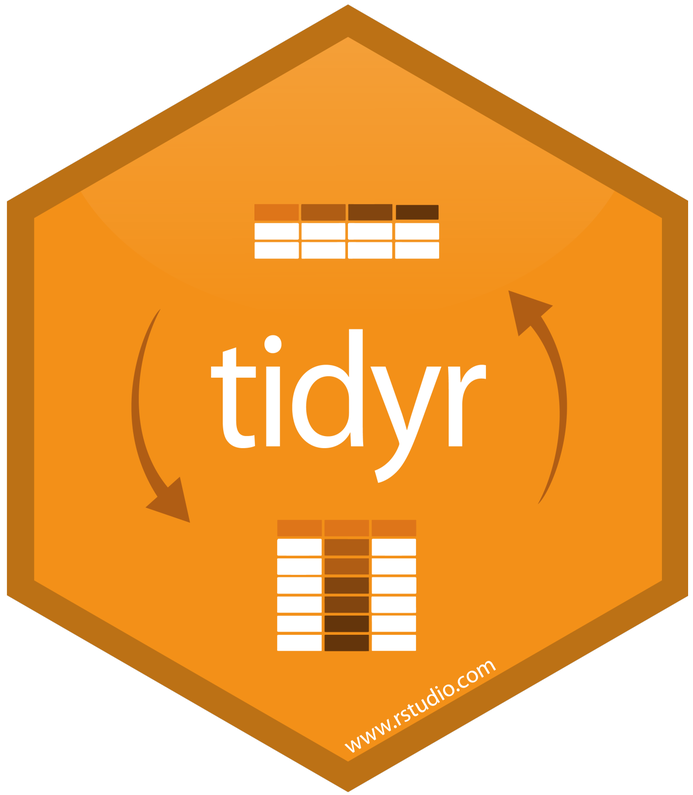
Tidy Data with



In R4DS

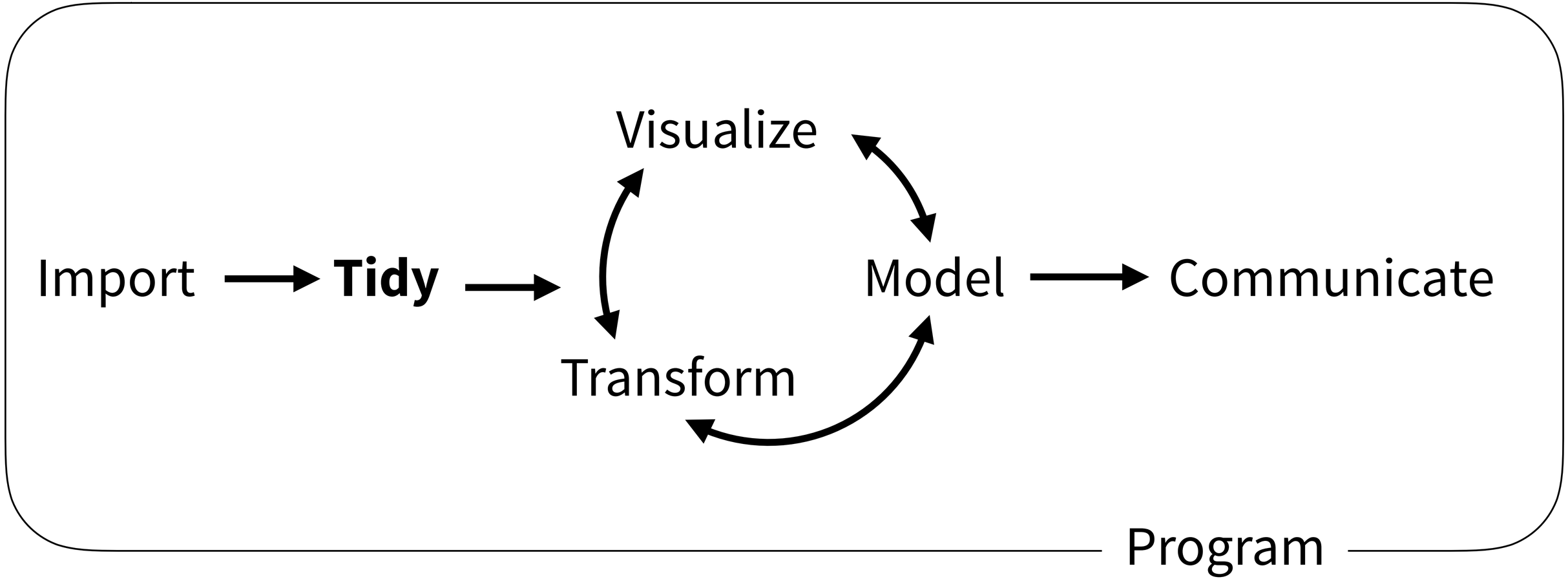
Tidy Data

Your Turn 0

Open 03-Tidy.Rmd

Run the setup chunk

(Applied) **Data Science**



Tidy tools

Tidy tools

Functions are easiest to use when they are:

1. **Simple** - They do one thing, and they do it well
2. **Composable** - They can be combined with other functions for multi-step operations
3. **Smart** - They can use R objects as input.

Tidy functions do these things in a specific way.

