Rasch time

Ottavia

2023-02-06

Contents

Prendo solo i dati che qualtrics identifica come persone che hanno finito, dopo aver applicato i criteri di pulizia come nell'altro file. L'analisi è quindi svolta su un dataset complessivo di 35.

Analisi separata SET A e SET B

Penso che userò solo i dati completi, anche se si riduce l'ampiezza campionaria.

In questo caso, stimo separatamente il modello di Rasch sul set A e sul set B.

Set A

```
## ------------------------------------------------------------
## TAM 4.0-16 (2022-05-13 13:23:23)
## R version 4.2.2 (2022-10-31 ucrt) x86_64, mingw32 | nodename=LAPTOP-OTTAVIA | login=huawei
##
## Date of Analysis: 2023-02-06 12:32:48
## Time difference of 0.05951405 secs
## Computation time: 0.05951405
##
## Multidimensional Item Response Model in TAM
##
## IRT Model: 1PL
## Call:
## tam.mml(resp = d.a.all[, -c(1:2)], verbose = F)
##
## ------------------------------------------------------------
## Number of iterations = 36
## Numeric integration with 21 integration points
##
## Deviance = 456.65
## Log likelihood = -228.32
## Number of persons = 35
## Number of persons used = 35
## Number of items = 14
```

```
## Number of estimated parameters = 15
##     Item threshold parameters = 14
##     Item slope parameters = 0
##     Regression parameters = 0
##     Variance/covariance parameters = 1
##
## AIC = 487  | penalty=30    | AIC=-2*LL + 2*p
## AIC3 = 502  | penalty=45    | AIC3=-2*LL + 3*p
## BIC = 510  | penalty=53.33    | BIC=-2*LL + log(n)*p
## aBIC = 461  | penalty=4.78    | aBIC=-2*LL + log((n-2)/24)*p  (adjusted BIC)
## CAIC = 525  | penalty=68.33    | CAIC=-2*LL + [log(n)+1]*p  (consistent AIC)
## AICc = 512  | penalty=55.26    | AICc=-2*LL + 2*p + 2*p*(p+1)/(n-p-1)  (bias corrected AIC)
## GHP = 0.49964     | GHP=( -LL + p ) / (#Persons * #Items)  (Gilula-Haberman log penalty)
##
## ------------------------------------------------------------
## EAP Reliability
## [1] 0.792
## ------------------------------------------------------------
## Covariances and Variances
##       [,1]
## [1,] 2.449
## ------------------------------------------------------------
## Correlations and Standard Deviations (in the diagonal)
##       [,1]
## [1,] 1.565
## ------------------------------------------------------------
## Regression Coefficients
##      [,1]
## [1,]    0
## ------------------------------------------------------------
## Item Parameters -A*Xsi
##         item  N     M xsi.item AXsi_.Cat1 B.Cat1.Dim1
## 1        a_1 35 0.714   -1.299     -1.299           1
## 2        a_2 35 0.914   -3.200     -3.200           1
## 3        a_3 35 0.914   -3.200     -3.200           1
## 4   a_logic1 35 0.486    0.063      0.063           1
## 5   a_logic2 35 0.629   -0.760     -0.760           1
## 6   a_logic3 35 0.829   -2.186     -2.186           1
## 7   a_logic4 35 0.800   -1.935     -1.935           1
## 8       a1_1 35 0.657   -0.933     -0.933           1
## 9       a1_2 35 0.857   -2.468     -2.468           1
## 10      a1_3 35 0.486    0.063      0.063           1
## 11 a1_logic1 33 0.515   -0.119     -0.119           1
## 12 a1_logic2 35 0.343    0.909      0.909           1
## 13 a1_logic3 34 0.765   -1.664     -1.664           1
## 14 a1_logic4 35 0.829   -2.186     -2.186           1
##
## Item Parameters in IRT parameterization
##         item alpha   beta
## 1        a_1     1 -1.299
## 2        a_2     1 -3.200
## 3        a_3     1 -3.200
## 4   a_logic1     1  0.063
## 5   a_logic2     1 -0.760
```

```
## 6    a_logic3      1 -2.186
## 7    a_logic4      1 -1.935
## 8        a1_1      1 -0.933
## 9        a1_2      1 -2.468
## 10       a1_3      1  0.063
## 11 a1_logic1      1 -0.119
## 12 a1_logic2      1  0.909
## 13 a1_logic3      1 -1.664
## 14 a1_logic4      1 -2.186
```

