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

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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

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```
import numpy as np
import pandas as pd

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

```
No of Features: 561
```

Obtain the train data

```
# get the data from txt files to pandas dataffame
X_train = pd.read_csv('UCI_HAR_dataset/train/X_train.txt', delim_whitespace=True, header=None, names=features)

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

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

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

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

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X	tBodyAcc-mad()-Y	tBodyAcc-mad()-Z	tBodyAcc-max()-X	...	angle(tBody/
6015	0.2797	-0.004397	-0.10952	0.359081	0.119909	-0.177541	0.337963	0.066883	-0.221876	0.474093	...	

1 rows × 564 columns

```
train.shape
```

```
(7352, 564)
```

Obtain the test data

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

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

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


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

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

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

1 rows × 564 columns

```
test.shape
```

```
(2947, 564)
```

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Data Cleaning

1. Check for Duplicates

```
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
```

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2. Checking for NaN/null values

```
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
```

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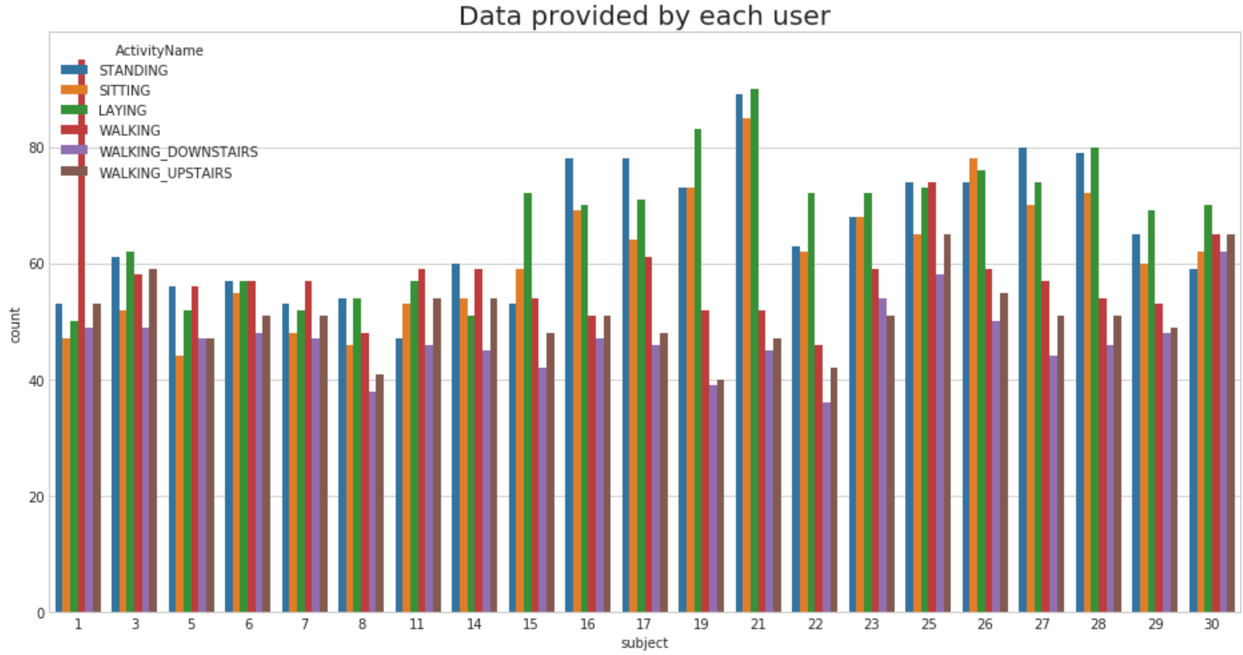
3. Check for data imbalance

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

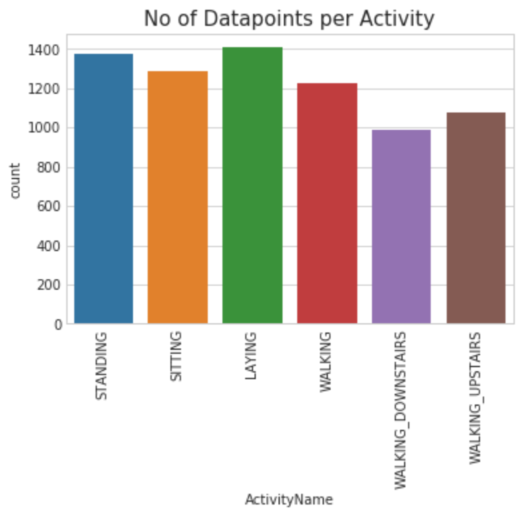
```
sns.set_style('whitegrid')
plt.rcParams['font.family'] = 'Dejavu Sans'