Tidy tools

Functions are easiest to use when they are:

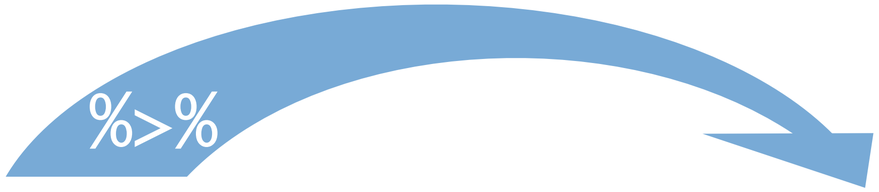
1. **Simple** - They do one thing, and they do it well
2. **Composable** - They can be combined with other functions for multi-step operations
3. **Smart** - They can use R objects as input.

Tidy functions do these things in a specific way.

1. Simple - They do one thing, and they do it well

filter() - extract **cases**
arrange() - reorder **cases**
group_by() - group **cases**
select() - extract **variables**
mutate() - create new **variables**
summarise() - summarise **variables** / create **cases**

2. **Composable** - They can be combined with other functions for multi-step operations




```
babynames          mutate(_____, percent = prop * 100)
```

Each dplyr function takes a data frame as its first argument and returns a data frame. As a result, you can directly pipe the output of one function into the next.

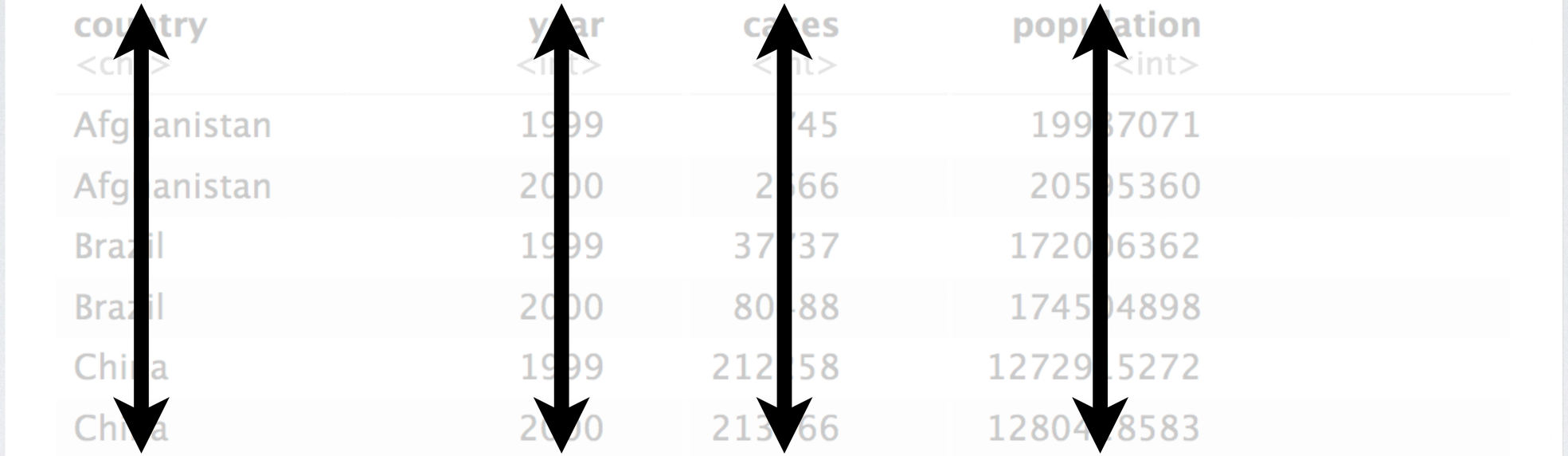
"Data are not just numbers,
they are numbers with a context."

- George Cobb and David Moore (1997)

