Ward Structured Hierarchical Clustering

Ward Clustering is a hierarchical clustering. Structured clustering is performed without connectivity constraints on the structure and is solely based on distance.

In [1]:
```
from sklearn import datasets
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn import cluster
from sklearn.cluster import KMeans
from sklearn.ensemble import IsolationForest
from sklearn.neighbors import LocalOutlierFactor
from sklearn import svm, neighbors
from sklearn.neighbors import NearestNeighbors

from sklearn.metrics import classification_report
from sklearn.metrics import confusion_matrix
from sklearn.metrics import recall_score
from sklearn.metrics import roc_auc_score
from sklearn.model_selection import GridSearchCV
from sklearn.metrics import make_scorer
from sklearn.metrics import accuracy_score

import pandas as pd
import numpy as np
import itertools
import matplotlib.pyplot as plt
import datetime

%matplotlib inline
```

In [2]:
```
train_split = 0.80
nrows = 250_000
path = 'c:/users/ugy1/abs/'
df=pd.read_csv(path+'datasets/processed_abs_loan_'+str(nrows)+'.csv',
               #usecols=use_list,
               #sep='\t',
               #compression=bz2,
               nrows=nrows,
               low_memory=False,
              index_col=0,
               parse_dates=True
              )
df.shape
```

Out[2]: (237024, 58)

In [3]:
```
column_list=df.columns.tolist()
```

In [4]:
```
df.head()
```

Out[4]:

	originalloanamount	originalloanterm	originalinterestratepercentage	graceperiodnumb
0	66711.84	60	3.29	1
1	16258.45	60	0.90	0
2	31930.41	72	2.90	1
3	26065.02	65	0.90	0
4	42091.00	72	3.90	0

5 rows × 58 columns

In [5]:
```
# prepare label for scikit-learn
Y=df.label.values
Y.shape
```

Out[5]: (237024,)

In [6]:
```
# prepare input data for scikit-learn
input=df.values
input.shape
```

Out[6]: (237024, 58)

In [7]:
```
# calculate train/test split

len_train = int(len(input)*train_split)
print(len_train)
```

189619

In [8]:
```
# apply train/test split to labels
y_train = Y[0:len_train]
y_test = Y[len_train:]
x_train = input[0:len_train]
x_test = input[len_train:]
x_train.shape
```

Out[8]: (189619, 58)

In [9]:
```
export_x_test = pd.DataFrame(data=x_test)
```

In [10]:
```
export_x_test.columns=column_list
export_x_test.rename(columns={'label':'True Label'}, inplace=True)
export_x_test.head()
```

Out[10]:

	originalloanamount	originalloanterm	originalinterestratepercentage	graceperiodnumb
0	36863.24	72.0	1.00	1.0
1	23811.32	60.0	1.90	0.0
2	30669.00	48.0	1.00	1.0
3	54083.21	72.0	1.00	0.0
4	31557.75	72.0	3.89	1.0

5 rows × 58 columns

In [11]:
```
#from sklearn.preprocessing import MinMaxScaler
# from sklearn.preprocessing import minmax_scale
# from sklearn.preprocessing import MaxAbsScaler
from sklearn.preprocessing import StandardScaler
# from sklearn.preprocessing import RobustScaler
# from sklearn.preprocessing import Normalizer
# from sklearn.preprocessing import QuantileTransformer
# from sklearn.preprocessing import PowerTransformer
```

In [12]:
```
x_scaler=StandardScaler()
x_train = x_scaler.fit_transform(x_train)
x_test = x_scaler.fit_transform(x_test)
```

In [13]:
```
#ward = cluster.Ward(n_clusters=2, memory=Memory(cachedir=None), connectivity=
None, copy=None, n_components=None, compute_full_tree='auto')
ward = cluster.AgglomerativeClustering(n_clusters=2, linkage='ward')
clf_ward= ward.fit(x_test)
```

In [14]:
```
#x_pred = x_test
```

In [15]:
```
prediction_ward = ward.labels_
```

In [16]:
```
np.unique(prediction_ward)
```

Out[16]:
```
array([0, 1], dtype=int64)
```

In [17]:
```
np.bincount(np.array(prediction_ward).reshape(1,prediction_ward.size)[0])
```

Out[17]:
```
array([37144, 10261], dtype=int64)
```

In [18]:
```
export_x_test['Predicted Label']=prediction_ward
```

In [19]:
```
export_x_test.head()
```

Out[19]:

	originalloanamount	originalloanterm	originalinterestratepercentage	graceperiodnuml
0	36863.24	72.0	1.00	1.0
1	23811.32	60.0	1.90	0.0
2	30669.00	48.0	1.00	1.0
3	54083.21	72.0	1.00	0.0
4	31557.75	72.0	3.89	1.0

5 rows × 59 columns

In [20]:
```
export_x_test.shape
```

Out[20]: (47405, 59)

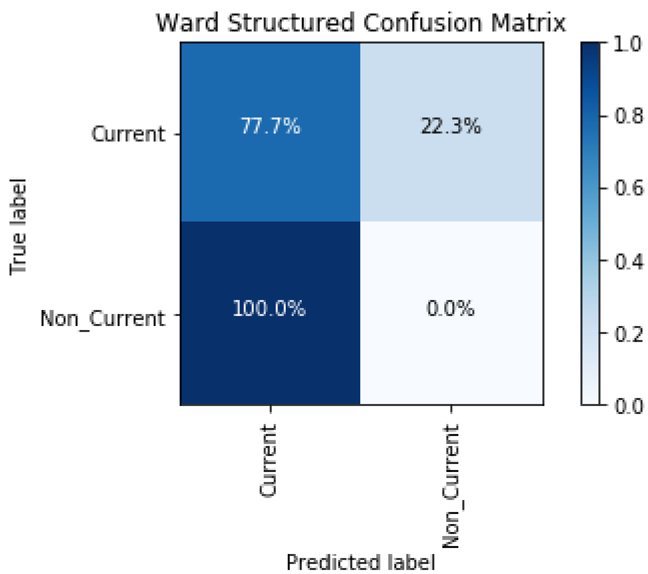
In [21]:
```
export_x_test.to_csv(path+"prediction/ward_s/predicated_ward_s_abs_loans_"+str
(nrows)+".csv", chunksize=10000)
```

