Data wrangling

Tame your data

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```r
knitr::opts_chunk$set(eval = T, # evaluate chunks
                      echo = T, # 'print code chunk?'
                      message = F, # 'print messages (e.g., warnings)?'
                      error = F, # stop when error encountered
                      warning = F) # don't print warnings
```

```r
# Create references.json file based on the citations in this script
# make sure you have 'bibliography: references.json' in the YAML
rbbt::bbt_update_bib("_wrangling.qmd")
```

```r
## play sound if error encountered
### from: https://sejohnston.com/2015/02/24/make-r-beep-when-r-markdown-finishes-or-when-i
options(error = function(){    # Beep on error
  beepr::beep(sound = "wilhelm")
  Sys.sleep(2) #
  }
 )
## and when knitting is complete
.Last <- function() {          # Beep on exiting session
  beepr::beep(sound = "ping")
  Sys.sleep(6) # allow to play for 6 seconds
  }
```

‘wrangle’ defined

/ raŋ l/

noun

a dispute or argument, typically one that is long and complicated. “an insurance wrangle is holding up compensation payments”

verb

1. have a long, complicated dispute or argument. “the bureaucrats continue wrangling over the fine print”
2. NORTH AMERICAN round up, herd, or take charge of (livestock). “the horses were wrangled early”

Wrangler

Jeep Wrangler 

Wrangler Jeans 

Cowboys 

Data Wrangling

- data wrangling = tidying + transforming
- an often long, arduous stage of analysis

Tidy

- re-shaping
  - e.g., from wide to long data
- outcome:
  - each column = a variable
  - each row = an observation

Transform

- filtering
- creating new variables based on observations (e.g., reaction times)
- computing summary statistics (e.g., means)

Why tidy data?

- helps future you
  - and collaborators
- facilitates sharing your data *and* code (Laurinavichyute et al., 2022)
- in short: facilitates reproducibility!

What does tidy data look like?

Three rules (Wickham et al., n.d.):

1. Each variable is a column, each column is a variable
2. Each observation is a row, each row is an observation
3. Each value is a cell, each cell is a single value

- N.B., how you define a *variable* or *observation* is relative to what you want to do
  - for now, let's consider a single trial per participant as an observation

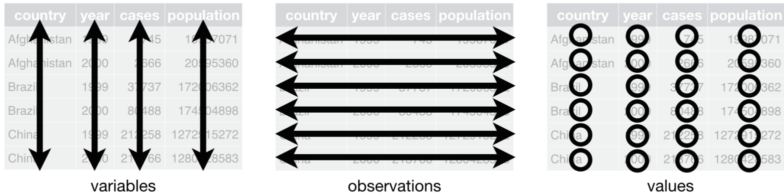


Figure 1: Image source: Wickham et al. (n.d.) (all rights reserved)

the `tidyverse`

- a collection of R packages for tidy data
- you need to load a package at the beginning of every session
    - today we will mostly use functions from the `dplyr` package
        * if you load the `tidyverse` you don't need to also load `dplyr`

```r
# load tidyverse
library(tidyverse)
```

package versions

- you can check the package version with:

```r
packageVersion("tidyverse")
```

```
[1] '2.0.0'
```

- need to update?

```r
# update a single package
install.packages("tidyverse")
```

- what about your other packages?

```
# which packages need updating?
old.packages()
# update all old packages
update.packages()
```

the magritrr pipe %>%

- takes the object before it and feeds it into the next command
  - the pipe could be read as "and then"
  - N.B., there's a new pipe in town! The R native `|>` (Ctrl/Cmd+Shift+M)

```
# take data frame and then...
iris %>%
  # print the head
  head()
```

```
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
6          5.4         3.9          1.7         0.4  setosa
```

Figure 2: Image source: magittr documentation (all rights reserved)

load our data

```r
# load lifetime data
readr::read_csv(here::here("data/data_lifetime_pilot.csv"))
```

