Illustration from the Openscapes blog Tidy Data for reproducibility, efficiency, and collaboration by Julia Lowndes and Allison Horst

Summarizing & Transforming Data in R

Saving you time and sanity

steffilazerte
@steffilazerte@fosstodon.org
@steffilazerte
steffilazerte.ca

Dr. Steffi LaZerte
Analysis and Data Tools for Science

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First things first

- 💾 Save previous script
- 📂 Open New File

  (make sure you're in the RStudio Project)
- ✏ Write `library(tidyverse)` at the top
- 💾 Save this new script

  (consider names like `summarizing.R` or `4_sum_and_trans.R`)

Types of Modifications

1. Subset

- `filter()` observations (rows)
- `select()` variables (columns)

2. Joining data sets

- `left_join()`, `right_join()`, etc.

3. Creating new columns

- Creating categories
- Column calculations
- By group
- `mutate()` and `group_by()`

4. Summarize existing columns

- Summarizing by group
- `summarize()` and `group_by()`

5. Transpose

- Going between **wide** and **long** data formats
  - `pivot_wider()` and `pivot_longer()`
- Transposing for analysis
- Transposing for visualizations

Getting ready

Check out the data:

```r
library(tidyverse)
size <- read_csv("data/grain_size2.csv")
size
```

Using data sets:

- grain_size2.csv
- grain_meta.csv

```
# A tibble: 114 × 9
   plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay
   <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl>
 1 CSP01     4       13.0        17.4      19.7        14.1        11.2       8.17  16.3
 2 CSP01    12       10.7        16.9      19.2        14.1        11.7       9.03  18.4
 3 CSP01    35       12.1        17.8      16.1        10.3         9.51      7.47  26.7
 4 CSP01    53       17.6        18.2      14.3         9.4         9.1       8.7   22.7
 5 CSP01    83       21.0        18.4      14.3         9.79        8.79      7.29  20.4
 6 CSP01   105       19.0        18.4      14.4        10.8         9.4       8.22  19.7
 7 CSP08    10       11.6        17.1      20.8        16.3         9.55      6.23  18.4
 8 CSP08    27       15.4        16.2      17.8        14.3        10.4       6.1   19.6
 9 CSP08    90       14.9        15.8      18.6        15.1        11.5       7.56  16.5
10 CSP02     5        8.75        8.64      8.66       12.0        18.3      15.2   28.5
# ℹ 104 more rows
```

Subsetting

By rows and column

filter() observations

filter() is from dplyr*

```r
filter(data, expression1, expression2, etc.)
```

- tidyverse functions always start with data
- Column expressions reference actual columns in data
- Here we use logical statements relating to column values

filter() observations

filter() by category

```r
filter(size, plot %in% c("CSP11", "CSP13"))
```

```
# A tibble: 9 × 9
  plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay
  <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl>
1 CSP13     2       22.1        17.5       18.3        11.9         7.92      6.05  16.3
2 CSP13    10       12.1        14.9       18          13.1        10.4       7.92  23.6
3 CSP13    25       13.7        12.7       14.3        11.7         9.67      6.31  31.6
4 CSP13    60       27.1         9.74      11.1         9.69        9.79      7.82  24.8
5 CSP13   140       10.4        15.3       16.0        12.4        12.4      10.2   23.5
6 CSP11    20        6.67        3.94       5.52       23.7        23        14.8   22.3
7 CSP11    30        5.27        4.23       6.11       23.6        23.9      15.3   21.6
8 CSP11    47        4.34        4.03       6.62       24.5        25.5      13.8   21.3
9 CSP11   143        5.28        4.26       7.07       22.8        28.0      12.4   20.2
```

Note: To save this as a separate object, don’t forget assignments:

```r
size_sub <- filter(size, plot %in% c("CSP11", "CSP13"))
```

filter() observations

filter() by measures

```r
filter(size, depth > 140 | depth < 4)
```

```
# A tibble: 9 × 9
  plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay
  <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl>
1 CSP13     2       22.1        17.5      18.3         11.9        7.92      6.05  16.3
2 CSP19   190        3.33        4.28     14.2         42.8       21.5       9.92   4  
3 CSP11   143        5.28        4.26      7.07        22.8       28.0      12.4   20.2
4 CSP14     3       16.1        15.0      17.5         12.2       12         9.88  17.3
5 CSP15   146       13.6        12.3      12.5         12.0       18.1      10.4   21.1
6 CSP20     3        5.12        5.09     17.9         25.9       14.3      11.8   19.9
7 CSP20   150       22.7        12.9      12.7         17.7       14.9       7.59  11.5
8 CSP21     3       14.1        11.6      11.9         14.1       15.5      10.4   22.4
9 CSP22   182       17.9        13.6      13.1         13.5       12.6       8.39  20.9
```

`filter()` observations

`filter()` by a combination → use comma for AND

```r
filter(size,
       depth > 100,
       plot %in% c("CSP11", "CSP13"))
```

```
# A tibble: 2 × 9
  plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay
  <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl>
1 CSP13   140       10.4        15.3      16.0         12.4        12.4      10.2  23.5
2 CSP11   143        5.28        4.26      7.07        22.8        28.0      12.4  20.2
```

Equivalent to using &

```r
filter(size,
       depth > 100 &
       plot %in% c("CSP11", "CSP13"))
```

Tangent

Logical Operators

Logical Operators

Possible options

Operator	Code
OR	|
AND	&
EQUAL	==
NOT EQUAL	!=
NOT	!
Greater than	>
Less than	<
Greater than or equal to	>=
Less than or equal to	<=
In	%in%

Your turn!

What do the following filters do?

```r
filter(size, depth == 20)
filter(size, depth == 20, clay < 20)
filter(size, depth %in% c(20, 100) & clay == 6)
filter(size, !plot %in% c("CSP01", "CSP13"))
filter(size, depth >= 146)
filter(size, depth > 146)
filter(size, coarse_silt < 9 | clay < 5)
```

`select()` variables

`select()` is from `dplyr`*

```
select(data, selection1, selection2, etc.)
```

- `tidyverse` functions always start with data
- Specify columns to keep or remove
- Column `selection`s reference actual columns in data

`select()` variables

`select()` by name

```r
select(size, coarse_sand, medium_sand, fine_sand)
```

```
# A tibble: 114 × 3
  coarse_sand medium_sand fine_sand
        <dbl>       <dbl>     <dbl>
1        13.0        17.4      19.7
2        10.7        16.9      19.2
3        12.1        17.8      16.1
4        17.6        18.2      14.3
# ℹ 110 more rows
```

Using helper functions

```r
select(size, ends_with("sand"))
```

```
# A tibble: 114 × 3
  coarse_sand medium_sand fine_sand
        <dbl>       <dbl>     <dbl>
1        13.0        17.4      19.7
2        10.7        16.9      19.2
3        12.1        17.8      16.1
4        17.6        18.2      14.3
# ℹ 110 more rows
```

Some other helper functions (`?select_helpers`):

Function	Usage
`starts_with()`	`starts_with("fine")`
`contains()`	`contains("sand")`
`everything()`	Useful for rearranging
`matches()`	Uses regular expressions

`select()` variables

Put it all together

To explore the data

```
size |>
  filter(depth > 100,
         plot %in% c("CSP13", "CSP25")) |>
  select(plot, depth, ends_with("sand"))
```

```
# A tibble: 2 × 5
  plot  depth coarse_sand medium_sand fine_sand
  <chr> <dbl>       <dbl>       <dbl>     <dbl>
1 CSP13   140        10.4        15.3      16.0
2 CSP25   130        18.6        21.3      13.8
```

To save as a separate object

```
size_sub_sand <- size |>
  filter(depth > 100,
         plot %in% c("CSP13", "CSP25")) |>
  select(plot, depth, ends_with("sand"))
```

Your turn: Subsetting

- Subset the data to variables **plot**, **depth** and all measures of **sand**
- Keep only values where there is **at least 30% clay**

```
size <- read_csv("data/grain_size2.csv") |>
  filter(???) |>
  select(???)
```

Note:
All particle values are percentages (depth is cm)

Too Easy?
What happens if you `select()` before you `filter()`?
How many different ways can you select these columns?

Your turn: Subsetting

- Subset the data to variables **plot**, **depth** and all measures of **sand**
- Keep only values where there is **<u>at least</u> 30% clay**

```r
size <- read_csv("data/grain_size2.csv") |>
  filter(clay >= 30) |>
  select(plot, depth, ends_with("sand"))

head(size)
```

```
# A tibble: 2 × 5
  plot  depth coarse_sand medium_sand fine_sand
  <chr> <dbl>       <dbl>       <dbl>     <dbl>
1 CSP02    36        8.15        9.24      8.55
2 CSP13    25       13.7        12.7      14.3
```

Select equivalents:

- `select(plot, depth, ends_with("sand"))`
- `select(plot, depth, contains("sand"))`
- `select(plot, depth, coarse_sand, medium_sand, fine_sand)`
- `select(-coarse_silt, -medium_silt, -fine_silt, -clay)`

Your turn: Subsetting (Too Easy?)

What happens if you `select()` before you `filter()`?

```r
size <- read_csv("data/grain_size2.csv") |>
  select(plot, depth, ends_with("sand")) |>
  filter(clay >= 30)
```

```
Error in `filter()`:
i In argument: `clay >= 30`.
Caused by error:
! object 'clay' not found
```

- Lines are sequential
- First `select()` removes column `clay`
- Then `filter()` cannot find `clay`
  - (`object 'clay' not found`)

Joining or Merging data

Joining data sets

Measurements

Plot	Date	n_birds
A	2025-01-12	1
A	2025-02-05	11
A	2025-03-01	2
B	2025-03-25	4
B	2025-04-18	10
B	2025-05-12	21

Metadata

Plot	Vegetation Density
A	50
B	76

Joining them together

Metadata is duplicated to line up with measurements

Plot	Date	n_birds	Vegetation Density
A	2025-01-12	1	50
A	2025-02-05	11	50
A	2025-03-01	2	50
B	2025-03-25	4	76
B	2025-04-18	10	76
B	2025-05-12	21	76

Joining data sets

Index or Metadata

```r
meta <- read_csv("data/grain_meta.csv")
meta
```

```
# A tibble: 27 × 4
   plot  habitat   technician date      
   <chr> <chr>     <chr>      <date>    
 1 CSP01 forest    Catharine  2009-04-23
 2 CSP02 forest    Catharine  2009-05-06
 3 CSP03 clearcut  Jason      2008-09-03
 4 CSP04 forest    Catharine  2008-09-29
 5 CSP05 grassland Catharine  2009-02-05
 6 CSP06 grassland Jason      2008-07-01
 7 CSP07 grassland Jason      2008-11-19
 8 CSP08 grassland Catharine  2009-03-02
 9 CSP09 forest    Catharine  2008-08-21
10 CSP10 grassland Jason      2009-02-17
11 CSP11 forest    Jason      2008-09-16
12 CSP12 grassland Catharine  2009-03-28
13 CSP13 grassland Catharine  2008-07-13
14 CSP14 clearcut  Jason      2009-06-01
15 CSP15 forest    Yasir      2008-12-02
# ℹ 12 more rows
```

Measurements

```r
size <- read_csv("data/grain_size2.csv")
size
```

```
# A tibble: 114 × 9
   plot  depth coarse_sand medium_sand fine_sand coarse_silt
   <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>
 1 CSP01     4       13.0        17.4      19.7        14.1 
 2 CSP01    12       10.7        16.9      19.2        14.1 
 3 CSP01    35       12.1        17.8      16.1        10.3 
 4 CSP01    53       17.6        18.2      14.3         9.4 
 5 CSP01    83       21.0        18.4      14.3         9.79
 6 CSP01   105       19.0        18.4      14.4        10.8 
 7 CSP08    10       11.6        17.1      20.8        16.3 
 8 CSP08    27       15.4        16.2      17.8        14.3 
 9 CSP08    90       14.9        15.8      18.6        15.1 
10 CSP02     5        8.75        8.64      8.66       12.0 
11 CSP02    11        9.89        8.68      8.34       10.7 
12 CSP02    36        8.15        9.24      8.55       10.7 
13 CSP02    56       12.0         8.63      8.06       11.1 
14 CSP02    70       17.5        10.5       8.45       11.2 
15 CSP02    78       23.3        15.0      11.0         9.97
# ℹ 99 more rows
# ℹ 3 more variables: medium_silt <dbl>, fine_silt <dbl>, clay <dbl>
```

`plot` (CSP01, CSP02, etc.) identifies data in both

Types of Join: Which rows to keep?

left_join(x, y)

- Keep all rows in x
- Keep rows in y only if they're also in x

right_join(x, y)

