scoring

February 11, 2016

1 Building a classifier for credit acceptance

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

Now, let's inspect the data.

In [1]:
```
%matplotlib inline
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(rc={"figure.figsize": (12, 6)})
```

```
/usr/local/lib/python2.7/site-packages/matplotlib/__init__.py:872: UserWarning: axes.color_cycle is depre
  warnings.warn(self.msg_depr % (key, alt_key))
```

In [2]:
```
data = pd.read_csv('all.tsv', sep=' ', header=None, names= ["bank_account_status","duration_mon

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[2]:   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]
```

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

```
In [3]: data_numeric = pd.read_csv('numeric.tsv', delim_whitespace=True, header=None)
        data_numeric.head()
```

```
Out[3]:     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]
```

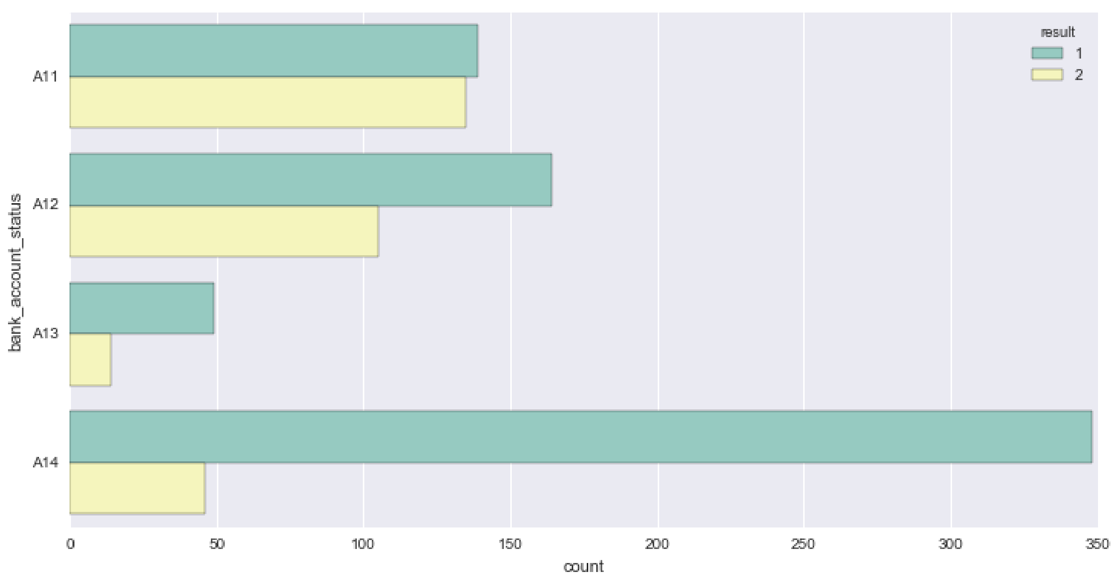
```
In [4]: print "credit average is : {0:.0f} DM".format(data['credit_amount'].mean())
```

```
credit average is : 3271 DM
```

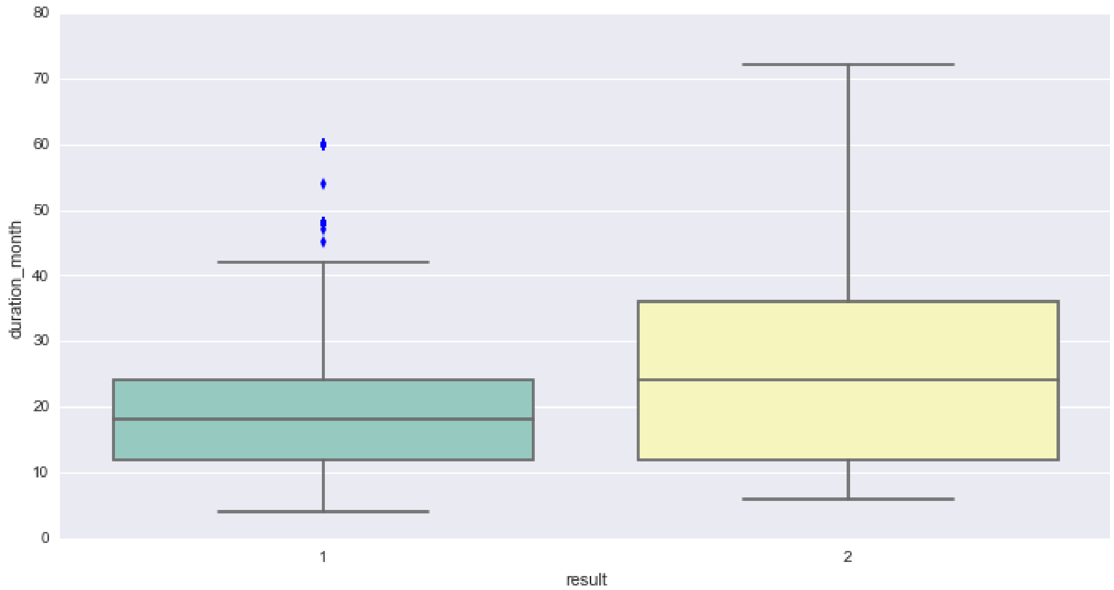
1.1 Exploring the data

Let's visualize the data and see if we can spot interesting patterns that could differenciate "good" and "bad" borrowers.

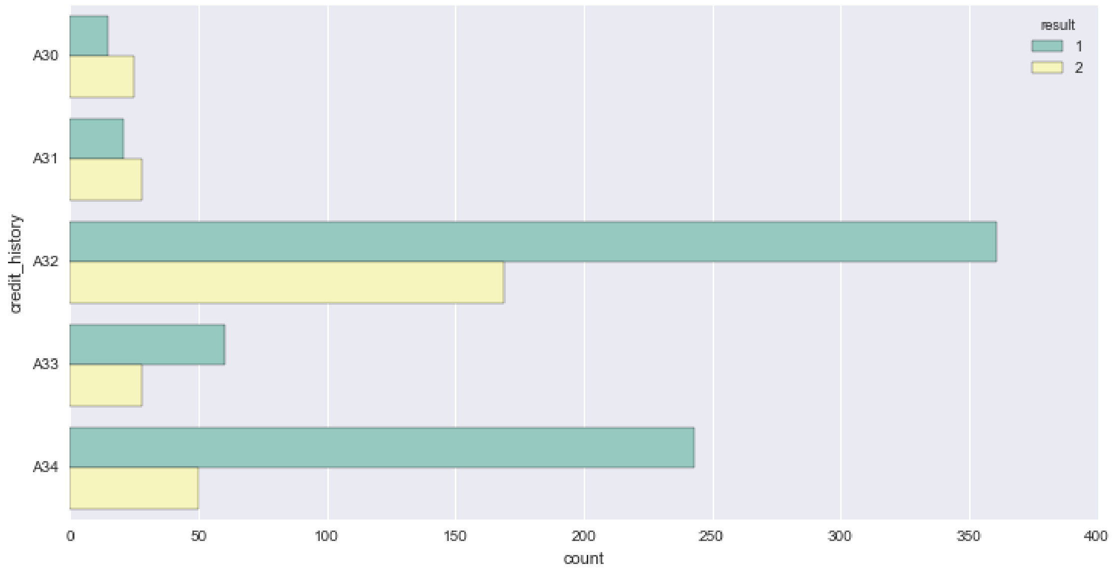
```
In [5]: features = data.ix[:,:-1]
        features = features.columns.tolist()
        a0 = sns.countplot(y=features[0], hue="result", data=data,order=np.unique(data[features[0]].valu
```



