Segmentation of Accelerometer-derived Time Series

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Introduction

- Segmentation helps describe and interpret accelerometer data
- Brief overview
- Cut-points and Bouts approach
- Hidden Semi-Markov Models

Brief Overview

Raw data:

As used with Deep Neural Networks
and

Template mapping techniques

https://github.com/NLeSC/mcfly

Signal Features:

e.g. Counts, Acceleration magnitude, Distribution percentiles

Epochs: Standard length

Defined as: Consecutive- or overlapping windows

Sojourn/Bouts: Variable length

Defined as: Knowledge-driven rules and/or Data-driven

Supervised

Given x and y, develop model that can predict y from x

Unsupervised

Given x, develop model that can subdivide into data-driven segments or clusters

Time spent in MVPA?

Strong need within research community for ‘time spent in levels of intensity (energy expenditure)’

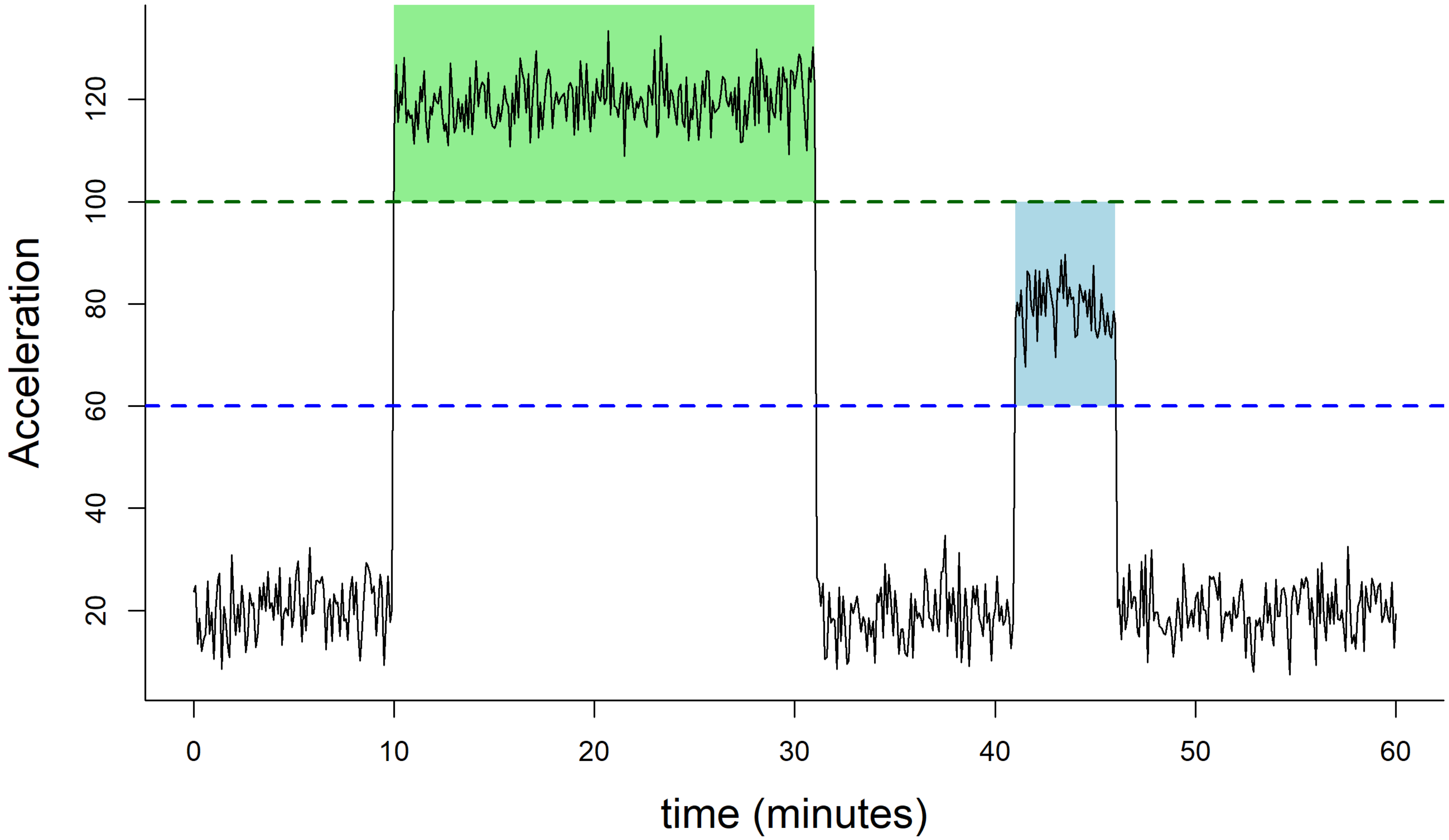
For example: time spent in Moderate or Vigorous Physical Activity (MVPA).

