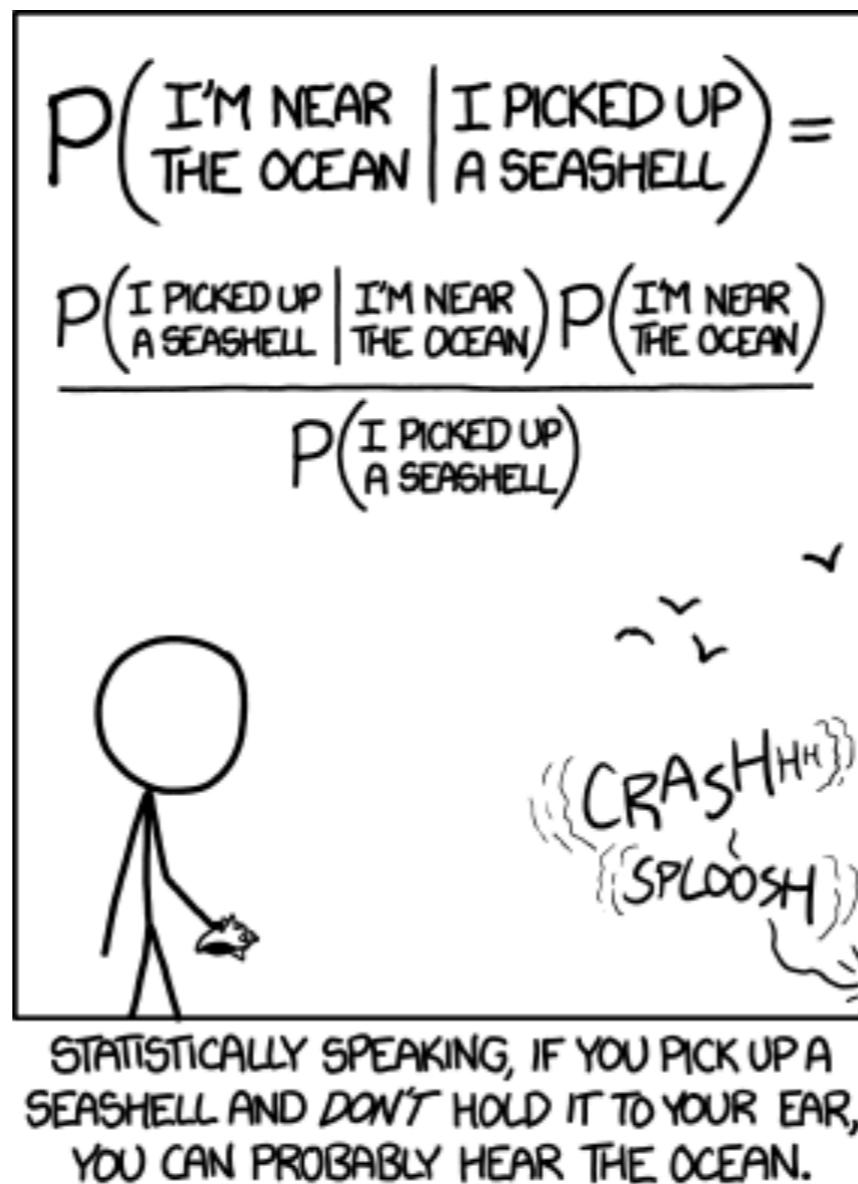


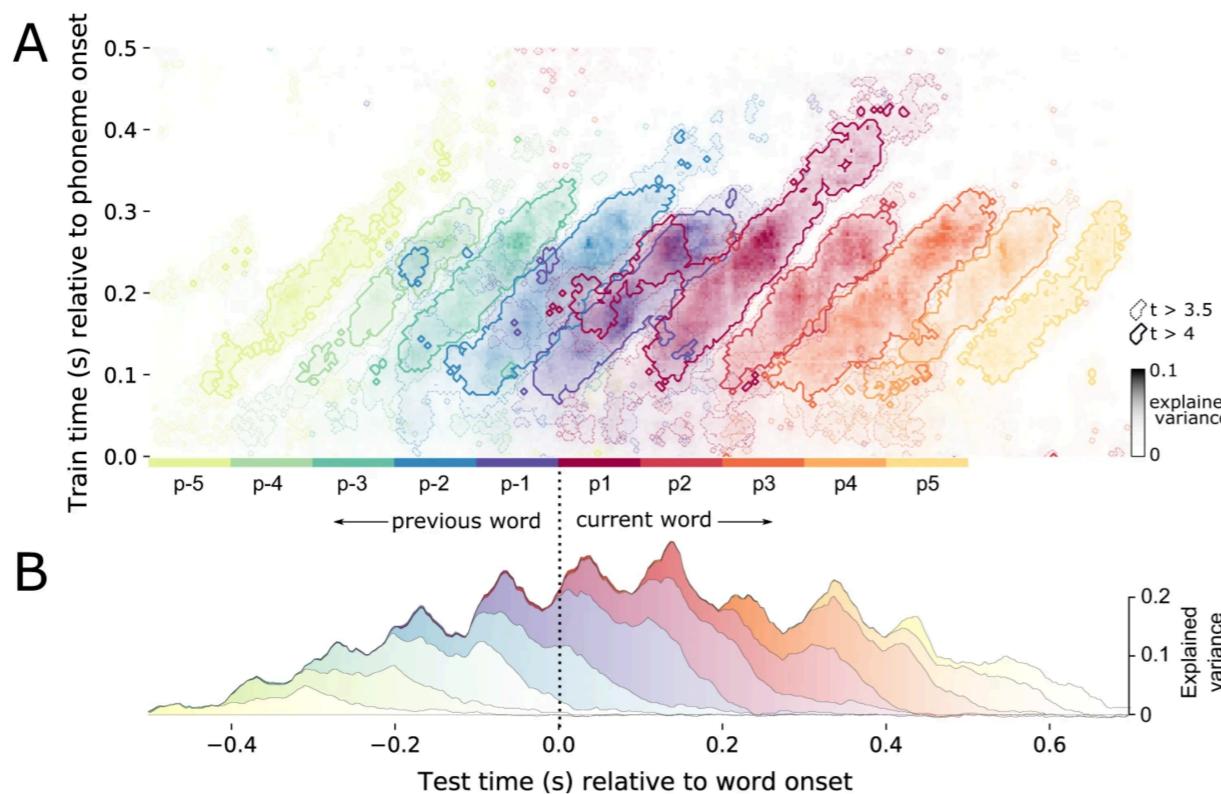
Summary and course outlook



COLLABORATIVE PLAYLIST
psych252
<https://tinyurl.com/psych252spotify24>
PLAY ...

Logistics

Guest lecture: Wednesday



Laura Gwilliams

Language is central to human life. The speed and accuracy with which typically-developing individuals acquire, produce and understand language is nothing short of remarkable - vastly outperforming even the most advanced artificial intelligence systems. My research aims to provide an algorithmically precise account of how the human brain achieves this feat. Such insight has the power to inform neuroscience (understanding the human brain) and engineering (building intelligent machines).

Course evaluations

The screenshot shows a web-based course evaluation system. At the top, there's a navigation bar with links for Home, Results, Custom Questions, Manage Courses, Instructor (Tobias Gerstenberg), and Help/Bell notifications. Below the navigation is a breadcrumb trail: Home / Custom Questions / Custom Question Surveys / Attach Surveys to Projects / Custom Question Survey. The main title is "Custom Question Survey Winter 2024 Course Feedback". There are three action buttons: "+ Add Custom Question Survey", "+ Create New Survey", and "View Main Survey for this Project". A table lists one survey entry: "PSYCH 252: Statistical Methods for Behavioral and Social Sciences 2" created by Tobias Gerstenberg on 3/10/2024 at 5:25 PM, associated with 1 course. The bottom of the page includes pagination controls showing "Total 1", "Records per page 50", "Page 1 of 1", and navigation arrows.

Survey Title	Created By	Updated By	Updated Date	Courses	Edit	Delete
PSYCH 252: Statistical Methods for Behavioral and Social Sciences 2	Tobias Gerstenberg	Tobias Gerstenberg	3/10/2024 5:25 PM	1		

Thank you for evaluating the course!!

<http://course-evaluations.stanford.edu>

Guest lecture: Friday

Satchel Grant



Shawn Schwartz



Plan for today

- What we've learned
- What shall I do now?
- Quick recap
- Going beyond with Bayes
 - Evidence for the null hypothesis
 - I only want positive coefficients!
 - Dealing with unequal variance
 - Better modeling Likert scale data
- Thanks!

What we've learned

Learning goals

What you will learn

You will learn how to **use R** to ...

- read, wrangle, and analyze data
- make publication-ready plots

Understand the philosophy behind null **hypothesis significance testing (NHST)** and **Bayesian statistics** through ...

- running computer simulations and visualizing the results

Formulate **research questions as statistical models** and ...

- determine which models work for different situations

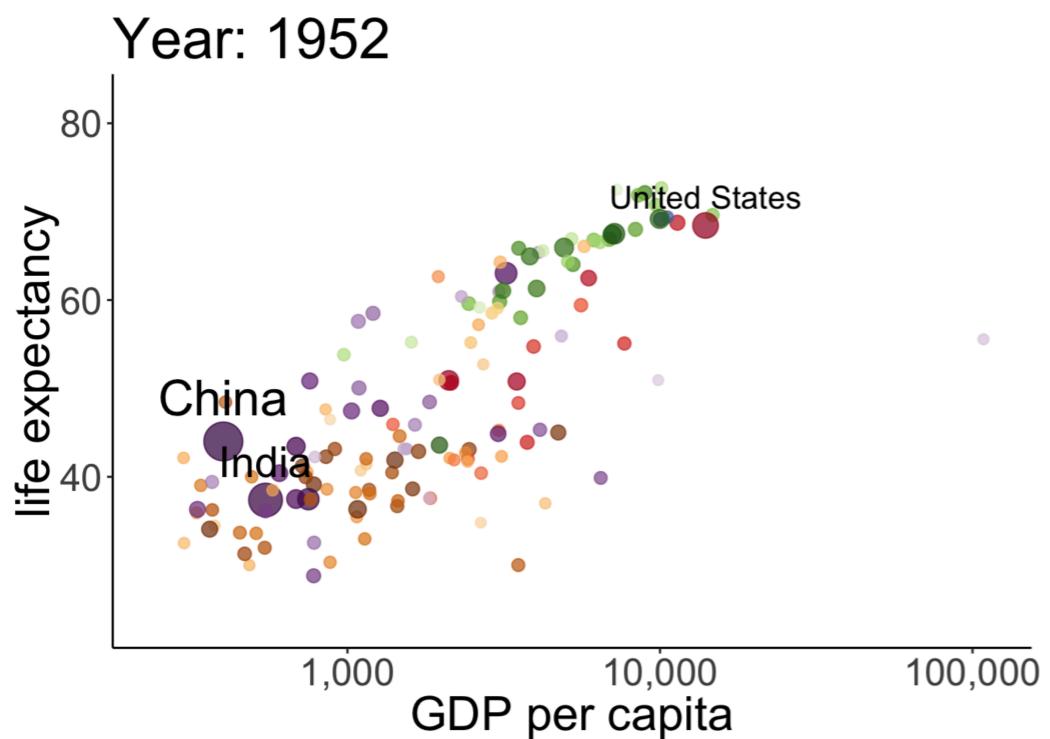
Communicate what you have learned about your data ...

- in short presentations in class, showcasing your visualization and analysis
- in written reports

Contribute to open and **reproducible science** through ...

- adopting good coding practices
- sharing your data and research reports online

You will learn to use R



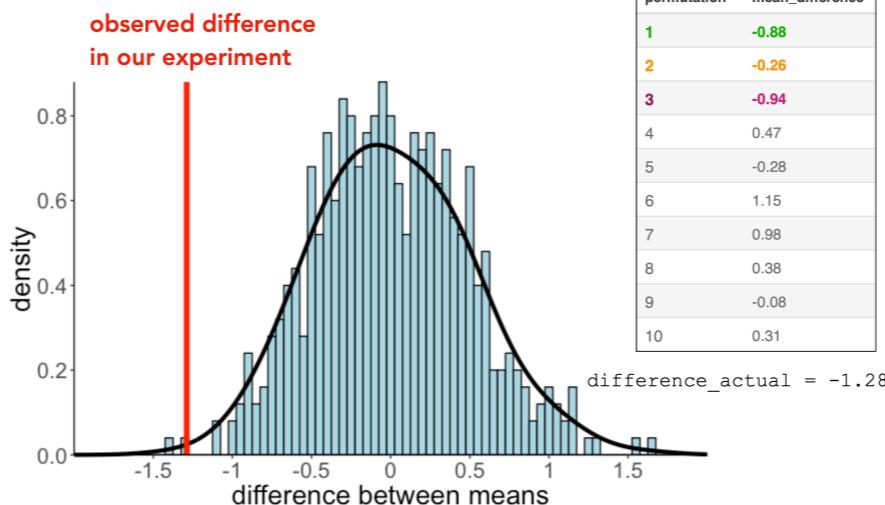
visualization

dplyr : go wrangling



data wrangling

Permutation test



```
1 #calculate p-value of our observed result  
2 df.permutations %>%  
3   summarise(p_value = sum(mean_difference <= difference_actual)/n())
```

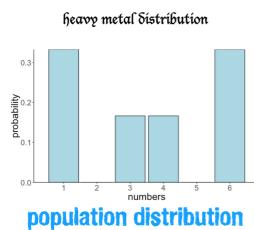
p-value = .002

64

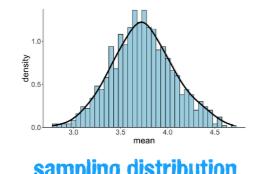
simulation

Philosophy behind frequentist and Bayesian stats

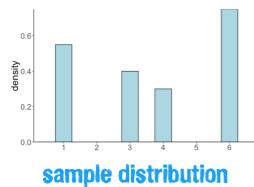
3 distributions in statistical inference



- unknown
- our target for inference
- e.g. we might be interested in the mean of the population distribution



- bridge between sample and population
- derived mathematically / computationally
- asymptotic distribution theory or resampling approaches
- shows how test statistic varies between samples



- our observed sample
- we compute statistics of interest (mean, variance, correlation, ...)
- make an inference about the population via the sampling distribution

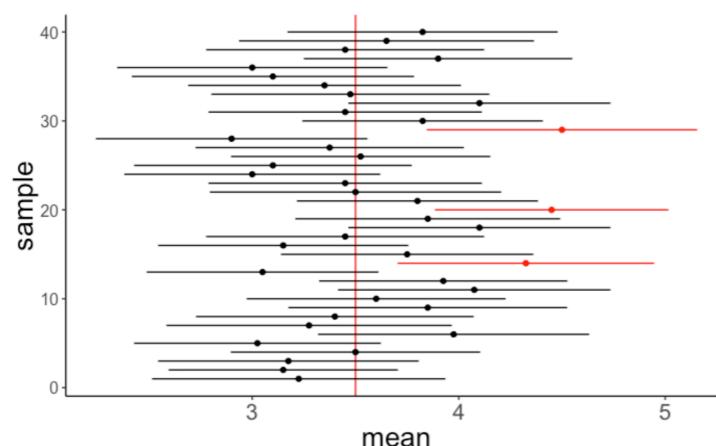
45

sampling distribution

95% confidence interval

Definition

"If we were to repeat the experiment over and over, then 95% of the time the confidence interval contains the estimate of interest."



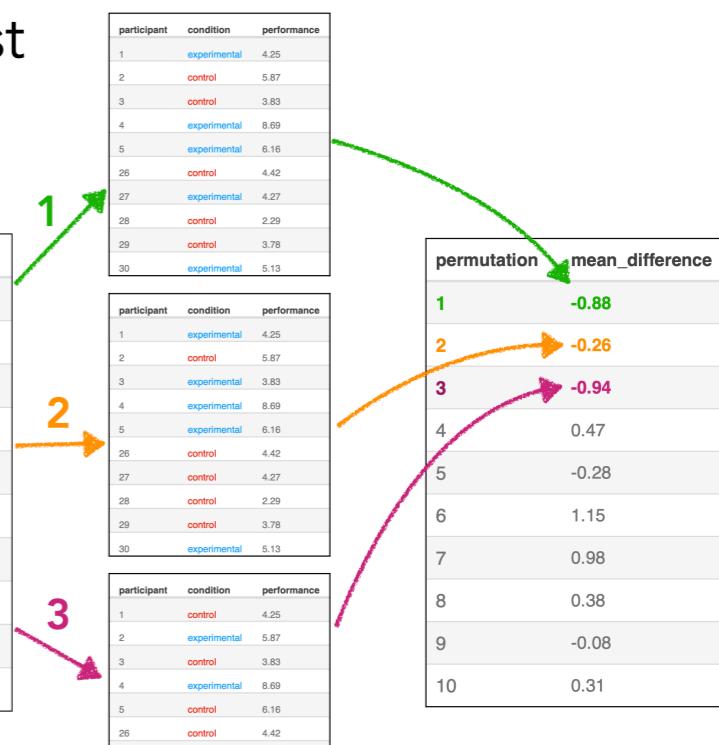
Hoekstra, R., Morey, R. D., Rouder, J. N., & Wagenmakers, E.-J. (2014). Robust Misinterpretation of Confidence Intervals. *Psychonomic Bulletin & Review*, 21(5), 1157-1164.

confidence interval

Permutation test

observed data

participant	condition	performance
1	control	4.25
2	control	5.87
3	control	3.83
4	control	8.69
5	experimental	6.16
26	control	4.42
27	experimental	4.27
28	control	2.29
29	experimental	3.78
30	experimental	5.13



p-value

61

The general procedure

1. Define H_0 as Model C (compact) and H_1 as Model A (augmented)
2. Fit model parameters to the data
3. Calculate the proportional reduction of error (PRE) in our sample
4. Decide whether the augmented model is **worth it** by comparing the observed PRE in our sample to the sampling distribution of PRE (assuming that H_0 is true)

model comparison

10

24

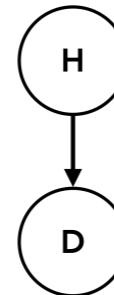
Philosophy behind frequentist and Bayesian stats

Clue guide to probability

$$p(B|A) = \frac{p(A|B) \cdot p(B)}{p(A)}$$

posterior $p(H|D) = \frac{\text{likelihood} \cdot \text{prior}}{p(D)} = \frac{p(D|H) \cdot p(H)}{p(D)}$

subjective probability interpretation
 H = Hypothesis
 D = Data



formal framework for learning from data

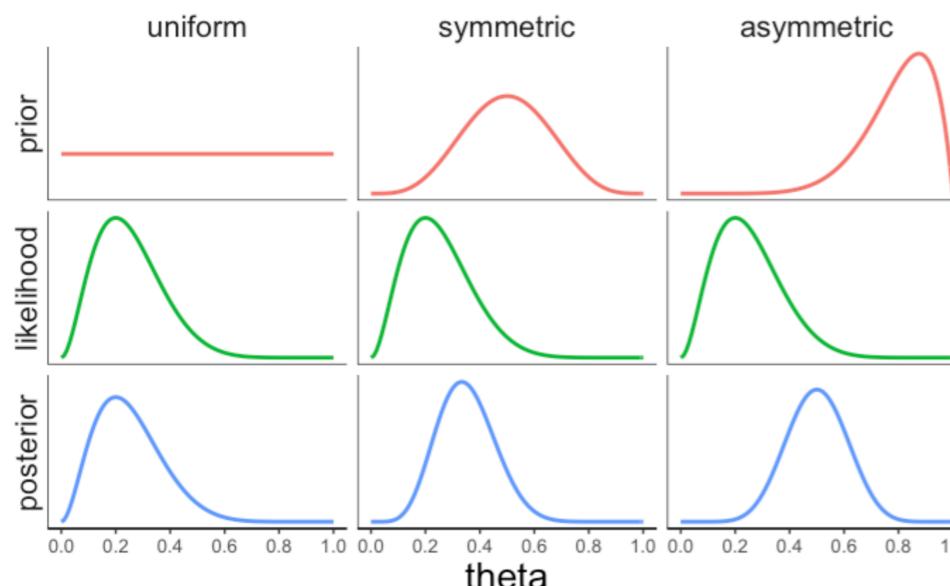
updating our prior belief $p(H)$, to a posterior belief $p(H|D)$ given some data

Bayes' theorem

44

The effect of the **prior**

same data, different priors



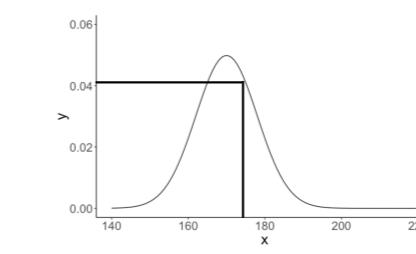
prior, likelihood, posterior

50

Summer camp

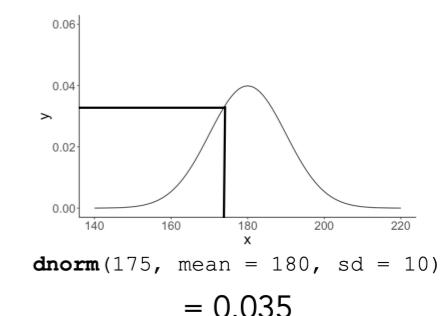
prior

$$p(\text{chess}) = \frac{1}{3}$$



likelihood

$$p(\text{basketball}) = \frac{2}{3}$$



posterior

$$p(\text{basketball}|175) = \frac{p(175|\text{basketball}) \cdot p(\text{basketball})}{p(175|\text{basketball}) \cdot p(\text{basketball}) + p(175|\text{chess}) \cdot p(\text{chess})}$$

$$p(\text{basketball}|175) = \frac{0.035 \cdot 2/3}{0.035 \cdot 2/3 + 0.041 \cdot 1/3} \approx 0.63$$

send the kid to the basketball gym!

36

Bayesian inference

Recipe for Bayesian analysis with `brms`

- 1. Visualize the data
- 2. Specify and fit the model
- 3. Model evaluation
- visualization is everywhere!**
 - a) Did the inference work?
 - b) Visualize model predictions
- 4. Interpret the model parameters
- 5. Test specific hypotheses
- 6. Report results

Bayesian data analysis

39

11

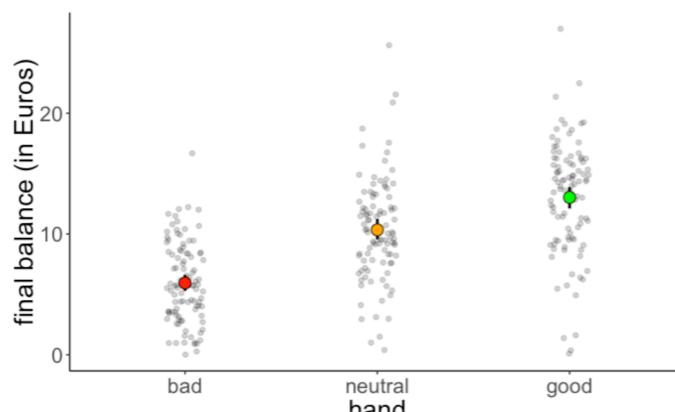
Formulate research questions as statistical models

Do better hands win more money?

participant	skill	hand	limit	balance
1	expert	bad	fixed	4.00
2	expert	bad	fixed	5.55
26	expert	bad	none	5.52
27	expert	bad	none	8.28
51	expert	neutral	fixed	11.74
52	expert	neutral	fixed	10.04
76	expert	neutral	none	21.55
77	expert	neutral	none	3.12
101	expert	good	fixed	10.86
102	expert	good	fixed	8.68

hand = {bad, neutral, good}

Visualize the data first

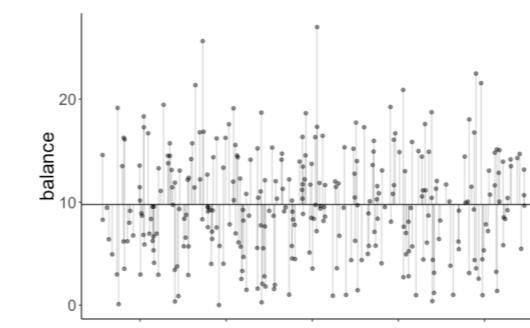


H_0 : Card quality does not affect the final balance.

Model C

$$\text{balance}_i = \beta_0 + \epsilon_i$$

Model prediction



Fitted model

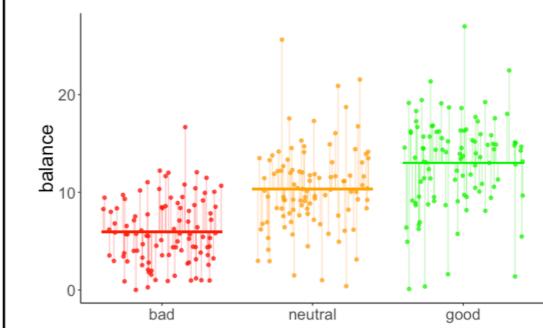
$$\widehat{\text{balance}}_i = 9.77$$

H_1 : Card quality affects the final balance.

Model A

$$\text{balance}_i = \beta_0 + \beta_1 \text{hand_neutral}_i + \beta_2 \text{hand_good}_i + \epsilon_i$$

Model prediction



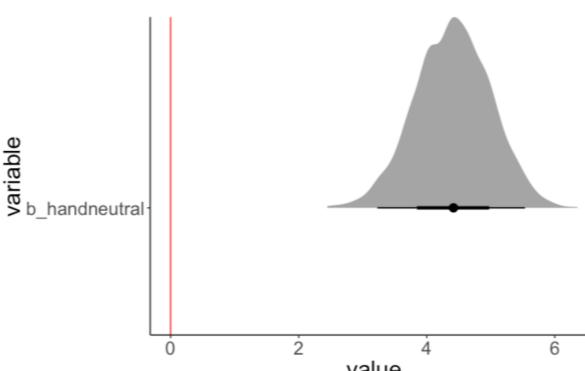
Fitted model

$$\widehat{\text{balance}}_i = 5.94 + 4.41 \cdot \text{hand_neutral}_i + 7.08 \cdot \text{hand_good}_i$$

31

Asking questions based on the posterior

Do neutral hands earn more money than bad hands?



What's the probability that handneutral is less than 0?

```
1 hypothesis(fit.brms,
2   hypothesis = "handneutral < 0")
```

p = 0

52

12

Communicate what you've learned about your data

2.1: Regressions (1.5 point)

Run three linear regression models that estimate the relationships between `quarter_of_birth` and `log_weekly_wage`, `education` and `log_weekly_wage`, and `quarter_of_birth` and `education`. Then run a multiple regression model that predicts `log_weekly_wage` based on both `quarter_of_birth` and `education`. Print the summaries of all four regressions and comment on their significances.

```
### YOUR CODE HERE ###
lm1 = lm(formula = log_weekly_wage ~ quarter_of_birth,
         data = df.qob)
lm2 = lm(formula = log_weekly_wage ~ education,
         data = df.qob)
lm3 = lm(formula = education ~ quarter_of_birth,
         data = df.qob)

lm_multi = lm(formula = log_weekly_wage ~ quarter_of_birth + education,
               data = df.qob)

summary(lm1)
```

Call:
`lm(formula = log_weekly_wage ~ quarter_of_birth, data = df.qob)`

Residuals:
Min 1Q Median 3Q Max
-8.2511 -0.2629 0.0605 0.3720 4.2099

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	5.887183	0.007114	827.584	<2e-16 ***
quarter_of_birth	0.007366	0.002913	2.529	0.0115 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.6908 on 49998 degrees of freedom
Multiple R-squared: 0.0001279, Adjusted R-squared: 0.0001079
F-statistic: 6.394 on 1 and 49998 DF, p-value: 0.01145

homework/midterm

A catchy project title goes here

My team's name goes here

The team members' names go here

2021-03-19 12:44:19

- 1 Introduction
 - 1.1 Research questions
 - 1.2 Hypotheses
- 2 Methods
- 3 Results
 - 3.1 Confirmatory analysis
 - 3.2 Exploratory analysis
- 4 Discussion
- References

The final project is due on **Friday, March 20th at 8pm**.

Here are some guidelines:

- The length of the final report should be around 2000 words per person in the group.
- All the code should be contained in this RMarkdown file (from reading in the messy data file, to making beautiful plots).
- Feel free to make the final report look like an actual paper. So you can hide all the code chunks that do data wrangling etc. from the output (by setting the code chunk option to `echo=F`), and only show the figures and tables that you need to explain your work.
- Show us what you've learned :) We're excited to read it!

For more information on how to do stuff in RMarkdown, check out:

- bookdown documentation
- RMarkdown code chunks
- RMarkdown cheat sheet
- Citations

final project (proposal, presentation, report)

Contribute to open and reproducible science

The screenshot shows the RStudio interface. On the left, the R script file '23-bayesian_data_analysis2.Rmd' is open, displaying R code for Bayesian data analysis. The code includes sections for model specification, posterior draws, and various plots like ggplots and geom_point. On the right, the terminal session shows the R environment, including the R version (R 4.3.2), the current working directory (~Documents/work/projects/psych252/psych252book/), and basic help information.

RStudio

The screenshot shows a GitHub repository page for 'final-projects'. The repository has 1 branch and 0 tags. The 'About' section describes it as a 'Starter code for the final project'. It lists several commits from 'tobiasgerstenberg' and 'sarahawu', each with a commit message and timestamp. The 'Releases' section indicates 'No releases published' and a link to 'Create a new release'. The 'Packages' section shows 'No packages published' and a link to 'Publish your first package'. The 'Contributors' section lists 'tobiasgerstenberg' and 'sarahawu'. The 'Languages' section shows 'HTML 99.4%' and 'TeX 0.6%'. The 'Repository structure' diagram shows a folder hierarchy: code (containing R), data, figures, papers, presentation, writeup (containing final_report and proposal).

github

What we've covered

visualization and data wrangling

probability, simulation, causality

linear model

power analysis

model comparison

linear mixed effects models

logistic regression

Bayesian data analysis

Date	Topic
January 8th	Introduction
January 10th	Visualization 1
January 12th	Visualization 2
January 15th	Martin Luther King Jr. Day
January 17th	Data wrangling 1
January 19th	Data wrangling 2
January 22nd	Probability
January 24th	Simulation 1
January 26th	Simulation 2
January 29th	Modeling data
January 31st	Linear model 1
February 2nd	Linear model 2
February 5th	Linear model 3
February 7th	Linear model 4
February 9th	Power analysis
February 12th	Model comparison
February 14th	No class (due to Midterm)
February 16th	Causation
February 19th	President's Day
February 21st	Linear mixed effects models 1
February 23rd	Linear mixed effects models 2
February 26th	Linear mixed effects models 3
February 28th	Linear mixed effects models 4
March 1st	Generalized linear model
March 4th	Bayesian data analysis 1
March 6th	Bayesian data analysis 2
March 8th	Bayesian data analysis 3
March 11th	Summary and course outlook
March 13th	Guest lecture: Laura Gwilliams
March 15th	Guest lecture: Satchel Grant & Shawn Schwartz

I'll keep updating the course notes!

PSYCH 252: STATISTICAL METHODS

Home Schedule Getting ready Information **Book**

This course offers an introduction to advanced topics in statistics with the focus of understanding data in the behavioral and social sciences. It is a practical course in which learning statistical concepts and building models in R go hand in hand. The course is organized into three parts: In the first part, we will learn how to visualize, wrangle, and simulate data in R. In the second part, we will cover topics in frequentist statistics (such as multiple regression, logistic regression, and mixed effects models) using the general linear model as an organizing framework. We will learn how to compare models using simulation methods such as bootstrapping and cross-validation. In the third part, we will focus on Bayesian data analysis as an alternative framework for answering statistical questions.

Requirement: [Psych 10, Stats 60](#), or equivalent.

Psych 252: Statistical Methods for Behavioral and Social Sciences

Tobias Gerstenberg

2024-01-06

Preface

This book contains the course notes for [Psych 252](#). The book is not intended to be self-explanatory and instead should be used in combination with the course lectures posted [here](#).

If you have any questions about the notes, please feel free to contact me at: gerstenberg@stanford.edu or post an issue on the book's [github repository](#).

<https://psych252.github.io/>

you'll still have access to the lecture recordings from 2022

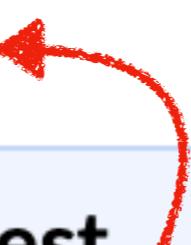
including the super accurate captions!



Tobi Gerstenberg

00:00:01

hi I am totally guest
America i'm an
assistant professor at
Stanford university



take a hint zoom!

Datacamp (available until ~ mid june)



What shall I do now?

PSYCH 253



Nilam Ram

COMM 369: Measurement and the Study of Change in Social Science Research (PSYCH 253)

This course is a survey of methodological issues associated with the measurement of psychological constructs and processes of change. General areas to be covered include use of latent variable models (structural equation modeling), classical test theory, generalizability theory, principal component analysis, factor analysis, item response theory and how these models facilitate and/or constrain the study of change processes. Students will work through application/implementation of the models through hands-on analysis of simulated and empirical data, acquire experiences in the formulation of research questions and study designs that are appropriately tethered to the different theoretical perspectives invoked by the different models.

Terms: Spr | **Units:** 3

Instructors: Ram, N. (PI) ; Mehta, A. (TA) ; Tan, A. (TA)

[Schedule for COMM 369](#)

CS109: Probability for Computer Scientists

Schedule

The class starts by providing a fundamental grounding in combinatorics, and then quickly moves into the basics of probability theory. We will then cover many essential concepts in probability theory, including particular probability distributions, properties of probabilities, and mathematical tools for analyzing probabilities. Finally, the last third of the class will focus on data analysis and Machine Learning as a means for seeing direct applications of probability in this exciting and quickly growing subfield of computer science.

Overview of Topics

 Counting Theory	 Core Probability	 Random Variables	 Probabilistic Models	 Uncertainty Theory	 Machine Learning
--	---	---	---	---	---

- learn more about probability theory through programming
- gain a deeper understanding of the fundamental underlying concepts

<http://web.stanford.edu/class/cs109/schedule.html>

PSYCH 204B: Computational Neuroimaging: Data Analyses and Experimental Designs

This course provides an in-depth survey and understanding of modern computational approaches to design and analyses of neuroimaging data. The course is a mixture of lectures and projects geared to give the student an understanding of the possibilities as well as limitations of different computational approaches. Topics include: signal and noise in MRI; general linear modeling; fMRI-adaptation; multivoxel pattern analyses; decoding and encoding algorithms; modeling population receptive fields. Required: Psych 204A; Recommended: Cognitive Neuroscience, Stats

Terms: Spr | **Units:** 1-3

Instructors: Grill-Spector, K. (PI)

[Schedule for PSYCH 204B](#)



Advanced regression analysis



Sanne Smith

EDUC 326: Advanced Regression Analysis (SOC 384)

Social science researchers often deal with complex data and research questions that traditional statistics models like linear regression cannot adequately address. This course offers the opportunity to understand and apply two widely used types of advanced regression analysis that allow the examination of 1) multilevel data structures (multilevel models) and 2) multivariate research questions (structural equation models).

Terms: Spr | **Units:** 3-5

Instructors: Smith, S. (PI) ; Bhat, K. (TA)

[Schedule for EDUC 326](#)

2023-2024 Spring

EDUC 326 | 3-5 units | UG Reqs: None | Class # 2200 | Section 01 | Grading: Letter or Credit/No Credit | LEC | Session: 2023-2024 Spring 1 | In Person | Students enrolled: 9

04/01/2024 - 06/05/2024 Thu 1:30 PM - 4:20 PM at [Ceras 108](#) with Smith, S. (PI); Bhat, K. (TA)

Instructors: Smith, S. (PI); Bhat, K. (TA)

Additional Resources: (Login to view additional resources)

and many more ...

- **EDUC 423B:** Introduction to Data Science II: Machine learning (SOC 302B) (overview of machine learning techniques)
- **EDUC 430A:** Experimental Research Design and Analysis (learn how to do field experiments and causal inference)
- **EDUC 430B:** Quasi-Experimental Research Design & Analysis (SOC 258B) ((seeking to) get causal inference without doing experiments)
- **MS&E 226:** Fundamentals of Data Science: Prediction, Inference, Causality (a bit redundant with this class but great if you want to reinforce this knowledge and get an intro to ML)
- **MS&E 231:** Introduction to Computational Social Science (SOC 278) (I heard this was very good. it hasn't been offered for a couple years though)
- **STATS 209A:** Topics in Causal Inference (MS&E 327) (haven't taken but seems like a good intro to causal inference)
- **STATS 216:** Introduction to Statistical Learning
- **CS 228:** Probabilistic Graphical Models: Principles and Techniques

What shall I not do?

Email the psych252 teaching team for stats questions I have in the future



We'd love to hear from you, but we can't help with stats questions.

Getting help with stats

for psych grads

for anyone

Consulting Services

The Department of Statistics offers a free online consulting service to members of the broader research community during each Stanford academic quarter.

Under the supervision of a senior faculty member, Statistics graduate students arrange Zoom meetings with clients to help with statistical research questions in areas such as:

- Experimental design and data acquisition
- Data exploration, analysis, and interpretation
- Modeling data and model fitting
- Statistical inference for estimation, testing, and prediction

Students taking statistics courses should understand that **this is not a tutoring service**.

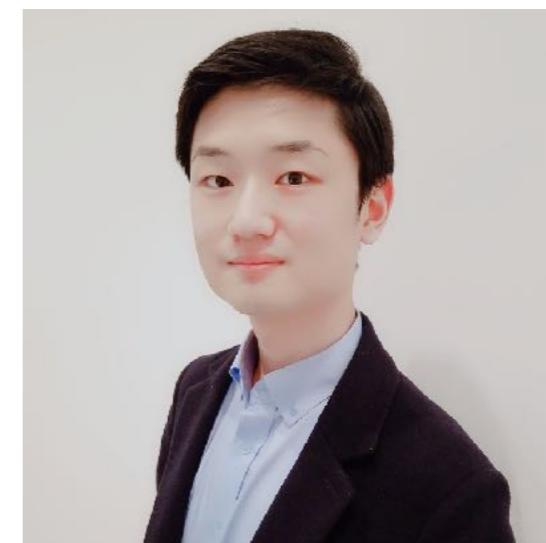
<https://statistics.stanford.edu/resources/consulting>



Shawn Schwartz
stschwartz@stanford.edu



Ari Beller
abeller@stanford.edu



Andrew Nam
ajhnam@stanford.edu

Quick recap

Quick recap: Testing hypotheses

Results

posterior samples			
b_Intercept	b_handneutral	b_handgood	sigma
5.97	4.27	7.49	3.94
5.11	5.25	7.40	3.91
7.03	3.78	5.80	4.48
5.72	4.18	7.25	4.00
6.01	4.44	6.15	4.57
5.94	4.69	6.72	4.36
6.39	3.84	6.40	3.92
5.24	5.15	7.69	4.16
6.12	4.51	7.20	4.14
6.43	3.71	6.37	4.13
5.85	5.01	7.32	4.00
6.51	3.58	6.62	3.95
5.85	4.45	7.62	4.17
5.80	5.45	6.36	4.10
5.48	5.51	7.22	3.99
⋮			

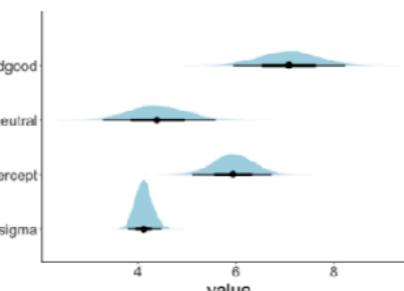
summary of posterior

parameter	lower	mode	upper
b_handgood	5.97	7.07	8.27
b_handneutral	3.21	4.43	5.51
b_intercept	5.17	5.95	6.77
sigma	3.81	4.12	4.47

maximum
a posteriori

MAP estimate and 95%
highest density interval

visualization



12

Testing hypothesis

```
1 df.hypothesis = fit_brm %>%
2   posterior_samples() %>%
3   clean_names() %>%
4   select(starts_with("b_")) %>%
5   mutate(neutral = b_intercept + b_handneutral,
6         bad_good_average = (b_intercept + b_intercept + b_handgood)/2,
7         hypothesis = neutral < bad_good_average)
```

samples
from the
posterior

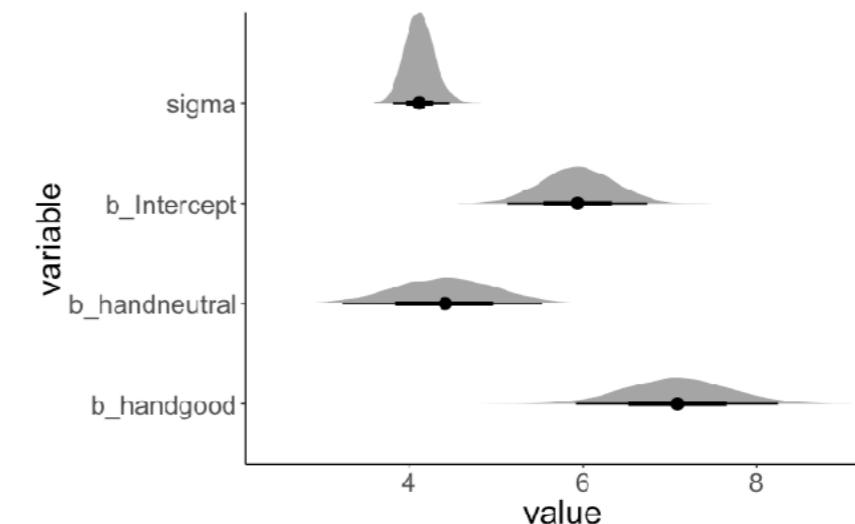
b_intercept	b_handneutral	b_handgood	neutral	bad_good_average	hypothesis
6.07	4.10	7.20	10.17	9.67	FALSE
6.06	4.44	6.95	10.19	9.53	FALSE
5.88	5.00	8.73	10.87	9.24	FALSE
5.85	4.78	6.18	10.63	8.94	FALSE
5.86	4.46	7.68	10.32	9.70	FALSE

```
1 df.hypothesis %>%
2   summarize(p = sum(hypothesis)/n())
```

p = 0.04

Asking questions based on the posterior

Do good hands make twice as much as bad hands?



```
1 hypothesis(fit_brm,
2   hypothesis = "handgood + Intercept > 2 * Intercept")
```

p = 0.89

16

The "emmeans" package is your friend!

```
1 fit_brm_poker %>%
2   emmeans(specs = consec ~ hand)
```

estimated
mean for
each group

contrasts →

```
$emmeans
hand    emmean lower.HPD upper.HPD
bad      5.94    5.16    6.78
neutral 10.34   9.55   11.15
good    13.02   12.22   13.82

Point estimate displayed: median
HPD interval probability: 0.95
```

```
$contrasts
contrast      estimate lower.HPD upper.HPD
neutral - bad     4.38    3.24    5.52
good - neutral    2.69    1.51    3.78

Point estimate displayed: median
HPD interval probability: 0.95
```

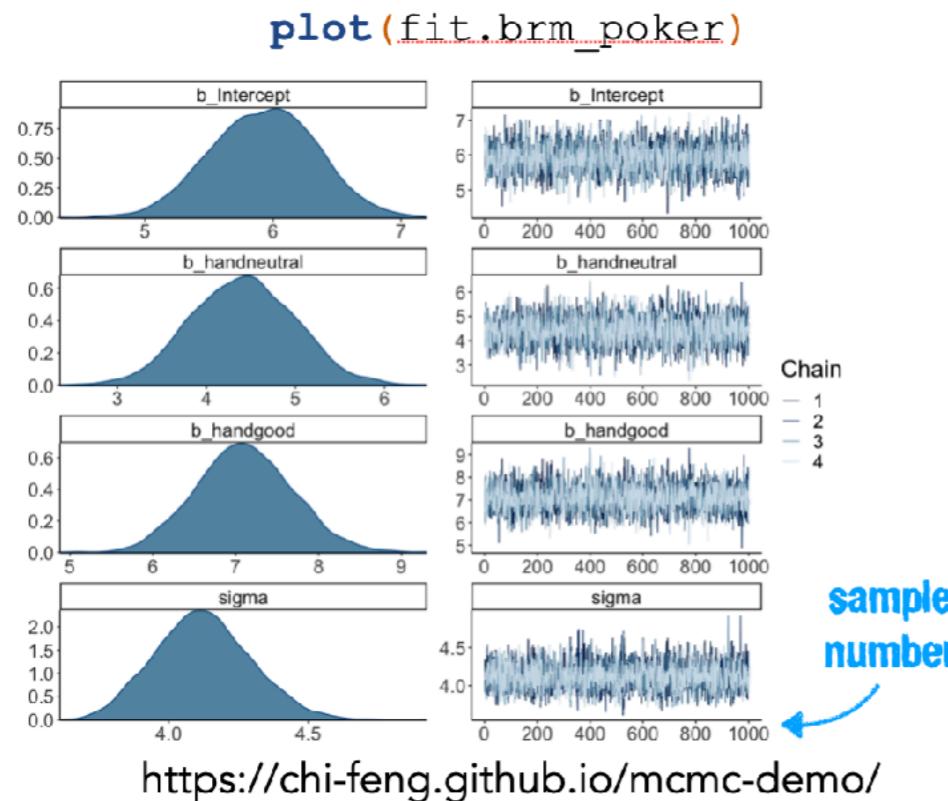
18

29

20

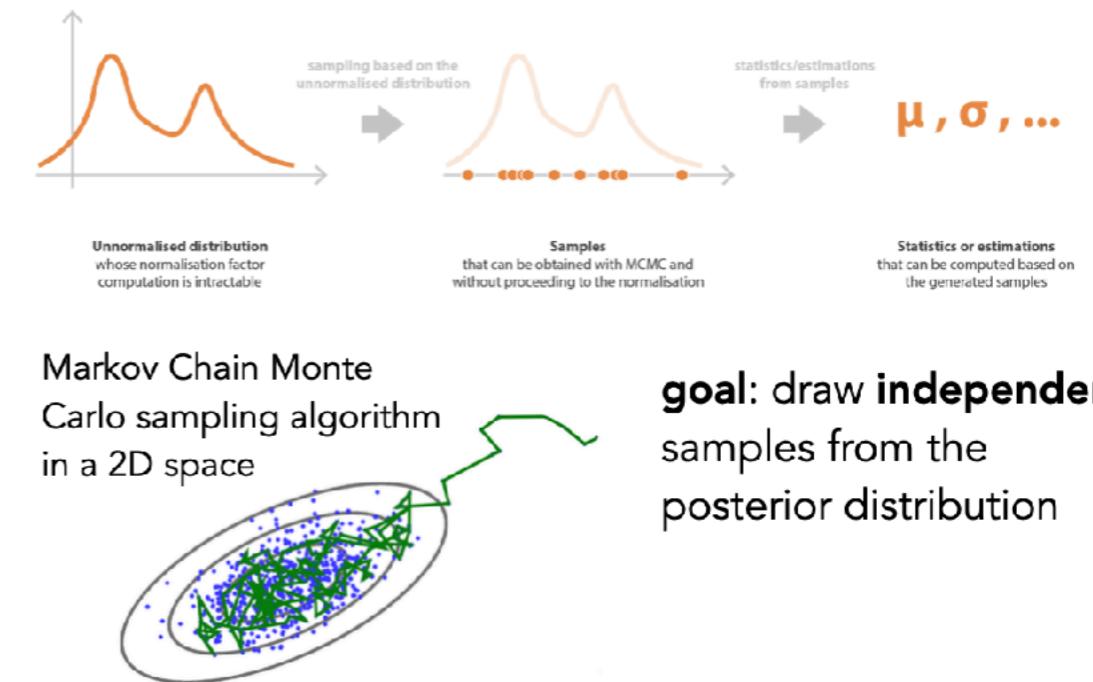
Quick recap: Model evaluation

Can we trust the model results?



Can we trust the model results?

