

CogLab: Manipulate More WEEK 8

logistics: formative assignments

- formative assignment #1: resubmission due Sunday
- formative assignment #2: descriptive statistics and plotting in R
 - due Nov 3

7	Monday, Oct 21, 2024	Project Milestone #4 (Full Experiment) Due
8	Tuesday, October 22, 2024	<u>W8: Manipulate Data</u>
8	Thursday, October 24, 2024	W8 continued
8	Sunday, October 27, 2024	Formative Assignment (jsPsych) Resubmission Due
9	Tuesday, October 29, 2024	<u>W9: Making Inferences</u>
9	Thursday, October 31, 2024	W9 continued
9	Sunday, November 3, 2024	Formative Assignment (R Descriptive) Due
10	Tuesday, November 5, 2024	Weeks 10-12: Data Collection
10	Thursday, November 7, 2024	Weeks 10-12: Data Collection
10	Sunday, November 10, 2024	Formative Assignment (R Inferential) Due
11	Tuesday, November 12, 2024	Weeks 10-12: Data Collection
11	Thursday, November 14, 2024	Weeks 10-12: Data Collection
11	Sunday, November 17, 2024	Formative Assignment (R Descriptive) Resubmission Due

project checklist

- create a checklist! work on provided feedback
- schedule a meeting with me before Tuesday

pre-registration

- next milestone #6: pre-registration (Nov 18: might move)
- **before** pre-registration:
 - providing accuracy feedback on priming trials
 - recording IP addresses
 - commenting the condition definition inside cognition.run
 - piloting your experiment (Uma + other group + 5 friends, N = 8), <u>pilot feedback</u> <u>sheet</u>
 - send cognition.run link by Nov 10
 - finalizing analysis plan + sample size

- 1. Data Collection: Have any data been collected for this study already?
- 2. **Main Question**: What is the main question being asked or hypothesis being tested in this study?
- 3. **Dependent Variable(s)**: Describe the key dependent variable(s) specifying how they will be measured.
- 4. **Condition(s)**: How many and which conditions will participants be assigned to? Please include an example trial of <u>each type of condition</u> you have in your experiment. Please also specify which independent variable will be within-participants or between-participants.
- 5. **Analyses**: Specify exactly which <u>analyses</u> you will conduct to examine the main question/hypothesis.
- 6. **Outliers & Exclusions**: Describe exactly how outliers will be defined and handled, and your precise rule(s) for excluding observations.
- 7. **Predicted Plot**: Please submit a predicted plot for your study based on what you expect the pattern to look like for your main hypothesis.
- 8. **Sample Size**: How many observations will be collected or what will determine sample size? No need to justify the decision, but be precise about <u>exactly</u> how the number will be determined.
- 9. **Exploratory details**: Anything else you would like to pre-register? (e.g., secondary analyses, variables collected for exploratory purposes, unusual analyses planned?)

recap

- what we covered:
 - tidyverse verbs
- your to-do's were:
 - brainstorm: group project code (accuracy feedback)
 - complete: formative assignment #1 resubmission
 - prep: <u>Transform Tables</u> recipes

today's agenda

- reviewing tidyverse verbs through your data
- learning a few more verbs/functions

wrangling your data

phase	measure	type	exclusion criteria
attention	accuracy	descriptive	< 0.75
priming	RT _{related} vs. RT _{unrelated} for direct and shared pairs	inferential (mixed effects model / ANOVA)	RT < 200 ms and RT > 1500 ms correct responses

analyses checklist

- □ confirm/correct all datatypes
- □ figure out how to "filter" certain types of trials
- $\hfill\square$ fix all typos in attention responses
- □ compute mean attention accuracy
- □ apply exclusions based on accuracy AND RTs
- Create RT bar graph
- □ fit a statistical model
- □ report statistics

open your RStudio project

- open the project and your .Rmd file
- run all chunks
- create new heading # class data analysis
- change data types for a few columns