```
# A tibble: 4,431 x 28
   RECORDING_SESSION_LABEL TRIAL_INDEX EYE_USED IA_DWELL_TIME
   <chr>                         <dbl> <chr>            <dbl>
 1 px3                               1 RIGHT                0
 2 px3                               2 RIGHT                0
 3 px3                               3 RIGHT                0
 4 px3                               3 RIGHT                0
 5 px3                               3 RIGHT                0
 6 px3                               3 RIGHT                0
 7 px3                               3 RIGHT                0
 8 px3                               3 RIGHT                0
 9 px3                               4 RIGHT                0
10 px3                               5 RIGHT                0
# i 4,421 more rows
# i 24 more variables: IA_FIRST_FIXATION_DURATION <dbl>,
#   IA_FIRST_RUN_DWELL_TIME <dbl>, IA_FIXATION_COUNT <dbl>, IA_ID <dbl>,
#   IA_LABEL <chr>, IA_REGRESSION_IN <dbl>, IA_REGRESSION_IN_COUNT <dbl>,
#   IA_REGRESSION_OUT <dbl>, IA_REGRESSION_OUT_COUNT <dbl>,
#   IA_REGRESSION_PATH_DURATION <dbl>, KeyPress <dbl>, rt <dbl>, bio <chr>,
#   critical <chr>, gender <chr>, item_id <dbl>, list <dbl>, match <chr>, ...
```

- was anything added to the Environment pane (top right box in RStudio)?

variable assignment with <-

- object_name <- code_output_to_be_saved_as_object_name

```r
# load lifetime data and store it under df_lifetime
df_lifetime <- readr::read_csv(here::here("data/data_lifetime_pilot.csv"),
                               # for special characters
                               locale = readr::locale(encoding = "latin1")
                               )
```

- you should now see the object `df_lifetime` in the Environment pane

A note on annotation

- annotate as you go: provide useful comments to describe your code (`# comment`)
- you always have at least one collaborator: future you!
    - comments

First we load required libraries.

```
# load libraries
library(tidyverse) # for e.g., wrangling and plotting
library(here) # for file-paths relative to project folder
```

Tidyverse verbs

- verbs are functions from the `tidyverse` package
- for data tidying and transforming we'll mostly use verbs from the `dplyr` package, which is part of the `tidyverse`
- check out [RLadies Freiburg]() to see a [YouTube video]() that covers most of these verbs

`rename()`

- one of the first things you'll often want to do is rename some variables
- let's start by re-naming some of our variables
    - e.g., `RECORDING_SESSION_LABEL` is a long way of saying 'participant'

```
# rename variables
df_lifetime <- df_lifetime %>% # make df_lifetime from df_lifetime BUT THEN
  rename("px" = RECORDING_SESSION_LABEL, # rename a variable and (comma = 'and')
         "trial" = TRIAL_INDEX) # another variable
```

Exercise

Change the following names:

- `EYE_USED` to `eye`
- `IA_DWELL_TIME` to `tt`

- `IA_FIRST_FIXATION_DURATION` to `ff`
- `IA_FIXATION_COUNT` to `fix_count`
- `IA_FIRST_RUN_DWELL_TIME` to `fp`
- `IA_ID` to `region_n`
- `IA_LABEL` to `region_text`

- `IA_REGRESSION_IN` to `reg_in`
- `IA_REGRESSION_IN_COUNT` to `reg_in_count`
- `IA_REGRESSION_OUT` to `reg_out`
- `IA_REGRESSION_OUT_COUNT` to `reg_out_count`
- `IA_REGRESSION_PATH_DURATION` to `rpd`
- `name_vital_status` to `lifetime`

```
# the names should then look like this:
names(df_lifetime)
```

```
 [1] "px"            "trial"         "eye"           "tt"
 [5] "ff"            "fp"            "fix_count"     "region_n"
 [9] "region_text"   "reg_in"        "reg_in_count"  "reg_out"
[13] "reg_out_count" "rpd"           "KeyPress"      "rt"
[17] "bio"           "critical"      "gender"        "item_id"
[21] "list"          "match"         "condition"     "name"
[25] "lifetime"      "tense"         "type"          "yes_press"
```

relocate

- the second step thing you might want to do is reorder your variables so the most important/relevant are near the beginning and ordered logically
  - let's order our continuous reading time variables from 'earliest' to 'latest' measure

