Decision Tree, Random Forest

Data: publicly available data from LendingClub.com (www.lendingclub.com).

Lending Club connects people who need money (borrowers) with people who have money (investors).

Goal: model that help investors to see if a borrower is reliable (high probability of paying back)

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

In [3]:
```
import numpy as np
import pandas as pd
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
```

Load data

In [33]:
```
loans = pd.read_csv('data/loan_data.csv')
print(loans.shape)
loans.head()
```

```
(9578, 14)
```

Out[33]:

	credit.policy	purpose	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.lin
0	1	debt_consolidation	0.1189	829.10	11.350407	19.48	737	5639.95833
1	1	credit_card	0.1071	228.22	11.082143	14.29	707	2760.00000
2	1	debt_consolidation	0.1357	366.86	10.373491	11.63	682	4710.00000
3	1	debt_consolidation	0.1008	162.34	11.350407	8.10	712	2699.95833
4	1	credit_card	0.1426	102.92	11.299732	14.97	667	4066.00000

In [56]:
```
loans.describe()
```

Out[56]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.wit
count	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578.000000	9578
mean	0.804970	0.122640	319.089413	10.932117	12.606679	710.846314	4560
std	0.396245	0.026847	207.071301	0.614813	6.883970	37.970537	2496
min	0.000000	0.060000	15.670000	7.547502	0.000000	612.000000	178
25%	1.000000	0.103900	163.770000	10.558414	7.212500	682.000000	2820
50%	1.000000	0.122100	268.950000	10.928884	12.665000	707.000000	4139
75%	1.000000	0.140700	432.762500	11.291293	17.950000	737.000000	5730
max	1.000000	0.216400	940.140000	14.528354	29.960000	827.000000	17639

In [58]:
```
loans.columns
```

Out[58]:
```
Index(['credit.policy', 'purpose', 'int.rate', 'installment', 'log.annual.in
c',
       'dti', 'fico', 'days.with.cr.line', 'revol.bal', 'revol.util',
       'inq.last.6mths', 'delinq.2yrs', 'pub.rec', 'not.fully.paid'],
      dtype='object')
```

In [61]:
```
loans['not.fully.paid'].value_counts()
```

Out[61]:
```
0    8045
1    1533
Name: not.fully.paid, dtype: int64
```

Check the data

In [11]:
```
loans.isnull().any()
```

Out[11]:
```
credit.policy        False
purpose              False
int.rate             False
installment          False
log.annual.inc       False
dti                  False
fico                 False
days.with.cr.line    False
revol.bal            False
revol.util           False
inq.last.6mths       False
delinq.2yrs          False
pub.rec              False
not.fully.paid       False
dtype: bool
```

In [174]:
```
s = (loans.dtypes=='object')
obj_col =  s[s].index
print(obj_col)
```

```
Index(['purpose'], dtype='object')
```

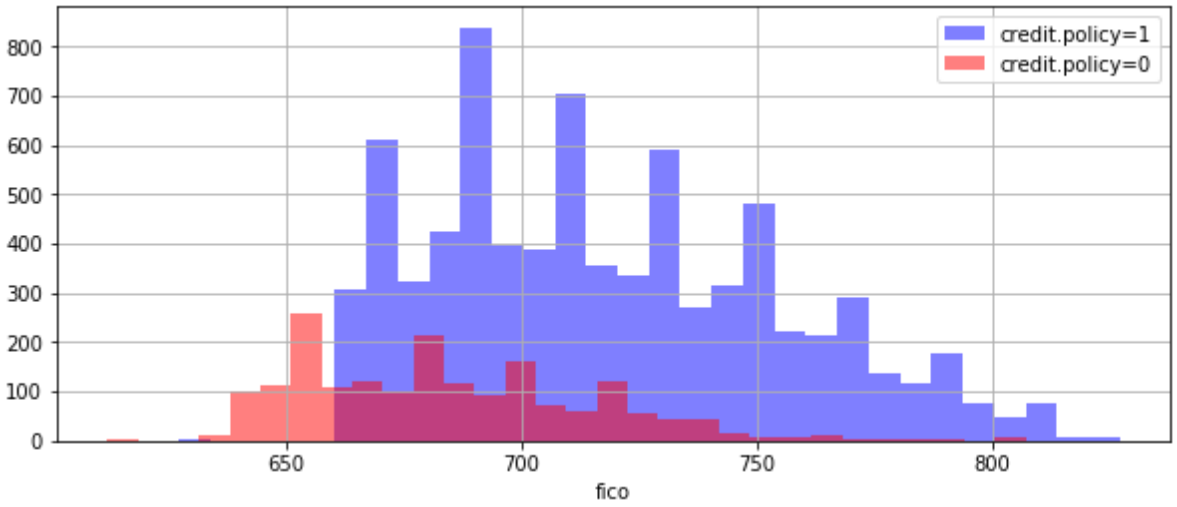
Explore Data

fico: The FICO credit score of the borrower.

credit.policy: 1 if the customer meets the credit underwriting criteria of LendingClub.com, and 0 otherwise.