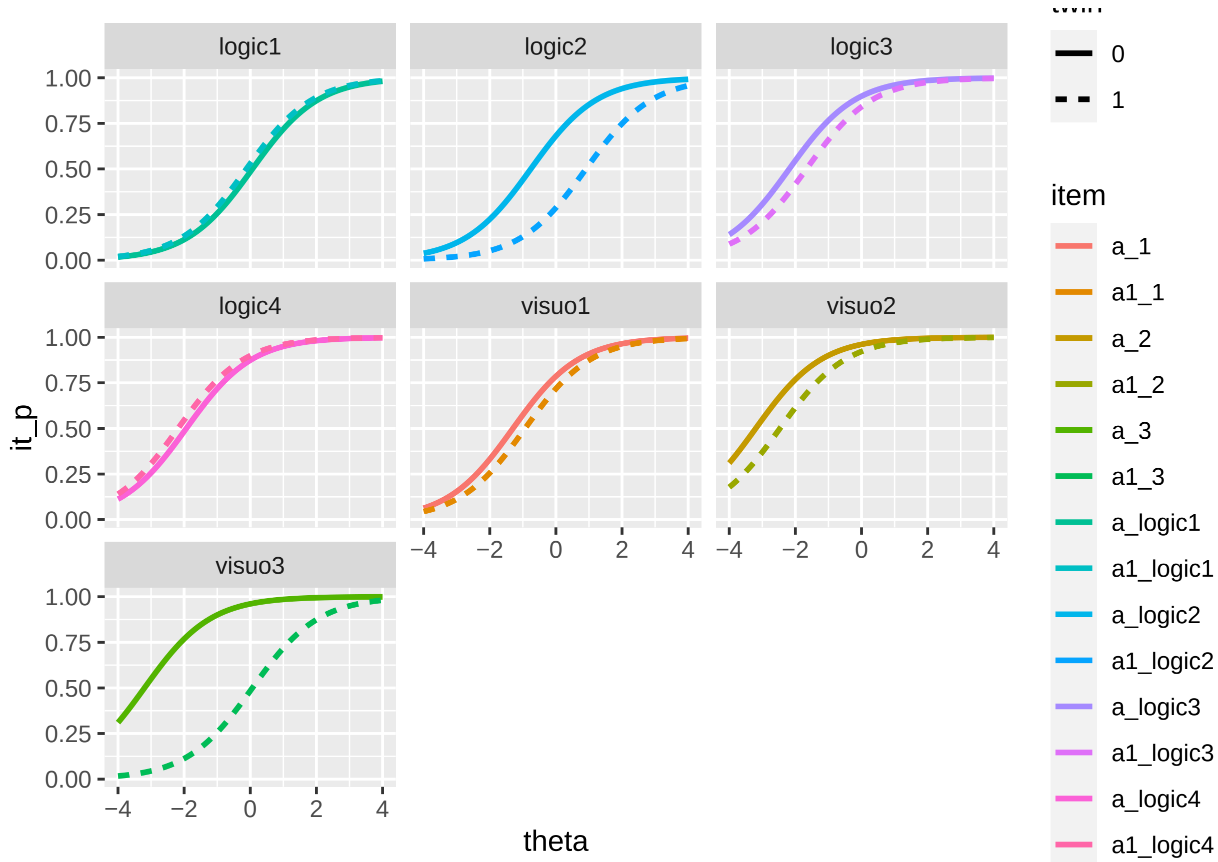


Figure 1: ICC set A con coppie equivalenti di item

Le persone:

Faccio il confronto delle difficoltà degli item gemelli ENTRO il set (Grafico a Pallini):

```
##                item set         b_A     se_bA  label         b_A1    se_bA1
## a_3             a_3   A -3.20017130 0.6736529 visuo3  0.06300724 0.4034019
## a_logic2 a_logic2   A -0.75984512 0.4132778 logic2  0.90930939 0.4249521
## a_2             a_2   A -3.20017130 0.6736529 visuo2 -2.46831372 0.5504129
## a_logic3 a_logic3   A -2.18551308 0.5147376 logic3 -1.66377782 0.4712228
## a_1             a_1   A -1.29946618 0.4378563 visuo1 -0.93311626 0.4195103
## a_logic1 a_logic1   A  0.06300724 0.4034019 logic1 -0.11925034 0.4183178
## a_logic4 a_logic4   A -1.93472790 0.4878911 logic4 -2.18551308 0.5147376
##                 diff
## a_3      -3.2631785
## a_logic2 -1.6691545
```

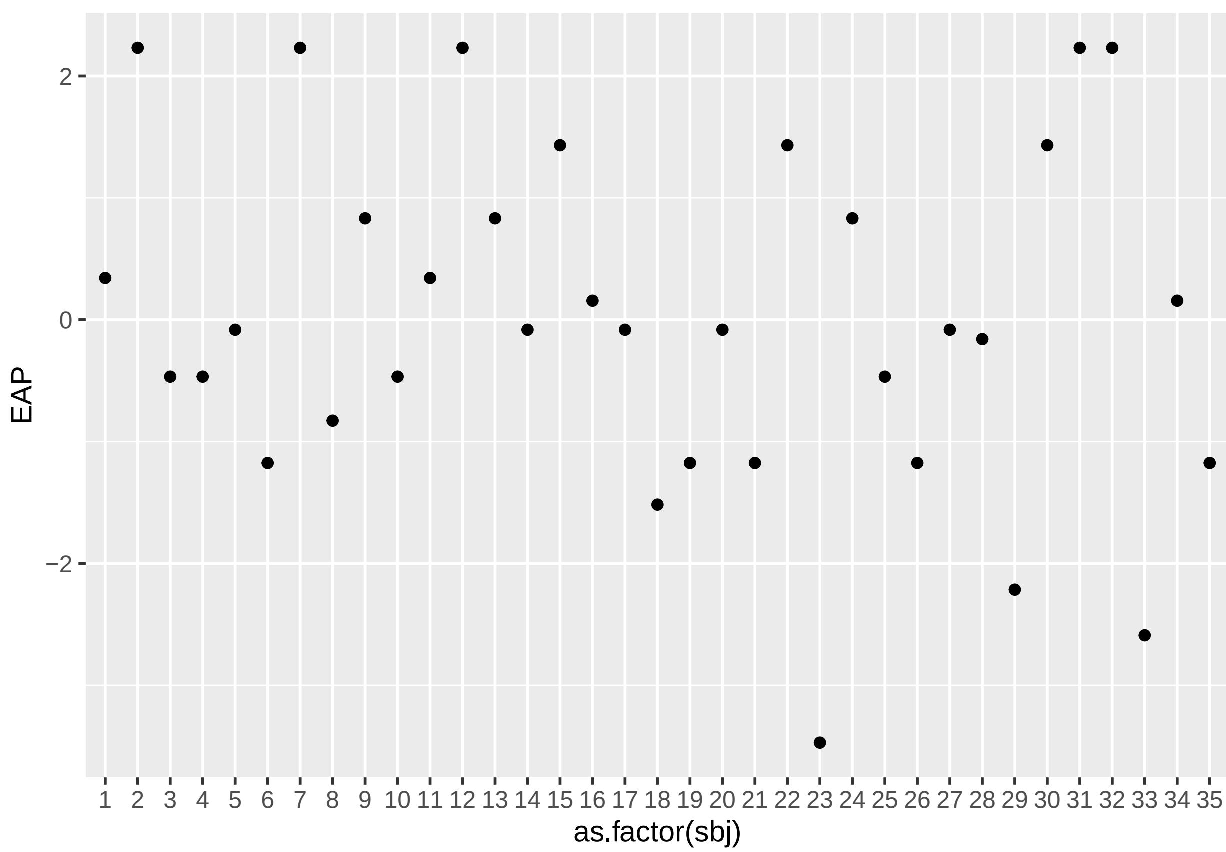
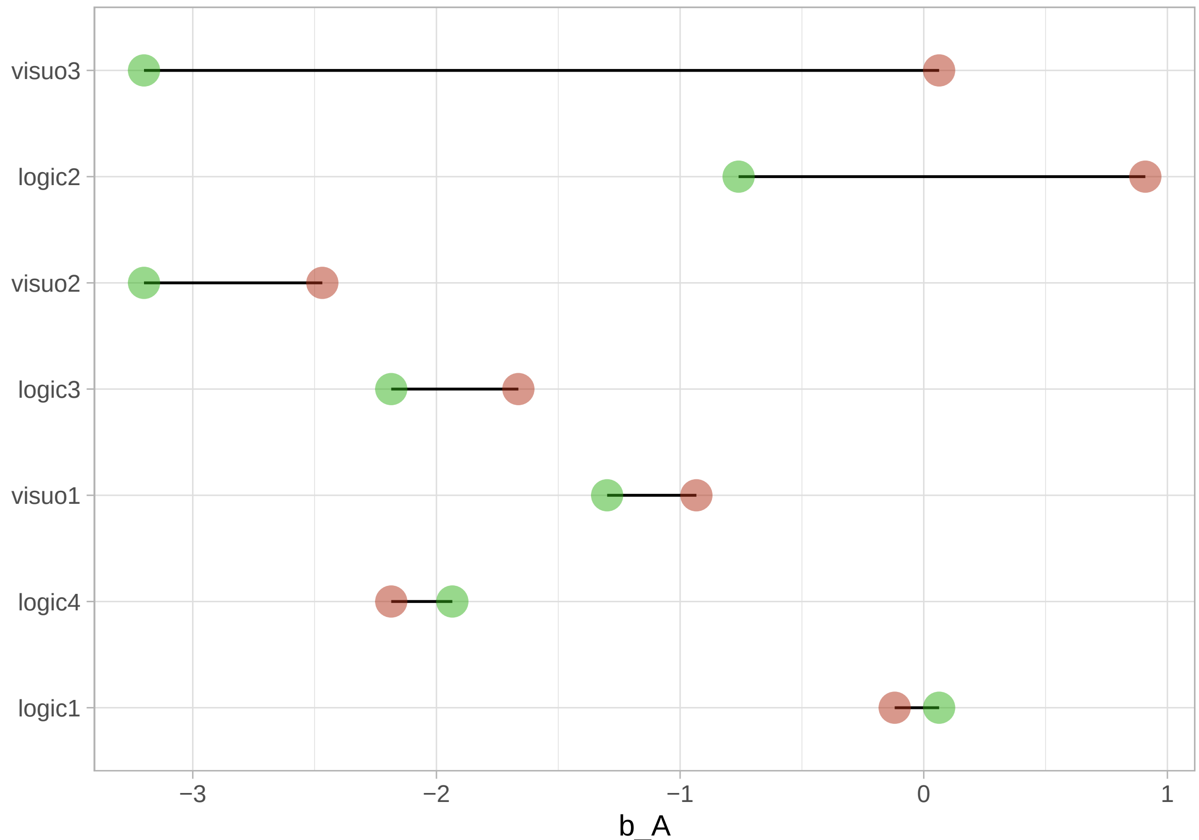


Figure 2: Distribuzione abilità delle persone

```
## a_2      -0.7318576
## a_logic3 -0.5217353
## a_1      -0.3663499
## a_logic1  0.1822576
## a_logic4  0.2507852
```



Set B

```
## ------------------------------------------------------------
## TAM 4.0-16 (2022-05-13 13:23:23)
## R version 4.2.2 (2022-10-31 ucrt) x86_64, mingw32 | nodename=LAPTOP-OTTAVIA | login=huawei
##
## Date of Analysis: 2023-02-06 12:32:50
## Time difference of 0.03081203 secs
## Computation time: 0.03081203
##
## Multidimensional Item Response Model in TAM
##
## IRT Model: 1PL
## Call:
## tam.mml(resp = d.b.all[, -c(1:2)], verbose = F)
##
## ------------------------------------------------------------
## Number of iterations = 41
## Numeric integration with 21 integration points
##
```

```
## Deviance = 367.6
## Log likelihood = -183.8
## Number of persons = 35
## Number of persons used = 35
## Number of items = 14
## Number of estimated parameters = 15
##     Item threshold parameters = 14
##     Item slope parameters = 0
##     Regression parameters = 0
##     Variance/covariance parameters = 1
##
## AIC = 398  | penalty=30    | AIC=-2*LL + 2*p
## AIC3 = 413  | penalty=45    | AIC3=-2*LL + 3*p
## BIC = 421  | penalty=53.33    | BIC=-2*LL + log(n)*p
## aBIC = 372  | penalty=4.78    | aBIC=-2*LL + log((n-2)/24)*p  (adjusted BIC)
## CAIC = 436  | penalty=68.33    | CAIC=-2*LL + [log(n)+1]*p  (consistent AIC)
## AICc = 423  | penalty=55.26    | AICc=-2*LL + 2*p + 2*p*(p+1)/(n-p-1)  (bias corrected AIC)
## GHP = 0.40571     | GHP=( -LL + p ) / (#Persons * #Items)  (Gilula-Haberman log penalty)
##
## ------------------------------------------------------------
## EAP Reliability
## [1] 0.737
## ------------------------------------------------------------
## Covariances and Variances
##       [,1]
## [1,] 2.561
## ------------------------------------------------------------
## Correlations and Standard Deviations (in the diagonal)
##      [,1]
## [1,]  1.6
## ------------------------------------------------------------
## Regression Coefficients
##      [,1]
## [1,]    0
## ------------------------------------------------------------
## Item Parameters -A*Xsi
##         item  N     M xsi.item AXsi_.Cat1 B.Cat1.Dim1
## 1  b1_visuo1 35 0.800   -1.986     -1.986           1
## 2   b_visuo1 35 0.486    0.064      0.064           1
## 3   b_visuo2 35 0.886   -2.847     -2.847           1
## 4   b_visuo3 35 0.914   -3.241     -3.241           1
## 5  b1_visuo3 35 0.943   -3.759     -3.759           1
## 6   b_logic1 35 0.714   -1.340     -1.340           1
## 7  b1_visuo2 35 0.971   -4.573     -4.573           1
## 8  b1_logic1 35 0.457    0.233      0.233           1
## 9  b1_logic2 35 0.857   -2.521     -2.521           1
## 10  b_logic2 35 0.686   -1.148     -1.148           1
## 11 b1_logic3 35 0.800   -1.986     -1.986           1
## 12  b_logic3 35 0.886   -2.847     -2.847           1
## 13 b1_logic4 35 0.886   -2.847     -2.847           1
## 14  b_logic4 35 0.914   -3.241     -3.241           1
##
## Item Parameters in IRT parameterization
##         item alpha   beta
```

```
## 1  b1_visuo1      1 -1.986
## 2   b_visuo1      1  0.064
## 3   b_visuo2      1 -2.847
## 4   b_visuo3      1 -3.241
## 5  b1_visuo3      1 -3.759
## 6   b_logic1      1 -1.340
## 7  b1_visuo2      1 -4.573
## 8  b1_logic1      1  0.233
## 9  b1_logic2      1 -2.521
## 10  b_logic2      1 -1.148
## 11 b1_logic3      1 -1.986
## 12  b_logic3      1 -2.847
## 13 b1_logic4      1 -2.847
## 14  b_logic4      1 -3.241
```

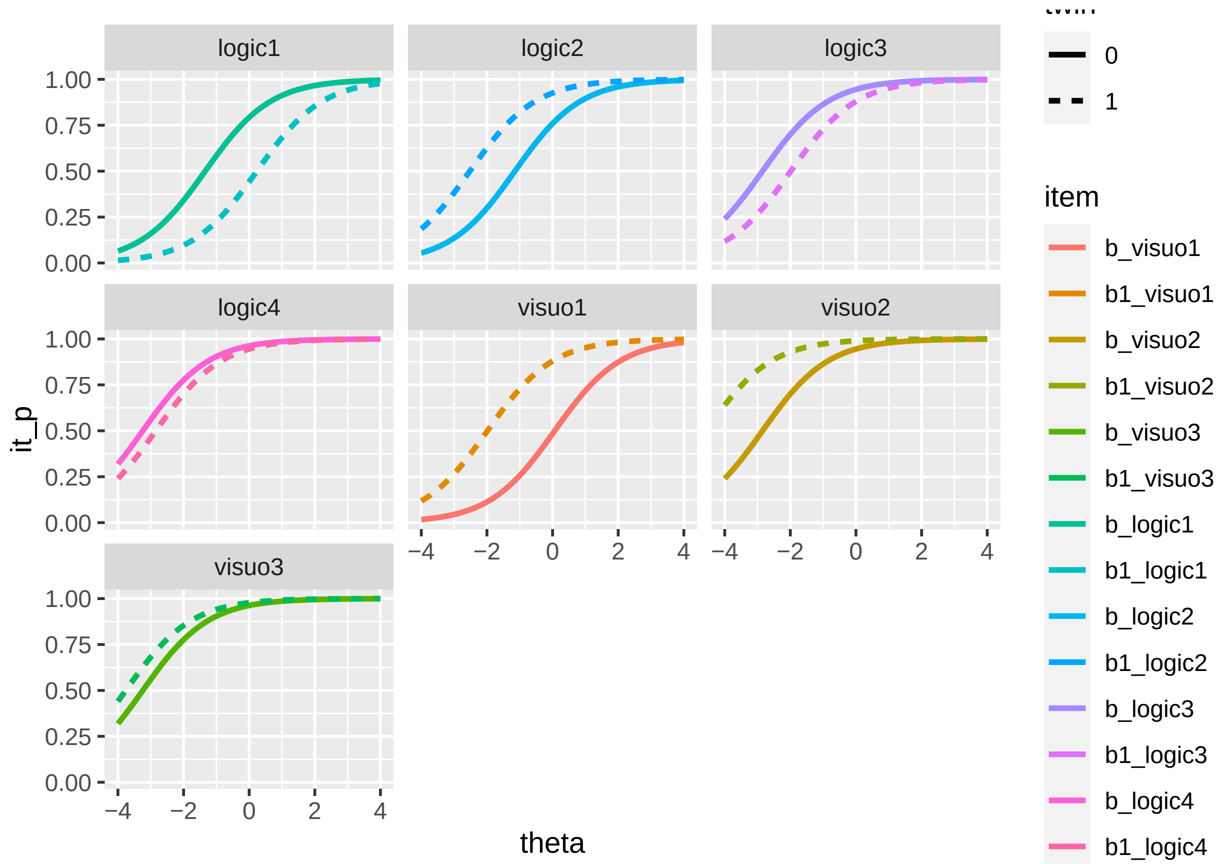


Figure 3: ICC set A con coppie equivalenti di item

Le persone:

Faccio il confronto delle difficoltà degli item gemelli ENTRO il set (Grafico a Pallini):

```
##                item set        b_B     se_bB  label       b_B1     se_bB1
## b_logic1 b_logic1   B -1.33992483 0.4430300 logic1  0.2329157 0.4113676
## b_logic3 b_logic3   B -2.84691103 0.5955275 logic3 -1.9860632 0.4902273
## b_logic4 b_logic4   B -3.24144896 0.6653049 logic4 -2.8469110 0.5955275
## b_visuo2 b_visuo2   B -2.84691103 0.5955275 visuo2 -3.7593642 0.7848552
## b_visuo3 b_visuo3   B -3.24144896 0.6653049 visuo3 -4.5733662 1.0613937
```