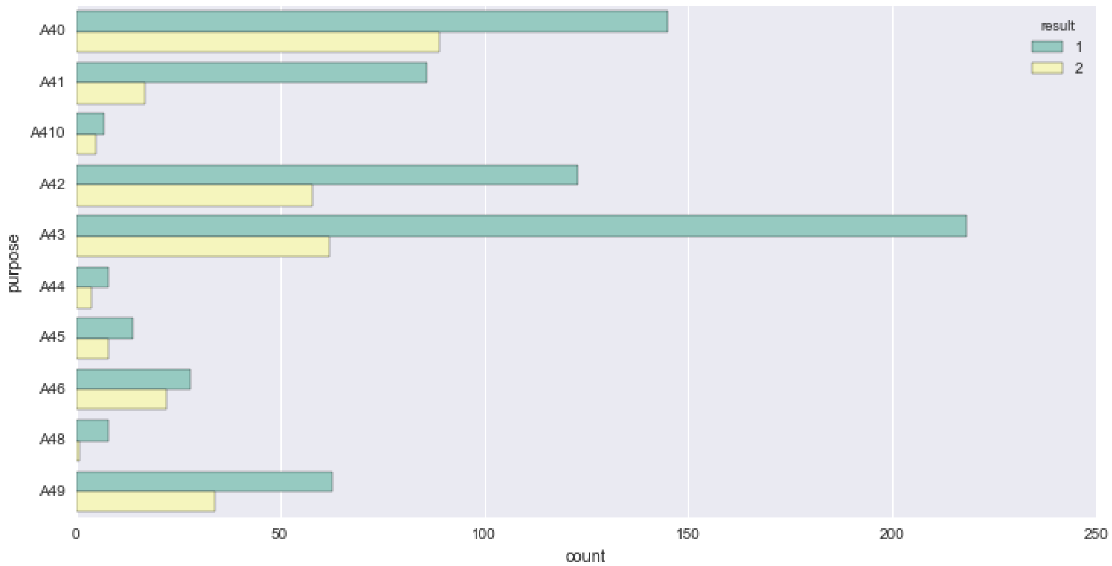

```
In [6]: a1 = sns.boxplot(x="result", y="duration_month", data=data,palette="Set3")
```



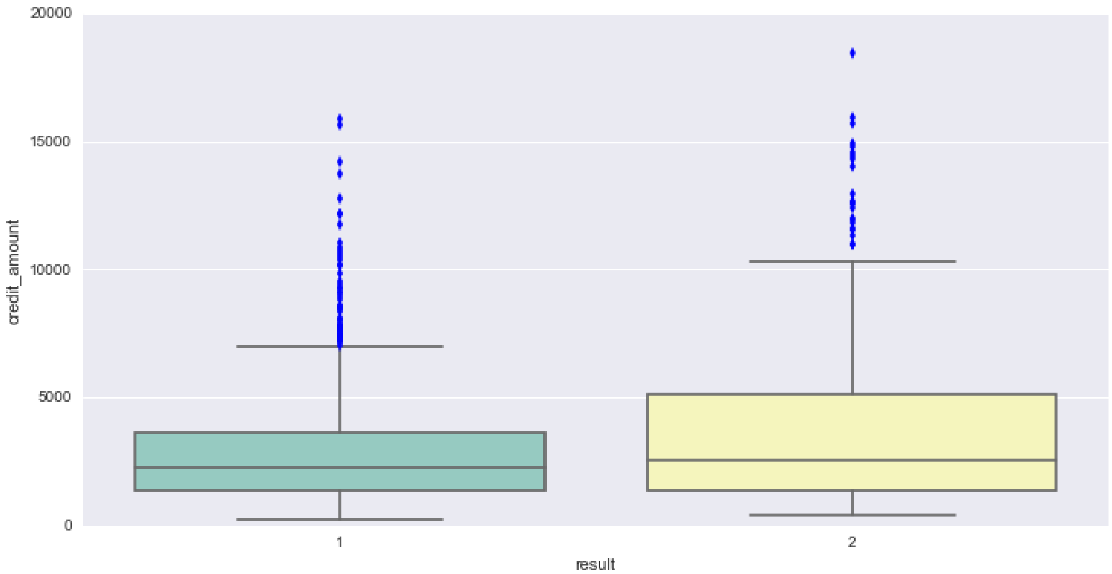

```
In [7]: a2 = sns.countplot(y=features[2], hue="result", order=np.unique(data[features[2]].values), data=
```



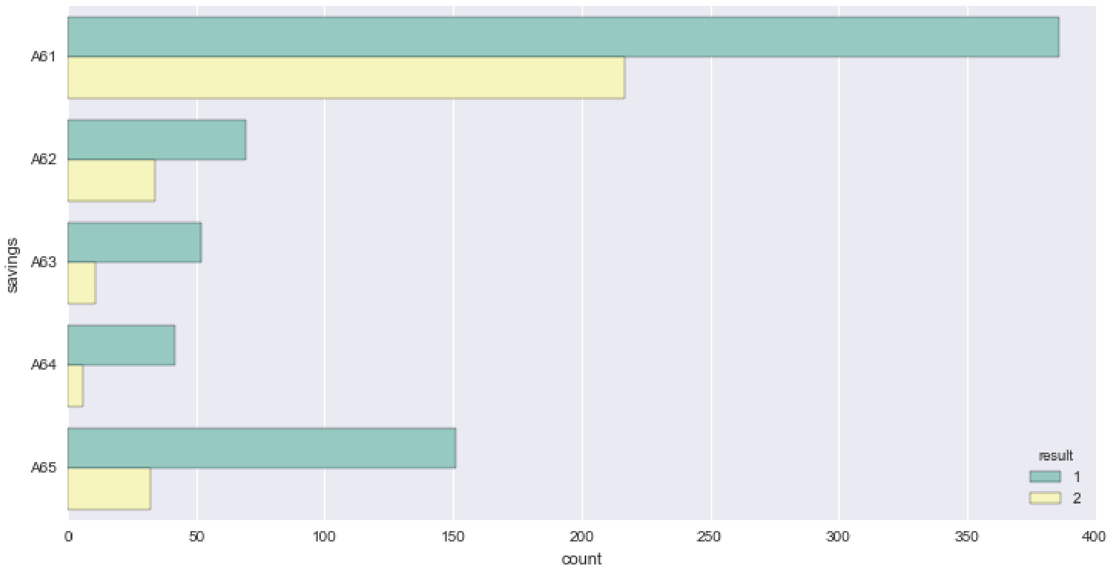

```
In [8]: a3 = sns.countplot(y=features[3], hue="result", order=np.unique(data[features[3]].values), data=
```



