Mood Prediction from Fitbit Data

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INTRODUCTION AND DESCRIPTION

Wearable sensors have become more and more ubiquitous and accurate in tracking biometrics such as steps, heart rate, and sleep. Massive amounts of quantitative biometric data has been collected through wearable devices such as Fitbit, Jawbone, smartwatches, and the like. However, users are often at a loss at how to translate that data into insights about other qualitative characteristics such as emotion, mood, or mental health. Since sleep has been shown to be highly correlated with mood and mood disorders, we aim to create an algorithm that will predict mood level based on Fitbit data.

We are aiming to assess how well a trained model can detect a mood from activity data collected by Fitbit. Inputs to our algorithm are a set of data collected by Fitbit, mood scores self-reported by participants, and surveys of depression before and after the study. We are collecting a dataset of two weeks of data from 16 participants from approximately March 28 - April 11. To establish sampling validity, our participants are a mix of male/female and come from various cities, schools, and are of varying ages.

Primary Data Sets

Sources:

1) Fitbit source data from the participants through the developer API: https://dev.fitbit.com/docs/
2) Mood sampling four times per day through EudaeSense (mobile app using an experience sampling method or ESM)
3) Surveys using PHQ-8, Beck's Depression Inventory, and Perceived Stress Scale before and after the mood and activity tracking, which are all overall measures of mental health.
4) Entry/Exit surveys asking about gender, age, and other general information

Size of the data:

1) Fitbit: Up to 500,000 instances from intraday time series data by minute
2) Mood ESM: Up to 896 instances (four times per day per participant)
3) Survey: 32 instances (before and after per participant)
4) Entry/Exit surveys: 16 instances of each

Nature of the data:

The Fibit data consists of JSON files reporting calories burned, number of steps, distance moved, number of floors, minutes for sedentary, minutes lightly active, minutes fairly active, minutes very active, calories burned by activities, minutes asleep, minutes awake, number of awakening while sleeping, and time in bed. A subset of the participants will also have GPS and heart rate data, but the amount of data is likely to be insignificant to our data analysis.

Mood ESM data consists of discrete self-reported measures of level of activity and degree of pleasure as well as continuous self-reported measures of sleepiness, stress, and feelings of positivity or negativity. This data can be collected up to four times per day per person.

The surveys consist of multiple choice (nominal) and likert scale (ordinal) responses. The questionnaire responses can also be evaluated as categorical classifications describing level of stress or depression.

APPROACHES AND POTENTIAL DISCOVERIES

Problem Statement: Predict mood scores at various times of the day from Fitbit activity data
Approach: We plan to approach this problem by training an LSTM (Long Short Term Memory) recurrent neural network using Keras and TensorFlow as the backend. We think this approach would work well for time-series prediction.
Potential Discovery: The potential discovery could be that mood can be predicted from Fitbit activity data.
Informed Action: If we were able to predict mood from Fitbit activity, then other apps could potentially offer various appropriately timed interventions to address or improve people's moods.

Other potential goals could be predicting post-survey mental evaluation results based on self-reported mood throughout the test period or predicting fitbit activity levels from self-reported mood scores.

TIMELINE / PLAN

Phase I: Data Collection, Engineering and Exploration (19 days)

March 28 - April 11: Data collection and engineering will be owned by April. The data collection is taking place from March 28 - April 11. During this time, the data will be uploaded and saved to an I School server, and the data engineering infrastructure has been designed and engineered by April.

April 4 - 15: As soon as we have collected a week's worth of data, we will begin extracting it and starting the data cleaning and exploration phase. We will work on cleaning the data by removing outliers or null values, normalizing the time series, and merge any datasets as needed. This portion of the project will be taken care of by Heidi, Audrey, and Laura.

Phase II: Feature Engineering and Classification (12 days)

April 16 - April 21: We will begin to engineer different features to see which combination are most correlated or predictive of mood or pre/post survey results and evaluating the outcomes of the algorithms using different features. This portion of the project will be done by all team members.

April 22 - April 27: We will apply ensembling methodology and grid search to choose the best features and combination of algorithms that give us the most predictive results. The ensembling will be done by Heidi and April and the grid search optimization will be done by Audrey and Laura.