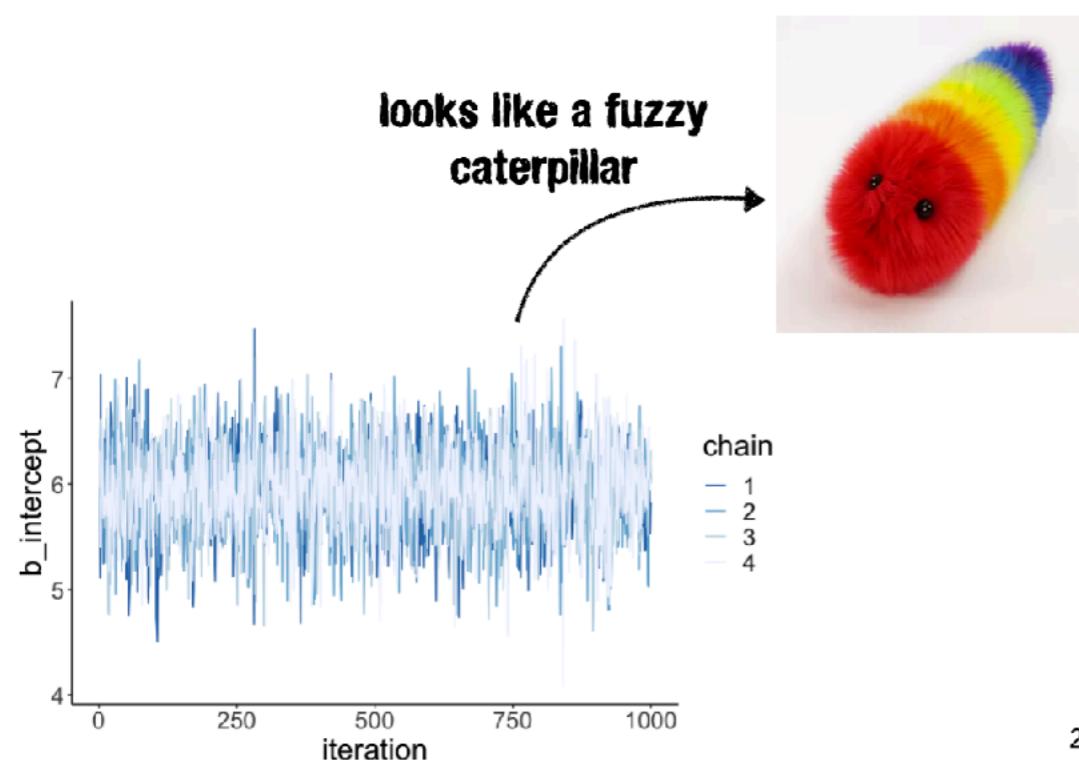
Inference via Markov Chain Monte Carlo (MCMC)



24

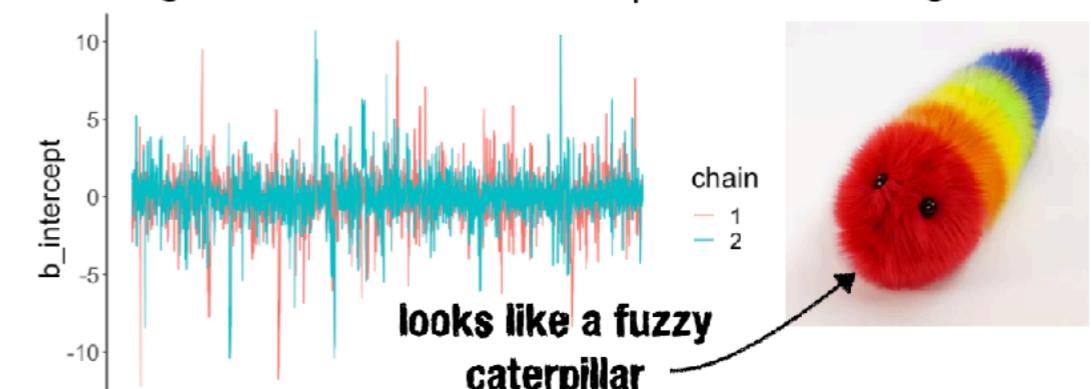
25

Can we trust the model results?



26

Having somewhat informative priors fixes things



if things go wrong:

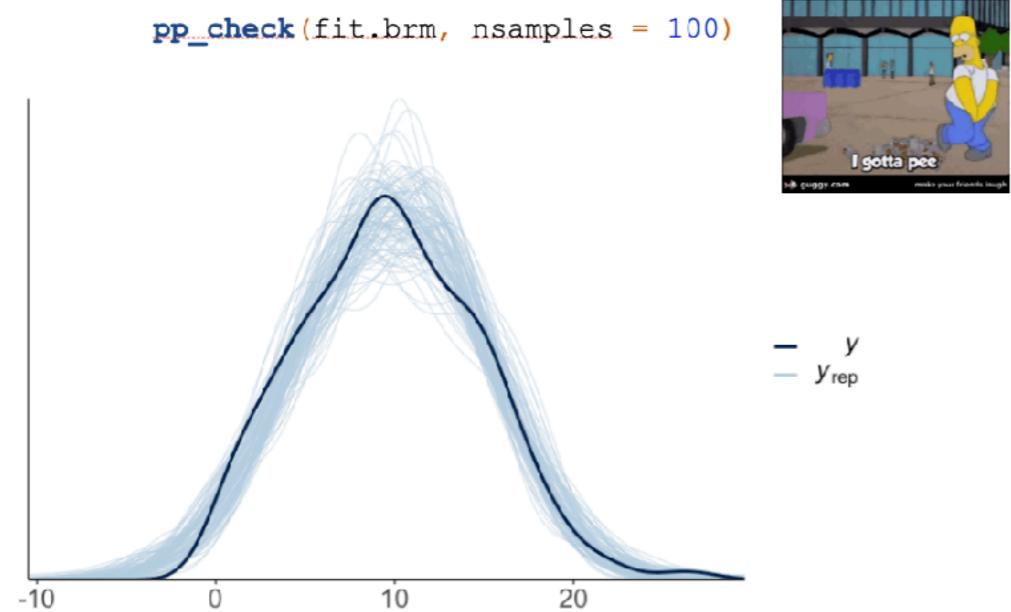
- set more informative priors
- run more warm-up samples
- adjust the sampling algorithm as suggested via the control argument

32

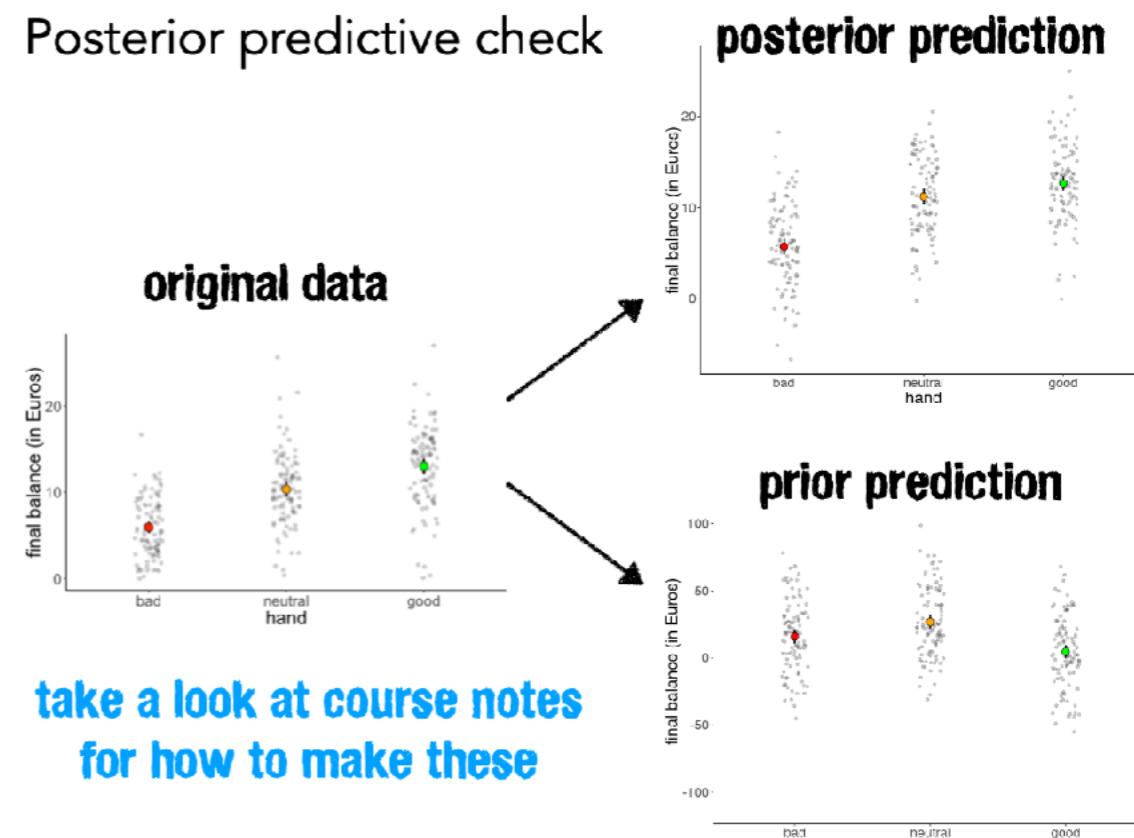
30

Quick recap: Posterior predictive check & reporting

Posterior predictive check



Posterior predictive check

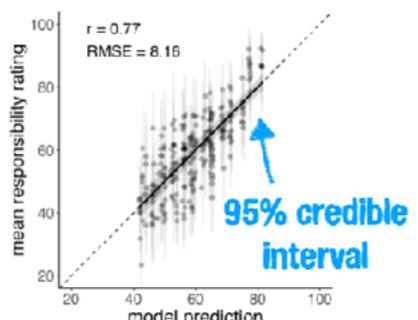


The model accurately captures the distribution of the response variable

34

Reporting results

Plots



Text

We computed a Bayesian mixed effects model with random intercepts and slopes to predict participants' responsibility judgments (see Table 1). Figure 6b shows a scatter plot of the model predictions and participants' responsibility judgments for the full set of 170 scenarios (with 250 judgments). Overall, the model predicts participants' responsibility judgments well with $r = .77$ and $RMSE = 8.16$. Table 1 shows the estimates of the different predictors. As can be seen, none of the predictors' 95% HDIs overlap with 0.¹

Tables

Table 1
Estimates of the mean, standard error, and 95% HDIs of the different predictors in the Bayesian mixed effects model. Note: n_causes = number of causes.

$$\text{responsibility} \sim 1 + \text{surprise} + \text{pivotality} + \text{n_causes} + (1 + \text{surprise} + \text{pivotality} + \text{n_causes}) | \text{participant}$$

term	estimate	std.error	lower 95% HDI	upper 95% HDI
intercept	59.94	3.25	54.70	65.22
surprise	21.08	4.57	14.17	29.23
pivotality	13.52	1.82	10.47	16.55
n_causes	5.72	0.50	6.55	4.90

model formula

parameter estimates

¹For any statistical claim, we report the mean of the posterior distribution together with the 95% highest-density interval (HDI). All Bayesian models were written in Stan (Carpenter et al., 2017) and accessed with the brms package (Bürkner, 2017) in R (R Core Team, 2019).

37

31

Quick recap: Sleep data

1. Specify and fit the model

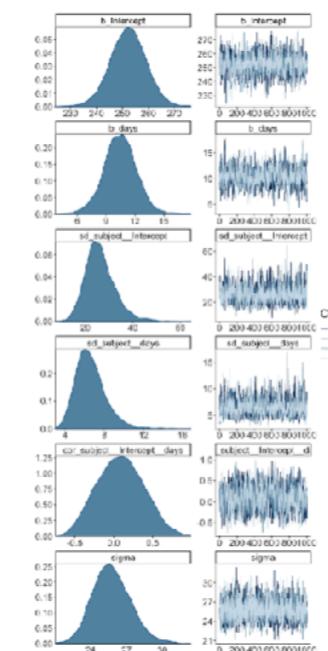
```
1 fit.brmsleep = brm(formula = reaction ~ 1 + days + (1 + days | subject),
2   data = df.sleep,
3   seed = 1,
4   file = "cache/brmsleep")
```



43

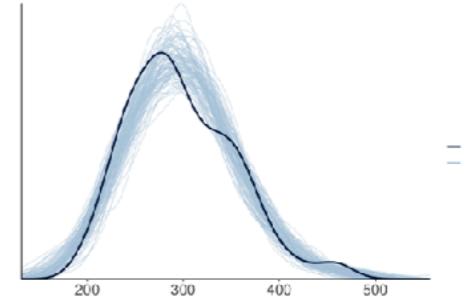
a) Did the inference work?

```
1 fit.brmsleep %>%
2   plot(N = 6)
```



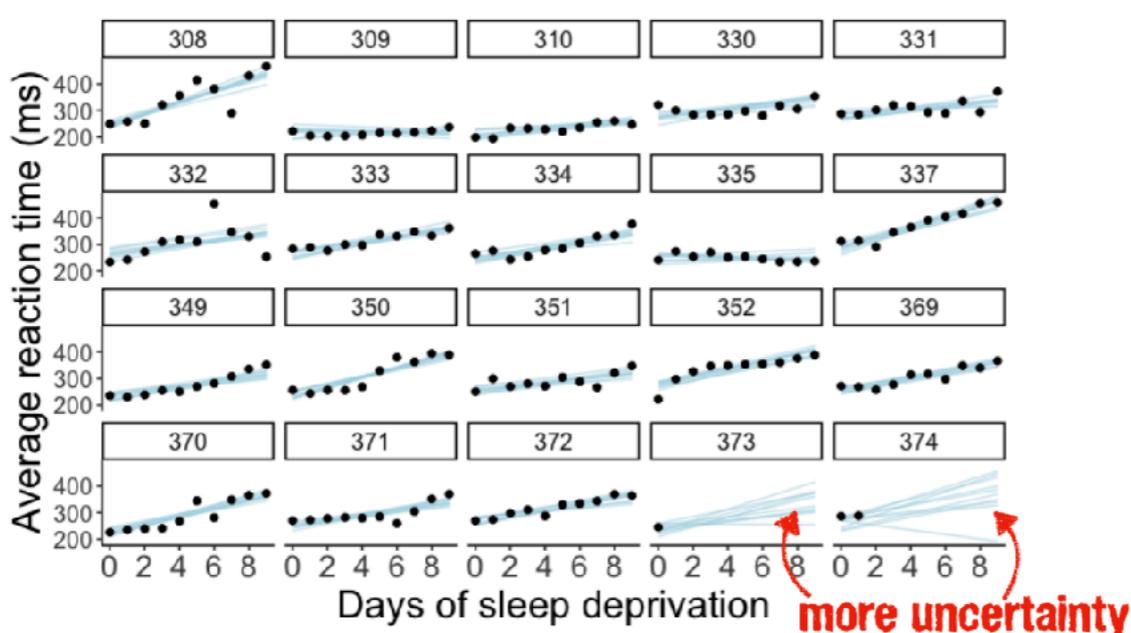
also looks good!

```
1 pp_check(fit.brmsleep,
2   nsamples = 100)
```



46

b) Visualize the model predictions



10 random samples from the posterior distribution

48

5. Test specific hypotheses

Did reaction times increase with the number of days of sleep deprivation?

```
1 fit.brmsleep %>%
2   summary()
```

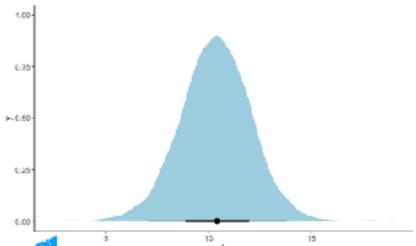
```
Family: gaussian
Links: mu = identity; sigma = identity
Formula: reaction ~ 1 + days + (1 + days | subject)
Data: df.sleep (Number of observations: 183)
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
total post-warmup samples = 4000

Group-Level Effects:
~subject (Number of levels: 2C)
Estimate Est.Error 1-95% CI 2.5-95% CI Rhat Bulk ESS Tail ESS
sd(Intercept) 26.16 6.25 15.65 40.54 1.00 1079 2463
sd(days) 5.55 1.52 4.14 10.13 1.00 1145 1625
cor(Intercept,days) 0.00 0.25 0.46 0.67 1.00 993 1526

Population-Level Effects:
Estimate Est.Error 1-95% CI 2.5-95% CI Rhat Bulk ESS Tail ESS
Intercept 252.18 6.86 238.47 265.42 1.00 1826 3766
days 10.46 1.84 7.13 13.78 1.00 1203 1782

Family Specific Parameters:
Estimate Est.Error 1-95% CI 2.5-95% CI Rhat Bulk ESS Tail ESS
sigma 25.77 1.57 22.93 29.14 1.00 5864 2773

Samples were drawn using sampling(NUTS). For each parameter, R_eff is a crude measure of effective sample size, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).
```



54

32

Quick recap: Titanic data

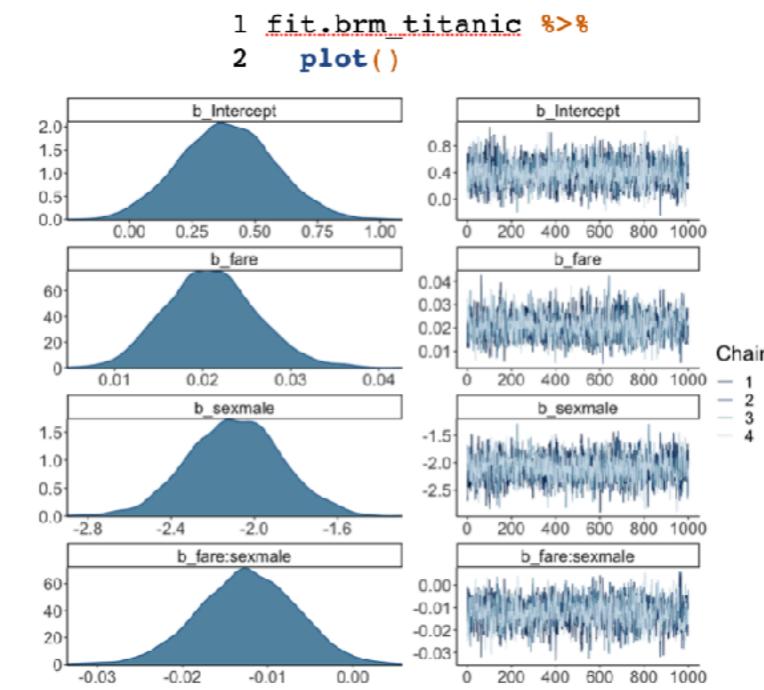
1. Specify and fit the model

```
1 fit.brm_titanic = brm(formula = survived ~ 1 + fare * sex,
2   family = "bernoulli",
3   data = df.titanic,
4   file = "cache/brm_titanic",
5   seed = 1)
```

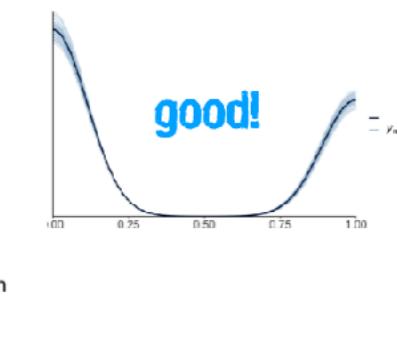
just need to
change the family

63

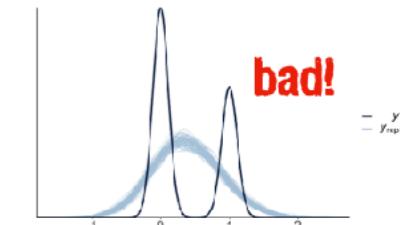
a) Did the inference work?



```
1 pp_check(fit.brm_titanic,
2 nsamples = 100)
```



model with Gaussian family



66

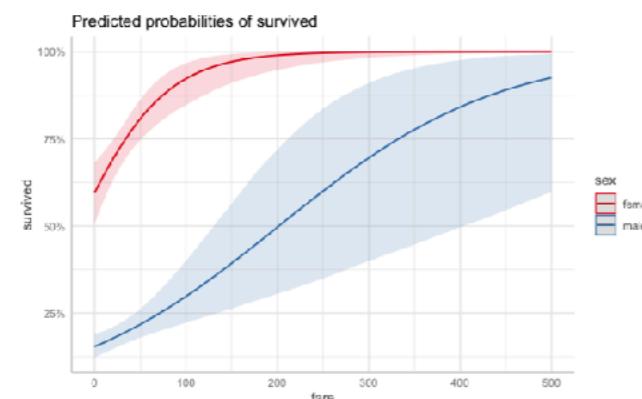
4. Interpret the model parameters



```
1 fit.brm_titanic %>%
2 ggpredict(terms = c("fare [0:500]", "sex"))
```

```
# Predicted probabilities of survived
# x = fare
# sex = female
x | Predicted | 95% CI
---|---|---
0 | 0.60 | [0.51, 0.68]
83 | 0.89 | [0.82, 0.95]
167 | 0.98 | [0.93, 1.00]
250 | 1.00 | [0.97, 1.00]
333 | 1.00 | [0.99, 1.00]
500 | 1.00 | [1.00, 1.00]

# sex = male
x | Predicted | 95% CI
---|---|---
0 | 0.15 | [0.12, 0.19]
83 | 0.27 | [0.21, 0.35]
167 | 0.43 | [0.28, 0.62]
250 | 0.60 | [0.35, 0.84]
333 | 0.75 | [0.43, 0.94]
500 | 0.93 | [0.60, 0.99]
```



70

5. Test specific hypotheses

Was the effect of fare on survival different for men vs women?

```
1 fit.brm_titanic %>%
2 emtrends(specs = pairwise ~ sex,
3           var = "fare")
```

```
$emtrends
sex      fare.trend lower.HPD upper.HPD
female    0.02083   0.01129   0.0316
male     0.00845   0.00385   0.0135

Point estimate displayed: median
HPD interval probability: 0.95

$contrasts
contrast      estimate lower.HPD upper.HPD
female - male  0.0124  0.000884  0.0232

Point estimate displayed: median
HPD interval probability: 0.95
```

the chance of survival
increased more with fare
for female than male
passengers

73

33

Going beyond

Evidence for the null hypothesis

Evidence for the null hypothesis



[Front Psychol. 2014; 5: 781.](#)

Published online 2014 Jul 29. doi: [10.3389/fpsyg.2014.00781](https://doi.org/10.3389/fpsyg.2014.00781)

PMCID: PMC4114196

PMID: [25120503](#)

Using Bayes to get the most out of non-significant results

[Zoltan Dienes*](#)

► Author information ► Article notes ► Copyright and License information [Disclaimer](#)

[HTML] Using Bayes to get the most out of non-significant results

[Z Dienes - Frontiers in psychology, 2014 - frontiersin.org](#)

No scientific conclusion follows automatically from a statistically non-significant result, yet people routinely use non-significant results to guide conclusions about the status of theories (or the effectiveness of practices). To know whether a non-significant result counts against a theory, or if it just indicates data insensitivity, researchers must use one of: power, intervals (such as confidence or credibility intervals), or else an indicator of the relative evidence for one theory over another, such as a Bayes factor. I argue Bayes factors allow theory to be ...

