

A DIRICHLET MODEL FOR INTERVAL RESPONSES

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International Meeting of the Psychometric Society 2022

1 - INTRODUCTION

„I like being around other people“

WHY USE INTERVAL RESPONSES?

Motivating Example:

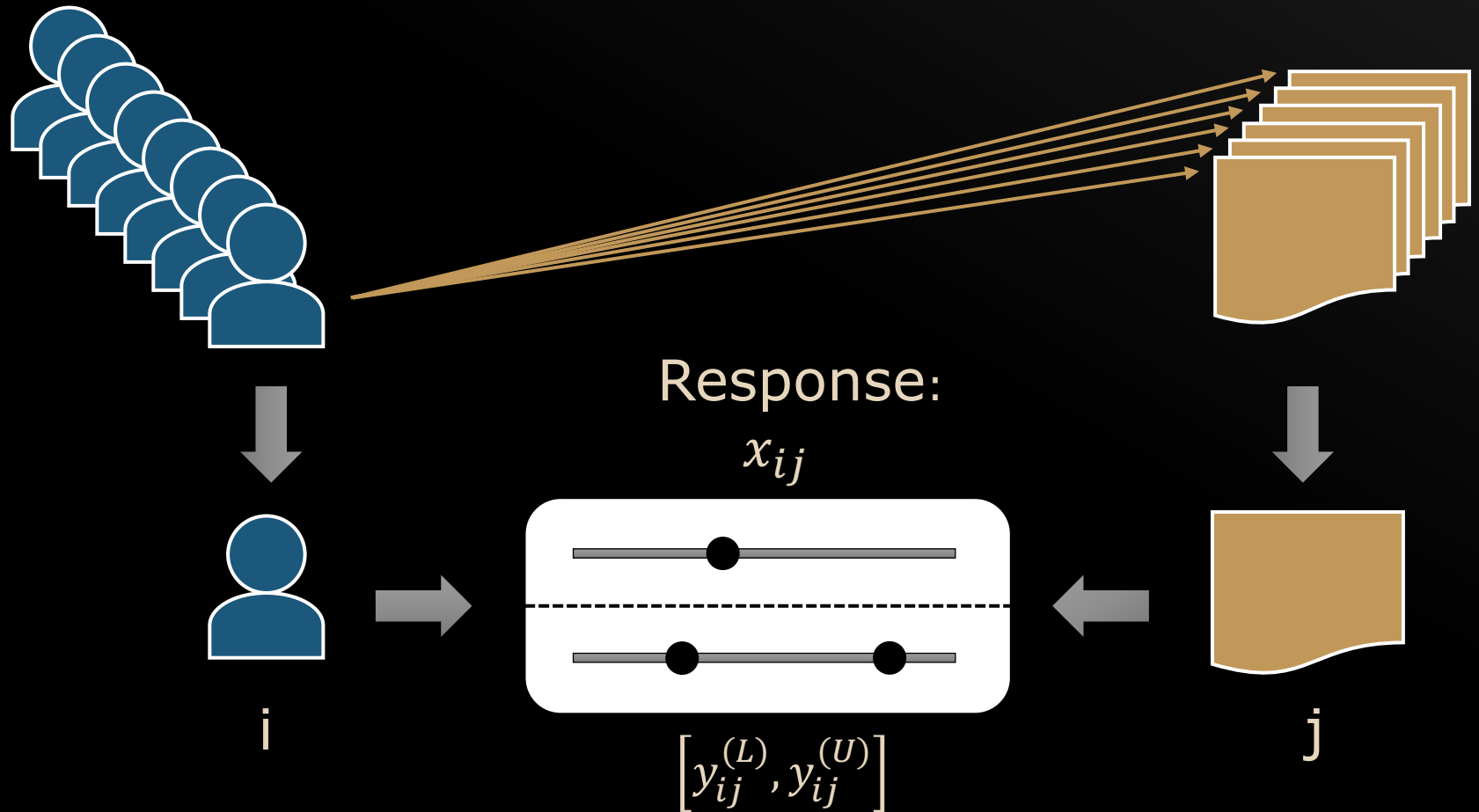
- Whole Trait Theory (Fleeson, 2001)
 - Trait: Distribution of states
- Accounting for variability
- Range of valid values

2 – IRT MODELS

TESTING SCENARIO

Respondents: 1 ... I

Items: 1 ... J

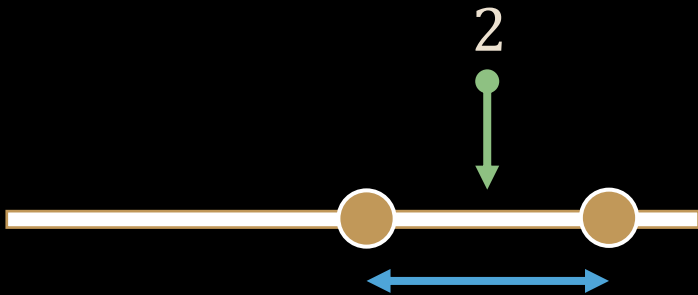


INTERVAL RESPONSE

Manifest Response:

Interval Location
(Midpoint):

$$\frac{y_{ij}^{(L)} + y_{ij}^{(U)}}{2}$$



Interval Width: $y_{ij}^{(U)} - y_{ij}^{(L)}$

INTERVAL RESPONSE

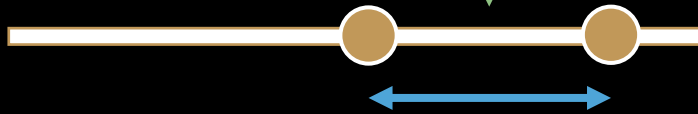
Manifest Response:

Latent Space:

Interval Location
(Midpoint):

$$\frac{y_{ij}^{(L)} + y_{ij}^{(U)}}{2}$$

Location
Dimension

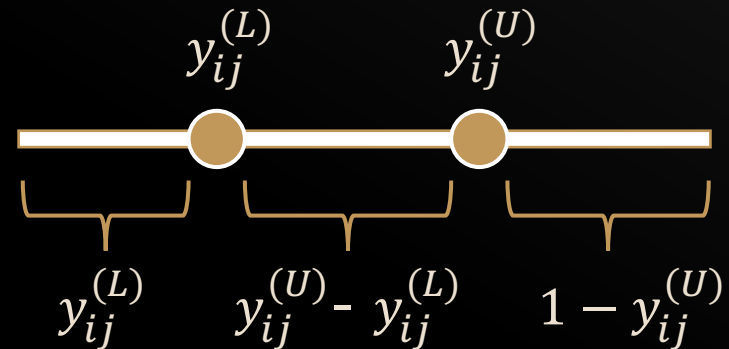
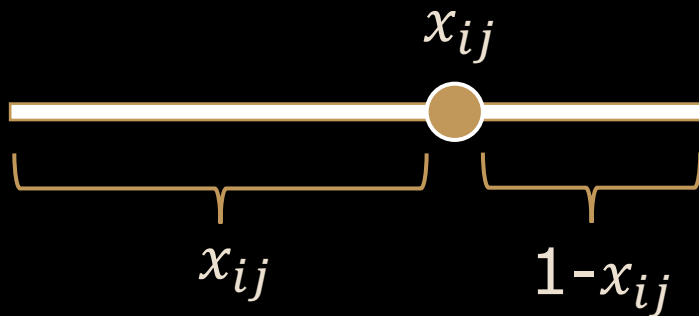


Interval Width: $y_{ij}^{(U)} - y_{ij}^{(L)}$

Expansion
Dimension

COMPOSITIONAL DATA

- Components must sum to one: simplex



RESTRICTIONS

No support for zero-components

➤ Single Response:

$$0 < x_{ij} < 1$$

➤ Interval Response:

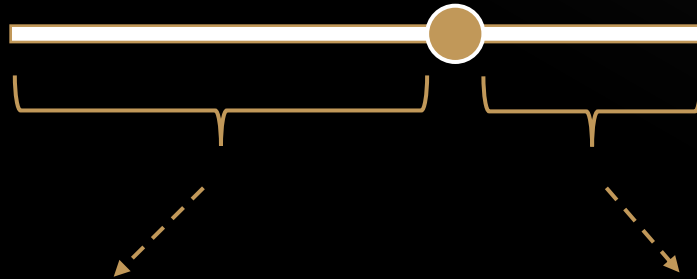
$$0 < y_{ij}^{(L)} < y_{ij}^{(U)} < 1$$

BETA RESPONSE MODEL (BRM)

Noel & Dauvier (2007)

$$x_{ij} \sim \text{Beta}(a_{ij}, d_{ij});$$

$$E(x_{ij}) = \frac{a_{ij}}{a_{ij} + d_{ij}}$$




$$a_{ij} = \exp[\alpha(\theta_i - \delta_j) + \tau_j]$$

$$d_{ij} = \exp[-\alpha(\theta_i - \delta_j) + \tau_j]$$

BETA RESPONSE MODEL (BRM)

Parameters: Ability / Difficulty



The diagram illustrates the Beta Response Model (BRM) with a horizontal line and a central point. Below the line, two brackets are shown, one on the left and one on the right, with dashed arrows pointing to the equations for a_{ij} and d_{ij} respectively.

$$a_{ij} = \exp\left[\alpha(\underbrace{\theta_i - \delta_j}) + \tau_j\right] \quad d_{ij} = \exp\left[-\alpha(\underbrace{\theta_i - \delta_j}) + \tau_j\right]$$


θ_i : Person ability

δ_j : Item difficulty

➤ Classic interpretation

BETA RESPONSE MODEL (BRM)

Parameters: Scaling

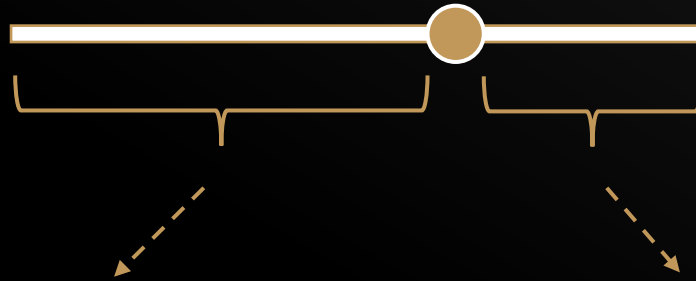

$$a_{ij} = \exp[\underbrace{\alpha(\theta_i - \delta_j)}_{\text{Scaling}} + \tau_j] \quad d_{ij} = \exp[\underbrace{-\alpha(\theta_i - \delta_j)}_{\text{Scaling}} + \tau_j]$$

$\pm\alpha > 0$: Scaling

- Continuous model:
Not a discrimination parameter!!

BETA RESPONSE MODEL (BRM)

Parameters: Precision



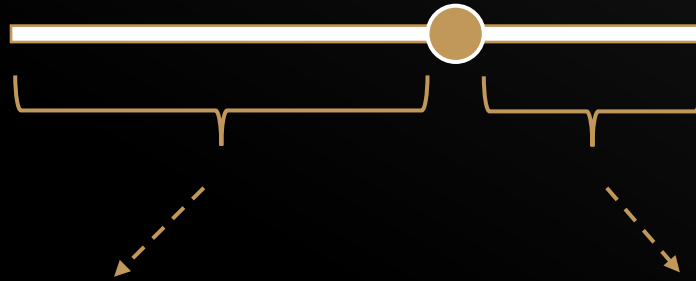
$$a_{ij} = \exp[\alpha(\theta_i - \delta_j) + \underbrace{\tau_j}] \quad d_{ij} = \exp[-\alpha(\theta_i - \delta_j) + \underbrace{\tau_j}]$$

$\tau_j > 0$: Item precision (both additive!)

➤ Steeper density curves

BETA RESPONSE MODEL (BRM)

Parameters: Exponential Link



$$a_{ij} = \exp[\underbrace{\alpha(\theta_i - \delta_j)} + \tau_j]$$

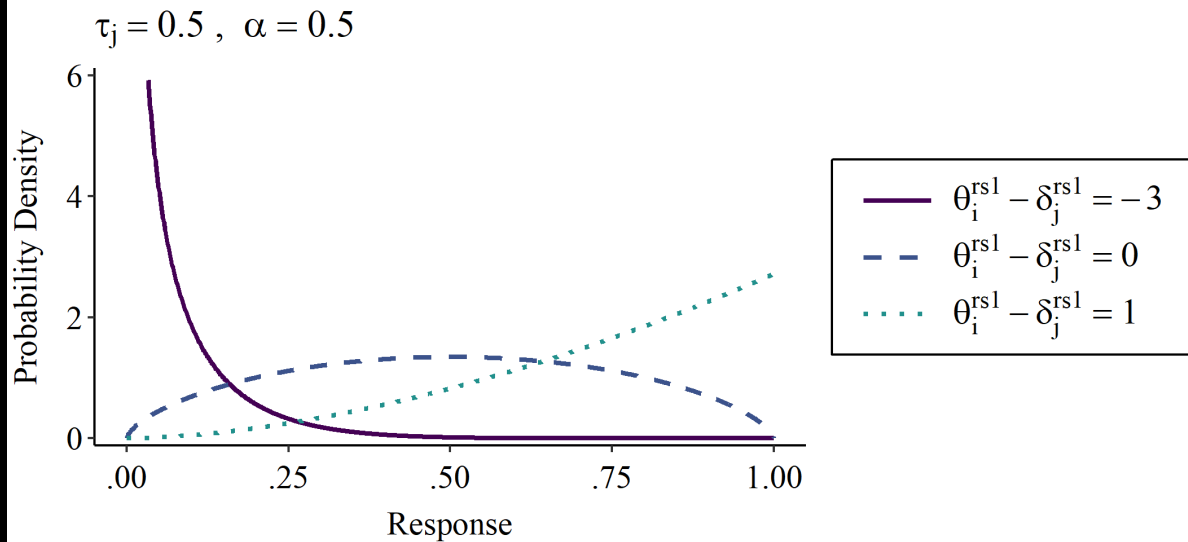
$$d_{ij} = \exp[\underbrace{-\alpha(\theta_i - \delta_j)} + \tau_j]$$

Example:

- $\theta_i - \delta_j = 0; \quad \tau_j = 0$
- $\exp(0) = 1$
- Beta(1, 1): uniform

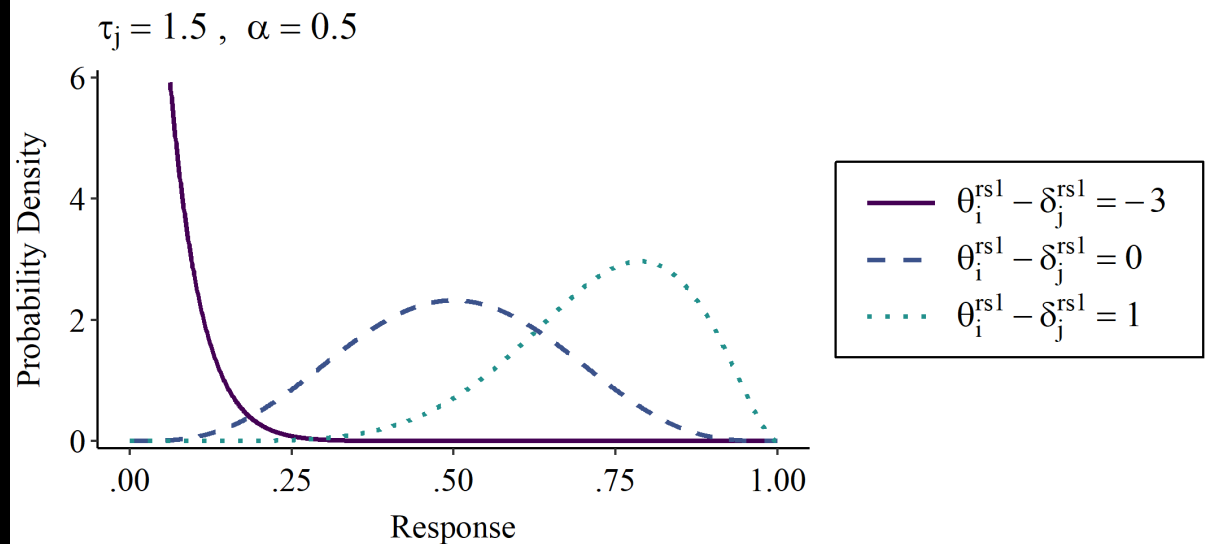
BRM: EXAMPLES

A



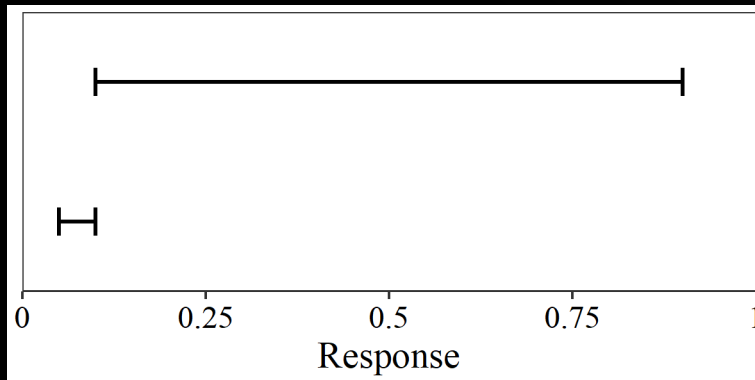
$$\tau_j = 0.5$$

B

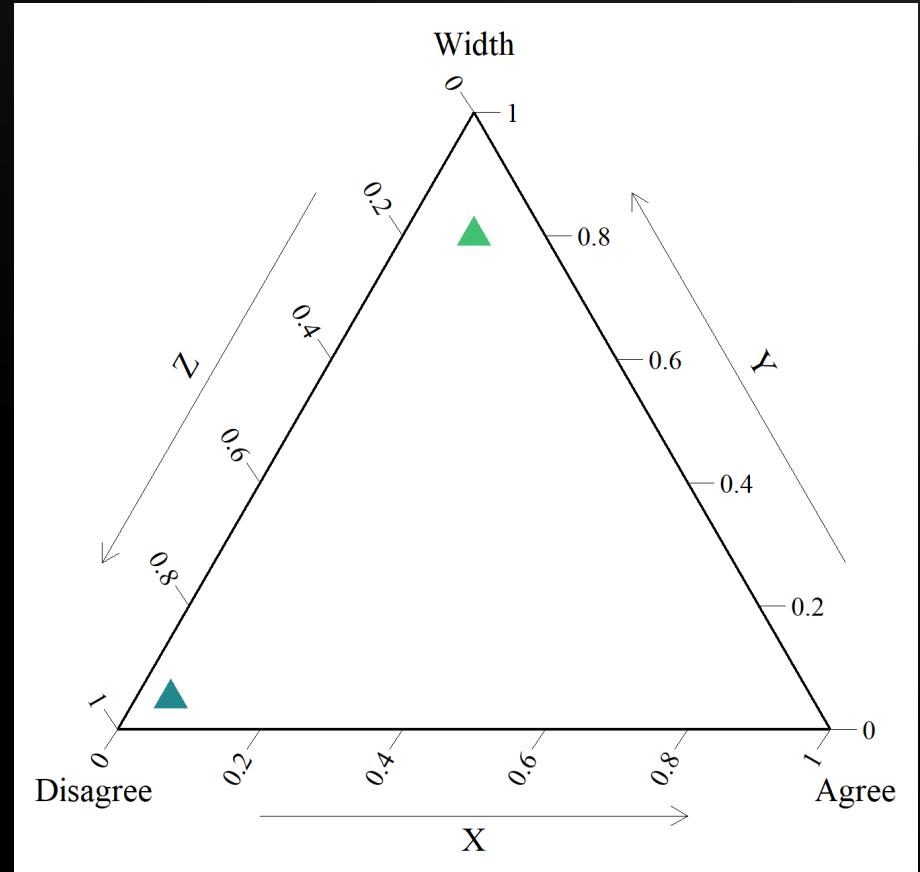


$$\tau_j = 1.5$$

RESPONSE INTERVALS - TERNARY SPACE

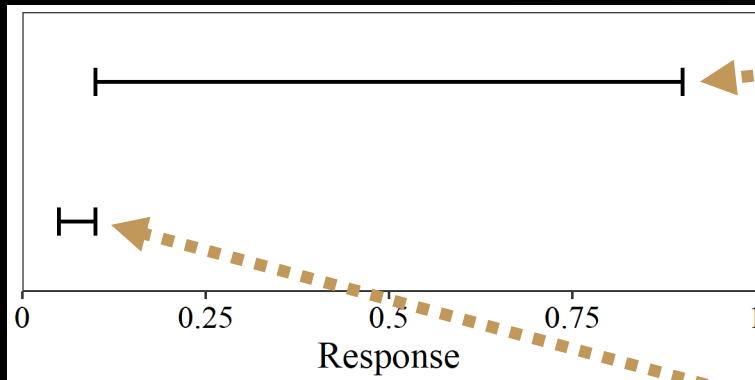


Response intervals

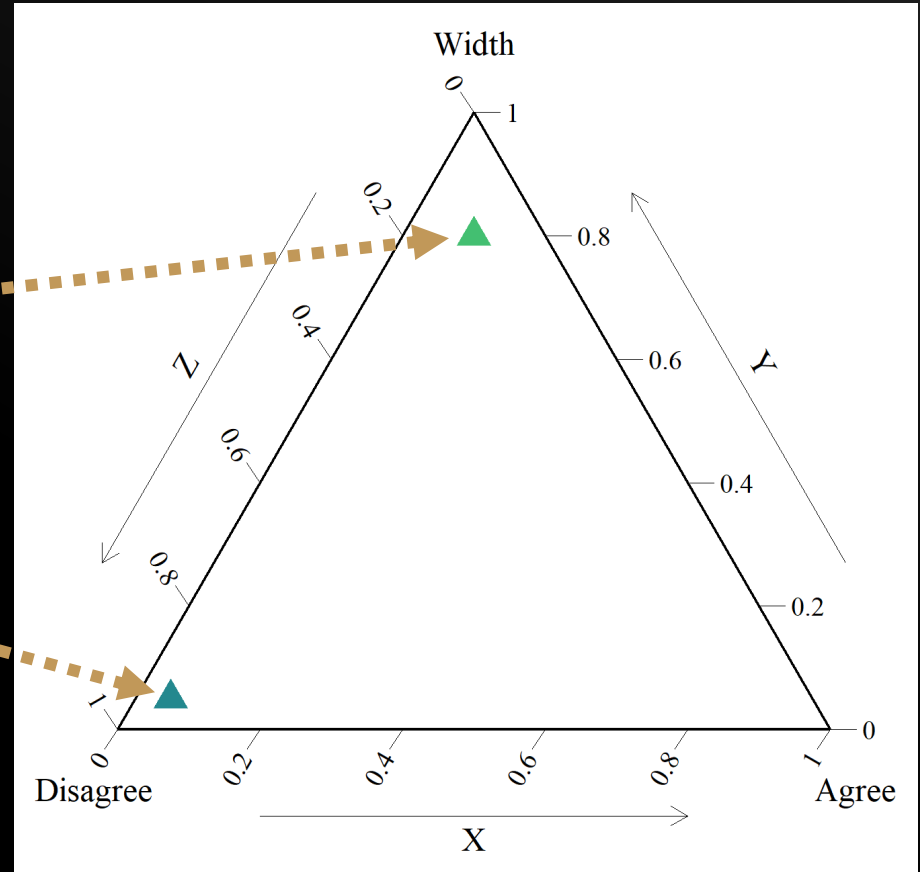


Location in ternary space

RESPONSE INTERVALS - TERNARY SPACE



Response intervals

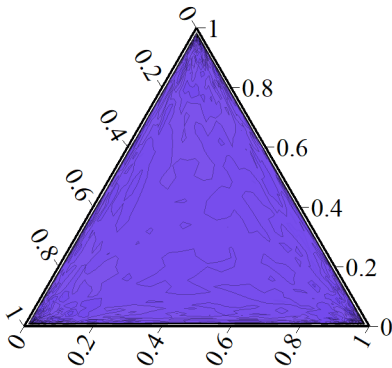


Location in ternary space

DIRICHLET DISTRIBUTION

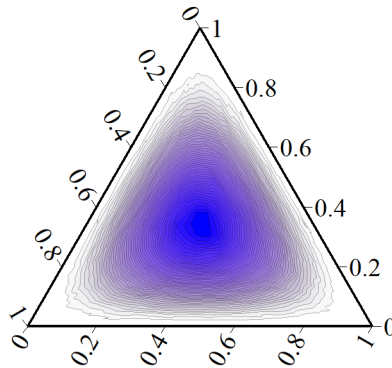
The beta distribution generalizes to the Dirichlet distribution.

A
Dir(1, 1, 1)



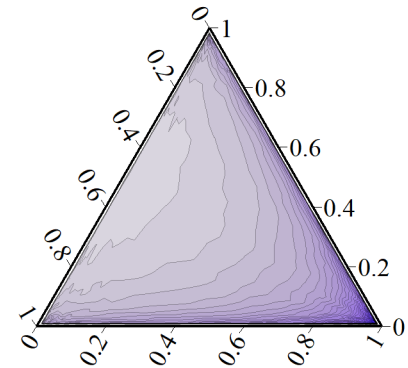
Uniform

B
Dir(3, 3, 3)



Unimodal

C
Dir(1, .7, .7)



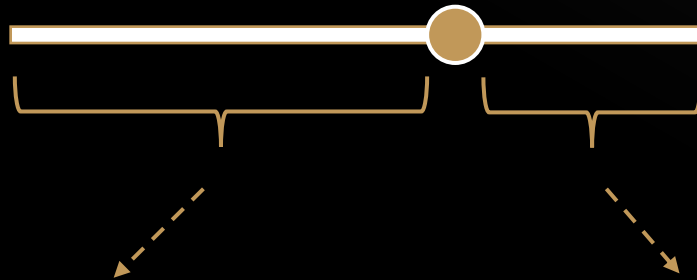
Multimodal

BETA RESPONSE MODEL (BRM)

Noel & Dauvier (2007)

$$x_{ij} \sim \text{Beta}(a_{ij}, d_{ij});$$

$$E(x_{ij}) = \frac{a_{ij}}{a_{ij} + d_{ij}}$$



$$a_{ij} = \exp[\alpha(\theta_i - \delta_j) + \tau_j]$$

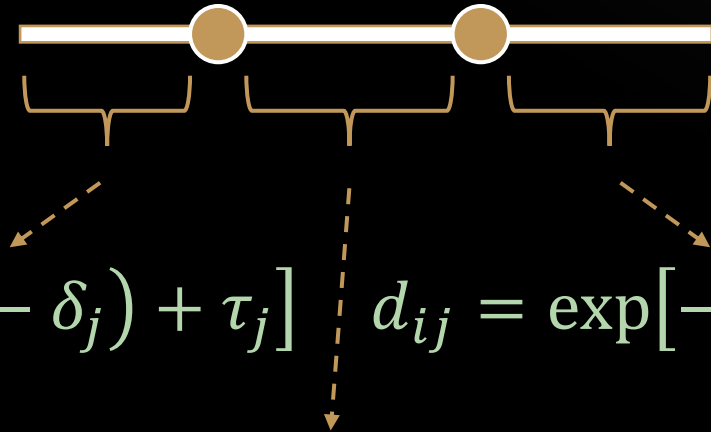
$$d_{ij} = \exp[-\alpha(\theta_i - \delta_j) + \tau_j]$$

DIRICHLET DUAL RESPONSE MODEL (DDRM)

Latent Parameterization

$$\mathbf{y}_{ij} \sim \text{Dirichlet}(a_{ij}, e_{ij}, d_{ij});$$

$$E(\mathbf{y}_{ij}) = \frac{a_{ij}}{a_{ij}+e_{ij}+d_{ij}}, \frac{e_{ij}}{a_{ij}+e_{ij}+d_{ij}}, \frac{d_{ij}}{a_{ij}+e_{ij}+d_{ij}}$$


$$a_{ij} = \exp[\alpha_\lambda(\theta_i - \delta_j) + \tau_j] \quad d_{ij} = \exp[-\alpha_\lambda(\theta_i - \delta_j) + \tau_j]$$
$$e_{ij} = \exp[\alpha_\epsilon(\eta_i + \gamma_j) + \tau_j]$$

DIRICHLET DUAL RESPONSE MODEL (DDRM)

Parameters: Precision



$$a_{ij} = \exp[\alpha_{\lambda}(\theta_i - \delta_j) + \tau_j] \quad d_{ij} = \exp[-\alpha_{\lambda}(\theta_i - \delta_j) + \tau_j]$$

$$e_{ij} = \exp[\alpha_{\epsilon}(\eta_i + \gamma_j) + \tau_j]$$

- Location dimension: equivalent to the BRM
- Expansion dimension: controls the interval width
- Scaling $\alpha_{\lambda}/\alpha_{\epsilon}$ per dimension
- Precision τ_j across both dimensions

DIRICHLET DUAL RESPONSE MODEL (DDRM)

Parameters: Expansion Dimension



$$a_{ij} = \exp[\alpha_\lambda(\theta_i - \delta_j) + \tau_j] \quad d_{ij} = \exp[-\alpha_\lambda(\theta_i - \delta_j) + \tau_j]$$

$$e_{ij} = \exp[\alpha_\epsilon(\underbrace{\eta_i + \gamma_j}_{\text{Expansion}}) + \tau_j]$$

η_i : Person expansion (preference for wider intervals)

γ_j : Item expansion (strength to evoke wider intervals)

➤ Higher values = wider response intervals

DIRICHLET DUAL RESPONSE MODEL (DDRM)

Exponential Link



$$a_{ij} = \exp[\underbrace{\alpha_\lambda(\theta_i - \delta_j)} + \underbrace{\tau_j}] \quad d_{ij} = \exp[\underbrace{-\alpha_\lambda(\theta_i - \delta_j)} + \underbrace{\tau_j}]$$

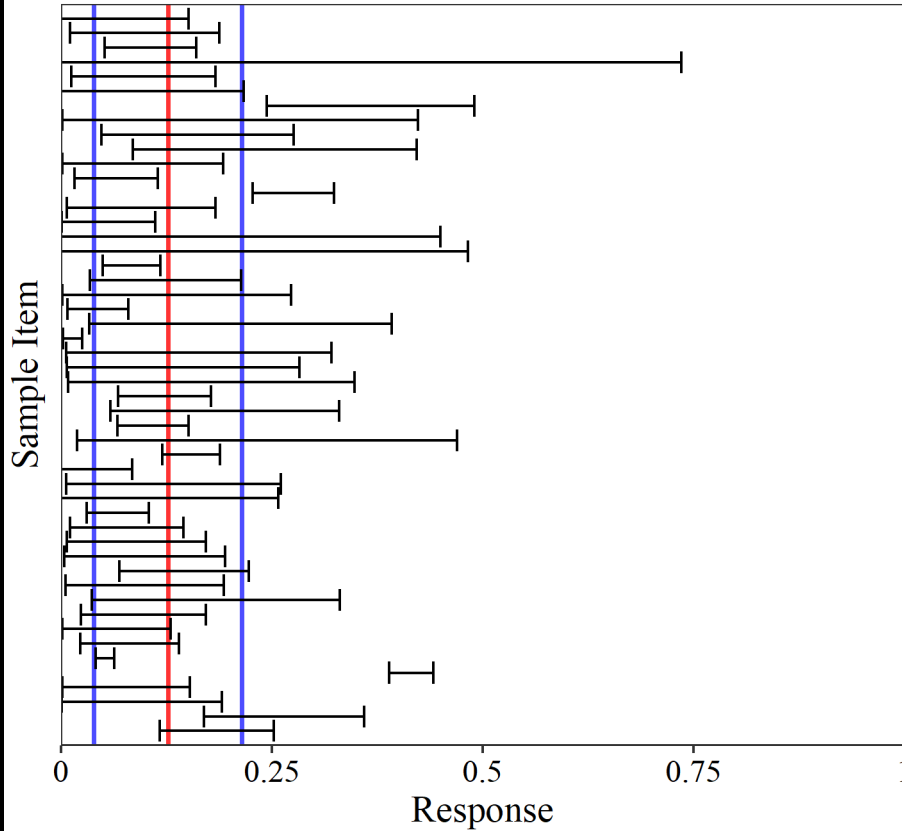
$$e_{ij} = \exp[\underbrace{\alpha_\epsilon(\eta_i + \gamma_j)} + \tau_j]$$

Example:

- $\theta_i - \delta_j = 0; \quad \eta_i + \gamma_j = 0; \quad \tau_j = 0$
- $\exp(0) = 1$
- *Dirichlet*(1,1,1): uniform distribution over the simplex

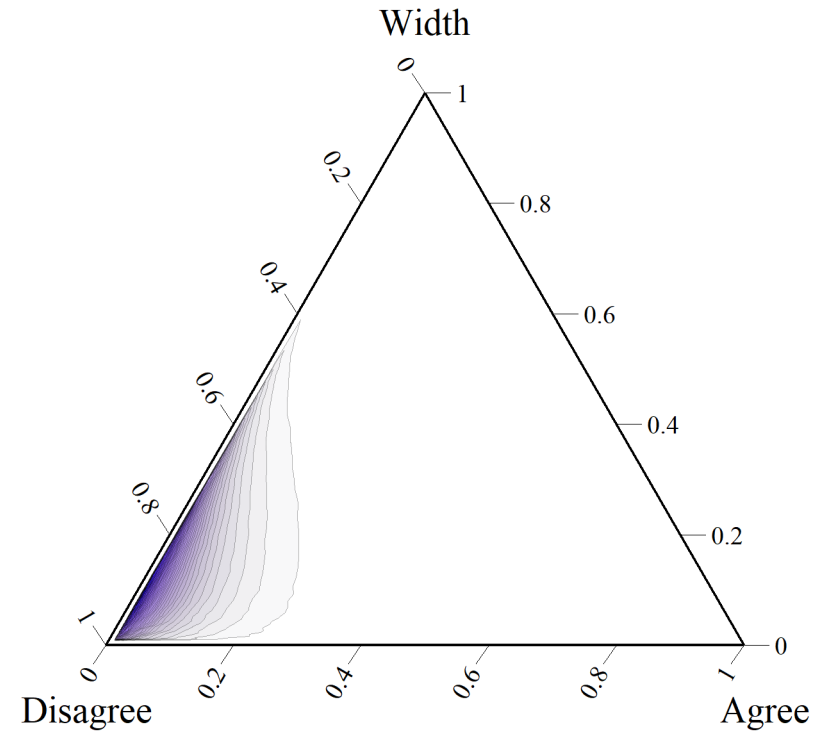
DDRM EXAMPLES

$$\theta_i - \delta_j = -3, \quad \eta_i - \gamma_j = 0, \quad \tau_j = 0.5, \quad \alpha_{\lambda, \varepsilon} = 0.5$$



50 randomly drawn intervals

- Red vertical line: expected interval location (midpoint)
- Blue vertical lines: expected lower and upper bound

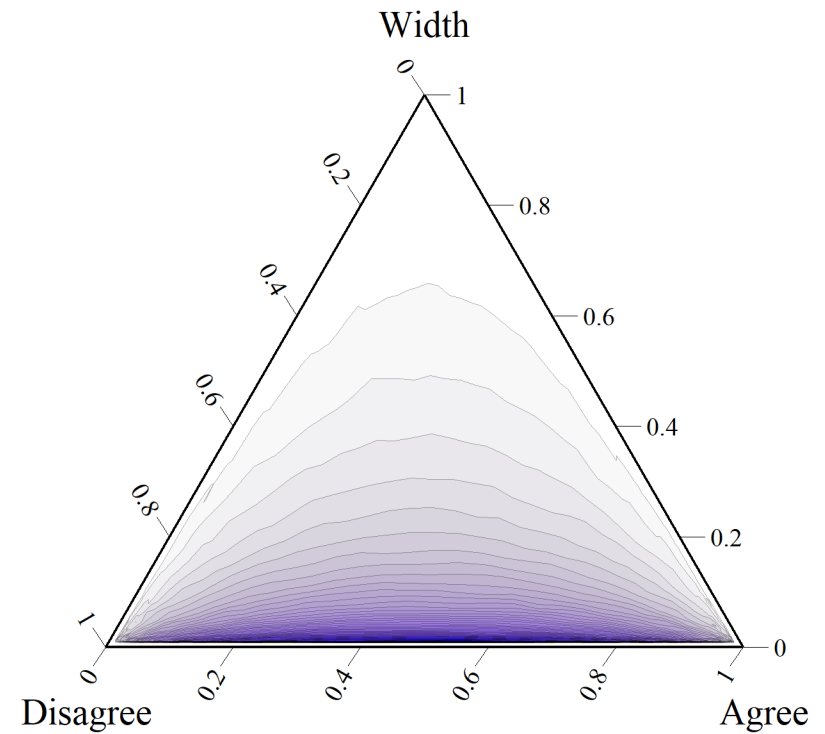
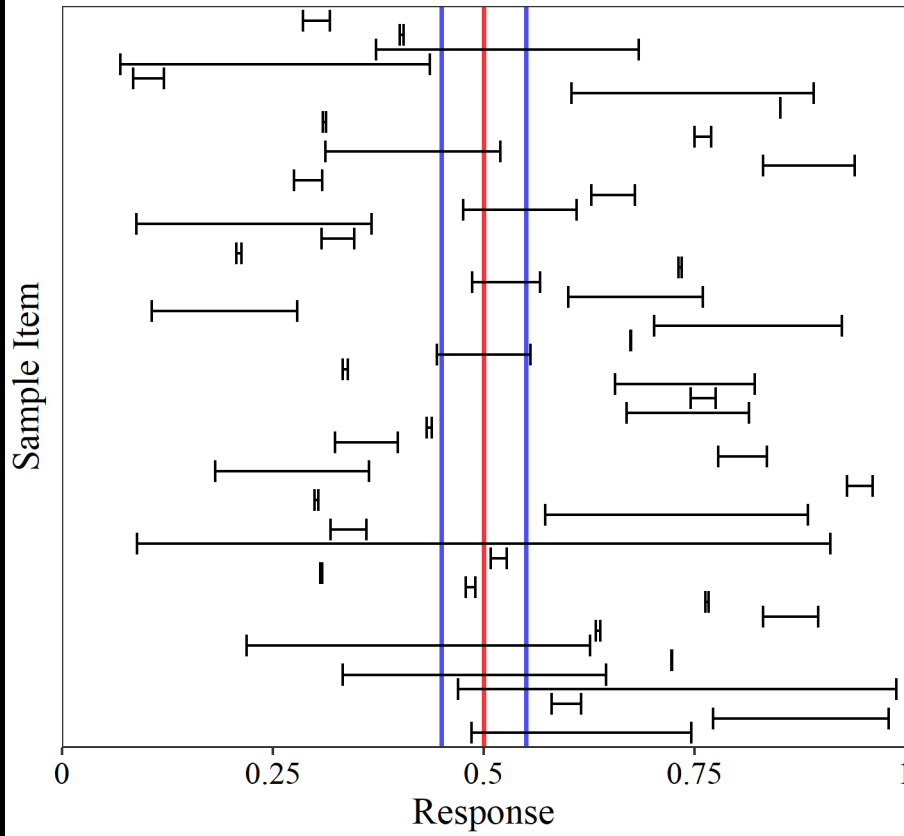


Response distribution density

DDRM EXAMPLES

Comparison: Precision

$$\theta_i - \delta_j = 0, \quad \eta_i - \gamma_j = -3, \quad \tau_j = 0.5, \quad \alpha_{\lambda, \varepsilon} = 0.5$$

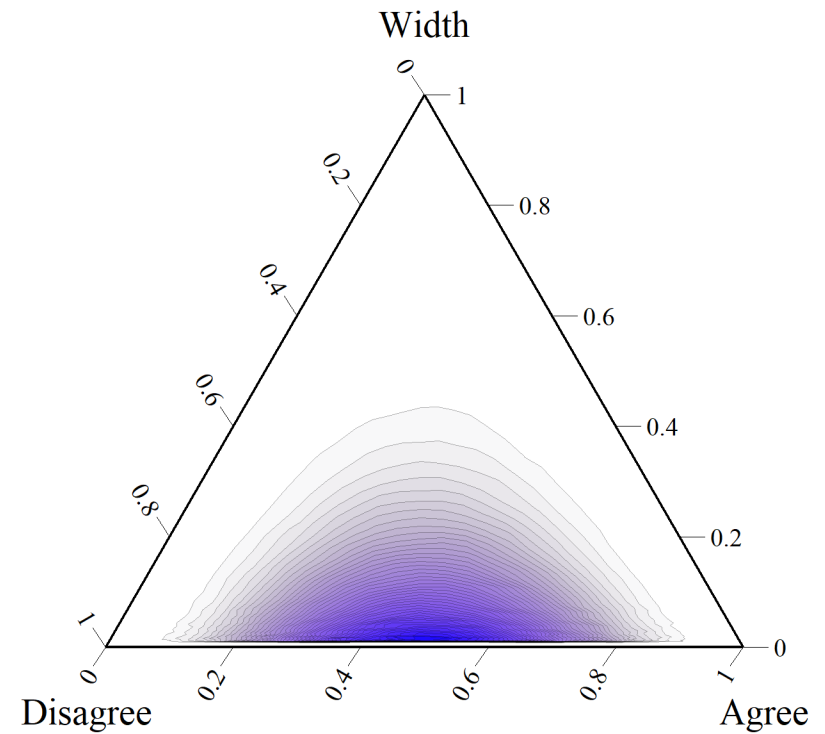
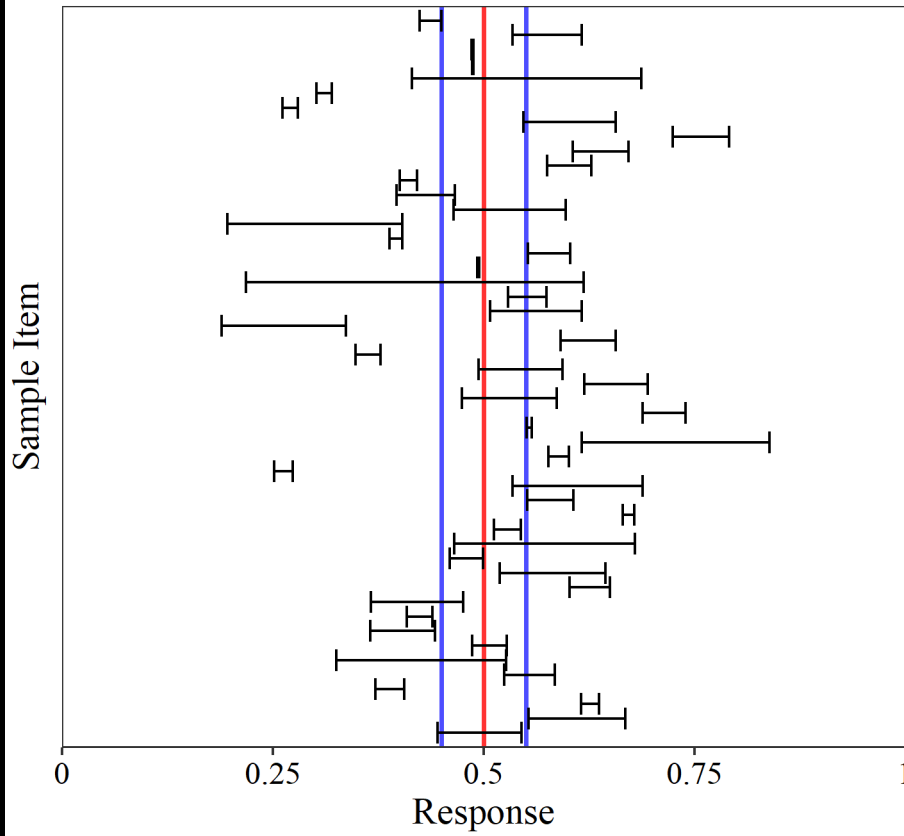


$$\tau_j = 0.5$$

DDRM EXAMPLES

Comparison: Precision

$\theta_i - \delta_j = 0$, $\eta_i - \gamma_j = -3$, $\tau_j = 1.5$, $\alpha_{\lambda, \varepsilon} = 0.5$



$$\tau_j = 1.5$$

3 – EMPIRICAL EXAMPLE

EMPIRICAL EXAMPLE

Methods

Two Extraversion scales:

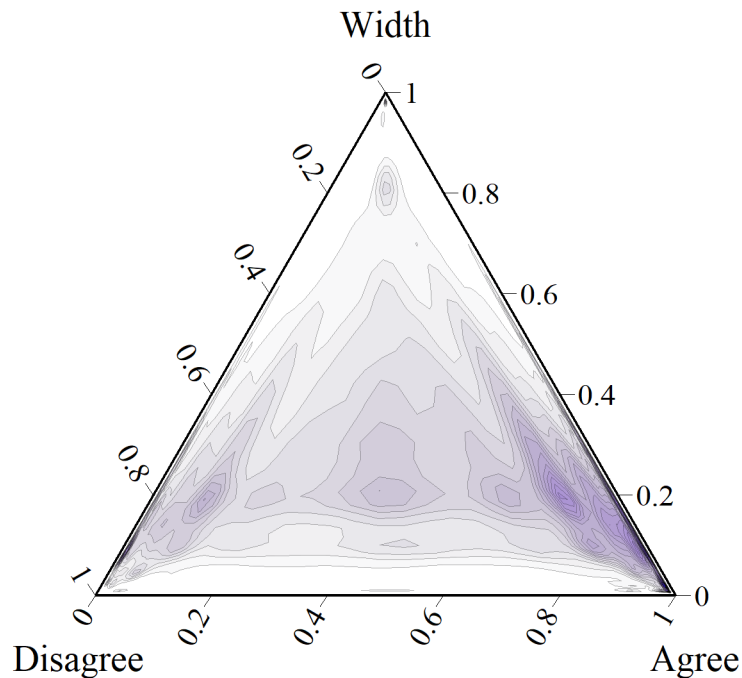
- IPIP: 36 items (Interval Responses)
- BFI-2: 12 items (Single Responses)

Sample: $n = 222$ (f: 140 , m: 80, d: 2)

POSTERIOR PREDICTIVE CHECKS

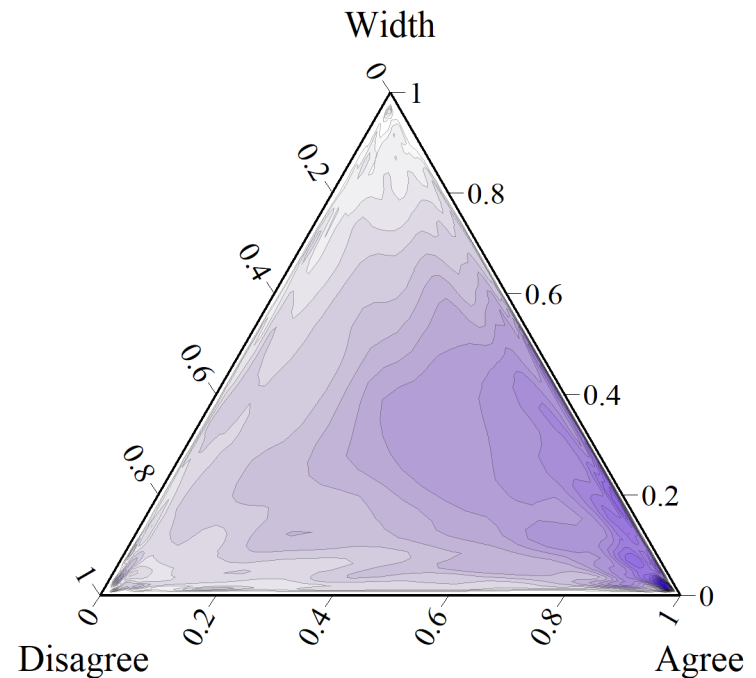
Ternary

A



Empirical

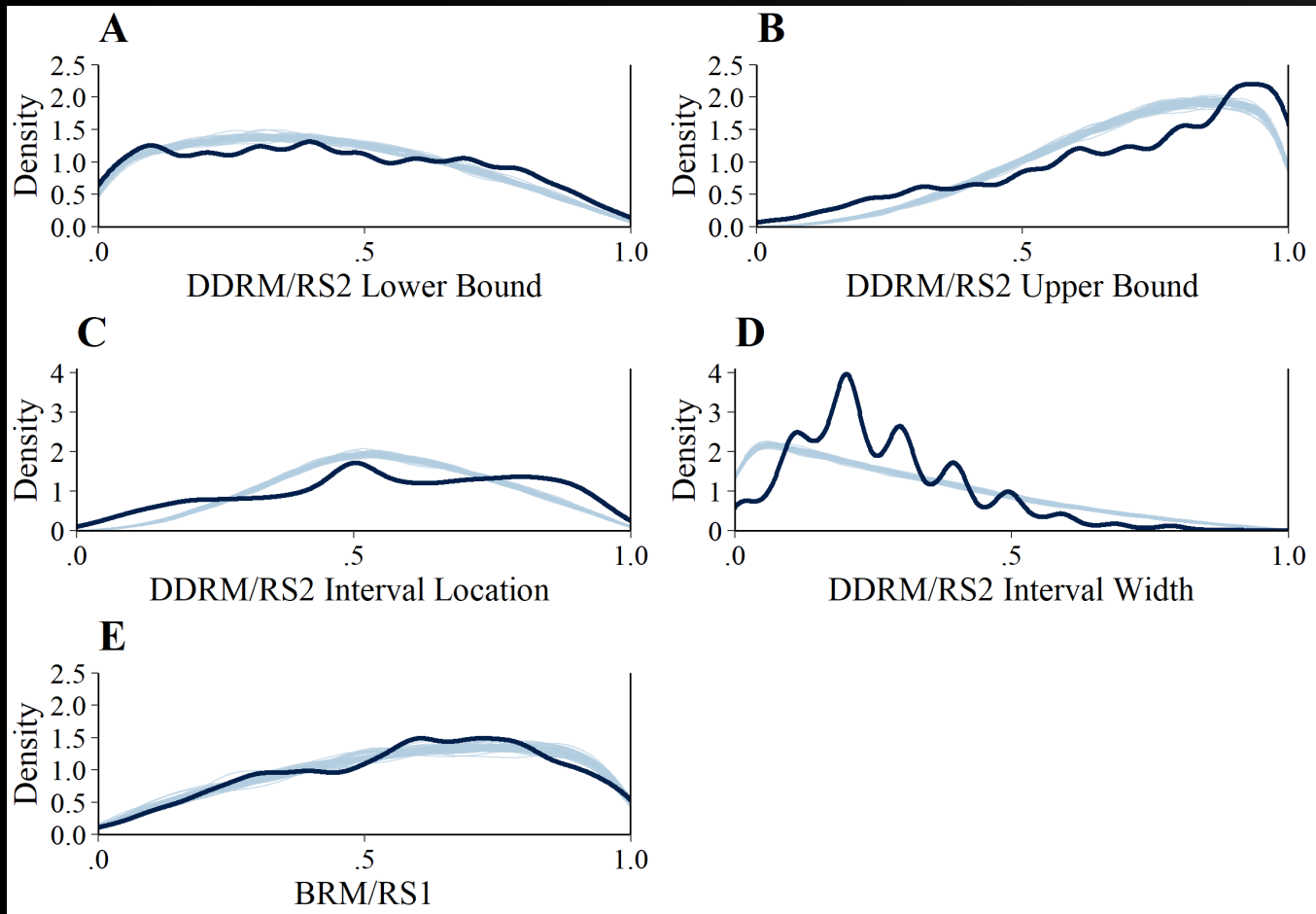
B



Replicated

POSTERIOR PREDICTIVE CHECKS

Binary Marginal Densities



Dark lines: empirical;

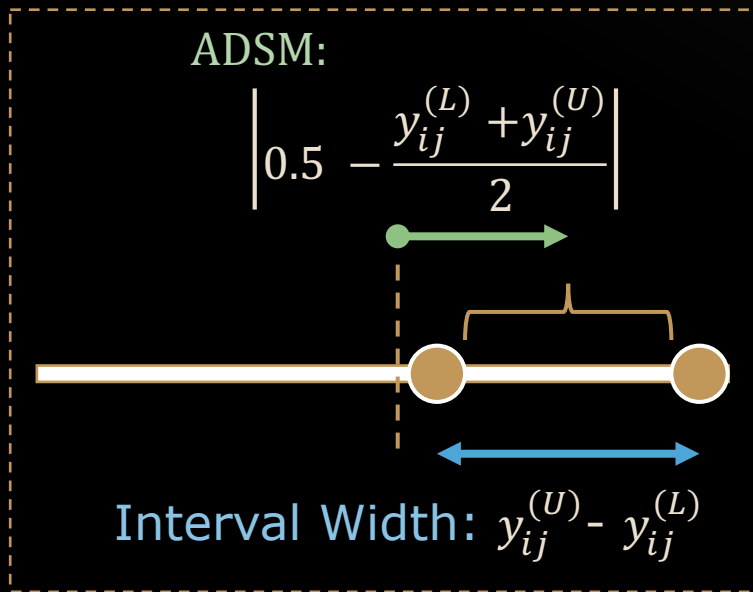
Lightlines: replicated

4 - WHY DO WE NEED A MODEL?

