# A MULTIVARIATE LOGIT-FUNCTION FOR MODELING CONTINUOUS BOUNDED INTERVAL RESPONSES

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International Meeting of the Psychometric Society 2024

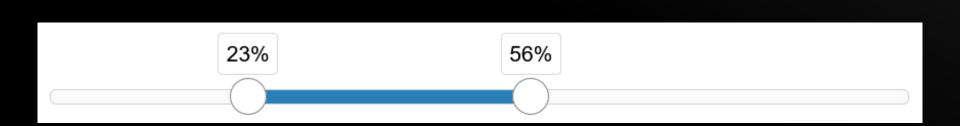
#### MOTIVATION

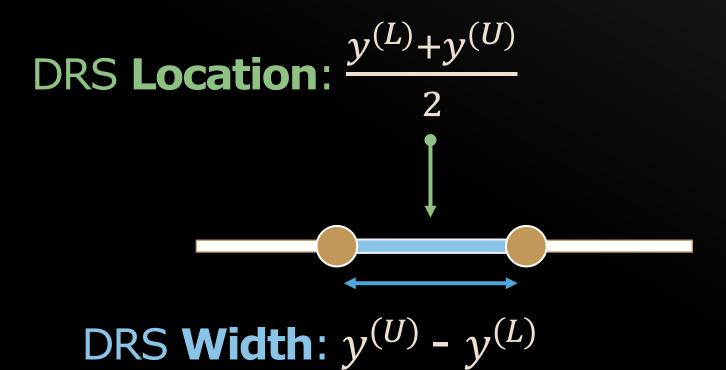
When **ONE** Response Value is **NOT** Enough

"What percentage of your daily work time did you spend on preparing for IMPS 2024 in the last week?"

Dual-range slider (DRS)

Dual-range slider (DRS)





#### Variability / plausible range:

Self-ratings, stimuli

#### **Uncertainty** / expertise:

Estimation (e.g, forecasting)

#### **Ambiguity:**

- Item content unclear
- No clear-cut true answer (e.g., verbal quantifiers like "seldom" or "likely")

#### TOPICS OF THE TALK

What is an appropriate link function for interval responses?

Smithson & Broomell (2024)

Application: consensus model

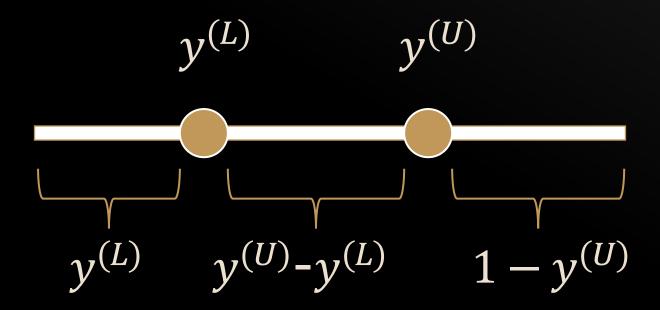
Kloft et al. (2024, in preparation)

## A LINK FUNCTION FOR INTERVAL RESPONSES

Smithson & Broomell (2024)