Consider

What are the variables in this data set?

```
table1
```



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

6 rows

Consider

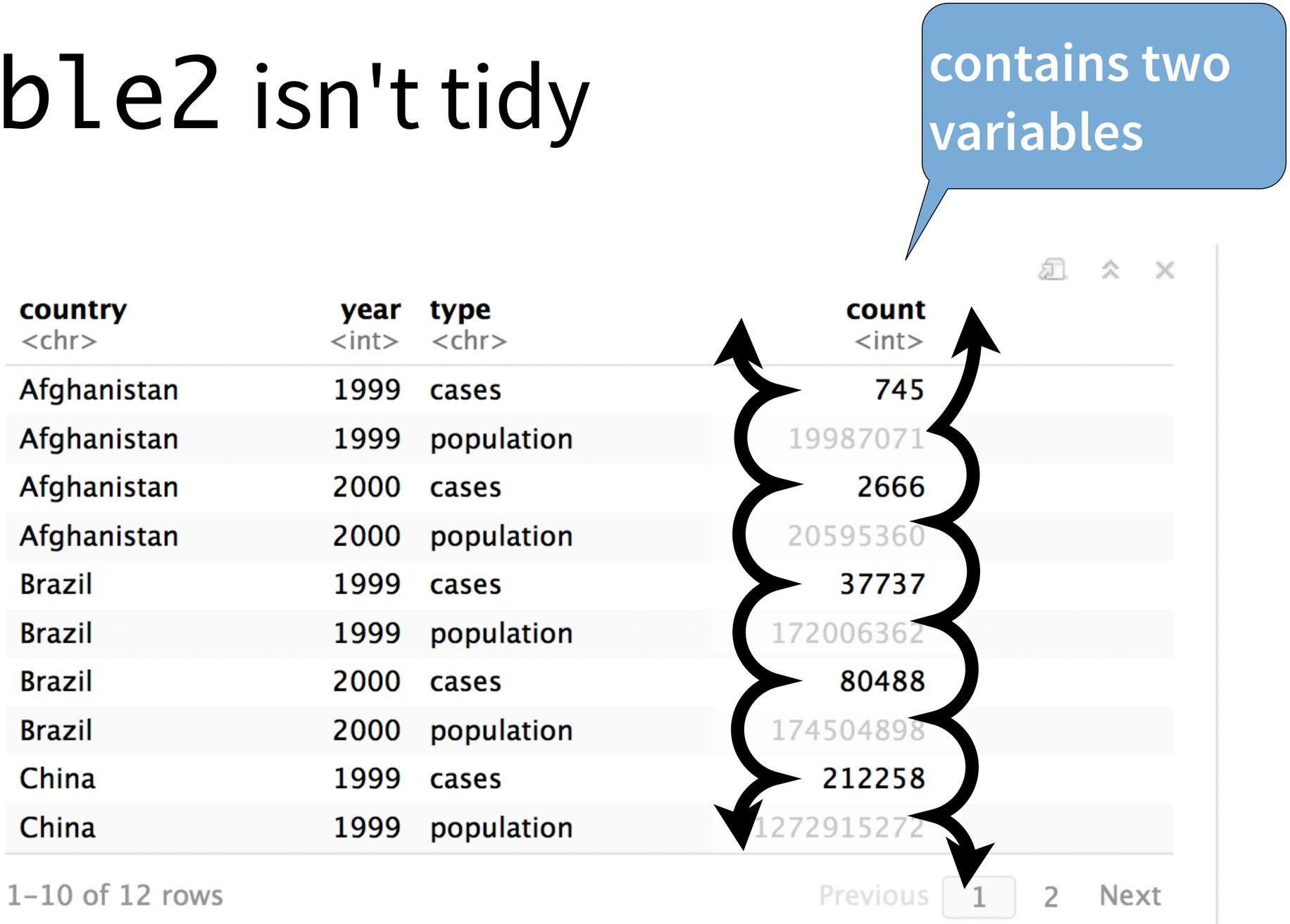
What are the variables in this data set?

```
table2
```

country	year	type	count
		<chr>	<int>
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

1–10 of 12 rows Previous 1 2 Next

`table2` isn't tidy



country <chr>	year <int>	type <chr>	count <int>
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

1–10 of 12 rows

Previous 1 2 Next

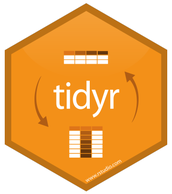
"Data comes in many formats, but R prefers just one: tidy data. "

- Garrett Grolemund

Tidy data

A data set is **tidy** iff:

1. Each **variable** is in its own **column**
2. Each **case** is in its own **row**
3. Each **value** is in its own **cell**



Your Turn 1

Is bp_systolic tidy? What are the variables?

Your Turn 1

Is bp_systolic tidy? What are the variables?

subject_id <dbl>	time_1 <dbl>	time_2 <dbl>	time_3 <dbl>
1	120	118	121
2	125	131	*NA*
3	141	*NA*	*NA*

3 rows

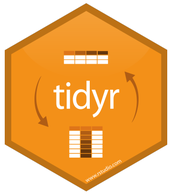
Variables:

- subject
- time
- systolic blood pressure

`bp_systolic2` is tidy

subject_id <dbl>	time <dbl>	systolic <dbl>
1	1	120
1	2	118
1	3	121
2	1	125
2	2	131
3	1	141

6 rows



Your Turn 2

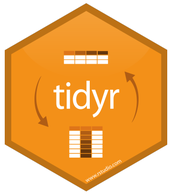
Using `bp_systolic2` with `group_by()` and `summarise()`:

- Find the average systolic blood pressure for each subject

- Find the last time each subject was measured

```
bp_systolic2 %>%
  group_by(subject_id) %>%
  summarise(avg_sys = mean(systolic),
    last_measurement = max(time))
```

```
# A tibble: 3 x 3
  subject_id avg_sys last_measurement
       <dbl>   <dbl>            <dbl>
1          1    120.                3
2          2    128                 2
3          3    141                 1
```

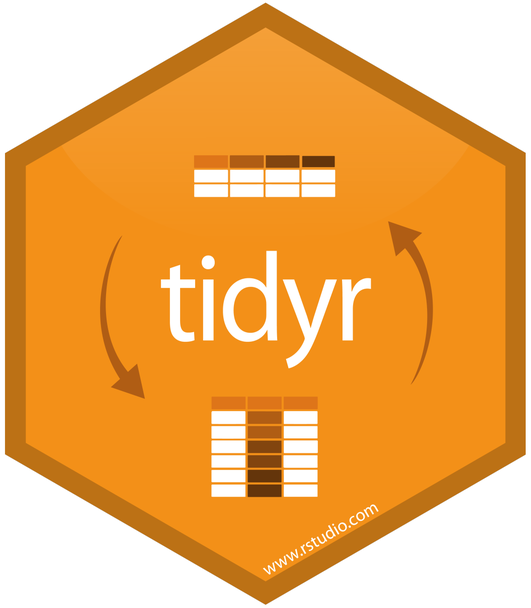


"Tidy data sets are all alike; but every messy data set is messy in its own way."

