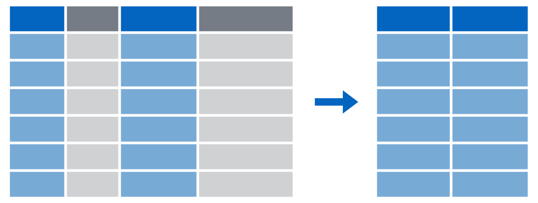
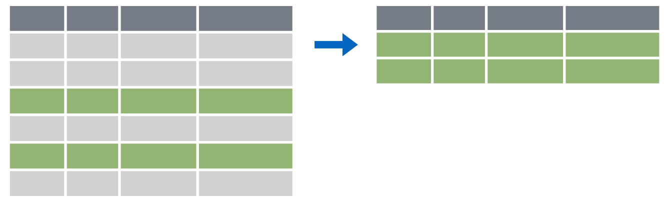
ANT 6973: DATA VISUALIZATION AND EXPLORATION

DATA MANIPULATION, PART 2

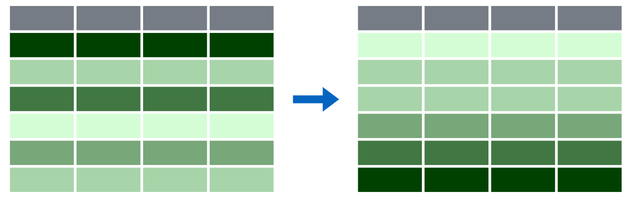
SINGLE TABLE VERBS



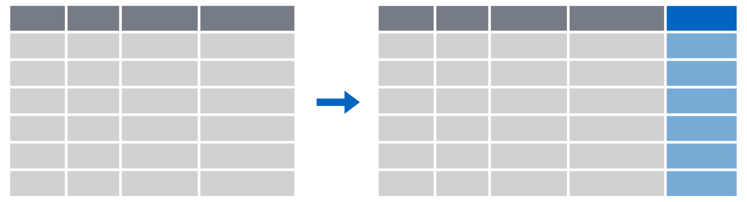
Extract variables with `select()`



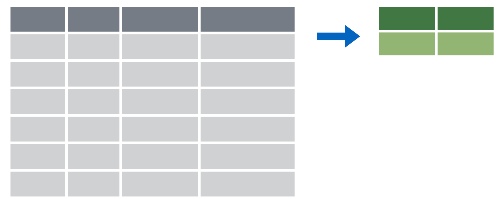
Extract cases with `filter()`



Arrange cases with `arrange()`



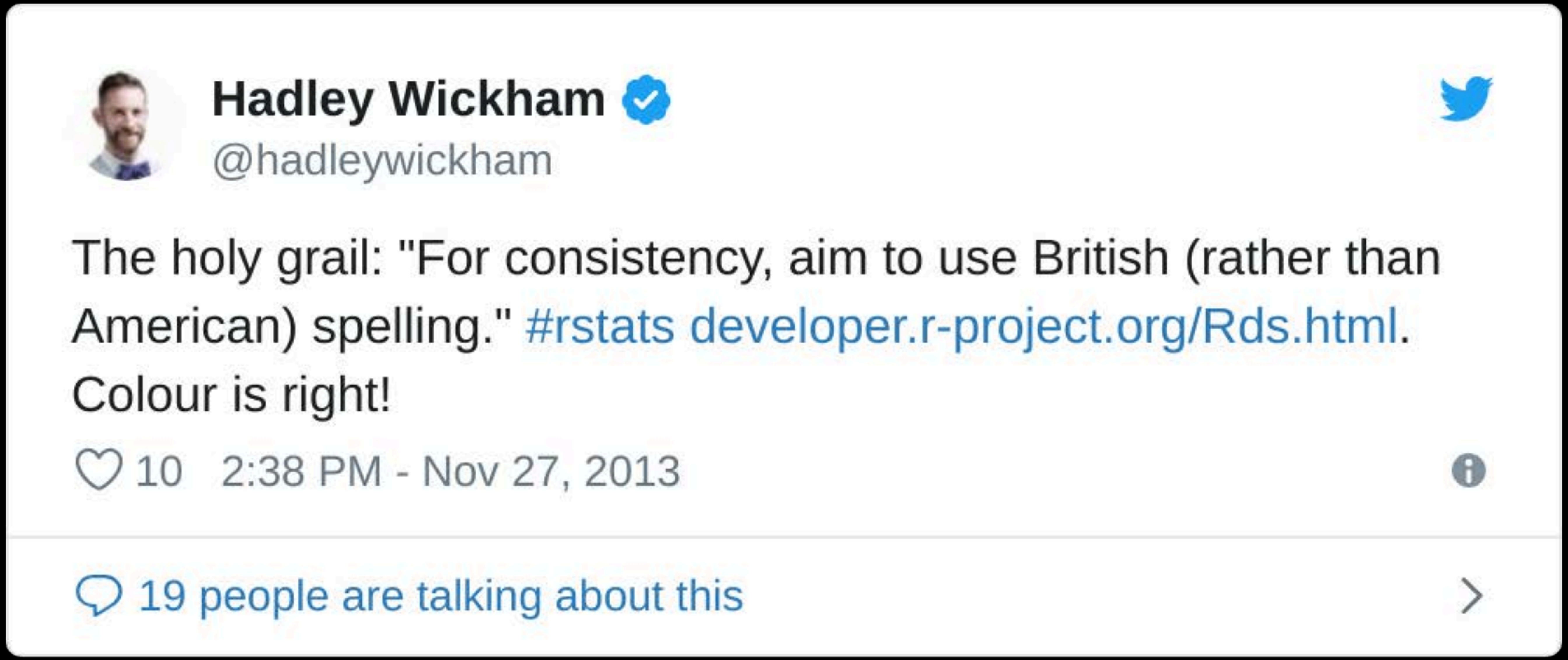
