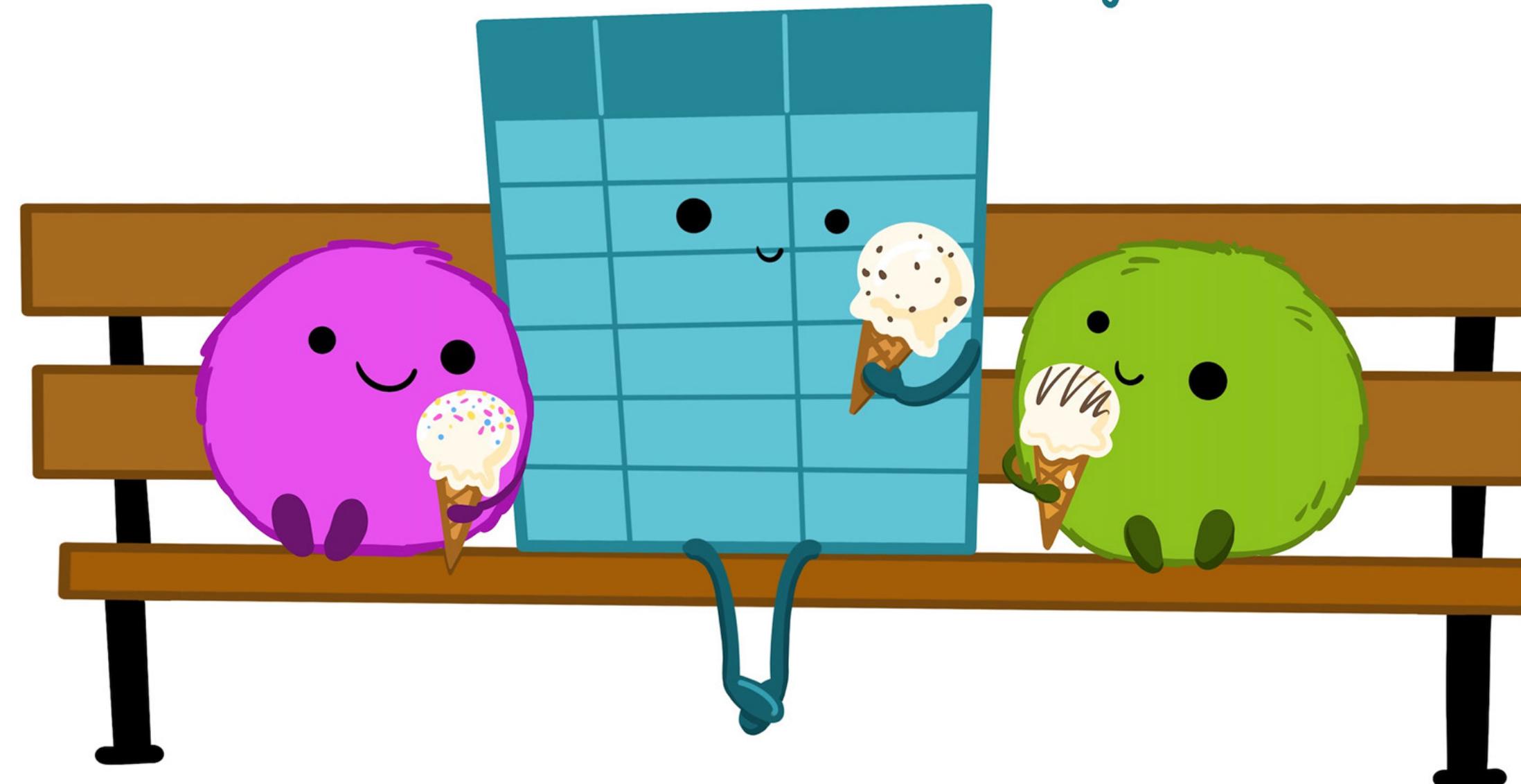


# Tidy Data and Data Joins

## Week 7 (11/12/25)

make friends with tidy data.



Artwork by Allison Horst

Stepfanie M. Aguillon

# Outline of today's class

- What is tidy data?
- Introduction to tidying data with `tidyverse`
- Introduction to joining datasets with `dplyr`

# What is tidy data?

# What is tidy data?

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

—HADLEY WICKHAM

variables

country	year	cases	population
Afghanistan	1999	745	19981071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	128042583

observations

country	year	cases	population
Afghanistan	1999	745	19981071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	128042583

values

country	year	cases	population
Afghanistan	1999	745	19981071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	128042583

# What is tidy data?

“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

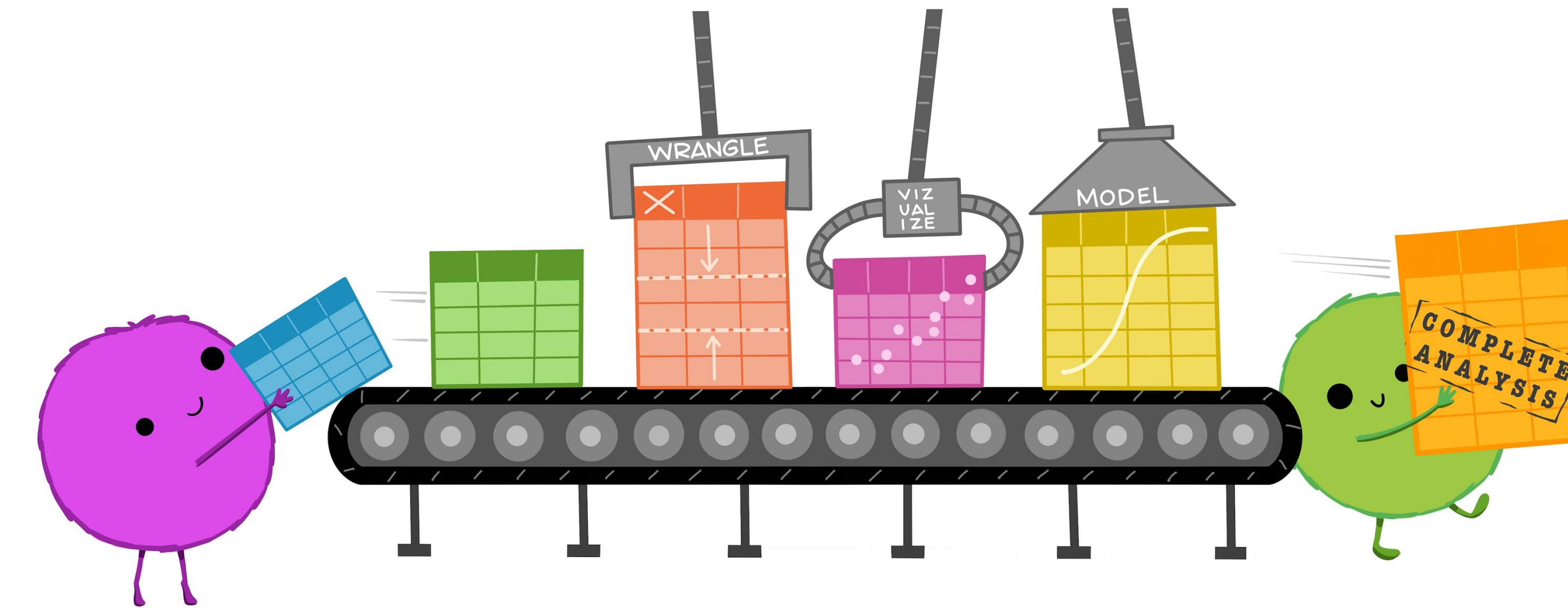
each column a variable

each row an observation

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

# So... why use tidy data?

“Tidy datasets are all alike, but every messy dataset is messy in its own way.” - Hadley Wickham



