Motor Activity Association with depression Episodes

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Introduction

- **Background**

  The use of on body sensors to monitor personal health has become quite normal these days. This data holds a lot of potential besides measuring the quantity of daily steps or calories burned, since continuous recordings of heart rate and activity levels usually are collected. For this there is an increasing awareness in the field of psychiatry on how these activity data relates to various mental health related issues such as changes in mood, personality, inability to cope with daily problems or stress, etc.

  In relation to mental health, depression is number one of the most frequent disorders and the current trend is indicating that its prevalence will increase even more in the coming years. Mental health problems are related to disturbance in internal biological systems. These are complex systems and, because relations between the sensor data and the mood are not well understood yet, changes within these systems are difficult to detect.

  In context to this, the state of biological systems is somehow measurable through recordings of motor-activity. Evidence indicates that a depressive state is associated with reduced daytime motor-activity, as well as increased nighttime activity when comparing to healthy controls .

  Activity and movement measurements have become an emerging topic in the field of mental health. Several studies use sensors to measure patients movements over time and connect them to diagnosis or self reports .

- **Objectives**

  The purpose of this analysis can be divided into three parts –

1) Determining the efficacy of psychiatric treatment and its degree for inpatient and outpatients' cases.

2) Comparing the activity behaviors of depressed and non-depressed subjects.

a) Identifying potential patterns that can help categorizing the subjects among the two based of their activity statistics.

b) Creating a model to categorize individuals as depressed and non-depressed.

3) Analysis of MADRS scores with respect to individuals motor activity performance. Further creating a model for MADRS score prediction based on motor activity data of a new patient.

- **Research questions**

  Corresponding to the objectives of this analysis, I will try to answer, first, if there is any difference in activity behaviour of depresses and non-depressed subjects and what are the statistical evidences that can prove those differences. And how those evidences can be leveraged to categorize the patients as depressed or non-depressed.

  Secondly, after analysing the association between the MADRS scores and activity data, what are the potential characteristic of activity data that can help correlating the initial & final MADRS score. And how can we predict the final MADRS score based on the initial MADRS score.

Data Description

- **Data collection**

  The analysed data has been taken from a research study for which it was originally collected for the study of motor activity in schizophrenia and major depression. Motor activity was monitored with an actigraph watch worn at the right wrist (Actiwatch, Cambridge Neurotechnology Ltd, England, model AW4). The actigraph watch measures activity by using a piezoelec tric accelerometer that is programmed to record the integration of intensity, amount and duration of movement in all directions.

- **Description**

  Data consists of actigraphy data collected from 23 unipolar and bipolar depressed patients(Condition group). Out of these subjects, 5 subjects were hospitalized during their data collection period, and 18 were outpatients. The severity level of their depression was rated by the Montgomery-Asberg Depression Rating Scale at the beginning and conclusion of the motor-activity recording.

  Additionally, the dataset also contains actigraphy data from 32 non-depressed (control group) without psychiatric symptoms.

  The dataset contains multiple CSV files for each subject (for Control and condition group), carrying their actigraphy data collected over time. The columns are: timestamp(one-minute intervals Data), date (date of measurement), activity (activity measurement from the actigraph watch). In addition, dataset also contain the MADRS

scores in the file *scores.csv.* It contains the following columns: ***number*** (patients identifier), ***days*** (number of days of measurements), ***gender*** (1 & 2 for female and male), ***age*** (in age groups), ***afftype*** (1:bipolar-II, 2:unipolar depressive, 3:bipolar-I), ***melanch*** (1:melancholia, 2: no melancholia), ***marriage*** (1: married, 2: single), ***work*** (1: working or studying, 2: unemployed/leave/pension), ***madrs1*** (MADRS score when measurement started), ***madrs2*** (MADRS when measurement stopped).

Methodology

- **Analytical methods** and **tools**For the presented analysis Python & R programming language were used. Python majorly performed due its diverse libraries & packages that were utilized such as NumPy, Seaborn, Pandas, Matplotlib, Statsmodels, Scikitlearn and Plotly.

