Prediction of toddler vocabulary from infant speech and non-speech processing

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Main version 2020-07-30

History

- 2020-07-30: First version

Read and preprocess data

```
##  [1] "Subject.."               "Gender"
##  [3] "X18mCDIAge"              "X18mCom"
##  [5] "X18mComAll"              "X18mComGenderSpec"
##  [7] "X18mSay"                 "X18mSayAll"
##  [9] "X18mSayGenderSpec"       "X24mCDIAge"
## [11] "X24mCom"                 "X24msay"
## [13] "X24mSayALL"              "X24mSayGenderSpec"
## [15] "Mullen.VR"               "MullenExL"
## [17] "stress...VRM.age"        "total.tro.pref.quotient"
## [19] "VRM.trials.completed"    "VRM.trials.coded"
## [21] "VRM.age"                 "Novelty.VRM"
## [23] "faces.VRM"               "Shapes.VRM"
## [25] "vowels.Age"              "Vowel.Alt.pref.quotient"
## [27] "A.not.B.Age"             "A.not.B.score"
## [29] "notes1"                  "notes2"
```

```
## [1] 97 30
```

```
##    Subject..    Gender   X18mCDIAge       X18mCom        X18mComAll
##  Min.   :3425   F:43   Min.   :17.40   Min.   : 15.0   Min.   : 5.00
##  1st Qu.:3587   M:54   1st Qu.:17.69   1st Qu.:174.0   1st Qu.:20.45
##  Median :3716          Median :17.96   Median :232.0   Median :35.42
##  Mean   :3676          Mean   :18.09   Mean   :231.1   Mean   :44.49
##  3rd Qu.:3771          3rd Qu.:18.32   3rd Qu.:304.0   3rd Qu.:69.62
##  Max.   :3874          Max.   :19.28   Max.   :395.0   Max.   :99.00
##                        NA's   :32      NA's   :32      NA's   :32
##  X18mComGenderSpec    X18mSay         X18mSayAll     X18mSayGenderSpec
##  Min.   : 5.00     Min.   :  2.00   Min.   : 5.556   Min.   : 6.25
##  1st Qu.:21.11     1st Qu.: 21.00   1st Qu.:10.625   1st Qu.:11.75
##  Median :33.06     Median : 52.00   Median :18.571   Median :21.88
##  Mean   :44.49     Mean   : 70.17   Mean   :34.826   Mean   :35.43
##  3rd Qu.:71.67     3rd Qu.:105.00   3rd Qu.:60.000   3rd Qu.:56.25
##  Max.   :99.00     Max.   :339.00   Max.   :97.894   Max.   :99.00
##  NA's   :32        NA's   :32       NA's   :32       NA's   :32
```

```
##    X24mCDIAge       X24mCom         X24msay        X24mSayALL
##  Min.   :22.93   Min.   : 50.0   Min.   :  4.0   Min.   : 5.00
##  1st Qu.:23.75   1st Qu.:350.5   1st Qu.:115.0   1st Qu.:17.96
##  Median :24.05   Median :490.0   Median :260.0   Median :45.34
##  Mean   :24.18   Mean   :468.9   Mean   :294.0   Mean   :47.54
##  3rd Qu.:24.42   3rd Qu.:586.8   3rd Qu.:473.5   3rd Qu.:78.50
##  Max.   :29.24   Max.   :684.0   Max.   :653.0   Max.   :98.70
##  NA's   :33      NA's   :33      NA's   :34      NA's   :34
##  X24mSayGenderSpec   Mullen.VR       MullenExL     stress...VRM.age
##  Min.   : 5.00     Min.   :32.00   Min.   :20.00   Min.   :5.000
##  1st Qu.:17.04     1st Qu.:46.00   1st Qu.:44.00   1st Qu.:5.330
##  Median :46.48     Median :49.00   Median :51.00   Median :5.560
##  Mean   :47.84     Mean   :53.38   Mean   :48.67   Mean   :5.675
##  3rd Qu.:82.05     3rd Qu.:60.50   3rd Qu.:57.00   3rd Qu.:6.020
##  Max.   :99.00     Max.   :80.00   Max.   :70.00   Max.   :6.910
##  NA's   :34        NA's   :71      NA's   :76
##  total.tro.pref.quotient VRM.trials.completed VRM.trials.coded    VRM.age
##  Min.   :0.2338          Min.   :2.000       Min.   :2.000    Min.   :5.000
##  1st Qu.:0.4070          1st Qu.:7.000       1st Qu.:6.000    1st Qu.:5.315
##  Median :0.4885          Median :9.000       Median :9.000    Median :5.560
##  Mean   :0.5074          Mean   :7.404       Mean   :7.277    Mean   :5.678
##  3rd Qu.:0.6219          3rd Qu.:9.000       3rd Qu.:9.000    3rd Qu.:6.035
##  Max.   :0.8202          Max.   :9.000       Max.   :9.000    Max.   :6.910
##                          NA's   :3           NA's   :3        NA's   :2
##   Novelty.VRM       faces.VRM        Shapes.VRM       vowels.Age
##  Min.   :0.3486   Min.   :0.2802   Min.   :0.3886   Min.   :6.350
##  1st Qu.:0.5550   1st Qu.:0.5271   1st Qu.:0.5584   1st Qu.:6.680
##  Median :0.5914   Median :0.5782   Median :0.6126   Median :6.810
##  Mean   :0.5934   Mean   :0.5756   Mean   :0.6194   Mean   :6.918
##  3rd Qu.:0.6296   3rd Qu.:0.6286   3rd Qu.:0.6670   3rd Qu.:7.110
##  Max.   :0.8349   Max.   :0.8883   Max.   :0.8938   Max.   :8.390
##  NA's   :2        NA's   :3        NA's   :3        NA's   :2
##  Vowel.Alt.pref.quotient  A.not.B.Age    A.not.B.score
##  Min.   :0.2576          Min.   :6.350   Min.   :1.000
##  1st Qu.:0.4585          1st Qu.:6.680   1st Qu.:1.000
##  Median :0.5083          Median :6.810   Median :2.000
##  Mean   :0.5170          Mean   :6.938   Mean   :1.862
##  3rd Qu.:0.5786          3rd Qu.:7.110   3rd Qu.:2.000
##  Max.   :0.7306          Max.   :8.060   Max.   :3.000
##  NA's   :2               NA's   :3       NA's   :3
##                    notes1       notes2
##                       :90          :94
##  incomplete infant data: 7   error=2: 1
##                              fail=1 : 1
##                              pass=3 : 1
##
##
##

##    Subject..   Gender  Vowel.Alt.pref.quotient A.not.B.score   vowels.Age
##  3425   :  3   F:129   Min.   :0.2576          1   :108      Min.   :6.350
##  3427   :  3   M:162   1st Qu.:0.4577          2   :105      1st Qu.:6.680
##  3435   :  3           Median :0.5083          3   : 69      Median :6.810
##  3436   :  3           Mean   :0.5170          NA's:  9      Mean   :6.918
```

```
##  3437   :  3           3rd Qu.:0.5842                        3rd Qu.:7.110
##  3438   :  3           Max.   :0.7306                        Max.   :8.390
##  (Other):273           NA's   :6                             NA's   :6
##  total.tro.pref.quotient  Novelty.VRM        VRM.age          values
##  Min.   :0.2338          Min.   :0.3486   Min.   :5.000   Min.   :-2.2646
##  1st Qu.:0.4070          1st Qu.:0.5537   1st Qu.:5.300   1st Qu.:-0.7612
##  Median :0.4885          Median :0.5914   Median :5.560   Median :-0.1084
##  Mean   :0.5074          Mean   :0.5934   Mean   :5.678   Mean   : 0.0000
##  3rd Qu.:0.6219          3rd Qu.:0.6301   3rd Qu.:6.050   3rd Qu.: 0.7315
##  Max.   :0.8202          Max.   :0.8349   Max.   :6.910   Max.   : 4.0585
##                          NA's   :6        NA's   :6       NA's   :99
##      ind
##  com18z:97
##  say18z:97
##  say24z:97
##
##
##
##
```

Correlation matrix

```r
cor.mat=rcorr(as.matrix(mydat[,c("total.tro.pref.quotient","Vowel.Alt.pref.quotient", "Novelty.VRM",
            "com18z","say18z","say24z")]))

# r values
cor.mat$r
```

```
##                         total.tro.pref.quotient Vowel.Alt.pref.quotient
## total.tro.pref.quotient            1.0000000000              0.23098790
## Vowel.Alt.pref.quotient            0.2309879016              1.00000000
## Novelty.VRM                        0.0002924873              0.03903981
## com18z                             0.0189075116              0.16547139
## say18z                             0.0320740429              0.21423357
## say24z                             0.1371903275              0.23559252
##                           Novelty.VRM      com18z      say18z     say24z
## total.tro.pref.quotient  0.0002924873  0.01890751  0.03207404 0.13719033
## Vowel.Alt.pref.quotient  0.0390398121  0.16547139  0.21423357 0.23559252
## Novelty.VRM              1.0000000000 -0.02086173 -0.02930042 0.09180731
## com18z                  -0.0208617293  1.00000000  0.59658044 0.58363815
## say18z                  -0.0293004167  0.59658044  1.00000000 0.70403815
## say24z                   0.0918073053  0.58363815  0.70403815 1.00000000
```

```r
# p values
cor.mat$p
```

```
## NULL
```

```r
# Ns
cor.mat$n
```

```
##                         total.tro.pref.quotient Vowel.Alt.pref.quotient
## total.tro.pref.quotient                      97                      95
## Vowel.Alt.pref.quotient                      95                      95
## Novelty.VRM                                  95                      93
```

```
## com18z                                        65                      64
## say18z                                        65                      64
## say24z                                        62                      60
##                          Novelty.VRM com18z say18z say24z
## total.tro.pref.quotient           95     65     65     62
## Vowel.Alt.pref.quotient           93     64     64     60
## Novelty.VRM                       95     64     64     61
## com18z                            64     65     65     56
## say18z                            64     65     65     56
## say24z                            61     56     56     62
```

```
write.table(cor.mat$r,file="cormat.txt")
write.table(cor.mat$p,file="cormat.txt",append=T)
```

```
## Warning in write.table(cor.mat$p, file = "cormat.txt", append = T): appending
## column names to file
```

```
write.table(cor.mat$n,file="cormat.txt",append=T)
```

```
## Warning in write.table(cor.mat$n, file = "cormat.txt", append = T): appending
## column names to file
```

Regressions for AnotB

```
regtab=NULL

for(thisvar in c("total.tro.pref.quotient","Vowel.Alt.pref.quotient", "Novelty.VRM",
            "com18z","say18z","say24z")) {
  myaov=summary(aov(mydat[,thisvar]~anotB,data=mydat))
  regtab=rbind(regtab,
               cbind(thisvar, unlist(myaov)["Df2"], unlist(myaov)["F value1"], unlist(myaov)["Pr(>F)1"]
                                                                                                                                                    

regtab
```

```
##     thisvar
## Df2 "total.tro.pref.quotient" "91" "1.29181253191765"  "0.279762523173808"
## Df2 "Vowel.Alt.pref.quotient" "89" "0.626866907795473" "0.536605208173023"
## Df2 "Novelty.VRM"             "89" "0.931269130562504" "0.397858659196074"
## Df2 "com18z"                  "62" "0.295359843031021" "0.745305064710345"
## Df2 "say18z"                  "62" "1.02942410802971"  "0.363236495029499"
## Df2 "say24z"                  "59" "2.15233718718851"  "0.125250323623545"
```

Setting up models

If RECALC is TRUE then the next chunk will not be done…

```
readRDS("vowel main_model.rds")->vowel
readRDS("anotb main_model.rds")->anb
readRDS("stress main_model.rds")->strs
readRDS("vrm main_model.rds")->vrm
readRDS("main_model.rds")->main
```

… but this one will:

```
niter=4000
nwarmup=500

#values for scaled variables -- this cannot be passed as a variable to stan, but it's noted here for cl
nu=3
s=1

our_priors <- c(prior("student_t(3,0,1)", class = b),
               prior("student_t(3,0,1)", class = Intercept)
              )
```

