```
In [0]:
import zipfile
In [0]:
zip ref = zipfile.ZipFile("/content/drive/My Drive/HAR data/HumanActivityRecognition.zip", 'r')
zip ref.extractall("/content/drive/My Drive/HAR data")
zip ref.close()
In [0]:
import pandas as pd
import numpy as np
In [0]:
import matplotlib.pyplot as plt
import numpy as np
import time
# 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()
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/drive/My Drive/HAR data/HAR/UCI HAR Dataset'
In [0]:
# Raw data signals
# Signals are from Accelerometer and Gyroscope
\# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
```

"body acc x",

```
"body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
In [0]:
# Utility function to read the data from csv file
def read csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)
# Utility function to load the load
def load signals(subset):
    signals data = []
    for signal in SIGNALS:
        filename = f'/content/drive/My Drive/HAR data/HAR/UCI HAR Dataset/{subset}/Inertial Signals
/{signal} {subset}.txt'
       signals data.append(
            read csv(filename).as matrix()
    # Transpose is used to change the dimensionality of the output,
    \ensuremath{\text{\#}} 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))
4
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/drive/My Drive/HAR data/HAR/UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = read csv(filename)[0]
    return pd.get dummies(y).as matrix()
In [0]:
def load data():
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    X train, X test = load signals('train'), load signals('test')
    y_train, y_test = load_y('train'), load_y('test')
    return X_train, X_test, y_train, y_test
In [0]:
# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set random seed(42)
In [0]:
# Configuring a session
session_conf = tf.ConfigProto(
    intra op parallelism threads=1,
```

inter_op_parallelism_threads=1

```
In [0]:
# Import Keras
from keras import backend as K
sess = tf.Session(graph=tf.get default graph(), config=session conf)
K.set_session(sess)
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
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]))
Train Test Split
In [0]:
# 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 [18]:
```

```
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

Store into pickle

```
In [0]:
```

```
%%time
import pickle

dbfile_1 = open('/content/drive/My Drive/HAR data/Xtrain', 'ab')
dbfile_2 = open('/content/drive/My Drive/HAR data/Xtest', 'ab')
```

```
dbfile 3 = open('/content/drive/My Drive/HAR data/ytrain', 'ab')
dbfile 4 = open('/content/drive/My Drive/HAR data/ytest', 'ab')
# source, destination
pickle.dump(X train, dbfile 1)
pickle.dump(X_test, dbfile_2)
pickle.dump(Y_train, dbfile_3)
pickle.dump(Y test, dbfile 4)
dbfile 1.close()
dbfile_2.close()
dbfile_3.close()
dbfile 4.close()
CPU times: user 128 ms, sys: 65 ms, total: 193 ms
Wall time: 356 ms
In [0]:
'''import pickle
dbfile_1 = open('/content/drive/My Drive/HAR data/Xtrain', 'rb')
X_train = pickle.load(dbfile_1)
dbfile 1.close()
dbfile 2 = open('/content/drive/My Drive/HAR data/Xtest', 'rb')
X test = pickle.load(dbfile 2)
dbfile_2.close()
dbfile 3 = open('/content/drive/My Drive/HAR data/ytrain', 'rb')
Y train = pickle.load(dbfile_3)
dbfile 3.close()
dbfile_4 = open('/content/drive/My Drive/HAR data/ytest', 'rb')
Y test = pickle.load(dbfile_4)
dbfile_4.close()'''
```

Model 1

• Defining the Architecture of LSTM

In [0]:

```
# 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_3 (LSTM)	(None,	32)	5376
dropout_3 (Dropout)	(None,	32)	0
dense_3 (Dense)	(None,	6)	198
Total params: 5,574 Trainable params: 5,574 Non-trainable params: 0			

```
# 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
: 1.1254 - val acc: 0.4662
Epoch 2/30
: 0.9491 - val acc: 0.5714
Epoch 3/30
7352/7352 [============== ] - 97s 13ms/step - loss: 0.7812 - acc: 0.6408 - val loss
: 0.8286 - val_acc: 0.5850
Epoch 4/30
7352/7352 [============== ] - 95s 13ms/step - loss: 0.6941 - acc: 0.6574 - val loss
: 0.7297 - val_acc: 0.6128
Epoch 5/30
: 0.7359 - val_acc: 0.6787
Epoch 6/30
: 0.7015 - val acc: 0.6939
Epoch 7/30
7352/7352 [============== ] - 95s 13ms/step - loss: 0.5692 - acc: 0.7477 - val_loss
: 0.5995 - val acc: 0.7387
Epoch 8/30
: 0.5762 - val acc: 0.7387
Epoch 9/30
: 0.7413 - val acc: 0.7126
Epoch 10/30
: 0.5048 - val_acc: 0.7513
Epoch 11/30
7352/7352 [============== ] - 89s 12ms/step - loss: 0.3985 - acc: 0.8274 - val loss
: 0.5234 - val acc: 0.7452
Epoch 12/30
: 0.4114 - val acc: 0.8833
Epoch 13/30
: 0.4386 - val acc: 0.8731
Epoch 14/30
: 0.3768 - val acc: 0.8921
Epoch 15/30
: 0.4441 - val acc: 0.8931
Epoch 16/30
: 0.4162 - val acc: 0.8968
Epoch 17/30
7352/7352 [============= ] - 89s 12ms/step - loss: 0.2028 - acc: 0.9404 - val_loss
: 0.4538 - val acc: 0.8962
Epoch 18/30
: 0.3964 - val acc: 0.8999
Epoch 19/30
7352/7352 [============= ] - 96s 13ms/step - loss: 0.1912 - acc: 0.9407 - val loss
: 0.3165 - val acc: 0.9030
Epoch 20/30
: 0.4546 - val acc: 0.8904
Epoch 21/30
: 0.3346 - val acc: 0.9063
```

```
Epoch 22/30
: 0.8164 - val acc: 0.8582
Epoch 23/30
: 0.4240 - val_acc: 0.9036
Epoch 24/30
: 0.4067 - val acc: 0.9148
Epoch 25/30
: 0.3396 - val acc: 0.9074
Epoch 26/30
: 0.3806 - val acc: 0.9019
Epoch 27/30
: 0.6464 - val acc: 0.8850
Epoch 28/30
7352/7352 [============== ] - 91s 12ms/step - loss: 0.1965 - acc: 0.9425 - val_loss
: 0.3363 - val_acc: 0.9203
Epoch 29/30
: 0.3737 - val_acc: 0.9158
Epoch 30/30
: 0.3088 - val_acc: 0.9097
Out[0]:
```

<keras.callbacks.History at 0x29b5ee36a20>

In [0]:

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

Pred	LAYING	SITTING	STANDING	WALKING	WALKING_DOWNSTAIRS	١
True						
LAYING	512	0	25	0	0	
SITTING	3	410	75	0	0	
STANDING	0	87	445	0	0	
WALKING	0	0	0	481	2	
WALKING_DOWNSTAIRS	0	0	0	0	382	
WALKING_UPSTAIRS	0	0	0	2	18	

Pred	WALKING_UPSTAIRS
True	
LAYING	0
SITTING	3
STANDING	0
WALKING	13
WALKING DOWNSTAIRS	38
WALKING_UPSTAIRS	451

In [0]:

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

2947/2947 [=========] - 4s 2ms/step

In [0]:

score

Out[0]:

[0.3087582236972612, 0.9097387173396675]

Model 2

In [30]:

```
# With One LSTM Layer Model 1

model = Sequential()

# 1 LSTM layer
model.add(LSTM(n_hidden, input_shape = (timesteps, input_dim)))
model.add(Dropout(0.25))
model.add(Dense(n_classes, activation = 'relu'))
model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
print(model.summary())
```

Model: "sequential 3"

Layer (type)	Output Shape	Param #
lstm_2 (LSTM)	(None, 32)	5376
dropout_2 (Dropout)	(None, 32)	0
dense_2 (Dense)	(None, 6)	198
Total params: 5,574		========

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

None

In [31]:

```
# Training the model
history = model.fit(X train,
    Y train,
    batch size=64,
    validation_data=(X_test, Y_test),
    epochs=epochs)
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
0.4062 - val_acc: 0.8537
Epoch 2/30
0.3853 - val_acc: 0.8613
Epoch 3/30
0.3690 - val acc: 0.8606
Epoch 4/30
7352/7352 [=============] - 9s 1ms/step - loss: 0.3640 - acc: 0.8465 - val loss:
0.3767 - val_acc: 0.8463
Epoch 5/30
0.3553 - val_acc: 0.8466
Epoch 6/30
0.3445 - val acc: 0.8430
Epoch 7/30
0.3386 - val acc: 0.8489
Epoch 8/30
0.3288 - val acc: 0.8465
Epoch 9/30
0.3330 - val_acc: 0.8414
Epoch 10/30
7352/7352 [===========] - 9s 1ms/step - loss: 0.2876 - acc: 0.8563 - val loss:
0.2848 - val acc: 0.8536
Epoch 11/30
0.2610 - val acc: 0.8743
Epoch 12/30
```

```
0.2659 - val acc: 0.8687
Epoch 13/30
0.2505 - val acc: 0.8721
Epoch 14/30
0.2575 - val acc: 0.8678
Epoch 15/30
0.2541 - val acc: 0.8685
Epoch 16/30
0.2426 - val_acc: 0.8730
Epoch 17/30
0.2799 - val acc: 0.8526
Epoch 18/30
0.2532 - val acc: 0.8554
Epoch 19/30
0.2320 - val acc: 0.8756
Epoch 20/30
0.2358 - val acc: 0.8738
Epoch 21/30
0.2349 - val acc: 0.8748
Epoch 22/30
0.4929 - val acc: 0.8196
Epoch 23/30
0.3371 - val acc: 0.8367
Epoch 24/30
0.3211 - val acc: 0.8519
Epoch 25/30
0.3072 - val acc: 0.8558
Epoch 26/30
7352/7352 [===========] - 9s 1ms/step - loss: 0.2366 - acc: 0.8631 - val loss:
0.2963 - val acc: 0.8589
Epoch 27/30
0.2749 - val_acc: 0.8649
Epoch 28/30
0.2722 - val acc: 0.8684
Epoch 29/30
0.2991 - val acc: 0.8760
Epoch 30/30
0.2719 - val acc: 0.8700
In [32]:
score = model.evaluate(X test, Y test)
print(score)
2947/2947 [============== ] - 1s 302us/step
[0.2719094553862105, 0.8700373047159452]
In [0]:
```

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

Pred	LAYING	SITTING	 WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
True				
LAYING	506	0	 4	27
SITTING	0	222	 0	26
STANDING	0	9	 0	111

```
      WALKING
      0
      28
      ...
      28
      184

      WALKING_DOWNSTAIRS
      0
      6
      ...
      363
      26

      WALKING_UPSTAIRS
      0
      0
      ...
      40
      428
```

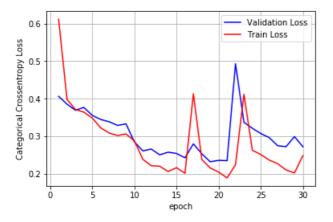
[6 rows x 6 columns]

In [0]:

```
%matplotlib inline
```

In [36]:

```
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 histrory.histrory 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)
```



Model 3

In [0]:

```
# With One LSTM Layer Model 1 #
n_hidden = 80

model = Sequential()

# 1 LSTM layer
model.add(LSTM(n_hidden, input_shape = (timesteps, input_dim))) # 1 LSTM

model.add(Dropout(0.25))
model.add(Dense(n_classes, activation = 'sigmoid'))
model.compile(loss = 'binary_crossentropy', optimizer = 'adam', metrics = ['accuracy'])
print(model.summary())
```

Model: "sequential_4"

```
lstm_4 (LSTM) (None, 80) 28800

dropout_4 (Dropout) (None, 80) 0

dense_4 (Dense) (None, 6) 486

Total params: 29,286
Trainable params: 29,286
Non-trainable params: 0
```

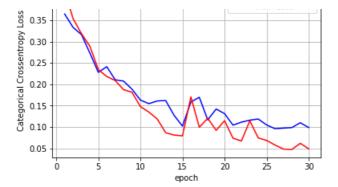
In [0]:

0.1695 - val acc: 0.9481

Epoch 18/30

```
# Training the model
history = model.fit(X train,
   Y train,
   batch size=64,
   validation_data=(X_test, Y_test),
   epochs=epochs)
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
0.3644 - val_acc: 0.8571
Epoch 2/30
0.3331 - val acc: 0.8613
Epoch 3/30
0.3162 - val acc: 0.8704
Epoch 4/30
0.2728 - val acc: 0.8806
Epoch 5/30
0.2279 - val acc: 0.8955
Epoch 6/30
0.2412 - val acc: 0.8933
Epoch 7/30
7352/7352 [============] - 30s 4ms/step - loss: 0.2087 - acc: 0.9015 - val loss:
0.2105 - val acc: 0.9009
Epoch 8/30
0.2073 - val acc: 0.9037
Epoch 9/30
0.1885 - val acc: 0.9164
Epoch 10/30
0.1629 - val acc: 0.9406
Epoch 11/30
0.1546 - val_acc: 0.9390
Epoch 12/30
0.1608 - val_acc: 0.9467
Epoch 13/30
0.1619 - val acc: 0.9440
Epoch 14/30
0.1272 - val acc: 0.9545
Epoch 15/30
0.1019 - val acc: 0.9637
Epoch 16/30
0.1586 - val acc: 0.9412
Epoch 17/30
```

```
0.1166 - val acc: 0.9592
Epoch 19/30
0.1421 - val acc: 0.9531
Epoch 20/30
0.1311 - val acc: 0.9570
Epoch 21/30
0.1042 - val acc: 0.9641
Epoch 22/30
0.1112 - val acc: 0.9606
Epoch 23/30
0.1159 - val acc: 0.9583
Epoch 24/30
0.1186 - val acc: 0.9601
Epoch 25/30
0.1046 - val acc: 0.9650
Epoch 26/30
0.0958 - val acc: 0.9663
Epoch 27/30
0.0974 - val_acc: 0.9646
Epoch 28/30
0.0986 - val acc: 0.9676
Epoch 29/30
0.1099 - val acc: 0.9645
Epoch 30/30
0.0985 - val acc: 0.9663
In [0]:
score = model.evaluate(X test, Y test)
print(score)
2947/2947 [============ ] - 8s 3ms/step
[0.09848940819087885, 0.9662934093908977]
In [0]:
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 histrory.histrory 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)
                 Validation Loss
```



Model 4

```
In [0]:
 # With One LSTM Layer Model 1 #
 n hidden = 80
model = Sequential()
 # 1 LSTM laver
 model.add(LSTM(n hidden, input shape = (timesteps, input dim), return sequences = True))
model.add(Dropout(0.25))
model.add(LSTM(n hidden))
model.add(Dense(n_classes, activation = 'sigmoid'))
model.compile(loss = 'binary crossentropy', optimizer = 'rmsprop', metrics = ['accuracy'])
print(model.summary())
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow backend.py:66: The name tf.get default graph is deprecated. Plea
se use tf.compat.vl.get default graph instead.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow backend.py:541: The name tf.placeholder is deprecated. Please us
e tf.compat.v1.placeholder instead.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow_backend.py:4432: The name tf.random_uniform is deprecated. Pleas
e use tf.random.uniform instead.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow backend.py:148: The name tf.placeholder with default is
deprecated. Please use tf.compat.v1.placeholder_with_default instead.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
{\tt packages/keras/backend/tensorflow\_backend.py:3733: calling dropout (from a constant of the constant of th
tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future
version.
Instructions for updating:
Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`.
```

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

WARNING:tensorflow:From /usr/local/lib/python3.6/distpackages/keras/backend/tensorflow backend.py:3657: The name tf.log is deprecated. Please use tf.ma th.log instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/distpackages/tensorflow/python/ops/nn_impl.py:180: add_dispatch_support.<locals>.wrapper (from tensorflow.python.ops.array_ops) is deprecated and will be removed in a future version. Instructions for updating:

Use tf.where in 2.0, which has the same broadcast rule as np.where Model: "sequential 1"

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 128, 80)	28800
dramate 1 (Dramate)	(Name 120 00)	

dropout_1 (propout)	(NONE, 120, 00)	U
lstm_2 (LSTM)	(None, 80)	51520
dense_1 (Dense)	(None, 6)	486
Total params: 80,806 Trainable params: 80,806 Non-trainable params: 0		

