

Brief Analysis of Tagu's 2025 Data

A Clarke

First, we need to get set up:

```
library(tidyverse)
library(cmdstanr)
library(patchwork)

source("../..//functions/import_data.R")
source("../..//functions/post_functions.R")
source("../..//functions/plot_model.R")

knitr::opts_chunk$set(echo = TRUE,
                      dev = "ragg_png",
                      dpi = 400)
```

Import

Loading Data

```
d <- import_data("tagu2025")

summary(d$found)
```

condition	trial	person	targ_type
negative:28800	Min. : 1.0	Min. : 1	Length:86400
neutral :28800	1st Qu.: 900.8	1st Qu.:19	Class :character
positive:28800	Median :1800.5	Median :38	Mode :character
	Mean :1800.5	Mean :38	
	3rd Qu.:2700.2	3rd Qu.:57	

	id	x	y	found
Max.	:3600.0	Max.	:75	
Min.	: 1.00	Min.	:0.0000	Min.
1st Qu.:	6.75	1st Qu.:	0.1831	1st Qu.:
Median	:12.50	Median	:0.4554	Median
Mean	:12.50	Mean	:0.4997	Mean
3rd Qu.:	18.25	3rd Qu.:	0.7277	3rd Qu.:
Max.	:24.00	Max.	:1.0000	Max.
	item_class	trial_p		
Min.	:1.0	Min.	: 1.00	
1st Qu.:	1.0	1st Qu.:	4.75	
Median	:1.5	Median	: 8.50	
Mean	:1.5	Mean	: 8.50	
3rd Qu.:	2.0	3rd Qu.:	12.25	
Max.	:2.0	Max.	:16.00	

```
summary(d$stim)
```

person	condition	trial	id
Min.	: 1	negative:28800	Min.
1st Qu.:	19	neutral :28800	1st Qu.:
Median	:38	positive:28800	Median
Mean	:38		Mean
3rd Qu.:	57		3rd Qu.:
Max.	:75		Max.
	x	y	item_class
Min.	:0.0000	Min.	:0.0000
1st Qu.:	0.1831	1st Qu.:	0.1368
Median	:0.4554	Median	:0.3410
Mean	:0.4997	Mean	:0.3077
3rd Qu.:	0.7277	3rd Qu.:	0.4785
Max.	:1.0000	Max.	:0.6153
			trial_p
Min.		Min.	: 1.00
1st Qu.:		1st Qu.:	4.75
Median		Median	: 8.50
Mean		Mean	: 8.50
3rd Qu.:		3rd Qu.:	12.25
Max.		Max.	:16.00

Loading Model

The model was previously run and saved

```
m <- readRDS("../1_fit_models/scratch/models/tagu2025all1_0.model")
m$summary()
```

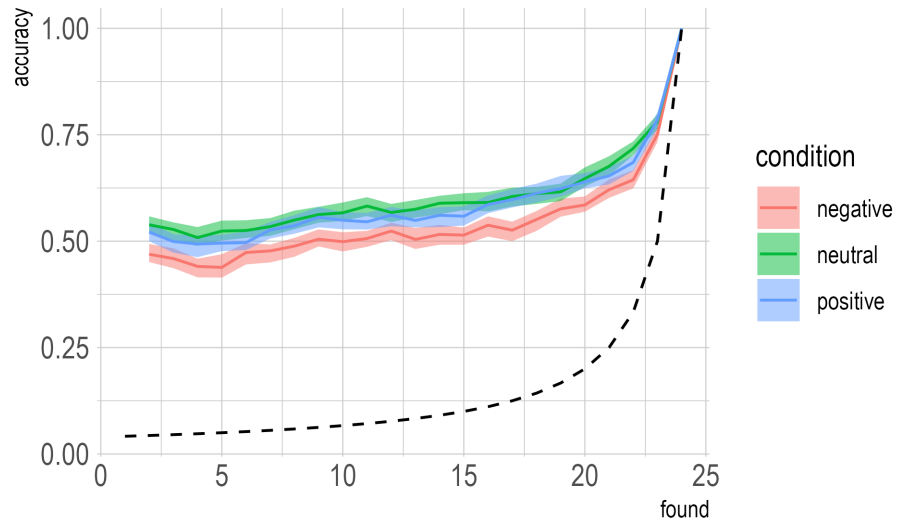
```
# A tibble: 262,073 x 10
  variable      mean  median    sd   mad    q5    q95  rhat ess_bulk
  <chr>      <dbl>   <dbl>  <dbl> <dbl>  <dbl>  <dbl> <dbl>   <dbl>
1 lp__      -8.15e+4 -8.15e+4 44.0    0   -8.15e+4 -8.14e+4 1.01    117.
2 b_a[1]    -8.20e-2 -8.34e-2 0.0283 0.0302 -1.27e-1 -3.68e-2 1.02    383.
3 b_a[2]     1.43e-1  1.43e-1 0.0200 0.0200  1.1 e-1  1.75e-1 1.01    356.
4 b_a[3]     6.63e-2  6.50e-2 0.0329 0.0328  1.48e-2  1.22e-1 1.01    399.
5 b_stick[1] 6.74e-1  6.74e-1 0.0459 0.0445  5.96e-1  7.49e-1 1.00    417.
6 b_stick[2] 4.52e-1  4.50e-1 0.0292 0.0274  4.09e-1  5.02e-1 1.01    310.
7 b_stick[3] 4.46e-1  4.47e-1 0.0322 0.0311  3.90e-1  5.01e-1 1.00    430.
8 rho_delta[~ 1.91e+1  1.91e+1 0.415  0.445  1.85e+1  1.98e+1 1.00    415.
9 rho_delta[~ 2.32e+1  2.32e+1 0.393  0.445  2.26e+1  2.38e+1 1.00    415.
10 rho_delta[~ 2.21e+1  2.21e+1 0.425  0.445  2.14e+1  2.28e+1 0.999    393.
# i 262,063 more rows
# i 1 more variable: ess_tail <dbl>
```

