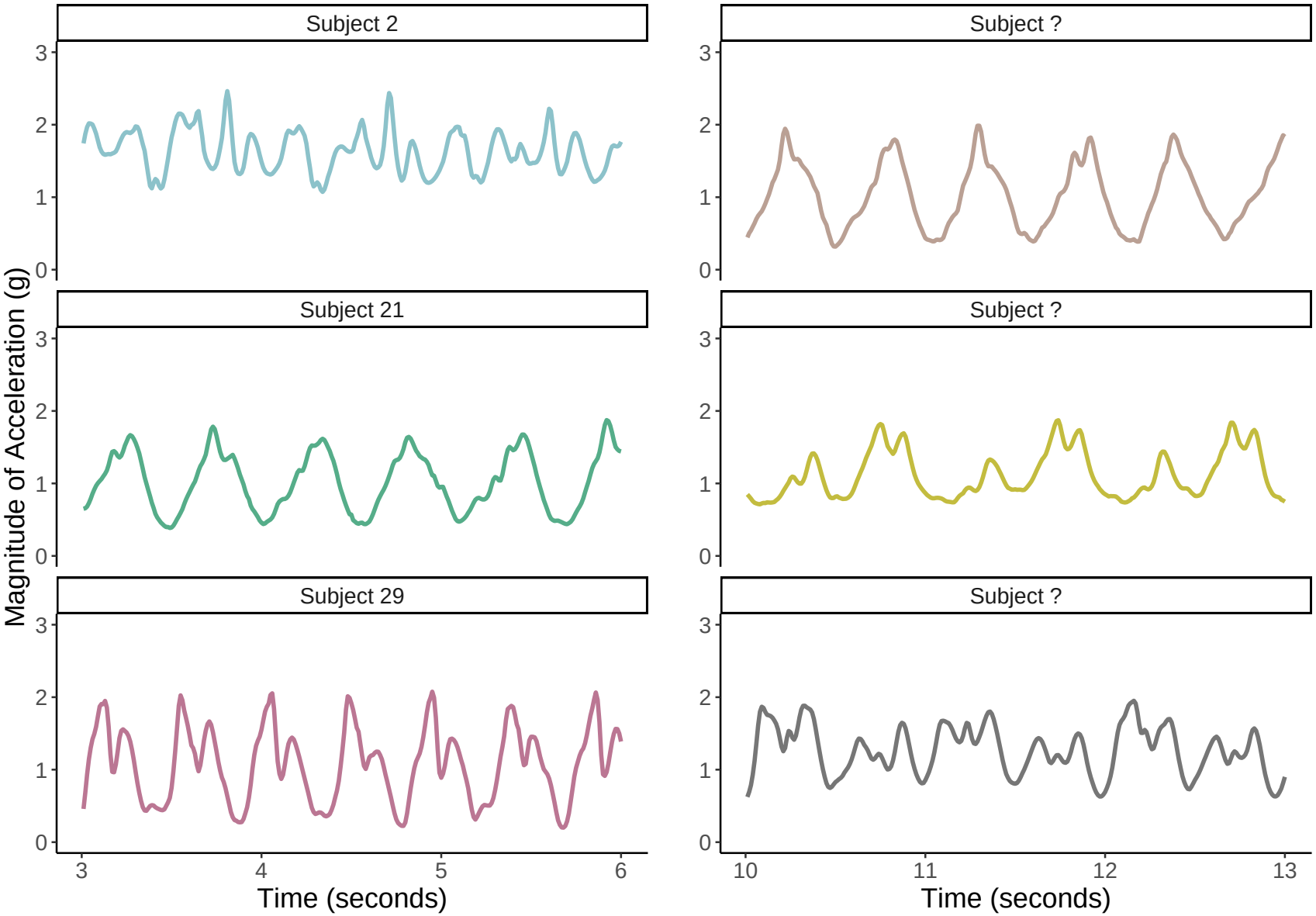
Fingerprinting Walking using High Density Accelerometer Data

ENAR 2024

Lily Koffman

The Problem: Can We Identify an Individual From Their Walking?



Why Do We Care?

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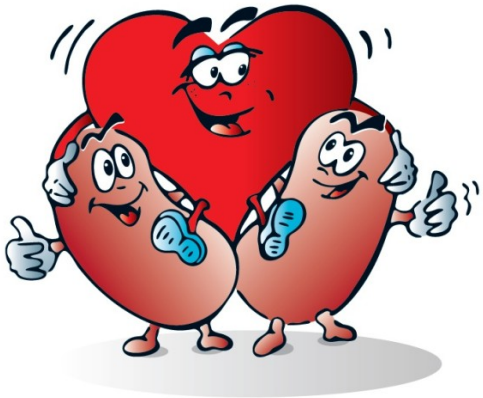

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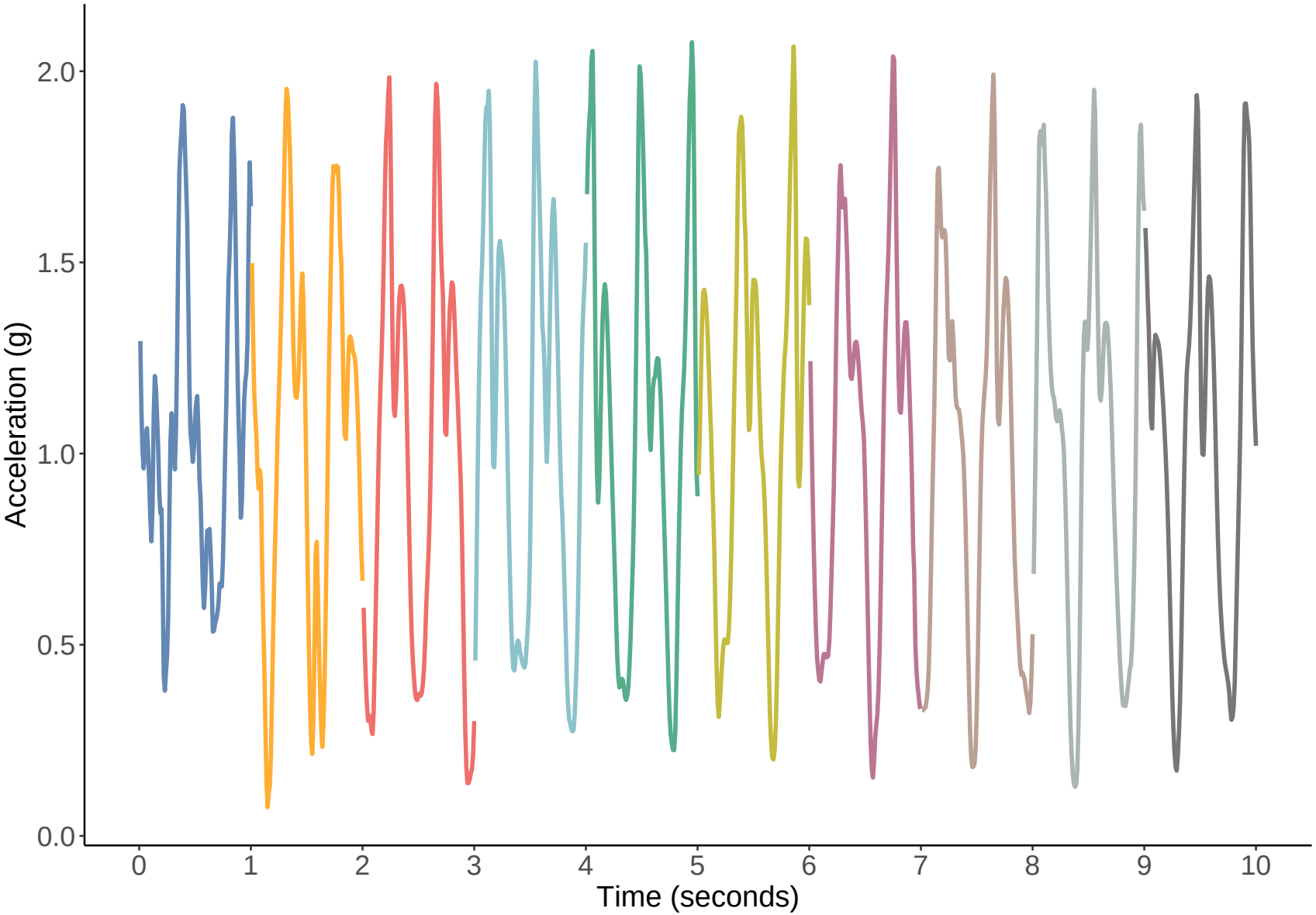
  - **Image partitioning**: compute summaries of the joint distribution, use summaries to predict identity
  - **Functional regression**: use joint distribution in trivariate functional regression to predict identity

Obtaining the joint distribution: segment the data



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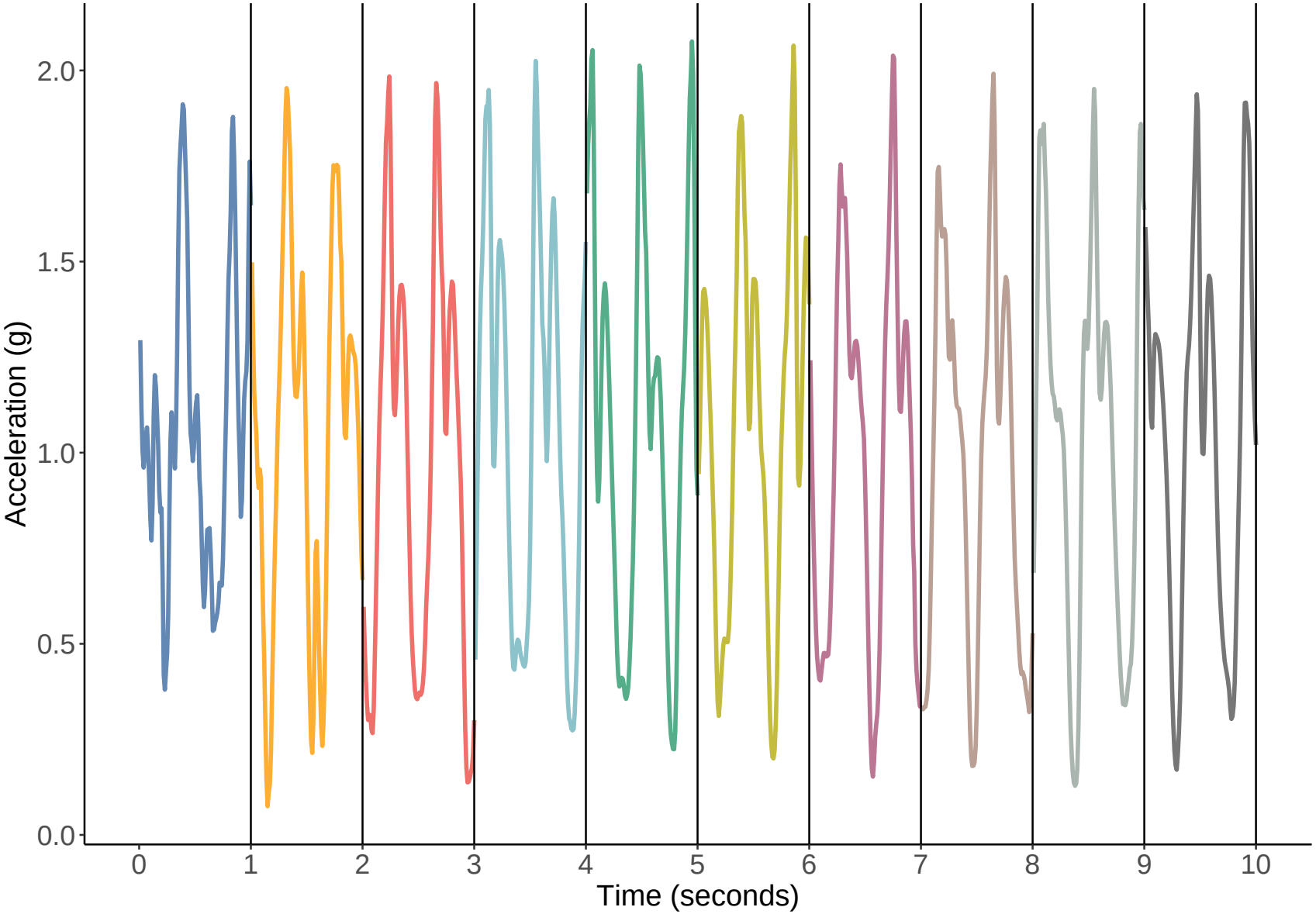
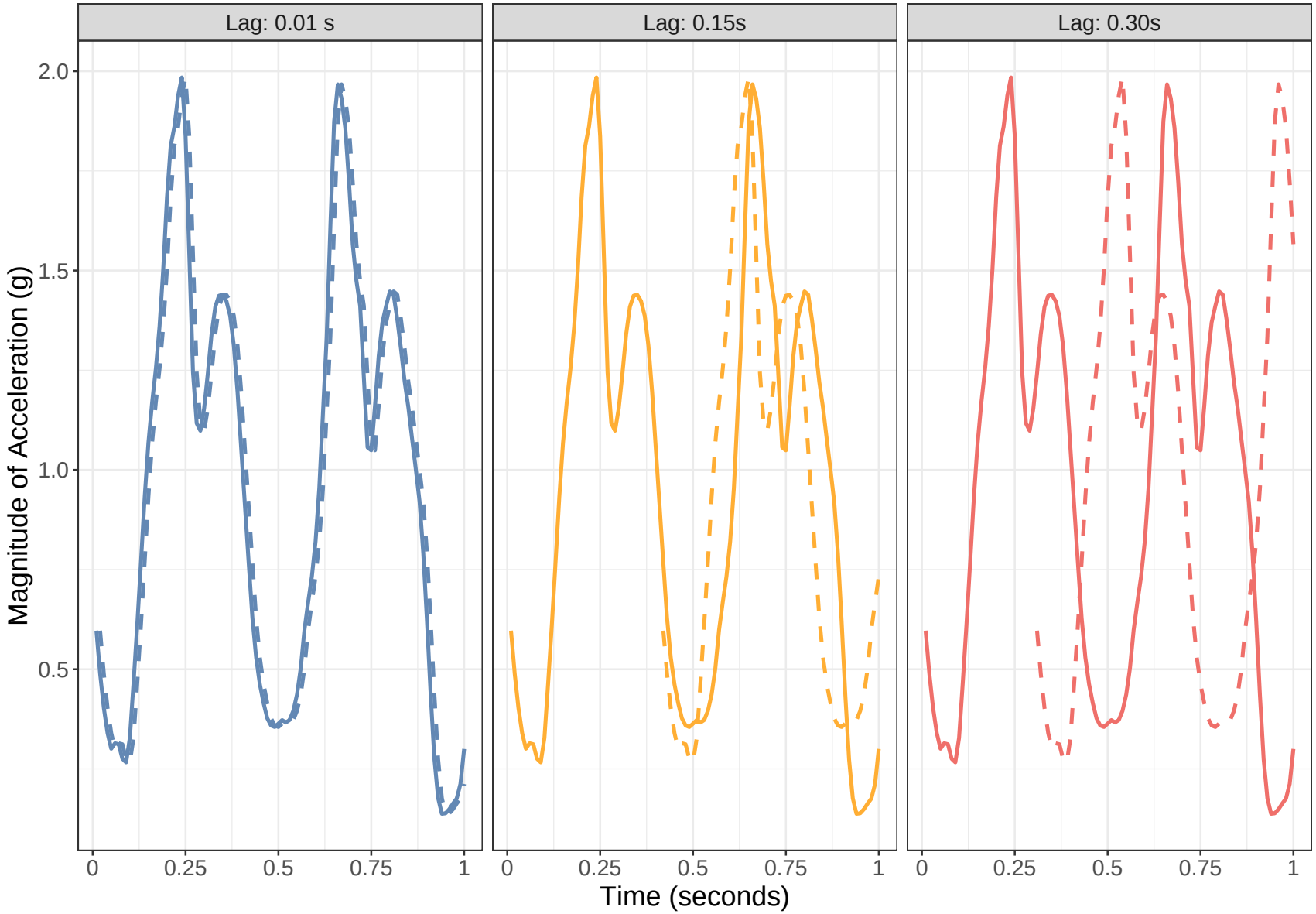


