

Summarizing & Transforming Data in R

Saving you time and sanity

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Analysis and Data Tools for Science



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()`

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



* part of the `tidyverse`

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

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

filter() observations

filter() by a combination → use comma for AND

```
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

filter() observations

filter() by a combination → use comma for AND

```
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 to using &

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

Tangent

Logical Operators

Logical Operators

Possible options

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

Your turn!

What do the following filters do?

```
1 size <- read_csv("data/grain_size2.csv")
2
3 filter(size, depth == 20)
4 filter(size, depth == 20, clay < 20)
5 filter(size, depth %in% c(20, 100) & clay == 6)
6 filter(size, !plot %in% c("CSP01", "CSP13"))
7 filter(size, depth >= 146)
8 filter(size, depth > 146)
9 filter(size, coarse_silt < 9 | clay < 5)
```

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



* part of the `tidyverse`

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
```

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
```


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
<code>starts_with()</code>	<code>starts_with("fine")</code>
<code>contains()</code>	<code>contains("sand")</code>
<code>everything()</code>	Useful for rearranging
<code>matches()</code>	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

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?

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
```

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

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

Joining or Merging data

Joining data sets

Measurements

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

Metadata

Plot	Vegetation Density
A	50
B	76

Joining data sets

Measurements

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

Metadata

Plot	Vegetation Density
A	50
B	76

Joining them together

Metadata is duplicated to line up with measurements

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

Joining data sets

Index or Metadata

```
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>
```

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  2009-07-12
14 CSP14 clearcut    Jason
15 CSP15 forest      Yasir
# i 12 more rows
```

Measurements

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

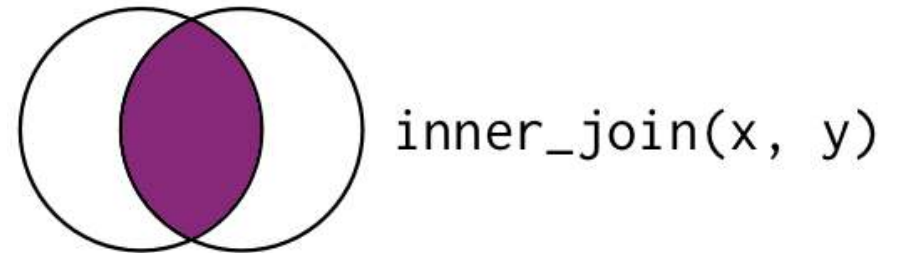
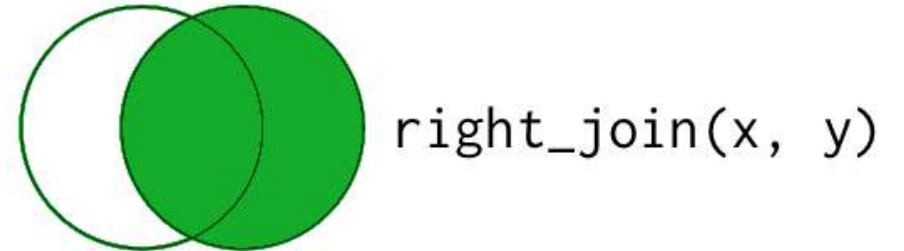
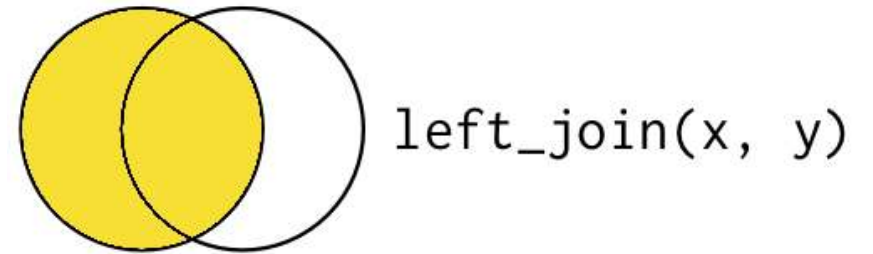
```
# A tibble: 114 × 9
  plot    depth coarse_sand medium_sand fine_sand coarse_silt
  <chr>   <dbl>         <dbl>         <dbl>         <dbl>         <dbl>
1 CSP01     4          13.0          17.4          19.7          14.1
2 CSP01    12          10.7          16.9          19.2          14.1
3 CSP01    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           8.0           8.63           8.06          11.1
14 CSP02    77           8.5           8.45           8.45          11.2
15 CSP02   100           8.0          11.0           9.97
```

```
# 1 3 more variables: medium_silt <dbl>, fine_silt <dbl>, clay
<dbl>
```

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`

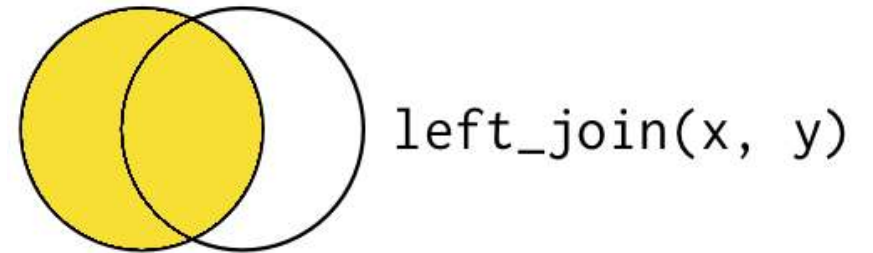


Adapted from “R for Data Science”

Types of Join: Which rows to keep?

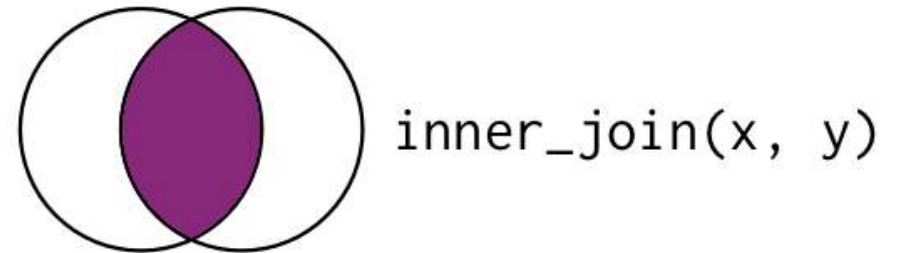
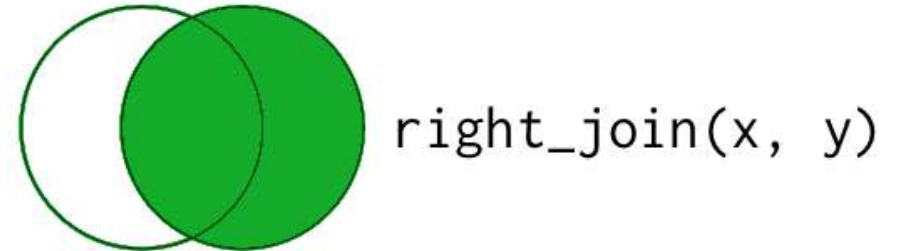
`left_join(x, y)`