Artwork by Allison Horst

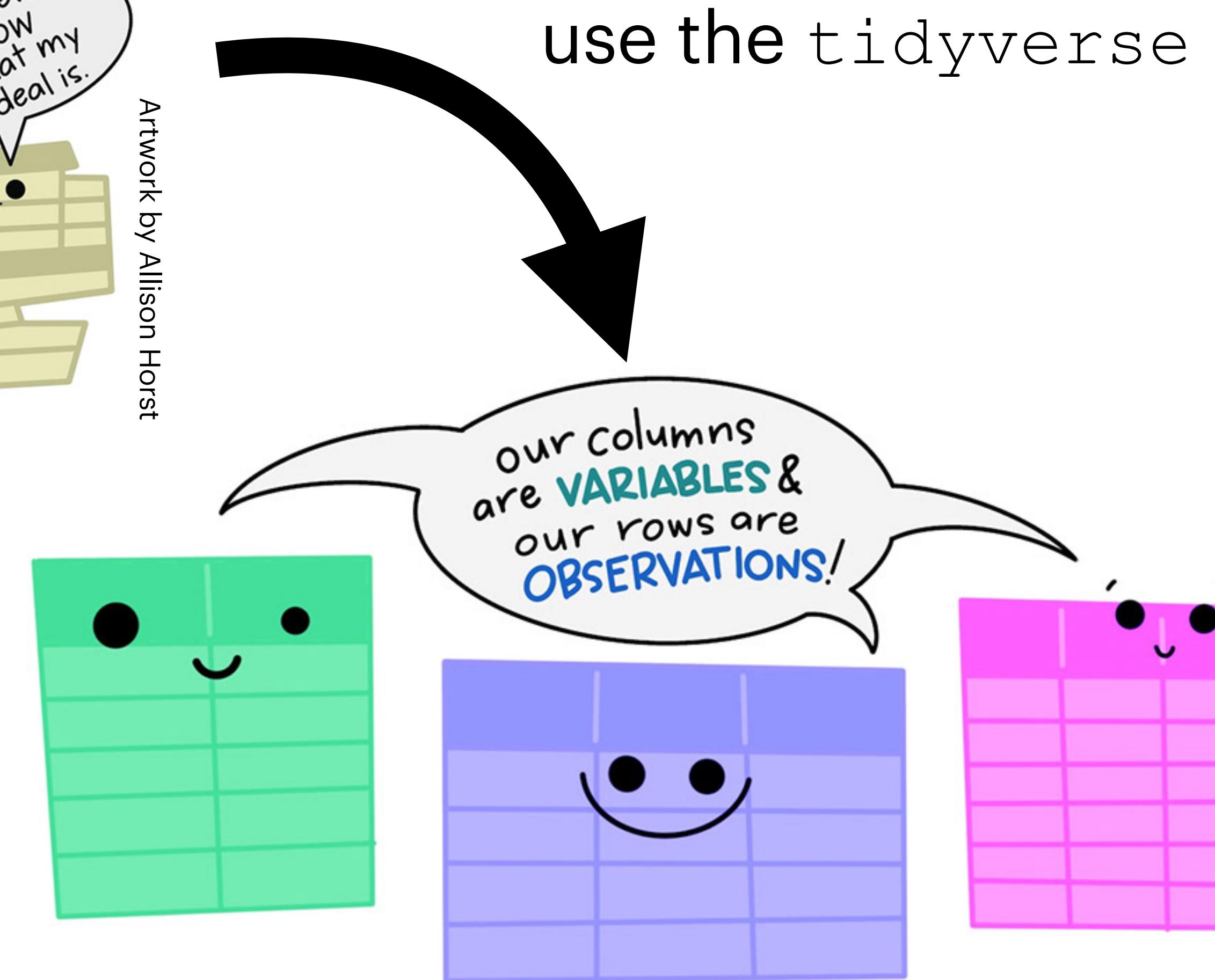
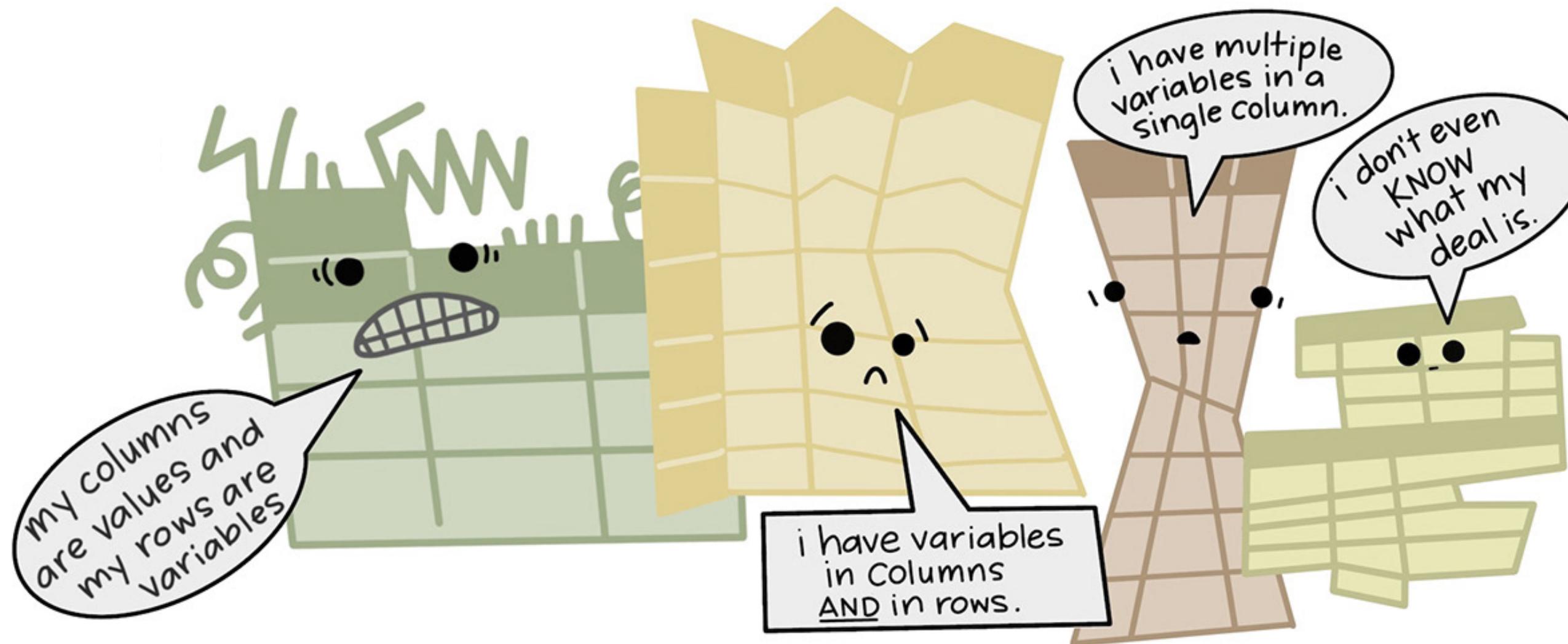
# Advantages to tidy data

- 1 With a consistent tidy data structure, tools you use or develop with one dataset will work with others.
- 2 R really likes vectors! Storing your variables as columns allows R to work with them as vectors more easily.
- 3 The tidyverse is designed to work with tidy data.

# Human readable data ≠ Tidy data

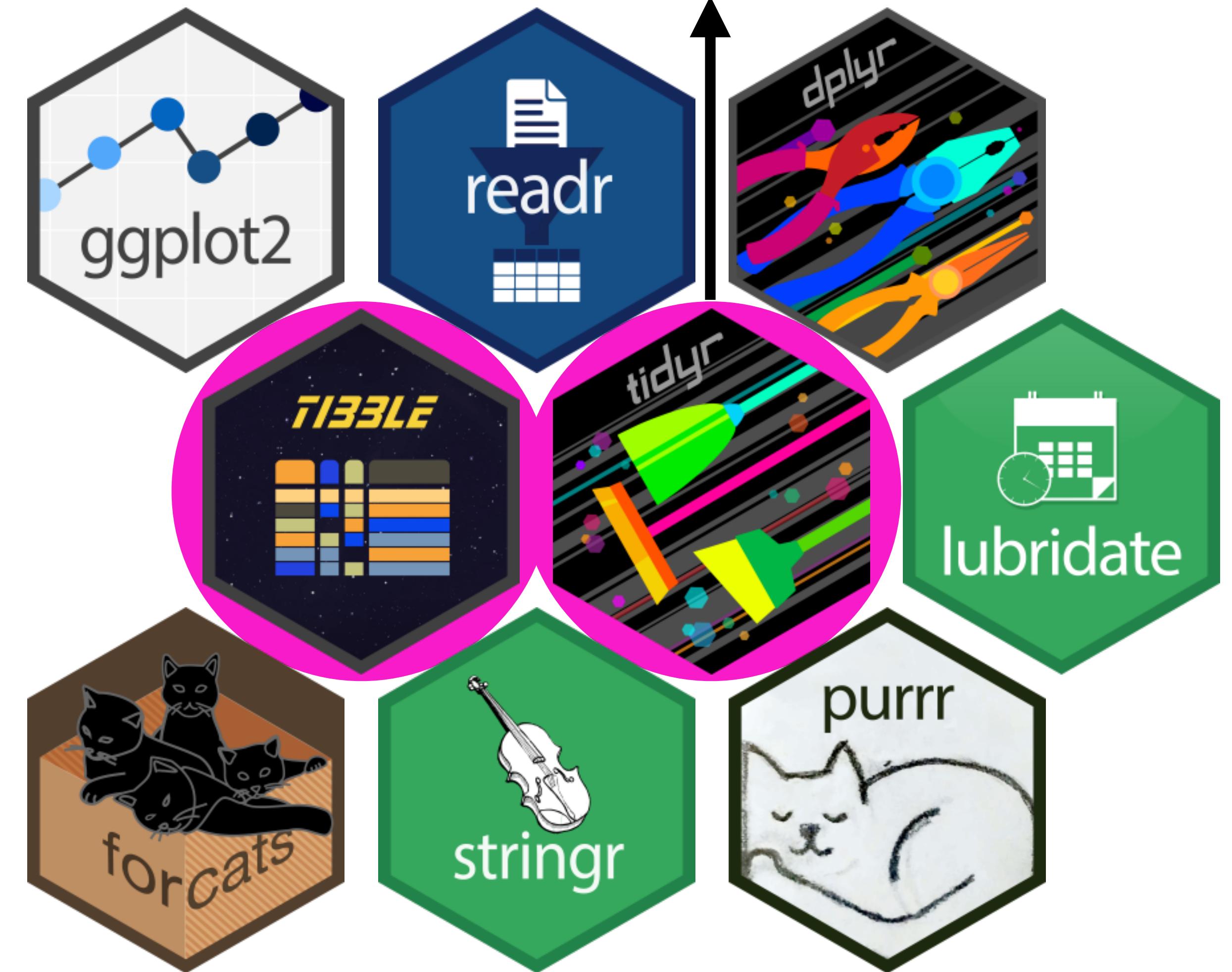
film_number	Dwarf	Elf	Hobbit	Man	Orc	Wizard
I	431	2200	3658	1995	27	2881
II	521	844	2463	3990	230	1273
III	313	693	2675	2727	466	1807

# Human readable data → Tidy data



# Tidying data with `tidyverse`

tidyverse package  
for tidying data

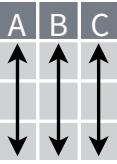


# Data tidying with `tidyr` :: CHEATSHEET



**Tidy data** is a way to organize tabular data in a consistent data structure across packages.

A table is tidy if:



&



Each **variable** is in its own **column**

Each **observation**, or **case**, is in its own **row**



Access **variables** as **vectors**

Preserve **cases** in vectorized operations

## Tibbles



### AN ENHANCED DATA FRAME

Tibbles are a table format provided by the **tibble** package. They inherit the data frame class, but have improved behaviors:

- **Subset** a new tibble with `]`, a vector with `[[` and `$`.
- **No partial matching** when subsetting columns.
- **Display** concise views of the data on one screen.

