Exploring DIF using explanatory IRT models

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Logistic mixed models for DIF

- IRT models can be regarded as logistic mixed models (e.g., Adams, Wilson, & Wu, 1997; de Bock & Wilson, 2004; Kamata, 2001)
- Formulation of the Rasch model (Rasch, 1960) as a logistic mixed model

Outline

- Logistic mixed models for DIF
- „Student PISA"
- Discussion

Logistic mixed models for DIF

- For Persons *j, …, J* and items *i, …, I*, the Rasch model can be specified as

$$Logit(\pi_{ij}) = \sum_{k=1}^{I} \beta_k X_{ki} + u_j$$

With

- $Y_{ij} \sim Bernoulli(\pi_{ij})$
- $X_{ki} = 1 \; if \; k = i, 0 \; otherwise$
- $u_j \sim N(0, {\sigma^2}_u)$

Logistic mixed models for DIF

- DIF is regarded as a group-specific difference in item parameter(s) (while controlling for overall group differences in ability)

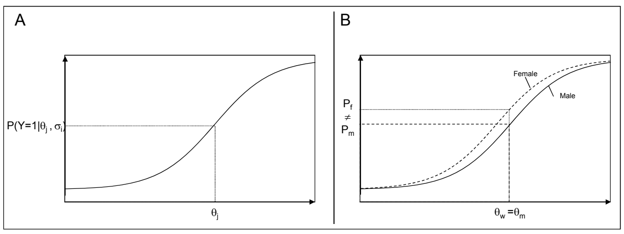
Logistic mixed models for DIF

- Specification of a (uniform) DIF model in the logistic mixed model (assuming items as fixed; cf. van den Noortgate & de Boeck, 2005)

$$Logit(\pi_{ijh}) = \sum_{k=1}^{I} \beta_k X_{ki} + \sum_{h=2}^{H} \alpha_h G_{hj} + \sum_{h=2}^{H} \gamma_{kh} G_{hj} X_{ki} + u_j$$

With
- G_{hj} as a group membership indicator,
- α_h as a group main effect,
- γ_{kh} as an item-specific indicator for (uniform) DIF

Logistic mixed models for DIF



Logistic mixed models for DIF

- Specification of a (uniform) DIF model in the logistic mixed model (assuming items as random; cf. van den Noortgate & de Boeck, 2005)

$$Logit(\pi_{ijh}) = \beta_0 + r_{0i} + \sum_{h=2}^{H} \alpha_h G_{hj} + \sum_{h=1}^{H} r_{hi} G_{hj} + u_j$$

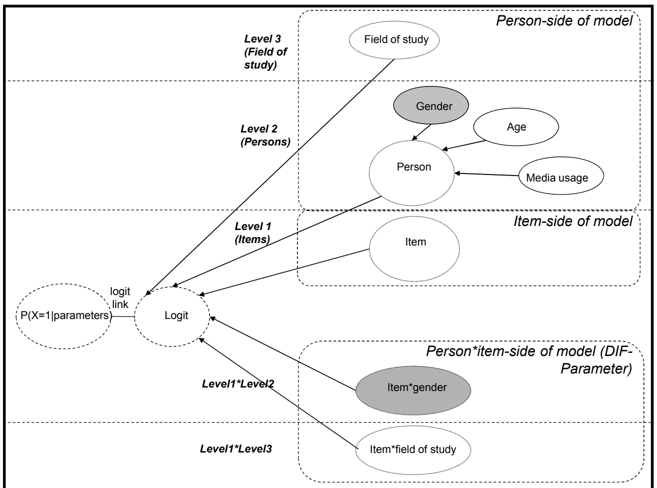
With
- G_{hj} as a group membership indicator,
- α_h as a group main effect,
- r_{0i} as the random main effect for item i , $r_{0i} \sim N(0, \sigma_i^2\ )$
- r_{hi} as the random effect of belonging to group h for item i , $r_{hi} \sim N(0, \sigma_i^2\ )$

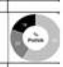
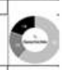
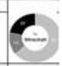
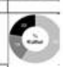
„Student PISA“

- Voluntary knowledge test for university students, conducted online by Spiegel magazine
- 700,000 participants (subsamples analysed here)
- Each participant received 45 items from 5 knowledge domains: politics, history, economics, culture and nature
- Question: Can manifest gender differences be attributed to item bias?

