



Hooray, significance! So what? Learning more about your data using Bayesian data analysis

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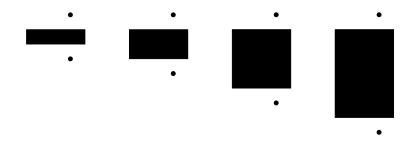
July 6, 2017, data science meetup Münster



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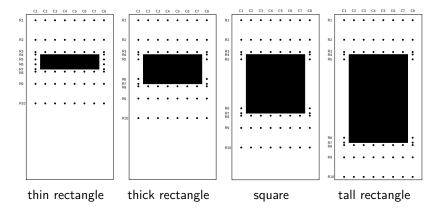


difference in acceptability?

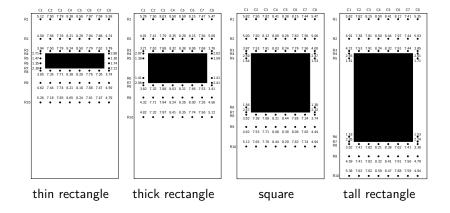


thin rectangle thick rectangle square tall rectangle

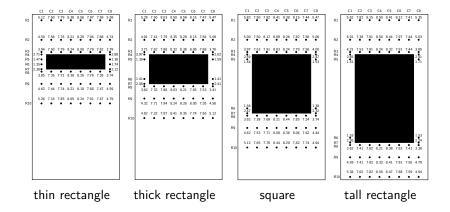
- lacksquare difference in acceptability? \longrightarrow empirical study
- 4 rectangles × 2 prepositions



- difference in acceptability? — empirical study
- 4 rectangles × 2 prepositions × 28 locations



- difference in acceptability? — empirical study
- 4 rectangles \times 2 prepositions \times 28 locations \times 34 subjects \longrightarrow 7616 ratings (1–9 rating scale)



- difference in acceptability? — empirical study
- 4 rectangles × 2 prepositions × 28 locations × 34 subjects → 7616 ratings (1–9 rating scale)
- prediction¹: lower ratings for taller rectangles

¹Kluth, Burigo, Schultheis, and Knoeferle (submitted); Regier (1996); Regier and Carlson (2001)





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- NHST → null hypothesis: **no** difference



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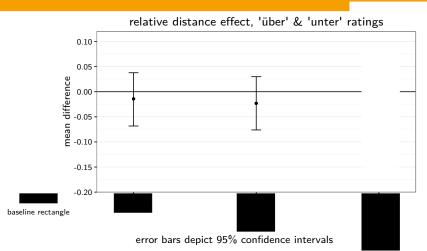


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- paired t-test





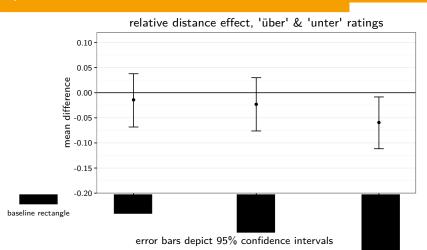
paired t-test // prediction confirmed?





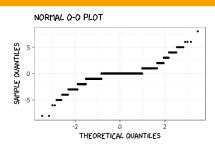


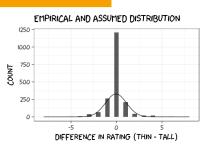
paired t-test // prediction confirmed!





Look at your data! // normality assumption violated

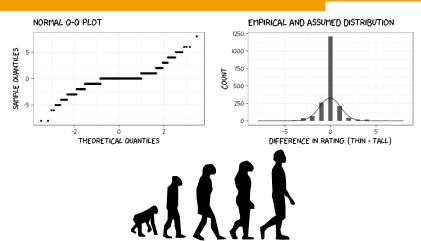








Look at your data! // normality assumption violated!