`options(tibble.print_max = n, tibble.print_min = m, tibble.width = Inf)` Control default display settings.

`View()` or `glimpse()` View the entire data set.

### CONSTRUCT A TIBBLE

**tibble(...)** Construct by columns.

`tibble(x = 1:3, y = c("a", "b", "c"))`

Both make this tibble

**tibble(...)** Construct by rows.

`tibble(~x, ~y,`

1, "a",

2, "b",

3, "c")

A tibble: 3 x 2  
x <int> <chr>  
y 1 a  
2 b  
3 c

**as\_tibble(x, ...)** Convert a data frame to a tibble.

**enframe(x, name = "name", value = "value")**

Convert a named vector to a tibble. Also **deframe()**.

**is\_tibble(x)** Test whether x is a tibble.

## Reshape Data

- Pivot data to reorganize values into a new layout.

table4a

country	1999	2000
A	0.7K	2K
B	37K	80K
C	212K	213K



→

table4a

country year cases

A 1999 0.7K

B 1999 37K

C 1999 212K

A 2000 2K

B 2000 80K

C 2000 213K

table2

country	year	type	count
A	1999	cases	0.7K
A	1999	pop	19M
A	2000	cases	2K
A	2000	pop	20M
B	1999	cases	37K
B	1999	pop	172M
B	2000	cases	80K
B	2000	pop	174M
C	1999	cases	212K
C	1999	pop	1T
C	2000	cases	213K
C	2000	pop	1T



→

table2

country year cases pop

A 1999 0.7K 19M

A 2000 2K 20M

B 1999 37K 172M

B 2000 80K 174M

C 1999 212K 1T

C 2000 213K 1T

## Split Cells

- Use these functions to split or combine cells into individual, isolated values.

table5

country	century	year
A	19	99
A	20	00



→

table5

country year

A 1999

A 2000

B 1999

B 2000

table3

country	year	rate
A	1999	0.7K/19M
A	2000	2K/20M



→

table3

country year cases pop

A 1999 0.7K 19M

A 2000 2K 20M

B 1999 37K 172M

B 2000 80K 174M

table3

country	year	rate
A	1999	0.7K
A	1999	19M



→

table3

country year

A 1999 0.7K

A 1999 19M

A 2000 2K

A 2000 20M

B 1999 37K

B 1999 172M

B 2000 80K

B 2000 174M

## Expand Tables

Create new combinations of variables or identify implicit missing values (combinations of variables not present in the data).

x	x1	x2	x3
A	1	3	
B	1	4	
B	2	3	

**expand(data, ...)** Create a new tibble with all possible combinations of the values of the variables listed in ...  
Drop other variables.  
`expand(mtcars, cyl, gear, carb)`

x	x1	x2	x3
A	1	3	
B	1	4	
B	2	3	

**complete(data, ..., fill = list())** Add missing possible combinations of values of variables listed in ... Fill remaining variables with NA.  
`complete(mtcars, cyl, gear, carb)`

## Handle Missing Values

Drop or replace explicit missing values (NA).

x	x1	x2
A	1	
B	NA	
C	NA	
D	3	
E	NA	

**drop\_na(data, ...)** Drop rows containing NA's in ... columns.  
`drop_na(x, x2)`

x	x1	x2
A	1	
B	NA	
C	NA	
D	3	
E	NA	

**fill(data, ..., .direction = "down")** Fill in NA's in ... columns using the next or previous value.  
`fill(x, x2)`

x	x1	x2
</tbl

# Types of datasets

WIDE

## Wide format

ID	X	Y	Z
1	a	b	c
2	d	e	f

TIDY!

