Exploring the Relationships Between Fitness Success and Levels of Physical Activity

By: Kevin Rouse and Anton Hung

Motivation

- Physical activity has shown to have positive impacts on people’s overall health and happiness[1]
- People who engage in higher levels of physical activity (vigorous > moderate > low) also have higher levels of life satisfaction[2]
- Given that higher levels of physical activity = higher life satisfaction, we wanted to explore the lagged relationships of physical activity level and how the level of physical activity one gets on a daily basis changes and how it impacts the amount of calories burned

1. United States Department of Health and Human Services (HHS). *Physical Activity Guidelines for Americans*. 2nd ed 2018. https://health.gov/paguidelines/second-edition/pdf/Physical_Activity_Guidelines_2nd_edition.pdf. [Google Scholar]
2. An, Hsin-Yu, et al. “The Relationships between Physical Activity and Life Satisfaction and Happiness among Young, Middle-Aged, and Older Adults.” *International Journal of Environmental Research and Public Health*, vol. 17, no. 13, Jan. 2020, p. 4817. *www.mdpi.com*, https://doi.org/10.3390/ijerph17134817.

Data

- The data is from the lifsenaps study[3], whose goal was to provide additional information on wearable fitness trackers that have not been studied much before by combining the data with surveys
- Contained data from 71 participants collected on a daily basis for up to four months for each participants
- One data point for each day, which were converted into discrete time intervals, each participant started at day 1

3. Yfantidou, Sofia, et al. "LifeSnaps, a 4-Month Multi-Modal Dataset Capturing Unobtrusive Snapshots of Our Lives in the Wild." *Scientific Data*, vol. 9, no. 1, Oct. 2022, p. 663. *www.nature.com*, https://doi.org/10.1038/s41597-022-01764-x.

Our Focus

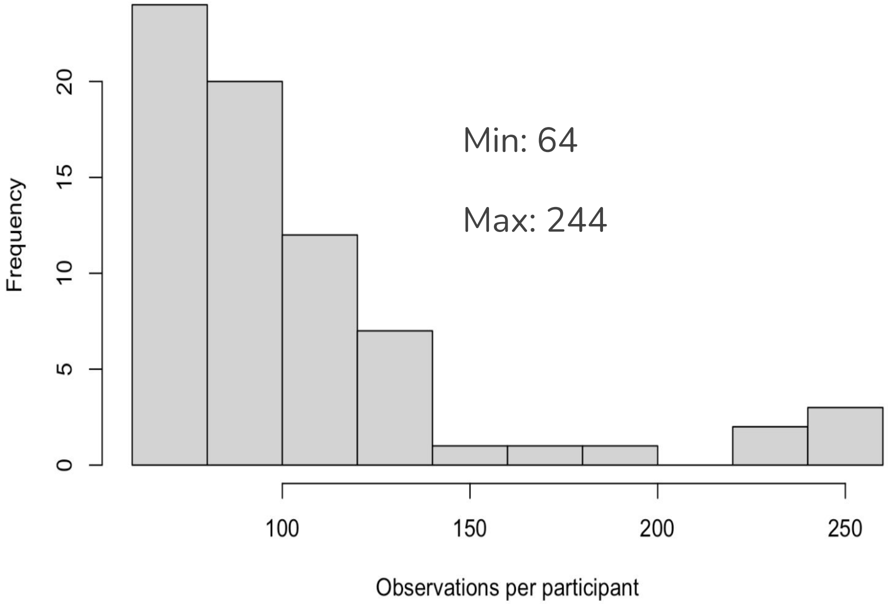
- Focused on the variables “very active minutes”, “moderately active minutes”, “lightly active minutes”, “sedentary minutes” to look at different levels of physical activity
- Focused on variable “calories” as a metric for fitness success
- Goal of analysis is to determine how these variables interact with each other on the same day, the next day, and a few days in the future
- Can hopefully give insight into what patterns of activity level lead to burning more calories and how levels of activity interact with each other

Data Preprocessing
Dates

- Discrete time. One observation per day per subject

- Different observation start dates between subjects
- Solution: Convert dates to relative days since the beginning of observation

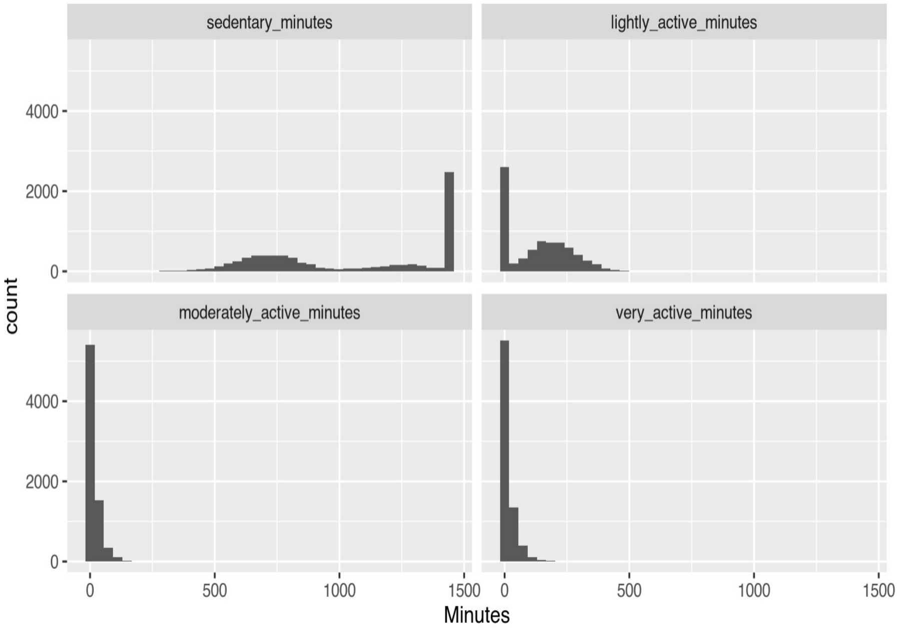
- Different number of observations per subject
- Solution: For a portion of our analysis (DTVEM), we subsetted the dataset to just the first 64 days



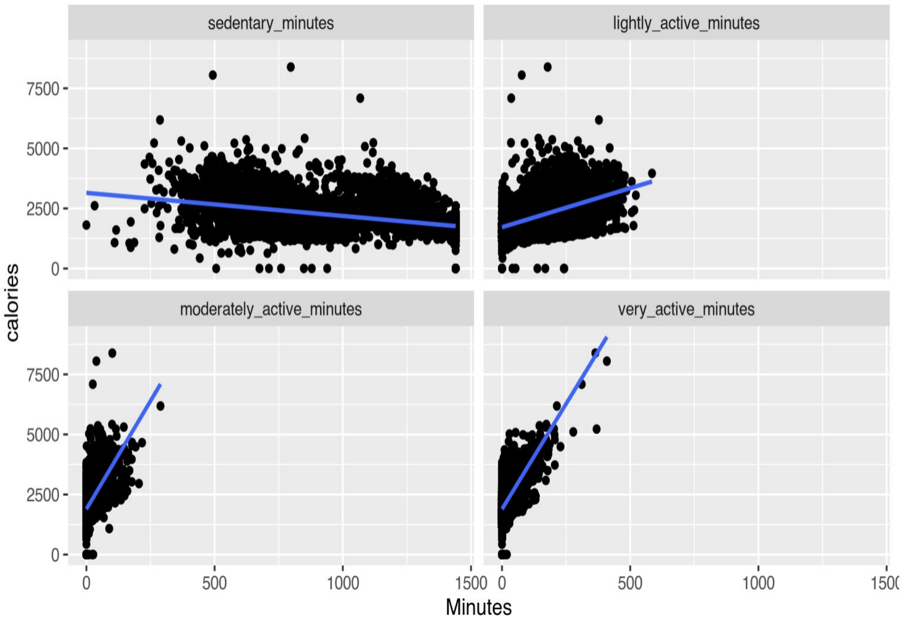
Data exploration

Preliminary exploration of our variables: sedentary, lightly active, moderately active, and very active minutes

Distributions of activity level minutes

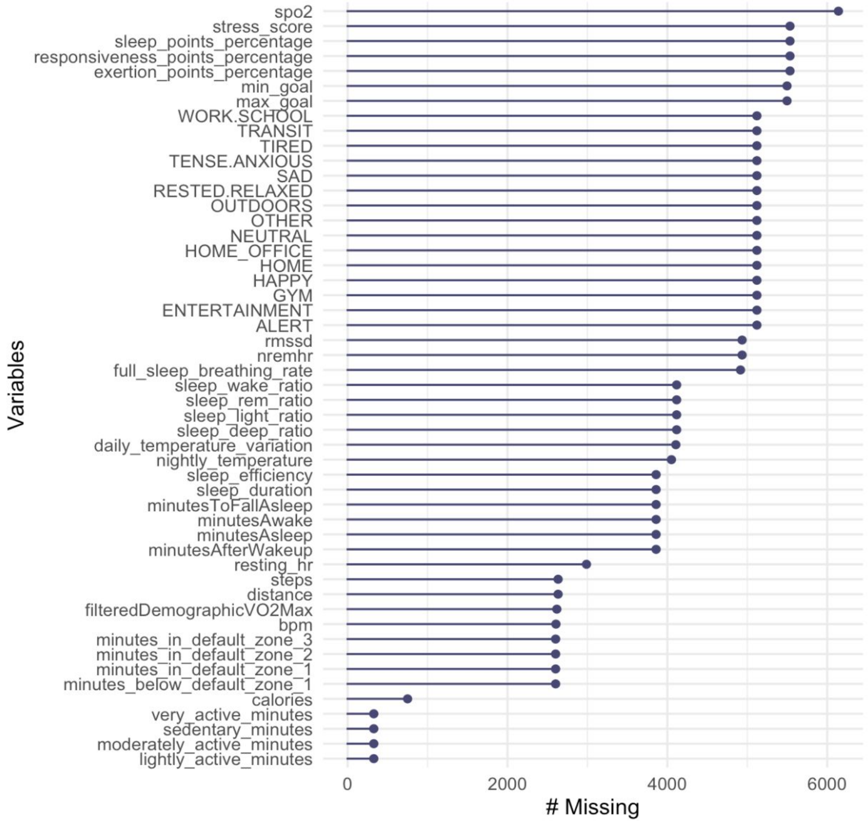


Relationship vs. calories burned



MICE

- Data contained a fair amount of missing values
- Variables of interest were amongst the least missing variables
- Used MICE with the CART method to impute missing data
- Only used first imputed dataset



Differential Time Varying Effect Model (DTVEM)

- DTVEM identifies the short and long term at which our predictor variables can predict our outcome variable (calories burned)
- Predictor variables:
  - Sedentary minutes
  - Lightly active minutes
  - Moderately active minutes
  - Very active minutes
  - Calories burned
- Outcome: calories burned
- Timepoints: 14

Jacobson NC, Chow SM, Newman MG. The Differential Time-Varying Effect Model (DTVEM): A tool for diagnosing and modeling time lags in intensive longitudinal data. Behav Res Methods. 2019 Feb;51(1):295-315. doi: 10.3758/s13428-018-1101-0. PMID: 30120682; PMCID: PMC6395514.

DTVEM results

Name	Estimate	Std.Error	tstat	p-value
calorieslagoncalorieslag1	0.153	0.0234	6.54	6.10e-11
calorieslagoncalorieslag6	0.0395	0.0167	2.37	1.78e-02
lightly_active_minuteslagoncalorieslag1	0.127	0.0237	5.34	9.20e-08
lightly_active_minuteslagoncalorieslag2	0.0655	0.0159	4.11	4.02e-05
lightly_active_minuteslagoncalorieslag4	0.0632	0.0157	4.03	5.54e-05
lightly_active_minuteslagoncalorieslag7	0.0714	0.0168	4.26	2.01e-05

Calories positively predicted itself 1 and 6 lags later

- Daily physical activity/non-activity
- Weekly physical activity

Lightly active minutes positively predicted calories 1,2,4, and 7 lags later

- Light activity is easier to participate in on a regular basis throughout the week

No significant lags for moderately and highly active minutes

DTVEM

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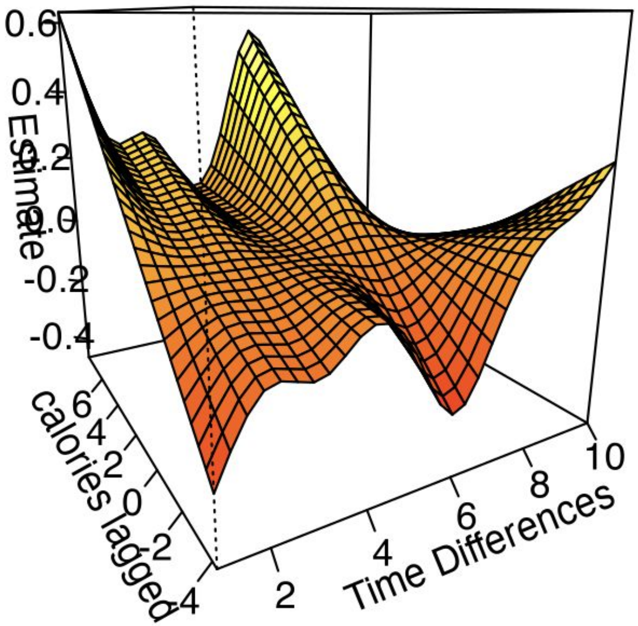
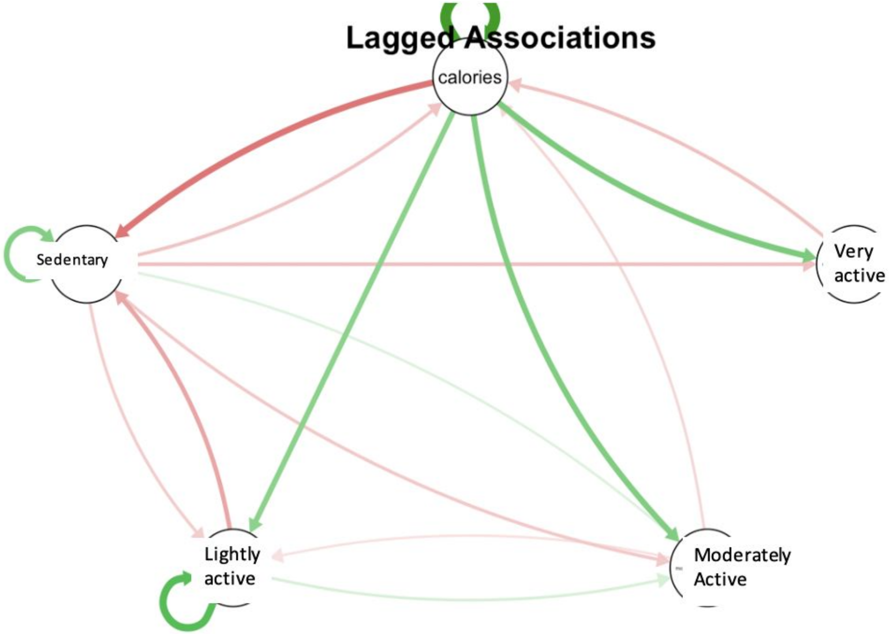


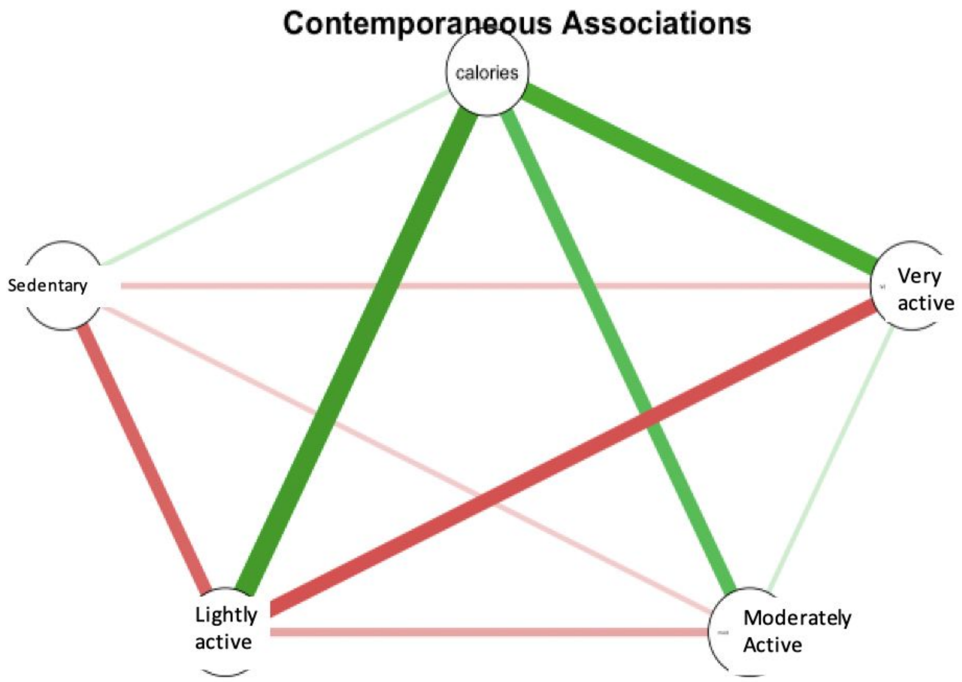
Vector Autoregression: Autoregressive and Cross-regressive Relationships

