UNIVERSITY OF AMSTERDAM

Does Everyone? Modeling Individual Differences in Cognitive Tasks.

Julia Haaf

September, 2019

Psychology and Statistics

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- Found scientific methods in theoretical considerations.

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- When combining methods and theory we can come up with new and interesting research questions and solutions.

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- Levels of processing (Craik & Lockhart, 1972): *Processing words semantically increases memory performance as compared to more shallow processing.*

Psychology Guiding Methods

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The Stroop Effect

ROT ROT

Psychology Guiding Methods

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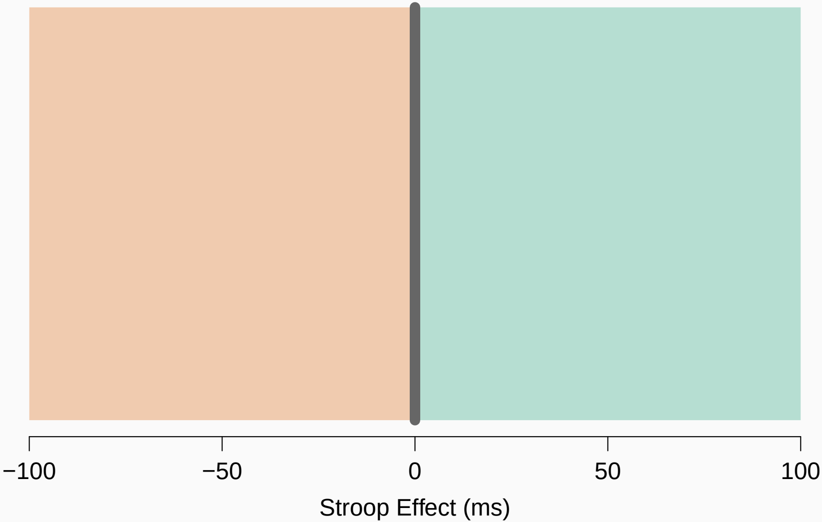
- Almost never metric predictions.

Ordinal Constraints and the Stroop Effect



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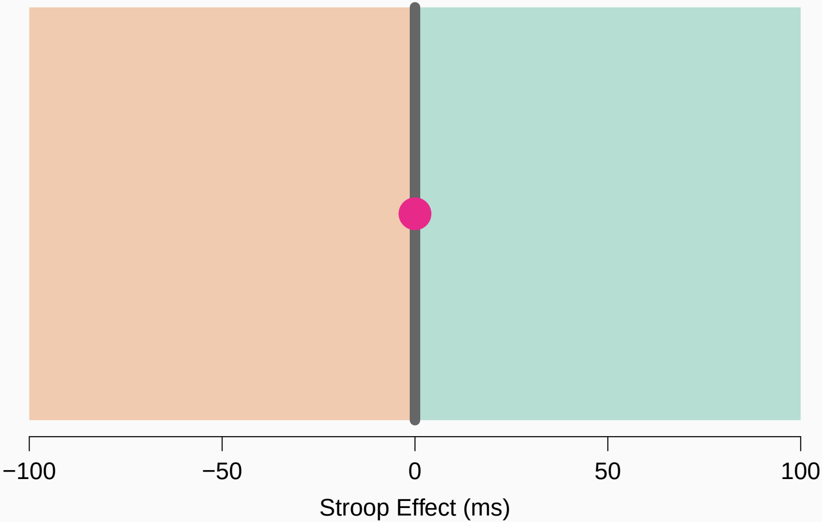

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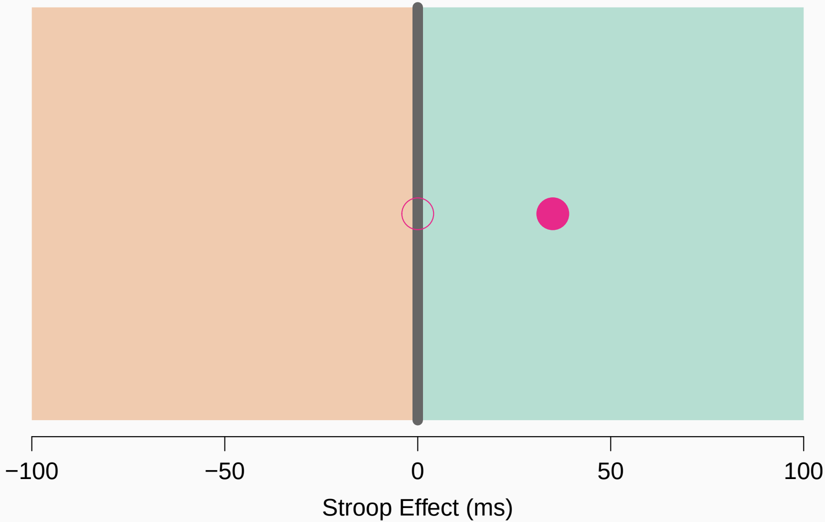

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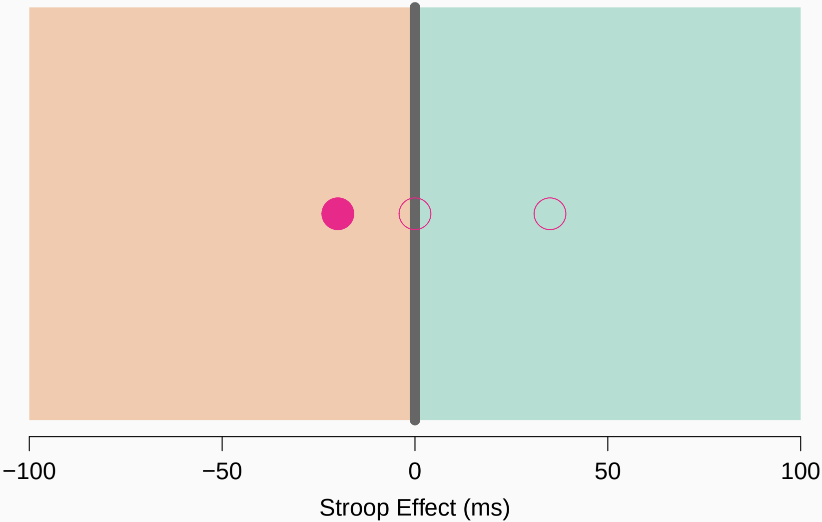
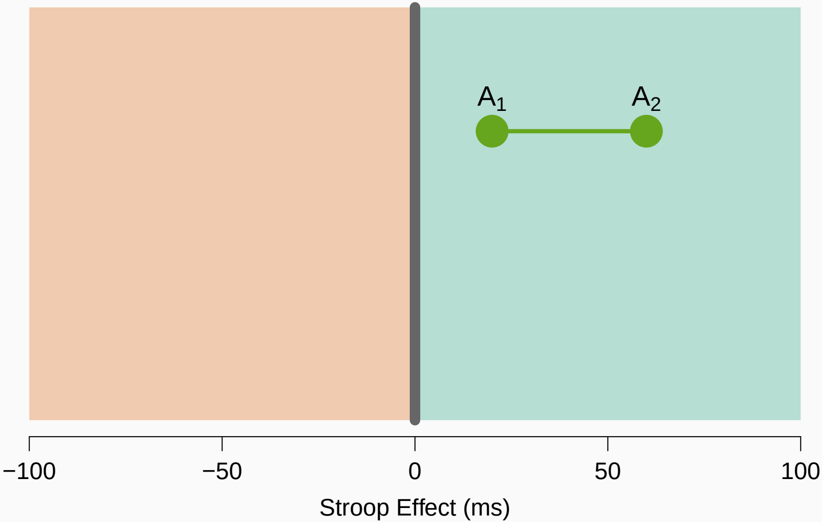


