





MAX PLANCK INSTITUTE
FOR DEMOGRAPHIC
RESEARCH

Alignment, clocking, and macro patterns of episodes in the life course

Tim Riffe

2 motivating observations:

1. sequence analysis of trajectories ending in death
2. matrix expression for average episode count

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1. sequence analysis of trajectories ending in death (**pattern detection**) (Y. Hu)
2. matrix expression for average episode count
(tenure statistics) (C. Dudel)

2 motivating questions:

1. would different patterns emerge if trajectories were aligned on moment of death rather than age?
2. what is the age pattern of average episode duration?

2 procedural solutions:

1. restructure wrt state transitions:
2. flexible episode recording:

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1. restructure wrt state transitions: alignment
2. flexible episode recording: clocking

An illustration

- Take transition matrix from Dudel & Myrsklä (2017).
- Simulate 10k trajectories using `rmarkovchain()` in `markovchain` package (Spedicato, 2017).
- Demonstrate concepts of **alignment** and **clocks**
- Generate (stationary) novel macro patterns

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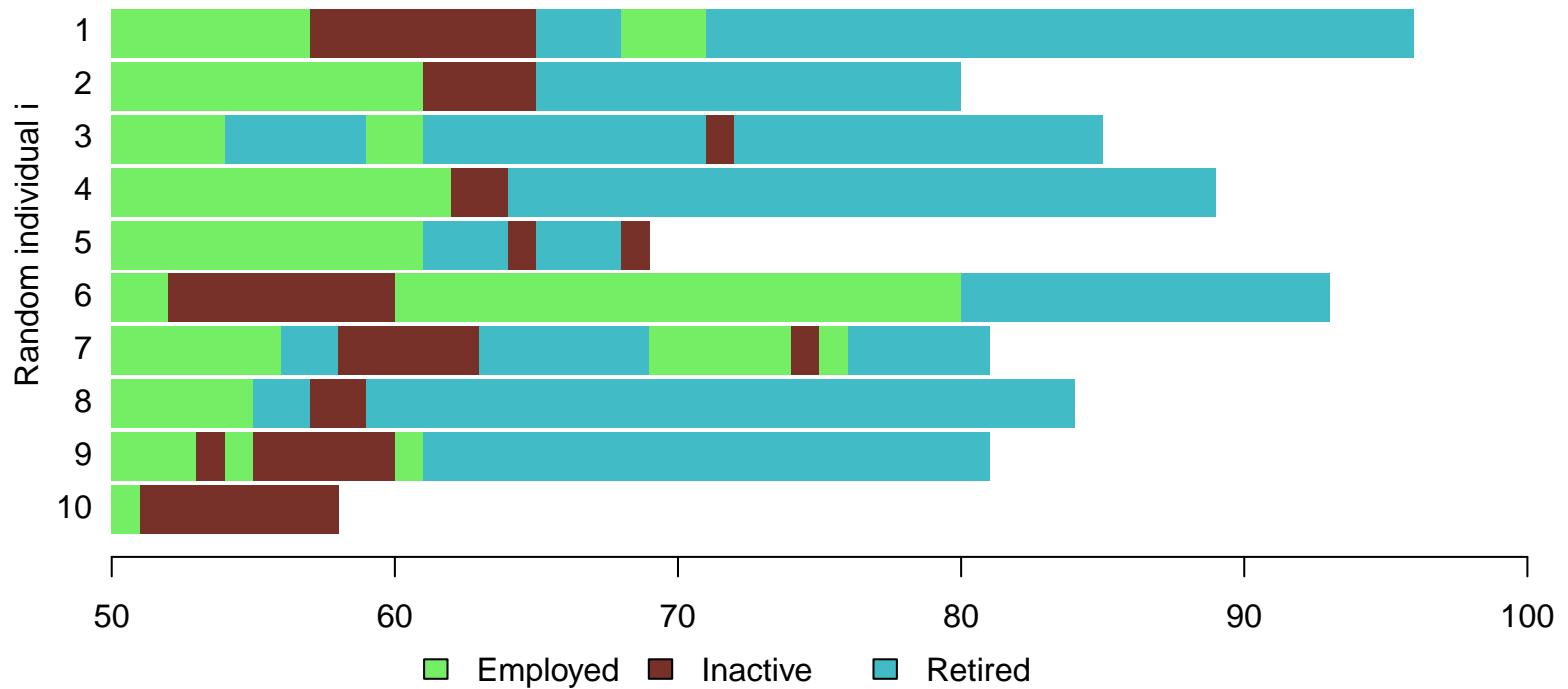
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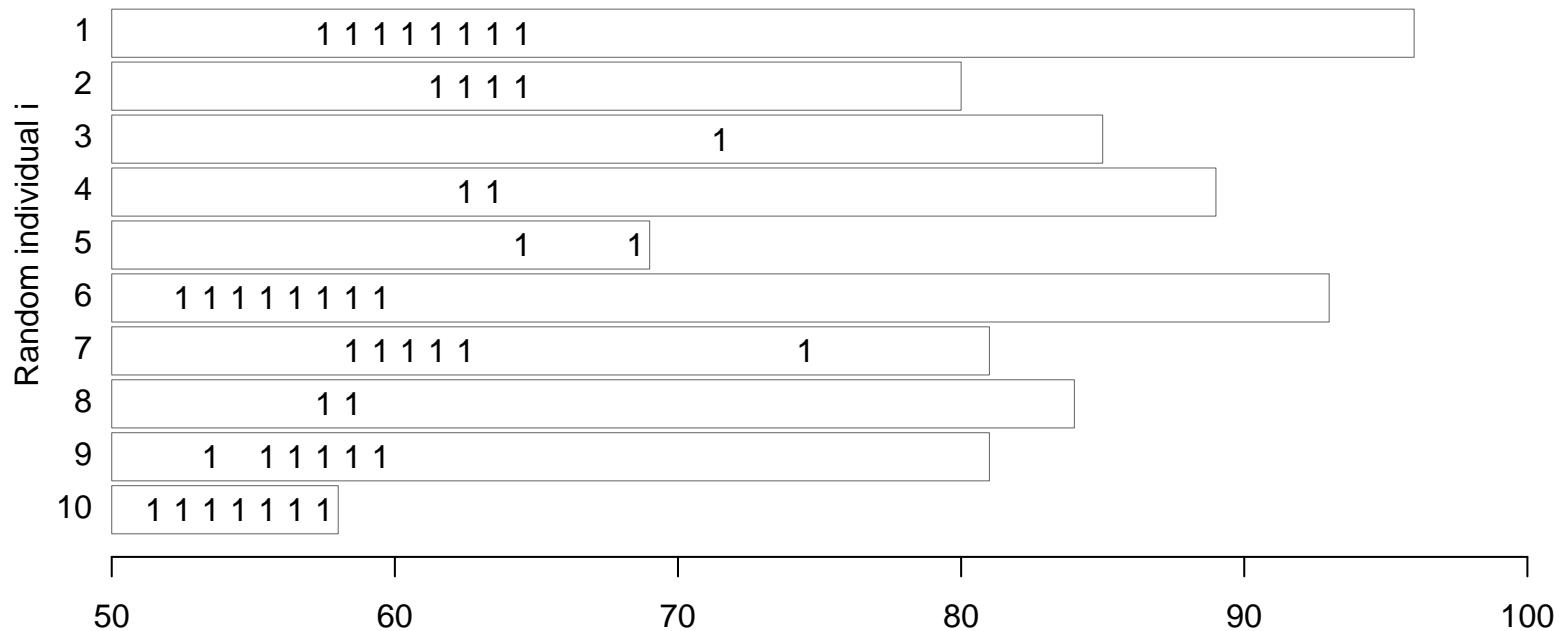
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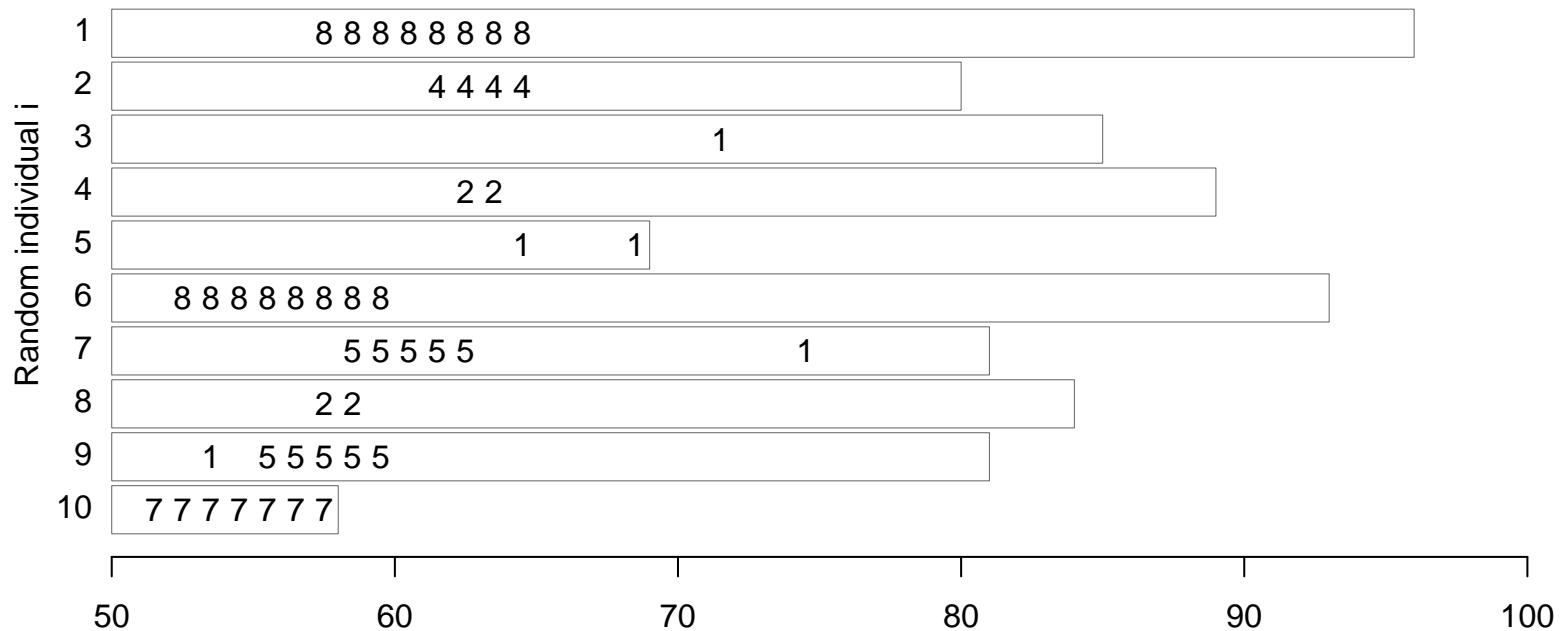
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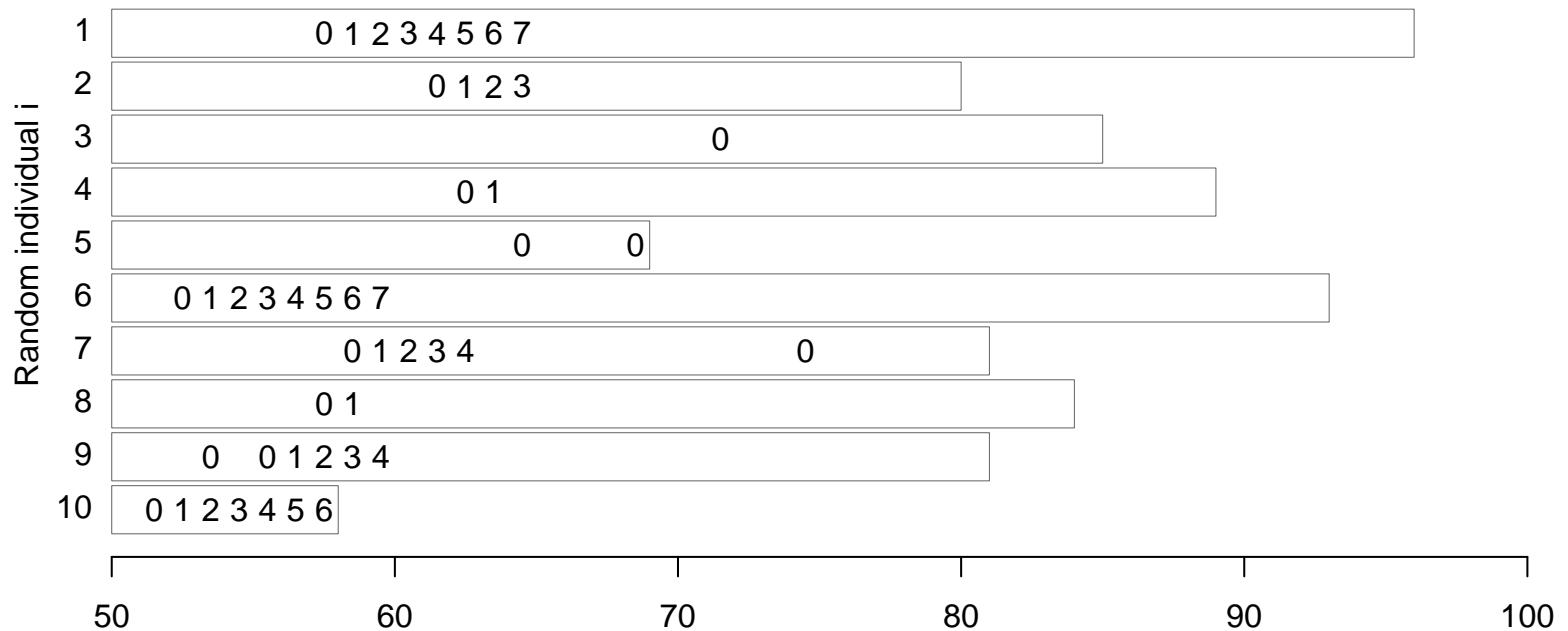
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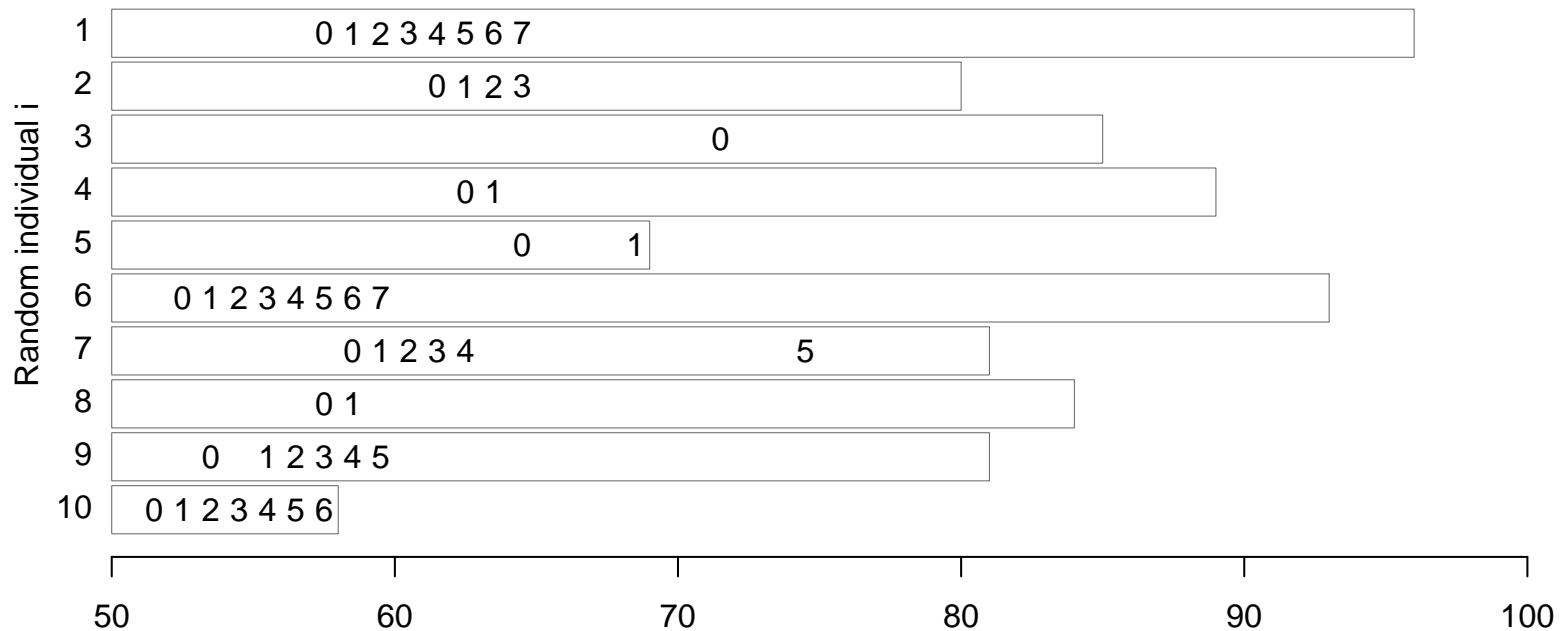
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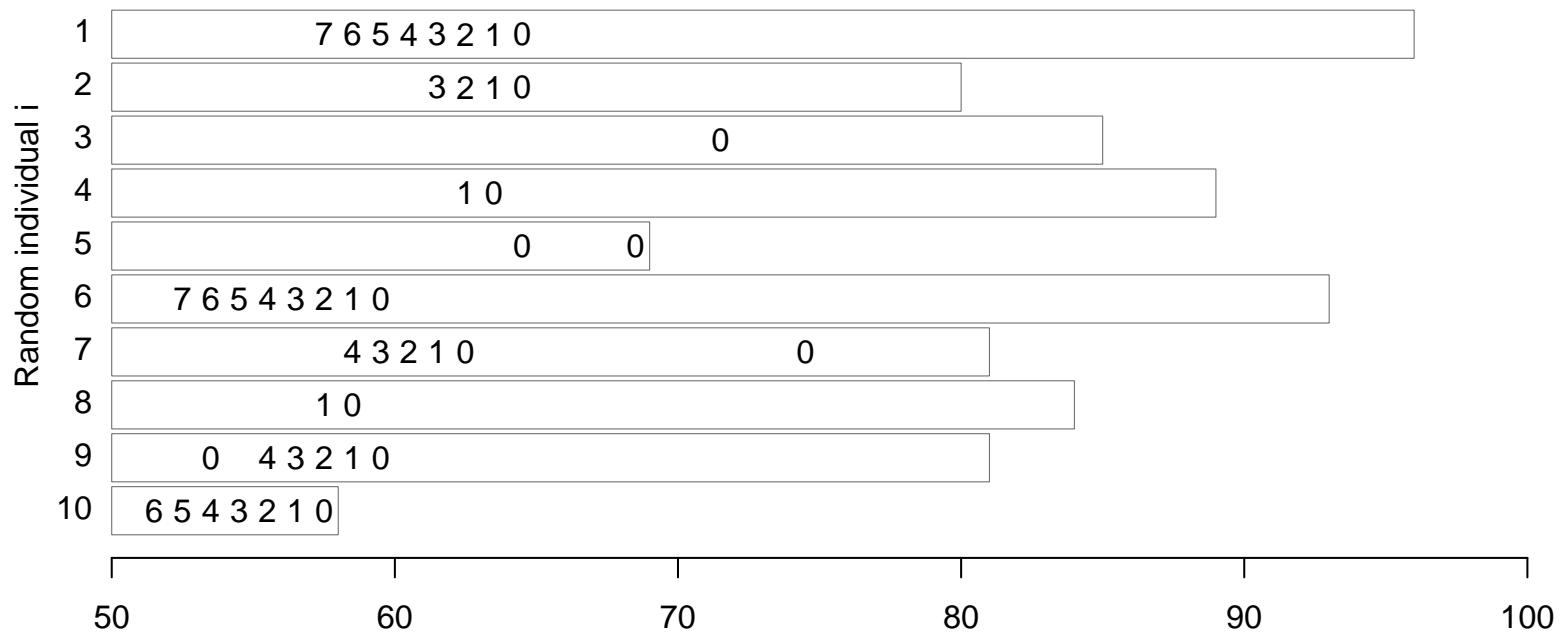
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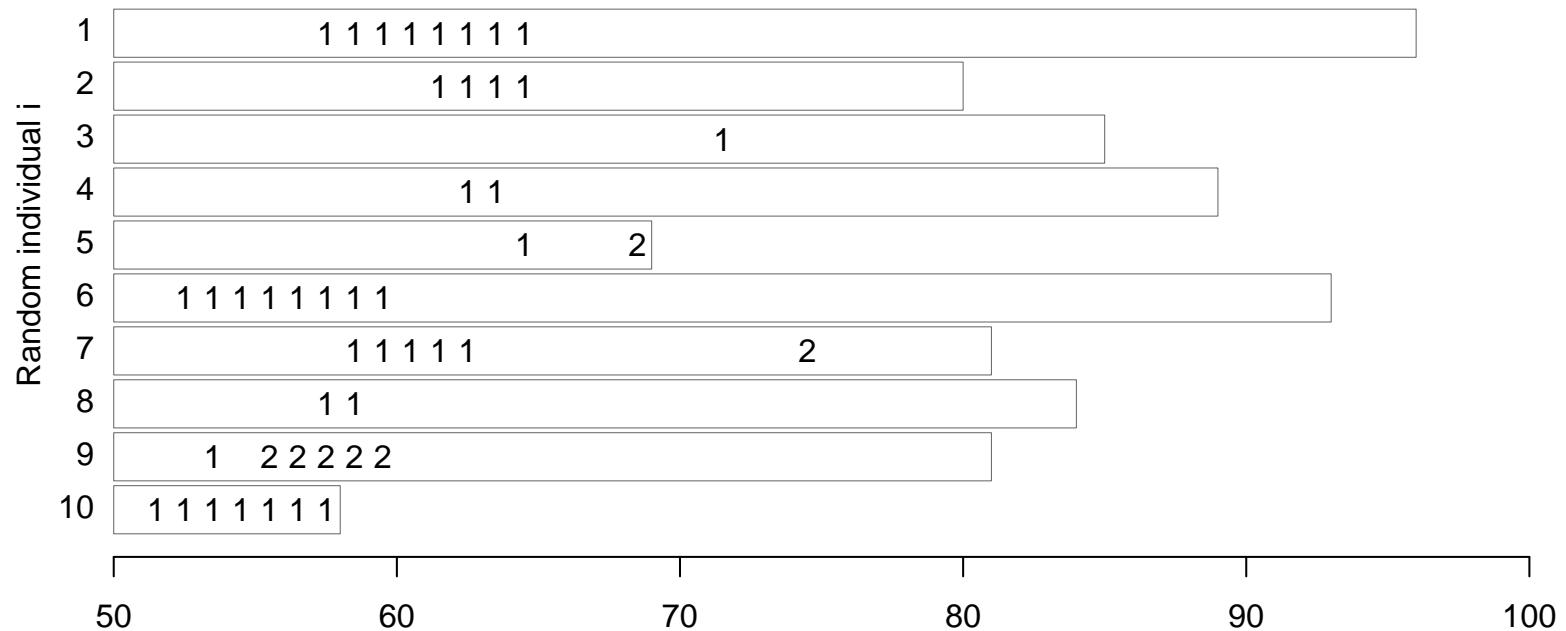
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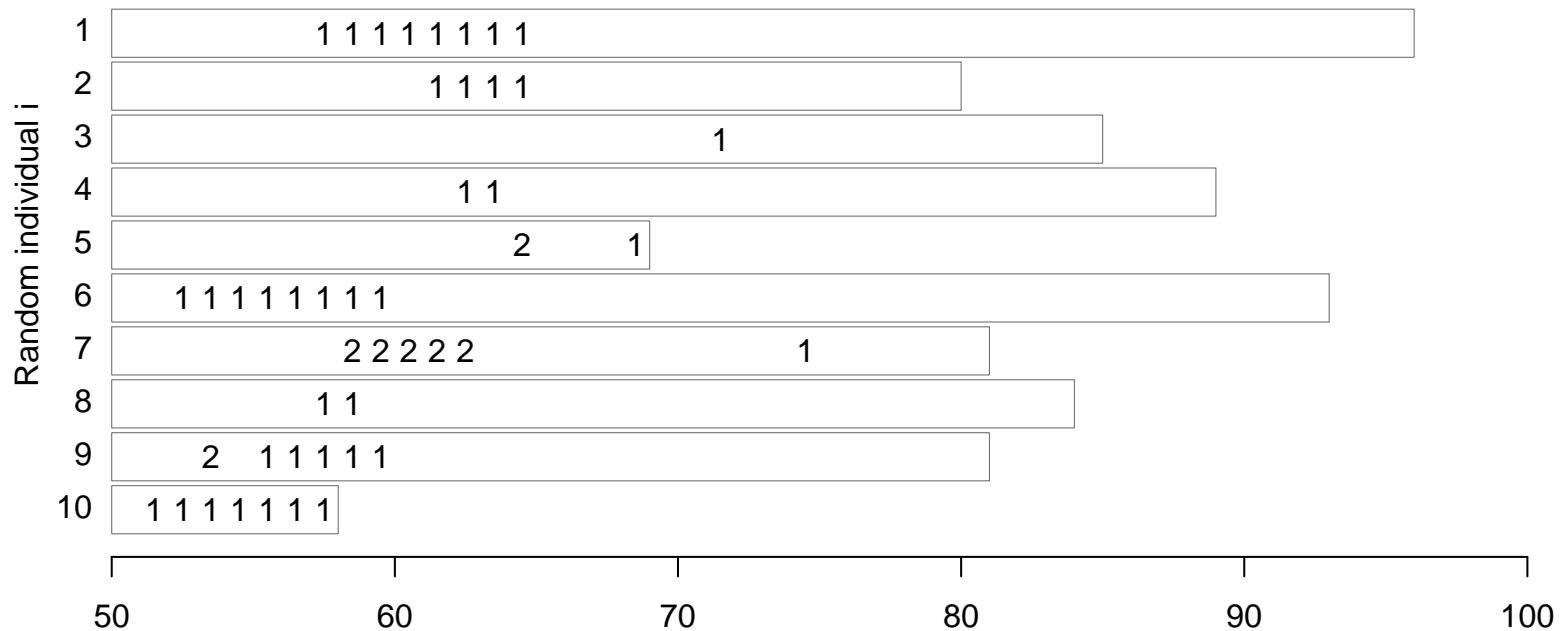
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Measures of scaling or total durations in episodes or cumulatively over episodes; Also measures of episode order, or even simply prevalence as a simple case.

