**Lab 4: IRT Fit**

**Mar 22, 2023**

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| Outline   * Estimation * Examples   1. IRT fit for binary responses using ‘irtoys’ and ‘ltm’ packages  2. IRT fit for polytomous responses using ‘eRm’ package |

* **Estimation**

**1. Installation of R package ‘irtoys’, ‘ltm’, and ‘eRm’**

**2. Functions in the R packages, ‘irtoys’, ‘ltm’, and ‘eRM’**

**[1] ‘irtoys’**

Refer to the following pages of the ‘eRm’ manual downloaded from <http://cran.r-project.org/web/packages/irtoys/irtoys.pdf>:

* ‘irf’ function [test item fit]
* ‘api’ function [the *Z3* appropriateness index]

**[2] ‘ltm’**

Refer to the following pages of the ‘ltm’ manual downloaded from <http://cran.r-project.org/web/packages/ltm/ltm.pdf>:

* ‘rasch’ function [Rasch model]
* ‘ltm’ function [latent trait model - latent variable model for binary data]
* ‘anova’ function [anova method for fitted IRT models]

**[3] ‘eRm’**

Refer to the following pages of the ‘eRm’ manual downloaded from <http://cran.r-project.org/web/packages/eRm/eRm.pdf>:

* ‘itemfit’ function [item fit statistics]
* ‘personfit’ function [person fit statistics]
* ‘IC’ function [information criteria]
* **Examples**

**1. IRT fit for binary responses using ‘irtoys’ and ‘ltm’ packages**

[1] Dataset

binary.txt

25-item, 250-person

Codes as 0 or 1

Note: Missing responses can be coded as **NA**.

[2] Scripts

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| ##########################################  ######### BINARY RESPONSES ###########  ##########################################  ## Import binary data (binary.txt)  binary <- read.table("C:/Teaching/IRT I\_2023 Spring/Labs/Lab 4/binary.txt",header=TRUE)  binary[1:10,]  ## Fit a Rasch model or 1PL model  # Item parameter estimates and SEs of item estimates  Rasch <- est(binary,model="1PL",engine="ltm",rasch=TRUE)  Rasch  ## Item fit for Item 2  itemfit <- itf(resp=binary, ip=Rasch$est, stat = "lr", item=2)  itemfit  ## Person fit  personfit <- api(binary, Rasch$est)  write.table(personfit,file="C:/Teaching/ IRT I\_2023 Spring/Labs/Lab 4/personfit.txt")  ## Model fit  # Fit a Rasch (1PL) model using ltm library to obtain a log-likelihood value  Rasch1 <- rasch(binary)  Rasch1  # Fit a 2PL model using ltm library to obtain a log-likelihood value  Two1 <- ltm(binary ~ z1, constr = rbind(c(1, 1, 1)))  Two1  # Model comparisons  anova(Rasch1, Two1) |

[3] Results

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| > ## Item fit for Item 2  > itemfit <- itf(resp=binary, ip=Rasch$est, stat = "lr", item=2)  > itemfit  Statistic DF P-value  H0: Item fits well to the data.  At alpha=0.05, there is evidence that H0 can be rejected. (Item 2 does not fit well to the data)  16.7636200 8.0000000 0.0326668      Results are saved as the file named as “personfit.txt.”  Estimated ICC: Solid line  Empirical ICC:  Dots  > personfit <- api(binary, Rasch$est)  >  > write.table(personfit,file="C:/Teaching/IRT I\_2018 Fall/Labs/Lab 4/personfit.txt")  Residual-based statistic  > personfit  [1] -0.186650969 (for person id 1) 0.576266851 (for person id 2) 0.201456170 1.296432461 1.035722607  [6] -0.170510454 -1.144249980 0.049289469 -1.054233539 0.412010665  [11] -0.336331554 0.696431715 -0.466450154 0.502220301 0.526937851  [16] -0.240101006 -0.369172446 1.086579822 -0.318136676 0.759713662 …  > ## Model fit  >  > # Fit a Rasch (1PL) model using ltm library to obtain a log-likelihood value  > Rasch1 <- rasch(binary)  > # Fit a 2PL model using ltm library to obtain a log-likelihood value  > Two1 <- ltm(binary ~ z1, constr = rbind(c(1, 1, 1)))  > # Model comparisons  > anova(Rasch1, Two1)  Likelihood Ratio Table  AIC BIC log.Lik LRT df p.value  H0: Simpler model (Rasch model) fits better.  At alpha=0.05, there is an evidence that H0 is rejected  (2-parameter model fits better to the data.)  Rasch1 6425.15 6516.71 -3186.57  Two1 6389.89 6562.44 -3145.94 81.26 23 <0.001  The smaller, the better  2-parameter model (Two1) fits better based on AIC while Rasch model fits better based on BIC. |

**2. IRT fit for polytomous responses using ‘eRm’ package**

[1] Dataset

Polytomous responses (polytomous.txt)

25-item, 316-person

Codes as 0, 1, or 2

Note: Missing responses can be coded as **NA**.