Obtaining the joint distribution: examine acceleration, lag acceleration for each segment and lag



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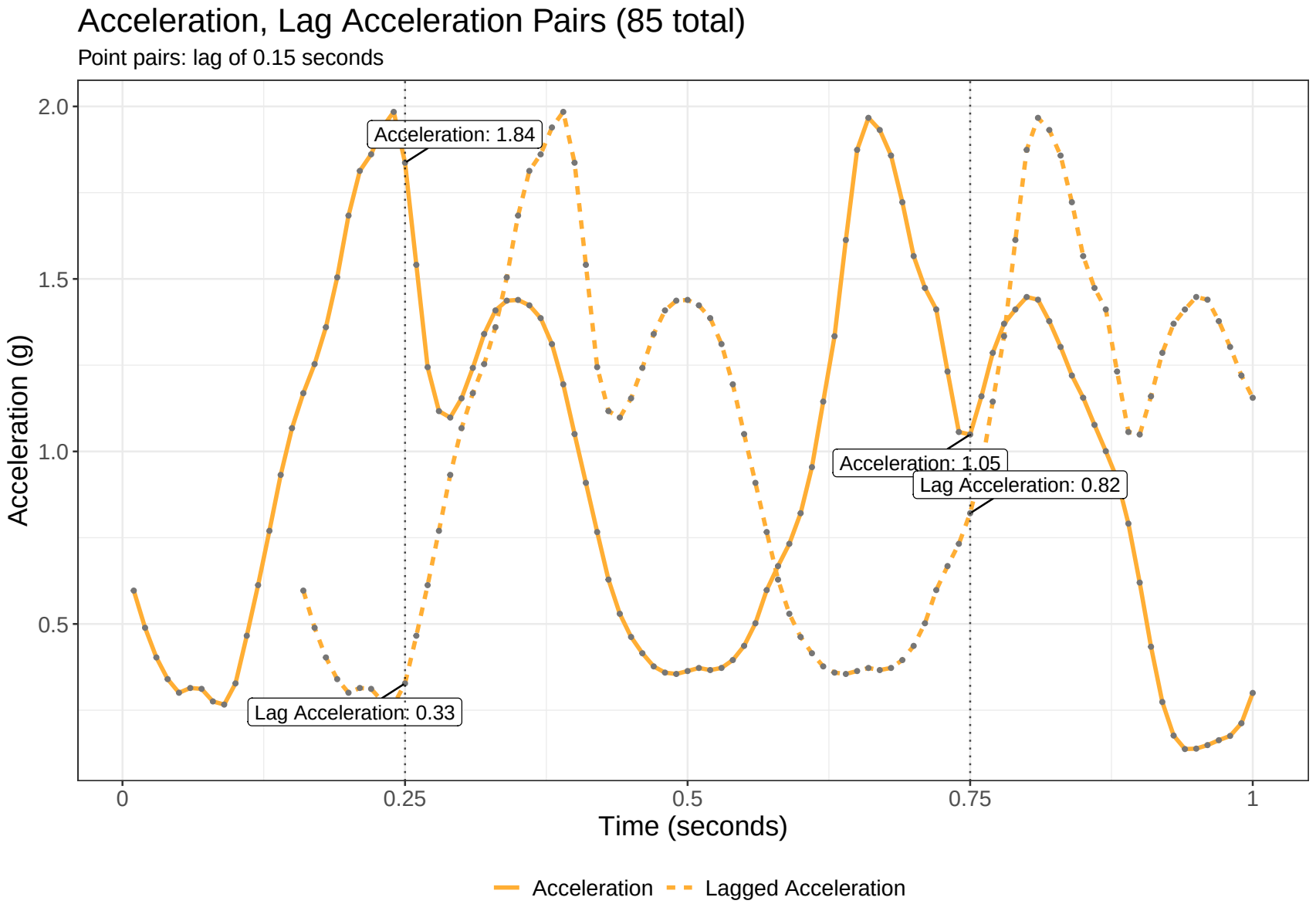

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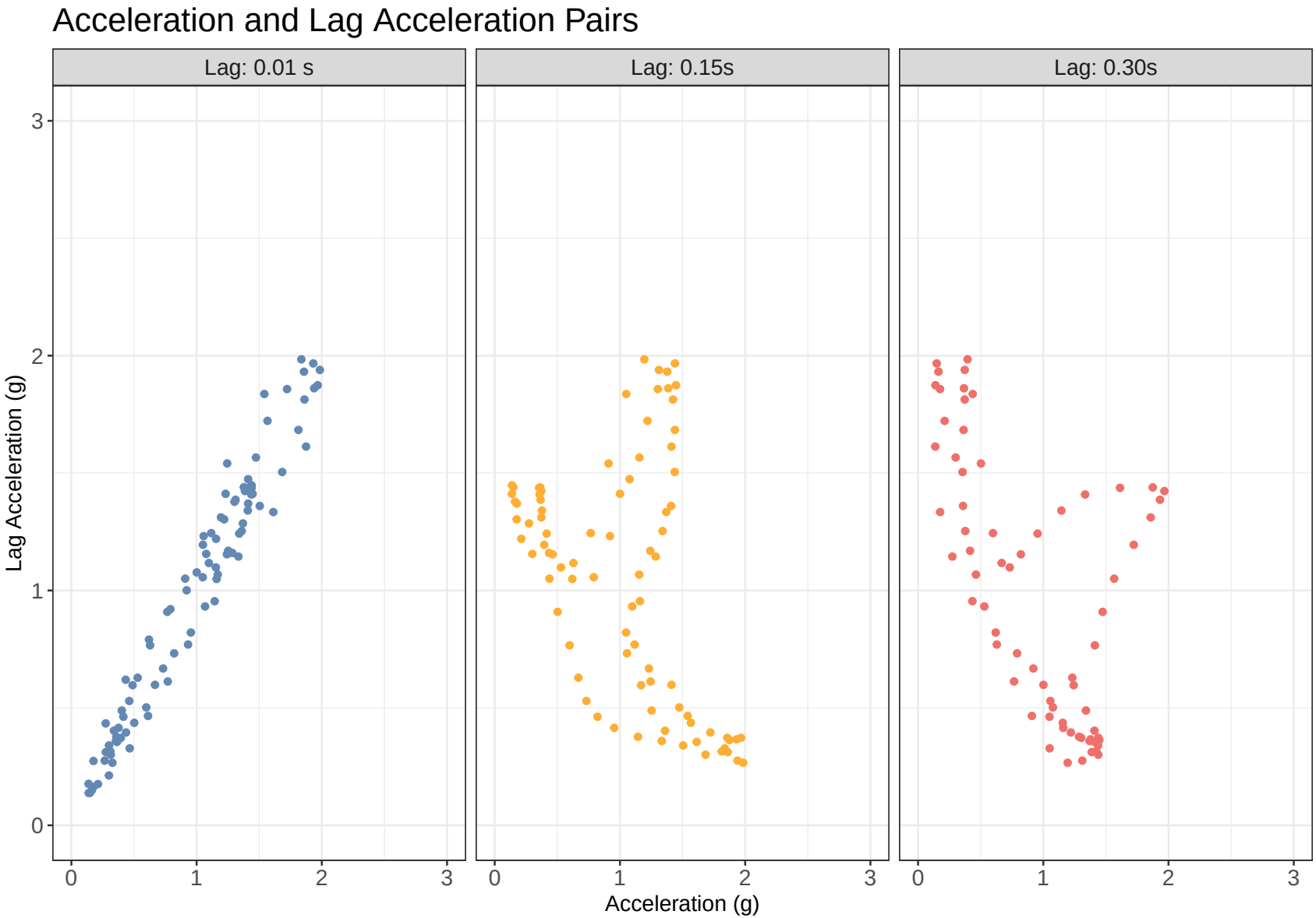

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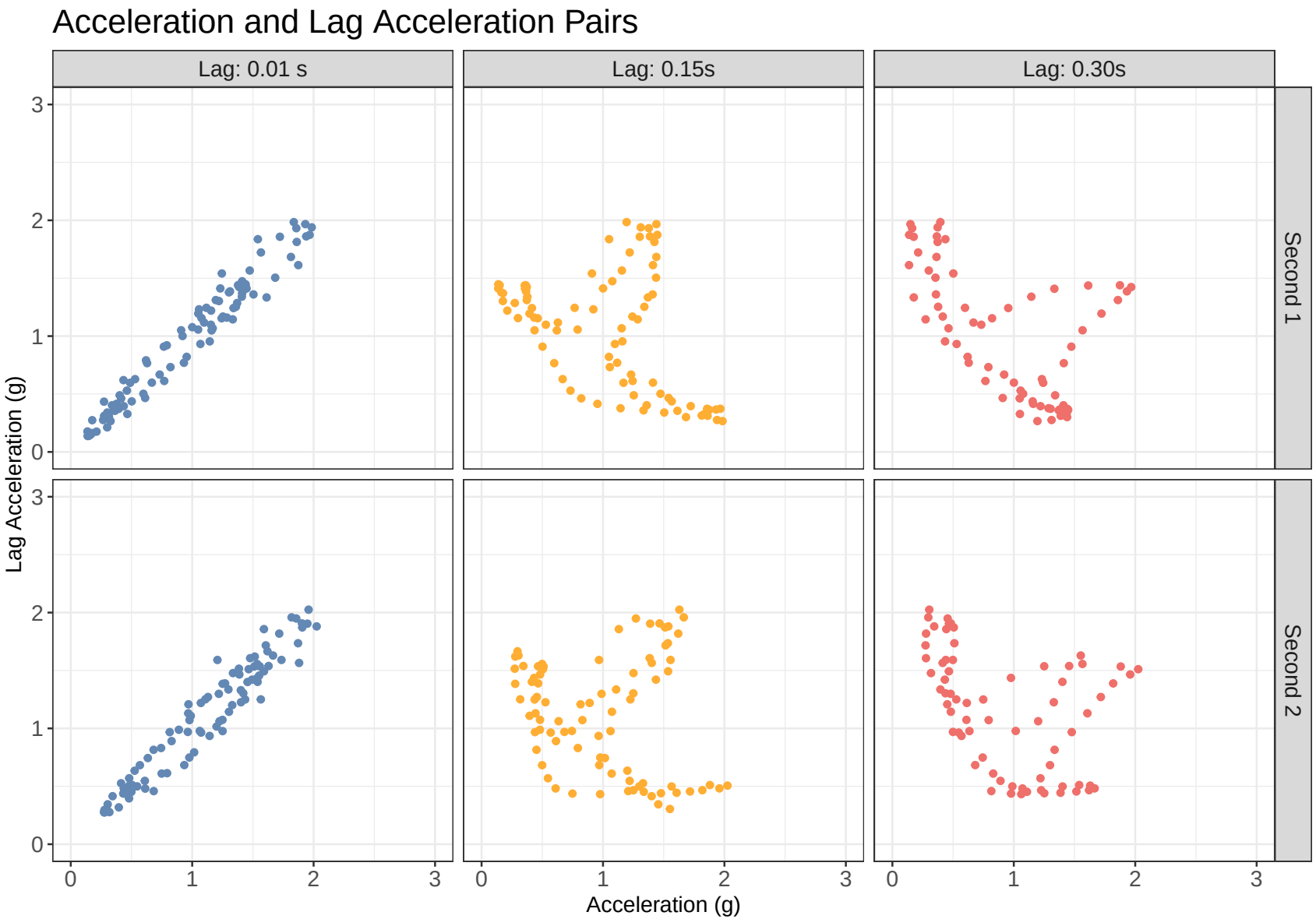


Image partitioning: partition grid into 2D cells

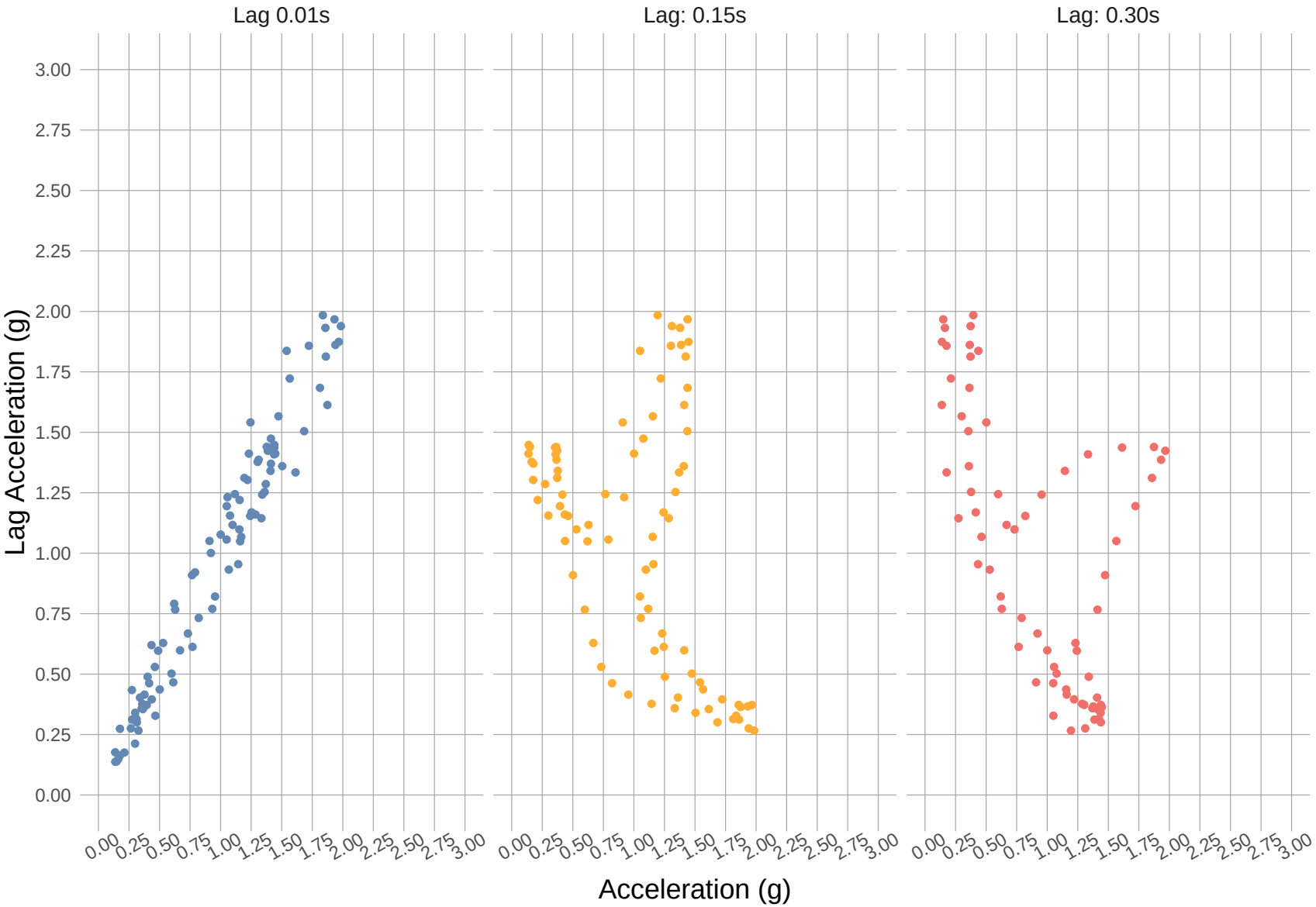
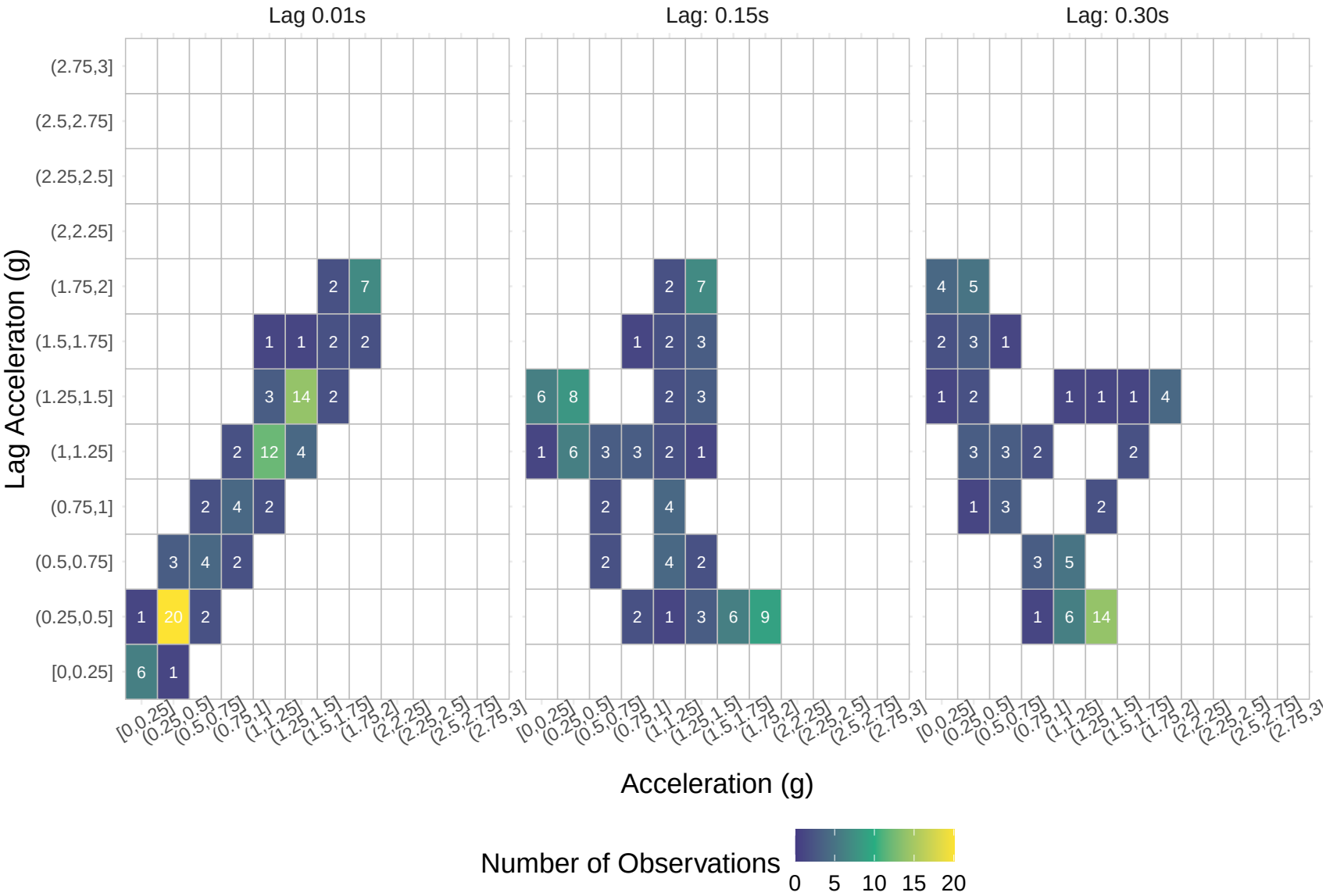


