Missing Data Imputation for Time Series Accelerometry Data

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Introduction

The wearable device has emerged as an important means of assessing human behaviors and served to define outcome measures in health observational and experimental studies. However, instances such as non-wearing of the device or partial wear can lead to an underestimation of total activity. Moreover, there might be potential disparities in activity levels between individuals with complete and incomplete or even no data, thereby rendering the estimated summary statistics from complete days susceptible to selection bias. This study focuses on the measurement of sedentary time during the day (8am–10pm).

This research aims to address this challenge by pioneering and assessing various imputation methods for the missing time series data to mitigate underreporting bias, a crucial factor influencing the quality of wearable tracking data. This effort not only carries immediate relevance for ongoing investigations but also offers enduring value for future researchers to contemplate, extending beyond the confines of the present analysis result.

Data and Methods

Data

We use data from the Physical Activity and Transit Survey (PAT). The survey asked adults in residential households in New York about their physical activity at work, home, commuting, and recreation. Among the 3811 respondents, 679 of them consented to wear accelerometer devices during all waking hours for one week. We created a concatenated dataset consisting of self-reported surveys and minute-level accelerometer data. The daytime raw accelerometer data has 3,992,520 observations, and the missing rate is about 20%.

Methods

We have two types of key measures to impute in the accelerometer data: 1) raw activity count; As an alternative, we also impute 2) a binary indicator of whether the missing minute is a sedentary minute, defined when the activity count falls between 0 and 99. There are several similar studies in the previous literature attempting to tackle the missing data problem in the time series accelerometry data. Two common methods are linear interpolation and zero-inflated Poisson models (R package 'accelmissing') (Lee et al, 2019).

In this research, we first analyze the relationship between missingness and minute-level variables and survey variables. Then, starts with logical imputation and is followed by stochastic imputation based on two different methods: 1) Multilevel regression for imputation using the 'mice' package, given the multilevel data structure, time points nested into individuals, we can impute the binary indicator for a sedentary minute; 2) Long Short Term Memory Neural Network. One advantage of using the deep learning method is that it does not require feature selections allowing us to directly feed all available data to the model. For instance, times series forecasting for finance with this method (Chen et al., 2016; Borovykh et al. 2017).

Once we have the completed imputation using the four methods mentioned above, we will split the data into 75% and 25% train-test datasets, and evaluate the prediction accuracy. This study answers the following research questions:

1. How does the imputation result in different key estimates compared to the complete cases method?
2. How do the accelerometry-based estimates compare to the self-reports in the survey?
3. How do different modeling approaches perform?
4. Does imputing activity count and determining sedentary status, as opposed to imputing sedentary status, enhance the accuracy and reliability of activity data imputation.

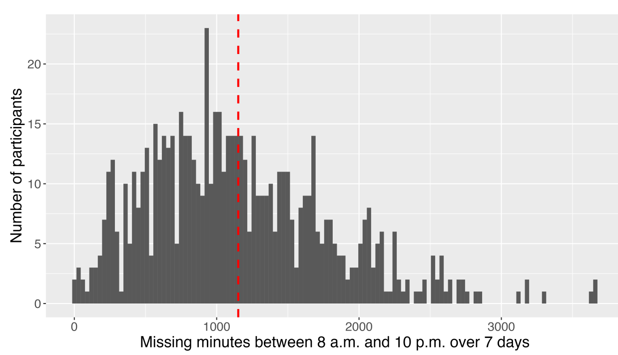
Computational challenge

Sensory digital traces are a new type of big data with a complex structure and relatively large size (approx. 1 GB). Multilevel regression can be challenging due to the nonconvergence because there are about 6,310 minute-level observations per participant and 678 participants. The computational intensity of these methods will be a focal point of our resource planning and execution strategy.

