HumanActivityRecognition

This project is to build a model that predicts the human activities such as Walking, Walking_Upstairs, Walking_Downstairs, Sitting, Standing or Laying. We are building a 6-class classifier.

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. accelerometer measures acceleration and gyroscope measures angular velocity. This experiment was video recorded to label the data manually.

Accelerometers are Tri-axial, which means, they measure accelaration on X-axis, Y-axis and Z-axis measured over time. Gyroscopes are also Tri-axial, which means, they measure velocity on X-axis, Y-axis and Z-axis and also there is time series for X,Y,Z axis.

As input there is 6 time series data for both Accelerometers and Gyroscopes for each axis. Using this input, we predict one of the 6 human activities mentioned above.

This is a multi-class classification problem. The metric we use is accuracy, confusion matrix (to see for which class model is performing well and for which class is it not), multi class log-loss.

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. We take each window of data and apply some filters like signal processing type, on the window data and then converted into a fixed length vector.
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

Next window of data is taken like, 50% of part from first window which is overlapping and 50% of part in second window. Then filter and sampling is applied on this data and is converted into numerical vector of fixed size.

This process is continued to all 6 time series data . Each vector is of size 128.

1. 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.
2. After that, the body linear acceleration and angular velocity were derived in time to obtian *jerk signals* (***tBodyAccJerk-XYZ*** and ***tBodyGyroJerk-XYZ***).
3. 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*.
4. 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.,.
5. These are the signals that we got so far.

   - tBodyAcc-XYZ
   - tGravityAcc-XYZ
   - tBodyAccJerk-XYZ -- Jerk is rate of change of acceleration
   - tBodyGyro-XYZ
   - tBodyGyroJerk-XYZ
   - tBodyAccMag -- Mag means magnitude of wave
   - tGravityAccMag
   - tBodyAccJerkMag
   - tBodyGyroMag
   - tBodyGyroJerkMag
   - fBodyAcc-XYZ
   - fBodyAccJerk-XYZ
   - fBodyGyro-XYZ
   - fBodyAccMag
   - fBodyAccJerkMag
   - fBodyGyroMag
   - fBodyGyroJerkMag

All the features start with 't' uses the time signal, and features that start with 'f' uses Fourier Transform.

1. 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.

2. 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

There are total 30 members from whom data is collected. These 30 people are divided into 70(21 users) - 30(9 users). We train models on the data from 21 users and test it on data of 9 users.

- 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

For each of the original data, it is converted into windows. On each window we apply signal processing filters and convert it into 128 dimensional vector. For all the raw values in the vector, many features are engineered as shown above.

This case had both the expert engineered features and raw time-series. We build models on both of these. We use deep learning to build models on raw time series data. Like RNN which can handle time series data.

To build models on expert engineered features we will use classical machine learning models

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

  The process we follow is :-
- First load expert generated data and perform Preprocessing and EDA then build models on this data.
- Next get raw 128-dimension time series data and we apply Deep leraning algorithms on this data.

In [1]:
```
import numpy as np
import pandas as pd

# get the features from the file features.txt
features = list()
with open('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_Dataset\\fea
tures.txt') as f:
    features = [line.split()[1] for line in f.readlines()]
print('No of Features: {}'.format(len(features)))
```

```
No of Features: 561
```

Obtain the train data

In [2]:
```
# get the data from txt files to pandas dataffame
X_train = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_
Dataset\\train\\X_train.txt', delim_whitespace=True, header=None, names=featur
es)

# add subject column to the dataframe
X_train['subject'] = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HA
R\\UCI_HAR_Dataset\\train\\subject_train.txt', header=None, squeeze=True)

y_train = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_
Dataset\\train\\y_train.txt', names=['Activity'], squeeze=True)
y_train_labels = y_train.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DO
WNSTAIRS',\
                       4:'SITTING', 5:'STANDING',6:'LAYING'})

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

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

Out[2]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X
6015	0.2797	-0.004397	-0.10952	0.359081	0.119909	-0.177541	0.337963

1 rows × 564 columns

In [3]:
```
train.shape
```

Out[3]: (7352, 564)

Obtain the test data

In [4]:
```
# get the data from txt files to pandas dataffame
X_test = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_D
ataset\\test\\X_test.txt', delim_whitespace=True, header=None, names=features)

# add subject column to the dataframe
X_test['subject'] = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HAR
\\UCI_HAR_Dataset\\test\\subject_test.txt', header=None, squeeze=True)

