Lösung Zettel 3

2023-06-02

Aufgabe 1

Libraries

```
set.seed(42)
library(dplyr)
library(bcogsci)
library(brms)
library(lme4)
```

Laden der Daten

```
data("sleepstudy")
```

(a)

Schaue dir die Daten im Datenssatz an. Welche Verteilung würdest du für die Reaktionszeit unterstellen? Gegeben der Daten welche Prior würdest du auswählen? (*Hinweis: Es gibt nicht die EINE richtige Antwort*)

```
summary(sleepstudy)
```

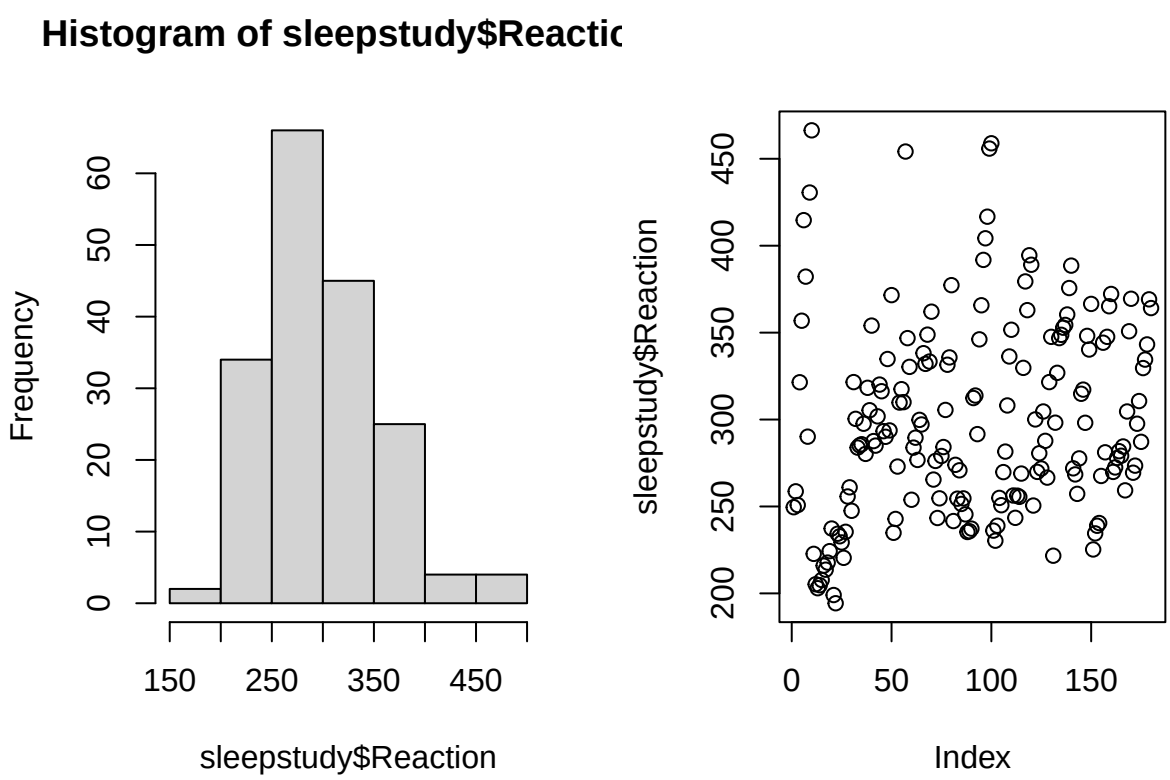
```
##     Reaction          Days        Subject
##  Min.   :194.3   Min.   :0.0   308    : 10
##  1st Qu.:255.4   1st Qu.:2.0   309    : 10
##  Median :288.7   Median :4.5   310    : 10
##  Mean   :298.5   Mean   :4.5   330    : 10
##  3rd Qu.:336.8   3rd Qu.:7.0   331    : 10
##  Max.   :466.4   Max.   :9.0   332    : 10
##                                (Other):120
```

```
mean(sleepstudy$Reaction); sd(sleepstudy$Reaction)
```

```
## [1] 298.5079
```

```
## [1] 56.32876
```

```
par(mfrow = c(1, 2)) # zwei Grafiken in einer Figure
hist(sleepstudy$Reaction)
plot(sleepstudy$Reaction)
```

