

# Two countries, twenty models and one secret weapon

Comparing change over time in convictions trajectories between Scotland and Queensland

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

# Two countries, lots of models and one secret weapon

Two applications of the “many models” workflow

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# 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?

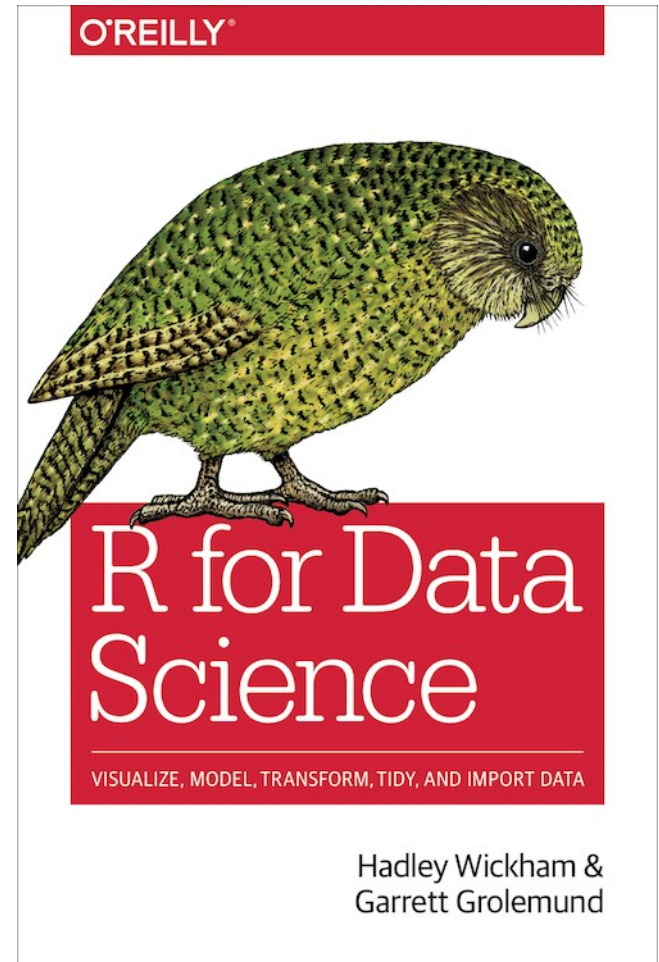
# Not going to cover

- 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

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« [Meritocracy won't happen: the problem's with the "ocracy"](#)

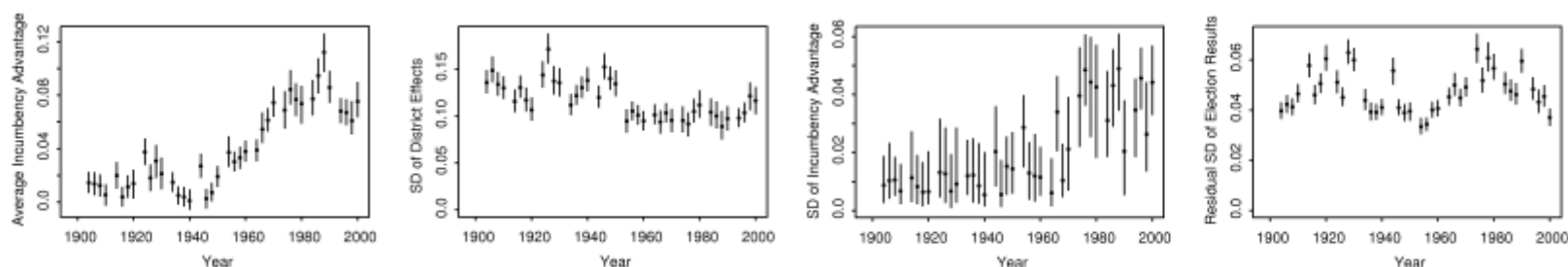
[Still more on R software for matching for causal inference](#) »

## 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:



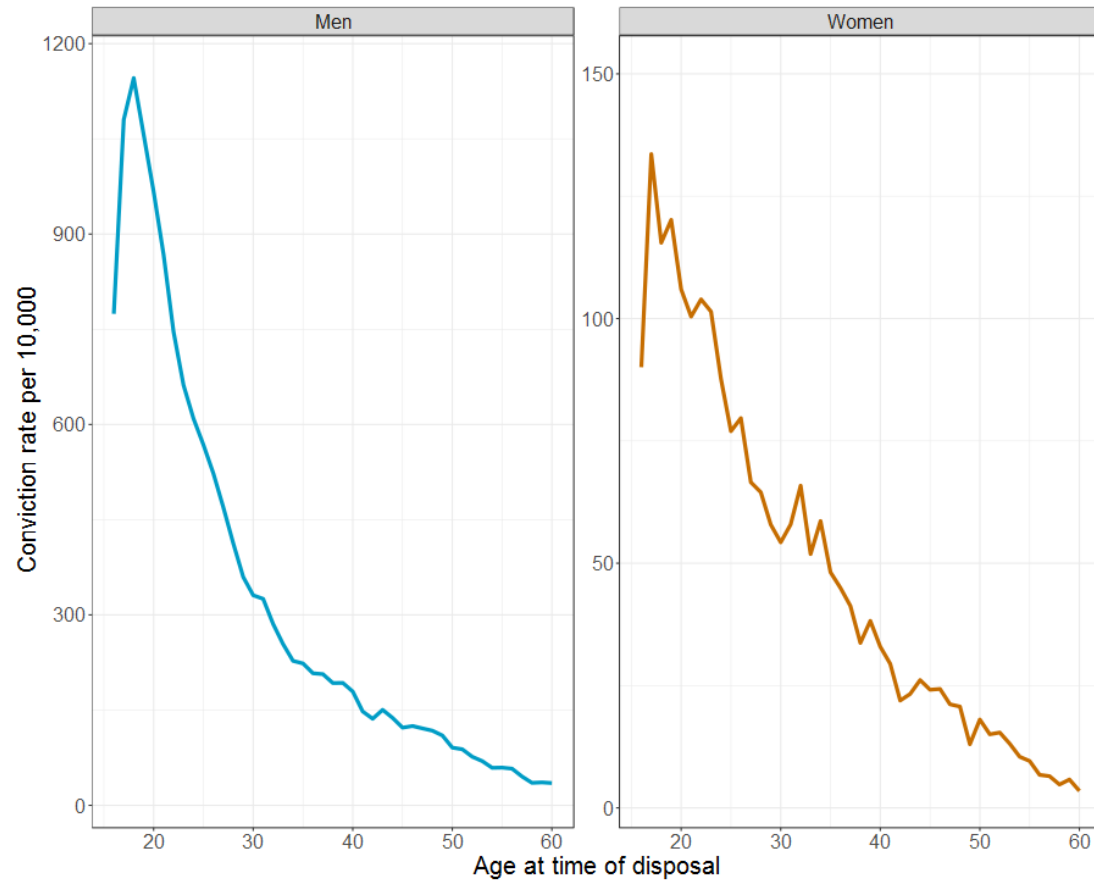
The idea is to fit a separate model for each year, or whatever, and then to look at all these estimates together to see trends. This can be considered as an approximation to multilevel modeling, with the partial pooling done by eye on the graphs rather than using a full statistical model.

