Class 1: Intro to Baysian thinking

Wiktor Soral, PhD

Class information

- **Instructor**: Wiktor Soral, PhD
- **E-mail**: wiktor.soral@psych.uw.edu.pl
- **Office**: room no. 96
- **Office hours**: Thursday, 1-3PM

Course outline

- Intro to Bayesian thinking
- Intro to Bayesian computation with R
- Intro to Markov Chain Monte Carlo
- Bayesian linear models:
  - simple and multiple regression
  - Bayesian factorial ANOVA
- Bayesian generalized linear models: logistic and Poisson regression
- Bayesian multilevel models
- Practices in model building: model comparison and model averaging

Assessment methods:

- Midterm exam (around November 25, 2019)
- Final exam (January 27, 2020)
- Home assignments (around 10)

Final score = 30% * (midterm score) + 40% * (home assignments) + 30% * (final exam score)

Total score and both exam scores should be at least at the 50% level to pass the course.

Attendace rules

Students are allowed to miss 2 classes without excuse, 2 more classes in case of excuse, but will not pass the course in case of more than 4 absences.

Additional work is assigned in case more than 2 classes are missed (even in cases of valid excuse).

Course website

https://github.com/wsoral/bam_2019

Typology of statistics

- **Frequentists:** From Neyman, Pearson, Wald. An approach you learned during basic statistics course. Is based on an imaginary sampling distributions and sharp decisiton rules (NHST = Null Hypothesis Significance Testing).
- **Bayesians:** From Bayes/Laplace/de Finetti. An approach that recently gains increasing popularity. Is based on an assumption that our knowledge regarding parameters in uncertain and can be always updated by new data.

Conceptually, Bayesian models are simple

$$\text{Posterior probability} \propto \text{Data given hypothesis} \times \text{Prior probability}$$

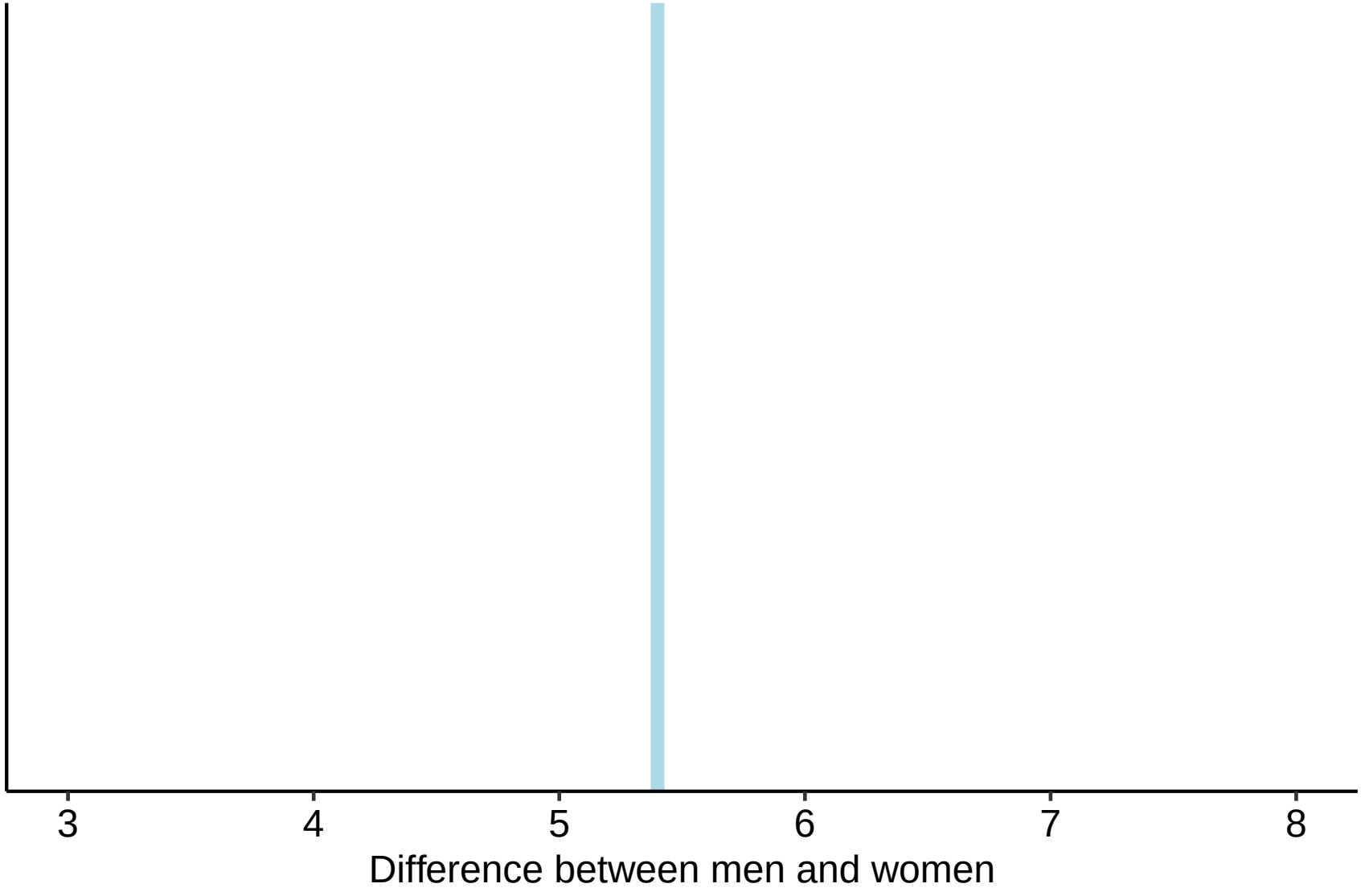
Conceptually, Bayesian models are simple, example

- A researcher is interested in differences in empathy between men and women. No past research examined this relationship.
- The researcher believes that the hypothesis that men are more empathic than women is just as likely as the hypothesis that women are more empathic than men (**prior**).
- Then the researcher conduct a study, and finds that in the collected sample women score higher on the empathy measures than men (**data given hypothesis**).
- The researcher updates his/her belief, and now finds hypothesis that women are more empathic than men more likely than the reverse (**posterior**).

Critical differences between Bayesian and Non-Bayesians: *Fixed/Variable*

- **Frequentists:** Data are random IID sample from a continuous stream, but parameters are fixed.
- **Bayesians:** Data are observed and therefore fixed, but parameters are unknown and described distributionally.

