Clustering and Feature Analysis of Smartphone Data for Depression Monitoring

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Problem Statement

- Depression is a common mental illness that affects more than 264 million people [1].
- While, there are many known methods and effective treatment options for mental disorders like depression, approximately 76% and 85% of people in low- and middle-income countries do not receive treatment, respectively [2].

Objectives

- Early detection and treatment of depression, promotes remission, reduces relapse and lowers financial burden of the disease [3]
- These benefit can be realized thanks to recent technological advancements which have given opportunity to digital phenotyping
- Analyze active and passive to monitor mental health in users

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Active and passive data

- Passive data
  - Collects data without user input
  - E.g GPS and Accelerometer
- Active
  - Collected data that requires user input
  - E.g Patient Health Questionnaire (PHQ) 9 survey that monitors the severity of depression

State-of-the-art

- Masud et al. [5]:
  - 33 subjects from Bangladesh
  - Collected with smartphone and PHQ-9 information
  - A support vector machine (SVM) classifier was trained using 12 features
  - Overall accuracy: 86.4% for prediction of depression levels
- Farhan et al. [6]:
  - Dartmouth StudentLife dataset
  - Collected with smartphone and PHQ-9 information
  - Wrapper method and 10-fold SVM
  - Multi-view bi-clustering (MVBC) to create behaviour subgroups
  - Overall accuracy: 87.1% for prediction of depression subgroups
- Grunerbl et al. [7]:
  - Psychiatric hospital patients
  - Collected accelerometer, sound, phone calls and GPS data
  - Overall accuracy: 76% for prediction of mental health state change

Dataset

- Dartmouth Studentlife dataset [8]
  - Smartphone data to collect passive and active data
    - Passive: physical activity, audio inferences, conversation inferences, Bluetooth scan, light sensor, global positioning system (GPS), phone charge, phone lock, WiFi, WiFi location
    - Active: PHQ-9
  - 60 college students for 10 weeks

Pre-processing

- Removal of incomplete data
    - Users that did not complete their second questionnaire

Feature extraction

- Composed of three views
  - Average
  - Trend
  - Location

Average view

- This view reflects the participant's overall behavior.
- The average view contains the average of a set of features over all the days that a participant is enrolled.

Sensor data	Feature description
Activity	Act_s, Act_w, and Act_r which represent activities for stationary, walking and running, in a day, respectively.
Conversation	$Convo_d$ and $Convo_c$ which represent conversation of total duration and number of conversations, per day, respectively.
Light	$Dark_d$ $Dark_c$ which represent the total duration and number of times when a user is in a dark environment, per day, respectively.
Audio	$Audio_q$, $Audio_n$, and $Audio_v$ which represent the duration of which user's are classified as quiet, noisy and voice, per day, respectively.
Phone lock	$PhoneLock_d$ and $PhoneLock_c$ which represent the total time for phone lock duration and the number of times phone is locked, per day, respectively.

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Trend view

- The trend view is calibrated to determine the variation of several sensors over the period of the study
- Pseudo steps
  - Wavelet transform
  - Fitted to least squares

$$\min_{c} \sum_{d} (f(\mathbf{c}, d) - \bar{y}_d)^2$$

$$\text{subject to} f(\mathbf{c}, x) = c_1 \sin(\frac{2\pi}{c_2} x + c_3) + c_4$$

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Location view

- The location view was inspired by previous works which showed a significant correlation between location and depressive mood disorder [4], [9].
- The features include
  - Location variance, time in top 3 cluster locations, entropy of (tc1; tc2; tc3) participant location, normalized entropy, percentage of time a participant is spent at their home, percentage of time a participant is spent moving, and total distance covered

Multi-view bi-clustering

- MVBC algorithm is to find subgroups of user behavior, which involves finding the same row clusters from all the view

