Better Anchoring and Ambiguity Measurement with Mixture Models

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V-Dem
VARIETIES OF DEMOCRACY
UNIVERSITAS GOTHOBURGENSIS 1891

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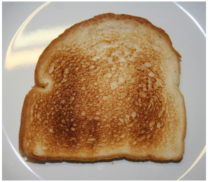
The Problem

Differential item functioning

How crunchy do you like your toast?

1. Very crunchy
2. Crunchy
3. Neither crunchy nor soft
4. Soft
5. Very soft

Anchoring items



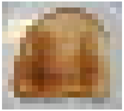
Source: Wikimedia Commons

How crunchy is this toast?

1. Very crunchy
2. Crunchy
3. Neither crunchy nor soft
4. Soft
5. Very soft

Anchoring batteries

Source: Wikimedia Commons



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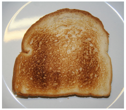
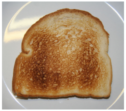


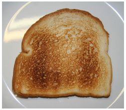
How [redacted] is this toast?

1. Very [redacted]
2. [redacted]
3. Neither [redacted] nor [redacted]
4. [redacted]
5. Very [redacted]



How ~~crunchy~~ **hot** is this toast?

1. Very ~~crunchy~~ **hot**
2. ~~Crunchy~~ **Hot**
3. Neither ~~crunchy~~ **hot** nor ~~soft~~ **cold**
4. ~~Soft~~ **Cold**
5. Very ~~soft~~ **cold**

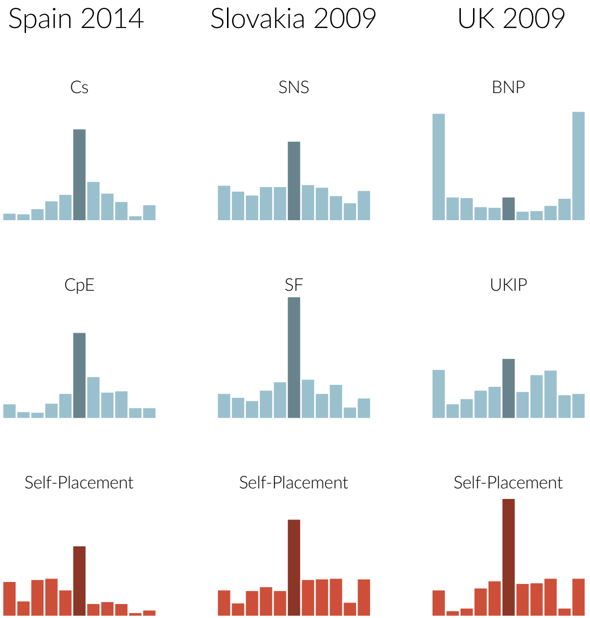


How crunchy is this toast?

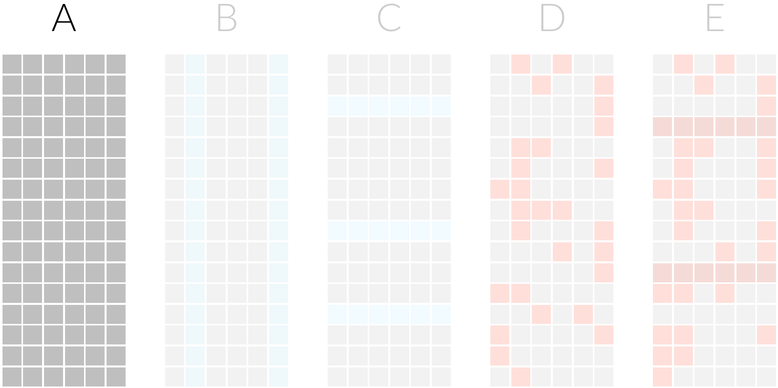
1. Very crunchy
2. Crunchy
3. Neither crunchy nor soft
4. Soft
5. Very soft