```
df_lifetime <- df_lifetime %>%
  relocate(ff,fp,rpd,tt, .after="eye") %>%
  relocate(region_n, region_text, .after="trial")
```

```
names(df_lifetime[1:10])
```

```
 [1] "px"          "trial"       "region_n"    "region_text" "eye"
 [6] "ff"          "fp"          "rpd"         "tt"          "fix_count"
```

`mutate()`

Make some change

- new columns

```
df_lifetime <- df_lifetime %>%
  mutate(new_column = "new")
```

- change existing column

```
df_lifetime <- df_lifetime %>%
  mutate(new_column = px,
         trial = trial + 5)
```

- but let's undo that…

```
df_lifetime <- df_lifetime %>%
  mutate(trial = trial - 5)
```

`if_else()`

- can be used inside `mutate()`
  - change values based on some logical condition
  - can be used to change an existing column, or create a new one
- `ifelse(condition, output_if_true, output_if_false)`

```
df_lifetime <- df_lifetime %>%
  mutate(new_column = if_else(name=="Aaliyah","name is Aaliyah","name is not Aaliyah"))
```

`case_when()`

- can be used inside `mutate()`
  - change values based on multiple logical conditions
  - can be used to change an existing column, or create a new one
- `case_when(condition & other_condition | other_condition ~ output, TRUE ~ output_otherwise)`
  - if you don't include `TRUE ~ output` then `NA`s will created

```r
df_lifetime <- df_lifetime %>%
  mutate(newer_column = case_when(
    name=="Aaliyah" & trial > 104 ~ "Aaliyah 2nd half",
    name=="Beyoncé" & (px == "px01" | px == "px04") ~ "Beyoncé px04 or px06",
    TRUE ~ "otherwise"))
```

Exercise

1. Create a new variable `accept` that checks whether the button pressed (`KeyPress`) equals the button that corresponds to an acceptance (`yes_press`)
   - if `KeyPress` and `yes_press` are the same, `accept` should be `1`. If not, `accept` should be `0`
   - hint: you will need `if_else()` or `case_when()`
2. Create a new variable `accuracy` where:
   - if `match` is `yes` and `accept` is `1`, `accuracy` is `1`
   - if `match` is `no` and `accept` is `0`, `accuracy` is `1`
   - if `match` is `yes` and `accept` is `0`, `accuracy` is `0`
   - if `match` is `no` and `accept` is `1`, `accuracy` is `0`

- the means and summaries should look like this:

```r
mean(df_lifetime$accept)
```

```
[1] 0.6068608
```

```r
summary(as_factor(df_lifetime$accept))
```

```
   0    1 
1742 2689 
```

```r
mean(df_lifetime$accuracy)
```

```
[1] 0.6267208
```

```r
summary(as_factor(df_lifetime$accuracy))
```

```
   0    1 
1654 2777 
```

Extra exercise

3. Create a new variable `region`, that has the following values based on `region_n`

- region_n `1` is region `verb-1`
- region_n `2` is region `verb`
- region_n `3` is region `verb+1`
- region_n `4` is region `verb+2`
- region_n `5` is region `verb+3`
- region_n `6` is region `verb+4`

```r
summary(as_factor(df_lifetime$region))
```

```
filler verb-1   verb verb+1 verb+2 verb+3 verb+4
  1024    639    639    639    639    639    212
```

4. Now relocate our new variables so that:

- `region` is before `region_n`
- `KeyPress` is after `yes_press`