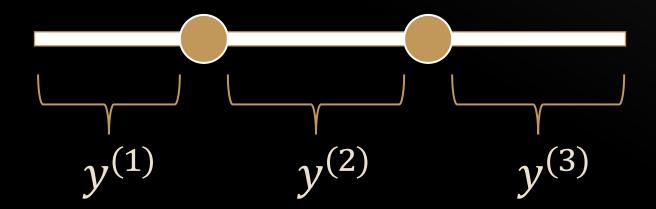
#### COMPOSITIONAL DATA

Components must sum to one: simplex



#### COMPOSITIONAL DATA

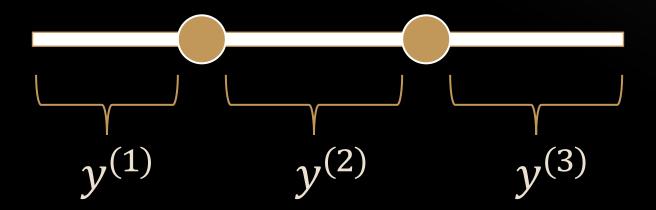
Components must sum to one: simplex



#### LOG-RATIOS

Unbounded **Location**: 
$$\log \left( \frac{y^{(1)}}{y^{(3)}} \right)$$

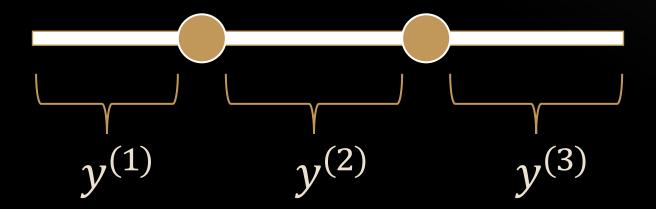
Compares outer components



#### LOG-RATIOS

Unbounded Width: 
$$\log \left( \frac{y^{(2)}}{\sqrt{y^{(1)} \times y^{(3)}}} \right)$$

Compares interval width to geometric mean of outer components



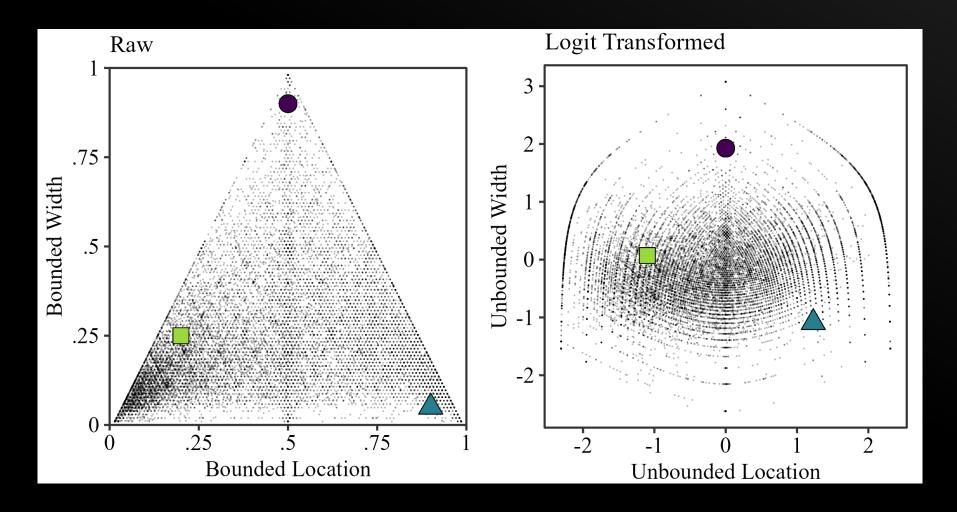
#### ISOMETRIC LOG-RATIO TRANSFORMATION

Smithson & Broomel (2024)

$$\mathbf{z} = \begin{pmatrix} z^{loc} \\ z^{wid} \end{pmatrix} = \begin{pmatrix} \sqrt{\frac{1}{2}} \log \left( \frac{y^{(1)}}{y^{(3)}} \right) \\ \sqrt{\frac{2}{3}} \log \left( \frac{y^{(2)}}{\sqrt{y^{(1)} \times y^{(3)}}} \right) \end{pmatrix}$$

#### DATA EXAMPLE

#### More suitable for models using a normal distribution



# APPLICATION: CONSENSUS MODEL

Kloft et al. (2024, in preparation)

## APPLICATIONS OF THE ISOMETRIC LOG-RATIO TRANSFORMATION

### Could just use transformed interval locations **or** widths

- Descriptive statistics
- Factor Analyses (Kloft & Heck, 2024)
  - Better model fit compared to untransformed intervals

#### Consensus Model

Joint model for location and width

#### INTERVAL TRUTH MODEL: OVERVIEW

- Extension of a univarite logit-normal model (Anders et al., 2014)
- ➤ Bivariate logit-normal model
  - Link function: isometric log-ratio

- Empirical applications:
  - Weighted aggregate of interval judgments
  - True value is an interval
  - Example: verbal quantifiers ("seldom", "often", "likely")

#### ASSUMPTIONS & PREREQUISITES

 Respondent makes a latent appraisal of the true consensus interval for a group

Variance in the expertise level

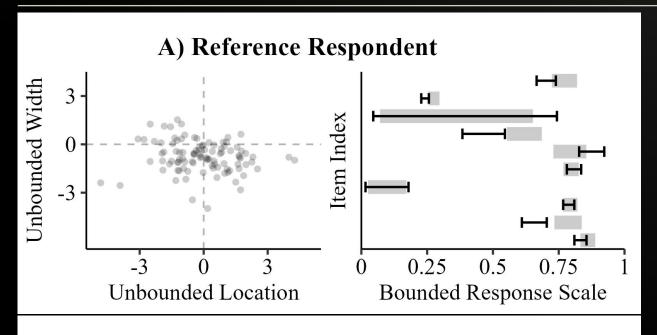
Multiple judgments per respondent

- Expertise can be used to weight judgments in the aggregation of responses
  - Joint estimation of expertise and latent consensus

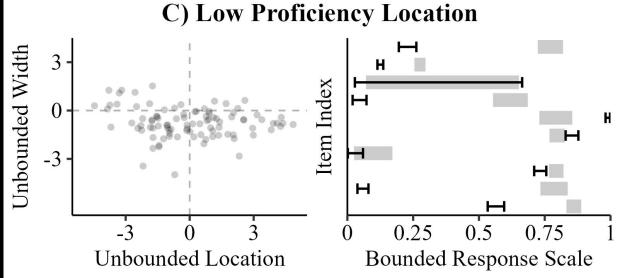
 Latent appraisal of the latent consensus plus some error

- Precision based on:
  - Proficiency of the respondent
  - Discernibility of the item

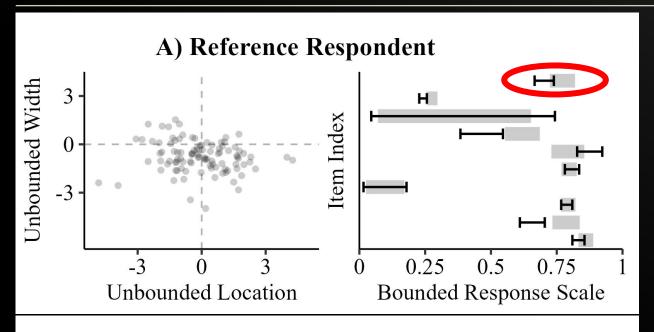
- Bivariate normal distribution for appraisals
  - 2D: location and width
  - Expected value: latent consensus



