predict credit risk by random forest model

June 12, 2019

1 Midterm project

We are giving you a dataset and asking you to create a model to make predictions. This assignment is less structured than the previous ones. It is intended to be similar to what a potential employer would give you to evaluate your skills.

So: time to show off ! Use the knowledge you have acquired in the first 7 weeks of the course to create a Jupyter notebook that presents your work (and you) in the best light.

As usual, a "correct answer" (e.g., highly predictive model) is only part of the goal. Your entire research methodology should be evident, as per the "Recipe for ML" we have discussed in class.

2 The problem

You are given a dataset of customers who have applied for credit. Each customer is associated with some number of attributes, and a rating of being a Good/Bad credit risk.

2.1 The dataset

- The dataset is given in the file "credit_data.csv".
- Each row corresponds to one customer.
- There are 20 attributes, some numeric and some categorical.
- The last column "Credit Risk" encodes whether the customer was judged to be a Good/Bad credit risk
  - 1: Good credit risk
  - 2: Bad credit risk

You will use this data to come up with a model that predicts "Credit Risk" for a customer from the customer's attributes.

2.1.1 Attributes

A description of the attributes is given in the plain text file "credit_data_attributes.txt".

You will notice that the values for many attributes are encoded as strings. For example, attribute 7 is the customer's Employment Status, having possible values A71, A72, .., A75. Per the file, "A71" means the customer is unemployed.

Currency The currency units are "DM" (old German currency: the Deutsche Mark).

As you might guess: this data is not recent; you may find anachronisms other than the currency.

2.2 Take a look at features. There are twenty features.

In [129]:
```
import pandas as pd
import numpy as np
import os

train_data=pd.read_csv("data/credit_data.csv")
train_data.head()
```

Out[129]:
```
  Attribute 1  Attribute 2 Attribute 3 Attribute 4  Attribute 5 Attribute 6  \
0         A11            6         A34         A43         1169         A65
1         A12           48         A32         A43         5951         A61
2         A14           12         A34         A46         2096         A61
3         A11           42         A32         A42         7882         A61
4         A11           24         A33         A40         4870         A61

  Attribute 7  Attribute 8 Attribute 9 Attribute 10     ...      Attribute 12  \
0         A75            4         A93         A101     ...              A121
1         A73            2         A92         A101     ...              A121
2         A74            2         A93         A101     ...              A121
3         A74            2         A93         A103     ...              A122
4         A73            3         A93         A101     ...              A124

  Attribute 13  Attribute 14 Attribute 15 Attribute 16  Attribute 17  \
0           67          A143         A152            2          A173
1           22          A143         A152            1          A173
2           49          A143         A152            1          A172
3           45          A143         A153            1          A173
4           53          A143         A153            2          A173

  Attribute 18  Attribute 19 Attribute 20 Credit Risk
0            1          A192         A201           1
1            1          A191         A201           2
2            2          A191         A201           1
3            2          A191         A201           1
4            2          A191         A201           2

[5 rows x 21 columns]
```

2.3 To be clearer, I change the features's name to their real meanings.

In [130]:
```
train_data.rename(columns={'Attribute 1' : 'Checking account','Attribute 2' : 'Durat
                           'Attribute 4' : 'Purpose','Attribute 5' : 'Credit amount'
                           'Attribute 7' : 'Present employment','Attribute 8' : 'Ins
```

```
                                'Attribute 10' : 'Other debtors / guarantors','Attribute 
                                'Attribute 13' : 'Age','Attribute 14' : 'Other installmen
                                'Attribute 16' : 'Existing credits','Attribute 17' : 'Job
                                'Attribute 19' : 'Telephone','Attribute 20' : 'Foreign wo
         train_data.head()
```

```
Out[130]:   Checking account  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 Present employment  Installment rate Status and sex  \
         0     A65                A75                 4            A93
         1     A61                A73                 2            A92
         2     A61                A74                 2            A93
         3     A61                A74                 2            A93
         4     A61                A73                 3            A93

           Other debtors / guarantors     ...      Property Age  \
         0                       A101     ...          A121  67
         1                       A101     ...          A121  22
         2                       A101     ...          A121  49
         3                       A103     ...          A122  45
         4                       A101     ...          A124  53

            Other installment plans Housing Existing credits   Job  \
         0                     A143    A152                2  A173
         1                     A143    A152                1  A173
         2                     A143    A152                1  A172
         3                     A143    A153                1  A173
         4                     A143    A153                2  A173

           Number of people being liable  Telephone Foreign worker Credit Risk
         0                             1       A192           A201           1
         1                             1       A191           A201           2
         2                             2       A191           A201           1
         3                             2       A191           A201           1
         4                             2       A191           A201           2

         [5 rows x 21 columns]
```

