Striatal Network Dynamics are Associated with Reinforcement Learning

Models

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Behavioral Learning Model

We ran a generalized mixed effects logit model predicting proportion correct with block. Subjects demonstrated significant learning across the task.

```r
flex_behav$block_int<-as.numeric(flex_behav$block)-2.5

mbehav<-glmer(correct~block_int+(block_int|subject),data=flex_behav,weights=weights,family=binomial)

summary(mbehav)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: correct ~ block_int + (block_int | subject)
##    Data: flex_behav
## Weights: weights
##
##      AIC      BIC   logLik deviance df.resid
##    468.1    480.5   -229.1    458.1       83
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -1.6088 -0.4340  0.1505  0.5624  1.6471
##
## Random effects:
##  Groups  Name        Variance Std.Dev. Corr
##  subject (Intercept) 1.0237   1.0118
##          block_int   0.2195   0.4685   0.81
## Number of obs: 88, groups:  subject, 22
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   1.1864     0.2250   5.272 1.35e-07 ***
## block_int     0.2820     0.1136   2.482   0.0131 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##           (Intr)
## block_int 0.748
```

Effect of Flexibility on Reinforcement Learning

Striatal flexibility- REML

We fit a mixed effects generalized linear model using a REML approximation to associate individual learning performance with striatal flexibility across blocks, using lme4.

```
mlearn_str<-glmer(correct~str_flex+(str_flex || subject),data=flex_behav,weights=weights,family=binomial

summary(mlearn_str)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: correct ~ str_flex + (str_flex || subject)
##    Data: flex_behav
## Weights: weights
##
##      AIC      BIC   logLik deviance df.resid
##    494.8    504.7   -243.4    486.8       84
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.63858 -0.73581 -0.02002  0.85468  2.43378
##
## Random effects:
##  Groups    Name        Variance  Std.Dev.
##  subject   (Intercept) 2.796e-08 0.0001672
##  subject.1 str_flex    6.196e+01 7.8715162
## Number of obs: 88, groups:  subject, 22
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.04581    0.23683   0.193  0.84662
## str_flex     9.45132    2.74667   3.441  0.00058 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##          (Intr)
## str_flex -0.772
```

```
flex_behav$str_flex_mean<-rep(tapply(flex_behav$str_flex,flex_behav$subject,mean),each=4)
mlearn_str_mean<-glmer(correct~str_flex+str_flex_mean+(str_flex || subject),data=flex_behav,weights=wei
summary(mlearn_str_mean)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: correct ~ str_flex + str_flex_mean + (str_flex || subject)
##    Data: flex_behav
## Weights: weights
##
```

```
##      AIC      BIC   logLik deviance df.resid
##    496.3    508.6   -243.1    486.3       83
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.52483 -0.74572 -0.05168  0.81802  2.43855
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  subject   (Intercept)  0.00    0.000
##  subject.1 str_flex    66.28    8.141
## Number of obs: 88, groups:  subject, 22
##
## Fixed effects:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)      1.236      1.671   0.740 0.459478
## str_flex         9.792      2.819   3.473 0.000514 ***
## str_flex_mean  -11.137     15.454  -0.721 0.471150
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) str_fl
## str_flex     0.053
## str_flex_mn -0.990 -0.162
```

