

#### Summer School in Applied Psychometric Principles

Peterhouse College 13<sup>th</sup> to 17<sup>th</sup> September 2010

#### Day 3

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#### Topics already covered

- We have...
  - Introduced IRT
  - Introduced simple models for binary responses
  - Discussed IRT assumptions
  - Introduced models for polytomous responses
  - Discussed assessment of fit for these models

Today

• We will spend a day with the Rasch Model

- Why that?
  - Rasch Model is a very simple test model
  - which has extraordinary measurement qualities
  - can be generalized to several applications
  - and which is testable

- The Rasch model can be seen as a very reduced / restricted version of the models we already encountered in the course:
  - the slopes for all items are constrained to be equal (usually  $D\alpha = 1$ )
  - no guessing parameter (c = 0)

$$P(u_{i} = 1 | \theta) = c_{i} + (1 - c_{i}) \frac{e^{Da_{i}(\theta - b_{i})}}{1 + e^{Da_{i}(\theta - b_{i})}}$$
$$P(u_{i} = 1 | \theta) = \frac{e^{(\theta - b_{i})}}{1 + e^{(\theta - b_{i})}}$$

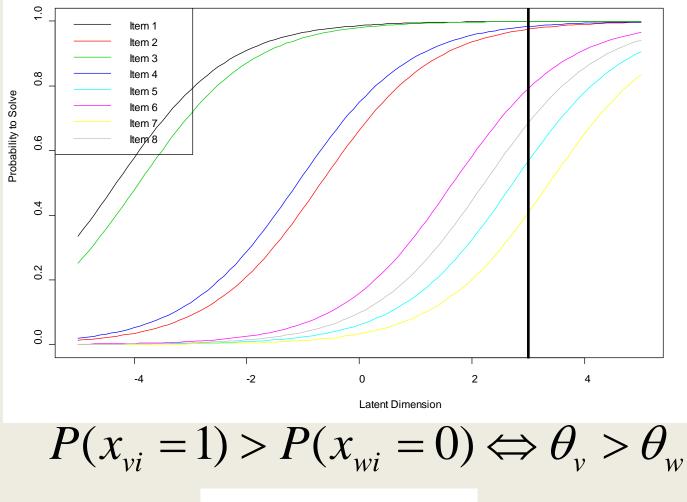
1.0 Item 1 ltem 2 Item 3 Item 4 0.8 ltem 5 Probability to Solve ltem 6 Item 7 0.6 Item 8 0.4 0.2 0.0 -2 2 0 4 -4 Latent Dimension

ICCs for Mobility survey items

- The fact that only one parameter is modeled leads to the models' most important consequence:
  - the ICCs are non-intersecting
  - thereby holds for any comparison of persons or items:

$$P(x_{vi} = 1) > P(x_{wi} = 0) \Leftrightarrow \theta_v > \theta_w$$

ICCs for Mobility survey items



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- This feature of the Rasch Model is called "specific objectivity"; when the Rasch model holds:
  - irrespective of which combination of items from a scale, the same ordering of persons is obtained
  - irrespective of what subsample of persons, the items are ordered the same way according to their difficulty

$$P(x_{vi} = 1) > P(x_{wi} = 0) \Leftrightarrow \theta_v > \theta_w$$

- because both these orderings are stable (within measurement error):
  - it is not important which combination of items was solved by a respondent;
  - and from that follows that the sum of solved items contains all information about the respondent's position on the latent trait

$$P(x_{vi} = 1) > P(x_{wi} = 0) \Leftrightarrow \theta_v > \theta_w$$

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- this principle of "specific objectivity" provides the possibility to construct two specific tests that test whether the data is Rasch-scalable or not:
  - the Andersen Likelihood Ratio Test: checks whether the invariance of item parameters in different subpopulation holds
  - the Martin Löf Test: checks whether the person parameters are invariant by splitting the scale into different subsets of items

### Sideline: Guttman Scaling

- In Guttman scaling only specific patterns allowed:
  - items ordered according to their difficulty
  - a person solving a more difficult item has to solve all items that are easier than that

Items () 1 1

#### Sideline: Guttman Scaling

Items

()

1

1 1

1 1

()

()

- "deterministic model"
- only ordinal measurement possible but score also represents all available information on respondents
- Measurement Theorem:

 $(x_{vi} = 1) \land (x_{wi} = 0) \Leftrightarrow \theta_v > \theta_w$ 

- In essence the Rasch Model does exactly the same:
  - looking for an ordering of the items that describes persons as well as items on the same scale

Items

()

1

1

1

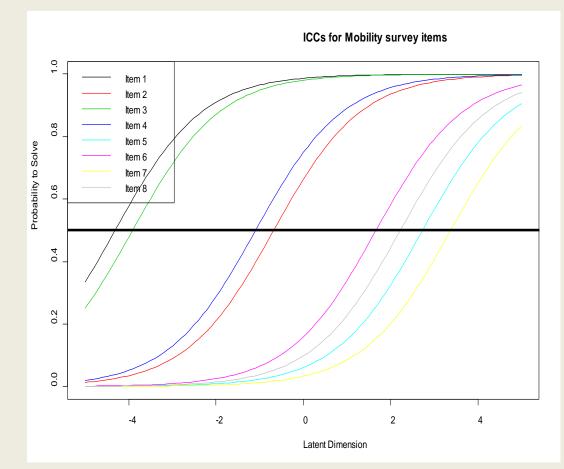
1

- the Rasch model is in a sense completely different:
  - it acknowledges
    measurement error:
    Guttman structure would be
    the ideal pattern, but
    deviations from that are
    possible
  - "probabilistic model"

Items

- the Rasch model is in a sense completely different:
  - by introducing a wellbehaved mathematical function to describe the relationship between the trait and the probability, it is possible to scale the items and scores on a (more than) interval continuum

- based on the data it can be assessed, where on the latent continuum the item is solved with a probability of 50%
- since the slope is defined by the mathematical function, distances between the locations can be measured



### Dimensionality or Local independence assumption

- Item responses are independent after controlling for (conditional on) the latent trait
- There is only one dimension explaining variance in the item responses
  - based on this assumption non-parametric tests can already be employed to check whether the data fits the model BEFORE we even estimate the model (e.g. Ponocny, I. (2001). *Psychometrika, 66,* 437-460.)

