

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



Compiled: 2023-04-19

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") == 2
```

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 FALSE TRUE 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()`?

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(clay >= 30) |>
3   select(plot, depth, ends_with("sand"))
4
5 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()`?

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

```
Error in `filter()`:  
! 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	2023-04-19	1
A	2023-05-13	11
A	2023-06-06	2
B	2023-07-01	4
B	2023-07-25	10
B	2023-08-19	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	2023-04-19	1	50
A	2023-05-13	11	50
A	2023-06-06	2	50
B	2023-07-01	4	76
B	2023-07-25	10	76
B	2023-08-19	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
```

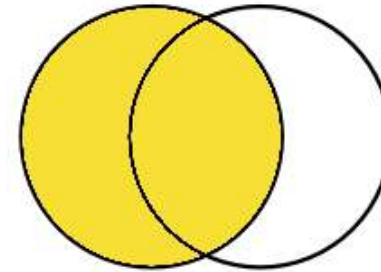
```
# A tibble: 114 × 9
  plot depth coarse_sand medium_sand fine_sand coarse_silt
  <chr> <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
1 CSP01     4      13.0      17.4      19.7      14.1
2 CSP01    12      10.7      16.9      19.2      14.1
3 CSP01    35      12.1      17.8      16.1      10.3
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)`

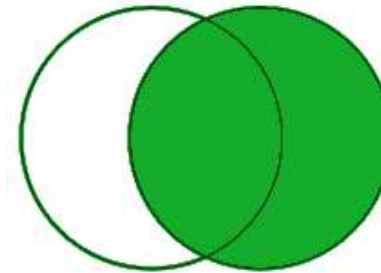
- Keep all rows in `x`
- Keep rows in `y` only if they're also in `x`



`left_join(x, y)`

`right_join(x, y)`

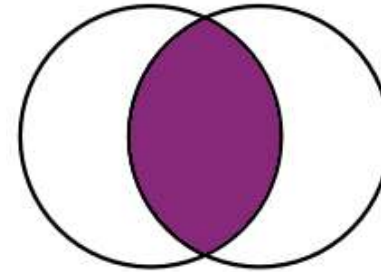
- Keep all rows in `y`
- Keep rows in `x` only if they're also in `y`



`right_join(x, y)`

`inner_join(x, y)`

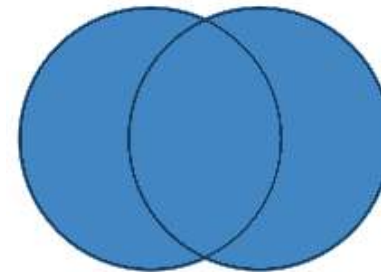
- Keep **only** rows that exist in **both** data frames



`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, only keep meta if we have a measurement

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

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

For more information see R for Data Science [Chapter 13.4 Mutating 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**
- Check your work

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

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**
- Check your work

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

Your turn: Creating new columns

- Add a calculation for **total silt**
- Check your work

```
1 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!

Your turn: Creating new columns

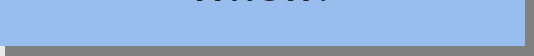
- Add a calculation for **total silt**
- Check your work

```
1 select(size, contains("silt")) |>  
2   as.data.frame()
```

	coarse_silt	medium_silt	fine_silt	total_silt
1	14.12	11.25	8.17	33.54
2	14.13	11.68	9.03	34.84
3	10.33	9.51	7.47	27.31
4	9.40	9.10	8.70	27.20
5	9.79	8.79	7.29	25.87
6	10.79	9.40	8.22	28.41
7	16.30	9.55	6.23	32.08
8	14.27	10.44	6.10	30.81
9	15.13	11.54	7.56	34.23
10	11.96	18.27	15.22	45.45
11	10.70	18.33	14.30	43.33
12	10.68	18.96	14.45	44.09
13	11.08	17.95	13.74	42.77
14	11.16	16.85	12.99	41.00
15	9.97	13.79	10.97	34.73
16	11.17	12.88	11.17	35.22
17	17.97	14.33	10.57	42.87
18	17.89	15.48	10.46	43.83
19	17.32	15.06	10.45	42.83
20	16.42	15.71	10.20	42.33
21	16.47	15.37	11.05	42.89
22	13.43	10.51	6.50	30.44
23	16.05	11.83	6.99	34.87
24	13.14	10.83	6.62	30.59
25	12.15	11.75	8.13	32.03

Whew!

26	13.30	10.84	7.06	31.20
27	18.03	14.17	7.62	39.82
28	16.70	12.24	8.71	37.65
29	17.64	12.65	8.08	38.37
30	17.26	13.75	8.37	39.38



Your turn: Creating new columns (Too Easy?)

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

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

Tangent

Decimal points

Where are...

... the decimal points?

- `tibble` rounds values for easy viewing

```
# A tibble: 114 × 15
  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 5 more variables: technician <chr>, date <date>, total_sand <dbl>, total_silt <dbl>,
#   total <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 × 15
  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 size <- read_csv("data/grain_size2.csv") |>
3   left_join(meta, by = "plot") |>
4   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
5          total_silt = coarse_silt + medium_silt + fine_silt) |>
6   ??? |>
7   ??? |>
8   ???
```


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

```
# 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

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

- sample sizes (`n()`)
- means (`mean()`)
- standard deviations (`sd()`)
- standard errors (`sd() / sqrt(n())`)
- total values (`sum()`)
- total counts (`n()`)

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

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

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

Your Turn: Calculate summary statistics

For each plot and habitat, calculate

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

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

Your Turn: Calculate summary statistics

Check your work

```
1 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

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

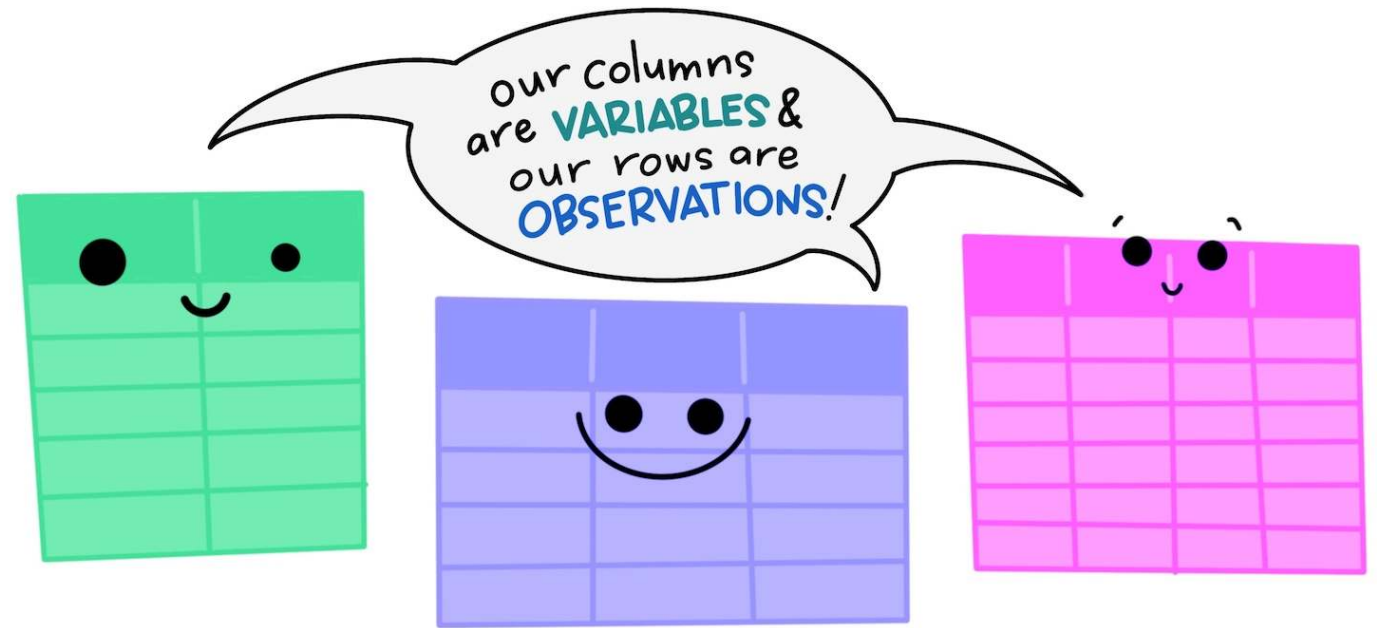
Un-tidy

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

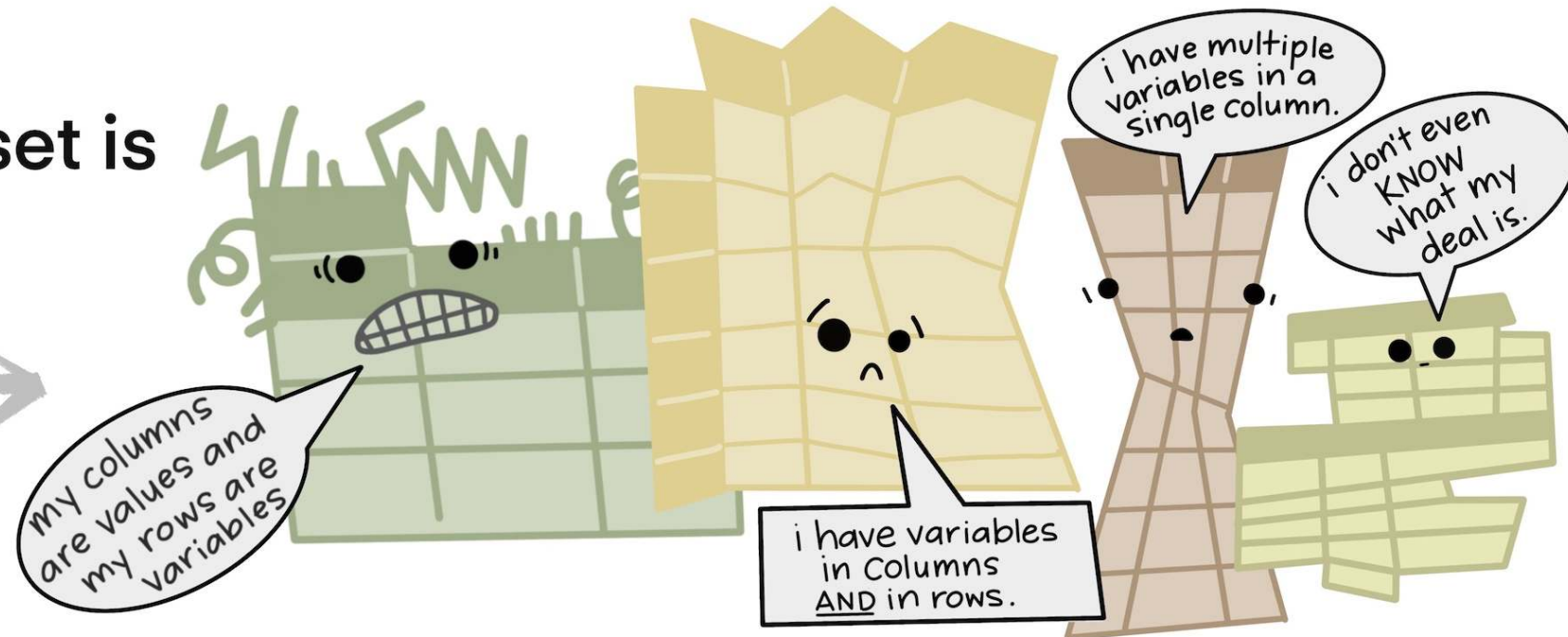
per row

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

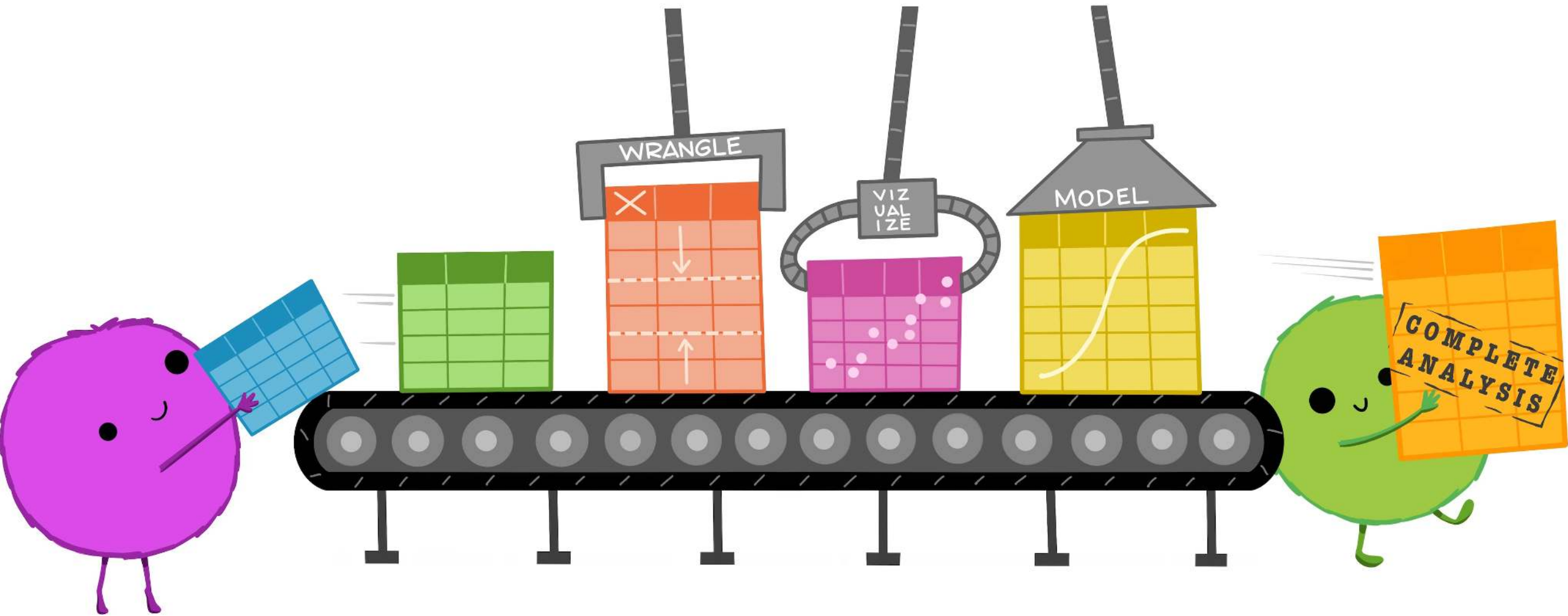


Tidy Data

Un-Tidy (wide)

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

Why do we care?



Why do we care?

How would you plot the untidy data?

(No. of cases by country for each year)

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

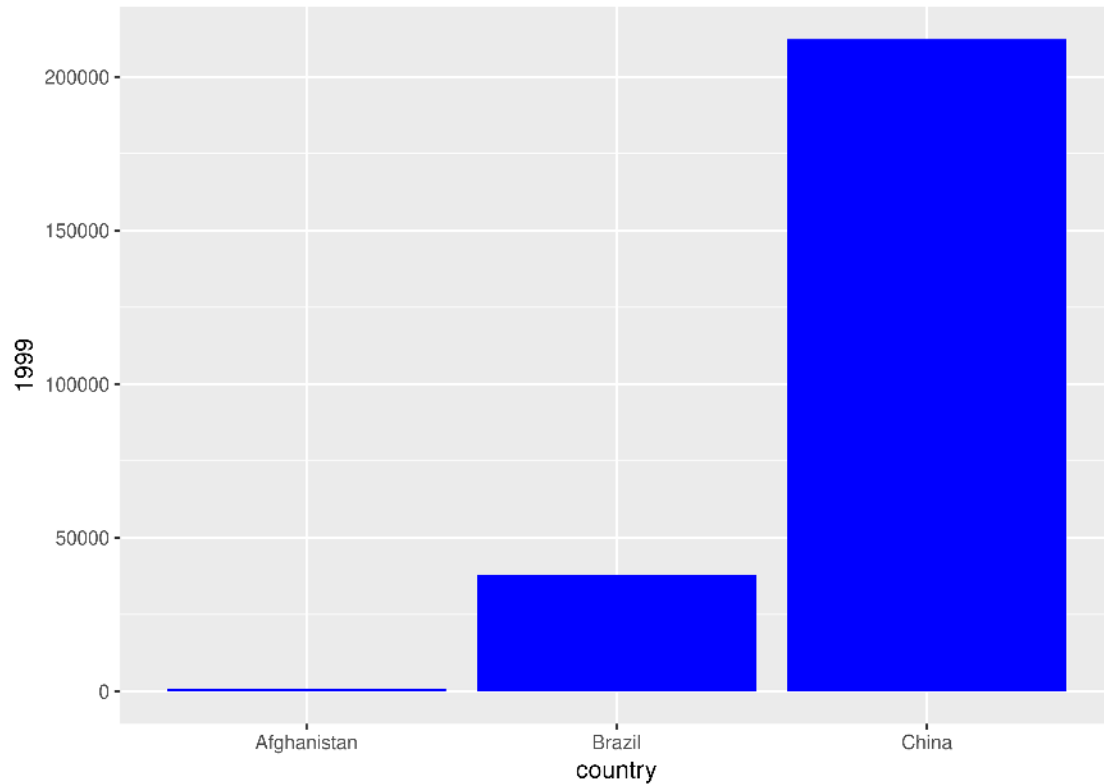
Note

- `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

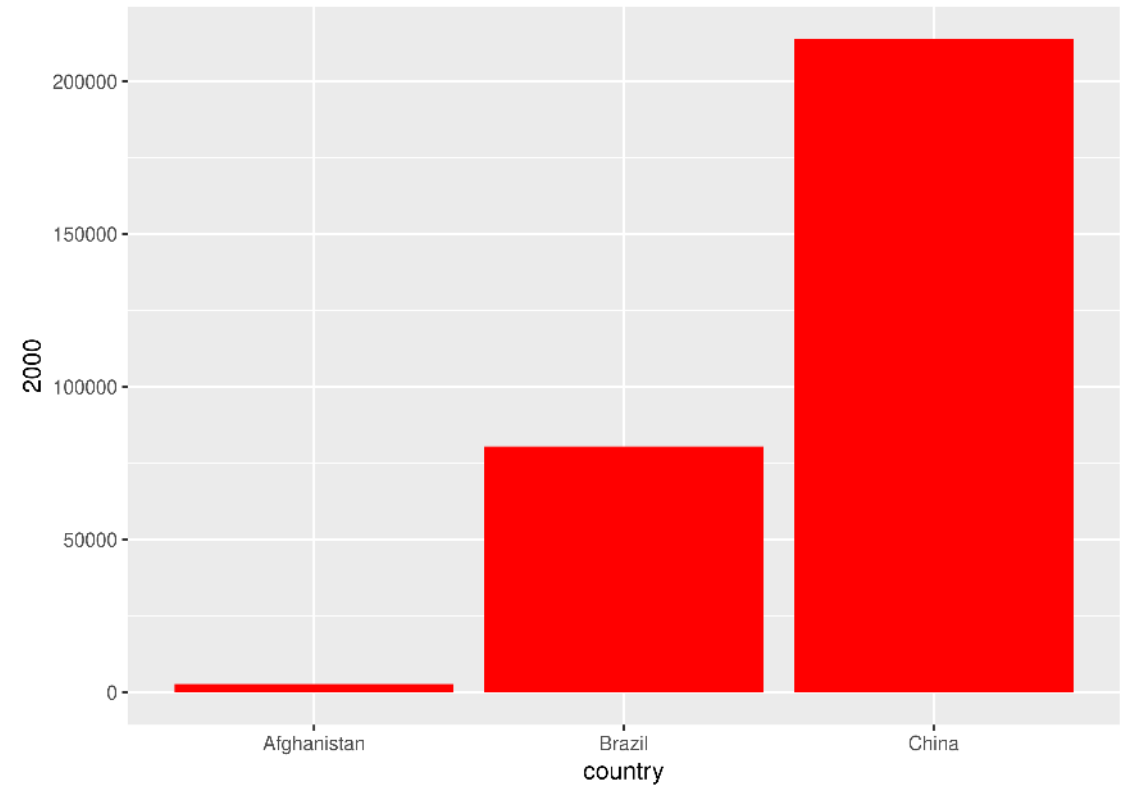
Why do we care?

With un-tidy data

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



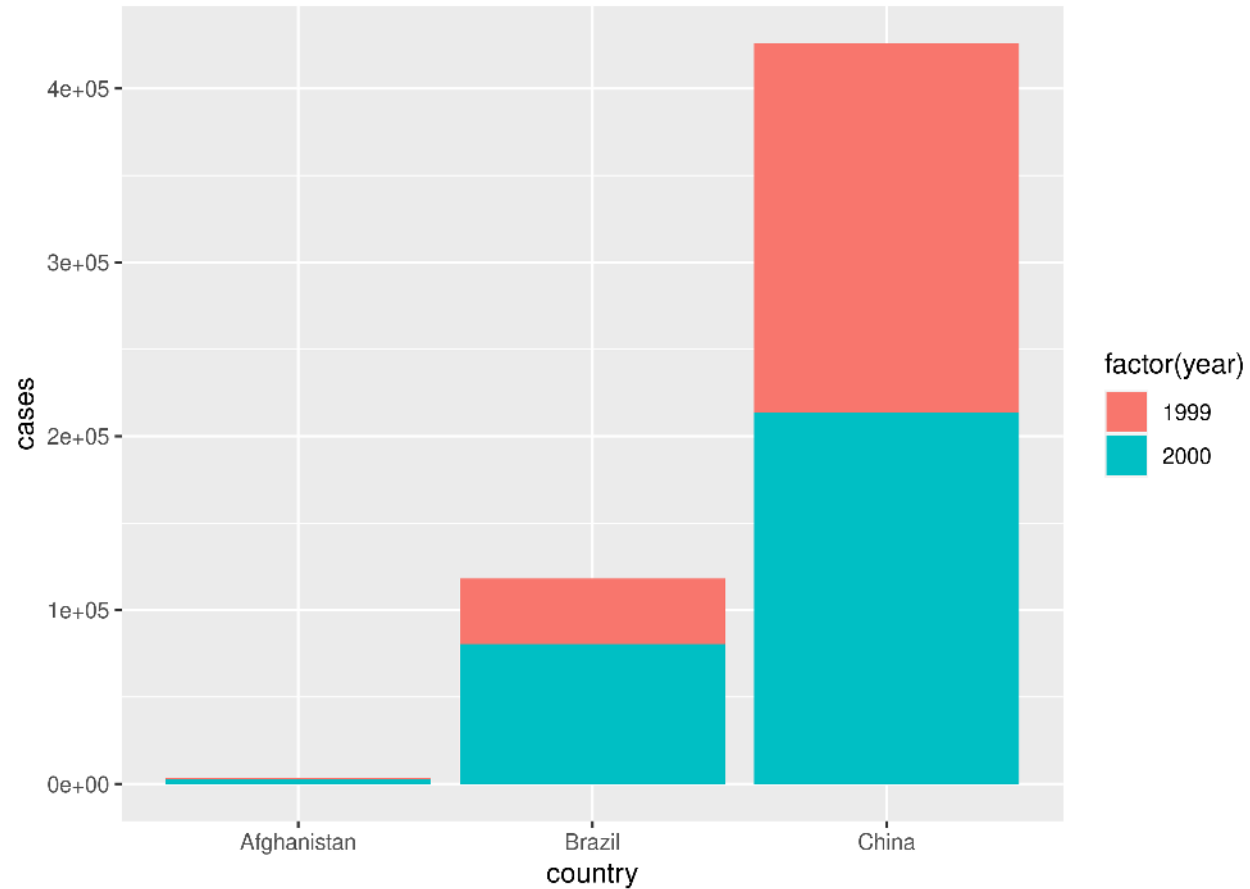
```
1 ggplot(data = table4a, aes(x = country, y = `2000`)) +  
2   geom_bar(stat = "identity", fill = "red")
```



Why do we care?

With tidy data

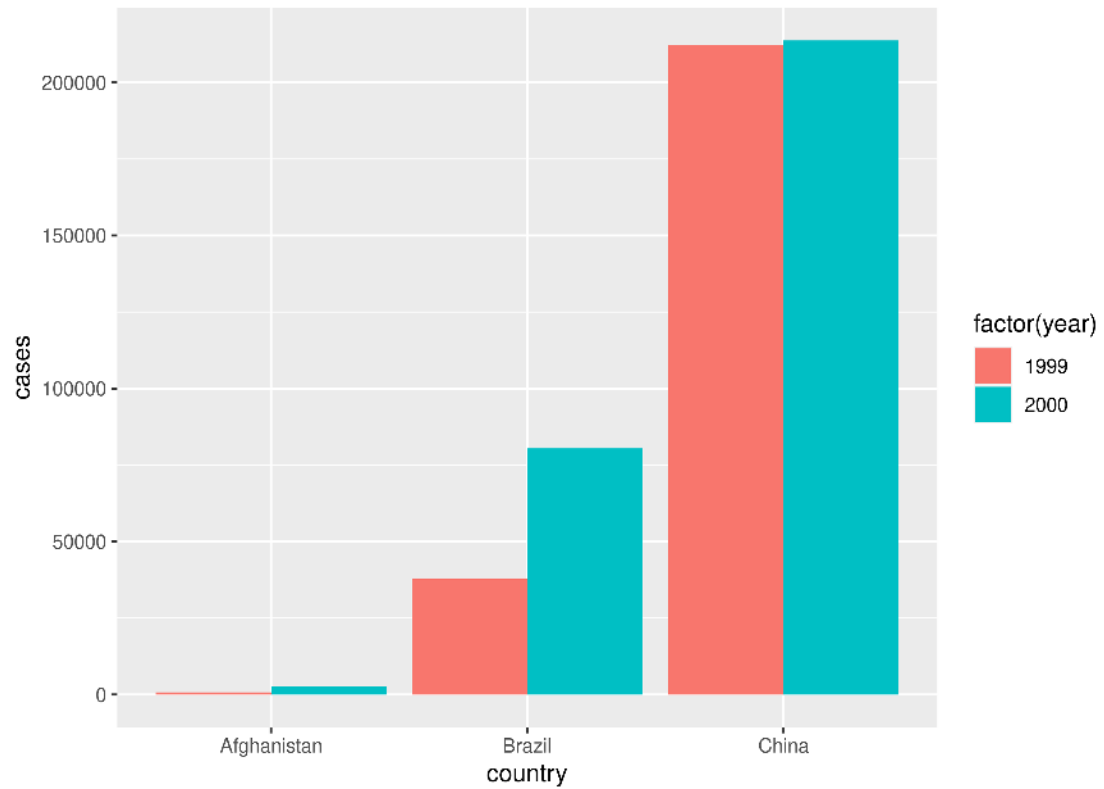
```
