Data Science Research of The PAMAP2 Physical Activity Monitoring Dataset

Overview

For this assignment, PAMAP2 Physical Activity Monitoring Dataset is used. This dataset contains data of 3 inertial measurement units and a heart rate monitor of 9 different subjects(1 female and 8 male) performing 18 various physical activities(running,rope jumping, lying etc) and the readings related to their hand,chest and ankle were noted down.

Source of dataset

The readings of individual subject is stored as text file in .dat format. This text file contains readings of 54 different attributes(including timestamp, activity ID, heart rate and IMU sensory data).

Outcome

The goal is to develop hardware and/or software which can determine the amount (using start/end times and heart rates) and type of physical activity carried out by an individual

Specific Requirements

You are required to:

1. carry out thorough exploratory data analysis and appropriately handle missing or dirty data;
2. develop and test at least one hypothesis for a relationship between a single pair of attributes;
3. develop and test at least one model which uses multiple attributes to make predictions.

Introduction

This report focuses on data analysis steps performed on the data of each individual. The PAMAP2 Physical Activity Monitoring Dataset will be analysed to develop hardware and/or software which can determine the amount (using start/end times and heart rates) and type of physical activity carried out by an individual. So I would go through various steps to perform data analysis and analyse the chest measurements and heartrate.

In the first step of data analysis, I will read and analyse data of description of activities and the readings of different inertial measurement of the subjects while carrying out the activities. Then I will load all the readings of the each subject into a single dataframe. In second step I will perform data cleaning in the obtained dataframe to handle missing values, data normalization etc.

In the next step, I will perform the exploratory data analysis to obtain relationship of activity Id with different attributes(like heartrate, chest magnetometer etc). After EDA, I will state an hypothesis and perform hypothesis testing for the stated hypothesis.

In the last step, I will build a model to predict heartrate and the activity Id from multiple readings of the chest after analysing the correlation of the data.

Content

Initial steps of importing all the required libraries and loading data from the list of files.

Data Cleaning:

```
Function : data_cleaning()
           Sub-Function :fill_null_heartrate() :- replace Null values
of heart rate column
```

Exploratory Data Analysis:

```
Train,Test data splitting
Function : train_test_splitting() :- Splitting into train and test set

Correlation through heatmap
Function : genrate_heatmap() :- Generate Heat-Map

Time and activity Analysis with respect to the actvities undertaken by
each subject
Function : elapsedtime_heartrate() :- Estimating Elapsed Time and mean
heart rate for each subject and
            their corresponding activities

           Sub-Function : change_milllisec() :- convert calculated
elapsedtime to seconds

Function : plot_scatter() :- Plotting a scatter plot between mean
heart rate and elapsedtime(sec)

Activity Heartrate Analysis
Function: activity_heartrate() :- Analyse the heart rate for each
activity for a subject at time
```

Hypothesis Testing:

```
Hypothesis stated : A hypothesis of dependency between activity and
human heartrate fluctiations.
Function : con_cat() :- perform concatenation as per the requirement
hypothesis testing
Function : t_test()  :- Perform t-test
Function : hypo_test() :- Result based on t-test()
```

Modelling :

Data Reading

```
import numpy as np
import pandas as pd
from matplotlib import pyplot as plt
import math
import scipy.stats as stats
%matplotlib inline
from sklearn.model_selection import train_test_split
import sklearn.model_selection as cross_validation
```

Here a list of files(list_of_files) is created to read and load the .dat file into single dataframe. A dictionary activityIDdict is created which maps each activityId with associated activity name so we can use the name in the further steps of processing. Then list of hand, chest and ankle inertial measurement units(IMU) are made to so as to have column names for the obtained dataframe. There will be total of 54 IMU which means 54 columnns in the dataframe.

```
# Load data
list_of_files = ['Dataset/Protocol/subject101.dat',
                 'Dataset/Protocol/subject102.dat',
                 'Dataset/Protocol/subject103.dat',
                 'Dataset/Protocol/subject104.dat',
                 'Dataset/Protocol/subject105.dat',
                 'Dataset/Protocol/subject106.dat',
                 'Dataset/Protocol/subject107.dat',
                 'Dataset/Protocol/subject108.dat',
                 'Dataset/Protocol/subject109.dat' ]

subjectID = [1,2,3,4,5,6,7,8,9]

activityIDdict = {0: 'transient',
              1: 'lying',
              2: 'sitting',
              3: 'standing',
              4: 'walking',
              5: 'running',
              6: 'cycling',
              7: 'Nordic_walking',
              9: 'watching_TV',
              10: 'computer_work',
```

```
                11: 'car driving',
                12: 'ascending_stairs',
                13: 'descending_stairs',
                16: 'vacuum_cleaning',
                17: 'ironing',
                18: 'folding_laundry',
                19: 'house_cleaning',
                20: 'playing_soccer',
                24: 'rope_jumping' }

colNames = ["timestamp", "activityID","heartrate"]

IMUhand = ['handTemperature',
           'hand_acc16_1', 'hand_acc16_2', 'hand_acc16_3',
           'hand_acc6_1', 'hand_acc6_2', 'hand_acc6_3',
           'hand_gyro1', 'hand_gyro2', 'hand_gyro3',
           'hand_magne1', 'hand_magne2', 'hand_magne3',
           'hand_orientation1', 'hand_orientation2',
'hand_orientation3', 'hand_orientation4']

IMUchest = ['chestTemperature',
           'chest_acc16_1', 'chest_acc16_2', 'chest_acc16_3',
           'chest_acc6_1', 'chest_acc6_2', 'chest_acc6_3',
           'chest_gyro1', 'chest_gyro2', 'chest_gyro3',
           'chest_magne1', 'chest_magne2', 'chest_magne3',
           'chest_orientation1', 'chest_orientation2',
'chest_orientation3', 'chest_orientation4']

IMUankle = ['ankleTemperature',
           'ankle_acc16_1', 'ankle_acc16_2', 'ankle_acc16_3',
           'ankle_acc6_1', 'ankle_acc6_2', 'ankle_acc6_3',
           'ankle_gyro1', 'ankle_gyro2', 'ankle_gyro3',
           'ankle_magne1', 'ankle_magne2', 'ankle_magne3',
           'ankle_orientation1', 'ankle_orientation2',
'ankle_orientation3', 'ankle_orientation4']

columns = colNames + IMUhand + IMUchest + IMUankle  #all columns in
one list


def create_dataframe(list_of_files):
    datafr = pd.DataFrame()
    for file in list_of_files:
        #procData = pd.read_table(file, header=None, sep='\s+')
        df = pd.read_csv(file,sep='\s+|\s+',engine='python')
        strfile=file[17:27]+'.csv'
        df.to_csv(strfile, index=None)
        phydf=pd.read_csv(strfile)
        phydf.columns = columns
        phydf['subject_id'] = int(file[-5])
```

```
        #dataCollection = dataCollection.append(procData,
ignore_index=True)
        datafr=pd.concat([datafr, phydf], ignore_index=True)
    return datafr

datafr=create_dataframe(list_of_files)
#dataCollection.reset_index(drop=True, inplace=True)
datafr.reset_index(drop=True, inplace=True)
#dataCollection.head()
datafr.head(10)
```

```
   timestamp  activityID  heartrate  handTemperature  hand_acc16_1  \
0       8.39           0        NaN             30.0       2.18837
1       8.40           0        NaN             30.0       2.37357
2       8.41           0        NaN             30.0       2.07473
3       8.42           0        NaN             30.0       2.22936
4       8.43           0        NaN             30.0       2.29959
5       8.44           0        NaN             30.0       2.33738
6       8.45           0        NaN             30.0       2.37142
7       8.46           0        NaN             30.0       2.33951
8       8.47           0        NaN             30.0       2.25966
9       8.48           0      104.0             30.0       2.29745

   hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  ...  \
0       8.56560       3.66179      2.39494      8.55081
3.64207  ...
1       8.60107       3.54898      2.30514      8.53644
3.73280  ...
2       8.52853       3.66021      2.33528      8.53622
3.73277  ...
3       8.83122       3.70000      2.23055      8.59741
3.76295  ...
4       8.82929       3.54710      2.26132      8.65762
3.77788  ...
5       8.82900       3.54767      2.27703      8.77828
3.73230  ...
6       9.05500       3.39347      2.39786      8.89814
3.64131  ...
7       9.13251       3.54668      2.44371      8.98841
3.62596  ...
8       9.09415       3.43015      2.42877      9.01871
3.61081  ...
9       8.90450       3.46984      2.39736      8.94335
3.53551  ...

   ankle_gyro2  ankle_gyro3  ankle_magne1  ankle_magne2  ankle_magne3
\
0    -0.004638     0.000368      -59.8479      -38.8919      -58.5253
```

```
1      0.000148     0.022495      -60.7361      -39.4138      -58.3999

2     -0.020301     0.011275      -60.4091      -38.7635      -58.3956

3     -0.014303    -0.002823      -61.5199      -39.3879      -58.2694

4     -0.016024     0.001050      -60.2954      -38.8778      -58.3977

5     -0.053934     0.015594      -60.6307      -38.8676      -58.2711

6     -0.039937    -0.000785      -60.5171      -38.9819      -58.2733

7     -0.010042     0.017701      -61.2916      -39.6182      -58.1499

8     -0.013923     0.014498      -60.8509      -39.0821      -58.1478

9      0.002283     0.020352      -61.5302      -38.7240      -58.3860

   ankle_orientation1  ankle_orientation2  ankle_orientation3  \
0                 1.0                 0.0                 0.0
1                 1.0                 0.0                 0.0
2                 1.0                 0.0                 0.0
3                 1.0                 0.0                 0.0
4                 1.0                 0.0                 0.0
5                 1.0                 0.0                 0.0
6                 1.0                 0.0                 0.0
7                 1.0                 0.0                 0.0
8                 1.0                 0.0                 0.0
9                 1.0                 0.0                 0.0

   ankle_orientation4  subject_id
0                 0.0           1
1                 0.0           1
2                 0.0           1
3                 0.0           1
4                 0.0           1
5                 0.0           1
6                 0.0           1
7                 0.0           1
8                 0.0           1
9                 0.0           1

[10 rows x 55 columns]
```

Data Cleaning

Here in data cleaning we will be focusing on four steps:

i) removing the rows with activityID=0: For further analysis I won't be considering the activities with activityID = 0 as the subjects are not doing any task.

ii) dropping the irrelevant columns: Going further, I won't require any of the orientation columns for analysis so I will remove those columns .

iii) converting values into numeric value: Since our data is all about different readings which are recorded in number type I will be converting all the values which are in non numeric format into numeric type

iv) removal of null values: Here to remove all the null values, I will use interpolate function. Since in the dataset records the reading is taken every millisecond and the various IMU reading won't change drastically so I will assume the null value will be similar to the above row.

```
def data_cleaning(datafr):
    #function : data_cleaning : perform all the datacleaing activites
    #parameter : datafr : dataframe

    dataout = datafr.drop(datafr[datafr['activityID'] == 0].index)

dataout=datafr.drop(['hand_orientation1','hand_orientation2','hand_ori
entation3','hand_orientation4','chest_orientation1',

'chest_orientation2','chest_orientation3','chest_orientation4','ankle_
orientation1','ankle_orientation2',
            'ankle_orientation3','ankle_orientation4'],axis=1)
    dataout=datafr.apply(pd.to_numeric,errors='coerce')
    dataout=datafr.interpolate()

    return datafr
```