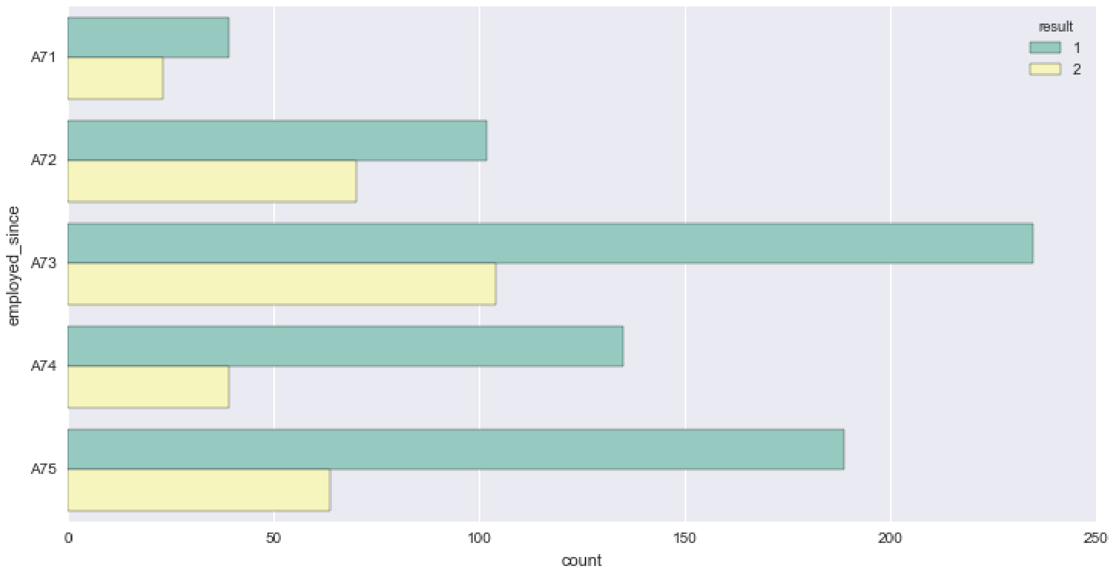

```
In [9]: a1 = sns.boxplot(x="result", y="credit_amount", data=data,palette="Set3")
```



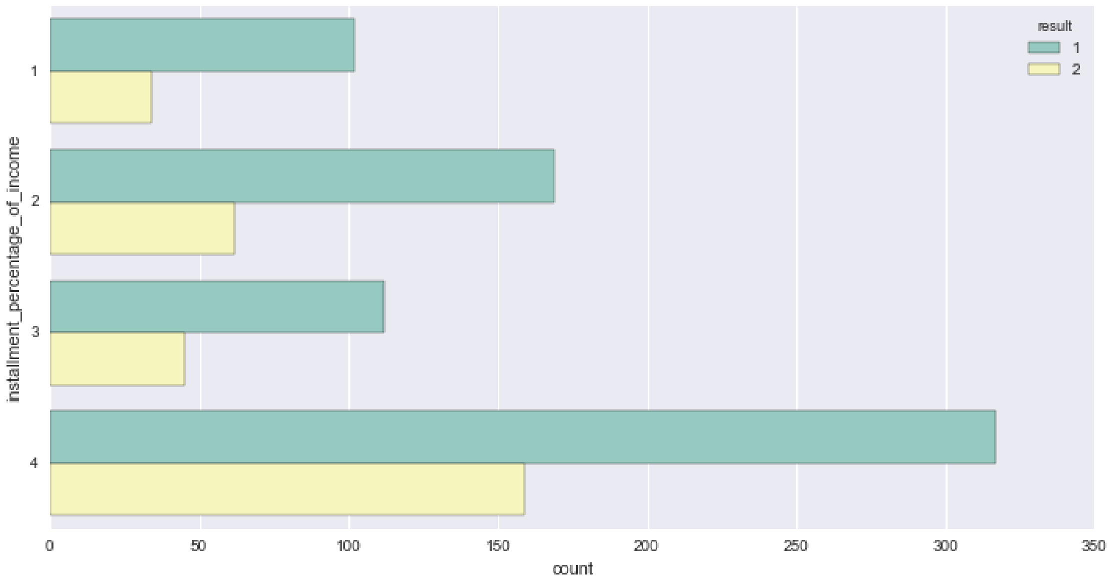

```
In [10]: a5 = sns.countplot(y=features[5], hue="result", order=np.unique(data[features[5]].values), data
```



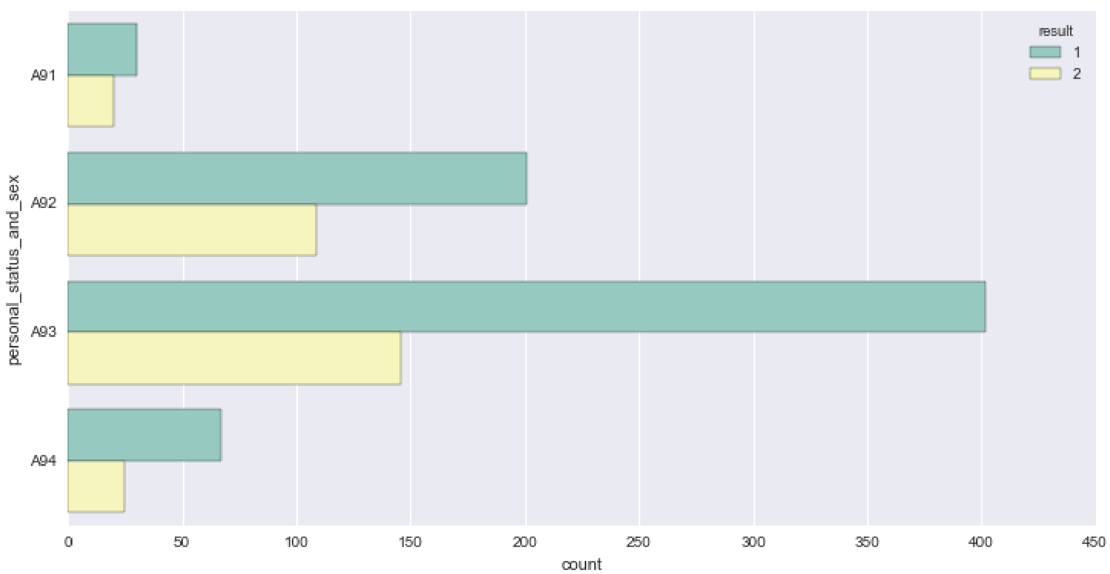

```
In [11]: a6 = sns.countplot(y=features[6], hue="result", order=np.unique(data[features[6]].values), data
```