#### Features of the Rasch-Model

- Two core differences to other IRT models:
  - it can be tested whether the respondents' patterns in the answer vectors comply with the assumtion of the Rasch Model (tests not based on "by-proxy" tests with factor analysis)
  - Compared to the other models the score is the "sufficient statistic"; in the other models it is a weighted sum

#### Estimating item parameters

- Joint maximum likelihood estimation (JML)
  - Uses *observed* frequencies of response patterns
  - Starting values for ability as proportion correct
    - 1. Estimate item parameters
    - 2. Use item parameters to re-estimate ability
  - Repeat last two steps until estimates do not change
- Marginal maximum likelihood (MML)
  - Uses expected frequencies of each response pattern
  - EM (Estimation and Maximisation) by Bock & Aitken (1981) is popular
- Conditional maximum likelihood (CML)
  - Uses sufficient statistics to exclude trait level parameters (only applies to the Rasch models)

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#### Estimating item parameters

• Conditional maximum likelihood (CML)

Formulas not important in detail, but: the estimator for every item parameter depends a) on the interaction of the location of all other items

b) conditional on all test scores

$$\hat{\delta}_{i} = \ln \left( \sum_{r=1}^{k} n_{r} \frac{\gamma_{r-1}^{(i)}(\epsilon)}{\gamma_{r}(\epsilon)} \right) - \ln(\mathbf{x}_{oi})$$

$$n(CL(X)) = \sum_{i=1}^{k} x_{oi} ln(\epsilon_{i}) - \sum_{r=0}^{k} n_{r} ln(\gamma_{r}(\epsilon))$$

(Wilhem Kempf, University of Konstanz)

#### Finding the examinee parameter

- Maximum likelihood (ML)
  - Maximising the likelihood function (iterative process)
  - ML estimator is unbiased, and its errors are normally distributed
  - Problems with ML is that convergence is not guaranteed with aberrant responses, and no estimator exists for all correct/incorrect responses
- Warm's Maximum Likelihood (WML)
  - often employed (e.g. WINMIRA) because it provides estimates for full/empty response patterns
  - more computational intensive than ML
  - more central estimates; SEs equal to ML
- Spline interpolation
  - estimator based on the relationship between scores and estimated person parameters
  - employed in eRm

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#### **EMPIRICAL EXAMPLE: BDI-DATA**

#### **PRACTICAL: MOBILITY DATA**

### Practical: Mobility survey

- The dimension of interest is women's mobility of social freedom.
- Women were asked whether they could engage in the following activities alone (1 = yes, 0 = no):

#### Estimation in R – eRm

library(eRm)

ResMob<-RM(*Itemmatrix*, se=TRUE, sum0=TRUE)

Itemmatrix is the Matrix containing the responses

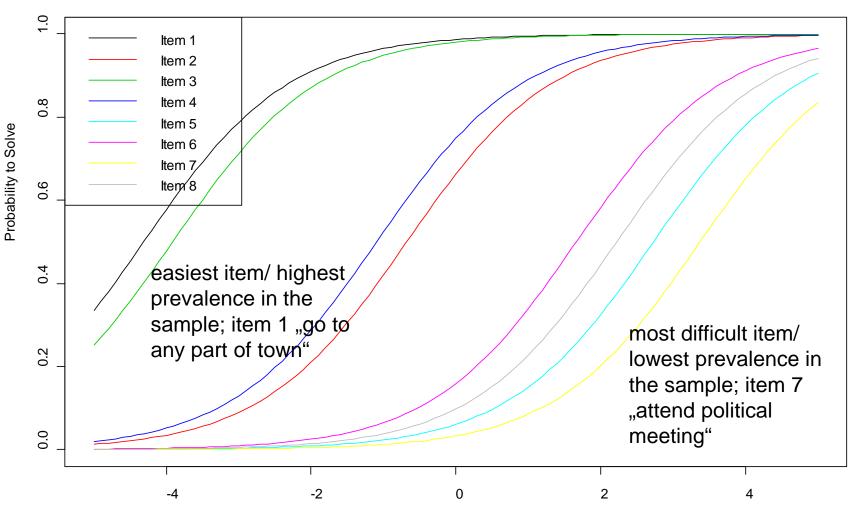
se=TRUE (standard errors are estimated)
sum0=TRUE (b's are normed on 0)

#### Plotting

#### 

#### **Item Characteristic Curves**

**ICCs for dichotomous Mobility items** 

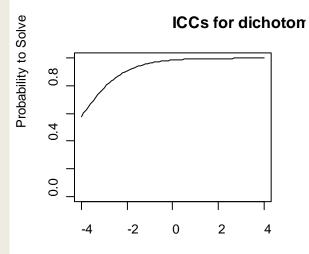


Latent Dimension

#### Plotting

plotICC(ResMob,empICC=list("kernel"),empCI=lis
 t(),main="ICCs for dichotomous Mobility
 items")

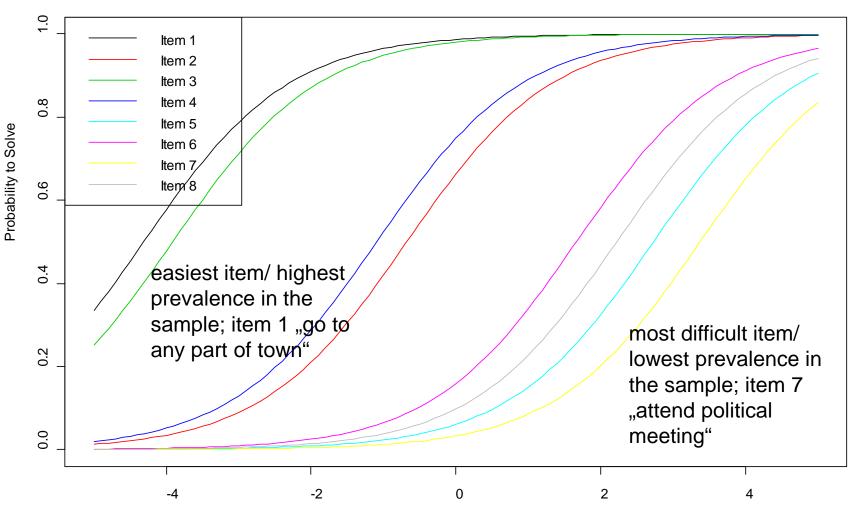
### Plotting



Latent Dimension

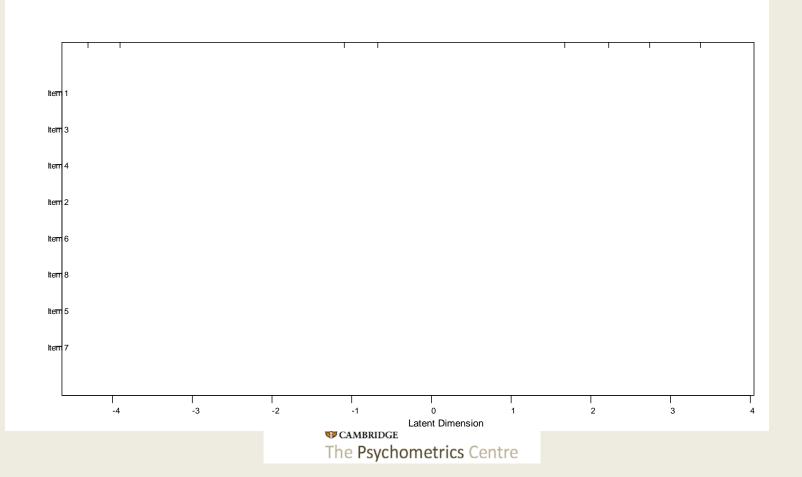
#### **Item Characteristic Curves**

**ICCs for dichotomous Mobility items** 



Latent Dimension

### Joint distribution of items and person parameters

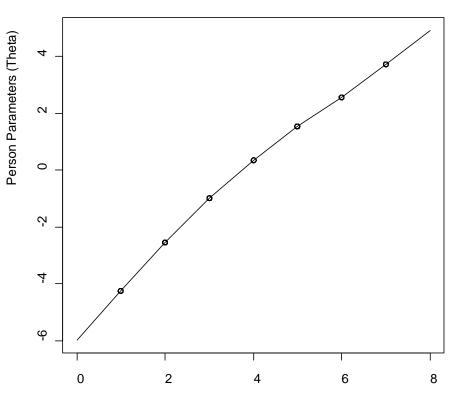


#### Estimating the person parameters

PersMob<-person.parameter(ResMob) plot(PersMob)

## Relationship between scores and person parameters

- every score can be transformed into the scale-free metric of the person parameters
- not related in linear fashion (esp. in the tails)
- also: there are only as many person parameters estimated as possible scores (unlike in the other IRT models)



Person Raw Scores

Plot of the Person Parameters

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#### What if...?

- What would be won if the Rasch-Model fitted the data?
  - we know that the summed item score can be used as a simple descriptive measure for the ability (was also used to estimate the model)
  - we also would have the person parameters to represent the ability on a (better than) equal interval level
  - we would know that the test is fair at any rate ("specific objectivity")
- The nice thing about the Rasch-Model is, that clear predictions about the nature of the data follow from the model formulation and these predictions can be easily tested

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### Testing the Rasch Model

- Non-Parametric tests:
  - Ponocny, I. (2001). Psychometrika, 66, 437-460.
  - before estimating the Rasch Model at all we could test whether the observed item responses of the persons would be expected if the test was Rasch scaled
  - not covered in detail here

# Testing the Rasch Model

- Parametric Tests based on "specific objectivity":
  - ANDERSEN'S LR-TEST: all estimated parameters are independent of the subgroup of the sample in which they are estimated (e.g. gender)
  - MARTIN LÖF-TEST: irrespective of which items are used, the comparison between two test persons should result in the same ordering

- Procedure:
  - The Rasch Model is estimated independently in both/all subgroups
  - and then the fit is compared using the likelihood:

 $\chi I = -2*(LN(Likelihood(full data set) + \sum (LN(Likelihood(Subgroup_g)))$ 

- with df=(g-1)\*(k-1); with g = number of subgroups and k = number of items
- these Likelihoods should be the same, if the itemparameters (δ<sub>i</sub>) were the same in all subgroups g<sub>i</sub>.
   the test should be non-significant

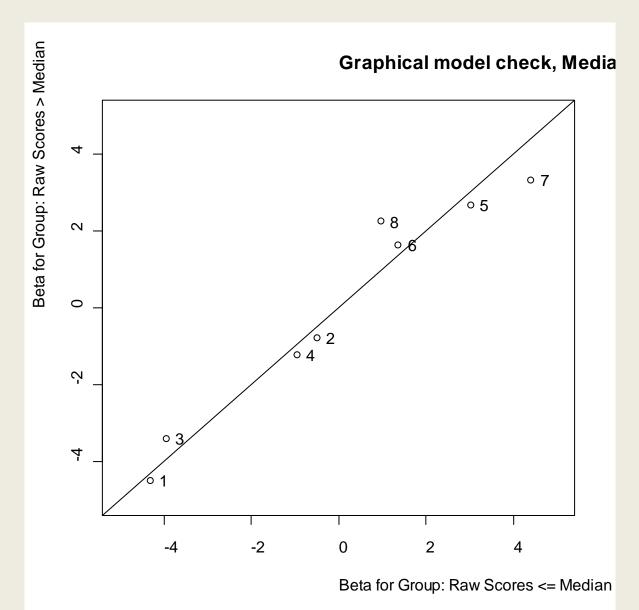
- the default test is with high vs. low scorer groups
- Sample is divided into two groups:
  - a: scores <= median;</pre>
  - b: scores > median

- Andersen1<-LRtest(ResMob,se=TRUE)</li>
- summary(Andersen1)

- the default test is with high vs. low scorer groups
- Sample is divided into two groups:
  - a: scores <= median;</pre>
  - b: scores > median
- χ<sup>2</sup> = 78.36 with df=7; p < .001
- the 8 items do not have the same difficulty parameters in both samples

• Plotting:

plotGOF(Andersen1,main="Graphical model check, Median",tlab="number", ctrline=list(gamma=0.95, col="blue", lty="dashed"), conf=list(),xlim=c(-5,5),ylim=c(-5,5))

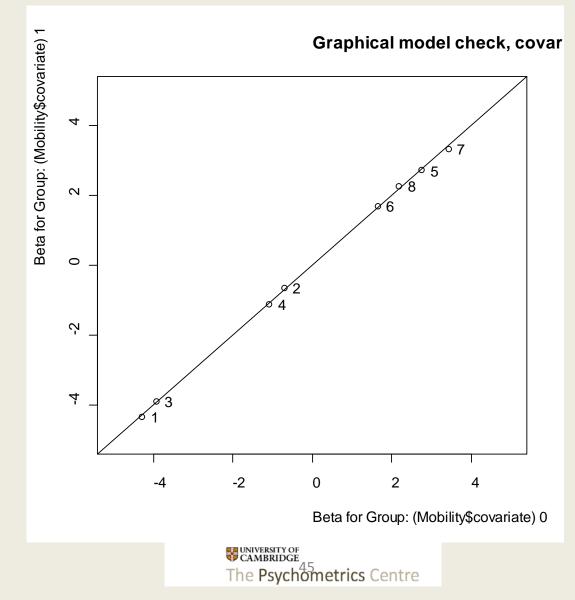


- no covariates in the data file; therefore simulate one:
- Mobility\$covariate<with(Mobility,rbinom(8445,1,.5))

Andersen2<-LRtest(ResMob,se=TRUE,splitcr=(Mobility\$cov ariate))

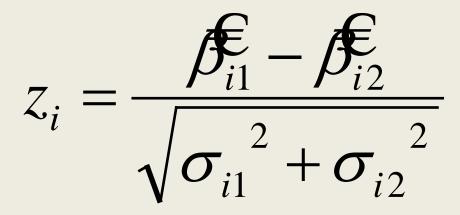
• the random split results in a non-significant test statistic:

- $\chi^2 = 3.15$  with df=7; p = .87
- the 8 items do have the same difficulty parameters in both samples



#### Wald Test

- Both tests provide only information on the fact that the difference between groups is at least for one item parameter big enough, to produce a significant test statistic
- Wald-Tests can be used to test the differences between the subgroups for every item



#### Wald Test

- Syntax for split with median raw score splitting:
- Wald1<-Waldtest(ResMob)</li>

### Wald Test

- In this example done for median of ability
- The following items fail this test:
  - Item 3: p = .002
  - Item 8: < .001

• typical post-hoc questions apply: Type I error, cross-validation,...



# **Differential Item Functioning**

- These ideas are closely connected to the question of Differential Item Functioning (DIF)
- DIF explores whether there are systematic differences between groups in the difficulty of endorsing specific item categories
- these should not be present (or corrected for), because they question the fairness of a specific test
- topic of tomorrow

# Martin Löf Test

- Procedure:
  - The Rasch Model is estimated independently in both ITEM subgroups
  - then the fit is compared using the likelihood:

 $\chi I = -2*(LN(Likelihood(full data set) + \sum_{i}(LN(Likelihood(Subgroup_1))))$ 

- For two subgroups with df=(l<sub>1</sub>\*l<sub>2</sub>-1); with l<sub>1</sub> = number of items in subgroup 1 and l<sub>2</sub> = number of items in subgroup 2
- these Likelihoods should be the same, if the itemparameters  $(\theta_j)$  were the same in all subgroups, i.e. the test should be non-significant

# Martin Löf Test

- the default test is with items high vs. Low in difficulty
- Sample is devided into two groups:
  - a: itemparameter <= median (Items: 1, 2, 3, 4);</p>
  - b: itemparameter > median (Items: 5, 6, 7, 8);
- $\chi^2 = ~3438$  with df=15; p <<< .001
- The items are (at least with this split criterion) not homogeneous

# Martin Löf Test

- Other splits possible, e.g.:
  - One has a hypothesis which items should be grouped together more closely
  - Random splits
- Please think of sub grouping / sub scaling! Then we will perform the test for this specific comparison!

#### Assessing Model Fit: Summary

- (Some) Ways to test the fit of the Rasch-Model:
  - Andersen's LR-Test: Itemparameters the same for different subgroups?
  - Wald-Tests: Itemparameters the same for different subgroups (pay attention to alpha-level!)
  - Martin-Löf-Test: Personparameters are the same when resulting from different item-sets



#### Assessing Model Fit: Summary

- Splits in this regard are usually only as good as the observed criteria
- Rost & von Davier (1997) proposed therefore:
  - estimate the Rasch-Model on your data
  - estimate a two class Mixed Rasch Model on the same data to identify the maximal possible differences between persons in response patterns
  - LR-test between these models or (my opinion)
     Andersen test with these groups

#### **POLYTOMOUS RASCH MODEL**

# **Polytomous Rasch Models**

- The question for polytomous IRT models is, how the different categories can be mapped on the latent continuum
- already seen: Graded Response Model
- In the Rasch perspective especially the *Partial Credit Model* is of interest
- and the constraint version of the so-called *Rating Scale Model*

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# **Generalized Partial Credit Model**

• The model is: 
$$P_{ix}(\theta) = \frac{\exp\sum_{s=0}^{x} a_i (\theta - b_{is})}{\sum_{r=0}^{m} \left[\exp\sum_{s=0}^{r} a_i (\theta - b_{is})\right]}$$

- Easier to see step by step (assume 3 categories):
  - Probability of completing 0 steps

$$P_{i0}(\theta) = \frac{\exp[0]}{\exp[0] + \exp[0 + a_i(\theta - b_{i1})] + \exp[0 + a_i(\theta - b_{i1}) + a_i(\theta - b_{i2})]}$$

Probability of completing 1 step

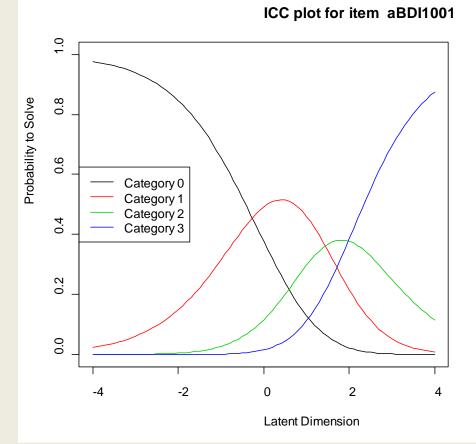
$$P_{i0}(\theta) = \frac{\exp\left[0 + a_i(\theta - b_{i1})\right]}{\exp\left[0\right] + \exp\left[a_i(\theta - b_{i1})\right] + \exp\left[0 + a_i(\theta - b_{i1}) + a_i(\theta - b_{i2})\right]}$$

# The Partial Credit logic

- Created specifically to handle items that require logical steps, and partial credit can be assigned for completing some steps (common in mathematical problems)
- Completing a step assumes completing below
- Computing probability of response to each category is direct ("divide-by-total"):
  - Probability of responding in category x (completing x steps) is associated with ratio of
    - odds of completing all steps before and including this one, and
    - odds of completing all steps
  - Each step's odds are modelled like in binary logistic models
    - For an item with m+1 response categories, m step difficulty parameters b<sub>1</sub>...b<sub>m</sub> are modelled

# Interpretation

- Step difficulty parameters have an easy graphical interpretation – they are points where the category lines cross
- Relative step difficulty reflects how easy it is to make transition from one step to another
  - Step difficulties do not have to be ordered
  - "Reversal" happens if a category has lower probability than any other at all levels of the latent trait



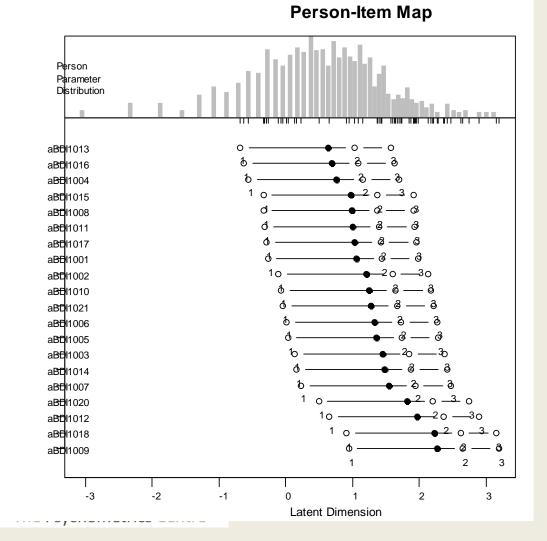
# Estimating a Rating Scale Model in eRm

• starting with the restricted case of the RSM:

• The function "RSM" is used:

#### Result<-RSM(data, se=TRUE, sum0=TRUE)

- circles: thresholds
- black dots: difficulty (comparable to item mean)

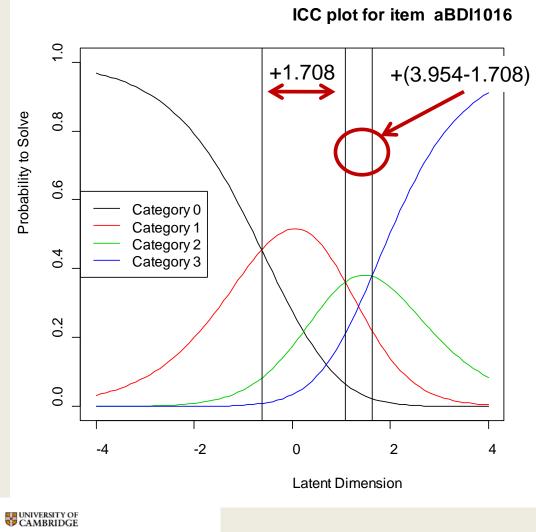


- the RSM imposes the exact same differences between category steps on every item
- in eRm estimated via
  - estimation of the first threshold
  - and estimation of difference parameters between first and second as well as first and third threshold

- Category parameter 0/1: first threshold, estimated
- Category parameter 1/2: second threshold, 1.708
- Category parameter 2/3: third threshold, 3.954