Quantitative and Qualitative Individual Differences



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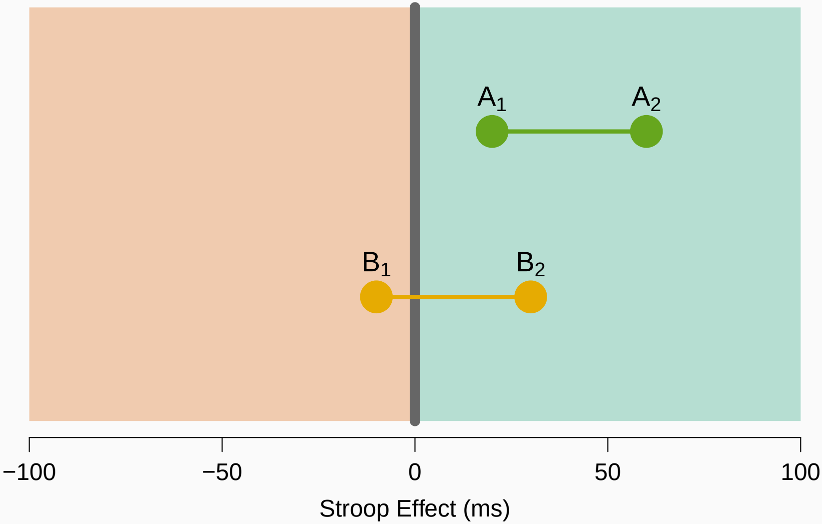

Psychology Guiding Methods

- Statistical models of Stroop interference should respect the theoretically important areas of negative, null, and positive effects.

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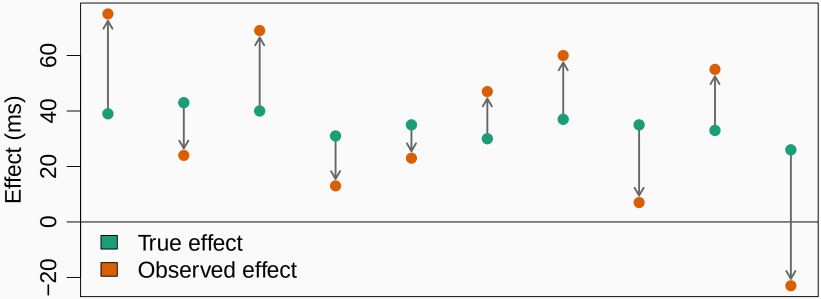
- Statistical models of Stroop interference should respect the theoretically important areas of negative, null, and positive effects.
- Statistical models should distinguish between qualitative and quantitative individual differences.

Methods Guiding Psychology

- Before modeling we need to consider the effect of sample noise in this setting.



Methods Guiding Psychology

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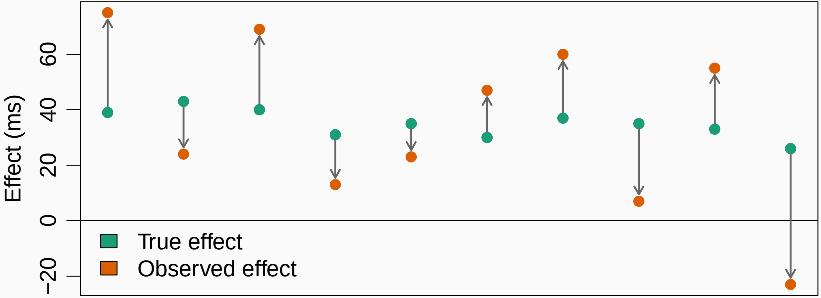
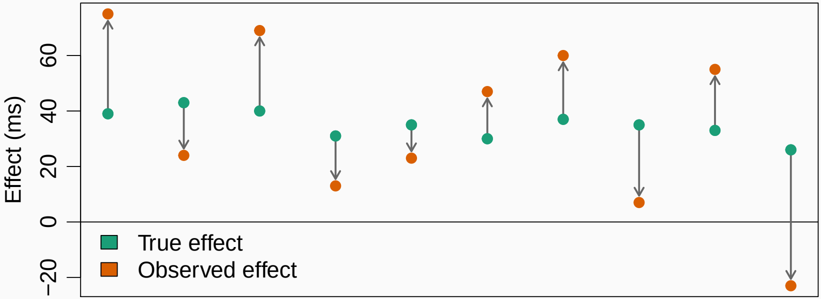
- *Observed effect = True effect + sample noise* $\rightarrow$ What we observe with limited numbers of trials.



Methods Guiding Psychology

- Before modeling we need to consider the effect of sample noise in this setting.
- *Observed effect = True effect + sample noise* → What we observe with limited numbers of trials.
- *True effect*: What we would obtain if we had an unlimited number of trials per person per condition.



The Research Question

Does everyone show a true effect in the same direction?

Is this an interesting question?

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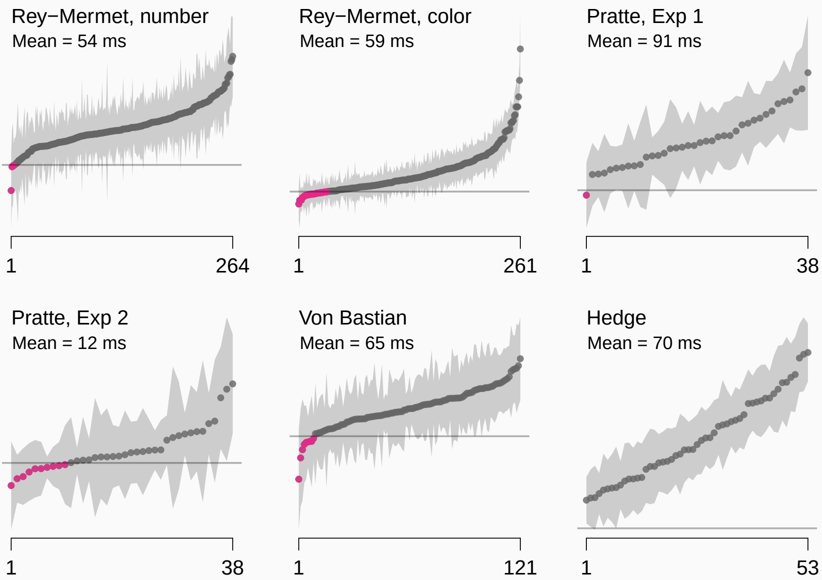

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Then

$$Y_{ijk} \sim \text{Normal}(\mu + \alpha_i + x_j\theta_i, \sigma^2).$$

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Then

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We care about the collection of θ_i.