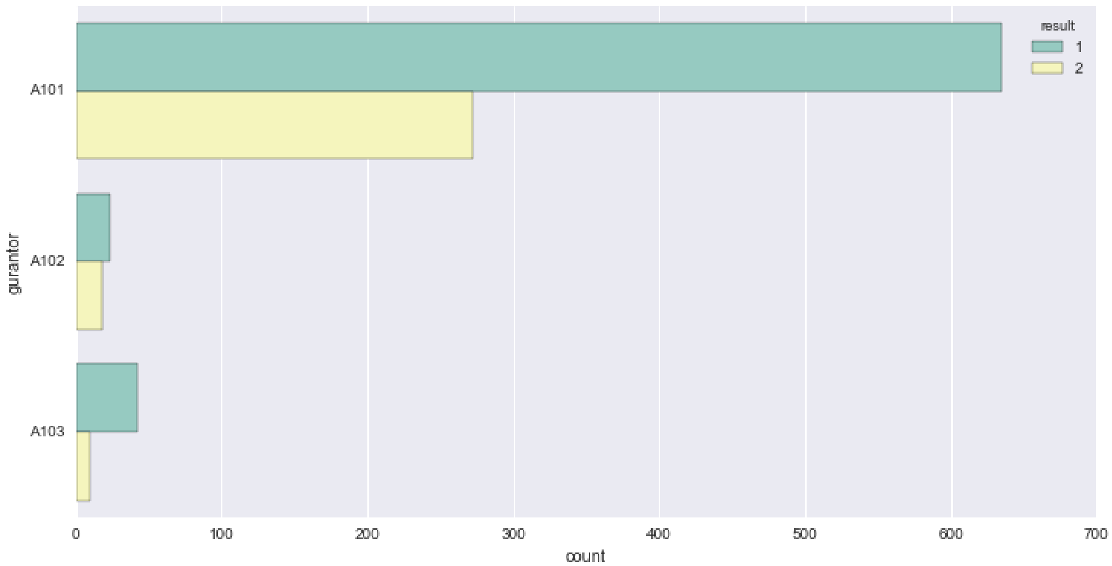

```
In [12]: a7 = sns.countplot(y=features[7], hue="result", order=np.unique(data[features[7]].values), data
```



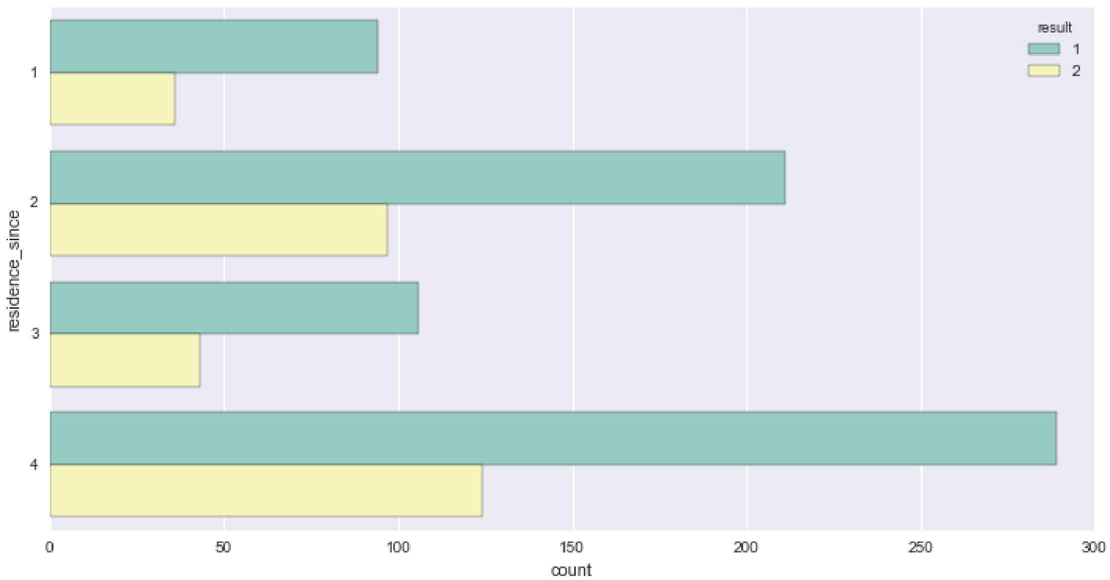

```
In [13]: a8 = sns.countplot(y=features[8], hue="result", order=np.unique(data[features[8]].values), data
```



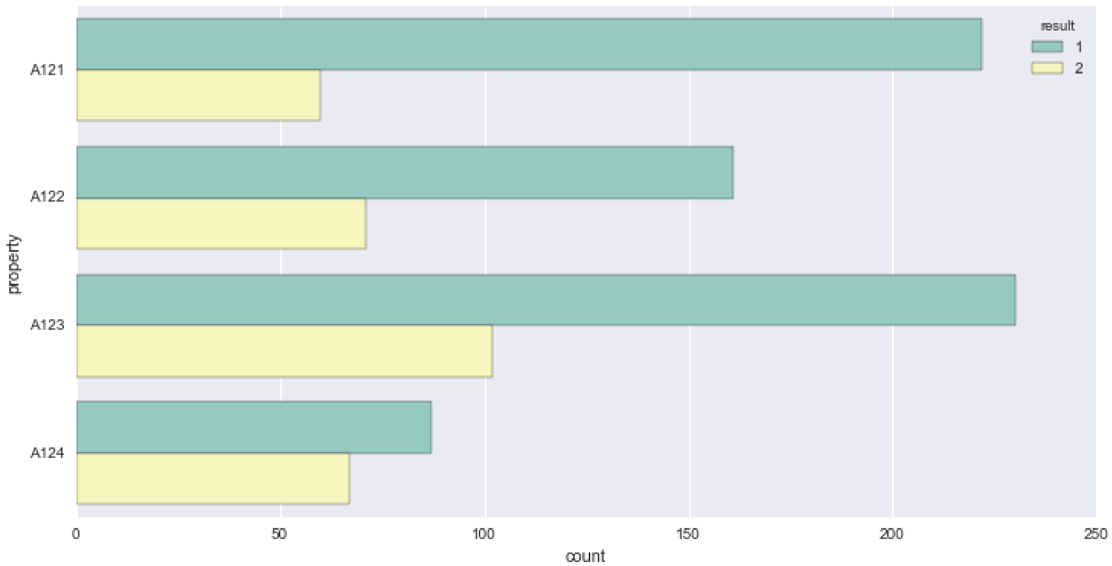

```
In [14]: a9 = sns.countplot(y=features[9], hue="result", order=np.unique(data[features[9]].values), data
```



