

Data Science Research : The PAMAP2 Physical Activity Monitoring Dataset

Introduction

In this report, we strive to devise software and hardware that can determine the amount of physical activity a person performs and provide insights gleaned from the data.

The PAMAP2 Physical Activity Monitoring Dataset contains the data carried out on 9 subjects which include an adult group of 8 males and 1 female and their corresponding readings were taken by wearing three different Inertial Measurements Units and Heart Rate monitor. There were 18 different physical activities (running, rope jumping, lying etc) performed on each subject, and their hand, chest, and ankle readings were recorded. The readings of individual subjects are stored in .dat files. This text file contains 54 different attributes (including timestamps, activity IDs, heart rates, and IMU sensory data). Analyses are carried out in various stages, such as exploratory data analysis, hypothesis testing, and modeling.

Content

Preparatory Task

- Importing libraries

Data Cleaning:

Functions involved:-

- Cleaning the data by removing the null values and the variables that are not used in this analysis using `data_cleaning()`
- Sub-Function : `fill_null_hearttrate()` :- replace Null values of heart rate column

Exploratory Data Analysis:

- Generation of test and train data
- Activity time analysis by subjectID
- Analysis on activity by hearttrate
- Analysis on activity by calorie burnt
- Analysis on activity by heart, chest and ankle temperature
- Correlation analysis

Hypothesis Testing:

- Hypothesis stated : A hypothesis of dependency between activity and human hearttrate fluctuations.

- Perform z-test
- Result based on z-test

Modelling :

- Polynomial Regression
- Random Forest algorithm

Preparatory Task

In this process, the libraries that are needed are imported, as well as the files that need to be loaded.

```
#standard imports for when working with pandas
import numpy as np
#matplotlib inline
from matplotlib import pyplot as plt
from scipy import stats
import math
import pandas as pd
import seaborn as sns
from pandas.plotting import scatter_matrix
pd.options.mode.chained_assignment = None
from sklearn.model_selection import train_test_split

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' }

#weight of the subjects
subject_weights={1:83,2:78,3:92,4:95,5:73,6:69,7:86,8:87,9:65}
```

#the metabolic equivalent of the activity, which is a measure of the intensity of the activity

```
MET_values = {1: 1,  
              2: 1.8,  
              3: 1.8,  
              4: 3.5,  
              5: 7.5,  
              6: 4,  
              7: 5.5,  
              12: 8,  
              13: 3,  
              16: 3.5,  
              17: 2.3,  
              24: 9}
```

```
List_of_Subjects=['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']
```

```
IMUhand = ['Temperature_hand',  
           '3D_hand_Accl_16_1', '3D_hand_Accl_16_2',  
           '3D_hand_Accl_16_3',  
           '3D_hand_Accl_6_1', '3D_hand_Accl_6_2', '3D_hand_Accl_6_3',  
           '3D_handGyro_1', '3D_handGyro_2', '3D_handGyro_3',  
           '3D_handmagneto_1', '3D_handmagneto_2', '3D_handmagneto_3',  
           'Orientation_hand_1', 'Orientation_hand_2',  
           'Orientation_hand_3', 'Orientation_hand_4']
```

```
IMUchest = ['Temperature_chest',  
            '3D_chest_Accl_16_1', '3D_chest_Accl_16_2',  
            '3D_chest_Accl_16_3',  
            '3D_chest_Accl_6_1', '3D_chest_Accl_6_2',  
            '3D_chest_Accl_6_3',  
            '3D_chestGyro_1', '3D_chestGyro_2', '3D_chestGyro_3',  
            '3D_chestmagneto_1', '3D_chestmagneto_2',  
            '3D_chestmagneto_3',  
            'Orientation_chest_1', 'Orientation_chest_2',  
            'Orientation_chest_3', 'Orientation_chest_4']
```

```
IMUankle = ['Temperature_ankle',  
            '3D_ankle_Accl_16_1', '3D_ankle_Accl_16_2',  
            '3D_ankle_Accl_16_3',
```

```

        '3D_ankle_Accl_6_1', '3D_ankle_Accl_6_2',
'3D_ankle_Accl_6_3',
        '3D_ankleGyro_1', '3D_ankleGyro_2', '3D_ankleGyro_3',
        '3D_anklemagneto_1', '3D_anklemagneto_2',
'3D_anklemagneto_3',
        'Orientation_ankle_1', 'Orientation_ankle_2',
'Orientation_ankle_3', 'Orientation_ankle_4']

```

```

columns=["timestamp", "activityID", "heartrate"]
+IMUhand+IMUchest+IMUankle

```

```
len(columns)
```

54

To read and load the .dat file into a single dataframe, a list of subjects (List_of_Subjects) is created. We create a dictionary activityIDdict that maps each activityId to its associated activity name for later processing steps. Following that, a list of hand, chest, and ankle inertial measurement units (IMU) is created so that column names can be assigned to the obtained dataframe. In total, 54 IMU will be present in the dataframe, which means 54 columns.

```

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_Subjects)
#dataCollection.reset_index(drop=True, inplace=True)
datafr.reset_index(drop=True, inplace=True)
#dataCollection.head()
datafr.head(10)

```

	timestamp	activityID	heartrate	Temperature_hand
3D_hand_Accl_16_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				

	3D_hand_Accl_16_2	3D_hand_Accl_16_3	3D_hand_Accl_6_1	
3D_hand_Accl_6_2 \				
0	8.56560	3.66179	2.39494	
8.55081				
1	8.60107	3.54898	2.30514	
8.53644				
2	8.52853	3.66021	2.33528	
8.53622				
3	8.83122	3.70000	2.23055	
8.59741				
4	8.82929	3.54710	2.26132	
8.65762				
5	8.82900	3.54767	2.27703	
8.77828				
6	9.05500	3.39347	2.39786	
8.89814				
7	9.13251	3.54668	2.44371	
8.98841				
8	9.09415	3.43015	2.42877	
9.01871				
9	8.90450	3.46984	2.39736	
8.94335				

	3D_hand_Accl_6_3	...	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1 \					
0	3.64207	...	-0.004638	0.000368	-
59.8479					
1	3.73280	...	0.000148	0.022495	-
60.7361					
2	3.73277	...	-0.020301	0.011275	-
60.4091					
3	3.76295	...	-0.014303	-0.002823	-
61.5199					
4	3.77788	...	-0.016024	0.001050	-

60.2954					
5	3.73230	...	-0.053934	0.015594	-
60.6307					
6	3.64131	...	-0.039937	-0.000785	-
60.5171					
7	3.62596	...	-0.010042	0.017701	-
61.2916					
8	3.61081	...	-0.013923	0.014498	-
60.8509					
9	3.53551	...	0.002283	0.020352	-
61.5302					

	3D_anklemagneto_2	3D_anklemagneto_3	Orientation_ankle_1	\
0	-38.8919	-58.5253	1.0	
1	-39.4138	-58.3999	1.0	
2	-38.7635	-58.3956	1.0	
3	-39.3879	-58.2694	1.0	
4	-38.8778	-58.3977	1.0	
5	-38.8676	-58.2711	1.0	
6	-38.9819	-58.2733	1.0	
7	-39.6182	-58.1499	1.0	
8	-39.0821	-58.1478	1.0	
9	-38.7240	-58.3860	1.0	

	Orientation_ankle_2	Orientation_ankle_3	Orientation_ankle_4
subject_id			
0	0.0	0.0	0.0
1			
1	0.0	0.0	0.0
1			
2	0.0	0.0	0.0
1			
3	0.0	0.0	0.0
1			
4	0.0	0.0	0.0
1			
5	0.0	0.0	0.0
1			
6	0.0	0.0	0.0
1			
7	0.0	0.0	0.0
1			
8	0.0	0.0	0.0
1			
9	0.0	0.0	0.0
1			

[10 rows x 55 columns]

Data Cleaning

The `data_cleaning()` takes `datafr`(dataframe created at the beginning of the process) as input and `phydata`(dataframe after cleaning) is obtained as its output. Here in data cleaning we will be focusing on four steps:

- Dropping the irrelevant columns: Going further, I won't require any of the orientation columns for analysis so I will remove those columns.
- 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.
- 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. For all columns, except heart rate, null values are removed using the `interpolate()` method. Heart rate has been replaced with the mean heart rate of each activity group in place of null values. Even after applying `interpolation()` to heart rate, there are NaN values that can either be filled with an assumed value, but instead I have replaced them with 100.
- 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

```
def fill_null_heartrate(datafr):  
    #function : fill_null_heartrate : replace the null values in  
heartrate column with 100  
    #parameters : datafr : dataframe  
  
    act_name=list(set(datafr['activityID'].values))  
    datedd=datafr  
    for act in act_name:  
  
        datedd.loc[datedd['activityID']== act,  
['heartrate']] = datedd.loc[datedd['activityID']== act,  
['heartrate']].fillna(100)  
    return datedd  
  
def data_cleaning(dataCollection):  
  
    # removal of orientation columns as they are not needed  
    dataCollection = dataCollection.drop(['Orientation_hand_1',  
'Orientation_hand_2', 'Orientation_hand_3', 'Orientation_hand_4',  
                                         'Orientation_chest_1',  
'Orientation_chest_2', 'Orientation_chest_3', 'Orientation_chest_4',  
                                         'Orientation_ankle_1',  
'Orientation_ankle_2', 'Orientation_ankle_3', 'Orientation_ankle_4'],  
                                         axis = 1)
```

```

#removal of any row of activity 0 as it is transient activity
which it is not used
dataCollection =
dataCollection.drop(dataCollection[dataCollection.activityID ==
0].index)

```

```

#removal of any remaining NaN value cells by constructing new
data points in known set of data points
dataCollection = dataCollection.interpolate()

```

```

#call fill_null_heartrate()
dataCollection=fill_null_heartrate(dataCollection)

```

```

#removal of non numeric data in cells
dataCollection = dataCollection.apply(pd.to_numeric, errors =
'coerce')

```

```

return dataCollection

```

```

phydata=data_cleaning(datafr)
phydata.reset_index(drop = True, inplace = True)
phydata

```

	timestamp	activityID	heartrate	Temperature_hand	\
2927	37.66	1	100.0	30.375	
2928	37.67	1	100.0	30.375	
2929	37.68	1	100.0	30.375	
2930	37.69	1	100.0	30.375	
2931	37.70	1	100.0	30.375	
...	
2872006	95.06	24	162.0	25.125	
2872007	95.07	24	162.0	25.125	
2872008	95.08	24	162.0	25.125	
2872009	95.09	24	162.0	25.125	
2872010	95.10	24	162.0	25.125	
	3D_hand_Acc1_16_1	3D_hand_Acc1_16_2	3D_hand_Acc1_16_3	\	
2927	2.21530	8.27915	5.58753		
2928	2.29196	7.67288	5.74467		
2929	2.29090	7.14240	5.82342		
2930	2.21800	7.14365	5.89930		
2931	2.30106	7.25857	6.09259		
...		
2872006	4.99466	6.01881	5.59830		
2872007	5.02764	5.90369	5.48372		
2872008	5.06409	5.71370	5.48491		
2872009	5.13914	5.63724	5.48629		
2872010	5.00812	5.40645	5.02326		

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
2927	2.24689	8.55387	5.77143	...	
2928	2.27373	8.14592	5.78739	...	
2929	2.26966	7.66268	5.78846	...	
2930	2.22177	7.25535	5.88000	...	
2931	2.20720	7.24042	5.95555	...	
...	
2872006	4.90787	6.05780	5.68357	...	
2872007	4.89090	5.95209	5.56301	...	
2872008	4.97981	5.87584	5.45738	...	
2872009	4.97690	5.69448	5.29167	...	
2872010	4.97362	5.45272	5.14120	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	...	\
2927	9.63162	-1.76757	0.265761	...	
2928	9.58649	-1.75247	0.250816	...	
2929	9.60196	-1.73721	0.356632	...	
2930	9.58674	-1.78264	0.311453	...	
2931	9.64677	-1.75240	0.295902	...	
...	
2872006	9.41274	-2.26922	-1.759580	...	
2872007	9.33733	-2.23908	-1.834950	...	
2872008	9.32243	-2.23905	-1.804610	...	
2872009	9.38220	-2.26938	-1.880500	...	
2872010	9.41250	-2.23905	-1.820220	...	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	...	\
3D_anklemagneto_1					
2927	0.002908	-0.027714	0.001752	...	-
61.1081					
2928	0.020882	0.000945	0.006007	...	-
60.8916					
2929	-0.035392	-0.052422	-0.004882	...	-
60.3407					
2930	-0.032514	-0.018844	0.026950	...	-
60.7646					
2931	0.001351	-0.048878	-0.006328	...	-
60.2040					
...	
...					
2872006	0.021288	-0.012885	0.005878	...	-
45.7855					
2872007	0.010715	0.003629	-0.004235	...	-
46.0331					
2872008	-0.016939	-0.035176	-0.002309	...	-
45.5140					
2872009	-0.028069	-0.036457	-0.007076	...	-
45.9093					
2872010	-0.013310	-0.030195	0.018229	...	-
46.1702					

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
2927	-36.863600	-58.369600	1
2928	-36.319700	-58.365600	1
2929	-35.784200	-58.611900	1
2930	-37.102800	-57.879900	1
2931	-37.122500	-57.884700	1
...
2872006	-0.831734	-0.170139	9
2872007	-0.817288	0.538134	9
2872008	-1.229410	0.540438	9
2872009	-0.565555	0.680109	9
2872010	-0.812965	-0.313346	9

[1942872 rows x 43 columns]

phydata.head()

	timestamp	activityID	heartrate	Temperature_hand
3D_hand_Acccl_16_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				

	3D_hand_Acccl_16_2	3D_hand_Acccl_16_3	3D_hand_Acccl_6_1
3D_hand_Acccl_6_2 \			
0	8.27915	5.58753	2.24689
8.55387			
1	7.67288	5.74467	2.27373
8.14592			
2	7.14240	5.82342	2.26966
7.66268			
3	7.14365	5.89930	2.22177
7.25535			
4	7.25857	6.09259	2.20720
7.24042			

