Decision Trees and Random Forest Project

June 10, 2018

1 Random Forest Project

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.

Lending club had a very interesting year in 2016, so let's check out some of their data and keep the context in mind. This data is from before they even went public.

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. You can download the data from here or just use the csv already provided. It's recommended you use the csv provided as it has been cleaned of NA values.

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

```
In [20]: import pandas as pd
         import matplotlib.pyplot as plt
         %matplotlib inline
         import seaborn as sns
```

2.1 Get the Data

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

```
In [6]: loans = pd.read_csv('loan_data.csv')
```

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

```
In [7]: 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 [8]: loans.head()

Out[8]:    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
```

```
In [9]: loans.describe()
```

```
Out[9]:        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
```

3 Exploratory Data Analysis

** Create a histogram of two FICO distributions on top of each other, one for each credit.policy outcome.**

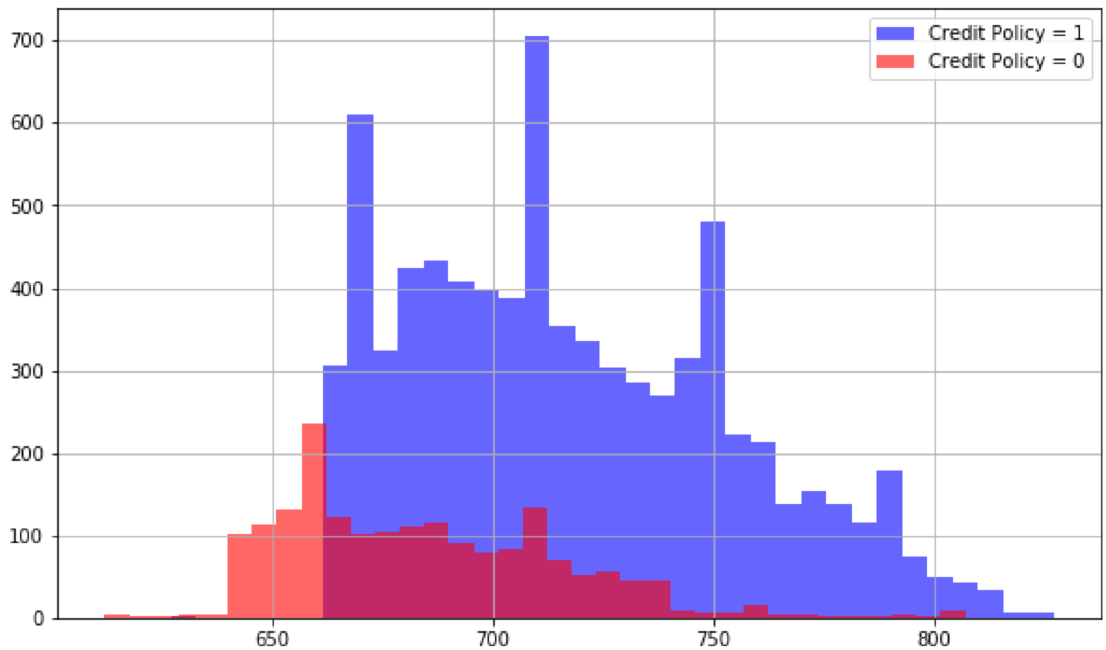
```
In [17]: plt.figure(figsize=(10,6))

         loans[loans['credit.policy']==1]['fico'].hist(bins=35,color='blue',
                                                        label='Credit Policy = 1',alpha=0.6)

         loans[loans['credit.policy']==0]['fico'].hist(bins=35,color='red',
```

```
                                               label='Credit Policy = 0',alpha=0.6)
plt.legend()
```