Make new variables with `mutate()`



Make tables of summaries with `summarize()`
along with `group_by()`

summarize()

A NOTE ON SPELLING…



Hadley Wickham @hadleywickham

The holy grail: "For consistency, aim to use British (rather than American) spelling." #rstats developer.r-project.org/Rds.html. Colour is right!

♡ 10 2:38 PM - Nov 27, 2013

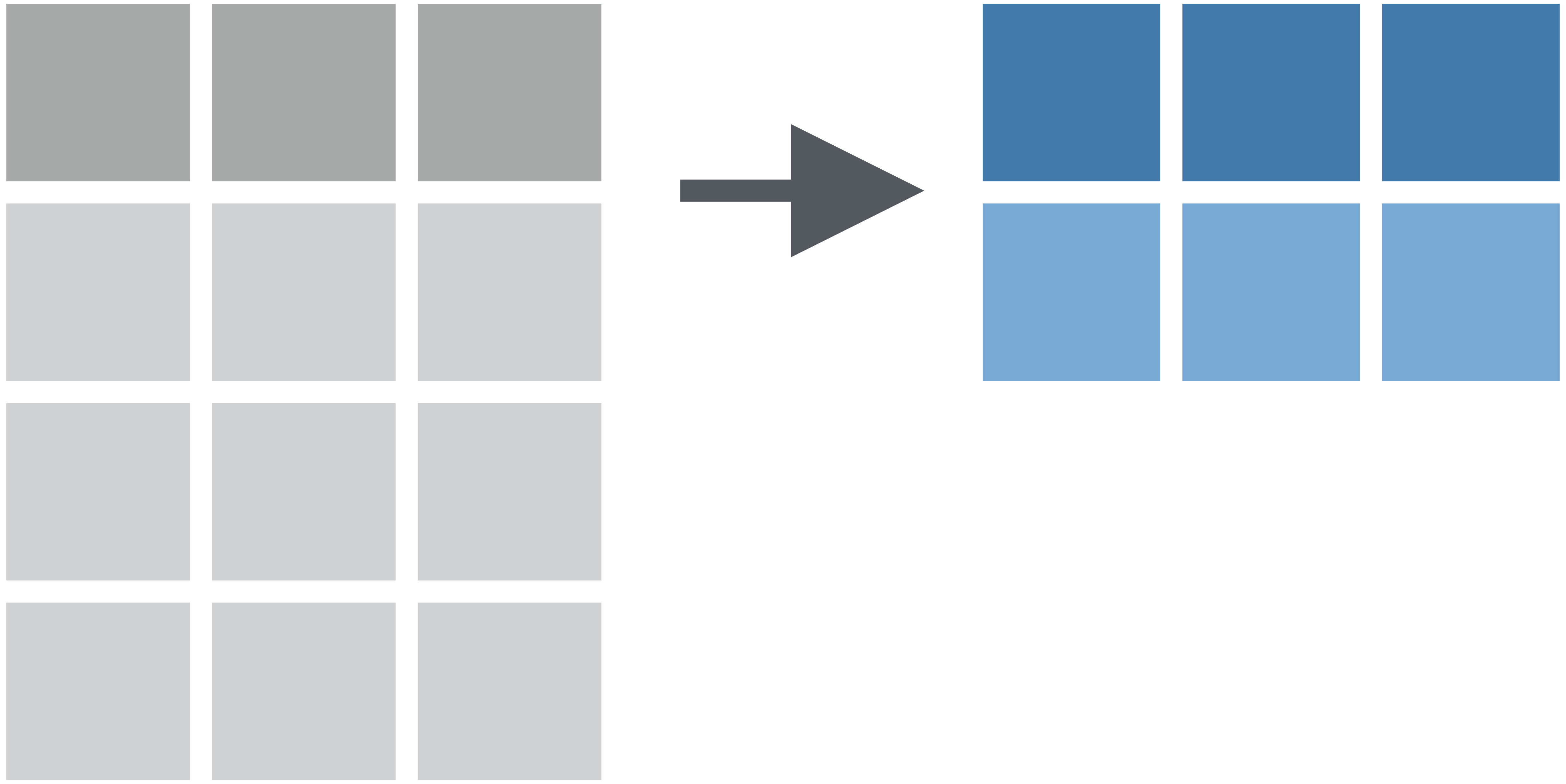
19 people are talking about this

But both the British and American spellings work:

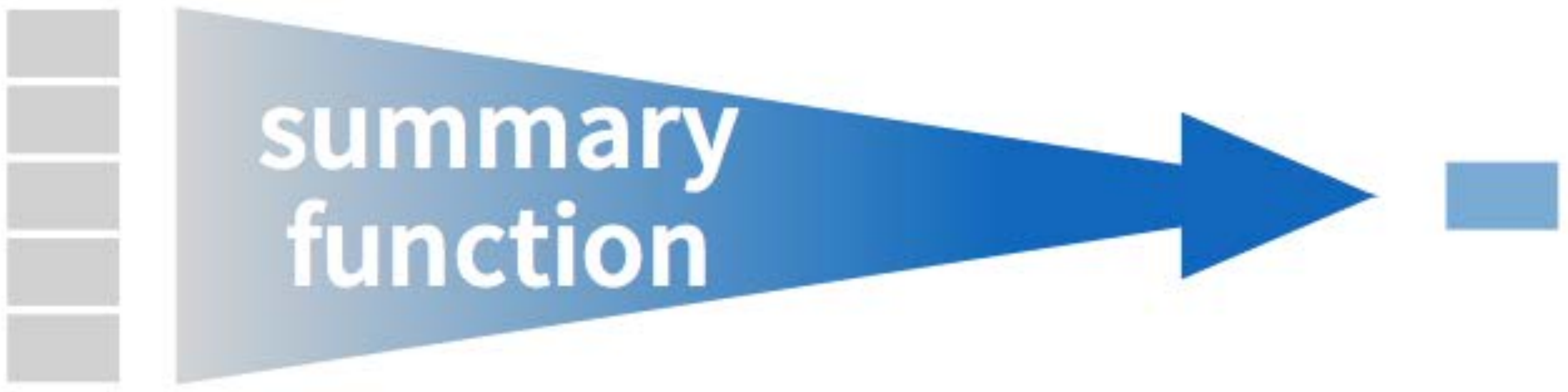
```
summarize() = summarise()
color() = colour()
```

SUMMARIZE()

Compute table of summaries.

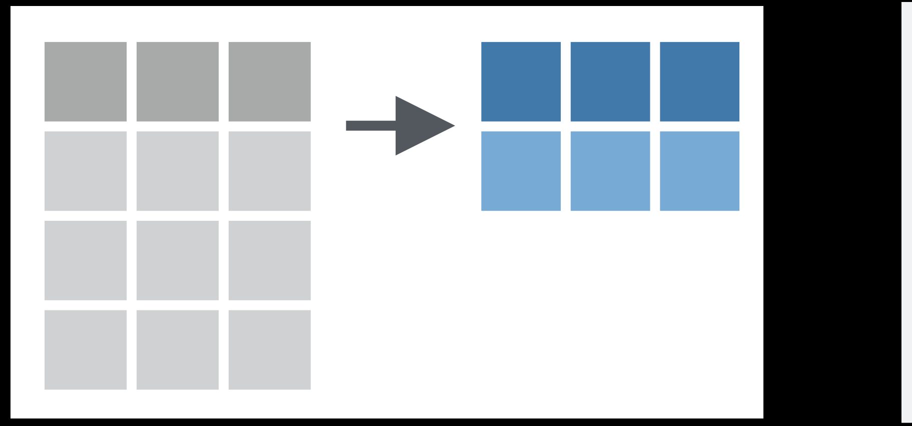


A *summary function* returns a *single value* that summarizes many values in a column



SUMMARIZE()

Compute table of summaries.