Data Cleaning process: data_cleaning():

Parameters passed(Input)-dataframe(datafr) to be cleaned created after reading the data

Output- returns dataframe(dataout) in which all the above mentioned steps are performed

Functions used:

i) drop(datafr[datafr['activityID'] == 0])-removing the rows with activityID=0

ii)drop()- dropping the irrelevant columns

iii) pd.to_numeric()-converting values into numeric value

iv)interpolate()-removal of null values

```
phydata=data_cleaning(datafr)
phydata
```

```
         timestamp  activityID  heartrate  handTemperature
hand_acc16_1  \
2927         37.66           1        NaN           30.375
2.21530
2928         37.67           1        NaN           30.375
2.29196
2929         37.68           1        NaN           30.375
2.29090
2930         37.69           1        NaN           30.375
2.21800
2931         37.70           1      100.0           30.375
2.30106
...            ...         ...        ...              ...           .
..
2872006      95.06          24      162.0           25.125
4.99466
2872007      95.07          24      162.0           25.125
5.02764
2872008      95.08          24      162.0           25.125
5.06409
2872009      95.09          24      162.0           25.125
5.13914
2872010      95.10          24      162.0           25.125
5.00812

         hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  \
2927          8.27915       5.58753      2.24689      8.55387
5.77143
2928          7.67288       5.74467      2.27373      8.14592
5.78739
2929          7.14240       5.82342      2.26966      7.66268
5.78846
2930          7.14365       5.89930      2.22177      7.25535
5.88000
2931          7.25857       6.09259      2.20720      7.24042
5.95555
...               ...           ...          ...          ...
...
2872006       6.01881       5.59830      4.90787      6.05780
5.68357
2872007       5.90369       5.48372      4.89090      5.95209
5.56301
2872008       5.71370       5.48491      4.97981      5.87584
5.45738
2872009       5.63724       5.48629      4.97690      5.69448
5.29167
2872010       5.40645       5.02326      4.97362      5.45272
5.14120
```

```
         ...  ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1  \
2927     ...       9.63162      -1.76757      0.265761     0.002908
2928     ...       9.58649      -1.75247      0.250816     0.020882
2929     ...       9.60196      -1.73721      0.356632    -0.035392
2930     ...       9.58674      -1.78264      0.311453    -0.032514
2931     ...       9.64677      -1.75240      0.295902     0.001351
...      ...           ...           ...           ...          ...
2872006  ...       9.41274      -2.26922     -1.759580     0.021288
2872007  ...       9.33733      -2.23908     -1.834950     0.010715
2872008  ...       9.32243      -2.23905     -1.804610    -0.016939
2872009  ...       9.38220      -2.26938     -1.880500    -0.028069
2872010  ...       9.41250      -2.23905     -1.820220    -0.013310

         ankle_gyro2  ankle_gyro3  ankle_magne1  ankle_magne2
ankle_magne3  \
2927       -0.027714     0.001752      -61.1081    -36.863600    -
58.369600
2928        0.000945     0.006007      -60.8916    -36.319700    -
58.365600
2929       -0.052422    -0.004882      -60.3407    -35.784200    -
58.611900
2930       -0.018844     0.026950      -60.7646    -37.102800    -
57.879900
2931       -0.048878    -0.006328      -60.2040    -37.122500    -
57.884700
...              ...          ...           ...           ...
...
2872006    -0.012885     0.005878      -45.7855     -0.831734     -
0.170139
2872007     0.003629    -0.004235      -46.0331     -0.817288
0.538134
2872008    -0.035176    -0.002309      -45.5140     -1.229410
0.540438
2872009    -0.036457    -0.007076      -45.9093     -0.565555
0.680109
2872010    -0.030195     0.018229      -46.1702     -0.812965     -
0.313346

         subject_id
2927              1
2928              1
2929              1
2930              1
2931              1
...             ...
2872006           9
2872007           9
2872008           9
2872009           9
2872010           9
```

```
[1942872 rows x 43 columns]
```

```
phydata.isnull().sum()
```

But since the top row will still have Nan values in heartrate we can see that the values should be 100 for the activityID=1 should be 100 so I filled the values with 100 in Nan value

```
phydata=phydata.fillna(100)
phydata.head()
```

```
      timestamp  activityID  heartrate  handTemperature  hand_acc16_1
\
2927      37.66           1      100.0           30.375       2.21530

2928      37.67           1      100.0           30.375       2.29196

2929      37.68           1      100.0           30.375       2.29090

2930      37.69           1      100.0           30.375       2.21800

2931      37.70           1      100.0           30.375       2.30106


      hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  ...  \
2927       8.27915       5.58753      2.24689      8.55387
5.77143  ...
2928       7.67288       5.74467      2.27373      8.14592
5.78739  ...
2929       7.14240       5.82342      2.26966      7.66268
5.78846  ...
2930       7.14365       5.89930      2.22177      7.25535
5.88000  ...
2931       7.25857       6.09259      2.20720      7.24042
5.95555  ...

      ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1
ankle_gyro2  \
2927       9.63162      -1.76757      0.265761     0.002908    -
0.027714
2928       9.58649      -1.75247      0.250816     0.020882
0.000945
2929       9.60196      -1.73721      0.356632    -0.035392    -
0.052422
2930       9.58674      -1.78264      0.311453    -0.032514    -
0.018844
2931       9.64677      -1.75240      0.295902     0.001351    -
0.048878
```

```
      ankle_gyro3  ankle_magne1  ankle_magne2  ankle_magne3
subject_id
2927     0.001752      -61.1081      -36.8636      -58.3696
1
2928     0.006007      -60.8916      -36.3197      -58.3656
1
2929    -0.004882      -60.3407      -35.7842      -58.6119
1
2930     0.026950      -60.7646      -37.1028      -57.8799
1
2931    -0.006328      -60.2040      -37.1225      -57.8847
1

[5 rows x 43 columns]
```

```
phydata.isnull().sum()
```

```
timestamp            0
activityID           0
heartrate            0
handTemperature      0
hand_acc16_1         0
hand_acc16_2         0
hand_acc16_3         0
hand_acc6_1          0
hand_acc6_2          0
hand_acc6_3          0
hand_gyro1           0
hand_gyro2           0
hand_gyro3           0
hand_magne1          0
hand_magne2          0
hand_magne3          0
chestTemperature     0
chest_acc16_1        0
chest_acc16_2        0
chest_acc16_3        0
chest_acc6_1         0
chest_acc6_2         0
chest_acc6_3         0
chest_gyro1          0
chest_gyro2          0
chest_gyro3          0
chest_magne1         0
chest_magne2         0
chest_magne3         0
ankleTemperature     0
ankle_acc16_1        0
ankle_acc16_2        0
```

```
ankle_acc16_3       0
ankle_acc6_1        0
ankle_acc6_2        0
ankle_acc6_3        0
ankle_gyro1         0
ankle_gyro2         0
ankle_gyro3         0
ankle_magne1        0
ankle_magne2        0
ankle_magne3        0
subject_id          0
dtype: int64
```

```
phydata.reset_index(drop = True, inplace = True)
phydata.head(10)
```

```
   timestamp  activityID  heartrate  handTemperature  hand_acc16_1  \
0      37.66           1      100.0           30.375       2.21530
1      37.67           1      100.0           30.375       2.29196
2      37.68           1      100.0           30.375       2.29090
3      37.69           1      100.0           30.375       2.21800
4      37.70           1      100.0           30.375       2.30106
5      37.71           1      100.0           30.375       2.07165
6      37.72           1      100.0           30.375       2.41148
7      37.73           1      100.0           30.375       2.32815
8      37.74           1      100.0           30.375       2.25096
9      37.75           1      100.0           30.375       2.14107

   hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  ...  \
0       8.27915       5.58753      2.24689      8.55387
5.77143  ...
1       7.67288       5.74467      2.27373      8.14592
5.78739  ...
2       7.14240       5.82342      2.26966      7.66268
5.78846  ...
3       7.14365       5.89930      2.22177      7.25535
5.88000  ...
4       7.25857       6.09259      2.20720      7.24042
5.95555  ...
5       7.25965       6.01218      2.19238      7.21038
6.01604  ...
6       7.59780       5.93915      2.23988      7.46679
6.03053  ...
7       7.63431       5.70686      2.31663      7.64745
6.01495  ...
8       7.78598       5.62821      2.28637      7.70801
5.93935  ...
9       7.52262       5.78141      2.31538      7.72276
5.78828  ...
```

```
   ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1  ankle_gyro2
\
0       9.63162      -1.76757      0.265761     0.002908    -0.027714

1       9.58649      -1.75247      0.250816     0.020882     0.000945

2       9.60196      -1.73721      0.356632    -0.035392    -0.052422

3       9.58674      -1.78264      0.311453    -0.032514    -0.018844

4       9.64677      -1.75240      0.295902     0.001351    -0.048878

5       9.60177      -1.75239      0.311276     0.003793    -0.026906

6       9.67694      -1.76748      0.326060     0.036814    -0.032277

7       9.61685      -1.76749      0.326380    -0.010352    -0.016621

8       9.61686      -1.72212      0.326234     0.039346     0.020393

9       9.63189      -1.70699      0.326105     0.029874    -0.010763


   ankle_gyro3  ankle_magne1  ankle_magne2  ankle_magne3  subject_id
0     0.001752      -61.1081      -36.8636      -58.3696           1
1     0.006007      -60.8916      -36.3197      -58.3656           1
2    -0.004882      -60.3407      -35.7842      -58.6119           1
3     0.026950      -60.7646      -37.1028      -57.8799           1
4    -0.006328      -60.2040      -37.1225      -57.8847           1
5     0.004125      -61.3257      -36.9744      -57.7501           1
6    -0.006866      -61.5520      -36.9632      -57.9957           1
7     0.006548      -61.5738      -36.1724      -59.3487           1
8    -0.011880      -61.7741      -37.1744      -58.1199           1
9     0.005133      -60.7680      -37.4206      -58.8735           1

[10 rows x 43 columns]
```

Conclusion of Data Cleaning

After doing data cleaning we got a dataframe(phydata) which we will use in the further steps of data analysis.

Exploratory Data Analysis

Here we will plot different graph for different readings.