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

```
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

```
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
```

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

5. Save this dataframe in a csv files

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

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Exploratory Data Analysis

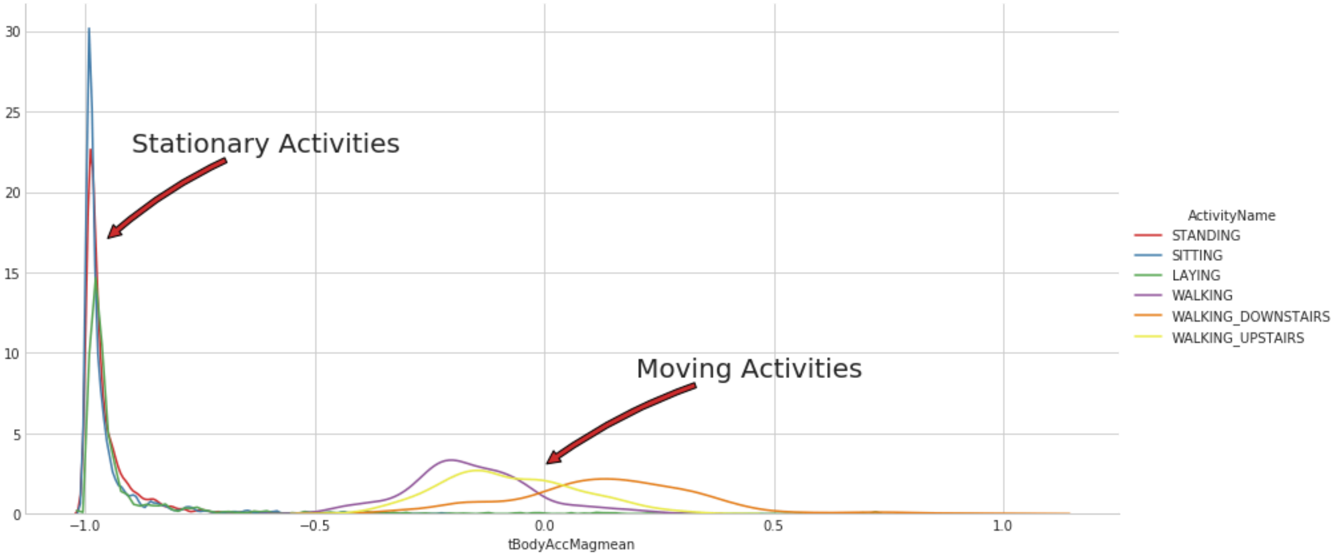
"***Without domain knowledge EDA has no meaning, without EDA a problem has no soul.***"

1. Featuring Engineering from Domain Knowledge

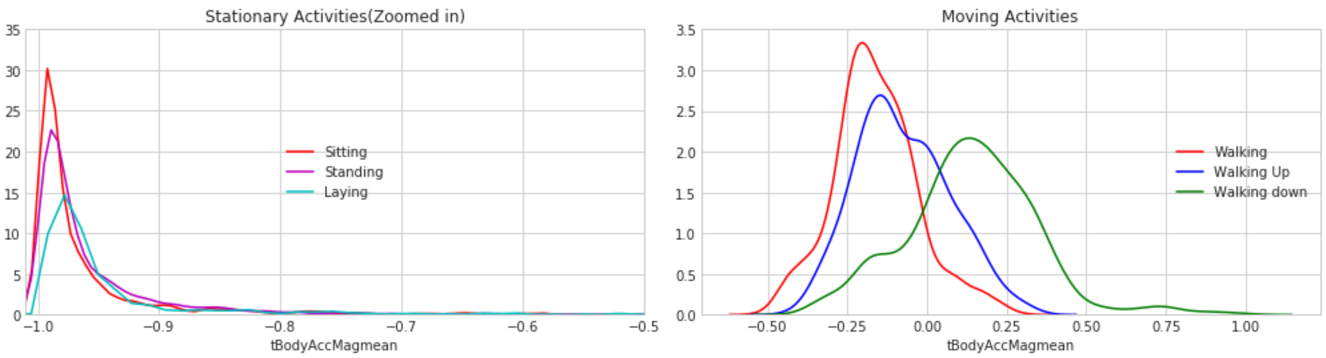
- **Static and Dynamic Activities**
  - In static activities (sit, stand, lie down) motion information will not be very useful.
  - In the dynamic activities (Walking, WalkingUpstairs,WalkingDownstairs) motion info will be significant.

2. Stationary and Moving activities are completely different

```
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()
```

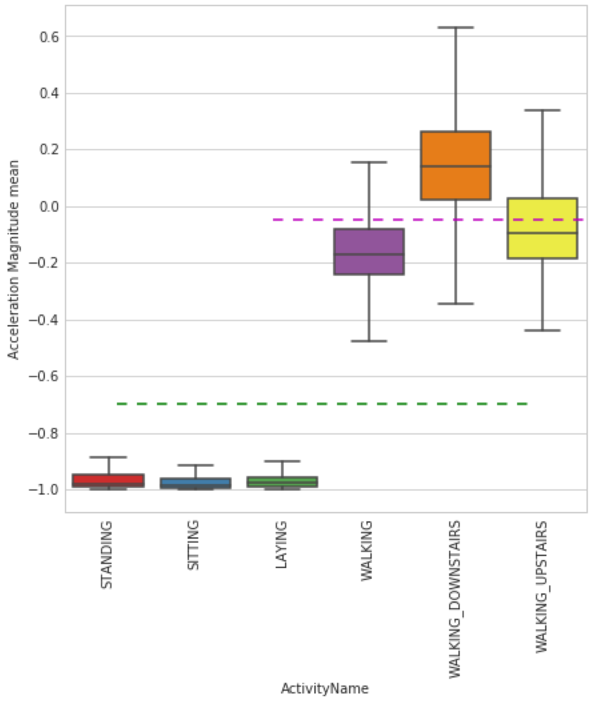



```
# for plotting purposes taking datapoints of each activity to a different dataframe
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

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

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


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



3. Magnitude of an acceleration can saperate it well

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

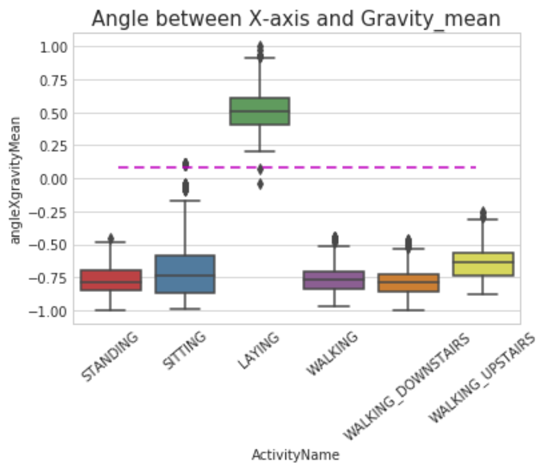


__ Observations__:

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

4. Position of GravityAccelerationComponants also matters

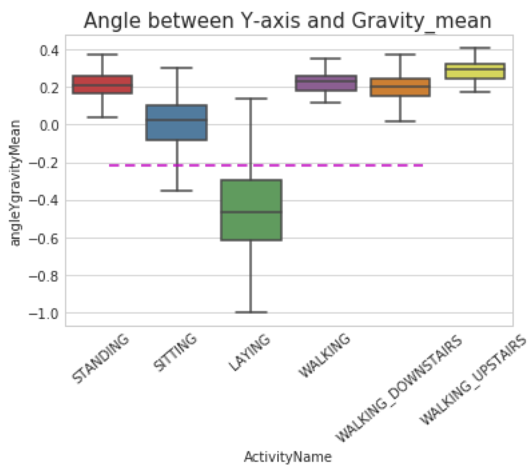
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



__ 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.

```
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()
```



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Apply t-sne on the data

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


# performs t-sne with different perplexity values and their repective plots..

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

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

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

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



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

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


```
Done

performing tsne with perplexity 5 and with 1000 iterations at max
[t-SNE] Computing 16 nearest neighbors...
[t-SNE] Indexed 7352 samples in 0.263s...
[t-SNE] Computed neighbors for 7352 samples in 48.983s...
[t-SNE] Computed conditional probabilities for sample 1000 / 7352
[t-SNE] Computed conditional probabilities for sample 2000 / 7352
[t-SNE] Computed conditional probabilities for sample 3000 / 7352
[t-SNE] Computed conditional probabilities for sample 4000 / 7352
[t-SNE] Computed conditional probabilities for sample 5000 / 7352
[t-SNE] Computed conditional probabilities for sample 6000 / 7352
[t-SNE] Computed conditional probabilities for sample 7000 / 7352
[t-SNE] Computed conditional probabilities for sample 7352 / 7352
[t-SNE] Mean sigma: 0.961265
[t-SNE] Computed conditional probabilities in 0.122s
```

```
import numpy as np
import pandas as pd
```

Obtain the train and test data

```
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)
```

```
train.head(3)
```

	tBodyAccmeanX	tBodyAccmeanY	tBodyAccmeanZ	tBodyAccstdX	tBodyAccstdY	tBodyAccstdZ	tBodyAccmadX	tBodyAccmadY	tBodyAccmadZ
0	0.288585	-0.020294	-0.132905	-0.995279	-0.983111	-0.913526	-0.995112	-0.983185	-0.923527
1	0.278419	-0.016411	-0.123520	-0.998245	-0.975300	-0.960322	-0.998807	-0.974914	-0.957686
2	0.279653	-0.019467	-0.113462	-0.995380	-0.967187	-0.978944	-0.996520	-0.963668	-0.977469

3 rows × 564 columns

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

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

```
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,))
```

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Let's model with our data

Labels that are useful in plotting confusion matrix

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

Function to plot the confusion matrix

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

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

    plt.imshow(cm, interpolation='nearest', cmap=cmap)
    plt.title(title)
    plt.colorbar()
    tick_marks = np.arange(len(classes))
```

```
    plt.xticks(tick_marks, classes, rotation=90)
    plt.yticks(tick_marks, classes)

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

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

Generic function to run any model specified

```
from datetime import datetime
def perform_model(model, X_train, y_train, X_test, y_test, class_labels, cm_normalize=True, \
                 print_cm=True, cm_cmap=plt.cm.Greens):


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

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


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


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


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

    # plot confusin matrix
    plt.figure(figsize=(8,8))
    plt.grid(b=False)
    plot_confusion_matrix(cm, classes=class_labels, normalize=True, title='Normalized confusion matrix', cmap = cm_cmap)
    plt.show()

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

    # add the trained  model to the results
```

```
    results['model'] = model

    return results
```

Method to print the gridsearch Attributes

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


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


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


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

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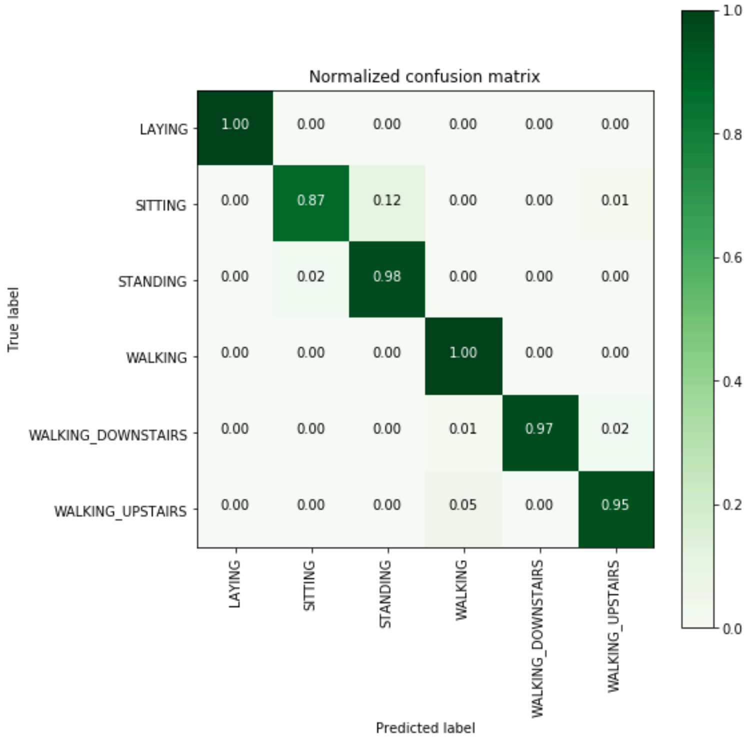
1. Logistic Regression with Grid Search

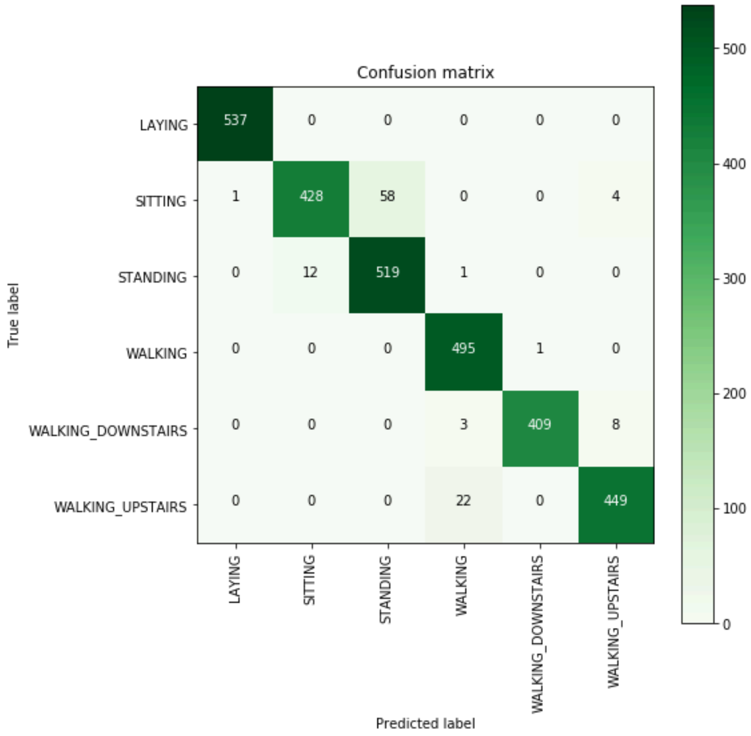
```
from sklearn import linear_model
from sklearn import metrics

from sklearn.model_selection import GridSearchCV



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

```
training the model..
Fitting 3 folds for each of 12 candidates, totalling 36 fits
[Parallel(n_jobs=-1)]: Done  36 out of  36 | elapsed:  1.2min finished
Done


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


Predicting test data
Done


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


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

    0.9626739056667798


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

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




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

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

       avg / total       0.96      0.96      0.96      2947
```

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




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

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

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

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

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

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9461371055495104
```

