scoring

February 22, 2016

1 Building a classifier for credit acceptance

In [93]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import make_scorer
from sklearn.metrics import confusion_matrix
sns.set(rc={"figure.figsize": (12, 6)})
```

The chosen dataset for this project represents 1000 individuals who took a credit.

With each observation an outcome is associated (1 for Good meaning the borrower did not default, 2 for Bad meaning the borrower defaulted).

This dataset is available on UCI Manchine Learning repository

It has comprehensive information about 1000 borrowers. Nonetheless, it does say anything about the time when the credit was authorized and the time when a creditor defaulted, nor about the interest rate of the issued credit.

This additional information could have been really handy to have a more comprehensive picture.

We are provided with two sets of data : - A set of data where Ordinal values are presented as categorical - A set of data with only numeric values (and added features)

The issue with the second dataset is that the meaning of the features are not documented. For this reason, we will focus on the first dataset.

During a credit application, a potential borrower provides personal information (generally along with documents) such as the information encountered in the dataset and get approved or rejected.

We intend to build a classification model that separates "good" borrowers who would be accepted by a financial institution from "bad" borrowers who would be rejected by the model.

In this particular case we want to minimize the false positive.

The reason is that giving a credit to someone who is not paying costs a lot.

The credit company gets the interests in case reimboursements are met.

It **looses the capital** (+ the expected interests) when not reimboursed!

[The page presenting the dataset](https://archive.ics.uci.edu/ml/datasets/Statlog+(German+Credit+Data) states that : It is worse to class a customer as good when they are bad (5), than it is to class a customer as bad when they are good (1).

We will stick to this 5 to 1 ratio and derive from it a cost function (see below) to evaluate our models

In [94]:
```
def cost(y,y_pred):
    confusion_m = confusion_matrix(y,y_pred)
    cost_matrix = np.array([[0,1],[5,0]])
    return float(np.diag(np.transpose(cost_matrix).dot(confusion_m)).sum()) / len(y)
cost_estimate = make_scorer(cost,greater_is_better=False)
```

How well does our classifier needs to perform in order to use it in production?

We defined the cost as: 5*fp + fn

It means that a fp costs us 5 times what a fn would have yielded in interets.

Given that in our dataset 70% of people are good borrowers, our score needs to be less than 0.7 in order for the credit insctruction to derive profit.

0.7 corresponds to the cost of turning down all customers, in which case there is no profit and no loss. We need our model to perform better than that!

Now, let's inspect the data.

```
In [95]: data = pd.read_csv('all.tsv', sep=' ', header=None, names= ["bank_account_status","duration_mo

         n_observations = data.shape[0]
         n_features = data.shape[1] - 1
         output = data.ix[:,-1]
         good_creditors = float(data.ix[:,-1][data.ix[:,-1] == 1].count()) / n_observations

         print 'Number of observations: {0}'.format(data.shape[0])
         print 'Number of features: {0}'.format(data.shape[1] - 1)
         print 'Percentage of good creditors: {0:.2f} % '.format(good_creditors * 100)

         data.head()
```

```
Number of observations: 1000
Number of features: 20
Percentage of good creditors: 70.00 %
```

```
Out[95]:   bank_account_status  duration_month credit_history purpose  credit_amount  \
         0                 A11               6            A34     A43           1169
         1                 A12              48            A32     A43           5951
         2                 A14              12            A34     A46           2096
         3                 A11              42            A32     A42           7882
         4                 A11              24            A33     A40           4870

           savings employed_since  installment_percentage_of_income  \
         0     A65            A75                                 4
         1     A61            A73                                 2
         2     A61            A74                                 2
         3     A61            A74                                 2
         4     A61            A73                                 3

           personal_status_and_sex gurantor  ...    property age  other_credits  \
         0                     A93     A101  ...        A121  67           A143
         1                     A92     A101  ...        A121  22           A143
         2                     A93     A101  ...        A121  49           A143
         3                     A93     A103  ...        A122  45           A143
         4                     A93     A101  ...        A124  53           A143

           housing nb_credit_at_bank  job_qualification nb_pp_cater_for  telephone?  \
         0    A152                 2               A173               1        A192
         1    A152                 1               A173               1        A191
         2    A152                 1               A172               2        A191
         3    A153                 1               A173               2        A191
         4    A153                 2               A173               2        A191

           foreigner? result
         0       A201      1
         1       A201      2
```

```
2       A201      1
3       A201      1
4       A201      2

[5 rows x 21 columns]
```

We don't have any missing data in our dataset:

```
In [158]: "The number of pieces of data missing is {0}".format(data.isnull().sum().sum())
```

```
Out[158]: 'The number of pieces of data missing is 0'
```

Below is the numeric dataset. 4 features have been added. But unfortunatelly, we don't know which ones!

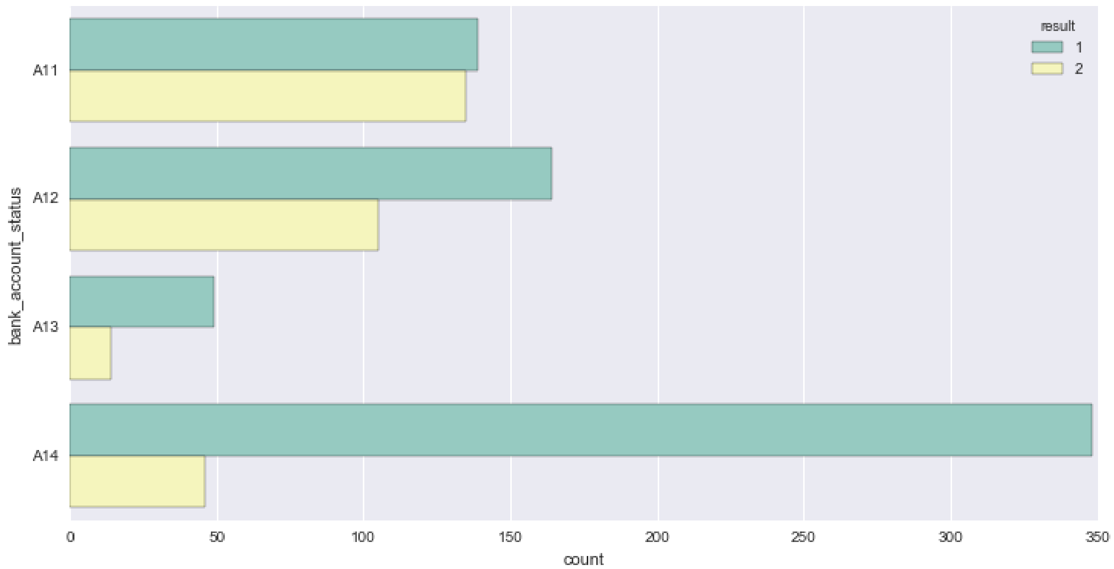
```
In [96]: data_numeric = pd.read_csv('numeric.tsv', delim_whitespace=True, header=None)
         data_numeric.head()
```

```
Out[96]:    0   1   2   3   4   5   6   7   8   9  ...  15  16  17  18  19  20  21  22  \
         0  1   6   4  12   5   5   3   4   1  67  ...   0   0   1   0   0   1   0   0
         1  2  48   2  60   1   3   2   2   1  22  ...   0   0   1   0   0   1   0   0
         2  4  12   4  21   1   4   3   3   1  49  ...   0   0   1   0   0   1   0   1
         3  1  42   2  79   1   4   3   4   2  45  ...   0   0   0   0   0   0   0   0
         4  1  24   3  49   1   3   3   4   4  53  ...   1   0   1   0   0   0   0   0

            23  24
         0   1   1
         1   1   2
         2   0   1
         3   1   1
         4   1   2

