Tracking physical activity with wearable sensors: considerations for data collection and analysis

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Disclosures

In the past my research has been funded by:

DELSYS®
WEARABLE SENSORS
FOR MOVEMENT SCIENCES

DE LUCA
FOUNDATION

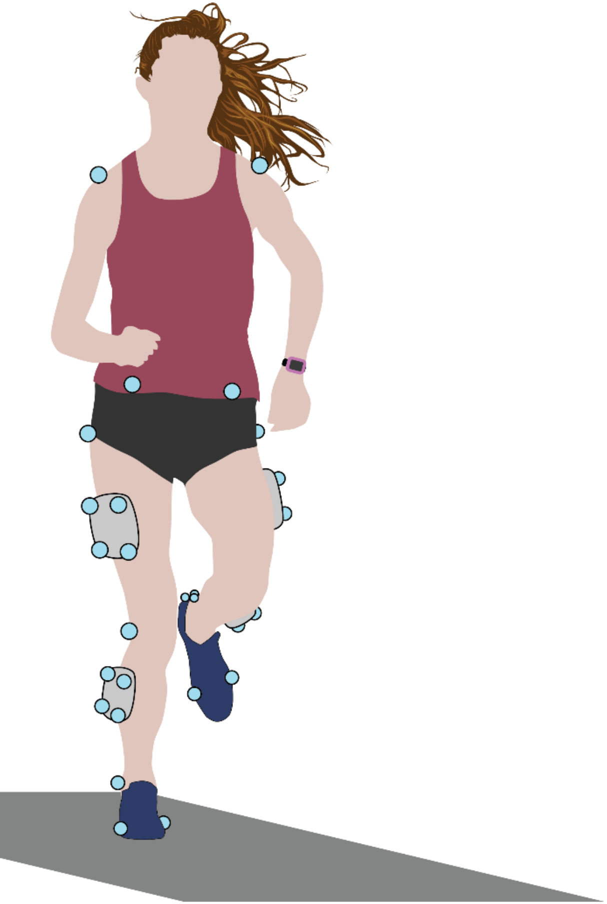
Summer/travel funding

STRYD

(Equipment)

I will be mentioning several brands in this talk; I have no current relationships with any of them

My background

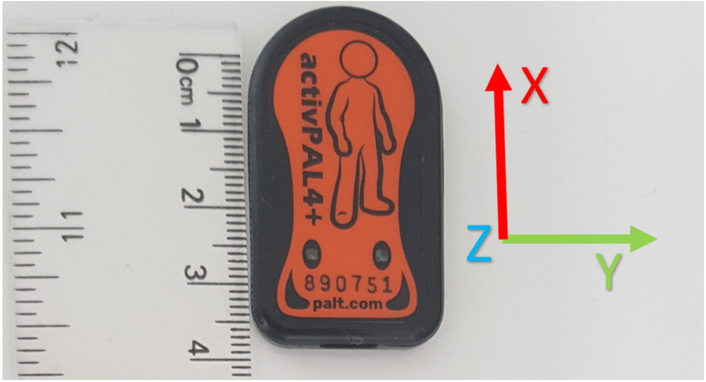


My background

- Biomechanics → what are we measuring?
- Sensors for activity recognition + gait analysis (many “scales” of data analysis!)

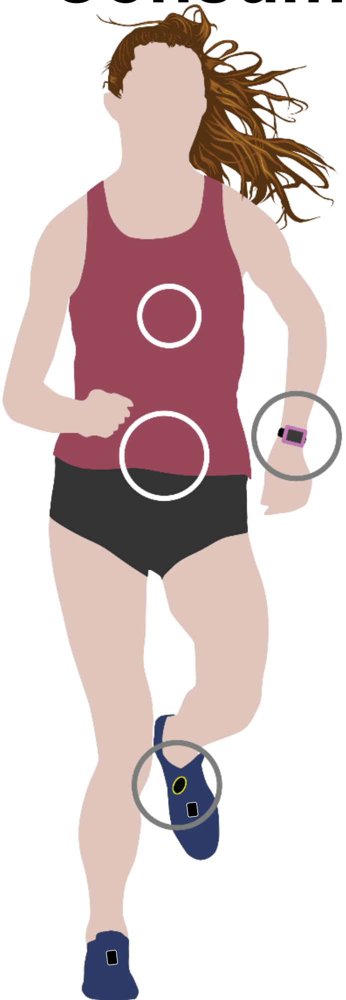
My goal for you

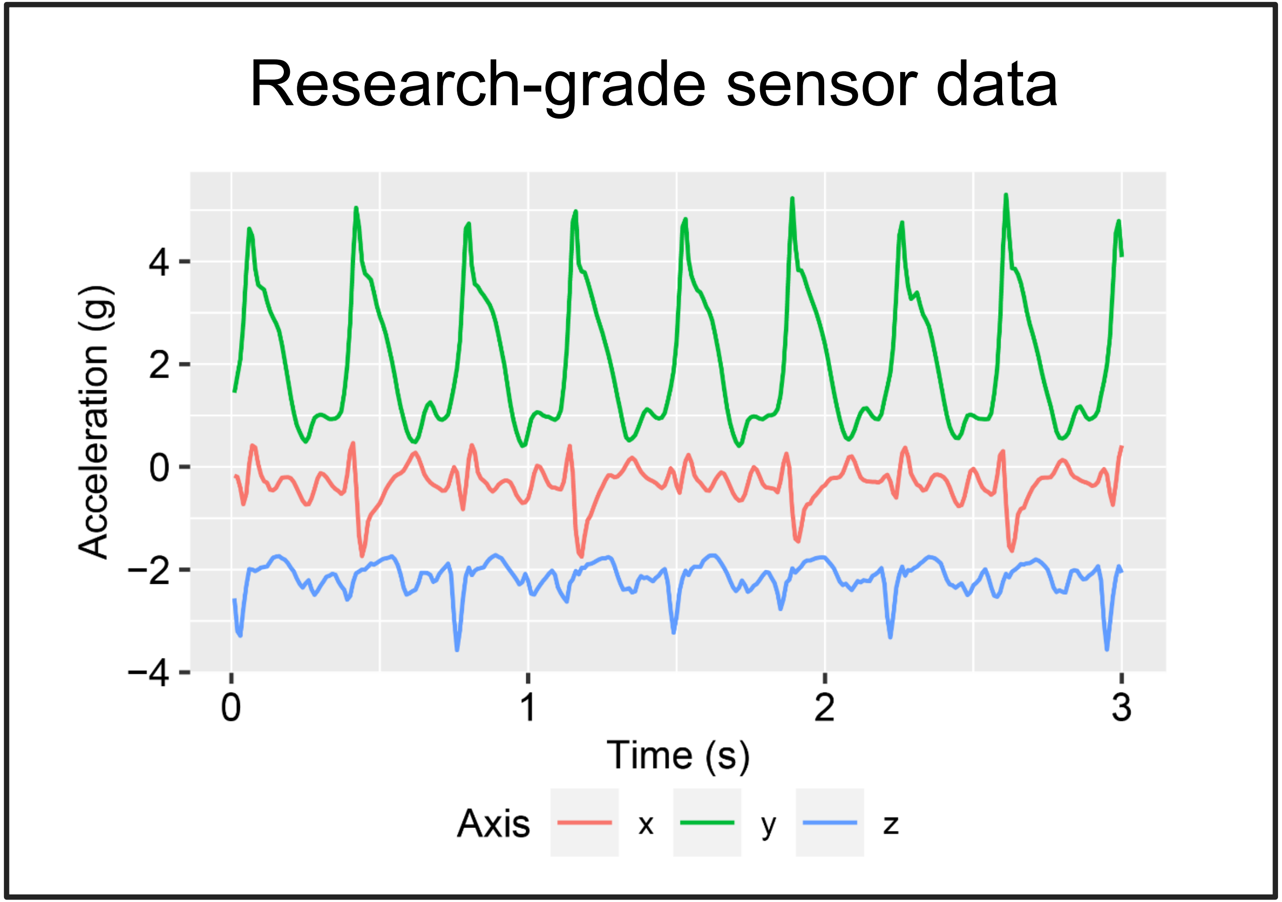
- A broad view of what you can do with sensors, and what you should keep in mind when working with sensor data



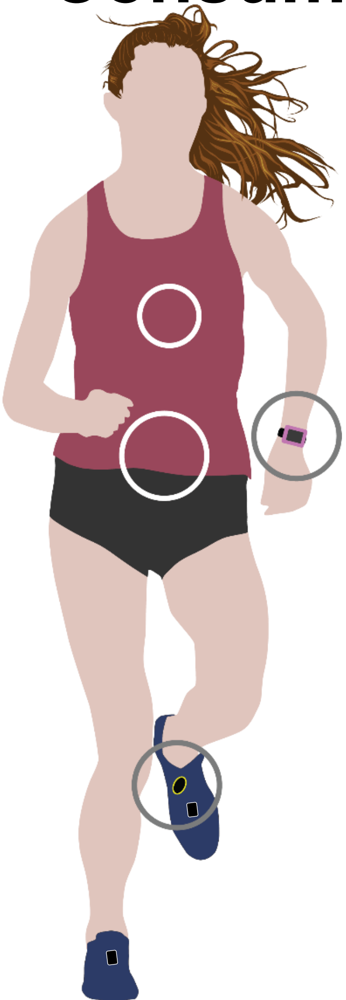
Which sensors? Consumer-grade vs. research-grade

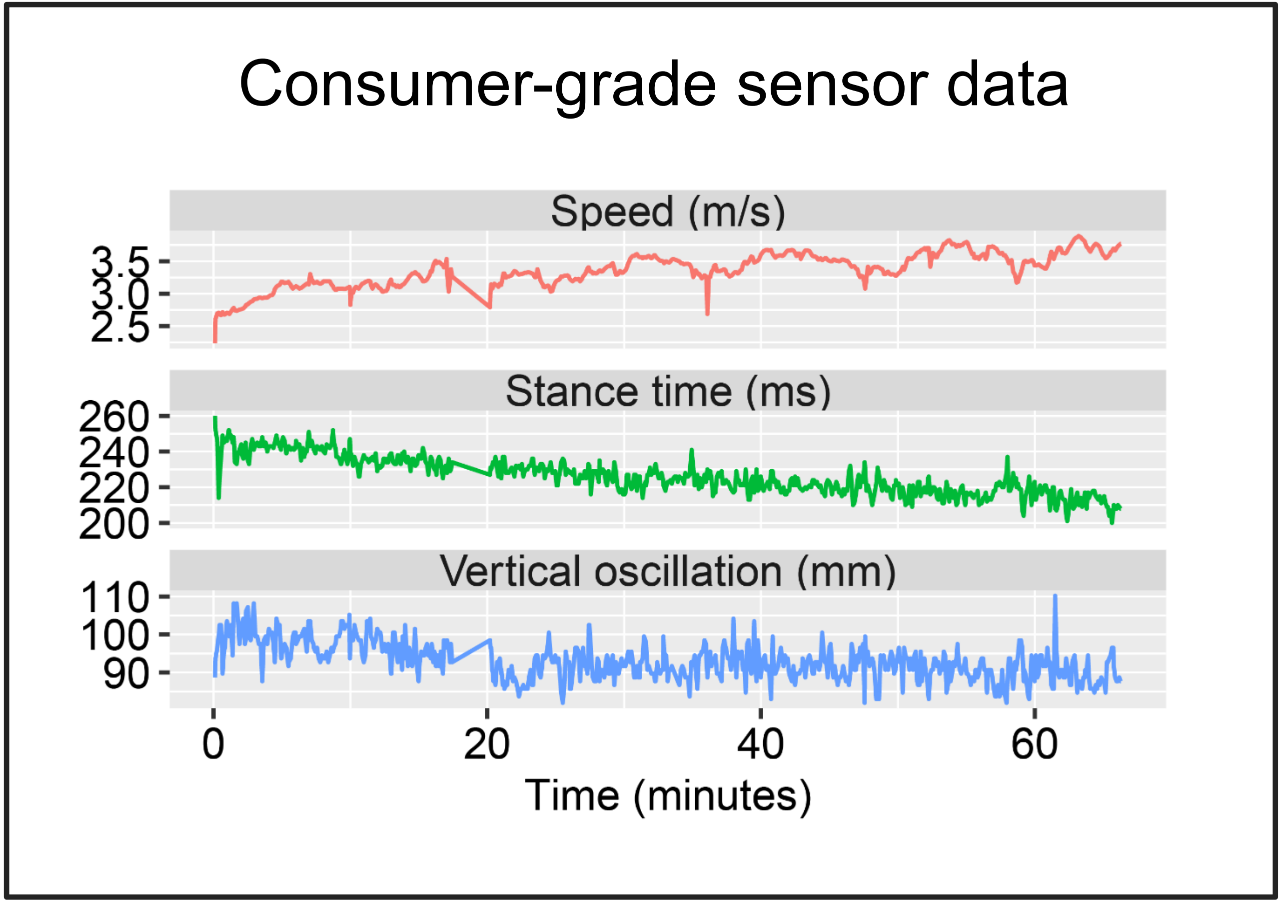
Consumer-grade vs. research-grade sensors





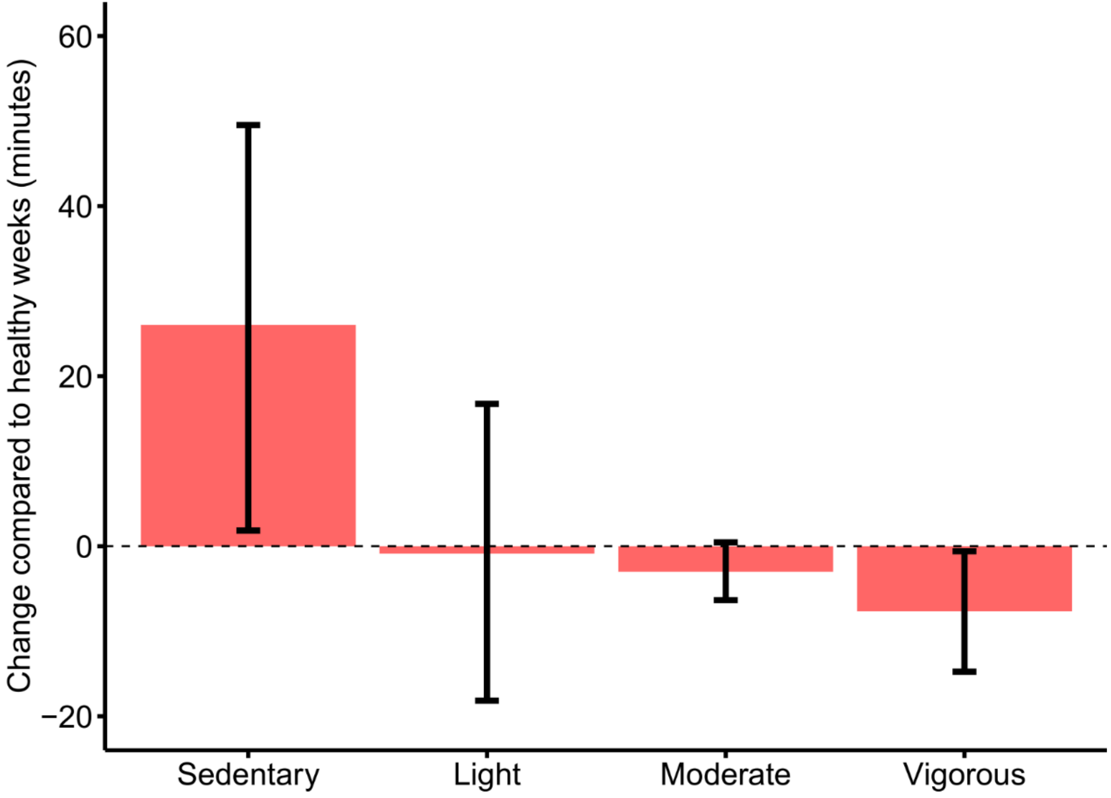
Consumer-grade vs. research-grade sensors





Sensors at different "scales"

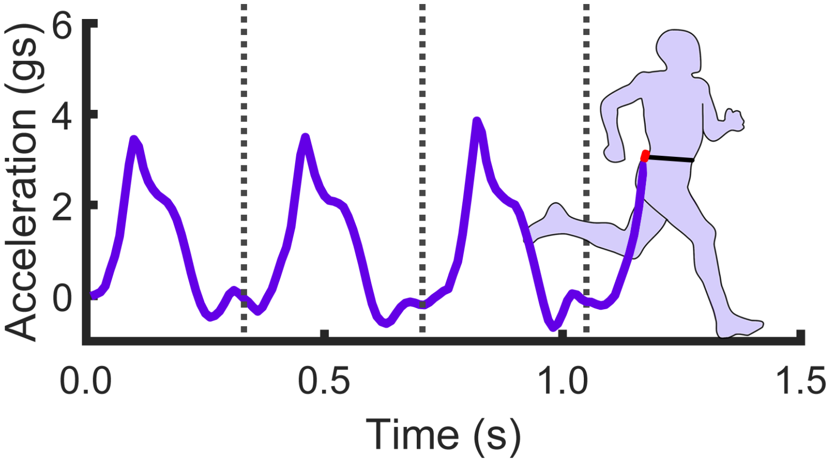
Total daily time in different activity levels

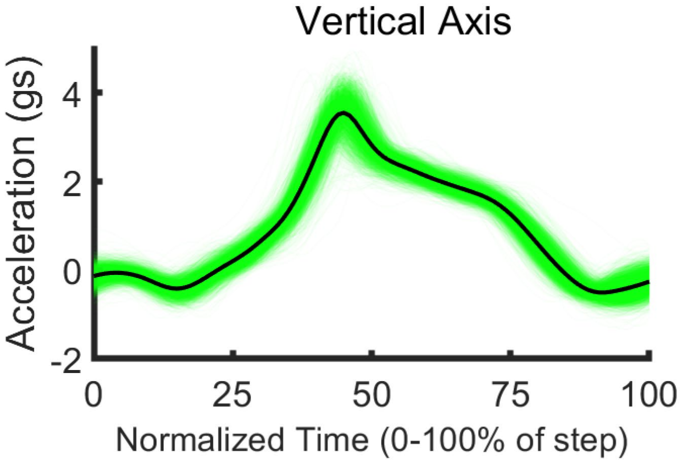


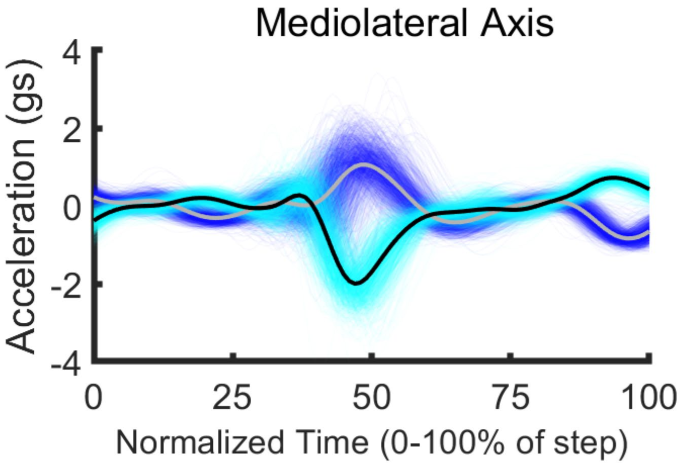
Davis & Gruber Med Sci Sports Exerc 2020 52(5)1163-68

Sensors at different "scales"

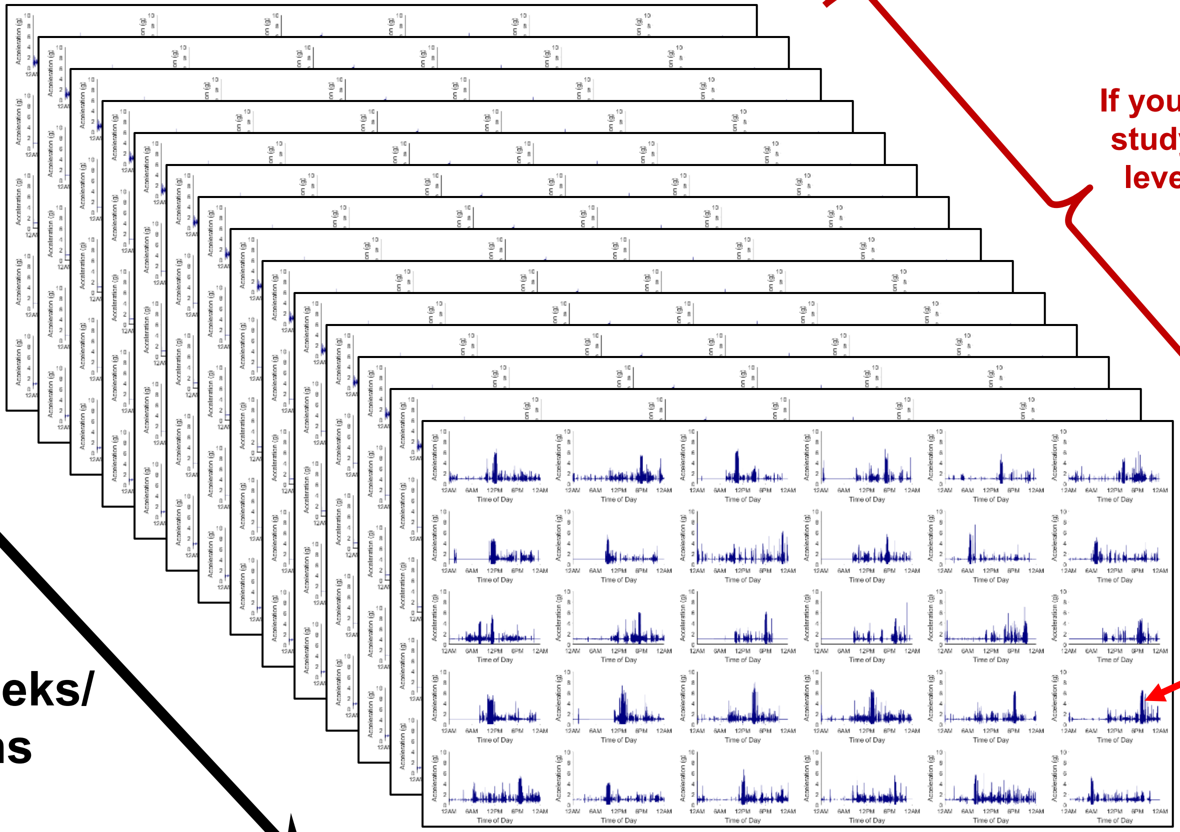
Sub-second movement pattern analysis





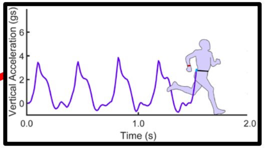


Sensors at different “scales”



If you want, you can study sub-second-level data across months

Days/Weeks/ Months



Sensors at different “scales”

<u>Some general tips about scale:</u>

The smaller the scale, the bigger the problems!

I *love* working with super-high-resolution sensor data.

<u>But</u> it is very, very tricky to do well.

Simple ain’t easy

Even something seemingly straightforward, like daily step count, will involve many careful methodological considerations

Sensors at different "scales"

Larger-scale metrics

- Total daily steps
- Total time asleep
- Total sitting time
- TDEE

Smaller-scale metrics

- Uninterrupted sedentary time
- "Exercise snacks"
- Sleep phases
- Continuous bouts of activity

Often need 'feature engineering' here

Decisions in some large studies to date

NHANES: ActiGraph on wrist

UK Biobank: Axivity on wrist

All of Us: 'Bring your own (wrist) device'

Summarizing raw acceleration data

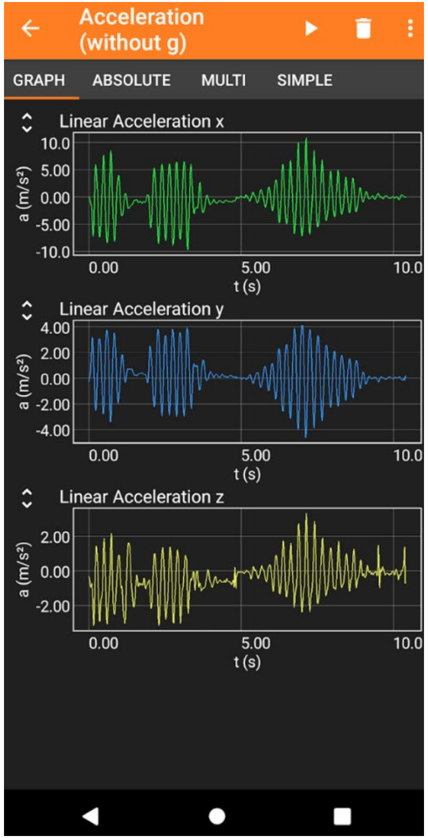
- Steps, counts, other units
  - In various ‘epochs’, e.g. 1 minute, 15 minutes, …
- *Total* daily steps / counts / units
  - *(epoch of 24 hrs)*
- Various ‘engineered features’
  - Non-wear time (according to what algorithm?)
  - Time spend asleep (according to what algorithm?)
  - Time spend in various “zones” or above “cut-points”
  - Probability of activity transition
  - ….

What **construct** are we trying to get at?

Energy expenditure?
Metabolic intensity?
At what scale? TDEE or more fine-grained?

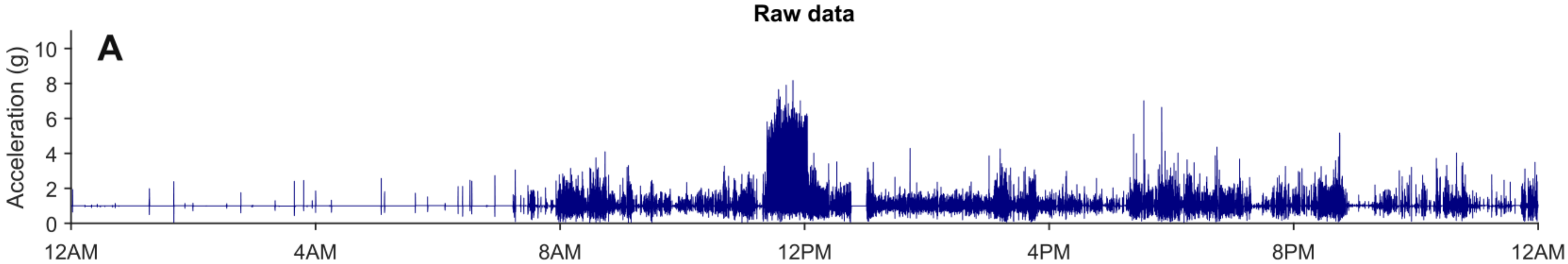
Note: often our construct of interest is *continuous,* even if we pretend it is categorical/ordinal/binary

What does a wearable sensor **actually** measure?

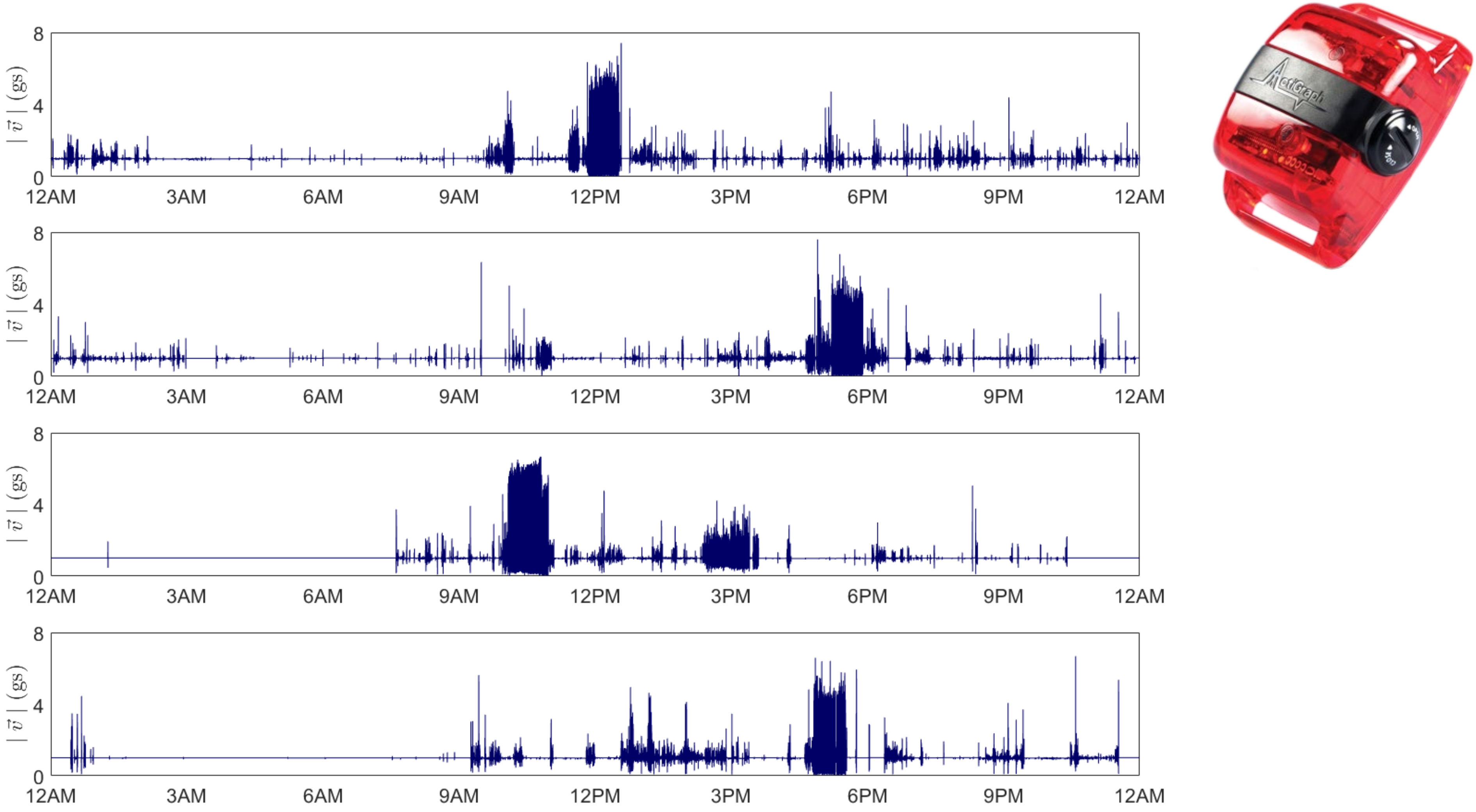


Linear acceleration (x/y/z)
Angular velocity (x/y/z)

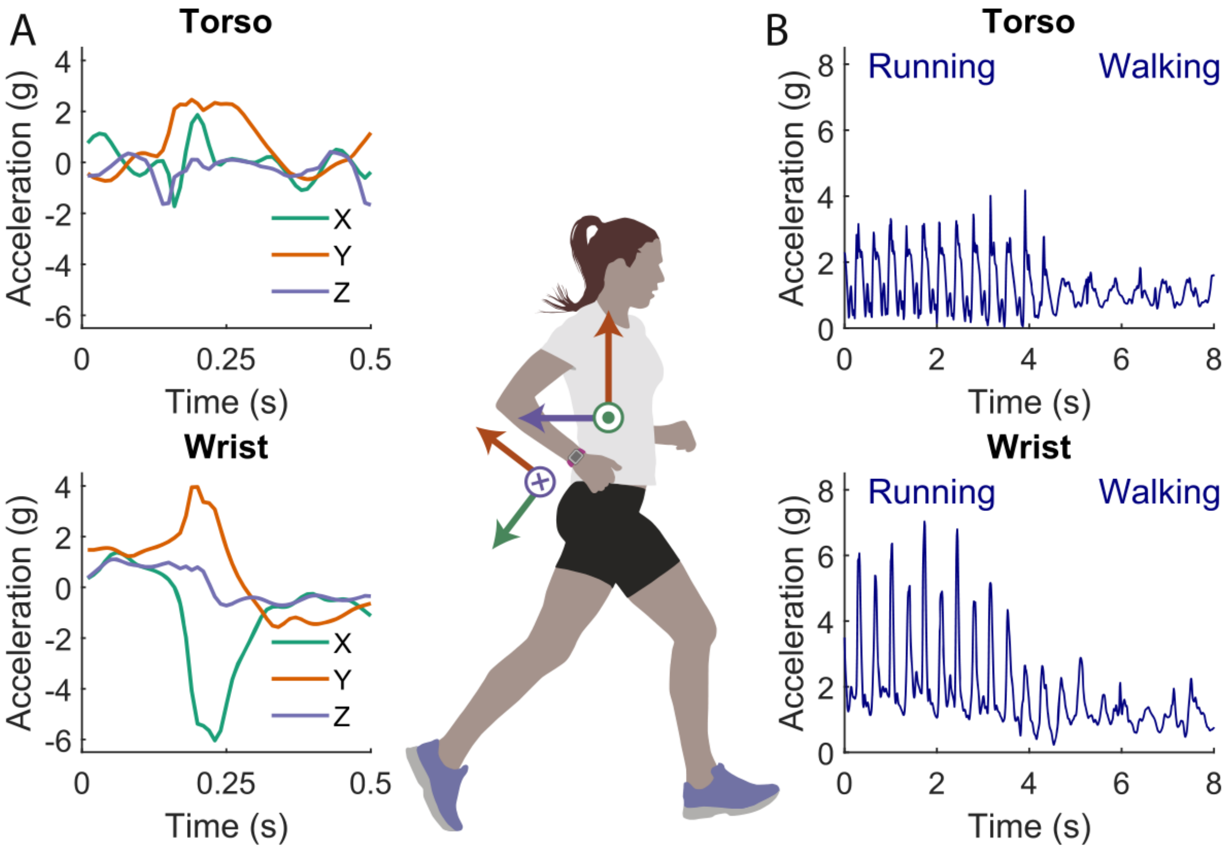
What does a wearable sensor **actually** measure?



You need to make sense of this ^^

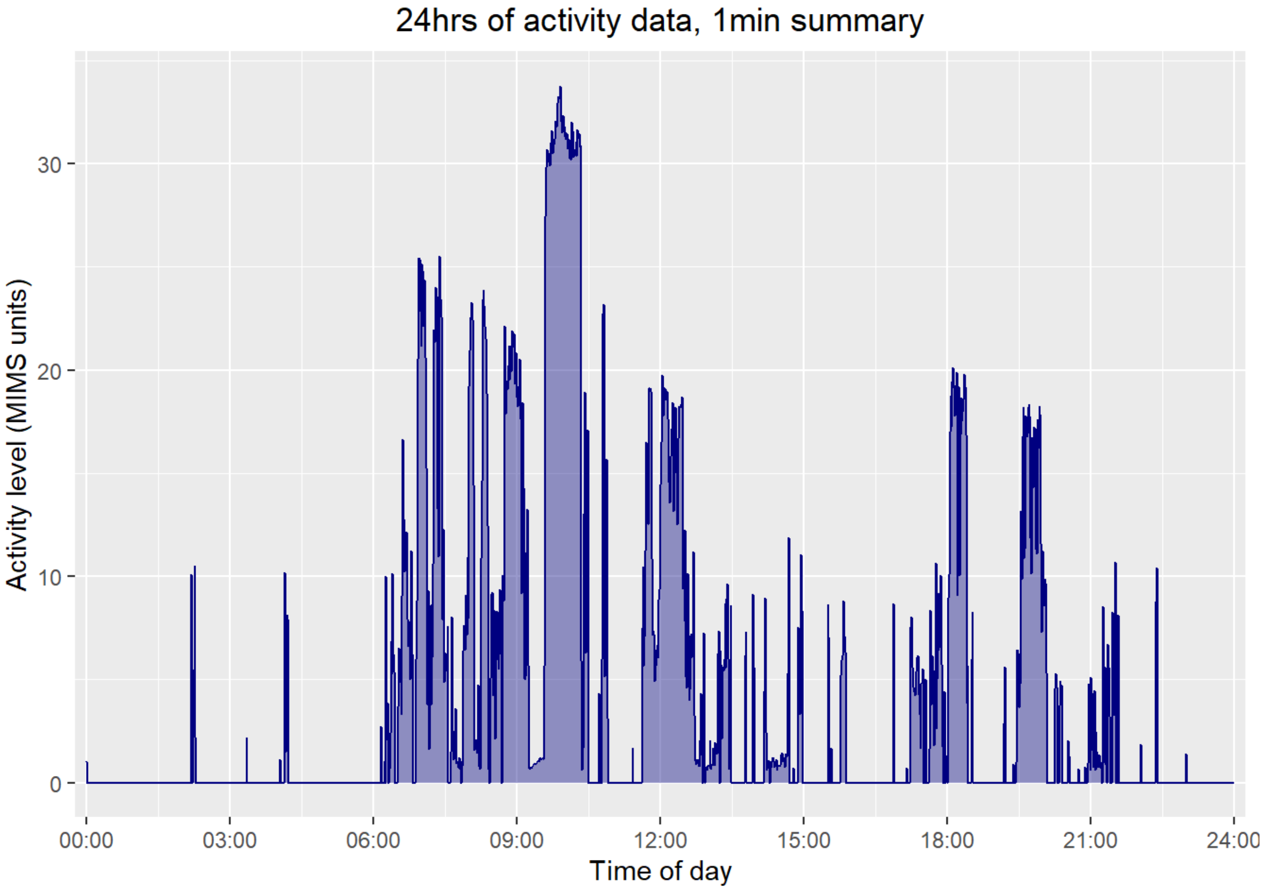

$|\vec{v}|$ (gs)
8
4
0
12AM
3AM
6AM
9AM
12PM
3PM
6PM
9PM
12AM
ActiGraph

Aside: acceleration signals are location-dependent!



