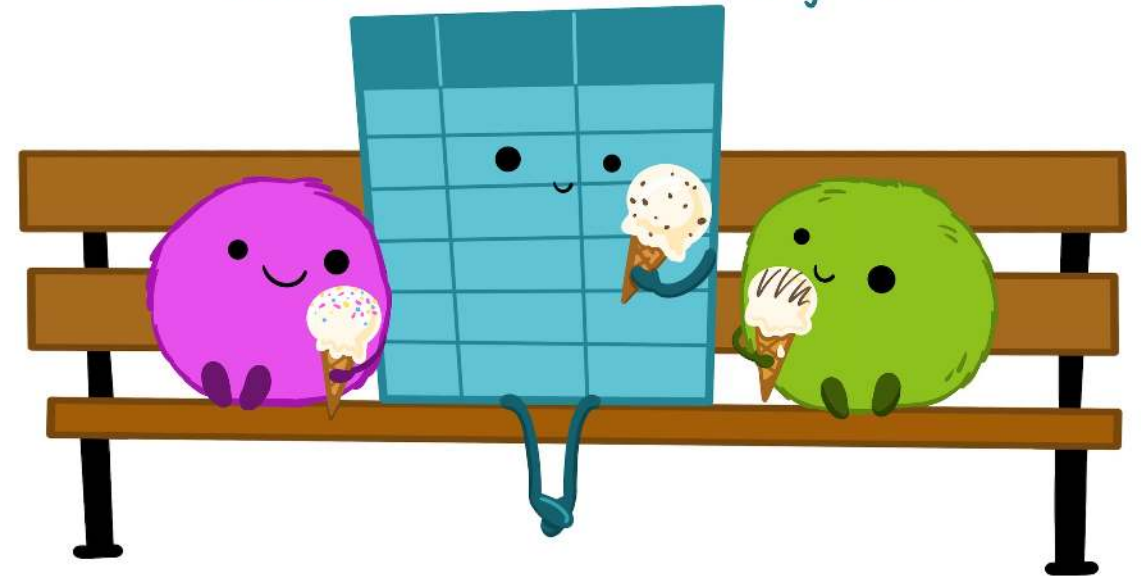



Summarizing & Transforming Data in R

Saving you time and sanity

make friends with tidy data.



 [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:

```
1 library(tidyverse)
2 size <- read_csv("data/grain_size2.csv")
3 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*

```
1 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

```
1 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:

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

filter() observations

filter() by measures

```
1 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



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%

Single comparisons

```
1 1 < 2
2 1 != 2
```

Multiple comparisons

```
1 1 == c(1, 2, 1, "apple")
2 1 %in% c(1, 2, 1, "apple")
3
4 c(1, 2, 1, "apple") == 1
5 c(1, 2, 1, "apple") %in% 1
6
7 c(1, 2, 1, "apple") == 1 | c(1, 2, 1, "apple") =
```

Your turn!

In each case, what are you asking?
Do you expect 1 or 4 values?

Back to `filter()`ing...

filter() observations

Which values are greater than 100 OR less than 4?

```
1 size$depth > 140 | size$depth < 4
```

```
[1] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[19] FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[37] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[55] TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE FALSE
[73] FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE TRUE
[91] FALSE FALSE FALSE TRUE TRUE FALSE FALSE FALSE FALSE FALSE FALSE FALSE TRUE FALSE FALSE FALSE FALSE FALSE
[109] FALSE FALSE FALSE FALSE FALSE FALSE
```

Return only rows with **TRUE**

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

filter() observations

filter() by a combination → use comma

```
1 filter(size,  
2       depth > 100,  
3       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 → use &

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

Separate arguments in filter() act like &

select() variables

select() is from dplyr*

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

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



select() variables

select() by name

```
1 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

```
1 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

```
1 size |>
2   filter(depth > 100,
3         plot %in% c("CSP13", "CSP25")) |>
4   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

```
1 size_sub_sand <- size |>
2   filter(depth > 100,
3         plot %in% c("CSP13", "CSP25")) |>
4   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

```
1 size <- read_csv("data/grain_size2.csv") |>  
2   filter(???) |>  
3   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?

Joining or Merging data

Joining data sets

Measurements

Plot	Date	n_birds
A	2024-02-21	1
A	2024-03-16	11
A	2024-04-09	2
B	2024-05-03	4
B	2024-05-27	10
B	2024-06-21	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	2024-02-21	1	50
A	2024-03-16	11	50
A	2024-04-09	2	50
B	2024-05-03	4	76
B	2024-05-27	10	76
B	2024-06-21	21	76

Joining data sets

Index or Metadata

```
1 meta <- read_csv("data/grain_meta.csv")
2 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

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

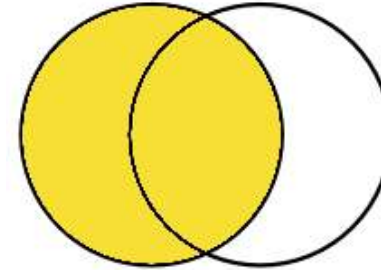
# A tibble: 114 × 9
  plot depth coarse_sand medium_sand fine_sand coarse_silt
  <chr> <dbl> <dbl> <dbl> <dbl> <dbl>
1 CSP01 4 13.0 17.4 19.7 14.1
2 CSP01 12 10.7 16.9 19.2 14.1
3 CSP01 35 12.1 17.8 16.1 10.3
4 CSP01 53 17.6 18.2 14.3 9.4
5 CSP01 83 21.0 18.4 14.3 9.79
6 CSP01 105 19.0 18.4 14.4 10.8
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)`

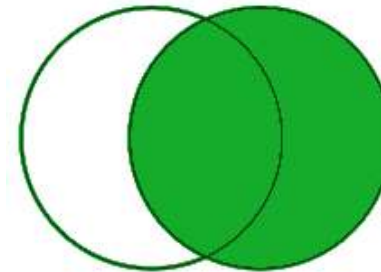
- Keep all rows in *x*
- Keep rows in *y* only if they're also in *x*



`left_join(x, y)`

`right_join(x, y)`

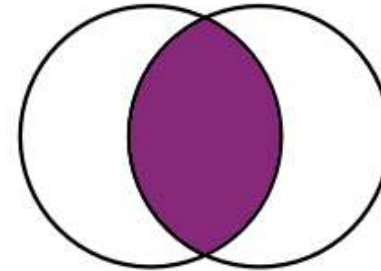
- Keep all rows in *y*
- Keep rows in *x* only if they're also in *y*



`right_join(x, y)`

`inner_join(x, y)`

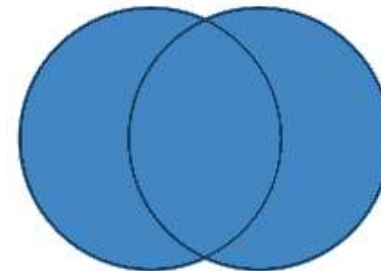
- Keep **only** rows that exist in **both** data frames



`inner_join(x, y)`

`full_join(x, y)`

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



`full_join(x, y)`

Joining data sets

`left_join()` is from `dplyr`*

