Xue_Jiangguangyu_MidTerm_Project

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1 Credit Risk 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.

3 Your submission

There are some ground rules, mainly to make grading easier for the GA and instructor.

Your `sklearn` model should be stored in the variable `credit_model`; this will allow the GA to apply `sklearn` methods to this variable to evaluate your predictions, e.g. `>credit_model.predict( ... )`

Your submission must contain a Jupyter notebook in a file named >LastName_FirstName_MidTerm_Project.ipynb

where `LastName` and `FirstName` should be replaced with your name (as it appears on the class roster).

IF your submission consists of files in addition to this one notebook, you can submit a *single* zip file. This file **must** conform to the following rules: - The notebook must execute, unchanged, when unzipped into *an arbitrary directory* - This means that all paths, e.g., to data files or modules, must be *relative* and not absolute.

4 Credit Risk Project

Brief Introduction: In this project, **Logistic Model** and **Random Forest** are implemented to do the prediction. - For Logistic Model, categorical features are transformed into **dummy variables** and then one of them are dropped to reduce muti-colinearity - For Random Forest, **unbalanced data** causes a high misclassified rate for low credit customers, while high accuracy for high credit customers. To deal with this problem, SMOTE method is used

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

5 0. Getting the data

5.0.1 Import data from csv file

```
In [2]: Credit_file = "./data/credit_data.csv"
        data_train = pd.read_csv(Credit_file)
        y = data_train["Credit Risk"] #Get the label for data
        data_train.head()
```

```
Out[2]:   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]
```

From the documentation of the data, we can see that there are 13 qulitative features and 7 numerical features. However,although "Attribute Age" is a numerical feature. I want to transfer into bucket, which might improve the performance of the models

6 1. Exploring data

In [3]:
```python
f = open("./data/credit_data_attributes.txt", "r")
print("The explaination of the Attributes are shown below:\n")
print(f.read())
```

```
The explaination of the Attributes are shown below:

Attribute 1:  (qualitative)
               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

Attribute 2:  (numerical)
              Duration in month

Attribute 3:  (qualitative)
              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)

Attribute 4:   (qualitative)
               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

Attribute 5:   (numerical)
               Credit amount

Attibute 6:   (qualitative)
               Savings account/bonds
               A61 :          ... <  100 DM
               A62 :   100 <= ... <  500 DM
               A63 :   500 <= ... < 1000 DM
               A64 :          .. >= 1000 DM
               A65 :   unknown/ no savings account

Attribute 7:   (qualitative)
               Present employment since
               A71 : unemployed
               A72 :       ... < 1 year
               A73 : 1  <= ... < 4 years
               A74 : 4  <= ... < 7 years
               A75 :       .. >= 7 years

Attribute 8:   (numerical)
               Installment rate in percentage of disposable income

Attribute 9:   (qualitative)
               Personal status and sex
               A91 : male   : divorced/separated
               A92 : female : divorced/separated/married
```

```
              A93 : male   : single
              A94 : male   : married/widowed
              A95 : female : single

Attribute 10: (qualitative)
              Other debtors / guarantors
              A101 : none
              A102 : co-applicant
              A103 : guarantor

Attribute 11: (numerical)
              Present residence since

Attribute 12: (qualitative)
              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

Attribute 13: (numerical)
              Age in years

Attribute 14: (qualitative)
              Other installment plans
              A141 : bank
              A142 : stores
              A143 : none

Attribute 15: (qualitative)
              Housing
              A151 : rent
              A152 : own
              A153 : for free

Attribute 16: (numerical)
              Number of existing credits at this bank

Attribute 17: (qualitative)
              Job
              A171 : unemployed/ unskilled  - non-resident
              A172 : unskilled - resident
              A173 : skilled employee / official
              A174 : management/ self-employed/
                     highly qualified employee/ officer

Attribute 18: (numerical)
```

```
                Number of people being liable to provide maintenance for

Attribute 19: (qualitative)
              Telephone
              A191 : none
              A192 : yes, registered under the customers name

Attribute 20: (qualitative)
              foreign worker
              A201 : yes
              A202 : no
```

In [4]: `data_train.describe()`

Out[4]:

	Attribute 2	Attribute 5	Attribute 8	Attribute 11	Attribute 13
count	1000.000000	1000.000000	1000.000000	1000.000000	1000.000000
mean	20.903000	3271.258000	2.973000	2.845000	35.546000
std	12.058814	2822.736876	1.118715	1.103718	11.375469
min	4.000000	250.000000	1.000000	1.000000	19.000000
25%	12.000000	1365.500000	2.000000	2.000000	27.000000
50%	18.000000	2319.500000	3.000000	3.000000	33.000000
75%	24.000000	3972.250000	4.000000	4.000000	42.000000
max	72.000000	18424.000000	4.000000	4.000000	75.000000

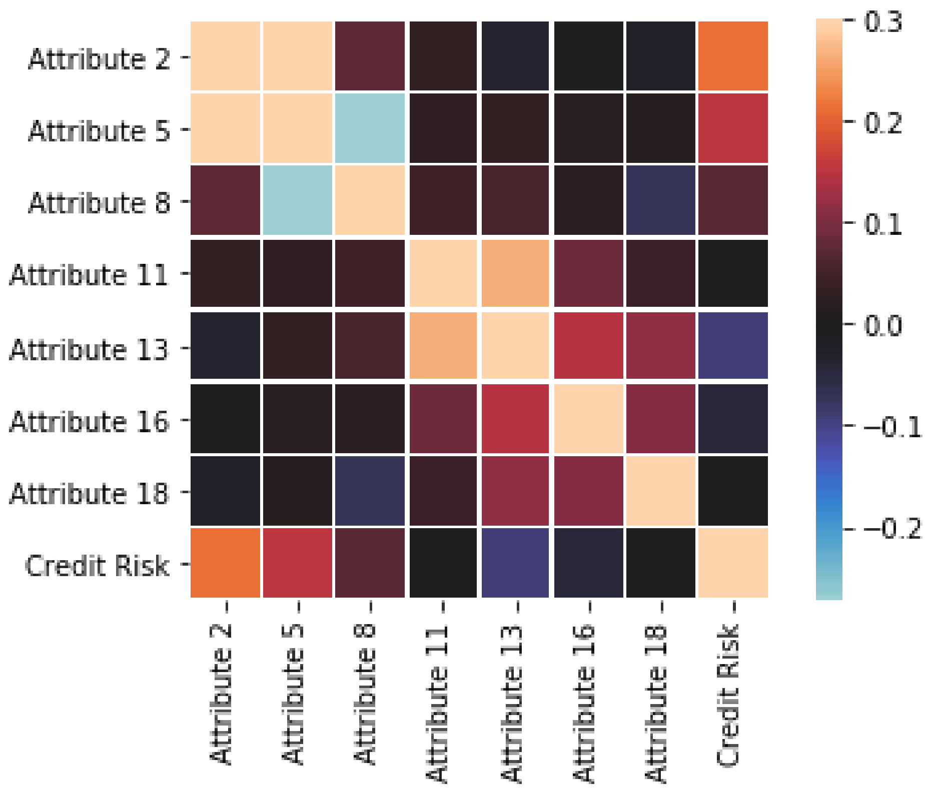
	Attribute 16	Attribute 18	Credit Risk
count	1000.000000	1000.000000	1000.000000
mean	1.407000	1.155000	1.300000
std	0.577654	0.362086	0.458487
min	1.000000	1.000000	1.000000
25%	1.000000	1.000000	1.000000
50%	1.000000	1.000000	1.000000
75%	2.000000	1.000000	2.000000
max	4.000000	2.000000	2.000000