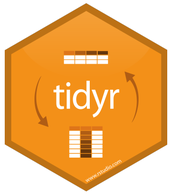
- Hadley Wickham

tidyr

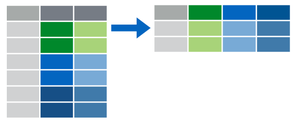
tidyr



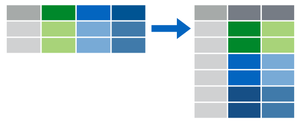
A package that reshapes the layout of tabular data.



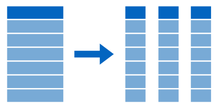
tidyr verbs



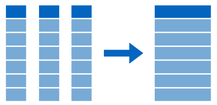
Make data wider with **pivot_wider()**



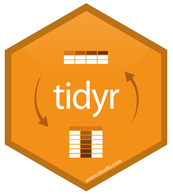
Make data longer with **pivot_longer()**



Split a column with **separate()** or **separate_rows()**

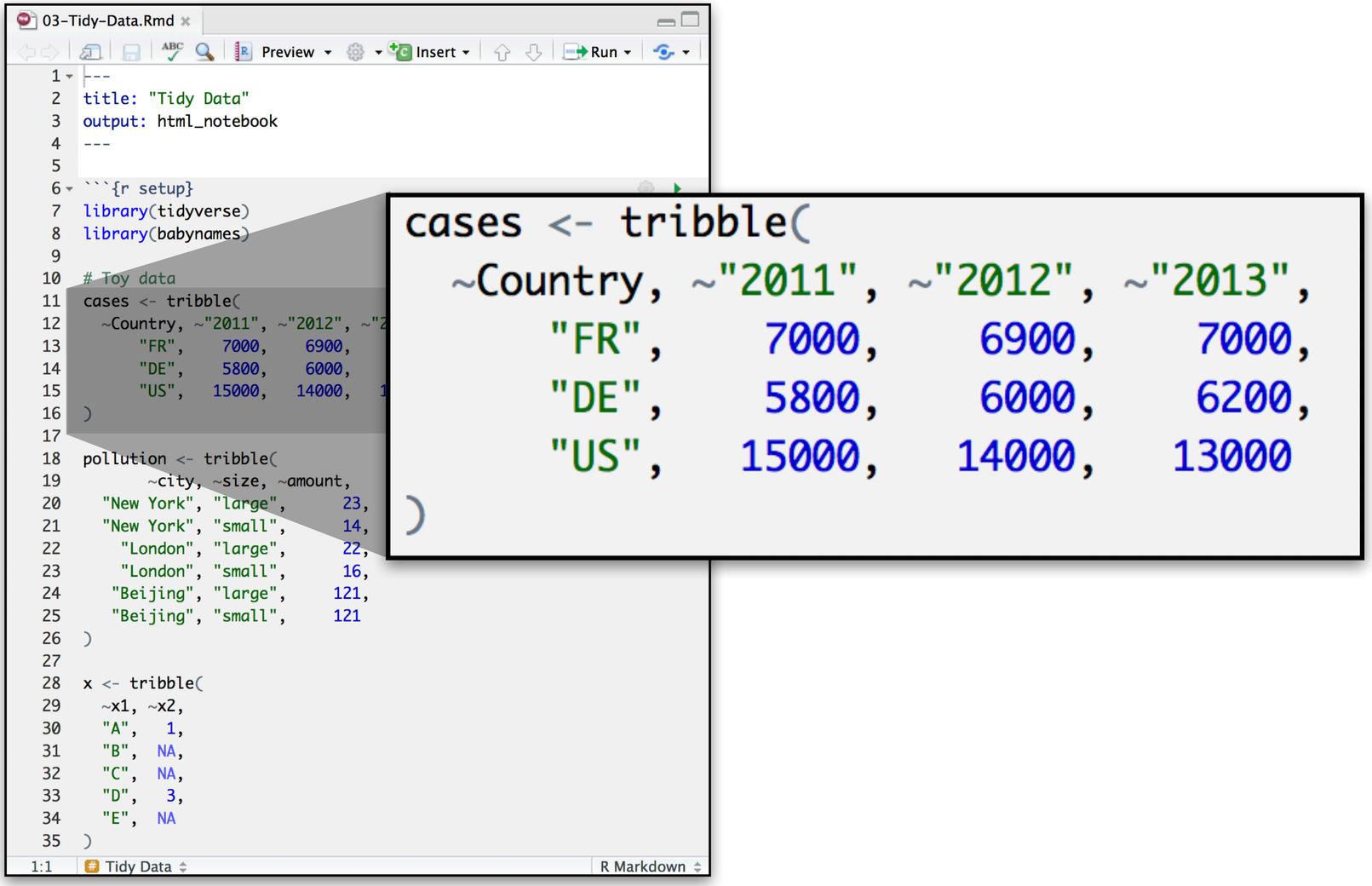


Unite columns with **unite()**



pivot_longer()