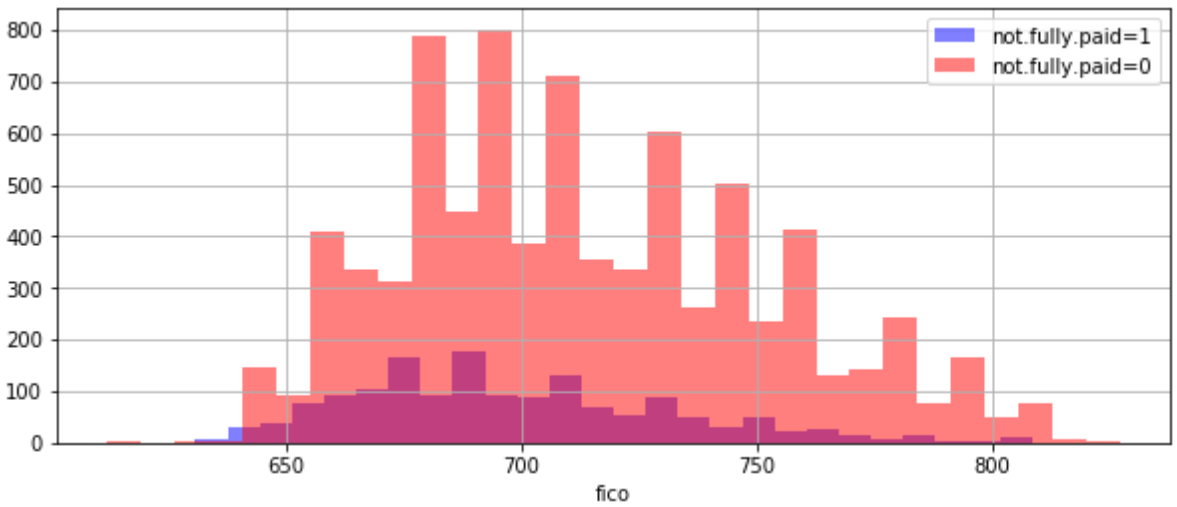
In [178]:
```
plt.figure(figsize=(10,4))
loans[loans['credit.policy'] == 1]['fico'].hist(color= 'blue', bins=30, alpha=
0.5, label='credit.policy=1')
loans[loans['credit.policy'] == 0]['fico'].hist(color= 'red', bins=30, alpha=
0.5, label='credit.policy=0')
plt.legend()
plt.xlabel('fico')
```

Out[178]: Text(0.5, 0, 'fico')



In [180]:
```
plt.figure(figsize=(10,4))
loans[loans['not.fully.paid'] == 1]['fico'].hist(color= 'blue', bins=30, alpha
=0.5, label='not.fully.paid=1')
loans[loans['not.fully.paid'] == 0]['fico'].hist(color= 'red', bins=30, alpha=
0.5, label='not.fully.paid=0')
plt.legend()
plt.xlabel('fico')
```

Out[180]: Text(0.5, 0, 'fico')



Handling categorical column

'purpose' column is a categorical data, convert to numerical values.

In [40]:
```
loans[obj_col[0]].value_counts()
```

Out[40]:
```
debt_consolidation    3957
all_other             2331
credit_card           1262
home_improvement       629
small_business         619
major_purchase         437
educational            343
Name: purpose, dtype: int64
```

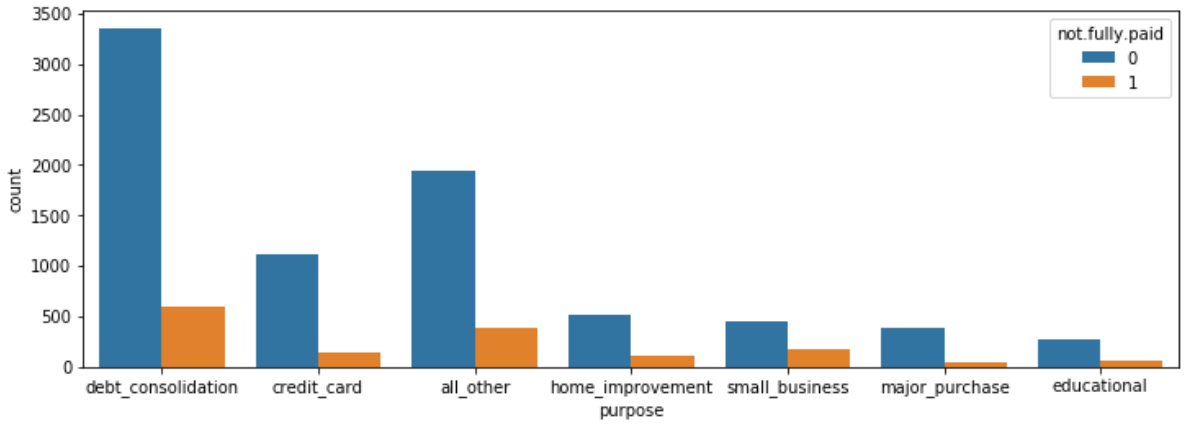
In [132]:
```
purpose_val = pd.get_dummies(loans['purpose'], drop_first=True)
purpose_val.head()
```

