```
In [1]:
# Importing Libraries
In [2]:
import pandas as pd
import numpy as np
In [3]:
# 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'])
Data
In [4]:
# Data directory
DATADIR = 'UCI_HAR_Dataset'
In [5]:
# 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 [6]:
# 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'UCI HAR Dataset/{subset}/Inertial Signals/{signal} {subset}.txt'

#### In [7]:

```
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'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    return pd.get_dummies(y).as_matrix()
```

#### In [8]:

```
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 [9]:

```
# Importing tensorflow
np.random.seed (42)
import tensorflow as tf
tf.set random seed(42)
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:526: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
     np qint8 = np.dtype([("qint8", np.int8, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:527: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
    np quint8 = np.dtype([("quint8", np.uint8, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:528: Fu
tureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / (1,)type'.
    np qint16 = np.dtype([("qint16", np.int16, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py: 529: Full of the control of the 
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / (1,)type'.
     _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:530: Fu
tureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
     np qint32 = np.dtype([("qint32", np.int32, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:535: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
   np_resource = np.dtype([("resource", np.ubyte, 1)])
```

# In [10]:

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

```
inter op parallelism threads=1
In [11]:
# Import Keras
import os
os.environ['KMP DUPLICATE LIB OK']='True'
from tensorflow.keras import backend as K
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set session(sess)
In [12]:
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
Using TensorFlow backend.
In [13]:
# Initializing parameters
epochs = 30
batch size = 16
n_hidden = 64
In [14]:
# Utility function to count the number of classes
def count classes(y):
    return len(set([tuple(category) for category in y]))
In [16]:
# Loading the train and test data
X train, X test, Y train, Y test = load data()
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:12: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
 if sys.path[0] == '':
/Users/bhawesh/anaconda3/lib/python3.7/site-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 [17]:
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
7352
In [18]:
X_train.shape
Out[18]:
(7352, 128, 9)
```

## • Defining the Architecture of LSTM

# In [19]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(32,return_sequences=True,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))

model.add(LSTM(28,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

WARNING:tensorflow:From /Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/ops/resource\_variable\_ops.py:435: colocate\_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version. Instructions for updating:
Colocations handled automatically by placer.

Madala Wasansatial 18

Model: "sequential\_1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 128, 32)	5376
dropout_1 (Dropout)	(None, 128, 32)	0
lstm_2 (LSTM)	(None, 28)	6832
dropout_2 (Dropout)	(None, 28)	0
dense_1 (Dense)	(None, 6)	174

Total params: 12,382 Trainable params: 12,382 Non-trainable params: 0

\_\_\_\_\_

## In [73]:

### In [74]:

```
Epoch 5/30
7352/7352 [===========] - 1078s 147ms/step - loss: 0.6872 - accuracy: 0.6834 -
val loss: 0.6223 - val accuracy: 0.7258
Epoch 6/30
l loss: 0.6051 - val accuracy: 0.7489
Epoch 7/30
1 loss: 0.7489 - val accuracy: 0.7248
Epoch 8/30
1_loss: 0.4933 - val_accuracy: 0.7669
Epoch 9/30
7352/7352 [============== ] - 240s 33ms/step - loss: 0.4596 - accuracy: 0.7954 - va
1 loss: 0.4845 - val accuracy: 0.7930
Epoch 10/30
l loss: 0.5197 - val accuracy: 0.8588
Epoch 11/30
1 loss: 0.3937 - val accuracy: 0.8748
Epoch 12/30
1_loss: 0.3701 - val_accuracy: 0.8989
Epoch 13/30
7352/7352 [============== ] - 249s 34ms/step - loss: 0.2819 - accuracy: 0.9169 - va
1 loss: 0.3248 - val accuracy: 0.8972
Epoch 14/30
7352/7352 [============= ] - 253s 34ms/step - loss: 0.2587 - accuracy: 0.9274 - va
l loss: 0.3103 - val accuracy: 0.9053
Epoch 15/30
1 loss: 0.3870 - val accuracy: 0.9030
Epoch 16/30
1_loss: 0.3751 - val_accuracy: 0.9019
Epoch 17/30
7352/7352 [============ ] - 230s 31ms/step - loss: 0.2133 - accuracy: 0.9369 - va
1_loss: 0.3343 - val_accuracy: 0.9050
Epoch 18/30
1 loss: 0.3600 - val accuracy: 0.9006
Epoch 19/30
1 loss: 0.3001 - val accuracy: 0.9230
Epoch 20/30
7352/7352 [============] - 2031s 276ms/step - loss: 0.1762 - accuracy: 0.9399 -
val loss: 0.3171 - val accuracy: 0.9131
Epoch 21/30
1 loss: 0.3270 - val accuracy: 0.9131
Epoch 22/30
1 loss: 0.3348 - val accuracy: 0.9199
Epoch 23/30
7352/7352 [============= ] - 303s 41ms/step - loss: 0.1847 - accuracy: 0.9440 - va
l loss: 0.3564 - val accuracy: 0.9148
Epoch 24/30
7352/7352 [============== ] - 272s 37ms/step - loss: 0.1776 - accuracy: 0.9418 - va
l loss: 0.5241 - val accuracy: 0.8975
Epoch 25/30
1 loss: 0.3894 - val accuracy: 0.9220
Epoch 26/30
7352/7352 [============== ] - 266s 36ms/step - loss: 0.1628 - accuracy: 0.9423 - va
1_loss: 0.3690 - val_accuracy: 0.9230
Epoch 27/30
7352/7352 [============= ] - 265s 36ms/step - loss: 0.1621 - accuracy: 0.9441 - va
1_loss: 0.3947 - val_accuracy: 0.9121
Epoch 28/30
1_loss: 0.3694 - val_accuracy: 0.9114
Epoch 29/30
1 loss: 0.3727 - val accuracy: 0.9182
Epoch 30/30
```

```
l_loss: 0.4158 - val_accuracy: 0.9101
Out[74]:
<keras.callbacks.callbacks.History at 0x639c9d5c0>
In [75]:
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
                   LAYING SITTING STANDING WALKING WALKING DOWNSTAIRS \
Pred
True
                       537
                               Ο
                                          0
                                                                        Ω
LAYING
                                                   Ω
                              420
                                                                        0
SITTING
                                         46
                                        400
                                                                       0
STANDING
                        0
                              132
                                                   0
                                         0
                       0
                               0
WALKING
                                                469
                                                                       2.1
                                          0
1
WALKING DOWNSTAIRS
                        0
                                 0
                                                   12
                                                                      401
                                                13
                       0
                                 2
WALKING_UPSTAIRS
                                                                        0
Pred
                   WALKING UPSTAIRS
True
LAYING
                                  0
SITTING
                                 21
STANDING
                                  Ω
WALKING
                                  6
WALKING DOWNSTAIRS
                                  7
WALKING_UPSTAIRS
                                455
In [76]:
score = model.evaluate(X_test, Y_test)
2947/2947 [============ ] - 18s 6ms/step
In [77]:
score
Out[77]:
[0.4158135156924696, 0.9100780487060547]
 • With a simple 2 layer architecture we got 90.09% accuracy and a loss of 0.30
 • We can further imporve the performace with Hyperparameter tuning
Assignment
Changing LSTM
In [116]:
# Initializing parameters
epochs = 30
batch size = 16
n_{hidden} = 32
In [118]:
```

# Initiliazing the sequential model

model.add(LSTM(n\_hidden, input\_shape=(timesteps, input\_dim)))

# Adding a dense output layer with sigmoid activation

# Configuring the parameters

# Adding a dropout layer
model.add(Dropout(0.4))

model = Sequential()

```
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

### Model: "sequential 9"

Layer (type)	Output Sh	hape	Param #
lstm_9 (LSTM)	(None, 32	2)	5376
dropout_9 (Dropout)	(None, 32	2)	0
dense_9 (Dense)	(None, 6)	) ========	198
Total params: 5,574 Trainable params: 5,574 Non-trainable params: 0			

# In [119]:

# In [120]:

# Training the model

```
model.fit(X_train,
        Y_train,
        batch size=batch size,
        validation_data=(X_test, Y_test),
        epochs=epochs)
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
l loss: 1.0321 - val accuracy: 0.6074
Epoch 2/30
7352/7352 [============== ] - 196s 27ms/step - loss: 0.8385 - accuracy: 0.6436 - va
1 loss: 0.8230 - val accuracy: 0.6308
Epoch 3/30
7352/7352 [============= ] - 175s 24ms/step - loss: 0.6884 - accuracy: 0.6912 - va
1_loss: 0.6510 - val_accuracy: 0.7435
Epoch 4/30
7352/7352 [============== ] - 178s 24ms/step - loss: 0.5859 - accuracy: 0.7564 - va
l loss: 0.5855 - val accuracy: 0.7611
Epoch 5/30
7352/7352 [============= ] - 149s 20ms/step - loss: 0.4952 - accuracy: 0.7969 - va
1 loss: 0.5028 - val accuracy: 0.7967
Epoch 6/30
1 loss: 0.5677 - val accuracy: 0.7869
Epoch 7/30
7352/7352 [=============] - 144s 20ms/step - loss: 0.4050 - accuracy: 0.8637 - va
1_loss: 0.7944 - val_accuracy: 0.7760
Epoch 8/30
7352/7352 [============= ] - 145s 20ms/step - loss: 0.3277 - accuracy: 0.8976 - va
l loss: 0.5426 - val accuracy: 0.8208
Epoch 9/30
7352/7352 [============== ] - 144s 20ms/step - loss: 0.3029 - accuracy: 0.9070 - va
l loss: 0.4130 - val accuracy: 0.8578
Epoch 10/30
7352/7352 [==========] - 1738s 236ms/step - loss: 0.2610 - accuracy: 0.9208 -
val loss: 0.4450 - val accuracy: 0.8571
Epoch 11/30
7352/7352 [============= ] - 145s 20ms/step - loss: 0.2344 - accuracy: 0.9244 - va
1_loss: 0.4185 - val_accuracy: 0.8792
Epoch 12/30
7352/7352 [============ ] - 146s 20ms/step - loss: 0.2109 - accuracy: 0.9305 - va
l loss: 0.3942 - val accuracy: 0.8812
Epoch 13/30
7352/7352 [============ ] - 147s 20ms/step - loss: 0.2157 - accuracy: 0.9332 - va
l loss: 0.5447 - val accuracy: 0.8609
```

