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

- Data set can be found here [https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones (https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones)](https://archive.ics.uci.edu/ml/datasets/Human+Activity+Recognition+Using+Smartphones)

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&response_type=code&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 (https://accounts.google.com/o/oauth2/auth?client_id=947318989803-6bn6qk8qdgf4n4g3pfee6491hc0brc4i.apps.googleusercontent.com&redirect_uri=urn%3aietf%3awg%3aoauth%3a2.0%3aoob&response_type=code&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)

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

In [2]:
```
import numpy as np
import pandas as pd

# get the features from the file features.txt
features = list()
with open('/content/drive/My Drive/HAR/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
```

In [7]:
```
print(features)
```

```
['tBodyAcc-mean()-X', 'tBodyAcc-mean()-Y', 'tBodyAcc-mean()-Z', 'tBodyAcc-std()-X', 'tBodyAcc-std()-Y', 'tBo
dyAcc-std()-Z', 'tBodyAcc-mad()-X', 'tBodyAcc-mad()-Y', 'tBodyAcc-mad()-Z', 'tBodyAcc-max()-X', 'tBodyAcc-ma
x()-Y', 'tBodyAcc-max()-Z', 'tBodyAcc-min()-X', 'tBodyAcc-min()-Y', 'tBodyAcc-min()-Z', 'tBodyAcc-sma()', 't
BodyAcc-energy()-X', 'tBodyAcc-energy()-Y', 'tBodyAcc-energy()-Z', 'tBodyAcc-iqr()-X', 'tBodyAcc-iqr()-Y',
'tBodyAcc-iqr()-Z', 'tBodyAcc-entropy()-X', 'tBodyAcc-entropy()-Y', 'tBodyAcc-entropy()-Z', 'tBodyAcc-arCoef
f()-X,1', 'tBodyAcc-arCoeff()-X,2', 'tBodyAcc-arCoeff()-X,3', 'tBodyAcc-arCoeff()-X,4', 'tBodyAcc-arCoeff()-
Y,1', 'tBodyAcc-arCoeff()-Y,2', 'tBodyAcc-arCoeff()-Y,3', 'tBodyAcc-arCoeff()-Y,4', 'tBodyAcc-arCoeff()-Z,
1', 'tBodyAcc-arCoeff()-Z,2', 'tBodyAcc-arCoeff()-Z,3', 'tBodyAcc-arCoeff()-Z,4', 'tBodyAcc-correlation()-X,
Y', 'tBodyAcc-correlation()-X,Z', 'tBodyAcc-correlation()-Y,Z', 'tGravityAcc-mean()-X', 'tGravityAcc-mean()-
Y', 'tGravityAcc-mean()-Z', 'tGravityAcc-std()-X', 'tGravityAcc-std()-Y', 'tGravityAcc-std()-Z', 'tGravityAc
c-mad()-X', 'tGravityAcc-mad()-Y', 'tGravityAcc-mad()-Z', 'tGravityAcc-max()-X', 'tGravityAcc-max()-Y', 'tGr
avityAcc-max()-Z', 'tGravityAcc-min()-X', 'tGravityAcc-min()-Y', 'tGravityAcc-min()-Z', 'tGravityAcc-sma()',
'tGravityAcc-energy()-X', 'tGravityAcc-energy()-Y', 'tGravityAcc-energy()-Z', 'tGravityAcc-iqr()-X', 'tGravi
tyAcc-iqr()-Y', 'tGravityAcc-iqr()-Z', 'tGravityAcc-entropy()-X', 'tGravityAcc-entropy()-Y', 'tGravityAcc-en
tropy()-Z', 'tGravityAcc-arCoeff()-X,1', 'tGravityAcc-arCoeff()-X,2', 'tGravityAcc-arCoeff()-X,3', 'tGravity
Acc-arCoeff()-X,4', 'tGravityAcc-arCoeff()-Y,1', 'tGravityAcc-arCoeff()-Y,2', 'tGravityAcc-arCoeff()-Y,3',
'tGravityAcc-arCoeff()-Y,4', 'tGravityAcc-arCoeff()-Z,1', 'tGravityAcc-arCoeff()-Z,2', 'tGravityAcc-arCoeff
()-Z,3', 'tGravityAcc-arCoeff()-Z,4', 'tGravityAcc-correlation()-X,Y', 'tGravityAcc-correlation()-X,Z', 'tGr
avityAcc-correlation()-Y,Z', 'tBodyAccJerk-mean()-X', 'tBodyAccJerk-mean()-Y', 'tBodyAccJerk-mean()-Z', 'tBo
```

Obtain the train data

In [0]:
```
# get the data from txt files to pandas dataffame
X_train = pd.read_csv("/content/drive/My Drive/HAR/UCI_HAR_dataset/train/X_train.txt", delim_whitespace=True, he
```

In [0]:
```
# add subject column to the dataframe
X_train['subject'] = pd.read_csv('/content/drive/My Drive/HAR/UCI_HAR_dataset/train/subject_train.txt', header=N

y_train = pd.read_csv('/content/drive/My Drive/HAR/UCI_HAR_dataset/train/y_train.txt', names=['Activity'], squee
y_train_labels = y_train.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWNSTAIRS',\
                       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()
```

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

Out[3]:
```
(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', header=None, squeeze=True)

# get y labels from the txt file
y_test = pd.read_csv('UCI_HAR_dataset/test/y_test.txt', names=['Activity'], squeeze=True)
y_test_labels = y_test.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWNSTAIRS',\
                       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()
```

```
D:\installed\Anaconda3\lib\site-packages\pandas\io\parsers.py:678: UserWarning: Duplicate names specified. Thi
s will raise an error in the future.
  return _read(filepath_or_buffer, kwds)
```

Out[4]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	angle(tBod
2261	0.279196	-0.018261	-0.103376	-0.996955	-0.982959	-0.988239	-0.9972	-0.982509	-0.986964	-0.940634	...	

1 rows × 564 columns

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

Out[5]:
```
(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

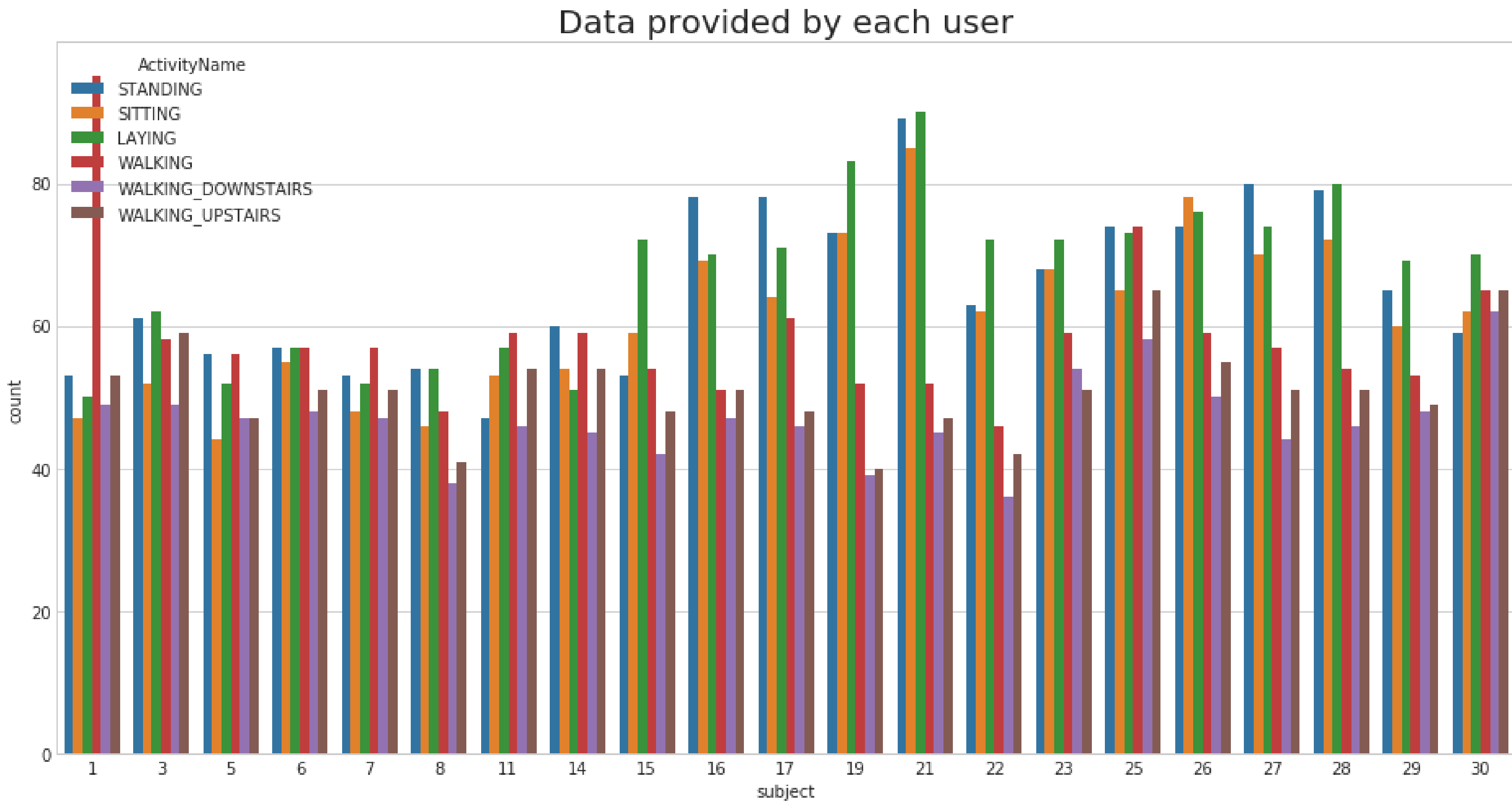
In [0]:
```
print('We have {} NaN/Null values in train'.format(train.isnull().values.sum()))
print('We have {} NaN/Null values in test'.format(test.isnull().values.sum()))
```

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

3. Check for data imbalance

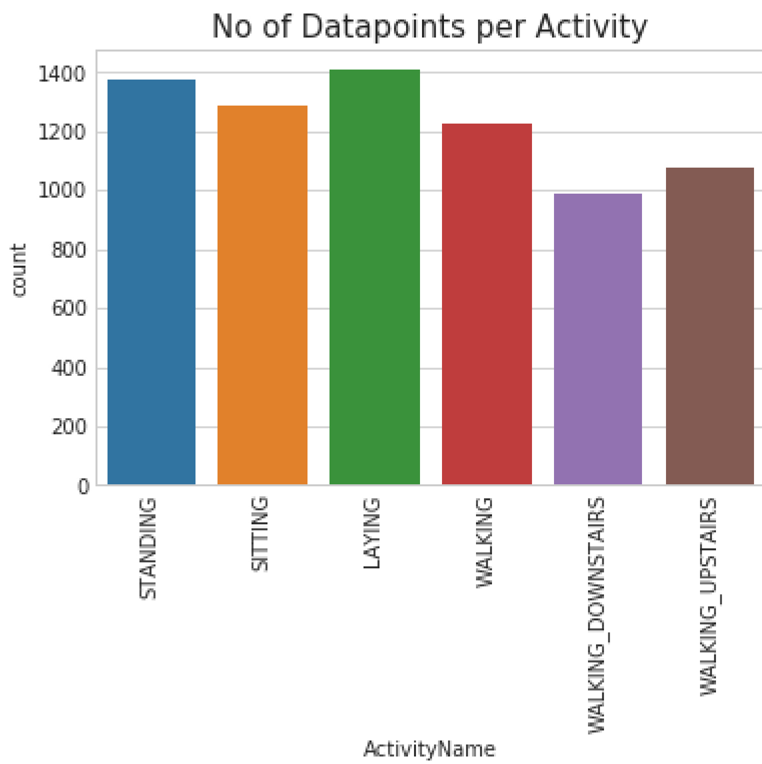
In [0]:
```
import matplotlib.pyplot as plt
import seaborn as sns

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[11]:
```
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/csv_files/train.csv', index=False)
test.to_csv('UCI_HAR_Dataset/csv_files/test.csv', index=False)
```

Exploratory Data Analysis

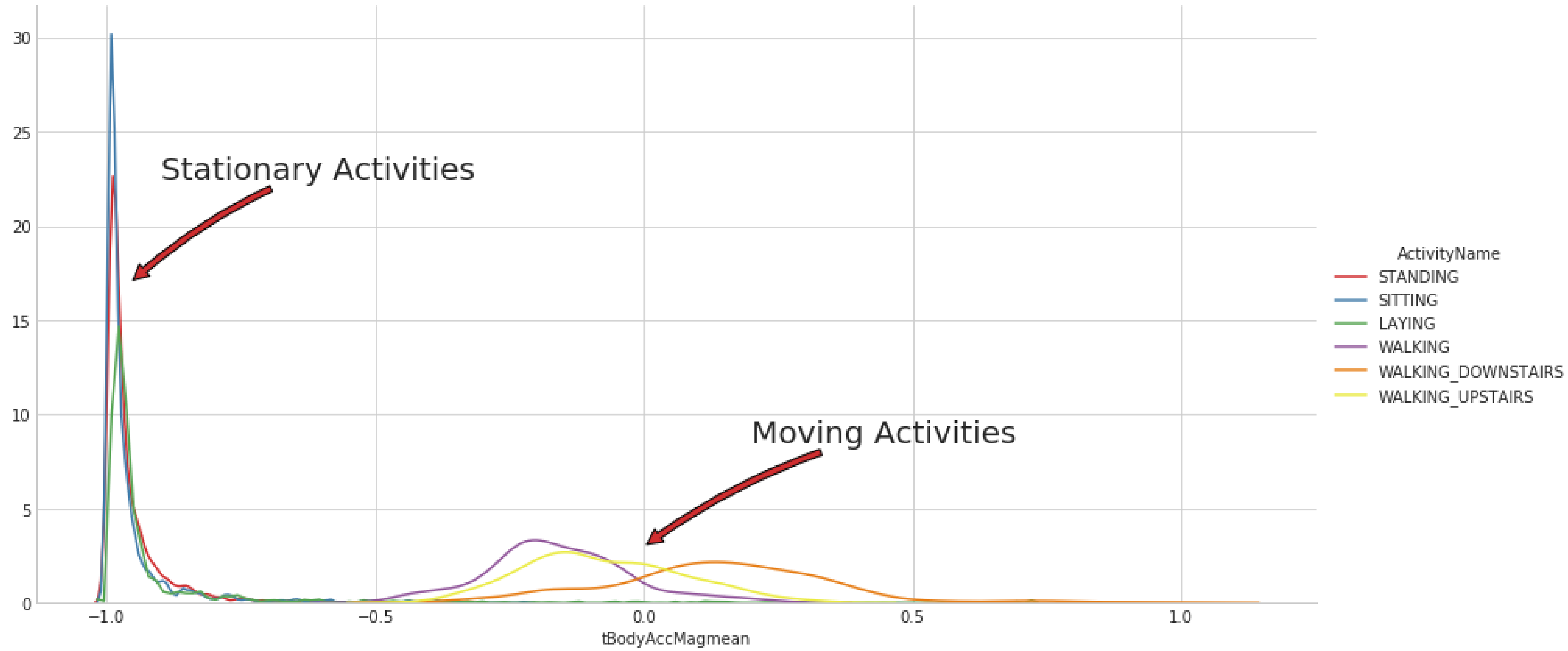
"***Without domain knowledge EDA has no meaning, without EDA a problem has no soul.***"

1. Featuring Engineering from Domain Knowledge

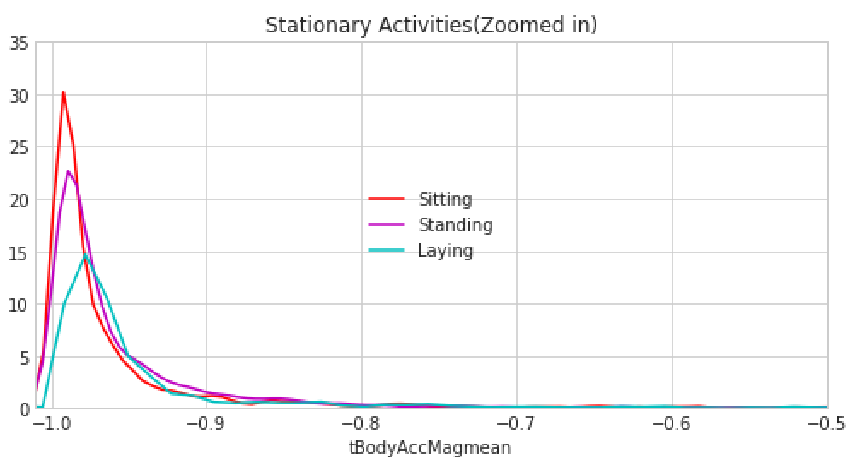
- **Static and Dynamic Activities**
  - In static activities (sit, stand, lie down) motion information will not be very useful.
  - In the dynamic activities (Walking, WalkingUpstairs,WalkingDownstairs) motion info will be significant.

