Gaussian Mixture Models / PCA - Unsupervised

A Gaussian mixture model is a probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. One can think of mixture models as generalizing k-means clustering to incorporate information about the covariance structure of the data as well as the centers of the latent Gaussians.

GMM has difficulty converging in higher diemensional space. Therefore PCA was applied as a dimensionality reduction technique. Refer the bottom after the initial GMM run. Accuracy did not improve even after dimensions were reduced to 15.

In [1]:
```
from sklearn import datasets
from sklearn import preprocessing
from sklearn.model_selection import train_test_split
from sklearn.decomposition import PCA

from sklearn.mixture import GaussianMixture
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.label.value_counts()
```

Out[4]:
```
0    229634
1      7390
Name: label, dtype: int64
```

In [5]:
```
df.head()
```

Out[5]:

	originalloanamount	originalloanterm	originalinterestratepercentage	graceperiodnuml
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 [6]:
```
# prepare label for scikit-learn
Y=df.label.values
Y.shape
```

Out[6]: (237024,)

In [7]:
```
# prepare input data for scikit-learn
input=df.values
input.shape
```

Out[7]: (237024, 58)

In [8]:
```
# calculate train/test split

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

```
189619
```

In [9]:
```
# 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[9]:
```
(189619, 58)
```

In [10]:
```
export_x_test = pd.DataFrame(data=x_test)
```

In [11]:
```
export_x_test.columns=column_list
export_x_test.rename(columns={'label':'True Label'}, inplace=True)
export_x_test.head()
```

Out[11]:

	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 × 58 columns

In [12]:
```
#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 [13]:
```
x_scaler=StandardScaler()
x_train = x_scaler.fit_transform(x_train)
x_test = x_scaler.fit_transform(x_test)
```

In [14]:
```
clf_gmm = GaussianMixture(n_components=2,
                          covariance_type='full',
                          #reg_covar=1e-6,
                          random_state=54,
                          max_iter= 100
                         ).fit(x_test)
```

In [15]:
```
x_pred=x_test
```

In [16]:
```
prediction_gmm = clf_gmm.predict(x_pred)
```

In [17]:
```
np.unique(prediction_gmm)
```

Out[17]:
```
array([0, 1], dtype=int64)
```

In [18]:
```
np.bincount(np.array(prediction_gmm).reshape(1,prediction_gmm.size)[0])
```

Out[18]:
```
array([10969, 36436], dtype=int64)
```

In [19]:
```
export_x_test['Predicted Label']=prediction_gmm
```

In [20]:
```
export_x_test.head()
```

Out[20]:

	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 [21]:
```
export_x_test.shape
```

Out[21]:
```
(47405, 59)
```

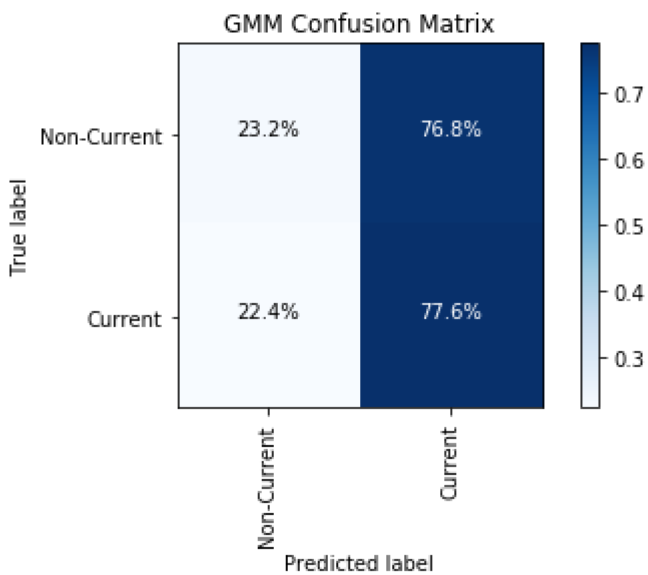
In [22]:
```
export_x_test.to_csv(path+"prediction/gmm/predicated_gmm_abs_loans_"+str(nrows
)+".csv", chunksize=10000)
```

In [23]:
```
def plot_confusion_matrix(cm, title, classes=['Non-Current', '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 [24]:
```
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()
```

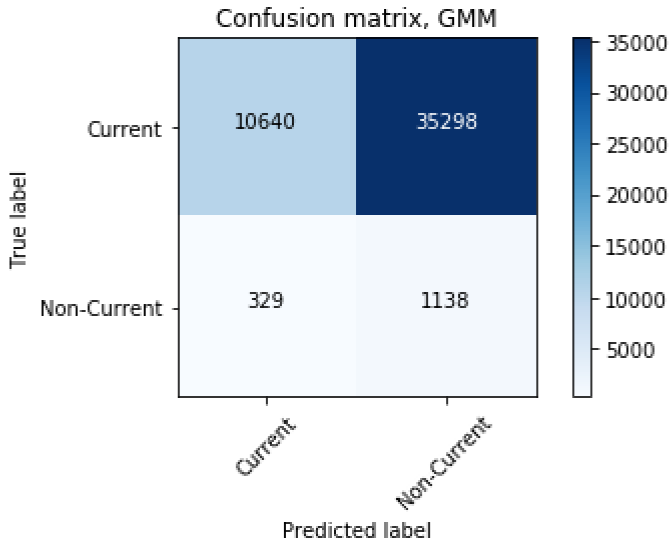
In [25]:
```
print(classification_report(y_test, prediction_gmm, target_names=['Non-Curren
t', 'Current']))
print ("AUC: ", "{:.1%}".format(roc_auc_score(y_test, prediction_gmm)))
cm = confusion_matrix(y_test, prediction_gmm)
plot_confusion_matrix(cm, title="GMM Confusion Matrix",save=True,
                      saveas='prediction/gmm/cm'+str(' GMM Accuracy-')+str(nro
ws)+'.jpg')
```

```
             precision    recall  f1-score   support

Non-Current       0.97      0.23      0.37     45938
    Current       0.03      0.78      0.06      1467

avg / total       0.94      0.25      0.36     47405

AUC:  50.4%
```



In [26]:
```
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_gmm))
# Compute confusion matrix
cnf_matrix = confusion_matrix(y_test, prediction_gmm)
np.set_printoptions(precision=2)

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

```
ROC_AUC_SCORE ;  0.503674657313
Confusion matrix, without normalization
[[10640 35298]
 [  329  1138]]
```



Applying PCA

In [27]:

```
pca = PCA(0.80, whiten=True)
pca_x_test = pca.fit_transform(x_test)
pca_x_test.shape
```

Out[27]: (47405, 15)

In [28]:

```
clf_gmm = GaussianMixture(n_components=2,
                          covariance_type='full',
                          #reg_covar=1e-6,
                          random_state=54,
                          max_iter= 100
                         ).fit(pca_x_test)
prediction_gmm = clf_gmm.predict(pca_x_test)
```

In [29]:

```
print(classification_report(y_test, prediction_gmm, target_names=['Non-Curren
t', 'Current']))
print ("AUC: ", "{:.1%}".format(roc_auc_score(y_test, prediction_gmm)))
cm = confusion_matrix(y_test, prediction_gmm)
```

```
             precision    recall  f1-score   support

Non-Current       0.97      0.23      0.37     45938
    Current       0.03      0.78      0.06      1467

avg / total       0.94      0.25      0.36     47405

AUC:  50.4%
```

```
In [ ]:
```