```
Epoch 14/30
1 loss: 0.5232 - val accuracy: 0.8748
Epoch 15/30
7352/7352 [============== ] - 170s 23ms/step - loss: 0.1824 - accuracy: 0.9389 - va
1 loss: 0.3321 - val accuracy: 0.8799
Epoch 16/30
1 loss: 0.4579 - val accuracy: 0.8663
Epoch 17/30
7352/7352 [===========] - 150s 20ms/step - loss: 0.1710 - accuracy: 0.9412 - va
1_loss: 0.3797 - val_accuracy: 0.9016
Epoch 18/30
7352/7352 [===========] - 150s 20ms/step - loss: 0.1726 - accuracy: 0.9437 - va
1_loss: 0.4645 - val_accuracy: 0.8924
Epoch 19/30
7352/7352 [============= ] - 161s 22ms/step - loss: 0.1719 - accuracy: 0.9389 - va
1_loss: 0.4814 - val_accuracy: 0.8860
Epoch 20/30
7352/7352 [============= ] - 160s 22ms/step - loss: 0.1550 - accuracy: 0.9444 - va
1 loss: 0.3362 - val accuracy: 0.8992
Epoch 21/30
7352/7352 [============== ] - 158s 22ms/step - loss: 0.1674 - accuracy: 0.9430 - va
1 loss: 0.3746 - val accuracy: 0.8945
Epoch 22/30
l loss: 0.4101 - val accuracy: 0.9016
Epoch 23/30
7352/7352 [============= ] - 167s 23ms/step - loss: 0.1529 - accuracy: 0.9452 - va
1 loss: 0.5036 - val accuracy: 0.8799
Epoch 24/30
7352/7352 [============== ] - 166s 23ms/step - loss: 0.1416 - accuracy: 0.9475 - va
1 loss: 0.3752 - val accuracy: 0.9077
Epoch 25/30
1 loss: 0.3901 - val accuracy: 0.9091
Epoch 26/30
7352/7352 [============== ] - 192s 26ms/step - loss: 0.1892 - accuracy: 0.9406 - va
1 loss: 0.6442 - val accuracy: 0.8697
Epoch 27/30
7352/7352 [============= ] - 189s 26ms/step - loss: 0.1508 - accuracy: 0.9493 - va
1_loss: 0.3408 - val_accuracy: 0.9043
Epoch 28/30
7352/7352 [============== ] - 170s 23ms/step - loss: 0.1324 - accuracy: 0.9491 - va
1_loss: 0.4604 - val_accuracy: 0.8904
Epoch 29/30
7352/7352 [===========] - 157s 21ms/step - loss: 0.1316 - accuracy: 0.9498 - va
1_loss: 0.5240 - val_accuracy: 0.8880
Epoch 30/30
7352/7352 [============= ] - 144s 20ms/step - loss: 0.1471 - accuracy: 0.9474 - va
1 loss: 0.7513 - val accuracy: 0.8755
```

# Out[120]:

<keras.callbacks.callbacks.History at 0x650f76f98>

# In [121]:

```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
                  LAYING SITTING STANDING WALKING WALKING DOWNSTAIRS \
Pred
True
                      513
                                0
                                         24
                                                   0
                                                                       0
LAYING
                               425
SITTING
                                          64
                                                   0
                                                                       1
                               117
                                                   2
STANDING
                        Ω
                                         405
                                                                       0
WALKING
                                0
                                         1
                                                 386
                                                                      49
                        0
WALKING DOWNSTAIRS
                                0
                                         0
                                                  0
                                                                     420
WALKING_UPSTAIRS
                                         1
                                                   4
                        0
                                4
                                                                      31
Pred
                   WALKING UPSTAIRS
```

Pred WALKING\_UPSTAIRS
True
LAYING 0
SITTING 1
STANDING 8

```
WALKING
                              60
WALKING DOWNSTAIRS
WALKING_UPSTAIRS
                             431
In [122]:
score = model.evaluate(X test, Y test)
In [123]:
score
Out[123]:
[0.751543751711401, 0.8754665851593018]
In [124]:
# Initializing parameters
epochs = 30
batch size = 16
n hidden = 64
In [125]:
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.55))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
Model: "sequential 10"
                          Output Shape
Layer (type)
                                                  Param #
_____
                        _____
lstm_10 (LSTM)
                          (None, 64)
                                                 18944
dropout_10 (Dropout)
                        (None, 64)
dense 10 (Dense)
                          (None, 6)
                                                  390
_____
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
In [126]:
# Compiling the model
model.compile(loss='categorical crossentropy',
            optimizer='rmsprop',
            metrics=['accuracy'])
In [127]:
# Training the model
model.fit(X train,
         Y train,
         batch size=batch size,
         validation data=(X test, Y test),
         epochs=epochs)
```

Train on 7352 samples. validate on 2947 samples

```
Epoch 1/30
l loss: 1.0838 - val accuracy: 0.5517
Epoch 2/30
7352/7352 [============== ] - 253s 34ms/step - loss: 0.8582 - accuracy: 0.6133 - va
1_loss: 0.7665 - val_accuracy: 0.6634
Epoch 3/30
7352/7352 [=============== ] - 210s 29ms/step - loss: 0.7849 - accuracy: 0.6678 - va
l loss: 0.7073 - val accuracy: 0.7150
Epoch 4/30
l loss: 0.6145 - val accuracy: 0.7737
Epoch 5/30
7352/7352 [============== ] - 270s 37ms/step - loss: 0.5641 - accuracy: 0.7807 - va
l loss: 0.4794 - val accuracy: 0.8276
Epoch 6/30
1 loss: 0.3470 - val accuracy: 0.8782
Epoch 7/30
7352/7352 [============= ] - 211s 29ms/step - loss: 0.2898 - accuracy: 0.9059 - va
1 loss: 0.4922 - val accuracy: 0.8653
Epoch 8/30
1 loss: 0.3282 - val accuracy: 0.8853
Epoch 9/30
1 loss: 0.4303 - val accuracy: 0.8785
Epoch 10/30
7352/7352 [===========] - 177s 24ms/step - loss: 0.2080 - accuracy: 0.9301 - va
1_loss: 0.3728 - val_accuracy: 0.8985
Epoch 11/30
7352/7352 [============= ] - 179s 24ms/step - loss: 0.1814 - accuracy: 0.9361 - va
1 loss: 0.4181 - val_accuracy: 0.9053
Epoch 12/30
1 loss: 0.4217 - val_accuracy: 0.8972
Epoch 13/30
7352/7352 [============= ] - 168s 23ms/step - loss: 0.1848 - accuracy: 0.9363 - va
l loss: 0.4813 - val accuracy: 0.9074
Epoch 14/30
1 loss: 0.6607 - val accuracy: 0.8585
Epoch 15/30
7352/7352 [===========] - 170s 23ms/step - loss: 0.1611 - accuracy: 0.9449 - va
1_loss: 0.2482 - val_accuracy: 0.9175
Epoch 16/30
7352/7352 [============= ] - 176s 24ms/step - loss: 0.1775 - accuracy: 0.9434 - va
l loss: 0.3645 - val accuracy: 0.9169
Epoch 17/30
l loss: 0.4787 - val accuracy: 0.9091
Epoch 18/30
1 loss: 0.3080 - val accuracy: 0.9172
Epoch 19/30
1 loss: 0.3242 - val accuracy: 0.9240
Epoch 20/30
7352/7352 [============== ] - 226s 31ms/step - loss: 0.1448 - accuracy: 0.9448 - va
1 loss: 0.3845 - val accuracy: 0.9179
Epoch 21/30
7352/7352 [============== ] - 184s 25ms/step - loss: 0.1441 - accuracy: 0.9491 - va
1_loss: 0.3254 - val_accuracy: 0.9138
Epoch 22/30
7352/7352 [============] - 154s 21ms/step - loss: 0.1370 - accuracy: 0.9493 - va
1_loss: 0.4371 - val_accuracy: 0.9138
Epoch 23/30
1 loss: 0.3453 - val_accuracy: 0.9074
Epoch 24/30
1 loss: 0.3688 - val accuracy: 0.9284
Epoch 25/30
7352/7352 [============== ] - 215s 29ms/step - loss: 0.1404 - accuracy: 0.9533 - va
1 loss: 0.4563 - val_accuracy: 0.9026
Epoch 26/30
```

```
1 1000 20m0/000p 1000. 0.1110 accaracy. 0.510/
1_loss: 0.4691 - val_accuracy: 0.9063
Epoch 27/30
1_loss: 0.4233 - val_accuracy: 0.9036
Epoch 28/30
1_loss: 0.2551 - val_accuracy: 0.9284
Epoch 29/30
1 loss: 0.3803 - val accuracy: 0.9162
Epoch 30/30
7352/7352 [============] - 176s 24ms/step - loss: 0.1666 - accuracy: 0.9467 - va
1 loss: 0.2756 - val accuracy: 0.9284
Out[127]:
<keras.callbacks.callbacks.History at 0x64f3f29b0>
In [131]:
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
              LAYING SITTING STANDING WALKING WALKING DOWNSTAIRS \
Pred
True
                 535
                        0
                               0
LAYING
SITTING
                 0
                       416
                               67
                                      0
                                                     0
STANDING
                  0
                        96
                               434
                                      1
                                                     0
WALKING
                  0
                        0
                                0
                                     491
                                                      3
WALKING DOWNSTAIRS
                  0
                        0
                               0
                                     6
                                                    413
                               1
                                     15
WALKING UPSTAIRS
                 0
                        0
                                                      8
              WALKING UPSTAIRS
Pred
True
LAYING
                         2
SITTING
                         8
STANDING
WALKING
                         2
WALKING DOWNSTAIRS
                         1
WALKING UPSTAIRS
                        447
In [132]:
score = model.evaluate(X test, Y test)
2947/2947 [=========] - 15s 5ms/step
In [133]:
score
Out[133]:
[0.27563241636243435, 0.92840176820755]
Changing Dropout
```

# In [41]:

```
# Initializing parameters
epochs = 30
batch_size = 16
n_hidden = 32
```

### In [42]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
```

```
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.7))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

### Model: "sequential 5"

Layer (type)	Output Shape	Param #
lstm_5 (LSTM)	(None, 32)	5376
dropout 5 (Dropout)	(None, 32)	0
dense 5 (Dense)	(None, 6)	198
Total params: 5,574		
The inchis no name E 574		

Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0

## In [43]:

### In [44]:

```
1 loss: 1.1522 - val_accuracy: 0.4951
Epoch 2/30
1 loss: 0.9802 - val accuracy: 0.5643
Epoch 3/30
7352/7352 [============= ] - 117s 16ms/step - loss: 0.9794 - accuracy: 0.5681 - va
1_loss: 0.9824 - val_accuracy: 0.5168
Epoch 4/30
7352/7352 [============= ] - 118s 16ms/step - loss: 1.0273 - accuracy: 0.5491 - va
1 loss: 0.9189 - val accuracy: 0.5775
Epoch 5/30
7352/7352 [============== ] - 119s 16ms/step - loss: 0.8047 - accuracy: 0.6411 - va
l loss: 0.8748 - val accuracy: 0.5969
Epoch 6/30
7352/7352 [============== ] - 119s 16ms/step - loss: 0.8253 - accuracy: 0.6299 - va
1 loss: 0.8473 - val accuracy: 0.6057
Epoch 7/30
l loss: 0.7836 - val accuracy: 0.6081
Epoch 8/30
7352/7352 [============ ] - 120s 16ms/step - loss: 0.7220 - accuracy: 0.6835 - va
1 loss: 0.8439 - val_accuracy: 0.6529
Epoch 9/30
1_loss: 0.8434 - val_accuracy: 0.7143
Epoch 10/30
7352/7352 [============] - 116s 16ms/step - loss: 0.6881 - accuracy: 0.7369 - va
l loss: 0.6961 - val_accuracy: 0.7479
Epoch 11/30
1 loss: 0.8060 - val accuracy: 0.7462
Epoch 12/30
```