class data analysis

```
```{r}
```

```
savic = read_csv("class_data.csv") %>%
mutate(rt = as.numeric(rt),
 relatedness = as.factor(relatedness),
 type = as.factor(type))
```

### basic descriptives

- how many levels does the relatedness variable have?
- what if you wanted the count the number of total trials per participant?

levels(savic\$relatedness)

## tidyverse: count()

- count() is another useful descriptive function like summarize() that tallies up counts of different things in your dataset while respecting groupings
- group by ID and count the trials
- how many target trials per ID?

<pre># Groups: ID [47] ID n <dbl> <int> 1 5418680 588 2 46356924 588 3 52271504 595 4 59881077 604 5 161705773 594 6 223076836 592 7 275998227 691 8 276772242 591 9 291529588 617 10 317312681 602 # with 37 more ro # i Use `print(n =</int></dbl></pre>		# A tibble: 47	x 2
<pre>ID n</pre>		# Groups: ID	[47]
<pre><dbl> <int>     1 5418680 588     2 46356924 588     3 52271504 595     4 59881077 604     5 161705773 594     6 223076836 592     7 275998227 691     8 276772242 591     9 291529588 617     10 317312681 602     # with 37 more ro     # i Use `print(n = </int></dbl></pre>		ID	n
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<pre>2 46<u>356</u>924 588 3 52<u>271</u>504 595 4 59<u>881</u>077 604 5 161<u>705</u>773 594 6 223<u>076</u>836 592 7 275<u>998</u>227 691 8 276<u>772</u>242 591 9 291<u>529</u>588 617 10 317<u>312</u>681 602 # with 37 more ro # i Use `print(n =</pre>		1 5 <u>418</u> 680	588
3 52 <u>271</u> 504 595 4 59 <u>881</u> 077 604 5 161 <u>705</u> 773 594 6 223 <u>076</u> 836 592 7 275 <u>998</u> 227 691 8 276 <u>772</u> 242 591 9 291 <u>529</u> 588 617 10 317 <u>312</u> 681 602 # with 37 more ro # i Use `print(n =		2 46 <u>356</u> 924	588
<pre>4 59<u>881</u>077 604 5 161<u>705</u>773 594 6 223<u>076</u>836 592 7 275<u>998</u>227 691 8 276<u>772</u>242 591 9 291<u>529</u>588 617 10 317<u>312</u>681 602 # with 37 more ro # i Use `print(n =</pre>		3 52 <u>271</u> 504	595
5 161 <u>705</u> 773 594 6 223 <u>076</u> 836 592 7 275 <u>998</u> 227 691 8 276 <u>772</u> 242 591 9 291 <u>529</u> 588 617 10 317 <u>312</u> 681 602 # with 37 more ro # i Use `print(n =		4 59 <u>881</u> 077	604
6 223 <u>076</u> 836 592 7 275 <u>998</u> 227 691 8 276 <u>772</u> 242 591 9 291 <u>529</u> 588 617 10 317 <u>312</u> 681 602 # with 37 more ro # i Use `print(n =		5 161 <u>705</u> 773	594
<pre>7 275<u>998</u>227 691 8 276<u>772</u>242 591 9 291<u>529588 617 10 317<u>312</u>681 602 # with 37 more ro # i Use `print(n =</u></pre>		6 223 <u>076</u> 836	592
<pre>% count()     8 276<u>772</u>242 591     9 291<u>529</u>588 617     10 317<u>312</u>681 602     # with 37 more ro     # i Use `print(n =</pre>		7 275 <u>998</u> 227	691
9 291 <u>529</u> 588 617 10 317 <u>312</u> 681 602 # with 37 more ro # i Use `print(n =	>% count()	8 276 <u>772</u> 242	591
10 317 <u>312</u> 681 602 # with 37 more ro # i Use `print(n =		9 291 <u>529</u> 588	617
# … with 37 more ro # i Use `print(n =		10 317 <u>312</u> 681	602
# i Use `print(n =		# with 37 mo	re row
a tooo prince		# i Use `print	(n = .

savic %>% group\_by(ID) %

5418680

46356924

52271504

4 59<u>881</u>077 5 161705773

6 223076836

7 275998227

104

104

104 104

104

104

104

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## tidyverse: pull()

- pull() is a convenient function that allows you to get the values inside one specific column as a vector
- extract the RTs from target trials

# savic %>% filter(typeoftrial == "target") %>% pull(rt)

>	savic	%>%									
+	fil	ter(typ	peoftr	ial ==	"targe	et") %	>%				
+	pul	l(rt)									
	[1]	NA	NA	75	NA	NA	NA	NA	214	NA	34
	[17]	242	NA	136	NA	NA	277	NA	294	NA	NA
	[33]	176	208	177	NA	254	NA	NA	NA	150	64
	[49]	NA	NA	227	223	302	NA	230	NA	88	253
	[65]	75	224	81	NA	98	NA	187	NA	NA	NA
	[81]	NA	133	NA	NA	NA	NA	NA	NA	246	214

## tidyverse: unique()

- unique() lets you see how many unique values are inside a particular column or vector
- how many subjects did the experiment?
- the length of a vector can be obtained using length()

savic %>%			
pull(ID)	%>%	unique()	

 [1]
 823806428
 275998227
 399427091
 617108779
 438881597
 59881077
 685459176
 789634588
 896801386
 636502299
 500683496

 [12]
 9793241458
 7008638007
 7840701730
 6636886676
 1804967059
 1017677598
 958013040
 223076836
 633750828
 713138680
 560469737

 [23]
 52271504
 983568245
 510710057
 343557222
 46356924
 5418680
 463680341
 27677242
 823472278
 291529588
 969332346

 [34]
 964433555
 648738364
 653349550
 161705773
 858059169
 317312681
 492031667
 768759264
 607043191
 794294242
 393616702

 [45]
 988749039
 366197048
 662530864
 4
 492031667
 768759264
 607043191
 794294242
 393616702

savic %>%
 pull(ID) %>% unique() %>% length()

### analyses checklist

- confirm/correct all datatypes
- □ figure out how to "filter" certain types of trials
- $\hfill\square$  fix all typos in attention responses
- compute mean attention accuracy
- apply exclusions based on accuracy AND RTs
- Create RT bar graph
- □ fit a statistical model
- report statistics

## attention

- create new heading # attention
- define a new dataframe attention\_trials that only consists of the attention check rows
- which columns are most relevant?
- only keep the relevant <u>columns</u>
- view this data

#### # attention