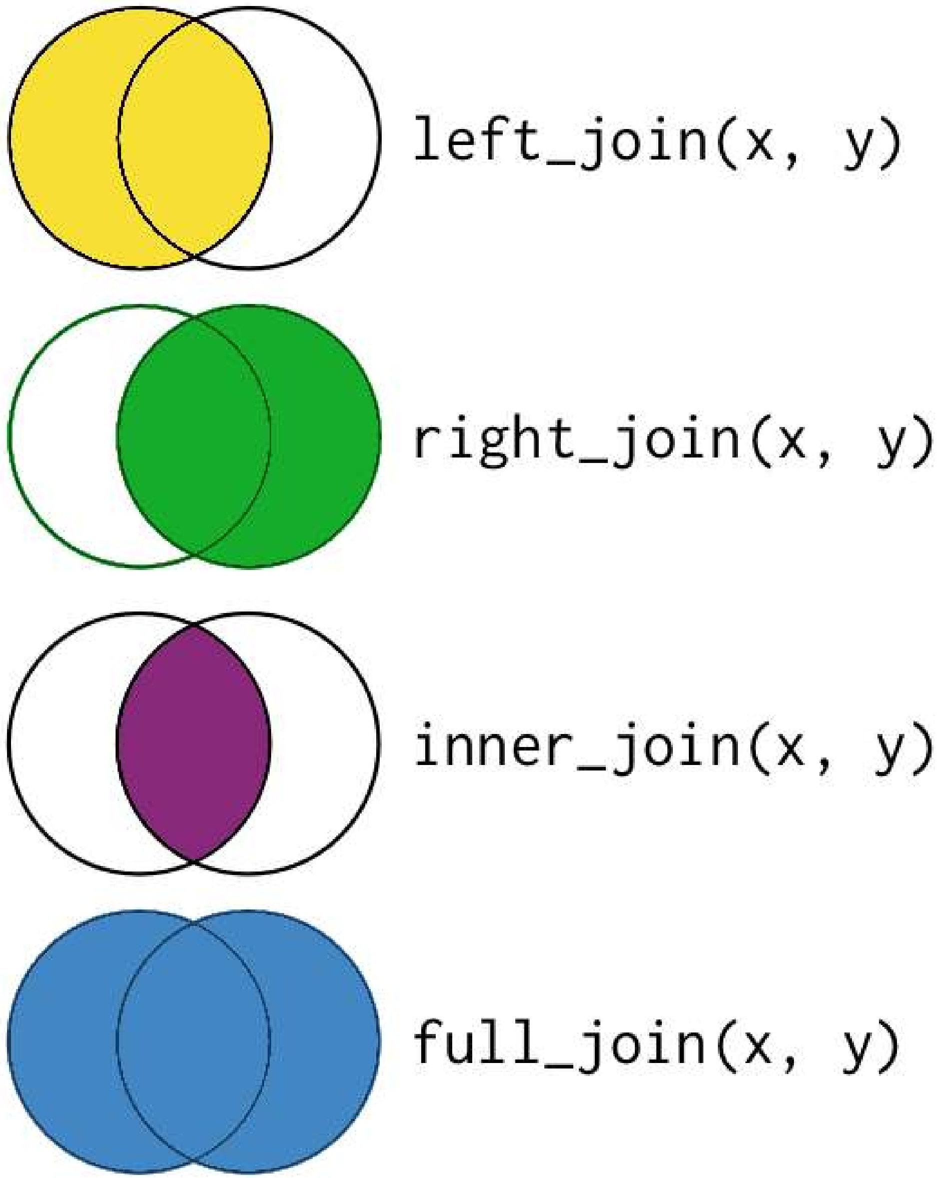
- Keep all rows in y
- Keep rows in x only if they're also in y

inner_join(x, y)

- Keep **only** rows that exist in **both** data frames

full_join(x, y)

- Keep **all** rows that exist in **either** x *or* y



Joining data sets

`left_join()` is from `dplyr`*

```r
left_join(x = data, y = data_to_join, by = c("column1", "column2"), ...)
```

- `tidyverse` functions always start with data (x)
- Here, also need second dataset (y)
- by refers columns in x and y used to join

Joining data sets

Keep all measurements (`size`), only keep `meta` if we have a measurement

```r
size <- left_join(x = size, y = meta, by = "plot")
```

```
# A tibble: 114 × 12
   plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay habitat   technician date
   <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl> <chr>     <chr>      <date>
 1 CSP01     4       13.0        17.4      19.7        14.1        11.2       8.17  16.3 forest    Catharine  2009-04-2
 2 CSP01    12       10.7        16.9      19.2        14.1        11.7       9.03  18.4 forest    Catharine  2009-04-2
 3 CSP01    35       12.1        17.8      16.1        10.3         9.51      7.47  26.7 forest    Catharine  2009-04-2
 4 CSP01    53       17.6        18.2      14.3         9.4         9.1       8.7   22.7 forest    Catharine  2009-04-2
 5 CSP01    83       21.0        18.4      14.3         9.79        8.79      7.29  20.4 forest    Catharine  2009-04-2
 6 CSP01   105       19.0        18.4      14.4        10.8         9.4       8.22  19.7 forest    Catharine  2009-04-2
 7 CSP08    10       11.6        17.1      20.8        16.3         9.55      6.23  18.4 grassland Catharine  2009-03-0
 8 CSP08    27       15.4        16.2      17.8        14.3        10.4       6.1   19.6 grassland Catharine  2009-03-0
 9 CSP08    90       14.9        15.8      18.6        15.1        11.5       7.56  16.5 grassland Catharine  2009-03-0
10 CSP02     5        8.75        8.64      8.66       12.0        18.3      15.2   28.5 forest    Catharine  2009-05-0
# ℹ 104 more rows
```

For more information see R for Data Science Chapter 19.3 Basic joins

Creating/modifying columns with `mutate()`

dplyr::mutate
add column(s), keep existing.
A
B
C
1
5
10
0
2
-3
4
9
6
3
2
14
9
8
THE PLAN:
A B C
+ =
Horst '18

Artwork by @allison_horst

Creating new columns

`mutate()` is from `dplyr`*

```r
mutate(data, column1 = expression1, column2 = expression2, ...)
```

- `tidyverse` functions always start with data
- Create new or modify existing `columns` in the `data`
- Columns filled according to `expression`

Creating new columns

```r
size <- read_csv("data/grain_size2.csv") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand)
```

Creates new column at the end, `total_sand`

```
# A tibble: 114 × 10
   plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay total_sand
   <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl>      <dbl>
 1 CSP01     4       13.0        17.4      19.7        14.1        11.2       8.17  16.3       50.1
 2 CSP01    12       10.7        16.9      19.2        14.1        11.7       9.03  18.4       46.8
 3 CSP01    35       12.1        17.8      16.1        10.3         9.51      7.47  26.7       46  
 4 CSP01    53       17.6        18.2      14.3         9.4         9.1       8.7   22.7       50.1
 5 CSP01    83       21.0        18.4      14.3         9.79        8.79      7.29  20.4       53.8
 6 CSP01   105       19.0        18.4      14.4        10.8         9.4       8.22  19.7       51.9
 7 CSP08    10       11.6        17.1      20.8        16.3         9.55      6.23  18.4       49.6
 8 CSP08    27       15.4        16.2      17.8        14.3        10.4       6.1   19.6       49.5
 9 CSP08    90       14.9        15.8      18.6        15.1        11.5       7.56  16.5       49.2
10 CSP02     5        8.75        8.64      8.66       12.0        18.3      15.2   28.5       26.0
# ℹ 104 more rows
```

Note: Column math is ***vectorized*** (i.e., row by row)

Tangent

Vectorizing

Tangent: Vectorized

Vectorized functions run in parallel across vectors

- Many functions in R are vectorized
- Makes them faster and easier

For example

```r
a <- c(1, 2, 3)
a + a
a * a
```

- But not all functions are vectorized

For example

```r
sum(a)
sum(a, a)
mean(a)
mean(c(a, a))
```

Back to `mutate()`...

Your turn: Creating new columns

- Add a calculation for **total** `silt`

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         ???)
```

Too Easy?

What happens if you add `total_sand` and `total_silt` together in the same `mutate()` function?

Your turn: Creating new columns

- Add a calculation for **total** `silt`

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)
```

Your turn: Creating new columns (Too Easy?)

- **What happens if you add `total_sand` and `total_silt` together in the same `mutate()`?**

```
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt,
         total = total_sand + total_silt)
```

- You get the sum!
- Lines within `mutate()` run sequentially
- You can create `total_sand` and `total_silt` in the first two lines then use them in the 3rd
- But you could not create `total_sand` and `total_silt` *after* using them

Your turn: Creating new columns

- Check your work

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)

select(size, contains("silt"))
```

```
# A tibble: 114 × 4
   coarse_silt medium_silt fine_silt total_silt
         <dbl>       <dbl>     <dbl>      <dbl>
 1       14.1        11.2       8.17       33.5
 2       14.1        11.7       9.03       34.8
 3       10.3         9.51      7.47       27.3
 4        9.4         9.1       8.7        27.2
 5        9.79        8.79      7.29       25.9
 6       10.8         9.4       8.22       28.4
 7       16.3         9.55      6.23       32.1
 8       14.3        10.4       6.1        30.8
 9       15.1        11.5       7.56       34.2
10       12.0        18.3      15.2        45.4
# i 104 more rows
```

Wait… that doesn't add up!

Tangent

Decimal points

Where are…

… the decimal points?

- `tibble` rounds values for easy viewing

```
# A tibble: 114 × 14
  plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay habitat
  <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl> <chr>
1 CSP01     4        13.0        17.4      19.7        14.1        11.2      8.17  16.3 forest
2 CSP01    12        10.7        16.9      19.2        14.1        11.7      9.03  18.4 forest
3 CSP01    35        12.1        17.8      16.1        10.3         9.51     7.47  26.7 forest
4 CSP01    53        17.6        18.2      14.3         9.4         9.1      8.7   22.7 forest
5 CSP01    83        21.0        18.4      14.3         9.79        8.79     7.29  20.4 forest
# i 109 more rows
# i 4 more variables: technician <chr>, date <date>, total_sand <dbl>, total_silt <dbl>
```

… my data?

```
# i 109 more rows
# i 5 more variables: technician <chr> ...
```

To see raw data

- Click on the name in the Environment pane
- Or use `as.data.frame()`

```r
as.data.frame(size)
```

```
    plot depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay   habitat
1  CSP01     4       13.04       17.37     19.71       14.12       11.25      8.17 16.30    forest
2  CSP01    12       10.74       16.90     19.15       14.13       11.68      9.03 18.40    forest
3  CSP01    35       12.11       17.75     16.14       10.33        9.51      7.47 26.70    forest
4  CSP01    53       17.61       18.16     14.32        9.40        9.10      8.70 22.70    forest
5  CSP01    83       21.05       18.38     14.34        9.79        8.79      7.29 20.40    forest
6  CSP01   105       19.02       18.43     14.44       10.79        9.40      8.22 19.70    forest
7  CSP08    10       11.60       17.14     20.81       16.30        9.55      6.23 18.40 grassland
8  CSP08    27       15.44       16.25     17.85       14.27       10.44      6.10 19.60 grassland
9  CSP08    90       14.88       15.79     18.57       15.13       11.54      7.56 16.50 grassland
10 CSP02     5        8.75        8.64      8.66       11.96       18.27     15.22 28.50    forest
11 CSP02    11        9.89        8.68      8.34       10.70       18.33     14.30 29.80    forest
12 CSP02    36        8.15        9.24      8.55       10.68       18.96     14.45 30.00    forest
13 CSP02    56       12.02        8.63      8.06       11.08       17.95     13.74 28.50    forest
14 CSP02    70       17.54       10.47      8.45       11.16       16.85     12.99 22.50    forest
15 CSP02    78       23.27       14.96     11.03        9.97       13.79     10.97 16.00    forest
16 CSP02   100       23.22       16.98      9.68       11.17       12.88     11.17 14.90    forest
17 CSP04     5        6.24        8.43     14.15       17.97       14.33     10.57 28.30    forest
18 CSP04    40        6.30        7.92     14.97       17.89       15.48     10.46 27.00    forest
19 CSP04    60        6.66        8.03     14.61       17.32       15.06     10.45 27.90    forest
20 CSP04    80        7.06        8.13     14.83       16.42       15.71     10.20 27.60    forest
21 CSP04   110       12.78        7.66     13.66       16.47       15.37     11.05 23.00    forest
22 CSP05     5       22.48       15.14     15.69       13.43       10.51      6.50 16.20 grassland
23 CSP05    13       13.81       14.24     17.95       16.05       11.83      6.99 19.10 grassland
24 CSP05    32       13.07       12.75     16.06       13.14       10.83      6.62 27.50 grassland
```

