Decision Trees and Random Forest Project II

October 26, 2016

1 Random Forest Project - Solutions

For this project we will be exploring publicly available data from LendingClub.com. Lending Club connects people who need money (borrowers) with people who have money (investors). Hopefully, as an investor you would want to invest in people who showed a profile of having a high probability of paying you back. We will try to create a model that will help predict this.

We will use lending data from 2007-2010 and be trying to classify and predict whether or not the borrower paid back their loan in full.

Here are what the columns represent: * credit.policy: 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise. * purpose: The purpose of the loan (takes values "credit_card", "debt_consolidation", "educational", "major_purchase", "small_business", and "all_other"). * int.rate: The interest rate of the loan, as a proportion (a rate of 11% would be stored as 0.11). Borrowers judged by LendingClub.com to be more risky are assigned higher interest rates. * installment: The monthly installments owed by the borrower if the loan is funded. * log.annual.inc: The natural log of the self-reported annual income of the borrower. * dti: The debt-to-income ratio of the borrower (amount of debt divided by annual income). * fico: The FICO credit score of the borrower. * days.with.cr.line: The number of days the borrower has had a credit line. * revol.bal: The borrower's revolving balance (amount unpaid at the end of the credit card billing cycle). * revol.util: The borrower's revolving line utilization rate (the amount of the credit line used relative to total credit available). * inq.last.6mths: The borrower's number of inquiries by creditors in the last 6 months. * delinq.2yrs: The number of times the borrower had been 30+ days past due on a payment in the past 2 years. * pub.rec: The borrower's number of derogatory public records (bankruptcy filings, tax liens, or judgments).

2 Import Libraries

Import the usual libraries for pandas and plotting. You can import sklearn later on.

```
In [1]: import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

2.1 Get the Data

** Use pandas to read loan_data.csv as a dataframe called loans.**

```
In [2]: loans = pd.read_csv('loan_data.csv')
```

** Check out the info(), head(), and describe() methods on loans.**

```
In [3]: loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
credit.policy        9578 non-null int64
purpose              9578 non-null object
int.rate             9578 non-null float64
installment          9578 non-null float64
log.annual.inc       9578 non-null float64
dti                  9578 non-null float64
fico                 9578 non-null int64
days.with.cr.line    9578 non-null float64
revol.bal            9578 non-null int64
revol.util           9578 non-null float64
inq.last.6mths       9578 non-null int64
delinq.2yrs          9578 non-null int64
pub.rec              9578 non-null int64
not.fully.paid       9578 non-null int64
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

In [4]:
```
loans.describe()
```

Out[4]:

	credit.policy	int.rate	installment	log.annual.inc	dti
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679
std	0.396245	0.026847	207.071301	0.614813	6.883970
min	0.000000	0.060000	15.670000	7.547502	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500
50%	1.000000	0.122100	268.950000	10.928884	12.665000
75%	1.000000	0.140700	432.762500	11.291293	17.950000
max	1.000000	0.216400	940.140000	14.528354	29.960000

	fico	days.with.cr.line	revol.bal	revol.util
count	9578.000000	9578.000000	9.578000e+03	9578.000000
mean	710.846314	4560.767197	1.691396e+04	46.799236
std	37.970537	2496.930377	3.375619e+04	29.014417
min	612.000000	178.958333	0.000000e+00	0.000000
25%	682.000000	2820.000000	3.187000e+03	22.600000
50%	707.000000	4139.958333	8.596000e+03	46.300000
75%	737.000000	5730.000000	1.824950e+04	70.900000
max	827.000000	17639.958330	1.207359e+06	119.000000

	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000
mean	1.577469	0.163708	0.062122	0.160054
std	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.000000	0.000000	0.000000
25%	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.000000	0.000000	0.000000
75%	2.000000	0.000000	0.000000	0.000000
max	33.000000	13.000000	5.000000	1.000000

In [5]:
```
loans.head()
```

Out[5]:

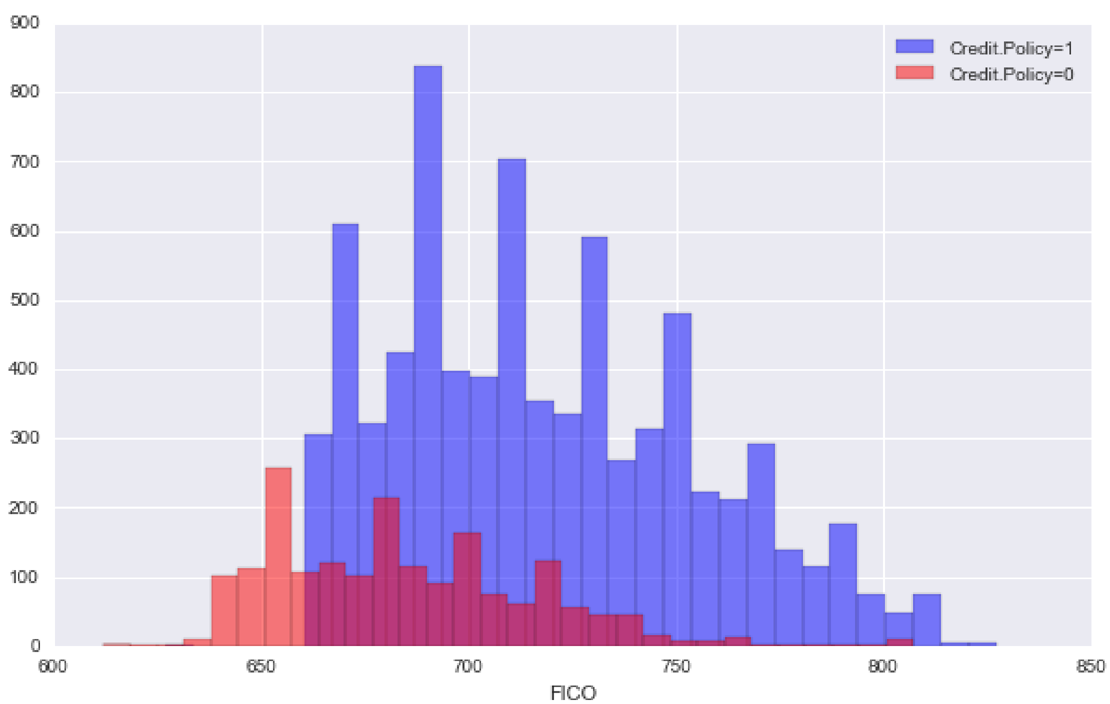
	credit.policy	purpose	int.rate	installment	log.annual.inc
0	1	debt_consolidation	0.1189	829.10	11.350407

```
1               1          credit_card    0.1071       228.22       11.082143
2               1  debt_consolidation    0.1357       366.86       10.373491
3               1  debt_consolidation    0.1008       162.34       11.350407
4               1          credit_card    0.1426       102.92       11.299732

     dti  fico  days.with.cr.line  revol.bal  revol.util  inq.last.6mths  \
0  19.48   737        5639.958333      28854        52.1               0
1  14.29   707        2760.000000      33623        76.7               0
2  11.63   682        4710.000000       3511        25.6               1
3   8.10   712        2699.958333      33667        73.2               1
4  14.97   667        4066.000000       4740        39.5               0

   delinq.2yrs  pub.rec  not.fully.paid
0            0        0               0
1            0        0               0
2            0        0               0
3            0        0               0
4            1        0               0
```

3 Exploratory Data Analysis

In [6]:
```python
plt.figure(figsize=(10,6))
loans[loans['credit.policy']==1]['fico'].hist(alpha=0.5,color='blue',
                                              bins=30,label='Credit.Policy=1')
loans[loans['credit.policy']==0]['fico'].hist(alpha=0.5,color='red',
                                              bins=30,label='Credit.Policy=0')
plt.legend()
plt.xlabel('FICO')
```