Source: telegraph.co.uk

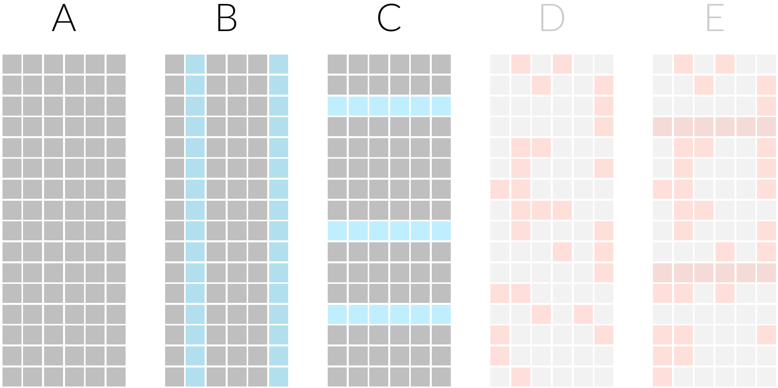
EES Left-Right batteries



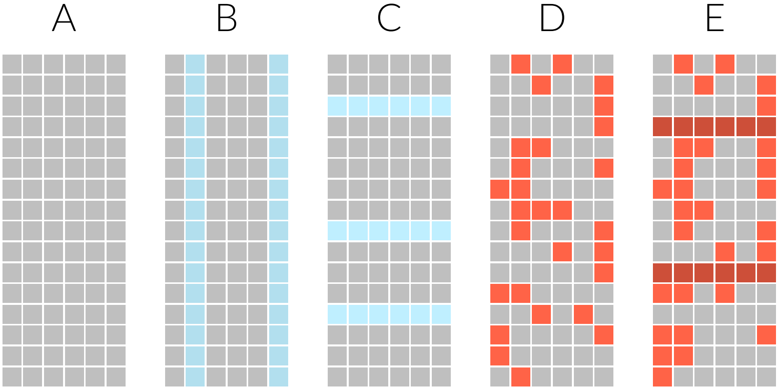
Low-quality responses



Low-quality responses



Low-quality responses



A Solution

A mixture framework

$$O = \pi M + (1 - \pi) C$$

O observed responses

M *informative* responses

C *uninformative* responses

π mixing weight, $\pi \in [0, 1]$

Modeling Informative Responses

Aldrich-McKelvey Scaling

Classical AMS

$$y_{ro} \sim \text{Normal}(\alpha_r + \beta_r \theta_o,\ \sigma)$$

Bayesian AMS (Hare at al. 2015)

$$y_{ro} \sim \text{Normal}(\alpha_r + \beta_r \theta_o,\ \sigma_r \sigma_o)$$

Scaling self-placements

$$\zeta_r = \frac{z_r - \alpha_r}{\beta_r}$$

Fitting complex latent variable models

Peter Fischli and David Weiss's The First Blush of Morning, 1984.
Source: https://www.wmagazine.com/story/peter-fischli-david-weiss-merry-pranksters

Measurement model

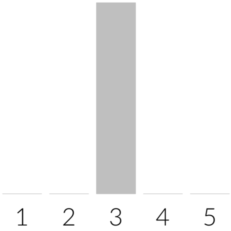
$$
\begin{aligned}
y_{ro} &\sim \text{Categorical}\left(\boldsymbol{p}_{ro}\right) \\
p_{rok} &= \text{OrdLogit}\left(\left(\tau_{rk} - \gamma_r \theta_o\right) \beta_o\right) \\
\boldsymbol{\tau_r} &\sim \text{Logistic}(0,\ 1),\ \tau_{rk} < \tau_{r,k+1} \\
P(\gamma_r = -1) &\sim \text{Beta}(0.5,\ 0.5),\ \gamma_r \in \{-1,\ +1\} \\
\ln \beta_o &\sim \text{Normal}(0,\ 1) \\
\theta_o &\sim \text{Normal}(0,\ \sigma) \\
\zeta_r &\sim \text{Normal}(0,\ \sqrt{R}\sigma) \\
\sigma &\sim \text{HalfNormal}^{+}(0,\ 1)
\end{aligned}
$$

Modeling Uninformative Responses

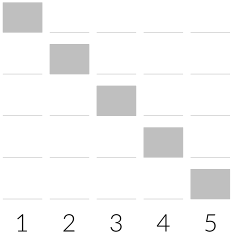
Contamination models

i. Pseudoguessing

ii. Midpoint



iii. Straightlining



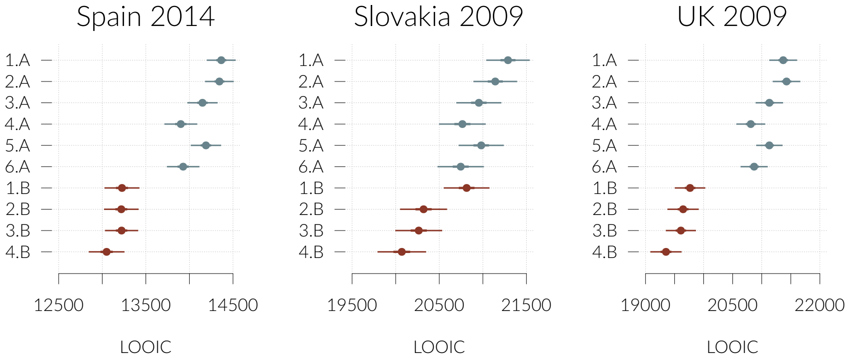
iv. Between-respondent multidimensionality

Building Mixture Models

10 mixture models

	Scale flipping	Midpoint inflation	Pseudo-guessing	Item slope
1.A				
2.A	Y			
3.A	Y	battery		
4.A	Y	item		
5.A	Y	battery	item	
6.A	Y	item	item	
1.B				Y
2.B	Y			Y
3.B	Y	battery		Y
4.B	Y	item		Y