```
25  CSP05    52         11.88         12.42     14.37         12.15         11.75       8.13 29.30 grassland
26  CSP05    90         13.16         14.13     16.04         13.30         10.84       7.06 25.50 grassland
27  CSP09     8          9.42         12.20     15.17         18.03         14.17       7.62 23.40    forest
28  CSP09    15         10.05         11.51     13.93         16.70         13.24       8.71 26.90    forest
```

To see all rows

- Use `print()`

```r
print(size, n = Inf)
```

```
# A tibble: 114 × 14
    plot  depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  clay habitat
    <chr> <dbl>       <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl> <chr>  
  1 CSP01     4       13.0        17.4      19.7        14.1        11.2       8.17  16.3 forest 
  2 CSP01    12       10.7        16.9      19.2        14.1        11.7       9.03  18.4 forest 
  3 CSP01    35       12.1        17.8      16.1        10.3         9.51      7.47  26.7 forest 
  4 CSP01    53       17.6        18.2      14.3         9.4         9.1       8.7   22.7 forest 
  5 CSP01    83       21.0        18.4      14.3         9.79        8.79      7.29  20.4 forest 
  6 CSP01   105       19.0        18.4      14.4        10.8         9.4       8.22  19.7 forest 
  7 CSP08    10       11.6        17.1      20.8        16.3         9.55      6.23  18.4 grassland
  8 CSP08    27       15.4        16.2      17.8        14.3        10.4       6.1   19.6 grassland
  9 CSP08    90       14.9        15.8      18.6        15.1        11.5       7.56  16.5 grassland
 10 CSP02     5        8.75        8.64      8.66       12.0        18.3      15.2   28.5 forest 
 11 CSP02    11        9.89        8.68      8.34       10.7        18.3      14.3   29.8 forest 
 12 CSP02    36        8.15        9.24      8.55       10.7        19.0      14.4   30   forest 
 13 CSP02    56       12.0         8.63      8.06       11.1        18.0      13.7   28.5 forest 
 14 CSP02    70       17.5        10.5       8.45       11.2        16.8      13.0   22.5 forest 
 15 CSP02    78       23.3        15.0      11.0         9.97       13.8      11.0   16   forest 
 16 CSP02   100       23.2        17.0       9.68       11.2        12.9      11.2   14.9 forest 
 17 CSP04     5        6.24        8.43     14.2        18.0        14.3      10.6   28.3 forest 
 18 CSP04    40        6.3         7.92     15.0        17.9        15.5      10.5   27   forest 
 19 CSP04    60        6.66        8.03     14.6        17.3        15.1      10.4   27.9 forest 
 20 CSP04    80        7.06        8.13     14.8        16.4        15.7      10.2   27.6 forest 
 21 CSP04   110       12.8         7.66     13.7        16.5        15.4      11.0   23   forest 
 22 CSP05     5       22.5        15.1      15.7        13.4        10.5       6.5   16.2 grassland
 23 CSP05    13       13.8        14.2      18.0        16.0        11.8       6.99  19.1 grassland
 24 CSP05    32       13.1        12.8      16.1        13.1        10.8       6.62  27.5 grassland
```

```
25 CSP05    52        11.9         12.4      14.4         12.2         11.8       8.13  29.3 grassland
26 CSP05    90        13.2         14.1      16.0         13.3         10.8       7.06  25.5 grassland
```

Back to `mutate()`...

Mutating by group

group_by() and ungroup() are from dplyr*

```r
group_by(data, column1, column2)
ungroup(data)
```

- tidyverse functions always start with data
- group_by() applies grouping according to specified data columns
- ungroup() removes grouping from data

Mutating by group

`mutate()` without grouping

```
size <- size |>
  mutate(mean_sand_all = mean(total_sand))
```

```
# A tibble: 114 × 3
   plot  total_sand mean_sand_all
   <chr>      <dbl>         <dbl>
 1 CSP01       50.1          39.6
 2 CSP01       46.8          39.6
 3 CSP01       46            39.6
 4 CSP01       50.1          39.6
 5 CSP01       53.8          39.6
 6 CSP01       51.9          39.6
 7 CSP08       49.6          39.6
 8 CSP08       49.5          39.6
 9 CSP08       49.2          39.6
10 CSP02       26.0          39.6
# i 104 more rows
```

Overall mean calculated

Grouping via `group_by()`:

```
size <- size |>
  group_by(plot) |>
  mutate(mean_sand_plot = mean(total_sand)) |>
  ungroup()
```

```
# A tibble: 114 × 3
  plot  total_sand mean_sand_
  <chr>      <dbl>          <
1 CSP01       50.1          49.8
2 CSP01       46.8          49.8
3 CSP01       46            49.8
4 CSP01       50.1          49.8
5 CSP01       53.8          49.8
6 CSP01       51.9          49.8
7 CSP08       49.6          49.4
8 CSP08       49.5          49.4
# i 106 more rows
```

Always remember to **`ungroup()`** your data!

Mean calculated for each group (i.e. plot)

(really important)
OTHER PARTS
SOLD
SEPARATELY!
dplyr::
ungroup
DPLYR::
group_by

Your turn: Mutating by group

Add a column containing the **mean amount of total silt *per* plot**

```
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt) |>
  ??? |>
  ??? |>
  ???
```

Too Easy?

See `?mutate`

Can you do the same thing without using `group_by()`?

Your turn: Mutating by group

Add a column containing the **mean amount of total silt *per* plot**

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt) |>
  group_by(plot) |>
  mutate(mean_silt = mean(total_silt)) |>
  ungroup()
```

Too Easy? You could also use

`mutate(mean_silt = mean(total_silt), .by = "plot")`

```
# A tibble: 114 × 6
   plot  coarse_silt medium_silt fine_silt total_silt mean_silt
   <chr>       <dbl>       <dbl>     <dbl>      <dbl>     <dbl>
 1 CSP01       14.1        11.2       8.17       33.5      29.5
 2 CSP01       14.1        11.7       9.03       34.8      29.5
 3 CSP01       10.3         9.51      7.47       27.3      29.5
 4 CSP01        9.4         9.1       8.7        27.2      29.5
 5 CSP01        9.79        8.79      7.29       25.9      29.5
 6 CSP01       10.8         9.4       8.22       28.4      29.5
 7 CSP08       16.3         9.55      6.23       32.1      32.4
 8 CSP08       14.3        10.4       6.1        30.8      32.4
 9 CSP08       15.1        11.5       7.56       34.2      32.4
10 CSP02       12.0        18.3      15.2        45.4      40.9
# ℹ 104 more rows
```

Put it all together

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt) |>
  group_by(plot) |>
  mutate(mean_sand = mean(total_sand),
         mean_silt = mean(total_silt)) |>
  ungroup()
```

Check it out

```r
select(size, plot, depth, total_sand, total_silt, mean_sand, mean_silt)
```

```
# A tibble: 114 × 6
   plot  depth total_sand total_silt mean_sand mean_silt
   <chr> <dbl>      <dbl>      <dbl>     <dbl>     <dbl>
 1 CSP01     4       50.1       33.5      49.8      29.5
 2 CSP01    12       46.8       34.8      49.8      29.5
 3 CSP01    35       46         27.3      49.8      29.5
 4 CSP01    53       50.1       27.2      49.8      29.5
 5 CSP01    83       53.8       25.9      49.8      29.5
 6 CSP01   105       51.9       28.4      49.8      29.5
 7 CSP08    10       49.6       32.1      49.4      32.4
 8 CSP08    27       49.5       30.8      49.4      32.4
 9 CSP08    90       49.2       34.2      49.4      32.4
10 CSP02     5       26.0       45.4      34.7      40.9
# ℹ 104 more rows
```

Summarizing

Summarizing by group

`summarize()` is from `dplyr`*

```
summarize(data, column1 = expression1, column2 = expression2)
```

- `tidyverse` functions always start with `data`
- `summarize()` collapses `data`
- Creates new `columns`
- Columns filled according to `expression`

Summarizing by group

- Similar to `mutate()`, but **collapses** rows whereas `mutate()` repeats data

`mutate()`

```r
size <- size |>
  group_by(plot) |>
  mutate(mean_sand = mean(total_sand)) |>
  ungroup()

select(size, plot, contains("sand"))
```

```
# A tibble: 114 × 6
   plot  coarse_sand medium_sand fine_sand total_sand mean_sand
   <chr>       <dbl>       <dbl>     <dbl>      <dbl>     <dbl>
 1 CSP01       13.0        17.4      19.7        50.1      49.8
 2 CSP01       10.7        16.9      19.2        46.8      49.8
 3 CSP01       12.1        17.8      16.1        46        49.8
 4 CSP01       17.6        18.2      14.3        50.1      49.8
 5 CSP01       21.0        18.4      14.3        53.8      49.8
 6 CSP01       19.0        18.4      14.4        51.9      49.8
 7 CSP08       11.6        17.1      20.8        49.6      49.4
 8 CSP08       15.4        16.2      17.8        49.5      49.4
 9 CSP08       14.9        15.8      18.6        49.2      49.4
10 CSP02        8.75        8.64      8.66       26.0      34.7
# i 104 more rows
```

Repeated values

Summarizing by group

- Similar to `mutate()`, but **collapses** rows whereas `mutate()` repeats data

`summarize()`

```
size <- size |>
  group_by(plot) |>
  summarize(mean_sand = mean(total_sand), .groups = "drop")

size
```

```
# A tibble: 27 × 2
   plot   mean_sand
   <chr>      <dbl>
 1 CSP01       49.8
 2 CSP02       34.7
 3 CSP03       29.9
 4 CSP04       30.3
 5 CSP05       44.6
 6 CSP06       37.8
 7 CSP07       36.6
 8 CSP08       49.4
 9 CSP09       37.9
10 CSP10       34.6
# i 17 more rows
```

Note:
We use `.groups = "drop"` to ungroup and avoid messages
You could also just use `ungroup()`

No repeated values **and** drops unused columns

Summarizing by group

- Keep other id columns by adding them to `group_by()`
- Beware: think carefully about grouping variables!

```r
size |>
  group_by(plot, depth) |>
  summarize(mean_sand = mean(total_sand), .groups = "drop")
```

```
# A tibble: 114 × 3
   plot  depth mean_sand
   <chr> <dbl>     <dbl>
 1 CSP01     4      50.1
 2 CSP01    12      46.8
 3 CSP01    35      46  
 4 CSP01    53      50.1
 5 CSP01    83      53.8
 6 CSP01   105      51.9
 7 CSP02     5      26.0
 8 CSP02    11      26.9
 9 CSP02    36      25.9
10 CSP02    56      28.7
# ℹ 104 more rows
```

`depth` is not a category, therefore not an appropriate grouping factor

Summarizing by group

- Use true groups of interest (e.g., Sex, Age)
- Or use factors which are on the same level (e.g., ID columns)

```r
size |>
  group_by(plot, habitat) |>
  summarize(mean_sand = mean(total_sand), .groups = "drop")
```

```
# A tibble: 27 × 3
   plot  habitat   mean_sand
   <chr> <chr>         <dbl>
 1 CSP01 forest         49.8
 2 CSP02 forest         34.7
 3 CSP03 clearcut       29.9
 4 CSP04 forest         30.3
 5 CSP05 grassland      44.6
 6 CSP06 grassland      37.8
 7 CSP07 grassland      36.6
 8 CSP08 grassland      49.4
 9 CSP09 forest         37.9
10 CSP10 grassland      34.6
# i 17 more rows
```

Better: `habitat` varies with `plot` (alternatively could have Joined later)

Summarizing by group

Summarizing is an excellent way to calculate statistics to describe your data

Statistic	Function(s)
sample sizes / total counts	`n()`*
means	`mean(x)`
standard deviations	`sd(x)`
standard errors	`sd(x)` / `sqrt(n())`**
total values	`sum(x)`

Where `x` is the column you want to calculate a summary statistic for
And no, `n()` is not missing an `x` 😉

Summarizing by group

`n()` is from `dplyr`*

```
n()
```

- *Helper* `tidyverse` function which **does NOT** start with data
- Returns row counts according to groups (if present)
- Can only be used *inside* `mutate()` or `summarize()`

For example…

```
size |>
  group_by(plot) |>
  summarize(samples_total = n(),
            .groups = "drop")
```

```
# A tibble: 27 × 2
  plot  samples_total
  <chr>         <int>
1 CSP01             6
2 CSP02             7
3 CSP03             4
4 CSP04             5
5 CSP05             5
6 CSP06             5
7 CSP07             3
8 CSP08             3
# ℹ 19 more rows
```

Your Turn: Calculate summary statistics

For each plot and habitat, calculate

- means for **total_silt** with `mean(x)`
- standard deviations for **total_silt** with `sd(x)`
- standard errors for **total_sand** and **total_silt** with `sd(x)/sqrt(n())`

