In [1]:

```
from google.colab import drive
drive.mount('/content/gdrive')
```

```
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%
b&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/gdrive
```

In [0]:

```
import pandas as pd
import numpy as np
import itertools
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
import matplotlib.pyplot as plt
import seaborn as sns
```

In [0]:

```
# Activities are the class labels
# It is a 6 class classification
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING_UPSTAIRS',
    2: 'WALKING_DOWNSTAIRS',
    3: 'SITTING',
    4: 'STANDING',
    5: 'LAYING',
}

# Utility function to print the confusion matrix
def confusion_matrix(Y_true, Y_pred):
    Y_true = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_true, axis=1)])
    Y_pred = pd.Series([ACTIVITIES[y] for y in np.argmax(Y_pred, axis=1)])

    return pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])



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=90)
    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')
```

```
    plt.xlabel('Predicted label')
```

Data

In [0]:

```
# Data directory
DATADIR = 'gdrive/My Drive/HAR/UCI_HAR_Dataset'
```

In [0]:

```
# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]
```

In [0]:

```
# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial
Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))
```

In [0]:

```
def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]

    return pd.get_dummies(y).as_matrix()
```

In [0]:

```
def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
```

```
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_test = load_y('train'), load_y('test')

    return X_train, X_test, y_train, y_test
```

In [0]:

```
# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)
```

In [0]:

```
# Configuring a session
session_conf = tf.ConfigProto(
   intra_op_parallelism_threads=1,inter_op_parallelism_threads=1)
```

In [11]:

```
#Import Keras
from keras import backend as K
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

```
Using TensorFlow backend.
```

In [0]:

```
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from keras.layers.normalization import BatchNormalization
```

In [0]:

```
# Initializing parameters
base_epochs = 30
base_batch_size = 32
base_n_hidden = 64
```

In [0]:

```
# Utility function to count the number of classes
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

In [15]:

```
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:11: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
  # This is added back by InteractiveShellApp.init_path()
```

In [16]:

```
timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)

print(timesteps)
print(input_dim)
print(len(X_train))
```

```
128
9
7352
```

LSTM_ Base_ Model

In [0]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(base_n_hidden, input_shape=(timesteps, input_dim)))
#adding a batch normalization layer
model.add(BatchNormalization())
# Adding a dropout layer
model.add(Dropout(0.4))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:66: The name tf.get_default_graph is deprecated. Plea
se use tf.compat.v1.get_default_graph instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:541: The name tf.placeholder is deprecated. Please us
e tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Pleas
e use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:148: The name tf.placeholder_with_default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3733: calling dropout (from
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future
version.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 64)                18944
_________________________________________________________________
batch_normalization_1 (Batch (None, 64)                256
_________________________________________________________________
dropout_1 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 390
=================================================================
Total params: 19,590
Trainable params: 19,462
Non-trainable params: 128
_________________________________________________________________
```

In [0]:

```
# Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='RMSprop',
              metrics=['accuracy'])
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimizers.py:793: The name t
f.train.Optimizer is deprecated. Please use tf.compat.v1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:3576: The name tf.log is deprecated. Please use tf.ma
th.log instead.
```

In [0]:

```
%%time
# Training the model
model.fit(X_train,
          Y_train,
          batch_size=32,
          validation_data=(X_test, Y_test),
          epochs=10)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from
tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 7352 samples, validate on 2947 samples
Epoch 1/10
7352/7352 [==============================] - 66s 9ms/step - loss: 1.0304 - acc: 0.5858 - val_loss:
0.7335 - val_acc: 0.7021
Epoch 2/10
7352/7352 [==============================] - 63s 9ms/step - loss: 0.5408 - acc: 0.7896 - val_loss:
0.6607 - val_acc: 0.8008
Epoch 3/10
7352/7352 [==============================] - 61s 8ms/step - loss: 0.3138 - acc: 0.8855 - val_loss:
0.9312 - val_acc: 0.7754
Epoch 4/10
7352/7352 [==============================] - 59s 8ms/step - loss: 0.2291 - acc: 0.9128 - val_loss:
0.4118 - val_acc: 0.8850
Epoch 5/10
7352/7352 [==============================] - 58s 8ms/step - loss: 0.1920 - acc: 0.9297 - val_loss:
0.3271 - val_acc: 0.8924
Epoch 6/10
7352/7352 [==============================] - 59s 8ms/step - loss: 0.1818 - acc: 0.9346 - val_loss:
0.3125 - val_acc: 0.8938
Epoch 7/10
7352/7352 [==============================] - 59s 8ms/step - loss: 0.1685 - acc: 0.9387 - val_loss:
0.3015 - val_acc: 0.8843
Epoch 8/10
7352/7352 [==============================] - 59s 8ms/step - loss: 0.1515 - acc: 0.9429 - val_loss:
0.3354 - val_acc: 0.8921
Epoch 9/10
7352/7352 [==============================] - 59s 8ms/step - loss: 0.1521 - acc: 0.9388 - val_loss:
0.3122 - val_acc: 0.9226
Epoch 10/10
7352/7352 [==============================] - 58s 8ms/step - loss: 0.1487 - acc: 0.9442 - val_loss:
0.2675 - val_acc: 0.9104
CPU times: user 11min 1s, sys: 38.8 s, total: 11min 40s
Wall time: 10min 1s
```

Out[0]:

```
<keras.callbacks.History at 0x7fe6010ddd68>
```

In [0]:

```
score = model.evaluate(X_test, Y_test,verbose=0)

print('Test loss:', score[0])
print('Test accuracy:', score[1]*100)
```

```
Test loss: 0.2675111037987024
Test accuracy: 91.04173736002714
```

In [0]:

```
#train_data
X_train=X_train[:6000]
Y_train=Y_train[:6000]
#cv_data
X_cv=X_train[:1352]
Y_cv=Y_train[:1352]
```

In [0]:

```
print(X_train.shape,Y_train.shape)
print(X_cv.shape,Y_cv.shape)
print(X_test.shape,Y_test.shape)
```

```
(6000, 128, 9) (6000, 6)
(1352, 128, 9) (1352, 6)
(2947, 128, 9) (2947, 6)
```

In [0]:

```
np.save("gdrive/My Drive/HAR/x_train",X_train)
np.save("gdrive/My Drive/HAR/y_train",Y_train)
np.save("gdrive/My Drive/HAR/x_cv",X_cv)
np.save("gdrive/My Drive/HAR/y_cv",Y_cv)
np.save("gdrive/My Drive/HAR/x_test",X_test)
np.save("gdrive/My Drive/HAR/y_test",Y_test)
```

In [0]:

```
X_train=np.load('gdrive/My Drive/HAR/x_train.npy')
Y_train=np.load('gdrive/My Drive/HAR/y_train.npy')
X_cv=np.load('gdrive/My Drive/HAR/x_cv.npy')
Y_cv=np.load('gdrive/My Drive/HAR/y_cv.npy')
X_test=np.load('gdrive/My Drive/HAR/x_test.npy')
Y_test=np.load('gdrive/My Drive/HAR/y_test.npy')
```

In [0]:

```
lstms = [12,36,64]
train_lstms_loss = []
cv_lstms_loss = []



for i in lstms:
  model = Sequential()
  model.add(LSTM(i, input_shape=(timesteps, input_dim)))
  model.add(BatchNormalization())
  model.add(Dropout(0.5))
  model.add(Dense(n_classes, activation='softmax'))
  model.compile(loss='categorical_crossentropy',optimizer='RMSprop',metrics=['accuracy'])
  model.fit(X_train,Y_train,batch_size=32,validation_data=(X_cv, Y_cv),epochs=10,verbose=0)
  train_score = model.evaluate(X_train, Y_train,verbose=0)
  train_lstms_loss.append(train_score)
  test_score = model.evaluate(X_cv, Y_cv,verbose=0)
  cv_lstms_loss.append(test_score)

print("============================================================================================
==============================================================")
  print("for lstm cells",i,"train_loss:",train_score[0],"train_acc:",train_score[1],"cv_loss:",test_score[0],"cv_acc:",test_score[1])

print("============================================================================================
==============================================================")
```

```
===================================================================================================
=======================================================
for lstm cells 12 train_loss: 0.5427719736178793 train_acc: 0.7983333333333333 cv_loss:
0.5774555450977659 cv_acc: 0.7943786982248521
===================================================================================================
=======================================================
===================================================================================================
=======================================================
for lstm cells 36 train_loss: 0.1419026134143011 train_acc: 0.948 cv_loss: 0.1471664534554336
cv_acc: 0.9312130177514792
===================================================================================================
=======================================================
===================================================================================================
```

```
=======================================================
for lstm cells 64 train_loss: 0.15687254037896248 train_acc: 0.9456666666666667 cv_loss: 0.1529195671973436 cv_acc: 0.9304733727810651
===================================================================================================
=======================================================
```

In [0]:

```
train_dropout_loss = []
cv_dropout_loss = []
dropouts = [0.2,0.4,0.6,0.9]

for i in dropouts:
  model = Sequential()
  model.add(LSTM(64, input_shape=(timesteps, input_dim)))
  model.add(BatchNormalization())
  model.add(Dropout(i))
  model.add(Dense(n_classes, activation='softmax'))
  model.compile(loss='categorical_crossentropy',optimizer='RMSprop',metrics=['accuracy'])
  model.fit(X_train,Y_train,batch_size=32,validation_data=(X_cv, Y_cv),epochs=10,verbose=0)
  train_score = model.evaluate(X_train, Y_train,verbose=0)
  train_dropout_loss.append(train_score[0])
  test_score = model.evaluate(X_cv, Y_cv,verbose=0)
  cv_dropout_loss.append(test_score[0])

print("===================================================================================================
========================================")
  print("for dropout",i,"train_loss:",train_score[0],"train_acc:",train_score[1],"cv_loss:",test_score[0],"cv_acc:",test_score[1])

print("===================================================================================================
========================================")
```

```
===================================================================================================
=================================
for dropout 0.2 train_loss: 0.09121699480417676 train_acc: 0.9618333333333333 cv_loss: 0.08054623748949032 cv_acc: 0.9556213017751479
===================================================================================================
=================================
===================================================================================================
=================================
for dropout 0.4 train_loss: 0.2927109430801174 train_acc: 0.9185 cv_loss: 0.22138404586332894 cv_acc: 0.9408284023668639
===================================================================================================
=================================
WARNING:tensorflow:Large dropout rate: 0.6 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead of keep_prob. Please ensure that this is intended.
===================================================================================================
=================================
for dropout 0.6 train_loss: 0.2663697602033571 train_acc: 0.9165 cv_loss: 0.2898362064807076 cv_acc: 0.915680473372781
===================================================================================================
=================================
WARNING:tensorflow:Large dropout rate: 0.9 (>0.5). In TensorFlow 2.x, dropout() uses dropout rate instead of keep_prob. Please ensure that this is intended.
===================================================================================================
=================================
for dropout 0.9 train_loss: 0.4850111870571758 train_acc: 0.8276666666666667 cv_loss: 0.42911438657158224 cv_acc: 0.8461538461538461
===================================================================================================
=================================
```

In [0]:

```
train_opt_loss = []
cv_opt_loss = []
optimizers = ['RMSprop','Adadelta','Adam']

for i in optimizers:
  model = Sequential()
  model.add(LSTM(64, input_shape=(timesteps, input_dim)))
  model.add(BatchNormalization())
  model.add(Dropout(0.2))
```

```
    model.add(Dense(n_classes, activation='softmax'))
    model.compile(loss='categorical_crossentropy',optimizer=i,metrics=['accuracy'])
    model.fit(X_train,Y_train,batch_size=32,validation_data=(X_cv, Y_cv),epochs=10,verbose=0)
    train_score = model.evaluate(X_train, Y_train,verbose=0)
    train_opt_loss.append(train_score[0])
    test_score = model.evaluate(X_cv, Y_cv,verbose=0)
    cv_opt_loss.append(test_score[0])

print("==========================================================================================================================================")
  print("for optimizer ",i,"train_loss:",train_score[0],"train_acc:",train_score[1],"cv_loss:",test_score[0],"cv_acc:",test_score[1])

print("==========================================================================================================================================")
```

```
=================================================================================================================================
for optimizer  RMSprop train_loss: 0.09372042466270614 train_acc: 0.9646666666666667 cv_loss:
0.08798773764093963 cv_acc: 0.9563609467455622
=================================================================================================================================
=================================================================================================================================
for optimizer  Adadelta train_loss: 0.10666192313204859 train_acc: 0.9461666666666667 cv_loss: 0.0
923617873280571 cv_acc: 0.9571005917159763
=================================================================================================================================
=================================================================================================================================
for optimizer  Adam train_loss: 0.09250945657089081 train_acc: 0.9641666666666666 cv_loss:
0.08666882475565281 cv_acc: 0.9548816568047337
=================================================================================================================================
```

In [0]:

```
model = Sequential()
model.add(LSTM(64, input_shape=(timesteps, input_dim)))
model.add(BatchNormalization())
model.add(Dropout(0.2))
model.add(Dense(n_classes, activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='RMSprop',metrics=['accuracy'])
model.fit(X_train,Y_train,batch_size=32,validation_data=(X_test, Y_test),epochs=20,verbose=1)
score = model.evaluate(X_test, Y_test,verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1]*100)
```

```
Train on 6000 samples, validate on 2947 samples
Epoch 1/20
6000/6000 [==============================] - 57s 10ms/step - loss: 0.7780 - acc: 0.6847 - val_loss
: 0.9274 - val_acc: 0.7065
Epoch 2/20
6000/6000 [==============================] - 48s 8ms/step - loss: 0.4287 - acc: 0.8255 - val_loss:
1.0003 - val_acc: 0.6176
Epoch 3/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.2508 - acc: 0.9037 - val_loss:
0.4645 - val_acc: 0.8490
Epoch 4/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1943 - acc: 0.9327 - val_loss:
1.4064 - val_acc: 0.7598
Epoch 5/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1708 - acc: 0.9363 - val_loss:
0.2106 - val_acc: 0.9179
Epoch 6/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1470 - acc: 0.9448 - val_loss:
0.2387 - val_acc: 0.9223
Epoch 7/20
6000/6000 [==============================] - 48s 8ms/step - loss: 0.1351 - acc: 0.9467 - val_loss:
0.3111 - val_acc: 0.9026
Epoch 8/20
6000/6000 [==============================] - 48s 8ms/step - loss: 0.1339 - acc: 0.9485 - val_loss:
0.3288 - val_acc: 0.9118
Epoch 9/20
```

```
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1201 - acc: 0.9497 - val_loss:
0.3280 - val_acc: 0.9148
Epoch 10/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1259 - acc: 0.9535 - val_loss:
0.3860 - val_acc: 0.9063
Epoch 11/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1137 - acc: 0.9552 - val_loss:
0.4017 - val_acc: 0.9043
Epoch 12/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1108 - acc: 0.9550 - val_loss:
0.3834 - val_acc: 0.9162
Epoch 13/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1060 - acc: 0.9552 - val_loss:
0.3190 - val_acc: 0.9077
Epoch 14/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1076 - acc: 0.9545 - val_loss:
0.3842 - val_acc: 0.9135
Epoch 15/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1084 - acc: 0.9550 - val_loss:
0.4441 - val_acc: 0.9080
Epoch 16/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1154 - acc: 0.9558 - val_loss:
0.4180 - val_acc: 0.9026
Epoch 17/20
6000/6000 [==============================] - 49s 8ms/step - loss: 0.1126 - acc: 0.9558 - val_loss:
0.4901 - val_acc: 0.8996
Epoch 18/20
6000/6000 [==============================] - 50s 8ms/step - loss: 0.1067 - acc: 0.9577 - val_loss:
0.4419 - val_acc: 0.9077
Epoch 19/20
6000/6000 [==============================] - 50s 8ms/step - loss: 0.1005 - acc: 0.9565 - val_loss:
0.7073 - val_acc: 0.8941
Epoch 20/20
6000/6000 [==============================] - 50s 8ms/step - loss: 0.1034 - acc: 0.9562 - val_loss:
0.3852 - val_acc: 0.9145
Test loss: 0.38519705226556006
Test accuracy: 91.44893111638956
```

In [0]:

```
model = Sequential()
model.add(LSTM(64, input_shape=(timesteps, input_dim),return_sequences=True))
model.add(BatchNormalization())
model.add(Dropout(0.2))
model.add(LSTM(128))
model.add(BatchNormalization())
model.add(Dropout(0.4))
model.add(Dense(n_classes, activation='softmax'))
model.compile(loss='categorical_crossentropy',optimizer='RMSprop',metrics=['accuracy'])
model.fit(X_train,Y_train,batch_size=32,validation_data=(X_test, Y_test),epochs=20,verbose=1)
score = model.evaluate(X_test, Y_test,verbose=0)
print('Test loss:', score[0])
print('Test accuracy:', score[1]*100)
```

```
Train on 6000 samples, validate on 2947 samples
Epoch 1/20
6000/6000 [==============================] - 107s 18ms/step - loss: 0.4946 - acc: 0.8167 - val_los
s: 1.9998 - val_acc: 0.6179
Epoch 2/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1874 - acc: 0.9323 - val_loss
: 0.5322 - val_acc: 0.8768
Epoch 3/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1426 - acc: 0.9450 - val_loss
: 0.4220 - val_acc: 0.8938
Epoch 4/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1465 - acc: 0.9477 - val_loss
: 0.2921 - val_acc: 0.9189
Epoch 5/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1209 - acc: 0.9503 - val_loss
: 0.3555 - val_acc: 0.9006
Epoch 6/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1279 - acc: 0.9492 - val_loss
: 0.4008 - val_acc: 0.9006
Epoch 7/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1165 - acc: 0.9545 - val_loss
```

