Loan Default Rate Prediction

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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. You can download the data from here.

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.

```
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.**

```
loans = pd.read_csv('loan_data.csv')
```

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

```
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
```

```
loans.describe()
```

```
       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
```

```
loans.head()
```

```
   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
```

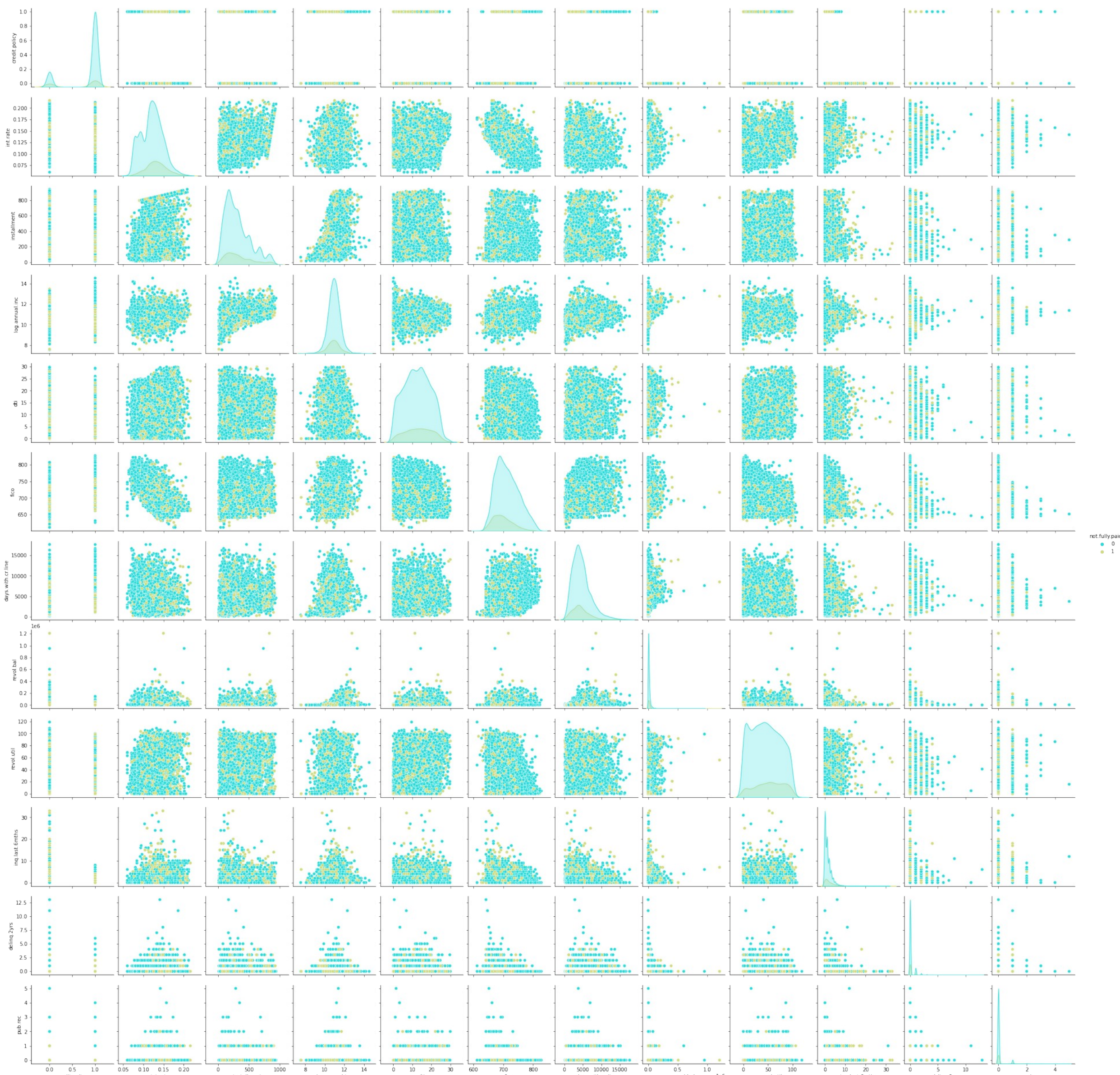
Exploratory Data Analysis

Let's do some data visualization! We'll use seaborn and pandas built-in plotting capabilities.

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

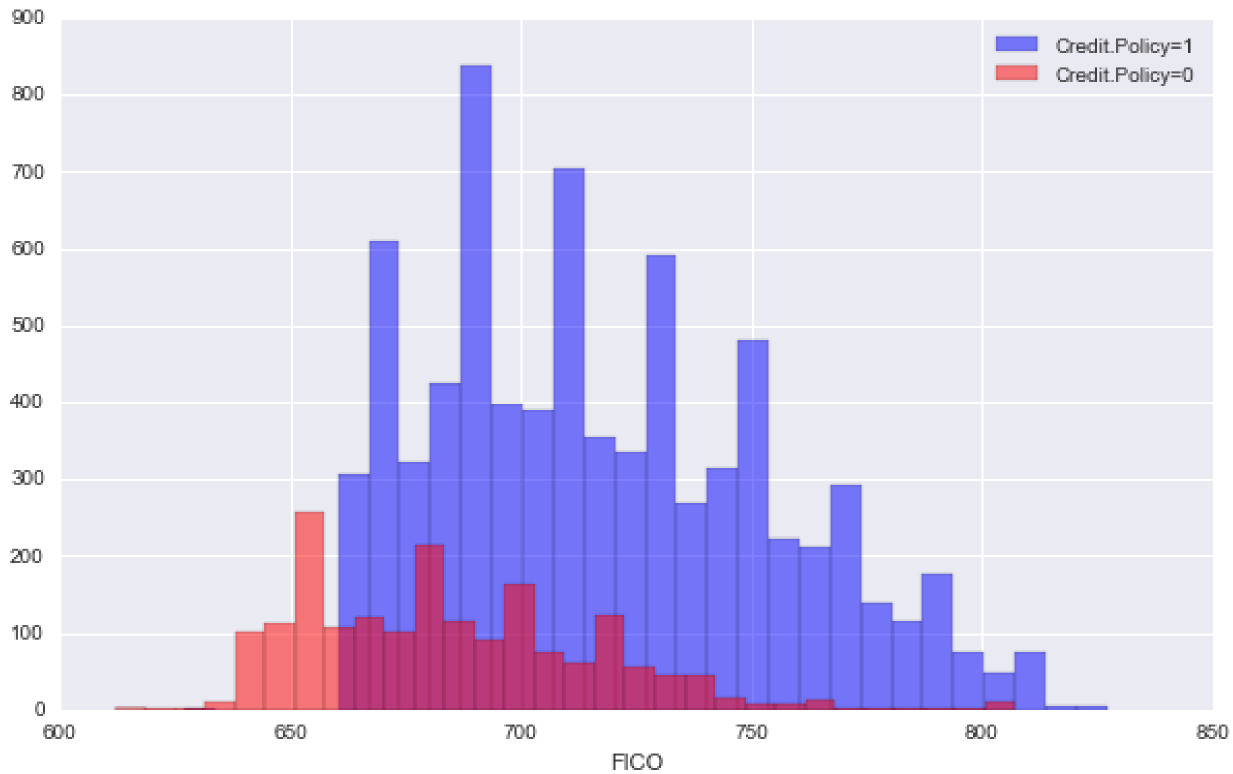
```
sns.pairplot(loans,palette = 'rainbow',hue = 'not.fully.paid')
```