  The utilised dataset contain large amount of data points in form of numeric, categorical , range and timestamp values, which provided the opportunity to use different types of analytical models and tests for desired study. It includes supervised learning methods like T-testing, F-testing, Multiple linear regression, etc. For prediction modelling two machine learning algorithms were performed, that are Gradient Boosting Regression and Random Forest Regression which helped in the third objective of the analysis to predict the final MADRS score.

  Apart from analytical tests and models a wide spectrum of visualization methods were also extensively utilized such as Scatter plot, 3D surface and scatter plot, box and Wisker plot, Bar plot, Histogram, Line plot, etc. These visualization methods were very useful to get initial insights and direct the study and also to explain the results of statistical analysis techniques.

- **Limitations and Assumptions**

  Here, a very rich data of actigraph was available in form of minute-resolution, but was limited for only 23 condition group and 32 control group. Which made me assume the 23 subject to be the representative of the condition population and 32 subjects for control population. So, the result of this analysis bear the limitation of sample size.

  In the minute resolution actigraph data, some dispcrepancies were observed in form of extremely low/no values for some extended period of time, which was assumed as abnormality possible because of the sensor was offline or not working properly during that phase. So, such abnormality were deleted avoid its effect on the actual data.

  During the process of developing the prediction model for MADRS score. As found from the prior literature available on this subject, the amount of sleep or rest can have some effect on patients' MADRS score. So, the duration of rest per day by the patient was taken on the assumption that during rest, patient's activity value will lie between 0 to 5. And hence its duration in minutes were calculated based on the volume of occurance of such values.

Results

Objective 1- Determining the efficacy of psychiatric treatment and its degree for inpatient and outpatients' cases.

For this the initial and final MADRS scores of 23 patients in condition group were compare and a paired T-test was performed to see their differences-

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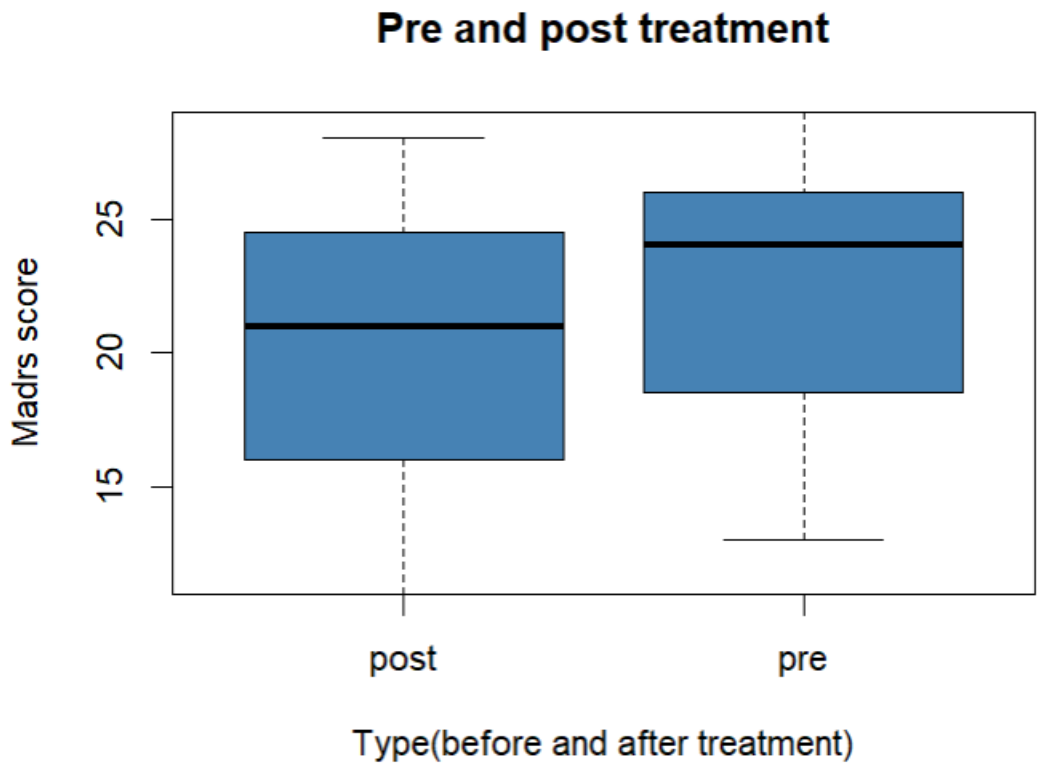


