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).

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
```

Get the Data

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

In [2]:
```
loans = pd.read_csv('16 Decision Trees and Random Forest Project.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):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   credit.policy      9578 non-null   int64  
 1   purpose            9578 non-null   object 
 2   int.rate           9578 non-null   float64
 3   installment        9578 non-null   float64
 4   log.annual.inc     9578 non-null   float64
 5   dti                9578 non-null   float64
 6   fico               9578 non-null   int64  
 7   days.with.cr.line  9578 non-null   float64
 8   revol.bal          9578 non-null   int64  
 9   revol.util         9578 non-null   float64
 10  inq.last.6mths     9578 non-null   int64  
 11  delinq.2yrs        9578 non-null   int64  
 12  pub.rec            9578 non-null   int64  
 13  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	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9.578000e+03	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560.767197	1.691396e+04	46.799236	1.577469	0.163708	0.062122	0.160054
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496.930377	3.375619e+04	29.014417	2.200245	0.546215	0.262126	0.366676
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178.958333	0.000000e+00	0.000000	0.000000	0.000000	0.000000	0.000000
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820.000000	3.187000e+03	22.600000	0.000000	0.000000	0.000000	0.000000
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139.958333	8.596000e+03	46.300000	1.000000	0.000000	0.000000	0.000000
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730.000000	1.824950e+04	70.900000	2.000000	0.000000	0.000000	0.000000
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639.958330	1.207359e+06	119.000000	33.000000	13.000000	5.000000	1.000000

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

Out[5]:

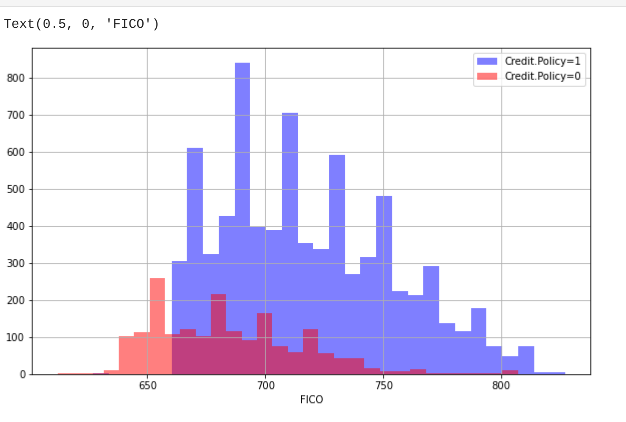
	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol.util	inq.last.6mths	delinq.2yrs	pub.rec	not.fully.paid
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	52.1	0	0	0	0
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	76.7	0	0	0	0
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	25.6	1	0	0	0
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	73.2	1	0	0	0
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	39.5	0	1	0	0

Exploratory Data Analysis

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

In [6]:
```
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')
```

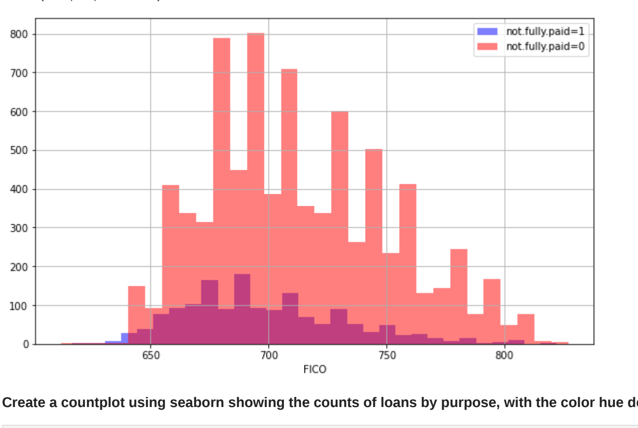
Out[6]: `Text(0.5, 0, 'FICO')`



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')
```

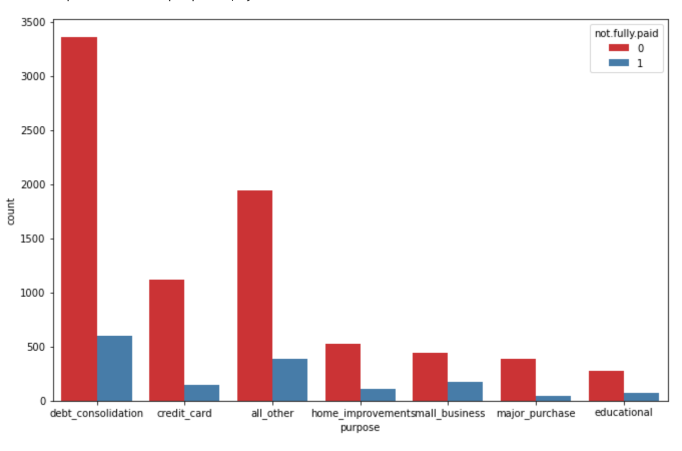
Out[7]: `Text(0.5, 0, 'FICO')`



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')
```

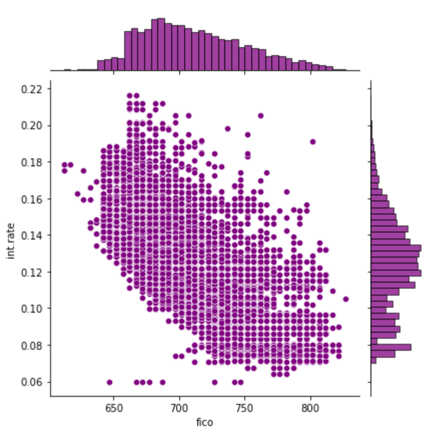
Out[8]: `<AxesSubplot:xlabel='purpose', ylabel='count'>`