## Long format

LONG

ID	variable	value
1	X	a
1	Y	b
1	Z	c
2	X	d
2	Y	e
2	Z	f

# tidyR lets you move between formats

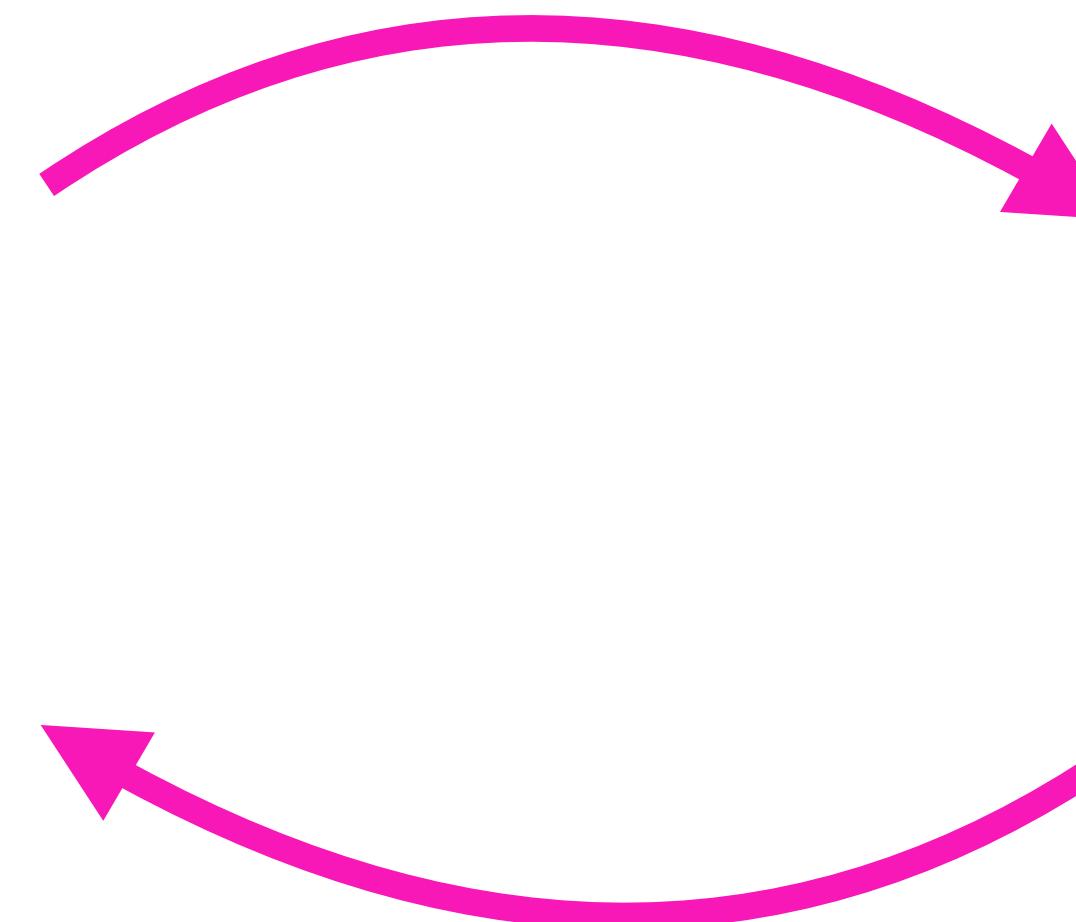
**Wide format**

WIDE DF

**Long format**

LONG DF

`pivot_longer()`



`pivot_wider()`

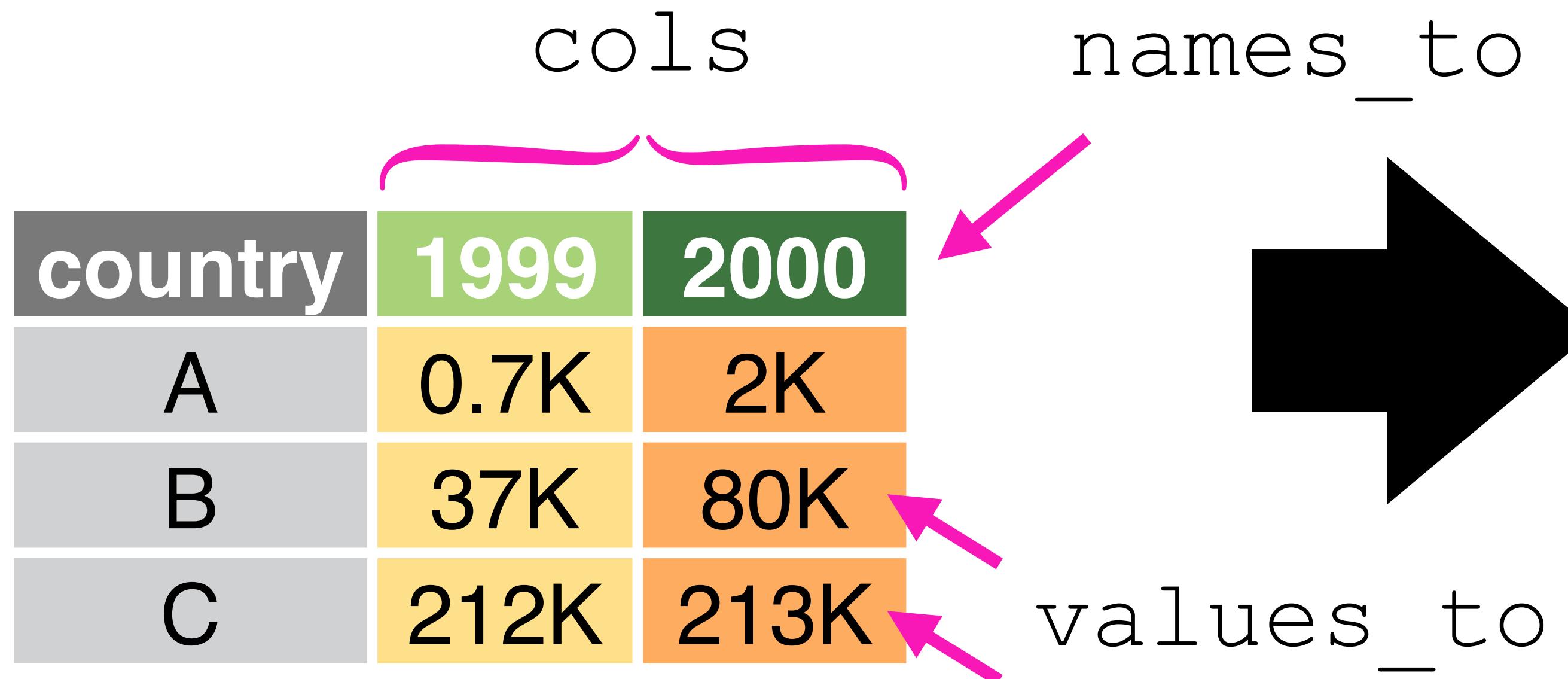
# What are the names? What are the values?

```
pivot_longer(df, cols, names_to = "", values_to = "")
```

```
pivot_wider(df, names_from = , values_from = )
```

# What are the names? What are the values?

```
pivot_longer(df, cols, names_to = "", values_to = "")
```



country	year	cases
A	1999	0.7K
B	1999	37K
C	1999	212K
A	2000	2K
B	2000	80K
C	2000	213K

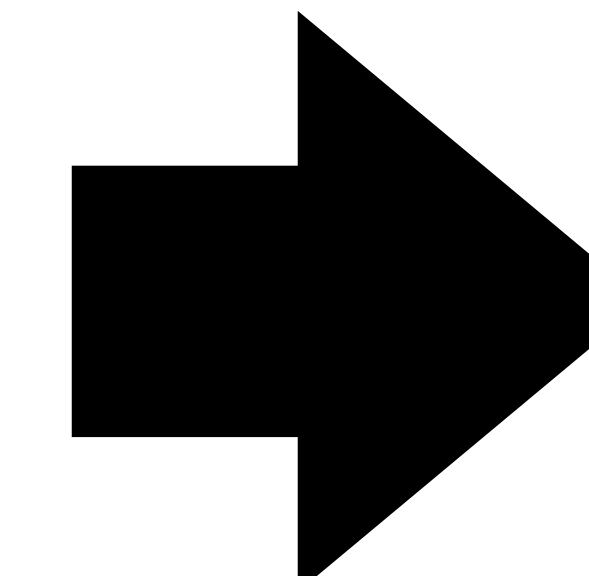
# What are the names? What are the values?

```
pivot_wider(df, names_from = , values_from = )
```

names\_from

country	year	type	count
A	1999	cases	0.7K
	1999	pop	19M
A	2000	cases	2K
	2000	pop	20M
B	1999	cases	37K
	1999	pop	172M
B	2000	cases	80K
	2000	pop	174M

values\_from



country	year	cases	pop
A	1999	0.7K	19M
	2000	2K	20M
B	1999	37K	172M
	2000	80K	174M

# What are the names? What are the values?

```
pivot_longer(df, cols, names_to = "", values_to = "")
```

names\_to/values\_to are the names we want for our new columns

```
pivot_wider(df, names_from = , values_from = )
```

names\_from/values\_from are the columns we're getting info from

Practice, practice, practice...

# Let's turn this into a tidy dataset!

`lotr_untidy_dataset.csv`

film_number	Dwarf	Elf	Hobbit	Man	Orc	Wizard
I	431	2200	3658	1995	27	2881
II	521	844	2463	3990	230	1273
III	313	693	2675	2727	466	1807

# Let's turn this into a tidy dataset!

```
lotr_wide <- read_csv("lotr_untidy_dataset.csv")  
  
lotr_long <- lotr_wide %>%  
  pivot_longer(2:7, names_to = "race", values_to  
  = "words_spoken")
```

# Let's turn this into a tidy dataset!

film_number	race	words_spoken
I	Dwarf	431
I	Elf	2200
I	Hobbit	3658
I	Man	1995
I	Orc	27
I	Wizard	2881