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



`right_join(x, y)`

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

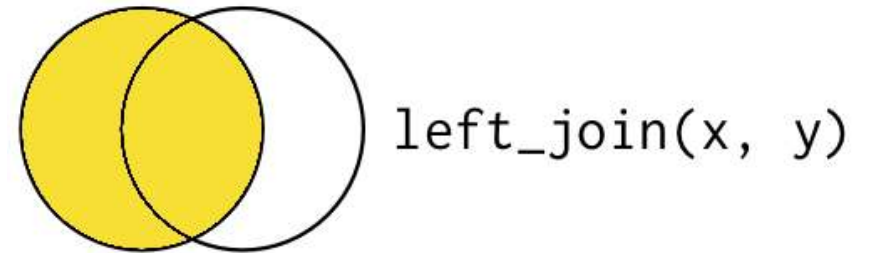


Adapted from “R for Data Science”

Types of Join: Which rows to keep?

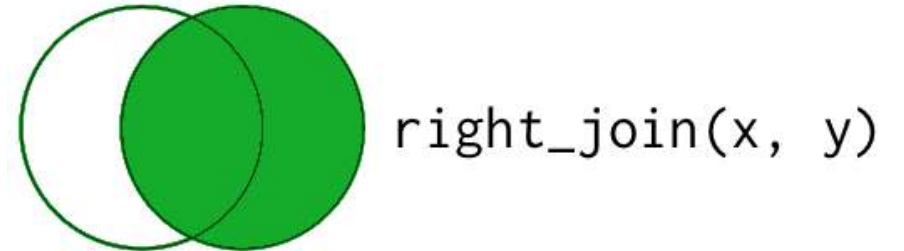
`left_join(x, y)`

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



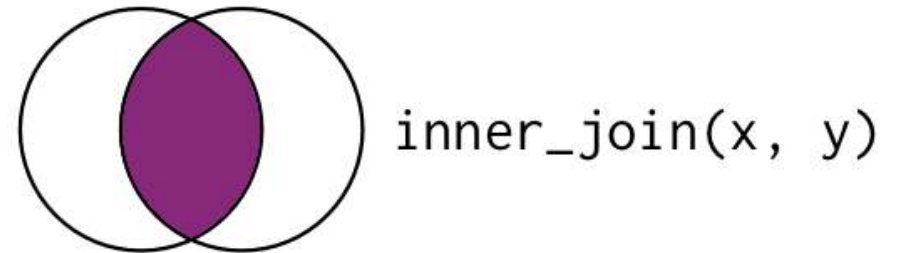
`right_join(x, y)`

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



`inner_join(x, y)`

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

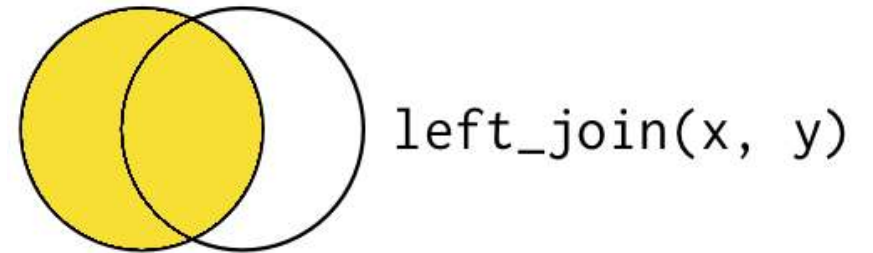


Adapted from “R for Data Science”

Types of Join: Which rows to keep?

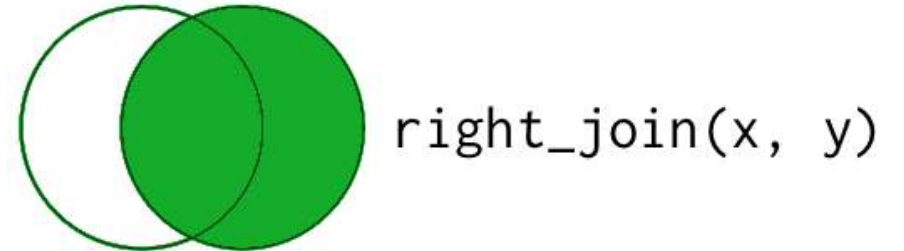
`left_join(x, y)`

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



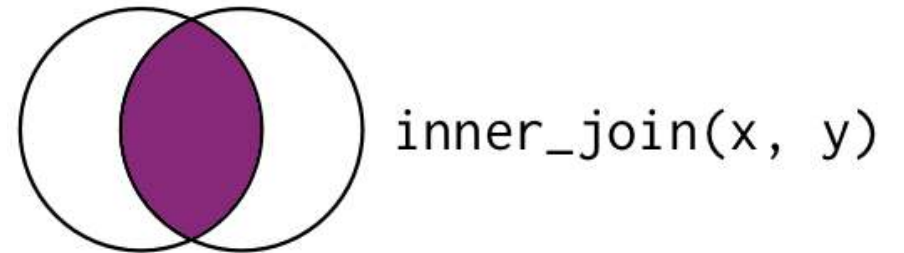
`right_join(x, y)`

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



`inner_join(x, y)`

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



`full_join(x, y)`

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



Adapted from “R for Data Science”

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



* part of the `tidyverse`

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")
```

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

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
3   <chr> <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl> <dbl> <chr>      <chr>
4 1 CSP01     4      13.0      17.4      19.7      14.1      11.2      8.17  16.3 forest    Catharine
5 2 CSP01    12      10.7      16.9      19.2      14.1      11.7      9.03  18.4 forest    Catharine
6 3 CSP01    35      12.1      17.8      16.1      10.3       9.51      7.47  26.7 forest    Catharine
7 4 CSP01    53      17.6      18.2      14.3       9.4       9.1       8.7   22.7 forest    Catharine
8 5 CSP01    83      21.0      18.4      14.3       9.79      8.79      7.29  20.4 forest    Catharine
9 6 CSP01   105      19.0      18.4      14.4      10.8       9.4       8.22  19.7 forest    Catharine
10 7 CSP08    10      11.6      17.1      20.8      16.3       9.55      6.23  18.4 grassland Catharine
11 8 CSP08    27      15.4      16.2      17.8      14.3      10.4       6.1   19.6 grassland Catharine
12 9 CSP08    90      14.9      15.8      18.6      15.1      11.5       7.56  16.5 grassland Catharine
13 10 CSP02     5       8.75       8.64       8.66      12.0      18.3      15.2  28.5 forest    Catharine
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`



* part of the `tidyverse`

Creating new columns

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

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
```


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

For example

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

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?