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 0x1aea6761df0>`

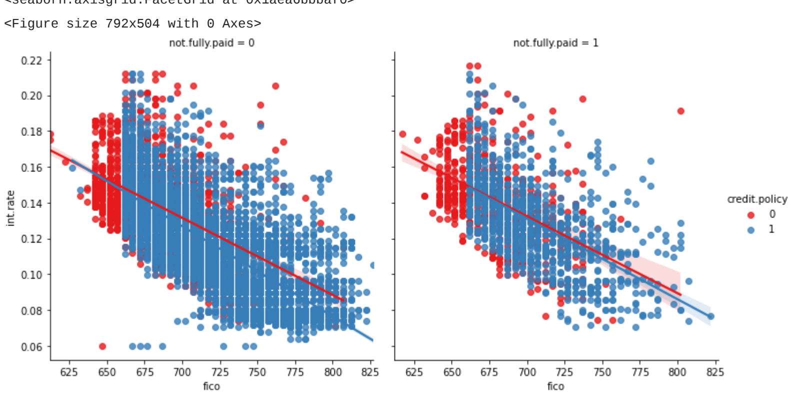


Create the following lmplots to see if the trend differed between not.fully.paid and credit.policy. Check the documentation for lmplot() if you can't figure out how to separate it into columns.

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 0x1aea6bbbaf0>`

`<Figure size 792x504 with 0 Axes>`



Setting up the Data

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

Check loans.info() again.

In [11]:
```
loans.info()
```

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

Categorical Features

Notice that the **purpose** column as categorical

That means we need to transform them using dummy variables so sklearn will be able to understand them. Let's do this in one clean step using pd.get_dummies.

Let's show you a way of dealing with these columns that can be expanded to multiple categorical features if necessary.

Create a list of 1 element containing the string 'purpose'. Call this list cat_feats.

In [12]:
```
cat_feats = ['purpose']
```

Now use pd.get_dummies(loans,columns=cat_feats,drop_first=True) to create a fixed larger dataframe that has new feature columns with dummy variables. Set this dataframe as final_data.

In [13]:
```
final_data = pd.get_dummies(loans,columns=cat_feats,drop_first=True)
```

In [14]:
```
final_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 9578 entries, 0 to 9577
Data columns (total 19 columns):
 #   Column                      Non-Null Count  Dtype  
---  ------                      --------------  -----  
 0   credit.policy               9578 non-null   int64  
 1   int.rate                    9578 non-null   float64
 2   installment                 9578 non-null   float64
 3   log.annual.inc              9578 non-null   float64
 4   dti                         9578 non-null   float64
 5   fico                        9578 non-null   int64  
 6   days.with.cr.line           9578 non-null   float64
 7   revol.bal                   9578 non-null   int64  
 8   revol.util                  9578 non-null   float64
 9   inq.last.6mths              9578 non-null   int64  
 10  delinq.2yrs                 9578 non-null   int64  
 11  pub.rec                     9578 non-null   int64  
 12  not.fully.paid              9578 non-null   int64  
 13  purpose_credit_card         9578 non-null   uint8  
 14  purpose_debt_consolidation  9578 non-null   uint8  
 15  purpose_educational         9578 non-null   uint8  
 16  purpose_home_improvement    9578 non-null   uint8  
 17  purpose_major_purchase      9578 non-null   uint8  
 18  purpose_small_business      9578 non-null   uint8  
dtypes: float64(6), int64(7), uint8(6)
memory usage: 1.0 MB
```

Train Test Split

Now its time to split our data into a training set and a testing set!

Use sklearn to split your data into a training set and a testing set as we've done in the past.

In [15]:
```
from sklearn.model_selection import train_test_split
```

In [16]:
```
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)
```

Training a Decision Tree Model

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

Import DecisionTreeClassifier

In [17]:
```
from sklearn.tree import DecisionTreeClassifier
```

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

In [18]:
```
dtree = DecisionTreeClassifier()
```

In [19]:
```
dtree.fit(X_train,y_train)
```

Out[19]: `DecisionTreeClassifier()`

Predictions and Evaluation of Decision Tree

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

In [20]:
```
predictions = dtree.predict(X_test)
```

In [21]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [22]:
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.85      0.82      0.84      2431
           1       0.19      0.24      0.21       443

    accuracy                           0.73      2874
   macro avg       0.52      0.53      0.52      2874
weighted avg       0.75      0.73      0.74      2874
```

In [23]:
```
print(confusion_matrix(y_test,predictions))
```

```
[[1987  444]
 [ 337  106]]
```

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 [24]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [25]:
```
rfc = RandomForestClassifier(n_estimators=600)
```

In [26]:
```
rfc.fit(X_train,y_train)
```

Out[26]: `RandomForestClassifier(n_estimators=600)`

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 [27]:
```
predictions = rfc.predict(X_test)
```

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

In [28]:
```
from sklearn.metrics import classification_report,confusion_matrix
```

In [29]:
```
print(classification_report(y_test,predictions))
```

```
              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.56      0.02      0.04       443

    accuracy                           0.85      2874
   macro avg       0.71      0.51      0.48      2874
weighted avg       0.80      0.85      0.78      2874
```

Show the Confusion Matrix for the predictions.

In [30]:
```
print(confusion_matrix(y_test,predictions))
```

```
[[2424    7]
 [ 434    9]]
```

What performed better the random forest or the decision tree?

In [31]:
```
# 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.
```

Great Job!