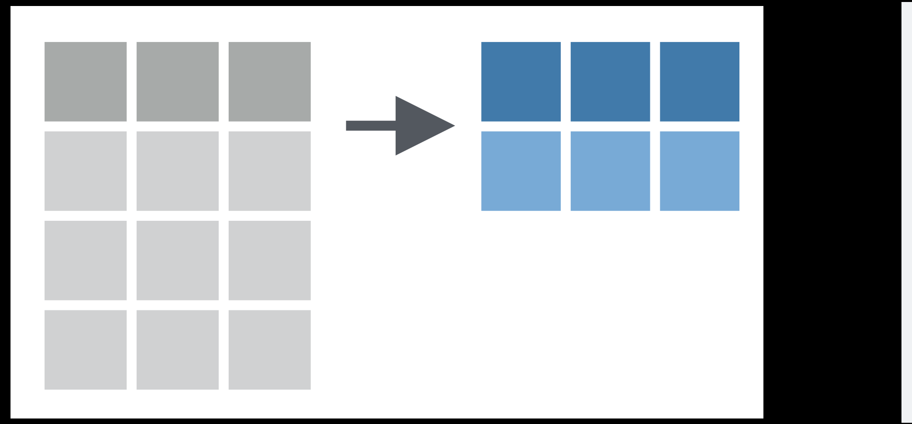
```
summarize(.data, …)
```

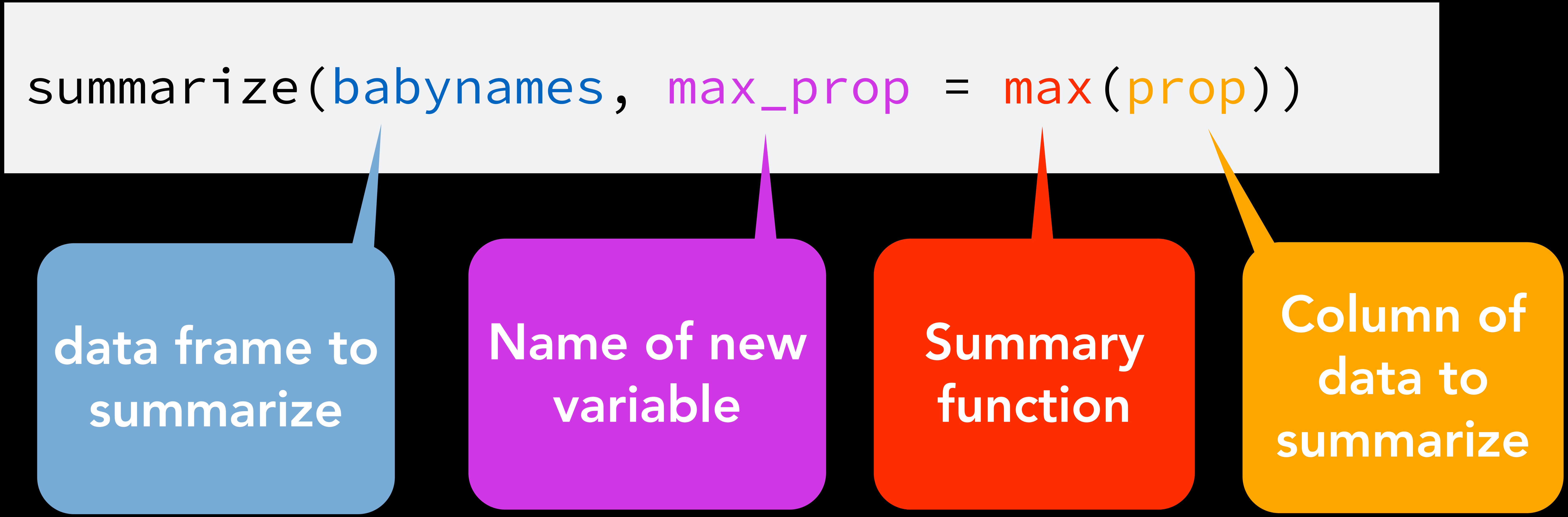
data frame to summarize

Name-value pairs of summary functions

SUMMARIZE()

Compute table of summaries.





```
summarize(babynames, max_prop = max(prop))
```

data frame to summarize

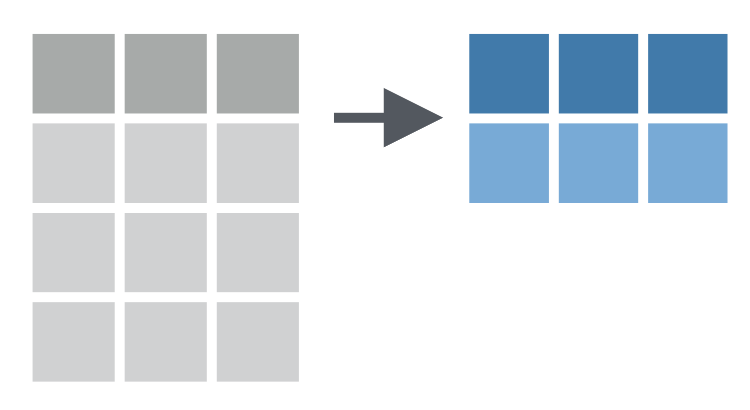
Name of new variable

Summary function

Column of data to summarize

SUMMARIZE()

Compute table of summaries.