Image partitioning: partition grid into 2D cells: count points in each cell



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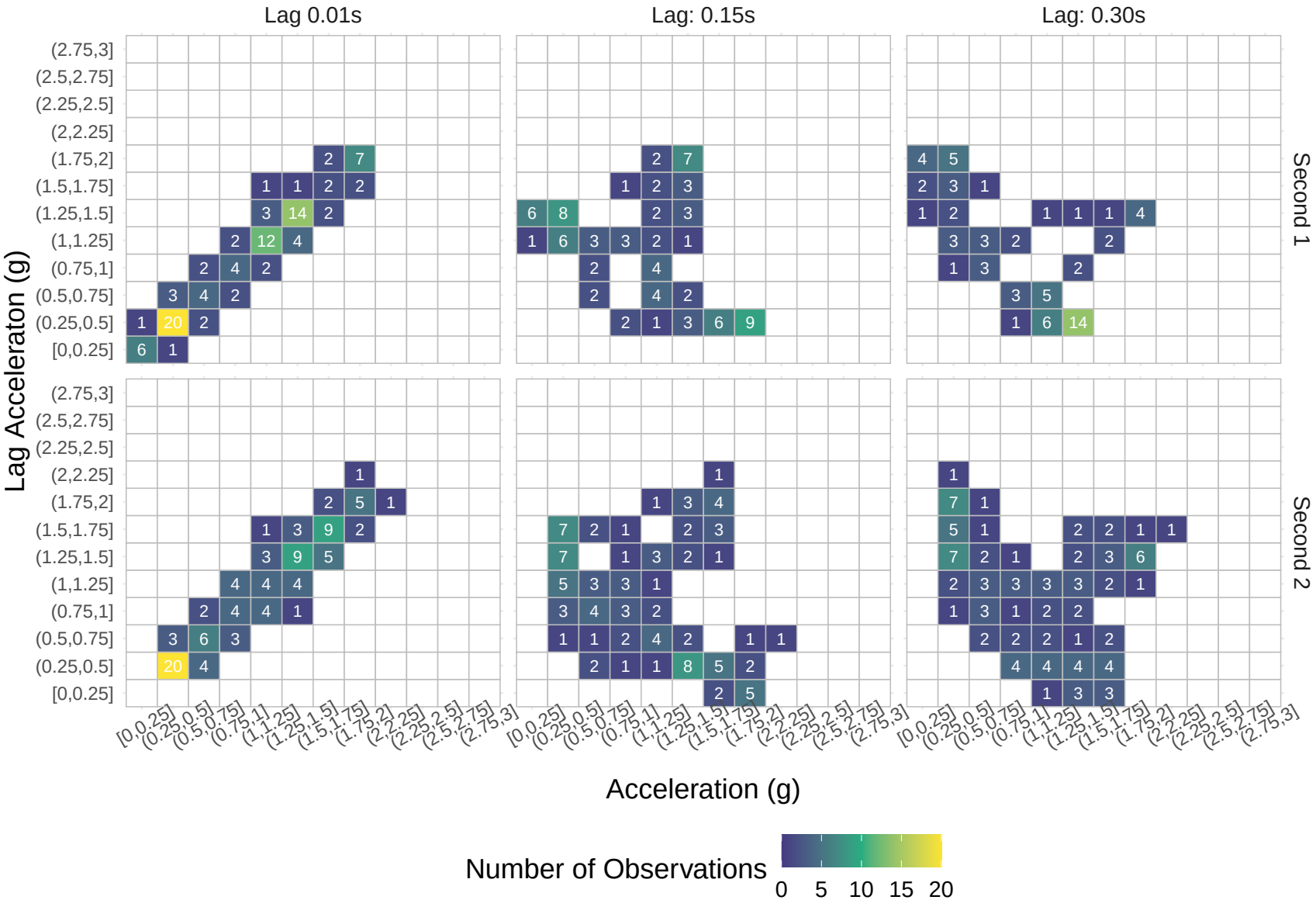

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- Remove predictors with near zero variance or few unique values

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- Use one vs. rest classification (separate model for each individual)
- Machine learning using `tidymodels`; logistic regression . . .
- For logistic regression models, use correlation and multiplicity adjusted (CMA) confidence intervals for coefficients to identify grid cells that are most predictive of identity

Functional regression

- Instead of summarizing joint distribution, use functional regression of the form:

$$\text{logit}\{p_{ij}^{i_0}\} = \int_{s,u} F\{v_{ij}(s-u), v_{ij}(s), u\} ds du$$

Where $Y_{ij}^{i_0} \sim$ Bernoulli$(p_{ij}^{i_0})$, $u = 1, \ldots, S-1 = 99$, $s = u+1, \ldots, S = 100$, $v_{ij}(s-u)$ is acceleration for subject i, second j, at $s-u$ and $v_{ij}(s)$ is acceleration for subject i, second j, at s.