Category

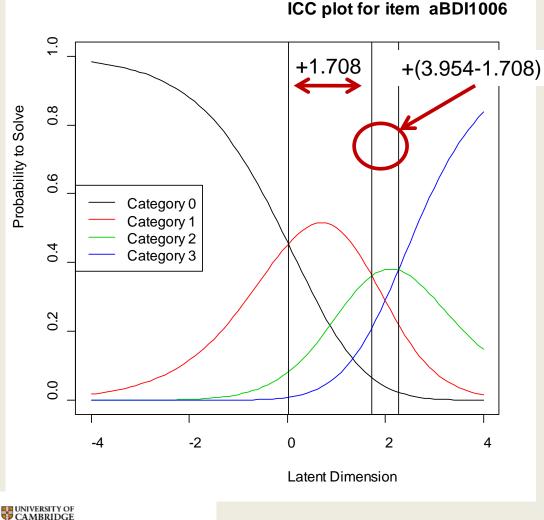
 parameter 0/1:
 first threshold,
 estimated; Item
 16 (sleep
 disturbances):
 .622



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Category

 parameter 0/1:
 first threshold,
 estimated; Item
 06 (feeling /
 waiting to be
 punished): .018

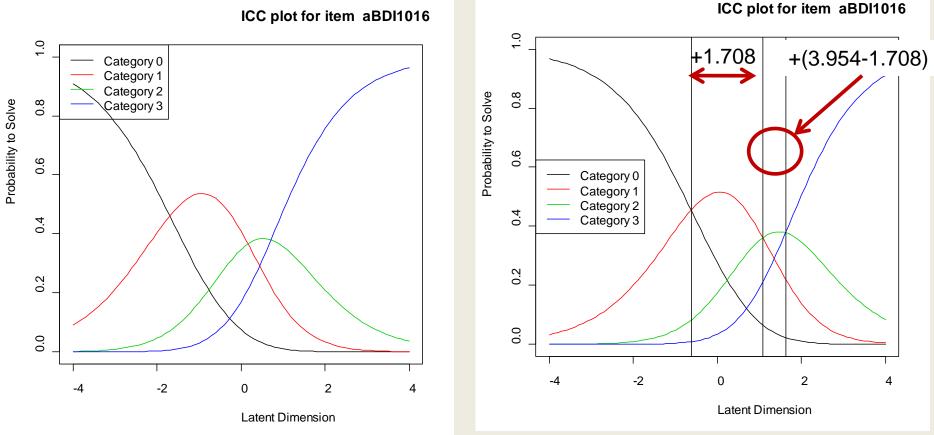


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- the major difference between these two models is
  - the PCM allows every item to have its own structure of category steps
  - whereas the RSM imposes the exact same differences between category steps on every item
  - (also models possible that use the same ratios etc)
  - AND every item can have its own number of categories

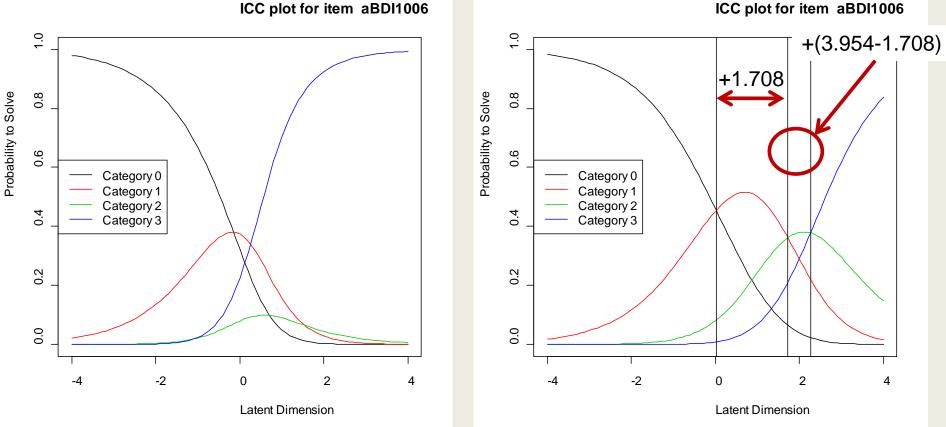
- the Partial Credit Model makes it possible that every item has its own pattern of thresholds
- in eRm estimated via
  - estimation of all thresholds of the items but one
  - (either parameterized that that have to sum to 0 or the first threshold is set to be 0)

- Category parameter 0/1: first threshold, estimated
- Category parameter 1/2: second threshold, estimated
- Category parameter 2/3: third threshold, estimated



