Calculating Effect Sizes for Single-Case Research

An Introduction to the SingleCaseES and scdhlm Web Applications and R Packages

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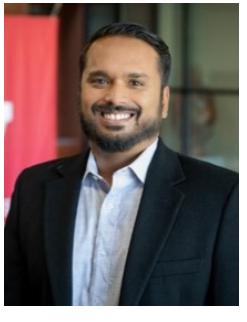

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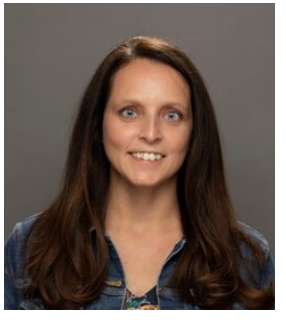


Jennifer Ledford

Outline

1. Organizing and curating data from single-case designs.
2. Within-study effect sizes.
    - Background
    - The `SingleCaseES` app
3. Between-case standardized mean differences
    - Background
    - The `scdhlm` app

Organizing and curating data from single-case designs

Why organize and curate your data?

1. So that you can do statistical analysis and effect size calculations.
2. So that you can share your data.
    - Make it easily accessible for inclusion in systematic reviews!
3. Because graphing data usually involves loss of information.
4. To fully document your research study.

Tidy SCD data

- One column per variable
- One row per observation session
- Descriptive labels for
  - Case (participant)
  - Phase of design or treatment condition

Case	Phase	Session	Outcome
Deborah's Group	Baseline	1	62.63
Deborah's Group	Baseline	2	40.22
Deborah's Group	Baseline	3	54.26
Deborah's Group	Baseline	4	40.26
Deborah's Group	Baseline	5	46.82
Deborah's Group	Baseline	6	52.45
Deborah's Group	Intervention	7	25.37
Deborah's Group	Intervention	8	26.32
Deborah's Group	Intervention	9	7.65
Deborah's Group	Intervention	10	11.41
Deborah's Group	Intervention	11	13.30
Deborah's Group	Intervention	12	22.66
Deborah's Group	Intervention	13	13.34
Amy's Group	Baseline	1	16.67
Amy's Group	Baseline	2	28.43
Amy's Group	Baseline	3	29.41
Amy's Group	Baseline	4	30.39
Amy's Group	Baseline	5	45.10
Amy's Group	Baseline	6	37.25

Multiple dependent variables

- **Wide format**: Use separate columns for multiple outcome variables

Case	Phase	Session	Problem_Behavior	On_Task_Behavior
Deborah's Group	Baseline	1	16.7	56.7
Deborah's Group	Baseline	2	20.0	70.0
Deborah's Group	Baseline	3	26.7	66.7
Deborah's Group	Baseline	4	20.0	86.7
Deborah's Group	Baseline	5	16.7	56.7
Deborah's Group	Baseline	6	13.3	70.0
Deborah's Group	Intervention	7	16.7	46.7
Deborah's Group	Intervention	8	20.0	73.3
Deborah's Group	Intervention	9	20.0	56.7
Deborah's Group	Intervention	10	30.0	50.0
Deborah's Group	Intervention	11	30.0	63.3
Deborah's Group	Intervention	12	13.3	63.3

Multiple dependent variables

- **Long format**: One row per outcome measure per session

Case	Phase	Session	DV	Outcome
Deborah's Group	Baseline	1	On Task Behavior	56.7
Deborah's Group	Baseline	1	Problem Behavior	16.7
Deborah's Group	Baseline	2	On Task Behavior	70.0
Deborah's Group	Baseline	2	Problem Behavior	20.0
Deborah's Group	Baseline	3	On Task Behavior	66.7
Deborah's Group	Baseline	3	Problem Behavior	26.7
Deborah's Group	Baseline	4	On Task Behavior	86.7
Deborah's Group	Baseline	4	Problem Behavior	20.0
Deborah's Group	Baseline	5	On Task Behavior	56.7
Deborah's Group	Baseline	5	Problem Behavior	16.7
Deborah's Group	Baseline	6	On Task Behavior	70.0
Deborah's Group	Baseline	6	Problem Behavior	13.3

Adding more detail

- Add furthers details about what happened in the study.
- Some ideas:
  - Actual session date + times (YYYY-MM-DD-HH:MM)
  - Observation session lengths
  - Clinician/therapist IDs
  - Notes about events

Case	Phase	Session	Problem Behavior	On-Task Behavior	Date	Session length	Notes
Deborah's Group	Baseline	1	16.7	56.7			
Deborah's Group	Baseline	2	20.0	70.0			
Deborah's Group	Baseline	3	26.7	66.7			

Share Your Data!

Within-case effect size indices

Within-case effect size indices

- Single-number summary of the **direction** and **magnitude** of intervention effect (functional relation) ***for each case*** within a study.
- Use these if you want to:
  - Describe results separately for each participant
  - Examine heterogeneity of effects or associations with individual-level characteristics
  - Compare results across participants and SCED studies that use various outcome measures
- Lots of proposed effect size indices. Today we'll focus on
  - Non-overlap of all pairs
  - Within-case standardized mean difference
  - Log-response ratio

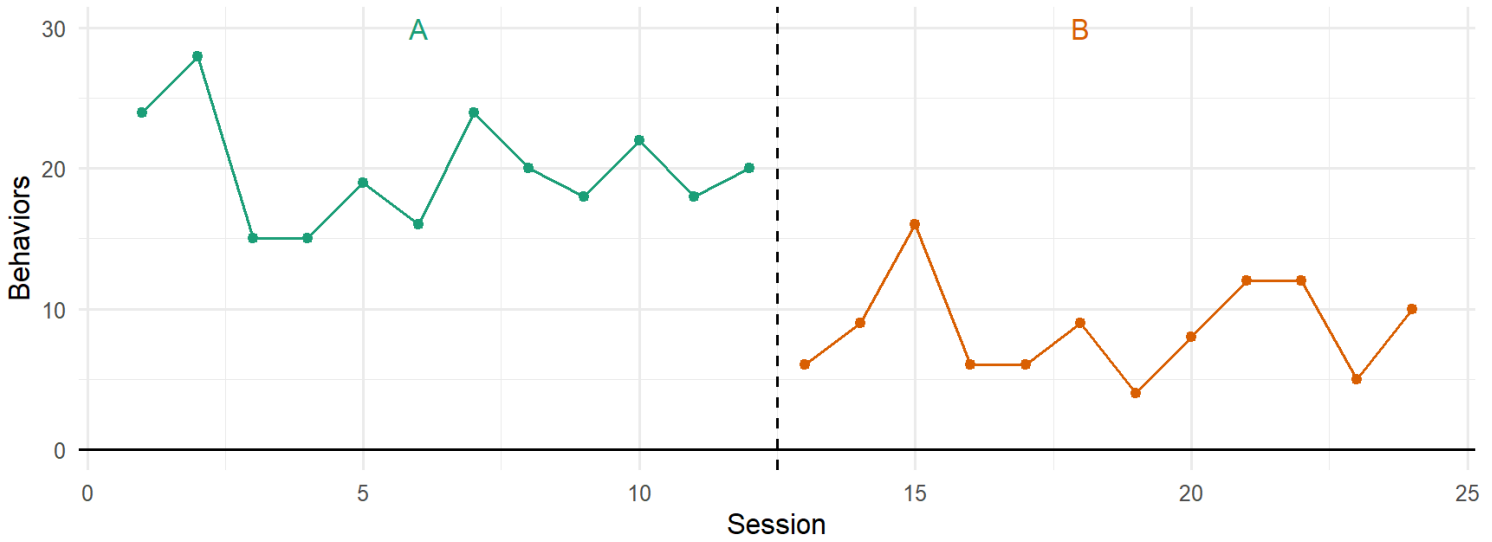
`SingleCaseES`: Single-series calculator