	3D_hand_Acccl_6_3	...	3D_ankle_Acccl_6_1	3D_ankle_Acccl_6_2 \
0	5.77143	...	9.63162	-1.76757
1	5.78739	...	9.58649	-1.75247
2	5.78846	...	9.60196	-1.73721
3	5.88000	...	9.58674	-1.78264
4	5.95555	...	9.64677	-1.75240

	3D_ankle_Acc1_6_3	3D_ankleGyro_1	3D_ankleGyro_2	
3D_ankleGyro_3 \				
0	0.265761	0.002908	-0.027714	0.001752
1	0.250816	0.020882	0.000945	0.006007
2	0.356632	-0.035392	-0.052422	-0.004882
3	0.311453	-0.032514	-0.018844	0.026950
4	0.295902	0.001351	-0.048878	-0.006328

	3D_anklemagneto_1	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
0	-61.1081	-36.8636	-58.3696	1
1	-60.8916	-36.3197	-58.3656	1
2	-60.3407	-35.7842	-58.6119	1
3	-60.7646	-37.1028	-57.8799	1
4	-60.2040	-37.1225	-57.8847	1

[5 rows x 43 columns]

phydata.isnull().sum()

timestamp	0
activityID	0
heartrate	0
Temperature_hand	0
3D_hand_Acc1_16_1	0
3D_hand_Acc1_16_2	0
3D_hand_Acc1_16_3	0
3D_hand_Acc1_6_1	0
3D_hand_Acc1_6_2	0
3D_hand_Acc1_6_3	0
3D_handGyro_1	0
3D_handGyro_2	0
3D_handGyro_3	0
3D_handmagneto_1	0
3D_handmagneto_2	0
3D_handmagneto_3	0
Temperature_chest	0
3D_chest_Acc1_16_1	0

```

3D_chest_Accl_16_2    0
3D_chest_Accl_16_3    0
3D_chest_Accl_6_1     0
3D_chest_Accl_6_2     0
3D_chest_Accl_6_3     0
3D_chestGyro_1        0
3D_chestGyro_2        0
3D_chestGyro_3        0
3D_chestmagneto_1     0
3D_chestmagneto_2     0
3D_chestmagneto_3     0
Temperature_ankle     0
3D_ankle_Accl_16_1    0
3D_ankle_Accl_16_2    0
3D_ankle_Accl_16_3    0
3D_ankle_Accl_6_1     0
3D_ankle_Accl_6_2     0
3D_ankle_Accl_6_3     0
3D_ankleGyro_1        0
3D_ankleGyro_2        0
3D_ankleGyro_3        0
3D_anklemagneto_1     0
3D_anklemagneto_2     0
3D_anklemagneto_3     0
subject_id            0
dtype: int64

```

The data cleaning phase is now complete. The final dataframe "phydata" contains all the information and is ready for the next phase "Exploratory data analysis".

Exploratory Data Analysis

During this phase, all EDA analyses are conducted. The analysis is conducted using 'phydata' as input and 'graphs based on the analysis' are generated as output.

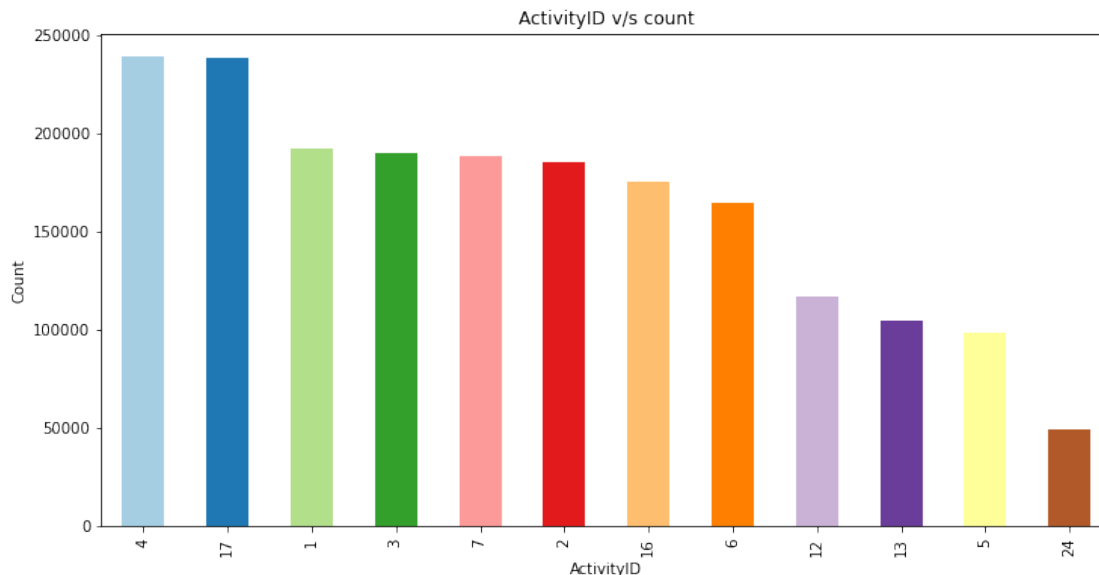
The process includes:-

- Generation of test and train data
- Activity time analysis by subjectID
- Analysis on activity by heartrate
- Analysis on activity by calorie burnt
- Analysis on activity by heart, chest and ankle temperature
- Correlation analysis

It is important to check if a dataframe is balanced before splitting it into a test and train set because unbalanced data can affect the performance of a machine learning model. If the data is unbalanced, meaning that one class is significantly more prevalent than the other

class, the model may be biased towards the more prevalent class. This can lead to poor performance on the less prevalent class.

```
size = range(len(phydata))
phydata['activityID'].value_counts().plot(kind = "bar",figsize =
(12,6),color=plt.cm.Paired(size))
plt.xlabel("ActivityID")
plt.ylabel("Count")
plt.title('ActivityID v/s count')
plt.show()
```



We can see from the bar graph that the dataframe is balanced, so we can split it into test and train sets.

Generation of test and train data

The test and train data are generated by splitting the data frame in half, i.e. 0.5.

```
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
```

```
training_data,testing_data = splitting_train_test(phydata,0.5)
```

```
training_data.describe()
```

	timestamp	activityID	heartrate	
Temperature_hand \				
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

	3D_hand_Accl_16_1	3D_hand_Accl_16_2	3D_hand_Accl_16_3	\
count	971436.000000	971436.000000	971436.000000	
mean	-4.956991	3.579835	3.612234	
std	6.244104	6.881571	3.962008	
min	-145.367000	-104.301000	-101.452000	
25%	-8.970760	1.060202	1.171568	
50%	-5.449225	3.525055	3.442250	
75%	-0.964139	6.451445	6.533720	
max	62.859600	155.699000	157.760000	

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
count	971436.000000	971436.000000	971436.000000	...	
mean	-4.890270	3.570034	3.796905	...	
std	6.249035	6.593962	3.946777	...	
min	-61.214700	-61.841700	-61.934700	...	
25%	-8.866962	1.060518	1.373687	...	
50%	-5.378790	3.566135	3.674970	...	
75%	-0.909503	6.458100	6.785285	...	
max	45.548400	62.259800	61.728000	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	\
count	971436.000000	971436.000000	971436.000000	
mean	9.370013	-0.046497	-2.176481	
std	6.068911	7.187835	3.477410	
min	-61.142000	-61.903500	-62.203800	
25%	8.394965	-2.073703	-3.398802	
50%	9.549240	-0.223893	-1.992215	
75%	10.278000	1.920240	-0.595102	
max	61.969300	62.049000	55.553400	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1	\			
count	971436.000000	971436.000000	971436.000000	
971436.000000				
mean	0.011323	-0.035935	0.007185	-
31.582509				

std	1.124865	0.637566	2.009187	
18.346495				
min	-13.592200	-7.324840	-12.977400	-
172.624000				
25%	-0.207035	-0.106357	-0.437332	-
41.694300				
50%	0.004692	-0.003908	-0.002289	-
33.998050				
75%	0.131925	0.116567	0.091502	-
17.897800				
max	16.442700	13.588200	14.482700	
91.551600				

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
count	971436.000000	971436.000000	971436.000000
mean	1.404674	17.253204	4.565264
std	21.685612	19.705747	2.332310
min	-137.908000	-102.716000	1.000000
25%	-12.443825	3.813545	2.000000
50%	0.779744	18.771850	5.000000
75%	17.840625	31.241150	7.000000
max	93.699200	139.787000	9.000000

[8 rows x 43 columns]

training_data.sort_index()

	timestamp	activityID	heartrate	Temperature_hand	\
0	37.66	1	100.0	30.375	
2	37.68	1	100.0	30.375	
3	37.69	1	100.0	30.375	
5	37.71	1	100.0	30.375	
6	37.72	1	100.0	30.375	
...	
1942859	94.98	24	162.0	25.125	
1942861	95.00	24	162.0	25.125	
1942862	95.01	24	162.0	25.125	
1942863	95.02	24	162.0	25.125	
1942865	95.04	24	162.0	25.125	
	3D_hand_Acc1_16_1	3D_hand_Acc1_16_2	3D_hand_Acc1_16_3	\	
0	2.21530	8.27915	5.58753		
2	2.29090	7.14240	5.82342		
3	2.21800	7.14365	5.89930		
5	2.07165	7.25965	6.01218		
6	2.41148	7.59780	5.93915		
...		
1942859	4.81452	6.51482	5.74788		
1942861	5.07290	6.39761	5.59819		
1942862	4.95472	6.28366	5.48134		

1942863	4.80517	6.32311	5.51746
1942865	4.95740	6.28434	5.55836

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
0	2.24689	8.55387	5.77143	...	
2	2.26966	7.66268	5.78846	...	
3	2.22177	7.25535	5.88000	...	
5	2.19238	7.21038	6.01604	...	
6	2.23988	7.46679	6.03053	...	
...	
1942859	4.89736	6.49594	5.78832	...	
1942861	4.94094	6.45017	5.63737	...	
1942862	4.93917	6.35946	5.51677	...	
1942863	4.89281	6.22387	5.51711	...	
1942865	4.81809	6.22448	5.59269	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	...	\
0	9.63162	-1.76757	0.265761	...	
2	9.60196	-1.73721	0.356632	...	
3	9.58674	-1.78264	0.311453	...	
5	9.60177	-1.75239	0.311276	...	
6	9.67694	-1.76748	0.326060	...	
...	
1942859	9.44267	-1.99702	-1.806020	...	
1942861	9.44276	-2.13311	-1.775310	...	
1942862	9.39788	-2.13306	-1.729670	...	
1942863	9.48793	-2.20869	-1.745040	...	
1942865	9.36713	-2.42063	-1.879930	...	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	...	\
0	0.002908	-0.027714	0.001752	...	
61.1081					
2	-0.035392	-0.052422	-0.004882	...	
60.3407					
3	-0.032514	-0.018844	0.026950	...	
60.7646					
5	0.003793	-0.026906	0.004125	...	
61.3257					
6	0.036814	-0.032277	-0.006866	...	
61.5520					
...	
...					
1942859	-0.036682	-0.011895	-0.017897	...	
45.9167					
1942861	0.027636	-0.024815	-0.022575	...	
46.2808					
1942862	-0.005801	-0.007817	0.009006	...	
45.9034					
1942863	-0.028744	-0.061156	0.033653	...	


```

46.0452
1942865      -0.041091      -0.019494      0.014317      -
45.8890

```

```

          3D_anklemagneto_2  3D_anklemagneto_3  subject_id
0          -36.863600      -58.369600          1
2          -35.784200      -58.611900          1
3          -37.102800      -57.879900          1
5          -36.974400      -57.750100          1
6          -36.963200      -57.995700          1
...
1942859      -0.437698          0.254439          9
1942861      -1.320750          0.254182          9
1942862      -1.211660      -0.028281          9
1942863      -0.690454      -0.313048          9
1942865      -1.596940          0.539545          9

```

[971436 rows x 43 columns]

Activity time analysis by subjectID

Let us consider the amount of time each subject spent performing different types of physical activity. As a result, the activityID is mapped with the activity's name to create a dataframe named phydatacop.

```

phydatacop=training_data.copy()
phydatacop.activityID=phydatacop.activityID.apply(lambda
x:activityIDdict[x])
phydatacop

```

```

          timestamp      activityID  heartrate  Temperature_hand \
312921      767.77      standing      90.000000      34.1875
141735     1926.37  ascending_stairs     167.909091      33.6875
1191085     3749.31    rope_jumping     181.000000      33.8125
1206914      255.84          lying      62.000000      33.4375
1710520      491.73      sitting      79.000000      34.3125
...
471794     3648.85      cycling     120.000000      29.7500
46078       498.44      sitting      92.000000      32.5625
495388     3961.26      running     139.000000      28.8750
1506095      783.52      ironing      74.000000      33.3750
699375      192.56          lying      72.000000      32.7500

```

```

          3D_hand_Accl_16_1  3D_hand_Accl_16_2  3D_hand_Accl_16_3 \
312921      -8.52981          4.712060          0.358276
141735     -11.23140          2.967660          2.325040
1191085     -1.77987          3.716760         -7.388680
1206914          4.89177         -0.216854          8.273420
1710520     -1.96494         -9.487270          0.889387
...