2.4 There is the description of data. We can see that there is no missing values.

```
In [131]: train_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
```

```
Data columns (total 21 columns):
Checking account                 1000 non-null object
Duration month                   1000 non-null int64
Credit history                   1000 non-null object
Purpose                          1000 non-null object
Credit amount                    1000 non-null int64
Savings                          1000 non-null object
Present employment               1000 non-null object
Installment rate                 1000 non-null int64
Status and sex                   1000 non-null object
Other debtors / guarantors       1000 non-null object
Present residence                1000 non-null int64
Property                         1000 non-null object
Age                              1000 non-null int64
Other installment plans          1000 non-null object
Housing                          1000 non-null object
Existing credits                 1000 non-null int64
Job                              1000 non-null object
Number of people being liable    1000 non-null int64
Telephone                        1000 non-null object
Foreign worker                   1000 non-null object
Credit Risk                      1000 non-null int64
dtypes: int64(8), object(13)
memory usage: 164.1+ KB
```

```
In [132]: num_features = ["Duration month", "Credit amount", "Installment rate",
                          "Present residence","Age","Existing credits","Number of people being l
          cal_features=["Checking account","Credit history","Purpose","Savings",
                        "Present employment","Status and sex","Other debtors / guarantors",
                        "Property","Other installment plans","Housing","Job","Telephone","Fore
```

2.5 There is the description of all numeric features. To eliminate the effects of scale, I need to rescale them.

```
In [133]: train_data.describe()
```

```
Out[133]:        Duration month  Credit amount  Installment rate  Present residence  \
          count     1000.000000    1000.000000       1000.000000        1000.000000
          mean        20.903000    3271.258000          2.973000           2.845000
          std         12.058814    2822.736876          1.118715           1.103718
          min          4.000000     250.000000          1.000000           1.000000
          25%         12.000000    1365.500000          2.000000           2.000000
          50%         18.000000    2319.500000          3.000000           3.000000
          75%         24.000000    3972.250000          4.000000           4.000000
          max         72.000000   18424.000000          4.000000           4.000000

                         Age  Existing credits  Number of people being liable  \
```

```
count  1000.000000       1000.000000                         1000.000000
mean     35.546000          1.407000                            1.155000
std      11.375469          0.577654                            0.362086
min      19.000000          1.000000                            1.000000
25%      27.000000          1.000000                            1.000000
50%      33.000000          1.000000                            1.000000
75%      42.000000          2.000000                            1.000000
max      75.000000          4.000000                            2.000000

       Credit Risk
count  1000.000000
mean      1.300000
std       0.458487
min       1.000000
25%       1.000000
50%       1.000000
75%       2.000000
max       2.000000
```

2.6 To use pipeline, I transfer the string to number in categorical features

In [134]:
```
def caltoint(df,cal_features):
    for i in range(0,len(cal_features)):
        val=df.loc[:,cal_features[i]].unique()
        for j in range(0,len(val)):
            df.loc[df[cal_features[i]]==val[j],cal_features[i]]=j
    return df
X_train=caltoint(train_data.iloc[:,:-1],cal_features)
X_train.head()
```

Out[134]:
```
   Checking account  Duration month  Credit history  Purpose  Credit amount  \
0                 0               6               0        0           1169
1                 1              48               1        0           5951
2                 2              12               0        1           2096
3                 0              42               1        2           7882
4                 0              24               2        3           4870

   Savings  Present employment  Installment rate  Status and sex  \
0        0                   0                 4               0
1        1                   1                 2               1
2        1                   2                 2               0
3        1                   2                 2               0
4        1                   1                 3               0

   Other debtors / guarantors  Present residence  Property  Age  \
0                           0                  4         0   67
1                           0                  2         0   22
2                           0                  3         0   49
```

```
3                            1                   4          1   45
4                            0                   4          2   53

   Other installment plans  Housing  Existing credits  Job  \
0                        0        0                 2    0
1                        0        0                 1    0
2                        0        0                 1    1
3                        0        1                 1    0
4                        0        1                 2    0

   Number of people being liable  Telephone  Foreign worker
0                              1          0               0
1                              1          1               0
2                              2          1               0
3                              2          1               0
4                              2          1               0
```