         [5 rows x 25 columns]
```

1.1 Exploring the data

Let's visualize the data and see if we can spot interesting patterns that could differenciate "good" (labelled as 1) and "bad" (labelled as 2) borrowers.

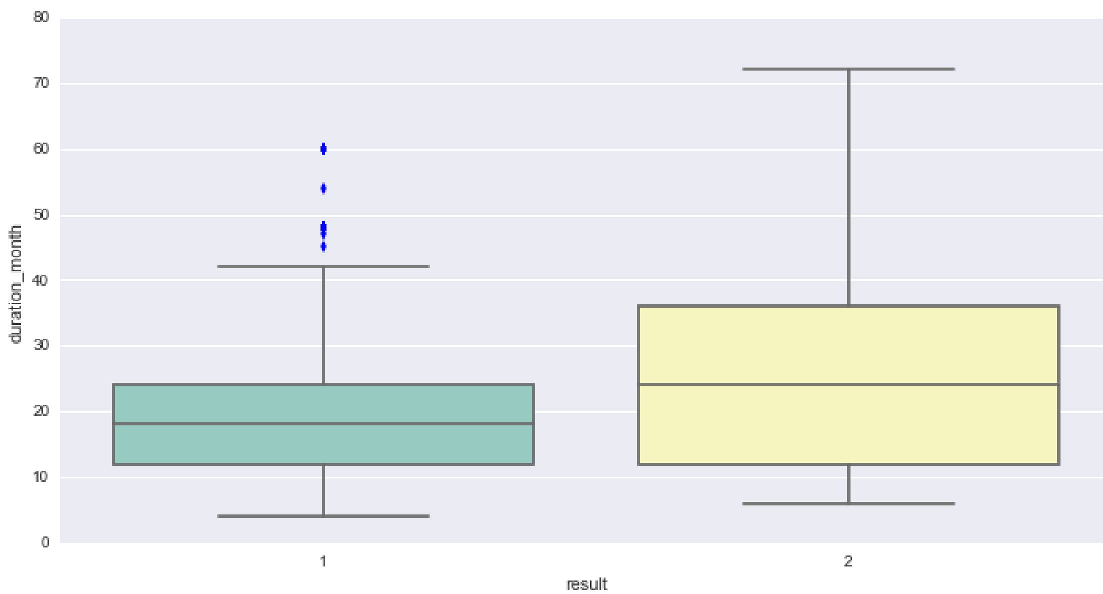
```
In [98]: features = data.ix[:,:-1]
         features = features.columns.tolist()
         a0 = sns.countplot(y=features[0], hue="result", data=data,order=np.unique(data[features[0]].val
```



Status of existing checking account A11 : ... < 0 DM A12 : 0 <= ... < 200 DM A13 : ... >= 200 DM / salary assignments for at least 1 year A14 : no checking account

Not having a checking account is a strong good signal

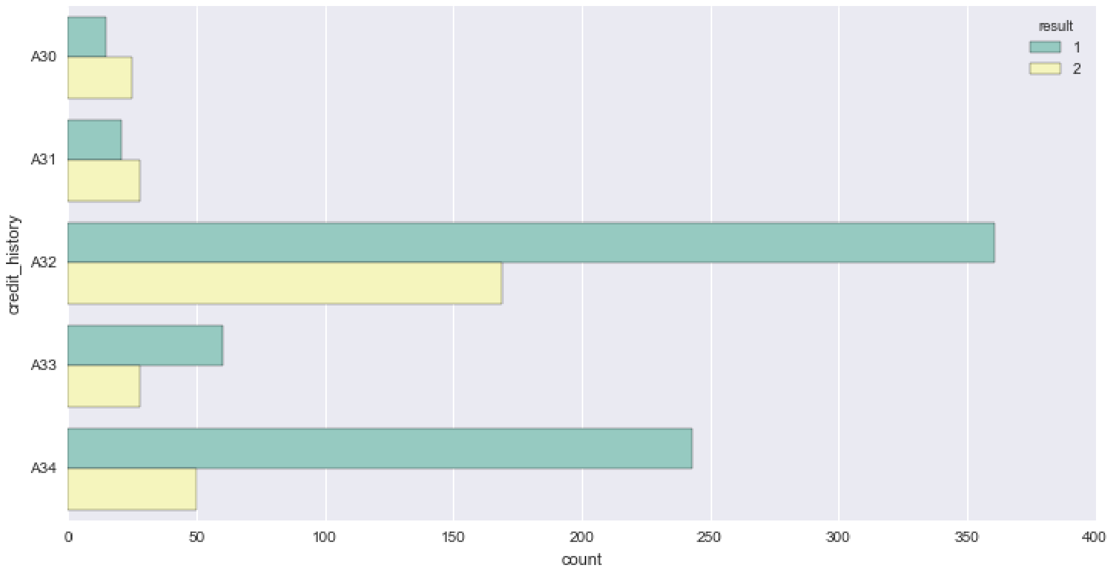
```
In [99]: a1 = sns.boxplot(x="result", y="duration_month", data=data,palette="Set3")
```



The boxplot above shows the duration of the credit for our 2 classes of borrowers.

A very long credit (more than 50 months) is bad signal.

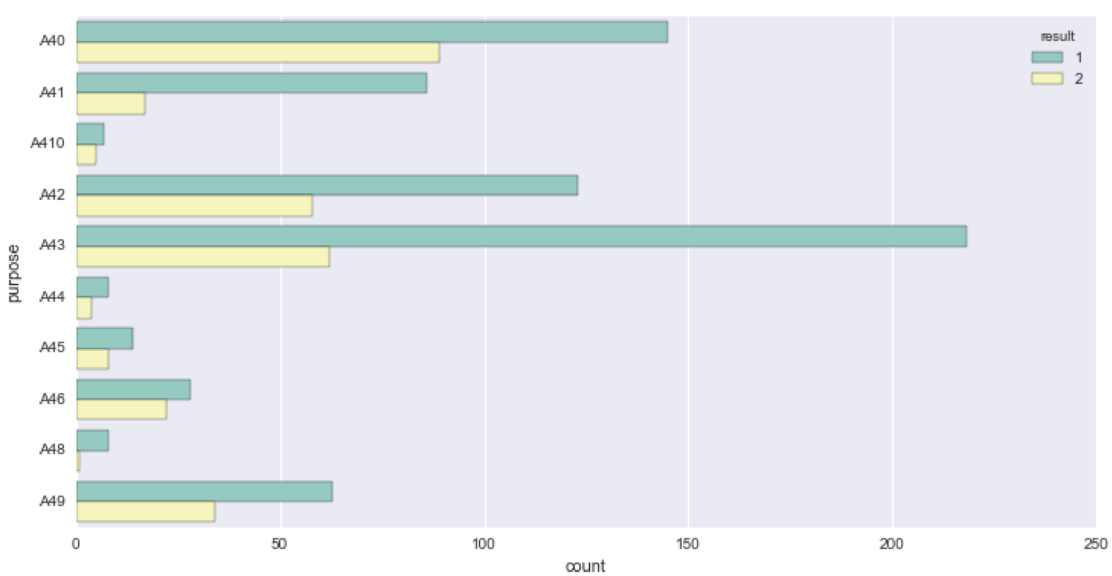
```
In [100]: a2 = sns.countplot(y=features[2], hue="result", order=np.unique(data[features[2]].values), da
```



Credit history A30 : no credits taken/ all credits paid back duly A31 : all credits at this bank paid back duly A32 : existing credits paid back duly till now A33 : delay in paying off in the past A34 : critical account/ other credits existing (not at this bank)

Havig a critical credit history is suprisingly a good signal.

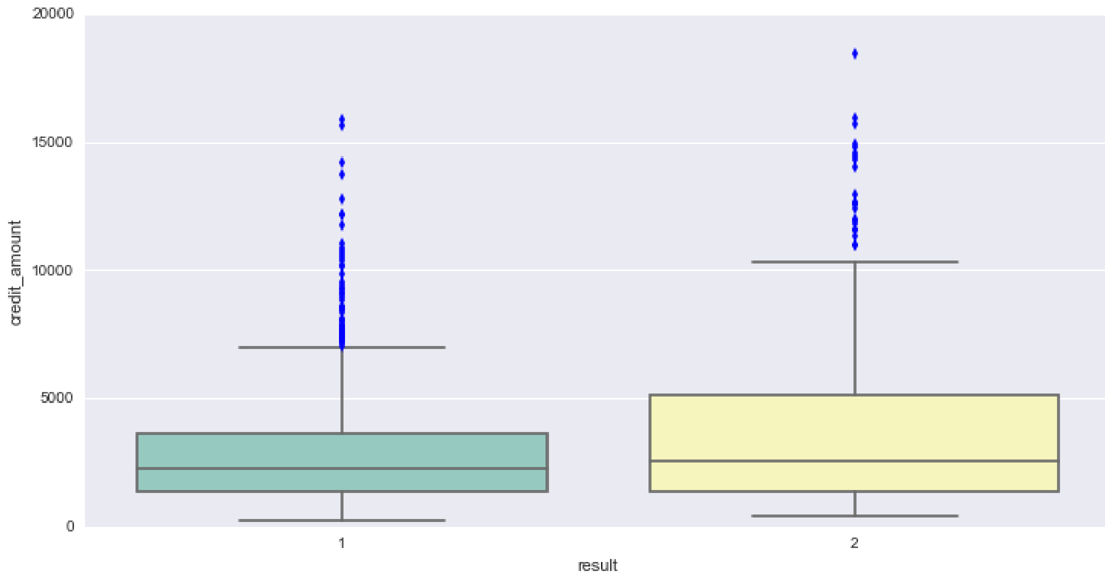
```
In [101]: a3 = sns.countplot(y=features[3], hue="result", order=np.unique(data[features[3]].values), da
```



Purpose A40 : car (new) A41 : car (used) A42 : furniture/equipment A43 : radio/television A44 : domestic appliances A45 : repairs A46 : education A47 : (vacation - does not exist?) A48 : retraining A49 : business A410 : others

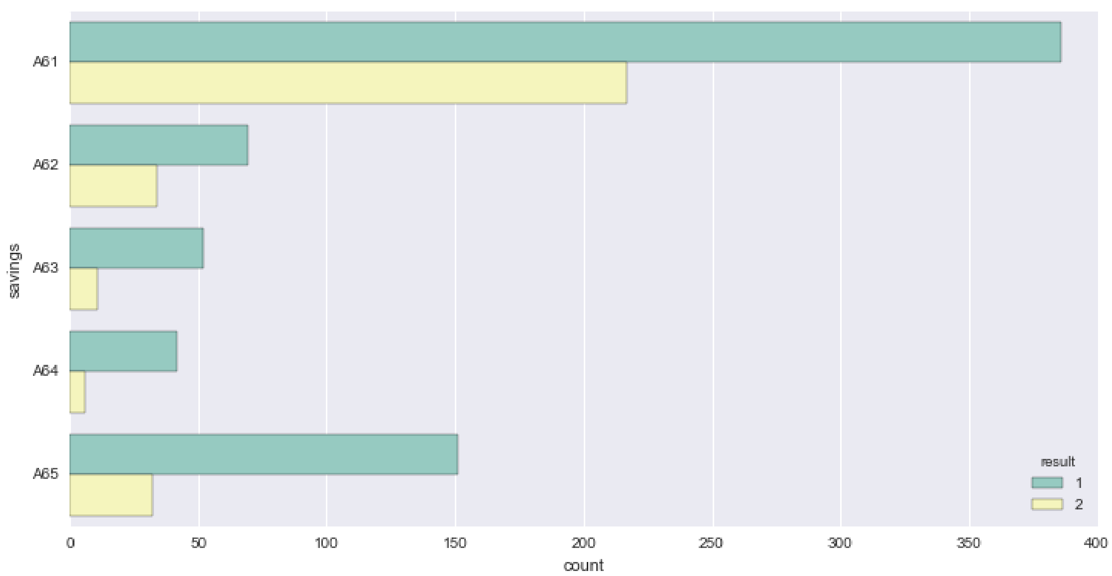
Asking a credit for a radio / television is a good signal