☆ 99 Cited by 966 Related articles All 14 versions Web of Science: 583 Import into BibTeX »

2070 now

- There is nothing special about H_0 compared to H_1 in Bayesian inference
- We can get evidence of H_0 over H_1 (e.g. using the Bayes factor approach)

Rolling the dice



Four sided



Six sided

both dice are equally likely to be picked
 $p(\text{blue die}) = p(\text{white die}) = 0.5$

both dice are equal sided
(uniform probability over the different numbers)

Which die do you think was rolled?

$$4 \quad p(\text{blue die} \mid \text{data}) = ?$$

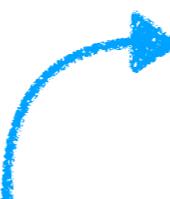
$$4, 2, 1 \quad p(\text{blue die} \mid \text{data}) = 0.77$$

$$4, 2, 1, 3, 1 \quad p(\text{blue die} \mid \text{data}) = 0.88$$

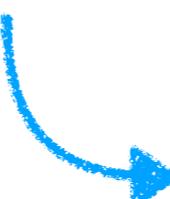
$$4, 2, 1, 3, 1, 5 \quad p(\text{blue die} \mid \text{data}) = 0$$

Bayes factor

$$BF_{01} = \frac{p(D | H_0)}{p(D | H_1)}$$



probability of the data
given H_0



probability of the data
given H_1

check this out

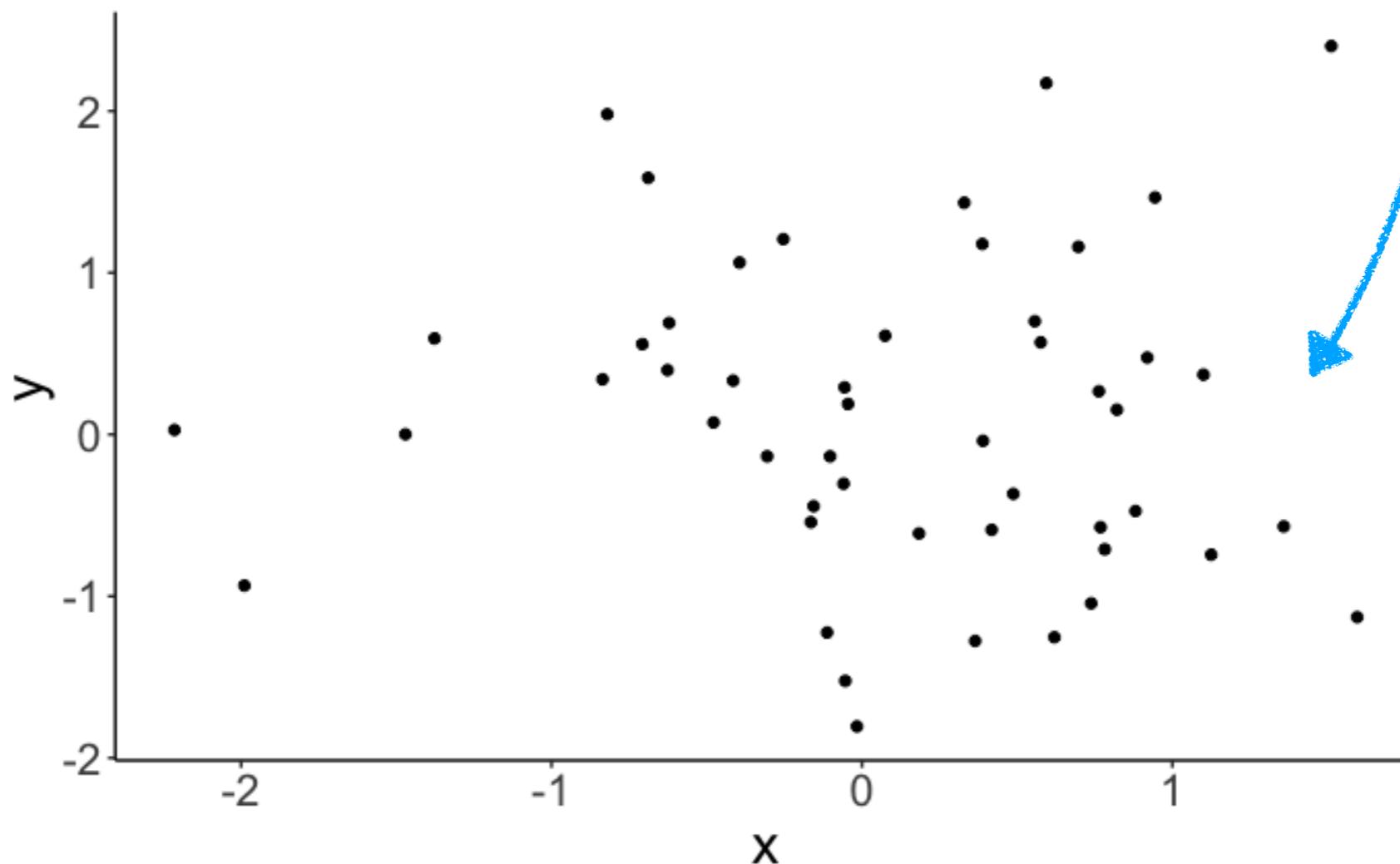


<https://vuorre.netlify.com/post/2017/03/21/bayes-factors-with-brms/>

Approximate LOO

Evidence for the null hypothesis

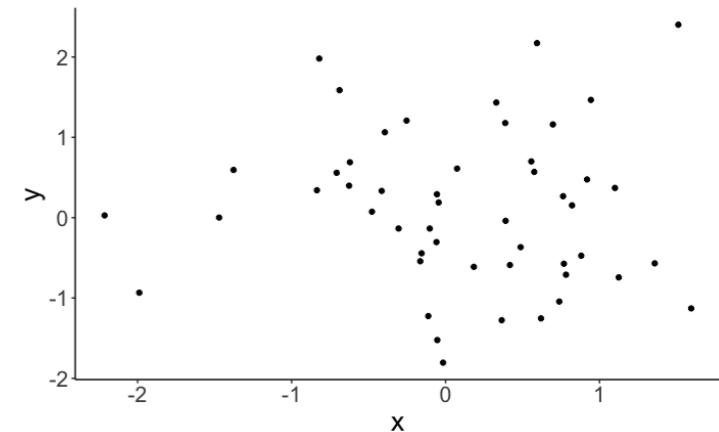
```
1 set.seed(1)
2 df.loo = tibble(x = rnorm(n = 50),
3                  y = rnorm(n = 50))
4
5 ggplot(data = df.loo,
6         mapping = aes(x = x,
7                         y = y)) +
8 geom_point()
```



no relationship
between x and y

Evidence for the null hypothesis

```
1 fit.lm_loo = lm(formula = y ~ 1 + x,  
2                   data = df.loo)  
3  
4 fit.lm_loo %>%  
5   summary()
```



```
Call:  
lm(formula = y ~ 1 + x, data = df.loo)
```

Residuals:

Min	1Q	Median	3Q	Max
-4.2185	-0.6735	0.0018	0.6734	4.2428

Coefficients:

	Estimate	Std. Error	t value	Pr(> t)
(Intercept)	0.0006437	0.0031639	0.203	0.839
x	-0.0019184	0.0031541	-0.608	0.543

```
Residual standard error: 1.001 on 99998 degrees of freedom  
Multiple R-squared:  3.7e-06, Adjusted R-squared:  -6.301e-06  
F-statistic: 0.37 on 1 and 99998 DF, p-value: 0.543
```

cannot reject the H_0 that the reduction in error due to x is what one would have expected by chance

Evidence for the null hypothesis

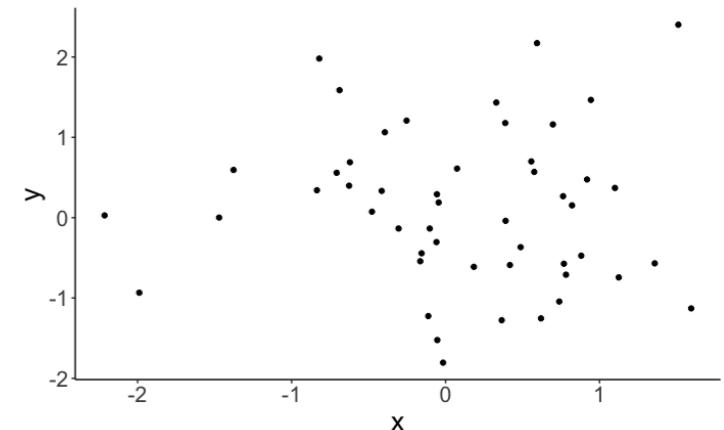
```
1 fit.brm_loo1 = brm(formula = y ~ 1, data = df.loo)
2
3 fit.brm_loo2 = brm(formula = y ~ 1 + x, data = df.loo)
4
5 fit.brm_loo1 = add_criterion(fit.brm_loo1, criterion = "loo")
6
7 fit.brm_loo2 = add_criterion(fit.brm_loo2, criterion = "loo")
```

loo_compare(fit.brm_loo1, fit.brm_loo2)

	elpd_diff	se_diff
fit.brm_loo1	0.0	0.0
fit.brm_loo2	-1.1	0.5

model_weights(fit.brm_loo1, fit.brm_loo2)

fit.brm_loo1	fit.brm_loo2
99.99999	0.00001



approximate
leave-one-out
cross-validation

I want only positive coefficients!

I only want positive coefficients!

```
1 brm(formula = how_much_i_love_stats ~ 1 + tobi + ari + beth + satchel + shawn,  
2       data = df.stats_love)
```

coefficients in the model

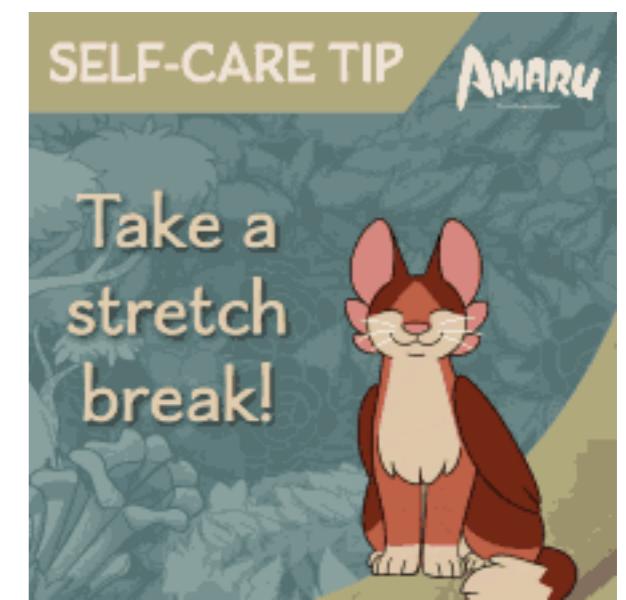
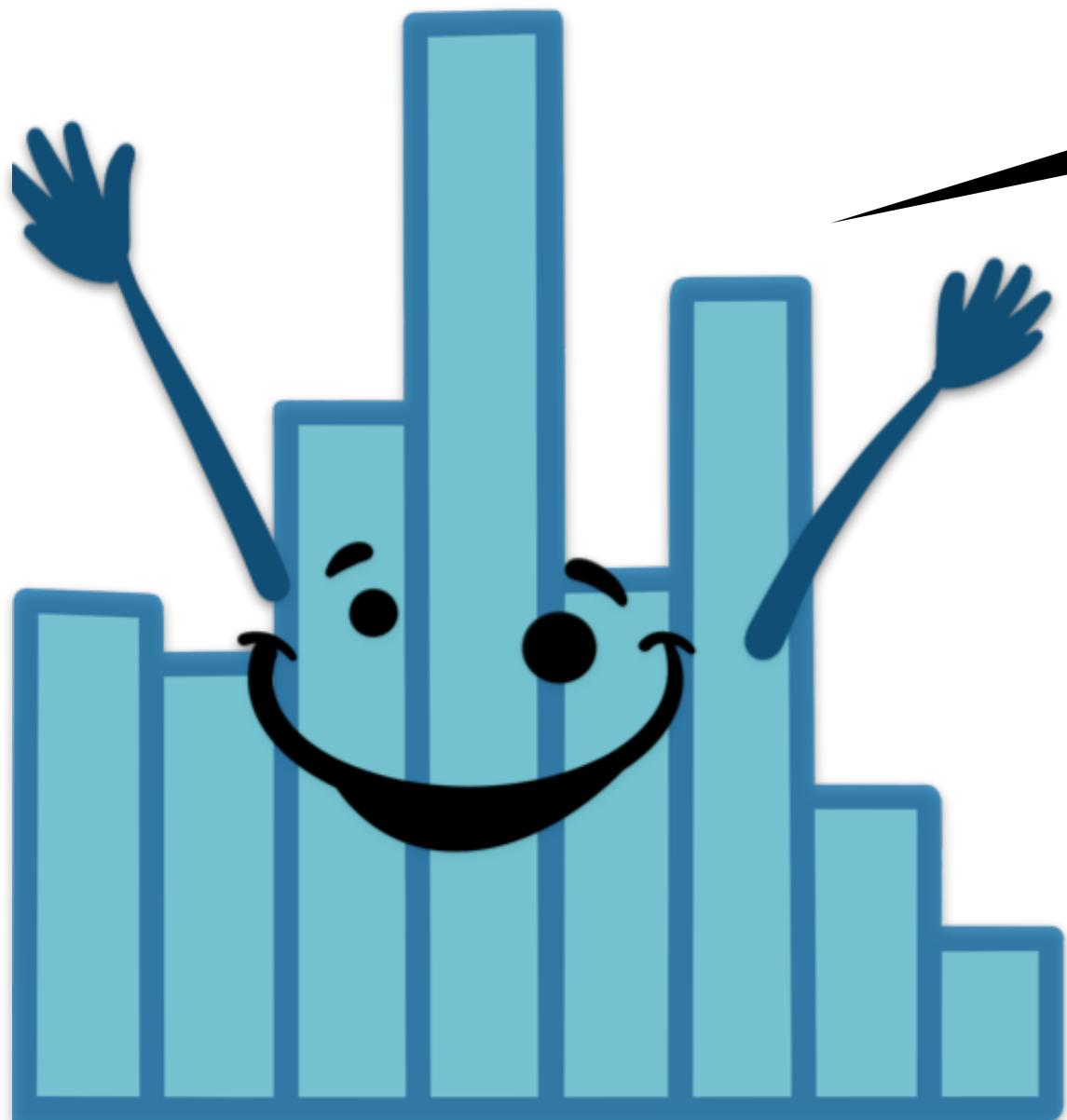
```
1 # priors  
2 priors = c(set_prior("normal(0,10)", class = "b", lb = 0))
```

lower bound = 0

```
1 brm(formula = how_much_i_love_stats ~ 1 + tobi + ari + beth + satchel + shawn,  
2       prior = priors,  
3       data = df.stats_love)
```

02:00

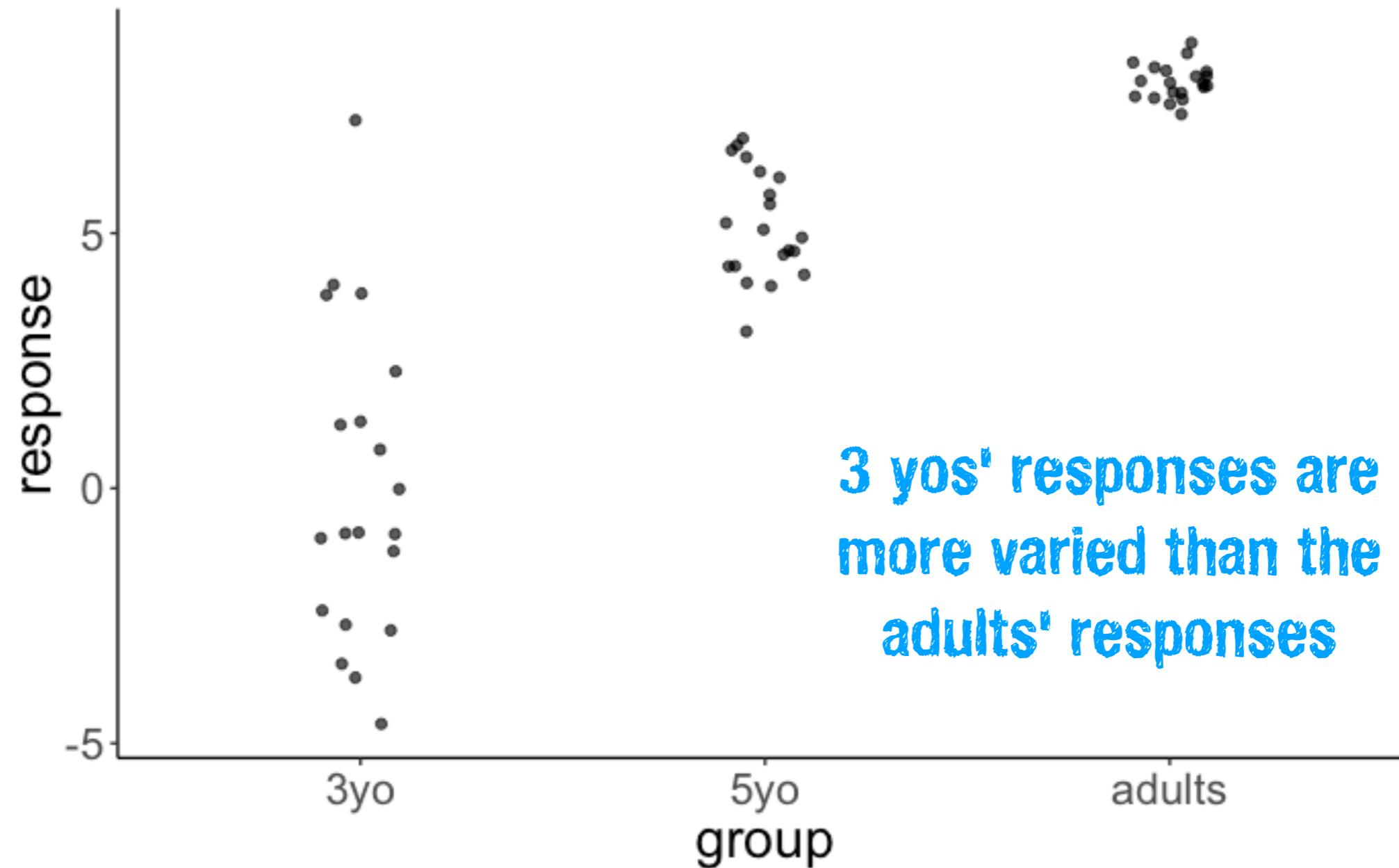
stretch break!



Dealing with unequal variance

Unequal variance aka heteroscedasticity

```
1 df.variance = tibble(group = rep(c("3yo", "5yo", "adults"), each = 20),  
2                         response = rnorm(n = 60,  
3                                         mean = rep(c(0, 5, 8), each = 20),  
4                                         sd = rep(c(3, 1.5, 0.3), each = 20)))
```



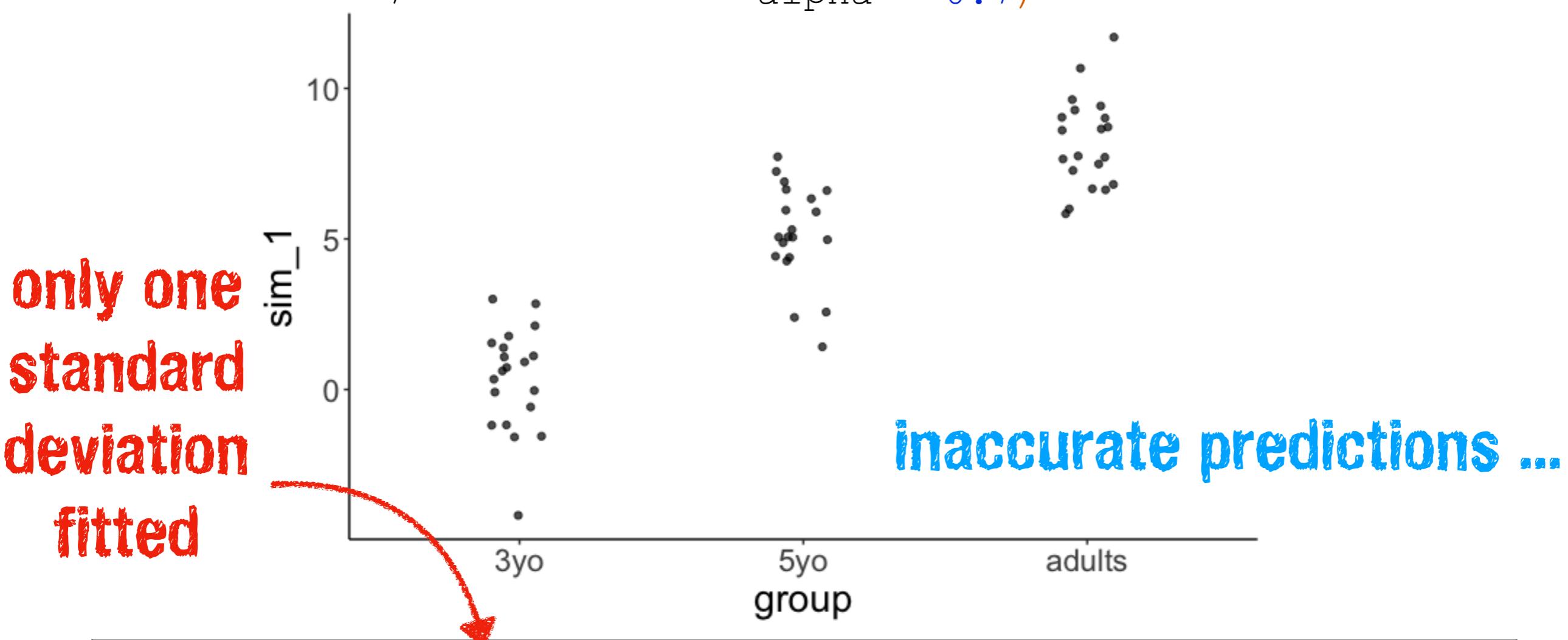
Unequal variance aka heteroscedasticity

```
1 fit.lm1 = lm(formula = response ~ 1 + group,  
2                         data = df.variance)  
3  
4 fit.lm1 %>%  
5   summary()
```

```
Call:  
lm(formula = response ~ 1 + group, data = df.variance)  
  
Residuals:  
    Min      1Q  Median      3Q     Max  
-4.6145 -0.8288 -0.0879  0.6315  7.2193  
  
Coefficients:  
              Estimate Std. Error t value Pr(>|t|)  
(Intercept) -0.005336  0.421618 -0.013    0.99  
group5yo      5.172810  0.596258  8.675 5.25e-12 ***  
groupadults   7.970655  0.596258 13.368 < 2e-16 ***  
---  
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1  
  
Residual standard error: 1.886 on 57 degrees of freedom  
Multiple R-squared:  0.7635, Adjusted R-squared:  0.7552  
F-statistic: 91.99 on 2 and 57 DF,  p-value: < 2.2e-16
```

Unequal variance aka heteroscedasticity

```
1 fit.lm1 %>%
2   simulate() %>%
3   bind_cols(df.variance) %>%
4   ggplot(aes(x = group, y = sim_1)) +
5   geom_jitter(height = 0,
6                 width = 0.1,
7                 alpha = 0.7)
```



r.squared	adj.r.squared	sigma	statistic	p.value	df	logLik	AIC	BIC	deviance	df.residual
0.76	0.76	1.89	91.99	0	3	-121.65	251.3	259.68	202.65	57

Unequal variance aka heteroscedasticity

```
1 fit.brml = brm(formula = bf(response ~ group,  
2                   sigma ~ group),  
3                   data = df.variance,  
4                   file = "cache/brml",  
5                   seed = 1)
```

modeling both the
means and variances

```
Family: gaussian  
Links: mu = identity; sigma = log  
Formula: response ~ group  
         sigma ~ group  
Data: df.variance (Number of observations: 60)  
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;  
         total post-warmup samples = 4000
```

Population-Level Effects:

	Estimate	Est.Error	l-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	-0.01	0.73	-1.41	1.51	1.01	1107	1072
sigma_Intercept	1.15	0.17	0.85	1.51	1.00	1991	1922
group5yo	5.18	0.77	3.60	6.65	1.00	1252	1327
groupadults	7.98	0.74	6.47	9.37	1.01	1110	1079
sigma_group5yo	-1.05	0.24	-1.51	-0.57	1.00	2249	2420
sigma_groupadults	-2.19	0.24	-2.66	-1.74	1.00	2171	2427

Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS and Tail_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

Unequal variance aka heteroscedasticity

```
Family: gaussian  
Links: mu = identity; sigma = log ← on a log scale!  
Formula: response ~ group  
         sigma ~ group  
Data: df.variance (Number of observations: 60)  
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;  
         total post-warmup samples = 4000
```

Population-Level Effects:

	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	-0.01	0.73	-1.41	1.51	1.01	1107	1072
sigma_Intercept	1.15	0.17	0.85	1.51	1.00	1991	1922
group5yo	5.18	0.77	3.60	6.65	1.00	1252	1327
groupadults	7.98	0.74	6.47	9.37	1.01	1110	1079
sigma_group5yo	-1.05	0.24	-1.51	-0.57	1.00	2249	2420
sigma_groupadults	-2.19	0.24	-2.66	-1.74	1.00	2171	2427

Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS and Tail_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

mean = **c(0, 5, 8)**

sd = **c(3, 1.5, 0.3)**

3 year olds $e^{1.15} = 3.16$

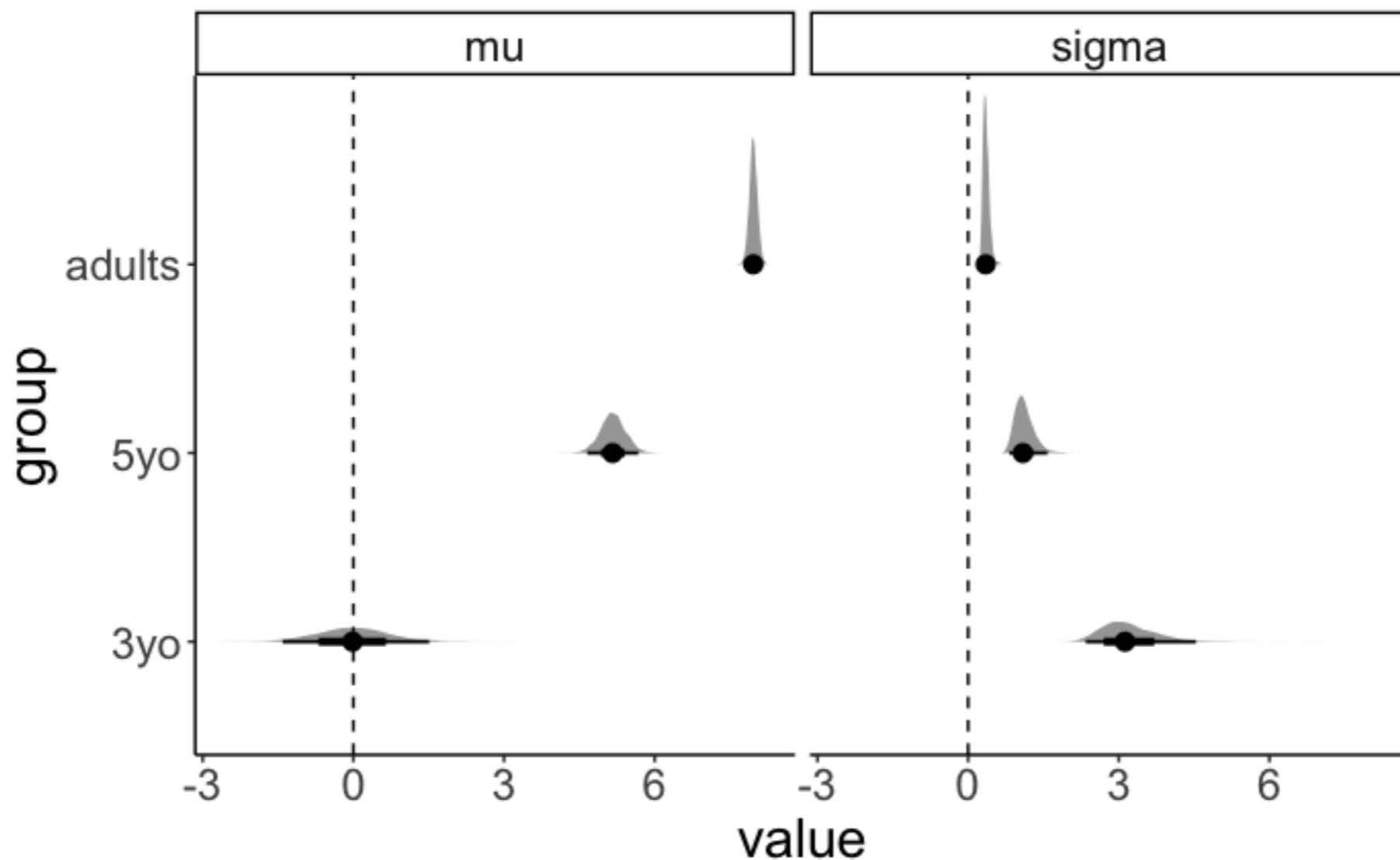


5 year olds $e^{1.15+(-1.05)} = 1.10$

adults $e^{1.15+(-2.19)} = 0.35$

Unequal variance aka heteroscedasticity

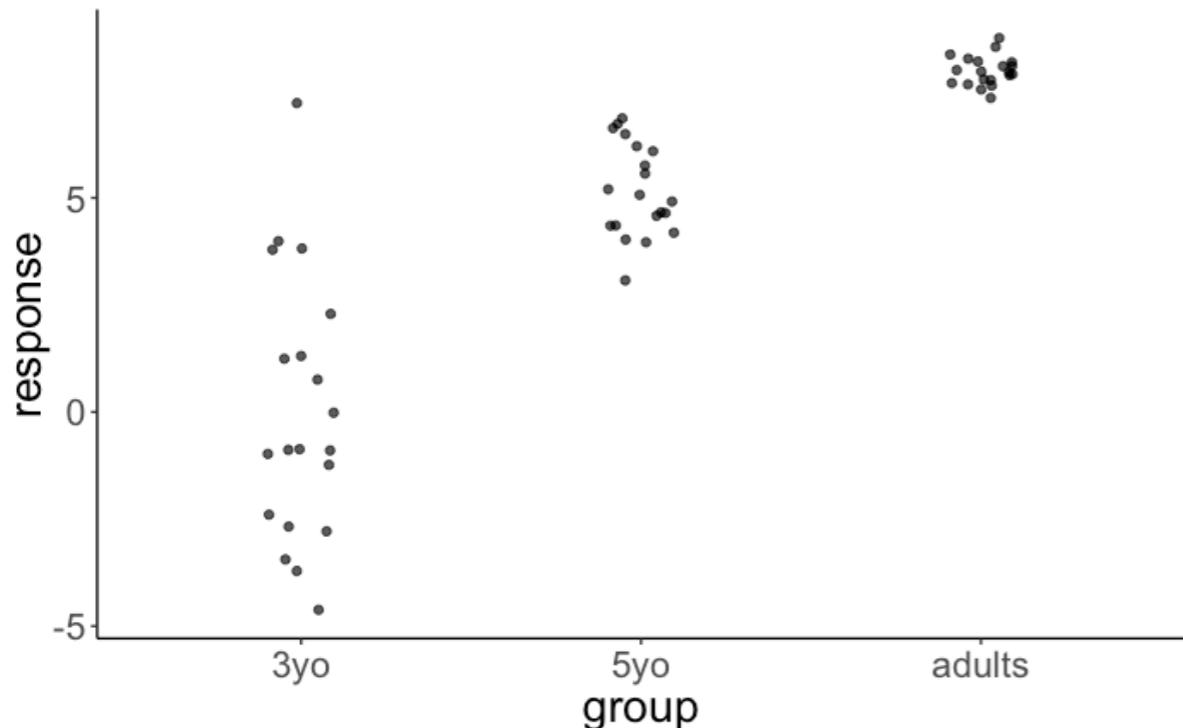
```
1 df.variance %>%
2   expand(group) %>%
3   add_fitted_draws(fit.brml, dpar = TRUE) %>%
4   select(group, .row, .draw, posterior = .value, mu, sigma) %>%
5   pivot_longer(cols = c(mu, sigma),
6                 names_to = "index",
7                 values_to = "value") %>%
8   ggplot(aes(x = value, y = group)) +
9   geom_halfeyeh() +
10  geom_vline(xintercept = 0, linetype = "dashed") +
11  facet_grid(cols = vars(index))
```



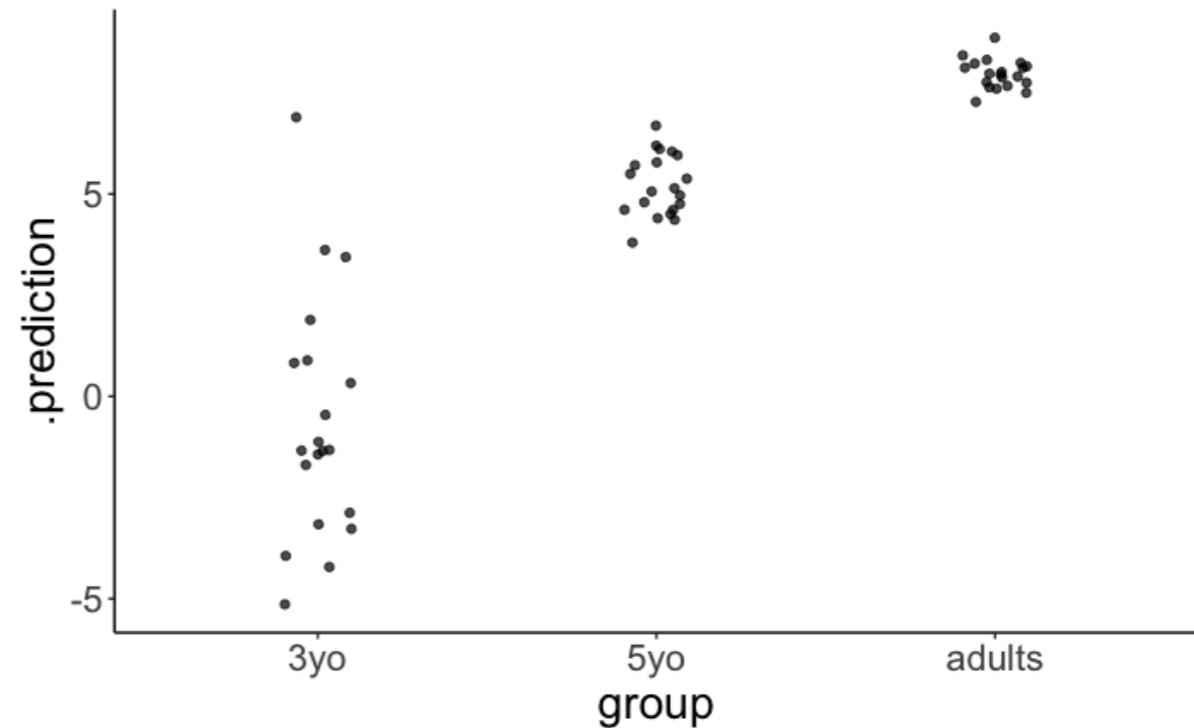
Unequal variance aka heteroscedasticity

```
1 df.variance %>%
2   add_predicted_draws(model = fit.brml,
3                       n = 1) %>%
4   ggplot(aes(x = group, y = .prediction)) +
5   geom_jitter(height = 0,
6                 width = 0.1,
7                 alpha = 0.7)
```

original data



predicted data



these predictions look good!

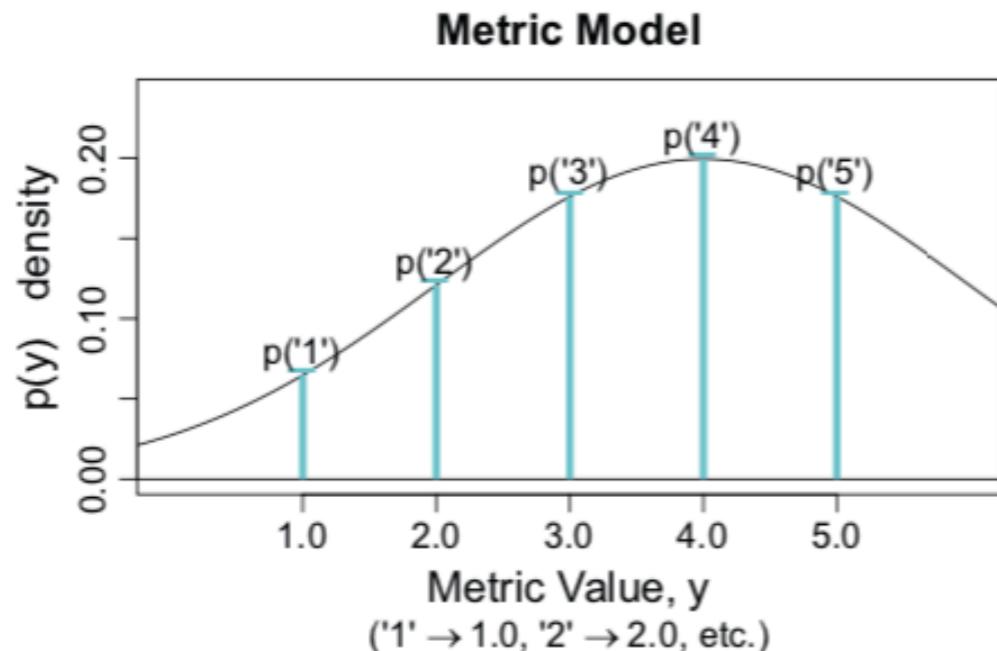
Better modeling Likert scale

We surveyed all articles in the *Journal of Personality and Social Psychology* (*JPSP*), *Psychological Science* (*PS*), and the *Journal of Experimental Psychology: General* (*JEP:G*) that mentioned the term “Likert,” and found that **100% of the articles** that analyzed ordinal data did so using a metric model.

great paper!

Liddell & Kruschke (2018) Analyzing ordinal data with metric models: What could possibly go wrong?. *Journal of Experimental Social Psychology*

Ordinal regression



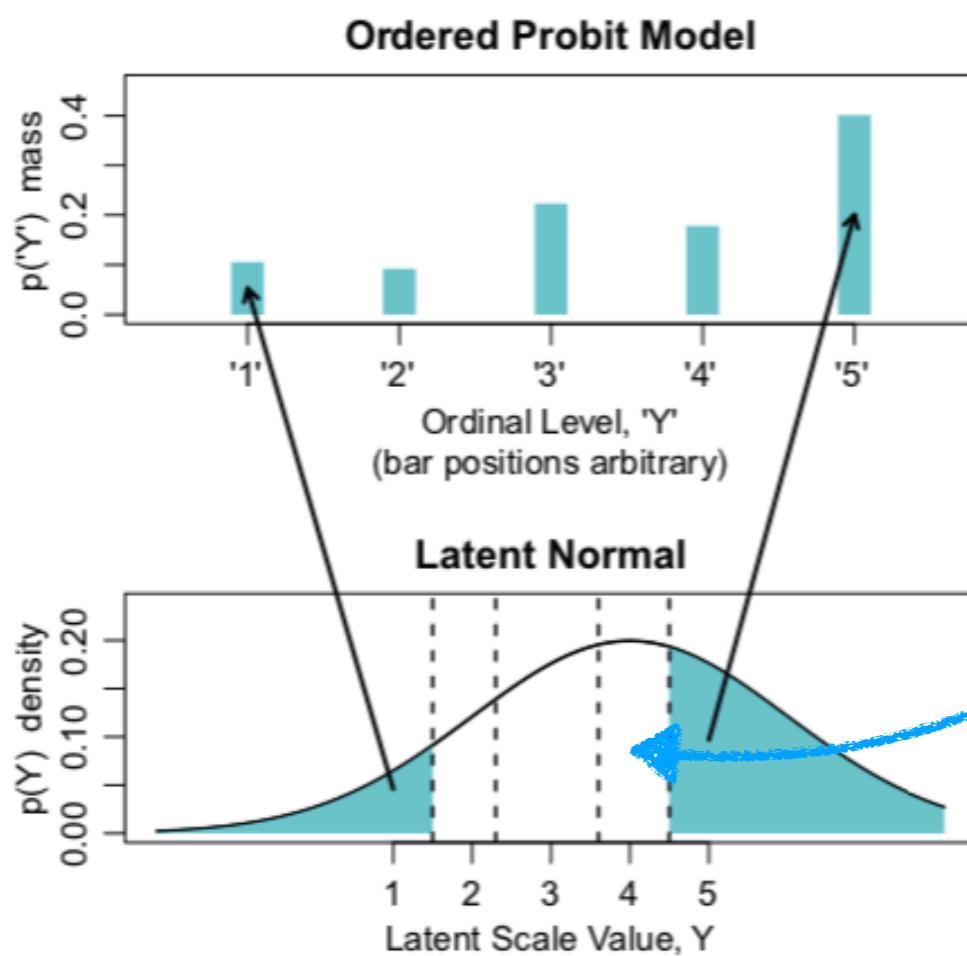
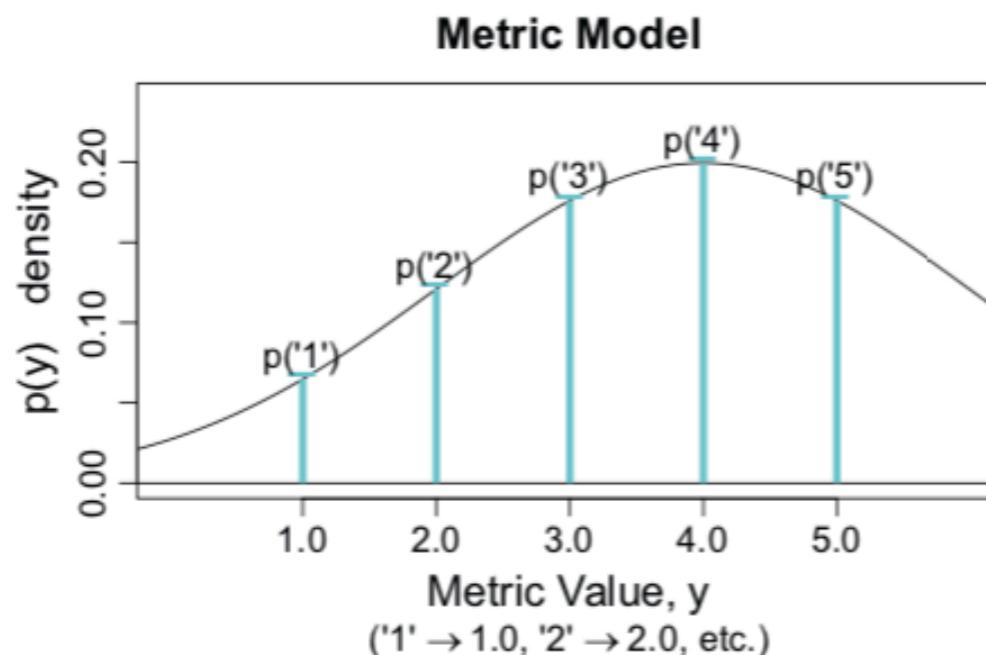
metric model

- fits a Gaussian distribution with mean and standard deviation
- makes the assumption that categories are **equidistant**

I loooove Bayesian statistics!

- completely disagree (1)
- moderately disagree (2)
- neither disagree nor agree (3)
- moderately agree (4)
- completely agree (5)

Ordinal regression



ordered probit model

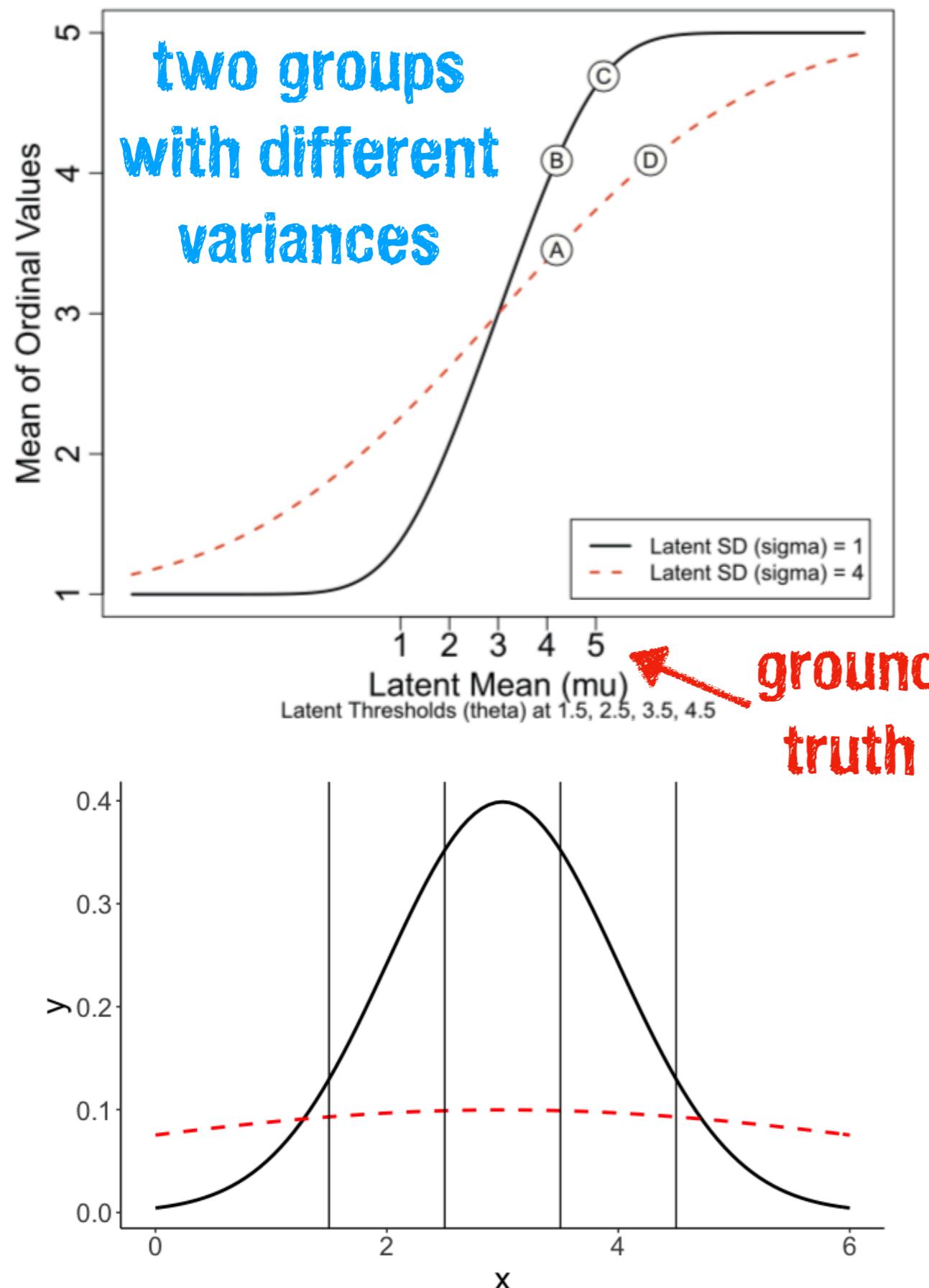
- assumes an ordering of the categories
- assumes a normal distribution in latent space
- finds a good mapping from that normal distribution in latent space to the ordered responses

finds thresholds that
separate the categories

Does it matter?