2.7 I use MinMaxScaler to rescale data

In [135]:
```
from sklearn.preprocessing import MinMaxScaler
for item in num_features:
    X_train.loc[:,item]=MinMaxScaler().fit_transform(X_train.loc[:,item].astype('floa
X_train.head()
```

Out[135]:
```
   Checking account  Duration month  Credit history  Purpose  Credit amount  \
0                 0        0.029412               0        0       0.050567
1                 1        0.647059               1        0       0.313690
2                 2        0.117647               0        1       0.101574
3                 0        0.558824               1        2       0.419941
4                 0        0.294118               2        3       0.254209

   Savings  Present employment  Installment rate  Status and sex  \
0        0                   0          1.000000               0
1        1                   1          0.333333               1
2        1                   2          0.333333               0
3        1                   2          0.333333               0
4        1                   1          0.666667               0

   Other debtors / guarantors  Present residence  Property       Age  \
0                           0           1.000000         0  0.857143
1                           0           0.333333         0  0.053571
2                           0           0.666667         0  0.535714
3                           1           1.000000         1  0.464286
4                           0           1.000000         2  0.607143

   Other installment plans  Housing  Existing credits  Job  \
0                        0        0          0.333333    0
1                        0        0          0.000000    0
```

```
2                         0        0          0.000000    1
3                         0        1          0.000000    0
4                         0        1          0.333333    0

   Number of people being liable  Telephone  Foreign worker
0                            0.0          0               0
1                            0.0          1               0
2                            1.0          1               0
3                            1.0          1               0
4                            1.0          1               0
```

In [136]:
```python
y_train=np.array(train_data.loc[:,"Credit Risk"])
y_train.shape
```

Out[136]:
```
(1000,)
```

2.8 After rescalor, I need to select important features, since there are so many features.

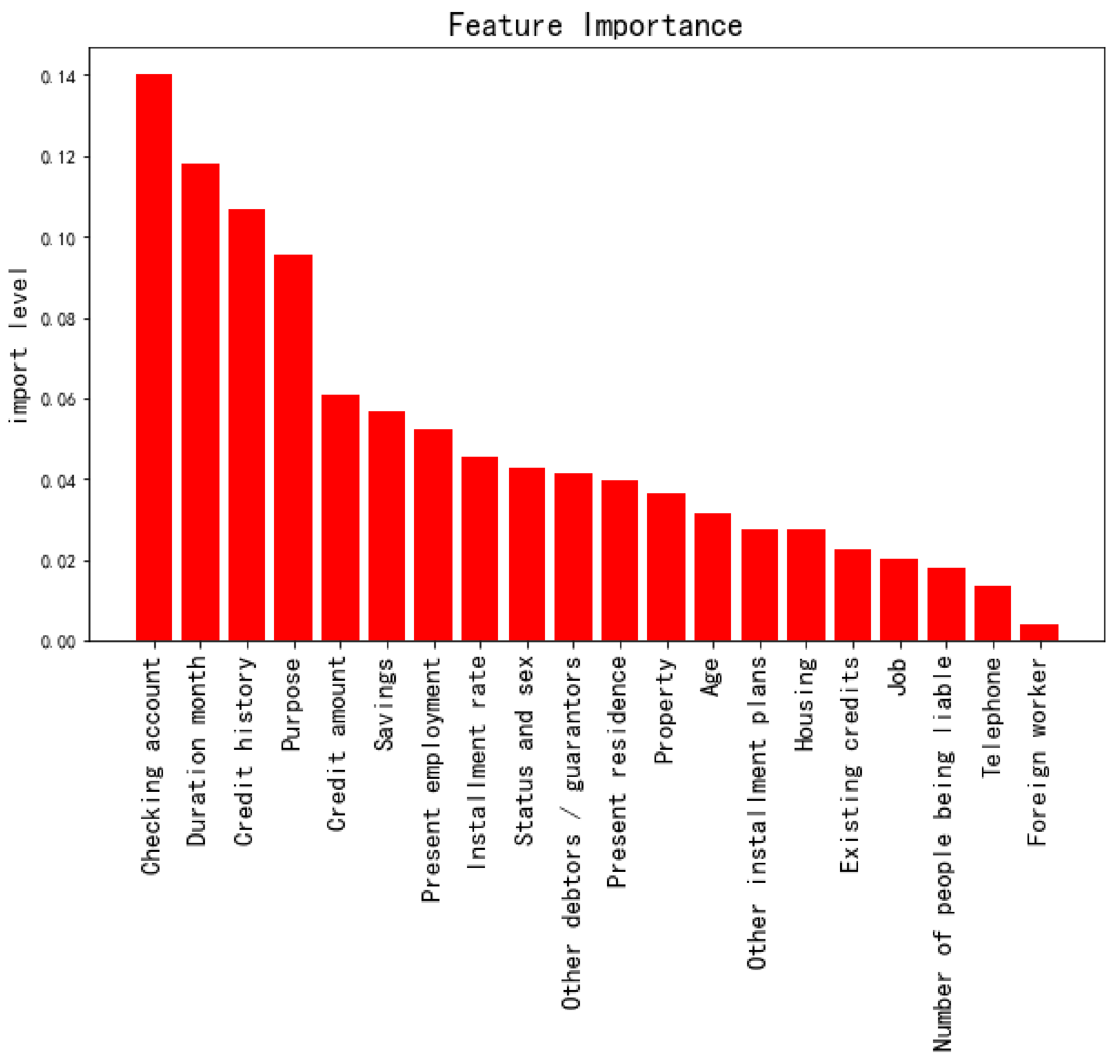
2.9 I used RandomForestClassifier to select important features by their gini scores.

