



Longitudinal Multidimensional Item Response Modelling in Preschool Children's Mental State Understanding

MSc. Vilma Susana Romero Romero

VI Congreso Bayesiano de América Latina



Mathematics
& Statistics

Lancaster
University





Theory of Mind (ToM)

Definition

Ability to perceive our own mental states as well as from others, such as beliefs, desires and intentions and know that they differ from one person to another.

Main Features

- Developed in the first years of life (4 years old).
- Understand social environment and how to interact in it.
- Mental state tasks to identify the acquisition of ToM.

Let's take a look:



Aim

Understanding of mental states in children over the 3rd year of life through MIRT and analyze each dimension under the Bayesian Longitudinal approach.



Data Description

Participants

86 British children (Female = 41, Male = 45) from different preschools and day nurseries located in Northern Lancashire. Age: Between 30 and 33 months when recruited.

Measures

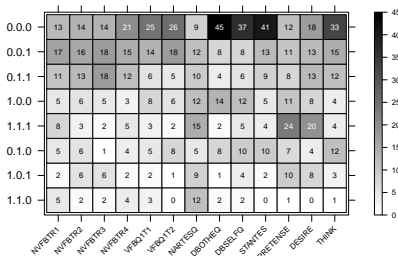
8 mental state tasks (13 questions three times in intervals of 4 months). A correct response scored '1' and an incorrect response scored '0'.

- Standard Location Change
- Deceptive Box
- Pretence, Desire and Think
- Narrative
- Verbal and Non-Verbal (2 and 4 trials respectively)



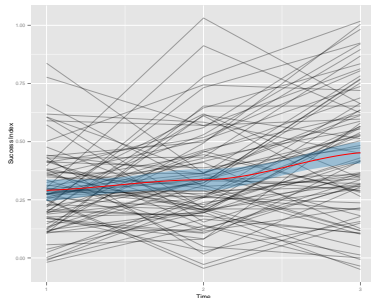
Exploratory Analysis

Response Patterns



- Only complete observations taken into account.
- Most difficult tasks: Standard Location Change and Deceptive Box.

Total Performance Trend



General trend is increasing

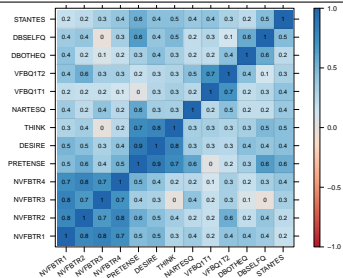
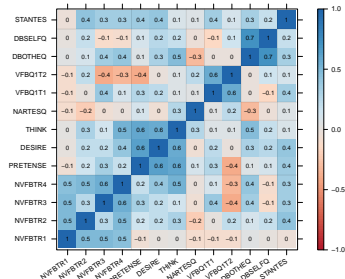
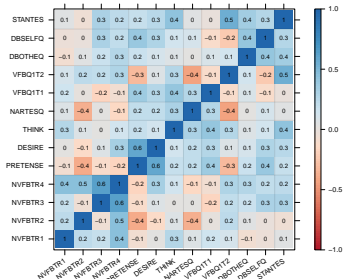


Correlation Analysis

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- Time 1 and 2 (Above)
- Time 3 (Below)
- Correlation across time.
- Correlation between possible latent factors.



Multidimensional Item Response Modeling

The probability of answering a dichotomous item correctly is:

$$\Phi(x_{ij} = 1 | \theta_i, \alpha_j, d_j) = \frac{1}{1 + \exp[-D(\alpha_j^T \theta_i + d_j)]}$$

Where, $i = 1, \dots, N$ participants, $j = 1, \dots, n$ test items, m latent factors $\theta_i = (\theta_{i1}, \dots, \theta_{im})$ with associated item slopes $\alpha_j = (\alpha_1, \dots, \alpha_m)$, d_j is the item intercept and D is a scaling adjustment (usually 1.702).

- The slopes are the multidimensional discrimination parameters (one for each latent factor).
- The intercept is proportional to the item difficulty.
- The higher (lower) the discrimination parameter, the (worst) better the item distinguishes low and high ability levels.

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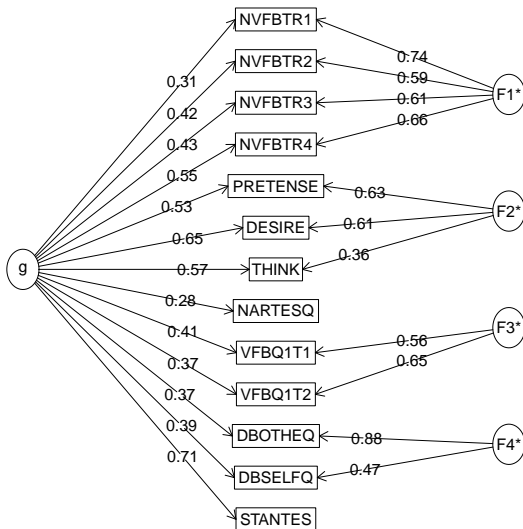
MIRT

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MIRT as Item Factor Analysis



Bifactor Model Path



Causality Analysis

First Stage: Bayesian Longitudinal Analysis

- **Correlation Structure:** Latent abilities on the same subject will be more correlated than among different subjects.

① Autoregressive AR(1)

- Constant variance across time.
- Correlation exponential decrease as the lag between times increases.

$$\Sigma_{\theta} = \sigma^2 \begin{pmatrix} 1 & \rho & \rho^2 \\ \rho & 1 & \rho \\ \rho^2 & \rho & 1 \end{pmatrix}$$

② Unstructured Covariance: Not specific pattern

③ Random Effects: $\theta_{ift} = \gamma_{if}^{(0)} + \gamma_{if}^{(1)}t$

- 3 chains of 10000 iterations with a burn-in phase of 5000 and final results pooled in a single chain.
- Employment of a **BUGS** (Bayesian inference Using Gibbs Sampling) code called from the free software R.



Prior Distributions

Choice of prior distributions for each f latent dimension

Parameters			AR(1)	Unstructured	Random Effects
Discrimination	α_j		$N(1, 1) \mathbb{I}[\alpha_j > 0]$	$N(1, 1) \mathbb{I}[\alpha_j > 0]$	$N(1, 1) \mathbb{I}[\alpha_j > 0]$
Difficulty	d_j		$N(0, 1)$	$N(0, 1)$	$N(0, 1)$
Latent Ability (θ_i)	μ_θ	$\mu_{\theta_{i1}}$	0	0	-
		$\mu_{\theta_{i2}}$	$N(0, 1)$	$N(0, 1)$	-
		$\mu_{\theta_{i3}}$	$N(0, 1)$	$N(0, 1)$	-
	Σ_θ	σ	1	-	-
		ρ	$U(-1, 1)$	-	-
		L_{ii}	-	$\text{Gamma}(1, 1)$	-
		$L_{ij} [i > j]$	-	$N(0, 1)$	-
		$\gamma_i^{(0)}$	-	-	$N(0, 1)$
	$\gamma_i^{(1)}$	$\mu_{\gamma_i^{(1)}}$	-	-	$N(0, 1)$
		$\tau_{\gamma_i^{(1)}}$	-	-	$\text{Gamma}(1, 1)$

Summary of DIC criterion

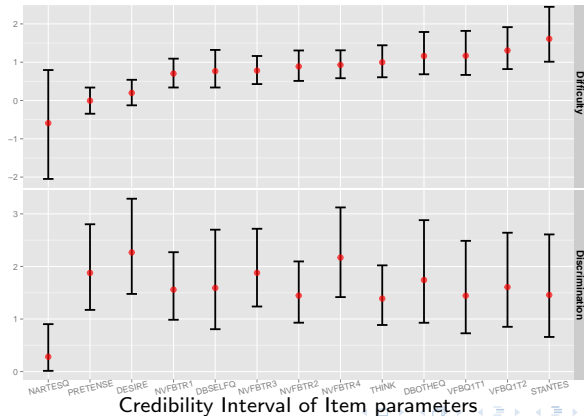
Model	DIC	Q _{0.025}	Q _{0.975}
AR(1) Covariance Structure	2312.46	2205.88	2418.96
Unstructured Covariance	2242.62	2124.69	2359.80
Random Effects	2337.56	2258.15	2415.93