```
<seaborn.axisgrid.PairGrid at 0x9e25533fd0>
```




```
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')
```

```
<matplotlib.text.Text at 0x119963f28>
```



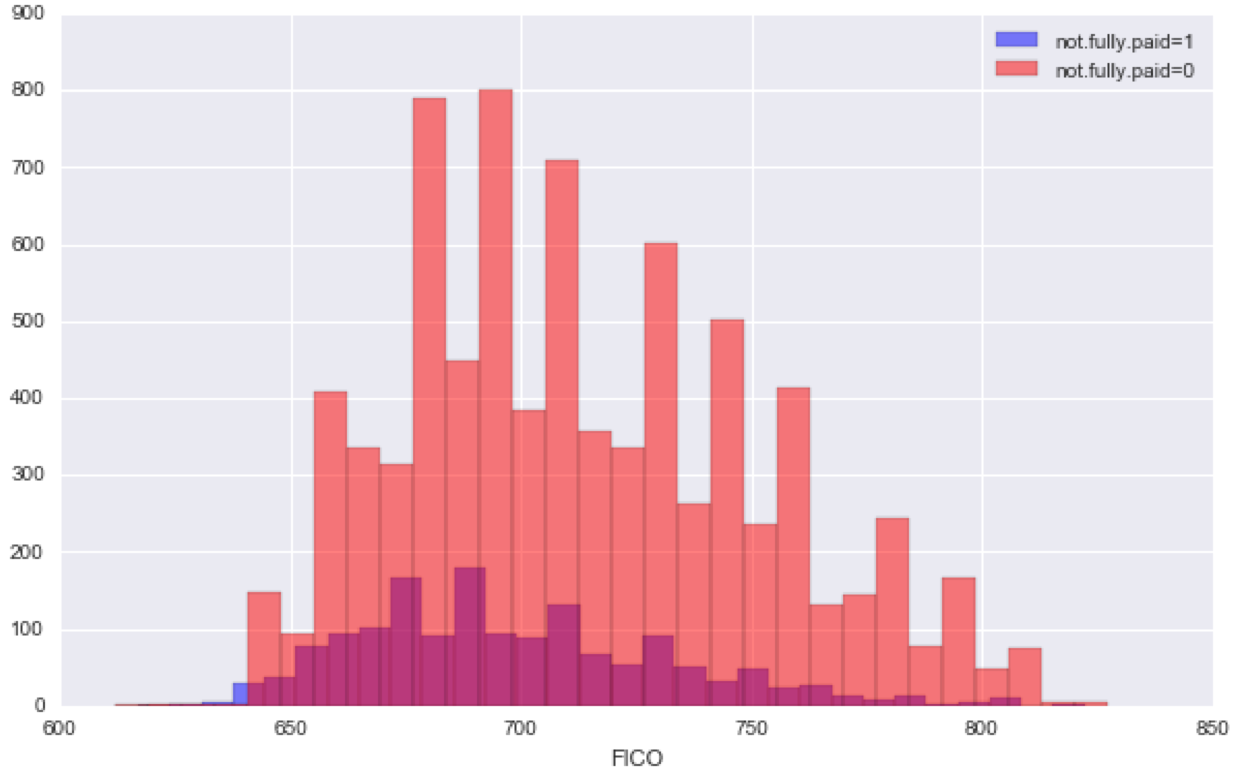
** Create a similar figure, except this time select by the not.fully.paid column.**