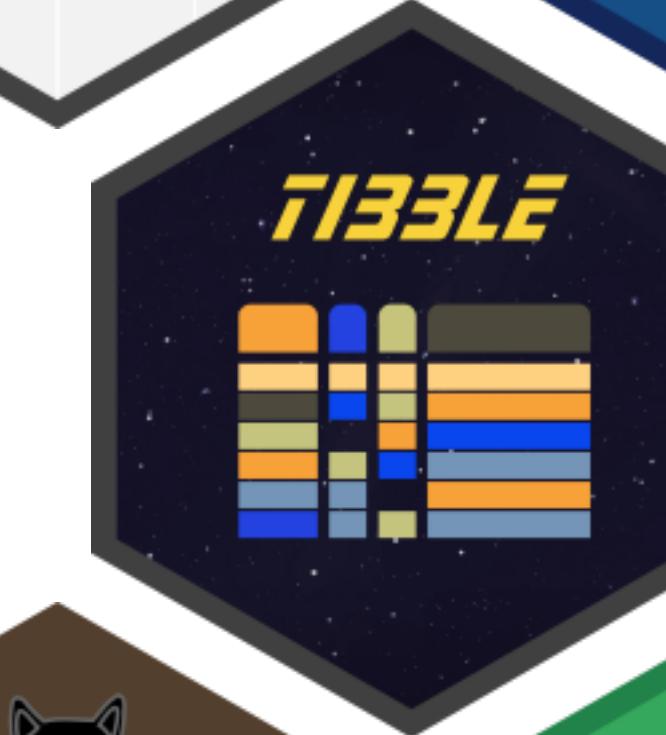
# Joining datasets with dplyr

# But what if you have *multiple* datasets?

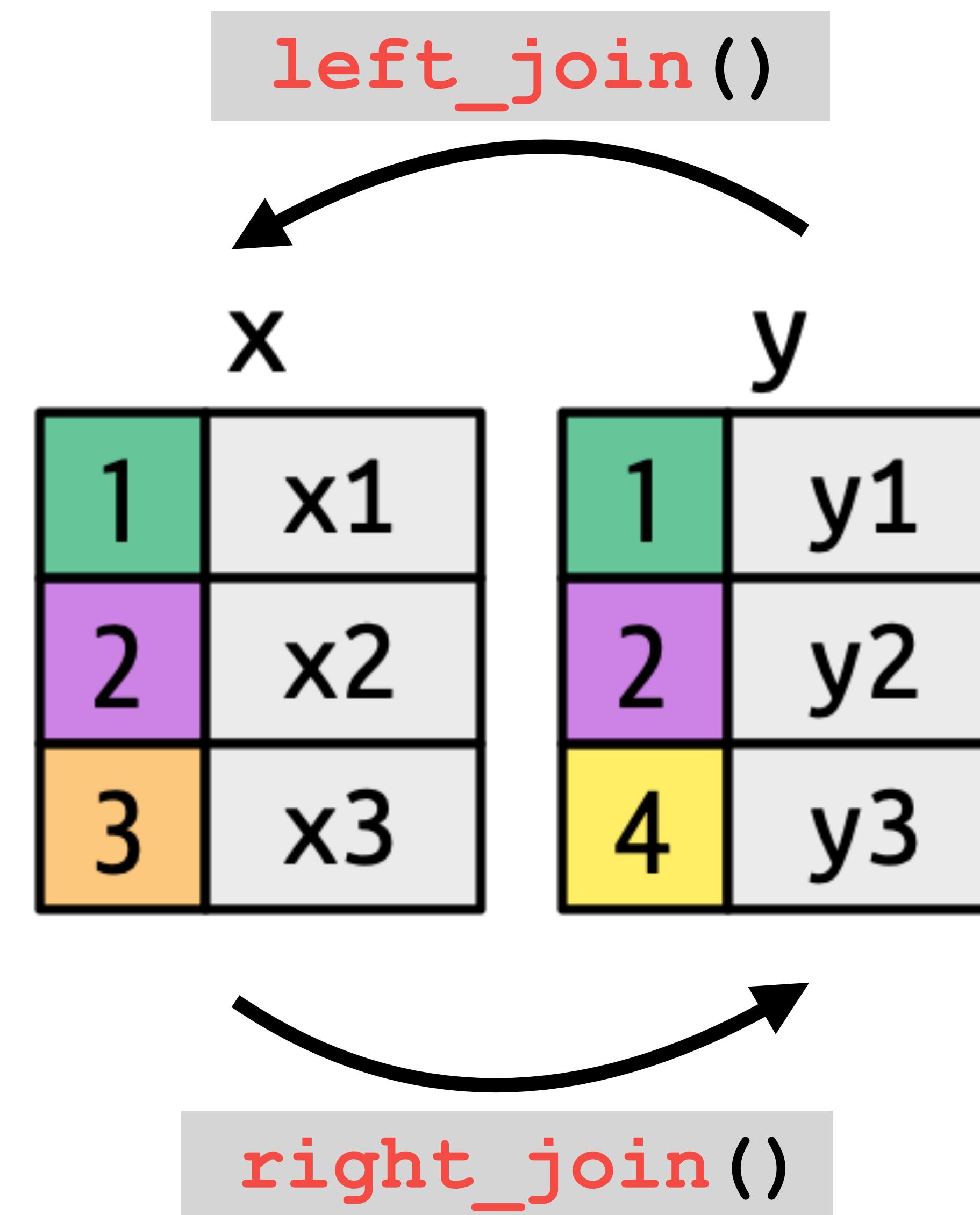
x		y	
1	x1	1	y1
2	x2	2	y2
3	x3	4	y3

same variable across different datasets

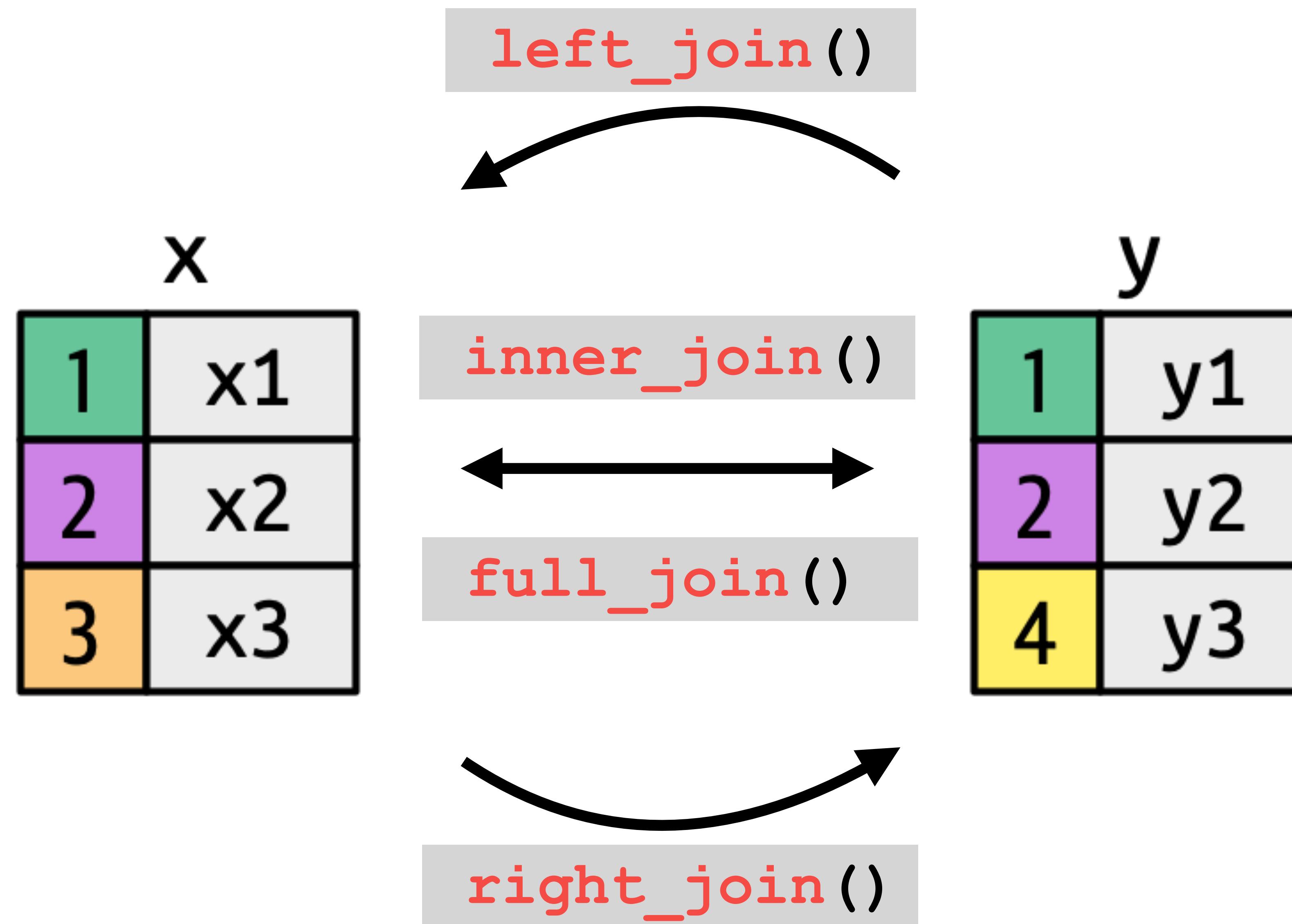
tidyverse package  
for manipulating data