Estimation Results - AR(1)

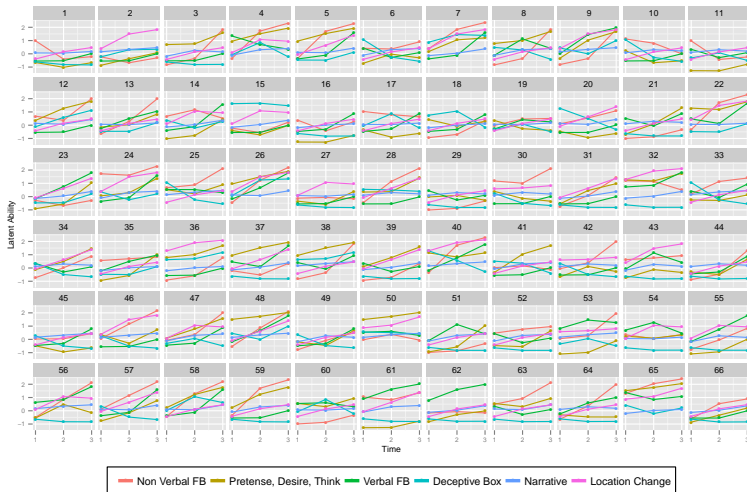
Summary of ρ estimate

Factor	$\bar{\rho}_f$	$Q_{0.025}$	$Q_{0.975}$
Non Verbal FB	0.44	0.22	0.63
Pretense, Desire, Think	0.65	0.43	0.83
Verbal FB	0.37	0.00	0.74
Deceptive Box	0.47	0.08	0.84
Narrative	0.06	-0.86	0.88
Location Change	0.62	-0.16	0.98





Estimation Results - AR(1)

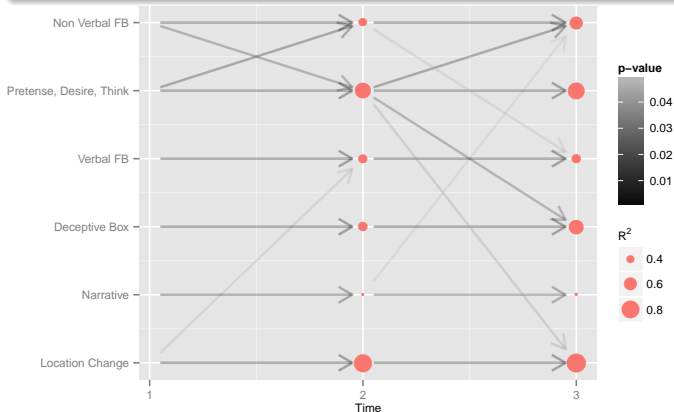


Estimated Latent Ability by subject



Second Stage: Ability Regression

Regression of the latent ability factors of $t = 2, 3$ against the latent ability of the previous instant of times.



Path Diagram of Causality - Model AR(1).

The p-values have not been adjusted for multiple comparison.

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Conclusions

- ① Children before 4 years old successfully passed Pretense, Desire and NVFB tasks.
- ② ToM reduced to 6 latent abilities through the Bifactor Model.
- ③ Easy items: Pretense and Desire.
Most difficult item: Standard Location Change.
- ④ Significant improvement across time: NVFB ability.
- ⑤ Causal analysis: Pretense, Desire and Think affects the development of most of the others abilities.

Future Work

- Consider the correlation between latent abilities in the model.
- Include a guessing parameter for each item.
- Covariates (age, sex and institution) could be included.
- Multilevel Modelling or Dynamic Latent Trait Models.



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Thank you!!!