```
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')
```

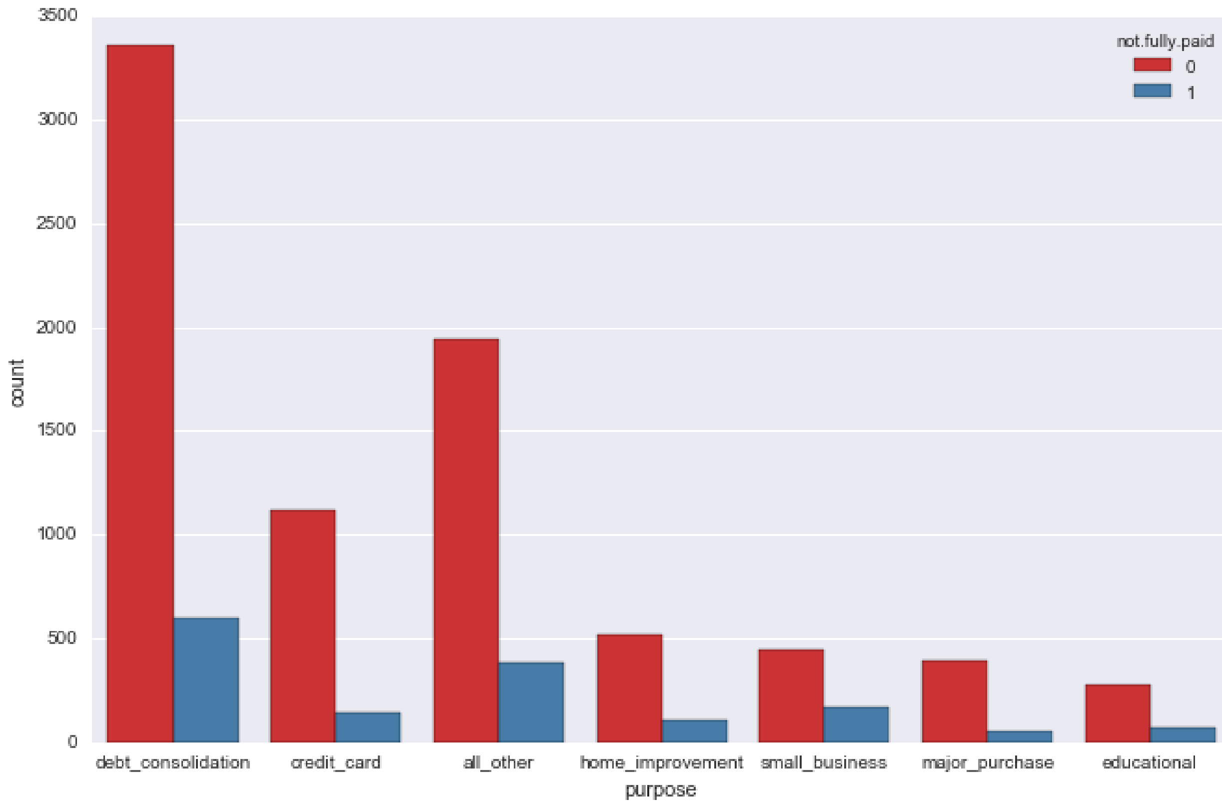
```
<matplotlib.text.Text at 0x11c47a7f0>
```



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