Models on Individuals' True Effects

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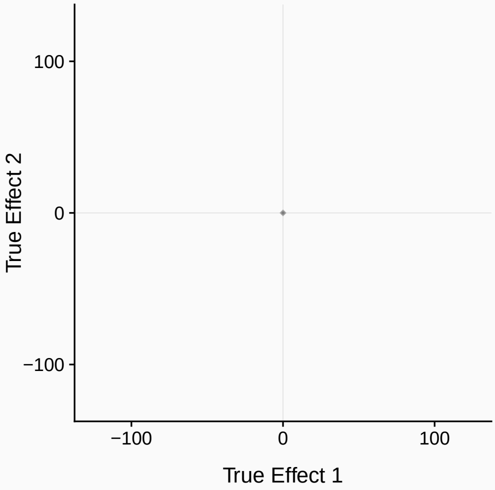
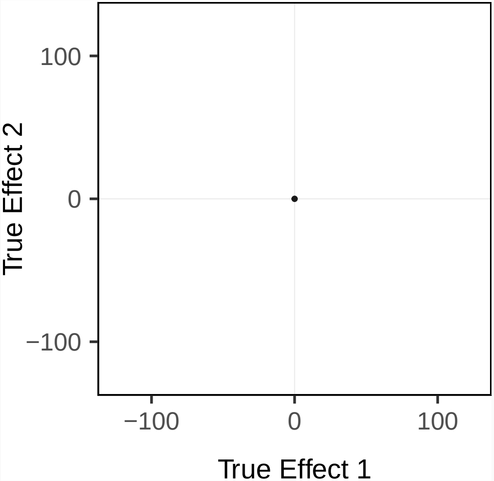
3. True Stroop effects vary in direction and size.

Models for Individual Differences and Ordinal Constraint



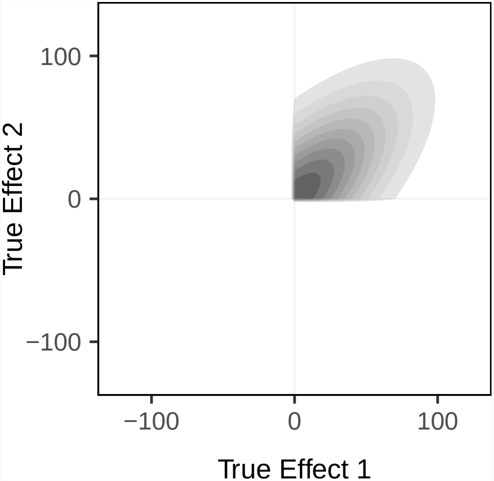
Haaf & Rouder (2017)

No One Shows a True Stroop Effect



Haaf & Rouder (2017)

Everyone Show a True Stroop Effect in the Same Direction



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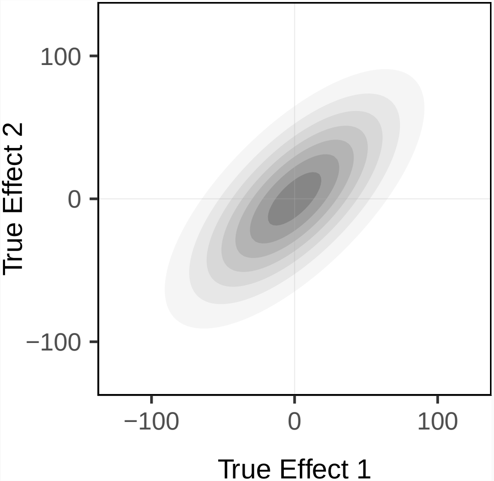

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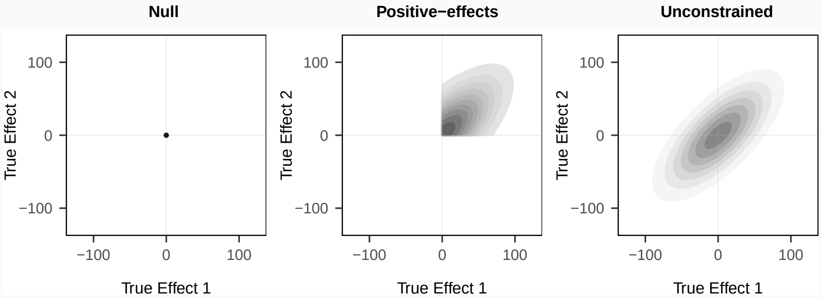
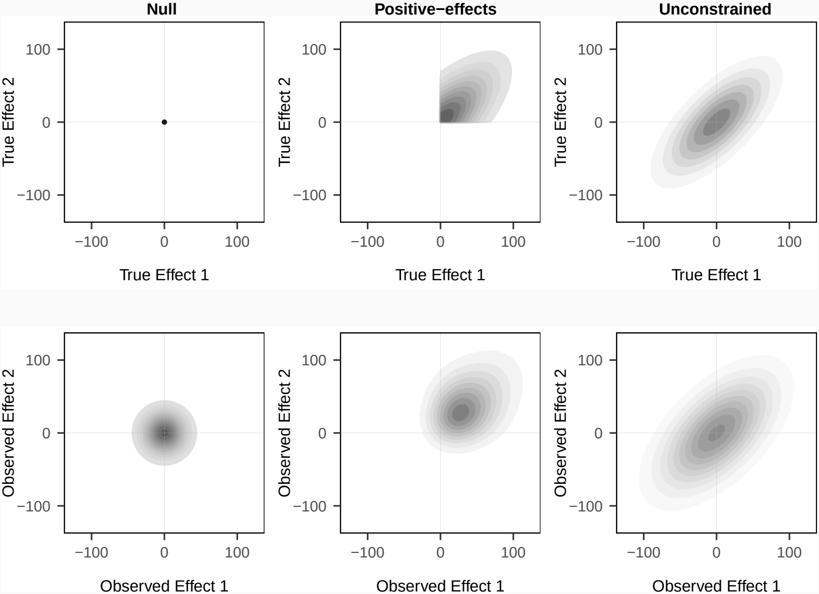
From Models. . .

