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#### A psychometric model for respondent-level anchoring on self-report rating scale instruments





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**Reporter: Yingshi Huang** 

- The self-report rating scale format
	- − low-stakes settings: a lack of respondent effort
	- − careless responses are less clear

What can be an indicator of insufficient respondent effort?

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#### What can be an indicator of insufficient respondent effort?



Self-Rating Anxiety Scale, SAS (Zung, 1971)

**same content (anchor):** select the same or a nearby response

**different content / reversed direction (without anchor):** go away

- The self-report rating scale format
	- − low-stakes settings: a lack of respondent effort
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#### What can be an indicator of insufficient respondent effort?



Self-Rating Anxiety Scale, SAS (Zung, 1971)

**same content (anchor):** select the same or a nearby response

**different content / reversed direction (with anchor):** lack of a justification

- The self-report rating scale format
	- − low-stakes settings: a lack of respondent effort
	- − careless responses are less clear

What can be an indicator of insufficient respondent effort?

- The solutions
	- − measuring anchoring behaviour
	- − consider response styles
	- − explore the potential for a shared underlying commonality

#### **Model**

• an extension of a multidimensional nominal model

$$
\mathbb{P}\big(X_{ij}\!=\!k\big) \!=\! \frac{\exp\Bigl(q_{ijk}\Bigr)}{\sum_{l=1}^{K}\exp\Bigl(q_{ijl}\Bigr)}
$$

 $-$  latent preference for category  $k$ 

$$
q_{ijk} = \begin{cases} a_{jk}\theta_i + c_{jk} + \eta_{ik}, & j = 1, \\ a_{jk}\theta_i + c_{jk} + \eta_{ik} + \rho_i\lambda_{|X_{i,j-1}-k|}, & j \ge 2 \end{cases}
$$



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$$

1 2 *j M* 1 1, 2, *l*, *K* 2 *i N* respondents categories items





*David Thissen, Li Cai, R. Darrell Bock, Book Chapter*

# Model 8

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$$

1 2 *j M* 1 1, 2, *l*, *K* categories 2 *i N* respondents  $M$  items

the strength of this anchoring effect for respondent *i* ( $\rho_i > 0$ ) the larger, the more likely to reduce effort

> potential anchoring effect:  $\lambda_0, \lambda_1, \dots, \lambda_{K-1}$  ( $\lambda_0 > \lambda_1 > \lambda_2 > \dots > \lambda_{K-1}$ ) distance from the category previous selected:  $X_{i, j-1}$  -  $k$

# Model 9

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\mathbb{P}\big(X_{ij}\!=\!k\big) \!=\! \frac{\exp\Bigl(q_{ijk}\Bigr)}{\sum_{l=1}^{K}\!\exp\Bigl(q_{ijl}\Bigr)}
$$

− latent preference for category

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q_{ijk} = \begin{cases} a_{jk}\theta_i + c_{jk} + \eta_{ik}, & j = 1, \\ a_{jk}\theta_i + c_{jk} + \eta_{ik} + \rho_i\lambda_{|X_{i,j-1}-k|}, & j \ge 2 \end{cases}
$$

choose category  $k$  for reasons unrelated to  $\theta_i$  (response style)





 $\frac{1}{2}$ 



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$$

− identification constraints

$$
\sum_{k=1}^{K} c_{jk} = 0 \text{ for all } j, \sum_{k=1}^{K} \eta_{ik} = 0 \text{ for all } i, \prod_{i=1}^{N} \rho_i = 1, \text{ and } \sum_{d=0}^{K-1} \lambda_d = 0
$$

− equal interval scoring for each item ( $\overline{a}_j$ >0)

$$
a_{jk} = k \cdot \overline{a}_j
$$

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$$

#### reversed items are in red



respondents

#### How to represent items that are reverse oriented?

#### What if the items are presented in random order?

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$$

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respondents

#### How to represent items that are reverse oriented?



latent trait level increase, preference decrease

#### What if the items are presented in random order?

the item index does not equal to the location

### Model 13

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$$

 $-$  latent preference for category  $k$ 

$$
q_{ijk} = \begin{cases} a_{jk}\theta_i + c_{jk} + \eta_{ik}, & j = 1, \\ a_{jk}\theta_i + c_{jk} + \eta_{ik} + \rho_i\lambda_{X_{i,j-1}-k}, & j \ge 2 \end{cases}
$$

#### reversed items are in red



respondents

- − **Step 1:** identify the previous item  $l_{ij}$  (the item index of the previous one item; the first item  $l_{ij} = 0$ )
- − **Step 2:** define the direction  $s_j =\begin{cases} 1, & \text{if item } j \text{ is oriented in the same direction as item 1,} \\ -1, & \text{if item } j \text{ is oriented in the opposite direction to item 1.} \end{cases}$

## Model and the set of  $14$

• an extension of a multidimensional nominal model

$$
\mathbb{P}\big(X_{ij}\!=\!k\big)\!=\!\frac{\exp\!\left(q_{ijk}\right)}{\sum_{l=1}^{K}\!\exp\!\left(q_{ijl}\right)}
$$

 $\lambda$  latent preference for category  $k$ 

$$
q_{ijk} = \begin{cases} a_{jk}\theta_i + c_{jk} + \eta_{ik}, & j = 1, \\ a_{jk}\theta_i + c_{jk} + \eta_{ik} + \rho_i\lambda_{|X_{i,j-1}-k|}, & j \ge 2 \end{cases}
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- − **Step 1:** identify the previous item  $l_{ij}$  (the item index of the previous one item; the first item  $l_{ij} = 0$ )
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- − **Step 3:** adjust the item directionality same direction different direction

# **Bayesian estimation**  $\frac{1}{1}$   $\frac{data}{1}$   $\frac{1}{2}$   $\frac{1}{2}$  15

• Stan (Hamiltonian Monte Carlo algorithm)

− the priors:

 $\theta_i \sim \mathcal{N}(0, 1), i = 1, 2, ..., N$  $\lambda_d \sim \mathcal{N}(0, 1), d = 0, 1, ..., K-1.$  $[\eta_{i1}, \eta_{i2}, \ldots, \eta_{iK}, \log \rho_i]^T \sim \mathcal{N}_{K+1}(0, \Sigma_n), i = 1, 2, \ldots, N,$  $[c_{i1}, c_{i2}, ..., c_{iK}, \log \overline{a}_i]^T \sim \mathcal{N}_{K+1}(0, \Sigma_c), j = 1, 2, ..., M,$  $\Sigma_c = \tau_c^{\rm T} \Omega_c \tau_c,$  $\Sigma_n = \tau_n^{\rm T} \Omega_n \tau_n$  $\tau_c$ ,  $\tau_n \sim \text{HalfCauchy}(1)$ ,  $\Omega_c$ ,  $\Omega_n \sim LKJCorr(2)$ ,

- − convergence:
- 1. the Gelman–Rubin  $\hat{R}$  (close to 1)
- 2. the ratio of the effective sample size  $N_{eff}$ to the total sample size  $N$

}

}

```
vector[N] theta; // latent trait
}
```

```
transformed parameters { // Transformed parameters block
vector[K] p[N, M]; // latent preferences
p[n, m, k] = u + rho[n] * lambda[1 + abs(y[n, z[n, w - 1]] - k)];}
```

```
model { // Model block
// priors
anc \sim normal(0, 1);
```
// target distribution

item-level parameters}

 $y[n, m] \sim$  categorical\_logit(p[n, m]);

generated quantities { // Generated quantities block

omega\_m = tcrossprod( $L$ \_omega\_m); // correlation matrix of

```
// Data block
int <lower = 1> N; // number of respondents
```
parameters { // Parameters block row\_vector[K] anc;  $\frac{1}{2}$  // uncentered anchoring effects

```
Just an example
```
### **Simulation**

- Purpose: examine the parameter recovery
	- − the number of items: M = 30, 50 or 100
	- − the anchoring effects:  $\lambda = [0.2, 0.1, 0, -0.1, -0.2]^T$  or  $\lambda = [0, 0, 0, 0, 0]^T$  (no anchor) Any false positive?
	- the content trait distribution:  $\theta \sim N(0,1)$  or  $\theta \sim N(1,1)$
	- − response categories per item: K = 5
	- − item parameters:  $s_j = 1$  &  $[\eta_{i1}, \eta_{i2}, ..., \eta_{iK}, \log \rho_i]^T \sim \mathcal{N}_{K+1}(0, \Sigma_{\eta}), i = 1, 2, ..., N$ ,
	- $[c_{j1}, c_{j2}, ..., c_{jK}, \log \overline{a}_{j}]^{T} \sim \mathcal{N}_{K+1}(0, \Sigma_{c}), i = 1, 2, ..., M,$ − examinees: N = 200



### **Simulation**

- Estimation
	- − 100 replications
	- − four chains (each chain 5,000 iterations)
	- − burn in: the first 2,500 iterations
	- convergence: the maximum  $\hat{R}$  across all parameters < 1.1
	- − the posterior means observed across 10,000 iterations were used

$\bm{M}$	$\mu_{\Theta}$	Anchoring	$\lambda_1$	$\lambda_2$	$\lambda_3$	$\lambda_4$	$\lambda_5$
30	$\bf{0}$	Present	$0.22 \pm 0.04$ $0.10 \pm 0.03$		$-0.01 \pm 0.03$	$-0.12 \pm 0.05$ $-0.19 \pm 0.07$	
	$\bf{0}$	Absent	$0.00 \pm 0.04$	$0.00 \pm 0.04$	$0.00 \pm 0.04$	$0.00 \pm 0.05$	$0.00 \pm 0.06$
	1	Present	$0.23 \pm 0.05$ $0.11 \pm 0.04$		$-0.01 \pm 0.04$	$-0.13 \pm 0.05$	$-0.21 \pm 0.08$
	1	Absent	$0.00 \pm 0.04$ 0.00 $\pm$ 0.05		$0.00 \pm 0.04$	$-0.22 \pm 0.05$	$0.01 \pm 0.08$
50	$\bf{0}$	Present	$0.21 \pm 0.03$	$0.11 \pm 0.02$	$0.00 \pm 0.02$	$-0.11 \pm 0.03$	$-0.21 \pm 0.05$
	$\mathbf{0}$	Absent	$0.00 \pm 0.03$ $0.00 \pm 0.03$		$0.00 \pm 0.03$	$0.00 \pm 0.04$	$0.00 \pm 0.06$
	1	Present	$0.23 \pm 0.04$ $0.11 \pm 0.03$		$-0.01 \pm 0.03$	$-0.12 \pm 0.04$	$-0.21 \pm 0.06$
	1	Absent	$0.00 \pm 0.03$	$0.01 \pm 0.03$	$-0.01 \pm 0.03$	$-0.01 \pm 0.04$	$0.01 \pm 0.06$
100	0	Present	$0.21 \pm 0.03$	$0.10 \pm 0.02$	$0.00 \pm 0.01$	$-0.11 \pm 0.02$	$-0.20 \pm 0.03$
	$\mathbf{0}$	Absent	$0.00 \pm 0.02$	$0.00 \pm 0.02$	$0.00 \pm 0.02$	$0.00 \pm 0.02$	$0.01 \pm 0.04$
	$\mathbf{1}$	Present	$0.22 \pm 0.03$	$0.12 \pm 0.02$	$0.00 \pm 0.02$	$-0.12 \pm 0.03$	$-0.22 \pm 0.05$
	1	Absent	$0.01 \pm 0.02$	$0.01 \pm 0.02$	$-0.01 \pm 0.02$	$-0.01 \pm 0.02$	$0.00 \pm 0.04$
True		Present	0.2	0.1	$\bf{0}$	$-0.1$	$-0.2$
		Absent	$\mathbf{0}$	$\mathbf{0}$	$\bf{0}$	$\bf{0}$	$\Omega$

Table 3. Parameter recovery of baseline anchoring effects

the mean and standard deviation across 100 replications

Table 4. Correlations of true and estimated parameters





#### Table 4. Correlations of true and estimated parameters

# **Empirical study**

- Purpose:
	- 1. Investigate the fitness of models & analyze parameter estimates
	- 2. Examine the validity of anchoring effects:

analyze the relationship between item directionality / response styles scrutinize representative respondents

3. Further determine the robustness of anchoring effects and response styles in detecting insufficient responses:

the effect of response times on anchoring and response styles

# **Empirical study**

- Data set
	- − the Introversion/Extraversion scale (five point scale, 1 = strongly disagree to 5 = strongly agree)
	- − M = 91 items
	- − 7,188 respondents (randomly choose 1,000)
	- − contain items from different directions

```
introversion items: 'I am quiet around strangers'
extraversion items: 'I talk to a lot of different people at parties'
single dimension: the first five eigenvalues (19.64, 3.68, 3.29, 3.18 and 2.41)
```
- − estimation: four chains with 10,000 (5,000 burn in)
- convergence:  $\hat{R}$  < 1.001 & the ratio  $N_{eff}/N$  > 0.5

### **Model fit and comparison**

- Is it necessary to include various components in the model?
	- − fit a series of nested models

1. Full model

\n
$$
q_{ijk} = \begin{cases} (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik}, & \text{if } l_{ij} = 0 \text{ or } s_j \neq s_{l_{ij}}, \\ (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik} + \rho_i \lambda_{\lvert x_{i, l_{ij}} - k \rvert}, & \text{otherwise.} \end{cases}
$$
\n2. Content, RS & Fixed Anc

\n
$$
q_{ijk} = \begin{cases} (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik}, & \text{if } l_{ij} = 0 \text{ or } s_j \neq s_{l_{ij}}, \\ (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik} + \lambda_{\lvert x_{i, l_{ij}} - k \rvert}, & \text{otherwise.} \end{cases}
$$
\n3. Content & RS

\n
$$
q_{ijk} = a_{jk}\theta_i + c_{jk} + \eta_{ik}
$$
\n4. Content & Anc

\n
$$
q_{ijk} = \begin{cases} (s_j a_{jk})\theta_i + c_{jk}, & \text{if } l_{ij} = 0 \text{ or } s_j \neq s_{l_{ij}}, \\ (s_j a_{jk})\theta_i + c_{jk} + \rho_i \lambda_{\lvert x_{i, l_{ij}} - k \rvert}, & \text{otherwise.} \end{cases}
$$
\n5. Content Only

\n
$$
q_{ijk} = a_{jk}\theta_i + c_{jk}
$$

## **Model fit and comparison**

- Evaluate criteria
	- − relative fit:

1. expected log pointwise predictive density (ELPD) based on the leave-one-out crossvalidation information criterion (LOOIC)

out-of-sample test train  $\textit{LOOIC} = -2 \times \text{elpd}_{\text{loo}}$ 

# Model fit and comparison 25

- Evaluate criteria
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out-of-sample test train  $\textit{LOOIC} = -2 \times \text{elpd}_{\text{loo}}$ 

− absolute fit: posterior predictive check

1. empirical data (not sure whether there is an anchoring) **vs** simulated data (with anchor)

the number of items that are in the same direction distance between successive item responses (calculate potential anchor)

$$
S_i = \left\{ j \geq 2 : s_j = s_{l_{ij}} \right\}
$$

whether the simulated  $f_i$  can cover the empirical one? **The actual coverage of 95%CI & 50%CI** 

#### **Results: model fit**

#### **1. Relative fit:**

#### Table 5. Comparison of models



#### **2. Absolute fit:**

The coverages: 55.7% (50%) and 96.0% (95%)

#### Results: parameter estimates (full) 27

#### Table 6. Posterior distributions of baseline anchoring effects



#### Results: parameter estimates (full)



Figure 1. Histogram of strengths of anchoring effects.

#### Anchor & item directionality / response styles

- Does anchoring apply only to successive items of the same content / direction?
	- − anchoring effect in items with opposite directions

$$
q_{ijk} = \begin{cases} (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik}, & \text{if } l_{ij} = 0, \\ (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik} + \mu_{\vert X_{i,l_{ij}} - k \vert}, & \text{if } l_{ij} \ge 1 \text{ and } s_j \ne s_{l_{ij}}, \text{ opposite direction} \\ (s_j a_{jk})\theta_i + c_{jk} + \eta_{ik} + \lambda_{\vert X_{i,l_{ij}} - k \vert}, & \text{otherwise}, \text{same direction} \end{cases}
$$

(the respondent-specific anchoring parameter  $\rho_i$  is omitted)

• What is the connection between anchoring effect and response styles?

