A loan default client portrait monitoring system based on decision tree and Logistic regression model

Loan Default with Decision Tree

Banks are concerned about the client's inability to repay the loan left the bank facing losses. They need to understand what characteristics users are at risk of defaulting on their loans.

About the dataset

We will use a loan default dataset for predicting. This is a historical dataset where each row represents one client. The data is relatively easy to understand. Typically, strengthening risk control when lending is the best way to reduce the number of clients defaulting on loans, so the focus of this analysis is to predict who is 'risky' for the bank.

The dataset includes information about:

- Income - monthly income of borrower;
- Balance - the amount of money deposited in the bank of the borrower;
- Student - if the borrower is a student;
- Default - if the borrower defaults on a loan

Information shows above is stored in the file 'LoanDefault.csv'

Import Needed Packages

In [3]:
```
import matplotlib.pyplot as plt
import pandas as pd
import pylab as pl
import numpy as np
%matplotlib inline
from sklearn.tree import DecisionTreeClassifier
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn import metrics
from sklearn.externals.six import StringIO
import pydotplus
import matplotlib.image as mpimg
from sklearn import tree
from sklearn.metrics import confusion_matrix
```

Load Data From CSV File

In [172]:
```
df = pd.read_csv("LoanDefault.csv")

# take a look at the dataset
df.head()
```

Out[172]:

	default	student	balance	income
0	No	No	729.526495	44361.625074
1	No	Yes	817.180407	12106.134700
2	No	No	1073.549164	31767.138947
3	No	No	529.250605	35704.493935
4	No	No	785.655883	38463.495879

Pre-processing

Before starting analysis and modeling, wrangling data by identifying if there is any missing value and checking if there is any wrong data by get a statistical summary of each column.

```
In [173]: print(df[df.isnull()==True].count())
          df.describe()
```

```
default    0
student    0
balance    0
income     0
dtype: int64
```

Out[173]:

	balance	income
count	10000.000000	10000.000000
mean	835.374886	33516.981876
std	483.714985	13336.639563
min	0.000000	771.967729
25%	481.731105	21340.462903
50%	823.636973	34552.644802
75%	1166.308386	43807.729272
max	2654.322576	73554.233495

It turns out that this dataframe has no missing values and the values in four columns are normal (i.e.no negative numbers in column 'balance' and 'income'). Now we can define X, and y for our dataset.

Using df as the LoanDefault.csv data read by pandas, declare the following variables:

```
X as the Feature Matrix (data)
y as the response vector (target)
```

```
In [11]: X = df[['student', 'balance', 'income']].values
         X[0:5]
```

```
Out[11]: array([['No', 729.5264952072861, 44361.62507426691],
                ['Yes', 817.180406555498, 12106.1347003149],
                ['No', 1073.54916401173, 31767.1389473999],
                ['No', 529.250604745278, 35704.4939350781],
                ['No', 785.655882930501, 38463.4958787229]], dtype=object)
```

Some features in this dataset are categorical such as 'student'. Since Sklearn Decision Trees do not handle categorical variables, we can convert these features to numerical values.

```
In [12]: le_student = preprocessing.LabelEncoder()
         le_student.fit(['No','Yes'])
         X[:,0] = le_student.transform(X[:,0])

         X[0:5]
```

```
Out[12]: array([[0, 729.5264952072861, 44361.62507426691],
                [1, 817.180406555498, 12106.1347003149],
                [0, 1073.54916401173, 31767.1389473999],
                [0, 529.250604745278, 35704.4939350781],
                [0, 785.655882930501, 38463.4958787229]], dtype=object)
```

Now we can fill the target variable.

```
In [13]: y = df["default"]
         y[0:5]
```

```
Out[13]: 0    No
         1    No
         2    No
         3    No
         4    No
         Name: default, dtype: object
```

Setting up the Decision Tree

We will be using train/test split on our decision tree. Import train_test_split from sklearn.cross_validation.

Train Test Split

For our model having a high, out-of-sample accuracy, we use an evaluation approach called Train/Test Split. Our train_test_split will return 4 different parameters. We will name them: X_trainset, X_testset, y_trainset, y_testset

The train_test_split will need the parameters: X, y, test_size=0.3, and random_state=4.