# get y labels from the txt file
y_test = pd.read_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_D
ataset\\test\\y_test.txt', names=['Activity'], squeeze=True)
y_test_labels = y_test.map({1: 'WALKING', 2:'WALKING_UPSTAIRS',3:'WALKING_DOWN
STAIRS',\
                       4:'SITTING', 5:'STANDING',6:'LAYING'})


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

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

Out[4]:

	tBodyAcc-mean()-X	tBodyAcc-mean()-Y	tBodyAcc-mean()-Z	tBodyAcc-std()-X	tBodyAcc-std()-Y	tBodyAcc-std()-Z	tBodyAcc-mad()-X
2261	0.279196	-0.018261	-0.103376	-0.996955	-0.982959	-0.988239	-0.9972

1 rows × 564 columns

In [5]:
```
test.shape
```

Out[5]: (2947, 564)

Data Cleaning

1. Check for Duplicates

In [6]:
```
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

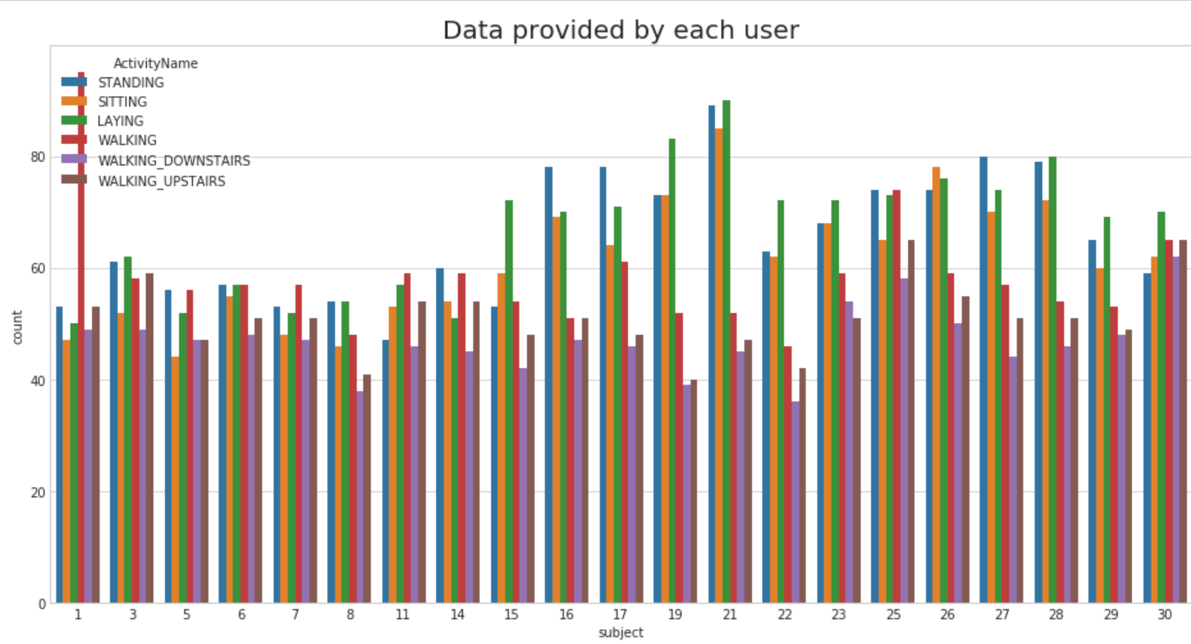
In [7]:
```
print('We have {} NaN/Null values in train'.format(train.isnull().values.sum
()))
print('We have {} NaN/Null values in test'.format(test.isnull().values.sum()))
```

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

3. Check for data imbalance

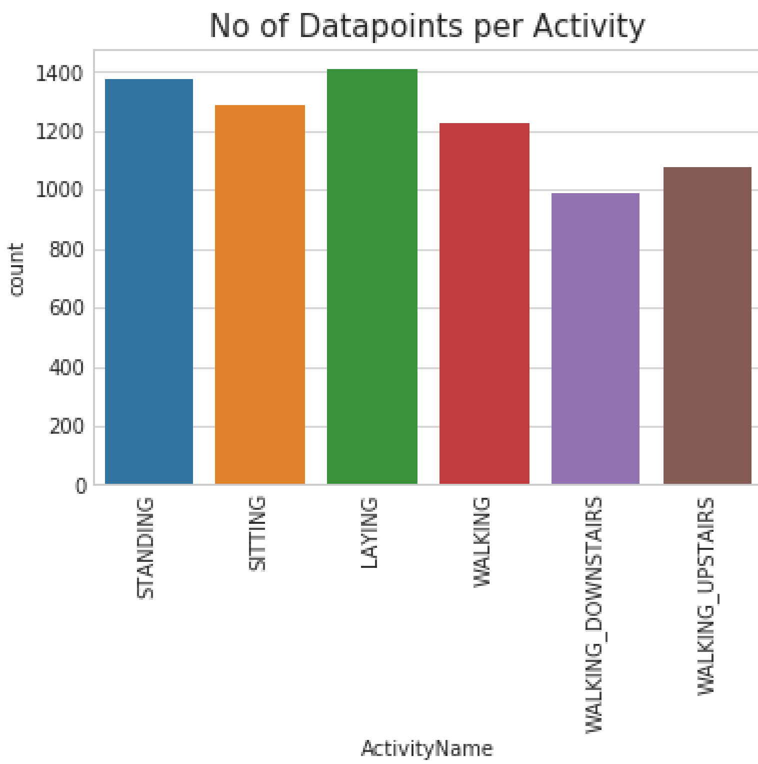
In [8]:
```
import matplotlib.pyplot as plt
import seaborn as sns