```
7352/7352 [============ ] - 136s 18ms/step - loss: 0.5308 - accuracy: 0.7969 - va
1 loss: 0.5615 - val accuracy: 0.7818
Epoch 13/30
1 loss: 0.6740 - val accuracy: 0.7665
Epoch 14/30
7352/7352 [============= ] - 119s 16ms/step - loss: 0.4805 - accuracy: 0.8300 - va
1_loss: 0.6425 - val_accuracy: 0.7920
Epoch 15/30
7352/7352 [============= ] - 115s 16ms/step - loss: 0.5441 - accuracy: 0.8162 - va
1 loss: 0.8308 - val accuracy: 0.7825
Epoch 16/30
7352/7352 [============= ] - 115s 16ms/step - loss: 0.4790 - accuracy: 0.8426 - va
l loss: 0.5679 - val accuracy: 0.8076
Epoch 17/30
7352/7352 [============== ] - 118s 16ms/step - loss: 0.4450 - accuracy: 0.8588 - va
1 loss: 0.8075 - val accuracy: 0.8022
Epoch 18/30
7352/7352 [============== ] - 130s 18ms/step - loss: 0.4052 - accuracy: 0.8829 - va
1 loss: 0.5603 - val accuracy: 0.8442
Epoch 19/30
7352/7352 [============== ] - 129s 18ms/step - loss: 0.3791 - accuracy: 0.8915 - va
1_loss: 0.4587 - val_accuracy: 0.8473
Epoch 20/30
7352/7352 [============ ] - 130s 18ms/step - loss: 0.3629 - accuracy: 0.8936 - va
1_loss: 0.4256 - val_accuracy: 0.8738
Epoch 21/30
7352/7352 [============== ] - 129s 18ms/step - loss: 0.3635 - accuracy: 0.9013 - va
1_loss: 0.6416 - val_accuracy: 0.8582
Epoch 22/30
7352/7352 [==============] - 135s 18ms/step - loss: 0.3661 - accuracy: 0.8950 - va
1 loss: 0.5373 - val_accuracy: 0.8371
Epoch 23/30
l loss: 0.4484 - val accuracy: 0.8744
Epoch 24/30
1 loss: 0.7172 - val accuracy: 0.8527
Epoch 25/30
7352/7352 [============= ] - 127s 17ms/step - loss: 0.2925 - accuracy: 0.9163 - va
l loss: 0.5847 - val accuracy: 0.8843
Epoch 26/30
7352/7352 [=============] - 130s 18ms/step - loss: 0.2644 - accuracy: 0.9212 - va
l loss: 0.6235 - val accuracy: 0.8707
Epoch 27/30
7352/7352 [============== ] - 132s 18ms/step - loss: 0.2724 - accuracy: 0.9223 - va
1 loss: 0.6380 - val accuracy: 0.8826
Epoch 28/30
7352/7352 [============== ] - 131s 18ms/step - loss: 0.2841 - accuracy: 0.9214 - va
1 loss: 0.5960 - val accuracy: 0.8829
Epoch 29/30
7352/7352 [============= ] - 130s 18ms/step - loss: 0.3320 - accuracy: 0.9125 - va
l loss: 0.8264 - val accuracy: 0.8514
Epoch 30/30
1_loss: 0.8671 - val_accuracy: 0.8476
```

## Out[44]:

<keras.callbacks.callbacks.History at 0x645d1ada0>

# In [45]:

```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	484	25	6	1	0	
SITTING	0	370	92	2	1	
STANDING	0	65	398	8	0	
WALKING	0	0	0	431	9	
WALKING_DOWNSTAIRS	0	0	0	25	388	
WALKING UPSTAIRS	0	2	0	30	12	
_						

```
WALKING UPSTAIRS
Pred
True
                                21
LAYING
SITTING
                                26
STANDING
                                61
                               56
WALKING
WALKING DOWNSTAIRS
                                7
WALKING UPSTAIRS
                               427
In [46]:
score = model.evaluate(X test, Y test)
2947/2947 [============ ] - 8s 3ms/step
In [47]:
score
Out[47]:
[0.8671318305163158, 0.84764164686203]
Adding More layers
In [48]:
# Initializing parameters
epochs = 30
batch size = 16
n hidden = 64
In [52]:
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.4))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
Model: "sequential_9"
Layer (type)
                          Output Shape
                                                   Param #
______
1stm 12 (LSTM)
                           (None, 64)
                                                   18944
dropout 9 (Dropout)
                           (None, 64)
dense 6 (Dense)
                         (None, 6)
                                                   390
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
In [53]:
```

### In [54]:

```
model.fit(X train,
       Y train,
      batch size=batch size,
       validation data=(X test, Y test),
       epochs=epochs)
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
l loss: 1.1095 - val accuracy: 0.5497
Epoch 2/30
7352/7352 [============== ] - 191s 26ms/step - loss: 0.8816 - accuracy: 0.6336 - va
l loss: 0.8614 - val accuracy: 0.6400
Epoch 3/30
1 loss: 1.2741 - val accuracy: 0.5185
Epoch 4/30
7352/7352 [============= ] - 180s 24ms/step - loss: 0.5214 - accuracy: 0.8161 - va
1 loss: 0.5649 - val accuracy: 0.8273
Epoch 5/30
1 loss: 0.3780 - val_accuracy: 0.8799
Epoch 6/30
7352/7352 [=============] - 176s 24ms/step - loss: 0.2669 - accuracy: 0.9116 - va
1 loss: 0.5281 - val accuracy: 0.8585
Epoch 7/30
7352/7352 [=============] - 172s 23ms/step - loss: 0.2330 - accuracy: 0.9207 - va
1 loss: 0.4112 - val accuracy: 0.8721
Epoch 8/30
1_loss: 0.3681 - val_accuracy: 0.8880
Epoch 9/30
7352/7352 [=============] - 189s 26ms/step - loss: 0.1992 - accuracy: 0.9309 - va
l loss: 0.3448 - val accuracy: 0.8935
Epoch 10/30
1 loss: 0.5202 - val accuracy: 0.8680
Epoch 11/30
1 loss: 0.3328 - val_accuracy: 0.9013
Epoch 12/30
7352/7352 [============== ] - 176s 24ms/step - loss: 0.1649 - accuracy: 0.9389 - va
1 loss: 0.3874 - val accuracy: 0.8846
Epoch 13/30
7352/7352 [============== ] - 177s 24ms/step - loss: 0.1559 - accuracy: 0.9450 - va
1_loss: 0.3335 - val_accuracy: 0.9111
Epoch 14/30
7352/7352 [============= ] - 181s 25ms/step - loss: 0.1632 - accuracy: 0.9431 - va
1 loss: 0.4399 - val accuracy: 0.9043
Epoch 15/30
7352/7352 [=========== ] - 174s 24ms/step - loss: 0.1525 - accuracy: 0.9436 - va
l loss: 0.3367 - val accuracy: 0.8958
Epoch 16/30
7352/7352 [============= ] - 184s 25ms/step - loss: 0.1397 - accuracy: 0.9472 - va
l loss: 0.4192 - val accuracy: 0.8958
Epoch 17/30
l loss: 0.3113 - val accuracy: 0.9087
Epoch 18/30
7352/7352 [============] - 173s 24ms/step - loss: 0.1371 - accuracy: 0.9497 - va
1_loss: 0.3204 - val_accuracy: 0.9057
Epoch 19/30
1 loss: 0.2370 - val accuracy: 0.9138
Epoch 20/30
7352/7352 [============= ] - 165s 22ms/step - loss: 0.1490 - accuracy: 0.9475 - va
l loss: 0.2868 - val accuracy: 0.9128
Epoch 21/30
7352/7352 [============= ] - 175s 24ms/step - loss: 0.1303 - accuracy: 0.9472 - va
l loss: 0.7616 - val accuracy: 0.8748
Epoch 22/30
1 loss: 0.3695 - val accuracy: 0.9019
Epoch 23/30
7352/7352 [============= ] - 186s 25ms/step - loss: 0.1287 - accuracy: 0.9490 - va
```

# Training the model

1 loce • 0 2724 - wal accuracy • 0 0101

```
1 1055. U.2/24 - Val accuracy. U.9101
Epoch 24/30
1 loss: 0.2277 - val accuracy: 0.9152
Epoch 25/30
1 loss: 0.3673 - val accuracy: 0.9158
Epoch 26/30
1 loss: 0.3518 - val accuracy: 0.9182
Epoch 27/30
7352/7352 [=============== ] - 180s 24ms/step - loss: 0.1389 - accuracy: 0.9461 - va
1 loss: 0.3393 - val accuracy: 0.9196
Epoch 28/30
7352/7352 [============== ] - 172s 23ms/step - loss: 0.1268 - accuracy: 0.9494 - va
l loss: 0.3260 - val accuracy: 0.8941
Epoch 29/30
7352/7352 [===========] - 170s 23ms/step - loss: 0.1226 - accuracy: 0.9529 - va
1_loss: 0.2653 - val_accuracy: 0.9223
Epoch 30/30
1_loss: 0.3104 - val_accuracy: 0.9131
Out[54]:
<keras.callbacks.callbacks.History at 0x6549c6320>
In [55]:
# Confusion Matrix
print(confusion matrix(Y test, model.predict(X test)))
             LAYING SITTING STANDING WALKING WALKING DOWNSTAIRS \
```

Pred	LAIING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS
True					
LAYING	510	0	27	0	0
SITTING	0	394	96	1	0
STANDING	0	63	468	1	0
WALKING	0	0	0	489	0
WALKING_DOWNSTAIRS	0	0	0	9	410
WALKING_UPSTAIRS	0	0	0	47	4

WALKING UPSTAIRS Pred True 0 LAYING SITTING 0 0 STANDING WALKING 7 WALKING DOWNSTAIRS WALKING\_UPSTAIRS 420

## In [56]:

```
score = model.evaluate(X test, Y test)
```

2947/2947 [============= ] - 12s 4ms/step

# In [57]:

score

# Out[57]:

[0.31043342269294943, 0.9131320118904114]

## In [24]:

```
# Initializing parameters
epochs = 30
batch size = 16
n hidden = 64
```

# In [125]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden,return_sequences=True,input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.55))
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

# Model: "sequential 29"

Layer (type)	Output Shape	Param #
lstm_45 (LSTM)	(None, 128, 64)	18944
dropout_39 (Dropout)	(None, 128, 64)	0
lstm_46 (LSTM)	(None, 64)	33024
dropout_40 (Dropout)	(None, 64)	0
dense_51 (Dense)	(None, 6)	390
Total params: 52,358		

Total params: 52,358
Trainable params: 52,358
Non-trainable params: 0

# In [126]:

# In [68]:

```
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	512	0	0	0	0	
SITTING	3	417	67	1	0	
STANDING	0	111	420	0	0	
WALKING	0	0	1	467	17	
WALKING DOWNSTAIRS	0	0	0	2	415	
WALKING UPSTAIRS	0	1	2	4	12	

Pred WALKING\_UPSTAIRS
True

LAYING 25
SITTING 3
STANDING 1
WALKING 11
WALKING\_DOWNSTAIRS 3
WALKING\_UPSTAIRS 452

### In [19]:

```
Y_train_dynamic=[]
X_train_dynamic=[]
Y_train_static=[]
X_train_static=[]
for i in range(0,len(Y_train)):
```

```
if(Y train[i][U]==1 or Y train[i][I]==1 or Y train[i][Z]==1):
        Y_train_dynamic.append(Y_train[i])
        X train dynamic.append(X_train[i])
    else:
       Y_train_static.append(Y_train[i])
        X train static.append(X train[i])
In [20]:
X train dynamic=np.array(X train dynamic)
Y train dynamic=np.array(Y train dynamic)
X_train_static=np.array(X_train_static)
Y_train_static=np.array(Y_train_static)
In [21]:
Y train dynamic=Y train dynamic[0:len(Y train dynamic),0:3]
In [22]:
Y_train_dynamic.shape
Out[22]:
(3285, 3)
In [27]:
Y test dynamic=Y test dynamic[0:len(Y test dynamic),0:3]
In [24]:
Y_test_dynamic=[]
X_test_dynamic=[]
Y test_static=[]
X test static=[]
for i in range(0,len(Y_test)):
    if(Y_test[i][0]==1 or Y_test[i][1]==1 or Y_test[i][2]==1):
        Y test dynamic.append(Y test[i])
        X_test_dynamic.append(X_test[i])
    else:
        Y test static.append(Y test[i])
        X_test_static.append(X_test[i])
In [26]:
X_test_dynamic=np.array(X_test_dynamic)
Y_test_dynamic=np.array(Y_test_dynamic)
X test static=np.array(X test static)
Y_test_static=np.array(Y_test_static)
In [28]:
score = model.evaluate(X test, Y test)
2947/2947 [=========] - 24s 8ms/step
In [29]:
score
Out[29]:
[0.3660856851979343, 0.9205971956253052]
In [257]:
```

```
# Initializing parameters
epochs = 30
batch_size = 32
n_hidden = 64
```

### In [258]:

```
{\bf from\ keras.regularizers\ import\ } 12
```

# In [259]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128,return_sequences=True,input_shape=(timesteps,
input_dim),bias_regularizer=12(0.001)))
# Adding a dropout layer
model.add(Dropout(0.2))

model.add(LSTM(64,input_shape=(timesteps, input_dim),bias_regularizer=12(0.001)))
# Adding a dropout layer
model.add(Dropout(0.5))
model.add(Dropout(0.5))
model.add(Dense(50, activation='sigmoid'))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

# Model: "sequential 78"

Layer (type)	Output Shape	Param #
lstm_53 (LSTM)	(None, 128, 128)	70656
dropout_81 (Dropout)	(None, 128, 128)	0
lstm_54 (LSTM)	(None, 64)	49408
dropout_82 (Dropout)	(None, 64)	0
dense_121 (Dense)	(None, 50)	3250
dense_122 (Dense)	(None, 6)	306
Total params: 123,620		

Total params: 123,620 Trainable params: 123,620 Non-trainable params: 0

# In [260]:

# In [261]:

```
print(X_train.shape)
print(Y_train.shape)
print(X_test.shape)
print(Y_test.shape)

(7352, 128, 9)
(7352, 6)
(2947, 128, 9)
(2947, 6)
```

# In [262]:

```
# Training the model
history=model.fit(X train,
```

```
Y_train,
batch_size=25,
validation_data=(X_test, Y_test),
epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
7352/7352 [=============] - 373s 51ms/step - loss: 1.4446 - accuracy: 0.4539 - va
l loss: 1.1004 - val accuracy: 0.5338
Epoch 2/30
l loss: 0.8570 - val accuracy: 0.6932
Epoch 3/30
1 loss: 0.6684 - val accuracy: 0.7472
Epoch 4/30
1 loss: 0.5975 - val accuracy: 0.7645
Epoch 5/30
7352/7352 [============== ] - 362s 49ms/step - loss: 0.5592 - accuracy: 0.7724 - va
1 loss: 0.7208 - val accuracy: 0.6715
Epoch 6/30
7352/7352 [============= ] - 351s 48ms/step - loss: 0.4514 - accuracy: 0.8458 - va
l loss: 0.4499 - val accuracy: 0.8751
Epoch 7/30
7352/7352 [=============== ] - 391s 53ms/step - loss: 0.3300 - accuracy: 0.9106 - va
1 loss: 0.3942 - val accuracy: 0.9016
Epoch 8/30
7352/7352 [=============] - 380s 52ms/step - loss: 0.2662 - accuracy: 0.9274 - va
l loss: 0.3214 - val accuracy: 0.8951
Epoch 9/30
7352/7352 [============== ] - 391s 53ms/step - loss: 0.2099 - accuracy: 0.9387 - va
1 loss: 0.3543 - val accuracy: 0.8918
Epoch 10/30
1_loss: 0.3606 - val_accuracy: 0.8938
Epoch 11/30
7352/7352 [=============] - 379s 52ms/step - loss: 0.1981 - accuracy: 0.9416 - va
l loss: 0.9166 - val accuracy: 0.8215
Epoch 12/30
l loss: 0.2741 - val accuracy: 0.9040
Epoch 13/30
1 loss: 0.2946 - val_accuracy: 0.9070
Epoch 14/30
1 loss: 0.3398 - val accuracy: 0.9023
Epoch 15/30
7352/7352 [============= ] - 386s 53ms/step - loss: 0.1457 - accuracy: 0.9489 - va
1_loss: 0.3091 - val_accuracy: 0.9169
Epoch 16/30
7352/7352 [===========] - 367s 50ms/step - loss: 0.1538 - accuracy: 0.9479 - va
1 loss: 0.4602 - val accuracy: 0.8870
Epoch 17/30
7352/7352 [============= ] - 394s 54ms/step - loss: 0.1433 - accuracy: 0.9501 - va
l loss: 0.2852 - val accuracy: 0.9179
Epoch 18/30
7352/7352 [============== ] - 379s 52ms/step - loss: 0.1330 - accuracy: 0.9501 - va
l loss: 0.3222 - val accuracy: 0.9145
Epoch 19/30
1 loss: 0.5332 - val accuracy: 0.9040
Epoch 20/30
7352/7352 [============ ] - 405s 55ms/step - loss: 0.1536 - accuracy: 0.9467 - va
1_loss: 0.4004 - val_accuracy: 0.9148
Epoch 21/30
1 loss: 0.3985 - val_accuracy: 0.8965
Epoch 22/30
7352/7352 [============== ] - 407s 55ms/step - loss: 0.1261 - accuracy: 0.9508 - va
1 loss: 0.3109 - val_accuracy: 0.9169
Epoch 23/30
7352/7352 [=========== ] - 393s 53ms/step - loss: 0.1416 - accuracy: 0.9497 - va
l loss: 0.4637 - val accuracy: 0.9070
Epoch 24/30
```

```
7352/7352 [============= ] - 388s 53ms/step - loss: 0.1351 - accuracy: 0.9529 - va
1 loss: 0.4951 - val accuracy: 0.9070
Epoch 25/30
1 loss: 0.7259 - val accuracy: 0.8707
Epoch 26/30
1_loss: 0.3463 - val_accuracy: 0.9128
Epoch 27/30
7352/7352 [============ ] - 375s 51ms/step - loss: 0.1289 - accuracy: 0.9540 - va
l loss: 0.3967 - val accuracy: 0.9131
Epoch 28/30
7352/7352 [============== ] - 394s 54ms/step - loss: 0.1193 - accuracy: 0.9525 - va
l loss: 0.4694 - val accuracy: 0.8972
Epoch 29/30
7352/7352 [============== ] - 391s 53ms/step - loss: 0.1182 - accuracy: 0.9543 - va
1 loss: 0.3567 - val accuracy: 0.9067
Epoch 30/30
l loss: 0.3985 - val accuracy: 0.9118
```

#### In [21]:

```
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.layers import Dense, Activation, Flatten
from keras.layers import LeakyReLU
model = Sequential()
model.add(Conv1D(filters=18,kernel size=1, activation=LeakyReLU(alpha=0.3)
                 , input shape=(timesteps,input dim),kernel initializer='glorot uniform'))
model.add(MaxPooling1D(pool_size=2))
model.add(Conv1D(filters=36, kernel size=3, kernel initializer='glorot uniform', activation=LeakyReL
U(alpha=0.3)))
model.add(MaxPooling1D(pool size=2,strides=2))
model.add(Conv1D(filters=36, kernel size=3, kernel initializer='glorot uniform',activation=LeakyReL
U(alpha=0.3)))
model.add(Dropout(0.5))
model.add(Conv1D(filters=144, kernel_size=3,kernel_initializer='glorot_uniform' ,activation=LeakyRe
LU(alpha=0.3), strides=2))
model.add(MaxPooling1D(pool size=2,strides=2))
model.add(Dropout(0.5))
model.add(Flatten())
model.add(Dense(32, activation='sigmoid'))
model.add(Dense(n classes, activation='sigmoid'))
```

WARNING:tensorflow:From /Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/ops/resource\_variable\_ops.py:435: colocate\_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version. Instructions for updating:
Colocations handled automatically by placer.

/Users/bhawesh/anaconda3/lib/python3.7/site-packages/keras/activations.py:235: UserWarning: Do not pass a layer instance (such as LeakyReLU) as the activation argument of another layer. Instead, ad vanced activation layers should be used just like any other layer in a model. identifier=identifier.\_\_class\_\_.\_\_name\_\_))

# Model: "sequential 2"

Layer (type)	Output	Shape	Param #
convld_1 (ConvlD)	(None,	128, 18)	180
max_pooling1d_1 (MaxPooling1	(None,	64, 18)	0
conv1d_2 (Conv1D)	(None,	62, 36)	1980
max_pooling1d_2 (MaxPooling1	(None,	31, 36)	0
convld_3 (ConvlD)	(None,	29, 36)	3924
dropout_1 (Dropout)	(None,	29, 36)	0

conv1d_4 (Conv1D)	(None,	14, 144)	15696
max_pooling1d_3 (MaxPooling1	(None,	7, 144)	0
dropout_2 (Dropout)	(None,	7, 144)	0
flatten_1 (Flatten)	(None,	1008)	0
dense_1 (Dense)	(None,	32)	32288
dense_2 (Dense)	(None,	6)	198
Total params: 54,266 Trainable params: 54,266 Non-trainable params: 0			

### In [30]:

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

# In [31]:

```
history=model.fit(X train,
      Y train,
     batch size=50,
     validation_data=(X_test, Y_test),
      epochs=15)
WARNING:tensorflow:From /Users/bhawesh/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math_ops.py:3066: to_int32 (from tensorflow.python.ops.math_ops) is
deprecated and will be removed in a future version.
Instructions for updating:
Use tf.cast instead.
Train on 7352 samples, validate on 2947 samples
Epoch 1/15
loss: 0.9130 - val accuracy: 0.6508
Epoch 2/15
loss: 0.5744 - val accuracy: 0.8235
Epoch 3/15
loss: 0.5086 - val_accuracy: 0.8181
Epoch 4/15
7352/7352 [=========] - 18s 2ms/step - loss: 0.3690 - accuracy: 0.9006 - val
loss: 0.4396 - val_accuracy: 0.8476
Epoch 5/15
loss: 0.3617 - val_accuracy: 0.8819
Epoch 6/15
loss: 0.3510 - val accuracy: 0.8758
Epoch 7/15
loss: 0.3206 - val accuracy: 0.8856
Epoch 8/15
loss: 0.3095 - val accuracy: 0.8863
Epoch 9/15
7352/7352 [===========] - 17s 2ms/step - loss: 0.1592 - accuracy: 0.9490 - val
loss: 0.3055 - val accuracy: 0.8924
Epoch 10/15
7352/7352 [=============] - 17s 2ms/step - loss: 0.1489 - accuracy: 0.9514 - val_
loss: 0.2877 - val accuracy: 0.9013
Epoch 11/15
7352/7352 [============= ] - 19s 3ms/step - loss: 0.1508 - accuracy: 0.9501 - val
loss: 0.2989 - val accuracy: 0.8951
Epoch 12/15
loss: 0.2901 - val accuracy: 0.9006
Epoch 13/15
loss: 0.2776 - val_accuracy: 0.9060
```

```
Epocn 14/15
loss: 0.3109 - val accuracy: 0.9067
Epoch 15/15
loss: 0.2777 - val accuracy: 0.9033
In [57]:
history=model.fit(X train,
    Y train,
    batch size=16,
    validation data=(X test, Y test),
     epochs=15)
Train on 7352 samples, validate on 2947 samples
Epoch 1/15
loss: 0.3262 - val accuracy: 0.9077
Epoch 2/15
loss: 0.3122 - val accuracy: 0.9182
Epoch 3/15
loss: 0.2787 - val accuracy: 0.9189
Epoch 4/15
loss: 0.3150 - val accuracy: 0.9148
Epoch 5/15
loss: 0.2987 - val accuracy: 0.9108
Epoch 6/15
7352/7352 [============== ] - 25s 3ms/step - loss: 0.0891 - accuracy: 0.9608 - val
loss: 0.3206 - val_accuracy: 0.9121
Epoch 7/15
loss: 0.2989 - val_accuracy: 0.9162
Epoch 8/15
loss: 0.2825 - val accuracy: 0.9152
Epoch 9/15
loss: 0.3459 - val_accuracy: 0.9172
Epoch 10/15
loss: 0.3192 - val accuracy: 0.9080
Epoch 11/15
loss: 0.3449 - val accuracy: 0.9186
Epoch 12/15
loss: 0.3526 - val accuracy: 0.9192
Epoch 13/15
loss: 0.3095 - val accuracy: 0.9206
Epoch 14/15
7352/7352 [==========] - 31s 4ms/step - loss: 0.0875 - accuracy: 0.9616 - val
loss: 0.3480 - val accuracy: 0.9023
Epoch 15/15
7352/7352 [=========] - 30s 4ms/step - loss: 0.0897 - accuracy: 0.9606 - val
loss: 0.3954 - val accuracy: 0.9046
In [249]:
print(confusion matrix(Y test, model.predict(X test)))
         LAYING SITTING STANDING WALKING WALKING_DOWNSTAIRS \
Pred
True
           537
                Ω
                     Ω
                         Ω
                                   0
LAYING
               424
                    60
                         0
                                   0
SITTING
            6
```

117

0

0

0

415

0

0

0

0

0

1

485

0

7

420

26

0

Ω

0

0

STANDING

WALKING DOWNSTAIRS

WALKING UPSTAIRS

WALKING