In [5]: `data_train.info()`

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 1000 entries, 0 to 999
Data columns (total 21 columns):
Attribute 1     1000 non-null object
Attribute 2     1000 non-null int64
Attribute 3     1000 non-null object
Attribute 4     1000 non-null object
Attribute 5     1000 non-null int64
Attribute 6     1000 non-null object
Attribute 7     1000 non-null object
Attribute 8     1000 non-null int64
```

```
Attribute 9      1000 non-null object
Attribute 10     1000 non-null object
Attribute 11     1000 non-null int64
Attribute 12     1000 non-null object
Attribute 13     1000 non-null int64
Attribute 14     1000 non-null object
Attribute 15     1000 non-null object
Attribute 16     1000 non-null int64
Attribute 17     1000 non-null object
Attribute 18     1000 non-null int64
Attribute 19     1000 non-null object
Attribute 20     1000 non-null object
Credit Risk      1000 non-null int64
dtypes: int64(8), object(13)
memory usage: 164.1+ KB
```

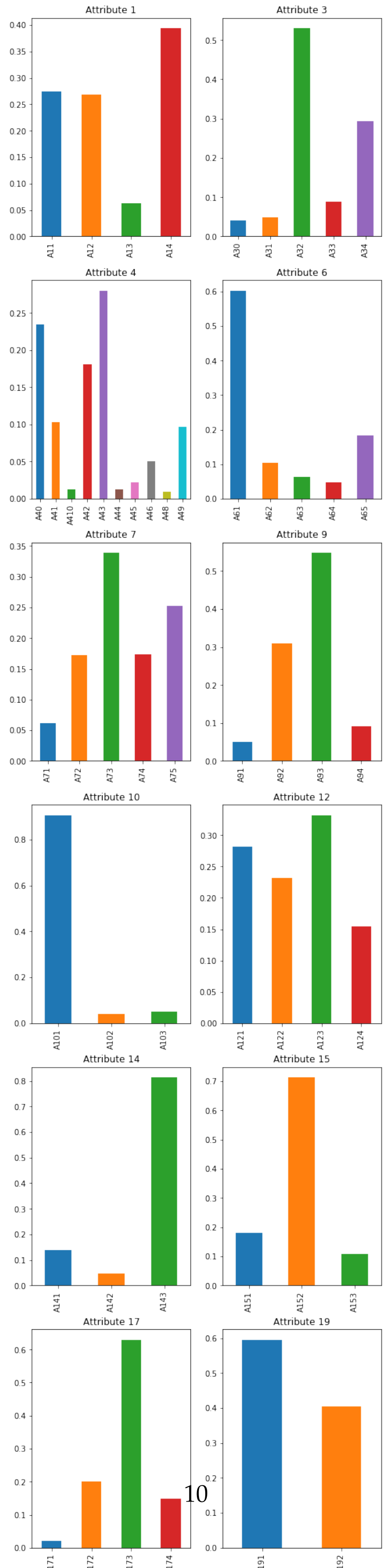
```
In [6]: import seaborn as sns
        _ = sns.heatmap(data_train.corr(), vmax=.3, center=0, square=True, linewidths=.5)
```



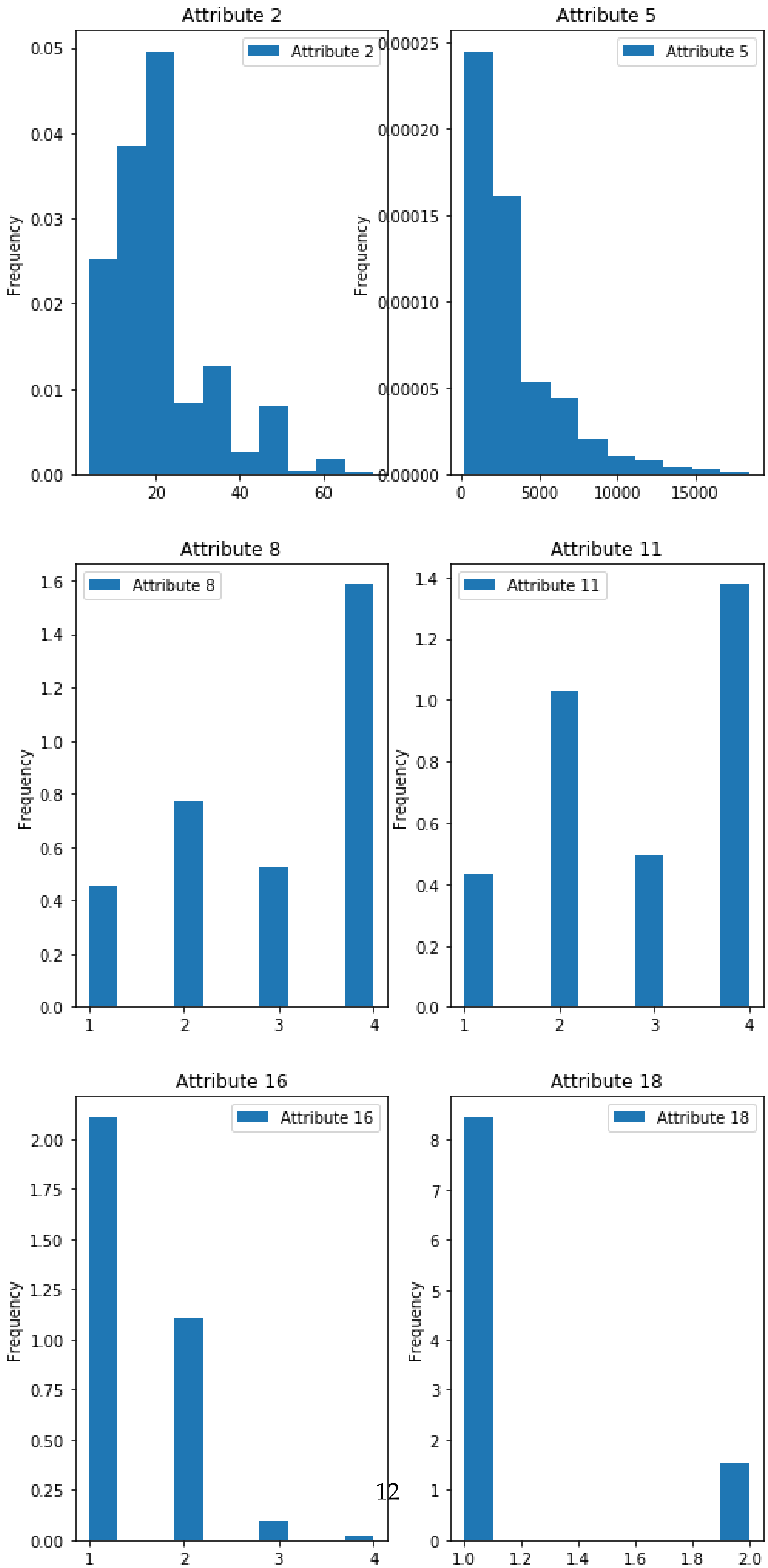
The correlation between is not high. Thus we don't need to reduce correlation by using method including PCA

