HumanActivityRecognition

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

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

How data was recorded

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

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

Feature names

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

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

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

- tBodyAcc-XYZ
- tGravityAcc-XYZ
- tBodyAccJerk-XYZ
- tBodyGyro-XYZ
- tBodyGyroJerk-XYZ
- tBodyAccMag
- tGravityAccMag

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

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

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

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

    - gravityMean
    - tBodyAccMean
    - tBodyAccJerkMean
    - tBodyGyroMean
    - tBodyGyroJerkMean

Y_Labels(Encoded)

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

Train and test data were saperated

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

Data

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

Data Size :

> 27 MB

Quick overview of the dataset :

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

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

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

Problem Framework

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

Problem Statement

- Given a new datapoint we have to predict the Activity

In [1]:

```
import numpy as np
import pandas as pd

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

```
No of Features: 561
```

Obtain the data

In [3]:

```
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)
```

Data Cleaning

1. Check for Duplicates

In [4]:

```
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 [5]:

```
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
```

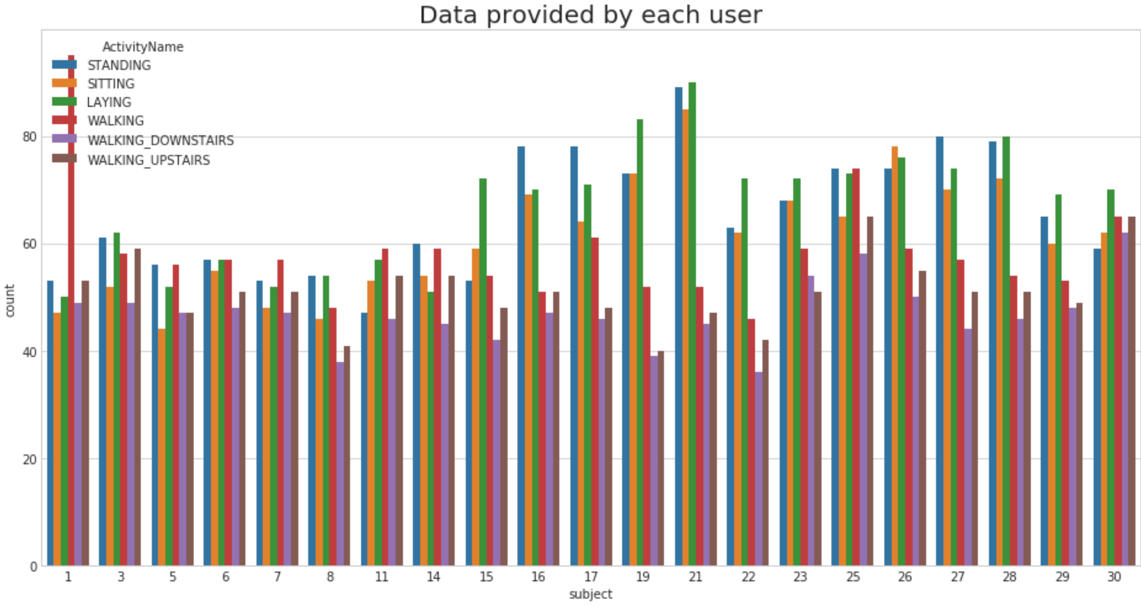
3. Check for data imbalance

In [6]:

```
import matplotlib.pyplot as plt
import seaborn as sns

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

In [7]:

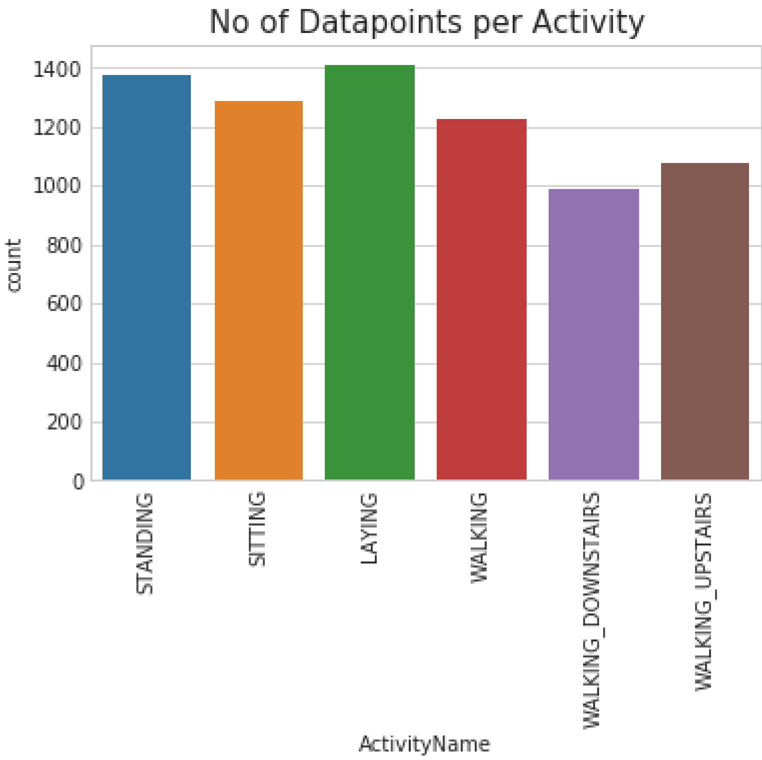
```
plt.figure(figsize=(16,8))
plt.title('Data provided by each user', fontsize=20)
sns.countplot(x='subject',hue='ActivityName', data = train)
plt.show()
```



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

In [8]:

```
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 [9]:

```
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[9]:

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

Exploratory Data Analysis

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

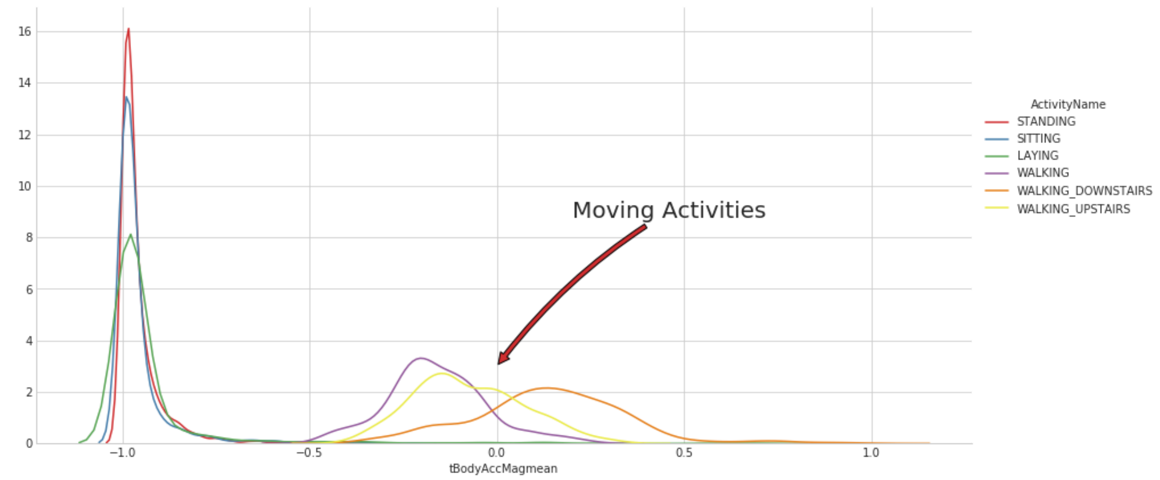
1. Featuring Engineering from Domain Knowledge

- **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

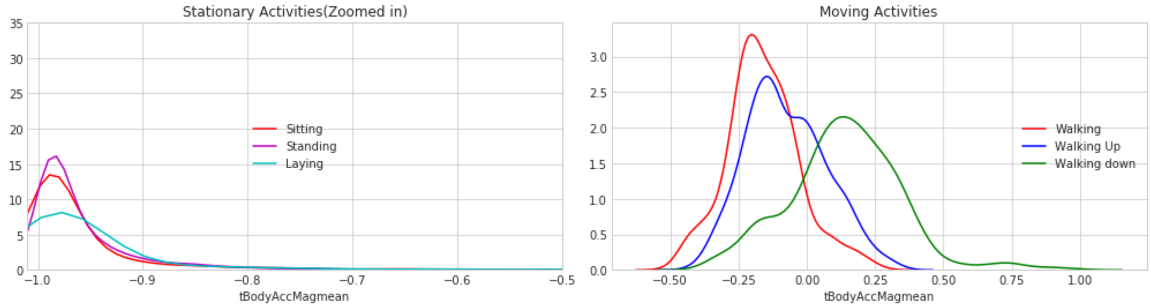
In [11]:

```
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 [12]:

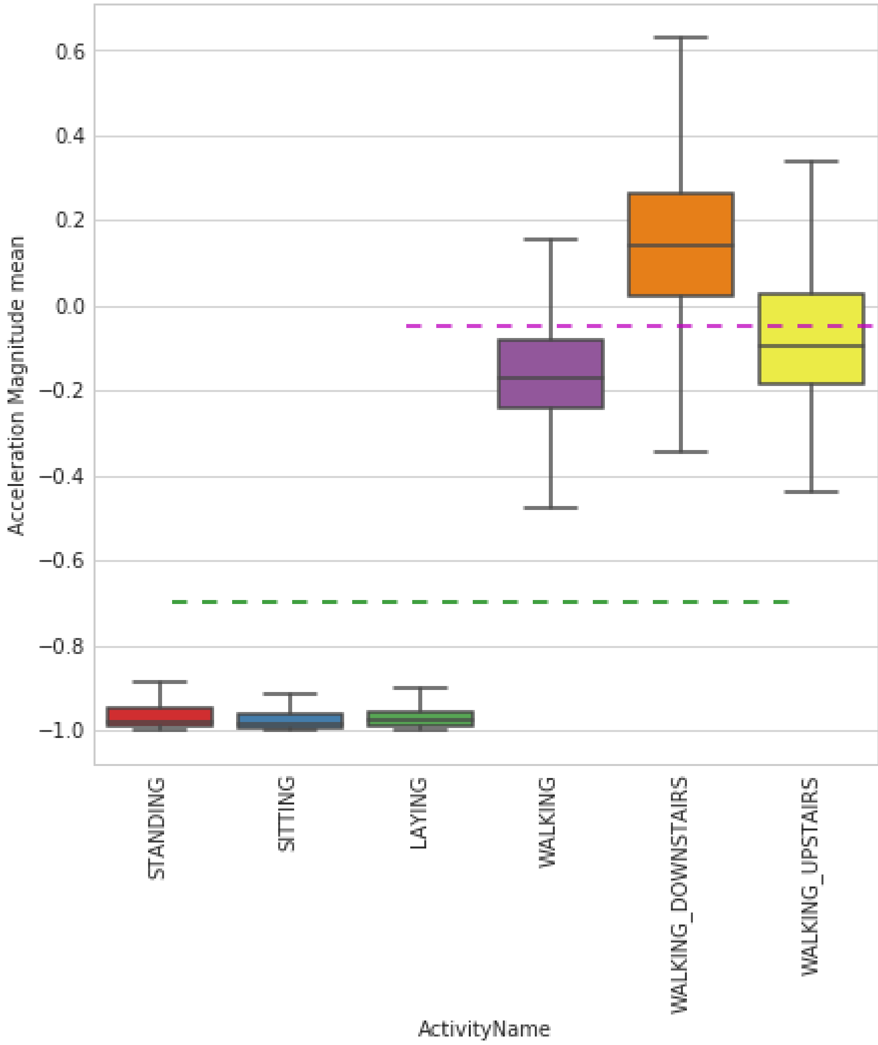
```
# for plotting purposes taking datapoints of each activity to a different dataframe
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

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 dow
n')
plt.legend(loc='center right')


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



3. Magnitude of an acceleration can saperate it well

In [13]:

```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMagmean',data=train, showfliers=False, saturat
ion=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()
```



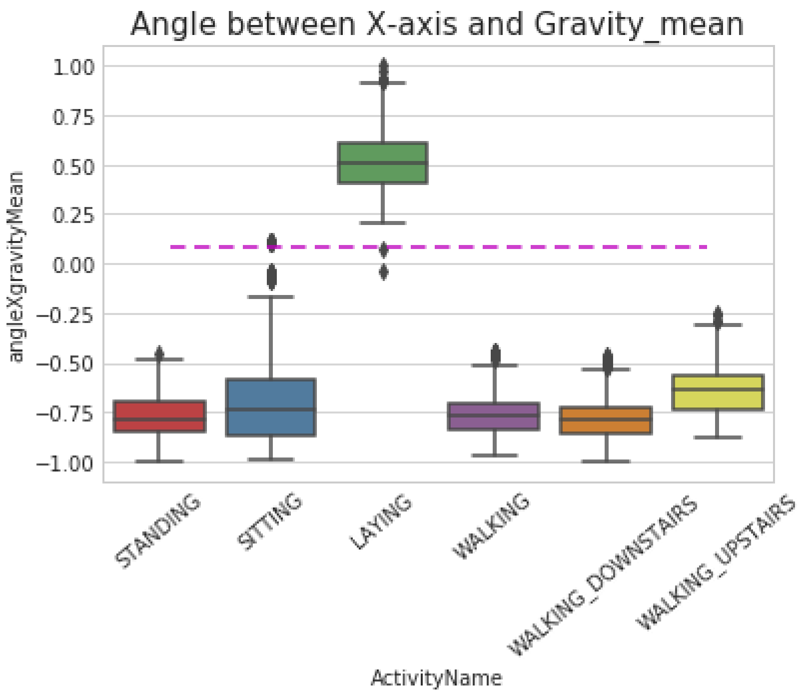
Observations:

- 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 [14]:

```
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()
```

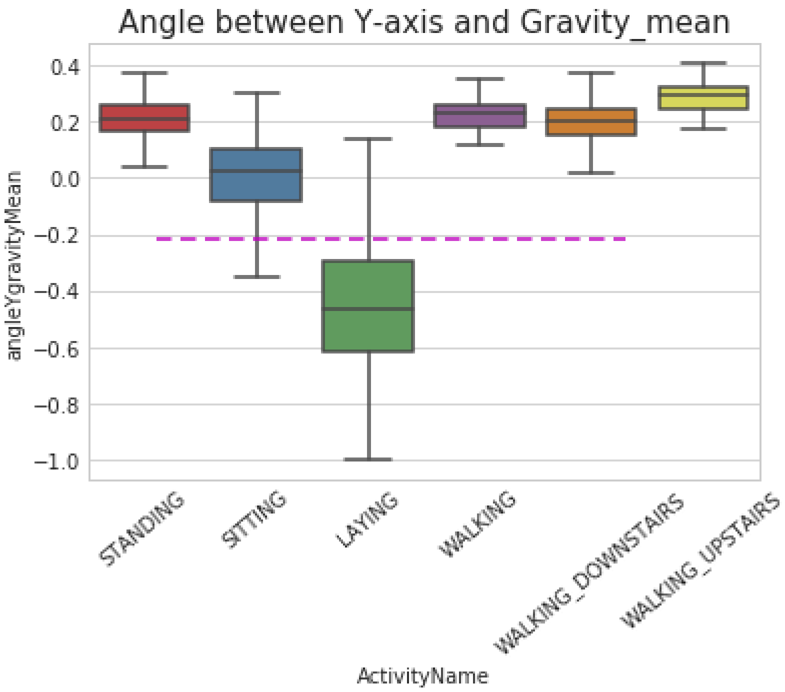


Observations:

- 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 [15]:

```
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 [16]:

```
import numpy as np
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns
```

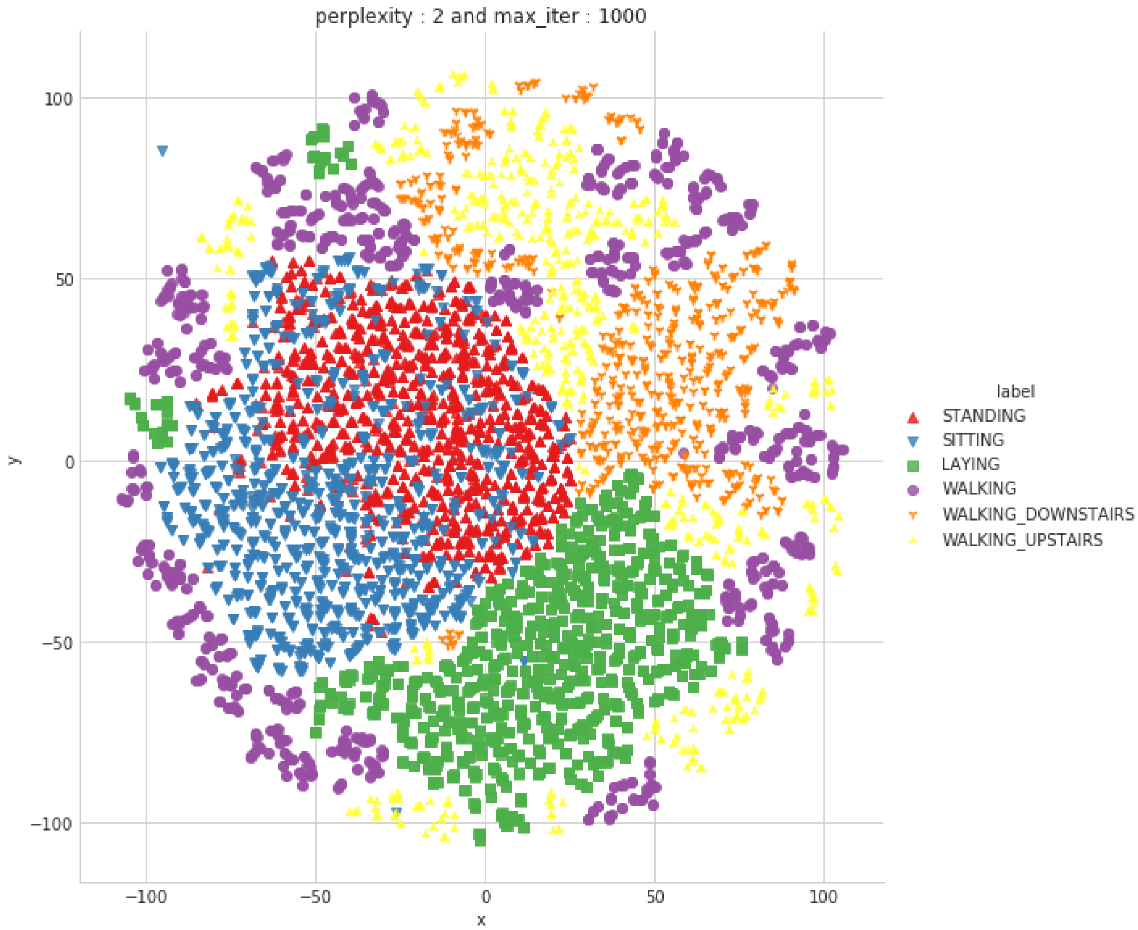
In [17]:

```
# 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'.form
at(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 [18]:

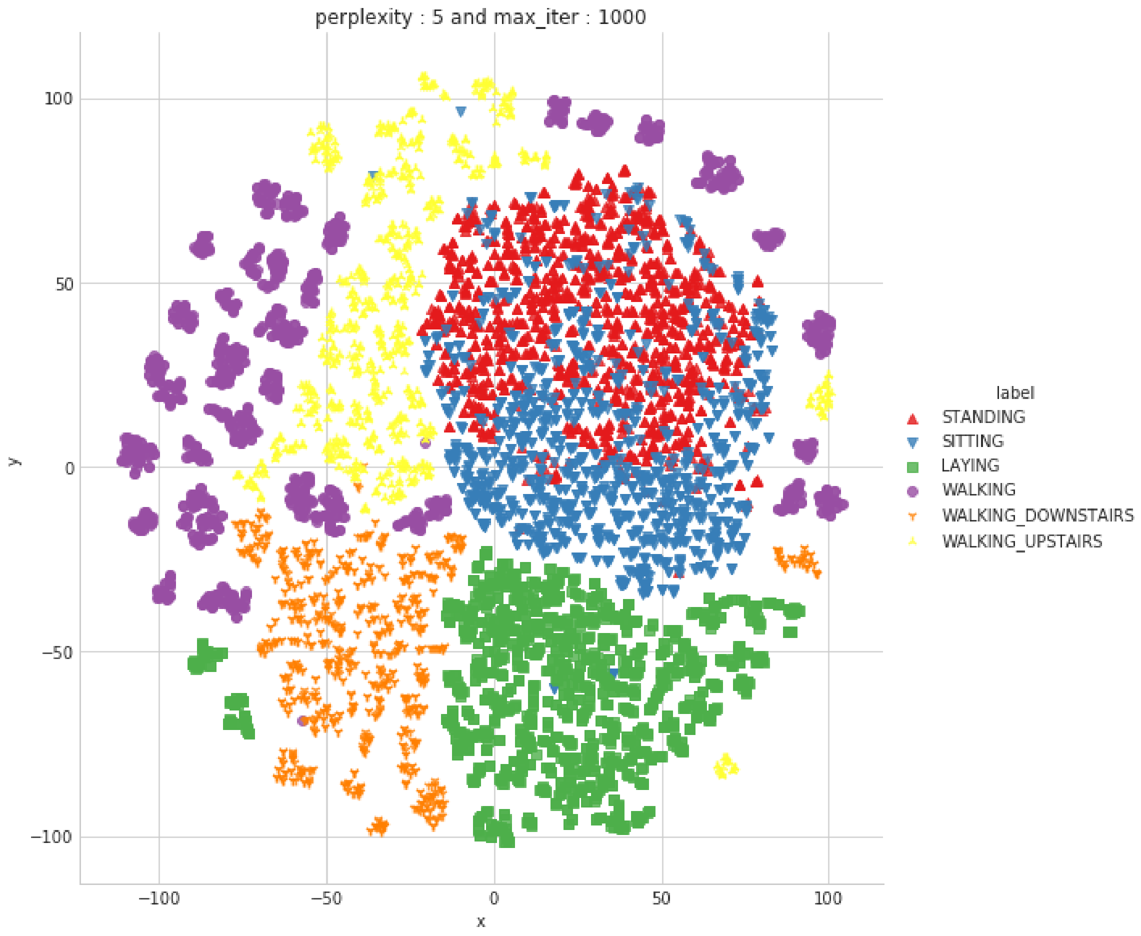
```
X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train['ActivityName']
perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[2,5,10,20,50])
```

