

My First Exposure to Accelerometer Data was for 100000 People from UK Biobank

John Muschelli, @StrictlyStat, Johns Hopkins University

presentation: http://johnmuschelli.com/CMStat_2018

source: http://github.com/muschellij2/CMStat_2018

Disclaimer (Acknowledgements?)

Work done with
[Andrew Leroux](#)

PhD Student at Johns
Hopkins



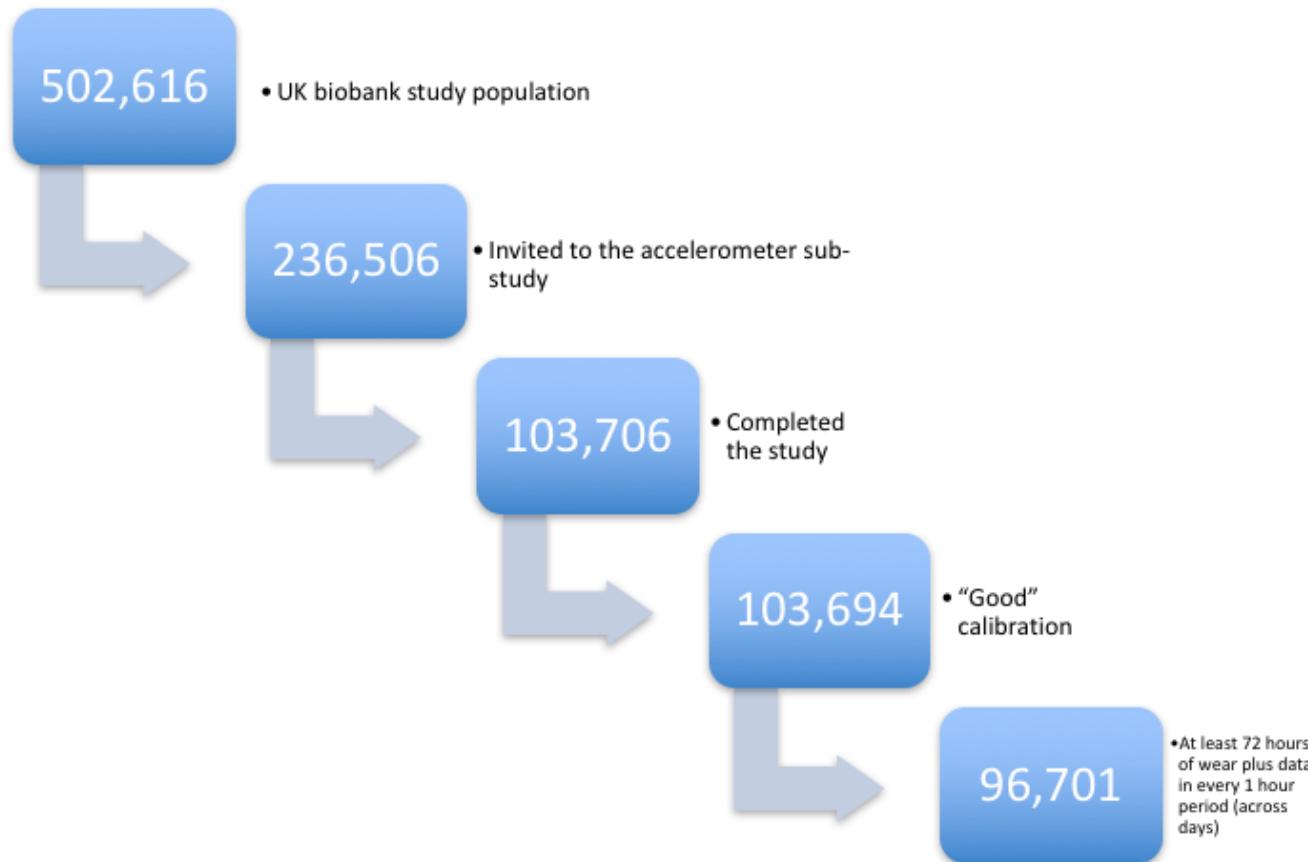
UK Biobank Data

- Overall 500,000 participants (UK), \approx 100,000 included in the sub-study

In this presentation:

- Explore the data
- Assess “bias” in different devices (see if “autocalibration” is working)
- Also discuss inclusion criteria “bias”
- Get similar findings (Doherty et al. 2017) analysis

Where do 100K come from?

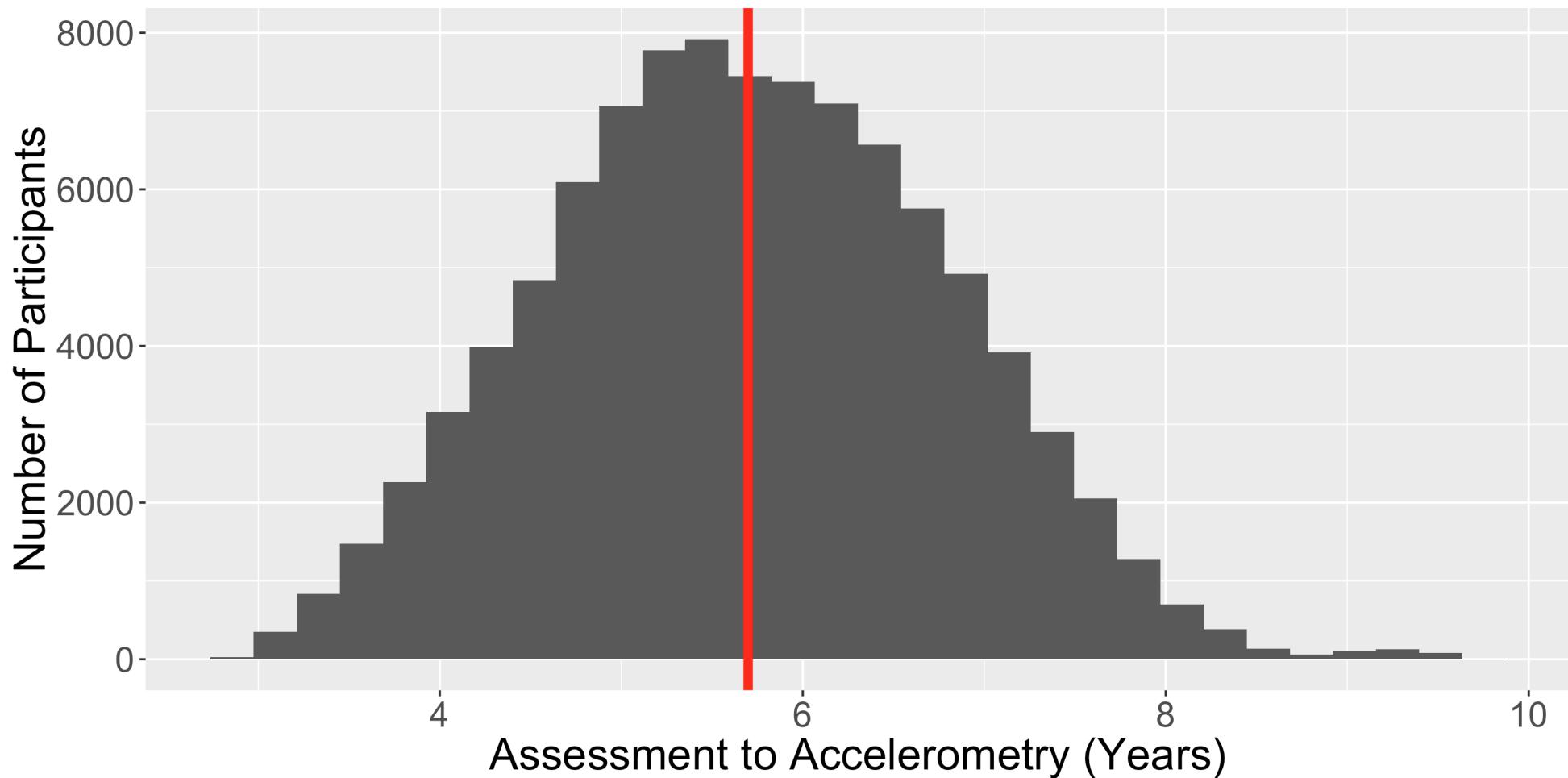


Demographics: Lots of Non-Response

	Completed: good data	Completed: bad data	No response	Not asked
n	96701	7005	132800	266110
Age at Initial Visit (mean (sd))	56.6 (7.8)	55.2 (7.9)	56.4 (8.0)	57.5 (8.1)
Male (% Male)	42255 (43.7)	3156 (45.1)	62601 (47.1)	121151 (45.5)
Ethnicity (% Non-White)	2983 (3.1)	335 (4.8)	7617 (5.8)	16102 (6.1)

Many people DIED before being able to be asked

Assessment to Accelerometry can be a WHILE



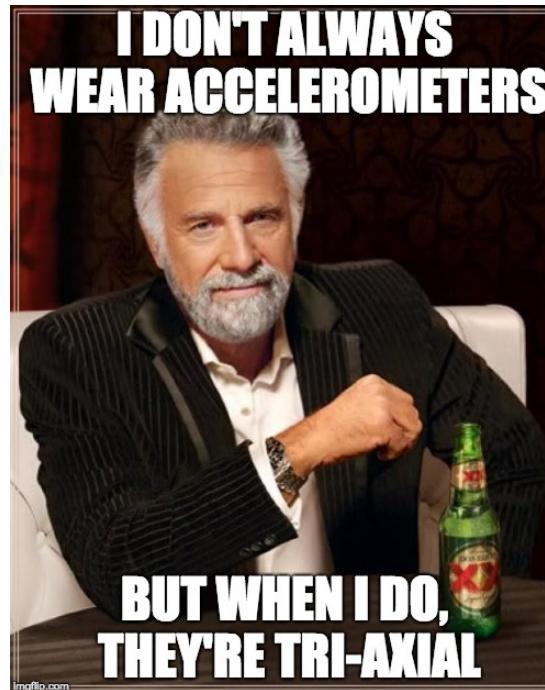
Responders are Healthier (Self-Reported)

Overall health (%)	Completed: good data	Completed: bad data	No response	Not asked
Excellent	20987 (21.8)	1464 (21.0)	21583 (16.3)	37849 (14.4)
Good	57849 (60.0)	4057 (58.1)	78968 (59.7)	148196 (56.2)
Fair	15149 (15.7)	1261 (18.0)	26669 (20.2)	62313 (23.6)
Poor	2482 (2.6)	205 (2.9)	4969 (3.8)	15124 (5.7)