‘Self-report method gives it to us, so accelerometer should be able to do better?’

Challenges:

- Acceleration is only one of various determinants of energy expenditure
- Lack of convincing real-life criterion methods
- Lack of clear construct definition

Is it this simple?



Defining what a bout/sojourn is

1. What should the cut-point be?
2. What should the epoch length be?
3. What should minimum duration of bout (sojourn) be?
4. Should we allow for gaps in a bout (sojourn)?
5. Should this be a percentage of the bout duration, an absolute minimum in seconds, or both?
6. Do the first and last epoch need to meet the threshold criteria?
7. Are bout gaps counted towards the time spent in bouts?
8. In what order are the bouts extracted, e.g. what if a 3-minute MVPA bout is part of a 30 minutes inactivity bout?
9. How many bout categories should there be? Inactive, light and MVPA?

Implementation in GGIR

User decides on:

- Acceleration thresholds (3 x)

- Fraction of time for which cut-point criteria need to be met (3 x)

- Bout duration ranges, e.g. [1, 5) [5, 10) and [10, ∞) minutes

- Epoch length

User does NOT decide on:

- Maximum bout gap of 1 minute

- First and last epoch need to meet cut-point criteria

- Number of intensity levels, which are always: inactive, light and MVPA

- Order in which bouts are calculated (1 MVPA; 2 inactive; 3 Light)

- Default code for detecting bout: https://github.com/wadpac/GGIR/blob/master/R/g.getbout.R -> where bout.metric==4

Reflections

Useful when interpreted as time spent in acceleration ranges

Unclear whether there is consensus on all these decisions

Unclear how to assess validity

Code validity and documentation probably most important, but never focus in related literature