Parameters passed: dataframe(phydata) which we got as output data cleaning Output: we will plot different graphs for different data

Process: Splitting into Test and Train set Correlation analysis

Splitting into Test and Train set

I will be splitting data into test and training sets in the ratio of 0.5. So we are dividing the test and train into two equal halves.

```
def splitting_train_test(dataframe,n=0.5):
    train_df = dataframe.sample(frac=n, random_state=1)
    test_df = dataframe.drop(train_df.index)
    return train_df,test_df
```

```
train_df,test_df = splitting_train_test(phydata,0.5)
```

```
train_df.describe()
```

```
           timestamp     activityID      heartrate  handTemperature  \
count  971436.000000  971436.000000  971436.000000    971436.000000
mean     1703.994666       8.081953     107.445857        32.751715
std      1093.247832       6.174908      26.975255         1.793871
min        31.220000       1.000000      57.000000        24.875000
25%       744.560000       3.000000      86.000000        31.687500
50%      1478.680000       6.000000     104.000000        33.125000
75%      2662.552500      13.000000     124.000000        34.062500
max      4245.680000      24.000000     202.000000        35.500000

         hand_acc16_1   hand_acc16_2   hand_acc16_3    hand_acc6_1  \
count   971436.000000  971436.000000  971436.000000  971436.000000
mean        -4.956991       3.579835       3.612234      -4.890270
std          6.244104       6.881571       3.962008       6.249035
min       -145.367000    -104.301000    -101.452000     -61.214700
25%         -8.970760       1.060202       1.171568      -8.866962
50%         -5.449225       3.525055       3.442250      -5.378790
75%         -0.964139       6.451445       6.533720      -0.909503
max         62.859600     155.699000     157.760000      45.548400

          hand_acc6_2    hand_acc6_3  ...    ankle_acc6_1   ankle_acc6_2
\
count   971436.000000  971436.000000  ...   971436.000000  971436.000000

mean         3.570034       3.796905  ...        9.370013      -0.046497

std          6.593962       3.946777  ...        6.068911       7.187835

min        -61.841700     -61.934700  ...      -61.142000     -61.903500
```

```
25%         1.060518       1.373687  ...       8.394965      -2.073703

50%         3.566135       3.674970  ...       9.549240      -0.223893

75%         6.458100       6.785285  ...      10.278000       1.920240

max        62.259800      61.728000  ...      61.969300      62.049000


        ankle_acc6_3    ankle_gyro1    ankle_gyro2    ankle_gyro3  \
count  971436.000000  971436.000000  971436.000000  971436.000000
mean       -2.176481       0.011323      -0.035935       0.007185
std         3.477410       1.124865       0.637566       2.009187
min       -62.203800     -13.592200      -7.324840     -12.977400
25%        -3.398802      -0.207035      -0.106357      -0.437332
50%        -1.992215       0.004692      -0.003908      -0.002289
75%        -0.595102       0.131925       0.116567       0.091502
max        55.553400      16.442700      13.588200      14.482700

        ankle_magne1   ankle_magne2   ankle_magne3     subject_id
count  971436.000000  971436.000000  971436.000000  971436.000000
mean      -31.582509       1.404674      17.253204       4.565264
std        18.346495      21.685612      19.705747       2.332310
min      -172.624000    -137.908000    -102.716000       1.000000
25%       -41.694300     -12.443825       3.813545       2.000000
50%       -33.998050       0.779744      18.771850       5.000000
75%       -17.897800      17.840625      31.241150       7.000000
max        91.551600      93.699200     139.787000       9.000000

[8 rows x 43 columns]
```

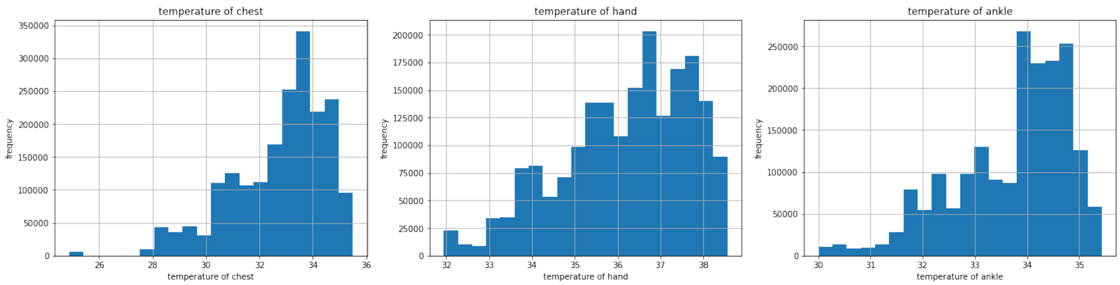
```python
plt.figure(figsize=(6,4))
plt.subplots_adjust(2,1,5,2)

plt.subplot(131)


phydata.handTemperature.hist(bins=20)
#dat0.price.plot(kind="hist",color='lightblue')
plt.xlabel("temperature of chest")
plt.ylabel("frequency")
plt.title('temperature of chest')
plt.subplot(132)
phydata.chestTemperature.hist(bins=20)
#dat0.price.plot(kind="hist",color='lightblue')
plt.xlabel("temperature of hand")
plt.ylabel("frequency")
plt.title('temperature of hand')
plt.subplot(133)
```

```
phydata.ankleTemperature.hist(bins=20)
#dat0.price.plot(kind="hist",color='lightblue')
plt.xlabel("temperature of ankle")
plt.ylabel("frequency")
plt.title('temperature of ankle')
```

```
Text(0.5, 1.0, 'temperature of ankle')
```



I will change the activityId into string values by mapping the activityId values in the activityIDdict dictionary.

```
phydatacop=train_df.copy()
phydatacop.activityID=phydatacop.activityID.apply(lambda
x:activityIDdict[x])
phydatacop
phydatacop[phydatacop['subject_id']==2]
```

```
        timestamp       activityID  heartrate  handTemperature
hand_acc16_1  \
312921     767.77         standing       90.0          34.1875      -
8.52981
361462    1390.52  vacuum_cleaning      104.0          34.5000     -
13.05990
349829    1193.29          ironing       84.0          34.4375
7.31548
460045    3470.56   Nordic_walking      124.0          30.1875      -
7.12054
342307    1118.07          ironing       84.0          34.3750      -
5.11778
...           ...              ...        ...              ...
...
368034    1456.24  vacuum_cleaning       98.0          34.5000      -
7.91946
253021      85.84            lying       87.0          33.5625
6.91583
427131    3017.77          walking      123.0          31.1875      -
5.27618
471794    3648.85          cycling      120.0          29.7500      -
6.10533
495388    3961.26          running      139.0          28.8750      -
5.33359
```

```
        hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  \
312921      4.712060      0.358276     -8.25446      4.95516
0.791698
361462      3.072090     -0.319846    -12.22260      3.66895    -
0.228277
349829      2.473040      5.722000      7.62250      2.44408
5.930320
460045     16.305200      8.114730    -13.94170     16.72250
8.171110
342307      6.224200      6.947140     -4.93868      5.55662
7.431330
...              ...           ...          ...          ...
...
368034      0.761547      4.614360     -7.57998     -1.23791
4.806280
253021      3.048350      6.060460      7.16291      3.06686
6.216340
427131      1.478520      2.265320     -5.39451      1.40183
2.140530
471794      3.427980      7.365140     -6.57784      4.30145
9.142140
495388     36.979800     -3.435980     -3.11945     34.86260    -
2.873060

        ...  ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1  \
312921  ...      9.716540     -1.511980     -1.006870     0.079272
361462  ...      9.554430      0.887316      6.811180    -0.159734
349829  ...      9.390110     -2.977860      0.074179     0.068208
460045  ...     16.377667     -6.851763     -2.755530    -3.576713
342307  ...      9.882050     -0.317092     -1.026730     0.275667
...     ...           ...           ...           ...          ...
368034  ...      9.609180     -0.620355     -1.599440     0.186945
253021  ...     -0.447090     -9.456720     -2.501390    -0.041407
427131  ...     14.693100     -3.067400      0.091707    -3.903790
471794  ...     10.602400     -2.752050     -1.022720     0.154275
495388  ...     11.857500      5.583830      0.381641    -1.355570

        ankle_gyro2  ankle_gyro3  ankle_magne1  ankle_magne2
ankle_magne3  \
312921    -0.003718    -0.076595      -18.7246    -16.879600
36.806500
361462     0.220180    -0.075913      -15.0970     -1.865220
26.292000
349829    -0.089438    -0.004169      -38.0109     21.364500
32.792400
460045     0.851214    -2.267850      -23.9823    -23.680833     -
2.502126
342307    -0.392800    -0.301082      -40.2248      5.940340
37.102000
```

```
...               ...           ...           ...           ...
...
368034     0.002653    -0.035290      -11.6386    -20.898600
4.523240
253021    -0.000295    -0.013074      -12.7842     22.638600     -
6.019310
427131     1.002250    -2.447160      -39.2733    -18.187900
15.175600
471794     0.059888     0.106166      -41.1119      5.348810
8.881400
495388     1.238730    -3.278750      -51.4954     -5.789500
36.450200

        subject_id
312921           2
361462           2
349829           2
460045           2
342307           2
...            ...
368034           2
253021           2
427131           2
471794           2
495388           2

[131684 rows x 43 columns]
```

Heatmap Generation

I will generate heatmap for train_data.

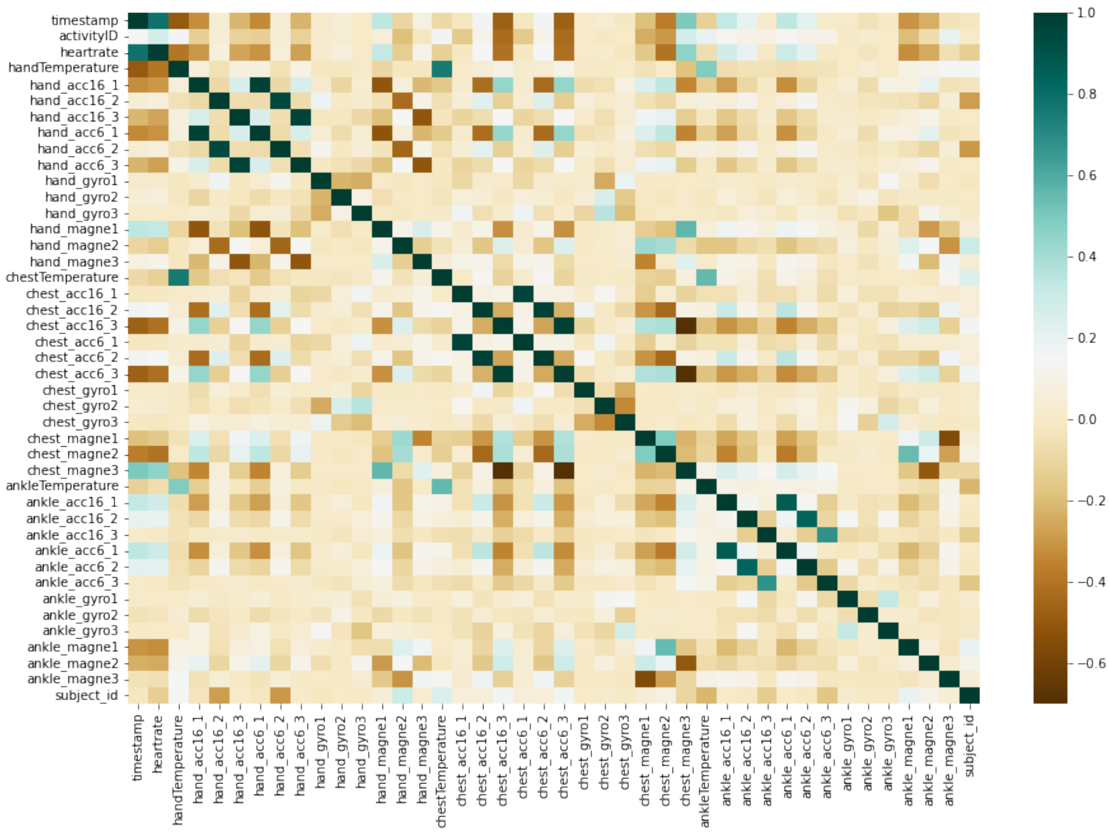
```
from pandas.plotting import scatter_matrix
def generate_heatmap(df):
    #Function : generate_heatmap : function to generate heatmap for
the dataframe train_data
    #parameter : train_data : dataframe
    #import seaborn as sns

    df_corr = df.corr()
    df_corr = df_corr.drop(['activityID'], axis = 1)

    f, ax = plt.subplots(figsize=(15, 10))
    sns.heatmap(df_corr, mask=np.zeros_like(df_corr, dtype=bool), cmap
= "BrBG",ax=ax)
    plt.show()
```