[2] Scripts

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| ##########################################  ####### POLYTOMOUS RESPONSES ###########  ##########################################  ## Call 'eRm' library  library(eRm)  ## Importing polytomous data (polytomous.txt)  poly <- read.table("C:/Teaching/ IRT I\_2023 Spring /Labs/Lab 4/polytomous.txt",header=TRUE)  ## Fitting a rating scale model using 'eRm': Conditional MLE  # RSM, estimation of item and person parameters  rsm <- RSM(poly, se = TRUE, sum0 = TRUE)  rsm  p.rsm <- person.parameter(rsm)  ## Item fit  itemfit <- itemfit(p.rsm)  itemfit  ## Person fit  personfit <- personfit(p.rsm)  personfit  ## Model comparisons: RSM vs. PCM  # Rating scale model  rsm <- RSM(poly, se = TRUE, sum0 = TRUE)  rsm  IC(p.rsm)  # Partial credit model  pcm <- PCM(poly, se = TRUE, sum0 = TRUE)  pcm  p.pcm <- person.parameter(pcm)  IC(p.pcm) |

[3] Results

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| > ## Item fit  > itemfit <- itemfit(p.rsm)  > itemfit    Adams and Khoo (1996) suggested that items with good fit have infit scores between 0.75 and 1.33.  Ho: Item fits well to the data.  Itemfit Statistics:  Chisq df p-value Outfit MSQ Infit MSQ Outfit t Infit t  item1 308.098 313 0.568 0.981 0.953 -0.18 -0.71  item2 298.993 313 0.706 0.952 0.954 -0.45 -0.66  item3 391.127 313 0.002 1.246 1.134 1.85 1.64  item4 291.406 313 0.804 0.928 0.961 -0.81 -0.58  item5 340.889 313 0.134 1.086 1.038 0.97 0.60  …  > ## Person fit  > personfit <- personfit(p.rsm)  > personfit  Adams and Khoo (1996) suggested that persons with good fit have infit scores between 0.75 and 1.33.  H0: Person fits well to the data.  Personfit Statistics:  Chisq df p-value Outfit MSQ Infit MSQ Outfit t Infit t  P1 42.569 24 0.011 1.703 1.915 0.94 1.21  P2 25.024 24 0.404 1.001 1.171 0.15 0.58  P3 18.482 24 0.779 0.739 0.677 -0.59 -1.10  P4 12.798 24 0.969 0.512 0.412 -1.89 -3.22  P5 14.891 24 0.924 0.596 0.611 -1.23 -1.60  P6 28.761 24 0.229 1.150 1.154 0.56 0.69  …  > # Rating scale model  > rsm <- RSM(poly, se = TRUE, sum0 = TRUE)  > rsm  Results of RSM estimation:  Call: RSM(X = poly, se = TRUE, sum0 = TRUE)  Conditional log-likelihood: -5720.688  Number of iterations: 33  Number of parameters: 25  >  > IC(p.rsm)  Information Criteria:  Please refer to values based on the marginal log-lik.  ‘cAIC’ is the AIC with the correction for consistency.  value npar AIC BIC cAIC  joint log-lik -6361.142 70 12862.28 13124.74 13194.74  marginal log-lik -6876.607 25 13803.21 13897.11 13922.11  conditional log-lik -5720.688 25 11491.38 11585.27 11610.27  >> # Partial credit model  > pcm <- PCM(poly, se = TRUE, sum0 = TRUE)  > pcm  Results of PCM estimation:  Call: PCM(X = poly, se = TRUE, sum0 = TRUE)  Conditional log-likelihood: -5698.104  Number of iterations: 74  Number of parameters: 49  ….  >  > p.pcm <- person.parameter(pcm)  >  > IC(p.pcm)  Information Criteria:  value npar AIC BIC cAIC  Please refer to values based on the marginal log-lik.  ‘cAIC’ is the AIC with the correction for consistency.  joint log-lik -6338.289 94 12864.58 13217.02 13311.02  marginal log-lik -6854.024 49 13806.05 13990.08 14039.08  conditional log-lik -5698.104 49 11494.21 11678.24 11727.24 |