```
: 0.4223 - val_acc: 0.9135
Epoch 8/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1215 - acc: 0.9515 - val_loss
: 0.4944 - val_acc: 0.9121
Epoch 9/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1096 - acc: 0.9523 - val_loss
: 0.3731 - val_acc: 0.9152
Epoch 10/20
6000/6000 [==============================] - 95s 16ms/step - loss: 0.1260 - acc: 0.9508 - val_loss
: 0.2140 - val_acc: 0.9325
Epoch 11/20
6000/6000 [==============================] - 96s 16ms/step - loss: 0.1070 - acc: 0.9530 - val_loss
: 0.4739 - val_acc: 0.9097
Epoch 12/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1110 - acc: 0.9533 - val_loss
: 0.9212 - val_acc: 0.8378
Epoch 13/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1084 - acc: 0.9577 - val_loss
: 0.2648 - val_acc: 0.9063
Epoch 14/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1055 - acc: 0.9533 - val_loss
: 0.6211 - val_acc: 0.8714
Epoch 15/20
6000/6000 [==============================] - 98s 16ms/step - loss: 0.1054 - acc: 0.9553 - val_loss
: 0.3850 - val_acc: 0.9002
Epoch 16/20
6000/6000 [==============================] - 96s 16ms/step - loss: 0.1110 - acc: 0.9538 - val_loss
: 0.3388 - val_acc: 0.9196
Epoch 17/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1026 - acc: 0.9537 - val_loss
: 0.2729 - val_acc: 0.9084
Epoch 18/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1027 - acc: 0.9552 - val_loss
: 0.2615 - val_acc: 0.9203
Epoch 19/20
6000/6000 [==============================] - 97s 16ms/step - loss: 0.1111 - acc: 0.9508 - val_loss
: 0.2883 - val_acc: 0.9080
Epoch 20/20
6000/6000 [==============================] - 95s 16ms/step - loss: 0.1073 - acc: 0.9550 - val_loss
: 0.2172 - val_acc: 0.9369
Test loss: 0.21721666411171675
Test accuracy: 93.68849677638276
```

1.By using LSTM 2 layer architecture we got 93% model accuracy so by refering this paper we use a divide and conquer apporach to get some more accuracy than LSTM models Refer: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5949027/

2.So we splitting the data into 2 models one model contains 3 class labels and another contains another 3 class labels like 'STANDING,SITTING,LYING' consider as one model called static model and 'WALKING UPSTSAIRS,WALKING DOWNSTAIRS,WALKING' as another model called dynamic model

3.First we create a binary model i.e.., we set >3 class labels as 1 and < 3 class labels as 0

4.second we create a model for > 3 class labels and predict also called as static model

5.Third we create a model for < 3 class labels and predict also called as dynamic model

Refer the above paper for to get some more better understading the way of implementation

Binary model

In [17]:

```
#https://github.com/UdiBhaskar/Human-Activity-Recognition--Using-Deep-NN/blob/master/Human%20Activity%20Detection-Without%20Verbose%20.ipynb
# Data directory
DATADIR = 'gdrive/My Drive/HAR/UCI_HAR_Dataset'

# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
```

```
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial
Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    y[y<=3] = 0 #here we scaling y_class labels 1,2,3 as 0
    y[y>3] = 1 #here we scaling y_class labels 4,5,6 as 1

    return pd.get_dummies(y).as_matrix()

def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_test = load_y('train'), load_y('test')

    return X_train, X_test, y_train, y_test

# Loading the train and test data
X_train_bin, X_test_bin, Y_train_bin, Y_test_bin = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:32: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:52: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
```

In [0]:

```
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.layers import Dense
from keras.layers import Flatten
```

In [23]:

```
binary_model = Sequential()
binary_model.add(Conv1D(filters=64, kernel_size=3, activation='relu',kernel_initializer='he_uniform
```

```
',input_shape=(timesteps, input_dim)))
binary_model.add(BatchNormalization())
binary_model.add(Dropout(0.5))
binary_model.add(Conv1D(filters=32, kernel_size=3, activation='relu',kernel_initializer='he_uniform
'))
binary_model.add(BatchNormalization())
binary_model.add(Dropout(0.5))
binary_model.add(MaxPooling1D(pool_size=2))
binary_model.add(Flatten())
binary_model.add(Dense(2, activation='softmax'))
binary_model.summary()
```

```
Model: "sequential_2"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv1d_3 (Conv1D)            (None, 126, 64)           1792      
_________________________________________________________________
batch_normalization_3 (Batch (None, 126, 64)           256       
_________________________________________________________________
dropout_3 (Dropout)          (None, 126, 64)           0         
_________________________________________________________________
conv1d_4 (Conv1D)            (None, 124, 32)           6176      
_________________________________________________________________
batch_normalization_4 (Batch (None, 124, 32)           128       
_________________________________________________________________
dropout_4 (Dropout)          (None, 124, 32)           0         
_________________________________________________________________
max_pooling1d_2 (MaxPooling1 (None, 62, 32)            0         
_________________________________________________________________
flatten_2 (Flatten)          (None, 1984)              0         
_________________________________________________________________
dense_2 (Dense)              (None, 2)                 3970      
=================================================================
Total params: 12,322
Trainable params: 12,130
Non-trainable params: 192
_________________________________________________________________
```

In [25]:

```
binary_model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
binary_model.fit(X_train_bin,Y_train_bin, epochs=30, batch_size=32,validation_data=(X_test_bin, Y_t
est_bin), verbose=1)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 6s 881us/step - loss: 0.0578 - acc: 0.9808 -
val_loss: 0.0087 - val_acc: 0.9986
Epoch 2/30
7352/7352 [==============================] - 3s 357us/step - loss: 0.0079 - acc: 0.9974 -
val_loss: 0.0073 - val_acc: 0.9983
Epoch 3/30
7352/7352 [==============================] - 3s 354us/step - loss: 0.0058 - acc: 0.9984 -
val_loss: 0.0106 - val_acc: 0.9956
Epoch 4/30
7352/7352 [==============================] - 3s 364us/step - loss: 0.0036 - acc: 0.9990 -
val_loss: 0.0030 - val_acc: 0.9990
Epoch 5/30
7352/7352 [==============================] - 3s 348us/step - loss: 0.0043 - acc: 0.9986 -
val_loss: 0.0028 - val_acc: 0.9993
Epoch 6/30
7352/7352 [==============================] - 3s 359us/step - loss: 0.0010 - acc: 0.9996 -
val_loss: 0.0041 - val_acc: 0.9993
Epoch 7/30
7352/7352 [==============================] - 3s 346us/step - loss: 9.2203e-04 - acc: 0.9997 - val_
loss: 0.0017 - val_acc: 0.9997
Epoch 8/30
7352/7352 [==============================] - 3s 356us/step - loss: 0.0042 - acc: 0.9988 -
val_loss: 8.5511e-04 - val_acc: 0.9997
Epoch 9/30
7352/7352 [==============================] - 3s 358us/step - loss: 0.0013 - acc: 0.9997 -
val_loss: 6.8389e-04 - val_acc: 0.9997
Epoch 10/30
7352/7352 [==============================] - 3s 375us/step - loss: 1.3490e-04 - acc: 1.0000 - val_
```