- Access `SingleCaseES` on the web at https://jepusto.shinyapps.io/SCD-effect-sizes/
- Or by opening RStudio and typing

```
library(SingleCaseES)
SCD_effect_sizes()
```

- Two parts to the app:
  - Single-series calculator (direct data entry)
  - Multiple-series calculator (using a data file)

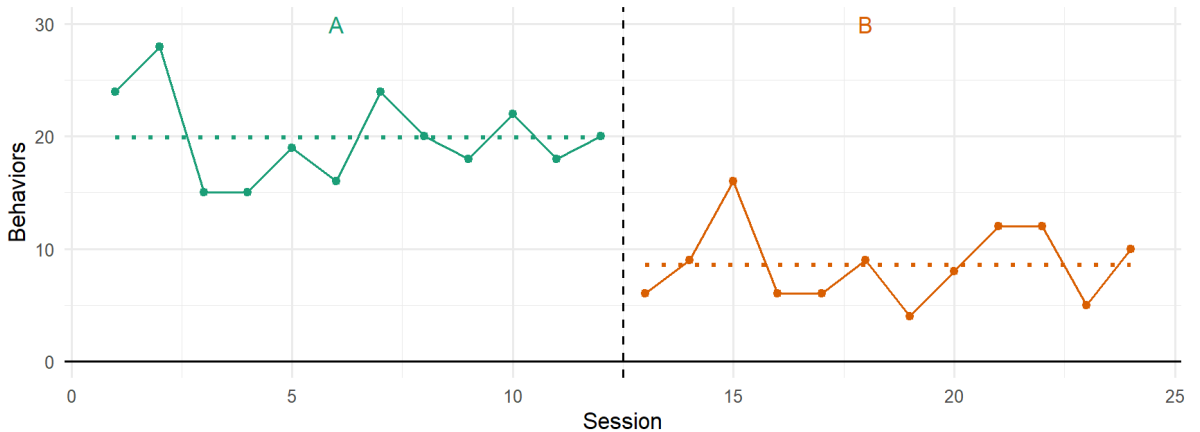
Simplest possible model



- Stable baseline and treatment phases (no time trends)
  - Immediate shift in level due to intervention
- Independence of outcome measurements

Notation

- n_A observations in phase A: $y_1^A, \ldots, y_{n_A}^A$
- n_B observations in phase B: $y_1^B, \ldots, y_{n_B}^B$
- Mean level of the outcome in each phase: μ_A, μ_B
  - Estimated by sample means $\bar{y}_A, \bar{y}_B$
- Standard deviation of the outcome in each phase: σ_A, σ_B
  - Estimated by sample standard deviations S_A, S_B



Non-overlap of all pairs

- Non-overlap measures are defined in terms of ***ordinal comparisons*** of outcomes
- Non-overlap of all pairs (Parker and Vannest, 2009) is defined in terms of all pairs of one observation from phase A and one observation from phase B.
- For every pair $i = 1, \ldots, n_A$ and $j = 1, \ldots, n_B$, take

$$q_{ij} = \begin{cases} 1 & \text{if} \quad y_j^B \text{ better than } y_i^A \\ \frac{1}{2} & \text{if} \quad y_j^B = y_i^A \\ 0 & \text{if} \quad y_j^B \text{ worse than } y_i^A \end{cases}$$

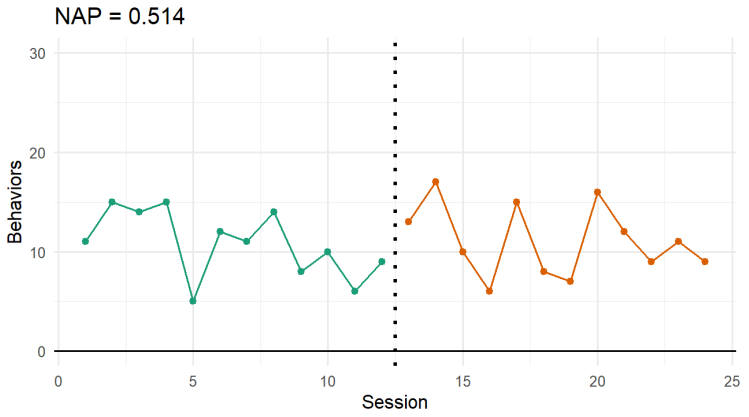
- NAP estimator:

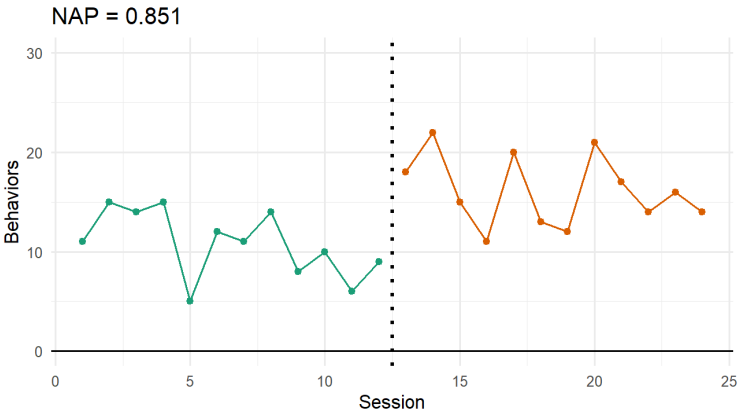
$$NAP = \frac{1}{mn} \sum_{i=1}^{n_A} \sum_{j=1}^{n_B} q_{ij}$$

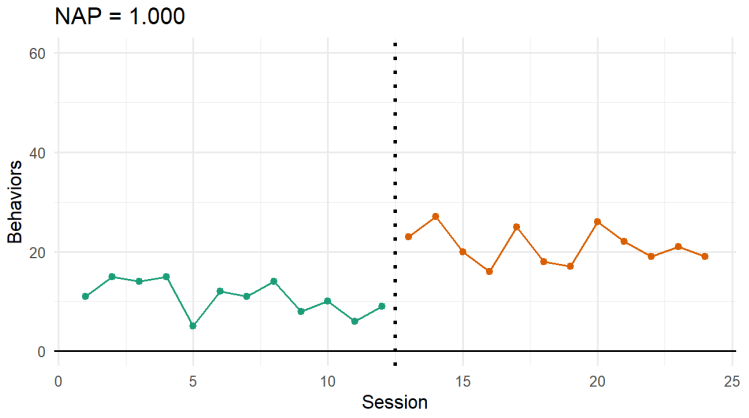
- Standard error based on unbiased estimator (Sen, 1967; Mee, 1990)
    - Methods assume that observations are independent and identically distributed within each phase.

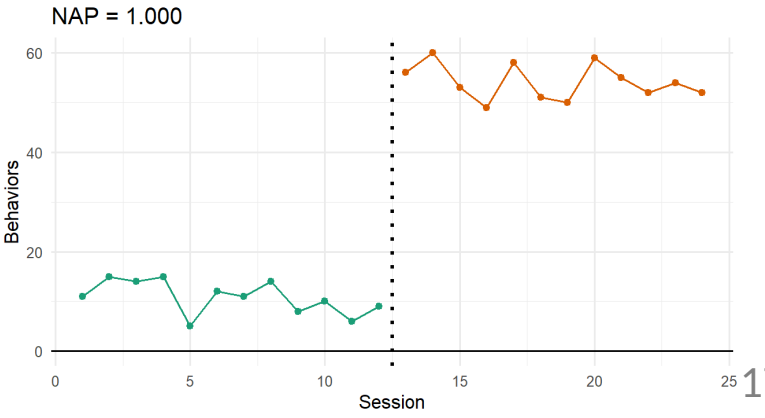
Limited range of sensitivity

- Limited range where NAP (and other non-overlap measures) sensitive to change.









Within-case standardized mean difference

- Proposed by Gingerich (1984) and Busk and Serlin (1992)
- Parameter definition:

$$\delta = \frac{\mu_B - \mu_A}{\sigma_A}$$

  - Difference in means, "standardized" by baseline variation
  - NOT equivalent to between-case SMD because σ_A includes only *within-case variation*.
- Appropriate for interval-scale outcomes
  - Is variability of outcomes approximately constant for different mean levels?
  - Standardizing by within-case variation means this measure will be strongly affected by reliability of measurements
  - Problematic for outcomes with restricted range in baseline

Within-case standardized mean difference: estimation

- Originally proposed estimator:

$$d = \frac{\bar{y}_B - \bar{y}_A}{S_A}$$

- Estimator with small-sample bias correction:

$$g = \left(1 - \frac{3}{4n_A - 5}\right) \times \frac{\bar{y}_B - \bar{y}_A}{S_A}$$

- Approximate standard error, ***assuming independent observations***:

$$SE_g = \left(1 - \frac{3}{4n_A - 5}\right) \sqrt{\frac{1}{n_A} + \frac{S_B^2}{n_B S_A^2} + \frac{d^2}{2(n_A - 1)}}$$

Proportional change in levels

- Percentage (proportional) change from baseline to intervention is an easily interpretable "informal" effect size (Campbell and Herzinger, 2010).
- The **log response ratio** is a formal measure of effect size that describes change in proportional terms (Pustejovsky, 2015; Pustejovsky, 2018).
- Parameter definition:

$$\psi = \log\left(\frac{\mu_B}{\mu_A}\right)$$

  - Appropriate for **ratio-scale** outcomes (frequency counts, percentage duration)
  - Natural logarithm is used to make the range unrestricted.

- Transformation to percentage change:

$$\%\ \text{change} = 100\% \times \left(e^{\psi} - 1\right)$$

Log response ratio: estimation

- Basic estimator (biased if m or n is small):

$$R_1 = \log\left(\frac{\tilde{y}_B}{\tilde{y}_A}\right)$$

- Bias-corrected estimator:

$$R_2 = \log\left(\frac{\tilde{y}_B}{\tilde{y}_A}\right) + \frac{\tilde{S}_B^2}{2n_B\tilde{y}_B^2} - \frac{\tilde{S}_A^2}{2n_A\tilde{y}_A^2}$$

- Approximate standard error for R_2, ***assuming independent observations***:

$$SE_R = \sqrt{\frac{\tilde{S}_A^2}{n_A\tilde{y}_A^2} + \frac{\tilde{S}_B^2}{n_B\tilde{y}_B^2}}$$

Direction of improvement

- Two versions of LRR:
  - **LRRi**: Positive numbers represent **increases** in **desirable outcomes**
  - **LRRd**: Negative numbers represent **decreases** in **undesirable outcomes**
- Use the version that corresponds to ***predominant valence*** of outcomes in your data.
- For count outcomes, LRRi $=$ -LRRd
- For proportion / percentage outcomes, the outcome valence is harmonized before calculation.
  - For proportion / percentage outcomes, LRRi $\neq$ -LRRd

Truncation constants

- If $\bar{y}_A = 0$ or $\bar{y}_B = 0$ then LRR is undefined.
  - If $S_A^2 = 0$ or $S_B^2 = 0$ then SE_R is undefined
- To handle such situations, the app uses **truncated mean** and **truncated SD** estimators:

$$\tilde{y}_A = \max\left\{\bar{y}_A, \frac{1}{2n_A D}\right\}, \qquad \tilde{y}_B = \max\left\{\bar{y}_B, \frac{1}{2n_B D}\right\}$$

and

$$\tilde{S}_A^2 = \max\left\{S_A^2, \frac{1}{n_A^3 D^2}\right\}, \qquad \tilde{S}_B^2 = \max\left\{S_B^2, \frac{1}{n_B^3 D^2}\right\}$$