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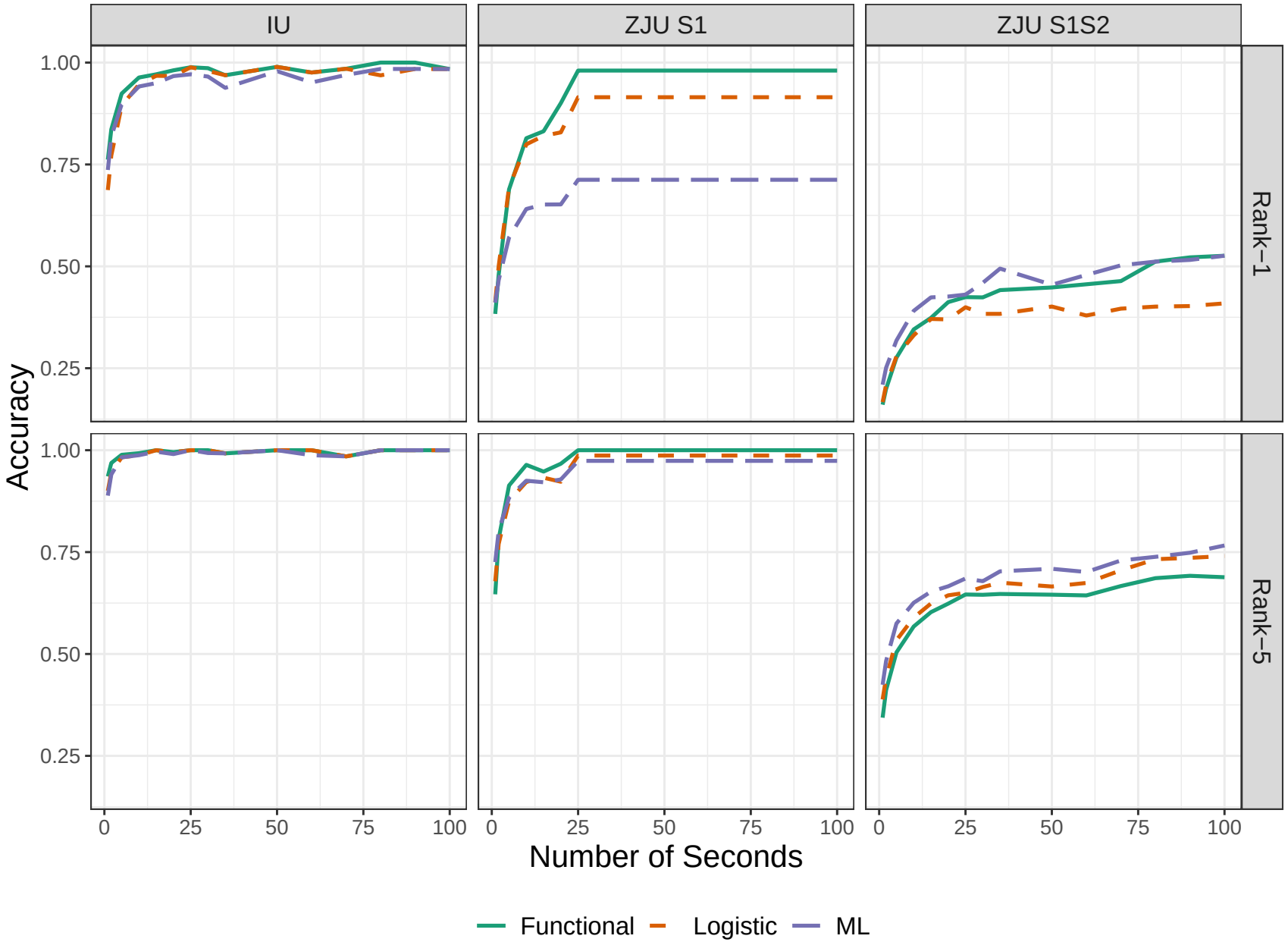
- Implement model using `mgcv::gam` after manipulating empirical joint distribution into matrices of acceleration, lag acceleration, and lag

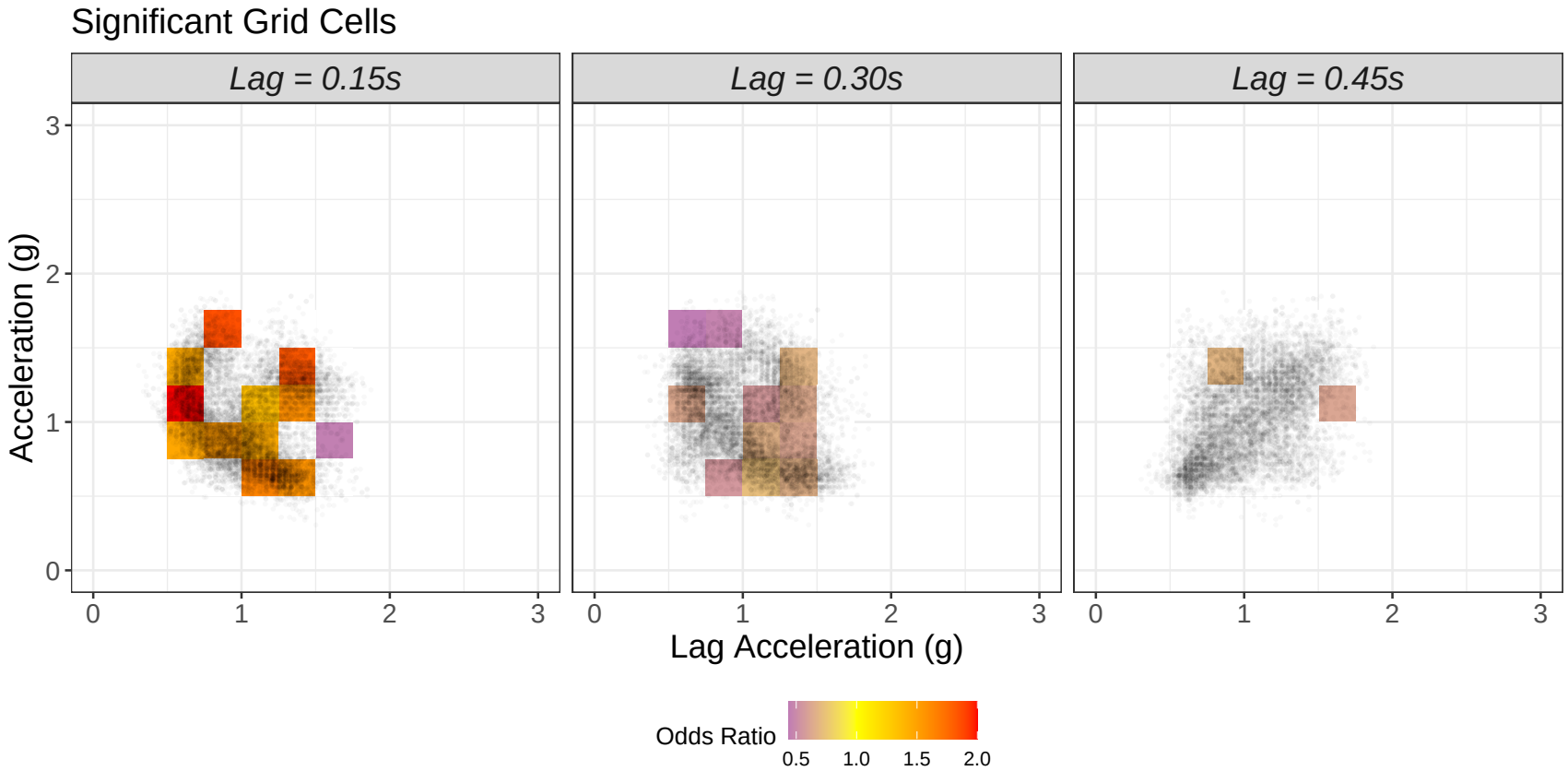
Application

- Two datasets:
  - Indiana Unversity (IU): 32 subjects, 8 min walking per subject
  - Zhejiang University (ZJU): 153 subjects, two trials at least one week and up to six months apart, 1 min walking per subject
    Use for two tasks: within session prediction (train on 75% of seconds in session 1, predict on other 25%)
    Out of session prediction: train on session 1, predict on session 2