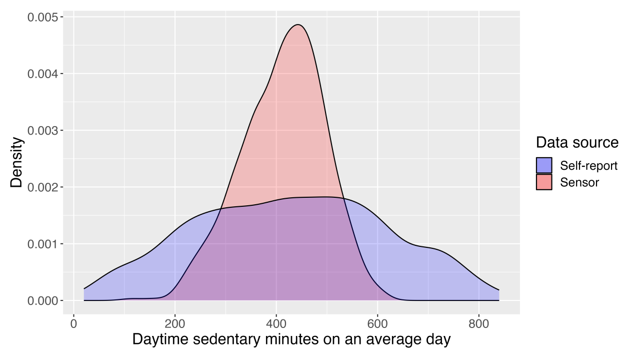
Results

Descriptive Analysis of Missing Data

Each participant has 5,880 minute observations (14 hours per day for 7 days). Of the 679 participants with accelerameter data, 678 participants have missing minute observations. The following figure shows the distribution of missing minute observations. On average, each participant has 1,153 missing minute observations (indicated by the red dashed line). In total, 781,940 minute observations are missing. It is computationally challenging to impute missing minute observations.



The measurement of interest is the daytime sedentary minutes. Besides the measure derived from the accelerameter data, a survey question asks about the minutes of sedentary activity on an average day. The following figure shows the densities of two variables measuring the daytime sedentary minutes on a day. Point estimates of average sedentary minutes converge between the two measures but the variance of the self-reported survey variable is greater than the variance of the accelerameter variable. It suggests that participants may under/over report sedentary activities due to recall bias. As accelerameter sensors collect more accurate data, it may be tempting to obtain complete acceleramter data.



Complete Case Approach

Complete cases approach is a straightforward method for handling missing data, which analyze only those observations for which there are no missing values in any of the variables of interest. We calculate the total sedetary minutes based on complete case, as reference to the estimates we obtain in the below using imputation approach. The result shows the an average individual had 2,894 minutes of day-time sedentary time in a week.

Linear Interpolation

Linear interpolation is a method of estimating values between two known values in a dataset. It assumes a linear relationship between the known values, and it calculates intermediate values based on this assumption. We found the average day time sedentary minutes based on linear interpolation is X, with a variance of X.

Multiple Imputation

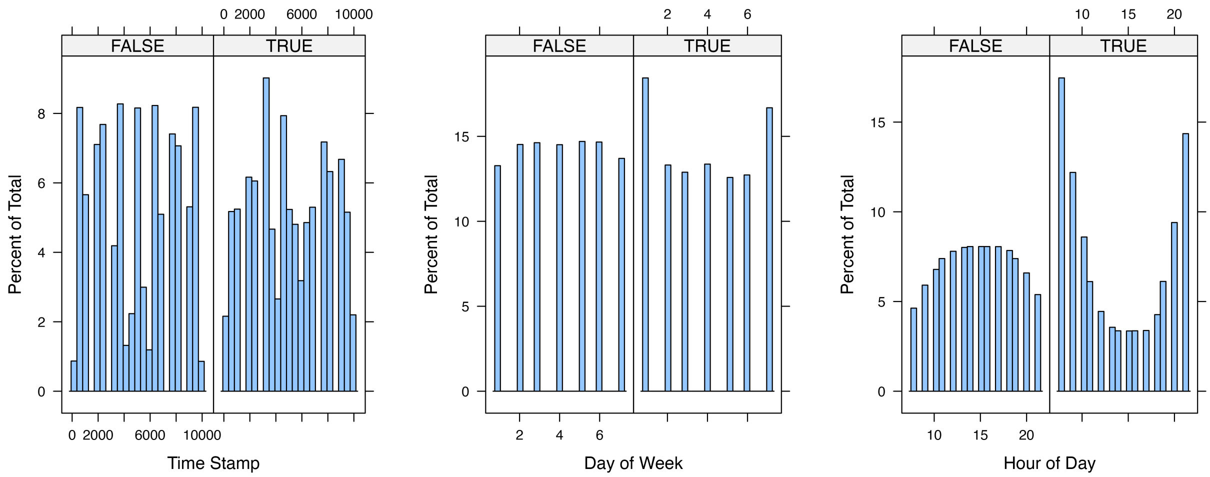
Activity count We first conducted the multiple imputation for minute-level activity count. To stabilize the variable, we used the square root transformation and back transformed after the imputation. The predictor in the imputation model include: 1) Time-varying variable lagged activity count (square-root transformed), which is the last activity count observed before the one at the missing time point; 2) Hour's position in the day; 3)Individual-level characteristics such as age, gender,race, activity limitation, income/poverty ratio, bmi range. They are the variables proven to be relevant to the sedentary behavior in the literature, and a result of backward covariate selection and variable importance test from the XGboost Tree in the below.