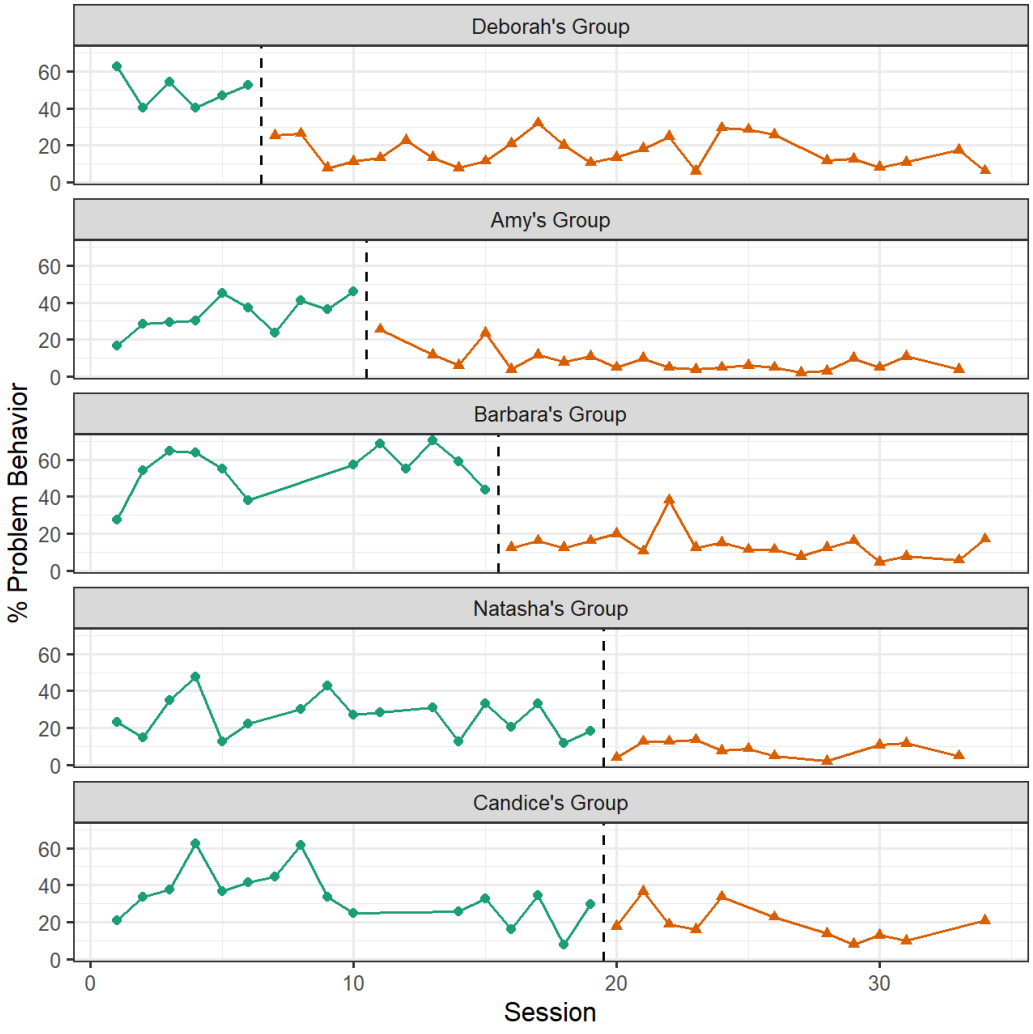
- D is a constant that depends on the outcome scale and measurement procedures
  - Number of intervals / items
  - Session length for direct observation
  - Can also define your own D

`SingleCaseES`: Multiple-series calculator

- Basic walk-through with data from Rodriguez and Anderson (2014)
- Calculating phase-pairs in ABAB designs
- Aggregating effect sizes

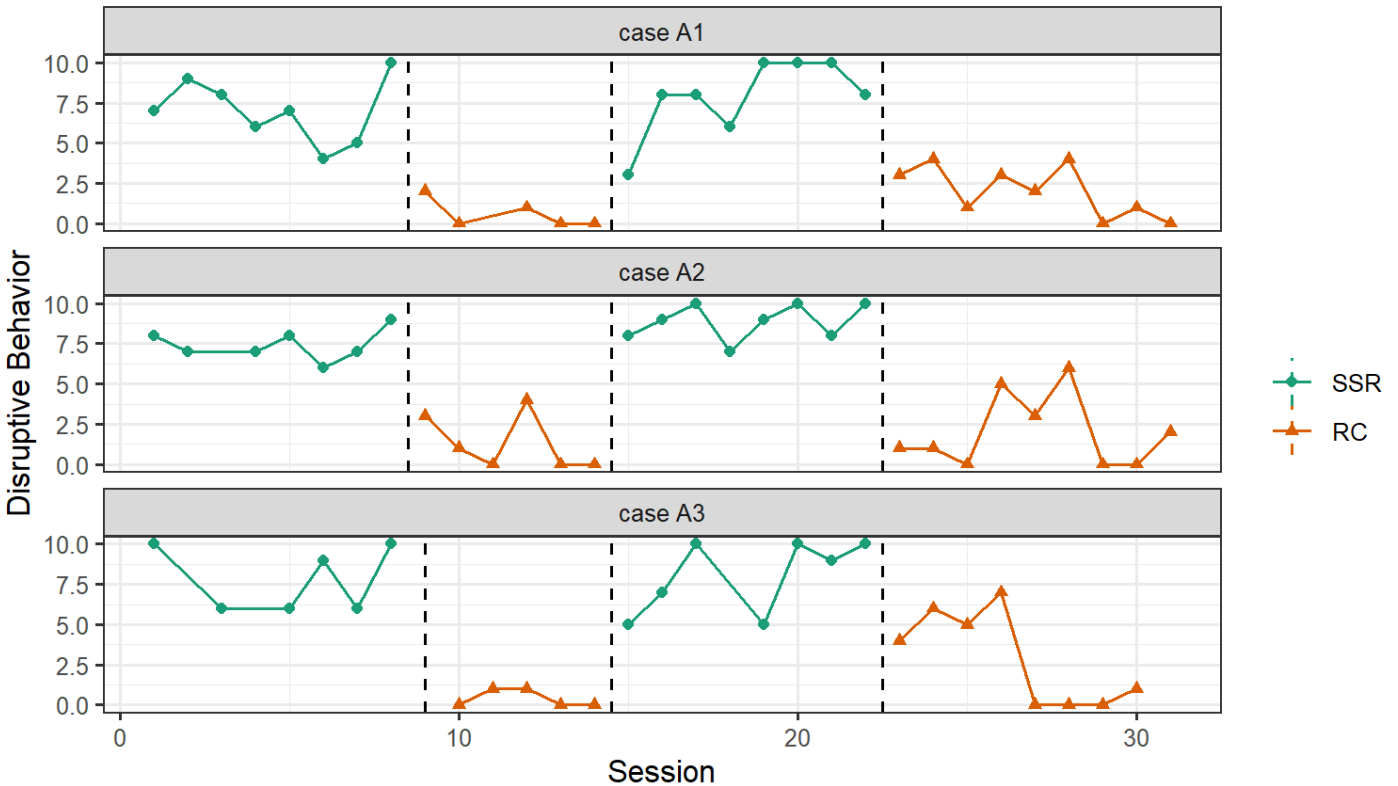
Rodriguez and Anderson (2014)