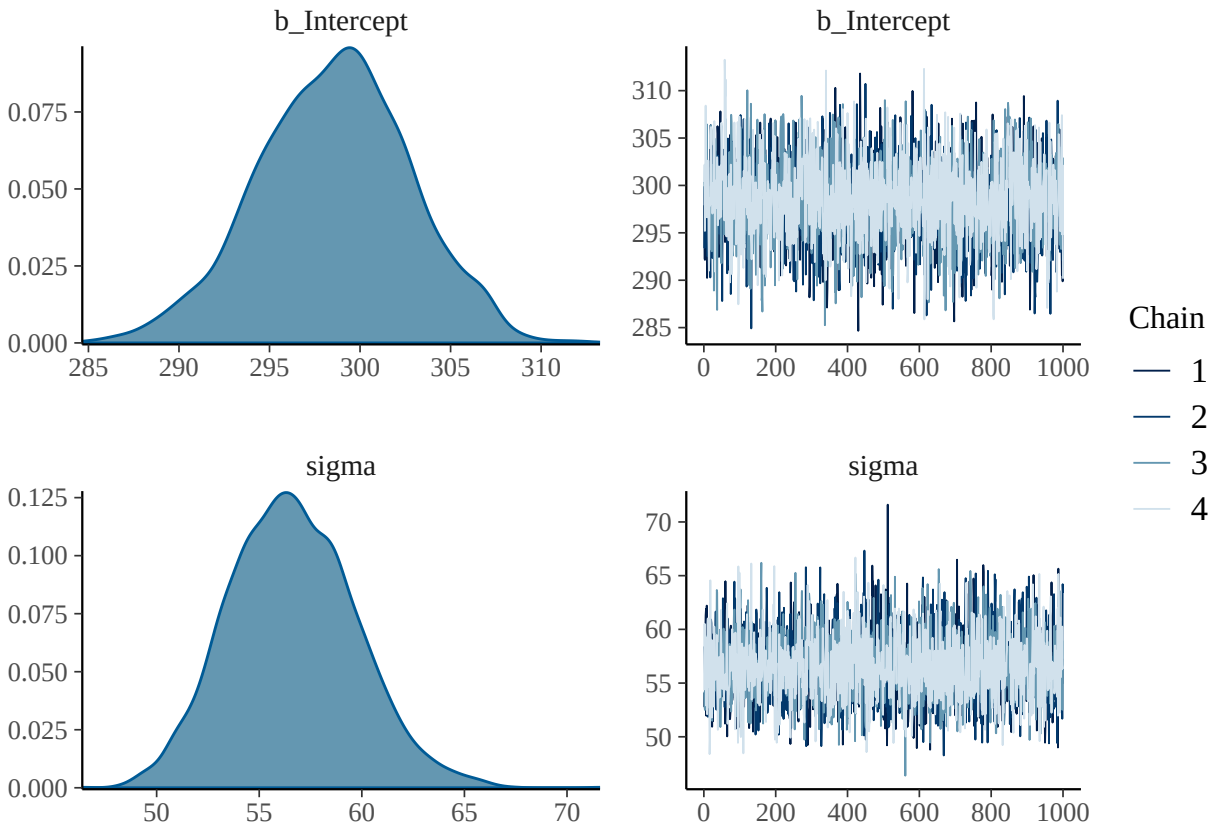


- die zu erklärende Variable scheint normalverteilt zu sein.
- ein gaussian prior scheint sinnvoll zu sein.