Heat map is graphical representation of the data in the form of coloured matrix. Heatmap can be used to show statistical similarity and correlation among the columns.

```
generate_heatmap(train_df)
```



Activity - Time and HeartRate Analysis

Now I will concentrate on exploring the time related to activities for each subject

```
def change_millisec(timest):
    calculated_time=timest/100
    return calculated_time
```

Here I am grouping the data of each subject according to the activity performed by them and calculating the time taken to perform each activity, the mean heartrate for each each task and we obtain dataframe ed.

```
def heartrate_elaptime(datafr):

ed1=datafr.groupby(['activityID','subject_id']).agg(elapsedtime=('time
stamp', 'size'), mean_hearrate=('heartrate', 'mean'))
    ed1['elapsedsec']=ed1['elapsedtime'].map(change_millisec)
    return ed1

ed= heartrate_elaptime(phydatacop)
ed
```

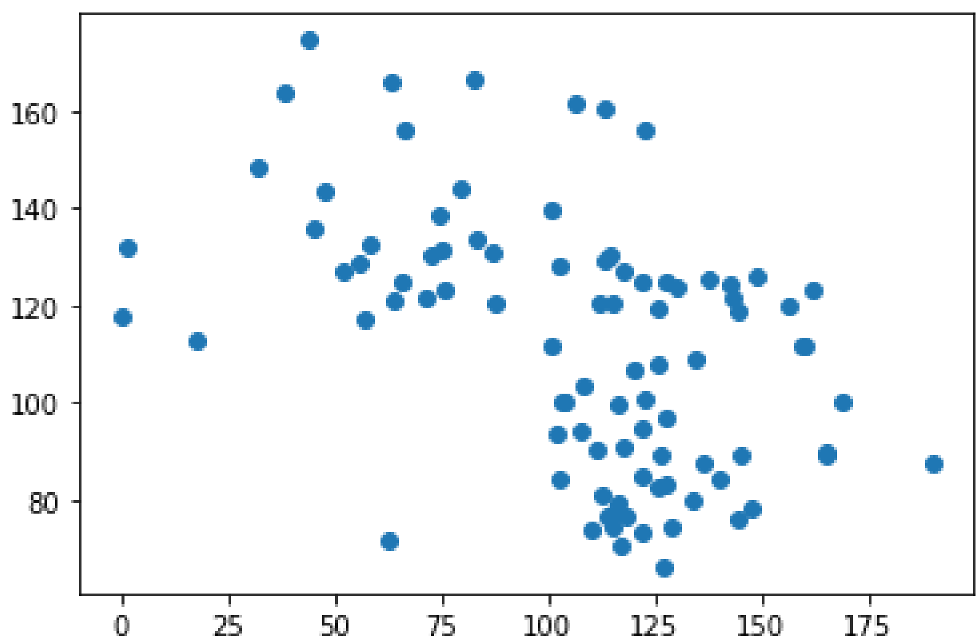
```
                          elapsedtime  mean_hearrate  elapsedsec
activityID     subject_id
Nordic_walking 1                10101     139.621696      101.01
               2                14908     125.738252      149.08
               4                13778     125.575527      137.78
               5                13030     124.040097      130.30
               6                13440     109.198536      134.40
...                               ...            ...         ...
walking        4                15947     111.816753      159.47
               5                16024     111.624311      160.24
               6                12802      97.064585      128.02
               7                16875     100.059832      168.75
               8                15651     120.107202      156.51

[91 rows x 3 columns]
```

Here I plot the scatter plot for the elapsed time and mean heartrate for each subject pursuing different physical activity.

```
plt.scatter(ed['elapsedsec'],ed['mean_hearrate'])
plt.show
```

```
<function matplotlib.pyplot.show(close=None, block=None)>
```




```
heart=ed['elapsedsec']
ctemp=ed['mean_hearrate']
spearmanr=stats.spearmanr(heart,ctemp)
print("Spearman correlation coefficient is {}".format(spearmanr))
```

```
Spearman correlation coefficient is SpearmanrResult(correlation=-
0.474120082815735, pvalue=2.0613166734956675e-06)
```

From the graph we can see that elapsed time is increasing then heartrate decreases.

```
heart=train_df['heartrate']
ctemp=train_df['chest_magne3']
spearmanr=stats.spearmanr(heart,ctemp)
print("Spearman correlation coefficient is {}".format(spearmanr))
```

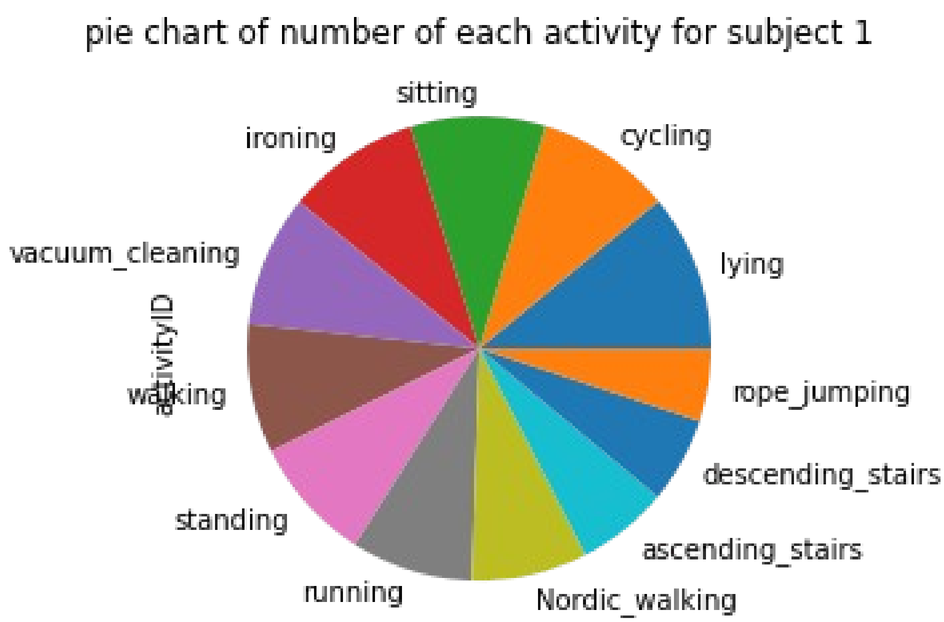
```
Spearman correlation coefficient is
SpearmanrResult(correlation=0.49059399116300434, pvalue=0.0)
```

Let us consider the time each subject devoted for carrying out different physical activity.

```
def plotpie(df,sub):
    print('time spend for each activity for subject{}\n'.format(sub))
    plt.title('pie chart of number of each activity for subject
{}'.format(sub))
    df.activityID.value_counts().plot(kind='pie')
    df.activityID.agg(['value_counts'])

#plt.subplots_adjust(2,1,5,2)
sub1=phydatacop[phydatacop['subject_id']==1]
sub=1
plotpie(sub1,sub)
```

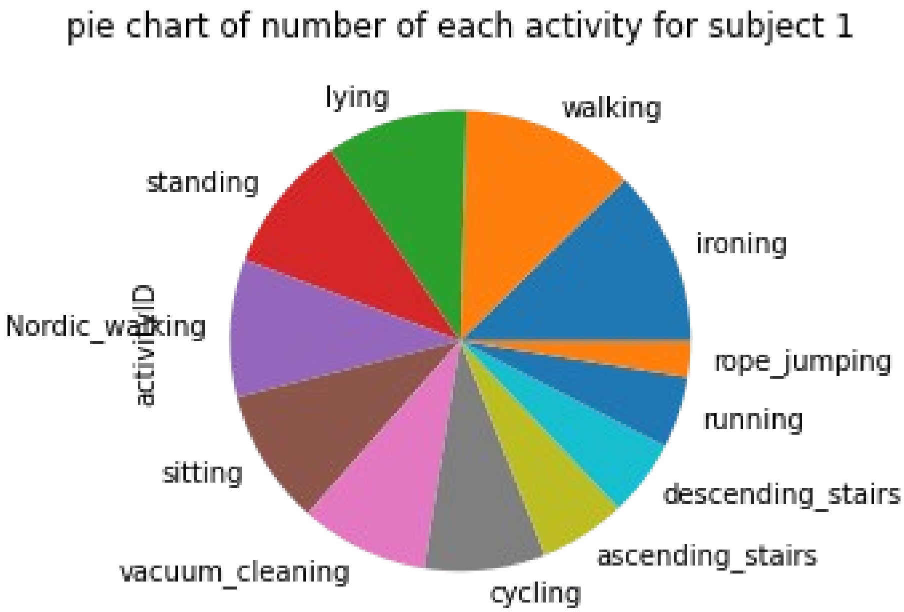
```
time spend for each activity for subject1
```




```
#plt.subplots_adjust(2,1,5,2)
sub1=phydatacop[phydatacop['subject_id']==4]
```

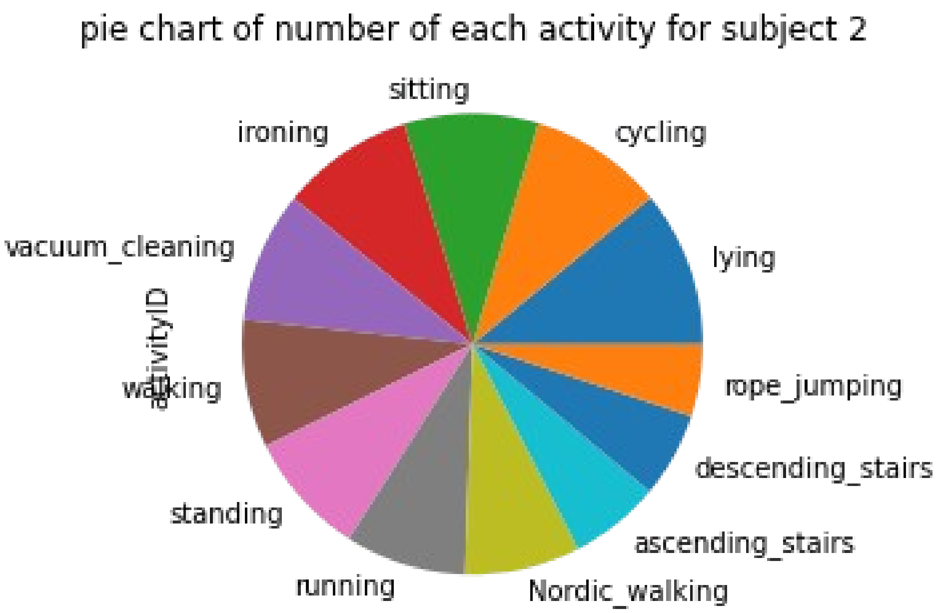
```
sub=4
plotpie(phydatacop,sub)
```

```
time spend for each activity for subject1
```




```
sub2=phydatacop[phydatacop['subject_id']==2]
sub2=2
plotpie(sub1,sub2)
```

```
time spend for each activity for subject2
```