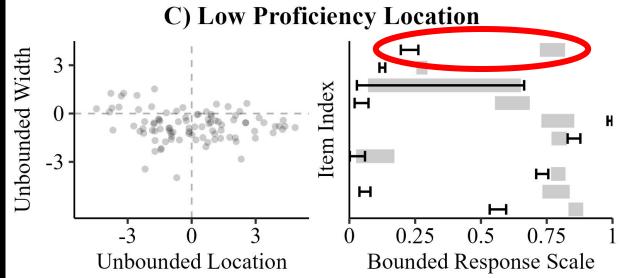
High proficiency, location



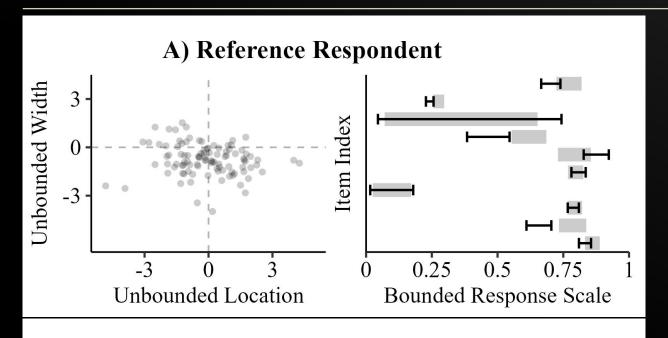
Low proficiency, location



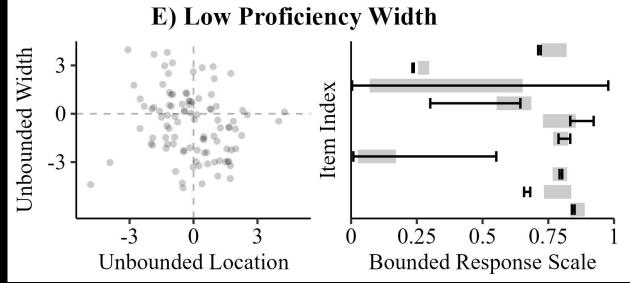
High proficiency, location



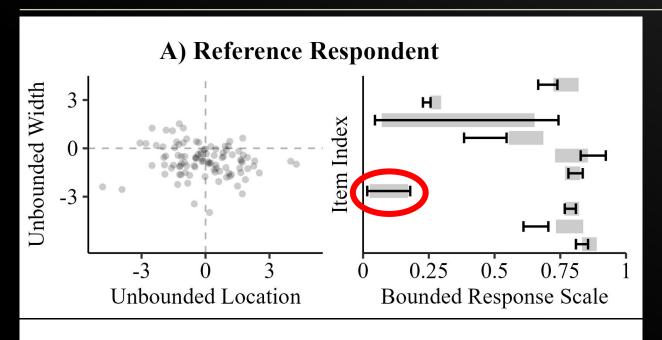
Low proficiency, location



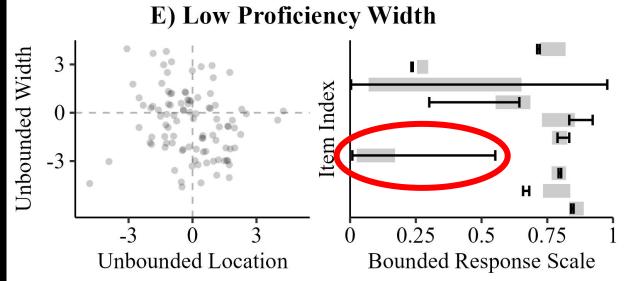
High proficiency, width



Low proficiency, width

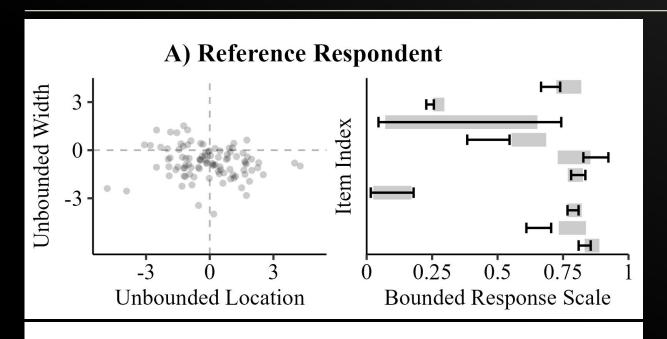


High proficiency, width

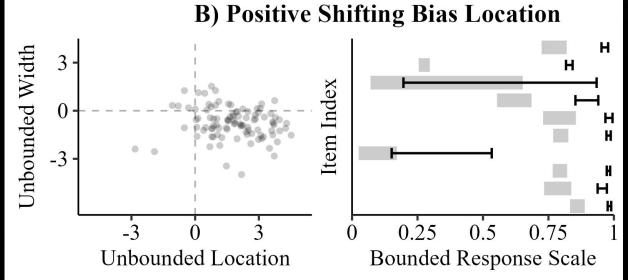


Low proficiency, width

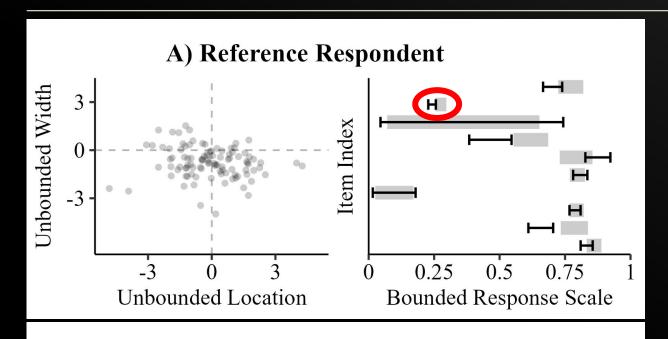
- Latent appraisal is scaled and shifted by respondent's biases
  - Affect all responses of a particular respondent
- Shifting Biases
  - Interval locations shift to the left/right on the response scale
  - Interval widths get wider/narrower
- Scaling Bias (extremity bias):
  - Pushes/pulls the location outwards/inwards with respect to the response scale's center