Out[17]: <matplotlib.legend.Legend at 0x10cf4c588>



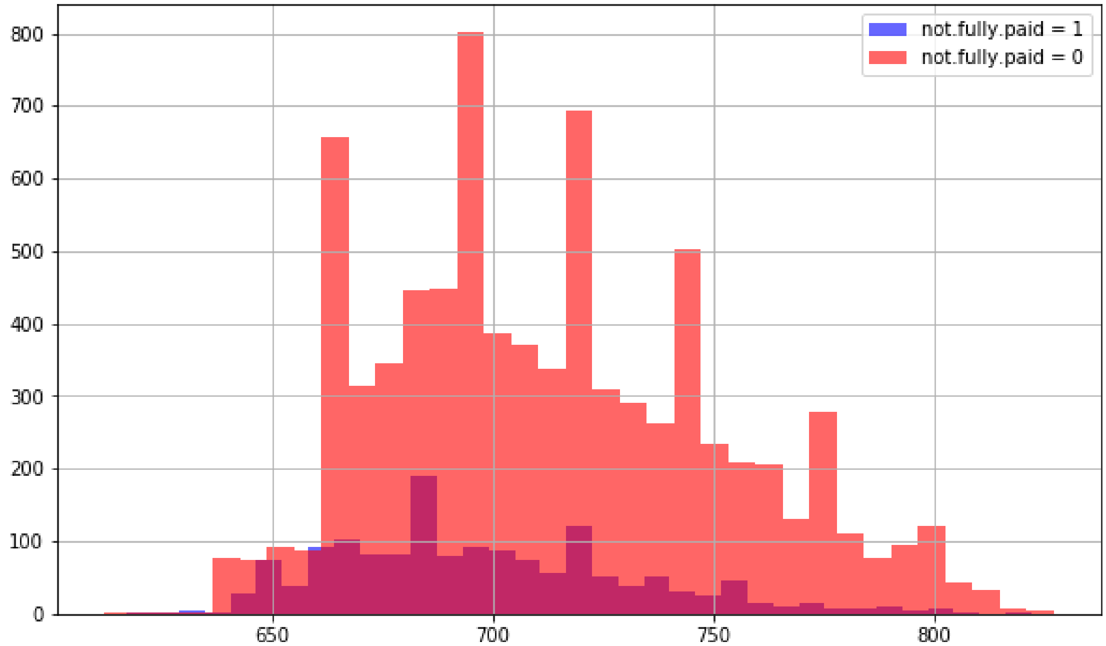
** Create a similar figure, except this time select by the not.fully.paid column.**

In [18]:
```
plt.figure(figsize=(10,6))

loans[loans['not.fully.paid']==1]['fico'].hist(bins=35,color='blue',
                                               label='not.fully.paid = 1',alpha=0.6)

loans[loans['not.fully.paid']==0]['fico'].hist(bins=35,color='red',
                                               label='not.fully.paid = 0',alpha=0.6)
plt.legend()
```

