Tugas Besar 2 IF3170 Inteligensi Buatan

Dibuat Oleh Kelompok 9 dengan anggota
1. 13516002 Antonio Setya
2. 13516039 Alvin Limassa
3. 13516068 Seperayo
4. 13516143 Juan Felix Parsaoran
5. 13516146 Aristoteles Swarna Wirahadi

Read the dataset

In [1]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import warnings
from sklearn.externals import joblib
warnings.filterwarnings('ignore')
pd.options.display.max_columns = 30
%matplotlib inline
```

In [2]:
```
df = pd.read_csv('tubes2_HeartDisease_train.csv')
df_eval = pd.read_csv('tubes2_HeartDisease_test.csv')
```

In [3]:
```
target = df['Column14']
df.drop("Column14" ,axis = 1,inplace=True)
```

Feature Engineering

Feature Engineering adalah suatu proses yang menggunakan domain knowledge dari suatu data untuk membuat fitur yang menjalankan algoritma *machine learning*. Proses ini sangat penting dalam pengaplikasian *machine learning*, namun proses ini cukup sulit dan mahal sifatnya.

Dalam tugas kali ini penanganan dan analisa data yang kami lakukan adalah dengan **Null Imputation, Change Data Type, Transform Data, Deal with Imbalance Data**. Selain itu, ukuran kinerja yang kami gunakan dalam eksperimen ini adalah *accuracy, precision, recall, dan F1*.

Null Imputation

Data yang diberikan dalam pengerjaan tugas ini memiliki beberapa bagian yang tidak tercantum atau bisa dibilang hilang. Terdapat beberapa cara dalam mengolah permasalahan ini, seperti mengabaikan, mengisi, dan menghapus data terkait. Pengabaian data dapat menimbulkan permasalahan dalam analisis data ditahap-tahap selanjutnya. Dalam tugas kali ini, kami memilih mengisikan data yang hilang dengan *fillna()*.

In [4]:
```
for column in list(df):
    temp = []
    for value in df[column]:
        if value == '?':
            temp.append(np.nan)
        else:
            temp.append(value)
    df[column] = temp

for column in list(df_eval):
    temp = []
    for value in df_eval[column]:
        if value == '?':
            temp.append(np.nan)
        else:
            temp.append(value)
    df_eval[column] = temp
```

In [5]:
```
#Filling the missing data
for column in list(df):
    df[column] = df[column].fillna(df[column].median())