We define the target variable activity count as nonnegative continuous variable. The imputation involved 10 iterations and generated m=5 datasets. Multiple imputation helps us to capture the variability between imputations. It is done with "mi" package i

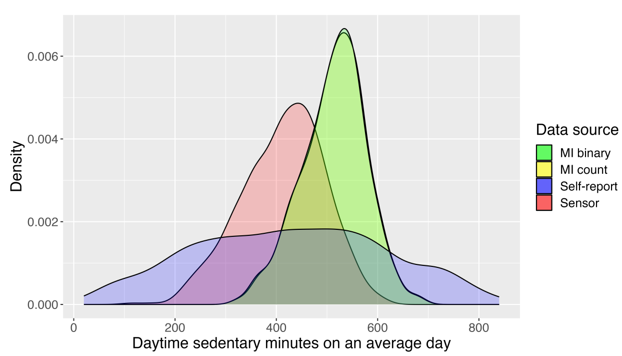
The observed activity count has a mean of 335, while the mean of the imputed value is 581. Given there are more than million data point, we random sampled 10% of them for the diagnostic plot visualizng the observed vs. imputed values diagnostic plot. We observe their distributions are similar.

After we have the complete dataset of 5, we pooled the estimate by taking the average of activity count from 5 datasets for each individual. Similar to what we have done earlier, we then use activity count threshold to determine whether a minute is a sedentary minutes. This approach multiply imputing activity count provided us a mean of 3,234 minutes of sedentary minutes in a week.

Binary sedentary status We use multiple imputation to fill the missing minute observations given the relationship between the activity count/binary indicator of sedentary status and three fully-observed minute-level variables (timestamp, day of week, and hour of day). In the following figures, the TRUE side indicates the distribution of participants with missing minute observations. We find that the missingness is not equally distributed across different values of the timestamp, day of week, and hour of day. Specifically, missingness is more likely to happen in the morning and evening, as well as on Saturday and Sunday.



We obtain five datasets with imputed activity counts and five datasets with imputed binary sedentary status. To improve the computational efficiency, five cores are used to generate the imputed datasets in parallel. Predictive mean matching is used to impute the activity count and logistic regression is used to impute the binary indicator of sedentary status.



XGBoost Tree

In addition to multiple imputation we use a machine learning approach where joined accelerometer and survey data are used as covariates to impute activity count/binary indicator. Unlike the previous models we use complete case data to train and test our models and then fill missing values based on the best performing model. For the binary indicator of sedentary minutes we use XGBoost, an efficient regularized boosting algorithm that uses a sequential ensemble of trees to improve model performance. The complete data are split into train (80%) and test (20%) datasets. Overall, to train the model we selected 60 complete case covariates (features) available for the datasets with missing and nonmissing target variable. The model was trained using 5-fold cross validation and the grid of hyperparameters specific to XGBoost with the subsequent selection of the best model based on the overall accuracy. The final model was used to predict the binary activity for the test as well as the data with missing sed_min status. For the test dataset we evaluated the model performance using balanced accuracy, sensitivity and specificity calculated based on the confusion matrix of predicted and observed sedentary behavior cases. Note that for this classification task we ignored the time-series nature of accelerometer data and treated sed_min as a cross-sectional indicator.

Autoregressive Integrated Moving Average and Kalman Smoothing

While the machine learning approach provided a convenient way of filling NAs using ensemble training we did not account for the time series nature of accelerometer count activity data. In this subsection we use ARIMA model for the univariate time series count together with Kalman smoothing (KS). While ARIMA model uses lagged moving average, KS can account for noisy measurement by incorporating information from past and future observations. For a sequence of missing values KS can make a best guess without the data stemming from the transition equation, hence the imputed NAs can take any value including the negative. For our imputed data we replaced all negative imputations with zeros.

Comparison of Estimates from Different Appraoches

Discussion

Author Contribution Statement

Deji Suolang is responsible for … Kaidar Nurumov is responsible for … Yongchao Ma is responsible for descriptive analysis, compilation of the final report, and maintenance of the GitHub repository.