#### **Results: item directionality**



#### Table 8. Posterior distributions of anchoring effects in both directions

#### $\log \rho_i$  $\eta_{i1}$  $\eta_{i2}$  $\eta_{i3}$  $\eta_{i4}$  $\eta_{i5}$ 1  $\eta_{i1}$  $-.09$ 1  $\eta_{i2}$ .09  $.01$  $\mathbf{1}$  $\eta_{i3}$  $.15$ .06  $-.09$  $\mathbf{1}$  $\eta_{i4}$ extreme  $.81$  $-.34$  $.04$  $.00.$ 1 response  $\eta_{i5}$ style  $-.04$  $\log \rho_i$  $-.08$  $.36$  $-.08$  $\mathbf{1}$ .07  $.75$  $.15$  $.78$  $.72$ .24 SD .91

#### **Table 7.** Posterior means of correlation matrix and standard deviations

avoid extreme avoid extreme avoid extreme



#### Table 7. Posterior means of correlation matrix and standard deviations



#### Table 7. Posterior means of correlation matrix and standard deviations



#### **Table 7.** Posterior means of correlation matrix and standard deviations

Both anchoring and response style can be manifestations of reduced respondent effort?



Figure 2. Scatter plot of strengths of anchoring effects against midpoint response styles.

No.	$\tilde{\eta}_3$	O	θ	Successive introversion items	Successive extraversion items
12	2.13	4.71	0.07	4,4,3,3,3,2,2,1	3,2,3,3,3
523	1.11	1.44	0.68	4,3,5,3,5	3,1,3,1,1
15	$-0.47$	2.04	1.37	4,4,5,4,5,5,4,5,5,5,2	1,4,4,4,3,2,1,1,1
265	$-1.44$	0.49	$-0.46$	1,4,1,2,5,1	1,4,1,5,5

Table 9. Response patterns of representative respondents



**Figure 3.** Absolute differences of consecutive responses for representative respondents.  $(MRS = midpoint$  response styles)

### **Relationship with response time**

- 
- Can response style and anchoring really reflect reduced respondent motivation?
	- − Hypothesis:

**reduced effort =** shorter response time + stronger response styles + stronger anchoring behaviour

− Model with response time:

 $t_{ij} = \frac{\text{time}_{ij}}{\frac{1}{M} \sum_{m=1}^{M} \text{time}_{im}}$  (standardization: different respondents spend different times)

$$
q_{ijk} = \begin{cases} (s_j a_{jk})\theta_i + c_{jk} + t_{ij}^{\alpha_{RS}}\eta_{ik}, & \text{if } l_{ij} = 0 \text{ or } s_j \neq s_{l_{ij}},\\ (s_j a_{jk})\theta_i + c_{jk} + t_{ij}^{\alpha_{RS}}\eta_{ik} + \rho_i t_{ij}^{\alpha_{AE}}\lambda_{X_{i,l_{ij}}-k}, & \text{otherwise}, \end{cases}
$$

measure the association with response time (strengthen or weaken the response styles / anchoring)

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$$

the shorter, the larger tendency



both should be negative

measure the association with response time (strengthen or weaken the response styles / anchoring)

Estimation: priors  $\mathcal{N}(0, 2)$ 

### **Relationship with response time**

- Response time data and preprocessing
	- − response times:

− 1% and 99% quantiles = 1.067 and 26.018 second

− winsorization:

763 response times that are >30 s were set at exactly 30 s

− (e.g., respondents who left the computer for a period of time before coming back)



Figure 4. Scatter plot of mean and standard deviation of response times for each item.



#### Table 10. Posterior distributions of coefficients for response time

### Discussion and limitations

- facilitate the design of rating scale instruments:
- − remove a midpoint category
- − intentionally intermixing items of different content types or widely varying mean scores

- the test-taking population: volunteers (more engaged)
- if the items possess a high level of parallelism, anchoring and response styles could become more easily confounded
- strengthening of both anchoring effects and response styles for items later in the test
- incorporate the content trait into the multivariate distribution assumed for respondent anchoring and response style parameters

The End. Thanks for Listening!



beijing normal university

谢谢大家 多谢晒~ ありがとう **Danke Merci** 

Reporter: Yingshi Huang