```
performing tsne with perplexity 2 and with 1000 iterations at max
[t-SNE] Computing 7 nearest neighbors...
[t-SNE] Indexed 7352 samples in 2.246s...
[t-SNE] Computed neighbors for 7352 samples in 55.349s...
[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: 0.635854
[t-SNE] Computed conditional probabilities in 0.082s
[t-SNE] Iteration 50: error = 124.7207642, gradient norm = 0.0274185 (50 i
terations in 3.753s)
[t-SNE] Iteration 100: error = 106.6979828, gradient norm = 0.0287408 (50
iterations in 2.929s)
[t-SNE] Iteration 150: error = 100.6062317, gradient norm = 0.0197489 (50
iterations in 2.557s)
[t-SNE] Iteration 200: error = 97.3068008, gradient norm = 0.0177662 (50 i
terations in 2.504s)
[t-SNE] Iteration 250: error = 95.0502472, gradient norm = 0.0150657 (50 i
terations in 2.967s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 95.050
247
[t-SNE] Iteration 300: error = 4.1168814, gradient norm = 0.0015664 (50 it
erations in 3.111s)
[t-SNE] Iteration 350: error = 3.2066424, gradient norm = 0.0009984 (50 it
erations in 3.222s)
[t-SNE] Iteration 400: error = 2.7760842, gradient norm = 0.0007171 (50 it
erations in 2.830s)
[t-SNE] Iteration 450: error = 2.5120215, gradient norm = 0.0005681 (50 it
erations in 2.553s)
[t-SNE] Iteration 500: error = 2.3287277, gradient norm = 0.0004781 (50 it
erations in 2.619s)
[t-SNE] Iteration 550: error = 2.1907609, gradient norm = 0.0004189 (50 it
erations in 2.559s)
[t-SNE] Iteration 600: error = 2.0814571, gradient norm = 0.0003726 (50 it
erations in 2.592s)
[t-SNE] Iteration 650: error = 1.9916465, gradient norm = 0.0003293 (50 it
erations in 2.609s)
[t-SNE] Iteration 700: error = 1.9160068, gradient norm = 0.0002977 (50 it
erations in 2.620s)
[t-SNE] Iteration 750: error = 1.8509090, gradient norm = 0.0002785 (50 it
erations in 2.594s)
[t-SNE] Iteration 800: error = 1.7944832, gradient norm = 0.0002541 (50 it
erations in 2.575s)
[t-SNE] Iteration 850: error = 1.7445557, gradient norm = 0.0002383 (50 it
erations in 2.588s)
[t-SNE] Iteration 900: error = 1.7001088, gradient norm = 0.0002229 (50 it
erations in 2.588s)
[t-SNE] Iteration 950: error = 1.6600125, gradient norm = 0.0002111 (50 it
erations in 2.598s)
[t-SNE] Iteration 1000: error = 1.6236660, gradient norm = 0.0001996 (50 i
terations in 2.748s)
[t-SNE] KL divergence after 1000 iterations: 1.623666
Done..
Creating plot for this t-sne visualization..
saving this plot as image in present working directory...
```


perplexity : 2 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

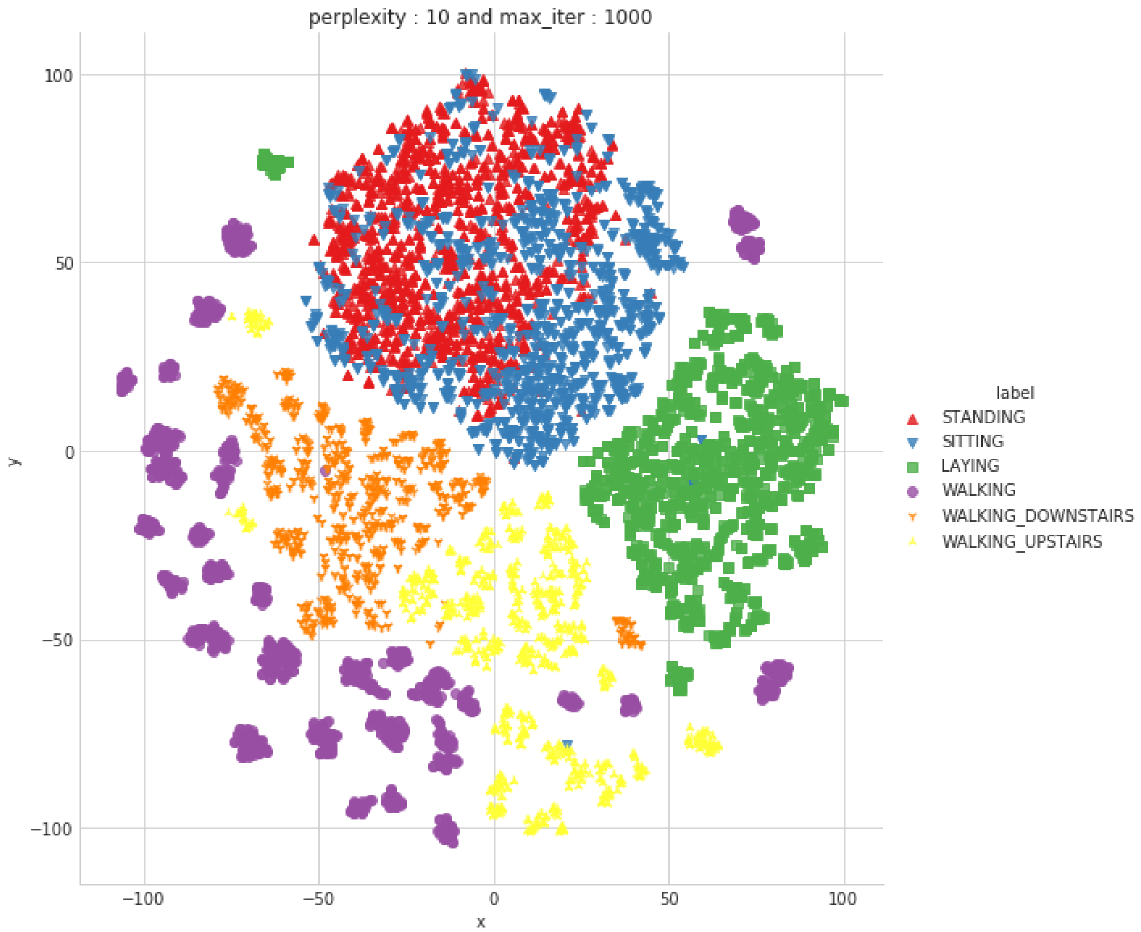
```
Done

performing tsne with perplexity 5 and with 1000 iterations at max
[t-SNE] Computing 16 nearest neighbors...
[t-SNE] Indexed 7352 samples in 2.203s...
[t-SNE] Computed neighbors for 7352 samples in 54.325s...
[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 0.078s
[t-SNE] Iteration 50: error = 114.0917969, gradient norm = 0.0206442 (50 i
terations in 7.072s)
[t-SNE] Iteration 100: error = 98.1152420, gradient norm = 0.0169837 (50 i
terations in 2.920s)
[t-SNE] Iteration 150: error = 93.3989410, gradient norm = 0.0095554 (50 i
terations in 2.510s)
[t-SNE] Iteration 200: error = 91.2936783, gradient norm = 0.0072150 (50 i
terations in 2.561s)
[t-SNE] Iteration 250: error = 90.0745392, gradient norm = 0.0054562 (50 i
terations in 2.538s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 90.074
539
[t-SNE] Iteration 300: error = 3.5757952, gradient norm = 0.0014640 (50 it
erations in 2.469s)
[t-SNE] Iteration 350: error = 2.8169851, gradient norm = 0.0007528 (50 it
erations in 2.459s)
[t-SNE] Iteration 400: error = 2.4356225, gradient norm = 0.0005280 (50 it
erations in 2.506s)
[t-SNE] Iteration 450: error = 2.2173913, gradient norm = 0.0004072 (50 it
erations in 2.520s)
[t-SNE] Iteration 500: error = 2.0720167, gradient norm = 0.0003329 (50 it
erations in 2.554s)
[t-SNE] Iteration 550: error = 1.9664084, gradient norm = 0.0002830 (50 it
erations in 2.531s)
[t-SNE] Iteration 600: error = 1.8850527, gradient norm = 0.0002455 (50 it
erations in 2.562s)
[t-SNE] Iteration 650: error = 1.8199900, gradient norm = 0.0002189 (50 it
erations in 2.539s)
[t-SNE] Iteration 700: error = 1.7663279, gradient norm = 0.0001978 (50 it
erations in 2.542s)
[t-SNE] Iteration 750: error = 1.7210433, gradient norm = 0.0001805 (50 it
erations in 2.555s)
[t-SNE] Iteration 800: error = 1.6822122, gradient norm = 0.0001643 (50 it
erations in 2.546s)
[t-SNE] Iteration 850: error = 1.6481471, gradient norm = 0.0001544 (50 it
erations in 2.573s)
[t-SNE] Iteration 900: error = 1.6184077, gradient norm = 0.0001427 (50 it
erations in 2.563s)
[t-SNE] Iteration 950: error = 1.5920080, gradient norm = 0.0001339 (50 it
erations in 2.553s)
[t-SNE] Iteration 1000: error = 1.5682036, gradient norm = 0.0001263 (50 i
terations in 2.553s)
[t-SNE] KL divergence after 1000 iterations: 1.568204
Done..
```

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



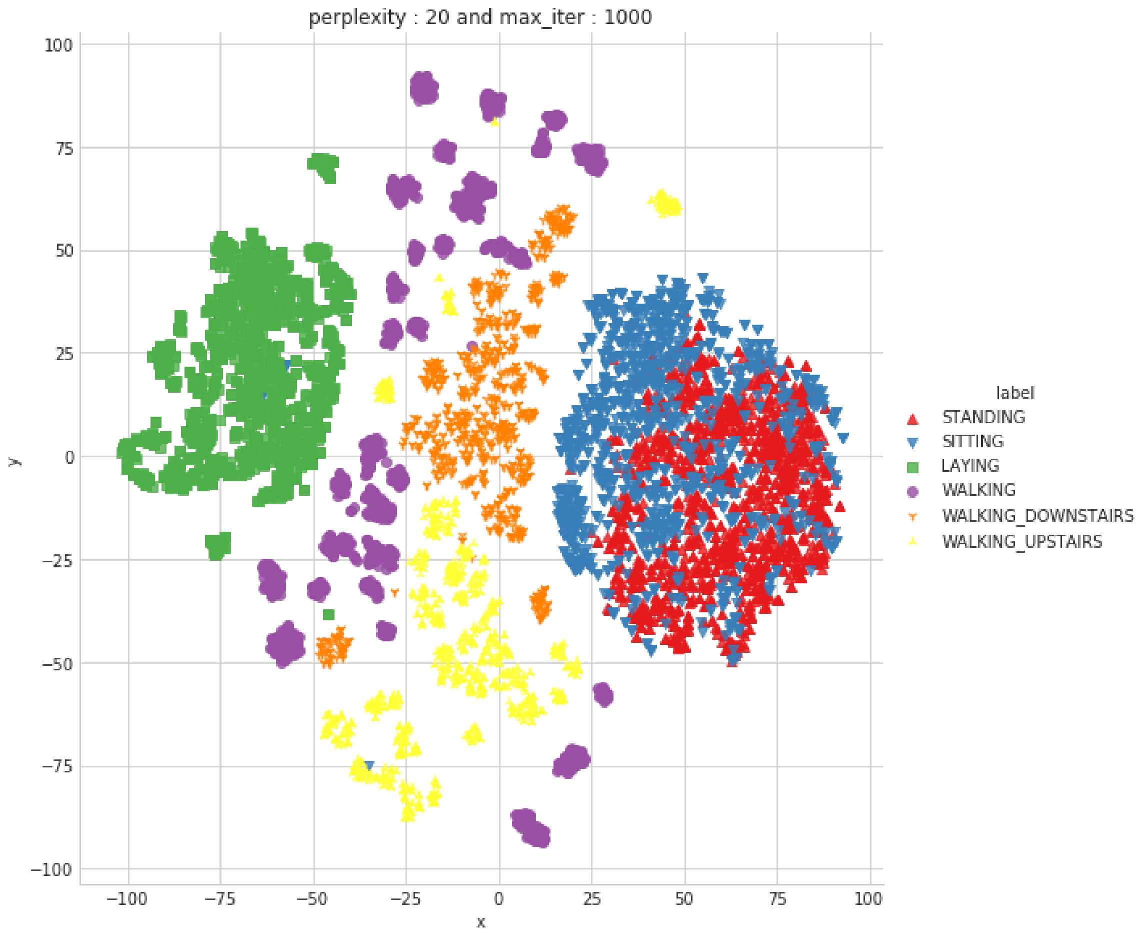
```
Done

performing tsne with perplexity 10 and with 1000 iterations at max
[t-SNE] Computing 31 nearest neighbors...
[t-SNE] Indexed 7352 samples in 1.853s...
[t-SNE] Computed neighbors for 7352 samples in 52.233s...
[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 0.151s
[t-SNE] Iteration 50: error = 105.7657013, gradient norm = 0.0189496 (50 i
terations in 4.364s)
[t-SNE] Iteration 100: error = 90.4657440, gradient norm = 0.0102857 (50 i
terations in 3.050s)
[t-SNE] Iteration 150: error = 87.3603058, gradient norm = 0.0058368 (50 i
terations in 2.679s)
[t-SNE] Iteration 200: error = 86.1050034, gradient norm = 0.0041631 (50 i
terations in 2.705s)
[t-SNE] Iteration 250: error = 85.3840866, gradient norm = 0.0033058 (50 i
terations in 2.734s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 85.384
087
[t-SNE] Iteration 300: error = 3.1321864, gradient norm = 0.0013912 (50 it
erations in 2.872s)
[t-SNE] Iteration 350: error = 2.4885402, gradient norm = 0.0006457 (50 it
erations in 2.833s)
[t-SNE] Iteration 400: error = 2.1695457, gradient norm = 0.0004207 (50 it
erations in 2.742s)
[t-SNE] Iteration 450: error = 1.9859039, gradient norm = 0.0003097 (50 it
erations in 2.677s)
[t-SNE] Iteration 500: error = 1.8677763, gradient norm = 0.0002503 (50 it
erations in 2.694s)
[t-SNE] Iteration 550: error = 1.7848721, gradient norm = 0.0002094 (50 it
erations in 2.687s)
[t-SNE] Iteration 600: error = 1.7225971, gradient norm = 0.0001809 (50 it
erations in 2.656s)
[t-SNE] Iteration 650: error = 1.6735473, gradient norm = 0.0001614 (50 it
erations in 2.652s)
[t-SNE] Iteration 700: error = 1.6340926, gradient norm = 0.0001441 (50 it
erations in 2.649s)
[t-SNE] Iteration 750: error = 1.6015133, gradient norm = 0.0001309 (50 it
erations in 2.648s)
[t-SNE] Iteration 800: error = 1.5745549, gradient norm = 0.0001194 (50 it
erations in 2.705s)
[t-SNE] Iteration 850: error = 1.5517440, gradient norm = 0.0001111 (50 it
erations in 2.653s)
[t-SNE] Iteration 900: error = 1.5320408, gradient norm = 0.0001037 (50 it
erations in 2.664s)
[t-SNE] Iteration 950: error = 1.5149099, gradient norm = 0.0000992 (50 it
erations in 2.644s)
[t-SNE] Iteration 1000: error = 1.5002866, gradient norm = 0.0000938 (50 i
terations in 2.662s)
[t-SNE] KL divergence after 1000 iterations: 1.500287
Done..
```

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



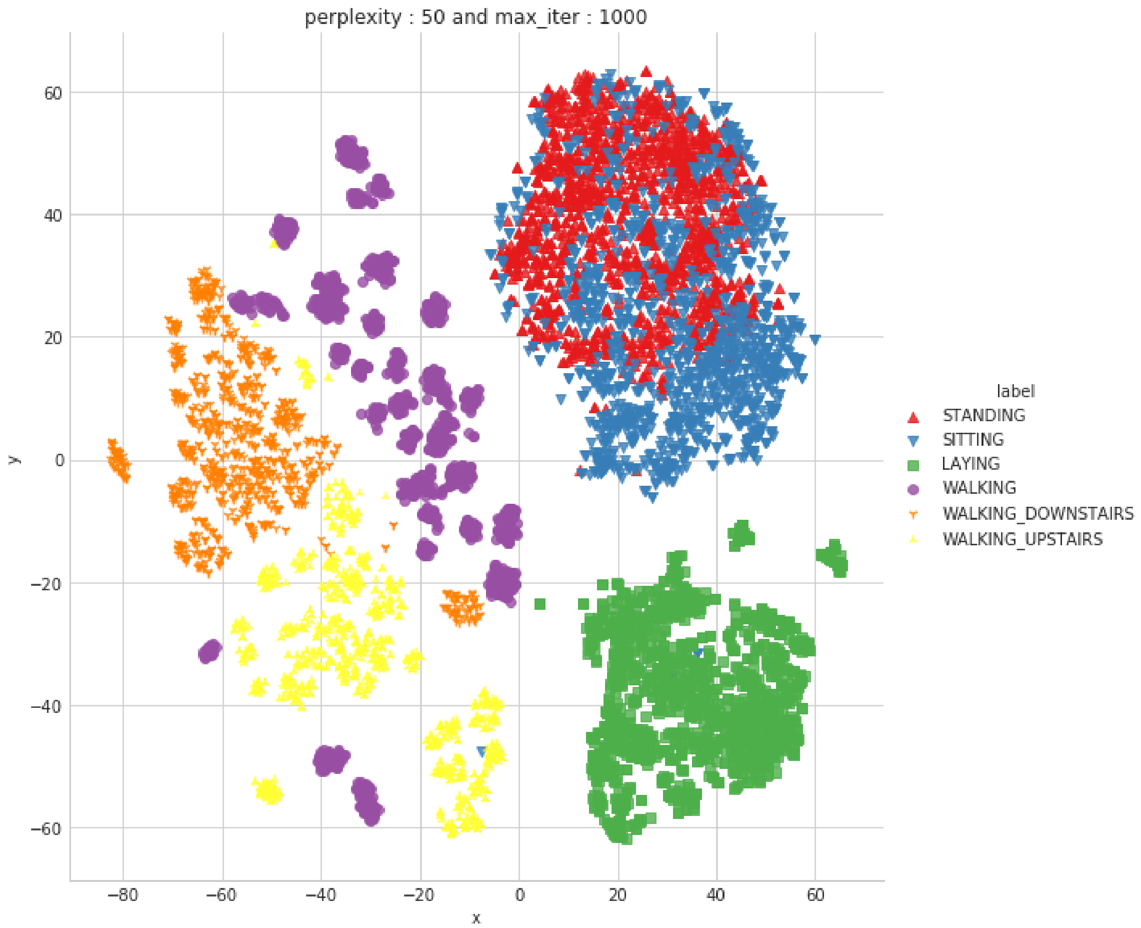
```
Done