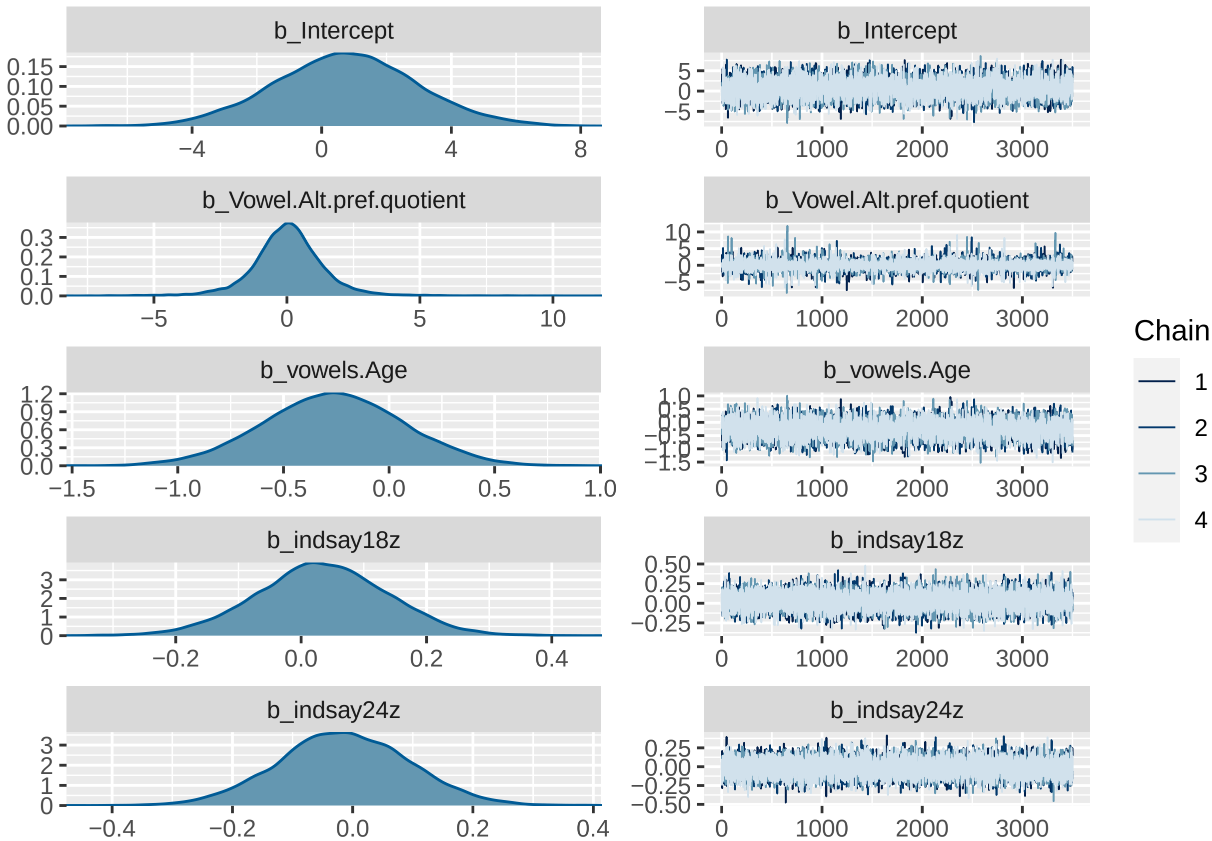
Univariate Bayesian models

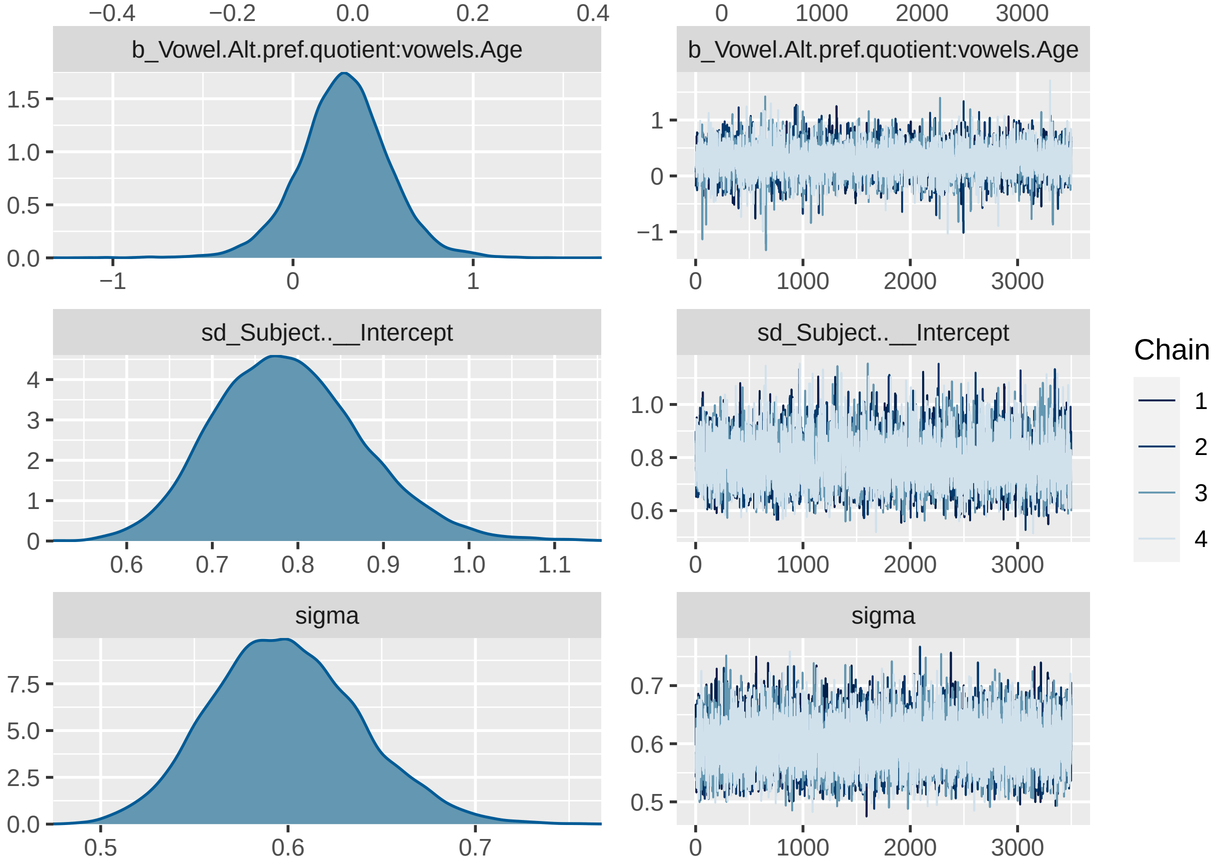
Vowels

```
vowel = brm(values ~
   Vowel.Alt.pref.quotient*vowels.Age +
  + ind + (1 | Subject..), data=stdatz,
  prior = our_priors,
             iter=niter, warmup=nwarmup, chains=4,cores=2,
             seed=12,
             save_all_pars = T,
             sample_prior = T
  )
```

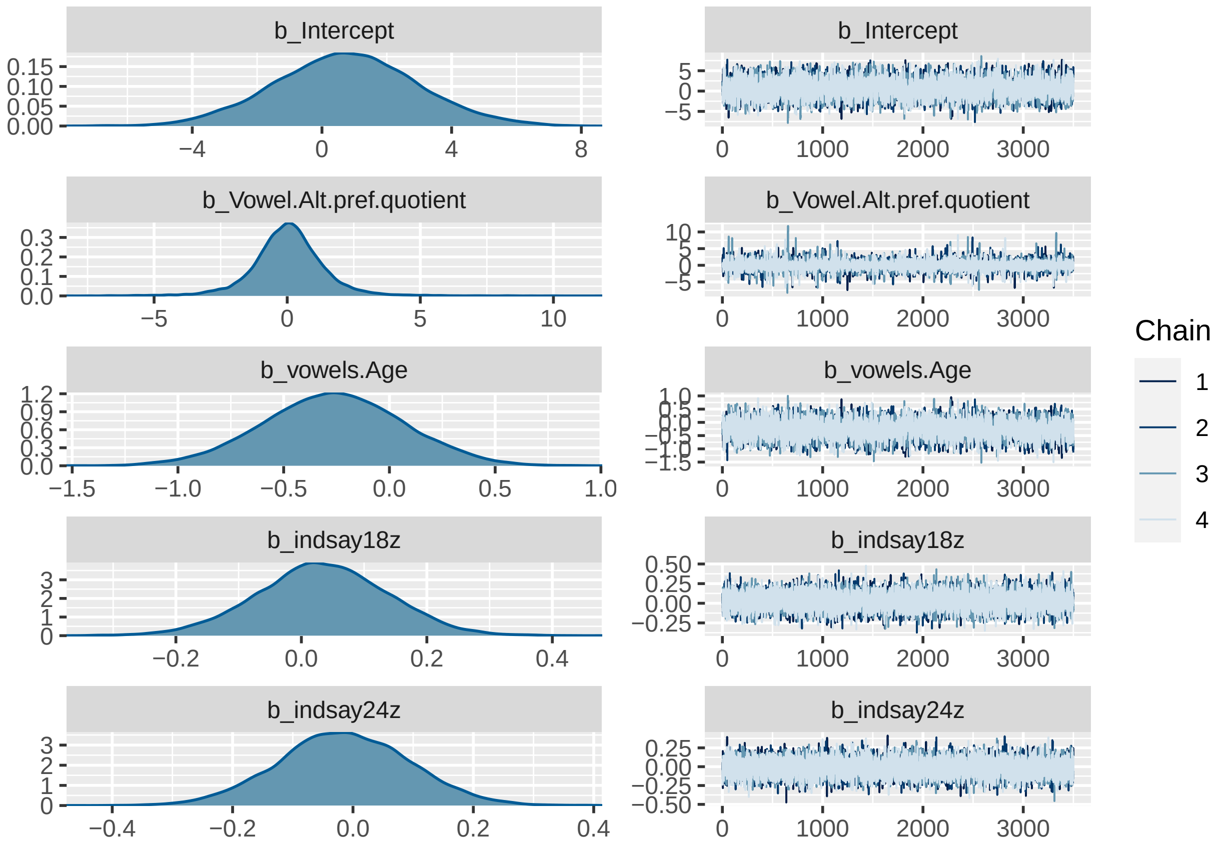
```
fit_uni_print(vowel,"vowel")
```

```
## [1] "vowel"
```


b_Intercept
b_Intercept
b_Vowel.Alt.pref.quotient
b_Vowel.Alt.pref.quotient
b_vowels.Age
b_vowels.Age
b_indsay18z
b_indsay18z
b_indsay24z
b_indsay24z
Chain
1
2
3
4