The X and y are the arrays required before the split, the test_size represents the ratio of the testing dataset, and the random_state ensures that we obtain the same splits.

```
In [14]: X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.3, random_state=4)
         print ('Train set:', X_train.shape,  y_train.shape)
         print ('Test set:', X_test.shape,  y_test.shape)

         Train set: (7000, 3) (7000,)
         Test set: (3000, 3) (3000,)
```

Modeling

We will first create an instance of the DecisionTreeClassifier called drugTree. Inside of the classifier, specify criterion="entropy" so we can see the information gain of each node.

```
In [15]: defaultTree = DecisionTreeClassifier(criterion="entropy", max_depth = 4)
         defaultTree # it shows the default parameters

Out[15]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                max_depth=4, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, presort='deprecated',
                                random_state=None, splitter='best')
```

Next, we will fit the data with the training feature matrix X_trainset and training response vector y_trainset

```
In [16]: defaultTree.fit(X_train,y_train)

Out[16]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                max_depth=4, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, presort='deprecated',
                                random_state=None, splitter='best')
```

Prediction

Let's make some predictions on the testing dataset and store it into a variable called predTree.

```
In [17]: predTree = defaultTree.predict(X_test)
```

You can print out predTree and y_testset if you want to visually compare the prediction to the actual values.

```
In [18]: print (predTree [0:5])
         print (y_test [0:5])

         ['No' 'No' 'No' 'No' 'No']
         1603    No
         8713    No
         4561    No
         6600    No
         2558    No
         Name: default, dtype: object
```

Evaluation

Next, let's import metrics from sklearn and check the accuracy of our model.

```
In [19]: print("DecisionTrees's Accuracy: ", metrics.accuracy_score(y_test, predTree))

         DecisionTrees's Accuracy:  0.973
```

Accuracy classification score computes subset accuracy: the set of labels predicted for a sample must exactly match the corresponding set of labels in y_true.

In multilabel classification, the function returns the subset accuracy. If the entire set of predicted labels for a sample strictly match with the true set of labels, then the subset accuracy is 1.0; otherwise it is 0.0.

Since the depth of decision tree affect the accuracy, traverse depth from 1 to 9 and computing the accracies, then select the most accurate depth.

```
In  [20]: for i in range(1,10):
              defaultTree = DecisionTreeClassifier(criterion="entropy", max_depth = i)
              defaultTree.fit(X_train,y_train)
              predTree = defaultTree.predict(X_test)
              print("Depth:", i, "-> DecisionTrees's Accuracy: ", metrics.accuracy_score(y_test, predTree))

          Depth: 1 -> DecisionTrees's Accuracy:  0.9666666666666667
          Depth: 2 -> DecisionTrees's Accuracy:  0.9723333333333334
          Depth: 3 -> DecisionTrees's Accuracy:  0.9736666666666667
          Depth: 4 -> DecisionTrees's Accuracy:  0.973
          Depth: 5 -> DecisionTrees's Accuracy:  0.973
          Depth: 6 -> DecisionTrees's Accuracy:  0.9733333333333334
          Depth: 7 -> DecisionTrees's Accuracy:  0.9686666666666667
          Depth: 8 -> DecisionTrees's Accuracy:  0.9686666666666667
          Depth: 9 -> DecisionTrees's Accuracy:  0.968
```

According to the output, now we can choose the optimal depth, that is, 3, for model.

```
In  [21]: defaultTree = DecisionTreeClassifier(criterion="entropy", max_depth = 3)
          defaultTree # it shows the default parameters

Out[21]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                max_depth=3, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, presort='deprecated',
                                random_state=None, splitter='best')
```

```
In  [22]: defaultTree.fit(X_train,y_train)

Out[22]: DecisionTreeClassifier(ccp_alpha=0.0, class_weight=None, criterion='entropy',
                                max_depth=3, max_features=None, max_leaf_nodes=None,
                                min_impurity_decrease=0.0, min_impurity_split=None,
                                min_samples_leaf=1, min_samples_split=2,
                                min_weight_fraction_leaf=0.0, presort='deprecated',
                                random_state=None, splitter='best')
```

```
In  [23]: predTree = defaultTree.predict(X_test)
          predTree

Out[23]: array(['No', 'No', 'No', ..., 'No', 'No', 'No'], dtype=object)
```