Other software that segments acc. data

accelerometry: https://CRAN.R-project.org/package=accelerometry

acc: https://CRAN.R-project.org/package=acc

pawacc: https://CRAN.R-project.org/package=pawacc

PASenseWear: https://CRAN.R-project.org/package=PASenseWear

Sojourn: https://CRAN.R-project.org/package=Sojourn

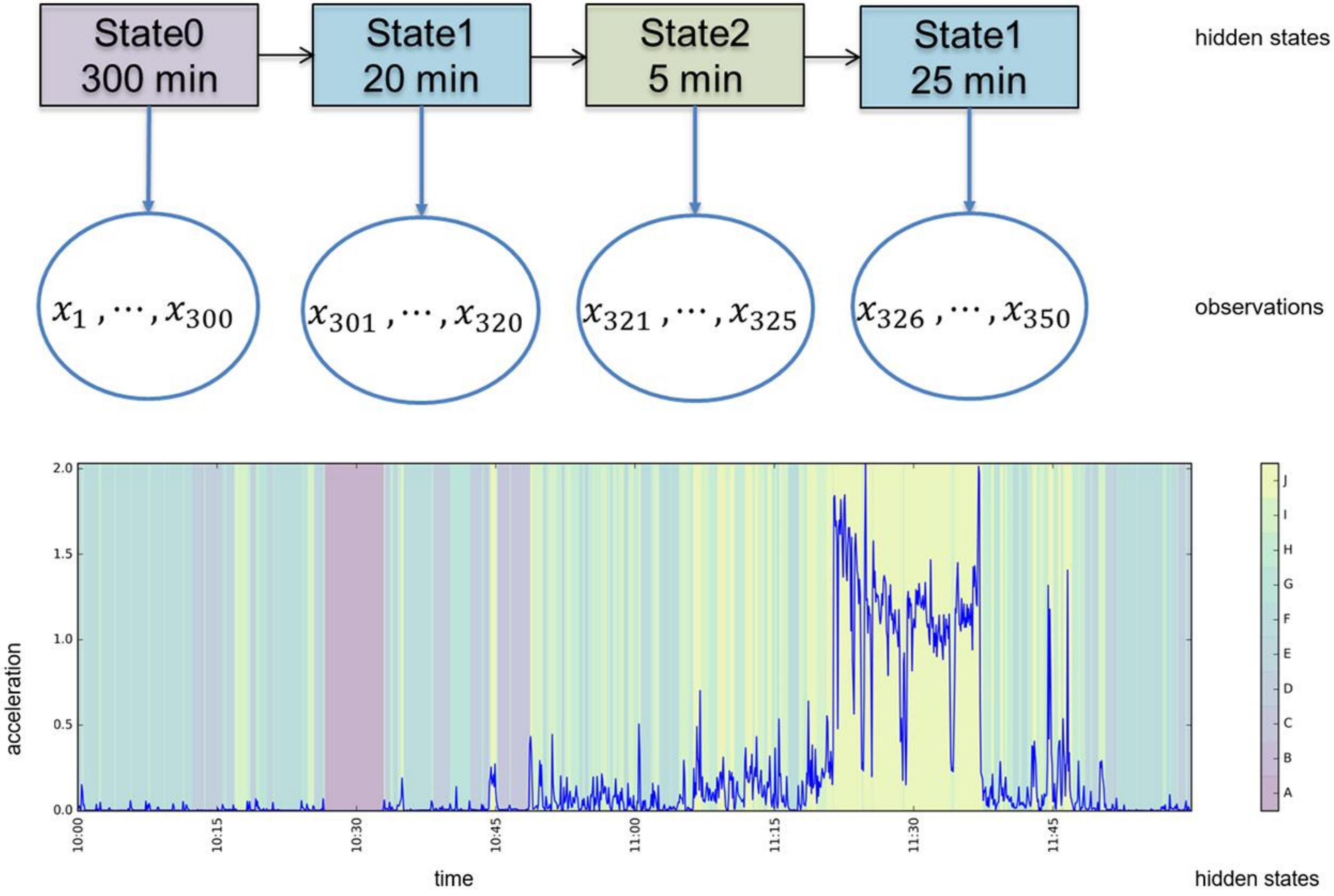
GENEAclassify: https://CRAN.R-project.org/package=GENEAclassify

adept: https://CRAN.R-project.org/package=adept

…?

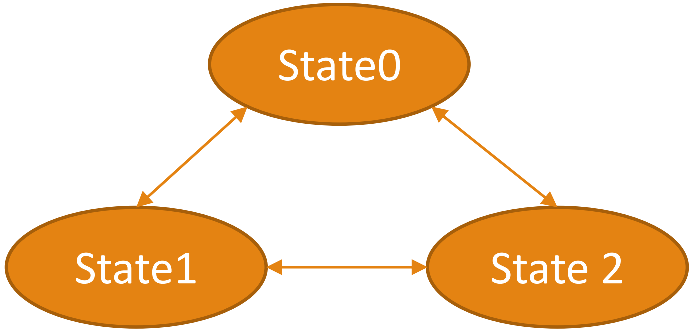
Unsupervised Hidden Semi-Markov Models (HSMM)

Unsupervised learning of abstract clusters (states)



van Kuppevelt et al. PLoSONE 2019, doi: 10.1371/journal.pone.0208692

Hidden Semi Markov Model



Initial state *i* and duration *h*.