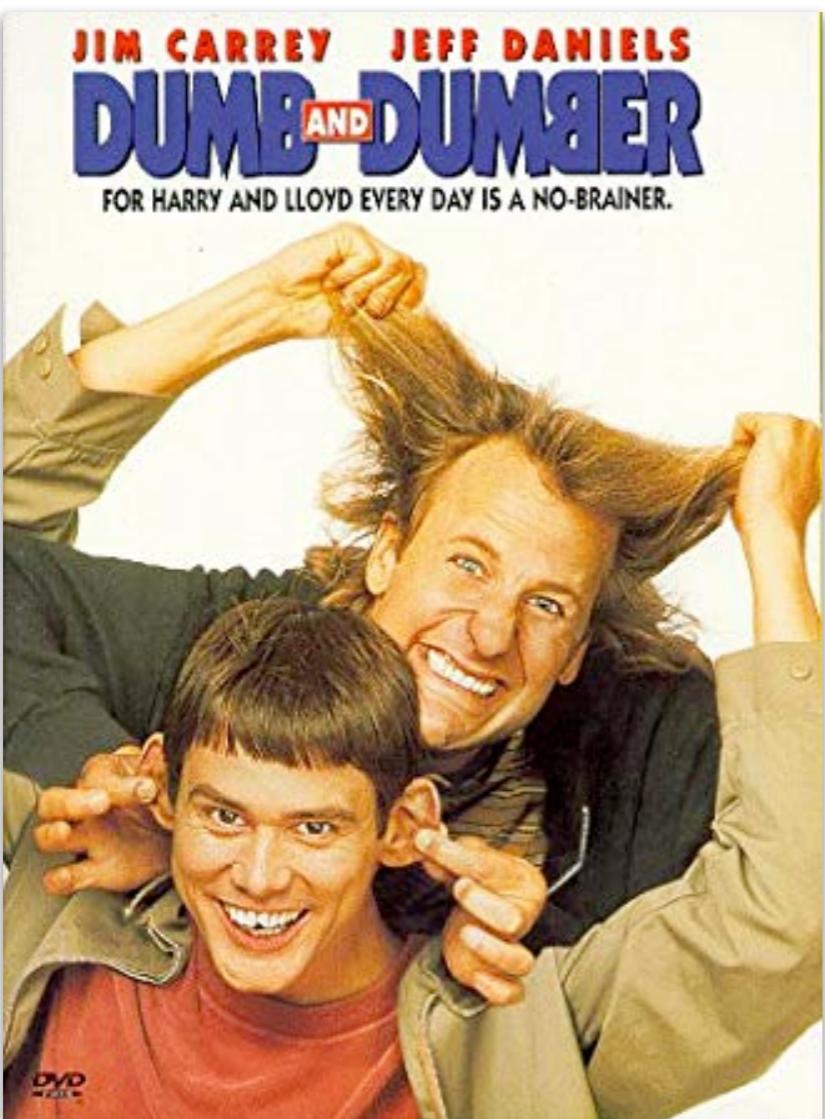
- treating ordinal data as metric can lead to:
 - low rates of correct detection (Type II error)
 - distorted effect size estimates
 - inflated false alarms (Type I error)
 - inversions of differences between groups
- main reasons for why this happens:
 - response categories may not be equidistant
 - response distribution may be non-normal
 - variances of unobserved variables may differ between groups, conditions, time points, ...

What could possibly go wrong?



- A vs. B: false positive (Type I error)
→ **no difference in latent space**
- B vs. D: false negative (Type II error)
→ **difference in latent space**
- C vs. D: reversal
→ **C is greater than D in metric space, but D is greater than C in latent space**

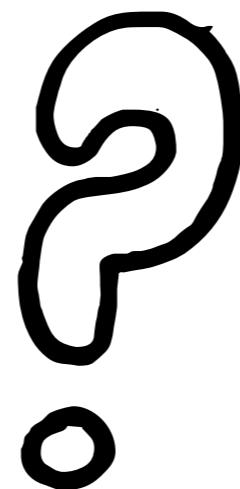
Which movie shall I watch?



Customer reviews

★★★★★ 4.5 out of 5

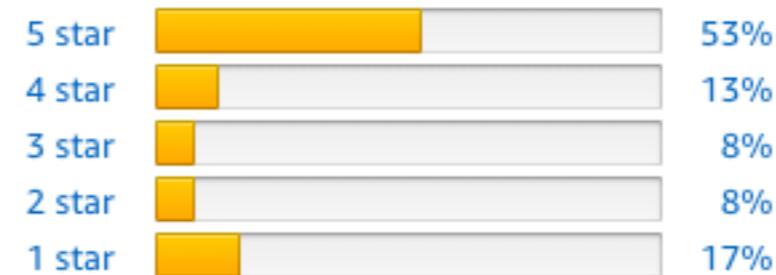
2,029 customer ratings



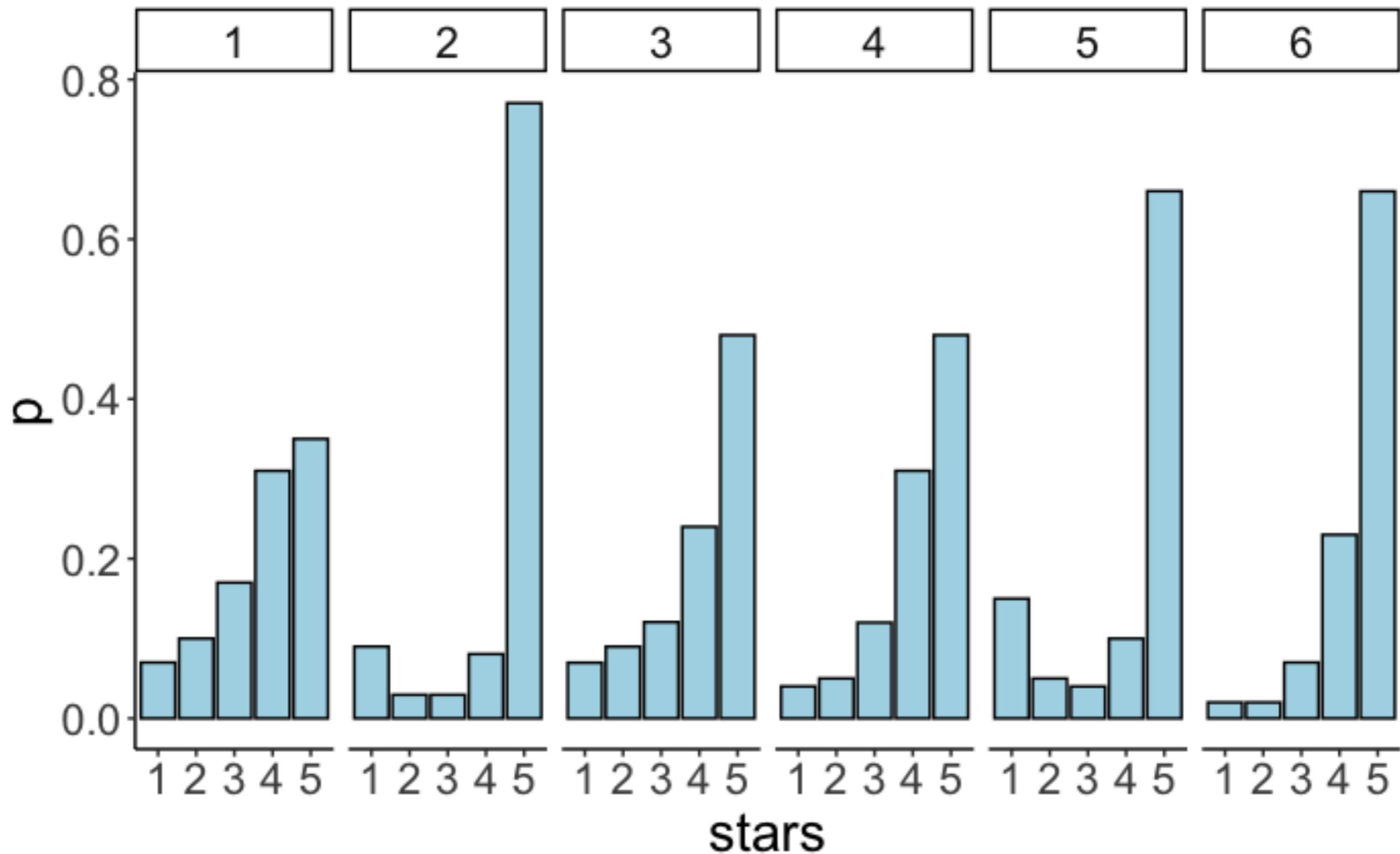
Customer reviews

★★★★☆ 3.8 out of 5

1,558 customer ratings



Amazon movie ratings



Fit the ordinal regression model

```
1 fit.brm5 = brm(formula = stars ~ 1 + id,  
2                   family = cumulative(link = "probit"),  
3                   data = df.movies,  
4                   file = "cache/brm5",  
5                   seed = 1)
```

linking function

thresholds

difference in
mean to
reference
category

```
Family: cumulative  
Links: mu = probit; disc = identity  
Formula: stars ~ 1 + id  
Data: df.movies (Number of observations: 21708)  
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;  
         total post-warmup samples = 4000
```

Population-Level Effects:

	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept[1]	-1.22	0.04	-1.31	-1.14	1.00	1877	2488
Intercept[2]	-0.90	0.04	-0.98	-0.82	1.00	1787	2419
Intercept[3]	-0.44	0.04	-0.52	-0.36	1.00	1692	2185
Intercept[4]	0.32	0.04	0.24	0.40	1.00	1634	2101
id2	0.84	0.06	0.71	0.96	1.00	2354	2553
id3	0.22	0.05	0.11	0.32	1.00	2146	2516
id4	0.33	0.04	0.24	0.41	1.00	1647	2315
id5	0.44	0.05	0.34	0.54	1.00	1982	2608
id6	0.75	0.04	0.67	0.83	1.00	1659	2158

Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS and Tail_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

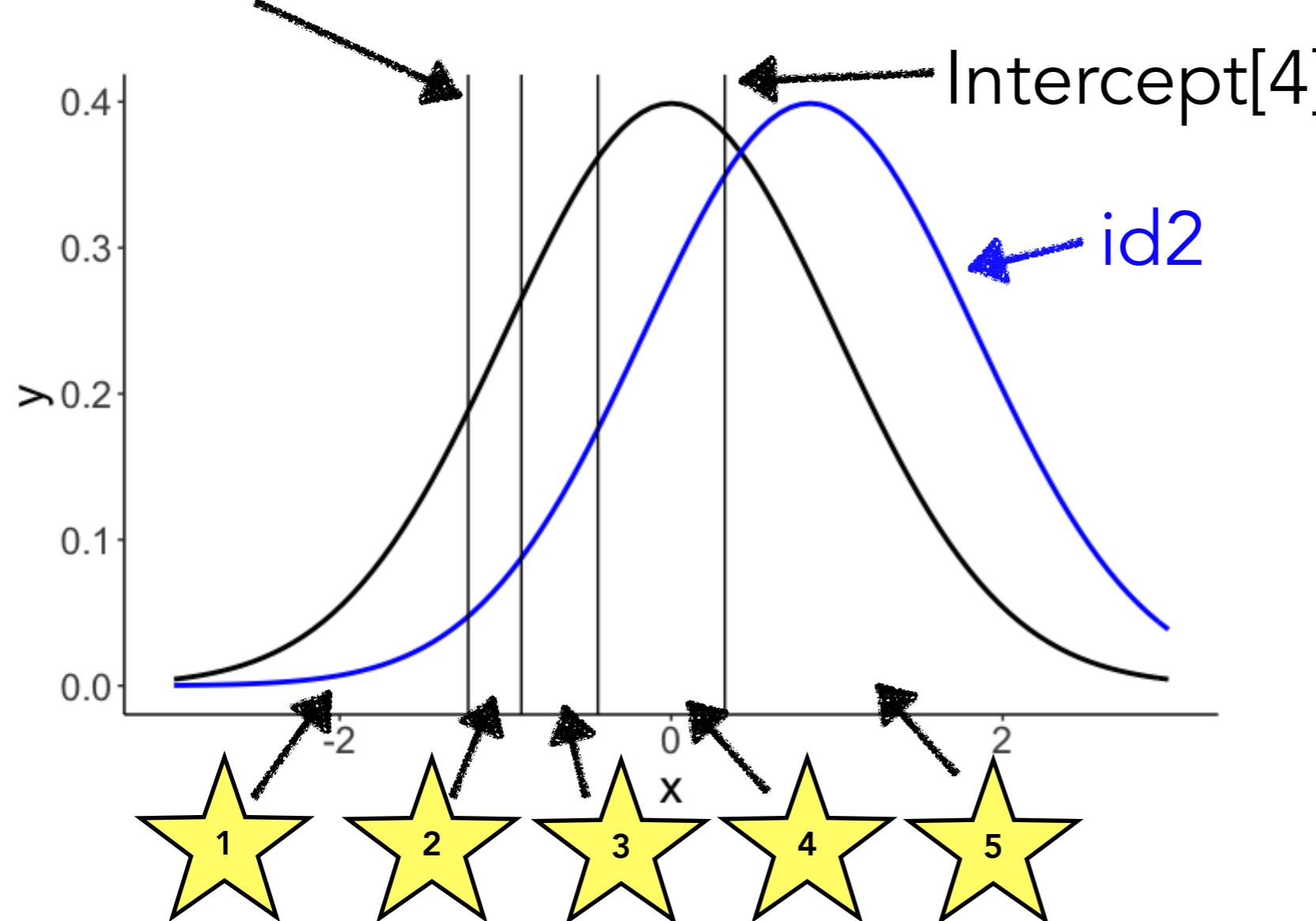
Interpretation

```
Family: cumulative  
Links: mu = probit; disc = identity  
Formula: stars ~ 1 + id  
Data: df.movies (Number of observations: 21708)  
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;  
total post-warmup samples = 4000
```

Population-Level Effects:

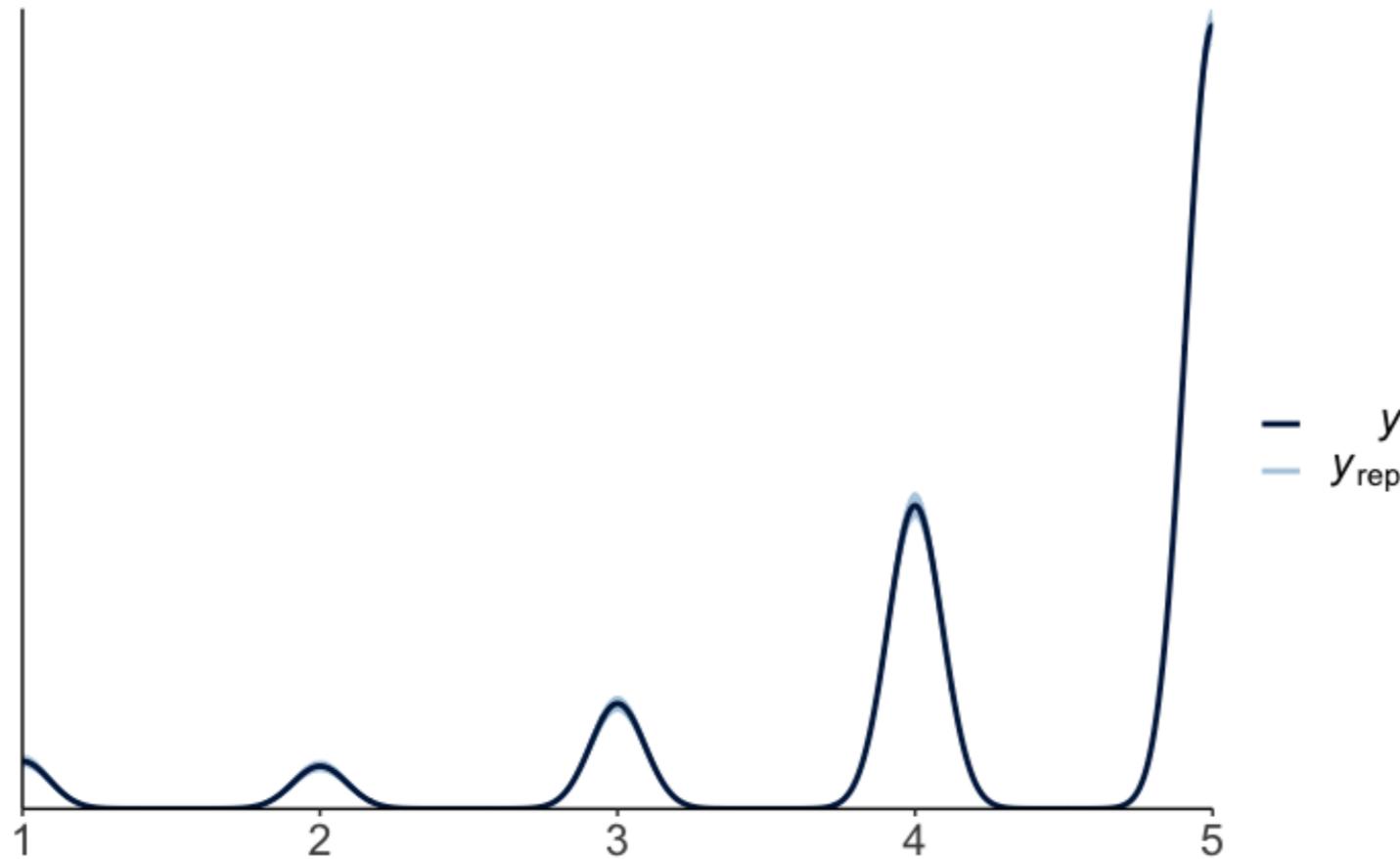
	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept[1]	-1.22	0.04	-1.31	-1.14	1.00	1877	2488
Intercept[2]	-0.90	0.04	-0.98	-0.82	1.00	1787	2419
Intercept[3]	-0.44	0.04	-0.52	-0.36	1.00	1692	2185
Intercept[4]	0.32	0.04	0.24	0.40	1.00	1634	2101
id2	0.84	0.06	0.71	0.96	1.00	2354	2553
id3	0.22	0.05	0.11	0.32	1.00	2146	2516
id4	0.33	0.04	0.24	0.41	1.00	1647	2315
id5	0.44	0.05	0.34	0.54	1.00	1982	2608
id6	0.75	0.04	0.67	0.83	1.00	1659	2158

Intercept[1]



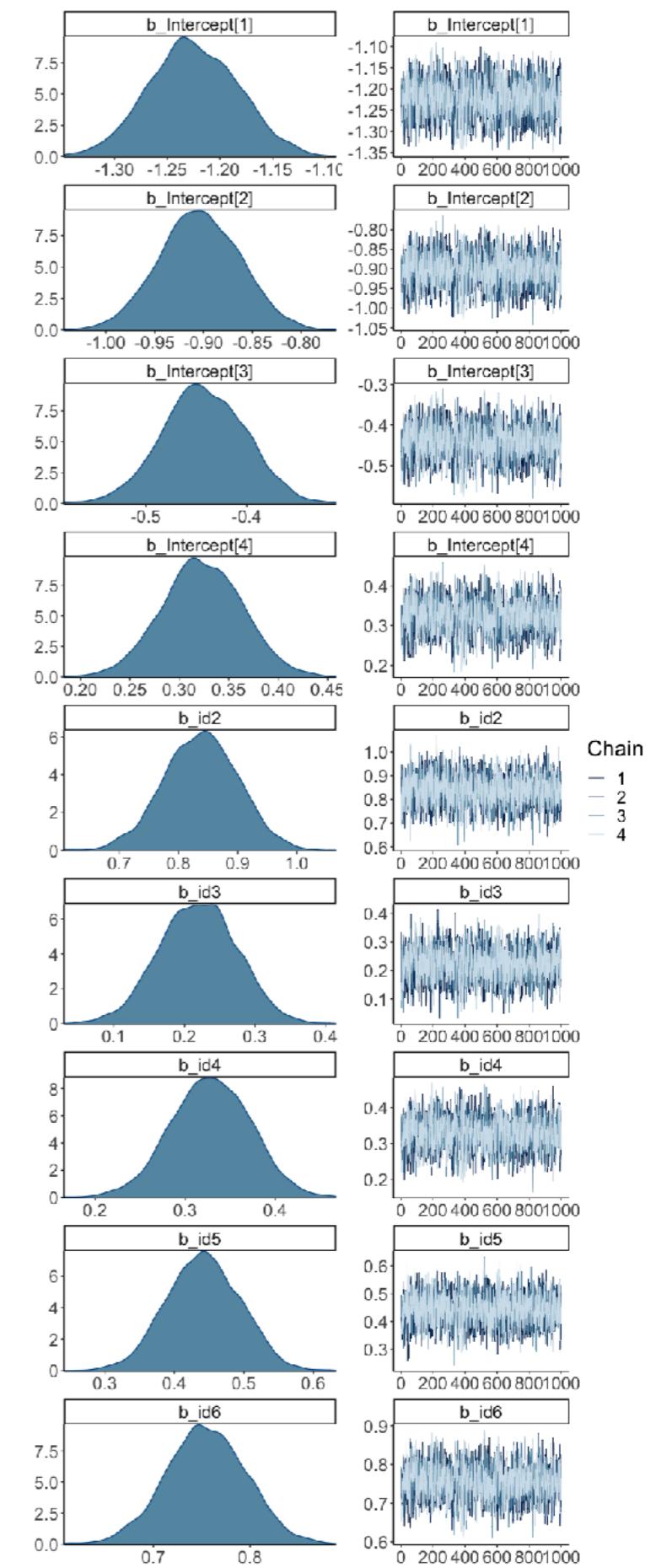
Check the model

```
1 fit.brms %>%  
2   plot(N = 9)
```

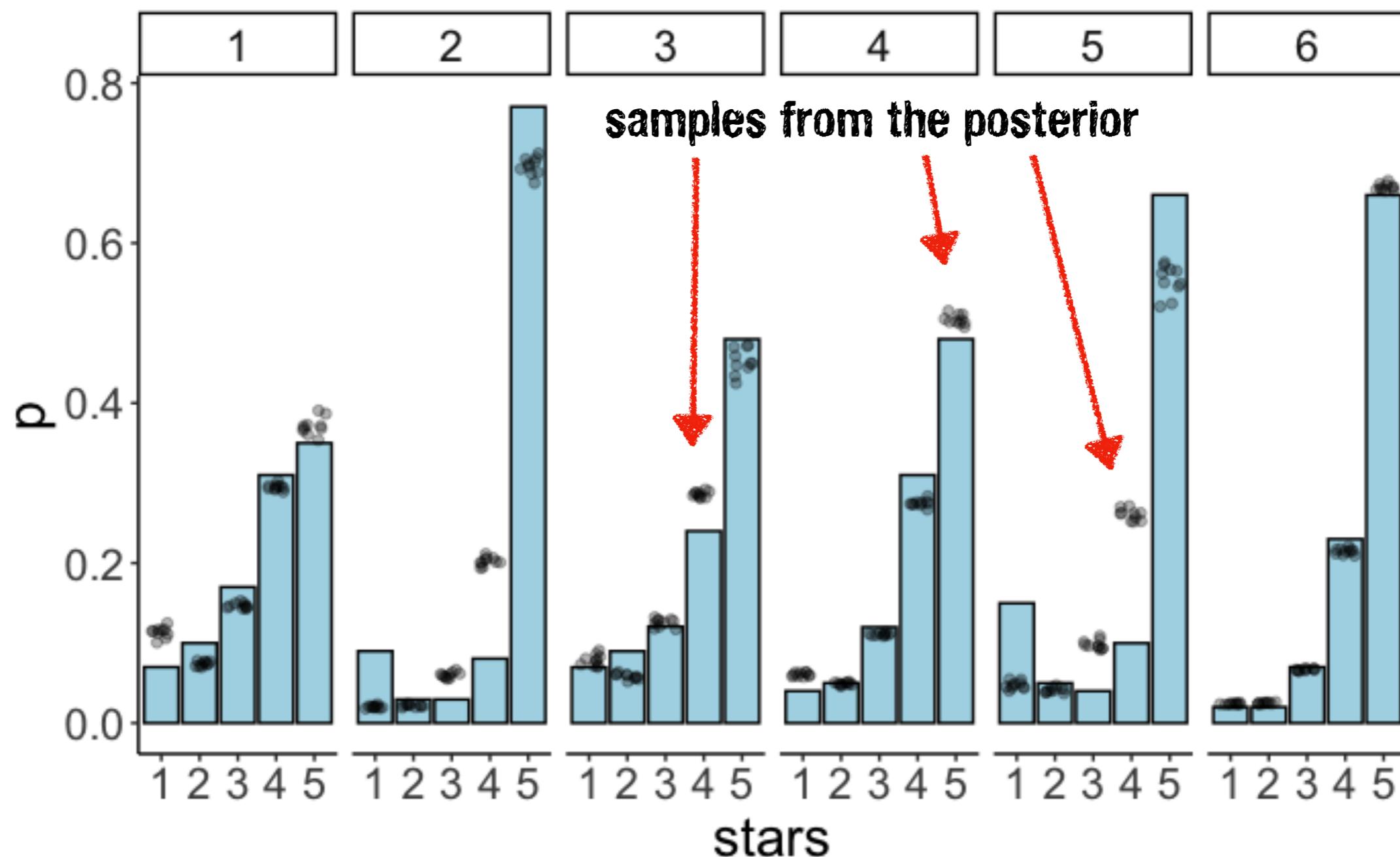


looking good!

```
1 fit.brms %>%  
2   plot(N = 9)
```



Illustrate the predictions



**predictions look pretty good but
maybe we can do better?**

Before doing better, let's do worse!

```
1 fit.brm6 = brm(formula = stars ~ 1 + id,  
2                   data = df.movies,  
3                   file = "cache/brm6",  
4                   seed = 1)
```

