## **DefTypNormTR** Results

## Preparing the data

```
# packages
library(Rmisc)
Loading required package: lattice
Loading required package: plyr
library(tidyverse)
-- Attaching core tidyverse packages ----- tidyverse 2.0.0.9000 --
v dplyr
           1.1.4 v readr
                                2.1.5
v forcats 1.0.0 v stringr
v ggplot2 3.5.1 v tibble
                                1.5.1
                                3.2.1
v lubridate 1.9.3 v tidyr
                                1.3.1
v purrr
          1.0.2
-- Conflicts -----
                                 ----- tidyverse_conflicts() --
x dplyr::arrange()
                    masks plyr::arrange()
x purrr::compact()
                    masks plyr::compact()
x dplyr::count()
                    masks plyr::count()
x dplyr::desc()
                    masks plyr::desc()
x dplyr::failwith() masks plyr::failwith()
                    masks stats::filter()
x dplyr::filter()
x dplyr::id()
                    masks plyr::id()
x dplyr::lag()
                    masks stats::lag()
x dplyr::mutate()
                    masks plyr::mutate()
```

```
x dplyr::rename()
                      masks plyr::rename()
x dplyr::summarise() masks plyr::summarise()
x dplyr::summarize() masks plyr::summarize()
i Use the conflicted package (<a href="http://conflicted.r-lib.org/">http://conflicted.r-lib.org/</a>) to force all conflicts to become
library(magrittr)
Attaching package: 'magrittr'
The following object is masked from 'package:purrr':
    set_names
The following object is masked from 'package:tidyr':
    extract
library(brms)
Loading required package: Rcpp
Loading 'brms' package (version 2.22.2). Useful instructions
can be found by typing help('brms'). A more detailed introduction
to the package is available through vignette('brms_overview').
Attaching package: 'brms'
The following object is masked from 'package:stats':
    ar
library(bridgesampling)
Attaching package: 'bridgesampling'
The following object is masked from 'package:brms':
    bf
```

```
#pcibex reading
source("read_pcibex.R")
df <- read.pcibex("results.csv")</pre>
# better column names
colnames(df) <- c("Time", "IP", "Controller", "Order", "ElementNum", "Label", "Group", "Penni
# retrieve the response times
df_rt <- df |> subset((PennElementType == "Selector" | Parameter == "play") & Type == "critical"
df_rt <- df_rt |>
    select(ProlificID, Parameter, item, EventTime) |>
    pivot_wider(names_from = Parameter, values_from = EventTime)
# only select selecions and critical items
# ! TODO: Check filler responses in the future.
df <- df |> subset(PennElementType == "Selector" & Type == "critical")
# check if left_join is working properly
stopifnot(nrow(df) == nrow(left_join(df, df_rt, by = c("ProlificID", "item"))))
# join RTs and selections
df <- left_join(df, df_rt, by = c("ProlificID", "item"))</pre>
df$DefType <- "TR"</pre>
n_subj <- length(unique(df$ProlificID))</pre>
n_subj
```

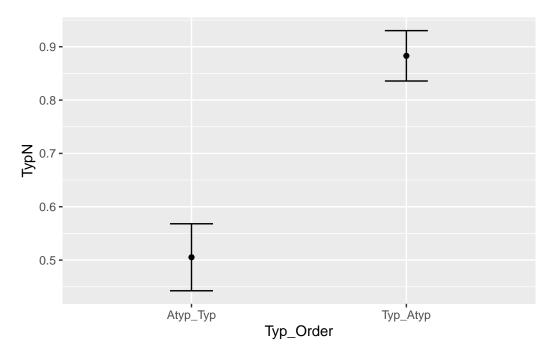
## [1] 46

```
# number of non-answers
no_answer <- nrow(subset(df, !(Value == "I1" | Value == "I2")))
no_answer</pre>
```

[1] 1

```
df <- df |> subset( Value == "I1" | Value == "I2")
# new column for the selection of Typ
df$Typ <- (df$Typ_Order == "Typ_Atyp" & df$Value == "I1") | (df$Typ_Order == "Atyp_Typ" & df
# Check mean proportion of typical answer as a function of condition
df %>%
   group_by(Typ_Order) %>%
   summarize(Typ = mean(Typ == "TRUE"), n = length(Value))
# A tibble: 2 x 3
  Typ_Order Typ
 <chr>
          <dbl> <int>
1 Atyp_Typ 0.505
                    368
2 Typ_Atyp 0.883
                    367
df$TypN <- as.numeric(df$Typ)</pre>
avgs <- summarySEwithin(df, measurevar = "TypN", withinvars = c("DefType", "Typ_Order"), idva</pre>
Automatically converting the following non-factors to factors: DefType, Typ_Order
avgs
 DefType Typ_Order N
                             TypN
                                         sd
       TR Atyp_Typ 368 0.5052906 0.6147353 0.03204529 0.06301544
1
2
       TR Typ Atyp 367 0.8829784 0.4614595 0.02408799 0.04736823
# do a plot with geom point and geom line and error bars using avgs
ggplot(avgs, aes(Typ_Order, TypN)) +
   geom_point() +
    geom_line() +
    geom_errorbar(aes(ymin = TypN - 1.96*se, ymax = TypN + 1.96*se), width = 0.2)
`geom_line()`: Each group consists of only one observation.
```

i Do you need to adjust the group aesthetic?



```
# get the Response time from selection time and play time
df$Selection <- as.numeric(df$Selection)
df$play <- as.numeric(df$play)
df$RT <- df$Selection - df$play

# percentage of really long response times
nrow(subset(df, RT > 10000)) / nrow(df)
```