Toy data


03-Tidy-Data.Rmd
Preview
Insert
Run
---
title: "Tidy Data"
output: html_notebook

```{r setup}
library(tidyverse)
library(babynames)
# Toy data
cases <- tribble(
~Country, ~"2011", ~"2012", ~"2013",
"FR", 7000, 6900, 7000,
"DE", 5800, 6000, 6200,
"US", 15000, 14000, 13000
)
pollution <- tribble(
~city, ~size, ~amount,
"New York", "large", 23,
"New York", "small", 14,
"London", "large", 22,
"London", "small", 16,
"Beijing", "large", 121,
"Beijing", "small", 121
)
x <- tribble(
~x1, ~x2,
"A", 1,
"B", NA,
"C", NA,
"D", 3,
"E", NA
)
1:1
Tidy Data
R Markdown
```

Consider

What are the variables in cases?

Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Consider

What are the variables in cases?

Country			
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14800	13000

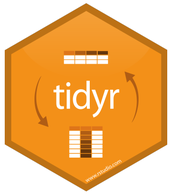
- Country
- Year
- Count

Your Turn 3

On a sheet of paper, draw how the cases data set would look if it had the same values grouped into three columns: *country*, *year*, *n*

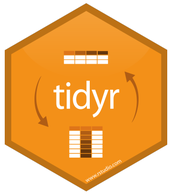
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000



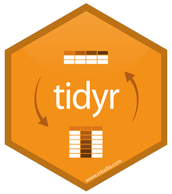
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n



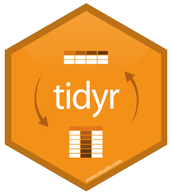
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000



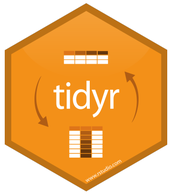
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800



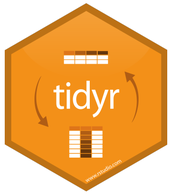
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000



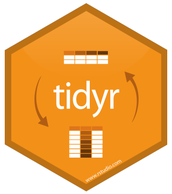
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900



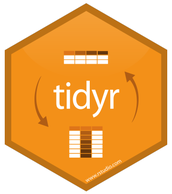
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000



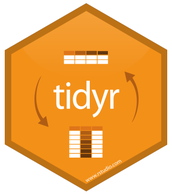
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000



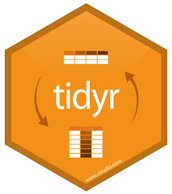
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000



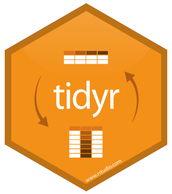
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200

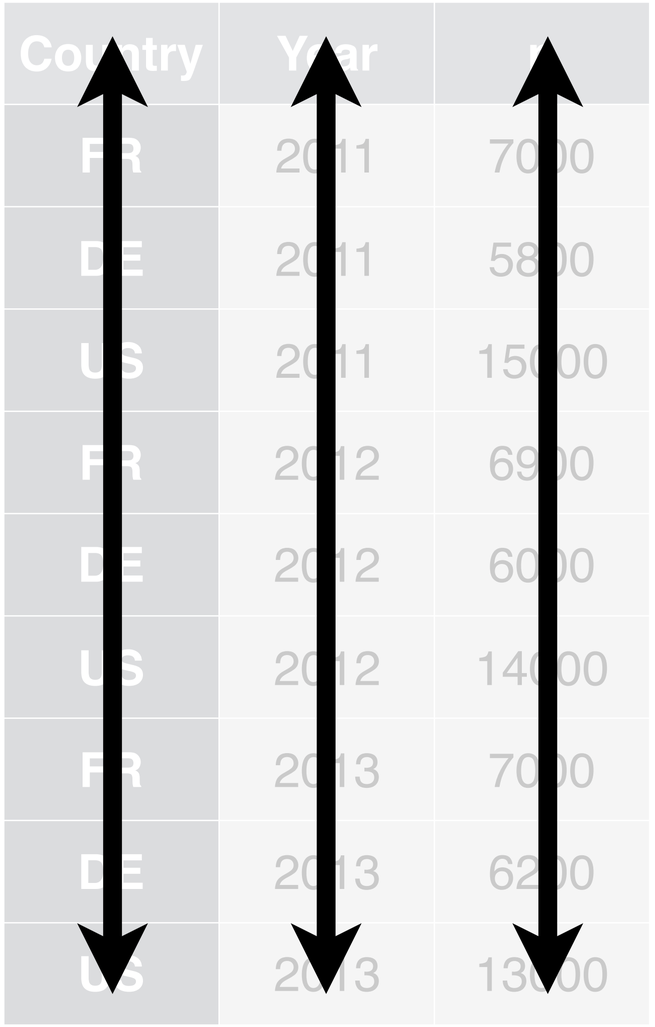


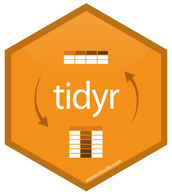
Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200
US	2013	13000