```{r}

attention_trials = savic %>% filter(typeoftrial == "attention")

attention_trials = savic %>% filter(typeoftrial == "attention") %>%
 select(ID, response, novel1, novel2, novel3, correct)

| 📄 first- | -R–notebook.Rr | nd × 🗌 atte | ntion_trials > | savic % | >% select(nove | l1, response, | | | | |
|------------------------------|----------------|-------------|----------------|-----------|----------------|------------------------------|--|--|--|--|
| ⟨□□⟩ <i>z</i> □ ¬ Filter | | | | | | | | | | |
| ^ | ID ‡ | response 🍦 | novel1 🍦 | novel2 🌼 | novel3 🌼 | correct $\ \ ^{\diamond}$ | | | | |
| 1 | 275998227 | apple | foobly | mipp | NOT_FOUND | 0 | | | | |
| 2 | 275998227 | foobly | foobly | Zimziland | NOT_FOUND | 1 | | | | |
| 3 | 275998227 | horse | foobly | NOT_FOUND | NOT_FOUND | 0 | | | | |
| 4 | 275998227 | dodish | dodish | geck | NOT_FOUND | 1 | | | | |
| | | | | | | | | | | |

fixing accuracy

 first, we make sure every response has some text and novel words do not have blanks

```
attention_trials = savic %>% filter(typeoftrial == "attention")# %>%
  select(ID, response, novel1, novel2, novel3, correct) %>%
  rowwise() %>%
  mutate(response = ifelse(is.na(response), "blank", response)) %>%
  mutate(across(c(novel1, novel2, novel3), ~ replace_na(., "NOT_FOUND")))
```

| 🕥 first | -R-notebook. | Rmd × at | tention_trial | 5 × | | |
|-----------------------------|--------------|------------|---------------|-----------|-----------|------------------|
| $\langle \Box \Box \rangle$ | an 🖓 Filte | r | | | | |
| ^ | id ÷ | response 🌐 | novel1 🍦 | novel2 🌐 | novel3 🌼 | correct $\hat{}$ |
| 1 | 366197048 | blank | dodish | geck | NOT_FOUND | 0 |
| 2 | 366197048 | blank | dodish | geck | NOT_FOUND | 0 |
| 3 | 366197048 | blank | foobly | mipp | NOT_FOUND | 0 |
| 4 | 366197048 | blank | foobly | NOT_FOUND | NOT_FOUND | 0 |
| 5 | 366197048 | blank | dodish | geck | NOT_FOUND | 0 |
| 6 | 366197048 | blank | foobly | mipp | Zimziland | 0 |
| 7 | 366197048 | blank | dodish | geck | NOT_FOUND | 0 |
| 8 | 366197048 | blank | dodish | NOT_FOUND | NOT_FOUND | 0 |
| 9 | 366197048 | blank | foobly | mipp | NOT_FOUND | 0 |
| 10 | 438881597 | blank | foobly | NOT_FOUND | NOT_FOUND | 0 |
| 11 | 768759264 | blank | dodish | NOT_FOUND | NOT_FOUND | 1 |

