

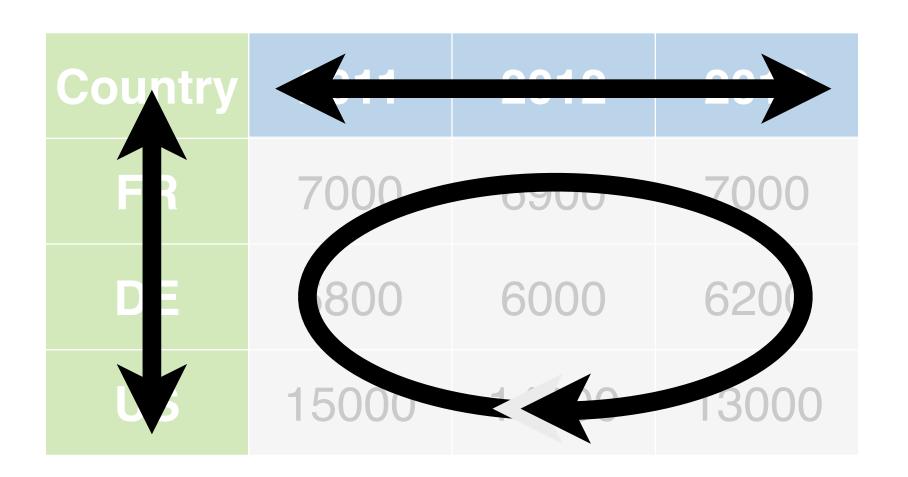
Email: info@rstudio.com
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## Data Wrangling with R

How to work with the structures of your data

Slides at:

bit.ly/wrangling-webinar



#### Garrett Grolemund

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## HELLO

my name is

## Garrett

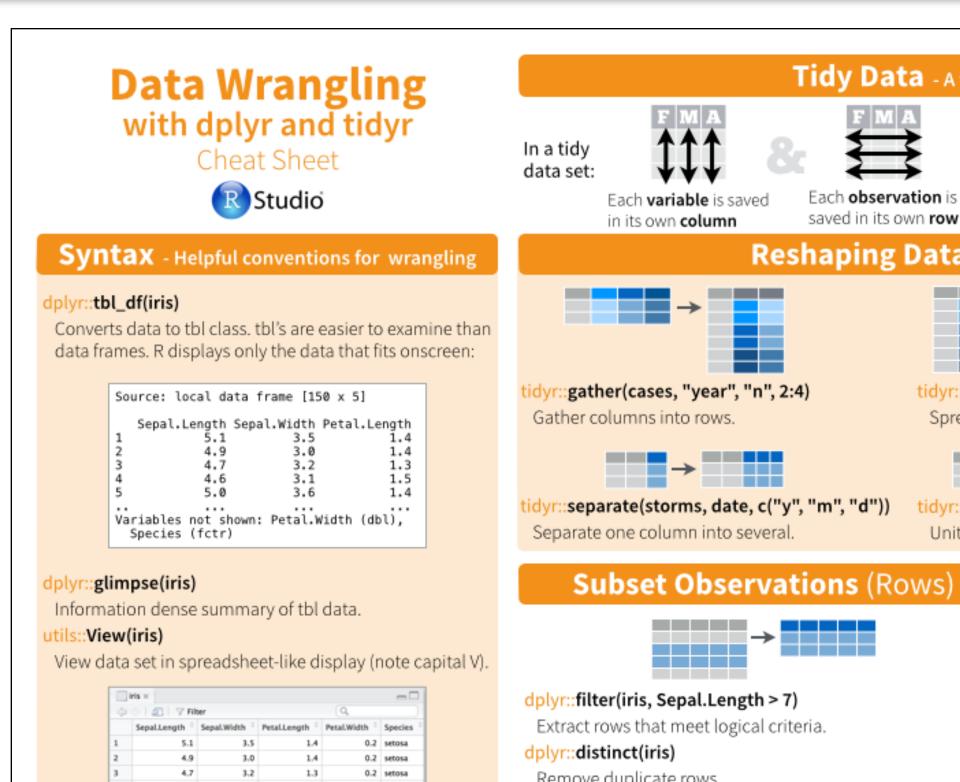
- garrett@rstudio.com
- StatGarrett

slides at: bit.ly/wrangling-webinar

## Two packages to help you work with the structure of data.







0.2 setosa

0.2 setosa

0.2 setosa

RStudio\* is a trademark of RStudio, Inc. • All rights reserved • info@rstudio.com • 844-448-1212 • rstudio.com devtools::install\_github("rstudio/EDAWR") for data sets

Passes object on left hand side as first argument (or .

x %% f(y) is the same as f(x, y)

 $y \gg f(x, ., z)$  is the same as f(x, y, z)

summarise(avg = mean(Sepal.Width)) %>%

"Piping" with %>% makes code more readable, e.g.

argument) of function on righthand side.

group\_by(Species) %>%

∷%>%

iris %>%

arrange(avg)

Remove duplicate rows.

#### dplyr::sample\_frac(iris, 0.5, replace = TRUE)

Randomly select fraction of rows.

#### dplyr::sample\_n(iris, 10, replace = TRUE)

Randomly select n rows.

#### dplyr::slice(iris, 10:15) Select rows by position.

dplyr::top\_n(storms, 2, date)

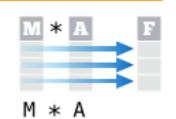
Select and order top n entries (by group if grouped data).

	Logic in R - ?	Comparison, ?base	::Logic
<	Less than	!=	Not equal to
>	Greater than	%in%	Group membership
==	Equal to	is.na	Is NA
<=	Less than or equal to	!is.na	Is not NA
>=	Greater than or equal to	&, ,!,xor,any,all	Boolean operators

#### Tidy Data - A foundation for wrangling in R



Tidy data complements R's vectorized operations. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R. M \* A



#### Reshaping Data - Change the layout of a data set



tidyr::spread(pollution, size, amount) Spread rows into columns.



::unite(data, col, ..., sep) Unite several columns into one.

::data\_frame(a = 1:3, b = 4:6) Combine vectors into data frame

#### dplyr::arrange(mtcars, mpg)

Order rows by values of a column (low to high).

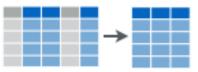
#### dplyr::arrange(.mtcars, desc(mpg))

Order rows by values of a column (high to low).

#### dplyr::rename(tb, y = year)

Rename the columns of a data frame.

#### **Subset Variables** (Columns)

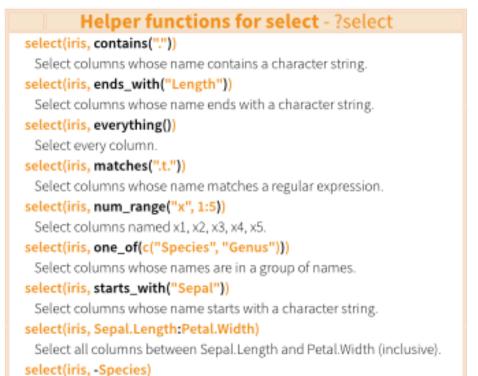


#### dplyr::select(iris, Sepal.Width, Petal.Length, Species)

Select columns by name or helper function.

Select all columns except Species.

Learn more with browseVignettes(package = c("dplyr", "tidyr")) • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15



## http://www.rstudio.com/resources/cheatsheets/

## Ground rules

5.96

5.88

53.0 2895 5.71 5.75 3.56

5.91 5.99 3.71

6.00

5.75 5.78 3.51

5.66 5.76 3.53

5.92 3.62

2894

2894

2894

2895

57.0

56.0

56.0



## tbl's

978

979

981

982

983

```
Just like data frames, but play better with the console window.
```

```
Source: local data frame [53,940 x 10]
              cut color clarity depth table
   carat
   0.23
            Ideal
                            SI2 61.5
                                         55
                            SI1 59.8
   0.21
          Premium
                                         61
                            VS1 56.9
   0.23
             Good
                                         65
                            VS2 62.4
   0.29
          Premium
                                         58
                            SI2 63.3
   0.31
             Good
                                         58
   0.24 Very Good
                           VVS2 62.8
                                         57
   0.24 Very Good
                           VVS1 62.3
                                         57
   0.26 Very Good
                            SI1 61.9
                                         55
   0.22
             Fair
                            VS2 65.1
                                         61
   0.23 Very Good
                            VS1 59.4
Variables not shown: price (int), x (dbl), y
 (dbl), z (dbl)
```

```
tbl
```

986	63.0	2896	6.00	6.05	3.51
987	56.0	2896	5.18	5.24	3.21
988	56.0	2896	5.91	5.96	3.65
989	55.0	2896	5.82	5.86	3.59
990	56.0	2896	5.83	5.89	3.64
991	58.0	2896	5.94	5.88	3.60
992	57.0	2896	6.39	6.35	4.02
993	57.0	2896	6.46	6.45	3.97
994	57.0	2897	5.48	5.51	3.33
995	58.0	2897	5.91	5.85	3.59
996	52.0	2897	5.30	5.34	3.26
997	55.0	2897	5.69	5.74	3.57
998	61.0	2897	5.82	5.89	3.48
999	58.0	2897	5.81	5.77	3.58
1000	59.0	2898	6.68	6.61	4.03
<pre>[ reached getOption("max.print")</pre>					
omitte	ed 5294	0 rows	]		

## data.frame

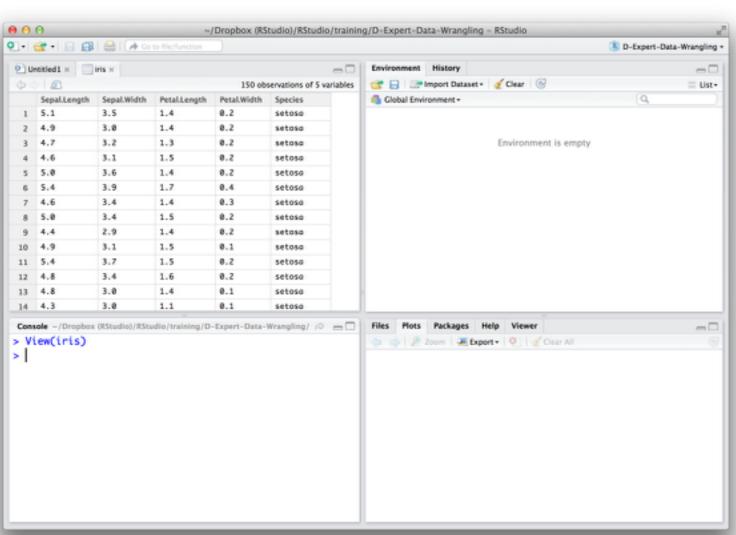




Examine any data set with the View() command (Capital V)