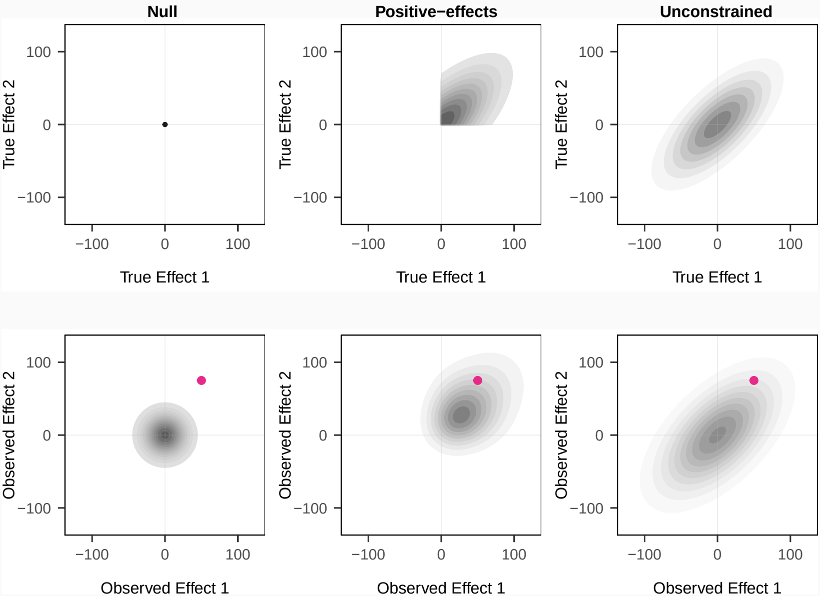


Null
Positive−effects
Unconstrained
100
0
−100
True Effect 2
True Effect 1

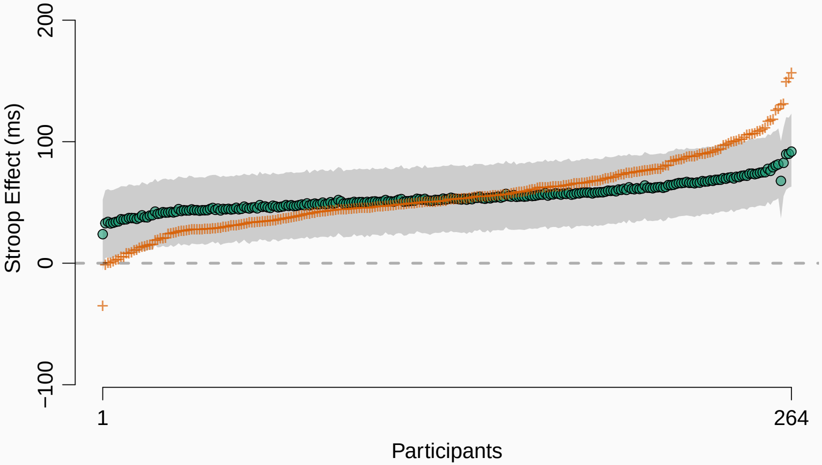
From Models... to Predictions



From Models... to Predictions... to Predictive Accuracy

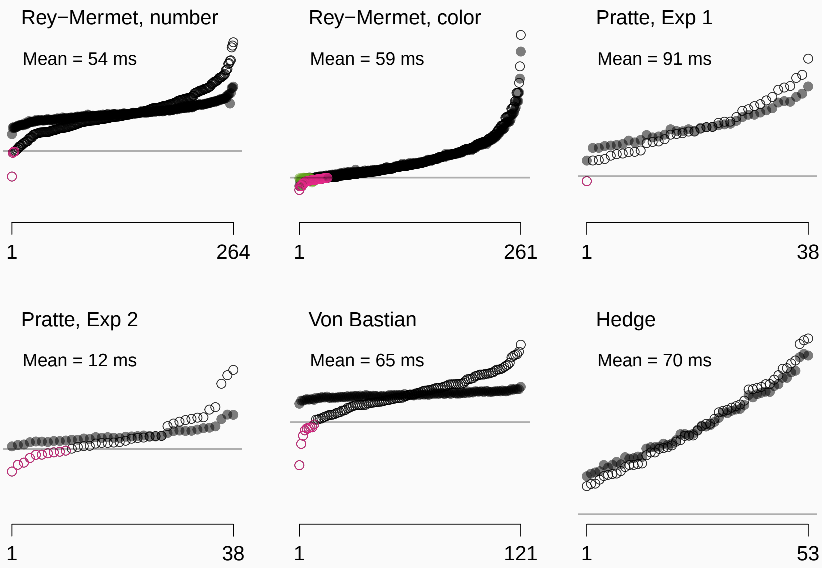


Ordinal Constraint for Individual Stroop Effects



Number-Stroop data by Rey-Mermet, Gade, & Oberauer (2018).

Does everyone Stroop?



Does everyone Stroop?

Study	Participants	Trials	Effect	BF_{pu}	BF_{p0}
Rey-Mermet, number	264	93	54 ms	**6.05**	$> 10^{300}$
Rey-Mermet, color	261	94	59 ms	10^{-4}	$> 10^{300}$
Pratte, Exp 1	38	146	90 ms	**4.75**	10^{73}
Pratte, Exp 2	38	165	12 ms	0.28	78.49
Von Bastian	121	46	64 ms	**6.38**	10^{62}
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Motivated by Pratte et al., Experiment 2

- Why do some people not show a Stroop effect?

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- Why do some people not show a Stroop effect?
- What is the nature of their non-Stroopiness?

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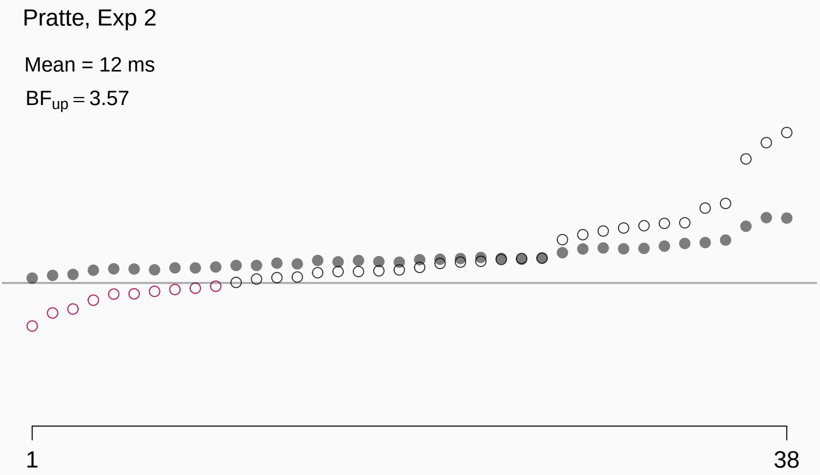
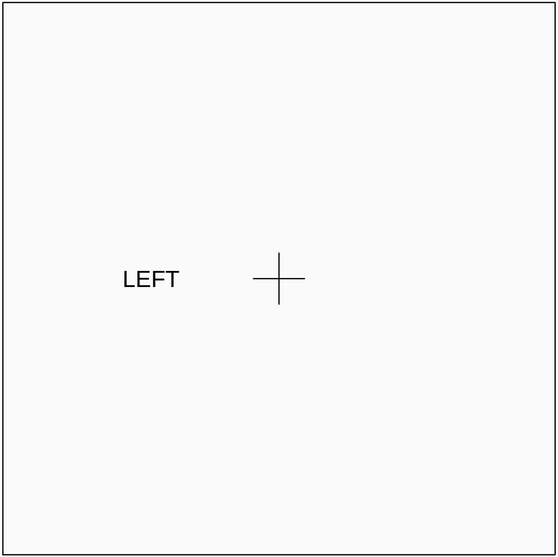


What could be different with the location Stroop?