```

471794	-6.10533	3.427980	7.365140
46078	-7.87425	4.095880	4.141940
495388	-5.33359	36.979800	-3.435980
1506095	2.11020	11.319200	-2.429680
699375	5.04452	0.198974	8.235820

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
312921	-8.254460	4.955160	0.791698	...	
141735	-10.353600	2.978210	2.293150	...	
1191085	-0.572605	3.958700	-4.197230	...	
1206914	5.134350	-0.344501	8.596710	...	
1710520	-1.802600	-9.468570	1.058310	...	
...	
471794	-6.577840	4.301450	9.142140	...	
46078	-7.704180	4.138990	4.356700	...	
495388	-3.119450	34.862600	-2.873060	...	
1506095	2.211510	12.367400	-2.346000	...	
699375	5.409190	0.227261	8.444170	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	\
312921	9.716540	-1.511980	-1.006870	
141735	11.137500	-1.301760	-2.513480	
1191085	-4.136650	-4.006830	2.162320	
1206914	-0.117976	-9.411680	-2.836260	
1710520	9.187270	2.903000	-2.153400	
...	
471794	10.602400	-2.752050	-1.022720	
46078	9.135820	1.192120	-3.570340	
495388	11.857500	5.583830	0.381641	
1506095	9.890210	-0.561093	-2.660590	
699375	2.514220	-9.420820	1.569270	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1	\			
312921	0.079272	-0.003718	-0.076595	-
18.7246				
141735	-0.276670	0.669698	-0.143689	-
51.7218				
1191085	1.877290	-0.176273	-0.654045	-
44.6465				
1206914	-0.008012	0.002114	0.017758	-
17.3221				
1710520	0.010209	0.011341	0.028921	-
19.4371				
...	
...				
471794	0.154275	0.059888	0.106166	-
41.1119				
46078	0.063705	0.008307	0.002250	-
85.4454				

495388	-1.355570	1.238730	-3.278750	-
51.4954				
1506095	0.426933	-0.741163	0.191537	-
33.2568				
699375	-0.070824	0.009968	0.010577	-
21.4016				

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
312921	-16.87960	36.806500	2
141735	33.83850	-6.571620	1
1191085	-12.21680	0.272571	5
1206914	26.44510	-4.782110	6
1710520	15.82690	26.000300	8
...
471794	5.34881	8.881400	2
46078	38.14700	16.401700	1
495388	-5.78950	36.450200	2
1506095	-1.96371	46.112500	7
699375	15.80880	-13.294100	4

[971436 rows x 43 columns]

Using a pie chart, we examine the time subjects spend on each activity (excluding the optional data given).

```
def plot(df, sub, ax):
```

```
    df.activityID.value_counts().plot(kind='pie', ax=ax)
    df.activityID.agg(['value_counts'])
    ax.set_title('Subject {}'.format(sub), fontsize=25)
```

```
# Add a title to the entire figure
```

```
print('Time spend for each activity by subjects')
```

```
# Create a figure with 3 rows and 3 columns of subplots, with a larger size
```

```
fig, ax = plt.subplots(3, 3, figsize=(9, 9))
```

```
# Iterate through the subject IDs
```

```
for i, sub in enumerate([1,2,3, 4,5,6,7,8,9]):
```

```
    # Plot the pie chart for the subject and assign it to the appropriate subplot
```

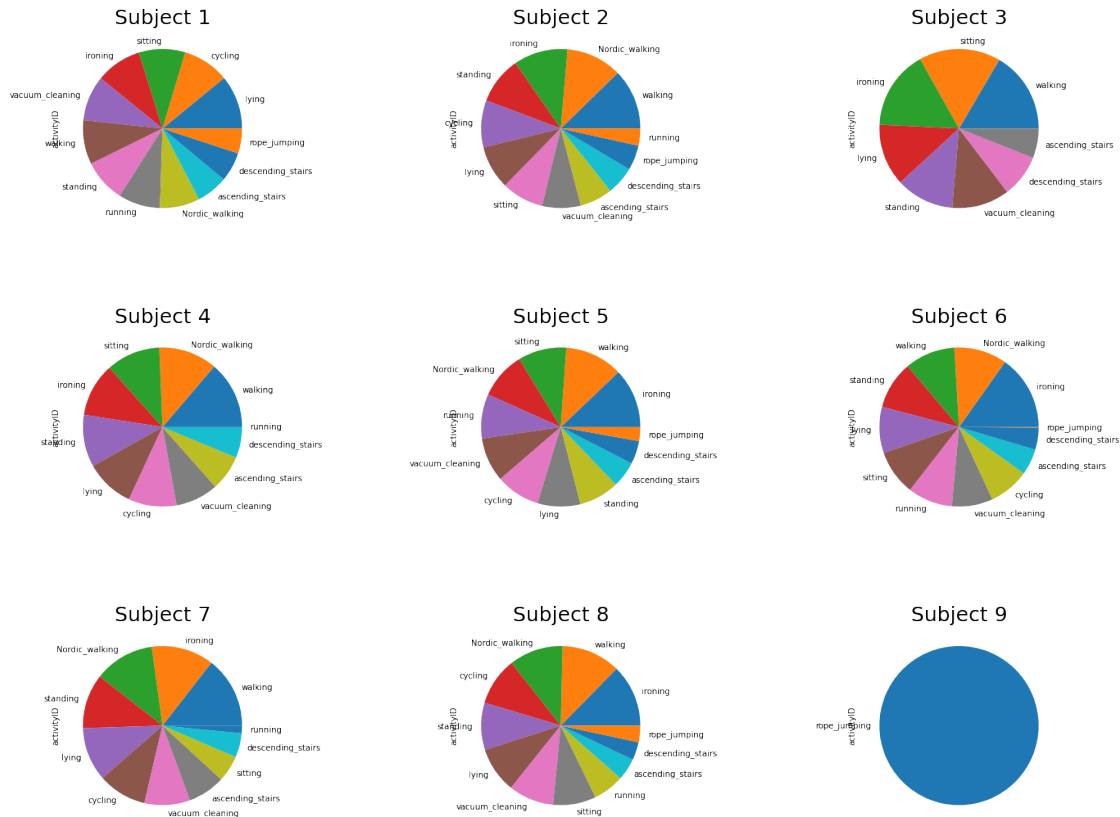
```
    plot(phydatacop[phydatacop['subject_id']==sub], sub, ax[i // 3][i % 3])
```

```
# Adjust the spacing between the subplots
```

```
plt.subplots_adjust(left=0, bottom=0.5, right=2, top=2, wspace=0.5, hspace=0.5)
```

```
# Show the plot
plt.show()
```

Time spend for each activity by subjects



Analysis on activity by heartrate

Let us consider now consider the average heartrate measured while performing various physical activities.

```
df_grouped=training_data.groupby(['activityID']).mean()
df_grouped=df_grouped.reset_index()
df_grouped
```

	activityID	timestamp	heartrate	Temperature_hand	
3D_hand_Accel_16_1	\				
0	1	205.810018	75.545557	32.728505	
3.679602					
1	2	506.308536	80.047179	33.258141	-
1.389341					
2	3	733.377930	88.536730	33.637740	-
7.075932					
3	4	2429.595921	112.779310	32.303069	-
10.107593					
4	5	3445.280586	156.609147	30.819405	-

6.504239					
5	6	3128.694951	124.830549	31.009282	-
5.154956					
6	7	2903.735748	123.775604	31.528332	-
4.737611					
7	12	1806.752318	129.518261	33.528458	-
8.733582					
8	13	1905.608580	129.094747	33.323658	-
6.282657					
9	16	1359.725161	104.182793	34.176997	-
7.162320					
10	17	1026.179980	90.045718	34.022595	-
3.375883					
11	24	3349.758610	161.966847	29.713111	-
4.206803					

	3D_hand_Accl_16_2	3D_hand_Accl_16_3	3D_hand_Accl_6_1
3D_hand_Accl_6_2 \			
0	2.061675	6.367305	3.791752
2.032754			
1	4.295544	5.173842	-1.262264
4.294076			
2	3.223117	2.675270	-6.939606
3.266560			
3	2.515623	1.922580	-10.100182
2.545913			
4	6.728369	0.287698	-6.624070
6.352816			
5	2.507518	7.122948	-5.158149
2.506534			
6	5.079735	2.543156	-4.736760
5.078315			
7	3.658778	1.603061	-8.643621
3.695112			
8	2.910228	3.656226	-6.184478
2.924561			
9	3.575758	1.913401	-7.031500
3.595148			
10	3.752365	5.447087	-3.246341
3.745548			
11	5.390808	-0.530344	-4.326484
5.410021			

	3D_hand_Accl_6_3	...	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2 \
0	6.588179	...	0.543936	-6.226228
1	5.383078	...	8.809982	-0.216851
2	2.893323	...	9.380298	-0.741048
3	2.092860	...	11.959444	0.632620
4	0.388420	...	13.193339	2.880917
5	7.262646	...	9.130031	2.129800

6	2.692999	...	12.262297	0.872126
7	1.801738	...	9.788651	1.604495
8	3.853605	...	10.742766	1.154140
9	2.132941	...	9.563327	0.435375
10	5.665965	...	9.601066	-0.401777
11	-0.539632	...	9.907947	1.084461

	3D_ankle_Accl_6_3	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3
\				
0	-3.316962	0.010893	-0.005854	0.006003
1	-2.089557	0.006796	-0.005329	0.005010
2	-1.643213	0.004367	-0.004551	0.004309
3	-2.693545	-0.005349	-0.113771	-0.000048
4	-3.189012	0.002644	-0.100271	-0.037299
5	-1.068567	0.085572	0.038773	0.003845
6	-2.906883	-0.004517	-0.140149	0.006245
7	-2.708451	0.385221	0.133281	-0.006582
8	-2.114203	-0.405388	-0.242240	0.111473
9	-1.281936	-0.002207	0.005179	0.004223
10	-1.457873	0.011071	-0.002973	0.002770
11	-2.047257	0.009809	-0.009883	0.012182

	3D_anklemagneto_1	3D_anklemagneto_2	3D_anklemagneto_3
subject_id			
0	-17.937375	20.577229	0.134306
4.485731			
1	-22.525800	2.503881	21.125203
4.306876			
2	-22.656027	-0.594149	24.427203
4.593166			
3	-36.985424	-0.592640	15.840951
4.623625			
4	-36.532773	-8.301071	13.229515
4.663884			
5	-38.848188	-6.929358	12.873313
4.701040			
6	-37.386417	-0.656277	14.345998

4.851653			
7	-35.736146	-4.829318	13.768898
4.402396			
8	-36.826082	-4.451120	20.214430
4.166409			
9	-24.416449	4.187497	11.367237
4.550262			
10	-38.835212	5.579286	34.094910
4.726989			
11	-40.243773	-8.196516	23.698923
4.221707			

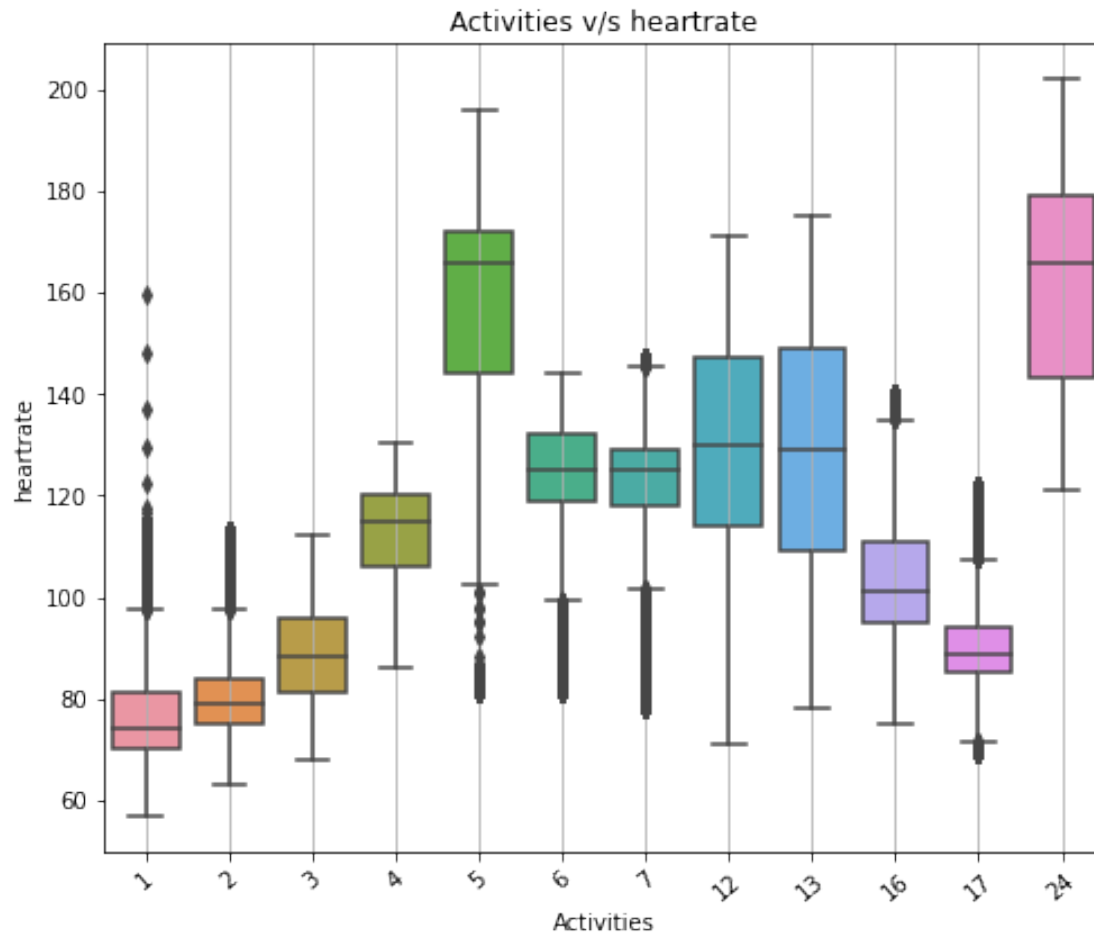
[12 rows x 43 columns]

```
df_grouped['activity_name']=1
for i in range(len(df_grouped['activityID'])):
    df_grouped['activity_name']
[i]=activityIDdict[df_grouped['activityID'][i]]
df_grouped[['activityID','activity_name','heartrate']]
```

	activityID	activity_name	heartrate
0	1	lying	75.545557
1	2	sitting	80.047179
2	3	standing	88.536730
3	4	walking	112.779310
4	5	running	156.609147
5	6	cycling	124.830549
6	7	Nordic_walking	123.775604
7	12	ascending_stairs	129.518261
8	13	descending_stairs	129.094747
9	16	vacuum_cleaning	104.182793
10	17	ironing	90.045718
11	24	rope_jumping	161.966847