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

In [9]:
```
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 [10]:
```
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 [11]:
```
columns = train.columns

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

train.columns = columns
test.columns = columns

test.columns
```

Out[11]:
```
Index(['tBodyAccmeanX', 'tBodyAccmeanY', 'tBodyAccmeanZ', 'tBodyAccstdX',
       'tBodyAccstdY', 'tBodyAccstdZ', 'tBodyAccmadX', 'tBodyAccmadY',
       'tBodyAccmadZ', 'tBodyAccmaxX',
       ...
       'angletBodyAccMeangravity', 'angletBodyAccJerkMeangravityMean',
       'angletBodyGyroMeangravityMean', 'angletBodyGyroJerkMeangravityMean',
       'angleXgravityMean', 'angleYgravityMean', 'angleZgravityMean',
       'subject', 'Activity', 'ActivityName'],
      dtype='object', length=564)
```

5. Save this dataframe in a csv files

In [13]:
```
# Train.csv and test.csv have expert generated features, we have not come to t
ime series data yet.

train.to_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_Dataset\\
csv_files\\train.csv', index=False)
test.to_csv('F:\\Python\\Appliedai\\Human recognition\\HAR\\UCI_HAR_Dataset\\c
sv_files\\test.csv', index=False)
```

Exploratory Data Analysis

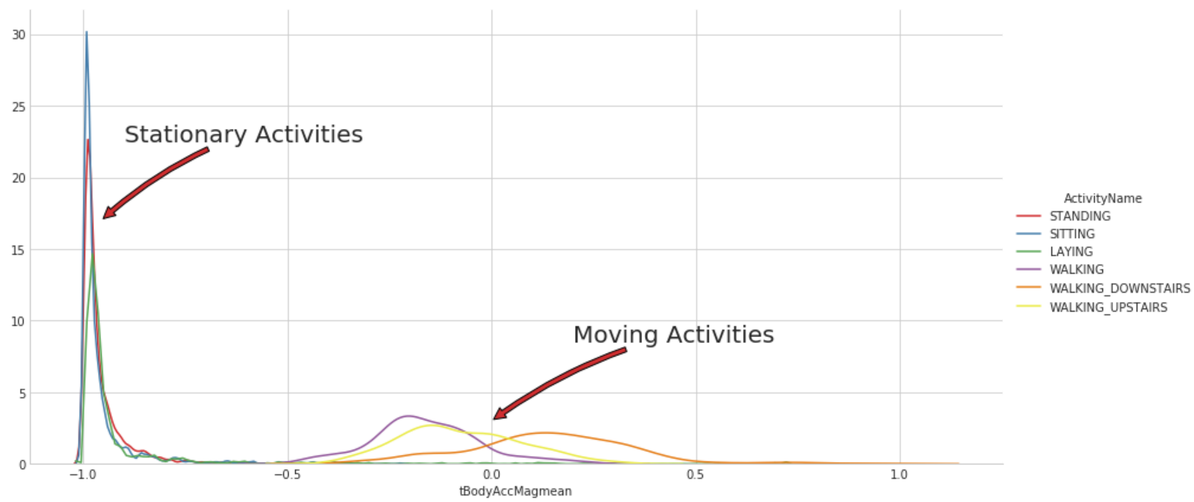
"***Without domain knowledge EDA has no meaning, without EDA a problem has no soul.***"