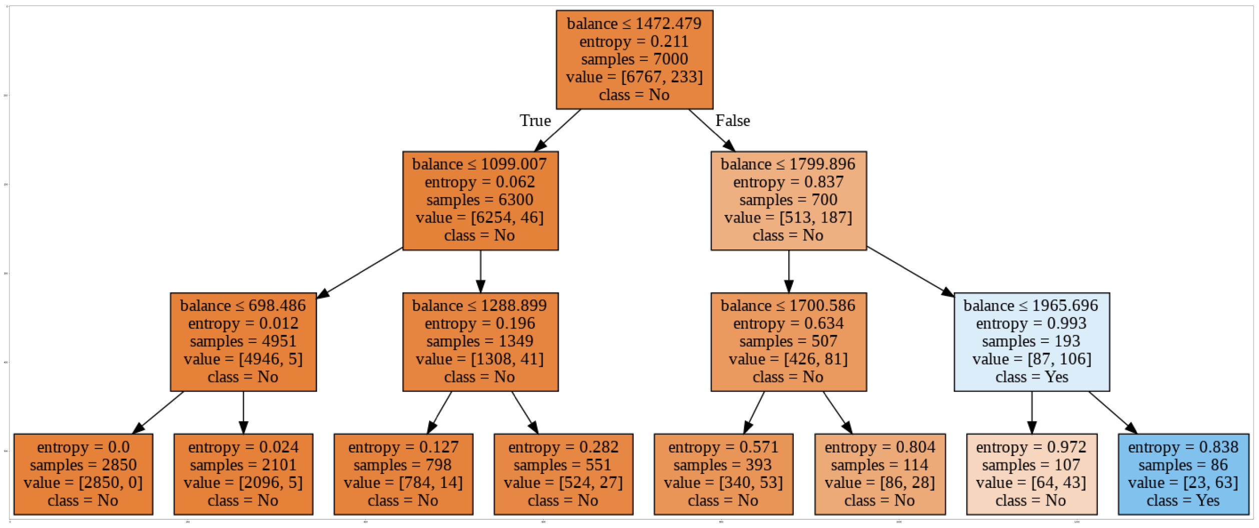
```
In  [24]: y_test

Out[24]: 1603    No
         8713    No
         4561    No
         6600    No
         2558    No
                 ..
         3458    No
         682     No
         3128    No
         8271    No
         1031    No
         Name: default, Length: 3000, dtype: object
```

Visualization

Lets visualize the tree

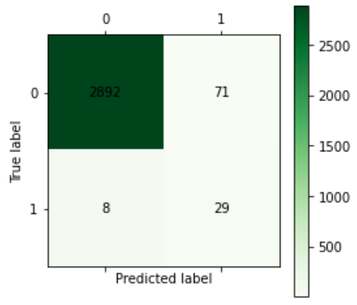
In [27]:
```
dot_data = StringIO()
filename = "defaulttree.png"
featureNames = df.columns[1:4]
targetNames = df["default"].unique().tolist()
out=tree.export_graphviz(defaultTree,feature_names=featureNames, out_file=dot_data, class_names= np.unique(y_train), filled=True, special_c
haracters=True,rotate=False)
graph = pydotplus.graph_from_dot_data(dot_data.getvalue())
graph.write_png(filename)
img = mpimg.imread(filename)
plt.figure(figsize=(100, 200))
plt.imshow(img,interpolation='nearest')
```

Out[27]:
```
<matplotlib.image.AxesImage at 0x7f0250b17f98>
```



Evaluation (Confusion Matrix)

In [30]:
```
def cm_plot(y, yp):

  cm = confusion_matrix(y, yp)

  plt.matshow(cm, cmap=plt.cm.Greens)
  plt.colorbar()

  for x in range(len(cm)):
    for y in range(len(cm)):
      plt.annotate(cm[x,y], xy=(x, y), horizontalalignment='center', verticalalignment='center')

  plt.ylabel('True label')
  plt.xlabel('Predicted label')
  return plt

cm_plot(y_test, defaultTree.predict(X_test)).show()
```



The first row is for borrowers whose actual default value in test set is 0. As you can calculate, out of 3000 borrowers, the default value of 2963 of them is 0. And out of these 2963, the classifier correctly predicted 2892 of them as 0, and 71 of them as 1.

It means, for 2892 borrowers, the actual default value were 0 in test set, and classifier also correctly predicted those as 0. However, while the actual label of 71 borrowers were 0, the classifier predicted those as 1, which is a good job in predicting the borrowers with default value 0.

What about the borrowers with default value 1? Lets look at the second row. It looks like there were 37 borrowers whom their default value were 1. The classifier correctly predicted 29 of them as 1, and 8 of them wrongly as 1, which is not very good. We can consider it as error of the model for second row.

```
In  [35]: print (classification_report(y_test, defaultTree.predict(X_test)))
```

```
              precision    recall  f1-score   support

          No       0.98      1.00      0.99      2900
         Yes       0.78      0.29      0.42       100

    accuracy                           0.97      3000
   macro avg       0.88      0.64      0.70      3000
weighted avg       0.97      0.97      0.97      3000
```

Based on the count of each section, we can calculate precision and recall of each label:

Precision is a measure of the accuracy provided that a class label has been predicted. It is defined by: precision = TP / (TP + FP)

Recall is true positive rate. It is defined as: Recall = TP / (TP + FN)

So, we can calculate precision and recall of each class.

Logistic Regression

The difference between Linear and Logistic Regression

While Linear Regression is suited for estimating continuous values (e.g. estimating house price), it is not the best tool for predicting the class of an observed data point. In order to estimate the class of a data point, we need some sort of guidance on what would be the most probable class for that data point. For this, we use Logistic Regression.