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          total_silt = coarse_silt + medium_silt + fine_silt)
```

Your turn: Creating new columns (Too Easy?)

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

```
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          total = total_sand + total_silt)
```

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

Your turn: Creating new columns

- Check your work

```
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 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
```

Your turn: Creating new columns

- Check your work

```
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 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
10     12.0       18.3      15.2
# i 104 more rows
```

Wait... that doesn't add up!

Tangent

Tibbles

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

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
```

Back to mutate() ...

Mutating by group

`mutate()` is from `dplyr`*

`mutate()` has a `.by` argument

```
1 mutate(data, column1 = expression1, column2 = expression2, ..., .by = c(group1, group2))
```

- Applies splits data frame by grouping columns *before* calculations



* part of the `tidyverse`

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

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 `.by = COLUMN`:

```
1 size <- size |>
2   mutate(mean_sand_plot = mean(total_sand),
3         .by = plot)
```

```
# 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
9 CSP08      49.2      49.4
# i 105 more rows
```

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

Mutating by group (alternative)

`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`



* part of the `tidyverse`

Mutating by group (alternative)

`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

Mutating by group (alternative)

`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
```

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

Mutating by group (alternative)

`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   ???
```

Too Easy?

Try both methods

Try grouping by multiple columns

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

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

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   group_by(plot) |>
8   mutate(mean_silt = mean(total_silt)) |>
9   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
```

Your turn: Mutating by group

Group by multiple columns

```
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   mutate(mean_silt = mean(total_silt), .by = c(habitat, technician))
```

```
# A tibble: 114 × 7
  habitat technician coarse_silt medium_silt fine_silt total_silt mean_silt
  <chr>      <chr>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
1 forest    Catharine      14.1       11.2       8.17       33.5       37.9
2 forest    Catharine      14.1       11.7       9.03       34.8       37.9
3 forest    Catharine      10.3        9.51       7.47       27.3       37.9
4 forest    Catharine       9.4        9.1        8.7        27.2       37.9
5 forest    Catharine       9.79       8.79       7.29       25.9       37.9
6 forest    Catharine      10.8        9.4        8.22       28.4       37.9
7 grassland Catharine      16.3        9.55       6.23       32.1       32.8
8 grassland Catharine      14.3       10.4        6.1       30.8       32.8
9 grassland Catharine      15.1       11.5        7.56       34.2       32.8
10 forest    Catharine      12.0       18.3       15.2       45.4       37.9
# i 104 more rows
```

Your turn: Mutating by group

Group by multiple columns

```
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(habitat, technician) |>
8   mutate(mean_silt = mean(total_silt)) |>
9   ungroup()
```

```
# A tibble: 114 × 7
  habitat technician coarse_silt medium_silt fine_silt total_silt mean_silt
  <chr>      <chr>          <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
1 forest    Catharine         14.1        11.2         8.17        33.5        37.9
2 forest    Catharine         14.1        11.7         9.03        34.8        37.9
3 forest    Catharine         10.3         9.51         7.47        27.3        37.9
4 forest    Catharine          9.4         9.1         8.7         27.2        37.9
5 forest    Catharine          9.79        8.79         7.29        25.9        37.9
6 forest    Catharine         10.8         9.4         8.22        28.4        37.9
7 grassland Catharine         16.3         9.55         6.23        32.1        32.8
8 grassland Catharine         14.3        10.4         6.1         30.8        32.8
9 grassland Catharine         15.1        11.5         7.56        34.2        32.8
10 forest   Catharine         12.0        18.3        15.2        45.4        37.9
# i 104 more rows
```

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   mutate(mean_sand = mean(total_sand),
8          mean_silt = mean(total_silt),
9          .by = plot)
```

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   mutate(mean_sand = mean(total_sand),
8          mean_silt = mean(total_silt),
9          .by = plot)
```

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,  
2           column1 = expression1, column2 = expression2, ...,  
3           .by = c(group1, group2))
```

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



* part of the `tidyverse`

Summarizing by group

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

`mutate()`

```
1 size <- size |>
2   mutate(mean_sand = mean(total_sand), .by = plot)
3
4 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   summarize(mean_sand = mean(total_sand), .by = plot)
3
4 size

# A tibble: 27 × 2
   plot    mean_sand
  <chr>    <dbl>
1 CSP01     49.8
2 CSP08     49.4
3 CSP02     34.7
4 CSP04     30.3
5 CSP05     44.6
6 CSP09     37.9
7 CSP12     43.1
8 CSP13     46.6
9 CSP16     43.9
10 CSP17     41.2
# i 17 more rows
```

No repeated values and
drops unused columns

Summarizing by group

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

```
1 size |>
2   summarize(mean_sand = mean(total_sand), .by = c(plot, depth))
```

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	CSP08	10	49.6
8	CSP08	27	49.5
9	CSP08	90	49.2
10	CSP02	5	26.0

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   summarize(mean_sand = mean(total_sand), .by = c(plot, habitat))

# A tibble: 27 × 3
  plot  habitat mean_sand
  <chr> <chr>      <dbl>
1 CSP01 forest      49.8
2 CSP08 grassland   49.4
3 CSP02 forest      34.7
4 CSP04 forest      30.3
5 CSP05 grassland   44.6
6 CSP09 forest      37.9
7 CSP12 grassland   43.1
8 CSP13 grassland   46.6
9 CSP16 forest      43.9
10 CSP17 forest      41.2
# 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` 😊

* Special function, can only be used *inside* of `mutate ()` or `summarize ()`

** There is no standard error function in R, but we can calculate it by hand

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   summarize(samples_total = n(), .by = plot)
```

```
# A tibble: 27 × 2
  plot  samples_total
<chr>          <int>
1 CSP01             6
2 CSP08             3
3 CSP02             7
4 CSP04             5
5 CSP05             5
6 CSP09             5
7 CSP12             5
8 CSP13             5
# i 19 more rows
```

Your Turn: Calculate summary statistics

For each plot and habitat, calculate

- standard error for **total_sand**
- mean for **total_silt**
- standard deviation for **total_silt**
- standard error for **total_silt**

Hint

Use `sd(x)/sqrt(n())` for standard error calculations

```
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   summarize(sample_size = n(),
10             mean_sand = mean(total_sand),
11             sd_sand = sd(total_sand),
12             se_sand = ???,
13             ???,
14             .by = c(plot, habitat))
```

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... can you use the `across()` function to do this elegantly?

Your Turn: Calculate summary statistics

For each plot and habitat, calculate

- standard error for **total_sand**
- mean for **total_silt**
- standard deviation for **total_silt**
- standard error 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          total_silt = coarse_silt + medium_silt + fine_silt)
7
8 size_sum <- size |>
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),
16             .by = c(plot, habitat))
```


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

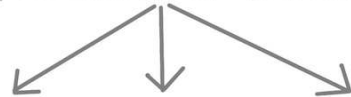
“**TIDY DATA** is a standard way of mapping the meaning of a dataset to its structure.”