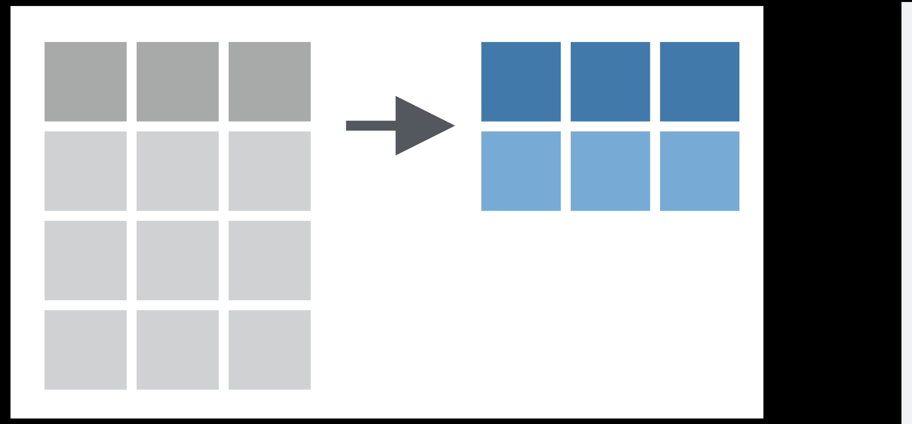
```
summarize(babynames, max_prop = max(prop))
```

year	sex	name	n	prop
1880	F	Mary	7065	0.07238
1880	F	Anna	2604	0.02667
1880	F	Emma	2003	0.02052
1880	F	Elizabet	1939	0.01986
1880	F	Minnie	1746	0.01788
1880	F	Margare	1578	0.01616

max_prop
0.0815

SUMMARIZE()

Compute table of summaries.



```
babynames |>
  summarize(max_n = max(n),
            min_n = min(n))
```

Multiple summaries separated by commas

year	sex	name	n	prop
1880	F	Mary	7065	0.07238
1880	F	Anna	2604	0.02667
1880	F	Emma	2003	0.02052
1880	F	Elizabet	1939	0.01986
1880	F	Minnie	1746	0.01788
1880	F	Margare	1578	0.01616

→

max_n	min_n
99686	5

USEFUL SUMMARY FUNCTIONS

- **Central tendency:** `mean()`, `median()`
- **Spread:** `sd()`, `var()`, `IQR()`, `mad()`
- **Range:** `min()`, `max()`, `quantile()`
- **Logical:** `any()`, `all()`
- **Position:** `first()`, `last()`, `nth()`
- **Count:** `n()`, `n_distinct()`

USEFUL SUMMARY FUNCTIONS

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Base R functions

USEFUL SUMMARY FUNCTIONS

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- **Spread:** `sd()`, `var()`, `IQR()`, `mad()`
- **Range:** `min()`, `max()`, `quantile()`
- **Logical:** `any()`, `all()`
- **Position:** `first()`, `last()`, `nth()`
- **Count:** `n()`, `n_distinct()`

dplyr functions

ACTIVITY 1

- Use `summarize()` to compute three statistics about babynames:
  - The smallest (minimum) year in the dataset
  - The largest (maximum) year in the dataset
  - The total number of children represented in the data

```
babynames |>
  summarize(first_yr = min(year),
            last_yr = max(year),
            total_n = sum(n))
first_yr last_yr  total_n
     <dbl>   <dbl>    <int>
1     1880    2017 348120517
```

ACTIVITY 2

- Extract the rows where name is "Khaleesi". Then use `summarize()` to find:
  - The total number of children named Khaleesi
  - The first year Khaleesi appeared in the data

```
babynames |>
  filter(name == "Khaleesi") |>
  summarize(total = sum(n),
            first_year = min(year))
  total first_year
  <int> <dbl>
1  1964  2011
```

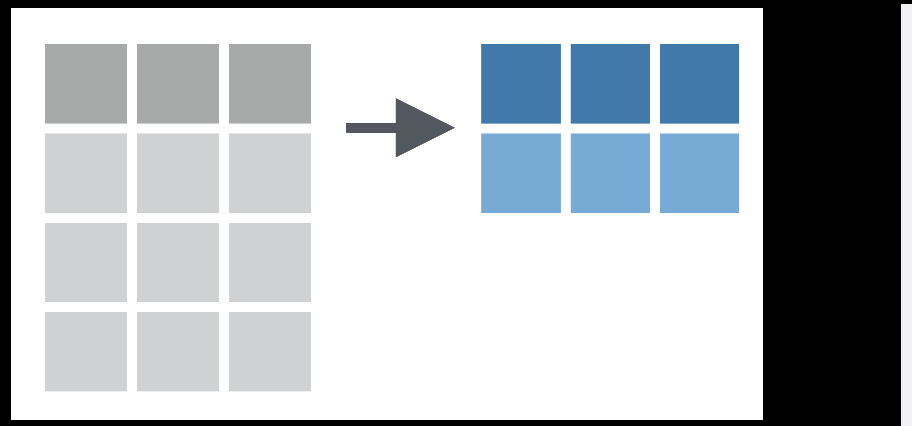
USEFUL SUMMARY FUNCTIONS

- **Center:** `mean()`, `median()`
- **Spread:** `sd()`, `var()`, `IQR()`, `mad()`
- **Range:** `min()`, `max()`, `quantile()`
- **Logical:** `any()`, `all()`
- **Position:** `first()`, `last()`, `nth()`
- **Count:** `n()`, `n_distinct()`

dplyr functions

n()