Outcome of T-test –

```
> t.test(value ~ type, data = melt1, paired = TRUE)

        Paired t-test

data:  value by type
t = -3.3104, df = 22, p-value = 0.003183
alternative hypothesis: true mean difference is not equal to 0
95 percent confidence interval:
 -4.455132 -1.023129
sample estimates:
mean difference
      -2.73913
```

The output shows that there is statistically significant difference between the initial MADRS score and MADRS score after the treatment with a significance level of 0.003183.

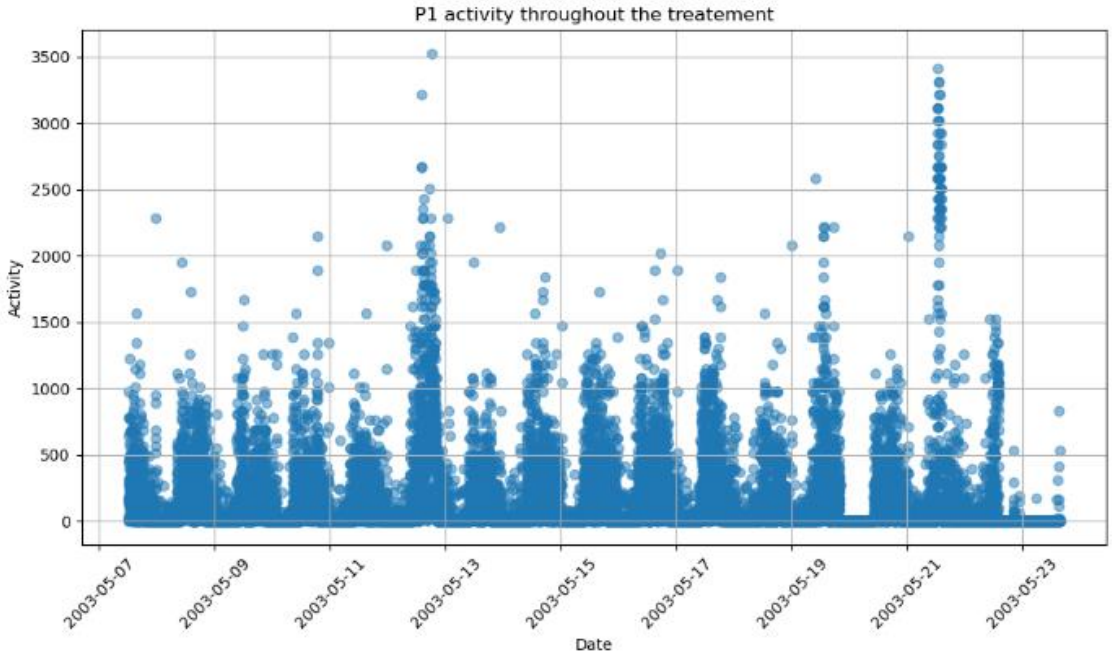
Further, the mean of improvement in MADRS score of hospitalized patients is found to be less than that of outpatients (i.e. 2.45 less than 3.8), which advocates that treatment of depression is far efficient when the patients and not hospitalized and treated in their normal environment.

Objective 2 - Comparing the activity behaviors of depressed and non-depressed subjects.