Values that get averaged *with respect to some structure*.

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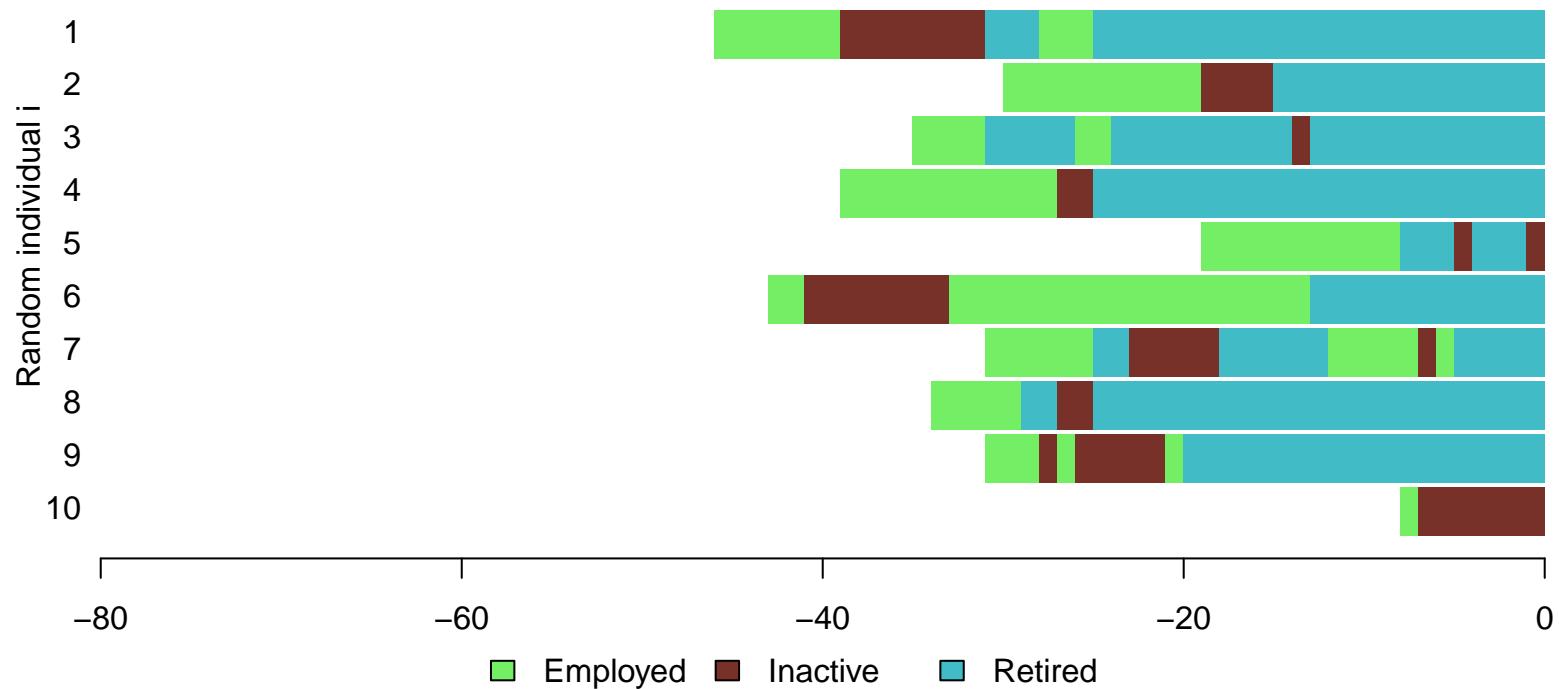
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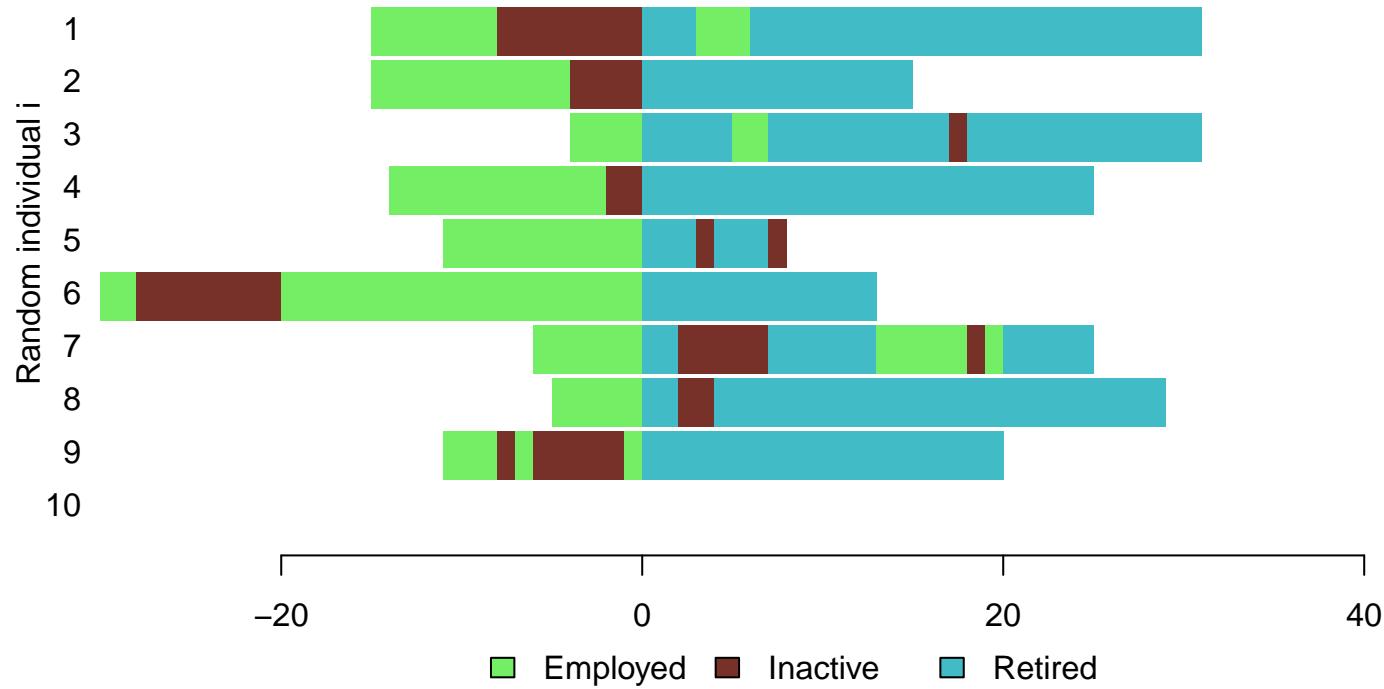