```r
names(df_lifetime)
```

```
 [1] "px"            "trial"         "region"        "region_n"
 [5] "region_text"   "eye"           "ff"            "fp"
 [9] "rpd"           "tt"            "fix_count"     "reg_in"
[13] "reg_in_count"  "reg_out"       "reg_out_count" "rt"
[17] "bio"           "critical"      "gender"        "item_id"
[21] "list"          "match"         "condition"     "name"
[25] "lifetime"      "tense"         "type"          "yes_press"
[29] "KeyPress"      "new_column"    "newer_column"  "accept"
[33] "accuracy"
```

`group_by()` and `ungroup()`

Group data by certain variable(s)

- then perform some mutation
- then ungroup the data

```r
df_lifetime <- df_lifetime |>
  group_by(px) |>
  mutate(px_accuracy = mean(accuracy)) %>%
  ungroup()
```

```r
round(
  range(df_lifetime$px_accuracy),
  2)
```

```
[1] 0.26 0.90
```

select()

- keep only certain column(s)

```r
df_lifetime %>%
  select(px)
```

```
# A tibble: 4,431 x 1
   px
   <chr>
 1 px3
 2 px3
 3 px3
 4 px3
 5 px3
 6 px3
 7 px3
 8 px3
 9 px3
10 px3
# i 4,421 more rows
```

```r
df_lifetime %>%
  select(px, trial)
```

```
# A tibble: 4,431 x 2
   px    trial
```

```
   <chr> <dbl>
 1 px3       1
 2 px3       2
 3 px3       3
 4 px3       3
 5 px3       3
 6 px3       3
 7 px3       3
 8 px3       3
 9 px3       4
10 px3       5
# i 4,421 more rows
```

`select()`

- or remove certain columns

```
df_lifetime %>%
  select(-px, -trial)
```

```
# A tibble: 4,431 x 32
   region region_n region_text    eye      ff    fp   rpd    tt fix_count reg_in
   <chr>     <dbl> <chr>          <chr> <dbl> <dbl> <dbl> <dbl>     <dbl>  <dbl>
 1 filler        1 He owned innu~ RIGHT     0     0     0     0         0      0
 2 filler        1 She is a moth~ RIGHT     0     0     0     0         0      0
 3 verb-1        1 She            RIGHT     0     0     0     0         0      0
 4 verb          2 will perform   RIGHT     0     0     0     0         0      0
 5 verb+1        3 in prestigiou~ RIGHT     0     0     0     0         0      0
 6 verb+2        4 in the future, RIGHT     0     0     0     0         0      0
 7 verb+3        5 as reported i~ RIGHT     0     0     0     0         0      0
 8 verb+4        6 as reported i~ RIGHT     0     0     0     0         0      0
 9 filler        1 He interviewe~ RIGHT     0     0     0     0         0      0
10 verb-1        1 She            RIGHT     0     0     0     0         0      0
# i 4,421 more rows
# i 22 more variables: reg_in_count <dbl>, reg_out <dbl>, reg_out_count <dbl>,
#   rt <dbl>, bio <chr>, critical <chr>, gender <chr>, item_id <dbl>,
#   list <dbl>, match <chr>, condition <chr>, name <chr>, lifetime <chr>,
#   tense <chr>, type <chr>, yes_press <dbl>, KeyPress <dbl>, new_column <chr>,
#   newer_column <chr>, accept <dbl>, accuracy <dbl>, px_accuracy <dbl>
```

Select criteria

You can also use criteria for `select`:

- `select(starts_with("x"))` select columns that start with a character string
- `select(ends_with("x"))` select columns that end with a character string
- `select(contains("x"))` select columns that contain a character string
- `select(num_range("prefix",10:20))` select columns with a `prefix` followed by a range of values

Exercise

Remove the example variables we created with `mutate`:

- `new_column` and `newer_column`

```
# should look like this after
names(df_lifetime)
```

```
 [1] "px"             "trial"          "region"         "region_n"
 [5] "region_text"    "eye"            "ff"             "fp"
 [9] "rpd"            "tt"             "fix_count"      "reg_in"
[13] "reg_in_count"   "reg_out"        "reg_out_count"  "rt"
[17] "bio"            "critical"       "gender"         "item_id"
[21] "list"           "match"          "condition"      "name"
[25] "lifetime"       "tense"          "type"           "yes_press"
[29] "KeyPress"       "accept"         "accuracy"       "px_accuracy"
```

`filter()`

- select certain rows based on certain criteria (`==`, `!=`, `>`, `<`, `|`)
  - N.B. when testing logical conditions `==` is needed

