Code

Tree-Based Differential Item Functioning (DIF) using Partial Credit Model

2022-10-19

Data Source

Real-world data to demonstrate the implementation of the methods discussed in this workshop were from a population-based Joint Replacement Registry for patients having a total or partial hip or knee replacement.

We selected 1391 individuals who had a total hip replacement and provided complete responses to the SF-12 (version 2) physical and mental components items prior to undergoing surgery (i.e., at the baseline clinic visit).

Objective

To test for DIF by age and sex on the physical and mental component items of the SF-12

Packages and Functions to Test for Tree-Based DIF in R

We would explore the **pctree** functions in the psychotree package.

Install the following packages, if not previously installed.

Hide

```
# install.packages(c("tidyverse","mirt","psychotree","partykit", "strucchange"))
```

Load the Libraries

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```
library(tidyverse) # For data manipulation
library(psychotree)  # For tree-based DIF Test
library(mirt)  # For traditional PCM
library(strucchange)    # For structural change test
```

Load the dataset and carry out the necessary data manipulation

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```
tha_data <- read_csv("SF12health_Complete_Hip.csv")

# glimpse(tha_data)

allitems_sex_age <- c("SF1_PH","SF2A_PH", "SF2B_PH", "SF3A_PH",
                      "SF3B_PH", "SF4A_MH","SF4B_MH", "SF5_PH",
                      "SF6A_MH", "SF6B_MH", "SF6C_MH", "SF7_MH","Sex","age")

allitems <- c("SF1_PH","SF2A_PH", "SF2B_PH", "SF3A_PH",
              "SF3B_PH", "SF4A_MH","SF4B_MH", "SF5_PH",
              "SF6A_MH", "SF6B_MH", "SF6C_MH", "SF7_MH")

tha_data_sx_ag <- tha_data[,allitems_sex_age]
tha_data_sx_ag$Sex <- factor(tha_data_sx_ag$Sex,levels = c(0,1),
                                                labels = c("Female","Male"))
```

Assumption: We assume that the PH and MH dimensions are unidimensional.

Select items associated with PH and MH

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```
tha_data_sx_ag$PH <- data.matrix(tha_data_sx_ag[,c(1,2,3,4,5,8)])
tha_data_sx_ag$MH <- data.matrix(tha_data_sx_ag[,c(6,7,9,10,11,12)])

# Recode the response usch that the minimum response becomes 0
# This is because of how the pctree function was developed.
# You can try not recoding and see warning you would get.

tha_data_sx_ag$PH <- data.matrix(tha_data_sx_ag[,c(1,2,3,4,5,8)]) - 1
tha_data_sx_ag$MH <- data.matrix(tha_data_sx_ag[,c(6,7,9,10,11,12)]) - 1
```

Before we proceed to test DIF using partial credit model (PCM) tree-based method, we would fit a conventional PCM to our data and assess the fit.

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```
#---------------------- PCM----------------------
mirtPHpcm <- mirt(data = tha_data_sx_ag$PH,
                  model = 1, # Default is 1, indicating that a                                        unidimensional model wi
ll be fitted
                  itemtype = "Rasch",
                  SE = TRUE,
                  verbose = FALSE)


mirtMHpcm <- mirt(data = tha_data_sx_ag$MH,
                  model = 1, # Default is 1, indicating that a                                        unidimensional model wi
ll be fitted
                  itemtype = "Rasch",
                  SE = TRUE,
                  verbose = FALSE)


# Obtain the model parameters
coefPHpcm <- coef(mirtPHpcm, IRTpars = T, simplify=TRUE)
coefMHpcm <- coef(mirtMHpcm, IRTpars = T, simplify=TRUE)
```

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```
## print the model parameters
mirtPHpcm
```

```
##
## Call:
## mirt(data = tha_data_sx_ag$PH, model = 1, itemtype = "Rasch",
##     SE = TRUE, verbose = FALSE)
##
## Full-information item factor analysis with 1 factor(s).
## Converged within 1e-04 tolerance after 29 EM iterations.
## mirt version: 1.37.1
## M-step optimizer: nlminb
## EM acceleration: Ramsay
## Number of rectangular quadrature: 61
## Latent density type: Gaussian
##
## Information matrix estimated with method: Oakes
## Second-order test: model is a possible local maximum
## Condition number of information matrix =  145.9544
##
## Log-likelihood = -7977.316
## Estimated parameters: 21
## AIC = 15996.63
## BIC = 16106.62; SABIC = 16039.92
## G2 (5603) = 2790.19, p = 1
## RMSEA = 0, CFI = NaN, TLI = NaN
```

Hide

```
mirtMHpcm
```

```
##
## Call:
## mirt(data = tha_data_sx_ag$MH, model = 1, itemtype = "Rasch",
##     SE = TRUE, verbose = FALSE)
##
## Full-information item factor analysis with 1 factor(s).
## Converged within 1e-04 tolerance after 23 EM iterations.
## mirt version: 1.37.1
## M-step optimizer: nlminb
## EM acceleration: Ramsay
## Number of rectangular quadrature: 61
## Latent density type: Gaussian
##
## Information matrix estimated with method: Oakes
## Second-order test: model is a possible local maximum
## Condition number of information matrix =  143.3808
##
## Log-likelihood = -10631.27
## Estimated parameters: 25
## AIC = 21312.53
## BIC = 21443.48; SABIC = 21364.06
## G2 (15599) = 4135.11, p = 1
## RMSEA = 0, CFI = NaN, TLI = NaN
```

Hide

```
coefPHpcm
```

```
## $items
##         a     b1     b2    b3    b4
## SF1_PH  1 -3.860 -2.528 0.256 2.815
## SF2A_PH 1  1.221  3.096    NA    NA
## SF2B_PH 1  1.487  3.145    NA    NA
## SF3A_PH 1 -0.350  1.288 2.477 3.130
## SF3B_PH 1 -0.320  1.376 2.802 3.235
## SF5_PH  1 -1.137  1.379 2.547 4.144
##
## $means
## F1
##  0
##
## $cov
##       F1
## F1 2.147
```

Hide

```
coefMHpcm
```

```
## $items
##         a     b1     b2     b3    b4
## SF4A_MH 1 -1.817 -0.894  0.152 0.445
## SF4B_MH 1 -1.798 -1.092 -0.035 0.325
## SF6A_MH 1 -2.607 -1.257 -0.278 3.155
## SF6B_MH 1 -1.704 -0.394  1.221 3.679
## SF6C_MH 1 -2.855 -2.502 -0.492 0.712
## SF7_MH  1 -1.845 -1.174  0.562 0.821
##
## $means
## F1
##  0
##
## $cov
##       F1
## F1 1.675
```

Visualize the results for all the items

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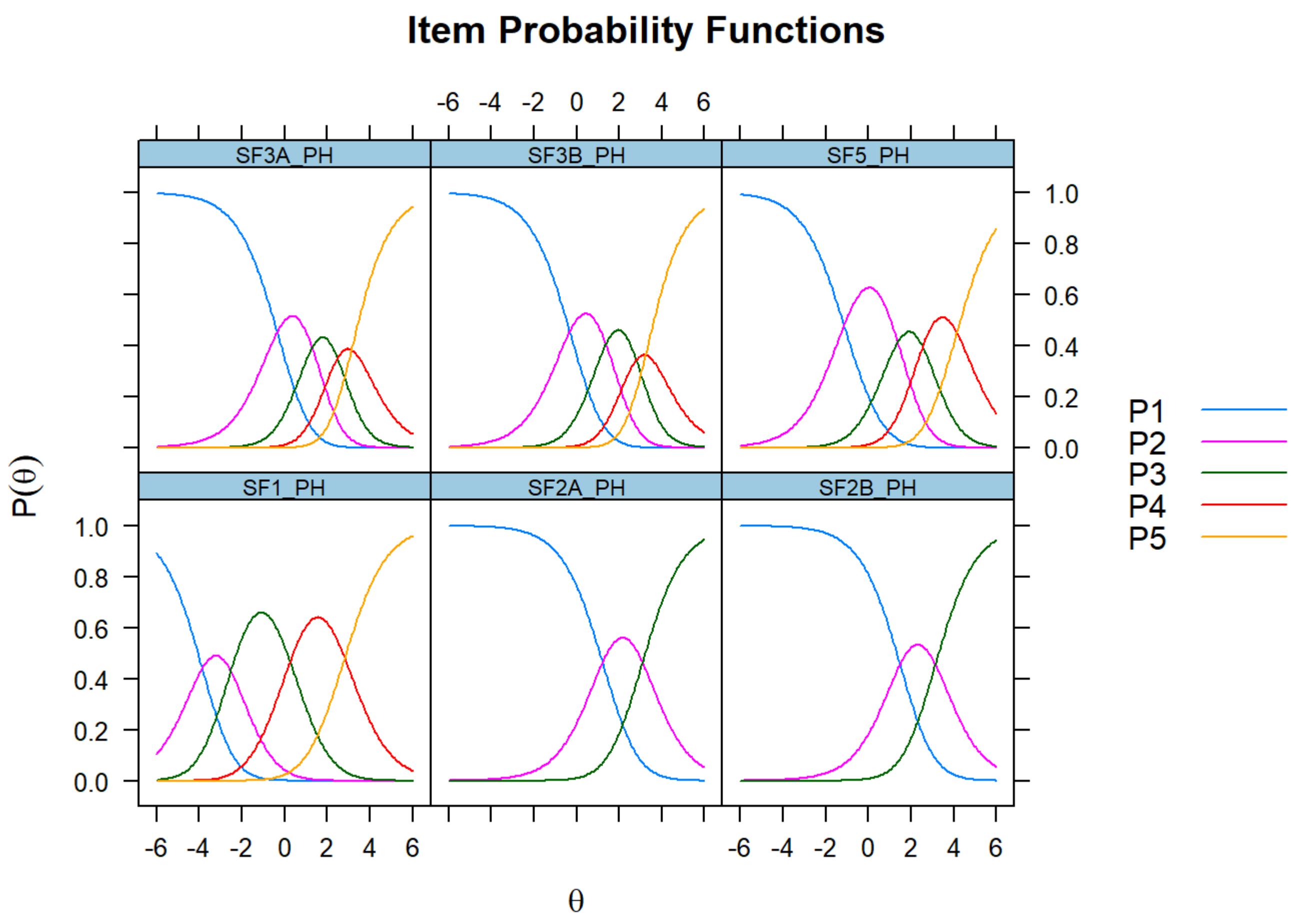
```
# Visualizations
plot(mirtPHpcm, type = 'trace') # the category response curves
```



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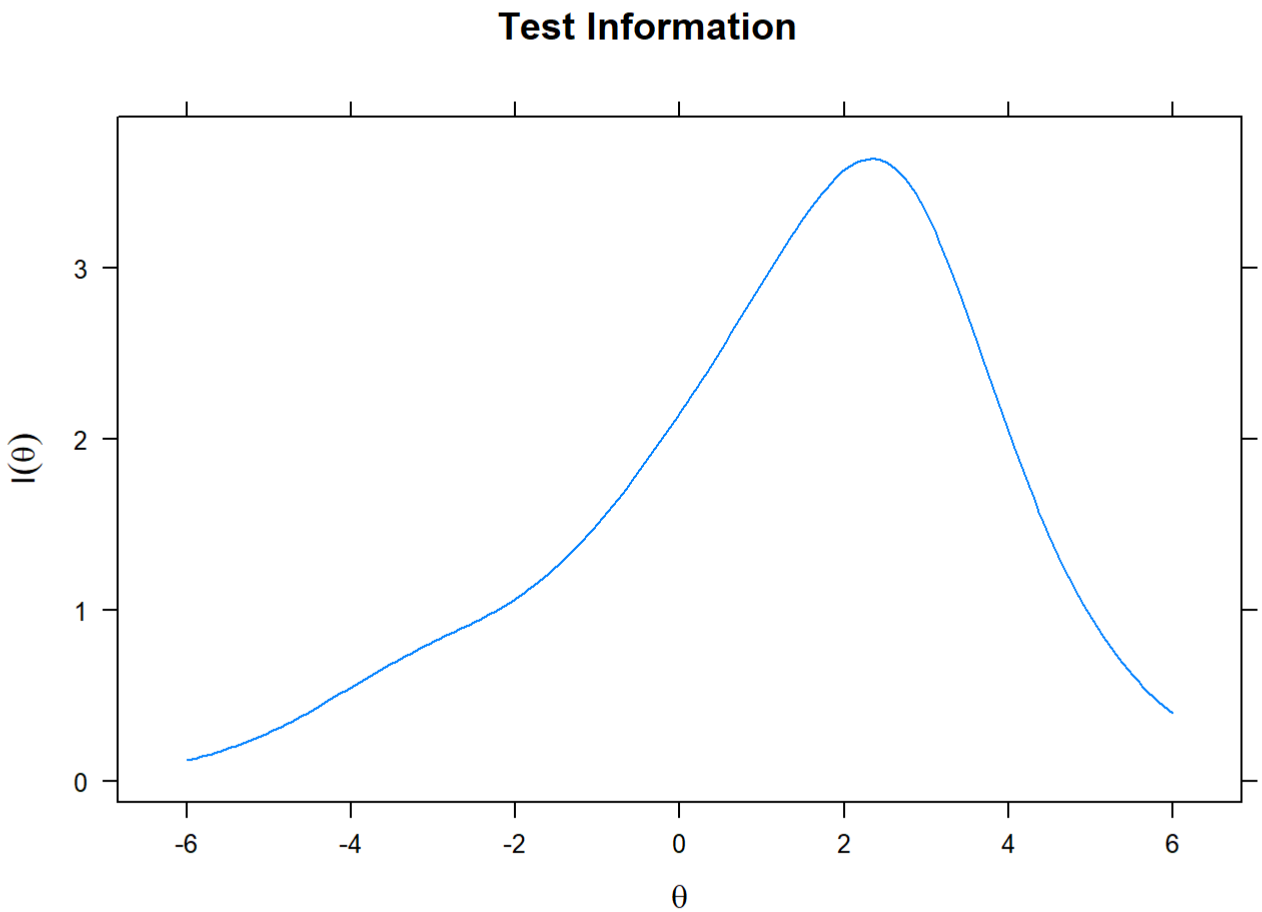
```
plot(mirtPHpcm, type = 'info')  # test information
```



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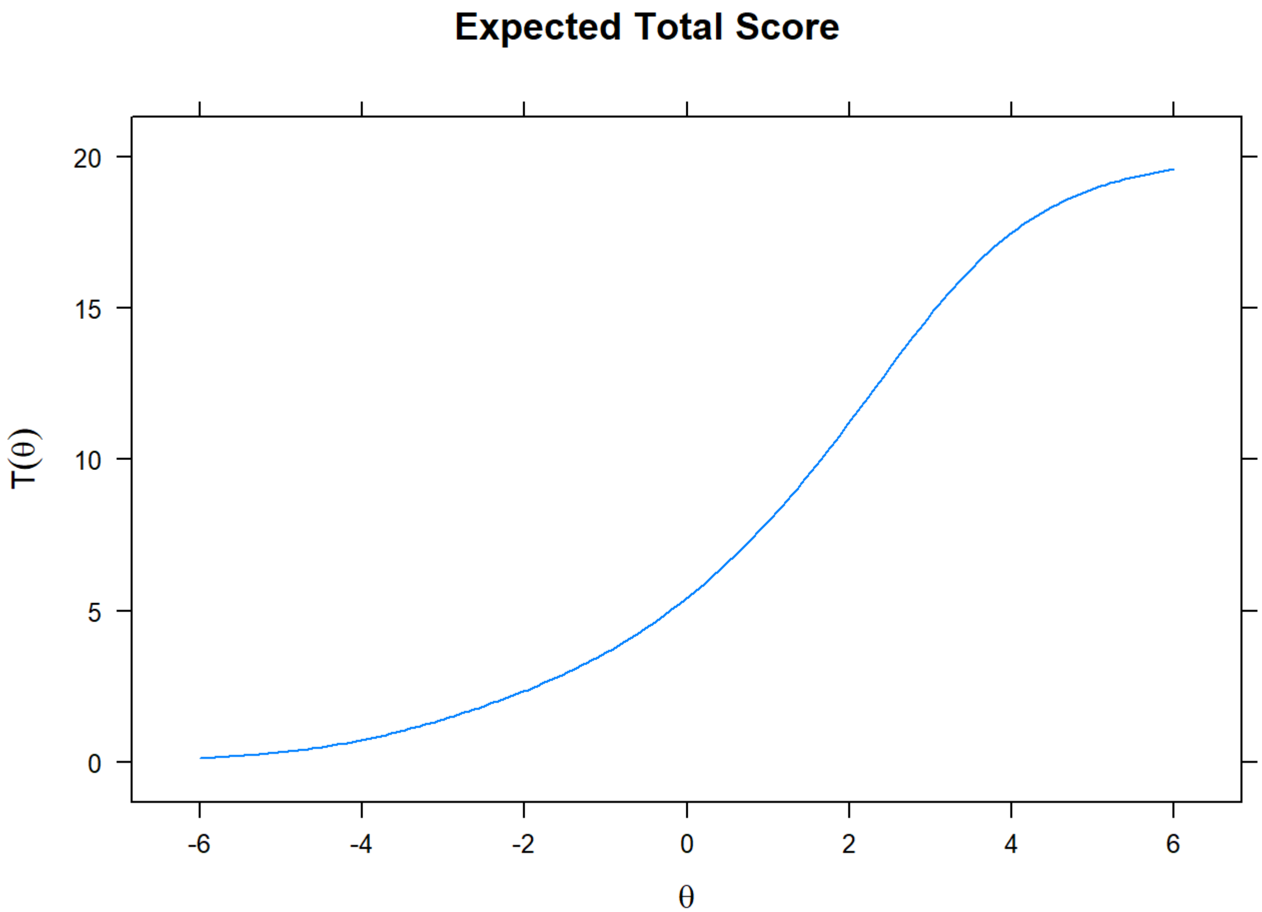
```
plot(mirtPHpcm)                  # test score function
```



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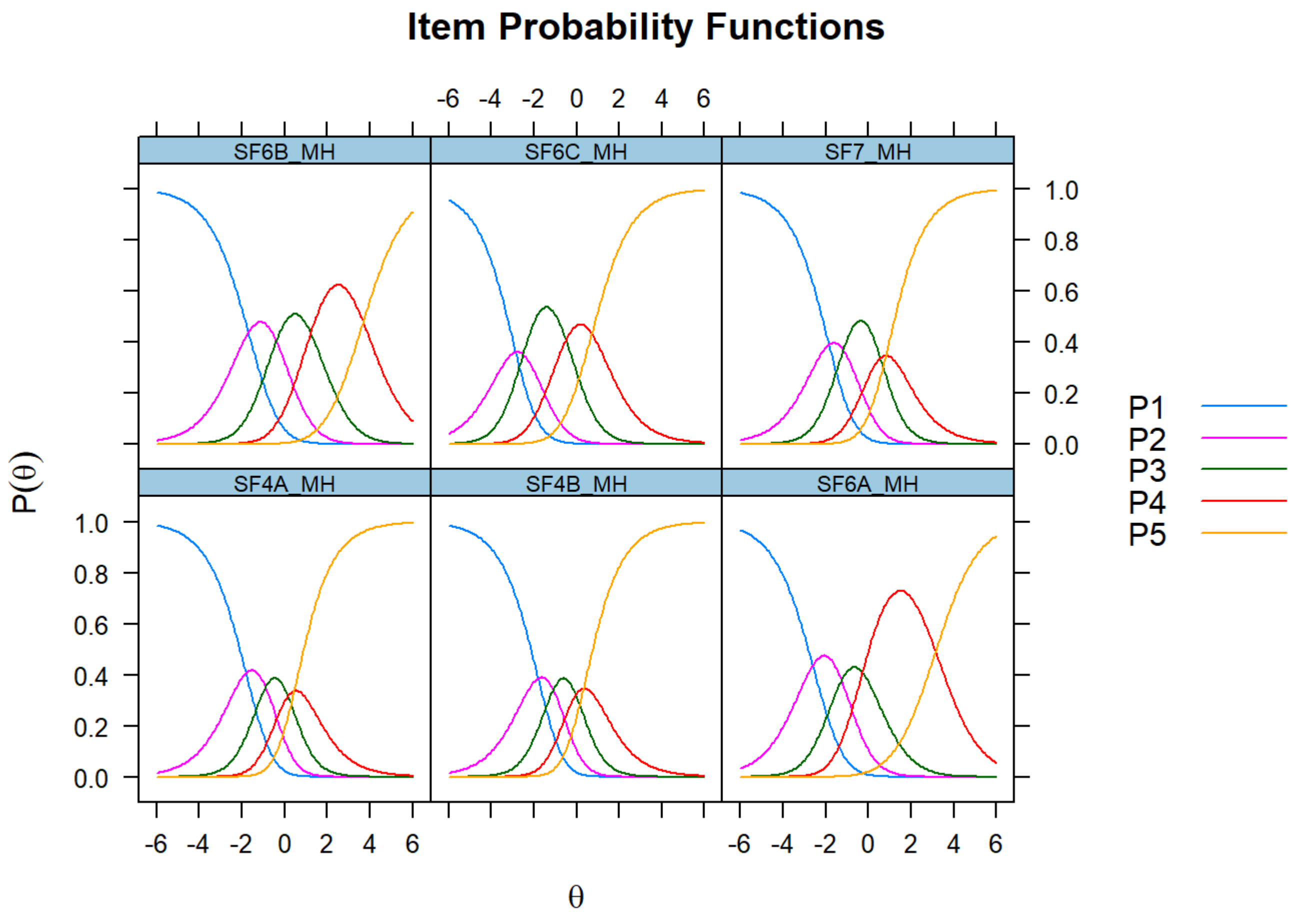
```
plot(mirtMHpcm, type = 'trace') # the category response curves
```



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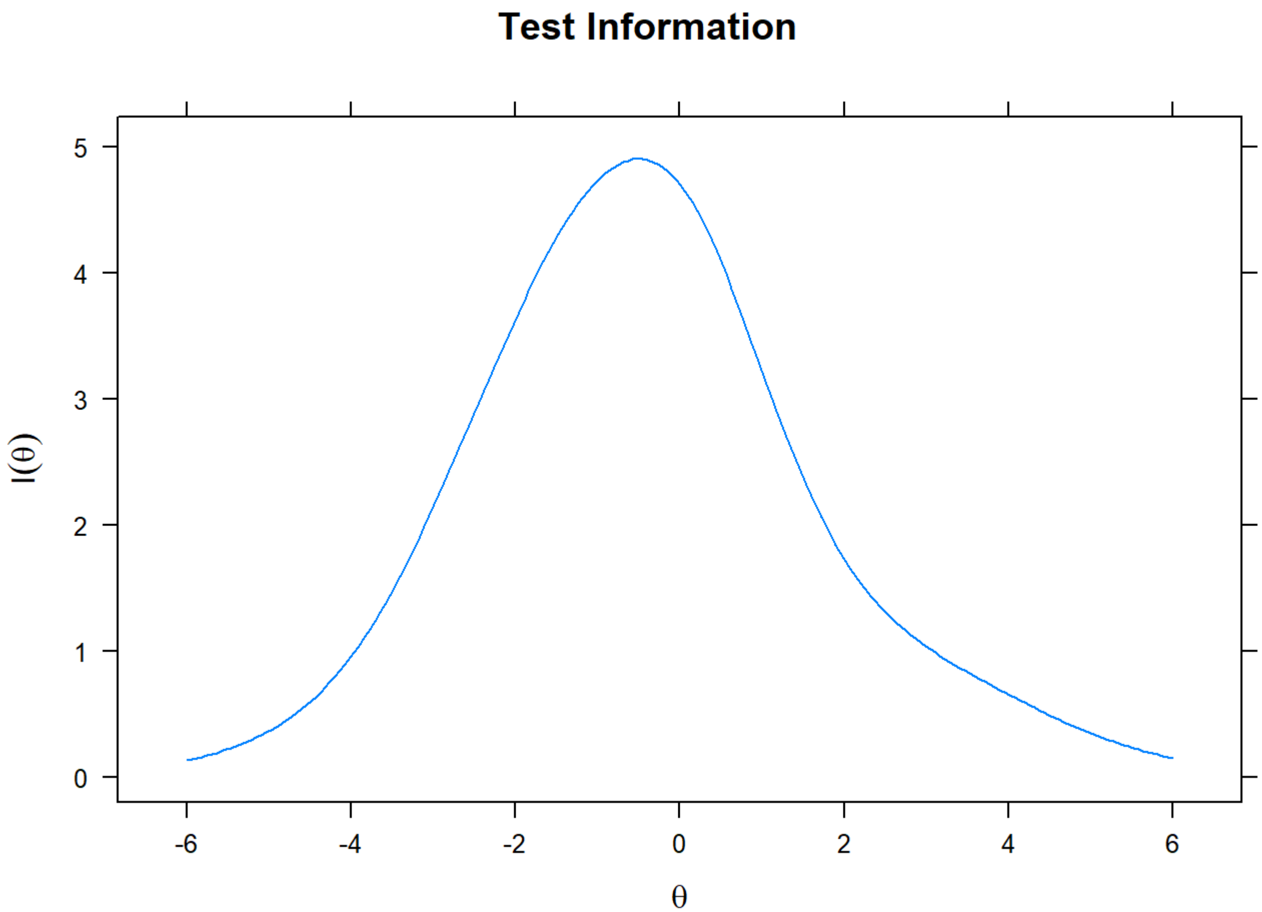
```
plot(mirtMHpcm, type = 'info')  # test information
```



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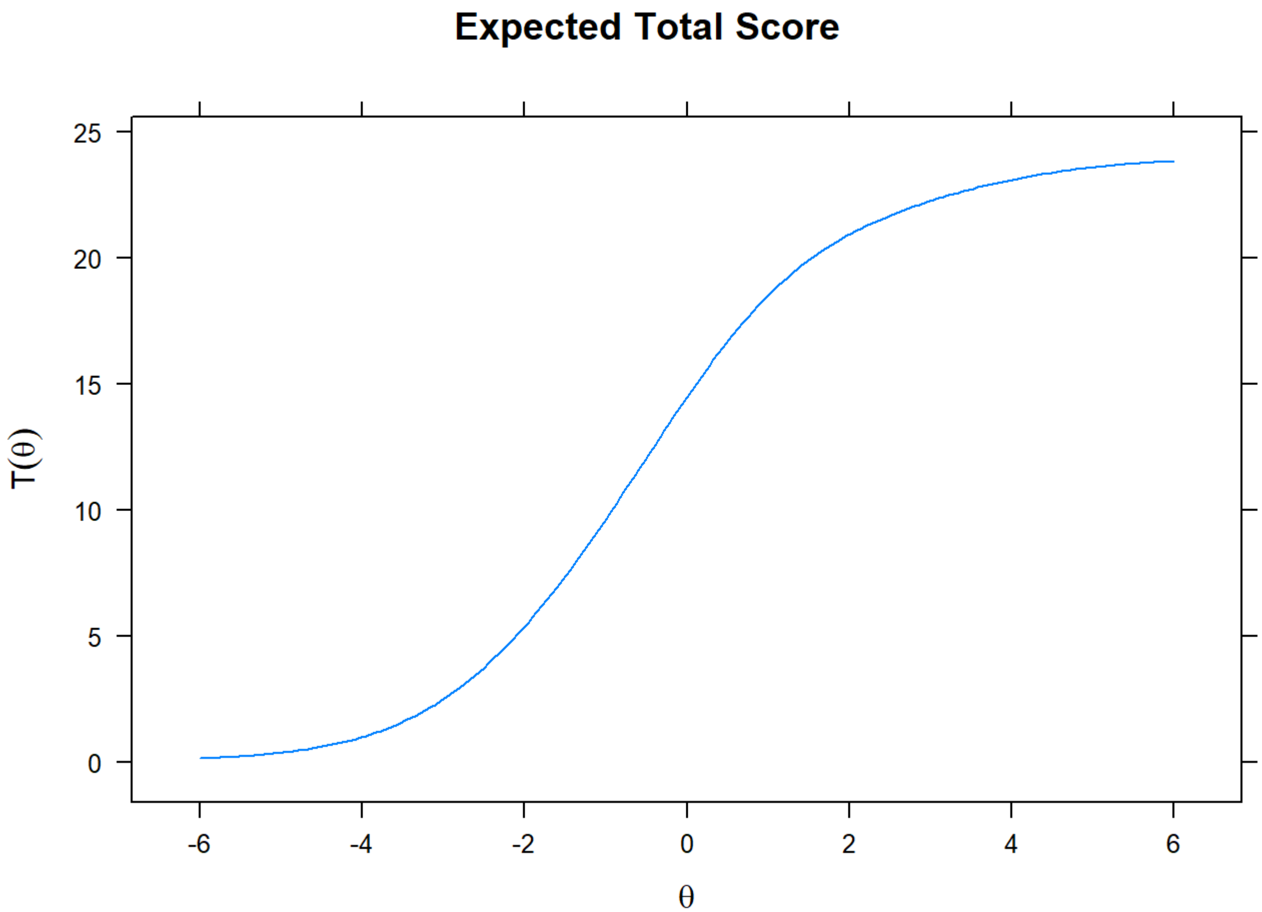
```
plot(mirtMHpcm)                    # test score function
```



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```
# Residuals
residuals(mirtPHpcm)
```

```
## LD matrix (lower triangle) and standardized values.
##
## Upper triangle summary:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -0.306  -0.248   0.184   0.058   0.226   0.352
##
##          SF1_PH SF2A_PH SF2B_PH SF3A_PH SF3B_PH SF5_PH
## SF1_PH       NA  -0.298  -0.259  -0.242  -0.253 -0.306
## SF2A_PH 246.884      NA   0.263   0.226   0.204  0.204
## SF2B_PH 186.390 192.856      NA   0.169   0.178  0.184
## SF3A_PH 326.103 142.687  79.087      NA   0.352  0.225
## SF3B_PH 355.958 115.903  88.535 688.821      NA  0.227
## SF5_PH  522.001 116.229  93.787 281.463 287.707     NA
```