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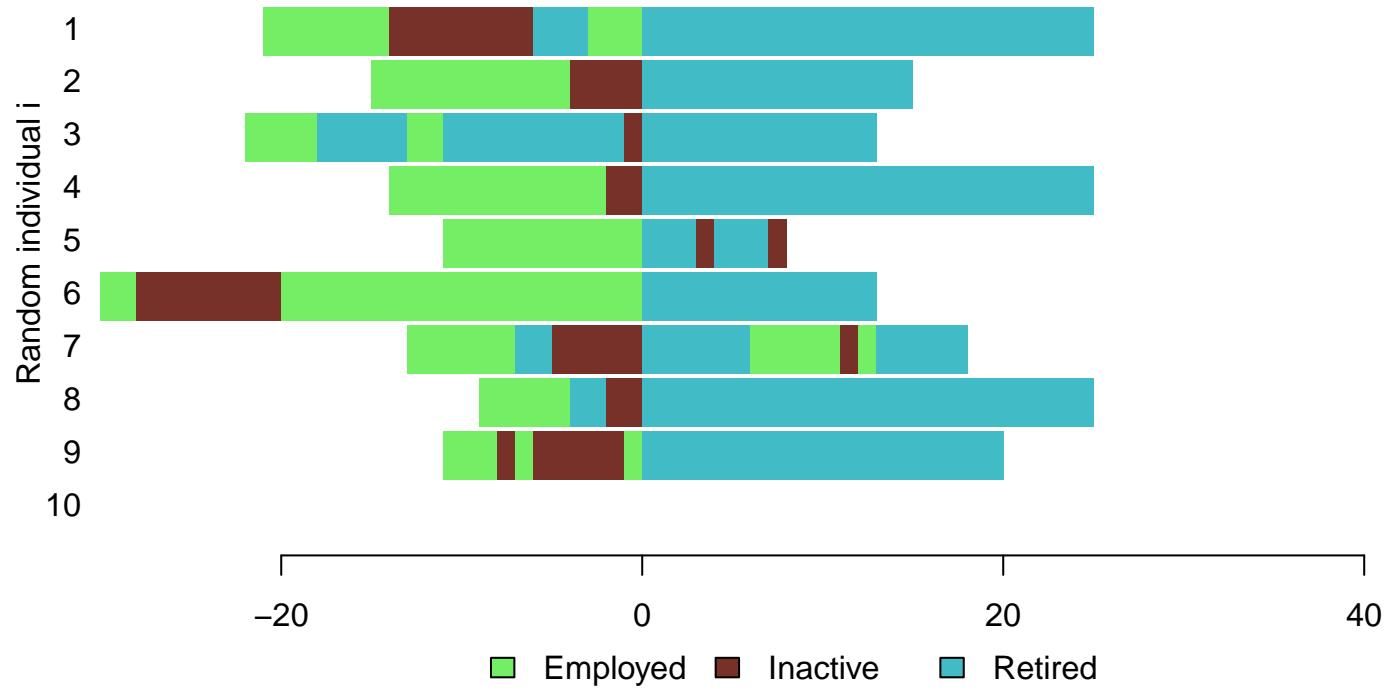
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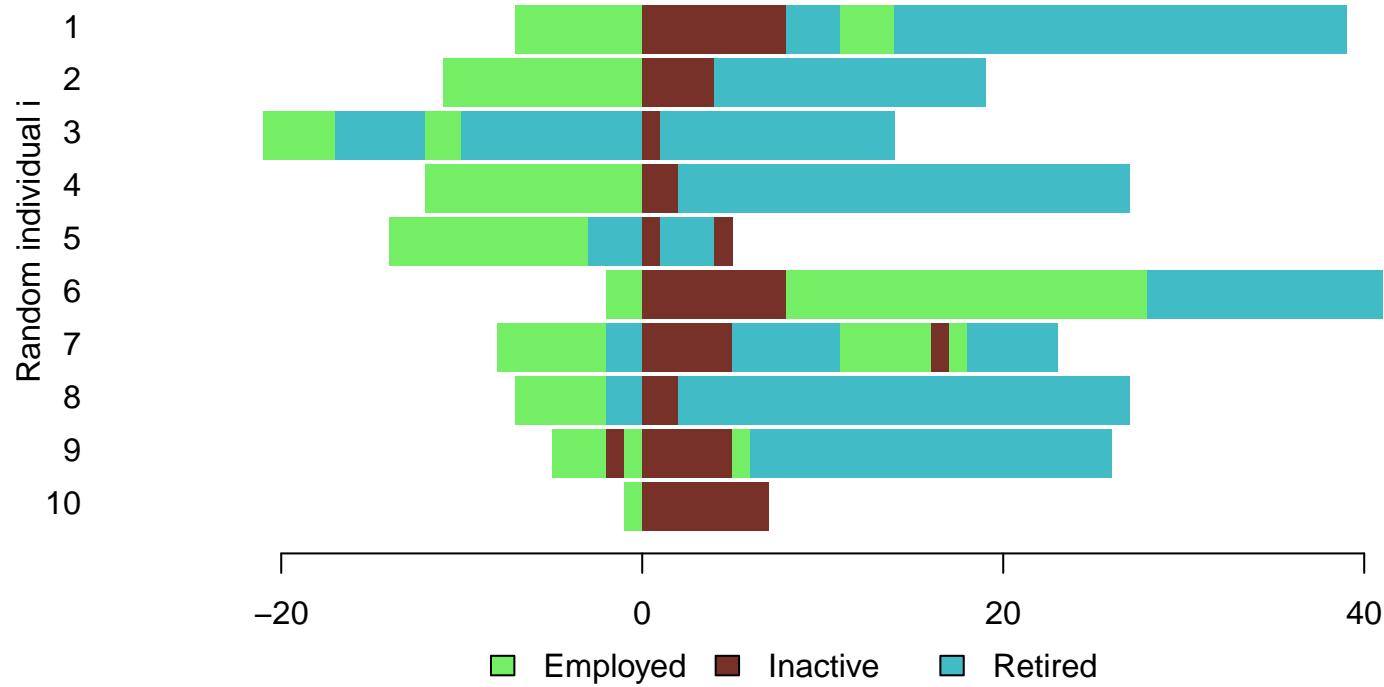
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