1 ggplot(data = table1, aes(x = country, y = cases, fill = factor(year))) +  
2   geom_bar(stat = "identity")
```



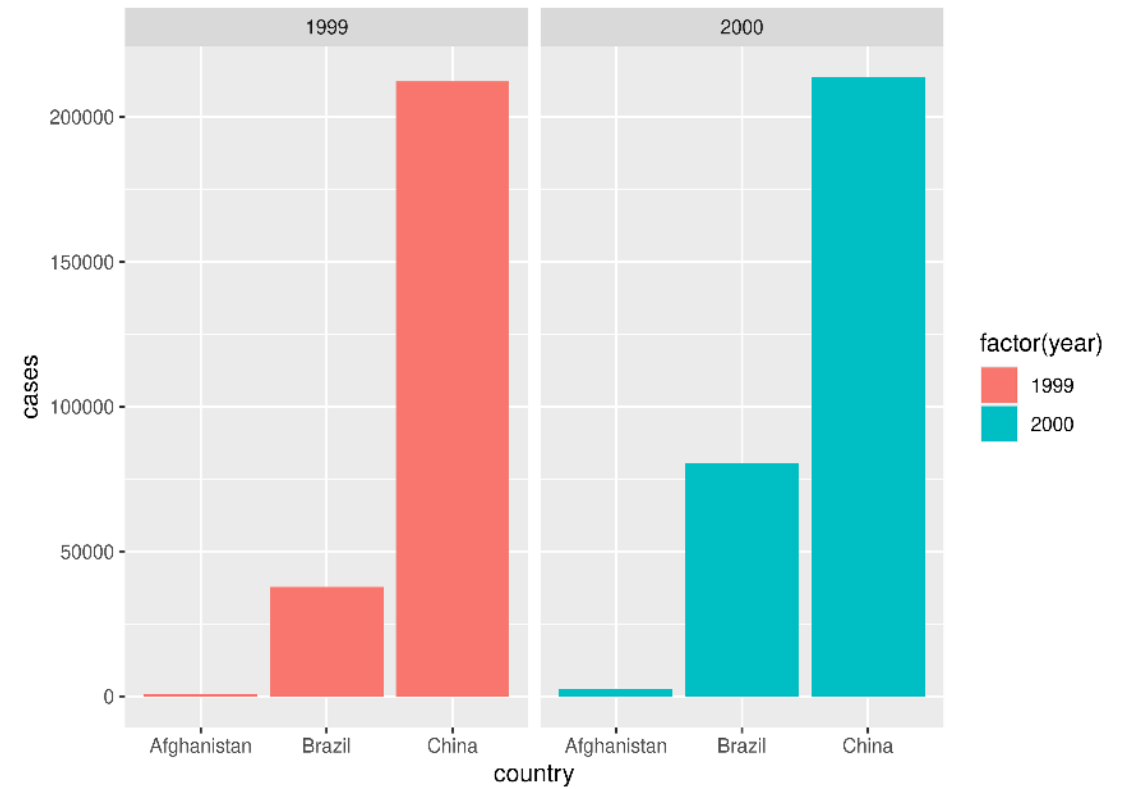
Why do we care?

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 that the 'country' column is mapped to 'country', the '1999' column is mapped to 'year' (with '1999' becoming the value in the 'year' column), and the '2000' column is mapped to 'year' (with '2000' becoming the value in the 'year' column). The 'cases' column in the long table contains the values from both the '1999' and '2000' columns of 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

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

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
# i 104 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
# i 446 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”



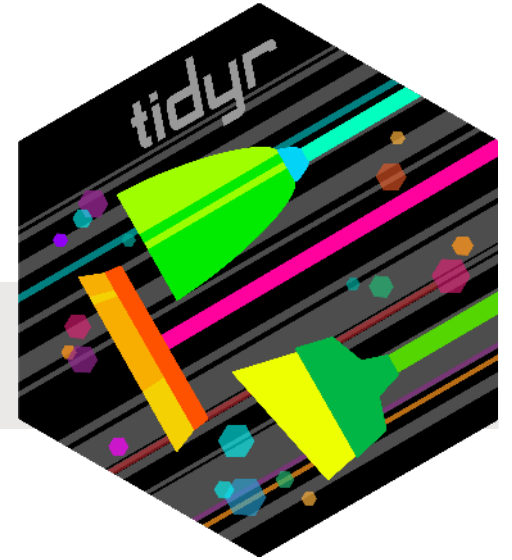
Going long

`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                           ???)
```