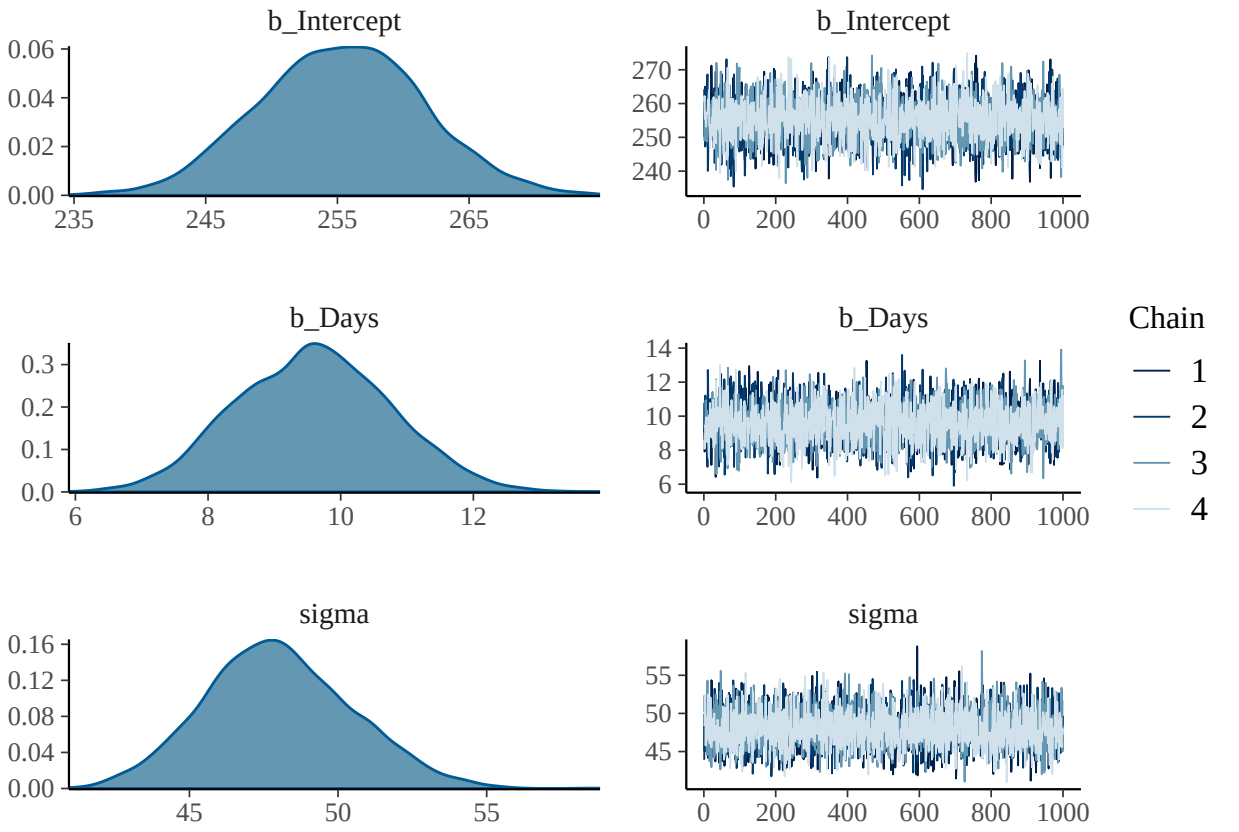
(b)

Fitte ein Intercept Model und ein Model welches die Tage als erklärende Variable in das Model mit aufnimmt. Vergleiche beide Modelle, welches scheint besser zu sein?

```
m_b1 = brm(Reaction ~ 1,
           family = gaussian(),
           data = sleepstudy,
           prior = c(prior(normal(300, 100), class = Intercept),
                     prior(normal(0, 60), class = sigma)))

m_b1

plot(m_b1)
```




```
m_b2 = brm(Reaction ~ 1 + Days,
           family = gaussian(),
           data = sleepstudy,
           prior = c(prior(normal(300, 100), class = Intercept),
                     prior(normal(0, 60), class = sigma),
                     prior(normal(4.5, 3), class = b, coef = Days)))

m_b2

plot(m_b2)
```



