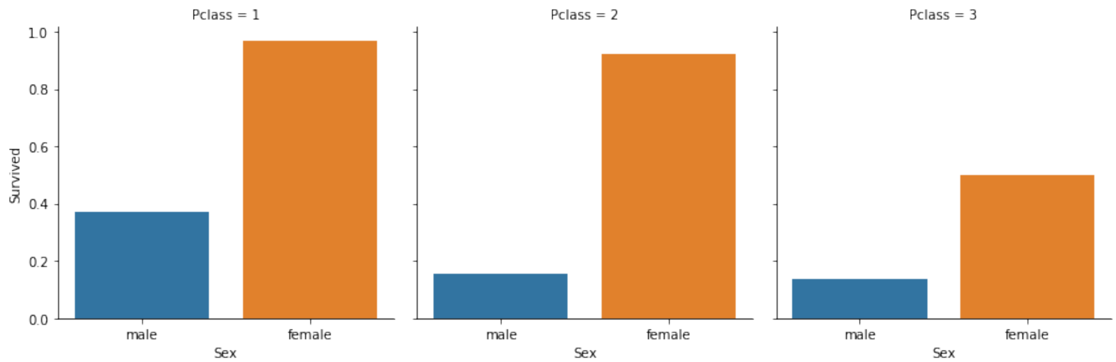
```
In [14]: #fill NaN in train_df.Age based on the median of each sex in train_df.Sex
         train_df.Age = train_df.groupby('Sex').Age.transform(lambda x: x.fillna(x.median()))
```

```
In [15]: import seaborn as sns

         #Visualize where most of the ages are by sex
         sns.violinplot("Sex", "Age", data=train_df,
                        palette=["lightblue", "lightpink"], )
```

```
Out[15]: <matplotlib.axes._subplots.AxesSubplot at 0x1d505aed470>
```




```
In [16]: #Double check missing values
         train_df.isnull().any()

Out[16]: PassengerId    False
         Survived       False
         Pclass         False
         Name           False
         Sex            False
         Age            False
         SibSp          False
         Parch          False
         Ticket         False
         Fare           False
         Embarked       False
         InCabin        False
         dtype: bool

In [17]: sex_survived = train_df.Sex.groupby(train_df.Survived).value_counts()

         #Break down by M/F per class based on who survived
         sns.factorplot(x='Sex', y='Survived', col='Pclass',
                        kind='bar', data=train_df, ci=None)

Out[17]: <seaborn.axisgrid.FacetGrid at 0x1d505afb358>
```