In [137]:
```python
from sklearn.ensemble import RandomForestClassifier
RFC = RandomForestClassifier(n_estimators=100,n_jobs= -1 ,random_state=0)
RFC.fit(X_train,y_train)
import_level = RFC.feature_importances_
index = np.argsort(import_level)[::-1]
index
```

Out[137]:
```
array([ 4,  0, 12,  1,  2,  3,  6,  5, 10, 11,  7,  8, 16, 14, 13, 15, 18,
        9, 17, 19], dtype=int64)
```

2.10 Here are histogram of features importance

In [138]:
```python
import matplotlib.pyplot as plt
x_columns = train_data.columns[:-1]
plt.figure(figsize=(10,6))
plt.title('Feature Importance',fontsize = 18)
plt.ylabel('import level',fontsize = 15,rotation = 90)
plt.rcParams['font.sans-serif']=['SimHei']
plt.rcParams['axes.unicode_minus']=False
for i in range(x_columns.shape[0]):
    plt.bar(i,import_level[index[i]],color = 'red',align = 'center')
    plt.xticks(np.arange(x_columns.shape[0]),x_columns,rotation = 90,fontsize = 15)
```



2.11 Here are the values of features importance

```
In [139]: print("The important level of")
          for each in range(X_train.shape[1]):
              print(x_columns[each]+ ':      '+ str(import_level[index[each]]))
```

```
The important level of
Checking account:      0.1400783155226069
Duration month:      0.11799221162699004
Credit history:      0.10682943185117172
Purpose:      0.09545929097057712
Credit amount:      0.06100176497095757
Savings:      0.05659289840799419
Present employment:      0.05230916562428683
Installment rate:      0.04548117755457917
```

```
Status and sex:      0.042633372579666685
Other debtors / guarantors:      0.041363198836470 85
Present residence:      0.03948671747006202
Property:      0.0364959264030821
Age:      0.03141480226134662
Other installment plans:      0.027667540127786258
Housing:      0.02747548362501513
Existing credits:      0.02230367836984267
Job:      0.020353084078643384
Number of people being liable:      0.017797811646398657
Telephone:      0.013335831492652028
Foreign worker:      0.003928296579870168
```

2.12 I use the features whose importance is bigger than the mean imporance

In [140]:
```
featuresel=np.array(import_level>=import_level.mean())
realfeatures=X_train.columns[featuresel]
realfeatures
```

Out[140]:
```
Index(['Checking account', 'Duration month', 'Credit history', 'Purpose',
       'Credit amount', 'Present employment', 'Age'],
      dtype='object')
```

2.13 I used pipelines to deal with categorical and numerical features. Through pipelines, I transform X_train dataframe to numpy ndarray.