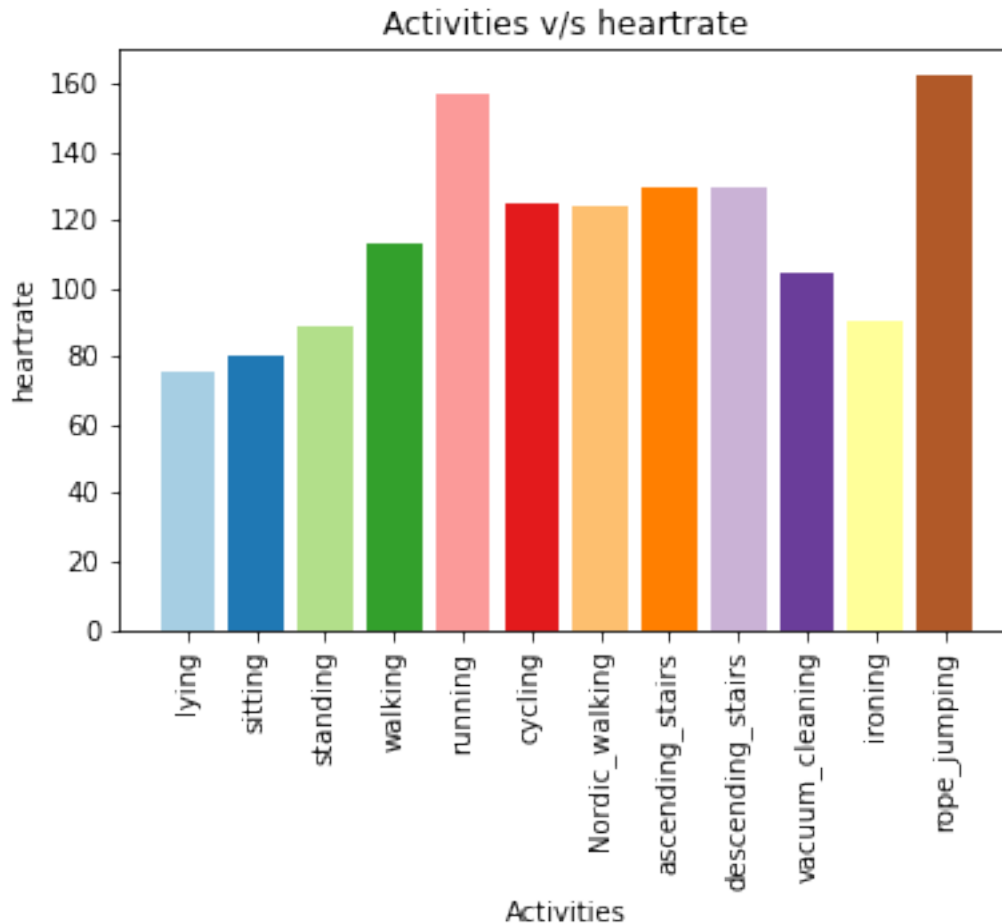
Boxplot for Activities v/s heartrate

```
import seaborn as sns
plt.figure(figsize=(7,5))
plt.subplots_adjust(2,1,5,2)
plt.subplot(131)
dat1=training_data[['activityID','heartrate']]
#dat1.activityID=dat1.activityID.astype("category")
plt.xticks(rotation=40)
sns.boxplot(x='activityID',y='heartrate',data=dat1)
plt.grid(axis='x')
plt.ylabel('heartrate')
plt.xlabel('Activities')
plt.title('Activities v/s heartrate')
plt.show()
```



Bar graph for Activities v/s heartrate

```
size = range(len(df_grouped))
plt.bar(df_grouped['activity_name'],df_grouped['heartrate'],color=plt.
cm.Paired(size))
plt.xticks(rotation=90)
plt.xlabel('Activities')
plt.ylabel('heartrate')
plt.title('Activities v/s heartrate')
plt.show()
```

Based on our analysis, we can conclude that rope jumping produces the highest heart rate, followed by running. Lying results in the lowest heart rate.

Analysis on activity by calorie burnt

As part of this analysis, we will consider how many calories the subjects burnt during various activities. Calorie_burnt is calculated in `calorie_calc()` based on the MET value and the weight of each subject. Next, a new dataframe `activity_subject_group` is created from `training_data` dataframe by grouping `activityID` and `subjectID`, then applying the mean, max, and min functions to the timestamp column for each group, and the value of calories burnt is added to that dataframe. Another dataframe `calorie_on_acti` is created by grouping the `activityID` and `subjectID` of `activity_subject_group` and taking their mean. The `activityID` is mapped to an `activityName` so that a clear understanding can be gained.

```
def calorie_calc(i):
```

```
    T=60
```

```
    MET=MET_values[activity_subject_group['activityID'][i]]
```

```
    W=subject_weights[activity_subject_group['subject_id'][i]]
```

```
    calories= T * MET * 3.5 * W / (200 * 60)
```

```

    return calories

activity_subject_group=training_data.groupby(['activityID','subject_id
'])['timestamp'].agg([np.mean,max,min])
activity_subject_group=activity_subject_group.reset_index()
activity_subject_group['calorie_burnt']=0
for i in range(len(activity_subject_group['activityID'])):
    activity_subject_group['calorie_burnt'][i]=calorie_calc(i)

calorie_on_acti=activity_subject_group.groupby(['activityID','subject_
id']).mean()
calorie_on_acti=calorie_on_acti.reset_index()
calorie_on_acti.activityID=calorie_on_acti.activityID.apply(lambda
x:activityIDdict[x])
calorie_on_acti

```

	activityID	subject_id	mean	max	min
calorie_burnt					
0	lying	1	174.045415	309.52	37.66
1.4525					
1	lying	2	171.966434	289.49	55.20
1.3650					
2	lying	3	276.886762	386.54	166.14
1.6100					
3	lying	4	190.067999	305.69	75.26
1.6625					
4	lying	5	223.699684	341.45	104.53
1.2775					
..
...					
86	rope_jumping	2	4178.977066	4245.68	4113.08
12.2850					
87	rope_jumping	5	3714.966443	3753.50	3676.20
11.4975					
88	rope_jumping	6	3622.808686	3624.05	3621.50
10.8675					
89	rope_jumping	8	3844.586316	3888.41	3800.36
13.7025					
90	rope_jumping	9	63.153766	95.04	31.22
10.2375					

[91 rows x 6 columns]

```

calor_df_for_graph=calorie_on_acti.groupby(['activityID']).mean()
calor_df_for_graph.reset_index(drop=False, inplace=True)
calor_df_for_graph

```

	activityID	subject_id	mean	max
min \				
0	Nordic_walking	4.714286	2885.966026	3020.291429

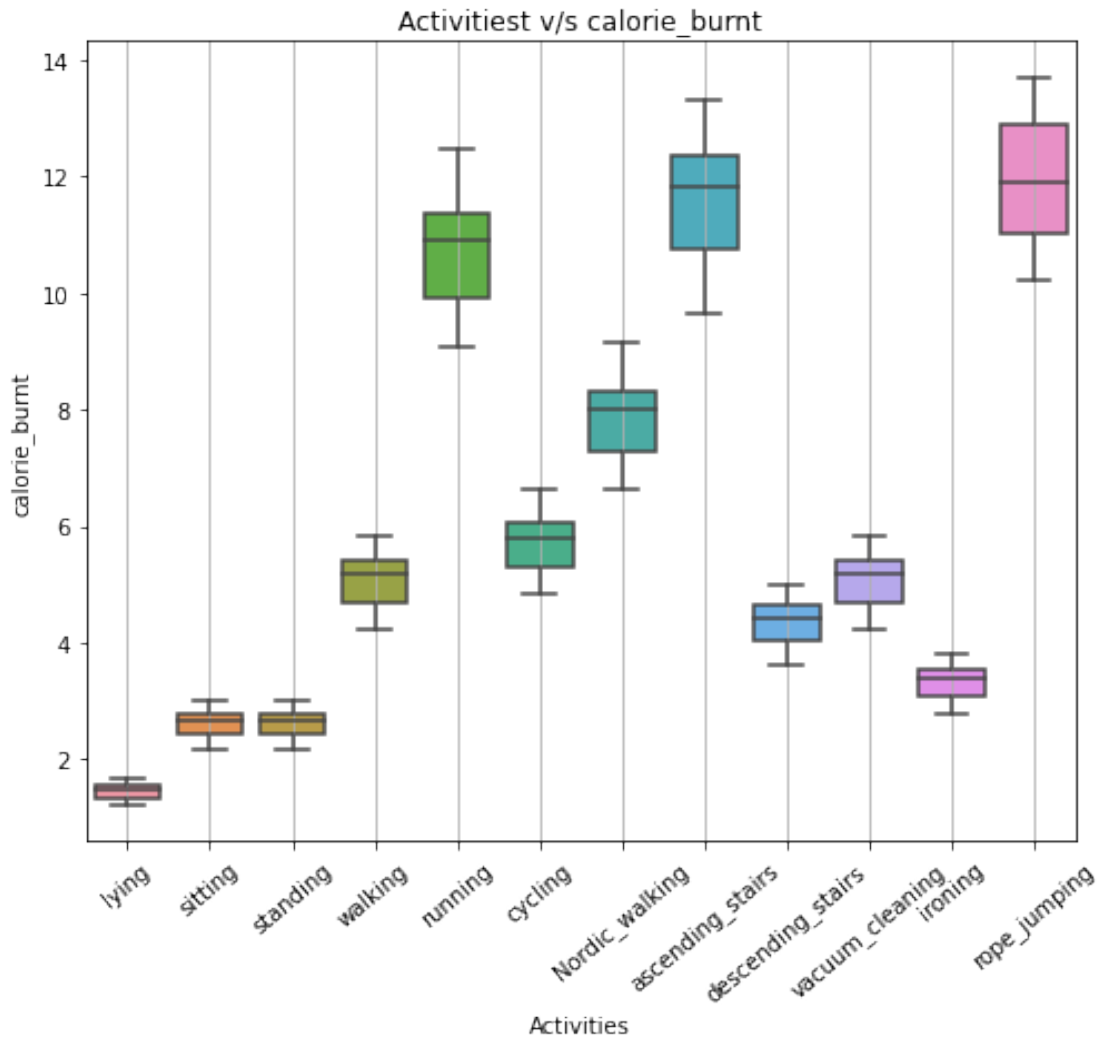
2751.590000				
1	ascending_stairs	4.500000	1807.821634	1999.022500
1615.946250				
2	cycling	4.714286	3124.079746	3241.817143
3006.704286				
3	descending_stairs	4.500000	1901.256871	2058.310000
1753.810000				
4	ironing	4.500000	1023.305778	1172.390000
874.068750				
5	lying	4.500000	206.958464	327.148750
86.527500				
6	rope_jumping	5.166667	3164.427640	3205.508333
3123.270000				
7	running	4.714286	3432.242946	3502.458571
3362.197143				
8	sitting	4.500000	499.172845	614.961250
383.506250				
9	standing	4.500000	736.287875	854.913750
617.530000				
10	vacuum_cleaning	4.500000	1358.443971	1468.221250
1249.055000				
11	walking	4.500000	2426.017357	2575.397500
2276.978750				

	calorie_burnt
0	7.851250
1	11.602500
2	5.710000
3	4.350937
4	3.335719
5	1.450312
6	11.943750
7	10.706250
8	2.610562
9	2.610562
10	5.076094
11	5.076094

Box plot for Activities v/s calorie_burnt

```
import seaborn as sns
plt.figure(figsize=(7,5))
plt.subplots_adjust(2,1,5,2)
plt.subplot(131)
dat1=calorie_on_acti[['activityID','calorie_burnt']]
#dat1.activityID=dat1.activityID.astype("category")
plt.xticks(rotation=40)
sns.boxplot(x='activityID',y='calorie_burnt',data=dat1)
plt.grid(axis='x')
plt.xlabel('Activities')
plt.ylabel('calorie_burnt')
```

```
# plt.title('Activities and Temperature of chest')
plt.title('Activitiest v/s calorie_burnt')
plt.show()
```



Based on our analysis, we can conclude that calorie_burnt is highest for rope jumping followed by ascending_stairs and running. Lying has the lowest value for calorie_burnt.

Analysis on activity by heart, chest and ankle temperature

Now let's take a look at the temperature analysis of the hand, chest, and ankle.

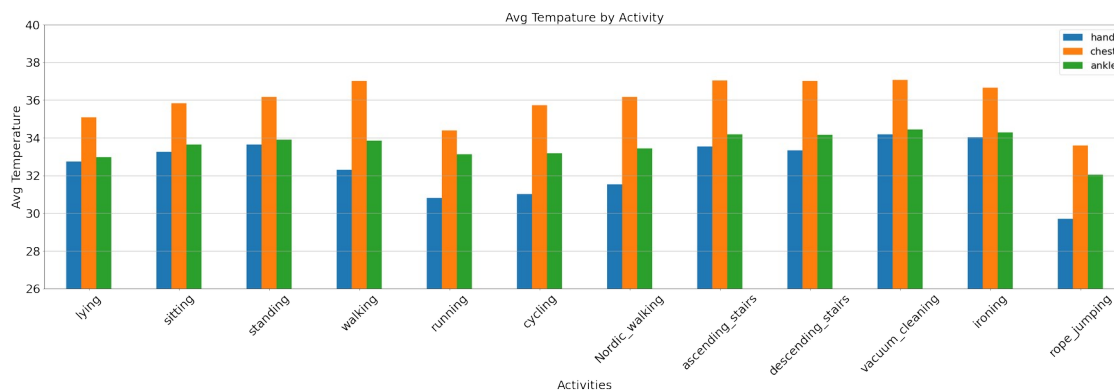
```
mean_tempreture = pd.DataFrame()
mean_tempreture['hand'] = df_grouped['Temperature_hand']
mean_tempreture['chest'] = df_grouped['Temperature_chest']
mean_tempreture['ankle'] = df_grouped['Temperature_ankle']

ax =mean_tempreture.plot(kind='bar', figsize=(40,10), title='Avg
Temputures by Activity',fontsize=25)
```

```

a = ax.set_xticklabels(df_grouped['activity_name'],rotation=45)
b = ax.legend(fontsize = 20)
c = ax.set_xticks(np.arange(len(samepls_tempreture)))
plt.title('Avg Tempature by Activity',fontsize = 25)
plt.ylim(26, 40)
plt.xlabel('Activities',fontsize=25)
plt.ylabel('Avg Temperature', fontsize=25)
plt.grid(axis='y')

```



According to this graph, we can conclude that the chest temperature is the highest compared to ankle and hand temperatures. The temperatures of the chest, hand, and ankle are higher when ascending_stairs, descending_stairs, Ironing and vacuum_cleaning. rope_jumping has the lowest values.