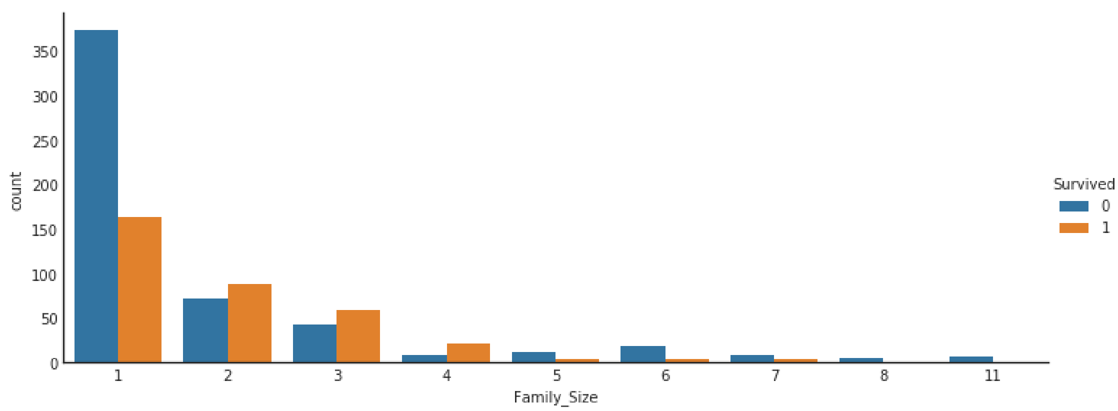



```
In [18]: #Factorize Embarked so they can be encoded
         embarked_encoded, embarked_categories = train_df.Embarked.factorize()

In [19]: from sklearn.preprocessing import OneHotEncoder

         encoder = OneHotEncoder()
         embarked_onehot = encoder.fit_transform(embarked_encoded.reshape(-1,1)).toarray()
         #Create separate encoded columns for each of the three Embarked values
         embarked_enc_df = pd.DataFrame(embarked_onehot, columns=['Embarked_S', 'Embarked_C',

In [20]: #Concatenate Tran_df and embarked encoded df
         df_train = pd.concat([train_df, embarked_enc_df], axis=1)

In [21]: #Use LabelEncoder for Sex encoded
         le = preprocessing.LabelEncoder()
         le.fit(train_df.Sex)

Out[21]: LabelEncoder()

In [22]: list(le.classes_)

Out[22]: ['female', 'male']

In [23]: sex_encoded = le.transform(train_df.Sex)

         df_train['Sex_Encoded'] = sex_encoded

In [24]: #Take a quick look at dataset correlations against Survived
         corr_matrix = df_train.corr()

In [25]: corr_matrix['Survived'].sort_values(ascending=False)

Out[25]: Survived       1.000000
         InCabin        0.316912
         Fare           0.257307
```

```
Embarked_C     0.168240
Parch          0.081629
Embarked_Q     0.003650
PassengerId   -0.005007
SibSp         -0.035322
Age           -0.073296
Embarked_S    -0.149683
Pclass        -0.338481
Sex_Encoded   -0.543351
Name: Survived, dtype: float64
```

In [26]:
```python
#Combined similar features to create a "Family Size" feature
df_train['Family_Size'] = df_train.Parch + df_train.SibSp + 1
```

In [27]:
```python
#Visualize Family Size and Survival
with sns.axes_style('white'):
    g = sns.factorplot("Family_Size", data=df_train, aspect=2.5, kind='count',
                       hue='Survived')
```



In [28]:
```python
#Check correlation after Family Size feature created
corr_matrix = df_train.corr()
corr_matrix['Survived'].sort_values(ascending=False)
```

Out[28]:
```
Survived       1.000000
InCabin        0.316912
Fare           0.257307
Embarked_C     0.168240
Parch          0.081629
Family_Size    0.016639
Embarked_Q     0.003650
PassengerId   -0.005007
SibSp         -0.035322
Age           -0.073296
Embarked_S    -0.149683
```

```
Pclass        -0.338481
Sex_Encoded   -0.543351
Name: Survived, dtype: float64
```

In [29]:
```
#Drop columns that won't be used(ie. no correlation or have been replaced by encoding
df_train.drop(['PassengerId', 'Name', 'Sex', 'SibSp','Parch', 'Ticket', 'Embarked'], a
```

In [30]:
```
df_train.dtypes
```

Out[30]:
```
Survived          int64
Pclass            int64
Age             float64
Fare            float64
InCabin           int64
Embarked_S      float64
Embarked_C      float64
Embarked_Q      float64
Sex_Encoded       int64
Family_Size       int64
dtype: object
```

