

HAR_LSTM_A_21 (2)

June 4, 2019

```
In [0]: import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
In [4]: from google.colab import drive
drive.mount('/content/drive')
```

Drive already mounted at /content/drive; to attempt to forcibly remount, call drive.mount("/content/drive")

```
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'])
```

0.0.1 Data

```
In [0]: # Data directory
DATADIR = 'drive/My Drive/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'drive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}.csv'
        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]: *#content/drive/My Drive/HAR/UCI_HAR_Dataset/train/Inertial Signals/body_acc_x_train.txt*

```

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'drive/My Drive/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 [13]: # 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 = 15
```

```
batch_size = 64
```

```
n_hidden = 64
```

```
In [0]: # Utility function to count the number of classes
```

```
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

```
In [17]: # 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
```

```
# This is added back by InteractiveShellApp.init_path()
```

```
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

```

0.1 Single Layer LSTM Model with dropout

```

In [18]: # Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(64, input_shape=(timesteps, input_dim), kernel_initializer = 'glorot_uni
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()

```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/framework/op_

Instructions for updating:

Colocations handled automatically by placer.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend

Instructions for updating:

Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.

Layer (type)	Output Shape	Param #
lstm_1 (LSTM)	(None, 64)	18944
dropout_1 (Dropout)	(None, 64)	0
dense_1 (Dense)	(None, 6)	390

Total params: 19,334
 Trainable params: 19,334
 Non-trainable params: 0

```

In [0]: # Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='Adam',
              metrics=['accuracy'])

```

```
In [20]: # Training the model
```

```
history = model.fit(X_train,  
                    Y_train,  
                    batch_size=64,  
                    validation_data=(X_test, Y_test),  
                    epochs=15)
```

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/python/ops/math_ops.py:

Instructions for updating:

Use tf.cast instead.

Train on 7352 samples, validate on 2947 samples

Epoch 1/15

7352/7352 [=====] - 23s 3ms/step - loss: 1.4317 - acc: 0.3792 - val_loss: 1.4317

Epoch 2/15

7352/7352 [=====] - 22s 3ms/step - loss: 1.3023 - acc: 0.4174 - val_loss: 1.3023

Epoch 3/15

7352/7352 [=====] - 22s 3ms/step - loss: 1.1832 - acc: 0.4973 - val_loss: 1.1832

Epoch 4/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.9123 - acc: 0.6004 - val_loss: 0.9123

Epoch 5/15

7352/7352 [=====] - 23s 3ms/step - loss: 0.7439 - acc: 0.6684 - val_loss: 0.7439

Epoch 6/15

7352/7352 [=====] - 23s 3ms/step - loss: 0.5865 - acc: 0.7497 - val_loss: 0.5865

Epoch 7/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.5060 - acc: 0.7860 - val_loss: 0.5060

Epoch 8/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.4841 - acc: 0.8184 - val_loss: 0.4841

Epoch 9/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.4050 - acc: 0.8191 - val_loss: 0.4050

Epoch 10/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.3426 - acc: 0.8715 - val_loss: 0.3426

Epoch 11/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.3795 - acc: 0.8697 - val_loss: 0.3795

Epoch 12/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.3427 - acc: 0.8719 - val_loss: 0.3427

Epoch 13/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.2352 - acc: 0.9212 - val_loss: 0.2352

Epoch 14/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.2383 - acc: 0.9193 - val_loss: 0.2383

Epoch 15/15

7352/7352 [=====] - 22s 3ms/step - loss: 0.1866 - acc: 0.9355 - val_loss: 0.1866

```
In [21]: # Confusion Matrix
```

```
print(confusion_matrix(Y_test, model.predict(X_test)))
```

```
Pred          LAYING  SITTING  ...  WALKING_DOWNSTAIRS  WALKING_UPSTAIRS  
True          ...
```

LAYING	537	0	...	0	0
SITTING	1	394	...	0	9
STANDING	0	94	...	0	0
WALKING	0	0	...	28	17
WALKING_DOWNSTAIRS	0	0	...	381	34
WALKING_UPSTAIRS	1	0	...	14	374

[6 rows x 6 columns]

```
In [22]: score = model.evaluate(X_test, Y_test)
         print("Accuracy: %.2f%%" % (score[1]*100))
```

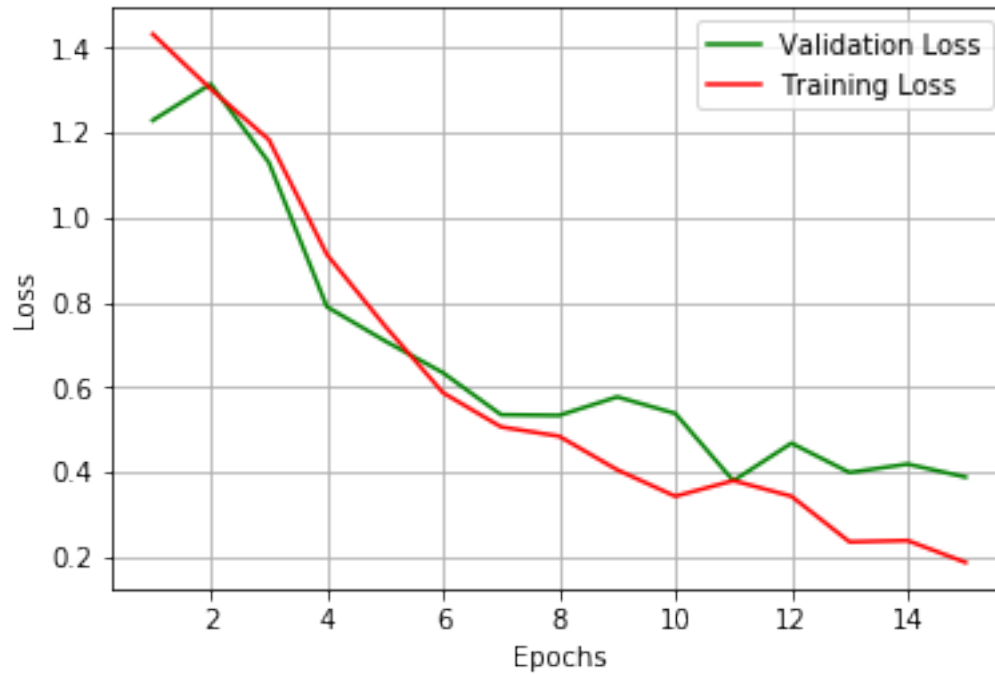
```
2947/2947 [=====] - 6s 2ms/step
Accuracy: 87.28%
```

```
In [24]: fig,ax = plt.subplots(1,1)
         ax.set_xlabel('Epochs') ; ax.set_ylabel('Loss')

         # list of epoch numbers
         list_of_epoch = list(range(1,15+1))

         train_loss = history.history['loss']
         val_loss = history.history['val_loss']

         ax.plot(list_of_epoch, val_loss, 'g', label="Validation Loss")
         ax.plot(list_of_epoch, train_loss, 'r', label="Training Loss")
         plt.legend()
         plt.grid()
         plt.show();
```



0.2 3 Layers LSTM Model with Dropout

```
In [21]: # Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(32, input_shape=(timesteps, input_dim), return_sequences=True))

#Adding another layer
model.add(LSTM(64, return_sequences=True)) # returns a sequence of vectors of dimens

# Adding a dropout layer
model.add(Dropout(0.5))

model.add(LSTM(128))

# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

Layer (type)	Output Shape	Param #
lstm_7 (LSTM)	(None, 128, 32)	5376
lstm_8 (LSTM)	(None, 128, 64)	24832
dropout_4 (Dropout)	(None, 128, 64)	0
lstm_9 (LSTM)	(None, 128)	98816
dense_3 (Dense)	(None, 6)	774
Total params: 129,798		
Trainable params: 129,798		
Non-trainable params: 0		

```
In [0]: # Compiling the model
import keras
model.compile(loss='categorical_crossentropy',
              optimizer='Adam',
              metrics=['accuracy'])
```

```
In [25]: # Training the model
history = model.fit(X_train,
                    Y_train,
                    batch_size=64,
                    validation_data=(X_test, Y_test),
                    epochs=15)
```

Train on 7352 samples, validate on 2947 samples

```
Epoch 1/15
7352/7352 [=====] - 66s 9ms/step - loss: 1.2921 - acc: 0.4124 - val_loss: 1.2921
Epoch 2/15
7352/7352 [=====] - 66s 9ms/step - loss: 1.2356 - acc: 0.4286 - val_loss: 1.2356
Epoch 3/15
7352/7352 [=====] - 65s 9ms/step - loss: 1.0627 - acc: 0.5389 - val_loss: 1.0627
Epoch 4/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.8606 - acc: 0.6353 - val_loss: 0.8606
Epoch 5/15
7352/7352 [=====] - 66s 9ms/step - loss: 0.6579 - acc: 0.6976 - val_loss: 0.6579
Epoch 6/15
7352/7352 [=====] - 66s 9ms/step - loss: 0.5128 - acc: 0.7633 - val_loss: 0.5128
Epoch 7/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.4824 - acc: 0.7983 - val_loss: 0.4824
Epoch 8/15
```



```

7352/7352 [=====] - 65s 9ms/step - loss: 0.3947 - acc: 0.8504 - val_loss: 0.3947
Epoch 9/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.2674 - acc: 0.9087 - val_loss: 0.2674
Epoch 10/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.1910 - acc: 0.9328 - val_loss: 0.1910
Epoch 11/15
7352/7352 [=====] - 66s 9ms/step - loss: 0.2482 - acc: 0.9124 - val_loss: 0.2482
Epoch 12/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.1845 - acc: 0.9376 - val_loss: 0.1845
Epoch 13/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.1662 - acc: 0.9377 - val_loss: 0.1662
Epoch 14/15
7352/7352 [=====] - 65s 9ms/step - loss: 0.1637 - acc: 0.9408 - val_loss: 0.1637
Epoch 15/15
7352/7352 [=====] - 66s 9ms/step - loss: 0.1476 - acc: 0.9433 - val_loss: 0.1476

```

```
In [26]: # Confusion Matrix
```

```
print(confusion_matrix(Y_test, model.predict(X_test)))
```

Pred \ True	LAYING	SITTING	...	WALKING_DOWNSTAIRS	WALKING_UPSTAIRS
LAYING	528	0	...	9	0
SITTING	1	421	...	1	3
STANDING	0	131	...	0	0
WALKING	0	0	...	7	28
WALKING_DOWNSTAIRS	0	0	...	401	19
WALKING_UPSTAIRS	0	0	...	17	428

```
[6 rows x 6 columns]
```

```
In [27]: score = model.evaluate(X_test, Y_test)
```

```
print("Accuracy: %.2f%%" % (score[1]*100))
```

```
2947/2947 [=====] - 18s 6ms/step
```

```
Accuracy: 89.41%
```

```
In [28]: fig,ax = plt.subplots(1,1)
```

```
ax.set_xlabel('Epochs') ; ax.set_ylabel('Loss')
```

```
# list of epoch numbers
```

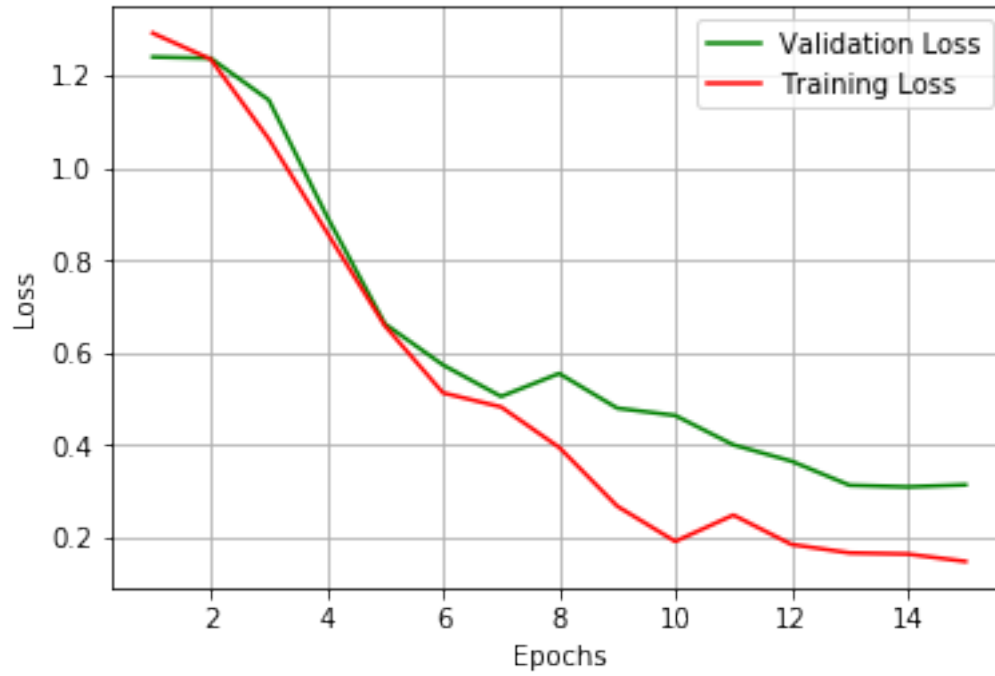
```
list_of_epoch = list(range(1,15+1))
```

```
train_loss = history.history['loss']
```

```
val_loss = history.history['val_loss']
```

```
ax.plot(list_of_epoch, val_loss, 'g', label="Validation Loss")
```

```
ax.plot(list_of_epoch, train_loss, 'r', label="Training Loss")
plt.legend()
plt.grid()
plt.show();
```



0.3 2 Layer LSTM Model with Dropout and Batch Normalization

```
In [0]: from keras.layers.normalization import BatchNormalization
```

```
model = Sequential()

model.add(LSTM(32, return_sequences=True, kernel_initializer='glorot_uniform'))
model.add(Dropout(0.5))
model.add(BatchNormalization())
model.add(LSTM(64, kernel_initializer='glorot_uniform'))
model.add(Dropout(0.5))

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

```
In [0]: # Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='Adam',
              metrics=['accuracy'])
```

```
In [0]: # Training the model
```

```
    model.fit(X_train,  
              Y_train,  
              batch_size=batch_size,  
              validation_data=(X_test, Y_test),  
              epochs=15)
```

Train on 7352 samples, validate on 2947 samples

Epoch 1/15

7352/7352 [=====] - 178s 24ms/step - loss: 0.0954 - acc: 0.9668 - val.

Epoch 2/15

7352/7352 [=====] - 176s 24ms/step - loss: 0.0729 - acc: 0.9730 - val.

Epoch 3/15

7352/7352 [=====] - 175s 24ms/step - loss: 0.0645 - acc: 0.9757 - val.

Epoch 4/15

7352/7352 [=====] - 174s 24ms/step - loss: 0.0623 - acc: 0.9768 - val.

Epoch 5/15

7352/7352 [=====] - 174s 24ms/step - loss: 0.0512 - acc: 0.9803 - val.

Epoch 6/15

7352/7352 [=====] - 174s 24ms/step - loss: 0.0526 - acc: 0.9792 - val.

Epoch 7/15

7352/7352 [=====] - 174s 24ms/step - loss: 0.0459 - acc: 0.9810 - val.

Epoch 8/15

7352/7352 [=====] - 173s 24ms/step - loss: 0.0571 - acc: 0.9769 - val.

Epoch 9/15

7352/7352 [=====] - 173s 23ms/step - loss: 0.0438 - acc: 0.9817 - val.

Epoch 10/15

7352/7352 [=====] - 173s 24ms/step - loss: 0.0553 - acc: 0.9801 - val.

Epoch 11/15

7352/7352 [=====] - 172s 23ms/step - loss: 0.0467 - acc: 0.9817 - val.

Epoch 12/15

7352/7352 [=====] - 172s 23ms/step - loss: 0.0513 - acc: 0.9814 - val.

Epoch 13/15

7352/7352 [=====] - 171s 23ms/step - loss: 0.0477 - acc: 0.9815 - val.

Epoch 14/15

7352/7352 [=====] - 172s 23ms/step - loss: 0.0432 - acc: 0.9834 - val.

Epoch 15/15

7352/7352 [=====] - 172s 23ms/step - loss: 0.0443 - acc: 0.9837 - val.

```
Out[0]: <keras.callbacks.History at 0x7f5e6d002d68>
```

```
In [0]: scores = model.evaluate(X_test, Y_test, verbose=1)
```

```
    print("Accuracy: %.2f%%" % (scores[1]*100))
```

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

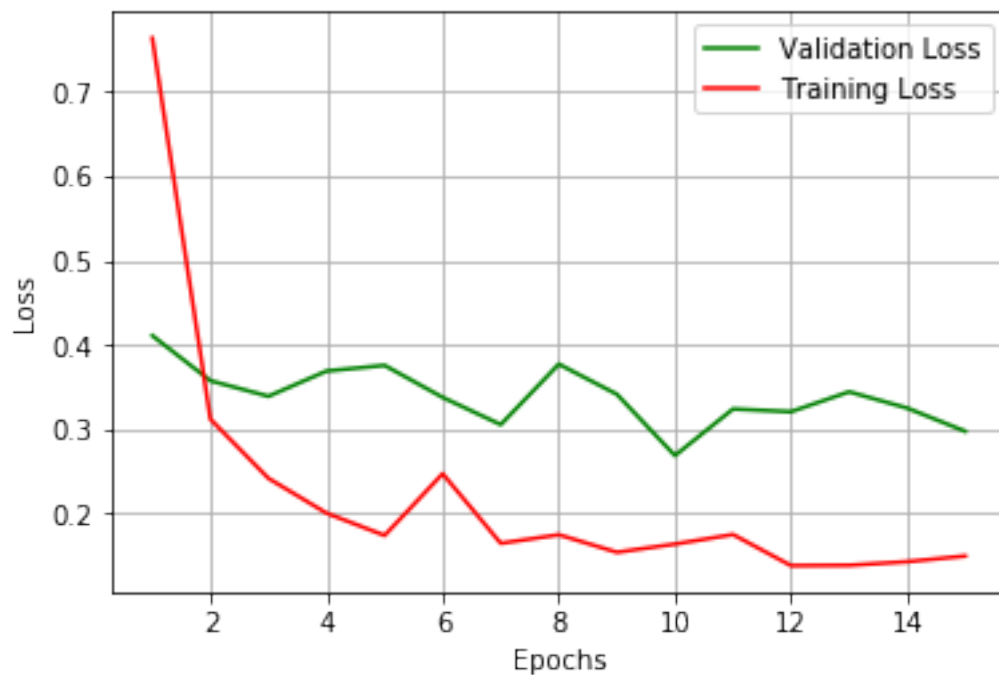
Accuracy: 96.35%

```
In [33]: fig,ax = plt.subplots(1,1)
         ax.set_xlabel('Epochs') ; ax.set_ylabel('Loss')

         # list of epoch numbers
         list_of_epoch = list(range(1,15+1))

         train_loss = history.history['loss']
         val_loss = history.history['val_loss']

         ax.plot(list_of_epoch, val_loss, 'g', label="Validation Loss")
         ax.plot(list_of_epoch, train_loss, 'r', label="Training Loss")
         plt.legend()
         plt.grid()
         plt.show();
```



1 Conclusion

- The use of simply a 2 Layer LSTM model with Batch Normalization and Dropout rate of 0.5 gives 96.35% accuracy which is comparable to those of the best performing ML models.

```
In [34]: from prettytable import PrettyTable
```

```
x = PrettyTable()
```

```

x.field_names = ["Number of Layers", "BN", "Dropout", "Accuracy"]

x.add_row(["1", 'NO', 0.5, '87.28%'])
x.add_row(["3", 'NO', 0.5, '89.41%'])
x.add_row(["2", 'YES', 0.5, '96.35%'])

print(x)

```

Number of Layers	BN	Dropout	Accuracy
1	NO	0.5	87.28%
3	NO	0.5	89.41%
2	YES	0.5	96.35%