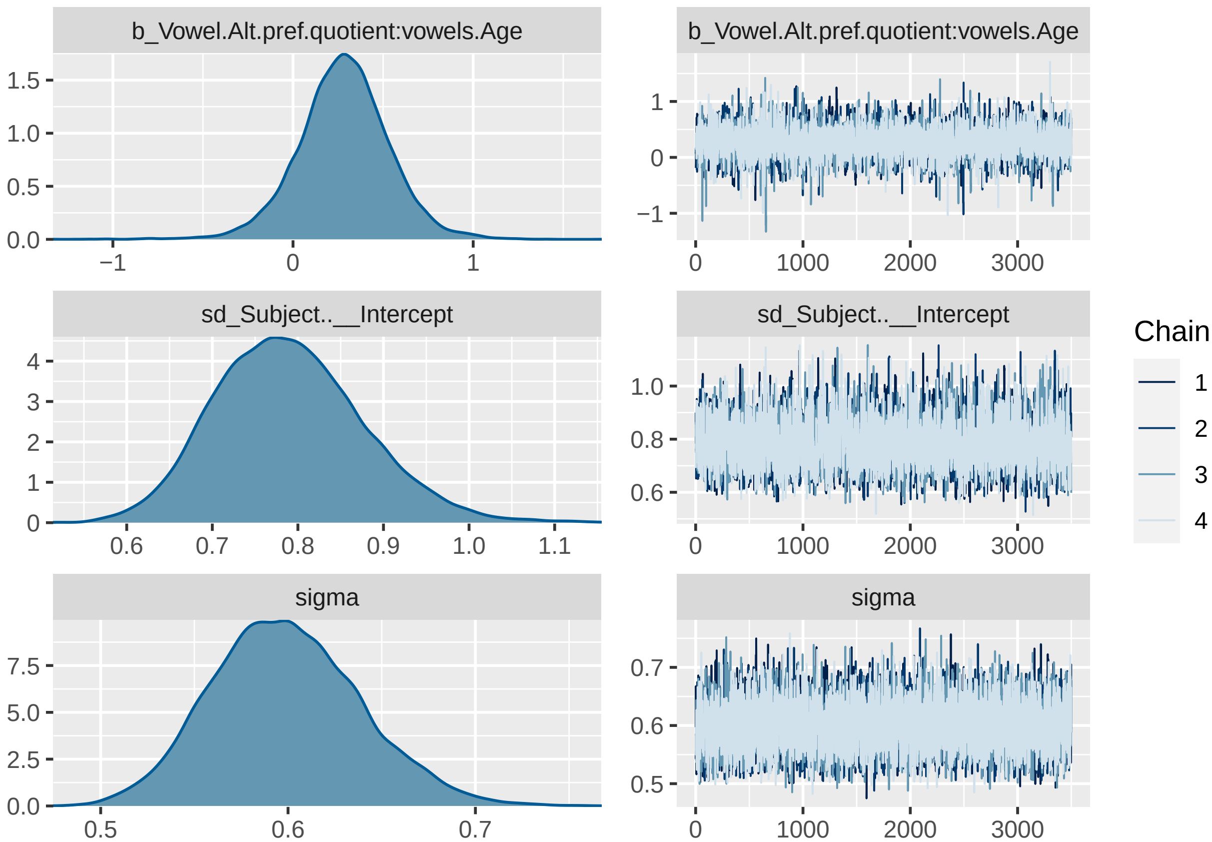

b_Vowel.Alt.pref.quotient:vowels.Age
b_Vowel.Alt.pref.quotient:vowels.Age
sd_Subject..__Intercept
sd_Subject..__Intercept
sigma
sigma
Chain
1
2
3
4

```
## [[1]]
```

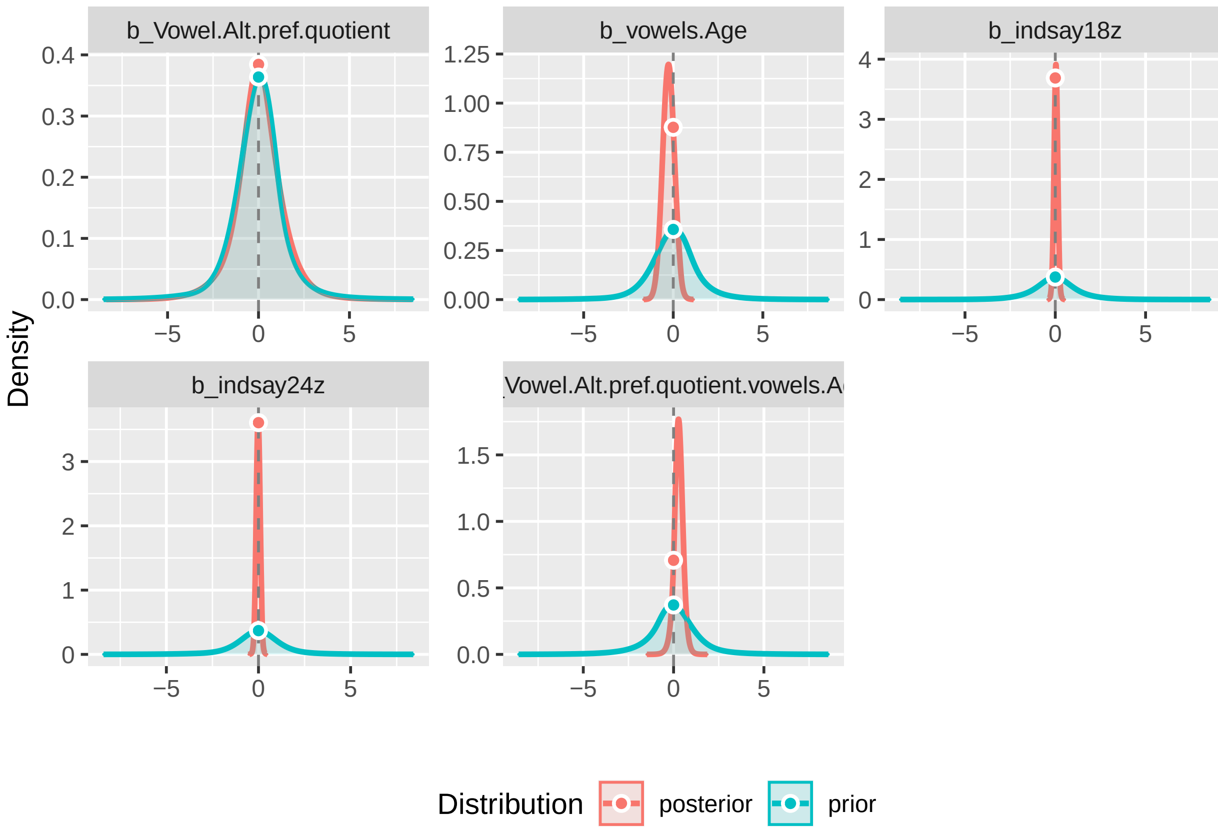



```
##
## [[2]]
##
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: values ~ Vowel.Alt.pref.quotient * vowels.Age + +ind + (1 | Subject..)
##    Data: stdatz (Number of observations: 188)
## Samples: 4 chains, each with iter = 4000; warmup = 500; thin = 1;
##          total post-warmup samples = 14000
##
## Group-Level Effects:
## ~Subject.. (Number of levels: 69)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.79      0.09     0.64     0.97 1.00     3907     6065
##
## Population-Level Effects:
##                                    Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept                              0.75      2.19    -3.54     5.17 1.00
## Vowel.Alt.pref.quotient                0.04      1.39    -2.77     2.82 1.00
## vowels.Age                            -0.26      0.33    -0.92     0.38 1.00
## indsay18z                              0.03      0.10    -0.17     0.24 1.00
## indsay24z                             -0.01      0.11    -0.23     0.20 1.00
## Vowel.Alt.pref.quotient:vowels.Age     0.28      0.25    -0.23     0.78 1.00
##                                    Bulk_ESS Tail_ESS
## Intercept                              4557     6439
## Vowel.Alt.pref.quotient               10828     6017
## vowels.Age                             4349     6051
```

```
## indsay18z                            15614    10392
## indsay24z                            14398    10723
## Vowel.Alt.pref.quotient:vowels.Age     5979     6749
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.60      0.04     0.53     0.68 1.00     8391    10182
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

## Computation of Bayes factors: sampling priors, please wait...

## Loading required namespace: logspline
```




```
## # Bayes Factor (Savage-Dickey density ratio)
##
## Parameter                            |   BF
## ------------------------------------------
## Intercept                            | 0.24
## Vowel.Alt.pref.quotient              | 0.95
## vowels.Age                           | 0.41
## indsay18z                            |  0.1
## indsay24z                            |  0.1
## Vowel.Alt.pref.quotient.vowels.Age   | 0.53
##
## * Evidence Against The Null: [0]
```