—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

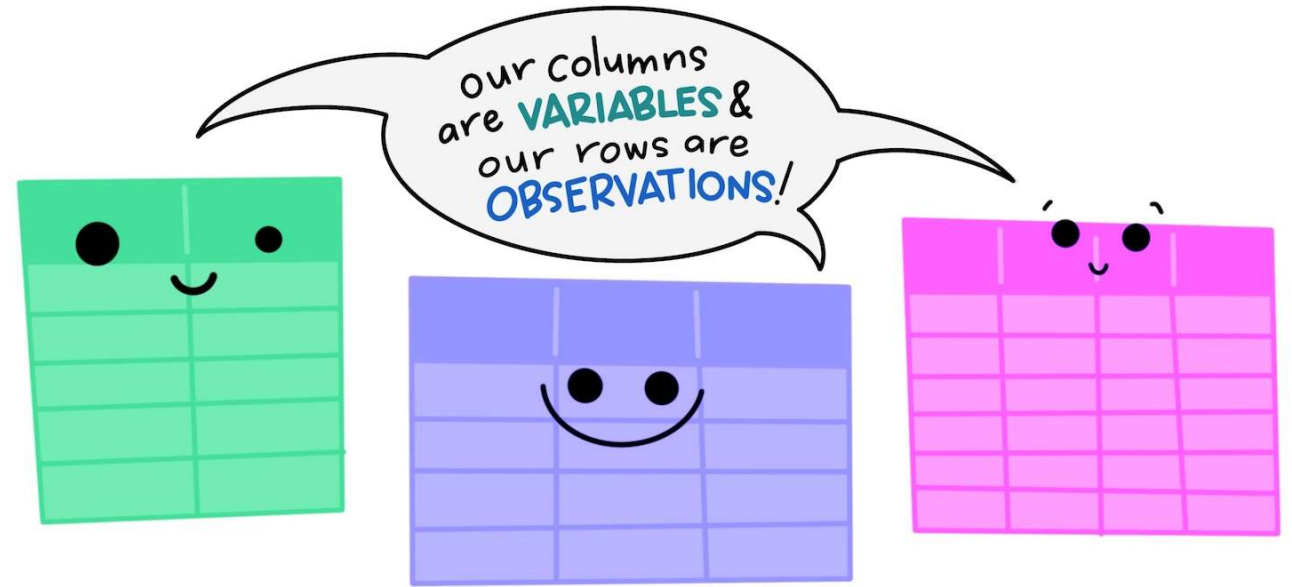
Long data
One measurement per row

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

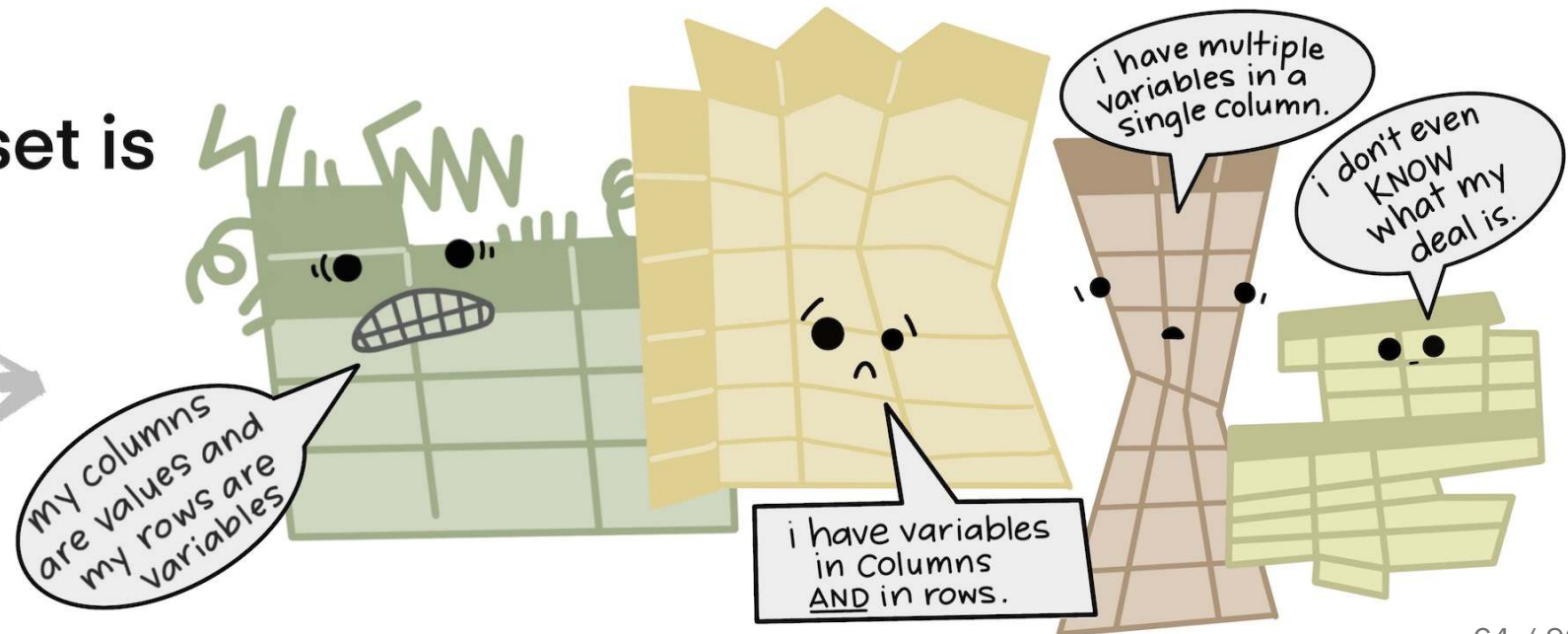
Wide data
Several measurements
per row

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

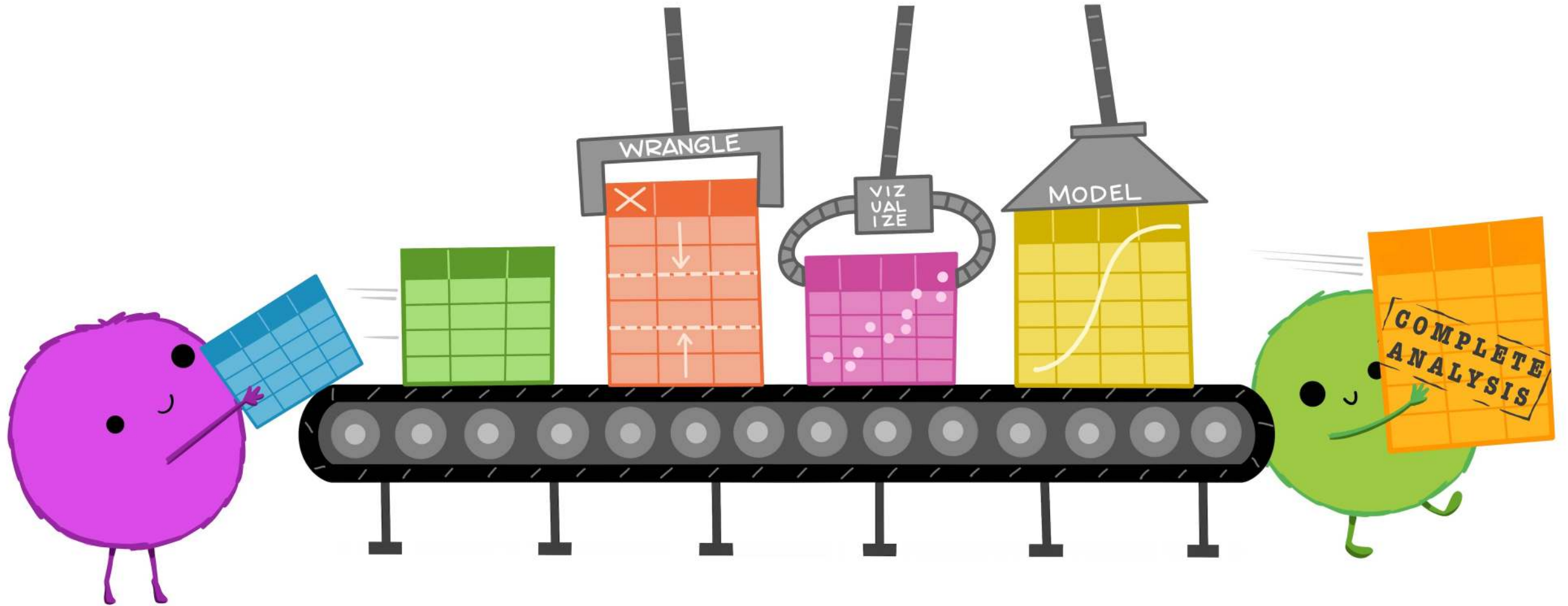


"...but every messy dataset is
messy in its own way."