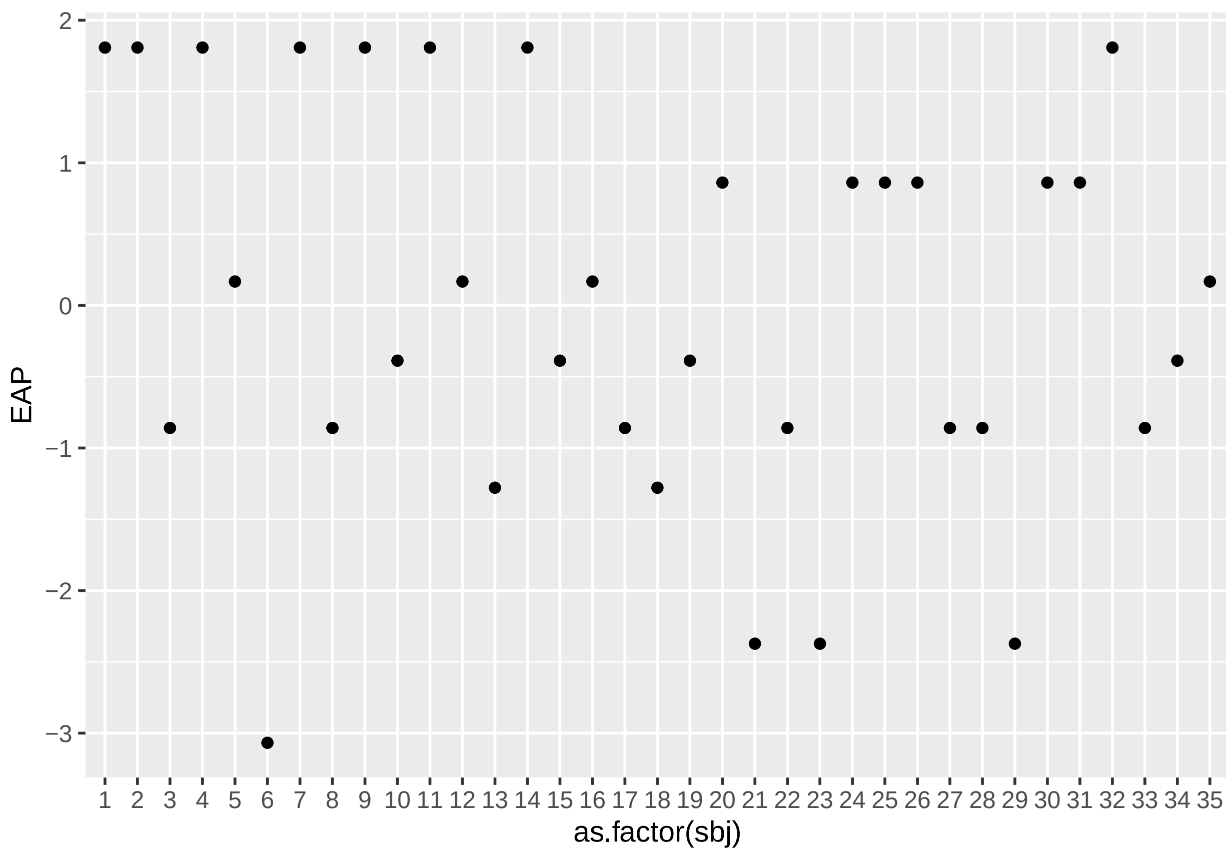
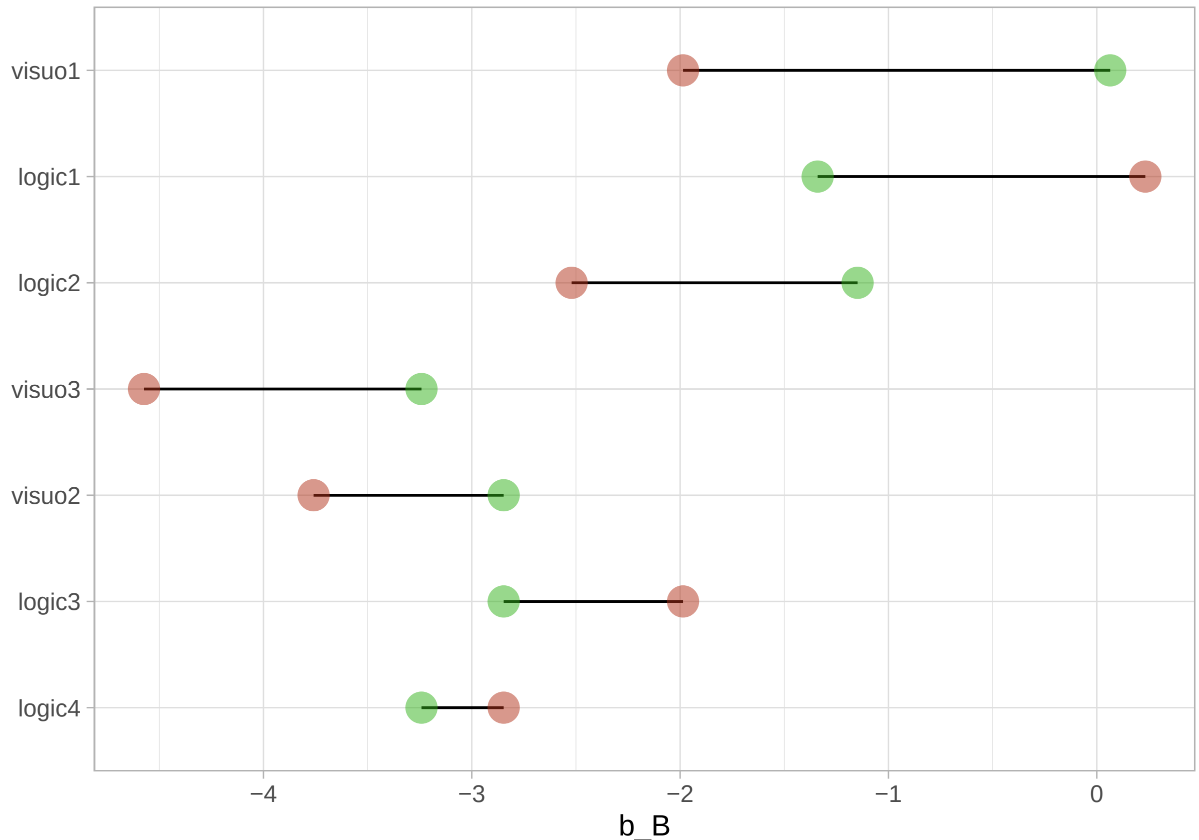


