HumanActivityRecognition

This project is to build a model that predicts the human activities such as Walking, Walking_Upstairs, Walking_Downstairs, Sitting, Standing or Laying.

This dataset is collected from 30 persons(referred as subjects in this dataset), performing different activities with a smartphone to their waists. The data is recorded with the help of sensors (accelerometer and Gyroscope) in that smartphone. This experiment was video recorded to label the data manually.

How data was recorded

By using the sensors(Gyroscope and accelerometer) in a smartphone, they have captured '3-axial linear acceleration'(*tAcc-XYZ*) from accelerometer and '3-axial angular velocity' (*tGyro-XYZ*) from Gyroscope with several variations.

> prefix 't' in those metrics denotes time.
>
> suffix 'XYZ' represents 3-axial signals in X , Y, and Z directions.

Feature names

1. These sensor signals are preprocessed by applying noise filters and then sampled in fixed-width windows(sliding windows) of 2.56 seconds each with 50% overlap. ie., each window has 128 readings.
2. From Each window, a feature vector was obtianed by calculating variables from the time and frequency domain.

> In our dataset, each datapoint represents a window with different readings

3. The accelertion signal was saperated into Body and Gravity acceleration signals(***tBodyAcc-XYZ*** and ***tGravityAcc-XYZ***) using some low pass filter with corner frequecy of 0.3Hz.
4. After that, the body linear acceleration and angular velocity were derived in time to obtian *jerk signals* (***tBodyAccJerk-XYZ*** and ***tBodyGyroJerk-XYZ***).
5. The magnitude of these 3-dimensional signals were calculated using the Euclidian norm. This magnitudes are represented as features with names like *tBodyAccMag*, *tGravityAccMag*, *tBodyAccJerkMag*, *tBodyGyroMag* and *tBodyGyroJerkMag*.
6. Finally, We've got frequency domain signals from some of the available signals by applying a FFT (Fast Fourier Transform). These signals obtained were labeled with ***prefix 'f'*** just like original signals with ***prefix 't'***. These signals are labeled as ***fBodyAcc-XYZ***, ***fBodyGyroMag*** etc.,.
7. These are the signals that we got so far.

- tBodyAcc-XYZ
- tGravityAcc-XYZ
- tBodyAccJerk-XYZ
- tBodyGyro-XYZ
- tBodyGyroJerk-XYZ

- tBodyAccMag
- tGravityAccMag
- tBodyAccJerkMag
- tBodyGyroMag
- tBodyGyroJerkMag
- fBodyAcc-XYZ
- fBodyAccJerk-XYZ
- fBodyGyro-XYZ
- fBodyAccMag
- fBodyAccJerkMag
- fBodyGyroMag
- fBodyGyroJerkMag

8. We can esitmate some set of variables from the above signals. ie., We will estimate the following properties on each and every signal that we recoreded so far.

    - ***mean()***: Mean value
    - ***std()***: Standard deviation
    - ***mad()***: Median absolute deviation
    - ***max()***: Largest value in array
    - ***min()***: Smallest value in array
    - ***sma()***: Signal magnitude area
    - ***energy()***: Energy measure. Sum of the squares divided by the number of values.
    - ***iqr()***: Interquartile range
    - ***entropy()***: Signal entropy
    - ***arCoeff()***: Autorregresion coefficients with Burg order equal to 4
    - ***correlation()***: correlation coefficient between two signals
    - ***maxInds()***: index of the frequency component with largest magnitude
    - ***meanFreq()***: Weighted average of the frequency components to obtain a mean frequency
    - ***skewness()***: skewness of the frequency domain signal
    - ***kurtosis()***: kurtosis of the frequency domain signal
    - ***bandsEnergy()***: Energy of a frequency interval within the 64 bins of the FFT of each window.
    - ***angle()***: Angle between to vectors.

9. We can obtain some other vectors by taking the average of signals in a single window sample. These are used on the angle() variable' `

    - gravityMean
    - tBodyAccMean
    - tBodyAccJerkMean
    - tBodyGyroMean
    - tBodyGyroJerkMean

Y_Labels(Encoded)

- In the dataset, Y_labels are represented as numbers from 1 to 6 as their identifiers.
    - WALKING as **1**
    - WALKING_UPSTAIRS as **2**
    - WALKING_DOWNSTAIRS as **3**
    - SITTING as **4**
    - STANDING as **5**

- LAYING as **6**

Train and test data were saperated

- The readings from ***70%*** of the volunteers were taken as ***trianing data*** and remaining ***30%*** subjects recordings were taken for ***test data***

Data

- All the data is present in 'UCI_HAR_dataset/' folder in present working directory.
  - Feature names are present in 'UCI_HAR_dataset/features.txt'
  - ***Train Data***
    - 'UCI_HAR_dataset/train/X_train.txt'
    - 'UCI_HAR_dataset/train/subject_train.txt'
    - 'UCI_HAR_dataset/train/y_train.txt'
  - ***Test Data***
    - 'UCI_HAR_dataset/test/X_test.txt'
    - 'UCI_HAR_dataset/test/subject_test.txt'
    - 'UCI_HAR_dataset/test/y_test.txt'

Data Size :

> 27 MB

Quick overview of the dataset :

- Accelerometer and Gyroscope readings are taken from 30 volunteers(referred as subjects) while performing the following 6 Activities.

  1. Walking
  2. WalkingUpstairs
  3. WalkingDownstairs
  4. Standing
  5. Sitting
  6. Lying.

- Readings are divided into a window of 2.56 seconds with 50% overlapping.
- Accelerometer readings are divided into gravity acceleration and body acceleration readings, which has x,y and z components each.
- Gyroscope readings are the measure of angular velocities which has x,y and z components.
- Jerk signals are calculated for BodyAcceleration readings.
- Fourier Transforms are made on the above time readings to obtain frequency readings.
- Now, on all the base signal readings., mean, max, mad, sma, arcoefficient, engerybands,entropy etc., are calculated for each window.
- We get a feature vector of 561 features and these features are given in the dataset.
- Each window of readings is a datapoint of 561 features.

Problem Framework

- 30 subjects(volunteers) data is randomly split to 70%(21) test and 30%(7) train data.
- Each datapoint corresponds one of the 6 Activities.

Problem Statement

- Given a new datapoint we have to predict the Activity

In [1]:
```
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=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3Aietf%3Awg%3Aoauth%3A2.0%3Aoob&scope=email%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdocs.test%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fdrive.photos.readonly%20https%3A%2F%2Fwww.googleapis.com%2Fauth%2Fpeopleapi.readonly&response_type=code

Enter your authorization code:
··········
Mounted at /content/drive
```

In [2]:
```
%cd /content/drive/My Drive/Colab Notebooks
```

```
/content/drive/My Drive/Colab Notebooks
```

In [3]:
```
import numpy as np
import pandas as pd

# get the features from the file features.txt
features = list()
with open('UCI_HAR_Dataset/features.txt') as f:
    features = [line.split()[1] for line in f.readlines()]
print('No of Features: {}'.format(len(features)))
```

```
No of Features: 561
```

Obtain the train data

In [0]:
```
# get the data from txt files to pandas dataffame
X_train = pd.read_csv('UCI_HAR_Dataset/train/X_train.txt', delim_whitespace=Tr
ue, header=None, names=features)

# add subject column to the dataframe
X_train['subject'] = pd.read_csv('UCI_HAR_Dataset/train/subject_train.txt', he
ader=None, squeeze=True)

y_train = pd.read_csv('UCI_HAR_Dataset/train/y_train.txt', names=['Activity'],
squeeze=True)
y_train_labels = y_train.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DO
WNSTAIRS',\
                       4:'SITTING', 5:'STANDING',6:'LAYING'})

# put all columns in a single dataframe
train = X_train
train['Activity'] = y_train
train['ActivityName'] = y_train_labels
train.sample()
```

```
/usr/local/lib/python3.6/dist-packages/pandas/io/parsers.py:702: UserWarning:
Duplicate names specified. This will raise an error in the future.
  return _read(filepath_or_buffer, kwds)
```

Out[0]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X
4771	0.286151	-0.018426	-0.103938	-0.983312	-0.986697	-0.988534	-0.983914

1 rows × 564 columns

In [0]:
```
train.shape
```

Out[0]: (7352, 564)

Obtain the test data

In [0]:
```
# get the data from txt files to pandas dataffame
X_test = pd.read_csv('UCI_HAR_Dataset/test/X_test.txt', delim_whitespace=True,
header=None, names=features)

# add subject column to the dataframe
X_test['subject'] = pd.read_csv('UCI_HAR_Dataset/test/subject_test.txt', heade
r=None, squeeze=True)

# get y labels from the txt file
y_test = pd.read_csv('UCI_HAR_Dataset/test/y_test.txt', names=['Activity'], sq
ueeze=True)
y_test_labels = y_test.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWN
STAIRS',\
                       4:'SITTING', 5:'STANDING',6:'LAYING'})


# put all columns in a single dataframe
test = X_test
test['Activity'] = y_test
test['ActivityName'] = y_test_labels
test.sample()
```

```
/usr/local/lib/python3.6/dist-packages/pandas/io/parsers.py:702: UserWarning:
Duplicate names specified. This will raise an error in the future.
  return _read(filepath_or_buffer, kwds)
```

Out[0]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	t
525	0.292245	-0.016466	-0.118074	-0.971879	-0.887577	-0.912186	-0.977585	-(

1 rows × 564 columns

In [0]:
```
test.shape
```

Out[0]: (2947, 564)

Data Cleaning

1. Check for Duplicates

In [0]:
```
print('No of duplicates in train: {}'.format(sum(train.duplicated())))
print('No of duplicates in test : {}'.format(sum(test.duplicated())))
```

```
No of duplicates in train: 0
No of duplicates in test : 0
```

2. Checking for NaN/null values

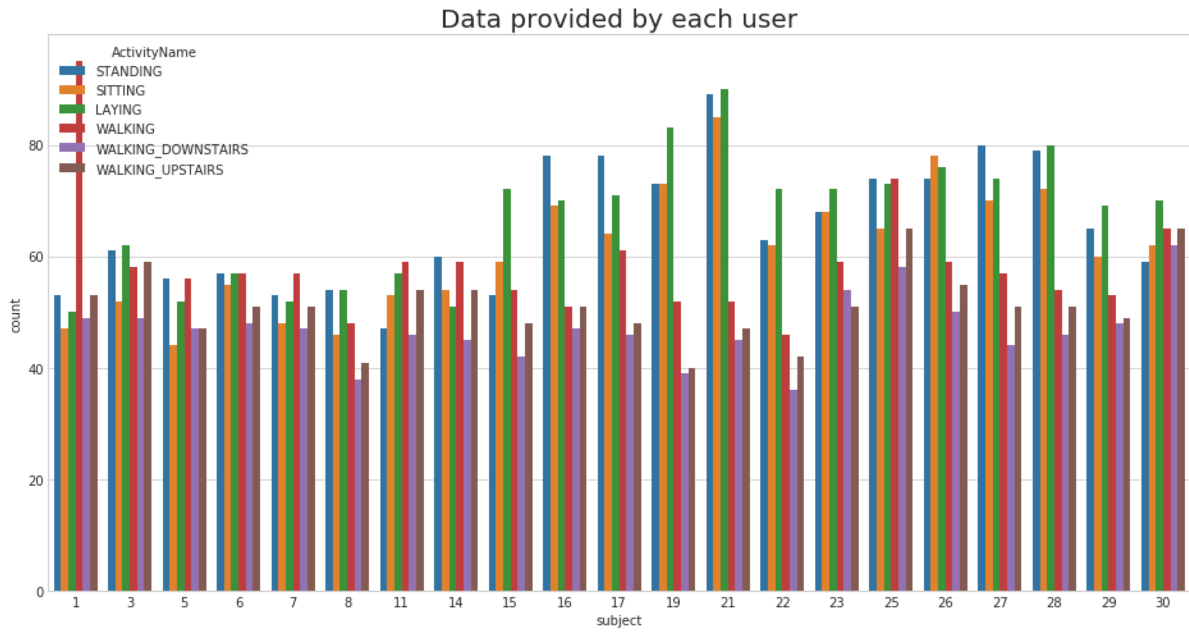
In [0]:
```
print('We have {} NaN/Null values in train'.format(train.isnull().values.sum
()))
print('We have {} NaN/Null values in test'.format(test.isnull().values.sum()))
```

```
We have 0 NaN/Null values in train
We have 0 NaN/Null values in test
```

3. Check for data imbalance

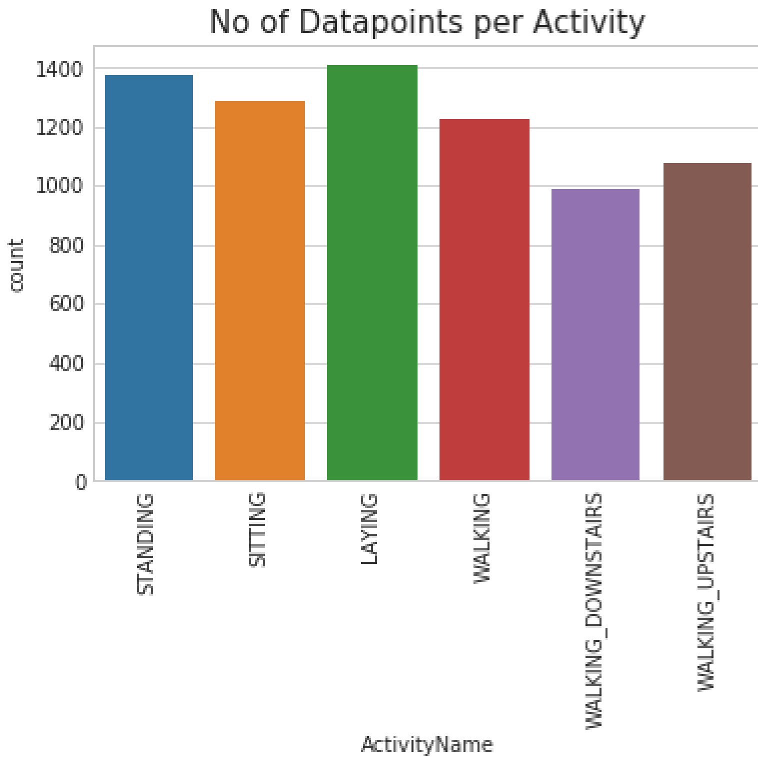
In [0]:
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set_style('whitegrid')
plt.rcParams['font.family'] = 'Dejavu Sans'
```

In [0]:
```
plt.figure(figsize=(16,8))
plt.title('Data provided by each user', fontsize=20)
sns.countplot(x='subject',hue='ActivityName', data = train)
plt.show()
```



We have got almost same number of reading from all the subjects

In [0]:
```
plt.title('No of Datapoints per Activity', fontsize=15)
sns.countplot(train.ActivityName)
plt.xticks(rotation=90)
plt.show()
```



Observation

> Our data is well balanced (almost)

4. Changing feature names

In [0]:
```
columns = train.columns

# Removing '()' from column names
columns = columns.str.replace('[()]','')
columns = columns.str.replace('[-]', '')
columns = columns.str.replace('[,]','')

train.columns = columns
test.columns = columns

test.columns
```

Out[0]:
```
Index(['tBodyAccmeanX', 'tBodyAccmeanY', 'tBodyAccmeanZ', 'tBodyAccstdX',
       'tBodyAccstdY', 'tBodyAccstdZ', 'tBodyAccmadX', 'tBodyAccmadY',
       'tBodyAccmadZ', 'tBodyAccmaxX',
       ...
       'angletBodyAccMeangravity', 'angletBodyAccJerkMeangravityMean',
       'angletBodyGyroMeangravityMean', 'angletBodyGyroJerkMeangravityMean',
       'angleXgravityMean', 'angleYgravityMean', 'angleZgravityMean',
       'subject', 'Activity', 'ActivityName'],
      dtype='object', length=564)
```

5. Save this dataframe in a csv files

In [0]:
```
train.to_csv('UCI_HAR_Dataset/train.csv', index=False)
test.to_csv('UCI_HAR_Dataset/test.csv', index=False)
```

Exploratory Data Analysis

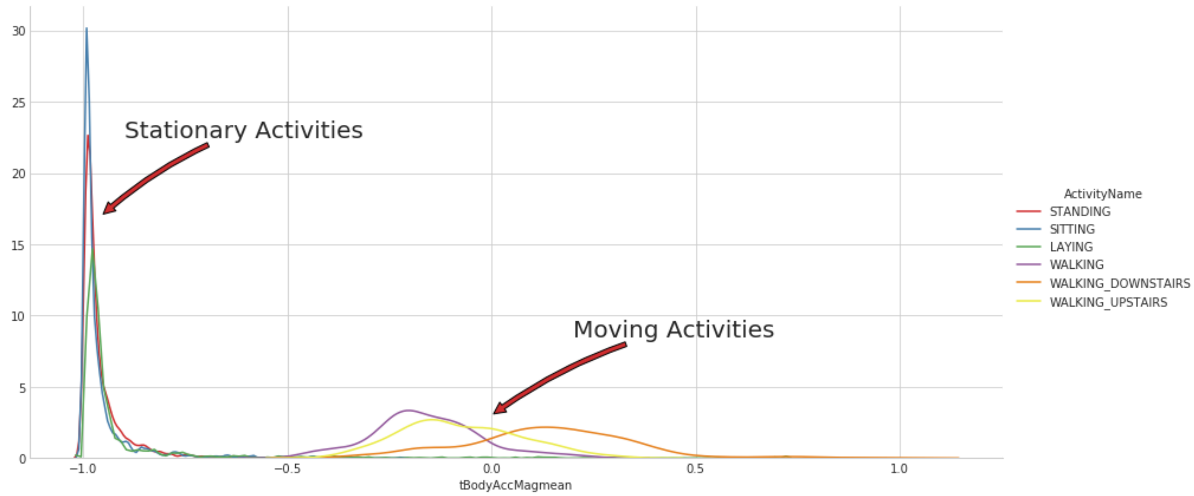
"***Without domain knowledge EDA has no meaning, without EDA a problem has no soul.***"

1. Featuring Engineering from Domain Knowledge

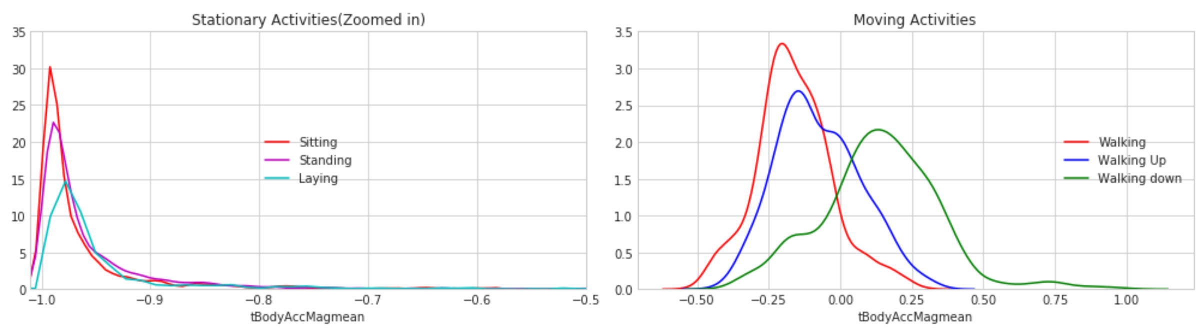
- **Static and Dynamic Activities**
  - In static activities (sit, stand, lie down) motion information will not be very useful.
  - In the dynamic activities (Walking, WalkingUpstairs,WalkingDownstairs) motion info will be significant.

2. Stationary and Moving activities are completely different

In [0]:
```
sns.set_palette("Set1", desat=0.80)
facetgrid = sns.FacetGrid(train, hue='ActivityName', size=6,aspect=2)
facetgrid.map(sns.distplot,'tBodyAccMagmean', hist=False)\
    .add_legend()
plt.annotate("Stationary Activities", xy=(-0.956,17), xytext=(-0.9, 23), size=
20,\
            va='center', ha='left',\
            arrowprops=dict(arrowstyle="simple",connectionstyle="arc3,rad=0.1"
))

plt.annotate("Moving Activities", xy=(0,3), xytext=(0.2, 9), size=20,\
            va='center', ha='left',\
            arrowprops=dict(arrowstyle="simple",connectionstyle="arc3,rad=0.1"
))
plt.show()
```

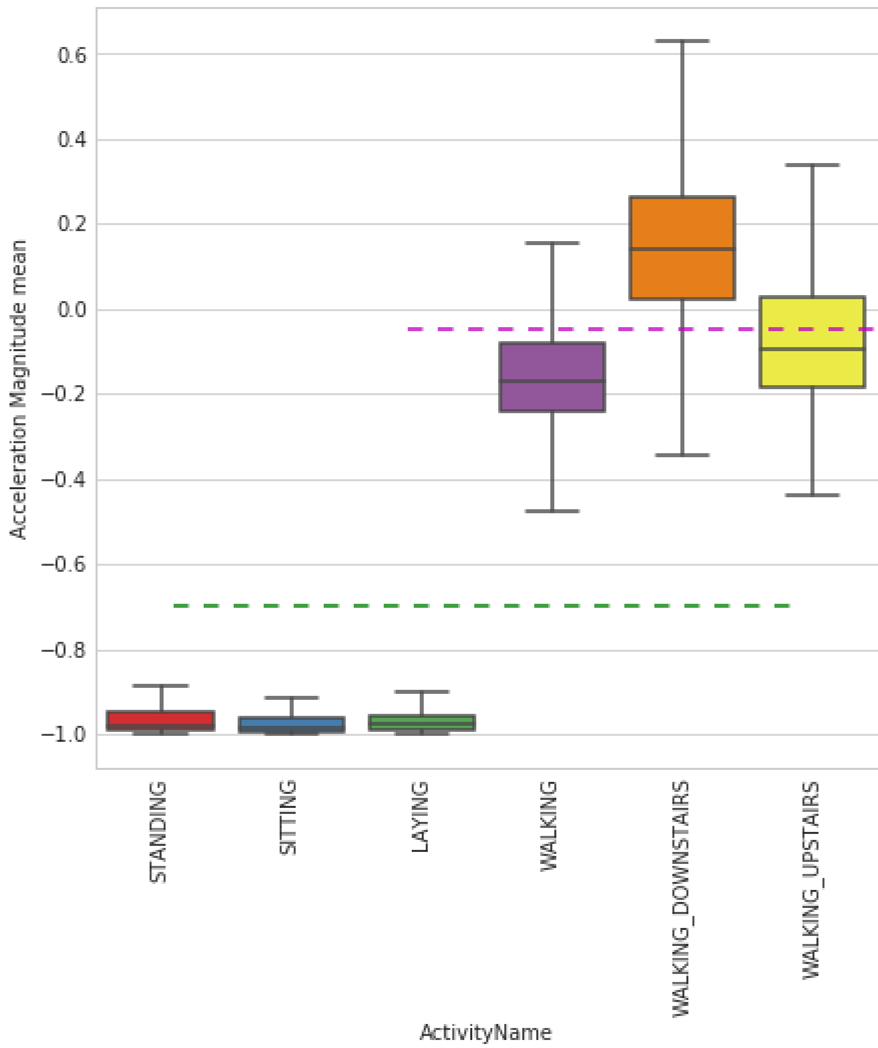


In [0]:
```
# for plotting purposes taking datapoints of each activity to a different data frame
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

plt.figure(figsize=(14,7))
plt.subplot(2,2,1)
plt.title('Stationary Activities(Zoomed in)')
sns.distplot(df4['tBodyAccMagmean'],color = 'r',hist = False, label = 'Sitting')
sns.distplot(df5['tBodyAccMagmean'],color = 'm',hist = False,label = 'Standing')
sns.distplot(df6['tBodyAccMagmean'],color = 'c',hist = False, label = 'Laying')
plt.axis([-1.01, -0.5, 0, 35])
plt.legend(loc='center')

plt.subplot(2,2,2)
plt.title('Moving Activities')
sns.distplot(df1['tBodyAccMagmean'],color = 'red',hist = False, label = 'Walking')
sns.distplot(df2['tBodyAccMagmean'],color = 'blue',hist = False,label = 'Walking Up')
sns.distplot(df3['tBodyAccMagmean'],color = 'green',hist = False, label = 'Walking down')
plt.legend(loc='center right')


plt.tight_layout()
plt.show()
```



3. Magnitude of an acceleration can saperate it well

In [0]:
```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMagmean',data=train, showfliers=False
, saturation=1)
plt.ylabel('Acceleration Magnitude mean')
plt.axhline(y=-0.7, xmin=0.1, xmax=0.9,dashes=(5,5), c='g')
plt.axhline(y=-0.05, xmin=0.4, dashes=(5,5), c='m')
plt.xticks(rotation=90)
plt.show()
```

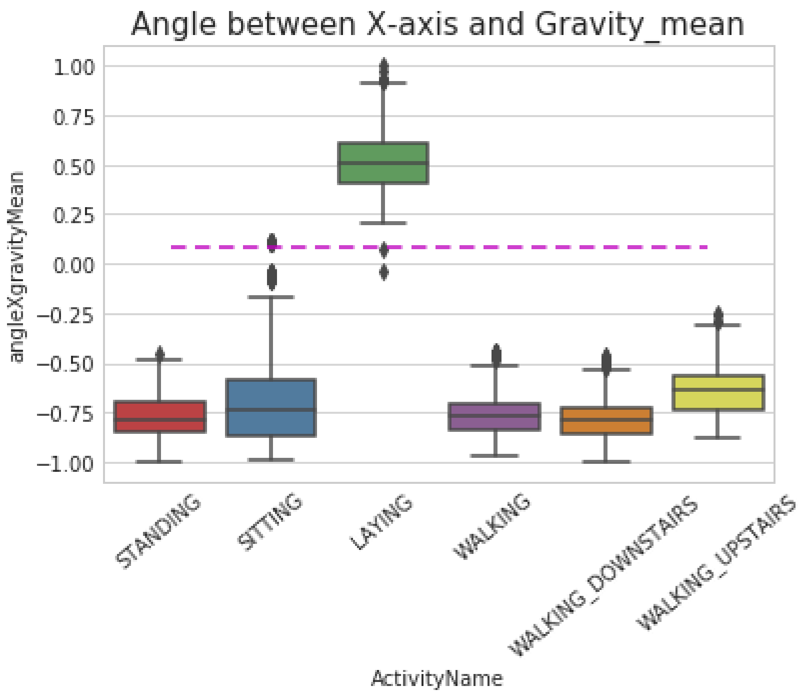


Observations:

- If tAccMean is < -0.8 then the Activities are either Standing or Sitting or Laying.
- If tAccMean is > -0.6 then the Activities are either Walking or WalkingDownstairs or WalkingUpstairs.
- If tAccMean > 0.0 then the Activity is WalkingDownstairs.
- We can classify 75% the Acitivity labels with some errors.

4. Position of GravityAccelerationComponants also matters

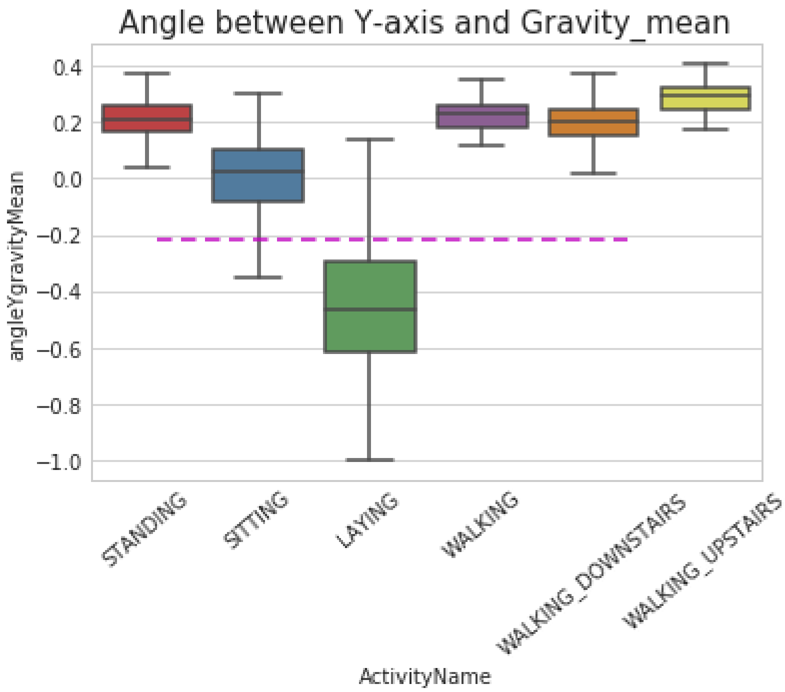
In [0]:
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



Observations:

- If angleX,gravityMean > 0 then Activity is Laying.
- We can classify all datapoints belonging to Laying activity with just a single if else statement.

In [0]:
```
sns.boxplot(x='ActivityName', y='angleYgravityMean', data = train, showfliers=
False)
plt.title('Angle between Y-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.axhline(y=-0.22, xmin=0.1, xmax=0.8, dashes=(5,3), c='m')
plt.show()
```



Apply t-sne on the data

In [0]:
```
import numpy as np
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns
```

In [0]:
```
# performs t-sne with different perplexity values and their repective plots..

def perform_tsne(X_data, y_data, perplexities, n_iter=1000, img_name_prefix='t
-sne'):

    for index,perplexity in enumerate(perplexities):
        # perform t-sne
        print('\nperforming tsne with perplexity {} and with {} iterations at
 max'.format(perplexity, n_iter))
        X_reduced = TSNE(verbose=2, perplexity=perplexity).fit_transform(X_dat
a)
        print('Done..')

        # prepare the data for seaborn
        print('Creating plot for this t-sne visualization..')
        df = pd.DataFrame({'x':X_reduced[:,0], 'y':X_reduced[:,1] ,'label':y_d
ata})

        # draw the plot in appropriate place in the grid
        sns.lmplot(data=df, x='x', y='y', hue='label', fit_reg=False, size=8,\
                   palette="Set1",markers=['^','v','s','o', '1','2'])
        plt.title("perplexity : {} and max_iter : {}".format(perplexity, n_ite
r))
        img_name = img_name_prefix + '_perp_{}_iter_{}.png'.format(perplexity,
n_iter)
        print('saving this plot as image in present working directory...')
        plt.savefig(img_name)
        plt.show()
        print('Done')
```

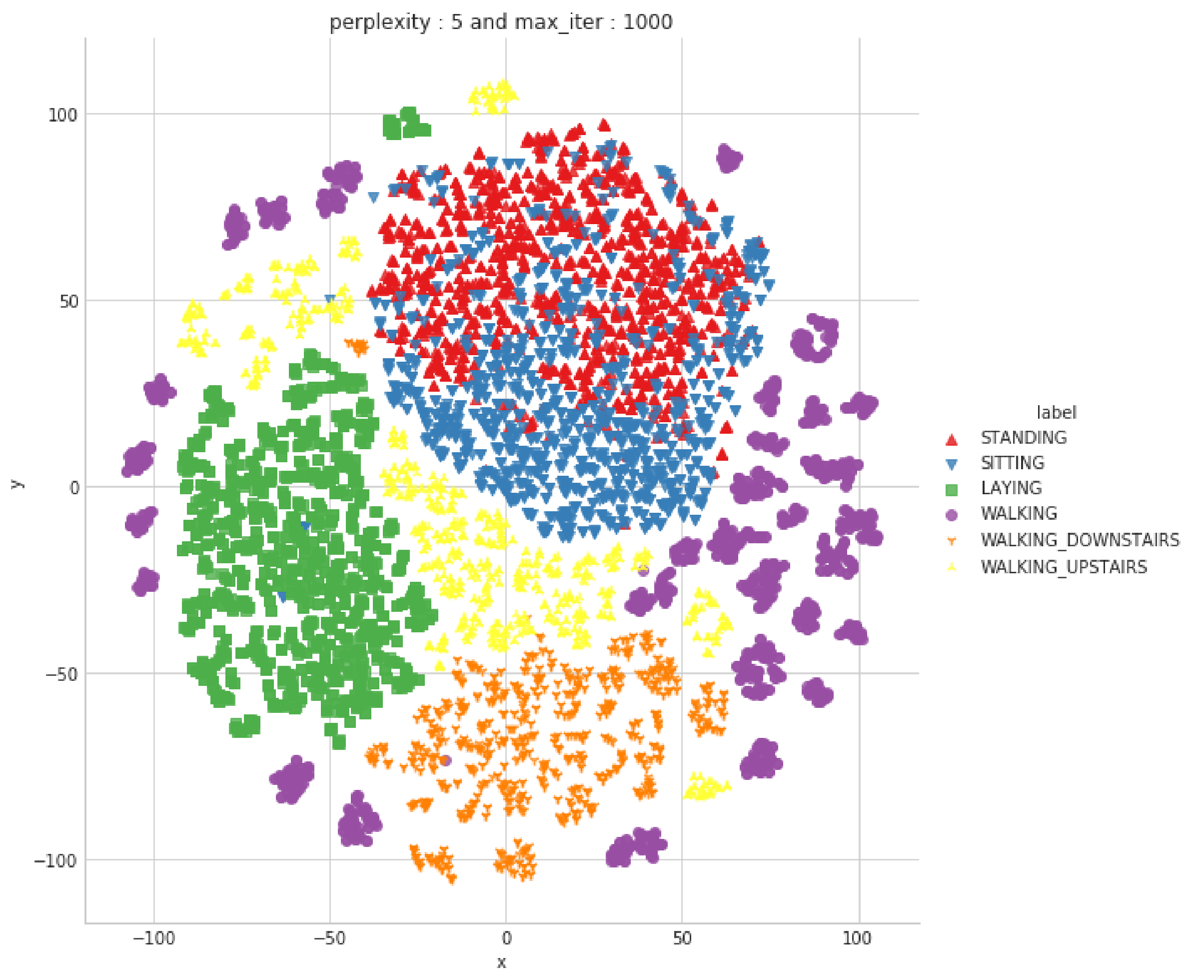
In [0]:
```
X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train['ActivityName']
perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[2,5,10,20,5
0])
```

```
performing tsne with perplexity 2 and with 1000 iterations at max
[t-SNE] Computing 7 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.426s...
[t-SNE] Computed neighbors for 7352 samples in 72.001s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.635855
[t-SNE] Computed conditional probabilities in 0.071s
[t-SNE] Iteration 50: error = 124.8017578, gradient norm = 0.0253939 (50 iter
ations in 16.625s)
[t-SNE] Iteration 100: error = 107.2019501, gradient norm = 0.0284782 (50 ite
rations in 9.735s)
[t-SNE] Iteration 150: error = 100.9872894, gradient norm = 0.0185151 (50 ite
rations in 5.346s)
[t-SNE] Iteration 200: error = 97.6054382, gradient norm = 0.0142084 (50 iter
ations in 7.013s)
[t-SNE] Iteration 250: error = 95.3084183, gradient norm = 0.0132592 (50 iter
ations in 5.703s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 95.308418
[t-SNE] Iteration 300: error = 4.1209540, gradient norm = 0.0015668 (50 itera
tions in 7.156s)
[t-SNE] Iteration 350: error = 3.2113254, gradient norm = 0.0009953 (50 itera
tions in 8.022s)
[t-SNE] Iteration 400: error = 2.7819963, gradient norm = 0.0007203 (50 itera
tions in 9.419s)
[t-SNE] Iteration 450: error = 2.5178111, gradient norm = 0.0005655 (50 itera
tions in 9.370s)
[t-SNE] Iteration 500: error = 2.3341548, gradient norm = 0.0004804 (50 itera
tions in 7.681s)
[t-SNE] Iteration 550: error = 2.1961622, gradient norm = 0.0004183 (50 itera
tions in 7.097s)
[t-SNE] Iteration 600: error = 2.0867445, gradient norm = 0.0003664 (50 itera
tions in 9.274s)
[t-SNE] Iteration 650: error = 1.9967778, gradient norm = 0.0003279 (50 itera
tions in 7.697s)
[t-SNE] Iteration 700: error = 1.9210005, gradient norm = 0.0002984 (50 itera
tions in 8.174s)
[t-SNE] Iteration 750: error = 1.8558111, gradient norm = 0.0002776 (50 itera
tions in 9.747s)
[t-SNE] Iteration 800: error = 1.7989457, gradient norm = 0.0002569 (50 itera
tions in 8.687s)
[t-SNE] Iteration 850: error = 1.7490212, gradient norm = 0.0002394 (50 itera
tions in 8.407s)
[t-SNE] Iteration 900: error = 1.7043383, gradient norm = 0.0002224 (50 itera
tions in 8.351s)
[t-SNE] Iteration 950: error = 1.6641431, gradient norm = 0.0002098 (50 itera
tions in 7.841s)
[t-SNE] Iteration 1000: error = 1.6279151, gradient norm = 0.0001989 (50 iter
ations in 5.623s)
[t-SNE] Error after 1000 iterations: 1.627915
Done..
```

```
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```

```
Done

performing tsne with perplexity 5 and with 1000 iterations at max
[t-SNE] Computing 16 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.263s...
[t-SNE] Computed neighbors for 7352 samples in 48.983s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.961265
[t-SNE] Computed conditional probabilities in 0.122s
[t-SNE] Iteration 50: error = 114.1862640, gradient norm = 0.0184120 (50 iter
ations in 55.655s)
[t-SNE] Iteration 100: error = 97.6535568, gradient norm = 0.0174309 (50 iter
ations in 12.580s)
[t-SNE] Iteration 150: error = 93.1900101, gradient norm = 0.0101048 (50 iter
ations in 9.180s)
[t-SNE] Iteration 200: error = 91.2315445, gradient norm = 0.0074560 (50 iter
ations in 10.340s)
[t-SNE] Iteration 250: error = 90.0714417, gradient norm = 0.0057667 (50 iter
ations in 9.458s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 90.071442
[t-SNE] Iteration 300: error = 3.5796804, gradient norm = 0.0014691 (50 itera
tions in 8.718s)
[t-SNE] Iteration 350: error = 2.8173938, gradient norm = 0.0007508 (50 itera
tions in 10.180s)
[t-SNE] Iteration 400: error = 2.4344938, gradient norm = 0.0005251 (50 itera
tions in 10.506s)
[t-SNE] Iteration 450: error = 2.2156141, gradient norm = 0.0004069 (50 itera
tions in 10.072s)
[t-SNE] Iteration 500: error = 2.0703306, gradient norm = 0.0003340 (50 itera
tions in 10.511s)
[t-SNE] Iteration 550: error = 1.9646366, gradient norm = 0.0002816 (50 itera
tions in 9.792s)
[t-SNE] Iteration 600: error = 1.8835558, gradient norm = 0.0002471 (50 itera
tions in 9.098s)
[t-SNE] Iteration 650: error = 1.8184001, gradient norm = 0.0002184 (50 itera
tions in 8.656s)
[t-SNE] Iteration 700: error = 1.7647167, gradient norm = 0.0001961 (50 itera
tions in 9.063s)
[t-SNE] Iteration 750: error = 1.7193680, gradient norm = 0.0001796 (50 itera
tions in 9.754s)
[t-SNE] Iteration 800: error = 1.6803776, gradient norm = 0.0001655 (50 itera
tions in 9.540s)
[t-SNE] Iteration 850: error = 1.6465144, gradient norm = 0.0001538 (50 itera
tions in 9.953s)
[t-SNE] Iteration 900: error = 1.6166563, gradient norm = 0.0001421 (50 itera
tions in 10.270s)
[t-SNE] Iteration 950: error = 1.5901035, gradient norm = 0.0001335 (50 itera
tions in 6.609s)
[t-SNE] Iteration 1000: error = 1.5664237, gradient norm = 0.0001257 (50 iter
ations in 8.553s)
```

```
[t-SNE] Error after 1000 iterations: 1.566424
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```

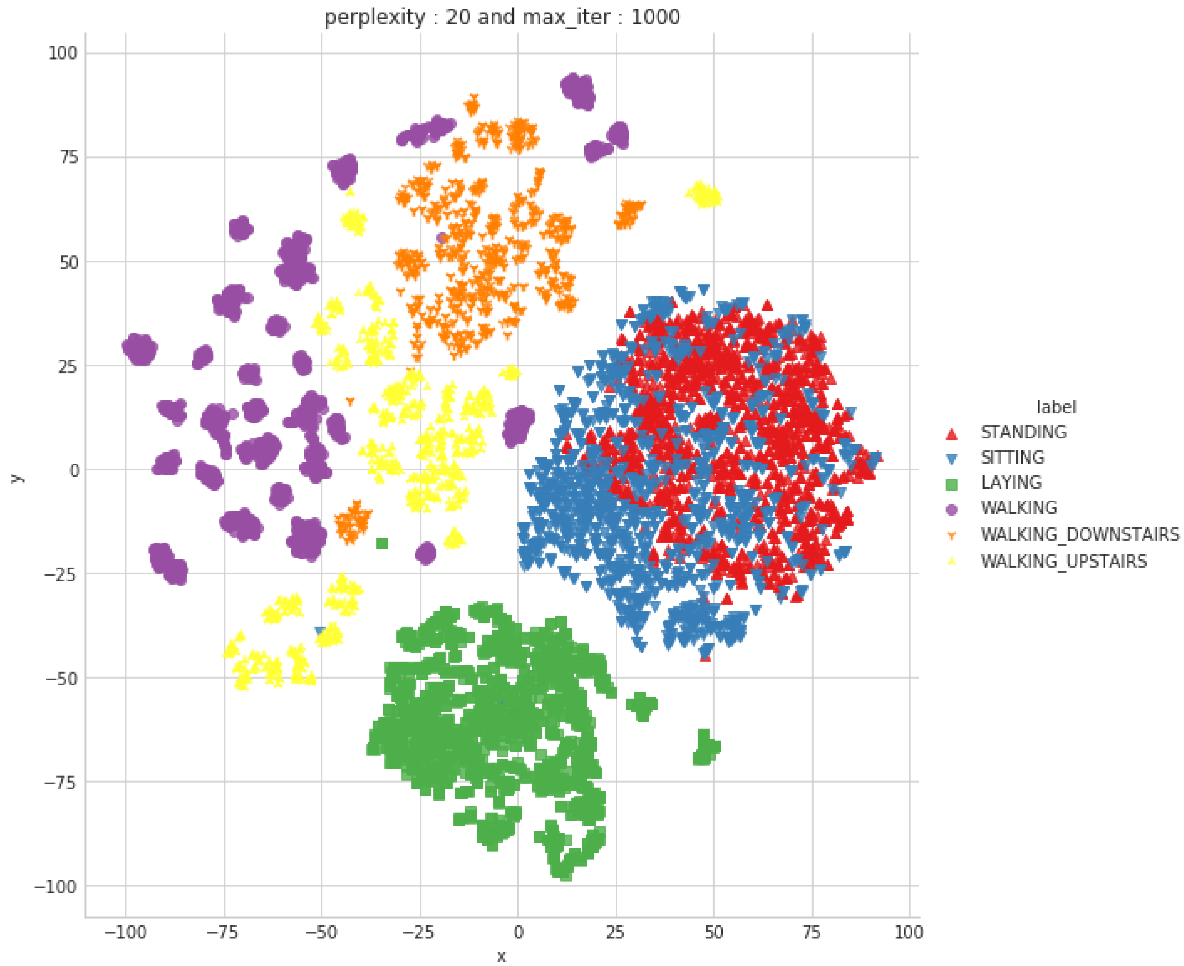


```
Done

performing tsne with perplexity 10 and with 1000 iterations at max
[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.410s...
[t-SNE] Computed neighbors for 7352 samples in 64.801s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.133828
[t-SNE] Computed conditional probabilities in 0.214s
[t-SNE] Iteration 50: error = 106.0169220, gradient norm = 0.0194293 (50 iter
ations in 24.550s)
[t-SNE] Iteration 100: error = 90.3036194, gradient norm = 0.0097653 (50 iter
ations in 11.936s)
[t-SNE] Iteration 150: error = 87.3132935, gradient norm = 0.0053059 (50 iter
ations in 11.246s)
[t-SNE] Iteration 200: error = 86.1169128, gradient norm = 0.0035844 (50 iter
ations in 11.864s)
[t-SNE] Iteration 250: error = 85.4133606, gradient norm = 0.0029100 (50 iter
ations in 11.944s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 85.413361
[t-SNE] Iteration 300: error = 3.1394315, gradient norm = 0.0013976 (50 itera
tions in 11.742s)
[t-SNE] Iteration 350: error = 2.4929206, gradient norm = 0.0006466 (50 itera
tions in 11.627s)
[t-SNE] Iteration 400: error = 2.1733041, gradient norm = 0.0004230 (50 itera
tions in 11.846s)
[t-SNE] Iteration 450: error = 1.9884514, gradient norm = 0.0003124 (50 itera
tions in 11.405s)
[t-SNE] Iteration 500: error = 1.8702440, gradient norm = 0.0002514 (50 itera
tions in 11.320s)
[t-SNE] Iteration 550: error = 1.7870129, gradient norm = 0.0002107 (50 itera
tions in 12.009s)
[t-SNE] Iteration 600: error = 1.7246909, gradient norm = 0.0001824 (50 itera
tions in 10.632s)
[t-SNE] Iteration 650: error = 1.6758548, gradient norm = 0.0001590 (50 itera
tions in 11.270s)
[t-SNE] Iteration 700: error = 1.6361949, gradient norm = 0.0001451 (50 itera
tions in 12.072s)
[t-SNE] Iteration 750: error = 1.6034756, gradient norm = 0.0001305 (50 itera
tions in 11.607s)
[t-SNE] Iteration 800: error = 1.5761518, gradient norm = 0.0001188 (50 itera
tions in 9.409s)
[t-SNE] Iteration 850: error = 1.5527289, gradient norm = 0.0001113 (50 itera
tions in 8.309s)
[t-SNE] Iteration 900: error = 1.5328671, gradient norm = 0.0001021 (50 itera
tions in 9.433s)
[t-SNE] Iteration 950: error = 1.5152045, gradient norm = 0.0000974 (50 itera
tions in 11.488s)
[t-SNE] Iteration 1000: error = 1.4999681, gradient norm = 0.0000933 (50 iter
ations in 10.593s)
```

```
[t-SNE] Error after 1000 iterations: 1.499968
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```

```
Done

performing tsne with perplexity 20 and with 1000 iterations at max
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.425s...
[t-SNE] Computed neighbors for 7352 samples in 61.792s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.274335
[t-SNE] Computed conditional probabilities in 0.355s
[t-SNE] Iteration 50: error = 97.5202179, gradient norm = 0.0223863 (50 itera
tions in 21.168s)
[t-SNE] Iteration 100: error = 83.9500732, gradient norm = 0.0059110 (50 iter
ations in 17.306s)
[t-SNE] Iteration 150: error = 81.8804779, gradient norm = 0.0035797 (50 iter
ations in 14.258s)
[t-SNE] Iteration 200: error = 81.1615143, gradient norm = 0.0022536 (50 iter
ations in 14.130s)
[t-SNE] Iteration 250: error = 80.7704086, gradient norm = 0.0018108 (50 iter
ations in 15.340s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 80.770409
[t-SNE] Iteration 300: error = 2.6957574, gradient norm = 0.0012993 (50 itera
tions in 13.605s)
[t-SNE] Iteration 350: error = 2.1637220, gradient norm = 0.0005765 (50 itera
tions in 13.248s)
[t-SNE] Iteration 400: error = 1.9143614, gradient norm = 0.0003474 (50 itera
tions in 14.774s)
[t-SNE] Iteration 450: error = 1.7684202, gradient norm = 0.0002458 (50 itera
tions in 15.502s)
[t-SNE] Iteration 500: error = 1.6744757, gradient norm = 0.0001923 (50 itera
tions in 14.808s)
[t-SNE] Iteration 550: error = 1.6101606, gradient norm = 0.0001575 (50 itera
tions in 14.043s)
[t-SNE] Iteration 600: error = 1.5641028, gradient norm = 0.0001344 (50 itera
tions in 15.769s)
[t-SNE] Iteration 650: error = 1.5291905, gradient norm = 0.0001182 (50 itera
tions in 15.834s)
[t-SNE] Iteration 700: error = 1.5024391, gradient norm = 0.0001055 (50 itera
tions in 15.398s)
[t-SNE] Iteration 750: error = 1.4809053, gradient norm = 0.0000965 (50 itera
tions in 14.594s)
[t-SNE] Iteration 800: error = 1.4631859, gradient norm = 0.0000884 (50 itera
tions in 15.025s)
[t-SNE] Iteration 850: error = 1.4486470, gradient norm = 0.0000832 (50 itera
tions in 14.060s)
[t-SNE] Iteration 900: error = 1.4367288, gradient norm = 0.0000804 (50 itera
tions in 12.389s)
[t-SNE] Iteration 950: error = 1.4270191, gradient norm = 0.0000761 (50 itera
tions in 10.392s)
[t-SNE] Iteration 1000: error = 1.4189968, gradient norm = 0.0000787 (50 iter
ations in 12.355s)
```

```
[t-SNE] Error after 1000 iterations: 1.418997
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```



```
Done

performing tsne with perplexity 50 and with 1000 iterations at max
[t-SNE] Computing 151 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.376s...
[t-SNE] Computed neighbors for 7352 samples in 73.164s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 1.437672
[t-SNE] Computed conditional probabilities in 0.844s
[t-SNE] Iteration 50: error = 86.1525574, gradient norm = 0.0242986 (50 itera
tions in 36.249s)
[t-SNE] Iteration 100: error = 75.9874649, gradient norm = 0.0061005 (50 iter
ations in 30.453s)
[t-SNE] Iteration 150: error = 74.7072296, gradient norm = 0.0024708 (50 iter
ations in 28.461s)
[t-SNE] Iteration 200: error = 74.2736282, gradient norm = 0.0018644 (50 iter
ations in 27.735s)
[t-SNE] Iteration 250: error = 74.0722427, gradient norm = 0.0014078 (50 iter
ations in 26.835s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 74.072243
[t-SNE] Iteration 300: error = 2.1539080, gradient norm = 0.0011796 (50 itera
tions in 25.445s)
[t-SNE] Iteration 350: error = 1.7567128, gradient norm = 0.0004845 (50 itera
tions in 21.282s)
[t-SNE] Iteration 400: error = 1.5888531, gradient norm = 0.0002798 (50 itera
tions in 21.015s)
[t-SNE] Iteration 450: error = 1.4956820, gradient norm = 0.0001894 (50 itera
tions in 23.332s)
[t-SNE] Iteration 500: error = 1.4359720, gradient norm = 0.0001420 (50 itera
tions in 23.083s)
[t-SNE] Iteration 550: error = 1.3947564, gradient norm = 0.0001117 (50 itera
tions in 19.626s)
[t-SNE] Iteration 600: error = 1.3653858, gradient norm = 0.0000949 (50 itera
tions in 22.752s)
[t-SNE] Iteration 650: error = 1.3441534, gradient norm = 0.0000814 (50 itera
tions in 23.972s)
[t-SNE] Iteration 700: error = 1.3284039, gradient norm = 0.0000742 (50 itera
tions in 20.636s)
[t-SNE] Iteration 750: error = 1.3171139, gradient norm = 0.0000700 (50 itera
tions in 20.407s)
[t-SNE] Iteration 800: error = 1.3085558, gradient norm = 0.0000657 (50 itera
tions in 24.951s)
[t-SNE] Iteration 850: error = 1.3017821, gradient norm = 0.0000603 (50 itera
tions in 24.719s)
[t-SNE] Iteration 900: error = 1.2962619, gradient norm = 0.0000586 (50 itera
tions in 24.500s)
[t-SNE] Iteration 950: error = 1.2914882, gradient norm = 0.0000573 (50 itera
tions in 24.132s)
[t-SNE] Iteration 1000: error = 1.2874244, gradient norm = 0.0000546 (50 iter
ations in 22.840s)
```

```
[t-SNE] Error after 1000 iterations: 1.287424
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```


```
Done
```

Obtain the train and test data

In [54]:
```
train = pd.read_csv('UCI_HAR_Dataset/train.csv')
test = pd.read_csv('UCI_HAR_Dataset/test.csv')
print(train.shape, test.shape)
```

```
(7352, 564) (2947, 564)
```

In [0]:
```
train.head(3)
```

Out[0]:

	tBodyAccmeanX	tBodyAccmeanY	tBodyAccmeanZ	tBodyAccstdX	tBodyAccstdY	tE
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-C
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-C
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-C

3 rows × 564 columns

In [0]:
```
# get X_train and y_train from csv files
X_train = train.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_train = train.ActivityName
```

In [0]:
```
# get X_test and y_test from test csv file
X_test = test.drop(['subject', 'Activity', 'ActivityName'], axis=1)
y_test = test.ActivityName
```

In [57]:
```
print('X_train and y_train : ({},{})'.format(X_train.shape, y_train.shape))
print('X_test  and y_test  : ({},{})'.format(X_test.shape, y_test.shape))
```

```
X_train and y_train : ((7352, 561),(7352,))
X_test  and y_test  : ((2947, 561),(2947,))
```

In [0]:
```
y_tr=y_train
y_te=y_test
```

Let's model with our data

Labels that are useful in plotting confusion matrix

In [0]:
```
labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING
_UPSTAIRS']
```

Function to plot the confusion matrix

In [0]:
```
import itertools
import numpy as np
import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
plt.rcParams["font.family"] = 'DejaVu Sans'

def plot_confusion_matrix(cm, classes,
                          normalize=False,
                          title='Confusion matrix',
                          cmap=plt.cm.Blues):
    if normalize:
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

    fmt = '.2f' if normalize else 'd'
    thresh = cm.max() / 2.
    for i, j in itertools.product(range(cm.shape[0]), range(cm.shape[1])):
        plt.text(j, i, format(cm[i, j], fmt),
                 horizontalalignment="center",
                 color="white" if cm[i, j] > thresh else "black")

    plt.tight_layout()
    plt.ylabel('True label')
    plt.xlabel('Predicted label')
```

Generic function to run any model specified

In [0]:
```
from datetime import datetime
def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_no
rmalize=True, \
                 print_cm=True, cm_cmap=plt.cm.Greens):


    # to store results at various phases
    results = dict()

    # time at which model starts training
    train_start_time = datetime.now()
    print('training the model..')
    model.fit(X_train, y_train)
    print('Done \n \n')
    train_end_time = datetime.now()
    results['training_time'] =  train_end_time - train_start_time
    print('training_time(HH:MM:SS.ms) - {}\n\n'.format(results['training_time'
]))


    # predict test data
    print('Predicting test data')
    test_start_time = datetime.now()
    y_pred = model.predict(X_test)
    test_end_time = datetime.now()
    print('Done \n \n')
    results['testing_time'] = test_end_time - test_start_time
    print('testing time(HH:MM:SS:ms) - {}\n\n'.format(results['testing_time'
]))
    results['predicted'] = y_pred


    # calculate overall accuracty of the model
    accuracy = metrics.accuracy_score(y_true=y_test, y_pred=y_pred)
    # store accuracy in results
    results['accuracy'] = accuracy
    print('---------------------')
    print('|      Accuracy      |')
    print('---------------------')
    print('\n    {}\n\n'.format(accuracy))


    # confusion matrix
    cm = metrics.confusion_matrix(y_test, y_pred)
    results['confusion_matrix'] = cm
    if print_cm:
        print('--------------------')
        print('| Confusion Matrix |')
        print('--------------------')
        print('\n {}'.format(cm))

    # plot confusin matrix
    plt.figure(figsize=(8,8))
    plt.grid(b=False)
    plot_confusion_matrix(cm, classes=class_labels, normalize=True, title='Nor
malized confusion matrix', cmap = cm_cmap)
```

```
    plt.show()

    # get classification report
    print('-------------------------')
    print('| Classifiction Report |')
    print('-------------------------')
    classification_report = metrics.classification_report(y_test, y_pred)
    # store report in results
    results['classification_report'] = classification_report
    print(classification_report)

    # add the trained  model to the results
    results['model'] = model

    return results
```

Method to print the gridsearch Attributes

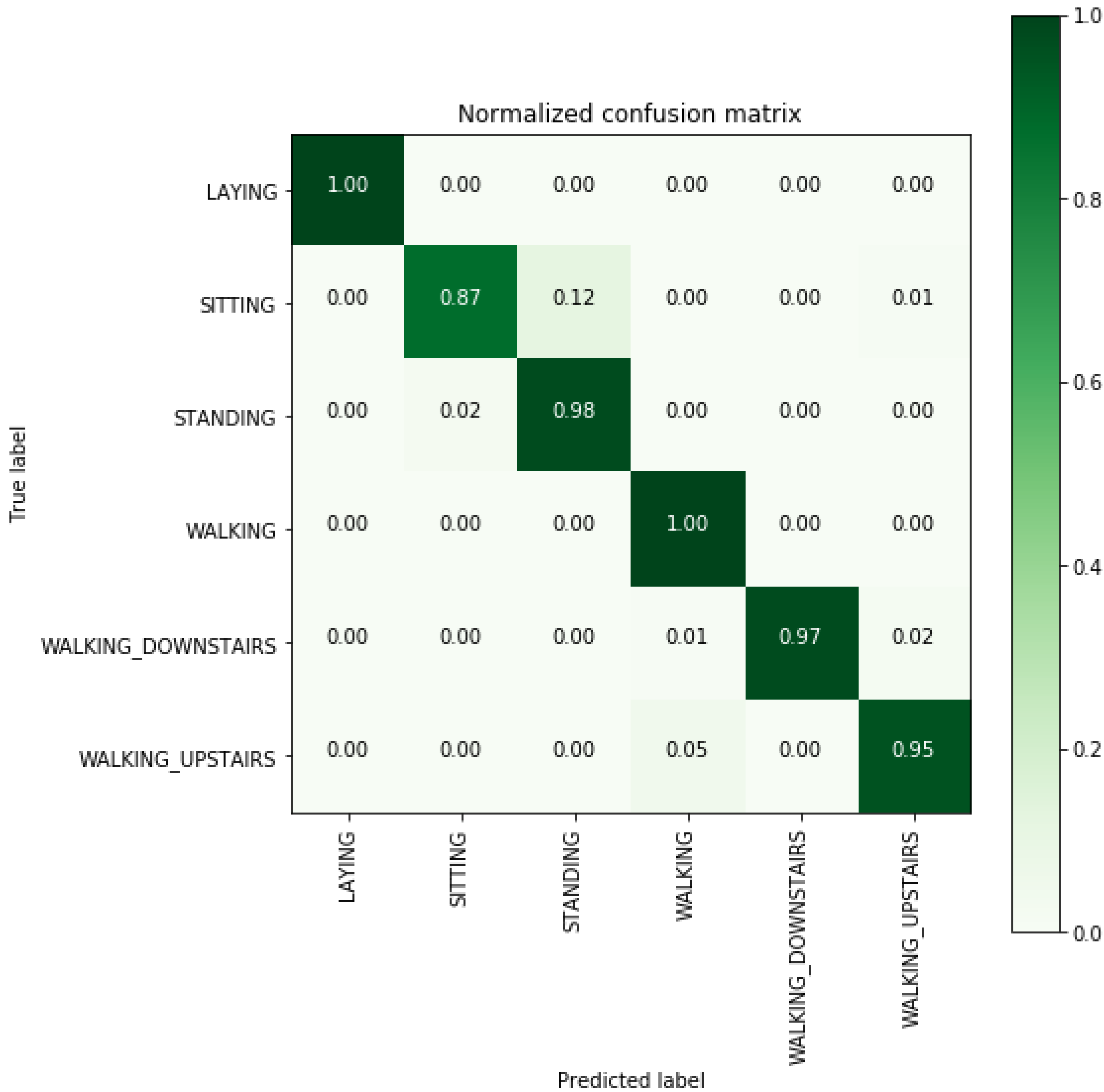
In [0]:
```
def print_grid_search_attributes(model):
    # Estimator that gave highest score among all the estimators formed in Gri
dSearch
    print('--------------------------')
    print('|      Best Estimator     |')
    print('--------------------------')
    print('\n\t{}\n'.format(model.best_estimator_))


    # parameters that gave best results while performing grid search
    print('--------------------------')
    print('|     Best parameters     |')
    print('--------------------------')
    print('\tParameters of best estimator : \n\n\t{}\n'.format(model.best_para
ms_))


    #  number of cross validation splits
    print('---------------------------------')
    print('|   No of CrossValidation sets   |')
    print('--------------------------------')
    print('\n\tTotal numbre of cross validation sets: {}\n'.format(model.n_spl
its_))


    # Average cross validated score of the best estimator, from the Grid Searc
h
    print('--------------------------')
    print('|        Best Score       |')
    print('--------------------------')
    print('\n\tAverage Cross Validate scores of best estimator : \n\n\t{}\n'.f
ormat(model.best_score_))
```

1. Logistic Regression with Grid Search

In [0]:
```
from sklearn import linear_model
from sklearn import metrics

from sklearn.model_selection import GridSearchCV
```

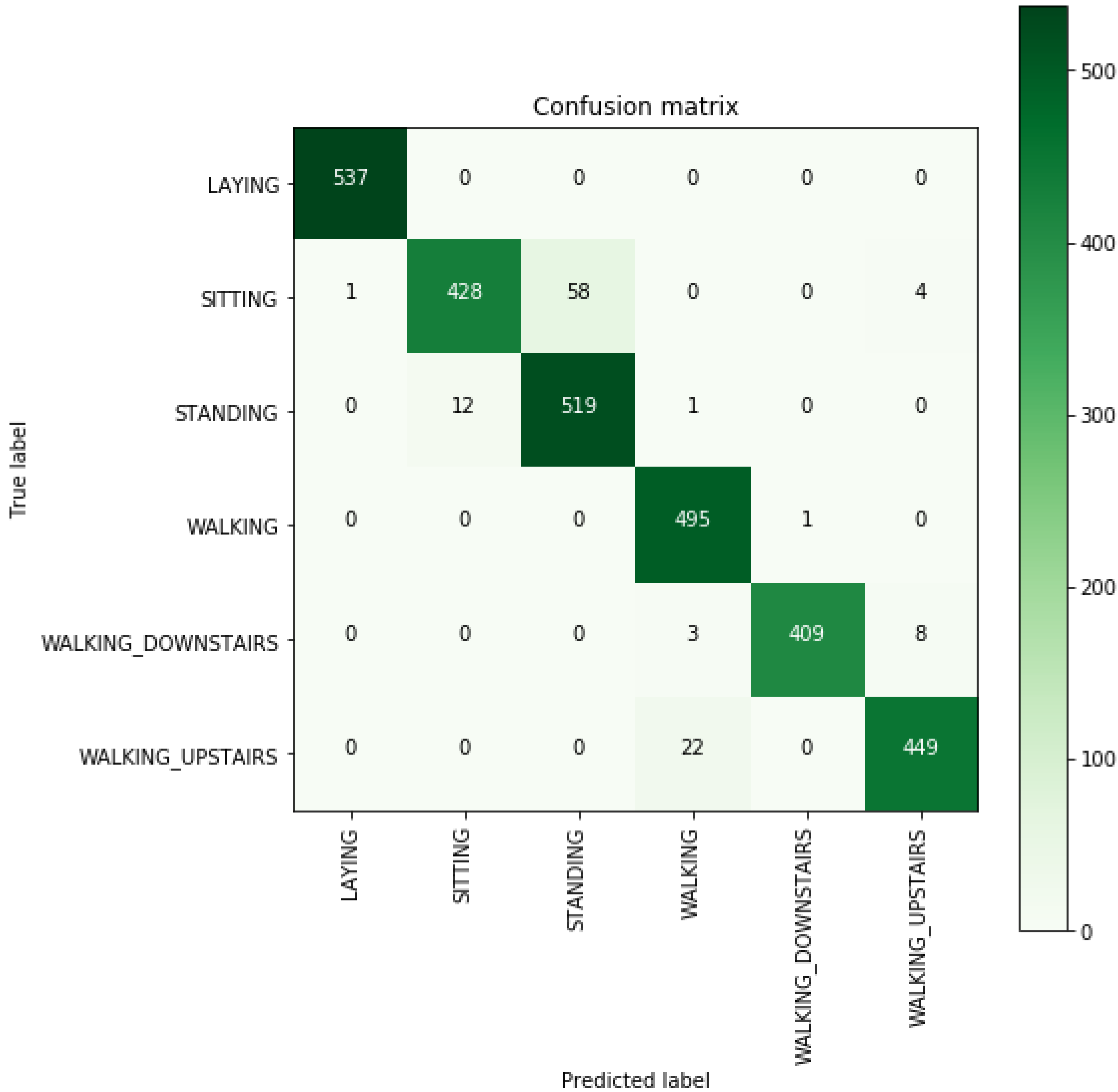
In [0]:
```
# start Grid search
parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1']}
log_reg = linear_model.LogisticRegression()
log_reg_grid = GridSearchCV(log_reg, param_grid=parameters, cv=3, verbose=1, n
_jobs=-1)
log_reg_grid_results =  perform_model(log_reg_grid, X_train, y_train, X_test,
y_test, class_labels=labels)
```

```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed:  1.2min finished

Done


training_time(HH:MM:SS.ms) - 0:01:25.843810


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.009192


---------------------
|      Accuracy      |
---------------------

    0.9626739056667798


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  1 428  58   0   0   4]
 [  0  12 519   1   0   0]
 [  0   0   0 495   1   0]
 [  0   0   0   3 409   8]
 [  0   0   0  22   0 449]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.87      0.92       491
          STANDING       0.90      0.98      0.94       532
           WALKING       0.95      1.00      0.97       496
WALKING_DOWNSTAIRS       1.00      0.97      0.99       420
  WALKING_UPSTAIRS       0.97      0.95      0.96       471

       avg / total       0.96      0.96      0.96      2947
```

In [0]:
```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(log_reg_grid_results['confusion_matrix'], classes=labels
, cmap=plt.cm.Greens, )
plt.show()
```



In [0]:
```
# observe the attributes of the model
print_grid_search_attributes(log_reg_grid_results['model'])
```

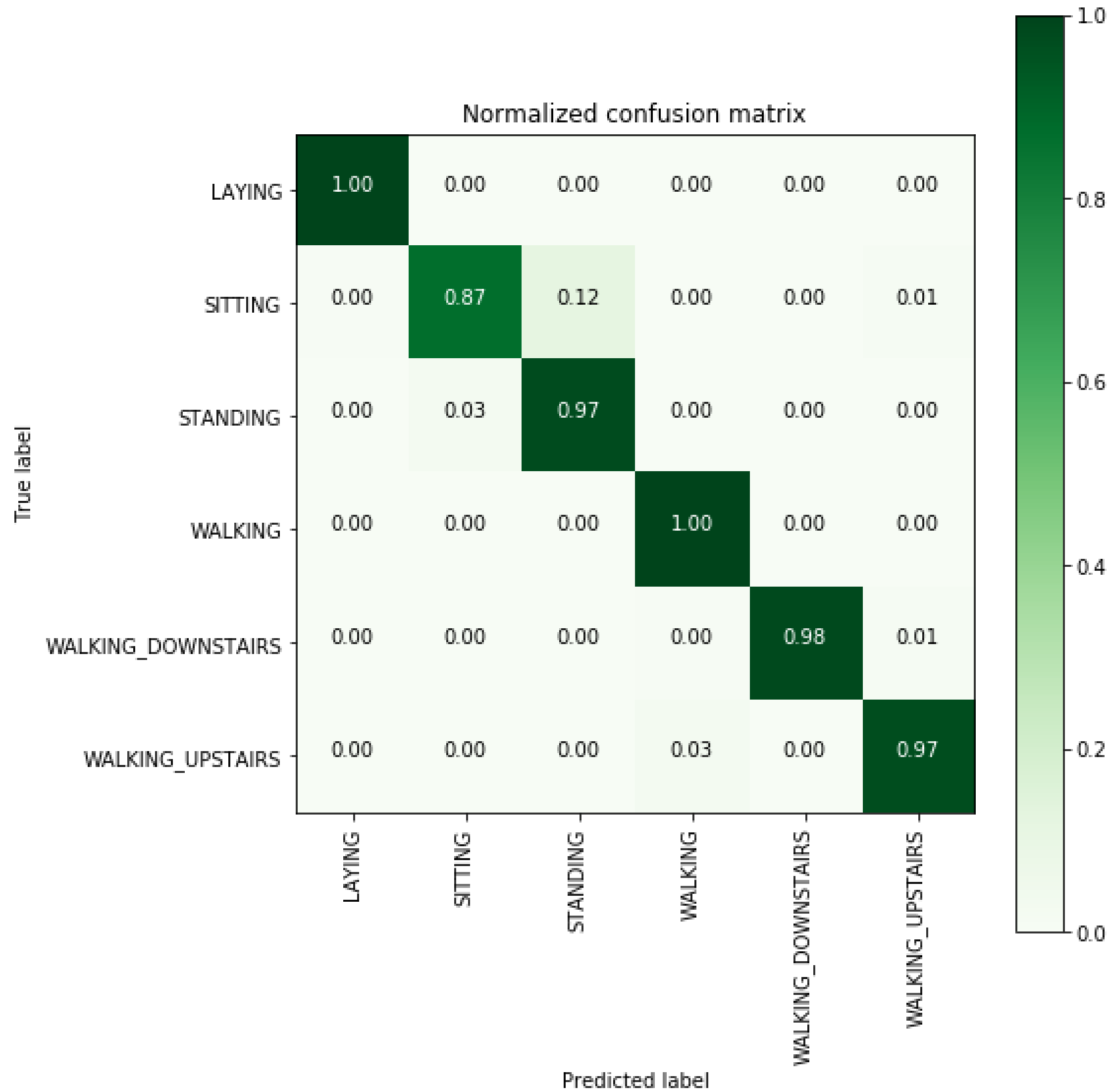
```
--------------------------
|      Best Estimator     |
--------------------------

        LogisticRegression(C=30, class_weight=None, dual=False, fit_intercept
=True,
          intercept_scaling=1, max_iter=100, multi_class='ovr', n_jobs=1,
          penalty='l2', random_state=None, solver='liblinear', tol=0.0001,
          verbose=0, warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'C': 30, 'penalty': 'l2'}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|       Best Score        |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9461371055495104
```

2. Linear SVC with GridSearch

In [0]:
```
from sklearn.svm import LinearSVC
```

In [0]:
```
parameters = {'C':[0.125, 0.5, 1, 2, 8, 16]}
lr_svc = LinearSVC(tol=0.00005)
lr_svc_grid = GridSearchCV(lr_svc, param_grid=parameters, n_jobs=-1, verbose=1
)
lr_svc_grid_results = perform_model(lr_svc_grid, X_train, y_train, X_test, y_t
est, class_labels=labels)
```

```
training the model..
Fitting 3 folds for each of 6 candidates, totalling 18 fits

[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:   24.9s finished

Done


training_time(HH:MM:SS.ms) - 0:00:32.951942


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.012182


---------------------
|      Accuracy      |
---------------------

    0.9660671869697998


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  2 426  58   0   0   5]
 [  0  14 518   0   0   0]
 [  0   0   0 495   0   1]
 [  0   0   0   2 413   5]
 [  0   0   0  12   1 458]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.87      0.92       491
          STANDING       0.90      0.97      0.94       532
           WALKING       0.97      1.00      0.99       496
WALKING_DOWNSTAIRS       1.00      0.98      0.99       420
  WALKING_UPSTAIRS       0.98      0.97      0.97       471

       avg / total       0.97      0.97      0.97      2947
```

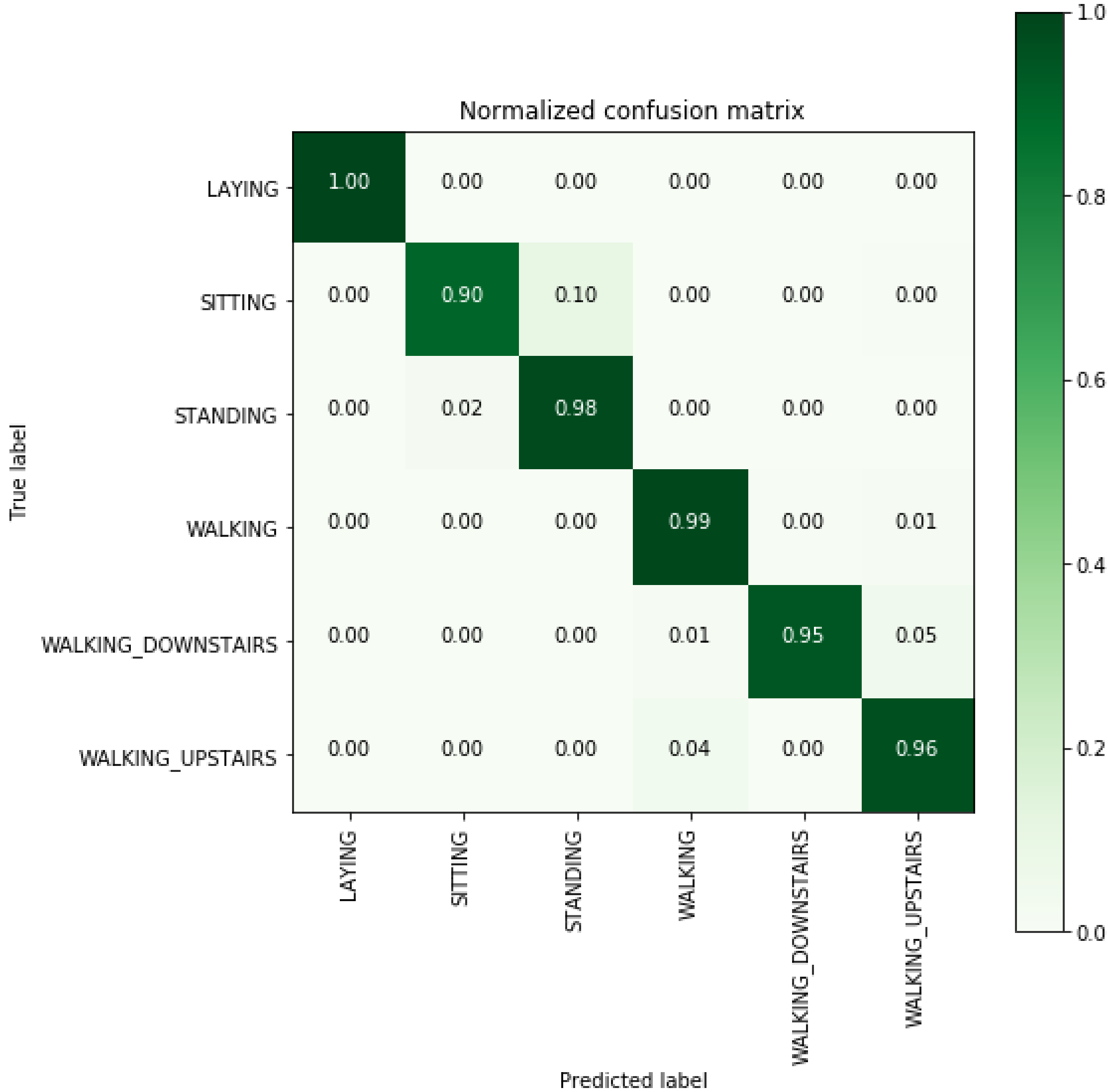
In [0]:
```
print_grid_search_attributes(lr_svc_grid_results['model'])
```

```
--------------------------
|      Best Estimator     |
--------------------------

        LinearSVC(C=8, class_weight=None, dual=True, fit_intercept=True,
     intercept_scaling=1, loss='squared_hinge', max_iter=1000,
     multi_class='ovr', penalty='l2', random_state=None, tol=5e-05,
     verbose=0)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'C': 8}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.9465451577801959
```

3. Kernel SVM with GridSearch

In [0]:
```
from sklearn.svm import SVC
parameters = {'C':[2,8,16],\
              'gamma': [ 0.0078125, 0.125, 2]}
rbf_svm = SVC(kernel='rbf')
rbf_svm_grid = GridSearchCV(rbf_svm,param_grid=parameters, n_jobs=-1)
rbf_svm_grid_results = perform_model(rbf_svm_grid, X_train, y_train, X_test, y
_test, class_labels=labels)
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:05:46.182889


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:05.221285


---------------------
|      Accuracy      |
---------------------

    0.9626739056667798


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  0 441  48   0   0   2]
 [  0  12 520   0   0   0]
 [  0   0   0 489   2   5]
 [  0   0   0   4 397  19]
 [  0   0   0  17   1 453]]
```




```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.90      0.93       491
          STANDING       0.92      0.98      0.95       532
           WALKING       0.96      0.99      0.97       496
WALKING_DOWNSTAIRS       0.99      0.95      0.97       420
  WALKING_UPSTAIRS       0.95      0.96      0.95       471

       avg / total       0.96      0.96      0.96      2947
```

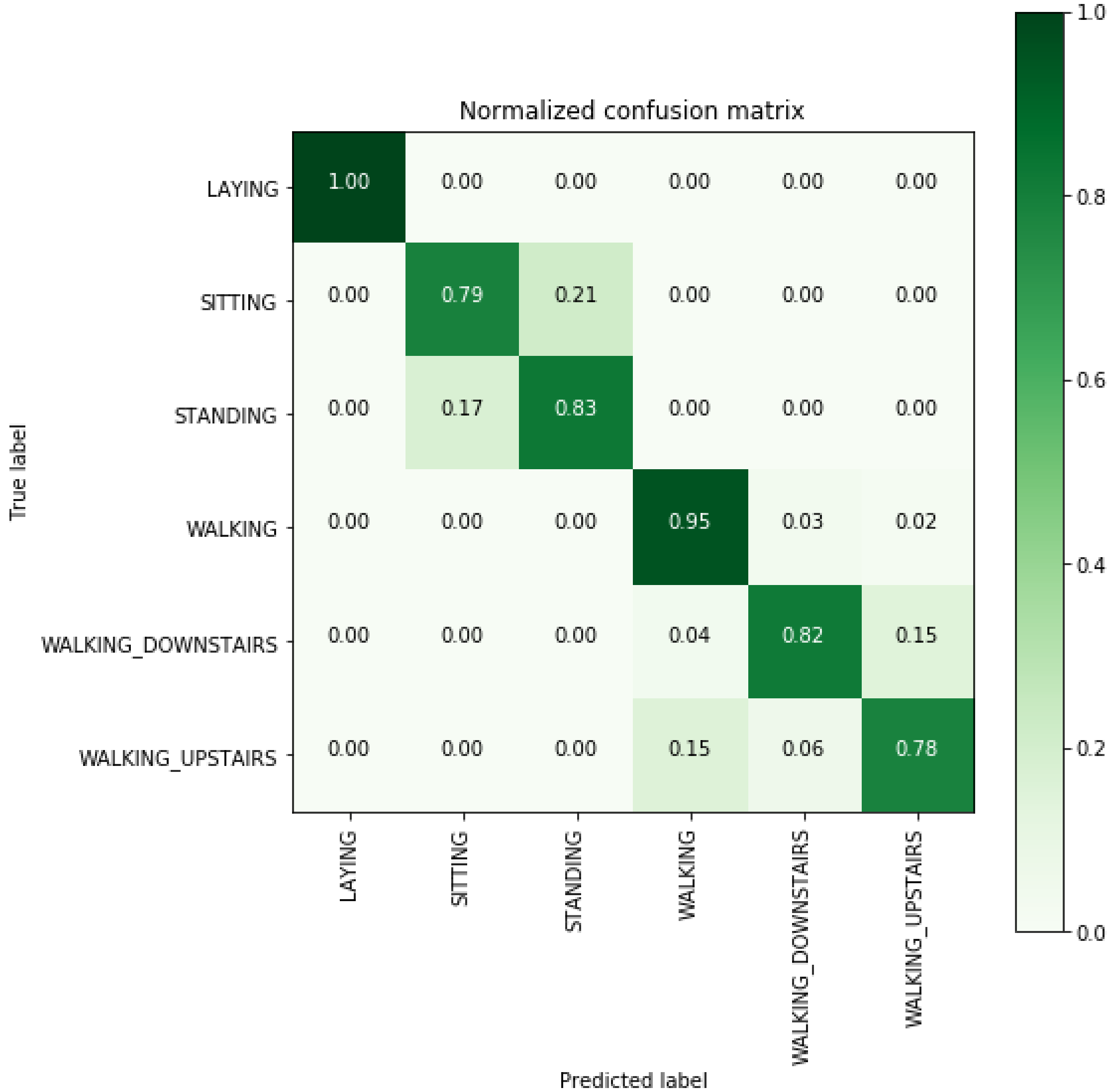
In [0]:
```
print_grid_search_attributes(rbf_svm_grid_results['model'])
```

```
--------------------------
|      Best Estimator     |
--------------------------

        SVC(C=16, cache_size=200, class_weight=None, coef0=0.0,
  decision_function_shape='ovr', degree=3, gamma=0.0078125, kernel='rbf',
  max_iter=-1, probability=False, random_state=None, shrinking=True,
  tol=0.001, verbose=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'C': 16, 'gamma': 0.0078125}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9440968443960827
```

4. Decision Trees with GridSearchCV

In [0]:
```
from sklearn.tree import DecisionTreeClassifier
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters, n_jobs=-1)
dt_grid_results = perform_model(dt_grid, X_train, y_train, X_test, y_test, cla
ss_labels=labels)
print_grid_search_attributes(dt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:00:19.476858


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.012858


---------------------
|      Accuracy      |
---------------------

    0.8642687478791992


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  0 386 105   0   0   0]
 [  0  93 439   0   0   0]
 [  0   0   0 472  16   8]
 [  0   0   0  15 344  61]
 [  0   0   0  73  29 369]]
```

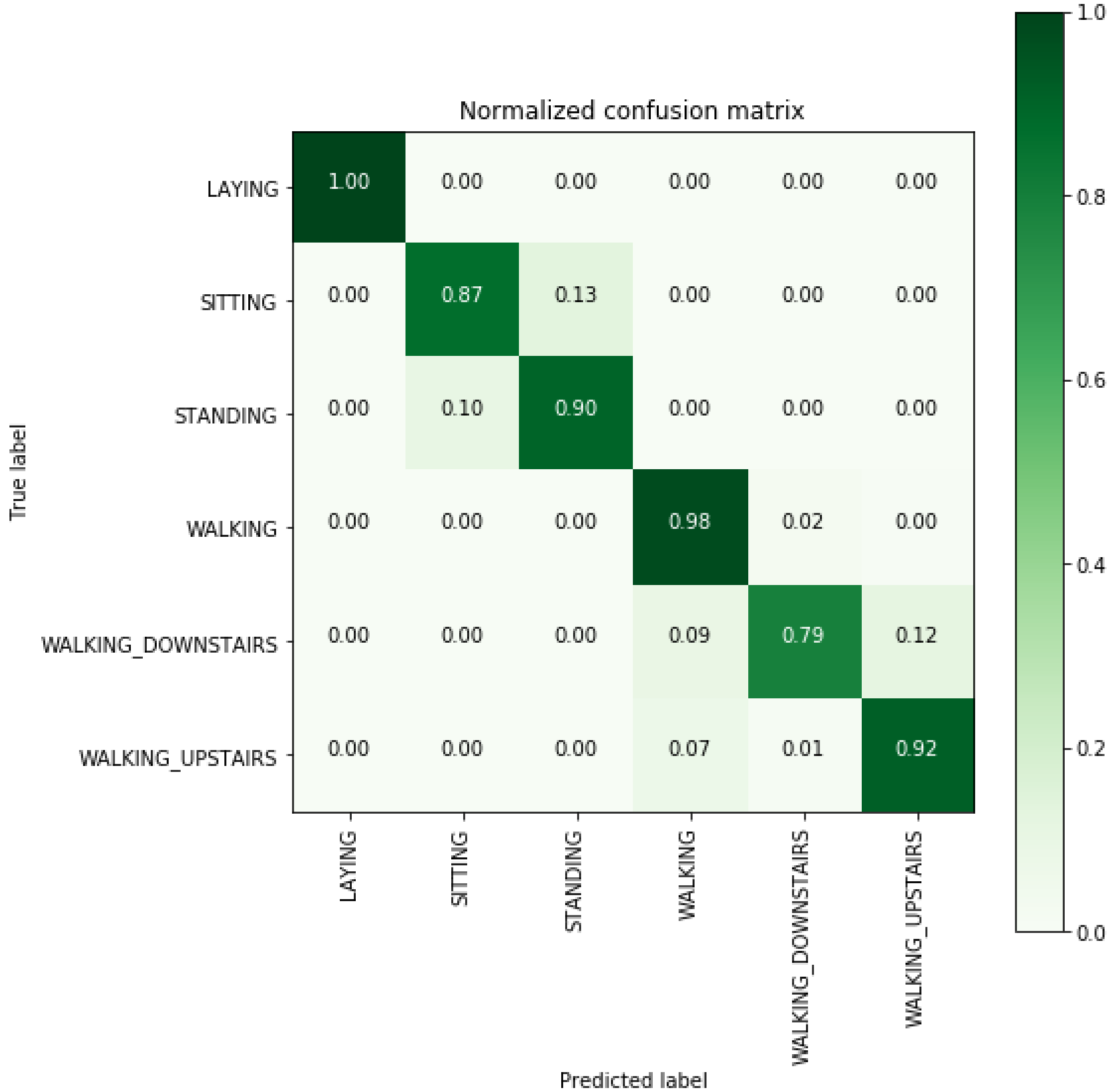

Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.79 0.21 0.00 0.00 0.00
0.00 0.17 0.83 0.00 0.00 0.00
0.00 0.00 0.00 0.95 0.03 0.02
0.00 0.00 0.00 0.04 0.82 0.15
0.00 0.00 0.00 0.15 0.06 0.78
1.0
0.8
0.6
0.4
0.2
0.0

```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.81      0.79      0.80       491
          STANDING       0.81      0.83      0.82       532
           WALKING       0.84      0.95      0.89       496
WALKING_DOWNSTAIRS       0.88      0.82      0.85       420
  WALKING_UPSTAIRS       0.84      0.78      0.81       471

       avg / total       0.86      0.86      0.86      2947

--------------------------
|      Best Estimator     |
--------------------------

        DecisionTreeClassifier(class_weight=None, criterion='gini', max_depth
=7,
            max_features=None, max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, presort=False, random_state=None,
            splitter='best')

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'max_depth': 7}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.8369151251360174
```

5. Random Forest Classifier with GridSearch

In [0]:
```
from sklearn.ensemble import RandomForestClassifier
params = {'n_estimators': np.arange(10,201,20), 'max_depth':np.arange(3,15,2)}
rfc = RandomForestClassifier()
rfc_grid = GridSearchCV(rfc, param_grid=params, n_jobs=-1)
rfc_grid_results = perform_model(rfc_grid, X_train, y_train, X_test, y_test, c
lass_labels=labels)
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:06:22.775270


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.025937


---------------------
|      Accuracy      |
---------------------

    0.9131319986426875


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  0 427  64   0   0   0]
 [  0  52 480   0   0   0]
 [  0   0   0 484  10   2]
 [  0   0   0  38 332  50]
 [  0   0   0  34   6 431]]
```

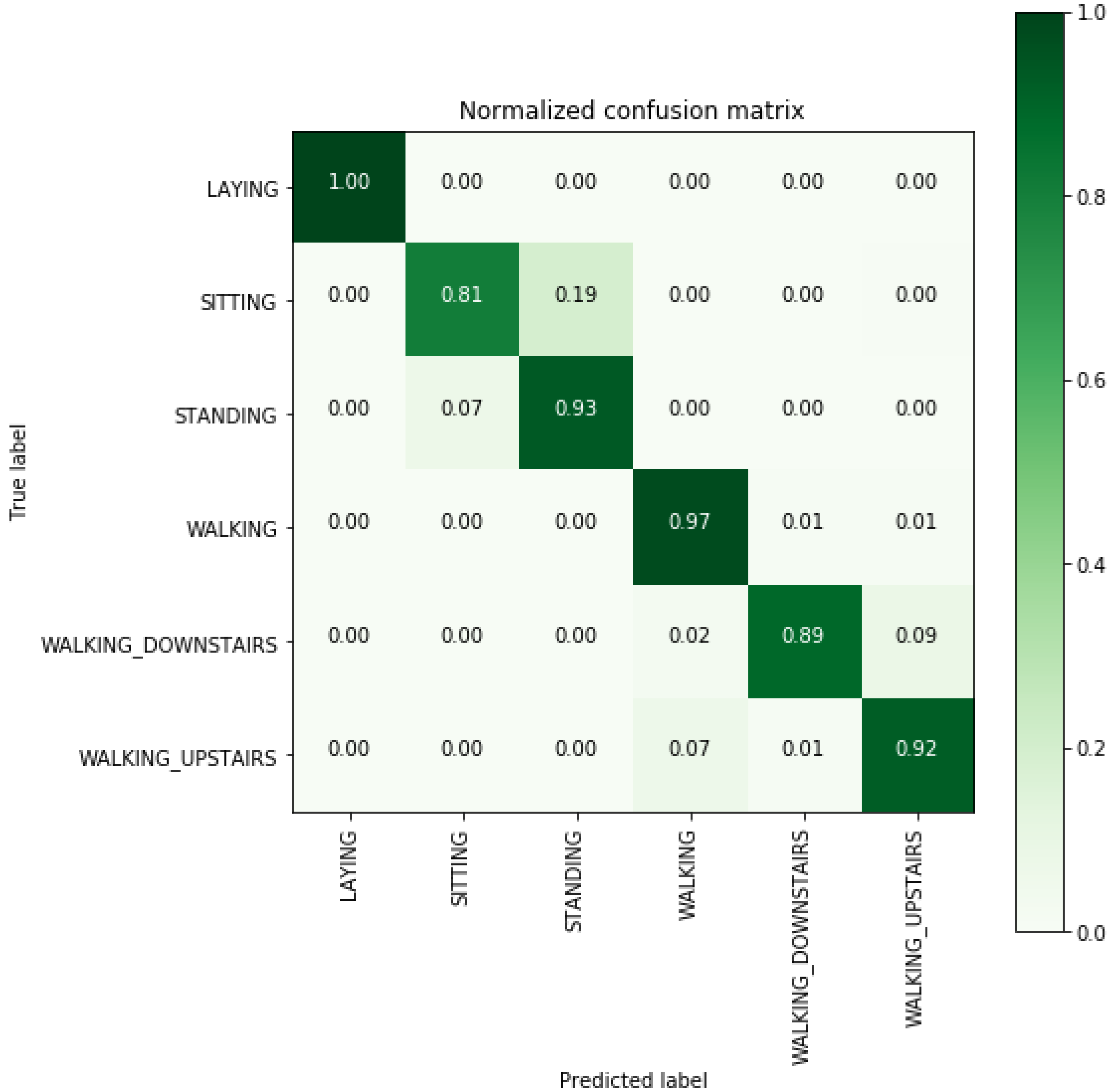

Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.87 0.13 0.00 0.00 0.00
0.00 0.10 0.90 0.00 0.00 0.00
0.00 0.00 0.00 0.98 0.02 0.00
0.00 0.00 0.00 0.09 0.79 0.12
0.00 0.00 0.00 0.07 0.01 0.92
0.0
0.2
0.4
0.6
0.8
1.0

```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.89      0.87      0.88       491
          STANDING       0.88      0.90      0.89       532
           WALKING       0.87      0.98      0.92       496
WALKING_DOWNSTAIRS       0.95      0.79      0.86       420
  WALKING_UPSTAIRS       0.89      0.92      0.90       471

       avg / total       0.92      0.91      0.91      2947

--------------------------
|      Best Estimator     |
--------------------------

        RandomForestClassifier(bootstrap=True, class_weight=None, criterion
='gini',
            max_depth=7, max_features='auto', max_leaf_nodes=None,
            min_impurity_decrease=0.0, min_impurity_split=None,
            min_samples_leaf=1, min_samples_split=2,
            min_weight_fraction_leaf=0.0, n_estimators=70, n_jobs=1,
            oob_score=False, random_state=None, verbose=0,
            warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator :

        {'max_depth': 7, 'n_estimators': 70}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator :

        0.9141730141458106
```

6. Gradient Boosted Decision Trees With GridSearch

In [0]:
```
from sklearn.ensemble import GradientBoostingClassifier
param_grid = {'max_depth': np.arange(5,8,1), \
             'n_estimators':np.arange(130,170,10)}
gbdt = GradientBoostingClassifier()
gbdt_grid = GridSearchCV(gbdt, param_grid=param_grid, n_jobs=-1)
gbdt_grid_results = perform_model(gbdt_grid, X_train, y_train, X_test, y_test,
class_labels=labels)
print_grid_search_attributes(gbdt_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 0:28:03.653432


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.058843


---------------------
|      Accuracy      |
---------------------

    0.9222938581608415


--------------------
| Confusion Matrix |
--------------------

 [[537   0   0   0   0   0]
 [  0 396  93   0   0   2]
 [  0  37 495   0   0   0]
 [  0   0   0 483   7   6]
 [  0   0   0  10 374  36]
 [  0   1   0  31   6 433]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.81 0.19 0.00 0.00 0.00
0.00 0.07 0.93 0.00 0.00 0.00
0.00 0.00 0.00 0.97 0.01 0.01
0.00 0.00 0.00 0.02 0.89 0.09
0.00 0.00 0.00 0.07 0.01 0.92
1.0
0.8
0.6
0.4
0.2
0.0

```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.91      0.81      0.86       491
          STANDING       0.84      0.93      0.88       532
           WALKING       0.92      0.97      0.95       496
WALKING_DOWNSTAIRS       0.97      0.89      0.93       420
  WALKING_UPSTAIRS       0.91      0.92      0.91       471

       avg / total       0.92      0.92      0.92      2947

--------------------------
|      Best Estimator     |
--------------------------

        GradientBoostingClassifier(criterion='friedman_mse', init=None,
              learning_rate=0.1, loss='deviance', max_depth=5,
              max_features=None, max_leaf_nodes=None,
              min_impurity_decrease=0.0, min_impurity_split=None,
              min_samples_leaf=1, min_samples_split=2,
              min_weight_fraction_leaf=0.0, n_estimators=140,
              presort='auto', random_state=None, subsample=1.0, verbose=0,
              warm_start=False)

--------------------------
|     Best parameters     |
--------------------------
        Parameters of best estimator : 

        {'max_depth': 5, 'n_estimators': 140}

---------------------------------
|   No of CrossValidation sets   |
--------------------------------

        Total numbre of cross validation sets: 3

--------------------------
|        Best Score       |
--------------------------

        Average Cross Validate scores of best estimator : 

        0.904379760609358
```

7. Comparing all models

In [0]:
```
print('\n                          Accuracy     Error')
print('                        ----------   --------')
print('Logistic Regression : {:.04}%      {:.04}%'.format(log_reg_grid_result
s['accuracy'] * 100,\
                                                  100-(log_reg_grid_results['a
ccuracy'] * 100)))

print('Linear SVC          : {:.04}%      {:.04}% '.format(lr_svc_grid_result
s['accuracy'] * 100,\
                                                        100-(lr_svc_grid_resul
ts['accuracy'] * 100)))

print('rbf SVM classifier  : {:.04}%     {:.04}% '.format(rbf_svm_grid_result
s['accuracy'] * 100,\
                                                          100-(rbf_svm_grid_re
sults['accuracy'] * 100)))

print('DecisionTree        : {:.04}%     {:.04}% '.format(dt_grid_results['ac
curacy'] * 100,\
                                                        100-(dt_grid_results[
'accuracy'] * 100)))

print('Random Forest       : {:.04}%     {:.04}% '.format(rfc_grid_results['a
ccuracy'] * 100,\
                                                           100-(rfc_grid_resul
ts['accuracy'] * 100)))
print('GradientBoosting DT : {:.04}%     {:.04}% '.format(rfc_grid_results['a
ccuracy'] * 100,\
                                                        100-(rfc_grid_results[
'accuracy'] * 100)))
```

```
                      Accuracy     Error
                      ----------   --------
Logistic Regression : 96.27%       3.733%
Linear SVC          : 96.61%       3.393%
rbf SVM classifier  : 96.27%      3.733%
DecisionTree        : 86.43%      13.57%
Random Forest       : 91.31%      8.687%
GradientBoosting DT : 91.31%      8.687%
```

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 = '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'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subse
t}.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 signa
ls)
    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_dummie
s.html)
    """
    filename = f'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
batch_size = 16
```

In [0]:
```
# Utility function to count the number of classes
def _count_classes(y):
    return len(set([tuple(category) for category in y]))
```

In [78]:
```
# 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: FutureWarnin
g: Method .as_matrix will be removed in a future version. Use .values instea
d.
  # This is added back by InteractiveShellApp.init_path()
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:12: FutureWarnin
g: Method .as_matrix will be removed in a future version. Use .values instea
d.
  if sys.path[0] == '':
```

In [60]:
```
X_train.shape
```

Out[60]:
```
(7352, 128, 9)
```

In [61]:
```
timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)
epochs=30

print(timesteps)
print(input_dim)
print(len(X_train))
```

```
128
9
7352
```

Hyperparameter Tuning of lstm architecture.

In [0]:
```
#https://machinelearningmastery.com/grid-search-hyperparameters-deep-learning-
models-python-keras/

def create_model(n_hidden, dropout_rate, init):
        # Initiliazing the sequential model
    model = Sequential()
    # Configuring the parameters
    model.add(LSTM(n_hidden,kernel_initializer=init, input_shape=(timesteps, i
nput_dim)))
    # Adding a dropout layer
    model.add(Dropout(dropout_rate))
    # Adding a dense output layer with sigmoid activation
    model.add(Dense(n_classes, activation='softmax'))

    print(model.summary())
    # Compile model
    model.compile(loss='categorical_crossentropy', optimizer='adam', metrics=[
'accuracy'])


    return model
```

In [0]:
```
from sklearn.model_selection import GridSearchCV
from keras.wrappers.scikit_learn import KerasClassifier

# Hyper parameter tuning the LSTM model using GridSearchCV
model = KerasClassifier(build_fn=create_model, epochs=epochs, batch_size=64, v
erbose=1)

# parameters for Gridsearchcv
n_hidden = [32, 64, 128]
dropout_rate = [0.4,0.5,0.7]
kernel_init=['glorot_normal','glorot_uniform','he_normal','he_uniform']

parameters = dict(n_hidden=n_hidden, dropout_rate=dropout_rate,init=kernel_ini
t)

grid = GridSearchCV(estimator=model, param_grid=parameters)
result = grid.fit(X_train, Y_train, validation_data=(X_test, Y_test))
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/
tensorflow_backend.py:66: The name tf.get_default_graph is deprecated. Please
use tf.compat.v1.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 use
tf.compat.v1.placeholder instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/
tensorflow_backend.py:4479: The name tf.truncated_normal is deprecated. Pleas
e use tf.random.truncated_normal instead.


/usr/local/lib/python3.6/dist-packages/sklearn/model_selection/_split.py:197
8: FutureWarning: The default value of cv will change from 3 to 5 in version
0.22. Specify it explicitly to silence this warning.
  warnings.warn(CV_WARNING, FutureWarning)
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/
tensorflow_backend.py:148: The name tf.placeholder_with_default is deprecate
d. Please use tf.compat.v1.placeholder_with_default instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/
tensorflow_backend.py:3733: calling dropout (from tensorflow.python.ops.nn_op
s) 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 - k
eep_prob`.
Model: "sequential_1"
_________________________________________________________________
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
_________________________________________________________________
None
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/optimize
rs.py:793: The name tf.train.Optimizer is deprecated. Please use tf.compat.v
1.train.Optimizer instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/tensorflow/pyt
hon/ops/math_grad.py:1250: add_dispatch_support.<locals>.wrapper (from tensor
flow.python.ops.array_ops) is deprecated and will be removed in a future vers
ion.
Instructions for updating:
Use tf.where in 2.0, which has the same broadcast rule as np.where
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 26s 5ms/step - loss: 1.5344 - ac
c: 0.3491 - val_loss: 1.3353 - val_acc: 0.4004
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.1741 - ac
c: 0.4997 - val_loss: 1.1172 - val_acc: 0.5260
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9631 - ac
c: 0.5931 - val_loss: 0.9056 - val_acc: 0.6101
Epoch 4/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7908 - ac
c: 0.6442 - val_loss: 0.8041 - val_acc: 0.6468
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7414 - ac
c: 0.6605 - val_loss: 0.8036 - val_acc: 0.6576
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7621 - ac
c: 0.6617 - val_loss: 0.7714 - val_acc: 0.6695
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6936 - ac
c: 0.6839 - val_loss: 0.7342 - val_acc: 0.6793
```

```
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6948 - ac
c: 0.6937 - val_loss: 0.7535 - val_acc: 0.6797
Epoch 9/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6519 - ac
c: 0.7184 - val_loss: 0.7252 - val_acc: 0.6970
Epoch 10/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.5886 - ac
c: 0.7690 - val_loss: 0.6878 - val_acc: 0.7245
Epoch 11/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.5196 - ac
c: 0.8043 - val_loss: 0.8217 - val_acc: 0.7173
Epoch 12/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4754 - ac
c: 0.8231 - val_loss: 0.6783 - val_acc: 0.7462
Epoch 13/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4089 - ac
c: 0.8531 - val_loss: 0.7604 - val_acc: 0.7526
Epoch 14/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.3720 - ac
c: 0.8696 - val_loss: 0.6239 - val_acc: 0.7791
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3573 - ac
c: 0.8737 - val_loss: 0.6209 - val_acc: 0.7940
Epoch 16/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4048 - ac
c: 0.8690 - val_loss: 1.2383 - val_acc: 0.6474
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6035 - ac
c: 0.7749 - val_loss: 0.5514 - val_acc: 0.7995
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3515 - ac
c: 0.8812 - val_loss: 0.4655 - val_acc: 0.8341
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3135 - ac
c: 0.8902 - val_loss: 0.5356 - val_acc: 0.8161
Epoch 20/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4047 - ac
c: 0.8629 - val_loss: 0.6531 - val_acc: 0.7421
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4031 - ac
c: 0.8490 - val_loss: 0.4567 - val_acc: 0.8320
Epoch 22/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.6358 - ac
c: 0.8035 - val_loss: 0.5841 - val_acc: 0.8188
Epoch 23/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4166 - ac
c: 0.8504 - val_loss: 0.4309 - val_acc: 0.8660
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3256 - ac
c: 0.9000 - val_loss: 0.3704 - val_acc: 0.8734
Epoch 25/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2805 - ac
c: 0.9153 - val_loss: 0.3785 - val_acc: 0.8758
Epoch 26/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2863 - ac
c: 0.9068 - val_loss: 0.4362 - val_acc: 0.8561
```

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Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2633 - ac
c: 0.9114 - val_loss: 0.3997 - val_acc: 0.8687
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2747 - ac
c: 0.9088 - val_loss: 0.3609 - val_acc: 0.8741
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2423 - ac
c: 0.9210 - val_loss: 0.3344 - val_acc: 0.8890
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2565 - ac
c: 0.9172 - val_loss: 0.7549 - val_acc: 0.7414
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_2"
_________________________________________________________________
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
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.4859 - ac
c: 0.3967 - val_loss: 1.2576 - val_acc: 0.5120
Epoch 2/30
4901/4901 [==============================] - 22s 5ms/step - loss: 1.0950 - ac
c: 0.5436 - val_loss: 1.0611 - val_acc: 0.5568
Epoch 3/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.9711 - ac
c: 0.5768 - val_loss: 1.1430 - val_acc: 0.5107
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8804 - ac
c: 0.5966 - val_loss: 1.0513 - val_acc: 0.5711
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9926 - ac
c: 0.5823 - val_loss: 1.0104 - val_acc: 0.5562
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8124 - ac
c: 0.6284 - val_loss: 0.8679 - val_acc: 0.5979
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7326 - ac
c: 0.6544 - val_loss: 0.8725 - val_acc: 0.5914
Epoch 8/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.7177 - ac
c: 0.6488 - val_loss: 0.8656 - val_acc: 0.6298
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7006 - ac
c: 0.6617 - val_loss: 0.8293 - val_acc: 0.6471
Epoch 10/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.6769 - ac
c: 0.6858 - val_loss: 0.8386 - val_acc: 0.6722
Epoch 11/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6436 - ac
c: 0.7115 - val_loss: 0.7842 - val_acc: 0.7038
Epoch 12/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6123 - ac
c: 0.7484 - val_loss: 0.7508 - val_acc: 0.7391
Epoch 13/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5491 - ac
c: 0.7923 - val_loss: 0.6909 - val_acc: 0.7794
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5244 - ac
c: 0.8190 - val_loss: 0.6402 - val_acc: 0.8032
Epoch 15/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5019 - ac
c: 0.8362 - val_loss: 0.6838 - val_acc: 0.7682
Epoch 16/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5133 - ac
c: 0.8241 - val_loss: 0.7844 - val_acc: 0.7384
Epoch 17/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5153 - ac
c: 0.8198 - val_loss: 0.6308 - val_acc: 0.7923
Epoch 18/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.4193 - ac
c: 0.8680 - val_loss: 0.6323 - val_acc: 0.8008
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7101 - ac
c: 0.7886 - val_loss: 0.8394 - val_acc: 0.7523
Epoch 20/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6591 - ac
c: 0.7802 - val_loss: 0.8987 - val_acc: 0.6328
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5032 - ac
c: 0.8372 - val_loss: 0.6238 - val_acc: 0.8140
Epoch 22/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6530 - ac
c: 0.7994 - val_loss: 1.5745 - val_acc: 0.5843
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9484 - ac
c: 0.7013 - val_loss: 0.8784 - val_acc: 0.6983
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6659 - ac
c: 0.7756 - val_loss: 0.7650 - val_acc: 0.7377
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5612 - ac
c: 0.8162 - val_loss: 0.7671 - val_acc: 0.7533
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5365 - ac
c: 0.8184 - val_loss: 0.7344 - val_acc: 0.7567
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7267 - ac
c: 0.7519 - val_loss: 1.0692 - val_acc: 0.6274
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6966 - ac
c: 0.7431 - val_loss: 0.7700 - val_acc: 0.7587
Epoch 29/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.5517 - ac
c: 0.8131 - val_loss: 0.7170 - val_acc: 0.7645
Epoch 30/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4995 - ac
c: 0.8323 - val_loss: 0.7298 - val_acc: 0.7523
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_3"
_________________________________________________________________
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
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.4870 - ac
c: 0.4064 - val_loss: 1.2822 - val_acc: 0.4625
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.1947 - ac
c: 0.4886 - val_loss: 1.2010 - val_acc: 0.4927
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0736 - ac
c: 0.5369 - val_loss: 1.0057 - val_acc: 0.5596
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8792 - ac
c: 0.6042 - val_loss: 0.9093 - val_acc: 0.5711
Epoch 5/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8029 - ac
c: 0.6328 - val_loss: 0.8185 - val_acc: 0.6471
Epoch 6/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8435 - ac
c: 0.6163 - val_loss: 0.9954 - val_acc: 0.5840
Epoch 7/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7962 - ac
c: 0.6479 - val_loss: 0.8169 - val_acc: 0.6485
Epoch 8/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7174 - ac
c: 0.6858 - val_loss: 0.7709 - val_acc: 0.6698
Epoch 9/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.6736 - ac
c: 0.6958 - val_loss: 0.7449 - val_acc: 0.6851
Epoch 10/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6506 - ac
c: 0.7138 - val_loss: 0.7114 - val_acc: 0.7214
Epoch 11/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.6388 - ac
c: 0.7389 - val_loss: 0.7272 - val_acc: 0.7302
Epoch 12/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.5674 - ac
```

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c: 0.7982 - val_loss: 1.3925 - val_acc: 0.5857
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6637 - ac
c: 0.7552 - val_loss: 0.6238 - val_acc: 0.7777
Epoch 14/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.4666 - ac
c: 0.8433 - val_loss: 0.5773 - val_acc: 0.8079
Epoch 15/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4415 - ac
c: 0.8513 - val_loss: 0.6459 - val_acc: 0.7930
Epoch 16/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.4226 - ac
c: 0.8703 - val_loss: 0.5627 - val_acc: 0.8015
Epoch 17/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.3505 - ac
c: 0.8935 - val_loss: 0.6915 - val_acc: 0.7923
Epoch 18/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.3313 - ac
c: 0.8992 - val_loss: 0.5439 - val_acc: 0.8324
Epoch 19/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3652 - ac
c: 0.8851 - val_loss: 0.7821 - val_acc: 0.7703
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3634 - ac
c: 0.8841 - val_loss: 0.5064 - val_acc: 0.8378
Epoch 21/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.3306 - ac
c: 0.8974 - val_loss: 0.4892 - val_acc: 0.8303
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2870 - ac
c: 0.9113 - val_loss: 0.4415 - val_acc: 0.8497
Epoch 23/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.2431 - ac
c: 0.9221 - val_loss: 0.4455 - val_acc: 0.8670
Epoch 24/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2437 - ac
c: 0.9259 - val_loss: 0.4196 - val_acc: 0.8687
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6432 - ac
c: 0.8244 - val_loss: 1.2253 - val_acc: 0.5667
Epoch 26/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.5213 - ac
c: 0.7921 - val_loss: 0.5274 - val_acc: 0.8626
Epoch 27/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3897 - ac
c: 0.8625 - val_loss: 0.5220 - val_acc: 0.8582
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3524 - ac
c: 0.8923 - val_loss: 0.4655 - val_acc: 0.8683
Epoch 29/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.2799 - ac
c: 0.9176 - val_loss: 0.4637 - val_acc: 0.8775
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2592 - ac
c: 0.9221 - val_loss: 0.4883 - val_acc: 0.8761
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_4"
```

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_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_4 (LSTM)                (None, 64)                18944     
_________________________________________________________________
dropout_4 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.3800 - ac
c: 0.4346 - val_loss: 1.2056 - val_acc: 0.4954
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.1029 - ac
c: 0.5289 - val_loss: 1.0935 - val_acc: 0.5365
Epoch 3/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.8753 - ac
c: 0.6254 - val_loss: 0.8716 - val_acc: 0.6468
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7850 - ac
c: 0.6550 - val_loss: 0.7935 - val_acc: 0.6729
Epoch 5/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.8454 - ac
c: 0.6564 - val_loss: 0.7843 - val_acc: 0.7004
Epoch 6/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7105 - ac
c: 0.7037 - val_loss: 0.7134 - val_acc: 0.7363
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6526 - ac
c: 0.7207 - val_loss: 0.7470 - val_acc: 0.7404
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9331 - ac
c: 0.6517 - val_loss: 0.9532 - val_acc: 0.6844
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6129 - ac
c: 0.7774 - val_loss: 0.5859 - val_acc: 0.7581
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4567 - ac
c: 0.8184 - val_loss: 0.5055 - val_acc: 0.7947
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4146 - ac
c: 0.8508 - val_loss: 0.5423 - val_acc: 0.7950
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4062 - ac
c: 0.8574 - val_loss: 0.5141 - val_acc: 0.8059
Epoch 13/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.3795 - ac
c: 0.8549 - val_loss: 0.5230 - val_acc: 0.8174
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3343 - ac
c: 0.8829 - val_loss: 0.4518 - val_acc: 0.8229
```

```
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2691 - ac
c: 0.9082 - val_loss: 0.4496 - val_acc: 0.8426
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2899 - ac
c: 0.9080 - val_loss: 0.4086 - val_acc: 0.8537
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2454 - ac
c: 0.9223 - val_loss: 0.4674 - val_acc: 0.8497
Epoch 18/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2286 - ac
c: 0.9227 - val_loss: 0.3724 - val_acc: 0.8602
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2199 - ac
c: 0.9210 - val_loss: 0.6325 - val_acc: 0.8001
Epoch 20/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.3399 - ac
c: 0.8833 - val_loss: 0.6927 - val_acc: 0.7964
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2931 - ac
c: 0.9014 - val_loss: 0.4277 - val_acc: 0.8398
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2540 - ac
c: 0.9121 - val_loss: 0.3490 - val_acc: 0.8690
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2003 - ac
c: 0.9235 - val_loss: 0.4145 - val_acc: 0.8415
Epoch 24/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2124 - ac
c: 0.9202 - val_loss: 0.3839 - val_acc: 0.8775
Epoch 25/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2124 - ac
c: 0.9225 - val_loss: 0.3479 - val_acc: 0.8863
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3093 - ac
c: 0.8857 - val_loss: 0.3675 - val_acc: 0.8806
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2934 - ac
c: 0.8774 - val_loss: 0.3996 - val_acc: 0.8524
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2394 - ac
c: 0.9153 - val_loss: 0.4338 - val_acc: 0.8741
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1982 - ac
c: 0.9290 - val_loss: 0.3865 - val_acc: 0.8541
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1978 - ac
c: 0.9196 - val_loss: 0.3877 - val_acc: 0.8561
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_5"
```

Layer (type)	Output Shape	Param #
lstm_5 (LSTM)	(None, 64)	18944
dropout_5 (Dropout)	(None, 64)	0

```
dense_5 (Dense)              (None, 6)                 390
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.4127 - ac
c: 0.3871 - val_loss: 1.1673 - val_acc: 0.5022
Epoch 2/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.9772 - ac
c: 0.5903 - val_loss: 1.1481 - val_acc: 0.5894
Epoch 3/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7721 - ac
c: 0.6919 - val_loss: 0.9315 - val_acc: 0.6814
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8899 - ac
c: 0.6697 - val_loss: 0.8500 - val_acc: 0.7394
Epoch 5/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.6070 - ac
c: 0.7811 - val_loss: 0.7694 - val_acc: 0.7458
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4810 - ac
c: 0.8392 - val_loss: 0.6555 - val_acc: 0.7957
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4146 - ac
c: 0.8721 - val_loss: 0.6445 - val_acc: 0.8168
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5265 - ac
c: 0.8264 - val_loss: 1.1292 - val_acc: 0.6064
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6456 - ac
c: 0.7749 - val_loss: 0.6607 - val_acc: 0.7323
Epoch 10/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3369 - ac
c: 0.8859 - val_loss: 0.4597 - val_acc: 0.8334
Epoch 11/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2490 - ac
c: 0.9280 - val_loss: 0.4623 - val_acc: 0.8622
Epoch 12/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2049 - ac
c: 0.9392 - val_loss: 0.4517 - val_acc: 0.8707
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1960 - ac
c: 0.9390 - val_loss: 0.4018 - val_acc: 0.8744
Epoch 14/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3778 - ac
c: 0.8737 - val_loss: 0.5857 - val_acc: 0.7557
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3051 - ac
c: 0.8984 - val_loss: 0.5063 - val_acc: 0.8537
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2277 - ac
c: 0.9312 - val_loss: 0.4690 - val_acc: 0.8707
Epoch 17/30
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4901/4901 [==============================] - 22s 5ms/step - loss: 0.3959 - ac
c: 0.8645 - val_loss: 0.4625 - val_acc: 0.8521
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2003 - ac
c: 0.9414 - val_loss: 0.4260 - val_acc: 0.8680
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1811 - ac
c: 0.9429 - val_loss: 0.4514 - val_acc: 0.8463
Epoch 20/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1656 - ac
c: 0.9463 - val_loss: 0.4526 - val_acc: 0.8711
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1737 - ac
c: 0.9427 - val_loss: 0.3990 - val_acc: 0.8768
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1446 - ac
c: 0.9508 - val_loss: 0.3638 - val_acc: 0.8867
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1646 - ac
c: 0.9486 - val_loss: 0.4135 - val_acc: 0.8897
Epoch 24/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1386 - ac
c: 0.9537 - val_loss: 0.4220 - val_acc: 0.8751
Epoch 25/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1407 - ac
c: 0.9469 - val_loss: 0.4276 - val_acc: 0.8768
Epoch 26/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.3929 - ac
c: 0.8731 - val_loss: 0.4606 - val_acc: 0.8619
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1801 - ac
c: 0.9398 - val_loss: 0.4340 - val_acc: 0.8666
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1454 - ac
c: 0.9521 - val_loss: 0.4386 - val_acc: 0.8795
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3185 - ac
c: 0.9102 - val_loss: 1.5057 - val_acc: 0.5898
Epoch 30/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5490 - ac
c: 0.8135 - val_loss: 0.6063 - val_acc: 0.7937
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_6"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_6 (LSTM)                (None, 64)                18944     
_________________________________________________________________
dropout_6 (Dropout)          (None, 64)                0         
_________________________________________________________________
dense_6 (Dense)              (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
```

```
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 25s 5ms/step - loss: 1.3947 - ac
c: 0.4315 - val_loss: 1.2867 - val_acc: 0.4513
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0800 - ac
c: 0.5255 - val_loss: 1.0851 - val_acc: 0.5229
Epoch 3/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.8005 - ac
c: 0.6577 - val_loss: 0.7814 - val_acc: 0.7170
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7053 - ac
c: 0.7042 - val_loss: 0.7834 - val_acc: 0.7319
Epoch 5/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6868 - ac
c: 0.7260 - val_loss: 1.0508 - val_acc: 0.6145
Epoch 6/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6398 - ac
c: 0.7507 - val_loss: 0.8034 - val_acc: 0.6834
Epoch 7/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.5591 - ac
c: 0.7785 - val_loss: 0.6991 - val_acc: 0.7391
Epoch 8/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.5807 - ac
c: 0.7809 - val_loss: 0.6539 - val_acc: 0.7737
Epoch 9/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4450 - ac
c: 0.8421 - val_loss: 0.6305 - val_acc: 0.7743
Epoch 10/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.4393 - ac
c: 0.8627 - val_loss: 0.7840 - val_acc: 0.7679
Epoch 11/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9534 - ac
c: 0.6891 - val_loss: 0.7297 - val_acc: 0.7102
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5231 - ac
c: 0.8184 - val_loss: 0.5631 - val_acc: 0.8096
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3826 - ac
c: 0.8851 - val_loss: 0.4520 - val_acc: 0.8493
Epoch 14/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3116 - ac
c: 0.9066 - val_loss: 0.3640 - val_acc: 0.8687
Epoch 15/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2496 - ac
c: 0.9241 - val_loss: 0.3475 - val_acc: 0.8775
Epoch 16/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2749 - ac
c: 0.9088 - val_loss: 0.3374 - val_acc: 0.8792
Epoch 17/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2240 - ac
c: 0.9245 - val_loss: 0.3700 - val_acc: 0.8812
Epoch 18/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2103 - ac
c: 0.9300 - val_loss: 0.4302 - val_acc: 0.8616
Epoch 19/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1855 - ac
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c: 0.9347 - val_loss: 0.3162 - val_acc: 0.8904
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1649 - ac
c: 0.9386 - val_loss: 0.2977 - val_acc: 0.8941
Epoch 21/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1577 - ac
c: 0.9394 - val_loss: 0.3086 - val_acc: 0.8962
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2193 - ac
c: 0.9190 - val_loss: 0.4008 - val_acc: 0.8612
Epoch 23/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1885 - ac
c: 0.9317 - val_loss: 0.2934 - val_acc: 0.8870
Epoch 24/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1690 - ac
c: 0.9351 - val_loss: 0.5360 - val_acc: 0.8269
Epoch 25/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2094 - ac
c: 0.9215 - val_loss: 0.6560 - val_acc: 0.7591
Epoch 26/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3050 - ac
c: 0.8796 - val_loss: 0.3738 - val_acc: 0.8656
Epoch 27/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1857 - ac
c: 0.9321 - val_loss: 0.3627 - val_acc: 0.8768
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2217 - ac
c: 0.9172 - val_loss: 0.4063 - val_acc: 0.8683
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1921 - ac
c: 0.9382 - val_loss: 0.3437 - val_acc: 0.8941
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1540 - ac
c: 0.9461 - val_loss: 0.3764 - val_acc: 0.8958
2450/2450 [==============================] - 4s 1ms/step
Model: "sequential_7"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_7 (LSTM)                (None, 128)               70656     
_________________________________________________________________
dropout_7 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_7 (Dense)              (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 25s 5ms/step - loss: 1.2966 - ac
c: 0.4619 - val_loss: 1.2307 - val_acc: 0.5137
Epoch 2/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.0551 - ac
c: 0.5666 - val_loss: 0.9510 - val_acc: 0.5898
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Epoch 3/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.1661 - ac
c: 0.5501 - val_loss: 0.9602 - val_acc: 0.5511
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8610 - ac
c: 0.6425 - val_loss: 1.0359 - val_acc: 0.6142
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9698 - ac
c: 0.5958 - val_loss: 0.8669 - val_acc: 0.6193
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7551 - ac
c: 0.6923 - val_loss: 0.7658 - val_acc: 0.6848
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7312 - ac
c: 0.7037 - val_loss: 0.8798 - val_acc: 0.6576
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6525 - ac
c: 0.7433 - val_loss: 0.7084 - val_acc: 0.7139
Epoch 9/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5356 - ac
c: 0.8084 - val_loss: 0.5609 - val_acc: 0.7940
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4871 - ac
c: 0.8321 - val_loss: 0.5704 - val_acc: 0.8161
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4531 - ac
c: 0.8470 - val_loss: 0.5622 - val_acc: 0.8120
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3521 - ac
c: 0.8792 - val_loss: 0.4934 - val_acc: 0.8436
Epoch 13/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3130 - ac
c: 0.8955 - val_loss: 0.5639 - val_acc: 0.8096
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2916 - ac
c: 0.8927 - val_loss: 0.5084 - val_acc: 0.8310
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2466 - ac
c: 0.9098 - val_loss: 0.5402 - val_acc: 0.8331
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.8285 - ac
c: 0.7188 - val_loss: 0.5505 - val_acc: 0.8090
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4746 - ac
c: 0.8151 - val_loss: 0.4236 - val_acc: 0.8419
Epoch 18/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2857 - ac
c: 0.9047 - val_loss: 0.4284 - val_acc: 0.8493
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2770 - ac
c: 0.9027 - val_loss: 0.4678 - val_acc: 0.8622
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3132 - ac
c: 0.8984 - val_loss: 0.4912 - val_acc: 0.8721
Epoch 21/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2889 - ac
c: 0.9002 - val_loss: 0.5022 - val_acc: 0.8510
```

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Epoch 22/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2085 - ac
c: 0.9216 - val_loss: 0.4051 - val_acc: 0.8829
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5216 - ac
c: 0.8435 - val_loss: 0.5504 - val_acc: 0.8541
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2988 - ac
c: 0.9012 - val_loss: 0.3569 - val_acc: 0.8850
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2444 - ac
c: 0.9212 - val_loss: 0.5373 - val_acc: 0.8666
Epoch 26/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3052 - ac
c: 0.8947 - val_loss: 0.3122 - val_acc: 0.9033
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2277 - ac
c: 0.9210 - val_loss: 0.3547 - val_acc: 0.8894
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5400 - ac
c: 0.8411 - val_loss: 0.6774 - val_acc: 0.6851
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3751 - ac
c: 0.8659 - val_loss: 0.3767 - val_acc: 0.8714
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2495 - ac
c: 0.9080 - val_loss: 0.4607 - val_acc: 0.8724
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_8"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_8 (LSTM)                (None, 128)               70656     
_________________________________________________________________
dropout_8 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_8 (Dense)              (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 25s 5ms/step - loss: 1.3855 - ac
c: 0.4183 - val_loss: 1.1731 - val_acc: 0.5093
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9256 - ac
c: 0.6148 - val_loss: 0.8738 - val_acc: 0.6413
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6669 - ac
c: 0.7209 - val_loss: 0.8781 - val_acc: 0.6362
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9042 - ac
c: 0.6184 - val_loss: 1.1373 - val_acc: 0.4754
Epoch 5/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.7935 - ac
c: 0.6911 - val_loss: 0.8008 - val_acc: 0.7197
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5099 - ac
c: 0.8137 - val_loss: 0.6977 - val_acc: 0.7377
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3685 - ac
c: 0.8692 - val_loss: 0.6822 - val_acc: 0.8012
Epoch 8/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5081 - ac
c: 0.8143 - val_loss: 0.5574 - val_acc: 0.8107
Epoch 9/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3472 - ac
c: 0.8831 - val_loss: 0.5396 - val_acc: 0.8402
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3832 - ac
c: 0.8866 - val_loss: 0.5143 - val_acc: 0.8375
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3088 - ac
c: 0.8998 - val_loss: 0.6303 - val_acc: 0.7838
Epoch 12/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4935 - ac
c: 0.8425 - val_loss: 0.5242 - val_acc: 0.8001
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3879 - ac
c: 0.8637 - val_loss: 0.3740 - val_acc: 0.8765
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2248 - ac
c: 0.9314 - val_loss: 0.4019 - val_acc: 0.8680
Epoch 15/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1660 - ac
c: 0.9435 - val_loss: 0.4405 - val_acc: 0.8697
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1370 - ac
c: 0.9539 - val_loss: 0.4219 - val_acc: 0.8636
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1564 - ac
c: 0.9412 - val_loss: 0.4037 - val_acc: 0.8853
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1220 - ac
c: 0.9551 - val_loss: 0.4807 - val_acc: 0.8823
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1197 - ac
c: 0.9549 - val_loss: 0.4877 - val_acc: 0.8877
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1134 - ac
c: 0.9565 - val_loss: 0.5853 - val_acc: 0.8833
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1405 - ac
c: 0.9504 - val_loss: 0.5537 - val_acc: 0.8826
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1212 - ac
c: 0.9535 - val_loss: 0.4517 - val_acc: 0.8901
Epoch 23/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1286 - ac
c: 0.9504 - val_loss: 0.3382 - val_acc: 0.8839
Epoch 24/30
```

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4901/4901 [==============================] - 24s 5ms/step - loss: 0.1186 - ac
c: 0.9539 - val_loss: 0.3579 - val_acc: 0.8904
Epoch 25/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1257 - ac
c: 0.9490 - val_loss: 0.4044 - val_acc: 0.8792
Epoch 26/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1122 - ac
c: 0.9553 - val_loss: 0.4433 - val_acc: 0.8860
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1203 - ac
c: 0.9553 - val_loss: 0.3550 - val_acc: 0.8951
Epoch 28/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1078 - ac
c: 0.9598 - val_loss: 0.4391 - val_acc: 0.8921
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1640 - ac
c: 0.9398 - val_loss: 0.5427 - val_acc: 0.8761
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1230 - ac
c: 0.9518 - val_loss: 0.4986 - val_acc: 0.8870
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_9"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_9 (LSTM)                (None, 128)               70656     
_________________________________________________________________
dropout_9 (Dropout)          (None, 128)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 26s 5ms/step - loss: 1.2598 - ac
c: 0.4576 - val_loss: 1.3062 - val_acc: 0.4839
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0285 - ac
c: 0.5357 - val_loss: 1.0400 - val_acc: 0.5402
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9671 - ac
c: 0.5785 - val_loss: 0.9964 - val_acc: 0.5633
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7761 - ac
c: 0.6685 - val_loss: 0.9133 - val_acc: 0.6600
Epoch 5/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7628 - ac
c: 0.6942 - val_loss: 0.9134 - val_acc: 0.6132
Epoch 6/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9121 - ac
c: 0.6324 - val_loss: 0.9667 - val_acc: 0.6546
Epoch 7/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8548 - ac
```

```
c: 0.6777 - val_loss: 1.1892 - val_acc: 0.5694
Epoch 8/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9289 - ac
c: 0.6283 - val_loss: 0.9790 - val_acc: 0.6189
Epoch 9/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.9163 - ac
c: 0.6257 - val_loss: 0.8977 - val_acc: 0.6128
Epoch 10/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0595 - ac
c: 0.6071 - val_loss: 0.9341 - val_acc: 0.6457
Epoch 11/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7631 - ac
c: 0.7191 - val_loss: 0.7711 - val_acc: 0.7251
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8286 - ac
c: 0.7034 - val_loss: 0.7603 - val_acc: 0.7760
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5741 - ac
c: 0.7976 - val_loss: 0.6481 - val_acc: 0.8029
Epoch 14/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6617 - ac
c: 0.7799 - val_loss: 1.0941 - val_acc: 0.4676
Epoch 15/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6489 - ac
c: 0.7570 - val_loss: 0.5092 - val_acc: 0.8066
Epoch 16/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.3695 - ac
c: 0.8760 - val_loss: 0.4874 - val_acc: 0.8286
Epoch 17/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2739 - ac
c: 0.9045 - val_loss: 0.4313 - val_acc: 0.8592
Epoch 18/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2905 - ac
c: 0.8925 - val_loss: 0.4185 - val_acc: 0.8500
Epoch 19/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2390 - ac
c: 0.9117 - val_loss: 0.4631 - val_acc: 0.8571
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2136 - ac
c: 0.9190 - val_loss: 0.3961 - val_acc: 0.8700
Epoch 21/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1825 - ac
c: 0.9323 - val_loss: 0.4745 - val_acc: 0.8595
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2289 - ac
c: 0.9098 - val_loss: 0.4138 - val_acc: 0.8636
Epoch 23/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1809 - ac
c: 0.9276 - val_loss: 0.3993 - val_acc: 0.8690
Epoch 24/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1825 - ac
c: 0.9278 - val_loss: 0.4204 - val_acc: 0.8683
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1647 - ac
c: 0.9347 - val_loss: 0.3742 - val_acc: 0.8799
Epoch 26/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1477 - ac
```

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c: 0.9390 - val_loss: 0.3962 - val_acc: 0.8707
Epoch 27/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1417 - ac
c: 0.9380 - val_loss: 0.3821 - val_acc: 0.8728
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1315 - ac
c: 0.9435 - val_loss: 0.3529 - val_acc: 0.8724
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1213 - ac
c: 0.9476 - val_loss: 0.3427 - val_acc: 0.8904
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1230 - ac
c: 0.9449 - val_loss: 0.3049 - val_acc: 0.8904
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_10"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_10 (LSTM)               (None, 32)                5376      
_________________________________________________________________
dropout_10 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_10 (Dense)             (None, 6)                 198       
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 26s 5ms/step - loss: 1.4785 - ac
c: 0.3877 - val_loss: 1.3519 - val_acc: 0.4082
Epoch 2/30
4901/4901 [==============================] - 22s 4ms/step - loss: 1.2161 - ac
c: 0.4889 - val_loss: 1.0050 - val_acc: 0.5762
Epoch 3/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.9200 - ac
c: 0.6046 - val_loss: 0.9028 - val_acc: 0.6105
Epoch 4/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.7600 - ac
c: 0.6686 - val_loss: 0.7923 - val_acc: 0.6569
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6884 - ac
c: 0.7023 - val_loss: 0.7578 - val_acc: 0.6698
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9933 - ac
c: 0.6172 - val_loss: 1.4232 - val_acc: 0.4605
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9250 - ac
c: 0.6258 - val_loss: 0.7714 - val_acc: 0.6926
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6135 - ac
c: 0.7539 - val_loss: 0.9048 - val_acc: 0.6518
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8099 - ac
c: 0.6711 - val_loss: 0.7477 - val_acc: 0.7350
```

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Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6354 - ac
c: 0.7341 - val_loss: 0.7470 - val_acc: 0.6773
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6186 - ac
c: 0.7290 - val_loss: 0.7350 - val_acc: 0.6892
Epoch 12/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.5472 - ac
c: 0.7727 - val_loss: 0.6111 - val_acc: 0.7760
Epoch 13/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5082 - ac
c: 0.8062 - val_loss: 0.6481 - val_acc: 0.7642
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4847 - ac
c: 0.8123 - val_loss: 0.7694 - val_acc: 0.7112
Epoch 15/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.5002 - ac
c: 0.8180 - val_loss: 0.5254 - val_acc: 0.8198
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.3513 - ac
c: 0.5680 - val_loss: 1.1230 - val_acc: 0.4822
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7861 - ac
c: 0.6468 - val_loss: 0.7161 - val_acc: 0.6916
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6617 - ac
c: 0.6870 - val_loss: 0.7516 - val_acc: 0.6695
Epoch 19/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7595 - ac
c: 0.6474 - val_loss: 0.7865 - val_acc: 0.6288
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7408 - ac
c: 0.6429 - val_loss: 0.7513 - val_acc: 0.6698
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6535 - ac
c: 0.7021 - val_loss: 0.6798 - val_acc: 0.7156
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5662 - ac
c: 0.7619 - val_loss: 0.6547 - val_acc: 0.7265
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4967 - ac
c: 0.7935 - val_loss: 0.6739 - val_acc: 0.7048
Epoch 24/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5200 - ac
c: 0.7721 - val_loss: 0.6020 - val_acc: 0.7248
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4462 - ac
c: 0.8096 - val_loss: 0.5819 - val_acc: 0.7486
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4363 - ac
c: 0.8109 - val_loss: 0.6075 - val_acc: 0.7428
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4029 - ac
c: 0.8223 - val_loss: 0.5813 - val_acc: 0.7581
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4046 - ac
c: 0.8233 - val_loss: 0.5597 - val_acc: 0.7676
```

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Epoch 29/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.3977 - ac
c: 0.8215 - val_loss: 0.5889 - val_acc: 0.7737
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3867 - ac
c: 0.8304 - val_loss: 0.5665 - val_acc: 0.7794
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_11"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_11 (LSTM)               (None, 32)                5376
_________________________________________________________________
dropout_11 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_11 (Dense)             (None, 6)                 198
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 25s 5ms/step - loss: 1.5232 - ac
c: 0.3677 - val_loss: 1.2898 - val_acc: 0.4262
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.1189 - ac
c: 0.5160 - val_loss: 1.1599 - val_acc: 0.5324
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9938 - ac
c: 0.5740 - val_loss: 1.0458 - val_acc: 0.5606
Epoch 4/30
4901/4901 [==============================] - 26s 5ms/step - loss: 0.9460 - ac
c: 0.5931 - val_loss: 1.1118 - val_acc: 0.5144
Epoch 5/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.8668 - ac
c: 0.6295 - val_loss: 0.9139 - val_acc: 0.6183
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7595 - ac
c: 0.6529 - val_loss: 0.8338 - val_acc: 0.6624
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6908 - ac
c: 0.6992 - val_loss: 0.8364 - val_acc: 0.6946
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7521 - ac
c: 0.6982 - val_loss: 1.1770 - val_acc: 0.5395
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7549 - ac
c: 0.6825 - val_loss: 0.8082 - val_acc: 0.6970
Epoch 10/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6705 - ac
c: 0.7176 - val_loss: 0.8510 - val_acc: 0.6403
Epoch 11/30
4901/4901 [==============================] - 22s 4ms/step - loss: 0.6776 - ac
c: 0.6901 - val_loss: 0.8119 - val_acc: 0.6759
Epoch 12/30
```

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4901/4901 [==============================] - 22s 4ms/step - loss: 0.6443 - ac
c: 0.6986 - val_loss: 0.7747 - val_acc: 0.6797
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6314 - ac
c: 0.7060 - val_loss: 0.8391 - val_acc: 0.6675
Epoch 14/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6507 - ac
c: 0.6895 - val_loss: 0.7589 - val_acc: 0.6929
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6081 - ac
c: 0.7296 - val_loss: 0.7511 - val_acc: 0.7027
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5987 - ac
c: 0.7313 - val_loss: 0.6971 - val_acc: 0.7207
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5744 - ac
c: 0.7529 - val_loss: 0.6762 - val_acc: 0.7357
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5351 - ac
c: 0.7749 - val_loss: 0.7163 - val_acc: 0.7486
Epoch 19/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4811 - ac
c: 0.8102 - val_loss: 0.6842 - val_acc: 0.7655
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4501 - ac
c: 0.8374 - val_loss: 0.6439 - val_acc: 0.8005
Epoch 21/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4090 - ac
c: 0.8580 - val_loss: 0.6528 - val_acc: 0.7998
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4249 - ac
c: 0.8498 - val_loss: 0.6693 - val_acc: 0.7954
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3576 - ac
c: 0.8819 - val_loss: 0.6195 - val_acc: 0.8110
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3200 - ac
c: 0.8990 - val_loss: 0.5914 - val_acc: 0.8263
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2904 - ac
c: 0.9092 - val_loss: 0.7119 - val_acc: 0.7991
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2745 - ac
c: 0.9155 - val_loss: 0.5532 - val_acc: 0.8361
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2470 - ac
c: 0.9245 - val_loss: 0.5336 - val_acc: 0.8371
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2259 - ac
c: 0.9288 - val_loss: 0.5786 - val_acc: 0.8453
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2239 - ac
c: 0.9251 - val_loss: 0.5449 - val_acc: 0.8456
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3725 - ac
c: 0.8743 - val_loss: 0.5381 - val_acc: 0.8449
2451/2451 [==============================] - 4s 2ms/step
```

```
Model: "sequential_12"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_12 (LSTM)               (None, 32)                5376      
_________________________________________________________________
dropout_12 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_12 (Dense)             (None, 6)                 198       
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 26s 5ms/step - loss: 1.5714 - ac
c: 0.3262 - val_loss: 1.3601 - val_acc: 0.3974
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.2428 - ac
c: 0.4643 - val_loss: 1.1789 - val_acc: 0.4832
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0871 - ac
c: 0.5330 - val_loss: 1.0696 - val_acc: 0.5426
Epoch 4/30
4902/4902 [==============================] - 22s 4ms/step - loss: 0.8963 - ac
c: 0.6212 - val_loss: 0.8876 - val_acc: 0.6091
Epoch 5/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.7883 - ac
c: 0.6428 - val_loss: 0.8180 - val_acc: 0.6515
Epoch 6/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7364 - ac
c: 0.6522 - val_loss: 0.8238 - val_acc: 0.6617
Epoch 7/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6934 - ac
c: 0.6705 - val_loss: 0.7620 - val_acc: 0.6725
Epoch 8/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6459 - ac
c: 0.7003 - val_loss: 0.7434 - val_acc: 0.6939
Epoch 9/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6557 - ac
c: 0.6903 - val_loss: 0.7431 - val_acc: 0.7319
Epoch 10/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6365 - ac
c: 0.7087 - val_loss: 0.7648 - val_acc: 0.6824
Epoch 11/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.7141 - ac
c: 0.6844 - val_loss: 0.7646 - val_acc: 0.7000
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5970 - ac
c: 0.7456 - val_loss: 0.7480 - val_acc: 0.7201
Epoch 13/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6473 - ac
c: 0.7124 - val_loss: 0.8088 - val_acc: 0.6790
Epoch 14/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6721 - ac
```

```
c: 0.6732 - val_loss: 0.7566 - val_acc: 0.6668
Epoch 15/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6163 - ac
c: 0.6991 - val_loss: 0.7044 - val_acc: 0.6926
Epoch 16/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5573 - ac
c: 0.7540 - val_loss: 0.6532 - val_acc: 0.7445
Epoch 17/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5038 - ac
c: 0.7987 - val_loss: 0.5991 - val_acc: 0.7879
Epoch 18/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7331 - ac
c: 0.7038 - val_loss: 0.7946 - val_acc: 0.7265
Epoch 19/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5900 - ac
c: 0.7815 - val_loss: 0.6745 - val_acc: 0.7740
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4667 - ac
c: 0.8435 - val_loss: 0.4801 - val_acc: 0.8517
Epoch 21/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4182 - ac
c: 0.8605 - val_loss: 0.4575 - val_acc: 0.8463
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4619 - ac
c: 0.8550 - val_loss: 0.4729 - val_acc: 0.8381
Epoch 23/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4339 - ac
c: 0.8576 - val_loss: 0.8463 - val_acc: 0.7479
Epoch 24/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.3384 - ac
c: 0.8943 - val_loss: 0.6456 - val_acc: 0.7713
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3092 - ac
c: 0.9021 - val_loss: 0.4802 - val_acc: 0.8320
Epoch 26/30
4902/4902 [==============================] - 22s 4ms/step - loss: 0.3803 - ac
c: 0.8856 - val_loss: 0.4590 - val_acc: 0.8439
Epoch 27/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2907 - ac
c: 0.9143 - val_loss: 0.4972 - val_acc: 0.8385
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2966 - ac
c: 0.9053 - val_loss: 0.4513 - val_acc: 0.8504
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2723 - ac
c: 0.9129 - val_loss: 0.5446 - val_acc: 0.8347
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2891 - ac
c: 0.9090 - val_loss: 0.4049 - val_acc: 0.8717
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_13"
```

Layer (type)	Output Shape	Param #
lstm_13 (LSTM)	(None, 64)	18944
dropout_13 (Dropout)	(None, 64)	0

```
_________________________________________________________________
dense_13 (Dense)             (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 26s 5ms/step - loss: 1.3752 - ac
c: 0.4338 - val_loss: 1.2056 - val_acc: 0.4778
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.0883 - ac
c: 0.5562 - val_loss: 0.9333 - val_acc: 0.5969
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8583 - ac
c: 0.6574 - val_loss: 0.8036 - val_acc: 0.6970
Epoch 4/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7194 - ac
c: 0.6994 - val_loss: 0.7294 - val_acc: 0.7262
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6583 - ac
c: 0.7321 - val_loss: 0.6773 - val_acc: 0.7411
Epoch 6/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.6090 - ac
c: 0.7511 - val_loss: 0.6999 - val_acc: 0.7051
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6140 - ac
c: 0.7545 - val_loss: 0.7064 - val_acc: 0.7021
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5936 - ac
c: 0.7574 - val_loss: 0.6143 - val_acc: 0.7604
Epoch 9/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4340 - ac
c: 0.8451 - val_loss: 0.5964 - val_acc: 0.7849
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3088 - ac
c: 0.8992 - val_loss: 0.4549 - val_acc: 0.8490
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2395 - ac
c: 0.9231 - val_loss: 0.4514 - val_acc: 0.8612
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2097 - ac
c: 0.9302 - val_loss: 0.4089 - val_acc: 0.8626
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2230 - ac
c: 0.9225 - val_loss: 0.3622 - val_acc: 0.8778
Epoch 14/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1859 - ac
c: 0.9331 - val_loss: 0.3769 - val_acc: 0.8738
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1990 - ac
c: 0.9345 - val_loss: 0.3679 - val_acc: 0.8856
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2947 - ac
c: 0.9017 - val_loss: 0.3796 - val_acc: 0.8768
```

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Epoch 17/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2371 - ac
c: 0.9229 - val_loss: 0.4780 - val_acc: 0.8361
Epoch 18/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2024 - ac
c: 0.9325 - val_loss: 0.3366 - val_acc: 0.8931
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1709 - ac
c: 0.9418 - val_loss: 0.4230 - val_acc: 0.8347
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2946 - ac
c: 0.9041 - val_loss: 0.3457 - val_acc: 0.8853
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1731 - ac
c: 0.9365 - val_loss: 0.3729 - val_acc: 0.8873
Epoch 22/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1602 - ac
c: 0.9410 - val_loss: 0.3419 - val_acc: 0.8599
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1715 - ac
c: 0.9243 - val_loss: 0.3504 - val_acc: 0.8873
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1520 - ac
c: 0.9359 - val_loss: 0.3232 - val_acc: 0.8931
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1437 - ac
c: 0.9372 - val_loss: 0.3003 - val_acc: 0.9040
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2083 - ac
c: 0.9331 - val_loss: 0.4008 - val_acc: 0.8873
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2254 - ac
c: 0.9145 - val_loss: 0.3092 - val_acc: 0.8979
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2448 - ac
c: 0.9121 - val_loss: 0.3625 - val_acc: 0.8816
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1628 - ac
c: 0.9347 - val_loss: 0.3821 - val_acc: 0.8921
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1569 - ac
c: 0.9370 - val_loss: 0.3334 - val_acc: 0.9006
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_14"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_14 (LSTM)               (None, 64)                18944     
_________________________________________________________________
dropout_14 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_14 (Dense)             (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
```

```
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 27s 5ms/step - loss: 1.4132 - ac
c: 0.3971 - val_loss: 1.2149 - val_acc: 0.4537
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.0593 - ac
c: 0.5262 - val_loss: 1.1417 - val_acc: 0.5368
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.0304 - ac
c: 0.6033 - val_loss: 0.9911 - val_acc: 0.6257
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7335 - ac
c: 0.7135 - val_loss: 0.9377 - val_acc: 0.6624
Epoch 5/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5358 - ac
c: 0.8002 - val_loss: 0.7619 - val_acc: 0.7496
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4902 - ac
c: 0.8251 - val_loss: 0.5934 - val_acc: 0.7988
Epoch 7/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4063 - ac
c: 0.8664 - val_loss: 0.6167 - val_acc: 0.7910
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3129 - ac
c: 0.9063 - val_loss: 0.4911 - val_acc: 0.8442
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2320 - ac
c: 0.9331 - val_loss: 0.5226 - val_acc: 0.8415
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8082 - ac
c: 0.7215 - val_loss: 0.7858 - val_acc: 0.7044
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4803 - ac
c: 0.8064 - val_loss: 0.6434 - val_acc: 0.7835
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4014 - ac
c: 0.8311 - val_loss: 0.6148 - val_acc: 0.8062
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3513 - ac
c: 0.8496 - val_loss: 0.5910 - val_acc: 0.8215
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3037 - ac
c: 0.8898 - val_loss: 0.5747 - val_acc: 0.8232
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3340 - ac
c: 0.8784 - val_loss: 0.6286 - val_acc: 0.7852
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4038 - ac
c: 0.8474 - val_loss: 0.5971 - val_acc: 0.8185
Epoch 17/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.2949 - ac
c: 0.8908 - val_loss: 0.5320 - val_acc: 0.8534
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2560 - ac
c: 0.9163 - val_loss: 0.4788 - val_acc: 0.8639
Epoch 19/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.2446 - ac
c: 0.9082 - val_loss: 0.5215 - val_acc: 0.8531
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2301 - ac
c: 0.9239 - val_loss: 0.4572 - val_acc: 0.8653
Epoch 21/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1769 - ac
c: 0.9457 - val_loss: 0.5147 - val_acc: 0.8436
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1762 - ac
c: 0.9423 - val_loss: 0.5929 - val_acc: 0.8327
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1640 - ac
c: 0.9478 - val_loss: 0.5056 - val_acc: 0.8609
Epoch 24/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1324 - ac
c: 0.9518 - val_loss: 0.4946 - val_acc: 0.8646
Epoch 25/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1461 - ac
c: 0.9484 - val_loss: 0.5222 - val_acc: 0.8463
Epoch 26/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1283 - ac
c: 0.9525 - val_loss: 0.4120 - val_acc: 0.8768
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1156 - ac
c: 0.9580 - val_loss: 0.4559 - val_acc: 0.8860
Epoch 28/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1261 - ac
c: 0.9533 - val_loss: 0.4015 - val_acc: 0.8938
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1703 - ac
c: 0.9457 - val_loss: 0.3505 - val_acc: 0.8979
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1441 - ac
c: 0.9455 - val_loss: 0.3355 - val_acc: 0.8904
2451/2451 [==============================] - 4s 1ms/step
Model: "sequential_15"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_15 (LSTM)               (None, 64)                18944     
_________________________________________________________________
dropout_15 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_15 (Dense)             (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 26s 5ms/step - loss: 1.3815 - ac
c: 0.4155 - val_loss: 1.2952 - val_acc: 0.4666
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.1267 - ac
```

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c: 0.5082 - val_loss: 1.1749 - val_acc: 0.4947
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9849 - ac
c: 0.5757 - val_loss: 0.9705 - val_acc: 0.5867
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7634 - ac
c: 0.6554 - val_loss: 0.8737 - val_acc: 0.6345
Epoch 5/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6776 - ac
c: 0.6824 - val_loss: 0.7582 - val_acc: 0.6763
Epoch 6/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6619 - ac
c: 0.7009 - val_loss: 0.7055 - val_acc: 0.6960
Epoch 7/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6617 - ac
c: 0.7232 - val_loss: 0.7142 - val_acc: 0.7401
Epoch 8/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.5235 - ac
c: 0.8082 - val_loss: 0.6327 - val_acc: 0.8076
Epoch 9/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4596 - ac
c: 0.8317 - val_loss: 0.5471 - val_acc: 0.8249
Epoch 10/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.3154 - ac
c: 0.9029 - val_loss: 0.5516 - val_acc: 0.8191
Epoch 11/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2782 - ac
c: 0.9092 - val_loss: 0.5187 - val_acc: 0.8320
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4354 - ac
c: 0.8643 - val_loss: 0.5270 - val_acc: 0.8595
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2723 - ac
c: 0.9096 - val_loss: 0.5271 - val_acc: 0.8459
Epoch 14/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2757 - ac
c: 0.8994 - val_loss: 0.6064 - val_acc: 0.8086
Epoch 15/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4195 - ac
c: 0.8388 - val_loss: 0.5328 - val_acc: 0.8473
Epoch 16/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2813 - ac
c: 0.9068 - val_loss: 0.5113 - val_acc: 0.8609
Epoch 17/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2138 - ac
c: 0.9247 - val_loss: 0.4462 - val_acc: 0.8823
Epoch 18/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1937 - ac
c: 0.9327 - val_loss: 0.4038 - val_acc: 0.8843
Epoch 19/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4348 - ac
c: 0.8366 - val_loss: 0.4769 - val_acc: 0.8470
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2572 - ac
c: 0.9184 - val_loss: 0.4119 - val_acc: 0.8782
Epoch 21/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2166 - ac
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c: 0.9270 - val_loss: 0.5740 - val_acc: 0.8480
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1967 - ac
c: 0.9359 - val_loss: 0.3810 - val_acc: 0.8836
Epoch 23/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1897 - ac
c: 0.9329 - val_loss: 0.4104 - val_acc: 0.8738
Epoch 24/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2086 - ac
c: 0.9300 - val_loss: 0.4326 - val_acc: 0.8629
Epoch 25/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2178 - ac
c: 0.9276 - val_loss: 0.3304 - val_acc: 0.8941
Epoch 26/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1782 - ac
c: 0.9345 - val_loss: 0.3163 - val_acc: 0.8928
Epoch 27/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1529 - ac
c: 0.9388 - val_loss: 0.3113 - val_acc: 0.8887
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1334 - ac
c: 0.9463 - val_loss: 0.3381 - val_acc: 0.9013
Epoch 29/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1260 - ac
c: 0.9500 - val_loss: 0.3958 - val_acc: 0.8826
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1386 - ac
c: 0.9433 - val_loss: 0.3395 - val_acc: 0.8897
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_16"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_16 (LSTM)               (None, 128)               70656     
_________________________________________________________________
dropout_16 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_16 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 27s 6ms/step - loss: 1.4120 - ac
c: 0.4016 - val_loss: 1.3689 - val_acc: 0.3285
Epoch 2/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.3915 - ac
c: 0.3971 - val_loss: 1.3565 - val_acc: 0.3658
Epoch 3/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.2662 - ac
c: 0.4677 - val_loss: 1.2719 - val_acc: 0.5490
Epoch 4/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.1063 - ac
c: 0.5478 - val_loss: 1.0562 - val_acc: 0.5891
```

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Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.1053 - ac
c: 0.5452 - val_loss: 1.0730 - val_acc: 0.5504
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9749 - ac
c: 0.6021 - val_loss: 0.9824 - val_acc: 0.5931
Epoch 7/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.8412 - ac
c: 0.6340 - val_loss: 0.9500 - val_acc: 0.5904
Epoch 8/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7840 - ac
c: 0.6556 - val_loss: 0.7712 - val_acc: 0.6522
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6772 - ac
c: 0.6999 - val_loss: 0.7126 - val_acc: 0.6709
Epoch 10/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.7440 - ac
c: 0.7027 - val_loss: 0.9696 - val_acc: 0.6013
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7803 - ac
c: 0.6890 - val_loss: 0.7352 - val_acc: 0.7360
Epoch 12/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5078 - ac
c: 0.8243 - val_loss: 0.4677 - val_acc: 0.8426
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3427 - ac
c: 0.8853 - val_loss: 0.4123 - val_acc: 0.8558
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2769 - ac
c: 0.9063 - val_loss: 0.3981 - val_acc: 0.8680
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2275 - ac
c: 0.9196 - val_loss: 0.4455 - val_acc: 0.8436
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2060 - ac
c: 0.9265 - val_loss: 0.3492 - val_acc: 0.8731
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1758 - ac
c: 0.9329 - val_loss: 0.4152 - val_acc: 0.8673
Epoch 18/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1925 - ac
c: 0.9308 - val_loss: 0.3697 - val_acc: 0.8734
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1707 - ac
c: 0.9341 - val_loss: 0.5271 - val_acc: 0.8476
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2078 - ac
c: 0.9249 - val_loss: 0.2958 - val_acc: 0.8931
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1685 - ac
c: 0.9343 - val_loss: 0.2821 - val_acc: 0.8897
Epoch 22/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1664 - ac
c: 0.9347 - val_loss: 0.3393 - val_acc: 0.8839
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1569 - ac
c: 0.9433 - val_loss: 0.3679 - val_acc: 0.8744
```

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Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2877 - ac
c: 0.9076 - val_loss: 0.3203 - val_acc: 0.8816
Epoch 25/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2302 - ac
c: 0.9231 - val_loss: 0.2710 - val_acc: 0.8992
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1802 - ac
c: 0.9384 - val_loss: 0.2855 - val_acc: 0.8887
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1606 - ac
c: 0.9425 - val_loss: 0.2484 - val_acc: 0.9101
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1542 - ac
c: 0.9429 - val_loss: 0.2695 - val_acc: 0.9030
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1673 - ac
c: 0.9370 - val_loss: 0.2991 - val_acc: 0.8877
Epoch 30/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1666 - ac
c: 0.9359 - val_loss: 0.3793 - val_acc: 0.8073
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_17 (LSTM)               (None, 128)               70656     
_________________________________________________________________
dropout_17 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_17 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 29s 6ms/step - loss: 1.3212 - ac
c: 0.4340 - val_loss: 1.2314 - val_acc: 0.4696
Epoch 2/30
4901/4901 [==============================] - 24s 5ms/step - loss: 1.1846 - ac
c: 0.5156 - val_loss: 1.0090 - val_acc: 0.5986
Epoch 3/30
4901/4901 [==============================] - 25s 5ms/step - loss: 0.8387 - ac
c: 0.6456 - val_loss: 0.9103 - val_acc: 0.6295
Epoch 4/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.9368 - ac
c: 0.6276 - val_loss: 1.1300 - val_acc: 0.5056
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.2675 - ac
c: 0.5107 - val_loss: 1.1756 - val_acc: 0.5310
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 1.0134 - ac
c: 0.5780 - val_loss: 0.9863 - val_acc: 0.5972
Epoch 7/30
```

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4901/4901 [==============================] - 24s 5ms/step - loss: 0.7221 - ac
c: 0.6974 - val_loss: 0.8926 - val_acc: 0.6420
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6677 - ac
c: 0.7194 - val_loss: 0.8019 - val_acc: 0.6834
Epoch 9/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.6299 - ac
c: 0.7560 - val_loss: 0.6991 - val_acc: 0.7255
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5159 - ac
c: 0.7943 - val_loss: 0.6529 - val_acc: 0.7893
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5797 - ac
c: 0.7688 - val_loss: 0.6632 - val_acc: 0.7750
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4471 - ac
c: 0.8400 - val_loss: 0.6782 - val_acc: 0.7299
Epoch 13/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4345 - ac
c: 0.8298 - val_loss: 0.5872 - val_acc: 0.8073
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6156 - ac
c: 0.7686 - val_loss: 0.8283 - val_acc: 0.6563
Epoch 15/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.6157 - ac
c: 0.7439 - val_loss: 0.7377 - val_acc: 0.7129
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4059 - ac
c: 0.8480 - val_loss: 0.5314 - val_acc: 0.8205
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2844 - ac
c: 0.9096 - val_loss: 0.4609 - val_acc: 0.8646
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2168 - ac
c: 0.9347 - val_loss: 0.4275 - val_acc: 0.8656
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1534 - ac
c: 0.9455 - val_loss: 0.4725 - val_acc: 0.8595
Epoch 20/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1434 - ac
c: 0.9482 - val_loss: 0.4166 - val_acc: 0.8619
Epoch 21/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1282 - ac
c: 0.9529 - val_loss: 0.4779 - val_acc: 0.8595
Epoch 22/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1941 - ac
c: 0.9353 - val_loss: 0.3799 - val_acc: 0.8741
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1582 - ac
c: 0.9431 - val_loss: 0.4298 - val_acc: 0.8619
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1418 - ac
c: 0.9472 - val_loss: 0.4592 - val_acc: 0.8704
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1483 - ac
c: 0.9453 - val_loss: 0.4005 - val_acc: 0.8687
Epoch 26/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.1563 - ac
c: 0.9431 - val_loss: 0.3862 - val_acc: 0.8812
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1471 - ac
c: 0.9490 - val_loss: 0.4336 - val_acc: 0.8789
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1496 - ac
c: 0.9414 - val_loss: 0.3982 - val_acc: 0.8734
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1306 - ac
c: 0.9463 - val_loss: 0.6795 - val_acc: 0.7784
Epoch 30/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2147 - ac
c: 0.9204 - val_loss: 0.4357 - val_acc: 0.8663
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_18"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_18 (LSTM)               (None, 128)               70656     
_________________________________________________________________
dropout_18 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_18 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 29s 6ms/step - loss: 1.2088 - ac
c: 0.4867 - val_loss: 1.5044 - val_acc: 0.4479
Epoch 2/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.0295 - ac
c: 0.5736 - val_loss: 1.2313 - val_acc: 0.5372
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9173 - ac
c: 0.6210 - val_loss: 1.6042 - val_acc: 0.4092
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.9024 - ac
c: 0.6522 - val_loss: 0.8432 - val_acc: 0.7126
Epoch 5/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8551 - ac
c: 0.7011 - val_loss: 1.2068 - val_acc: 0.5002
Epoch 6/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8066 - ac
c: 0.6816 - val_loss: 0.8728 - val_acc: 0.6834
Epoch 7/30
4902/4902 [==============================] - 23s 5ms/step - loss: 1.1880 - ac
c: 0.5796 - val_loss: 1.1733 - val_acc: 0.5310
Epoch 8/30
4902/4902 [==============================] - 24s 5ms/step - loss: 1.1259 - ac
c: 0.5496 - val_loss: 1.3131 - val_acc: 0.4544
Epoch 9/30
4902/4902 [==============================] - 24s 5ms/step - loss: 1.0193 - ac
```

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c: 0.5720 - val_loss: 0.9377 - val_acc: 0.6203
Epoch 10/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.7380 - ac
c: 0.7122 - val_loss: 0.7586 - val_acc: 0.7221
Epoch 11/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6188 - ac
c: 0.7742 - val_loss: 0.7039 - val_acc: 0.7516
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5140 - ac
c: 0.8127 - val_loss: 0.6289 - val_acc: 0.7822
Epoch 13/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.4988 - ac
c: 0.8235 - val_loss: 1.0158 - val_acc: 0.6810
Epoch 14/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.6008 - ac
c: 0.7734 - val_loss: 0.6216 - val_acc: 0.7805
Epoch 15/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.4181 - ac
c: 0.8458 - val_loss: 0.6750 - val_acc: 0.7655
Epoch 16/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3850 - ac
c: 0.8652 - val_loss: 0.6019 - val_acc: 0.7835
Epoch 17/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.3234 - ac
c: 0.8876 - val_loss: 0.5702 - val_acc: 0.7927
Epoch 18/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.3056 - ac
c: 0.8886 - val_loss: 0.5233 - val_acc: 0.8341
Epoch 19/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.2754 - ac
c: 0.9041 - val_loss: 0.4982 - val_acc: 0.8317
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2399 - ac
c: 0.9125 - val_loss: 0.6715 - val_acc: 0.7913
Epoch 21/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2507 - ac
c: 0.9072 - val_loss: 0.4517 - val_acc: 0.8622
Epoch 22/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2491 - ac
c: 0.9064 - val_loss: 0.3799 - val_acc: 0.8687
Epoch 23/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1948 - ac
c: 0.9280 - val_loss: 0.5213 - val_acc: 0.8419
Epoch 24/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1956 - ac
c: 0.9292 - val_loss: 0.4349 - val_acc: 0.8653
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1800 - ac
c: 0.9310 - val_loss: 0.4105 - val_acc: 0.8731
Epoch 26/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1761 - ac
c: 0.9302 - val_loss: 0.4003 - val_acc: 0.8734
Epoch 27/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1574 - ac
c: 0.9382 - val_loss: 0.4155 - val_acc: 0.8683
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1582 - ac
```

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c: 0.9343 - val_loss: 0.4268 - val_acc: 0.8802
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1845 - ac
c: 0.9274 - val_loss: 0.5139 - val_acc: 0.8392
Epoch 30/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1763 - ac
c: 0.9245 - val_loss: 0.3796 - val_acc: 0.8843
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_19"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_19 (LSTM)               (None, 32)                5376      
_________________________________________________________________
dropout_19 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_19 (Dense)             (None, 6)                 198       
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 27s 6ms/step - loss: 1.4685 - ac
c: 0.4256 - val_loss: 1.2720 - val_acc: 0.4703
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9930 - ac
c: 0.5893 - val_loss: 0.9727 - val_acc: 0.5752
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9143 - ac
c: 0.6107 - val_loss: 0.8639 - val_acc: 0.6471
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7465 - ac
c: 0.6703 - val_loss: 0.8046 - val_acc: 0.6471
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7009 - ac
c: 0.6850 - val_loss: 0.8820 - val_acc: 0.6413
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6553 - ac
c: 0.7084 - val_loss: 0.7397 - val_acc: 0.6929
Epoch 7/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6558 - ac
c: 0.7109 - val_loss: 0.7959 - val_acc: 0.7011
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6375 - ac
c: 0.7168 - val_loss: 0.7128 - val_acc: 0.7119
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5823 - ac
c: 0.7554 - val_loss: 0.6780 - val_acc: 0.7370
Epoch 10/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5352 - ac
c: 0.7872 - val_loss: 0.6685 - val_acc: 0.7482
Epoch 11/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.4886 - ac
c: 0.8082 - val_loss: 0.6443 - val_acc: 0.7713
```

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Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4542 - ac
c: 0.8351 - val_loss: 0.6281 - val_acc: 0.7950
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4177 - ac
c: 0.8527 - val_loss: 0.5475 - val_acc: 0.8096
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3778 - ac
c: 0.8731 - val_loss: 0.5214 - val_acc: 0.8269
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3496 - ac
c: 0.8843 - val_loss: 0.4917 - val_acc: 0.8344
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3137 - ac
c: 0.8982 - val_loss: 0.4839 - val_acc: 0.8514
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2933 - ac
c: 0.9021 - val_loss: 0.4833 - val_acc: 0.8487
Epoch 18/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.3077 - ac
c: 0.9021 - val_loss: 0.5973 - val_acc: 0.8164
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2807 - ac
c: 0.9125 - val_loss: 0.5523 - val_acc: 0.8371
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2565 - ac
c: 0.9176 - val_loss: 0.4112 - val_acc: 0.8690
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2410 - ac
c: 0.9247 - val_loss: 0.4135 - val_acc: 0.8721
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2237 - ac
c: 0.9245 - val_loss: 0.4009 - val_acc: 0.8755
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2169 - ac
c: 0.9263 - val_loss: 0.3794 - val_acc: 0.8765
Epoch 24/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.2039 - ac
c: 0.9312 - val_loss: 0.3882 - val_acc: 0.8809
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1872 - ac
c: 0.9404 - val_loss: 0.4174 - val_acc: 0.8741
Epoch 26/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1827 - ac
c: 0.9380 - val_loss: 0.3905 - val_acc: 0.8792
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1843 - ac
c: 0.9367 - val_loss: 0.4022 - val_acc: 0.8744
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1830 - ac
c: 0.9402 - val_loss: 0.4299 - val_acc: 0.8731
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2026 - ac
c: 0.9312 - val_loss: 0.3355 - val_acc: 0.8839
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1803 - ac
c: 0.9412 - val_loss: 0.3559 - val_acc: 0.8782
```

```
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_20"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_20 (LSTM)               (None, 32)                5376      
_________________________________________________________________
dropout_20 (Dropout)         (None, 32)                0         
_________________________________________________________________
dense_20 (Dense)             (None, 6)                 198       
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 28s 6ms/step - loss: 1.4186 - ac
c: 0.4344 - val_loss: 1.1785 - val_acc: 0.5711
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.9935 - ac
c: 0.6017 - val_loss: 0.9974 - val_acc: 0.6094
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.8033 - ac
c: 0.6635 - val_loss: 0.8472 - val_acc: 0.6627
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7101 - ac
c: 0.6923 - val_loss: 0.8017 - val_acc: 0.6637
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6939 - ac
c: 0.6999 - val_loss: 0.7621 - val_acc: 0.6895
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7591 - ac
c: 0.6848 - val_loss: 0.9000 - val_acc: 0.6617
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7193 - ac
c: 0.7315 - val_loss: 0.7378 - val_acc: 0.7581
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5803 - ac
c: 0.7788 - val_loss: 0.6725 - val_acc: 0.7655
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.5184 - ac
c: 0.8125 - val_loss: 0.6237 - val_acc: 0.8100
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4651 - ac
c: 0.8464 - val_loss: 0.5898 - val_acc: 0.8042
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.4099 - ac
c: 0.8719 - val_loss: 0.5775 - val_acc: 0.8178
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3478 - ac
c: 0.8929 - val_loss: 0.5537 - val_acc: 0.8208
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2916 - ac
c: 0.9157 - val_loss: 0.6577 - val_acc: 0.8039
Epoch 14/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.2756 - ac
c: 0.9196 - val_loss: 0.4769 - val_acc: 0.8402
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2304 - ac
c: 0.9310 - val_loss: 0.5080 - val_acc: 0.8409
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2799 - ac
c: 0.9202 - val_loss: 0.4854 - val_acc: 0.8354
Epoch 17/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1993 - ac
c: 0.9439 - val_loss: 0.4864 - val_acc: 0.8473
Epoch 18/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1946 - ac
c: 0.9410 - val_loss: 0.4909 - val_acc: 0.8483
Epoch 19/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1863 - ac
c: 0.9457 - val_loss: 0.5473 - val_acc: 0.8310
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1763 - ac
c: 0.9465 - val_loss: 0.5513 - val_acc: 0.8415
Epoch 21/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1651 - ac
c: 0.9508 - val_loss: 0.5150 - val_acc: 0.8521
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1652 - ac
c: 0.9496 - val_loss: 0.5156 - val_acc: 0.8483
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1693 - ac
c: 0.9459 - val_loss: 0.5373 - val_acc: 0.8527
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1556 - ac
c: 0.9480 - val_loss: 0.5140 - val_acc: 0.8487
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1641 - ac
c: 0.9441 - val_loss: 0.4782 - val_acc: 0.8487
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1642 - ac
c: 0.9427 - val_loss: 0.5124 - val_acc: 0.8422
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1434 - ac
c: 0.9549 - val_loss: 0.4898 - val_acc: 0.8673
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1404 - ac
c: 0.9541 - val_loss: 0.4530 - val_acc: 0.8639
Epoch 29/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1268 - ac
c: 0.9565 - val_loss: 0.5224 - val_acc: 0.8575
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2161 - ac
c: 0.9296 - val_loss: 0.4249 - val_acc: 0.8639
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_21"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_21 (LSTM)               (None, 32)                5376
_________________________________________________________________
```

```
dropout_21 (Dropout)         (None, 32)                0
_________________________________________________________________
dense_21 (Dense)             (None, 6)                 198
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 28s 6ms/step - loss: 1.5489 - ac
c: 0.3754 - val_loss: 1.2330 - val_acc: 0.5416
Epoch 2/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.9691 - ac
c: 0.6285 - val_loss: 0.8376 - val_acc: 0.6994
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.8029 - ac
c: 0.6905 - val_loss: 0.9036 - val_acc: 0.6552
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.6496 - ac
c: 0.7419 - val_loss: 0.7295 - val_acc: 0.7353
Epoch 5/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.5465 - ac
c: 0.7797 - val_loss: 0.6476 - val_acc: 0.7598
Epoch 6/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.4987 - ac
c: 0.7942 - val_loss: 0.6451 - val_acc: 0.7618
Epoch 7/30
4902/4902 [==============================] - 22s 4ms/step - loss: 0.4667 - ac
c: 0.8184 - val_loss: 0.6680 - val_acc: 0.7689
Epoch 8/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4298 - ac
c: 0.8356 - val_loss: 0.6175 - val_acc: 0.7876
Epoch 9/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4053 - ac
c: 0.8529 - val_loss: 0.6078 - val_acc: 0.7845
Epoch 10/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3392 - ac
c: 0.8827 - val_loss: 0.6321 - val_acc: 0.8073
Epoch 11/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.3126 - ac
c: 0.8892 - val_loss: 0.5250 - val_acc: 0.8432
Epoch 12/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2453 - ac
c: 0.9186 - val_loss: 0.5119 - val_acc: 0.8442
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2231 - ac
c: 0.9298 - val_loss: 0.5700 - val_acc: 0.8361
Epoch 14/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2458 - ac
c: 0.9186 - val_loss: 0.5216 - val_acc: 0.8537
Epoch 15/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.2175 - ac
c: 0.9198 - val_loss: 0.6689 - val_acc: 0.8164
Epoch 16/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1902 - ac
```

```
c: 0.9300 - val_loss: 0.5541 - val_acc: 0.8198
Epoch 17/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2020 - ac
c: 0.9276 - val_loss: 0.5505 - val_acc: 0.8442
Epoch 18/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1566 - ac
c: 0.9435 - val_loss: 0.5362 - val_acc: 0.8565
Epoch 19/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1524 - ac
c: 0.9457 - val_loss: 0.6673 - val_acc: 0.8049
Epoch 20/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1662 - ac
c: 0.9423 - val_loss: 0.4752 - val_acc: 0.8605
Epoch 21/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1567 - ac
c: 0.9398 - val_loss: 0.4738 - val_acc: 0.8690
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1385 - ac
c: 0.9433 - val_loss: 0.4991 - val_acc: 0.8629
Epoch 23/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1457 - ac
c: 0.9417 - val_loss: 0.6247 - val_acc: 0.8510
Epoch 24/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1612 - ac
c: 0.9419 - val_loss: 0.5628 - val_acc: 0.8643
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1509 - ac
c: 0.9417 - val_loss: 0.6441 - val_acc: 0.8490
Epoch 26/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1698 - ac
c: 0.9282 - val_loss: 0.5852 - val_acc: 0.8402
Epoch 27/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1577 - ac
c: 0.9364 - val_loss: 0.5098 - val_acc: 0.8663
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1909 - ac
c: 0.9290 - val_loss: 0.4133 - val_acc: 0.8731
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1749 - ac
c: 0.9390 - val_loss: 0.4292 - val_acc: 0.8775
Epoch 30/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1784 - ac
c: 0.9353 - val_loss: 0.4981 - val_acc: 0.8639
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_22"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_22 (LSTM)               (None, 64)                18944     
_________________________________________________________________
dropout_22 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_22 (Dense)             (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
```

```
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 29s 6ms/step - loss: 1.2708 - ac
c: 0.4938 - val_loss: 0.8568 - val_acc: 0.6423
Epoch 2/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.7133 - ac
c: 0.6899 - val_loss: 0.7525 - val_acc: 0.6994
Epoch 3/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.6069 - ac
c: 0.7488 - val_loss: 0.7826 - val_acc: 0.7387
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.6260 - ac
c: 0.7843 - val_loss: 0.6629 - val_acc: 0.7727
Epoch 5/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4535 - ac
c: 0.8423 - val_loss: 0.6537 - val_acc: 0.7458
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.3300 - ac
c: 0.8910 - val_loss: 0.5521 - val_acc: 0.8069
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2612 - ac
c: 0.9133 - val_loss: 0.5539 - val_acc: 0.8222
Epoch 8/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2182 - ac
c: 0.9253 - val_loss: 0.4416 - val_acc: 0.8341
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2549 - ac
c: 0.9141 - val_loss: 0.5025 - val_acc: 0.8188
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2231 - ac
c: 0.9276 - val_loss: 0.3810 - val_acc: 0.8734
Epoch 11/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1935 - ac
c: 0.9251 - val_loss: 0.4960 - val_acc: 0.8388
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2501 - ac
c: 0.9063 - val_loss: 0.4253 - val_acc: 0.8470
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2365 - ac
c: 0.9247 - val_loss: 0.3981 - val_acc: 0.8595
Epoch 14/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2333 - ac
c: 0.9182 - val_loss: 0.9518 - val_acc: 0.6814
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2095 - ac
c: 0.9225 - val_loss: 0.4136 - val_acc: 0.8612
Epoch 16/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1602 - ac
c: 0.9410 - val_loss: 0.4067 - val_acc: 0.8666
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1495 - ac
c: 0.9443 - val_loss: 0.4242 - val_acc: 0.8575
Epoch 18/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1482 - ac
c: 0.9421 - val_loss: 0.3942 - val_acc: 0.8697
```

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Epoch 19/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1748 - ac
c: 0.9333 - val_loss: 0.3937 - val_acc: 0.8690
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1485 - ac
c: 0.9449 - val_loss: 0.4501 - val_acc: 0.8565
Epoch 21/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1446 - ac
c: 0.9398 - val_loss: 0.4519 - val_acc: 0.8643
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1538 - ac
c: 0.9414 - val_loss: 0.4425 - val_acc: 0.8626
Epoch 23/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1681 - ac
c: 0.9243 - val_loss: 0.4173 - val_acc: 0.8554
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1642 - ac
c: 0.9357 - val_loss: 0.4110 - val_acc: 0.8605
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1471 - ac
c: 0.9400 - val_loss: 0.4015 - val_acc: 0.8663
Epoch 26/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1389 - ac
c: 0.9414 - val_loss: 0.4398 - val_acc: 0.8636
Epoch 27/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1603 - ac
c: 0.9406 - val_loss: 0.4711 - val_acc: 0.8551
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1450 - ac
c: 0.9437 - val_loss: 0.4468 - val_acc: 0.8619
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1290 - ac
c: 0.9508 - val_loss: 0.4223 - val_acc: 0.8755
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1287 - ac
c: 0.9500 - val_loss: 0.5815 - val_acc: 0.8320
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_23"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_23 (LSTM)               (None, 64)                18944
_________________________________________________________________
dropout_23 (Dropout)         (None, 64)                0
_________________________________________________________________
dense_23 (Dense)             (None, 6)                 390
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 29s 6ms/step - loss: 1.2206 - ac
c: 0.5070 - val_loss: 0.9054 - val_acc: 0.6634
Epoch 2/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.6476 - ac
c: 0.7425 - val_loss: 0.6557 - val_acc: 0.7689
Epoch 3/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.4097 - ac
c: 0.8727 - val_loss: 0.5942 - val_acc: 0.7869
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2505 - ac
c: 0.9239 - val_loss: 0.4888 - val_acc: 0.8426
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2006 - ac
c: 0.9378 - val_loss: 0.5330 - val_acc: 0.8249
Epoch 6/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2076 - ac
c: 0.9345 - val_loss: 0.4092 - val_acc: 0.8626
Epoch 7/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1833 - ac
c: 0.9361 - val_loss: 0.5659 - val_acc: 0.8456
Epoch 8/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1589 - ac
c: 0.9429 - val_loss: 0.5382 - val_acc: 0.8415
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2041 - ac
c: 0.9312 - val_loss: 0.4492 - val_acc: 0.8711
Epoch 10/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1539 - ac
c: 0.9553 - val_loss: 0.4202 - val_acc: 0.8758
Epoch 11/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1237 - ac
c: 0.9594 - val_loss: 0.4353 - val_acc: 0.8799
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1300 - ac
c: 0.9572 - val_loss: 0.4622 - val_acc: 0.8741
Epoch 13/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1284 - ac
c: 0.9588 - val_loss: 0.3810 - val_acc: 0.8819
Epoch 14/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1719 - ac
c: 0.9347 - val_loss: 0.3973 - val_acc: 0.8758
Epoch 15/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1205 - ac
c: 0.9535 - val_loss: 0.4112 - val_acc: 0.8697
Epoch 16/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1055 - ac
c: 0.9594 - val_loss: 0.4762 - val_acc: 0.8751
Epoch 17/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1060 - ac
c: 0.9578 - val_loss: 0.4748 - val_acc: 0.8823
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1087 - ac
c: 0.9590 - val_loss: 0.4762 - val_acc: 0.8772
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1097 - ac
c: 0.9549 - val_loss: 0.4954 - val_acc: 0.8728
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.0971 - ac
c: 0.9563 - val_loss: 0.5026 - val_acc: 0.8826
Epoch 21/30
```

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4901/4901 [==============================] - 23s 5ms/step - loss: 0.1384 - ac
c: 0.9463 - val_loss: 0.7910 - val_acc: 0.8229
Epoch 22/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1207 - ac
c: 0.9572 - val_loss: 0.6629 - val_acc: 0.8636
Epoch 23/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1298 - ac
c: 0.9574 - val_loss: 0.4932 - val_acc: 0.8697
Epoch 24/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1092 - ac
c: 0.9578 - val_loss: 0.5813 - val_acc: 0.8660
Epoch 25/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1103 - ac
c: 0.9572 - val_loss: 0.4709 - val_acc: 0.8768
Epoch 26/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1181 - ac
c: 0.9539 - val_loss: 0.4664 - val_acc: 0.8778
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1012 - ac
c: 0.9580 - val_loss: 0.5119 - val_acc: 0.8714
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1230 - ac
c: 0.9557 - val_loss: 0.4253 - val_acc: 0.8724
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1329 - ac
c: 0.9439 - val_loss: 0.6467 - val_acc: 0.7268
Epoch 30/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1926 - ac
c: 0.9219 - val_loss: 0.4469 - val_acc: 0.8717
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_24"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_24 (LSTM)               (None, 64)                18944     
_________________________________________________________________
dropout_24 (Dropout)         (None, 64)                0         
_________________________________________________________________
dense_24 (Dense)             (None, 6)                 390       
=================================================================
Total params: 19,334
Trainable params: 19,334
Non-trainable params: 0
_________________________________________________________________
None
Train on 4902 samples, validate on 2947 samples
Epoch 1/30
4902/4902 [==============================] - 29s 6ms/step - loss: 1.2446 - ac
c: 0.5063 - val_loss: 0.8953 - val_acc: 0.6390
Epoch 2/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.7683 - ac
c: 0.6705 - val_loss: 0.7350 - val_acc: 0.7004
Epoch 3/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.5848 - ac
c: 0.7462 - val_loss: 0.6862 - val_acc: 0.7455
Epoch 4/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.4259 - ac
```

```
c: 0.8386 - val_loss: 0.5207 - val_acc: 0.8178
Epoch 5/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2935 - ac
c: 0.9058 - val_loss: 0.5166 - val_acc: 0.8320
Epoch 6/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.2770 - ac
c: 0.9109 - val_loss: 0.4559 - val_acc: 0.8541
Epoch 7/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1916 - ac
c: 0.9323 - val_loss: 0.4278 - val_acc: 0.8683
Epoch 8/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1761 - ac
c: 0.9364 - val_loss: 0.3920 - val_acc: 0.8765
Epoch 9/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1644 - ac
c: 0.9390 - val_loss: 0.4141 - val_acc: 0.8806
Epoch 10/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1508 - ac
c: 0.9366 - val_loss: 0.3964 - val_acc: 0.8758
Epoch 11/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1622 - ac
c: 0.9398 - val_loss: 0.3970 - val_acc: 0.8765
Epoch 12/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1779 - ac
c: 0.9378 - val_loss: 0.3948 - val_acc: 0.8860
Epoch 13/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.2238 - ac
c: 0.9231 - val_loss: 0.3750 - val_acc: 0.8850
Epoch 14/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1589 - ac
c: 0.9404 - val_loss: 0.3229 - val_acc: 0.8972
Epoch 15/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1548 - ac
c: 0.9390 - val_loss: 0.3837 - val_acc: 0.8639
Epoch 16/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1510 - ac
c: 0.9376 - val_loss: 0.3132 - val_acc: 0.9033
Epoch 17/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1675 - ac
c: 0.9323 - val_loss: 0.3380 - val_acc: 0.9030
Epoch 18/30
4902/4902 [==============================] - 22s 5ms/step - loss: 0.1638 - ac
c: 0.9380 - val_loss: 0.4540 - val_acc: 0.8504
Epoch 19/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1416 - ac
c: 0.9472 - val_loss: 0.4620 - val_acc: 0.8697
Epoch 20/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1208 - ac
c: 0.9525 - val_loss: 0.4882 - val_acc: 0.8812
Epoch 21/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1228 - ac
c: 0.9498 - val_loss: 0.4189 - val_acc: 0.8765
Epoch 22/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1024 - ac
c: 0.9598 - val_loss: 0.4222 - val_acc: 0.8826
Epoch 23/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1071 - ac
```

```
c: 0.9521 - val_loss: 0.4033 - val_acc: 0.8877
Epoch 24/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1167 - ac
c: 0.9480 - val_loss: 0.3914 - val_acc: 0.8962
Epoch 25/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1047 - ac
c: 0.9551 - val_loss: 0.4562 - val_acc: 0.8802
Epoch 26/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1095 - ac
c: 0.9551 - val_loss: 0.4109 - val_acc: 0.8982
Epoch 27/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1955 - ac
c: 0.9264 - val_loss: 0.4433 - val_acc: 0.8690
Epoch 28/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1206 - ac
c: 0.9529 - val_loss: 0.6180 - val_acc: 0.8490
Epoch 29/30
4902/4902 [==============================] - 23s 5ms/step - loss: 0.1421 - ac
c: 0.9449 - val_loss: 0.4366 - val_acc: 0.8985
Epoch 30/30
4902/4902 [==============================] - 24s 5ms/step - loss: 0.1144 - ac
c: 0.9504 - val_loss: 0.4239 - val_acc: 0.8914
2450/2450 [==============================] - 4s 2ms/step
Model: "sequential_25"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_25 (LSTM)               (None, 128)               70656     
_________________________________________________________________
dropout_25 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_25 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 29s 6ms/step - loss: 0.9542 - ac
c: 0.6182 - val_loss: 0.8693 - val_acc: 0.6498
Epoch 2/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5647 - ac
c: 0.7960 - val_loss: 0.5274 - val_acc: 0.8045
Epoch 3/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2985 - ac
c: 0.8980 - val_loss: 0.4171 - val_acc: 0.8568
Epoch 4/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2067 - ac
c: 0.9278 - val_loss: 0.4451 - val_acc: 0.8395
Epoch 5/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1961 - ac
c: 0.9276 - val_loss: 0.3291 - val_acc: 0.8694
Epoch 6/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1678 - ac
c: 0.9351 - val_loss: 0.3749 - val_acc: 0.8653
```

```
Epoch 7/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1976 - ac
c: 0.9267 - val_loss: 0.4665 - val_acc: 0.8490
Epoch 8/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1479 - ac
c: 0.9418 - val_loss: 0.4340 - val_acc: 0.8612
Epoch 9/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1551 - ac
c: 0.9418 - val_loss: 0.3435 - val_acc: 0.8755
Epoch 10/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1829 - ac
c: 0.9243 - val_loss: 0.3574 - val_acc: 0.8907
Epoch 11/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1340 - ac
c: 0.9445 - val_loss: 0.3484 - val_acc: 0.8901
Epoch 12/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1672 - ac
c: 0.9388 - val_loss: 0.3540 - val_acc: 0.8738
Epoch 13/30
4901/4901 [==============================] - 22s 5ms/step - loss: 0.1334 - ac
c: 0.9494 - val_loss: 0.3960 - val_acc: 0.8918
Epoch 14/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1263 - ac
c: 0.9510 - val_loss: 0.3436 - val_acc: 0.8907
Epoch 15/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1419 - ac
c: 0.9433 - val_loss: 0.4624 - val_acc: 0.8809
Epoch 16/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1727 - ac
c: 0.9345 - val_loss: 0.4598 - val_acc: 0.8663
Epoch 17/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1610 - ac
c: 0.9433 - val_loss: 0.2876 - val_acc: 0.9104
Epoch 18/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1245 - ac
c: 0.9504 - val_loss: 0.3160 - val_acc: 0.9063
Epoch 19/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.2457 - ac
c: 0.9229 - val_loss: 0.3852 - val_acc: 0.8918
Epoch 20/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1279 - ac
c: 0.9496 - val_loss: 0.3718 - val_acc: 0.8799
Epoch 21/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1472 - ac
c: 0.9408 - val_loss: 0.4326 - val_acc: 0.8945
Epoch 22/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1313 - ac
c: 0.9494 - val_loss: 0.4681 - val_acc: 0.8846
Epoch 23/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1172 - ac
c: 0.9547 - val_loss: 0.4872 - val_acc: 0.8911
Epoch 24/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1363 - ac
c: 0.9508 - val_loss: 0.4664 - val_acc: 0.8890
Epoch 25/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1600 - ac
c: 0.9347 - val_loss: 0.4758 - val_acc: 0.8836
```

```
Epoch 26/30
4901/4901 [==============================] - 31s 6ms/step - loss: 0.1356 - ac
c: 0.9455 - val_loss: 0.5322 - val_acc: 0.8792
Epoch 27/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1288 - ac
c: 0.9498 - val_loss: 0.3986 - val_acc: 0.8992
Epoch 28/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.1180 - ac
c: 0.9535 - val_loss: 0.4902 - val_acc: 0.8951
Epoch 29/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1515 - ac
c: 0.9478 - val_loss: 0.4360 - val_acc: 0.8979
Epoch 30/30
4901/4901 [==============================] - 23s 5ms/step - loss: 0.1236 - ac
c: 0.9523 - val_loss: 0.4217 - val_acc: 0.9060
2451/2451 [==============================] - 4s 2ms/step
Model: "sequential_26"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_26 (LSTM)               (None, 128)               70656     
_________________________________________________________________
dropout_26 (Dropout)         (None, 128)               0         
_________________________________________________________________
dense_26 (Dense)             (None, 6)                 774       
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
None
Train on 4901 samples, validate on 2947 samples
Epoch 1/30
4901/4901 [==============================] - 30s 6ms/step - loss: 1.0078 - ac
c: 0.5850 - val_loss: 0.7571 - val_acc: 0.7089
Epoch 2/30
4901/4901 [==============================] - 24s 5ms/step - loss: 0.5416 - ac
c: 0.8031 - val_loss: 0.6674 - val_acc: 0.7665
Epoch 3/30
 320/4901 [>.............................] - ETA: 16s - loss: 0.3546 - acc:
 0.8906Buffered data was truncated after reaching the output size limit.
```

Using CNN-1D

In [0]:

```
from keras.layers.convolutional import Conv1D
from keras.layers import Dense, Activation, Flatten, MaxPooling1D
from keras.layers.normalization import BatchNormalization
```

In [79]:
```
model = Sequential()
model.add(Conv1D(64, kernel_size=3,activation='relu', padding='same', input_shape=(timesteps, input_dim)))
model.add(Conv1D(64, kernel_size=3,activation='relu', padding='same', input_shape=(timesteps, input_dim)))
model.add(MaxPooling1D(pool_size=2))


model.add(Conv1D(32, 3, activation='relu', padding='same'))
model.add(Conv1D(32, 3, activation='relu', padding='same'))
model.add(MaxPooling1D(pool_size=2))
model.add(BatchNormalization())
model.add(Dropout(0.5))

model.add(Flatten())
model.add(Dense(32, activation='relu'))
model.add(Dense(n_classes, activation='softmax'))

model.summary()
```

```
Model: "sequential_17"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_9 (Conv1D)            (None, 128, 64)           1792
_________________________________________________________________
conv1d_10 (Conv1D)           (None, 128, 64)           12352
_________________________________________________________________
max_pooling1d_5 (MaxPooling1 (None, 64, 64)            0
_________________________________________________________________
conv1d_11 (Conv1D)           (None, 64, 32)            6176
_________________________________________________________________
conv1d_12 (Conv1D)           (None, 64, 32)            3104
_________________________________________________________________
max_pooling1d_6 (MaxPooling1 (None, 32, 32)            0
_________________________________________________________________
batch_normalization_23 (Batc (None, 32, 32)            128
_________________________________________________________________
dropout_39 (Dropout)         (None, 32, 32)            0
_________________________________________________________________
flatten_15 (Flatten)         (None, 1024)              0
_________________________________________________________________
dense_31 (Dense)             (None, 32)                32800
_________________________________________________________________
dense_32 (Dense)             (None, 6)                 198
=================================================================
Total params: 56,550
Trainable params: 56,486
Non-trainable params: 64
_________________________________________________________________
```

In [0]:
```
model.compile(loss="binary_crossentropy",
              optimizer="adam",
              metrics=['accuracy'])
```

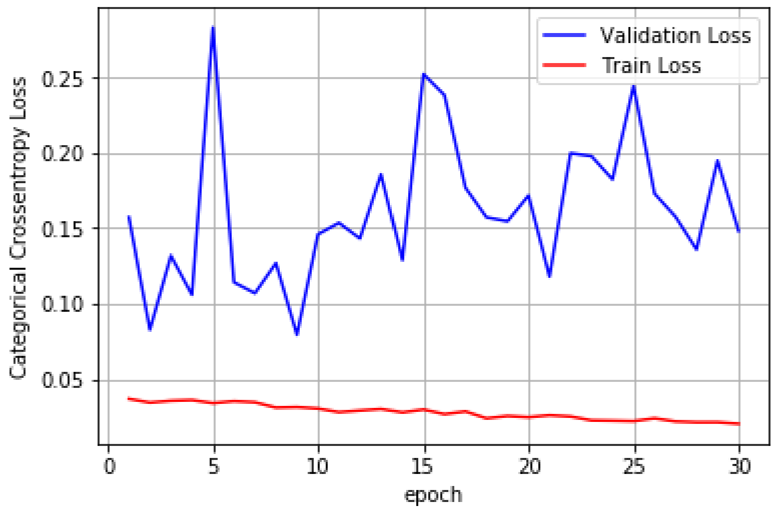
In [82]:
```
history= model.fit(X_train, Y_train, batch_size=64, epochs=epochs, verbose=1,
validation_data=(X_test, Y_test))
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 2s 218us/step - loss: 0.0367 - a
cc: 0.9841 - val_loss: 0.1573 - val_acc: 0.9636
Epoch 2/30
7352/7352 [==============================] - 2s 223us/step - loss: 0.0342 - a
cc: 0.9846 - val_loss: 0.0827 - val_acc: 0.9713
Epoch 3/30
7352/7352 [==============================] - 2s 225us/step - loss: 0.0355 - a
cc: 0.9837 - val_loss: 0.1320 - val_acc: 0.9638
Epoch 4/30
7352/7352 [==============================] - 2s 225us/step - loss: 0.0359 - a
cc: 0.9836 - val_loss: 0.1060 - val_acc: 0.9675
Epoch 5/30
7352/7352 [==============================] - 2s 224us/step - loss: 0.0339 - a
cc: 0.9849 - val_loss: 0.2837 - val_acc: 0.9341
Epoch 6/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0352 - a
cc: 0.9842 - val_loss: 0.1144 - val_acc: 0.9713
Epoch 7/30
7352/7352 [==============================] - 2s 224us/step - loss: 0.0345 - a
cc: 0.9854 - val_loss: 0.1071 - val_acc: 0.9760
Epoch 8/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.0309 - a
cc: 0.9860 - val_loss: 0.1271 - val_acc: 0.9695
Epoch 9/30
7352/7352 [==============================] - 2s 224us/step - loss: 0.0312 - a
cc: 0.9862 - val_loss: 0.0794 - val_acc: 0.9702
Epoch 10/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.0303 - a
cc: 0.9873 - val_loss: 0.1459 - val_acc: 0.9621
Epoch 11/30
7352/7352 [==============================] - 2s 215us/step - loss: 0.0279 - a
cc: 0.9863 - val_loss: 0.1536 - val_acc: 0.9651
Epoch 12/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.0290 - a
cc: 0.9866 - val_loss: 0.1432 - val_acc: 0.9720
Epoch 13/30
7352/7352 [==============================] - 2s 221us/step - loss: 0.0300 - a
cc: 0.9857 - val_loss: 0.1859 - val_acc: 0.9705
Epoch 14/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0277 - a
cc: 0.9866 - val_loss: 0.1291 - val_acc: 0.9709
Epoch 15/30
7352/7352 [==============================] - 2s 217us/step - loss: 0.0296 - a
cc: 0.9865 - val_loss: 0.2526 - val_acc: 0.9576
Epoch 16/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0265 - a
cc: 0.9872 - val_loss: 0.2386 - val_acc: 0.9516
Epoch 17/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0283 - a
cc: 0.9865 - val_loss: 0.1769 - val_acc: 0.9694
Epoch 18/30
7352/7352 [==============================] - 2s 228us/step - loss: 0.0237 - a
cc: 0.9883 - val_loss: 0.1573 - val_acc: 0.9618
Epoch 19/30
7352/7352 [==============================] - 2s 221us/step - loss: 0.0253 - a
```

```
cc: 0.9873 - val_loss: 0.1546 - val_acc: 0.9656
Epoch 20/30
7352/7352 [==============================] - 2s 215us/step - loss: 0.0245 - a
cc: 0.9882 - val_loss: 0.1718 - val_acc: 0.9674
Epoch 21/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0258 - a
cc: 0.9872 - val_loss: 0.1181 - val_acc: 0.9683
Epoch 22/30
7352/7352 [==============================] - 2s 223us/step - loss: 0.0250 - a
cc: 0.9878 - val_loss: 0.2000 - val_acc: 0.9727
Epoch 23/30
7352/7352 [==============================] - 2s 226us/step - loss: 0.0224 - a
cc: 0.9885 - val_loss: 0.1980 - val_acc: 0.9672
Epoch 24/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0222 - a
cc: 0.9892 - val_loss: 0.1825 - val_acc: 0.9679
Epoch 25/30
7352/7352 [==============================] - 2s 218us/step - loss: 0.0219 - a
cc: 0.9892 - val_loss: 0.2449 - val_acc: 0.9606
Epoch 26/30
7352/7352 [==============================] - 2s 221us/step - loss: 0.0238 - a
cc: 0.9889 - val_loss: 0.1731 - val_acc: 0.9681
Epoch 27/30
7352/7352 [==============================] - 2s 225us/step - loss: 0.0217 - a
cc: 0.9895 - val_loss: 0.1576 - val_acc: 0.9712
Epoch 28/30
7352/7352 [==============================] - 2s 226us/step - loss: 0.0212 - a
cc: 0.9903 - val_loss: 0.1358 - val_acc: 0.9707
Epoch 29/30
7352/7352 [==============================] - 2s 224us/step - loss: 0.0212 - a
cc: 0.9898 - val_loss: 0.1950 - val_acc: 0.9589
Epoch 30/30
7352/7352 [==============================] - 2s 215us/step - loss: 0.0201 - a
cc: 0.9900 - val_loss: 0.1482 - val_acc: 0.9696
```

In [84]:
```
score_ = model.evaluate(X_test, Y_test)
print('loss:', score_[0])
print('Accuracy:', score_[1])
x = list(range(1,epochs+1))
fig,ax = plt.subplots(1,1)
ax.set_xlabel('epoch') ; ax.set_ylabel('Categorical Crossentropy Loss')
vy = history.history['val_loss']
ty = history.history['loss']
plt_dynamic(x, vy, ty, ax)
```

```
2947/2947 [==============================] - 1s 196us/step
loss: 0.14820250596297643
Accuracy: 0.9695735862791478
```



In [83]:
```
from prettytable import PrettyTable

x = PrettyTable()

x.field_names = ["Model", "Loss","Test ACC"]

x.add_row(["LSTM","categorical", 0.89])
x.add_row(["CNN:1D","binary", 0.9696])

print(x)
```

```
+--------+------------+----------+
| Model  |    Loss    | Test ACC |
+--------+------------+----------+
|  LSTM  | categorical|   0.89   |
| CNN:1D |   binary   |  0.9696  |
+--------+------------+----------+
```

Conclusions:

1) Used Various ML model with features extracted by domain experts.

2) Linear SVM performed well with 96% accuracy.

3) Tried simple LSTM model with only 128 features given by sensors. Performed GridSearch to fine tune hyperparameters.LSTM Model performed good but not that great like Linear SVM.It gave 0.89 accuracy.

4) Then CNN 1D was tried and it yield almost 97% accuracy when used binary cross ectropy.

5) All models were run for 30 epochs.