Lesson #1: The devil is
in the inclusion criteria
(or can be)

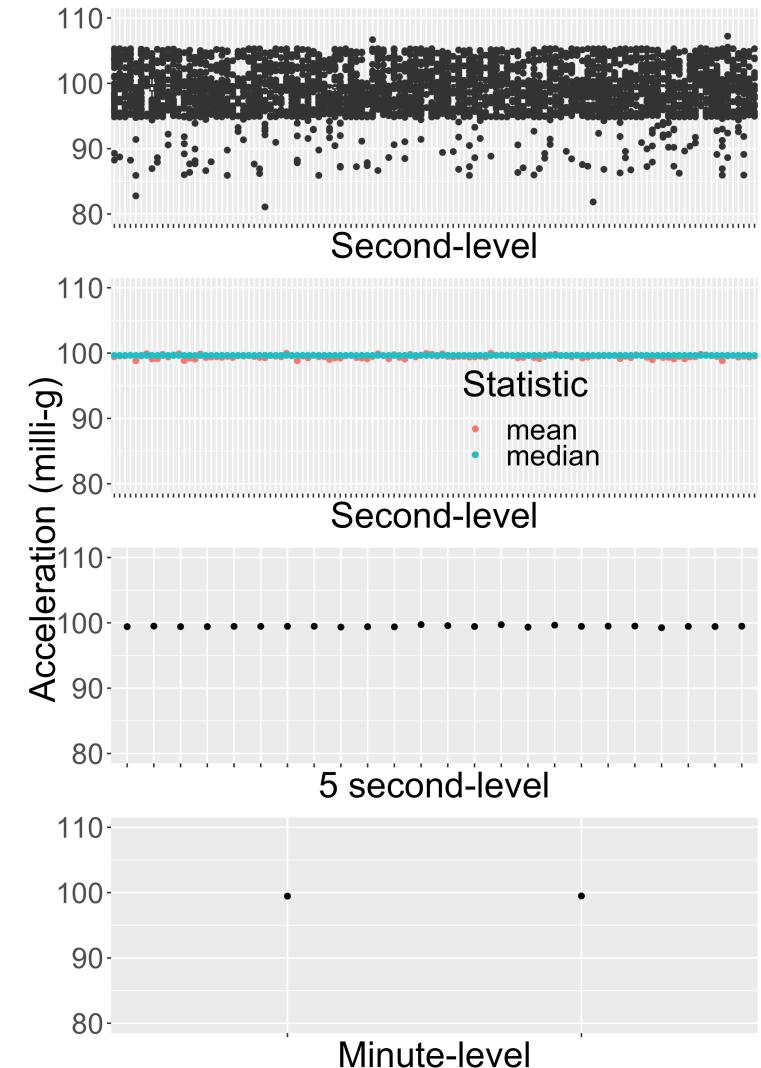
Data Gathered

- Tri-axial Axtivity 100Hz over 7 days
- Started at 10AM and ended at 10PM (spoiler: will be important)
- Data measured in milli-g ($1g = 9.80665 \text{ ms}^2$)
 - not counts or steps as other devices



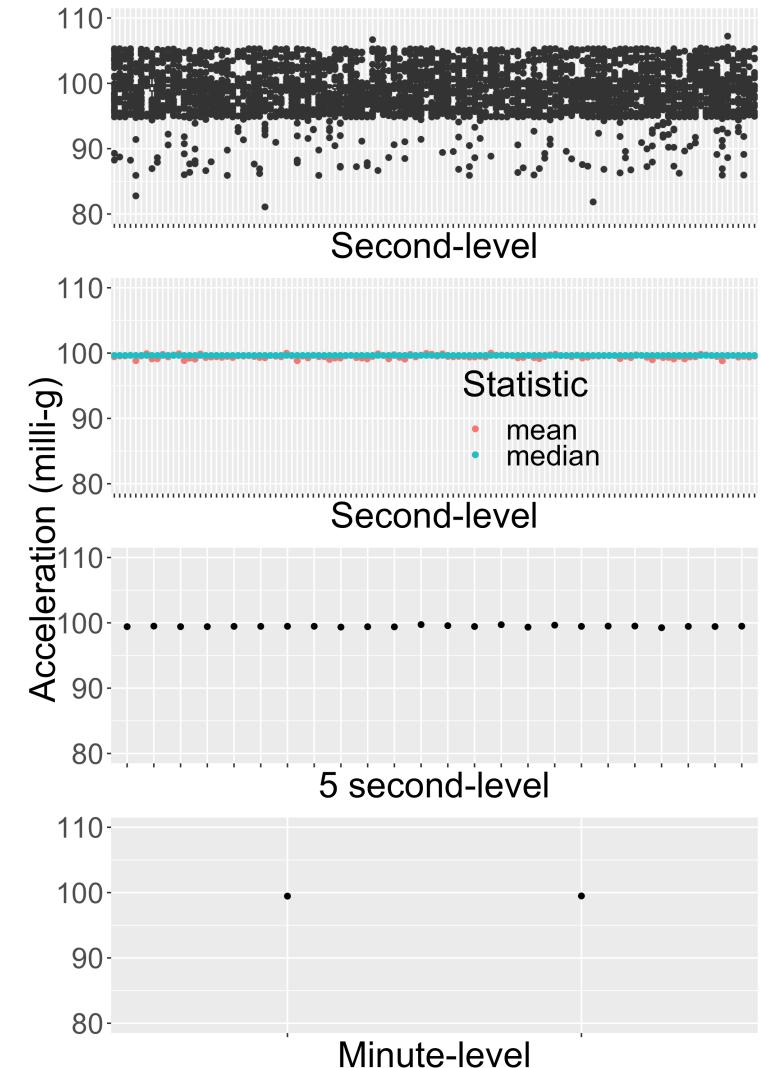
Accelerometry Data Available

- Data at varying levels
 - Axtivity CWA format (Highest resolution, 100Hz) (200Mb per user)
 - very large for 100K subjects (20Tb)
- 5 second level data
 - UKBB imputation/processing done
 - averaged into 1440 minute-level data
- Overall statistics (mean/median): overall, daily, hourly, day of week
 - removed “non-wear” periods



Accelerometry Data Available

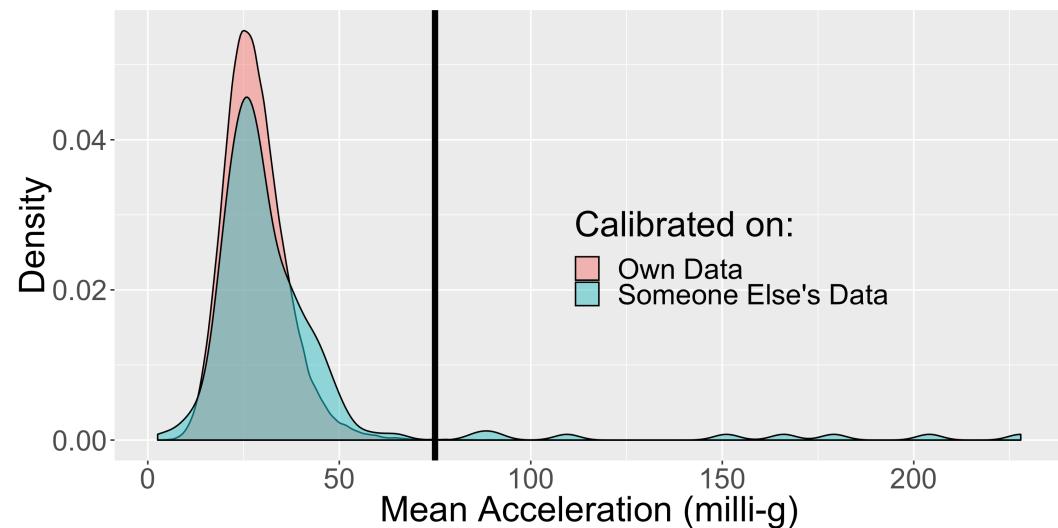
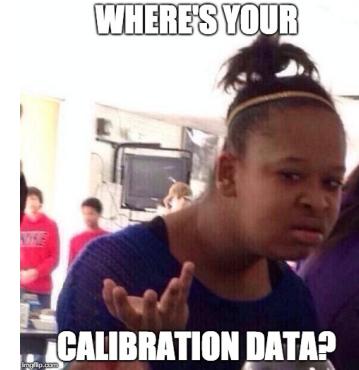
- Data at varying levels
 - Axtivity CWA format (Highest resolution, 100Hz) (200Mb per user)
 - very large for 100K subjects (20Tb)
- 5 second level data
 - UKBB imputation/processing done
 - averaged into 1440 minute-level data
- Overall statistics (mean/median): overall, daily, hourly, day of week
 - removed “non-wear” periods



UKBB Processing: Auto-calibration

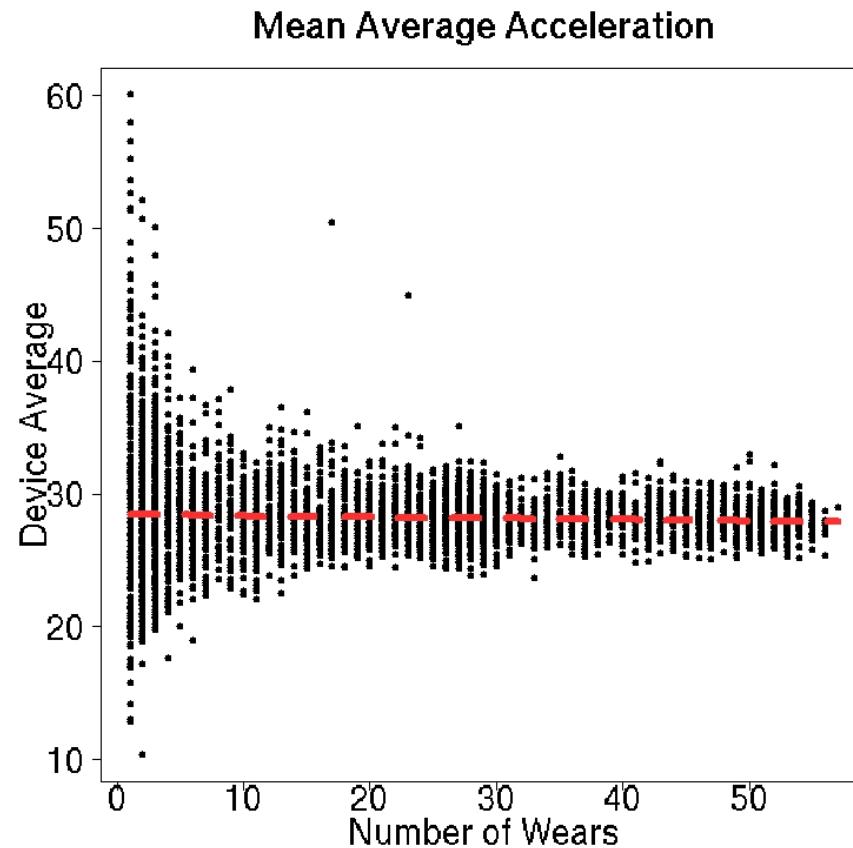
(Hees et al. 2014)

1. Use 10s window all axes
SD < 13.0 mg.
2. Fit a unit gravity sphere
using OLS.
3. If 3 axes had values
outside a ± 300 mg range
- use calibration
coefficient
4. If not, use **next person's**
calibration coefficient
from the same device



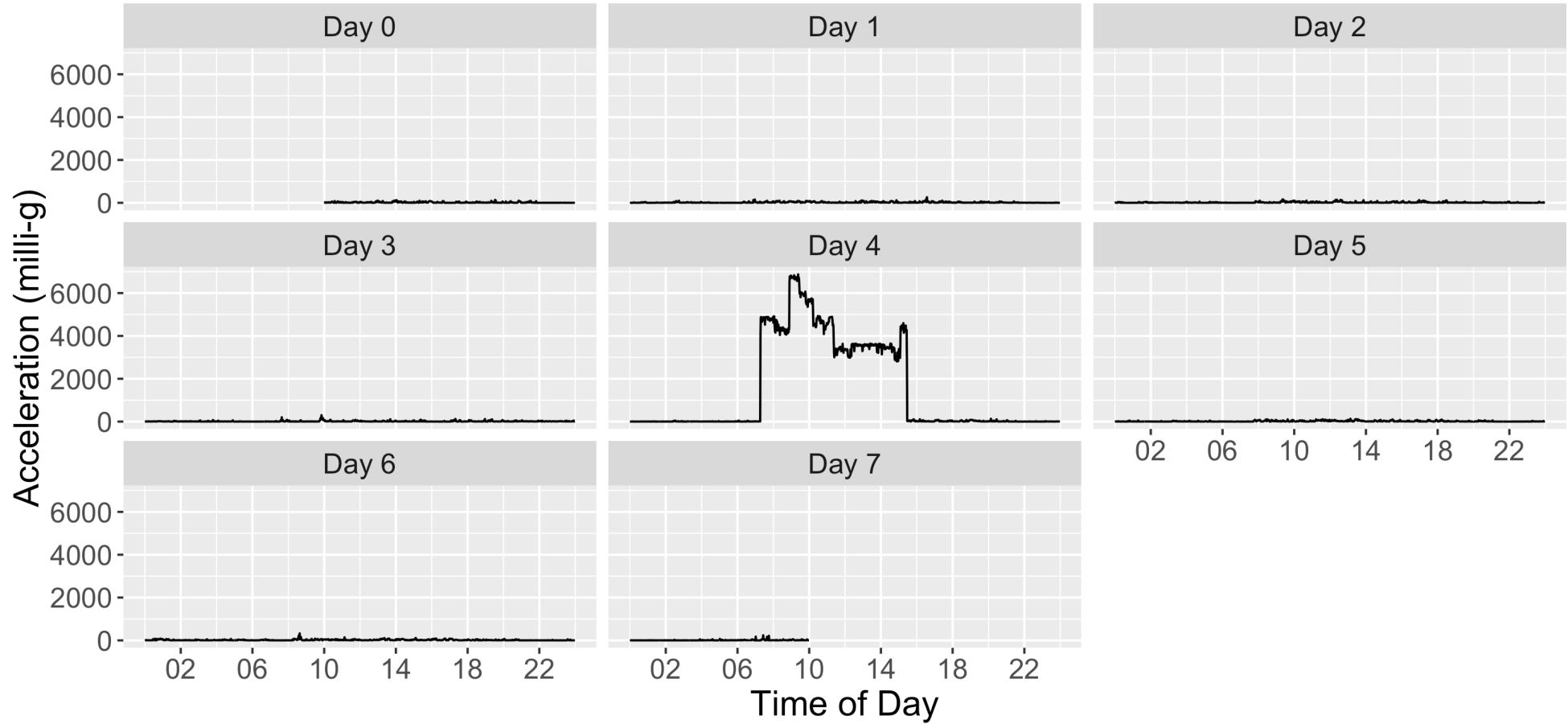
Auto-calibration seems to “work”

- Within-person average, within-device average (one point per device)
- Plotted against # of wears per device (σ should decrease with \sqrt{n})



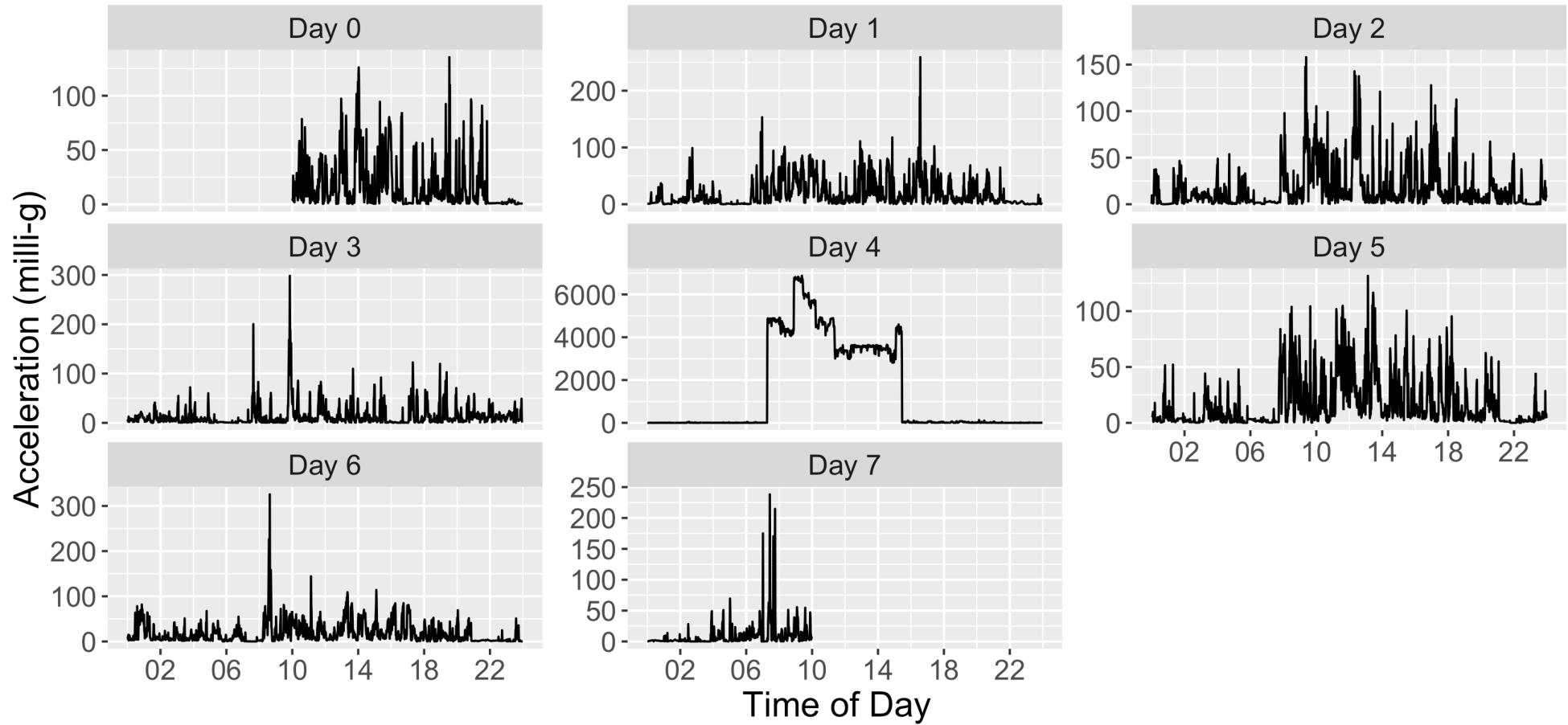
Doesn't work for all cases

Participant 2586235 Calibrated on Someone Else's Data



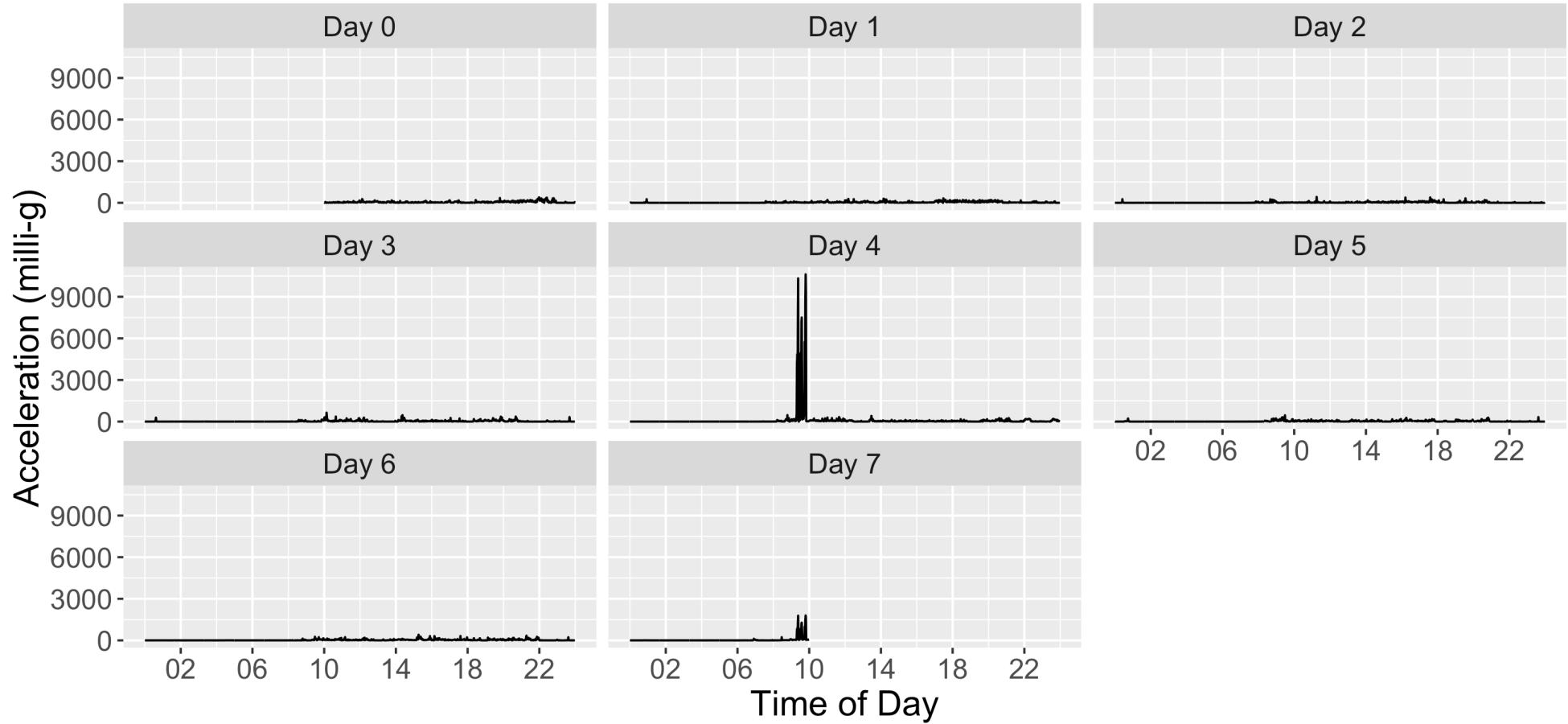
Doesn't work for all cases

Participant 2586235 Calibrated on Someone Else's Data



Doesn't work for all cases

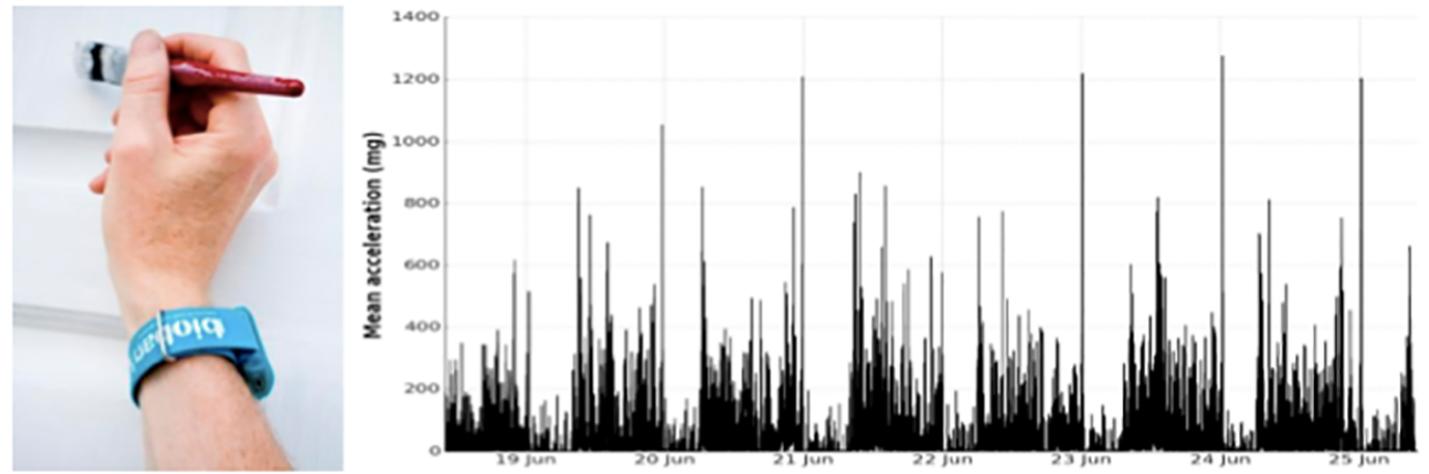
Participant 3462861 Calibrated on Own Data



Lesson #2: If magnitude is important, need calibration (“batch effect” correction), but may not be perfect

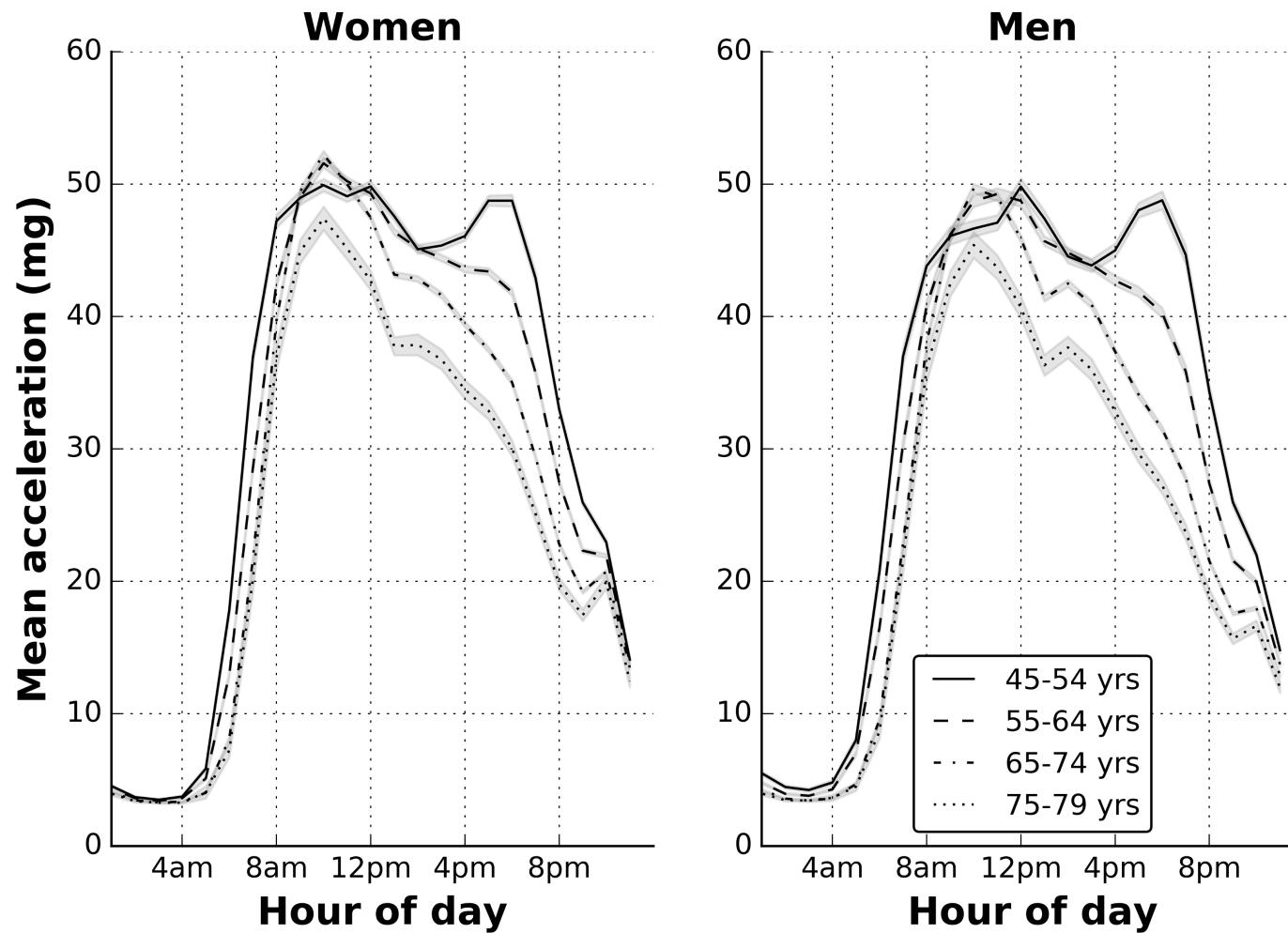
UKBB Processing: Doherty et al. (2017)

- Recording errors and 'interrupts' flagged (plug in accelerometer to computer)
- \pm8g flagged
- Resampled to 100 Hz (interrupts > 5 seconds set to missing)
- Euclidean norm, fourth order Butterworth low pass filter ($f = 20\text{Hz}$).
- Subtract 1g, negative values set to 0



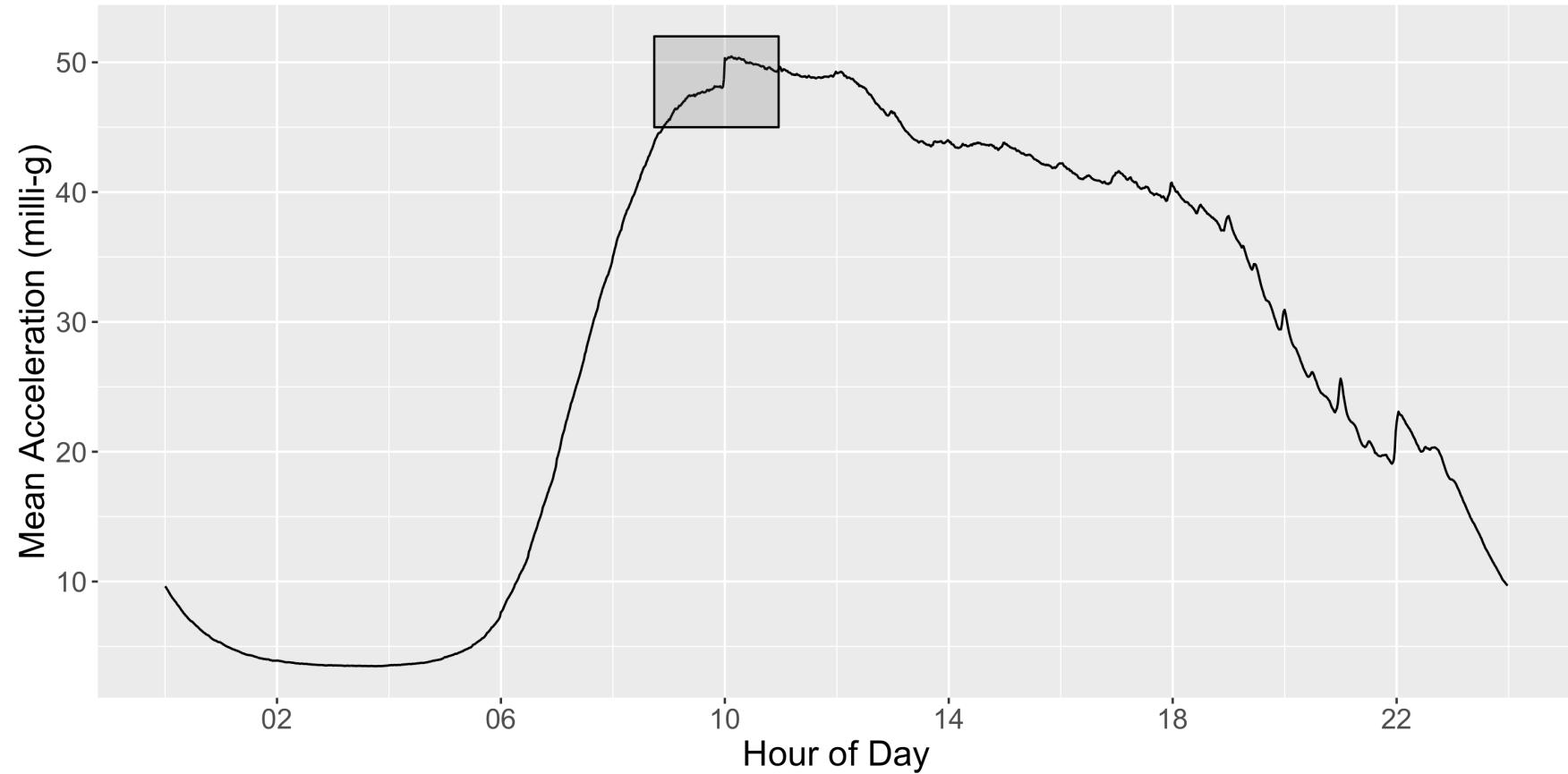
They have software (Python) on
GitHub

One result from (Doherty et al. 2017) analysis



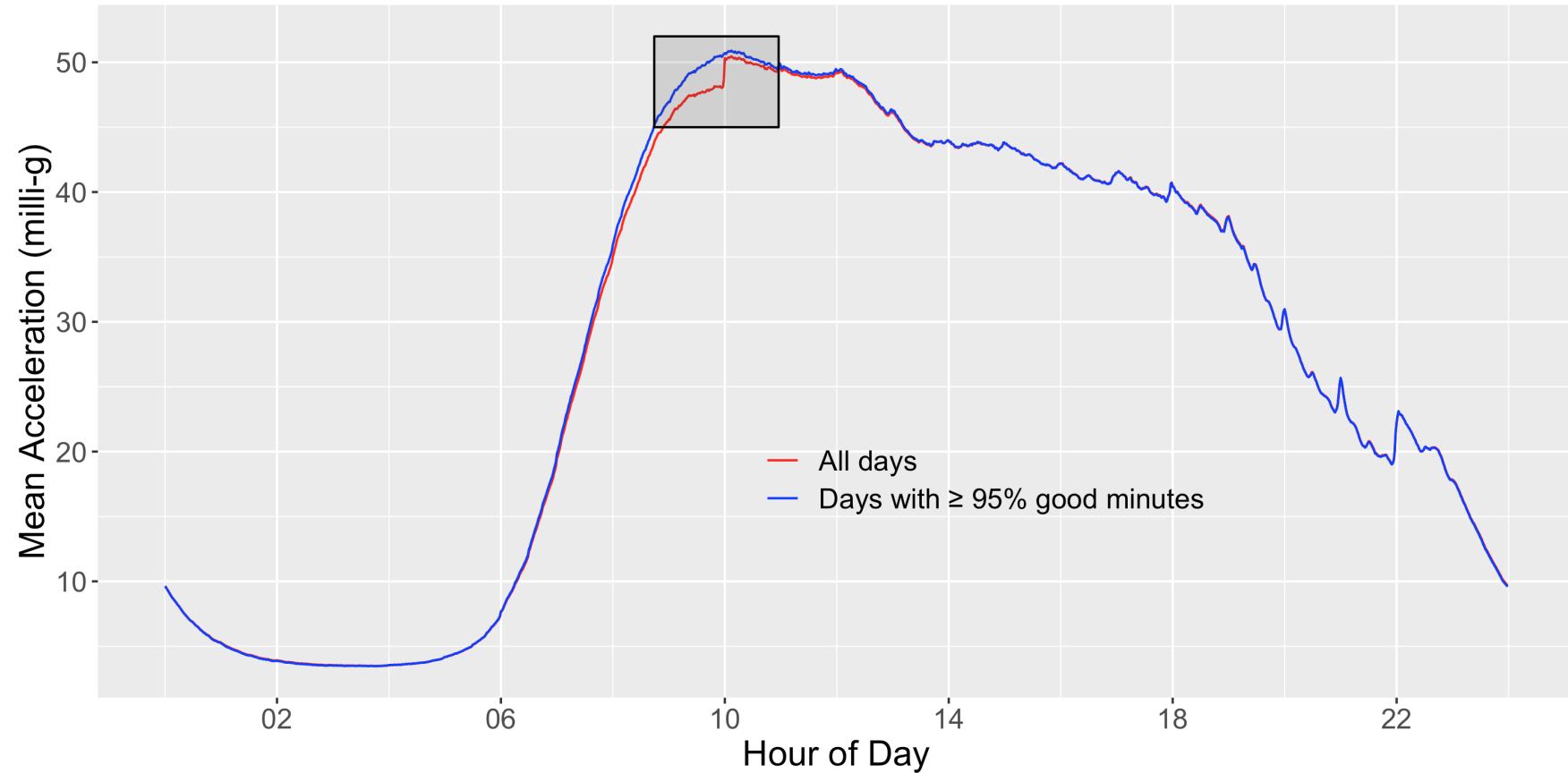
How do people typically move?

- Average over minute - regardless of multiple visits per person



How do people typically move?

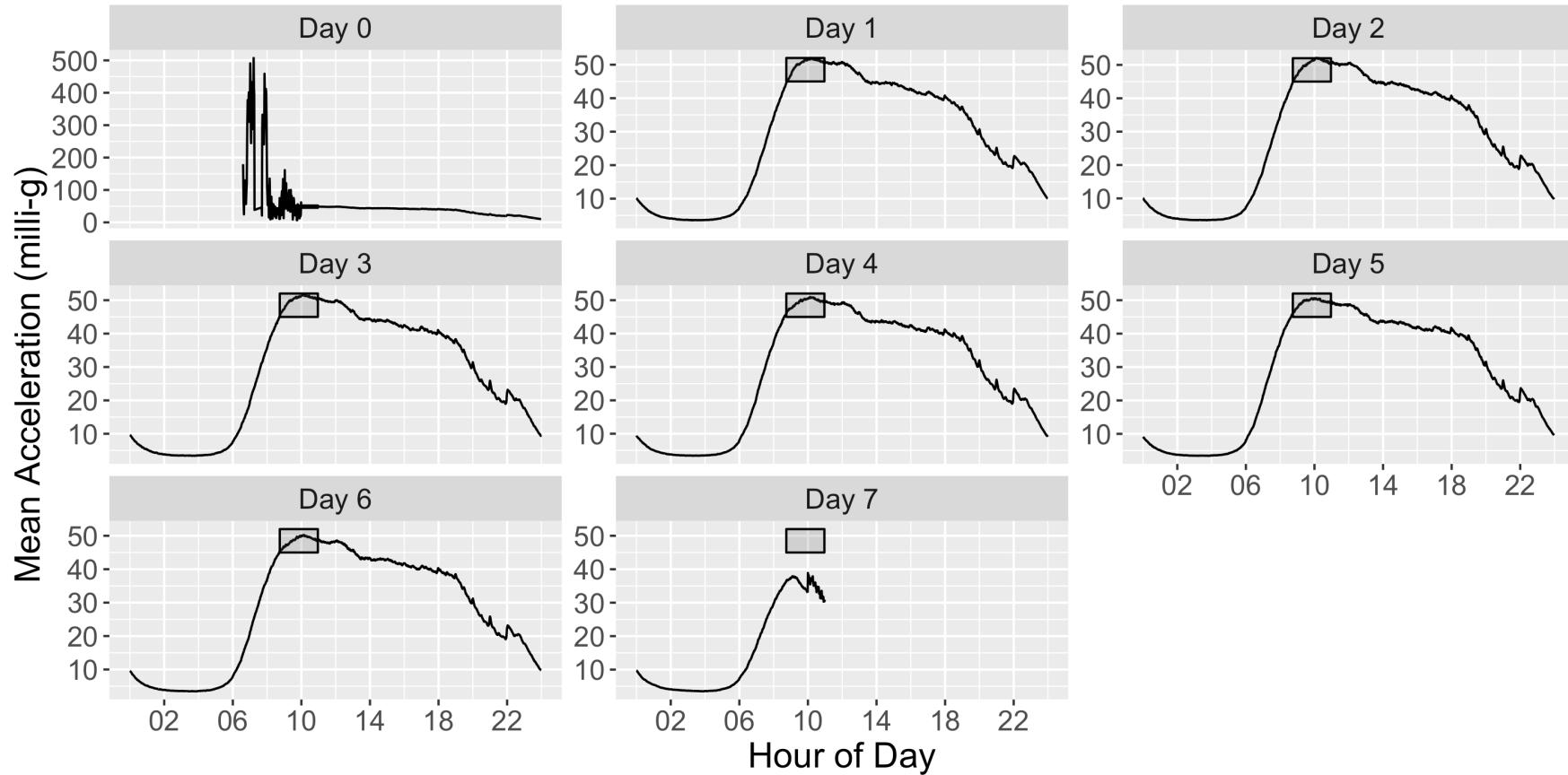
- Average over minute with days > 95% non-missing data