Correlation Analysis

Correlation analysis is a statistical technique that is used to evaluate the strength and direction of the relationship between two variables. It measures the degree to which a change in one variable is associated with a change in another variable.

We are mapping the activity ID and activity name here.

```

df_grouped['activity_name']=1
for i in range(len(df_grouped['activityID'])):
    df_grouped['activity_name']
[i]=activityIDdict[df_grouped['activityID'][i]]
df_grouped

```

activityID	timestamp	heartrate	Temperature_hand
3D_hand_Accl_16_1	\		
0	1 205.810018	75.545557	32.728505
3.679602			
1	2 506.308536	80.047179	33.258141
1.389341			-
2	3 733.377930	88.536730	33.637740
7.075932			-
3	4 2429.595921	112.779310	32.303069
10.107593			-
4	5 3445.280586	156.609147	30.819405
			-

6.504239					
5	6	3128.694951	124.830549	31.009282	-
5.154956					
6	7	2903.735748	123.775604	31.528332	-
4.737611					
7	12	1806.752318	129.518261	33.528458	-
8.733582					
8	13	1905.608580	129.094747	33.323658	-
6.282657					
9	16	1359.725161	104.182793	34.176997	-
7.162320					
10	17	1026.179980	90.045718	34.022595	-
3.375883					
11	24	3349.758610	161.966847	29.713111	-
4.206803					

	3D_hand_Accl_16_2	3D_hand_Accl_16_3	3D_hand_Accl_6_1
3D_hand_Accl_6_2 \			
0	2.061675	6.367305	3.791752
2.032754			
1	4.295544	5.173842	-1.262264
4.294076			
2	3.223117	2.675270	-6.939606
3.266560			
3	2.515623	1.922580	-10.100182
2.545913			
4	6.728369	0.287698	-6.624070
6.352816			
5	2.507518	7.122948	-5.158149
2.506534			
6	5.079735	2.543156	-4.736760
5.078315			
7	3.658778	1.603061	-8.643621
3.695112			
8	2.910228	3.656226	-6.184478
2.924561			
9	3.575758	1.913401	-7.031500
3.595148			
10	3.752365	5.447087	-3.246341
3.745548			
11	5.390808	-0.530344	-4.326484
5.410021			

	3D_hand_Accl_6_3	...	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	\
0	6.588179	...	-6.226228	-3.316962	
1	5.383078	...	-0.216851	-2.089557	
2	2.893323	...	-0.741048	-1.643213	
3	2.092860	...	0.632620	-2.693545	
4	0.388420	...	2.880917	-3.189012	
5	7.262646	...	2.129800	-1.068567	

6	2.692999	...	0.872126	-2.906883
7	1.801738	...	1.604495	-2.708451
8	3.853605	...	1.154140	-2.114203
9	2.132941	...	0.435375	-1.281936
10	5.665965	...	-0.401777	-1.457873
11	-0.539632	...	1.084461	-2.047257

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	3D_anklemagneto_1
\				
0	0.010893	-0.005854	0.006003	-17.937375
1	0.006796	-0.005329	0.005010	-22.525800
2	0.004367	-0.004551	0.004309	-22.656027
3	-0.005349	-0.113771	-0.000048	-36.985424
4	0.002644	-0.100271	-0.037299	-36.532773
5	0.085572	0.038773	0.003845	-38.848188
6	-0.004517	-0.140149	0.006245	-37.386417
7	0.385221	0.133281	-0.006582	-35.736146
8	-0.405388	-0.242240	0.111473	-36.826082
9	-0.002207	0.005179	0.004223	-24.416449
10	0.011071	-0.002973	0.002770	-38.835212
11	0.009809	-0.009883	0.012182	-40.243773

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
activity_name			
0	20.577229	0.134306	4.485731
lying			
1	2.503881	21.125203	4.306876
sitting			
2	-0.594149	24.427203	4.593166
standing			
3	-0.592640	15.840951	4.623625
walking			
4	-8.301071	13.229515	4.663884
running			
5	-6.929358	12.873313	4.701040
cycling			
6	-0.656277	14.345998	4.851653

Nordic_walking			
7	-4.829318	13.768898	4.402396
ascending_stairs			
8	-4.451120	20.214430	4.166409
descending_stairs			
9	4.187497	11.367237	4.550262
vacuum_cleaning			
10	5.579286	34.094910	4.726989
ironing			
11	-8.196516	23.698923	4.221707
rope_jumping			

[12 rows x 44 columns]

In order to reduce the columns we have `axis_reducer()`, in which we take the sum of the square roots for each of the three values provided. In this way, the heatmap can be easily interpreted.

```
def axis_reducer(df,a,b,c,d):
    ref=df.copy()
    ref[d]=1
    for i in range(len(ref[a])):
        # x=ref[a][i]
        # y=ref[b][i]
        # z=ref[c][i]
        # print(ref[b][i])

        ref[d][i]=(ref[a][i]**2 + ref[b][i]**2 + ref[c][i]**2)**0.5

    # ref[d][i]=dist
    ref=ref.drop([a,b,c], axis=1)

    return ref
```

```
df_correlation=training_data.copy()
df_correlation.reset_index(drop=True, inplace=True)
df_correlation
```

	timestamp	activityID	heartrate	Temperature_hand	\
0	767.77	3	90.000000	34.1875	
1	1926.37	12	167.909091	33.6875	
2	3749.31	24	181.000000	33.8125	
3	255.84	1	62.000000	33.4375	
4	491.73	2	79.000000	34.3125	
...	
971431	3648.85	6	120.000000	29.7500	
971432	498.44	2	92.000000	32.5625	
971433	3961.26	5	139.000000	28.8750	

971434	783.52	17	74.000000	33.3750
971435	192.56	1	72.000000	32.7500

	3D_hand_Accl_16_1	3D_hand_Accl_16_2	3D_hand_Accl_16_3	\
0	-8.52981	4.712060	0.358276	
1	-11.23140	2.967660	2.325040	
2	-1.77987	3.716760	-7.388680	
3	4.89177	-0.216854	8.273420	
4	-1.96494	-9.487270	0.889387	
...	
971431	-6.10533	3.427980	7.365140	
971432	-7.87425	4.095880	4.141940	
971433	-5.33359	36.979800	-3.435980	
971434	2.11020	11.319200	-2.429680	
971435	5.04452	0.198974	8.235820	

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
0	-8.254460	4.955160	0.791698	...	
1	-10.353600	2.978210	2.293150	...	
2	-0.572605	3.958700	-4.197230	...	
3	5.134350	-0.344501	8.596710	...	
4	-1.802600	-9.468570	1.058310	...	
...	
971431	-6.577840	4.301450	9.142140	...	
971432	-7.704180	4.138990	4.356700	...	
971433	-3.119450	34.862600	-2.873060	...	
971434	2.211510	12.367400	-2.346000	...	
971435	5.409190	0.227261	8.444170	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	\
0	9.716540	-1.511980	-1.006870	
1	11.137500	-1.301760	-2.513480	
2	-4.136650	-4.006830	2.162320	
3	-0.117976	-9.411680	-2.836260	
4	9.187270	2.903000	-2.153400	
...	
971431	10.602400	-2.752050	-1.022720	
971432	9.135820	1.192120	-3.570340	
971433	11.857500	5.583830	0.381641	
971434	9.890210	-0.561093	-2.660590	
971435	2.514220	-9.420820	1.569270	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1 \				
0	0.079272	-0.003718	-0.076595	-
18.7246				
1	-0.276670	0.669698	-0.143689	-
51.7218				
2	1.877290	-0.176273	-0.654045	-
44.6465				

3	-0.008012	0.002114	0.017758	-
17.3221				
4	0.010209	0.011341	0.028921	-
19.4371				
...	
...				
971431	0.154275	0.059888	0.106166	-
41.1119				
971432	0.063705	0.008307	0.002250	-
85.4454				
971433	-1.355570	1.238730	-3.278750	-
51.4954				
971434	0.426933	-0.741163	0.191537	-
33.2568				
971435	-0.070824	0.009968	0.010577	-
21.4016				

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
0	-16.87960	36.806500	2
1	33.83850	-6.571620	1
2	-12.21680	0.272571	5
3	26.44510	-4.782110	6
4	15.82690	26.000300	8
...
971431	5.34881	8.881400	2
971432	38.14700	16.401700	1
971433	-5.78950	36.450200	2
971434	-1.96371	46.112500	7
971435	15.80880	-13.294100	4

[971436 rows x 43 columns]

```

ref=axis_reducer(df_correlation,'3D_hand_Accl_16_1','3D_hand_Accl_16_2',
,'3D_hand_Accl_16_3','Hand_Acceleration_16')
ref=axis_reducer(ref,'3D_hand_Accl_6_1','3D_hand_Accl_6_2','3D_hand_Accl_6_3','Hand_Acceleration_6')
ref=axis_reducer(ref,'3D_handGyro_1','3D_handGyro_2','3D_handGyro_3','Hand_Gyrometer')
ref=axis_reducer(ref,'3D_ankle_Accl_6_1','3D_ankle_Accl_6_2','3D_ankle_Accl_6_3','Ankle_Acceleration')
ref=axis_reducer(ref,'3D_handmagneto_1','3D_handmagneto_2','3D_handmagneto_3','Hand_magnetometer')
ref=axis_reducer(ref,'3D_ankle_Accl_16_1','3D_ankle_Accl_16_2','3D_ankle_Accl_16_3','Ankle_Acceleration_16')
ref=axis_reducer(ref,'3D_ankleGyro_1','3D_ankleGyro_2','3D_ankleGyro_3','Ankle_Gyrometer')
ref=axis_reducer(ref,'3D_anklemagneto_1','3D_anklemagneto_2','3D_anklemagneto_3','Ankle_Magnetometer')
ref=axis_reducer(ref,'3D_chest_Accl_16_1','3D_chest_Accl_16_2','3D_chest_Accl_16_3','Chest_Acceleration_16')

```

st_Accl_16_3','Chest_Acceleration_16')

ref

	timestamp	activityID	heartrate	Temperature_hand	\
0	767.77	3	90.000000	34.1875	
1	1926.37	12	167.909091	33.6875	
2	3749.31	24	181.000000	33.8125	
3	255.84	1	62.000000	33.4375	
4	491.73	2	79.000000	34.3125	
...	
971431	3648.85	6	120.000000	29.7500	
971432	498.44	2	92.000000	32.5625	
971433	3961.26	5	139.000000	28.8750	
971434	783.52	17	74.000000	33.3750	
971435	192.56	1	72.000000	32.7500	

	Temperature_chest	3D_chest_Accl_6_1	3D_chest_Accl_6_2	\
0	37.5000	0.726417	9.00292	
1	36.9375	1.029990	12.11190	
2	36.4375	0.823781	7.44068	
3	35.5625	0.426480	-1.29363	
4	37.6250	0.323531	9.94835	
...	
971431	34.7500	-2.415180	3.05996	
971432	34.1875	0.954195	9.73556	
971433	32.2500	3.928670	22.06030	
971434	36.1250	2.309780	10.08320	
971435	34.7500	-0.757257	1.78800	

	3D_chest_Accl_6_3	3D_chestGyro_1	3D_chestGyro_2	...
subject_id \				
0	-3.942390	-0.032422	-0.058200	...
2				
1	-4.267670	0.197389	-0.299194	...
1				
2	1.432570	2.479190	-0.082051	...
5				
3	9.676190	-0.026513	-0.017288	...
6				
4	0.641904	-0.074353	0.035903	...
8				
...
...				
971431	-12.388600	0.063543	0.134901	...
2				
971432	0.682817	-0.018283	0.019778	...
1				
971433	-10.543100	3.670570	0.764957	...
2				
971434	-1.908610	-0.331533	1.281290	...

7				
971435	9.692280	-0.004381	0.001607	...
4				

	Hand_Acceleration_16	Hand_Acceleration_6	Hand_Gyrometer	\
0	9.751386	9.660047	0.164967	
1	11.847243	11.014777	2.181952	
2	8.460191	5.797924	4.643583	
3	9.613840	10.019164	0.062214	
4	9.729352	9.696556	0.057963	
...	
971431	10.162253	12.056085	0.268151	
971432	9.794678	9.770694	0.041158	
971433	37.520111	35.119600	2.651422	
971434	11.767777	12.780731	4.275455	
971435	9.659995	10.030702	0.039176	

	Ankle_Acceleration	Hand_magnetometer	
Ankle_Acceleration_16	\		
0	9.884888	34.928264	9.853628
1	11.491565	48.546151	11.880628
2	6.151600	46.379032	7.628115
3	9.830463	48.484174	10.163821
4	9.872713	29.258687	9.926956
...
971431	11.001392	53.481398	10.488048
971432	9.880875	56.686076	10.033660
971433	13.112022	56.899400	11.042984
971434	10.257184	44.155289	10.479384
971435	9.876019	53.783521	9.848968

	Ankle_Gyrometer	Ankle_Magnetometer	Chest_Acceleration_16
0	0.110294	44.612218	10.060474
1	0.738707	62.156053	13.478711
2	1.995762	46.288600	11.259950
3	0.019596	31.972911	9.440225
4	0.032699	36.115194	9.970973
...