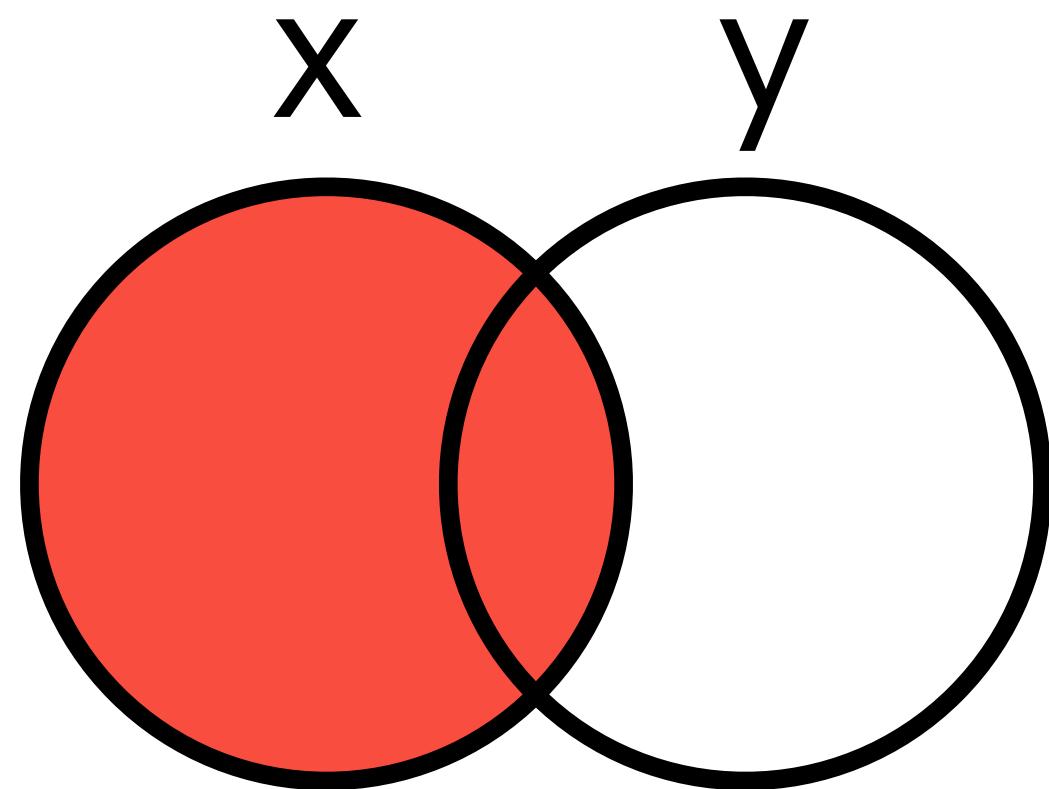
# Many different join options in dplyr



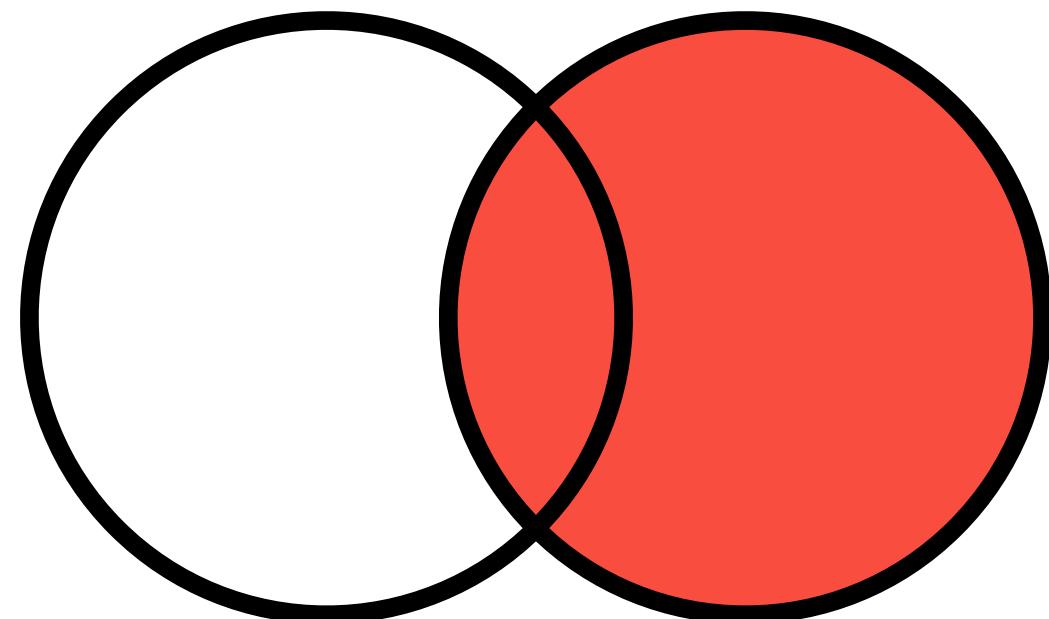
# Many different join options in dplyr



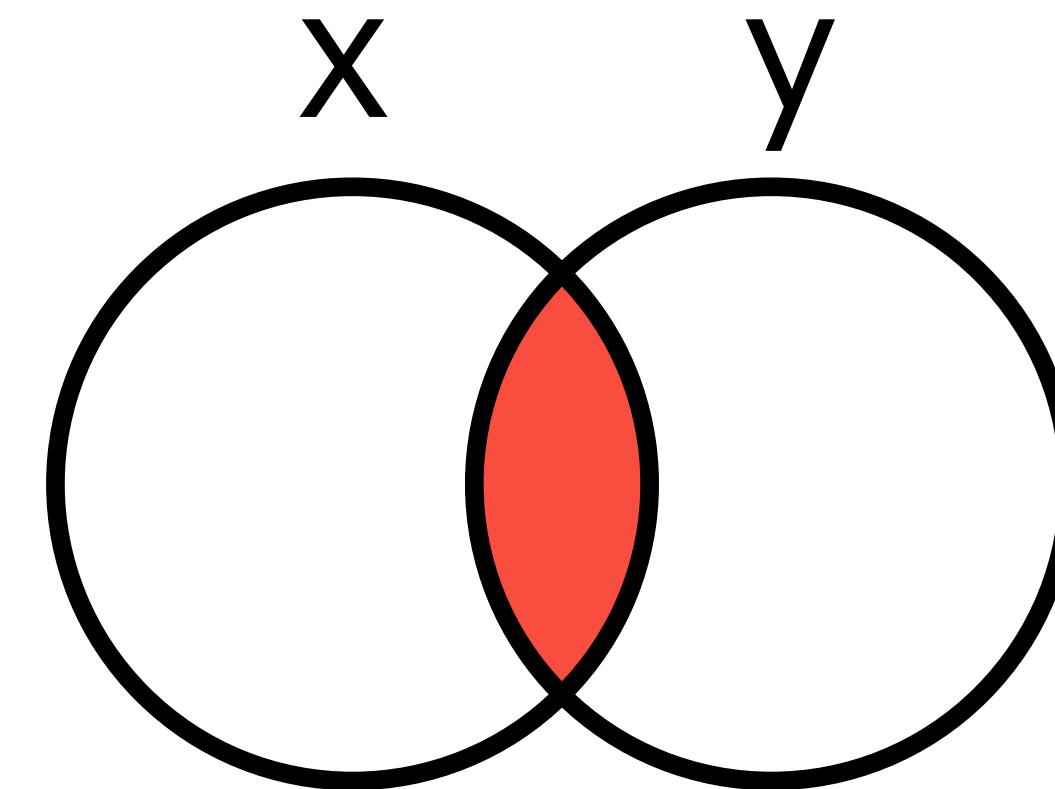
# Many different join options in dplyr



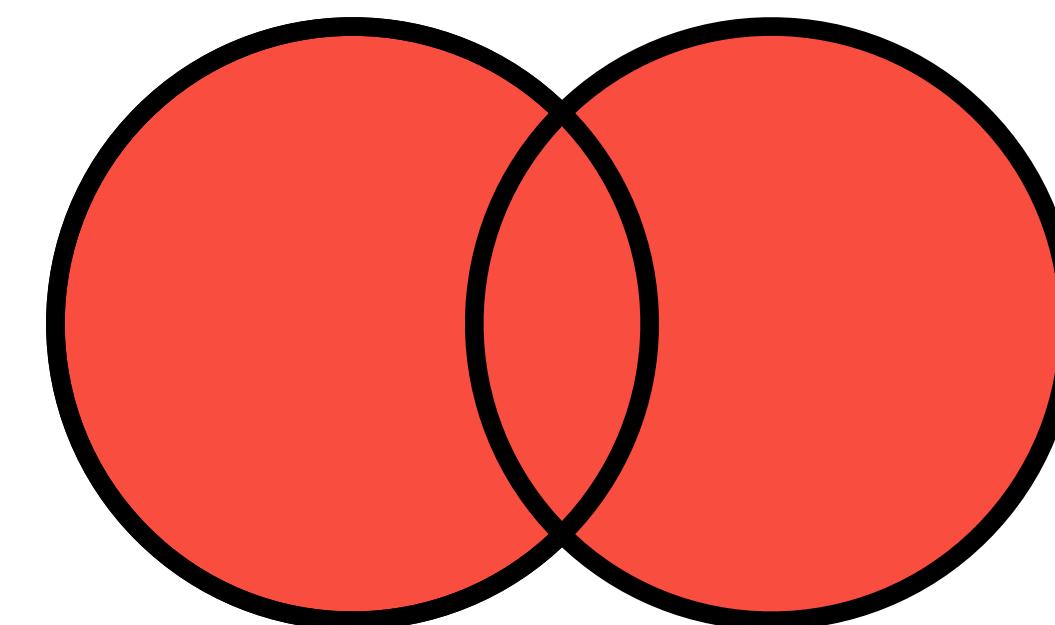
`left_join(x,y)`



`right_join(x,y)`



`inner_join(x,y)`

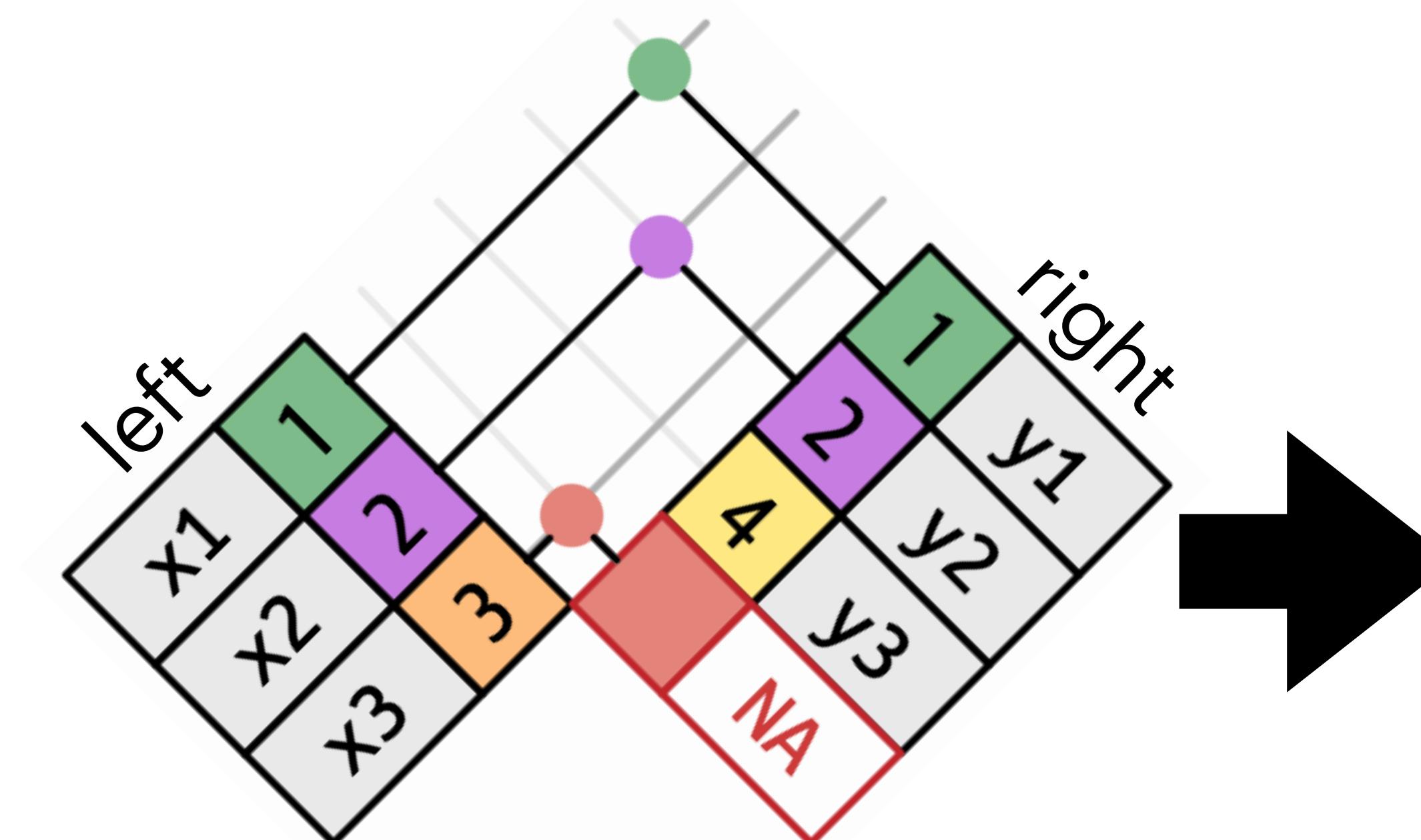


`full_join(x,y)`