```
plt.figure(figsize=(11,7))
sns.countplot(x='purpose',hue='not.fully.paid',data=loans,palette='Set
1')
```

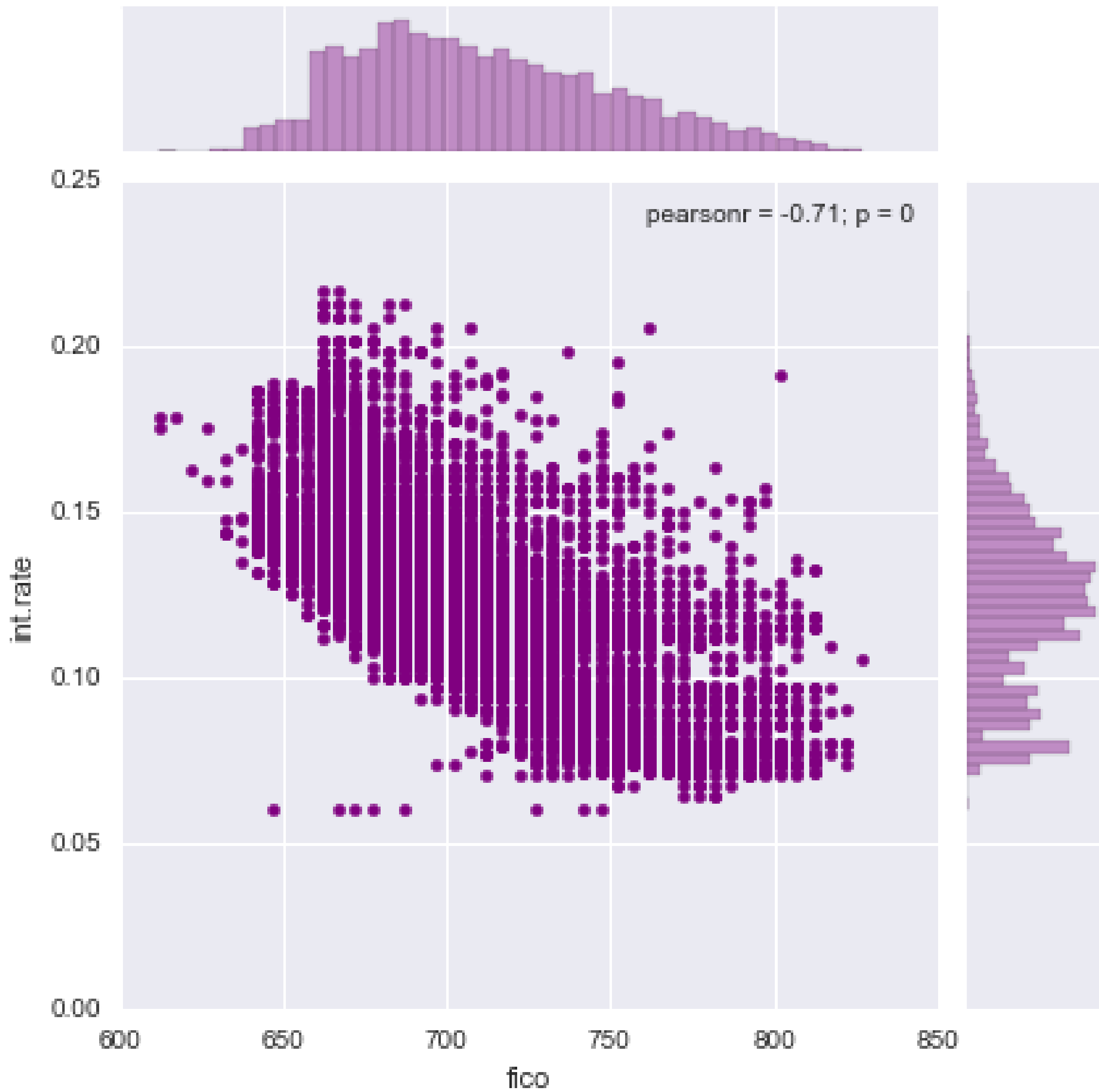
```
<matplotlib.axes._subplots.AxesSubplot at 0x119996828>
```



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

