HTW E1

```
pacman::p_load(dplyr,purrr,tidyr,tibble,ggplot2,
  brms,tidybayes, rstanarm,emmeans,broom,bayestestR,
  stringr, here,conflicted, patchwork, knitr,kableExtra)
#options(brms.backend="cmdstanr",mc.cores=4)
walk(c("brms","dplyr","bayestestR"), conflict_prefer_all, quiet = TRUE)
walk(c("Display_Functions","org_functions"), ~ source(here::here(paste0("Functions/", .x, ".R
e1 <- readRDS(here("data/e1_08-21-23.rds"))
e1Sbjs <- e1 |> group_by(id,condit) |> summarise(n=n())
testE1 <- e1 |> filter(expMode2 == "Test")
nbins=5
trainE1 <-  e1 |> filter(expMode2=="Train") |> group_by(id,condit, vb) |>
    mutate(Trial_Bin = cut( gt.train, breaks = seq(1, max(gt.train),length.out=nbins+1),inclu
trainE1_max <- trainE1 |> filter(Trial_Bin == nbins, bandInt==800)
trainE1_avg <- trainE1_max |> group_by(id,condit) |> summarise(avg = mean(dist))
```

Analyses Strategy

All data processing and statistical analyses were performed in R version 4.32 Team (2020). To assess differences between groups, we used Bayesian Mixed Effects Regression. Model fitting was performed with the brms package in R Bürkner (2017), and descriptive stats and tables were extracted with the BayestestR package Makowski et al. (2019). Mixed effects regression enables us to take advantage of partial pooling, simultaneously estimating parameters at the individual and group level. Our use of Bayesian, rather than frequentist methods allows us to directly quantify the uncertainty in our parameter estimates, as well as circumventing convergence issues common to the frequentist analogues of our mixed models.

Each model was set to run with 4 chains, 5000 iterations per chain, with the first 2500 discarded as warmup chains. Rhat values were within an acceptable range, with values <=1.02 (see appendix for diagnostic plots). We used uninformative priors for the fixed effects of the model (condition and velocity band), and weakly informative Student T distributions for for the random effects. For each model, we report the median values of the posterior distribution, and

95% credible intervals. EXPLAIN WHAT PARAMETERS REPRESENT AND WHAT HDI & PD

For the testing phase of all experiments, we compare varied and constant performance across two measures, deviation and discrimination. Deviation was quantified as the absolute deviation from the nearest boundary of the velocity band, or set to 0 if the throw velocity fell anywhere inside the target band. Thus, when the target band was 600-800, throws of 400, 650, and 1100 would result in deviation values of 200, 0, and 300, respectively. The degree of discrimination between bands was measured by fitting a linear model to the testing throws of each subjects, with the lower end of the target velocity band as the predicted variable, and the x velocity produced by the participants as the predictor variable. Participants who reliably discriminated between velocity bands tended to have positive slopes with values ~1, while participants who made throws irrespective of the current target band would have slopes ~0.

$$dist_{ij} = \beta_0 + \beta_1 \cdot condit_{ij} + \beta_2 \cdot band_{ij} + \beta_3 \cdot condit_{ij} \cdot band_{ij} + b_{0i} + b_{1i} \cdot band_{ij} + \epsilon_{ij} \quad (1)$$

Results

```
p1 <- trainE1 |> ggplot(aes(x = Trial_Bin, y = dist, color = condit)) +
    stat_summary(geom = "line", fun = mean) +
    stat_summary(geom = "errorbar", fun.data = mean_se, width = .4, alpha = .7) +
    facet_wrap(~vb)+
    scale_x_continuous(breaks = seq(1, nbins + 1)) +
    theme(legend.title=element_blank()) +
    labs(y = "Deviation", x="Training Block")
#ggsave(here("Assets/figs/e1_train_deviation.png"), p1, width = 8, height = 6,bg="white")
```

```
##| label: tbl-e1-train-dist
##| tbl-cap: "Experiment 1 - Learning curves. "
##| output: asis

bmm_e1_train<- trainE1_max %>%
  brm(dist ~ condit,
      file=here("data/model_cache/e1_train_deviation"),
      data = .,
      iter = 2000,
      chains = 4,
      control = list(adapt_delta = .94, max_treedepth = 13))
mtr1 <- as.data.frame(describe_posterior(bmm_e1_train, centrality = "Mean"))[, c(1,2,4,5,6)]
```