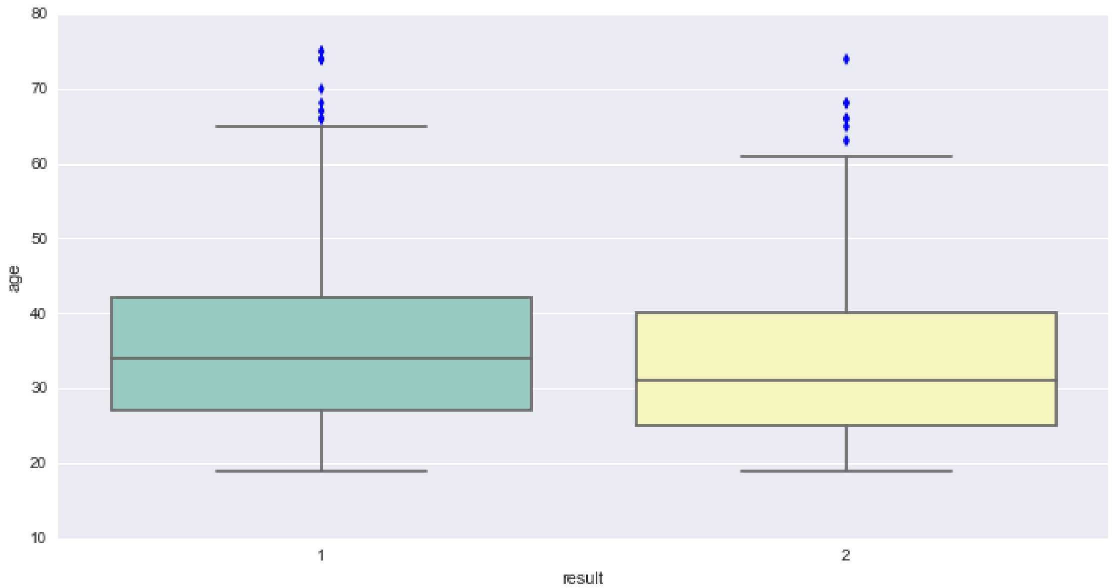

```
In [15]: a10 = sns.countplot(y=features[10], hue="result", order=np.unique(data[features[10]].values), d
```



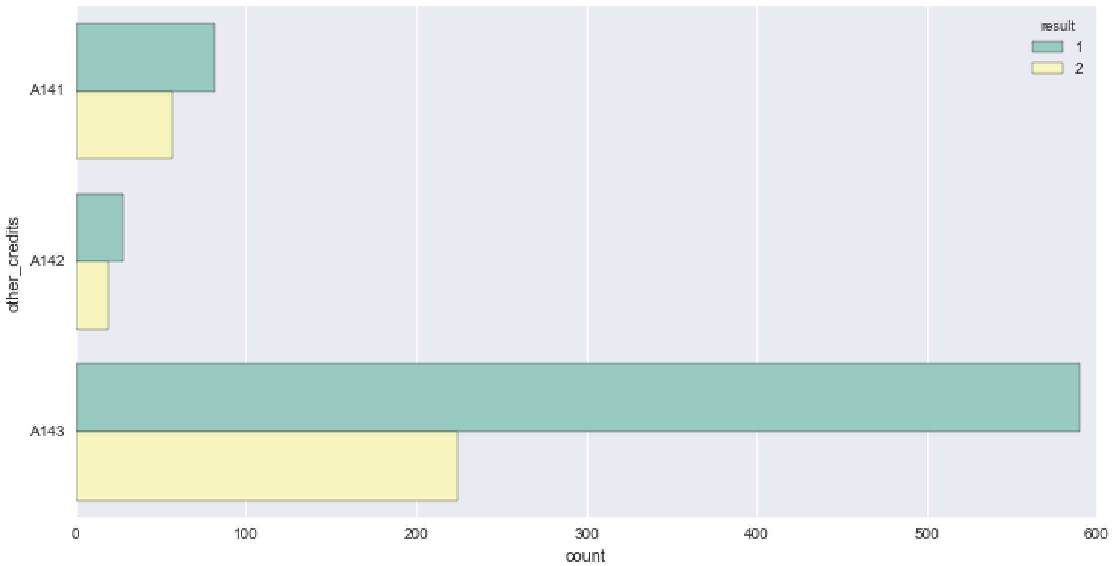

```
In [16]: a11 = sns.countplot(y=features[11], hue="result", order=np.unique(data[features[11]].values), d
```



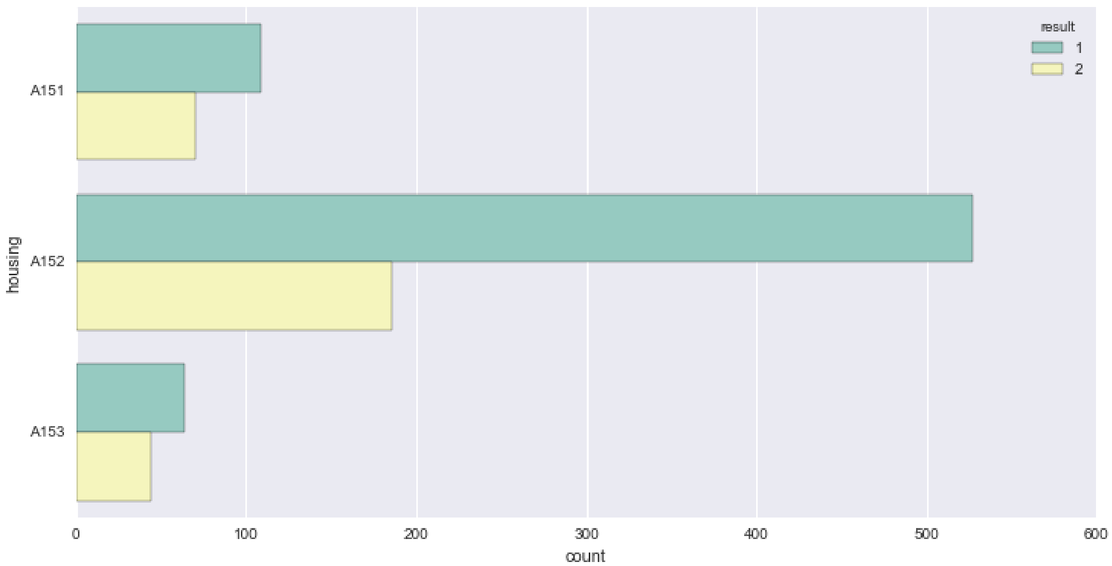

```
In [17]: a12 = sns.boxplot(x="result", y="age", data=data,palette="Set3")
```



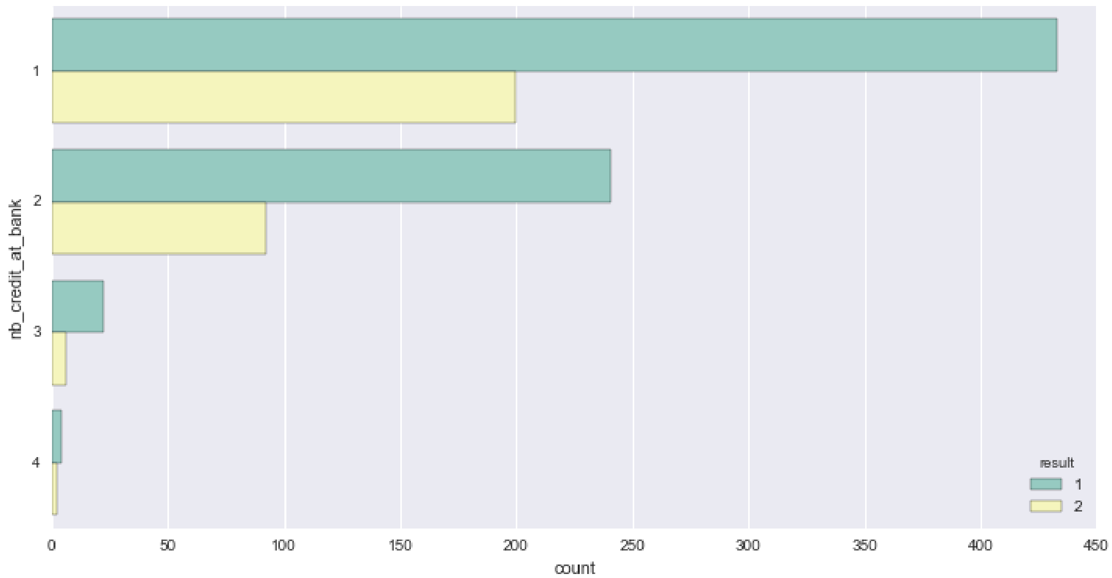

```
In [18]: a13 = sns.countplot(y=features[13], hue="result", order=np.unique(data[features[13]].values), c
```