Integrating a social behavior intervention during small group academic instruction using a total group criterion intervention



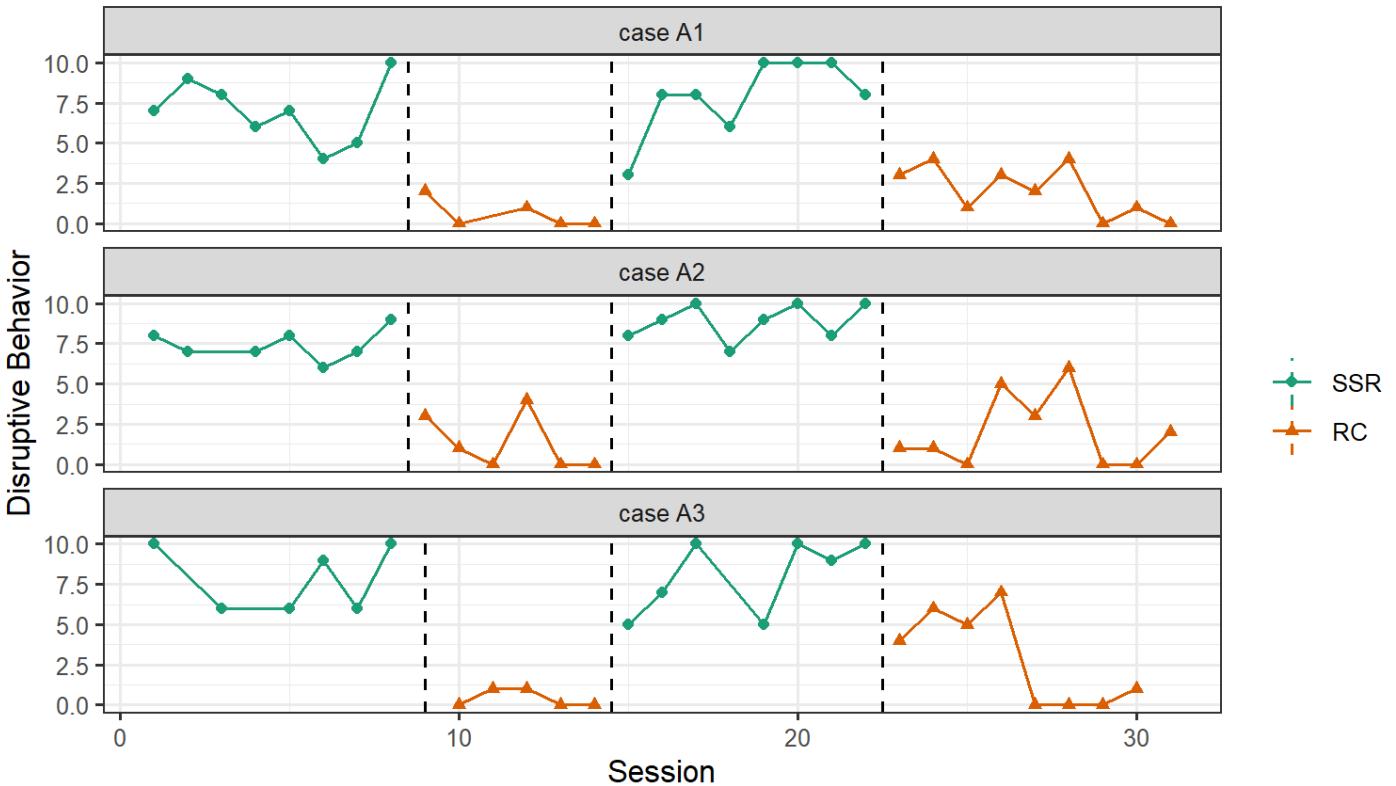
Lambert, Cartledge, Heward et al. (2006)

Effects of response cards on disruptive behavior and academic responding during math lessons by fourth-grade urban students



Calculating phase pairs

- Might want to calculate effect sizes for adjacent pairs of baseline and intervention phases.
- SingleCaseES provides an option to determine phase pairs automatically.



Aggregating effect sizes

- After calculating effect sizes for adjacent pairs of phases, we might want to **average them together** to simplify reporting or further analysis.
  - Average across phase pairs in an ABAB design
  - Average across cases to generate an overall summary effect size estimate
- Several options for taking weighted averages
  - Equal weighting
  - Inverse-variance weighting: $\frac{1}{V}$ (use for LRR)
  - n_A
  - n_B
  - $n_A n_B$ (use for NAP)
  - $\frac{1}{n_A} + \frac{1}{n_B}$ (use for SMD)

Replication code

```r
# Load packages
library(SingleCaseES)

# Load data
library(readxl)
library(janitor)

dat <-
  read_excel(path = "Small-is-Beautiful-effect-size-workshop.xlsx", sheet = "Lambert") %>%
  clean_names(case = "parsed")

# clean data
library(dplyr)

dat <-
  dat %>%
  group_by(case) %>%
  mutate(phase_pair_calculated = calc_phase_pairs(treatment, session = day)) %>%
  ungroup()

# Batch calculation
res <- batch_calc_ES(dat = dat,
                     grouping = c(case),
                     condition = treatment,
                     outcome = outcome,
                     aggregate = c(phase_pair_calculated),
                     weighting = "1/nA + 1/nB",
                     session_number = day,
                     baseline_phase = "SSR",
```

Between-case standardized mean differences

Premises

- **Goal**: Estimate an effect size using data from a single-case design that is *in the same metric* as the standardized mean difference effect size from a between-group experimental design.
- **Why?** (Shadish, Hedges, Horner et al., 2015)
  - **Translation** of single-case research for researchers who work primarily with between-groups designs
  - **Comparison** of results from single-case studies and between-groups studies, for purposes of understanding the utility and limitations of each type of design
  - **Synthesis** involving both single-case and between-groups designs