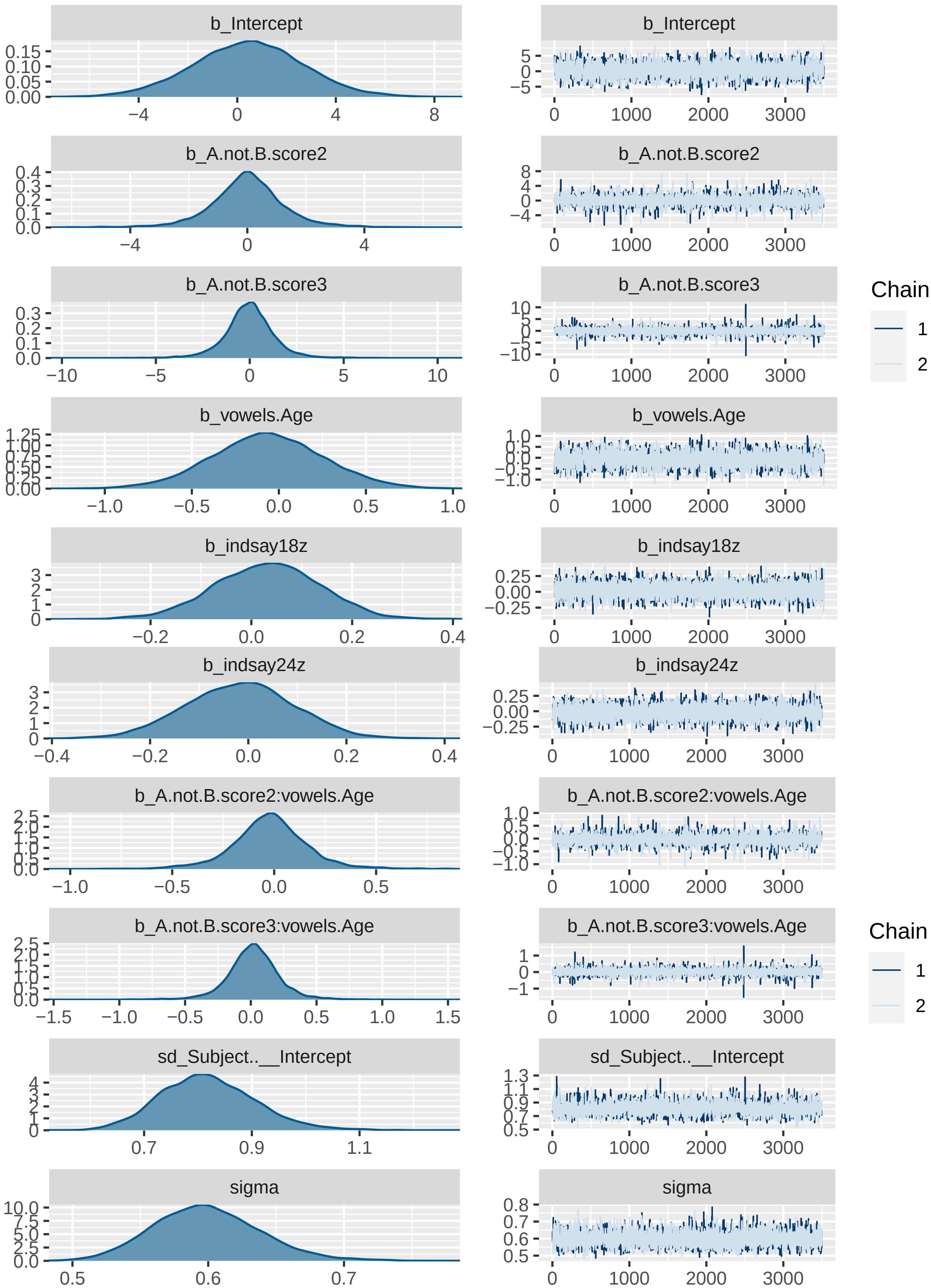


A-not-B

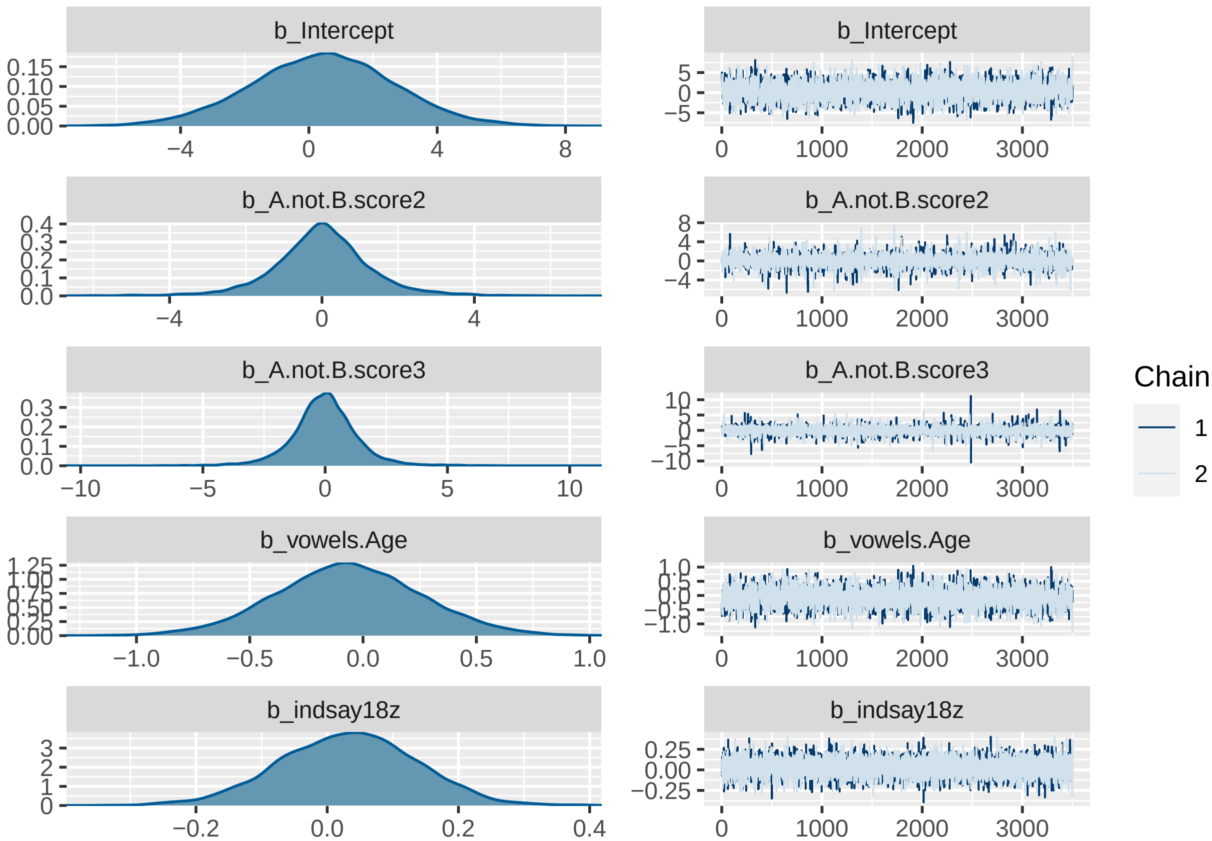
```
anb = brm(values ~
   A.not.B.score*vowels.Age +
  + ind + (1 | Subject..), data=stdatz,
  prior = our_priors,
             iter=niter, warmup=nwarmup, chains=4,cores=2,
             seed=12,
             save_all_pars = T,
             sample_prior = T
  )
```

```
fit_uni_print(anb,"anotb")
```

```
## [1] "anotb"
```

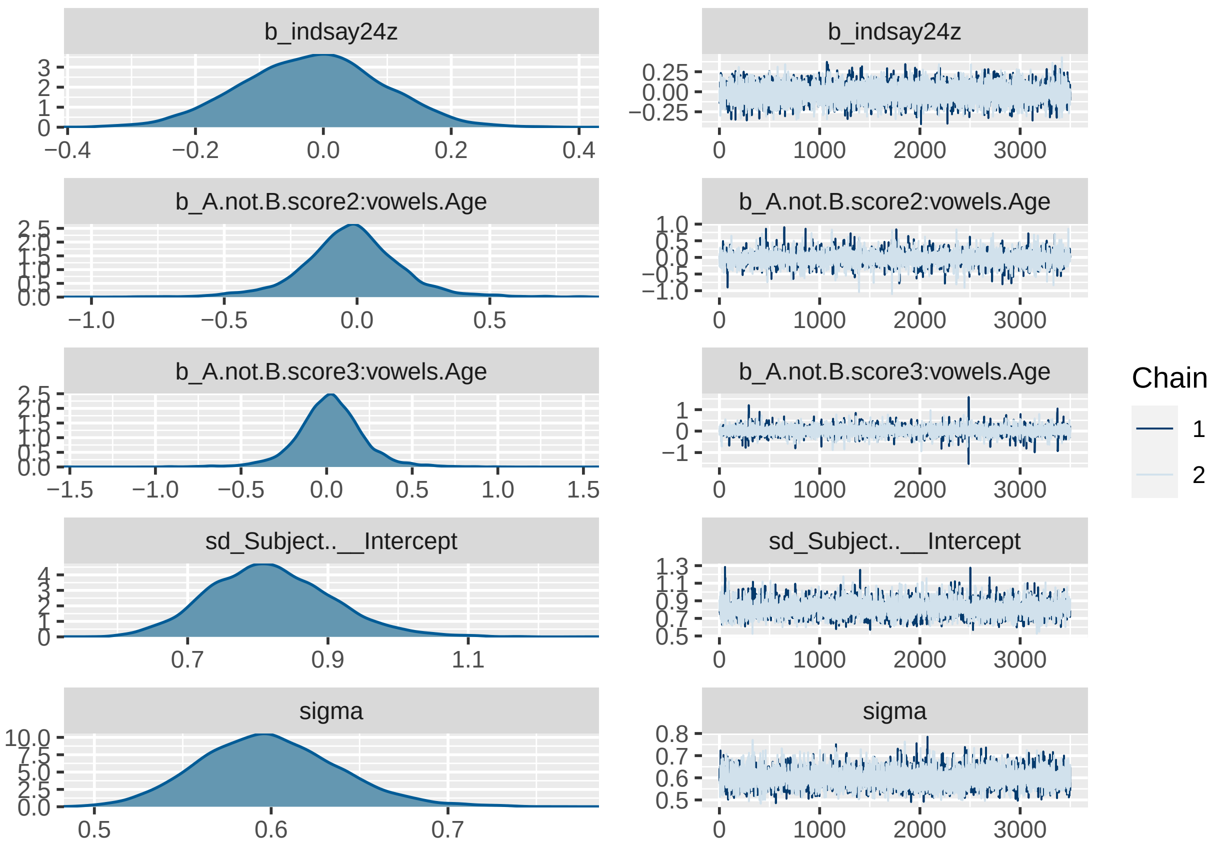

b_Intercept
b_A.not.B.score2
b_A.not.B.score3
b_vowels.Age
b_indsay18z
b_indsay24z
b_A.not.B.score2:vowels.Age
b_A.not.B.score3:vowels.Age
sd_Subject..__Intercept
sigma
Chain
1
2

```
## [[1]]
```



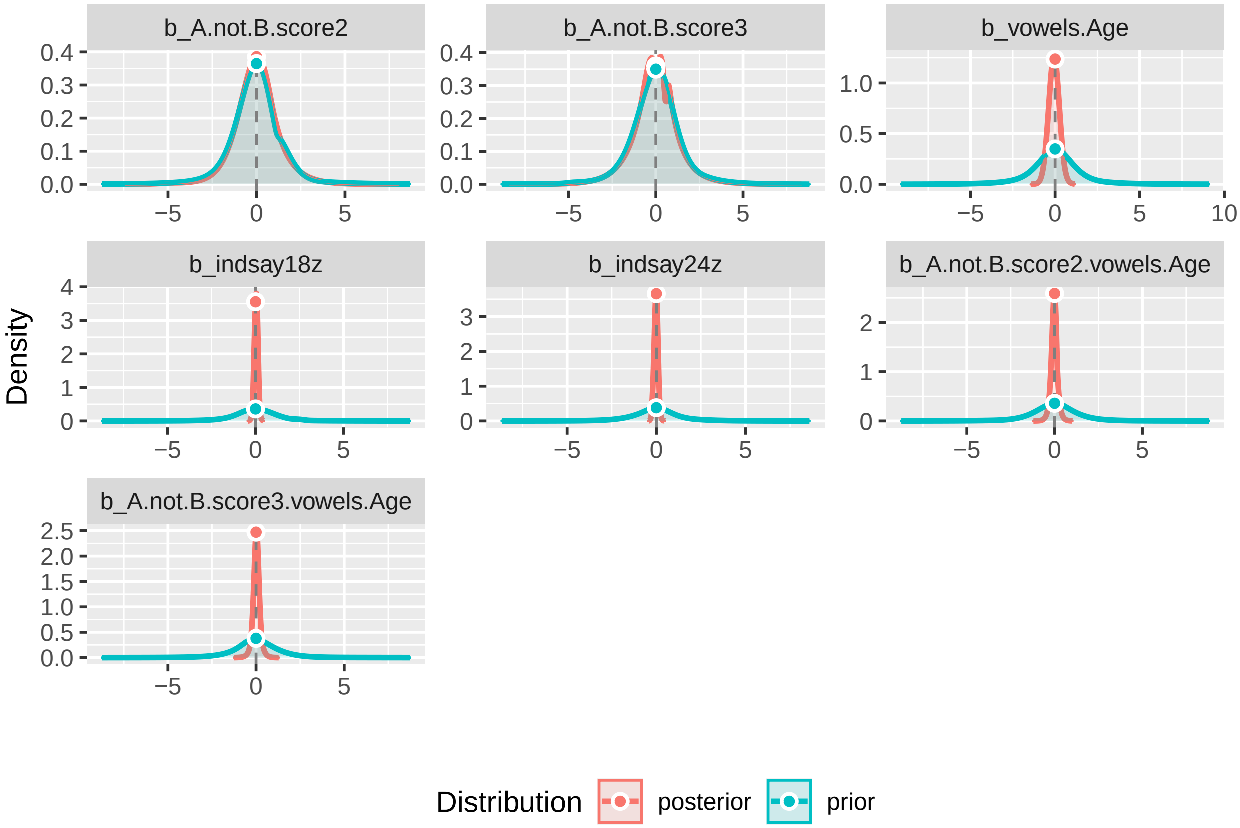

```
##
## [[2]]

##
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: values ~ A.not.B.score * vowels.Age + +ind + (1 | Subject..)
##    Data: stdatz (Number of observations: 188)
## Samples: 2 chains, each with iter = 4000; warmup = 500; thin = 1;
##          total post-warmup samples = 7000
##
## Group-Level Effects:
## ~Subject.. (Number of levels: 69)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.82      0.09     0.66     1.01 1.00     1986     3055
##
## Population-Level Effects:
##                          Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## Intercept                    0.44      2.21    -3.98     4.75 1.00     2705
## A.not.B.score2               0.01      1.31    -2.64     2.75 1.00     4990
## A.not.B.score3              -0.02      1.36    -2.75     2.72 1.00     4689
## vowels.Age                  -0.06      0.32    -0.69     0.57 1.00     2728
## indsay18z                    0.03      0.10    -0.17     0.23 1.00     9679
## indsay24z                   -0.02      0.11    -0.23     0.19 1.00     8690
## A.not.B.score2:vowels.Age   -0.02      0.19    -0.42     0.37 1.00     4877
## A.not.B.score3:vowels.Age    0.02      0.20    -0.39     0.43 1.00     4479
##                          Tail_ESS
## Intercept                    3530
```

```
## A.not.B.score2                  3248
## A.not.B.score3                  3009
## vowels.Age                      3562
## indsay18z                       5751
## indsay24z                       5729
## A.not.B.score2:vowels.Age       3248
## A.not.B.score3:vowels.Age       2859
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.60      0.04     0.53     0.68 1.00     3867     4412
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

## Computation of Bayes factors: sampling priors, please wait...
```




```
## # Bayes Factor (Savage-Dickey density ratio)
##
## Parameter                  |   BF
## -------------------------------
## Intercept                  | 0.23
## A.not.B.score2             | 0.95
## A.not.B.score3             | 0.98
## vowels.Age                 | 0.28
## indsay18z                  |  0.1
## indsay24z                  |  0.1
```

```
## A.not.B.score2.vowels.Age | 0.14
## A.not.B.score3.vowels.Age | 0.15
##
## * Evidence Against The Null: [0]
```