View(iris)
View(mtcars)
View(pressure)





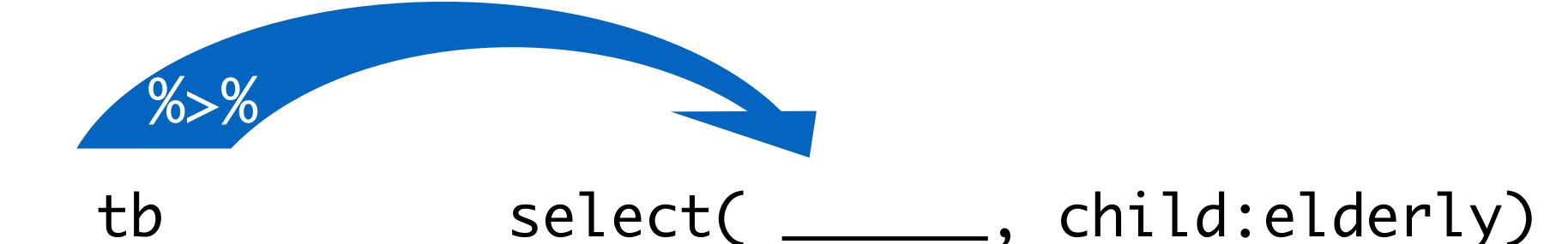


## The pipe 0/50/0

library(dplyr)

select(tb, child:elderly)
tb %>% select(child:elderly)





## Data Wrangling

## Wramgling Mungimg Janitor Work Manipulation Iranstormation

50-80% of your time?



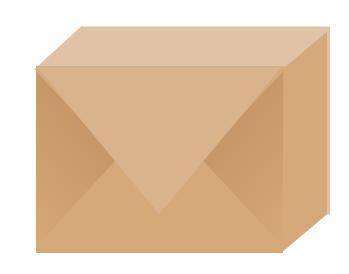
## Two goals

- Make data suitable to use with a particular piece of software
- Reveal information

## Data sets come in many formats

...but R prefers just one.

## EDAWR



An R package with all of the data sets that we will use today.

## storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

#### cases

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

city	particle size	amount (μg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

## storms

#### wind pressure date 110 1007 2000-08-12 1009 1998-07-30 45 1005 65 1995-06-04 1013 40 1997-07-01 1010 1999-06-13 50 45 1010 1996-06-21

## cases

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

## pollution

city	particle size	amount (μg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

Storm name

### storms

## sterm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ala 40 1013 1997-07-01 Arline 50 1010 1999-06-13 Arline 1010 1996-06-21

## cases

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

city	particle size	amount (μg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

- Storm name
- Wind Speed (mph)

### storms

# sterm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ala 40 1013 1997-07-01 Arlane 50 1010 1999-06-13 Alviur 3 100 1996-06-21

## cases

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

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

- Storm name
- Wind Speed (mph)
- Air Pressure

## storms

# sterm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ana 40 1013 1997-07-01 Arlene 50 1010 1999-06-13 Arran 43 1070 1996-36-21

## cases

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

city	particle size	amount (μg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

### storms

# sterm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ana 40 1013 1997-07-01 Arlane 50 1010 1999-06-13 Arran 43 1070 1996-36-21

## cases

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

## pollution

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

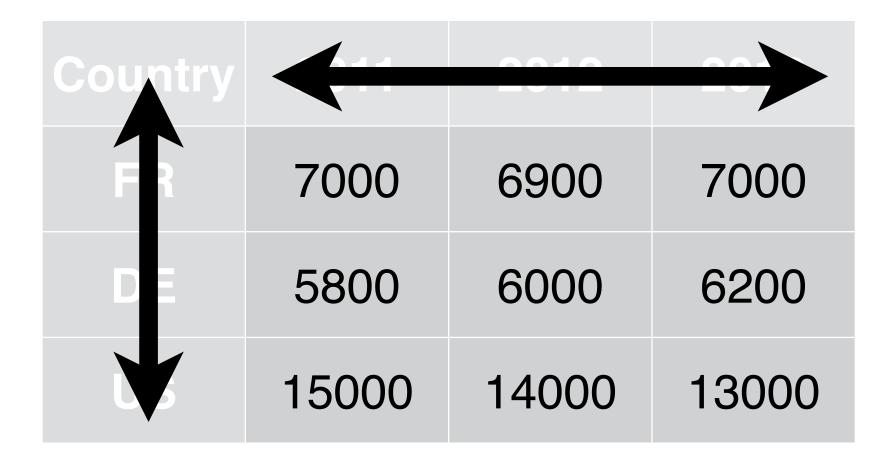
- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

Country

#### storms

# sterm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ana 40 1013 1997-07-01 Arlane 50 1010 1999-06-13 Arran 43 1070 1996-36-21

#### cases

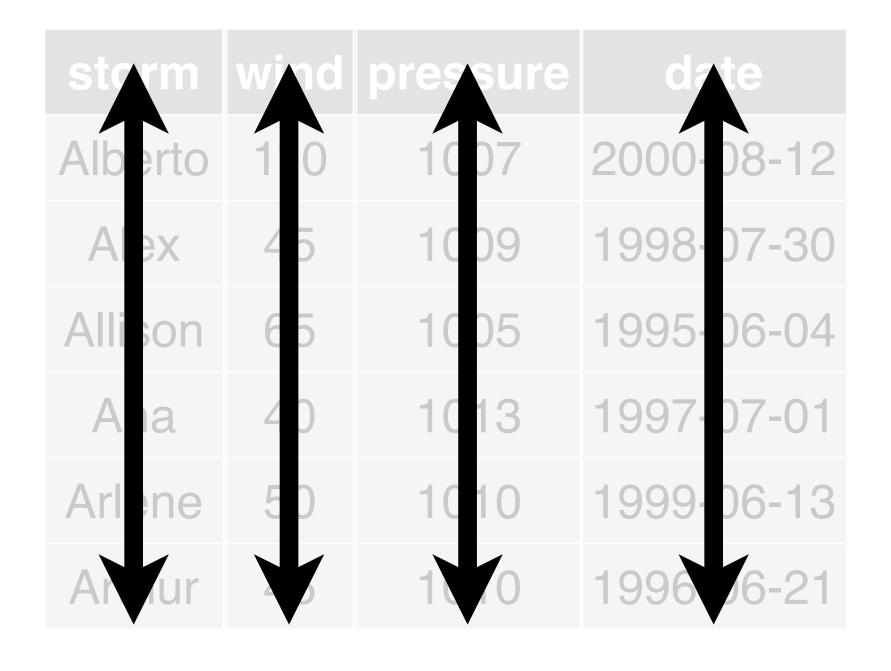


city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

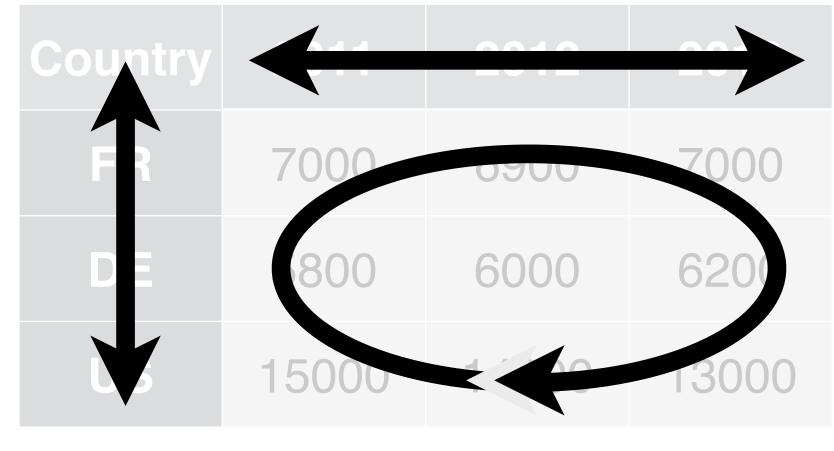
- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

- Country
- Year

#### storms



#### cases



city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

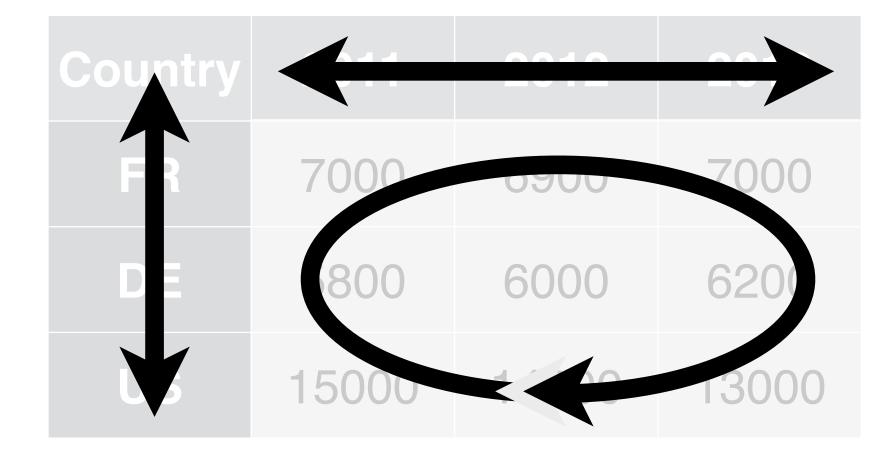
- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

- Country
- Year
- Count

### storms

storm	wind	pressure	date
Alberto	10	1007	date 2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Alia	40	1013	1997-01
Arlene	50	1010	1999-06-13
Artur		100	1996 6-21