(Maybe) Lesson #3: Keep only “full” days

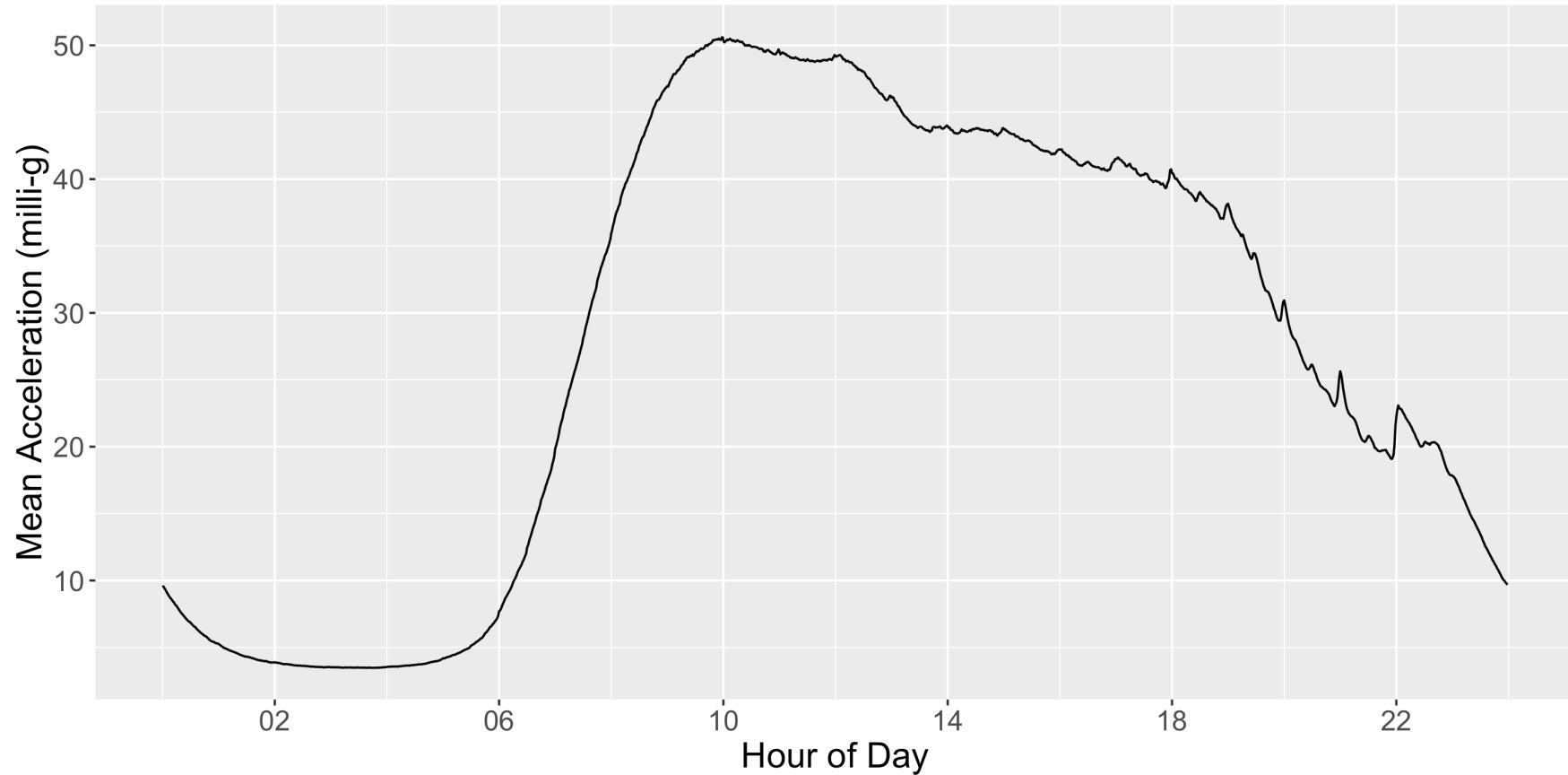
Not so fast, let's look day by day

- Average over minute for days separately, one row per subject



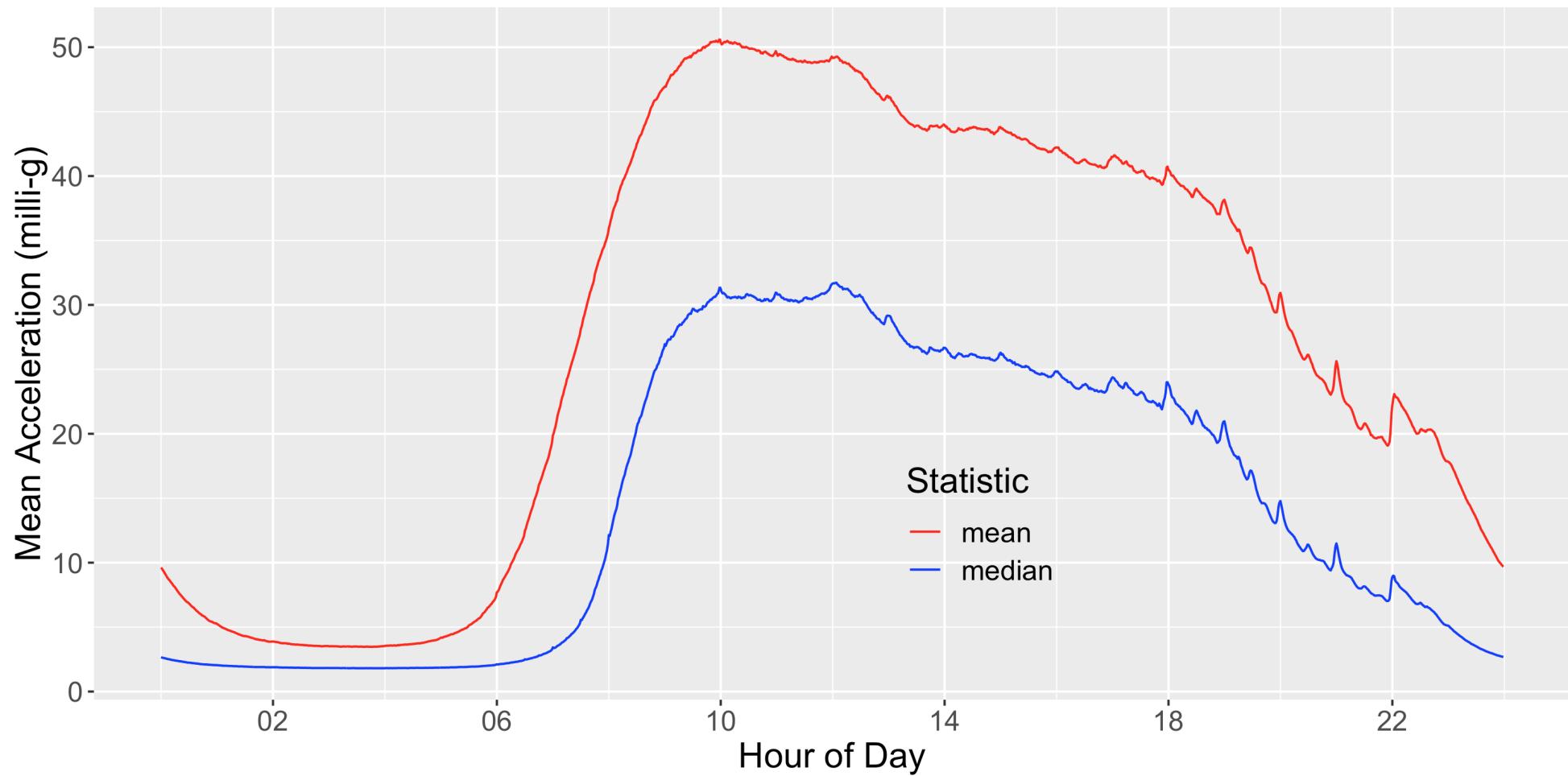
Removing Day 7

- Average over minute for days 0 - 6



Lesson #3: Explore days before averaging across individual?

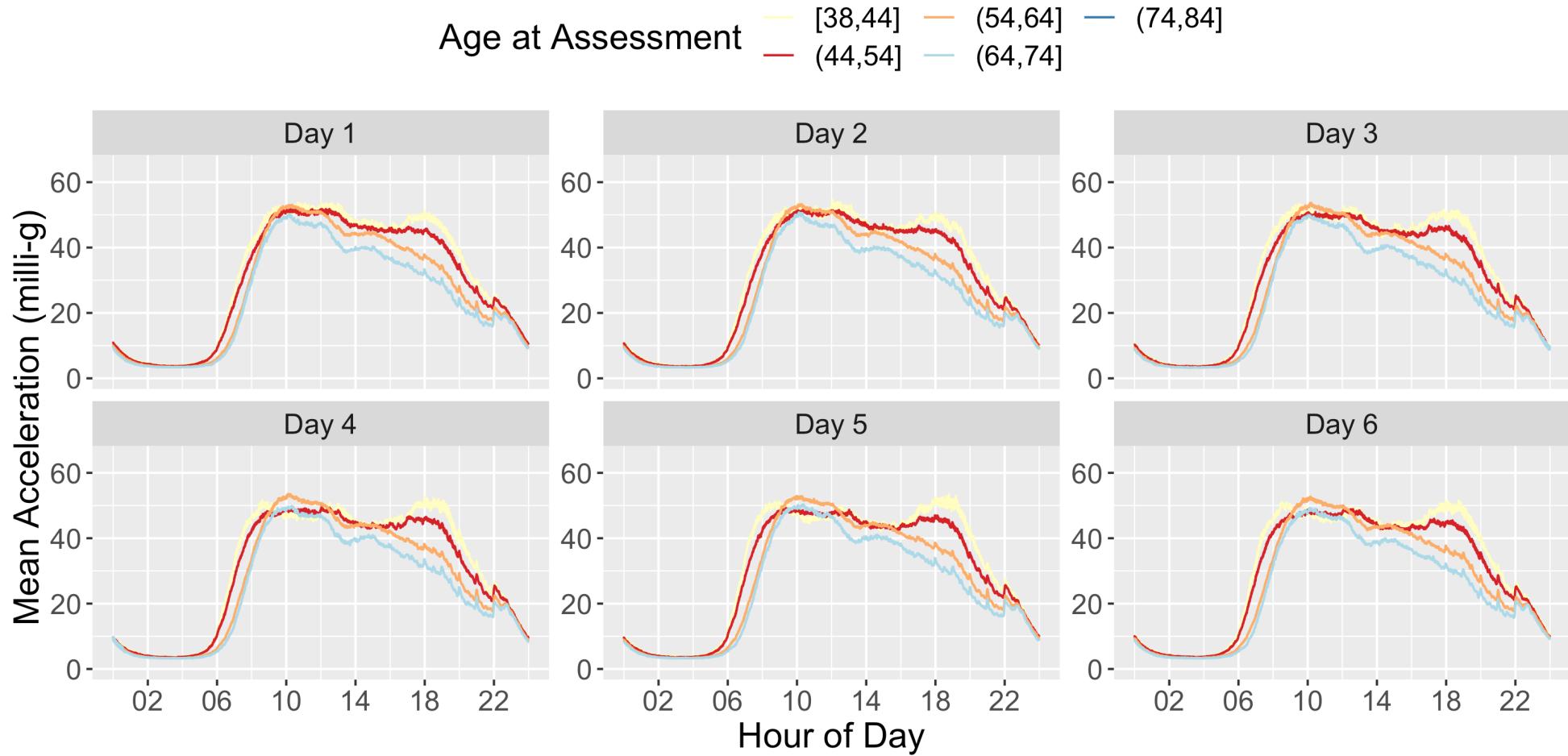
Well use the MEDIAN then!