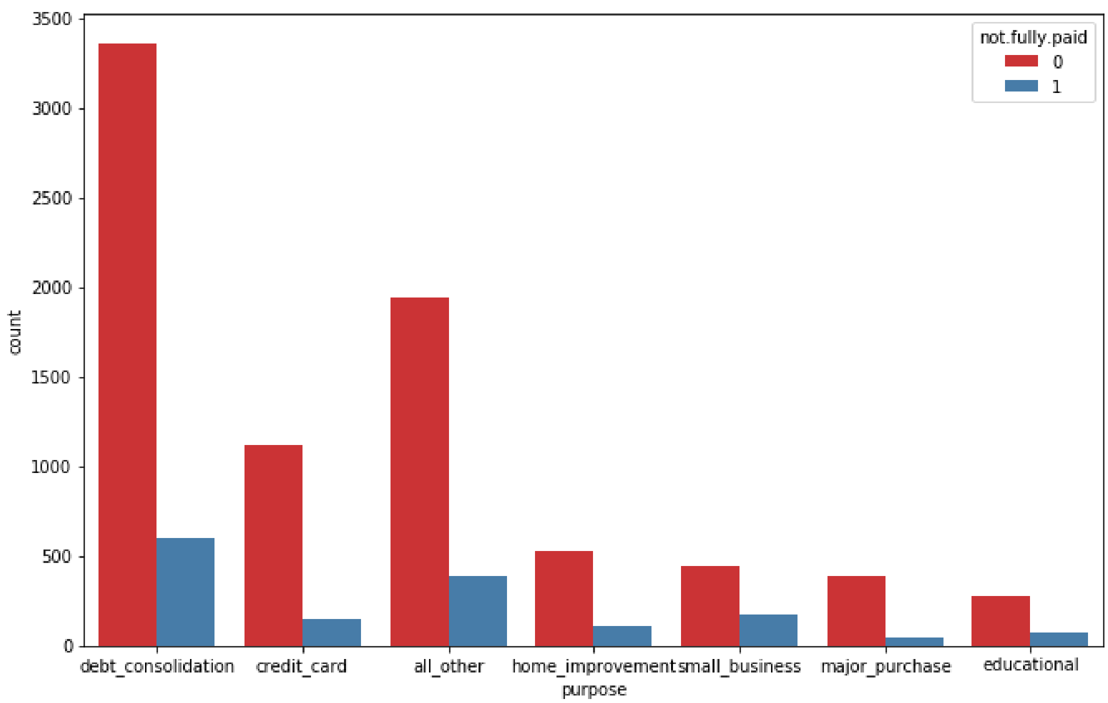
Out[18]: <matplotlib.legend.Legend at 0x11448ca90>



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

In [22]:
```
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=loans,palette='Set1')
```

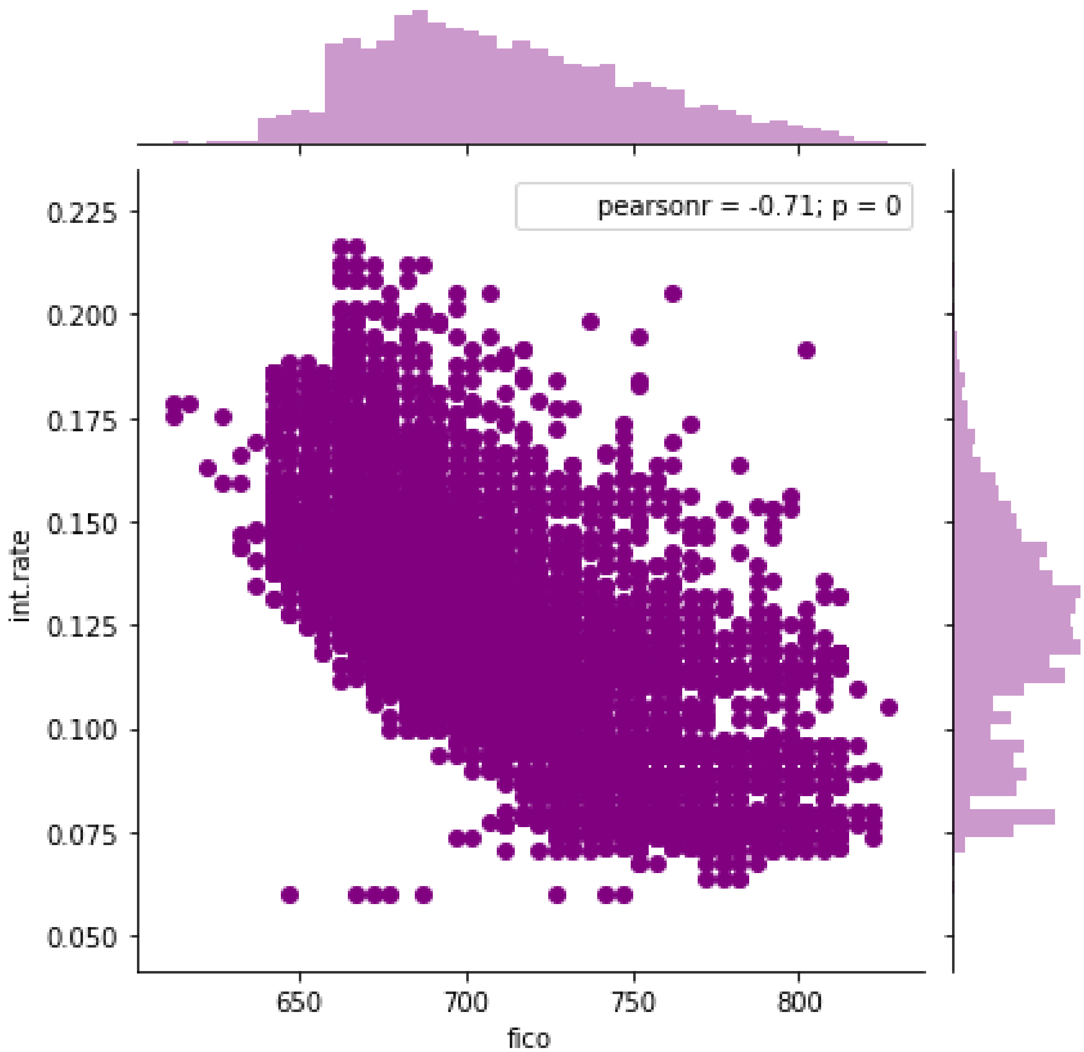
Out[22]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x11470a358>
```



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