The number of rows in a dataset/group



```
babynames |>
  summarize(n_rows = n())
```

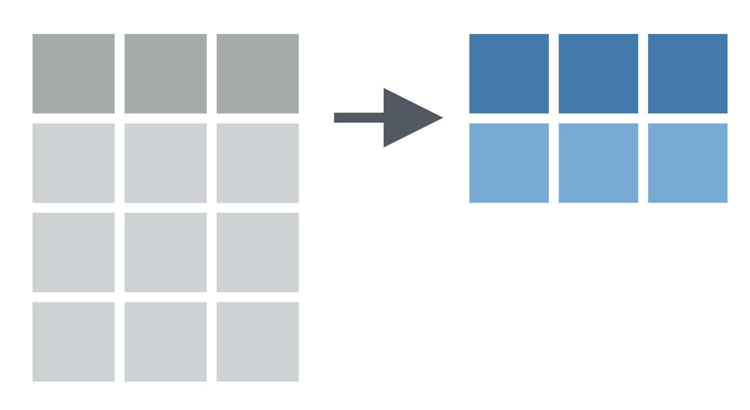
year	sex	name	n	prop
1880	F	Mary	7065	0.07238
1880	F	Anna	2604	0.02667
1880	F	Emma	2003	0.02052
1880	F	Elizabet	1939	0.01986
1880	F	Minnie	1746	0.01788
1880	F	Margare	1578	0.01616

→

n_rows
1924665

n_distinct()

The number of distinct values in a column/group.



```
babynames |>
  summarize(n_rows = n(),
            n_names = n_distinct(name))
```

year	sex	name	n	prop
1880	F	Mary	7065	0.07238
1880	F	Anna	2604	0.02667
1880	F	Emma	2003	0.02052
1880	F	Elizabet	1939	0.01986
1880	F	Minnie	1746	0.01788
1880	F	Margare	1578	0.01616

→

n_rows	n_names
1924665	97310

group_by()

Grouping cases

GROUP_BY()

- `group_by()` changes the unit of analysis to *groups* in the data
- Any `dplyr` verbs used on a *grouped tibble* will be applied "by group"
- Especially useful when paired with `summarize()`
- To remove the grouping, either use `ungroup()` or use the optional argument `.groups` in the `summarize()` function for finer control

GROUP_BY()

Groups cases by common values of one or more columns.

```
babynames |>
  group_by(sex)
```

```
Source: local data frame [1,825,433 x 5]
Groups: sex [2]

    year   sex        name     n        prop
   <dbl> <chr>       <chr> <int>       <dbl>
1   1880     F        Mary  7065 0.07238359
```

GROUP_BY()

Groups cases by common values of one or more columns.

```
babynames |>
  group_by(sex) |>
  summarize(total = sum(n))
```

