

Human Activity Recognition

In [0]:

```
import pandas as pd
import numpy as np
```

In [0]:

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

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

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

Data

In [0]:

```
# Data directory
DATADIR = '/content/gdrive/My Drive/Colab Notebooks/UCI_HAR_Dataset'
```

In [0]:

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

In [0]:

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

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

    for signal in SIGNALS:
        filename = f'/content/gdrive/My Drive/Colab Notebooks/UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.txt'
```

```

        signals_data.append(
            _read_csv(filename).as_matrix()
        )

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

```

In [0]:

```

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

    return pd.get_dummies(y).as_matrix()

```

In [0]:

```

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

    return X_train, X_test, y_train, y_test

```

In [0]:

```

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

```

In [0]:

```

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

```

In [11]:

```

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

```

Using TensorFlow backend.

In [0]:

```

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

```

In [0]:

```

# Initializing parameters
epochs = 30

```

```
epochs = 50
batch_size = 16
n_hidden = 32
```

In [0]:

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

In [15]:

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

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:11: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
# This is added back by InteractiveShellApp.init_path()
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:12: FutureWarning: Method .as_matrix
will be removed in a future version. Use .values instead.
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 [49]:

```
# Initiliazng the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(50, input_shape=(timesteps, input_dim), return_sequences=True))

model.add(Dropout(0.6))

#model.add(LSTM(24, return_sequences=True))
# Adding a dropout layer
#model.add(Dropout(0.6))

#model.add(LSTM(24))
# Adding a dropout layer
model.add(LSTM(50))

model.add(Dense(50, activation='relu'))
#model.add(Dropout(0.6))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='softmax'))

model.summary()

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

Layer (type)	Output Shape	Param #
=====		
lstm_29 (LSTM)	(None, 128, 50)	12000

dropout_23 (Dropout)	(None, 128, 50)	0
lstm_30 (LSTM)	(None, 50)	20200
dense_17 (Dense)	(None, 50)	2550
dense_18 (Dense)	(None, 6)	306
=====		
Total params: 35,056		
Trainable params: 35,056		
Non-trainable params: 0		
=====		

In [50]:

```
# Training the model
history=model.fit(X_train,
                  Y_train,
                  batch_size=batch_size,
                  validation_data=(X_test, Y_test),
                  epochs=30)
```

Train on 7352 samples, validate on 2947 samples

```
Epoch 1/30
7352/7352 [=====] - 72s 10ms/step - loss: 0.9071 - acc: 0.6130 - val_loss:
: 0.6927 - val_acc: 0.6946
Epoch 2/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.4859 - acc: 0.7926 - val_loss:
0.5751 - val_acc: 0.7957
Epoch 3/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.3356 - acc: 0.8896 - val_loss:
0.3452 - val_acc: 0.8775
Epoch 4/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.2871 - acc: 0.8989 - val_loss:
0.3946 - val_acc: 0.8636
Epoch 5/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1822 - acc: 0.9365 - val_loss:
0.4466 - val_acc: 0.8636
Epoch 6/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.2011 - acc: 0.9294 - val_loss:
0.3249 - val_acc: 0.8901
Epoch 7/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.1716 - acc: 0.9344 - val_loss:
0.2948 - val_acc: 0.8873
Epoch 8/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1593 - acc: 0.9384 - val_loss:
0.2852 - val_acc: 0.8982
Epoch 9/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1459 - acc: 0.9430 - val_loss:
0.3868 - val_acc: 0.8863
Epoch 10/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1853 - acc: 0.9302 - val_loss:
0.2953 - val_acc: 0.8935
Epoch 11/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1326 - acc: 0.9461 - val_loss:
0.3094 - val_acc: 0.9009
Epoch 12/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1174 - acc: 0.9535 - val_loss:
0.2808 - val_acc: 0.9148
Epoch 13/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.1560 - acc: 0.9392 - val_loss:
0.2873 - val_acc: 0.9046
Epoch 14/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1442 - acc: 0.9418 - val_loss:
0.2448 - val_acc: 0.9077
Epoch 15/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1781 - acc: 0.9297 - val_loss:
0.3365 - val_acc: 0.9013
Epoch 16/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.1579 - acc: 0.9346 - val_loss:
0.3181 - val_acc: 0.9053
Epoch 17/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1251 - acc: 0.9411 - val_loss:
0.2864 - val_acc: 0.9097
Epoch 18/30
```

```

Epoch 18/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1323 - acc: 0.9459 - val_loss:
0.3096 - val_acc: 0.9080
Epoch 19/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1166 - acc: 0.9508 - val_loss:
0.3583 - val_acc: 0.9080
Epoch 20/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.1184 - acc: 0.9512 - val_loss:
0.3624 - val_acc: 0.9111
Epoch 21/30
7352/7352 [=====] - 69s 9ms/step - loss: 0.1543 - acc: 0.9418 - val_loss:
0.4119 - val_acc: 0.8914
Epoch 22/30
7352/7352 [=====] - 69s 9ms/step - loss: 0.1360 - acc: 0.9472 - val_loss:
0.3722 - val_acc: 0.8884
Epoch 23/30
7352/7352 [=====] - 69s 9ms/step - loss: 0.1323 - acc: 0.9471 - val_loss:
0.3051 - val_acc: 0.9108
Epoch 24/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1232 - acc: 0.9527 - val_loss:
0.2921 - val_acc: 0.9182
Epoch 25/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1187 - acc: 0.9524 - val_loss:
0.3590 - val_acc: 0.9087
Epoch 26/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1154 - acc: 0.9543 - val_loss:
0.2936 - val_acc: 0.9186
Epoch 27/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.2073 - acc: 0.9248 - val_loss:
0.2432 - val_acc: 0.9203
Epoch 28/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1192 - acc: 0.9524 - val_loss:
0.2608 - val_acc: 0.9155
Epoch 29/30
7352/7352 [=====] - 68s 9ms/step - loss: 0.1190 - acc: 0.9517 - val_loss:
0.2679 - val_acc: 0.9104
Epoch 30/30
7352/7352 [=====] - 67s 9ms/step - loss: 0.1113 - acc: 0.9540 - val_loss:
0.2848 - val_acc: 0.9148

```

In [55]:

```

%matplotlib inline

import matplotlib.pyplot as plt
import numpy as np
import time

plt.style.use('classic')
# https://gist.github.com/greydanus/f6eee59eaf1d90fcb3b534a25362cea4
# https://stackoverflow.com/a/14434334
# this function is used to update the plots for each epoch and error
def plt_dynamic(x, vy, ty, ax, colors=['b']):
    ax.plot(x, vy, 'b', label="Validation Loss")
    ax.plot(x, ty, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
    fig.canvas.draw()

fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')

# list of epoch numbers
x = list(range(1,epochs+1))

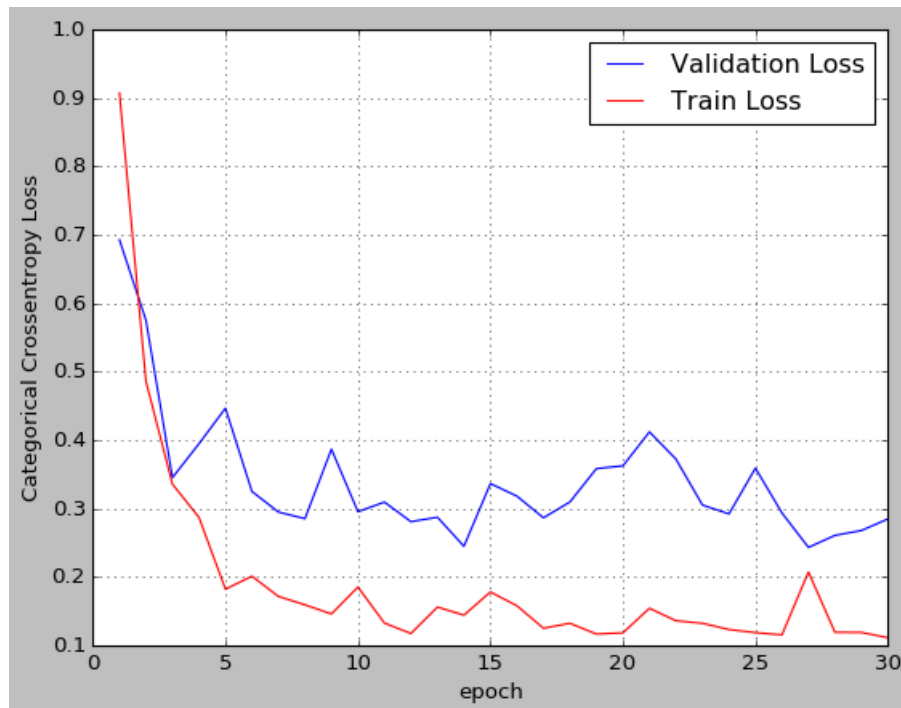
# print(history.history.keys())
# dict_keys(['val_loss', 'val_acc', 'loss', 'acc'])
# history = model_drop.fit(X_train, Y_train, batch_size=batch_size, epochs=nb_epoch, verbose=1, va
lidation_data=(X_test, Y_test))

# we will get val_loss and val_acc only when you pass the paramter validation_data
# val_loss : validation loss
# val_acc : validation accuracy

# loss : training loss
# acc : train accuracy
# for each key in history.history we will have a list of length equal to number of epochs

```

```
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```



In [51]:

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

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	\
True						
LAYING	520	0	0	0	0	
SITTING	4	404	81	0	0	
STANDING	0	100	430	1	0	
WALKING	0	0	0	464	27	
WALKING_DOWNSTAIRS	0	0	0	0	420	
WALKING_UPSTAIRS	0	0	0	0	13	

Pred	WALKING_UPSTAIRS
True	
LAYING	17
SITTING	2
STANDING	1
WALKING	5
WALKING_DOWNSTAIRS	0
WALKING_UPSTAIRS	458

In [52]:

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

2947/2947 [=====] - 3s 961us/step

In [53]:

```
score
```

Out[53]:

```
[0.28479463859741877, 0.9148286392941974]
```

- I got a accuracy of 0.9148 and a loss of 0.284 on Test data
- although at epoch 27 I got a accuracy of 0.9203 and a loss of 0.243