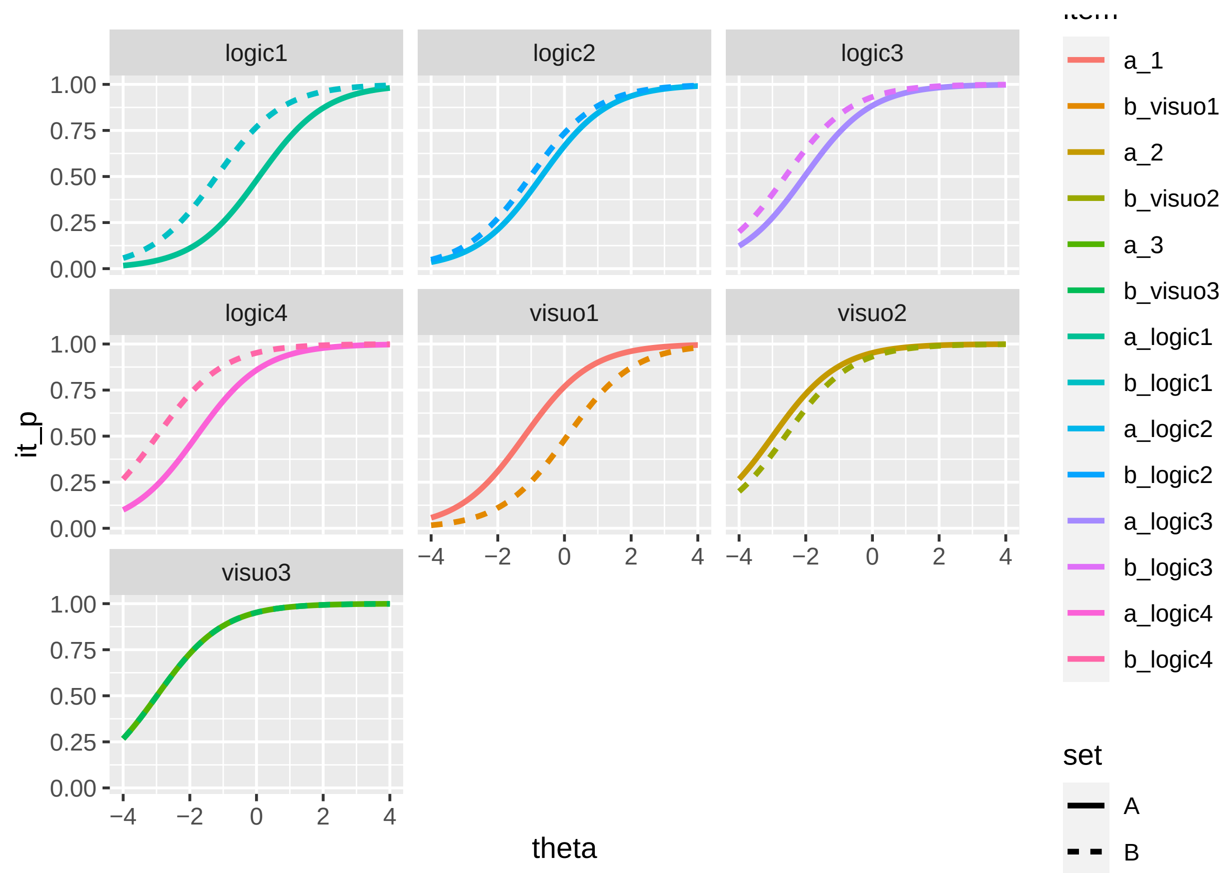
Figure 4: Distribuzione abilità delle persone

```
## b_logic2 b_logic2   B -1.14809656 0.4332855 logic2 -2.5208500 0.5489522
## b_visuo1 b_visuo1   B  0.06439019 0.4098571 visuo1 -1.9860632 0.4902273
##                diff
## b_logic1 -1.5728406
## b_logic3 -0.8608478
## b_logic4 -0.3945379
## b_visuo2  0.9124532
## b_visuo3  1.3319173
## b_logic2  1.3727534
## b_visuo1  2.0504534
```