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```
residuals(mirtMHpcm)
```

```
## LD matrix (lower triangle) and standardized values.
##
## Upper triangle summary:
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  -0.633  -0.180  -0.108  -0.031   0.190   0.390
##
##         SF4A_MH SF4B_MH SF6A_MH  SF6B_MH SF6C_MH SF7_MH
## SF4A_MH      NA   0.390   0.156   -0.208   0.206 -0.127
## SF4B_MH 846.429      NA  -0.194   -0.248   0.174 -0.166
## SF6A_MH 135.638 208.972      NA    0.208   0.339 -0.108
## SF6B_MH 240.363 341.574 240.481       NA  -0.633 -0.099
## SF6C_MH 236.085 168.537 640.397 2229.350      NA -0.152
## SF7_MH   90.421 152.700  65.197   54.789 128.132     NA
```

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```
#-------------- Fit a partial credit tree model ------------------#
PHtree <- pctree(PH ~ Sex + age,  data = tha_data_sx_ag, minsize = 200)
MHtree <- pctree(MH ~ Sex + age,  data = tha_data_sx_ag, minsize = 200)

# Note: The minsize is an integer specification of minimum number of
#       observations in each node
```

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```
## print tree (with and without parameters)
print(PHtree)
```

```
## Partial credit tree
##
## Model formula:
## PH ~ Sex + age
##
## Fitted party:
## [1] root
## |   [2] Sex in Female: n = 717
## |        PHSF1_PH-C2  PHSF1_PH-C3  PHSF1_PH-C4 PHSF2A_PH-C1 PHSF2A_PH-C2 PHSF2B_PH-C1
## |           1.536073     5.525677    12.171975     5.421650    12.512268     5.820207
## |       PHSF2B_PH-C2 PHSF3A_PH-C1 PHSF3A_PH-C2 PHSF3A_PH-C3 PHSF3A_PH-C4 PHSF3B_PH-C1
## |          12.827443     3.753218     9.115246    15.666805    22.389673     3.745519
## |       PHSF3B_PH-C2 PHSF3B_PH-C3 PHSF3B_PH-C4  PHSF5_PH-C1  PHSF5_PH-C2  PHSF5_PH-C3
## |           9.103598    16.139197    22.789791     3.067056     8.416160    14.888342
## |        PHSF5_PH-C4
## |          23.265543
## |   [3] Sex in Male: n = 674
## |        PHSF1_PH-C2  PHSF1_PH-C3  PHSF1_PH-C4 PHSF2A_PH-C1 PHSF2A_PH-C2 PHSF2B_PH-C1
## |          0.5219573    4.0154517   10.0005184    4.0101747   10.1810146    4.1882881
## |       PHSF2B_PH-C2 PHSF3A_PH-C1 PHSF3A_PH-C2 PHSF3A_PH-C3 PHSF3A_PH-C4 PHSF3B_PH-C1
## |         10.4872277    2.4768077    6.6753057   12.1897425   18.6450957    2.5608968
## |       PHSF3B_PH-C2 PHSF3B_PH-C3 PHSF3B_PH-C4  PHSF5_PH-C1  PHSF5_PH-C2  PHSF5_PH-C3
## |          6.9300133   12.6806723   19.3311263    1.5606909    5.9414716   11.6042808
## |        PHSF5_PH-C4
## |         18.7363059
##
## Number of inner nodes:    1
## Number of terminal nodes: 2
## Number of parameters per node: 19
## Objective function (negative log-likelihood): 4320.052
```

Hide

```
print(PHtree, FUN = function(x) " *")
```

```
## Partial credit tree
##
## Model formula:
## PH ~ Sex + age
##
## Fitted party:
## [1] root
## |   [2] Sex in Female *
## |   [3] Sex in Male *
##
## Number of inner nodes:    1
## Number of terminal nodes: 2
## Number of parameters per node: 19
## Objective function (negative log-likelihood): 4320.052
```

Hide

```
print(MHtree)
```

```
## Partial credit tree
##
## Model formula:
## MH ~ Sex + age
##
## Fitted party:
## [1] root
## |   [2] age <= 60: n = 477
## |       MHSF4A_MH-C2 MHSF4A_MH-C3 MHSF4A_MH-C4 MHSF4B_MH-C1 MHSF4B_MH-C2 MHSF4B_MH-C3
## |          1.3893052    3.8042314    6.6118448   -0.0485260    0.9971401    3.2940881
## |       MHSF4B_MH-C4 MHSF6A_MH-C1 MHSF6A_MH-C2 MHSF6A_MH-C3 MHSF6A_MH-C4 MHSF6B_MH-C1
## |          5.7857295   -0.4747603    0.5790457    2.7890057    8.6615263    0.1535538
## |       MHSF6B_MH-C2 MHSF6B_MH-C3 MHSF6B_MH-C4 MHSF6C_MH-C1 MHSF6C_MH-C2 MHSF6C_MH-C3
## |          1.8507865    5.0786605   11.7771317   -0.9949791   -1.0588313    0.5212918
## |       MHSF6C_MH-C4  MHSF7_MH-C1  MHSF7_MH-C2  MHSF7_MH-C3  MHSF7_MH-C4
## |          3.8730677    0.6135342    1.4594904    4.3958609    7.4761197
## |   [3] age > 60: n = 914
## |       MHSF4A_MH-C2 MHSF4A_MH-C3 MHSF4A_MH-C4 MHSF4B_MH-C1 MHSF4B_MH-C2 MHSF4B_MH-C3
## |         0.61316619   2.22217588   4.15798449   0.03197709   0.55133092   1.93717938
## |       MHSF4B_MH-C4 MHSF6A_MH-C1 MHSF6A_MH-C2 MHSF6A_MH-C3 MHSF6A_MH-C4 MHSF6B_MH-C1
## |         3.82968172  -0.95168920  -0.69085971   0.40946232   5.08450781   0.05243723
## |       MHSF6B_MH-C2 MHSF6B_MH-C3 MHSF6B_MH-C4 MHSF6C_MH-C1 MHSF6C_MH-C2 MHSF6C_MH-C3
## |         1.23238944   4.11561215   9.37028998  -1.11298126  -2.11690155  -1.00447004
## |       MHSF6C_MH-C4  MHSF7_MH-C1  MHSF7_MH-C2  MHSF7_MH-C3  MHSF7_MH-C4
## |         1.05696985  -0.35223221   0.12666708   2.09673303   4.48712398
##
## Number of inner nodes:    1
## Number of terminal nodes: 2
## Number of parameters per node: 23
## Objective function (negative log-likelihood): 6351.613
```

Hide

```
print(MHtree, FUN = function(x) " *")
```

```
## Partial credit tree
##
## Model formula:
## MH ~ Sex + age
##
## Fitted party:
## [1] root
## |   [2] age <= 60 *
## |   [3] age > 60 *
##
## Number of inner nodes:    1
## Number of terminal nodes: 2
## Number of parameters per node: 23
## Objective function (negative log-likelihood): 6351.613
```

Hide