# What do we get if we join these datasets?

x	y
1	x1
2	x2
3	x3

`left_join(x, y)`

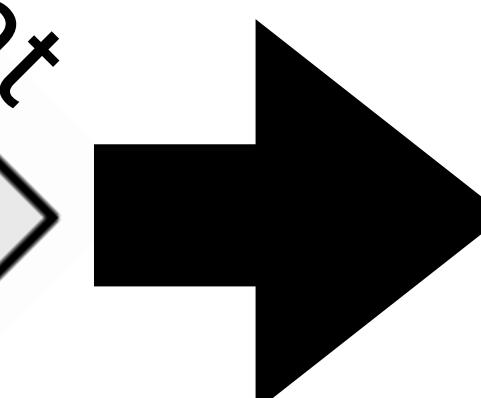
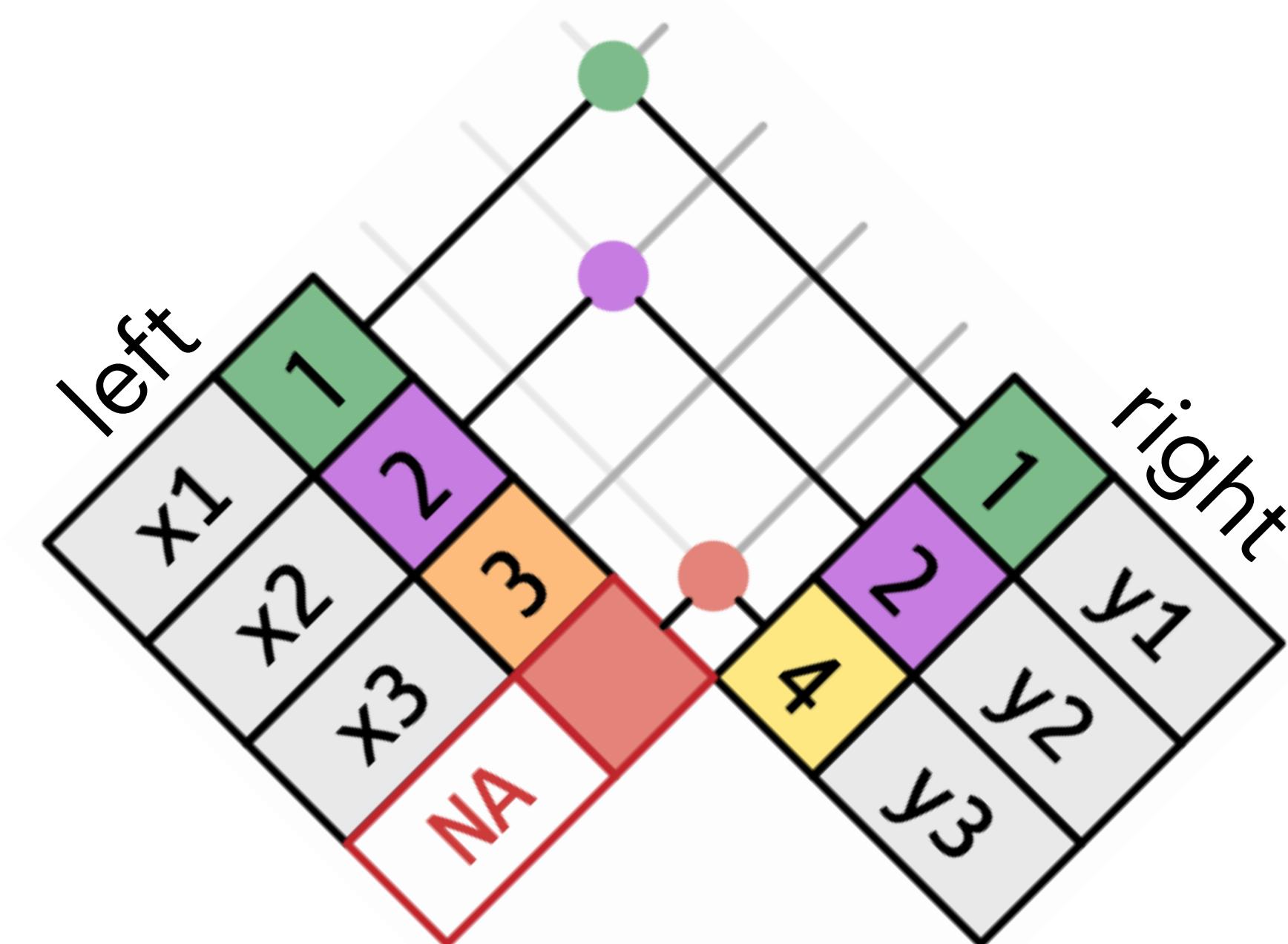


key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA

# What do we get if we join these datasets?

x	y
1	x1
2	x2
3	x3

right\_join(x, y)

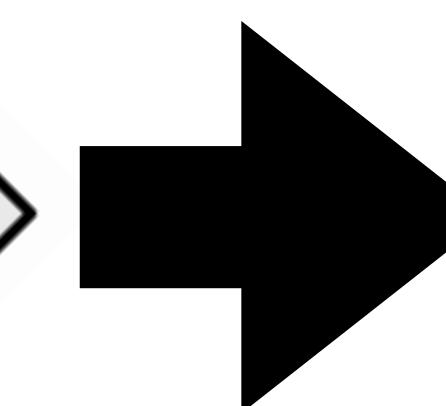
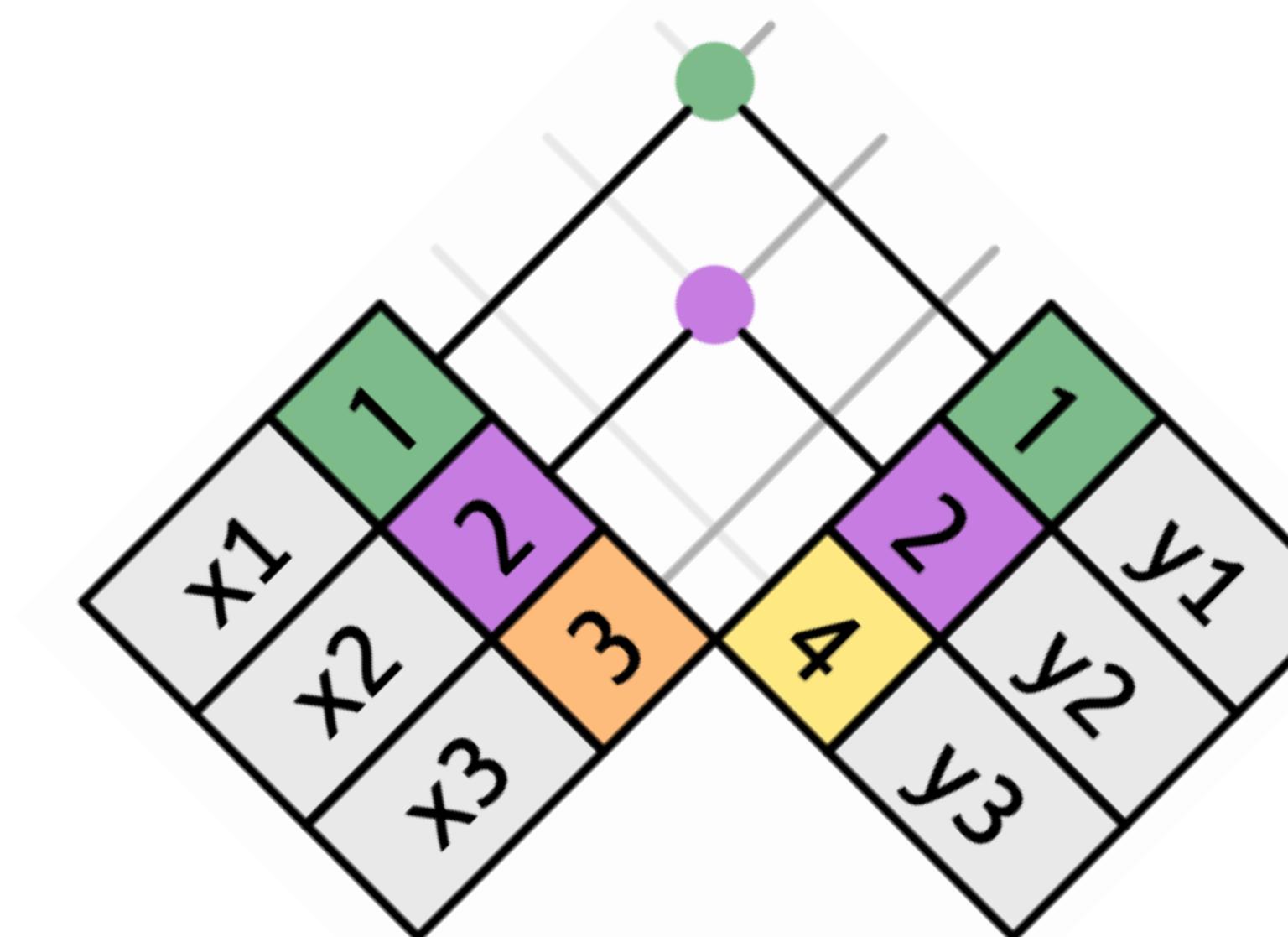