```
df_lifetime %>%
  filter(trial == 1)
```

```
# A tibble: 8 x 32
  px    trial region region_n region_text          eye      ff    fp   rpd    tt
  <chr> <dbl> <chr>     <dbl> <chr>                <chr> <dbl> <dbl> <dbl> <dbl>
1 px3       1 filler        1 He owned innumerabl~ RIGHT     0     0     0     0
2 px5       1 filler        1 She is a mother of ~ RIGHT   145  1603  1603  1603
3 px6       1 filler        1 He is a father of t~ RIGHT   147  1224  1224  1224
4 px2       1 filler        1 She made innumerabl~ RIGHT    84  1829  1829  1829
5 px7       1 filler        1 In the '70s, he own~ RIGHT   138  2456  2456  2456
6 px1       1 filler        1 Beloved morning sho~ RIGHT   160  1708  1708  1708
7 px8       1 filler        1 She was a mother of~ RIGHT   220   806   806   806
8 px4       1 filler        1 In the '70s, he own~ LEFT    171  3557  3557  3557
# i 22 more variables: fix_count <dbl>, reg_in <dbl>, reg_in_count <dbl>,
#   reg_out <dbl>, reg_out_count <dbl>, rt <dbl>, bio <chr>, critical <chr>,
#   gender <chr>, item_id <dbl>, list <dbl>, match <chr>, condition <chr>,
#   name <chr>, lifetime <chr>, tense <chr>, type <chr>, yes_press <dbl>,
#   KeyPress <dbl>, accept <dbl>, accuracy <dbl>, px_accuracy <dbl>
```

`filter()`

What are these code chunks doing?

```
df_lifetime %>%
  filter(px_accuracy > .5)
```

```
df_lifetime %>%
  filter(px == "px3")
```

```
df_lifetime %>%
  filter(px == "px3" | trial == "3")
```

```
df_lifetime %>%
  filter(px == "px3" & trial != "3")
```

Logical operators

- symbols used to describe a logical condition
- `==` is idential (`1 == 1`)
- `!=` is not identical (`1 != 2`)
- `>` is greater than (`2 > 1`)
- `<` is less than (`1 < 2`)
- `&` and also (for multiple conditions)
- `|` or (for multiple conditions)

Exercise

1. Create a new dataframe `df_crit` that includes only critical trials
2. Create a new dataframe `df_fill` that includes only filler trials

- Tip: trial type is stored in the column `type`

```
df_crit |> select(type) |> head()
```

```
# A tibble: 6 x 1
  type
  <chr>
1 critical
2 critical
3 critical
4 critical
5 critical
6 critical
```

```
df_fill |> select(type) |> head()
```

```
# A tibble: 6 x 1
  type
```

```
  <chr>
1 filler
2 filler
3 filler
4 filler
5 filler
6 filler
```

`distinct()`

- like `filter()`, but for *distinct values* of a variable
  - "select rows with distinct values for some row(s)"

```r
df_crit %>%
  distinct(px)
```

```
# A tibble: 8 x 1
  px
  <chr>
1 px3
2 px5
3 px6
4 px2
5 px7
6 px1
7 px8
8 px4
```

```r
df_crit %>%
  distinct(px, name)
```

```
# A tibble: 639 x 2
   px    name
   <chr> <chr>
 1 px3   Edith Piaf
 2 px3   Aaliyah
 3 px3   David Beckham
 4 px3   Jana Novotna
 5 px3   Grace Kelly
```

```
 6 px3   Nigella Lawson
 7 px3   Coco Chanel
 8 px3   Ben Kingsley
 9 px3   Jim Carrey
10 px3   Judy Garland
# i 629 more rows
```