performing tsne with perplexity 20 and with 1000 iterations at max
[t-SNE] Computing 61 nearest neighbors...
[t-SNE] Indexed 7352 samples in 1.784s...
[t-SNE] Computed neighbors for 7352 samples in 435.508s...
[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 0.308s
[t-SNE] Iteration 50: error = 97.9048996, gradient norm = 0.0117818 (50 it
erations in 5.540s)
[t-SNE] Iteration 100: error = 84.7624588, gradient norm = 0.0079371 (50 i
terations in 4.266s)
[t-SNE] Iteration 150: error = 82.4843903, gradient norm = 0.0041068 (50 i
terations in 3.884s)
[t-SNE] Iteration 200: error = 81.6530991, gradient norm = 0.0027784 (50 i
terations in 4.056s)
[t-SNE] Iteration 250: error = 81.1977234, gradient norm = 0.0025771 (50 i
terations in 4.211s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 81.197
723
[t-SNE] Iteration 300: error = 2.7249007, gradient norm = 0.0013041 (50 it
erations in 3.691s)
[t-SNE] Iteration 350: error = 2.1888509, gradient norm = 0.0005860 (50 it
erations in 3.259s)
[t-SNE] Iteration 400: error = 1.9365268, gradient norm = 0.0003542 (50 it
erations in 3.416s)
[t-SNE] Iteration 450: error = 1.7885538, gradient norm = 0.0002507 (50 it
erations in 3.376s)
[t-SNE] Iteration 500: error = 1.6930069, gradient norm = 0.0001997 (50 it
erations in 3.187s)
[t-SNE] Iteration 550: error = 1.6278261, gradient norm = 0.0001608 (50 it
erations in 3.337s)
[t-SNE] Iteration 600: error = 1.5803468, gradient norm = 0.0001360 (50 it
erations in 3.354s)
[t-SNE] Iteration 650: error = 1.5444452, gradient norm = 0.0001205 (50 it
erations in 3.386s)
[t-SNE] Iteration 700: error = 1.5162125, gradient norm = 0.0001074 (50 it
erations in 3.728s)
[t-SNE] Iteration 750: error = 1.4938722, gradient norm = 0.0000993 (50 it
erations in 3.606s)
[t-SNE] Iteration 800: error = 1.4762194, gradient norm = 0.0000902 (50 it
erations in 3.567s)
[t-SNE] Iteration 850: error = 1.4615550, gradient norm = 0.0000850 (50 it
erations in 3.495s)
[t-SNE] Iteration 900: error = 1.4493594, gradient norm = 0.0000822 (50 it
erations in 3.226s)
[t-SNE] Iteration 950: error = 1.4392700, gradient norm = 0.0000754 (50 it
erations in 3.488s)
[t-SNE] Iteration 1000: error = 1.4305348, gradient norm = 0.0000741 (50 i
terations in 3.393s)
[t-SNE] KL divergence after 1000 iterations: 1.430535
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 2.027s...
[t-SNE] Computed neighbors for 7352 samples in 58.141s...
[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 0.858s
[t-SNE] Iteration 50: error = 85.2329178, gradient norm = 0.0307021 (50 it
erations in 5.797s)
[t-SNE] Iteration 100: error = 75.5017700, gradient norm = 0.0047555 (50 i
terations in 5.446s)
[t-SNE] Iteration 150: error = 74.6227646, gradient norm = 0.0023487 (50 i
terations in 4.992s)
[t-SNE] Iteration 200: error = 74.2893906, gradient norm = 0.0015089 (50 i
terations in 5.891s)
[t-SNE] Iteration 250: error = 74.1173096, gradient norm = 0.0011702 (50 i
terations in 5.698s)
[t-SNE] KL divergence after 250 iterations with early exaggeration: 74.117
310
[t-SNE] Iteration 300: error = 2.1518736, gradient norm = 0.0011859 (50 it
erations in 4.961s)
[t-SNE] Iteration 350: error = 1.7544440, gradient norm = 0.0004853 (50 it
erations in 4.397s)
[t-SNE] Iteration 400: error = 1.5862771, gradient norm = 0.0002793 (50 it
erations in 4.414s)
[t-SNE] Iteration 450: error = 1.4919926, gradient norm = 0.0001925 (50 it
erations in 3.989s)
[t-SNE] Iteration 500: error = 1.4319952, gradient norm = 0.0001408 (50 it
erations in 4.491s)
[t-SNE] Iteration 550: error = 1.3911310, gradient norm = 0.0001109 (50 it
erations in 4.701s)
[t-SNE] Iteration 600: error = 1.3618691, gradient norm = 0.0000936 (50 it
erations in 4.793s)
[t-SNE] Iteration 650: error = 1.3404288, gradient norm = 0.0000800 (50 it
erations in 4.452s)
[t-SNE] Iteration 700: error = 1.3245654, gradient norm = 0.0000805 (50 it
erations in 4.663s)
[t-SNE] Iteration 750: error = 1.3127260, gradient norm = 0.0000654 (50 it
erations in 4.180s)
[t-SNE] Iteration 800: error = 1.3036268, gradient norm = 0.0000605 (50 it
erations in 4.834s)
[t-SNE] Iteration 850: error = 1.2964762, gradient norm = 0.0000596 (50 it
erations in 4.416s)
[t-SNE] Iteration 900: error = 1.2909524, gradient norm = 0.0000558 (50 it
erations in 4.263s)
[t-SNE] Iteration 950: error = 1.2865924, gradient norm = 0.0000525 (50 it
erations in 4.459s)
[t-SNE] Iteration 1000: error = 1.2825896, gradient norm = 0.0000490 (50 i
terations in 4.337s)
[t-SNE] KL divergence after 1000 iterations: 1.282590
Done..
```

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




```
Done
```

In [19]:

```
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 [20]:

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

In [21]:

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

In [22]:

```
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,))
```

function to plot confusion matrix

In [24]:

```
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')
```

function to run any model specified

In [25]:

```
from datetime import datetime
def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_normalize=T
rue, \
                 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 c
onfusion matrix', cmap = cm_cmap)
    plt.show()

    # get classification report
    print('-------------------------')
    print('| Classifiction Report |')
```

```
    print('-------------------------')
    classification_report = metrics.classification_report(y_test, y_pred)
    # store report in results
    results['classification_report'] = classification_report
    print(classification_report)

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

    return results
```

method to print grid search attributes

In [26]:

```
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 number 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(mod
el.best_score_))
```

1. Logistic Regression with Grid Search

In [27]:

```
from sklearn import linear_model
from sklearn import metrics

from sklearn.model_selection import GridSearchCV
```

In [28]:

```
labels=['LAYING', 'SITTING','STANDING','WALKING','WALKING_DOWNSTAIRS','WALKING_UPSTAIR
S']
```

In [29]:

```
# start Grid search
parameters = {'C':[0.01, 0.1, 1, 10, 20, 30], 'penalty':['l2','l1'], 'max_iter':[500,75
0,1000]}
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, c
lass_labels=labels)
```

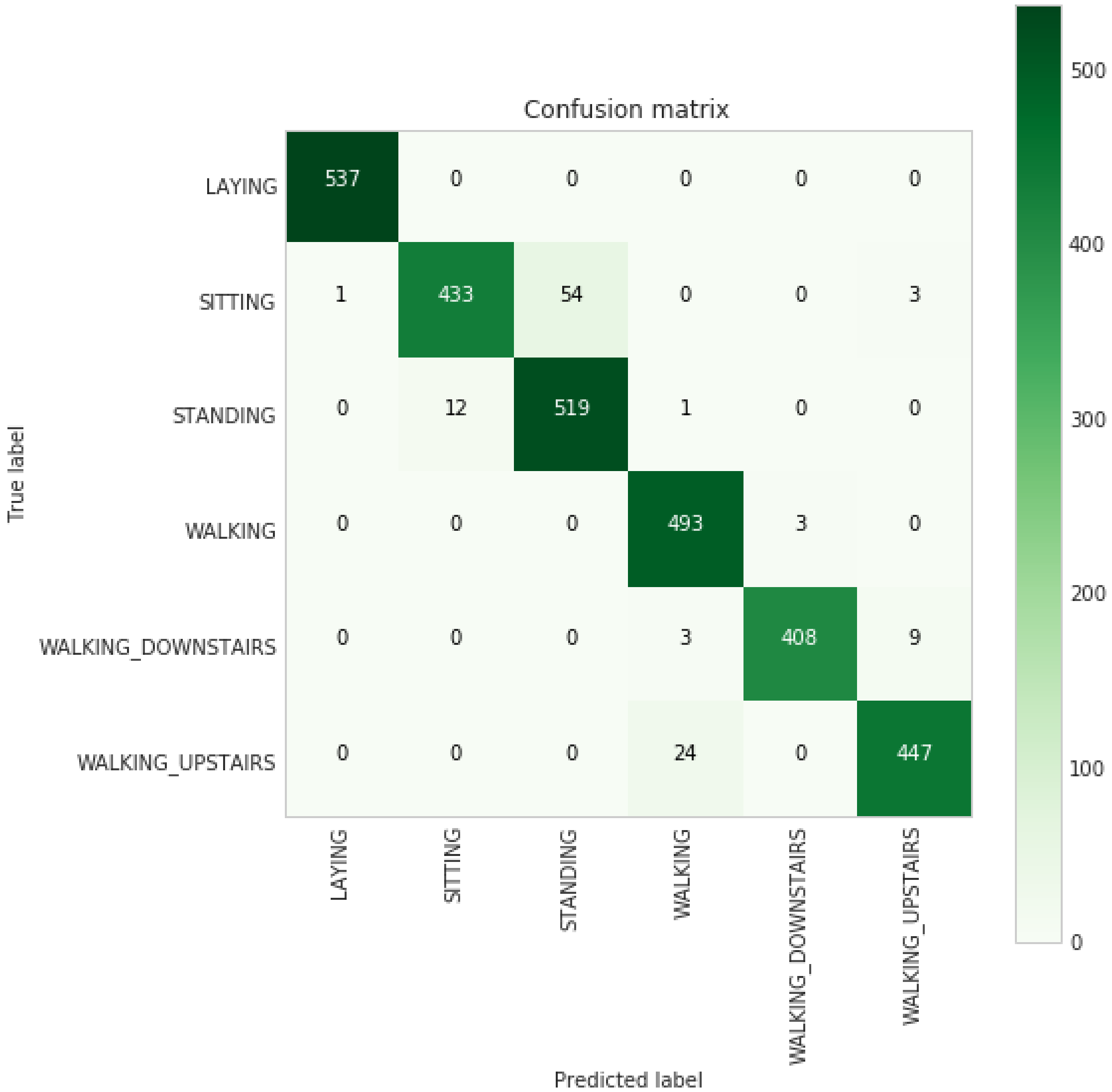
```
training the model..
Fitting 3 folds for each of 36 candidates, totalling 108 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  2.4min
[Parallel(n_jobs=-1)]: Done 108 out of 108 | elapsed:  8.6min finished
C:\Users\SUBHODAYA KUMAR\Anaconda3\lib\site-packages\sklearn\linear_model
\_logistic.py:940: ConvergenceWarning: lbfgs failed to converge (status=
1):
STOP: TOTAL NO. of ITERATIONS REACHED LIMIT.

Increase the number of iterations (max_iter) or scale the data as shown i
n:
    https://scikit-learn.org/stable/modules/preprocessing.html
Please also refer to the documentation for alternative solver options:
    https://scikit-learn.org/stable/modules/linear_model.html#logistic-reg
ression
  extra_warning_msg=_LOGISTIC_SOLVER_CONVERGENCE_MSG)

Done


training_time(HH:MM:SS.ms) - 0:08:54.277253


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.016991


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

    0.9626739056667798


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

 [[537   0   0   0   0   0]
 [  1 433  54   0   0   3]
 [  0  12 519   1   0   0]
 [  0   0   0 493   3   0]
 [  0   0   0   3 408   9]
 [  0   0   0  24   0 447]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.88 0.11 0.00 0.00 0.01
0.00 0.02 0.98 0.00 0.00 0.00
0.00 0.00 0.00 0.99 0.01 0.00
0.00 0.00 0.00 0.01 0.97 0.02
0.00 0.00 0.00 0.05 0.00 0.95
1.0
0.8
0.6
0.4
0.2
0.0

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      0.88      0.93       491
          STANDING       0.91      0.98      0.94       532
           WALKING       0.95      0.99      0.97       496
WALKING_DOWNSTAIRS       0.99      0.97      0.98       420
  WALKING_UPSTAIRS       0.97      0.95      0.96       471

          accuracy                           0.96      2947
         macro avg       0.96      0.96      0.96      2947
      weighted avg       0.96      0.96      0.96      2947
```

In [30]:

```
plt.figure(figsize=(8,8))
plt.grid(b=False)
plot_confusion_matrix(log_reg_grid_results['confusion_matrix'], classes=labels, cmap=pl
t.cm.Greens, )
plt.show()
```



In [31]:

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

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

        LogisticRegression(C=10, class_weight=None, dual=False, fit_interc
ept=True,
                   intercept_scaling=1, l1_ratio=None, max_iter=500,
                   multi_class='auto', n_jobs=None, penalty='l2',
                   random_state=None, solver='lbfgs', tol=0.0001, verbose=
0,
                   warm_start=False)

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

        {'C': 10, 'max_iter': 500, 'penalty': 'l2'}

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

        Total number of cross validation sets: 3

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

        Average Cross Validate scores of best estimator : 

        0.9434188461186187
```

2. Linear SVC with GridSearch

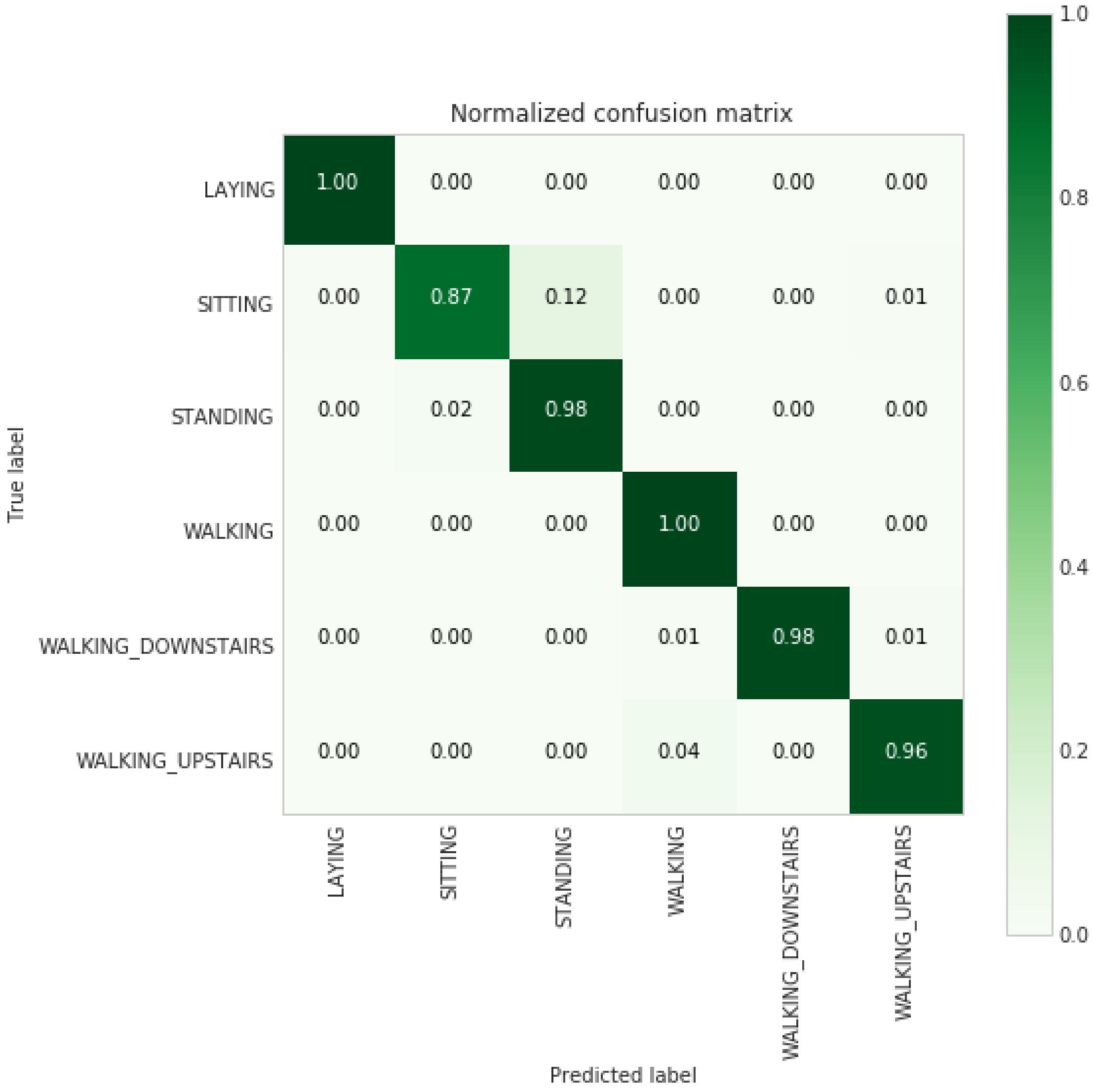
In [32]:

```
from sklearn.svm import LinearSVC
```

In [33]:

```
parameters = {'C':[0.125, 0.5, 1, 2, 8, 16], 'max_iter':[2500,5000]}
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, clas
s_labels=labels)
```