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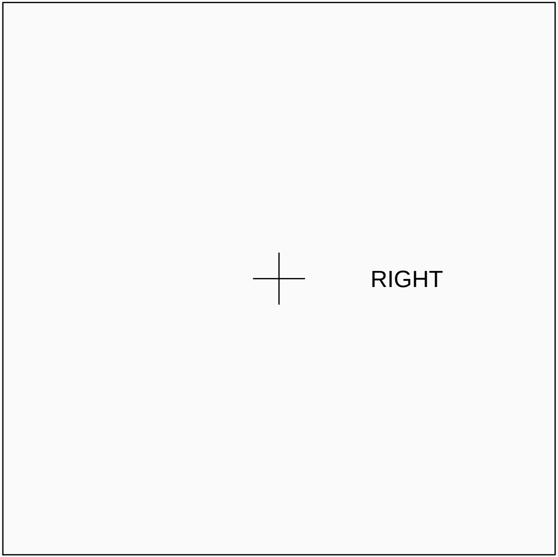

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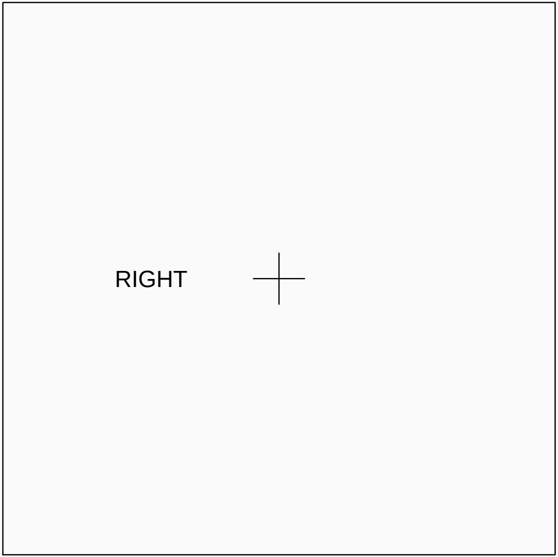

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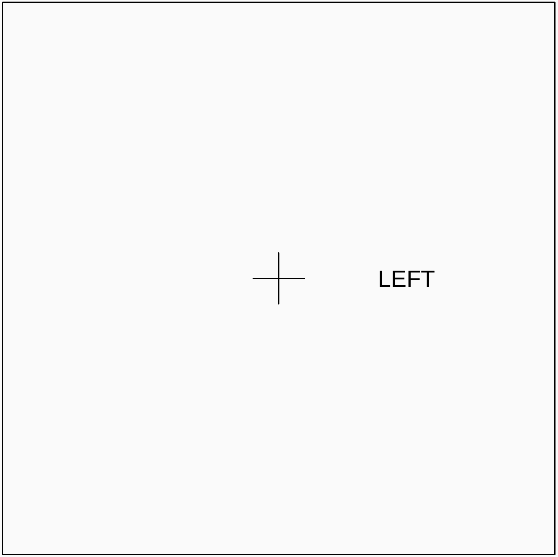

What could be different with the location Stroop?

- Different participants use different strategies.

What could be different with the location Stroop?

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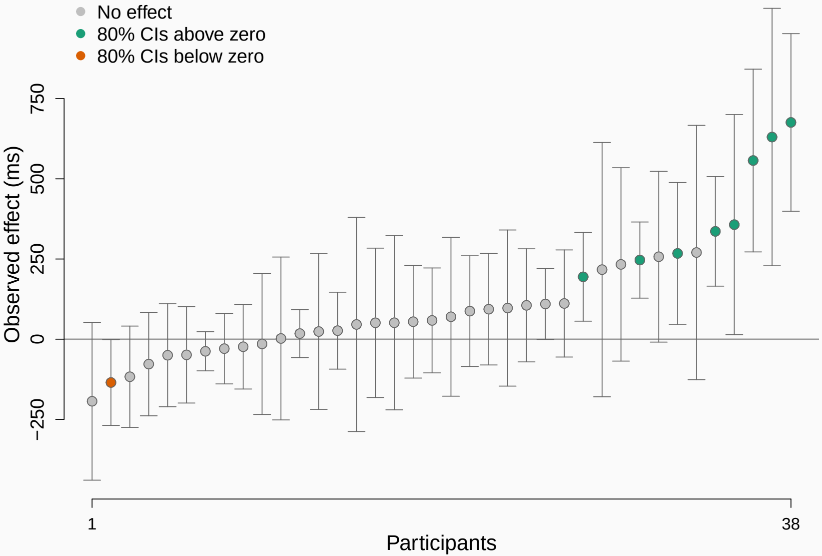
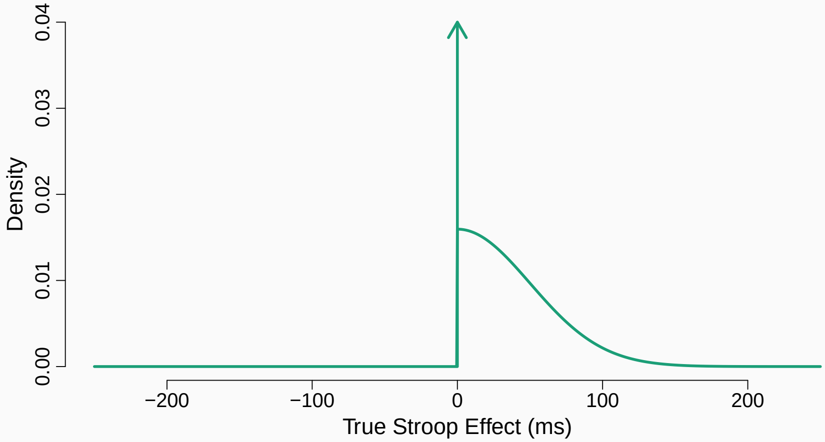
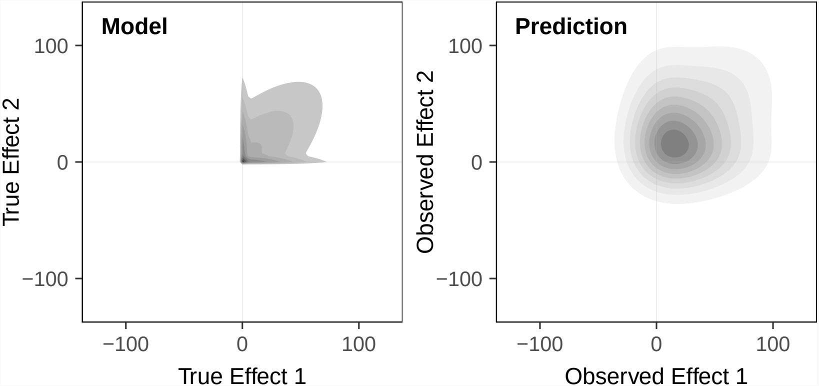


Some Do Some Don't



Haaf & Rouder (2019)

Modeling Approach: Some Do Some Don't Model



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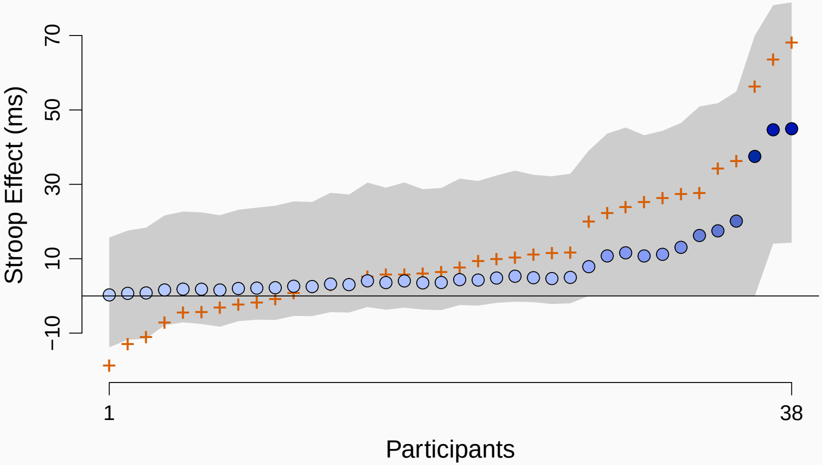
- Which participants do and which don't?

