# Better Anchoring and Ambiguity Measurement with Mixture Models

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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



#### How crunchy is this toast?

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



How is this toast?

- 1. Very
- 2.
- 3. Neither nor
- 4.
- 5. Very



#### How <del>crunchy</del> **hot** is this toast?

- 1. Very <del>crunchy</del> hot
- 2. Crunchy Hot
- 3. Neither <del>crunchy</del> hot nor <del>soft</del> cold
- 4. Soft Cold
- 5. Very soft cold



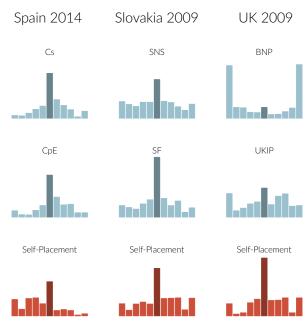
Howenundhwisthistoast??

- 11. Verycrumably
- 22. Crumabby
- 33. Neitilbler crumabhyynon softt
- 44. Søftft
- 55. Verysoftt

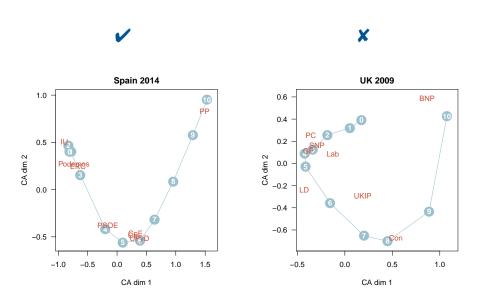


Source: telegraph.co.uk

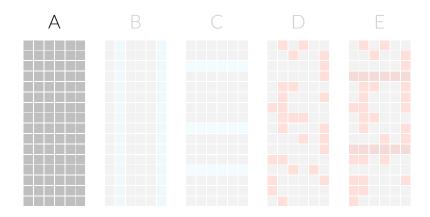
EES Left-Right batteries



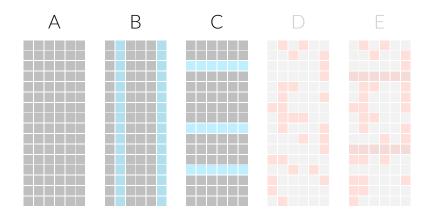
#### Diagnostics with correspondence analysis



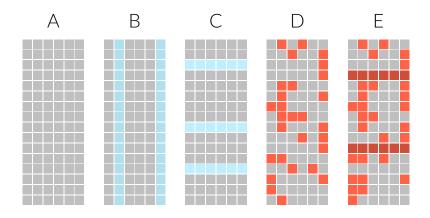
#### Low-quality responses



#### 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
- $\pi$  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

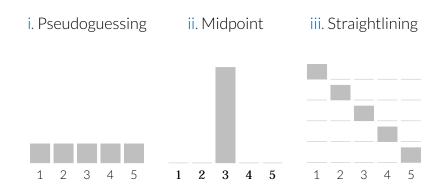
#### Measurement model

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

Modeling Uninformative

Responses

#### Contamination models



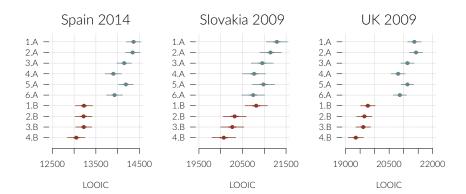
iv. Between-respondent multidimensionality