(c) - (d)

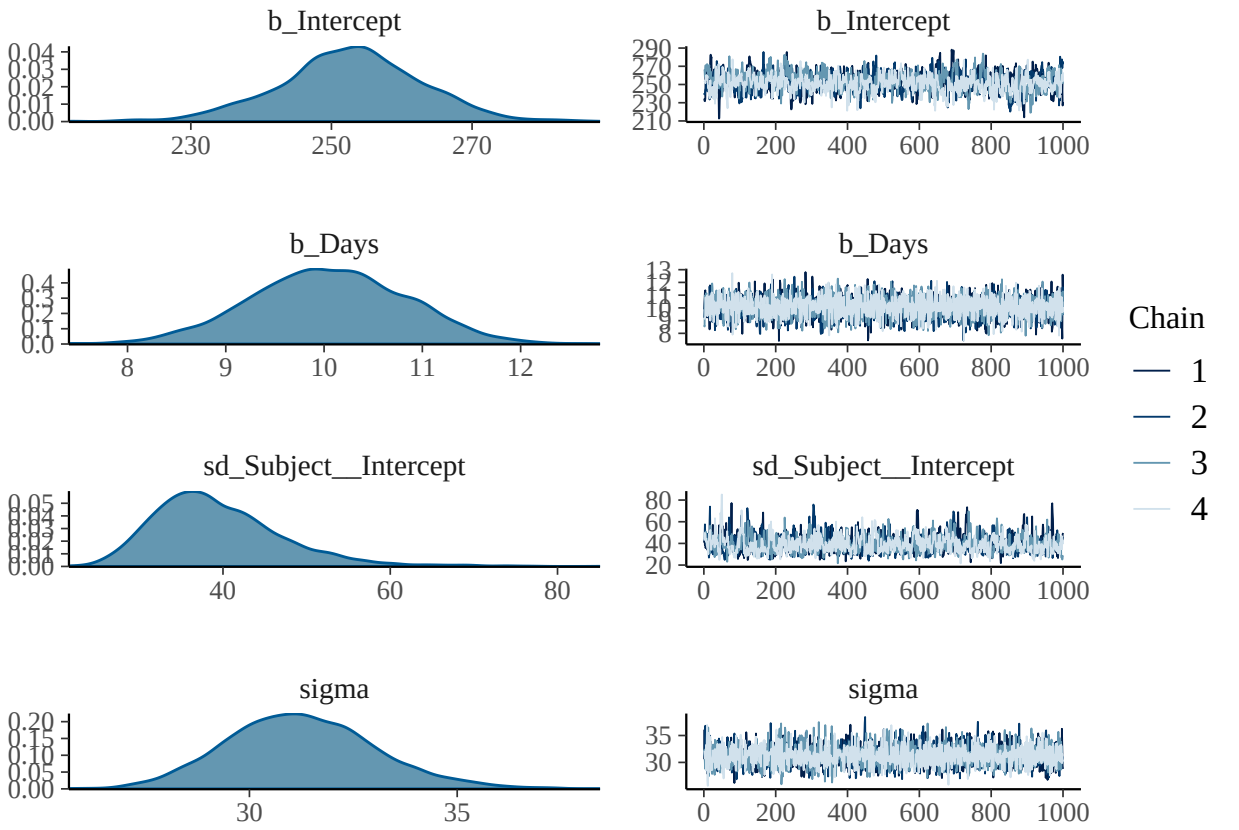
In den Daten ist die Variable `Subject` enthalten. Wir haben also wiederholte Messungen. Wie würdest du damit umgehen? Wie angebracht sind die bisherigen Modelle, wenn du bedenkst, dass es wiederholte Messungen gibt?

```
test = aggregate(sleepstudy$Reaction, list(sleepstudy$Subject), FUN=sd)     # SD pro Gruppe
mean(test$x); sd(sleepstudy$Reaction)
```

```
## [1] 40.23369
```

```
## [1] 56.32876
```

```
m_c1 = brm(Reaction ~ 1 + Days + (1 | Subject),
           family = gaussian(),
           data = sleepstudy,
           prior = c(prior(normal(300, 100), class = Intercept),
                     prior(normal(0, 60), class = sigma),
                     prior(normal(4.5, 3), class = b, coef = Days),
                     prior(normal(0, 60), class = sd, coef = Intercept, group = Subject)))

m_c1

plot(m_c1)
```

