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FACULTY OF PSYCHOLOGY AND EDUCATIONAL SCIENCES

Analyzing an experiment on involuntary attention using `brms`

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OUTLINE

- background
- experimental paradigm
- data and results
- conclusions

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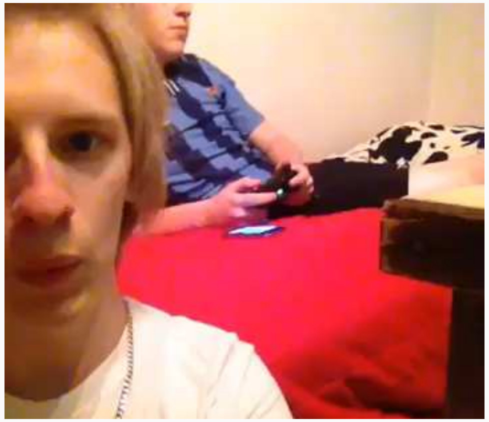
Involuntary attention



source: https://www.youtube.com/watch?v=0M2L9XNYfLs

What happened?

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- The guy in the background was attracted to the phone…
- … despite *knowing* that his friend was making the notification sounds
- His attention was **automatically** attracted to ~~uninformative~~ **counterproductive** sounds (distraction from current task: watching TV)

Why study involuntary attention?

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- Involuntary attentional orienting can be dangerous in some real-life situations
- Car driver distracted by flashing mobile phone, worker operating heavy machinery distracted by blinking lights, ...
- How to study this phenomenon in the lab?

Temporal Order Judgment (TOJ)

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- Flash two stimuli on screen

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- Task: which stimulus appeared **first**?

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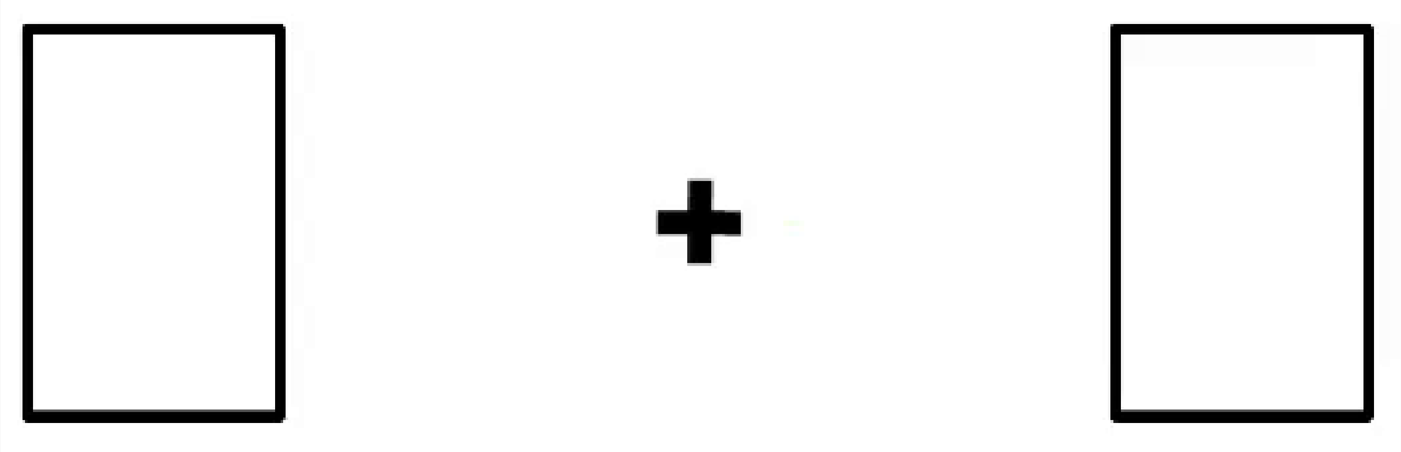
- Flash two stimuli on screen
- Task: which stimulus appeared **first**?
- Difficulty depends on the time between the onset of the stimuli (**SOA**)