—HADLEY WICKHAM



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   ???
```

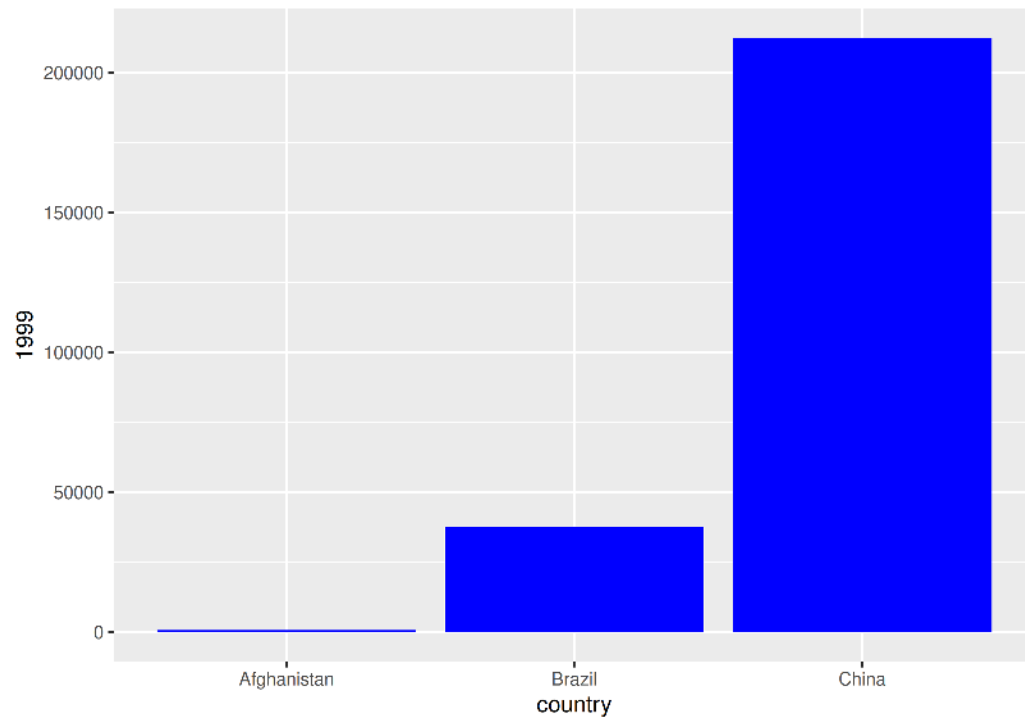
Note

- `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

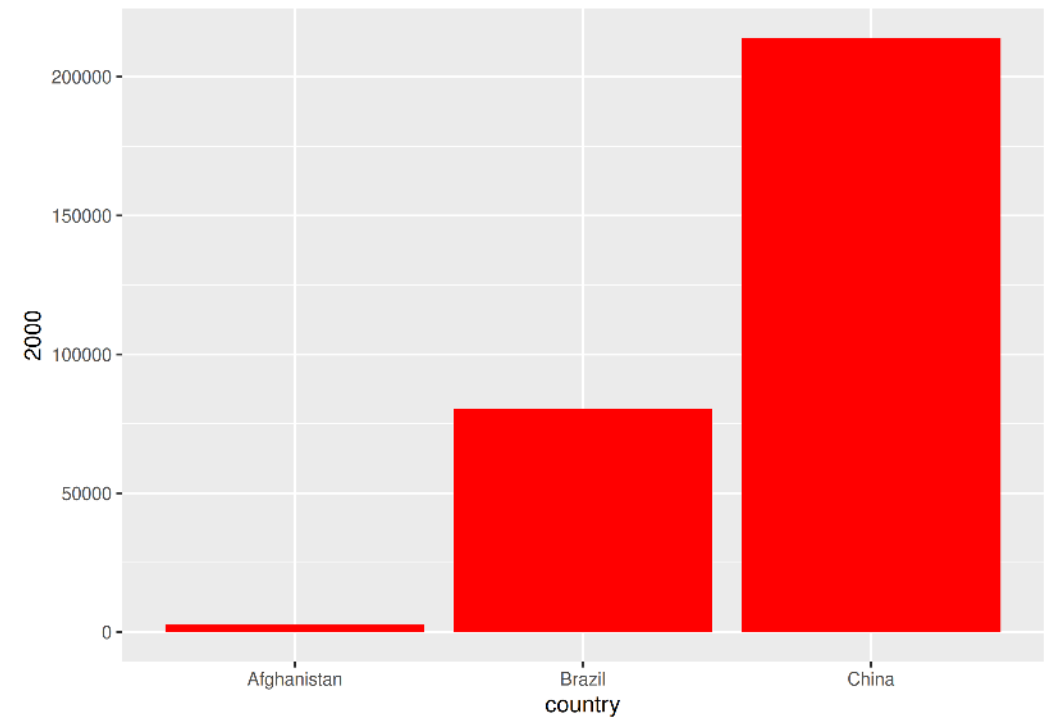
Why do we care?

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

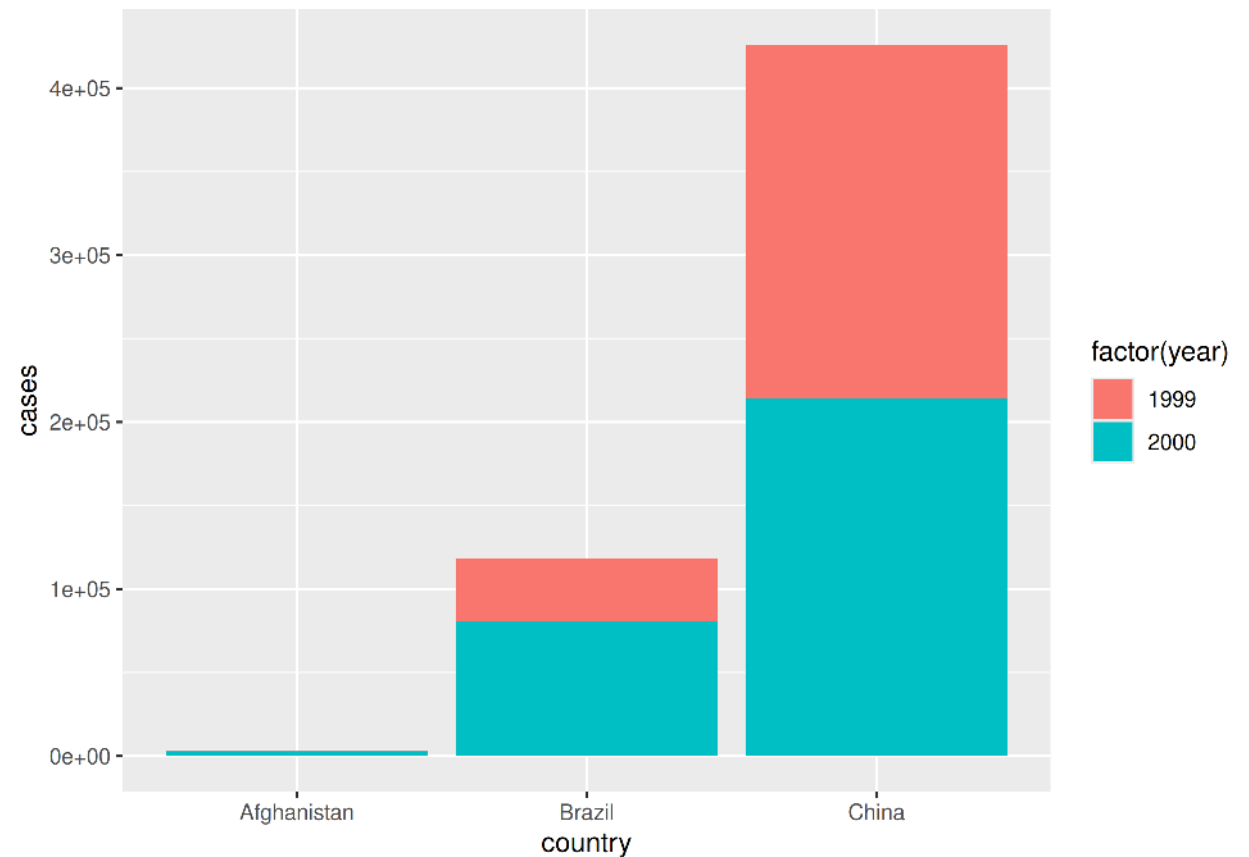