Classification Based on the Hierarchical Model



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Summary

- Quantitative vs. qualitative individual differences.
- If everyone shows an effect in the same direction we can rely on simple, universal theoretical accounts.
- If some individuals robustly show no effect it can have implications for experimental methods and theory.
- If some individuals robustly show an opposite effect we may prefer more complex theories.
- In this case, answering *why* there are qualitative individual differences is key for theory development.

Do it yourself: The Does-Everyone t-Test

Function `quid()`: The Qualitative-Individual-Differences Test Function

- `quid()` is available on github:
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- `quid()` is available on github: https://github.com/jstbcs/play/
- The function may be installed as follows:

```
install.packages(c("BayesFactor", "MCMCpack", "curl"))
filename <- curl::curl("https://bit.ly/2ZqGOik")
source(filename)
```

Function `quid()`: The Qualitative-Individual-Differences Test Function

- Let's look at some data: Von Bastian, Souza, & Gade (2015), Experiment 1.

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```
devtools::source_url("https://bit.ly/2SxyKtq")
```

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The data are now loaded as a data frame called `stroop`.

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- The participant identification number is the variable `stroop$ID` (from 1 to 121).
- The condition is the variable `stroop$cond` (values are 1 for congruent and 2 for incongruent)
- The response time for each trial in seconds is stored in the variable `stroop$rt`

Function `quid()`: The Qualitative-Individual-Differences Test Function

Now we are ready to use `quid()`:

```
res <- quid(id = stroop$ID
            , condition = stroop$cond
            , rt = stroop$rt)
```

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The output, `res`, is a list containing

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```
res$bfs
```

```
##       bf.1u        bf.pu        bf.0u
## 9.777135e-01 6.310874e+00 1.002935e-62
```

Function `quid()`: Prior Settings

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(b) about how much we expect individuals to differ from this mean effect.

Function `quid()`: Prior Settings

- An important input to `quid()` is `prior`.
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```
largeVals <- c(80/200, 40/200)
resB <- quid(id = stroop$ID
             , condition = stroop$cond
             , rt = stroop$rt
             , prior = largeVals)
resB$bfs
```