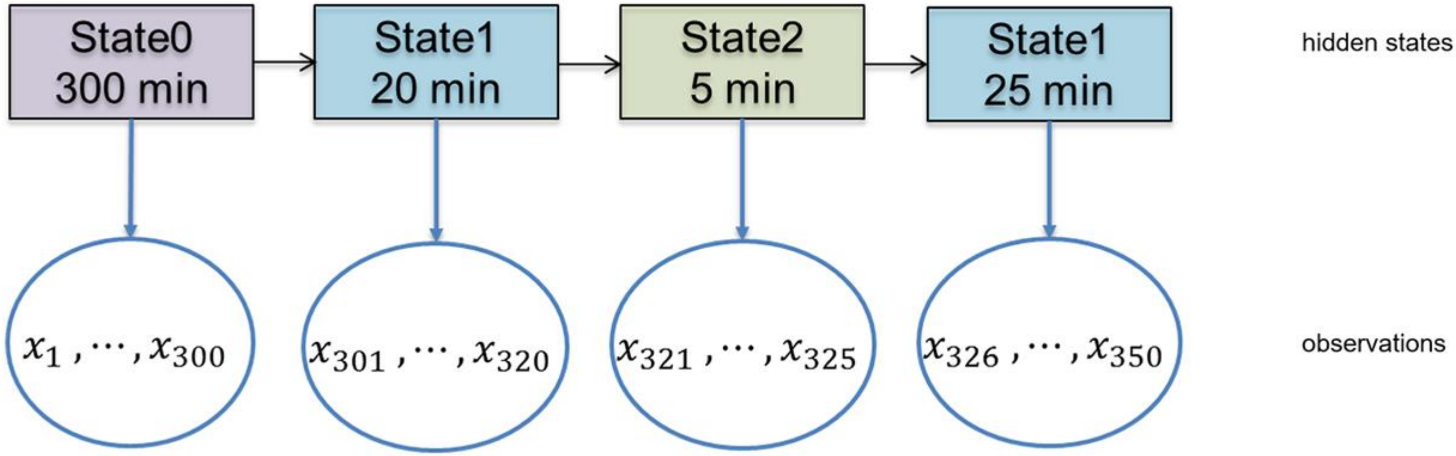
Transition probability matrix (i, h)(j,d) that state *i* with duration *h* generates state $j \neq i$ having duration *d*:

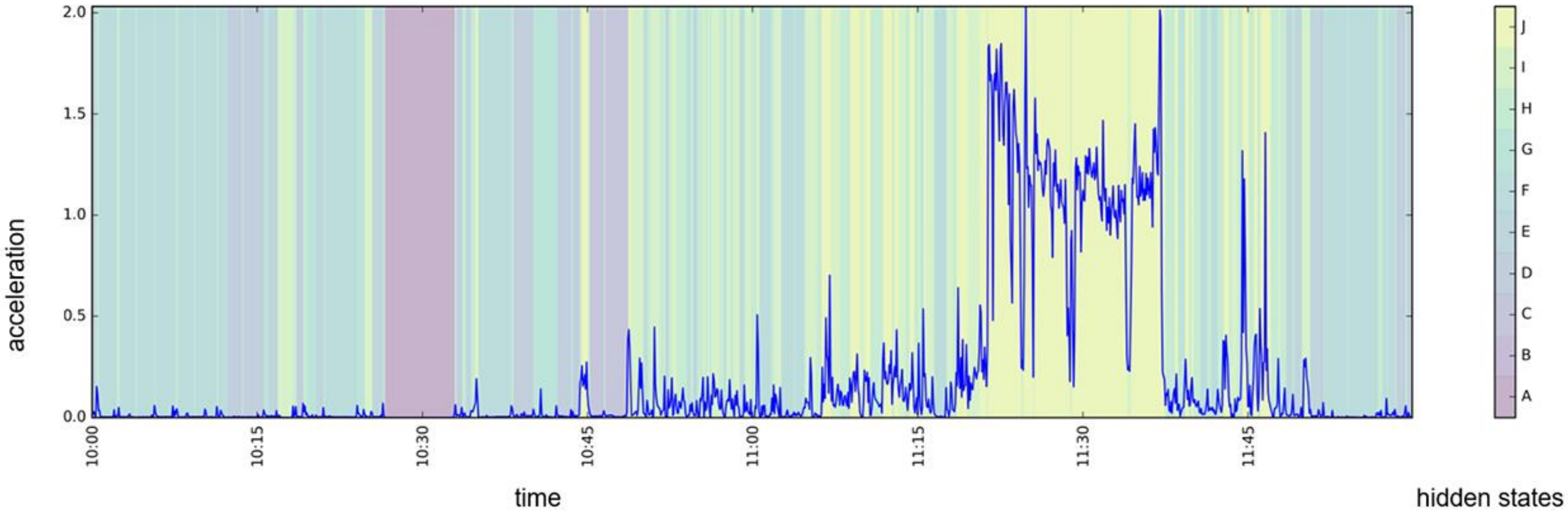
While in state *j* there will be *d* observations being **emitted**, independent of time *t*.

Distribution of durations: We choose Poisson, where each state holds its own lambda parameter.

Distribution of observations: We choose multivariate Gaussian distributions.

Number of states





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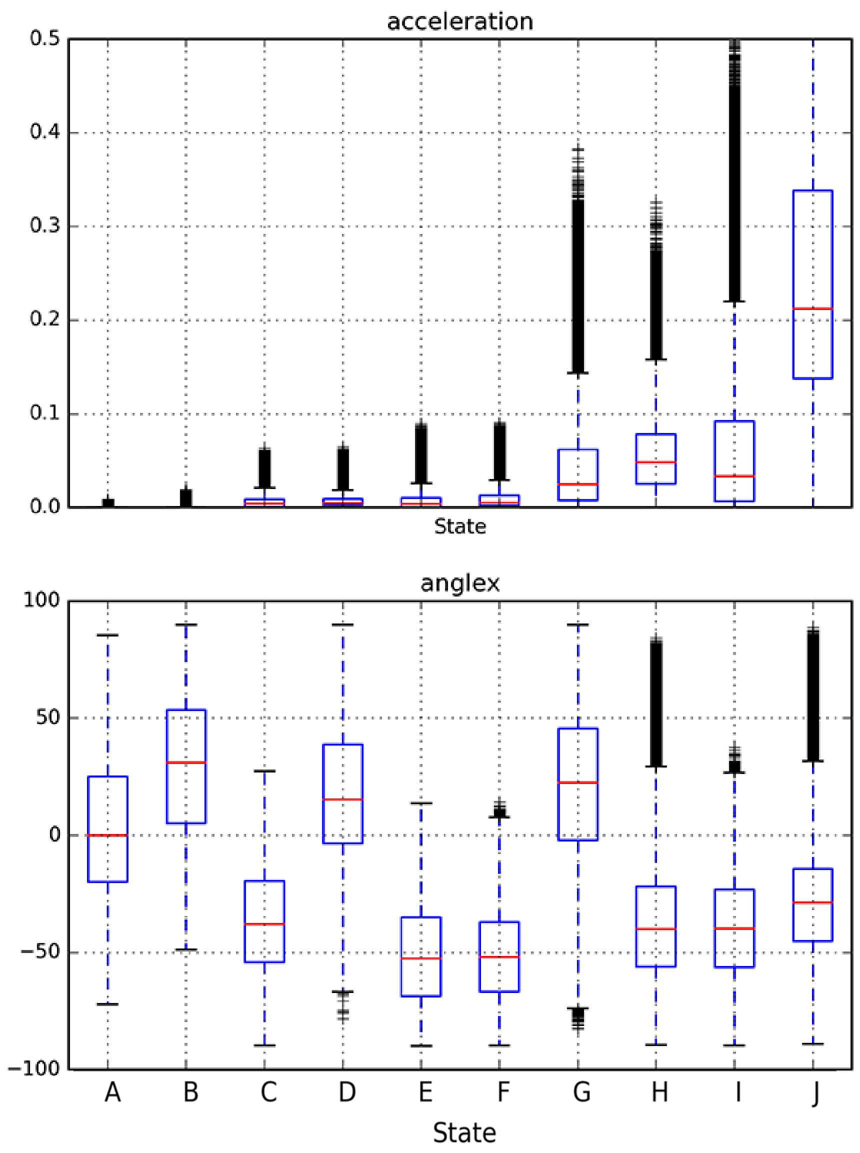