EES: Model fit

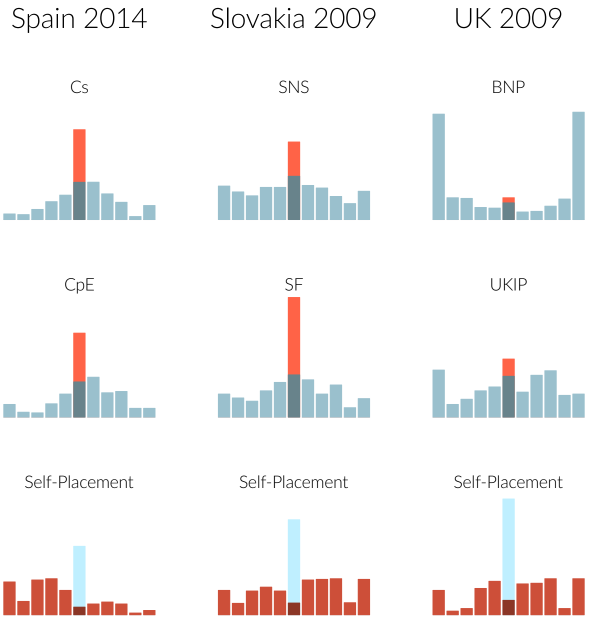


EES: Best fit

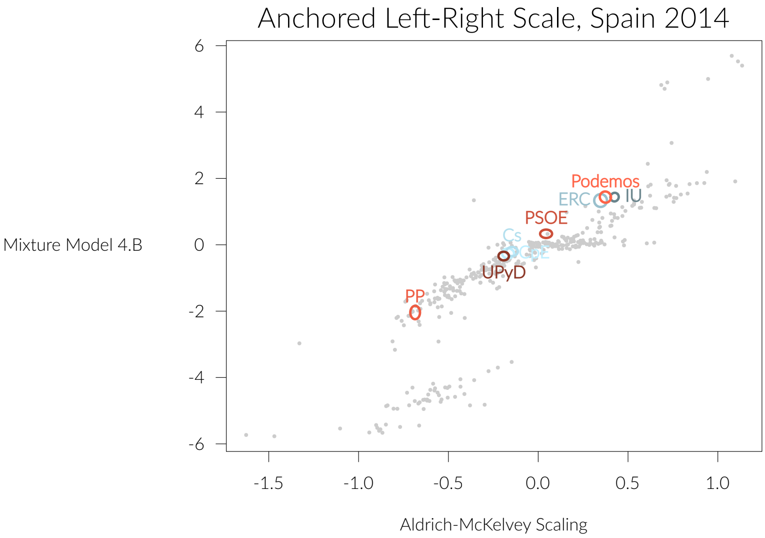
Model 4.B

- Respondent thresholds
- Scale flipping by respondent, population rate
- Midpoint inflation by response, item rate
- Item discrimination

EES: Midpoint inflation estimated by model 4.B



Model-based anchoring



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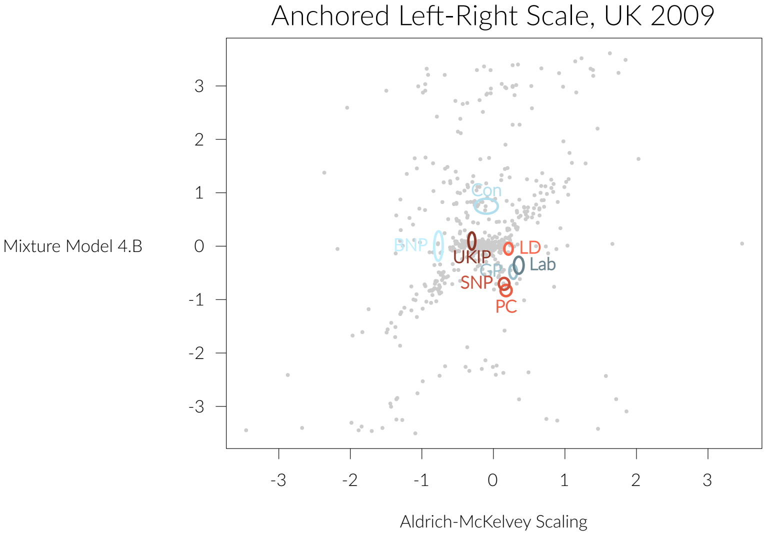

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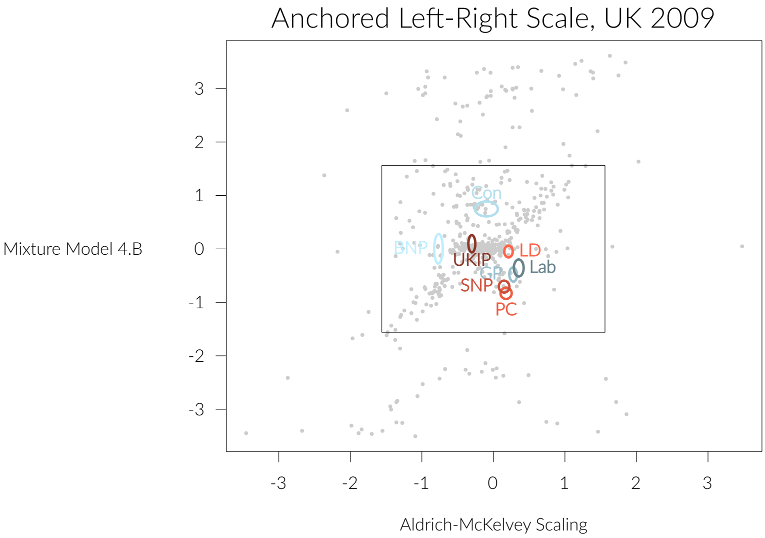