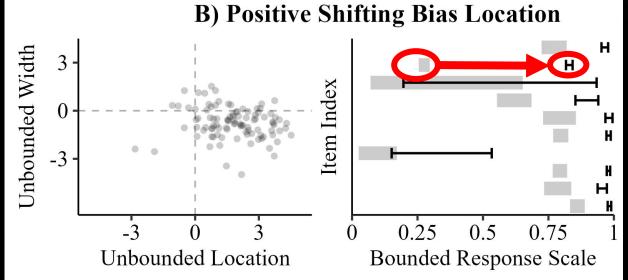
No biases



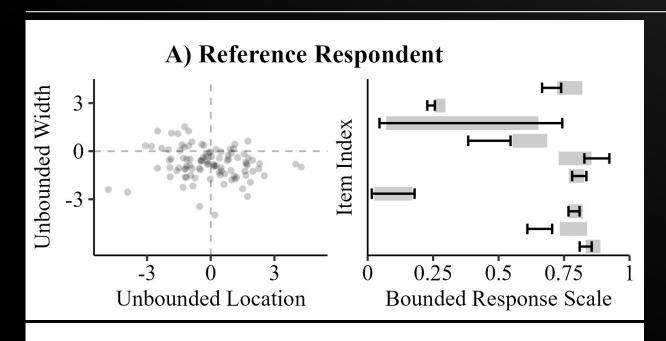
Positive
location
shifting
bias



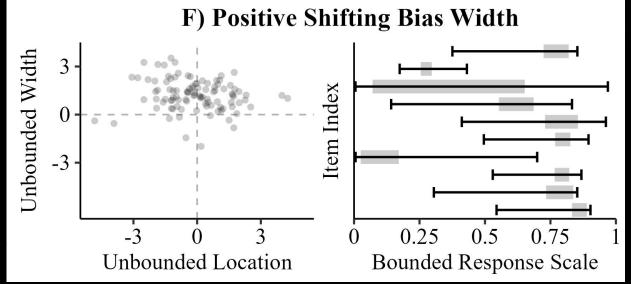
No biases



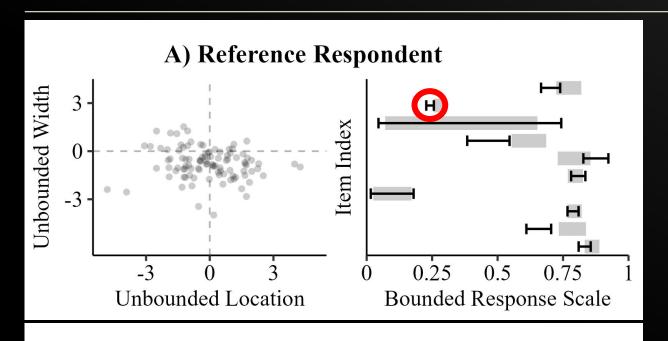
Positive
location
shifting
bias



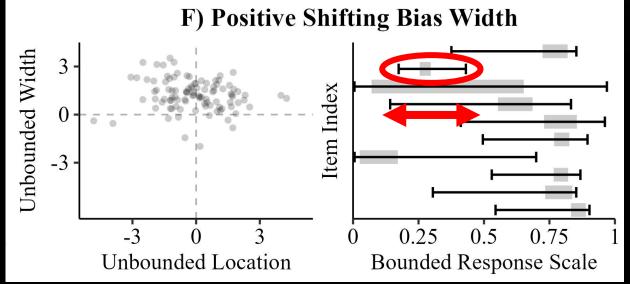
No biases



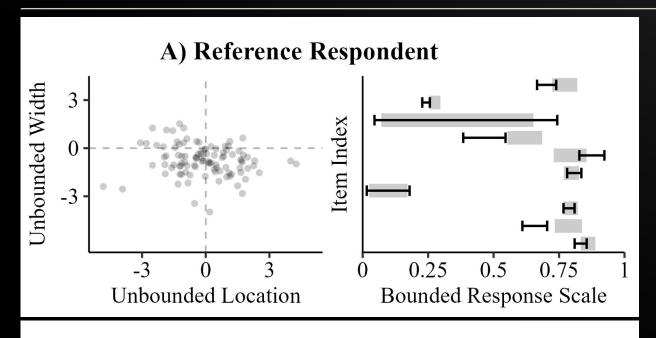
Positive width shifting bias



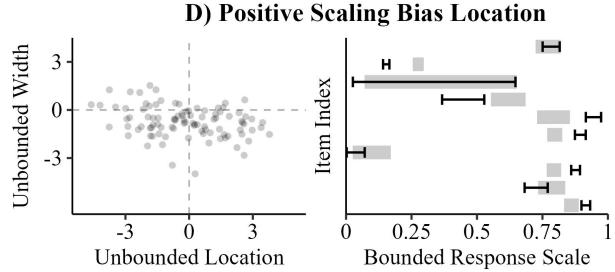
No biases



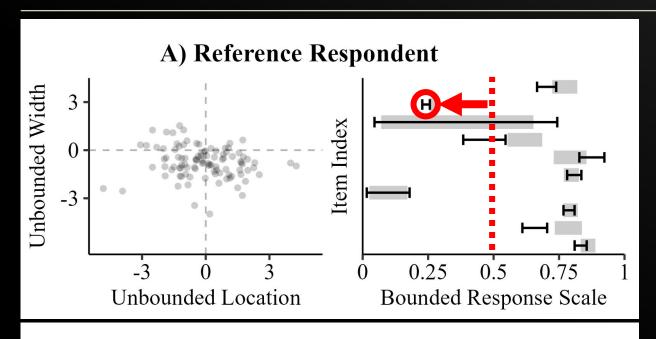
Positive width shifting bias



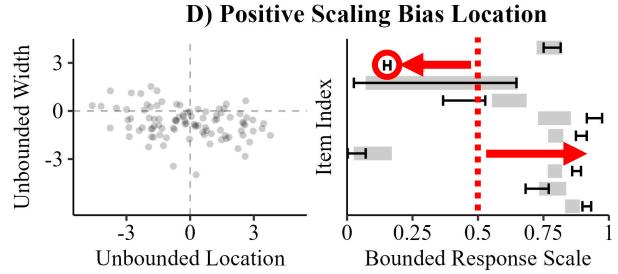
No biases



Positive
location
scaling
bias



No biases

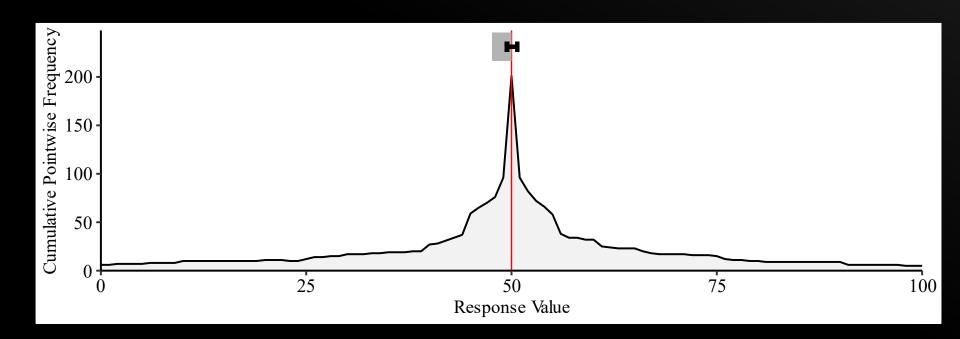


Positive
location
scaling
bias

#### EMPRICAL EXAMPLE: VERBAL QUANTIFIERS

#### "50-50 Chance"

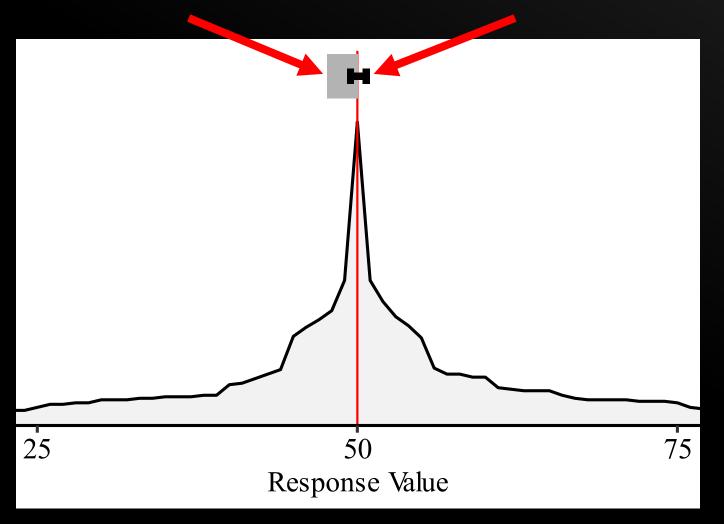
- Control Item in the study
- Should be centered on x = 50 and narrow



#### Emprical Example: Verba Quantifiers

Mean of logit-transformed location and width

Estimated consensus interval



#### TAKE-HOME POINTS

 Isometric log-ratio transformation makes interval responses more suitable for modeling frameworks using normal distributions