```
loss: 9.8621e-04 - val_acc: 0.9997
Epoch 11/30
7352/7352 [==============================] - 3s 392us/step - loss: 0.0030 - acc: 0.9990 -
val_loss: 3.6772e-04 - val_acc: 1.0000
Epoch 12/30
7352/7352 [==============================] - 3s 374us/step - loss: 0.0019 - acc: 0.9995 -
val_loss: 9.7679e-04 - val_acc: 0.9997
Epoch 13/30
7352/7352 [==============================] - 3s 356us/step - loss: 0.0054 - acc: 0.9993 -
val_loss: 0.0021 - val_acc: 0.9993
Epoch 14/30
7352/7352 [==============================] - 3s 350us/step - loss: 4.5302e-04 - acc: 0.9999 - val_
loss: 0.0010 - val_acc: 0.9997
Epoch 15/30
7352/7352 [==============================] - 3s 355us/step - loss: 3.4219e-04 - acc: 0.9997 - val_
loss: 0.0020 - val_acc: 0.9997
Epoch 16/30
7352/7352 [==============================] - 3s 388us/step - loss: 9.7779e-04 - acc: 0.9997 - val_
loss: 0.0014 - val_acc: 0.9997
Epoch 17/30
7352/7352 [==============================] - 3s 352us/step - loss: 8.1858e-04 - acc: 0.9996 - val_
loss: 6.5504e-04 - val_acc: 0.9997
Epoch 18/30
7352/7352 [==============================] - 3s 357us/step - loss: 0.0121 - acc: 0.9978 -
val_loss: 0.0086 - val_acc: 0.9986
Epoch 19/30
7352/7352 [==============================] - 3s 348us/step - loss: 0.0026 - acc: 0.9993 -
val_loss: 0.0115 - val_acc: 0.9980
Epoch 20/30
7352/7352 [==============================] - 3s 370us/step - loss: 2.2864e-04 - acc: 1.0000 - val_
loss: 0.0104 - val_acc: 0.9983
Epoch 21/30
7352/7352 [==============================] - 3s 372us/step - loss: 8.2877e-04 - acc: 0.9995 - val_
loss: 0.0092 - val_acc: 0.9983
Epoch 22/30
7352/7352 [==============================] - 3s 358us/step - loss: 0.0013 - acc: 0.9995 -
val_loss: 0.0095 - val_acc: 0.9986
Epoch 23/30
7352/7352 [==============================] - 3s 352us/step - loss: 7.6134e-04 - acc: 0.9997 - val_
loss: 0.0140 - val_acc: 0.9980
Epoch 24/30
7352/7352 [==============================] - 3s 369us/step - loss: 6.4754e-04 - acc: 0.9997 - val_
loss: 0.0075 - val_acc: 0.9986
Epoch 25/30
7352/7352 [==============================] - 3s 350us/step - loss: 4.1572e-05 - acc: 1.0000 - val_
loss: 0.0092 - val_acc: 0.9980
Epoch 26/30
7352/7352 [==============================] - 3s 377us/step - loss: 4.3807e-05 - acc: 1.0000 - val_
loss: 0.0075 - val_acc: 0.9986
Epoch 27/30
7352/7352 [==============================] - 3s 355us/step - loss: 6.6887e-05 - acc: 1.0000 - val_
loss: 0.0074 - val_acc: 0.9986
Epoch 28/30
7352/7352 [==============================] - 3s 356us/step - loss: 6.9065e-06 - acc: 1.0000 - val_
loss: 0.0071 - val_acc: 0.9990
Epoch 29/30
7352/7352 [==============================] - 3s 353us/step - loss: 0.0018 - acc: 0.9995 -
val_loss: 0.0046 - val_acc: 0.9990
Epoch 30/30
7352/7352 [==============================] - 3s 350us/step - loss: 0.0026 - acc: 0.9995 -
val_loss: 0.0015 - val_acc: 0.9997
```

Out[25]:

```
<keras.callbacks.History at 0x7f7061515588>
```

In [26]:

```
binary_model_score = binary_model.evaluate(X_test_bin,Y_test_bin,verbose=0)
print('Test loss:', binary_model_score[0])
print('Test accuracy:', binary_model_score[1]*100)
```

```
Test loss: 0.001487480033914023
Test accuracy: 99.9660671869698
```

In [0]:

```
binary_model.save('gdrive/My Drive/HAR/final_binary_model.ml')
```

sharpening test data

In [0]:

```
'''from scipy import ndimage
def sharpen(x_test, sigma, alpha):
    r = x_test.shape[0]
    c = x_test.shape[1]
    d = x_test.shape[2]
    container = np.empty((r, c, d))
    i = 0

    for row in x_test:
        test = np.array([row])
        blurred = ndimage.gaussian_filter(test, sigma)
        sharpened = test + alpha * (test - blurred)
        container[i] = sharpened
        i = i + 1
    return container'''
```

Out[0]:

```
'from scipy import ndimage\ndef sharpen(x_test, sigma, alpha):\n    r = x_test.shape[0]\n    c =
x_test.shape[1]\n    d = x_test.shape[2]\n    container = np.empty((r, c, d))\n    i = 0\n\n    for
row in x_test:\n        test = np.array([row])\n        blurred = ndimage.gaussian_filter(test, sig
ma)\n        sharpened = test + alpha * (test - blurred)\n        container[i] = sharpened\n
i = i + 1\n    return container'
```

Static_Model

In [87]:

```
# Data directory
DATADIR = 'gdrive/My Drive/HAR/UCI_HAR_Dataset'

# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial
Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )
```

```
    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    y_subset = y > 3 #taking y_class labels greater than 3
    y = y[y_subset]
    return pd.get_dummies(y).as_matrix(),y_subset

def load_static_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_train_sub  = load_y('train')
    y_test,y_test_sub = load_y('test')
    X_train = X_train[y_train_sub]
    X_test = X_test[y_test_sub]

    return X_train, X_test, y_train, y_test

# Loading the train and test data
X_train_static, X_test_static, Y_train_static, Y_test_static = load_static_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:32: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:51: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
```

In [88]:

```
print('X:shape',X_train_static.shape,'Y:shape',Y_train_static.shape)
#print('X:shape',X_cv_static.shape,'Y:shape',Y_cv_static.shape)
print('X:shape',X_test_static.shape,'Y:shape',Y_test_static.shape)
```

```
X:shape (4067, 128, 9) Y:shape (4067, 3)
X:shape (1560, 128, 9) Y:shape (1560, 3)
```

In [0]:

```
import numpy
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
import keras
import keras.utils
from keras import utils as np_utils
from keras.wrappers.scikit_learn import KerasClassifier
```

In [0]:

```
%%time
def
create_model(filters=1,filters2=1,kernel_size2=1,kernel_size=1,dropout_rate2=0.0,dropout_rate=0.0):

  model = Sequential()
  model.add(keras.layers.Conv1D(filters=filters,
kernel_size=kernel_size,kernel_regularizer=keras.regularizers.l2(0.55),
                                activation='relu',kernel_initializer='he_uniform',input_shape=
(timesteps, input_dim)))
```

```
  model.add(BatchNormalization())
  model.add(Dropout(dropout_rate))
  model.add(keras.layers.Conv1D(filters=filters2,
kernel_size=kernel_size2,kernel_regularizer=keras.regularizers.l2(0.28),
                                activation='relu',kernel_initializer='he_uniform'))
  model.add(BatchNormalization())
  model.add(Dropout(dropout_rate2))
  model.add(MaxPooling1D(pool_size=2))
  model.add(Flatten())
  model.add(Dense(3, activation='softmax'))
  model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
  return model
seed = 7
numpy.random.seed(seed)

model = KerasClassifier(build_fn=create_model, epochs=30, batch_size=16, verbose=0)
# define the grid search parameters
filters = [1,32,64]
filters2 = [1,26,36]
kernel_size = [1,3,5,7]
kernel_size2 = [1,2,6,8]
dropout_rate = [0.0,0.2,0.4,0.6,0.8]
dropout_rate2 = [0.0,0.1,0.3,0.5,0.9]
param = dict(filters=filters,kernel_size=kernel_size,dropout_rate=dropout_rate,filters2=filters2,
             dropout_rate2=dropout_rate2,kernel_size2=kernel_size2)
rand = RandomizedSearchCV(estimator=model,param_distributions=param,cv=3)
rand_result = rand.fit(X_train_static, Y_train_static)
# summarize results
print("Best: %f using %s" % (rand_result.best_score_, rand_result.best_params_))
```

```
Best: 0.889599 using {'kernel_size2': 1, 'kernel_size': 7, 'filters2': 26, 'filters': 32,
'dropout_rate2': 0.9, 'dropout_rate': 0.2}
CPU times: user 55min, sys: 2min 12s, total: 57min 12s
Wall time: 48min 57s
```

In [92]:

```
static_model = Sequential()
static_model.add(Conv1D(filters=32, kernel_size=7, activation='relu',kernel_initializer='he_uniform
',input_shape=(timesteps, input_dim)))
static_model.add(BatchNormalization())
static_model.add(Dropout(0.0))
static_model.add(Conv1D(filters=32, kernel_size=1, activation='relu',kernel_initializer='he_uniform
'))
static_model.add(BatchNormalization())
static_model.add(Dropout(0.2))
static_model.add(Conv1D(filters=32, kernel_size=7, activation='relu',kernel_initializer='he_uniform
'))
static_model.add(MaxPooling1D(pool_size=2))
static_model.add(Flatten())
static_model.add(Dense(32,activation='relu'))
static_model.add(Dense(3, activation='softmax'))
static_model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
static_model.fit(X_train_static,Y_train_static, epochs=59, batch_size=32,
                 validation_data=(X_test_static, Y_test_static), verbose=1)
```

```
Train on 4067 samples, validate on 1560 samples
Epoch 1/59
4067/4067 [==============================] - 6s 1ms/step - loss: 0.2940 - acc: 0.8788 - val_loss:
0.2683 - val_acc: 0.8910
Epoch 2/59
4067/4067 [==============================] - 2s 415us/step - loss: 0.2222 - acc: 0.9112 -
val_loss: 0.3736 - val_acc: 0.8756
Epoch 3/59
4067/4067 [==============================] - 2s 404us/step - loss: 0.2306 - acc: 0.9046 -
val_loss: 0.3486 - val_acc: 0.8545
Epoch 4/59
4067/4067 [==============================] - 2s 404us/step - loss: 0.2051 - acc: 0.9115 -
val_loss: 0.3071 - val_acc: 0.8750
Epoch 5/59
4067/4067 [==============================] - 2s 422us/step - loss: 0.2001 - acc: 0.9134 -
val_loss: 0.2938 - val_acc: 0.8929
Epoch 6/59
4067/4067 [==============================] - 2s 396us/step - loss: 0.1903 - acc: 0.9211 -
val_loss: 0.2835 - val_acc: 0.9038
```