Temporal Order Judgment (TOJ)



Counterproductive TOJ

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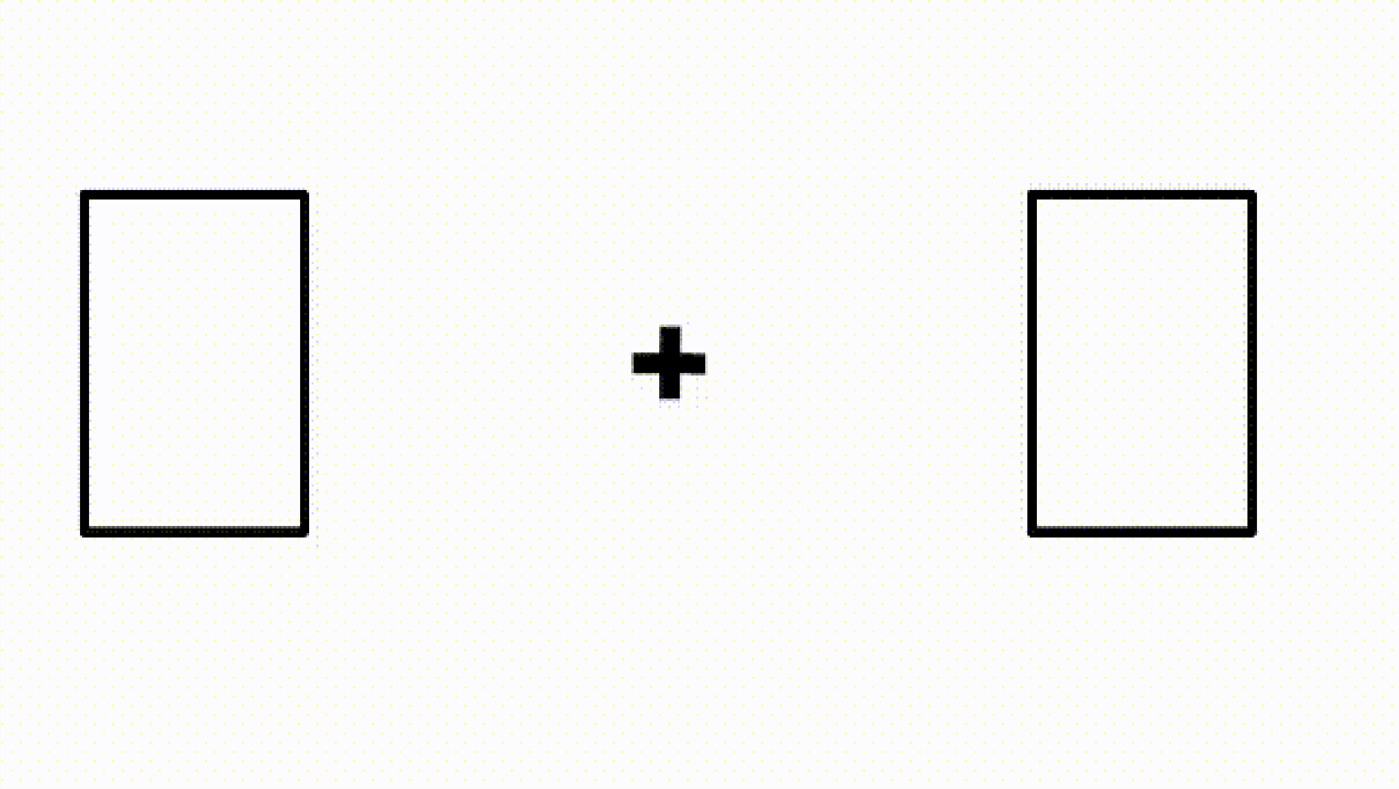
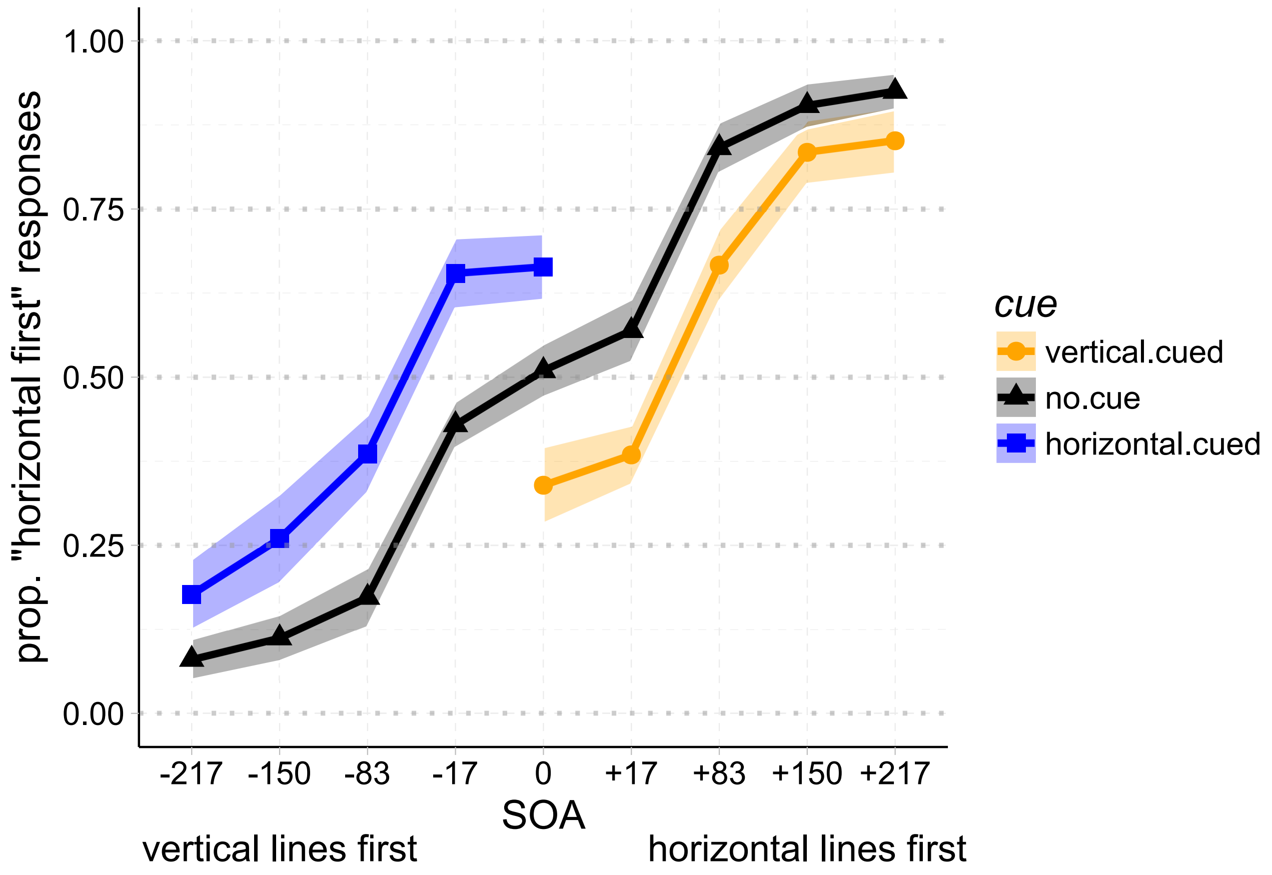
Counterproductive TOJ

- An **exogenous cue** is used to attract attention towards one placeholder
- The stimulus on the attended location is perceived as **first** even when appearing second
- What if the cue is **always wrong**, i.e., appearing on the location of the *second* stimulus?

Counterproductive TOJ



TOJ - Data


prop. "horizontal first" responses
1.00
0.75
0.50
0.25
0.00
-217
-150
-83
-17
0
+17
+83
+150
+217
SOA
vertical lines first
horizontal lines first
cue
vertical.cued
no.cue
horizontal.cued

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- model comparison:
  1. full model (**SOA** + **cue** + **SOA** x **cue**)
  2. main effects (**SOA** + **cue**)
  3. main effect of **SOA**
  4. main effect of **cue**
  5. **null** model (intercept only)

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    5. **null** model (intercept only)
- on the winning model:
    - diagnostics & posterior predictive checks
    - hypothesis testing

Bayesian multilevel modeling with `brms`

```r
###################### full model (SOA * cue) ######################
model.full <- brm(num.horiz1st | trials(tot.trials) ~ SOA * cue +
              (SOA * cue || participant),
              data = data.TOJ,
              family = binomial("logit"),
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              sample_prior = TRUE,
              inits = "random",
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Bayesian multilevel modeling with `brms`

```
##################### main effect of SOA #####################
    model.SOA <- brm(num.horiz1st | trials(tot.trials) ~ SOA +
                  (SOA || participant),
              data = data.TOJ,
              family = binomial("logit"),
                  prior = priors.SOA,
              sample_prior = TRUE,
              inits = "random",
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```

Model comparison with `brms`

(*leave-one-out* cross-validation)

```
model.comparison <- LOO( # list with all models
                      model.full, model.mains, model.SOA, model.cue, model.null,
                      reloo = TRUE, # exact CV for problematic observations
                      compare = FALSE) # do not compare models with each other
```

```
##    models  LOO.IC
## 1  mains 2727.31
## 2   full 2844.49
## 3    SOA 3628.22
## 4    cue 7998.10
## 5   null 8275.49
```

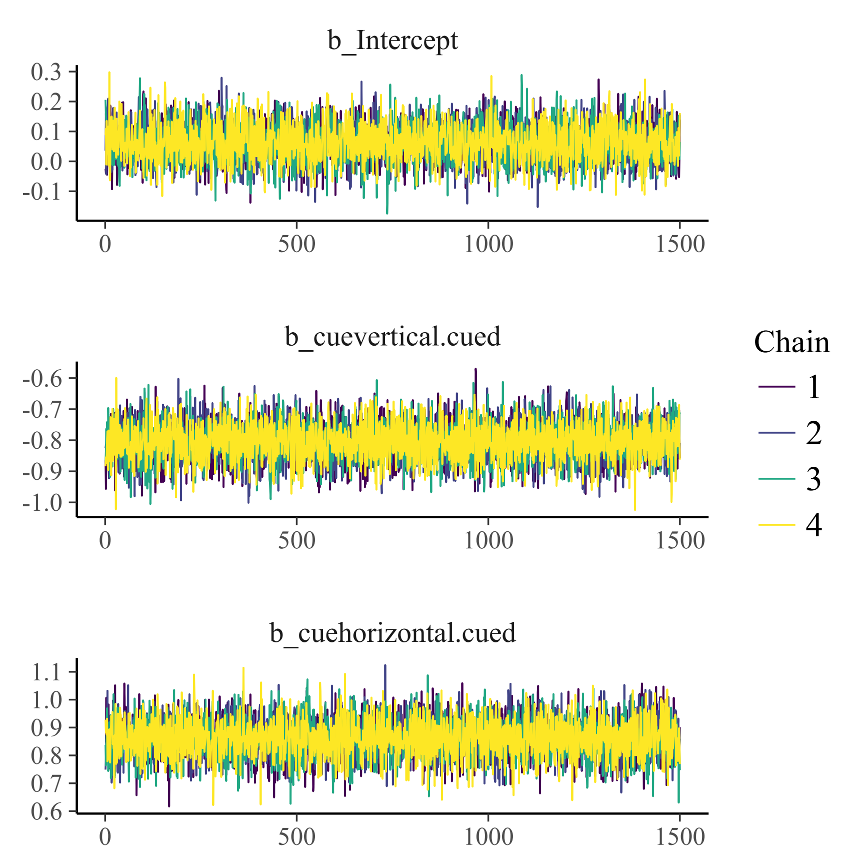
brms output

(**main effects** model, only **constant** effects)

```
##  [1] "Population-Level Effects: "
##  [2] "                   Estimate Est.Error l-95% CI u-95% CI Eff.Sample Rhat"
##  [3] "Intercept              0.06      0.06    -0.06     0.19       4716 1.00"
##  [4] "SOAM217               -2.64      0.13    -2.89    -2.38       4256 1.00"
##  [5] "SOAM150               -2.23      0.13    -2.50    -1.97       3727 1.00"
##  [6] "SOAM83                -1.53      0.10    -1.73    -1.34       4928 1.00"
##  [7] "SOAM17                -0.35      0.06    -0.47    -0.22       6000 1.00"
##  [8] "SOAP17                 0.21      