Some summary metrics, e.g. MIMS units, try to account for this

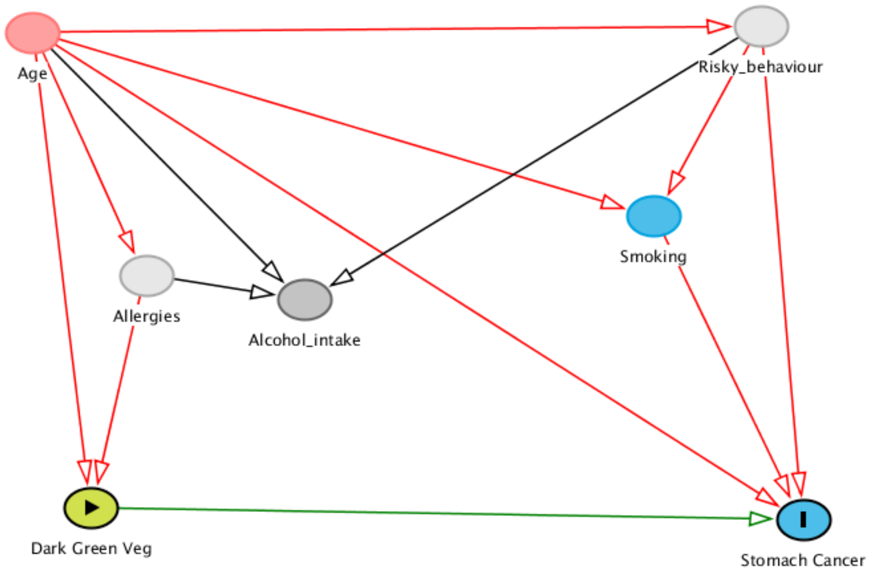
Modest reduction: to minute-level epochs



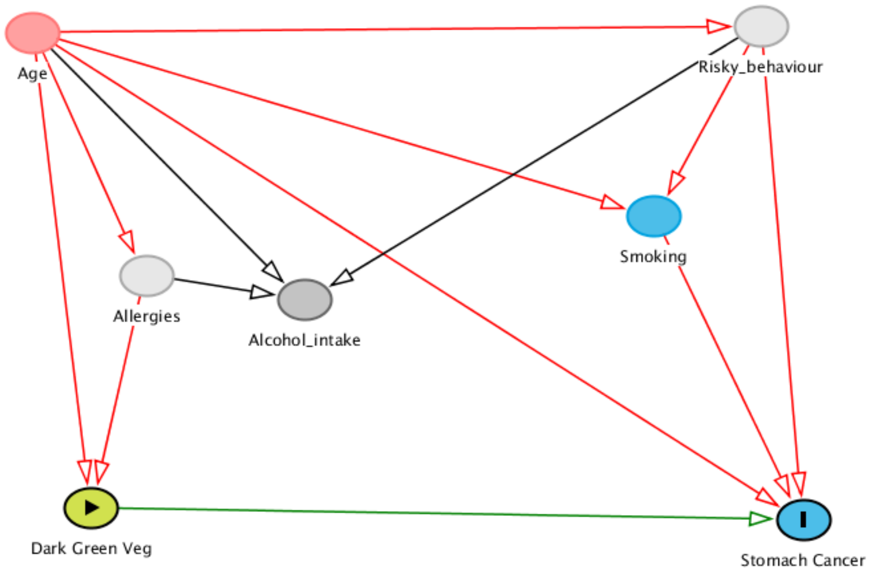
Is sensor-measured activity / metabolic expenditure:

- Your exposure of interest?
- Your outcome of interest?
- A confounder or effect modifier?

This might affect how you collect and analyze data!



Often the challenge is the ***other*** (non-sensor) half of the analysis (need x *and* y!)



Some analytical considerations

Even summary metrics (e.g. total daily steps) from accelerometer data are…

- ***Less*** (not *un-*) biased or confounded with other variables of interest than self-report data
  - *e.g. causal DAG: education / self-reported PA*
- Challenging to align with other sources of data
- Generally not normally distributed (*sometimes not even continuous, e.g. S-L-M-V cutoffs!*)
- Often non-linearly associated with outcomes
- Not a perfect representation of the underlying construct you're trying to measure

Some analytical considerations

Raw accelerometer data are…

- **Very** large (many gigabytes!)
- **Very** challenging to work with unless you have strong data-crunching skills
    - MATLAB / R / Python basically mandatory
- **Very** information-rich!

So you need to think carefully about how you'll 'reduce' your raw accelerometer data to summary metrics

Some analytical considerations

Consumer-grade sensor data are…

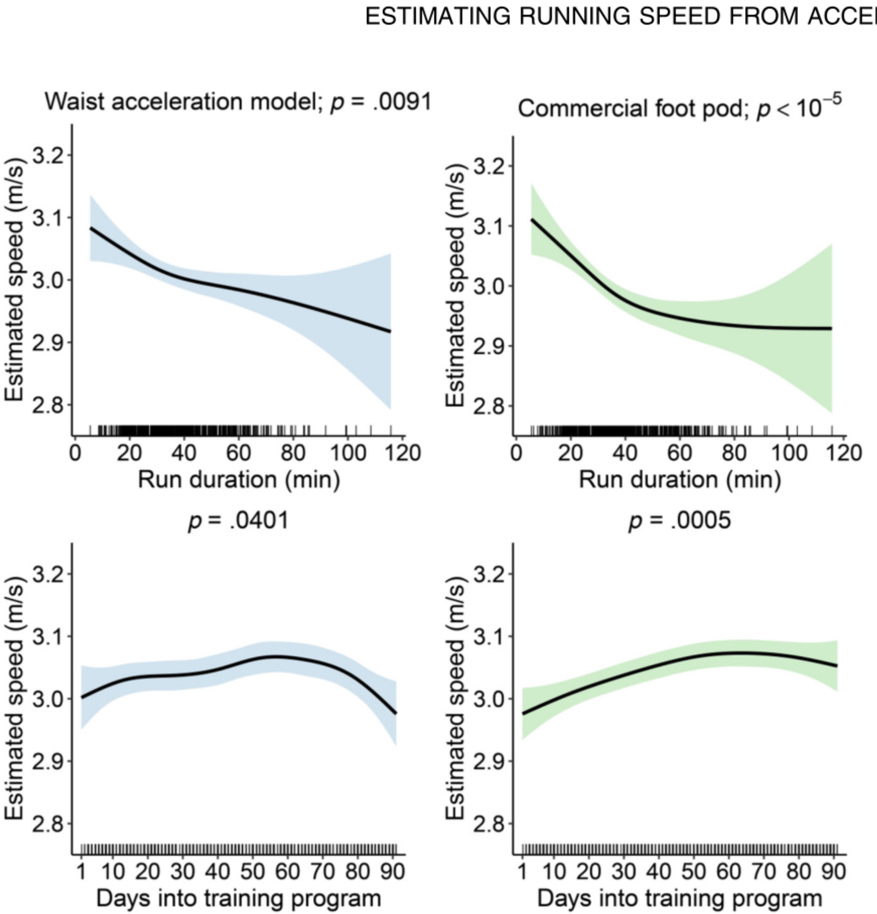
- **Somewhat** easier to work with
- Reliant on ‘**black box**’ algorithms
- Sometimes **‘free’** – if people bring their own (watch out for selection bias!)
- Not usually validated in population of interest
- Not usually the focus of the company making the devices

So you need to think carefully about costs/benefits of the consumer-grade sesors

Did you think about…

- Weekdays vs. weekends? Holidays?
- Non-wear time?
  - (both detecting it and what to do about it)
- When the day starts? Is midnight to midnight “right”?
  - Night shift, night owls
- Circadian cycles?
  - Should you “register” 24-hour days?
- …all the other corner cases and gotchas?
  - Probably makes sense to train up / collab with 1-2 people who can be highly skilled in sensor data analysis
- In-lab vs. real-world differences?

Linearity: not a great assumption



Davis, J.J., et al. 2023. *Journal for the Measurement of Physical Behaviour*, *6*(1) 24-36.