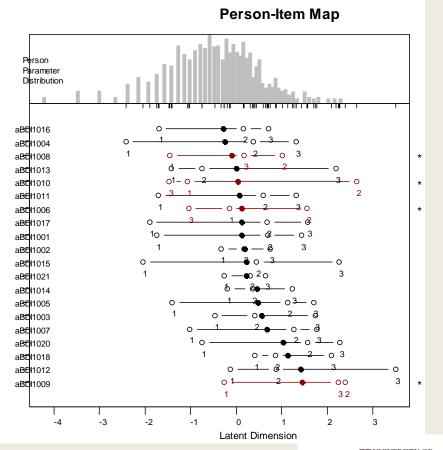
ICC plot for item aBDI1016

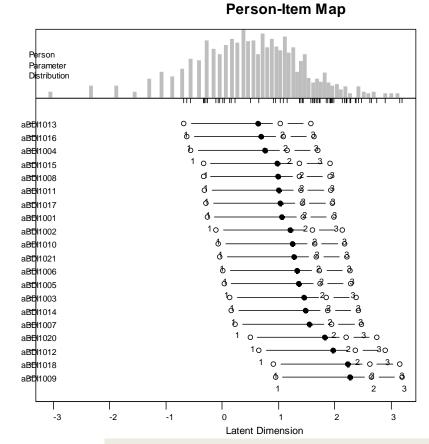
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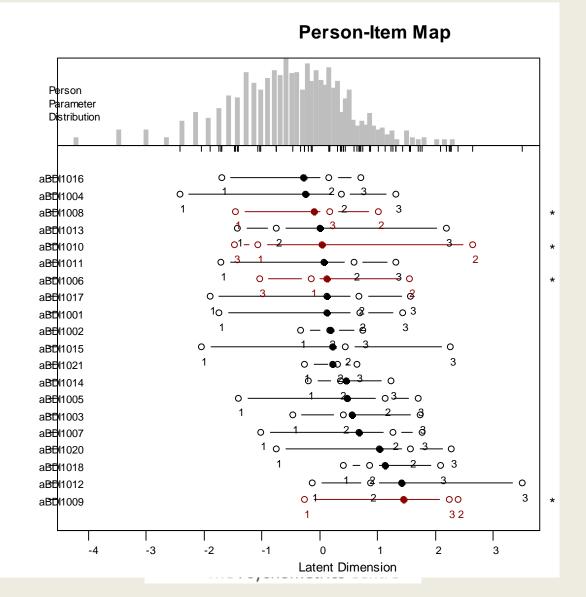


ICC plot for item aBDI1006

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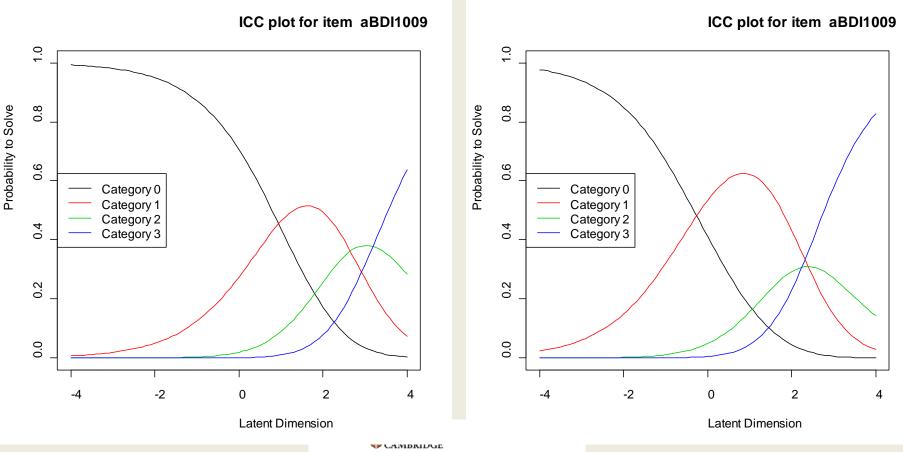






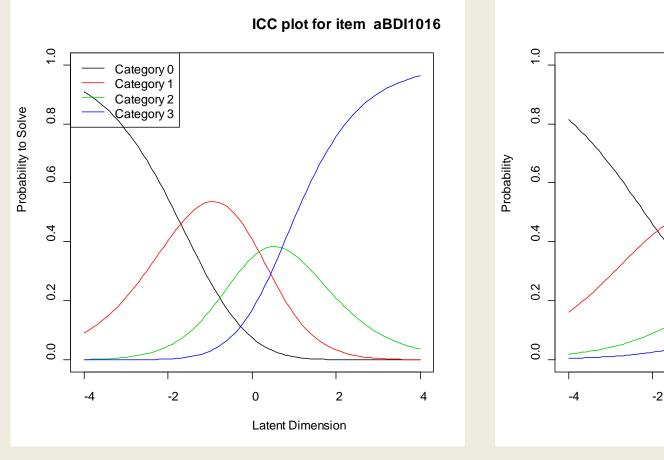
### Differences RSM & PCM

• BDI item 9, suicidal ideation



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## Differences PCM & \_\_\_\_