Confronto TRA set

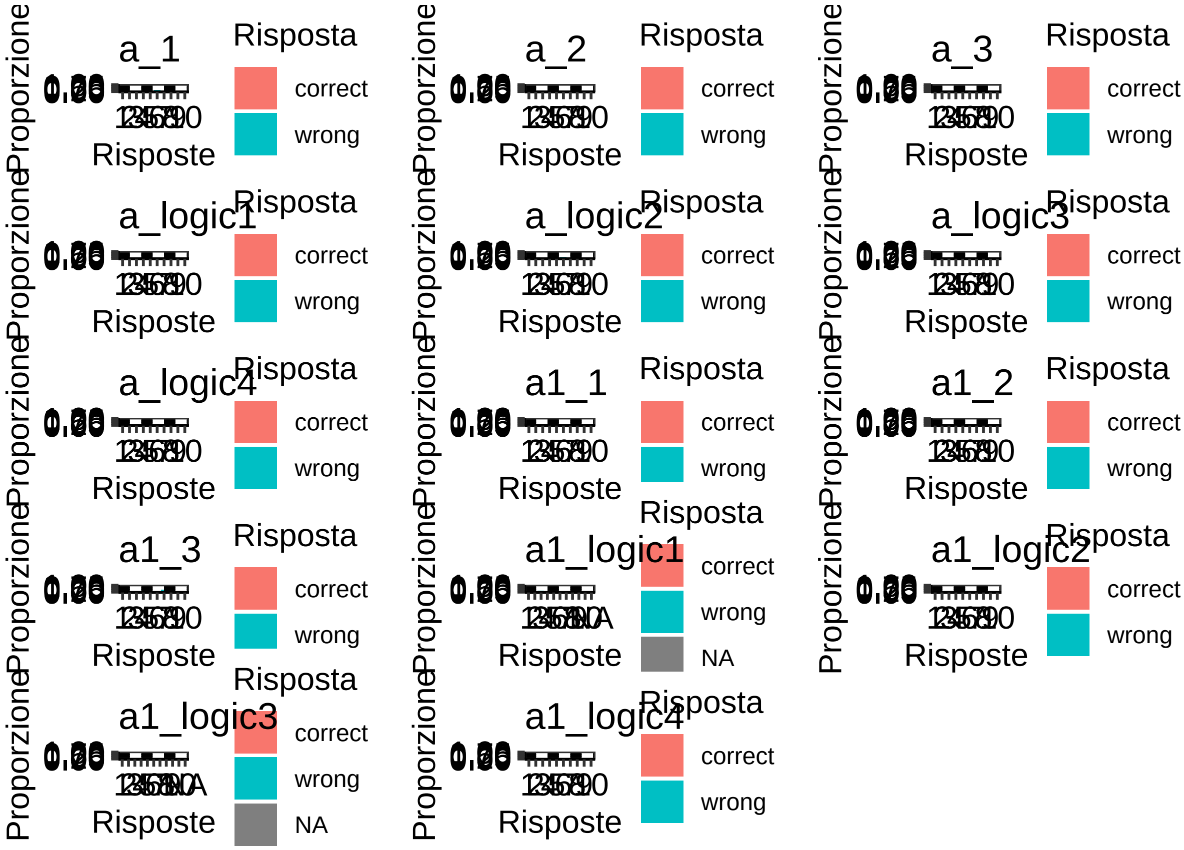
Siccome al momento ho 35 soggetti e mettere insieme i 28 item vorrebbe dire provare a stimare un modello con 29 parametri, per fare i confronti tra i set mi muovo come ho fatto per il calcolo dell'accordo TRA set, ossia appaiando A-B e A1-B1

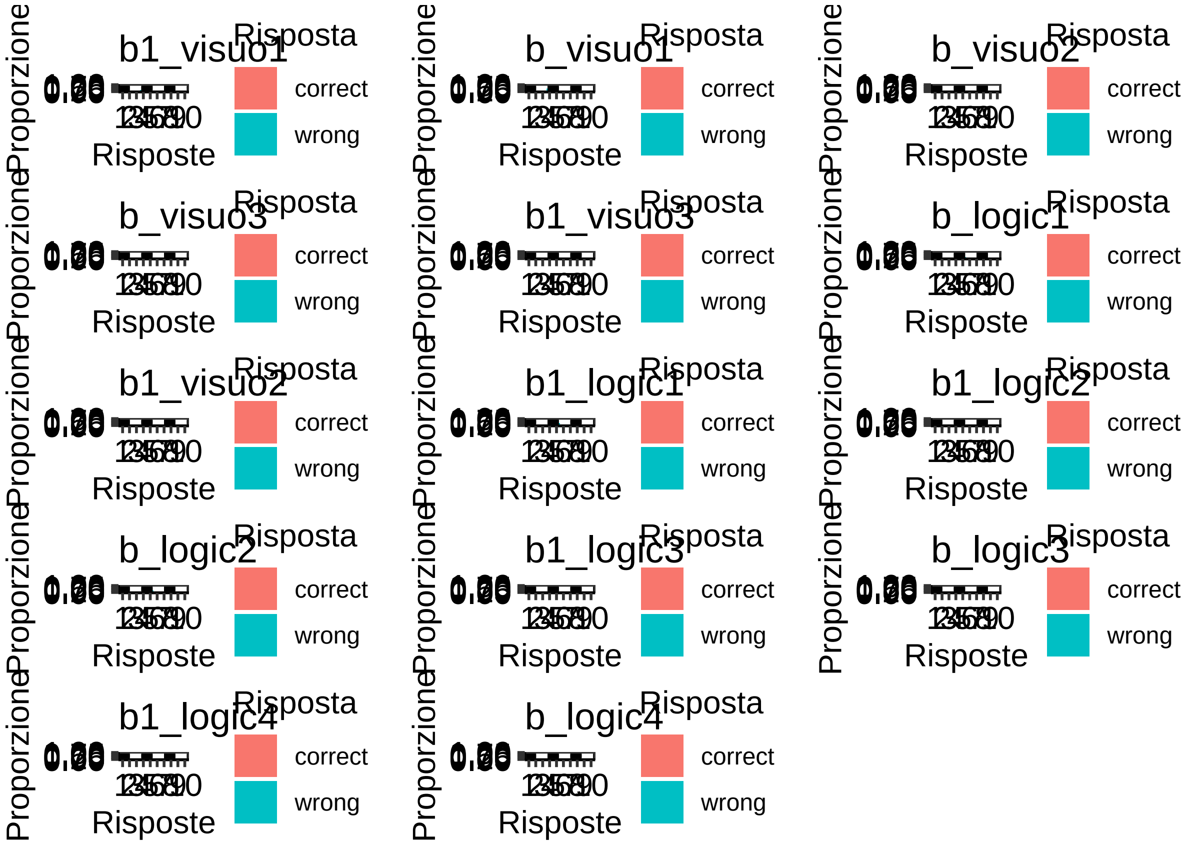


Analisi distrattori come diceva Pasquale

```
##
## Caricamento pacchetto: 'patchwork'

## Il seguente oggetto è mascherato da 'package:MASS':
##
##     area
```


a_1
a_2
a_3
a_logic1
a_logic2
a_logic3
a_logic4
a1_1
a1_2
a1_3
a1_logic1
a1_logic2
a1_logic3
a1_logic4
Proporzione
Risposte
Risposta
correct
wrong
NA