fixing accuracy

- now create 3 new columns that measure the distance between the response and novel1, novel2, novel3
- what do you think these columns contain?

```
attention_trials = savic %>% filter(typeoftrial == "attention") %>%
select(ID, response, novel1, novel2, novel3, correct) %>%
rowwise() %>%
mutate(response = ifelse(is.na(response), "blank", response)) %>%
mutate(across(c(novel1, novel2, novel3), ~ replace_na(., "NOT_FOUND"))) %>%
mutate(edit_novel1 = adist(novel1, response),
        edit_novel2 = adist(novel2, response),
        edit_novel3 = adist(novel3, response))
```

| first | -R-notebook.Rı | md × atte | ention_trials > | < | | | | | | _ |
|----------|----------------|------------|-----------------|-----------|-----------|-----------|--------------------|--------------------|------------------|---|
| | 🔊 🛛 🖓 Filter | | | | | | | | Q | |
| ^ | ID ‡ | response 🗘 | novel1 🌻 | novel2 🌼 | novel3 🌼 | correct 🌼 | edit_novel1[, 1] 🗦 | edit_novel2[, 1] 🗦 | edit_novel3[, 1] | ÷ |
| 1 | 275998227 | apple | foobly | mipp | NOT_FOUND | 0 | 5 | 4 | | 9 |
| 2 | 275998227 | foobly | foobly | Zimziland | NOT_FOUND | 1 | 0 | 8 | | 9 |
| 3 | 275998227 | horse | foobly | NOT_FOUND | NOT_FOUND | 0 | 5 | 9 | | 9 |
| 4 | 275998227 | dodish | dodish | geck | NOT_FOUND | 1 | 0 | 6 | | 9 |
| 5 | 275998227 | dodish | dodish | NOT_FOUND | NOT_FOUND | 1 | 0 | 9 | | 9 |
| | | | | | | | | | | |

fixing accuracy

 now we create a revised_correct column with an edit distance cut-off of 2 and a mismatch column to track where our accuracy has changed

```
attention_trials = savic %>% filter(typeoftrial == "attention") %>%
select(ID, response, novel1, novel2, novel3, correct) %>%
mutate(response = ifelse(is.na(response), "blank", response)) %>%
mutate(across(c(novel1, novel2, novel3), ~ replace_na(., "NOT_FOUND"))) %>%
mutate(edit_novel1 = adist(novel1, response),
    edit_novel2 = adist(novel2, response),
    edit_novel3 = adist(novel3, response)) %>%
mutate(revised_correct = ifelse(edit_novel1 < 2 |
        edit_novel2 < 2 |
        edit_novel3 < 2,
        1, 0),
mismatch = ifelse(correct == revised_correct, 0, 1)) %>%
```

| r | | | | | | | | | | Q, | |
|---|----------|------------|-----------|-----------|------------------|------------------|------------------|--------------------|----------------------|-----------------|--|
| | response | 🗘 novel1 🔅 | novel2 🌐 | novel3 🌼 | correct $\hat{}$ | edit_novel1[, 1] | edit_novel2[, 1] | edit_novel3[, 1] 🔅 | revised_correct[, 1] | mismatch[, 1] 🍼 | |
|) | mipp | foobly | mipp | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
|) | geck | dodish | geck | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
| 5 | dodish | dodish | NOT_FOUND | NOT_FOUND | 0 | 0 | 9 | 9 | 1 | 1 | |
| 5 | geck | dodish | geck | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
| 3 | foobly | foobly | mipp | NOT_FOUND | 0 | 0 | 6 | 9 | 1 | 1 | |
| 3 | mipp | foobly | mipp | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
| 3 | mipp | foobly | mipp | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
| 3 | dodish | dodish | geck | NOT_FOUND | 0 | 0 | 6 | 9 | 1 | 1 | |
| ŀ | foobly | foobly | NOT_FOUND | NOT_FOUND | 0 | 0 | 9 | 9 | 1 | 1 | |
| ł | dodish | dodish | NOT_FOUND | NOT_FOUND | 0 | 0 | 9 | 9 | 1 | 1 | |
|) | Heck | dodish | geck | NOT_FOUND | 0 | 6 | 1 | 9 | 1 | 1 | |
| L | Dodish | dodish | T_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |
| 3 | floobly | foobly | NOT_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |
| 3 | dodidh | dodish | NOT_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |
| 5 | fooblu | foobly | NOT_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |
| ; | godish | dodish | NOT_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |
| ŀ | geck | dodish | geck | NOT_FOUND | 0 | 6 | 0 | 9 | 1 | 1 | |
| 5 | Foobly | foobly | NOT_FOUND | NOT_FOUND | 0 | 1 | 9 | 9 | 1 | 1 | |

analyses checklist

- confirm/correct all datatypes
- □ figure out how to "filter" certain types of trials
- □ fix all typos in attention responses
- Compute mean attention accuracy
- apply exclusions based on accuracy AND RTs
- Create RT bar graph
- □ fit a statistical model
- □ report statistics

summarizing accuracy

- calculate the mean accuracy and standard deviation across all attention trials
- how do we do this for each participant?