```
Epoch 7/59
4067/4067 [==============================] - 2s 401us/step - loss: 0.2079 - acc: 0.9122 -
val_loss: 0.3417 - val_acc: 0.8776
Epoch 8/59
4067/4067 [==============================] - 2s 403us/step - loss: 0.1784 - acc: 0.9230 -
val_loss: 0.2629 - val_acc: 0.9038
Epoch 9/59
4067/4067 [==============================] - 2s 399us/step - loss: 0.1901 - acc: 0.9191 -
val_loss: 0.2487 - val_acc: 0.9122
Epoch 10/59
4067/4067 [==============================] - 2s 400us/step - loss: 0.1725 - acc: 0.9235 -
val_loss: 0.2527 - val_acc: 0.9135
Epoch 11/59
4067/4067 [==============================] - 2s 422us/step - loss: 0.1767 - acc: 0.9213 -
val_loss: 0.2374 - val_acc: 0.9006
Epoch 12/59
4067/4067 [==============================] - 2s 428us/step - loss: 0.1789 - acc: 0.9203 -
val_loss: 0.3060 - val_acc: 0.8808
Epoch 13/59
4067/4067 [==============================] - 2s 442us/step - loss: 0.1597 - acc: 0.9277 -
val_loss: 0.2390 - val_acc: 0.9147
Epoch 14/59
4067/4067 [==============================] - 2s 424us/step - loss: 0.1491 - acc: 0.9363 -
val_loss: 0.3087 - val_acc: 0.9103
Epoch 15/59
4067/4067 [==============================] - 2s 418us/step - loss: 0.1483 - acc: 0.9361 -
val_loss: 0.4047 - val_acc: 0.8910
Epoch 16/59
4067/4067 [==============================] - 2s 429us/step - loss: 0.1495 - acc: 0.9363 -
val_loss: 0.2725 - val_acc: 0.9179
Epoch 17/59
4067/4067 [==============================] - 2s 412us/step - loss: 0.1294 - acc: 0.9439 -
val_loss: 0.2909 - val_acc: 0.9077
Epoch 18/59
4067/4067 [==============================] - 2s 417us/step - loss: 0.1539 - acc: 0.9378 -
val_loss: 0.2716 - val_acc: 0.9109
Epoch 19/59
4067/4067 [==============================] - 2s 424us/step - loss: 0.1431 - acc: 0.9373 -
val_loss: 0.3384 - val_acc: 0.9173
Epoch 20/59
4067/4067 [==============================] - 2s 447us/step - loss: 0.1407 - acc: 0.9390 -
val_loss: 0.3228 - val_acc: 0.9160
Epoch 21/59
4067/4067 [==============================] - 2s 436us/step - loss: 0.1416 - acc: 0.9329 -
val_loss: 0.3610 - val_acc: 0.8923
Epoch 22/59
4067/4067 [==============================] - 2s 457us/step - loss: 0.1274 - acc: 0.9489 -
val_loss: 0.3253 - val_acc: 0.9192
Epoch 23/59
4067/4067 [==============================] - 2s 447us/step - loss: 0.1183 - acc: 0.9501 -
val_loss: 0.2975 - val_acc: 0.9135
Epoch 24/59
4067/4067 [==============================] - 2s 434us/step - loss: 0.1357 - acc: 0.9432 -
val_loss: 0.2616 - val_acc: 0.9218
Epoch 25/59
4067/4067 [==============================] - 2s 419us/step - loss: 0.1325 - acc: 0.9471 -
val_loss: 0.3600 - val_acc: 0.9026
Epoch 26/59
4067/4067 [==============================] - 2s 427us/step - loss: 0.1318 - acc: 0.9457 -
val_loss: 0.3595 - val_acc: 0.8955
Epoch 27/59
4067/4067 [==============================] - 2s 436us/step - loss: 0.1570 - acc: 0.9368 -
val_loss: 0.3598 - val_acc: 0.8923
Epoch 28/59
4067/4067 [==============================] - 2s 422us/step - loss: 0.1253 - acc: 0.9484 -
val_loss: 0.3379 - val_acc: 0.9006
Epoch 29/59
4067/4067 [==============================] - 2s 412us/step - loss: 0.1274 - acc: 0.9457 -
val_loss: 0.3340 - val_acc: 0.9147
Epoch 30/59
4067/4067 [==============================] - 2s 420us/step - loss: 0.1058 - acc: 0.9555 -
val_loss: 0.3280 - val_acc: 0.9212
Epoch 31/59
4067/4067 [==============================] - 2s 415us/step - loss: 0.1356 - acc: 0.9479 -
val_loss: 0.2701 - val_acc: 0.9263
Epoch 32/59
4067/4067 [==============================] - 2s 417us/step - loss: 0.1217 - acc: 0.9511 -
```

```
val_loss: 0.4524 - val_acc: 0.8897
Epoch 33/59
4067/4067 [==============================] - 2s 440us/step - loss: 0.1173 - acc: 0.9501 -
val_loss: 0.3675 - val_acc: 0.8904
Epoch 34/59
4067/4067 [==============================] - 2s 420us/step - loss: 0.1057 - acc: 0.9575 -
val_loss: 0.4708 - val_acc: 0.8718
Epoch 35/59
4067/4067 [==============================] - 2s 411us/step - loss: 0.1195 - acc: 0.9464 -
val_loss: 0.4662 - val_acc: 0.8853
Epoch 36/59
4067/4067 [==============================] - 2s 431us/step - loss: 0.1507 - acc: 0.9361 -
val_loss: 0.5384 - val_acc: 0.8923
Epoch 37/59
4067/4067 [==============================] - 2s 403us/step - loss: 0.1281 - acc: 0.9484 -
val_loss: 0.5009 - val_acc: 0.8981
Epoch 38/59
4067/4067 [==============================] - 2s 402us/step - loss: 0.1100 - acc: 0.9552 -
val_loss: 0.5386 - val_acc: 0.9019
Epoch 39/59
4067/4067 [==============================] - 2s 392us/step - loss: 0.1115 - acc: 0.9523 -
val_loss: 0.4056 - val_acc: 0.9128
Epoch 40/59
4067/4067 [==============================] - 2s 402us/step - loss: 0.0984 - acc: 0.9589 -
val_loss: 0.5095 - val_acc: 0.9026
Epoch 41/59
4067/4067 [==============================] - 2s 415us/step - loss: 0.1013 - acc: 0.9567 -
val_loss: 0.2972 - val_acc: 0.9006
Epoch 42/59
4067/4067 [==============================] - 2s 412us/step - loss: 0.1159 - acc: 0.9498 -
val_loss: 0.5124 - val_acc: 0.9026
Epoch 43/59
4067/4067 [==============================] - 2s 416us/step - loss: 0.1022 - acc: 0.9557 -
val_loss: 0.5227 - val_acc: 0.9026
Epoch 44/59
4067/4067 [==============================] - 2s 399us/step - loss: 0.0983 - acc: 0.9597 -
val_loss: 0.4954 - val_acc: 0.8987
Epoch 45/59
4067/4067 [==============================] - 2s 426us/step - loss: 0.1254 - acc: 0.9479 -
val_loss: 0.2917 - val_acc: 0.9199
Epoch 46/59
4067/4067 [==============================] - 2s 407us/step - loss: 0.1186 - acc: 0.9525 -
val_loss: 0.2711 - val_acc: 0.9199
Epoch 47/59
4067/4067 [==============================] - 2s 394us/step - loss: 0.0978 - acc: 0.9604 -
val_loss: 0.3164 - val_acc: 0.9269
Epoch 48/59
4067/4067 [==============================] - 2s 396us/step - loss: 0.0956 - acc: 0.9594 -
val_loss: 0.3670 - val_acc: 0.9186
Epoch 49/59
4067/4067 [==============================] - 2s 428us/step - loss: 0.0930 - acc: 0.9614 -
val_loss: 0.3123 - val_acc: 0.9224
Epoch 50/59
4067/4067 [==============================] - 2s 410us/step - loss: 0.1012 - acc: 0.9582 -
val_loss: 0.2761 - val_acc: 0.9179
Epoch 51/59
4067/4067 [==============================] - 2s 406us/step - loss: 0.1213 - acc: 0.9496 -
val_loss: 0.4582 - val_acc: 0.8821
Epoch 52/59
4067/4067 [==============================] - 2s 425us/step - loss: 0.0881 - acc: 0.9658 -
val_loss: 0.3291 - val_acc: 0.9141
Epoch 53/59
4067/4067 [==============================] - 2s 415us/step - loss: 0.1036 - acc: 0.9533 -
val_loss: 0.3199 - val_acc: 0.9167
Epoch 54/59
4067/4067 [==============================] - 2s 419us/step - loss: 0.0873 - acc: 0.9639 -
val_loss: 0.2934 - val_acc: 0.9154
Epoch 55/59
4067/4067 [==============================] - 2s 410us/step - loss: 0.0863 - acc: 0.9636 -
val_loss: 0.3316 - val_acc: 0.9154
Epoch 56/59
4067/4067 [==============================] - 2s 400us/step - loss: 0.0863 - acc: 0.9597 -
val_loss: 0.4001 - val_acc: 0.9179
Epoch 57/59
4067/4067 [==============================] - 2s 411us/step - loss: 0.0892 - acc: 0.9648 -
val_loss: 0.3249 - val_acc: 0.9231
Epoch 58/59
```