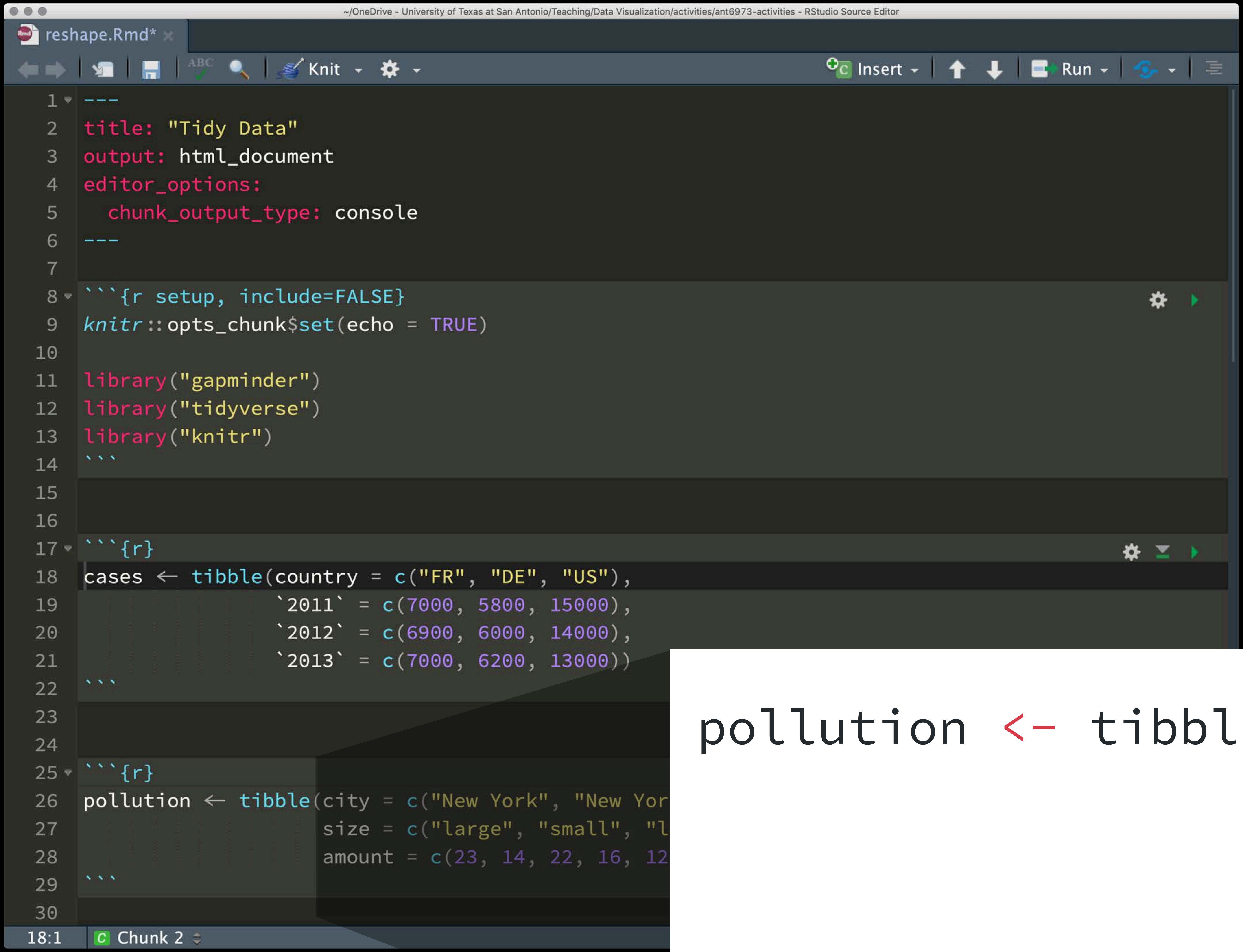
Grouping variable

sex	total
F	172371079
M	175749438

New summary variable

Note that all other columns in original data are not in summary

PRACTICE DATA


~/OneDrive - University of Texas at San Antonio/Teaching/Data Visualization/activities/ant6973-activities - RStudio Source Editor
reshape.Rmd*
Knit
Insert
Run
18:1
Chunk 2

~~~
---
title: "Tidy Data"
output: html_document
editor_options:
  chunk_output_type: console
---

```{r setup, include=FALSE}
knitr::opts_chunk$set(echo = TRUE)

library("gapminder")
library("tidyverse")
library("knitr")
~~~

```{r}
cases <- tibble(country = c("FR", "DE", "US"),
                `2011` = c(7000, 5800, 15000),
                `2012` = c(6900, 6000, 14000),
                `2013` = c(7000, 6200, 13000))
```

```{r}
pollution <- tibble(city = c("New York", "New Yor
                    size = c("large", "small", "l
                    amount = c(23, 14, 22, 16, 12
```

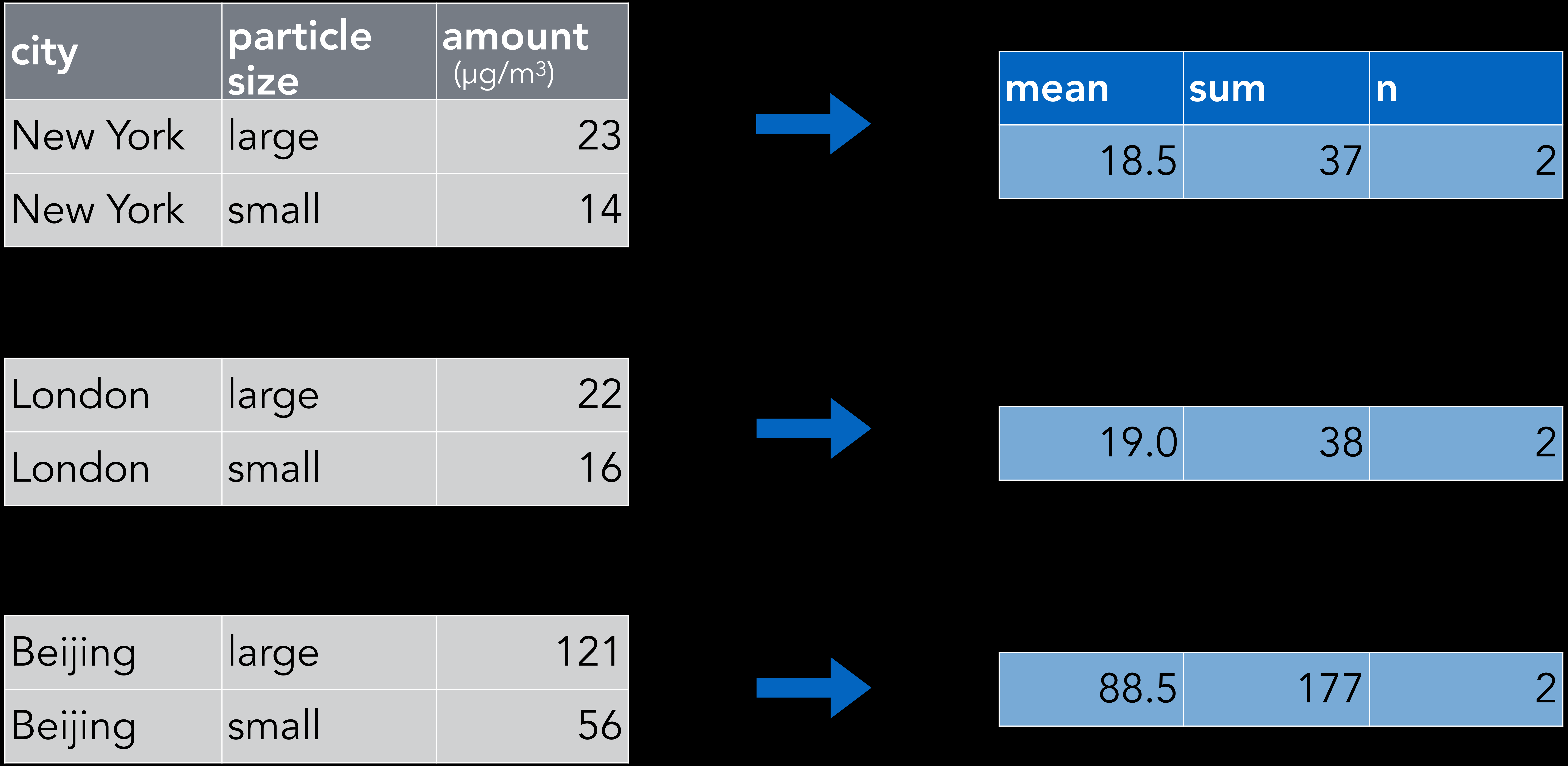
```