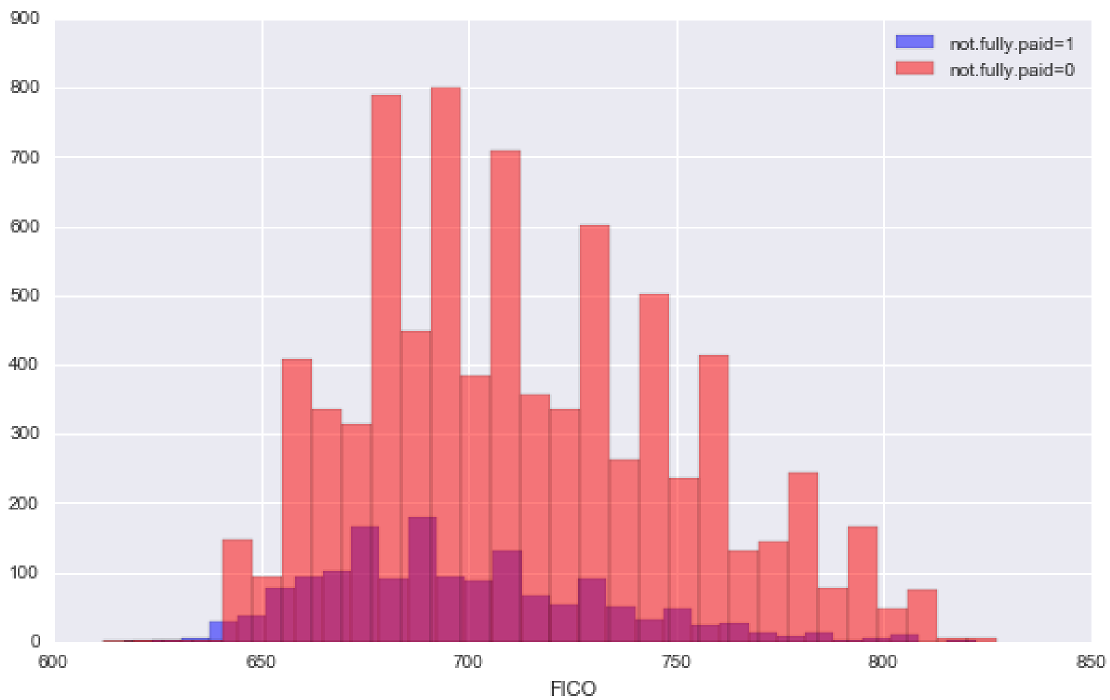
Out[6]: <matplotlib.text.Text at 0xa1bb5cdd8>



** Create a similar figure, except this time select by the not.fully.paid column.**

```
In [7]: plt.figure(figsize=(10,6))
        loans[loans['not.fully.paid']==1]['fico'].hist(alpha=0.5,color='blue',
                                                      bins=30,label='not.fully.paid=1')
        loans[loans['not.fully.paid']==0]['fico'].hist(alpha=0.5,color='red',
                                                      bins=30,label='not.fully.paid=0')
        plt.legend()
        plt.xlabel('FICO')
```

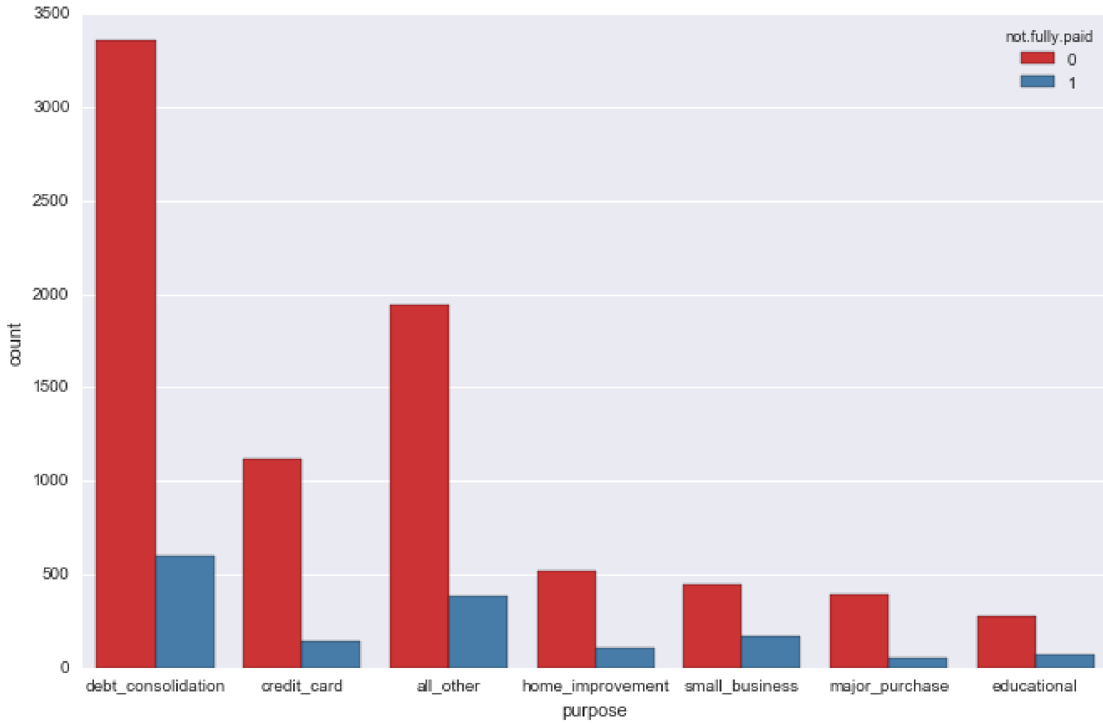
```
Out[7]: <matplotlib.text.Text at 0xa1c006a90>
```