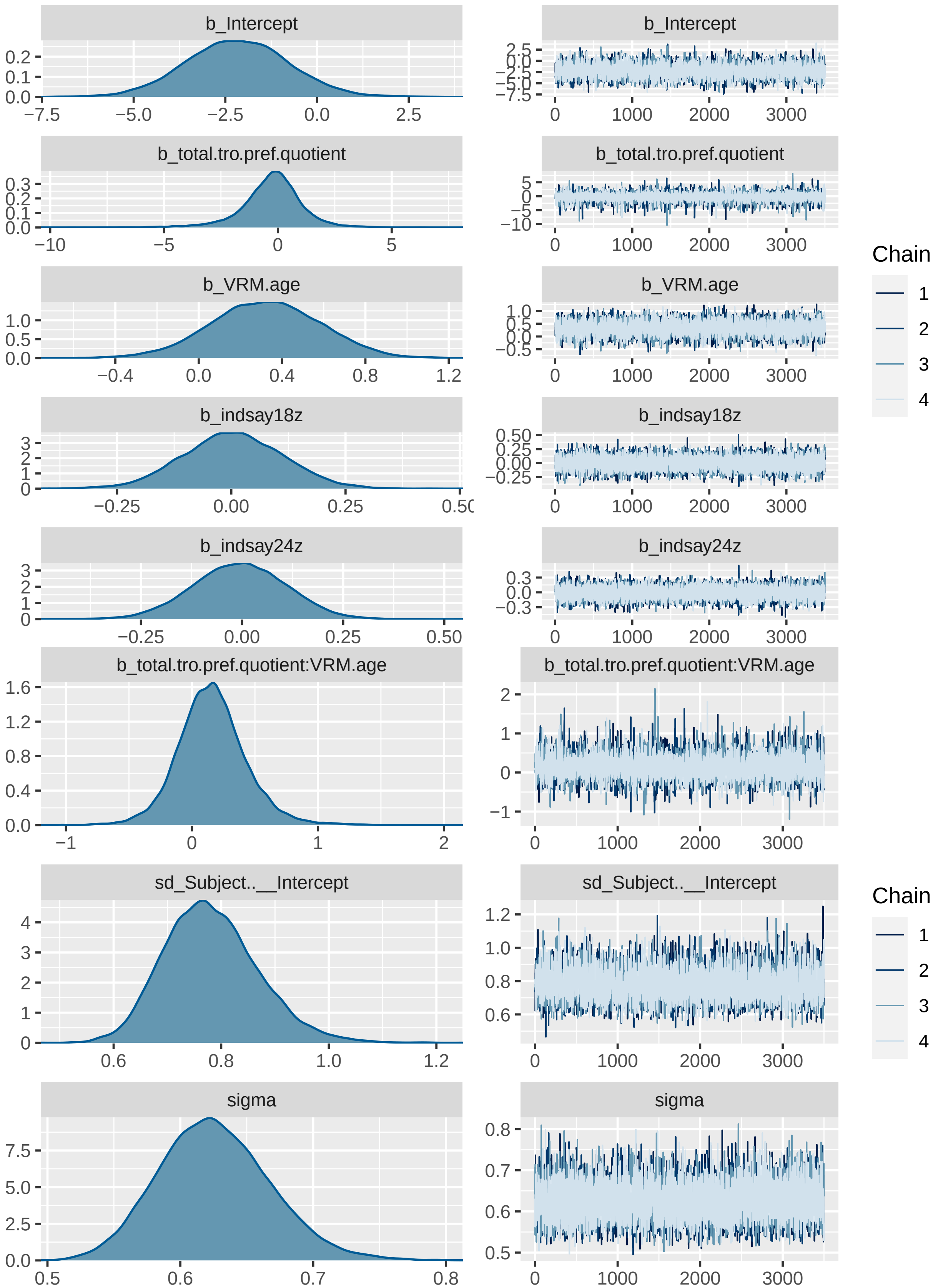


Stress

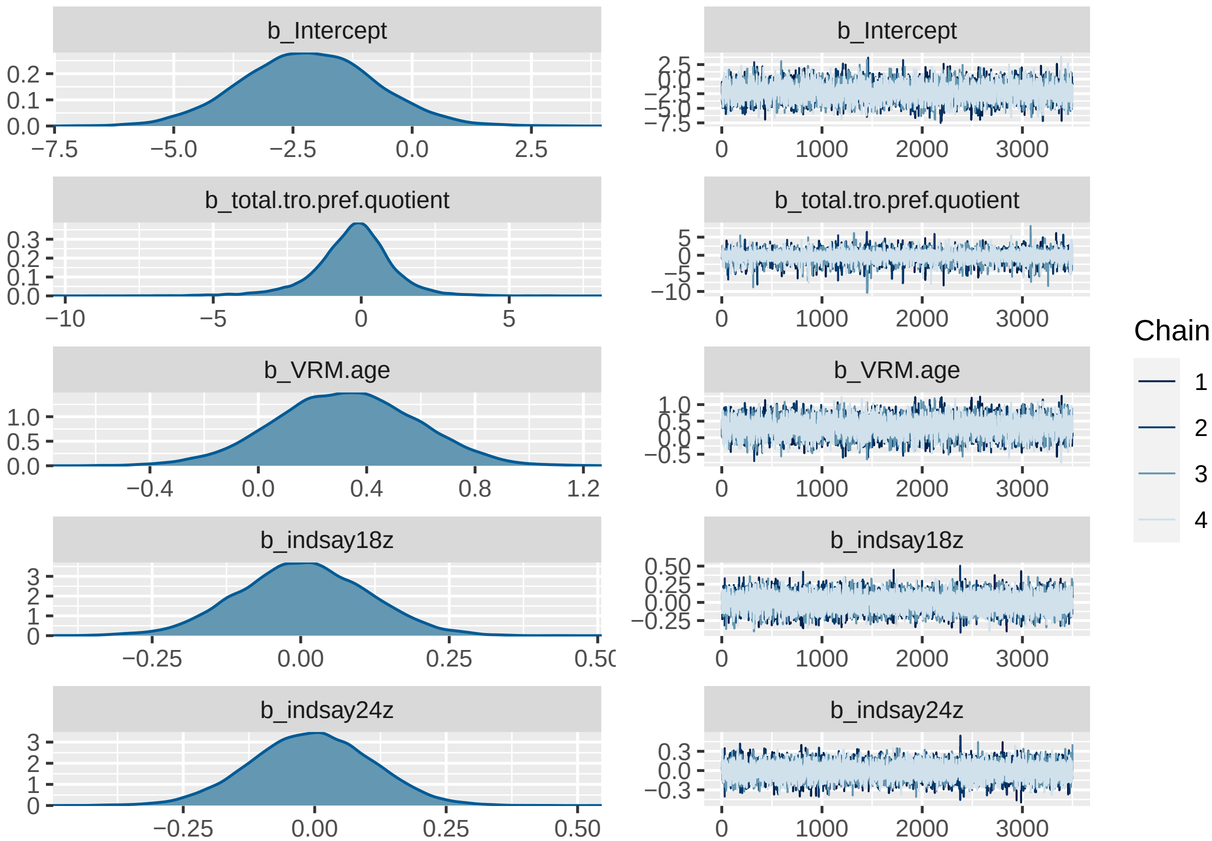
```
strs = brm(values ~
   total.tro.pref.quotient*VRM.age +
  + ind + (1 | Subject..), data=stdatz,
  prior = our_priors,
             iter=niter, warmup=nwarmup, chains=4,cores=2,
             seed=12,
             save_all_pars = T,
             sample_prior = T
  )
```

```
fit_uni_print(strs,"stress")
```

```
## [1] "stress"
```


b_Intercept
b_total.tro.pref.quotient
b_VRM.age
b_indsay18z
b_indsay24z
b_total.tro.pref.quotient:VRM.age
sd_Subject..__Intercept
sigma
Chain
1
2
3
4