SMD in between-group experiment

- What is the SMD from a between-group experiment?

$$\delta_{BC} = \frac{\left(\begin{array}{c}\text{Average outcome if}\\ \text{everybody gets intervention}\end{array}\right) - \left(\begin{array}{c}\text{Average outcome if}\\ \text{nobody gets intervention}\end{array}\right)}{\left(\begin{array}{c}\text{SD of outcome if}\\ \text{nobody gets intervention}\end{array}\right)}$$

$$\delta_{BC} = \frac{\left(\begin{array}{c}\text{Average outcome if}\\ \text{everybody gets intervention}\end{array}\right) - \left(\begin{array}{c}\text{Average outcome if}\\ \text{nobody gets intervention}\end{array}\right)}{\sqrt{\left(\begin{array}{c}\text{Between-participant}\\ \text{variance}\end{array}\right) + \left(\begin{array}{c}\text{Within-participant}\\ \text{variance}\end{array}\right)}}$$

- We aim to estimate these component quantities using data from a single-case experimental design.

The broad strategy

(Pustejovsky, Hedges, and Shadish, 2014) described a general strategy for estimating BC-SMD:

1. Develop a hierarchical linear model that describes:
    - The form of time trends and intervention effects
    - How the trends and intervention effects vary across participants
2. Imagine a **hypothetical between-group experiment** with the same population of participants, same intervention, same dependent variable.
    - When is treatment initiated?
    - When are outcomes assessed?
3. Use the hierarchal model to estimate the components of δ_{BC} for the hypothetical experiment.
4. Make a small-sample correction (similar to Hedges' g)

Design translation

A multiple baseline across participants:

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18
X	X	X	X	X	T	X	X	X	X	X	X	X	X	X	X	X	X
X	X	X	X	X	X	X	X	T	X	X	X	X	X	X	X	X	X
X	X	X	X	X	X	X	X	X	X	X	T	X	X	X	X	X	X
X	X	X	X	X	X	X	X	X	X	X	X	X	X	T	X	X	X

A hypothetical between-group design (with pre-test):

T1	T2	T3	T4	T5	T6	T7	T8	T9	T10	T11	T12	T13	T14	T15	T16	T17	T18
				X	T										X		
				X	T										X		
				X											X		
				X											X		

Overview of methods literature

- BC-SMD estimators for a basic hierarchical linear model with no time trends:
  - Hedges, Pustejovsky, and Shadish (2012): Treatment reversal (ABAB) design replicated across 3+ participants
  - Hedges, Pustejovsky, and Shadish (2013): Multiple baseline / multiple probe design with 3+ participants
  - Shadish, Hedges, and Pustejovsky (2014): More worked examples
- Pustejovsky, Hedges, and Shadish (2014) described a more general strategy for multiple baseline / multiple probe designs across participants
  - Valentine, Tanner-Smith, Pustejovsky et al. (2016): Tutorial and practical guidance
- Swaminathan, Rogers, and Horner (2014) proposed Bayesian estimation methods
- Chen, Pustejovsky, Klingbeil et al. (2023) proposed BC-SMD methods for more complex designs:
  - Multiple baseline across behaviors, replicated across 3+ participants
  - Clustered multiple baseline design across participants (3+ clusters)
  - Multivariate multiple baseline design across 3+ participants

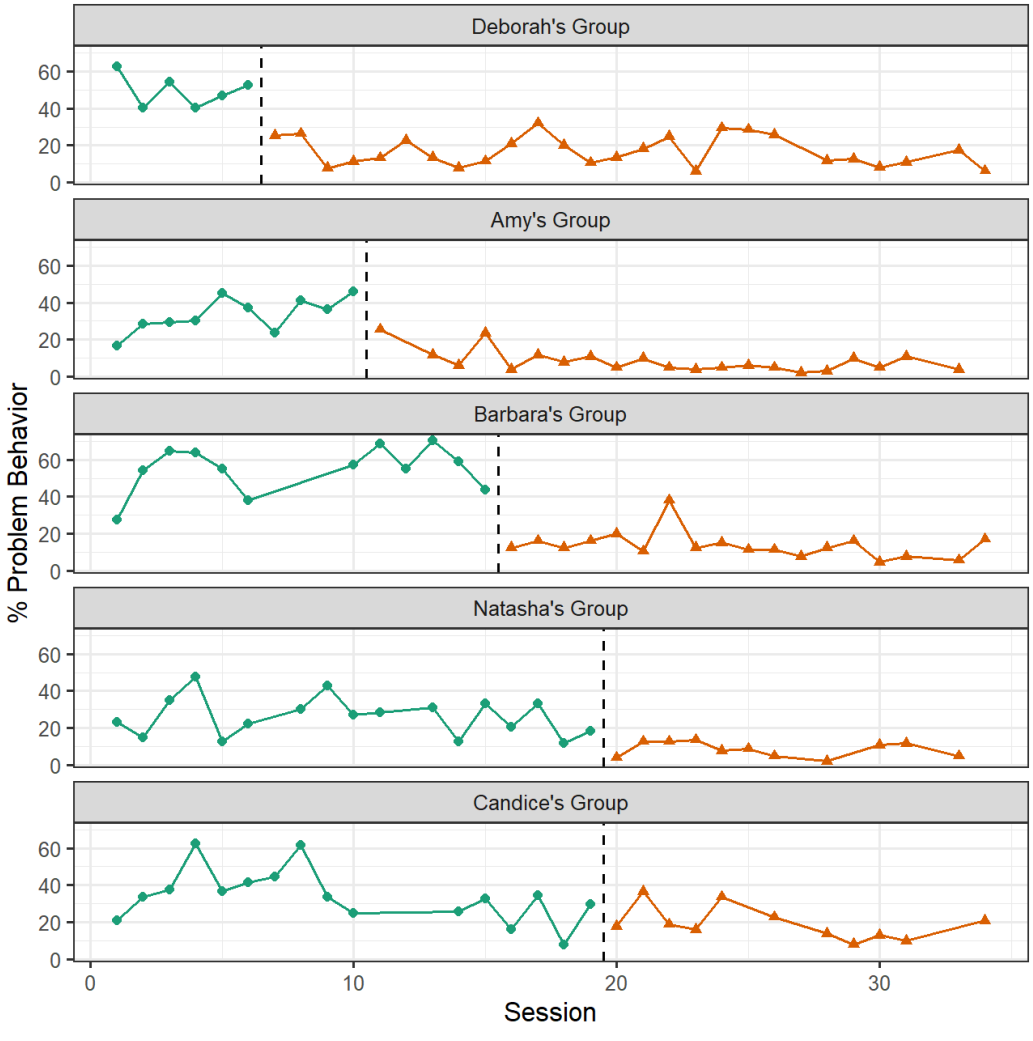
`scdhlm` web app

- Access `scdhlm` on the web at https://jepusto.shinyapps.io/scdhlm/
- Or by opening RStudio and typing

```
library(scdhlm)
shine_scd()
```