Critical differences between Bayesian and Non-Bayesians: *Fixed/Variable*



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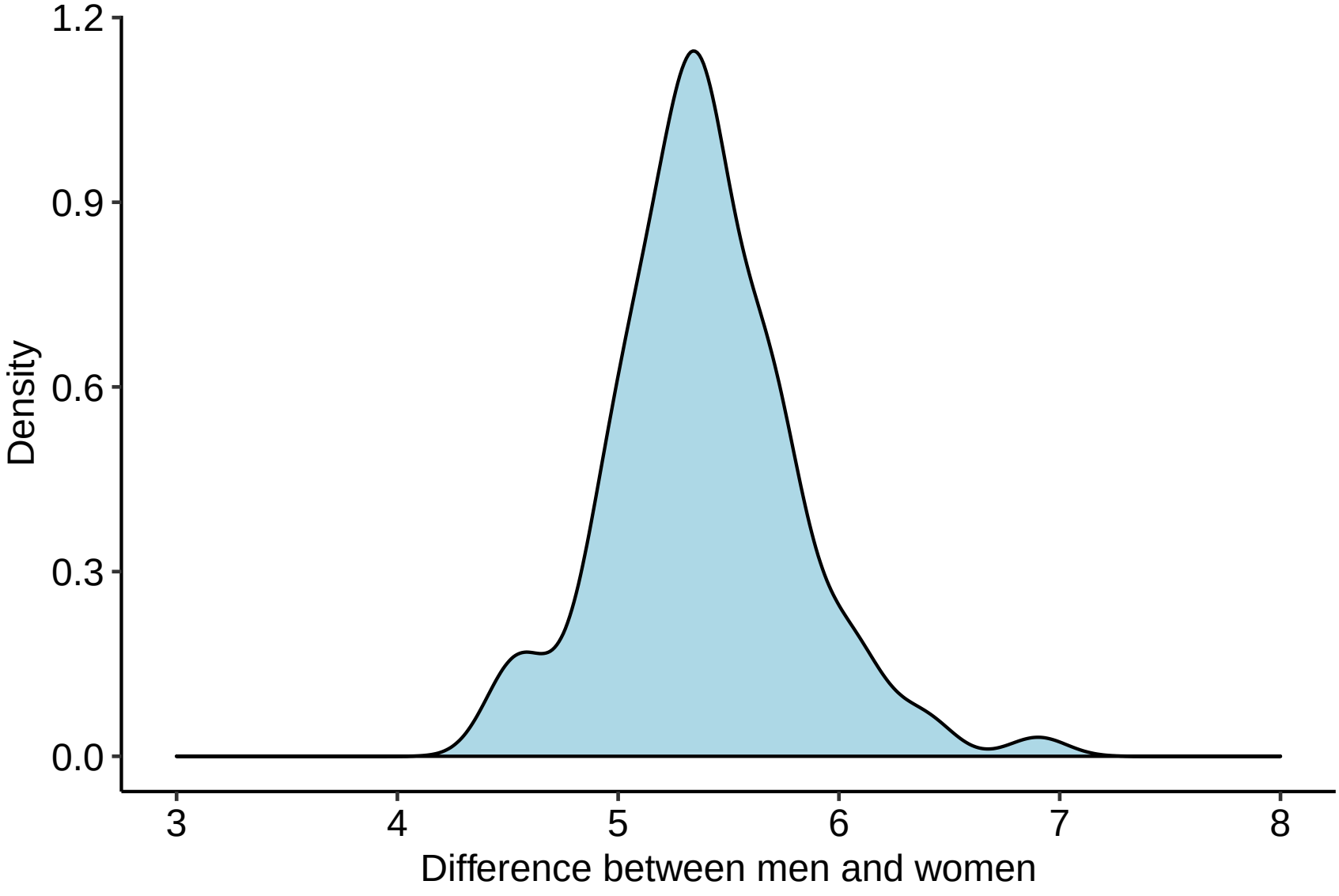
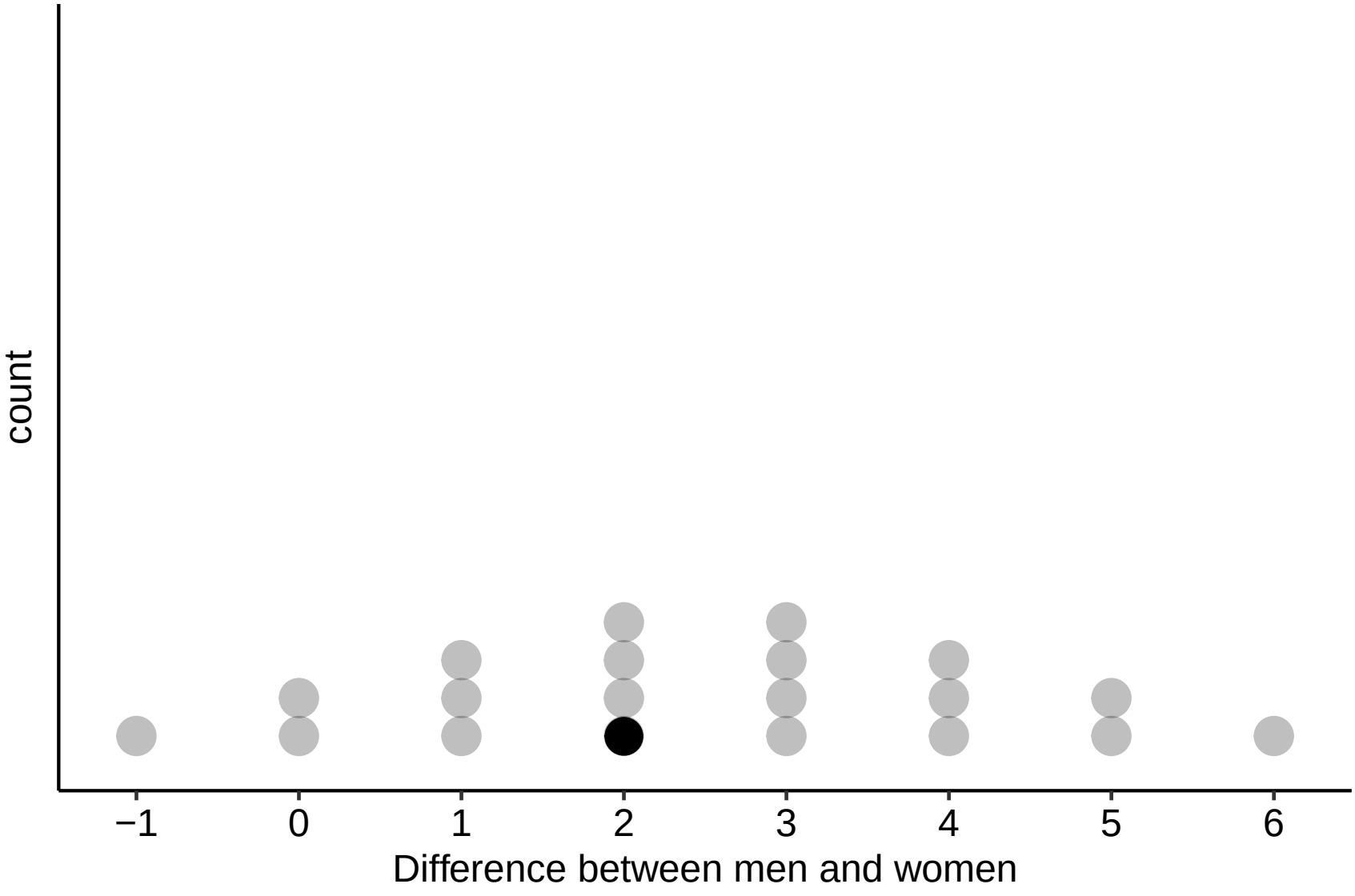


Critical differences between Bayesian and Non-Bayesians: *Interpretation of probability*

- **Frequentists:** Probability is observed result from an infinite series of trials performed under identical conditions.
- **Bayesians:** Probability is the researcher 'degree of belief' before or after the data are observed.

Critical differences between Bayesian and Non-Bayesians:
Interpretation of probability