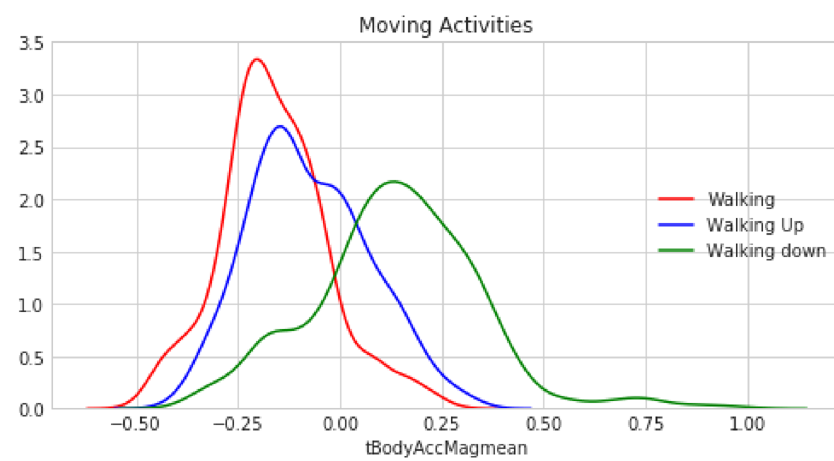
2. Stationary and Moving activities are completely different

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()
```



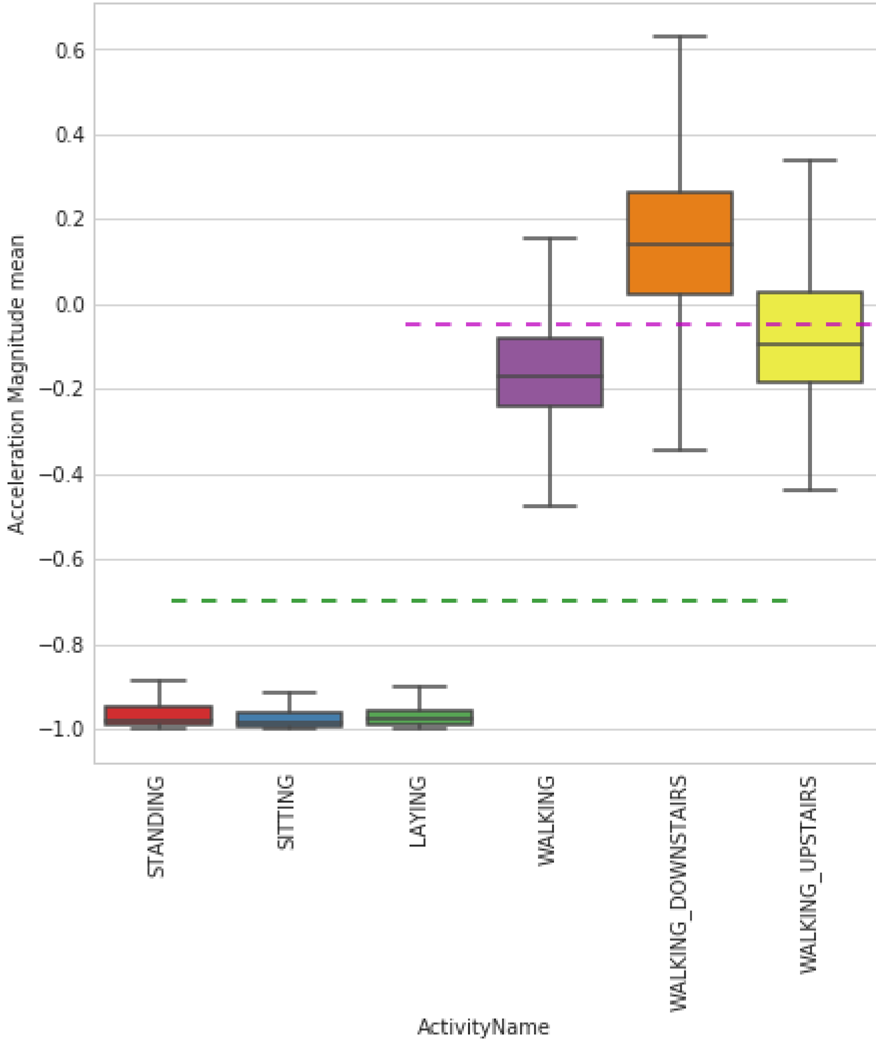
In [0]:
```
# for plotting purposes taking datapoints of each activity to a different dataframe
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

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()
```

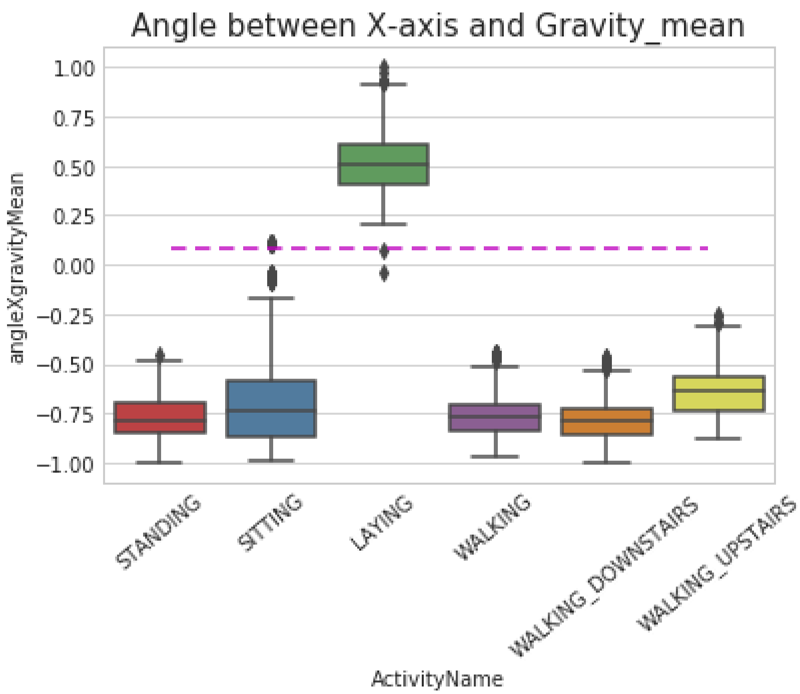


__ Observations__:

- 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

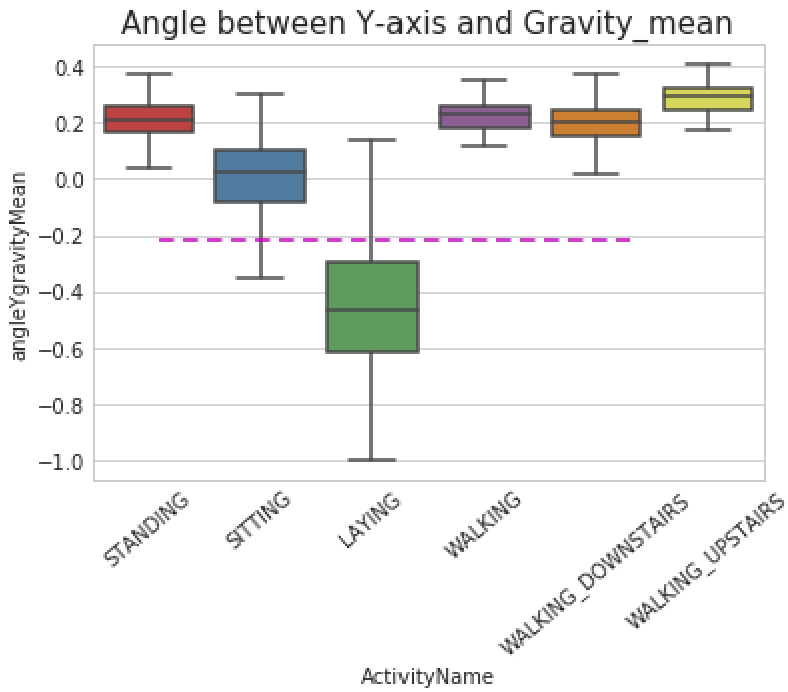
In [0]:
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



__ 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

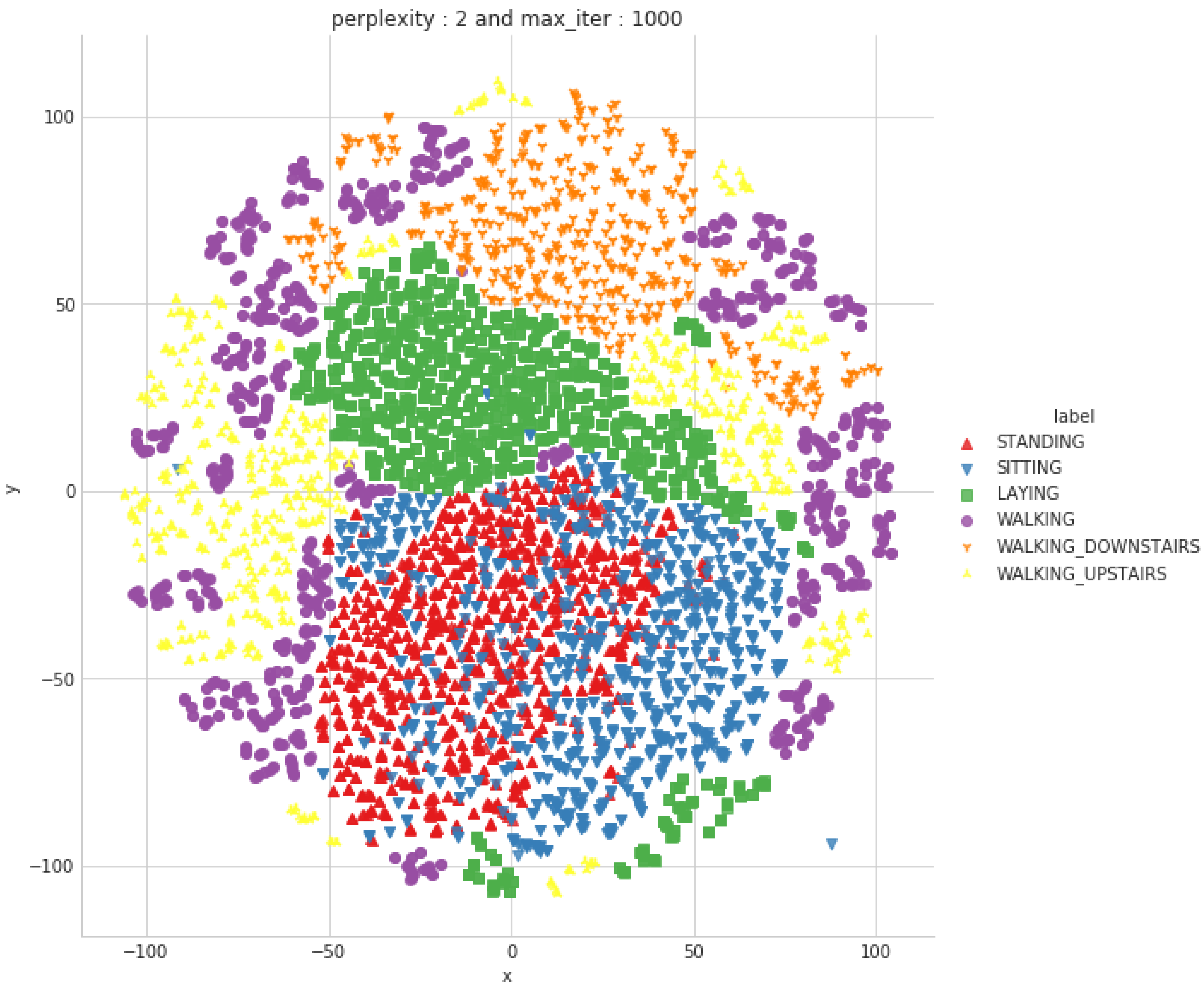
In [0]:
```
import numpy as np
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns
```

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_data)
        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_data})

        # 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_iter))
        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 =[2,5,10,20,50])
```

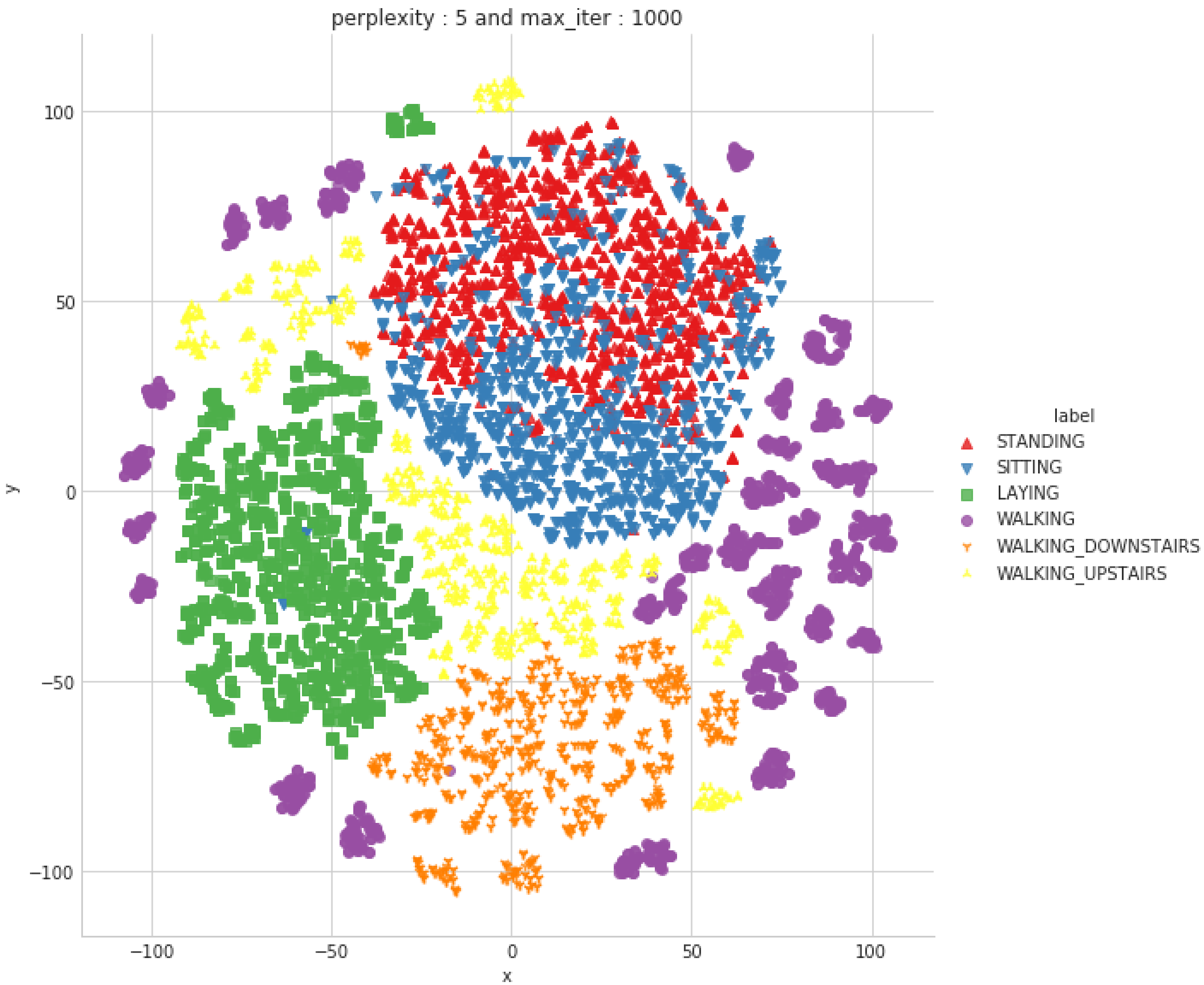
```
performing tsne with perplexity 2 and with 1000 iterations at max
[t-SNE] Computing 7 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.426s...
[t-SNE] Computed neighbors for 7352 samples in 72.001s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional 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 iterations in 16.625s)
[t-SNE] Iteration 100: error = 107.2019501, gradient norm = 0.0284782 (50 iterations in 9.735s)
[t-SNE] Iteration 150: error = 100.9872894, gradient norm = 0.0185151 (50 iterations in 5.346s)
[t-SNE] Iteration 200: error = 97.6054382, gradient norm = 0.0142084 (50 iterations in 7.013s)
[t-SNE] Iteration 250: error = 95.3084183, gradient norm = 0.0132592 (50 iterations 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 iterations in 7.156s)
[t-SNE] Iteration 350: error = 3.2113254, gradient norm = 0.0009953 (50 iterations in 8.022s)
[t-SNE] Iteration 400: error = 2.7819963, gradient norm = 0.0007203 (50 iterations in 9.419s)
[t-SNE] Iteration 450: error = 2.5178111, gradient norm = 0.0005655 (50 iterations in 9.370s)
[t-SNE] Iteration 500: error = 2.3341548, gradient norm = 0.0004804 (50 iterations in 7.681s)
[t-SNE] Iteration 550: error = 2.1961622, gradient norm = 0.0004183 (50 iterations in 7.097s)
[t-SNE] Iteration 600: error = 2.0867445, gradient norm = 0.0003664 (50 iterations in 9.274s)
[t-SNE] Iteration 650: error = 1.9967778, gradient norm = 0.0003279 (50 iterations in 7.697s)
[t-SNE] Iteration 700: error = 1.9210005, gradient norm = 0.0002984 (50 iterations in 8.174s)
[t-SNE] Iteration 750: error = 1.8558111, gradient norm = 0.0002776 (50 iterations in 9.747s)
[t-SNE] Iteration 800: error = 1.7989457, gradient norm = 0.0002569 (50 iterations in 8.687s)
[t-SNE] Iteration 850: error = 1.7490212, gradient norm = 0.0002394 (50 iterations in 8.407s)
[t-SNE] Iteration 900: error = 1.7043383, gradient norm = 0.0002224 (50 iterations in 8.351s)
[t-SNE] Iteration 950: error = 1.6641431, gradient norm = 0.0002098 (50 iterations in 7.841s)
[t-SNE] Iteration 1000: error = 1.6279151, gradient norm = 0.0001989 (50 iterations 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...
```