### cases



## pollution

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
Lordon	large	22
London	small	16
Being	large	121
Being	small	56

- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

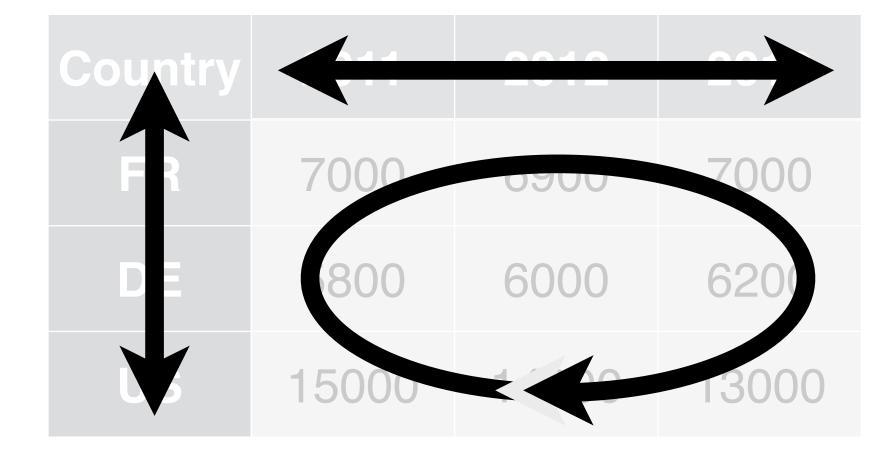
- Country
- Year
- Count

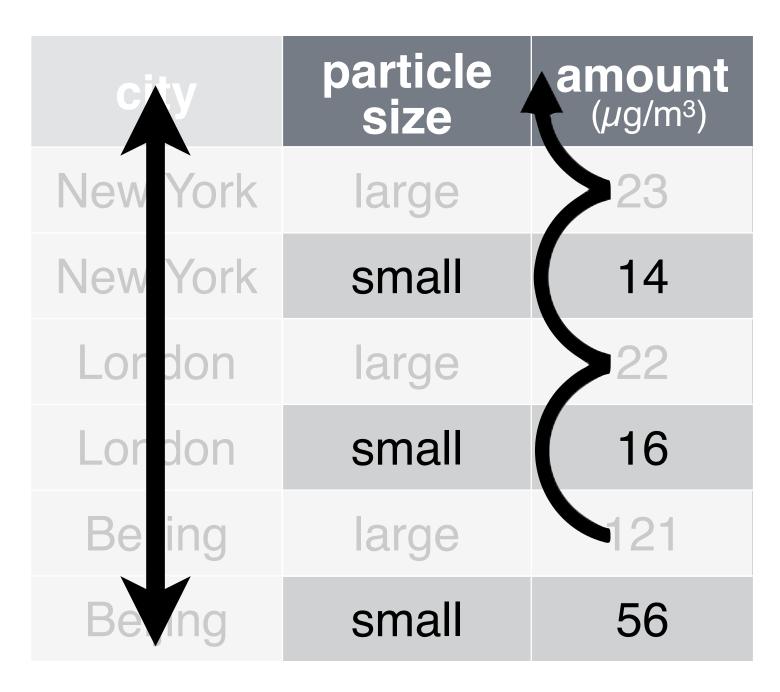
City

### storms

# storm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ana 40 1013 1997-07-01 Arlane 50 1010 1999-06-13 Arvaur 43 1070 1996-36-21

## cases





- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

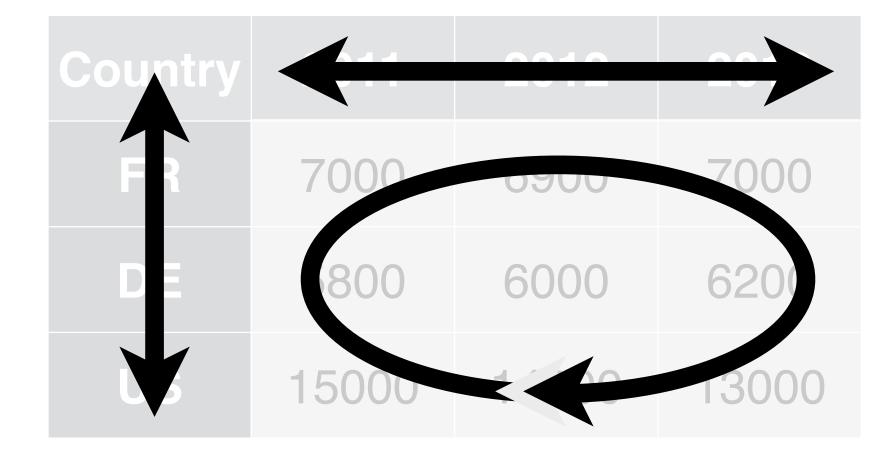
- Country
- Year
- Count

- City
- Amount of large particles

### storms

# storm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ala 40 1013 1997-07-01 Arlene 50 1010 1999-06-13 Arlan 43 1070 1996-36-21

### cases



city	particle size	amount (µg/m³)
New York	large	<b>&gt;</b> 23
New York	small	14
Lordon	large	>22
Lordon	small	16
Being	large	121
Bering	small	56

- Storm name
- Wind Speed (mph)
- Air Pressure
- Date

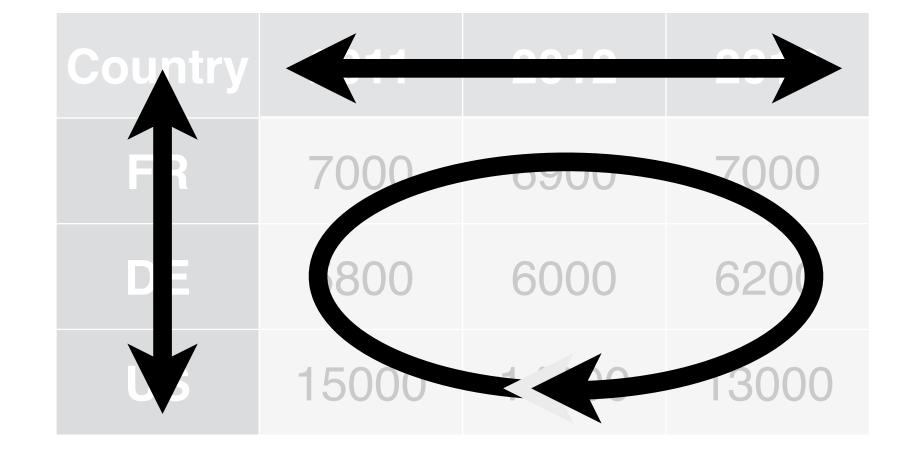
- Country
- Year
- Count

- City
- Amount of large particles
- Amount of small particles

### storms

# storm wind pressure date Alberto 1 0 1007 2000-08-12 Alex 45 1009 1998-07-30 Allison 65 1005 1995-06-04 Ala 40 1013 1997-07-01 Arlene 50 1010 1999-06-13 Arlan 43 1070 1996-36-21

## cases



## pollution

city	particle size	amount (µg/m³)
New York	large	<b>&gt;</b> 23 <b>4</b>
New York	small	14
London	large	>22
London	small	16
Being	large	121
Being	small	56

storms\$storm
storms\$wind
storms\$pressure
storms\$date

cases\$country
names(cases)[-1]
unlist(cases[1:3, 2:4])

pollution\$city[c(1,3,5)]
pollution\$amount[c(1,3,5)]
pollution\$amount[c(2,4,6)]

## storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



## storms\$pressure / storms\$wind

950	110	8.6
1003	45	22.3
987	65	15.2
1004	40	25.1
1006	50	20.1
1000	45	22.2

# storms

## Tidy data

- Each variable is saved in its own column.
- Each observation is saved in its own row.
- Each "type" of observation stored in a **single table** (here, storms).

## Recap: Tidy data

123 Variables in columns, observations in rows, each type in a table



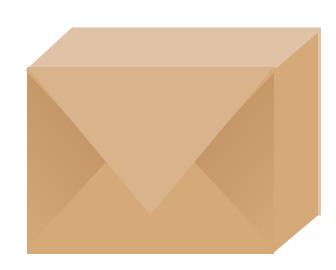
Easy to access variables



Automatically preserves observations

## 

## tidyr



A package that reshapes the layout of tables.

Two main functions: gather() and spread()

```
# install.packages("tidyr")
```

library(tidyr)

?gather

?spread

## Your Turn

Imagine how this data would look if it were tidy with three variables: country, year, n

cases

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	Ygar	
FR	2011	7000
DE	2011	5800
US	2011	15(00
FR	2012	6900
DE	2012	6000
US	2012	14(00
FR	2013	7000
	2013	6200
	2013	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

Countr	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 FR DE US

#### 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 FR DE US

#### 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

Collapses multiple columns into two columns:

- 1. a key column that contains the former column names
- 2. a value column that contains the former column cells

```
gather(cases, "year", "n", 2:4)
```

Collapses multiple columns into two columns:

- 1. a key column that contains the former column names
- 2. a value column that contains the former column cells

```
gather(cases, "year", "n", 2:4)
```

data frame to reshape

Collapses multiple columns into two columns:

- 1. a key column that contains the former column names
- 2. a value column that contains the former column cells

```
gather(cases, "year", "n", 2:4)
```

data frame to reshape name of the new key column (a character string)

Collapses multiple columns into two columns:

- 1. a key column that contains the former column names
- 2. a value column that contains the former column cells

```
gather(cases, "year", "n", 2:4)
```

data frame to reshape name of the new key column (a character string)

name of the new value column (a character string)

Collapses multiple columns into two columns:

- 1. a key column that contains the former column names
- 2. a value column that contains the former column cells

gather(cases, "year", "n", 2:4)

data frame to reshape name of the new key column (a character string)

name of the new value column (a character string)

names or numeric indexes of columns to collapse



```
##
                                             country year
                          2013
##
     country
                    2012
              2011
                                       ## 1
                                                   FR 2011
                                                             7000
              7000
                    6900
## 1
                          7000
          FR
                                       ## 2
                                                   DE 2011
                                                             5800
          DE
              5800
                    6000
                          6200
## 2
## 3
          US 15000 14000 13000
                                       ## 3
                                                   US 2011 15000
                                       ## 4
                                                   FR 2012
                                                             6900
                                                             6000
                                       ## 5
                                                   DE 2012
                                       ## 6
                                                   US 2012 14000
                                       ## 7
                                                   FR 2013
                                                             7000
                                       ## 8
                                                             6200
                                                   DE 2013
                                                   US 2013 13000
                                       ## 9
```

gather(cases, "year", "n", 2:4)

#### Your Turn

Imagine how the pollution data set would look tidy with three variables: *city, large, small* pollution

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

city	particle size	amount (μg/m³)
New York	large	<b>&gt;</b> 23 <b>+</b>
New York	small	14
Lordon	large	>22
Lordon	small	16
Beling	large	121
Bering	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

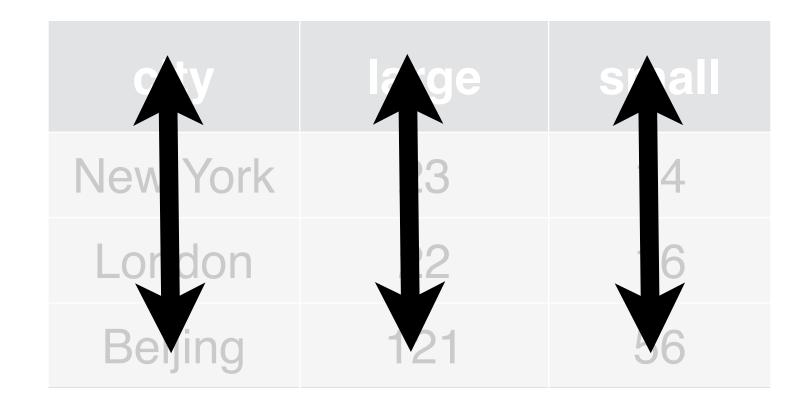
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

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

#### 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

Generates multiple columns from two columns:

- 1. each unique value in the key column becomes a column name
- 2. each value in the value column becomes a cell in the new columns

```
spread(pollution, size, amount)
```

Generates multiple columns from two columns:

- 1. each unique value in the key column becomes a column name
- 2. each value in the value column becomes a cell in the new columns

```
spread(pollution, size, amount)
```

data frame to reshape

Generates multiple columns from two columns:

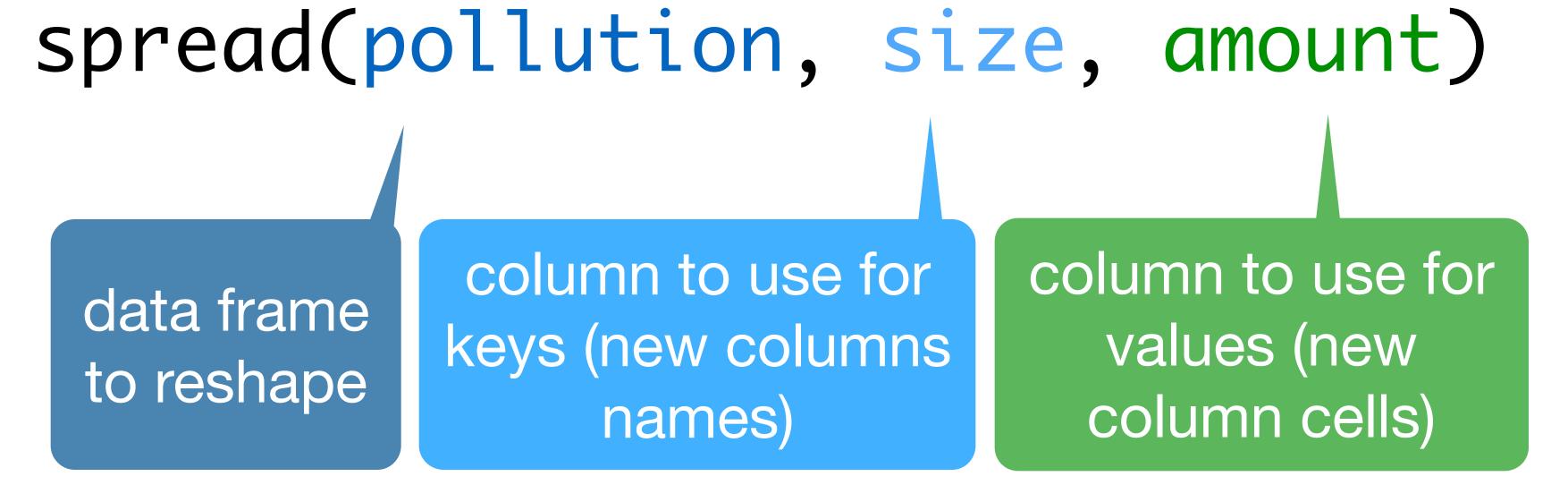
- 1. each unique value in the key column becomes a column name
- 2. each value in the value column becomes a cell in the new columns

spread(pollution, size, amount)

data frame to reshape column to use for keys (new columns names)

Generates multiple columns from two columns:

- 1. each unique value in the key column becomes a column name
- 2. each value in the value column becomes a cell in the new columns



121

56

16

14



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

spread(pollution, size, amount)

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

# unite() and separate()

There are three more variables hidden in storms:

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

- Year
- Month
- Day

# separate()

Separate splits a column by a character string separator.

separate(storms, date, c("year", "month", "day"), sep = "-")

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

storm	wind	pressure	year	month	day
Alberto	110	1007	2000	08	12
Alex	45	1009	1998	07	30
Allison	65	1005	1995	06	04
Ana	40	1013	1997	07	1
Arlene	50	1010	1999	06	13
Arthur	45	1010	1996	06	21

# unite()

Unite unites columns into a single column.

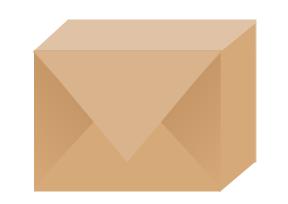
unite(storms2, "date", year, month, day, sep = "-")

### storms2

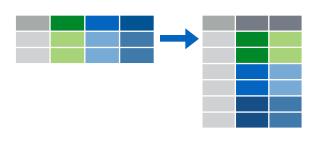
storm	wind	pressure	year	month	day
Alberto	110	1007	2000	08	12
Alex	45	1009	1998	07	30
Allison	65	1005	1995	06	04
Ana	40	1013	1997	07	1
Arlene	50	1010	1999	06	13
Arthur	45	1010	1996	06	21

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

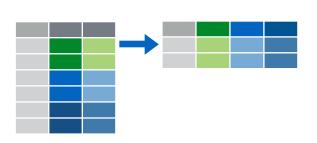
# Recap: tidyr



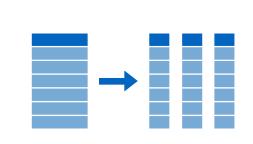
A package that reshapes the layout of data sets.



Make observations from variables with gather()



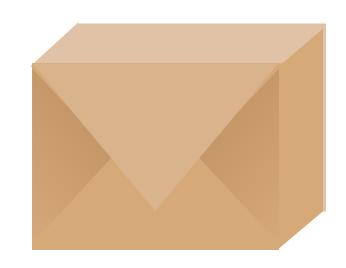
Make variables from observations with spread()



Split and merge columns with unite() and separate()

# Data sets contain more information than they display

# dplyr



A package that helps transform tabular data.

```
# install.packages("dplyr")
```

library(dplyr)

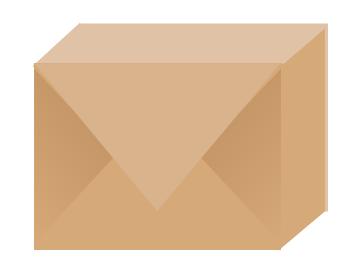
?select ?mutate

?filter ?summarise

?arrange ?group\_by



# nycflights13



# Data sets related to flights that departed from NYC in 2013

```
# install.packages("nycflights13")
```

library(nycflights13)

?airlines ?planes

?airports ?weather

?flights



# Ways to access information

Extract existing variables.

select()

Extract existing observations.

filter()

Derive new variables (from existing variables)

mutate()

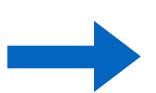
Change the unit of analysis

summarise()



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



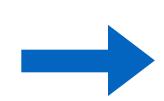
storm	pressure
Alberto	1007
Alex	1009
Allison	1005
Ana	1013
Arlene	1010
Arthur	1010

select(storms, storm, pressure)



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



wind	pressure	date
110	1007	2000-08-12
45	1009	1998-07-30
65	1005	1995-06-04
40	1013	1997-07-01
50	1010	1999-06-13
45	1010	1996-06-21

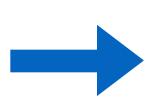
select(storms, -storm)

# see ?select for more



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



wind	pressure	date
110	1007	2000-08-12
45	1009	1998-07-30
65	1005	1995-06-04
40	1013	1997-07-01
50	1010	1999-06-13
45	1010	1996-06-21

select(storms, wind:date)

# see ?select for more

### Useful select functions

\* Blue functions come in dplyr

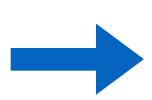
	Select everything but
-	Select range
contains()	Select columns whose name contains a character string
ends_with()	Select columns whose name ends with a string
everything()	Select every column
matches()	Select columns whose name matches a regular expression
num_range()	Select columns named x1, x2, x3, x4, x5
one_of()	Select columns whose names are in a group of names
starts_with()	Select columns whose name starts with a character string



# filter()

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13

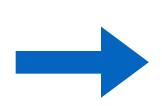
filter(storms, wind >= 50)



# filter()

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04

filter(storms, wind >= 50,
 storm %in% c("Alberto", "Alex", "Allison"))

# logical tests in R

### ?Comparison

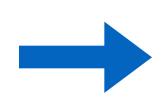
<	Less than
>	Greater than
==	Equal to
<=	Less than or equal to
>=	Greater than or equal to
!=	Not equal to
%in%	Group membership
is.na	Is NA
!is.na	Is not NA

### ?base::Logic

&	boolean and
	boolean or
xor	exactly or
	not
any	any true
all	all true

# mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date	ratio
Alberto	110	1007	2000-08-12	9.15
Alex	45	1009	1998-07-30	22.42
Allison	65	1005	1995-06-04	15.46
Ana	40	1013	1997-07-01	25.32
Arlene	50	1010	1999-06-13	20.20
Arthur	45	1010	1996-06-21	22.44

mutate(storms, ratio = pressure / wind)

# mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date	ratio	inverse
Alberto	110	1007	2000-08-12	9.15	0.11
Alex	45	1009	1998-07-30	22.42	0.04
Allison	65	1005	1995-06-04	15.46	0.06
Ana	40	1013	1997-07-01	25.32	0.04
Arlene	50	1010	1999-06-13	20.20	0.05
Arthur	45	1010	1996-06-21	22.44	0.04

mutate(storms, ratio = pressure / wind, inverse = ratio $^-1$ )

### Useful mutate functions

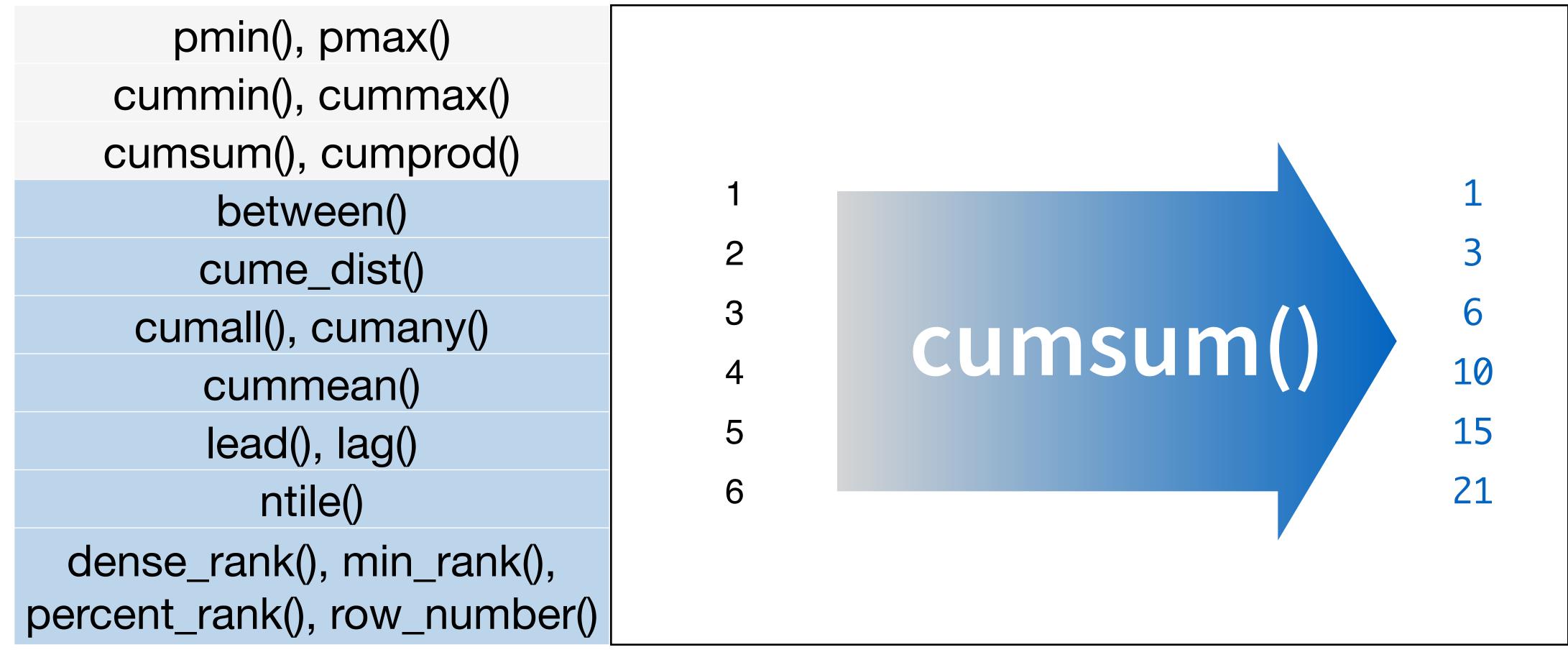
\* All take a vector of values and return a vector of values

\*\* Blue functions come in dplyr

pmin(), pmax()	Element-wise min and max
cummin(), cummax()	Cumulative min and max
cumsum(), cumprod()	Cumulative sum and product
between()	Are values between a and b?
cume_dist()	Cumulative distribution of values
cumall(), cumany()	Cumulative all and any
cummean()	Cumulative mean
lead(), lag()	Copy with values one position
ntile()	Bin vector into n buckets
dense_rank(), min_rank(), percent_rank(), row_number()	Various ranking methods

### "Window" functions

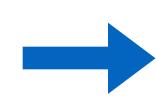
\* All take a vector of values and return a vector of values





# summarise()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



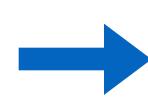
median	variance
22.5	1731.6

pollution %>% summarise(median = median(amount), variance = var(amount))



# summarise()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



mean	sum	n
42	252	6

pollution %>% summarise(mean = mean(amount), sum = sum(amount), n = n())

# Useful summary functions

\* All take a vector of values and return a single value

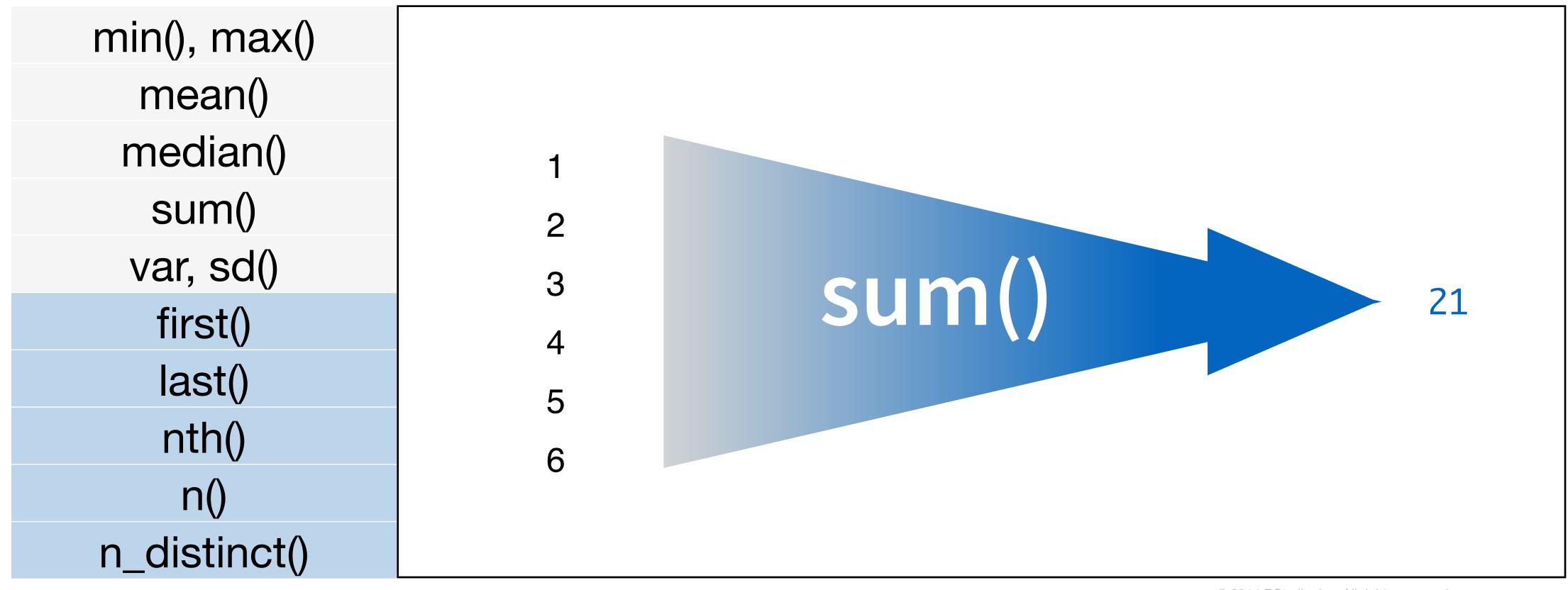
\*\* Blue functions come in dplyr

min(), max()	Minimum and maximum values
mean()	Mean value
median()	Median value
sum()	Sum of values
var, sd()	Variance and standard deviation of a vector
first()	First value in a vector
last()	Last value in a vector
nth()	Nth value in a vector
n()	The number of values in a vector
n_distinct()	The number of distinct values in a vector



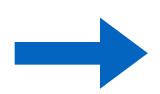
# "Summary" functions

\* All take a vector of values and return a single value



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



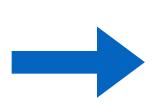
storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

arrange(storms, wind)



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



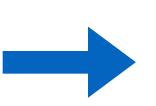
storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

arrange(storms, wind)



### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

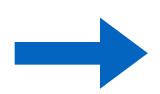


storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21
Alex	45	1009	1998-07-30
Ana	40	1013	1997-07-01

arrange(storms, desc(wind))

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

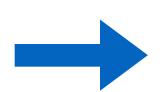


storm	wind	pressure	date
Ana	40	1013	1997-07-01
Alex	45	1009	1998-07-30
Arthur	45	1010	1996-06-21
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12

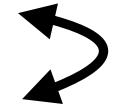
arrange(storms, wind)

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date
Ana	40	1013	1997-07-01
Arthur	45	1010	1996-06-21
Alex	45	1009	1998-07-30
Arlene	50	1010	1999-06-13
Allison	65	1005	1995-06-04
Alberto	110	1007	2000-08-12



arrange(storms, wind, date)