```
In [102]: a1 = sns.boxplot(x="result", y="credit_amount", data=data,palette="Set3")
```



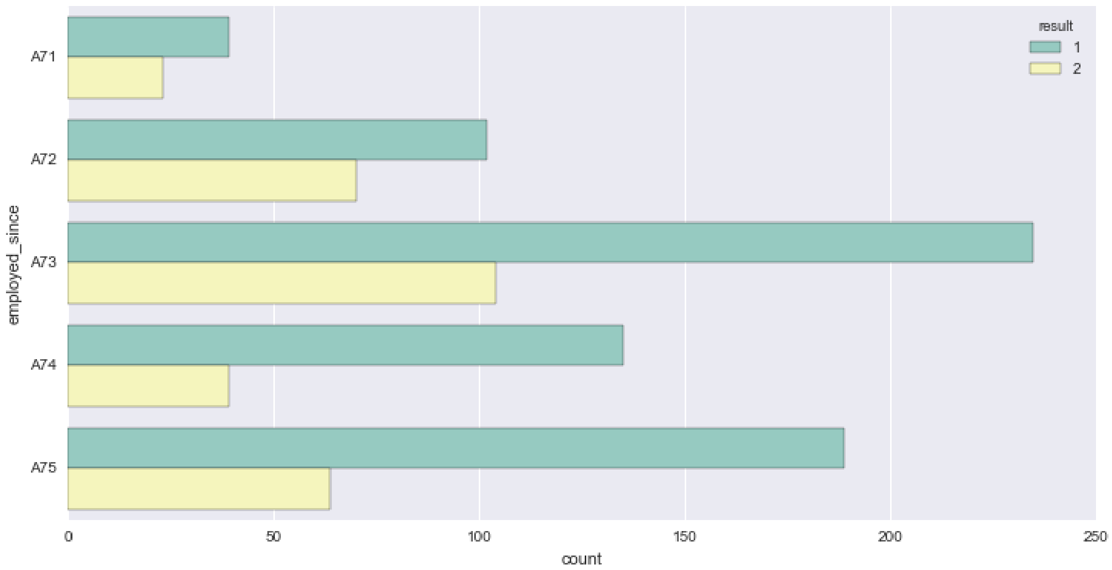
For both classes medians of the credit amount are similar. It will be hard to derive meaninful information to classify our borrowers from this feature.

```
In [103]: a5 = sns.countplot(y=features[5], hue="result", order=np.unique(data[features[5]].values), da
```



“‘ Savings account/bonds A61 : . . . < 100 DM A62 : 100 <= . . . < 500 DM A63 : 500 <= . . . < 1000 DM A64 : .. >= 1000 DM A65 : unknown/ no savings account ““ Borrowers’ savings do not appear to be very insightful.

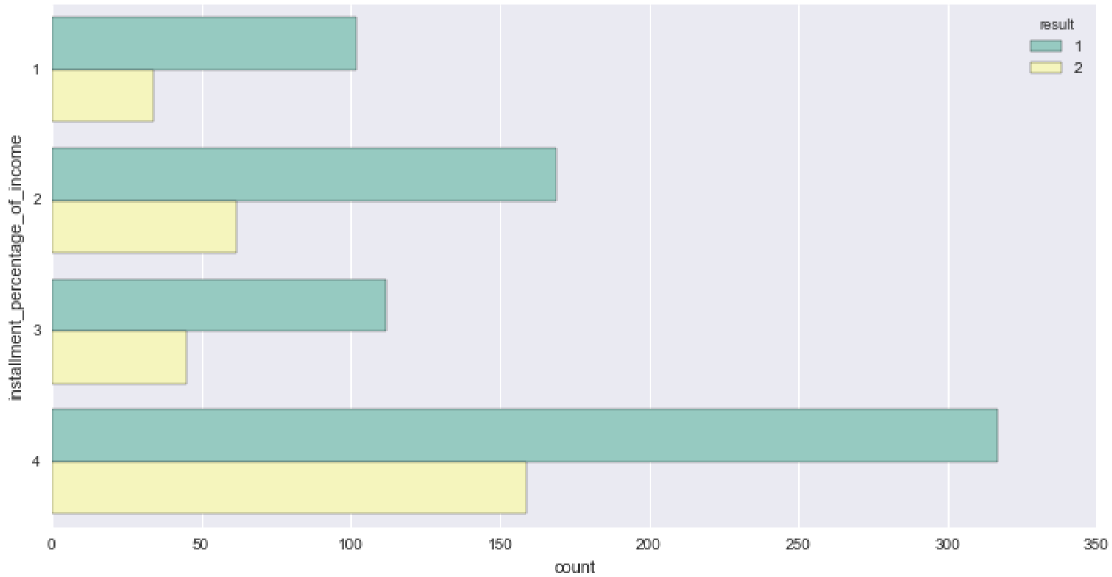
```
In [104]: a6 = sns.countplot(y=features[6], hue="result", order=np.unique(data[features[6]].values), da
```



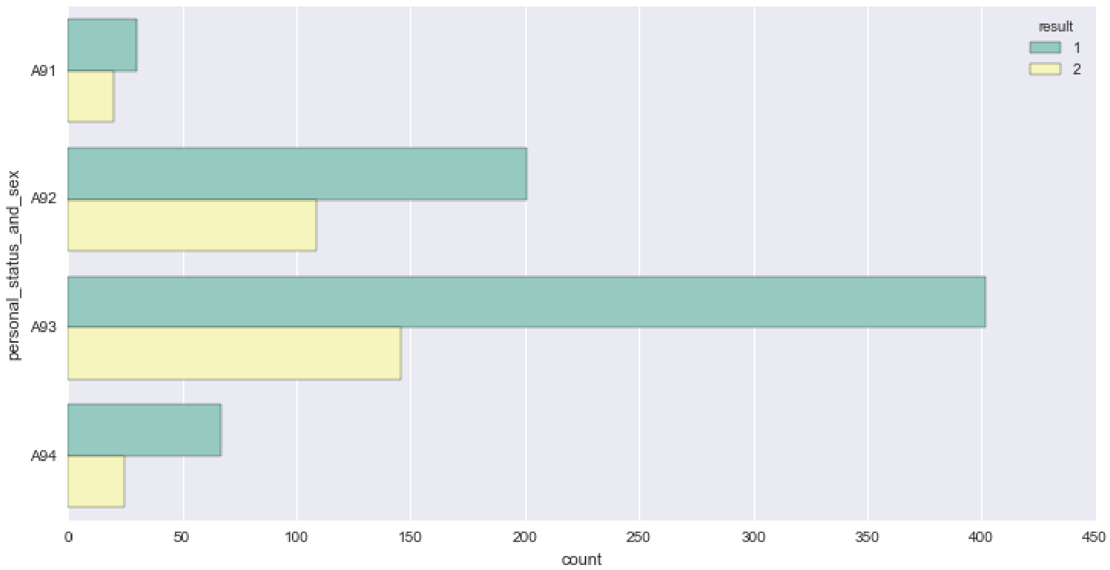

```
Present employment since
A71 : unemployed
A72 : ... < 1 year
A73 : 1 <= ... < 4 years
A74 : 4 <= ... < 7 years
A75 : .. >= 7 years
```

Borrowers who have been working for the same employer for a long time is a good signal.