for column in list(df_eval):
    df_eval[column] = df_eval[column].fillna(df_eval[column].median())
```

In [6]:
```
df['Column7'] = df['Column7'].fillna(df['Column7'].median())
```

Change data type

Selain Null Imputation, kami juga menerapkan Change Data Type dengan method *astype()*. Method ini memungkinkan kita untuk secara *explicit* melakukan konversi *dtype* yang diinginkan. Penggunaan method ini juga memberikan tingkat serba guna yang tinggi dalam proses konversi ke berbagai tipe.

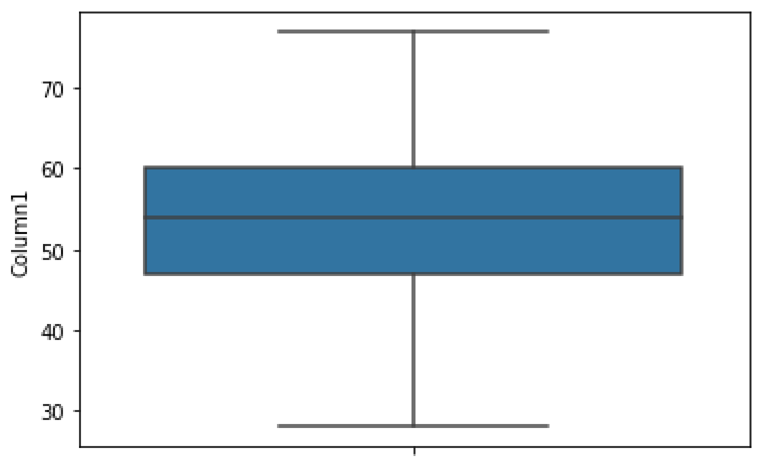
In [7]:
```
df['Column4'] = df['Column4'].astype('int64')
df['Column5'] = df['Column5'].astype('int64')
df['Column6'] = df['Column6'].astype('int64')
df['Column7'] = df['Column7'].astype('int64')
df['Column8'] = df['Column8'].astype('int64')
df['Column9'] = df['Column9'].astype('int64')
df['Column10'] = df['Column10'].astype('float64')
df['Column11'] = df['Column11'].astype('int64')
df['Column12'] = df['Column12'].astype('int64')
df['Column13'] = df['Column13'].astype('int64')
```

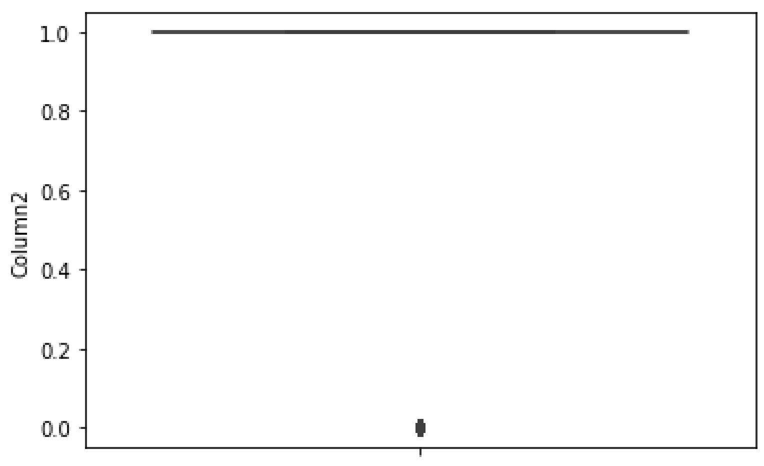
In [8]:
```
df_eval['Column4'] = df_eval['Column4'].astype('int64')
df_eval['Column5'] = df_eval['Column5'].astype('int64')
df_eval['Column6'] = df_eval['Column6'].astype('int64')
df_eval['Column7'] = df_eval['Column7'].astype('int64')
df_eval['Column8'] = df_eval['Column8'].astype('int64')
df_eval['Column9'] = df_eval['Column9'].astype('int64')
df_eval['Column10'] = df_eval['Column10'].astype('float64')
df_eval['Column11'] = df_eval['Column11'].astype('int64')