0.06     0.09     0.33       6000 1.00"
##  [9] "SOAP83                 1.60      0.11     1.39     1.81       4528 1.00"
## [10] "SOAP150                2.42      0.16     2.11     2.72       3422 1.00"
## [11] "SOAP217                2.73      0.16     2.41     3.06       3851 1.00"
## [12] "cuevertical.cued      -0.80      0.06    -0.93    -0.68       6000 1.00"
## [13] "cuehorizontal.cued     0.86      0.07     0.73     1.00       5145 1.00"
```

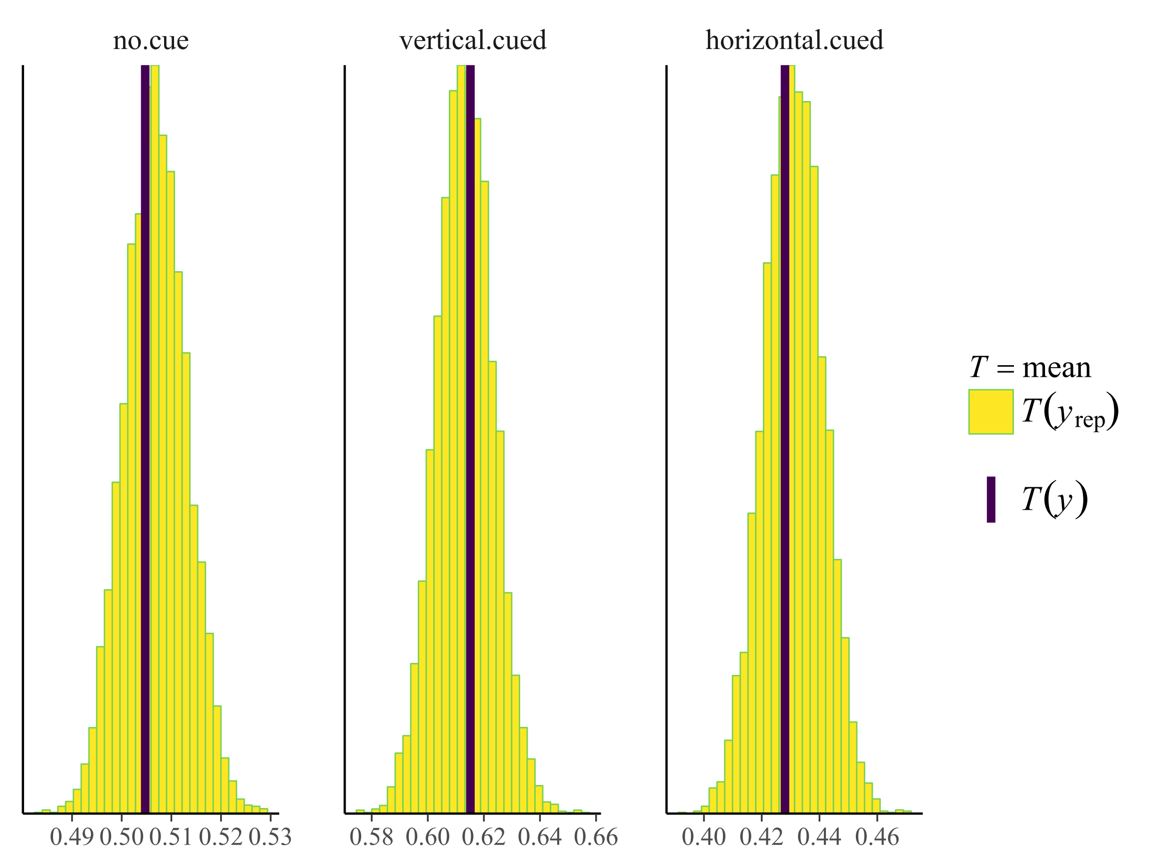
MCMC chains

```
library(bayesplot)
mcmc_trace(as.array(model.mains),
pars = c("b_Intercept",
  "b_cuevertical.cued",
  "b_cuehorizontal.cued"),
facet_args = list(ncol=1))
```