Now extract posterior samples and predictions.

```
pred <- extract_pred(m, d)
post <- extract_post(m, d)
```

Accuracy

```
acc <- summarise_acc(pred)
plot_model_accuracy(acc)
```

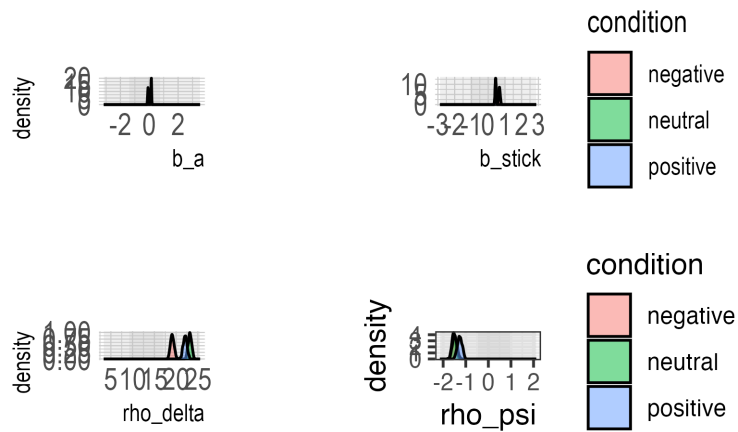


Looks like the model does a pretty good job of predicting which item will be selected next in all three conditions.

Posterior Distributions

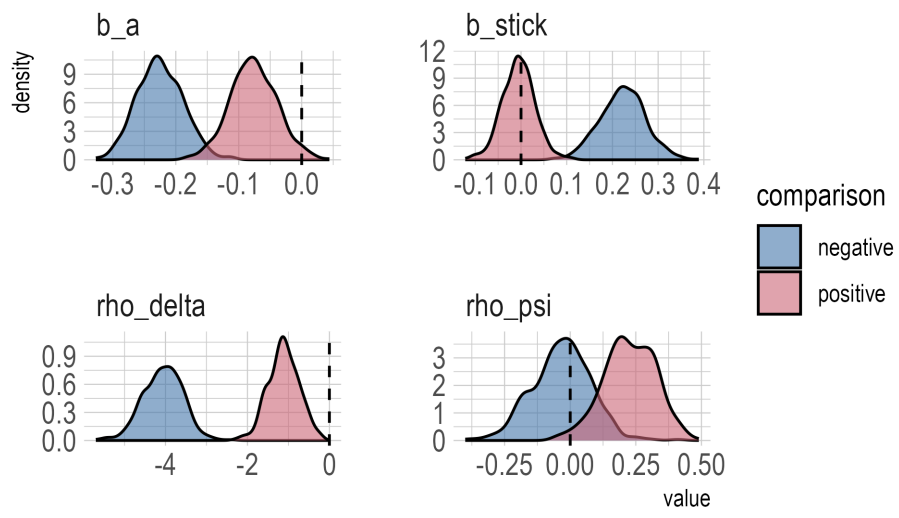
Parameter Estimates

```
plot_model_fixed(post) + theme_bw()
```



Differences between Conditions

```
# are there differences between conditions?
post$fixed %>%
  pivot_longer(-c(.draw, condition), names_to = "param") %>%
  pivot_wider(names_from = "condition") %>%
  group_by(.draw, param) %>%
  mutate(negative = negative - neutral,
         positive = positive - neutral,
         .keep = "none") %>%
  pivot_longer(c(negative, positive), names_to = "comparison") %>%
  ggplot(aes(value, fill = comparison)) +
  geom_density(alpha = 0.6) +
  geom_vline(xintercept = 0, linetype = 2) +
  facet_wrap(~param, scales = "free")
```



Individual Differences

```
plot_model_random(post)
```