df_eval['Column12'] = df_eval['Column12'].astype('int64')
df_eval['Column13'] = df_eval['Column13'].astype('int64')
```

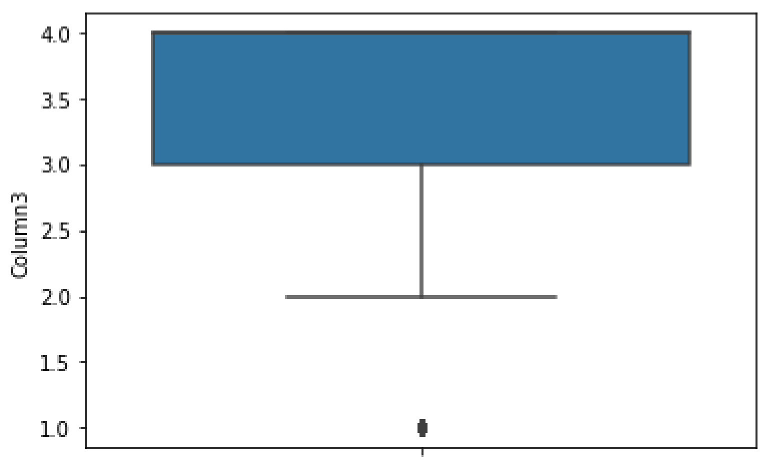
Transform Data

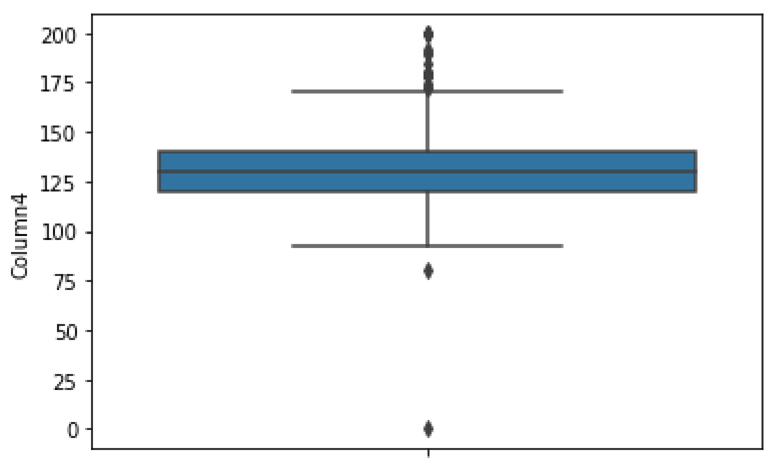
Kami menstandarisasi data dengan mentransform data. Disini kami menggunakan RobustScaler yang akan menghilangkan dan menskalakan data dengan interkuartil data. RobustScaler digunakan karena data ini memiliki banyak outlier. Sehingga jika menskalakan data dengan mean atau variansi tidak akan menghasilkan prediksi yang baik

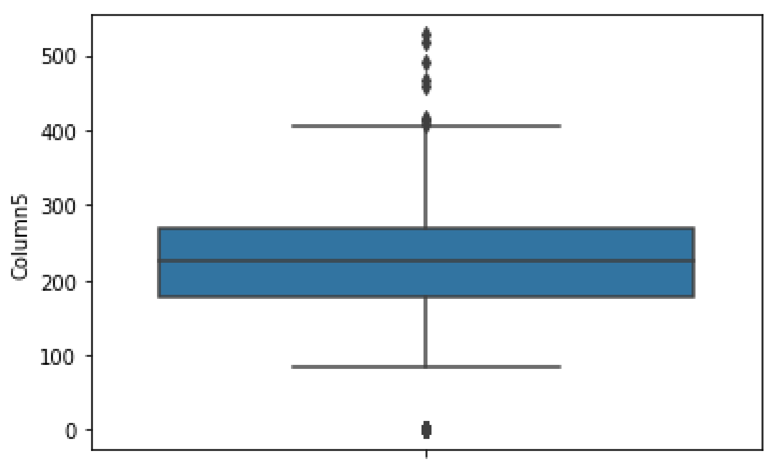
In [9]:
```
#memeriksa outlier
plt.figure()
for x in list(df):
    if(df.dtypes[x]=='int64' or df.dtypes[x]=='float64'):
        sns.boxplot(df[x], orient='v')
        plt.show()
```

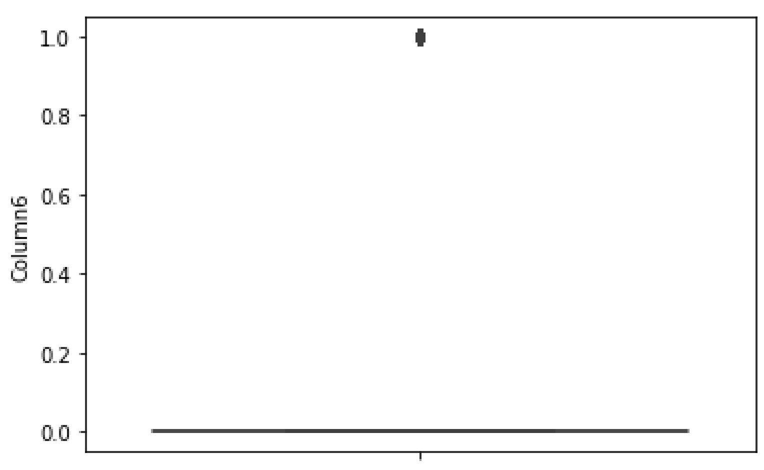

Column1
70
60
50
40
30

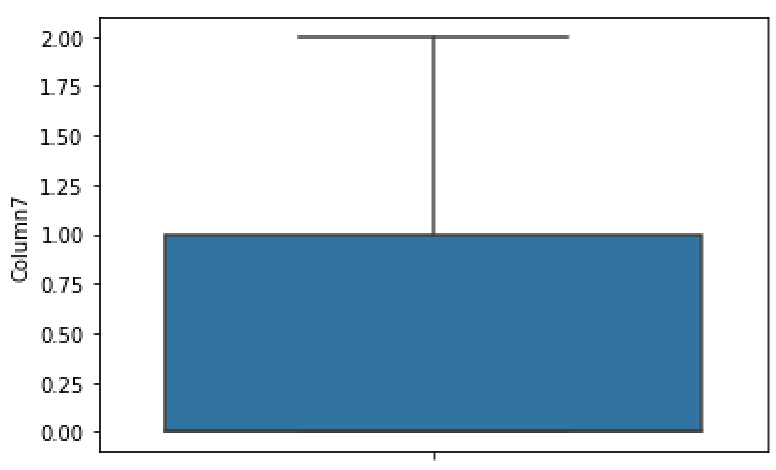

Column2
1.0
0.8
0.6
0.4
0.2
0.0

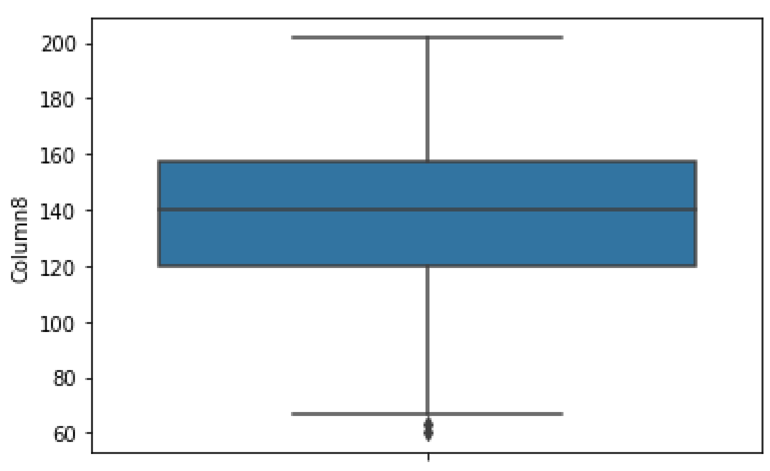

Column3
4.0
3.5
3.0
2.5
2.0
1.5
1.0

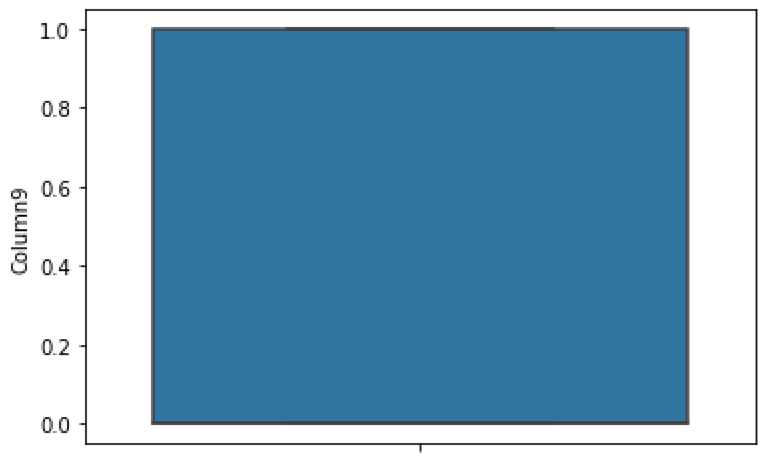

Column4
200
175
150
125
100
75
50
25
0

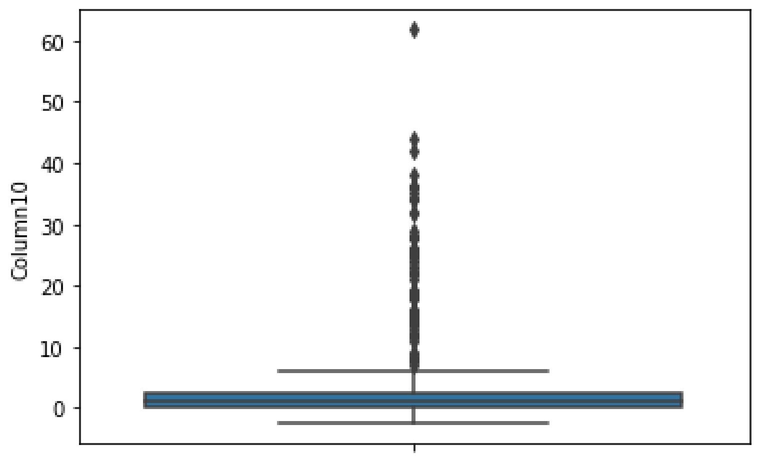

Column5
500
400
300
200
100
0

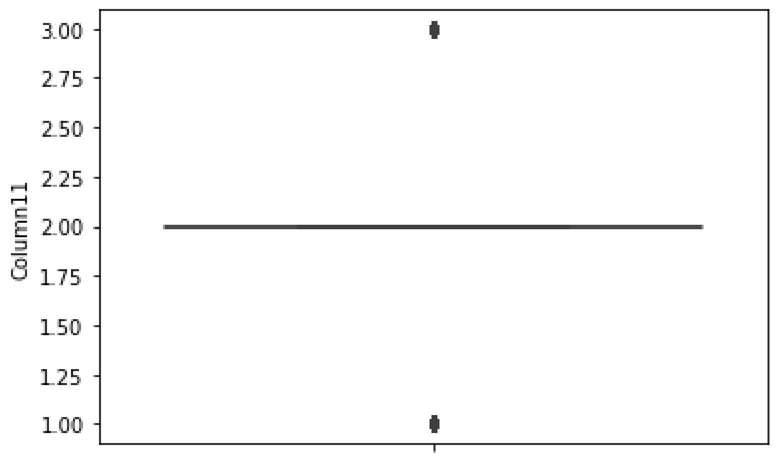

Column6
1.0
0.8
0.6
0.4
0.2
0.0

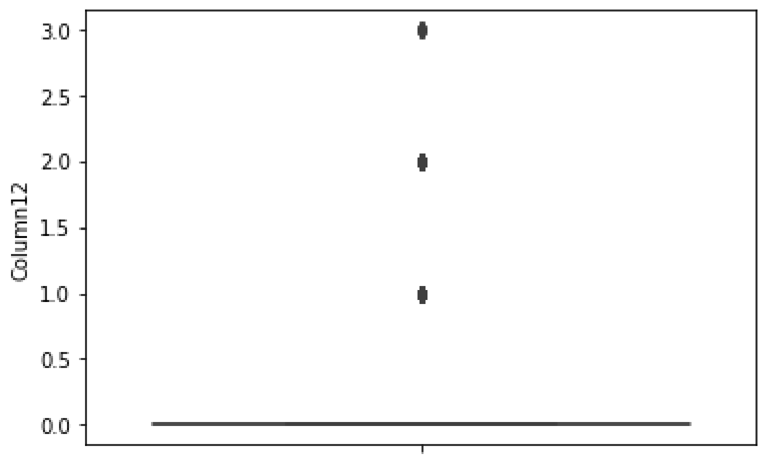

Column7
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00

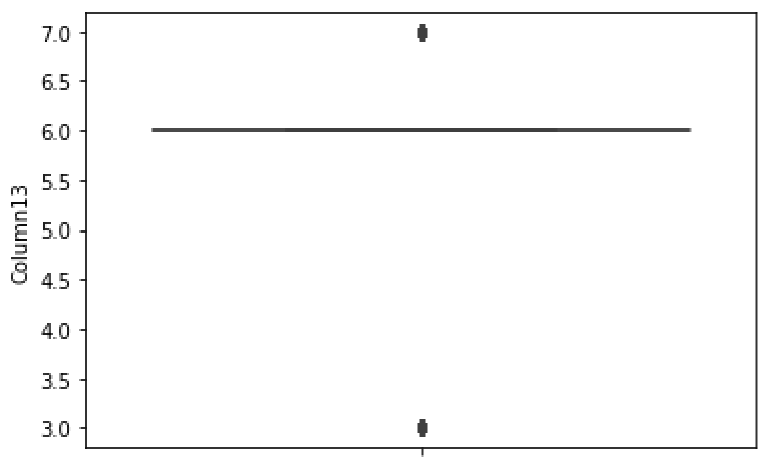

Column8
200
180
160
140
120
100
80
60











In [10]:
```
from sklearn.preprocessing import RobustScaler
transformer = RobustScaler().fit(df)
df = transformer.transform(df)