```
training the model..
Fitting 5 folds for each of 12 candidates, totalling 60 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  4.8min
[Parallel(n_jobs=-1)]: Done  60 out of  60 | elapsed:  6.8min finished
C:\Users\SUBHODAYA KUMAR\Anaconda3\lib\site-packages\sklearn\svm\_base.py:
947: ConvergenceWarning: Liblinear failed to converge, increase the number
of iterations.
  "the number of iterations.", ConvergenceWarning)


Done


training_time(HH:MM:SS.ms) - 0:07:05.225342


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.013992


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

    0.9667458432304038


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

 [[537   0   0   0   0   0]
 [  2 428  58   0   0   3]
 [  0   9 522   1   0   0]
 [  0   0   0 496   0   0]
 [  0   0   0   3 412   5]
 [  0   0   0  17   0 454]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.87 0.12 0.00 0.00 0.01
0.00 0.02 0.98 0.00 0.00 0.00
0.00 0.00 0.00 1.00 0.00 0.00
0.00 0.00 0.00 0.01 0.98 0.01
0.00 0.00 0.00 0.04 0.00 0.96
1.0
0.8
0.6
0.4
0.2
0.0

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

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

          accuracy                           0.97      2947
         macro avg       0.97      0.97      0.97      2947
      weighted avg       0.97      0.97      0.97      2947
```

In [34]:

```
print_grid_search_attributes(lr_svc_grid_results['model'])
```

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

        LinearSVC(C=0.5, class_weight=None, dual=True, fit_intercept=True,
          intercept_scaling=1, loss='squared_hinge', max_iter=2500,
          multi_class='ovr', penalty='l2', random_state=None, tol=5e-05,
          verbose=0)

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

        {'C': 0.5, 'max_iter': 2500}

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

        Total number of cross validation sets: 5

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

        Average Cross Validate scores of best estimator :

        0.9420644015594
```

3. Kernel SVM with GridSearch

In [35]:

```
from sklearn.svm import SVC
parameters = {'C':[2,8,16],\
              'gamma': [ 0.0078125, 0.125, 2],\
             'max_iter':[2500,5000]}
rbf_svm = SVC(kernel='rbf')
rbf_svm_grid = GridSearchCV(rbf_svm,param_grid=parameters, verbose=1, n_jobs=-1)
rbf_svm_grid_results = perform_model(rbf_svm_grid, X_train, y_train, X_test, y_test, cl
ass_labels=labels)
```

```
training the model..
Fitting 5 folds for each of 18 candidates, totalling 90 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  42 tasks      | elapsed:  9.0min
[Parallel(n_jobs=-1)]: Done  90 out of  90 | elapsed: 24.7min finished
C:\Users\SUBHODAYA KUMAR\Anaconda3\lib\site-packages\sklearn\svm\_base.py:
231: ConvergenceWarning: Solver terminated early (max_iter=2500).  Conside
r pre-processing your data with StandardScaler or MinMaxScaler.
  % self.max_iter, ConvergenceWarning)

Done


training_time(HH:MM:SS.ms) - 0:24:48.975221


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:03.859448


---------------------
|      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]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.90 0.10 0.00 0.00 0.00
0.00 0.02 0.98 0.00 0.00 0.00
0.00 0.00 0.00 0.99 0.00 0.01
0.00 0.00 0.00 0.01 0.95 0.05
0.00 0.00 0.00 0.04 0.00 0.96
1.0
0.8
0.6
0.4
0.2
0.0

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.97      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

          accuracy                           0.96      2947
         macro avg       0.96      0.96      0.96      2947
      weighted avg       0.96      0.96      0.96      2947
```

In [36]:

```
print_grid_search_attributes(rbf_svm_grid_results['model'])
```

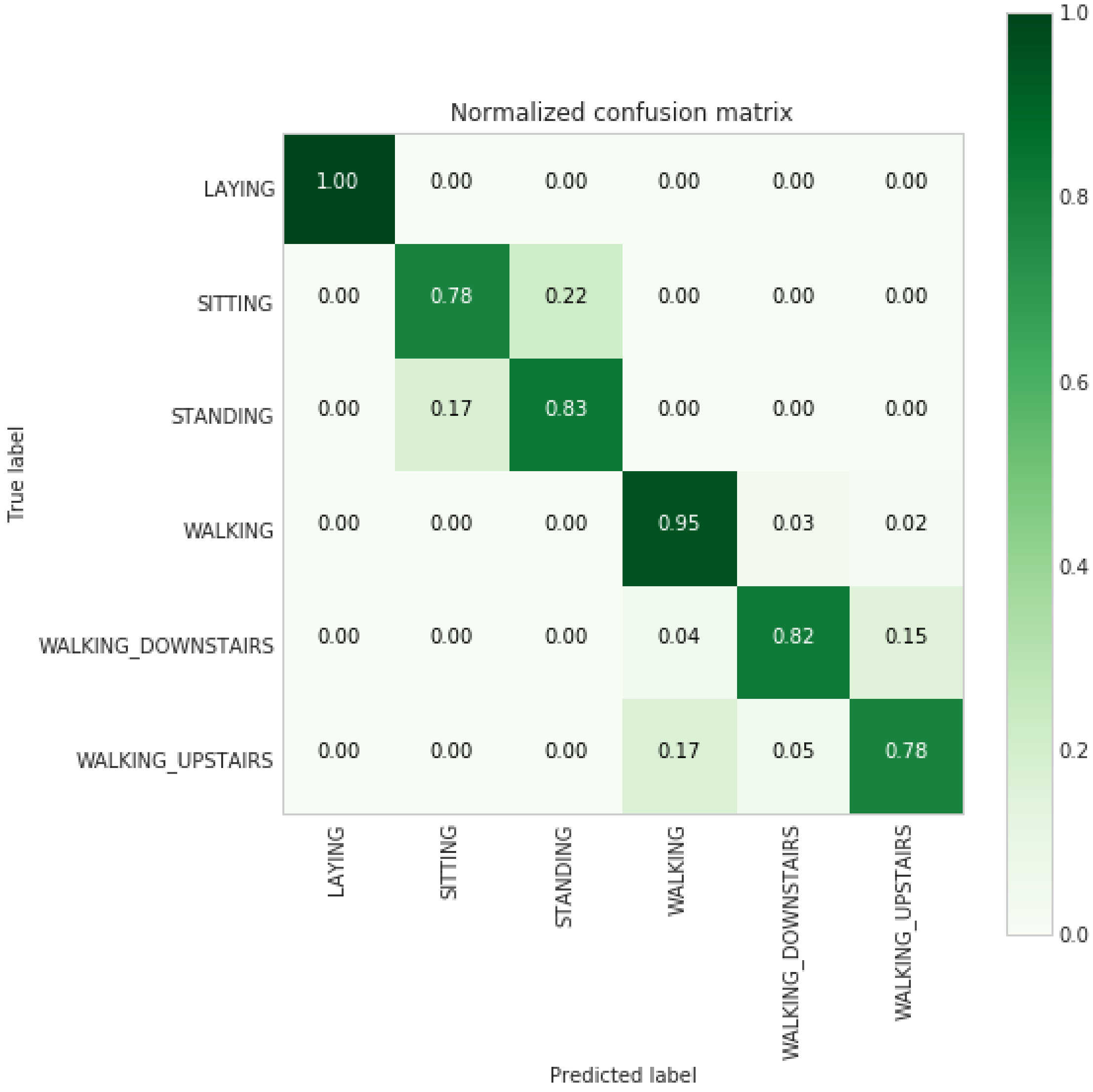
```
--------------------------
|      Best Estimator     |
--------------------------

        SVC(C=16, break_ties=False, cache_size=200, class_weight=None, coe
f0=0.0,
    decision_function_shape='ovr', degree=3, gamma=0.0078125, kernel='rb
f',
    max_iter=2500, probability=False, random_state=None, shrinking=True,
    tol=0.001, verbose=False)

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

        {'C': 16, 'gamma': 0.0078125, 'max_iter': 2500}

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

        Total number of cross validation sets: 5

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

        Average Cross Validate scores of best estimator : 

        0.9447834551903698
```

4. Decision Trees with GridSearchCV

In [37]:

```
from sklearn.tree import DecisionTreeClassifier
parameters = {'max_depth':np.arange(3,10,2)}
dt = DecisionTreeClassifier()
dt_grid = GridSearchCV(dt,param_grid=parameters,verbose =1, 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..
Fitting 5 folds for each of 4 candidates, totalling 20 fits

[Parallel(n_jobs=-1)]: Using backend LokyBackend with 4 concurrent worker
s.
[Parallel(n_jobs=-1)]: Done  20 out of  20 | elapsed:   27.7s finished

Done


training_time(HH:MM:SS.ms) - 0:00:32.422666


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.013007


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

    0.8635900916185952


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

 [[537   0   0   0   0   0]
 [  0 385 106   0   0   0]
 [  0  93 439   0   0   0]
 [  0   0   0 472  16   8]
 [  0   0   0  16 343  61]
 [  0   0   0  78  24 369]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.78 0.22 0.00 0.00 0.00
0.00 0.17 0.83 0.00 0.00 0.00
0.00 0.00 0.00 0.95 0.03 0.02
0.00 0.00 0.00 0.04 0.82 0.15
0.00 0.00 0.00 0.17 0.05 0.78
1.0
0.8
0.6
0.4
0.2
0.0

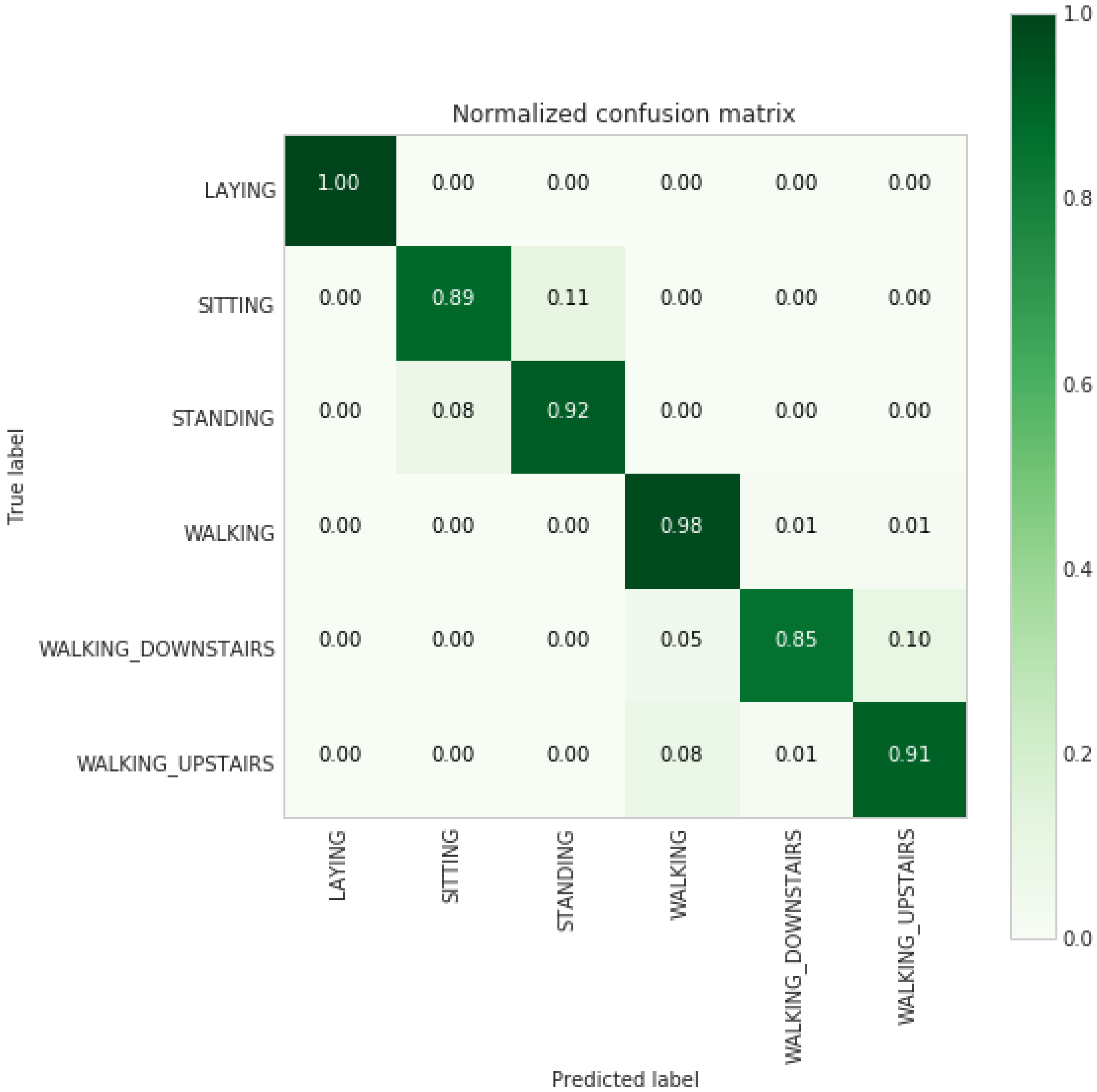
```
-------------------------
| Classifiction Report |
-------------------------
                    precision    recall  f1-score   support

            LAYING       1.00      1.00      1.00       537
           SITTING       0.81      0.78      0.79       491
          STANDING       0.81      0.83      0.82       532
           WALKING       0.83      0.95      0.89       496
WALKING_DOWNSTAIRS       0.90      0.82      0.85       420
  WALKING_UPSTAIRS       0.84      0.78      0.81       471

          accuracy                           0.86      2947
         macro avg       0.86      0.86      0.86      2947
      weighted avg       0.86      0.86      0.86      2947

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

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

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

        {'max_depth': 7}

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

        Total number of cross validation sets: 5

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

        Average Cross Validate scores of best estimator :

        0.8522920684249226
```

5. Random Forest Classifier with GridSearch

In [38]:

```
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_labe
ls=labels)
print_grid_search_attributes(rfc_grid_results['model'])
```

```
training the model..
Done


training_time(HH:MM:SS.ms) - 6:33:24.344915


Predicting test data
Done


testing time(HH:MM:SS:ms) - 0:00:00.065963


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

    0.9280624363759755


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

 [[537   0   0   0   0   0]
 [  0 437  54   0   0   0]
 [  0  41 491   0   0   0]
 [  0   0   0 485   7   4]
 [  0   0   0  20 358  42]
 [  0   0   0  38   6 427]]
```


Normalized confusion matrix
True label
Predicted label
LAYING
SITTING
STANDING
WALKING
WALKING_DOWNSTAIRS
WALKING_UPSTAIRS
1.00 0.00 0.00 0.00 0.00 0.00
0.00 0.89 0.11 0.00 0.00 0.00
0.00 0.08 0.92 0.00 0.00 0.00
0.00 0.00 0.00 0.98 0.01 0.01
0.00 0.00 0.00 0.05 0.85 0.10
0.00 0.00 0.00 0.08 0.01 0.91
1.0
0.8
0.6
0.4
0.2
0.0

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

            LAYING       1.00      1.00      1.00       537
           SITTING       0.91      0.89      0.90       491
          STANDING       0.90      0.92      0.91       532
           WALKING       0.89      0.98      0.93       496
WALKING_DOWNSTAIRS       0.96      0.85      0.91       420
  WALKING_UPSTAIRS       0.90      0.91      0.90       471

          accuracy                           0.93      2947
         macro avg       0.93      0.92      0.93      2947
      weighted avg       0.93      0.93      0.93      2947

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

        RandomForestClassifier(bootstrap=True, ccp_alpha=0.0, class_weight
=None,
                       criterion='gini', max_depth=11, max_features='aut
o',
                       max_leaf_nodes=None, max_samples=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=None, oob_score=False, random_state=None,
                       verbose=0, warm_start=False)

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

        {'max_depth': 11, 'n_estimators': 70}

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

        Total number of cross validation sets: 5

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

        Average Cross Validate scores of best estimator :

        0.9205694677599116
```

Using LSTM

In [2]:

```
# 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 [3]:

```
# 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',
}
```

In [4]:

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

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

    for signal in SIGNALS:
        filename = f'UCI_HAR_Dataset/{subset}/Inertial Signals/{signal}_{subset}.txt'
        signals_data.append(
            _read_csv(filename).to_numpy()
        )

    # 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 [5]:

```
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'UCI_HAR_Dataset/{subset}/y_{subset}.txt'
    y = _read_csv(filename)[0]

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

In [6]:

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

    return X_train, X_test, y_train, y_test
```

In [7]:

```
# Loading the train and test data
X_train, X_test, Y_train, Y_test = load_data()
```

In [8]:

```
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, 128, 9),(7352, 6))
X_test  and Y_test  : ((2947, 128, 9),(2947, 6))
```

In [9]:

```
# Importing tensorflow
np.random.seed(42)
import tensorflow as tf
tf.set_random_seed(42)
```

```
C:\Users\SUBHODAYA KUMAR\Anaconda3\lib\site-packages\h5py\__init__.py:36:
FutureWarning: Conversion of the second argument of issubdtype from `float
` to `np.floating` is deprecated. In future, it will be treated as `np.flo
at64 == np.dtype(float).type`.
  from ._conv import register_converters as _register_converters
```

In [10]:

```
# Configuring a session
session_conf = tf.ConfigProto(
    intra_op_parallelism_threads=1,
    inter_op_parallelism_threads=1
)
```

In [11]:

```
# Import Keras
from keras import backend as K
sess = tf.Session(graph=tf.get_default_graph(), config=session_conf)
K.set_session(sess)
```

```
Using TensorFlow backend.
```

In [12]:

```
# Importing libraries
from keras.models import Sequential
from keras.layers import LSTM
from keras.layers.core import Dense, Dropout
from keras.layers import BatchNormalization

import matplotlib.pyplot as plt
from sklearn.metrics import confusion_matrix
```

In [13]:

```
# Plot train and cross validation loss
def plot_train_cv_loss(trained_model, epochs, colors=['b']):
    fig, ax = plt.subplots(1,1)
    ax.set_xlabel('epoch')
    ax.set_ylabel('Categorical Crossentropy Loss')
    x_axis_values = list(range(1,epochs+1))

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

    ax.plot(x_axis_values, validation_loss, 'b', label="Validation Loss")
    ax.plot(x_axis_values, train_loss, 'r', label="Train Loss")
    plt.legend()
    plt.grid()
```

In [14]:

```
# Initializing parameters
epochs = 20
batch_size = 16
n_hidden = 32
```

In [15]:

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

In [16]:

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

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