1. Featuring Engineering from Domain Knowledge

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

2. Stationary and Moving activities are completely different

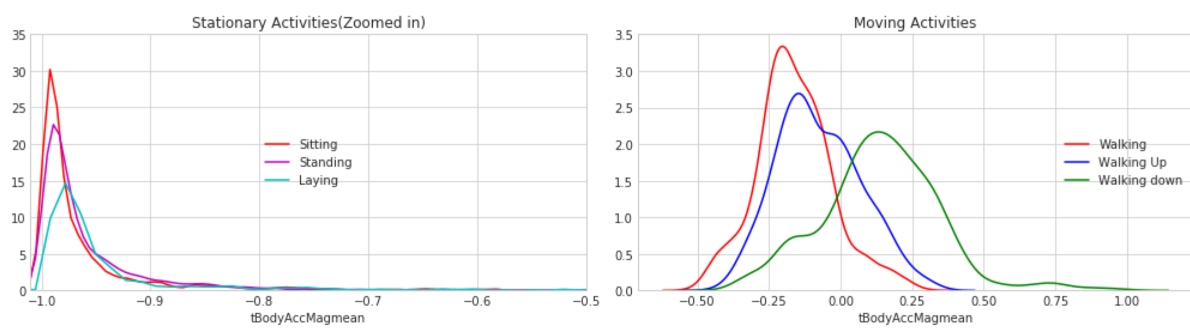
In [14]:
```
sns.set_palette("Set1", desat=0.80)
facetgrid = sns.FacetGrid(train, hue='ActivityName', size=6,aspect=2)
facetgrid.map(sns.distplot,'tBodyAccMagmean', hist=False)\
    .add_legend()
plt.annotate("Stationary Activities", xy=(-0.956,17), xytext=(-0.9, 23), size=
20,\
            va='center', 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()
```



Observation:-

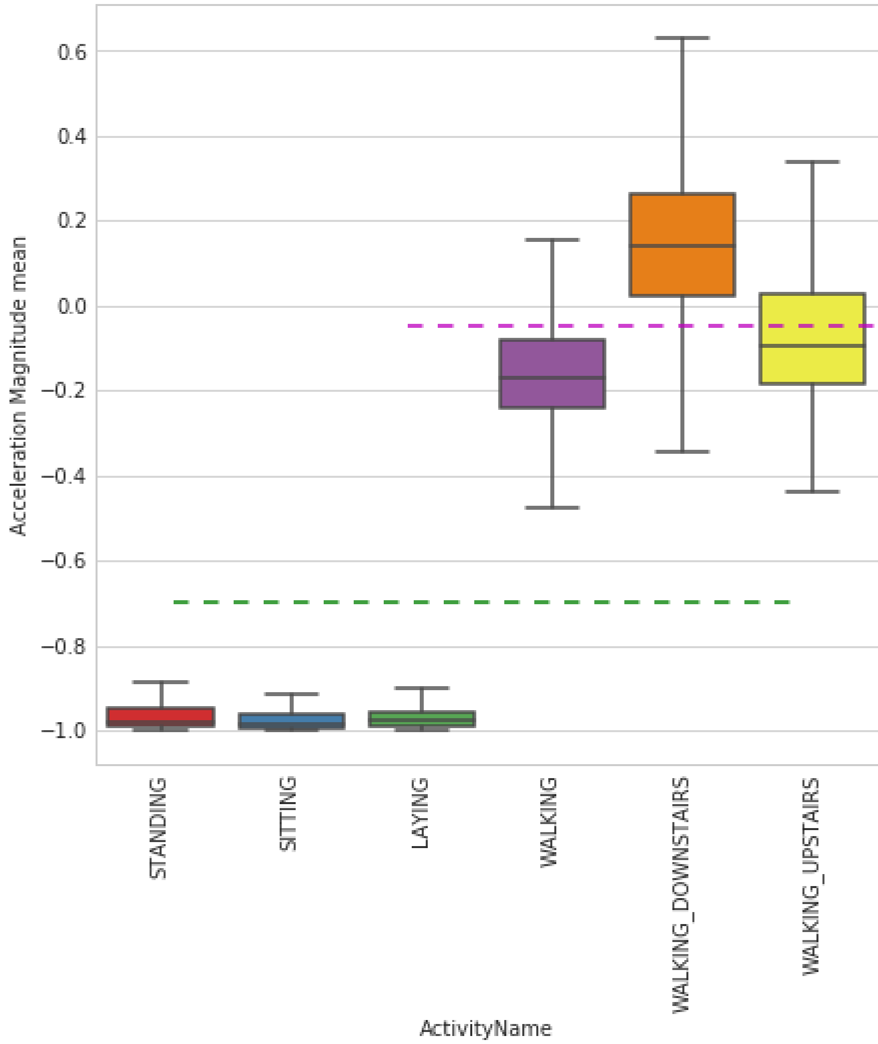
1. The feature tBodyAccMagmean clearly seperated Stationary/static and Moving activities/dynamic activities.