```
## show summary for terminal panel nodes
summary(PHtree)
```

```
## $`2`
##
## Partial credit model
##
## Item category parameters:
##              Estimate Std. Error z value Pr(>|z|)
## PHSF1_PH-C2    1.5361     0.5533   2.776   0.0055 **
## PHSF1_PH-C3    5.5257     1.0644   5.191 2.09e-07 ***
## PHSF1_PH-C4   12.1720     1.5893   7.659 1.88e-14 ***
## PHSF2A_PH-C1   5.4216     0.5306  10.218  < 2e-16 ***
## PHSF2A_PH-C2  12.5123     1.0720  11.672  < 2e-16 ***
## PHSF2B_PH-C1   5.8202     0.5331  10.917  < 2e-16 ***
## PHSF2B_PH-C2  12.8274     1.0755  11.927  < 2e-16 ***
## PHSF3A_PH-C1   3.7532     0.5245   7.155 8.35e-13 ***
## PHSF3A_PH-C2   9.1152     1.0479   8.699  < 2e-16 ***
## PHSF3A_PH-C3  15.6668     1.5796   9.918  < 2e-16 ***
## PHSF3A_PH-C4  22.3897     2.1151  10.586  < 2e-16 ***
## PHSF3B_PH-C1   3.7455     0.5245   7.141 9.23e-13 ***
## PHSF3B_PH-C2   9.1036     1.0477   8.689  < 2e-16 ***
## PHSF3B_PH-C3  16.1392     1.5844  10.186  < 2e-16 ***
## PHSF3B_PH-C4  22.7898     2.1204  10.748  < 2e-16 ***
## PHSF5_PH-C1    3.0671     0.5224   5.872 4.32e-09 ***
## PHSF5_PH-C2    8.4162     1.0443   8.059 7.67e-16 ***
## PHSF5_PH-C3   14.8883     1.5741   9.458  < 2e-16 ***
## PHSF5_PH-C4   23.2655     2.1564  10.789  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log-likelihood: -2088 (df = 19)
## Number of iterations in BFGS optimization: 31
##
##
## $`3`
##
## Partial credit model
##
## Item category parameters:
##              Estimate Std. Error z value Pr(>|z|)
## PHSF1_PH-C2    0.5220     0.4166   1.253     0.21
```

```
## PHSF1_PH-C3    4.0155     0.7630   5.263 1.42e-07 ***
## PHSF1_PH-C4   10.0005     1.1287   8.860  < 2e-16 ***
## PHSF2A_PH-C1   4.0102     0.3726  10.764  < 2e-16 ***
## PHSF2A_PH-C2  10.1810     0.7509  13.559  < 2e-16 ***
## PHSF2B_PH-C1   4.1883     0.3735  11.215  < 2e-16 ***
## PHSF2B_PH-C2  10.4872     0.7542  13.904  < 2e-16 ***
## PHSF3A_PH-C1   2.4768     0.3675   6.740 1.59e-11 ***
## PHSF3A_PH-C2   6.6753     0.7275   9.175  < 2e-16 ***
## PHSF3A_PH-C3  12.1897     1.0966  11.116  < 2e-16 ***
## PHSF3A_PH-C4  18.6451     1.4786  12.610  < 2e-16 ***
## PHSF3B_PH-C1   2.5609     0.3676   6.966 3.27e-12 ***
## PHSF3B_PH-C2   6.9300     0.7287   9.510  < 2e-16 ***
## PHSF3B_PH-C3  12.6807     1.1001  11.527  < 2e-16 ***
## PHSF3B_PH-C4  19.3311     1.4874  12.997  < 2e-16 ***
## PHSF5_PH-C1    1.5607     0.3633   4.295 1.74e-05 ***
## PHSF5_PH-C2    5.9415     0.7210   8.241  < 2e-16 ***
## PHSF5_PH-C3   11.6043     1.0900  10.646  < 2e-16 ***
## PHSF5_PH-C4   18.7363     1.4859  12.610  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log-likelihood: -2232 (df = 19)
## Number of iterations in BFGS optimization: 30
```

Hide

```
summary(MHtree)
```

```
## $`2`
##
## Partial credit model
##
## Item category parameters:
##                 Estimate Std. Error z value Pr(>|z|)
## MHSF4A_MH-C2  1.38931    0.28349   4.901 9.55e-07 ***
## MHSF4A_MH-C3  3.80423    0.48802   7.795 6.43e-15 ***
## MHSF4A_MH-C4  6.61184    0.70432   9.388  < 2e-16 ***
## MHSF4B_MH-C1 -0.04853    0.30058  -0.161   0.8717
## MHSF4B_MH-C2  0.99714    0.46515   2.144   0.0321 *
## MHSF4B_MH-C3  3.29409    0.66342   4.965 6.86e-07 ***
## MHSF4B_MH-C4  5.78573    0.87121   6.641 3.12e-11 ***
## MHSF6A_MH-C1 -0.47476    0.31601  -1.502   0.1330
## MHSF6A_MH-C2  0.57905    0.47494   1.219   0.2228
## MHSF6A_MH-C3  2.78901    0.66845   4.172 3.01e-05 ***
## MHSF6A_MH-C4  8.66153    0.91636   9.452  < 2e-16 ***
## MHSF6B_MH-C1  0.15355    0.26863   0.572   0.5676
## MHSF6B_MH-C2  1.85079    0.45238   4.091 4.29e-05 ***
## MHSF6B_MH-C3  5.07866    0.66474   7.640 2.17e-14 ***
## MHSF6B_MH-C4 11.77713    0.97357  12.097  < 2e-16 ***
## MHSF6C_MH-C1 -0.99498    0.43570  -2.284   0.0224 *
## MHSF6C_MH-C2 -1.05883    0.55313  -1.914   0.0556 .
## MHSF6C_MH-C3  0.52129    0.71665   0.727   0.4670
## MHSF6C_MH-C4  3.87307    0.90890   4.261 2.03e-05 ***
## MHSF7_MH-C1   0.61353    0.28038   2.188   0.0287 *
## MHSF7_MH-C2   1.45949    0.45078   3.238   0.0012 **
## MHSF7_MH-C3   4.39586    0.65992   6.661 2.72e-11 ***
## MHSF7_MH-C4   7.47612    0.87539   8.540  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log-likelihood: -2122 (df = 23)
## Number of iterations in BFGS optimization: 34
##
##
## $`3`
##
## Partial credit model
```