Linearity: not a great assumption

Sriram et al / Am J Prev Med 2021;60(1):95−103 **99**

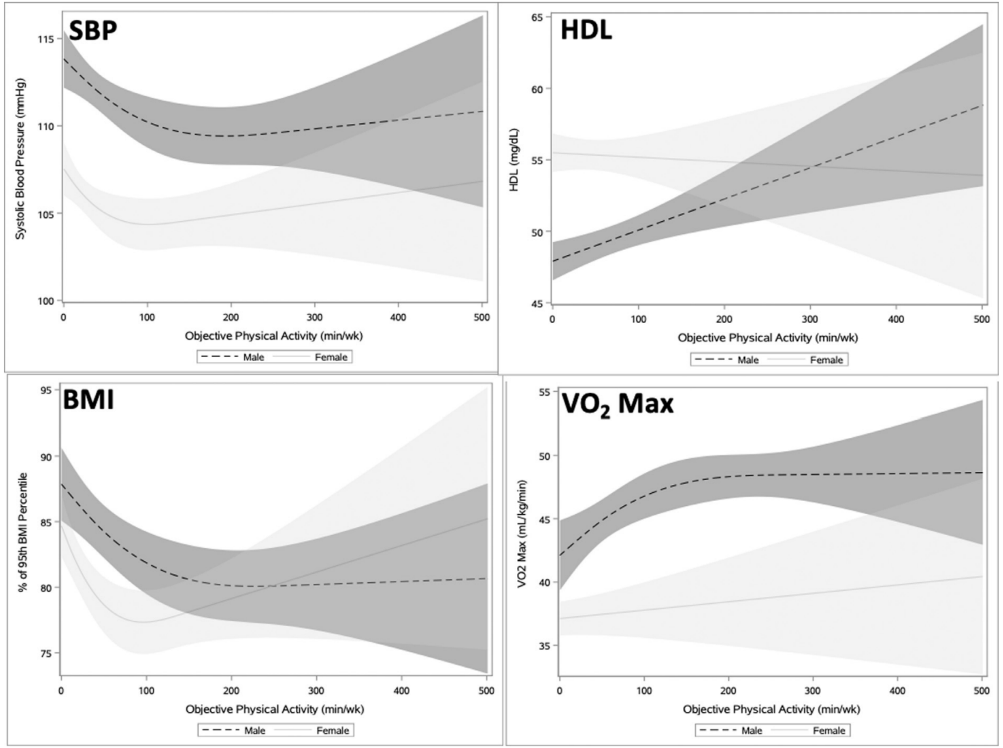


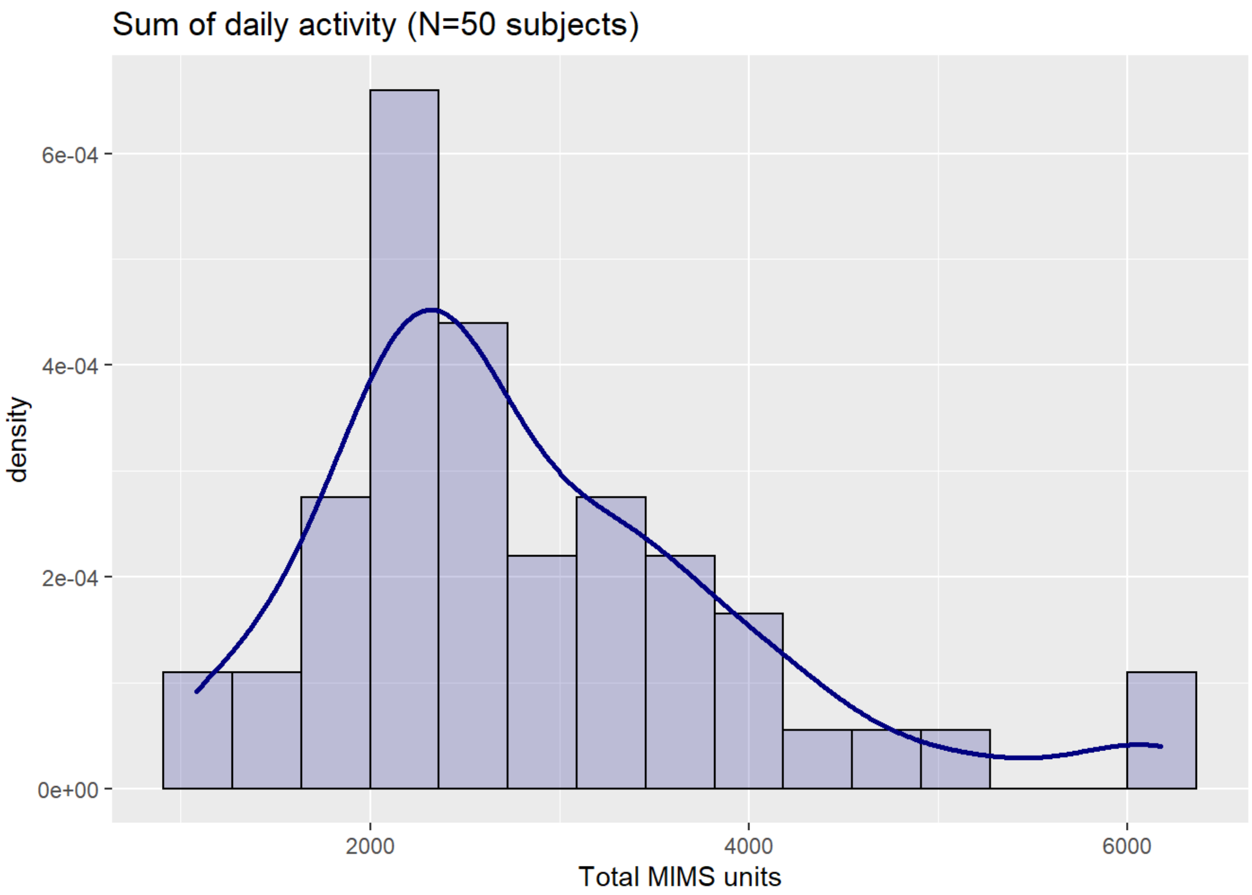
Figure 1. Association between objective PA and cardiometabolic outcomes among adolescents (aged 12–19 years), NHANES 2003–2006.

Note: Unadjusted Models. Shading represents 95% CI.

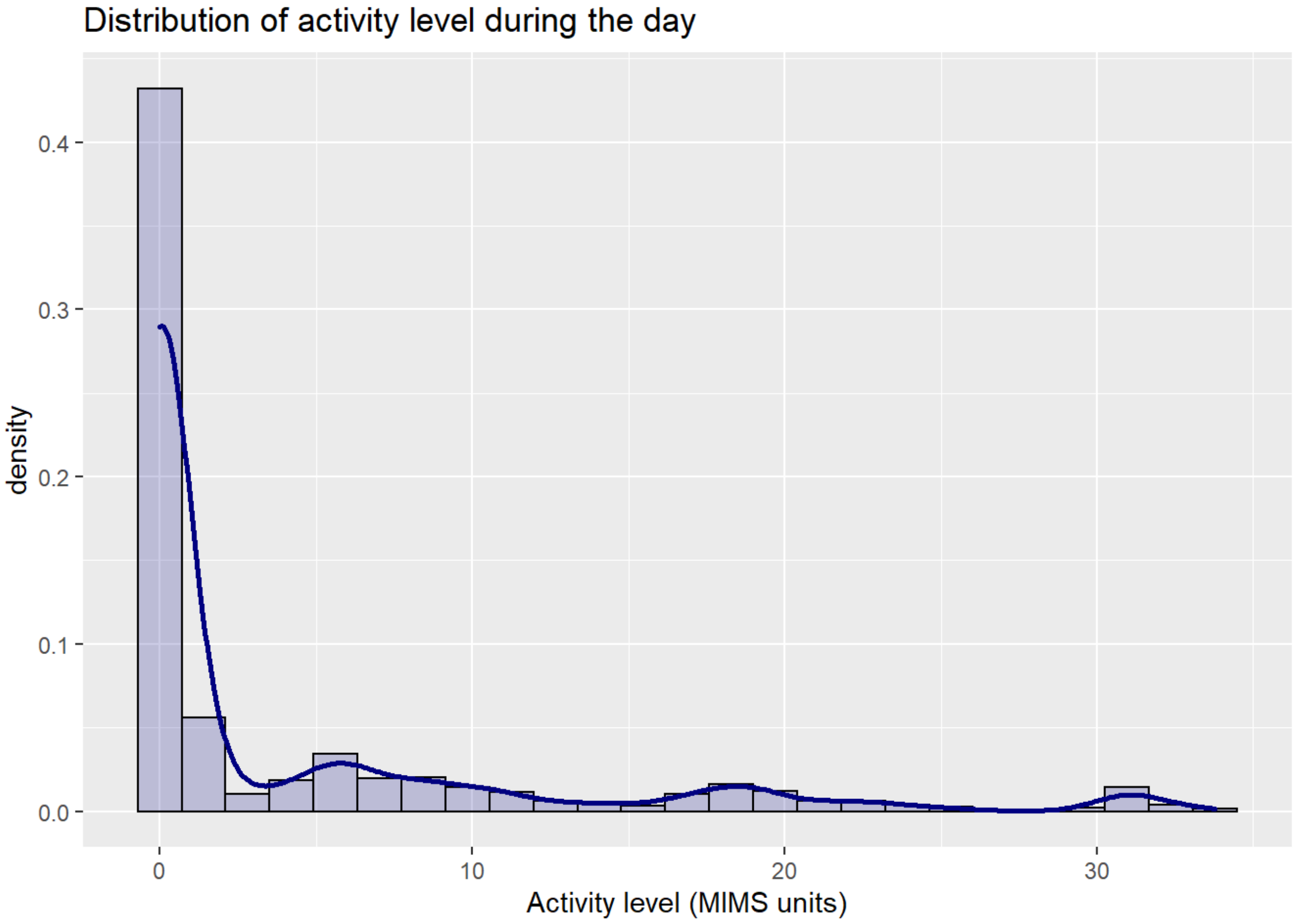
BP, blood pressure; HDL, high-density lipoprotein; min, minute; NHANES, National Health and Nutrition Examination Survey; PA, physical activity; SBP, systolic BP; VO$_2$ Max, maximum rate of oxygen consumption; wk, week.

Small question: why are CIs wide at high activity levels?