## [1] 0.01360544

```
# filter out really long response times and get the averages
rt_avgs <- df %>%
    filter(RT < 10000) %>%
    summarySEwithin(., measurevar = "RT", withinvars = c("Typ", "DefType", "Typ_Order"), idvalage.
```

Automatically converting the following non-factors to factors: Typ, DefType, Typ\_Order

```
rt_avgs
```

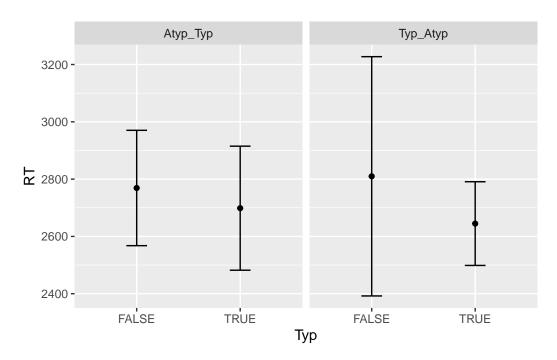
```
Typ DefType Typ_Order N RT sd se ci 1 FALSE TR Atyp_Typ 178 2769.040 1370.227 102.70287 202.6797
```

```
2 FALSE TR Typ_Atyp 43 2809.837 1397.110 213.05729 429.9670
3 TRUE TR Atyp_Typ 183 2698.550 1494.157 110.45129 217.9297
4 TRUE TR Typ_Atyp 321 2644.798 1335.458 74.53799 146.6464
```

```
# plot the credible intervals and means
ggplot(rt_avgs, aes(Typ, RT)) +
    geom_point() +
    geom_line() +
    geom_errorbar(aes(ymin = RT - 1.96*se, ymax = RT + 1.96*se), width = 0.2) +
    facet_wrap(~Typ_Order)
```

`geom\_line()`: Each group consists of only one observation.
i Do you need to adjust the group aesthetic?

`geom\_line()`: Each group consists of only one observation.
i Do you need to adjust the group aesthetic?



# read typdatadiff to include in the model
diff <- read\_csv("TypDataItemDiff.csv")</pre>

Rows: 16 Columns: 5

```
-- Column specification ------
Delimiter: ","
chr (1): noun_en
dbl (4): item, 1, 2, Diff
i Use `spec()` to retrieve the full column specification for this data.
i Specify the column types or set `show_col_types = FALSE` to quiet this message.
df$item <- as.factor(df$item)</pre>
diff$item <- as.factor(diff$item)</pre>
# join differences in typicality and our experient data
stopifnot(nrow(left_join(df, diff, by = "item")) == nrow(df))
df <- left_join(df, diff, by = "item")</pre>
df$Typ_Order <- as.factor(df$Typ_Order)</pre>
contrasts(df$Typ_Order) <- contr.sum(2) / 2</pre>
# fit models with interaction and no interactions.
m.int <- brm(Typ ~ Typ_Order * Diff + (Typ_Order * Diff | ProlificID) + (Typ_Order * Diff | ...</pre>
    data = df,
    family = bernoulli("probit"),
    chains = 4, cores = 8,
    iter = 12000, warmup = 2000, control = list(adapt_delta = 0.99),
    file = "Typ_int_full", save_pars = save_pars(all = TRUE)
)
m.noint <- brm(Typ ~ Typ_Order + Diff + (Typ_Order + Diff | ProlificID)+ (Typ_Order + Diff |
    data = df,
    family = bernoulli("probit"),
    chains = 4, cores = 8,
    iter = 12000, warmup = 2000, control = list(adapt_delta = 0.99),
    file = "Typ_no_int_full", save_pars = save_pars(all = TRUE)
# compare model using bridgesampling
# compute log marginal likelihood via bridge sampling for HO
```

```
H0.bridge <- bridge_sampler(m.int, silent = TRUE)</pre>
Warning: 1075 of the 15000 log_prob() evaluations on the proposal draws
produced -Inf/Inf.
# compute log marginal likelihood via bridge sampling for H1
H1.bridge <- bridge_sampler(m.noint, silent = TRUE)</pre>
Warning: 674 of the 20000 log prob() evaluations on the proposal draws produced
-Inf/Inf.
# compute percentage errors to compute an approximate percentage error of the estimates:
(H0.error <- error_measures(H0.bridge)$percentage)</pre>
[1] "96%"
(H1.error <- error_measures(H1.bridge)$percentage)</pre>
[1] "14%"
# compute Bayes factor, H! is preferred
BF <- exp(H0.bridge$logml - H1.bridge$logml)</pre>
print(BF)
[1] 0.01010287
# strong evidence against HO (the null hypothesis) and in favor of H1
# compute posterior model probabilities (assuming equal prior model probabilities)
post1 <- post_prob(H0.bridge, H1.bridge)</pre>
print(post1)
 HO.bridge H1.bridge
0.01000183 0.98999817
```

```
# 99 percent probability for H1 to be true if their initial probabilities are 0.5-0.5
# Maybe one can use other experiments to give a more informed probability

# compute posterior model probabilities (using specified prior model probabilities)
# post2 <- post_prob(H0.bridge, H1.bridge, prior_prob = c(.6, .4))
# print(post2)</pre>
```