In [ ]:
```
train_set = df_train.values
```

In [32]:
```
#Process all the above preprocessing on the test set by creating a function called cl
def clean(df):

    df.Embarked.fillna("S", inplace=True)

    df['InCabin'] = df['Cabin'].apply(lambda x: 0 if type(x) == float else 1)
    df.drop('Cabin', axis=1, inplace=True)

    df.Age = df.groupby('Sex').Age.transform(lambda x: x.fillna(x.median()))

    df.Fare = df.groupby('Pclass').Fare.transform(lambda x: x.fillna(x.median()))

    embarked_enc, embarked_cat = df.Embarked.factorize()
    encoder = OneHotEncoder()
    embarked_oh = encoder.fit_transform(embarked_enc.reshape(-1,1)).toarray()
    embarked_enc = pd.DataFrame(embarked_oh, columns=['Embarked_S', 'Embarked_C', 'Em

    df = pd.concat([df, embarked_enc], axis=1)

    le = preprocessing.LabelEncoder()
    sex_encoded = le.fit_transform(df.Sex.astype(str))
    df['Sex_Encoded'] = sex_encoded

    df['Famile_Size'] = df.Parch + df.SibSp + 1

    df.drop(['PassengerId', 'Name', 'Sex', 'SibSp','Parch', 'Ticket', 'Embarked'], ax
```

```
    return df
```

In [33]:
```
#Load Test Set
test_df = pd.read_csv('test.csv')
#Check for NULL values
test_df.isnull().any()
```

Out[33]:
```
PassengerId    False
Pclass         False
Name           False
Sex            False
Age             True
SibSp          False
Parch          False
Ticket         False
Fare            True
Cabin           True
Embarked       False
dtype: bool
```

In [34]:
```
#Run test set through "clean" function for preprocessing
test_set = clean(test_df)
```

In [35]:
```
test_set.isnull().any()
```

Out[35]:
```
Pclass         False
Age            False
Fare           False
InCabin        False
Embarked_S     False
Embarked_C     False
Embarked_Q     False
Sex_Encoded    False
Famile_Size    False
dtype: bool
```

In [36]:
```
from  sklearn.ensemble import RandomForestClassifier
#Random Forest Classifier
clf = RandomForestClassifier(n_estimators=500, random_state=19,
                             n_jobs=-1)
```

In [37]:
```
# Training data features, skip the first column 'Survived'
train_features = train_set[:, 1:]

# 'Survived' column values
train_target = train_df.Survived.values

# Fit the model to our training data
```

```
clf = clf.fit(train_features, train_target)
score = clf.score(train_features, train_target)
"Mean accuracy of Random Forest: {0:.3g}".format(score)
```

Out[37]: 'Mean accuracy of Random Forest: 0.982'

In [38]:
```
# Predict the Survival values for the test data
test_y = clf.predict(test_set)
```

In [39]:
```
from sklearn import metrics
from sklearn.cross_validation import train_test_split

# Split 80-20 train vs test data
train_x, test_x, train_y, test_y = train_test_split(train_features,
                                                    train_target,
                                                    test_size=0.20,
                                                    random_state=11)
print (train_features.shape, train_target.shape)
print (train_x.shape, train_y.shape)
print (test_x.shape, test_y.shape)
```

```
(891, 9) (891,)
(712, 9) (712,)
(179, 9) (179,)


D:\Anaconda\lib\site-packages\sklearn\cross_validation.py:41: DeprecationWarning: This module w
  "This module will be removed in 0.20.", DeprecationWarning)
```

In [40]:
```
clf = clf.fit(train_x, train_y)
predict_y = clf.predict(test_x)
#Random Forest Classifier Accuracy Score
from sklearn.metrics import accuracy_score
print ("Accuracy = %.2f" % (accuracy_score(test_y, predict_y)))
```

```
Accuracy = 0.85
```

In [41]:
```
#RFC Model Score
model_score = clf.score(test_x, test_y)
print ("Model Score %.2f \n" % (model_score))

#Confucion Matrix
confusion_matrix = metrics.confusion_matrix(test_y, predict_y)
print ("Confusion Matrix Results:")

print ("TP:", confusion_matrix[0, 0])
print ("FN:", confusion_matrix[0, 1])
print ("FP:", confusion_matrix[1, 0])
print ("TN:",confusion_matrix[1, 1])
```

```
Model Score 0.85

Confusion Matrix Results:
TP: 107
FN: 11
FP: 15
TN: 46
```