```
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)

size_sum <- size |>
  group_by(plot, habitat) |>
  summarize(sample_size = n(),
            mean_sand = mean(total_sand),
            sd_sand = sd(total_sand),
            se_sand = ???,
            ???)
```

Too Easy?

Can you recycle some of the calculated values into the next statistic?

Challenging

What if you only wanted to calculate the mean of each column…

Your Turn: Calculate summary statistics

For each plot and habitat, calculate

- sample sizes with `n()`
- means for **total_sand** and **total_silt** with `mean(x)`
- standard deviations for **total_sand** and **total_silt** with `sd(x)`
- standard errors for **total_sand** and **total_silt** with `sd(x)/sqrt(n(x))`

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)

size_sum <- size |>
  group_by(plot, habitat) |>
  summarize(sample_size = n(),
            mean_sand = mean(total_sand),
            sd_sand = sd(total_sand),
            se_sand = sd_sand / sqrt(sample_size),
            mean_silt = mean(total_silt),
            sd_silt = sd(total_silt),
            se_silt = sd_silt / sqrt(sample_size))
```

Your Turn: Calculate summary statistics

Check your work

```r
size_sum
```

```
# A tibble: 27 × 9
# Groups:   plot [27]
   plot  habitat   sample_size mean_sand sd_sand se_sand mean_silt sd_silt se_silt
   <chr> <chr>           <int>     <dbl>   <dbl>   <dbl>     <dbl>   <dbl>   <dbl>
 1 CSP01 forest              6      49.8   2.96    1.21       29.5   3.72    1.52 
 2 CSP02 forest              7      34.7  10.8     4.06       40.9   4.29    1.62 
 3 CSP03 clearcut            4      29.9   4.89    2.45       43.6   3.25    1.63 
 4 CSP04 forest              5      30.3   2.18    0.973      43.0   0.544   0.243
 5 CSP05 grassland           5      44.6   5.52    2.47       31.8   1.81    0.811
 6 CSP06 grassland           5      37.8   4.10    1.83       48.1   3.32    1.49 
 7 CSP07 grassland           3      36.6   7.30    4.21       39.8   1.05    0.609
 8 CSP08 grassland           3      49.4   0.176   0.102      32.4   1.73    0.998
 9 CSP09 forest              5      37.9   2.98    1.33       38.4   1.17    0.524
10 CSP10 grassland           3      34.6   9.71    5.61       44.1   5.41    3.13 
# i 17 more rows
```

Transposing

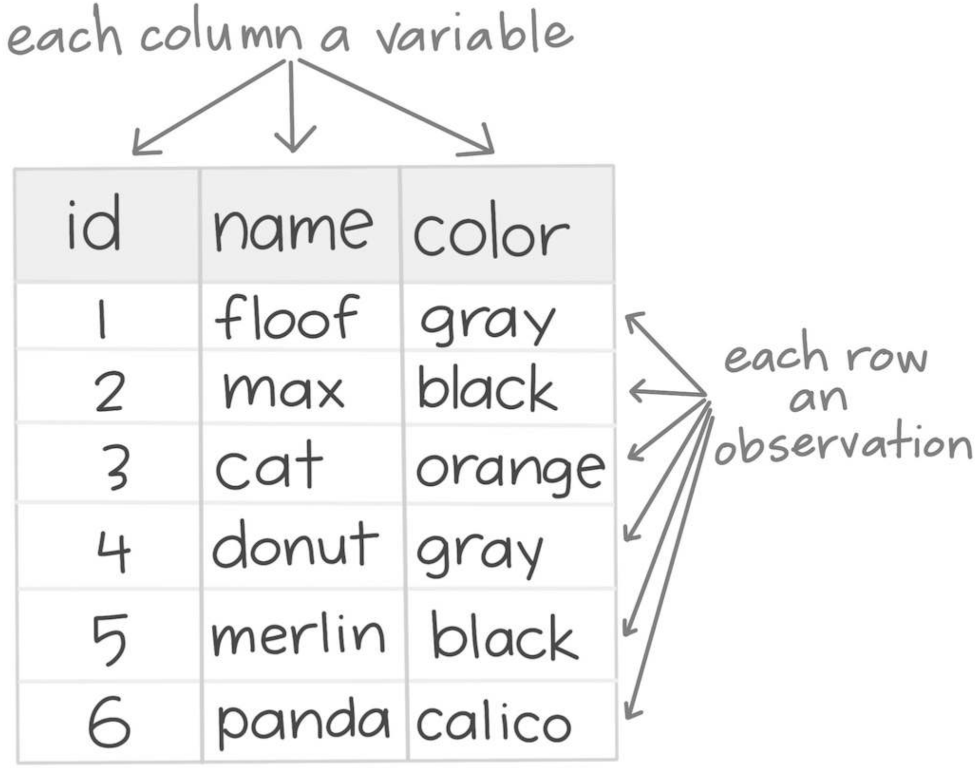
Let’s talk about tidy data

Upcoming illustrations from the Openscapes blog *Tidy Data for reproducibility, efficiency, and collaboration*
by Julia Lowndes and Allison Horst

> "TIDY DATA is a standard way of mapping the meaning of a dataset to its structure."
>
> —HADLEY WICKHAM

In tidy data:

- each variable forms a column
- each observation forms a row
- each cell is a single measurement



id	name	color
1	floof	gray
2	max	black
3	cat	orange
4	donut	gray
5	merlin	black
6	panda	calico

Wickham, H. (2014). Tidy Data. Journal of Statistical Software 59 (10). DOI: 10.18637/jss.v059.i10

Tidy Data

id	name	colour	age	mass (lb)
1	floof	grey	10	7
1	floof	grey	12	7.5
2	max	black	1	5
2	max	black	2	6
3	cat	orange	5	10
3	cat	orange	7	12

Long data
One measurement per row

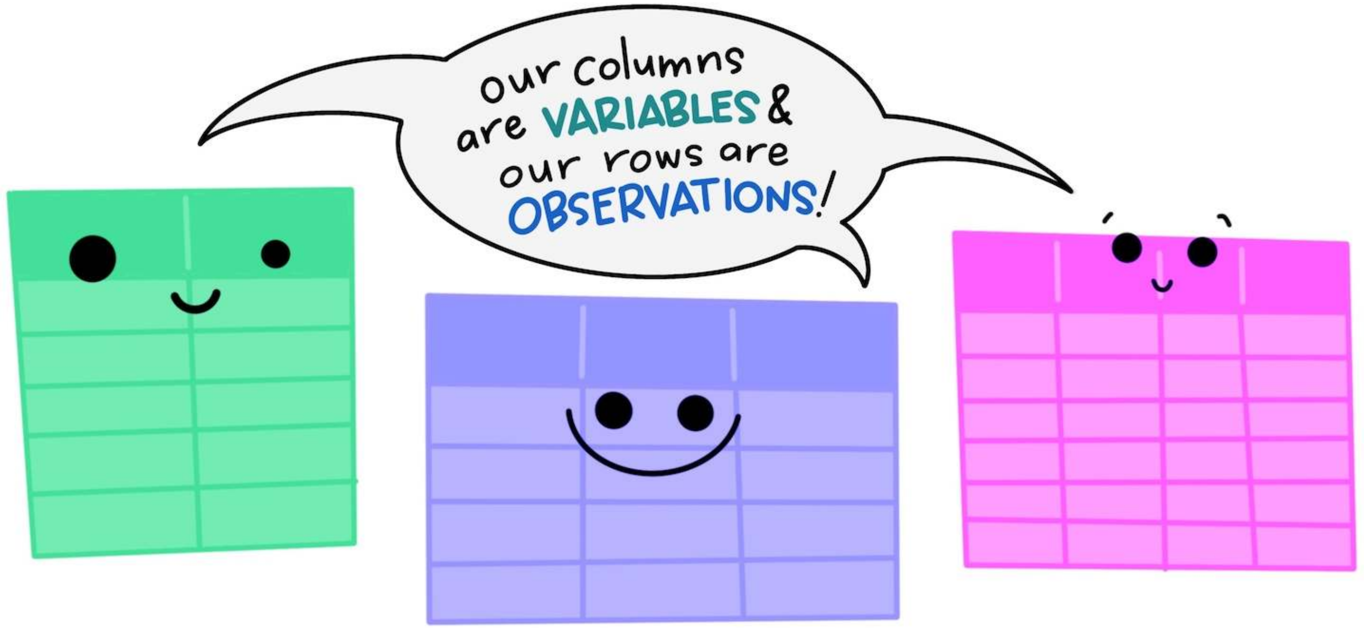
Un-tidy

id	name	colour	age1	mass1	age2	mass2
1	floof	grey	10	7	12	7.5
2	max	black	1	5	2	6
3	cat	orange	5	10	7	12

Wide data
Several measurements

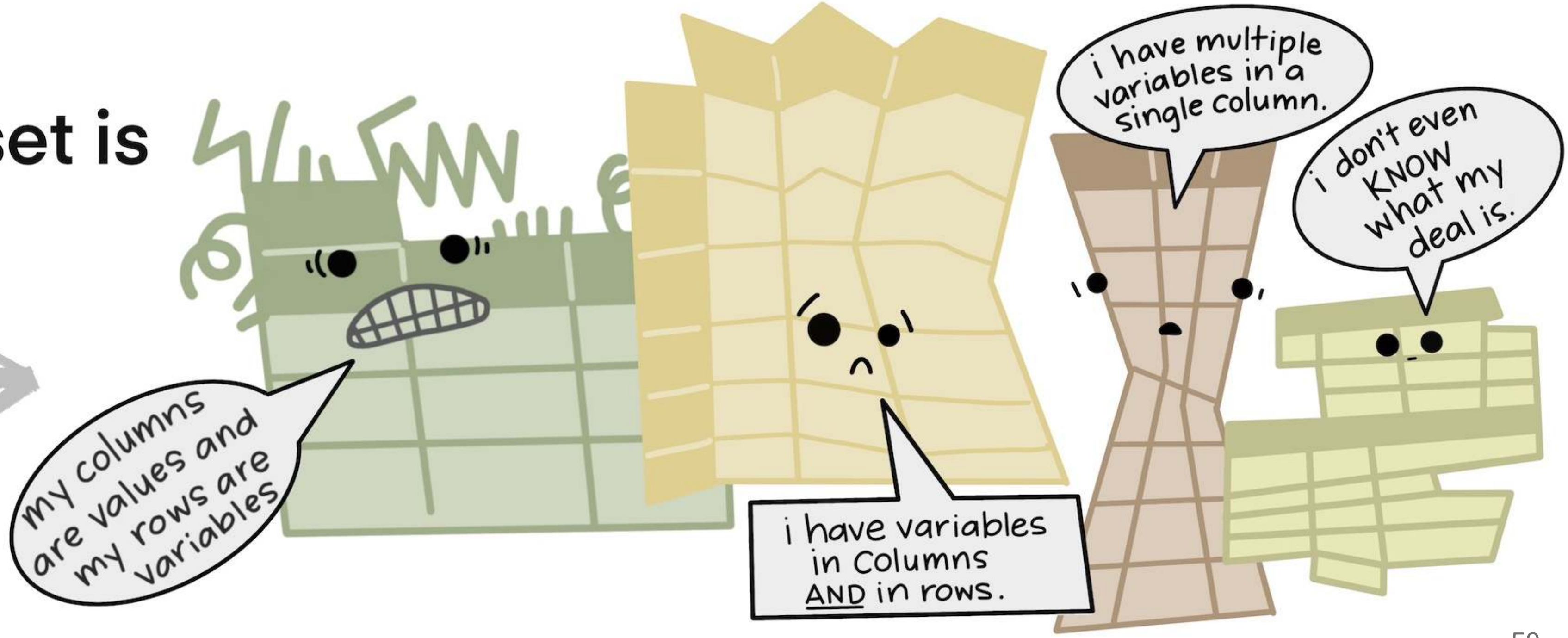
per row

The standard structure of tidy data means that "tidy datasets are all alike…"

