



Lecture

„Item Response Theory“

The two parameter logistic Birnbaum model

29. November 2016



2-PL-Birnbaum model

- Model equation

$$P(Y_i = 1 | U) = P(Y_i = 1 | \xi) = \frac{\exp[\alpha_i \cdot (\xi - \beta_i)]}{1 + \exp[\alpha_i \cdot (\xi - \beta_i)]}$$

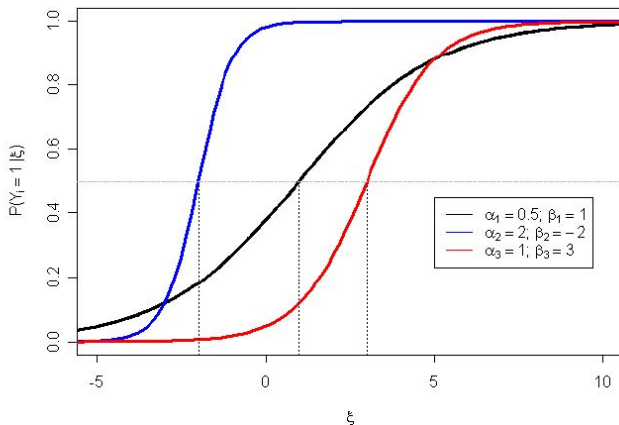
- Local stochastic independence

$$P(Y_i = 1 | U, Y_1, \dots, Y_{i-1}, Y_{i+1}, \dots, Y_m) = P(Y_i = 1 | U)$$



2-PL-Birnbaum model

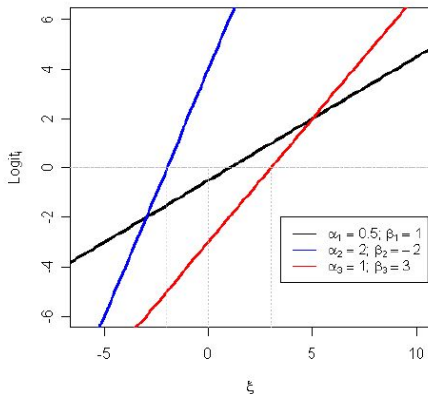
■ Item characteristic curves





2-PL-Birnbaum model

- Logits are linear functions of ξ and of each other



\Rightarrow The 2-PL-Birnbaum model is analog to the model of τ -congeneric variables

$$\ln \left(\frac{P(Y_i = 1 | \xi)}{P(Y_i = 0 | \xi)} \right) = \alpha_i \cdot (\xi - \beta_i)$$



2-PL-Birnbaum model

- Meaning of the model parameters:

- 1 latent variable ξ (e.g., ability, ...)

- 2 Item parameter:

β_i : Item difficulty (same interpretation as in the Rasch model)

α_i : Item discrimination



2-PL-Birnbaum model

- Item information function: If we specify $\alpha_1 \equiv 1$ and :

$$P_i(\xi) := \frac{\exp[\alpha_i \cdot (\xi - \beta_i)]}{1 + \exp[\alpha_i \cdot (\xi - \beta_i)]}, \quad i = 1, \dots, m,$$

then the information function

$$I_{Y_i}(\xi) := \frac{[P'_i(\xi)]^2}{P_i(\xi) \cdot [1 - P_i(\xi)]}$$

satisfies

$$I_{Y_i}(\xi) = \alpha_i^2 \cdot P_i(\xi) \cdot [1 - P_i(\xi)], \quad i = 1, \dots, m.$$

- In the 2-PL-model, the conditional variance $\text{Var}(Y_i | \xi)$ is *not* identical to the information function, if $\alpha_i \neq 1$, that is,

$$\alpha_i \neq 1 \Rightarrow \text{Var}(Y_i | \xi) \neq I_{Y_i}(\xi).$$

The term $P'_i(\xi)$ denotes the first derivative of $P_i(\xi)$ with respect to ξ .