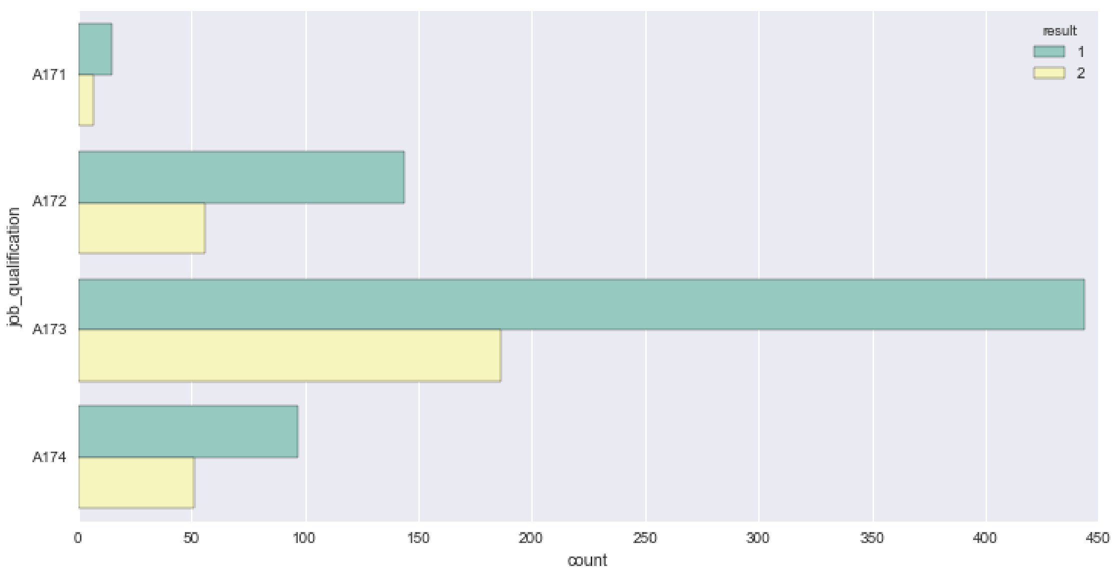

```
In [19]: a14 = sns.countplot(y=features[14], hue="result", order=np.unique(data[features[14]].values), c
```



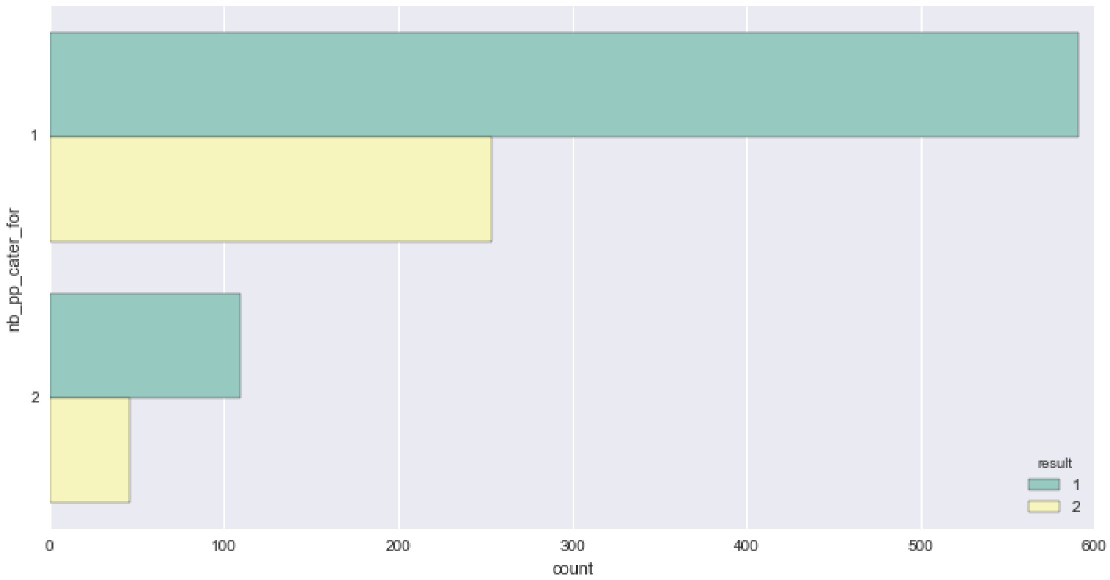

```
In [20]: a15 = sns.countplot(y=features[15], hue="result", order=np.unique(data[features[15]].values), c
```



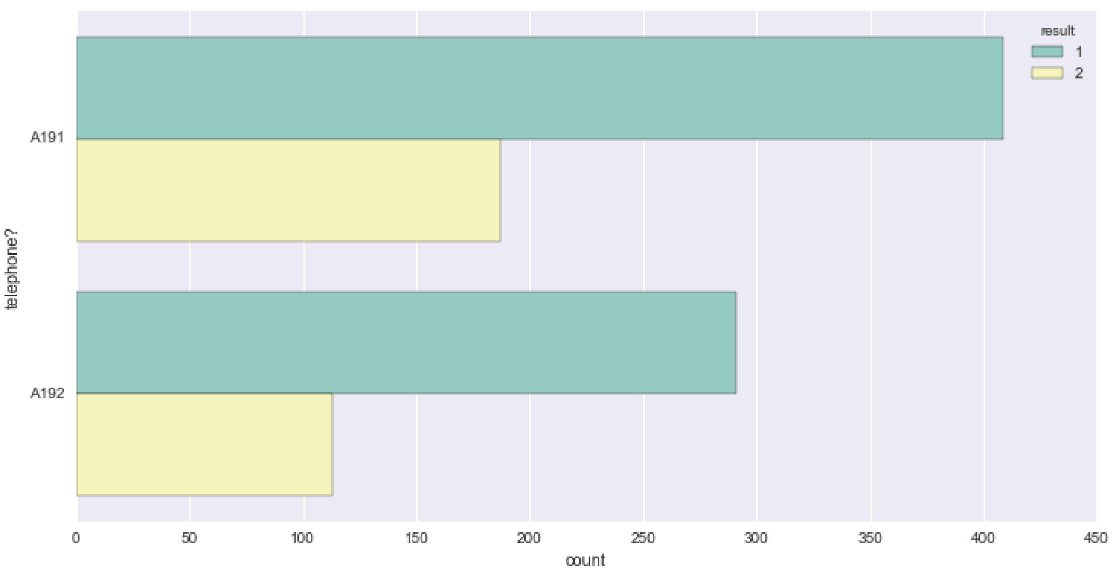

```
In [21]: a16 = sns.countplot(y=features[16], hue="result", order=np.unique(data[features[16]].values), c
```