```
WALKING UPSTAIRS
Pred
True
                                 0
LAYING
SITTING
                                 1
STANDING
                                 0
WALKING
                                 4
WALKING DOWNSTAIRS
                                 0
WALKING UPSTAIRS
                                444
In [250]:
score = model.evaluate(X test, Y test)
2947/2947 [============ ] - 3s 1ms/step
In [251]:
score
Out[251]:
[0.3760031298141544, 0.9246691465377808]
```

# **Divide and Conquor**

# In [ ]:

#https://scholarcommons.usf.edu/cgi/viewcontent.cgi?article=8755&context=etd

# Model for prediction of Static or dynamic

# In [22]:

```
model_d = Sequential()
model_d.add(Conv1D(filters=64, kernel_size=5, activation='relu', kernel_initializer='lecun_uniform',
input_shape=(128,9)))
model_d.add(Conv1D(filters=32, kernel_size=3, activation='relu', kernel_initializer='lecun_uniform')
)
model_d.add(Dropout(0.45))
model_d.add(MaxPooling1D(pool_size=3))
model_d.add(Flatten())
model_d.add(Dense(32, activation='relu'))
model_d.add(Dense(2, activation='softmax'))
model_d.summary()
```

Model: "sequential 3"

Layer (type)	Output	Shape	Param #
conv1d_5 (Conv1D)	(None,	124, 64)	2944
convld_6 (ConvlD)	(None,	122, 32)	6176
dropout_3 (Dropout)	(None,	122, 32)	0
max_pooling1d_4 (MaxPooling1	(None,	40, 32)	0
flatten_2 (Flatten)	(None,	1280)	0
dense_3 (Dense)	(None,	32)	40992
dense_4 (Dense)	(None,	2)	66
Total params: 50,178	=====		

Total params: 50,178 Trainable params: 50,178 Non-trainable params: 0

```
## Classifying data as 2 class dynamic vs static
##data preparation
def data scaled 2class():
   # Data directory
   DATADIR = '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'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'UCI HAR Dataset/{subset}/y {subset}.txt'
       y = read csv(filename)[0]
       for i in range(0,len(y)):
           if(y[i]<=3):
               y[i] = 0
           else:
               v[i]=1
        return pd.get_dummies(y).as_matrix()
   X train 2c, X val 2c = load signals('train'), load signals('test')
   Y train 2c, Y val 2c = load y('train'), load y('test')
   return X_train_2c, Y_train_2c, X_val_2c, Y_val_2c
```

# In [24]:

```
X_train_2c, Y_train_2c, X_val_2c, Y_val_2c = data_scaled_2class()

/Users/bhawesh/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:35: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/ipykernel_launcher.py:56: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
```

```
In [25]:
print(X train 2c.shape)
print(Y val 2c.shape)
(7352, 128, 9)
(2947, 2)
In [202]:
from keras.callbacks import *
filepath="epochs:{epoch:03d}-val acc:{val_accuracy:.3f}.hdf7"
checkpoint 2 = ModelCheckpoint(filepath, monitor='val accuracy', verbose=1, mode='max')
In [203]:
callbacks_list=[checkpoint_2]
In [204]:
model d.compile(loss='categorical crossentropy', optimizer='adam', metrics=['accuracy'])
In [205]:
model d.fit(X train 2c, Y train 2c, epochs=20, batch size=16, validation data=(X val 2c, Y val 2c),
           verbose=1,callbacks=callbacks list)
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [============= ] - 23s 3ms/step - loss: 0.0246 - accuracy: 0.9895 - val
loss: 0.0512 - val accuracy: 0.9885
Epoch 00001: saving model to epochs:001-val acc:0.988.hdf7
Epoch 2/20
7352/7352 [===========] - 23s 3ms/step - loss: 9.4761e-04 - accuracy: 0.9996 -
val loss: 0.0492 - val accuracy: 0.9878
Epoch 00002: saving model to epochs:002-val_acc:0.988.hdf7
Epoch 3/20
7352/7352 [============= ] - 22s 3ms/step - loss: 0.0064 - accuracy: 0.9985 - val
loss: 0.0075 - val_accuracy: 0.9976
Epoch 00003: saving model to epochs:003-val acc:0.998.hdf7
Epoch 4/20
7352/7352 [===========] - 22s 3ms/step - loss: 8.6226e-04 - accuracy: 0.9997 -
val loss: 0.0025 - val accuracy: 0.9990
Epoch 00004: saving model to epochs:004-val acc:0.999.hdf7
Epoch 5/20
7352/7352 [==========] - 24s 3ms/step - loss: 8.3795e-04 - accuracy: 0.9997 -
val loss: 0.0024 - val accuracy: 0.9997
Epoch 00005: saving model to epochs:005-val acc:1.000.hdf7
Epoch 6/20
7352/7352 [==========] - 21s 3ms/step - loss: 1.5161e-04 - accuracy: 1.0000 -
val loss: 0.0037 - val accuracy: 0.9990
Epoch 00006: saving model to epochs:006-val acc:0.999.hdf7
Epoch 7/20
7352/7352 [===========] - 21s 3ms/step - loss: 1.6798e-05 - accuracy: 1.0000 -
val loss: 0.0063 - val accuracy: 0.9983
Epoch 00007: saving model to epochs:007-val acc:0.998.hdf7
Epoch 8/20
7352/7352 [==========] - 21s 3ms/step - loss: 7.9455e-06 - accuracy: 1.0000 -
val loss: 0.0046 - val accuracy: 0.9986
Epoch 00008: saving model to epochs:008-val acc:0.999.hdf7
Epoch 9/20
7352/7352 [===========] - 21s 3ms/step - loss: 3.7265e-06 - accuracy: 1.0000 -
val loss: 0.0043 - val_accuracy: 0.9986
```

```
Epoch 00009: saving model to epochs:009-val acc:0.999.hdf7
Epoch 10/20
7352/7352 [==========] - 23s 3ms/step - loss: 3.1222e-06 - accuracy: 1.0000 -
val loss: 0.0039 - val accuracy: 0.9990
Epoch 00010: saving model to epochs:010-val acc:0.999.hdf7
Epoch 11/20
7352/7352 [==========] - 21s 3ms/step - loss: 4.5465e-06 - accuracy: 1.0000 -
val loss: 0.0042 - val accuracy: 0.9986
Epoch 00011: saving model to epochs:011-val_acc:0.999.hdf7
7352/7352 [==========] - 21s 3ms/step - loss: 2.7394e-06 - accuracy: 1.0000 -
val_loss: 0.0041 - val_accuracy: 0.9986
Epoch 00012: saving model to epochs:012-val acc:0.999.hdf7
Epoch 13/20
7352/7352 [===========] - 24s 3ms/step - loss: 1.2381e-06 - accuracy: 1.0000 -
val loss: 0.0044 - val accuracy: 0.9986
Epoch 00013: saving model to epochs:013-val acc:0.999.hdf7
Epoch 14/20
val loss: 0.0042 - val accuracy: 0.9986
Epoch 00014: saving model to epochs:014-val acc:0.999.hdf7
Epoch 15/20
7352/7352 [============] - 22s 3ms/step - loss: 1.1284e-06 - accuracy: 1.0000 -
val loss: 0.0055 - val accuracy: 0.9986
Epoch 00015: saving model to epochs:015-val acc:0.999.hdf7
7352/7352 [===========] - 22s 3ms/step - loss: 1.3785e-06 - accuracy: 1.0000 -
val loss: 0.0051 - val accuracy: 0.9986
Epoch 00016: saving model to epochs:016-val acc:0.999.hdf7
Epoch 17/20
7352/7352 [===========] - 22s 3ms/step - loss: 6.9404e-07 - accuracy: 1.0000 -
val loss: 0.0047 - val accuracy: 0.9986
Epoch 00017: saving model to epochs:017-val acc:0.999.hdf7
Epoch 18/20
7352/7352 [==========] - 22s 3ms/step - loss: 5.4426e-07 - accuracy: 1.0000 -
val_loss: 0.0044 - val_accuracy: 0.9986
Epoch 00018: saving model to epochs:018-val acc:0.999.hdf7
Epoch 19/20
7352/7352 [===========] - 23s 3ms/step - loss: 4.5994e-07 - accuracy: 1.0000 -
val loss: 0.0043 - val accuracy: 0.9986
Epoch 00019: saving model to epochs:019-val acc:0.999.hdf7
Epoch 20/20
val loss: 0.0040 - val accuracy: 0.9990
Epoch 00020: saving model to epochs:020-val acc:0.999.hdf7
Out[2051:
<keras.callbacks.callbacks.History at 0x1a6989cb00>
In [221:
best model division = load model('epochs:009-val acc:0.999.hdf7')
WARNING:tensorflow:From /Users/bhawesh/anaconda3/lib/python3.7/site-
packages/tensorflow/python/ops/math ops.py:3066: to int32 (from tensorflow.python.ops.math ops) is
deprecated and will be removed in a future version.
```

# In [3]:

Instructions for updating:
Use tf.cast instead.

```
DATADIR = 'UCI_HAR_Dataset'
```

## In [4]:

```
# 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
   "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"
1
```

# In [5]:

```
# 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'UCT_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 [6]:

```
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'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]
    return pd.get_dummies(y).as_matrix()
```

### In [7]:

```
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 [10]:

```
# Importing tensorflow
```

```
np.random.seed(42)
import tensorflow as tf
tf.set random seed(42)
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:526: Fu
tureWarning: Passing (type, 1) or '1type' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np qint8 = np.dtype([("qint8", np.int8, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:527: Fu
\hbox{tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version}\\
of numpy, it will be understood as (type, (1,)) / (1,)type'.
  _np_quint8 = np.dtype([("quint8", np.uint8, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:528: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  np qint16 = np.dtype([("qint16", np.int16, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:529: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / (1,)type'.
  _np_quint16 = np.dtype([("quint16", np.uint16, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:530: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
  _np_qint32 = np.dtype([("qint32", np.int32, 1)])
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/framework/dtypes.py:535: Fu
tureWarning: Passing (type, 1) or 'ltype' as a synonym of type is deprecated; in a future version
of numpy, it will be understood as (type, (1,)) / '(1,)type'.
 np resource = np.dtype([("resource", np.ubyte, 1)])
In [11]:
# Configuring a session
session conf = tf.ConfigProto(
   intra op parallelism threads=1,
    inter op parallelism threads=1
In [12]:
# Import Keras
import os
os.environ['KMP DUPLICATE LIB OK']='True'
from tensorflow.keras import backend as K
sess = tf.Session(graph=tf.get default graph(), config=session conf)
K.set session(sess)
In [21]:
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from keras.models import Model, load model
In [14]:
# Initializing parameters
epochs = 30
batch size = 16
n hidden = 64
In [15]:
# Utility function to count the number of classes
def count classes(y):
    return len(set([tuple(category) for category in y]))
In [16]:
# Loading the train and test data
```

