Logistic Regression

Will create a model for a telecommunication company, to predict when its customers will leave for a competitor, so that they can take some action to retain the customers.

Required libraries:

In [1]:

```
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
```

About the dataset
Will use telecommunications dataset for predicting customer churn. This is a historical customer dataset where each row represents one customer. Typically it is less expensive to keep customers than acquire new ones, so the focus of this analysis is to predict the customers who will stay with the company.

This data set provides information to predict what behavior will help you to retain customers. Will analyze all relevant customer data and develop focused customer retention programs.

The dataset includes information about:

- Customers who left within the last month – the column is called Churn
- Services that each customer has signed up for – phone, multiple lines, internet, online security, online backup, device protection, tech support, and streaming TV and movies
- Customer account information – how long they had been a customer, contract, payment method, paperless billing, monthly charges, and total charges
- Demographic info about customers – gender, age range, and if they have partners and dependents

A telecommunications company is concerned about the number of customers leaving their land-line business for cable competitors. They need to understand who is leaving.

Load Data From CSV File

In [2]:

```
df = pd.read_csv("ChurnData.csv")
df.head()
```

Out[2]:

	tenure	age	address	income	ed	employ	equip	callcard	wireless	longmon	...	page
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0	1.0	4.40	...	1.
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0	0.0	9.45	...	0.
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0	0.0	6.30	...	0.
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0	1.0	6.05	...	1.
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0	0.0	7.10	...	0.

5 rows × 28 columns

Data pre-processing and selection

In [3]:

```
df = df[['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip',   'callcard',
'wireless','churn']]
df['churn'] = df['churn'].astype('int')
df.head()
```

Out[3]:

	tenure	age	address	income	ed	employ	equip	callcard	wireless	churn
0	11.0	33.0	7.0	136.0	5.0	5.0	0.0	1.0	1.0	1
1	33.0	33.0	12.0	33.0	2.0	0.0	0.0	0.0	0.0	1
2	23.0	30.0	9.0	30.0	1.0	2.0	0.0	0.0	0.0	0
3	38.0	35.0	5.0	76.0	2.0	10.0	1.0	1.0	1.0	0
4	7.0	35.0	14.0	80.0	2.0	15.0	0.0	1.0	0.0	0

In [4]:

```
X = np.asarray(df[['tenure', 'age', 'address', 'income', 'ed', 'employ', 'equip']])
X[0:5]
```

Out[4]:

```
array([[ 11.,  33.,   7., 136.,   5.,   5.,   0.],
       [ 33.,  33.,  12.,  33.,   2.,   0.,   0.],
       [ 23.,  30.,   9.,  30.,   1.,   2.,   0.],
       [ 38.,  35.,   5.,  76.,   2.,  10.,   1.],
       [  7.,  35.,  14.,  80.,   2.,  15.,   0.]])
```

In [5]:

```
y = np.asarray(df['churn'])
y [0:5]
```

Out[5]:

```
array([1, 1, 0, 0, 0])
```

Also, we normalize the dataset:

In [6]:

```
from sklearn import preprocessing
X = preprocessing.StandardScaler().fit(X).transform(X)
X[0:5]
```

Out[6]:

```
array([[-1.13518441, -0.62595491, -0.4588971 ,  0.4751423 ,  1.6961288 ,
        -0.58477841, -0.85972695],
       [-0.11604313, -0.62595491,  0.03454064, -0.32886061, -0.6433592 ,
        -1.14437497, -0.85972695],
       [-0.57928917, -0.85594447, -0.261522  , -0.35227817, -1.42318853,
        -0.92053635, -0.85972695],
       [ 0.11557989, -0.47262854, -0.65627219,  0.00679109, -0.6433592 ,
        -0.02518185,  1.16316   ],
       [-1.32048283, -0.47262854,  0.23191574,  0.03801451, -0.6433592 ,
         0.53441472, -0.85972695]])
```

Train/Test dataset
Okay, we split our dataset into train and test set:

In [7]:

```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split( X, y, test_size=0.2, random_state=
4)
print ('Train set:', X_train.shape,  y_train.shape)
print ('Test set:', X_test.shape,  y_test.shape)
```

```
Train set: (160, 7) (160,)
Test set: (40, 7) (40,)
```

Modeling (Logistic Regression with Scikit-learn)

This function implements logistic regression and can use different numerical optimizers to find parameters, including ‘newton-cg’, ‘lbfgs’, ‘liblinear’, ‘sag’, ‘saga’ solvers.**C** parameter indicates **inverse of regularization strength** which must be a positive float.