country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

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

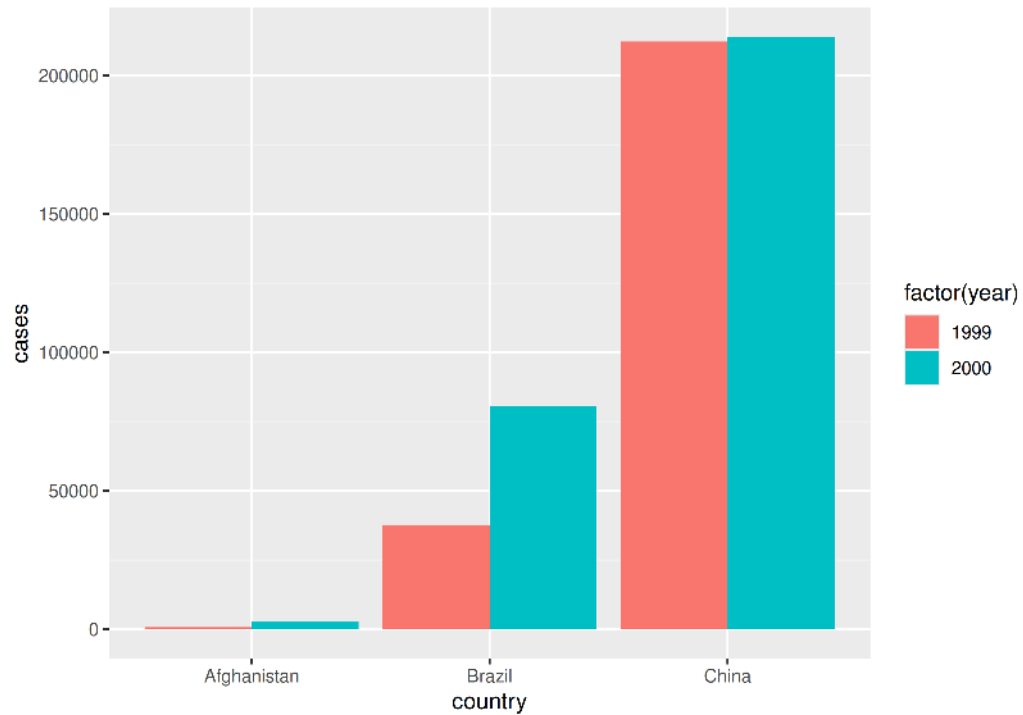
```
1 ggplot(data = table1, aes(x = country, y = cases, fill = factor(year))) +  
2   geom_bar(stat = "identity")
```



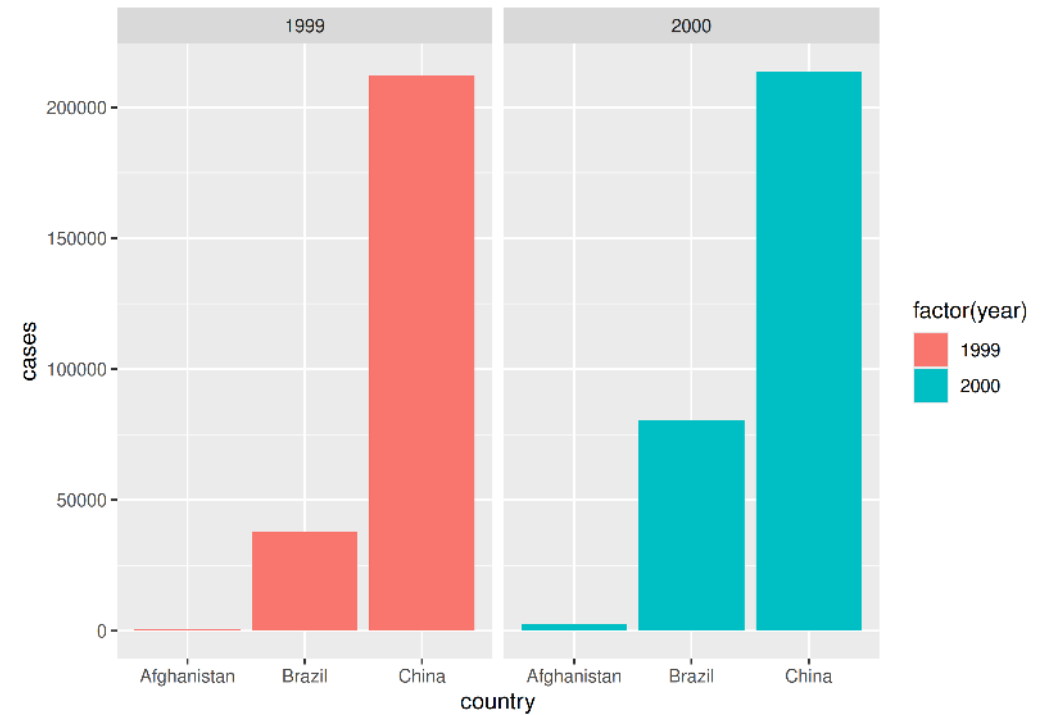
Why do we care?

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)
```