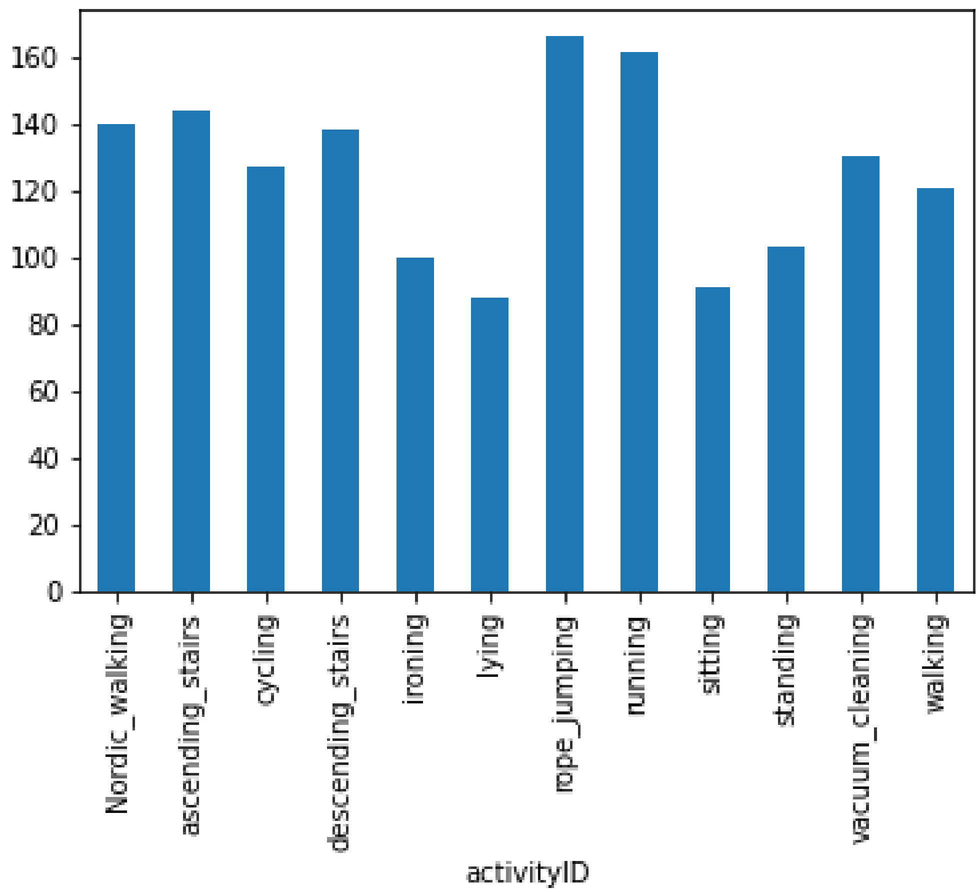


Now we will plot bar graph for each subject the average heartrate while performing different physical activities.

```
def activity_heartrate(train_data,sub_id):
    #Function:activity_heartrate() : plot graph based on average heartrate
    #parameters : train_data : dataframe
    #              sub_id: subject_id
    ttrain_data = train_data.loc[(train_data["subject_id"] == sub_id)]
    data_graph = ttrain_data['heartrate'].groupby(ttrain_data['activityID']).mean()
    #data_graph.index = data_graph.index.map(activityIDdict)
    data_graph.plot(kind='bar')
```

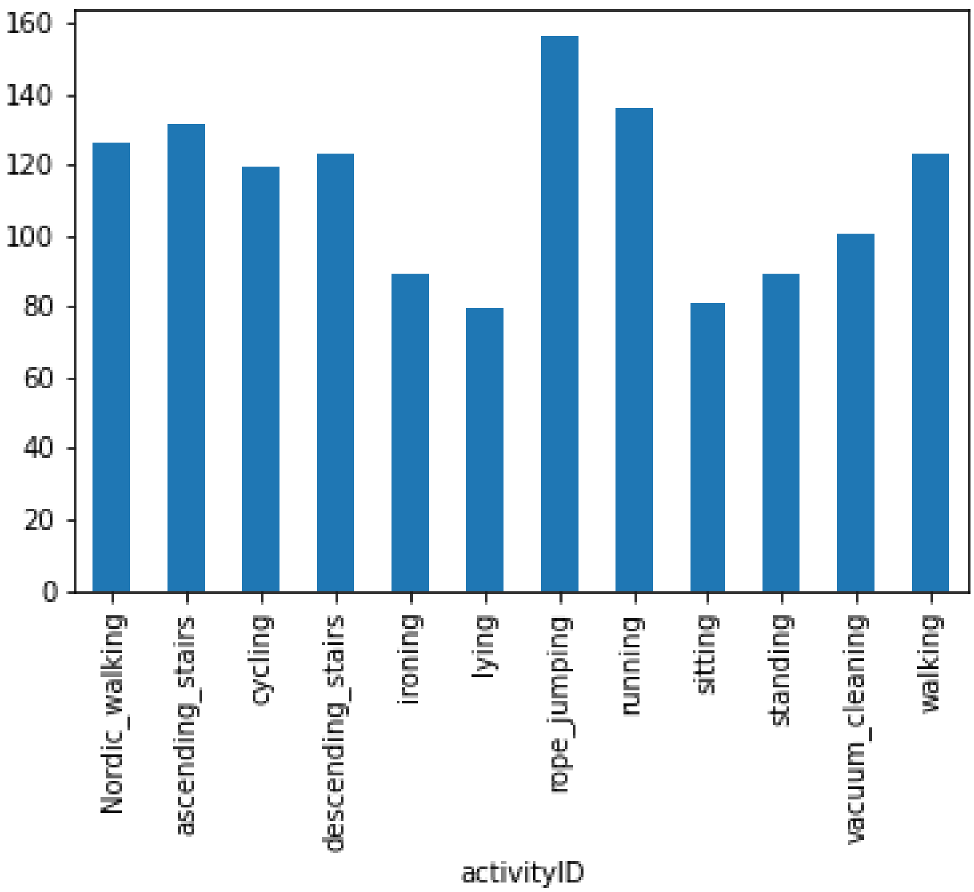
Consider the first subject_id -> subject_id=1 (a male of age 27 height: 182 weight :83)

```
activity_heartrate(phydatacop,1)
```



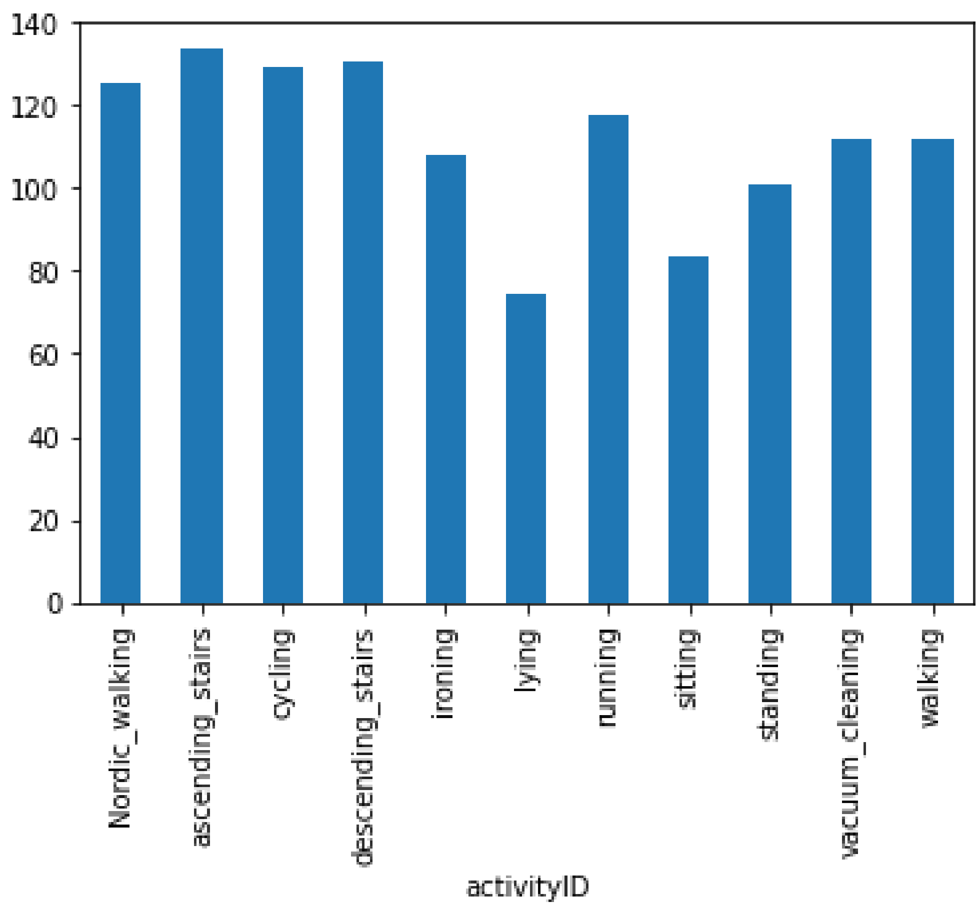
Let us also consider the observation when the subjectid=2(a female age:25 height:169 weight:78)

```
activity_heartrate(phydatacop,2)
```



Similarly let us now consider another subject_id ,4 (a male age: 24 height:194 weight:95)