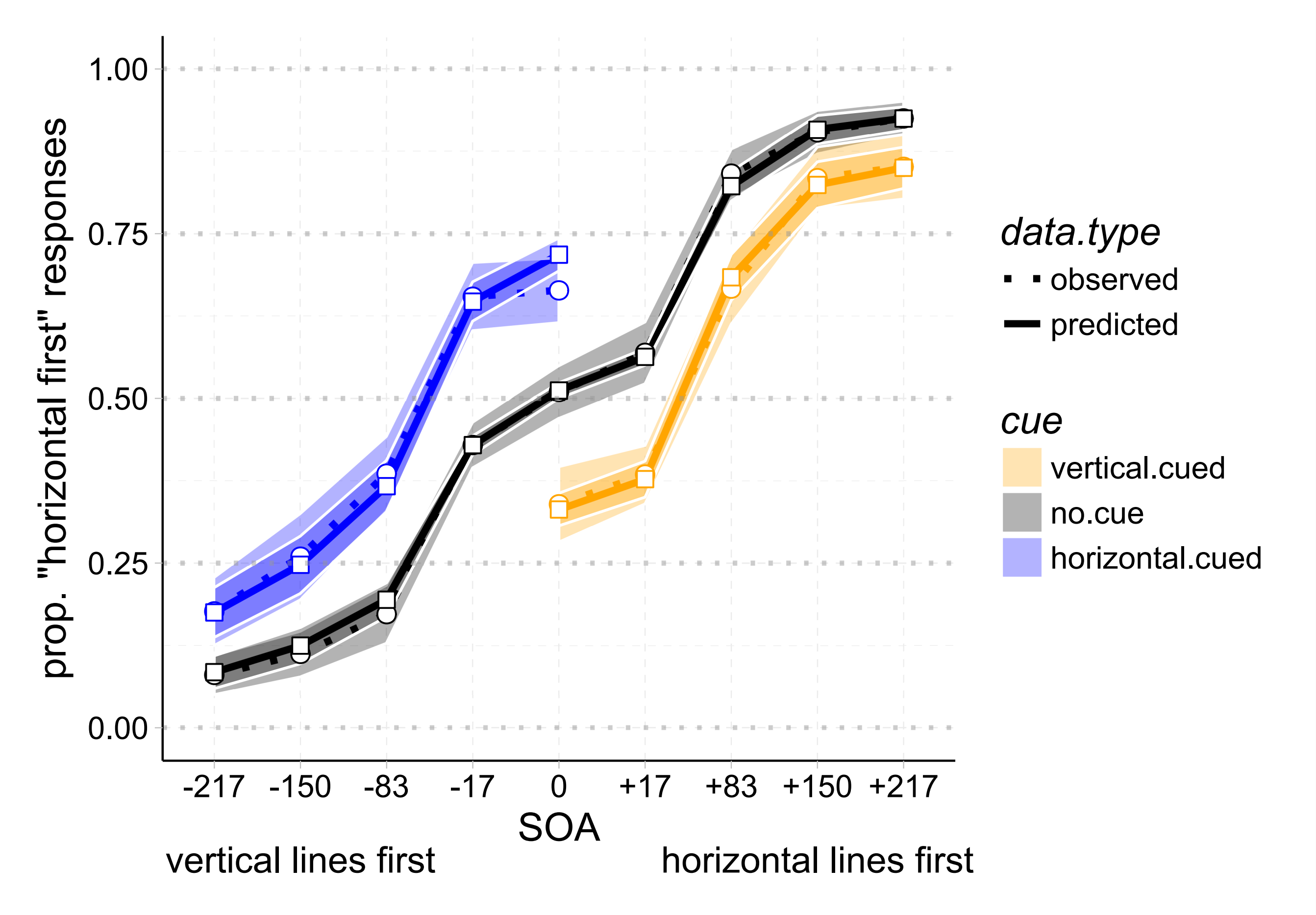


Posterior Predictive Checks

```
pp_check(model.mains,
nsamples = NULL,
type = "stat_grouped",
group = "cue")
```



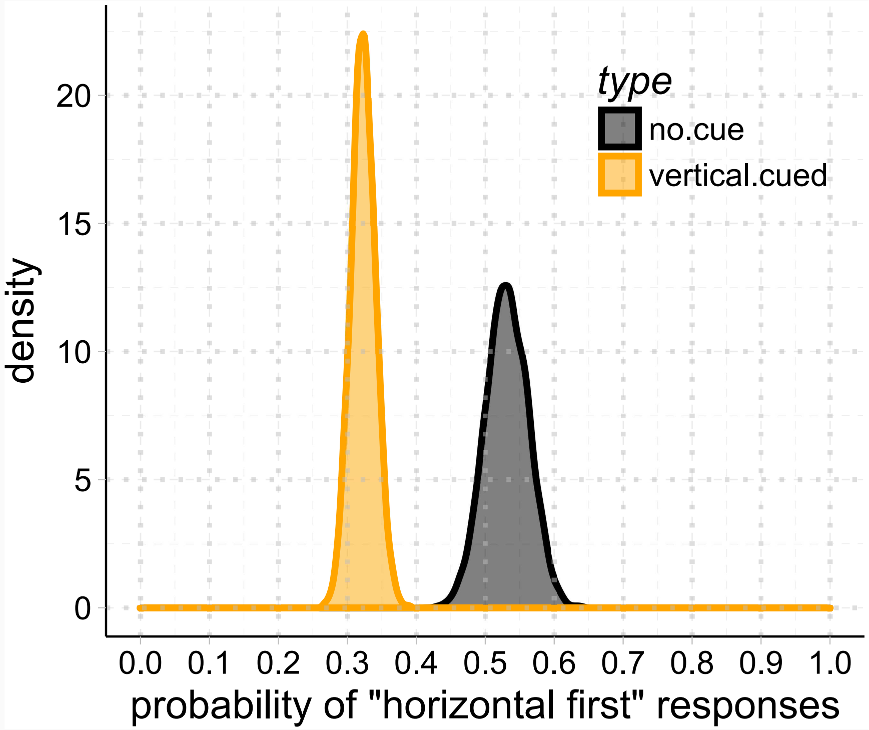
Observed vs. predicted data



Hypothesis testing

(**no cue** vs. **vertical cued** conditions)

```
# posterior probability
# under the hypothesis
# (no.cue=vertical.cued)
# against its alternative
# (no.cue=/=vertical.cued)
hypothesis(model.mains,
"Intercept = Intercept + cuevertical.cued")
```