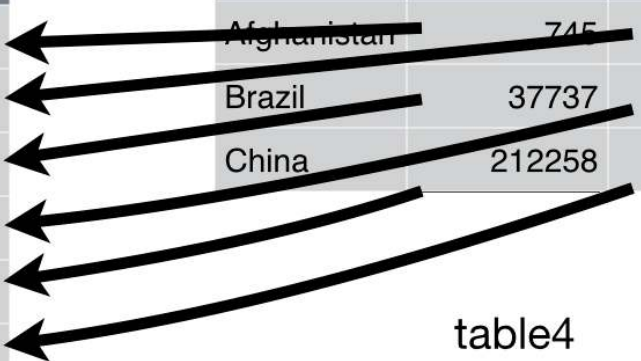


Going long

`pivot_longer()`

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

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”



* part of the `tidyverse`

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"`

* part of the `tidyverse`

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   summarize(sample_size = n(),
4             mean_sand = mean(total_sand),
5             sd_sand = sd(total_sand),
6             se_sand = sd_sand / sqrt(sample_size),
7             .by = plot)
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 CSP08         3     49.4   0.176  0.102
3 CSP02         7     34.7  10.8   4.06
4 CSP04         5     30.3   2.18   0.973
5 CSP05         5     44.6   5.52   2.47
6 CSP09         5     37.9   2.98   1.33
7 CSP12         5     43.1   3.24   1.45
8 CSP13         5     46.6   6.91   3.09
9 CSP16         5     43.9  14.9   6.67
10 CSP17         3     41.2   3.46   2.00
# 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 = ???)
```

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  
11 CSP04         5 sd_sand    2.18  
12 CSP04         5 se_sand    0.973  
13 CSP05         5 mean_sand  44.6  
14 CSP05         5 sd_sand    5.52  
15 CSP05         5 se_sand    2.47  
# i 66 more rows
```

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  
11 CSP04         5 sd_sand    2.18  
12 CSP04         5 se_sand    0.973  
13 CSP05         5 mean_sand  44.6  
14 CSP05         5 sd_sand    5.52  
15 CSP05         5 se_sand    2.47  
# i 66 more rows
```

Remember tidy selectors!

Could also use...

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

Going wide

`pivot_wider()`

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

table2

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

Going wide

From long ...

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

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



* part of the `tidyverse`

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`



* part of the `tidyverse`

Going wide

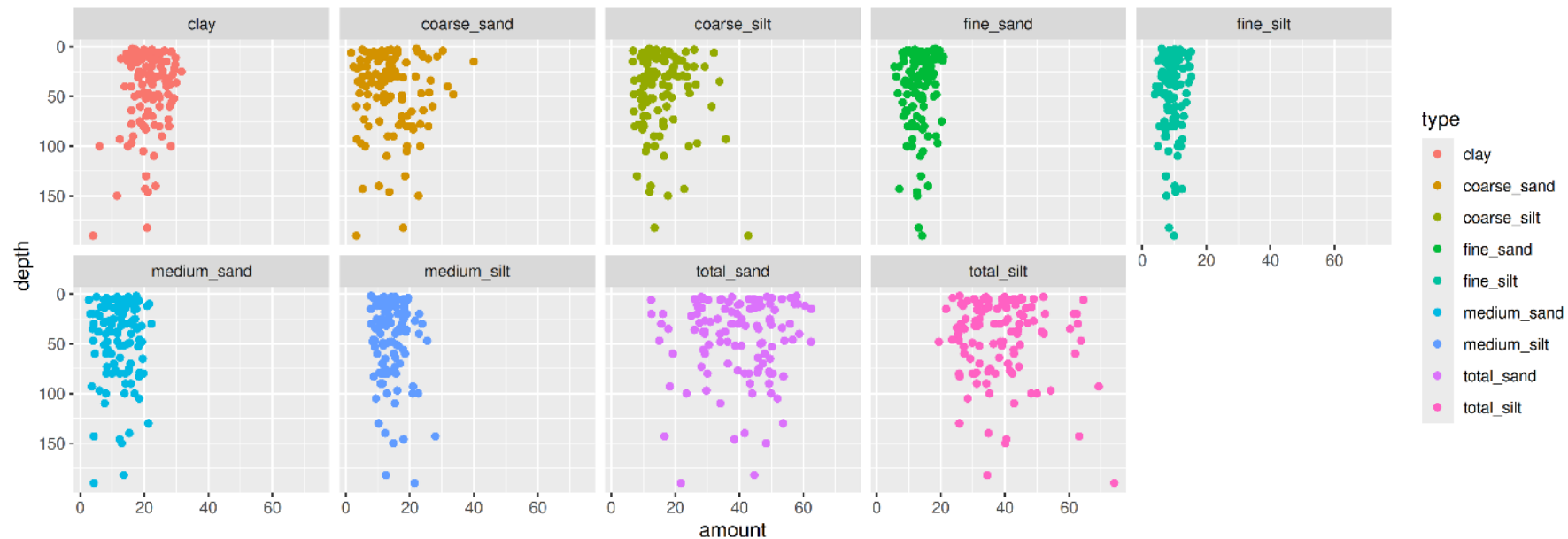
```
1 size_wide <- pivot_wider(size_long, names_from = type, values_from = amount)
```

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

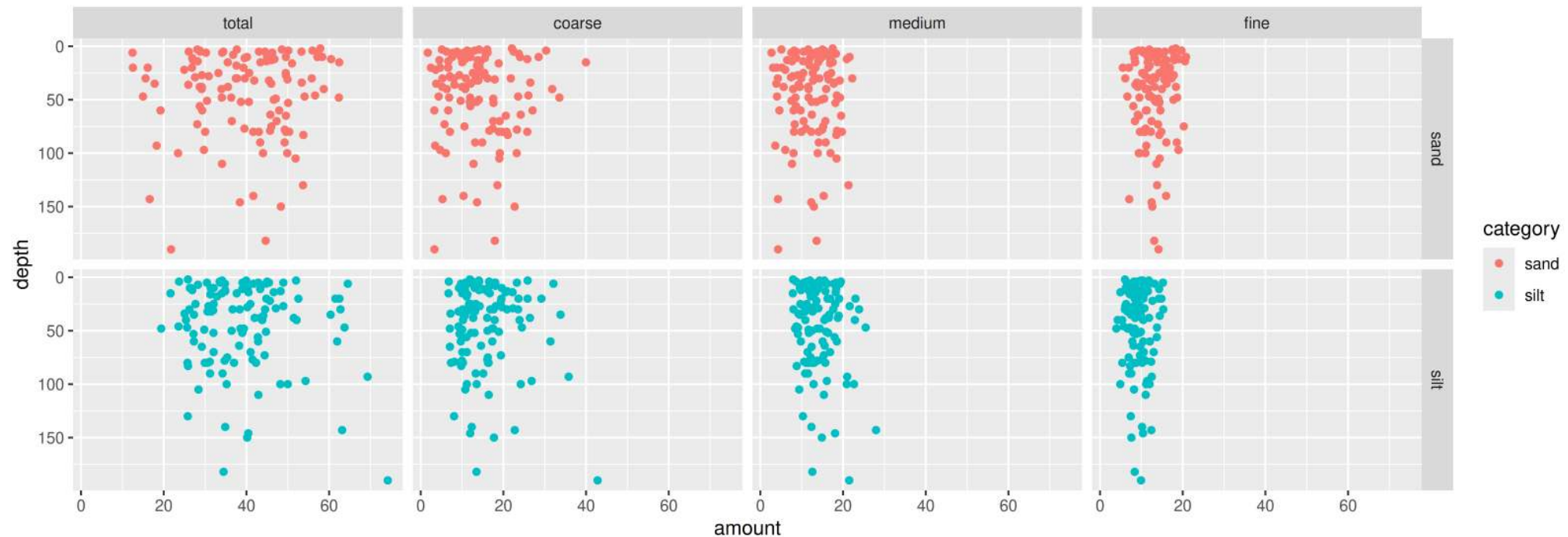
```
1 size <- read_csv("data/grain_size2.csv") |>
2   left_join(meta, by = "plot") |>
3   mutate(total_sand = coarse_sand + medium_sand + fine_sand,
4          total_silt = coarse_silt + medium_silt + fine_silt)
5
6 size_long <- pivot_longer(size, cols = c(-plot, -depth, -technician, -habitat, -date,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