```
In [23]: sns.jointplot(x='fico',y='int.rate',data=loans,color='purple')
```

```
Out[23]: <seaborn.axisgrid.JointGrid at 0x1a1684f3c8>
```

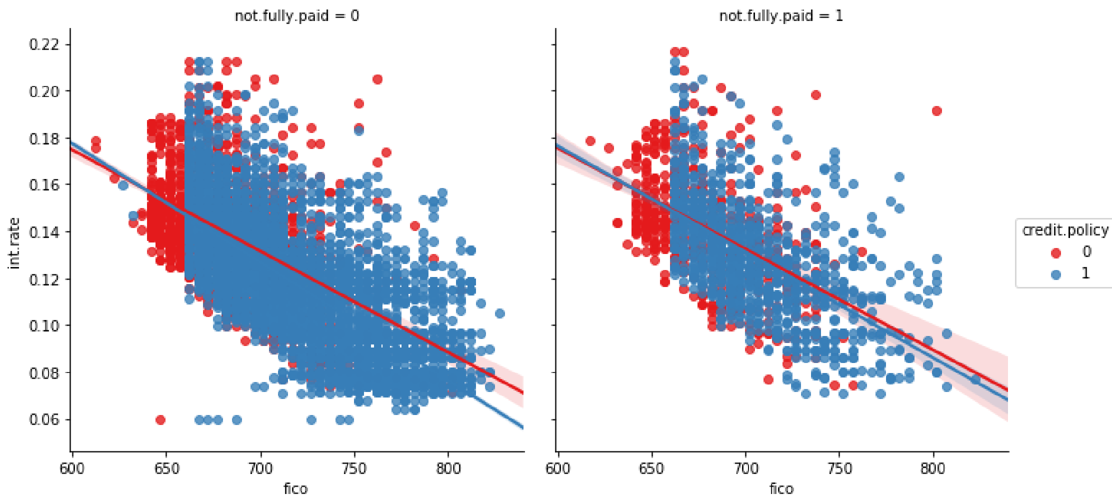


** Create the following lmplots to see if the trend differed between not.fully.paid and credit.policy.**

```
In [26]: plt.figure(figsize=(11,7))
         sns.lmplot(y='int.rate',x='fico',data=loans,hue='credit.policy',
                    col='not.fully.paid',palette='Set1')
```