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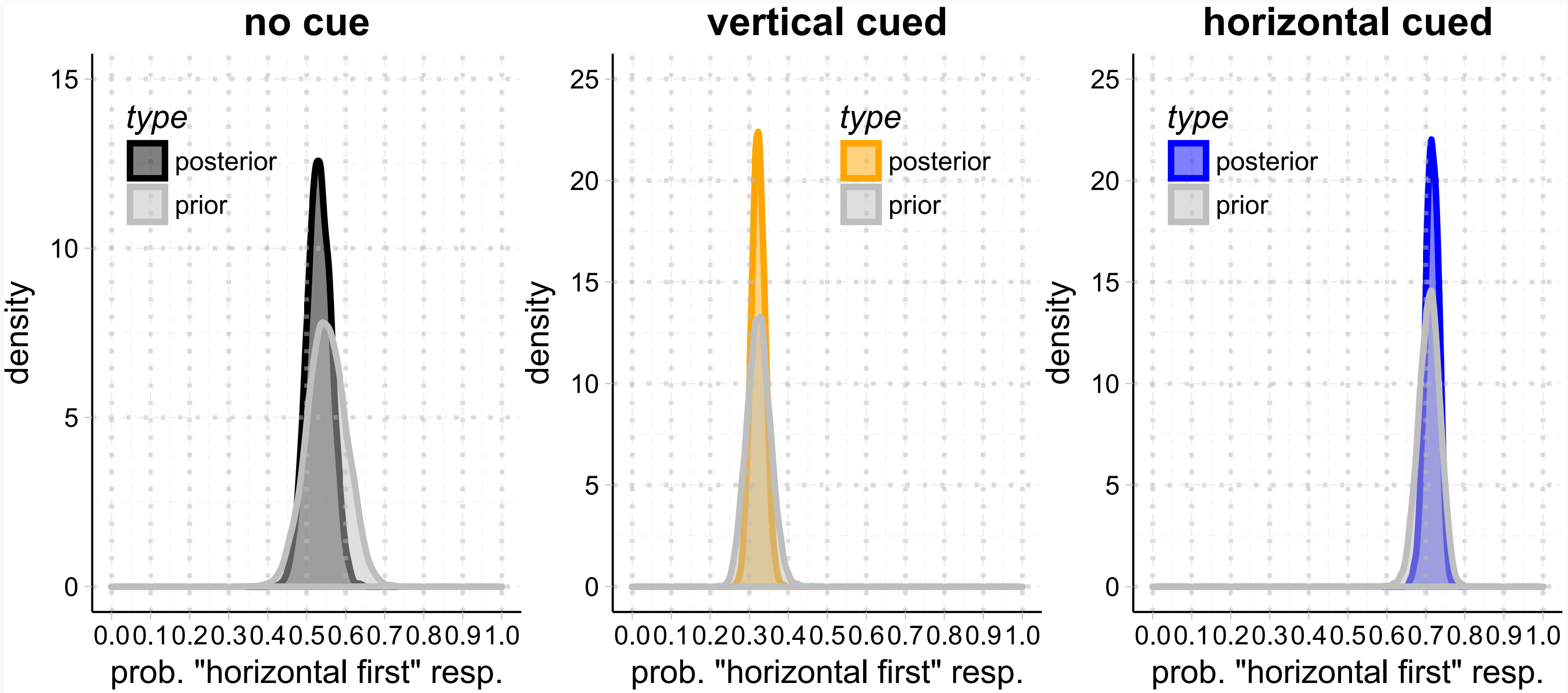
Hypothesis testing

(**pilot** vs. **current** experiment)



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  - comparison of prior and posterior distributions of cue conditions
- … and much more! Thanks for `brms`, @paulbuerkner!

Thanks for your attention!

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Slides available here:

https://asch3tti.netlify.com/post/bayesatlund2018/