```
df_crit %>%
  distinct(px, name,
           .keep_all=T)
```

```
# A tibble: 639 x 32
   px    trial region region_n region_text eye      ff    fp   rpd    tt
   <chr> <dbl> <chr>     <dbl> <chr>       <chr> <dbl> <dbl> <dbl> <dbl>
 1 px3       3 verb-1        1 She         RIGHT     0     0     0     0
 2 px3       5 verb-1        1 She         RIGHT     0     0     0     0
 3 px3       8 verb-1        1 He          RIGHT     0     0     0     0
 4 px3      10 verb-1        1 She         RIGHT     0     0     0     0
 5 px3      13 verb-1        1 She         RIGHT     0     0     0     0
 6 px3      16 verb-1        1 She         RIGHT     0     0     0     0
 7 px3      18 verb-1        1 She         RIGHT     0     0     0     0
 8 px3      21 verb-1        1 He          RIGHT     0     0     0     0
 9 px3      23 verb-1        1 He          RIGHT     0     0     0     0
10 px3      26 verb-1        1 She         RIGHT     0     0     0     0
# i 629 more rows
# i 22 more variables: fix_count <dbl>, reg_in <dbl>, reg_in_count <dbl>,
#   reg_out <dbl>, reg_out_count <dbl>, rt <dbl>, bio <chr>, critical <chr>,
#   gender <chr>, item_id <dbl>, list <dbl>, match <chr>, condition <chr>,
#   name <chr>, lifetime <chr>, tense <chr>, type <chr>, yes_press <dbl>,
#   KeyPress <dbl>, accept <dbl>, accuracy <dbl>, px_accuracy <dbl>
```

`arrange()`

- sort column(s) in ascending or descending order
  - this is really just for ease of reading

```
# default: ascending order (A-Z)
df_crit %>%
  distinct(px, trial, name, condition) %>%
  arrange(px, trial)
```

```
# A tibble: 639 x 4
   px    trial name            condition
   <chr> <dbl> <chr>           <chr>
 1 px1       3 Amy Winehouse   deadPP
 2 px1       5 John Wayne      deadPP
 3 px1       8 Abraham Lincoln deadPP
 4 px1      10 Helen Mirren    livingSF
 5 px1      13 Paul McCartney  livingSF
 6 px1      16 Ariana Grande   livingPP
 7 px1      18 Kate Middleton  livingSF
 8 px1      21 Johan Cruyff    deadSF
 9 px1      23 Marilyn Monroe  deadPP
10 px1      26 Biggie Smalls   deadSF
# i 629 more rows
```

```r
# descending order (Z-A)
df_crit %>%
  distinct(px, trial, name, condition) %>%
  arrange(desc(px), trial)
```

```
# A tibble: 639 x 4
   px    trial name            condition
   <chr> <dbl> <chr>           <chr>
 1 px8       3 Whitney Houston deadPP
 2 px8       5 Elton John      livingSF
 3 px8       8 Jackie Chan     livingPP
 4 px8      10 Romy Schneider  deadPP
 5 px8      13 James Cameron   livingSF
 6 px8      16 Ella Fitzgerald deadSF
 7 px8      18 Kathryn Hepburn deadPP
 8 px8      21 Kate Middleton  livingPP
 9 px8      23 Janis Joplin    deadPP
10 px8      26 Serena Williams livingSF
# i 629 more rows
```

`separate()`

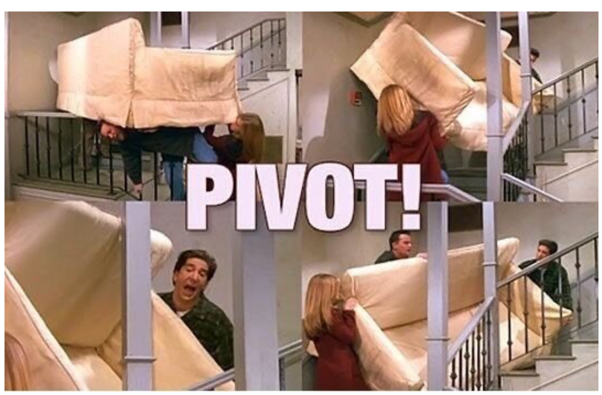
- create new columns from a single column