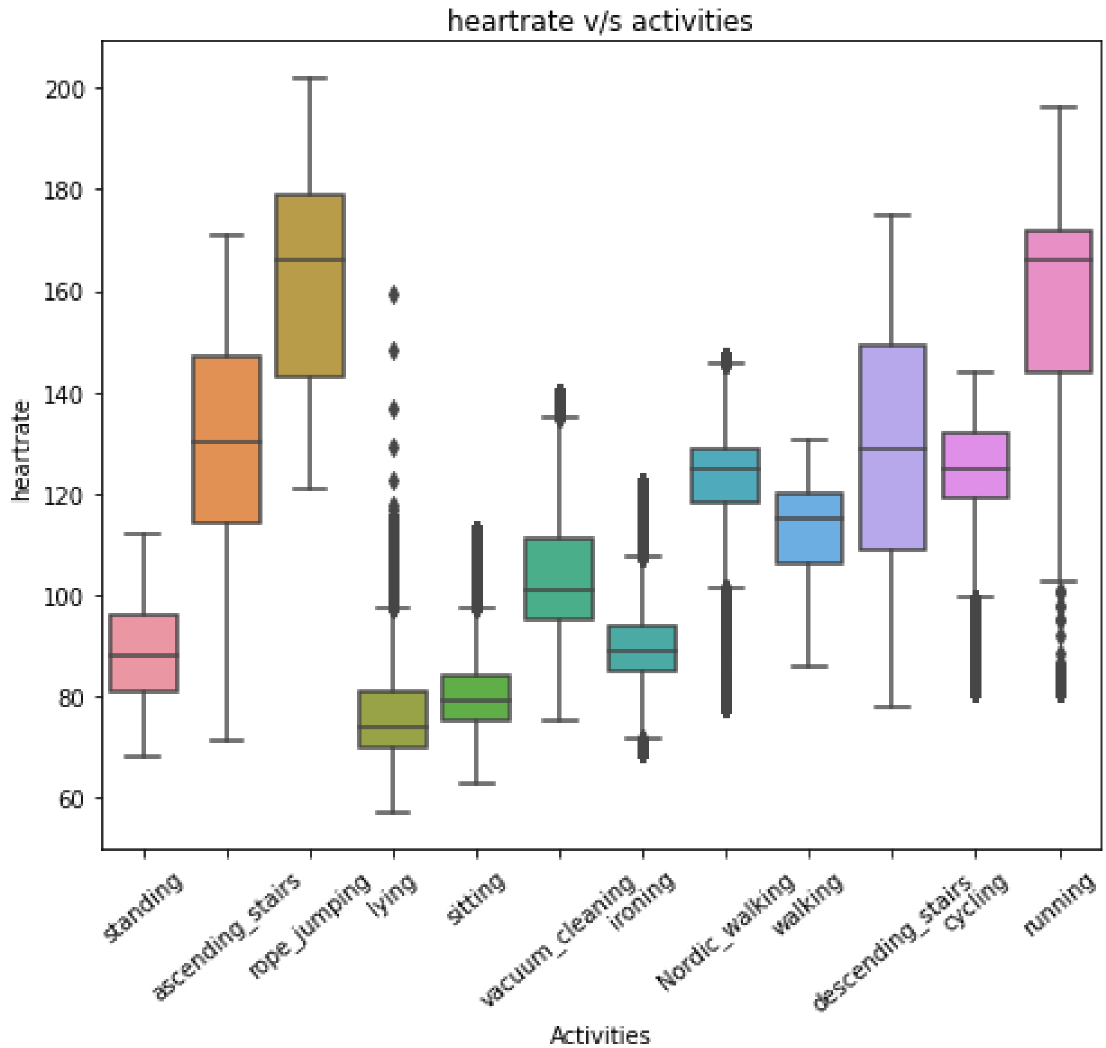
```
activity_heartrate(phydatacop,4)
```



Now I will plot a boxplot of the average heartrate measured while performing various physical activities.

```
import seaborn as sns
def heartrate_boxplot(phydatacop):
    plt.figure(figsize=(7,5))
    plt.subplots_adjust(2,1,5,2)
    plt.subplot(131)
    dat1=phydatacop[['activityID','heartrate']]
    #dat1.activityID=dat1.activityID.astype("category")
    plt.xticks(rotation=40)
    sns.boxplot(x='activityID',y='heartrate',data=dat1)
    plt.ylabel('heartrate')
    plt.xlabel('Activities')
#   plt.title('Activities and Temperature of chest')
    plt.title('heartrate v/s activities')

heartrate_boxplot(phydatacop)
```



Further in the data analysis I will take into consideration the average heartrate while performing activities to state hypothesis.

Hypothesis Testing

I will be performing the hypothesis testing based on the below scenario

Hypothesis: If the subject is performing cumbersome activities like rope jumping and running then average heartrate of the subject will be more than 110.

Null Hypothesis :The average heartrate of the subject while performing cumbersome activities is less than or equal to 110

$H0$: µ <= 110

Alternate Hypothesis:The average heartrate of the subject while performing cumbersome activities is less than or equal to 110

$H1 : \mu > 110$

Here I am considering the activity running and rope jumping as independent variable and average heartrate as dependent variable.

```
running_data = train_df[train_df["activityID"] == 5]
ropejumping_data = train_df[train_df["activityID"] == 24]
cumbersome_data=pd.DataFrame()
cumbersome_data =
pd.concat([cumbersome_data,running_data,ropejumping_data],
ignore_index=False)
cumbersome_data
```

```
         timestamp  activityID  heartrate  handTemperature
hand_acc16_1  \
1436799    3466.15           5      176.0          28.0625    -
11.614500
1165461    3392.82           5      152.0          33.8125     -
4.625630
1427969    3377.85           5      167.0          28.1875    -
32.151100
233529     3313.29           5      173.0          30.4375    -
30.378100
1422642    3324.58           5      145.0          28.3125
8.240610
...            ...         ...        ...              ...           .
..
247533     3602.14          24      181.0          30.1875     -
1.027870
511742     4230.05          24      179.0          28.5000
0.634975
1184329    3681.75          24      139.0          33.8750     -
9.025420
501024     4122.87          24      123.0          28.3125     -
0.539344
237828     3505.09          24      129.0          30.1875     -
1.603240

         hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  \
1436799     12.199200     -5.178400   -18.146800    21.783800    -
6.030400
1165461     -4.954130      0.564829    -4.227810    -5.102200
0.416994
1427969     54.792300     -3.820800   -43.525800    62.126600    -
3.238780
233529      53.540200      6.178220   -35.598200    45.132200
4.914560
1422642      5.953630      1.182600     6.741310     6.221660
1.256810
...               ...           ...          ...          ...
```

```
...
247533       7.147790     -4.925800    -1.094920     6.650410    -
4.489510
511742      -0.968486      1.130520     1.424530    -2.712040    -
0.137652
1184329      3.777730      1.508630    -8.812540     3.887880
1.821460
501024      -1.067640    -10.933300    -0.241368     0.023247   -
11.120200
237828       7.814620      1.221310    -1.494780     7.609710
0.824271

         ...  ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1  \
1436799  ...     24.685000     12.452400     -0.480484    -0.516671
1165461  ...     11.119500     -5.265060     -2.954690    -0.163015
1427969  ...     19.176400     13.552100     -3.073160    -0.252656
233529   ...     11.916575     -2.005432     -2.950493    -0.130902
1422642  ...      7.763660      0.499046     -1.139180     3.702880
...      ...           ...           ...           ...          ...
247533   ...      2.476990     -2.874380     -0.615926     1.523360
511742   ...      7.196820      1.316780     -0.230692    -0.532160
1184329  ...      9.242210      0.678307     -3.236270    -0.143172
501024   ...      5.258980      5.559860      6.713020    -0.230153
237828   ...     25.244600     -2.021600     12.276700     0.664214

         ankle_gyro2  ankle_gyro3  ankle_magne1  ankle_magne2
ankle_magne3  \
1436799    -0.102250    -1.742000    -41.216200       3.27400
28.63310
1165461    -0.412381    -3.518760    -19.752800     -35.30170
14.99560
1427969     0.118389    -2.155950    -44.974600       5.13008
26.91570
233529      0.464649    -1.483988    -45.024525     -50.20960
13.76705
1422642    -2.506820     7.659240    -44.596100       2.52040
21.53050
...              ...          ...           ...           ...
...
247533      0.133100     2.189300    -51.879500     -34.34670
36.14870
511742     -0.233961    -1.513260    -38.235700      -1.37933
34.65590
1184329    -0.223484    -0.306898    -46.121900      19.94060
9.16550
501024      0.232471     2.192700    -36.096500     -12.53920
30.18710
237828      0.278529     1.631470    -65.969600      12.86130     -
17.57140
```

```
         subject_id
1436799           6
1165461           5
1427969           6
233529            1
1422642           6
...             ...
247533            1
511742            2
1184329           5
501024            2
237828            1

[73482 rows x 43 columns]
```

```
cumbersome_mean=cumbersome_data['heartrate'].mean()
cumbersome_std=cumbersome_data['heartrate'].std()
cumbersome_count=cumbersome_data['heartrate'].count()
cumbersome_std
```

```
22.60876807693868
```

```
cumbersome_count
```

```
73482
```

```
z=(cumbersome_mean-110)/(cumbersome_std/np.sqrt(cumbersome_count))
p_value_from_normal=(1-stats.norm.cdf(z))
print('Mean German film budget from data: ',cumbersome_mean)
print ('one tail p value from normal: ', p_value_from_normal)
print ('one tail p value from normal: ', z)
```

```
Mean German film budget from data:  158.40277581348565
one tail p value from normal:  0.0
one tail p value from normal:  580.3418016636251
```

```
0.0
```

I will be considering the significance level of 5%.The p_value that I obtained from the z-test is <0.05, that less than probability of null hypothesis will get accepted.Hence, I will reject my null hypothesis which is the average heartrate while subject is performing cumbersome activities is less or equal to than 110. I will accept my alternate hypothesis that states the average heartrate of the subject while carrying out roping jumping and running is more than 110.

Modelling

Here I will be performing modelling to predict the values. I will focus on predicting the heartrate and activity ID. I will use Polynomial Regression to predict the heartrate using the IMU readings of the chest. First I will calculate Pearson correlation coefficient among the different attributes.

```
phydata.corr()
```

```
                  timestamp  activityID  heartrate  handTemperature  \
timestamp          1.000000    0.145244   0.781018        -0.490511
activityID         0.145244    1.000000   0.266168         0.161482
heartrate          0.781018    0.266168   1.000000        -0.392719
handTemperature   -0.490511    0.161482  -0.392719         1.000000
hand_acc16_1      -0.326419   -0.132573  -0.304767         0.060560
hand_acc16_2       0.035387    0.040441   0.061473        -0.048200
hand_acc16_3      -0.215841   -0.116720  -0.268230         0.076189
hand_acc6_1       -0.337584   -0.132422  -0.314024         0.074848
hand_acc6_2        0.032966    0.044040   0.059788        -0.044556
hand_acc6_3       -0.225717   -0.117646  -0.277322         0.091445
hand_gyro1         0.012714    0.017877   0.013709        -0.023747
hand_gyro2         0.050323    0.027396   0.063663        -0.026927
hand_gyro3         0.002185    0.000997  -0.002162        -0.000591
hand_magne1        0.336791    0.056011   0.323093        -0.094556
hand_magne2       -0.098353   -0.188580  -0.136681        -0.023572
hand_magne3        0.081404   -0.024137   0.104108        -0.019437
chestTemperature  -0.078469    0.164711  -0.121405         0.756932
chest_acc16_1     -0.027182   -0.149190  -0.017360         0.003434
chest_acc16_2      0.165152    0.106193   0.158603         0.031876
chest_acc16_3     -0.470486   -0.430837  -0.410932         0.096407
chest_acc6_1      -0.026794   -0.147995  -0.017705         0.017779
chest_acc6_2       0.165293    0.104523   0.159775         0.030089
chest_acc6_3      -0.472758   -0.432678  -0.415184         0.105311
chest_gyro1        0.007220   -0.000092   0.008466        -0.002885
chest_gyro2        0.025081   -0.020024   0.015662        -0.013703
chest_gyro3       -0.020470    0.003799  -0.023344         0.007507
chest_magne1      -0.189935   -0.241435  -0.157423        -0.044514
chest_magne2      -0.369113   -0.300498  -0.404140        -0.002912
chest_magne3       0.501184    0.267184   0.451494        -0.178856
ankleTemperature  -0.118076    0.198320  -0.057182         0.495801
ankle_acc16_1      0.318519    0.134564   0.277960        -0.060309
ankle_acc16_2      0.203938    0.097455   0.198062        -0.045794
ankle_acc16_3      0.005226    0.081944  -0.005200        -0.042369
ankle_acc6_1       0.341460    0.147599   0.296503        -0.058351
ankle_acc6_2       0.221526    0.106010   0.217162        -0.052726
ankle_acc6_3       0.002138    0.099209  -0.010363        -0.037033
ankle_gyro1        0.001015   -0.005895   0.000925        -0.002130
ankle_gyro2       -0.038416    0.010039  -0.022244         0.029378
ankle_gyro3        0.001527    0.002653   0.005877         0.001300
ankle_magne1      -0.307658   -0.200735  -0.325040         0.090922
ankle_magne2      -0.236989   -0.069130  -0.249641         0.112931
ankle_magne3      -0.041782    0.209294  -0.057358         0.154702
subject_id        -0.021916   -0.000546  -0.128235         0.152991
```