** Create a countplot using seaborn showing the counts of loans by purpose, with the color hue defined by not.fully.paid. **

```
In [8]: plt.figure(figsize=(11,7))
        sns.countplot(x='purpose',hue='not.fully.paid',data=loans,palette='Set1')
```

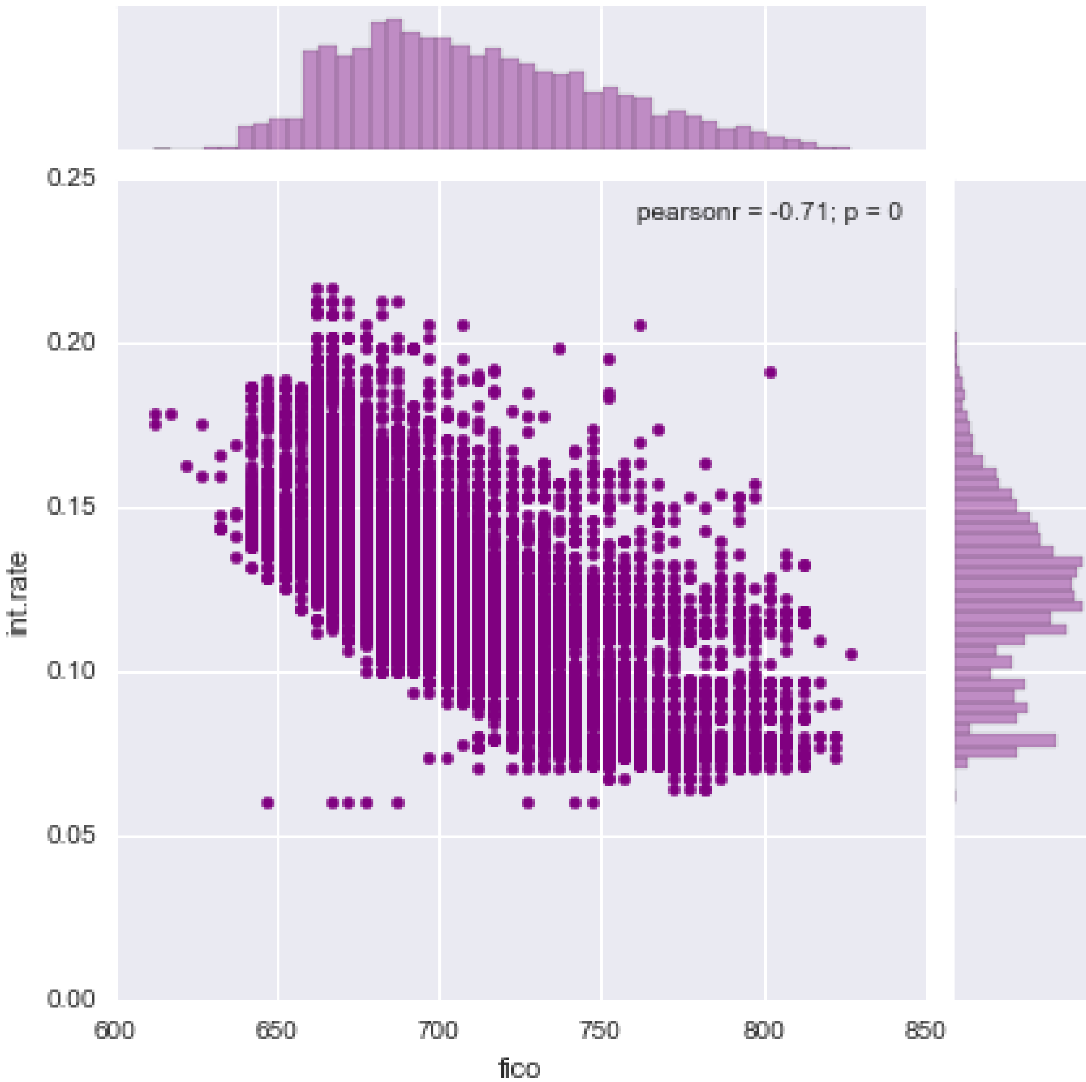
```
Out[8]: <matplotlib.axes._subplots.AxesSubplot at 0xa1bb8d438>
```