```r
df_crit<- df_crit %>%
  separate(name,
           sep=" ",
           into = c("First","Last"),
           remove = F, # don't remove original column (name)
           extra = "merge") # if extra chunks, combine in 'Last' (von der...)
```

- opposite: `unite()`

Reshape data

- this is the major step of data tidying
  - make each column a variable
  - make each row an observation
  - make each cell a data point
- what variable and observation mean will depend on what you want to do, and will change at different steps of your analyses
- you typically want *long* data
  - but our dataset isn't as long as it could be



`pivot_longer()`

- takes wide data and makes it longer
  - converts headers of columns into values of a new column
  - combines the values of those columns into a new condensed column
- takes a few arguments:
  - `cols`: which columns do we want to combine into a single column?
  - `names_to`: what should we call the new column containing the previous column names?
  - `values_to`: what should we call the new column containing the values from the previous columns?

`pivot_longer()`

```
df_lifetime %>%
  select(px,trial,region,ff,fp,rpd,tt,rt,type,accept,condition) %>%
  filter(type=="critical",region=="verb",px!="px3") %>%
  pivot_longer(
  cols = c(ff,fp,rpd,tt,rt), # columns to make long
  names_to = "measure", # new column name for headers
  values_to = "time" # new column name for values
)
```

```
# A tibble: 2,795 x 8
   px    trial region type     accept condition measure  time
   <chr> <dbl> <chr>  <chr>     <dbl> <chr>     <chr>   <dbl>
 1 px5       3 verb   critical      1 livingPP  ff        175
 2 px5       3 verb   critical      1 livingPP  fp        175
 3 px5       3 verb   critical      1 livingPP  rpd       175
 4 px5       3 verb   critical      1 livingPP  tt        321
 5 px5       3 verb   critical      1 livingPP  rt       4736
 6 px5       5 verb   critical      1 livingPP  ff        207
 7 px5       5 verb   critical      1 livingPP  fp        413
 8 px5       5 verb   critical      1 livingPP  rpd       413
 9 px5       5 verb   critical      1 livingPP  tt        413
10 px5       5 verb   critical      1 livingPP  rt       4622
# i 2,785 more rows
```

Source: PsyTeachR

`pivot_wider()`

- takes long data and makes it wider
- takes a few arguments:
  - `id_cols`: identifying columns
  - `names_from`: what should we call the new column containing the previous column names?
  - `names_prefix`:
  - `values_from`: new column values

`pivot_wider()`

```
df_lifetime %>%
  select(px,trial,region,ff,fp,rpd,tt,rt,type,accept,condition) %>%
  filter(type=="critical",px!="px3") %>%
  pivot_wider(
  id_cols = c(px,trial), # columns to make long
  names_from = region, # new column name for headers
  names_prefix = "reg_", # new column name for values
  values_from = tt
)
```

```
# A tibble: 559 x 8
   px    trial `reg_verb-1` reg_verb `reg_verb+1` `reg_verb+2` `reg_verb+3`
   <chr> <dbl>        <dbl>    <dbl>        <dbl>        <dbl>        <dbl>
 1 px5       3          190      321         1723          672          575
 2 px5       5            0      413          476          279         2441
 3 px5       8          246     1892          967          450          981
 4 px5      10            0      601          932          243          702
 5 px5      13            0      407         1115            0            0
 6 px5      16            0     1010         1502          337         1426
 7 px5      18          238      389         1415          359          584
 8 px5      21            0      376          584          475         2015
 9 px5      23          231      215          717          184          255
10 px5      26          125      347          400          317          981
# i 549 more rows
# i 1 more variable: `reg_verb+4` <dbl>
```

Source: PsyTeachR

Save your tidy data

- once your data is nice and tidy, save it with a **new filename**
  - this way you always have the same starting point for your data exploration/analyses