Out[132]:

	credit_card	debt_consolidation	educational	home_improvement	major_purchase	small_busin
0	0	1	0	0	0	
1	1	0	0	0	0	
2	0	1	0	0	0	
3	0	1	0	0	0	
4	1	0	0	0	0	

In [133]:
```
plt.figure(figsize=(12,4))
sns.countplot(x='purpose', data=loans, hue='not.fully.paid')
```

Out[133]:
```
<matplotlib.axes._subplots.AxesSubplot at 0x197f8088ba8>
```



Make Data ready

purpose categorical data droped and numerical version of it been added.

In [167]:
```
loans.drop(columns=['purpose'], axis =1).shape
```

Out[167]: (9578, 13)

In [169]:
```
purpose_val.shape
```

Out[169]: (9578, 6)

In [172]:
```
data = pd.concat([loans.drop(columns=['purpose'], axis=1), purpose_val], axis=1)
```

In [173]:
```
data.shape
```

Out[173]: (9578, 19)

In [171]:
```
data.head()
```

Out[171]:

	credit.policy	int.rate	installment	log.annual.inc	dti	fico	days.with.cr.line	revol.bal	revol
0	1	0.1189	829.10	11.350407	19.48	737	5639.958333	28854	5
1	1	0.1071	228.22	11.082143	14.29	707	2760.000000	33623	7
2	1	0.1357	366.86	10.373491	11.63	682	4710.000000	3511	2
3	1	0.1008	162.34	11.350407	8.10	712	2699.958333	33667	7
4	1	0.1426	102.92	11.299732	14.97	667	4066.000000	4740	3

In [62]:
```
X = data.drop(columns='not.fully.paid', axis=1)

y = data['not.fully.paid']
```

Make the Random Forest Model

In [64]:
```
from sklearn.model_selection import train_test_split
```

In [65]:
```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.30, random_state=42)
```

In [66]:
```
from sklearn.tree import DecisionTreeClassifier
```

In [67]:
```
dtree =  DecisionTreeClassifier()
dtree.fit(X_train, y_train)
```

Out[67]:
```
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')
```

Predict

In [68]:
```
pred =  dtree.predict(X_test)
```

Evaluate

In [100]:
```
from sklearn.metrics import  classification_report, confusion_matrix, accuracy
_score
```

In [108]:
```
print(confusion_matrix(y_test, pred))
print('\n')
print(classification_report(y_test, pred))
```

```
[[2319   89]
 [ 427   39]]


              precision    recall  f1-score   support

           0       0.84      0.96      0.90      2408
           1       0.30      0.08      0.13       466

   micro avg       0.82      0.82      0.82      2874
   macro avg       0.57      0.52      0.52      2874
weighted avg       0.76      0.82      0.78      2874
```

Playing with the parameters in Decision Tree

min_samples_split

In [76]:
```
from sklearn.model_selection import GridSearchCV
```

In [95]:
```
param_grid = { 'min_samples_split': [2, 5, 10, 20, 30, 50, 100]}

grid = GridSearchCV(DecisionTreeClassifier(), param_grid, refit=True, verbose=
0, cv=3)
grid.fit(X_train, y_train)
```

Out[95]:
```
GridSearchCV(cv=3, error_score='raise-deprecating',
       estimator=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'),
       fit_params=None, iid='warn', n_jobs=None,
       param_grid={'min_samples_split': [2, 5, 10, 20, 30, 50, 100]},
       pre_dispatch='2*n_jobs', refit=True, return_train_score='warn',
       scoring=None, verbose=0)
```

In [96]:
```
pred_bestParam = grid.predict(X_test)
```

In [98]:
```
print(confusion_matrix(y_test, pred_bestParam))
print('\n')
print(classification_report(y_test, pred_bestParam))
```

```
[[2320   88]
 [ 436   30]]


              precision    recall  f1-score   support

           0       0.84      0.96      0.90      2408
           1       0.25      0.06      0.10       466

   micro avg       0.82      0.82      0.82      2874
   macro avg       0.55      0.51      0.50      2874
weighted avg       0.75      0.82      0.77      2874
```

Changing the max_depth

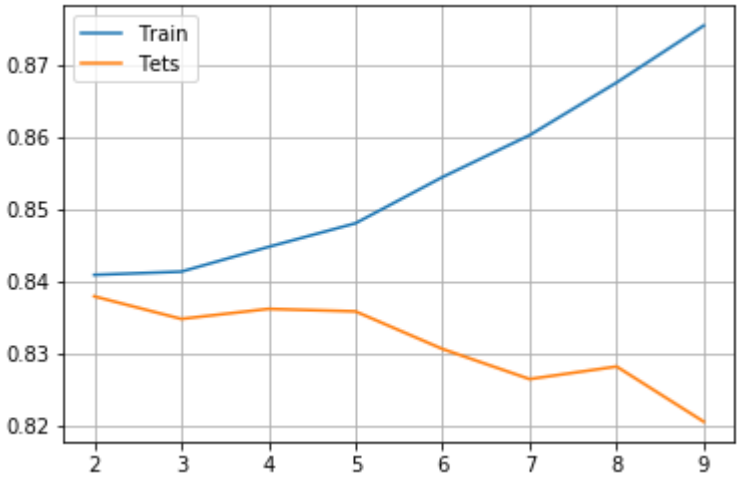
In general the approach allow the the tree to grow until it overfits and then prune it.

Preventing the tree from growing too deep by stopping it before it perfectly classifies the training data.

In [103]:
```
train_Acu =[]
test_Acu = []
index = []
for i in range(2,10):
    dtree = DecisionTreeClassifier(max_depth  = i)
    dtree.fit(X_train, y_train)
    pred = dtree.predict(X_test)
    train_Acu.append( accuracy_score(y_train, dtree.predict(X_train)))
    test_Acu.append(accuracy_score(y_test, pred))
    index.append(i)
```

In [104]:
```
print(train_Acu)
print(test_Acu)
plt.plot(index, train_Acu, index, test_Acu)
plt.legend(['Train', 'Tets'])
plt.grid(b = True)
```

```
[0.8408412887828163, 0.8412887828162291, 0.8447195704057279, 0.84800119331742
24, 0.8544152744630071, 0.8602326968973747, 0.8675417661097852, 0.87544749403
34129]
[0.83785664578984, 0.8347251217814892, 0.8361169102296451, 0.835768963117606
2, 0.8305497564370216, 0.826374391092554, 0.8281141266527487, 0.8204592901878
914]
```



RandomForest

In [119]:
```
from sklearn.ensemble import RandomForestClassifier
```

In [126]:
```
model =RandomForestClassifier( )
model.fit(X_train, y_train)
pred = model.predict(X_test)
print('train_accuracy=%.2f' %(accuracy_score(y_train, model.predict(X_train
))))
print('test_accuracy=%.2f' %(accuracy_score(y_test, pred)))

print(confusion_matrix(y_test, pred))
print('\n')
print(classification_report(y_test, pred))
print('\n')
```

```
train_accuracy=0.98
test_accuracy=0.83
[[2363   45]
 [ 448   18]]


              precision    recall  f1-score   support

           0       0.84      0.98      0.91      2408
           1       0.29      0.04      0.07       466

   micro avg       0.83      0.83      0.83      2874
   macro avg       0.56      0.51      0.49      2874
weighted avg       0.75      0.83      0.77      2874



C:\Users\FirouzehPC\Anaconda3\lib\site-packages\sklearn\ensemble\forest.py:24
6: FutureWarning: The default value of n_estimators will change from 10 in ve
rsion 0.20 to 100 in 0.22.
  "10 in version 0.20 to 100 in 0.22.", FutureWarning)
```

In [127]:
```
model =RandomForestClassifier(n_estimators=10,max_features=5 )
model.fit(X_train, y_train)
pred = model.predict(X_test)
print('train_accuracy=%.2f' %(accuracy_score(y_train, model.predict(X_train
))))
print('test_accuracy=%.2f' %(accuracy_score(y_test, pred)))
print(confusion_matrix(y_test, pred))
print('\n')
print(classification_report(y_test, pred))
```

```
train_accuracy=0.98
test_accuracy=0.83
[[2359   49]
 [ 444   22]]


              precision    recall  f1-score   support

           0       0.84      0.98      0.91      2408
           1       0.31      0.05      0.08       466

   micro avg       0.83      0.83      0.83      2874
   macro avg       0.58      0.51      0.49      2874
weighted avg       0.76      0.83      0.77      2874
```

In [ ]:

In [ ]:

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In [ ]: