Modeling student retention

An example of project presentation slides

Aki Vehtari
Aalto University

Modeling student retention

An example of project presentation slides

Aki Vehtari
Aalto University

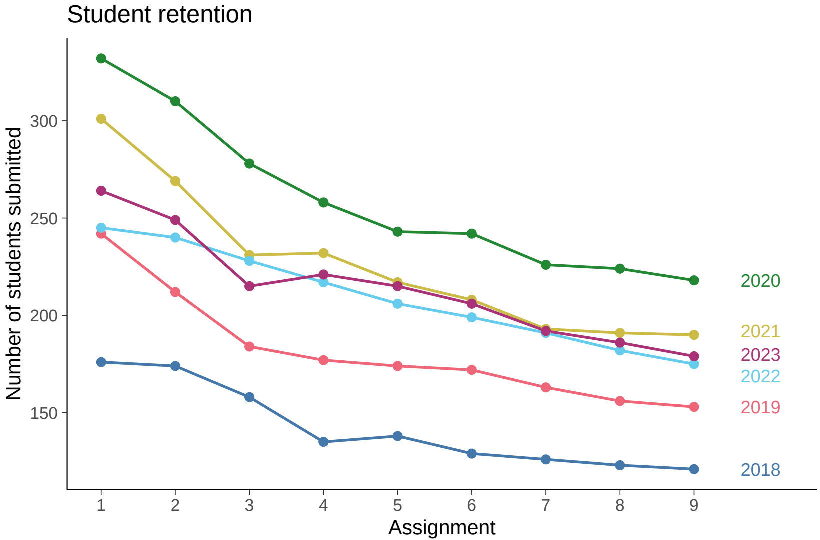
Introduce yourself

Modeling student retention

- Is there difference in student retention in different years?
- When making changes to the course and assignment it is useful to follow changes in retention
  - although external effects (like pandemic) make it difficult to make precise conclusions

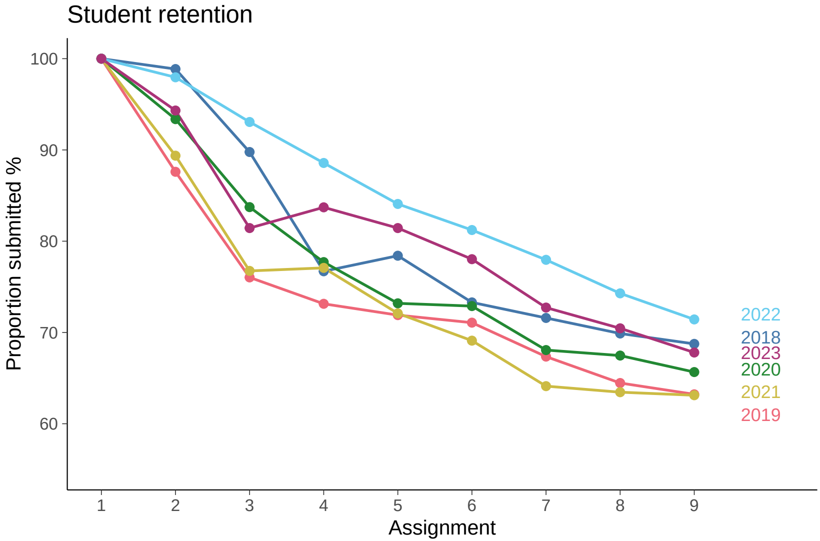
Modeling student retention

Is there difference in student retention in different years?



Modeling student retention

Is there difference in student retention in different years?



Student retention

- As we want to compare different years, we use hierarchical models and compare

1. Latent hierarchical linear model

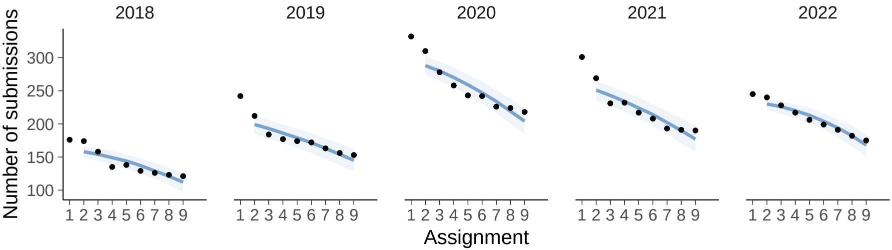
```
nstudents | trials(nstudents1) ~ (assignment | year),
  family=binomial()
```

2. Latent hierarchical linear model + spline

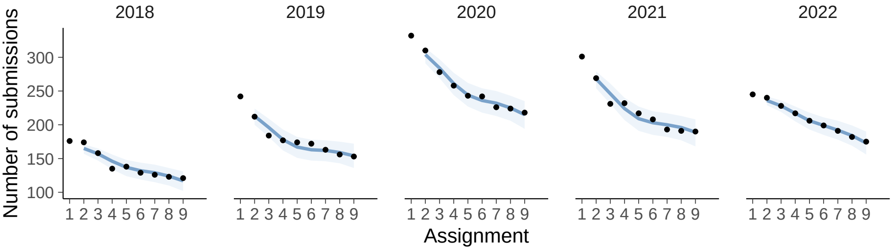
```
nstudents | trials(nstudents1) ~ (assignment | year) +
  s(assignment, k=4), family=binomial()
```

Student retention – Posterior predictive distributions

Latent hierarchical linear model

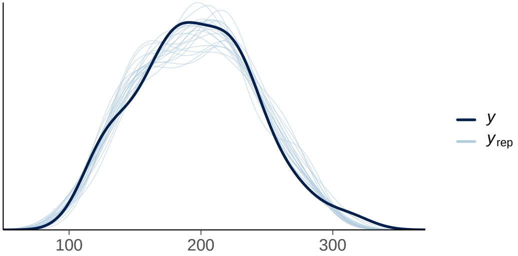


Latent hierarchical linear model + spline

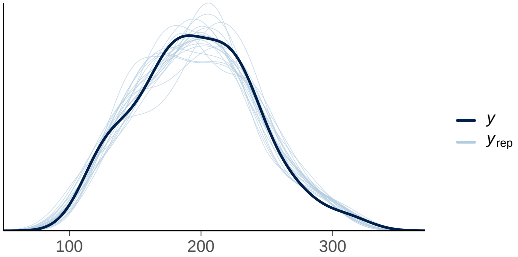


Student retention – Marginal PPC

Latent hierarchical linear model

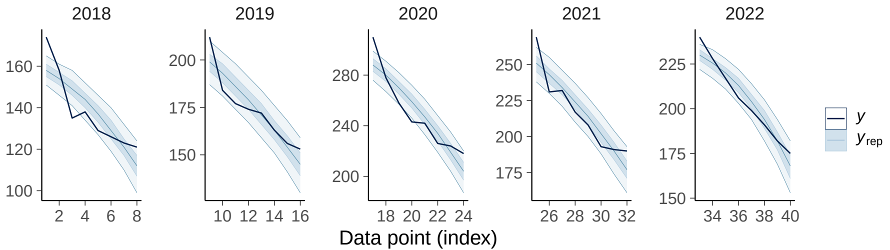


Latent hierarchical linear model + spline

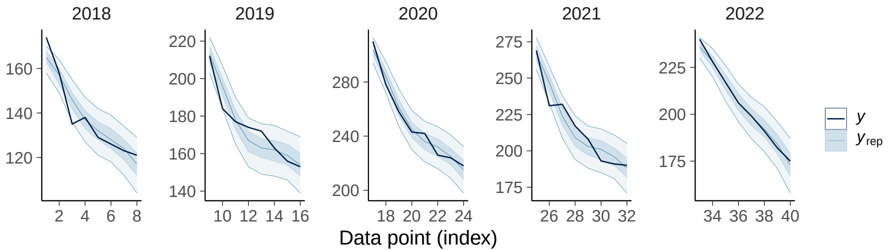


Student retention – Posterior predictive ribbon

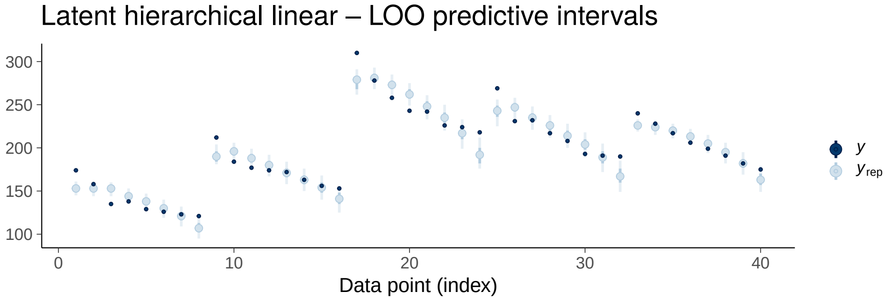
Latent hierarchical linear model

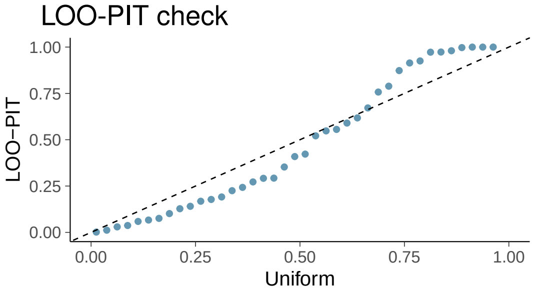


Latent hierarchical linear model + spline

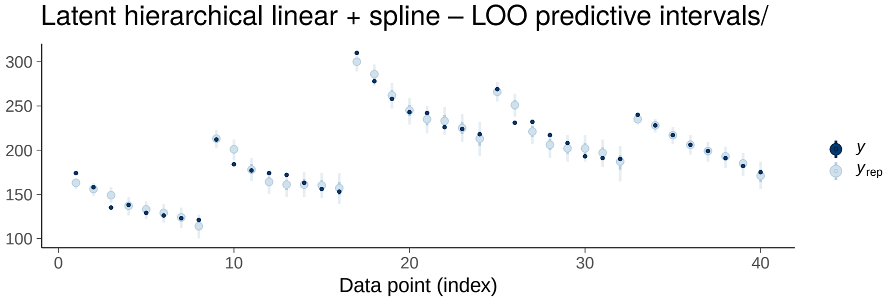


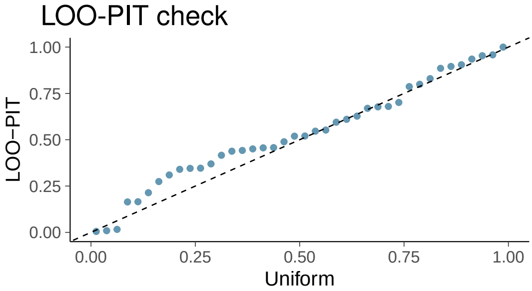
Student retention – LOO-PIT checking





Student retention – LOO-PIT checking



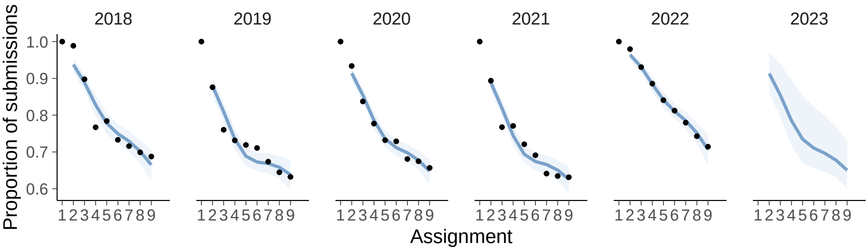


Student retention – LOO model comparison

Latent hierarchical linear vs. latent hierarchical linear + spline

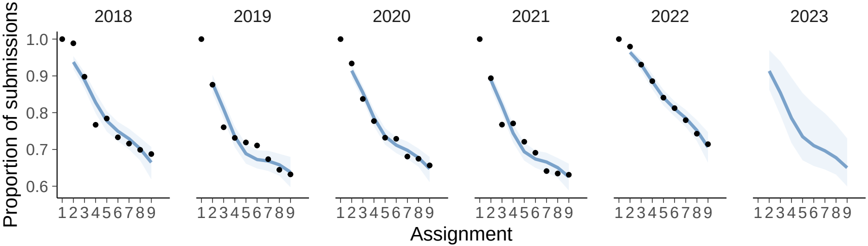
- R^2: 0.92 vs 0.97 in favor of +spline
- ELPD-difference: 43 (SE 14) in favor of +spline

Student retention latent spline model, year 2023?



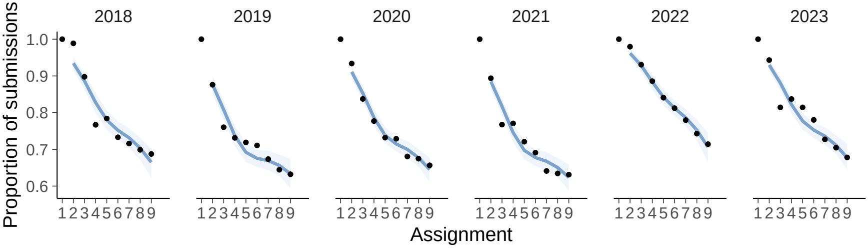
- 90% posterior predictive interval for assignment 9 $(155, 193)$

Student retention latent spline model, year 2023?

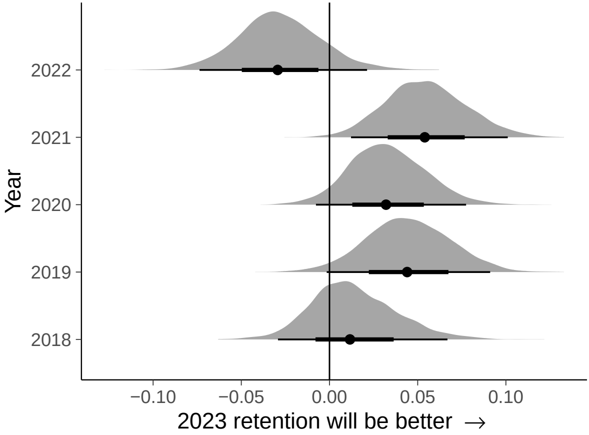


- 90% posterior predictive interval for assignment 9 $(155, 193)$
- Actually observed 179

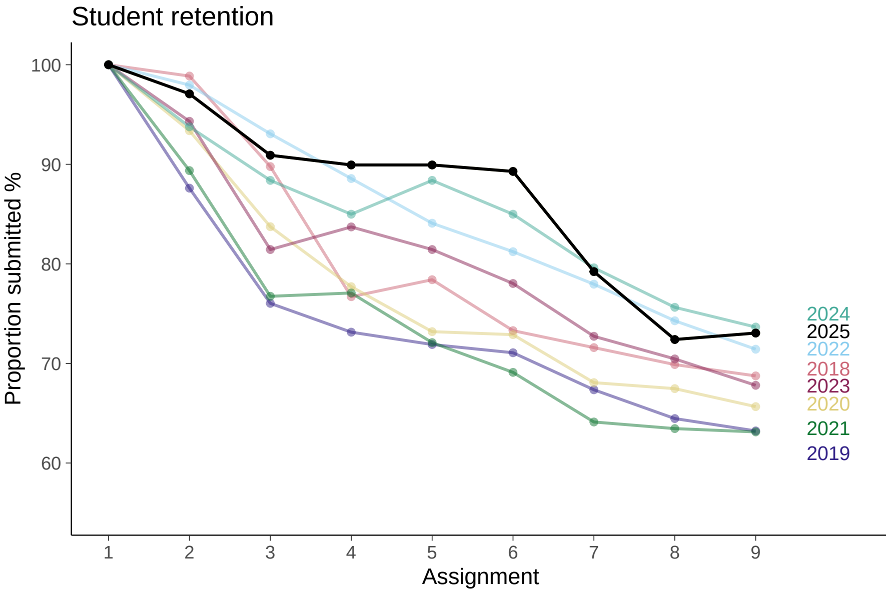
How does year 2023 compare to others?



How does year 2023 compare to others?

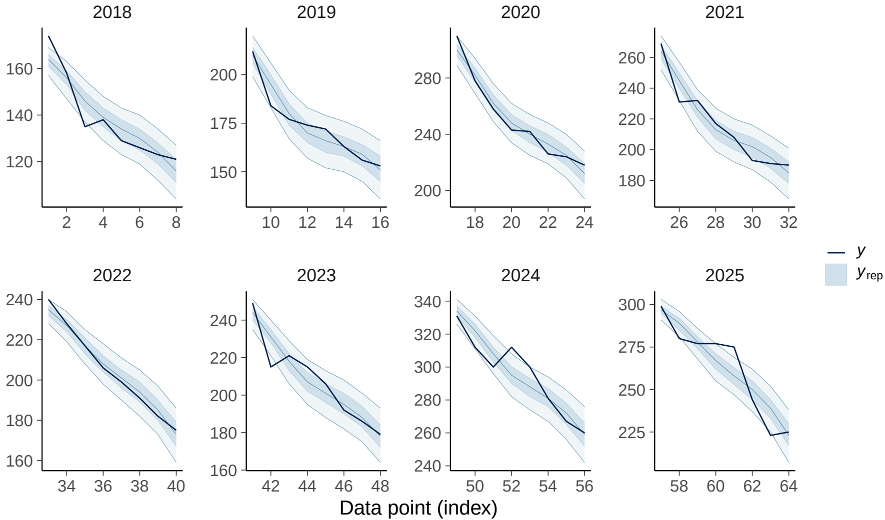


More data



Student retention
Proportion submitted %
100
90
80
70
60
1
2
3
4
5
6
7
8
9
Assignment
2024
2025
2022
2018
2023
2020
2021
2019

More data



2018
2019
2020
2021
2022
2023
2024
2025
160
140
120
200
175
150
280
240
200
260
240
220
200
180
2
4
6
8
10
12
14
16
18
20
22
24
26
28
30
32
y
y rep
240
220
200
180
160
240
220
200
180
160
340
320
300
280
260
240
300
275
250
225
34
36
38
40
42
44
46
48
50
52
54
56
58
60
62
64
Data point (index)

Convergence diagnostics

- MCMC sampling performed well based on the usual convergence diagnostics

Conclusions

- Latent hierarchical model with spline can model 98% of the variation submission numbers
- Based on the model checking diagnostics, the model is reasonable
- Year 2023 retention was slightly above average

Extra hints

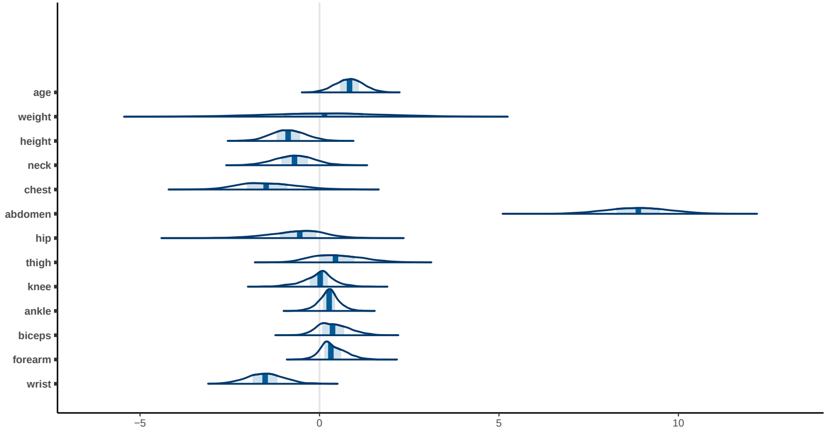
- Following slides discuss some presentation hints

Slide number

- Slide number helps after the presentation as question askers can refer to a specific slide

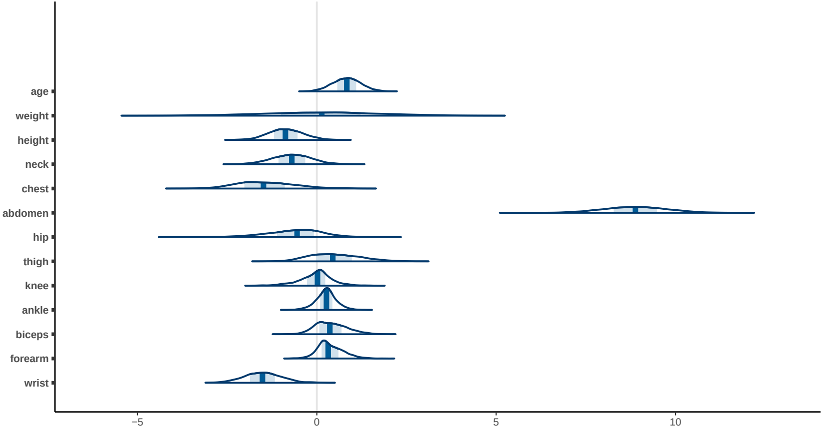
Bodyfat

Marginal posteriors of coefficients



Bodyfat

Check that the font in all figures is big enough!



Bodyfat

Marginal posteriors of coefficients (Much better!)

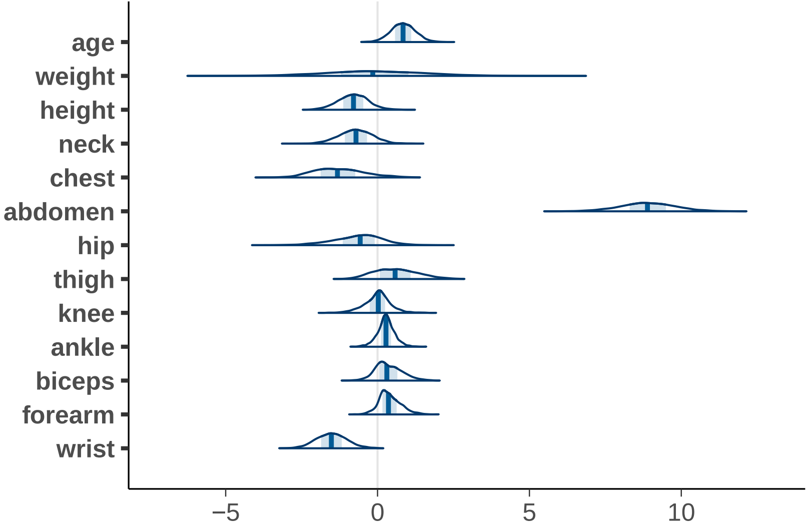


Figure font size

For example:

```
theme_set(bayesplot::theme_default(base_family = "sans",
          base_size=16))
```