```
1 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

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

```
1 # A tibble: 114 × 12
2   plot depth coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt clay habitat technician da
3   <chr> <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl>   <dbl> <dbl> <chr>   <chr>   <c
4 1 CSP01     4    13.0    17.4    19.7    14.1    11.2    8.17  16.3 forest Catharine 20
5 2 CSP01    12    10.7    16.9    19.2    14.1    11.7    9.03  18.4 forest Catharine 20
6 3 CSP01    35    12.1    17.8    16.1    10.3    9.51    7.47  26.7 forest Catharine 20
7 4 CSP01    53    17.6    18.2    14.3     9.4     9.1    8.7   22.7 forest Catharine 20
8 5 CSP01    83    21.0    18.4    14.3     9.79    8.79    7.29  20.4 forest Catharine 20
9 6 CSP01   105    19.0    18.4    14.4    10.8     9.4    8.22  19.7 forest Catharine 20
10 7 CSP08    10    11.6    17.1    20.8    16.3     9.55    6.23  18.4 grassland Catharine 20
11 8 CSP08    27    15.4    16.2    17.8    14.3    10.4     6.1   19.6 grassland Catharine 20
12 9 CSP08    90    14.9    15.8    18.6    15.1    11.5     7.56  16.5 grassland Catharine 20
13 10 CSP02     5     8.75     8.64     8.66    12.0    18.3    15.2   28.5 forest Catharine 20
14 # i 104 more rows
```

For more information see R for Data Science [Chapter 19.3 Basic joins](#)

Creating/modifying columns with mutate()



Artwork by @allison_horst

Creating new columns

`mutate()` is from `dplyr`*

```
1 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

```
1 size <- read_csv("data/grain_size2.csv") |>
2   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
- But not all functions are vectorized

For example

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

For example

```
1 sum(a)
2 sum(a, a)
3 mean(a)
4 mean(c(a, a))
```

Back to mutate()...

Your turn: Creating new columns

- Add a calculation for **total silt**

```
1 meta <- read_csv("data/grain_meta.csv")
2
3 size <- read_csv("data/grain_size2.csv") |>
4   left_join(meta, by = "plot") |>
5   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
6          ???)
```

Too Easy?

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

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()`

```
1 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	13.92	16.70	12.24	8.71	26.90	forest
29	CSP09	30	16.17	9.88	11.67	17.64	12.65	8.08	23.90	forest
30	CSP09	48	11.96	11.67	12.70	17.26	13.75	8.37	24.30	forest

To see all rows

- Use `print()`

```
1 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

27	CSP09	8	9.42	12.2	15.2	18.0	14.2	7.62	23.4	forest
28	CSP09	15	10.0	11.5	13.9	16.7	12.2	8.71	26.9	forest

Back to mutate()...

Mutating by group

`group_by()` and `ungroup()` are from `dplyr`*

```
1 group_by(data, column1, column2)
2 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

```
1 size <- size |>
2   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():

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

```
# A tibble: 114 × 3
  plot total_sand mean_sand_plot
  <chr>    <dbl>    <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)



Your turn: Mutating by group

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

```
1 meta <- read_csv("data/grain_meta.csv")
2
3 size <- read_csv("data/grain_size2.csv") |>
4   left_join(meta, by = "plot") |>
5   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
6          total_silt = coarse_silt + medium_silt + fine_silt) |>
7   ??? |>
8   ??? |>
9   ???
```

Too Easy?

See `?mutate`

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

Put it all together

```
1 meta <- read_csv("data/grain_meta.csv")
2
3 size <- read_csv("data/grain_size2.csv") |>
4   left_join(meta, by = "plot") |>
5   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
6          total_silt = coarse_silt + medium_silt + fine_silt) |>
7   group_by(plot) |>
8   mutate(mean_sand = mean(total_sand),
9          mean_silt = mean(total_silt)) |>
10  ungroup()
```

Check it out

```
1 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`*

```
1 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()`

```
1 size <- size |>
2   group_by(plot) |>
3   mutate(mean_sand = mean(total_sand)) |>
4   ungroup()
5
6 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()`

```
1 size <- size |>
2   group_by(plot) |>
3   summarize(mean_sand = mean(total_sand), .groups = "drop")
4
5 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!