** Let's see the trend between FICO score and interest rate. Recreate the following jointplot.**

```
In [9]: sns.jointplot(x='fico',y='int.rate',data=loans,color='purple')
```

```
Out[9]: <seaborn.axisgrid.JointGrid at 0xa1bb77518>
```

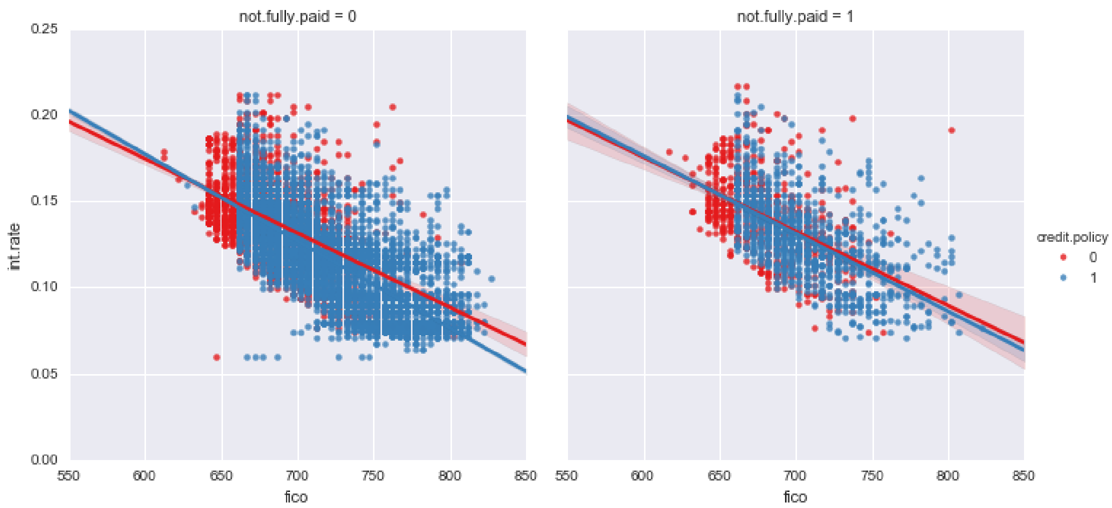


** Create the following lmplots to see if the trend differed between not.fully.paid and credit.policy. Check the documentation for lmplot() if you can't figure out how to separate it into columns.**

```
In [10]: plt.figure(figsize=(11,7))
         sns.lmplot(y='int.rate',x='fico',data=loans,hue='credit.policy',
                    col='not.fully.paid',palette='Set1')
```

```
Out[10]: <seaborn.axisgrid.FacetGrid at 0xa1c992710>
```

```
<matplotlib.figure.Figure at 0xa1c95ba20>
```



4 Setting up the Data

Let's get ready to set up our data for our Random Forest Classification Model!