Rodriguez and Anderson (2014)

Integrating a social behavior intervention during small group academic instruction using a total group criterion intervention



The most basic HLM

- Level-1 model for each participant:

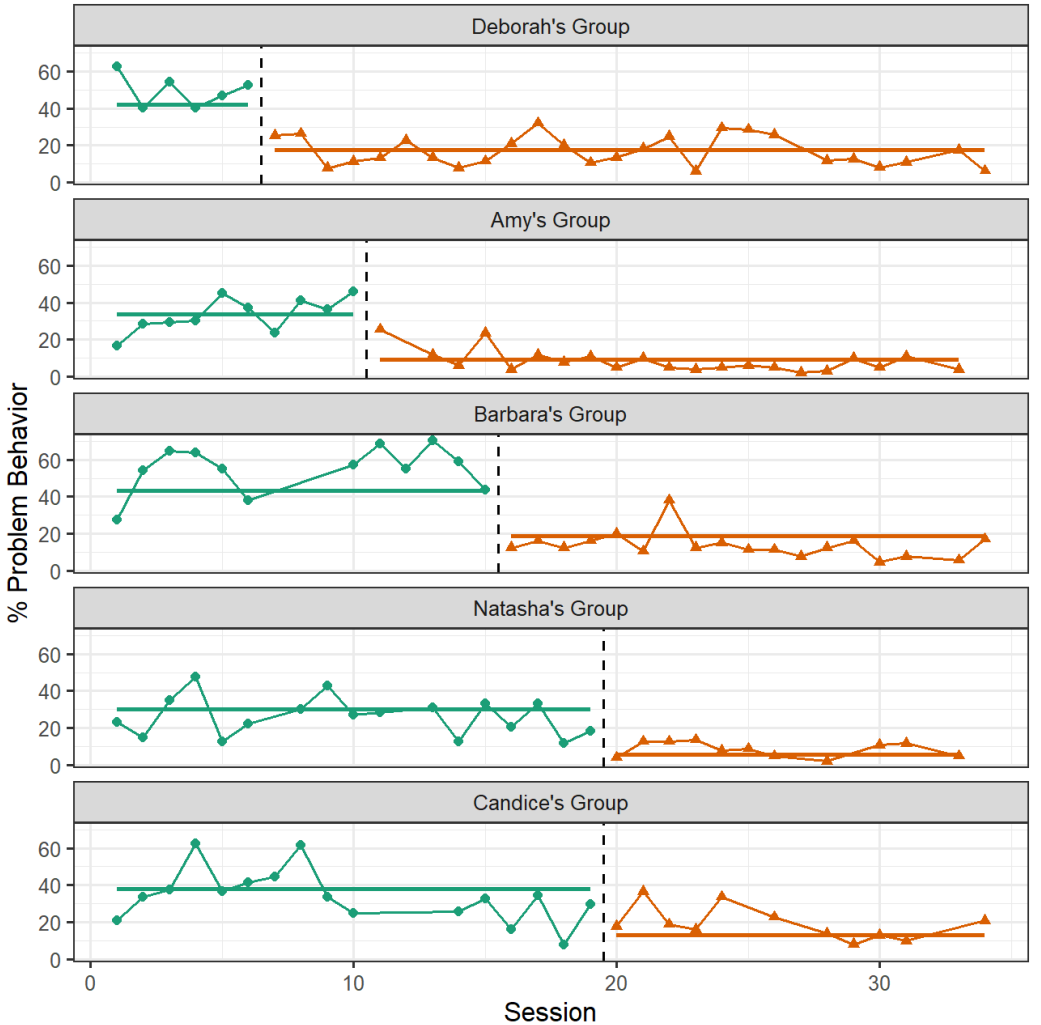
$$Y_{ij} = \beta_{0j} + \beta_{1j}(Tx)_{ij} + e_{ij}$$

  where $\mathrm{Var}(e_{ij}) = \sigma_e^2$ and $e_{1j}, \ldots, e_{Tj} \sim AR_1(\phi)$

- Level-2 model:

$$\begin{aligned} \beta_{0j} &= \theta_{00} + u_{0j}, \qquad u_{0j} \sim N(0, \sigma_{u0}^2) \\ \beta_{1j} &= \theta_{10} \end{aligned}$$

- Under this model:
  - Average outcome if nobody gets intervention: θ_{00}
  - Average outcome if everybody gets intervention: $\theta_{00} + \theta_{10}$
  - SD of outcome if nobody gets intervention: $\sqrt{\sigma_{u0}^2 + \sigma_e^2}$
  - BC-SMD effect size: $\delta_{BC} = \dfrac{\theta_{10}}{\sqrt{\sigma_{u0}^2 + \sigma_e^2}}$



- $\hat{\theta}_{00} = 37.5$
- $\hat{\theta}_{10} = -24.7$
- $\hat{\sigma}^2_e = 112.1$
- $\hat{\sigma}^2_{u0} = 36.7$

$$\hat{\delta}_{BC} = \frac{-24.7}{\sqrt{112.1 + 36.7}} = -2.03$$

$$g_{BC}\ (SE) = -1.99\ (0.31)$$

A more flexible HLM

- Level-1 model for each participant:

$$Y_{ij} = \beta_{0j} + \beta_{1j}(\text{Time})_{ij} + \beta_{2j}(Tx)_{ij} + \beta_{3j}(Tx)_{ij} \times \big((\text{Time})_{ij} - k_j\big) + e_{ij}$$

  where $\text{Var}(e_{ij}) = \sigma_e^2$ and $e_{1j}, \ldots, e_{Tj} \sim AR_1(\phi)$ and k_j is last baseline session.