In [15]:
```
# for plotting purposes taking datapoints of each activity to a different data
frame
df1 = train[train['Activity']==1]
df2 = train[train['Activity']==2]
df3 = train[train['Activity']==3]
df4 = train[train['Activity']==4]
df5 = train[train['Activity']==5]
df6 = train[train['Activity']==6]

plt.figure(figsize=(14,7))
plt.subplot(2,2,1)
plt.title('Stationary Activities(Zoomed in)')
sns.distplot(df4['tBodyAccMagmean'],color = 'r',hist = False, label = 'Sittin
g')
sns.distplot(df5['tBodyAccMagmean'],color = 'm',hist = False,label = 'Standin
g')
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 = 'Walki
ng')
sns.distplot(df2['tBodyAccMagmean'],color = 'blue',hist = False,label = 'Walki
ng Up')
sns.distplot(df3['tBodyAccMagmean'],color = 'green',hist = False, label = 'Wal
king down')
plt.legend(loc='center right')


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



3. Magnitude of an acceleration can saperate it well

In [16]:
```
plt.figure(figsize=(7,7))
sns.boxplot(x='ActivityName', y='tBodyAccMagmean',data=train, showfliers=False
, saturation=1)
plt.ylabel('Acceleration Magnitude mean')
plt.axhline(y=-0.7, xmin=0.1, xmax=0.9,dashes=(5,5), c='g')
plt.axhline(y=-0.05, xmin=0.4, dashes=(5,5), c='m')
plt.xticks(rotation=90)
plt.show()
```

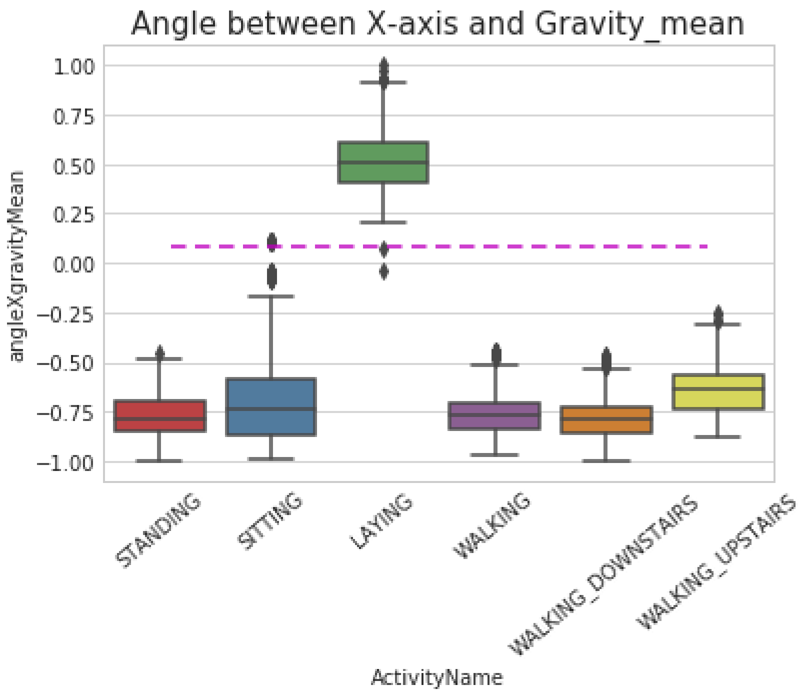


Observations:

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

4. Position of GravityAccelerationComponants also matters

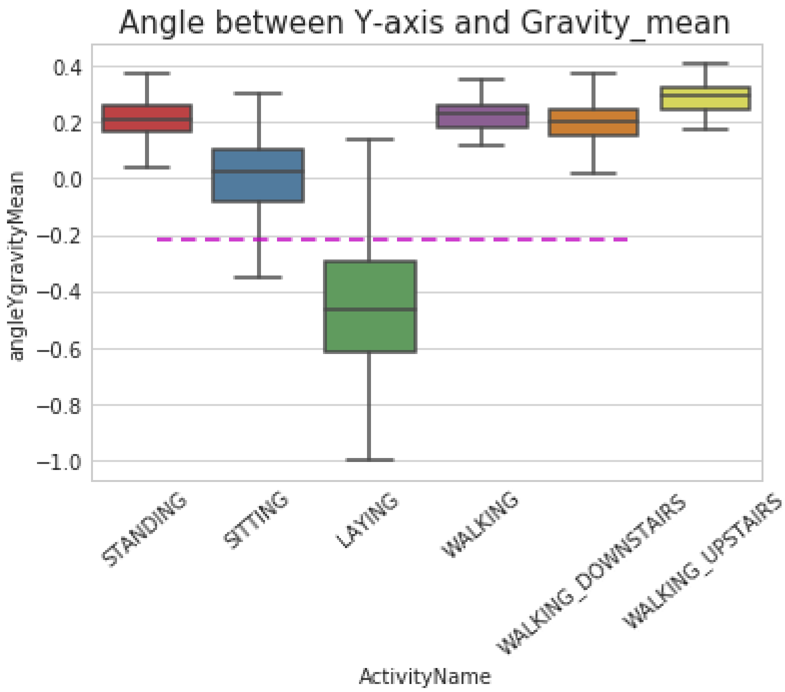
In [17]:
```
sns.boxplot(x='ActivityName', y='angleXgravityMean', data=train)
plt.axhline(y=0.08, xmin=0.1, xmax=0.9,c='m',dashes=(5,3))
plt.title('Angle between X-axis and Gravity_mean', fontsize=15)
plt.xticks(rotation = 40)
plt.show()
```



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 [18]:
```
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 [46]:
```
import numpy as np
from sklearn.manifold import TSNE
import matplotlib.pyplot as plt
import seaborn as sns
```