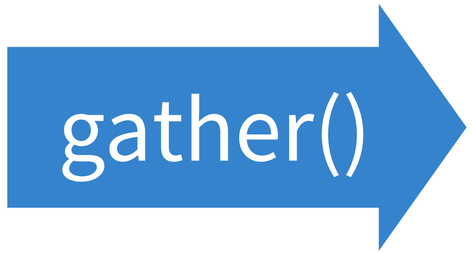


Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

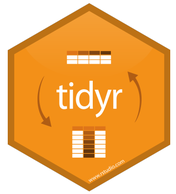




Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000



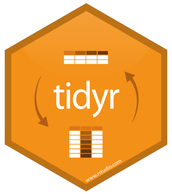
Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200
US	2013	13000



Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

1 2

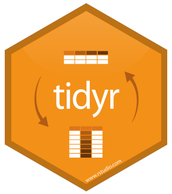
Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200
US	2013	13000



Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

key (former column names)

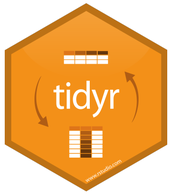
Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200
US	2013	13000



Country	2011	2012	2013
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

key **value** (former cells)

Country	Year	n
FR	2011	7000
DE	2011	5800
US	2011	15000
FR	2012	6900
DE	2012	6000
US	2012	14000
FR	2013	7000
DE	2013	6200
US	2013	13000



pivot_longer()

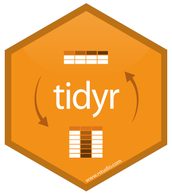
```
cases %>%
    pivot_longer(2:4, names_to = "year", values_to = "n")
```

data frame to reshape

numeric indexes of columns to collapse (or names)

name of the new variable created from column names (a character string)

name of the new variable created from cell values (a character string)

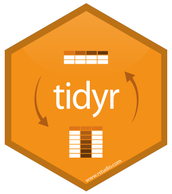


pivot_longer()

```
cases %>%
    pivot_longer(2:4, names_to = "year", values_to = "count")
```

numeric indexes

	2	3	4
Country <chr>	**2011** <dbl>	**2012** <dbl>	**2013** <dbl>
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000

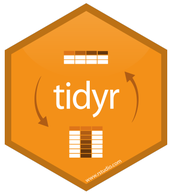


pivot_longer()

names

```
cases %>%
    pivot_longer(cols=c("2011","2012","2013"),
                 names_to = "year", values_to = "count")
```

	2011	2012	2013
Country	**2011**	**2012**	**2013**
<chr>	<dbl>	<dbl>	<dbl>
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000



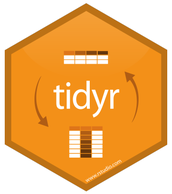
pivot_longer()

```
cases %>%
    pivot_longer(-Country, names_to = "year", values_to = "count")
```

Everything except...

Not Country **Not Country** **Not Country**

Country <chr>	2011 <dbl>	2012 <dbl>	2013 <dbl>
FR	7000	6900	7000
DE	5800	6000	6200
US	15000	14000	13000



Your Turn 4

recall

```
cases %>%
    pivot_longer(-Country, names_to = "year", values_to = "count")
```

Use **pivot_longer()** to reorganize **table4a** into three columns: *country*, *year*, and *cases*.

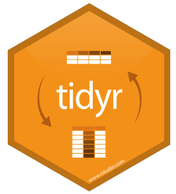
	country <chr>	1999 <int>	2000 <int>
1	Afghanistan	745	2666
2	Brazil	37737	80488
3	China	212258	213766

3 rows

```
table4a %>%
  gather(key = "year", value = "n", 2:3)
```

country <chr>	year <chr>	n <int>
Afghanistan	1999	745
Brazil	1999	37737
China	1999	212258
Afghanistan	2000	2666
Brazil	2000	80488
China	2000	213766

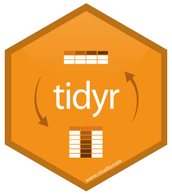
6 rows



```
table4a %>%
  gather(key = "year", value = "n", 2:3, convert = TRUE)
```