transformer = RobustScaler().fit(df_eval)
joblib.dump(transformer,"data_transformer.dat")
X_res_eval = transformer.transform(df_eval)
df_eval = pd.DataFrame({'Column1':X_res_eval[:,0],'Column2':X_res_eval[:,1],'Column3':X_res_eval[:,2],'Column4':X_res_eval[:,3],'Column5':X_res_eval[:,4],'Column6':X_res_eval[:,5
],'Column7':X_res_eval[:,6],'Column8':X_res_eval[:,7],'Column9':X_res_eval[:,8],'Column10':X_res_eval[:,9],'Column11':X_res_eval[:,10],'Column12':X_res_eval[:,11],'Column13':X_re
s_eval[:,12]})
```

Dealing with imbalance data

Kami menggunakan teknik *oversampling* dalam meningkatkan kualitas *predictive modelling*, dimana model dapat melakukan pembelajaran pola yang membedakan kelas dengan lebih baik. Sesuai namanya, teknik ini akan meningkatkan jumlah sample dalam data set dengan menggunakan data sintetik. Tujuannya adalah untuk meningkatkan kelas dengan jumlah sample yang sedikit atau *minority*, sehingga data set menjadi lebih seimbang. Method yang kami gunakan adalah *smote()*, method ini akan mencari *n-nearest neighbors* dari kelas minority untuk setiap sample di kelas, kemudian berdasarkan hasil pencarian method *smote()* akan menarik garis ke setiap tetangga terdekat dan membuat random point pada setiap garis itu. Titik inilah yang menjadi sample sintetik.

In [11]:
```
from collections import Counter
from sklearn.datasets import make_classification
from imblearn.over_sampling import SMOTE
sm = SMOTE(random_state=42)
X_res, y_res = sm.fit_resample(df, target)
print('Resampled data train shape %s' % Counter(y_res))
```