```
1 size |>
2   group_by(plot, depth) |>
3   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)

```
1 size |>
2   group_by(plot, habitat) |>
3   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	<code>n()</code> *
means	<code>mean(x)</code>
standard deviations	<code>sd(x)</code>
standard errors	<code>sd(x) / sqrt(n())</code> **
total values	<code>sum(x)</code>

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`*

```
1 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...

```
1 size |>
2   group_by(plot) |>
3   summarize(samples_total = n(),
4             .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())`

```
1 meta <- read_csv("data/grain_meta.csv")
2
3 size <- read_csv("data/grain_size2.csv") |>
4   left_join(meta, by = "plot") |>
5   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
6          total_silt = coarse_silt + medium_silt + fine_silt)
7
8 size_sum <- size |>
9   group_by(plot, habitat) |>
10  summarize(sample_size = n(),
11            mean_sand = mean(total_sand),
12            sd_sand = sd(total_sand),
13            se_sand = ???,
14            ???)
```

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... 60

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

each column a variable



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

each row an observation



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

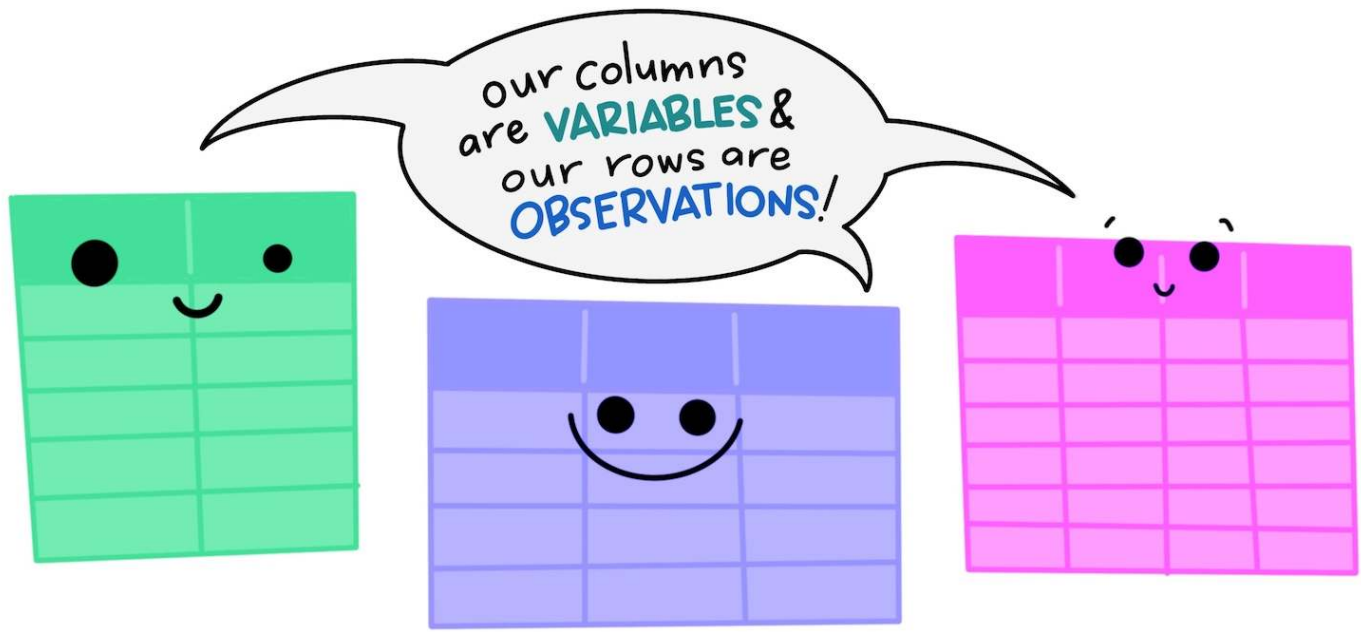
Un-tidy

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

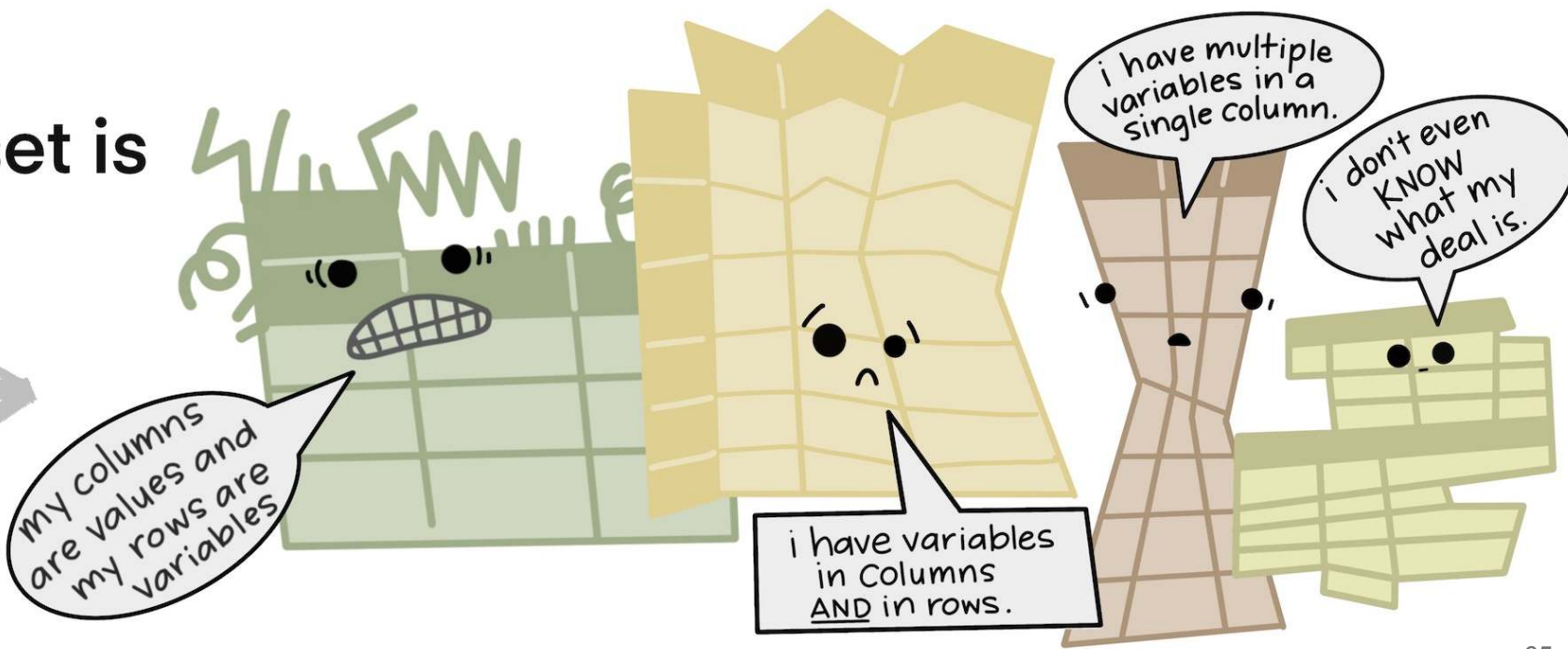
per row

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

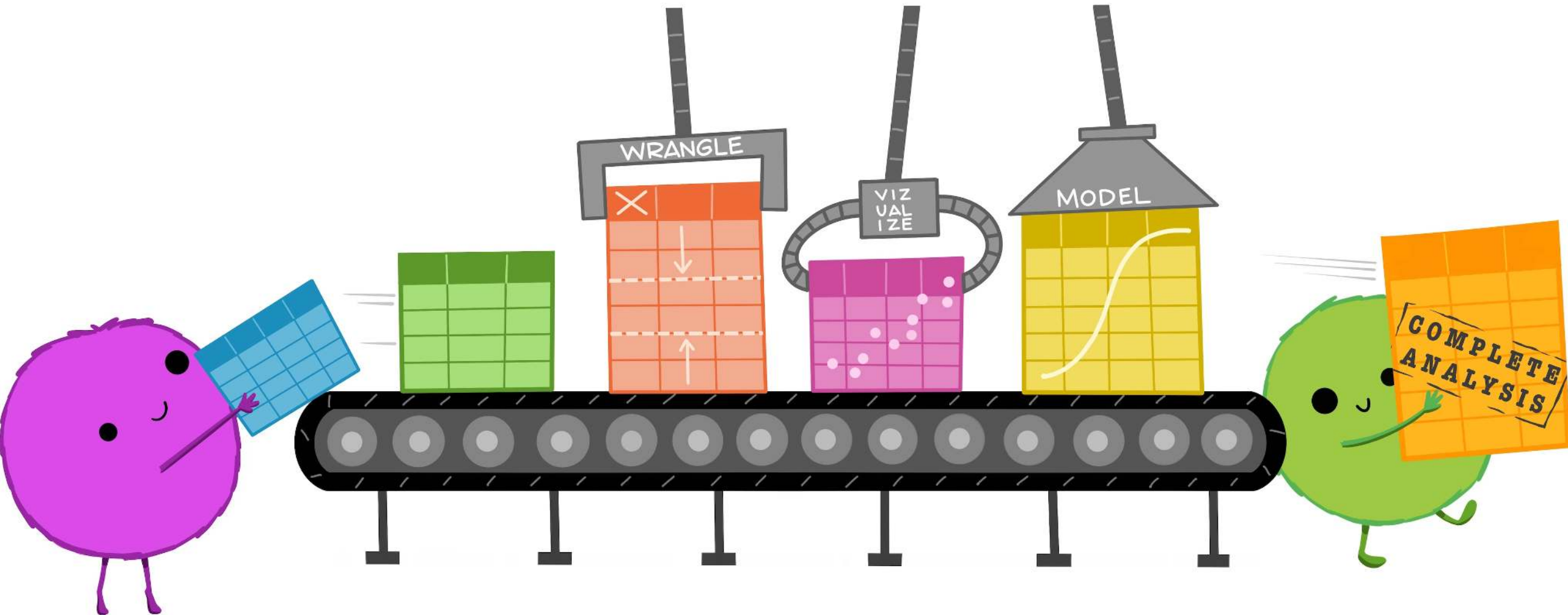


"...but every messy dataset is messy in its own way."

-HADLEY WICKHAM



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?