```
4067/4067 [==============================] - 2s 410us/step - loss: 0.0854 - acc: 0.9651 -
val_loss: 0.4786 - val_acc: 0.9058
Epoch 59/59
4067/4067 [==============================] - 2s 399us/step - loss: 0.1172 - acc: 0.9557 -
val_loss: 0.2501 - val_acc: 0.9269
```

Out[92]:

```
<keras.callbacks.History at 0x7f7054309b70>
```

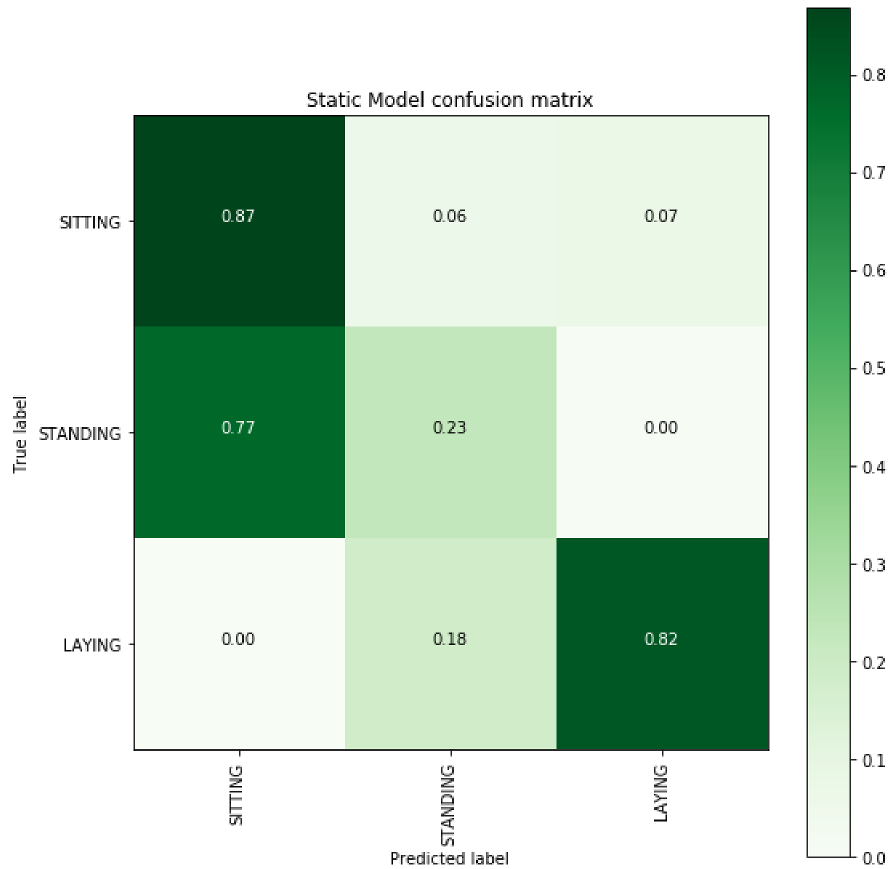
In [93]:

```
static_model_score = static_model.evaluate(X_test_static,Y_test_static,verbose=0)
print('Test loss:', static_model_score[0])
print('Test accuracy:', static_model_score[1]*100)
```

```
Test loss: 0.25014383807258894
Test accuracy: 92.6923076923077
```

In [94]:

```
from sklearn.metrics import confusion_matrix
predict_static = dynamic_model.predict(X_test_static)
f_predict_static = np.argmax(predict_static,axis=1)
cm = confusion_matrix(np.argmax(Y_test_static,axis=1), f_predict_static)
plt.figure(figsize=(8,8))
labels=['SITTING','STANDING','LAYING']
plot_confusion_matrix(cm, classes=labels,
                      normalize=True, title='Static Model confusion matrix', cmap = plt.cm.Greens)
plt.show()
```



Based on above confusion matrix results the class sitting and standing labels more confuse to predict

In [0]:

```
static_model.save('gdrive/My Drive/HAR/final_static_model.m2')
```

Dynamic model

In [35]:

```
# Data directory
DATADIR = 'gdrive/My Drive/HAR/UCI_HAR_Dataset'

# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial 
Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    y_subset = y <= 3 #taking y_class labels less than 3
    y = y[y_subset]
    return pd.get_dummies(y).as_matrix(),y_subset

def load_dynamic_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_train_sub  = load_y('train')
    y_test,y_test_sub = load_y('test')
    X_train = X_train[y_train_sub]
    X_test = X_test[y_test_sub]

    return X_train, X_test, y_train, y_test

# Loading the train and test data
X_train_dynamic, X_test_dynamic, Y_train_dynamic, Y_test_dynamic = load_dynamic_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:32: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:51: FutureWarning: Method .as_matrix
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:51: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
```

In [36]:

```
print(X_train_dynamic.shape,Y_train_dynamic.shape)
print(X_test_dynamic.shape,Y_test_dynamic.shape)
```

```
(3285, 128, 9) (3285, 3)
(1387, 128, 9) (1387, 3)
```

In [0]:

```
import numpy
from sklearn.model_selection import RandomizedSearchCV
from sklearn.model_selection import GridSearchCV
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Dropout
import keras
import keras.utils
from keras import utils as np_utils
from keras.wrappers.scikit_learn import KerasClassifier
def create_model(filters=1,filters2=1,kernel_size2=1,kernel_size=1,dropout_rate2=0.0,dropout_rate=0
.0):
  model = Sequential()
  model.add(keras.layers.Conv1D(filters=filters, kernel_size=kernel_size, activation='relu',kernel_
initializer='he_uniform',input_shape=(timesteps, input_dim)))
  model.add(BatchNormalization())
  model.add(Dropout(dropout_rate))
  model.add(keras.layers.Conv1D(filters=filters2, kernel_size=kernel_size2, activation='relu',kerne
l_initializer='he_uniform'))
  model.add(BatchNormalization())
  model.add(Dropout(dropout_rate2))
  model.add(MaxPooling1D(pool_size=2))
  model.add(Flatten())
  model.add(Dense(3, activation='softmax'))
  model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
  return model

# fix random seed for reproducibility
seed = 7
numpy.random.seed(seed)
model = KerasClassifier(build_fn=create_model, epochs=30, batch_size=16, verbose=0)
# define the grid search parameters
filters = [1,32,64]
filters2 = [1,32,64]
kernel_size = [1,3,5,7]
kernel_size2 = [1,3,5,7]
dropout_rate = [0.0,0.2,0.4,0.6,0.8]
dropout_rate2 = [0.0,0.2,0.4,0.6,0.8]
param =
dict(filters=filters,kernel_size=kernel_size,dropout_rate=dropout_rate,filters2=filters2,dropout_ra
te2=dropout_rate2,kernel_size2=kernel_size2)
random = RandomizedSearchCV(estimator=model,param_distributions=param,cv=3)
rand_result = random.fit(X_train_dynamic, Y_train_dynamic)
# summarize results
print("Best: %f using %s" % (rand_result.best_score_, rand_result.best_params_))
```

```
Best: 0.954642 using {'kernel_size2': 7, 'kernel_size': 1, 'filters2': 32, 'filters': 32,
'dropout_rate2': 0.2, 'dropout_rate': 0.0}
```

In [37]:

```
dynamic_model = Sequential()
dynamic_model.add(Conv1D(filters=32, kernel_size=1, activation='relu',kernel_initializer='he_unifor
m',input_shape=(timesteps, input_dim)))
dynamic_model.add(BatchNormalization())
dynamic_model.add(Dropout(0.0))
dynamic_model.add(Conv1D(filters=32, kernel_size=7, activation='relu',kernel_initializer='he_unifor
m'))
dynamic_model.add(BatchNormalization())
dynamic_model.add(Dropout(0.2))
dynamic_model.add(MaxPooling1D(pool_size=2))
```

```
dynamic_model.add(MaxPooling1D(pool_size=2))
dynamic_model.add(Flatten())
dynamic_model.add(Dense(3, activation='softmax'))
dynamic_model.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
conv1d_8 (Conv1D)            (None, 128, 32)           320       
_________________________________________________________________
batch_normalization_7 (Batch (None, 128, 32)           128       
_________________________________________________________________
dropout_7 (Dropout)          (None, 128, 32)           0         
_________________________________________________________________
conv1d_9 (Conv1D)            (None, 122, 32)           7200      
_________________________________________________________________
batch_normalization_8 (Batch (None, 122, 32)           128       
_________________________________________________________________
dropout_8 (Dropout)          (None, 122, 32)           0         
_________________________________________________________________
max_pooling1d_4 (MaxPooling1 (None, 61, 32)            0         
_________________________________________________________________
flatten_4 (Flatten)          (None, 1952)              0         
_________________________________________________________________
dense_5 (Dense)              (None, 3)                 5859      
=================================================================
Total params: 13,635
Trainable params: 13,507
Non-trainable params: 128
_________________________________________________________________
```

In [38]:

```
dynamic_model.compile(loss='categorical_crossentropy', optimizer='Adam', metrics=['accuracy'])
dynamic_model.fit(X_train_dynamic,Y_train_dynamic, epochs=30, batch_size=32,validation_data=(X_test_dynamic, Y_test_dynamic),verbose=1)
```

```
Train on 3285 samples, validate on 1387 samples
Epoch 1/30
3285/3285 [==============================] - 2s 722us/step - loss: 0.6781 - acc: 0.7367 - val_loss: 0.4249 - val_acc: 0.8717
Epoch 2/30
3285/3285 [==============================] - 1s 342us/step - loss: 0.1024 - acc: 0.9650 - val_loss: 0.2290 - val_acc: 0.9229
Epoch 3/30
3285/3285 [==============================] - 1s 347us/step - loss: 0.0371 - acc: 0.9924 - val_loss: 0.1777 - val_acc: 0.9430
Epoch 4/30
3285/3285 [==============================] - 1s 353us/step - loss: 0.0223 - acc: 0.9948 - val_loss: 0.1433 - val_acc: 0.9560
Epoch 5/30
3285/3285 [==============================] - 1s 344us/step - loss: 0.0124 - acc: 0.9973 - val_loss: 0.1282 - val_acc: 0.9589
Epoch 6/30
3285/3285 [==============================] - 1s 347us/step - loss: 0.0138 - acc: 0.9973 - val_loss: 0.1320 - val_acc: 0.9553
Epoch 7/30
3285/3285 [==============================] - 1s 342us/step - loss: 0.0061 - acc: 0.9991 - val_loss: 0.1366 - val_acc: 0.9618
Epoch 8/30
3285/3285 [==============================] - 1s 360us/step - loss: 0.0046 - acc: 1.0000 - val_loss: 0.1017 - val_acc: 0.9632
Epoch 9/30
3285/3285 [==============================] - 1s 365us/step - loss: 0.0044 - acc: 0.9997 - val_loss: 0.0724 - val_acc: 0.9726
Epoch 10/30
3285/3285 [==============================] - 1s 352us/step - loss: 0.0031 - acc: 0.9994 - val_loss: 0.0766 - val_acc: 0.9740
Epoch 11/30
3285/3285 [==============================] - 1s 341us/step - loss: 0.0071 - acc: 0.9979 - val_loss: 0.1750 - val_acc: 0.9394
Epoch 12/30
3285/3285 [==============================] - 1s 353us/step - loss: 0.0091 - acc: 0.9967 - val_loss: 0.1148 - val_acc: 0.9589
```

```
Epoch 13/30
3285/3285 [==============================] - 1s 346us/step - loss: 0.0023 - acc: 1.0000 -
val_loss: 0.0986 - val_acc: 0.9683
Epoch 14/30
3285/3285 [==============================] - 1s 359us/step - loss: 0.0015 - acc: 0.9997 -
val_loss: 0.0990 - val_acc: 0.9640
Epoch 15/30
3285/3285 [==============================] - 1s 366us/step - loss: 0.0011 - acc: 1.0000 -
val_loss: 0.1133 - val_acc: 0.9618
Epoch 16/30
3285/3285 [==============================] - 1s 346us/step - loss: 0.0023 - acc: 0.9997 -
val_loss: 0.0685 - val_acc: 0.9784
Epoch 17/30
3285/3285 [==============================] - 1s 351us/step - loss: 0.0019 - acc: 0.9997 -
val_loss: 0.0845 - val_acc: 0.9704
Epoch 18/30
3285/3285 [==============================] - 1s 347us/step - loss: 6.9701e-04 - acc: 1.0000 - val_
loss: 0.0715 - val_acc: 0.9755
Epoch 19/30
3285/3285 [==============================] - 1s 350us/step - loss: 6.2882e-04 - acc: 1.0000 - val_
loss: 0.0593 - val_acc: 0.9784
Epoch 20/30
3285/3285 [==============================] - 1s 347us/step - loss: 8.1471e-04 - acc: 0.9997 - val_
loss: 0.0672 - val_acc: 0.9748
Epoch 21/30
3285/3285 [==============================] - 1s 357us/step - loss: 6.5646e-04 - acc: 1.0000 - val_
loss: 0.0700 - val_acc: 0.9719
Epoch 22/30
3285/3285 [==============================] - 1s 357us/step - loss: 4.3850e-04 - acc: 1.0000 - val_
loss: 0.0651 - val_acc: 0.9740
Epoch 23/30
3285/3285 [==============================] - 1s 342us/step - loss: 0.0032 - acc: 0.9994 -
val_loss: 0.1153 - val_acc: 0.9704
Epoch 24/30
3285/3285 [==============================] - 1s 391us/step - loss: 0.0052 - acc: 0.9982 -
val_loss: 0.0806 - val_acc: 0.9697
Epoch 25/30
3285/3285 [==============================] - 1s 367us/step - loss: 0.0045 - acc: 0.9985 -
val_loss: 0.1324 - val_acc: 0.9654
Epoch 26/30
3285/3285 [==============================] - 1s 363us/step - loss: 0.0099 - acc: 0.9967 -
val_loss: 0.1710 - val_acc: 0.9632
Epoch 27/30
3285/3285 [==============================] - 1s 353us/step - loss: 0.0060 - acc: 0.9976 -
val_loss: 0.0965 - val_acc: 0.9712
Epoch 28/30
3285/3285 [==============================] - 1s 353us/step - loss: 0.0011 - acc: 0.9997 -
val_loss: 0.0491 - val_acc: 0.9827
Epoch 29/30
3285/3285 [==============================] - 1s 343us/step - loss: 4.6941e-04 - acc: 0.9997 - val_
loss: 0.0625 - val_acc: 0.9798
Epoch 30/30
3285/3285 [==============================] - 1s 345us/step - loss: 1.9695e-04 - acc: 1.0000 - val_
loss: 0.0615 - val_acc: 0.9820
```

Out[38]:

```
<keras.callbacks.History at 0x7f7061785a90>
```

In [39]:

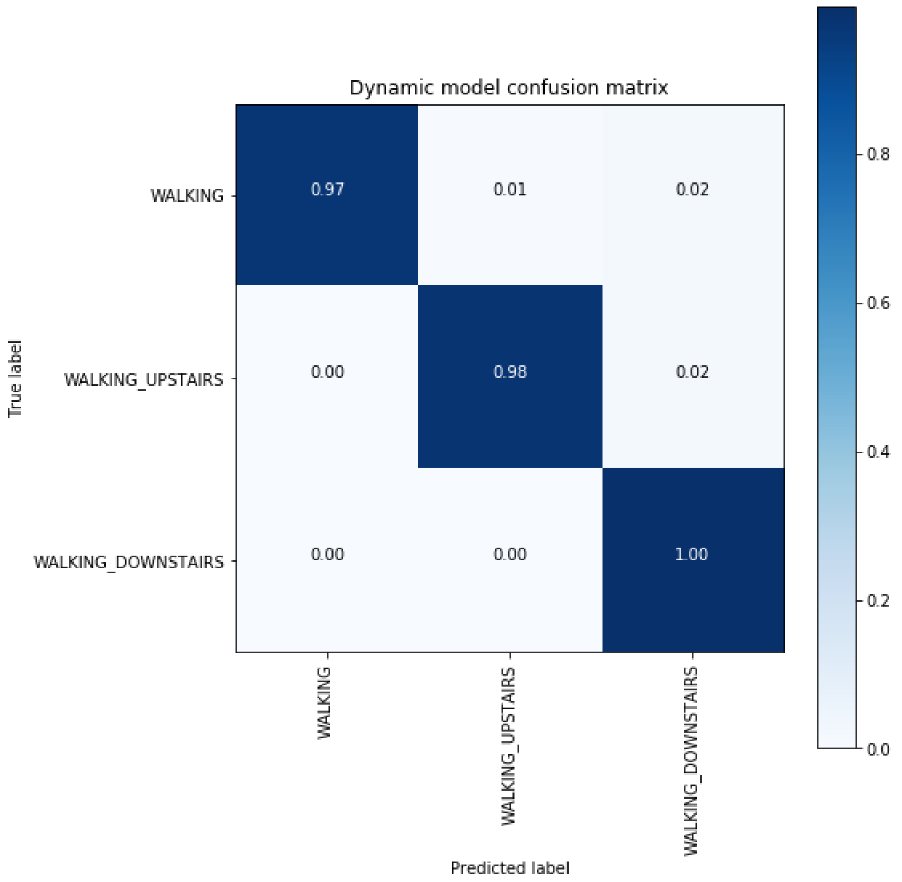
```
dynamic_model_score = dynamic_model.evaluate(X_test_dynamic,Y_test_dynamic,verbose=0)
print('Test loss:', dynamic_model_score[0])
print('Test accuracy:', dynamic_model_score[1]*100)
```