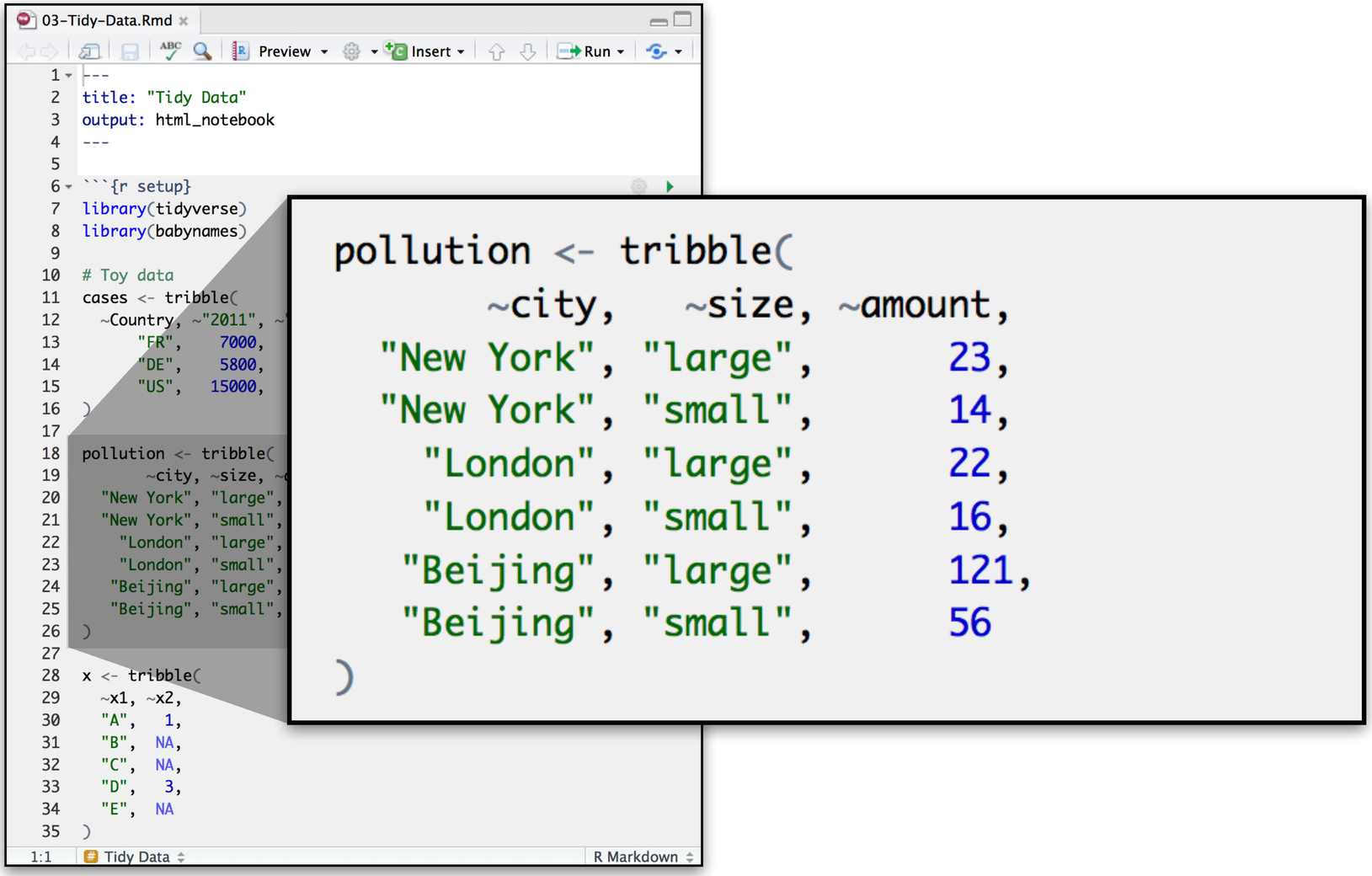
country <chr>	year <int>	n <int>
Afghanistan	1999	745
Brazil	1999	37737
China	1999	212258
Afghanistan	2000	2666
Brazil	2000	80488
China	2000	213766

6 rows



pivot_wider()

Toy data


03-Tidy-Data.Rmd
Preview
Insert
Run
1 ---
2 title: "Tidy Data"
3 output: html_notebook
4 ---
5
6 ```{r setup}
7 library(tidyverse)
8 library(babynames)
9
10 # Toy data
11 cases <- tribble(
12 ~Country, ~"2011", ~
13 "FR", 7000,
14 "DE", 5800,
15 "US", 15000,
16)
17
18 pollution <- tribble(
19 ~city, ~size, ~
20 "New York", "large",
21 "New York", "small",
22 "London", "large",
23 "London", "small",
24 "Beijing", "large",
25 "Beijing", "small",
26)
27
28 x <- tribble(
29 ~x1, ~x2,
30 "A", 1,
31 "B", NA,
32 "C", NA,
33 "D", 3,
34 "E", NA
35)
1:1
Tidy Data
R Markdown
pollution <- tribble(
~city, ~size, ~amount,
"New York", "large", 23,
"New York", "small", 14,
"London", "large", 22,
"London", "small", 16,
"Beijing", "large", 121,
"Beijing", "small", 56
)

Consider

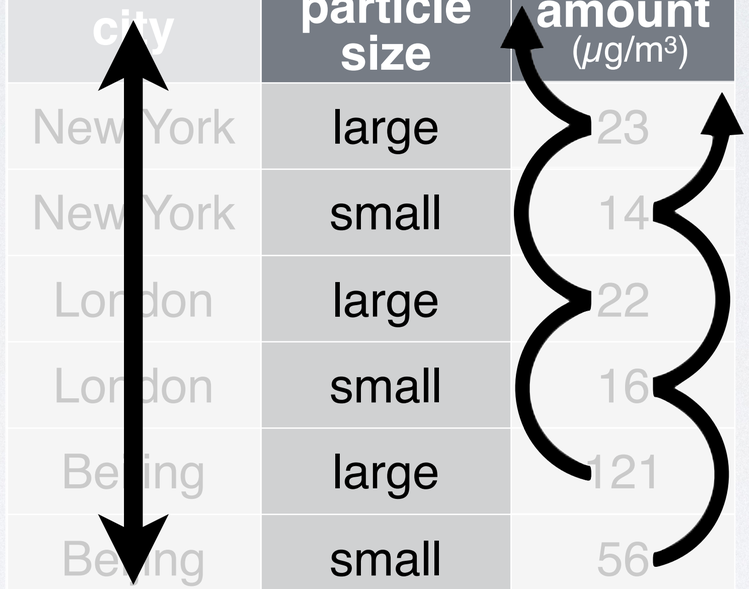
What are the variables in pollution?