```
sns.jointplot(x='fico',y='int.rate',data=loans,color='purple')
```

```
<seaborn.axisgrid.JointGrid at 0x119963320>
```

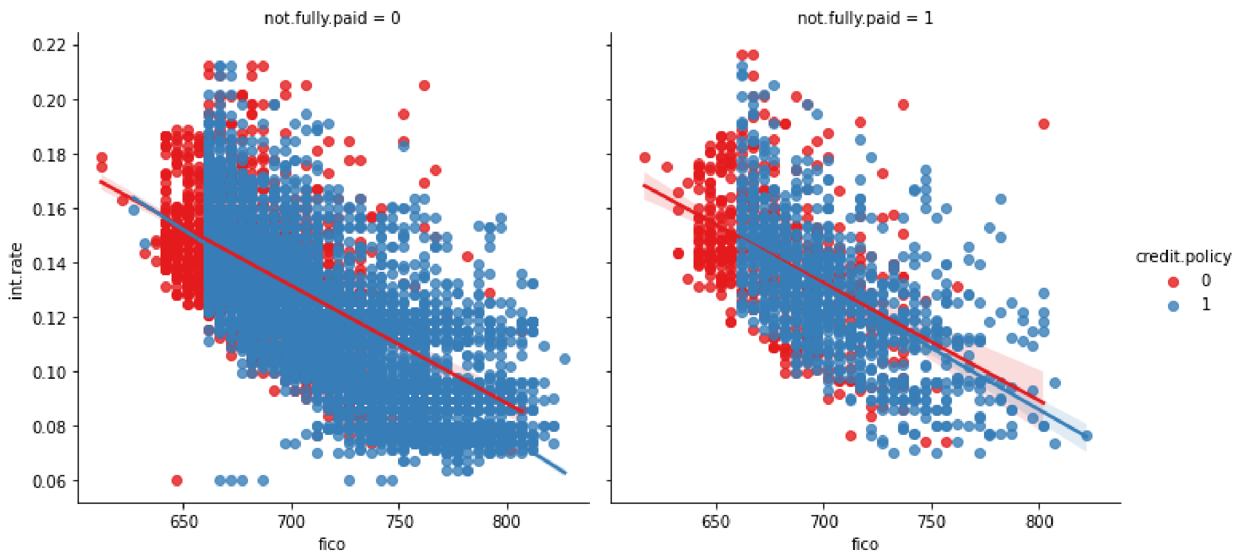


** Create the following lmplots to see if the trend differed between not.fully.paid and credit.policy.

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

```
<seaborn.axisgrid.FacetGrid at 0x9e37e22790>
```

```
<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.

```
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.

The 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.

```
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.

```
final_data = pd.get_dummies(loans,columns=cat_feats,drop_first=True)
```

```
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.**

```
from sklearn.model_selection import train_test_split

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 logistic Regression model

** import logistic regressor from sklearn

```
from sklearn.linear_model import LogisticRegression
```

** Train and fit a logistic regression model on the training set.**

```
lm = LogisticRegression()

lm.fit(X_train,y_train)

C:\Users\Gaurav\AppData\Roaming\Python\Python39\site-packages\sklearn\
linear_model\_logistic.py:814: ConvergenceWarning: lbfgs failed to
converge (status=1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as
shown in:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:

https://scikit-learn.org/stable/modules/linear_model.html#logistic-
regression
  n_iter_i = _check_optimize_result(

LogisticRegression()
```

Predictions and Evaluations

** Now predict values for the testing data.**

```
predict=lm.predict(X_test)
```

** Create a classification report for the model.**

```
from sklearn.metrics import classification_report,confusion_matrix

print(classification_report(y_test,predict))

              precision    recall  f1-score   support

           0       0.85      1.00      0.92      2431
           1       0.62      0.02      0.04       443

    accuracy                           0.85      2874
   macro avg       0.74      0.51      0.48      2874
weighted avg       0.81      0.85      0.78      2874


print(confusion_matrix(y_test,predict))

[[2425    6]
 [ 433   10]]
```

Training a Decision Tree Model

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

** Import DecisionTreeClassifier**

```
from sklearn.tree import DecisionTreeClassifier
```

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

```
dtree = DecisionTreeClassifier()

dtree.fit(X_train,y_train)

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')
```

Predictions and Evaluation of Decision Tree

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

```
predictions = dtree.predict(X_test)

from sklearn.metrics import classification_report,confusion_matrix

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
```

```
print(confusion_matrix(y_test,predictions))
```

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

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.

```
from sklearn.ensemble import RandomForestClassifier

rfc = RandomForestClassifier(n_estimators=600)

rfc.fit(X_train,y_train)
```

```
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)
```

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.**

```
predictions = rfc.predict(X_test)
```

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

```
from sklearn.metrics import classification_report,confusion_matrix

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.

```
print(confusion_matrix(y_test,predictions))

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

What performed better the random forest or the decision tree?

```
# Depends what metric we try to optimize for.
# Notice the recall for each class for the models.
# Neither did very well, more feature engineering is needed.
```

Great Job!