```
Resampled data train shape Counter({1: 349, 0: 349, 3: 349, 2: 349, 4: 349})
```

In [12]:
```
df = pd.DataFrame({'Column1':X_res[:,0],'Column2':X_res[:,1],'Column3':X_res[:,2],'Column4':X_res[:,3],'Column5':X_res[:,4],'Column6':X_res[:,5],'Column7':X_res[:,6],'Column8':X_
res[:,7],'Column9':X_res[:,8],'Column10':X_res[:,9],'Column11':X_res[:,10],'Column12':X_res[:,11],'Column13':X_res[:,12]})
df['Column14'] = y_res
target = df['Column14']
df.drop("Column14" ,axis = 1,inplace=True)
```

Modeling

Confusion Matrix

In [13]:
```
import itertools
from sklearn.metrics import confusion_matrix

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

classes = ['0','1','2','3','4']
```

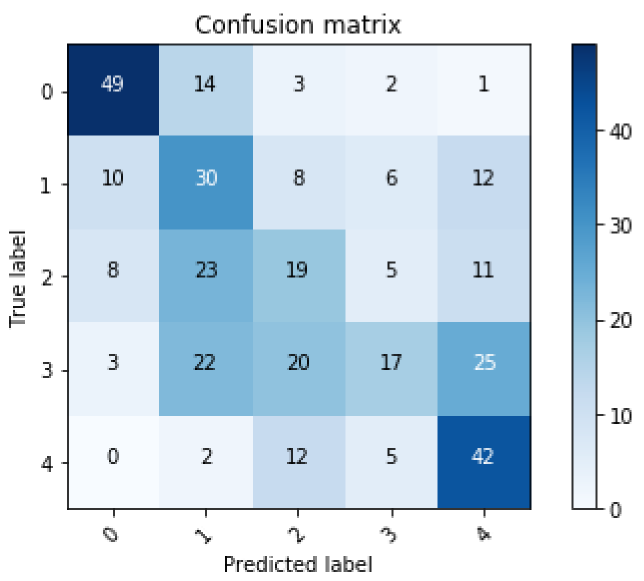
Split the data

In [14]:
```
from sklearn.model_selection import train_test_split
```

In [15]:
```
X_train, X_test, y_train, y_test = train_test_split(df, target, test_size=0.20, random_state=42)
```

Naive Bayes

In [16]:
```
from sklearn.naive_bayes import GaussianNB

naivebayes = GaussianNB()
model_nb = naivebayes.fit(X_train,y_train)
nb_predict = model_nb.predict(X_test)
plot_confusion_matrix(confusion_matrix(y_test, nb_predict), classes)
```

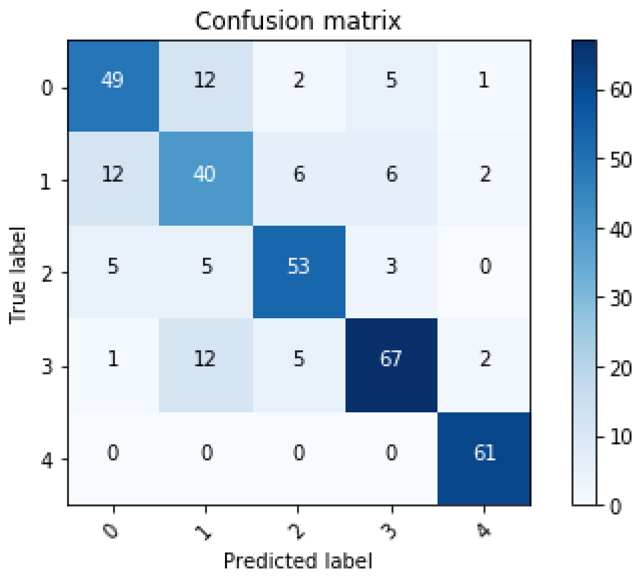


In [17]:
```
from sklearn.model_selection import cross_val_score
from sklearn.metrics import accuracy_score
from sklearn.metrics import precision_score
from sklearn.metrics import recall_score
from sklearn.metrics import f1_score
from sklearn.metrics import precision_recall_fscore_support

print("Without CV")
report_lr = precision_recall_fscore_support(y_test, nb_predict, average='weighted')
print ("Precision = %0.6f\nRecall = %0.6f\nF1 = %0.6f\nAccuracy = %0.6f\n" % \
        (report_lr[0], report_lr[1], report_lr[2], accuracy_score(y_test,nb_predict)))

print("Cross Validation 10")
acc_scores = cross_val_score(model_nb, df, target, cv=10, scoring='accuracy')
print("Accuracy: %0.6f (+/- %0.6f)" % (acc_scores.mean(), acc_scores.std() * 2))

prec_scores = cross_val_score(model_nb, df, target, cv=10, scoring='precision_weighted')
print("Precision: %0.6f (+/- %0.6f)" % (prec_scores.mean(), prec_scores.std() * 2))

recall_scores = cross_val_score(model_nb, df, target, cv=10, scoring='recall_weighted')
print("Recall: %0.6f (+/- %0.6f)" % (recall_scores.mean(), recall_scores.std() * 2))

f1_scores = cross_val_score(model_nb, df, target, cv=10, scoring='f1_weighted')
print("F1: %0.6f (+/- %0.6f)" % (f1_scores.mean(), f1_scores.std() * 2))
```

```
Without CV
Precision = 0.460444
Recall = 0.449857
F1 = 0.433870
Accuracy = 0.449857

Cross Validation 10
Accuracy: 0.465378 (+/- 0.063703)
Precision: 0.453334 (+/- 0.071175)
Recall: 0.465378 (+/- 0.063703)
F1: 0.446851 (+/- 0.060313)
```

MLP

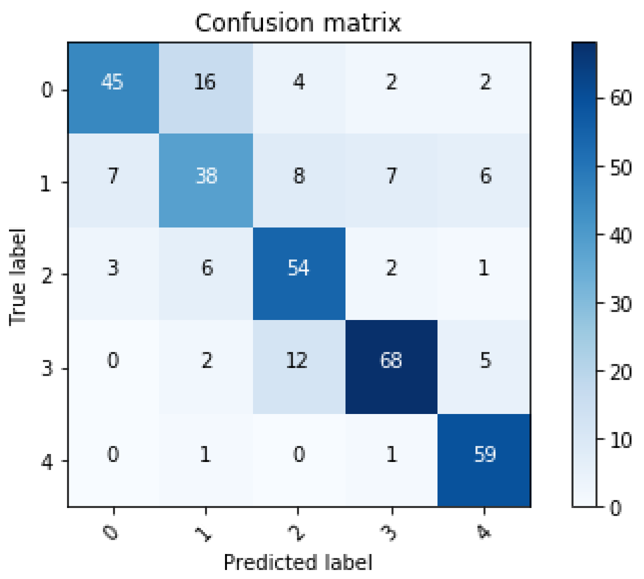
In [18]:
```
#mlp
from sklearn.neural_network import MLPClassifier
mlp = MLPClassifier(solver='lbfgs', alpha=1e-5,hidden_layer_sizes=(36),random_state=1, max_iter = 1000)
model_mlp = mlp.fit(X_train,y_train)
mlp_predict = model_mlp.predict(X_test)
plot_confusion_matrix(confusion_matrix(y_test, mlp_predict), classes)
```



In [19]:
```
# print("Without CV")
# report_lr = precision_recall_fscore_support(y_test, mlp_predict, average='weighted')
# print ("Precision = %0.6f\nRecall = %0.6f\nF1 = %0.6f\nAccuracy = %0.6f\n" % \
#            (report_lr[0], report_lr[1], report_lr[2], accuracy_score(y_test,mlp_predict)))