```
# run this manually!
write.csv(df_lifetime, here::here("data/tidy_data_lifetime_pilot.csv"),row.names=FALSE)
```

Summary

- we saw that the equation for a straight line boils down to its intercept and slope
- we fit our first linear model with a categorical predictor
- next, we'll look at a case with more than one predictor: **multiple** regression

Important terms

wrangle	have a long dispute
data wrangling	tidying and transforming your data
tidy data	data where each column is a variable and each row is an observation
the tidyverse	a group of packages for tidy data
dplyr	a package within the tidyverse for data wrangling
pipe operator (`%>%` or `|>`)	operational function, passes the result of one function/argument to the next
logical operators	compare values of two arguments: `&`, `|`, `==`, `!=`, >, <

Important functions

`read_csv()`	read-in a csv as a tibble (from `readr` package)
`rename()`	rename variables
`relocate()`	move variables
`mutate()`	change or create new variables
`if_else()`	condition for 'mutate()'
`case_when()`	handle multiple conditions for 'mutate()'
`group_by()`	group by a certain variable
`select()`	keep (or exclude) certain variables

`filter()`	keep (or exclude) rows based on some criteria
`distinct()`	keep rows with distinct value of given variable(s)
`arrange()`	sort variable(s) in ascending or descending order
`separate()`	split a variable into multiple variables
`pivot_longer()`	make wide data longer
`pivot_wider()`	make long data wider

Session Info

```
sessionInfo()
```

```
R version 4.2.3 (2023-03-15)
Platform: aarch64-apple-darwin20 (64-bit)
Running under: macOS Ventura 13.2.1

Matrix products: default
BLAS:   /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/lib/libRblas.0.dylib
LAPACK: /Library/Frameworks/R.framework/Versions/4.2-arm64/Resources/lib/libRlapack.dylib

locale:
[1] en_US.UTF-8/en_US.UTF-8/en_US.UTF-8/C/en_US.UTF-8/en_US.UTF-8

attached base packages:
[1] stats     graphics  grDevices utils     datasets  methods   base

other attached packages:
 [1] lubridate_1.9.2 forcats_1.0.0   stringr_1.5.0   dplyr_1.1.1
 [5] purrr_1.0.1     readr_2.1.4     tidyr_1.3.0     tibble_3.2.1
 [9] ggplot2_3.4.2   tidyverse_2.0.0

loaded via a namespace (and not attached):
 [1] tidyselect_1.2.0 xfun_0.38        colorspace_2.1-0 vctrs_0.6.1
 [5] generics_0.1.3   htmltools_0.5.5  yaml_2.3.7       utf8_1.2.3
 [9] rlang_1.1.0      pillar_1.9.0     glue_1.6.2       withr_2.5.0
[13] bit64_4.0.5      lifecycle_1.0.3  munsell_0.5.0    gtable_0.3.3
[17] evaluate_0.20    knitr_1.42       tzdb_0.3.0       fastmap_1.1.1
[21] curl_5.0.0       parallel_4.2.3   fansi_1.0.4      Rcpp_1.0.10
[25] scales_1.2.1     vroom_1.6.1      magick_2.7.4     jsonlite_1.8.4
[29] fs_1.6.1         bit_4.0.5        rbbt_0.0.0.9000  hms_1.1.3
```

```
[33] png_0.1-8        digest_0.6.31    stringi_1.7.12   grid_4.2.3
[37] rprojroot_2.0.3  here_1.0.1       cli_3.6.1        tools_4.2.3
[41] magrittr_2.0.3   crayon_1.5.2     pkgconfig_2.0.3  timechange_0.2.0
[45] rmarkdown_2.21   httr_1.4.5       rstudioapi_0.14  R6_2.5.1
[49] compiler_4.2.3
```

References

Laurinavichyute, A., Yadav, H., & Vasishth, S. (2022). Share the code, not just the data: A case study of the reproducibility of articles published in the Journal of Memory and Language under the open data policy. *Journal of Memory and Language*, *125*, 12.

Wickham, H., Çetinkaya-Rundel, M., & Grolemund, G. (n.d.). *R for Data Science* (2nd ed.). https://r4ds.hadley.nz/