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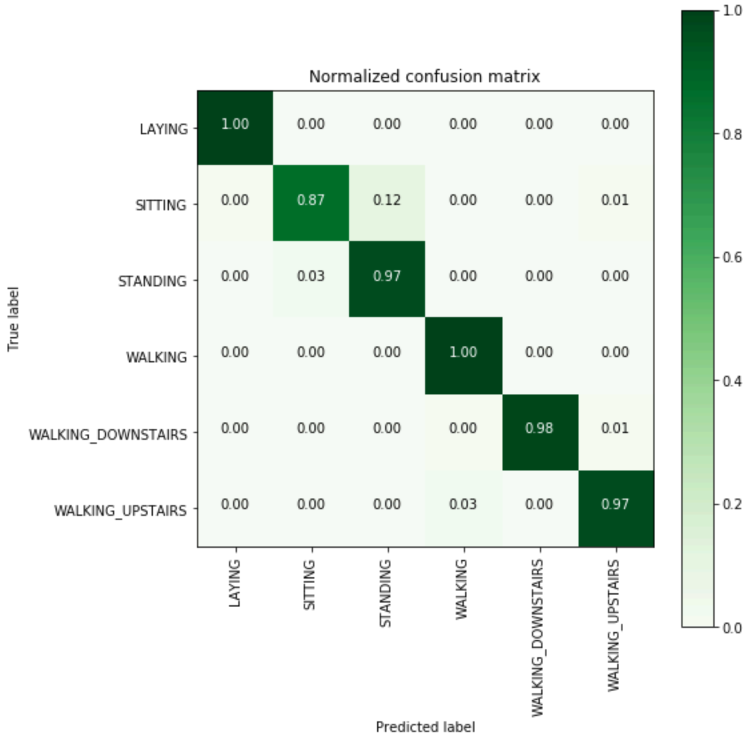
2. Linear SVC with GridSearch

```
from sklearn.svm import LinearSVC


parameters = {'C':[0.125, 0.5, 1, 2, 8, 16]}
lr_svc = LinearSVC(tol=0.00005)
```

```
lr_svc_grid = GridSearchCV(lr_svc, param_grid=parameters, n_jobs=-1, verbose=1)
lr_svc_grid_results = perform_model(lr_svc_grid, X_train, y_train, X_test, y_test, class_labels=labels)
```

```
training the model..
Fitting 3 folds for each of 6 candidates, totalling 18 fits
[Parallel(n_jobs=-1)]: Done  18 out of  18 | elapsed:   24.9s finished
Done


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


Predicting test data
Done


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


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

    0.9660671869697998


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

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




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

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

       avg / total       0.97      0.97      0.97      2947
```

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

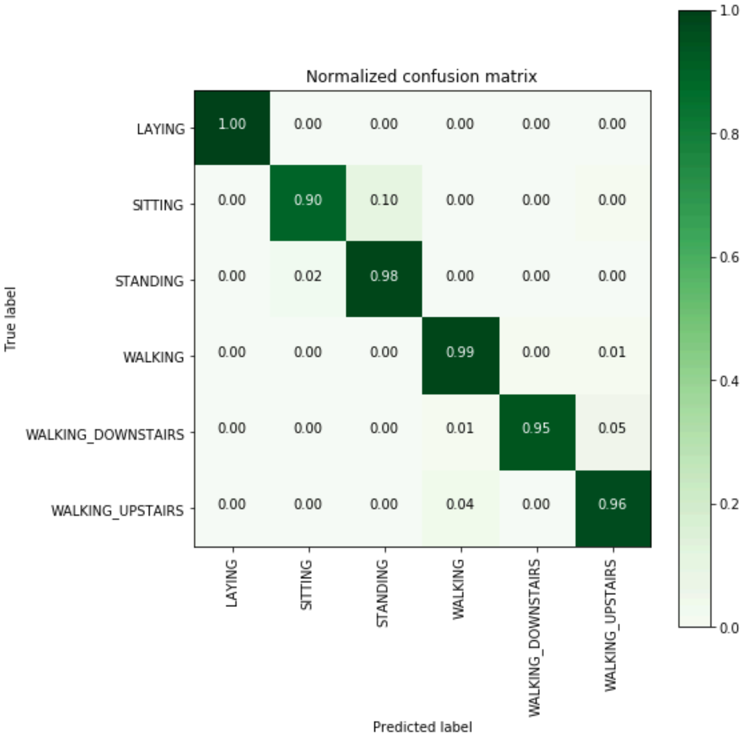
```
--------------------------
|      Best Estimator     |
--------------------------
```

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

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

        {'C': 8}

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9465451577801959
```

3. Kernel SVM with GridSearch

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