Feature ranking

- Followed by clustering the subgroups
- Minimum redundancy maximum relevance (mRMR) was selected

$$\max \Phi(D, R), \Phi = D - R$$

$$\max D(S, c), D = \frac{1}{|S|} \sum_{x_i \in S} I(x_i; c))$$

$$\min R(S), R = \frac{1}{|s|^2} \sum_{x_i, x_j \in S} I(x_i; x_j)$$

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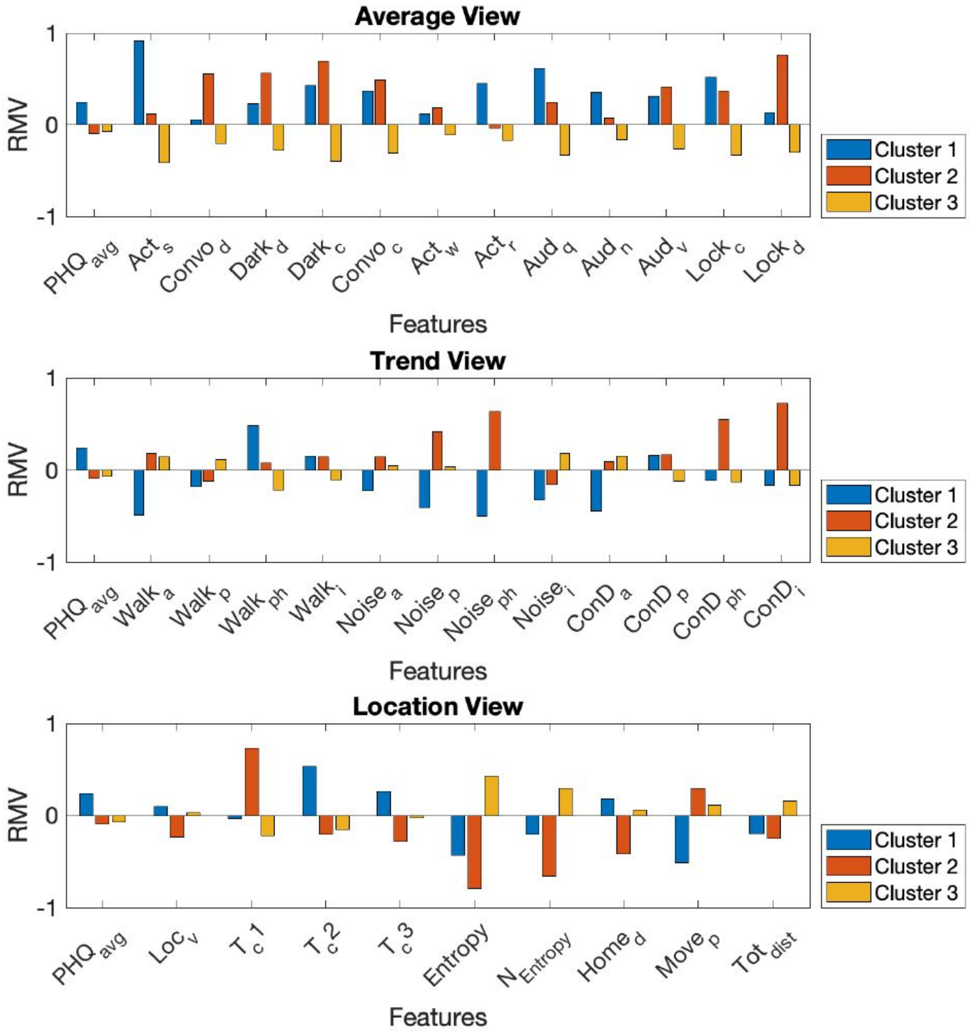
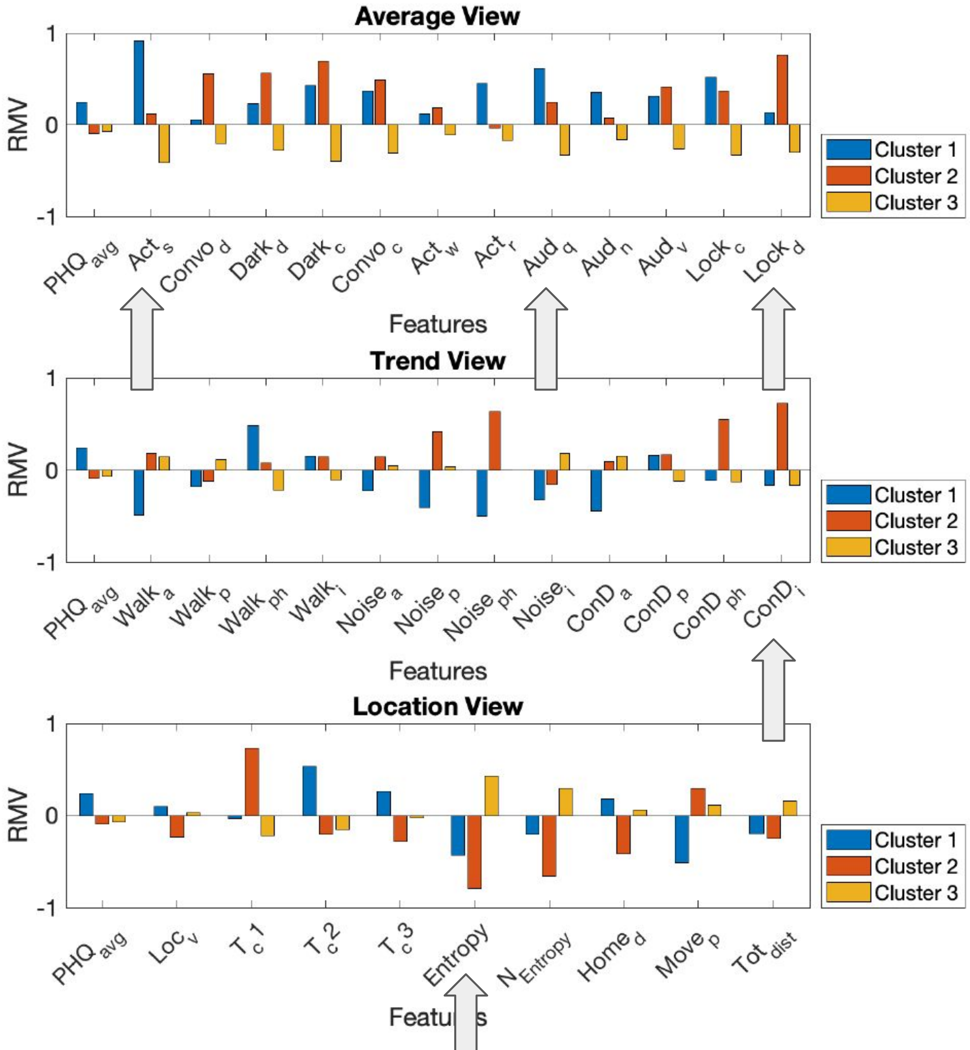
Results