971431	0.196618	42.399025	12.667246
971432	0.064284	95.000662	9.771799
971433	3.757955	63.355439	30.175062
971434	0.876516	56.887903	10.583624
971435	0.072300	29.743566	9.600552

[971436 rows x 25 columns]

```
ref=axis_reducer(ref,'3D_chest_Acc1_6_1','3D_chest_Acc1_6_2','3D_chest_Acc1_6_3','Chest_Acceleration_6')
```

```
ref=axis_reducer(ref,'3D_chestGyro_1','3D_chestGyro_2','3D_chestGyro_3','Chest_Gyrometer')
```

```
ref=axis_reducer(ref,'3D_chestmagneto_1','3D_chestmagneto_2','3D_chestmagneto_3','Chest_Magnetometer')
```

```
ref
```

	timestamp	activityID	heartrate	Temperature_hand \
0	767.77	3	90.000000	34.1875
1	1926.37	12	167.909091	33.6875
2	3749.31	24	181.000000	33.8125
3	255.84	1	62.000000	33.4375
4	491.73	2	79.000000	34.3125
...
971431	3648.85	6	120.000000	29.7500
971432	498.44	2	92.000000	32.5625
971433	3961.26	5	139.000000	28.8750
971434	783.52	17	74.000000	33.3750
971435	192.56	1	72.000000	32.7500

	Temperature_chest	Temperature_ankle	subject_id \
0	37.5000	34.8125	2
1	36.9375	34.9375	1
2	36.4375	34.1250	5
3	35.5625	34.6250	6
4	37.6250	33.9375	8
...
971431	34.7500	33.6250	2
971432	34.1875	32.9375	1
971433	32.2500	31.7500	2
971434	36.1250	32.5625	7
971435	34.7500	33.4375	4

	Hand_Acceleration_16	Hand_Acceleration_6	Hand_Gyrometer \
0	9.751386	9.660047	0.164967
1	11.847243	11.014777	2.181952
2	8.460191	5.797924	4.643583
3	9.613840	10.019164	0.062214
4	9.729352	9.696556	0.057963
...
971431	10.162253	12.056085	0.268151

971432	9.794678	9.770694	0.041158
971433	37.520111	35.119600	2.651422
971434	11.767777	12.780731	4.275455
971435	9.659995	10.030702	0.039176

	Ankle_Acceleration	Hand_magnetometer	
Ankle_Acceleration_16 \			
0	9.884888	34.928264	9.853628
1	11.491565	48.546151	11.880628
2	6.151600	46.379032	7.628115
3	9.830463	48.484174	10.163821
4	9.872713	29.258687	9.926956
...
971431	11.001392	53.481398	10.488048
971432	9.880875	56.686076	10.033660
971433	13.112022	56.899400	11.042984
971434	10.257184	44.155289	10.479384
971435	9.876019	53.783521	9.848968

	Ankle_Gyrometer	Ankle_Magnetometer	Chest_Acceleration_16 \
0	0.110294	44.612218	10.060474
1	0.738707	62.156053	13.478711
2	1.995762	46.288600	11.259950
3	0.019596	31.972911	9.440225
4	0.032699	36.115194	9.970973
...
971431	0.196618	42.399025	12.667246
971432	0.064284	95.000662	9.771799
971433	3.757955	63.355439	30.175062
971434	0.876516	56.887903	10.583624
971435	0.072300	29.743566	9.600552

	Chest_Acceleration_6	Chest_Gyrometer	Chest_Magnetometer
0	9.855084	0.084096	27.869222
1	12.883012	0.474735	43.174891
2	7.621981	2.515189	49.537940
3	9.771592	0.034585	49.229344
4	9.974286	0.083730	26.310660

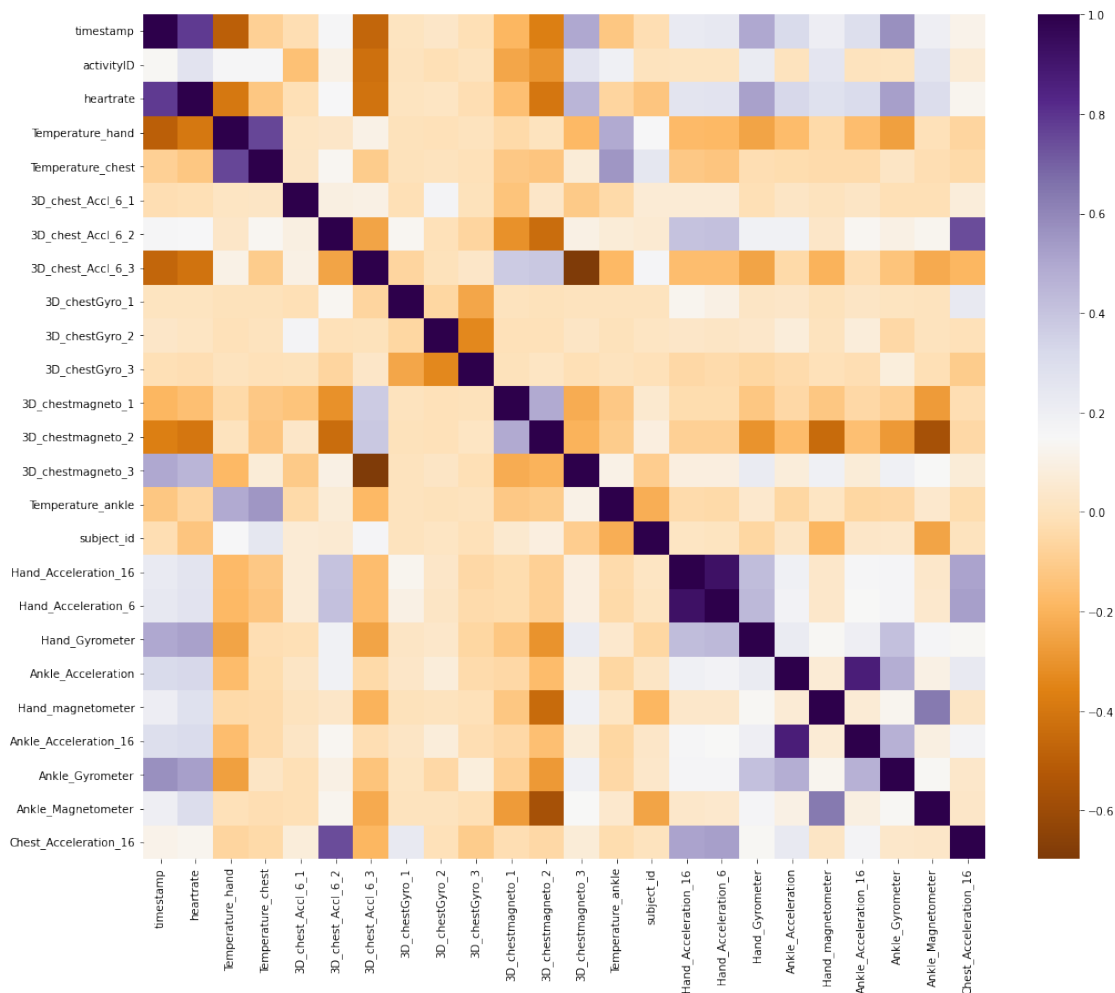
971431	12.987450	0.233825	41.916091
971432	9.806011	0.033836	74.998591
971433	24.763849	4.356266	53.524002
971434	10.518973	1.351819	37.290062
971435	9.884871	0.055825	49.388521

[971436 rows x 19 columns]

A heatmap is a visual representation of data displayed in coloured matrix form. By plotting a heatmap, we can see how much statistical similarity exists between columns. Heatmaps can be used to check whether a correlation exists between columns of a dataframe.

```
df_corr = ref.corr(method='pearson')
df_corr = df_corr.drop(['activityID'], axis = 1)
```

```
f, ax = plt.subplots(figsize=(17, 14))
sns.heatmap(df_corr, cmap = "PuOr", mask=np.zeros_like(df_corr,
dtype=bool))
plt.show()
```



Based on the heatmap, we can conclude that Ankle_Gyrometer, 3D_chestmagneto_3, and Hand_Gyrometer are positively correlated since the value for pearson coefficient is higher, while 3D_chest_Accl_6_3 and Temperature_hand are negatively correlated.

Hypothesis Testing

Hypothesis: "IF, the subject is performing cumbersome activities like rope jumping and running THEN average heartrate of the subject will be more than 100."

- Independent Variable : Running and rope jumping (Physical activity)
- Dependent Variable : Average Heart rate

Null Hypothesis(H0) : The average heartrate of the subject while performing running and rope jumping is less than or equal to 100 ($\mu \leq 100$).

Alternate Hypothesis(H1) :The average heartrate of the subject while performing running and rope jumping is greater than 100 ($\mu > 100$).

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

	timestamp	activityID	heartrate	Temperature_hand \
1436799	3466.15	5	176.0	28.0625
1165461	3392.82	5	152.0	33.8125
1427969	3377.85	5	167.0	28.1875
233529	3313.29	5	173.0	30.4375
1422642	3324.58	5	145.0	28.3125
...
247533	3602.14	24	181.0	30.1875
511742	4230.05	24	179.0	28.5000
1184329	3681.75	24	139.0	33.8750
501024	4122.87	24	123.0	28.3125
237828	3505.09	24	129.0	30.1875

	3D_hand_Accl_16_1	3D_hand_Accl_16_2	3D_hand_Accl_16_3 \
1436799	-11.614500	12.199200	-5.178400
1165461	-4.625630	-4.954130	0.564829
1427969	-32.151100	54.792300	-3.820800
233529	-30.378100	53.540200	6.178220
1422642	8.240610	5.953630	1.182600
...
247533	-1.027870	7.147790	-4.925800
511742	0.634975	-0.968486	1.130520
1184329	-9.025420	3.777730	1.508630

501024	-0.539344	-1.067640	-10.933300
237828	-1.603240	7.814620	1.221310

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
1436799	-18.146800	21.783800	-6.030400	...	
1165461	-4.227810	-5.102200	0.416994	...	
1427969	-43.525800	62.126600	-3.238780	...	
233529	-35.598200	45.132200	4.914560	...	
1422642	6.741310	6.221660	1.256810	...	
...	
247533	-1.094920	6.650410	-4.489510	...	
511742	1.424530	-2.712040	-0.137652	...	
1184329	-8.812540	3.887880	1.821460	...	
501024	-0.241368	0.023247	-11.120200	...	
237828	-1.494780	7.609710	0.824271	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	...	\
1436799	24.685000	12.452400	-0.480484	...	
1165461	11.119500	-5.265060	-2.954690	...	
1427969	19.176400	13.552100	-3.073160	...	
233529	11.916575	-2.005432	-2.950493	...	
1422642	7.763660	0.499046	-1.139180	...	
...	
247533	2.476990	-2.874380	-0.615926	...	
511742	7.196820	1.316780	-0.230692	...	
1184329	9.242210	0.678307	-3.236270	...	
501024	5.258980	5.559860	6.713020	...	
237828	25.244600	-2.021600	12.276700	...	

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1	\			
1436799	-0.516671	-0.102250	-1.742000	-
41.216200				
1165461	-0.163015	-0.412381	-3.518760	-
19.752800				
1427969	-0.252656	0.118389	-2.155950	-
44.974600				
233529	-0.130902	0.464649	-1.483988	-
45.024525				
1422642	3.702880	-2.506820	7.659240	-
44.596100				
...	
...				
247533	1.523360	0.133100	2.189300	-
51.879500				
511742	-0.532160	-0.233961	-1.513260	-
38.235700				
1184329	-0.143172	-0.223484	-0.306898	-
46.121900				
501024	-0.230153	0.232471	2.192700	-

36.096500				
237828	0.664214	0.278529	1.631470	-
65.969600				

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
1436799	3.27400	28.63310	6
1165461	-35.30170	14.99560	5
1427969	5.13008	26.91570	6
233529	-50.20960	13.76705	1
1422642	2.52040	21.53050	6
...
247533	-34.34670	36.14870	1
511742	-1.37933	34.65590	2
1184329	19.94060	9.16550	5
501024	-12.53920	30.18710	2
237828	12.86130	-17.57140	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-100)/(cumbersome_std/np.sqrt(cumbersome_count))
p_value_from_normal=(1-stats.norm.cdf(z))
print('Mean from data: ',cumbersome_mean)
print ('one tail p value from normal: ', format(p_value_from_normal,
'.2f'))
#print ('one tail p value from normal: ', z)
```

Mean from data: 158.40277581348565

one tail p value from normal: 0.00

In my analysis, I will take 5% significance levels into account. Due to the p_value of 0.05 from the z-test, I will reject my null hypothesis, which is that the subject's heart rate is less than 100 while performing cumbersome activities. I will accept my alternate hypothesis that states the average heart rate of the subject when performing rope jumping and running is greater than 100.

Modelling

By using modeling, I will be able to predict the values. My main focus will be on predicting heart rate and activity ID. In order to predict the heart rate based on the IMU readings of the chest, I will use Polynomial Regression.