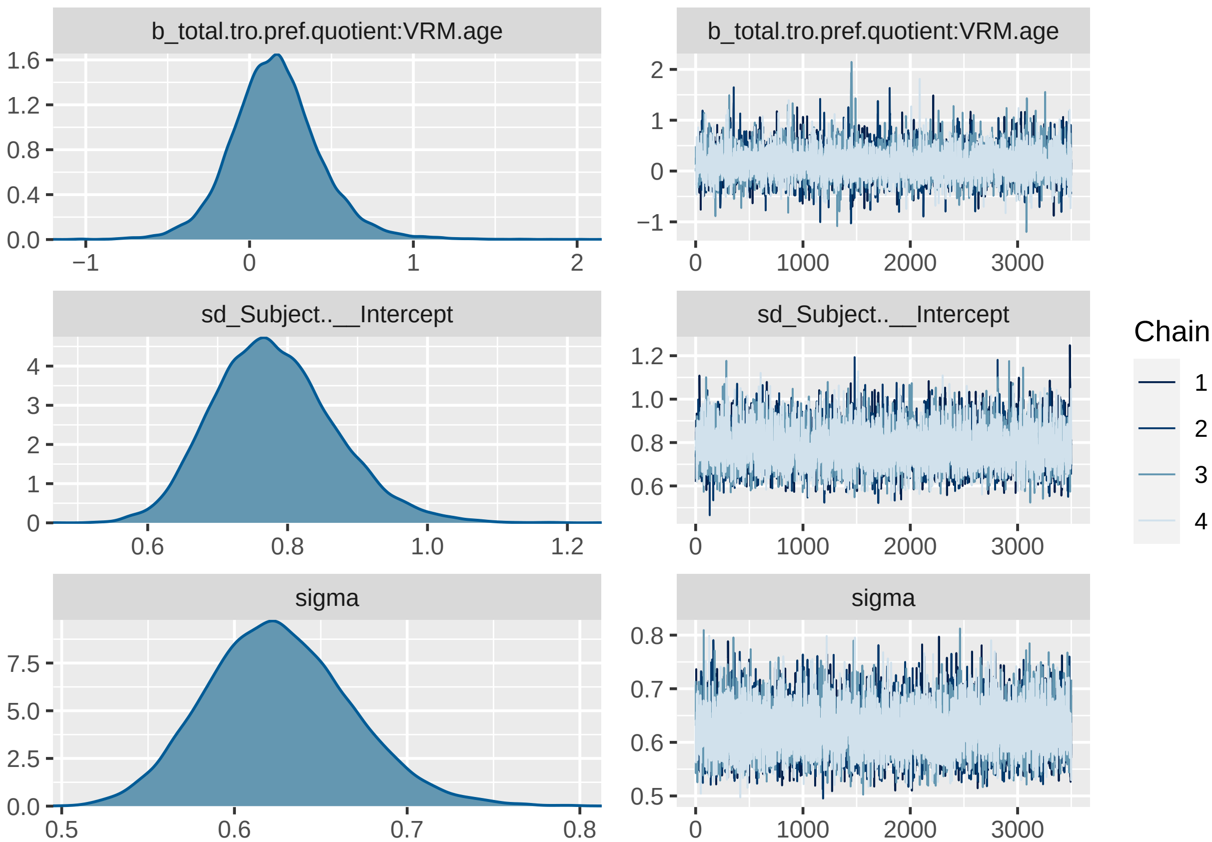
```
## [[1]]
```



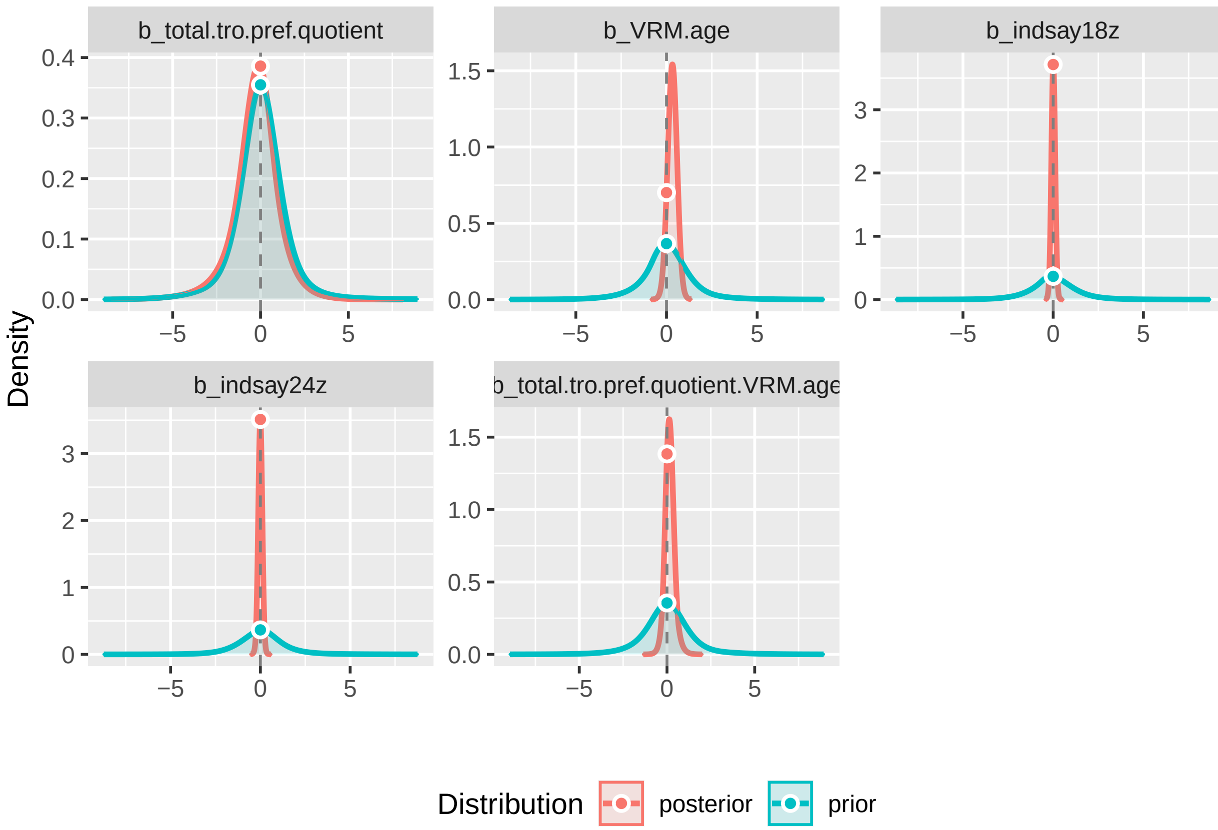

```
##
## [[2]]

##
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: values ~ total.tro.pref.quotient * VRM.age + +ind + (1 | Subject..)
##    Data: stdatz (Number of observations: 189)
## Samples: 4 chains, each with iter = 4000; warmup = 500; thin = 1;
##          total post-warmup samples = 14000
##
## Group-Level Effects:
## ~Subject.. (Number of levels: 70)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.78      0.09     0.63     0.97 1.00     4212     7235
##
## Population-Level Effects:
##                                 Estimate Est.Error l-95% CI u-95% CI Rhat
## Intercept                          -2.17      1.40    -4.89     0.59 1.00
## total.tro.pref.quotient            -0.27      1.37    -3.34     2.29 1.00
## VRM.age                             0.32      0.26    -0.19     0.83 1.00
## indsay18z                           0.00      0.11    -0.21     0.22 1.00
## indsay24z                          -0.01      0.12    -0.23     0.21 1.00
## total.tro.pref.quotient:VRM.age     0.16      0.28    -0.36     0.74 1.00
##                                 Bulk_ESS Tail_ESS
## Intercept                           5236     7774
## total.tro.pref.quotient            12368     5896
## VRM.age                             4926     7385
```

```
## indsay18z                             15867    11041
## indsay24z                             14584     9907
## total.tro.pref.quotient:VRM.age        7690     6142
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.63      0.04     0.55     0.71 1.00     8395    10117
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
## Computation of Bayes factors: sampling priors, please wait...
```




```
## # Bayes Factor (Savage-Dickey density ratio)
##
## Parameter                             |   BF
## ---------------------------------------------
## Intercept                             | 0.57
## total.tro.pref.quotient               | 0.92
## VRM.age                               | 0.52
## indsay18z                             |  0.1
## indsay24z                             |  0.1
## total.tro.pref.quotient.VRM.age       | 0.26
##
## * Evidence Against The Null: [0]
```

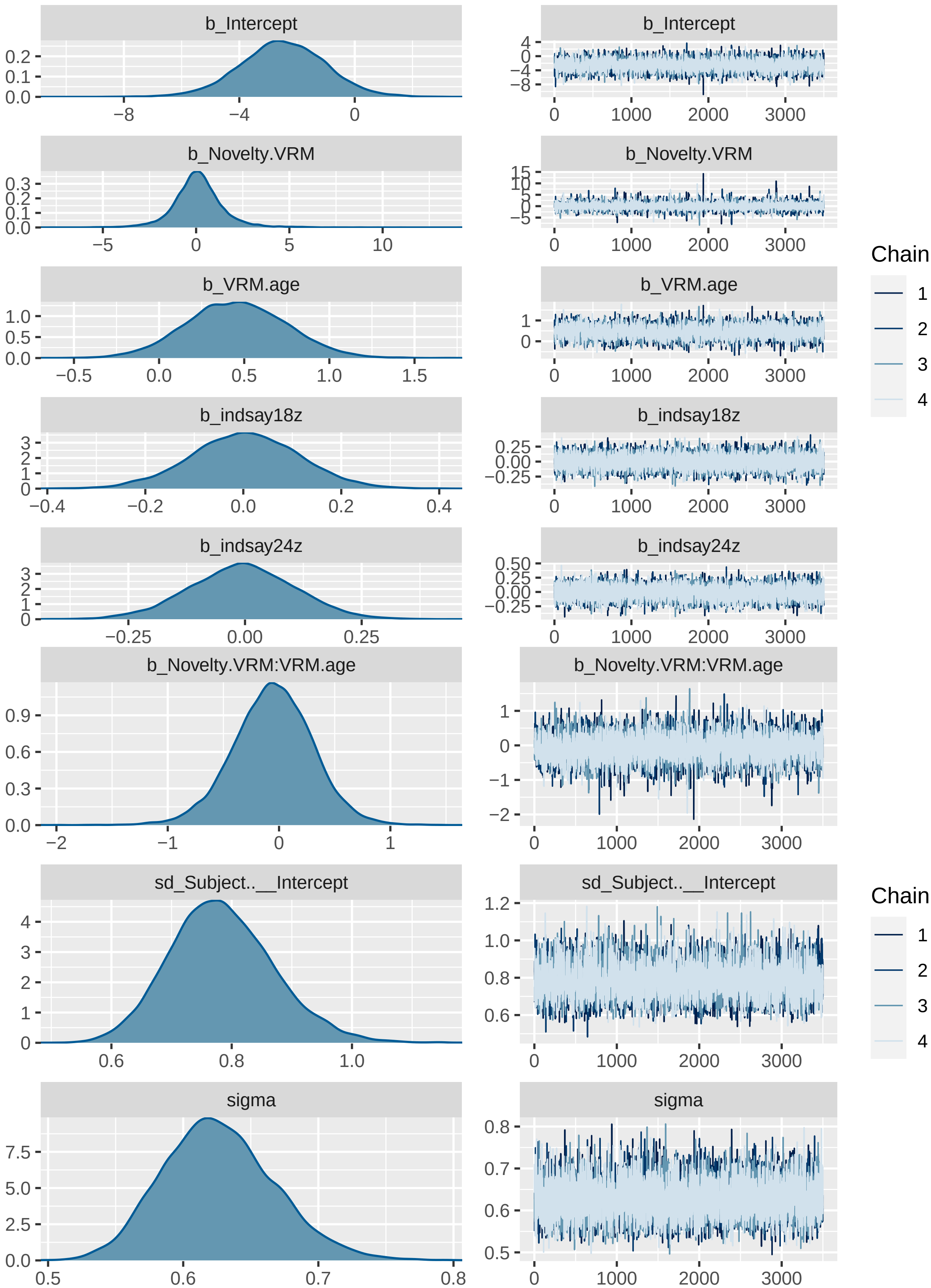


VRM

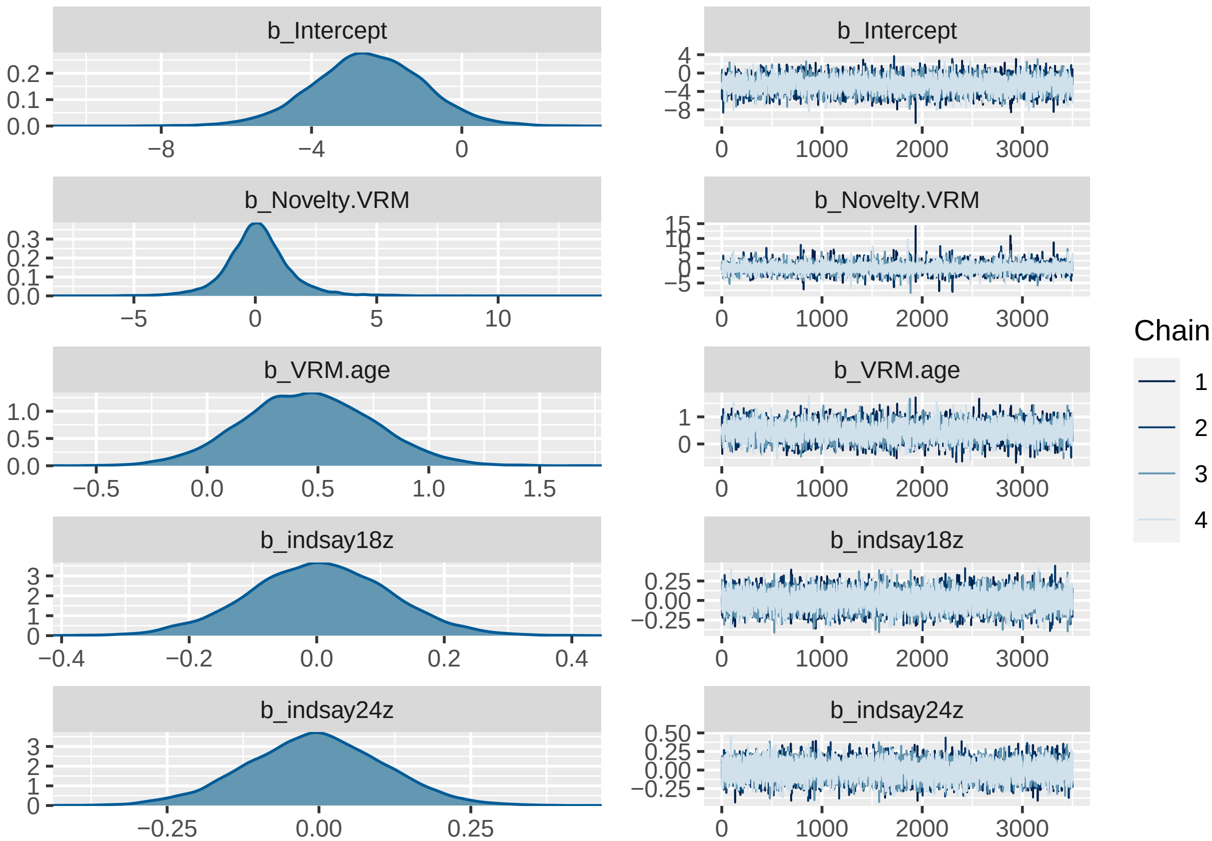
```
vrm = brm(values ~
   Novelty.VRM*VRM.age +
  + ind + (1 | Subject..), data=stdatz,
  prior = our_priors,
             iter=niter, warmup=nwarmup, chains=4,cores=2,
             seed=12,
             save_all_pars = T,
             sample_prior = T
  )
```

```
fit_uni_print(vrm,"vrm")
```

```
## [1] "vrm"
```