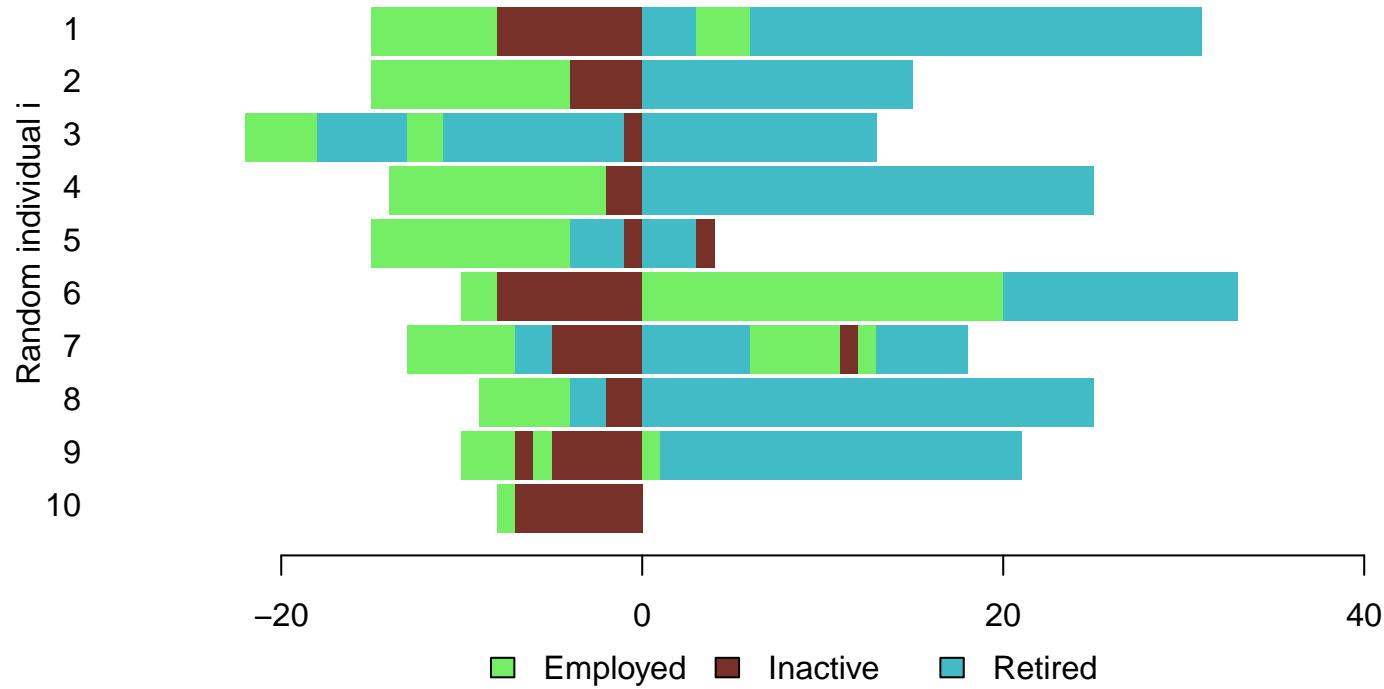
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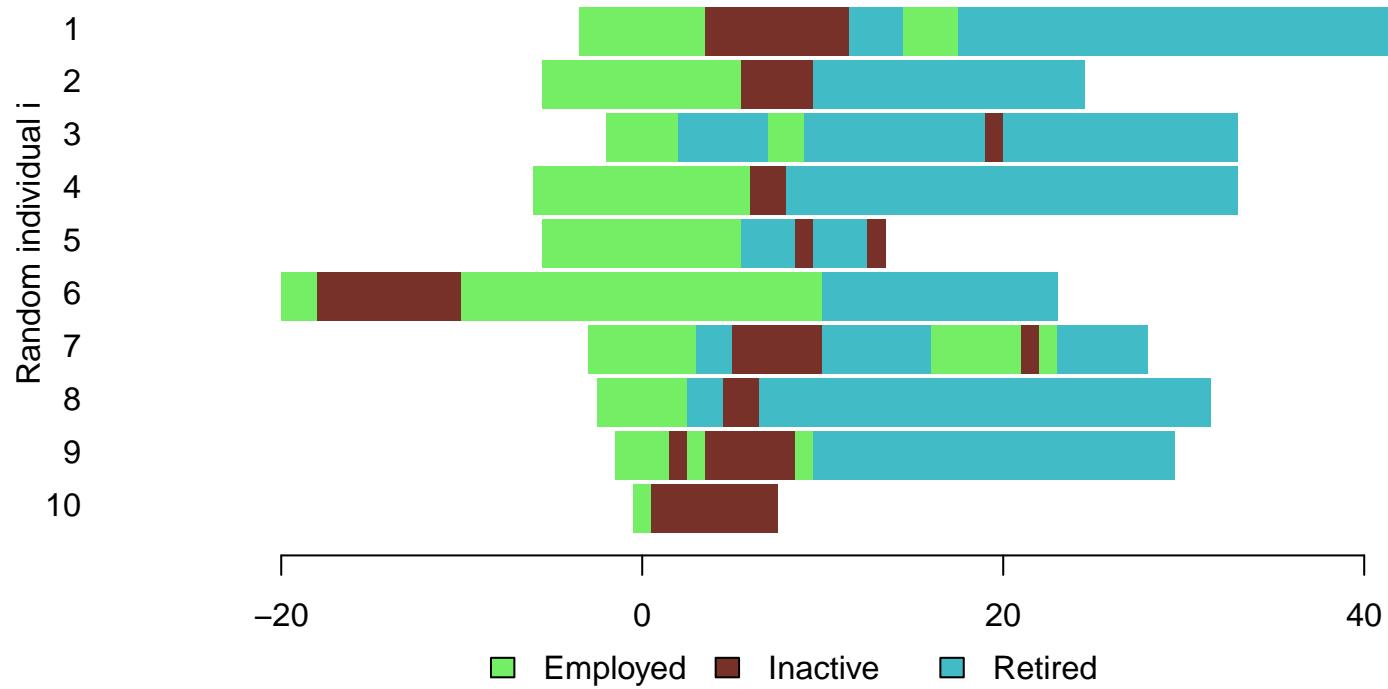
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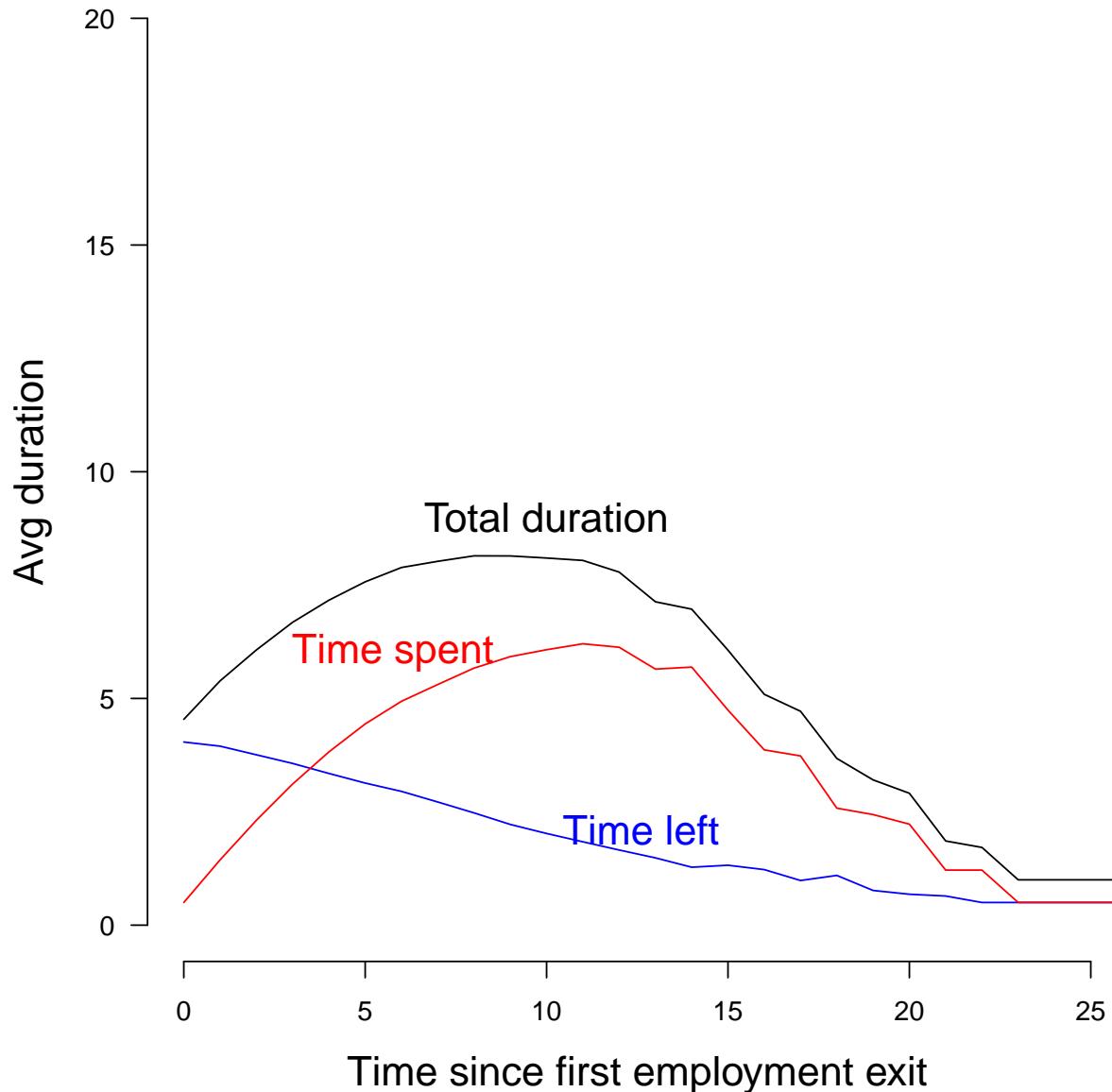
Alignment