```
phydata.corr()
```

\	timestamp	activityID	heartrate	Temperature_hand
timestamp	1.000000	0.143712	0.781720	-0.493674
activityID	0.143712	1.000000	0.265348	0.159352
heartrate	0.781720	0.265348	1.000000	-0.395932
Temperature_hand	-0.493674	0.159352	-0.395932	1.000000
3D_hand_Accl_16_1	-0.321940	-0.129905	-0.298458	0.059130
3D_hand_Accl_16_2	0.039321	0.038609	0.065728	-0.053288
3D_hand_Accl_16_3	-0.215706	-0.116724	-0.268278	0.077812
3D_hand_Accl_6_1	-0.332616	-0.129179	-0.307739	0.073200
3D_hand_Accl_6_2	0.036865	0.042104	0.063252	-0.048332
3D_hand_Accl_6_3	-0.226055	-0.118394	-0.277938	0.094127
3D_handGyro_1	0.011050	0.019513	0.012257	-0.025622
3D_handGyro_2	0.047300	0.027951	0.059773	-0.023345
3D_handGyro_3	0.002810	0.001211	-0.001140	-0.001049
3D_handmagneto_1	0.337544	0.053005	0.322611	-0.096713
3D_handmagneto_2	-0.095922	-0.188841	-0.134859	-0.024213
3D_handmagneto_3	0.084492	-0.023507	0.106754	-0.022195
Temperature_chest	-0.084272	0.159571	-0.127371	0.757514
3D_chest_Accl_16_1	-0.027998	-0.150098	-0.018564	0.005239
3D_chest_Accl_16_2	0.157065	0.105353	0.151197	0.034396

3D_chest_Accl_16_3	-0.469099	-0.428336	-0.409800	0.098116
3D_chest_Accl_6_1	-0.026889	-0.147677	-0.018807	0.019417
3D_chest_Accl_6_2	0.158540	0.103335	0.153499	0.032130
3D_chest_Accl_6_3	-0.471208	-0.429389	-0.412970	0.107511
3D_chestGyro_1	0.005108	0.000238	0.007120	-0.001823
3D_chestGyro_2	0.025507	-0.020597	0.016387	-0.013415
3D_chestGyro_3	-0.018143	0.003579	-0.021720	0.004979
3D_chestmagneto_1	-0.189442	-0.241078	-0.157438	-0.043054
3D_chestmagneto_2	-0.368725	-0.298399	-0.403923	-0.001476
3D_chestmagneto_3	0.499251	0.265201	0.449597	-0.180812
Temperature_ankle	-0.123084	0.195023	-0.062178	0.495376
3D_ankle_Accl_16_1	0.324924	0.133338	0.283501	-0.062394
3D_ankle_Accl_16_2	0.200998	0.097188	0.193728	-0.047370
3D_ankle_Accl_16_3	0.006021	0.083855	-0.004164	-0.041712
3D_ankle_Accl_6_1	0.343229	0.144746	0.297939	-0.061476
3D_ankle_Accl_6_2	0.218812	0.103893	0.211036	-0.053106
3D_ankle_Accl_6_3	0.003066	0.099199	-0.009076	-0.042125
3D_ankleGyro_1	0.001594	-0.004876	0.001228	-0.000417
3D_ankleGyro_2	-0.045435	0.012900	-0.028440	0.033085
3D_ankleGyro_3	-0.001125	0.001905	0.001550	0.001882
3D_anklemagneto_1	-0.308442	-0.199631	-0.325755	0.092230
3D_anklemagneto_2	-0.234251	-0.069626	-0.247339	0.112293
3D_anklemagneto_3	-0.041953	0.209897	-0.056973	0.154059
subject_id	-0.022949	-0.001891	-0.127993	0.154094

	3D_hand_Accl_16_1	3D_hand_Accl_16_2	
3D_hand_Accl_16_3 \			
timestamp	-0.321940	0.039321	-
0.215706			
activityID	-0.129905	0.038609	-
0.116724			
heartrate	-0.298458	0.065728	-
0.268278			
Temperature_hand	0.059130	-0.053288	
0.077812			
3D_hand_Accl_16_1	1.000000	-0.085483	
0.257433			
3D_hand_Accl_16_2	-0.085483	1.000000	-
0.067639			
3D_hand_Accl_16_3	0.257433	-0.067639	
1.000000			
3D_hand_Accl_6_1	0.978695	-0.070139	
0.254849			
3D_hand_Accl_6_2	-0.080322	0.945219	-
0.067663			
3D_hand_Accl_6_3	0.261275	-0.070711	
0.964548			
3D_handGyro_1	0.020572	0.181804	-
0.028435			
3D_handGyro_2	-0.094400	-0.007236	-
0.023842			
3D_handGyro_3	0.030422	0.018463	-
0.084107			
3D_handmagneto_1	-0.509092	-0.043630	-
0.192428			
3D_handmagneto_2	0.055012	-0.430874	
0.145735			
3D_handmagneto_3	-0.210788	0.103437	-
0.506023			
Temperature_chest	-0.161275	-0.054717	-
0.030131			
3D_chest_Accl_16_1	0.020788	0.039300	-
0.102546			
3D_chest_Accl_16_2	-0.424136	0.229222	-
0.068293			
3D_chest_Accl_16_3	0.436363	-0.120776	
0.143100			
3D_chest_Accl_6_1	0.019807	0.036088	-
0.105307			
3D_chest_Accl_6_2	-0.430063	0.243264	-
0.068802			
3D_chest_Accl_6_3	0.436456	-0.127795	
0.142996			
3D_chestGyro_1	-0.071869	0.060359	

0.008060			
3D_chestGyro_2	-0.048675	0.001573	-
0.058523			
3D_chestGyro_3	0.080158	0.033692	
0.031157			
3D_chestmagneto_1	0.248302	-0.052192	
0.175672			
3D_chestmagneto_2	0.340194	-0.088579	
0.199710			
3D_chestmagneto_3	-0.343251	0.055371	-
0.136653			
Temperature_ankle	-0.134254	0.074205	-
0.024140			
3D_ankle_Accl_16_1	-0.284793	0.048992	-
0.158171			
3D_ankle_Accl_16_2	-0.091788	0.112923	-
0.069671			
3D_ankle_Accl_16_3	-0.009622	0.008100	
0.019459			
3D_ankle_Accl_6_1	-0.320398	0.060863	-
0.164375			
3D_ankle_Accl_6_2	-0.101164	0.127373	-
0.075457			
3D_ankle_Accl_6_3	-0.013885	0.007775	
0.023768			
3D_ankleGyro_1	0.038499	-0.004623	
0.012820			
3D_ankleGyro_2	-0.072116	-0.031042	-
0.011710			
3D_ankleGyro_3	0.093352	-0.037152	
0.023692			
3D_anklemagneto_1	0.084533	-0.049024	
0.060863			
3D_anklemagneto_2	0.206595	-0.096015	
0.108253			
3D_anklemagneto_3	-0.042602	0.041010	-
0.011762			
subject_id	-0.030536	-0.281382	-
0.002032			

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	
3D_hand_Accl_6_3 ... \			
timestamp	-0.332616	0.036865	-
0.226055 ...			
activityID	-0.129179	0.042104	-
0.118394 ...			
heartrate	-0.307739	0.063252	-
0.277938 ...			
Temperature_hand	0.073200	-0.048332	
0.094127 ...			

3D_hand_Accl_16_1	0.978695	-0.080322	
0.261275 ...			
3D_hand_Accl_16_2	-0.070139	0.945219	-
0.070711 ...			
3D_hand_Accl_16_3	0.254849	-0.067663	
0.964548 ...			
3D_hand_Accl_6_1	1.000000	-0.075857	
0.258160 ...			
3D_hand_Accl_6_2	-0.075857	1.000000	-
0.057245 ...			
3D_hand_Accl_6_3	0.258160	-0.057245	
1.000000 ...			
3D_handGyro_1	0.026733	0.127434	-
0.018062 ...			
3D_handGyro_2	-0.070609	-0.018114	-
0.046556 ...			
3D_handGyro_3	0.026827	0.047140	-
0.081414 ...			
3D_handmagneto_1	-0.513296	-0.042100	-
0.193052 ...			
3D_handmagneto_2	0.054776	-0.448265	
0.148578 ...			
3D_handmagneto_3	-0.212629	0.108379	-
0.508750 ...			
Temperature_chest	-0.151743	-0.051863	-
0.018037 ...			
3D_chest_Accl_16_1	0.022197	0.040047	-
0.100536 ...			
3D_chest_Accl_16_2	-0.422319	0.225210	-
0.071394 ...			
3D_chest_Accl_16_3	0.439236	-0.126056	
0.148525 ...			
3D_chest_Accl_6_1	0.018233	0.038100	-
0.103556 ...			
3D_chest_Accl_6_2	-0.431257	0.240070	-
0.070809 ...			
3D_chest_Accl_6_3	0.439120	-0.132640	
0.147878 ...			
3D_chestGyro_1	-0.056542	0.039675	
0.002391 ...			
3D_chestGyro_2	-0.040470	0.004696	-
0.057784 ...			
3D_chestGyro_3	0.074419	0.040766	
0.034933 ...			
3D_chestmagneto_1	0.248276	-0.055658	
0.177742 ...			
3D_chestmagneto_2	0.342390	-0.092798	
0.203156 ...			
3D_chestmagneto_3	-0.347580	0.058728	-
0.142154 ...			

Temperature_ankle	-0.127711	0.077988	-
0.014209 ...			
3D_ankle_Accl_16_1	-0.279327	0.046976	-
0.162560 ...			
3D_ankle_Accl_16_2	-0.090862	0.113708	-
0.071240 ...			
3D_ankle_Accl_16_3	-0.009980	0.009954	
0.018408 ...			
3D_ankle_Accl_6_1	-0.314685	0.057046	-
0.170112 ...			
3D_ankle_Accl_6_2	-0.100935	0.130811	-
0.075637 ...			
3D_ankle_Accl_6_3	-0.013800	0.009622	
0.021927 ...			
3D_ankleGyro_1	0.039194	-0.002519	
0.012257 ...			
3D_ankleGyro_2	-0.070733	-0.032122	-
0.011419 ...			
3D_ankleGyro_3	0.082080	-0.013802	
0.025473 ...			
3D_anklemagneto_1	0.085498	-0.052534	
0.062323 ...			
3D_anklemagneto_2	0.211722	-0.099627	
0.112929 ...			
3D_anklemagneto_3	-0.039436	0.043655	-
0.009647 ...			
subject_id	-0.028407	-0.299075	
0.003984 ...			

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	
3D_ankle_Accl_6_3 \			
timestamp	0.343229	0.218812	
0.003066			
activityID	0.144746	0.103893	
0.099199			
heartrate	0.297939	0.211036	-
0.009076			
Temperature_hand	-0.061476	-0.053106	-
0.042125			
3D_hand_Accl_16_1	-0.320398	-0.101164	-
0.013885			
3D_hand_Accl_16_2	0.060863	0.127373	
0.007775			
3D_hand_Accl_16_3	-0.164375	-0.075457	
0.023768			
3D_hand_Accl_6_1	-0.314685	-0.100935	-
0.013800			
3D_hand_Accl_6_2	0.057046	0.130811	
0.009622			
3D_hand_Accl_6_3	-0.170112	-0.075637	

0.021927			
3D_handGyro_1	0.024639	0.007832	-
0.015512			
3D_handGyro_2	0.056241	0.011126	-
0.036083			
3D_handGyro_3	-0.029619	0.067769	
0.040395			
3D_handmagneto_1	0.183855	0.133716	
0.077258			
3D_handmagneto_2	-0.177566	-0.100271	-
0.071410			
3D_handmagneto_3	0.120442	0.101405	-
0.025222			
Temperature_chest	0.117682	0.063606	-
0.058572			
3D_chest_Accl_16_1	-0.057189	0.034964	-
0.077985			
3D_chest_Accl_16_2	0.350883	0.123827	-
0.012490			
3D_chest_Accl_16_3	-0.351082	-0.245606	-
0.150507			
3D_chest_Accl_6_1	-0.056746	0.050902	-
0.085095			
3D_chest_Accl_6_2	0.346028	0.127759	-
0.008315			
3D_chest_Accl_6_3	-0.332360	-0.252244	-
0.148667			
3D_chestGyro_1	-0.015835	0.033178	-
0.017601			
3D_chestGyro_2	0.050787	0.080787	-
0.015170			
3D_chestGyro_3	-0.080334	0.067386	
0.007946			
3D_chestmagneto_1	-0.277185	-0.172659	-
0.046764			
3D_chestmagneto_2	-0.376887	-0.206097	-
0.011048			
3D_chestmagneto_3	0.274268	0.208268	
0.157367			
Temperature_ankle	0.103990	0.079747	
0.109705			
3D_ankle_Accl_16_1	0.865992	0.136564	-
0.127484			
3D_ankle_Accl_16_2	0.173266	0.830114	-
0.100162			
3D_ankle_Accl_16_3	0.026540	-0.131144	
0.680237			
3D_ankle_Accl_6_1	1.000000	0.160784	-
0.011388			
3D_ankle_Accl_6_2	0.160784	1.000000	-

0.149378			
3D_ankle_Accl_6_3	-0.011388	-0.149378	
1.000000			
3D_ankleGyro_1	-0.026946	0.119640	-
0.082210			
3D_ankleGyro_2	0.019751	-0.067823	
0.011974			
3D_ankleGyro_3	-0.064276	0.080396	-
0.015923			
3D_anklemagneto_1	-0.214861	-0.119502	-
0.034605			
3D_anklemagneto_2	-0.122585	-0.055327	-
0.065216			
3D_anklemagneto_3	0.125014	0.104612	-
0.024594			
subject_id	0.000232	-0.016663	-
0.165449			

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	\
timestamp	0.001594	-0.045435	-0.001125	
activityID	-0.004876	0.012900	0.001905	
heartrate	0.001228	-0.028440	0.001550	
Temperature_hand	-0.000417	0.033085	0.001882	
3D_hand_Accl_16_1	0.038499	-0.072116	0.093352	
3D_hand_Accl_16_2	-0.004623	-0.031042	-0.037152	
3D_hand_Accl_16_3	0.012820	-0.011710	0.023692	
3D_hand_Accl_6_1	0.039194	-0.070733	0.082080	
3D_hand_Accl_6_2	-0.002519	-0.032122	-0.013802	
3D_hand_Accl_6_3	0.012257	-0.011419	0.025473	
3D_handGyro_1	0.029073	-0.034873	0.138108	
3D_handGyro_2	0.049503	0.098756	-0.034400	
3D_handGyro_3	-0.049996	-0.017408	-0.168897	
3D_handmagneto_1	0.049010	-0.084133	0.055356	
3D_handmagneto_2	0.072884	-0.017045	0.051156	
3D_handmagneto_3	0.007752	-0.047867	0.011586	
Temperature_chest	-0.001082	-0.003040	0.002490	
3D_chest_Accl_16_1	0.069913	-0.042724	-0.042076	
3D_chest_Accl_16_2	-0.038563	0.027827	-0.110185	
3D_chest_Accl_16_3	0.012151	-0.022057	0.069666	
3D_chest_Accl_6_1	0.059285	-0.031758	-0.042266	
3D_chest_Accl_6_2	-0.043967	0.031758	-0.100427	
3D_chest_Accl_6_3	0.011869	-0.020204	0.063494	
3D_chestGyro_1	0.017133	-0.018961	-0.046690	
3D_chestGyro_2	0.125529	0.066578	-0.100307	
3D_chestGyro_3	0.148984	-0.126513	0.274436	
3D_chestmagneto_1	0.004302	0.014061	0.000785	
3D_chestmagneto_2	-0.001941	0.019354	-0.002909	
3D_chestmagneto_3	0.007541	0.004453	0.002670	
Temperature_ankle	-0.011002	0.008862	0.005253	
3D_ankle_Accl_16_1	-0.005604	-0.049563	-0.036485	

3D_ankle_Accl_16_2	0.149641	-0.052329	0.141475
3D_ankle_Accl_16_3	-0.090419	-0.070966	-0.019770
3D_ankle_Accl_6_1	-0.026946	0.019751	-0.064276
3D_ankle_Accl_6_2	0.119640	-0.067823	0.080396
3D_ankle_Accl_6_3	-0.082210	0.011974	-0.015923
3D_ankleGyro_1	1.000000	-0.066244	0.323950
3D_ankleGyro_2	-0.066244	1.000000	0.021793
3D_ankleGyro_3	0.323950	0.021793	1.000000
3D_anklemagneto_1	-0.022029	0.021425	-0.005423
3D_anklemagneto_2	0.055971	-0.028698	0.010361
3D_anklemagneto_3	-0.016857	-0.025478	-0.017639
subject_id	0.015888	-0.006887	-0.004433

	3D_anklemagneto_1	3D_anklemagneto_2	
3D_anklemagneto_3 \			
timestamp	-0.308442	-0.234251	-
0.041953			
activityID	-0.199631	-0.069626	
0.209897			
heartrate	-0.325755	-0.247339	-
0.056973			
Temperature_hand	0.092230	0.112293	
0.154059			
3D_hand_Accl_16_1	0.084533	0.206595	-
0.042602			
3D_hand_Accl_16_2	-0.049024	-0.096015	
0.041010			
3D_hand_Accl_16_3	0.060863	0.108253	-
0.011762			
3D_hand_Accl_6_1	0.085498	0.211722	-
0.039436			
3D_hand_Accl_6_2	-0.052534	-0.099627	
0.043655			
3D_hand_Accl_6_3	0.062323	0.112929	-
0.009647			
3D_handGyro_1	0.012532	-0.066293	-
0.000633			
3D_handGyro_2	-0.007820	-0.003256	-
0.014572			
3D_handGyro_3	-0.062962	0.128163	
0.036106			
3D_handmagneto_1	-0.067752	-0.293229	-
0.157725			
3D_handmagneto_2	0.237363	0.152785	-
0.307834			
3D_handmagneto_3	0.164784	-0.204457	
0.176941			
Temperature_chest	0.003403	-0.023325	
0.137156			
3D_chest_Accl_16_1	0.031638	0.034772	

0.022563			
3D_chest_Accl_16_2	-0.095474	-0.158283	
0.177911			
3D_chest_Accl_16_3	0.241516	0.291592	-
0.123356			
3D_chest_Accl_6_1	0.029862	0.032687	
0.025687			
3D_chest_Accl_6_2	-0.096078	-0.163369	
0.176566			
3D_chest_Accl_6_3	0.241334	0.293496	-
0.120431			
3D_chestGyro_1	0.011577	-0.009814	-
0.001900			
3D_chestGyro_2	-0.047100	0.071318	-
0.007137			
3D_chestGyro_3	0.036327	-0.013329	-
0.016635			
3D_chestmagneto_1	0.173865	0.298685	-
0.561354			
3D_chestmagneto_2	0.544165	0.189275	-
0.276592			
3D_chestmagneto_3	-0.162404	-0.500480	-
0.100202			
Temperature_ankle	-0.046966	-0.078861	
0.092491			
3D_ankle_Accl_16_1	-0.206725	-0.113579	
0.118556			
3D_ankle_Accl_16_2	-0.111039	-0.051984	
0.096681			
3D_ankle_Accl_16_3	-0.027784	-0.054434	-
0.020188			
3D_ankle_Accl_6_1	-0.214861	-0.122585	
0.125014			
3D_ankle_Accl_6_2	-0.119502	-0.055327	
0.104612			
3D_ankle_Accl_6_3	-0.034605	-0.065216	-
0.024594			
3D_ankleGyro_1	-0.022029	0.055971	-
0.016857			
3D_ankleGyro_2	0.021425	-0.028698	-
0.025478			
3D_ankleGyro_3	-0.005423	0.010361	-
0.017639			
3D_anklemagneto_1	1.000000	0.062097	-
0.031615			
3D_anklemagneto_2	0.062097	1.000000	
0.020617			
3D_anklemagneto_3	-0.031615	0.020617	
1.000000			
subject_id	0.193853	0.105505	

0.045997

	subject_id
timestamp	-0.022949
activityID	-0.001891
heartrate	-0.127993
Temperature_hand	0.154094
3D_hand_Accl_16_1	-0.030536
3D_hand_Accl_16_2	-0.281382
3D_hand_Accl_16_3	-0.002032
3D_hand_Accl_6_1	-0.028407
3D_hand_Accl_6_2	-0.299075
3D_hand_Accl_6_3	0.003984
3D_handGyro_1	-0.027199
3D_handGyro_2	0.004104
3D_handGyro_3	-0.001531
3D_handmagneto_1	0.050043
3D_handmagneto_2	0.307351
3D_handmagneto_3	0.031566
Temperature_chest	0.250471
3D_chest_Accl_16_1	0.054456
3D_chest_Accl_16_2	0.055383
3D_chest_Accl_16_3	0.160612
3D_chest_Accl_6_1	0.061794
3D_chest_Accl_6_2	0.054672
3D_chest_Accl_6_3	0.168062
3D_chestGyro_1	-0.001165
3D_chestGyro_2	0.014272
3D_chestGyro_3	-0.012408
3D_chestmagneto_1	0.047993
3D_chestmagneto_2	0.084797
3D_chestmagneto_3	-0.096166
Temperature_ankle	-0.215867
3D_ankle_Accl_16_1	0.002171
3D_ankle_Accl_16_2	-0.015104
3D_ankle_Accl_16_3	-0.142385
3D_ankle_Accl_6_1	0.000232
3D_ankle_Accl_6_2	-0.016663
3D_ankle_Accl_6_3	-0.165449
3D_ankleGyro_1	0.015888
3D_ankleGyro_2	-0.006887
3D_ankleGyro_3	-0.004433
3D_anklemagneto_1	0.193853
3D_anklemagneto_2	0.105505
3D_anklemagneto_3	0.045997
subject_id	1.000000

[43 rows x 43 columns]

Polynomial Regression

Polynomial regression models the relationship between a dependent and independent variable as an nth-degree polynomial. Data points that do not fit linear regression is analyzed using polynomial regression. We calculated the correlation between the columns of the dataframe in the above section. As a result of the dataframe observed above, we can conclude that heartrate has a higher correlation with 3D_chest_Accl_16_2, 3D_chestmagneto_3 respectively. Hence, X will be an independent variable which includes both 3D_chest_Accl_16_2 and 3D_chestmagneto_3, and tar will be the list of variables that includes heartrate as a dependent variable.

- Independent Variable : X :- Includes 3D_chest_Accl_16_2,3D_chestmagneto_3
- Dependent Variable. : tar :-Includes heartrate

The Process involves:

- Transform the independent variable X by calculating till nth degree polynomial where n=8
- Obtain train test data by applying train_test_split inbuilt 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.

We compute the root mean squared error and the mean squared error in order to obtain the error. I have also provided an example for the same considering two values of X from the dataframe and predicted the heart rate.