# print("Cross Validation 10")
# acc_scores = cross_val_score(model_mlp, df, target, cv=10, scoring='accuracy')
# print("Accuracy: %0.6f (+/- %0.6f)" % (acc_scores.mean(), acc_scores.std() * 2))

# prec_scores = cross_val_score(model_mlp, df, target, cv=10, scoring='precision_weighted')
# print("Precision: %0.6f (+/- %0.6f)" % (prec_scores.mean(), prec_scores.std() * 2))

# recall_scores = cross_val_score(model_mlp, df, target, cv=10, scoring='recall_weighted')
# print("Recall: %0.6f (+/- %0.6f)" % (recall_scores.mean(), recall_scores.std() * 2))

# f1_scores = cross_val_score(model_mlp, df, target, cv=10, scoring='f1_weighted')
# print("F1: %0.6f (+/- %0.6f)" % (f1_scores.mean(), f1_scores.std() * 2))
```

K-NN

In [20]:
```
#knn
from sklearn.neighbors import KNeighborsClassifier

knn = KNeighborsClassifier()
model_knn = knn.fit(X_train,y_train)
knn_predict = model_knn.predict(X_test)
plot_confusion_matrix(confusion_matrix(y_test, knn_predict), classes)
```

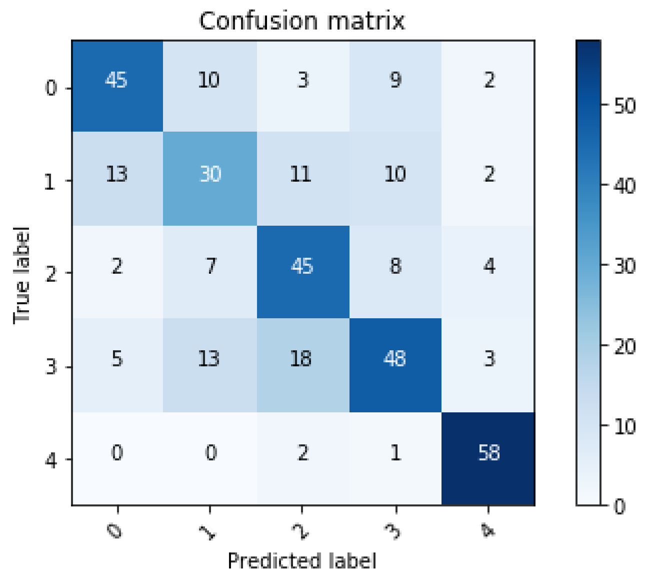


In [21]:
```
print("Without CV")
report_lr = precision_recall_fscore_support(y_test, knn_predict, average='weighted')
print ("Precision = %0.6f\nRecall = %0.6f\nF1 = %0.6f\nAccuracy = %0.6f\n" % \
           (report_lr[0], report_lr[1], report_lr[2], accuracy_score(y_test,knn_predict)))

print("Cross Validation 10")
acc_scores = cross_val_score(model_knn, df, target, cv=10, scoring='accuracy')
print("Accuracy: %0.6f (+/- %0.6f)" % (acc_scores.mean(), acc_scores.std() * 2))

prec_scores = cross_val_score(model_knn, df, target, cv=10, scoring='precision_weighted')
print("Precision: %0.6f (+/- %0.6f)" % (prec_scores.mean(), prec_scores.std() * 2))

recall_scores = cross_val_score(model_knn, df, target, cv=10, scoring='recall_weighted')
print("Recall: %0.6f (+/- %0.6f)" % (recall_scores.mean(), recall_scores.std() * 2))

f1_scores = cross_val_score(model_knn, df, target, cv=10, scoring='f1_weighted')
print("F1: %0.6f (+/- %0.6f)" % (f1_scores.mean(), f1_scores.std() * 2))
```

```
Without CV
Precision = 0.759908
Recall = 0.756447
F1 = 0.753671
Accuracy = 0.756447

Cross Validation 10
Accuracy: 0.804723 (+/- 0.064448)
Precision: 0.801153 (+/- 0.067982)
Recall: 0.804723 (+/- 0.064448)
F1: 0.798131 (+/- 0.068448)
```

Decision Tree Learning

In [22]:
```
from sklearn import tree

tree_dtl = tree.DecisionTreeClassifier()
model_tree = tree_dtl.fit(X_train,y_train)
tree_predict = model_tree.predict(X_test)
plot_confusion_matrix(confusion_matrix(y_test, tree_predict), classes)
```



In [23]:
```
print("Without CV")
report_lr = precision_recall_fscore_support(y_test, tree_predict, average='weighted')
print ("Precision = %0.6f\nRecall = %0.6f\nF1 = %0.6f\nAccuracy = %0.6f\n" % \
           (report_lr[0], report_lr[1], report_lr[2], accuracy_score(y_test,tree_predict)))

print("Cross Validation 10")
acc_scores = cross_val_score(model_tree, df, target, cv=10, scoring='accuracy')
print("Accuracy: %0.6f (+/- %0.6f)" % (acc_scores.mean(), acc_scores.std() * 2))

prec_scores = cross_val_score(model_tree, df, target, cv=10, scoring='precision_weighted')
print("Precision: %0.6f (+/- %0.6f)" % (prec_scores.mean(), prec_scores.std() * 2))

recall_scores = cross_val_score(model_tree, df, target, cv=10, scoring='recall_weighted')
print("Recall: %0.6f (+/- %0.6f)" % (recall_scores.mean(), recall_scores.std() * 2))

f1_scores = cross_val_score(model_tree, df, target, cv=10, scoring='f1_weighted')
print("F1: %0.6f (+/- %0.6f)" % (f1_scores.mean(), f1_scores.std() * 2))
```