```
X train, X test, Y train, Y test = load data()
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/ipykernel launcher.py:12: FutureWarning:
Method .as matrix will be removed in a future version. Use .values instead.
 if sys.path[0] == '':
/Users/bhawesh/anaconda3/lib/python3.7/site-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 [17]:
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
7352
In [18]:
X train[0].shape
Out[18]:
(128, 9)
In [34]:
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.layers import Dense, Activation, Flatten
from keras.layers import LeakyReLU
model1 = Sequential()
model1.add(Conv1D(filters=18,kernel size=1, activation=LeakyReLU(alpha=0.3)
                 , input_shape=(timesteps,input_dim),kernel_initializer='he_uniform'))
model1.add(MaxPooling1D(pool size=2))
model1.add(Conv1D(filters=36, kernel size=3, kernel initializer='he uniform', activation=LeakyReLU(a
lpha=0.3)))
model1.add(Dropout(0.5))
model1.add(Conv1D(filters=144, kernel_size=3,kernel_initializer='he_uniform',activation=LeakyReLU(
alpha=0.3), strides=2))
model1.add(MaxPooling1D(pool_size=2,strides=2))
model1.add(Dropout(0.5))
model1.add(Flatten())
model1.add(Dense(32, activation='relu'))
model1.add(Dense(3, activation='sigmoid'))
model1.summary()
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/keras/activations.py:235: UserWarning: Do not
pass a layer instance (such as LeakyReLU) as the activation argument of another layer. Instead, ad
vanced activation layers should be used just like any other layer in a model.
  identifier=identifier.__class__.__name__))
```

Model: "sequential 3"

Layer (type)	Output Shape	Param #
convld_1 (ConvlD)	(None, 128, 18)	180
max_pooling1d_1 (MaxPooling1	(None, 64, 18)	0
convld_2 (ConvlD)	(None, 62, 36)	1980
dropout_3 (Dropout)	(None, 62, 36)	0

convld_3 (ConvlD)	(None,	30, 144)	15696
max_pooling1d_2 (MaxPooling1	(None,	15, 144)	0
dropout_4 (Dropout)	(None,	15, 144)	0
flatten_1 (Flatten)	(None,	2160)	0
dense_2 (Dense)	(None,	32)	69152
dense_3 (Dense)	(None,	3)	99
Total params: 87,107 Trainable params: 87,107 Non-trainable params: 0			

### In [44]:

```
model1 = Sequential()
model1.add(Conv1D(filters=64, kernel_size=5, activation='relu', kernel_initializer='lecun_uniform', i
nput_shape=(128,9)))
model1.add(Conv1D(filters=32, kernel_size=3, activation='relu', kernel_initializer='lecun_uniform'))
model1.add(Dropout(0.45))
model1.add(MaxPooling1D(pool_size=3))
model1.add(Flatten())
model1.add(Dense(32, activation='relu'))
model1.add(Dense(3, activation='softmax'))
model1.summary()
```

# Model: "sequential\_5"

Layer (type)	Output	Shape	Param #
conv1d_6 (Conv1D)	(None,	124, 64)	2944
conv1d_7 (Conv1D)	(None,	122, 32)	6176
dropout_6 (Dropout)	(None,	122, 32)	0
max_pooling1d_4 (MaxPooling1	(None,	40, 32)	0
flatten_3 (Flatten)	(None,	1280)	0
dense_6 (Dense)	(None,	32)	40992
dense_7 (Dense)	(None,	3)	99

Total params: 50,211 Trainable params: 50,211 Non-trainable params: 0

# In [23]:

```
Y_pred_train=best_model_division.predict(X_train)
Y_pred_test=best_model_division.predict(X_test)
```

### In [25]:

```
Y_pred_train = np.argmax(Y_pred_train, axis=1)
Y_pred_test = np.argmax(Y_pred_test, axis=1)
```

# In [26]:

```
Y_static_tr=Y_train[Y_pred_train==1]
Y_dynamic_tr=Y_train[Y_pred_train==0]
Y_static_test=Y_test[Y_pred_test==1]
Y_dynamic_test=Y_test[Y_pred_test==0]
```

# In [39]:

```
Y dynamic tr=Y dynamic tr[0:len(Y dynamic tr),0:3]
Y dynamic test=Y dynamic test[0:len(Y dynamic test), 0:3]
Y_static_tr=Y_static_tr[0:len(Y_static_tr),3:6]
Y static test=Y static test[0:len(Y static test), 3:6]
In [28]:
X static tr=X train[Y pred train==1]
X dynamic tr=X train[Y pred train==0]
X_static_test=X_test[Y_pred_test==1]
X dynamic test=X test[Y pred test==0]
In [ ]:
In [29]:
from keras.callbacks import *
filepath="epochs:{epoch:03d}-val_acc:{val_accuracy:.3f}.hdf5"
checkpoint 2 = ModelCheckpoint(filepath, monitor='val accuracy', verbose=1, mode='max')
In [30]:
callbacks list = [checkpoint 2]
In [45]:
model1.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
In [46]:
history=model1.fit(X dynamic tr,
        Y dynamic tr,
        batch size=20,
        validation data=(X dynamic test, Y dynamic test),
        epochs=20, callbacks=callbacks list)
Train on 3285 samples, validate on 1391 samples
Epoch 1/20
loss: 0.3071 - val_accuracy: 0.9037
Epoch 00001: saving model to epochs:001-val acc:0.904.hdf5
Epoch 2/20
loss: 0.2010 - val accuracy: 0.9303
Epoch 00002: saving model to epochs:002-val acc:0.930.hdf5
Epoch 3/20
loss: 0.3736 - val accuracy: 0.8778
Epoch 00003: saving model to epochs:003-val acc:0.878.hdf5
Epoch 4/20
3285/3285 [============= ] - 10s 3ms/step - loss: 0.0099 - accuracy: 0.9976 - val
loss: 0.1543 - val accuracy: 0.9490
Epoch 00004: saving model to epochs:004-val acc:0.949.hdf5
Epoch 5/20
3285/3285 [===========] - 10s 3ms/step - loss: 9.9896e-04 - accuracy: 1.0000 -
val loss: 0.1406 - val accuracy: 0.9561
Epoch 00005: saving model to epochs:005-val acc:0.956.hdf5
Epoch 6/20
3285/3285 [===========] - 10s 3ms/step - loss: 5.9479e-04 - accuracy: 1.0000 -
val_loss: 0.1455 - val accuracy: 0.9547
Epoch 00006: saving model to epochs:006-val_acc:0.955.hdf5
Epoch 7/20
```

```
3285/3285 [===========] - 10s 3ms/step - loss: 4.6674e-04 - accuracy: 1.0000 -
val loss: 0.1500 - val accuracy: 0.9547
Epoch 00007: saving model to epochs:007-val acc:0.955.hdf5
Epoch 8/20
3285/3285 [===========] - 10s 3ms/step - loss: 2.3807e-04 - accuracy: 1.0000 -
val loss: 0.1495 - val accuracy: 0.9540
Epoch 00008: saving model to epochs:008-val acc:0.954.hdf5
3285/3285 [============] - 10s 3ms/step - loss: 0.0012 - accuracy: 1.0000 - val
loss: 0.1095 - val accuracy: 0.9648
Epoch 00009: saving model to epochs:009-val_acc:0.965.hdf5
Epoch 10/20
val_loss: 0.1404 - val_accuracy: 0.9590
Epoch 00010: saving model to epochs:010-val acc:0.959.hdf5
Epoch 11/20
3285/3285 [============] - 11s 3ms/step - loss: 2.1276e-04 - accuracy: 1.0000 -
val loss: 0.1587 - val_accuracy: 0.9569
Epoch 00011: saving model to epochs:011-val acc:0.957.hdf5
Epoch 12/20
3285/3285 [===========] - 11s 3ms/step - loss: 1.3620e-04 - accuracy: 1.0000 -
val loss: 0.1735 - val accuracy: 0.9554
Epoch 00012: saving model to epochs:012-val acc:0.955.hdf5
Epoch 13/20
3285/3285 [============] - 11s 3ms/step - loss: 9.3560e-05 - accuracy: 1.0000 -
val loss: 0.1607 - val accuracy: 0.9605
Epoch 00013: saving model to epochs:013-val acc:0.960.hdf5
Epoch 14/20
3285/3285 [============= ] - 11s 3ms/step - loss: 0.0064 - accuracy: 0.9985 - val
loss: 0.4949 - val accuracy: 0.8914
Epoch 00014: saving model to epochs:014-val acc:0.891.hdf5
Epoch 15/20
loss: 0.3351 - val accuracy: 0.9281
Epoch 00015: saving model to epochs:015-val acc:0.928.hdf5
Epoch 16/20
3285/3285 [============ ] - 11s 3ms/step - loss: 0.0040 - accuracy: 0.9997 - val
loss: 0.2164 - val_accuracy: 0.9475
Epoch 00016: saving model to epochs:016-val acc:0.948.hdf5
Epoch 17/20
3285/3285 [============] - 11s 3ms/step - loss: 8.2682e-04 - accuracy: 1.0000 -
val loss: 0.1670 - val accuracy: 0.9590
Epoch 00017: saving model to epochs:017-val acc:0.959.hdf5
Epoch 18/20
3285/3285 [===========] - 11s 3ms/step - loss: 1.4110e-04 - accuracy: 1.0000 -
val loss: 0.1244 - val accuracy: 0.9641
Epoch 00018: saving model to epochs:018-val acc:0.964.hdf5
Epoch 19/20
3285/3285 [===========] - 10s 3ms/step - loss: 1.0327e-04 - accuracy: 1.0000 -
val loss: 0.1471 - val accuracy: 0.9633
Epoch 00019: saving model to epochs:019-val acc:0.963.hdf5
Epoch 20/20
val loss: 0.1413 - val accuracy: 0.9648
Epoch 00020: saving model to epochs:020-val acc:0.965.hdf5
In [47]:
best_model_d = load_model('epochs:020-val_acc:0.965.hdf5')
```

\_ ....

```
In [48]:
# Activities are the class labels
# It is a 6 class classification
ACTIVITIES = {
    0: 'WALKING',
    1: 'WALKING UPSTAIRS',
    2: 'WALKING DOWNSTAIRS',
# 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'])
In [51]:
print(confusion_matrix(Y_dynamic_test, best_model_d.predict(X_dynamic_test)))
Pred
                    WALKING WALKING DOWNSTAIRS WALKING UPSTAIRS
True
WALKING
                        478
                                             18
                                                                 4
WALKING DOWNSTAIRS
                         2
                                            418
                                                                 0
WALKING_UPSTAIRS
                                             24
                                                               446
In [55]:
score = best model d.evaluate(X dynamic test, Y dynamic test)
1391/1391 [============ ] - 2s lms/step
In [56]:
score
Out[56]:
[0.1413168757945732, 0.9647735357284546]
Static
In [90]:
Y train static=Y train static[0:len(Y train static),3:6]
Y test static=Y test static[0:len(Y test static), 3:6]
In [19]:
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.layers import Dense, Activation, Flatten
from keras.layers import LeakyReLU
model = Sequential()
model.add(Conv1D(filters=18,kernel_size=1, activation=LeakyReLU(alpha=0.3)
                 , input shape=(timesteps,input dim),kernel initializer='glorot uniform'))
model.add(MaxPooling1D(pool size=2))
model.add(Conv1D(filters=36, kernel size=3,kernel initializer='glorot uniform',activation=LeakyReL
U(alpha=0.3)))
model.add(Dropout(0.5))
model.add(Conv1D(filters=144, kernel_size=3,kernel initializer='glorot uniform' ,activation=LeakyRe
LU(alpha=0.3), strides=2))
model.add(MaxPooling1D(pool size=2,strides=2))
model.add(Dropout(0.5))
```

model.add(Flatten())

model.summarv()

model.add(Dense(32, activation='relu'))
model.add(Dense(3, activation='sigmoid'))

WARNING:tensorflow:From /Users/bhawesh/anaconda3/lib/python3.7/site-packages/tensorflow/python/ops/resource\_variable\_ops.py:435: colocate\_with (from tensorflow.python.framework.ops) is deprecated and will be removed in a future version. Instructions for updating:

Colocations handled automatically by placer.

/Users/bhawesh/anaconda3/lib/python3.7/site-packages/keras/activations.py:235: UserWarning: Do not pass a layer instance (such as LeakyReLU) as the activation argument of another layer. Instead, ad vanced activation layers should be used just like any other layer in a model. identifier=identifier.\_\_class\_\_.\_\_name\_\_))

### Model: "sequential 2"

Layer (type)	Output	Shape	Param #
convld_1 (ConvlD)	(None,	128, 18)	180
max_pooling1d_1 (MaxPooling1	(None,	64, 18)	0
conv1d_2 (Conv1D)	(None,	62, 36)	1980
dropout_1 (Dropout)	(None,	62, 36)	0
conv1d_3 (Conv1D)	(None,	30, 144)	15696
max_pooling1d_2 (MaxPooling1	(None,	15, 144)	0
dropout_2 (Dropout)	(None,	15, 144)	0
flatten_1 (Flatten)	(None,	2160)	0
dense_1 (Dense)	(None,	32)	69152
dense_2 (Dense)	(None,	3)	99

Total params: 87,107 Trainable params: 87,107 Non-trainable params: 0

# In [167]:

model.compile(loss='categorical\_crossentropy', optimizer='adam', metrics=['accuracy'])

## In [67]:

```
history=model.fit(X_static_tr,
	Y_train_static,
	batch_size=300,
	validation_data=(X_static_test, Y_static_test),
	epochs=15)
```

```
Train on 4067 samples, validate on 1560 samples
Epoch 1/15
loss: 0.3313 - val_accuracy: 0.8577
Epoch 2/15
loss: 0.4369 - val accuracy: 0.8327
Epoch 3/15
loss: 0.3389 - val accuracy: 0.8885
Epoch 4/15
loss: 0.3526 - val accuracy: 0.8679
Epoch 5/15
loss: 0.3836 - val accuracy: 0.8744
Epoch 6/15
loss: 0.3504 - val accuracy: 0.8891
```

```
Epoch 7/15
loss: 0.3327 - val accuracy: 0.8782
Epoch 8/15
loss: 0.3239 - val accuracy: 0.8853
Epoch 9/15
loss: 0.3431 - val accuracy: 0.8769
Epoch 10/15
loss: 0.3342 - val accuracy: 0.8814
Epoch 11/15
loss: 0.3906 - val accuracy: 0.8885
Epoch 12/15
loss: 0.3355 - val accuracy: 0.8872
Epoch 13/15
loss: 0.3002 - val accuracy: 0.8885
Epoch 14/15
loss: 0.3527 - val_accuracy: 0.8936
Epoch 15/15
loss: 0.3506 - val_accuracy: 0.8878
```

# In [57]:

```
model = Sequential()
model.add(Conv1D(filters=64, kernel_size=5, activation='relu', kernel_initializer='glorot_uniform',i
nput_shape=(128,9)))
model.add(Conv1D(filters=32, kernel_size=3, activation='relu', kernel_initializer='glorot_uniform'))
model.add(Dropout(0.45))
model.add(MaxPooling1D(pool_size=3))
model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(3, activation='relu'))
model.add(Dense(3, activation='softmax'))
model.summary()
```

# Model: "sequential 6"

Layer (type)	Output	Shape	Param #
conv1d_8 (Conv1D)	(None,	124, 64)	2944
conv1d_9 (Conv1D)	(None,	122, 32)	6176
dropout_7 (Dropout)	(None,	122, 32)	0
max_pooling1d_5 (MaxPooling1	(None,	40, 32)	0
flatten_4 (Flatten)	(None,	1280)	0
dense_8 (Dense)	(None,	32)	40992
dense_9 (Dense)	(None,	3)	99
Total params: 50,211			

Trainable params: 50,211
Non-trainable params: 0

# In [60]:

```
from keras.callbacks import *
filepath="epochs:{epoch:03d}-val_acc:{val_accuracy:.3f}.hdf6"
checkpoint_2 = ModelCheckpoint(filepath, monitor='val_accuracy', verbose=1, mode='max')
```

# In [61]:

```
callbacks_list = [checkpoint_2]
```

# In [62]:

```
model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=['accuracy'])
```

## In [64]:

history=model.fit(X static tr,

```
Y static tr,
     batch size=50,
     validation_data=(X_static_test, Y_static_test),
     epochs=15,callbacks=callbacks list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.3406 - val accuracy: 0.8599
Epoch 00001: saving model to epochs:001-val acc:0.860.hdf6
Epoch 2/15
loss: 0.3242 - val accuracy: 0.8683
Epoch 00002: saving model to epochs:002-val acc:0.868.hdf6
Epoch 3/15
loss: 0.3095 - val accuracy: 0.8817
Epoch 00003: saving model to epochs:003-val acc:0.882.hdf6
loss: 0.3133 - val accuracy: 0.8760
Epoch 00004: saving model to epochs:004-val acc:0.876.hdf6
Epoch 5/15
loss: 0.3005 - val accuracy: 0.8721
Epoch 00005: saving model to epochs:005-val acc:0.872.hdf6
Epoch 6/15
loss: 0.3236 - val_accuracy: 0.8702
Epoch 00006: saving model to epochs:006-val acc:0.870.hdf6
Epoch 7/15
loss: 0.3563 - val accuracy: 0.8650
Epoch 00007: saving model to epochs:007-val acc:0.865.hdf6
Epoch 8/15
loss: 0.3095 - val accuracy: 0.8856
Epoch 00008: saving model to epochs:008-val acc:0.886.hdf6
Epoch 9/15
loss: 0.3105 - val accuracy: 0.8798
Epoch 00009: saving model to epochs:009-val acc:0.880.hdf6
Epoch 10/15
loss: 0.3306 - val accuracy: 0.8933
Epoch 00010: saving model to epochs:010-val acc:0.893.hdf6
Epoch 11/15
loss: 0.3567 - val accuracy: 0.8843
Epoch 00011: saving model to epochs:011-val acc:0.884.hdf6
Epoch 12/15
loss: 0.3717 - val_accuracy: 0.8753
Epoch 00012: saving model to epochs:012-val_acc:0.875.hdf6
Epoch 13/15
```

```
loss: 0.3280 - val accuracy: 0.9055
Epoch 00013: saving model to epochs:013-val acc:0.906.hdf6
Epoch 14/15
loss: 0.3891 - val accuracy: 0.8946
Epoch 00014: saving model to epochs:014-val acc:0.895.hdf6
4067/4067 [============] - 10s 2ms/step - loss: 0.1066 - accuracy: 0.9498 - val
loss: 0.3448 - val accuracy: 0.8901
Epoch 00015: saving model to epochs:015-val_acc:0.890.hdf6
In [65]:
history=model.fit(X static tr,
       Y_static_tr,
       batch size=50,
       validation_data=(X_static_test, Y_static_test),
       epochs=15,callbacks=callbacks_list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.3441 - val accuracy: 0.8959
Epoch 00001: saving model to epochs:001-val acc:0.896.hdf6
Epoch 2/15
4067/4067 [============ ] - 9s 2ms/step - loss: 0.1069 - accuracy: 0.9489 - val 1
oss: 0.3390 - val accuracy: 0.9042
Epoch 00002: saving model to epochs:002-val acc:0.904.hdf6
Epoch 3/15
loss: 0.4258 - val accuracy: 0.8888
Epoch 00003: saving model to epochs:003-val_acc:0.889.hdf6
Epoch 4/15
loss: 0.4983 - val_accuracy: 0.8830
Epoch 00004: saving model to epochs:004-val acc:0.883.hdf6
Epoch 5/15
4067/4067 [============== ] - 10s 2ms/step - loss: 0.0913 - accuracy: 0.9594 - val
loss: 0.5533 - val accuracy: 0.8772
Epoch 00005: saving model to epochs:005-val acc:0.877.hdf6
Epoch 6/15
loss: 0.3399 - val accuracy: 0.8914
Epoch 00006: saving model to epochs:006-val acc:0.891.hdf6
Epoch 7/15
4067/4067 [============ ] - 9s 2ms/step - loss: 0.1008 - accuracy: 0.9567 - val 1
oss: 0.3362 - val accuracy: 0.8869
Epoch 00007: saving model to epochs:007-val acc:0.887.hdf6
Epoch 8/15
4067/4067 [============ ] - 9s 2ms/step - loss: 0.1028 - accuracy: 0.9584 - val_1
oss: 0.2660 - val accuracy: 0.9165
Epoch 00008: saving model to epochs:008-val acc:0.916.hdf6
Epoch 9/15
4067/4067 [=========== ] - 9s 2ms/step - loss: 0.0864 - accuracy: 0.9639 - val 1
oss: 0.3291 - val_accuracy: 0.8997
Epoch 00009: saving model to epochs:009-val_acc:0.900.hdf6
Epoch 10/15
oss: 0.3717 - val_accuracy: 0.8817
Epoch 00010: saving model to epochs:010-val acc:0.882.hdf6
Epoch 11/15
```

```
4067/4067 [============== ] - 9s 2ms/step - loss: 0.0808 - accuracy: 0.9639 - val 1
oss: 0.3663 - val accuracy: 0.9049
Epoch 00011: saving model to epochs:011-val acc:0.905.hdf6
Epoch 12/15
oss: 0.3521 - val accuracy: 0.9023
Epoch 00012: saving model to epochs:012-val acc:0.902.hdf6
loss: 0.3425 - val_accuracy: 0.8850
Epoch 00013: saving model to epochs:013-val_acc:0.885.hdf6
Epoch 14/15
loss: 0.3595 - val_accuracy: 0.9120
Epoch 00014: saving model to epochs:014-val acc:0.912.hdf6
Epoch 15/15
oss: 0.3424 - val accuracy: 0.9049
Epoch 00015: saving model to epochs:015-val acc:0.905.hdf6
In [66]:
history=model.fit(X static tr,
     Y static tr,
     batch size=20,
     validation data=(X static test, Y static test),
     epochs=15, callbacks=callbacks list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.3711 - val accuracy: 0.8843
Epoch 00001: saving model to epochs:001-val acc:0.884.hdf6
Epoch 2/15
loss: 0.3037 - val accuracy: 0.9132
Epoch 00002: saving model to epochs:002-val acc:0.913.hdf6
Epoch 3/15
loss: 0.2716 - val_accuracy: 0.9017
Epoch 00003: saving model to epochs:003-val_acc:0.902.hdf6
Epoch 4/15
loss: 0.2659 - val accuracy: 0.9068
Epoch 00004: saving model to epochs:004-val acc:0.907.hdf6
Epoch 5/15
loss: 0.3229 - val accuracy: 0.9120
Epoch 00005: saving model to epochs:005-val acc:0.912.hdf6
Epoch 6/15
loss: 0.2726 - val accuracy: 0.9177
Epoch 00006: saving model to epochs:006-val acc:0.918.hdf6
Epoch 7/15
loss: 0.2923 - val accuracy: 0.9216
Epoch 00007: saving model to epochs:007-val_acc:0.922.hdf6
Epoch 8/15
loss: 0.3132 - val_accuracy: 0.9203
Epoch 00008: saving model to epochs:008-val acc:0.920.hdf6
Epoch 9/15
                       - - - - -
```