Bayesian regression model // using brms

predict rating by rectangle (thin, thick, square, tall)

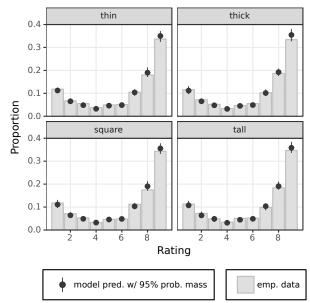


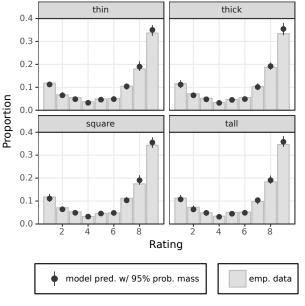
Bayesian regression model // using brms

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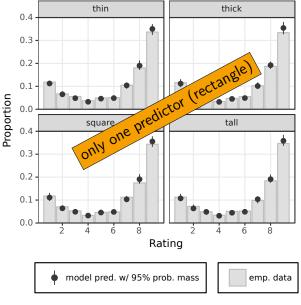
```
R code
regressionModel = brm(
          rating ~ rectangle + (1 | subject),
          family = cumulative(), # ordinal regression
          data = ratingDataFrame)
```

```
necessary R packages: brms, rstan
(Bürkner, in press; Stan Development Team, 2016)
```





no regression slope is credibly different from zero \longrightarrow no credible difference in ratings \longrightarrow prediction not confirmed



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Learn from your data! // beyond binary answers ...

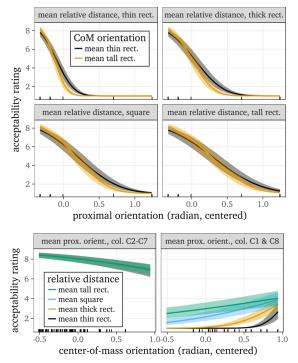
- factors hypothesized to affect rating:
 - center-of-mass orientation
 - proximal orientation
 - relative distance



Learn from your data! // beyond binary answers ...

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R code





regression more powerful than standard tests, but why *Bayesian* regression?



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- Bayesian parameter estimation allows to interpret the whole probability distribution of regression parameters
- Bayesian statistics allows to **intuitively discuss** the results
 - valid² statement: $\geq 95\%$ probability that prediction is true

²depends on the results





regression more powerful than standard tests, but why *Bayesian* regression?

- Bayesian parameter estimation allows to interpret the whole probability distribution of regression parameters
- Bayesian statistics allows to **intuitively discuss** the results
 - ullet valid² statement: $\geq 95\%$ probability that prediction is true
- including prior information from previous studies directly into the regression analysis is part of the Bayesian framework

²depends on the results





Thank you!

list of useful resources follows on the next slides

References

- Kluth, T., Burigo, M., Schultheis, H., & Knoeferle, P. (submitted). Does direction matter? Linguistic asymmetries reflected in visual attention. Cognition.
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- Mass.: MIT Press.
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- Stan Development Team. (2016). RStan: the R interface to Stan. (R package version 2.14.1)





Useful resources // selected R packages

- rstan (R interface for STAN),
 https://cran.r-project.org/package=rstan, STAN is a programming
 language itself, for more information including interfaces to other
 languages see mc-stan.org
- brms (Bayesian regression modeling using STAN), well documented, very responsive package author, https://cran.r-project.org/package=brms, Bürkner (in press)
- rstanarm, similar to brms; faster but less flexible, https://cran.r-project.org/package=rstanarm
- bayesplot, provides great visualizations, compatible with brms and rstanarm, https://cran.r-project.org/package=bayesplot
- BEST (Bayesian estimation supersedes the t-test), https://cran.r-project.org/package=BEST
- Bayesian First Aid, http://sumsar.net/blog/2014/01/bayesian-first-aid/





Useful resources // selected tutorials & literature

- tutorial: https://mvuorre.github.io/post/2017/
 how-to-compare-two-groups-with-robust-bayesian
 -estimation-using-r-stan-and-brms/, based on
 Kruschke (2013)
- full data set including working and commented R scripts: Kluth (2017); accompanying the article Kluth et al. (submitted); not available yet, but stay tuned, should be online in a few months (check https://www.techfak.de/~tkluth)
- books: Kruschke (2015); McElreath (2016)
- annotated reading list: Etz, Gronau, Dablander, Edelsbrunner, and Baribault (in press)