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TEXAS Education
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Log response ratio effect sizes

Rationale and methods for single-case designs with behavioral outcomes

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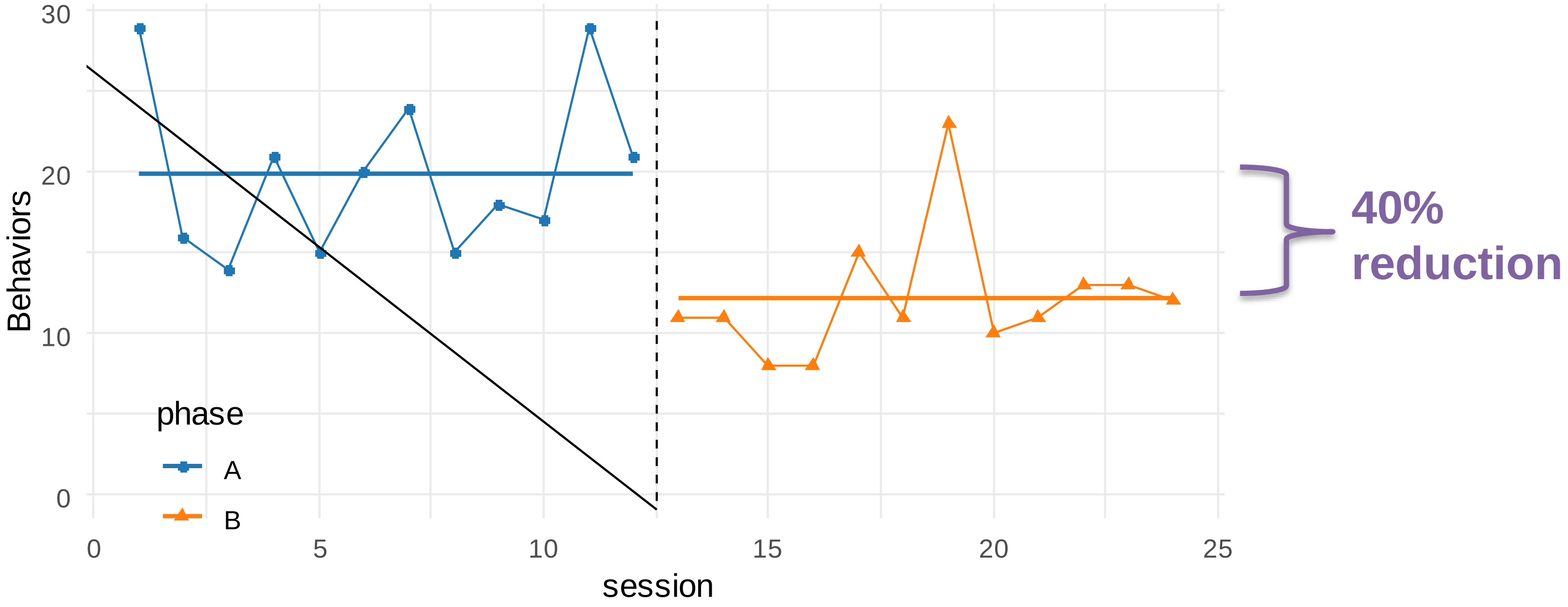
Effect size

- ***A numerical index quantifying the magnitude and direction of an intervention effect on an outcome, on a scale that is comparable across cases/studies*** (Pustejovsky & Ferron, 2017).
- Not influenced by arbitrary aspects of a study's design.

Proportionate change in levels



- Proportionate change makes sense for outcomes that are ***on a ratio scale***.
- Assuming stable baseline and treatment phase (no trends).

Log Response Ratio (LRR)

- The ***log response ratio*** (LRR) is a formal effect size measure that quantifies functional relationships ***in terms of proportionate change:***

$$LRR = log\left(\frac{Mean\ level\ in\ phase\ B}{Mean\ level\ in\ phase\ A}\right)$$

$$LRR = log\left(\frac{12}{20}\right) = \log(0.6) = -0.22$$

- Relationship to percentage change:

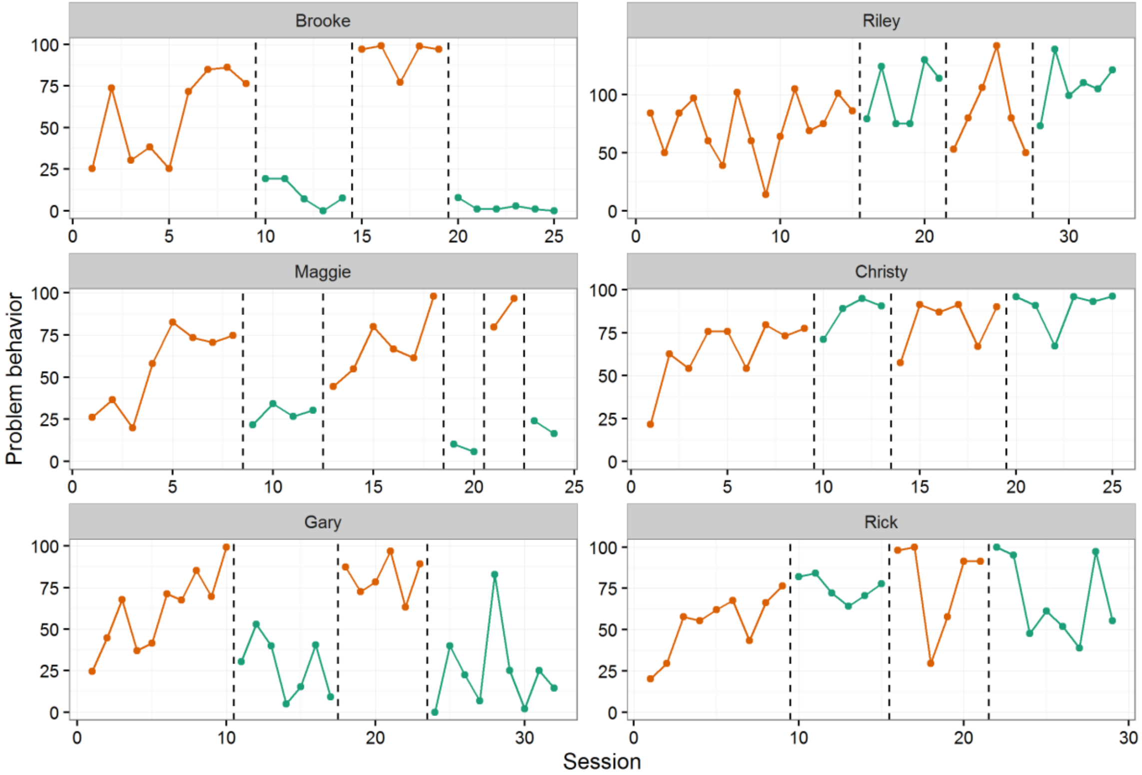
$$\%\ Change = 100\% \times (e^{LRR} - 1)$$

Advantages & limitations of LRR

+ Appropriate for ratio scale outcomes (most systematic direct observation of behavior).
+ Scale-free, comparable across studies that use different measurement systems.
+ Interpretable by converting into % change.

- Not interpretable for behaviors with near-zero baselines.
- Behaviors measured as percentages need to be defined in consistent direction.
- Standard errors assume independent observations (no auto-correlation)

Romaniuk et al. (2002). The influence of activity choice on problem behaviors maintained by escape versus attention.



Case	Function	LRR (SE)
Brooke	Escape	-2.39 (0.37)
Gary	Escape	-0.96 (0.23)
Maggie	Escape	-1.09 (0.19)
Christy	Attention	0.22 (0.08)
Rick	Attention	0.12 (0.13)
Riley	Attention	0.31 (0.10)
Meta-analysis	Escape	-1.22 (0.13)
	Attention	0.23 (0.06)

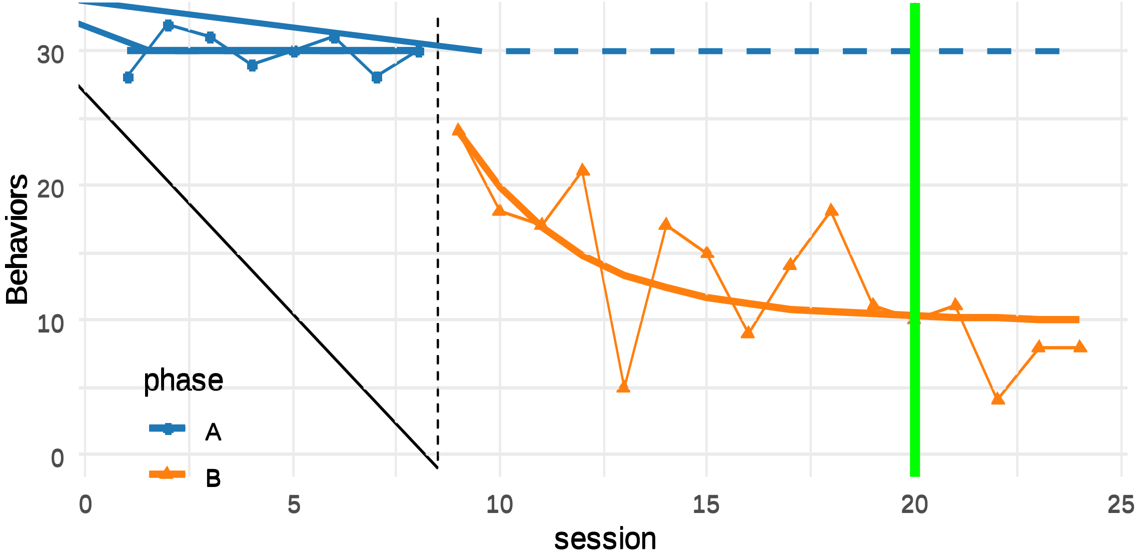
Escape: 66-77% ***reduction*** in behavior