Family: gaussian
Links: mu = identity; sigma = identity
Formula: stars ~ 1 + id
Data: df.movies (Number of observations: 21708)
Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
total post-warmup samples = 4000

Population-Level Effects:

	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept	3.77	0.04	3.70	3.84	1.00	1203	1621
id2	0.64	0.05	0.54	0.75	1.00	1605	2335
id3	0.20	0.05	0.10	0.30	1.00	1558	2147
id4	0.37	0.04	0.29	0.45	1.00	1267	1862
id5	0.30	0.05	0.21	0.40	1.00	1441	2154
id6	0.72	0.04	0.65	0.79	1.00	1205	1720

Family Specific Parameters:

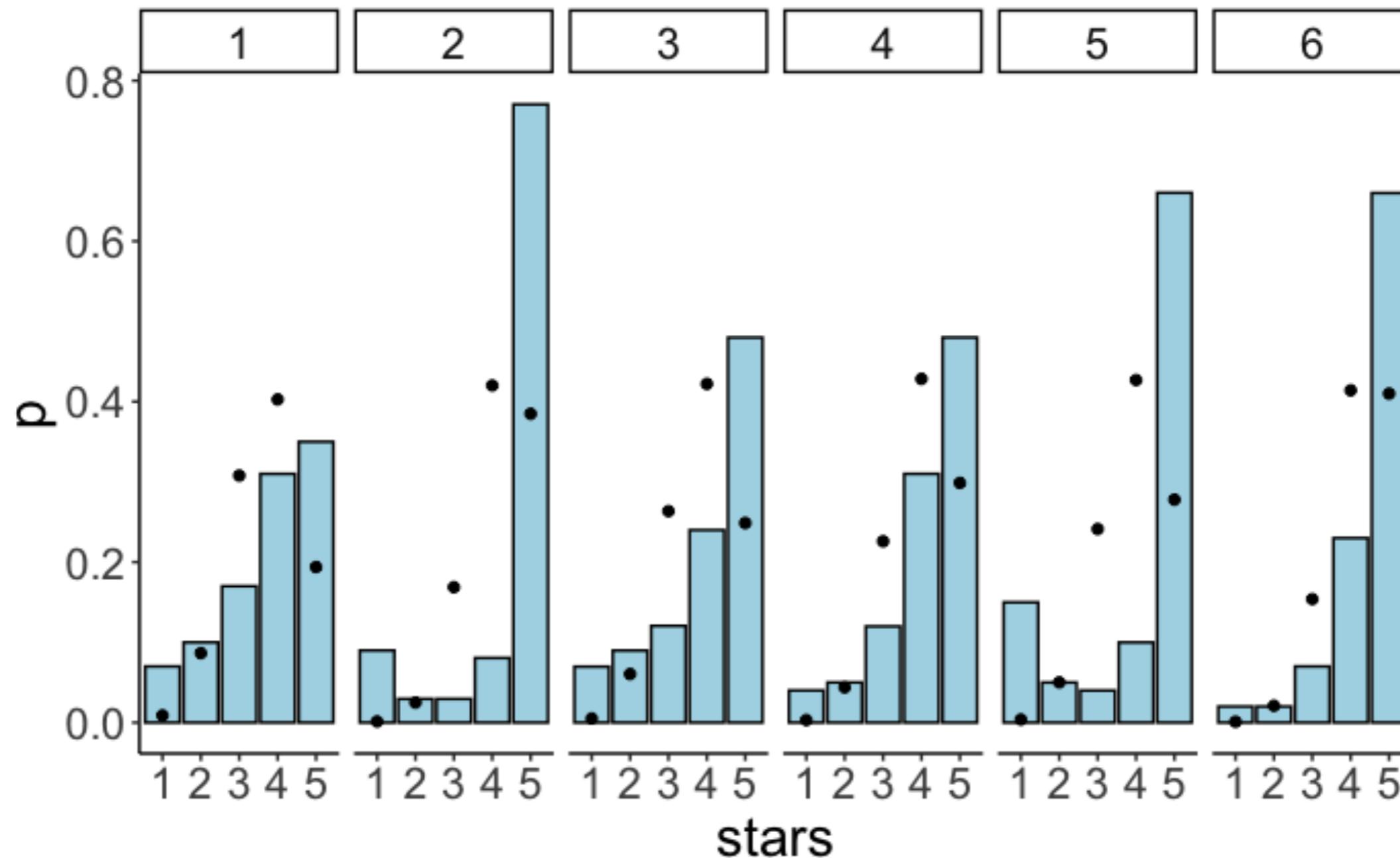
	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
sigma	1.00	0.00	0.99	1.01	1.00	3300	2723

Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS and Tail_ESS are effective sample size measures, and Rhat is the potential scale reduction factor on split chains (at convergence, Rhat = 1).

mean for the reference category

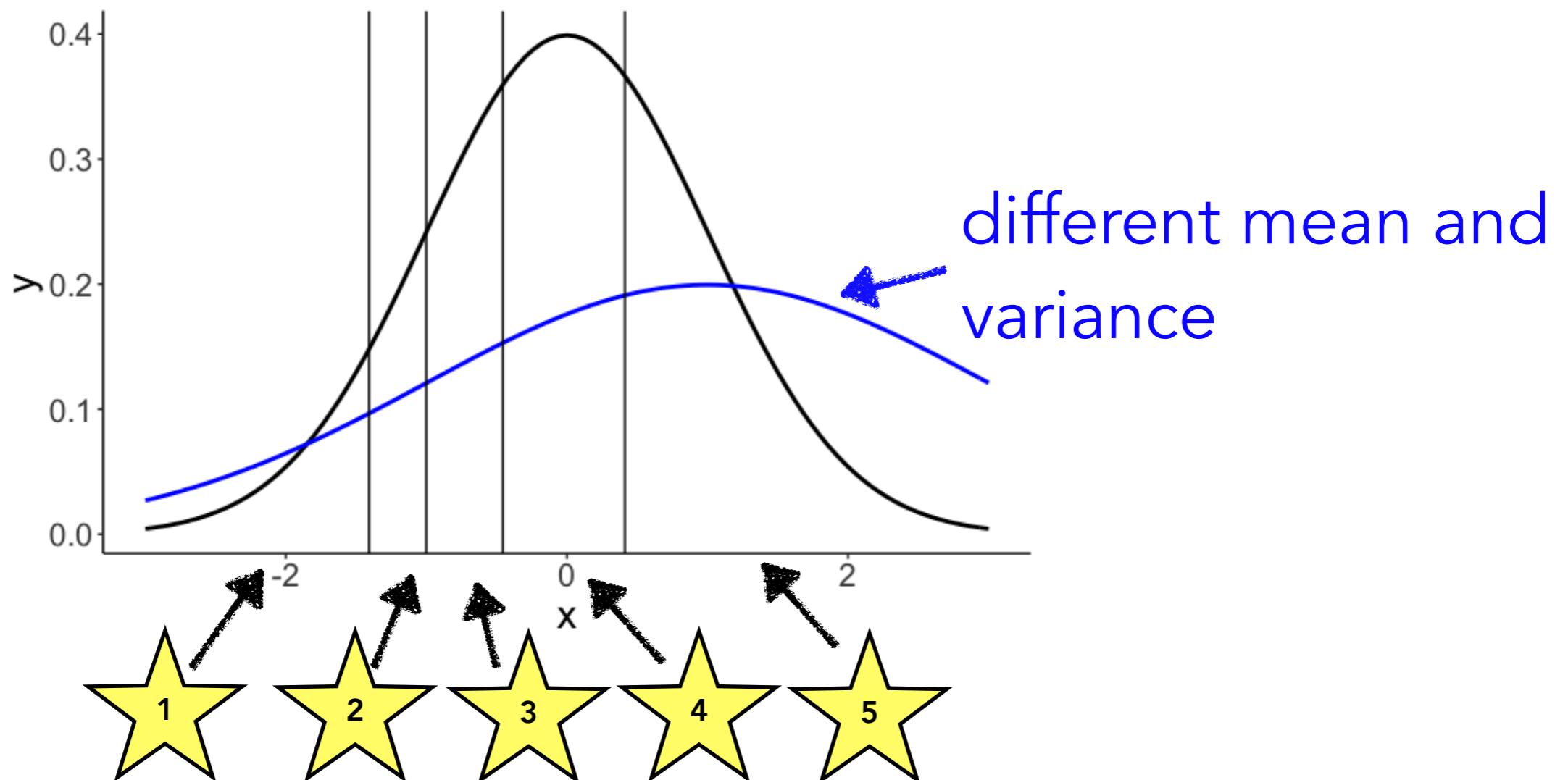
difference in mean to reference category

Predictions from the metric model



that's not looking good ...

Let's relax the assumption of equal variances



Fit a model that doesn't assume equal variance

```
1 fit.brm7 = brm(formula = bf(stars ~ 1 + id) + lf(disc ~ 0 + id, cmc = FALSE),  
2 family = cumulative(link = "probit"),  
3 data = df.movies,  
4 file = "cache/brm7",  
5 seed = 1)
```

tricky formula

thresholds

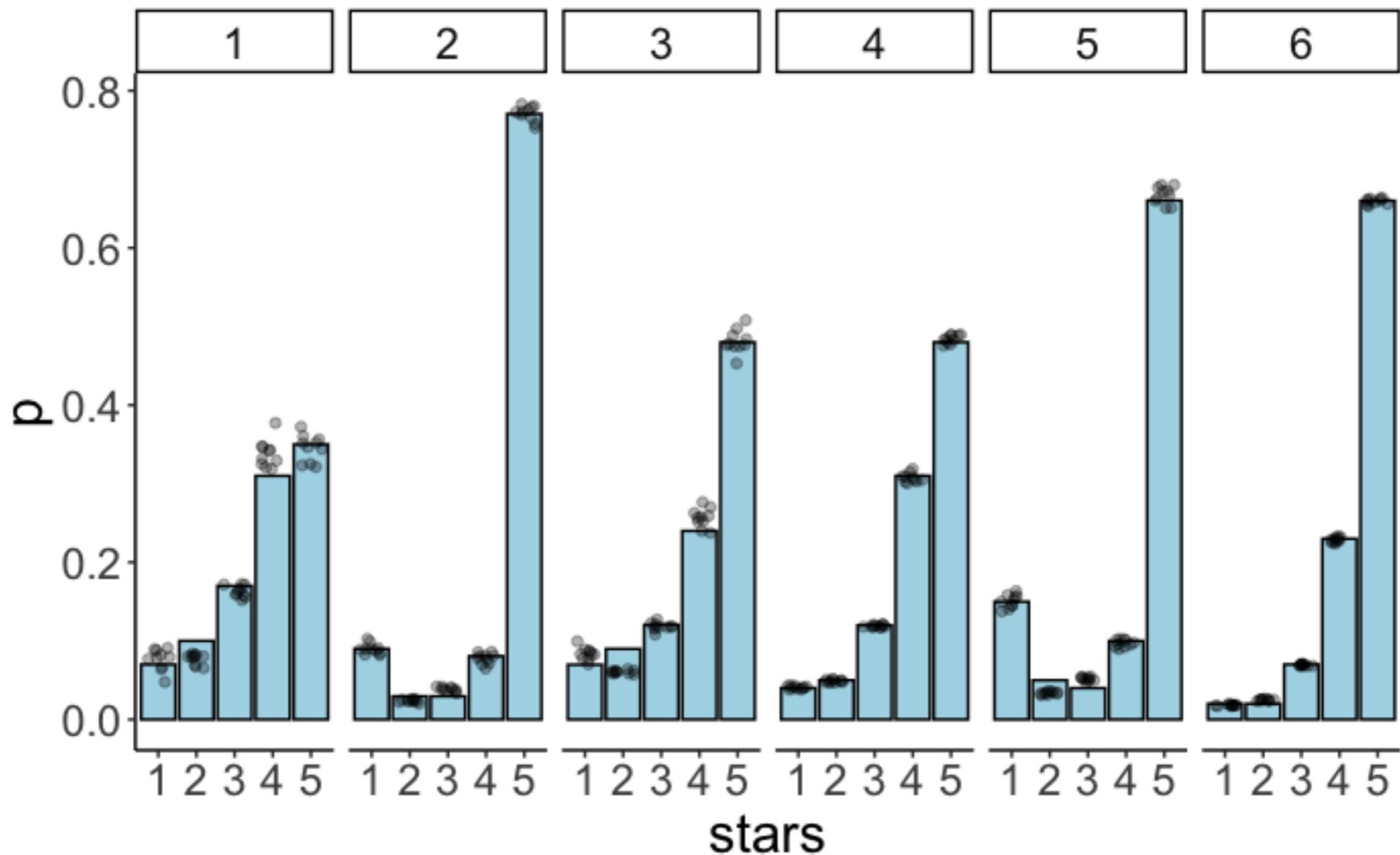
difference in
mean

difference in
variance

	Estimate	Est.Error	1-95% CI	u-95% CI	Rhat	Bulk_ESS	Tail_ESS
Intercept[1]	-1.41	0.06	-1.53	-1.29	1.00	1484	2421
Intercept[2]	-1.00	0.05	-1.10	-0.90	1.00	1852	2561
Intercept[3]	-0.46	0.04	-0.54	-0.37	1.00	2405	2684
Intercept[4]	0.41	0.05	0.32	0.51	1.00	1336	2161
id2	2.71	0.33	2.14	3.44	1.00	1681	1865
id3	0.33	0.07	0.20	0.47	1.00	1961	2618
id4	0.36	0.05	0.26	0.46	1.00	1525	2753
id5	1.65	0.17	1.34	2.00	1.00	1929	2281
id6	0.86	0.06	0.74	0.98	1.00	1112	1769
disc_id2	-1.12	0.10	-1.33	-0.94	1.00	1672	1943
disc_id3	-0.23	0.06	-0.34	-0.11	1.00	1342	1955
disc_id4	-0.01	0.04	-0.09	0.07	1.00	1043	1747
disc_id5	-1.09	0.07	-1.23	-0.95	1.00	1681	1996
disc_id6	-0.08	0.04	-0.15	0.00	1.00	941	1489

see for
details

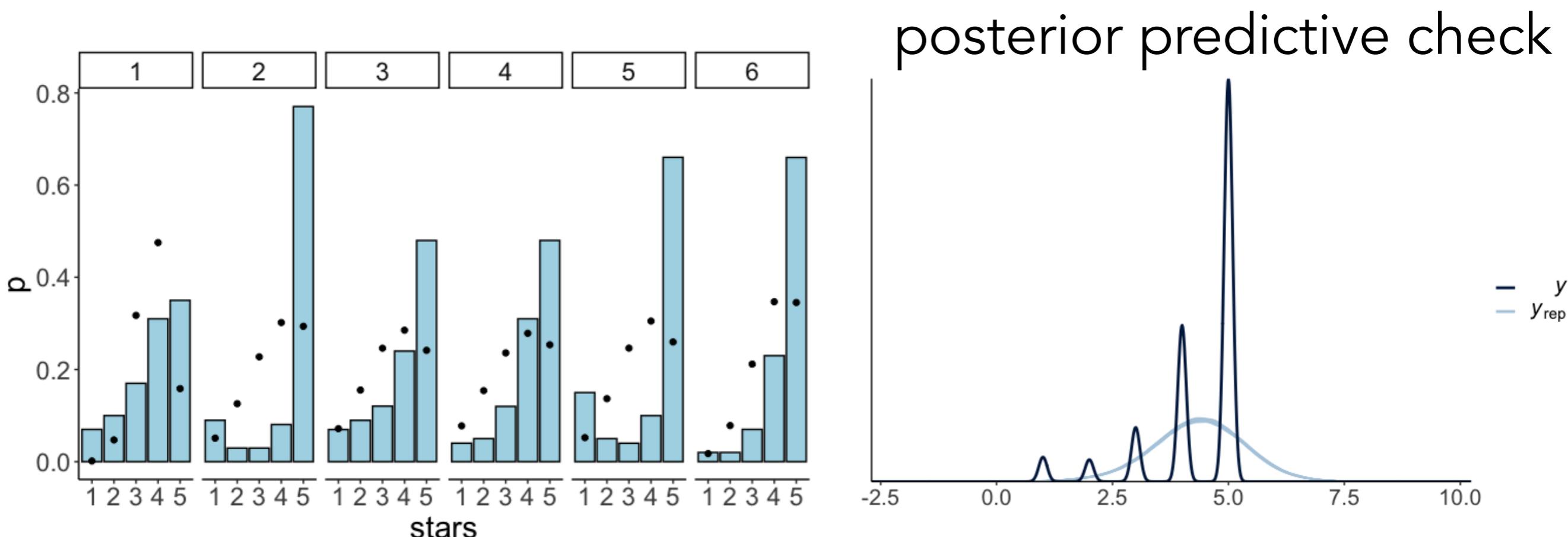
Illustrate the predictions



this looks excellent!

Metric model with different variances still doesn't work well ...

```
1 fit.brms = brm(formula = bf(stars ~ 1 + id,  
2                               sigma ~ 1 + id),  
3                               data = df.movies,  
4                               file = "cache/brms",  
5                               seed = 1)
```



still no good ...

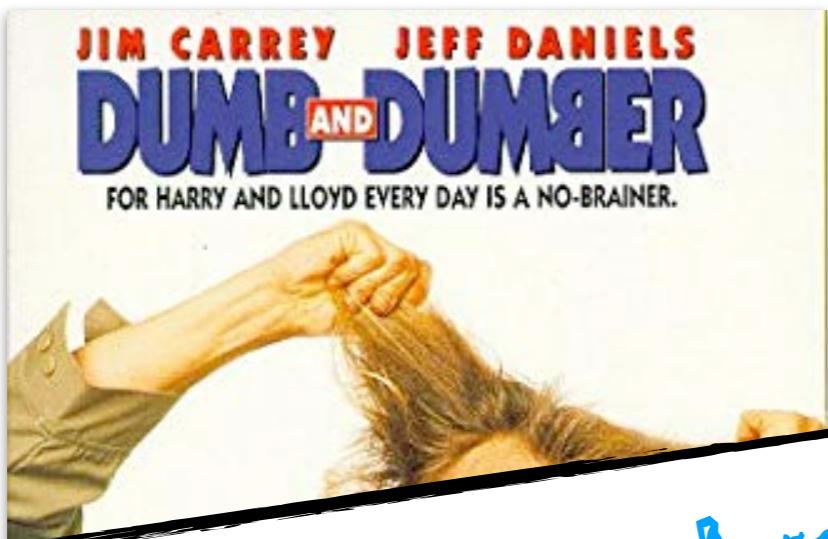
Model comparison

```
1 fit.brm5 = add_criterion(fit.brm5,  
2                           criterion = "loo")  
3  
4 fit.brm6 = add_criterion(fit.brm6,  
5                           criterion = "loo")  
6  
7 loo_compare(fit.brm5, fit.brm6)
```

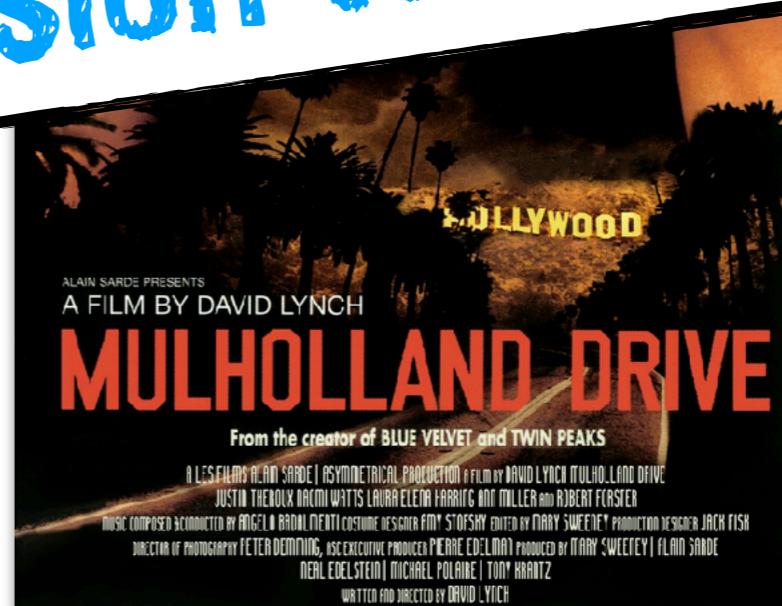
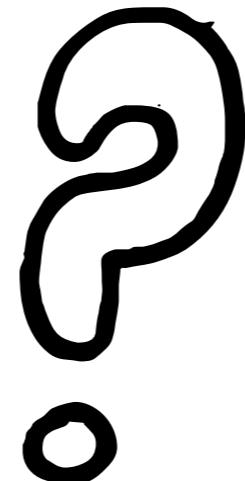
	elpd_diff	se_diff
fit.brm5	0.0	0.0
fit.brm6	-7657.1	109.2

the ordinal regression model is muuuuuuch better!

Which movie shall I watch?



run an ordinal regression to find out!



Customer reviews

★★★★★ 4.5 out of 5

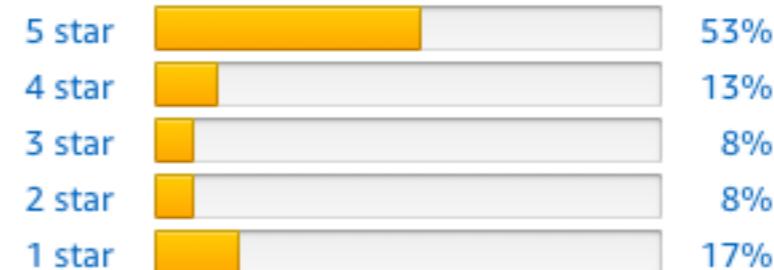
2,029 customer ratings



Customer reviews

★★★★★ 3.8 out of 5

1,558 customer ratings



Better modeling slider data

Example taken from ...

How to analyze visual analog (slider) scale data?

A reasonable choice might be the zero-one-inflated beta model

Feb 18, 2019 · 25 min read · psychology, statistics

- [Introduction](#)
- [The zero-one-inflated beta model](#)
- [ZOIB regression](#)
- [Simulation: Compare ZOIB and t-test performances](#)
- [Discussion](#)
- [References](#)

Introduction

In psychological experiments, subjective responses are often collected using two types of response scales: ordinal and visual analog scales. These scales are unlikely to provide normally distributed data. However, researchers often analyze responses from these scales with models that assume normality of the data.¹

Ordinal scales, of which binary ratings are a special case, provide ordinal data and are thus better analyzed using ordinal models (Bürkner and Vuorre 2018; Liddell and Kruschke 2018).

<https://vuorre.netlify.com/post/2019/02/18/analyze-analog-scale-ratings-with-zero-one-inflated-beta-models/#zoib-regression>

In general, what is more important to you?