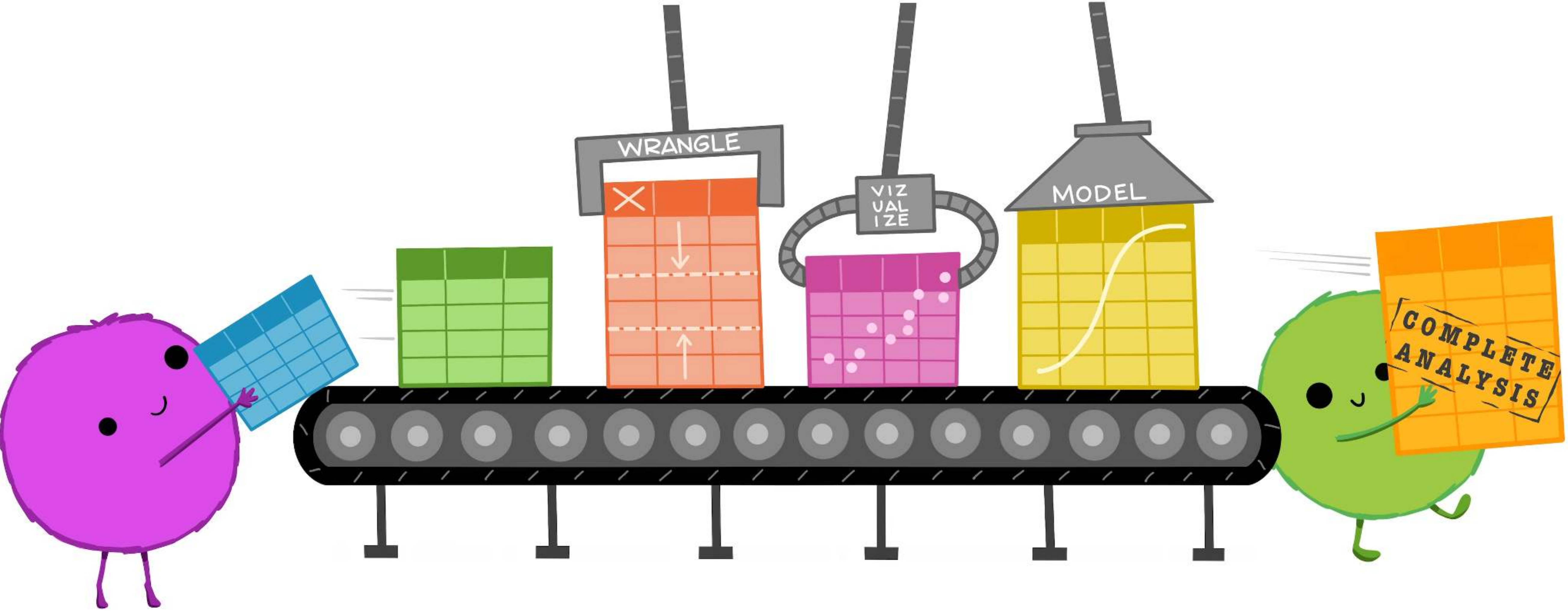


"…but every messy dataset is messy in its own way."

—HADLEY WICKHAM


my columns are values and my rows are variables
i have variables in columns AND in rows.
i have multiple variables in a single column.
i don't even KNOW what my deal is.

Why do we care?



Why do we care?

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

Tuberculosis cases per year per country

How would you plot this untidy data as the number of cases by country for each year?

```r
ggplot(data = table4a, aes(x = ???, y = ???)) +
  ???
```

Note

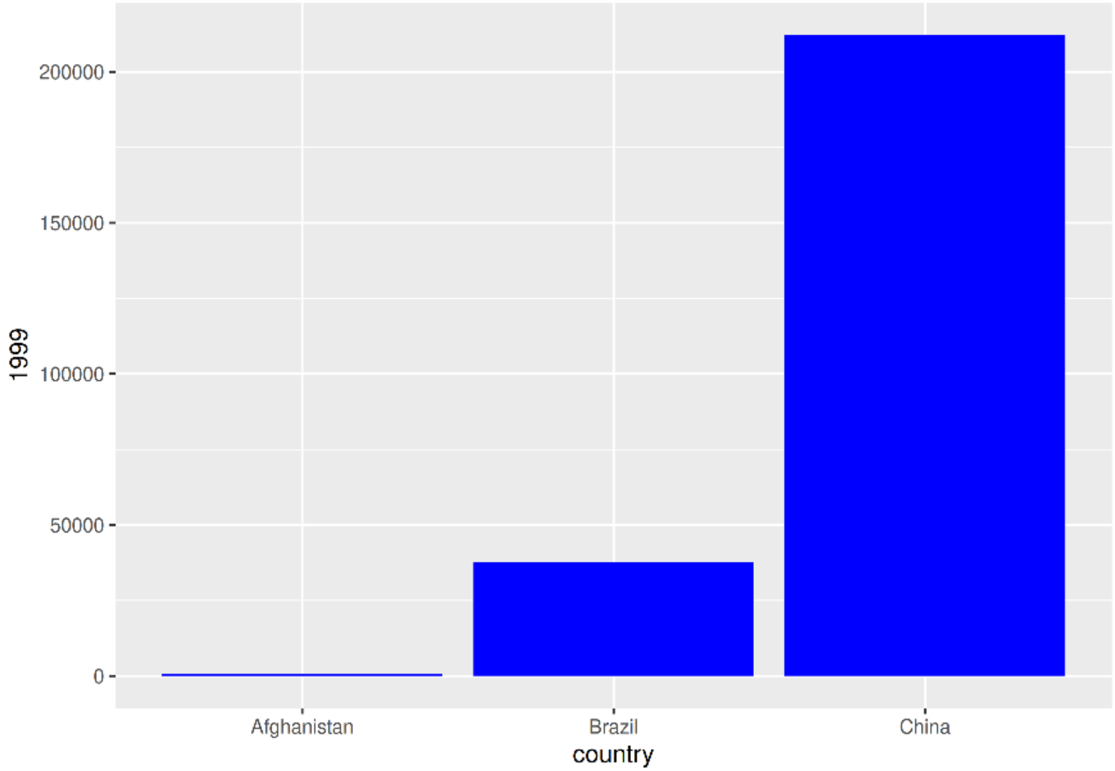
- `table4a` is a built-in data frame
- Type `table4a` in the console to take a look
- Type `?table4a` to pull up the help file with information

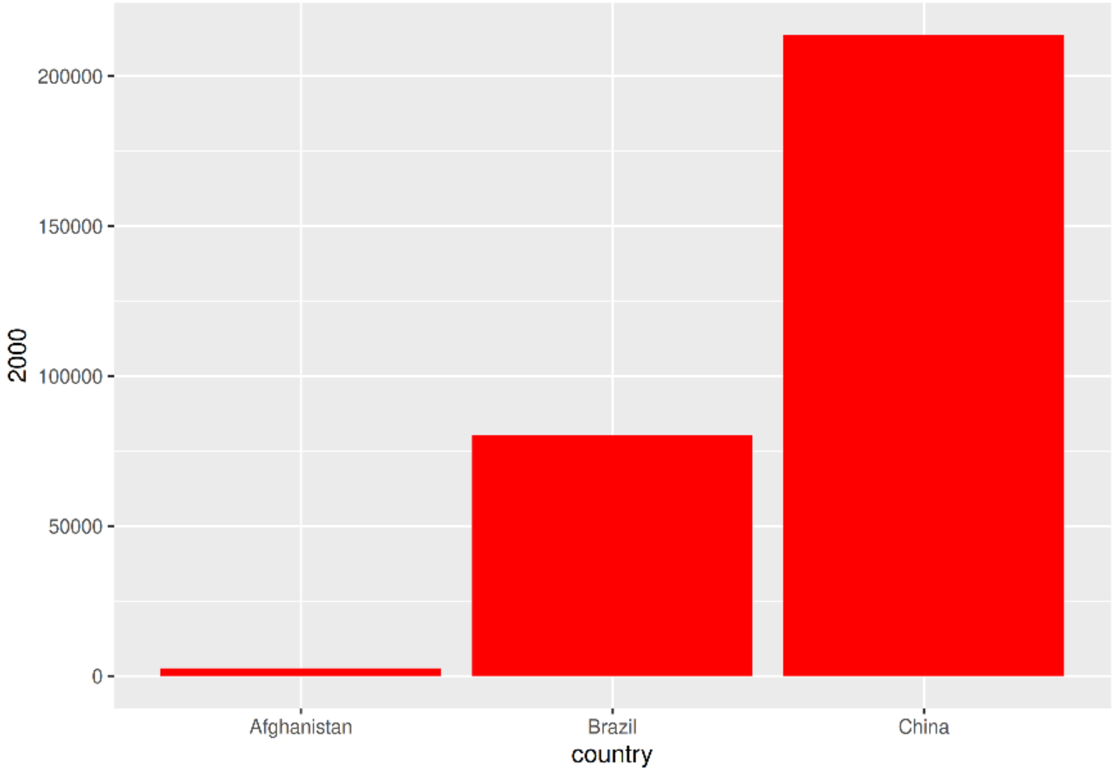
Why do we care?

With un-tidy data

```r
ggplot(data = table4a, aes(x = country, y = `1999`)) +
  geom_bar(stat = "identity", fill = "blue")
```

```r
ggplot(data = table4a, aes(x = country, y = `2000`)) +
  geom_bar(stat = "identity", fill = "red")
```





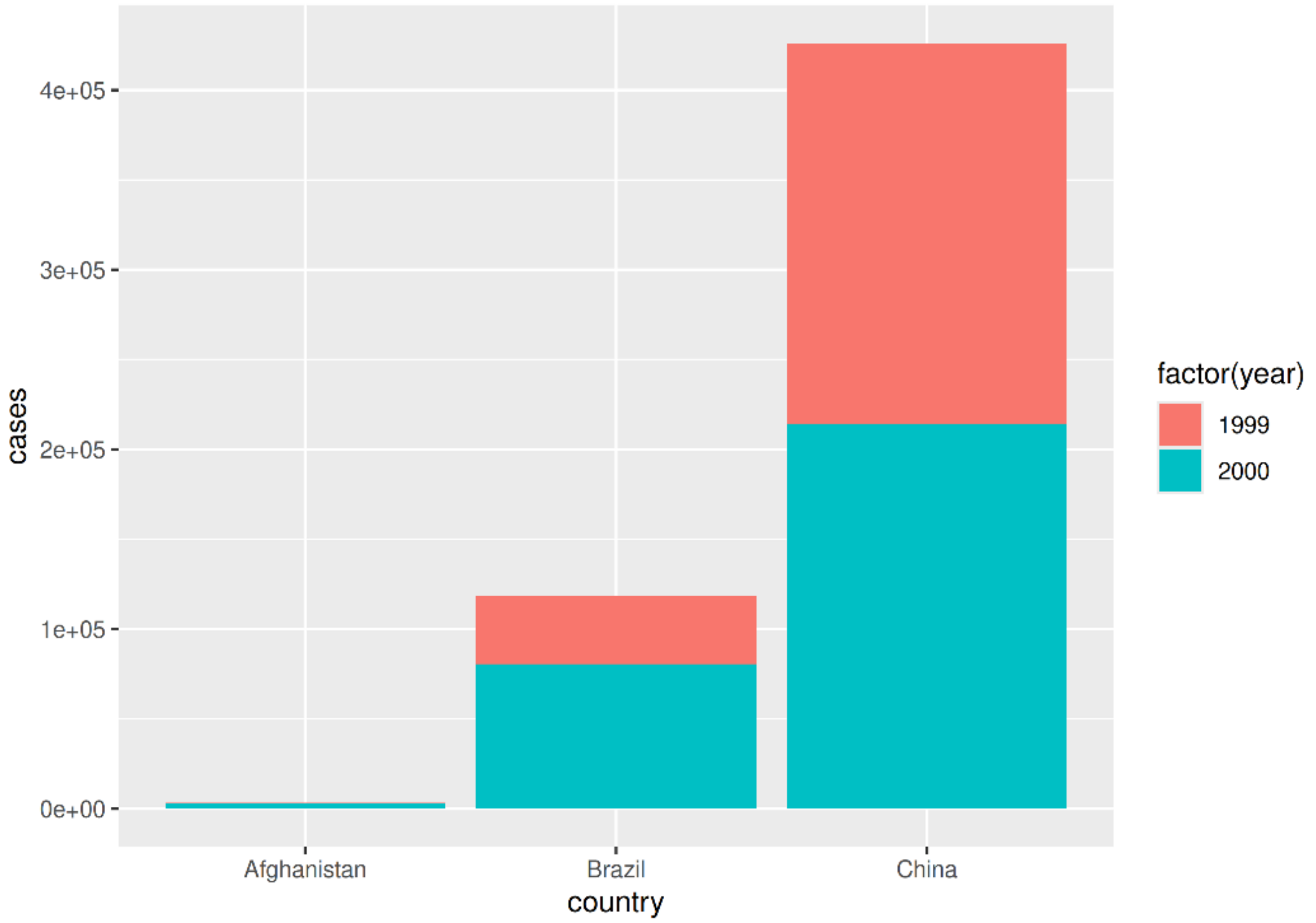
We have to plot it twice!

Why do we care?