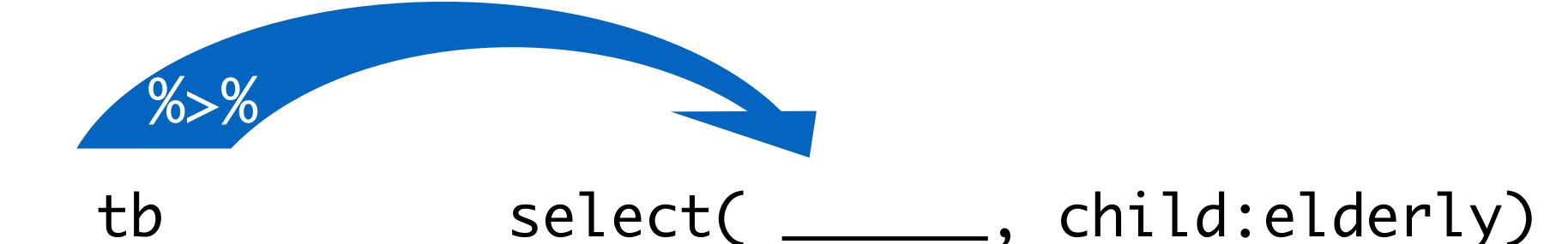


# The pipe 0/50/0

library(dplyr)

select(tb, child:elderly)
tb %>% select(child:elderly)







### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

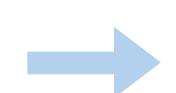


storm	pressure
Alberto	1007
Alex	1009
Allison	1005
Ana	1013
Arlene	1010
Arthur	1010

select(storms, storm, pressure)

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	pressure
Alberto	1007
Alex	1009
Allison	1005
Ana	1013
Arlene	1010
Arthur	1010

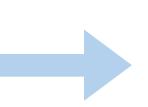
storms %>% select(storm, pressure)



# filter()

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13

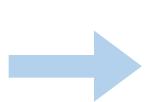
filter(storms, wind >= 50)



# filter()

### storms

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21

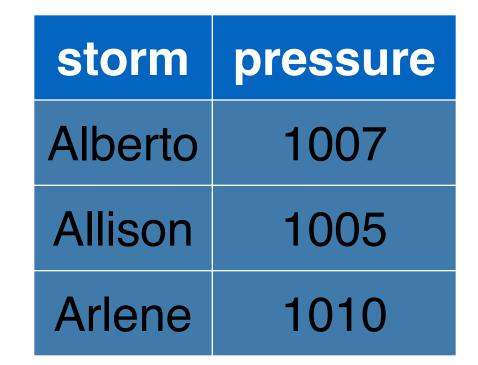


storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Allison	65	1005	1995-06-04
Arlene	50	1010	1999-06-13

storms %>% filter(wind >= 50)



storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21





# mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storms %>%

mutate(ratio = pressure / wind) %>%
select(storm, ratio)



## mutate()

storm	wind	pressure	date
Alberto	110	1007	2000-08-12
Alex	45	1009	1998-07-30
Allison	65	1005	1995-06-04
Ana	40	1013	1997-07-01
Arlene	50	1010	1999-06-13
Arthur	45	1010	1996-06-21



storm	ratio
Alberto	9.15
Alex	22.42
Allison	15.46
Ana	25.32
Arlene	20.20
Arthur	22.44

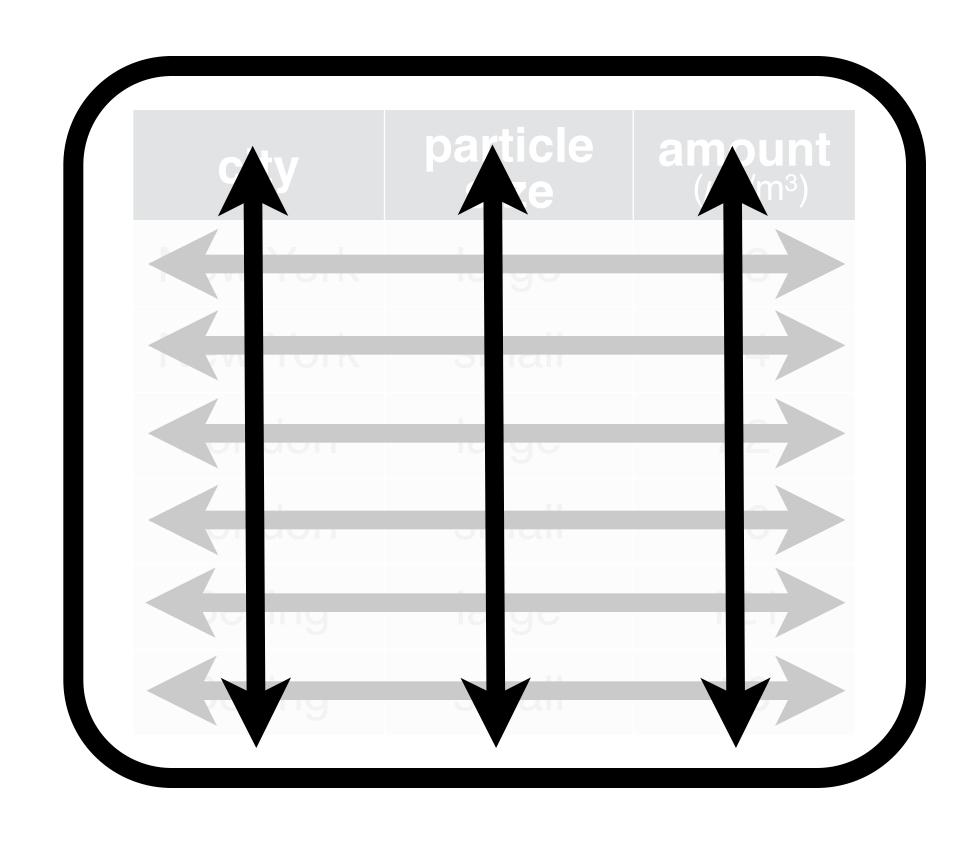
storms %>%

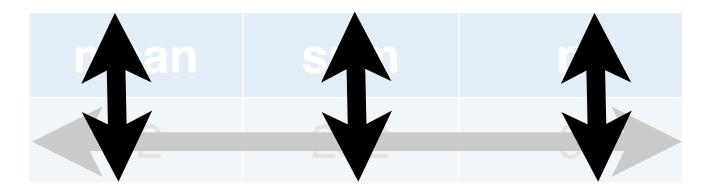
mutate(ratio = pressure / wind) %>%
select(storm, ratio)



## Shortcut to type %>%

# Unit of analysis

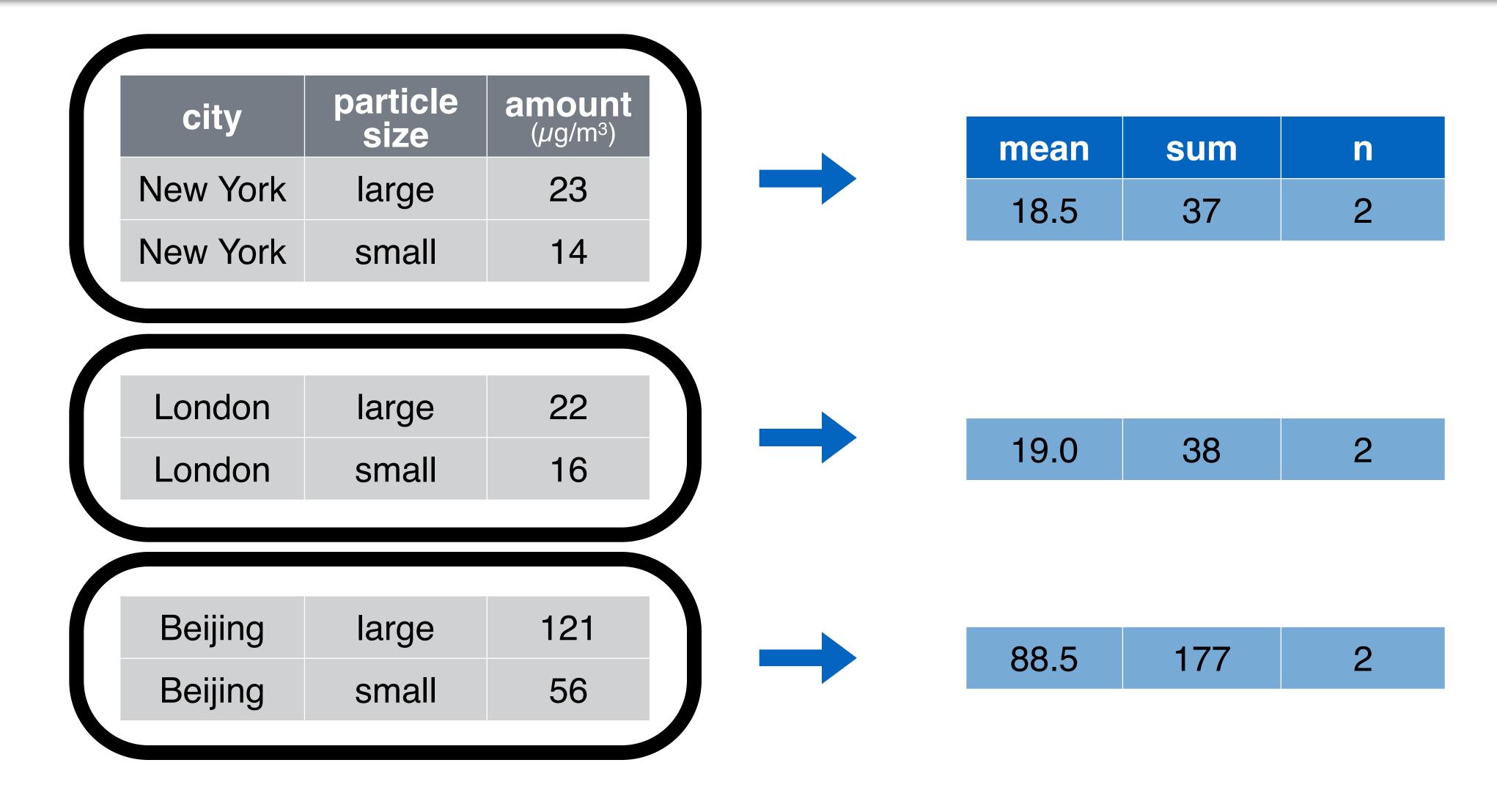




city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

mean	sum	n
42	252	6

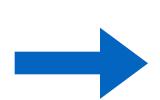




group\_by() + summarise()

## group\_by()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



city	particle size	amount (μg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

pollution %>% group\_by(city)

```
pollution %>% group_by(city)
## Source: local data frame [6 x 3]
## Groups: city
##
##
       city size amount
                       23
## 1 New York large
                   14
## 2 New York small
                      22
## 3 London large
                       16
## 4 London small
## 5 Beijing large
                      121
## 6 Beijing small
                       56
```



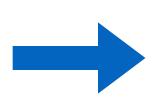
## group\_by() + summarise()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

```
pollution %>% group_by(city) %>%
  summarise(mean = mean(amount), sum = sum(amount), n = n())
```

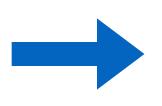


city	particle size	amount (µg/m³)
New York	large	23
New York	small	14



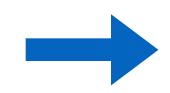
city	mean	sum	n
New York	18.5	37	2

London	large	22
London	small	16



London	19.0	38	2

Beijing	large	121
Beijing	small	56



Beijing 88.5 177 2



city	particle size	amount (µg/m³)
New York	large	23
New York	small	14

London	large	22
London	small	16

Beijing	large	121
Beijing	small	56

city	mean	sum	n
New York	18.5	37	2

city	mean	sum	n
New York	18.5	37	2
London	19.0	38	2
Beijing	88.5	177	2

Beijing 88.5 177 2



city	particle size	amount (µg/m³)
New York	large	23
New York	small	14

London	large	22
London	small	16

Beijing	large	121
Beijing	small	56

city	mean	sum	n
New York	18.5	37	2
London	19.0	38	2
Beijing	88.5	177	2



city	particle size	amount (µg/m³)
New York	large	23
New York	small	14

London	large	22
London	small	16

Beijing	large	121
Beijing	small	56

city	mean	sum	n
New York	18.5	37	2
London	19.0	38	2
Beijing	88.5	177	2

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

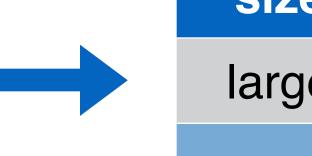
city	size	amount
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	mean
New York	18.5
London	19.0
Beiiina	88.5

pollution %>% group\_by(city) %>% summarise(mean = mean(amount))

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

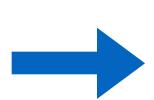


size	mean
large	55.3
small	28.6

pollution %>% group\_by(size) %>% summarise(mean = mean(amount))

## ungroup()

city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56



city	particle size	amount (µg/m³)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

pollution %>% ungroup()

country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3



tb

country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3

country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3

tb %>%
 group\_by(country, year)

country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3

year	sex	cases
1999	female	1
1999	male	1
2000	female	1
2000	male	1
1999	female	2
1999	male	2
2000	female	2
2000	male	2
1999	female	3
1999	male	3
2000	female	3
2000	male	3
	1999 2000 2000 1999 1999 2000 2000 1999 1999	1999 female 2000 female 2000 male 1999 male 1999 male 1999 male 2000 female 2000 female 1999 female 1999 female 2000 male 1999 female

country	year	cases
Afghanistan	1999	2
Afghanistan	2000	2
Brazil	1999	4
Brazil	2000	4
China	1999	6
China	1999	6

tb %>%
 group\_by(country, year) %>%
 summarise(cases = sum(cases))



country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3

year	sex	cases
1999	female	1
1999	male	1
2000	female	1
2000	male	1
1999	female	2
1999	male	2
2000	female	2
2000	male	2
1999	female	3
1999	male	3
2000	female	3
2000	male	3
	1999 2000 2000 1999 1999 2000 2000 1999 1999	1999 female 2000 female 2000 male 1999 male 1999 male 1999 male 2000 female 2000 female 1999 female 1999 female 2000 male 1999 female

country	year	cases
Afghanistan	1999	2
Afghanistan	2000	2
Brazil	1999	4
Brazil	2000	4
China	1999	6
China	1999	6



tb %>%
 group\_by(country, year) %>%
 summarise(cases = sum(cases)) %>%
 summarise(cases = sum(cases))



## Hierarchy of information

country	year	sex	cases
Afghanistan	1999	female	1
Afghanistan	1999	male	1
Afghanistan	2000	female	1
Afghanistan	2000	male	1
Brazil	1999	female	2
Brazil	1999	male	2
Brazil	2000	female	2
Brazil	2000	male	2
China	1999	female	3
China	1999	male	3
China	2000	female	3
China	2000	male	3

country	year	cases
Afghanistan	1999	2
Afghanistan	2000	2
Brazil	1999	4
Brazil	2000	4
China	1999	6
China	2000	6

country	cases
Afghanistan	4
Brazil	8
China	12

cases 24

## Larger units of analysis



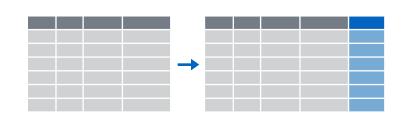
## Recap: Information



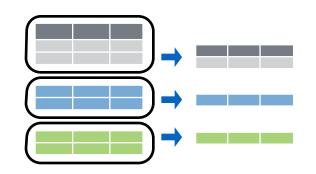
Extract variables and observations with select() and filter()



Arrange observations, with arrange().



Make new variables, with mutate().



Make groupies observations with group\_by() and summarise().

## Joining data



## dplyr::bind\_cols()

y

<b>x</b> 1	<b>x2</b>
A	1
В	2
C	3

Z

<b>x</b> 1	<b>x2</b>
В	2
C	3
D	4

<b>x</b> 1	<b>x2</b>	<b>x</b> 1	<b>x2</b>
A	1	В	2
В	2	C	3
C	3	D	4

bind\_cols(y, z)

**x**1

A

**x2** 



## dplyr::bind\_rows()

y

<b>x</b> 1	<b>x2</b>	
A	1	
В	2	
C	3	

Z

<b>x</b> 1	<b>x2</b>	
В	2	
C	3	
D	4	

=

3
2
3
4

bind\_rows(y, z)



## dplyr::union()

y

<b>x</b> 1	<b>x2</b>	
A	1	
В	2	
C	3	

Z

<b>x</b> 1	<b>x2</b>	
В	2	
C	3	
D	4	

<b>x</b> 1	<b>x2</b>	
A	1	
В	2	
C	3	
D	4	

union(y, z)



## dplyr::intersect()

y		
<b>x</b> 1	<b>x2</b>	
A	1	
В	2	
C	3	

	<b>x</b> 1	<b>x2</b>
	В	2
+	C	3
	D	4

<b>x</b> 1	<b>x2</b>	
В	2	
C	3	

intersect(y, z)



## dplyr::setdif()

x1 x2 A 1 B 2

 x1
 x2

 B
 2

 C
 3

 D
 4

 x1
 x2

 A
 1

 D
 4

setdiff(y, z)

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

name	plays	
George	sitar	
John	guitar	
Paul	bass	
Ringo	drums	

song	name	plays
Across the Universe	John	guitar
Come Together	John	guitar
Hello, Goodbye	Paul	bass
Peggy Sue	Buddy	<na></na>

left\_join(songs, artists, by = "name")

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

name	plays
George	sitar
John	guitar
Paul	bass
Ringo	drums

song	name	plays
Across the Universe	John	guitar
Come Together	John	guitar
Hello, Goodbye	Paul	bass
Peggy Sue	Buddy	<na></na>

left\_join(songs, artists, by = "name")



#### songs2

song	first	last
Across the Universe	John	Lennon
Come Together	John	Lennon
Hello, Goodbye	Paul	McCartney
Peggy Sue	Buddy	Holly

#### artists2

first	last	plays
George	Harrison	sitar
John	Lennon	guitar
Paul	McCartney	bass
Ringo	Starr	drums
Paul	Simon	guitar
John	Coltranee	sax

song	first	last	plays
Across the Universe	John	Lennon	guitar
Come Together	John	Lennon	guitar
Hello, Goodbye	Paul	McCartney	bass
Peggy Sue	Buddy	Holly	<na></na>

left\_join(songs2, artists2, by = c("first", "last"))



#### songs2

song	first	last
Across the Universe	John	Lennon
Come Together	John	Lennon
Hello, Goodbye	Paul	McCartney
Peggy Sue	Buddy	Holly

#### artists2

first	last	plays
George	Harrison	sitar
John	Lennon	guitar
Paul	McCartney	bass
Ringo	Starr	drums
Paul	Simon	guitar
John	Coltrane	sax

song	first	last	plays
Across the Universe	John	Lennon	guitar
Come Together	John	Lennon	guitar
Hello, Goodbye	Paul	McCartney	bass
Peggy Sue	Buddy	Holly	<na></na>

left\_join(songs2, artists2, by = c("first", "last"))



## left\_join()

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

name	plays
George	sitar
John	guitar
Paul	bass
Ringo	drums

song	name	plays
Across the Universe	John	guitar
Come Together	John	guitar
Hello, Goodbye	Paul	bass
Peggy Sue	Buddy	<na></na>

left\_join(songs, artists, by = "name")

## inner\_join()

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

name	plays
George	sitar
John	guitar
Paul	bass
Ringo	drums



song	name	plays
Across the Universe	John	guitar
Come Together	John	guitar
Hello, Goodbye	Paul	bass

inner\_join(songs, artists, by = "name")



## semi\_join()

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

name	plays
George	sitar
John	guitar
Paul	bass
Ringo	drums

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul

semi\_join(songs, artists, by = "name")



## anti\_join()

#### songs

song	name
Across the Universe	John
Come Together	John
Hello, Goodbye	Paul
Peggy Sue	Buddy