BOUNDEDNESS

Scale-Inherent Correlation

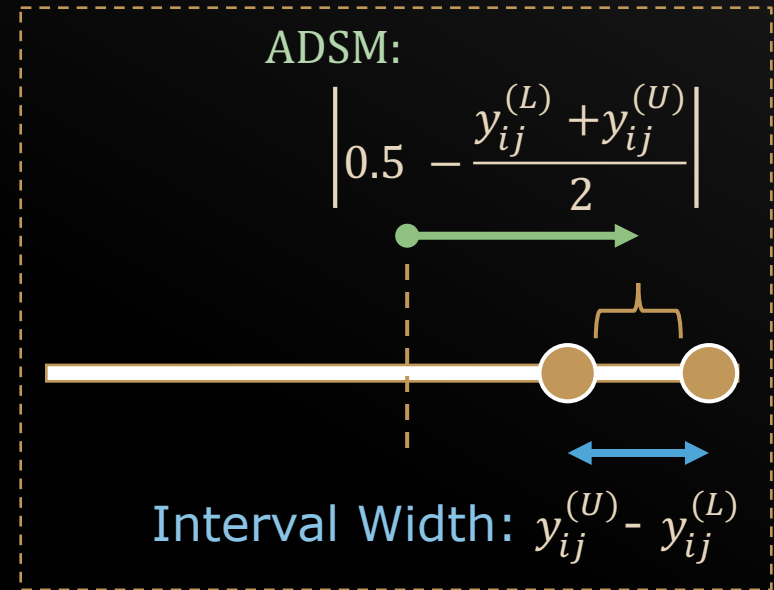
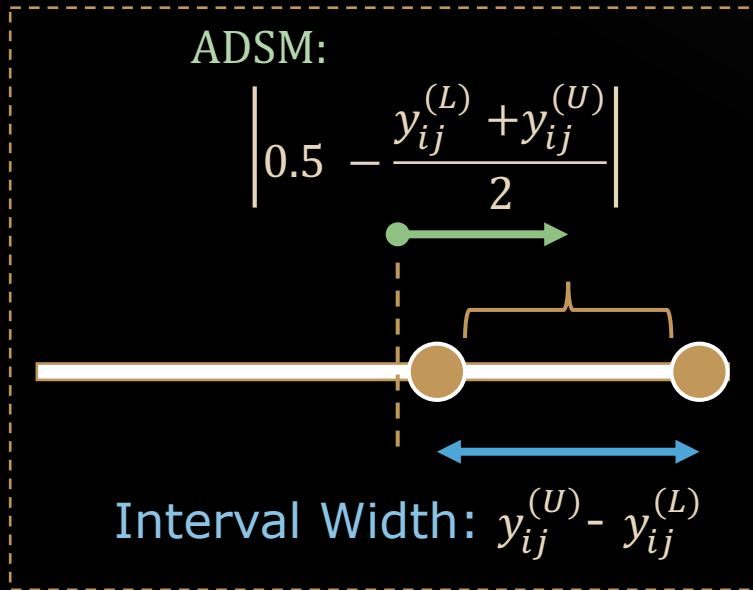
- ADSM: Absolute Distance from Scale Midpoint



BOUNDEDNESS

Scale-Inherent Correlation

- ADSM: Absolute Distance from Scale Midpoint



- Negative correlation between ADMS and Interval Width

BOUNDEDNESS

Comparison of Correlations

Manifest correlation: person mean scores

- ADSM
- Interval Width

Latent variable correlation: person parameters

- Absolute Location ($|\theta|$; remember: $M(\theta) = 0$)
- Expansion (η)

BOUNDEDNESS

Comparison of Correlations

	Mean scores	Model parameters
Empirical:	$r = -.57$	$r = -.19$
Simulation:	$r = -.74$	$r = -.02$
True:		$(r = -.002)$

➤ The model accounts for the scale-inherent correlation

CONVERGENT VALIDITY: RESPONSE FORMATS

Mean Scores vs. Estimates

Manifest correlation: person mean scores

- Single response
- Interval location (midpoint)

Latent variable correlation: person parameters

- Person location θ_{BRM}
- Person location θ_{DDRM}

CONVERGENT VALIDITY: RESPONSE FORMATS

Correlations in the Empirical Study:

Mean scores: $r = .81$

Model Parameters: $r = .87$

➤ Latent model improves convergence

TAKE HOME POINTS

- High **convergent validity** of response formats
- Model **accounts** for **boundedness**
- **Additional information**: expansion dimension
 - Validity? What does it measure?
- Useful tool for analysis of interval responses

THANKS TO:



- Prof. Dr. Daniel W. Heck



- Prof. Dr. Andreas Voss



- Dr. Raphael Hartmann

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Slides: <https://github.com/matthiaskloft/>

REFERENCES

- Danner, D., Rammstedt, B., Bluemke, M., Lechner, C., Berres, S., Knopf, T., Soto, C. J., & John, O. P. (2019). Das Big Five Inventar 2: Validierung eines Persönlichkeitsinventars zur Erfassung von 5 Persönlichkeitsdomänen und 15 Facetten. *Diagnostica*, 1–12. <https://doi.org/10.1026/0012-1924/a000218>
- Fleeson, W. (2001). Toward a structure- and process-integrated view of personality: Traits as density distributions of states. *Journal of Personality and Social Psychology*, 80(6), 1011–1027. APA PsycArticles. <https://doi.org/10.1037/0022-3514.80.6.1011>
- Goldberg, L. R. (1999). A broad-bandwidth, public domain, personality inventory measuring the lower-level facets of several five-factor models. *Personality psychology in Europe*, 7(1), 7–28.
- Noel, Y. (2014). A beta unfolding model for continuous bounded responses. *Psychometrika*, 79(4), 647–674. <https://doi.org/10.1007/s11336-013-9361-1>
- Noel, Y., & Dauvier, B. (2007). A beta item response model for continuous bounded responses. *Applied Psychological Measurement*, 31(1), 47–73. <https://doi.org/10.1177/0146621605287691>
- Samejima, F. (1973). Homogeneous case of the continuous response model. *Psychometrika*, 38(2), 203–219. <https://doi.org/10.1007/BF02291114>
- Soto, C. J., & John, O. P. (2017). The Next Big Five Inventory (BFI-2): Developing and Assessing a Hierarchical Model With 15 Facets to Enhance Bandwidth, Fidelity, and Predictive Power. *Journal of Personality & Social Psychology*, 113(1), 117–143. <https://doi.org/10.1037/pspp0000096>