With tidy data

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

```r
ggplot(data = table1, aes(x = country, y = cases, fill = factor(year))) +
  geom_bar(stat = "identity")
```

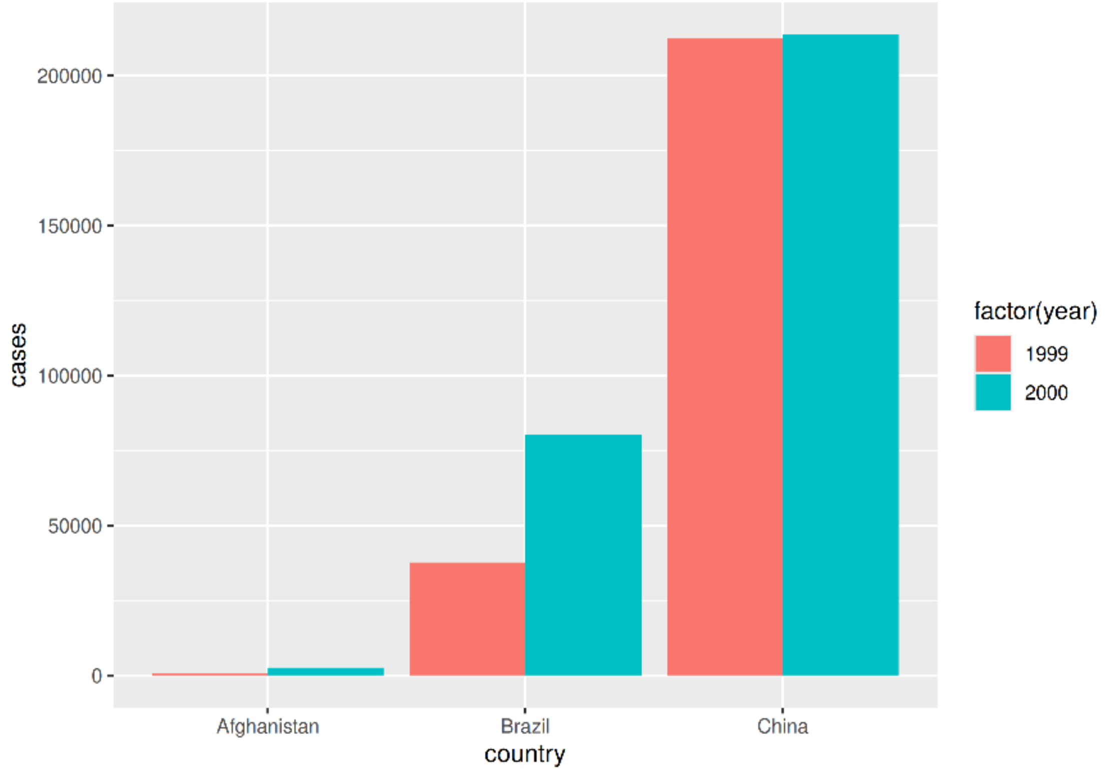


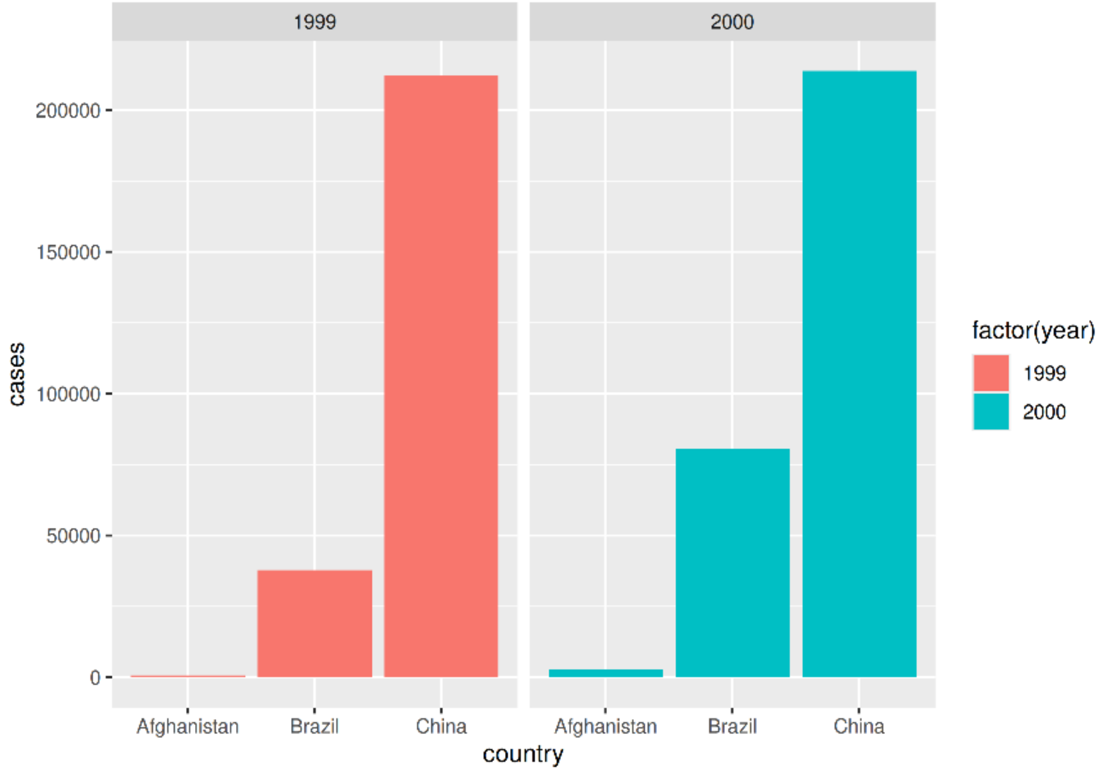
Why do we care?

With tidy data

```r
ggplot(data = table1,
       aes(x = country, y = cases, fill = factor(year))) +
  geom_bar(stat = "identity", position = "dodge")
```

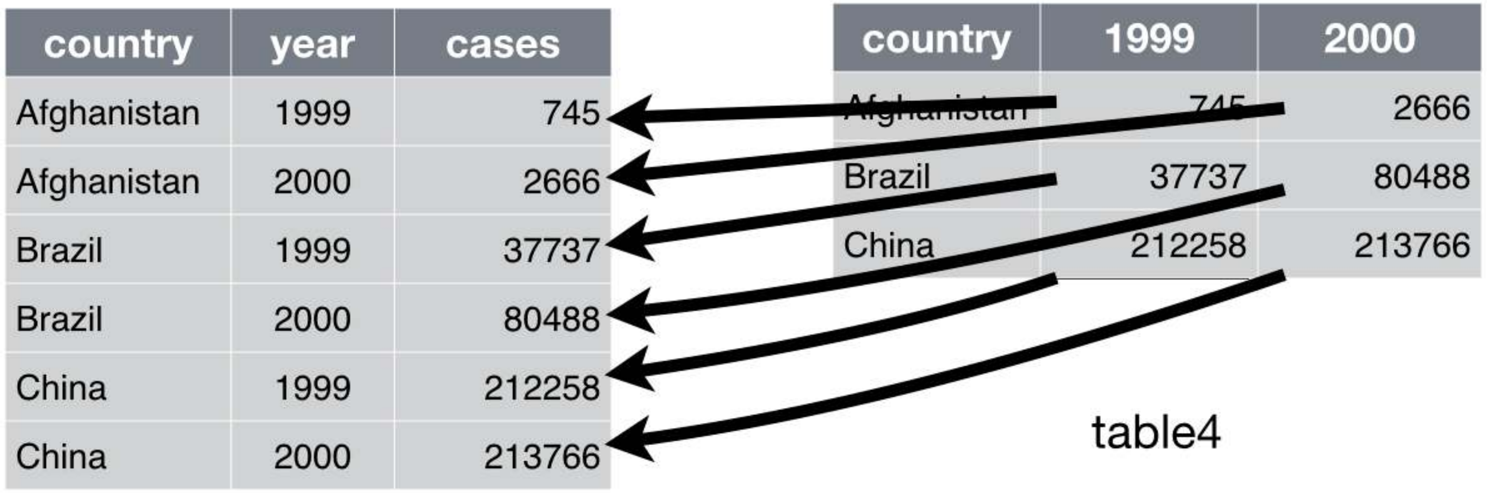
```r
ggplot(data = table1,
       aes(x = country, y = cases, fill = factor(year))) +
  geom_bar(stat = "identity") + facet_wrap(~year)
```





Going long

`pivot_longer()`



country	year	cases
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

table4

Going long

From wide …

```
# A tibble: 114 × 6
   plot  depth coarse_silt medium_silt fine_silt total_silt
   <chr> <dbl>       <dbl>       <dbl>     <dbl>      <dbl>
 1 CSP01     4       14.1        11.2       8.17       33.5
 2 CSP01    12       14.1        11.7       9.03       34.8
 3 CSP01    35       10.3         9.51      7.47       27.3
 4 CSP01    53        9.4         9.1       8.7        27.2
 5 CSP01    83        9.79        8.79      7.29       25.9
 6 CSP01   105       10.8         9.4       8.22       28.4
 7 CSP08    10       16.3         9.55      6.23       32.1
 8 CSP08    27       14.3        10.4       6.1        30.8
 9 CSP08    90       15.1        11.5       7.56       34.2
10 CSP02     5       12.0        18.3      15.2        45.4
11 CSP02    11       10.7        18.3      14.3        43.3
12 CSP02    36       10.7        19.0      14.4        44.1
13 CSP02    56       11.1        18.0      13.7        42.8
14 CSP02    70       11.2        16.8      13.0        41  
15 CSP02    78        9.97       13.8      11.0        34.7
# i 99 more rows
```

… to long

```
# A tibble: 456 × 4
   plot  depth type        amount
   <chr> <dbl> <chr>        <dbl>
 1 CSP01     4 coarse_silt  14.1 
 2 CSP01     4 medium_silt  11.2 
 3 CSP01     4 fine_silt     8.17
 4 CSP01     4 total_silt   33.5 
 5 CSP01    12 coarse_silt  14.1 
 6 CSP01    12 medium_silt  11.7 
 7 CSP01    12 fine_silt     9.03
 8 CSP01    12 total_silt   34.8 
 9 CSP01    35 coarse_silt  10.3 
10 CSP01    35 medium_silt   9.51
11 CSP01    35 fine_silt     7.47
12 CSP01    35 total_silt   27.3 
13 CSP01    53 coarse_silt   9.4 
14 CSP01    53 medium_silt   9.1 
15 CSP01    53 fine_silt     8.7 
16 CSP01    53 total_silt   27.2 
17 CSP01    83 coarse_silt   9.79
18 CSP01    83 medium_silt   8.79
19 CSP01    83 fine_silt     7.29
20 CSP01    83 total_silt   25.9 
# i 436 more rows
```

Going long

pivot_longer() is from tidyr*

```r
pivot_longer(data, cols = c(column1, column2),
             names_to = "new_categorical_column",
             values_to = "new_numerical_column")
```

- tidyverse functions always start with data
- Takes columns and converts to long data
- Column names (column1 and column2) go into “new_categorical_column”
- Column values (*contents* of column1 and column2) go into “new_numerical_column”

Going long

pivot_longer() is from tidyr*

```
pivot_longer(data, cols = c(column1, column2),
             names_to = "new_categorical_column",
             values_to = "new_numerical_column")
```

In our example:

- **data** = `size`
- **cols** = `c(-plot, -depth, -habitat, -technician, -date)`
  - Here, easiest to exclude columns
- **names_to** = `"type"`
- **values_to** = `"amount"`

Going long

```
size_long <- pivot_longer(size, cols = c(-plot, -depth, -habitat, -technician, -date),
                          names_to = "type", values_to = "amount")
```

```
# A tibble: 1,026 × 7
   plot  depth habitat technician date       type        amount
   <chr> <dbl> <chr>   <chr>      <date>     <chr>        <dbl>
 1 CSP01     4 forest  Catharine  2009-04-23 coarse_sand  13.0
 2 CSP01     4 forest  Catharine  2009-04-23 medium_sand  17.4
 3 CSP01     4 forest  Catharine  2009-04-23 fine_sand    19.7
 4 CSP01     4 forest  Catharine  2009-04-23 coarse_silt  14.1
 5 CSP01     4 forest  Catharine  2009-04-23 medium_silt  11.2
 6 CSP01     4 forest  Catharine  2009-04-23 fine_silt     8.17
 7 CSP01     4 forest  Catharine  2009-04-23 clay         16.3
 8 CSP01     4 forest  Catharine  2009-04-23 total_sand   50.1
 9 CSP01     4 forest  Catharine  2009-04-23 total_silt   33.5
10 CSP01    12 forest  Catharine  2009-04-23 coarse_sand  10.7
11 CSP01    12 forest  Catharine  2009-04-23 medium_sand  16.9
12 CSP01    12 forest  Catharine  2009-04-23 fine_sand    19.2
# ℹ 1,014 more rows
```