In [141]:
```
from sklearn.base import BaseEstimator, TransformerMixin
from sklearn.preprocessing import OneHotEncoder# A class to select numerical or cate
from sklearn.pipeline import FeatureUnion
# since Scikit-Learn doesn't handle DataFrames yet
from sklearn.pipeline import Pipeline

class DataFrameSelector(BaseEstimator, TransformerMixin):
    def __init__(self, attribute_names):
        self.attribute_names = attribute_names
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        return X[self.attribute_names]

try:
    from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
except ImportError:
    from sklearn.preprocessing import Imputer as SimpleImputer

num_features = ["Duration month", "Credit amount", "Age"]
num_pipeline = Pipeline([("select_numeric", DataFrameSelector( num_features )),("impu
                                                            SimpleImputer(strategy="me
```

```
In [142]: class MostFrequentImputer(BaseEstimator, TransformerMixin):
              def fit(self, X, y=None):
                  self.most_frequent_ = pd.Series([X[c].value_counts().index[0] for c in X],
                                                  index=X.columns)
                  return self
              def transform(self, X, y=None):
                  return X.fillna(self.most_frequent_)

          cat_features = ["Checking account", "Credit history", "Purpose","Present employment"]
          cat_pipeline = Pipeline([("select_cat", DataFrameSelector( cat_features )),
                                   ("imputer", MostFrequentImputer()),
                                   ("cat_encoder", OneHotEncoder(sparse=False))])
```

```
In [143]: from sklearn.pipeline import FeatureUnion
          preprocess_pipeline = FeatureUnion(transformer_list=[("num_pipeline", num_pipeline),

          X = preprocess_pipeline.fit_transform(X_train)
```

```
D:\anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:368: FutureWarning: The handl
If you want the future behaviour and silence this warning, you can specify "categories='auto'"
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integers
  warnings.warn(msg, FutureWarning)
```

2.14 Therefore, we get our final training data, which is x, and final target data, which is y_train.

2.15 Before choosing model, I selects the baseline model.

```
In [144]: from sklearn.dummy import DummyClassifier
          from sklearn.model_selection import cross_val_score
          from sklearn.model_selection import cross_val_predict
          strats = { "stratified": {},"uniform": {},"constant": {"constant": 1}}
          plt_num = 1
          # Compute Accuracy for various baseline classifiers
          for strat, args in strats.items():
              dmy_clf = DummyClassifier(strategy=strat, **args)
              print(dmy_clf)
              acc_scores_dmy = cross_val_score(dmy_clf, X, y_train,scoring="accuracy",cv=5)
              SCORE_BASELINE=acc_scores_dmy.mean()
              print("{s}: SCORE_BASELINE = {a:.2f}".format(s=strat, a=SCORE_BASELINE))
```

```
DummyClassifier(constant=None, random_state=None, strategy='stratified')
stratified: SCORE_BASELINE = 0.59
DummyClassifier(constant=None, random_state=None, strategy='uniform')
uniform: SCORE_BASELINE = 0.50
DummyClassifier(constant=1, random_state=None, strategy='constant')
constant: SCORE_BASELINE = 0.70
```

2.16 We can see that when the constant model is the best when it always predicts credit risk 1.

2.17 Then I use logistic regression to predict at first. We can see that the cross_val_score is 0.739.

```
In [145]: from sklearn.linear_model import LogisticRegression
          from sklearn.model_selection import cross_val_score
          from sklearn.model_selection import cross_val_predict
          clf = LogisticRegression(C=200. / len(X),solver='saga', tol=0.0001)
          SCORE_1 = cross_val_score(clf, X, y_train,scoring="accuracy",cv=5).mean()
          SCORE_1

Out[145]: 0.739
```