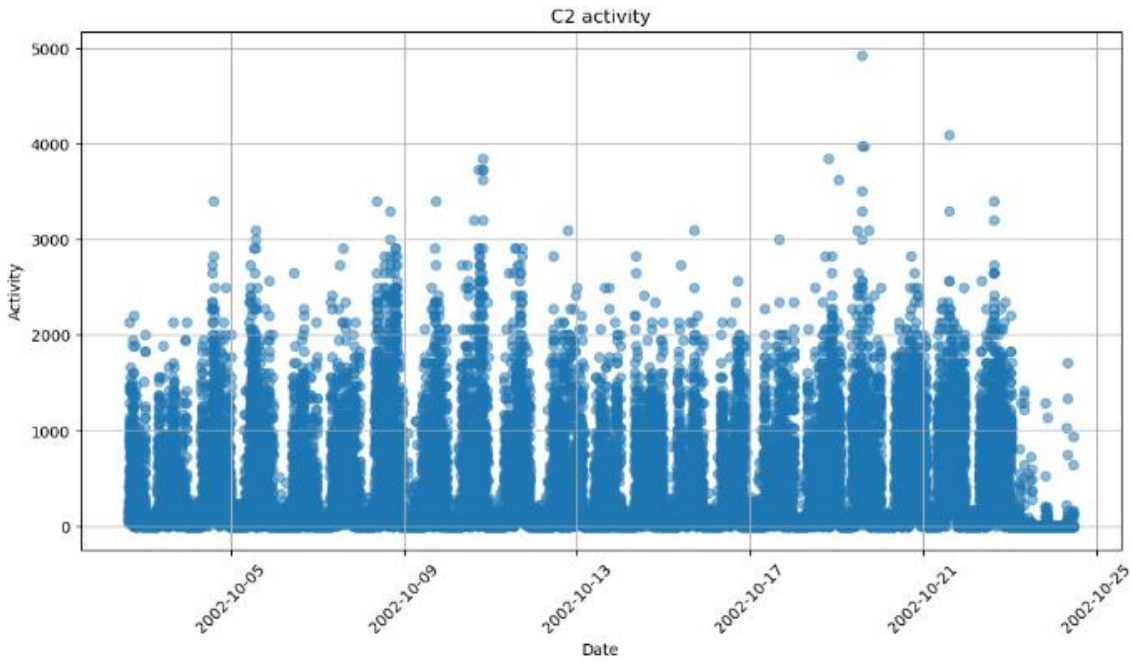
a) Identifying potential patterns that can help categorizing the subjects among the two based of their activity statistics.
b) Creating a model to categorize individuals as depressed and non-depressed.

The scatter plot of activity data of individual subjects of condition and control group was drawn (below are two examples)-

Condition1-



Control2-



To represent these large amount of data points of each individual in a generalized manner, six numeric representatives were taken – Mean of activity, 75 Quartile mean, 99 Quartile mean, Standard deviation of activity, Standard deviation at 75 quartile, Standard deviation at 99 quartile. These numeric parameters were calculated for each individual from their activity data for a generalized comparison between the condition and control group.

Combining all the parameters two table were constructed for both condition and control group. The description of the two table is given below.

Condition group table –

	mean_of_meanact	mean_of_Q75act	mean_of_Q99act	std_of_meanact	std_of_Q75act	std_of_Q99act
count	23.000000	23.000000	23.000000	23.000000	23.000000	23.000000
mean	177.359263	239.771178	1293.282746	60.221801	116.235225	318.413688
std	75.725958	137.580750	335.760931	39.333135	75.837742	168.601320
min	65.370585	37.288462	665.491429	9.301415	20.827523	96.547265
25%	120.196612	126.054167	1030.523544	28.137077	61.546887	190.752177
50%	172.622371	223.000000	1300.538571	60.377039	117.073784	287.349708
75%	235.399106	354.801471	1574.730899	73.919049	143.678425	389.201044
max	296.403373	495.942308	1804.810000	166.280241	317.549671	745.719621

Control group table –

	mean_of_meanact	mean_of_Q75act	mean_of_Q99act	std_of_meanact	std_of_Q75act	std_of_Q99act
count	32.000000	32.000000	32.000000	32.000000	32.000000	32.000000
mean	263.666975	374.478207	1696.860976	81.291596	148.062548	410.943519
std	71.689552	124.541947	405.953265	31.768637	52.523207	309.473258
min	139.782917	167.400000	915.619333	43.967642	82.669024	134.236127
25%	201.082937	287.116964	1401.476008	54.296764	104.532570	213.154471
50%	262.758110	372.544643	1729.681104	70.213031	129.261063	307.159779
75%	315.547474	470.230082	1867.617679	119.680854	195.159923	497.436726
max	407.458697	652.559524	2635.942143	137.730227	261.527268	1520.288118