```
loss: 0.3696 - val accuracy: 0.9036
Epoch 00009: saving model to epochs:009-val acc:0.904.hdf6
Epoch 10/15
loss: 0.3251 - val accuracy: 0.9222
Epoch 00010: saving model to epochs:010-val acc:0.922.hdf6
Epoch 11/15
loss: 0.3887 - val accuracy: 0.9036
Epoch 00011: saving model to epochs:011-val acc:0.904.hdf6
Epoch 12/15
4067/4067 [============] - 14s 3ms/step - loss: 0.0735 - accuracy: 0.9715 - val
loss: 0.3849 - val_accuracy: 0.9100
Epoch 00012: saving model to epochs:012-val_acc:0.910.hdf6
Epoch 13/15
loss: 0.3262 - val_accuracy: 0.9229
Epoch 00013: saving model to epochs:013-val acc:0.923.hdf6
Epoch 14/15
loss: 0.3206 - val accuracy: 0.9242
Epoch 00014: saving model to epochs:014-val acc:0.924.hdf6
Epoch 15/15
loss: 0.3893 - val accuracy: 0.9023
Epoch 00015: saving model to epochs:015-val acc:0.902.hdf6
In [68]:
history=model.fit(X static tr,
     Y static tr,
     batch size=20,
     validation data=(X static test, Y static test),
     epochs=15, callbacks=callbacks list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.3624 - val_accuracy: 0.9235
Epoch 00001: saving model to epochs:001-val acc:0.924.hdf6
Epoch 2/15
loss: 0.3420 - val accuracy: 0.9171
Epoch 00002: saving model to epochs:002-val acc:0.917.hdf6
Epoch 3/15
loss: 0.4323 - val accuracy: 0.9242
Epoch 00003: saving model to epochs:003-val_acc:0.924.hdf6
Epoch 4/15
loss: 0.4035 - val accuracy: 0.9120
Epoch 00004: saving model to epochs:004-val acc:0.912.hdf6
Epoch 5/15
loss: 0.4302 - val_accuracy: 0.9100
Epoch 00005: saving model to epochs:005-val acc:0.910.hdf6
Epoch 6/15
loss: 0.4064 - val accuracy: 0.9190
Epoch 00006: saving model to epochs:006-val_acc:0.919.hdf6
Epoch 7/15
```

```
-----] - 115 JMS/SCEP - 1055. U.V413 - accuracy. U.9023 - Val
1001/1001
loss: 0.4155 - val accuracy: 0.9254
Epoch 00007: saving model to epochs:007-val acc:0.925.hdf6
Epoch 8/15
loss: 0.3827 - val accuracy: 0.9210
Epoch 00008: saving model to epochs:008-val acc:0.921.hdf6
Epoch 9/15
loss: 0.3935 - val accuracy: 0.9229
Epoch 00009: saving model to epochs:009-val acc:0.923.hdf6
loss: 0.3929 - val_accuracy: 0.9171
Epoch 00010: saving model to epochs:010-val_acc:0.917.hdf6
Epoch 11/15
loss: 0.3933 - val_accuracy: 0.9299
Epoch 00011: saving model to epochs:011-val acc:0.930.hdf6
Epoch 12/15
loss: 0.4470 - val accuracy: 0.9094
Epoch 00012: saving model to epochs:012-val acc:0.909.hdf6
Epoch 13/15
loss: 0.6168 - val_accuracy: 0.9132
Epoch 00013: saving model to epochs:013-val acc:0.913.hdf6
Epoch 14/15
loss: 0.7143 - val accuracy: 0.8965
Epoch 00014: saving model to epochs:014-val acc:0.897.hdf6
Epoch 15/15
loss: 0.6869 - val accuracy: 0.9087
Epoch 00015: saving model to epochs:015-val acc:0.909.hdf6
In [70]:
history=model.fit(X static tr,
     Y static_tr,
     batch size=16,
     validation_data=(X_static_test, Y_static_test),
     epochs=15, callbacks=callbacks list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.6696 - val accuracy: 0.9055
Epoch 00001: saving model to epochs:001-val acc:0.906.hdf6
Epoch 2/15
loss: 0.6728 - val accuracy: 0.9030
Epoch 00002: saving model to epochs:002-val acc:0.903.hdf6
Epoch 3/15
loss: 0.7011 - val accuracy: 0.8972
Epoch 00003: saving model to epochs:003-val acc:0.897.hdf6
loss: 0.7002 - val_accuracy: 0.9100
Epoch 00004: saving model to epochs:004-val_acc:0.910.hdf6
4067/4067 [============] - 12s 3ms/step - loss: 0.1032 - accuracy: 0.9830 - val
```

```
loss: 0.6342 - val accuracy: 0.9139
Epoch 00005: saving model to epochs:005-val acc:0.914.hdf6
Epoch 6/15
loss: 0.7298 - val accuracy: 0.9049
Epoch 00006: saving model to epochs:006-val acc:0.905.hdf6
Epoch 7/15
loss: 0.6854 - val accuracy: 0.9055
Epoch 00007: saving model to epochs:007-val acc:0.906.hdf6
Epoch 8/15
loss: 0.6970 - val_accuracy: 0.8991
Epoch 00008: saving model to epochs:008-val_acc:0.899.hdf6
Epoch 9/15
loss: 0.7512 - val_accuracy: 0.9017
Epoch 00009: saving model to epochs:009-val acc:0.902.hdf6
Epoch 10/15
loss: 0.6946 - val accuracy: 0.9030
Epoch 00010: saving model to epochs:010-val acc:0.903.hdf6
Epoch 11/15
loss: 0.7945 - val accuracy: 0.8940
Epoch 00011: saving model to epochs:011-val acc:0.894.hdf6
Epoch 12/15
loss: 0.7454 - val accuracy: 0.9132
Epoch 00012: saving model to epochs:012-val acc:0.913.hdf6
Epoch 13/15
loss: 0.7262 - val accuracy: 0.8997
Epoch 00013: saving model to epochs:013-val_acc:0.900.hdf6
Epoch 14/15
loss: 0.7007 - val_accuracy: 0.9094
Epoch 00014: saving model to epochs:014-val acc:0.909.hdf6
Epoch 15/15
loss: 0.6904 - val accuracy: 0.9100
Epoch 00015: saving model to epochs:015-val acc:0.910.hdf6
In [73]:
history=model.fit(X static tr,
     Y static_tr,
     batch size=20,
     validation data=(X static test, Y static test),
     epochs=15,callbacks=callbacks_list)
Train on 4067 samples, validate on 1556 samples
Epoch 1/15
loss: 0.7688 - val accuracy: 0.9177
Epoch 00001: saving model to epochs:001-val acc:0.918.hdf6
loss: 0.7692 - val_accuracy: 0.9139
Epoch 00002: saving model to epochs:002-val acc:0.914.hdf6
Epoch 3/15
```

```
loss: 0.7468 - val accuracy: 0.9107
Epoch 00003: saving model to epochs:003-val acc:0.911.hdf6
Epoch 4/15
loss: 0.7810 - val accuracy: 0.9126
Epoch 00004: saving model to epochs:004-val acc:0.913.hdf6
Epoch 5/15
loss: 0.7787 - val accuracy: 0.9152
Epoch 00005: saving model to epochs:005-val acc:0.915.hdf6
Epoch 6/15
loss: 0.7761 - val accuracy: 0.9132
Epoch 00006: saving model to epochs:006-val acc:0.913.hdf6
loss: 0.8016 - val accuracy: 0.9120
Epoch 00007: saving model to epochs:007-val_acc:0.912.hdf6
Epoch 8/15
loss: 0.7982 - val_accuracy: 0.9145
Epoch 00008: saving model to epochs:008-val acc:0.915.hdf6
Epoch 9/15
loss: 0.7980 - val accuracy: 0.9087
Epoch 00009: saving model to epochs:009-val acc:0.909.hdf6
Epoch 10/15
loss: 0.8433 - val accuracy: 0.9126
Epoch 00010: saving model to epochs:010-val acc:0.913.hdf6
Epoch 11/15
loss: 0.7659 - val accuracy: 0.9094
Epoch 00011: saving model to epochs:011-val acc:0.909.hdf6
Epoch 12/15
loss: 0.8215 - val accuracy: 0.9126
Epoch 00012: saving model to epochs:012-val_acc:0.913.hdf6
Epoch 13/15
loss: 0.7749 - val accuracy: 0.9062
Epoch 00013: saving model to epochs:013-val acc:0.906.hdf6
Epoch 14/15
loss: 0.7737 - val_accuracy: 0.9152
Epoch 00014: saving model to epochs:014-val acc:0.915.hdf6
Epoch 15/15
loss: 0.8425 - val accuracy: 0.9010
Epoch 00015: saving model to epochs:015-val acc:0.901.hdf6
In [74]:
best model s = load model('epochs:011-val acc:0.930.hdf6')
In [75]:
# Activities are the class labels
# It is a 6 class classification
ACTIVITIES = {
  0: 'SITTING',
```

1: 'STANDING',

```
2: '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'])
In [76]:
print(confusion matrix(Y static test, model.predict(X static test)))
Pred
        LAYING SITTING STANDING
True
                     0
           512 0
0 389
0 27
LAYING
                             102
SITTING
STANDING
                     27
                              501
In [78]:
score = best_model_s.evaluate(X_static_test, Y_static_test)
1556/1556 [============ ] - 2s 1ms/step
In [79]:
score
Out[79]:
[0.39326874985088, 0.9299485683441162]
```

# **Final Pipelining**

In [80]:

```
# 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'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'UCI HAR Dataset/{subset}/y {subset}.txt'
    y = _read_csv(filename)[0]
    return v
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 [81]:
X_train, X_test, Y_train, Y_test = load_data()
/Users/bhawesh/anaconda3/lib/python3.7/site-packages/ipykernel launcher.py:29: FutureWarning:
Method .as_matrix will be removed in a future version. Use .values instead.
In [82]:
len(Y train)
Out[82]:
7352
In [83]:
Y pred train=best model division.predict(X train)
Y pred test=best model division.predict(X test)
In [84]:
Y_pred_train = np.argmax(Y_pred_train, axis=1)
Y pred test = np.argmax(Y pred test, axis=1)
In [85]:
X static tr=X train[Y pred train==1]
X dynamic_tr=X_train[Y_pred_train==0]
X static test=X test[Y pred test==1]
X dynamic test=X test[Y pred test==0]
In [86]:
Y pred static tr=best model s.predict(X static tr)
Y_pred_static_test=best_model_s.predict(X_static_test)
In [88]:
Y pred dynamic tr=best model d.predict(X dynamic tr)
Y pred dynamic test=best model d.predict(X dynamic test)
```

In [89]:

```
Y pred dynamic tr=np.argmax(Y pred dynamic tr, axis=1)
Y_pred_dynamic_test=np.argmax(Y_pred_dynamic_test, axis=1)
Y_pred_static_tr=np.argmax(Y_pred_static_tr, axis=1)
Y pred static test=np.argmax(Y pred static test, axis=1)
In [90]:
{\tt Y\_pred\_static\_tr=Y\_pred\_static\_tr+4}
Y_pred_static_test=Y_pred_static_test+4
In [91]:
Y pred dynamic tr=Y pred dynamic tr+1
{\tt Y\_pred\_dynamic\_test=Y\_pred\_dynamic\_test+1}
In [92]:
k,j = 0,0
final_pred_tr = []
for i in Y_pred_train:
    if i == 1:
        final_pred_tr.append(Y_pred_static_tr[k])
    else:
       final_pred_tr.append(Y_pred_dynamic_tr[j])
        j = j + 1
In [93]:
k, j = 0, 0
final pred test = []
for i in Y_pred_test:
    if i == 1:
       final_pred_test.append(Y_pred_static_test[k])
        k = k + 1
       final_pred_test.append(Y_pred_dynamic_test[j])
        j = j + 1
In [94]:
##accuracy of train and test
from sklearn.metrics import accuracy score
print('Accuracy of train data',accuracy_score(Y_train,final_pred_tr))
print('Accuracy of validation data',accuracy score(Y test,final pred test))
Accuracy of train data 0.9944232861806311
Accuracy of validation data 0.9463861554122837
In [ ]:
```