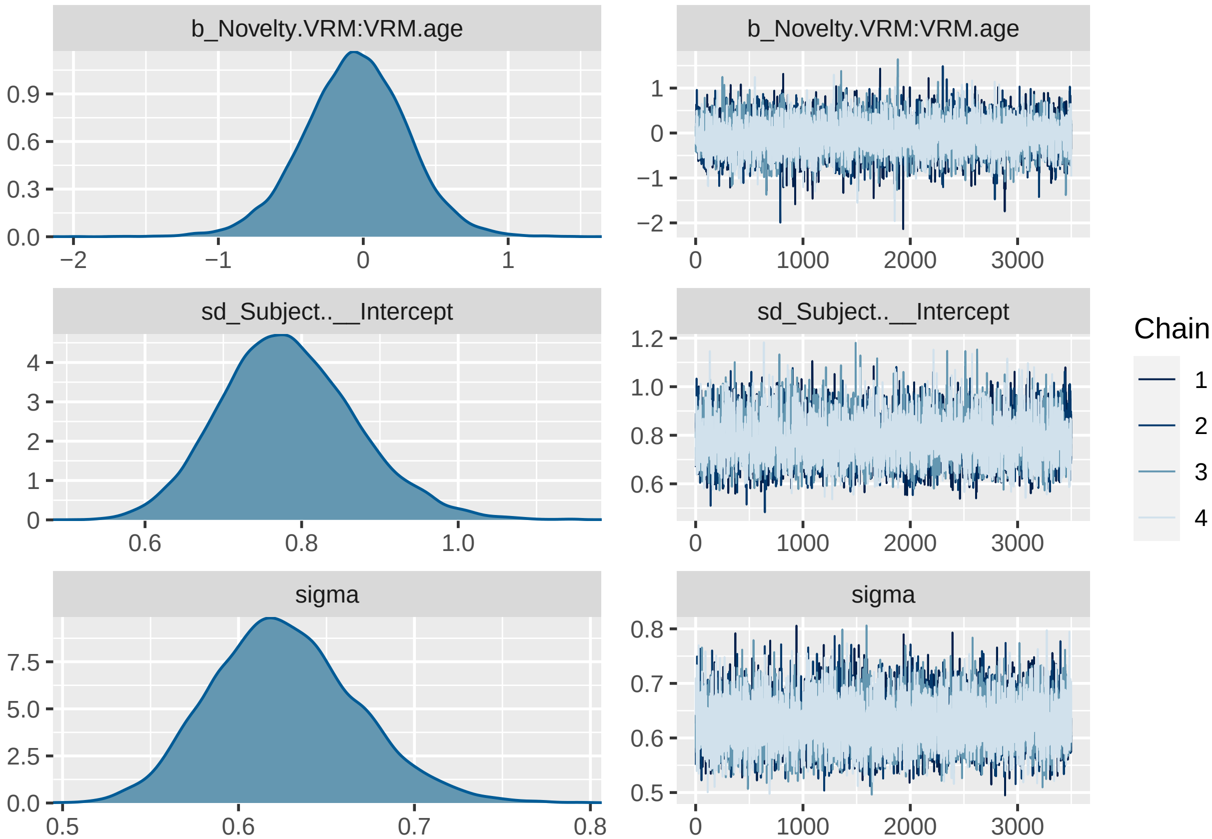

b_Intercept
b_Intercept
b_Novelty.VRM
b_Novelty.VRM
b_VRM.age
b_VRM.age
b_indsay18z
b_indsay18z
b_indsay24z
b_indsay24z
b_Novelty.VRM:VRM.age
b_Novelty.VRM:VRM.age
sd_Subject..__Intercept
sd_Subject..__Intercept
sigma
sigma
Chain
1
2
3
4
Chain
1
2
3
4

```
## [[1]]
```

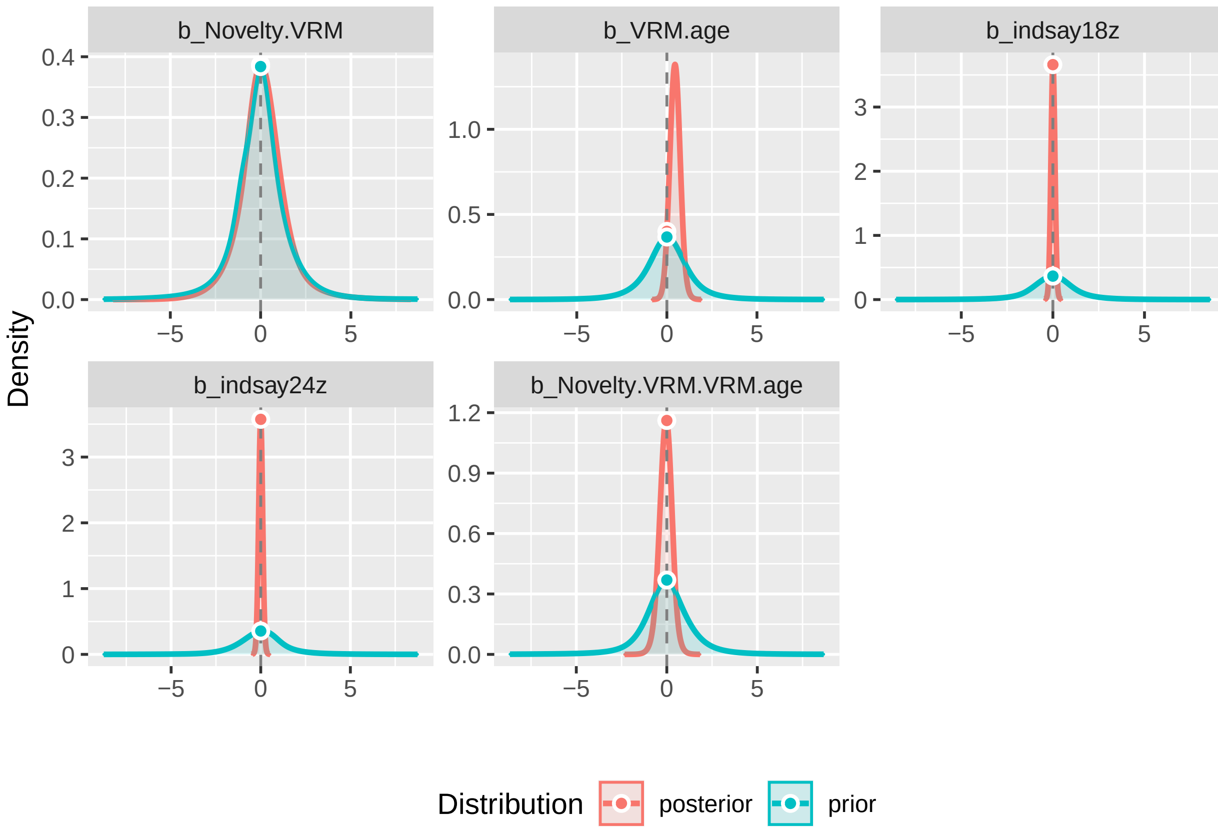



```
##
## [[2]]
##
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: values ~ Novelty.VRM * VRM.age + +ind + (1 | Subject..)
##    Data: stdatz (Number of observations: 189)
## Samples: 4 chains, each with iter = 4000; warmup = 500; thin = 1;
##          total post-warmup samples = 14000
##
## Group-Level Effects:
## ~Subject.. (Number of levels: 70)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.78      0.09     0.63     0.97 1.00     4262     7975
##
## Population-Level Effects:
##                     Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept              -2.49      1.48    -5.45     0.40 1.00     4817     7481
## Novelty.VRM             0.11      1.38    -2.57     3.09 1.00     9895     5813
## VRM.age                 0.46      0.29    -0.11     1.04 1.00     4099     6404
## indsay18z               0.00      0.11    -0.22     0.22 1.00    13633    10245
## indsay24z              -0.01      0.11    -0.23     0.21 1.00    12337    10628
## Novelty.VRM:VRM.age    -0.06      0.36    -0.77     0.64 1.00     5011     6789
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.63      0.04     0.55     0.71 1.00     7826    10576
```

```
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).

## Computation of Bayes factors: sampling priors, please wait...
```



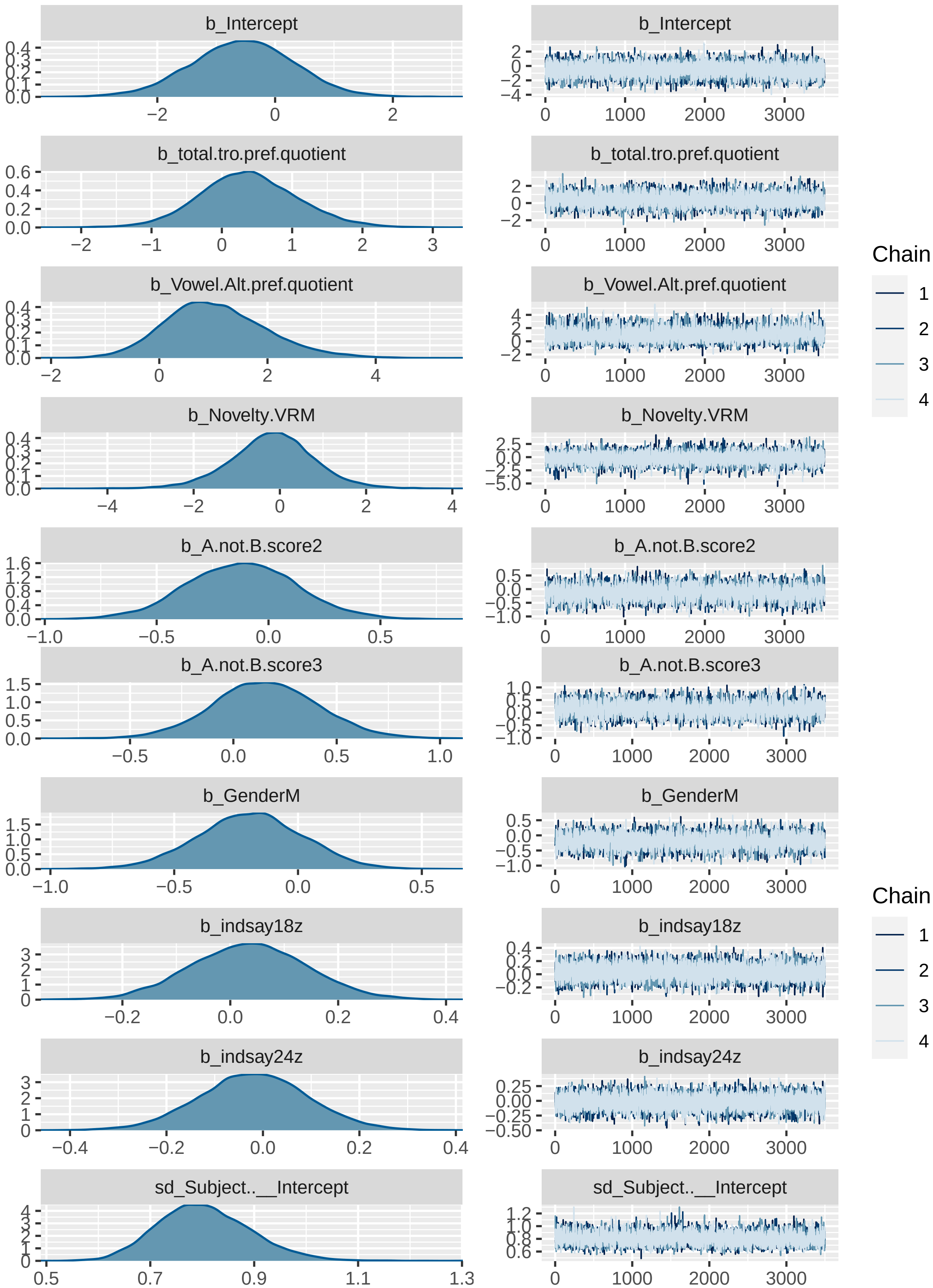

```
## # Bayes Factor (Savage-Dickey density ratio)
##
## Parameter           |   BF
## --------------------------
## Intercept           | 0.78
## Novelty.VRM         | 0.99
## VRM.age             | 0.92
## indsay18z           |  0.1
## indsay24z           |  0.1
## Novelty.VRM.VRM.age | 0.32
##
## * Evidence Against The Null: [0]
```