[https://statmodeling.stat.columbia.edu/2005/03/07/the\\_secret\\_weapon/](https://statmodeling.stat.columbia.edu/2005/03/07/the_secret_weapon/)

# Changing Criminal Careers

- Well-established relationship between age and crime as far back as Quetelet (1832)
- 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



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)



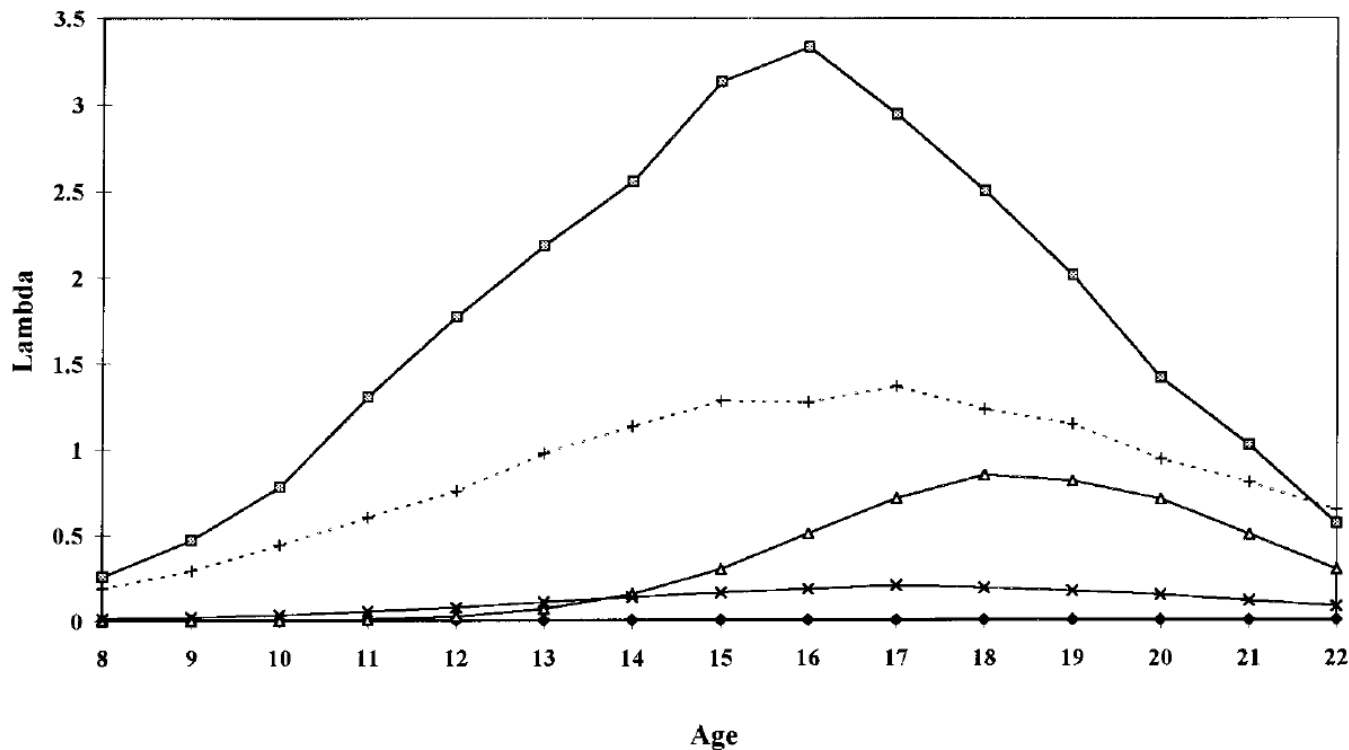
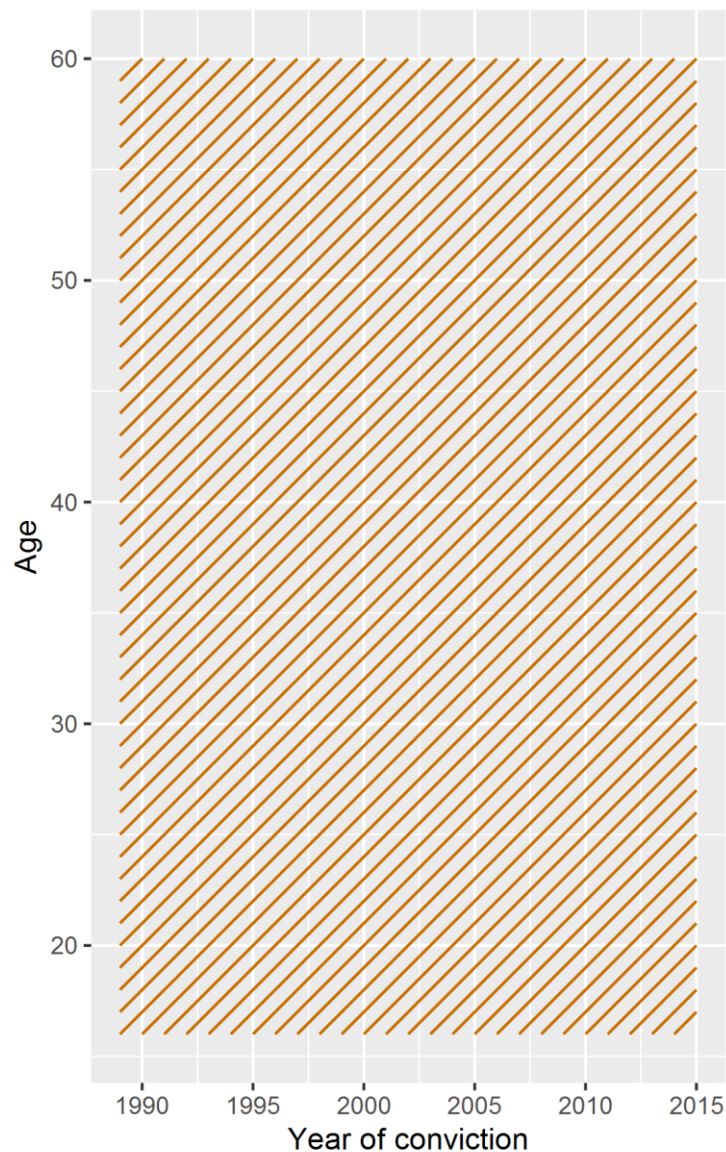


FIG. 5.—Predicted misdemeanor/felony rates by age for the Racine 1955 five-class model

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

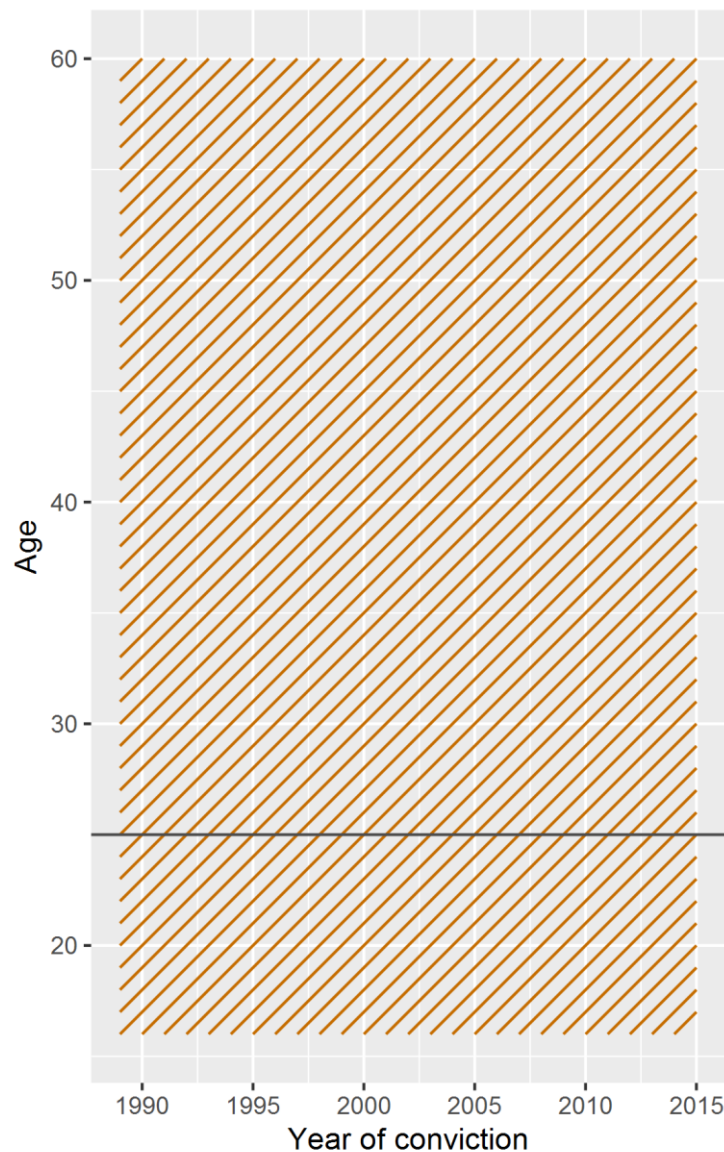
# Many LCGMs

For each cohort,  
fit LCGM



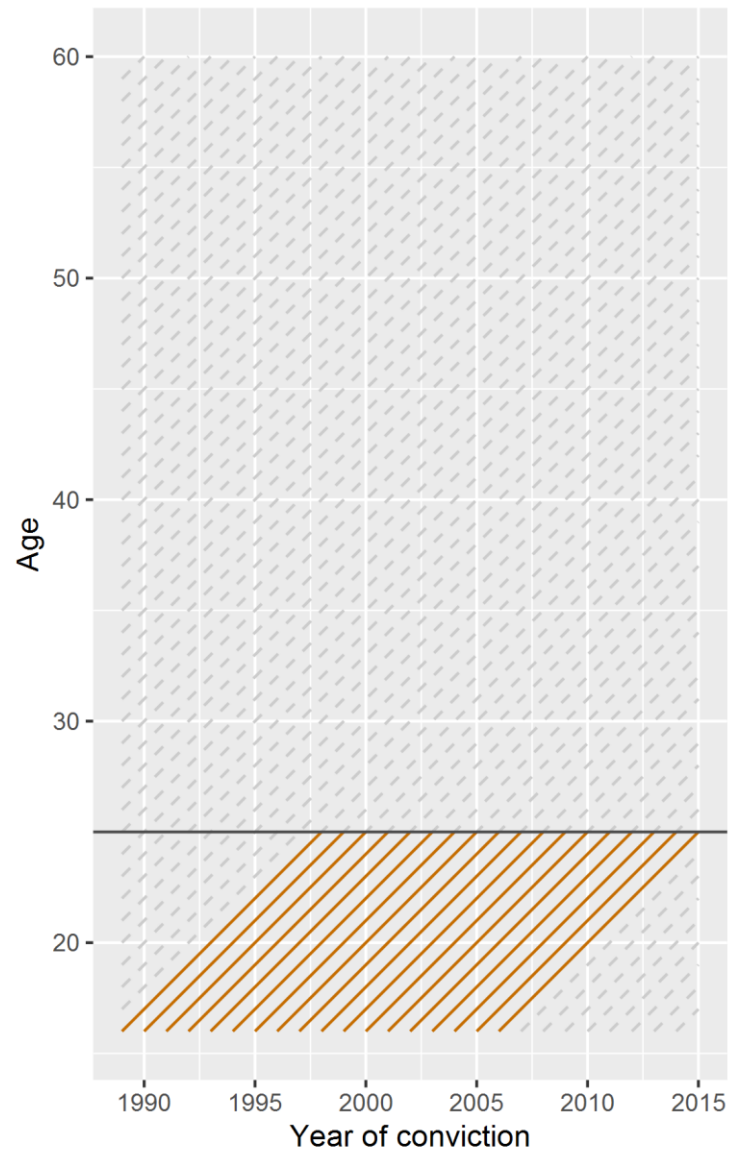
# Many LCGMs

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For each cohort,  
fit LCGM



# Modelling strategy

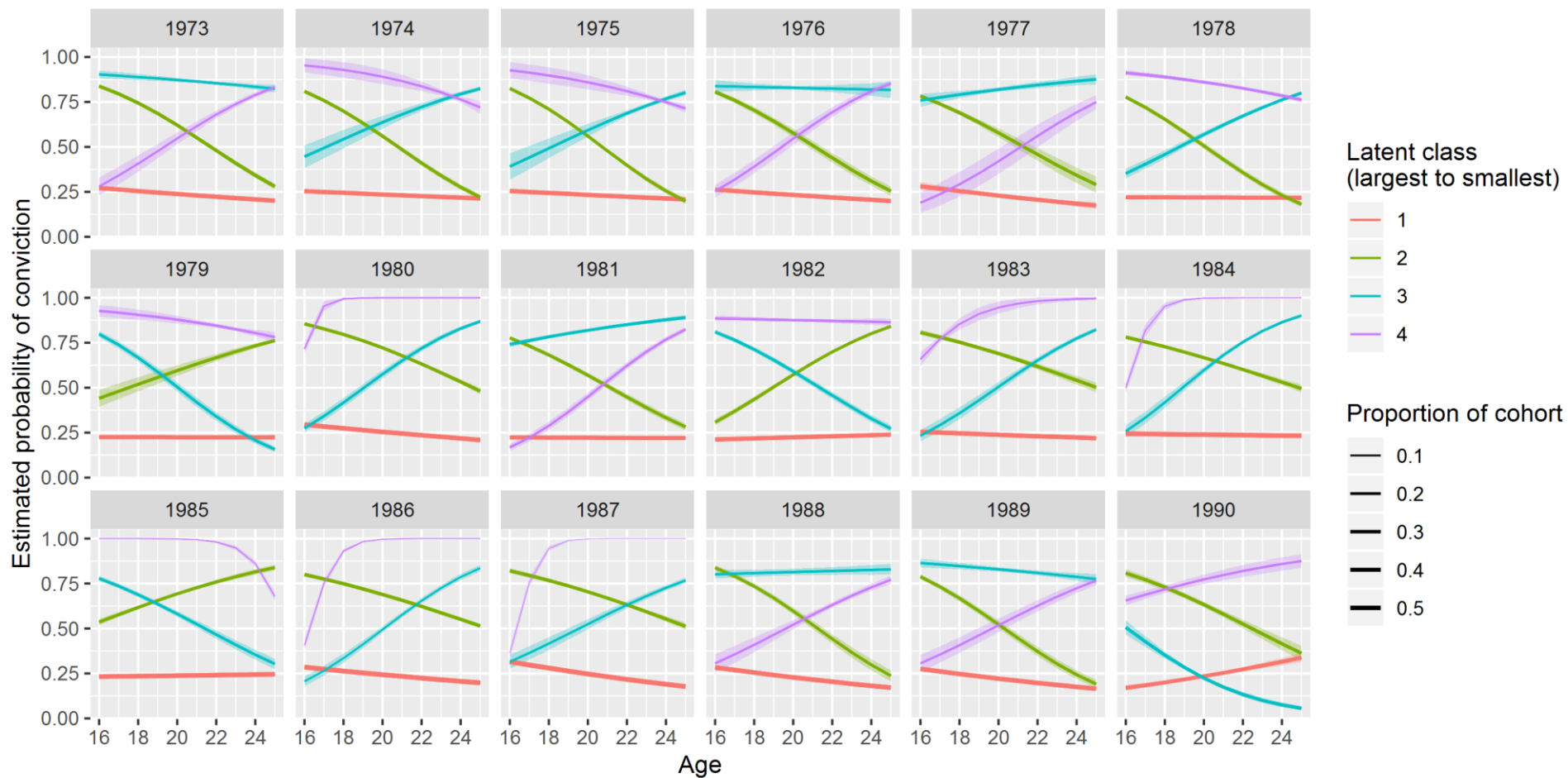
- Models fit in Mplus 8.2 using the `MplusAutomation` (Hallquist and Wiley 2018) R package to call Mplus, fit the models and then pull the results back into R
- This lets you use R's standard iteration tools with Mplus
- Results here from a subset of data from Scottish Offenders Index

# Parameters of interest

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

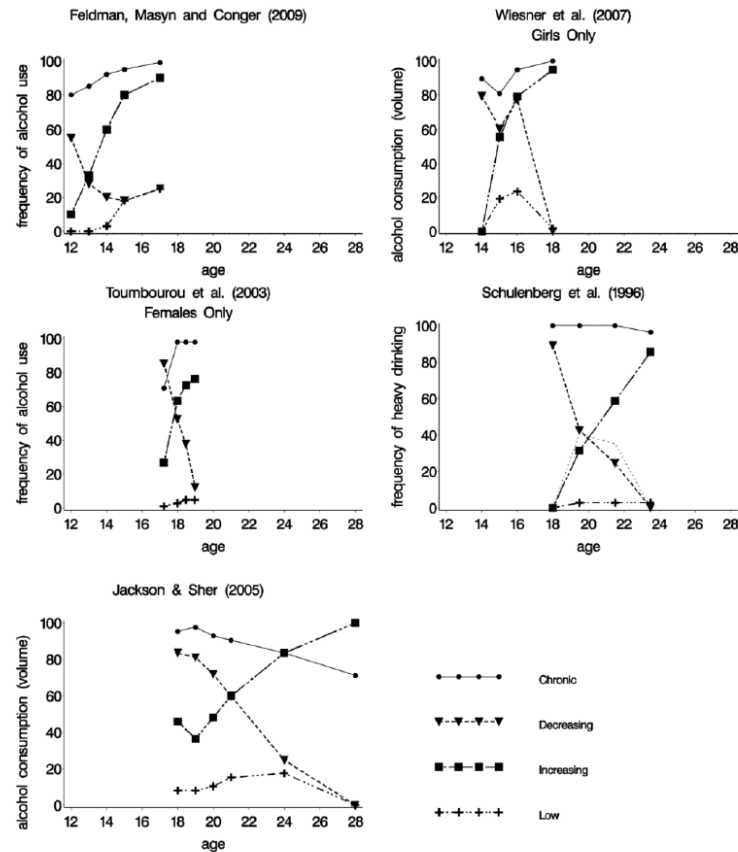
# How many latent classes?

- 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?



Note: Trajectories do not include the full SOI dataset so should not be interpreted substantively





**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 been 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

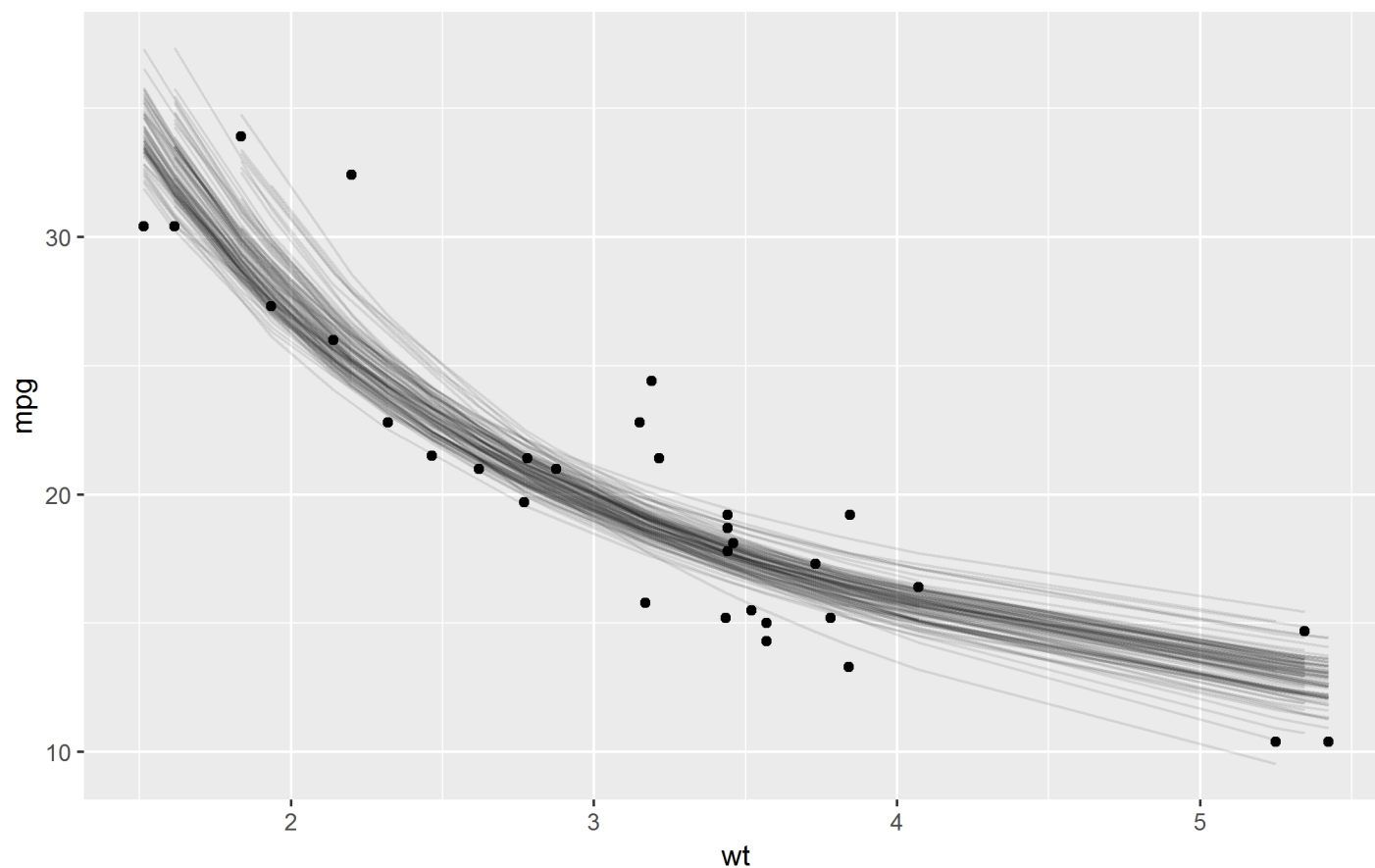
- Does look like there's *some* differences between cohorts in the trajectory shapes, but cat's cradle means it's hard to tell
- ... but are these differences meaningful? Many models approach means we don't know statistically
- One model per cohort means class definitions change – can't really compare 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!



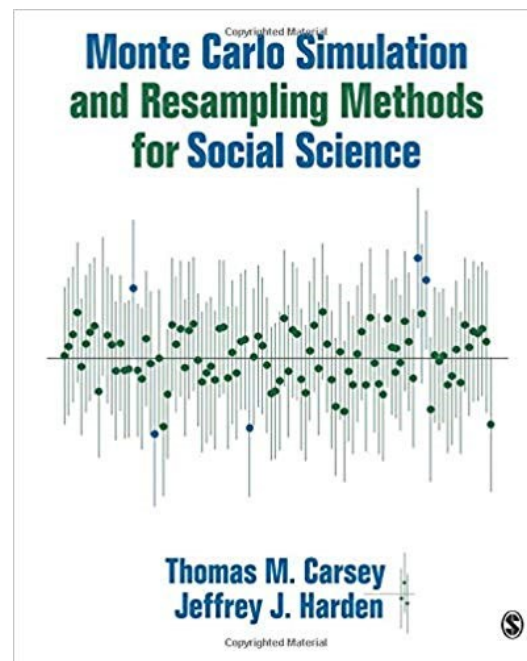
<https://cran.r-project.org/web/packages/broom/vignettes/bootstrapping.html>

# 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)

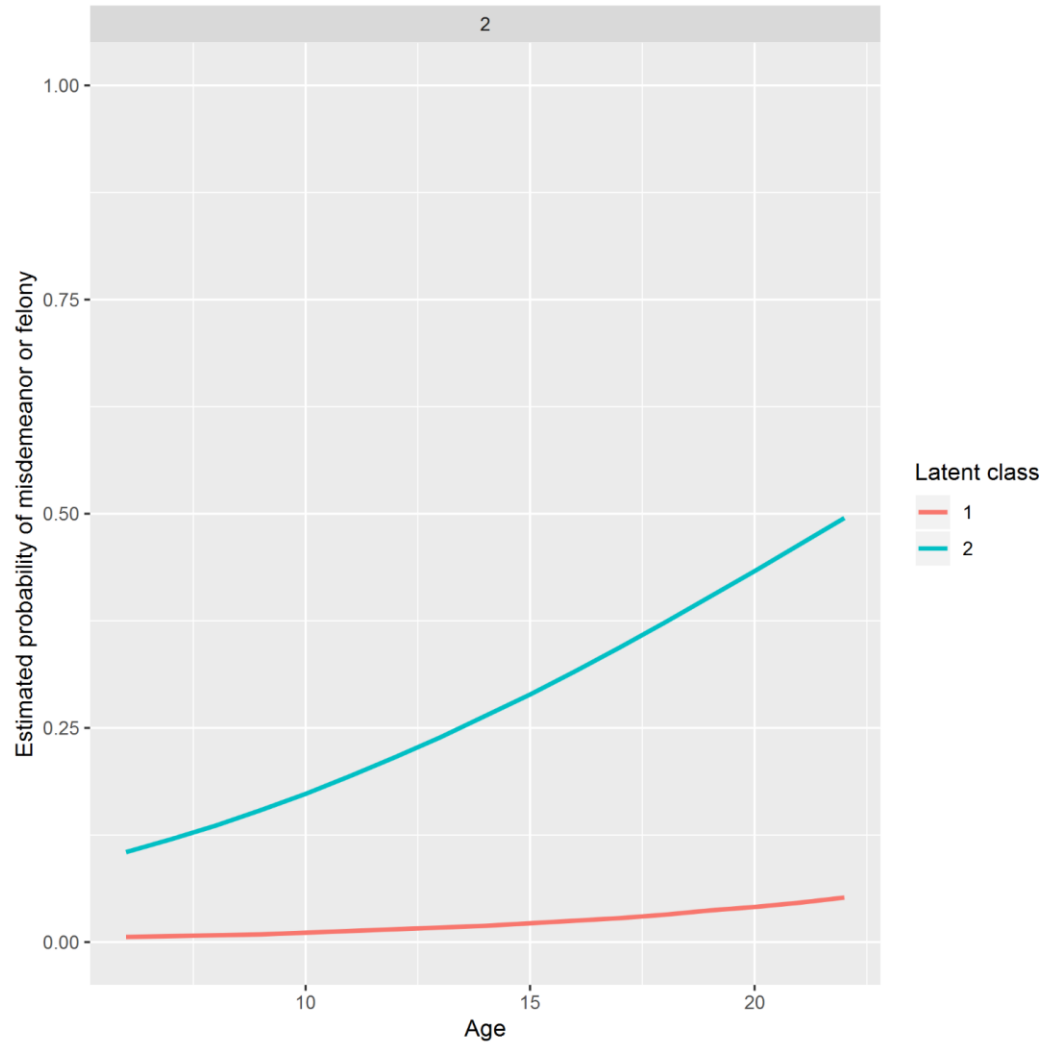
- Data from Racine, Wisconsin 1955 birth cohort (downloaded from <https://www.icpsr.umich.edu/icpsrweb/>)
- Remember: substantive interest in the **shape** of the different trajectories, art of model selection
- Not going to discuss substantive meaning of these trajectories

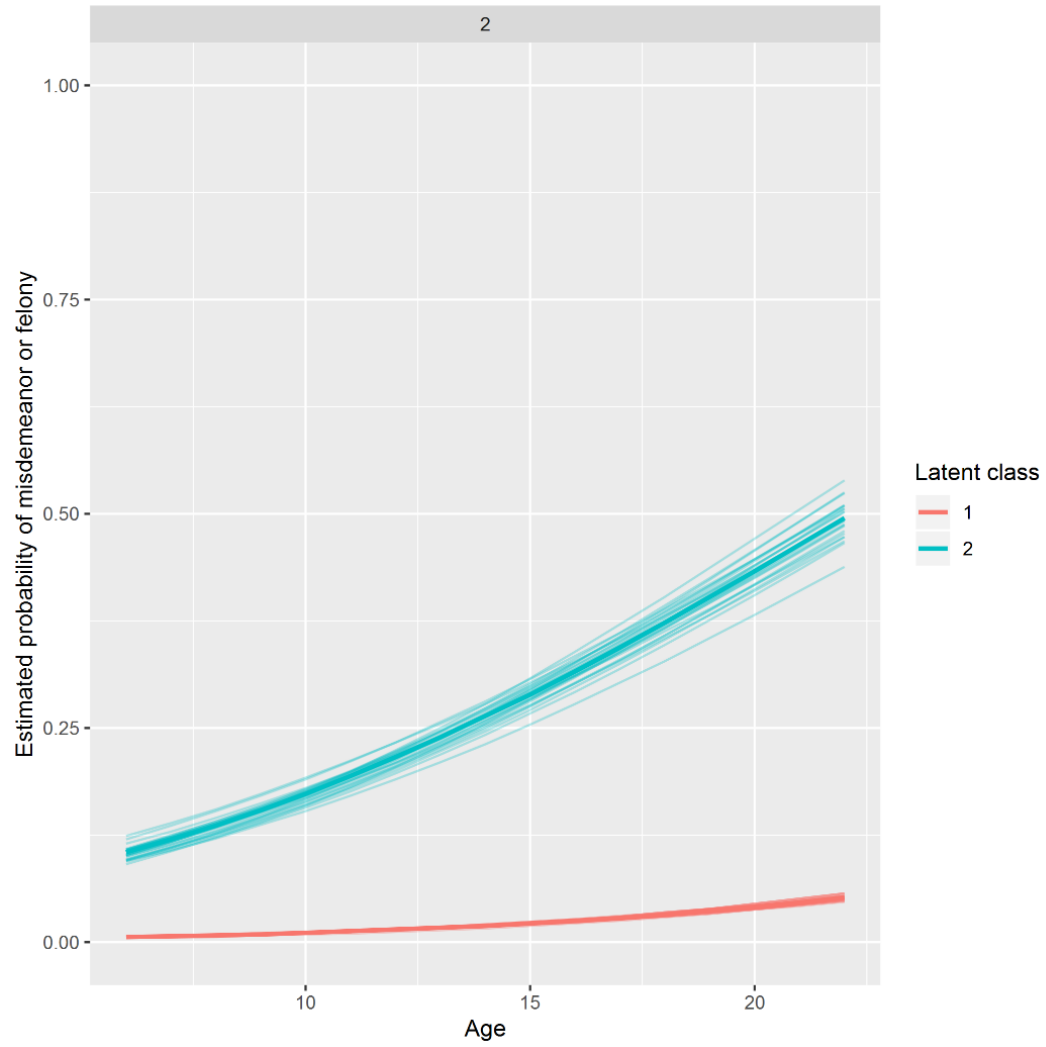
# How many latent classes?

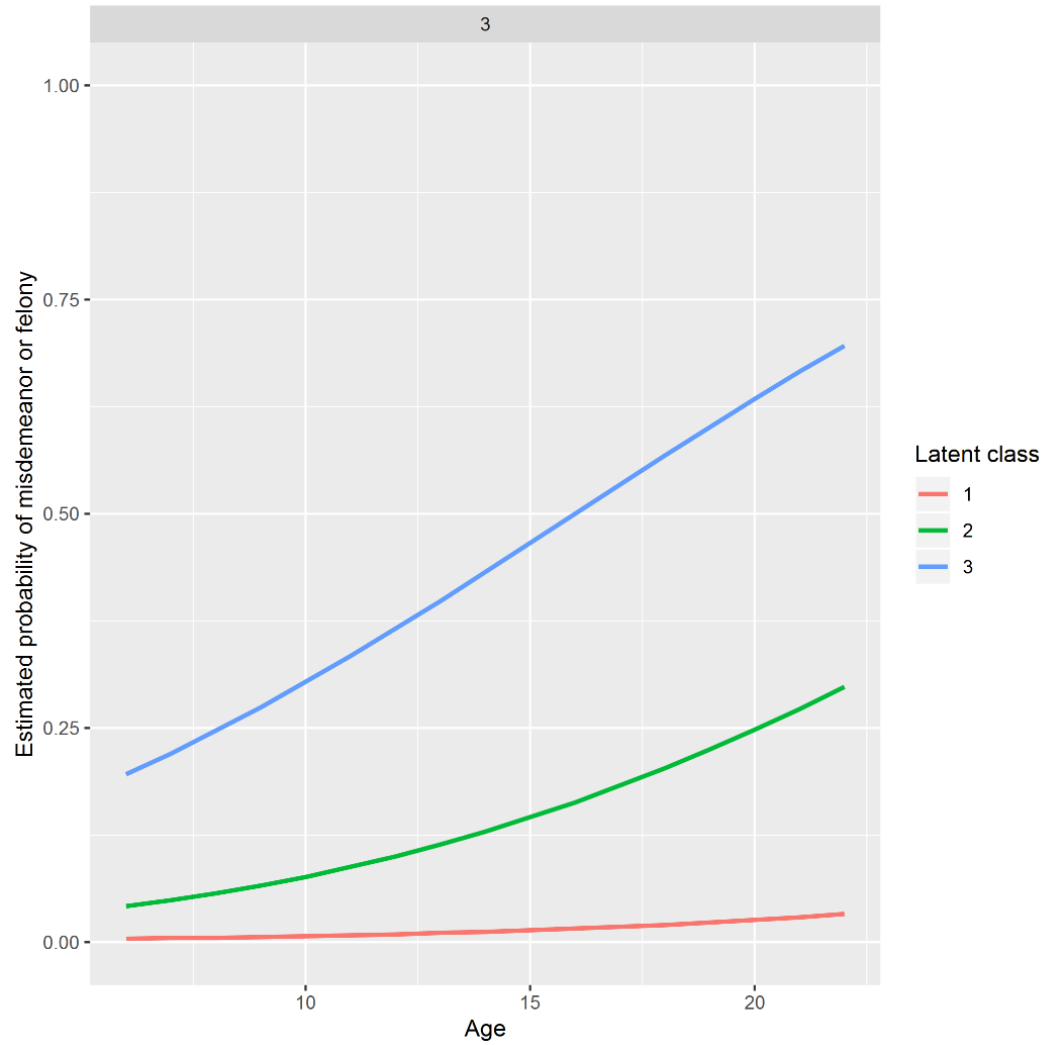
Model selection process:

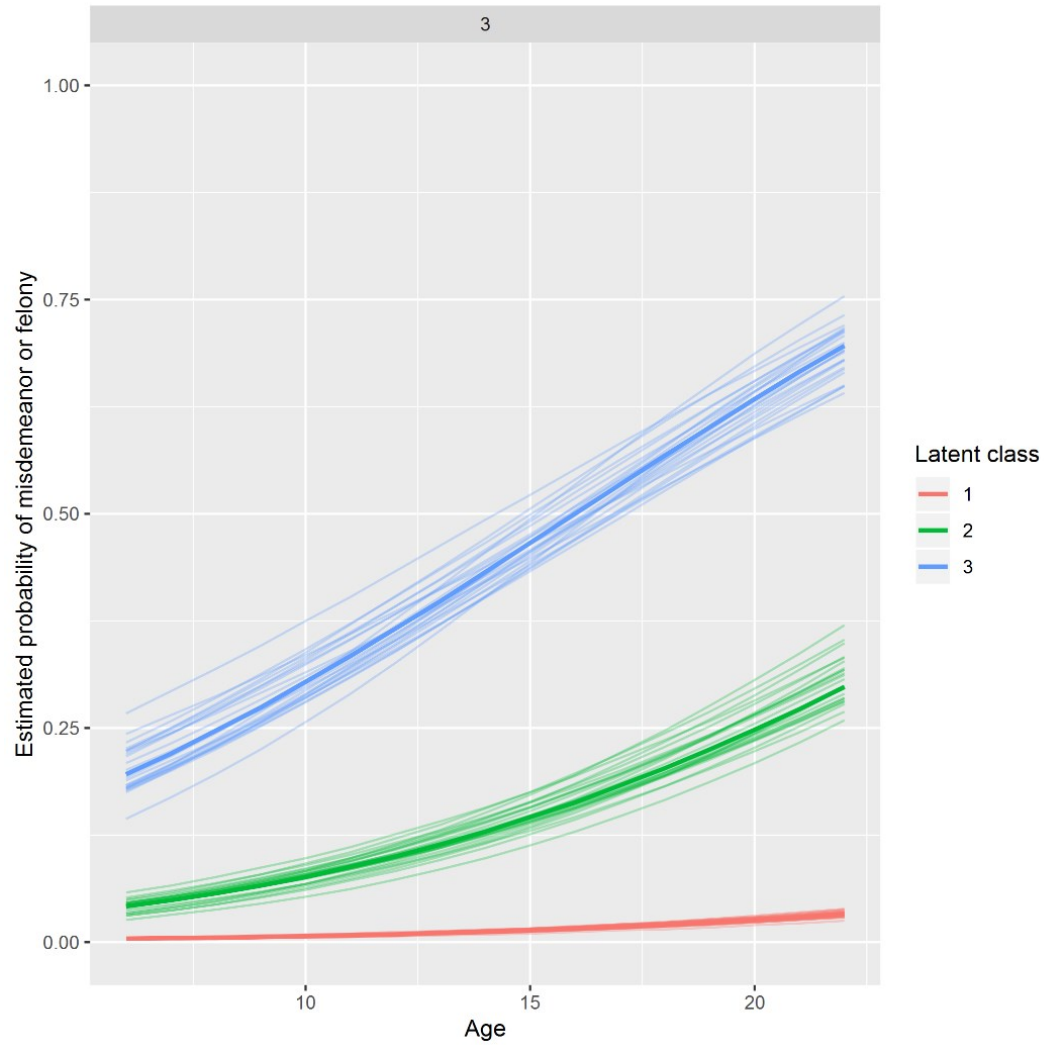
1. AIC/BIC/aBIC
2. (VLMR test)
3. (BLRT test)
4. Substantive interpretation
5. “Norris method” (see Norris, 2009)
6. ... Consistency of trajectory shapes across bootstrap replications?

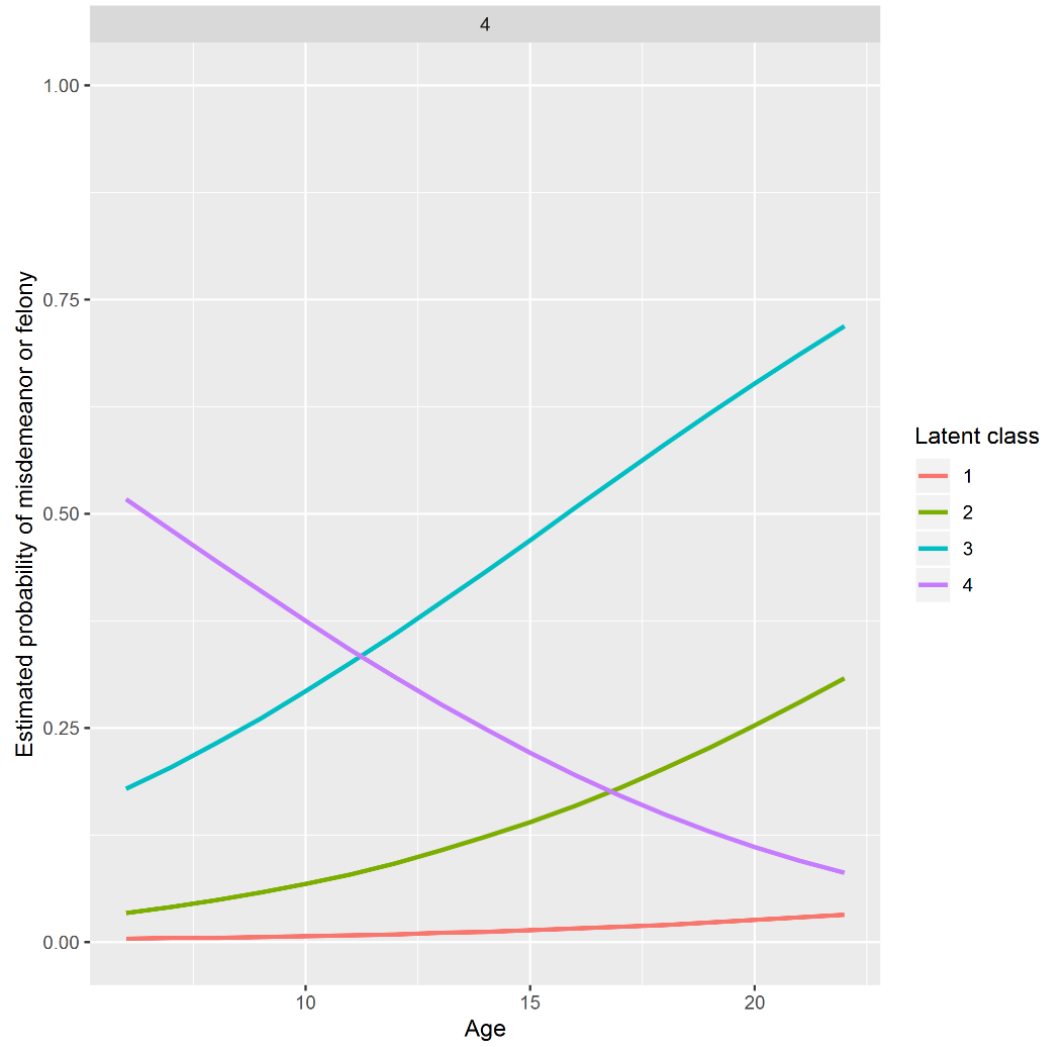


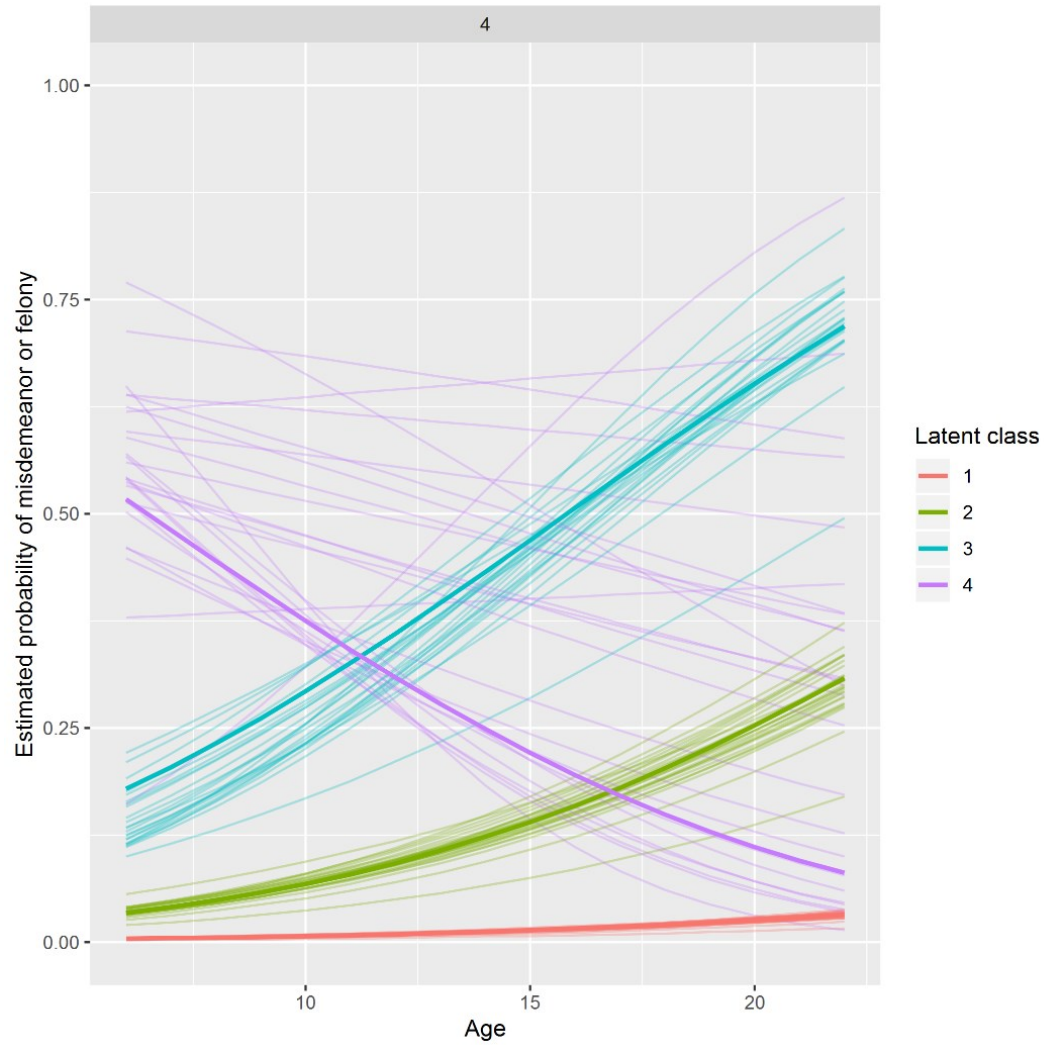


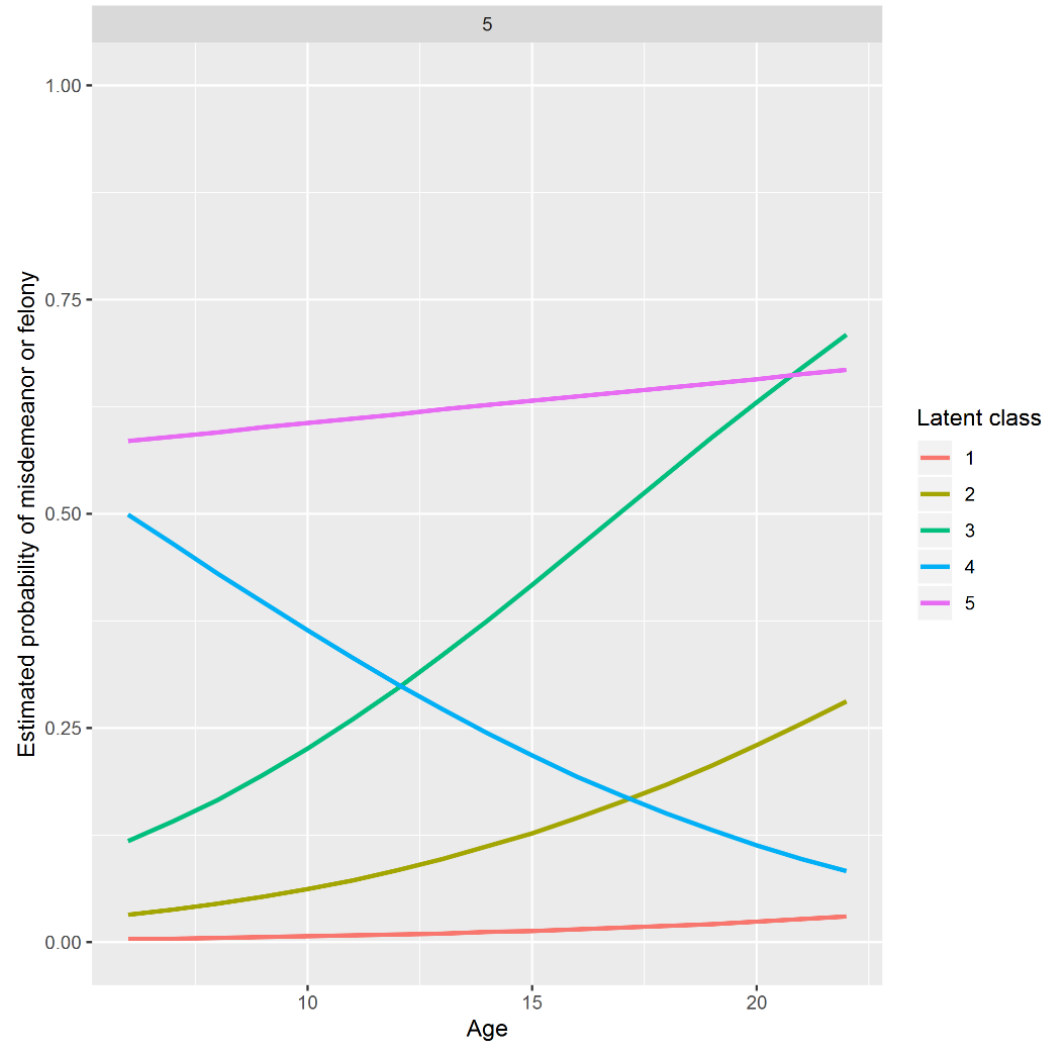


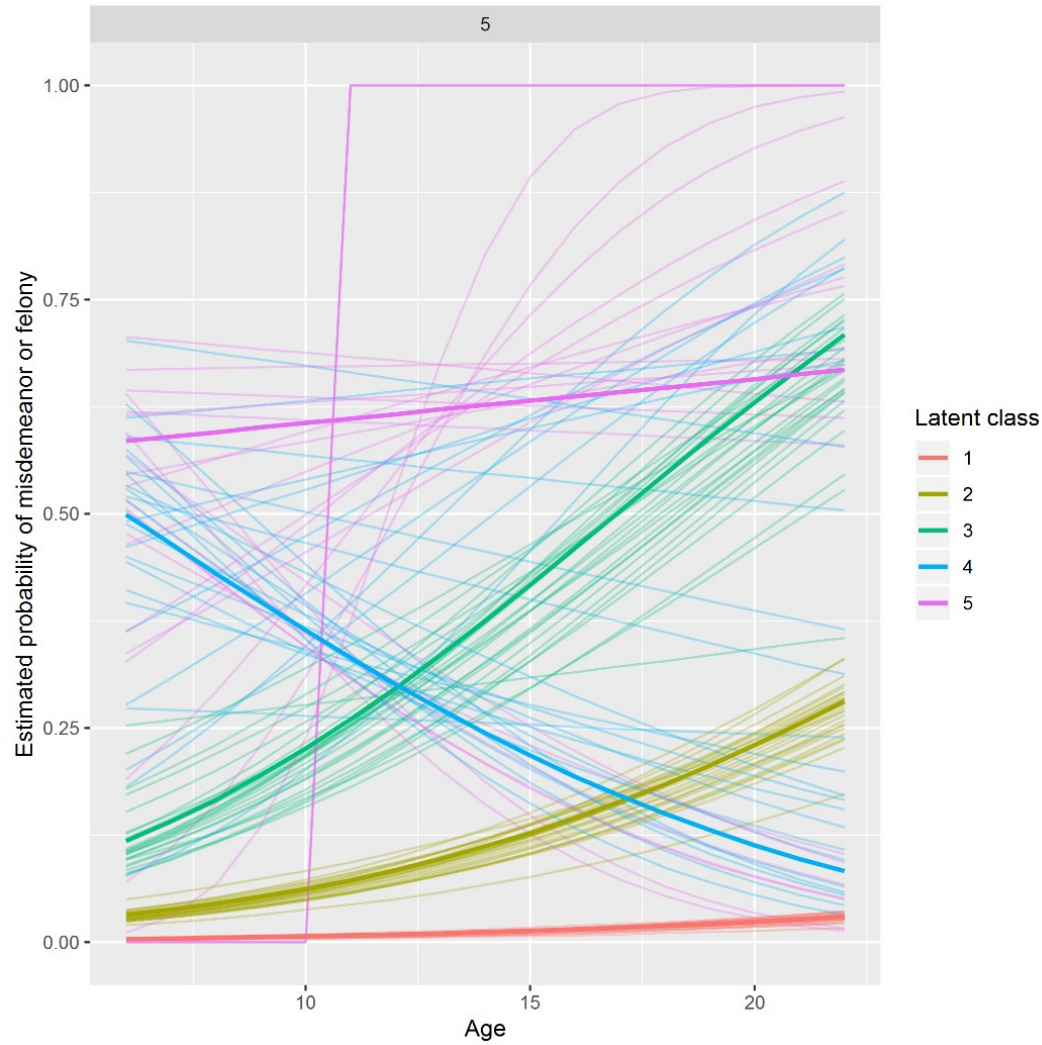




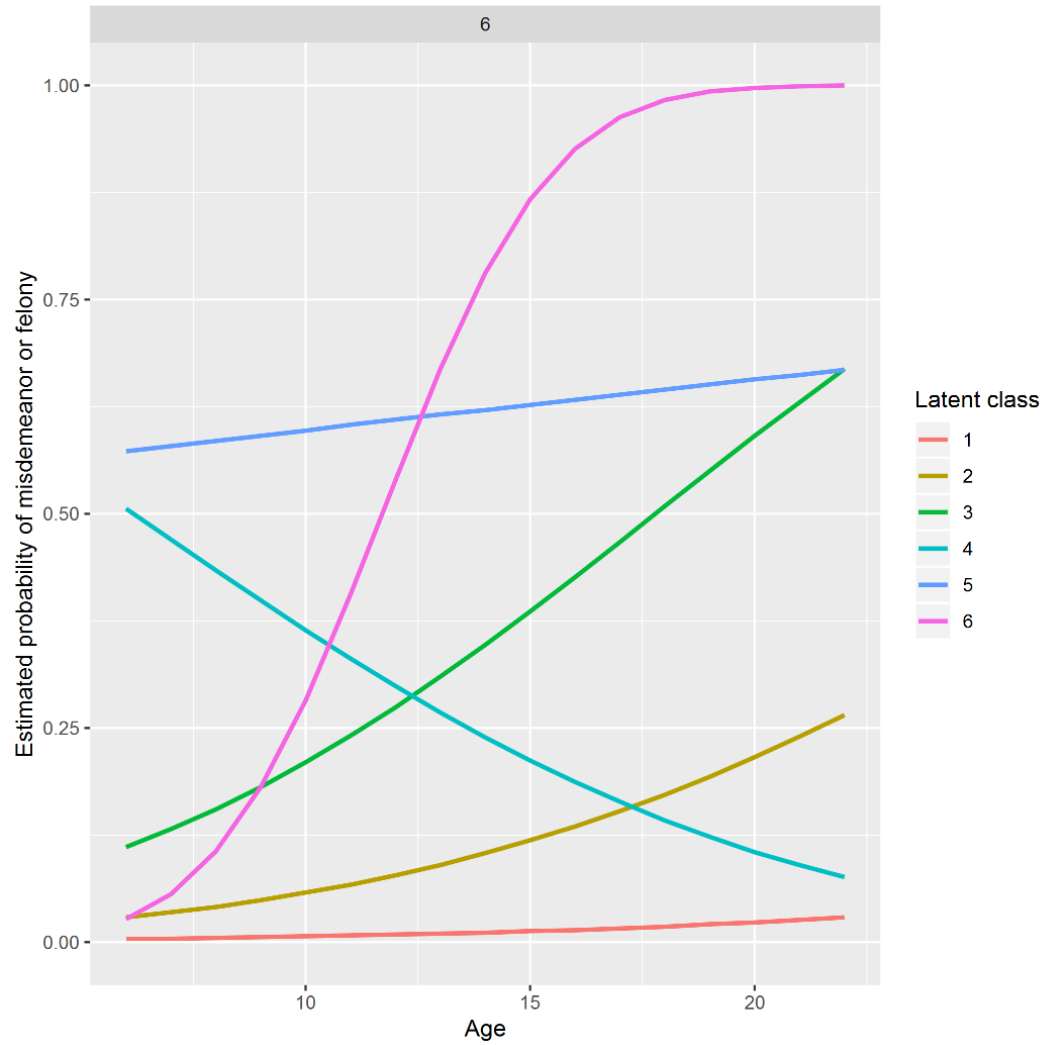


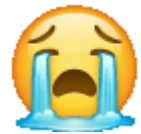
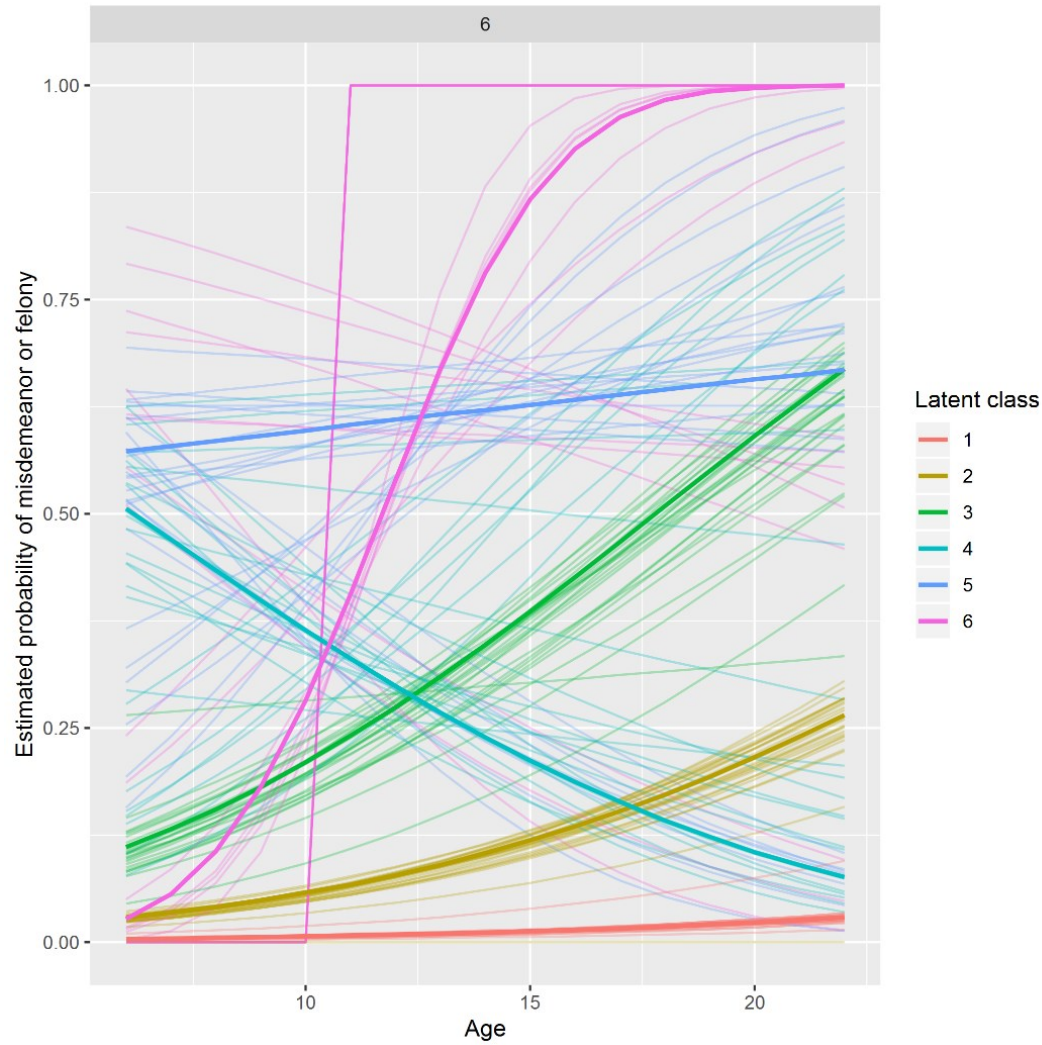












# Results

- 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!

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

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