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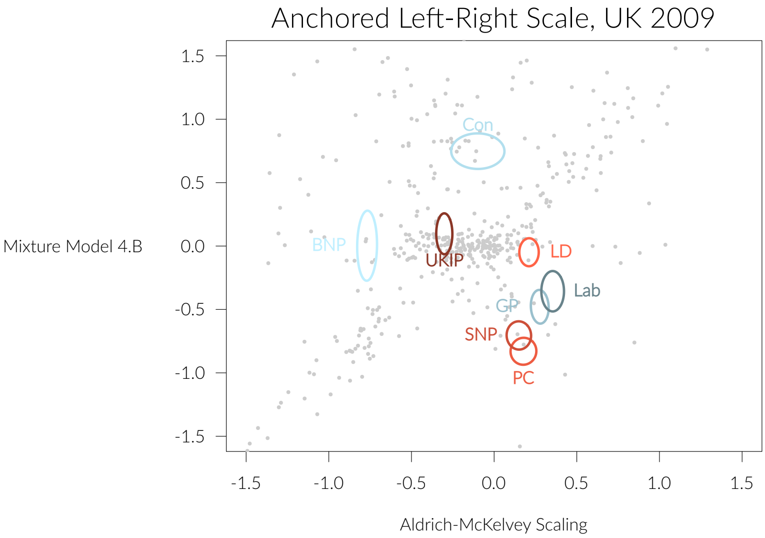
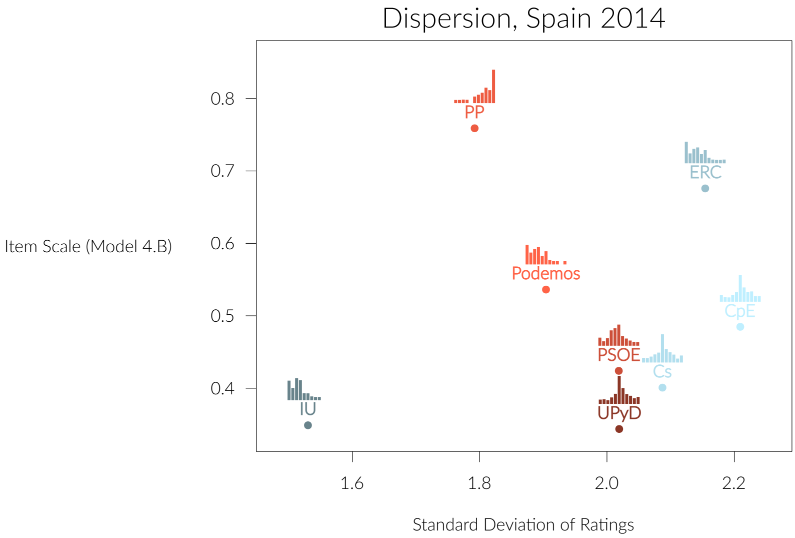
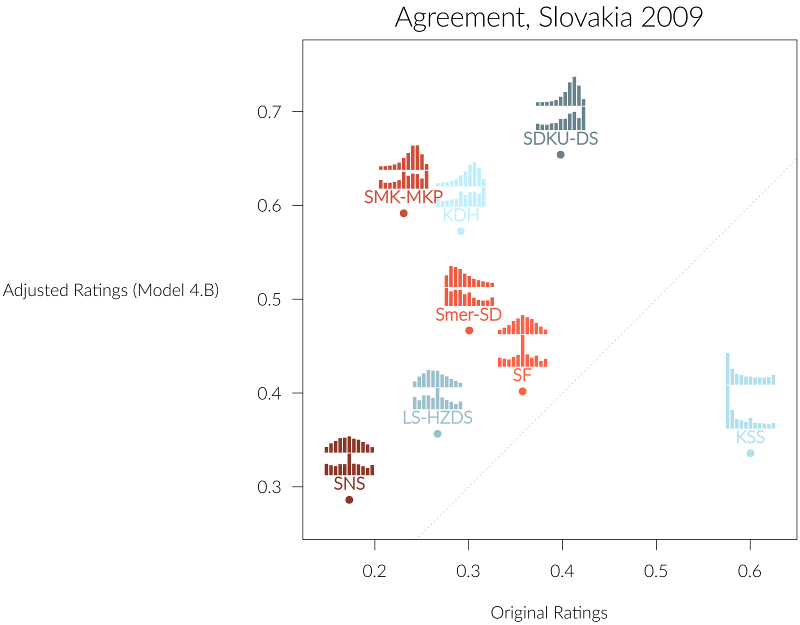