#### Item Response Category Char

2

3

4

0

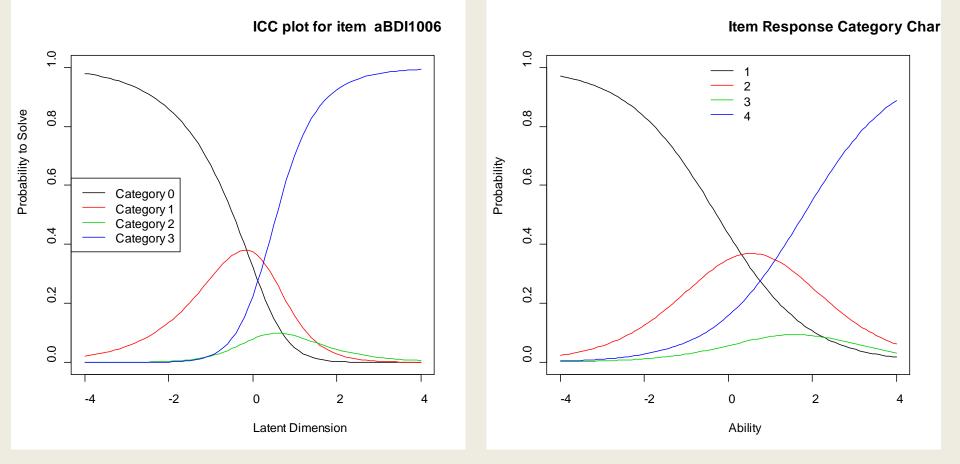
Ability

2

4

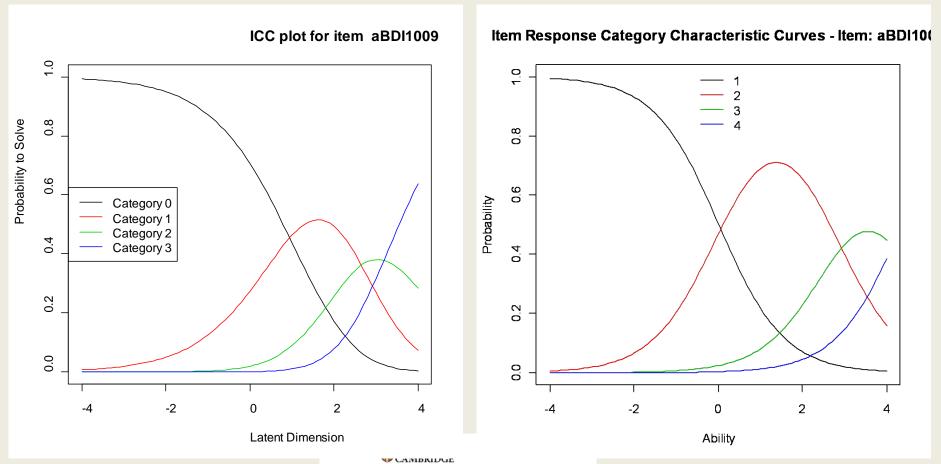
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## Differences PCM & \_\_\_\_



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### Differences PCM & \_



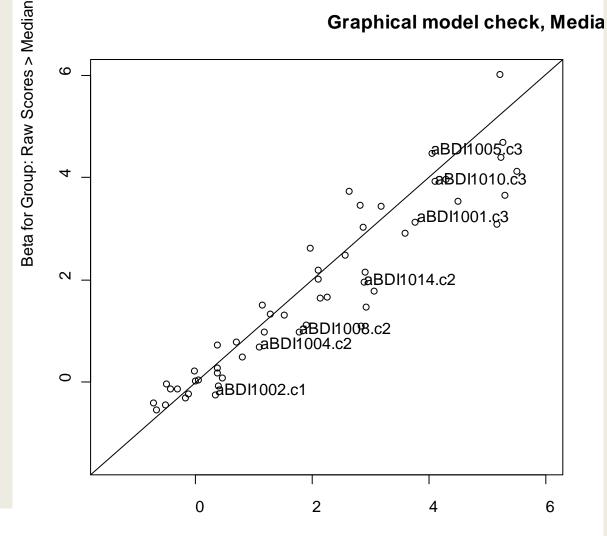
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# Testing polytomous Rasch Models

- since in the estimation process for CML polytomous items are treated as if they were dichotomous items
- polytomous Rasch Models are testable in the same way as dichotomous Rasch Models

# Testing polytomous Rasch Models

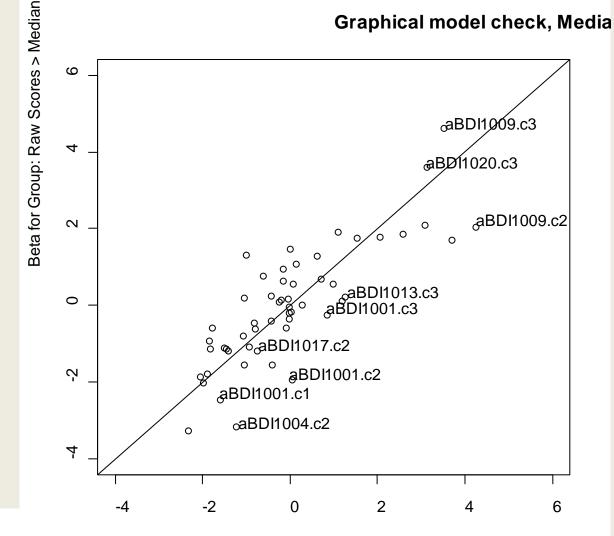
- Test with RSM
- p < .001



Beta for Group: Raw Scores <= Median

# Testing polytomous Rasch Models

- Test with PCM
- p < .001



Beta for Group: Raw Scores <= Median

#### RSM vs PCM

- RSM needs substantially less parameters
- this was before the 2000s a substantial advantage

- today in my opinion no reason to use this model anymore
- (despite the case in which LR test between RSM and PCM shows no significant difference)

#### Rasch vs. 2PL or 3PL Model? (or PC vs. GR and GPCM?)

- This comparison has been of interest for many years, and generated quite emotional debate.
- Rasch model has many desirable properties
  - estimation of parameters is straightforward,
  - sample size does not need to be big,
  - number of items correct is the sufficient statistic for person's score,
  - measurement is completely additive,
  - specific objectivity (more on this tomorrow).
- But your data might not fit the Rasch model...

# Why Rasch?

- often critique: there are no data, that fit that model
- several responses are possible:
  - bad theories produce bad empirics
  - Rasch is a very simple model and reality is not simple (LLTM, LLRA, Mix-Rasch, Multidimensional-/ Nominal-Rasch model,...)
  - BUT it is a model where in detail can be tested, whether it fits the data, or not

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# Rasch vs. 2PL or 3PL Model? (Cont.)

- Two-parameter logistic model is more complex
  - Often fits data better than the Rasch model
  - Requires larger samples (500+)
- Three-parameter logistic model is even more complex
  - Fits data where guessing is common better
  - Estimation is complex and estimates are not guaranteed without constraints
  - Sample needs to be large in applications.

## Choice of model must be pragmatic

- Desirable measurement properties of the Rasch model may make it a target model to achieve when constructing measures
  - Rasch maintained that if items have different discriminations, the latent trait is not unidimensional
- However, in many applications it is impossible to change the nature of the data
  - Take school exams with a lot of varied curriculum content to be squeezed in the test items
- There must be a pragmatic balance between the parsimony of the model and the complexity of the application

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# Rasch as model of choice

 for many applications also models with more parameters might be able to reliably discriminate between different levels of a continuous latent trait

# Rasch as model of choice

- but the Rasch Model it is the only test model that ensures specific objectivity and in which the local stochastic independence assumption is testable
- therefore, especially in high stakes testing situations the Rasch model proves to be extremely useful