```
128
9
7352
```

- Defining the Architecture of LSTM

1. Using Categorical cross entropy

Lstm with 32 Neurons and dropout = 0.5

In [26]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

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

In [27]:

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

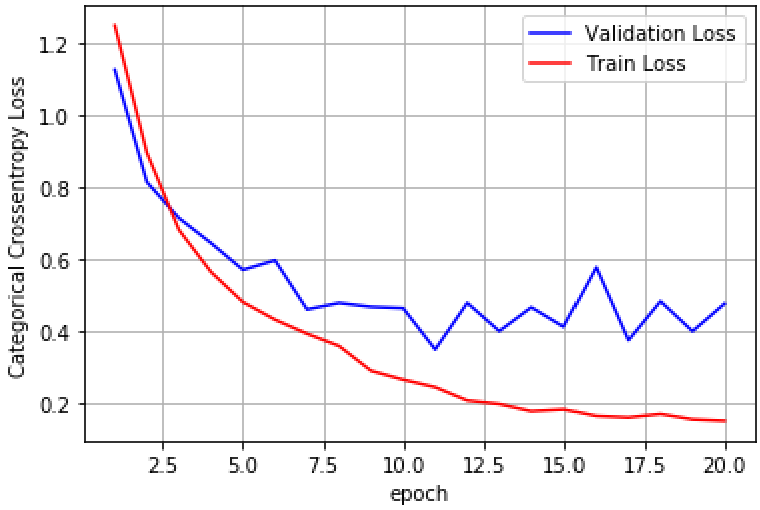
In [28]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 63s 9ms/step - loss: 1.2493 -
acc: 0.4771 - val_loss: 1.1263 - val_acc: 0.5249
Epoch 2/20
7352/7352 [==============================] - 64s 9ms/step - loss: 0.8962 -
acc: 0.6400 - val_loss: 0.8150 - val_acc: 0.6583
Epoch 3/20
7352/7352 [==============================] - 78s 11ms/step - loss: 0.6823
- acc: 0.7270 - val_loss: 0.7150 - val_acc: 0.7089
Epoch 4/20
7352/7352 [==============================] - 70s 9ms/step - loss: 0.5654 -
acc: 0.7847 - val_loss: 0.6458 - val_acc: 0.7598
Epoch 5/20
7352/7352 [==============================] - 75s 10ms/step - loss: 0.4815
- acc: 0.8341 - val_loss: 0.5712 - val_acc: 0.8083
Epoch 6/20
7352/7352 [==============================] - 78s 11ms/step - loss: 0.4328
- acc: 0.8677 - val_loss: 0.5977 - val_acc: 0.8157
Epoch 7/20
7352/7352 [==============================] - 64s 9ms/step - loss: 0.3939 -
acc: 0.8774 - val_loss: 0.4612 - val_acc: 0.8507
Epoch 8/20
7352/7352 [==============================] - 63s 9ms/step - loss: 0.3599 -
acc: 0.8856 - val_loss: 0.4794 - val_acc: 0.8531
Epoch 9/20
7352/7352 [==============================] - 61s 8ms/step - loss: 0.2909 -
acc: 0.9027 - val_loss: 0.4683 - val_acc: 0.8626
Epoch 10/20
7352/7352 [==============================] - 60s 8ms/step - loss: 0.2663 -
acc: 0.9170 - val_loss: 0.4647 - val_acc: 0.8704
Epoch 11/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2455 -
acc: 0.9197 - val_loss: 0.3502 - val_acc: 0.8833
Epoch 12/20
7352/7352 [==============================] - 60s 8ms/step - loss: 0.2087 -
acc: 0.9350 - val_loss: 0.4795 - val_acc: 0.8714
Epoch 13/20
7352/7352 [==============================] - 61s 8ms/step - loss: 0.1989 -
acc: 0.9368 - val_loss: 0.4011 - val_acc: 0.8846
Epoch 14/20
7352/7352 [==============================] - 59s 8ms/step - loss: 0.1789 -
acc: 0.9377 - val_loss: 0.4671 - val_acc: 0.8792
Epoch 15/20
7352/7352 [==============================] - 58s 8ms/step - loss: 0.1841 -
acc: 0.9358 - val_loss: 0.4134 - val_acc: 0.8809
Epoch 16/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.1656 -
acc: 0.9403 - val_loss: 0.5781 - val_acc: 0.8558
Epoch 17/20
7352/7352 [==============================] - 54s 7ms/step - loss: 0.1615 -
acc: 0.9423 - val_loss: 0.3758 - val_acc: 0.8785
Epoch 18/20
7352/7352 [==============================] - 53s 7ms/step - loss: 0.1711 -
acc: 0.9412 - val_loss: 0.4839 - val_acc: 0.8989
Epoch 19/20
7352/7352 [==============================] - 52s 7ms/step - loss: 0.1561 -
acc: 0.9444 - val_loss: 0.4008 - val_acc: 0.8880
Epoch 20/20
7352/7352 [==============================] - 52s 7ms/step - loss: 0.1521 -
acc: 0.9456 - val_loss: 0.4773 - val_acc: 0.9013
```

In [29]:

```
import matplotlib.pyplot as plt
%matplotlib inline

plot_train_cv_loss(training,epochs)
```



- best epoch is 5. It starts overfitting from epoch 6. Best accuracy is 80.83%

In [30]:

```
# 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'])
```

In [31]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 513        0         0        0                   0
SITTING                  0      362       123        2                   0
STANDING                 0       43       481        2                   0
WALKING                  0        0         0      440                  43
WALKING_DOWNSTAIRS       0        0         0        3                 413
WALKING_UPSTAIRS         0        2         0       10                  12

Pred                WALKING_UPSTAIRS
True
LAYING                            24
SITTING                            4
STANDING                           6
WALKING                           13
WALKING_DOWNSTAIRS                 4
WALKING_UPSTAIRS                 447
```

In [32]:

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

```
2947/2947 [==============================] - 2s 743us/step
```

In [33]:

```
score
```

Out[33]:

```
[0.4773142791923584, 0.9012555140821175]
```

In [35]:

```
# Initializing parameters
epochs = 20
batch_size = 25
n_hidden = 100
```

1 LSTM neuron, dropout = 0.5

In [36]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.5))
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 100)               44000
_________________________________________________________________
dropout_3 (Dropout)          (None, 100)               0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 606
=================================================================
Total params: 44,606
Trainable params: 44,606
Non-trainable params: 0
_________________________________________________________________
```

In [37]:

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

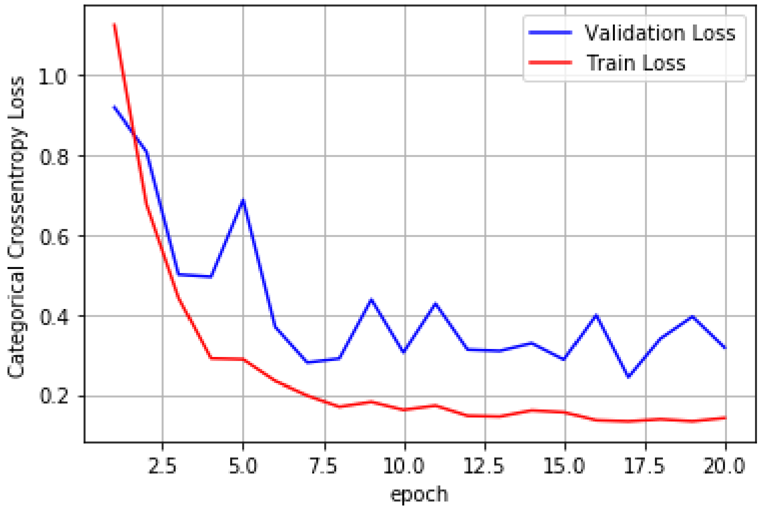
In [38]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 69s 9ms/step - loss: 1.1250 -
acc: 0.5233 - val_loss: 0.9185 - val_acc: 0.6284
Epoch 2/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.6764 -
acc: 0.7339 - val_loss: 0.8082 - val_acc: 0.7160
Epoch 3/20
7352/7352 [==============================] - 64s 9ms/step - loss: 0.4409 -
acc: 0.8459 - val_loss: 0.4999 - val_acc: 0.8385
Epoch 4/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.2895 -
acc: 0.9045 - val_loss: 0.4942 - val_acc: 0.8487
Epoch 5/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.2874 -
acc: 0.9091 - val_loss: 0.6874 - val_acc: 0.8035
Epoch 6/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.2332 -
acc: 0.9210 - val_loss: 0.3685 - val_acc: 0.8670
Epoch 7/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.1972 -
acc: 0.9276 - val_loss: 0.2790 - val_acc: 0.8880
Epoch 8/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1691 -
acc: 0.9389 - val_loss: 0.2891 - val_acc: 0.9070
Epoch 9/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1814 -
acc: 0.9346 - val_loss: 0.4373 - val_acc: 0.8724
Epoch 10/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.1615 -
acc: 0.9444 - val_loss: 0.3042 - val_acc: 0.9043
Epoch 11/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.1722 -
acc: 0.9395 - val_loss: 0.4271 - val_acc: 0.8792
Epoch 12/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.1467 -
acc: 0.9463 - val_loss: 0.3115 - val_acc: 0.9080
Epoch 13/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.1448 -
acc: 0.9476 - val_loss: 0.3082 - val_acc: 0.9172
Epoch 14/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1601 -
acc: 0.9450 - val_loss: 0.3276 - val_acc: 0.8965
Epoch 15/20
7352/7352 [==============================] - 62s 8ms/step - loss: 0.1555 -
acc: 0.9450 - val_loss: 0.2865 - val_acc: 0.9158
Epoch 16/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.1355 -
acc: 0.9474 - val_loss: 0.3982 - val_acc: 0.9087
Epoch 17/20
7352/7352 [==============================] - 64s 9ms/step - loss: 0.1327 -
acc: 0.9494 - val_loss: 0.2422 - val_acc: 0.9216
Epoch 18/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1380 -
acc: 0.9482 - val_loss: 0.3390 - val_acc: 0.9138
Epoch 19/20
7352/7352 [==============================] - 71s 10ms/step - loss: 0.1330
- acc: 0.9487 - val_loss: 0.3944 - val_acc: 0.9108
Epoch 20/20
7352/7352 [==============================] - 75s 10ms/step - loss: 0.1411
- acc: 0.9479 - val_loss: 0.3169 - val_acc: 0.9186
```

In [39]:

```
plot_train_cv_loss(training,epochs)
```



- best epoch is 4. It starts overfitting from 5. Best accuracy is 84.87%

In [40]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 513        0         0        0
0
SITTING                  0      412        77        0
0
STANDING                 0       91       440        0
0
WALKING                  0        1         0      467
2
WALKING_DOWNSTAIRS       0        0         0        7
412
WALKING_UPSTAIRS         0        0         0        7
1

Pred                WALKING_UPSTAIRS
True
LAYING                            24
SITTING                            2
STANDING                           1
WALKING                           26
WALKING_DOWNSTAIRS                 1
WALKING_UPSTAIRS                 463
```

In [41]:

```
score1 = model.evaluate(X_test, Y_test)
```

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

In [42]:

```
score1
```

Out[42]:

```
[0.31687591483809235, 0.9185612487275195]
```

1 LSTM neuron and dropout = 0.8

In [43]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.8))
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_4 (LSTM)                (None, 100)               44000     
_________________________________________________________________
dropout_4 (Dropout)          (None, 100)               0         
_________________________________________________________________
dense_4 (Dense)              (None, 6)                 606       
=================================================================
Total params: 44,606
Trainable params: 44,606
Non-trainable params: 0
_________________________________________________________________
```

In [44]:

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

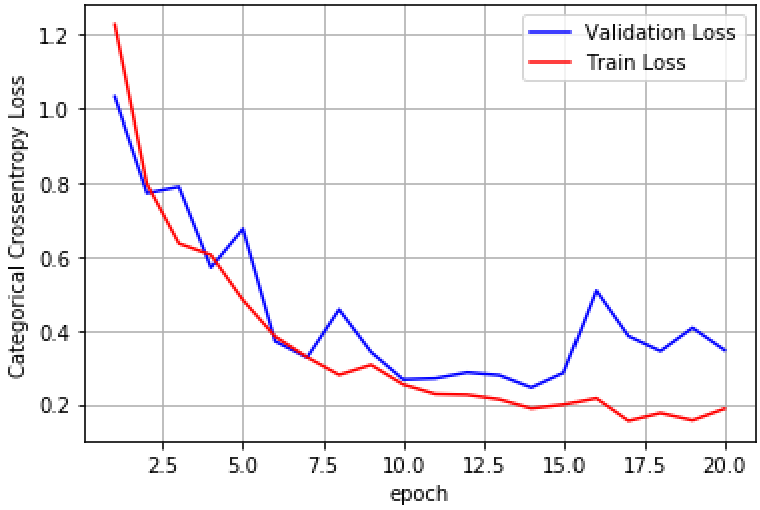
In [45]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 68s 9ms/step - loss: 1.2264 -
acc: 0.4887 - val_loss: 1.0311 - val_acc: 0.5487
Epoch 2/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.7971 -
acc: 0.6697 - val_loss: 0.7719 - val_acc: 0.7177
Epoch 3/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.6355 -
acc: 0.7565 - val_loss: 0.7894 - val_acc: 0.7414
Epoch 4/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.6046 -
acc: 0.7780 - val_loss: 0.5702 - val_acc: 0.7842
Epoch 5/20
7352/7352 [==============================] - 111s 15ms/step - loss: 0.4820
- acc: 0.8453 - val_loss: 0.6750 - val_acc: 0.7913
Epoch 6/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.3836 -
acc: 0.8856 - val_loss: 0.3708 - val_acc: 0.8856
Epoch 7/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.3273 -
acc: 0.9033 - val_loss: 0.3263 - val_acc: 0.8945
Epoch 8/20
7352/7352 [==============================] - 61s 8ms/step - loss: 0.2793 -
acc: 0.9161 - val_loss: 0.4566 - val_acc: 0.8728
Epoch 9/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.3065 -
acc: 0.9117 - val_loss: 0.3411 - val_acc: 0.8975
Epoch 10/20
7352/7352 [==============================] - 61s 8ms/step - loss: 0.2533 -
acc: 0.9244 - val_loss: 0.2669 - val_acc: 0.9084
Epoch 11/20
7352/7352 [==============================] - 63s 9ms/step - loss: 0.2275 -
acc: 0.9293 - val_loss: 0.2700 - val_acc: 0.9141
Epoch 12/20
7352/7352 [==============================] - 61s 8ms/step - loss: 0.2254 -
acc: 0.9294 - val_loss: 0.2860 - val_acc: 0.8975
Epoch 13/20
7352/7352 [==============================] - 64s 9ms/step - loss: 0.2130 -
acc: 0.9317 - val_loss: 0.2784 - val_acc: 0.9111
Epoch 14/20
7352/7352 [==============================] - 74s 10ms/step - loss: 0.1885
- acc: 0.9382 - val_loss: 0.2451 - val_acc: 0.9226
Epoch 15/20
7352/7352 [==============================] - 9698s 1s/step - loss: 0.1989
- acc: 0.9359 - val_loss: 0.2850 - val_acc: 0.9179
Epoch 16/20
7352/7352 [==============================] - 71s 10ms/step - loss: 0.2160
- acc: 0.9355 - val_loss: 0.5077 - val_acc: 0.8870
Epoch 17/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.1547 -
acc: 0.9457 - val_loss: 0.3843 - val_acc: 0.9101
Epoch 18/20
7352/7352 [==============================] - 70s 10ms/step - loss: 0.1759
- acc: 0.9449 - val_loss: 0.3438 - val_acc: 0.9189
Epoch 19/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.1563 -
acc: 0.9442 - val_loss: 0.4069 - val_acc: 0.9009
Epoch 20/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.1877 -
acc: 0.9406 - val_loss: 0.3464 - val_acc: 0.9220
```

In [46]:

```
plot_train_cv_loss(training,epochs)
```



- best epoch is 2. It starts overfitting from 3. Best accuracy is 71.77%

In [47]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 514        0        23        0
0
SITTING                  0      376       113        0
0
STANDING                 0       60       467        3
0
WALKING                  0        0         0      485
2
WALKING_DOWNSTAIRS       0        0         2        2
415
WALKING_UPSTAIRS         0        4         0        7
0

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            2
STANDING                           2
WALKING                            9
WALKING_DOWNSTAIRS                 1
WALKING_UPSTAIRS                 460
```

In [48]:

```
score2 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 4s 1ms/step
```

In [49]:

```
score2
```

Out[49]:

```
[0.34641228316512473, 0.9219545300305395]
```

2 LSTM Neurons, dropout = 0.3

In [50]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.3))
#Adding another LSTM layer
model.add(LSTM(200,))
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_5 (LSTM)                (None, 128, 100)          44000     
_________________________________________________________________
dropout_5 (Dropout)          (None, 128, 100)          0         
_________________________________________________________________
lstm_6 (LSTM)                (None, 200)               240800    
_________________________________________________________________
dense_5 (Dense)              (None, 6)                 1206      
=================================================================
Total params: 286,006
Trainable params: 286,006
Non-trainable params: 0
_________________________________________________________________
```

In [51]:

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

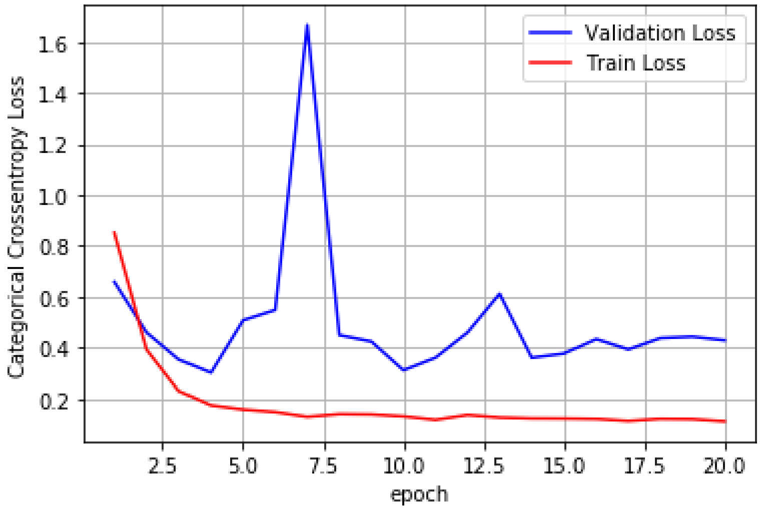
In [52]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 275s 37ms/step - loss: 0.8513
- acc: 0.6474 - val_loss: 0.6581 - val_acc: 0.7591
Epoch 2/20
7352/7352 [==============================] - 263s 36ms/step - loss: 0.3927
- acc: 0.8628 - val_loss: 0.4598 - val_acc: 0.8714
Epoch 3/20
7352/7352 [==============================] - 264s 36ms/step - loss: 0.2300
- acc: 0.9214 - val_loss: 0.3534 - val_acc: 0.8884
Epoch 4/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1738
- acc: 0.9336 - val_loss: 0.3017 - val_acc: 0.8938
Epoch 5/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1575
- acc: 0.9402 - val_loss: 0.5074 - val_acc: 0.8582
Epoch 6/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1477
- acc: 0.9459 - val_loss: 0.5478 - val_acc: 0.8945
Epoch 7/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1292
- acc: 0.9479 - val_loss: 1.6674 - val_acc: 0.7577
Epoch 8/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1397
- acc: 0.9487 - val_loss: 0.4490 - val_acc: 0.9013
Epoch 9/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1385
- acc: 0.9486 - val_loss: 0.4238 - val_acc: 0.8941
Epoch 10/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1310
- acc: 0.9494 - val_loss: 0.3110 - val_acc: 0.9084
Epoch 11/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1174
- acc: 0.9523 - val_loss: 0.3603 - val_acc: 0.9091
Epoch 12/20
7352/7352 [==============================] - 254s 34ms/step - loss: 0.1365
- acc: 0.9482 - val_loss: 0.4595 - val_acc: 0.9138
Epoch 13/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1263
- acc: 0.9532 - val_loss: 0.6116 - val_acc: 0.8901
Epoch 14/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1229
- acc: 0.9521 - val_loss: 0.3600 - val_acc: 0.8989
Epoch 15/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1224
- acc: 0.9524 - val_loss: 0.3764 - val_acc: 0.9226
Epoch 16/20
7352/7352 [==============================] - 256s 35ms/step - loss: 0.1209
- acc: 0.9531 - val_loss: 0.4333 - val_acc: 0.9013
Epoch 17/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1130
- acc: 0.9543 - val_loss: 0.3927 - val_acc: 0.9002
Epoch 18/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1213
- acc: 0.9536 - val_loss: 0.4373 - val_acc: 0.9002
Epoch 19/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1200
- acc: 0.9533 - val_loss: 0.4428 - val_acc: 0.9050
Epoch 20/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1115
- acc: 0.9559 - val_loss: 0.4286 - val_acc: 0.8901
```

In [53]:

```
plot_train_cv_loss(training,epochs)
```



- Best epoch is 6. It starts overfitting from 7. Best accuracy is 88.43%

In [54]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 537        0         0        0
0
SITTING                  7      303       164        0
0
STANDING                 0       62       470        0
0
WALKING                  1        0         0      466
28
WALKING_DOWNSTAIRS       0        0         0        5
415
WALKING_UPSTAIRS         0        0         3        2
34

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                           17
STANDING                           0
WALKING                            1
WALKING_DOWNSTAIRS                 0
WALKING_UPSTAIRS                 432
```

In [55]:

```
score3 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 20s 7ms/step
```

In [56]:

```
score3
```

Out[56]:

```
[0.4285913717844088, 0.8900576857821514]
```

2 LSTM Neurons, 2 dropouts

In [57]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.8))
#Adding another LSTM layer
model.add(LSTM(200,))
#Adding another dropout
model.add(Dropout(0.9))
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_7 (LSTM)                (None, 128, 100)          44000     
_________________________________________________________________
dropout_6 (Dropout)          (None, 128, 100)          0         
_________________________________________________________________
lstm_8 (LSTM)                (None, 200)               240800    
_________________________________________________________________
dropout_7 (Dropout)          (None, 200)               0         
_________________________________________________________________
dense_6 (Dense)              (None, 6)                 1206      
=================================================================
Total params: 286,006
Trainable params: 286,006
Non-trainable params: 0
_________________________________________________________________
```

In [58]:

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

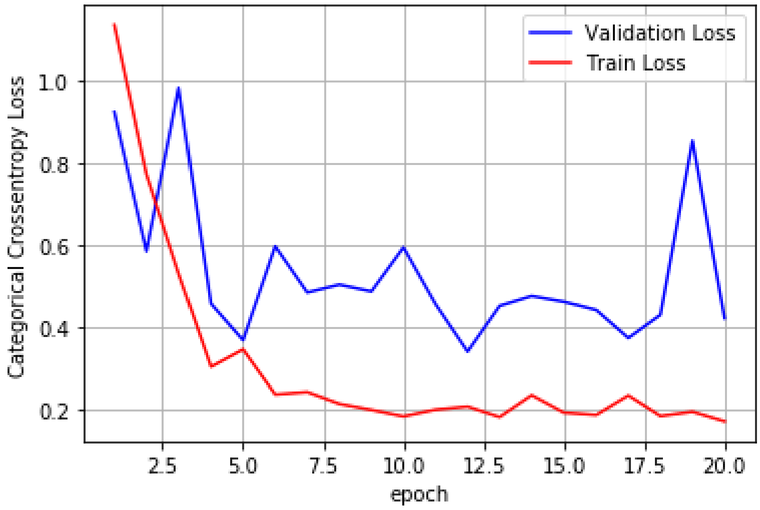
In [59]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 252s 34ms/step - loss: 1.1332
- acc: 0.5339 - val_loss: 0.9220 - val_acc: 0.5969
Epoch 2/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.7717
- acc: 0.7016 - val_loss: 0.5850 - val_acc: 0.7944
Epoch 3/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.5305
- acc: 0.8384 - val_loss: 0.9801 - val_acc: 0.7336
Epoch 4/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.3049
- acc: 0.9064 - val_loss: 0.4577 - val_acc: 0.8673
Epoch 5/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.3470
- acc: 0.9059 - val_loss: 0.3690 - val_acc: 0.8968
Epoch 6/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.2379
- acc: 0.9268 - val_loss: 0.5971 - val_acc: 0.8877
Epoch 7/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.2438
- acc: 0.9241 - val_loss: 0.4849 - val_acc: 0.8863
Epoch 8/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.2152
- acc: 0.9309 - val_loss: 0.5039 - val_acc: 0.8975
Epoch 9/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.2007
- acc: 0.9358 - val_loss: 0.4874 - val_acc: 0.8979
Epoch 10/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.1851
- acc: 0.9411 - val_loss: 0.5944 - val_acc: 0.8799
Epoch 11/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.2013
- acc: 0.9380 - val_loss: 0.4567 - val_acc: 0.8975
Epoch 12/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.2087
- acc: 0.9373 - val_loss: 0.3415 - val_acc: 0.9141
Epoch 13/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1835
- acc: 0.9403 - val_loss: 0.4524 - val_acc: 0.9172
Epoch 14/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.2363
- acc: 0.9327 - val_loss: 0.4763 - val_acc: 0.8962
Epoch 15/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1942
- acc: 0.9392 - val_loss: 0.4625 - val_acc: 0.9138
Epoch 16/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1886
- acc: 0.9372 - val_loss: 0.4423 - val_acc: 0.9050
Epoch 17/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.2356
- acc: 0.9363 - val_loss: 0.3744 - val_acc: 0.9165
Epoch 18/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1859
- acc: 0.9419 - val_loss: 0.4307 - val_acc: 0.9053
Epoch 19/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.1963
- acc: 0.9388 - val_loss: 0.8534 - val_acc: 0.8823
Epoch 20/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1731
- acc: 0.9422 - val_loss: 0.4226 - val_acc: 0.9186
```

In [60]:

```
plot_train_cv_loss(training,epochs)
```



- Best epoch is 2. It starts overfitting from 3. Best accuracy is 79.44%

In [61]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 535        0         0        0
0
SITTING                  0      383        84       20
0
STANDING                 0       70       462        0
0
WALKING                  0        0         0      453
32
WALKING_DOWNSTAIRS       0        0         0        1
417
WALKING_UPSTAIRS         0        0         2       12
0

Pred                WALKING_UPSTAIRS
True
LAYING                             2
SITTING                            4
STANDING                           0
WALKING                           11
WALKING_DOWNSTAIRS                 2
WALKING_UPSTAIRS                 457
```

In [62]:

```
score4 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 20s 7ms/step
```

In [63]:

```
score4
```

Out[63]:

```
[0.4225864914956355, 0.9185612487275195]
```

LSTM with 2 Neurons, 2 dropouts, BatchNormalization

In [64]:

```
from keras.layers import BatchNormalization

# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.4))
#Adding another LSTM layer
model.add(LSTM(200,))
model.add(Dropout(0.3))
model.add(BatchNormalization())
# Adding a dense output layer with softmax activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_9 (LSTM)                (None, 128, 100)          44000     
_________________________________________________________________
dropout_8 (Dropout)          (None, 128, 100)          0         
_________________________________________________________________
lstm_10 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dropout_9 (Dropout)          (None, 200)               0         
_________________________________________________________________
batch_normalization_1 (Batch (None, 200)               800       
_________________________________________________________________
dense_7 (Dense)              (None, 6)                 1206      
=================================================================
Total params: 286,806
Trainable params: 286,406
Non-trainable params: 400
_________________________________________________________________
```

In [65]:

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

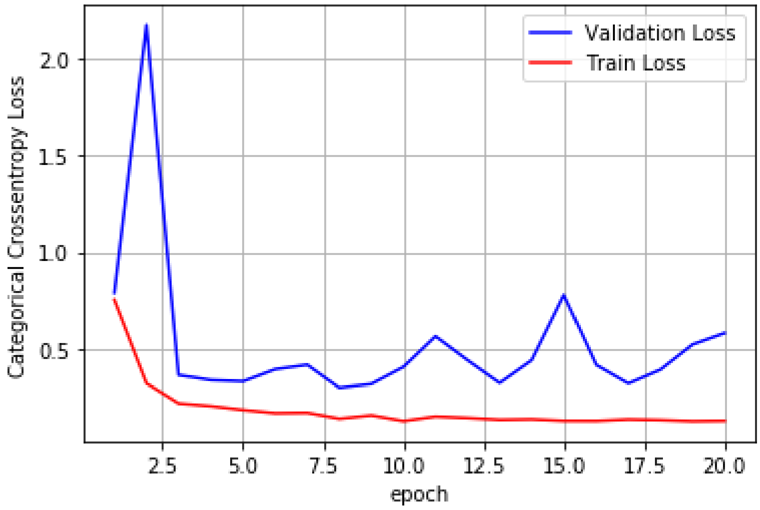
In [66]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 258s 35ms/step - loss: 0.7539
- acc: 0.6946 - val_loss: 0.7905 - val_acc: 0.8168
Epoch 2/20
7352/7352 [==============================] - 254s 34ms/step - loss: 0.3233
- acc: 0.8832 - val_loss: 2.1740 - val_acc: 0.6749
Epoch 3/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.2190
- acc: 0.9219 - val_loss: 0.3659 - val_acc: 0.8887
Epoch 4/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.2049
- acc: 0.9253 - val_loss: 0.3399 - val_acc: 0.8873
Epoch 5/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1851
- acc: 0.9346 - val_loss: 0.3335 - val_acc: 0.8979
Epoch 6/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1688
- acc: 0.9388 - val_loss: 0.3956 - val_acc: 0.8951
Epoch 7/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1707
- acc: 0.9381 - val_loss: 0.4188 - val_acc: 0.9016
Epoch 8/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1402
- acc: 0.9455 - val_loss: 0.2998 - val_acc: 0.9192
Epoch 9/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1574
- acc: 0.9436 - val_loss: 0.3202 - val_acc: 0.9084
Epoch 10/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1282
- acc: 0.9510 - val_loss: 0.4077 - val_acc: 0.9131
Epoch 11/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1514
- acc: 0.9442 - val_loss: 0.5656 - val_acc: 0.9002
Epoch 12/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1442
- acc: 0.9508 - val_loss: 0.4424 - val_acc: 0.9087
Epoch 13/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1350
- acc: 0.9502 - val_loss: 0.3248 - val_acc: 0.9138
Epoch 14/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1374
- acc: 0.9483 - val_loss: 0.4426 - val_acc: 0.8867
Epoch 15/20
7352/7352 [==============================] - 254s 34ms/step - loss: 0.1296
- acc: 0.9506 - val_loss: 0.7787 - val_acc: 0.8918
Epoch 16/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1291
- acc: 0.9518 - val_loss: 0.4181 - val_acc: 0.8609
Epoch 17/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1367
- acc: 0.9524 - val_loss: 0.3223 - val_acc: 0.9114
Epoch 18/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1335
- acc: 0.9499 - val_loss: 0.3935 - val_acc: 0.9141
Epoch 19/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1276
- acc: 0.9509 - val_loss: 0.5231 - val_acc: 0.9040
Epoch 20/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1295
- acc: 0.9510 - val_loss: 0.5820 - val_acc: 0.9050
```

In [67]:

```
plot_train_cv_loss(training,epochs)
```



- best epoch is 4. It starts overfitting from 5. Best accuracy is 61.18%

In [68]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 537        0         0        0
0
SITTING                  5      416        66        2
0
STANDING                 0       97       421       13
0
WALKING                  0        0         0      481
15
WALKING_DOWNSTAIRS       0        0         0       38
378
WALKING_UPSTAIRS         0        0         0       33
4

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            2
STANDING                           1
WALKING                            0
WALKING_DOWNSTAIRS                 4
WALKING_UPSTAIRS                 434
```

In [69]:

```
score5 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 20s 7ms/step
```

In [70]:

```
score5
```

Out[70]:

```
[0.5819538532469711, 0.9049881235154394]
```

2. Using Binary CrossEntropy

1 LSTM Neuron and dropout = 0.4

In [71]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.4))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_11 (LSTM)               (None, 100)               44000     
_________________________________________________________________
dropout_10 (Dropout)         (None, 100)               0         
_________________________________________________________________
dense_8 (Dense)              (None, 6)                 606       
=================================================================
Total params: 44,606
Trainable params: 44,606
Non-trainable params: 0
_________________________________________________________________
```

In [72]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='rmsprop',
              metrics=['categorical_accuracy'])
```

In [73]:

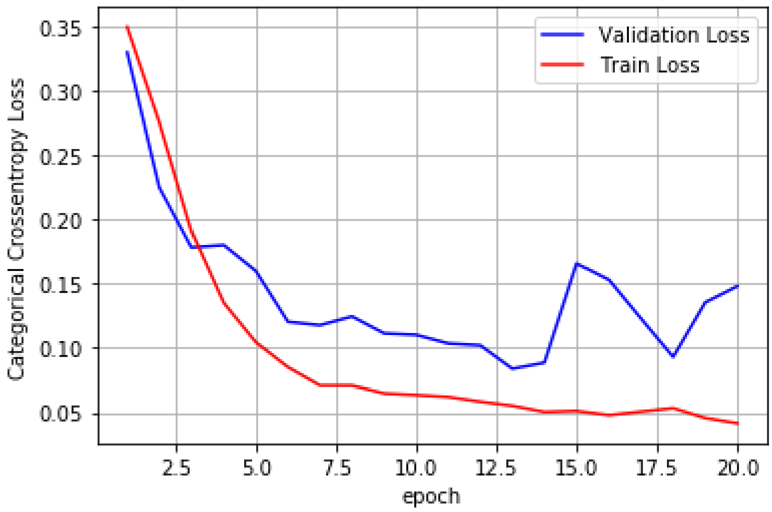
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 73s 10ms/step - loss: 0.3492
- categorical_accuracy: 0.4448 - val_loss: 0.3294 - val_categorical_accura
cy: 0.4781
Epoch 2/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.2753 -
categorical_accuracy: 0.6064 - val_loss: 0.2249 - val_categorical_accurac
y: 0.6902
Epoch 3/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.1906 -
categorical_accuracy: 0.7786 - val_loss: 0.1782 - val_categorical_accurac
y: 0.7659
Epoch 4/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1351 -
categorical_accuracy: 0.8610 - val_loss: 0.1799 - val_categorical_accurac
y: 0.7852
Epoch 5/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.1045 -
categorical_accuracy: 0.8945 - val_loss: 0.1598 - val_categorical_accurac
y: 0.8303
Epoch 6/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.0852 -
categorical_accuracy: 0.9121 - val_loss: 0.1204 - val_categorical_accurac
y: 0.8856
Epoch 7/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.0710 -
categorical_accuracy: 0.9276 - val_loss: 0.1177 - val_categorical_accurac
y: 0.8894
Epoch 8/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0709 -
categorical_accuracy: 0.9280 - val_loss: 0.1245 - val_categorical_accurac
y: 0.8931
Epoch 9/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0648 -
categorical_accuracy: 0.9308 - val_loss: 0.1114 - val_categorical_accurac
y: 0.8989
Epoch 10/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0636 -
categorical_accuracy: 0.9350 - val_loss: 0.1102 - val_categorical_accurac
y: 0.8901
Epoch 11/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.0621 -
categorical_accuracy: 0.9370 - val_loss: 0.1035 - val_categorical_accurac
y: 0.8850
Epoch 12/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.0585 -
categorical_accuracy: 0.9382 - val_loss: 0.1021 - val_categorical_accurac
y: 0.8941
Epoch 13/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0553 -
categorical_accuracy: 0.9433 - val_loss: 0.0839 - val_categorical_accurac
y: 0.9237
Epoch 14/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.0505 -
categorical_accuracy: 0.9446 - val_loss: 0.0886 - val_categorical_accurac
y: 0.9158
Epoch 15/20
7352/7352 [==============================] - 76s 10ms/step - loss: 0.0513
- categorical_accuracy: 0.9468 - val_loss: 0.1656 - val_categorical_accura
cy: 0.9002
```

```
Epoch 16/20
7352/7352 [==============================] - 71s 10ms/step - loss: 0.0481
- categorical_accuracy: 0.9491 - val_loss: 0.1529 - val_categorical_accura
cy: 0.8904
Epoch 17/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0508 -
categorical_accuracy: 0.9430 - val_loss: 0.1228 - val_categorical_accurac
y: 0.9097
Epoch 18/20
7352/7352 [==============================] - 67s 9ms/step - loss: 0.0535 -
categorical_accuracy: 0.9437 - val_loss: 0.0930 - val_categorical_accurac
y: 0.9057
Epoch 19/20
7352/7352 [==============================] - 70s 9ms/step - loss: 0.0458 -
categorical_accuracy: 0.9505 - val_loss: 0.1354 - val_categorical_accurac
y: 0.8965
Epoch 20/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.0417 -
categorical_accuracy: 0.9523 - val_loss: 0.1480 - val_categorical_accurac
y: 0.9060
```

In [74]:

```
import matplotlib.pyplot as plt
plot_train_cv_loss(training,epochs)
```



- best epoch is 3. It starts overfitting from epoch 4. Best accuracy is 76.59%

In [75]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 510        0        27        0                   0
SITTING                  0      411        77        1                   0
STANDING                 0      102       430        0                   0
WALKING                  0        0         0      448                  45
WALKING_DOWNSTAIRS       0        0         0        1                 418
WALKING_UPSTAIRS         0        1         0        9                   8

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            2
STANDING                           0
WALKING                            3
WALKING_DOWNSTAIRS                 1
WALKING_UPSTAIRS                 453
```

In [76]:

```
score6 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 5s 2ms/step
```

In [77]:

```
score6
```

Out[77]:

```
[0.14798565943513792, 0.9060061079063454]
```

1 LSTM neuron , dropout = 0.8

In [78]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim)))
# Adding a dropout layer
model.add(Dropout(0.8))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_12 (LSTM)               (None, 100)               44000     
_________________________________________________________________
dropout_11 (Dropout)         (None, 100)               0         
_________________________________________________________________
dense_9 (Dense)              (None, 6)                 606       
=================================================================
Total params: 44,606
Trainable params: 44,606
Non-trainable params: 0
_________________________________________________________________
```