Watch out for skewed distributions



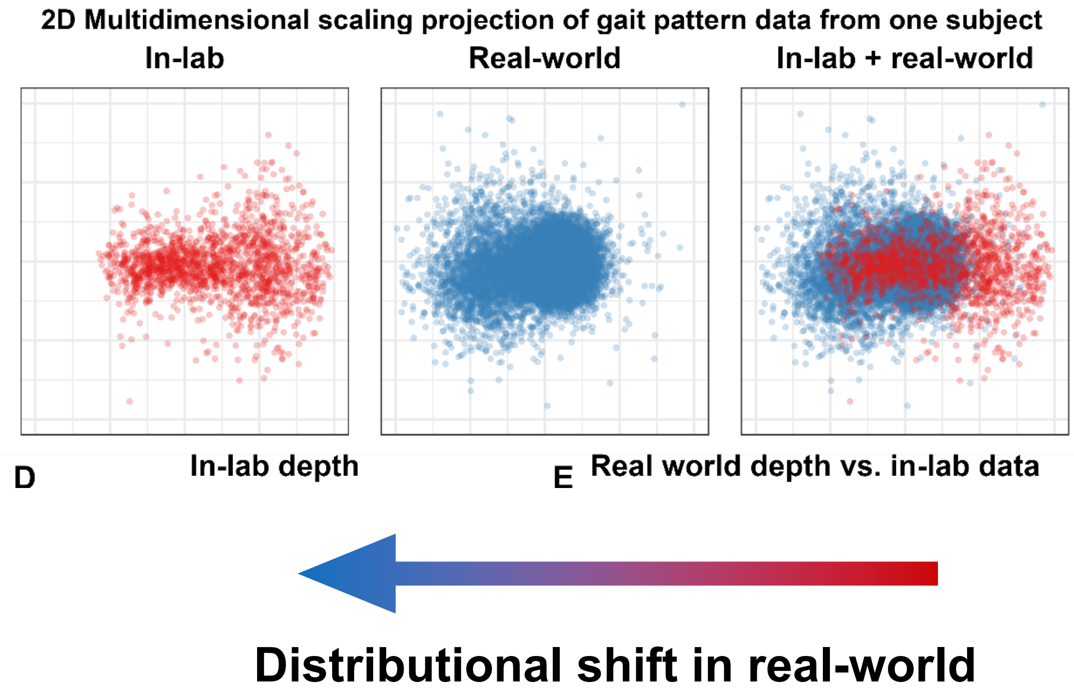
Watch out for skewed distributions



Lots of inactive time, a little bit of active & very active time

Another gotcha – in-lab vs. real-world shifts in behavior/movement

‘Distribution shift’ when comparing in-lab vs. real-world data from the same person



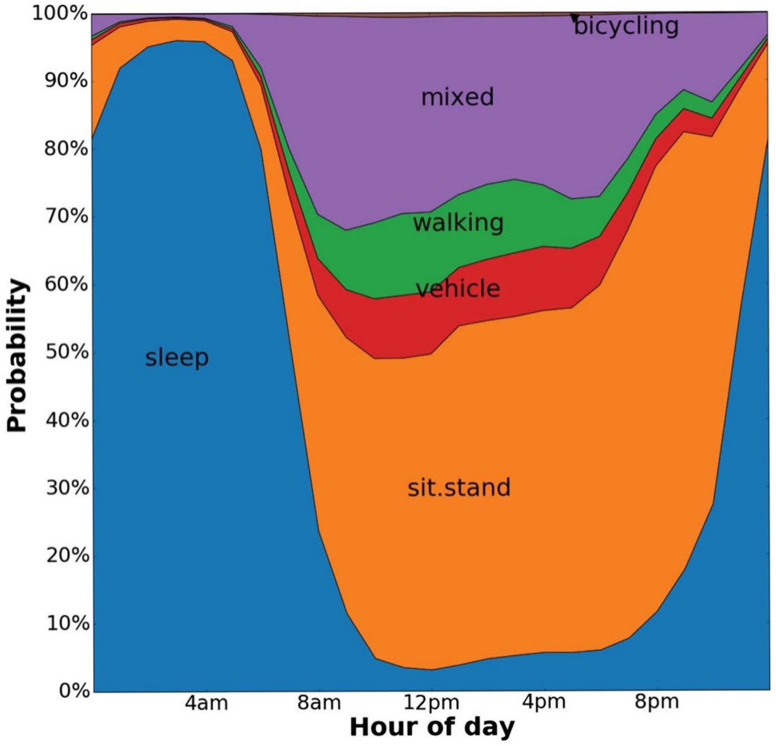
Options for more advanced analysis

Activity recognition & activity-specific analysis

Massive-scale analysis

FDA methods

Advanced analysis: Activity recognition



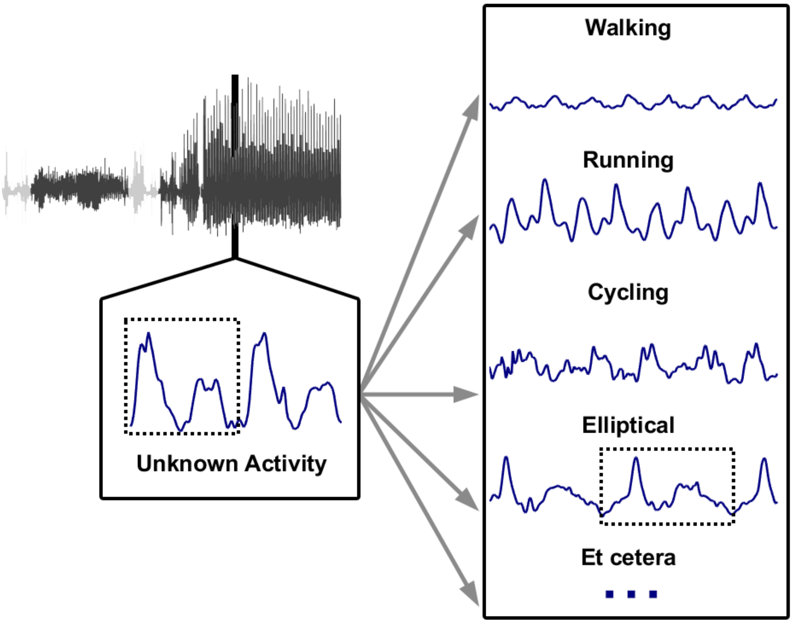
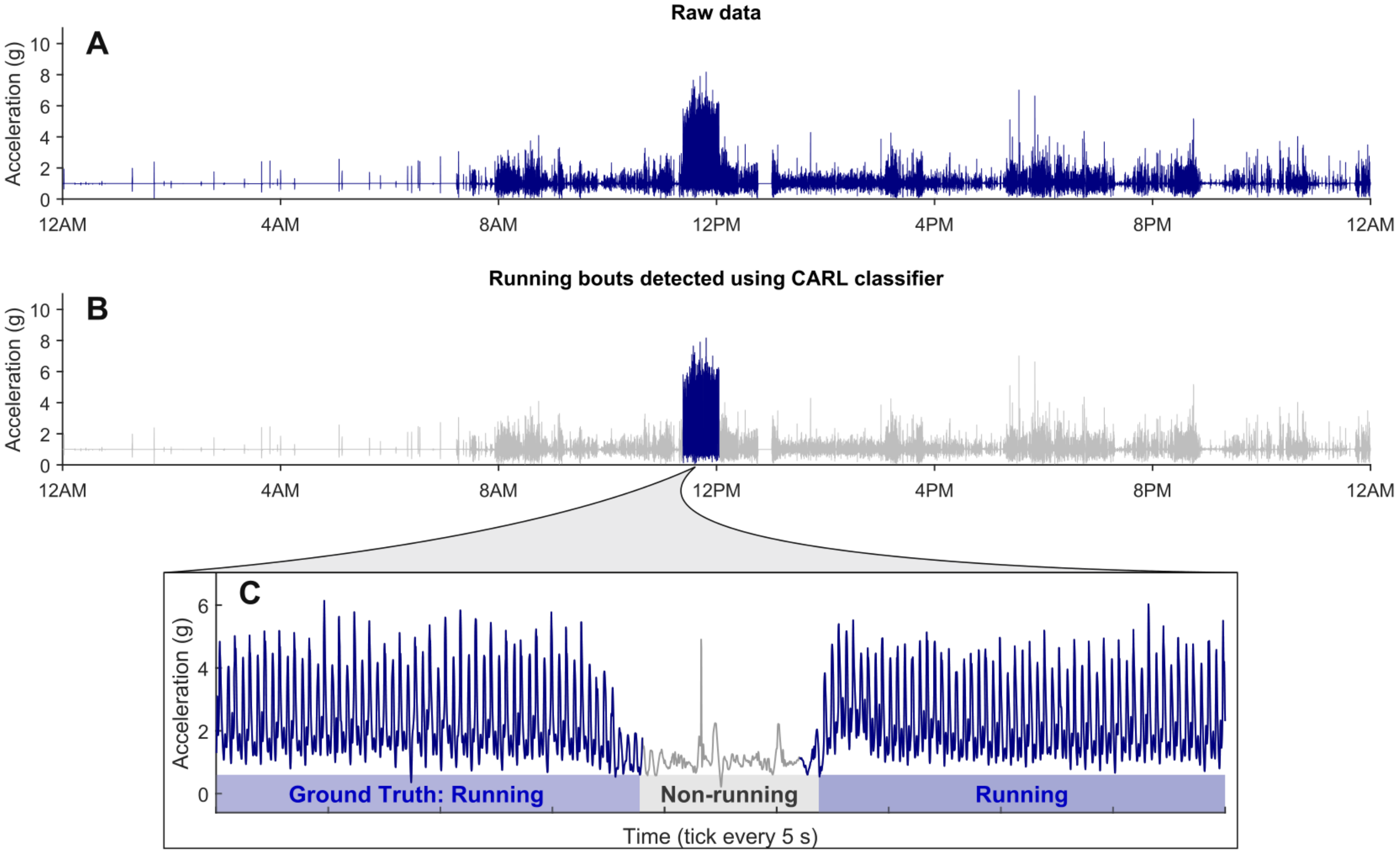


Figure 2. Variation in accelerometer-measured time by activity type: the UK Biobank study 2013–2015 (n = 96,220).

