

Mixtures of Rasch Models

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Introduction

- Rasch model for measuring latent traits
- Model assumption: Item parameters estimates do not depend on person sample
- Violated in case of differential item functioning (DIF)
- Several approaches to test for DIF:
 - LR tests, Wald tests
 - Rasch trees
 - Mixture models
- Here: Two versions of the mixture model approach

Rasch Model

Probability for person *i* to solve item *j*:

$$P(Y_{ij} = y_{ij}|\theta_i, \beta_j) = \frac{e^{y_{ij}(\theta_i - \beta_j)}}{1 + e^{\theta_i - \beta_j}}$$

- y_{ij} : Response by person *i* to item *j*
- θ_i : Ability of person *i*
- β_j : Difficulty of item *j*

ML Estimation

Factorization of the full likelihood on basis of the scores $r_i = \sum_{j=1}^m y_{ij}$

$$L(\theta, \beta) = f(\mathbf{y}|\theta, \beta)$$

= $h(\mathbf{y}|\mathbf{r}, \theta, \beta)g(\mathbf{r}|\theta, \beta)$
= $h(\mathbf{y}|\mathbf{r}, \beta)g(\mathbf{r}|\theta, \beta)$

- Joint ML: Joint estimation of β and θ is inconsistent
- Marginal ML: Assume distribution for θ and integrate out in $g(\mathbf{r}|\theta,\beta)$
- Conditional ML: Assume $g(\mathbf{r}) = g(\mathbf{r}|\theta,\beta)$ as given or that it does not depend on θ,β (but potentially other parameters). Hence, $g(\mathbf{r})$ is a nuisance term and only $h(\mathbf{y}|\mathbf{r},\beta)$ needs to be maximized.

Mixture Models

Mixtures of Rasch Models

• Mixture of the full likelihoods by Rost (1990):

- Mixture density = \sum weight \times component
- Weights are a priori probabilities for the components
- Components are densities or (regression) models

$$f(\boldsymbol{y}|\boldsymbol{\pi},\boldsymbol{\psi},\boldsymbol{\beta}) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_{k} \psi_{r_{i},k} h(\boldsymbol{y}_{i}|r_{i},\boldsymbol{\beta}_{k})$$

with $\psi_{r_i,k} = g_k(r_i)$

• Mixture of the conditional likelihoods:

$$f(\boldsymbol{y}|\boldsymbol{\pi},\boldsymbol{\beta}) = \prod_{i=1}^{n} \sum_{k=1}^{K} \pi_{k} h(\boldsymbol{y}_{i}|r_{i},\boldsymbol{\beta}_{k})$$

Parameter Estimation

EM algorithm by Dempster, Laird and Rubin (1977)

- Group membership is seen as a missing value
- Optimization is done iteratively by alternate estimation of group membership (E-step) and component densities (M-step)
- E-step:

$$\hat{p}_{ik} = \frac{\hat{\pi}_k h(\boldsymbol{y}_i | \boldsymbol{r}_i, \hat{\boldsymbol{\beta}}_k)}{\sum_{g=1}^{K} \hat{\pi}_g h(\boldsymbol{y}_i | \boldsymbol{r}_i, \hat{\boldsymbol{\beta}}_g)}$$

M-step:

For each component separately

$$\hat{\boldsymbol{\beta}}_{k} = \operatorname*{argmax}_{\boldsymbol{\beta}_{k}} \sum_{i=1}^{n} \hat{\boldsymbol{p}}_{ik} \log h(\boldsymbol{y}_{i}|r_{i}, \hat{\boldsymbol{\beta}}_{k})$$

Number of Components

How can the number of components *k* be established?

- A priori known number of groups in the data
- LR test: Regularity conditions are not fulfilled
 - \rightarrow Distribution under H_0 unknown
 - ightarrow Bootstrap necessary
- Information criteria: AIC, BIC, ICL

Simulation Design

Item Parameters

- 10 items, 1800 people, equal group sizes
- Latent groups in item and/or person parameters:





Person Parameters





Criteria for Goodness of Fit

- Number of components
- Rand index:

Agreement between true and estimated partition

• Mean residual sum of squares:

Agreement between true and estimated (item) parameter vector



Latent Structure in Item and Person Parameters (DIF + Ability Differences)





Latent Structure in Item and Person Parameters (DIF + Ability Differences)



Latent Structure in Item and Person Parameters (DIF + Ability Differences)



Literature

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Summary and Outlook

- Model suitable for detecting latent classes with DIF
- Model also suitable when a latent structure in the person parameters is present
- AIC tends to overestimate the correct number of classes, BIC and ICL work well
- Clustering of the observations works well
- Estimation of the item parameters in the components works reasonably well
- Comparison with Rost's MRM to follow