```
##
## Item category parameters:
##              Estimate Std. Error z value Pr(>|z|)
## MHSF4A_MH-C2  0.61317    0.20926   2.930 0.003388 **
## MHSF4A_MH-C3  2.22218    0.34343   6.471 9.76e-11 ***
## MHSF4A_MH-C4  4.15798    0.48604   8.555  < 2e-16 ***
## MHSF4B_MH-C1  0.03198    0.19533   0.164 0.869960
## MHSF4B_MH-C2  0.55133    0.30819   1.789 0.073630 .
## MHSF4B_MH-C3  1.93718    0.44177   4.385 1.16e-05 ***
## MHSF4B_MH-C4  3.82968    0.58240   6.576 4.84e-11 ***
## MHSF6A_MH-C1 -0.95169    0.22666  -4.199 2.68e-05 ***
## MHSF6A_MH-C2 -0.69086    0.32682  -2.114 0.034523 *
## MHSF6A_MH-C3  0.40946    0.45158   0.907 0.364549
## MHSF6A_MH-C4  5.08451    0.60784   8.365  < 2e-16 ***
## MHSF6B_MH-C1  0.05244    0.17648   0.297 0.766372
## MHSF6B_MH-C2  1.23239    0.30266   4.072 4.66e-05 ***
## MHSF6B_MH-C3  4.11561    0.44903   9.166  < 2e-16 ***
## MHSF6B_MH-C4  9.37029    0.64621  14.500  < 2e-16 ***
## MHSF6C_MH-C1 -1.11298    0.30533  -3.645 0.000267 ***
## MHSF6C_MH-C2 -2.11690    0.37275  -5.679 1.35e-08 ***
## MHSF6C_MH-C3 -1.00447    0.48332  -2.078 0.037683 *
## MHSF6C_MH-C4  1.05697    0.60975   1.733 0.083014 .
## MHSF7_MH-C1  -0.35223    0.19741  -1.784 0.074384 .
## MHSF7_MH-C2   0.12667    0.30943   0.409 0.682280
## MHSF7_MH-C3   2.09673    0.44546   4.707 2.52e-06 ***
## MHSF7_MH-C4   4.48712    0.58841   7.626 2.42e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Log-likelihood: -4230 (df = 23)
## Number of iterations in BFGS optimization: 30
```

Visualize the results for all the items

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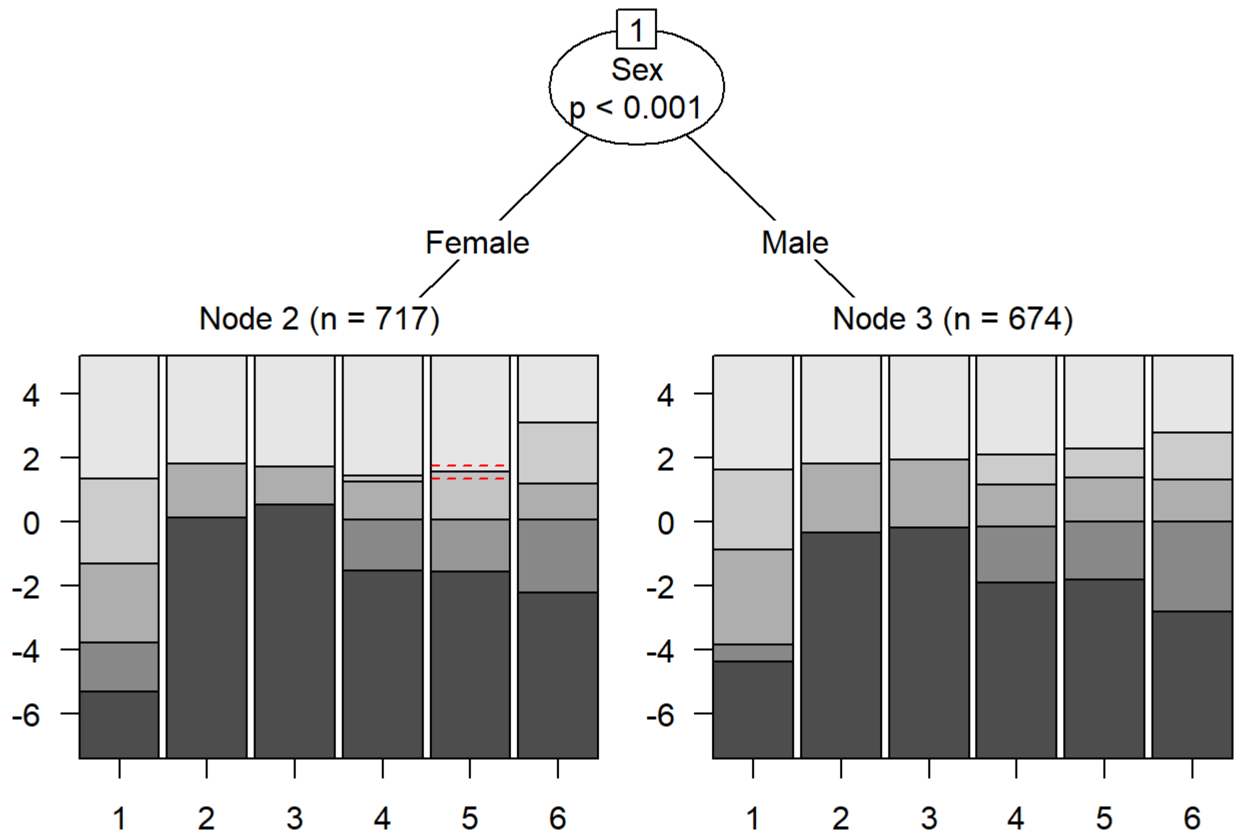
```
plot(PHtree, type = "regions")
```



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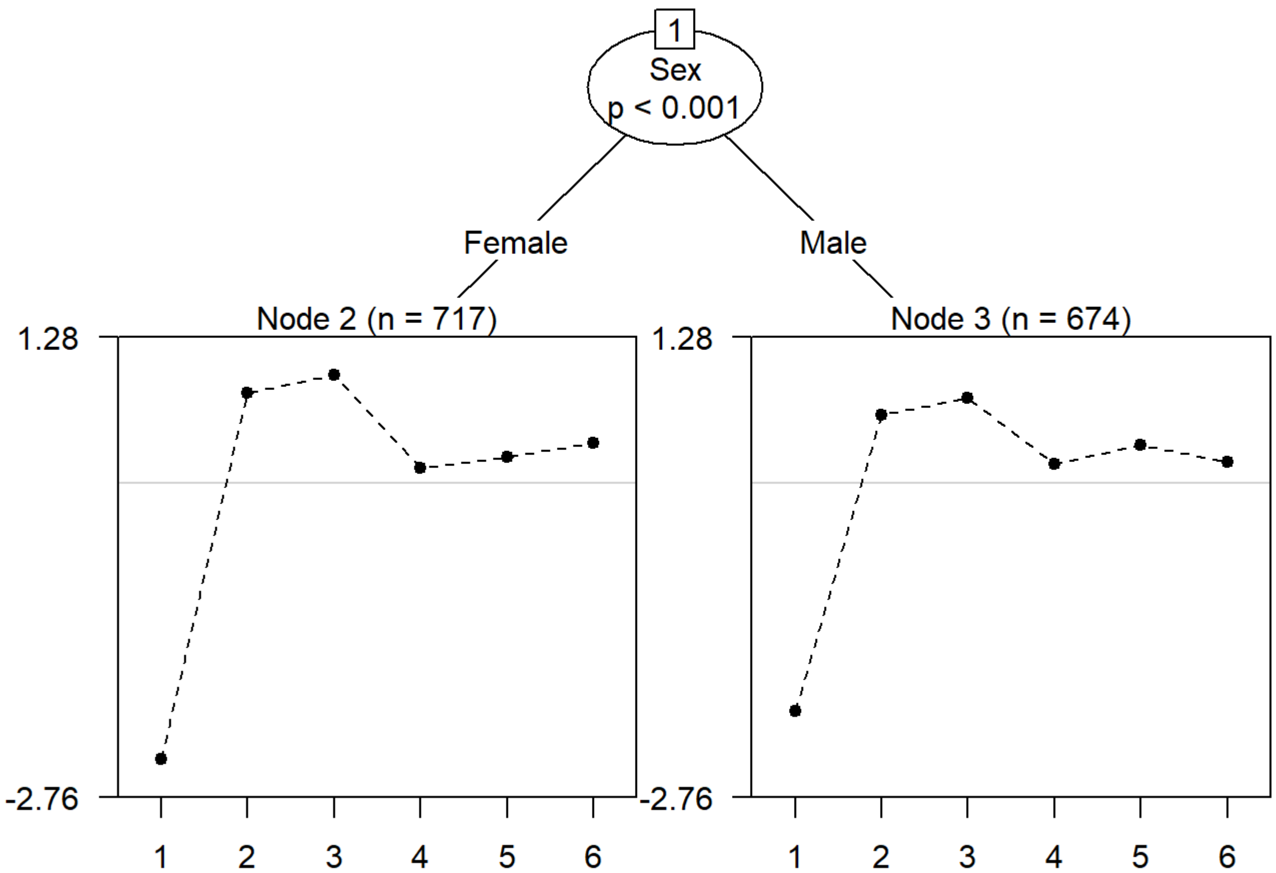
```
plot(PHtree, type = "profile")
```



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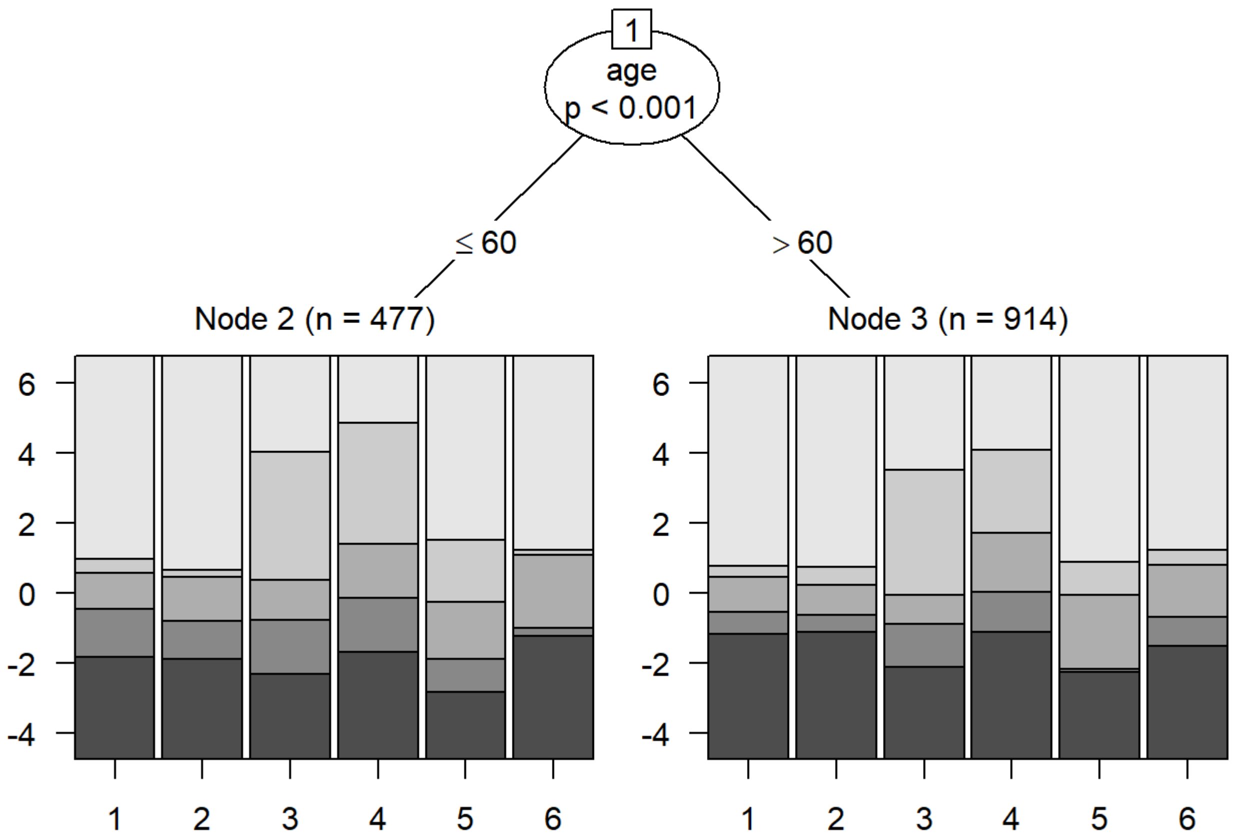
```
plot(MHtree, type = "regions")
```



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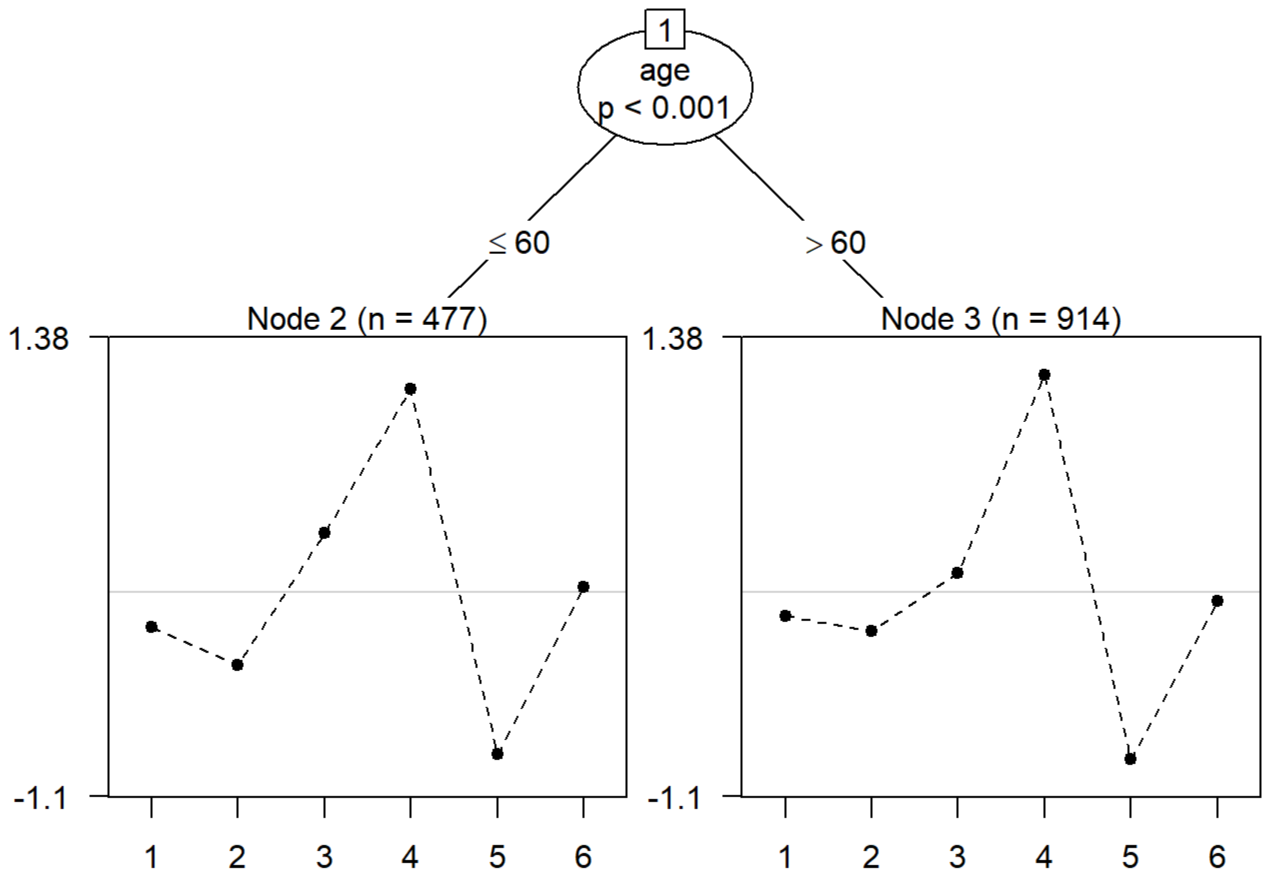
```
plot(MHtree, type = "profile")
```



Inspect parameter stability tests in the splitting node

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```
sctest(PHtree, node = 1)
```

```
##                    Sex         age
## statistic 4.723498e+01 49.55706284
## p.value   6.610836e-04  0.01104046
```

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```r
sctest(MHtree, node = 1)
```

```
##                    Sex          age
## statistic 43.8877030 6.621059e+01
## p.value    0.0108204 2.808721e-04
```