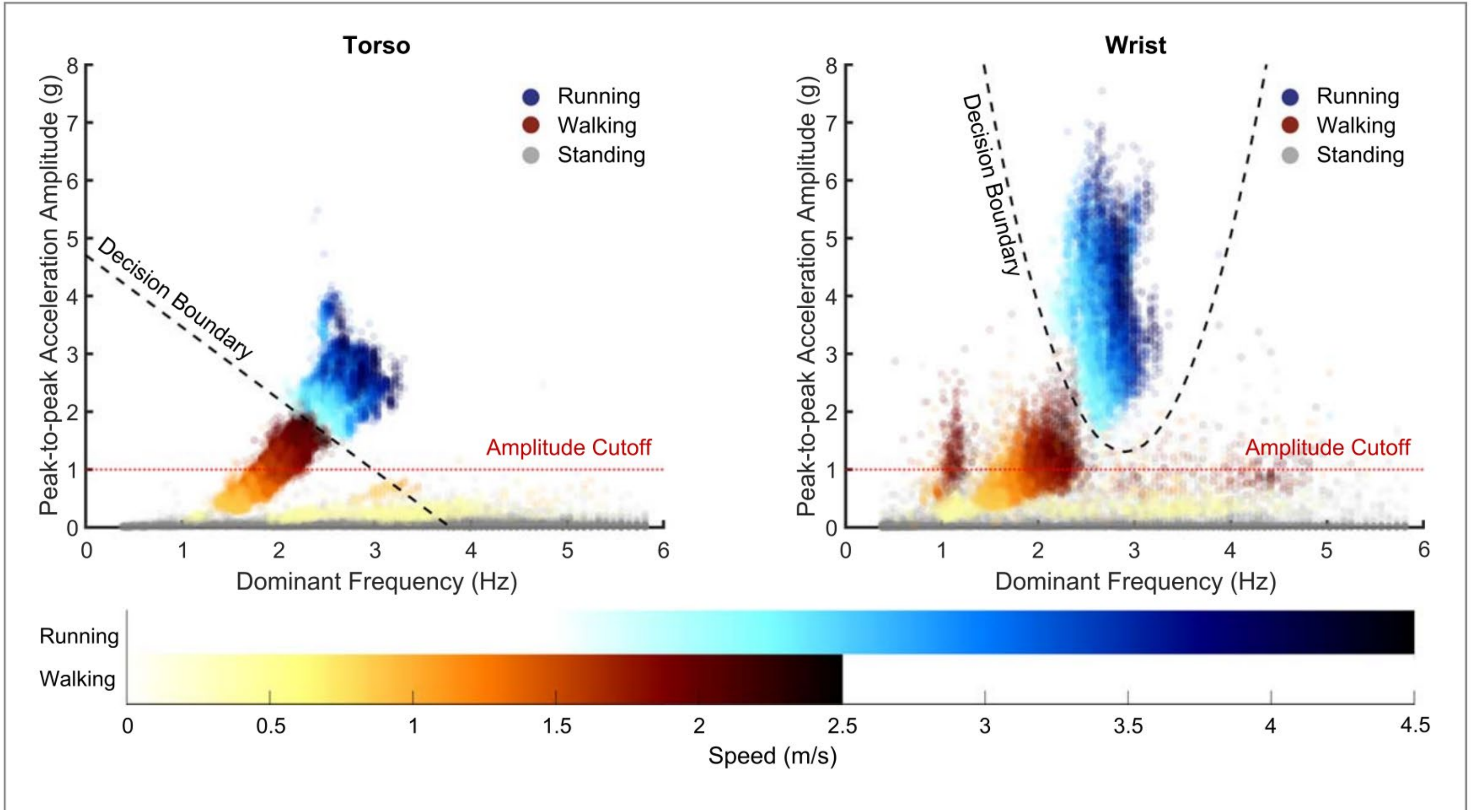
Willetts, M., Hollowell, S., Aslett, L., Holmes, C. and Doherty, A., 2018. *Scientific Reports*, *8*(1),7961.

Advanced analysis: Activity recognition



Davis, Straczkiewicz, Harezlak, and Gruber. *Physiol Meas*. doi: 10.1088/1361-6579/ac41b8

Advanced analysis: Activity recognition



Davis, Straczkiewicz, Harezlak, and Gruber. *Physiol Meas*. doi: 10.1088/1361-6579/ac41b8

Advanced analysis: Massive-scale studies

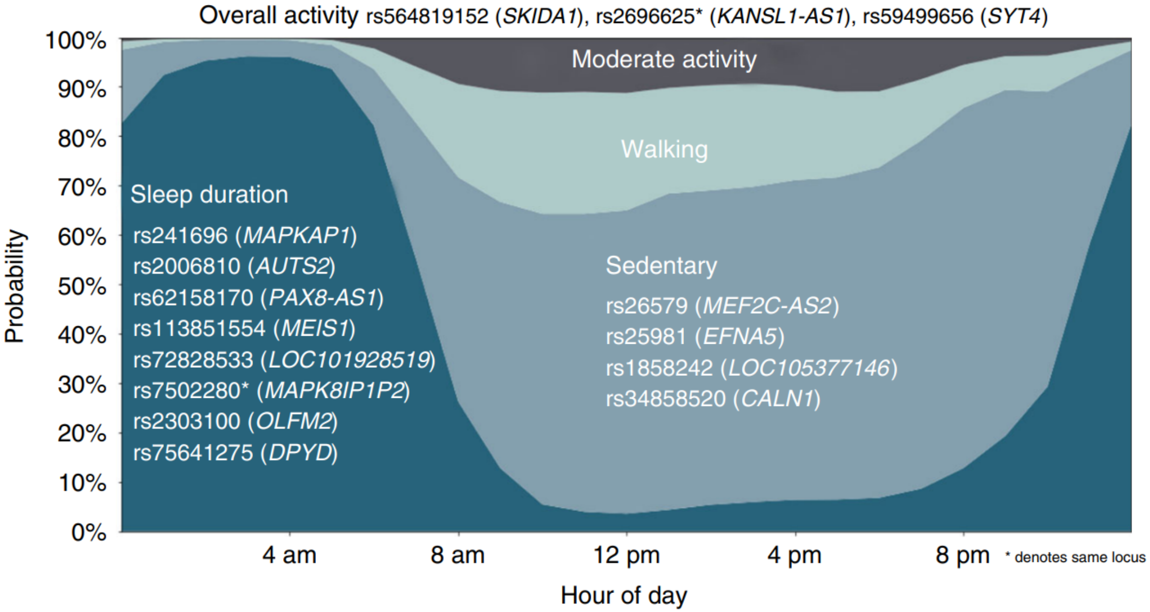
nature COMMUNICATIONS

ARTICLE

https://doi.org/10.1038/s41467-018-07743-4 OPEN

GWAS identifies 14 loci for device-measu
physical activity and sleep duration

Aiden Doherty[1,2,3,4], Karl Smith-Byrne[5], Teresa Ferreira[1,6], Michael V. Holmes[4,7,8], Chris
Sara L. Pulit[1,6,10,11] & Cecilia M. Lindgren[1,4,6,11]



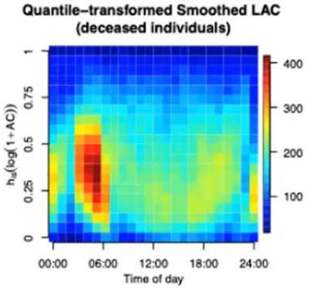
Doherty, A.,et al. *Nature Communications* 2018, *9*(1),5257.

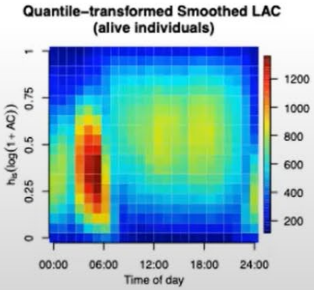
Advanced analysis: Functional data methods

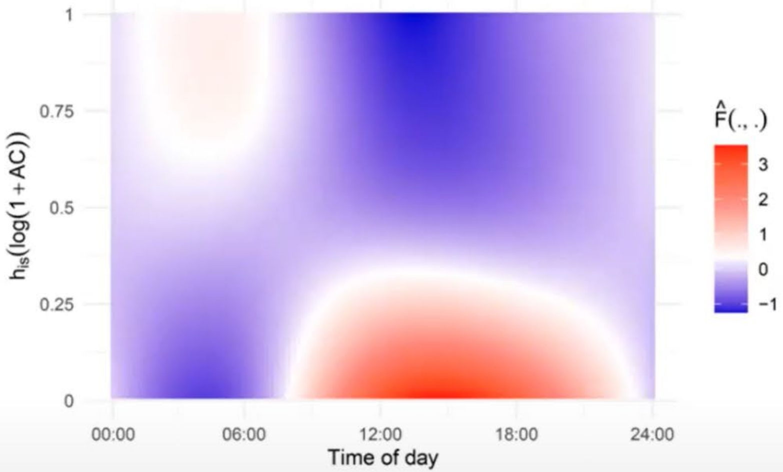
NHANES Population

- 50 to 85 years old
- Have >= 3 valid days
- No missing covariates

2816 individuals with 659 events within 10 years







Take home message:
Higher daytime physical activity and lower nighttime physical activity are associated with lower risk of all-cause mortality

Cui, Erjia, Ciprian M. Crainiceanu, and Andrew Leroux. *Journal of Computational and Graphical Statistics* 2021, 30(3):780-793.

A worked example!

Database | Open Access

Long Term Movement Monitoring Database

Jeffrey Hausdorff

Published: June 20, 2016. Version: 1.0.0

New Database Added: LTMM *(June 20, 2016, midnight)*

The Long Term Movement Monitoring database contains 3-day 3D accelerometer recordings of 71 elder community residents, used to study gait, stability, and fall risk.

A worked example!

johnjdavisiv.github.io/2023-short-course

Code at: github.com/johnjdavisiv/2023-short-course

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code + data:

github.com/johnjdavisiv/2023-short-course