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 = contains("sand"),  
3                           names_to = "type",  
4                           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  
# i 71 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

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

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
# i 446 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
# i 104 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`**
- **`names_from`** = **`type`**
- **`values_from`** = **`amount`**



Going wide

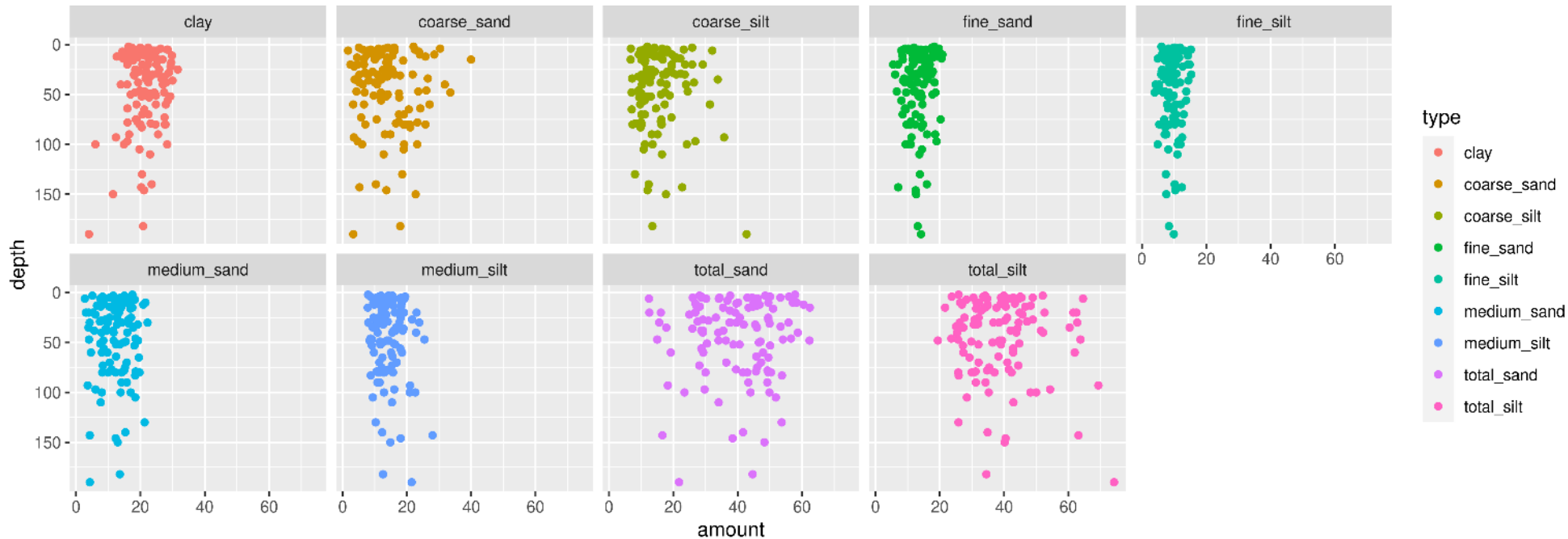
```
1 size_wide <- size_long |>
2   pivot_wider(names_from = type, values_from = amount)
```

```
1 # A tibble: 114 × 14
2   plot depth habitat technician date coarse_sand medium_sand fine_sand coarse_silt medium_silt fine_silt clay
3   <chr> <dbl> <chr>    <chr>    <date>    <dbl>    <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     8.17 16.3
5 2 CSP01    12 forest Catharine 2009-04-23 10.7     16.9     19.2     14.1     11.7     9.03 18.4
6 3 CSP01    35 forest Catharine 2009-04-23 12.1     17.8     16.1     10.3     9.51     7.47 26.7
7 4 CSP01    53 forest Catharine 2009-04-23 17.6     18.2     14.3      9.4      9.1      8.7 22.7
8 5 CSP01    83 forest Catharine 2009-04-23 21.0     18.4     14.3      9.79     8.79     7.29 20.4
9 6 CSP01   105 forest Catharine 2009-04-23 19.0     18.4     14.4     10.8      9.4      8.22 19.7
10 7 CSP08    10 grassland Catharine 2009-03-02 11.6     17.1     20.8     16.3      9.55     6.23 18.4
11 8 CSP08    27 grassland Catharine 2009-03-02 15.4     16.2     17.8     14.3     10.4      6.1 19.6
12 9 CSP08    90 grassland Catharine 2009-03-02 14.9     15.8     18.6     15.1     11.5      7.56 16.5
13 10 CSP02     5 forest Catharine 2009-05-06 8.75      8.64      8.66     12.0     18.3     15.2 28.5
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

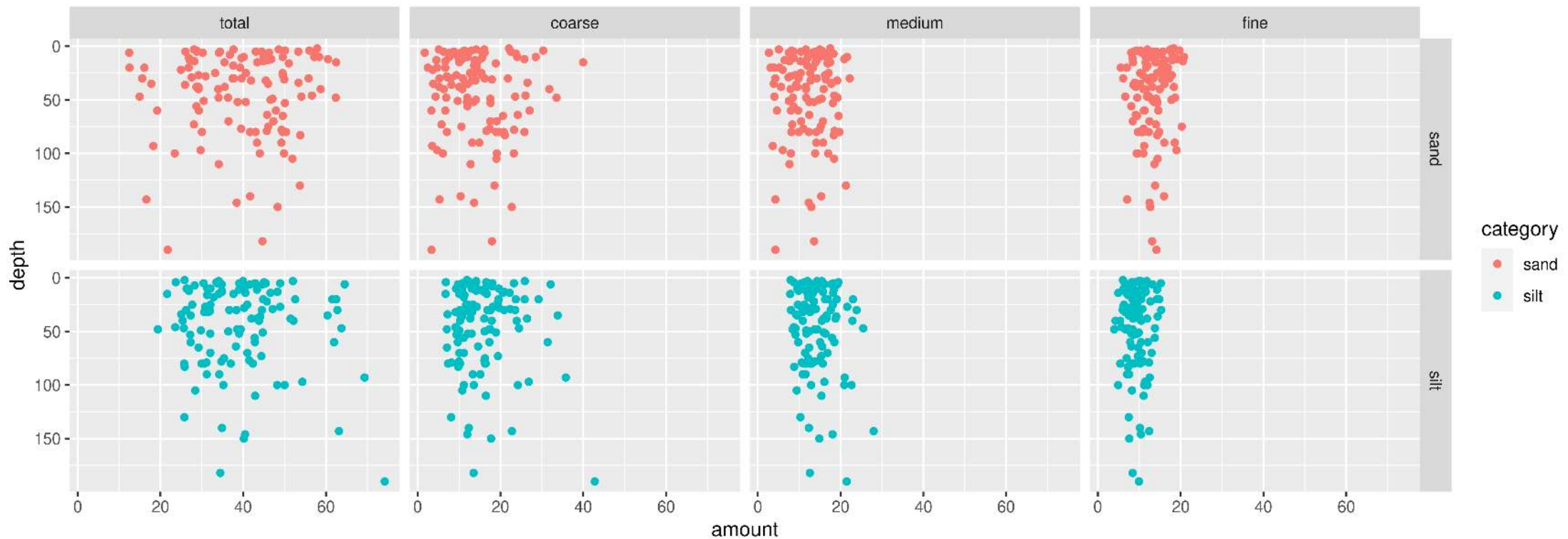
```
1 size <- read_csv("data/grain_size2.csv") |>
2   left_join(meta, by = "plot") |>
3   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
4          total_silt = coarse_silt + medium_silt + fine_silt)
5
6 size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date, -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 it's 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