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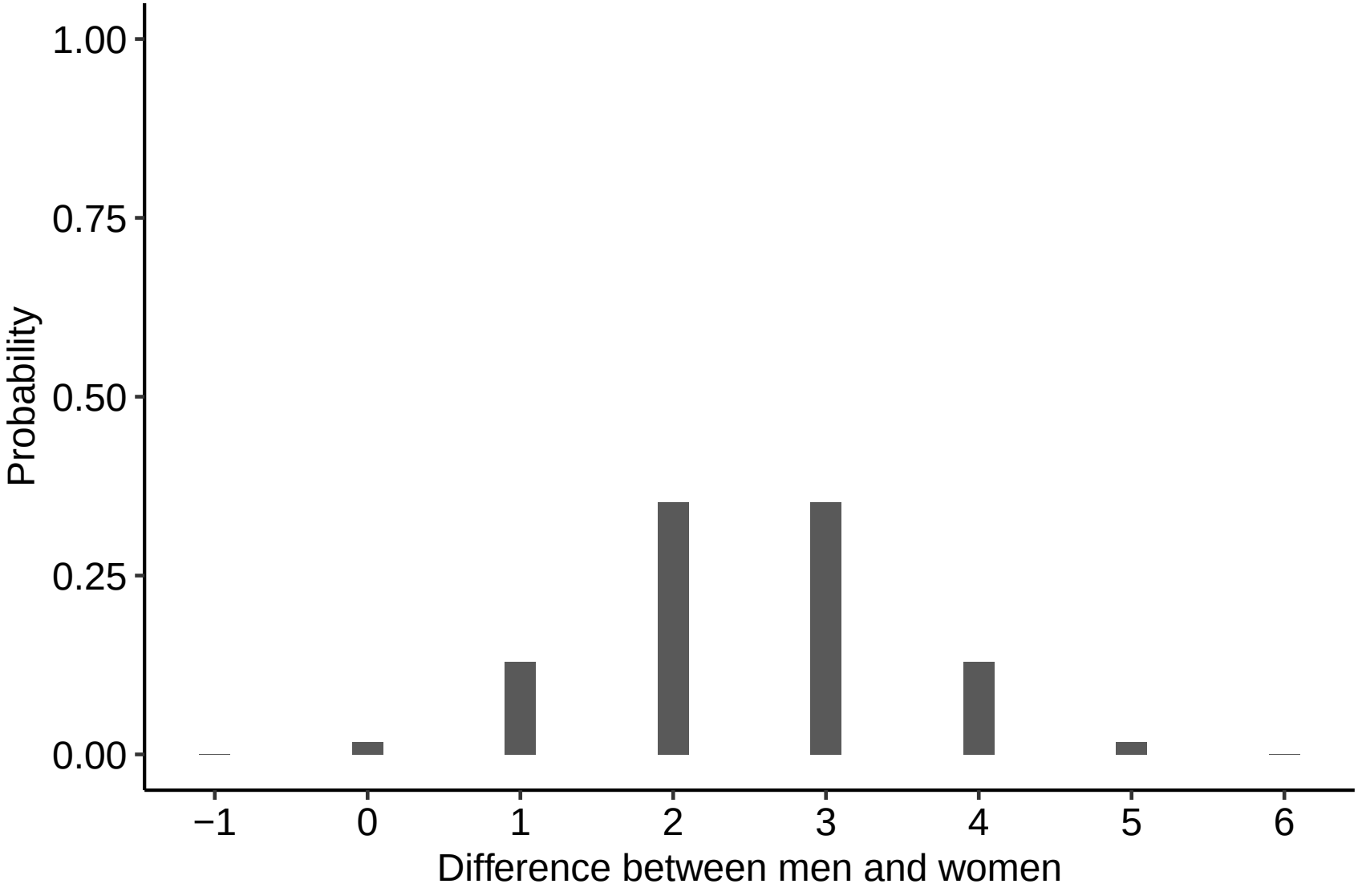

Critical differences between Bayesian and Non-Bayesians: *Model summaries*

- **Frequentists:** Point estimates and standard errors. Confidence intervals: 95% CI indicating that 19/20 times intervals covers the true parameter value.
- **Bayesians:** Various ways of describing parameters distribution (means, medians, quantiles). Credible intervals, HPDIs (highest posterior density intervals).

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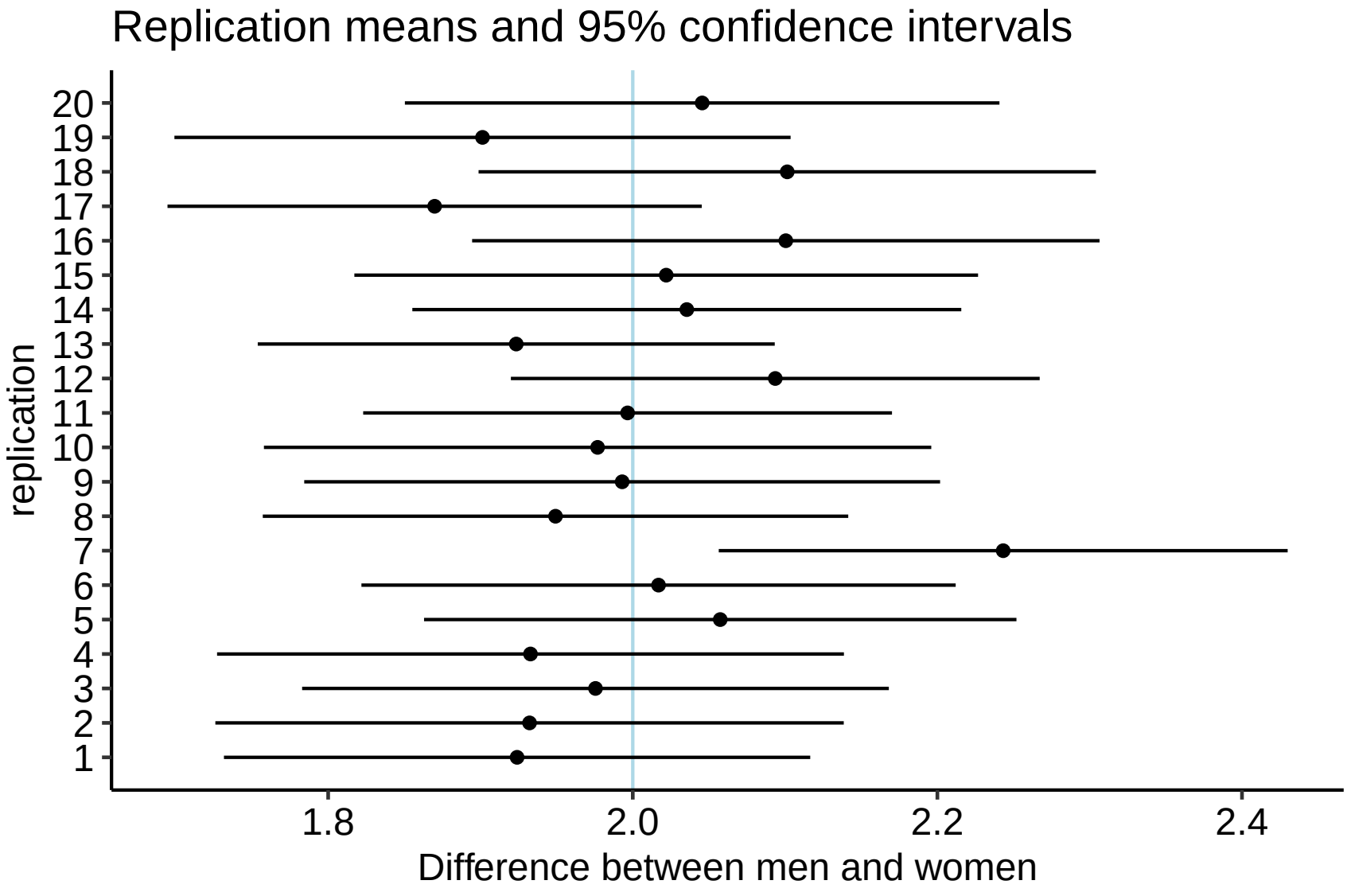