In [47]:
```
# performs t-sne with different perplexity values and their repective plots..
# TSNE on 561 features /dimensions expert engineered features
# we mapped 561 dim to 2 dim space using TSNE

def perform_tsne(X_data, y_data, perplexities, n_iter=1000, img_name_prefix='t
-sne'):
    for index,perplexity in enumerate(perplexities):
        # perform t-sne
        print('\nperforming tsne with perplexity {} and with {} iterations at
 max'.format(perplexity, n_iter))
        X_reduced = TSNE(verbose=2, perplexity=perplexity).fit_transform(X_dat
a)
        print('Done..')

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

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

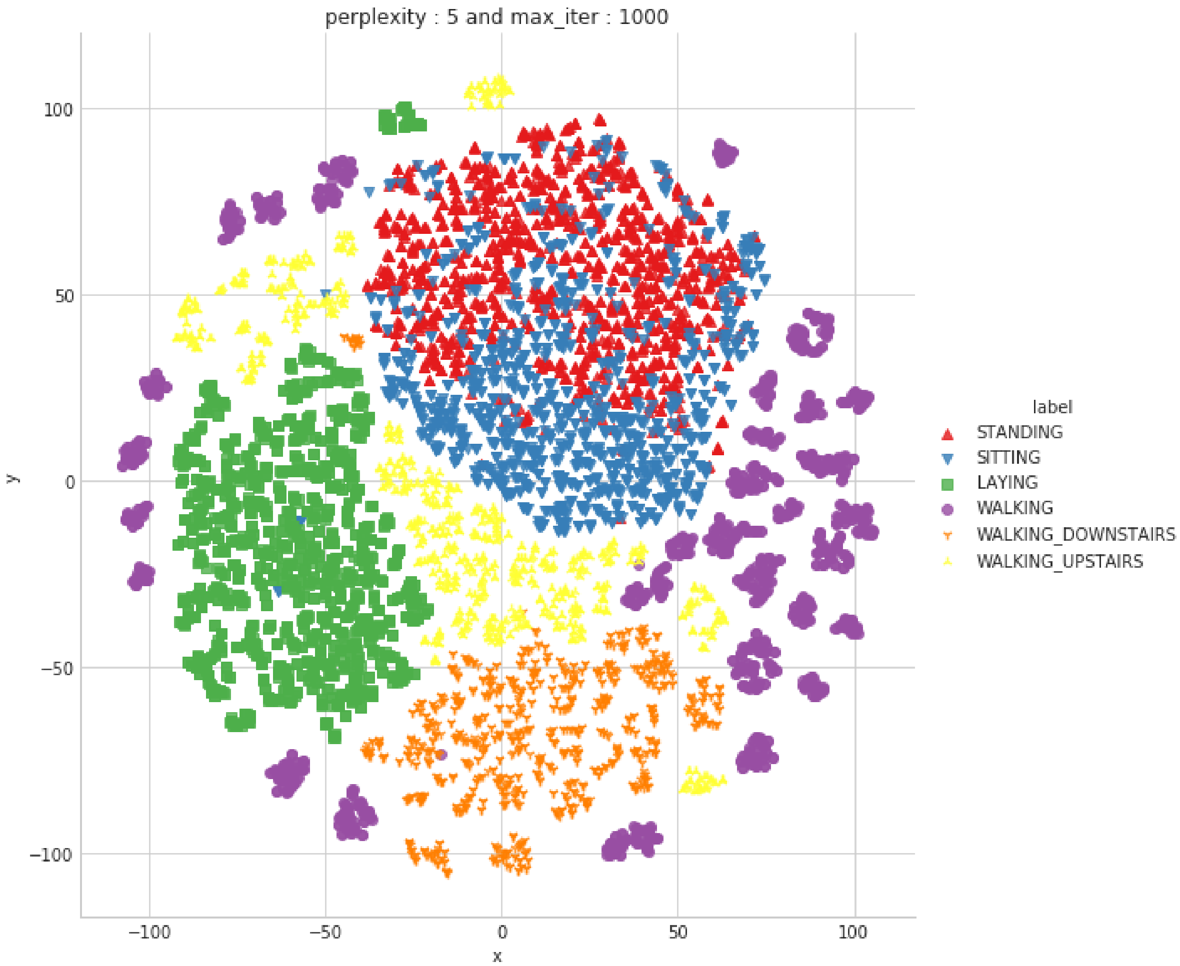
In [48]:
```
X_pre_tsne = train.drop(['subject', 'Activity','ActivityName'], axis=1)
y_pre_tsne = train['ActivityName']
perform_tsne(X_data = X_pre_tsne,y_data=y_pre_tsne, perplexities =[2,5,10,20,5
0])
```

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

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