```
In [142]: a7 = sns.countplot(y=features[7], hue="result", order=np.unique(data[features[7]].values), da
```



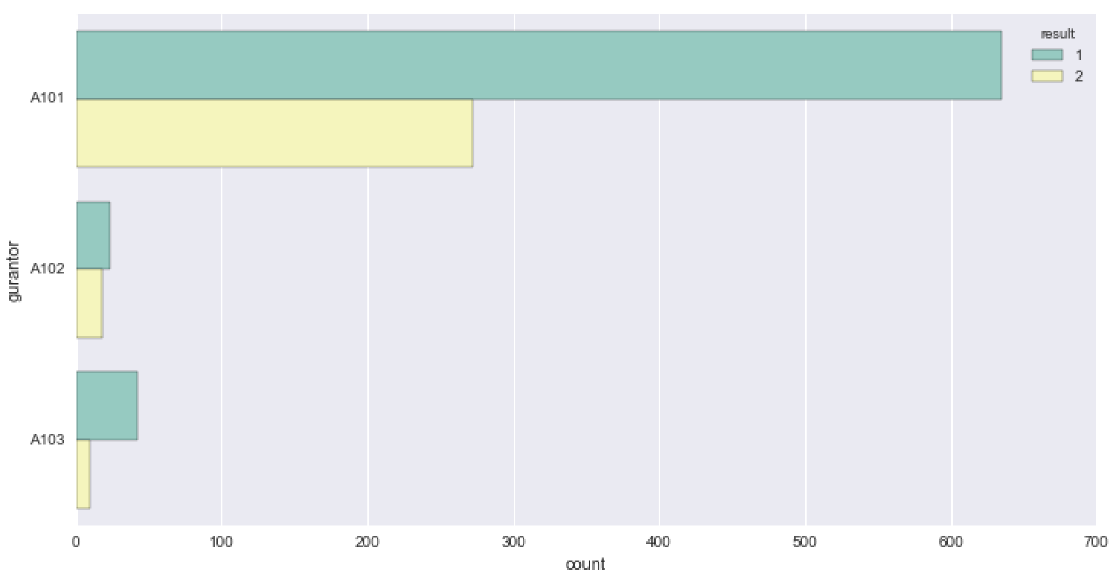
```
In [143]: a8 = sns.countplot(y=features[8], hue="result", order=np.unique(data[features[8]].values), da
```



`Personal status and sex  A91 : male : divorced/separated  A92 : female : divorced/separated/married  A93 : male : single  A94 : male : married/widowed  A95 : female : single`

Males are more likely to pay their debts than women.

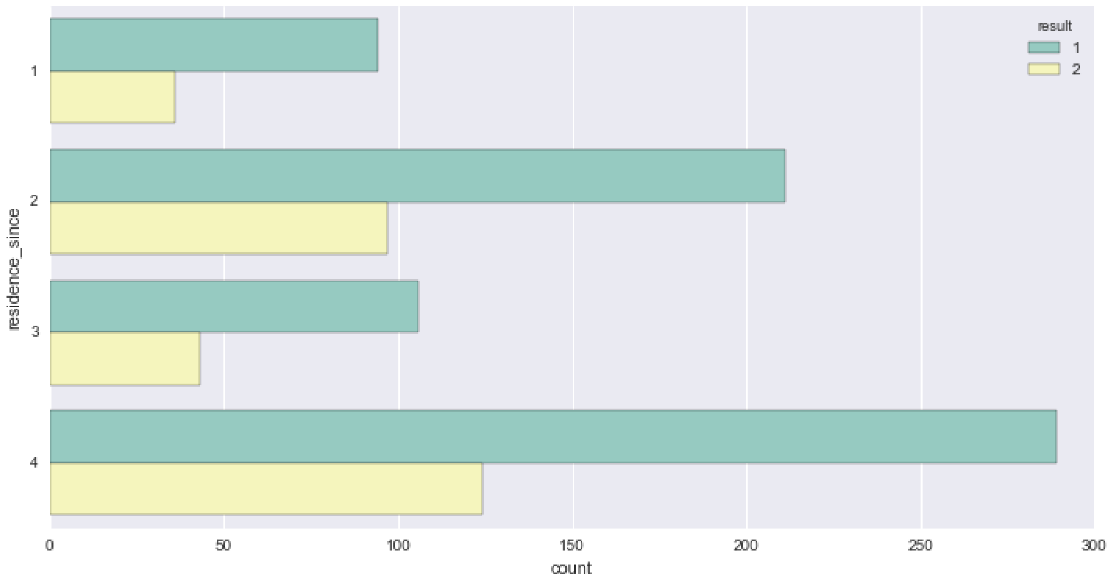
```
In [107]: a9 = sns.countplot(y=features[9], hue="result", order=np.unique(data[features[9]].values), da
```



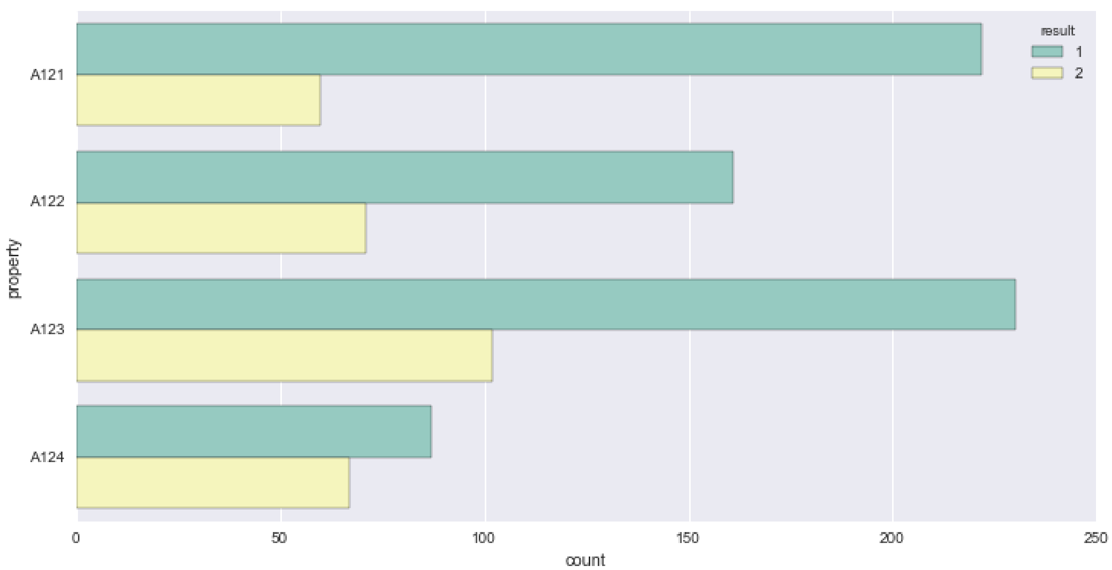
`Other debtors / guarantors  A101 : none  A102 : co-applicant  A103 : guarantor`

The wide majority does have guarantor nor debtor. This feature won't help much.

```
In [108]: a10 = sns.countplot(y=features[10], hue="result", order=np.unique(data[features[10]].values),
```



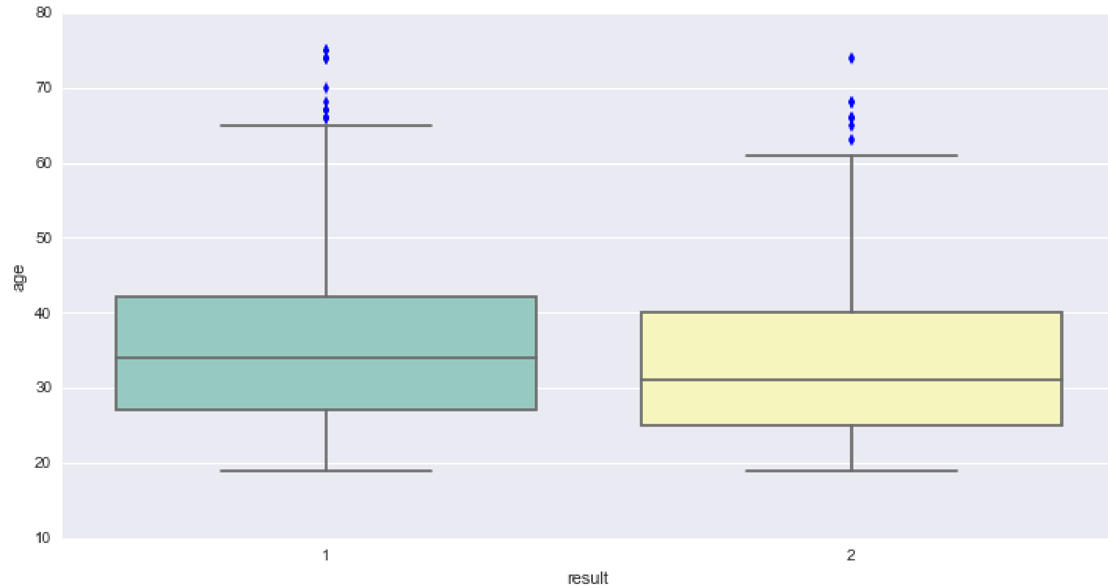