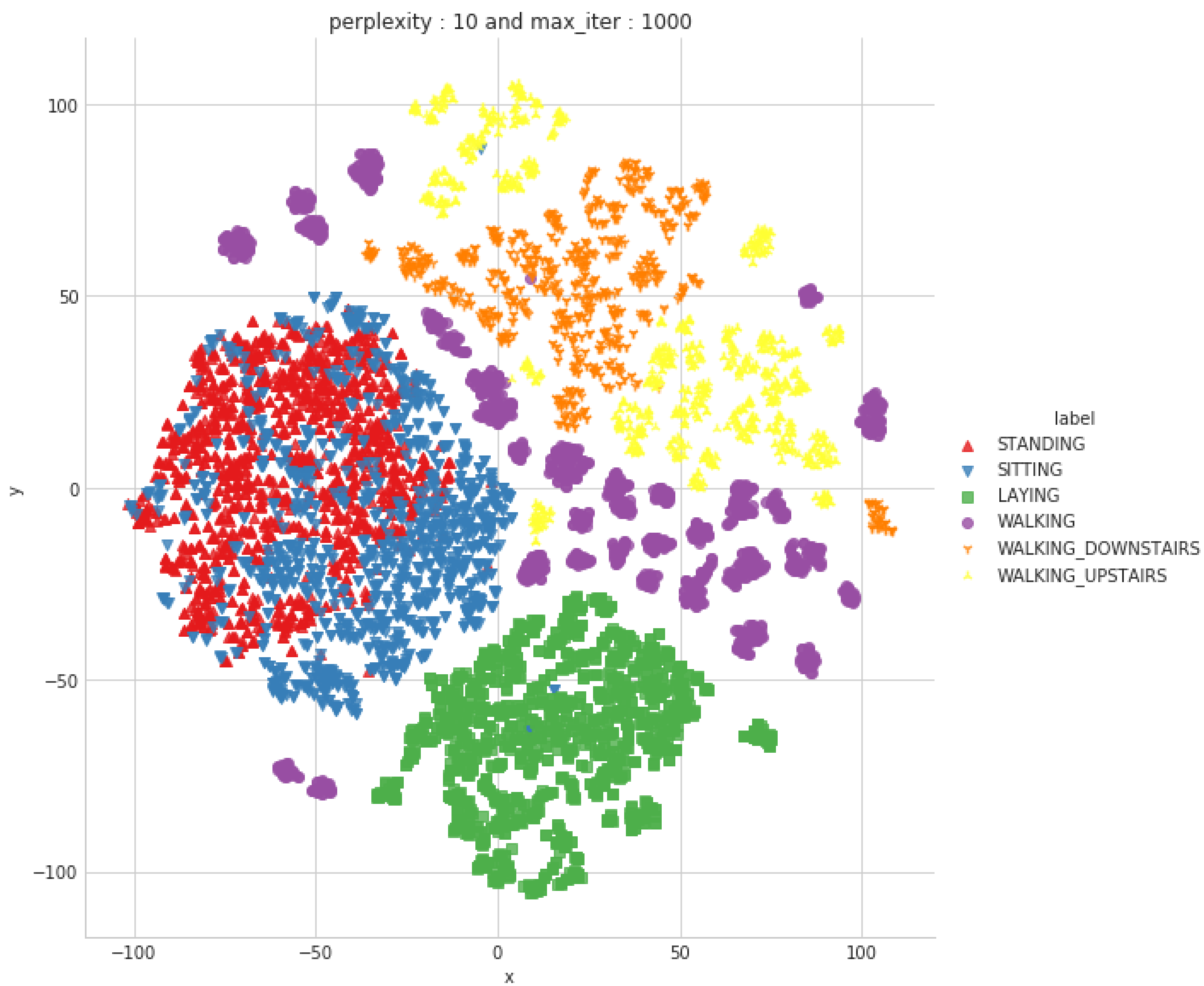



```
Done

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 iterations in 55.655s)
[t-SNE] Iteration 100: error = 97.6535568, gradient norm = 0.0174309 (50 iterations in 12.580s)
[t-SNE] Iteration 150: error = 93.1900101, gradient norm = 0.0101048 (50 iterations in 9.180s)
[t-SNE] Iteration 200: error = 91.2315445, gradient norm = 0.0074560 (50 iterations in 10.340s)
[t-SNE] Iteration 250: error = 90.0714417, gradient norm = 0.0057667 (50 iterations 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 iterations in 8.718s)
[t-SNE] Iteration 350: error = 2.8173938, gradient norm = 0.0007508 (50 iterations in 10.180s)
[t-SNE] Iteration 400: error = 2.4344938, gradient norm = 0.0005251 (50 iterations in 10.506s)
[t-SNE] Iteration 450: error = 2.2156141, gradient norm = 0.0004069 (50 iterations in 10.072s)
[t-SNE] Iteration 500: error = 2.0703306, gradient norm = 0.0003340 (50 iterations in 10.511s)
[t-SNE] Iteration 550: error = 1.9646366, gradient norm = 0.0002816 (50 iterations in 9.792s)
[t-SNE] Iteration 600: error = 1.8835558, gradient norm = 0.0002471 (50 iterations in 9.098s)
[t-SNE] Iteration 650: error = 1.8184001, gradient norm = 0.0002184 (50 iterations in 8.656s)
[t-SNE] Iteration 700: error = 1.7647167, gradient norm = 0.0001961 (50 iterations in 9.063s)
[t-SNE] Iteration 750: error = 1.7193680, gradient norm = 0.0001796 (50 iterations in 9.754s)
[t-SNE] Iteration 800: error = 1.6803776, gradient norm = 0.0001655 (50 iterations in 9.540s)
[t-SNE] Iteration 850: error = 1.6465144, gradient norm = 0.0001538 (50 iterations in 9.953s)
[t-SNE] Iteration 900: error = 1.6166563, gradient norm = 0.0001421 (50 iterations in 10.270s)
[t-SNE] Iteration 950: error = 1.5901035, gradient norm = 0.0001335 (50 iterations in 6.609s)
[t-SNE] Iteration 1000: error = 1.5664237, gradient norm = 0.0001257 (50 iterations 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...
```

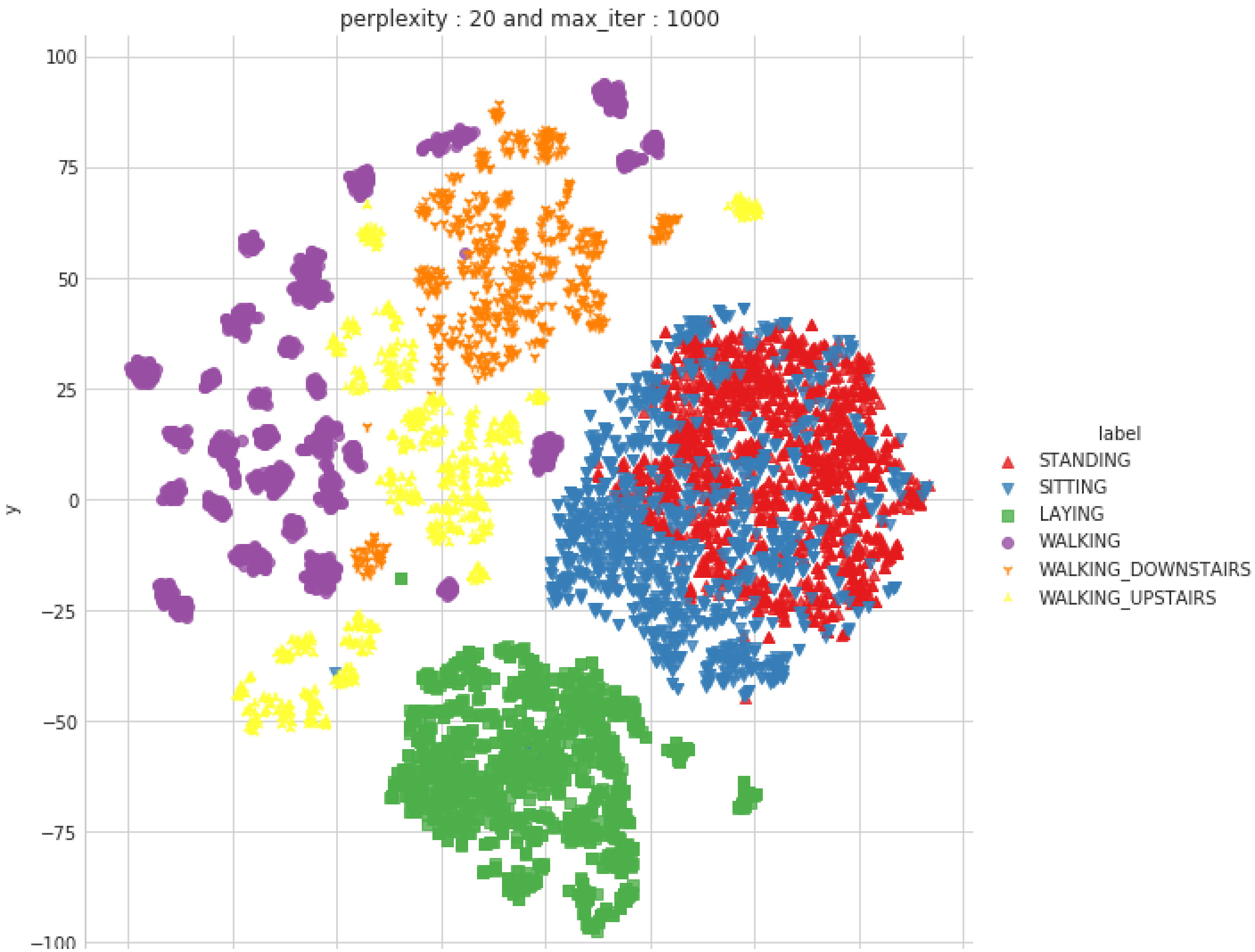

perplexity : 5 and max_iter : 1000
100
50
0
−50
−100
y
−100
−50
0
50
100
x
label
STANDING
SITTING
LAYING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS

```
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 iterations in 24.550s)
[t-SNE] Iteration 100: error = 90.3036194, gradient norm = 0.0097653 (50 iterations in 11.936s)
[t-SNE] Iteration 150: error = 87.3132935, gradient norm = 0.0053059 (50 iterations in 11.246s)
[t-SNE] Iteration 200: error = 86.1169128, gradient norm = 0.0035844 (50 iterations in 11.864s)
[t-SNE] Iteration 250: error = 85.4133606, gradient norm = 0.0029100 (50 iterations 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 iterations in 11.742s)
[t-SNE] Iteration 350: error = 2.4929206, gradient norm = 0.0006466 (50 iterations in 11.627s)
[t-SNE] Iteration 400: error = 2.1733041, gradient norm = 0.0004230 (50 iterations in 11.846s)
[t-SNE] Iteration 450: error = 1.9884514, gradient norm = 0.0003124 (50 iterations in 11.405s)
[t-SNE] Iteration 500: error = 1.8702440, gradient norm = 0.0002514 (50 iterations in 11.320s)
[t-SNE] Iteration 550: error = 1.7870129, gradient norm = 0.0002107 (50 iterations in 12.009s)
[t-SNE] Iteration 600: error = 1.7246909, gradient norm = 0.0001824 (50 iterations in 10.632s)
[t-SNE] Iteration 650: error = 1.6758548, gradient norm = 0.0001590 (50 iterations in 11.270s)
[t-SNE] Iteration 700: error = 1.6361949, gradient norm = 0.0001451 (50 iterations in 12.072s)
[t-SNE] Iteration 750: error = 1.6034756, gradient norm = 0.0001305 (50 iterations in 11.607s)
[t-SNE] Iteration 800: error = 1.5761518, gradient norm = 0.0001188 (50 iterations in 9.409s)
[t-SNE] Iteration 850: error = 1.5527289, gradient norm = 0.0001113 (50 iterations in 8.309s)
[t-SNE] Iteration 900: error = 1.5328671, gradient norm = 0.0001021 (50 iterations in 9.433s)
[t-SNE] Iteration 950: error = 1.5152045, gradient norm = 0.0000974 (50 iterations in 11.488s)
[t-SNE] Iteration 1000: error = 1.4999681, gradient norm = 0.0000933 (50 iterations 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...
```


perplexity : 10 and max_iter : 1000
100
50
0
−50
−100
y
−100
−50
0
50
100
x
label
STANDING
SITTING
LAYING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS

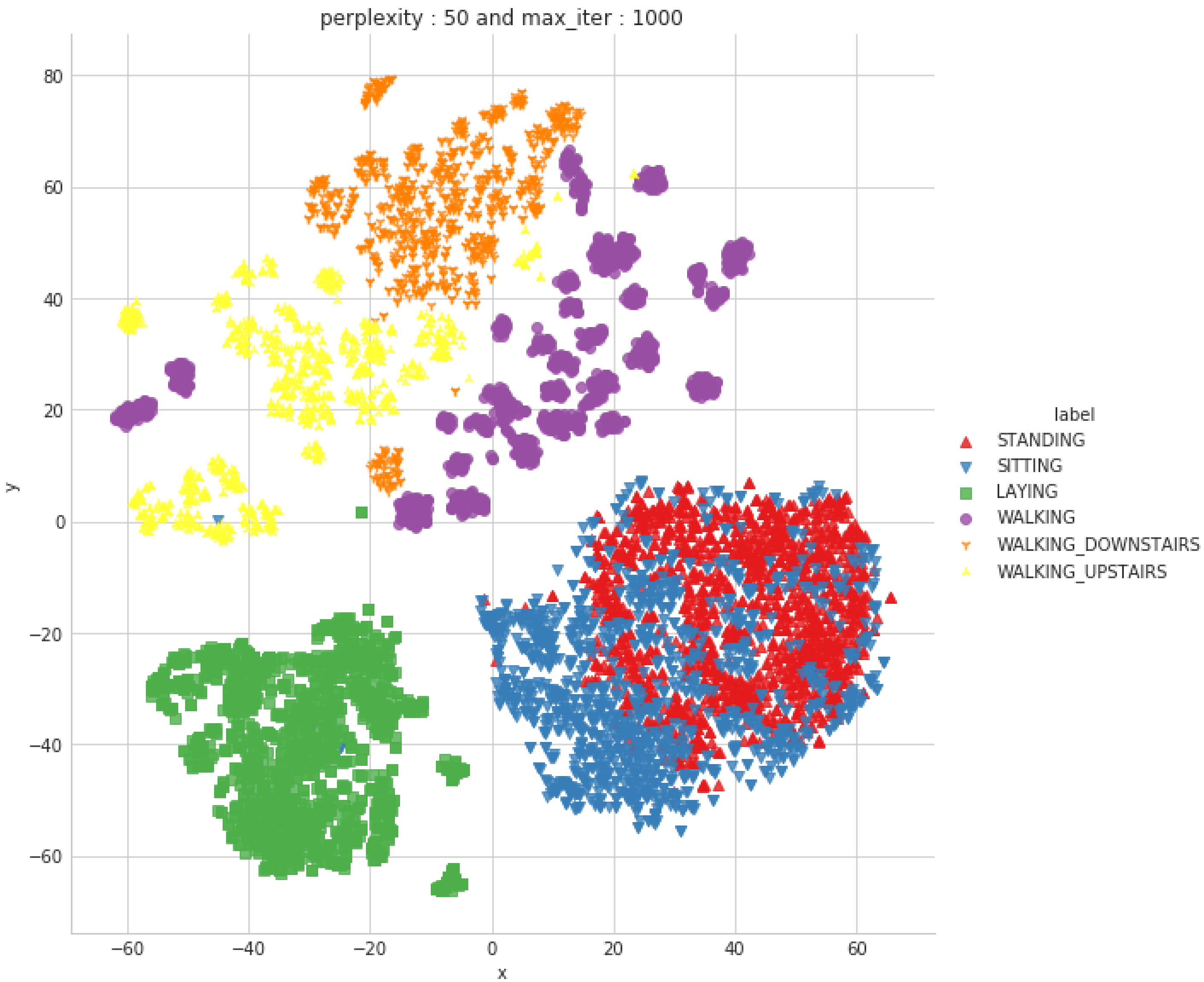
```
Done

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 iterations in 21.168s)
[t-SNE] Iteration 100: error = 83.9500732, gradient norm = 0.0059110 (50 iterations in 17.306s)
[t-SNE] Iteration 150: error = 81.8804779, gradient norm = 0.0035797 (50 iterations in 14.258s)
[t-SNE] Iteration 200: error = 81.1615143, gradient norm = 0.0022536 (50 iterations in 14.130s)
[t-SNE] Iteration 250: error = 80.7704086, gradient norm = 0.0018108 (50 iterations 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 iterations in 13.605s)
[t-SNE] Iteration 350: error = 2.1637220, gradient norm = 0.0005765 (50 iterations in 13.248s)
[t-SNE] Iteration 400: error = 1.9143614, gradient norm = 0.0003474 (50 iterations in 14.774s)
[t-SNE] Iteration 450: error = 1.7684202, gradient norm = 0.0002458 (50 iterations in 15.502s)
[t-SNE] Iteration 500: error = 1.6744757, gradient norm = 0.0001923 (50 iterations in 14.808s)
[t-SNE] Iteration 550: error = 1.6101606, gradient norm = 0.0001575 (50 iterations in 14.043s)
[t-SNE] Iteration 600: error = 1.5641028, gradient norm = 0.0001344 (50 iterations in 15.769s)
[t-SNE] Iteration 650: error = 1.5291905, gradient norm = 0.0001182 (50 iterations in 15.834s)
[t-SNE] Iteration 700: error = 1.5024391, gradient norm = 0.0001055 (50 iterations in 15.398s)
[t-SNE] Iteration 750: error = 1.4809053, gradient norm = 0.0000965 (50 iterations in 14.594s)
[t-SNE] Iteration 800: error = 1.4631859, gradient norm = 0.0000884 (50 iterations in 15.025s)
[t-SNE] Iteration 850: error = 1.4486470, gradient norm = 0.0000832 (50 iterations in 14.060s)
[t-SNE] Iteration 900: error = 1.4367288, gradient norm = 0.0000804 (50 iterations in 12.389s)
[t-SNE] Iteration 950: error = 1.4270191, gradient norm = 0.0000761 (50 iterations in 10.392s)
[t-SNE] Iteration 1000: error = 1.4189968, gradient norm = 0.0000787 (50 iterations 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 iterations in 36.249s)
[t-SNE] Iteration 100: error = 75.9874649, gradient norm = 0.0061005 (50 iterations in 30.453s)
[t-SNE] Iteration 150: error = 74.7072296, gradient norm = 0.0024708 (50 iterations in 28.461s)
[t-SNE] Iteration 200: error = 74.2736282, gradient norm = 0.0018644 (50 iterations in 27.735s)
[t-SNE] Iteration 250: error = 74.0722427, gradient norm = 0.0014078 (50 iterations 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 iterations in 25.445s)
[t-SNE] Iteration 350: error = 1.7567128, gradient norm = 0.0004845 (50 iterations in 21.282s)
[t-SNE] Iteration 400: error = 1.5888531, gradient norm = 0.0002798 (50 iterations in 21.015s)
[t-SNE] Iteration 450: error = 1.4956820, gradient norm = 0.0001894 (50 iterations in 23.332s)
[t-SNE] Iteration 500: error = 1.4359720, gradient norm = 0.0001420 (50 iterations in 23.083s)
[t-SNE] Iteration 550: error = 1.3947564, gradient norm = 0.0001117 (50 iterations in 19.626s)
[t-SNE] Iteration 600: error = 1.3653858, gradient norm = 0.0000949 (50 iterations in 22.752s)
[t-SNE] Iteration 650: error = 1.3441534, gradient norm = 0.0000814 (50 iterations in 23.972s)
[t-SNE] Iteration 700: error = 1.3284039, gradient norm = 0.0000742 (50 iterations in 20.636s)
[t-SNE] Iteration 750: error = 1.3171139, gradient norm = 0.0000700 (50 iterations in 20.407s)
[t-SNE] Iteration 800: error = 1.3085558, gradient norm = 0.0000657 (50 iterations in 24.951s)
[t-SNE] Iteration 850: error = 1.3017821, gradient norm = 0.0000603 (50 iterations in 24.719s)
[t-SNE] Iteration 900: error = 1.2962619, gradient norm = 0.0000586 (50 iterations in 24.500s)
[t-SNE] Iteration 950: error = 1.2914882, gradient norm = 0.0000573 (50 iterations in 24.132s)
[t-SNE] Iteration 1000: error = 1.2874244, gradient norm = 0.0000546 (50 iterations 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...
```


perplexity : 50 and max_iter : 1000
label
STANDING
SITTING
LAYING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
x
y

Done

In [0]:
```
import numpy as np
import pandas as pd
```

Obtain the train and test data

In [0]:
```
train = pd.read_csv('UCI_HAR_dataset/csv_files/train.csv')
test = pd.read_csv('UCI_HAR_dataset/csv_files/test.csv')
print(train.shape, test.shape)
```

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

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

Out[3]:

	tBodyAccmeanX	tBodyAccmeanY	tBodyAccmeanZ	tBodyAccstdX	tBodyAccstdY	tBodyAccstdZ	tBodyAccmadX	tBodyAccmadY	tBoc
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	

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 [0]:
```
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,))
```

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_normalize=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='Normalized confusion matrix', 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 GridSearch
            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_params_))


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


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

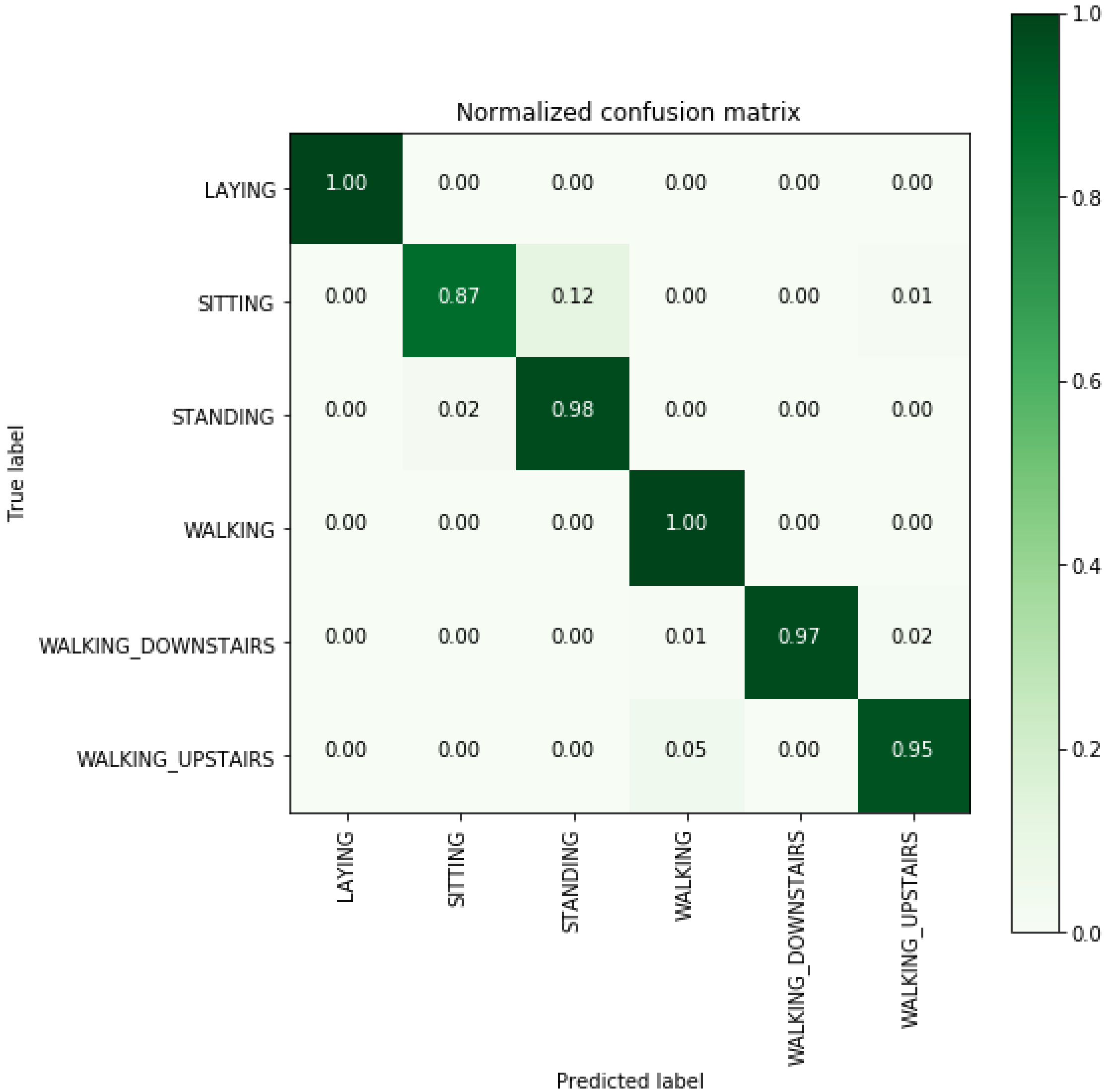
1. Logistic Regression with Grid Search

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)
```

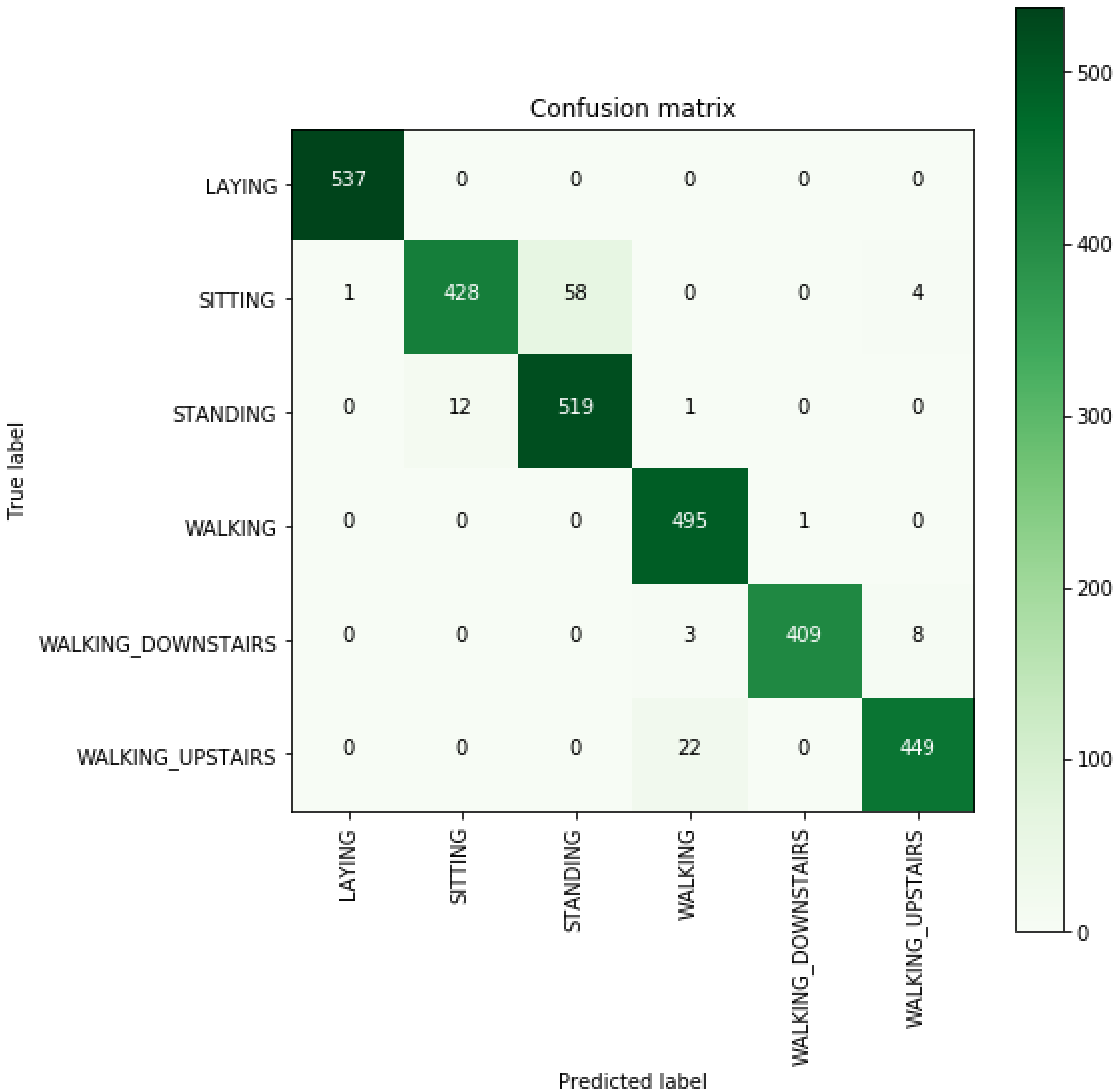
```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits

[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()
```



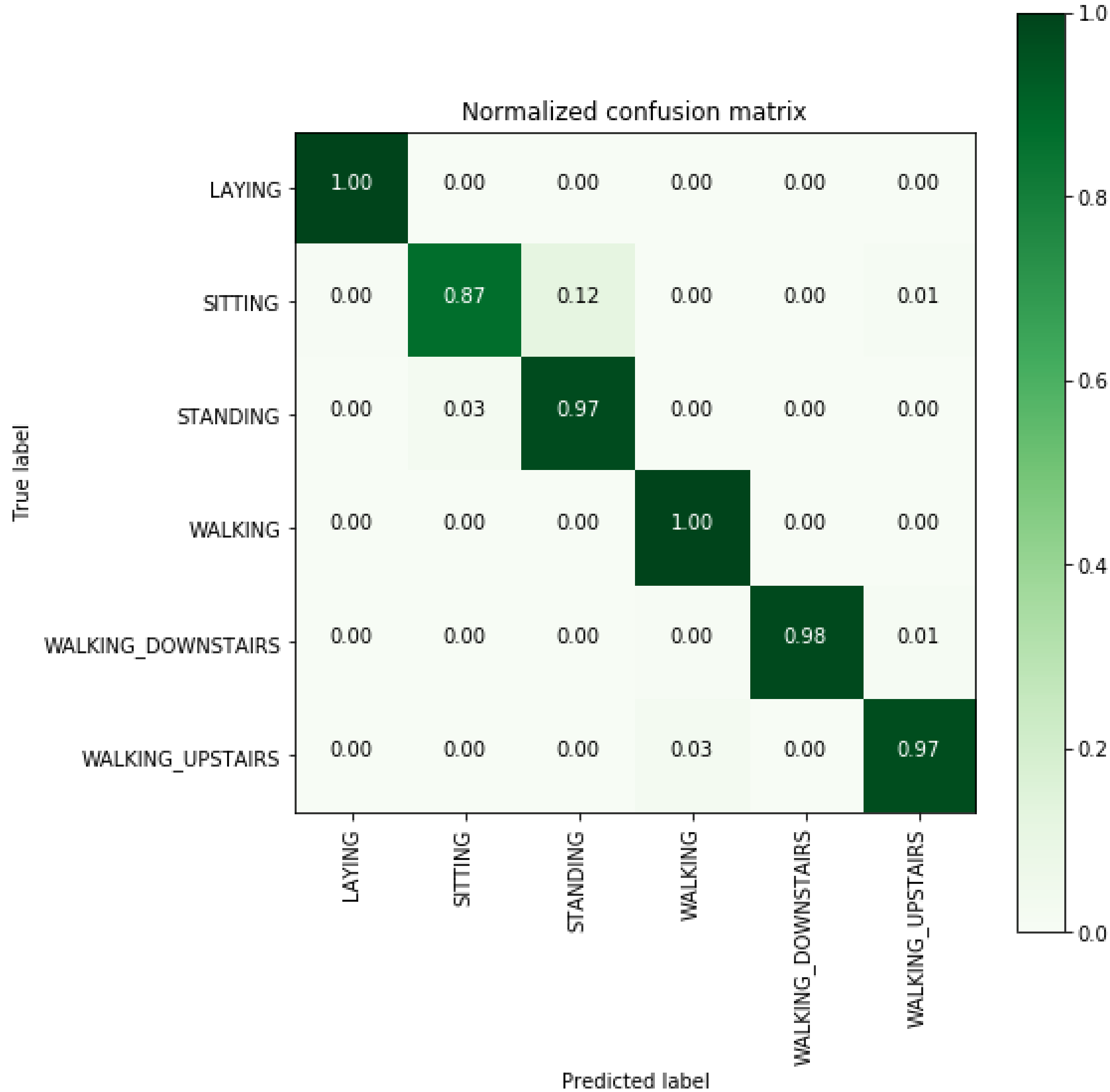
In [0]:
```
# observe the attributes of the model
print_grid_search_attributes(log_reg_grid_results['model'])
```