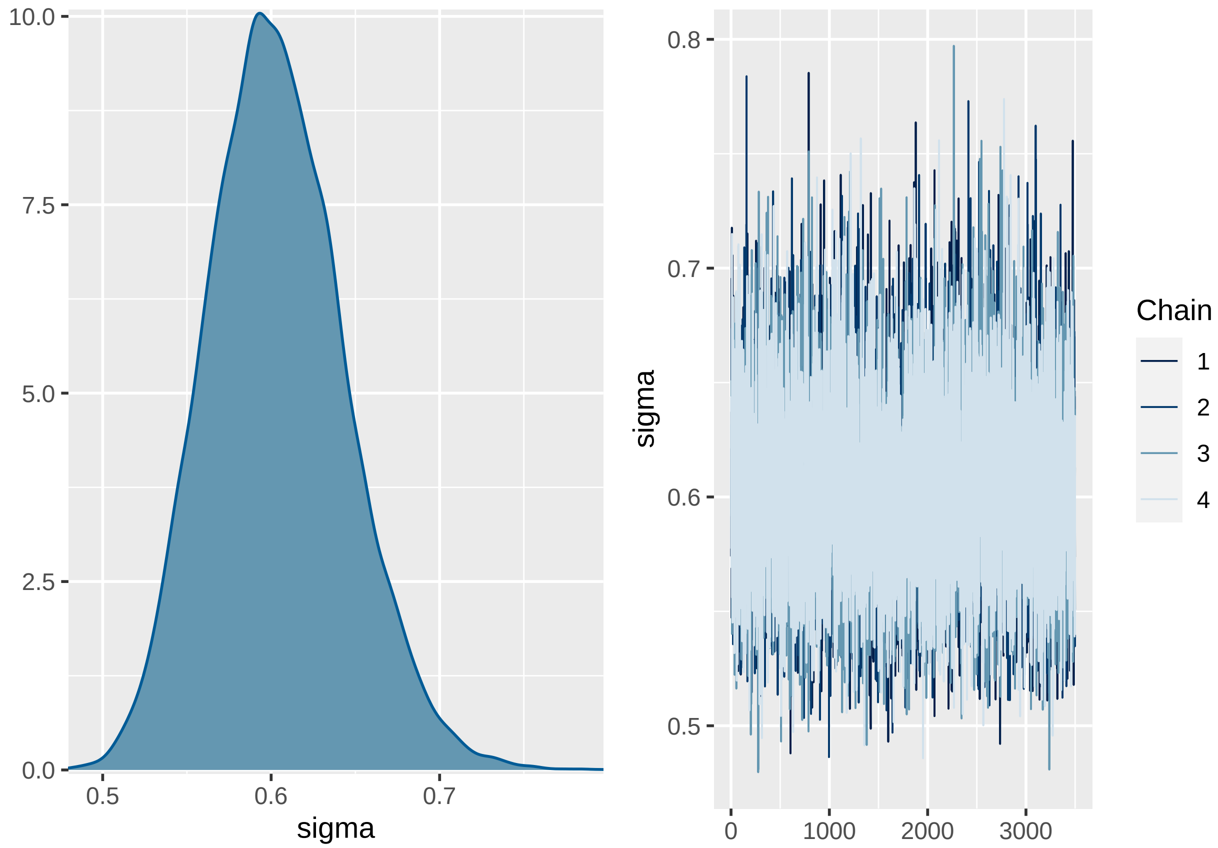


Multivariate Bayesian model

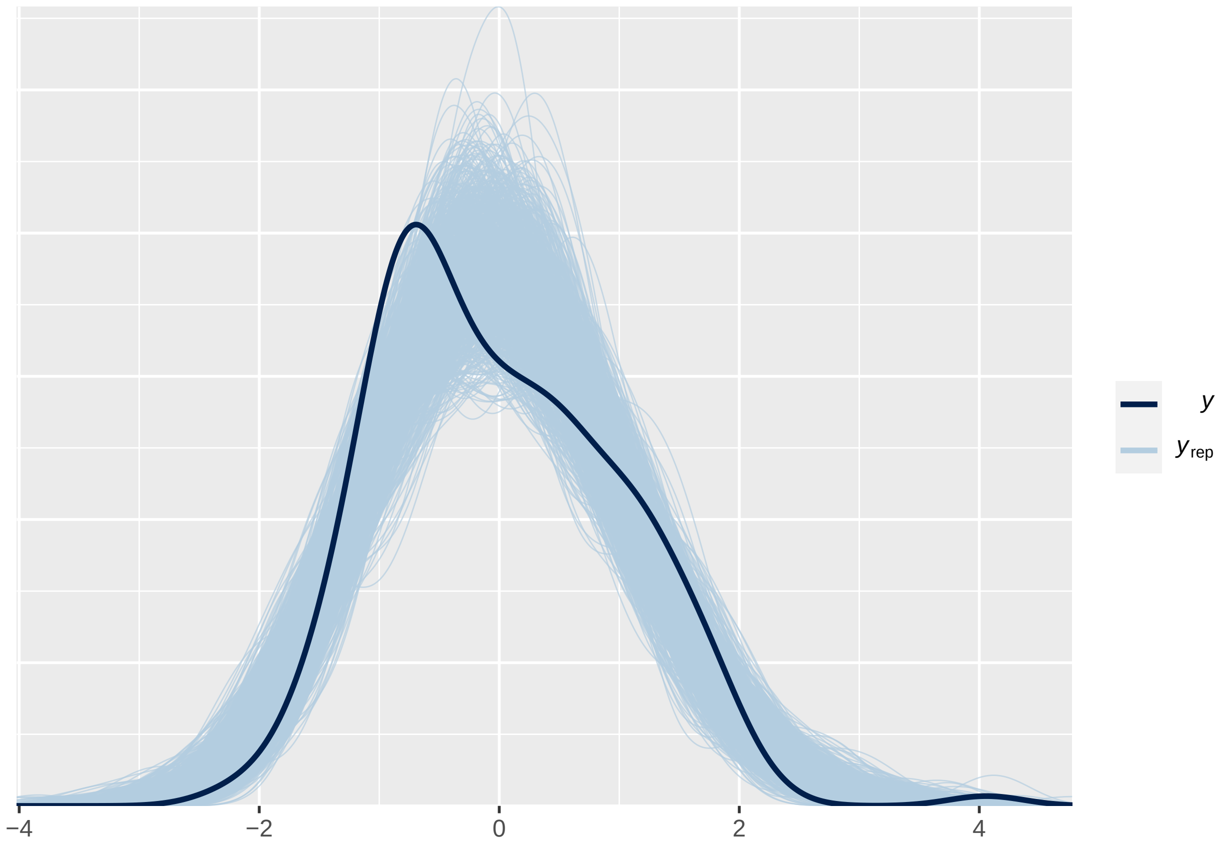
```
main = brm(values ~
   total.tro.pref.quotient + Vowel.Alt.pref.quotient + Novelty.VRM + A.not.B.score +
     Gender + ind + (1 | Subject..), data = stdatz,
  prior = our_priors,
             iter=niter, warmup=nwarmup, chains=4,cores=2,
             seed=12,
             save_all_pars = T,
             sample_prior = T
  )
```

```
saveRDS(main,file="main_model.rds")

plot(main)
```


b_Intercept
b_total.tro.pref.quotient
b_Vowel.Alt.pref.quotient
b_Novelty.VRM
b_A.not.B.score2
b_A.not.B.score3
b_GenderM
b_indsay18z
b_indsay24z
sd_Subject..__Intercept
Chain
1
2
3
4




```
pp_check(main, nsamples = 1000)
```




```
main
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: values ~ total.tro.pref.quotient + Vowel.Alt.pref.quotient + Novelty.VRM + A.not.B.score + G
##    Data: stdatz (Number of observations: 185)
## Samples: 4 chains, each with iter = 4000; warmup = 500; thin = 1;
##          total post-warmup samples = 14000
##
## Group-Level Effects:
## ~Subject.. (Number of levels: 68)
##               Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sd(Intercept)     0.80      0.09     0.64     0.99 1.00     4483     8262
##
## Population-Level Effects:
##                         Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## Intercept                  -0.55      0.87    -2.28     1.14 1.00     7559
## total.tro.pref.quotient     0.38      0.70    -0.94     1.82 1.00     7414
## Vowel.Alt.pref.quotient     1.06      0.94    -0.60     3.09 1.00     5956
## Novelty.VRM                -0.18      0.99    -2.20     1.79 1.00     9721
## A.not.B.score2             -0.12      0.25    -0.61     0.38 1.00     4807
## A.not.B.score3              0.16      0.26    -0.34     0.67 1.00     4791
## GenderM                    -0.19      0.21    -0.61     0.22 1.00     4968
## indsay18z                   0.04      0.11    -0.17     0.25 1.00    19170
## indsay24z                  -0.02      0.11    -0.24     0.20 1.00    18908
##                         Tail_ESS
## Intercept                   9703
## total.tro.pref.quotient     8596
```

```
## Vowel.Alt.pref.quotient     7178
## Novelty.VRM                 8943
## A.not.B.score2              7238
## A.not.B.score3              7569
## GenderM                     8018
## indsay18z                  10329
## indsay24z                  10727
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.60      0.04     0.53     0.69 1.00    10228    10728
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

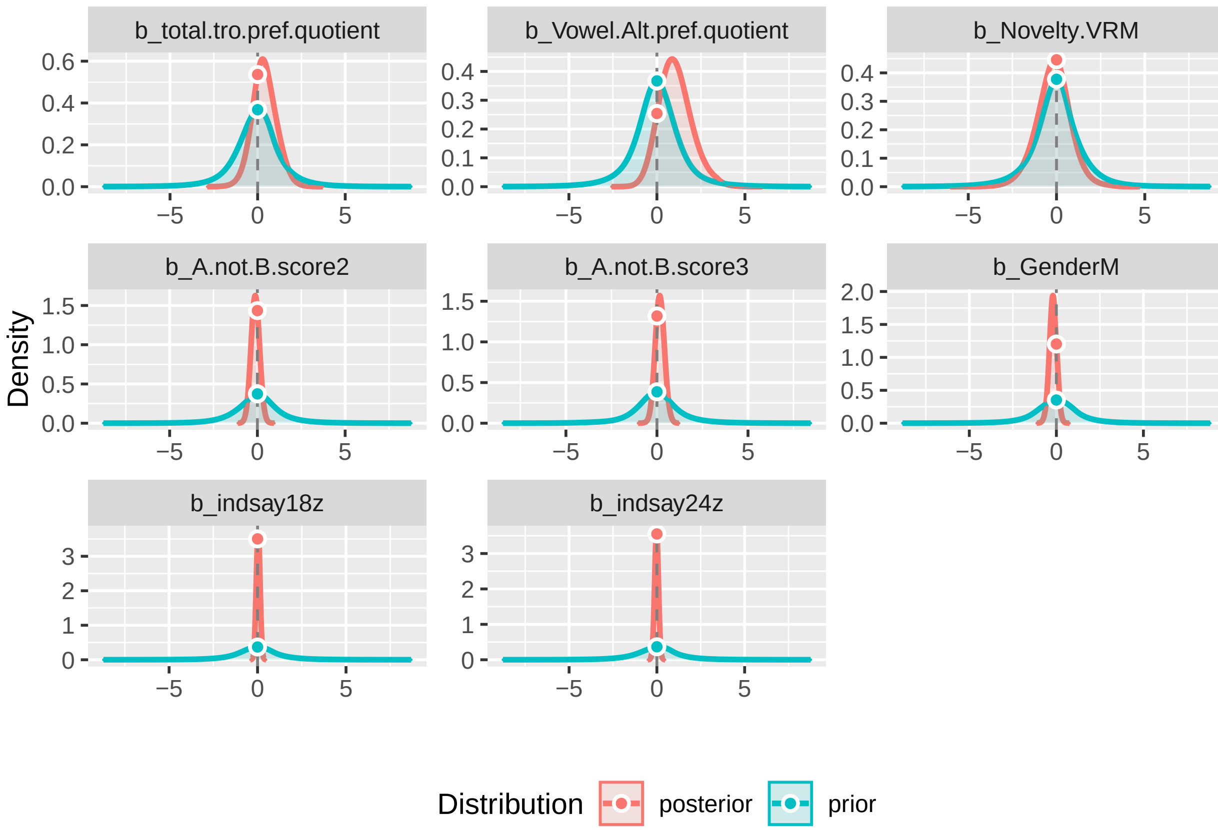
```r
saveRDS(summary(main),file="main_model_summary.rds")


in_bf = bayesfactor_parameters(main, null = 0,effects="fixed")
```

```
## Computation of Bayes factors: sampling priors, please wait...
```

```r
in_bf
```

```
## # Bayes Factor (Savage-Dickey density ratio)
##
## Parameter               |   BF
## ------------------------------
## Intercept               | 0.46
## total.tro.pref.quotient | 0.69
## Vowel.Alt.pref.quotient | 1.45
## Novelty.VRM             | 0.85
## A.not.B.score2          | 0.26
## A.not.B.score3          | 0.29
## GenderM                 | 0.29
## indsay18z               | 0.11
## indsay24z               |  0.1
##
## * Evidence Against The Null: [0]
```

```r
plot(in_bf)
```




```r
saveRDS(in_bf,file="main_model_bf.rds")
```

Relating strength of population effect to predictive power

```r
d_vow=cohensd(mydat$Vowel.Alt.pref.quotient)
d_strs=cohensd(mydat$total.tro.pref.quotient)
d_vrm=cohensd(mydat$Novelty.VRM)

print(rbind(cbind(d_vow,d_strs,d_vrm),
                cbind(fixef(vowel)["Vowel.Alt.pref.quotient","Estimate"],
                fixef(strs)["total.tro.pref.quotient","Estimate"],
               fixef(vrm)["Novelty.VRM","Estimate"])))
```

```
##            d_vow      d_strs     d_vrm
## [1,] 0.17306686  0.05258105 1.3915207
## [2,] 0.04292277 -0.26900880 0.1142419
```