Attention: 13-40% ***increase*** in behavior

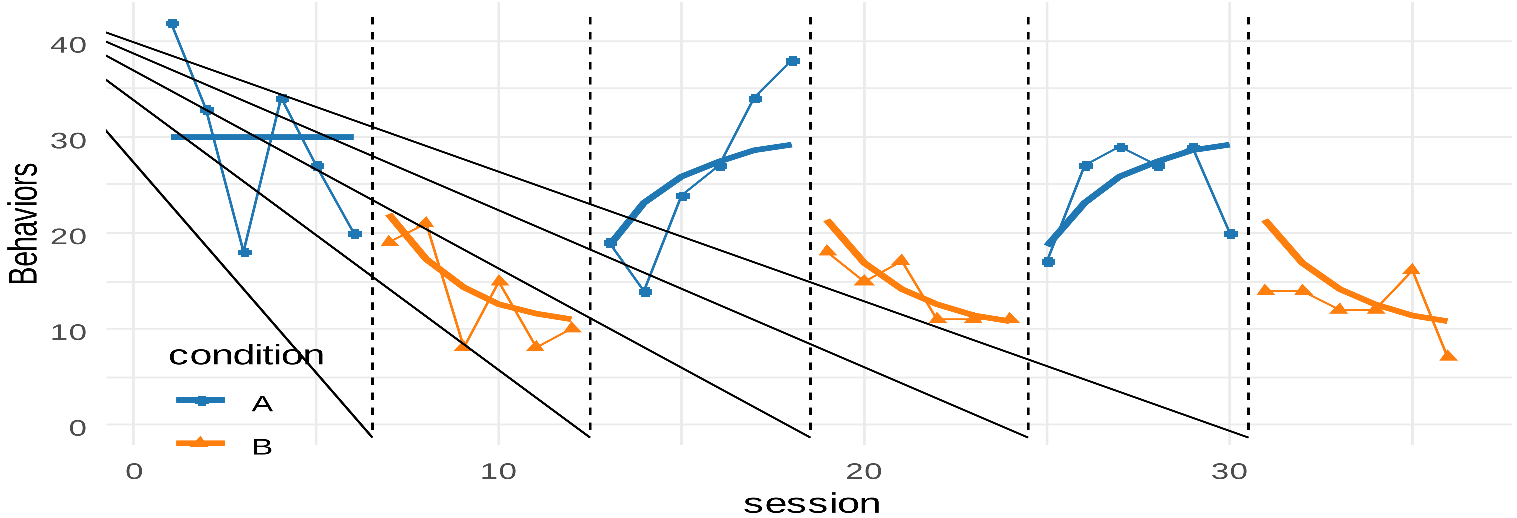
Non-linear models for gradual effects

$$Y_i = \beta_0 + \beta_1 (1 - \omega^{U_i})$$

where U_i is cumulative number of treatment sessions



Extension for treatment reversal designs



- Works with LRR and other parametric effect sizes
- See Swan and Pustejovsky (2018) for further details

Resources

Contact
Email: pusto@austin.utexas.edu
Twitter: @jepusto
Web: https://jepusto.com

- Web applications
  - for calculating LRR (and other basic ES indices): https://jepusto.shinyapps.io/SCD-effect-sizes/
  - for the gradual effects model: https://jepusto.shinyapps.io/gem-scd/

- Pustejovsky, J. E. (2018). Using response ratios for meta-analyzing single-case designs with behavioral outcomes. *Journal of School Psychology, 68*, 99-112. https://psyarxiv.com/nj28d/
- Price, C. L., Pustejovsky, J. E., Ostrosky, M. M., & Santos, R. M. (2019). Examining the Effects of Social Stories on Challenging Behavior and Prosocial Skills in Young Children: A Systematic Review and Meta-Analysis. *Topics in Early Childhood Special Education,* forthcoming. https://psyarxiv.com/fch6t/