```
--------------------------
|      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]:
```
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_test, 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
```

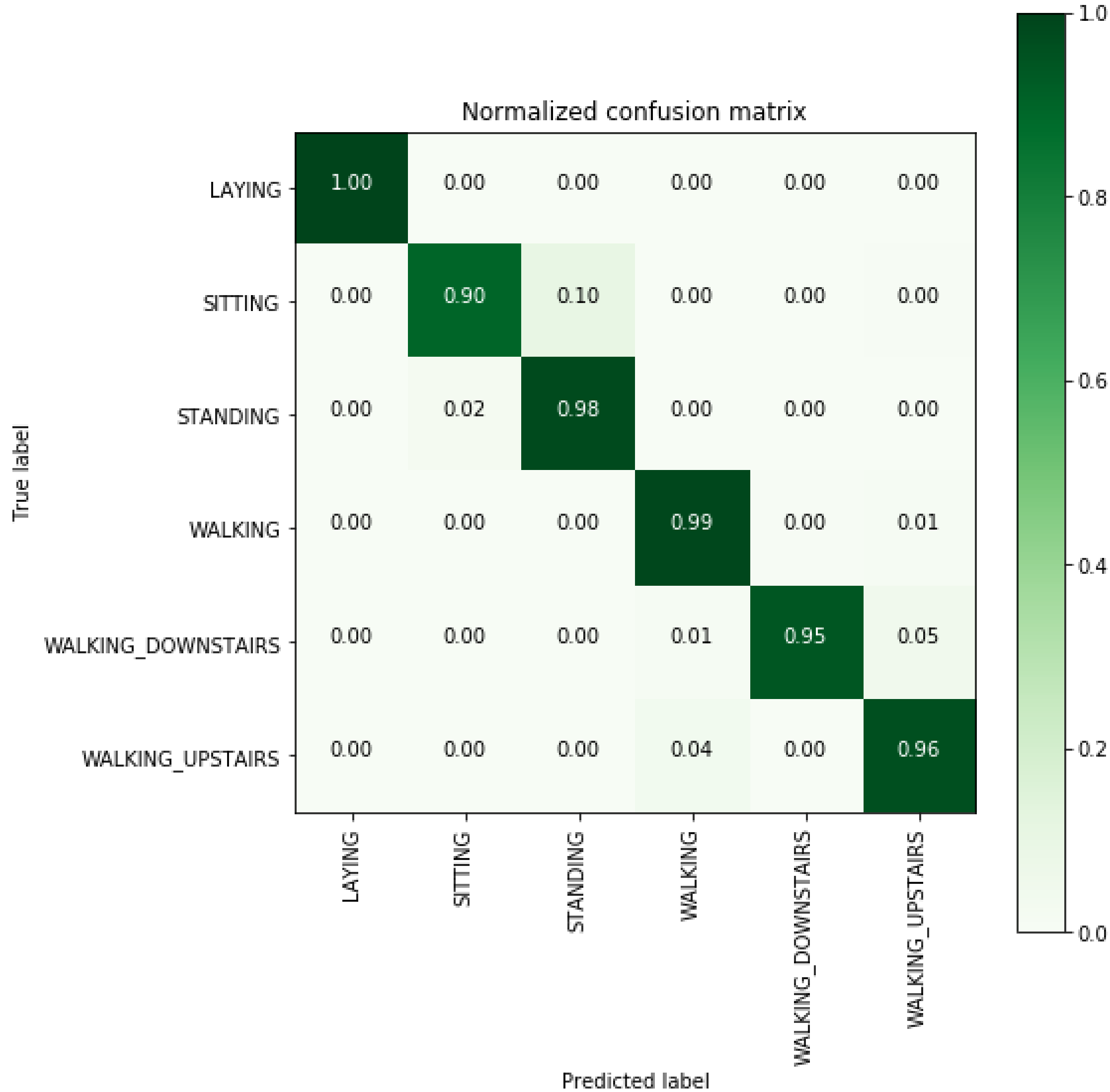
In [0]:
```
print_grid_search_attributes(lr_svc_grid_results['model'])
```

```
--------------------------
|      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
```

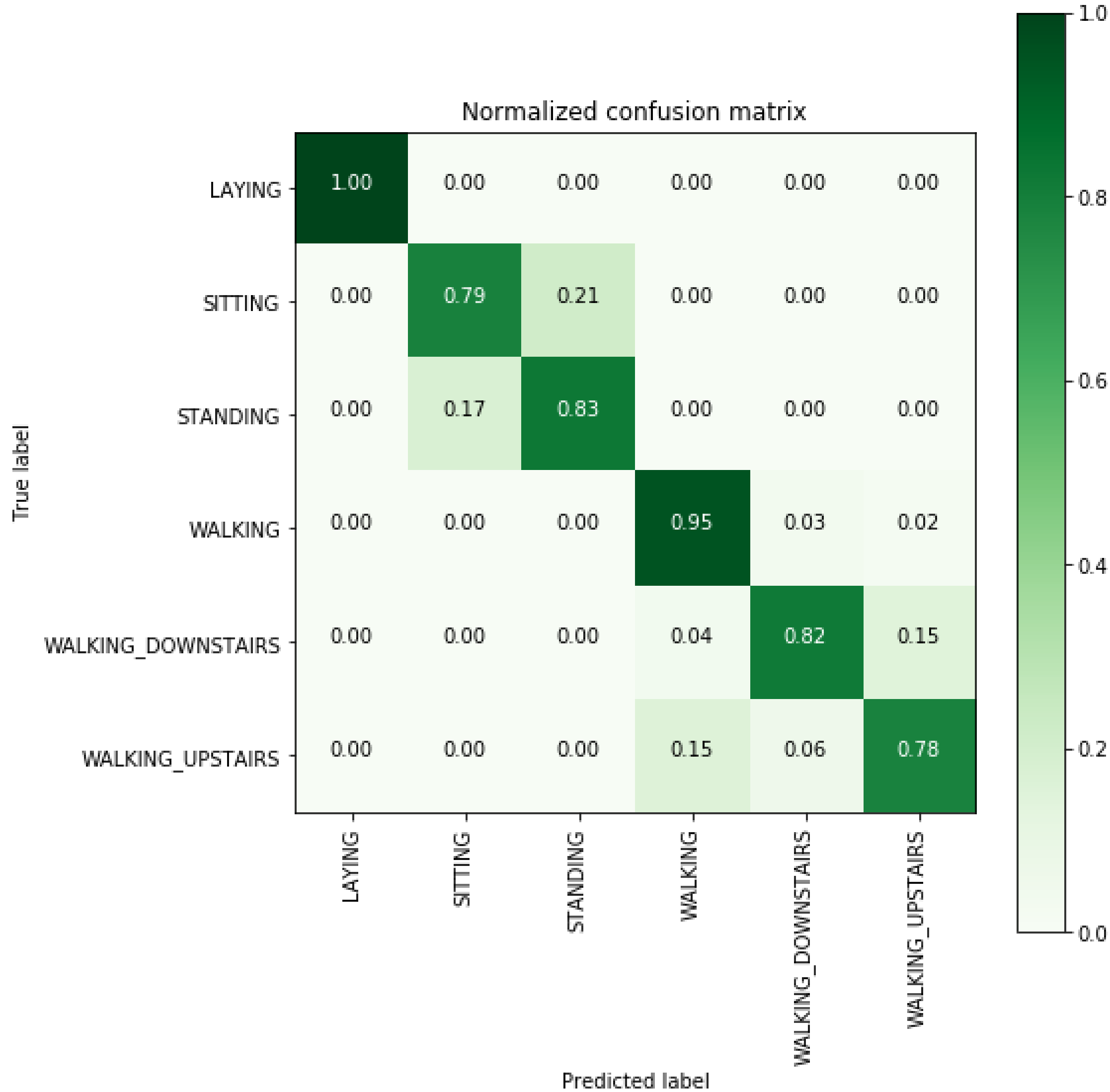
In [0]:
```
print_grid_search_attributes(rbf_svm_grid_results['model'])
```

```
--------------------------
|      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, class_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]]
```



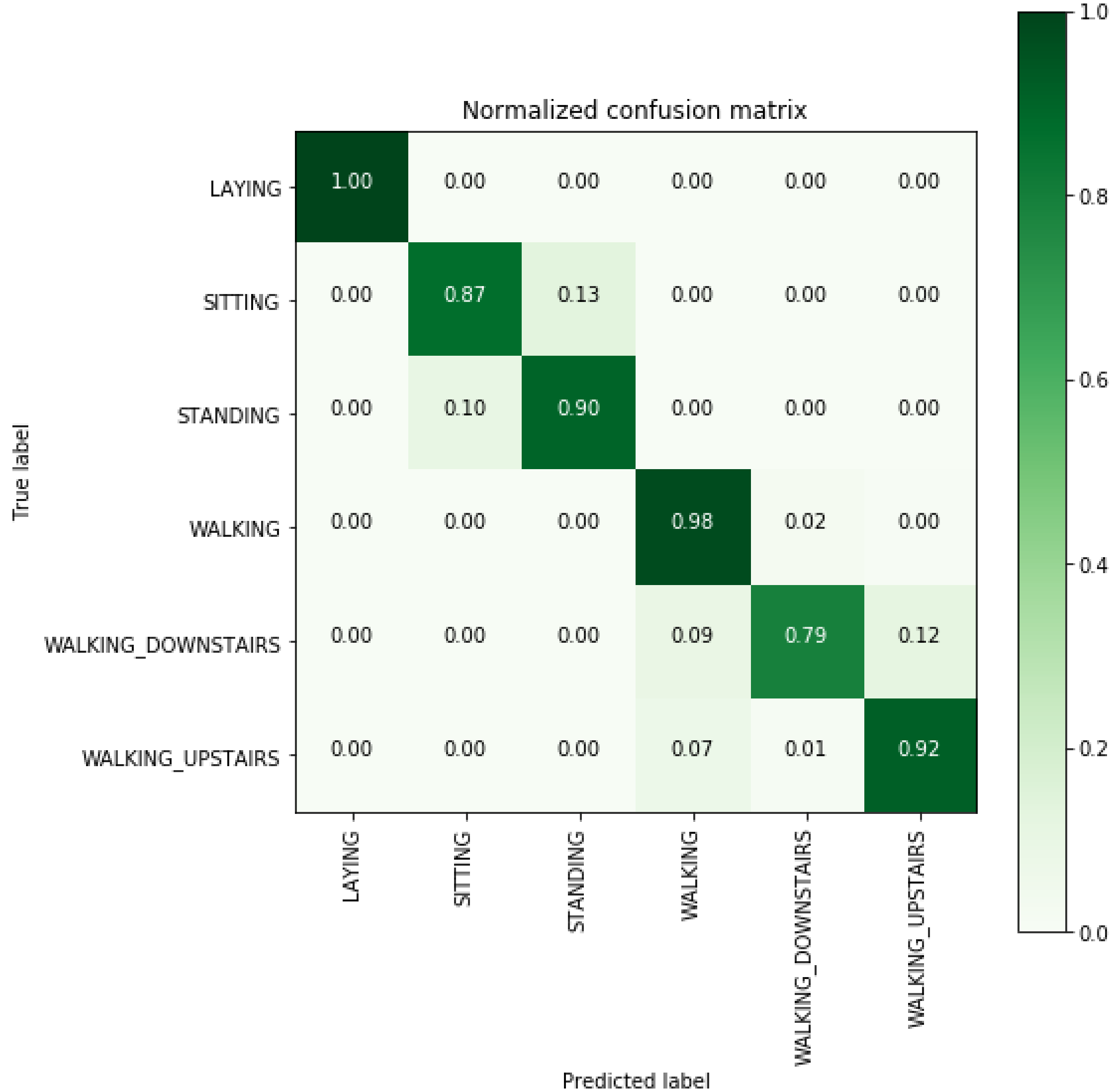

```
------------------------
| Classifiction Report |
------------------------
                    precision    recall  f1-score   support

            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, class_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]]
```



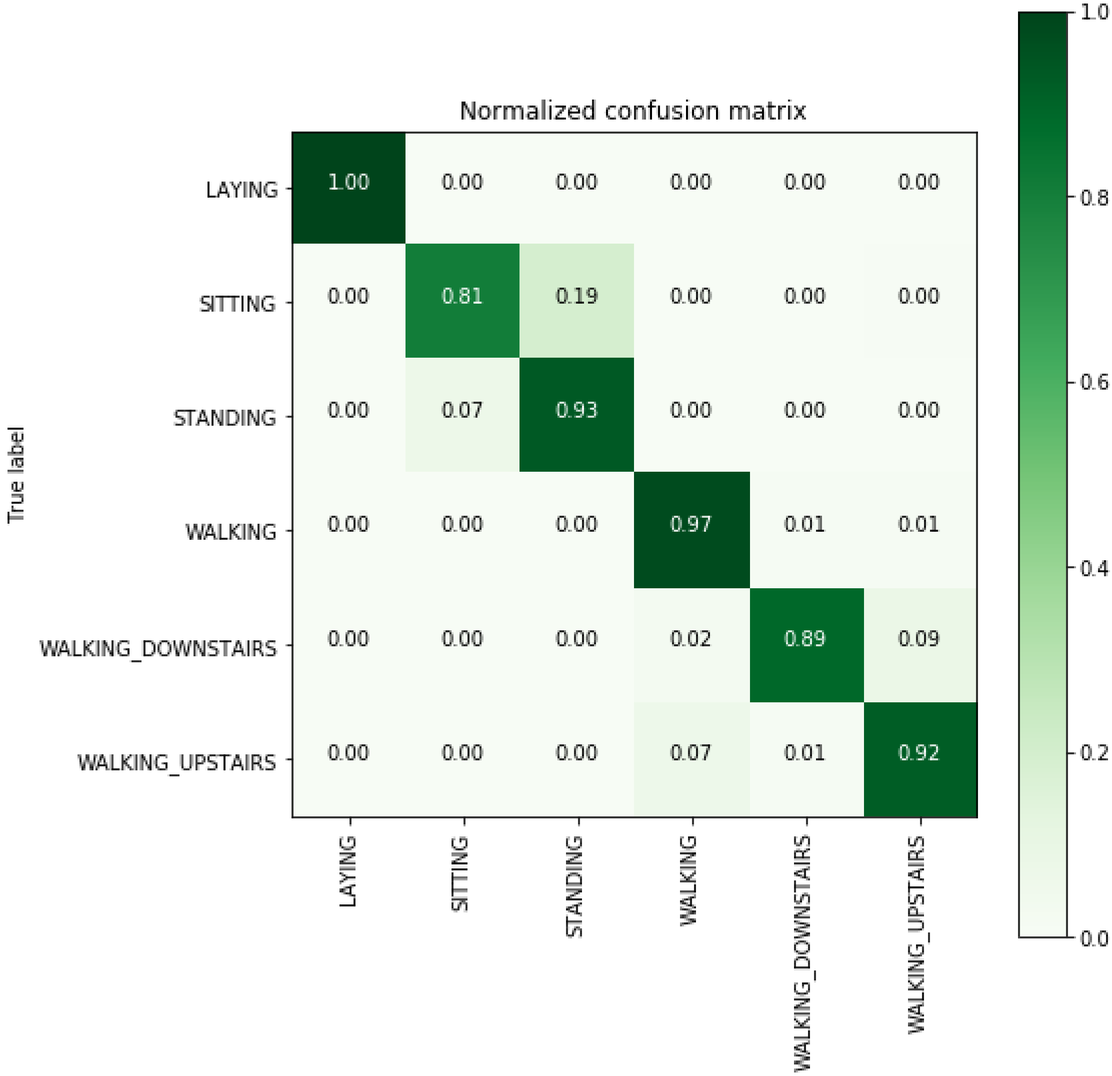

```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            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]]
```




```
------------------------
| 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_results['accuracy'] * 100,\
                                                  100-(log_reg_grid_results['accuracy'] * 100)))

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

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

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

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

We can choose ***Logistic regression*** or ***Linear SVC*** or ***rbf SVM***.

Conclusion :

In the real world, domain-knowledge, EDA and feature-engineering matter most.

In [0]:
```
import pandas as pd
import numpy as np
```

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

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

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

Data

In [0]:
```
# Data directory
DATADIR = '/content/drive/My Drive/HAR/UCI_HAR_Dataset'
```

In [0]:
```
# Raw data signals
# Signals are from Accelerometer and Gyroscope
# The signals are in x,y,z directions
# Sensor signals are filtered to have only body acceleration
# excluding the acceleration due to gravity
# Triaxial acceleration from the accelerometer is total acceleration
SIGNALS = [
    "body_acc_x",
    "body_acc_y",
    "body_acc_z",
    "body_gyro_x",
    "body_gyro_y",
    "body_gyro_z",
    "total_acc_x",
    "total_acc_y",
    "total_acc_z"
]
```

In [0]:
```
# Utility function to read the data from csv file
def _read_csv(filename):
    return pd.read_csv(filename, delim_whitespace=True, header=None)