```
X=phydata[['3D_chest_Accl_16_2','3D_chestmagneto_3']]
#phytarget=phydata['heartrate']
tar = phydata['heartrate']

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 21.549188895804267
The mean squared error is 464.3675420670539

```
array([93.95065891])
```

Random Forest Algorithm

The Random Forest algorithm can be used for both classification and regression, making it extremely versatile. As the name implies, Random Forest is a forest of trees, decision trees that are randomly populated. The algorithms create and combine decision trees, and the more trees in the forest, the better the accuracy of the predictions. The process includes:-

- A dataframe data created by dropping activityID and timestamp and target which includes activityID
- Train test data split is done for both data and target
- Import RandomForestClassifier and create a gaussian classifier clf and train the model
- Obtain the root mean squared 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
0.12492301228595215

```
from sklearn import metrics
```

```
# Model Accuracy shows how often is the classifier correct?
```

```
print("Accuracy:",metrics.accuracy_score(test_target, y_pred))
```

Accuracy: 0.9998250013832611

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

	timestamp	activityID	heartrate	Temperature_hand	\
513306	166.11	1	142.600000	31.0000	
513307	166.12	1	134.000000	31.0000	
513308	166.13	1	125.400000	31.0000	
513309	166.14	1	116.800000	31.0000	
513310	166.15	1	108.200000	31.0000	
...	
687639	2443.15	4	122.000000	28.6875	
687640	2443.16	4	122.000000	28.6875	
687641	2443.17	4	122.000000	28.6875	
687642	2443.18	4	122.000000	28.6875	
687643	2443.19	4	120.545455	28.6875	

	3D_hand_Accl_16_1	3D_hand_Accl_16_2	3D_hand_Accl_16_3	\
513306	-1.43105	5.40588	7.774870	
513307	-1.57471	5.14382	8.043010	
513308	-1.88156	4.50119	8.040590	
513309	-1.84377	4.50090	8.041150	
513310	-1.78781	5.18687	8.424550	
...	
687639	-1.20135	9.90925	-1.781750	
687640	-1.23218	9.94916	-1.589910	
687641	-1.34154	9.95104	-1.476090	
687642	-1.02451	9.95240	-1.047990	
687643	-1.16711	9.65274	-0.741214	

	3D_hand_Accl_6_1	3D_hand_Accl_6_2	3D_hand_Accl_6_3	...	\
513306	-1.25869	5.42474	7.86577	...	
513307	-1.42397	5.42599	7.92634	...	
513308	-1.62143	5.06513	8.10854	...	
513309	-1.62562	4.58187	8.09451	...	
513310	-1.73035	4.59780	8.17008	...	
...	
687639	-1.26926	10.12770	-1.79391	...	
687640	-1.30068	9.88640	-1.70274	...	
687641	-1.28472	9.91656	-1.62732	...	
687642	-1.28208	9.97719	-1.37075	...	
687643	-1.18977	9.91638	-1.08379	...	

	3D_ankle_Accl_6_1	3D_ankle_Accl_6_2	3D_ankle_Accl_6_3	\
513306	9.70353	0.999148	-0.697040	
513307	9.68799	0.953621	-0.817893	
513308	9.71766	0.968642	-0.908910	
513309	9.73190	1.074280	-1.106080	
513310	9.73166	1.134700	-1.166820	
...	
687639	9.89845	1.029330	-0.788984	

687640	9.77915	1.044690	-0.576507
687641	9.95965	0.954051	-0.516633
687642	10.00460	0.863293	-0.531715
687643	10.06470	0.742307	-0.531645

	3D_ankleGyro_1	3D_ankleGyro_2	3D_ankleGyro_3	
3D_anklemagneto_1 \				
513306	-0.201402	-0.059007	0.107266	-
43.6954				
513307	-0.240913	-0.067527	0.091327	-
42.7963				
513308	-0.372723	-0.060329	0.094986	-
42.8046				
513309	-0.345057	-0.102539	0.114357	-
42.9115				
513310	-0.435516	-0.078463	0.089137	-
42.7882				
...	
...				
687639	-0.157561	0.077097	0.775084	-
22.6451				
687640	-0.100678	0.100662	0.740007	-
22.8618				
687641	-0.064701	0.054579	0.731004	-
22.5340				
687642	-0.063496	0.039095	0.730862	-
22.6406				
687643	-0.005480	0.017985	0.700883	-
22.9847				

	3D_anklemagneto_2	3D_anklemagneto_3	subject_id
513306	1.163090	57.3792	3
513307	0.696723	56.8717	3
513308	1.573020	57.3762	3
513309	0.921397	56.8751	3
513310	0.467699	57.4881	3
...
687639	-6.823270	12.4377	3
687640	-6.935700	13.1809	3
687641	-6.825550	12.3130	3
687642	-6.938610	12.8077	3
687643	-6.374950	12.8166	3

[174338 rows x 43 columns]

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

```
array([3], dtype=int64)
```

Summary

As a result of this report, software and hardware are designed that can quantify physical activity and provide insights based on the data. In order to achieve this, we went through several phases, including data cleaning, exploratory data analysis, hypothesis testing, and modelling. Since the data provided didn't have linear correlation, we used polynomial regression and a random forest algorithm for modeling.

As a result of this analysis, we were able to analyze each variable and derive a conclusion based on it. My analysis included heartrate, calorie burnt, a heatmap showing the correlation between the variables, and a comparison of the chest, ankle, and hand temperatures. In this analysis, we gained a greater understanding of the variables and how they relate to one another.

Other algorithms such as KNN and K-Mean can also be considered for modeling, which will also yield the desired results. The models we used are polynomial regression and the random forest algorithm which has an accuracy greater than 90% that will accurately predict the models. In conclusion, all report requirements have been met.