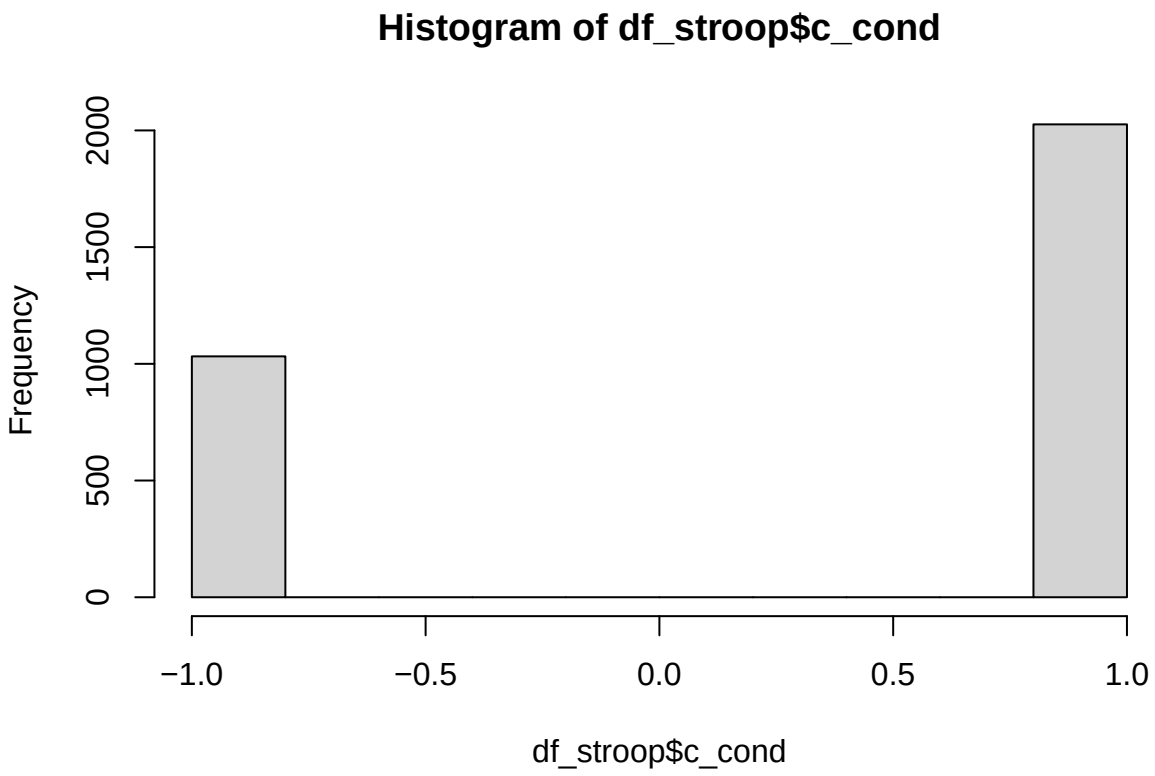


Aufgabe 2