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

    for signal in SIGNALS:
        filename = f'/content/drive/My Drive/HAR/UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.txt
        signals_data.append(
            _read_csv(filename).as_matrix()
        )

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

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

    return pd.get_dummies(y).as_matrix()
```

In [0]:
```
def load_data():
    """
    Obtain the dataset from multiple files.
    Returns: X_train, X_test, y_train, y_test
    """
    X_train, X_test = load_signals('train'), load_signals('test')
    y_train, y_test = load_y('train'), load_y('test')

    return X_train, X_test, y_train, y_test
```

Model 1-Single hidden layer(LSTM)

In [21]:
```
# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)
```

The default version of TensorFlow in Colab will soon switch to TensorFlow 2.x.
We recommend you upgrade (https://www.tensorflow.org/guide/migrate) now or ensure your notebook will continue to use TensorFlow 1.x via the `%tensorflow_version 1.x` magic: more info (https://colab.research.google.com/notebooks/tensorflow_version.ipynb).

In [0]:
```
# Configuring a session
session_conf = tf.ConfigProto(
    intra_op_parallelism_threads=1,
    inter_op_parallelism_threads=1
)
```

In [23]:
```
# 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 = 32
n_hidden = 128
```

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

In [27]:
```
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

```
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:11: FutureWarning: Method .as_matrix will be remo
ved in a future version. Use .values instead.
  # This is added back by InteractiveShellApp.init_path()
/usr/local/lib/python3.6/dist-packages/ipykernel_launcher.py:12: FutureWarning: Method .as_matrix will be remo
ved in a future version. Use .values instead.
  if sys.path[0] == '':
```

In [28]:
```
timesteps = len(X_train[0])
input_dim = len(X_train[0][0])
n_classes = _count_classes(Y_train)

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

```
128
9
7352
```

- Defining the Architecture of LSTM

In [30]:
```
# Initiliazing the sequential model
model1 = Sequential()
# Configuring the parameters
model1.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model1.add(Dropout(0.25))
# Adding a dense output layer with sigmoid activation
model1.add(Dense(n_classes, activation='sigmoid'))
model1.summary()
```

```
WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:541: The na
me 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:4432: The n
ame tf.random_uniform is deprecated. Please use tf.random.uniform instead.

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:148: The na
me tf.placeholder_with_default is deprecated. 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: calli
ng dropout (from tensorflow.python.ops.nn_ops) with keep_prob is deprecated and will be removed in a future ve
rsion.
Instructions for updating:
Please use `rate` instead of `keep_prob`. Rate should be set to `rate = 1 - keep_prob`.
Model: "sequential_1"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_1 (LSTM)                (None, 128)               70656
_________________________________________________________________
dropout_1 (Dropout)          (None, 128)               0
_________________________________________________________________
dense_1 (Dense)              (None, 6)                 774
=================================================================
Total params: 71,430
Trainable params: 71,430
Non-trainable params: 0
_________________________________________________________________
```

In [31]:
```
# Compiling the model
model1.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

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

WARNING:tensorflow:From /usr/local/lib/python3.6/dist-packages/keras/backend/tensorflow_backend.py:3576: The n
ame tf.log is deprecated. Please use tf.math.log instead.
```

In [39]:
```
# Training the model
model1.fit(X_train,
         Y_train,
         batch_size=batch_size,
         validation_data=(X_test, Y_test),
         epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1188 - acc: 0.9543 - val_loss: 0.3531 -
val_acc: 0.9158
Epoch 2/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1115 - acc: 0.9566 - val_loss: 0.5706 -
val_acc: 0.9070
Epoch 3/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1355 - acc: 0.9491 - val_loss: 0.3601 -
val_acc: 0.9186
Epoch 4/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1243 - acc: 0.9513 - val_loss: 0.3061 -
val_acc: 0.9070
Epoch 5/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1191 - acc: 0.9525 - val_loss: 0.3169 -
val_acc: 0.9199
Epoch 6/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1191 - acc: 0.9516 - val_loss: 0.3737 -
val_acc: 0.9111
Epoch 7/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1165 - acc: 0.9542 - val_loss: 0.5156 -
val_acc: 0.9063
Epoch 8/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1244 - acc: 0.9524 - val_loss: 0.4450 -
val_acc: 0.9077
Epoch 9/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1250 - acc: 0.9517 - val_loss: 0.2826 -
val_acc: 0.9199
Epoch 10/30
7352/7352 [==============================] - 55s 8ms/step - loss: 0.1109 - acc: 0.9553 - val_loss: 0.2723 -
val_acc: 0.9233
Epoch 11/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1114 - acc: 0.9559 - val_loss: 0.3496 -
val_acc: 0.9091
Epoch 12/30
```

```
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1073 - acc: 0.9547 - val_loss: 0.3396 -
val_acc: 0.9226
Epoch 13/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1043 - acc: 0.9563 - val_loss: 0.4597 -
val_acc: 0.9026
Epoch 14/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1114 - acc: 0.9562 - val_loss: 0.4190 -
val_acc: 0.9033
Epoch 15/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1070 - acc: 0.9559 - val_loss: 0.3808 -
val_acc: 0.9053
Epoch 16/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1001 - acc: 0.9567 - val_loss: 0.3728 -
val_acc: 0.9199
Epoch 17/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1215 - acc: 0.9544 - val_loss: 0.2742 -
val_acc: 0.9216
Epoch 18/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1065 - acc: 0.9570 - val_loss: 0.3464 -
val_acc: 0.9165
Epoch 19/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.1185 - acc: 0.9513 - val_loss: 0.2733 -
val_acc: 0.9253
Epoch 20/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.1072 - acc: 0.9557 - val_loss: 0.3301 -
val_acc: 0.9189
Epoch 21/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.1011 - acc: 0.9561 - val_loss: 0.3663 -
val_acc: 0.9213
Epoch 22/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.1138 - acc: 0.9559 - val_loss: 0.2481 -
val_acc: 0.9264
Epoch 23/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.0990 - acc: 0.9580 - val_loss: 0.3128 -
val_acc: 0.9203
Epoch 24/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.1053 - acc: 0.9585 - val_loss: 0.3290 -
val_acc: 0.9230
Epoch 25/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.0982 - acc: 0.9565 - val_loss: 0.3091 -
val_acc: 0.9253
Epoch 26/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1262 - acc: 0.9557 - val_loss: 0.2557 -
```

```
val_acc: 0.9325
Epoch 27/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1062 - acc: 0.9570 - val_loss: 0.4628 -
val_acc: 0.9084
Epoch 28/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1034 - acc: 0.9585 - val_loss: 0.3246 -
val_acc: 0.9165
Epoch 29/30
7352/7352 [==============================] - 56s 8ms/step - loss: 0.1023 - acc: 0.9542 - val_loss: 0.4690 -
val_acc: 0.9094
Epoch 30/30
7352/7352 [==============================] - 57s 8ms/step - loss: 0.0984 - acc: 0.9572 - val_loss: 0.3615 -
val_acc: 0.9253
```

Out[39]:

```
<keras.callbacks.History at 0x7f718de9a6d8>
```

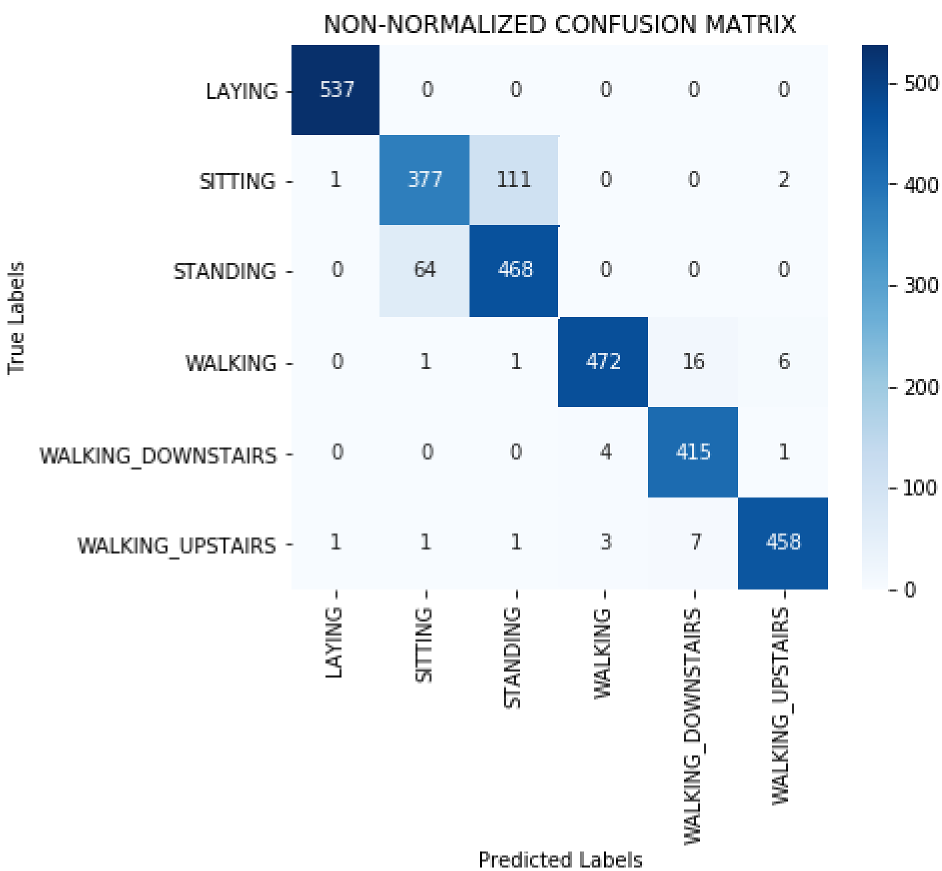
In [0]:

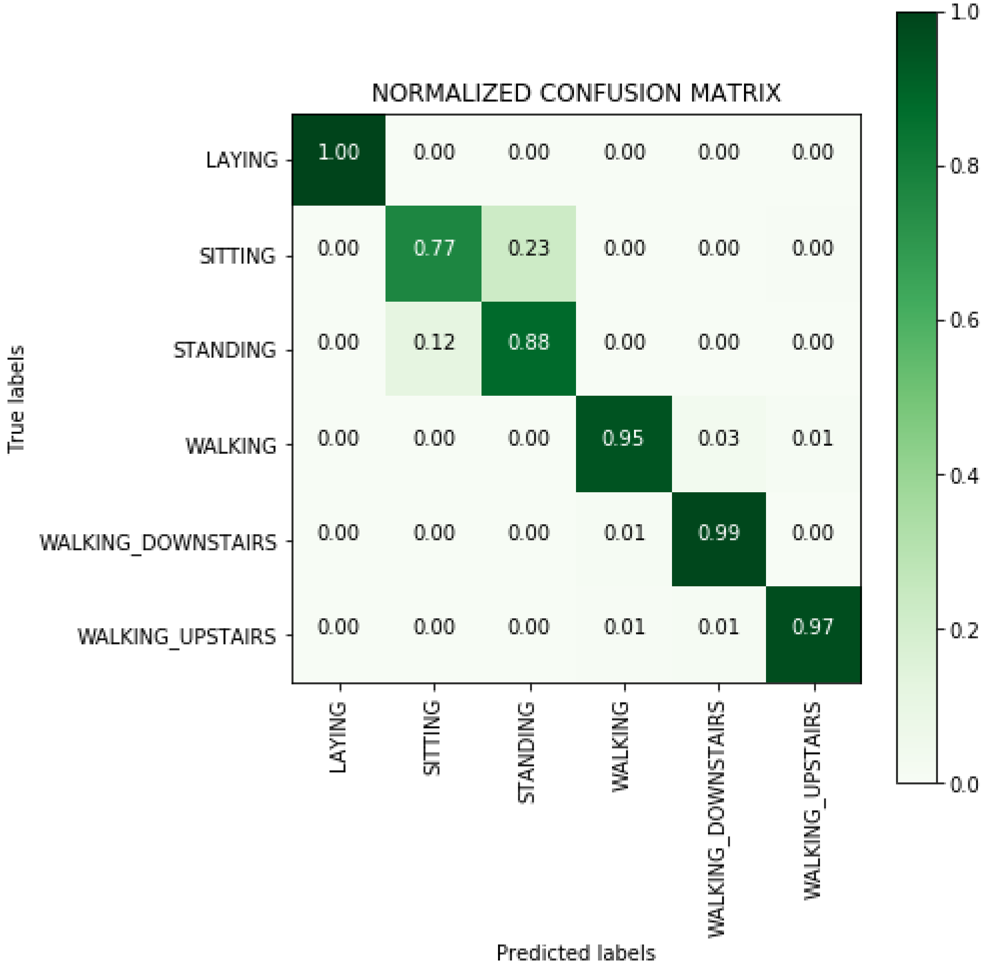
```
history1=model1.history
```

In [0]:
```
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix
import itertools

#Utility function to plot the confusion matrices
#https://scikit-learn.org/stable/modules/generated/sklearn.metrics.confusion_matrix.html
def plot_confusion_matrix(cm_df, classes, normalize, title):
    if normalize:
        cm = cm_df.values
        cm = cm.astype('float') / cm.sum(axis=1)[:, np.newaxis]

        plt.figure(figsize = (7,7))
        plt.imshow(cm, interpolation='nearest', cmap=plt.cm.Greens)
        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
        plt.tight_layout()
        plt.xlabel('Predicted labels')
        plt.ylabel('True labels')

    else:
        import seaborn as sn
        plt.figure(figsize = (6,5))
        ax = sn.heatmap(cm_df, annot=True, fmt='d', cmap=plt.cm.Blues)   #fmt='d' for decimal integer.
        ax.set_xlabel("Predicted Labels")
        ax.set_ylabel("True Labels")
        ax.set_title(title)


#Utility function to design the confusion matrix DF
def get_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)])
    cm_df =  pd.crosstab(Y_true, Y_pred, rownames=['True'], colnames=['Pred'])
```

```
    return cm_df
```

In [63]:
```
y_pred=model1.predict(X_test)
cm_df=get_confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using get_confusion_matrix() definec
classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df

#Plot a Non-Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED CONFUSION MATRIX")

#Plot a Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFUSION MATRIX")
```





In [64]:
```
score1 = model1.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 8s 3ms/step
```

In [66]:
```
print('The Test loss is',score1[0],'and Test accuracy is',score1[1])
```

```
The Test loss is 0.36151349165593255 and Test accuracy is 0.9253478113335596
```

Model 2

Layer 1-128 lstm ,dropout=0.2

Layer 2-64 lstm ,dropout=0.5

In [47]:
```
epochs_1 = 30
batch_size_1= 32
n_hidden_1 = 128
n_hidden_2 =64

model1 = Sequential()
# Configuring the parameters
model1.add(LSTM(n_hidden_1, return_sequences=True, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model1.add(Dropout(0.2))
model1.add(LSTM(n_hidden_2))
# Adding a dropout layer
model1.add(Dropout(0.5))
# Adding a dense output layer with sigmoid activation
model1.add(Dense(n_classes, activation='sigmoid'))
model1.summary()
```