In [8]:

```
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import confusion_matrix
LR = LogisticRegression(C=0.01, solver='liblinear').fit(X_train,y_train)
LR
```

Out[8]:

```
LogisticRegression(C=0.01, class_weight=None, dual=False, fit_intercept=Tr
ue,
          intercept_scaling=1, max_iter=100, multi_class='warn',
          n_jobs=None, penalty='l2', random_state=None, solver='liblinea
r',
          tol=0.0001, verbose=0, warm_start=False)
```

In [9]:

```
yhat = LR.predict(X_test)
yhat
```

Out[9]:

```
array([0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1, 0, 0, 0, 1, 1, 0, 0, 0,
       0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1, 0, 0, 0])
```

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 [10]:

```
yhat_prob = LR.predict_proba(X_test)
yhat_prob
```

Out[10]:

```
array([[0.54132919, 0.45867081],
       [0.60593357, 0.39406643],
       [0.56277713, 0.43722287],
       [0.63432489, 0.36567511],
       [0.56431839, 0.43568161],
       [0.55386646, 0.44613354],
       [0.52237207, 0.47762793],
       [0.60514349, 0.39485651],
       [0.41069572, 0.58930428],
       [0.6333873 , 0.3666127 ],
       [0.58068791, 0.41931209],
       [0.62768628, 0.37231372],
       [0.47559883, 0.52440117],
       [0.4267593 , 0.5732407 ],
       [0.66172417, 0.33827583],
       [0.55092315, 0.44907685],
       [0.51749946, 0.48250054],
       [0.485743  , 0.514257  ],
       [0.49011451, 0.50988549],
       [0.52423349, 0.47576651],
       [0.61619519, 0.38380481],
       [0.52696302, 0.47303698],
       [0.63957168, 0.36042832],
       [0.52205164, 0.47794836],
       [0.50572852, 0.49427148],
       [0.70706202, 0.29293798],
       [0.55266286, 0.44733714],
       [0.52271594, 0.47728406],
       [0.51638863, 0.48361137],
       [0.71331391, 0.28668609],
       [0.67862111, 0.32137889],
       [0.50896403, 0.49103597],
       [0.42348082, 0.57651918],
       [0.71495838, 0.28504162],
       [0.59711064, 0.40288936],
       [0.63808839, 0.36191161],
       [0.39957895, 0.60042105],
       [0.52127638, 0.47872362],
       [0.65975464, 0.34024536],
       [0.5114172 , 0.4885828 ]])
```

Evaluation

jaccard index

jaccard is the size of the intersection divided by the size of the union of two label sets. 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.

In [11]:

```
from sklearn.metrics import jaccard_similarity_score
jaccard_similarity_score(y_test, yhat)
```

Out[11]:

```
0.75
```

confusion matrix

Another way of looking at accuracy of classifier is to look at **confusion matrix**.

In [12]:

```
from sklearn.metrics import classification_report, confusion_matrix
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:
        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]))
```

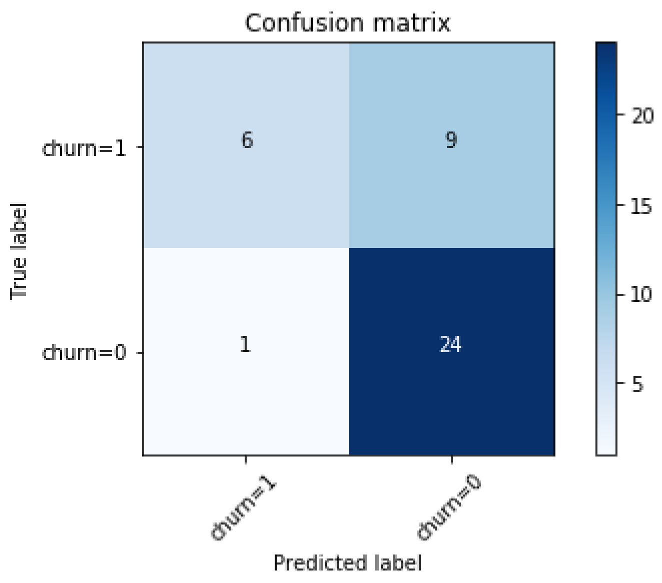
```
[[ 6  9]
 [ 1 24]]
```

In [13]:

```
# 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=['churn=1','churn=0'],normalize= False,  titl
e='Confusion matrix')
```

```
Confusion matrix, without normalization
[[ 6  9]
 [ 1 24]]
```



In [14]:

```
print (classification_report(y_test, yhat))
```

```
              precision    recall  f1-score   support

           0       0.73      0.96      0.83        25
           1       0.86      0.40      0.55        15

   micro avg       0.75      0.75      0.75        40
   macro avg       0.79      0.68      0.69        40
weighted avg       0.78      0.75      0.72        40
```

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.

F1 score: Now we are in the position to calculate the F1 scores for each label based on the precision and recall of that label.

The F1 score is the harmonic average of the precision and recall, where an F1 score reaches its best value at 1 (perfect precision and recall) and worst at 0. It is a good way to show that a classifer has a good value for both recall and precision.

And finally, we can tell the average accuracy for this classifier is the average of the F1-score for both labels, which is 0.72 in our case.

log loss Now, lets try log loss for evaluation. In logistic regression, the output can be the probability of customer churn is yes (or equals to 1). This probability is a value between 0 and 1. Log loss(Logarithmic loss) measures the performance of a classifier where the predicted output is a probability value between 0 and 1.

log loss

Now, lets try **log loss** for evaluation. In logistic regression, the output can be the probability of customer churn is yes (or equals to 1). This probability is a value between 0 and 1. Log loss(Logarithmic loss) measures the performance of a classifier where the predicted output is a probability value between 0 and 1.

In [15]:

```
from sklearn.metrics import log_loss
log_loss(y_test, yhat_prob)
```

Out[15]:

```
0.6017092478101186
```

In [ ]:

```

```