In [42]:
```python
from sklearn.metrics import classification_report
print(classification_report(test_y,
                            predict_y,
                            target_names=['Not Survived', 'Survived']))
```

```
              precision    recall  f1-score   support

Not Survived       0.88      0.91      0.89       118
    Survived       0.81      0.75      0.78        61

 avg / total       0.85      0.85      0.85       179
```

In [43]:
```python
#Create an SVM model
from sklearn.svm import SVC
svm_clf = SVC(kernel='rbf', C=6, gamma=0.3)
svm_clf.fit(train_x, train_y)
```

Out[43]:
```
SVC(C=6, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.3, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)
```

In [44]:
```python
svm_clf.score(train_features, train_target)
```

Out[44]:
```
0.9214365881032548
```

In [45]:
```python
svm_predict_y = svm_clf.predict(test_x)
acc_score = accuracy_score(test_y, svm_predict_y)
#SVM Accuracy
print("Accuracy = {0:.3g}".format(acc_score))
```

```
Accuracy = 0.754
```

In [46]:
```python
print(classification_report(test_y,
                            svm_predict_y,
                            target_names=['Not Survived', 'Survived']))
```

```
              precision    recall  f1-score   support

Not Survived       0.78      0.88      0.83       118
    Survived       0.69      0.51      0.58        61

 avg / total       0.75      0.75      0.74       179
```

```
In [47]: #Decision Tree Classifier
         from sklearn.tree import DecisionTreeClassifier

         tree_clf = DecisionTreeClassifier(max_depth=3)
         tree_clf.fit(train_x, train_y)

Out[47]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=3,
                     max_features=None, max_leaf_nodes=None,
                     min_impurity_decrease=0.0, min_impurity_split=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, presort=False, random_state=None,
                     splitter='best')

In [48]: tree_clf.score(train_features, train_target)

Out[48]: 0.8237934904601572

In [49]: from sklearn.ensemble import VotingClassifier
         from sklearn.linear_model import LogisticRegression

         #Experimenting with a voting classifier (LR, RFC, SVC)
         log_clf = LogisticRegression()
         rnd_clf = RandomForestClassifier()
         svm_clf = SVC()
         voting_clf = VotingClassifier(
             estimators=[('lr', log_clf), ('rf', rnd_clf), ('svc', svm_clf)],
             voting='hard')
         voting_clf.fit(train_x, train_y)

Out[49]: VotingClassifier(estimators=[('lr', LogisticRegression(C=1.0, class_weight=None, dual=
                   intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                   penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                   verbose=0, warm_start=False)), ('rf', RandomF...,
           max_iter=-1, probability=False, random_state=None, shrinking=True,
           tol=0.001, verbose=False))],
                  flatten_transform=None, n_jobs=1, voting='hard', weights=None)

In [50]: #Output for Voting Classifier
         for clf in (log_clf, rnd_clf, svm_clf, voting_clf):
             clf.fit(train_x, train_y)
             y_pred = clf.predict(test_x)
             print(clf.__class__.__name__, accuracy_score(test_y, y_pred))
```