```
training the model..
Done


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


Predicting test data
Done


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


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

    0.9626739056667798


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

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




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

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

       avg / total       0.96      0.96      0.96      2947
```

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

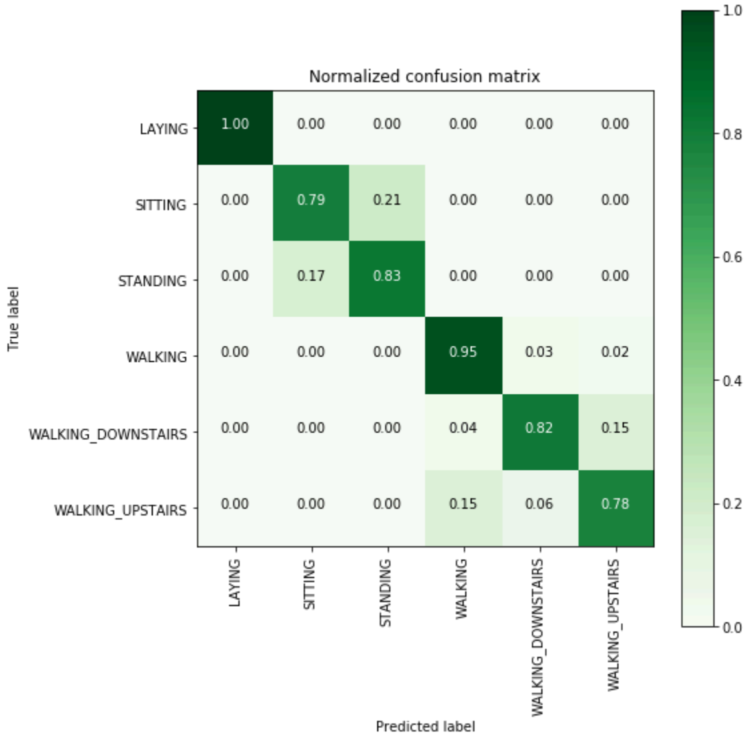
```
--------------------------
|      Best Estimator     |
--------------------------

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

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

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

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

        Total numbre of cross validation sets: 3

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

        Average Cross Validate scores of best estimator :

        0.9440968443960827
```

4. Decision Trees with GridSearchCV

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

```
training the model..
Done


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


Predicting test data
Done


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


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

    0.8642687478791992


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

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




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

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

       avg / total       0.86      0.86      0.86      2947

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

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

--------------------------
|     Best parameters     |
```

```
# Importing Libraries


import pandas as pd
import numpy as np


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

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

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

Data

```
# Data directory
DATADIR = 'UCI_HAR_Dataset'


# 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"
]


# 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).as_matrix()
        )

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



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).as_matrix()


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


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


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


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


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


# Initializing parameters
epochs = 30
batch_size = 16
n_hidden = 32


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


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


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

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

```
_________________________________________________________________
Layer (type)                 Output Shape              Param #
=================================================================
lstm_3 (LSTM)                (None, 32)                5376
_________________________________________________________________
```

```
dropout_3 (Dropout)          (None, 32)                0
_________________________________________________________________
dense_3 (Dense)              (None, 6)                 198
=================================================================
Total params: 5,574
Trainable params: 5,574
Non-trainable params: 0
_________________________________________________________________
```

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

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