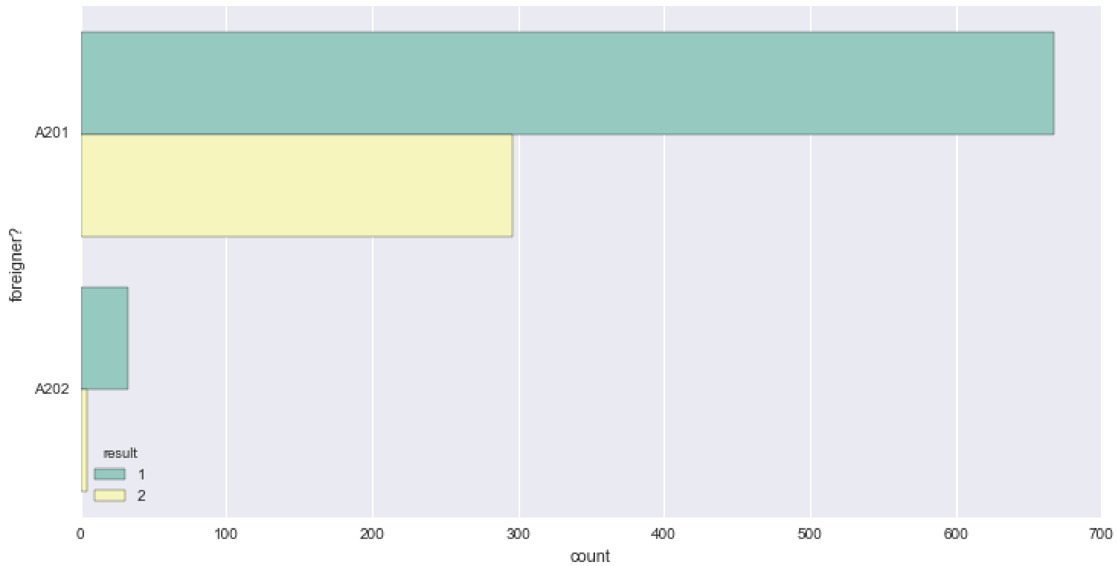

```
In [22]: a17 = sns.countplot(y=features[17], hue="result", order=np.unique(data[features[17]].values), c
```




```
In [23]: a18 = sns.countplot(y=features[18], hue="result", order=np.unique(data[features[18]].values), c
```




```
In [24]: a19 = sns.countplot(y=features[19], hue="result", order=np.unique(data[features[19]].values), c
```



Those are the most important findings we can derive from below: - Borrowers with no checking account seem to be risker - It is confirmed that if the credit history reflects a critical situation, borrower is riskier - People taking a credit for a radio/television are riskier - People without a saving account are riskier - Surprisingly, people more than 7 years on a job seem to be riskier - Foreigners are also 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 III. 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 [25]: X = data.ix[:,:-1]
         y = data['result']
```

```
In [26]: X.columns.tolist()
```

```
Out[26]: ['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 [27]:
```
def preprocess(X,convert_numeric=False):
    outX = pd.DataFrame(index=X.index)
    target_cols = ['credit_history','employed_since','gurantor','property','other_credits','jol
    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 [28]:
```
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 [29]:
```
feature_index = [3,9,14,25,30,58]
corr_df = X_all.corr()
corr_df.iloc[feature_index,feature_index]
```

Out[29]:

	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 [30]: from sklearn.tree import DecisionTreeClassifier
         from sklearn.tree import export_graphviz
         from sklearn import cross_validation
         from sklearn.metrics import make_scorer
         from sklearn.metrics import confusion_matrix
         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
```

The cost function discussed earler that will be used to assess the performace of our models

```
In [31]: def cost(y,y_pred):
             confusion_m = confusion_matrix(y,y_pred)
             cost_matrix = np.array([[0,1],[5,0]])
             return np.diag(np.transpose(cost_matrix).dot(confusion_m)).sum()
         cost_estimate = make_scorer(cost,greater_is_better=False)
```

Some convinience methods

```
In [32]: 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 [33]: 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 [34]: 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 [35]: 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_num
```

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

```
In [37]: 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}
-149.17125
```

```
In [38]: 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): 0.001
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for training set: 112
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 138
------------------------------------------
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: 259
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 134
------------------------------------------
Training set size: 600
Training GaussianNB...
Done!
Training time (secs): 0.002
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for training set: 413
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 133
------------------------------------------
Training set size: 800
Training GaussianNB...
Done!
Training time (secs): 0.007
Predicting labels using GaussianNB...
```

```
Done!
Prediction time (secs): 0.003
Cost estimation for training set: 529
Predicting labels using GaussianNB...
Done!
Prediction time (secs): 0.001
Cost estimation for test set: 135
------------------------------------------
Training set size: 200
Training GridSearchCV...
Done!
Training time (secs): 4.917
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 154
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 205
------------------------------------------
Training set size: 400
Training GridSearchCV...
Done!
Training time (secs): 5.526
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 206
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 152
------------------------------------------
Training set size: 600
Training GridSearchCV...
Done!
Training time (secs): 6.245
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for training set: 384
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 197
------------------------------------------
Training set size: 800
Training GridSearchCV...
Done!
Training time (secs): 7.173
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.001
```

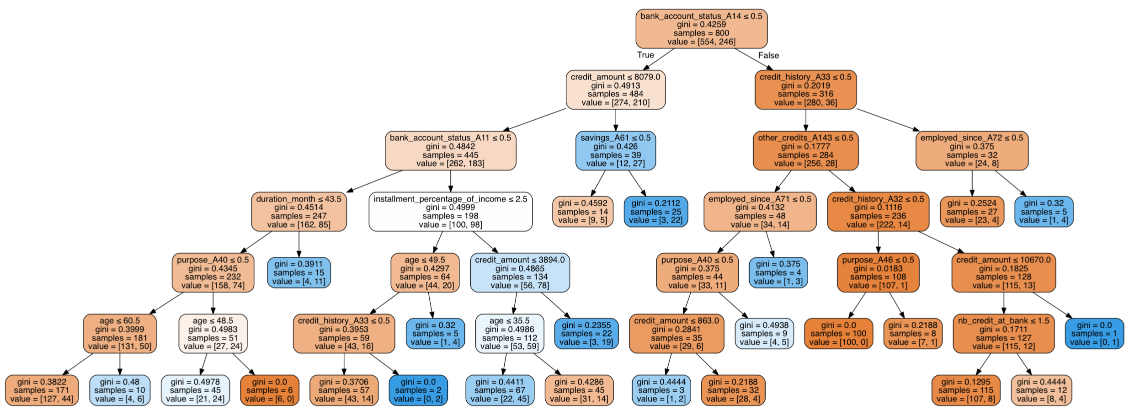
```
Cost estimation for training set: 555
Predicting labels using GridSearchCV...
Done!
Prediction time (secs): 0.000
Cost estimation for test set: 197
```

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 [39]:
```
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[39]:



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 [40]:
```
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','1.5
                   }
nb_model = RandomizedSearchCV(estimators,parameters,scoring=cost_estimate,verbose=1,n_jobs=-1,r
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 128 tasks      | elapsed:    2.0s
[Parallel(n_jobs=-1)]: Done 728 tasks      | elapsed:    9.5s
[Parallel(n_jobs=-1)]: Done 1728 tasks      | elapsed:   19.7s
[Parallel(n_jobs=-1)]: Done 2000 out of 2000 | elapsed:   22.3s finished
```

```
Out[40]: [mean: -117.03625, std: 12.94604, params: {'sel__estimator__min_samples_split': 15, 'sel__estimat
          mean: -118.79250, std: 7.83326, params: {'sel__estimator__min_samples_split': 29, 'sel__estimato
          mean: -119.58750, std: 7.49933, params: {'sel__estimator__min_samples_split': 19, 'sel__estimato
          mean: -119.80375, std: 6.67533, params: {'sel__estimator__min_samples_split': 15, 'sel__estimato
          mean: -119.98500, std: 7.45654, params: {'sel__estimator__min_samples_split': 19, 'sel__estimato
          mean: -120.18375, std: 7.46726, params: {'sel__estimator__min_samples_split': 19, 'sel__estimato
          mean: -120.80250, std: 15.19737, params: {'sel__estimator__min_samples_split': 25, 'sel__estimat
          mean: -120.78000, std: 7.62627, params: {'sel__estimator__min_samples_split': 19, 'sel__estimato
          mean: -120.96375, std: 10.71448, params: {'sel__estimator__min_samples_split': 23, 'sel__estimat
          mean: -121.37125, std: 8.06474, params: {'sel__estimator__min_samples_split': 17, 'sel__estimato
```

```
In [41]: 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
135
Naive Bayes combined with tree for feature selection
135
```

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.

So in this situation, we would 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 [43]: def chooseThreshold(model,new_threshold):
             prediction = []
             probas = model.predict_proba(X_test)
             for proba in probas:
                 if proba[0] > new_threshold:
                     prediction.append(1)
```

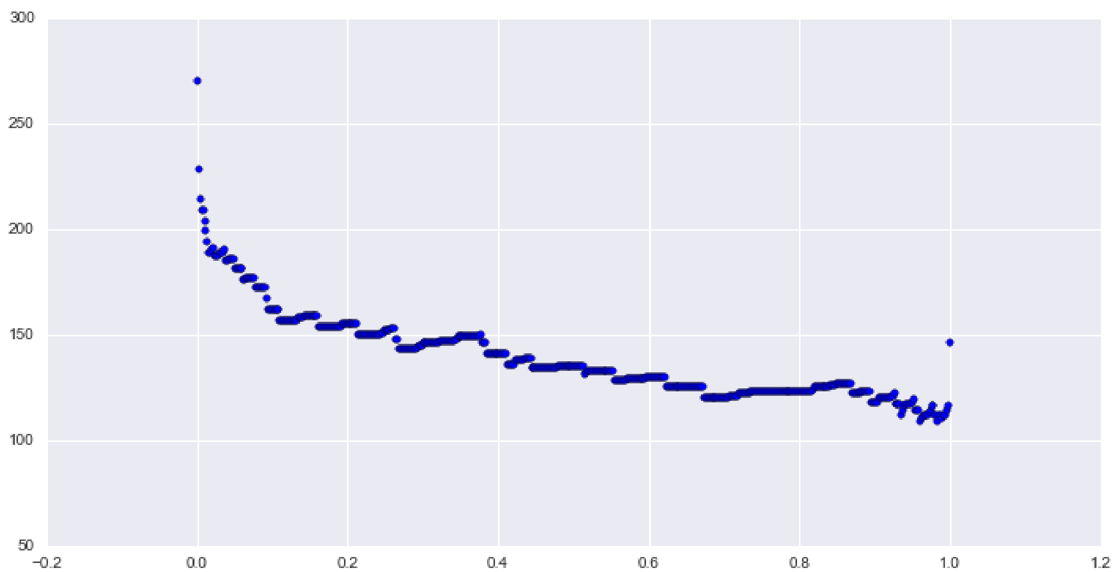
```
            else:
                prediction.append(2)
        return prediction
```

```
In [44]: 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,0.7))
         std_cost = float(135)
         increase = (std_cost - new_cost) / std_cost
         print 'Changing the threshold to {0} improves our cost by {1:.2f} %'.format(0.7,increase *100
```

```
Changing the threshold to 0.7 improves our cost by 11.11 %
```



5.1 Ordinal Values turned to numeric attributes

```
In [45]: 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
127
```

```
In [46]: def chooseThreshold(model,new_threshold):
             prediction = []
```

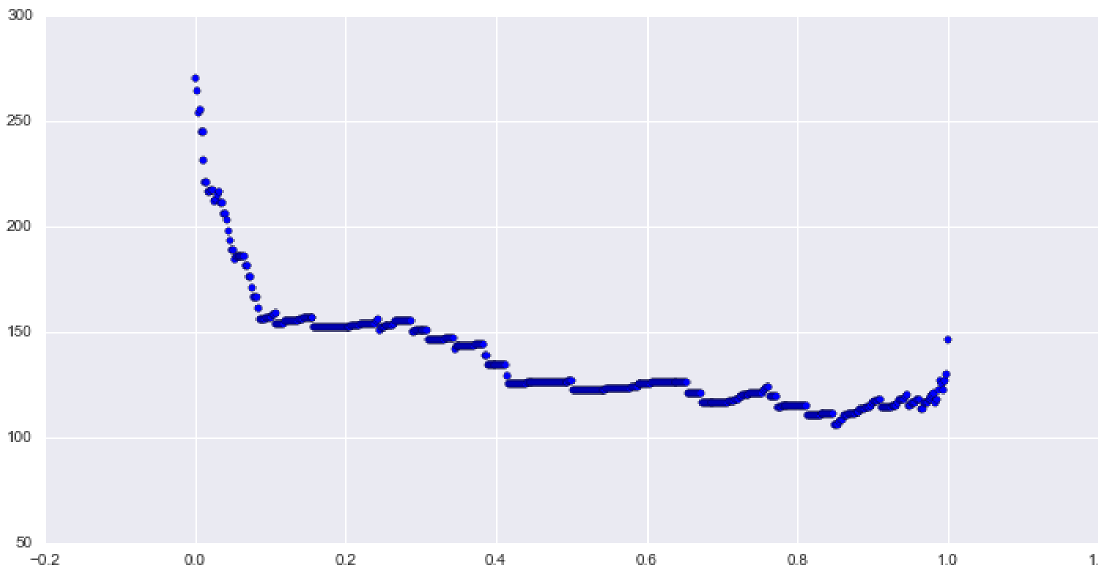
```
        probas = model.predict_proba(X_test_num)
        for proba in probas:
            if proba[0] > new_threshold:
                prediction.append(1)
            else:
                prediction.append(2)
        return prediction
```

In [47]:
```
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,0.8))
```

```
115
```



Converting categorical into ordinal values in this present case did not yield any improvement.