Projective predictive covariate selection

- The full model predictive distribution represents our best knowledge about future $\tilde{y}$

$$p(\tilde{y}|D) = \int p(\tilde{y}|\boldsymbol{\theta})p(\boldsymbol{\theta}|D)d\boldsymbol{\theta},$$

  where $\boldsymbol{\theta} = (\boldsymbol{\beta}, \sigma^2))$ and $\boldsymbol{\beta}$ is in general non-sparse (all $\boldsymbol{\beta}_j \neq 0$)
- What is the best distribution $q_\perp(\boldsymbol{\theta})$ given a constraint that only selected covariates have nonzero coefficient
- Optimization problem:

$$q_\perp = \arg\min_q \frac{1}{n} \sum_{i=1}^{n} \mathrm{KL}\left(p(\tilde{y}_i \mid D) \parallel \int p(\tilde{y}_i \mid \boldsymbol{\theta})q(\boldsymbol{\theta})d\boldsymbol{\theta}\right)$$

- Optimal projection from the full posterior to a sparse posterior (with minimal predictive loss)

For 10min presentation, too much information

- The full model predictive distribution represents our best knowledge about future $\tilde{y}$

$$p(\tilde{y}|D) = \int p(\tilde{y}|\boldsymbol{\theta}) p(\boldsymbol{\theta}|D) d\boldsymbol{\theta},$$

  where $\boldsymbol{\theta} = (\boldsymbol{\beta}, \sigma^2))$ and $\boldsymbol{\beta}$ is in general non-sparse (all $\boldsymbol{\beta}_j \neq 0$)
- What is the best distribution $q_\perp(\boldsymbol{\theta})$ given a constraint that only selected covariates have nonzero coefficient
- Optimization problem:

$$q_\perp = \arg\min_q \frac{1}{n} \sum_{i=1}^{n} \mathrm{KL}\left(p(\tilde{y}_i \mid D) \parallel \int p(\tilde{y}_i \mid \boldsymbol{\theta}) q(\boldsymbol{\theta}) d\boldsymbol{\theta} \right)$$

- Optimal projection from the full posterior to a sparse posterior (with minimal predictive loss)

THANKS!

NO “THANKS”!

NO “THANKS”!

- Don’t ever end with a slide having just “THANKS”

NO “THANKS”!

- Don’t ever end with a slide having just “THANKS”
- “THANKS” slide has zero information content

NO "THANKS"!

- Don't ever end with a slide having just "THANKS"
- "THANKS" slide has zero information content
- Leave the conclusion slide or contact information slide

Conclusions

- Latent hierarchical model with spline can model 98% of the variation submission numbers
- Based on the model checking diagnostics, the model is reasonable
- Year 2023 retention was slightly above average

Additional information

- You can have additional slides after the conclusion for supporting material to answer questions
  - for example, in this course, include Stan code and additional convergence and model checking results

Gaussian linear model with regularized horseshoe prior

```
// generated with brms 2.14.4
functions {
  vector horseshoe(vector z, vector lambda, real tau, real c2) {
    int K = rows(z);
    vector[K] lambda2 = square(lambda);
    vector[K] lambda_tilde = sqrt(c2 * lambda2 ./ (c2 + tau^2 * lambda2));
    return z .* lambda_tilde * tau;
  }
}
data {
  int<lower=1> N;  // total number of observations
  vector[N] Y;  // response variable
  int<lower=1> K;  // number of population-level effects
  matrix[N, K] X;  // population-level design matrix
  // data for the horseshoe prior
  real<lower=0> hs_df;  // local degrees of freedom
  real<lower=0> hs_df_global;  // global degrees of freedom
  real<lower=0> hs_df_slab;  // slab degrees of freedom
  real<lower=0> hs_scale_global;  // global prior scale
  real<lower=0> hs_scale_slab;  // slab prior scale
  int prior_only;  // should the likelihood be ignored?
}
transformed data {
  int Kc = K - 1;
```