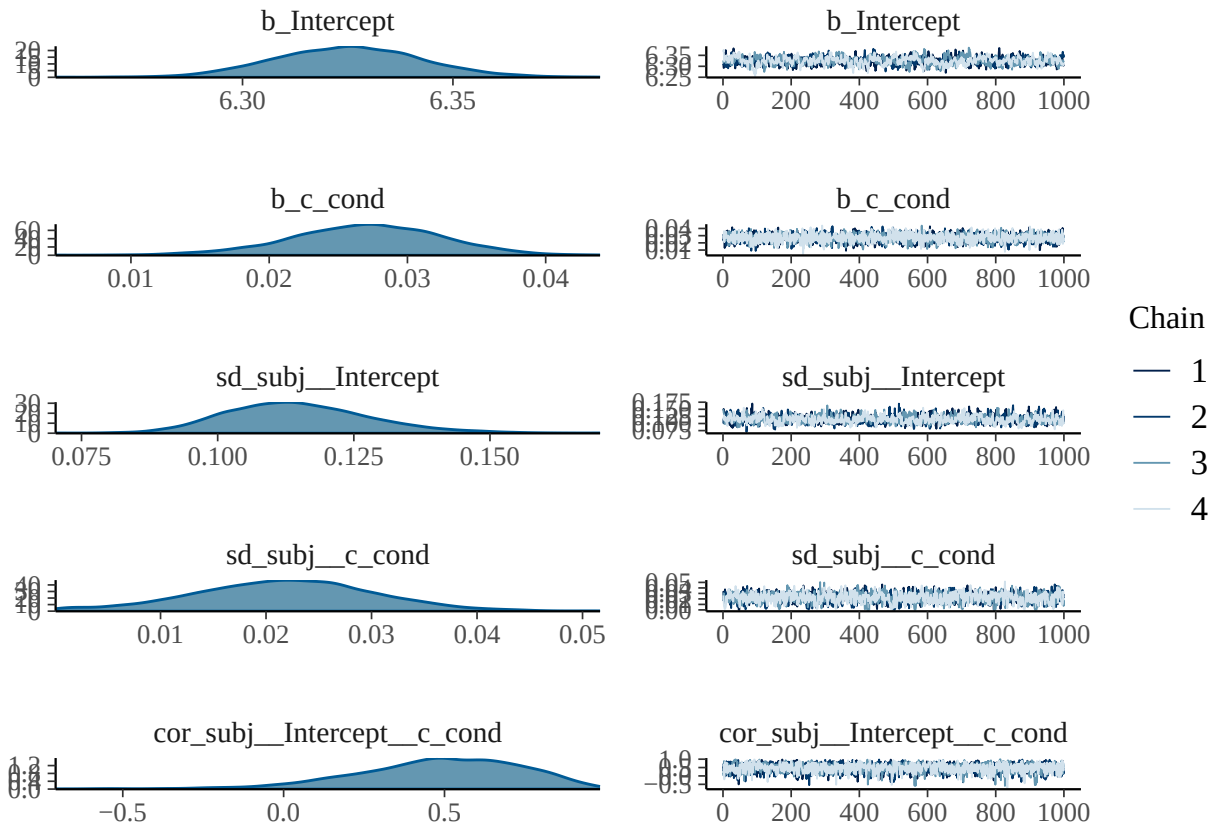
(a)

