

HAR_LSTM

March 16, 2019

```
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'])
```

0.0.1 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'
        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 [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)

In [10]: # 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 [12]: # Importing libraries
        from keras.models import Sequential
        from keras.layers import LSTM
        from keras.layers.core import Dense, Dropout

In [13]: # Initializing parameters
        epochs = 30
        batch_size = 16
        n_hidden = 32

In [14]: # 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()

c:\users\dell\appdata\local\programs\python\python36\lib\site-packages\ipykernel_launcher.py:1:
    if sys.path[0] == '':

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

- Defining the Architecture of LSTM

```
In [17]: # 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(0.5))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
-----
Layer (type)                 Output Shape          Param #
-----
lstm_1 (LSTM)                 (None, 32)            5376
-----
dropout_1 (Dropout)          (None, 32)            0
-----
dense_1 (Dense)               (None, 6)             198
=====
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
-----
```

```
In [18]: # Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

```
In [20]: # 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

7352/7352 [=====] - 28s 4ms/step - loss: 0.6905 - acc: 0.6606 - val_loss: 0.6850

Epoch 2/30

7352/7352 [=====] - 28s 4ms/step - loss: 0.6376 - acc: 0.6732 - val_loss: 0.6850

Epoch 3/30

7352/7352 [=====] - 26s 3ms/step - loss: 0.6057 - acc: 0.6850 - val_loss: 0.6850

Epoch 4/30

7352/7352 [=====] - 27s 4ms/step - loss: 0.5705 - acc: 0.7044 - val_loss: 0.6850

Epoch 5/30

7352/7352 [=====] - 28s 4ms/step - loss: 0.5582 - acc: 0.7179 - val_loss: 0.5582
 Epoch 6/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.5528 - acc: 0.7349 - val_loss: 0.5528
 Epoch 7/30
 7352/7352 [=====] - 26s 3ms/step - loss: 0.4966 - acc: 0.7831 - val_loss: 0.4966
 Epoch 8/30
 7352/7352 [=====] - 26s 3ms/step - loss: 0.4583 - acc: 0.7956 - val_loss: 0.4583
 Epoch 9/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.4308 - acc: 0.8048 - val_loss: 0.4308
 Epoch 10/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.4154 - acc: 0.8111 - val_loss: 0.4154
 Epoch 11/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.4117 - acc: 0.8105 - val_loss: 0.4117
 Epoch 12/30
 7352/7352 [=====] - 27s 4ms/step - loss: 0.4004 - acc: 0.8403 - val_loss: 0.4004
 Epoch 13/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.3604 - acc: 0.8645 - val_loss: 0.3604
 Epoch 14/30
 7352/7352 [=====] - 25s 3ms/step - loss: 0.3069 - acc: 0.9023 - val_loss: 0.3069
 Epoch 15/30
 7352/7352 [=====] - 26s 3ms/step - loss: 0.2778 - acc: 0.9195 - val_loss: 0.2778
 Epoch 16/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.2440 - acc: 0.9270 - val_loss: 0.2440
 Epoch 17/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.2062 - acc: 0.9361 - val_loss: 0.2062
 Epoch 18/30
 7352/7352 [=====] - 27s 4ms/step - loss: 0.2099 - acc: 0.9376 - val_loss: 0.2099
 Epoch 19/30
 7352/7352 [=====] - 30s 4ms/step - loss: 0.2098 - acc: 0.9339 - val_loss: 0.2098
 Epoch 20/30
 7352/7352 [=====] - 29s 4ms/step - loss: 0.1825 - acc: 0.9442 - val_loss: 0.1825
 Epoch 21/30
 7352/7352 [=====] - 28s 4ms/step - loss: 0.2035 - acc: 0.9402 - val_loss: 0.2035
 Epoch 22/30
 7352/7352 [=====] - 29s 4ms/step - loss: 0.2215 - acc: 0.9338 - val_loss: 0.2215
 Epoch 23/30
 7352/7352 [=====] - 31s 4ms/step - loss: 0.1811 - acc: 0.9433 - val_loss: 0.1811
 Epoch 24/30
 7352/7352 [=====] - 32s 4ms/step - loss: 0.1776 - acc: 0.9430 - val_loss: 0.1776
 Epoch 25/30
 7352/7352 [=====] - 31s 4ms/step - loss: 0.1702 - acc: 0.9427 - val_loss: 0.1702
 Epoch 26/30
 7352/7352 [=====] - 27s 4ms/step - loss: 0.1818 - acc: 0.9463 - val_loss: 0.1818
 Epoch 27/30
 7352/7352 [=====] - 26s 4ms/step - loss: 0.1806 - acc: 0.9438 - val_loss: 0.1806
 Epoch 28/30
 7352/7352 [=====] - 29s 4ms/step - loss: 0.2104 - acc: 0.9404 - val_loss: 0.2104
 Epoch 29/30

```
7352/7352 [=====] - 26s 4ms/step - loss: 0.2942 - acc: 0.9336 - val_1
Epoch 30/30
7352/7352 [=====] - 32s 4ms/step - loss: 0.1822 - acc: 0.9422 - val_1
```

```
Out[20]: <keras.callbacks.History at 0x1a443cffe80>
```

```
In [21]: # Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
```

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	510	0	27	0		0
SITTING	2	443	46	0		0
STANDING	0	166	365	1		0
WALKING	0	1	0	454		22
WALKING_DOWNSTAIRS	0	0	0	0		411
WALKING_UPSTAIRS	0	0	0	17		21

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	0
STANDING	0
WALKING	19
WALKING_DOWNSTAIRS	9
WALKING_UPSTAIRS	433

```
In [22]: score = model.evaluate(X_test, Y_test)
```

```
2947/2947 [=====] - 1s 376us/step
```

```
In [23]: score
```

```
Out[23]: [0.33535143116306826, 0.8876823888700374]
```

- With a simple 2 layer architecture we got 88.76% accuracy and a loss of 0.33
- We can further improve the performance with Hyperparameter tuning

```
In [ ]:
```