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

Consider

What are the variables in pollution?

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



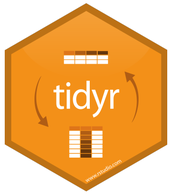
- City
- Amount of large particulate
- Amount of small particulate

Your Turn 5

On a sheet of paper, draw how this data set would look if it had the same values grouped into three columns: *city*, *large*, *small*

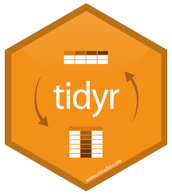
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



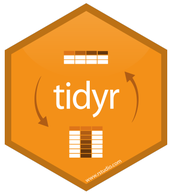
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small



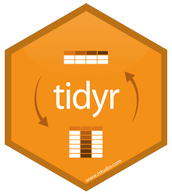
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	



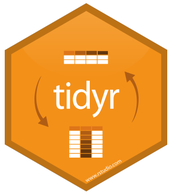
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14



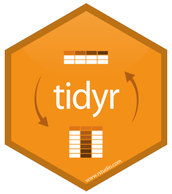
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14
London	22	



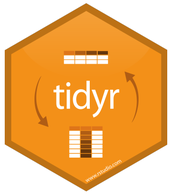
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14
London	22	16



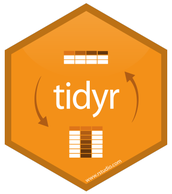
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14
London	22	16
Beijing	121	



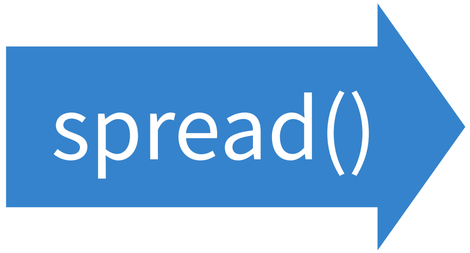
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14
London	22	16
Beijing	121	56

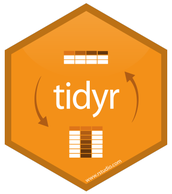


city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

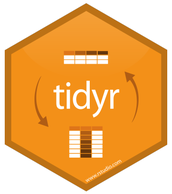


city	large	small
New York	23	14
London	22	16
Beijing	121	56



	1	2
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

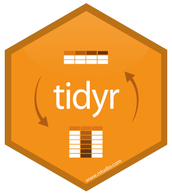
city	large	small
New York	23	14
London	22	16
Beijing	121	56



key (new column names)

city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

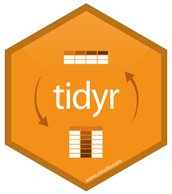
city	large	small
New York	23	14
London	22	16
Beijing	121	56



key **value** (new cells)

city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	large	small
New York	23	14
London	22	16
Beijing	121	56



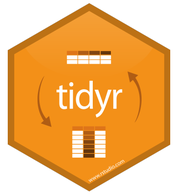
pivot_wider()

```
pollution %>% pivot_wider(names_from = size, values_from = amount)
```

data frame to reshape

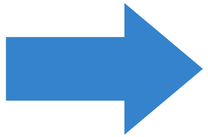
new columns from names in this variable

values for these columns from this variable

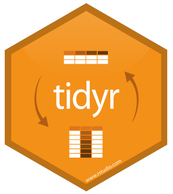


```
pollution %>% pivot_wider(names_from = size,
                          values_from = amount)
```

```
      city  size amount
1 New York large     23
2 New York small     14
3   London large     22
4   London small     16
5  Beijing large    121
6  Beijing small     56
```



```
     city large small
1  Beijing   121    56
2   London    22    16
3 New York    23    14
```



Your Turn 6

```
pollution %>% pivot_wider(names_from = size,
                          values_from = amount)
```

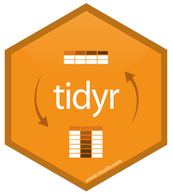
Use **pivot_wider()** to reorganize **table2** into four columns: *country*, *year*, *cases*, and *population*.

country <chr>	year <int>	type <chr>	count <int>
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362

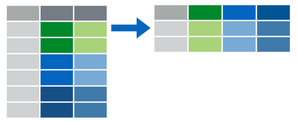
```
table2 %>%
    pivot_wider(names_from = type, values_from = count)
```

	country <chr>	year <int>	cases <int>	population <int>
1	Afghanistan	1999	745	19987071
2	Afghanistan	2000	2666	20595360
3	Brazil	1999	37737	172006362
4	Brazil	2000	80488	174504898
5	China	1999	212258	1272915272
6	China	2000	213766	1280428583

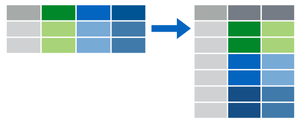
6 rows



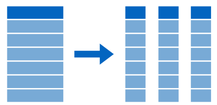
tidyr verbs



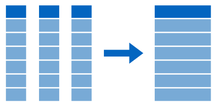
Make data wider with **pivot_wider()**



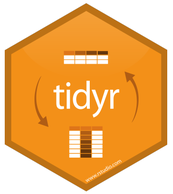
Make data longer with **pivot_longer()**



Split a column with **separate()** or **separate_rows()**



Unite columns with **unite()**



Tidy Data with