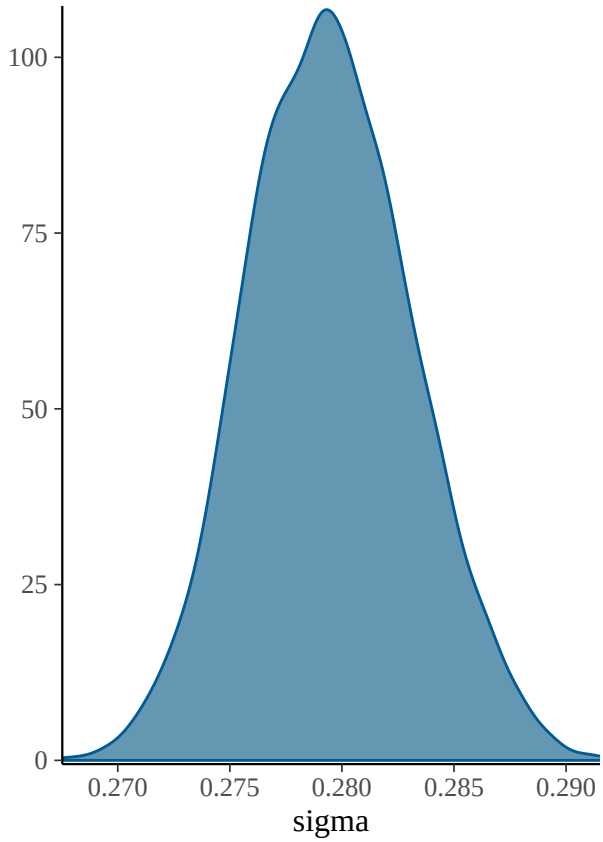
```
library(bcogsci)
data("df_stroop")

df_stroop = df_stroop %>%
  mutate(c_cond = if_else(condition == 'Incongruent', 1, -1))
```

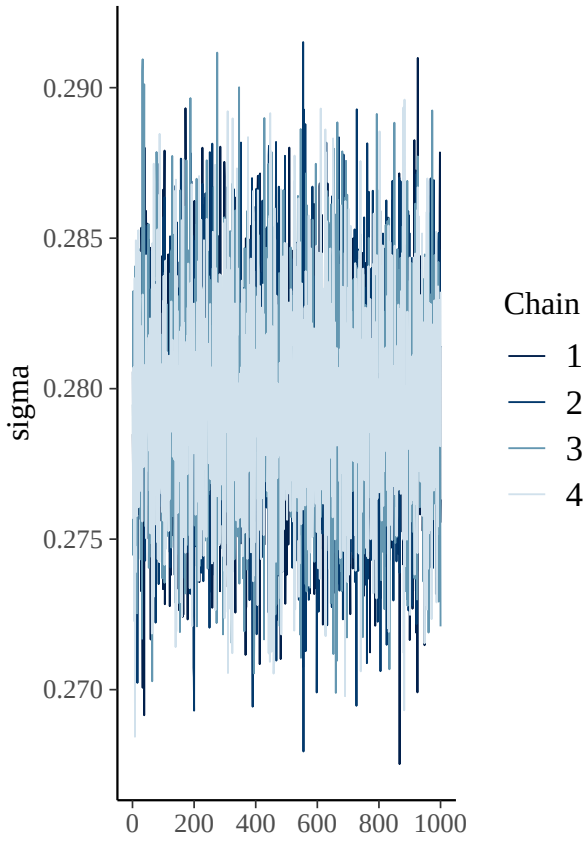
```
hist(df_stroop$c_cond)
```




```
m_2a <- brm(RT ~ c_cond + (c_cond | subj),
  family = lognormal(),
  prior =
    c(
      prior(normal(6, 1.5), class = Intercept),
      prior(normal(0, .01), class = b),
      prior(normal(0, 1), class = sigma),
      prior(normal(0, 1), class = sd),
      prior(lkj(2), class = cor)
    ),
  data = df_stroop
)
m_2a
plot(m_2a)
```


b_Intercept
b_Intercept
b_c_cond
b_c_cond
sd_subj__Intercept
sd_subj__Intercept
sd_subj__c_cond
sd_subj__c_cond
cor_subj__Intercept__c_cond
cor_subj__Intercept__c_cond
Chain
1
2
3
4






```
posterior_summary(m_2a, variable = "b_c_cond")
```