```
1 ggplot(data = table4a, aes(x = ???, y = ???)) +  
2   ???
```

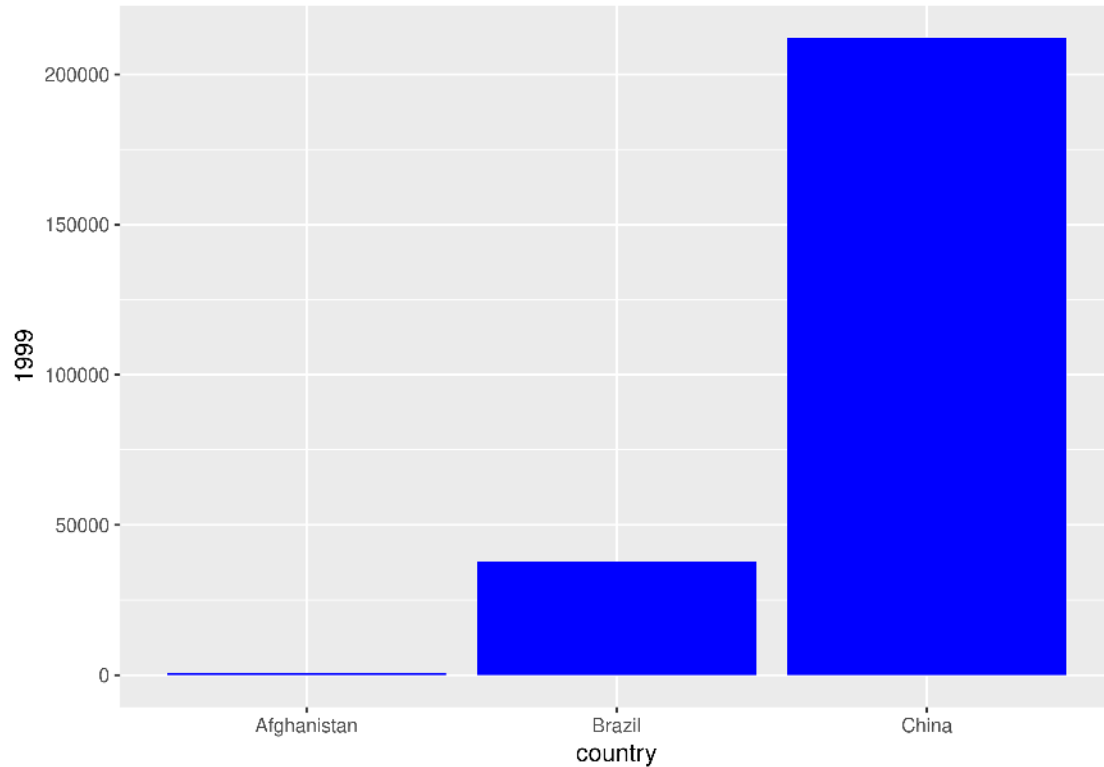
Note

- `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

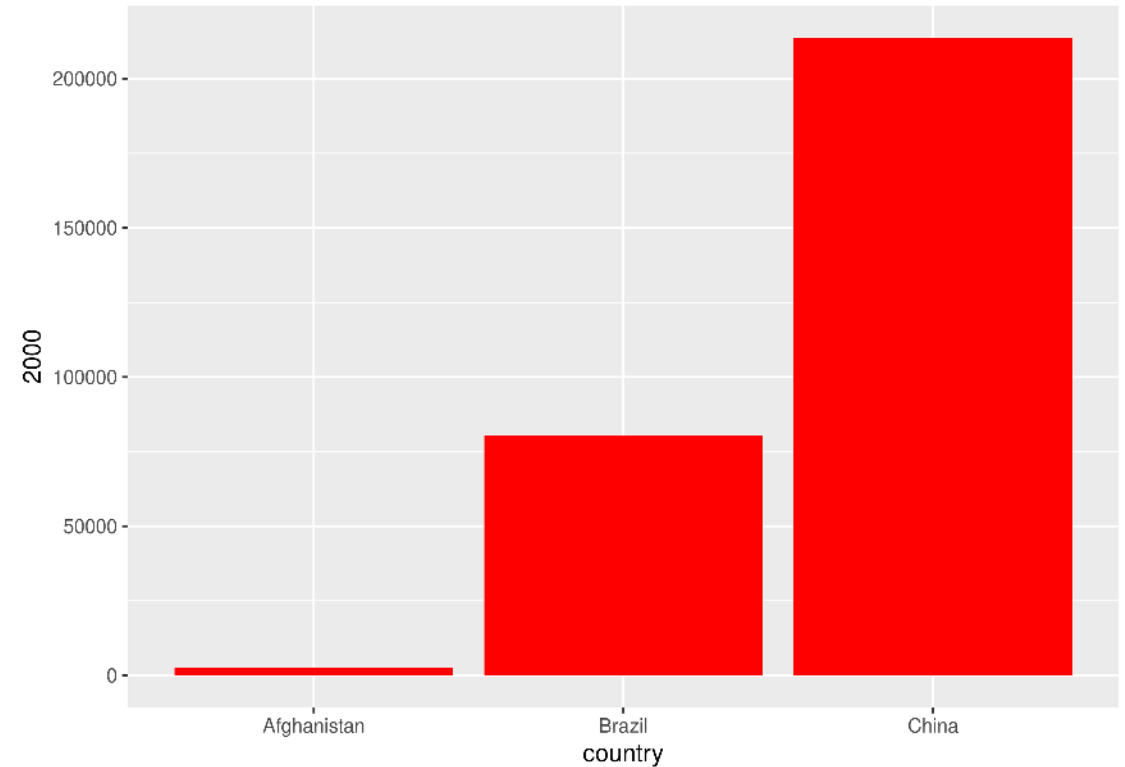
Why do we care?

With un-tidy data

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



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



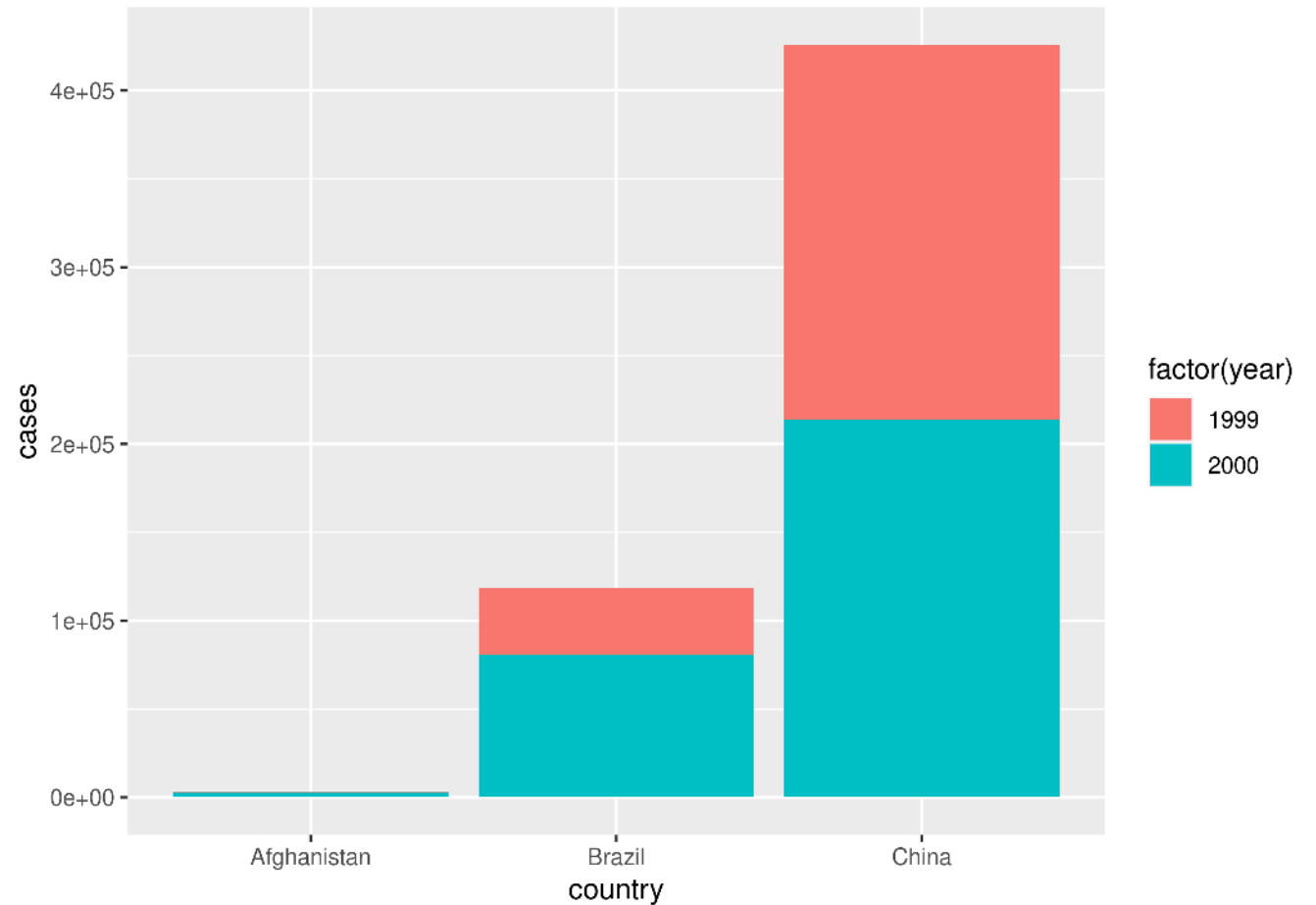
We have to plot it twice!

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

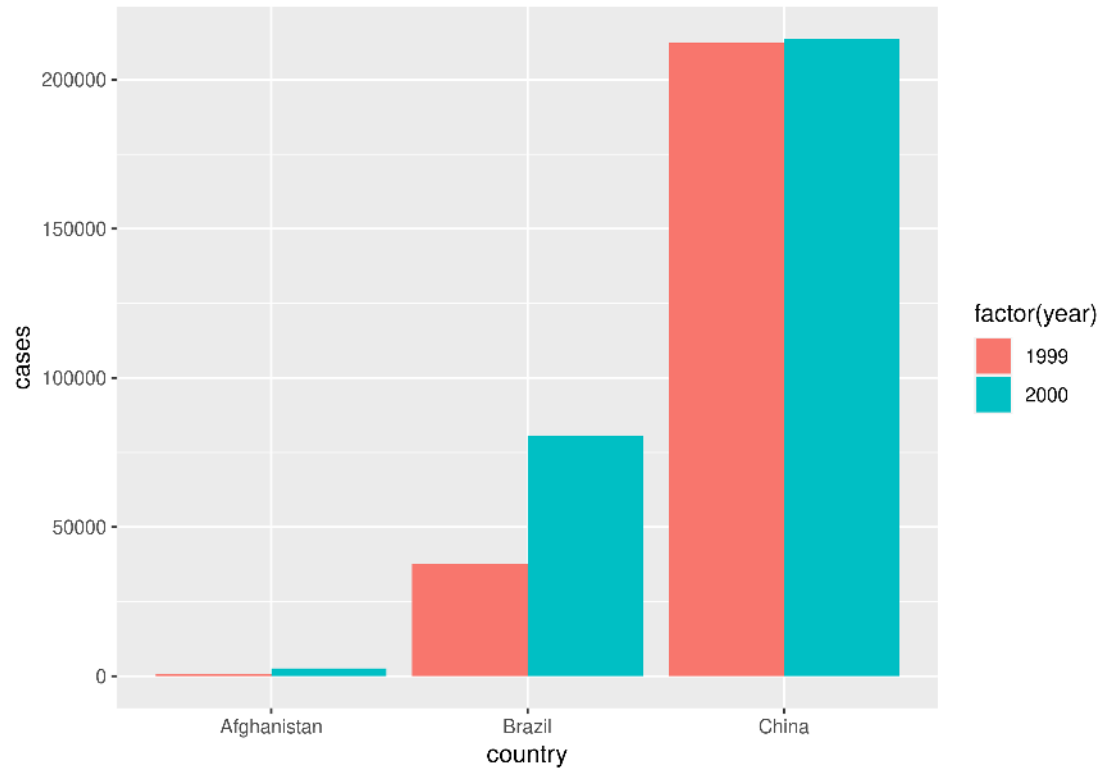
```
1 ggplot(data = table1, aes(x = country, y = cases, fill = factor(year))) +  
2   geom_bar(stat = "identity")
```



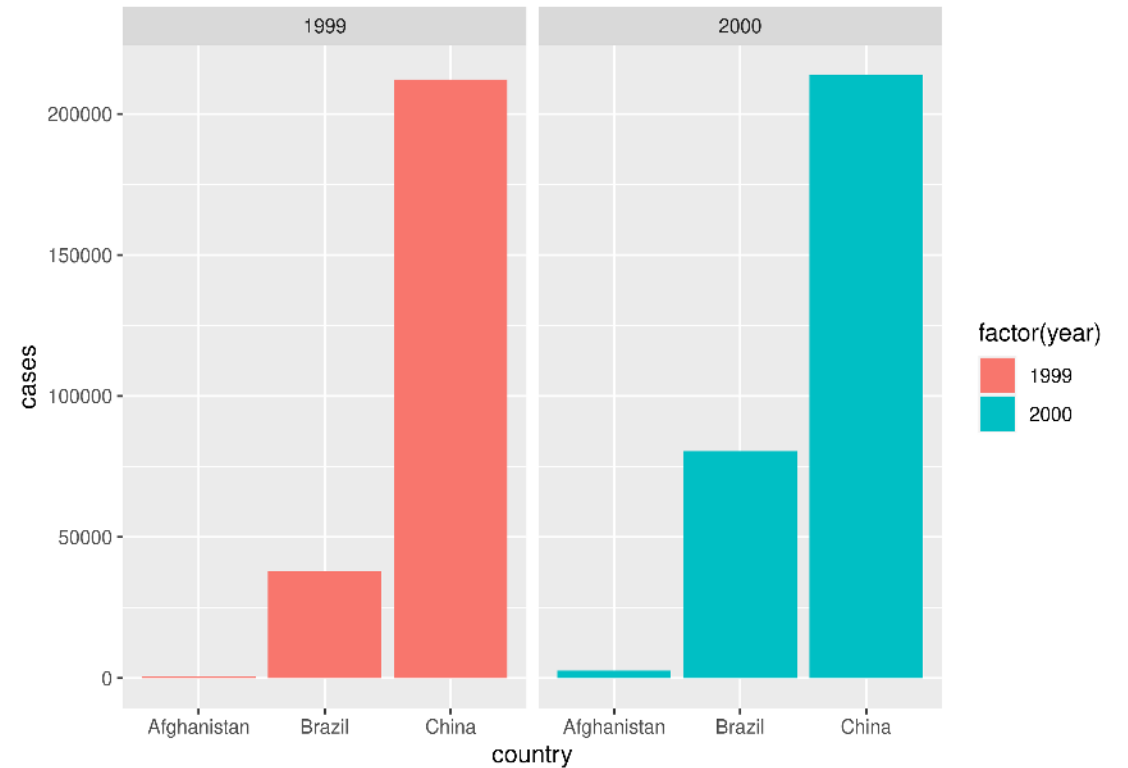
Why do we care?

With tidy data

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



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



Going long

`pivot_longer()`

The diagram illustrates the transformation of a wide table into a long table using the `pivot_longer()` function. The wide table on the right has columns for country, 1999, and 2000. The long table on the left has columns for country, year, and cases. Arrows show the mapping: the 'country' column remains the same, the '1999' column maps to the 'year' column, and the '2000' column maps to the 'cases' column. The label 'table4' is positioned below the wide table.

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`*