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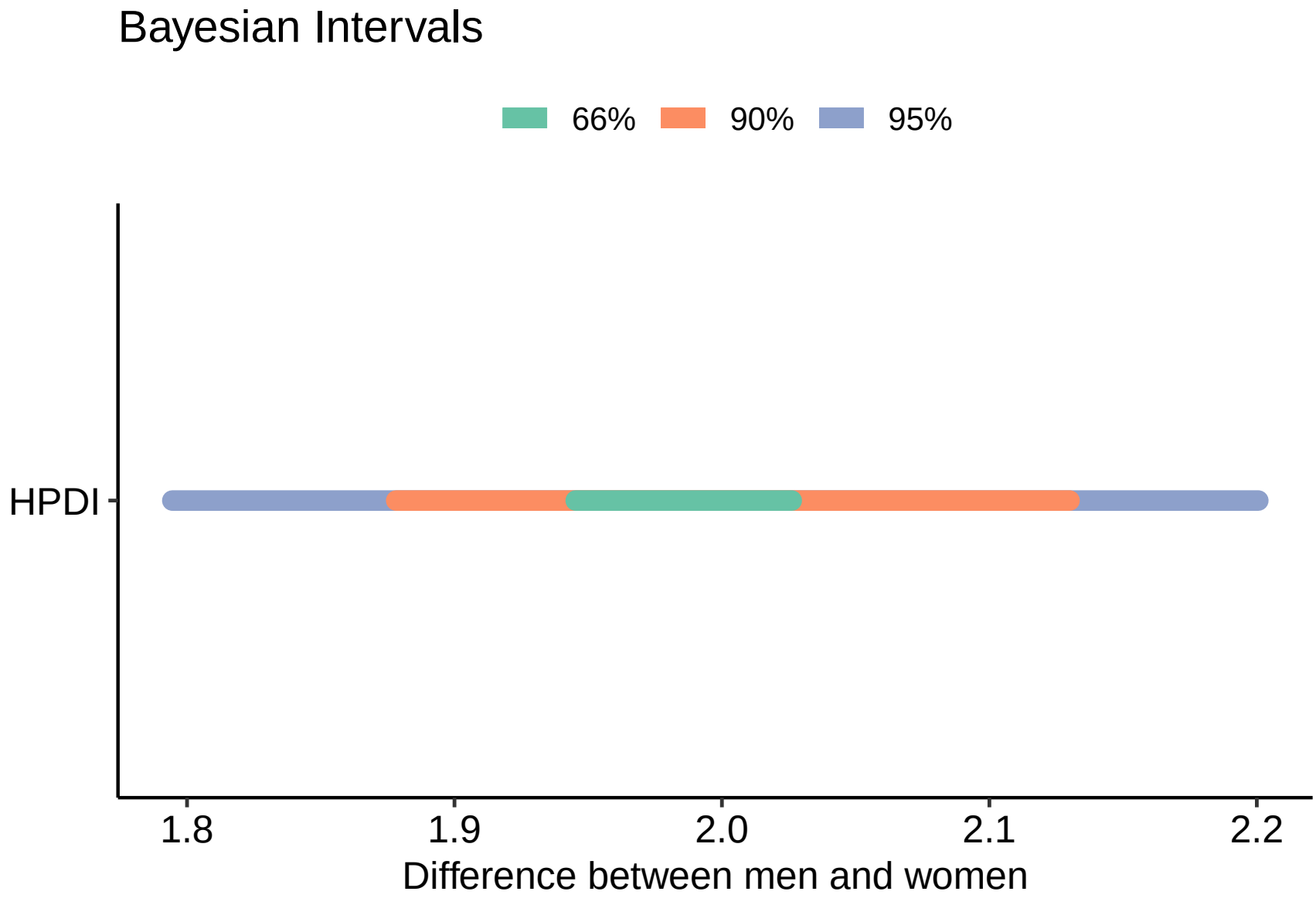
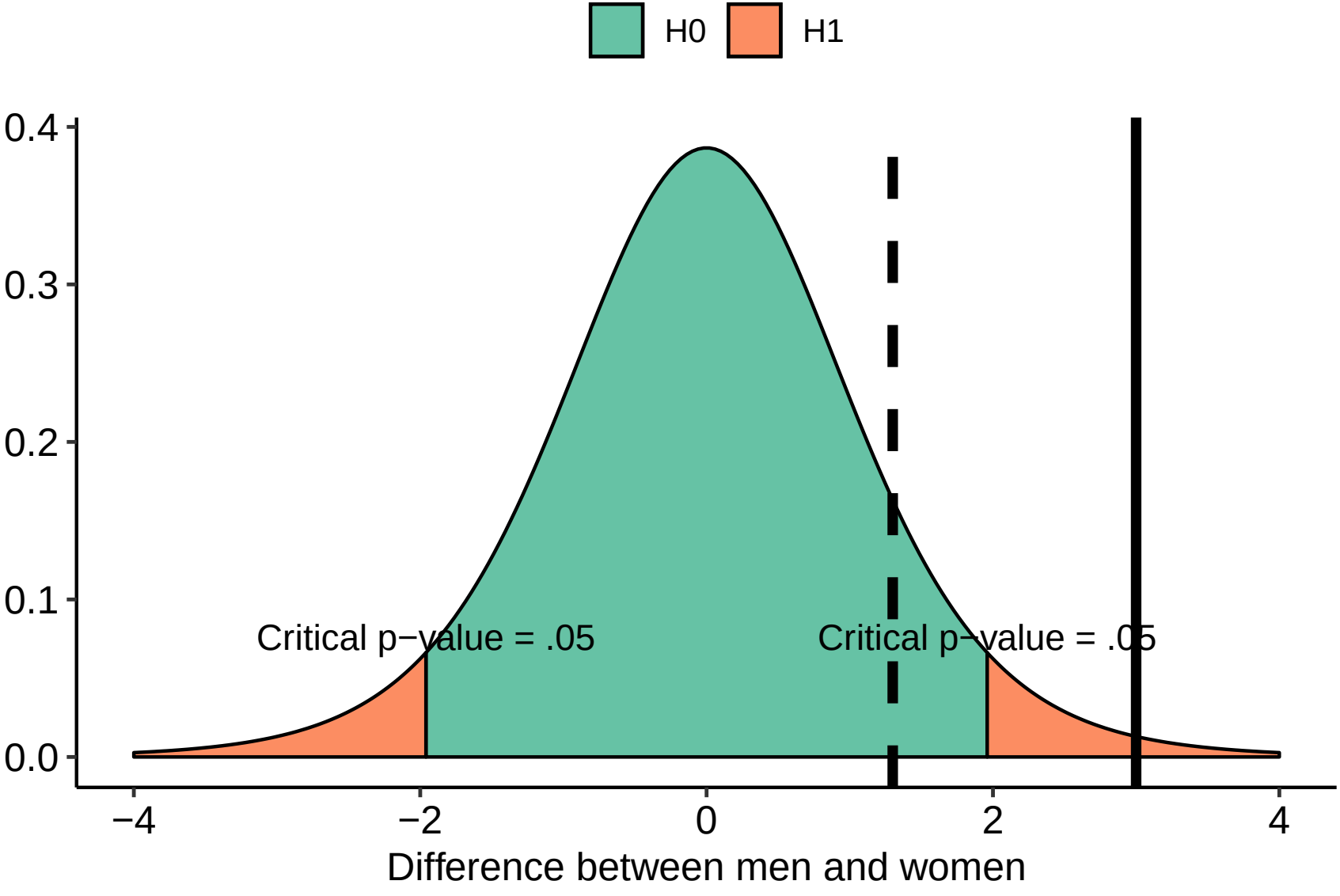
Model summaries



Critical differences between Bayesian and Non-Bayesians: *General inference*

- **Frequentists:** Deduction from the data given H_0, by setting α in advance. Reject H_0 if $Pr(data|H_0) < \alpha$, not reject H_0 if $Pr(data|H_0) \geq \alpha$.
- **Bayesians:** Induction from posterior given prior knowledge.