	hand_acc16_1	hand_acc16_2	hand_acc16_3	hand_acc6_1
timestamp	-0.326419	0.035387	-0.215841	-0.337584
activityID	-0.132573	0.040441	-0.116720	-0.132422
heartrate	-0.304767	0.061473	-0.268230	-0.314024
handTemperature	0.060560	-0.048200	0.076189	0.074848
hand_acc16_1	1.000000	-0.075153	0.258193	0.977927
hand_acc16_2	-0.075153	1.000000	-0.064802	-0.063314
hand_acc16_3	0.258193	-0.064802	1.000000	0.255113
hand_acc6_1	0.977927	-0.063314	0.255113	1.000000
hand_acc6_2	-0.072598	0.943875	-0.064305	-0.069088
hand_acc6_3	0.261183	-0.065532	0.965348	0.258474
hand_gyro1	0.024890	0.178876	-0.030262	0.031604
hand_gyro2	-0.092303	-0.015090	-0.021081	-0.070053
hand_gyro3	0.025095	0.020113	-0.078287	0.022075
hand_magne1	-0.511406	-0.044221	-0.194918	-0.516012
hand_magne2	0.054865	-0.433211	0.145604	0.054522
hand_magne3	-0.211730	0.103455	-0.507012	-0.213472
chestTemperature	-0.157314	-0.049040	-0.032047	-0.148163
chest_acc16_1	0.018428	0.040275	-0.102355	0.020416
chest_acc16_2	-0.424266	0.217422	-0.071932	-0.421792
chest_acc16_3	0.438326	-0.118614	0.145014	0.441849
chest_acc6_1	0.018547	0.037151	-0.106891	0.017793
chest_acc6_2	-0.428782	0.234024	-0.072254	-0.429740
chest_acc6_3	0.438220	-0.124418	0.143730	0.441573
chest_gyro1	-0.075419	0.060966	0.009136	-0.060244

```
chest_gyro2          -0.050872     0.002803    -0.058657    -
0.043507
chest_gyro3           0.081714     0.033917     0.035606
0.076212
chest_magne1          0.251469    -0.052196     0.176186
0.251136
chest_magne2          0.341614    -0.088291     0.198857
0.344269
chest_magne3         -0.345545     0.054173    -0.138832    -
0.350289
ankleTemperature     -0.131383     0.076508    -0.025875    -
0.124988
ankle_acc16_1        -0.281450     0.054351    -0.154606    -
0.276782
ankle_acc16_2        -0.089554     0.112317    -0.065574    -
0.089580
ankle_acc16_3        -0.006652     0.004290     0.018489    -
0.007543
ankle_acc6_1         -0.322109     0.065009    -0.163218    -
0.317713
ankle_acc6_2         -0.097172     0.123091    -0.072858    -
0.098036
ankle_acc6_3         -0.017180     0.010547     0.024442    -
0.017108
ankle_gyro1           0.043247    -0.005346     0.013903
0.043473
ankle_gyro2          -0.070603    -0.037732    -0.010423    -
0.069087
ankle_gyro3           0.095700    -0.047358     0.024114
0.085104
ankle_magne1          0.082812    -0.049515     0.060617
0.084416
ankle_magne2          0.207467    -0.098225     0.109933
0.212333
ankle_magne3         -0.042793     0.041686    -0.011914    -
0.039334
subject_id           -0.034171    -0.280354    -0.002883    -
0.032079

                  hand_acc6_2  hand_acc6_3  ...  ankle_acc6_1
ankle_acc6_2  \
timestamp            0.032966    -0.225717  ...      0.341460
0.221526
activityID           0.044040    -0.117646  ...      0.147599
0.106010
heartrate            0.059788    -0.277322  ...      0.296503
0.217162
handTemperature     -0.044556     0.091445  ...     -0.058351     -
0.052726
hand_acc16_1        -0.072598     0.261183  ...     -0.322109     -
```

```
0.097172
hand_acc16_2        0.943875    -0.065532  ...       0.065009
0.123091
hand_acc16_3       -0.064305     0.965348  ...      -0.163218     -
0.072858
hand_acc6_1        -0.069088     0.258474  ...      -0.317713     -
0.098036
hand_acc6_2         1.000000    -0.054614  ...       0.059645
0.127686
hand_acc6_3        -0.054614     1.000000  ...      -0.168814     -
0.071399
hand_gyro1          0.123651    -0.020103  ...       0.023396
0.006876
hand_gyro2         -0.023764    -0.042611  ...       0.059358
0.003256
hand_gyro3          0.050964    -0.076043  ...      -0.025916
0.063300
hand_magne1        -0.041747    -0.194345  ...       0.184068
0.135213
hand_magne2        -0.451040     0.148734  ...      -0.181960     -
0.096657
hand_magne3         0.108571    -0.510017  ...       0.120072
0.101082
chestTemperature   -0.049100    -0.020922  ...       0.121279
0.064278
chest_acc16_1       0.040540    -0.100822  ...      -0.053022
0.034564
chest_acc16_2       0.214224    -0.076263  ...       0.356602
0.119510
chest_acc16_3      -0.125215     0.149670  ...      -0.356285     -
0.250668
chest_acc6_1        0.038158    -0.105748  ...      -0.054455
0.050685
chest_acc6_2        0.231261    -0.075353  ...       0.352101
0.124227
chest_acc6_3       -0.130963     0.148020  ...      -0.335630     -
0.257637
chest_gyro1         0.039037     0.003769  ...      -0.011384
0.035767
chest_gyro2         0.005874    -0.057728  ...       0.049916
0.080695
chest_gyro3         0.039931     0.037977  ...      -0.080335
0.064818
chest_magne1       -0.055434     0.178756  ...      -0.279168     -
0.173353
chest_magne2       -0.091661     0.202947  ...      -0.376469     -
0.208064
chest_magne3        0.058632    -0.142845  ...       0.277004
0.211484
ankleTemperature    0.079797    -0.016026  ...       0.108993
```

```
0.080106
ankle_acc16_1        0.050456    -0.159030  ...      0.855427
0.135428
ankle_acc16_2        0.113186    -0.065228  ...      0.181058
0.819482
ankle_acc16_3        0.009592     0.019161  ...      0.035145     -
0.134853
ankle_acc6_1         0.059645    -0.168814  ...      1.000000
0.160849
ankle_acc6_2         0.127686    -0.071399  ...      0.160849
1.000000
ankle_acc6_3         0.013536     0.024410  ...     -0.007721     -
0.151902
ankle_gyro1         -0.002637     0.014917  ...     -0.022677
0.119081
ankle_gyro2         -0.038893    -0.009964  ...      0.027792     -
0.073778
ankle_gyro3         -0.021830     0.027247  ...     -0.067599
0.073176
ankle_magne1        -0.053114     0.061756  ...     -0.213810     -
0.120948
ankle_magne2        -0.100473     0.113399  ...     -0.125642     -
0.062752
ankle_magne3         0.044490    -0.009567  ...      0.125622
0.105460
subject_id          -0.299409     0.003545  ...     -0.000580     -
0.011625

                  ankle_acc6_3  ankle_gyro1  ankle_gyro2  ankle_gyro3
\
timestamp             0.002138     0.001015    -0.038416     0.001527

activityID            0.099209    -0.005895     0.010039     0.002653

heartrate            -0.010363     0.000925    -0.022244     0.005877

handTemperature      -0.037033    -0.002130     0.029378     0.001300

hand_acc16_1         -0.017180     0.043247    -0.070603     0.095700

hand_acc16_2          0.010547    -0.005346    -0.037732    -0.047358

hand_acc16_3          0.024442     0.013903    -0.010423     0.024114

hand_acc6_1          -0.017108     0.043473    -0.069087     0.085104

hand_acc6_2           0.013536    -0.002637    -0.038893    -0.021830

hand_acc6_3           0.024410     0.014917    -0.009964     0.027247
```

hand_gyro1	-0.016318	0.025890	-0.038144	0.132647
hand_gyro2	-0.031014	0.042430	0.093068	-0.037502
hand_gyro3	0.041402	-0.052242	-0.023284	-0.168722
hand_magne1	0.079182	0.048675	-0.078373	0.055630
hand_magne2	-0.072149	0.074338	-0.015224	0.056252
hand_magne3	-0.024915	0.007227	-0.045110	0.012188
chestTemperature	-0.051722	-0.003375	-0.005819	-0.000393
chest_acc16_1	-0.076255	0.069288	-0.043691	-0.043553
chest_acc16_2	-0.007499	-0.041766	0.028173	-0.109453
chest_acc16_3	-0.152217	0.010585	-0.023962	0.068377
chest_acc6_1	-0.082543	0.058928	-0.032454	-0.043607
chest_acc6_2	-0.004602	-0.046428	0.031008	-0.101776
chest_acc6_3	-0.149047	0.010196	-0.021303	0.062761
chest_gyro1	-0.016610	0.016670	-0.014966	-0.042759
chest_gyro2	-0.014719	0.130569	0.067987	-0.096745
chest_gyro3	0.008519	0.143755	-0.130711	0.265811
chest_magne1	-0.046129	0.004497	0.012853	0.000342
chest_magne2	-0.013304	-0.000325	0.016637	-0.003283
chest_magne3	0.157525	0.007514	0.005421	0.002865
ankleTemperature	0.113402	-0.011682	0.004036	-0.000124
ankle_acc16_1	-0.137495	-0.001117	-0.048875	-0.045776
ankle_acc16_2	-0.094675	0.146941	-0.056544	0.131754
ankle_acc16_3	0.659641	-0.082166	-0.066440	-0.011612
ankle_acc6_1	-0.007721	-0.022677	0.027792	-0.067599

ankle_acc6_2	-0.151902	0.119081	-0.073778	0.073176
ankle_acc6_3	1.000000	-0.076834	0.017771	-0.012474
ankle_gyro1	-0.076834	1.000000	-0.072977	0.313138
ankle_gyro2	0.017771	-0.072977	1.000000	0.018438
ankle_gyro3	-0.012474	0.313138	0.018438	1.000000
ankle_magne1	-0.036558	-0.020931	0.018665	-0.005307
ankle_magne2	-0.065403	0.054899	-0.028986	0.012702
ankle_magne3	-0.026070	-0.017219	-0.026331	-0.017464
subject_id	-0.165760	0.018648	-0.005422	0.000918