```
Out[26]: <seaborn.axisgrid.FacetGrid at 0x1a17f1a240>
```

<matplotlib.figure.Figure at 0x1a17f2eeb8>



4 Setting up the Data

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

In [27]: 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 [28]:
```python
cat_feats = ['purpose']
```

In [29]:
```python
final_data = pd.get_dummies(loans,columns=cat_feats,drop_first=True)
```

In [30]:
```python
final_data.head()
```

Out[30]:

```
   credit.policy  int.rate  installment  log.annual.inc    dti  fico  \
0              1    0.1189       829.10       11.350407  19.48   737
1              1    0.1071       228.22       11.082143  14.29   707
2              1    0.1357       366.86       10.373491  11.63   682
3              1    0.1008       162.34       11.350407   8.10   712
4              1    0.1426       102.92       11.299732  14.97   667

   days.with.cr.line  revol.bal  revol.util  inq.last.6mths  delinq.2yrs  \
0        5639.958333      28854        52.1               0            0
1        2760.000000      33623        76.7               0            0
2        4710.000000       3511        25.6               1            0
3        2699.958333      33667        73.2               1            0
4        4066.000000       4740        39.5               0            1

   pub.rec  not.fully.paid  purpose_credit_card  purpose_debt_consolidation  \
0        0               0                    0                           1
1        0               0                    1                           0
2        0               0                    0                           1
3        0               0                    0                           1
4        0               0                    1                           0

   purpose_educational  purpose_home_improvement  purpose_major_purchase  \
0                    0                         0                       0
1                    0                         0                       0
2                    0                         0                       0
3                    0                         0                       0
4                    0                         0                       0

   purpose_small_business
0                       0
1                       0
2                       0
3                       0
4                       0
```

4.2 Train Test Split

** Use sklearn to split data into a training set and a testing set.**

In [31]:
```python
from sklearn.cross_validation import train_test_split
```

```
/Users/Momin/anaconda3/lib/python3.6/site-packages/sklearn/cross_validation.py:41: Deprecation
  "This module will be removed in 0.20.", DeprecationWarning)
```

```
In [32]: 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=0.3, random_state
```

4.3 Training a Decision Tree Model

Let's start by training a single decision tree first!
** Import DecisionTreeClassifier**

```
In [33]: from sklearn.tree import DecisionTreeClassifier
```

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

```
In [34]: dtree = DecisionTreeClassifier()

In [35]: dtree.fit(X_train,y_train)

Out[35]: DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth=None,
                     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')
```

4.4 Predictions and Evaluation of Decision Tree

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

```
In [38]: predictions = dtree.predict(X_test)

In [39]: from sklearn.metrics import classification_report, confusion_matrix

In [40]: print(classification_report(y_test,predictions))

             precision    recall  f1-score   support

          0       0.85      0.84      0.84      2408
          1       0.20      0.21      0.21       466

avg / total       0.74      0.74      0.74      2874


In [41]: print(confusion_matrix(y_test,predictions))

[[2015  393]
 [ 366  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 [42]: from sklearn.ensemble import RandomForestClassifier
```

```
In [43]: rfc = RandomForestClassifier(n_estimators=300)
         rfc.fit(X_train,y_train)
```

```
Out[43]: RandomForestClassifier(bootstrap=True, class_weight=None, criterion='gini',
                     max_depth=None, max_features='auto', 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, n_estimators=300, 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 [44]: predictions = rfc.predict(X_test)
```

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

```
In [45]: print(classification_report(y_test,predictions))
```

```
             precision    recall  f1-score   support

          0       0.84      0.99      0.91      2408
          1       0.28      0.01      0.02       466

avg / total       0.75      0.84      0.77      2874
```

```
In [46]: print(confusion_matrix(y_test,predictions))
```

```
[[2395   13]
 [ 461    5]]
```

What performed better the random forest or the decision tree?

```
In [36]: # Depends what metric you are trying to optimize for.
         # Notice the recall for each class for the models.
         # Neither did very well, more feature engineering is needed.
```