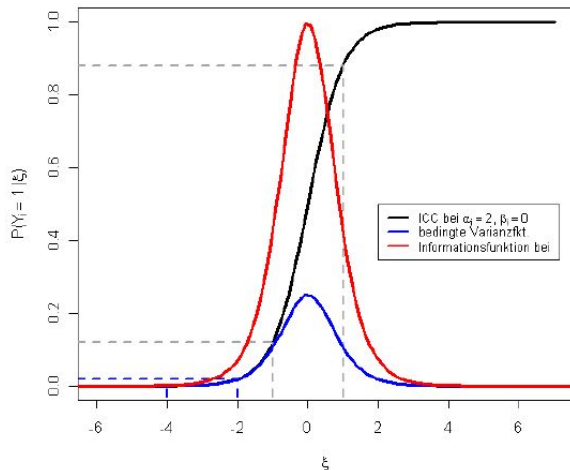
- Test information function:

$$I_{Y_1, \dots, Y_m}(\xi) = \sum_{i=1}^m I_{Y_i}(\xi)$$



2-PL-Birnbaum model

■ ICC and Information function



$$\alpha_i = 2$$

$$\beta_i = 0$$



2-PL-Birnbaum model

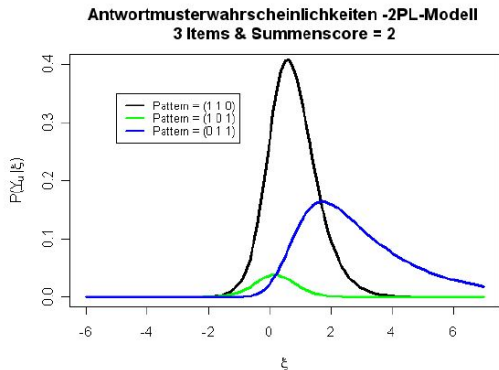
- The asymptotic standard errors are again (as in the Rasch model):

$$\begin{aligned}
 SE_{\hat{\xi}}(\xi) &\approx \sqrt{\frac{1}{I_{Y_1, \dots, Y_m}(\xi)}} \\
 &= \frac{1}{\sqrt{\sum_{i=1}^m I_{Y_i}(\xi)}} \\
 &= \frac{1}{\sqrt{\sum_{i=1}^m \alpha_i^2 \cdot P_i(\xi) \cdot [1 - P_i(\xi)]}}
 \end{aligned}$$



Parameter estimation

- Maximum likelihood estimation:



3 items:

$$\alpha_1 = 0.5, \beta_1 = -1$$

$$\alpha_2 = 3, \beta_2 = 0$$

$$\alpha_3 = 0.5, \beta_3 = 1$$



Parameter estimation

- Maximum likelihood estimation:
 - Sum score is not a sufficient statistic for the estimation of the person parameter
 - now it is important, *which* items are solved.
 - Persons with identical sum scores, but different response patterns can now have different estimates of their person parameters as well as different standard errors
 - Winmira cannot be used for the 2PL-Birnbaum model



2-PL-Birnbaum model – Mplus

■ Model specification in Mplus:

```

Mplus_16items_2p.inp
TITLE:    16 Items 1 latente Dimension 2PL;
DATA:    FILE IS 16items_2pl_1latent.dat;
         TYPE IS INDIVIDUAL;
VARIABLE: NAMES ARE i1-i16;
         USEVARIABLES ARE i1-i16;
         CATEGORICAL ARE i1-i16;
ANALYSIS: Estimator=MLR;
MODEL:   XI BY i1-i15*;
         XI@1;
         [XI@0];
OUTPUT:  TECH1;
SAVE:    FILE IS person_est.dat;
         SAVE=FSCORES;
  
```

Logistisches IRT-Modell

BY – Statement für
Itemdiskriminationen

Speichern der Personenparameter
(EAP)



2-PL-Birnbaum model – Mplus

■ Output:

factor analytic parametrization: $\text{logit}_i = \alpha_i \cdot \xi - \gamma_i$

