Joint Modeling of Feedback-Use and Time Data Advances in Bayesian Item Response Modeling

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- Introduction
 - Feedback Behavior Study
 - ${\color{red} \bullet}$ Bayesian Response Modeling

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 - Bayesian Response Modeling
- Complex Multivariate Count Data
 - Multivariate Zero-Inflated Poisson Modeling
 - Results
 - Feedback Behavior Study: Use (Latent) Predictors
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Formative Computer-Based Assessment

- ▶ Two-stage testing: Ability feedback use
- ▶ Observe response times (speed) and feedback times (reading)
- ▶ Dutch study: Differential use of feedback in test assessment



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Bayesian Modeling of Multivariate Count Data

A Bayesian Modeling Approach:

- ► Hierarchical Structured Data, uncertainty/sampling error at different levels
- ► Use Powerful Simulation Techniques
- ▶ Use Prior Knowledge

Bayesian Modeling of Multivariate Count Data

A Bayesian Modeling Approach:

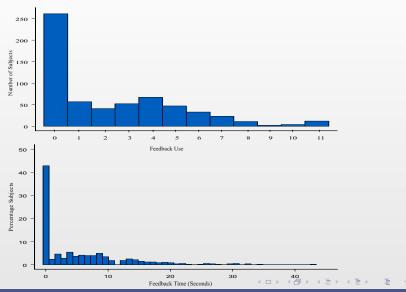
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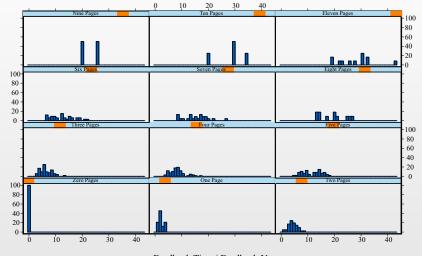
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Feedback-Use and Feedback-Time Data



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Modeling Multivariate Count Data

Count Data

	No. Pages	Total Times
Subjects	2	7
Subjects	0	0
	÷	÷
	y_i^f	y_i^t

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Count Data

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Summary Statistics

	Mean	SD	% Zeros	Mean No Zeros
Feedback Use	2.35	5.35	.43	4.11
Feedback Times	2.75	6.19	.43	9.35

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Feedback-Use No. Pages

The idea is to model feedback use (yes or no), feedback pages (count pages), feedback times (count seconds)

Mixture of Observed Feedback Pages

$$Y_i^f \sim \begin{cases} 0, & \text{with probability } 1 - \phi_i \\ Poisson\left(\lambda_i^{(f)}\right), & \text{with probability } \phi_i, \end{cases}$$

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Model Feedback Count Data

$$P\left(Y_i^f = 0 \mid \lambda_i = \lambda_i^{(f)}\right) = (1 - \phi_i) + \phi_i e^{-\lambda_i}$$

$$P\left(Y_i^f = j \mid \lambda_i = \lambda_i^{(f)}\right) = \phi_i \frac{e^{-\lambda_i} \lambda_i^j}{j!},$$

Feedback Times

Mixture of Observed Feedback Times

$$T_i^f \sim \begin{cases} 0, & \text{with probability } 1 - \phi_i \\ Poisson\left(\lambda_i^{(t)}\right), & \text{with probability } \phi_i, \end{cases}$$

Feedback Times

Mixture of Observed Feedback Times

$$T_i^f \sim \begin{cases} 0, & \text{with probability } 1 - \phi_i \\ Poisson\left(\lambda_i^{(t)}\right), & \text{with probability } \phi_i, \end{cases}$$

Model Feedback Time Count Data

$$P\left(T_i^f = 0 \mid \lambda_i = \lambda_i^{(t)}\right) = (1 - \phi_i) + \phi_i e^{-\lambda_i}$$

$$P\left(T_i^f = j \mid \lambda_i = \lambda_i^{(t)}\right) = \phi_i \frac{e^{-\lambda_i} \lambda_i^j}{i!},$$



Feedback Use

Identify (non-)users of feedback pages using explanatory subject information

Observed Feedback Use

$$Z_i \mid \lambda_i^{(t)}, \lambda_i^{(f)} \sim \begin{cases} 0, & \text{with probability } (1 - \phi_i) P\left(Y_i^f = 0, T_i^f = 0\right) \\ 1, & \text{with probability } \phi_i \left(1 - P\left(Y_i^f = 0, T_i^f = 0\right)\right) \end{cases}$$

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Feedback Use

$$\phi_i = P(Z_i = 1) = \frac{\exp(\mathbf{x}_i^t \boldsymbol{\alpha})}{1 + \exp(\mathbf{x}_i^t \boldsymbol{\alpha})}$$



Population Model Subjects

Respondents are sampled independently and identically distributed.

Stage 2: Prior Expected Counts

$$\log \lambda_i^{(f)} = \mathbf{x}_i^t \boldsymbol{\beta}_f$$
$$\log \lambda_i^{(t)} = \mathbf{x}_i^t \boldsymbol{\beta}_t$$

Population Model Subjects

Respondents are sampled independently and identically distributed.

Stage 2: Prior Expected Counts

$$\log \lambda_i^{(f)} = \mathbf{x}_i^t \boldsymbol{\beta}_f$$
$$\log \lambda_i^{(t)} = \mathbf{x}_i^t \boldsymbol{\beta}_t$$

Stage 2: Multivariate Prior Expected Counts

$$\left(egin{array}{c} \log \lambda_i^{(f)} \ \log \lambda_i^{(t)} \end{array}
ight) \;\; \sim \;\; \mathcal{N}\left(\mathbf{x}oldsymbol{eta}, oldsymbol{\Sigma}_{\lambda}
ight)$$



Population Results

	Joint Model (No Predictors)			
Component	Parameter	Mean	HPD	
Feedback Use (Bernoulli part)				
Use Feedback	Intercept, α_0	.30	(.13,.45)	
No Feedback	o Feedback $1-\phi$		(.38, .46)	
Feedback Behavior (Poisson part)				
No. Pages	Intercept, μ_1	3.06	(2.69, 3.46)	
Time	Intercept, μ_2	7.09	(6.35, 7.92)	
	Correlation, Σ_{12}	.20	(.13,.27)	
			,	

[–] HPD: 95% Highest Posterior Density interval

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Ability-Speed Model

Collection of Responses and Response Times, N persons and K items

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Measuring Ability

$$P(Y_{ik}^a = 1 \mid \theta_i, a_k, b_k) = \Phi(a_k \theta_i - b_k) \text{ IRT Model}$$

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Measuring Ability

$$P(Y_{ik}^a = 1 \mid \theta_i, a_k, b_k) = \Phi(a_k \theta_i - b_k)$$
 IRT Model

Measuring Speed of Working

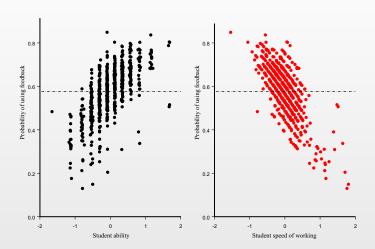
$$\log T_{ik}^a \mid \zeta_i, c_k, d_k \sim \mathcal{N}(d_k - c_k \zeta_i, \sigma_{\epsilon}^2)$$
 RT Model

Joint Model Results

	Joint Model (Latent Predictors Speed and Ability)			
Component	Parameter	Mean	HPD	
Feedback Use (Bernoulli part)				
	Intercept, α_0	.32	(.15,.47)	
	$1 - \phi$.42	(.36, .48)	
	Ability, α_1	.68	(.33, 1.00)	
	Speed, α_2	95	(-1.32,50)	

⁻ Latent predictors are grand-mean centered

Feedback-Use

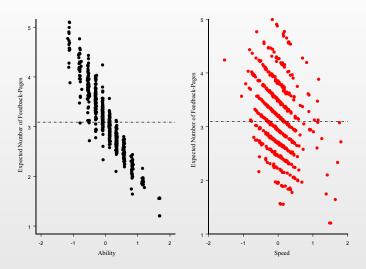


Joint Model Results

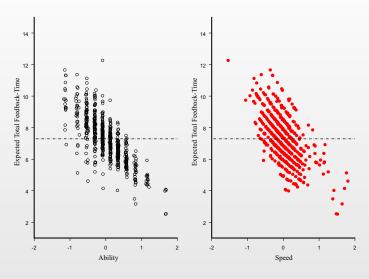
	Joint Model (latent Predictors Speed and Ability)			
Component	Parameter Mean		HPD	
Feedback Behavior (Poisson part)				
Feedback				
	Intercept, β_0	1.13(3.09)	(1.00, 1.25)	
	Ability, β_1	40	(69,11)	
	Speed, β_2	16	(52, .16)	
Feedback-Time				
	Intercept, β_0	1.97(7.17)	(1.85, 2.08)	
	Ability, β_1	33	(59,07)	
	Speed, β_2	32	(63,03)	
Correlation	Σ_{12}	.18	(.11,.24)	

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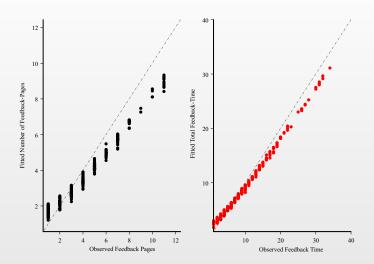
Feedback Page Counts



Feedback Times



Model Fit



► Flexible joint model for multivariate zero-inflated discrete count data



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- ▶ Use (higher-level) latent predictor variables



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 - ▶ Ability positively and speed negatively related to feedback use



- ► Flexible joint model for multivariate zero-inflated discrete count data
- ▶ Use (higher-level) latent predictor variables
- ▶ Feedback Behavior Study
 - Heterogeneity in feedback-use versus feedback to improve learning
 - ▶ Ability positively and speed negatively related to feedback use
 - ▶ Ability and speed negatively related to feedback counts and times



Some References

- ▶ Jean-Paul Fox (2010) Bayesian Item Response Modeling, Springer-Science, New-York.
- ▶ Fox, J.-P., Klein Entink, R.H., van der Linden, W.J. (2007). Modeling of responses and response times with the package cirt. *Journal of Statistical Software*, 20, issue 7.
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