```
In [0]:
  # Importing Libraries
 In [1]:
  import pandas as pd
  import numpy as np
   # Load the Drive helper and mount
  from google.colab import drive
 drive.mount('/content/drive')
Go to this URL in a browser: https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6
\verb|qk8qdgf4n4g3pfee6491hc0brc4i.apps.google user content.com&redirect\_uri=urn&3Aietf&3Awg&3Aoauth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&3A2.0&auth&
b\&scope=email \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$20 https \$3A \$2F \$2F www.googleap is.com \$2F auth \$2F docs.test \$2F auth \$2F 
2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fww
ogleapis.com%2Fauth%2Fpeopleapi.readonly&response type=code
Enter your authorization code:
Mounted at /content/drive
 In [0]:
  # Activities are the class labels
  # It is a 6 class classification
  ACTIVITIES = {
```

```
# 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 = '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'drive/My Drive/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)
    11 11 11
    filename = f'drive/My Drive/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 [10]:
# 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
batch size = 16
n_{hidden} = [16, 32, 74, 128]
dropout = [0.25, 0.5]
In [0]:
# Utility function to count the number of classes
def count classes(y):
    return len(set([tuple(category) for category in y]))
In [0]:
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
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
7352

    Defining the Architecture of LSTM

In [0]:
from keras.optimizers import Adam,RMSprop,SGD
def best_hyperparameters(n_hidden,dropout):
    model = Sequential()
    model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
    model.add(Dropout(dropout))
    model.add(Dense(n classes, activation='sigmoid'))
    model.compile(loss='categorical_crossentropy',
             optimizer='rmsprop',
              metrics=['accuracy'])
    return model
```

```
from keras.wrappers.scikit_learn import KerasClassifier
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import LSTM
from keras.layers.embeddings import Embedding
```

```
trom keras.preprocessing import sequence
from sklearn.model_selection import GridSearchCV
model = KerasClassifier(build fn=best hyperparameters,epochs=epochs, batch size=batch size, verbose
param grid = dict(n hidden=n hidden,dropout = dropout)
# if you are using CPU
# grid = GridSearchCV(estimator=model, param grid=param grid, n jobs=-1)
# if you are using GPU dont use the n_jobs parameter
grid = GridSearchCV(estimator=model, param grid=param grid)
grid_result = grid.fit(X_train,Y_train)
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/framework/op_def_library.py:263: 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.
/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:2053: FutureWarning: You
should specify a value for 'cv' instead of relying on the default value. The default value will ch
ange from 3 to 5 in version 0.22.
 warnings.warn(CV_WARNING, FutureWarning)
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/keras/backend/tensorflow backend.py:3445: calling dropout (from
tensorflow.python.ops.nn ops) with keep prob is deprecated and will be removed in a future
version.
Instructions for updating:
Please use `rate` instead of `keep prob`. Rate should be set to `rate = 1 - keep prob`.
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
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.
In [0]:
grid result.best params
Out[0]:
{'dropout': 0.25, 'n hidden': 74}
In [0]:
dropout=0.25
n hidden = 74
# 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(dropout))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
Layer (type)
                             Output Shape
                                                       Param #
```

lstm_26 (LSTM)	(None,	74)	24864
dropout_26 (Dropout)	(None,	74)	0
dense_26 (Dense)	(None,	6)	450
Total params: 25,314 Trainable params: 25,314 Non-trainable params: 0			

In [0]:

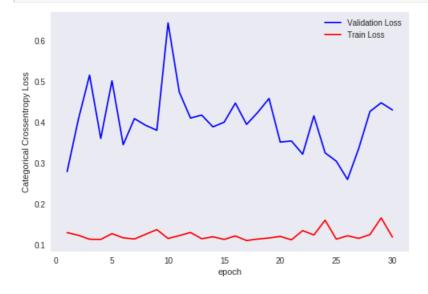
Training the model

```
history = 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
0.2794 - val acc: 0.9091
Epoch 2/30
0.4070 - val acc: 0.9121
Epoch 3/30
0.5153 - val acc: 0.9036
Epoch 4/30
0.3607 - val acc: 0.9077
Epoch 5/30
0.5015 - val acc: 0.8965
Epoch 6/30
0.3453 - val acc: 0.9162
Epoch 7/30
0.4091 - val acc: 0.9199
Epoch 8/30
0.3926 - val acc: 0.9125
Epoch 9/30
0.3806 - val acc: 0.9101
Epoch 10/30
0.6433 - val_acc: 0.9026
Epoch 11/30
0.4740 - val_acc: 0.9026
Epoch 12/30
0.4104 - val acc: 0.9135
Epoch 13/30
0.4176 - val acc: 0.9169
Epoch 14/30
0.3889 - val acc: 0.9175
Epoch 15/30
0.4002 - val acc: 0.9175
Epoch 16/30
0.4470 - val acc: 0.9057
Epoch 17/30
0.3949 - val acc: 0.9199
Epoch 18/30
0.4245 - val acc: 0.9111
Epoch 19/30
0.4583 - val_acc: 0.9131
```

```
Epocn ZU/3U
0.3517 - val acc: 0.9226
Epoch 21/30
0.3543 - val acc: 0.9213
Epoch 22/30
0.3221 - val acc: 0.9125
Epoch 23/30
0.4157 - val_acc: 0.9152
Epoch 24/30
0.3254 - val acc: 0.9260
Epoch 25/30
0.3048 - val acc: 0.9226
Epoch 26/30
0.2602 - val_acc: 0.9206
Epoch 27/30
0.3362 - val acc: 0.9213
Epoch 28/30
0.4265 - val acc: 0.9111
Epoch 29/30
7352/7352 [============= ] - 41s 6ms/step - loss: 0.1663 - acc: 0.9404 - val loss:
0.4478 - val acc: 0.9281
Epoch 30/30
0.4303 - val acc: 0.9172
In [0]:
# Confusion Matrix
print(confusion_matrix(Y_test, model.predict(X_test)))
           LAYING SITTING STANDING WALKING WALKING DOWNSTAIRS \
Pred
True
LAYING
             510
                  0
                       18
SITTING
             0
                 415
                       74
                             0
                                        0
                  99
                             Ω
                                        Ω
STANDING
             0
                       433
WALKING
             0
                  0
                       0
                            477
                                        2
WALKING DOWNSTAIRS
             0
                  0
                        0
                             2
                                       409
WALKING UPSTAIRS
                       2
                            9
                  0
                                        0
             1
Pred
           WALKING UPSTAIRS
True
LAYING
                   9
SITTING
                   2
STANDING
                   0
WALKING
                  17
WALKING DOWNSTAIRS
                   9
WALKING UPSTAIRS
                  459
In [0]:
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()
import matplotlib.pyplot as plt
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))
```

vy = history.history['val_loss']
ty = history.history['loss']

```
plt_dynamic(x, vy, ty, ax)
```



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

2947/2947 [=======] - 2s 676us/step

In [0]:

score

Out[0]:

[0.43029451220163206, 0.9172039362063115]

In [19]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(128, input_shape=(timesteps, input_dim),return_sequences=True))
# Adding a dropout layer
model.add(Dropout(0.75))
model.add(LSTM(74, input_shape=(timesteps, input_dim),return_sequences=True))
model.add(LSTM(32, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.75))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

Layer (type)	Output Shape	Param #
lstm_6 (LSTM)	(None, 128, 128)	70656
dropout_3 (Dropout)	(None, 128, 128)	0
lstm_7 (LSTM)	(None, 128, 74)	60088
lstm_8 (LSTM)	(None, 32)	13696
dropout_4 (Dropout)	(None, 32)	0
dense_1 (Dense)	(None, 6)	198

Total params: 144,638 Trainable params: 144,638 Non-trainable params: 0

In [21]:

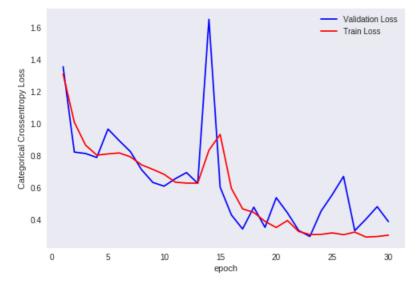
```
# Training the model
history = model.fit(X train,
       Y train,
       batch size=batch size,
       validation_data=(X_test, Y_test),
       epochs=epochs)
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
packages/tensorflow/python/ops/math ops.py:3066: to int32 (from tensorflow.python.ops.math 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 1/30
7352/7352 [===============] - 139s 19ms/step - loss: 1.3099 - acc: 0.4483 - val los
s: 1.3566 - val acc: 0.4028
Epoch 2/30
7352/7352 [===============] - 136s 19ms/step - loss: 1.0093 - acc: 0.5641 - val los
s: 0.8225 - val acc: 0.5945
Epoch 3/30
s: 0.8138 - val acc: 0.5904
Epoch 4/30
s: 0.7889 - val acc: 0.6183
Epoch 5/30
s: 0.9668 - val acc: 0.5908
Epoch 6/30
s: 0.8942 - val acc: 0.6013
Epoch 7/30
7352/7352 [============== ] - 141s 19ms/step - loss: 0.7930 - acc: 0.6367 - val los
s: 0.8254 - val acc: 0.6179
Epoch 8/30
7352/7352 [============= ] - 138s 19ms/step - loss: 0.7426 - acc: 0.6401 - val los
s: 0.7119 - val acc: 0.6284
Epoch 9/30
7352/7352 [============= ] - 135s 18ms/step - loss: 0.7144 - acc: 0.6499 - val los
s: 0.6327 - val_acc: 0.6257
Epoch 10/30
7352/7352 [=============] - 134s 18ms/step - loss: 0.6836 - acc: 0.6514 - val los
s: 0.6094 - val_acc: 0.6284
Epoch 11/30
7352/7352 [============] - 136s 18ms/step - loss: 0.6348 - acc: 0.6706 - val los
s: 0.6560 - val_acc: 0.6250
Epoch 12/30
7352/7352 [============] - 135s 18ms/step - loss: 0.6283 - acc: 0.6874 - val los
s: 0.6945 - val_acc: 0.6193
Epoch 13/30
7352/7352 [=========== ] - 134s 18ms/step - loss: 0.6285 - acc: 0.7089 - val los
s: 0.6274 - val acc: 0.7370
Epoch 14/30
s: 1.6528 - val_acc: 0.3312
Epoch 15/30
s: 0.6034 - val acc: 0.7635
Epoch 16/30
7352/7352 [============ ] - 141s 19ms/step - loss: 0.5959 - acc: 0.7915 - val los
s: 0.4300 - val acc: 0.8877
Epoch 17/30
7352/7352 [============] - 140s 19ms/step - loss: 0.4676 - acc: 0.8553 - val los
s: 0.3415 - val acc: 0.8985
Epoch 18/30
```

```
7352/7352 [============== ] - 141s 19ms/step - loss: 0.4450 - acc: 0.8634 - val los
s: 0.4780 - val acc: 0.8755
Epoch 19/30
s: 0.3519 - val acc: 0.9016
Epoch 20/30
s: 0.5373 - val acc: 0.8809
Epoch 21/30
480/7352 [>.....] - ETA: 2:03 - loss: 0.4117 - acc:
0.8750WARNING:tensorflow:From /usr/local/lib/python3.6/dist-
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 1/30
7352/7352 [============== ] - 139s 19ms/step - loss: 1.3099 - acc: 0.4483 - val los
s: 1.3566 - val acc: 0.4028
Epoch 2/30
7352/7352 [===========] - 136s 19ms/step - loss: 1.0093 - acc: 0.5641 - val los
s: 0.8225 - val_acc: 0.5945
Epoch 3/30
s: 0.8138 - val acc: 0.5904
Epoch 4/30
7352/7352 [===========] - 145s 20ms/step - loss: 0.8036 - acc: 0.6298 - val los
s: 0.7889 - val acc: 0.6183
Epoch 5/30
7352/7352 [============== ] - 138s 19ms/step - loss: 0.8112 - acc: 0.6182 - val los
s: 0.9668 - val_acc: 0.5908
Epoch 6/30
7352/7352 [===========] - 141s 19ms/step - loss: 0.8174 - acc: 0.6302 - val los
s: 0.8942 - val acc: 0.6013
Epoch 7/30
s: 0.8254 - val_acc: 0.6179
Epoch 8/30
7352/7352 [==============] - 138s 19ms/step - loss: 0.7426 - acc: 0.6401 - val_los
s: 0.7119 - val acc: 0.6284
Epoch 9/30
s: 0.6327 - val acc: 0.6257
Epoch 10/30
s: 0.6094 - val acc: 0.6284
Epoch 11/30
s: 0.6560 - val acc: 0.6250
Epoch 12/30
s: 0.6945 - val_acc: 0.6193
Epoch 13/30
7352/7352 [============ ] - 134s 18ms/step - loss: 0.6285 - acc: 0.7089 - val los
s: 0.6274 - val_acc: 0.7370
Epoch 14/30
s: 1.6528 - val acc: 0.3312
Epoch 15/30
7352/7352 [===========] - 135s 18ms/step - loss: 0.9332 - acc: 0.6107 - val los
s: 0.6034 - val acc: 0.7635
Epoch 16/30
s: 0.4300 - val acc: 0.8877
Epoch 17/30
7352/7352 [=============] - 140s 19ms/step - loss: 0.4676 - acc: 0.8553 - val los
s: 0.3415 - val_acc: 0.8985
Epoch 18/30
s: 0.4780 - val_acc: 0.8755
Epoch 19/30
7352/7352 [============= ] - 142s 19ms/step - loss: 0.3892 - acc: 0.8776 - val los
s: 0.3519 - val acc: 0.9016
Epoch 20/30
s: 0.5373 - val acc: 0.8809
Epoch 21/30
```

```
s: 0.4426 - val acc: 0.8860
s: 0.4426 - val acc: 0.8860
Epoch 22/30
Epoch 22/30
s: 0.3322 - val acc: 0.9036
s: 0.3322 - val_acc: 0.9036
Epoch 23/30
Epoch 23/30
s: 0.2949 - val acc: 0.9179
7352/7352 [===============] - 136s 19ms/step - loss: 0.3067 - acc: 0.9008 - val los
s: 0.2949 - val acc: 0.9179
Epoch 24/30
Epoch 24/30
s: 0.4534 - val acc: 0.9057
s: 0.4534 - val acc: 0.9057
Epoch 25/30
Epoch 25/30
s: 0.5568 - val_acc: 0.8778
7352/7352 [============= ] - 139s 19ms/step - loss: 0.3173 - acc: 0.9033 - val los
s: 0.5568 - val acc: 0.8778
Epoch 26/30
Epoch 26/30
s: 0.6705 - val acc: 0.8744
7352/7352 [============== ] - 138s 19ms/step - loss: 0.3059 - acc: 0.8985 - val los
s: 0.6705 - val acc: 0.8744
Epoch 27/30
Epoch 27/30
s: 0.3312 - val_acc: 0.9182
7352/7352 [===========] - 140s 19ms/step - loss: 0.3222 - acc: 0.8969 - val los
s: 0.3312 - val_acc: 0.9182
Epoch 28/30
Epoch 28/30
s: 0.4033 - val acc: 0.9148
s: 0.4033 - val acc: 0.9148
Epoch 29/30
Epoch 29/30
7352/7352 [============== ] - 138s 19ms/step - loss: 0.2944 - acc: 0.9097 - val los
s: 0.4813 - val acc: 0.8928
s: 0.4813 - val acc: 0.8928
Epoch 30/30
Epoch 30/30
7352/7352 [============= ] - 137s 19ms/step - loss: 0.3028 - acc: 0.9056 - val los
s: 0.3878 - val_acc: 0.9125
s: 0.3878 - val acc: 0.9125
In [22]:
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()
import matplotlib.pyplot as plt
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))
```

vy = history.history['val loss']

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



In [23]:

In [24]:

```
score
```

Out[24]:

 $\hbox{\tt [0.3877914281657706, 0.9124533423820834]}$

Exploratory Data Analysis

1)Importing all the packages which are required 2)Load the data 3)features are given by the experts 4)Remove duplicates 5)Remove null values 6)Checking for the data imbalance 7)Do some violin plots, box plots and twin plots on some features 8)try TSNE on data with different perplexities

Prediction models

1)Split the data in train and test 2)Apply Logistic regression on the data with hyper parameter tuning 3)Apply Linear SVC on the data with hyper parameter tuning 4)Apply Kernal SVM on the data with hyper parameter tuning 5)Apply Decision tree, Random forest classifier and Gradient boosted decision tree on the data with hyper parameter tuning 6)Comparing all the models

LSTM

1)Take the data and the time-series data and get the features from those time series data 2)Apply the LSTM with hyperparameter tuning and only with 2 layers 3)Trying it with more layers and getting the accuracy

In [1]:

```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["layers", "Train loss", "Test loss"]

x.add_row(["2",".11",".43"])

x.add_row(["4",".302",".387"])

print(x)
```

+	Train	loss	 Test	
2	.1	_		43 387

- 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