- After pre-processing, 38 users were used
- We visualize the bar plot that present the relative mean values (RMV) of the PHQ-9 scores (average of pre and post) and the features for each of the three clusters



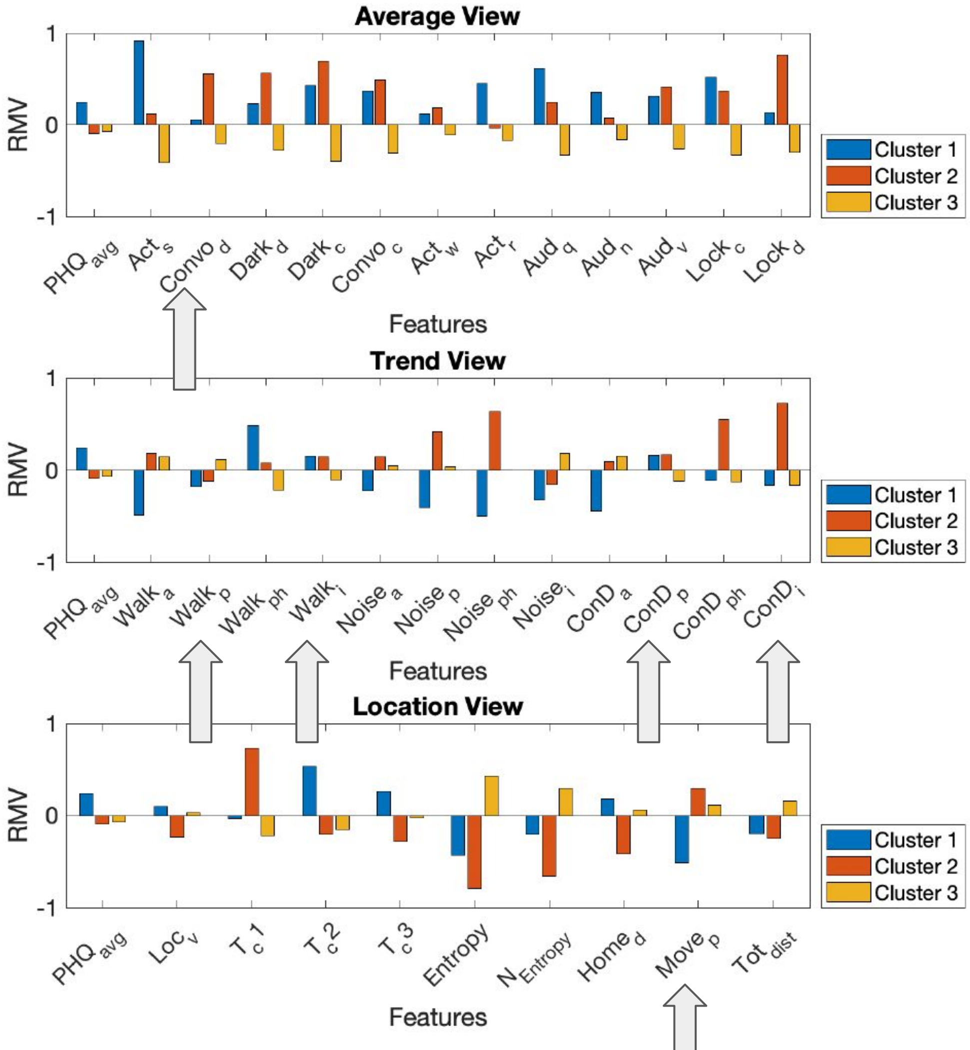
PHQ-9

- Cluster 1 (+)
- Cluster 2 (-)
- Cluster 3 (/)



PHQ-9

- Cluster 1 (+)
- Cluster 2 (-)
- Cluster 3 (/)



PHQ-9

- Cluster 1 (+)
- Cluster 2 (-)
- Cluster 3 (/)

Results continue

- Reduced feature set (n=16) achieved 94.7±1.62%

Predicted Classes

Actual Classes	C1	C2	C3
C1	9	0	0
C2	0	6	1
C3	0	1	21

Discussion and Conclusion

- The MVBC algorithm was applied to the sensing data from the smartphone followed by mRMR feature ranking was used to obtain the rank of the key features
- Of the reduced feature set, trend view seems to be the most significant as 8 of the 16 features pertain to this view.
  - Noise_i, Walk_a, Walk_ph, Noise_a, ConD_i, Walk_p, ConD_p, and ConD_a
- Due to the high accuracy with the use of a reduced feature set, detection of depression may be done locally on smartphones with future opportunities for low power secured connected healthcare and continuous human activity monitoring applications [10], [11].

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