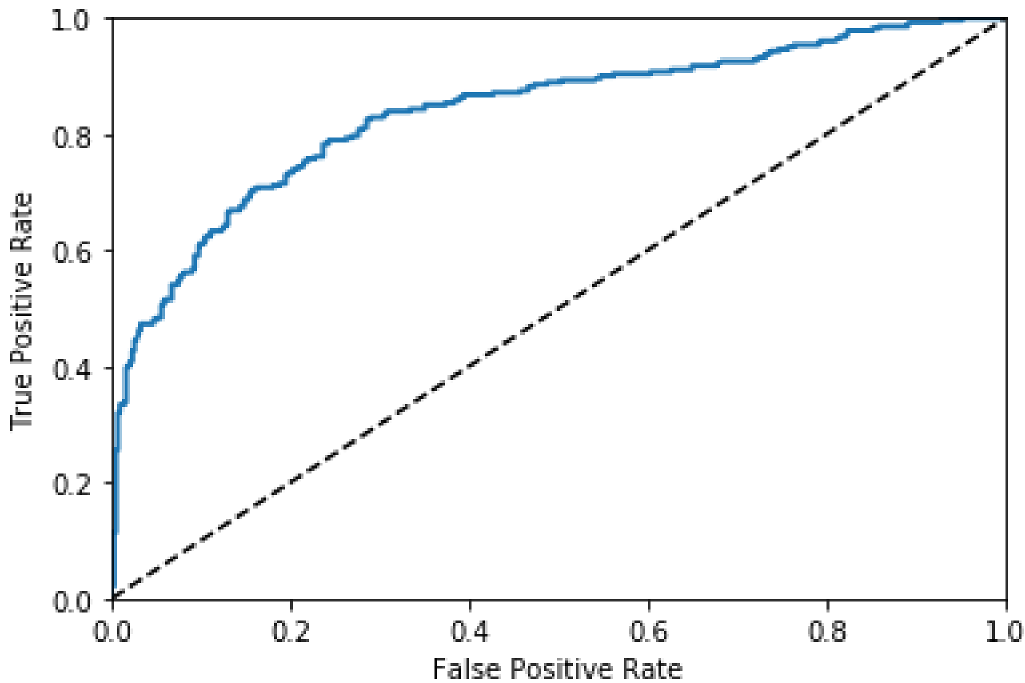
```
LogisticRegression 0.8659217877094972
RandomForestClassifier 0.8547486033519553
SVC 0.7486033519553073
VotingClassifier 0.8659217877094972
```

```
D:\Anaconda\lib\site-packages\sklearn\preprocessing\label.py:151: DeprecationWarning: The truth
  if diff:
```

In [51]:
```python
y_hat_log = log_clf.predict(test_x)
acc_log = accuracy_score(test_y, y_hat_log)
#Voting Classifier Accuracy
acc_log
```

Out[51]: 0.8659217877094972

In [52]:
```python
from sklearn.metrics import roc_curve, roc_auc_score
from sklearn.model_selection import cross_val_predict
y_probas_forest = cross_val_predict(log_clf, train_x, train_y, cv=3,
                                    method="predict_proba")
y_scores_forest = y_probas_forest[:, 1]

fpr, tpr, thresholds = roc_curve(train_y, y_scores_forest)

#Plot the ROC Curve
def plot_roc_curve(fpr, tpr, label=None):
    plt.plot(fpr, tpr, linewidth=2, label=label)
    plt.plot([0, 1], [0, 1], 'k--')
    plt.axis([0, 1, 0, 1])
    plt.xlabel('False Positive Rate')
    plt.ylabel('True Positive Rate')

plot_roc_curve(fpr, tpr,'Random Forest')
plt.show()

print("ROC AUC Score: {0:.3f}".format(roc_auc_score(train_y, y_scores_forest)))
```




```
ROC AUC Score: 0.838
```

```
In [53]: # Bagging Classifier
         from sklearn.ensemble import BaggingClassifier

         bag_clf = BaggingClassifier(
                 DecisionTreeClassifier(), n_estimators=500,
                 max_samples=100, bootstrap=True, n_jobs=-1)
         bag_clf.fit(train_x, train_y)
         bag_y_hat = bag_clf.predict(test_x)
```

```
In [54]: bag_accuracy = accuracy_score(test_y, bag_y_hat)
```

```
In [55]: confusion_matrix = metrics.confusion_matrix(test_y, bag_y_hat)
         print('The Bagging accuracy score: {0:.3f}'.format(bag_accuracy))

         confusion_matrix
```

```
The Bagging accuracy score: 0.894
```

```
Out[55]: array([[112,   6],
                [ 13,  48]], dtype=int64)
```