Shift trajectories to match on a state entry (left) or exit (right) event. The reference event is selected based on a criteria (first, last, longest episode).

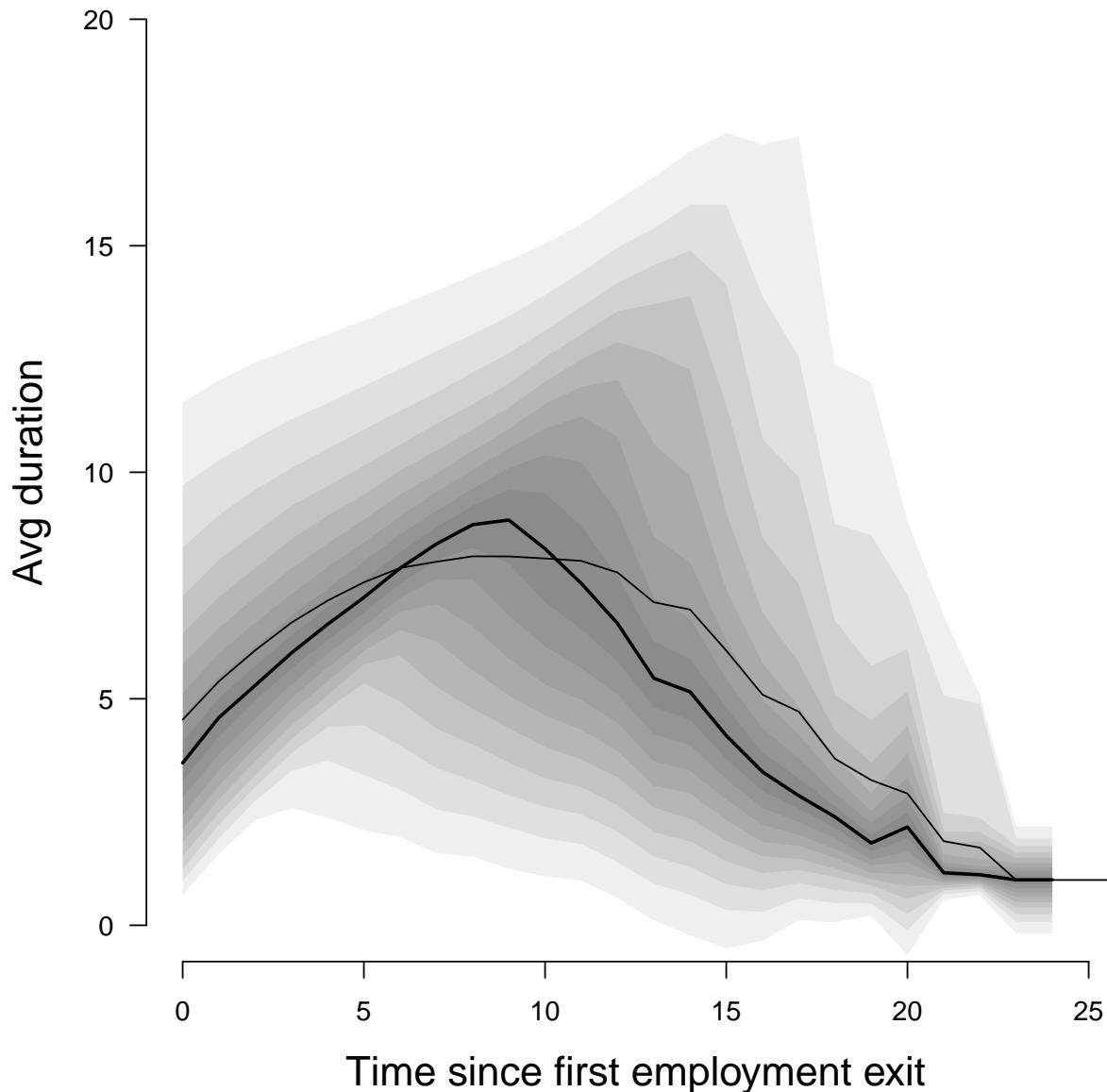
Macro patterns

Macro patterns can be derived by aggregating (e.g. means) over clock measures by some structure defined by an alignment operation. Clocking and alignment do not need to be with respect to the same state.