Your turn: Lengthen data

- We’ll first create a summary dataset for sand variables

```r
sand_sum <- read_csv("data/grain_size2.csv") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand) |>
  group_by(plot) |>
  summarize(sample_size = n(),
            mean_sand = mean(total_sand),
            sd_sand = sd(total_sand),
            se_sand = sd_sand / sqrt(sample_size))

sand_sum
```

```
# A tibble: 27 × 5
   plot  sample_size mean_sand sd_sand se_sand
   <chr>       <int>     <dbl>   <dbl>   <dbl>
 1 CSP01           6      49.8   2.96    1.21 
 2 CSP02           7      34.7  10.8     4.06 
 3 CSP03           4      29.9   4.89    2.45 
 4 CSP04           5      30.3   2.18    0.973
 5 CSP05           5      44.6   5.52    2.47 
 6 CSP06           5      37.8   4.10    1.83 
 7 CSP07           3      36.6   7.30    4.21 
 8 CSP08           3      49.4   0.176   0.102
 9 CSP09           5      37.9   2.98    1.33 
10 CSP10           3      34.6   9.71    5.61 
# i 17 more rows
```

Your turn: Lengthen data

- Gather all variables except `plot` and `sample_size` into a long format

```r
sand_long <- pivot_longer(sand_sum,
                          cols = ???,
                          names_to = ???,
                          values_to = ???)
```

Your turn: Lengthen data

- Gather all variables except `plot` and `sample_size` into a long format

```r
sand_long <- pivot_longer(sand_sum,
                          cols = contains("sand"),
                          names_to = "type",
                          values_to = "amount")
```

```
# A tibble: 81 × 4
   plot  sample_size type      amount
   <chr>       <int> <chr>      <dbl>
 1 CSP01           6 mean_sand 49.8
 2 CSP01           6 sd_sand    2.96
 3 CSP01           6 se_sand    1.21
 4 CSP02           7 mean_sand 34.7
 5 CSP02           7 sd_sand   10.8
 6 CSP02           7 se_sand    4.06
 7 CSP03           4 mean_sand 29.9
 8 CSP03           4 sd_sand    4.89
 9 CSP03           4 se_sand    2.45
10 CSP04           5 mean_sand 30.3
11 CSP04           5 sd_sand    2.18
12 CSP04           5 se_sand    0.973
13 CSP05           5 mean_sand 44.6
14 CSP05           5 sd_sand    5.52
15 CSP05           5 se_sand    2.47
# ℹ 66 more rows
```

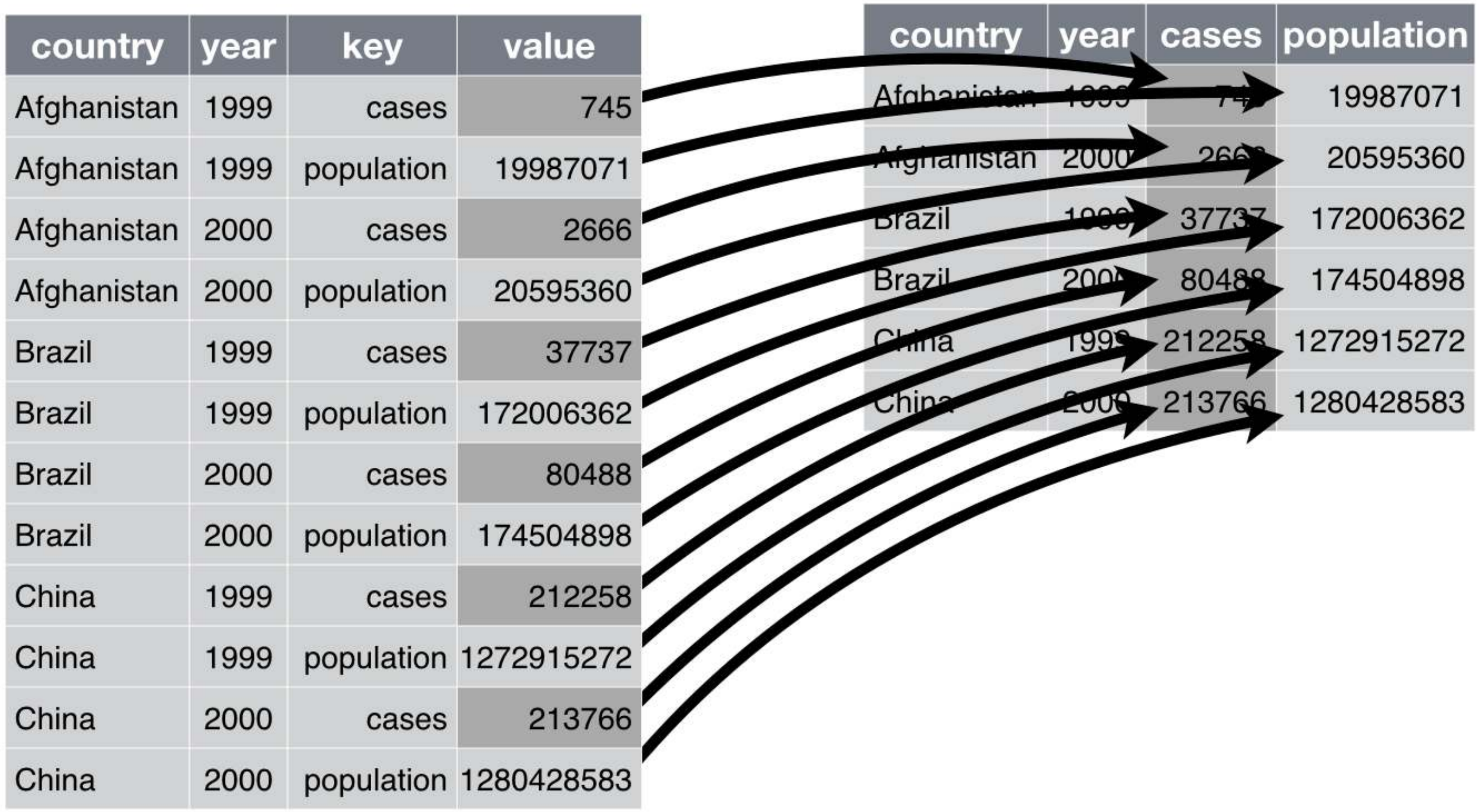
Remember tidy selectors!

Could also use…

- `cols = ends_with("sand")`
- `cols = c(mean_sand, sd_sand, se_sand)`
- `cols = c(-plot, -sample_size)`

Going wide

`pivot_wider()`



country	year	key	value
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898
China	1999	cases	212258
China	1999	population	1272915272
China	2000	cases	213766
China	2000	population	1280428583

table2

country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

Going wide

From long …

```
# A tibble: 456 × 4
   plot  depth type         amount
   <chr> <dbl> <chr>         <dbl>
 1 CSP01     4 coarse_silt  14.1
 2 CSP01     4 medium_silt  11.2
 3 CSP01     4 fine_silt     8.17
 4 CSP01     4 total_silt   33.5
 5 CSP01    12 coarse_silt  14.1
 6 CSP01    12 medium_silt  11.7
 7 CSP01    12 fine_silt     9.03
 8 CSP01    12 total_silt   34.8
 9 CSP01    35 coarse_silt  10.3
10 CSP01    35 medium_silt   9.51
11 CSP01    35 fine_silt     7.47
12 CSP01    35 total_silt   27.3
13 CSP01    53 coarse_silt   9.4
14 CSP01    53 medium_silt   9.1
15 CSP01    53 fine_silt     8.7
16 CSP01    53 total_silt   27.2
17 CSP01    83 coarse_silt   9.79
18 CSP01    83 medium_silt   8.79
19 CSP01    83 fine_silt     7.29
20 CSP01    83 total_silt   25.9
# i 436 more rows
```

… to wide

```
# A tibble: 114 × 6
   plot  depth coarse_silt medium_silt fine_silt total_silt
   <chr> <dbl>       <dbl>       <dbl>     <dbl>      <dbl>
 1 CSP01     4        14.1        11.2        8.17       33.5
 2 CSP01    12        14.1        11.7        9.03       34.8
 3 CSP01    35        10.3         9.51       7.47       27.3
 4 CSP01    53         9.4         9.1        8.7        27.2
 5 CSP01    83         9.79        8.79       7.29       25.9
 6 CSP01   105        10.8         9.4        8.22       28.4
 7 CSP08    10        16.3         9.55       6.23       32.1
 8 CSP08    27        14.3        10.4        6.1        30.8
 9 CSP08    90        15.1        11.5        7.56       34.2
10 CSP02     5        12.0        18.3       15.2        45.4
11 CSP02    11        10.7        18.3       14.3        43.3
12 CSP02    36        10.7        19.0       14.4        44.1
13 CSP02    56        11.1        18.0       13.7        42.8
14 CSP02    70        11.2        16.8       13.0        41
15 CSP02    78         9.97       13.8       11.0        34.7
# i 99 more rows
```

Going wide

pivot_wider() is from tidyr*

```r
pivot_wider(data,
            names_from = existing_categorical_column,
            values_from = existing_numerical_column)
```

- tidyverse functions always start with data
- Takes columns and converts to wide data
- Values in existing_categorical_column become column names
- Values in existing_numerical_column become column contents

In our example:

- **data** = size_long
- **names_from** = type
- **values_from** = amount

Going wide

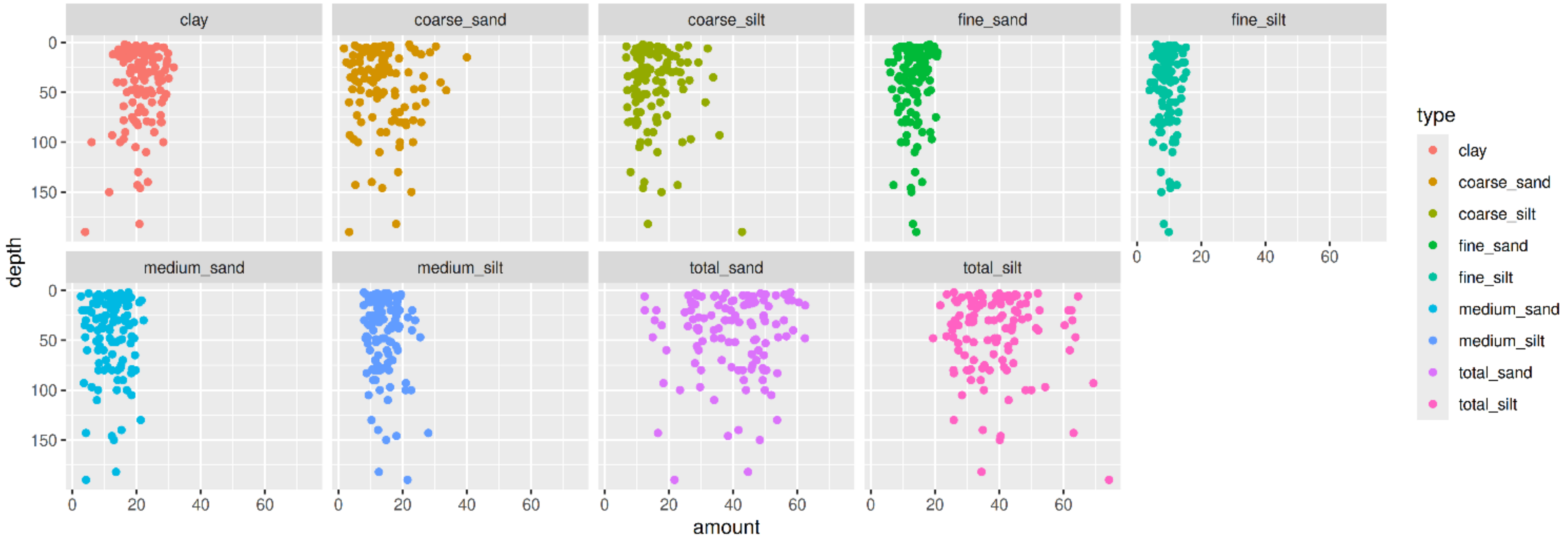
```r
size_wide <- pivot_wider(size_long, names_from = type, values_from = amount)
```

```
# A tibble: 114 × 14
   plot  depth habitat   technician date       coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt  cla
   <chr> <dbl> <chr>     <chr>      <date>           <dbl>       <dbl>     <dbl>       <dbl>       <dbl>     <dbl> <dbl
 1 CSP01     4 forest    Catharine  2009-04-23       13.0        17.4      19.7        14.1        11.2       8.17  16.
 2 CSP01    12 forest    Catharine  2009-04-23       10.7        16.9      19.2        14.1        11.7       9.03  18.
 3 CSP01    35 forest    Catharine  2009-04-23       12.1        17.8      16.1        10.3         9.51      7.47  26.
 4 CSP01    53 forest    Catharine  2009-04-23       17.6        18.2      14.3         9.4         9.1       8.7   22.
 5 CSP01    83 forest    Catharine  2009-04-23       21.0        18.4      14.3         9.79        8.79      7.29  20.
 6 CSP01   105 forest    Catharine  2009-04-23       19.0        18.4      14.4        10.8         9.4       8.22  19.
 7 CSP08    10 grassland Catharine  2009-03-02       11.6        17.1      20.8        16.3         9.55      6.23  18.
 8 CSP08    27 grassland Catharine  2009-03-02       15.4        16.2      17.8        14.3        10.4       6.1   19.
 9 CSP08    90 grassland Catharine  2009-03-02       14.9        15.8      18.6        15.1        11.5       7.56  16.
10 CSP02     5 forest    Catharine  2009-05-06        8.75        8.64      8.66       12.0        18.3      15.2   28.
# ℹ 104 more rows
```

Again: Why transpose?