- Used vector autoregression with lags of 1 day to analyze short term relationships between the variables.
- Autoregressive and cross-regressive relationships:



From	To	Beta	SE	p-value
Calories	Calories	0.518	0.064	0.000
Calories	Very Active Mins	0.263	0.063	0.000
Calories	Mod. Active Mins	0.254	0.055	0.000
Calories	Lightly Active Mins	0.231	0.077	0.003
Calories	Sedentary Mins	-0.277	0.080	0.001
Very Active Mins	Calories	-0.123	0.027	0.000
Very Active Mins	Very Active Mins	-0.009	0.037	0.805
Very Active Mins	Mod. Active Mins	-0.027	0.035	0.443
Very Active Mins	Lightly Active Mins	-0.035	0.031	0.253
Very Active Mins	Sedentary Mins	0.054	0.031	0.085
Mod. Active Mins	Calories	-0.079	0.018	0.000
Mod. Active Mins	Very Active Mins	-0.043	0.026	0.102
Mod. Active Mins	Mod. Active Mins	-0.008	0.026	0.748
Mod. Active Mins	Lightly Active Mins	-0.059	0.018	0.001
Mod. Active Mins	Sedentary Mins	0.066	0.018	0.000
Lightly Active Mins	Calories	0.031	0.040	0.430
Lightly Active Mins	Very Active Mins	0.018	0.048	0.710
Lightly Active Mins	Mod. Active Mins	0.078	0.040	0.049
Lightly Active Mins	Lightly Active Mins	0.340	0.049	0.000
Lightly Active Mins	Sedentary Mins	-0.179	0.052	0.001
Sedentary Mins	Calories	-0.119	0.030	0.000
Sedentary Mins	Very Active Mins	-0.128	0.035	0.000
Sedentary Mins	Mod. Active Mins	-0.109	0.032	0.001
Sedentary Mins	Lightly Active Mins	-0.099	0.030	0.001
Sedentary Mins	Sedentary Mins	0.248	0.034	0.000

Vector Autoregression: Contemporaneous Relationships



Discussion: DTVEM

Calories positively predicts itself: People who burn a lot of calories are more likely to burn a lot of calories regularly.

Aside from calories burned, **lightly active minutes were the strongest predictor of calories burned**

- Light activity can be repeated regularly
- Intense activity is difficult to sustain for long periods of time. May be too tired to exercise the following day. Difficult to fit into a busy work/life schedule

Discussion: Vector autoregression

Vector Autoregression relationships:

Sedentary minutes positively predicts itself: inactivity predicts further inactivity

Light activity negatively predicts sedentary minutes

Intense activity positively predicts sedentary minutes and negatively predicts calories burned

- Light physical activity means less time spent being inactive
- Intense physical activity is difficult to make time for, and can leave you too tired to engage in activity the following day.

Conclusions

- Regular light activity is the best predictor of calories burned
    - Walking and going outside means less time sitting on the couch at home
    - Habit of avoiding sedentary lifestyle
    - More calories burned

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Merci

Thank YOU!!!!!!!!
Questions?

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