For the purpose of creating a model to categorize patients based on these numeric representators, two multiple linear regressions were performed for the condition and control group separately, with 'Mean of activity' as dependent variable and 'Standard deviation of activity' and '75 Quartile mean' as independent variables. The two regression models were represented in a 3D scatter plot shown below-

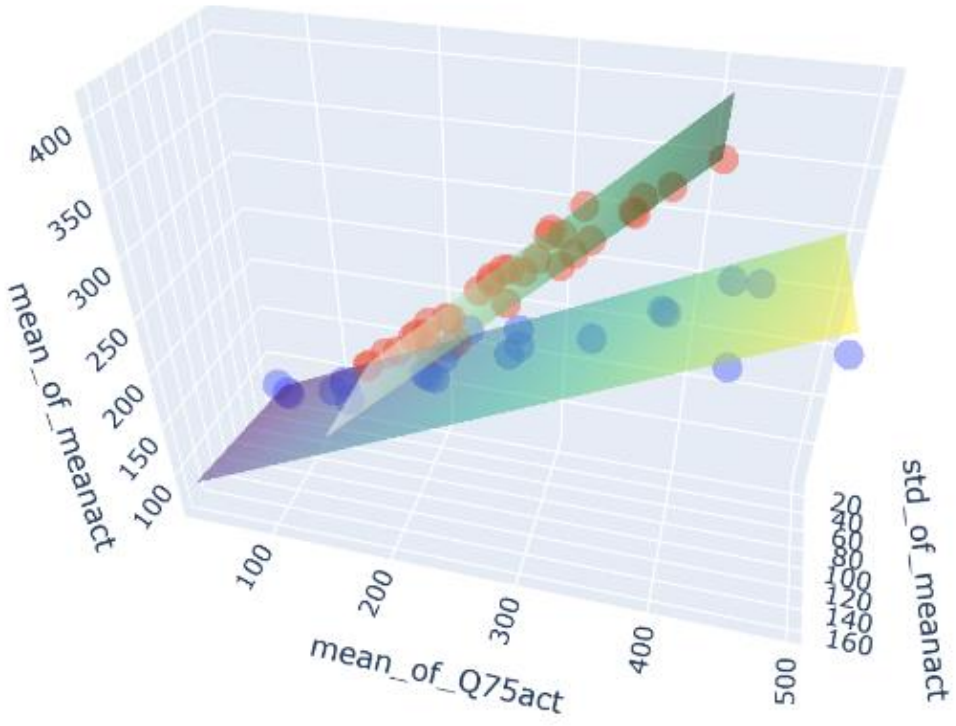


Fig: 3D representation of regression model plan for Control (Red points) and Condition group (Blue points).project

From the plot it was evident that the models have no intersection and can explain the data point of the two groups with great precision.

The regression model of Control group can be resented as the following equation-

Mean of activity = -1.715166 -0.012684(Std of meanact) + 1.008805(Mean of Q75act)

With R square value of 0.9989370230534083, which predicts a high precision of 99.8 percent of the model.

The regression model of Condition group can be resented as the following equation-

Mean of activity = 45.696502 + 0.162151(Std of meanact) + 0.508392(Mean of Q75act)

With R square value of 0.973278688721822, which predicts a high precision of 97.3 percent of the model.

Using these models, we can precisely diagnose new subject as a depressed and non-depressed based on its activity data representators association with the Condition and Control model.

Objective 3 – Analysis of MADRS scores with respect to individuals motor activity performance. Further creating a model for MADRS score prediction based on motor activity of a new patient.