None

```
# Training the model
history = model.fit(X train,
    Y train,
    batch size= 64,
    validation data=(X test, Y test),
    epochs=epochs)
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
0.0949 - val acc: 0.9742
Epoch 2/30
0.1142 - val acc: 0.9724
Epoch 3/30
0.1288 - val_acc: 0.9688
Epoch 4/30
0.0962 - val_acc: 0.9751
Epoch 5/30
0.1185 - val acc: 0.9722
Epoch 6/30
0.1057 - val acc: 0.9723
Epoch 7/30
0.1143 - val acc: 0.9738
Epoch 8/30
0.1110 - val acc: 0.9671
Epoch 9/30
0.1210 - val acc: 0.9723
Epoch 10/30
0.1088 - val acc: 0.9736
Epoch 11/30
0.1426 - val acc: 0.9748
Epoch 12/30
7352/7352 [=============== ] - 58s 8ms/step - loss: 0.0331 - acc: 0.9860 - val loss:
0.2099 - val acc: 0.9475
Epoch 13/30
0.1255 - val acc: 0.9623
Epoch 14/30
0.1483 - val acc: 0.9718
Epoch 15/30
7352/7352 [=============== ] - 58s 8ms/step - loss: 0.0304 - acc: 0.9877 - val loss:
0.1413 - val_acc: 0.9688
Epoch 16/30
0.1288 - val_acc: 0.9744
Epoch 17/30
0.1279 - val acc: 0.9727
7352/7352 [==============] - 58s 8ms/step - loss: 0.0301 - acc: 0.9886 - val loss:
```

```
0.1383 - val_acc: 0.9695
Epoch 19/30
0.1219 - val_acc: 0.9738
Epoch 20/30
0.1546 - val acc: 0.9686
Epoch 21/30
0.1032 - val acc: 0.9755
Epoch 22/30
0.1271 - val acc: 0.9674
Epoch 23/30
0.1098 - val acc: 0.9737
Epoch 24/30
0.1386 - val acc: 0.9716
Epoch 25/30
0.1342 - val acc: 0.9760
Epoch 26/30
0.1325 - val acc: 0.9699
Epoch 27/30
0.1163 - val_acc: 0.9701
Epoch 28/30
0.1486 - val acc: 0.9640
Epoch 29/30
0.1134 - val_acc: 0.9759
Epoch 30/30
0.1277 - val acc: 0.9695
CPU times: user 32min 43s, sys: 1min 43s, total: 34min 27s
Wall time: 29min 1s
In [0]:
score = model.evaluate(X test, Y test)
print(score)
2947/2947 [==========] - 17s 6ms/step
[0.1007159318419772, 0.9716095518248745]
In [0]:
# Confusion Matrix
print(confusion matrix(Y test, model.predict(X test)))
```

Pred	LAYING	SITTING	 WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
True				
LAYING	511	0	 0	0
SITTING	0	351	 0	2
STANDING	0	22	 1	0
WALKING	0	0	 43	1
WALKING_DOWNSTAIRS	0	0	 420	0
WALKING_UPSTAIRS	0	4	 14	440

[6 rows x 6 columns]

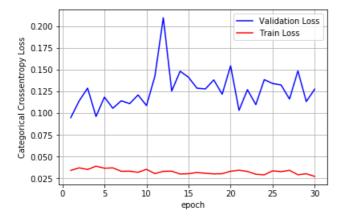
```
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
# list of epoch numbers
x = list(range(1, epochs+1))
# print(history.history.keys())
```

```
# 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)
```



Conclusion

In [3]:

```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model","Hidden layer","activation","Optimizer", "Test accuracy in %"]

x.add_row(["Lstm + dropout(0.5)","32","sigmoid","rmsprop" ,"90.97%"])
x.add_row(["Lstm + dropout(0.25)","32","relu","Adam" ,"87%"])
x.add_row(["Lstm + dropout(0.25)","80","sigmoid" ,"Adam", "96.62%"])
x.add_row(["Lstm + dropout(0.25)","80","sigmoid","rmsprop" ,"97.16%"])

print(x)
```

Model	H	idden layer	+- +-	activation	 +-	Optimizer	Test	accuracy in	% +
Lstm + dropout(0.5) Lstm + dropout(0.25) Lstm + dropout(0.25) Lstm + dropout(0.25)		32 32 80 80	 	sigmoid relu sigmoid sigmoid	 	rmsprop Adam Adam rmsprop	 	90.97% 87% 96.62% 97.16%	

- By increasing the hidden layers to 80 we got a very good result.
- Lstm + dropout(0.25) model ,with 80 hidden layers with "sigmoid" activation function we got a test acccuracy of 97.16%.
- We can further imporve the performace with Hyperparameter tuning.