```
In [109]: a11 = sns.countplot(y=features[11], hue="result", order=np.unique(data[features[11]].values),
```



`Property  A121 : real estate  A122 : if not A121 : building society savings agreement/ life insurance  A123 : if not A121/A122 : car or other, not in attribute 6  A124 : unknown / no property`

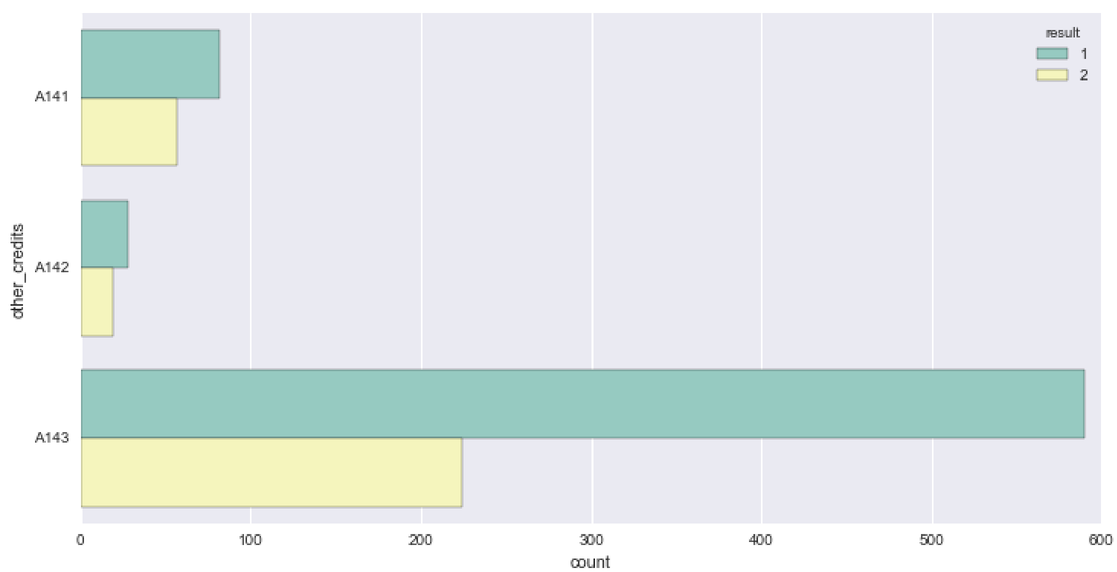
The more real estate or properties you have, the more likely to pay back your loan you are.

```
In [110]: a12 = sns.boxplot(x="result", y="age", data=data,palette="Set3")
```



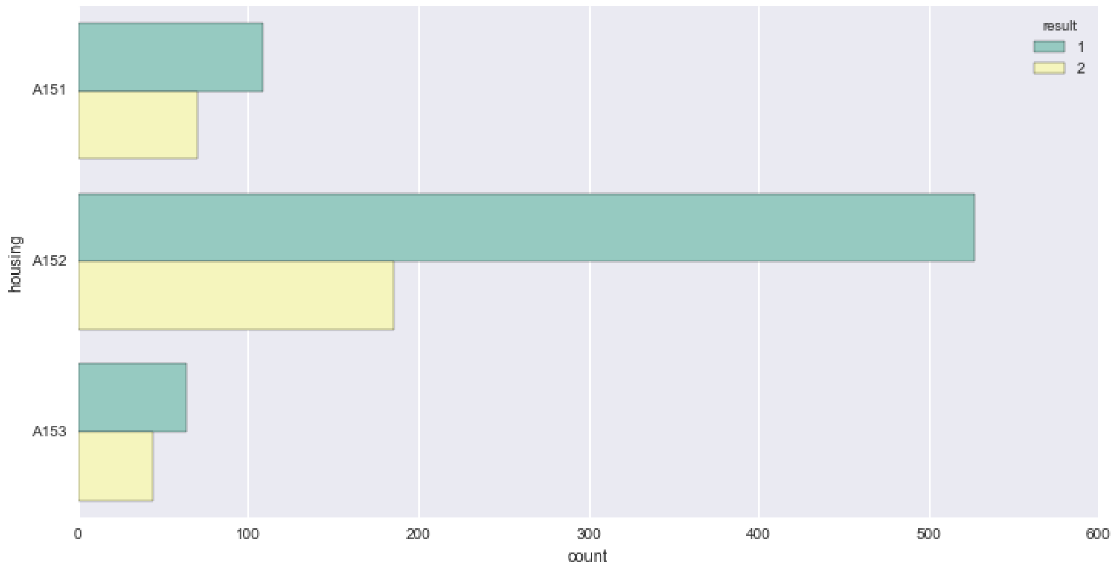
Our two classes are very similar when it comes to age.

```
In [111]: a13 = sns.countplot(y=features[13], hue="result", order=np.unique(data[features[13]].values),
```



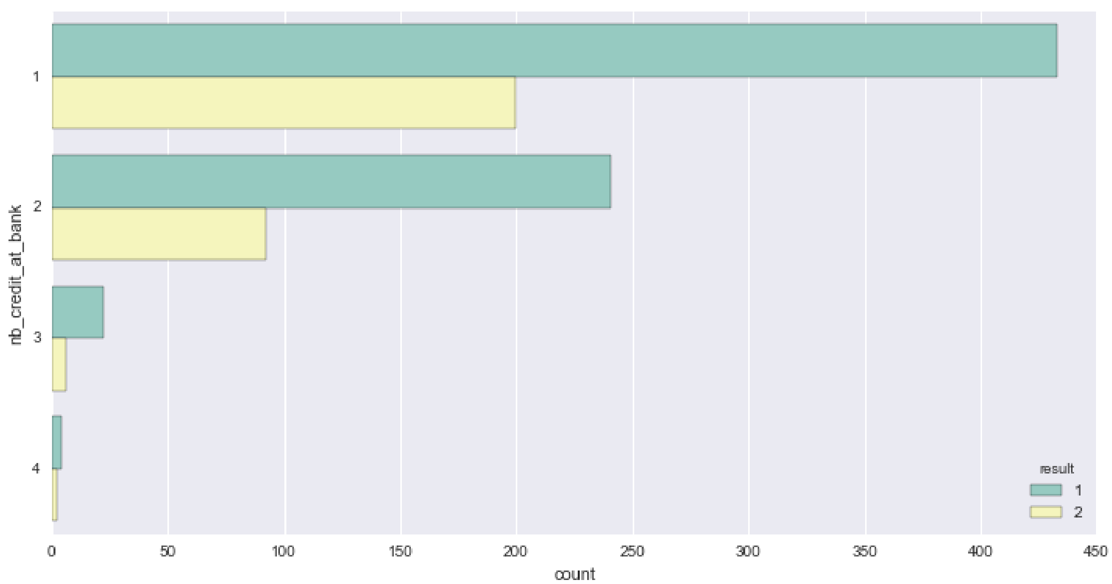
Other installment plans A141 : bank A142 : stores A143 : none

```
In [112]: a14 = sns.countplot(y=features[14], hue="result", order=np.unique(data[features[14]].values),
```

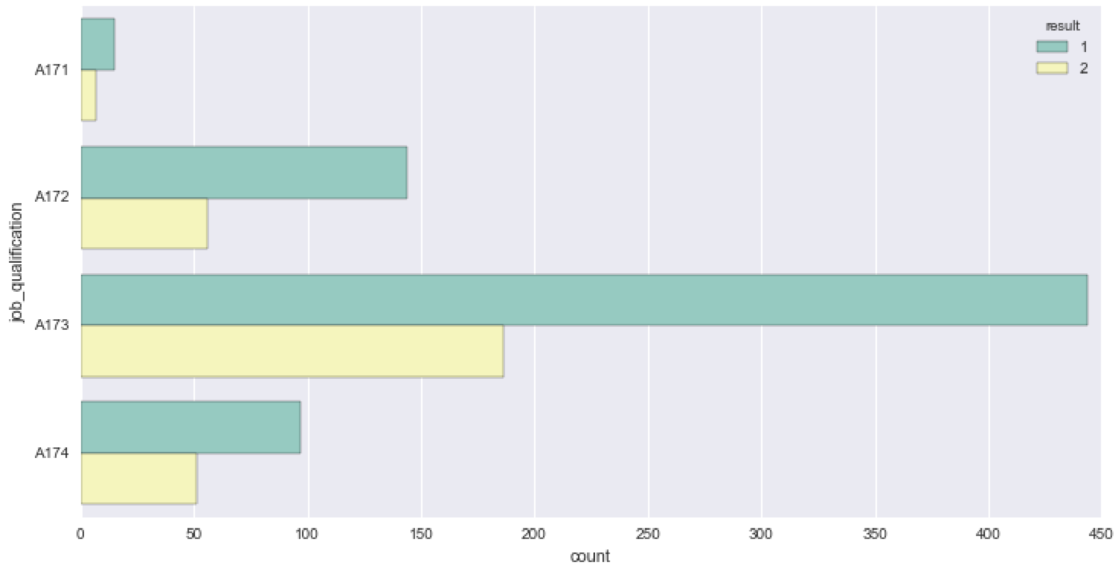


Housing A151 : rent A152 : own A153 : for free
Again owning your home tends to be a positive signal.