For building up prediction model, dataset of individual actigraph and that of demographic details and initial & final MADRS scores of all 23 patients were utilized. During the treatment process, it can be very helpful to know the final MADRS score of patients. So, for predicting the final MADRS, the approach of building a supervised machine learning model was adopted where the final MADRS score of given patients were taken as dependent variable and important parameter of actigraph data and demographic details with initial MADRS score were taken as independent variables.

Included demographic variables are patients' gender, number of days of treatment and marital status. Apart from these factors, several studies have pointed out the bidirectional relationship between the depression and sleep. So, it was essential to include some metric of sleep as the independent variable. For that, duration of rest per day (in minutes) by assuming the activity value to be between 0 to 5 during the rest time of the patient and calculated accordingly.

Finally, nine independent variables were chosen for training the model and predicting the final MADRS score. These independent variables included 'madrs1', 'gender', 'marriage', 'days_treatment', 'rest_duration', 'mean_of_meanact', 'mean_of_Q75act', 'mean_of_Q99act' and 'std_of_meanact' of each patient.

Input table for training of the prediction model-

	patients	madrs1	madrs2	gender	marriage	days_treatement
0	condition_1	19.0	19.0	0	1.0	16.141667
1	condition_2	24.0	11.0	0	0.0	19.064583
2	condition_3	24.0	25.0	1	0.0	15.033333
3	condition_4	20.0	16.0	0	1.0	14.969444
4	condition_5	26.0	26.0	0	0.0	14.925694
5	condition_6	18.0	15.0	1	1.0	14.884028
6	condition_7	24.0	25.0	1	0.0	15.399306
7	condition_8	20.0	16.0	0	1.0	13.402083
8	condition_9	26.0	26.0	0	1.0	14.109722
9	condition_10	28.0	21.0	0	1.0	14.968750
10	condition 11	24.0	24.0	1	1.0	15.965278

rest_duration	mean_of_meanact	mean_of_Q75act	mean_of_Q99act	std_of_meanact
703.582860	152.199630	194.433333	1248.365333	59.218240
595.711944	211.470872	275.694444	1538.437778	83.266168
755.454545	280.810714	423.910714	1605.270000	61.577770
758.678790	286.064732	427.321429	1710.240714	166.280241
760.902619	172.622371	212.500000	1300.538571	46.444164
763.032707	194.754861	267.875000	1428.765000	38.794611
737.500789	275.251141	460.732143	1538.089286	162.503395
847.405565	184.412095	205.416667	1671.409167	106.385888
804.905995	177.031624	223.000000	1420.541538	25.805786
758.713987	296.403373	441.785714	1691.552143	84.898469
711.356242	130.193472	125.483333	1250.976000	64.907332

Under the ScikitLearn library, Random Forest Regressor was used as the supervised machine learning model. The data was divided into train and test subset, with 85% data for training the model. The prediction model was built under the name of “rf_model”, which on testing over the test data subsetperform s reasonably well, with a relatively low MSE value of 3.0883 and a moderately high R-square value of 0.7239.

Mean Squared Error: 3.0883250000000038
R-squared Score: 0.723948603351955

For prediction of the final MADRS score of new subjects, the above mentioned nine independent variables (i.e. 'madrs1', 'gender', 'marriage', 'days_treatment', 'rest_duration', 'mean_of_meanact', 'mean_of_Q75act', 'mean_of_Q99act' and 'std_of_meanact') are required to taken as input in the form of an array for the model.

For manual prediction trial of the model, the input data of patient 'condition_16', which was not part of training data subset, pulled in in form of array into the model and the prediction made i.e. 17.75 is very close to the actual final MADRS score i.e. 17. Hence the model is accurate in predicting the final MADRS score.

```
test28 = X_test[X_test['madrs1']==13]
test28_array = test28.values.flatten()
test28_array
```

```
array([1.30000000e+01, 1.00000000e+00, 1.00000000e+00, 1.65895833e+01,
       6.84586211e+02, 2.44083594e+02, 3.71968750e+02, 1.60244562e+03,
       5.11259837e+01])
```

```
Prediction = rf_model.predict(test28)
Prediction
```

```
array([17.75])
```

References

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