 We can adapt existing models to interval reponses by using the isometric log-ratio transformation as a link function

#### THANKS TO:



Prof. Dr. Daniel W. Heck



Björn Siepe

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Slides:

https://github.com/matthiaskloft/

#### REFERENCES

- Anders, R., Oravecz, Z., & Batchelder, W. H. (2014). Cultural consensus theory for continuous responses: A latent appraisal model for information pooling. *Journal of Mathematical Psychology*, 61, 1–13. <a href="https://doi.org/10.1016/j.jmp.2014.06.001">https://doi.org/10.1016/j.jmp.2014.06.001</a>
- Kloft, M., & Heck, D. W. (2024). Discriminant validity of interval response formats: Investigating the dimensional structure of interval widths. PsyArXiv. https://doi.org/10.31234/osf.io/esvxk
- **Kloft, M.**, Siepe, B.S., & Heck, D.W. (2024). The interval truth model: A consensus model for continuous bounded interval responses [Manuscript in preparation]. Department of Psychology, University of Marburg
- Smithson, M., & Broomell, S. B. (2024). Compositional data analysis tutorial: Psychological Methods. *Psychological Methods*, *29* (2), 362–378. https://doi.org/10.1037/met0000464

#### ADDITIONAL SLIDES

Model Equations

Bivariate logit-normal model:

ILR(
$$\mathbf{y}_{ij}$$
)~ $BVN(\boldsymbol{\mu}_{ij}, \boldsymbol{\Sigma}_{ij})$ 

### Latent Appraisal

$$\begin{pmatrix} A_{ij}^{loc} \\ A_{ij}^{wid} \end{pmatrix} = \begin{pmatrix} T_{j}^{loc} \\ T_{j}^{wid} \end{pmatrix} + \begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix}$$

$$\begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix} \sim BVN \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{\Sigma}_{ij} \end{pmatrix}$$

### Latent Appraisal

$$\begin{pmatrix} A_{ij}^{loc} \\ A_{ij}^{wid} \end{pmatrix} = \begin{pmatrix} T_{j}^{loc} \\ T_{j}^{wid} \end{pmatrix} + \begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix}$$

$$\begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix} \sim BVN \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{\Sigma}_{ij} \end{pmatrix}$$

#### Latent True Consensus

$$\begin{pmatrix} A_{ij}^{loc} \\ A_{ij}^{wid} \end{pmatrix} = \begin{pmatrix} T_j^{loc} \\ T_j^{wid} \end{pmatrix} + \begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix}$$

$$\begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix} \sim BVN \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{\Sigma}_{ij} \end{pmatrix}$$