#### artists

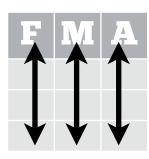
name	plays
George	sitar
John	guitar
Paul	bass
Ringo	drums

song	name
Peggy Sue	Buddy

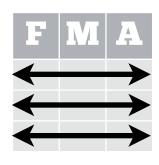
anti\_join(songs, artists, by = "name")



## Recap: Best format for analysis



Variables in columns



**Observations** in rows



Separate all variables implied by law, formula or goal



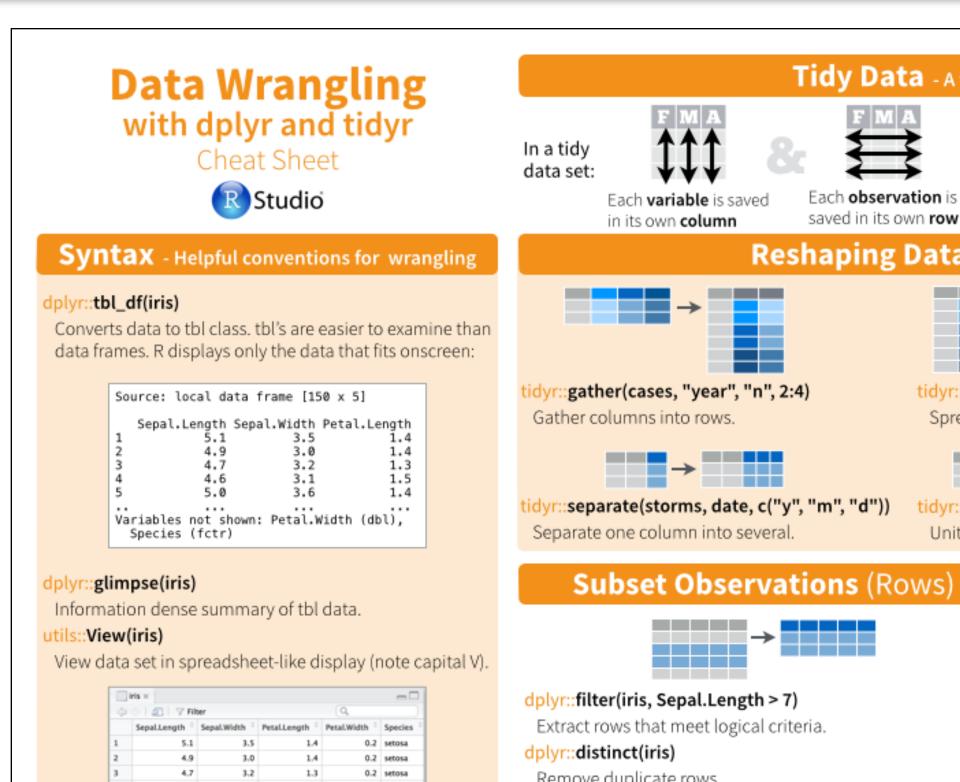
Unit of analysis matches the unit of analysis implied by law, formula or goal



Single table

# How to learn more





0.2 setosa

0.2 setosa

0.2 setosa

RStudio\* is a trademark of RStudio, Inc. • All rights reserved • info@rstudio.com • 844-448-1212 • rstudio.com devtools::install\_github("rstudio/EDAWR") for data sets

Passes object on left hand side as first argument (or .

x %% f(y) is the same as f(x, y)

 $y \gg f(x, ., z)$  is the same as f(x, y, z)

summarise(avg = mean(Sepal.Width)) %>%

"Piping" with %>% makes code more readable, e.g.

argument) of function on righthand side.

group\_by(Species) %>%

∷%>%

iris %>%

arrange(avg)

Remove duplicate rows.

#### dplyr::sample\_frac(iris, 0.5, replace = TRUE)

Randomly select fraction of rows.

#### dplyr::sample\_n(iris, 10, replace = TRUE)

Randomly select n rows.

#### dplyr::slice(iris, 10:15) Select rows by position.

dplyr::top\_n(storms, 2, date)

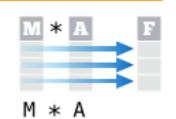
Select and order top n entries (by group if grouped data).

	Logic in R - ?Comparison, ?base::Logic		
<	Less than	!=	Not equal to
>	Greater than	%in%	Group membership
==	Equal to	is.na	Is NA
<=	Less than or equal to	!is.na	Is not NA
>=	Greater than or equal to	&, ,!,xor,any,all	Boolean operators

#### Tidy Data - A foundation for wrangling in R



Tidy data complements R's vectorized operations. R will automatically preserve observations as you manipulate variables. No other format works as intuitively with R. M \* A



#### Reshaping Data - Change the layout of a data set



tidyr::spread(pollution, size, amount) Spread rows into columns.



::unite(data, col, ..., sep) Unite several columns into one.

::data\_frame(a = 1:3, b = 4:6) Combine vectors into data frame

#### dplyr::arrange(mtcars, mpg)

Order rows by values of a column (low to high).

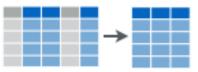
#### dplyr::arrange(.mtcars, desc(mpg))

Order rows by values of a column (high to low).

#### dplyr::rename(tb, y = year)

Rename the columns of a data frame.

#### **Subset Variables** (Columns)

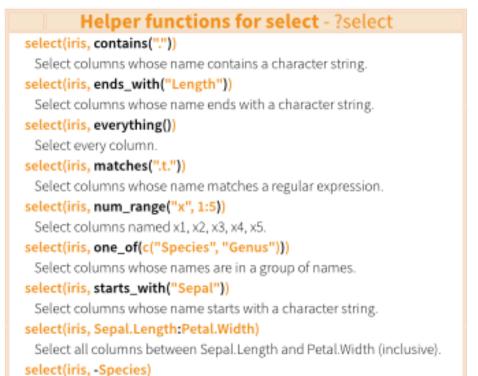


#### dplyr::select(iris, Sepal.Width, Petal.Length, Species)

Select columns by name or helper function.

Select all columns except Species.

Learn more with browseVignettes(package = c("dplyr", "tidyr")) • dplyr 0.4.0• tidyr 0.2.0 • Updated: 1/15



#### http://www.rstudio.com/resources/cheatsheets/

## dplyr and more



Four courses that teach dplyr, ggvis, rmarkdown, and the RStudio IDE.

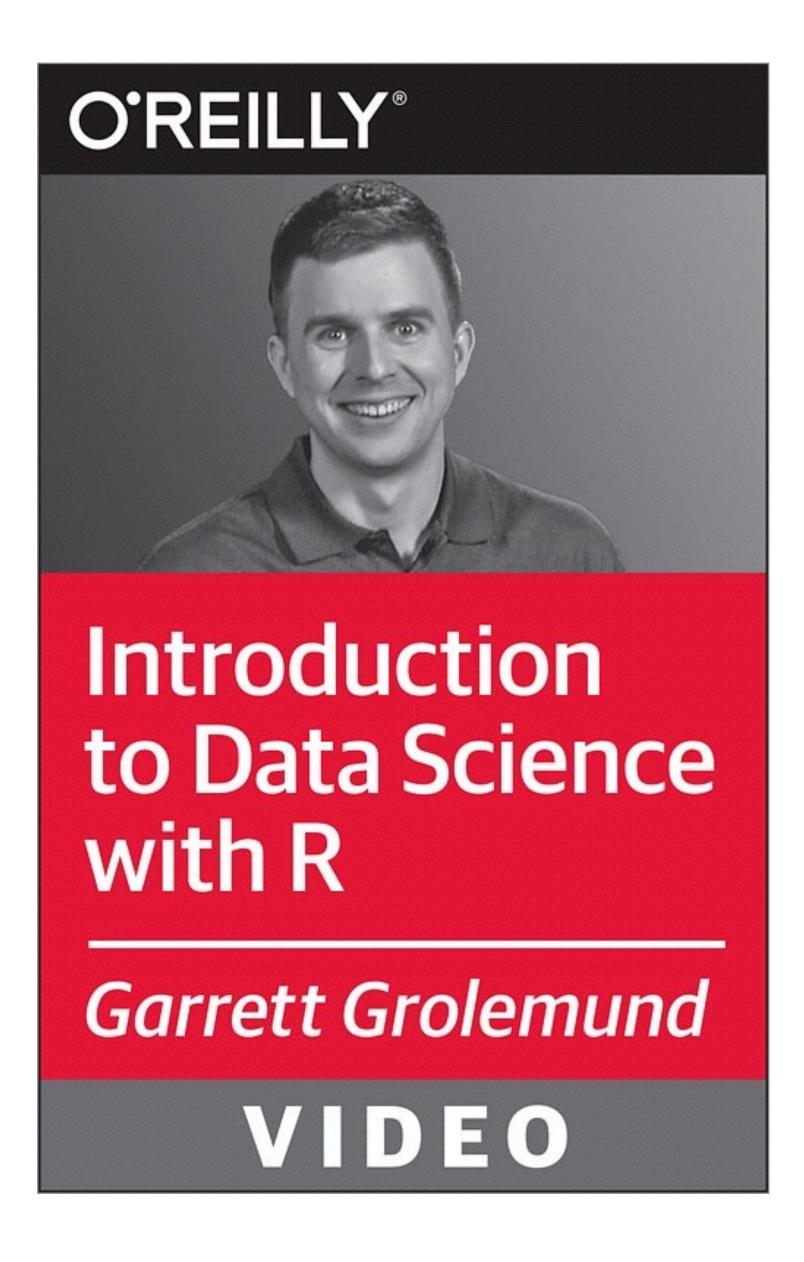
Video lessons

Live coding environment

Interactive practice

(~4 hrs worth of content for dplyr)

www.datacamp.com/tracks/rstudio-track



### Data Science with R

R's tools for data science. Reshape2, dplyr, and ggplot2 packages.

- Tidy data
- Data visualization and customizing graphics
- Statistical modeling with R

bit.ly/intro-to-data-science-with-R



## Expert Data Science

Coming Spring 2015

- Foundations of Data Science
- tidyr
- dplyr
- ggvis

## Thank you

### Data Wrangling with R

Slides at: <a href="mailto:bit.ly/wrangling-webinar">bit.ly/wrangling-webinar</a>