In [79]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='rmsprop',
              metrics=['categorical_accuracy'])
```

In [80]:

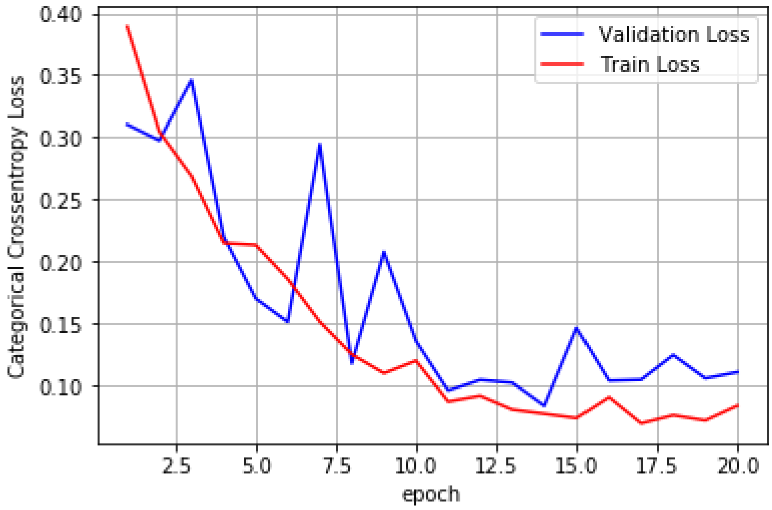
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 71s 10ms/step - loss: 0.3891
- categorical_accuracy: 0.4019 - val_loss: 0.3101 - val_categorical_accura
cy: 0.5175
Epoch 2/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.3044 -
categorical_accuracy: 0.5692 - val_loss: 0.2972 - val_categorical_accurac
y: 0.5304
Epoch 3/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.2688 -
categorical_accuracy: 0.6567 - val_loss: 0.3458 - val_categorical_accurac
y: 0.4785
Epoch 4/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.2147 -
categorical_accuracy: 0.7466 - val_loss: 0.2199 - val_categorical_accurac
y: 0.7333
Epoch 5/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.2131 -
categorical_accuracy: 0.7892 - val_loss: 0.1698 - val_categorical_accurac
y: 0.8124
Epoch 6/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.1855 -
categorical_accuracy: 0.8305 - val_loss: 0.1508 - val_categorical_accurac
y: 0.8344
Epoch 7/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1510 -
categorical_accuracy: 0.8727 - val_loss: 0.2943 - val_categorical_accurac
y: 0.6892
Epoch 8/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.1246 -
categorical_accuracy: 0.8974 - val_loss: 0.1174 - val_categorical_accurac
y: 0.8744
Epoch 9/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1095 -
categorical_accuracy: 0.9075 - val_loss: 0.2075 - val_categorical_accurac
y: 0.8198
Epoch 10/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.1195 -
categorical_accuracy: 0.9081 - val_loss: 0.1354 - val_categorical_accurac
y: 0.8744
Epoch 11/20
7352/7352 [==============================] - 69s 9ms/step - loss: 0.0866 -
categorical_accuracy: 0.9270 - val_loss: 0.0954 - val_categorical_accurac
y: 0.9030
Epoch 12/20
7352/7352 [==============================] - 91s 12ms/step - loss: 0.0912
- categorical_accuracy: 0.9251 - val_loss: 0.1041 - val_categorical_accura
cy: 0.8999
Epoch 13/20
7352/7352 [==============================] - 75s 10ms/step - loss: 0.0802
- categorical_accuracy: 0.9300 - val_loss: 0.1019 - val_categorical_accura
cy: 0.8863
Epoch 14/20
7352/7352 [==============================] - 76s 10ms/step - loss: 0.0768
- categorical_accuracy: 0.9369 - val_loss: 0.0832 - val_categorical_accura
cy: 0.9067
Epoch 15/20
7352/7352 [==============================] - 70s 10ms/step - loss: 0.0734
- categorical_accuracy: 0.9397 - val_loss: 0.1460 - val_categorical_accura
cy: 0.8897
```

```
Epoch 16/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.0901 -
categorical_accuracy: 0.9317 - val_loss: 0.1035 - val_categorical_accurac
y: 0.9101
Epoch 17/20
7352/7352 [==============================] - 66s 9ms/step - loss: 0.0691 -
categorical_accuracy: 0.9404 - val_loss: 0.1043 - val_categorical_accurac
y: 0.9152
Epoch 18/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.0757 -
categorical_accuracy: 0.9381 - val_loss: 0.1241 - val_categorical_accurac
y: 0.9016
Epoch 19/20
7352/7352 [==============================] - 65s 9ms/step - loss: 0.0715 -
categorical_accuracy: 0.9399 - val_loss: 0.1053 - val_categorical_accurac
y: 0.9019
Epoch 20/20
7352/7352 [==============================] - 68s 9ms/step - loss: 0.0834 -
categorical_accuracy: 0.9348 - val_loss: 0.1103 - val_categorical_accurac
y: 0.9036
```

In [81]:

```
plot_train_cv_loss(training,epochs)
```



- Best epoch is 1. It start overfitting from epoch 2. Best accuracy 84.01%

In [82]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS
\
True
LAYING                 522        0        13        0                   0
SITTING                  0      407        83        1                   0
STANDING                 0      104       423        5                   0
WALKING                  0        0         1      491                   4
WALKING_DOWNSTAIRS       0        0         0       10                 410
WALKING_UPSTAIRS         0        0         4       55                   2

Pred                WALKING_UPSTAIRS
True
LAYING                             2
SITTING                            0
STANDING                           0
WALKING                            0
WALKING_DOWNSTAIRS                 0
WALKING_UPSTAIRS                 410
```

In [83]:

```
score7 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 4s 1ms/step
```

In [84]:

```
score7
```

Out[84]:

```
[0.11029730399505142, 0.9036308109942314]
```

2 LSTM neurons, dropout = 0.8

In [85]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.8))
#Adding another LSTM layer
model.add(LSTM(200,))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_13 (LSTM)               (None, 128, 100)          44000     
_________________________________________________________________
dropout_12 (Dropout)         (None, 128, 100)          0         
_________________________________________________________________
lstm_14 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dense_10 (Dense)             (None, 6)                 1206      
=================================================================
Total params: 286,006
Trainable params: 286,006
Non-trainable params: 0
_________________________________________________________________
```

In [86]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='rmsprop',
              metrics=['categorical_accuracy'])
```

In [87]:

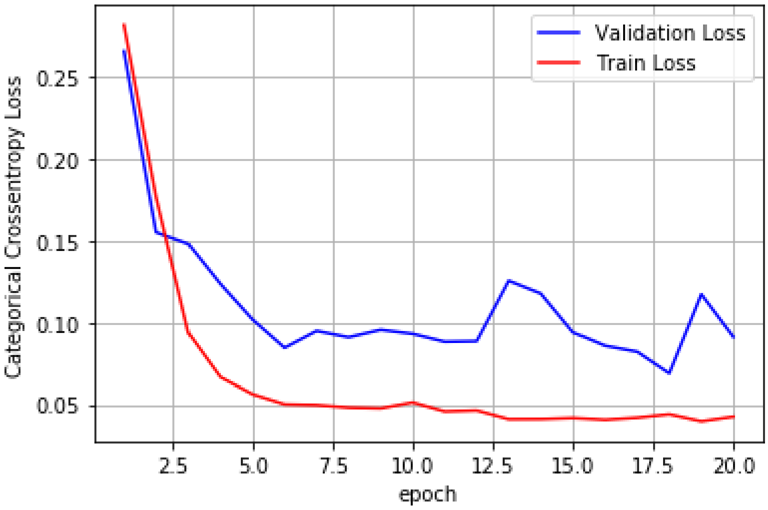
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.2815
- categorical_accuracy: 0.5559 - val_loss: 0.2655 - val_categorical_accura
cy: 0.5931
Epoch 2/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.1768
- categorical_accuracy: 0.7587 - val_loss: 0.1551 - val_categorical_accura
cy: 0.8208
Epoch 3/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0937
- categorical_accuracy: 0.8915 - val_loss: 0.1480 - val_categorical_accura
cy: 0.8571
Epoch 4/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0667
- categorical_accuracy: 0.9261 - val_loss: 0.1235 - val_categorical_accura
cy: 0.8768
Epoch 5/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0562
- categorical_accuracy: 0.9365 - val_loss: 0.1018 - val_categorical_accura
cy: 0.8948
Epoch 6/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0501
- categorical_accuracy: 0.9422 - val_loss: 0.0845 - val_categorical_accura
cy: 0.9002
Epoch 7/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0496
- categorical_accuracy: 0.9455 - val_loss: 0.0948 - val_categorical_accura
cy: 0.9084
Epoch 8/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0481
- categorical_accuracy: 0.9483 - val_loss: 0.0909 - val_categorical_accura
cy: 0.9067
Epoch 9/20
7352/7352 [==============================] - 244s 33ms/step - loss: 0.0477
- categorical_accuracy: 0.9475 - val_loss: 0.0955 - val_categorical_accura
cy: 0.9148
Epoch 10/20
7352/7352 [==============================] - 261s 35ms/step - loss: 0.0512
- categorical_accuracy: 0.9460 - val_loss: 0.0930 - val_categorical_accura
cy: 0.9152
Epoch 11/20
7352/7352 [==============================] - 262s 36ms/step - loss: 0.0458
- categorical_accuracy: 0.9490 - val_loss: 0.0882 - val_categorical_accura
cy: 0.9013
Epoch 12/20
7352/7352 [==============================] - 262s 36ms/step - loss: 0.0464
- categorical_accuracy: 0.9464 - val_loss: 0.0885 - val_categorical_accura
cy: 0.9077
Epoch 13/20
7352/7352 [==============================] - 265s 36ms/step - loss: 0.0411
- categorical_accuracy: 0.9510 - val_loss: 0.1254 - val_categorical_accura
cy: 0.8982
Epoch 14/20
7352/7352 [==============================] - 268s 36ms/step - loss: 0.0411
- categorical_accuracy: 0.9504 - val_loss: 0.1176 - val_categorical_accura
cy: 0.9118
Epoch 15/20
7352/7352 [==============================] - 266s 36ms/step - loss: 0.0418
- categorical_accuracy: 0.9505 - val_loss: 0.0939 - val_categorical_accura
cy: 0.9172
```

```
Epoch 16/20
7352/7352 [==============================] - 265s 36ms/step - loss: 0.0407
- categorical_accuracy: 0.9486 - val_loss: 0.0857 - val_categorical_accura
cy: 0.9250
Epoch 17/20
7352/7352 [==============================] - 287s 39ms/step - loss: 0.0420
- categorical_accuracy: 0.9518 - val_loss: 0.0821 - val_categorical_accura
cy: 0.9209
Epoch 18/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.0440
- categorical_accuracy: 0.9508 - val_loss: 0.0689 - val_categorical_accura
cy: 0.9247
Epoch 19/20
7352/7352 [==============================] - 250s 34ms/step - loss: 0.0398
- categorical_accuracy: 0.9525 - val_loss: 0.1172 - val_categorical_accura
cy: 0.9013
Epoch 20/20
7352/7352 [==============================] - 263s 36ms/step - loss: 0.0426
- categorical_accuracy: 0.9513 - val_loss: 0.0911 - val_categorical_accura
cy: 0.9175
```

In [88]:

```
plot_train_cv_loss(training,epochs)
```



- best epoch is 6. It starts overfitting from epoch 7. Best accuracy 90.02%

In [89]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS
\
True
LAYING                 537        0         0        0                   0
SITTING                  5      382        85        0                   0
STANDING                 0       90       438        0                   0
WALKING                  0        0         0      468                  11
WALKING_DOWNSTAIRS       0        0         0        1                 415
WALKING_UPSTAIRS         0        0         0        4                   3

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                           19
STANDING                           4
WALKING                           17
WALKING_DOWNSTAIRS                 4
WALKING_UPSTAIRS                 464
```

In [90]:

```
score8 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 22s 8ms/step
```

In [91]:

```
score8
```

Out[91]:

```
[0.09114118609929235, 0.9175432643366135]
```

2 LSTM neurons, 2 dropouts

In [92]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.8))
#Adding another LSTM layer
model.add(LSTM(200,))
model.add(Dropout(0.9))
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_15 (LSTM)               (None, 128, 100)          44000     
_________________________________________________________________
dropout_13 (Dropout)         (None, 128, 100)          0         
_________________________________________________________________
lstm_16 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dropout_14 (Dropout)         (None, 200)               0         
_________________________________________________________________
dense_11 (Dense)             (None, 6)                 1206      
=================================================================
Total params: 286,006
Trainable params: 286,006
Non-trainable params: 0
_________________________________________________________________
```

In [93]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='rmsprop',
              metrics=['categorical_accuracy'])
```

In [94]:

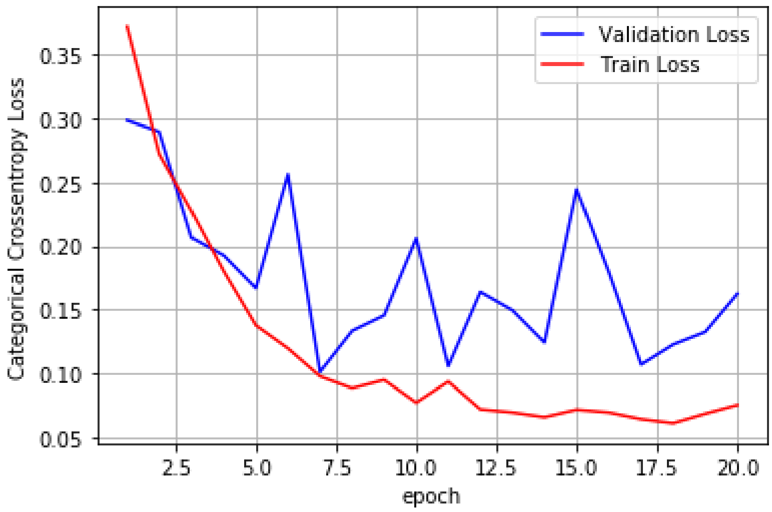
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 290s 40ms/step - loss: 0.3722
- categorical_accuracy: 0.4351 - val_loss: 0.2986 - val_categorical_accura
cy: 0.5019
Epoch 2/20
7352/7352 [==============================] - 256s 35ms/step - loss: 0.2721
- categorical_accuracy: 0.6160 - val_loss: 0.2896 - val_categorical_accura
cy: 0.6142
Epoch 3/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.2273
- categorical_accuracy: 0.7029 - val_loss: 0.2065 - val_categorical_accura
cy: 0.7564
Epoch 4/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1801
- categorical_accuracy: 0.7909 - val_loss: 0.1925 - val_categorical_accura
cy: 0.8093
Epoch 5/20
7352/7352 [==============================] - 254s 35ms/step - loss: 0.1376
- categorical_accuracy: 0.8803 - val_loss: 0.1668 - val_categorical_accura
cy: 0.8517
Epoch 6/20
7352/7352 [==============================] - 254s 34ms/step - loss: 0.1195
- categorical_accuracy: 0.9147 - val_loss: 0.2563 - val_categorical_accura
cy: 0.7933
Epoch 7/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.0976
- categorical_accuracy: 0.9212 - val_loss: 0.1010 - val_categorical_accura
cy: 0.8945
Epoch 8/20
7352/7352 [==============================] - 256s 35ms/step - loss: 0.0883
- categorical_accuracy: 0.9276 - val_loss: 0.1332 - val_categorical_accura
cy: 0.8935
Epoch 9/20
7352/7352 [==============================] - 290s 40ms/step - loss: 0.0949
- categorical_accuracy: 0.9267 - val_loss: 0.1454 - val_categorical_accura
cy: 0.8690
Epoch 10/20
7352/7352 [==============================] - 256s 35ms/step - loss: 0.0769
- categorical_accuracy: 0.9334 - val_loss: 0.2060 - val_categorical_accura
cy: 0.8670
Epoch 11/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.0935
- categorical_accuracy: 0.9282 - val_loss: 0.1055 - val_categorical_accura
cy: 0.9186
Epoch 12/20
7352/7352 [==============================] - 264s 36ms/step - loss: 0.0716
- categorical_accuracy: 0.9407 - val_loss: 0.1638 - val_categorical_accura
cy: 0.8714
Epoch 13/20
7352/7352 [==============================] - 259s 35ms/step - loss: 0.0692
- categorical_accuracy: 0.9396 - val_loss: 0.1494 - val_categorical_accura
cy: 0.8965
Epoch 14/20
7352/7352 [==============================] - 267s 36ms/step - loss: 0.0656
- categorical_accuracy: 0.9437 - val_loss: 0.1240 - val_categorical_accura
cy: 0.9125
Epoch 15/20
7352/7352 [==============================] - 287s 39ms/step - loss: 0.0713
- categorical_accuracy: 0.9415 - val_loss: 0.2444 - val_categorical_accura
cy: 0.8907
```

```
Epoch 16/20
7352/7352 [==============================] - 260s 35ms/step - loss: 0.0692
- categorical_accuracy: 0.9430 - val_loss: 0.1789 - val_categorical_accura
cy: 0.9057
Epoch 17/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.0640
- categorical_accuracy: 0.9425 - val_loss: 0.1068 - val_categorical_accura
cy: 0.9175
Epoch 18/20
7352/7352 [==============================] - 260s 35ms/step - loss: 0.0609
- categorical_accuracy: 0.9455 - val_loss: 0.1225 - val_categorical_accura
cy: 0.9179
Epoch 19/20
7352/7352 [==============================] - 252s 34ms/step - loss: 0.0683
- categorical_accuracy: 0.9429 - val_loss: 0.1324 - val_categorical_accura
cy: 0.9141
Epoch 20/20
7352/7352 [==============================] - 268s 36ms/step - loss: 0.0750
- categorical_accuracy: 0.9380 - val_loss: 0.1623 - val_categorical_accura
cy: 0.8972
```

In [95]:

```
plot_train_cv_loss(training,epochs)
```



- best epoch is 6. It starts overfitting from epoch 7. Best accuraccy is 96.53%

In [96]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS
\
True
LAYING                 523        0        14        0                   0
SITTING                  5      375       105        0                   0
STANDING                 0       90       441        0                   0
WALKING                  0        1         1      473                  10
WALKING_DOWNSTAIRS       0        0         1       25                 390
WALKING_UPSTAIRS         0        0         0       28                   1

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            6
STANDING                           1
WALKING                           11
WALKING_DOWNSTAIRS                 4
WALKING_UPSTAIRS                 442
```

In [97]:

```
score9 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 20s 7ms/step
```

In [98]:

```
score9
```

Out[98]:

```
[0.16230833367408035, 0.8971835765184933]
```

2 LSTM neurons, 2 dropouts, BatchNormaliztion

In [99]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.8))
#Adding another LSTM layer
model.add(LSTM(200,))
model.add(Dropout(0.9))
model.add(BatchNormalization())
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_17 (LSTM)               (None, 128, 100)          44000     
_________________________________________________________________
dropout_15 (Dropout)         (None, 128, 100)          0         
_________________________________________________________________
lstm_18 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dropout_16 (Dropout)         (None, 200)               0         
_________________________________________________________________
batch_normalization_2 (Batch (None, 200)               800       
_________________________________________________________________
dense_12 (Dense)             (None, 6)                 1206      
=================================================================
Total params: 286,806
Trainable params: 286,406
Non-trainable params: 400
_________________________________________________________________
```