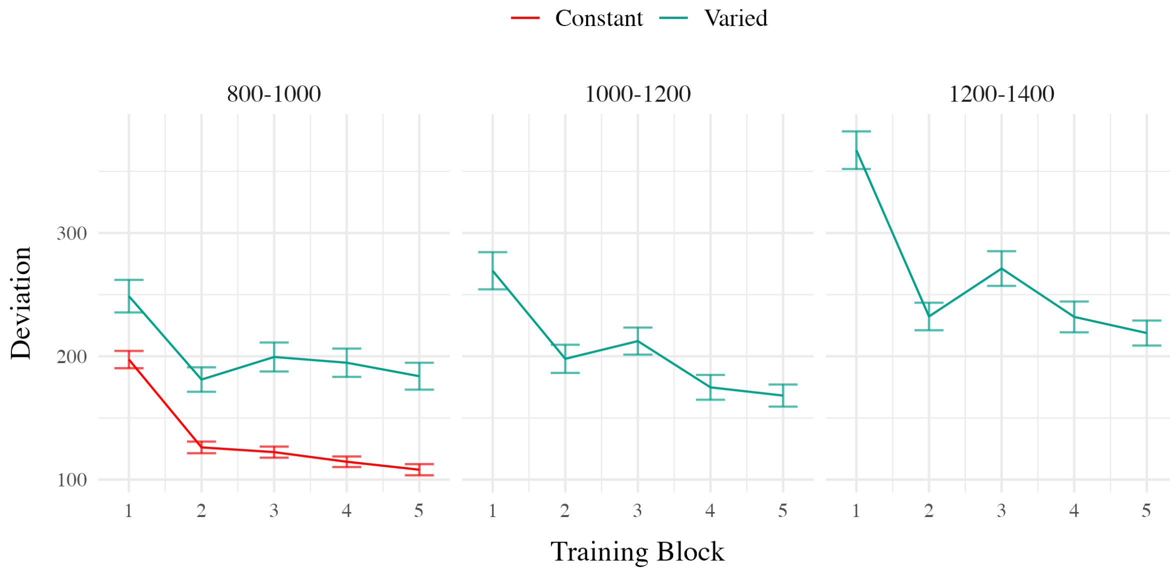

Figure 1: E1. Deviations from target band during training

```
colnames(mtr1) <- c("Term", "Estimate","95% CrI Lower", "95% CrI Upper", "pd")

# mtr1 |> mutate(across(where(is.numeric), \(x) round(x, 2))) |>
#   tibble::remove_rownames() |>
#   mutate(Term = stringr::str_remove(Term, "b_")) |>
#    kable(booktabs = TRUE)

cdtr1 <- get_coef_details(bmm_e1_train, "conditVaried")
```

Bürkner, P.-C. (2017). Brms: An R Package for Bayesian Multilevel Models Using Stan. *Journal of Statistical Software*, *80*, 1–28. https://doi.org/10.18637/jss.v080.i01

Makowski, D., Ben-Shachar, M. S., & Lüdecke, D. (2019). bayestestR: Describing Effects and their Uncertainty, Existence and Significance within the Bayesian Framework. *Journal of Open Source Software*, *4*(40), 1541. https://doi.org/10.21105/joss.01541

Team, R. C. (2020). *R: A Language and Environment for Statistical Computing*. R: A Language and Environment for Statistical Computing.