In [22]:
```
def plot_confusion_matrix(cm, title, classes=['Current', 'Non_Current'],
                          cmap=plt.cm.Blues, save=False, saveas="MyFigure.png"
):

    # print Confusion matrix with blue gradient colours

    cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    fmt = '.1%'
    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')

    if save:
        plt.savefig(saveas, dpi=100)
```

In [23]:
```
def plot_gridsearch_cv(results, estimator, x_min, x_max, y_min, y_max,save=F
alse, saveas="MyFigure.png"):

    # print GridSearch cross-validation for parameters

    plt.figure(figsize=(10,8))
    plt.title("GridSearchCV for "+estimator, fontsize=24)

    plt.xlabel(estimator)
    plt.ylabel("Score")
    plt.grid()

    ax = plt.axes()
    ax.set_xlim(x_min, x_max)
    ax.set_ylim(y_min, y_max)

    pad = 0.005
    X_axis = np.array(results["param_"+estimator].data, dtype=float)

    for scorer, color in zip(sorted(scoring), ['b', 'k']):
        for sample, style in (('train', '--'), ('test', '-')):
            sample_score_mean = results['mean_%s_%s' % (sample, scorer)]
            sample_score_std = results['std_%s_%s' % (sample, scorer)]
            ax.fill_between(X_axis, sample_score_mean - sample_score_std,
                            sample_score_mean + sample_score_std,
                            alpha=0.1 if sample == 'test' else 0, color=color)
            ax.plot(X_axis, sample_score_mean, style, color=color,
                alpha=1 if sample == 'test' else 0.7,
                label="%s (%s)" % (scorer, sample))

        best_index = np.nonzero(results['rank_test_%s' % scorer] == 1)[0][0]
        best_score = results['mean_test_%s' % scorer][best_index]

        # Plot a dotted vertical line at the best score for that scorer mark
ed by x
        ax.plot([X_axis[best_index], ] * 2, [0, best_score],
            linestyle='-.', color=color, marker='x', markeredgewidth=3, ms=8
)

        # Annotate the best score for that scorer
        ax.annotate("%0.2f" % best_score,
                (X_axis[best_index], best_score+pad))

    plt.legend(loc="best")
    plt.grid('off')
    plt.tight_layout()
    if save:
        plt.savefig(saveas, dpi=100)

    plt.show()
```

In [24]:
```
print(classification_report(y_test, prediction_ward, target_names=['Current'
, 'Non_Current']))
print ("AUC: ", "{:.1%}".format(roc_auc_score(y_test, prediction_ward)))
cm = confusion_matrix(y_test, prediction_ward)
plot_confusion_matrix(cm, title="Ward Structured Confusion Matrix",save=True
,
                      saveas='prediction/ward_s/cm'+str(' Ward Structured Ac
curacy-')+str(nrows)+'.jpg')
```

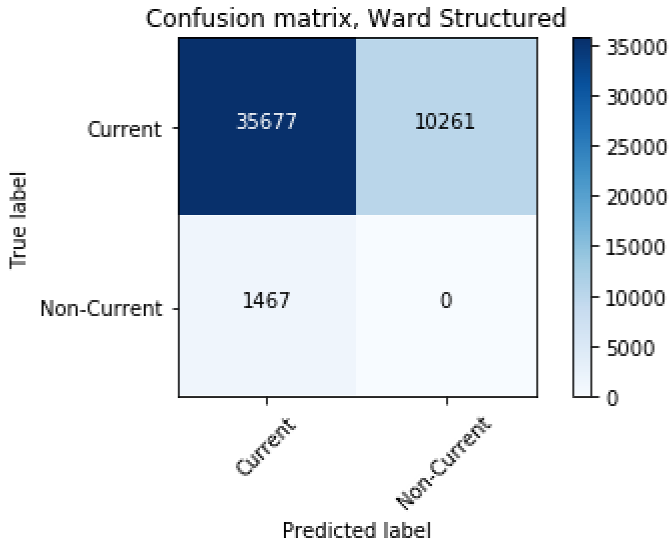
```
             precision    recall  f1-score   support

    Current       0.96      0.78      0.86     45938
Non_Current       0.00      0.00      0.00      1467

avg / total       0.93      0.75      0.83     47405

AUC:  38.8%
```



In [25]:

```
class_names = ['Current', 'Non-Current']

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


print('ROC_AUC_SCORE ; ', roc_auc_score(y_test, prediction_ward))
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, prediction_ward)
np.set_printoptions(precision=2)

# Plot non-normalized confusion matrix
plt.figure()
plot_confusion_matrix(cnf_matrix, classes=class_names, title= 'Confusion matri
x, Ward Structured')
plt.savefig('prediction/ward_s/cm'+str(' Ward Structured-')+str(nrows)+'.jpg')
plt.show()
```

```
ROC_AUC_SCORE ;  0.388316861857
Confusion matrix, without normalization
[[35677 10261]
 [ 1467     0]]
```



In [ ]: