Two countries, twenty models and one secret weapon

CANCELLED!

Comparing change over time in convictions trajectories between Scotland and Queensland

Ben Matthews, University of Edinburgh | Edinburgh Q-step Seminar Series | 25th March 2019

Two countries, lots of models and one secret weapon

Two applications of the “many models” workflow

Ben Matthews, University of Edinburgh | Edinburgh Q-step Seminar Series | 25th March 2019

Overview

- The many models workflow
- Why do this to yourself?
    - The secret weapon
        - Change over time in criminal careers
        - One latent class growth model per cohort
    - Visualizing uncertainty
        - How many latent classes?
        - One latent class growth model per bootstrap
- What have we learned?

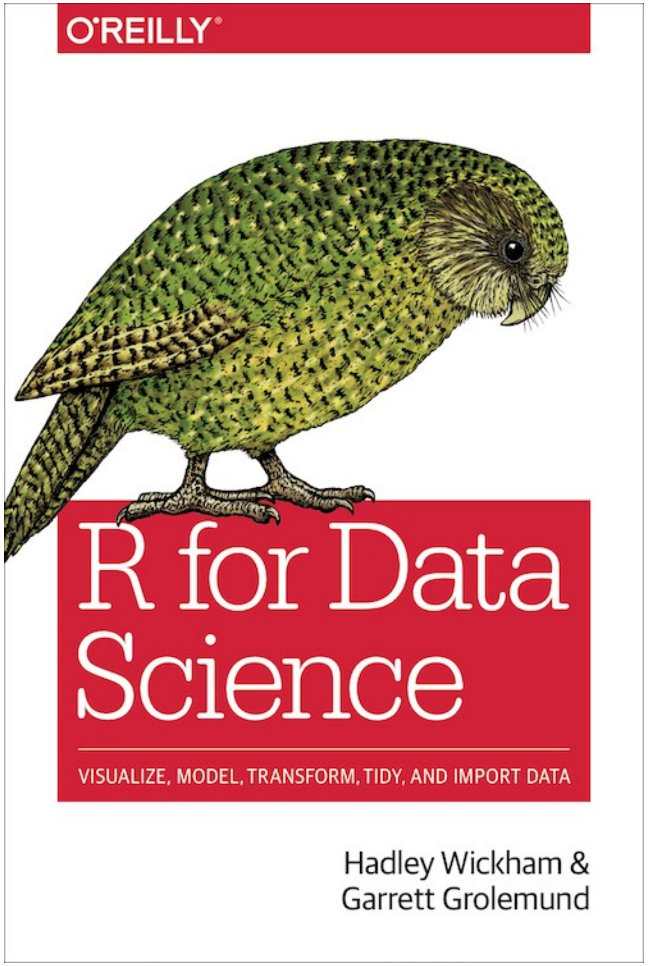
Not going to cover

- How latent class growth models work
- Too much detail on the data sources used
- What the results mean substantively
- Too much on how you would implement this workflow (but see example R code at https://github.com/benmatthewsed/qstep-march-2019)

Many models

Many models

```
1. Use many simple models
   to better understand
   complex datasets.
2. Use list-columns to
   store arbitrary data
   structures in a data
   frame.
3. Turn models into tidy
   data so you can work
   with model results like
   any other dataset.
```



https://r4ds.had.co.nz/many-models.html

List-columns?

- “Arbitrary data” can include, well anything!
- A dataset, a model call, model results…

```
# A tibble: 18 x 4
   birth_year data                   mplus_command    k_2
        <int> <list>                 <list>           <list>
 1       1973 <tibble [1,114 x 12]> <S3: mplusObject> <S3: mplusObject>
 2       1974 <tibble [1,102 x 12]> <S3: mplusObject> <S3: mplusObject>
 3       1975 <tibble [1,072 x 12]> <S3: mplusObject> <S3: mplusObject>
...
18       1990 <tibble [770 x 12]>   <S3: mplusObject> <S3: mplusObject>
```

List-columns and iteration

- For each one of a group of things do some thing to them
- For each birth year, fit a two class model to that cohort's data using the appropriate Mplus command

```
# A tibble: 18 x 4
   birth_year data                       mplus_command     k_2
        <int> <list>                     <list>            <list>
 1       1973 <tibble [1,114 x 12]> <S3: mplusObject> <S3: mplusObject>
 2       1974 <tibble [1,102 x 12]> <S3: mplusObject> <S3: mplusObject>
 3       1975 <tibble [1,072 x 12]> <S3: mplusObject> <S3: mplusObject>
...
18       1990 <tibble [770 x 12]>   <S3: mplusObject> <S3: mplusObject>
```

Iteration in R

- I used R's `purrr` package to iterate (there are other ways too)
- Lots of great resources to learn about iteration using `purrr`:
  - https://github.com/cwickham/purrr-tutorial/blob/master/slides.pdf
  - https://speakerdeck.com/jennybc/purrr-workshop
  - https://github.com/jenniferthompson/RLadiesIntroToPurrr

Why do this to yourself?

“The Secret Weapon”

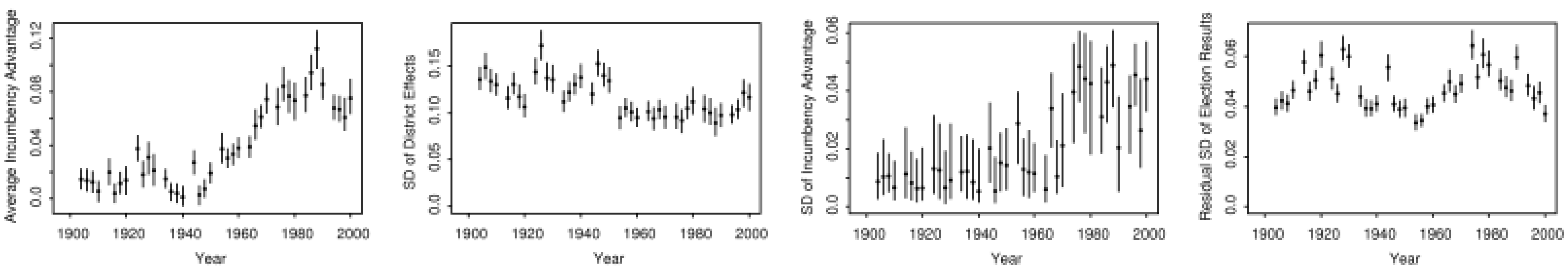
Statistical Modeling, Causal Inference, and Social Science

The secret weapon

Posted by Andrew on 7 March 2005, 12:52 am

An incredibly useful method is to fit a statistical model repeatedly on several different datasets and then display all these estimates together. For example, running a regression on data on each of 50 states (see here as discussed here), or running a regression on data for several years and plotting the estimated coefficients over time.

Here's another example:

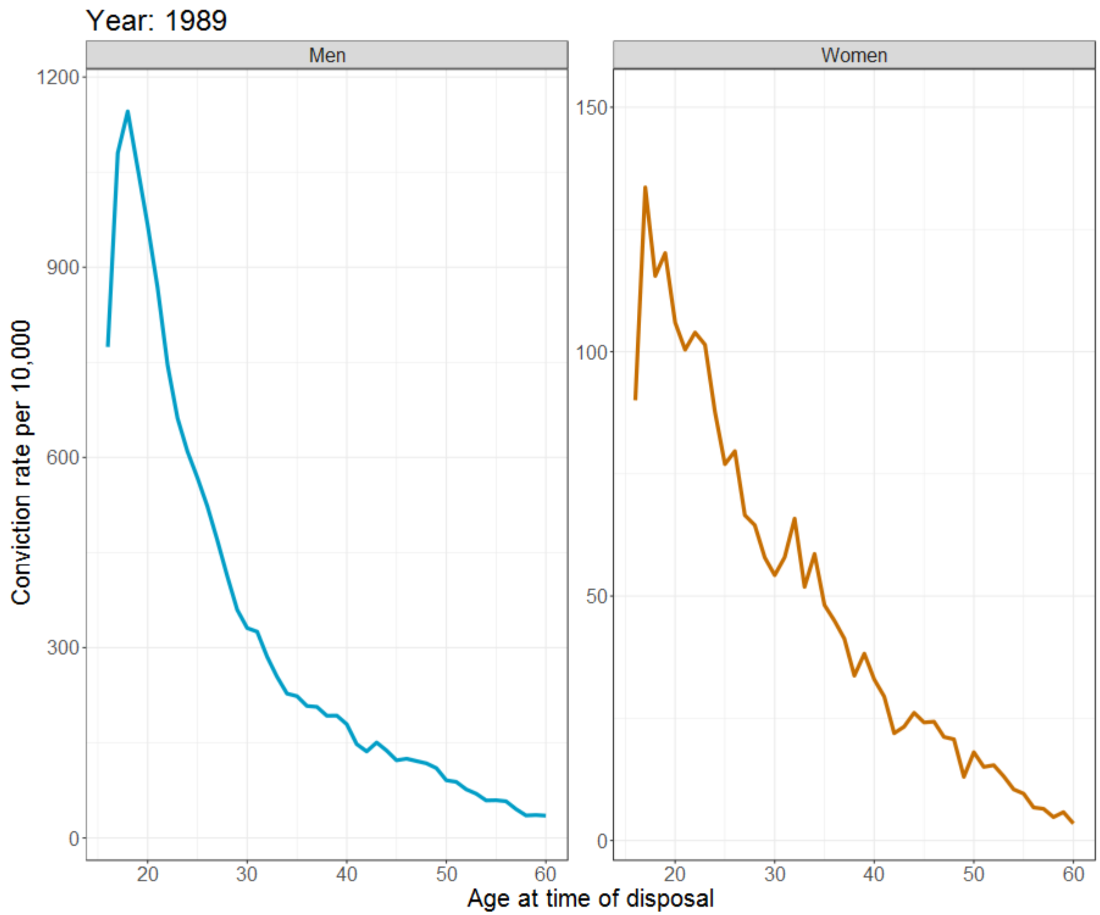


The idea is to fit a separate model for each year, or whatever, and then to look at all these estimates together to see trends. This can be considered as an approximation to multilevel modeling, with the partial pooling done by eye on the graphs rather than using a full statistical model.

https://statmodeling.stat.columbia.edu/2005/03/07/the_secret_weap/

Changing Criminal Careers

- Well-established relationship between age and crime as far back as Quetelet in 1831
- Significant change in last 25 or so years in Scotland (Matthews and Minton 2018)
- Fit a model to successive cohorts in the Scottish Offenders Index and compare results!



Year: 1989
Men
Women
Conviction rate per 10,000
1200
900
600
300
0
150
100
50
0
20
30
40
50
60
Age at time of disposal

A core issue in the criminal careers debate is the shape of the age-crime curve at the level of the individual. Is it single peaked, as argued by Gottfredson and Hirschi, or age invariant, as argued by Blumstein and Cohen? The results reported in Table 4 support the Gottfredson and Hirschi position. The debate over the shape of the age-crime curve, however, neglects a possibility that fundamentally alters the nature of the phenomenon to be explained—individuals may not only consistently differ in their rate of offending at any given age but may also have distinctive trajectories of offending over age.

Nagin and Land (1993:346) *Age, Criminal Careers, and Population Heterogeneity: Specification and Estimation of a Nonparametric, Mixed Poisson Model*, Criminology, *Vol. 31, No. 3, pp. 327:362*

Identifying conviction trajectories

- Latent Class Growth Mixture Model (LCGM, Nagin and Land 1993), makes groups out of data based on a repeated measures dependent variable
- Each group gets a trajectory (in our case, probability of conviction in a given year)
- LCGMs are very popular (if divisive) in criminology (Nagin and Land 2005a, 2005b; Sampson and Laub 2005)

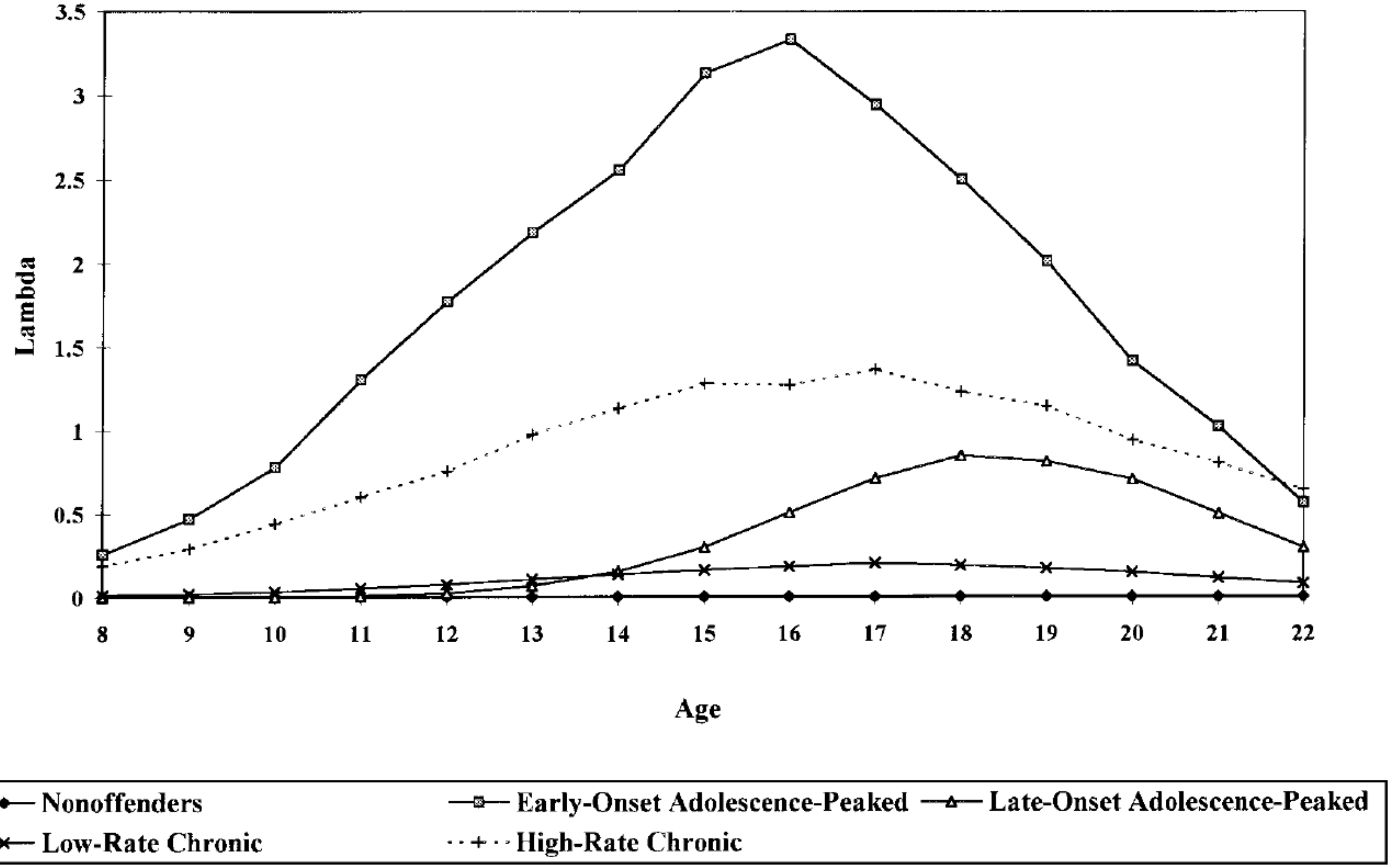
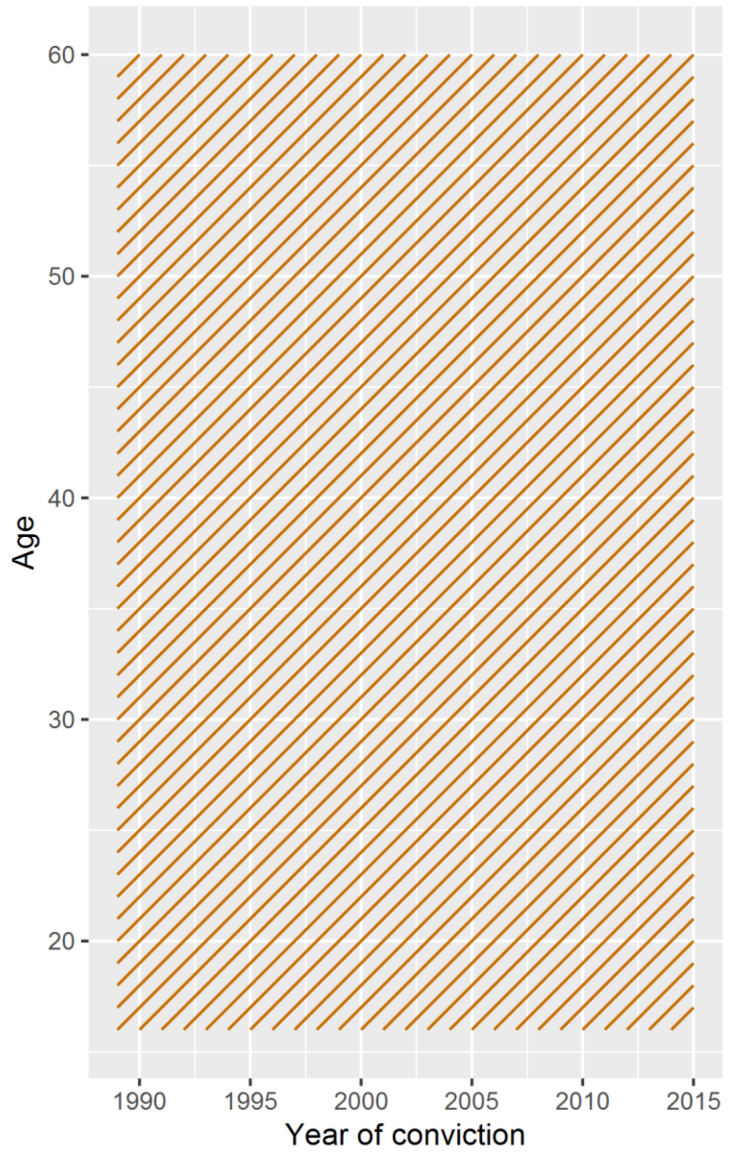


FIG. 5.—Predicted misdemeanor/felony rates by age for the Racine 1955 five-class model

D'Unger et al. (1998), *How Many Latent Classes of Delinquent/Criminal Careers? Results from Mixed Poisson Regression Analyses,* American Journal of Sociology, *Vol. 103, No. 6, pp. 1593-1630*

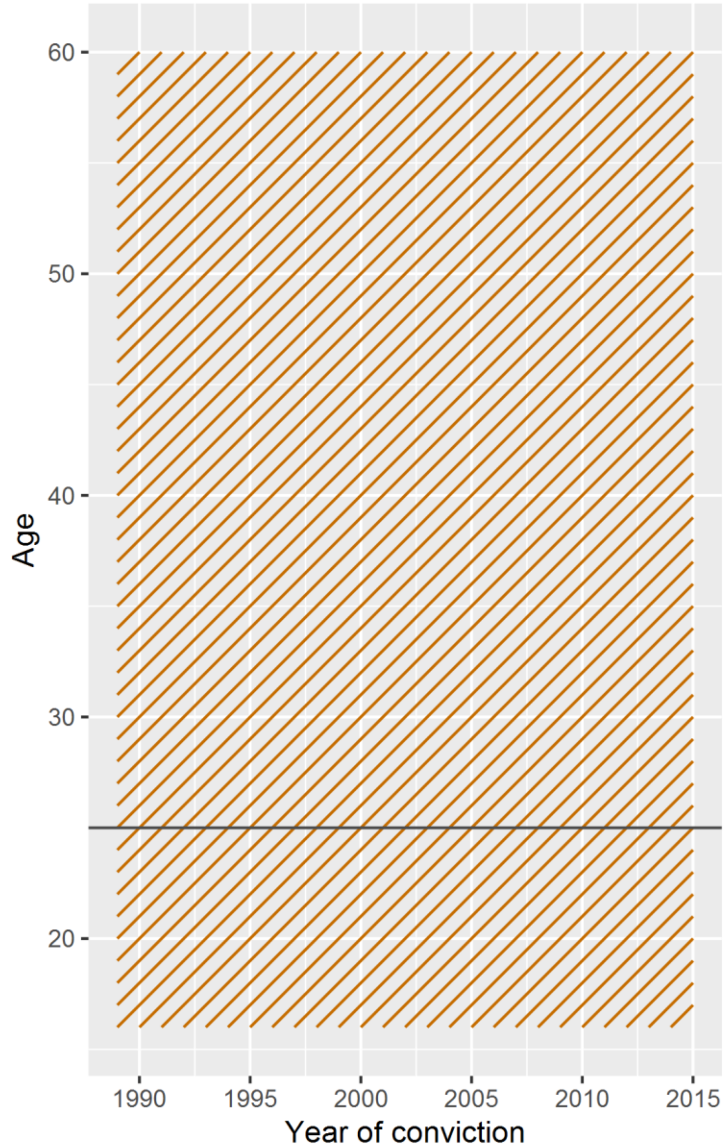
Many LCGMs

For each cohort,
fit LCGM



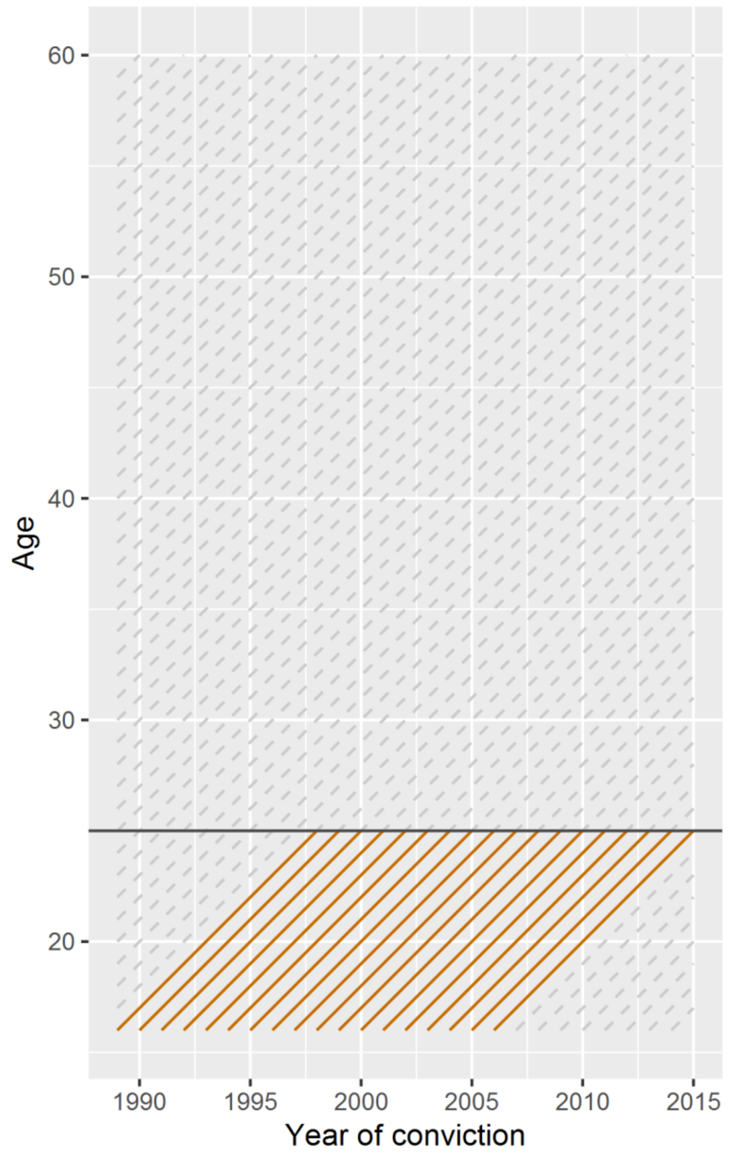
Many LCGMs

For each cohort,
fit LCGM



Many LCGMs

For each cohort,
fit LCGM



Modelling strategy

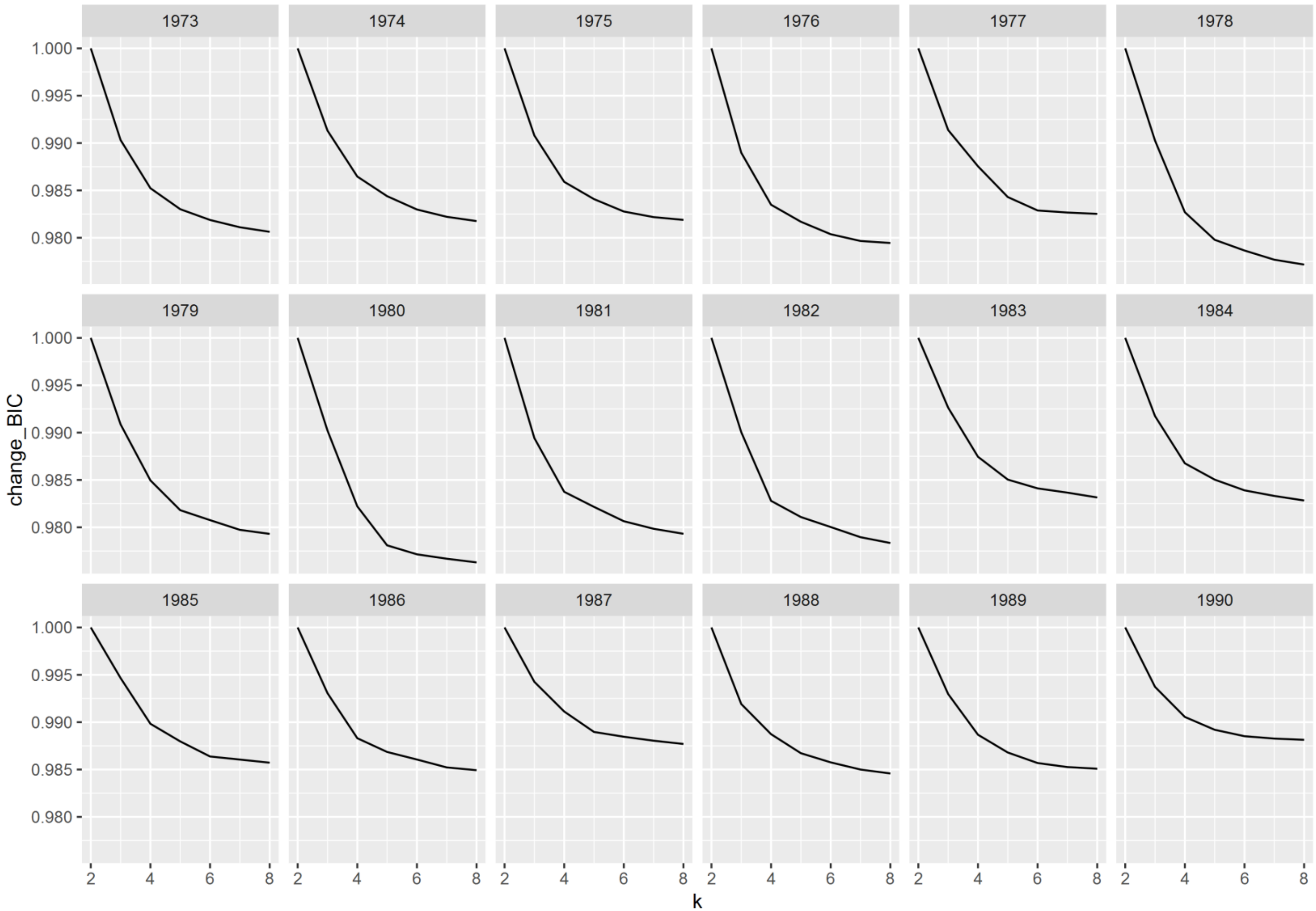
- Models fit in Mplus 8.2 using the MplusAutomation (Hallquist and Wiley 2018) R package to call Mplus, fit the models and then pull the results back into R
- This lets you use R’s standard iteration tools with Mplus
- Results here from a subset of data from Scottish Offenders Index

Parameters of interest

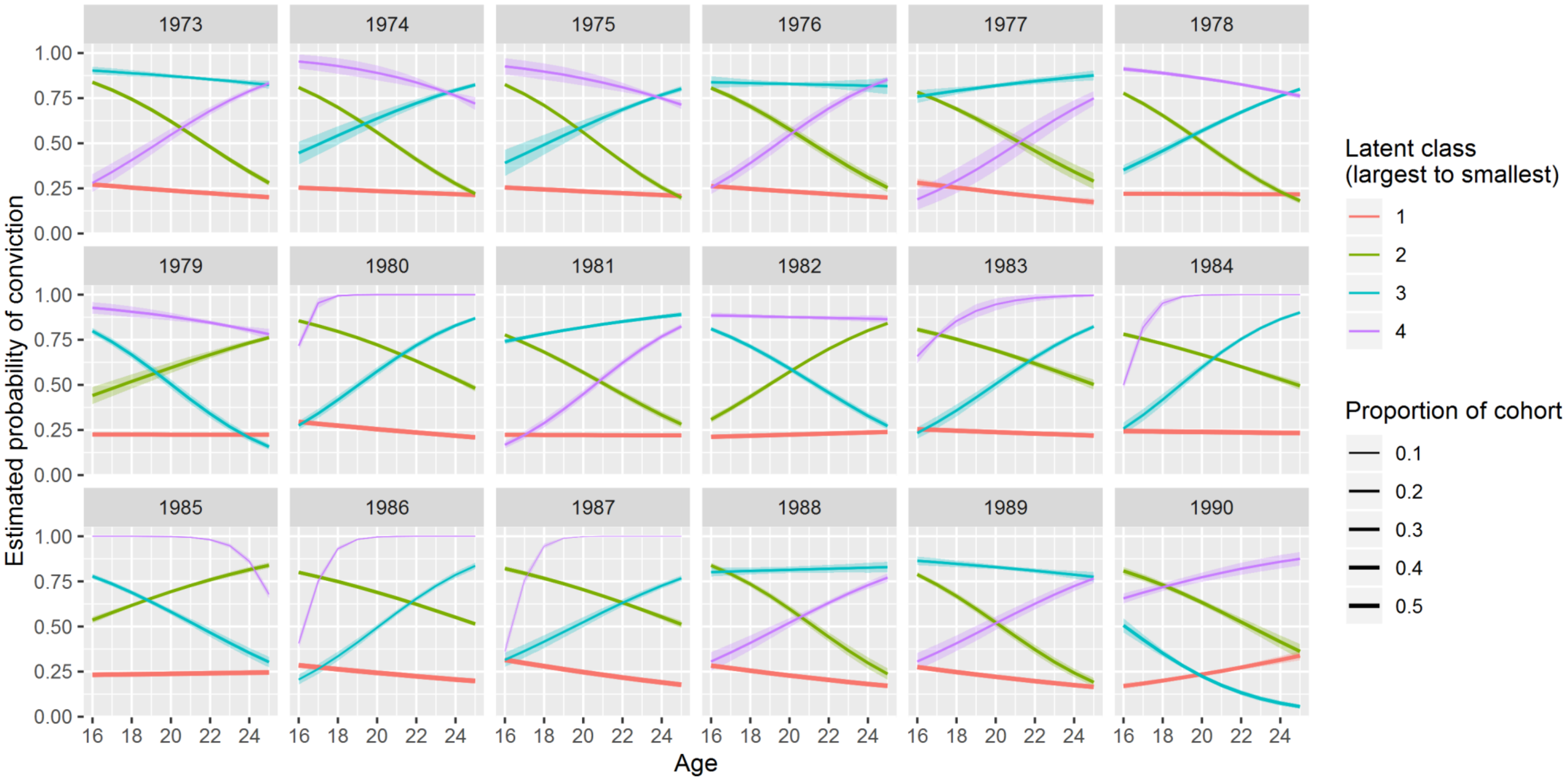
- Shape of trajectories
- Number of classes in “best” model
- Proportion of people assigned to each class

How many latent classes?

- Model selection process:
  1. AIC/BIC/aBIC
  2. (VLMR test)
  3. (BLRT test)
  4. Substantive interpretation
  5. Norris method (see Norris, 2009)
- More art than science?
- Tricky enough with one model!



Note: Analysis does not include the full SOI dataset and so should not be interpreted substantively



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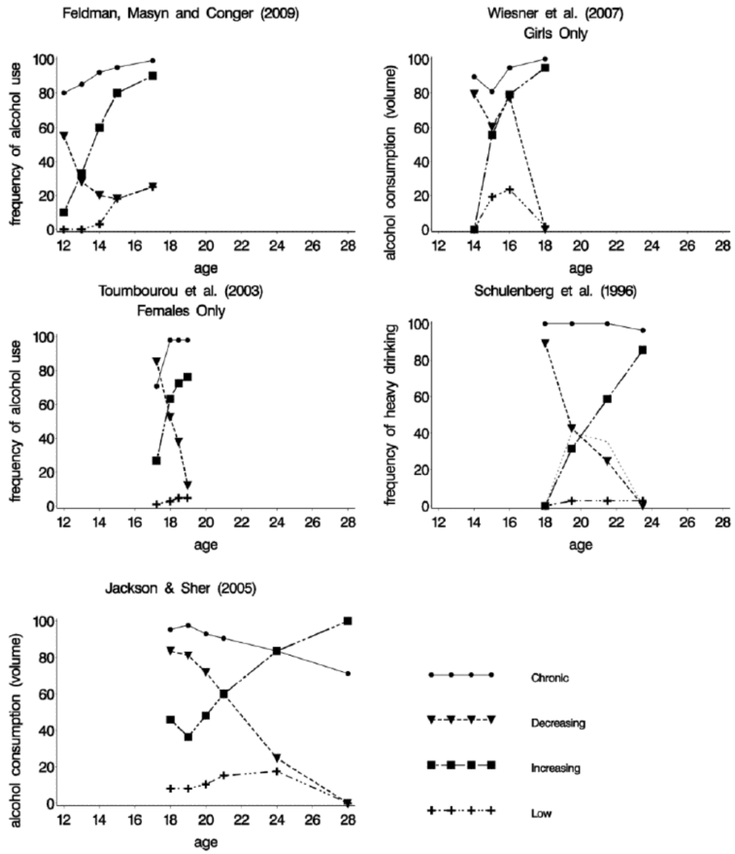


Figure 1.
Trajectories of various measures of alcohol involvement spanning ages 13-29 illustrating the "soldier's bed cat's cradle" phenomenon in five studies. All data have beeen scaled so that lowest reported value is a 0 and the highest reported value is 100 in each study.

Sher et al. (2011), *Alcohol Use Trajectories and the Ubiquitous Cat's Cradle: Cause for Concern?,* J Abnorm Psychol, *Vol. 120, No. 2, pp. 322-335*

Results

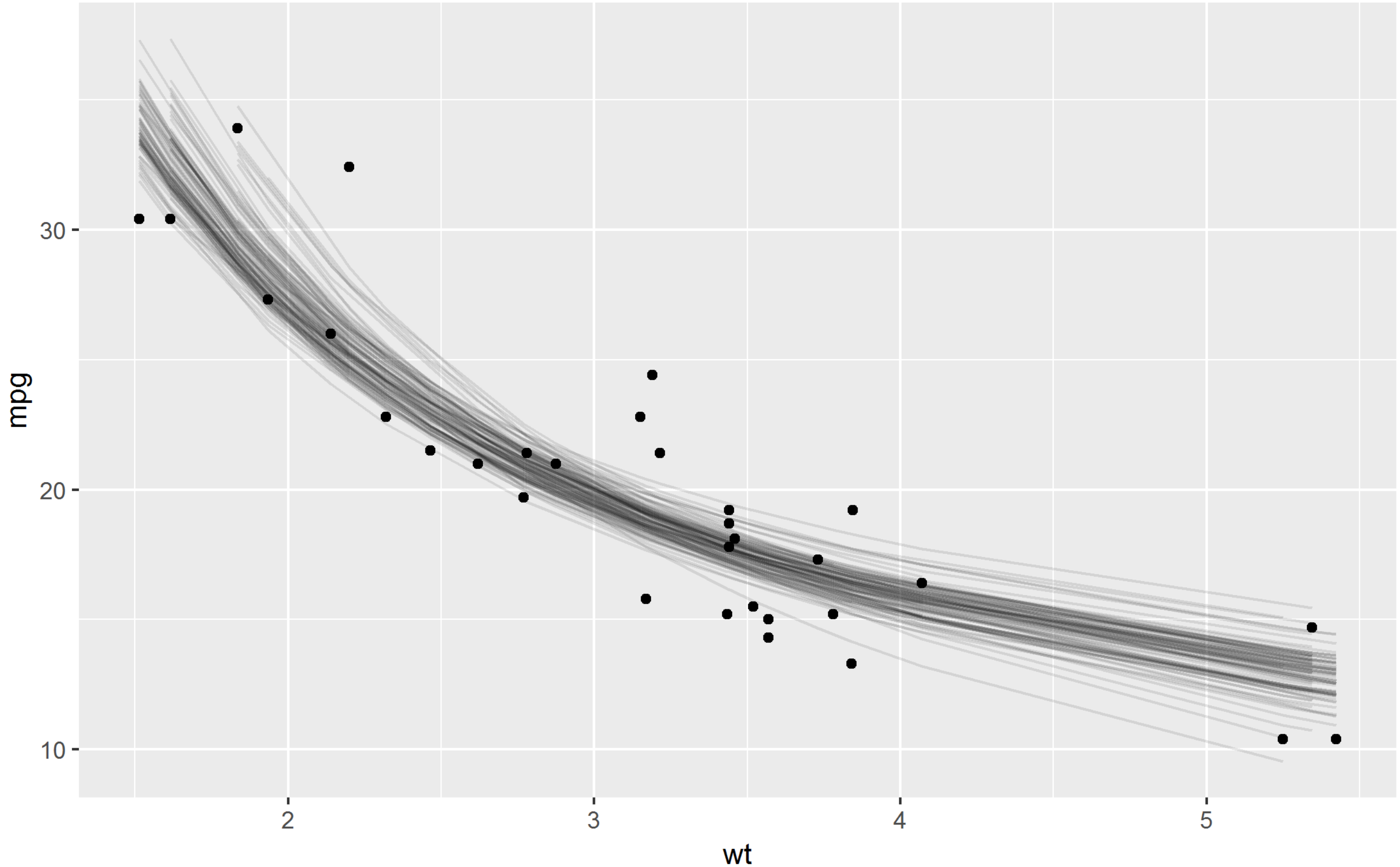
- Does look like there's *some* differences between cohorts in the trajectory shapes, but cat's cradle means it's hard to tell
- … but are these differences meaningful? Many models approach means we don't know statistically
- One model per cohort means class definitions change – can't really compare proportion assigned
- Are there different number of classes across cohorts? Selection is very subjective!

Visualizing uncertainty in LCGMs

“Point estimates should be accompanied by information on precision!!!”

- Vernon Gayle

Motivation 1: Lots of lines!



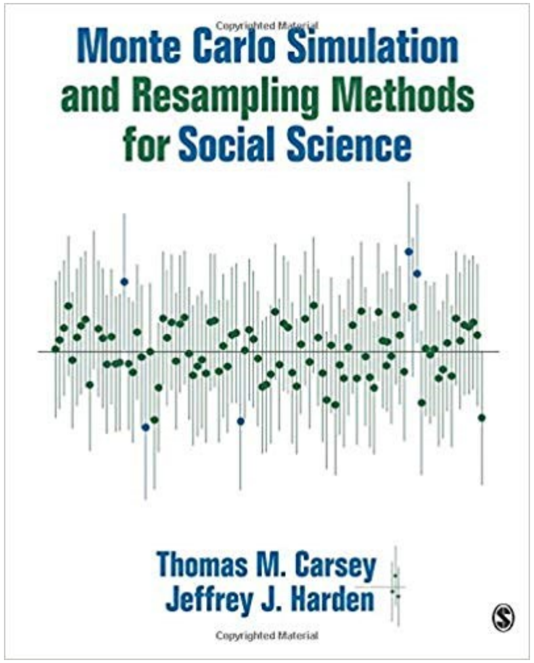
https://cran.r-project.org/web/packages/broom/vignettes/bootstrapping.html

Motivation 2: What do these latent groups **mean**?

- Direct (LCGM groups are real!) and indirect interpretations (LCGM groups are statistical shorthand!) (Bauer 2007:779)
- In some cases, aetiology of groups is theorized **after** they have been identified by LCGM (Krohn et al. 2013:194)
- Are we just chasing noise?

Many LCGMs (again)

- Sample with replacement 25 times from original dataset using `rsample` package
- For each bootstrap replication, fit LCGM
- Work with bootstrap replications as with any (nested/list-column) dataset
- See Carsey and Harden (2014) on bootstrapping methods



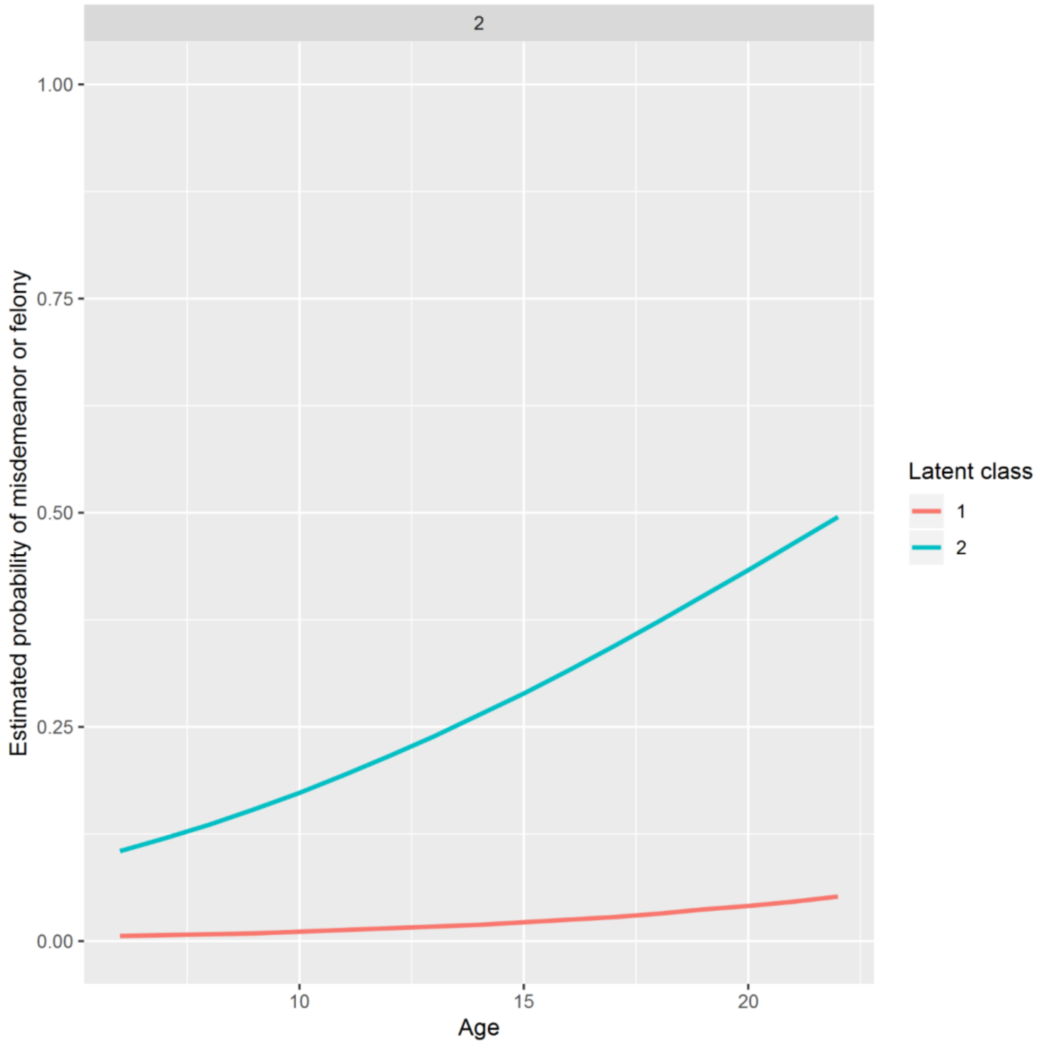
Many LCGMs (again)

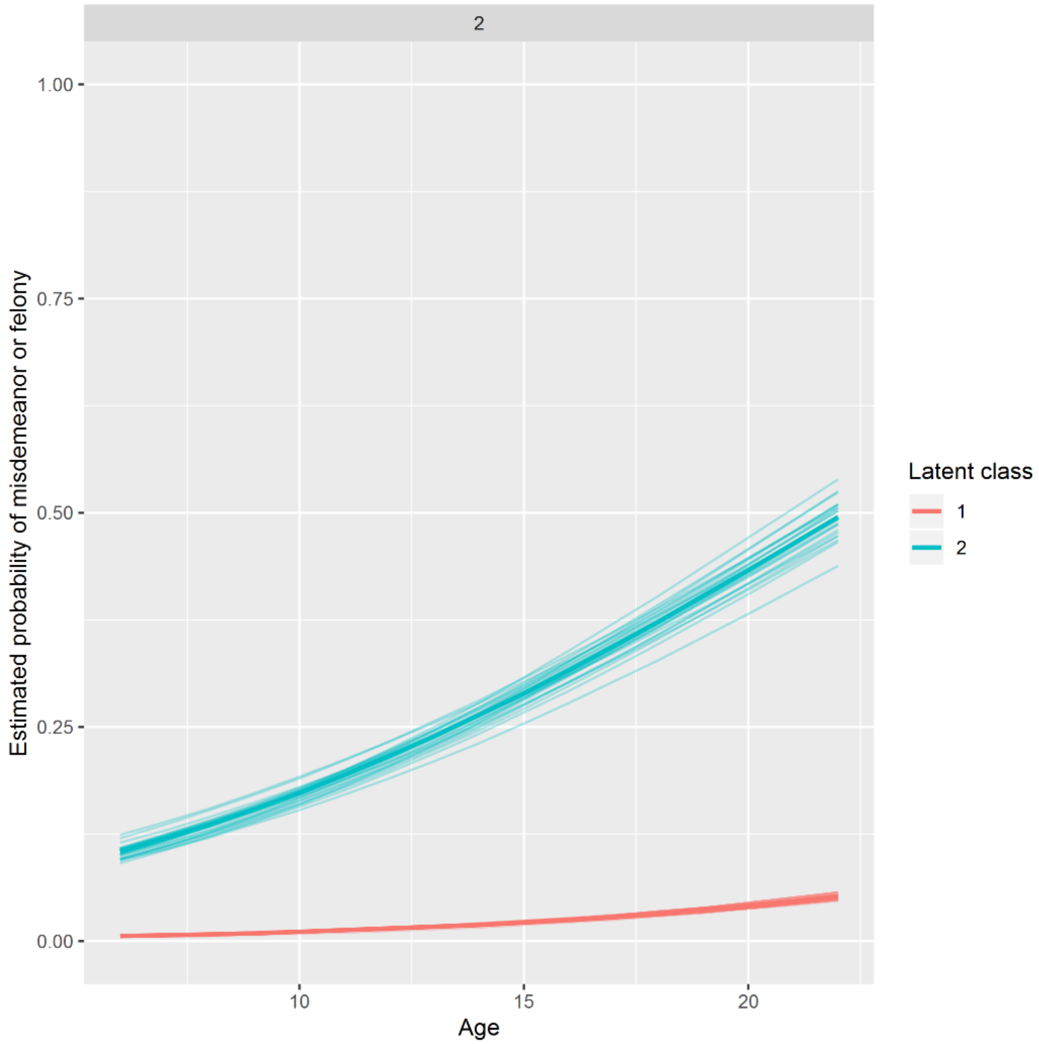
- Data from Racine, Wisonsin 1955 birth cohort (downloaded from https://www.icpsr.umich.edu/icpsrweb/)
- Remember: substantive interest in the **shape** of the different trajectories, art of model selection
- Not going to discuss substantive meaning of these trajectories

How many latent classes?

Model selection process:

1. AIC/BIC/aBIC
2. (VLMR test)
3. (BLRT test)
4. Substantive interpretation
5. “Norris method” (see Norris, 2009)
6. ... Consistency of trajectory shapes across bootstrap replications?


2
1.00
0.75
0.50
0.25
0.00
Estimated probability of misdemeanor or felony
10
15
20
Age
Latent class
1
2



Understanding Inequalities

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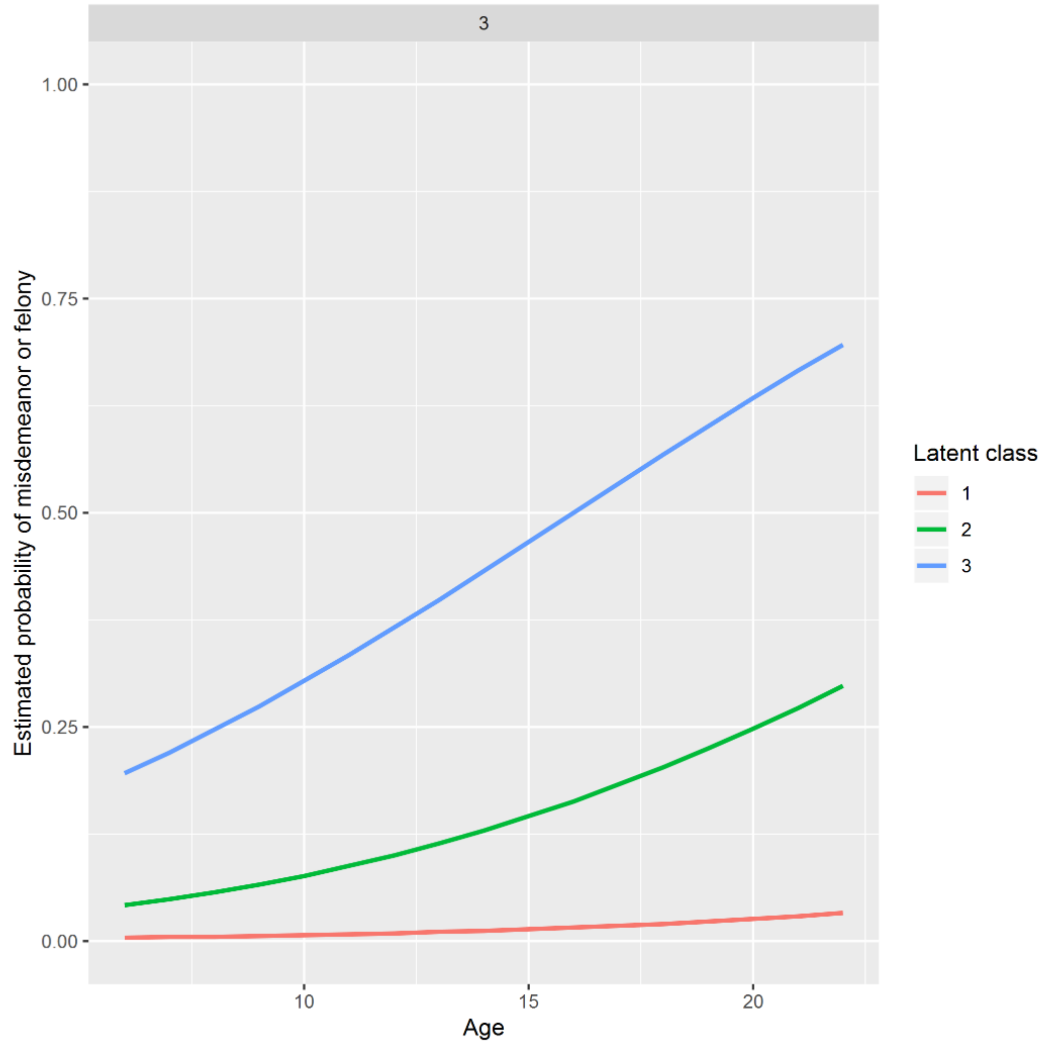

Understanding Inequalities

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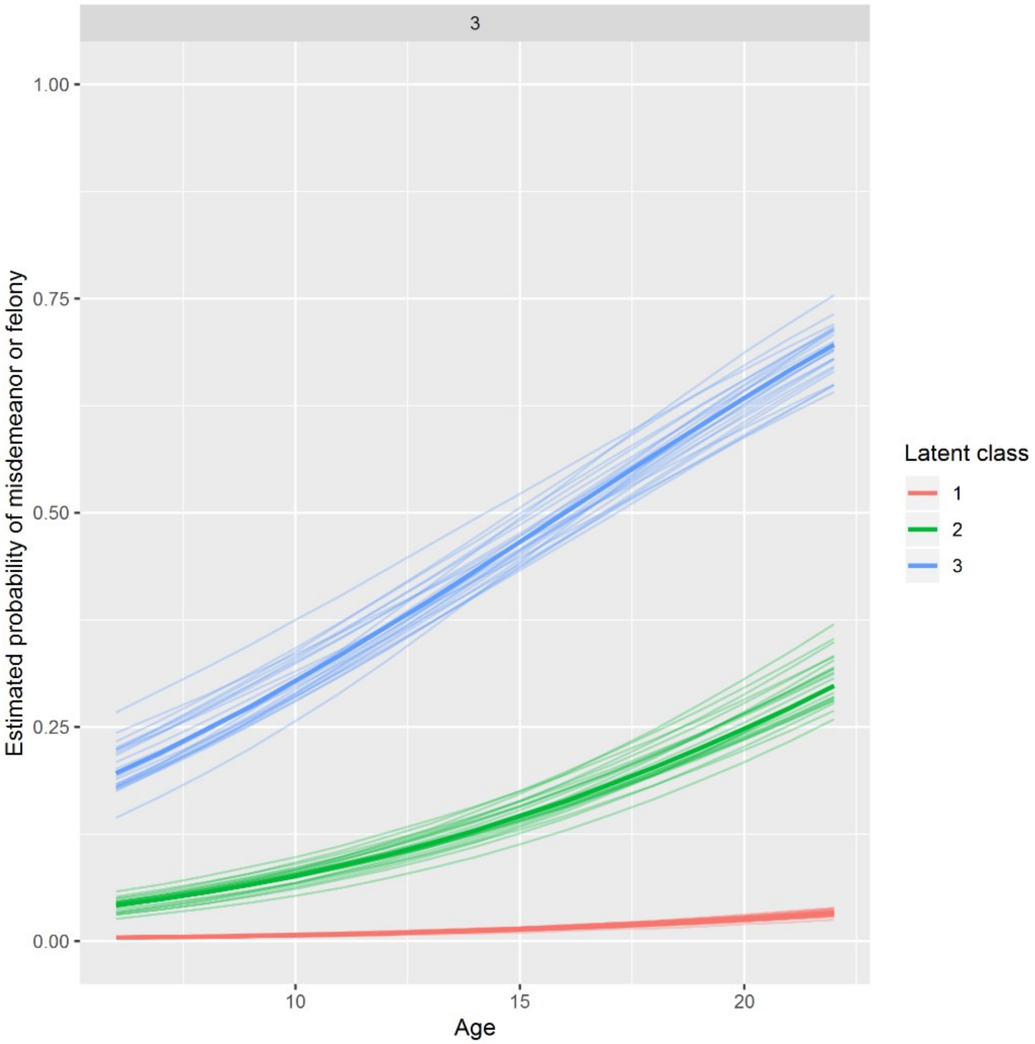
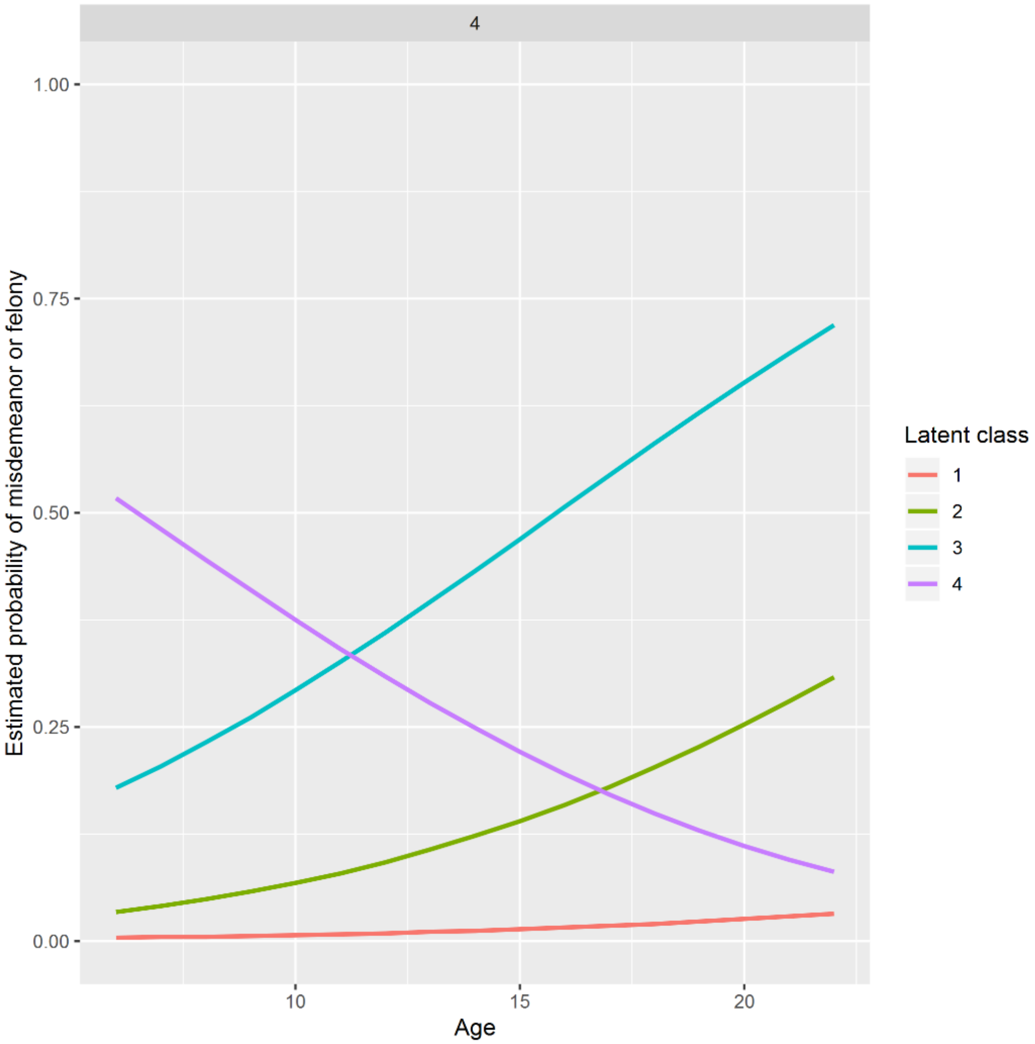
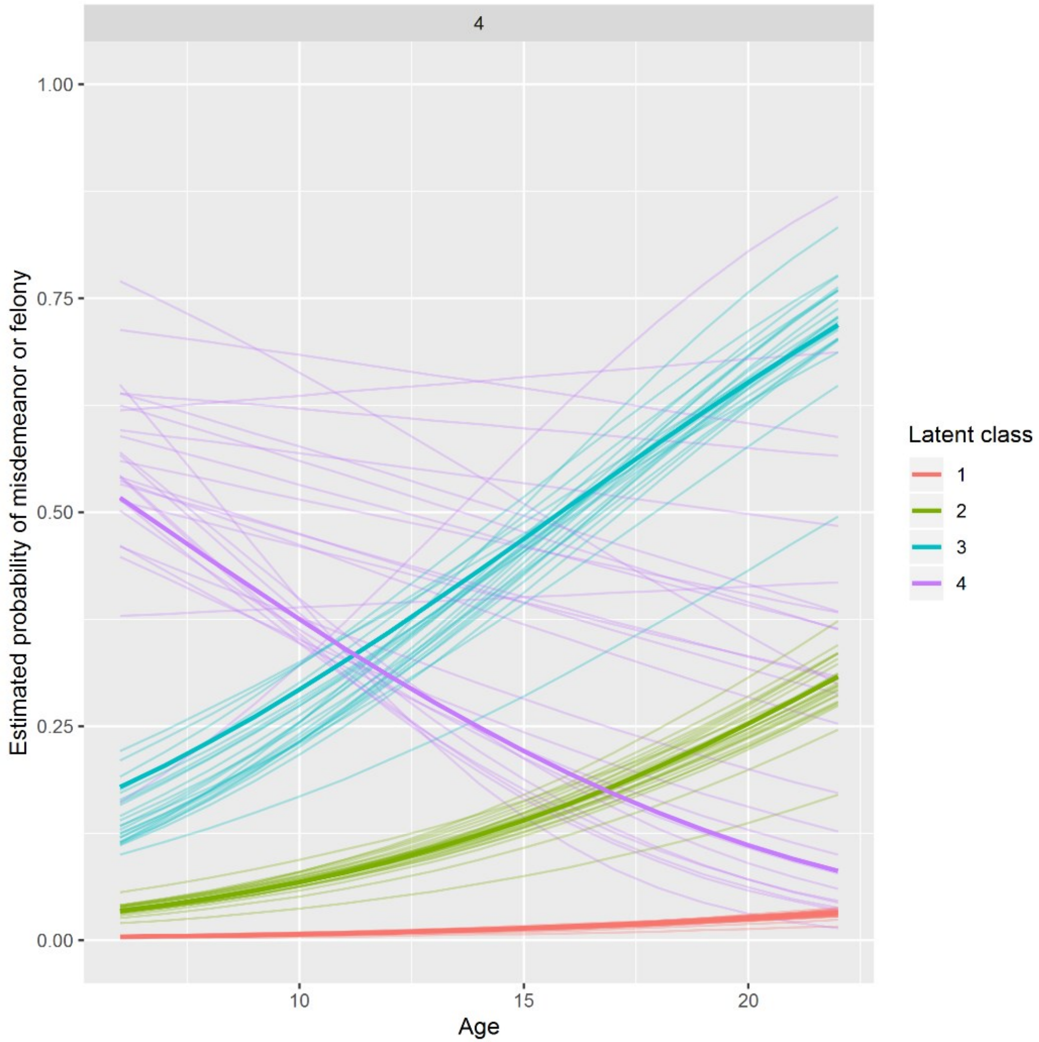

3
1.00
0.75
0.50
0.25
0.00
Estimated probability of misdemeanor or felony
10
15
20
Age
Latent class
1
2
3


4
Estimated probability of misdemeanor or felony
1.00
0.75
0.50
0.25
0.00
10
15
20
Age
Latent class
1
2
3
4



Understanding Inequalities

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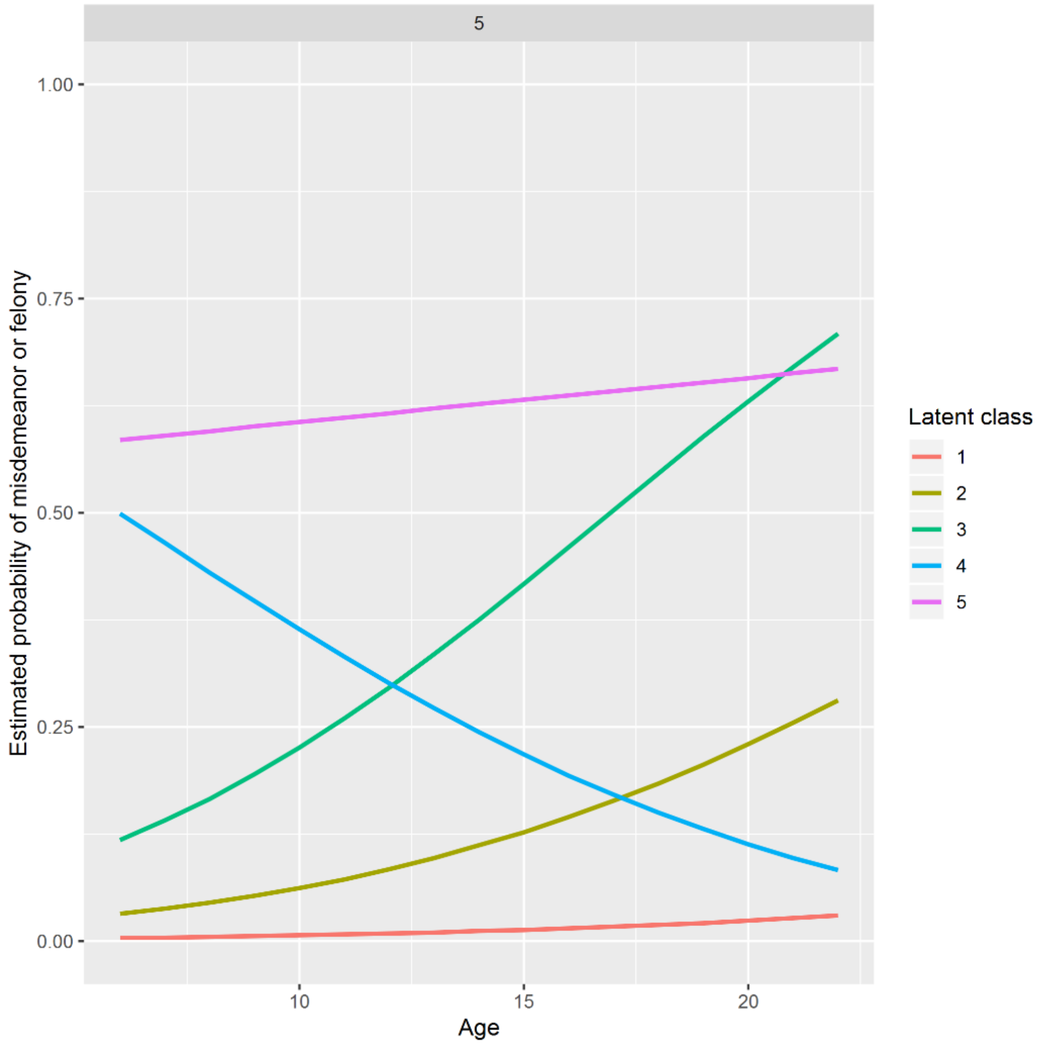
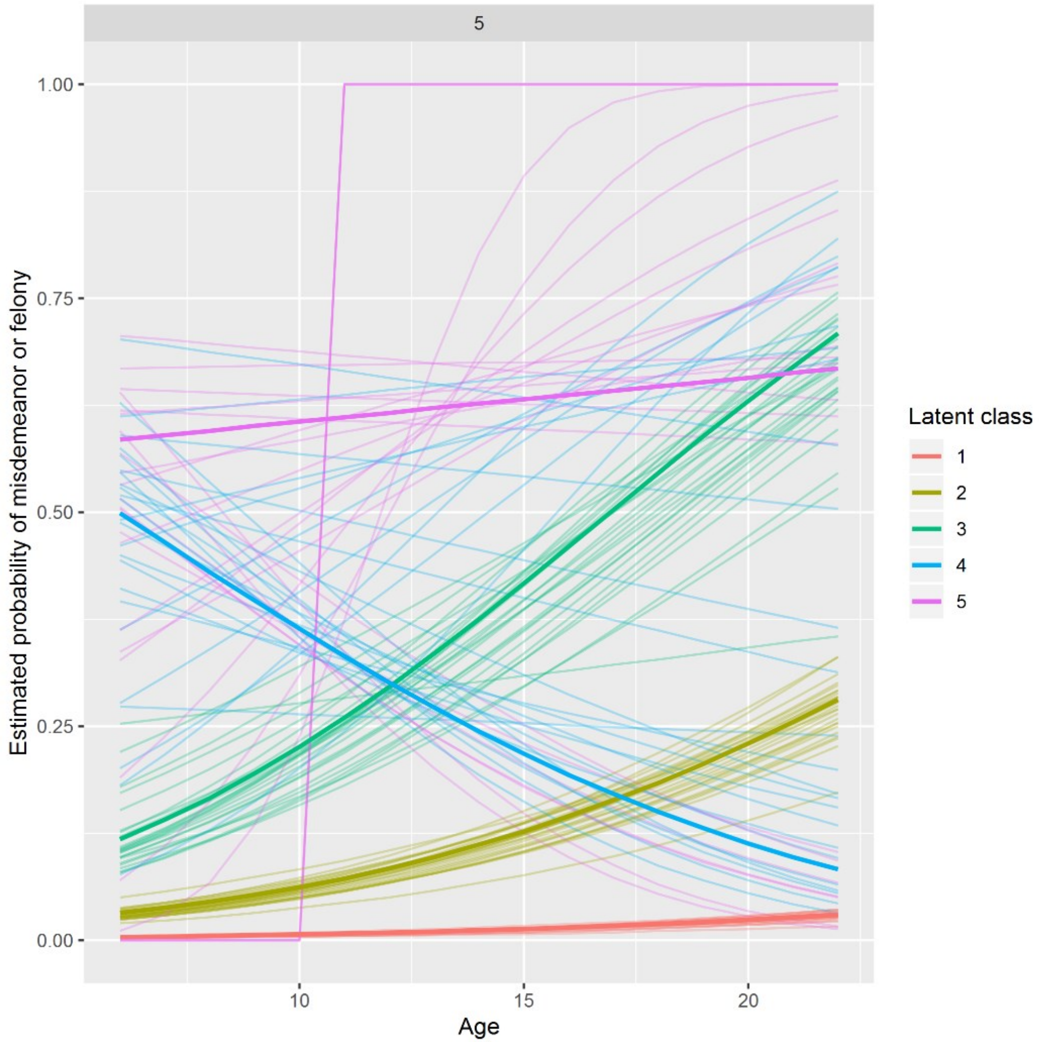

5
1.00
0.75
0.50
0.25
0.00
Estimated probability of misdemeanor or felony
10
15
20
Age
Latent class
1
2
3
4
5



Understanding Inequalities

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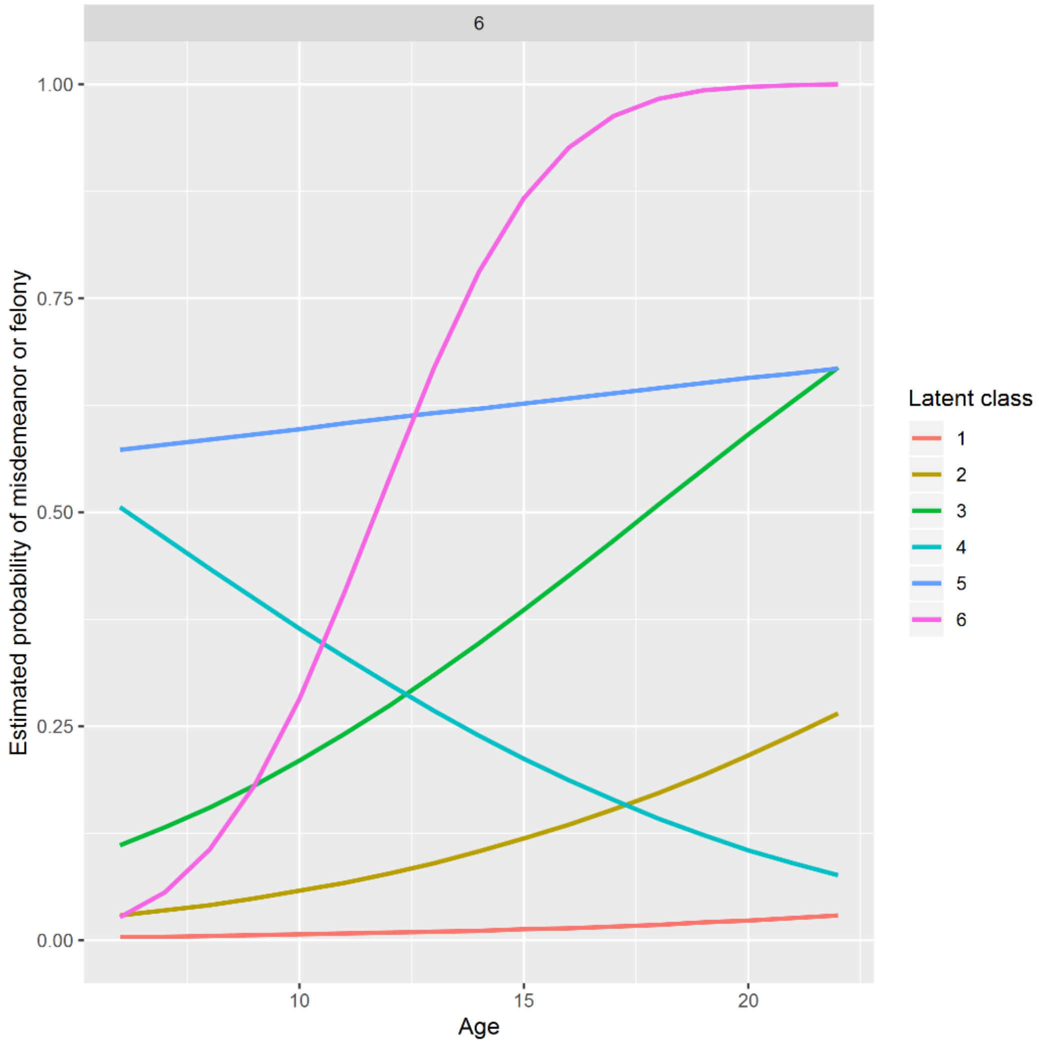
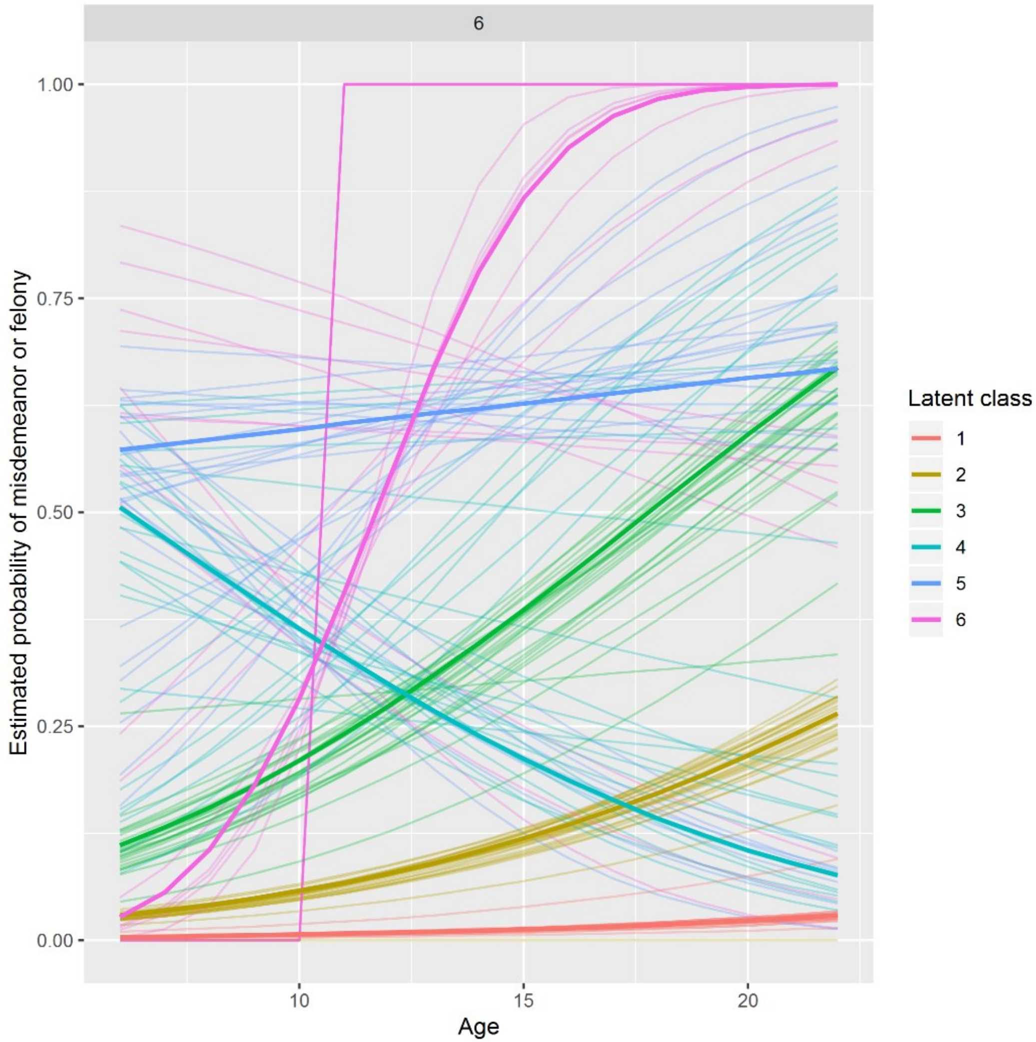

6
1.00
0.75
0.50
0.25
0.00
Estimated probability of misdemeanor or felony
10
15
20
Age
Latent class
1
2
3
4
5
6


6
Estimated probability of misdemeanor or felony
1.00
0.75
0.50
0.25
0.00
10
15
20
Age
Latent class
1
2
3
4
5
6

Results

- These figures would suggest maybe a three or *possibly* a four-class model?
- Trajectory shapes from five- and six-class models aren’t stable across replications
- … But is it appropriate to move from bootstrapping to visualizing uncertainty to model selection?

What have we learned?

Summary

- Many models workflow has positives and negatives
- Not so sure the ‘secret weapon’ was useful for me
- It was useful for re-fitting models to bootstrap replications to see what the LCGM was doing

Questions for you

- Is this a useful approach to look at change over time in the LCGMs?
- Is bootstrapping to select number of classes a valuable technique?
  - If so, how many bootstrap replications do you need?
    - For hypothetical outcome plots (Hullman et al. 2015) ~20
    - To calculate CIs usually 999 or 1999 (Carsey and Harden 2014)
  - Limitation – time and processing power!

Thank you!

@benmatthewsed | ben.matthews@ed.ac.uk

These slides and bootstrapping code at: https://github.com/benmatthewsed/qstep-march-2019

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