Recall linear regression:

Linear regression finds a function that relates a continuous dependent variable, y, to some predictors (independent variables x1 , x2 , etc.). For example, Simple linear regression assumes a function of the form:

> y=θ0+θ1x1+θ2x2+⋯

and finds the values of parameters θ0,θ1,θ2 , etc, where the term θ0 is the "intercept". It can be generally shown as:

> hθ(x)=θTX

Logistic Regression is a variation of Linear Regression, useful when the observed dependent variable, y, is categorical. It produces a formula that predicts the probability of the class label as a function of the independent variables.

Logistic regression fits a special s-shaped curve by taking the linear regression and transforming the numeric estimate into a probability with the following function, which is called sigmoid function σ:

> hθ(x)=σ(θTX)=e(θ0+θ1x1+θ2x2+...)1+e(θ0+θ1x1+θ2x2+⋯)

Or:

> ProbabilityOfaClass1=P(Y=1|X)=σ(θTX)=eθTX1+eθTX

In this equation, θTX is the regression result (the sum of the variables weighted by the coefficients), exp is the exponential function and σ(θTX) is the sigmoid or logistic function, also called logistic curve. It is a common "S" shape (sigmoid curve).

So, briefly, Logistic Regression passes the input through the logistic/sigmoid but then treats the result as a probability. The objective of Logistic Regression algorithm, is to find the best parameters θ, for hθ(x) = σ(θTX) , in such a way that the model best predicts the class of each case.

Loan Default with Logistic Regression

Banks are concerned about the client's inability to repay the loan left the bank facing losses. They need to understand what characteristics users are at risk of defaulting on their loans.

About the dataset

We will use a loan default dataset for predicting. This is a historical dataset where each row represents one client. The data is relatively easy to understand. Typically, strengthening risk control when lending is the best way to reduce the number of clients defaulting on loans, so the focus of this analysis is to predict who is 'risky' for the bank.

The dataset includes information about:

- Income - monthly income of borrower;
- Balance - the amount of money deposited in the bank of the borrower;
- Student - if the borrower is a student;
- Default - if the borrower defaults on a loan

Information shows above is stored in the file 'LoanDefault.csv'

Firstly, import needed packages.

```
In [ ]: import statsmodels.api as sm
        import pandas as pd
        import pylab as pl
        import numpy as np
        import scipy.optimize as opt
        from sklearn import preprocessing
        %matplotlib inline
        import matplotlib.pyplot as plt
        from sklearn.model_selection import train_test_split
        from sklearn.linear_model import LogisticRegression
        from sklearn.metrics import classification_report, confusion_matrix
        import itertools
```

Load Data From CSV File

```
In [139]: df = pd.read_csv("LoanDefault.csv")

          # take a look at the dataset
          df.head()
```

Out[139]:

	default	student	balance	income
0	No	No	729.526495	44361.625074
1	No	Yes	817.180407	12106.134700
2	No	No	1073.549164	31767.138947
3	No	No	529.250605	35704.493935
4	No	No	785.655883	38463.495879

Data pre-processing and selection

As dataframe shows, some features in this dataset are categorical such as 'student' or 'default'. We can convert these features to numerical values. pandas.get_dummies() Convert categorical variable into dummy/indicator variables and select useful features for modeling.

In [140]:
```
df = pd.get_dummies(df)
df.drop(df.columns[[2, 4]],axis=1, inplace=True)
df
```

Out[140]:

	balance	income	default_Yes	student_Yes
0	729.526495	44361.625074	0	0
1	817.180407	12106.134700	0	1
2	1073.549164	31767.138947	0	0
3	529.250605	35704.493935	0	0
4	785.655883	38463.495879	0	0
5	919.588530	7491.558572	0	1
6	825.513331	24905.226578	0	0
7	808.667504	17600.451344	0	1
8	1161.057854	37468.529288	0	0
9	0.000000	29275.268293	0	0
10	0.000000	21871.073089	0	1
11	1220.583753	13268.562221	0	1
12	237.045114	28251.695345	0	0
13	606.742343	44994.555849	0	0
14	1112.968401	23810.174050	0	0
15	286.232560	45042.413036	0	0
16	0.000000	50265.312354	0	0
17	527.540184	17636.539617	0	1
18	485.936864	61566.106118	0	0
19	1095.072735	26464.631389	0	0
20	228.952550	50500.182198	0	0
21	954.261793	32457.509075	0	0
22	1055.956605	51317.883082	0	0
23	641.984389	30466.103257	0	0
24	773.211725	34353.314305	0	0
25	855.008523	25211.332161	0	0
26	642.999739	41473.511801	0	0
27	1454.863272	32189.094952	0	0
28	615.704277	39376.394619	0	0
29	1119.569353	16556.070205	0	1
...	...	...	...	...
9970	1294.500408	25687.326050	0	1
9971	180.620128	20975.560495	0	1
9972	755.432801	14455.865365	0	0
9973	876.119027	37668.366788	0	0
9974	933.332025	26051.398320	0	1
9975	908.315934	21287.942487	0	0
9976	218.417559	25401.133121	0	0
9977	915.439827	16624.339111	0	1
9978	2202.462395	47287.257108	1	0
9979	173.249172	30697.245062	0	0
9980	770.015741	13684.789952	0	1
9981	739.418018	40656.951448	0	0
9982	623.526119	59441.309981	0	0
9983	506.625454	49861.003411	0	0
9984	875.241640	52861.744197	0	0
9985	842.949429	39957.127855	0	0
9986	401.332674	15332.017833	0	1
9987	1092.906583	45479.466985	0	0
9988	0.000000	41740.686597	0	0
9989	999.281112	20013.350644	0	1
9990	372.379239	25374.899085	0	0
9991	658.799558	54802.078221	0	0