Figures: Long data are great for graphing

```r
size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date),
                          names_to = "type", values_to = "amount")

ggplot(data = size_long, aes(y = depth, x = amount, colour = type)) +
  geom_point() +
  scale_y_reverse() +
  facet_wrap(~ type, nrow = 2)
```



Again: Why transpose?

Figures: Take it to the next step

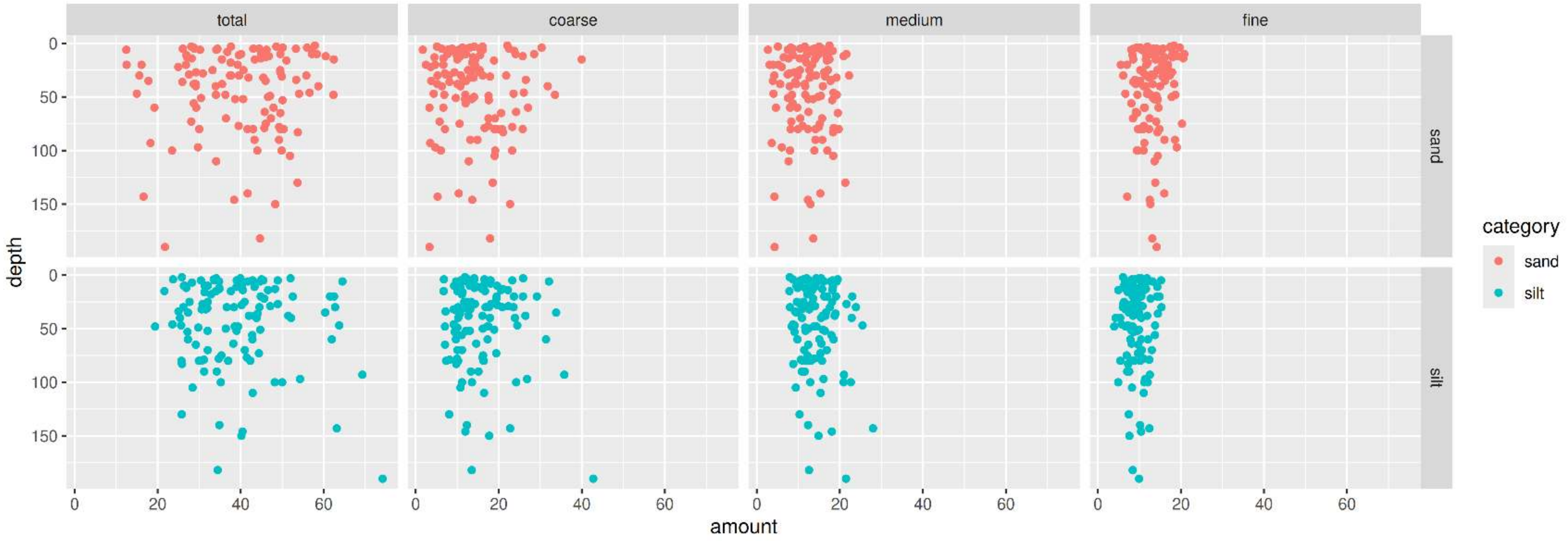
```r
size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)

size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date, -clay),
                          names_to = c("size", "category"), values_to = "amount",
                          names_sep = "_") |>
  mutate(size = factor(size, levels = c("total", "coarse", "medium", "fine")))
```

```
# A tibble: 912 × 9
   plot  depth  clay habitat technician date       size   category amount
   <chr> <dbl> <dbl> <chr>   <chr>      <date>     <fct>  <chr>     <dbl>
 1 CSP01     4  16.3 forest  Catharine  2009-04-23 coarse sand      13.0
 2 CSP01     4  16.3 forest  Catharine  2009-04-23 medium sand      17.4
 3 CSP01     4  16.3 forest  Catharine  2009-04-23 fine   sand      19.7
 4 CSP01     4  16.3 forest  Catharine  2009-04-23 coarse silt      14.1
 5 CSP01     4  16.3 forest  Catharine  2009-04-23 medium silt      11.2
 6 CSP01     4  16.3 forest  Catharine  2009-04-23 fine   silt       8.17
 7 CSP01     4  16.3 forest  Catharine  2009-04-23 total  sand      50.1
 8 CSP01     4  16.3 forest  Catharine  2009-04-23 total  silt      33.5
 9 CSP01    12  18.4 forest  Catharine  2009-04-23 coarse sand      10.7
10 CSP01    12  18.4 forest  Catharine  2009-04-23 medium sand      16.9
# ℹ 902 more rows
```

Again: Why transpose?

Figures: Take it to the next step

```
ggplot(data = size_long,
       aes(y = depth, x = amount, colour = category)) +
  geom_point() +
  scale_y_reverse() +
  facet_grid(category ~ size)
```



Again: Why transpose?

Anlyses: Linear models `lm(y ~ x, data)`

Use `pivot_longer()` in analysis where grouping variables are important

- i.e., do amounts of different size classes differ with depth? (need size classes in “type” column)

```r
lm(amount ~ type + depth, data = size_long)
```

Use `pivot_wider()` in analyses where each variable must be in it’s own column

- i.e., does the amount of sand differ with depth? (need size classes in separate columns)

```r
lm(total_sand ~ depth, data = size_wide)
```

If you can’t figure out how to plot or analyse your data,

they probably need to be transposed

Your Turn: Transpose for plotting

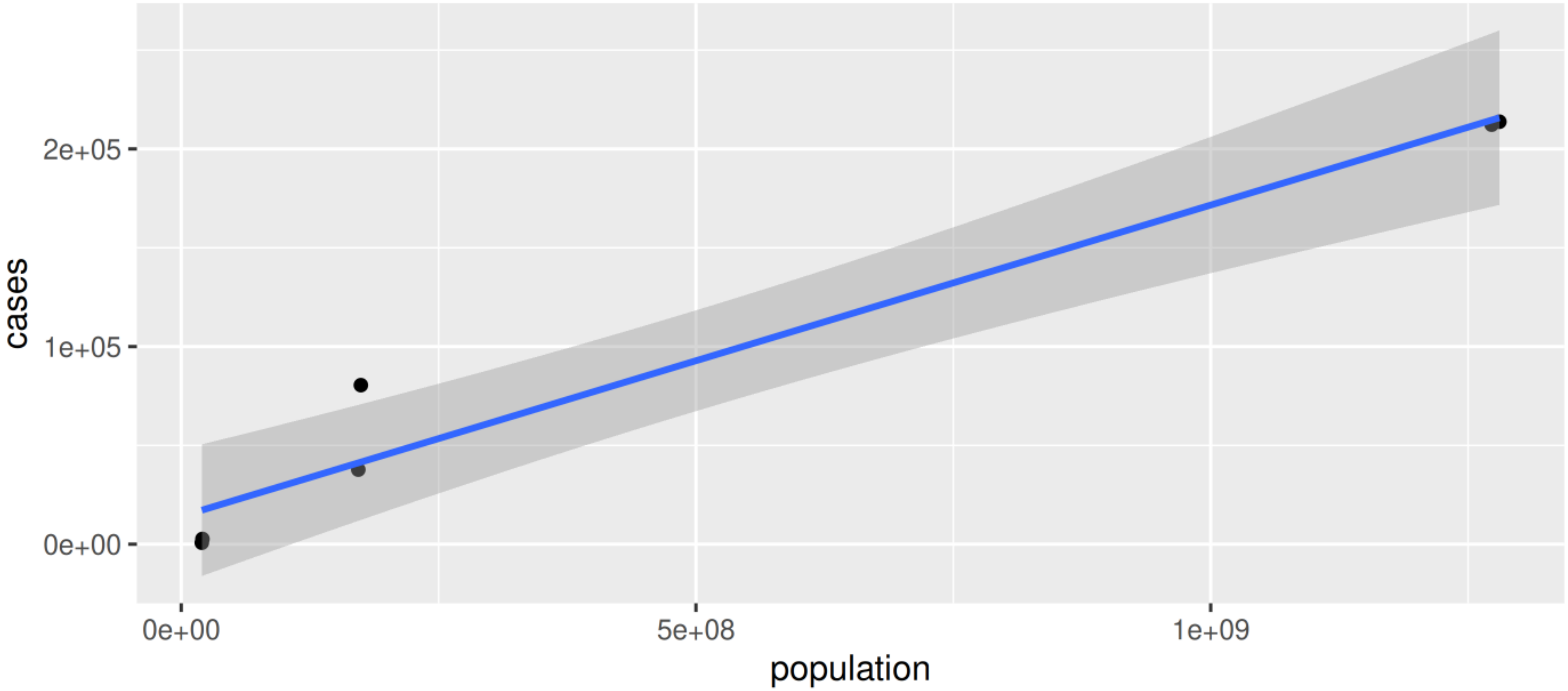
Plot the number of Tuberculosis `cases` vs. the `population` in data frame `table2`

```
temp <- pivot_???(table2, ???)

ggplot(data = temp, ???) +
  ???
```

Your Turn: Transpose for plotting

Plot the number of Tuberculosis cases (`cases`) vs. the `population` in data frame `table2`

```r
temp <- pivot_wider(table2, names_from = "type", values_from = "count")

ggplot(data = temp, aes(x = population, y = cases)) +
  geom_point() +
  stat_smooth(method = "lm")
```



Put it all together

```r
meta <- read_csv("data/grain_meta.csv")

size <- read_csv("data/grain_size2.csv") |>
  left_join(meta, by = "plot") |>
  mutate(total_sand = coarse_sand + medium_sand + fine_sand,
         total_silt = coarse_silt + medium_silt + fine_silt)

size_sum <- size |>
  group_by(plot, habitat) |>
  summarize(sample_size = n(),
            total_sand = sum(total_sand),
            mean_sand = mean(total_sand),
            sd_sand = sd(total_sand),
            se_sand = sd_sand / sqrt(sample_size),
            total_silt = sum(total_silt),
            mean_silt = mean(total_silt),
            sd_silt = sd(total_silt),
            se_silt = sd_silt / sqrt(sample_size))

size_long <- size |>
  pivot_longer(cols = c(-plot, -depth, -technician, -habitat, -date, -clay),
               values_to = "amount", names_to = c("size", "category"), names_sep = "_") |>
  mutate(size = factor(size, levels = c("total", "coarse", "medium", "fine")))
```

Put it all together

Save your data

```r
write_csv(size, "datasets/size_total.csv")
write_csv(size_sum, "datasets/size_summary.csv")
write_csv(size_long, "datasets/size_long.csv")
```

Keep yourself organized

- Keep your R-created data in a **different** folder from your ‘raw’ data
- If you have a lot going on, split your work into several scripts, and number the both the scripts AND the data sets produced:
- `1_cleaned.csv`
- `2_summarized.csv`
- `3_graphing.csv`

Wrapping up: Common mistakes

- `select()` doesn’t work
  - You may have the `MASS` package loaded, it also has a `select()` function
  - Make sure you loaded `tidyverse` or `dplyr` packages
  - Try using `dplyr::select()`
- I can’t figure out how to `pivot_wider()` my data in the way I want it
  - Sometimes you need to `pivot_longer()` before you can widen it
- `mutate()` is giving me weird results
  - Is your data grouped when it shouldn’t be?
  - Try using `ungroup()` first
- I get a warning when I join data sets
  - Can be because multiple joins
  - Can be because mismatched factor levels
    - If the category levels in one data frame do not match the other data frame
    - They will be transformed to character
    - If that’s a problem, use `as.factor()` to turn them back

Wrapping up: Further reading

- R for Data Science
  - Chapter 3: Data transformation
  - Chapter 5: Data tidying
  - Chapter 19: Joins
- RStudio Data Manipulation with `dplyr`
  - Or Help > Cheatsheets > Data Transformation with dplyr