```
Test loss: 0.06151885367722327
Test accuracy: 98.19754866618601
```

In [60]:

```
from sklearn.metrics import confusion_matrix
predict_dynamic = dynamic_model.predict(X_test_dynamic)
f_predict_dynamic = np.argmax(predict_dynamic,axis=1)
cm = confusion_matrix(np.argmax(Y_test_dynamic,axis=1), f_predict_dynamic)
plt.figure(figsize=(8,8))
```

```
plt.figure(figsize=(8,8))
labels=['WALKING','WALKING_UPSTAIRS','WALKING_DOWNSTAIRS']
plot_confusion_matrix(cm, classes=labels,
                      normalize=True, title='Dynamic model confusion matrix', cmap = plt.cm.Blues)
plt.show()
```



In above confusion matrix results states that 98% of class labels are correctly predicted

In [0]:

```
dynamic_model.save('gdrive/My Drive/HAR/final_dynamic_model.m3')
```

Normal model

In [41]:

```
# Data directory
DATADIR = 'gdrive/My Drive/HAR/UCI_HAR_Dataset'

# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]

# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)
```

```
# Utility function to load the load
def load_signals(subset):
    signals_data = []

    for signal in SIGNALS:
        filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

    # Transpose is used to change the dimensionality of the output,
    # aggregating the signals by combination of sample/timestep.
    # Resultant shape is (7352 train/2947 test samples, 128 timesteps, 9 signals)
    return np.transpose(signals_data, (1, 2, 0))

def load_y(subset):
    """
    The objective that we are trying to predict is a integer, from 1 to 6,
    that represents a human activity. We return a binary representation of
    every sample objective as a 6 bits vector using One Hot Encoding
    (https://pandas.pydata.org/pandas-docs/stable/generated/pandas.get_dummies.html)
    """
    filename = f'gdrive/My Drive/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    return pd.get_dummies(y).as_matrix()

def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train,y_test = load_y('train'), load_y('test')

    return X_train, X_test, y_train, y_test

# Loading the train and test data
Q_X_train, Q_X_test, Q_Y_train, Q_Y_test = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:32: FutureWarning: Method .as_matrix will be removed in a future version. Use .values instead.
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:49: FutureWarning: Method .as_matrix will be removed in a future version. Use .values instead.
```

In [0]:

```
from keras.models import load_model
b_model = load_model('gdrive/My Drive/HAR/final_binary_model.m1')
s_model = load_model('gdrive/My Drive/HAR/final_static_model.m2')
d_model = load_model('gdrive/My Drive/HAR/final_dynamic_model.m3')
```

In [0]:

```
#predicting output activity
def predict(X):
    ##predicting whether dynamic or static
    predict_binary = binary_model.predict(X)
    f_predict_binary =  np.argmax(predict_binary, axis=1)
    #static data filter
    X_static = X[f_predict_binary==1]
    #dynamic data filter
    X_dynamic = X[f_predict_binary==0]
    #predicting static activities
    predict_static = static_model.predict(X_static)
    f_predict_static = np.argmax(predict_static,axis=1)
    #adding 3 because need to get inal prediction lable as output
    f_predict_static = f_predict_static + 3
    #predicting dynamic activites
    predict_dynamic = dynamic_model.predict(X_dynamic)
    f_predict_dynamic = np.argmax(predict_dynamic,axis=1)
    #adding 1 because need to get inal prediction lable as output
    f_predict_dynamic = f_predict_dynamic
```

```
    ##appending final output to one list in the same sequence of input data
    i,j = 0,0
    final_predict = []
    for q_p in f_predict_binary:
        if q_p == 1:
            final_predict.append(f_predict_static[i])
            i = i + 1
        else:
            final_predict.append(f_predict_dynamic[j])
            j = j + 1
    return final_predict
```

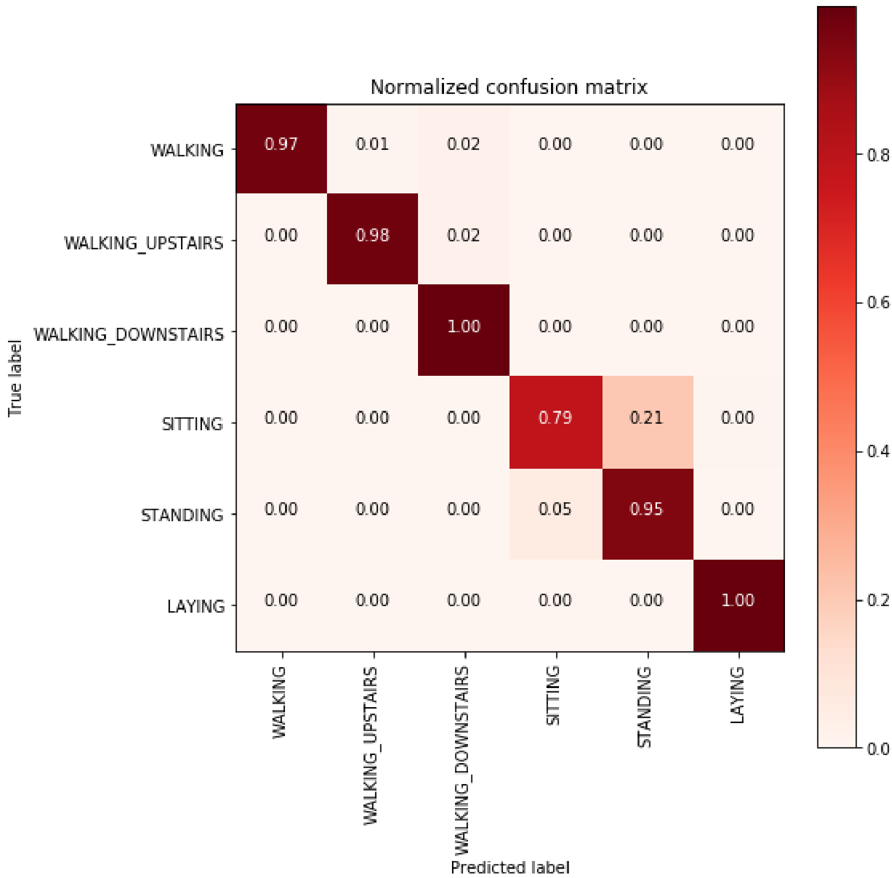
In [44]:

```
from sklearn.metrics import accuracy_score
train_pred = predict(Q_X_train)
test_pred = predict(Q_X_test)
print('Accuracy of train data',accuracy_score(np.argmax(Q_Y_train,axis=1),train_pred))
print('Accuracy of validation data',accuracy_score(np.argmax(Q_Y_test,axis=1),test_pred))
```

```
Accuracy of train data 0.9802774755168662
Accuracy of validation data 0.9460468272819816
```

In [47]:

```
from sklearn.metrics import confusion_matrix
cm = confusion_matrix(np.argmax(Q_Y_test,axis=1), test_pred)
plt.figure(figsize=(8,8))
labels=['WALKING','WALKING_UPSTAIRS','WALKING_DOWNSTAIRS','SITTING','STANDING','LAYING']
plot_confusion_matrix(cm, classes=labels,
                      normalize=True, title='Normalized confusion matrix', cmap = plt.cm.Reds)
plt.show()
```



In [96]:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model", "Accuracy"]
x.add_row(["LSTM BASE MODEL ",  '91%'])
x.add_row(["LSTM 2 Layer ", '93%'])
```

```
x.add_row(["Static model ", '92%'])
x.add_row(["Dynamic model ", '98%'])
x.add_row(["Binary + static + dynamic ", '94%'])
print(x)
```

```
+---------------------------+----------+
|           Model           | Accuracy |
+---------------------------+----------+
|      LSTM BASE MODEL      |   91%    |
|       LSTM 2 Layer        |   93%    |
|       Static model        |   92%    |
|       Dynamic model       |   98%    |
| Binary + static + dynamic |   94%    |
+---------------------------+----------+
```

Observations

1. In this dataset about Human activity Recoginition using smart phones data, Various LSTM and CNN deep learning techniques are applied
2. We got the results by using LSTM we got 93% accuracy
3. By applying the new concept called Divide and conquer we dividede te data into two parts
4. Applied first 3 class labels as one model and remaining 3 class labels as another model and predicted individually
5. first 3 class label models called dynamic models and last 3 class labels called as static models
6. Applied as 2 models and we got Static model as 92% accuracy and dynamic model as 98% accuracy
7. In static model there is a lot of confusion between standing and sitting class labels because of that confusion it gives lower accuracy
8. But in dynamic models it gives excellent classification it gaves 98% accuracy
9. Overall by combing all these 6 labels we got 94% as final accuracy by using concept called divde and conquer