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

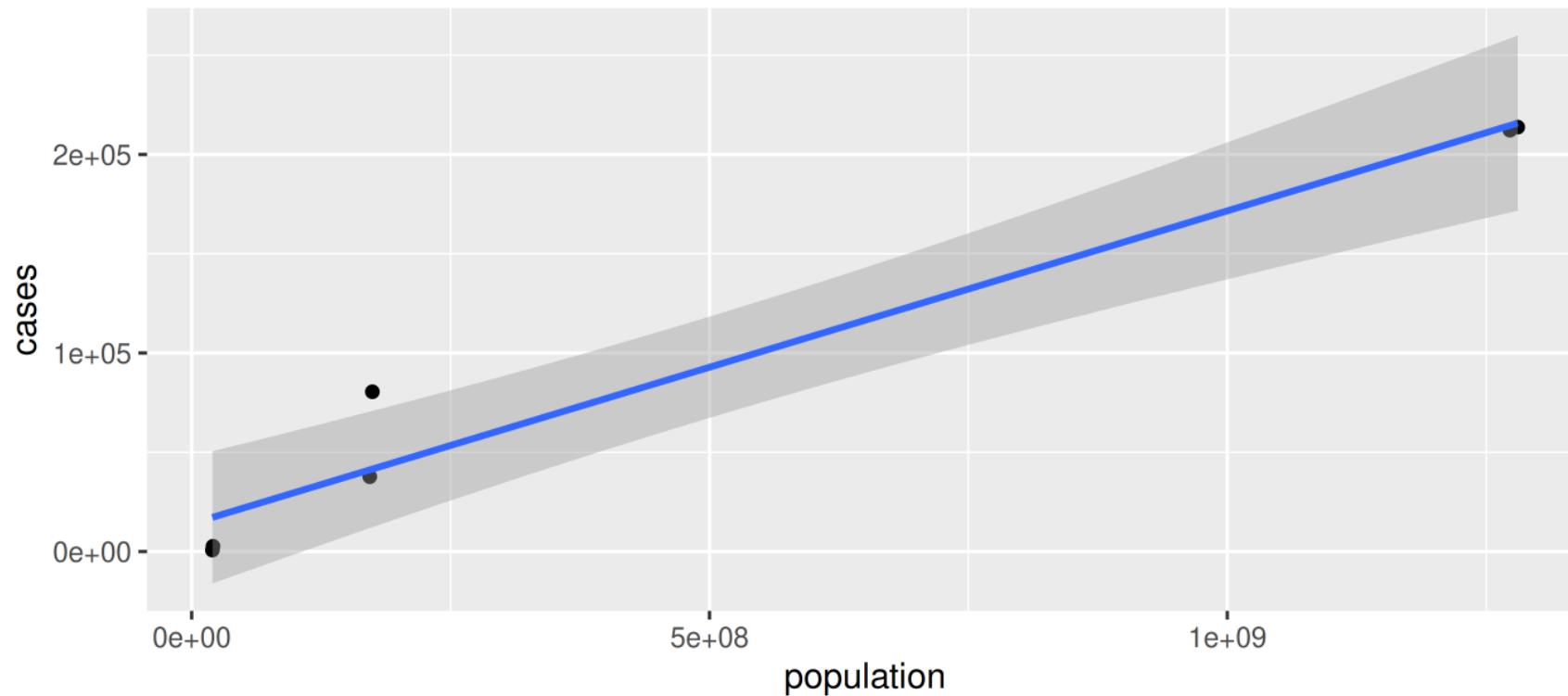
Plot the number of Tuberculosis `cases` vs. the `population` in data frame `table2`

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

Your Turn: Transpose for plotting

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

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



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   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             .by = c(plot, habitat))
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

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- Make sure you loaded `tidyverse` or `dplyr` packages
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Joins use `by`, mutate/summarizes use `.by`

Wrapping up: Common mistakes

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