Results: Accuracies over Varying Amount of Testing Data



Inference


Significant Grid Cells
Lag = 0.15s
Lag = 0.30s
Lag = 0.45s
Acceleration (g)
Lag Acceleration (g)
0
1
2
3
Odds Ratio
0.5
1.0
1.5
2.0

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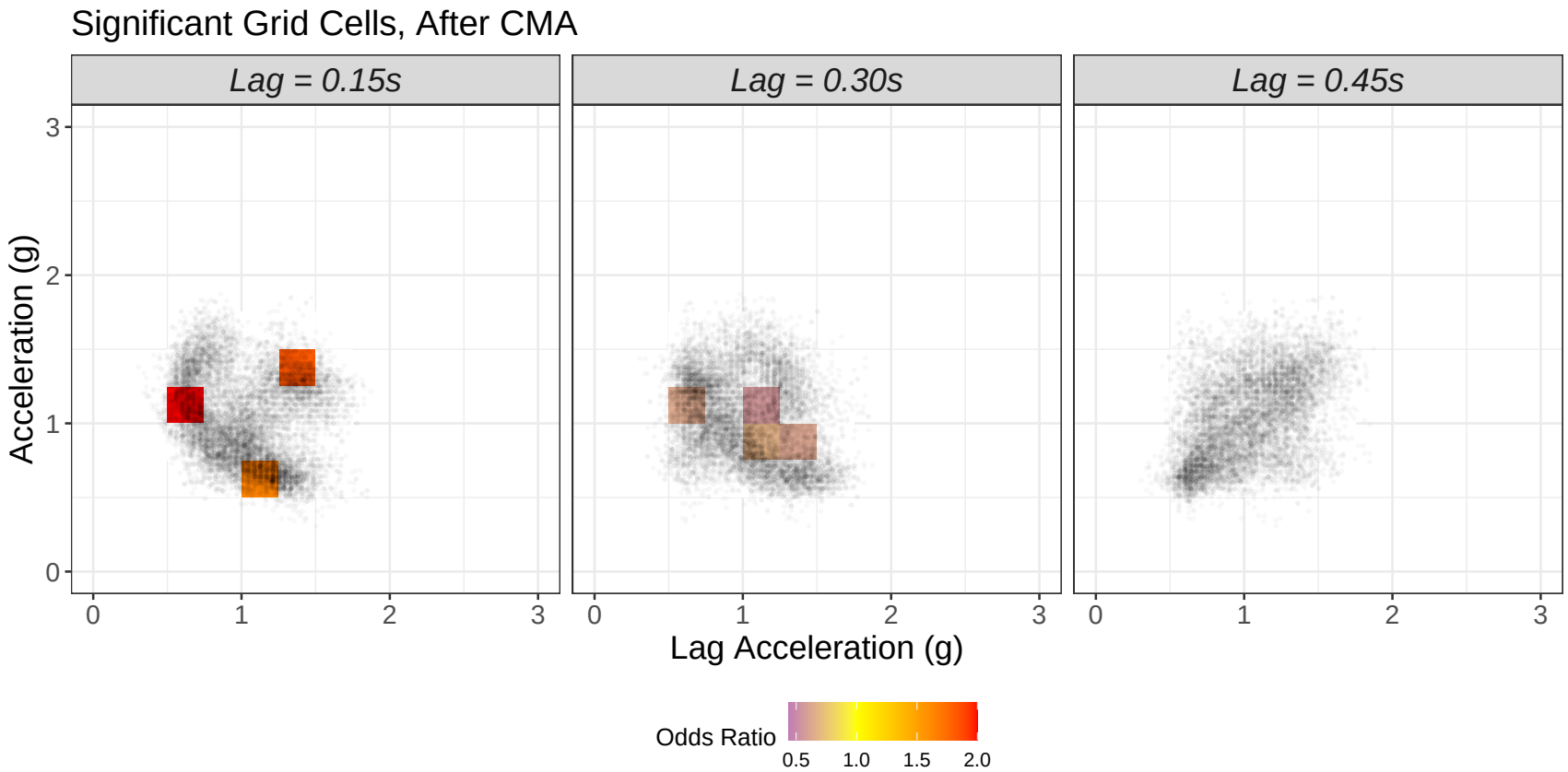
Significant Grid Cells, After CMA
Lag = 0.15s
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Lag = 0.45s
Acceleration (g)
Lag Acceleration (g)
0
1
2
3
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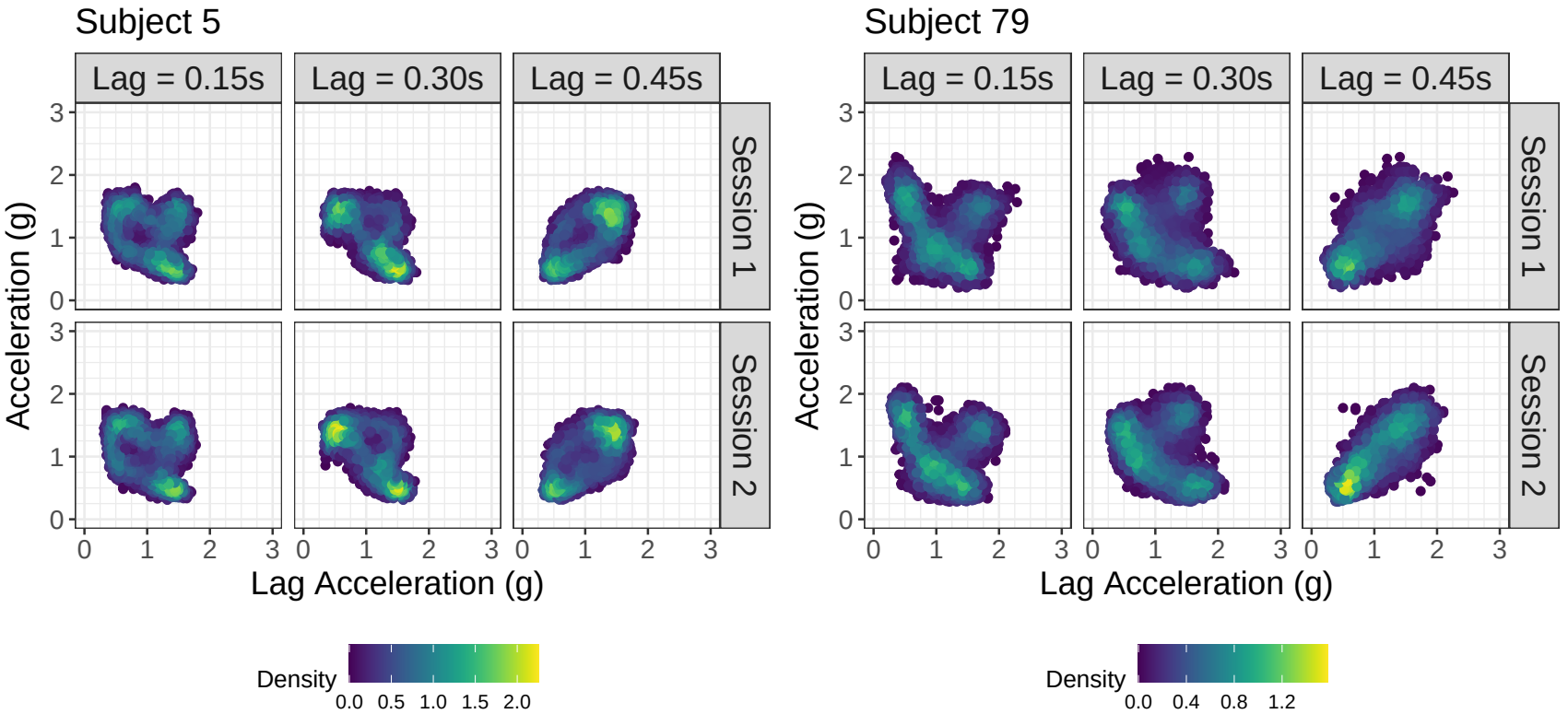
Fingerprints: well-predicted subject



