Clustering Discrete State Trajectories of Varying Lengths: Health Care Utilization Patterns

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#### Thank you to my collaborators



## Health care utilization trajectories



Can we use clustering to **discover** and **illustrate** variation in experiences?



Source: Schuler et al (2017) Health Affairs. doi: 10.1377/hlthaff.2017.0448

#### Feature extraction + LCA



# Latent class analysis

For response pattern  $\mathbf{y}$  and class  $c_k$ 

$$\Pr(\mathbf{Y} = \mathbf{y}) = \sum_{k=1}^{K} \Pr(C = c_k) \prod_{j=1}^{J} \Pr(Y_j = y_j | C = c_k)$$

The class indicators are missing data.

#### Four distinct classes



Source: Schuler et al (2017) Health Affairs. doi: 10.1377/hlthaff.2017.0448



### Classes have distinct trajectories

Source: Schuler et al (2017) Health Affairs. doi: 10.1377/hlthaff.2017.0448

#### Remaining methods gaps



Distance is a weighted combination of

- 1. moving average of discordant days and
- 2. length difference

$$d(\mathbf{a}, \mathbf{b}) = w \frac{1}{K} \sum_{k=1}^{K} \frac{\sum |s(a_t| t \in (k, k+\tau)) - s(b_t| t \in (k, k+\tau))|}{2\tau} + (1-w) \frac{|l(\mathbf{a}) - l(\mathbf{b})|}{\max\{l(\mathbf{a}), l(\mathbf{b})\}}$$

 $s(a_t | t \in (k, k + \tau))$ Vector number of "days" in each<br/>state during time window of width  $\tau$  $\tau, w$ Bandwidth and weight tuning<br/>parameters



 Standardized time
 Original time



### Conclusions

- Clustering can show variation in longitudinal data
- Feature extraction enables use of LCA clustering
- Custom distance measure enables other clustering methods