In [100]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='rmsprop',
              metrics=['categorical_accuracy'])
```

In [101]:

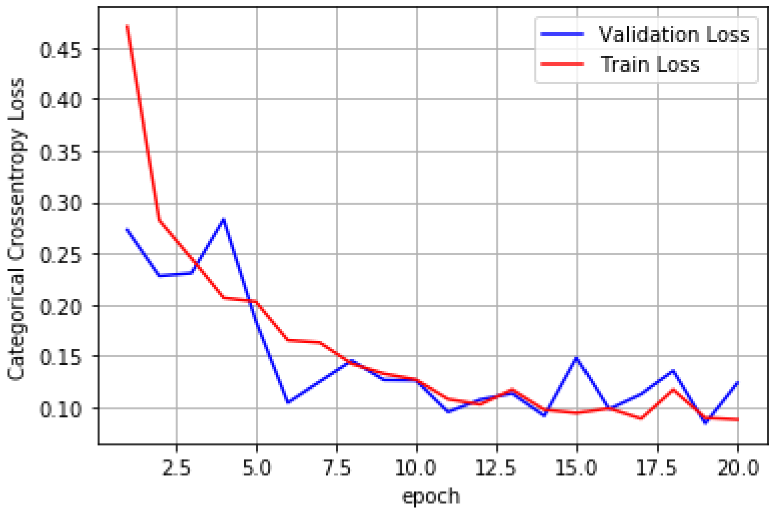
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 273s 37ms/step - loss: 0.4707
- categorical_accuracy: 0.4347 - val_loss: 0.2730 - val_categorical_accura
cy: 0.6237
Epoch 2/20
7352/7352 [==============================] - 266s 36ms/step - loss: 0.2824
- categorical_accuracy: 0.6347 - val_loss: 0.2280 - val_categorical_accura
cy: 0.7034
Epoch 3/20
7352/7352 [==============================] - 275s 37ms/step - loss: 0.2453
- categorical_accuracy: 0.6997 - val_loss: 0.2308 - val_categorical_accura
cy: 0.7299
Epoch 4/20
7352/7352 [==============================] - 277s 38ms/step - loss: 0.2067
- categorical_accuracy: 0.7930 - val_loss: 0.2833 - val_categorical_accura
cy: 0.6702
Epoch 5/20
7352/7352 [==============================] - 264s 36ms/step - loss: 0.2030
- categorical_accuracy: 0.8020 - val_loss: 0.1844 - val_categorical_accura
cy: 0.8130
Epoch 6/20
7352/7352 [==============================] - 289s 39ms/step - loss: 0.1653
- categorical_accuracy: 0.8770 - val_loss: 0.1046 - val_categorical_accura
cy: 0.8914
Epoch 7/20
7352/7352 [==============================] - 290s 39ms/step - loss: 0.1630
- categorical_accuracy: 0.8662 - val_loss: 0.1250 - val_categorical_accura
cy: 0.8850
Epoch 8/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.1423
- categorical_accuracy: 0.8870 - val_loss: 0.1454 - val_categorical_accura
cy: 0.8531
Epoch 9/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.1326
- categorical_accuracy: 0.9033 - val_loss: 0.1265 - val_categorical_accura
cy: 0.8877
Epoch 10/20
7352/7352 [==============================] - 247s 34ms/step - loss: 0.1268
- categorical_accuracy: 0.9045 - val_loss: 0.1261 - val_categorical_accura
cy: 0.8751
Epoch 11/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.1081
- categorical_accuracy: 0.9222 - val_loss: 0.0956 - val_categorical_accura
cy: 0.8996
Epoch 12/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.1030
- categorical_accuracy: 0.9255 - val_loss: 0.1077 - val_categorical_accura
cy: 0.8999
Epoch 13/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.1173
- categorical_accuracy: 0.9202 - val_loss: 0.1137 - val_categorical_accura
cy: 0.9033
Epoch 14/20
7352/7352 [==============================] - 247s 34ms/step - loss: 0.0978
- categorical_accuracy: 0.9323 - val_loss: 0.0919 - val_categorical_accura
cy: 0.9114
Epoch 15/20
7352/7352 [==============================] - 245s 33ms/step - loss: 0.0946
- categorical_accuracy: 0.9340 - val_loss: 0.1482 - val_categorical_accura
cy: 0.8870
```

```
Epoch 16/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.0991
- categorical_accuracy: 0.9297 - val_loss: 0.0985 - val_categorical_accura
cy: 0.9141
Epoch 17/20
7352/7352 [==============================] - 247s 34ms/step - loss: 0.0891
- categorical_accuracy: 0.9374 - val_loss: 0.1129 - val_categorical_accura
cy: 0.9155
Epoch 18/20
7352/7352 [==============================] - 248s 34ms/step - loss: 0.1171
- categorical_accuracy: 0.9197 - val_loss: 0.1354 - val_categorical_accura
cy: 0.8863
Epoch 19/20
7352/7352 [==============================] - 247s 34ms/step - loss: 0.0900
- categorical_accuracy: 0.9392 - val_loss: 0.0846 - val_categorical_accura
cy: 0.9131
Epoch 20/20
7352/7352 [==============================] - 246s 33ms/step - loss: 0.0882
- categorical_accuracy: 0.9385 - val_loss: 0.1236 - val_categorical_accura
cy: 0.9182
```

In [102]:

```
plot_train_cv_loss(training,epochs)
```



In [103]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 536        0         1        0                   0
SITTING                  1      369       119        0                   0
STANDING                 0       55       477        0                   0
WALKING                  0        0         0      455                  37
WALKING_DOWNSTAIRS       0        0         0        0                 420
WALKING_UPSTAIRS         0        0         0        0                  22

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            2
STANDING                           0
WALKING                            4
WALKING_DOWNSTAIRS                 0
WALKING_UPSTAIRS                 449
```

In [104]:

```
score10 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 20s 7ms/step
```

In [105]:

```
score10
```

Out[105]:

```
[0.12357697055033087, 0.9182219205972175]
```

In [128]:

```
from prettytable import PrettyTable
pt = PrettyTable()
pt.title = " categorical cross entropy "
pt.field_names = ["LSTM Layers",'Neurons','Dropout', 'Best Epoch','Accuracy']
pt.add_row(["1","32","0.5","5","80.83"])
pt.add_row(["1","100","0.5","4","84.87"])
pt.add_row(["1","100","0.8","2","71.77"])
pt.add_row(["2","100,200","0.3","4","89.38"])
pt.add_row(["2","100,200","0.8,0.9","1","79.44"])
print(pt)

pt = PrettyTable()
pt.title ="Binary cross entropy"
pt.field_names = ["LSTM Layers",'Neurons','Dropout', 'Best Epoch','Accuracy']
pt.add_row(["1","100","0.4","3","76.59"])
pt.add_row(["1","100","0.8","1","53.04"])
pt.add_row(["2","100,200","0.8","6","90.02"])
pt.add_row(["2","100,200","0.8,0.9","5","85.97"])
print(pt)

pt= PrettyTable()
pt.title="With batch normalization"
pt.field_names = ["LSTM Layers",'Neurons','Dropout', 'Best Epoch','Accuracy','entropy']
pt.add_row(["2","100,200","0.4,0.3","1","81.68","categorical cross entropy"])
pt.add_row(["2","100,200","0.8,0.9","2","70.34","binary cross entropy"])
print(pt)
```

```
+-------------+---------+---------+------------+----------+
| LSTM Layers | Neurons | Dropout | Best Epoch | Accuracy |
+-------------+---------+---------+------------+----------+
|      1      |    32   |   0.5   |     5      |  80.83   |
|      1      |   100   |   0.5   |     4      |  84.87   |
|      1      |   100   |   0.8   |     2      |  71.77   |
|      2      | 100,200 |   0.3   |     4      |  89.38   |
|      2      | 100,200 | 0.8,0.9 |     1      |  79.44   |
+-------------+---------+---------+------------+----------+
+-------------+---------+---------+------------+----------+
| LSTM Layers | Neurons | Dropout | Best Epoch | Accuracy |
+-------------+---------+---------+------------+----------+
|      1      |   100   |   0.4   |     3      |  76.59   |
|      1      |   100   |   0.8   |     1      |  53.04   |
|      2      | 100,200 |   0.8   |     6      |  90.02   |
|      2      | 100,200 | 0.8,0.9 |     5      |  85.97   |
+-------------+---------+---------+------------+----------+
+-------------+---------+---------+------------+----------+---------------
------------+
| LSTM Layers | Neurons | Dropout | Best Epoch | Accuracy |          entro
py          |
+-------------+---------+---------+------------+----------+---------------
------------+
|      2      | 100,200 | 0.4,0.3 |     1      |  81.68   | categorical cr
oss entropy |
|      2      | 100,200 | 0.8,0.9 |     2      |  70.34   |    binary cros
s entropy   |
+-------------+---------+---------+------------+----------+---------------
------------+
```

In [109]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.3))
#Adding another LSTM layer
model.add(LSTM(200,))
model.add(Dropout(0.4))
model.add(BatchNormalization())
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='softmax'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_21 (LSTM)               (None, 128, 100)          44000     
_________________________________________________________________
dropout_19 (Dropout)         (None, 128, 100)          0         
_________________________________________________________________
lstm_22 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dropout_20 (Dropout)         (None, 200)               0         
_________________________________________________________________
batch_normalization_4 (Batch (None, 200)               800       
_________________________________________________________________
dense_14 (Dense)             (None, 6)                 1206      
=================================================================
Total params: 286,806
Trainable params: 286,406
Non-trainable params: 400
_________________________________________________________________
```

In [110]:

```
# Compiling the model
model.compile(loss='categorical_crossentropy',
              optimizer='adam',
              metrics=['accuracy'])
```

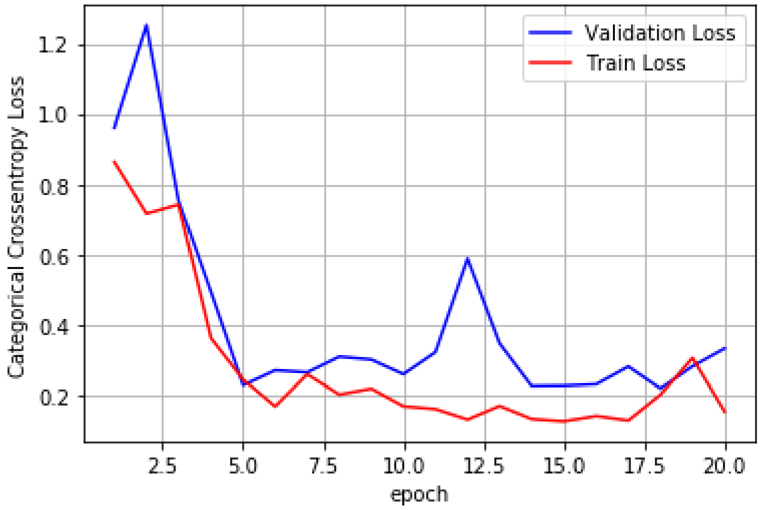
In [111]:

```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 253s 34ms/step - loss: 0.8634
- acc: 0.6472 - val_loss: 0.9614 - val_acc: 0.7163
Epoch 2/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.7165
- acc: 0.7318 - val_loss: 1.2530 - val_acc: 0.5460
Epoch 3/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.7420
- acc: 0.7140 - val_loss: 0.7530 - val_acc: 0.6983
Epoch 4/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.3615
- acc: 0.8697 - val_loss: 0.4929 - val_acc: 0.8388
Epoch 5/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.2442
- acc: 0.9155 - val_loss: 0.2279 - val_acc: 0.9152
Epoch 6/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1674
- acc: 0.9384 - val_loss: 0.2702 - val_acc: 0.9148
Epoch 7/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.2590
- acc: 0.9109 - val_loss: 0.2643 - val_acc: 0.9094
Epoch 8/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.2010
- acc: 0.9274 - val_loss: 0.3088 - val_acc: 0.8636
Epoch 9/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.2177
- acc: 0.9264 - val_loss: 0.3006 - val_acc: 0.9006
Epoch 10/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1677
- acc: 0.9359 - val_loss: 0.2591 - val_acc: 0.9152
Epoch 11/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1599
- acc: 0.9391 - val_loss: 0.3217 - val_acc: 0.9016
Epoch 12/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1303
- acc: 0.9461 - val_loss: 0.5883 - val_acc: 0.8337
Epoch 13/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1687
- acc: 0.9369 - val_loss: 0.3465 - val_acc: 0.9057
Epoch 14/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1318
- acc: 0.9457 - val_loss: 0.2254 - val_acc: 0.9206
Epoch 15/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1255
- acc: 0.9495 - val_loss: 0.2264 - val_acc: 0.9128
Epoch 16/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1403
- acc: 0.9444 - val_loss: 0.2309 - val_acc: 0.9220
Epoch 17/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.1276
- acc: 0.9482 - val_loss: 0.2810 - val_acc: 0.9169
Epoch 18/20
7352/7352 [==============================] - 242s 33ms/step - loss: 0.2007
- acc: 0.9257 - val_loss: 0.2184 - val_acc: 0.9203
Epoch 19/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.3053
- acc: 0.8913 - val_loss: 0.2817 - val_acc: 0.9016
Epoch 20/20
7352/7352 [==============================] - 243s 33ms/step - loss: 0.1529
- acc: 0.9397 - val_loss: 0.3320 - val_acc: 0.8904
```

In [112]:

```
plot_train_cv_loss(training,epochs)
```



In [113]:

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTA
IRS  \
True
LAYING                 537        0         0        0
0
SITTING                  3      376       109        3
0
STANDING                 0      103       427        2
0
WALKING                  0        0         0      465
31
WALKING_DOWNSTAIRS       0        0         0        0
420
WALKING_UPSTAIRS         0        0         0       54
18

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            0
STANDING                           0
WALKING                            0
WALKING_DOWNSTAIRS                 0
WALKING_UPSTAIRS                 399
```

In [114]:

```
score11 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 21s 7ms/step
```

In [115]:

```
score11
```

Out[115]:

```
[0.332028348539614, 0.8903970139124533]
```

In [116]:

```
# Initiliazing the sequential model
model = Sequential()
# Configuring the parameters
model.add(LSTM(n_hidden, input_shape=(timesteps, input_dim), return_sequences = True))
# Adding a dropout layer
model.add(Dropout(0.8))
#Adding another LSTM layer
model.add(LSTM(200,))
model.add(Dropout(0.9))
model.add(BatchNormalization())
# Adding a dense output layer with sigmoid activation
model.add(Dense(n_classes, activation='sigmoid'))
model.summary()
```

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #   
=================================================================
lstm_23 (LSTM)               (None, 128, 100)          44000     
_________________________________________________________________
dropout_21 (Dropout)         (None, 128, 100)          0         
_________________________________________________________________
lstm_24 (LSTM)               (None, 200)               240800    
_________________________________________________________________
dropout_22 (Dropout)         (None, 200)               0         
_________________________________________________________________
batch_normalization_5 (Batch (None, 200)               800       
_________________________________________________________________
dense_15 (Dense)             (None, 6)                 1206      
=================================================================
Total params: 286,806
Trainable params: 286,406
Non-trainable params: 400
_________________________________________________________________
```

In [117]:

```
# Compiling the model
model.compile(loss='binary_crossentropy',
              optimizer='adam',
              metrics=['categorical_accuracy'])
```

In [118]:

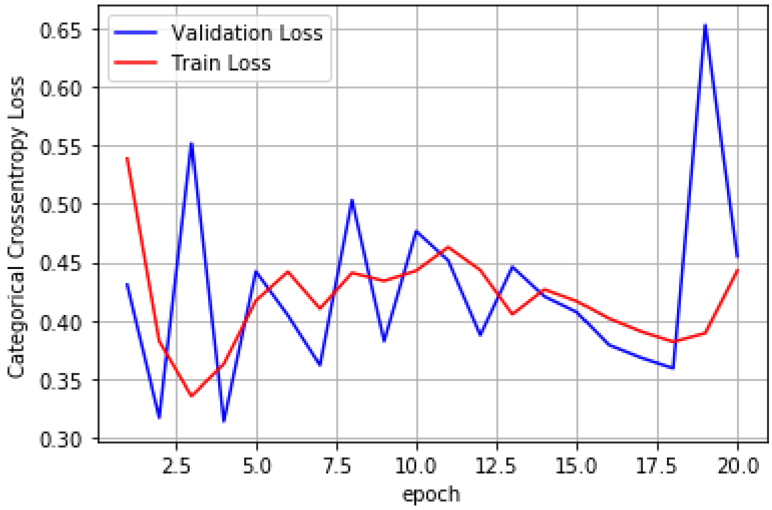
```
# Training the model
training = model.fit(X_train,
          Y_train,
          batch_size=batch_size,
          validation_data=(X_test, Y_test),
          epochs=epochs)
```

```
Train on 7352 samples, validate on 2947 samples
Epoch 1/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.5388
- categorical_accuracy: 0.3150 - val_loss: 0.4306 - val_categorical_accura
cy: 0.2698
Epoch 2/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.3821
- categorical_accuracy: 0.4459 - val_loss: 0.3170 - val_categorical_accura
cy: 0.4968
Epoch 3/20
7352/7352 [==============================] - 248s 34ms/step - loss: 0.3356
- categorical_accuracy: 0.5049 - val_loss: 0.5517 - val_categorical_accura
cy: 0.1761
Epoch 4/20
7352/7352 [==============================] - 248s 34ms/step - loss: 0.3626
- categorical_accuracy: 0.4368 - val_loss: 0.3139 - val_categorical_accura
cy: 0.4676
Epoch 5/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4169
- categorical_accuracy: 0.3202 - val_loss: 0.4420 - val_categorical_accura
cy: 0.1731
Epoch 6/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4417
- categorical_accuracy: 0.2417 - val_loss: 0.4043 - val_categorical_accura
cy: 0.3824
Epoch 7/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4101
- categorical_accuracy: 0.3207 - val_loss: 0.3615 - val_categorical_accura
cy: 0.4245
Epoch 8/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4408
- categorical_accuracy: 0.2549 - val_loss: 0.5032 - val_categorical_accura
cy: 0.1870
Epoch 9/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4339
- categorical_accuracy: 0.2561 - val_loss: 0.3822 - val_categorical_accura
cy: 0.3478
Epoch 10/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4426
- categorical_accuracy: 0.2549 - val_loss: 0.4765 - val_categorical_accura
cy: 0.1653
Epoch 11/20
7352/7352 [==============================] - 248s 34ms/step - loss: 0.4628
- categorical_accuracy: 0.1870 - val_loss: 0.4514 - val_categorical_accura
cy: 0.3302
Epoch 12/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4431
- categorical_accuracy: 0.2395 - val_loss: 0.3873 - val_categorical_accura
cy: 0.3566
Epoch 13/20
7352/7352 [==============================] - 250s 34ms/step - loss: 0.4052
- categorical_accuracy: 0.3054 - val_loss: 0.4459 - val_categorical_accura
cy: 0.1948
Epoch 14/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.4265
- categorical_accuracy: 0.2446 - val_loss: 0.4205 - val_categorical_accura
cy: 0.2406
Epoch 15/20
7352/7352 [==============================] - 255s 35ms/step - loss: 0.4165
- categorical_accuracy: 0.2818 - val_loss: 0.4072 - val_categorical_accura
cy: 0.2769
```

```
Epoch 16/20
7352/7352 [==============================] - 250s 34ms/step - loss: 0.4016
- categorical_accuracy: 0.3210 - val_loss: 0.3789 - val_categorical_accura
cy: 0.3573
Epoch 17/20
7352/7352 [==============================] - 250s 34ms/step - loss: 0.3905
- categorical_accuracy: 0.3385 - val_loss: 0.3680 - val_categorical_accura
cy: 0.3573
Epoch 18/20
7352/7352 [==============================] - 249s 34ms/step - loss: 0.3816
- categorical_accuracy: 0.3554 - val_loss: 0.3589 - val_categorical_accura
cy: 0.3627
Epoch 19/20
7352/7352 [==============================] - 251s 34ms/step - loss: 0.3891
- categorical_accuracy: 0.3307 - val_loss: 0.6528 - val_categorical_accura
cy: 0.1822
Epoch 20/20
7352/7352 [==============================] - 2542s 346ms/step - loss: 0.44
27 - categorical_accuracy: 0.2388 - val_loss: 0.4549 - val_categorical_acc
uracy: 0.2121
```

In [119]:

```
plot_train_cv_loss(training,epochs)
```



In [120]:

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

```
Pred                LAYING  STANDING
True
LAYING                  93       444
SITTING                 17       474
STANDING                 0       532
WALKING                  9       487
WALKING_DOWNSTAIRS      10       410
WALKING_UPSTAIRS        35       436
```

In [121]:

```
score12 = model.evaluate(X_test, Y_test)
```

```
2947/2947 [==============================] - 21s 7ms/step
```

In [122]:

```
score12
```

Out[122]:

```
[0.4549274587068956, 0.21208008143875126]
```

In [129]:

```
pt= PrettyTable()
pt.title="With batch normalization"
pt.field_names = ["LSTM Layers",'Neurons','Dropout', 'Best Epoch','Accuracy','entropy']
pt.add_row(["2","100,200","0.4,0.3","1","71.63","categorical cross entropy"])
pt.add_row(["2","100,200","0.8,0.9","2","49.68","binary cross entropy"])
print(pt)
```

```
+-------------+---------+---------+------------+----------+---------------
------------+
| LSTM Layers | Neurons | Dropout | Best Epoch | Accuracy |          entro
py          |
+-------------+---------+---------+------------+----------+---------------
------------+
|      2      | 100,200 | 0.4,0.3 |     1      |  71.63   | categorical cr
oss entropy |
|      2      | 100,200 | 0.8,0.9 |     2      |  49.68   |    binary cros
s entropy   |
+-------------+---------+---------+------------+----------+---------------
------------+
```

Conclusion:

- Best accuracy obtained while using categorical cross entropy is 89.38%
- Best accuracy obtained while using binary cross entropy is 90.02%
- By using BatchNormalization the performance hadn't improved.