```
Model: "sequential_4"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_4 (LSTM)                (None, 128, 128)          70656
_________________________________________________________________
dropout_4 (Dropout)          (None, 128, 128)          0
_________________________________________________________________
lstm_5 (LSTM)                (None, 64)                49408
_________________________________________________________________
dropout_5 (Dropout)          (None, 64)                0
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 390
=================================================================
Total params: 120,454
Trainable params: 120,454
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
model1.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [49]:
```
model1.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 118s 16ms/step - loss: 1.3030 - acc: 0.4301 - val_loss: 1.3862
- val_acc: 0.3895
Epoch 2/30
7352/7352 [==============================] - 117s 16ms/step - loss: 0.9816 - acc: 0.5615 - val_loss: 0.9725
- val_acc: 0.4618
Epoch 3/30
7352/7352 [==============================] - 115s 16ms/step - loss: 0.7327 - acc: 0.6774 - val_loss: 0.6773
- val_acc: 0.7282
Epoch 4/30
7352/7352 [==============================] - 114s 16ms/step - loss: 0.5335 - acc: 0.8138 - val_loss: 0.4658
- val_acc: 0.8480
Epoch 5/30
7352/7352 [==============================] - 114s 16ms/step - loss: 0.3052 - acc: 0.9036 - val_loss: 0.3758
- val_acc: 0.8744
Epoch 6/30
7352/7352 [==============================] - 116s 16ms/step - loss: 0.2487 - acc: 0.9249 - val_loss: 0.4137
- val_acc: 0.8646
Epoch 7/30
7352/7352 [==============================] - 116s 16ms/step - loss: 0.2270 - acc: 0.9310 - val_loss: 0.4726
- val_acc: 0.8772
Epoch 8/30
7352/7352 [==============================] - 114s 15ms/step - loss: 0.1966 - acc: 0.9348 - val_loss: 0.4432
- val_acc: 0.8863
Epoch 9/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1915 - acc: 0.9351 - val_loss: 0.3289
- val_acc: 0.9108
Epoch 10/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1797 - acc: 0.9382 - val_loss: 0.4094
- val_acc: 0.8955
Epoch 11/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1745 - acc: 0.9385 - val_loss: 0.3330
- val_acc: 0.9060
Epoch 12/30
7352/7352 [==============================] - 114s 15ms/step - loss: 0.1483 - acc: 0.9455 - val_loss: 0.3915
```

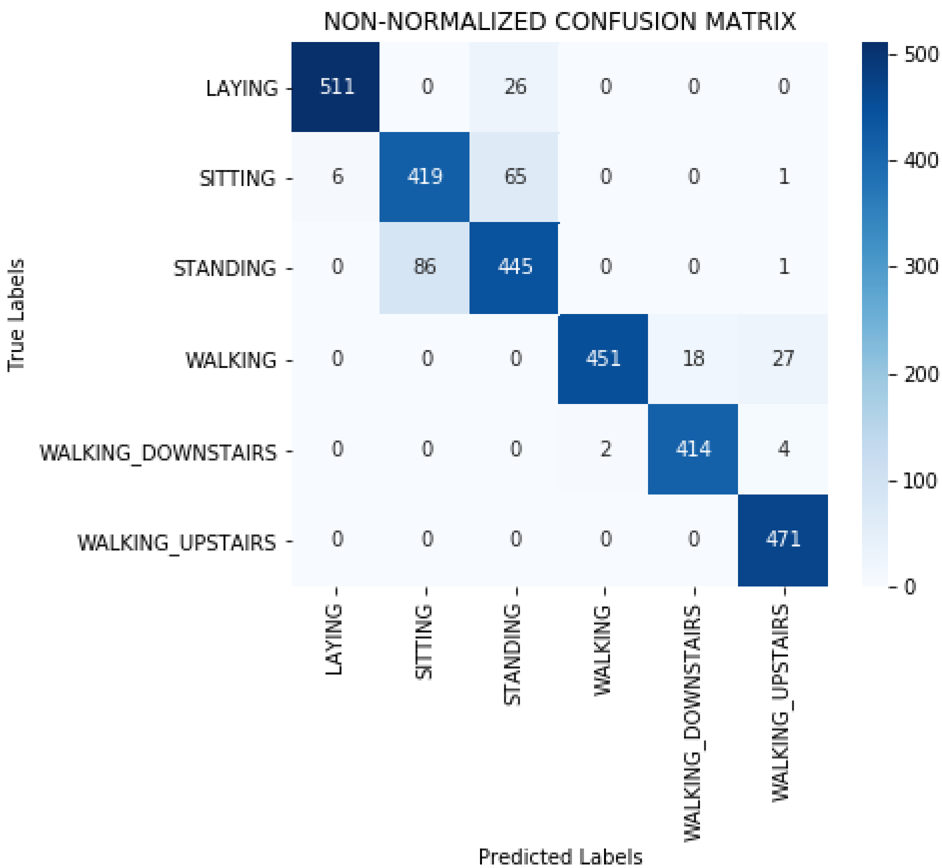
```
- val_acc: 0.9046
Epoch 13/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1488 - acc: 0.9441 - val_loss: 0.3256
- val_acc: 0.9199
Epoch 14/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1426 - acc: 0.9494 - val_loss: 0.3743
- val_acc: 0.8955
Epoch 15/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1537 - acc: 0.9448 - val_loss: 0.3020
- val_acc: 0.9074
Epoch 16/30
7352/7352 [==============================] - 114s 15ms/step - loss: 0.1371 - acc: 0.9513 - val_loss: 0.4267
- val_acc: 0.9013
Epoch 17/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1366 - acc: 0.9493 - val_loss: 0.4202
- val_acc: 0.9043
Epoch 18/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1283 - acc: 0.9501 - val_loss: 0.5280
- val_acc: 0.9033
Epoch 19/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1413 - acc: 0.9516 - val_loss: 0.3282
- val_acc: 0.9084
Epoch 20/30
7352/7352 [==============================] - 111s 15ms/step - loss: 0.1255 - acc: 0.9493 - val_loss: 0.3423
- val_acc: 0.9131
Epoch 21/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1188 - acc: 0.9529 - val_loss: 0.3482
- val_acc: 0.9101
Epoch 22/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1244 - acc: 0.9509 - val_loss: 0.3297
- val_acc: 0.9206
Epoch 23/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1243 - acc: 0.9543 - val_loss: 0.3478
- val_acc: 0.9220
Epoch 24/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1398 - acc: 0.9493 - val_loss: 0.4187
- val_acc: 0.9070
Epoch 25/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1187 - acc: 0.9517 - val_loss: 0.4044
- val_acc: 0.9179
Epoch 26/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1150 - acc: 0.9520 - val_loss: 0.4547
- val_acc: 0.9101
```

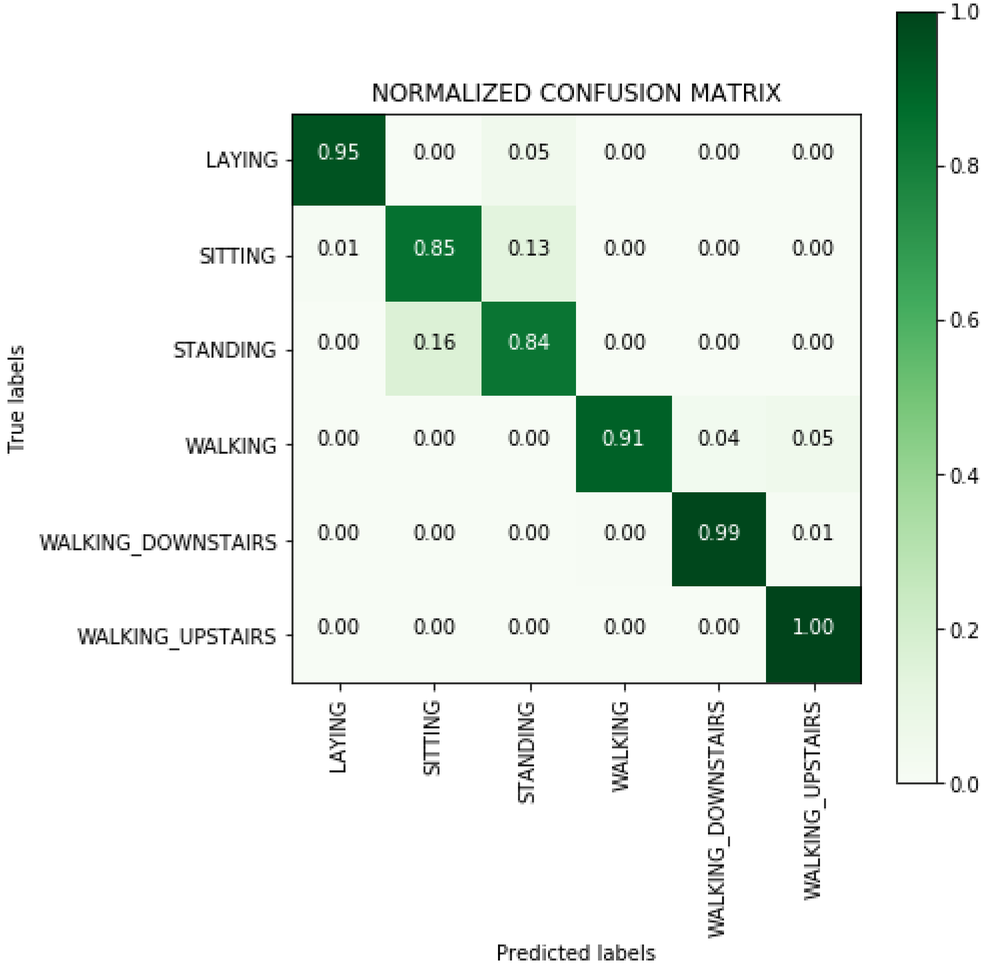
```
Epoch 27/30
7352/7352 [==============================] - 112s 15ms/step - loss: 0.1132 - acc: 0.9567 - val_loss: 0.3021
- val_acc: 0.9216
Epoch 28/30
7352/7352 [==============================] - 115s 16ms/step - loss: 0.1163 - acc: 0.9529 - val_loss: 0.3718
- val_acc: 0.9209
Epoch 29/30
7352/7352 [==============================] - 114s 15ms/step - loss: 0.1163 - acc: 0.9532 - val_loss: 0.4651
- val_acc: 0.9091
Epoch 30/30
7352/7352 [==============================] - 113s 15ms/step - loss: 0.1232 - acc: 0.9565 - val_loss: 0.3248
- val_acc: 0.9199
```

Out[49]:
```
<keras.callbacks.History at 0x7f71808f7c50>
```

In [0]:
```
history1=model1.history
```

In [58]:
```
y_pred=model2.predict(X_test)
cm_df=get_confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using get_confusion_matrix() definec
classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df

#Plot a Non-Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED CONFUSION MATRIX")

#Plot a Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFUSION MATRIX")
```





NORMALIZED CONFUSION MATRIX
True labels
Predicted labels
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
0.95 0.00 0.05 0.00 0.00 0.00
0.01 0.85 0.13 0.00 0.00 0.00
0.00 0.16 0.84 0.00 0.00 0.00
0.00 0.00 0.00 0.91 0.04 0.05
0.00 0.00 0.00 0.00 0.99 0.01
0.00 0.00 0.00 0.00 0.00 1.00
1.0
0.8
0.6
0.4
0.2
0.0

In [67]:
```
score2 = model2.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 16s 5ms/step
```

In [68]:
```
print('The Test loss is',score2[0],'and Test accuracy is',score2[1])
```

```
The Test loss is 0.3247978840465356 and Test accuracy is 0.9199185612487275
```

Classification using Conv1D

In [0]:
```
import pandas as pd
from matplotlib import pyplot
from sklearn.preprocessing import StandardScaler
from keras.models import Sequential
from keras.layers import Dense
from keras.layers import Flatten
from keras.layers import Dropout
from keras.layers.convolutional import Conv1D
from keras.layers.convolutional import MaxPooling1D
from keras.utils import to_categorical
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
```

In [127]:
```
model3 = Sequential()
model3.add(Conv1D(filters=128, kernel_size=5, activation='relu',kernel_initializer='glorot_normal',input_shape=(
model3.add(Conv1D(filters=64, kernel_size=5, activation='relu',kernel_initializer='glorot_normal'))
model3.add(Dropout(0.2))
model3.add(MaxPooling1D(pool_size=2))
model3.add(Flatten())
model3.add(Dense(50, activation='relu'))
model3.add(Dense(6, activation='softmax'))
model3.summary()
```

```
Model: "sequential_21"
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
conv1d_33 (Conv1D)           (None, 124, 128)          5888
_________________________________________________________________
conv1d_34 (Conv1D)           (None, 120, 64)           41024
_________________________________________________________________
dropout_22 (Dropout)         (None, 120, 64)           0
_________________________________________________________________
max_pooling1d_17 (MaxPooling (None, 60, 64)            0
_________________________________________________________________
flatten_17 (Flatten)         (None, 3840)              0
_________________________________________________________________
dense_35 (Dense)             (None, 50)                192050
_________________________________________________________________
dense_36 (Dense)             (None, 6)                 306
=================================================================
Total params: 239,268
Trainable params: 239,268
Non-trainable params: 0
_________________________________________________________________
```

In [0]:
```
model3.compile(loss='categorical_crossentropy',
              optimizer='rmsprop',
              metrics=['accuracy'])
```

In [129]:
```
model3.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test,Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/30
7352/7352 [==============================] - 4s 563us/step - loss: 0.3941 - acc: 0.8462 - val_loss: 0.3727 -
val_acc: 0.8955
Epoch 2/30
7352/7352 [==============================] - 2s 222us/step - loss: 0.1601 - acc: 0.9416 - val_loss: 0.3579 -
val_acc: 0.9165
Epoch 3/30
7352/7352 [==============================] - 2s 216us/step - loss: 0.1292 - acc: 0.9509 - val_loss: 0.3888 -
val_acc: 0.9094
Epoch 4/30
7352/7352 [==============================] - 2s 212us/step - loss: 0.1124 - acc: 0.9523 - val_loss: 0.3493 -
val_acc: 0.9033
Epoch 5/30
7352/7352 [==============================] - 2s 221us/step - loss: 0.0988 - acc: 0.9566 - val_loss: 0.5167 -
val_acc: 0.9060
Epoch 6/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0931 - acc: 0.9608 - val_loss: 0.5551 -
val_acc: 0.9253
Epoch 7/30
7352/7352 [==============================] - 2s 216us/step - loss: 0.0859 - acc: 0.9659 - val_loss: 0.5420 -
val_acc: 0.9097
Epoch 8/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.1113 - acc: 0.9627 - val_loss: 0.5450 -
val_acc: 0.9172
Epoch 9/30
7352/7352 [==============================] - 2s 213us/step - loss: 0.0921 - acc: 0.9668 - val_loss: 0.6792 -
val_acc: 0.8877
Epoch 10/30
7352/7352 [==============================] - 2s 212us/step - loss: 0.0788 - acc: 0.9676 - val_loss: 0.5242 -
val_acc: 0.9199
Epoch 11/30
7352/7352 [==============================] - 2s 212us/step - loss: 0.0772 - acc: 0.9706 - val_loss: 0.5694 -
val_acc: 0.9053
Epoch 12/30
7352/7352 [==============================] - 2s 212us/step - loss: 0.0614 - acc: 0.9740 - val_loss: 0.5803 -
```