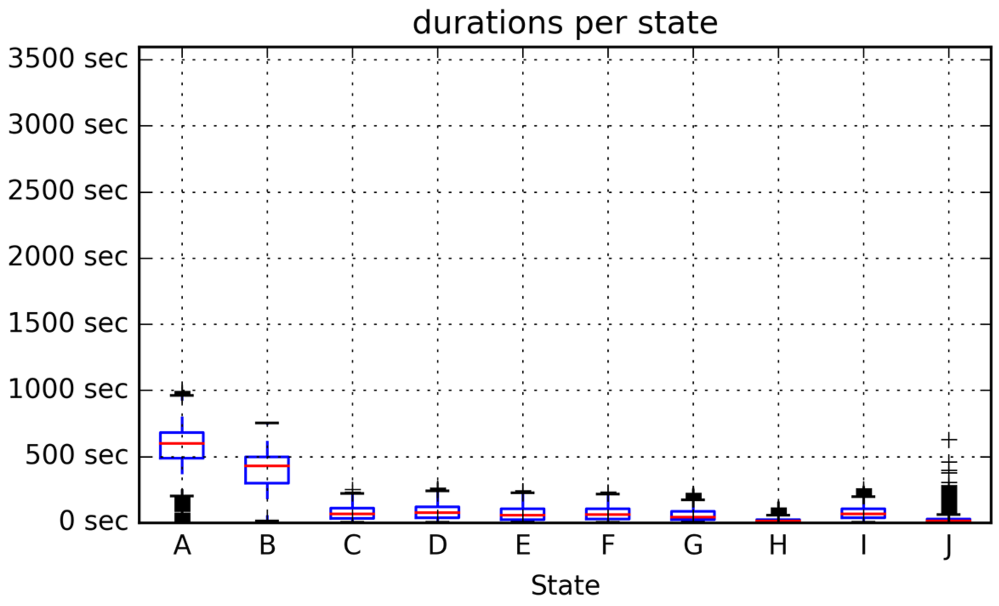

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Open Source Software for HSMM

Library	**Estimation**	**Multi-variate observations**
R package hsmm https://CRAN.R-project.org/package=hsmm	Maximum Likelihood	No
R package mhsmm https://CRAN.R-project.org/package=mhsmm	Maximum Likelihood	Yes
Python library pyhsmm https://github.com/mattjj/pyhsmm	Bayesian	Yes

Reflections on HSMM

- Lower dependence on lab calibration studies needed for cut-points approach

- States are interpretable based on underlying observations

- Communication challenge: Community wants “time spent in MVPA”, which is not exactly what HSMM gives

- Large dataset: Train in representative subsample and then apply to remaining data?

- Multivariate: Ease of interpretation will decrease with more input variables

Questions?

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