2.18 Then I calculate confusion matrix and make a picture.

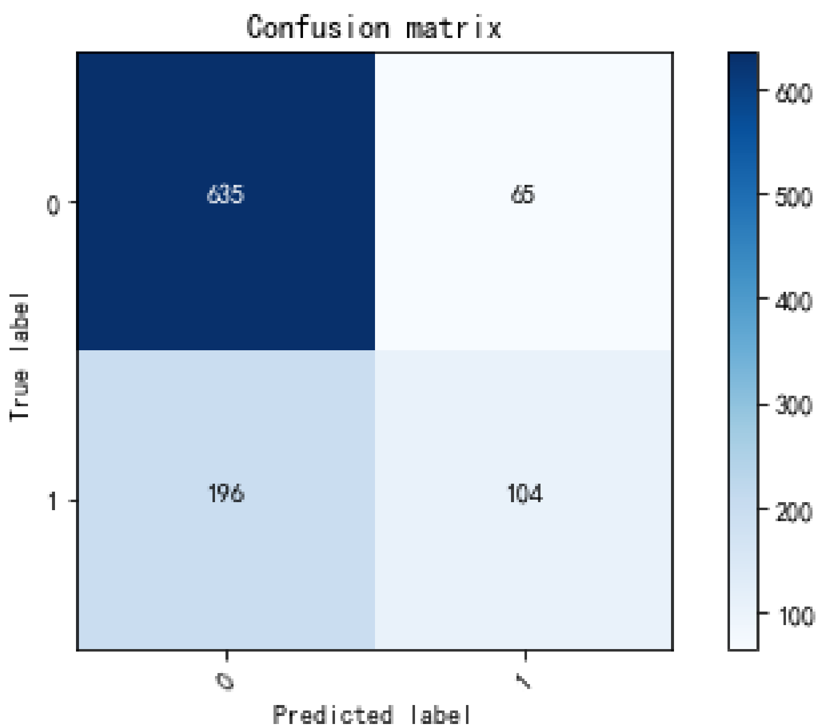
```
In [146]: import matplotlib.pyplot as plt
          import itertools
          def plot_confusion_matrix(cm, classes,normalize=False,title='Confusion matrix',cmap=
              """This function prints and plots the confusion matrix.
              Normalization can be applied by setting `normalize=True`.
              """
              if normalize:
              # Normalize by row sums
                  cm_pct = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                  cm = np.around( 100 * cm_pct, decimals=0).astype(int)
                  print("Normalized confusion matrix")
              else:
                  print('Confusion matrix, without normalization')
              plt.imshow(cm, interpolation='nearest', cmap=cmap)
              plt.title(title)
              plt.colorbar()
              tick_marks = np.arange(len(classes))
              plt.xticks(tick_marks, classes, rotation=45)
              plt.yticks(tick_marks, classes)
              fmt = '.2f' if normalize else 'd'
              fmt = 'd'
              thresh = cm.max() / 2.
              for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  # Plot coordinate system has origin in upper left corner
                  # - coordinates are (horizontal offset, vertical offset)
                  # - so cm[i,j] should appear in plot coordinate (j,i)
                  plt.text(j, i, format(cm[i, j], fmt),horizontalalignment="center",
                           color="white" if cm[i, j] > thresh else "black")
              plt.ylabel('True label')
              plt.xlabel('Predicted label')
              plt.tight_layout()
```

```
from sklearn.metrics import confusion_matrix
y_pred=cross_val_predict(clf, X, y_train,cv=5)
conf_mx=confusion_matrix(y_train,y_pred)
print(conf_mx)
```

```
[[635  65]
 [196 104]]
```

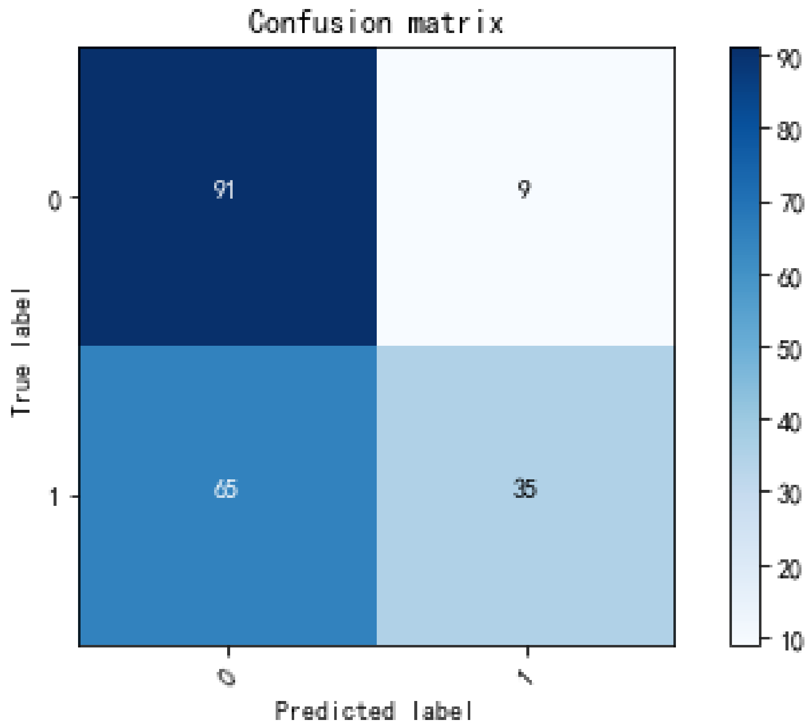
```
In [147]: plot_confusion_matrix(conf_mx, range(2))
```

```
Confusion matrix, without normalization
```




```
In [148]: plot_confusion_matrix(conf_mx, range(2),normalize=True)
```

```
Normalized confusion matrix
```



2.19 We can see that for credit risk 1, our prediction is really good. However, for credit risk 2, our predition performs badly.