Critical differences between Bayesian and Non-Bayesians:
General inference



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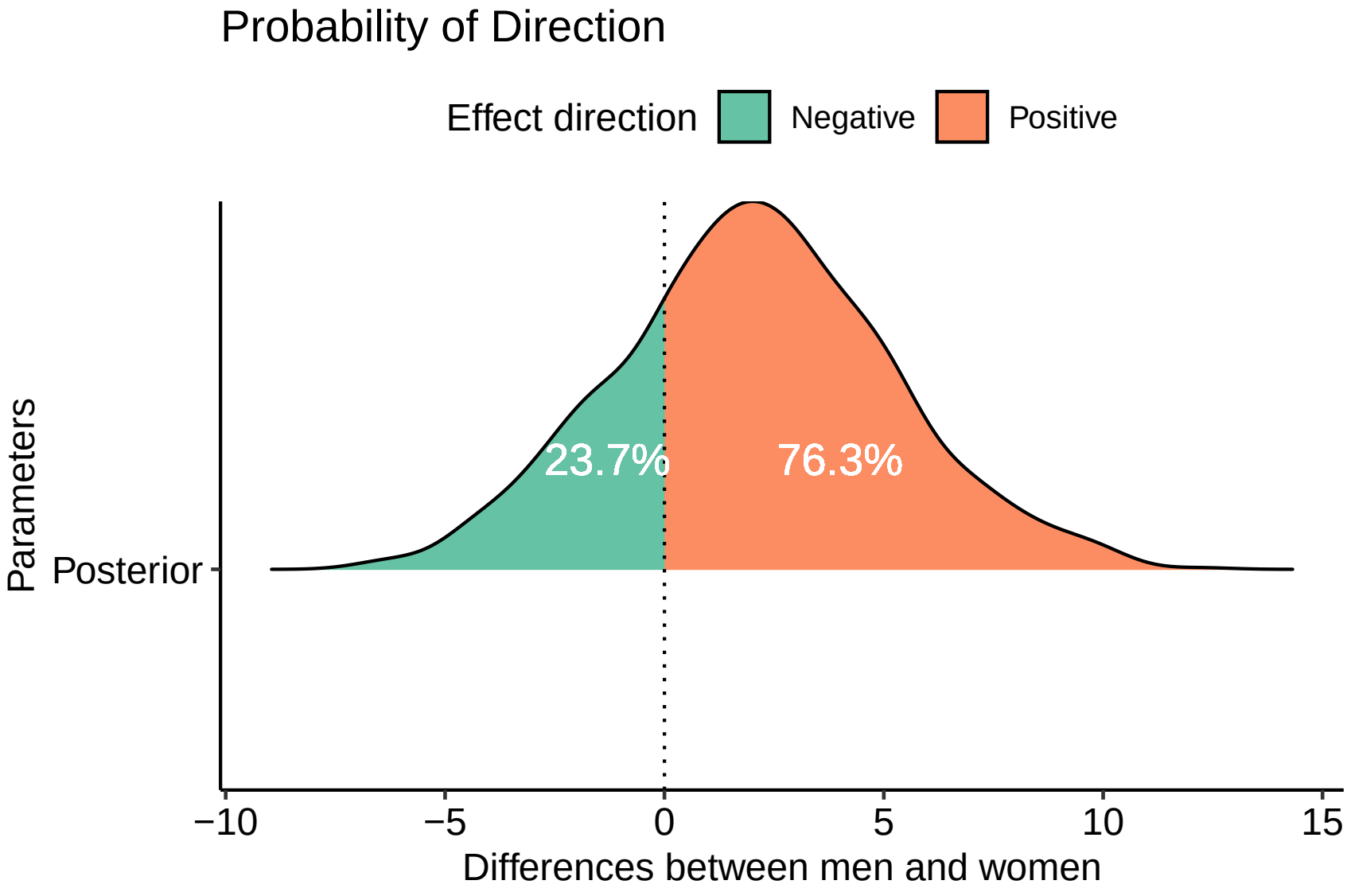

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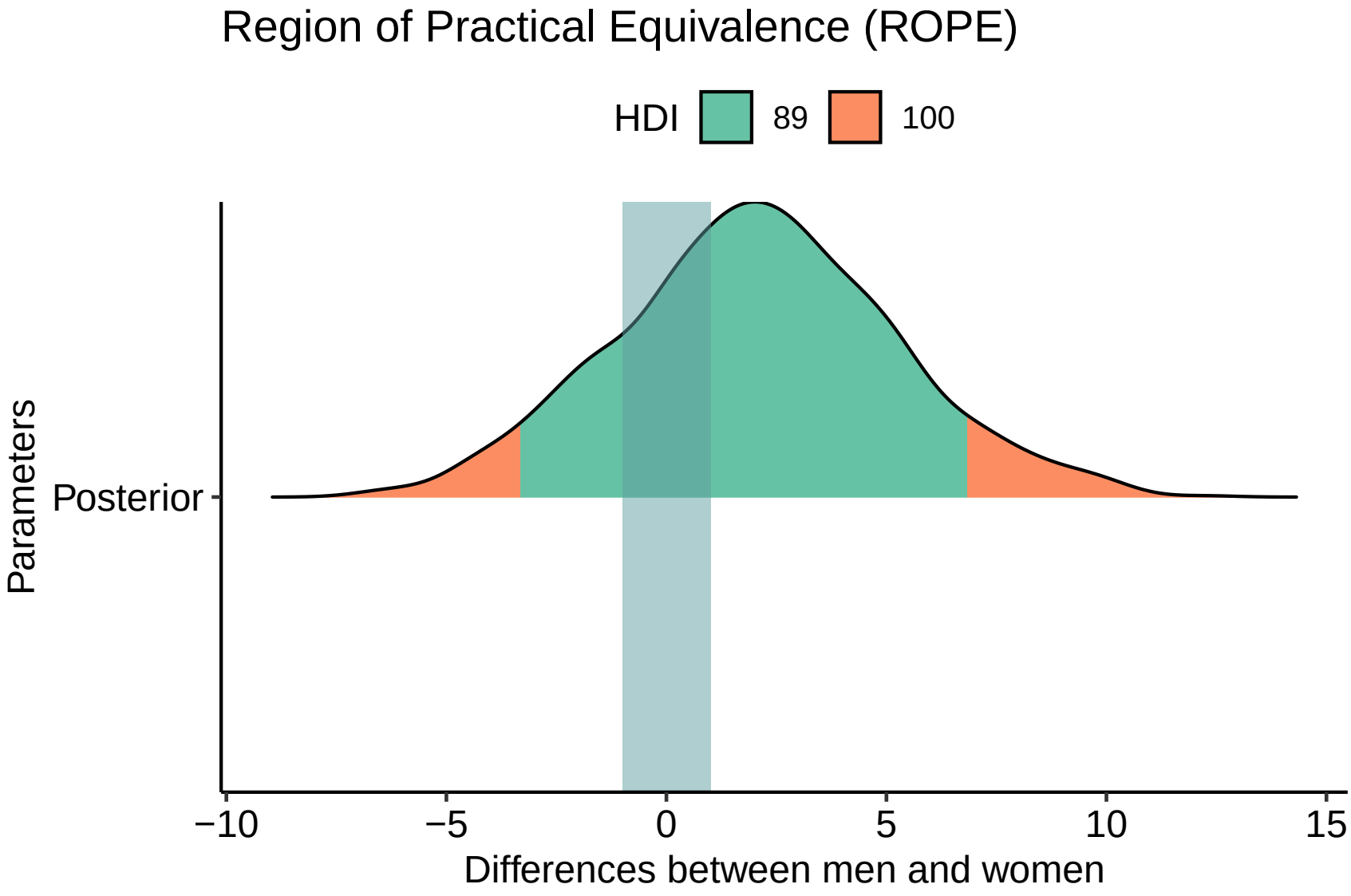