```
Done

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

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

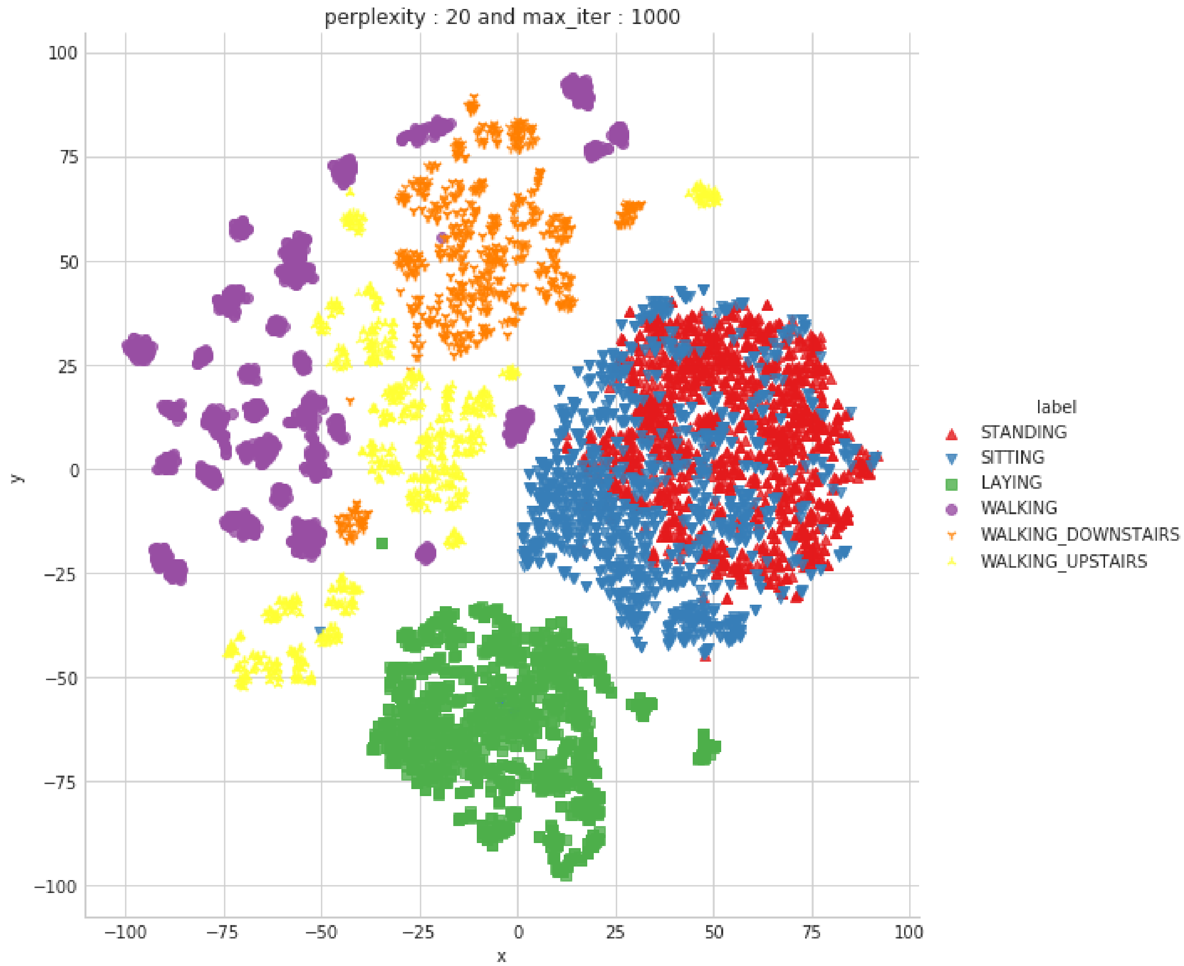


```
Done

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

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