```
##        bf.1u        bf.pu        bf.0u
## 3.077463e+00 4.664942e+00 2.570078e-62
```

Function `quid()`: Other Priors

$$(\mu, \sigma^2) \propto \frac{1}{\sigma^2},$$

$$\alpha_i \sim \text{Normal}(0, g_\alpha \sigma^2),$$

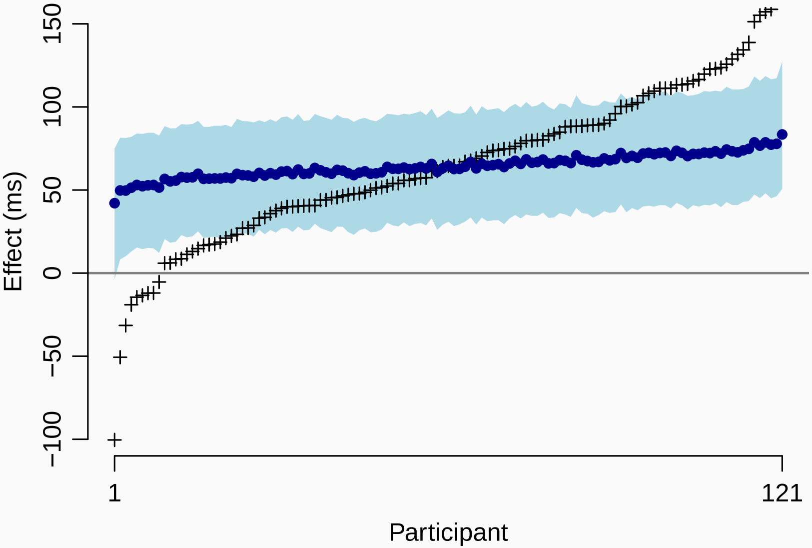
Most important priors:

$$\theta_i \sim \text{Normal}(\mu_\theta, g_\theta \sigma^2),$$

$$\mu_\theta \sim \text{Normal}(0, g_{\mu\theta}, \sigma^2).$$

gs have scaled χ^2-distributions, and the scales are set by `prior`.

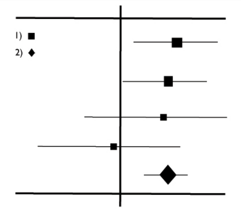
Function `quid()`: You can make nice plots!



Does every study show an effect in the expected direction?

Why This Is A Good Question For Meta-analysis

- The usual meta-analytic question: What is the overall effect combined over a bunch of studies?



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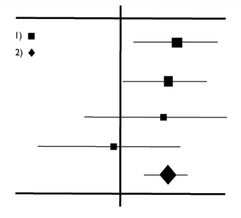

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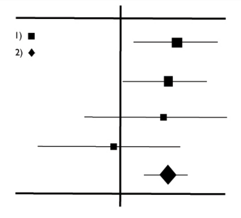

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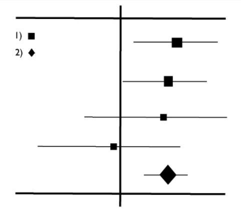

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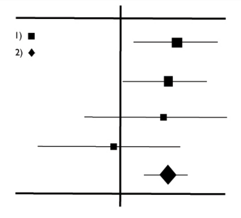
- What is currently hot in the field.
- If the target contrast is robust the *direction* of the effect should not be affected.

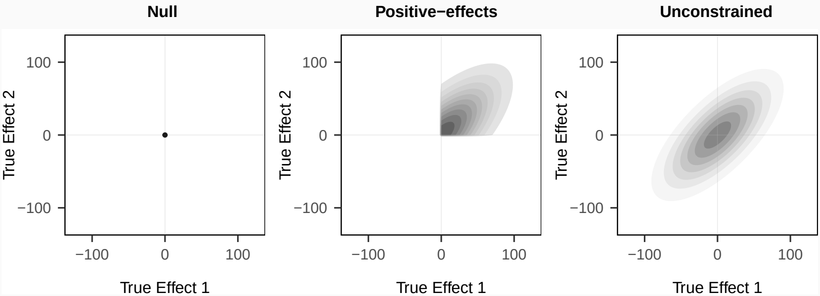


New Meta-Analytic Question

Does Every Study In A Collection Plausibly Show an Effect in the Same Direction?

(Haaf, 2018; Rouder, Haaf, Davis-Stober, & Hilgard, 2019)

Meta-Analytic Models



Application: Early language development

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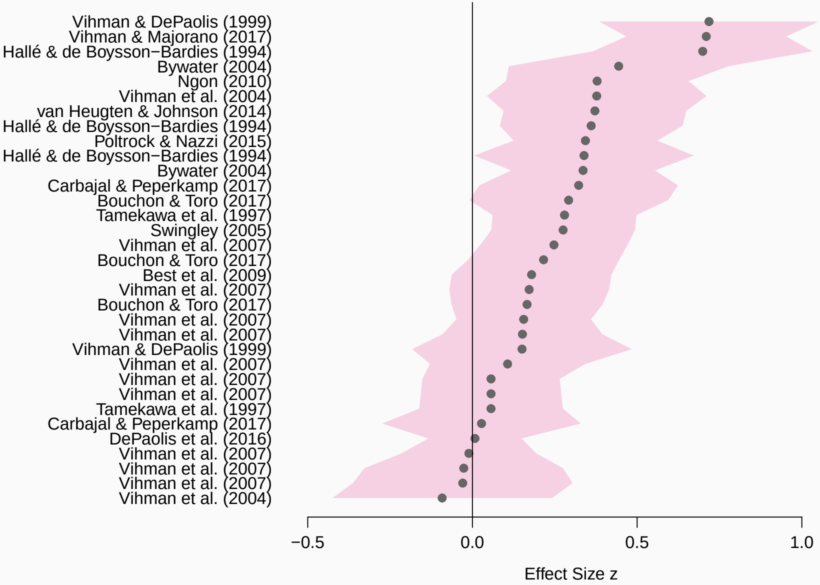
- General finding: Toddlers (∼11-20 months) pay longer attention to familiar words than novel ones.
- Carbajal (2018) conducted a meta-analysis with 33 studies.

Application: Early language development



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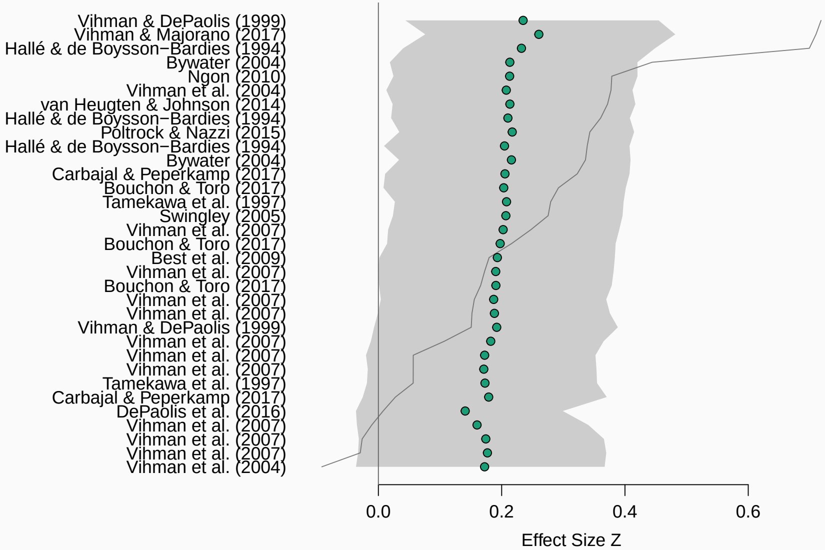

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- The Bayes factor of the every-study-does over the unconstrained model is 8.01 to 1.

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- The Bayes factor of the every-study-does over the unconstrained model is 8.01 to 1.
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Summary II

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- Evidence that every study shows the familiar-words effect.
- The average effect size is 0.2 (Fisher's Z).
- Qualitative interactions (Gail & Simon, 1985).
- Does-every-study approach is now implemented in the `metaBMA` package in `R`.

Back to Individual Differences

- Cognitive Psychology is more complicated than the Stroop effect.

Back to Individual Differences

- Cognitive Psychology is more complicated than the Stroop effect.
- Developing individual differences approaches for more diverse data patterns.

Example: How do we represent numbers internally?

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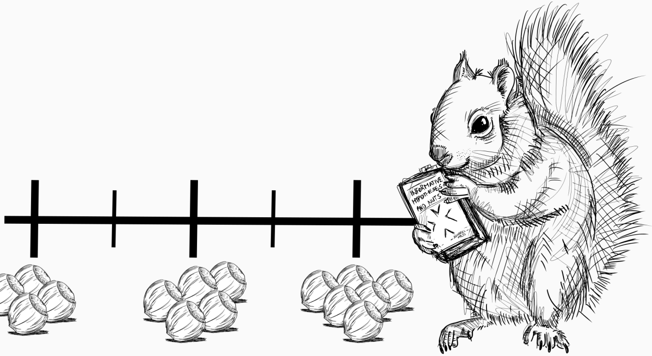
1. Analog representation.



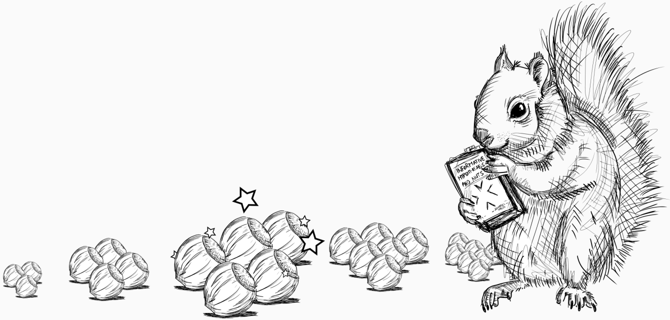
How do we represent numbers internally?

1. Analog representation.
2. Propositional representation.

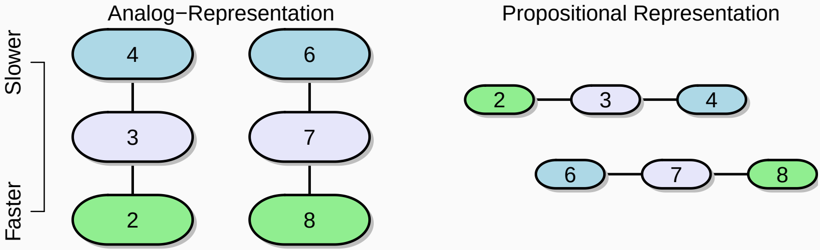
 <  = true

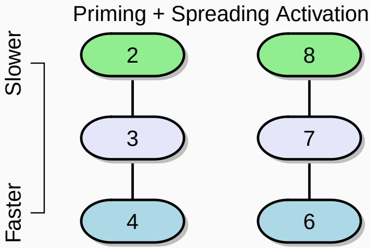
How do we represent numbers internally?

1. Analog representation.
2. Propositional representation.
3. Priming + spreading activation.

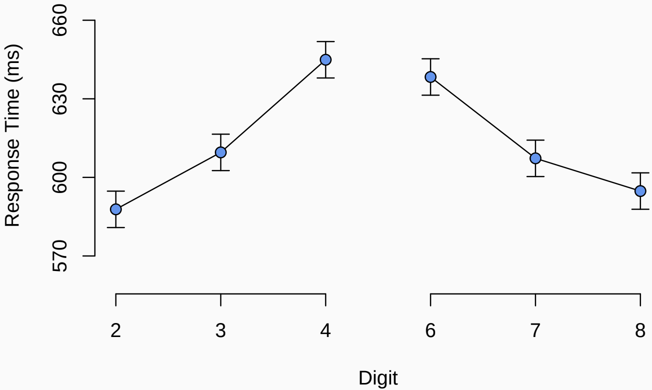


Theoretical positions as ordinal models





Rouder, Lu, Speckman, Sun, & Jiang (2005)



Individual Differences in Number Representation

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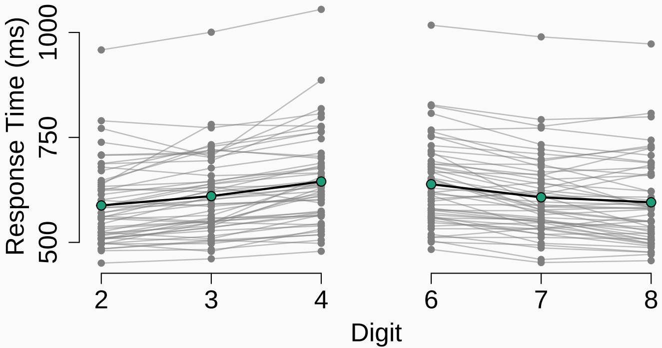
- Common mechanism $\rightarrow$ common processing architecture.
