HTW

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In project 1, we applied model-based techniques to quantify and control for the similarity between training and testing experience, which in turn enabled us to account for the difference between varied and constant training via an extended version of a similarity based generalization model. In project 2, we will go a step further, implementing a full process model capable of both 1) producing novel responses and 2) modeling behavior in both the learning and testing stages of the experiment. Project 2 also places a greater emphasis on extrapolation performance following training - as varied training has often been purported to be particularly beneficial in such situations.

````
```{r}
#| label: tbl-example
#| tbl-cap: "Example"
#| tbl-subcap:
#|   - "Cars1"
#|   - "Pressure1"
library(knitr)
kable(head(cars))
kable(head(pressure))

pacman::p_load(tidyverse,tidybayes,brms, lme4, bayesplot,bayestestR,parameters,marginaleffec
                emmeans, equatiomatic, here, pacman,  broom,
               broom.mixed,lme4,emmeans,here,knitr)




walk(c(here("Functions/Display_Functions.R"), here("Functions/org_functions.R"),
       here("Functions/Table_Functions.R")), source)
```
````

Table 1: Example

(a) Cars1

speed	dist
4	2
4	10
7	4
7	22
8	16
9	10

(b) Pressure1

temperature	pressure
0	0.0002
20	0.0012
40	0.0060
60	0.0300
80	0.0900
100	0.2700

Methods

Participants

Data was collected from 647 participants (after exclusions). The results shown below consider data from subjects in our initial experiment, which consisted of 196 participants (106 constant, 90 varied). The follow-up experiments entailed minor manipulations: 1) reversing the velocity bands that were trained on vs. novel during testing; 2) providing ordinal rather than numerical feedback during training (e.g. correct, too low, too high). The data from these subsequent experiments are largely consistently with our initial results shown below.

Procedure

````
```{r}
#| label: tbl-examplelllll
#| tbl-cap: "Example"
#| tbl-subcap:
#|   - "Cars1l"
#|   - "Pressure1l"
````
````

Table 2: Example

(a) Cars1l

speed	dist
4	2
4	10
7	4
7	22
8	16
9	10

(b) Pressure1l

temperature	pressure
0	0.0002
20	0.0012
40	0.0060
60	0.0300
80	0.0900
100	0.2700

````
library(knitr)
kable(head(cars))
kable(head(pressure))
```
````

extra

```
pacman::p_load(tidyverse,knitr,tidybayes,brms, lme4, bayesplot,bayestestR,parameters,marginal
                emmeans, equatiomatic, here, pacman,  broom,
               broom.mixed,lme4,emmeans,here,
                wesanderson,glue, ggdist,ggforce,patchwork,gghalves,ggh4x,
                install = TRUE,
                update = FALSE
               )
```

````
```{r}
#| label: tbl-example2vvv
#| tbl-cap: "Example"
````

Table 3: Example

(a) Cars2vv

speed	dist
4	2
4	10
7	4
7	22
8	16
9	10

(b) Pressure2vv

temperature	pressure
0	0.0002
20	0.0012
40	0.0060
60	0.0300
80	0.0900
100	0.2700

````
#| tbl-subcap:
#|   - "Cars2vv"
#|   - "Pressure2vv"
library(knitr)
kable(head(cars))
kable(head(pressure))
```
````

Analyses Strategy

All data processing and statistical analyses were performed in R version 4.31 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 (**?**). 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. For each model, we report the median values of the posterior distribution, and 95% credible intervals.
````

load data

```
library(here)
library(dplyr)
here::set_here(path='..')
```

```
File .here already exists in /Users/thomasgorman/Library/CloudStorage/GoogleDrive-tegorman13
```

```
test <- readRDS(here("data/e1_08-21-23.rds")) |> filter(expMode2 == "Test")
#options(brms.backend="cmdstanr",mc.cores=4)
e1Sbjs <- test |> group_by(id,condit) |> summarise(n=n())
testAvg <- test %>% group_by(id, condit, vb, bandInt,bandType,tOrder) %>%
  summarise(nHits=sum(dist==0),vx=mean(vx),dist=mean(dist),sdist=mean(sdist),n=n(),Percent_Hi
```

````
```{r}
#| label: tbl-htw
#| tbl-cap: "Example"
#| tbl-subcap:
#|   - "Cars2"
#|   - "Pressure2"
library(knitr)
kable(head(e1Sbjs))
kable(head(testAvg))
```
````

source functions

Test tables

```
result <- test_summary_table(test, "dist","Deviation", mfun = list(mean = mean, median = medi


result$constant |>kable(booktabs = TRUE,
                        linesep = "\\addlinespace[0.5em]")
                        #caption = paste("Summary of Deviation- Constant"))
# |>
#   kable_styling(font_size = ifelse(fmt_out == "latex", 8.5, NA))
```

Table 4: Example

(a) Cars2

id	condit	n
1	Varied	63
2	Varied	55
3	Constant	58
4	Varied	63
5	Constant	63
6	Varied	63

(b) Pressure2

id	condit	vb	bandInt	bandType	tOrder	nHits	vx	dist	sdist	
1	Varied	100-300	100	Extrapolation	trainFirst	0	564.8623	264.8623	264.86235	1
1	Varied	350-550	350	Extrapolation	trainFirst	1	791.2064	243.6982	243.69821	1
1	Varied	600-800	600	Extrapolation	trainFirst	2	984.5210	233.5615	209.09513	1
1	Varied	800-1000	800	Trained	trainFirst	2	1060.7720	155.5877	102.60470	
1	Varied	1000-1200	1000	Trained	trainFirst	1	1187.2458	296.8225	118.81533	
1	Varied	1200-1400	1200	Trained	trainFirst	2	1378.7755	136.2681	83.08371	

```r
result$varied |> kable(booktabs = TRUE,
                        linesep = "\\addlinespace[0.5em]")
                        #caption = paste("Summary of Deviation- Varied"))
```

```r
library(gt)
```

````
```{r}
#| label: tbl-example2bbb
#| tbl-cap: "Example"
#| tbl-subcap:
#|   - "Cars2bb"
#|   - "Pressure2bb"
library(knitr)
kable(head(cars))
kable(head(pressure))
```
````

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

Table 5: Testing Deviation - Empirical Summary

(a) Full datasets

Band	Band Type	Mean	Median	Sd
100-300	Extrapolation	254	148	298
350-550	Extrapolation	191	110	229
600-800	Extrapolation	150	84	184
800-1000	Trained	184	106	242
1000-1200	Extrapolation	233	157	282
1200-1400	Extrapolation	287	214	290

(b) Intersection of samples with all labels available

Band	Band Type	Mean	Median	Sd
100-300	Extrapolation	386	233	426
350-550	Extrapolation	285	149	340
600-800	Extrapolation	234	144	270
800-1000	Trained	221	149	248
1000-1200	Trained	208	142	226
1200-1400	Trained	242	182	235

Table 6: Example

(a) Cars2bb

speed	dist
4	2
4	10
7	4
7	22
8	16
9	10

(b) Pressure2bb

temperature	pressure
0	0.0002
20	0.0012
40	0.0060
60	0.0300
80	0.0900
100	0.2700

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