MODEL RESULTS				
		Estimate	Two-Tailed	
			S.E. Est./S.E.	P-Value
XI	BY			
	Y0	3.868	1.371	2.822 0.005
	Y1	1.903	0.277	6.861 0.000
	Y2	1.110	0.133	8.362 0.000
	Y3	1.205	0.141	8.552 0.000
	...			
	Y10	3.187	0.833	3.824 0.000
Means				
	XI	0.000	0.000	999.000 999.000
Thresholds				
	Y0\$1	-8.729	2.512	-3.475 0.001
	Y1\$1	-3.598	0.317	-11.338 0.000
	Y2\$1	-1.390	0.103	-13.452 0.000
	Y3\$1	-1.047	0.097	-10.808 0.000
	...			
	Y10\$1	7.623	1.482	5.142 0.000
Variances				
	XI	1.000	0.000	999.000 999.000

Diskriminationsparameter (α_i)
in der logistischen Metrik

transformierte
Itemschwierigkeitsparameter (γ_i)



2-PL-Birnbaum model – Mplus

■ Output(continued):

2-PL-Birnbaum model parametrization: $\text{logit}_i = \alpha_i \cdot (\xi^* - \beta_i)$

IRT PARAMETERIZATION IN TWO-PARAMETER LOGISTIC METRIC
WHERE THE LOGIT IS DISCRIMINATION*(THETA - DIFFICULTY)

Item Discriminations				
XI	BY			
Y0	3.868	1.371	2.822	0.005
Y1	1.903	0.277	6.861	0.000
Y2	1.110	0.133	8.362	0.000
Y3	1.205	0.141	8.552	0.000
...				
Y10	3.187	0.833	3.824	0.000
Means				
XI	0.000	0.000	0.000	1.000
Item Difficulties				
Y0\$1	-2.257	0.187	-12.047	0.000
Y1\$1	-1.891	0.153	-12.396	0.000
Y2\$1	-1.253	0.130	-9.663	0.000
Y3\$1	-0.869	0.097	-8.948	0.000
...				
Y10\$1	2.392	0.204	11.711	0.000
Variances				
XI	1.000	0.000	0.000	1.000

Diskriminationsparameter (α_i)
in der logistischen Metrik

Itemschwierigkeitsparameter (β_i)



2PL-Birnbaum model

■ Uniqueness

The item parameters α_i , β_i , and the latent variable ξ are not uniquely defined by the assumptions of the 2PL-Birnbaum model. This is easily seen from

$$\alpha_i \cdot (\xi - \beta_i) = \frac{\alpha_i}{a} \cdot [(a \cdot \xi + b) - (a \cdot \beta_i + b)] = \alpha_i^* \cdot (\xi^* - \beta_i^*), \quad a, b \in \mathbb{R},$$

with $\alpha_i^* := \frac{\alpha_i}{a}$, $\xi^* := a \cdot \xi + b$, and $\beta_i^* := a \cdot \beta_i + b$.

■ Admissible transformations

The item parameters β_i and the latent variable ξ have an **interval scale**. Admissible transformations are the linear transformations. The discrimination parameters α_i have a **ratio scale**. Admissible transformations are multiplications by a real number $\left(\frac{1}{a}\right)$.

■ Meaningful propositions, that is, propositions with invariant truth values:

- about ratios of differences between values of the latent variable ξ
- about ratios of differences between item parameters β_i
- about ratios of the discrimination parameters α_i



2PL-Birnbaum model

Scale fixing via:

- Fixing via item parameters. For example, $\beta_1 = 0$ and $\alpha_1 = 1$. In this case, the latent variable ξ is defined by

$$\xi := \text{logit}_1 = \ln \left(\frac{P(Y_1 = 1 | U)}{1 - P(Y_1 = 1 | U)} \right).$$

- Fixing the expectation and the variance of the latent variable. For example, $E(\xi) = 0$ and $\text{Var}(\xi) = 1$.

In both cases, the logit of each item is a (deterministic) linear function of the latent variable, and vice versa, the latent variable is a (deterministic) linear function of the logit of each item.