Ambiguity and dispersion



Ambiguity and agreement



Conclusion

Conclusion

Developing the paper

- Two-step version
- Bayesian model validation
- Replicate causal analyses

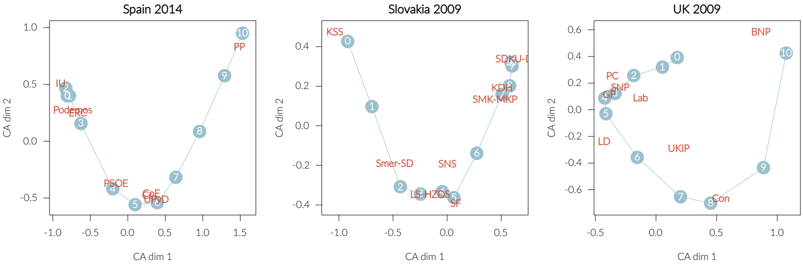
Future research

- Modeling rationalization bias (Bølstad 2020)
- Nonresponse and ambiguity (Rozenas 2013)
- More structured component memberships

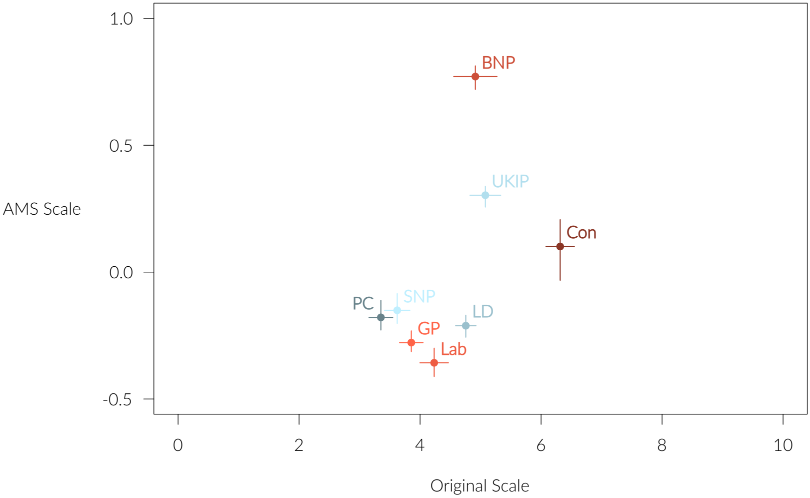
Thank you!

APPENDIX

Three EES Left-Right batteries



AMS: EES UK 2009 Left-Right battery



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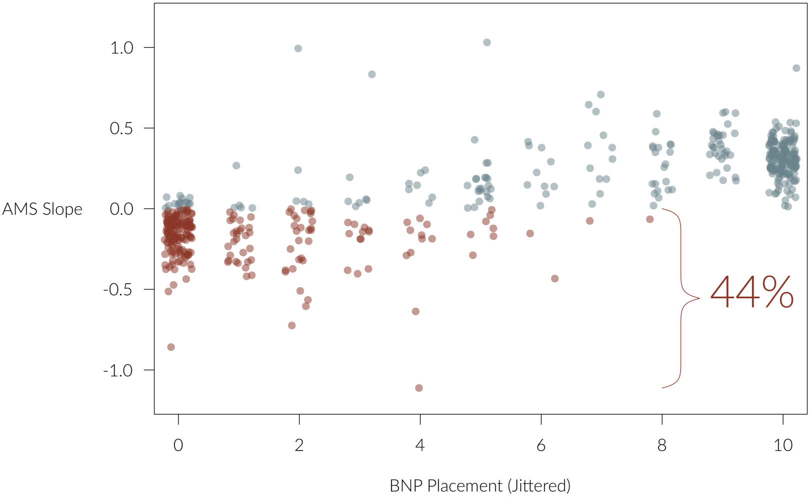

THE END