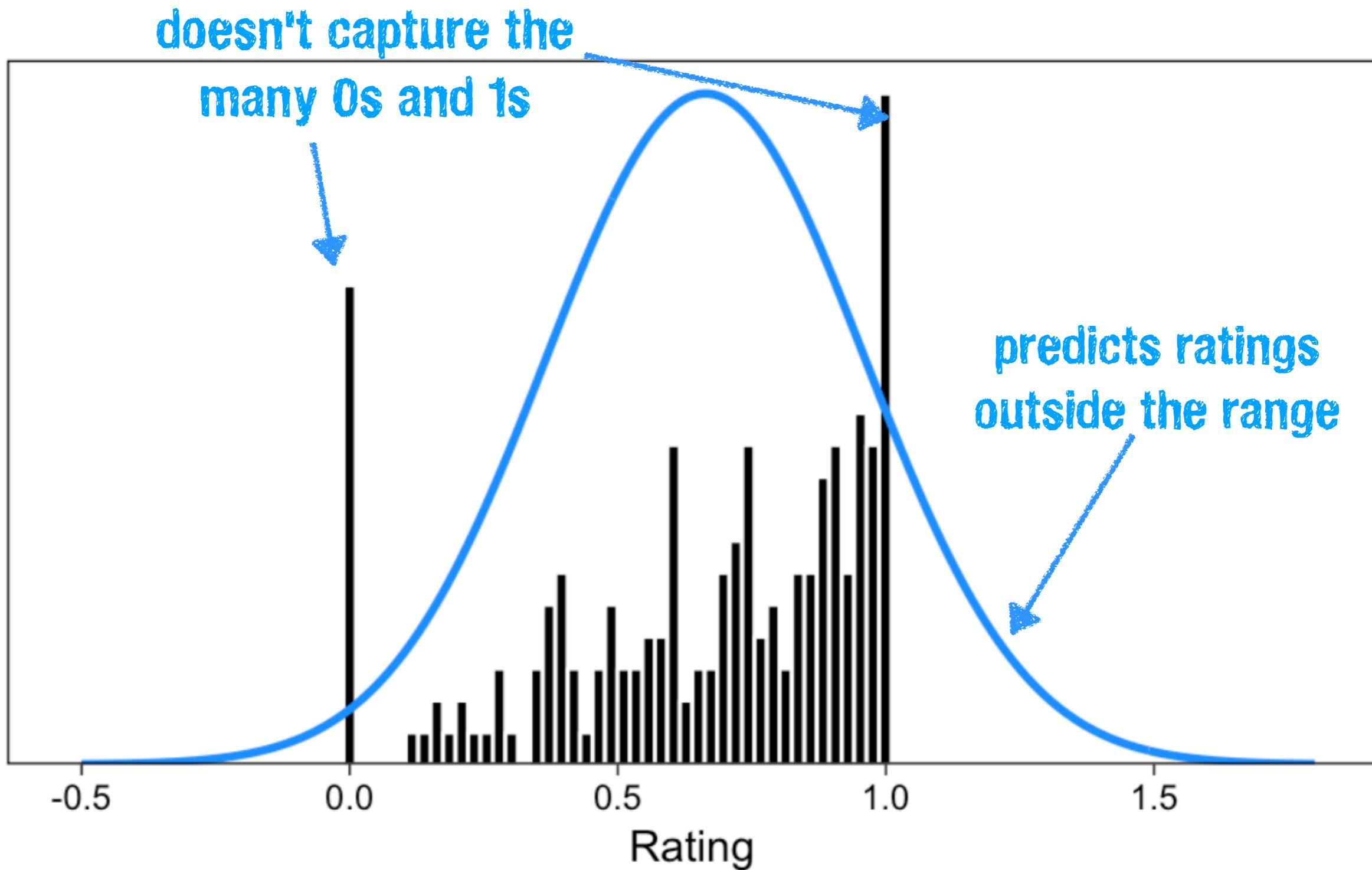
Leisure

Money



Next

Normality assumption is (almost always) violated



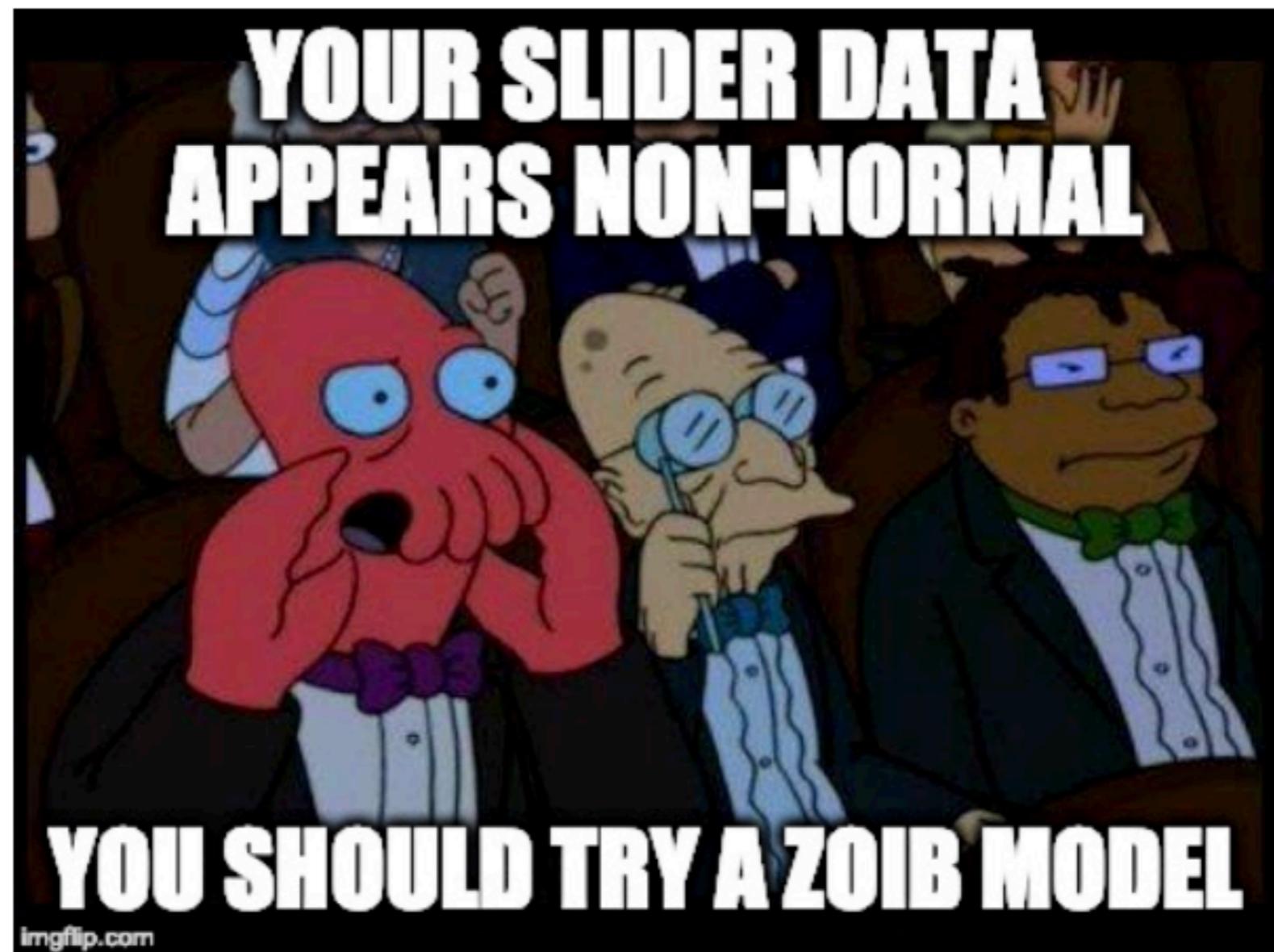
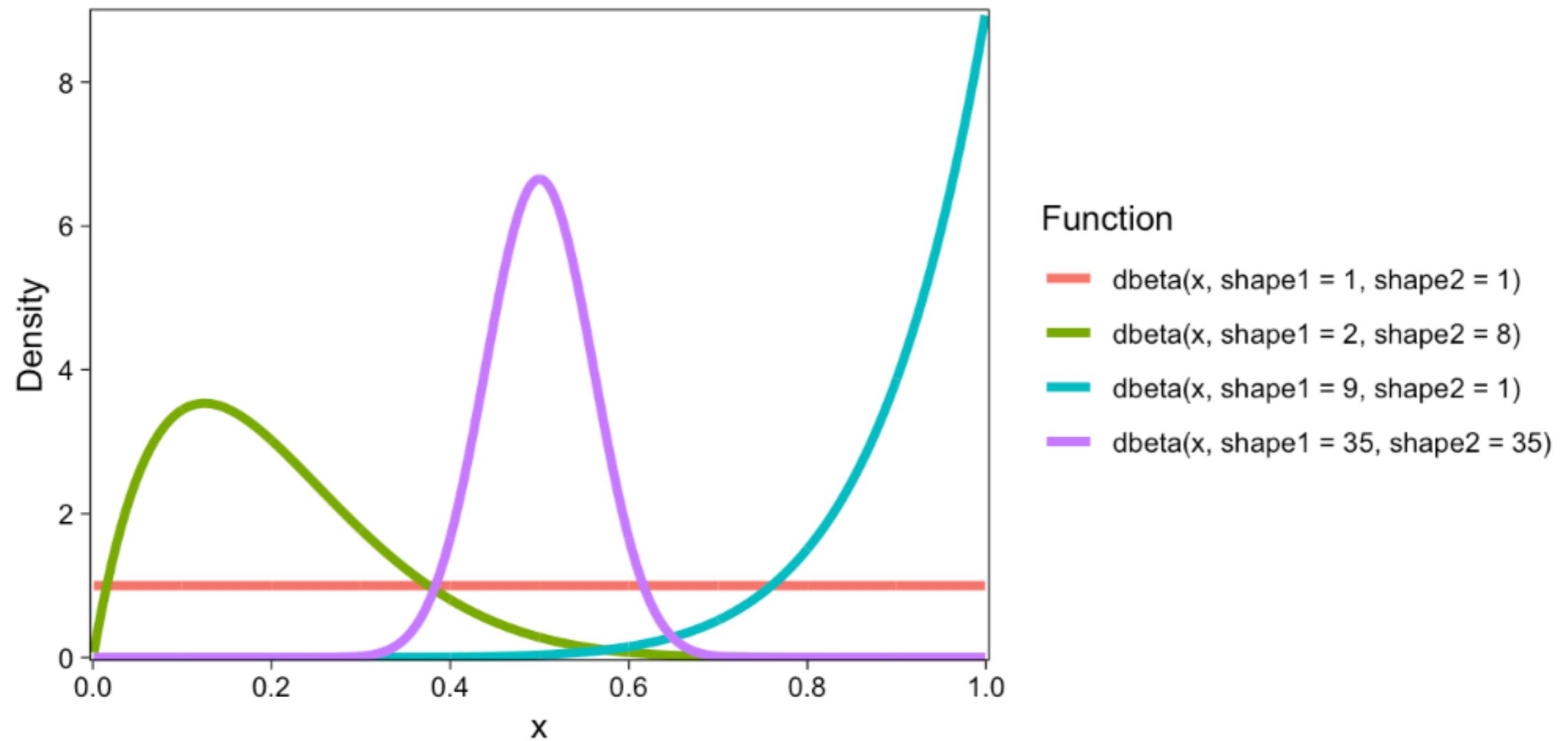


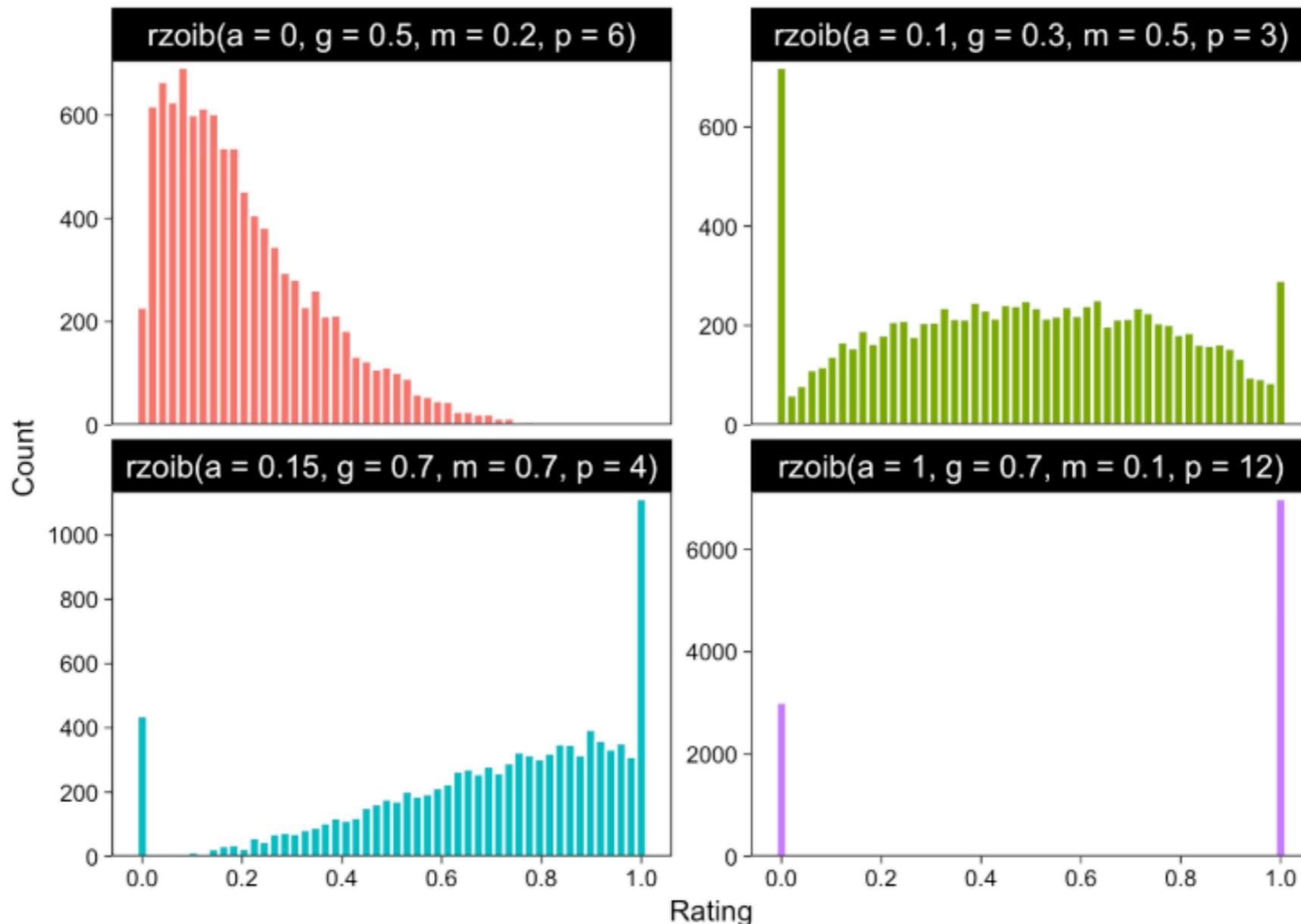
Figure 3: Dr. John A. Zoidberg thinks you should try a ZOIB model on your slider scale data.

Beta distribution



Zero-one inflated **beta** binomial model

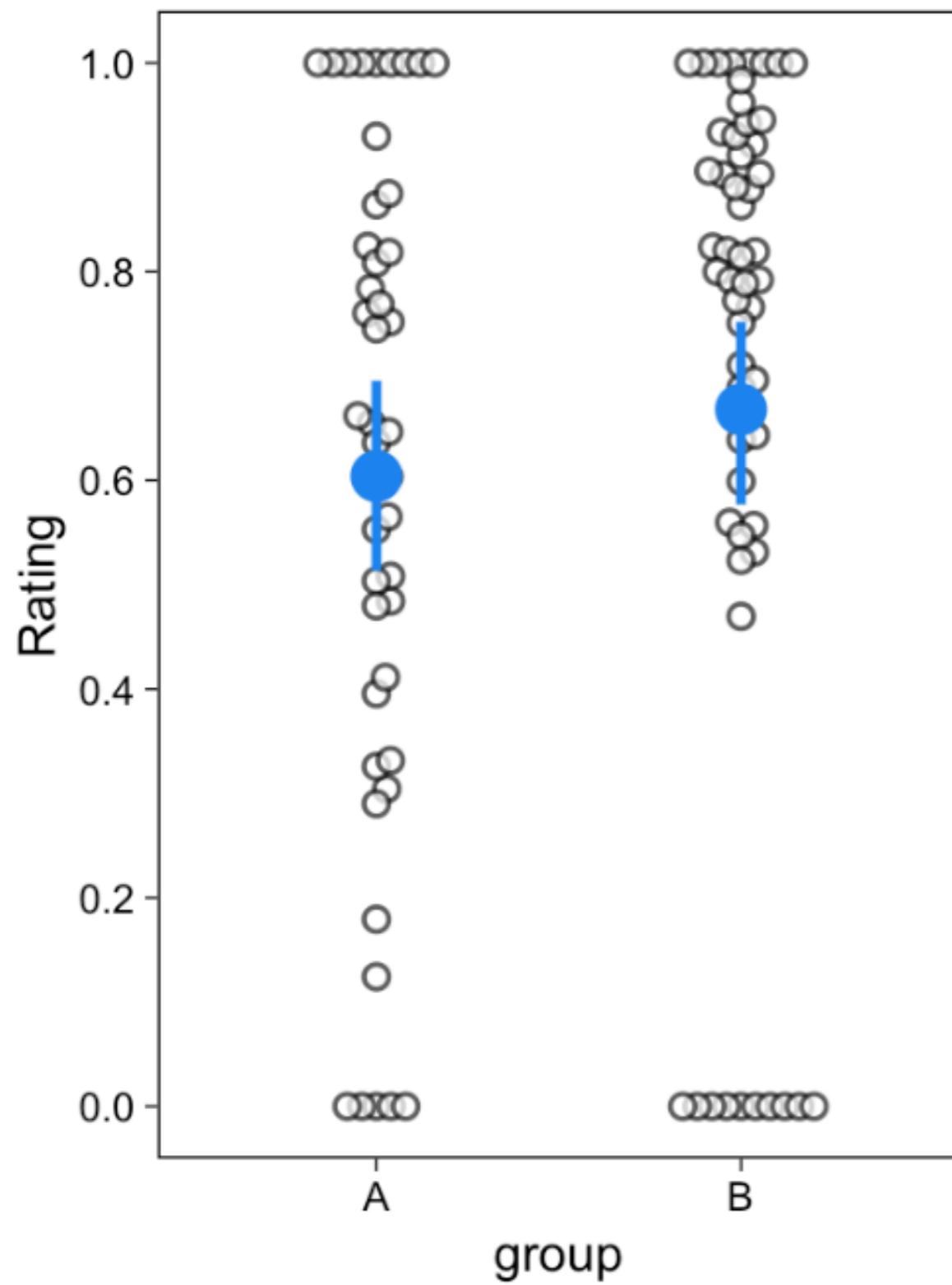
Zero-one inflated beta binomial model



Generative process

Some chance the a person will pick a 0 or 1, if not then response is determined by the beta distribution.

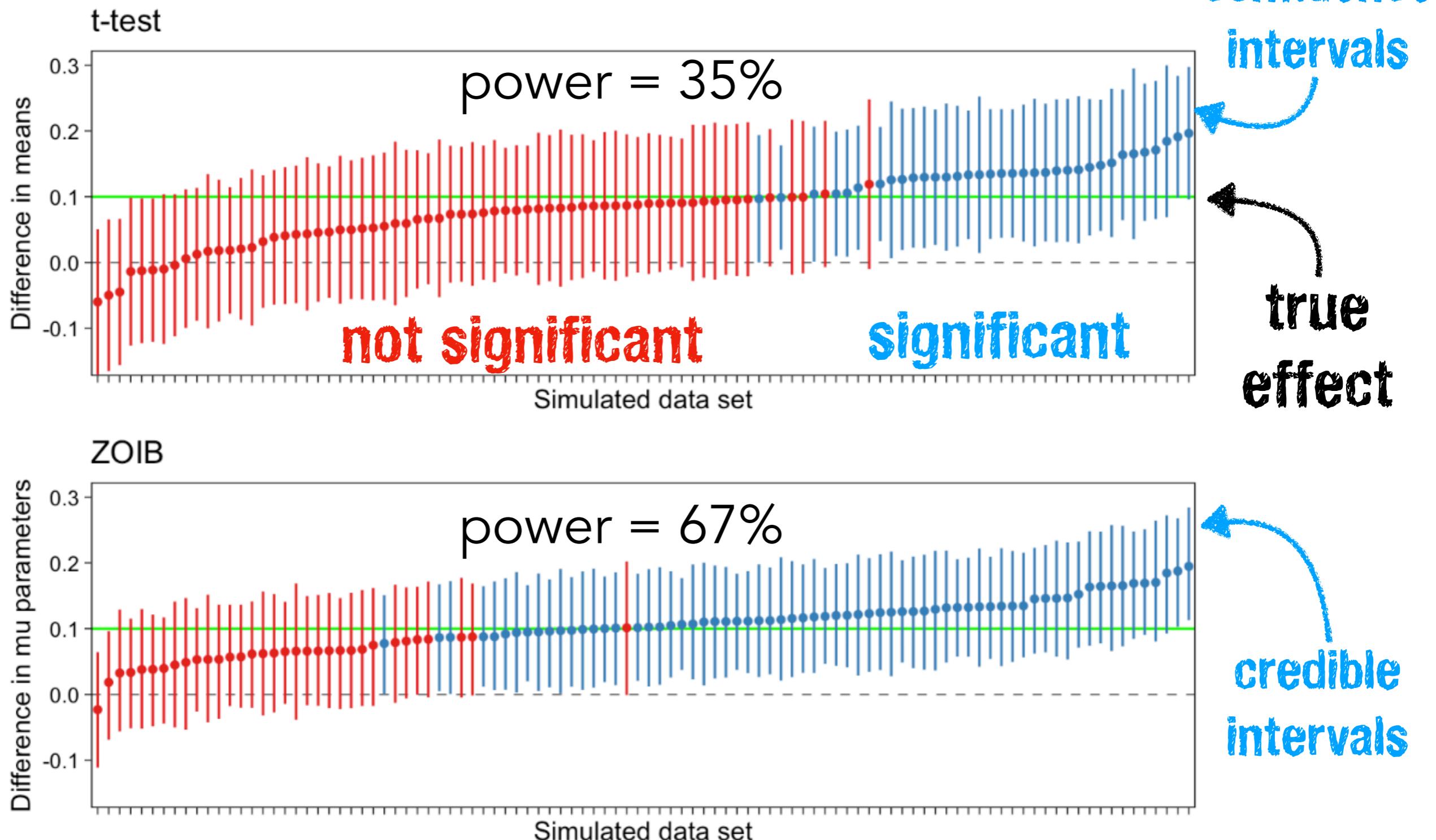
Example data



Fit the ZOIB

```
zoib_model = bf(  
  Rating ~ group,  
  phi ~ group,  
  zoi ~ group,  
  coi ~ group,  
  family = zero_one_inflated_beta()  
)  
  
fit = brm(  
  formula = zoib_model,  
  data = dat  
)
```

Capturing the data-generating process gives you power



Thanks

Psych 252 Team

Ari Beller



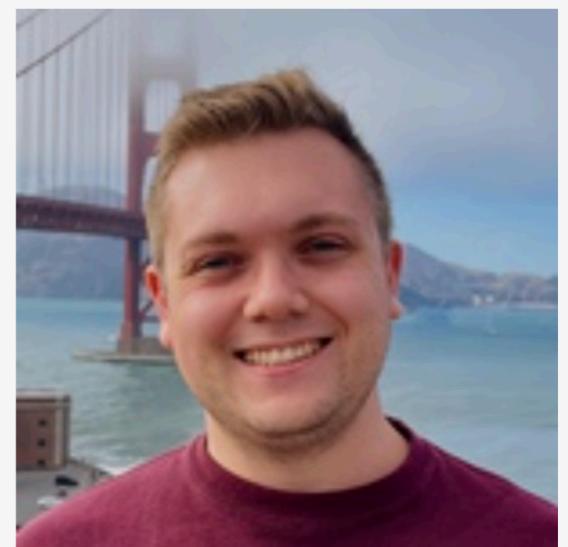
Beth Rispoli



Satchel Grant



Shawn Schwartz



Teaching assistant

they/them

Teaching assistant

she/her

Teaching assistant

he/him

Teaching assistant

he/him

All of you!

Abutto, Adani

Bennett

Anderson, Sean Paul

Blakey, Will William

Chen, Emily M

Chi, Howard

Decatur, Cid Halsey-
Steve

Dhingra, Monisha

Ergin, Irmak

Fang, David

Fendrich, Sarah

Fischer, Stephanie

Goodwin, Emily

Gupta, Anmol

Hu, Sherry

Johnson, Katherine

Abigail

Kemmann, Bendix

Klevak, Nastasia

Ruth

Lai, Wilson Cyrus Shi

Hao

Lepp, Haley

Li, Qianqian

Morante Mazzaferro,

Mateus

Myoung, Eunjung

Park, Joon

Portillo, Sofia

Analise

Rajagopalan, Neha

Tao, Yujie

Tufts, L'Nard Evan

Travis, II

Tung, Sarah Shi

Uricher, Raphael

Zamora, Tatiana Iza