```
1 pivot_longer(data, cols = c(column1, column2),  
2             names_to = "new_categorical_column",  
3             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`*

```
1 pivot_longer(data, cols = c(column1, column2),  
2               names_to = "new_categorical_column",  
3               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

```
1 size_long <- pivot_longer(size, cols = c(-plot, -depth, -habitat, -technician, -date),  
2                             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

```
1 sand_sum <- read_csv("data/grain_size2.csv") |>
2   mutate(total_sand = coarse_sand + medium_sand + fine_sand) |>
3   group_by(plot) |>
4   summarize(sample_size = n(),
5             mean_sand = mean(total_sand),
6             sd_sand = sd(total_sand),
7             se_sand = sd_sand / sqrt(sample_size))
8
9 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

```
1 sand_long <- pivot_longer(sand_sum,  
2                           cols = ???,  
3                           names_to = ???,  
4                           values_to = ???)
```

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

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

table2

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`*

```
1 pivot_wider(data,  
2             names_from = existing_categorical_column,  
3             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

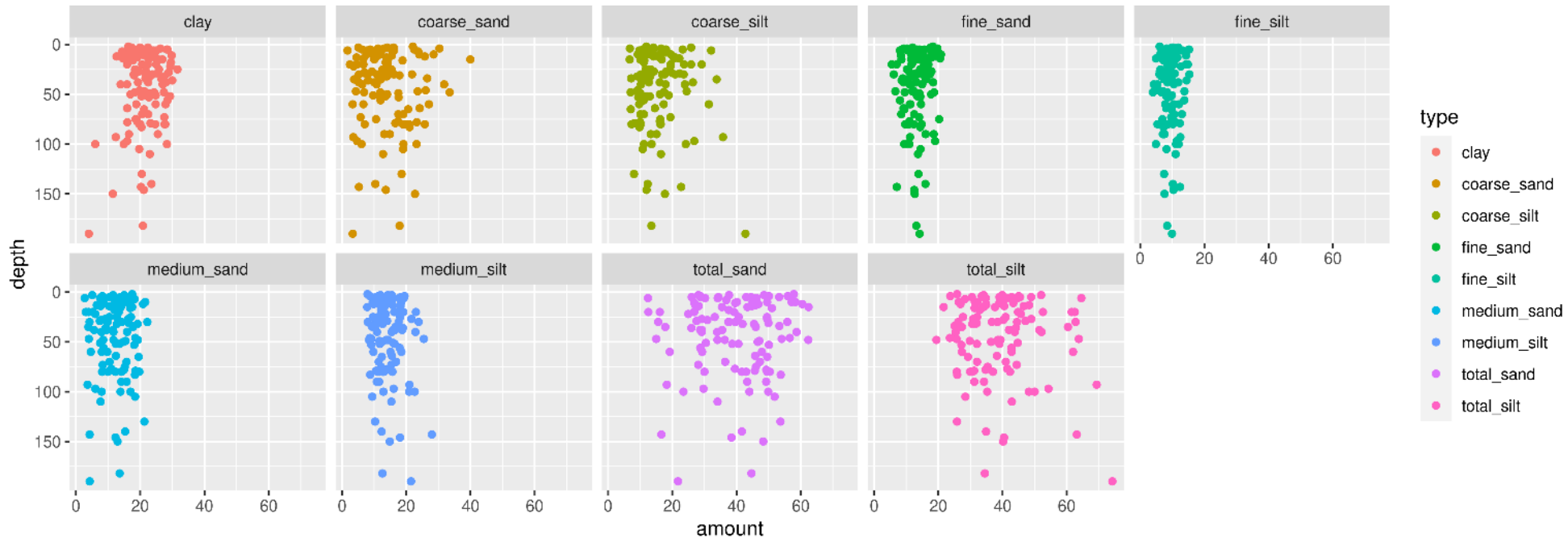
```
1 size_wide <- pivot_wider(size_long, names_from = type, values_from = amount)
```

```
1 # A tibble: 114 × 14
2   plot depth habitat technician date coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_si
3   <chr> <dbl> <chr> <chr> <date> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
4 1 CSP01 4 forest Catharine 2009-04-23 13.0 17.4 19.7 14.1 11.2 8.
5 2 CSP01 12 forest Catharine 2009-04-23 10.7 16.9 19.2 14.1 11.7 9.
6 3 CSP01 35 forest Catharine 2009-04-23 12.1 17.8 16.1 10.3 9.51 7.
7 4 CSP01 53 forest Catharine 2009-04-23 17.6 18.2 14.3 9.4 9.1 8.
8 5 CSP01 83 forest Catharine 2009-04-23 21.0 18.4 14.3 9.79 8.79 7.
9 6 CSP01 105 forest Catharine 2009-04-23 19.0 18.4 14.4 10.8 9.4 8.
10 7 CSP08 10 grassland Catharine 2009-03-02 11.6 17.1 20.8 16.3 9.55 6.
11 8 CSP08 27 grassland Catharine 2009-03-02 15.4 16.2 17.8 14.3 10.4 6.
12 9 CSP08 90 grassland Catharine 2009-03-02 14.9 15.8 18.6 15.1 11.5 7.
13 10 CSP02 5 forest Catharine 2009-05-06 8.75 8.64 8.66 12.0 18.3 15.
14 # i 104 more rows
```