# Building Mixture Models

#### 10 mixture models

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

#### EES: Model fit

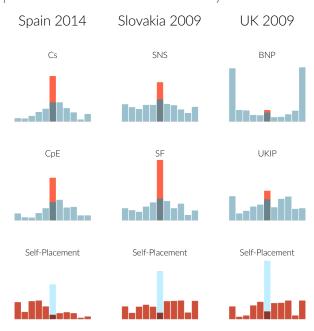


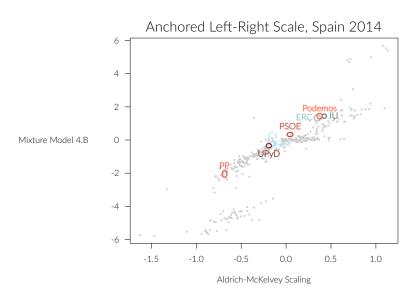
EES: Best fit

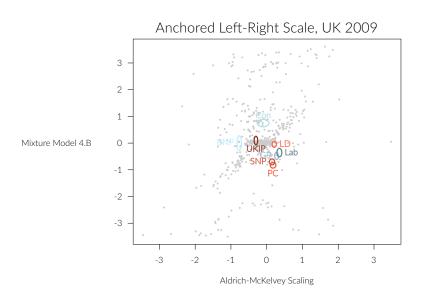
#### Model 4.B

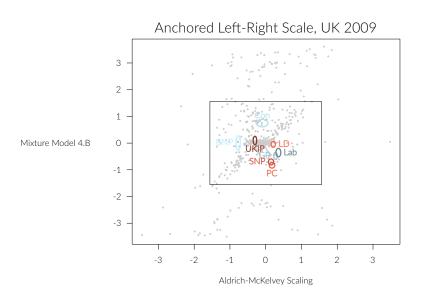
- Respondent thresholds
- Scale flipping by respondent, population rate
- Midpoint inflation by response, item rate
- Item discrimination

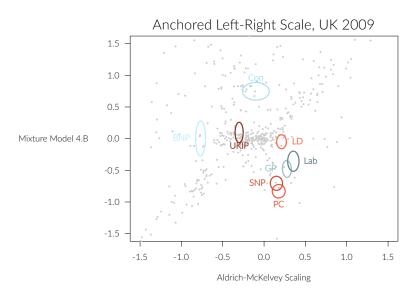
EES: Midpoint inflation estimated by model 4.B



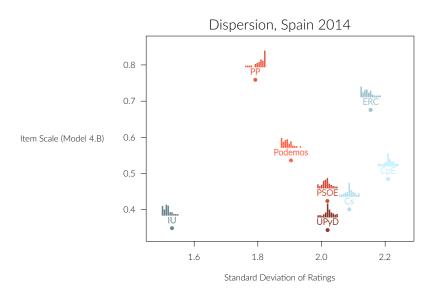




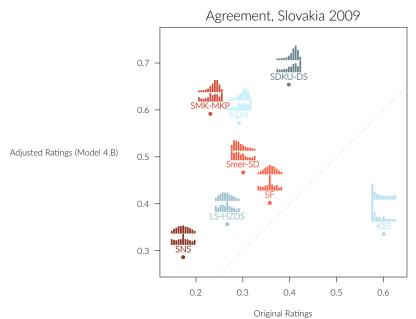




#### Ambiguity and dispersion



#### Ambiguity and agreement



## Conclusion

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#### Developing the paper

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

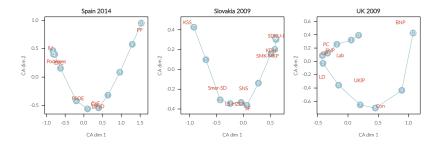
#### Future research

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

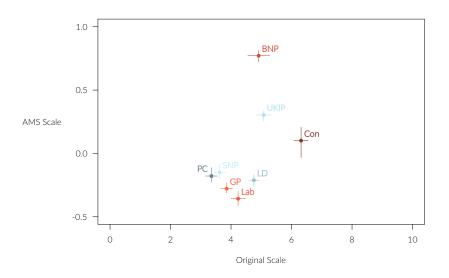
Thank you!

# APPENDIX

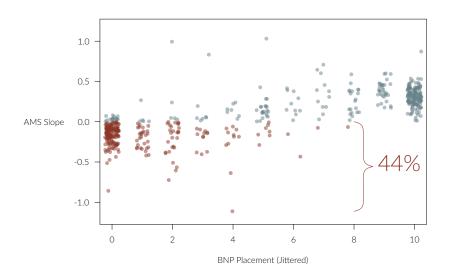
## Three EES Left-Right batteries



#### AMS: EES UK 2009 Left-Right battery



#### AMS: EES UK 2009 Left-Right battery



# THE END