mean

summarize participant accuracy

subject_attention_accuracy = attention_trials %>%
group_by(ID) %>%
summarize(mean_accuracy = mean(revised_correct))

| 🕥 first- | tention_accuracy | | |
|----------|------------------|-----------------|--|
| 1.00000 | 000 🖓 Filter | | |
| * | ID ‡ | mean_accuracy 🚊 | |
| 1 | 5418680 | 0.8888889 | |
| 2 | 46356924 | 1.0000000 | |
| 3 | 52271504 | 0.7777778 | |
| 4 | 59881077 | 0.2222222 | |
| 5 | 161705773 | 0.1111111 | |
| 6 | 223076836 | 0.8888889 | |
| 7 | 275998227 | 0.5555556 | |
| 8 | 276772242 | 1.0000000 | |
| 9 | 291529588 | 0.6666667 | |
| 10 | 317312681 | 1.0000000 | |
| 11 | 343557222 | 0.8888889 | |
| 12 | 366197048 | 0.0000000 | |

excluding participants

- what was our exclusion criteria for attention check?
- how do we find IDs that have accuracy less than 75%?
- storing these IDs in a vector will be useful later on

find IDs that have less than 75% accuracy

low_acc_IDs = subject_attention_accuracy %>%
filter(mean_accuracy < 0.75) %>%
pull(ID)

analyses checklist

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priming data plan

- list out all the steps we will need to take to get to our intended plot from the raw data
- also list the tidyverse functions you may need to use for each step



priming data plan

- filter for target trials
- select only relevant columns
- apply exclusions: filter, %in%
 - remove NA trials
 - RT > 200 and RT < 1500
 - correct responses
 - non-practice trials
 - relatedness is related/unrelated
 - type is direct/shared
 - remove low accuracy IDs
- compute means per condition
 - summarize



priming trials: filtering

• filter for target trials

priming_data = savic %>% filter(typeoftrial == "target")

priming trials: selecting

• filter for target trials

priming_data = savic %>% filter(typeoftrial == "target") %>%
 select(ID, rt, relatedness, prime, response, type, correct, block_number, target, correct_key)

select only relevant columns

priming trials: filtering/exclusions

- filter for target trials
- select only relevant columns
- apply exclusions: filter, %in%
 - remove NA trials
 - RT > 200 and RT < 1500
 - correct responses
 - non-practice trials
 - relatedness is related/unrelated
 - type is direct/shared
 - remove low accuracy IDs

```
priming_data = savic %>% filter(typeoftrial == "target") %>%
    select(ID, rt, relatedness, prime, response, type, correct, block_number, target, correct_key)%>%
    filter(!is.na(rt))
```

filter(!is.na(rt), rt > 200 , rt < 1500)

filter(!is.na(rt), rt > 200 , rt < 1500, correct == "TRUE")</pre>

filter(!is.na(rt), rt > 200 , rt < 1500, correct == "TRUE", block_number == 1)</pre>

filter(!is.na(rt), rt > 200 , rt < 1500, correct == "TRUE", block_number == 1) %>%
filter(relatedness %in% c("related", "unrelated") & type %in% c("direct", "shared"))

priming trials: compute means

475 Direct Shared Prime Type

• use the priming data to compute means for each condition

plot

```{r}

priming_data %>%
 group_by(type, relatedness) %>%
 summarise(mean_rt = mean(rt))

| | | - · · · | |
|---|-------------|-------------|-------------|
| | type | relatedness | mean_rt |
| | <fct></fct> | <fct></fct> | <dbl></dbl> |
| 1 | direct | related | 544. |
| 2 | direct | unrelated | 560. |
| 3 | shared | related | 541. |
| 4 | shared | unrelated | 545. |
| | 1 | | |

plot priming data

- directly pass the data from the means into ggplot()
- interpretation?







analyses checklist

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- □ fit a statistical model
- $\hfill\square$ report statistics

next class

• before class

- work on: project checklist
- schedule: a meeting with me before Tuesday next week
- apply: formative assignment #2 (R descriptive)
- during class
 - making statistical inferences from data!