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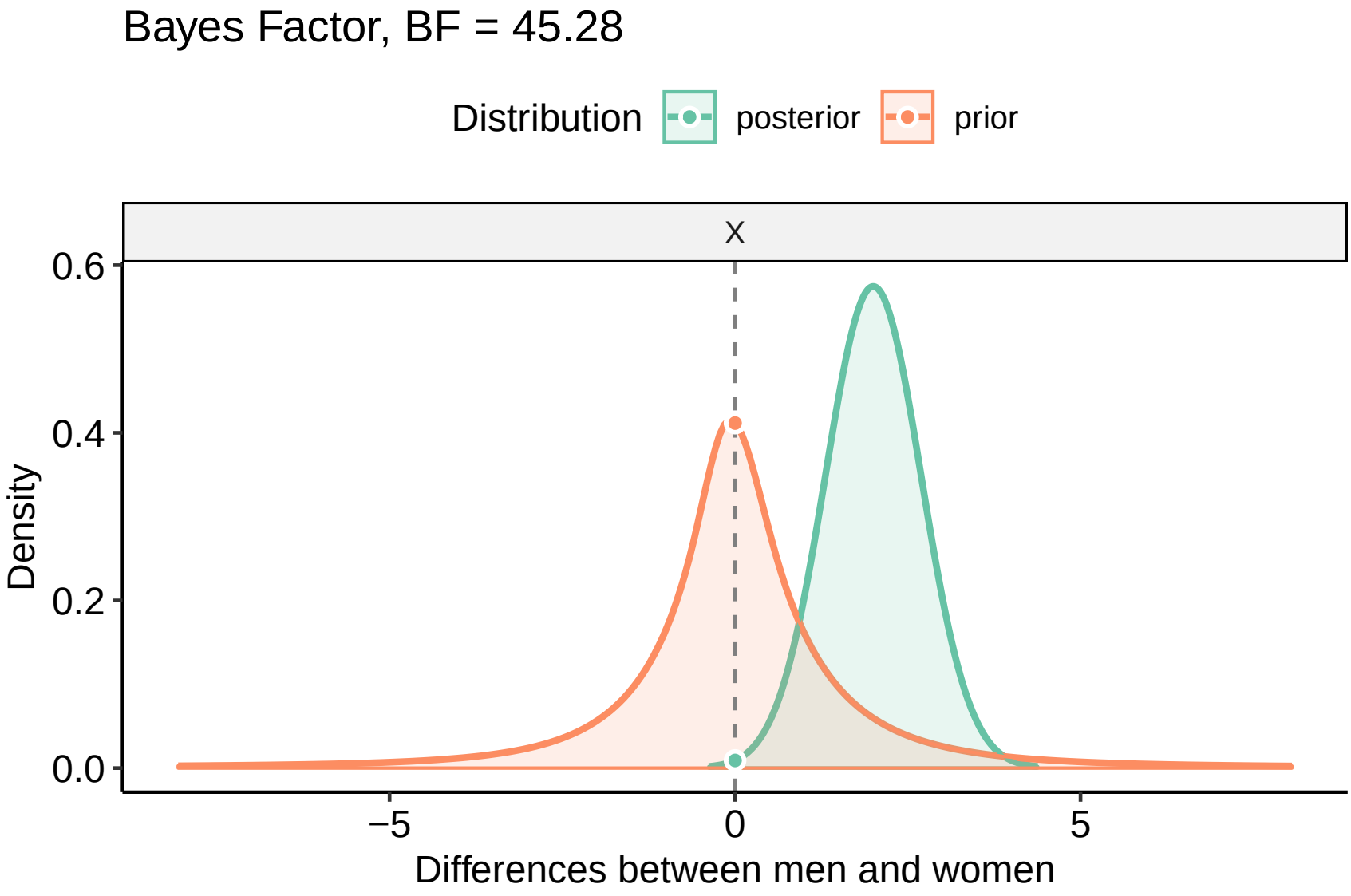


Critical differences between Bayesian and Non-Bayesians: *Quality checks*

- **Frequentists:** Type I and type II errors. Effect size and power. Fixation on p-values.
- **Bayesians:** Posterior predictive checks. Sensitivity to forms of the prior. Bayes factors, information criteria (DIC, WAIC, LOOIC).

Reasons NOT to use Bayesian inference

- The population parameters are truly fixed and unchanging under realistic circumstances
- We care more about "significance" than effect size
- Computers are slow and rarely available
- We want automated, "cookbook" type procedures

Reasons to use Bayesian inference

- We want to be very careful about stipulating assumptions and are willing to defend them.
- We view the world probabilistically, rather than as a set of fixed phenomena that are known or unknown.
- Every statistical model ever created in the history of human kind is subjective; we are willing to admit it.
- Prior information abound in the social sciences and it is important and helpful to use it.

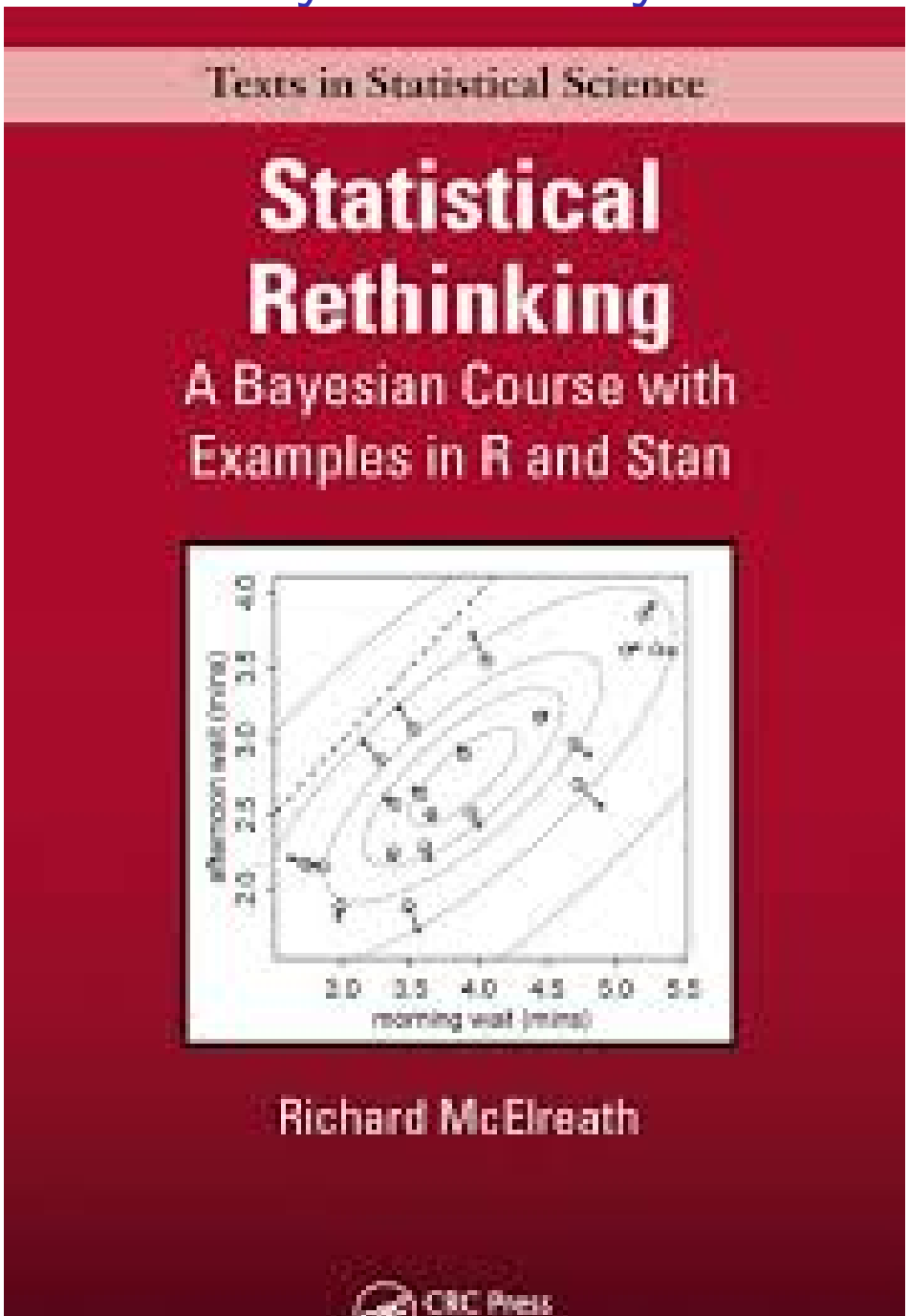
When Bayesian inference is extremely useful

- We have small sample sizes, with a lot of noise.
- Populations we sample from have complex, hierarchical structure (e.g. students within classes, classes within schools, schools within districts, etc.).
- We want to account for various sources of uncertainty (missing data, measurement errors, violated assumptioms, e.g. non-homogeneous variances, non-normal distribution of response variable, autocorrelation of residuals).
- We are trying to replicate previously observed results.
- We want to estimate whether our study supports hypothesis of no differnce (or zero correlation).
- We want to use our models not only for inference, but also for prediction.

Software for Bayesian modeling

- Majority of contemporary software offer functionalities for Baysian analysis
- Stata
- SAS
- MPlus
- SPSS/Amos
- JASP
- WinBUGS
- **R**
  - JAGS
  - **Stan**
  - **brms**
- Python - Pymc3
- Julia - Turing

Books on Bayesian analysis



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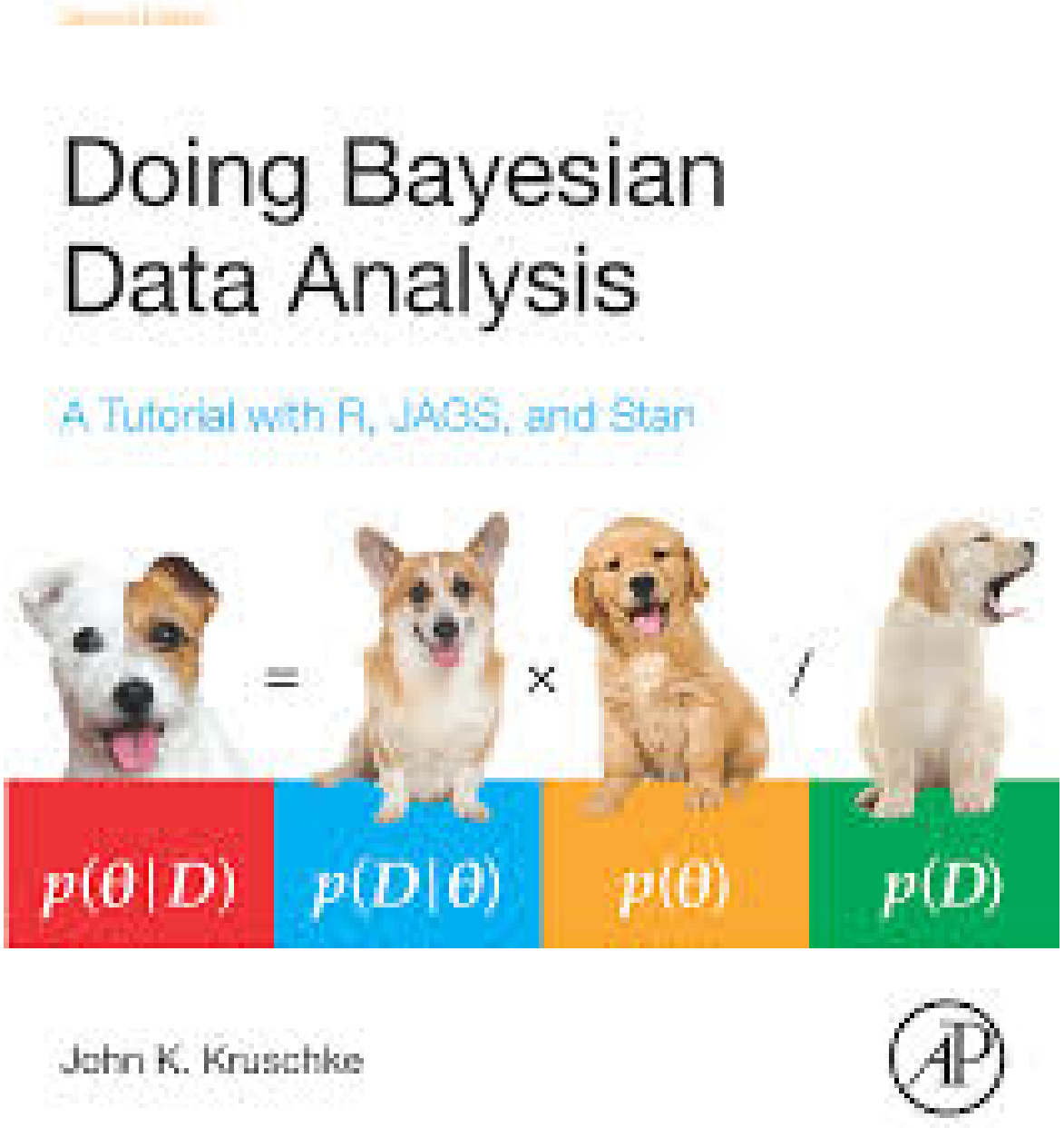

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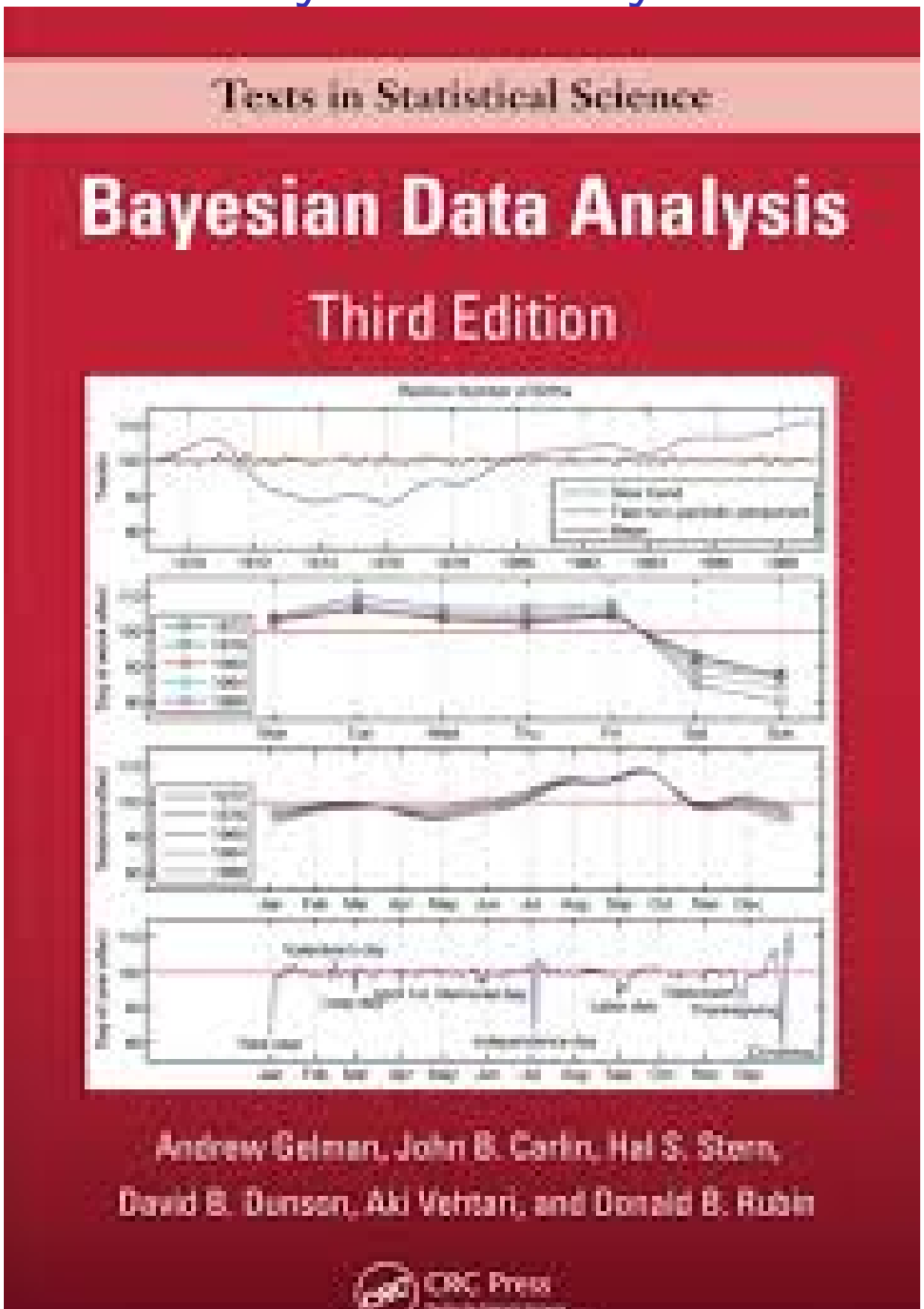

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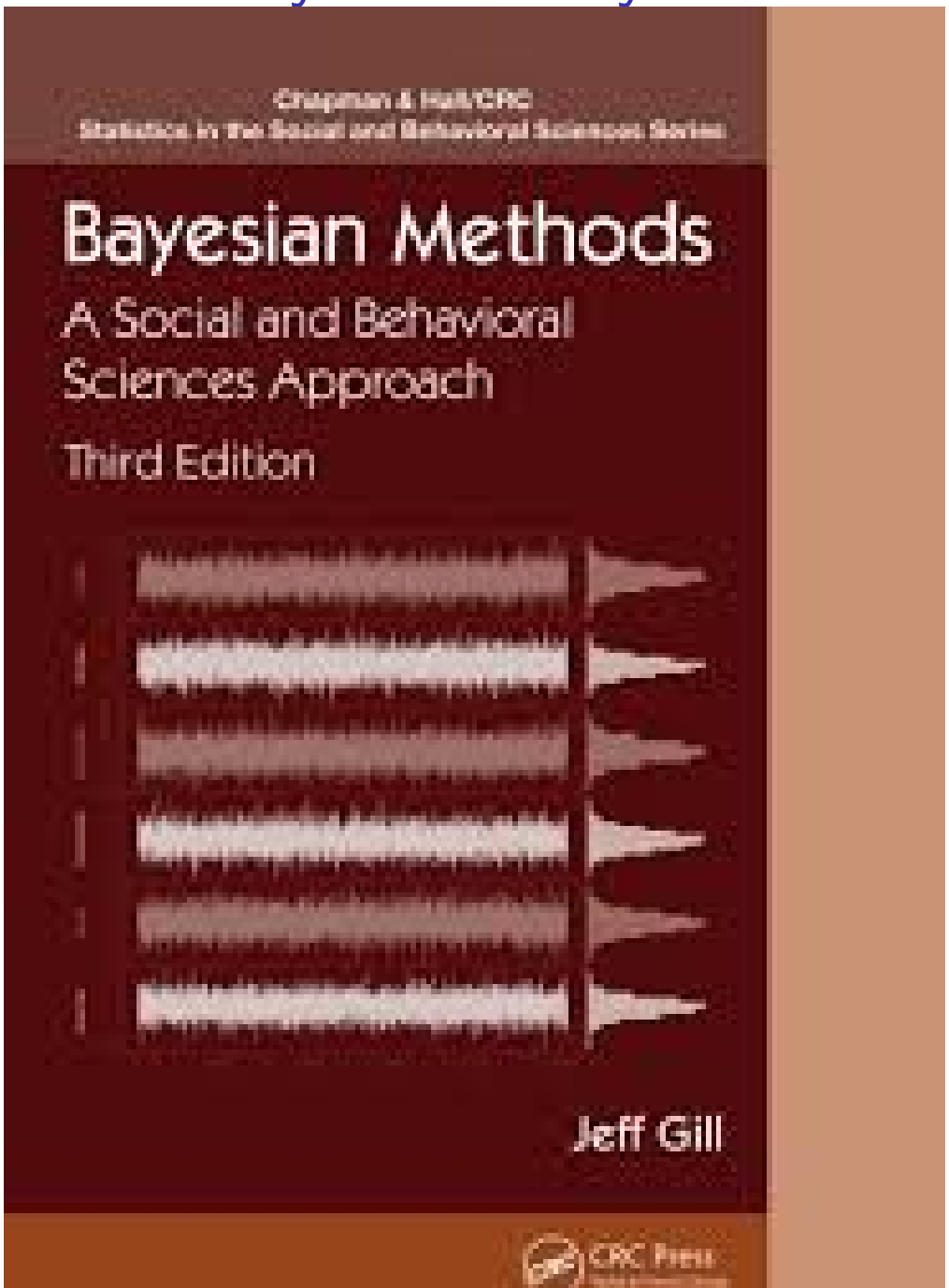

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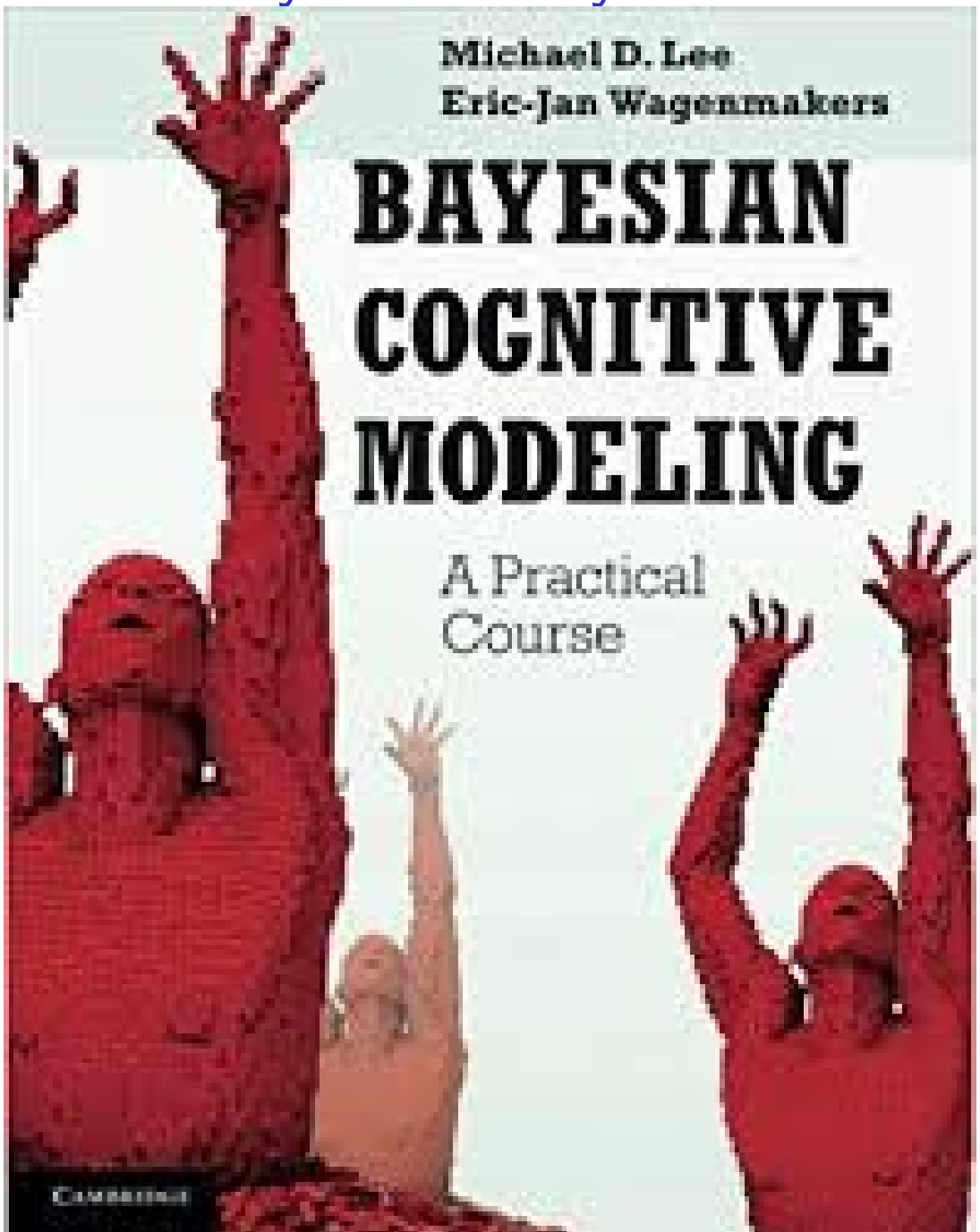

Online resources:

- List of blog posts about brms on Paul Bürkner site: here
- Case studies using Stan: here
- A. Solomon Kurz online book with examples from Statistical rethinking translated into brms: here
- A. Solomon Kurz online book with examples from Andrew Hayes (mediation and moderation analysis) book translated into brms: here
- A. Solomon Kurz online book with examples from Kruscke book translated into brms: here