2.20 Maybe I can try another model. I use random forest model to predict. Since this is classificaiton problem, I make the max_features equal to sqrt of total features.

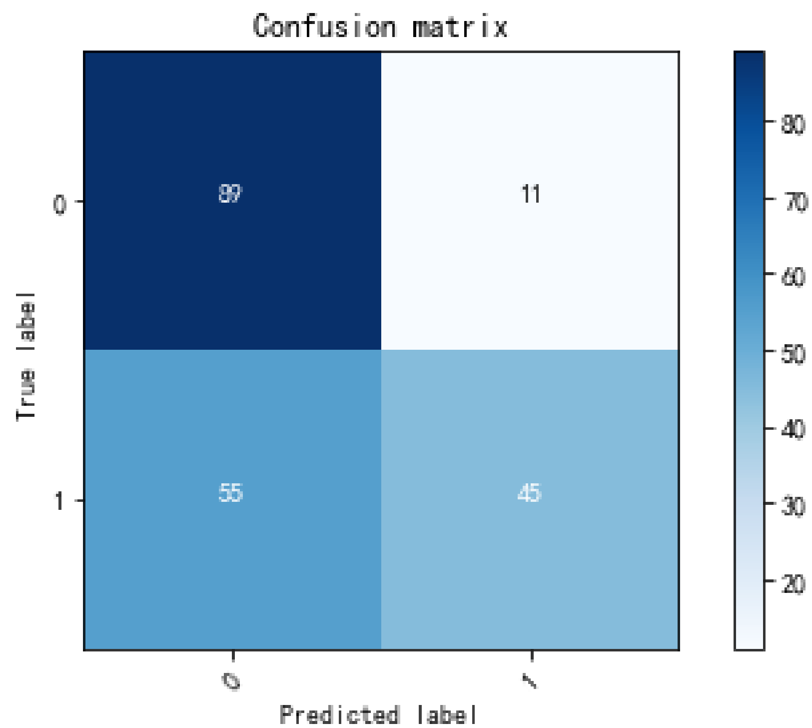
In [149]:
```
from sklearn.tree import DecisionTreeRegressor
from sklearn.ensemble import RandomForestClassifier
import math

from sklearn.datasets import load_iris
rf=RandomForestClassifier(n_estimators=100,max_features=round(math.sqrt(X.shape[1]))
rf.fit(X,y_train)
SCORE_2 = cross_val_score(rf, X, y_train,scoring="accuracy",cv=5).mean()
SCORE_2
```

Out[149]:
```
0.755
```

2.21 We can see that final score is 0.755, whichi is better than logistic regression.

In [150]:
```
y_pred=cross_val_predict(rf, X, y_train,cv=5)
conf_mx=confusion_matrix(y_train,y_pred)
print(conf_mx)
plot_confusion_matrix(conf_mx, range(2),normalize=True)
```

```
[[621  79]
 [166 134]]
Normalized confusion matrix
```



2.22 We can see that prediction for credit risk 2 is much better although the prediciton for credit risk 1 is a little worse. There is some trade off between two predictions.