	balance	income	default_Yes	student_Yes
9992	1111.647317	45490.682463	0	0
9993	938.836241	56633.448744	0	0
9994	172.412987	14955.941689	0	1
9995	711.555020	52992.378914	0	0
9996	757.962918	19660.721768	0	0
9997	845.411989	58636.156984	0	0
9998	1569.009053	36669.112365	0	0
9999	200.922183	16862.952321	0	1

10000 rows × 4 columns

Before starting analysis and modeling, wrangling data by identifying if there is any missing value and checking if there is any wrong data by get a statistical summary of each column.

```
In  [141]: print(df[df.isnull()==True].count())
           df.describe()
```

```
balance        0
income         0
default_Yes    0
student_Yes    0
dtype: int64
```

Out[141]:

	balance	income	default_Yes	student_Yes
count	10000.000000	10000.000000	10000.000000	10000.000000
mean	835.374886	33516.981876	0.033300	0.294400
std	483.714985	13336.639563	0.179428	0.455795
min	0.000000	771.967729	0.000000	0.000000
25%	481.731105	21340.462903	0.000000	0.000000
50%	823.636973	34552.644802	0.000000	0.000000
75%	1166.308386	43807.729272	0.000000	1.000000
max	2654.322576	73554.233495	1.000000	1.000000

It turns out that this dataframe has no missing values and the values in four columns are normal (i.e.no negative numbers in column 'balance' and 'income'). Now we can define X, and y for our dataset.

```
In  [149]: X = np.asarray(df[['income', 'balance', 'student_Yes']])
           X[0:5]
```

```
Out[149]: array([[4.43616251e+04, 7.29526495e+02, 0.00000000e+00],
                 [1.21061347e+04, 8.17180407e+02, 1.00000000e+00],
                 [3.17671389e+04, 1.07354916e+03, 0.00000000e+00],
                 [3.57044939e+04, 5.29250605e+02, 0.00000000e+00],
                 [3.84634959e+04, 7.85655883e+02, 0.00000000e+00]])
```

```
In  [150]: y = np.asarray(df['default_Yes'])
           y [0:5]
```

```
Out[150]: array([0, 0, 0, 0, 0], dtype=uint8)
```

Also, we normalize the dataset:

```
In  [151]: X = preprocessing.StandardScaler().fit(X).transform(X)
           X[0:5]
```

```
Out[151]: array([[ 0.81318727, -0.21883482, -0.64593619],
                 [-1.60549572, -0.03761593,  1.54814054],
                 [-0.13121225,  0.49241019, -0.64593619],
                 [ 0.16403093, -0.6328925 , -0.64593619],
                 [ 0.37091513, -0.10279088, -0.64593619]])
```

Train/Test dataset

Split the dataset into train and test set:

```
In [152]: X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.3, random_state=2)
          print ('Train set:', X_train.shape,  y_train.shape)
          print ('Test set:', X_test.shape,  y_test.shape)

          Train set: (7000, 3) (7000,)
          Test set: (3000, 3) (3000,)
```

Modeling (Logistic Regression with Scikit-learn)

Build our model using LogisticRegression from Scikit-learn package. This function implements logistic regression and can use different numerical optimizers to find parameters, including ‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers. Here the solver 'liblinear' is used due to the scale of the dataset. Now fit our model with train set:

```
In [153]: LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
          LR

Out[153]: LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=True,
                    intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
                    penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
                    verbose=0, warm_start=False)
```

Now we can predict using our test set:

```
In [154]: yhat = LR.predict(X_test)
          yhat

Out[154]: array([0, 0, 0, ..., 0, 0, 0], dtype=uint8)
```

predict_proba returns estimates for all classes, ordered by the label of classes. So, the first column is the probability of class 1, P(Y=1|X), and second column is probability of class 0, P(Y=0|X):