key	val_x	val_y
1	x1	y1
2	x2	y2
4	NA	y3

# What do we get if we join these datasets?

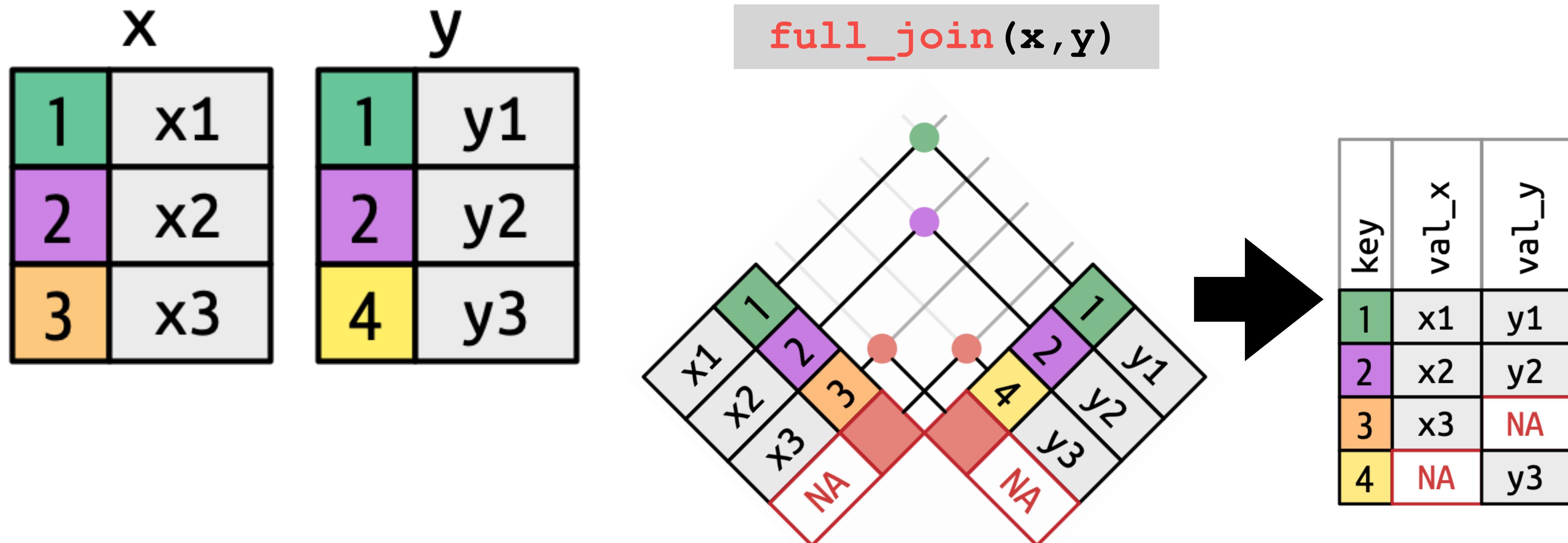
x	y
1	x1
2	x2
3	x3

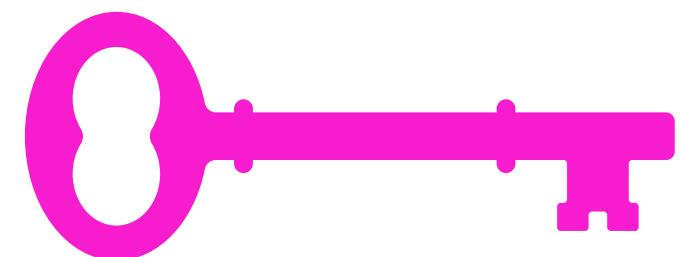
inner\_join(x, y)



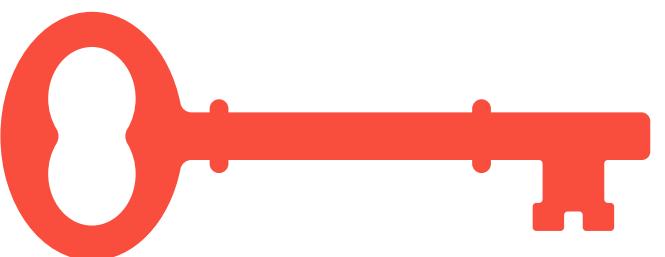
key	val_x	val_y
1	x1	y1
2	x2	y2

# What do we get if we join these datasets?





# These functions use a “key”



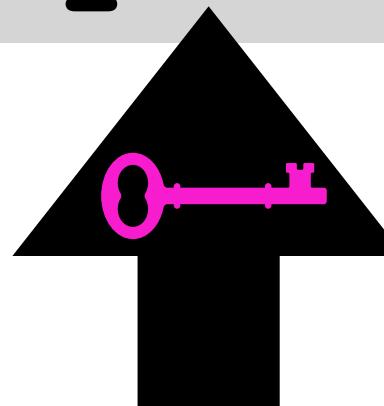
Key = the column shared between the datasets

Diagram illustrating the shared key between datasets x and y. The key column is the first column of both datasets, labeled '0' on the arrows.

	x	y
1	x1	y1
2	x2	y2
3	x3	y3

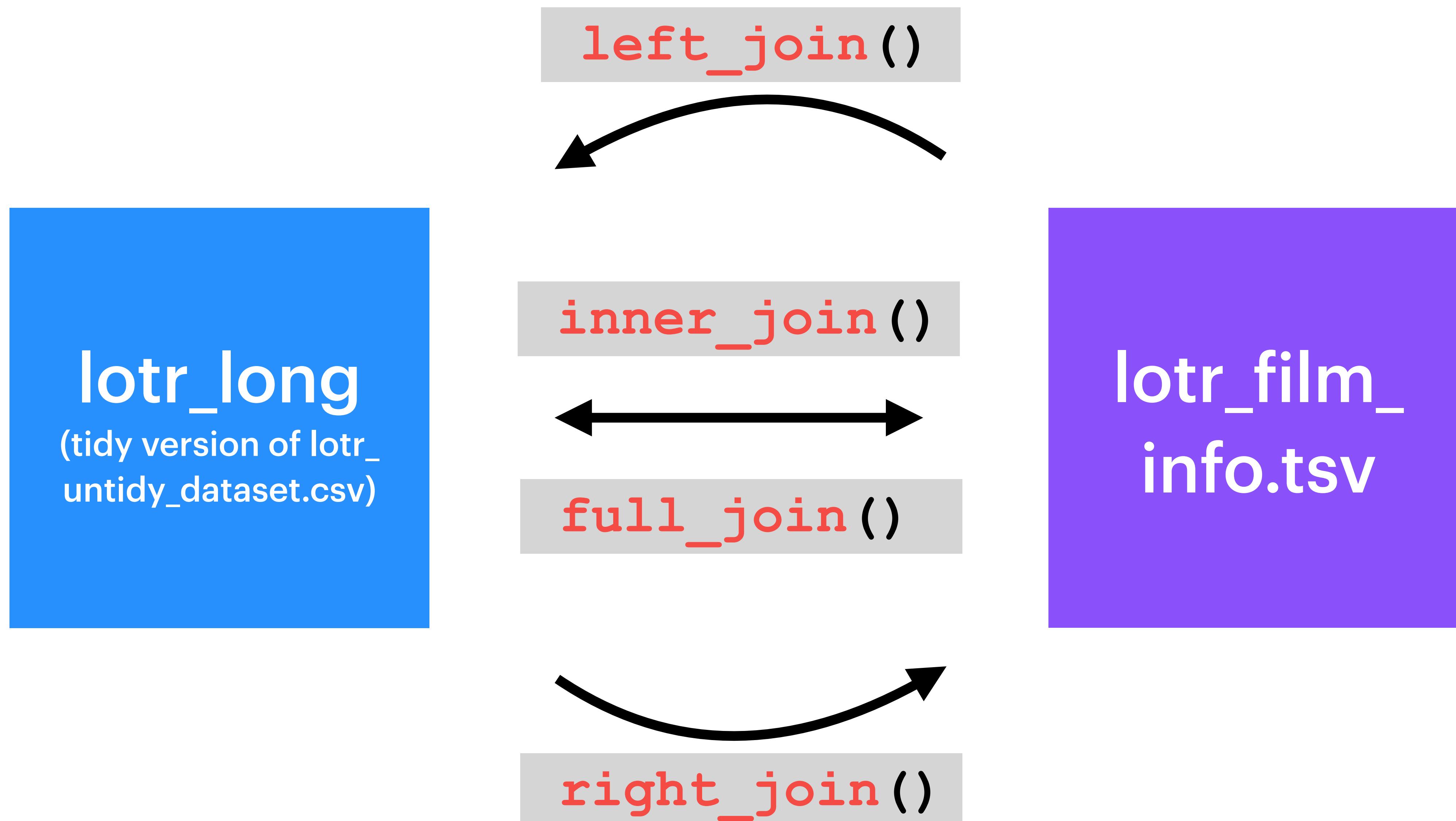
You don't need to specify the key if the columns have the same names, otherwise...

```
<TYPE>_join(x, y, by = )
```



Practice, practice, practice...

# Let's practice joining two datasets!



# Further reading

- Wickham & Grolemund 2017, *R for Data Science*, [Chapter 5](#)
- Wickham 2014, [Tidy Data](#), *Journal of Statistical Software*
- Data tidying with `tidyverse` [Cheatsheet](#)