	ankle_magne1	ankle_magne2	ankle_magne3	subject_id
timestamp	-0.307658	-0.236989	-0.041782	-0.021916
activityID	-0.200735	-0.069130	0.209294	-0.000546
heartrate	-0.325040	-0.249641	-0.057358	-0.128235
handTemperature	0.090922	0.112931	0.154702	0.152991
hand_acc16_1	0.082812	0.207467	-0.042793	-0.034171
hand_acc16_2	-0.049515	-0.098225	0.041686	-0.280354
hand_acc16_3	0.060617	0.109933	-0.011914	-0.002883
hand_acc6_1	0.084416	0.212333	-0.039334	-0.032079
hand_acc6_2	-0.053114	-0.100473	0.044490	-0.299409
hand_acc6_3	0.061756	0.113399	-0.009567	0.003545
hand_gyro1	0.011851	-0.065075	-0.000670	-0.025337
hand_gyro2	-0.007805	-0.002934	-0.014939	0.006286
hand_gyro3	-0.061264	0.127946	0.035480	-0.001432

hand_magne1	-0.066001	-0.295443	-0.158423	0.051578
hand_magne2	0.239298	0.155272	-0.307207	0.306676
hand_magne3	0.166220	-0.206654	0.176160	0.032379
chestTemperature	0.001807	-0.024831	0.138394	0.250849
chest_acc16_1	0.030678	0.035793	0.023467	0.054026
chest_acc16_2	-0.097550	-0.158155	0.178840	0.059554
chest_acc16_3	0.242145	0.292483	-0.123476	0.159185
chest_acc6_1	0.029459	0.033947	0.026666	0.061961
chest_acc6_2	-0.098480	-0.163757	0.177536	0.058501
chest_acc6_3	0.241889	0.294382	-0.121168	0.166347
chest_gyro1	0.013040	-0.010439	-0.003074	-0.000370
chest_gyro2	-0.046459	0.071446	-0.007592	0.013570
chest_gyro3	0.037248	-0.011397	-0.015693	-0.011296
chest_magne1	0.173531	0.301376	-0.560974	0.046902
chest_magne2	0.543522	0.191019	-0.277400	0.084613
chest_magne3	-0.162493	-0.502327	-0.098198	-0.094658
ankleTemperature	-0.048627	-0.079925	0.093914	-0.214171
ankle_acc16_1	-0.204053	-0.115939	0.118349	0.001004
ankle_acc16_2	-0.112638	-0.056165	0.097198	-0.011798
ankle_acc16_3	-0.028416	-0.052443	-0.019791	-0.139104
ankle_acc6_1	-0.213810	-0.125642	0.125622	-0.000580
ankle_acc6_2	-0.120948	-0.062752	0.105460	-0.011625
ankle_acc6_3	-0.036558	-0.065403	-0.026070	-0.165760
ankle_gyro1	-0.020931	0.054899	-0.017219	0.018648

```
ankle_gyro2            0.018665     -0.028986     -0.026331   -0.005422
ankle_gyro3           -0.005307      0.012702     -0.017464    0.000918
ankle_magne1           1.000000      0.062428     -0.032131    0.193458
ankle_magne2           0.062428      1.000000      0.019299    0.105547
ankle_magne3          -0.032131      0.019299      1.000000    0.046106
subject_id             0.193458      0.105547      0.046106    1.000000

[43 rows x 43 columns]
```

Polynomial Regression

From the above obtained dataframe we can notice that readings of chest_magne3 and chest_acc16_2 are more correlated to heartrate than other attributes. So I will take them as dependant variable for polynomial regression. I will create dataframe X with the dependant value. And since we are predicting heartrate from chest_magne3 and chest_acc16_2, I will take heartrate as independent variable and take it as list.

```
X=phydata[['chest_acc16_2','chest_magne3']]
#phytarget=phydata['heartrate']
tar = phydata['heartrate']
```

Since the variable are not linearly dependant I will use Polynomial Regression. Polynomial Regression $f(x;\mathbf{w}) = w0 + w1x + \cdots + wnxn$. But here we will take multiple attributes chest_magne3 and chest_acc16_2 as dependent variable. And using PolynomialFeatures we will find the values of dependant variable upto power of n which we will pass as parameter degree. We will convert the features into the power. Independent Variable : X :- Includes chest_acc16_2,chest_magne3 Dependent Variable. : tar :-Includes heartrate

Process involves: Transform the independent Variable X by calculatin till nth degree polynomial where n=8 Obtain train test data by applying train_test_split inbult function to both X and tar. Apply poly_reg_model.fit(X_train,y_train) for fitting the data. Hence the corresponding model is created.

```
later on,
we compute the root mean squared error and the mean squared error
inoerder to
obtain the error.
I have also provided an example for the same considering two values of
X from the dataframe and
prected the heart rate.
```

```
from sklearn.preprocessing import PolynomialFeatures
poly = PolynomialFeatures(degree=8, include_bias=False)
poly_features = poly.fit_transform(X)
X_train, X_test, y_train, y_test = train_test_split(poly_features, 
tar, test_size=0.4,train_size=0.6,random_state=4798)
```

```
from sklearn.linear_model import LinearRegression
poly_reg_model = LinearRegression()
poly_reg_model.fit(X_train, y_train)
```

```
LinearRegression()
```

```
poly_reg_y_predicted = poly_reg_model.predict(X_test)
from sklearn.metrics import mean_squared_error
poly_reg_rmse = np.sqrt(mean_squared_error(y_test, 
poly_reg_y_predicted))
print('The root mean squared error is {}'.format(poly_reg_rmse))
poly_mse=mean_squared_error(y_test, poly_reg_y_predicted)
print('The mean squared error is {}'.format(poly_mse))
poly_feat = poly.fit_transform([[1.930140,-54.463000]])
predict_heart= poly_reg_model.predict(poly_feat)
predict_heart
```

```
The root mean squared error is 21.4802172441862
The mean squared error is 461.3997328574342
```

```
array([93.77671844])
```

Random Forest Algorithm

Random Forest algorithm can be used for both classification and regression which makes it a very versatile modelling algorithm. As the name implies, Random Forest is a forest of trees, decision trees which are randomly populating the forest. The algorithms creates and combines decision trees together, the more trees in the forest, the better the accuracy of its predictions will be.

The process involves:

A dataframe data created by dropping activityID and timestamp and target which includes activityID Train test data split is done for both data_1 and target

Import RandomForestClassifier and create a gaussian classifier clf and train the model Obtain the root mean sqaured error Accuracy of the model is also obtained

```
data=phydata.drop(['activityID','timestamp'], axis=1)
target = phydata['activityID']
train_data,test_data,train_target,test_target = 
cross_validation.train_test_split(data,target,test_size=0.4,train_size
=0.6,random_state=12345)
```

```
from sklearn.ensemble import RandomForestClassifier

#Create a Gaussian Classifier
clf=RandomForestClassifier(n_estimators=100)

#Train the model using the training sets y_pred=clf.predict(X_test)
clf.fit(train_data,train_target)

y_pred=clf.predict(test_data)

rand_rmse = np.sqrt(mean_squared_error(test_target, y_pred))
print('The root mean squared error for Random Forest Classifier is
{}'.format(rand_rmse))
```

```
The root mean squared error for Random Forest Classifier is
0.5945502741484764
```

```
from sklearn import metrics
# Model Accuracy, how often is the classifier correct?
print("Accuracy:",metrics.accuracy_score(test_target, y_pred))
```

```
Accuracy: 0.9942450142450142
```

```
tes=phydata[phydata['subject_id']==3]
tes
```

```
       timestamp  activityID  heartrate  handTemperature  hand_acc16_1
\
46281     166.17           1       91.0          31.0000     -2.316980

46282     166.27           1       91.0          31.0000     -1.353890

46283     166.39           1       91.0          31.0000     -1.201360

46284     166.49           1       91.0          31.0000     -0.737192

46285     166.60           1       90.0          31.0000     -0.403772

...          ...         ...        ...              ...           ...

62117    2442.74           4      122.0          28.6875     -2.452420

62118    2442.85           4      122.0          28.6875     -2.901860

62119    2442.96           4      122.0          28.6875     -2.406590

62120    2443.07           4      122.0          28.6875     -1.759920

62121    2443.18           4      122.0          28.6875     -1.024510
```

```
       hand_acc16_2  hand_acc16_3  hand_acc6_1  hand_acc6_2
hand_acc6_3  ...  \
46281       6.75346       9.18109    -2.117760      6.23230
8.86153  ...
46282       6.39038       7.61876    -1.773730      6.68216
8.09006  ...
46283       4.68530       8.01167    -1.409040      5.19955
8.13824  ...
46284       5.06320       8.24827    -0.504560      5.11760
8.24319  ...
46285       5.05890       8.06084    -0.264815      5.10063
8.09198  ...
...             ...           ...          ...          ...          .
..  ...
62117      10.29660      -1.99423    -2.383700     10.40740     -
1.97459  ...
62118       9.16494      -1.65076    -3.237720      8.96402     -
1.71384  ...
62119       9.73024      -1.64525    -2.536620      9.59354     -
1.41392  ...
62120      10.90040      -1.75497    -2.047700     10.93360     -
1.97609  ...
62121       9.95240      -1.04799    -1.282080      9.97719     -
1.37075  ...

       ankle_acc6_1  ankle_acc6_2  ankle_acc6_3  ankle_gyro1
ankle_gyro2  \
46281       9.71673      1.013740     -1.136080    -0.637220    -
0.074219
46282      10.01330      2.812390     -2.187770    -0.113422    -
0.545321
46283       9.17755      1.165330     -0.755322    -0.285889    -
0.552679
46284       8.42732      0.227757     -0.475887    -0.315613    -
0.332036
46285      10.78790      2.436960     -0.132287     0.113989    -
0.085076
...             ...           ...           ...          ...
...
62117       9.32376      3.013710      1.765540     2.046050
0.147897
62118       6.60552      2.838120     -5.257340     3.574080    -
0.051112
62119       8.25500      4.898860     -2.502980    -0.972910
0.007421
62120      10.66470      2.027690     -0.841671    -0.127264    -
0.057552
62121      10.00460      0.863293     -0.531715    -0.063496
0.039095
```

```
       ankle_gyro3  ankle_magne1  ankle_magne2  ankle_magne3
subject_id
46281     0.113066      -42.6776      0.574123       57.4883
3
46282    -0.572943      -40.8283     -2.814860       58.5511
3
46283    -0.619155      -36.2752     -6.535780       60.8259
3
46284    -0.107497      -32.9984     -7.554590       62.3974
3
46285     0.448154      -32.5742     -5.913210       62.2877
3
...            ...           ...           ...           ...          .
..
62117    -0.698613      -21.0772     -8.924000        8.5653
3
62118    -0.386876      -20.5655    -10.445800       13.8674
3
62119     0.657275      -20.3344    -10.249600       15.1054
3
62120     0.961383      -21.0434     -8.333120       13.8938
3
62121     0.730862      -22.6406     -6.938610       12.8077
3

[15841 rows x 43 columns]
```

```python
tes=phydata.iloc[[62117]]
tes1=tes.drop(['activityID','timestamp'], axis=1)
pred=clf.predict(tes1)
pred
```

```
array([4], dtype=int64)
```