Again: Why transpose?

Figures: Long data are great for graphing

```
1 size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date),
2                             names_to = "type", values_to = "amount")
3
4 ggplot(data = size_long, aes(y = depth, x = amount, colour = type)) +
5   geom_point() +
6   scale_y_reverse() +
7   facet_wrap(~ type, nrow = 2)
```



Again: Why transpose?

Figures: Take it to the next step

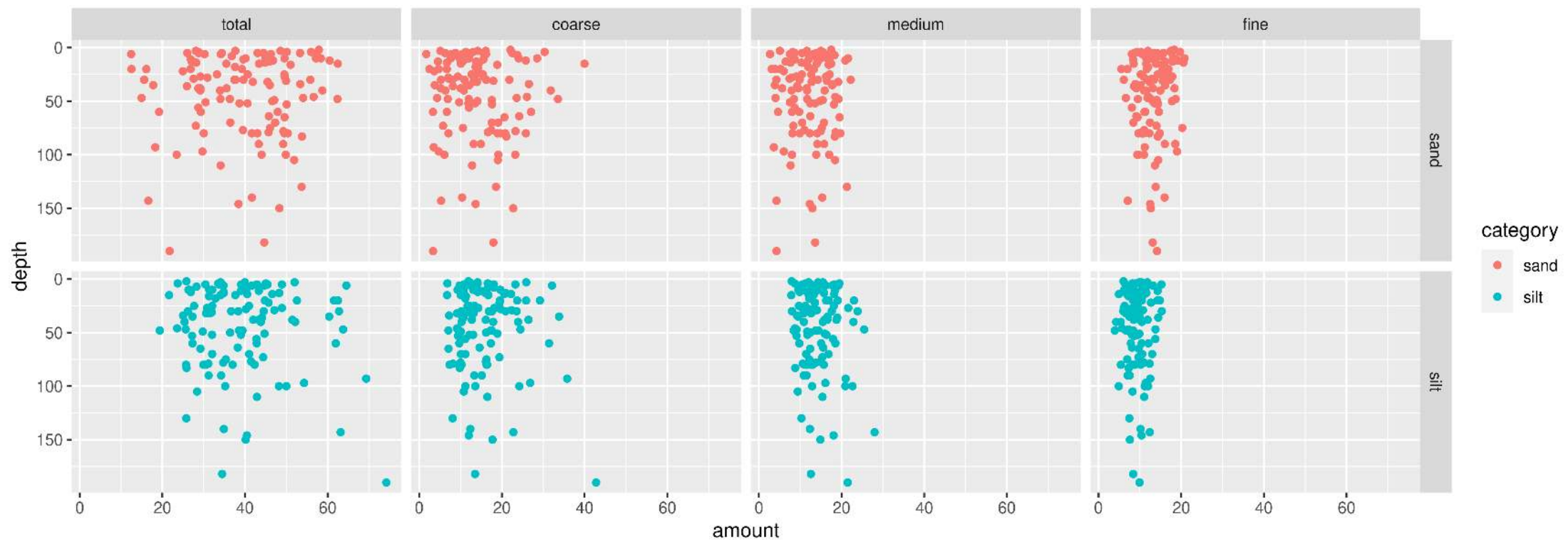
```
1 size <- read_csv("data/grain_size2.csv") |>
2   left_join(meta, by = "plot") |>
3   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
4          total_silt = coarse_silt + medium_silt + fine_silt)
5
6 size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date, -clay),
7                             names_to = c("size", "category"), values_to = "amount",
8                             names_sep = "_") |>
9   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

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



Again: Why transpose?

Analyses: 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)

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

Use `pivot_wider()` in analyses where each variable must be in its own column

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

```
1 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`

```
1 temp <- pivot_???(table2, ???)
2
3 ggplot(data = temp, ???) +
4   ???
```

Put it all together

```
1 meta <- read_csv("data/grain_meta.csv")
2
3 size <- read_csv("data/grain_size2.csv") |>
4   left_join(meta, by = "plot") |>
5   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
6          total_silt = coarse_silt + medium_silt + fine_silt)
7
8 size_sum <- size |>
9   group_by(plot, habitat) |>
10  summarize(sample_size = n(),
11            total_sand = sum(total_sand),
12            mean_sand = mean(total_sand),
13            sd_sand = sd(total_sand),
14            se_sand = sd_sand / sqrt(sample_size),
15            total_silt = sum(total_silt),
16            mean_silt = mean(total_silt),
17            sd_silt = sd(total_silt),
18            se_silt = sd_silt / sqrt(sample_size))
19
20 size_long <- size |>
21   pivot_longer(cols = c(-plot, -depth, -technician, -habitat, -date, -clay),
22               values_to = "amount", names_to = c("size", "category"), names_sep = "_") |>
23   mutate(size = factor(size, levels = c("total", "coarse", "medium", "fine")))
```

Put it all together

Save your data

```
1 write_csv(size, "Datasets/size_total.csv")
2 write_csv(size_sum, "Datasets/size_summary.csv")
3 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](#)