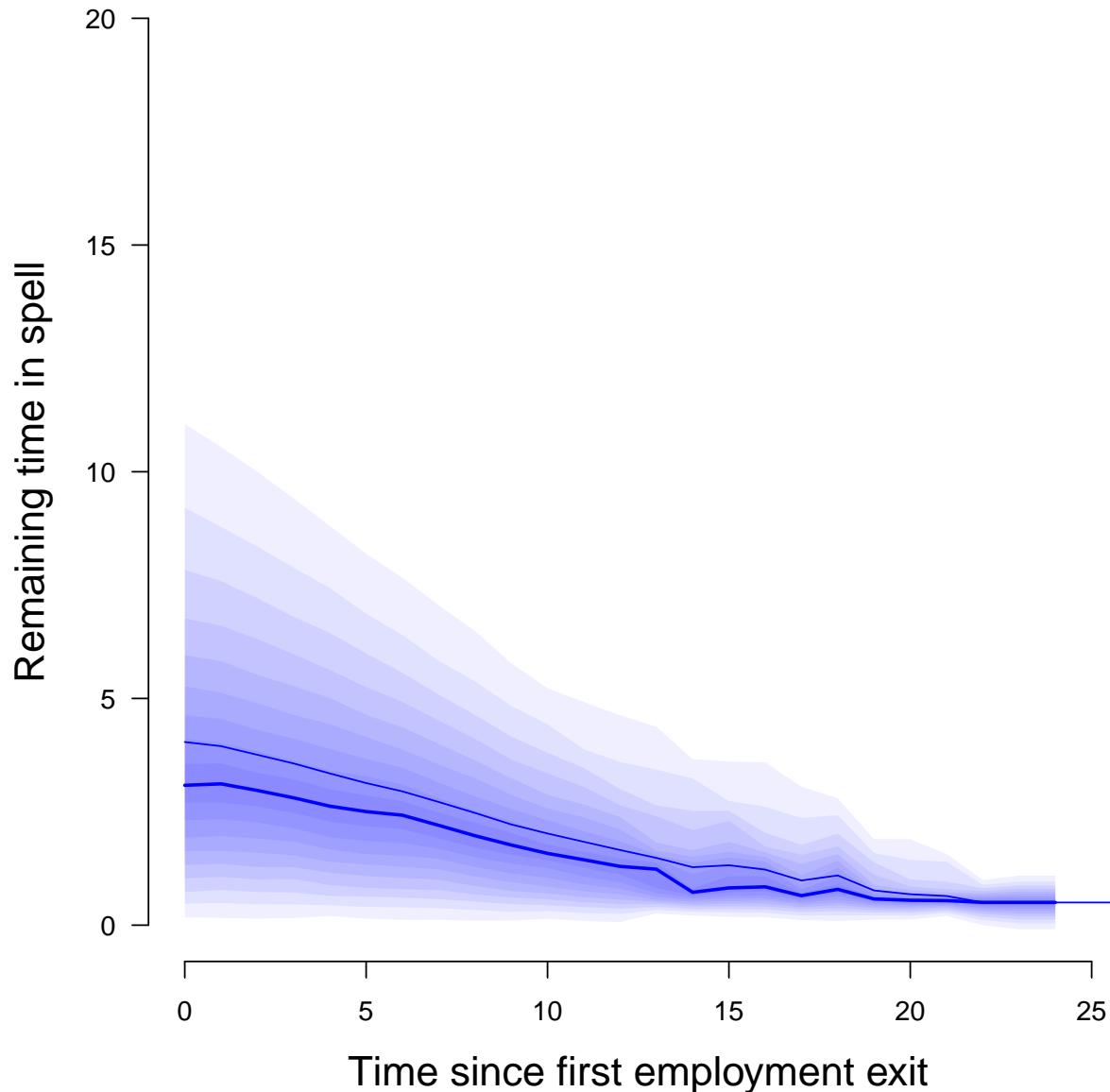
Inactivity clocks aligned on exit from first retirement



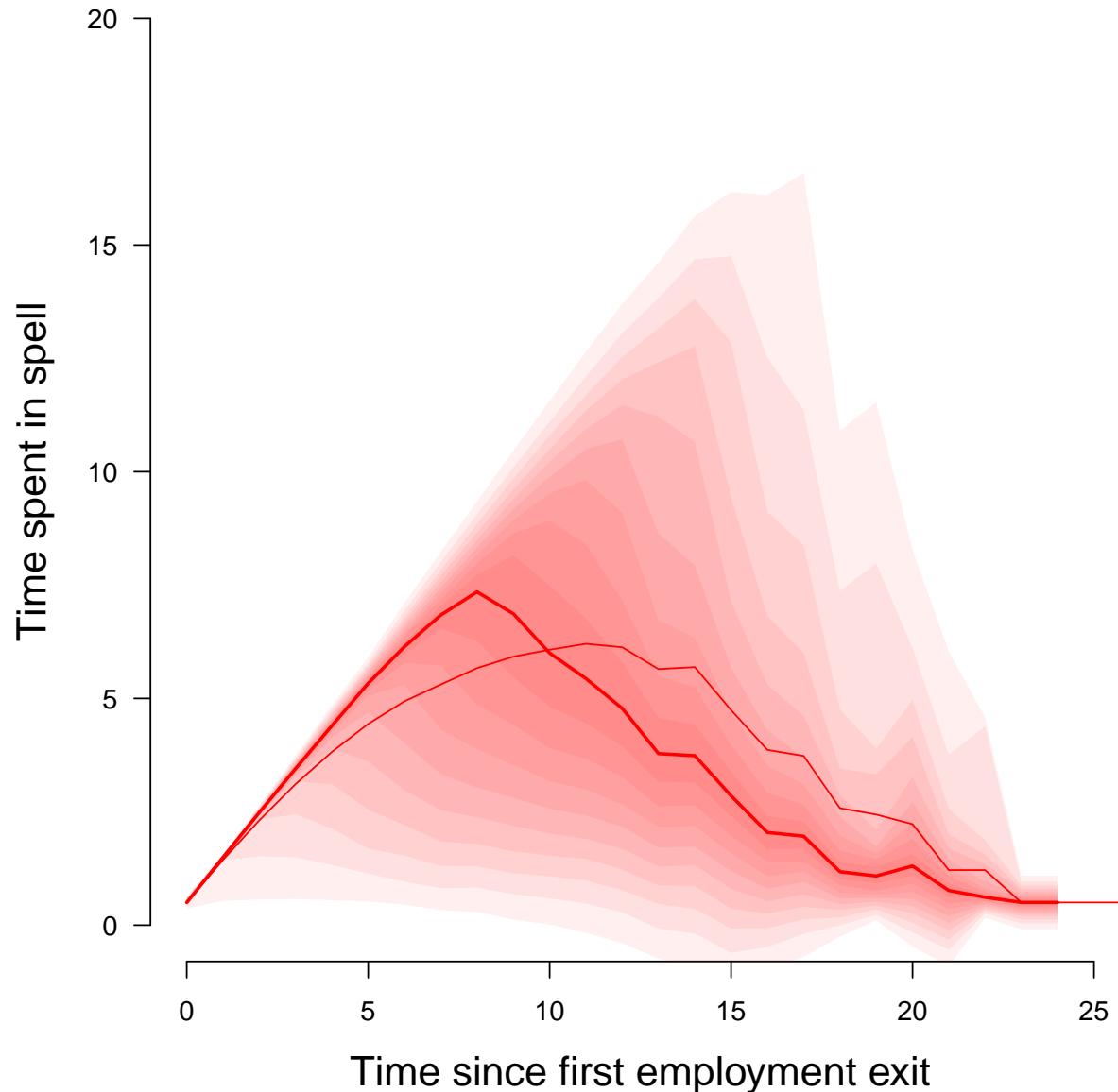
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How many macro patterns from the same data?

- **s** states
- **a** possible alignments (entry, exit, center, *justified*, ...)
- **e** possible episode choices (first, last, longest episode, ...)
- **c** possible clock types (up, down, total, order, *fractional*, *relative*, ...)
- **s × a × e × c = p** possible clock/structure combinations from which to derive macro patterns.

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Why again?

- Preprocessing steps for sequence analyses
- Pattern detection in general
- More completely characterize demographic phenomena
- Expand set of possible tenure statistics

Thanks!

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