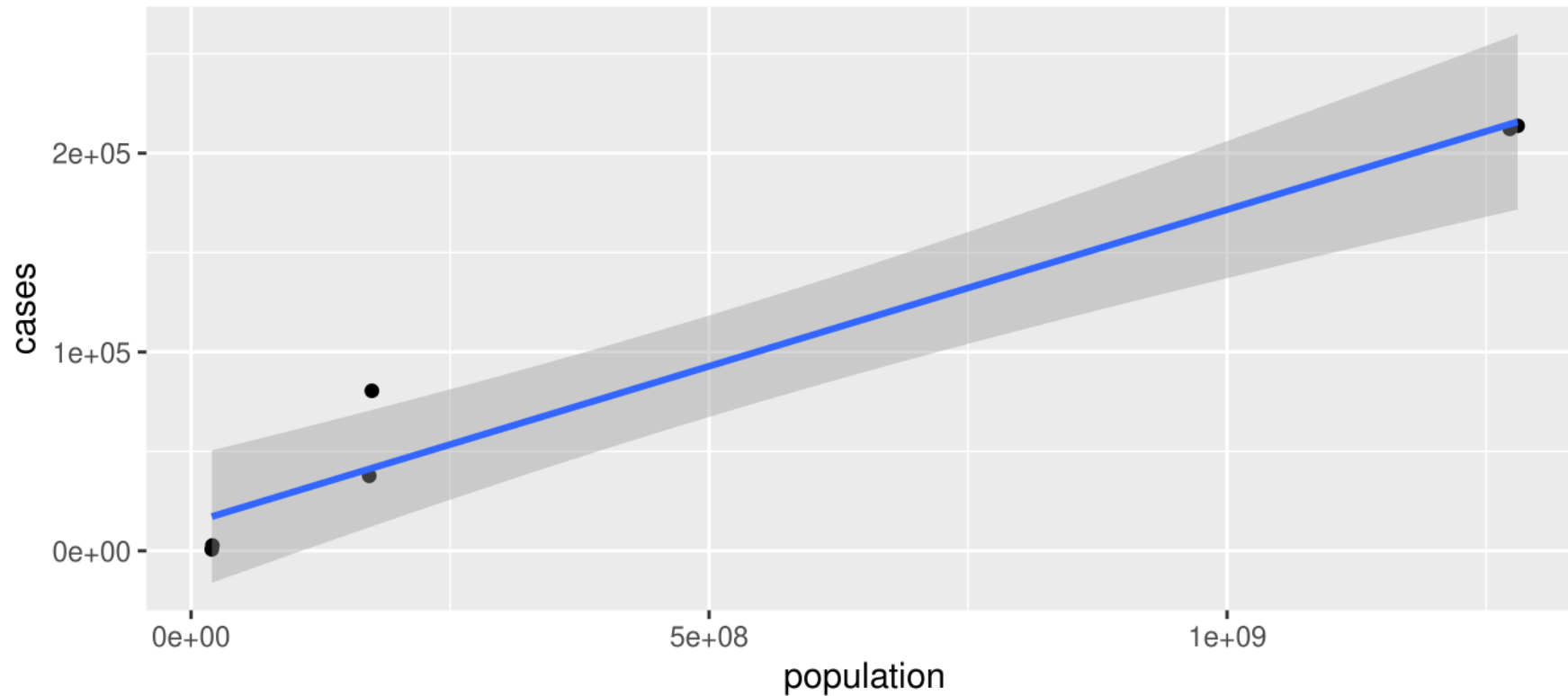
Plot the number of Tuberculosis cases (`cases`) vs. the `population` in data frame `table2`

```
1 temp <- table2 |>
2   ???(???)
3
4 ggplot(data = temp, ???) +
5   ???
```


Your Turn: Transpose for plotting

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

```
1 temp <- table2 |>
2   pivot_wider(names_from = "type", values_from = "count")
3
4 ggplot(data = temp, aes(x = population, y = cases)) +
5   geom_point() +
6   stat_smooth(method = "lm")
```



Put it all together

```
1 meta <- read_csv("data/grain_meta.csv")
2 size <- read_csv("data/grain_size2.csv") |>
3   left_join(meta, by = "plot") |>
4   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
5          total_silt = coarse_silt + medium_silt + fine_silt)
6
7 size_sum <- size |>
8   group_by(plot, habitat) |>
9   summarize(sample_size = n(),
10             total_sand = sum(total_sand),
11             mean_sand = mean(total_sand),
12             sd_sand = sd(total_sand),
13             se_sand = sd_sand / sqrt(sample_size),
14             total_silt = sum(total_silt),
15             mean_silt = mean(total_silt),
16             sd_silt = sd(total_silt),
17             se_silt = sd_silt / sqrt(sample_size))
18
19 size_long <- size |>
20   pivot_longer(cols = c(-plot, -depth, -technician, -habitat, -date, -clay),
21               values_to = "amount", names_to = c("size", "category"), names_sep = "_") |>
22   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`
 - 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 5: Transforming data](#)
 - [Chapter 12: Tidy data](#)
 - [Chapter 13: Relational data](#)
- [RStudio Data Manipulation with dplyr, tidyr](#)
 - Or Help > Cheatsheets > Data Manipulation