Maybe it's a “few bad apples”

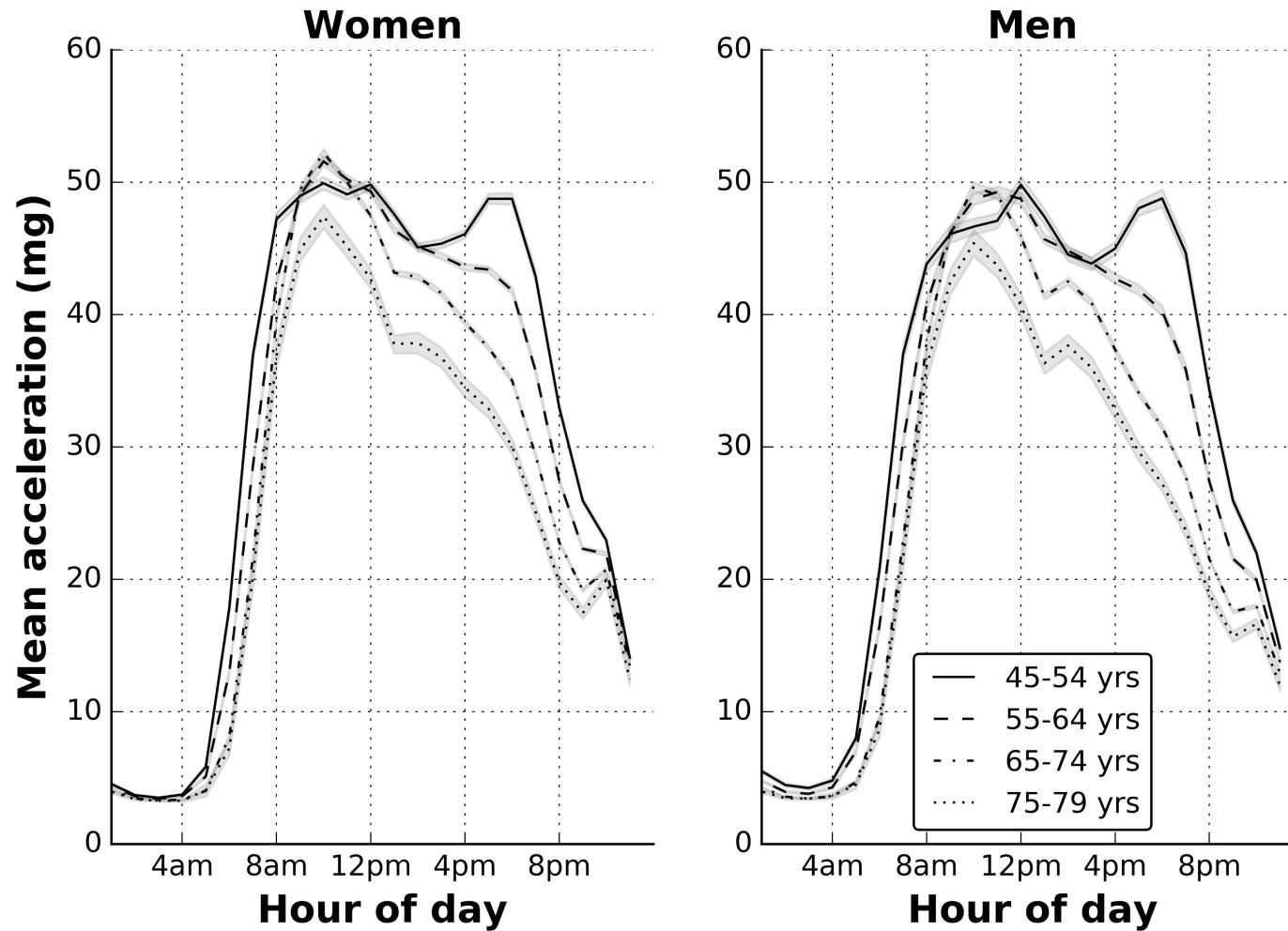
Heatmap of 2000 randomly sampled people

Age at Assessment Plot

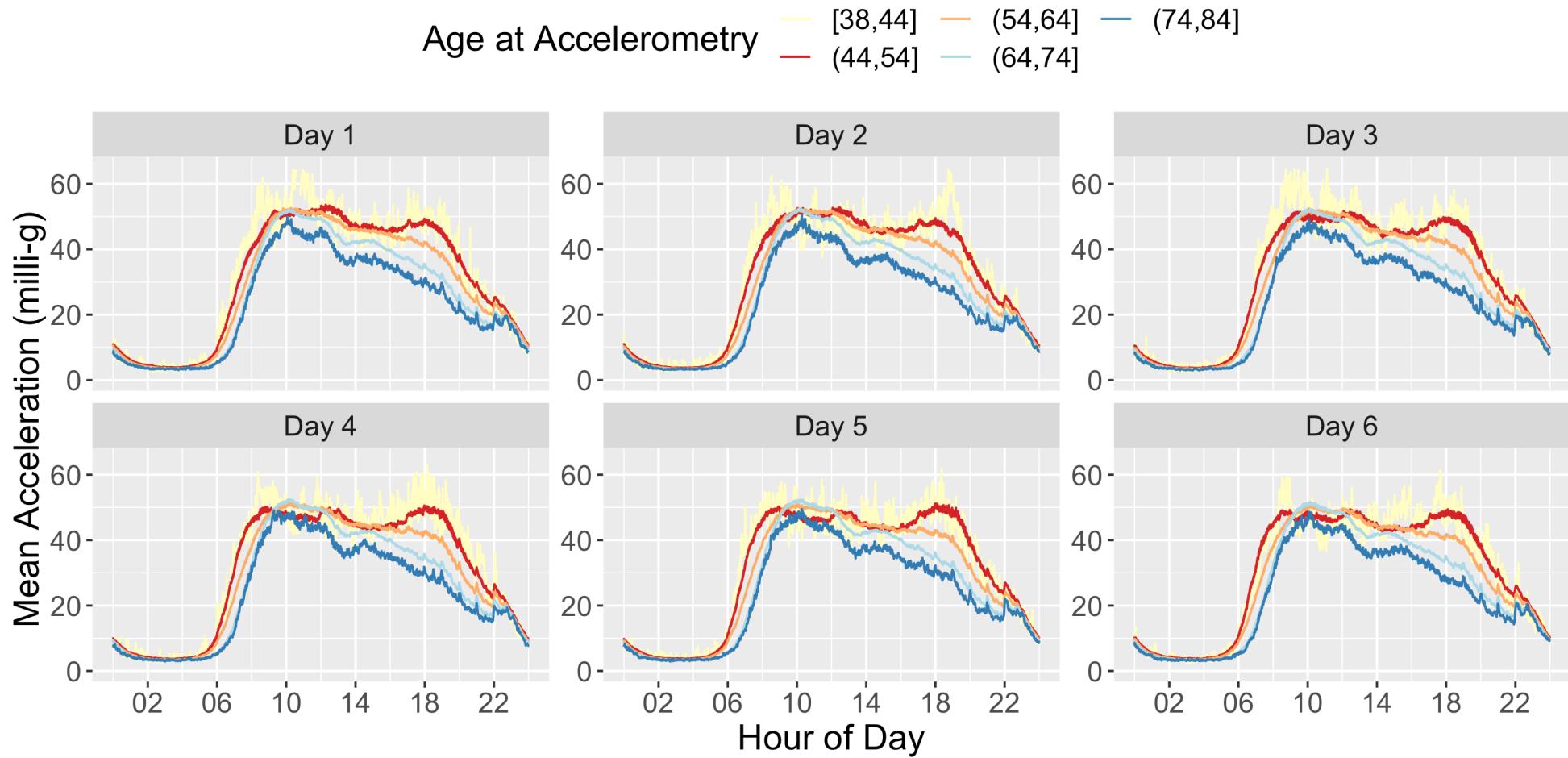


One result from (Doherty et al. 2017) analysis

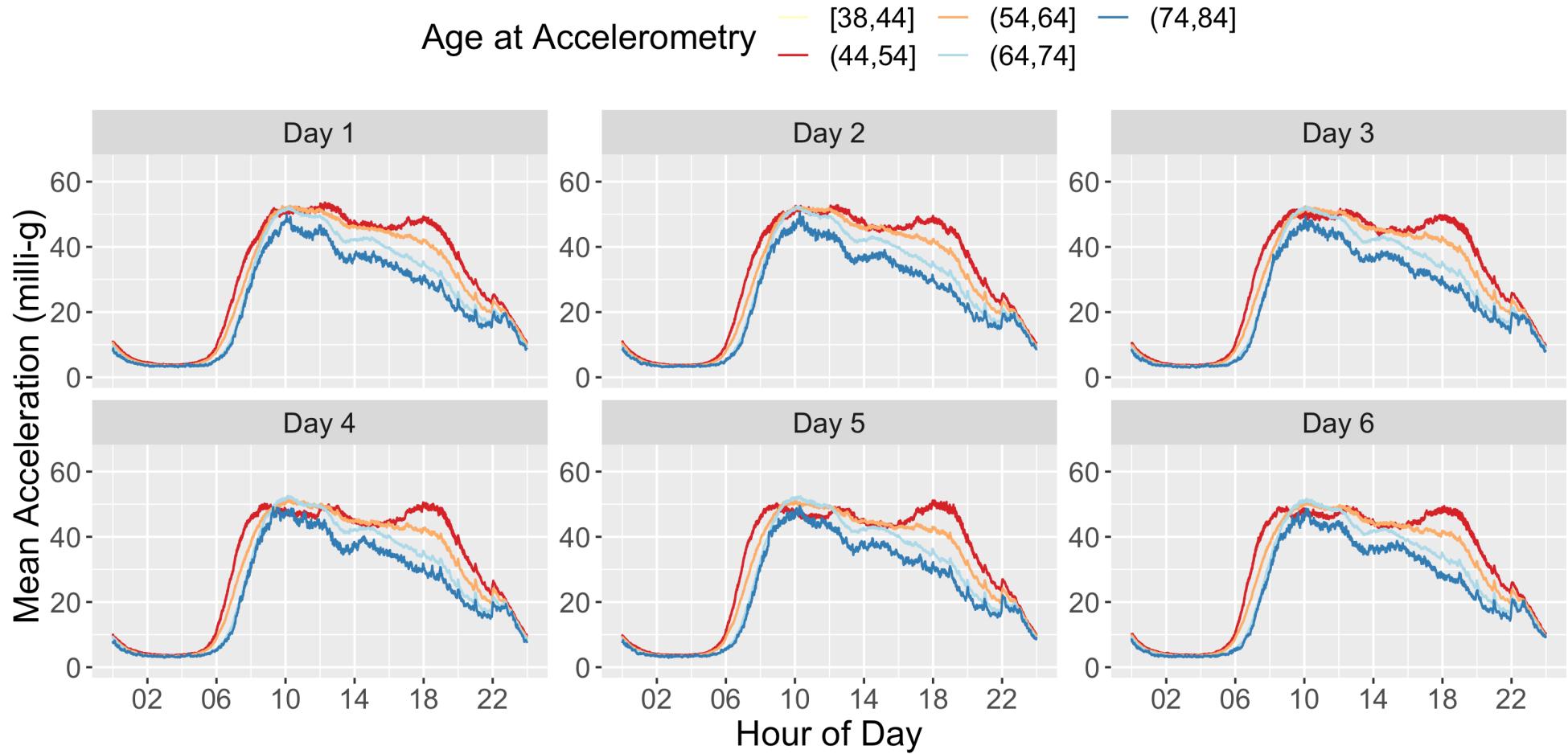
- Look at age range



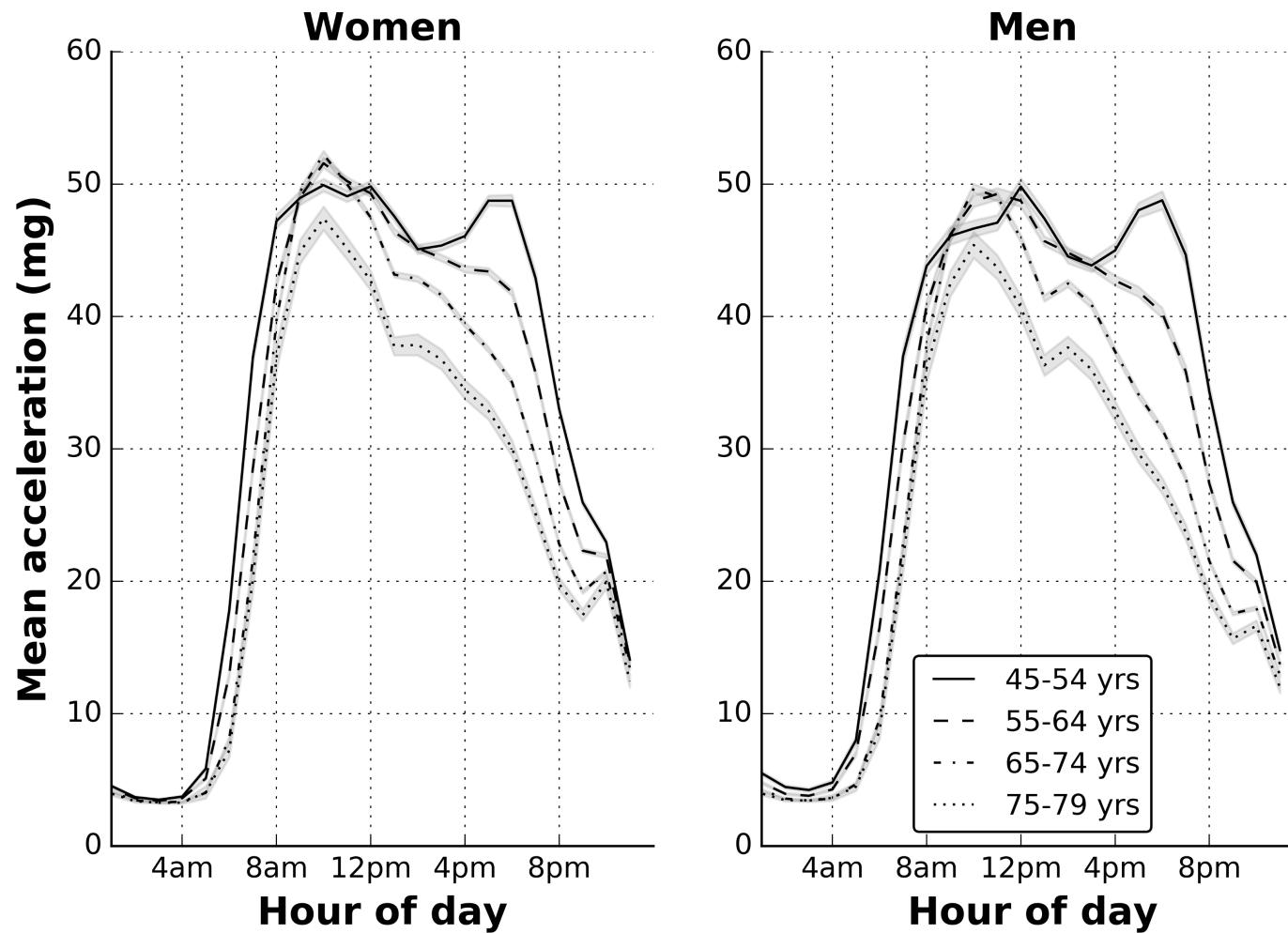
Age at Acceleration Plot



Age at Acceleration Plot - Remove 38-44 y/o



One result from (Doherty et al. 2017) analysis

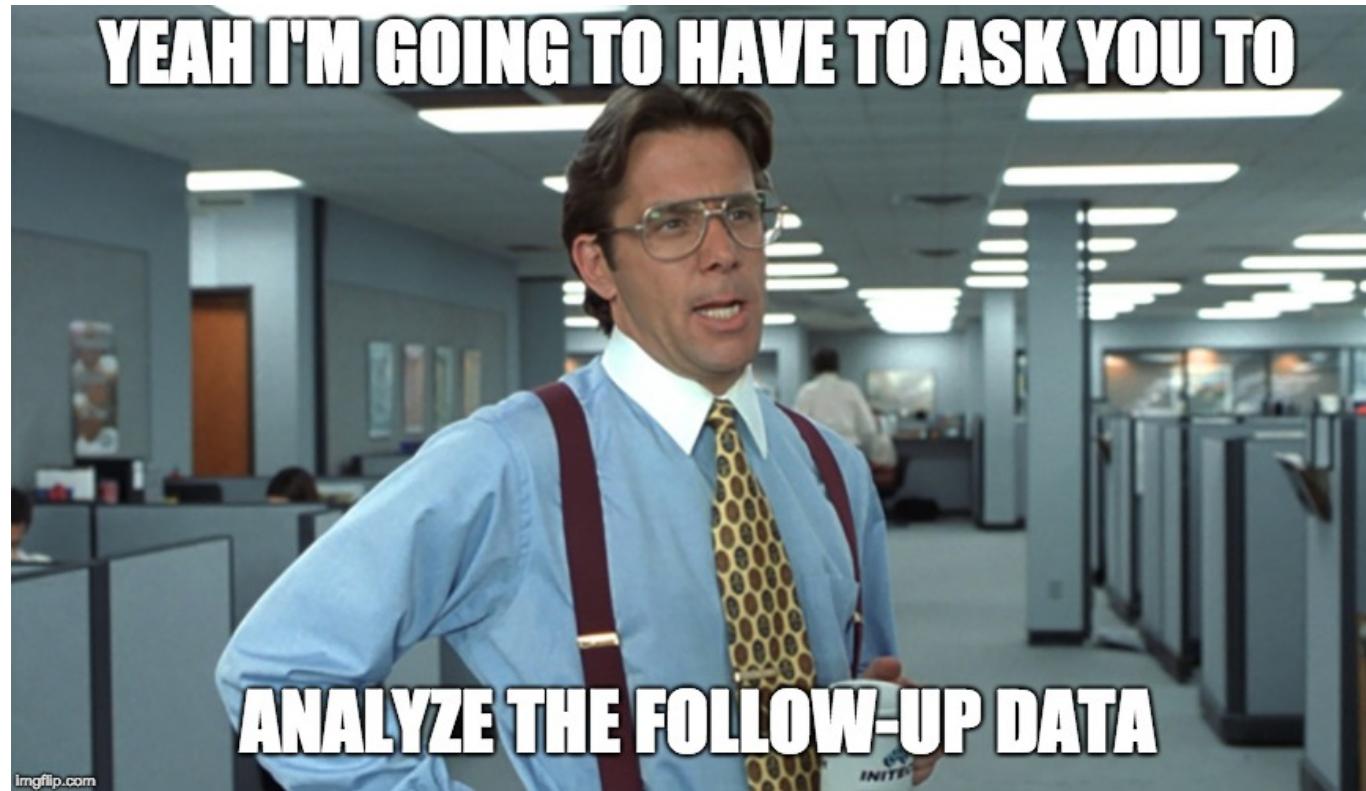


Takehome Messages

1. Start off smaller than 100K people
 2. Inspect the raw(ish) data
 3. Processing highly affects results
 - Autocalibration seems to work well on gross features (with 100K people)
 - Artifacts still seem present in the data
1. Inclusion criteria matters (esp. for inference)
 2. Back to the 100Hz data we go!

Next data installment

"We invited some participants to wear an activity monitor for a week, four times a year. ... finished in early 2019."



References (and Thanks)

- Doherty, Aiden, Dan Jackson, Nils Hammerla, Thomas Plötz, Patrick Olivier, Malcolm H Granat, Tom White, et al. 2017. "Large Scale Population Assessment of Physical Activity Using Wrist Worn Accelerometers: The Uk Biobank Study." 12 (2): e0169649.
- Hees, Vincent T van, Zhou Fang, Joss Langford, Felix Assah, Anwar Mohammad, Inacio CM da Silva, Michael I Trenell, Tom White, Nicholas J Wareham, and Søren Brage. 2014. "Autocalibration of Accelerometer Data for Free-Living Physical Activity Assessment Using Local Gravity and Temperature: An Evaluation on Four Continents." 117 (7): 738-44.