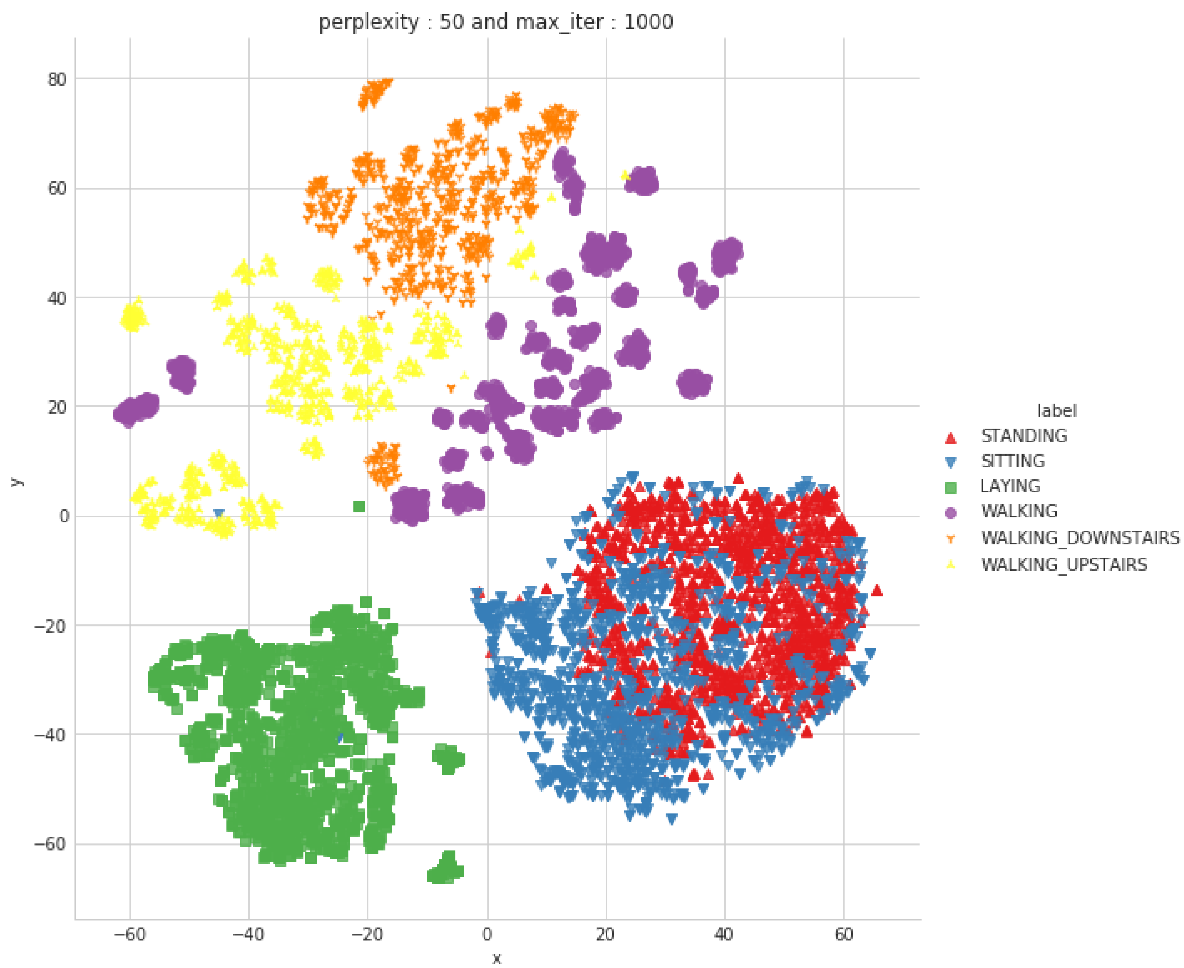
```
Done

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

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



```
Done

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

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




```
Done
```