### Error / Precision of appraisal

$$egin{pmatrix} A_{ij}^{
m loc} \ A_{ij}^{
m wid} \end{pmatrix} = egin{pmatrix} T_{
m j}^{
m loc} \ T_{
m j}^{
m wid} \end{pmatrix} + egin{pmatrix} \epsilon_{ij}^{
m loc} \ \epsilon_{ij}^{
m wid} \end{pmatrix}$$

$$\begin{pmatrix} \epsilon_{ij}^{loc} \\ \epsilon_{ij}^{wid} \end{pmatrix} \sim BVN \begin{pmatrix} 0 \\ 0 \end{pmatrix}, \mathbf{\Sigma}_{ij} \end{pmatrix}$$

### Error / Precision of appraisal

$$\mathbf{\Sigma}_{ij} = \begin{pmatrix} \left(\frac{1}{E_i^{loc}} \frac{1}{\lambda_j^{loc}}\right)^2 & \rho_{ij} \\ \rho_{ij} & \left(\frac{1}{E_i^{wid}} \frac{1}{\lambda_j^{wid}}\right)^2 \end{pmatrix}$$

$$\rho_{ij} = \sqrt{\omega_j \left(\frac{1}{E_i^{loc}} \frac{1}{\lambda_j^{loc}}\right)^2 \left(\frac{1}{E_i^{wid}} \frac{1}{\lambda_j^{wid}}\right)^2}$$

#### Person proficiency to detect consensus

$$oldsymbol{\Sigma}_{ij} = egin{pmatrix} \left( rac{1}{E_i^{loc}} rac{1}{\lambda_j^{loc}} 
ight)^2 & 
ho_{ij} \ 
ho_{ij} & \left( rac{1}{E_i^{wid}} rac{1}{\lambda_j^{wid}} 
ight)^2 \end{pmatrix}$$

$$\rho_{ij} = \sqrt{\omega_j \left(\frac{1}{E_i^{loc}} \frac{1}{\lambda_j^{loc}}\right)^2 \left(\frac{1}{E_i^{wid}} \frac{1}{\lambda_j^{wid}}\right)^2}$$

### Item discernibility/difficulty

$$oldsymbol{\Sigma}_{ij} = egin{pmatrix} \left( rac{1}{E_i^{loc}} rac{1}{\lambda_j^{loc}} 
ight)^2 & 
ho_{ij} \ 
ho_{ij} & \left( rac{1}{E_i^{wid}} rac{1}{\lambda_j^{wid}} 
ight)^2 \end{pmatrix}$$

$$\rho_{ij} = \sqrt{\omega_j \left(\frac{1}{E_i^{loc}} \frac{1}{\lambda_j^{loc}}\right)^2 \left(\frac{1}{E_i^{wid}} \frac{1}{\lambda_j^{wid}}\right)^2}$$

#### Residual correlation between location and width

$$oldsymbol{\Sigma}_{ij} = egin{pmatrix} \left( rac{1}{E_i^{loc}} rac{1}{\lambda_j^{loc}} 
ight)^2 & 
ho_{ij} \ 
ho_{ij} & \left( rac{1}{E_i^{wid}} rac{1}{\lambda_j^{wid}} 
ight)^2 \end{pmatrix}$$

$$\rho_{ij} = \sqrt{\omega_j \left(\frac{1}{E_i^{loc}} \frac{1}{\lambda_j^{loc}}\right)^2 \left(\frac{1}{E_i^{wid}} \frac{1}{\lambda_j^{wid}}\right)^2}$$

A respondent's biases shift and scale the latent appraisal

$$ILR(\mathbf{y}_{ij}) = \left(A_{ij}^{loc}a_i^{loc} + b_i^{loc}, A_{ij}^{wid} + b_i^{wid}\right)^{\top}$$

## Shifting biases

$$ILR(\mathbf{y}_{ij}) = \left(A_{ij}^{loc}a_i^{loc} + b_i^{loc}, A_{ij}^{wid} + b_i^{wid}\right)^{T}$$

## Scaling bias

$$ILR(\mathbf{y}_{ij}) = \left(A_{ij}^{loc}a_i^{loc} + b_i^{loc}, A_{ij}^{wid} + b_i^{wid}\right)^{\top}$$