- Mixture of representations $\rightarrow$ what is the underlying mechanism?

Individual Differences in Number Representation



Data by Rouder, Lu, Speckman, Sun, & Jiang (2005).

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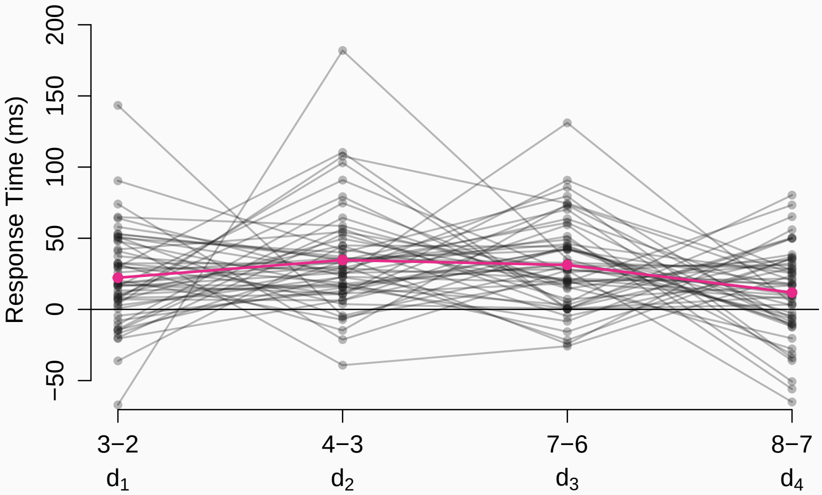

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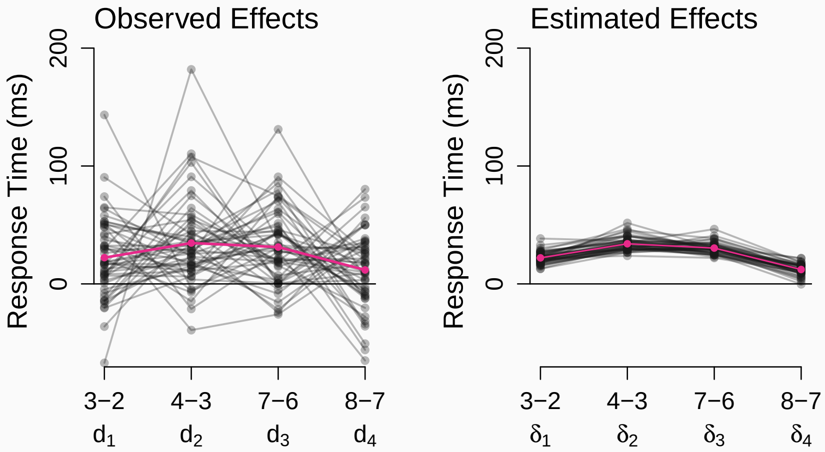
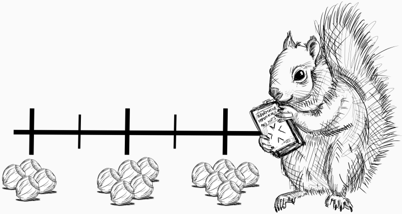


Individual Differences in Number Representation

- Preferred model: **Analog representation** model



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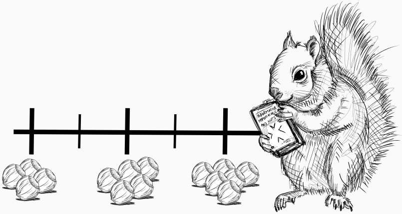

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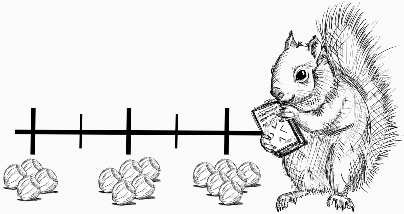

Individual Differences in Number Representation

- Preferred model: **Analog representation** model
- Preferred 9.78-to-1 over the **None of the above** model
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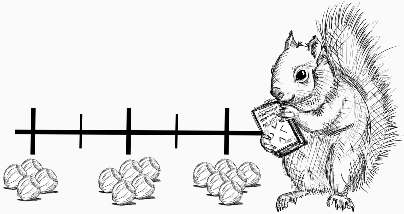
- Bayes factor for **Priming + spreading activation** model cannot be estimated



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Does everyone show an effect in the same direction?

- To answer this question we need a combination of new methods and theoretical considerations.
- Everyone Stroops.
- Qualitative vs. quantitative individual differences is a useful distrinction in cognitive psychology.
- For individual differences research: Assessing how individuals vary without overstating individual differences.
- We first need to know *that people have a similar processing architecture* before we can report average effects.

Thank you!

Are there any questions?

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- Advantage of the normal specification:

1. The normal is computationally convenient
2. The effect is easily parameterized and the placement of constraint is straightforward to implement.

References

Carbajal, M. J. (2018). *Separation and acquisition of two languages in earlychildhood: A multidisciplinary approach* (PhD thesis). Université Paris Sciences et Lettres.

Gail, M., & Simon, R. (1985). Testing for qualitative interactions between treatment effects and patient subsets. *Biometrics*, *41*(2), 361–372.

Haaf, J. M. (2018). *A hierarchical Bayesian analysis of multiple order constraints in behavioral science* (PhD thesis). University of Missouri.

Haaf, J. M., & Rouder, J. N. (2017). Developing constraint in Bayesian mixed models. *Psychological Methods*, *22*(4), 779–798.

Haaf, J. M., & Rouder, J. N. (2019). Some do and some don't? Accounting for variability of individual difference structures. *Psychonomic Bulletin and Review*, *26*, 772–789. Retrieved from https://doi.org/10.3758/s13423-018-1522-x

Pratte, M. S., Rouder, J. N., Morey, R. D., & Feng, C. (2010). Exploring the differences in distributional properties between Stroop and Simon effects using delta plots. *Attention, Perception & Psychophysics*, *72*, 2013–2025.

Rey-Mermet, A., Gade, M., & Oberauer, K. (2018). Should we stop thinking about inhibition? Searching for individual and age differences in inhibition ability. *Journal of Experimental Psychology: Learning, Memory, and Cognition*. Retrieved from http://dx.doi.org/10.1037/xlm0000450

Rouder, J. N., Haaf, J. M., Davis-Stober, C. P., & Hilgard, J. (2019). Beyond overall effects: A Bayesian approach to finding constraints in meta-analysis. *Psychological Methods*.

Rouder, J. N., Lu, J., Speckman, P. L., Sun, D., & Jiang, Y. (2005). A hierarchical model for estimating response time distributions. *Psychonomic Bulletin and Review*, *12*, 195–223.

Von Bastian, C. C., Souza, A. S., & Gade, M. (2015). No evidence for bilingual cognitive advantages: A test of