```
In [7]: def plot_attrs(df, attrs, attr_type="Cat", normalize=True, plot=True):
            """
            Plot/print the distribution of one or more attributes of DataFrame

            Parameters
            ----------
            df: DataFrame
            attrs: List of attributes (i.e., column names)

            Optional
            --------
            attr_type: String;
              "Cat" to indicate that the attributes in attrs are Categorical (so use value_cou
              Otherwise: the attributes must be numeric columns (so use histogram)
            """
            num_attrs = len(attrs)
            ncols=2
            nrows = max(1,round(num_attrs/ncols))
            if num_attrs==1:
                fig, axes = plt.subplots(nrows=nrows, ncols=1, figsize=(4, num_attrs*3))
            else:
                fig, axes = plt.subplots(nrows=nrows, ncols=ncols, figsize=(ncols*4, num_attrs
            # Make sure axes is an array (special case when num_attrs==1)
            if num_attrs == 1:
                axes =np.array( [ axes ])

            for i, attr in enumerate(attrs):
                if attr_type == "Cat":
                    alpha_bar_chart = 0.55
                    plot_data = df.loc[:, attr ].value_counts(normalize=normalize).sort_index(

                    args = { "kind":"bar" } #, "alpha":alpha_bar_chart}
                    kind="bar"
                else:
                    plot_data = df.loc[:, [attr] ]

                    args = { "kind":"hist"}
                    if normalize:
                        args["density"] = True
                    kind="hist"

                if plot:
                    _ = plot_data.plot(title=attr, ax=axes.flatten()[i], **args)
                else:
                    print(attr + "\n")
                    print(plot_data)
                    print("\n")
```

```
In [8]: plot_attrs(data_train, [ "Attribute 1", "Attribute 3", "Attribute 4","Attribute 6","Att
                "Attribute 10","Attribute 12","Attribute 14","Attribute 15","Attribute
```


Attribute 1
A11 A12 A13 A14
Attribute 3
A30 A31 A32 A33 A34
Attribute 4
A40 A41 A410 A42 A43 A44 A45 A46 A48 A49
Attribute 6
A61 A62 A63 A64 A65
Attribute 7
A71 A72 A73 A74 A75
Attribute 9
A91 A92 A93 A94
Attribute 10
A101 A102 A103
Attribute 12
A121 A122 A123 A124
Attribute 14
A141 A142 A143
Attribute 15
A151 A152 A153
Attribute 17
A171 A172 A173 A174
Attribute 19
A191 A192

```
In [9]: plot_attrs(data_train, ["Attribute 2","Attribute 5","Attribute 8","Attribute 11","Attr
```


Attribute 2
Attribute 2
Frequency
0.05
0.04
0.03
0.02
0.01
0.00
20
40
60
Attribute 5
Attribute 5
Frequency
0.00025
0.00020
0.00015
0.00010
0.00005
0.00000
0
5000
10000
15000
Attribute 8
Attribute 8
Frequency
1.6
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
Attribute 11
Attribute 11
Frequency
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
1
2
3
4
Attribute 16
Attribute 16
Frequency
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
1
2
3
4
Attribute 18
Attribute 18
Frequency
8
7
6
5
4
3
2
1
0
1.0
1.2
1.4
1.6
1.8
2.0

7 2. Making pipeline and prepocessing of data

7.0.1 2.1 Pipelines

Three main pipelines: - Numerical pipeline - Categorical pipeline - Agebucket pipeline

Create several base pipelines: - `DataFrameSelector`: select several columns of data, return DataFrame (input:DataFrame,output: DataFrame) - `DataFramSelector_toarray`: select several columns of data and transform and return an array (input:DataFrame,output: array) - `strtoint`: transform Categorical data into int by Removing A from every string (input:DataFrame,output: array) - `todummy_drop`: utilize OneHotEncoder to transform "int" form categorical data into several dummy variables and drop the first column of each set of dummy varaibles (input:array,output: array)

```
In [10]: from sklearn.base import BaseEstimator, TransformerMixin
         from sklearn.pipeline import Pipeline
         try:
             from sklearn.impute import SimpleImputer # Scikit-Learn 0.20+
         except ImportError:
             from sklearn.preprocessing import Imputer as SimpleImputer
         from sklearn.preprocessing import OneHotEncoder
         from sklearn.pipeline import FeatureUnion

         #Select the data
         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]

         class DataFrameSelector_toarray(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].values

         class strtoint(BaseEstimator, TransformerMixin):
             def fit(self,X,y = None):
                 return self
             def transform(self,X):
                 temp = X.values
                 for i,item_1 in enumerate(temp):
```

```
            for j,item_2 in enumerate(item_1):
                temp[i][j] = int(item_2[1:])
        return temp

class todummy_drop(BaseEstimator, TransformerMixin):
    def fit(self,X,y = None):
        return self
    def transform(self,X):
        temp = X.T
        res = np.delete(OneHotEncoder(sparse=False,categories='auto').fit_transform(te
        for i,item in enumerate(temp[1:]):
            dm_0 = np.delete(OneHotEncoder(sparse=False,categories='auto').fit_transfo
            res =np.concatenate((res,dm_0),axis = 1)
        return res

class Age_bucket(BaseEstimator, TransformerMixin):
    def __init__(self, n):# n is interval length for each bucket
        self.n = n
    def fit(self, X, y=None):
        return self
    def transform(self, X):
        X = X.values

        max_0,min_0 = int(X.max()),int(X.min())
        len_0 = self.n
        bkt_num = np.floor((max_0-min_0+1)/ len_0)    #determine how many buckets acc

        if  ((max_0-min_0+1) % len_0) != 0 :
            bkt_num+=1                       #if there are remainder, bucket number+1

        print("Transform age into {t} buckets and {m} dummy variables".format(t = bkt_

        j = 0
        while(j<bkt_num):
            for i,item in enumerate(X):
                if (j*len_0+min_0)<= int(item) and  int(item) <(j+1)*len_0+min_0:

                    X[i]=j
            j +=1

        return X

features_age = ["Attribute 13"]
age_pipeline = Pipeline([
        ("select_numeric", DataFrameSelector( features_age )), #set the parameter for
        ("Agebucket",  Age_bucket(n =10)),
        (" todummy_drop",  todummy_drop())
```

```
        ])

    cat_features = ["Attribute 1", "Attribute 3", "Attribute 4","Attribute 6","Attribute 
                    "Attribute 10","Attribute 12","Attribute 14","Attribute 15","Attribute
    cat_pipeline = Pipeline([
            ("select_cat", DataFrameSelector( cat_features )), #set the parameter for Data
            ("strtoint", strtoint()),          #set the parameter for SimpleImputer, Use m
            ("todummy_drop",todummy_drop())
        ])

    num_features=["Attribute 2","Attribute 5","Attribute 8","Attribute 11","Attribute 16"
    num_pipeline = Pipeline([
            ("select_numeric", DataFrameSelector_toarray( num_features )), #set the param
        ])

    preprocess_pipeline_logistic = FeatureUnion(transformer_list=[
            ("num_pipeline", num_pipeline),
            ("cat_pipeline", cat_pipeline),
            ("age_pipeline", age_pipeline)
        ])
```

```
In [11]: X = preprocess_pipeline_logistic.fit_transform(data_train)
```

```
Transform age into 6.0 buckets and 5.0 dummy variables
```

7.0.2 2.2 Training set and Testing set

Spliting data set into two - Training set: size of 700 - Testing set: size of 300 - Futhermore, Training set is divided into 5, using cross validation. This will help us to determine what is the best parameter in models(especially for `Random Forest` to find optimal `n_estimators` and `max_depth`)

```
In [12]: from sklearn.model_selection import train_test_split
         X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.3,random_state=
```

```
In [13]: X.shape
```

```
Out[13]: (1000, 54)
```

8 3. Logistic Model

8.0.1 Logistic Model with unbalanced data

In Logistic Model, wen need to transform categorical data into dummy variables. After that, one of the dummy variables need to be dropped to eliminate colinearity. Utilizing the pipeline above, there are 54 features in logistic model after transformation.

8.0.2 3.1 Using cross validation

Cross Validation is used here to evaluate the performance of logistic model

```
In [14]: from sklearn import linear_model, preprocessing, model_selection
         from sklearn.model_selection import cross_val_score
         logistic_clf_1 = linear_model.LogisticRegression(solver='liblinear')
         SCORE_1 = cross_val_score(logistic_clf_1, X_train, y_train, cv=5, scoring="accuracy")
         SCORE_1 = SCORE_1.mean()
         SCORE_1

Out[14]: 0.755790820231353

In [15]: print("{s}: Accuracy = {a:.4f}".format(s="Logistic Model  ", a=SCORE_1.mean()))

Logistic Model  : Accuracy = 0.7558
```

8.0.3 3.2 Fiting model and predit on the testing set

I also try the method without using Cross validation. Just to compare the result with other model below.

In other words, I use training set to train the data and testing set to evaluate the data

```
In [16]: logistic_clf_2 = linear_model.LogisticRegression(solver='liblinear')
         logistic_clf_2.fit(X_train,y_train)
         print("On the training set, the accuracy is {t:.4f}".format(t = logistic_clf_2.score(X
         print("On the testing set, the accuracy is {t:.4f}".format(t = logistic_clf_2.score(X_

On the training set, the accuracy is 0.7943
On the testing set, the accuracy is 0.7633
```

Conclusion: The accuracy of cross validation and testing set are similar to each other as expected

8.0.4 3.3 Confusion Matrics

We can't only focus on the accuracy.

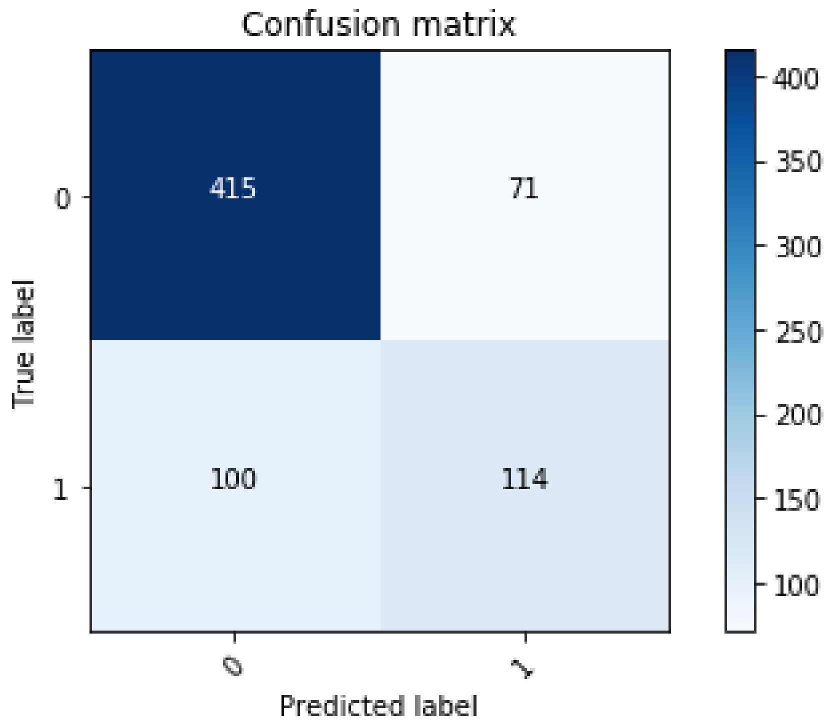
In this case, **a poor credit customer classfied as good credit one** is very undesirable. We will lose a lot of money if a large amount of poor credit customers are classified as good credit ones.

```
In [17]: from sklearn.model_selection import cross_val_predict
         from sklearn import datasets, svm, metrics
         from sklearn.metrics import precision_recall_curve
         expected_1 = y_train
         predicted_1 = cross_val_predict(logistic_clf_1, X_train, y_train, cv=5)
         confusion_mat_L_1 = metrics.confusion_matrix(expected_1, predicted_1)
```

In [18]:
```python
# %load mnist_plot_confusion.py
import itertools

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    """
    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()
```

In [19]:
```python
plot_confusion_matrix(confusion_mat_L_1, range(2))
```

```
Confusion matrix, without normalization
```




```
In [20]: t1 = confusion_mat_L_1[0][0]/(confusion_mat_L_1[0][0]+confusion_mat_L_1[0][1])
         t2 = confusion_mat_L_1[1][1]/(confusion_mat_L_1[1][1]+confusion_mat_L_1[1][0])
         print("Given good credit customer,prediction accuracy is {t1}".format(t1 =t1))
         print("Given poor credit customer,prediction accuracy(Precision) is {t2}".format(t2 =

Given good credit customer,prediction accuracy is 0.8539094650205762
Given poor credit customer,prediction accuracy(Precision) is 0.5327102803738317
```

Discussion: These accuracy above are just very bad in practice. We don't want to see so many **poor credit people classified as qualified customers**, which may bring **huge loss** if the company lend money to them base on this prediction.

I guess this result is because of the **unbalanced data**. There are more people with good credit in our sample as shown below

```
In [21]: y_train.value_counts()

Out[21]: 1    486
         2    214
         Name: Credit Risk, dtype: int64
```

Good credit people are far more that the poor credit ones!

For the data in the training set, And this ratio is around 7:3. **The unbalanced data might cause our model to tend to predict more 1(low risk**

8.0.5 3.4 Deal with unbalanced data problem

Here, we try to **assign different weights** to the sample to crack the unbalanced data problem.

When deciding weights, two factors are considered: - The original data, good credit people: poor credit people = 7:3. So we need to assign a weight of {1:0.3,2:0.7} to keep a perfect balance - However, we tend to consider the accuracy for poor credit people more important than that for good credit people. So even more weights should be assigned to class 2(poor credit people).

So I will try **{1:0.25,2:0.75}**.

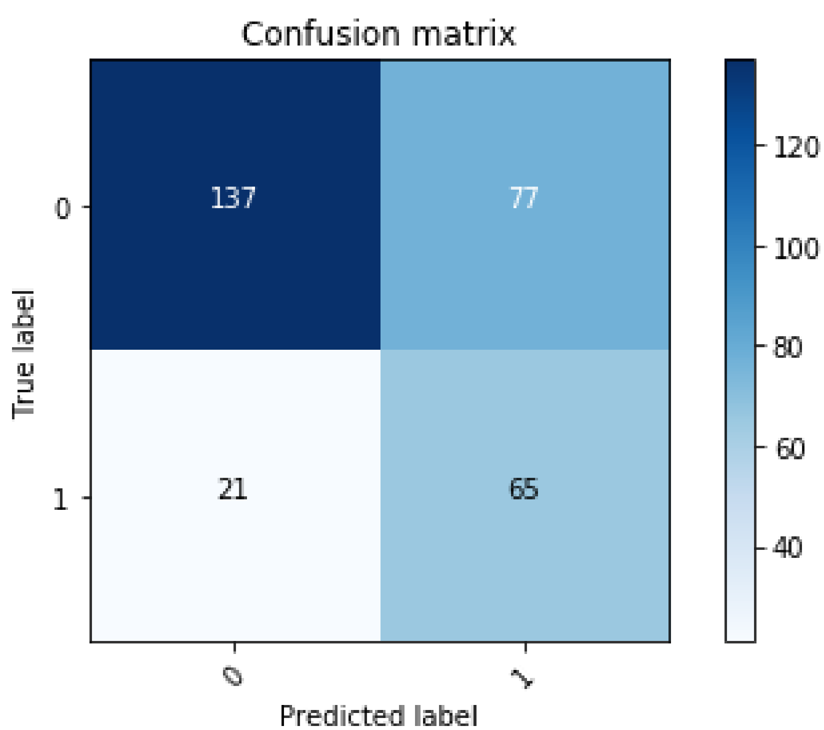
But we have to say that, if weights are assigned, the overall accuracy will be sacrificed

```
In [22]: logistic_clf_ba = linear_model.LogisticRegression(solver='liblinear',class_weight = {
         logistic_clf_ba.fit(X_train,y_train)
         print("On the training set, the accuracy is {t:.4f}".format(t = logistic_clf_ba.score
         print("On the testing set, the accuracy is {t:.4f}".format(t = logistic_clf_ba.score(
```

```
On the training set, the accuracy is 0.7143
On the testing set, the accuracy is 0.6733
```

```
In [23]: expected_L_ba = y_test
         predicted_L_ba = logistic_clf_ba.predict(X_test)
         confusion_mat_L_ba = metrics.confusion_matrix(expected_L_ba, predicted_L_ba)
         plot_confusion_matrix(confusion_mat_L_ba, range(2))
```

```
Confusion matrix, without normalization
```



```
In [24]: t1 = confusion_mat_L_ba[0][0]/(confusion_mat_L_ba[0][0]+confusion_mat_L_ba[0][1])
         t2 = confusion_mat_L_ba[1][1]/(confusion_mat_L_ba[1][1]+confusion_mat_L_ba[1][0])
         print("Given good credit customer,prediction accuracy is {t1}".format(t1 =t1))
         print("Given poor credit customer,prediction accuracy(Precision) is {t2}".format(t2 =
```

```
Given good credit customer,prediction accuracy is 0.6401869158878505
Given poor credit customer,prediction accuracy(Precision) is 0.7558139534883721
```

Conclusion: After assigning different weights({1:0.25,2:0.75}) to sample, I achieved a much better matrics. Of course, the price to that is sacrifice some of the accuracy

The overall acuuracy drops around 10 percents, but the accuracy for poor credit customer **increases over 23 percents.**

Accuracy of overall is **sacrificed for** accuracy for poor credit people!

In this way, the unbalanced data problem is solved.

9 4. Random Forest

9.0.1 4.1 Random Forest Pipeline

We no longer need to transform categorical data into dummy variables bacause no scale effects here. So slight changes are made here for previous pipelines.

```
In [25]: from sklearn.ensemble import RandomForestClassifier
```

```
In [26]: cat_pipeline_rf = Pipeline([
                 ("select_cat", DataFrameSelector( cat_features )), #set the parameter for Dat
                 ("strtoint", strtoint()),         #set the parameter for SimpleImputer, Use m
                 #("todummy_drop",todummy_drop())
             ])

         num_pipeline_rf = Pipeline([
                 ("select_numeric", DataFrameSelector_toarray( num_features )), #set the param
             ])

         age_pipeline_rf = Pipeline([
                 ("select_numeric", DataFrameSelector( features_age )), #set the parameter for
                 ("Agebucket",  Age_bucket(n =10)),
                 #(" todummy_drop",  todummy_drop())

             ])

         preprocess_pipeline_rf = FeatureUnion(transformer_list=[
                 ("num_pipeline", num_pipeline_rf),
                 ("cat_pipeline", cat_pipeline_rf),
                 ("age_pipeline", age_pipeline_rf)
             ])
```

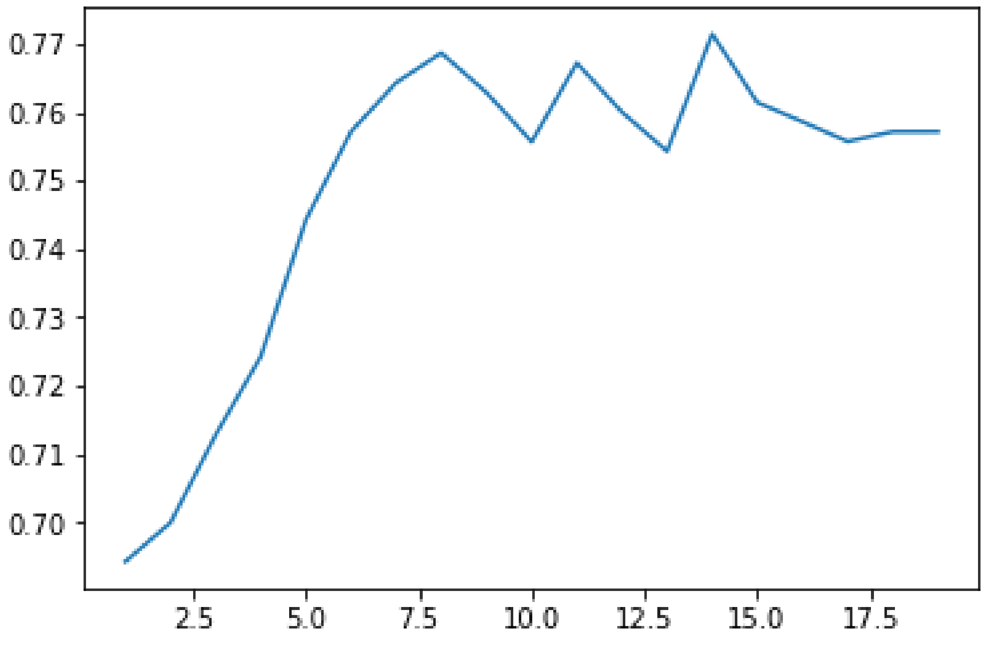
```
In [27]: X_2 = preprocess_pipeline_rf.fit_transform(data_train)
         X_train_2, X_test_2, y_train_2, y_test_2 = train_test_split(X_2, y, test_size=0.3,ranc
```

```
Transform age into 6.0 buckets and 5.0 dummy variables
```

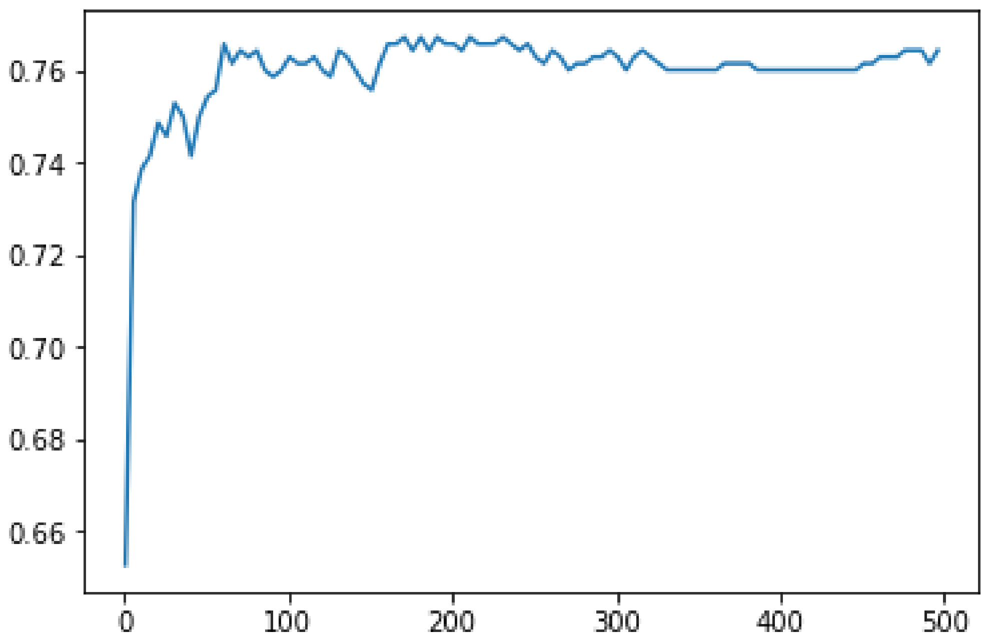
9.0.2 4.2 Finding the optimal number and depth of trees using cross validation

```
In [28]: def find_optimal_maxdep(X_train, y_train):
             res = []
             opt = 0
             for i in np.arange(1,20):
                 rf = RandomForestClassifier(n_estimators=100, max_depth=i,random_state=1)
                 SCORE = cross_val_score(rf, X_train_2, y_train_2, cv=5, scoring="accuracy")
                 res.append(SCORE.mean())
             plt.plot(np.arange(1,20),res)
             return res

         def find_optimal_nest(X_train_2, y_train_2):
             res = []
             for i in np.arange(1,500,5):
                 rf = RandomForestClassifier(n_estimators=i, max_depth=7,random_state=1)
                 SCORE = cross_val_score(rf, X_train_2, y_train_2, cv=5, scoring="accuracy")
                 res.append(SCORE.mean())
             plt.plot(np.arange(1,500,5),res)
             return res
```

```
In [29]: Score_rf_all =find_optimal_maxdep(X_train_2, y_train_2)
```



```
In [30]: Score_rf_nest =find_optimal_nest(X_train_2, y_train_2)
```

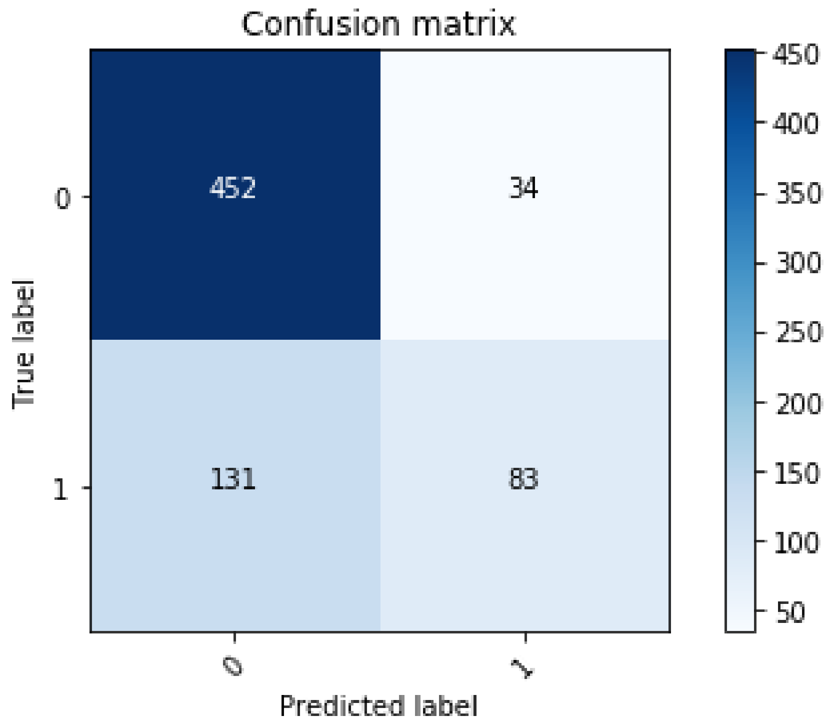


After observation of the two graphes above, I decide to choose **100** for `n_estimators` and **7** for `max_depth`

9.0.3 4.3 Cross validation and prediction on testing set

```
In [31]: rf_clf = RandomForestClassifier(n_estimators=100, max_depth=7,random_state=1)
         SCORE_2 = cross_val_score(rf_clf, X_train, y_train, cv=5, scoring="accuracy")
         SCORE_2 = SCORE_2.mean()
         SCORE_2

Out[31]: 0.7271475949939137

In [32]: print("{s}: Accuracy = {a:.4f}".format(s="Random Forest Model  ", a=SCORE_2.mean()))

Random Forest Model  : Accuracy = 0.7271


In [33]: expected_2 = y_train_2
         predicted_2 = cross_val_predict(rf_clf, X_train_2, y_train_2, cv=5)
         confusion_mat_rf_1 = metrics.confusion_matrix(expected_2, predicted_2)

In [34]: plot_confusion_matrix(confusion_mat_rf_1, range(2))
```

```
Confusion matrix, without normalization
```




```
In [35]: rf_clf_test = RandomForestClassifier(n_estimators=100, max_depth=7,random_state=1)
         rf_clf_test.fit(X_train_2,y_train_2)
         print("On the training set, the accuracy is {t:.4f}".format(t =rf_clf_test.score(X_tra
         print("On the testing set, the accuracy is {t:.4f}".format(t = rf_clf_test.score(X_tes

On the training set, the accuracy is 0.9029
On the testing set, the accuracy is 0.7500
```

```
In [36]: t1 = confusion_mat_rf_1[0][0]/(confusion_mat_rf_1[0][0]+confusion_mat_rf_1[0][1])
         t2 = confusion_mat_rf_1[1][1]/(confusion_mat_rf_1[1][1]+confusion_mat_rf_1[1][0])
         print("Given good credit customer,prediction accuracy is {t1}".format(t1 =t1))
         print("Given poor credit customer,prediction accuracy(Precision) is {t2}".format(t2 =

Given good credit customer,prediction accuracy is 0.9300411522633745
Given poor credit customer,prediction accuracy(Precision) is 0.3878504672897196
```

Comparison of Random Forest and Logistic Model: - Accuracy: The accuracy in both models are similar. - Precision: As we can see in the confusion matrix. Random Forest has even **more serious problem predicting poor credit customers.(low precision)**

9.0.4 4.4 Dealing with unbalanced data problem

I use the same weight as Logistic Model.

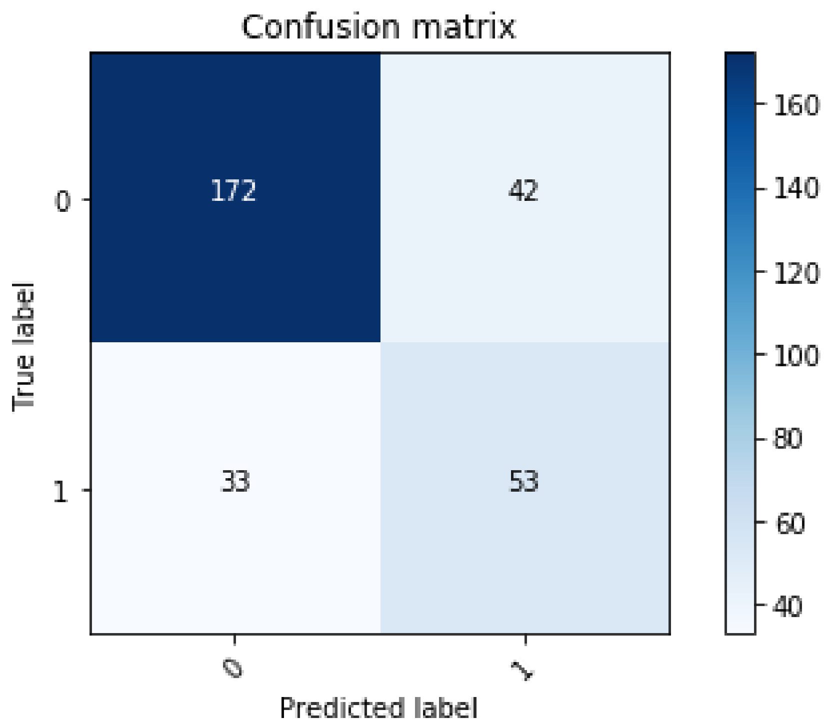
```
In [37]: rf_clf_test_ba = RandomForestClassifier(n_estimators=100, max_depth=7,random_state=1,c
         rf_clf_test_ba.fit(X_train_2,y_train_2)
         rf_clf_test_ba.score(X_test_2,y_test_2)
```

```
Out[37]: 0.75
```

```
In [38]: expected_rf_ba = y_test_2
         predicted_rf_ba = rf_clf_test_ba.predict(X_test_2)
         confusion_mat_rf_ba = metrics.confusion_matrix(expected_rf_ba, predicted_rf_ba)
```

```
In [39]: plot_confusion_matrix(confusion_mat_rf_ba, range(2))
```

```
Confusion matrix, without normalization
```




```
In [40]: t1 = confusion_mat_rf_ba[0][0]/(confusion_mat_rf_ba[0][0]+confusion_mat_rf_ba[0][1])
         t2 = confusion_mat_rf_ba[1][1]/(confusion_mat_rf_ba[1][1]+confusion_mat_rf_ba[1][0])
         print("Given good credit customer,prediction accuracy is {t1}".format(t1 =t1))
         print("Given poor credit customer,prediction accuracy(Precision) is {t2}".format(t2 =t
```

```
Given good credit customer,prediction accuracy is 0.8037383177570093
Given poor credit customer,prediction accuracy(Precision) is 0.6162790697674418
```

Conclusion: Using the same weights in Logistic Model may not be enough in Random Forest. We actually here should change the weight into something with larger diference like {0:0.2,1:0.8} or {0:0.1,1:0.9}

9.0.5 4.5 Deciding the weights for Random Forest

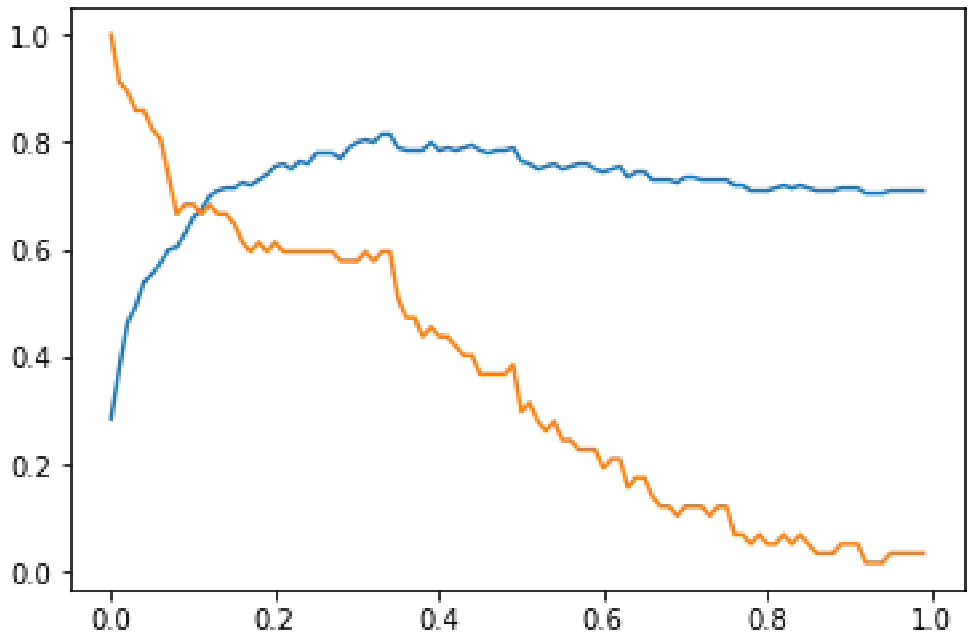
To determine what the weight should be, we need to have another set to test the optimal weights.(Testing set should be used only once. If we now still use testing set and change weights, **We have already peeked on data!**

So the data set should be split into **three** from at the first place. Let's call them Train set, Test set and final set. **Test set** is used to determin the weights and **final set** is used to evluate the result.

```
In [41]: X_train_3, X_test_3, y_train_3, y_test_3 = train_test_split(X_2, y, test_size=0.3,ranc
         X_test_3, X_final_3, y_test_3, y_final_3 = train_test_split(X_test_3, y_test_3, test_s
```

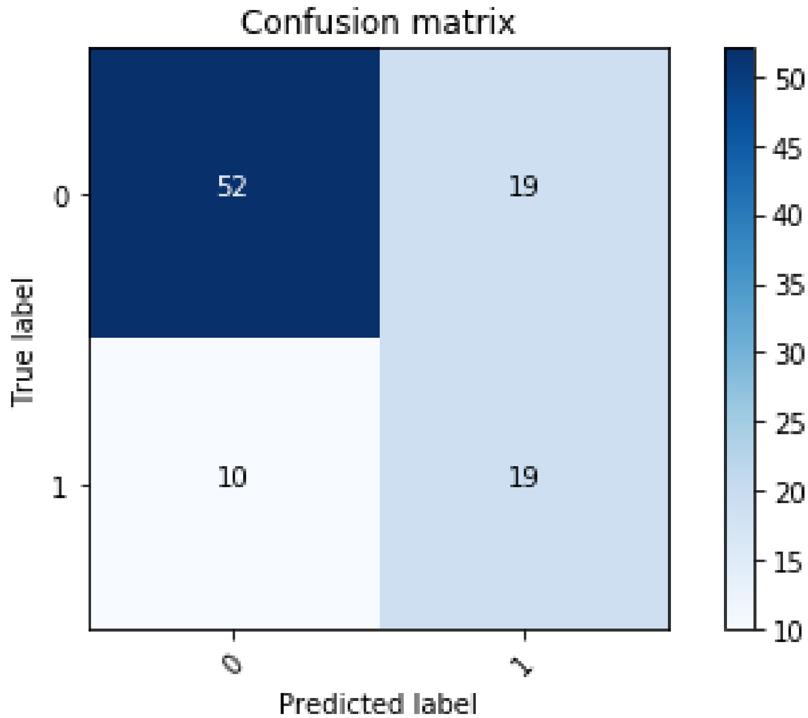
```
In [42]: def precision_weights(X_train_2,y_train_2,X_test_2,y_test_2):
             score = []
             precision = []
             for i in np.arange(0,1,0.01):
                 rf_clf_test_ba = RandomForestClassifier(n_estimators=170, max_depth=7,random_s
                 rf_clf_test_ba.fit(X_train_2,y_train_2)
                 score.append(rf_clf_test_ba.score(X_test_2,y_test_2))
                 expected_rf_ba = y_test_2
                 predicted_rf_ba = rf_clf_test_ba.predict(X_test_2)
                 confusion_mat_rf_ba = metrics.confusion_matrix(expected_rf_ba, predicted_rf_ba
                 precision.append(confusion_mat_rf_ba[1][1]/(confusion_mat_rf_ba[1][1]+confusio
             plt.plot(np.arange(0,1,0.01),score,label='Score')
             plt.plot(np.arange(0,1,0.01),precision,label='Precision')
             return [score, precision]
```

```
In [43]: score,precision = precision_weights(X_train_3,y_train_3,X_test_3,y_test_3)
```



According to the graph above, weights of{1:0.1,2:0.9} is chosen

```
In [44]: rf_clf_test_ba_2 = RandomForestClassifier(n_estimators=100, max_depth=7,random_state=
         rf_clf_test_ba_2.fit(X_train_3,y_train_3)
         rf_clf_test_ba_2.score(X_final_3,y_final_3)

Out[44]: 0.59

In [45]: expected_rf_ba_2 = y_final_3
         predicted_rf_ba_2 = rf_clf_test_ba.predict(X_final_3)
         confusion_mat_rf_ba_2 = metrics.confusion_matrix(expected_rf_ba_2, predicted_rf_ba_2)

In [46]: plot_confusion_matrix(confusion_mat_rf_ba_2, range(2))

Confusion matrix, without normalization
```




```
In [47]: t1 = confusion_mat_rf_ba_2[0][0]/(confusion_mat_rf_ba_2[0][0]+confusion_mat_rf_ba_2[0]
         t2 = confusion_mat_rf_ba_2[1][1]/(confusion_mat_rf_ba_2[1][1]+confusion_mat_rf_ba_2[1]
         print("Given good credit customer,prediction accuracy is {t1}".format(t1 =t1))
         print("Given poor credit customer,prediction accuracy(Precision) is {t2}".format(t2 =
```

```
Given good credit customer,prediction accuracy is 0.7323943661971831
Given poor credit customer,prediction accuracy(Precision) is 0.6551724137931034
```

10 5. Summary

10.0.1 5.1 Accuracy Model

If we only evaluate the model by accuracy,`Logistic Model` without changing weight is a good choice

```
In [48]: credit_model = logistic_clf_2
```

10.0.2 5.2 Balanced Model

```
In [49]: credit_model_2 = rf_clf_test_ba
```

Conclusion: - In terms of unbalanced, Random Forest has more serious problem than Logistic Model. It seems that it is a must for Random Forest to address unbalanced data. - Assigning different weights to the sample is really helpful if our goal is not soly on maximizing the accuracy but on both accuracy and percision.