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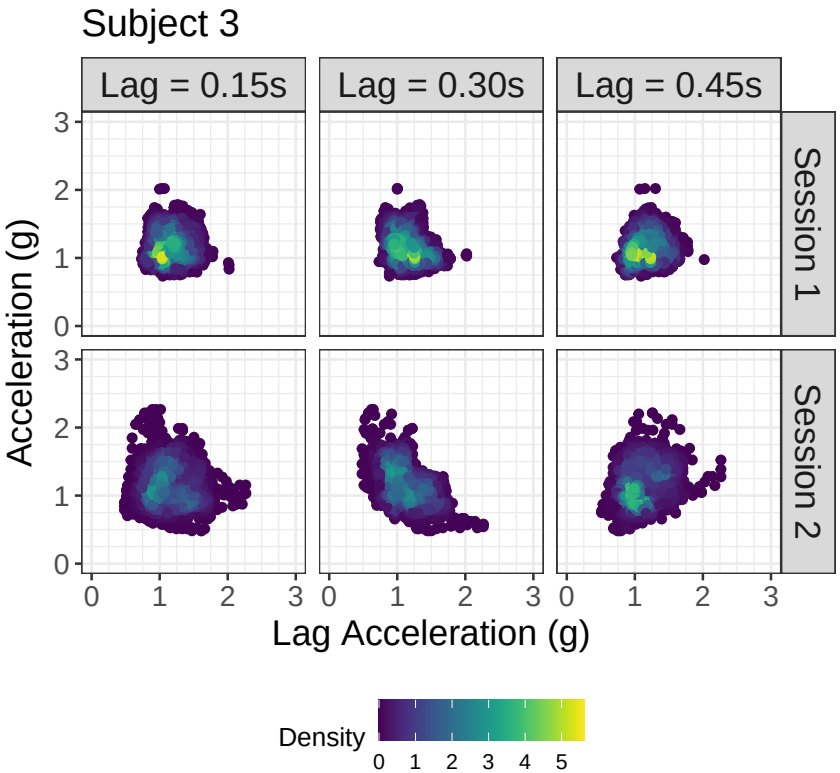
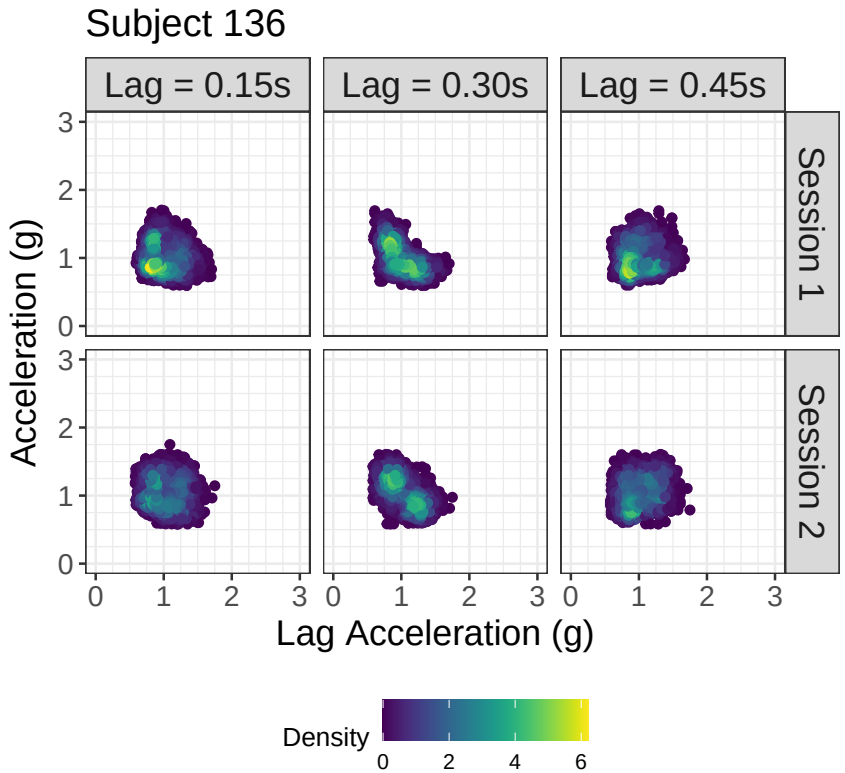
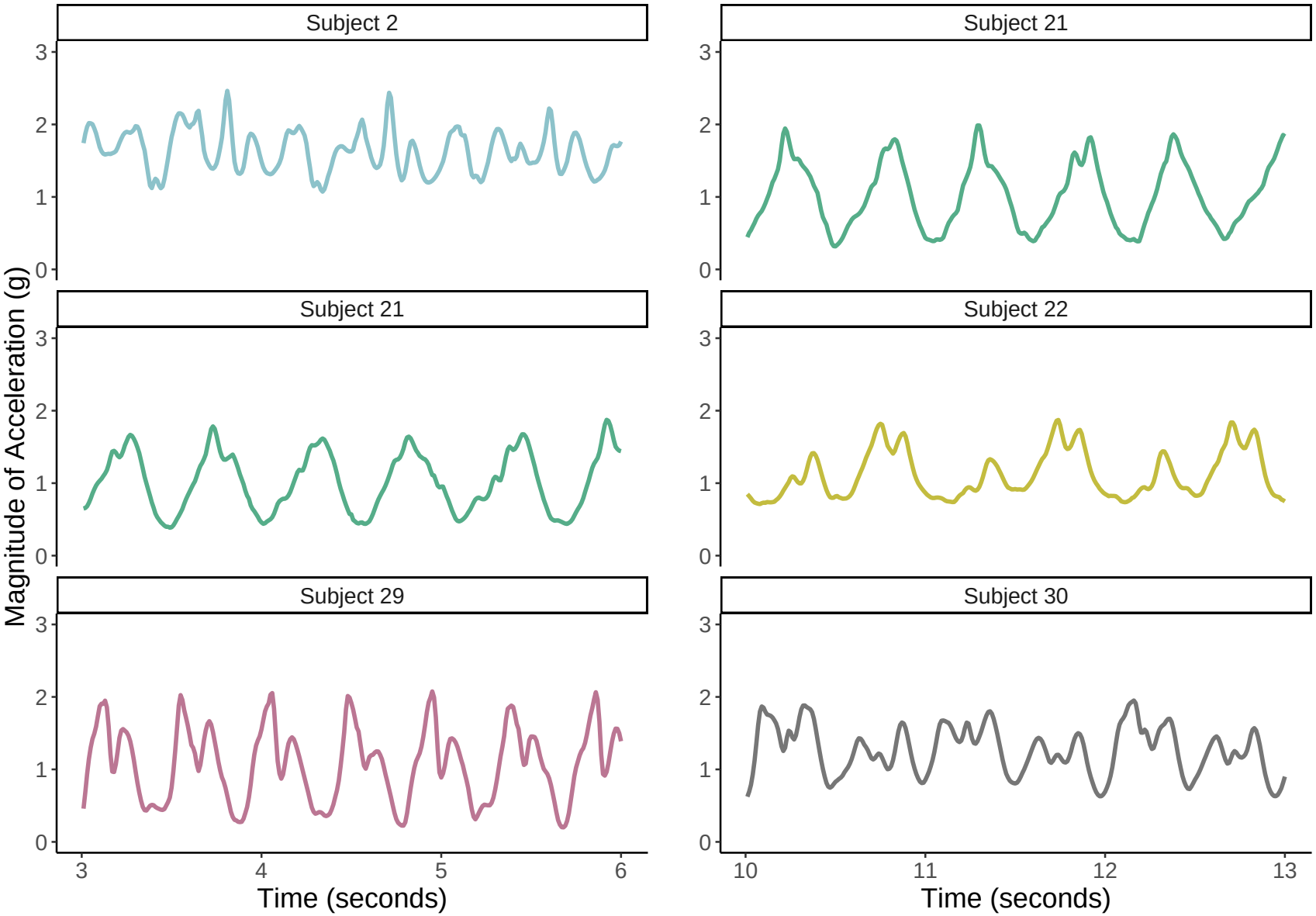




Revisiting problem statement



Acknowledgements

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- Ciprian Crainiceanu, PhD, Johns Hopkins Bloomberg School of Public Health