2.23 For higher accuracy, I choose random forest model.

2.24 Below are credit_medel.predict

```
In [151]: class credit_model(object):
              def __init__(self, X_train, y_train): #X_train is dataframe, y_train is ndarray
                  self.X_train = X_train
                  self.y_train = y_train
              def predict(self):
                  from sklearn.base import BaseEstimator, TransformerMixin
                  from sklearn.preprocessing import OneHotEncoder# A class to select numerical
                  from sklearn.pipeline import FeatureUnion
                  # since Scikit-Learn doesn't handle DataFrames yet
                  from sklearn.pipeline import Pipeline
                  class DataFrameSelector(BaseEstimator, TransformerMixin):
                      def __init__(self, attribute_names):
```

```
            self.attribute_names = attribute_names
        def fit(self, X, y=None):
            return self
        def transform(self, X):
            return X[self.attribute_names]

    try:
        from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
    except ImportError:
        from sklearn.preprocessing import Imputer as SimpleImputer

    num_features = ["Duration month", "Credit amount", "Age"]
    num_pipeline = Pipeline([("select_numeric", DataFrameSelector( num_features )
                                                    SimpleImputer(strategy="me

    class MostFrequentImputer(BaseEstimator, TransformerMixin):
        def fit(self, X, y=None):
            self.most_frequent_ = pd.Series([X[c].value_counts().index[0] for c i
                                            index=X.columns)
            return self
        def transform(self, X, y=None):
            return X.fillna(self.most_frequent_)

    cat_features = ["Checking account", "Credit history", "Purpose","Present empl
    cat_pipeline = Pipeline([("select_cat", DataFrameSelector( cat_features )),
                     ("imputer", MostFrequentImputer()),
                     ("cat_encoder", OneHotEncoder(sparse=False))])
    from sklearn.pipeline import FeatureUnion
    preprocess_pipeline = FeatureUnion(transformer_list=[("num_pipeline", num_pip

    X = preprocess_pipeline.fit_transform(self.X_train)
    from sklearn.tree import DecisionTreeRegressor
    from sklearn.ensemble import RandomForestClassifier
    import math
    from sklearn.datasets import load_iris
    rf=RandomForestClassifier(n_estimators=100,max_features=round(math.sqrt(X.sha
    rf.fit(X,self.y_train)
    y_pred=cross_val_predict(rf, X, self.y_train,cv=5)
    return y_pred
```

2.25 Here is our prediction array.

```
In [152]: exp=credit_model(X_train,y_train)
          exp.predict()
```

```
D:\anaconda3\lib\site-packages\sklearn\preprocessing\_encoders.py:368: FutureWarning: The handl
If you want the future behaviour and silence this warning, you can specify "categories='auto'"
```

```
In case you used a LabelEncoder before this OneHotEncoder to convert the categories to integers
  warnings.warn(msg, FutureWarning)
```

```
Out[152]: array([1, 2, 1, 2, 1, 1, 1, 1, 1, 2, 2, 2, 2, 1, 2, 2, 1, 2, 2, 2, 1, 1,
                 1, 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1,
                 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 2, 1, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2,
                 2, 2, 1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2, 1,
                 1, 2, 2, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1,
                 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 2, 1,
                 1, 1, 1, 1, 2, 1, 2, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1,
                 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1,
                 1, 2, 1, 1, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1,
                 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1,
                 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2,
                 2, 1, 1, 2, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                 1, 1, 2, 1, 1, 2, 1, 2, 1, 2, 1, 1, 2, 2, 1, 2, 1, 1, 1, 1, 1, 1,
                 1, 1, 2, 1, 1, 1, 2, 2, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2,
                 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1,
                 2, 2, 1, 1, 2, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,
                 1, 2, 1, 1, 1, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 2,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1,
                 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 2,
                 1, 2, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 2, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 2, 1, 1, 2, 1,
                 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1,
                 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 1,
                 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 2, 2, 1, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 2, 2, 1, 1, 1, 1, 2,
                 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 2, 1, 1, 2, 1, 2,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 2, 2, 1, 2, 1, 1, 1,
                 1, 2, 2, 1, 1, 1, 1, 2, 2, 1, 1, 1, 2, 1, 2, 1, 1, 2, 2, 1, 2, 1,
                 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1,
                 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1,
                 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1,
                 1, 2, 2, 1, 1, 2, 1, 1, 1, 2, 2, 2, 1, 2, 2, 2, 1, 2, 2, 1, 2, 1,
                 1, 1, 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,
                 1, 2, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1,
                 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 2, 1, 2, 2, 1, 1, 2, 2, 1, 1, 1, 2,
                 1, 2, 1, 1, 2, 2, 2, 1, 2, 1, 1, 1, 1, 1, 2, 1, 1, 2, 2, 1, 1, 2,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1,
                 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 1,
                 1, 1, 2, 1, 1, 2, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1,
                 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 2, 2, 1, 1, 1, 1, 1,
                 2, 2, 2, 1, 1, 2, 2, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2,
                 2, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 2, 1, 1,
```

```
       1, 1, 1, 1, 2, 2, 1, 1, 1, 1, 1, 2, 1, 1, 1, 1, 1, 1, 2, 1, 1, 1,
       1, 1, 2, 1, 1, 1, 1, 1, 2, 1], dtype=int64)
```

2.26 Thanks for you reviewing!

2.27 Have a nice day!