Check loans.info() again.

```
In [12]: loans.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 14 columns):
credit.policy        9578 non-null int64
purpose              9578 non-null object
int.rate             9578 non-null float64
installment          9578 non-null float64
log.annual.inc       9578 non-null float64
dti                  9578 non-null float64
fico                 9578 non-null int64
days.with.cr.line    9578 non-null float64
revol.bal            9578 non-null int64
revol.util           9578 non-null float64
inq.last.6mths       9578 non-null int64
delinq.2yrs          9578 non-null int64
pub.rec              9578 non-null int64
not.fully.paid       9578 non-null int64
dtypes: float64(6), int64(7), object(1)
memory usage: 1.0+ MB
```

4.1 Categorical Features

Notice that the **purpose** column as categorical

```
In [36]: cat_feats = ['purpose']
```

```
In [37]: final_data = pd.get_dummies(loans,columns=cat_feats,drop_first=True)
```

```
In [38]: final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 19 columns):
credit.policy                 9578 non-null int64
int.rate                      9578 non-null float64
installment                   9578 non-null float64
log.annual.inc                9578 non-null float64
dti                           9578 non-null float64
fico                          9578 non-null int64
days.with.cr.line             9578 non-null float64
revol.bal                     9578 non-null int64
revol.util                    9578 non-null float64
inq.last.6mths                9578 non-null int64
delinq.2yrs                   9578 non-null int64
pub.rec                       9578 non-null int64
not.fully.paid                9578 non-null int64
purpose_credit_card           9578 non-null float64
purpose_debt_consolidation    9578 non-null float64
purpose_educational           9578 non-null float64
purpose_home_improvement      9578 non-null float64
purpose_major_purchase        9578 non-null float64
purpose_small_business        9578 non-null float64
dtypes: float64(12), int64(7)
memory usage: 1.4 MB
```

4.2 Train Test Split

```
In [20]: from sklearn.cross_validation import train_test_split
```

```
In [21]: X = final_data.drop('not.fully.paid',axis=1)
         y = final_data['not.fully.paid']
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=101)
```

4.3 Training a Decision Tree Model

```
In [22]: from sklearn.tree import DecisionTreeClassifier
```

Create an instance of DecisionTreeClassifier() called dtree and fit it to the training data.

```
In [23]: dtree = DecisionTreeClassifier()
```

```
In [24]: dtree.fit(X_train,y_train)
```

```
Out[24]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     max_features=None, max_leaf_nodes=None, min_samples_leaf=1,
                     min_samples_split=2, min_weight_fraction_leaf=0.0,
                     presort=False, random_state=None, splitter='best')
```

4.4 Predictions and Evaluation of Decision Tree

Create predictions from the test set and create a classification report and a confusion matrix.

```
In [25]: predictions = dtree.predict(X_test)
```

```
In [26]: from sklearn.metrics import classification_report,confusion_matrix
```

```
In [27]: print(classification_report(y_test,predictions))
```

```
precision    recall  f1-score   support

          0       0.85      0.82      0.84      2431
          1       0.19      0.23      0.20       443

avg / total       0.75      0.73      0.74      2874
```

```
In [28]: print(confusion_matrix(y_test,predictions))
```

```
[[1995  436]
 [ 343  100]]
```

4.5 Training the Random Forest model

Now its time to train our model!

Create an instance of the RandomForestClassifier class and fit it to our training data from the previous step.

```
In [29]: from sklearn.ensemble import RandomForestClassifier
```

```
In [30]: rfc = RandomForestClassifier(n_estimators=600)
```

```
In [31]: rfc.fit(X_train,y_train)
```

```
Out[31]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', max_leaf_nodes=None,
                     min_samples_leaf=1, min_samples_split=2,
                     min_weight_fraction_leaf=0.0, n_estimators=600, n_jobs=1,
                     oob_score=False, random_state=None, verbose=0,
                     warm_start=False)
```

4.6 Predictions and Evaluation

Let's predict off the y_test values and evaluate our model.

** Predict the class of not.fully.paid for the X_test data.**

```
In [32]: predictions = rfc.predict(X_test)
```

Now create a classification report from the results. Do you get anything strange or some sort of warning?

```
In [33]: from sklearn.metrics import classification_report,confusion_matrix
```

```
In [34]: print(classification_report(y_test,predictions))
```

```
precision    recall  f1-score   support

          0       0.85      1.00      0.92      2431
          1       0.57      0.03      0.05       443

avg / total       0.81      0.85      0.78      2874
```

Show the Confusion Matrix for the predictions.

```
In [35]: print(confusion_matrix(y_test,predictions))
```

```
[[2422    9]
 [ 431   12]]
```