```
In [113]: a15 = sns.countplot(y=features[15], hue="result", order=np.unique(data[features[15]].values),
```



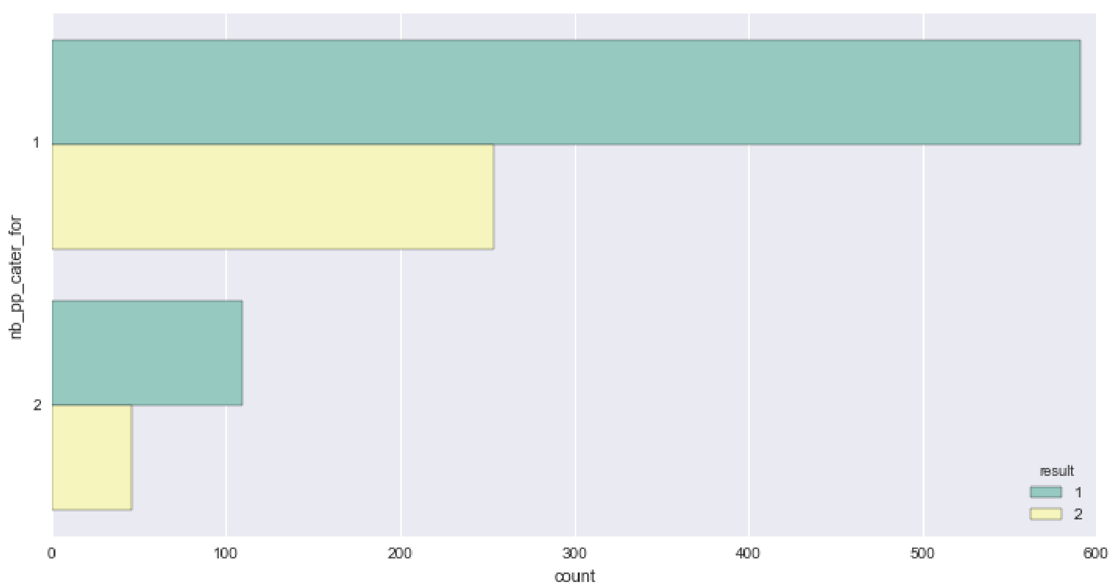

```
In [114]: a16 = sns.countplot(y=features[16], hue="result", order=np.unique(data[features[16]].values),
```



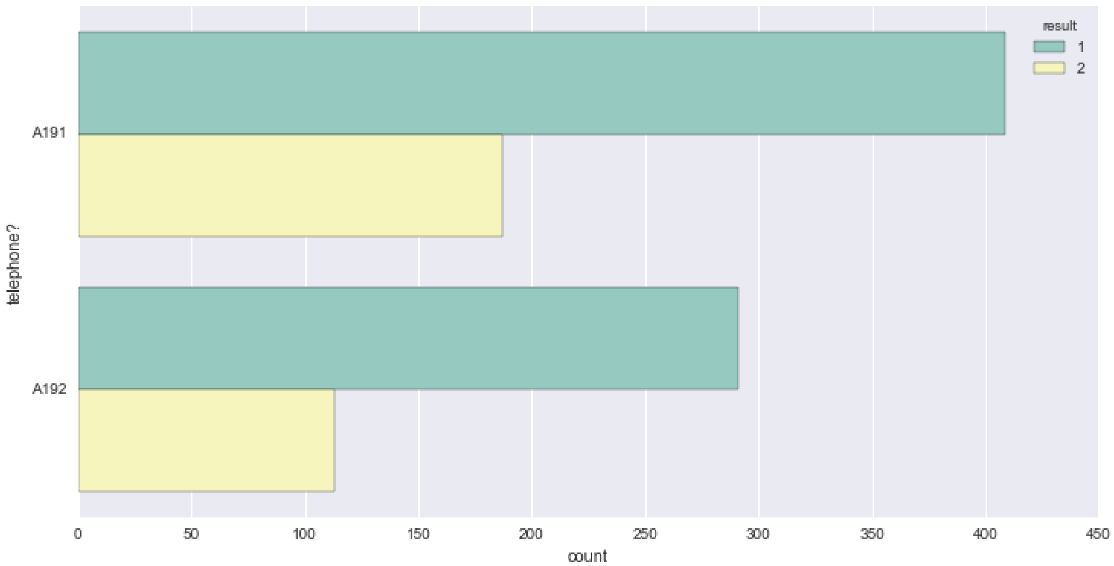
Job A171 : unemployed/ unskilled - non-resident A172 : unskilled - resident A173 : skilled employee / official A174 : management/ self-employed/ highly qualified employee/ officer

A higher the job qualification does not imply you are better borrower. This is not a strong signal though.

```
In [144]: a17 = sns.countplot(y=features[17], hue="result", order=np.unique(data[features[17]].values),
```

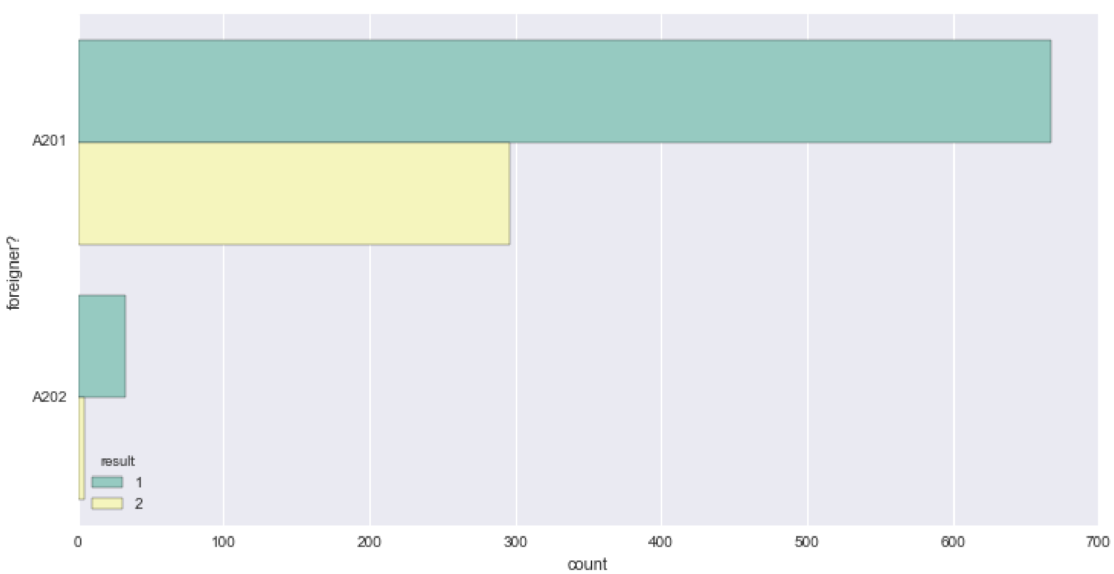



```
In [116]: a18 = sns.countplot(y=features[18], hue="result", order=np.unique(data[features[18]].values),
```



Telephone
A191 : none
A192 : yes, registered under the customers name

```
In [117]: a19 = sns.countplot(y=features[19], hue="result", order=np.unique(data[features[19]].values),
```



foreign worker
A201 : yes
A202 : no

This bank seems to be specialized in granting credits to foreigners. Locals have less risk though!

Those are the most important findings we can derive from below: - Borrowers with no checking account seem to be less risky - If the credit history reflects a critical situation, borrower is surprisingly less risky - People taking a credit for a radio/television are less risky - People without a saving account are less risky - People more than 4 (and 7 years) on a job are less risky

On the contrary, features like the age of the person don't seem to be related to the pay back ability of borrowers. It is interesting since we could test getting rid of those.

2 Preprocessing

2.1 Categorical or ordinal features

6 out of 20 features are ordinal.

For instance : `Present employment since A71 : unemployed A72 : ... < 1 year A73 : 1 <= ... < 4 years A74 : 4 <= ... < 7 years A75 : .. >= 7 years`

We will first treat them as categorical to find out the type of model that performs better our classification task. After that, we will try to see if converting those to ordinal helps to be more accurate.

```
In [118]: X = data.ix[:,:-1]
          y = data['result']
```

```
In [119]: X.columns.tolist()
```

```
Out[119]: ['bank_account_status',
           'duration_month',
           'credit_history',
           'purpose',
           'credit_amount',
           'savings',
           'employed_since',
           'installment_percentage_of_income',
           'personal_status_and_sex',
           'gurantor',
           'residence_since',
           'property',
           'age',
           'other_credits',
           'housing',
           'nb_credit_at_bank',
           'job_qualification',
           'nb_pp_cater_for',
           'telephone?',
           'foreigner?']
```

```
In [120]: def preprocess(X,convert_numeric=False):
              outX = pd.DataFrame(index=X.index)
              target_cols = ['credit_history','employed_since','gurantor','property','other_credits','jo
              for col in X.columns:
                  if convert_numeric == True and col in target_cols:
                      distinct_val = sorted(X[col].unique())
                      new_col = X[col].replace(distinct_val,range(0,len(distinct_val)))
                  elif X[col].dtype == object:
                      values = X[col].value_counts()
                      nb_values = len(values)
                      if nb_values == 2:
```

```
                new_col = X[col].replace([values.index[0],values.index[1]],[0,1])
            else:
                new_col = pd.get_dummies(X[col],prefix=col)
        else:
            new_col = X[col]

        outX = outX.join(new_col)
    return outX
```

In [121]:
```
X_all = preprocess(X) # with categorical features
X_all_num = preprocess(X,convert_numeric=True) # with ordinal features
```

3 Correlation between variables

With our preprocessing done, we can look for correlations between the variables we identified above as being good candidates for separating borrowers

In [122]:
```
feature_index = [3,9,14,25,30,58]
corr_df = X_all.corr()
corr_df.iloc[feature_index,feature_index]
```

Out[122]:
```
                        bank_account_status_A14  credit_history_A34  \
bank_account_status_A14                1.000000            0.168879
credit_history_A34                     0.168879            1.000000
purpose_A43                            0.076027           -0.009983
savings_A65                            0.142364            0.013529
employed_since_A75                     0.072110            0.150968
foreigner?                            -0.017108            0.036770