- Level-2 model:

$$\begin{aligned}
\beta_{0j} &= \theta_{00} + u_{0j}, \qquad & u_{0j} \sim N(0, \sigma^2_{u0}) \\
\beta_{1j} &= \theta_{10} + u_{1j}? \\
\beta_{2j} &= \theta_{20} + u_{2j}? \\
\beta_{3j} &= \theta_{30} + u_{3j}?
\end{aligned}$$

  - Adding a random effect $\rightarrow$ allowing slope / Tx effect to ***vary across cases***
  - Omitting a random effect $\rightarrow$ assuming slope / Tx effect is ***constant***
  - Models with more random effects require more cases

A more flexible HLM

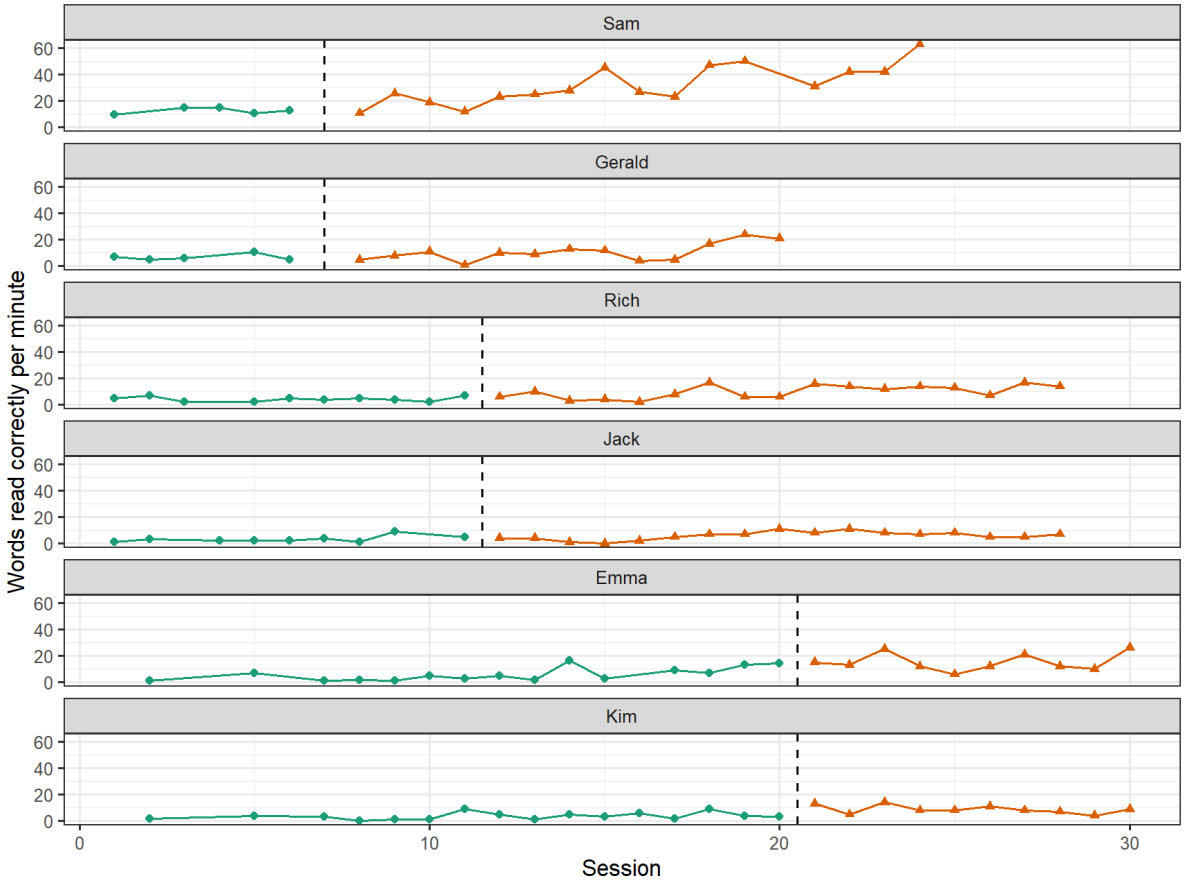
- Can also modify assumptions about level-1 errors
- Different variance by treatment phase:

$$\text{Var}(e_{ij}) = \begin{cases} \sigma^2_{eC} & \text{if} \quad (Tx)_{ij} = 0 \\ \sigma^2_{eT} & \text{if} \quad (Tx)_{ij} = 1 \end{cases}$$

- Correlation structure of level-1 errors:
  - First order auto-regression $(AR_1(\phi))$
  - First order moving average $(MA_1(\phi))$
  - Independent

Model should be informed by **theoretical expectations** and **visual inspection**

Barton-Arwood, Wehby, and Falk (2005) Reading instruction for elementary-age students with emotional and behavioral disorders: Academic and behavioral outcomes



Models with time trends

- For models with time trends, we need to specify ***timing*** of pre-test and post-test for the hypothetical between-group design.
- **Initial treatment time**: Last session of baseline phase before being assigned to intervention or comparison condition.
  - Default: Length of shortest baseline phase
- **Focal follow-up time**: Session during which outcomes would be assessed in hypothetical experiment.
  - Default: Last measurement occasion for first case to enter intervention
  - This is not a particularly good default
  - Ideally, pick a focal follow-up time based on a meaningful or typical treatment duration

Barton-Arwood, Wehby, and Falk (2005) effect size calculations

- Model specification
  - Baseline level (random)
  - Baseline time trends (constant)
  - Treatment level change (constant)
  - Treatment trend change (random)
  - Level-1 variance differs by phase
- Initial treatment time: After 6 sessions
- Focal follow-up time of session 16 (10 sessions of treatment).
- BC-SMD estimate:

$$g_{BC}\ (SE) = 0.82\ (0.75)$$

Illustrative application of BC-SMDs

- Calder and colleagues (2020, 2021) studied an explicit grammar instruction intervention for children with developmental language disorder.
- Calder, Claessen, Ebbels et al. (2020): multiple baseline across nine participants
  - Data available in the Excel workbook
  - Try calculating a BC-SMD estimate after 10 weeks of intervention
- Calder, Claessen, Ebbels et al. (2021): crossover randomized trial with $N = 21$ participants
  - 10 weekly intervention sessions
  - $g = 1.97, SE = 0.11$ for expressive morphosyntax
  - $g = 0.06, SE = 0.06$ for grammaticality judgements

Limitations of between-case SMD

- Tool for translating from single-case logic to group-design logic.
    - Premised on the idea that a hypothetical group design is theoretically plausible
- Describes a **summary**, **average effect** across a set of cases
    - Potentially concealing individual-level heterogeneity
- For some models, magnitude depends on the features (timing) of hypothetical between-group design
- Technical limitations
    - Only available for some designs
    - Requires at least 3 participants (preferably more!)
    - Models assume normal (Gaussian) errors
    - Care needed for model selection

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