„Student PISA“

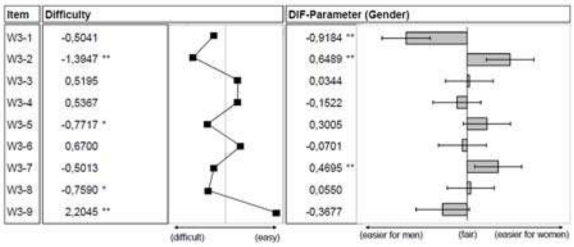
	Politics		History		Economics		Culture		Nature	
Fixed effects	M	SE	M	SE	M	SE	M	SE	M	SE
Constant	0,7665	0,31	0,5611	0,40	0,6211	0,37	0,3068	0,32	0,5319	0,32
Gender	-0,6773	0,14	-0,5173	0,12	-0,5575	0,16	-0,1716	0,12	-0,1953	0,18
Media usage	-0,1212	0,02	-0,0788	0,01	-0,0834	0,01	-0,0644	0,01	-0,0043	0,01
Age	0,1146	0,02	0,1221	0,02	0,1575	0,02	0,1317	0,02	0,1081	0,02
Random effects	VAR	SE	VAR	SE	VAR	SE	VAR	SE	VAR	SE
Main effects										
Item	0,7090	0,36	1,0406	0,52	1,1281	0,57	0,8648	0,43	0,8194	0,41
Person	0,7087	0,04	0,5481	0,03	0,3298	0,03	0,3812	0,03	0,3920	0,03
Field of study	0,0759	0,03	0,0784	0,03	0,0397	0,02	0,0383	0,01	0,0582	0,02
Interactions										
Item*gender	0,1476	0,08	0,1255	0,07	0,2259	0,12	0,1283	0,07	0,2849	0,15
Item*field of study	0,0369	0,01	0,0291	0,01	0,0444	0,01	0,0329	0,01	0,0718	0,01
Residual Variance	0,8688	0,01	0,8740	0,01	0,8988	0,01	0,9115	0,01	0,8871	0,01



Subtest		No DIF		DIF				GESAMT
				advantage for men		advantage for women		
		abs.	rel.	abs.	rel.	abs.	rel.	
Politics	P1	6	67%	2	22%	1	11%	
	P2	6	67%	1	11%	2	22%	
	P3	5	56%	2	22%	2	22%	
	P4	4	44%	3	33%	2	22%	
History	G1	4	44%	3	33%	2	22%	
	G2	7	78%	1	11%	1	11%	
	G3	5	56%	2	22%	2	22%	
	G4	6	67%	1	11%	2	22%	
Economics	W1	5	56%	2	22%	2	22%	
	W2	7	78%	1	11%	1	11%	
	W3	6	67%	1	11%	2	22%	
	W4	5	56%	1	11%	3	33%	
Culture	K1	6	67%	2	22%	1	11%	
	K2	5	56%	3	33%	1	11%	
	K3	8	89%	0	0%	1	11%	
	K4	5	56%	3	33%	1	11%	
Nature	N1	5	56%	2	22%	2	22%	
	N2	5	56%	2	22%	2	22%	
	N3	4	44%	2	22%	3	33%	
	N4	7	78%	1	11%	1	11%	

No DIF   advantage for men   advantage for women

„Student PISA“



Thanks for your attention

Discussion

- Logistic mixed models can be used to test for DIF
- Flexible model specification is possible
- Estimation of complex logistic mixed using ML: quasi-likelihood prcodures are usually preferred
- Extension of the framework (Bayesian modeling) feasible