```
7352/7352 [==============================] - 94s 13ms/step - loss: 0.9666 - acc: 0.5880 - val_loss: 0.9491 - val_acc: 0.5714
Epoch 3/30
7352/7352 [==============================] - 97s 13ms/step - loss: 0.7812 - acc: 0.6408 - val_loss: 0.8286 - val_acc: 0.5850
Epoch 4/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.6941 - acc: 0.6574 - val_loss: 0.7297 - val_acc: 0.6128
Epoch 5/30
7352/7352 [==============================] - 92s 13ms/step - loss: 0.6336 - acc: 0.6912 - val_loss: 0.7359 - val_acc: 0.6787
Epoch 6/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.5859 - acc: 0.7134 - val_loss: 0.7015 - val_acc: 0.6939
Epoch 7/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.5692 - acc: 0.7477 - val_loss: 0.5995 - val_acc: 0.7387
Epoch 8/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.4899 - acc: 0.7809 - val_loss: 0.5762 - val_acc: 0.7387
Epoch 9/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.4482 - acc: 0.7886 - val_loss: 0.7413 - val_acc: 0.7126
Epoch 10/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.4132 - acc: 0.8077 - val_loss: 0.5048 - val_acc: 0.7513
Epoch 11/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.3985 - acc: 0.8274 - val_loss: 0.5234 - val_acc: 0.7452
Epoch 12/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.3378 - acc: 0.8638 - val_loss: 0.4114 - val_acc: 0.8833
Epoch 13/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.2947 - acc: 0.9051 - val_loss: 0.4386 - val_acc: 0.8731
Epoch 14/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.2448 - acc: 0.9291 - val_loss: 0.3768 - val_acc: 0.8921
Epoch 15/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.2157 - acc: 0.9331 - val_loss: 0.4441 - val_acc: 0.8931
Epoch 16/30
7352/7352 [==============================] - 90s 12ms/step - loss: 0.2053 - acc: 0.9366 - val_loss: 0.4162 - val_acc: 0.8968
Epoch 17/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.2028 - acc: 0.9404 - val_loss: 0.4538 - val_acc: 0.8962
Epoch 18/30
7352/7352 [==============================] - 93s 13ms/step - loss: 0.1911 - acc: 0.9419 - val_loss: 0.3964 - val_acc: 0.8999
Epoch 19/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1912 - acc: 0.9407 - val_loss: 0.3165 - val_acc: 0.9030
Epoch 20/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1732 - acc: 0.9446 - val_loss: 0.4546 - val_acc: 0.8904
Epoch 21/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.1782 - acc: 0.9444 - val_loss: 0.3346 - val_acc: 0.9063
Epoch 22/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1812 - acc: 0.9418 - val_loss: 0.8164 - val_acc: 0.8582
Epoch 23/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1824 - acc: 0.9426 - val_loss: 0.4240 - val_acc: 0.9036
Epoch 24/30
7352/7352 [==============================] - 94s 13ms/step - loss: 0.1726 - acc: 0.9429 - val_loss: 0.4067 - val_acc: 0.9148
Epoch 25/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1737 - acc: 0.9411 - val_loss: 0.3396 - val_acc: 0.9074
Epoch 26/30
7352/7352 [==============================] - 96s 13ms/step - loss: 0.1650 - acc: 0.9461 - val_loss: 0.3806 - val_acc: 0.9019
Epoch 27/30
7352/7352 [==============================] - 89s 12ms/step - loss: 0.1925 - acc: 0.9415 - val_loss: 0.6464 - val_acc: 0.8850
Epoch 28/30
7352/7352 [==============================] - 91s 12ms/step - loss: 0.1965 - acc: 0.9425 - val_loss: 0.3363 - val_acc: 0.9203
Epoch 29/30
7352/7352 [==============================] - 92s 12ms/step - loss: 0.1889 - acc: 0.9431 - val_loss: 0.3737 - val_acc: 0.9158
Epoch 30/30
7352/7352 [==============================] - 95s 13ms/step - loss: 0.1945 - acc: 0.9414 - val_loss: 0.3088 - val_acc: 0.9097
<keras.callbacks.History at 0x29b5ee36a20>
```

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

```
Pred                LAYING  SITTING  STANDING  WALKING  WALKING_DOWNSTAIRS  \
True
LAYING                 512        0        25        0                   0
SITTING                  3      410        75        0                   0
```

```
STANDING                 0       87       445       0                    0
WALKING                  0        0         0     481                    2
WALKING_DOWNSTAIRS       0        0         0       0                  382
WALKING_UPSTAIRS         0        0         0       2                   18

Pred                WALKING_UPSTAIRS
True
LAYING                             0
SITTING                            3
STANDING                           0
WALKING                           13
WALKING_DOWNSTAIRS                38
WALKING_UPSTAIRS                 451
```

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

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

```
score
```

```
[0.3087582236972612, 0.9097387173396675]
```

- With a simple 2 layer architecture we got 90.09% accuracy and a loss of 0.30
- We can further imporve the performace with Hyperparameter tuning