```
Without CV
Precision = 0.643515
Recall = 0.647564
F1 = 0.643001
Accuracy = 0.647564

Cross Validation 10
Accuracy: 0.701076 (+/- 0.124198)
Precision: 0.705777 (+/- 0.143868)
Recall: 0.708605 (+/- 0.126961)
F1: 0.697063 (+/- 0.127605)
```

Save best model to external file

Menurut hasil percobaan kami, model terbaik yang sesuai dengan data set adalah model **KNN** (Skor terbesar dengan standar deviasi pada cross validation lebih kecil). Oleh karena itu model disimpan pada file eksternal

In [24]:
```
#Saving Model to KNN.dat
from sklearn.externals import joblib
joblib.dump(model_knn, 'KNN.dat')
```

Out[24]:
```
['KNN.dat']
```

Load Data Model

In [25]:
```
model_knn = joblib.load('KNN.dat')
```

In [26]:
```
prob = model_knn.predict(df_eval)
```

Predict test data

In [27]:
```
diagnose = []
for probitem in prob:
    if (probitem == 0):
        diagnose.append('absence')
    else:
        diagnose.append('presence')
```

In [28]:
```
df_eval['predict'] = prob
df_eval['diagnose'] = diagnose
```

In [29]:
```
df_eval['predict'].value_counts()
```

Out[29]:
```
1    44
0    38
3    26
2    20
4    13
Name: predict, dtype: int64
```

In [30]:
```
df_eval
```

Out[30]:

	Column1	Column2	Column3	Column4	Column5	Column6	Column7	Column8	Column9	Column10	Column11	Column12	Column13	predict	diagnose
0	0.545455	0.0	-0.5	1.250000	0.746667	1.0	1.0	0.75000	0.0	-0.25	0.0	0.0	0.0	3	presence
1	0.636364	0.0	0.5	0.750000	-0.106667	0.0	0.0	0.87500	0.0	-0.50	-1.0	1.0	0.0	0	absence
2	0.000000	0.0	0.5	0.000000	0.413333	0.0	0.0	-1.31250	1.0	0.00	0.0	0.0	0.0	1	presence
3	-0.545455	0.0	0.5	-0.416667	0.653333	0.0	0.0	-0.56250	0.0	0.50	0.0	0.0	0.0	1	presence
4	0.272727	-1.0	-1.0	0.000000	1.293333	0.0	0.0	-1.09375	0.0	0.00	0.0	0.0	0.0	0	absence
5	0.090909	0.0	0.0	0.000000	0.226667	0.0	1.0	0.00000	0.0	0.00	0.0	0.0	0.0	2	presence
6	-0.272727	0.0	0.5	0.416667	1.160000	0.0	0.0	-0.34375	1.0	20.50	0.0	3.0	0.0	4	presence
7	0.727273	0.0	0.5	0.000000	-0.546667	0.0	1.0	-0.40625	1.0	1.00	0.0	0.0	0.0	2	presence
8	-0.454545	-1.0	0.0	1.250000	-0.413333	0.0	0.0	0.71875	0.0	0.00	0.0	0.0	0.0	0	absence
9	1.181818	-1.0	0.0	-0.625000	4.706667	0.0	2.0	0.84375	0.0	7.50	0.0	0.0	0.0	1	presence
10	-1.000000	0.0	0.5	-0.625000	-2.813333	0.0	0.0	0.37500	1.0	0.50	0.0	0.0	0.0	3	presence
11	0.090909	0.0	0.5	0.625000	0.493333	0.0	0.0	-1.15625	1.0	0.50	0.0	0.0	0.0	2	presence
12	-0.272727	0.0	-0.5	0.000000	0.173333	0.0	0.0	0.53125	0.0	-0.50	0.0	0.0	0.0	1	presence
13	1.000000	0.0	0.5	-0.833333	0.493333	0.0	2.0	0.78125	0.0	2.50	-1.0	2.0	-1.0	2	presence
14	-0.363636	0.0	-0.5	1.666667	-0.026667	0.0	1.0	-0.53125	0.0	-0.50	0.0	0.0	0.0	2	presence
15	0.272727	0.0	0.5	1.458333	1.040000	1.0	2.0	-0.28125	0.0	0.00	0.0	3.0	0.0	4	presence
16	0.272727	0.0	0.5	-0.083333	-2.813333	1.0	1.0	0.46875	1.0	0.00	0.0	0.0	0.0	2	presence
17	-2.272727	0.0	-0.5	-0.416667	0.426667	0.0	0.0	0.84375	0.0	-0.50	0.0	0.0	0.0	0	absence
18	-0.272727	0.0	0.0	0.000000	1.706667	0.0	0.0	0.00000	0.0	0.00	0.0	0.0	0.0	1	presence
19	0.363636	0.0	0.5	-1.250000	0.306667	0.0	0.0	0.71875	0.0	0.00	-1.0	1.0	0.0	1	presence
20	2.000000	-1.0	0.0	0.416667	-0.186667	0.0	1.0	-0.53125	0.0	5.00	0.0	0.0	-4.0	1	presence
21	1.272727	0.0	0.5	0.333333	-2.813333	0.0	0.0	-0.09375	1.0	1.00	0.0	0.0	0.0	2	presence
22	-0.636364	0.0	0.5	-0.750000	-0.093333	0.0	0.0	0.31250	0.0	0.00	-1.0	0.0	-4.0	0	absence