LMM

Voglio andare a (almeno provare) a fare un'analisi più comprensiva. Voglio considerare in un unico modello:

- il set (A vs. B)
- Il tipo di item (posso considerare visuo, visuo1, visuo2 eccetera o come item equivalente)
- Gli item

Prima cosa: devo sistemare il dataset in modo da avere in formato Long tutte le risposte (sempre codificate come 1/0)

```
##                                     sbj item resp set type.gen   type twin
## R_3q0JtfuxCV2Ee0Y.a_1 R_3q0JtfuxCV2Ee0Y  a_1    1   A    visuo visuo1    0
## R_3PFEEF9VwLkdjbI.a_1 R_3PFEEF9VwLkdjbI  a_1    1   A    visuo visuo1    0
## R_2Y9cnG6WCGqIPPd.a_1 R_2Y9cnG6WCGqIPPd  a_1    0   A    visuo visuo1    0
## R_3qJPfVWV4m3ioEh.a_1 R_3qJPfVWV4m3ioEh  a_1    1   A    visuo visuo1    0
## R_2CN61fltHFydjPs.a_1 R_2CN61fltHFydjPs  a_1    0   A    visuo visuo1    0
## R_p5hhdn6Hxb7j5xT.a_1 R_p5hhdn6Hxb7j5xT  a_1    1   A    visuo visuo1    0
```

Il modello più semplice che mi vien in mente va a specificare l'effetto random sia dei soggetti sia degli item ma considera l'effetto fisso dei

```
m1 = glmer(resp ~ 0 + type.gen + (1|sbj) + (1|item),
           data = ab.l,
           family = "binomial")
summary(m1)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: resp ~ 0 + type.gen + (1 | sbj) + (1 | item)
##    Data: ab.l
##
##      AIC      BIC   logLik deviance df.resid
##    468.3    485.0   -230.1    460.3      486
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.1856  0.1406  0.2910  0.4642  2.0007
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  sbj    (Intercept) 1.4865   1.2192
##  item   (Intercept) 0.9037   0.9506
## Number of obs: 490, groups:  sbj, 35; item, 14
##
## Fixed effects:
##                 Estimate Std. Error z value Pr(>|z|)
## type.genlogic   1.4807     0.4321   3.427 0.000611 ***
## type.genvisuo   2.0298     0.4971   4.083 4.44e-05 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             typ.gnl
## type.genvis 0.233
```

```
m2 = glmer(resp ~ 0 + type.gen + set + (1|sbj) + (1|item),
           data = ab.l,
           family = "binomial")
summary(m2)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: resp ~ 0 + type.gen + set + (1 | sbj) + (1 | item)
##    Data: ab.l
##
##      AIC      BIC   logLik deviance df.resid
##    470.1    491.1   -230.0    460.1      485
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.1151  0.1430  0.2960  0.4681  1.9831
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  sbj    (Intercept) 1.4864   1.2192
##  item   (Intercept) 0.8929   0.9449
## Number of obs: 490, groups:  sbj, 35; item, 14
##
## Fixed effects:
```

```
##                 Estimate Std. Error z value Pr(>|z|)
## type.genlogic   1.3686     0.5113   2.677 0.007439 **
## type.genvisuo   1.9133     0.5705   3.354 0.000798 ***
## setB            0.2284     0.5662   0.403 0.686631
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##               typ.gnl typ.gnv
## type.genvis  0.439
## setB        -0.539  -0.496
```

```
m3 = glmer(resp ~ 0 + type.gen*set + (1|sbj) + (1|item),
           data = ab.l,
           family = "binomial")
summary(m3)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: resp ~ 0 + type.gen * set + (1 | sbj) + (1 | item)
##    Data: ab.l
##
##      AIC      BIC   logLik deviance df.resid
##    470.5    495.7   -229.3    458.5      484
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -4.3279  0.1382  0.2896  0.4597  2.0101
##
## Random effects:
##  Groups Name        Variance Std.Dev.
##  sbj    (Intercept) 1.4849   1.2186
##  item   (Intercept) 0.7717   0.8785
## Number of obs: 490, groups:  sbj, 35; item, 14
##
## Fixed effects:
##                     Estimate Std. Error z value Pr(>|z|)
## type.genlogic        1.0796     0.5324   2.028 0.042591 *
## type.genvisuo        2.3233     0.6379   3.642 0.000271 ***
## setB                 0.8101     0.7001   1.157 0.247240
## type.genvisuo:setB  -1.4131     1.0868  -1.300 0.193509
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##               typ.gnl typ.gnv setB
## type.genvis  0.143
## setB        -0.632   0.009
## typ.gnvs:sB  0.405  -0.517  -0.645
```

```
# per stimare semplicemente la difficoltà degli item posso metterli come effetti fissi
# per come è scritto il modello 1, ho le stime di difficoltà degli item

ranef(m1)$item
```

```
##          (Intercept)
## a_1       -0.7547717
## a_2        0.5486805
## a_3        0.5486805
## a_logic1  -1.3193488
## a_logic2  -0.7018771
## a_logic3   0.3422708
## a_logic4   0.1692263
## b_logic1  -0.2939832
## b_logic2  -0.4346913
## b_logic3   0.7297656
## b_logic4   0.9512762
## b_visuo1  -1.7957057
## b_visuo2   0.3125375
## b_visuo3   0.5486805
```