Striatal flexibility- Bayesian model

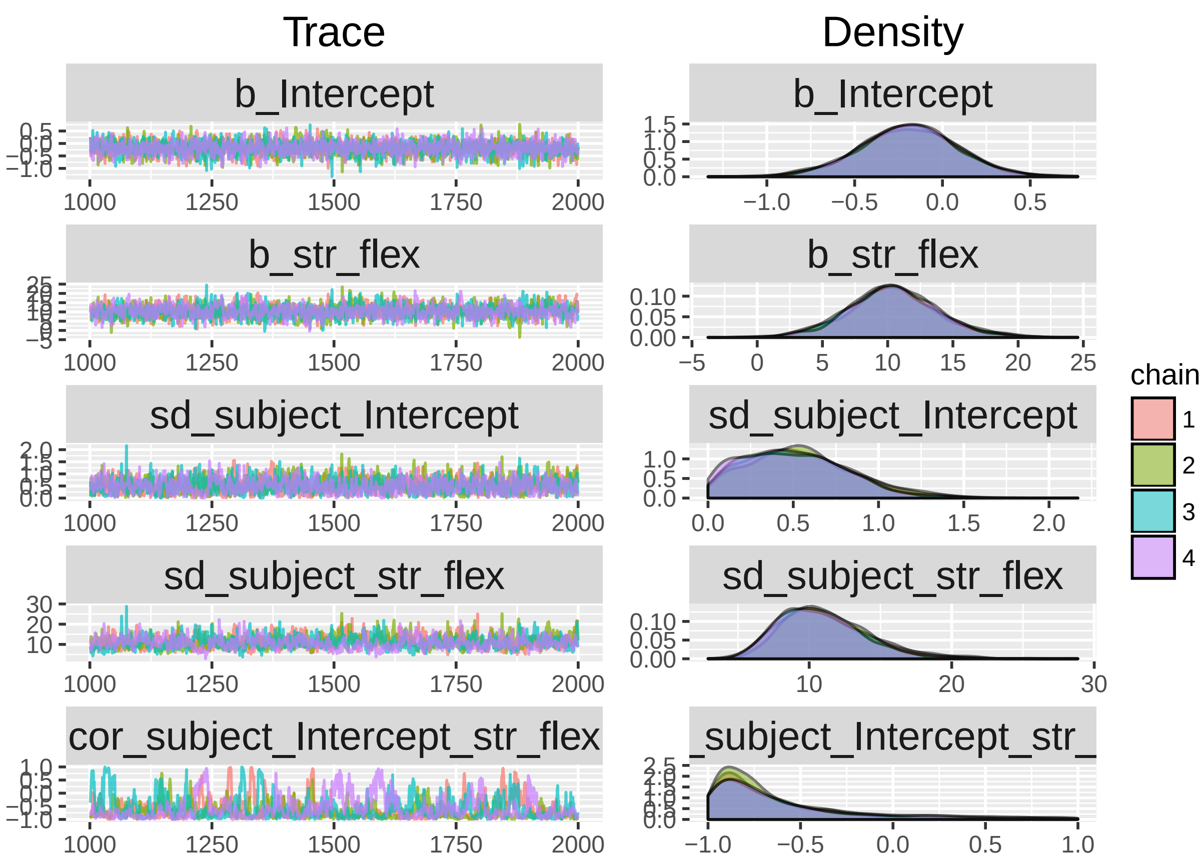
For appropriate posterior inference, we fit the same model using Hamiltonian Monte Carlo to generate a full posterior distribution for the effect of striatal flexibility on learning performance.

```
options(mc.cores = parallel::detectCores())
flex_behav$numcorr<-as.integer(flex_behav$correct*flex_behav$weights)

mlearn_str_stan<-brm(numcorr~str_flex+(str_flex|subject),data=flex_behav,family=binomial)

summary(mlearn_str_stan)
```

```
##  Family: binomial (logit)
## Formula: numcorr ~ str_flex + (str_flex | subject)
##    Data: flex_behav (Number of observations: 88)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup samples = 4000
##    WAIC: Not computed
##
## Random Effects:
## ~subject (Number of levels: 22)
##                        Estimate Est.Error l-95% CI u-95% CI Eff.Sample
## sd(Intercept)              0.52      0.31     0.04     1.20       1079
## sd(str_flex)              11.03      3.09     6.19    18.23        347
## cor(Intercept,str_flex)   -0.62      0.39    -0.99     0.56        176
##                        Rhat
## sd(Intercept)          1.01
```

```
## sd(str_flex)            1.02
## cor(Intercept,str_flex) 1.03
##
## Fixed Effects:
##           Estimate Est.Error l-95% CI u-95% CI Eff.Sample Rhat
## Intercept    -0.19      0.28    -0.75     0.35       2489    1
## str_flex     10.42      3.42     3.65    17.56       1628    1
##
## Samples were drawn using sampling(NUTS). For each parameter, Eff.Sample
## is a crude measure of effective sample size, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```
plot(mlearn_str_stan)
```



Whole-brain flexibility

Because a global measure of flexibility has also been shown to relate to a number of cogitive processes (Bassett et al 2011, Braun et al 2015), we fit another mixed-effects model with this whole-brain metric as a predictor.

```
mlearn_wb<-glmer(correct~wb_flex+(wb_flex || subject),data=flex_behav,weights=weights,family=binomial)

summary(mlearn_wb)
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
```

```
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: correct ~ wb_flex + (wb_flex || subject)
##    Data: flex_behav
## Weights: weights
##
##      AIC      BIC   logLik deviance df.resid
##    511.5    521.4   -251.8    503.5       84
##
## Scaled residuals:
##      Min       1Q   Median       3Q      Max
## -2.67954 -0.71005 -0.01157  0.81079  2.72652
##
## Random effects:
##  Groups    Name        Variance Std.Dev.
##  subject   (Intercept)  0.00    0.000
##  subject.1 wb_flex     64.94    8.058
## Number of obs: 88, groups:  subject, 22
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  -0.1104     0.3506  -0.315  0.75287
## wb_flex      11.8486     3.9126   3.028  0.00246 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##         (Intr)
## wb_flex -0.889
```