23	0.000000	0.0	0.5	0.000000	-0.120000	1.0	0.0	-0.65625	1.0	0.50	0.0	0.0	0.0	1	presence
24	0.181818	0.0	0.5	-0.625000	-2.813333	0.0	1.0	-1.59375	0.0	-1.00	-1.0	0.0	0.0	4	presence
25	-0.090909	-1.0	0.0	-0.083333	0.066667	0.0	2.0	-0.56250	0.0	-0.50	-1.0	0.0	0.0	0	absence
26	-1.636364	0.0	0.5	-0.833333	-2.813333	0.0	0.0	-0.25000	1.0	0.00	0.0	0.0	-1.0	1	presence
27	0.818182	0.0	0.5	1.250000	0.253333	1.0	0.0	-0.87500	1.0	0.00	0.0	0.0	0.0	3	presence
28	1.090909	0.0	0.5	-0.750000	0.013333	0.0	2.0	-0.03125	1.0	0.00	-1.0	1.0	-4.0	1	presence
29	0.272727	0.0	0.0	-1.041667	-2.813333	0.0	0.0	0.46875	0.0	-0.35	0.0	0.0	0.0	1	presence
...	...	...	...	...	...	...	...	...	...	...	...	...	...	...	...
111	-0.454545	0.0	-1.0	0.000000	-2.813333	0.0	1.0	0.37500	0.0	1.00	0.0	0.0	0.0	2	presence
112	-0.090909	0.0	0.0	0.000000	-0.186667	1.0	2.0	0.59375	0.0	5.50	1.0	0.0	-4.0	0	absence
113	-1.090909	-1.0	0.5	-1.166667	0.720000	0.0	2.0	-0.34375	0.0	2.50	0.0	0.0	-4.0	0	absence
114	-1.727273	-1.0	0.5	0.416667	-0.586667	0.0	0.0	0.53125	0.0	-0.50	0.0	0.0	0.0	0	absence
115	-0.090909	0.0	0.5	0.416667	-0.106667	1.0	2.0	0.68750	1.0	15.00	1.0	0.0	0.0	4	presence
116	-1.090909	0.0	-0.5	-0.416667	-0.200000	0.0	0.0	0.53125	0.0	-0.50	0.0	0.0	0.0	0	absence
117	1.090909	0.0	0.0	-0.833333	0.026667	1.0	2.0	-1.06250	1.0	0.15	0.0	0.0	0.0	2	presence
118	0.000000	0.0	-1.0	-0.416667	-0.533333	0.0	0.0	0.12500	0.0	0.50	-1.0	0.0	0.0	3	presence
119	0.636364	0.0	0.0	0.833333	0.426667	1.0	0.0	0.12500	1.0	0.00	0.0	0.0	-4.0	0	absence
120	1.363636	0.0	0.5	0.000000	-0.013333	1.0	1.0	0.00000	0.0	0.00	0.0	0.0	0.0	3	presence
121	-0.363636	0.0	0.5	0.583333	1.840000	0.0	2.0	-0.40625	1.0	0.00	-1.0	0.0	0.0	3	presence
122	-0.909091	0.0	-0.5	-0.416667	0.693333	0.0	0.0	1.25000	0.0	-0.50	-1.0	0.0	0.0	1	presence
123	-1.272727	0.0	0.0	-1.000000	0.386667	0.0	0.0	-1.65625	1.0	-0.50	0.0	0.0	0.0	1	presence
124	1.636364	0.0	0.0	-0.416667	0.040000	0.0	0.0	-0.96875	1.0	0.00	0.0	0.0	0.0	3	presence
125	-0.272727	0.0	-0.5	-0.208333	-0.306667	0.0	0.0	0.37500	0.0	-0.50	0.0	0.0	0.0	1	presence
126	-0.454545	0.0	0.0	-0.416667	-0.306667	0.0	0.0	0.18750	0.0	0.50	0.0	3.0	0.0	3	presence
127	0.727273	0.0	0.5	1.166667	-0.013333	1.0	0.0	-0.65625	1.0	1.00	1.0	0.0	0.0	4	presence
128	0.363636	0.0	0.5	0.000000	2.320000	1.0	2.0	0.00000	0.0	0.00	0.0	0.0	0.0	3	presence
129	1.090909	0.0	0.0	-0.416667	-2.813333	0.0	1.0	-0.40625	0.0	-0.75	-1.0	0.0	0.0	1	presence
130	-0.454545	-1.0	-0.5	-0.833333	0.000000	0.0	0.0	0.84375	0.0	-0.50	0.0	0.0	0.0	1	presence
131	-0.272727	-1.0	0.5	0.000000	1.253333	0.0	0.0	0.28125	1.0	5.50	0.0	0.0	0.0	1	presence
132	0.727273	0.0	0.5	0.833333	-2.813333	0.0	1.0	-1.71875	0.0	0.50	0.0	0.0	0.0	3	presence
133	0.818182	0.0	0.5	0.833333	-2.813333	0.0	1.0	0.65625	0.0	1.35	-1.0	0.0	0.0	2	presence
134	1.000000	0.0	0.5	1.666667	0.693333	1.0	0.0	-0.65625	1.0	0.50	0.0	0.0	0.0	4	presence
135	0.454545	0.0	0.5	1.416667	-0.466667	1.0	2.0	-1.34375	0.0	0.00	0.0	2.0	-1.0	4	presence
136	0.818182	0.0	-0.5	0.000000	-0.613333	0.0	1.0	0.00000	0.0	0.00	0.0	0.0	0.0	1	presence
137	-1.090909	0.0	0.0	1.250000	-0.853333	0.0	0.0	0.40625	0.0	-0.50	0.0	0.0	0.0	0	absence
138	1.000000	0.0	-1.0	0.000000	0.546667	0.0	0.0	0.00000	0.0	0.00	0.0	0.0	0.0	3	presence
139	-0.090909	0.0	0.5	0.000000	-0.386667	0.0	0.0	0.46875	0.0	-0.50	0.0	0.0	0.0	1	presence
140	-1.363636	0.0	-0.5	-0.416667	0.000000	0.0	1.0	0.40625	0.0	0.50	-1.0	0.0	0.0	0	absence

141 rows × 15 columns