                        purpose_A43  savings_A65  employed_since_A75  \
bank_account_status_A14    0.076027     0.142364            0.072110
credit_history_A34        -0.009983     0.013529            0.150968
purpose_A43                1.000000     0.004378            0.046928
savings_A65                0.004378     1.000000            0.105303
employed_since_A75         0.046928     0.105303            1.000000
foreigner?                -0.063242     0.003138           -0.053144

                        foreigner?
bank_account_status_A14  -0.017108
credit_history_A34        0.036770
purpose_A43              -0.063242
savings_A65               0.003138
employed_since_A75       -0.053144
foreigner?                1.000000
```

There is little correlation between the above features (max is 0.17) but interestingly there are mostly positive values showing that there are going in the same direction.

Here method like PCA will probably not perform very well, on the contrary a Naive Bayes model is a good candidate.

4 Models considered

4.0.1 Naive Bayes

We only have 1000 data points to train our algorithm. Naive Bayes is known to perform well when we don't have much data to train our model. That's why it makes a good candidate. It also have the advantage of being fast when compared to more complicated models. The disadvantage is that it assumes that features are independent from one another which does not make it a good candidate for cases when we most probably have highly correlated input variables (it is not the case here).

4.0.2 Decision Trees

Decision trees require little data preparation (for instance, it copes with our unscaled vectors) and it is easy to understand. Our data is not too unbalanced (67% of one class, 33% of another) to be a serious problem to this technique. On the other side, It is prone to overfitting if we don't limit the size of the tree (minimum sample per node, per leaf, max depth of the tree). A tree leaves setting apart small number of instance is specialized in the training data and hence won't generalize well.

For all models, we will tune our parameters on the train set thanks to cross-validation.

For the Naive Bayes approach, we will experiment on reducing the number features considered and see if we obtain better results on our cost function.

```
In [123]: from sklearn.tree import DecisionTreeClassifier
          from sklearn.tree import export_graphviz
          from sklearn import cross_validation
          from sklearn import metrics
          import time
          from IPython.display import Image
          from sklearn.externals.six import StringIO
          from sklearn import tree
          import pydot
          from sklearn.ensemble import ExtraTreesClassifier
          from sklearn.feature_selection import SelectFromModel
          from sklearn.pipeline import Pipeline
          from sklearn.svm import SVC
          from sklearn.preprocessing import StandardScaler
          from sklearn.grid_search import RandomizedSearchCV
          from sklearn.naive_bayes import GaussianNB
```

Some convinience methods

```
In [124]: def train_classifier(clf, X_train, y_train):
              print "Training {}...".format(clf.__class__.__name__)
              start = time.time()
              clf.fit(X_train, y_train)
              end = time.time()
              print "Done!\nTraining time (secs): {:.3f}".format(end - start)
```

```
In [125]: def predict_labels(clf, features, target):
              print "Predicting labels using {}...".format(clf.__class__.__name__)
              start = time.time()
              y_pred = clf.predict(features)
              end = time.time()
              print "Done!\nPrediction time (secs): {:.3f}".format(end - start)
              return cost(target.values, y_pred)
```

```
In [126]: def train_predict(clf, X_train, y_train, X_test, y_test):
              print "------------------------------------------"
```

```
        print "Training set size: {}".format(len(X_train))
        train_classifier(clf, X_train, y_train)
        print "Cost estimation for training set: {}".format(predict_labels(clf, X_train, y_train)
        print "Cost estimation for test set: {}".format(predict_labels(clf, X_test, y_test))
```

We split our data between a test and train set.

```
In [127]: X_train, X_test, y_train, y_test = cross_validation.train_test_split(X_all, y, test_size=0.2,r

          X_train_num, X_test_num, y_train_num, y_test_num = cross_validation.train_test_split(X_all_nu
```

Now let's benchmarch a Decision tree and a Naive Bayes model. According to the result, we will elaborate on one of them.

```
In [128]: from sklearn.grid_search import GridSearchCV
          parameters = {'max_depth': range(6,9,1),
                        'min_samples_split': range(5,61,5),
                        'max_features' : range(15,26,2)}
          clf = DecisionTreeClassifier(random_state=15)

          tree_model = GridSearchCV(clf,parameters, scoring=cost_estimate,cv=5)
          tree_model.fit(X_train, y_train)
          print tree_model.best_params_
          print tree_model.best_score_
```

```
{'max_features': 25, 'min_samples_split': 30, 'max_depth': 6}
-0.9325
```

```
In [129]: NB_alone = GaussianNB()
          sizes = range(200,801,200)

          for i,v in enumerate(sizes):
              train_predict(NB_alone,X_train[:v],y_train[:v],X_test,y_test)

          for i,v in enumerate(sizes):
              train_predict(tree_model,X_train[:v],y_train[:v],X_test,y_test)
```

```
------------------------------------------
Training set size: 200
Training GaussianNB...
Done!
Training time (secs): 0.002
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for training set: 0.56
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 0.69
------------------------------------------
Training set size: 400
Training GaussianNB...
Done!
Training time (secs): 0.001
Predicting labels using GaussianNB...
```

```
Done!
Prediction time (secs): 0.001
Cost estimation for training set: 0.6475
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 0.67
------------------------------------------
Training set size: 600
Training GaussianNB...
Done!
Training time (secs): 0.003
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.004
Cost estimation for training set: 0.688333333333
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 0.665
------------------------------------------
Training set size: 800
Training GaussianNB...
Done!
Training time (secs): 0.002
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.002
Cost estimation for training set: 0.66125
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 0.675
------------------------------------------
Training set size: 200
Training GridSearchCV...
Done!
Training time (secs): 4.353
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 0.77
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 1.025
------------------------------------------
Training set size: 400
Training GridSearchCV...
Done!
Training time (secs): 5.151
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.001
```

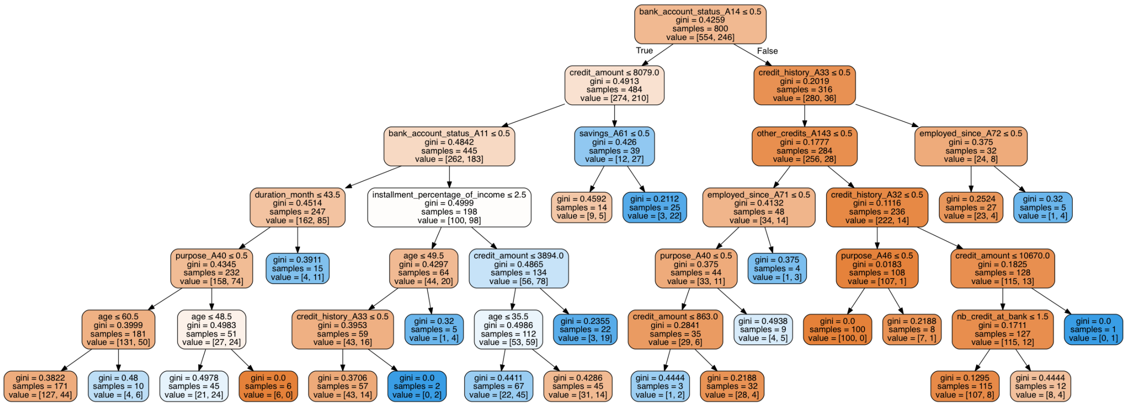
```
Cost estimation for training set: 0.515
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 0.76
------------------------------------------
Training set size: 600
Training GridSearchCV...
Done!
Training time (secs): 5.654
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 0.64
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 0.985
------------------------------------------
Training set size: 800
Training GridSearchCV...
Done!
Training time (secs): 6.282
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 0.69375
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 0.985
```

Our Naive Bayes model performs consistently better than the Decision tree.

First let's have a look at the features considered as important by the Descision tree, and then we will to conbine both models!

```
In [130]: dot_data = StringIO()
          tree.export_graphviz(tree_model.best_estimator_, out_file=dot_data,
                               feature_names=X_all.columns.tolist(),
                               filled=True, rounded=True,
                               special_characters=True)
          graph = pydot.graph_from_dot_data(dot_data.getvalue())
          Image(graph.create_png())
```

Out[130]:



If we take the couple first criteria used by the tree we have : - Bank account status A14 : we spotted it earlier - Credit history A 33 : also shows differences between borrowers. - Credit Amount < 8079 : The tree uses the outliers depicted in our boxplot

Now, let's experiment combining both models.