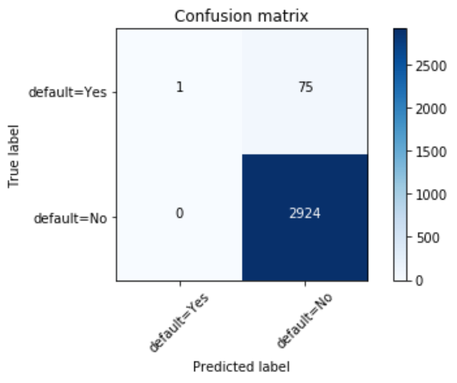
```
In [155]: yhat_prob = LR.predict_proba(X_test)
          yhat_prob

Out[155]: array([[0.95240624, 0.04759376],
                 [0.94934741, 0.05065259],
                 [0.95950125, 0.04049875],
                 ...,
                 [0.87913474, 0.12086526],
                 [0.98455597, 0.01544403],
                 [0.91853669, 0.08146331]])
```

Evaluation (Confusion Matrix)

```
In [156]: 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:
                  cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]
                  print("Normalized confusion matrix")
              else:
                  print('Confusion matrix, without normalization')

              print(cm)

              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'
              thresh = cm.max() / 2.
              for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
                  plt.text(j, i, format(cm[i, j], fmt),
                           horizontalalignment="center",
                           color="white" if cm[i, j] > thresh else "black")

              plt.tight_layout()
              plt.ylabel('True label')
              plt.xlabel('Predicted label')
          print(confusion_matrix(y_test, yhat, labels=[1,0]))

          [[   1   75]
           [   0 2924]]
```

```
In  [171]: # Compute confusion matrix
           cnf_matrix = confusion_matrix(y_test, yhat, labels=[1,0])
           np.set_printoptions(precision=2)


           # Plot non-normalized confusion matrix
           plt.figure()
           plot_confusion_matrix(cnf_matrix, classes=['default=Yes','default=No'],normalize= False,  title='Confusion matrix')
```

```
Confusion matrix, without normalization
[[   1   75]
 [   0 2924]]
```



The first row is for borrowers whose actual default value in test set is 1. As you can calculate, out of 3000 borrowers, the default value of 76 of them is 1. And out of these 76, the classifier correctly predicted 1 of them as 1, and 75 of them as 0.

It means, for 1 borrowers, the actual default value were 1 in test set, and classifier also correctly predicted those as 1. However, while the actual label of 75 borrowers were 1, the classifier predicted those as 0, which is not very good. We can consider it as error of the model for first row.

What about the borrowers with default value 0? Lets look at the second row. It looks like there were 2924 borrowers whom their default value were 0. The classifier correctly predicted 2924 of them as 0, and none of them wrongly as 1. So, it has done a good job in predicting the borrowers with default value 0.

```
In  [158]: print (classification_report(y_test, yhat))
```

```
             precision    recall  f1-score   support

          0       0.97      1.00      0.99      2924
          1       1.00      0.01      0.03        76

avg / total       0.98      0.97      0.96      3000
```

Based on the count of each section, we can calculate precision and recall of each label:

Precision is a measure of the accuracy provided that a class label has been predicted. It is defined by: precision = TP / (TP + FP)

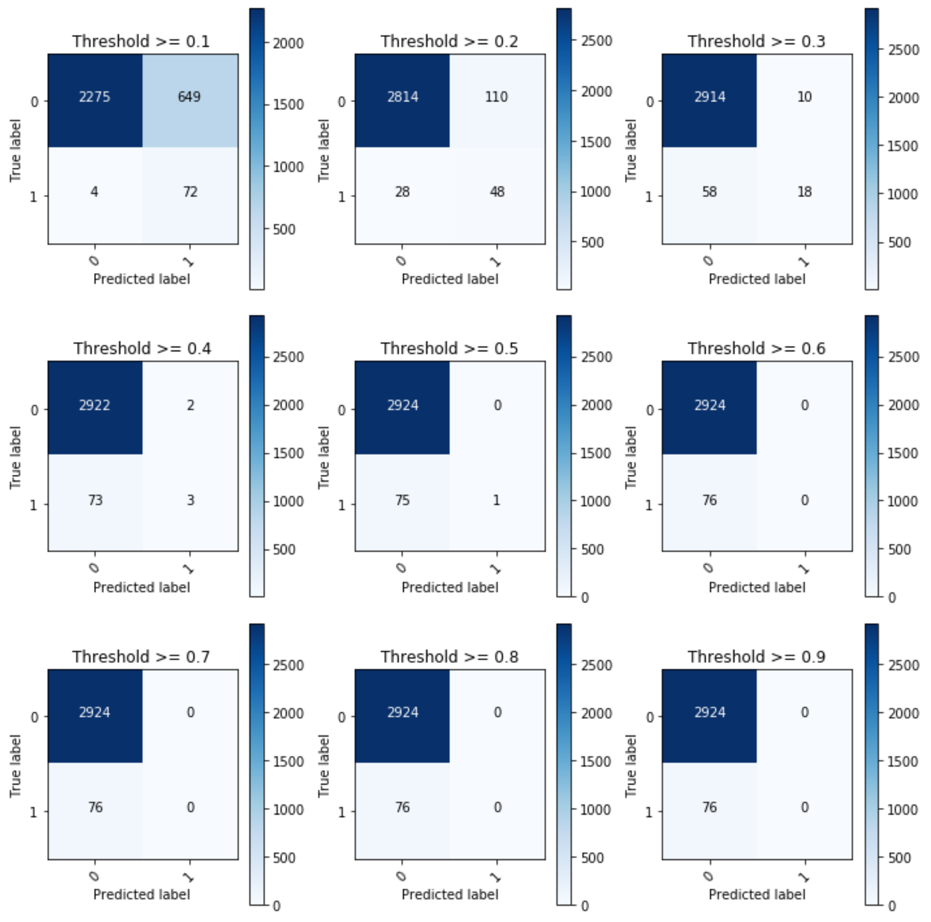
Recall is true positive rate. It is defined as: Recall = TP / (TP + FN)

So, we can calculate precision and recall of each class.

The calculation above demonstrated a normal logistic regression modeling process, which is based on a default threshold: 0.5. However, our target is to block borrowers who cannot repay the loan rather than losing potential clients. Now we do this by adjusting the threshold. Here I illustrate all confusion matrices with threshold from 0.1 to 0.9.

In [160]:
```
lr = LogisticRegression(C = 0.01,  solver='liblinear')
lr.fit(X_train,y_train)
Y_pred_proba = lr.predict_proba(X_test)

thresholds = [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]

plt.figure(figsize=(10,10))

j = 1
for i in thresholds:
    Y_test_predictions_high_recall = Y_pred_proba[:,1] > i

    plt.subplot(3,3,j)
    j += 1

    # Compute confusion matrix
    cnf_matrix = confusion_matrix(y_test,Y_test_predictions_high_recall)
    np.set_printoptions(precision=2)

    print("Recall metric in the testing dataset: ", cnf_matrix[1,1]/(cnf_matrix[1,0]+cnf_matrix[1,1]))

    # Plot non-normalized confusion matrix
    class_names = [0,1]
    plot_confusion_matrix(cnf_matrix
                          , classes=class_names
                          , title='Threshold >= %s'%i)
plt.savefig("threshold_nonpen.jpg")
```

```
Recall metric in the testing dataset:  0.9473684210526315
Confusion matrix, without normalization
[[2275  649]
 [   4   72]]
Recall metric in the testing dataset:  0.631578947368421
Confusion matrix, without normalization
[[2814  110]
 [  28   48]]
Recall metric in the testing dataset:  0.23684210526315788
Confusion matrix, without normalization
[[2914   10]
 [  58   18]]
Recall metric in the testing dataset:  0.039473684210526314
Confusion matrix, without normalization
[[2922    2]
 [  73    3]]
Recall metric in the testing dataset:  0.013157894736842105
Confusion matrix, without normalization
[[2924    0]
 [  75    1]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
```



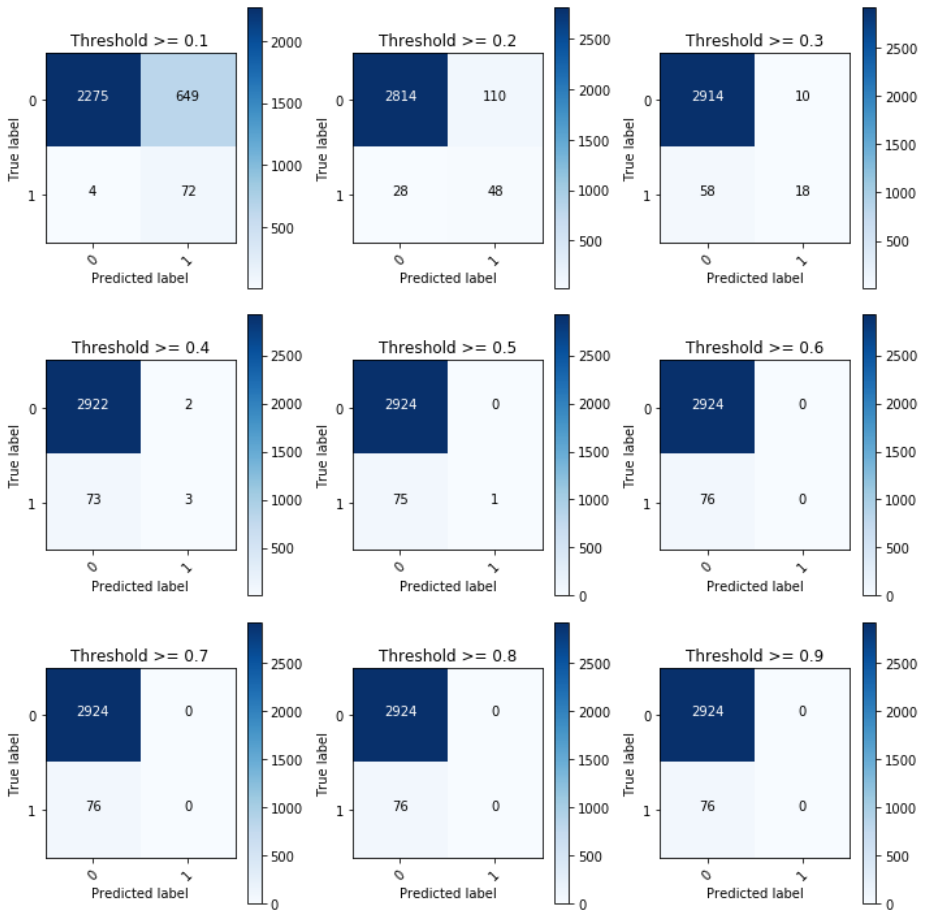
```
In  [165]: Y_test_predictions_high_recall = Y_pred_proba[:,1] > 0.1
           print ('Threshold=0.1')
           print(classification_report(y_test, Y_test_predictions_high_recall))
           print('Accuracy when threshold = 0.1: ',metrics.accuracy_score(y_test, Y_test_predictions_high_recall))
           Y_test_predictions_high_recall = Y_pred_proba[:,1] > 0.2
           print('---------------------------------------------------------')
           print ('Threshold=0.2')
           print(classification_report(y_test, Y_test_predictions_high_recall))
           print('Accuracy when threshold = 0.2: ',metrics.accuracy_score(y_test, Y_test_predictions_high_recall))
```

```
Threshold=0.1
             precision    recall  f1-score   support

          0       1.00      0.78      0.87      2924
          1       0.10      0.95      0.18        76

avg / total       0.98      0.78      0.86      3000

Accuracy when threshold = 0.1:  0.7823333333333333
---------------------------------------------------------
Threshold=0.2
             precision    recall  f1-score   support

          0       0.99      0.96      0.98      2924
          1       0.30      0.63      0.41        76

avg / total       0.97      0.95      0.96      3000

Accuracy when threshold = 0.2:  0.954
```

In dealing with larger dataset, we can add a paremeter **penalty = 'l2'** in LogisticRegression(),which is used to avoid overfits to improve the generalization of functions.

In [159]:
```python
#lr = LogisticRegression(C = 0.01, penalty = 'l2')
#lr.fit(X_train,y_train)
#Y_pred_proba = lr.predict_proba(X_test)

#thresholds = [0.1,0.2,0.3,0.4,0.5,0.6,0.7,0.8,0.9]

#plt.figure(figsize=(10,10))

#j = 1
#for i in thresholds:
    #Y_test_predictions_high_recall = Y_pred_proba[:,1] > i

    #plt.subplot(3,3,j)
    #j += 1

    # Compute confusion matrix
    #cnf_matrix = confusion_matrix(y_test,Y_test_predictions_high_recall)
    #np.set_printoptions(precision=2)

    #print("Recall metric in the testing dataset: ", cnf_matrix[1,1]/(cnf_matrix[1,0]+cnf_matrix[1,1]))

    # Plot non-normalized confusion matrix
    class_names = [0,1]
    plot_confusion_matrix(cnf_matrix
                          , classes=class_names
                          , title='Threshold >= %s'%i)
#plt.savefig("threshold cm.jpg")
```

```
Recall metric in the testing dataset:  0.9473684210526315
Confusion matrix, without normalization
[[2275  649]
 [   4   72]]
Recall metric in the testing dataset:  0.631578947368421
Confusion matrix, without normalization
[[2814  110]
 [  28   48]]
Recall metric in the testing dataset:  0.23684210526315788
Confusion matrix, without normalization
[[2914   10]
 [  58   18]]
Recall metric in the testing dataset:  0.039473684210526314
Confusion matrix, without normalization
[[2922    2]
 [  73    3]]
Recall metric in the testing dataset:  0.013157894736842105
Confusion matrix, without normalization
[[2924    0]
 [  75    1]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
Recall metric in the testing dataset:  0.0
Confusion matrix, without normalization
[[2924    0]
 [  76    0]]
```


Threshold >= 0.1
Threshold >= 0.2
Threshold >= 0.3
Threshold >= 0.4
Threshold >= 0.5
Threshold >= 0.6
Threshold >= 0.7
Threshold >= 0.8
Threshold >= 0.9
True label
Predicted label