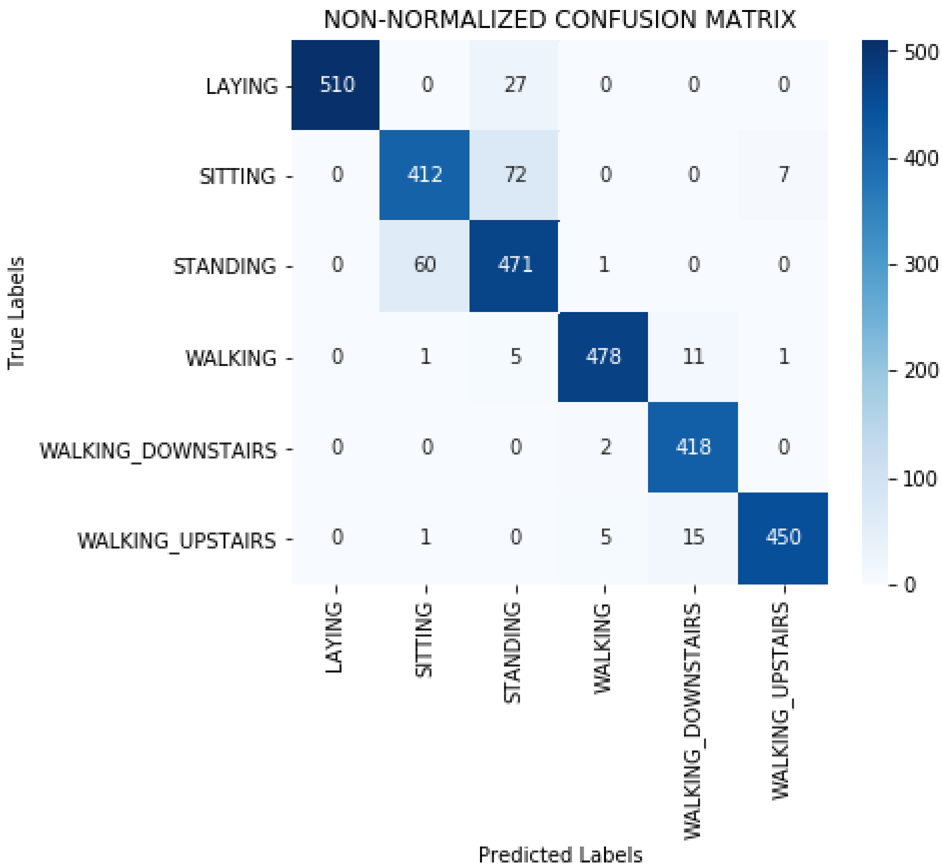
```
val_acc: 0.9128
Epoch 13/30
7352/7352 [==============================] - 2s 216us/step - loss: 0.1023 - acc: 0.9709 - val_loss: 0.5897 -
val_acc: 0.9104
Epoch 14/30
7352/7352 [==============================] - 2s 222us/step - loss: 0.0790 - acc: 0.9717 - val_loss: 0.6685 -
val_acc: 0.9033
Epoch 15/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.0916 - acc: 0.9744 - val_loss: 0.6572 -
val_acc: 0.9013
Epoch 16/30
7352/7352 [==============================] - 2s 217us/step - loss: 0.0654 - acc: 0.9769 - val_loss: 0.5758 -
val_acc: 0.9114
Epoch 17/30
7352/7352 [==============================] - 2s 220us/step - loss: 0.0785 - acc: 0.9784 - val_loss: 0.5604 -
val_acc: 0.9169
Epoch 18/30
7352/7352 [==============================] - 2s 229us/step - loss: 0.0648 - acc: 0.9770 - val_loss: 0.5914 -
val_acc: 0.9063
Epoch 19/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0597 - acc: 0.9785 - val_loss: 0.6276 -
val_acc: 0.9121
Epoch 20/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0815 - acc: 0.9780 - val_loss: 0.5772 -
val_acc: 0.9118
Epoch 21/30
7352/7352 [==============================] - 2s 215us/step - loss: 0.0619 - acc: 0.9793 - val_loss: 0.7351 -
val_acc: 0.9152
Epoch 22/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0584 - acc: 0.9803 - val_loss: 0.6469 -
val_acc: 0.9186
Epoch 23/30
7352/7352 [==============================] - 2s 217us/step - loss: 0.0476 - acc: 0.9825 - val_loss: 0.9449 -
val_acc: 0.8799
Epoch 24/30
7352/7352 [==============================] - 2s 213us/step - loss: 0.0501 - acc: 0.9815 - val_loss: 0.7045 -
val_acc: 0.9158
Epoch 25/30
7352/7352 [==============================] - 2s 229us/step - loss: 0.0656 - acc: 0.9831 - val_loss: 0.7857 -
val_acc: 0.9046
Epoch 26/30
7352/7352 [==============================] - 2s 218us/step - loss: 0.0473 - acc: 0.9853 - val_loss: 0.7560 -
val_acc: 0.9226
```

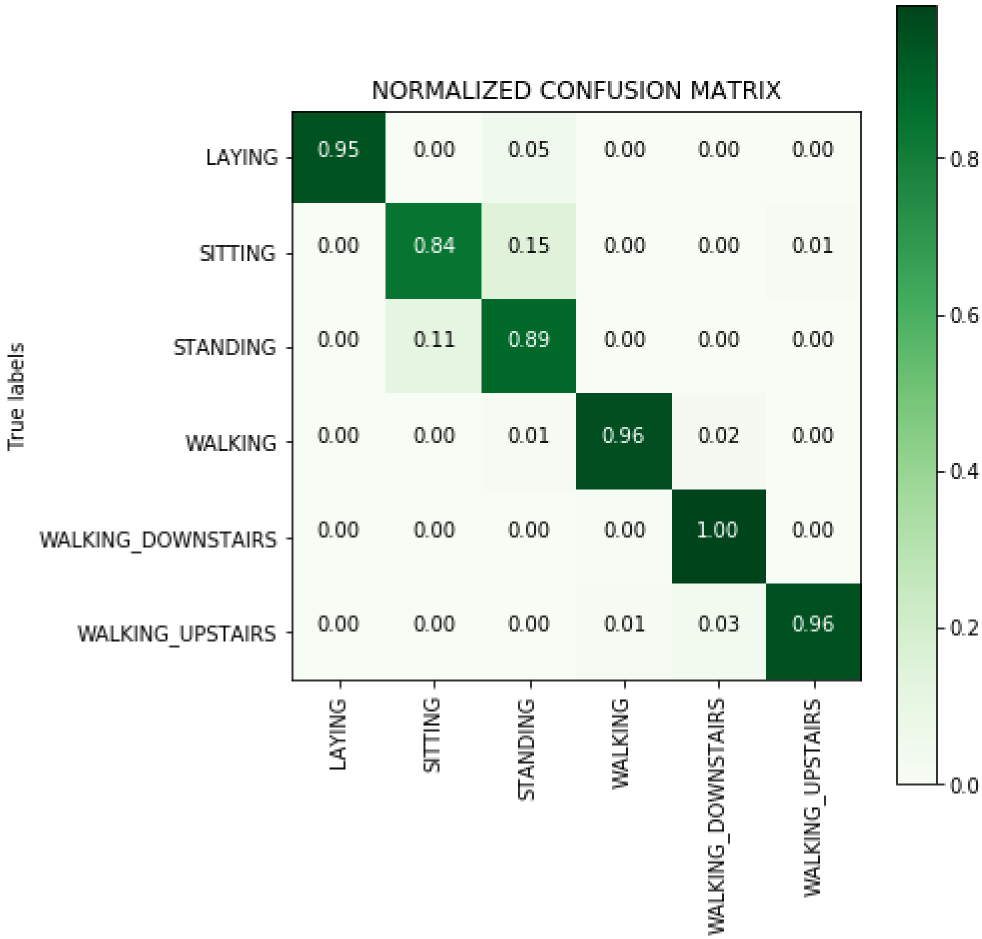
```
Epoch 27/30
7352/7352 [==============================] - 2s 211us/step - loss: 0.0749 - acc: 0.9811 - val_loss: 0.7486 -
val_acc: 0.9165
Epoch 28/30
7352/7352 [==============================] - 2s 213us/step - loss: 0.0604 - acc: 0.9839 - val_loss: 0.6515 -
val_acc: 0.9274
Epoch 29/30
7352/7352 [==============================] - 2s 219us/step - loss: 0.0450 - acc: 0.9835 - val_loss: 0.6664 -
val_acc: 0.9294
Epoch 30/30
7352/7352 [==============================] - 2s 225us/step - loss: 0.0806 - acc: 0.9812 - val_loss: 0.6447 -
val_acc: 0.9294
```

Out[129]:

```
<keras.callbacks.History at 0x7f6f6f43be10>
```

In [130]:
```
y_pred=model3.predict(X_test)
cm_df=get_confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using get_confusion_matrix() definec
classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df

#Plot a Non-Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED CONFUSION MATRIX")

#Plot a Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFUSION MATRIX")
```




NORMALIZED CONFUSION MATRIX
True labels
Predicted labels
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
0.95 0.00 0.05 0.00 0.00 0.00
0.00 0.84 0.15 0.00 0.00 0.01
0.00 0.11 0.89 0.00 0.00 0.00
0.00 0.00 0.01 0.96 0.02 0.00
0.00 0.00 0.00 0.00 1.00 0.00
0.00 0.00 0.00 0.01 0.03 0.96
0.0
0.2
0.4
0.6
0.8

In [131]:
```
score3 = model3.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 0s 92us/step
```

In [132]:
```
print('The Test loss is',score3[0],'and Test accuracy is',score3[1])
```

```
The Test loss is 0.6447151533074668 and Test accuracy is 0.9294197488971836
```

In [142]:
```
from keras.layers import Bidirectional
model4 = Sequential()
model4.add(Bidirectional(LSTM(128, activation='relu'),input_shape=(timesteps, input_dim)))
model4.add(Dropout(0.2))
# Adding a dense output layer with sigmoid activation
model4.add(Dense(n_classes, activation='sigmoid'))
model4.summary()
```

```
Model: "sequential_24"
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
bidirectional_3 (Bidirection (None, 256)               141312    
_________________________________________________________________
dropout_25 (Dropout)         (None, 256)               0         
_________________________________________________________________
dense_39 (Dense)             (None, 6)                 1542      
=================================================================
Total params: 142,854
Trainable params: 142,854
Non-trainable params: 0
_________________________________________________________________
```

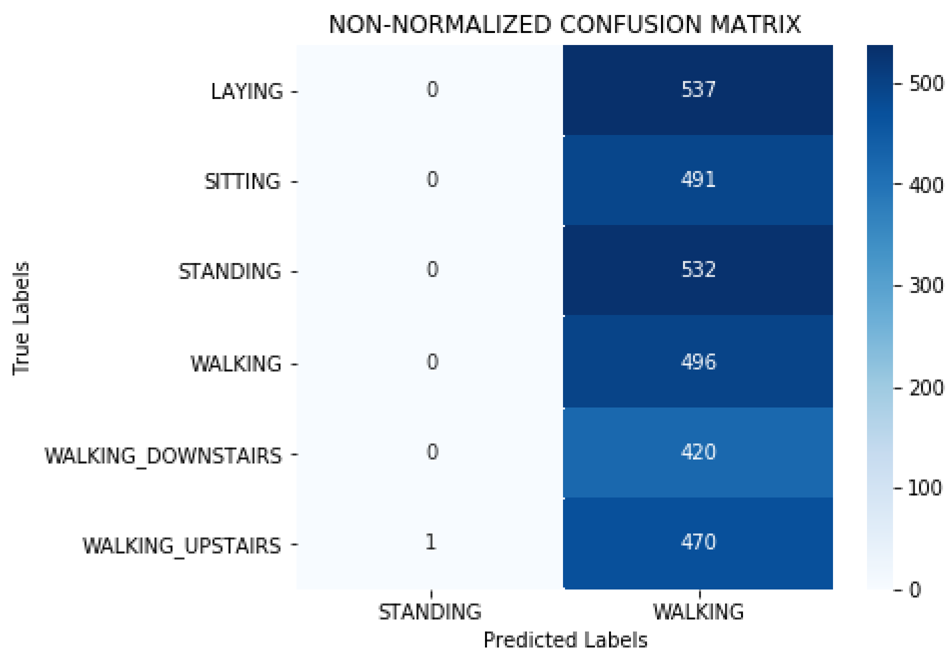
In [0]:
```
model4.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

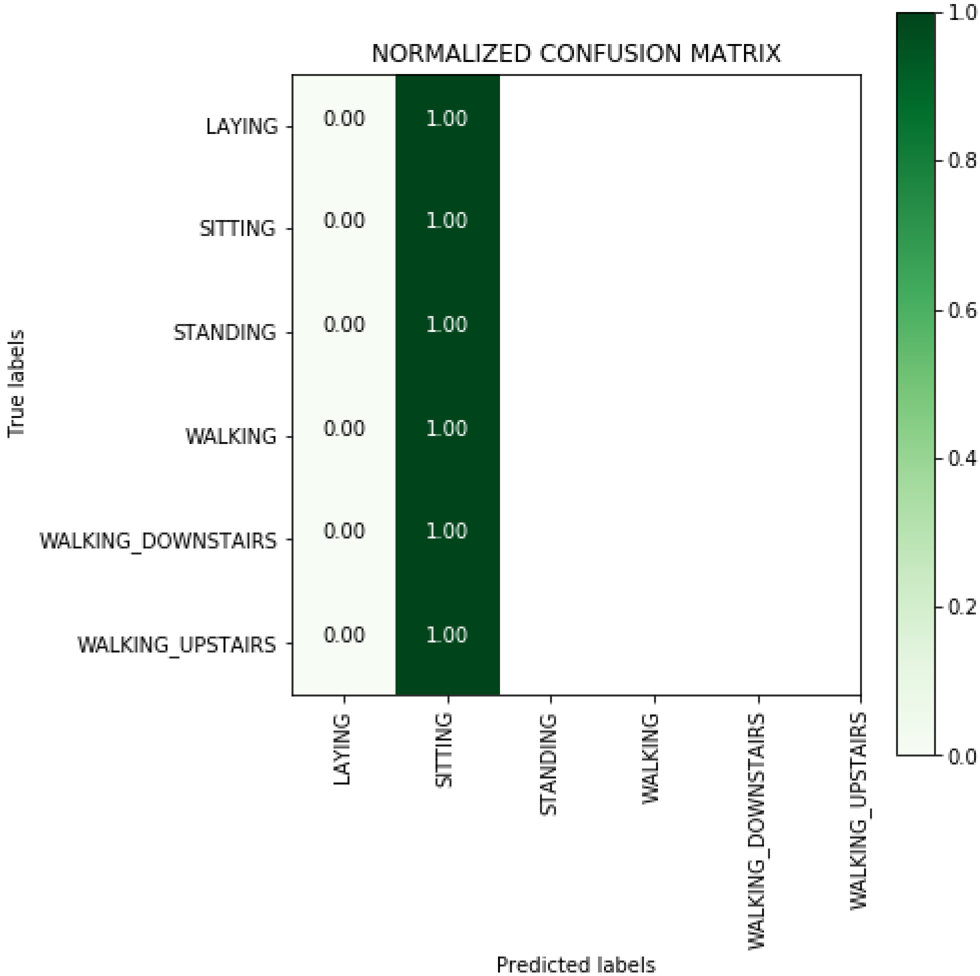
In [145]:
```
model4.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test,Y_test),
          epochs=5)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/5
7352/7352 [==============================] - 107s 15ms/step - loss: 1.7918 - acc: 0.1668 - val_loss: 1.7912 - val_acc: 0.1683
Epoch 2/5
7352/7352 [==============================] - 106s 14ms/step - loss: 1.7918 - acc: 0.1668 - val_loss: 1.7912 - val_acc: 0.1683
Epoch 3/5
7352/7352 [==============================] - 106s 14ms/step - loss: 1.7918 - acc: 0.1668 - val_loss: 1.7912 - val_acc: 0.1683
Epoch 4/5
7352/7352 [==============================] - 106s 14ms/step - loss: 1.7918 - acc: 0.1668 - val_loss: 1.7912 - val_acc: 0.1683
Epoch 5/5
7352/7352 [==============================] - 106s 14ms/step - loss: 1.7918 - acc: 0.1668 - val_loss: 1.7912 - val_acc: 0.1683
```

Out[145]:
```
<keras.callbacks.History at 0x7f6f6df81358>
```

In [146]:
```
y_pred=model4.predict(X_test)
cm_df=get_confusion_matrix(Y_test, y_pred) #Prepare the confusion matrix by using get_confusion_matrix() defined
classes=list(cm_df.index) #Class names = Index Names or Column Names in cm_df

#Plot a Non-Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=False, title="NON-NORMALIZED CONFUSION MATRIX")

#Plot a Normalized confusion matrix
plot_confusion_matrix(cm_df, classes, normalize=True, title="NORMALIZED CONFUSION MATRIX")
```




NORMALIZED CONFUSION MATRIX
True labels
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
0.00
1.00
Predicted labels
1.0
0.8
0.6
0.4
0.2
0.0

In [147]:
```
score4 = model4.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 15s 5ms/step
```

In [148]:
```
print('The Test loss is',score4[0],'and Test accuracy is',score4[1])
```

```
The Test loss is 1.7911514966496784 and Test accuracy is 0.168306752629793
```

In [150]:
```
from prettytable import PrettyTable
x = PrettyTable()
x.field_names = ["Model", "Test Accuracy(%)", "Test error(%)"]
x.add_row(["Lstm-single layer",92.53 ,7.47])
x.add_row(["Lstm-double layer",91.99, 8.01])
x.add_row(["CNN 1D", 92.94,7.06])
x.add_row(["Bidirectional Lstm", 16.83,83.17])
print(x)
```

```
+--------------------+------------------+-----------------+
|       Model        | Test Accuracy(%) |  Test error(%)  |
+--------------------+------------------+-----------------+
| Lstm-single layer  |      92.53       |       7.47      |
| Lstm-double layer  |      91.99       |       8.01      |
|       CNN 1D       |      92.94       |       7.06      |
| Bidirectional Lstm |      16.83       |      83.17      |
+--------------------+------------------+-----------------+
```

Conclusion:

In video the accuracy was 90.09% and by doing some tuning in parameters it has been leveraged to 92.53%

Single layer Lstm performed better than double layer

To improve test accuracy we used a 1D CNN model which performed better than 2 layer Lstm and slightly better than Lstm of single layer

I also tried Bidierectional LSTM but it performed very poorly, test accuracy and train accuracy is less than 17%.It is a dumb model it predicted majority activities as sitting.