```
In [131]: NB = GaussianNB()

          x_tree = DecisionTreeClassifier(random_state=15)


          estimators = Pipeline([
              ('sel',SelectFromModel(x_tree)),
              ('classifier',NB)
          ])

          parameters = {
                          'sel__estimator__max_depth':range(3,10,1),
                          'sel__estimator__min_samples_split': range(15,30,2),
                          'sel__estimator__max_features' : range(15,25,2),
                          'sel__estimator__criterion' : ['gini','entropy'],
                          'sel__estimator__max_leaf_nodes': range(50,90,5),
                          'sel__threshold':['median','0.5*median','0.75*median','mean','1.25*median','1
                       }
          nb_model = RandomizedSearchCV(estimators,parameters,scoring=cost_estimate,verbose=1,n_jobs=-1
          nb_model.fit(X_train,y_train)
          scores = nb_model.grid_scores_
          sorted(scores, key= lambda x: np.mean(x[2]),reverse=True )[:10]
```

```
Fitting 5 folds for each of 400 candidates, totalling 2000 fits

[Parallel(n_jobs=-1)]: Done 212 tasks      | elapsed:    2.1s
[Parallel(n_jobs=-1)]: Done 1112 tasks      | elapsed:    9.9s
[Parallel(n_jobs=-1)]: Done 2000 out of 2000 | elapsed:   17.3s finished
```

```
Out[131]: [mean: -0.74250, std: 0.04964, params: {'sel__estimator__min_samples_split': 29, 'sel__estimator
           mean: -0.74375, std: 0.09209, params: {'sel__estimator__min_samples_split': 19, 'sel__estimator
           mean: -0.74500, std: 0.04858, params: {'sel__estimator__min_samples_split': 23, 'sel__estimator
           mean: -0.74500, std: 0.04858, params: {'sel__estimator__min_samples_split': 23, 'sel__estimator
           mean: -0.74500, std: 0.04858, params: {'sel__estimator__min_samples_split': 29, 'sel__estimator
           mean: -0.75125, std: 0.04820, params: {'sel__estimator__min_samples_split': 17, 'sel__estimator
```

```
mean: -0.75250, std: 0.04852, params: {'sel__estimator__min_samples_split': 27, 'sel__estimator
mean: -0.75500, std: 0.06385, params: {'sel__estimator__min_samples_split': 23, 'sel__estimator
mean: -0.75500, std: 0.06385, params: {'sel__estimator__min_samples_split': 23, 'sel__estimator
mean: -0.75625, std: 0.05022, params: {'sel__estimator__min_samples_split': 25, 'sel__estimator
```

In [132]:
```python
NB_alone_predictions = NB_alone.predict(X_test)
NB_predictions = nb_model.predict(X_test)

print "Simple Naive Bayes"
print cost(y_test,NB_alone_predictions)

print "Naive Bayes combined with tree for feature selection"
print cost(y_test,NB_predictions)
```

```
Simple Naive Bayes
0.675
Naive Bayes combined with tree for feature selection
0.675
```

The model with feature selection performs slighly better but if we run the grid search several times, we sometimes get worse results on the test set.

In this situation, we favor the **simpler Naive Bayes model**.

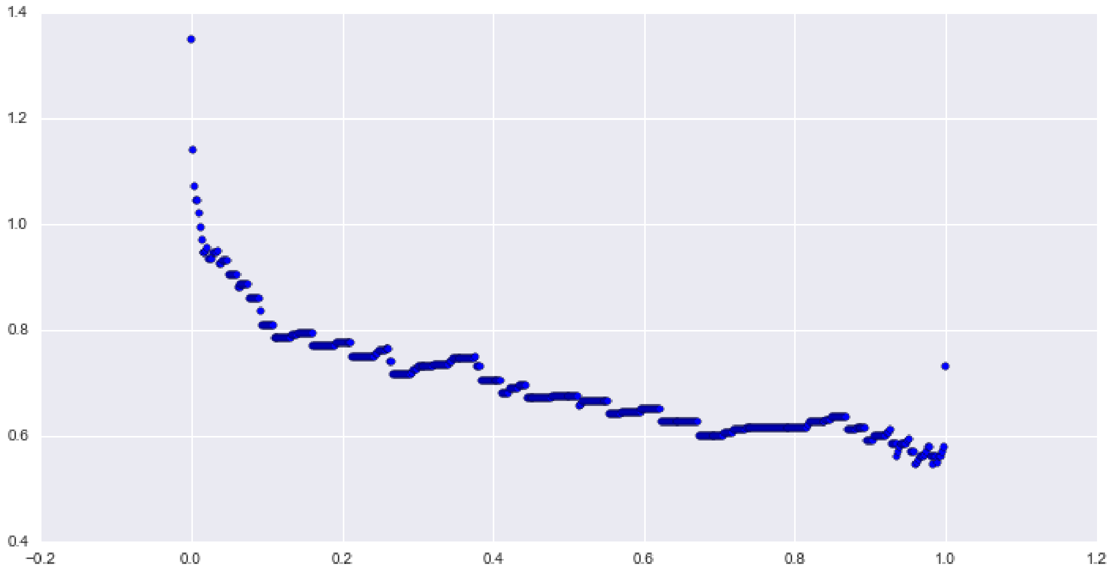
5 Changing the 0.5 probabilistic threshold

As shown below we manage to lower the cost by being a lot more conservative than the model and allowing the credit only when the model is very confident about its prediction.

In [133]:
```python
def chooseThreshold(model,new_threshold):
    prediction = []
    probas = model.predict_proba(X_test)
    for proba in probas:
        if proba[0] > new_threshold:
            prediction.append(1)
        else:
            prediction.append(2)
    return prediction
```

In [138]:
```python
thresholds = np.linspace(0,1,500)

for t in thresholds:
    plt.scatter(t,cost(y_test,chooseThreshold(NB_alone,t)))

new_cost = cost(y_test,chooseThreshold(nb_model,0.95))
std_cost = float(0.675)
increase = (std_cost - new_cost) / std_cost
print 'Changing the threshold to {0} improves our cost by {1:.2f} %. Making it {2}'.format(0.
```

```
Changing the threshold to 0.95 improves our cost by 12.59 %. Making it 0.59
```



5.1 Ordinal Values turned to numeric attributes

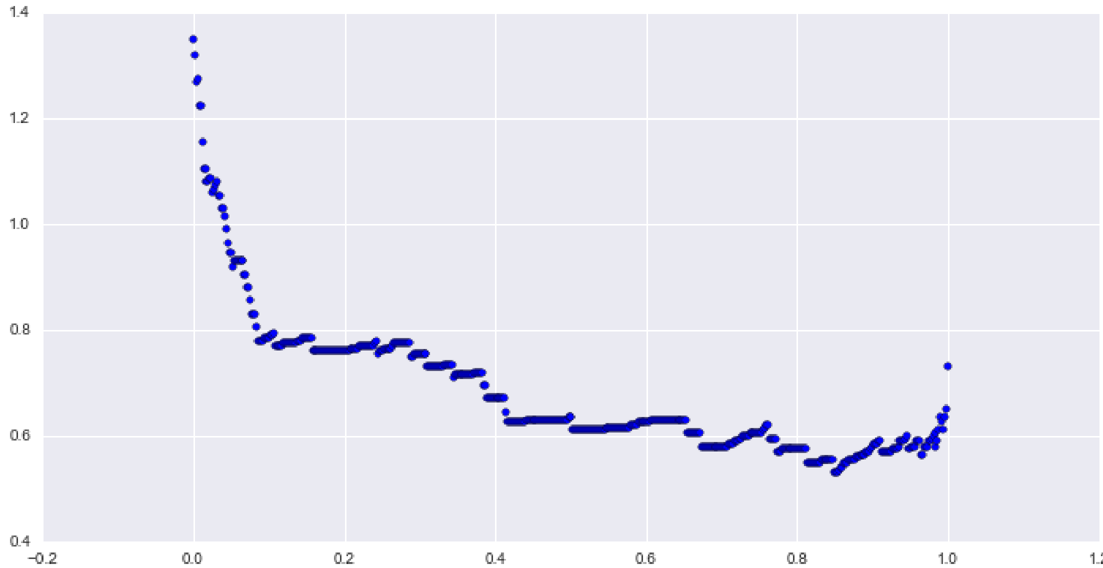
In [139]:
```
NB_num = GaussianNB()
NB_num.fit(X_train_num,y_train_num)

NB_num_predictions = NB_num.predict(X_test_num)

print "Naive Bayes 2"
print cost(y_test_num,NB_num_predictions)
```

```
Naive Bayes 2
0.635
```

In [140]:
```
def chooseThreshold(model,new_threshold):
    prediction = []
    probas = model.predict_proba(X_test_num)
    for proba in probas:
        if proba[0] > new_threshold:
            prediction.append(1)
        else:
            prediction.append(2)
    return prediction
```

In [141]:
```
thresholds = np.linspace(0,1,500)

for t in thresholds:
    plt.scatter(t,cost(y_test_num,chooseThreshold(NB_num,t)))

print cost(y_test,chooseThreshold(NB_num,0.85))
```

```
0.53
```



Below we can have a look at the predictions that did match the test data against which we tested our model.

```
In [225]: wrong_predictions = []

          for i,v in enumerate(y_test):
              if v != chooseThreshold(NB_num,0.85)[i]:
                  wrong_predictions.append(y_test.index[i])

          wrong = data.iloc[wrong_predictions,:]
```

```
In [229]: #wrong[wrong['result'] == 2]
```

```
In [228]: #wrong[wrong['result'] == 1]
```

6 Conclusion

In this Capstone project we manage to develop a model allowing a bank to profitably screen borrowers' applications.

Our final model performed 0.53 versus 0.7 which was the target we wanted to beat in order for a finantial institution to earn money.

Along the way, we discovered that using ordinal values on a set of 6 features out of 20 helped us improve our model. Before running our Naive Bayes model we tried to reduce the number of features keeping only the features considered as important for a Decision Tree but the results were not sufficiantly significant to justify for the increased complexity.

As it is costly to have borrowers defaulting, we also decided to change the treshold of the model so that it predicts that someone should be accepted when it more certain about this decision.