From week 10

```
pollution <- tibble(city = ...,
                    size = ...,
                    amount = ...)
```
```

```
pollution |>
 summarize(mean = mean(amount), sum = sum(amount), n = n())
```

city	particle size	amount (µg/m^3)
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



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

mean	sum	n
18.5	37	2
19.0	38	2
88.5	177	2

`group_by() + summarize()`

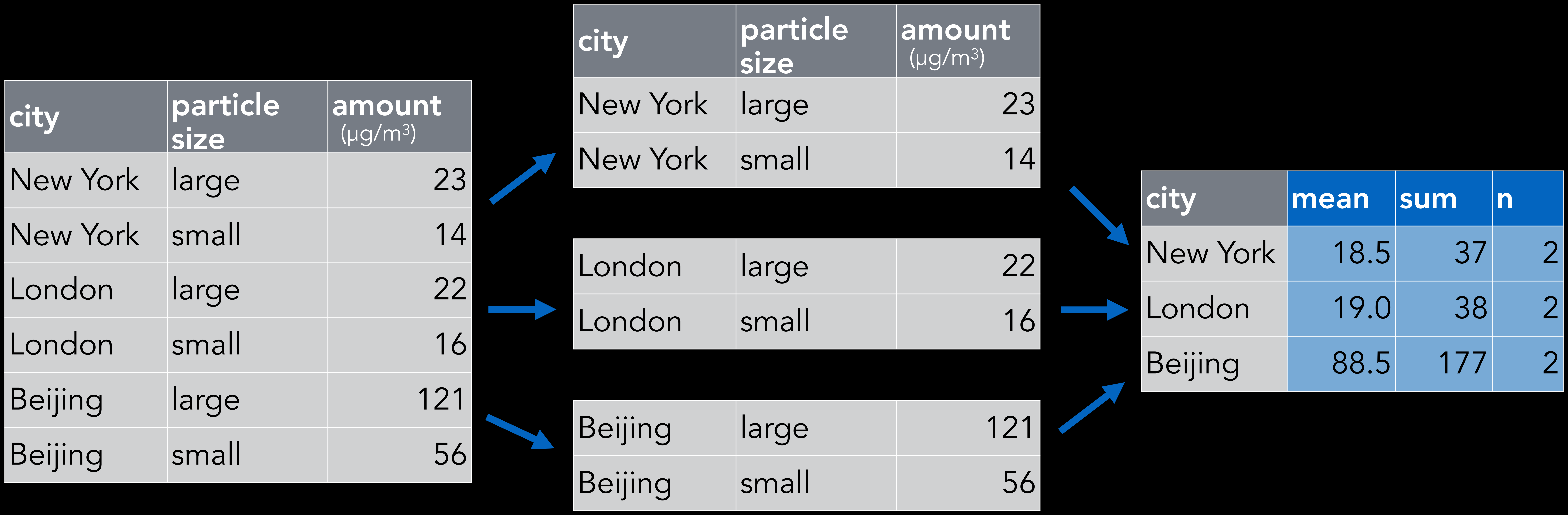
city	particle size	amount (µg/m^3)
New York	large	23
New York	small	14

London	large	22
London	small	16

Beijing	large	121
Beijing	small	56

mean	sum	n
18.5	37	2
19.0	38	2
88.5	177	2

```
group_by() + summarize()
```



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

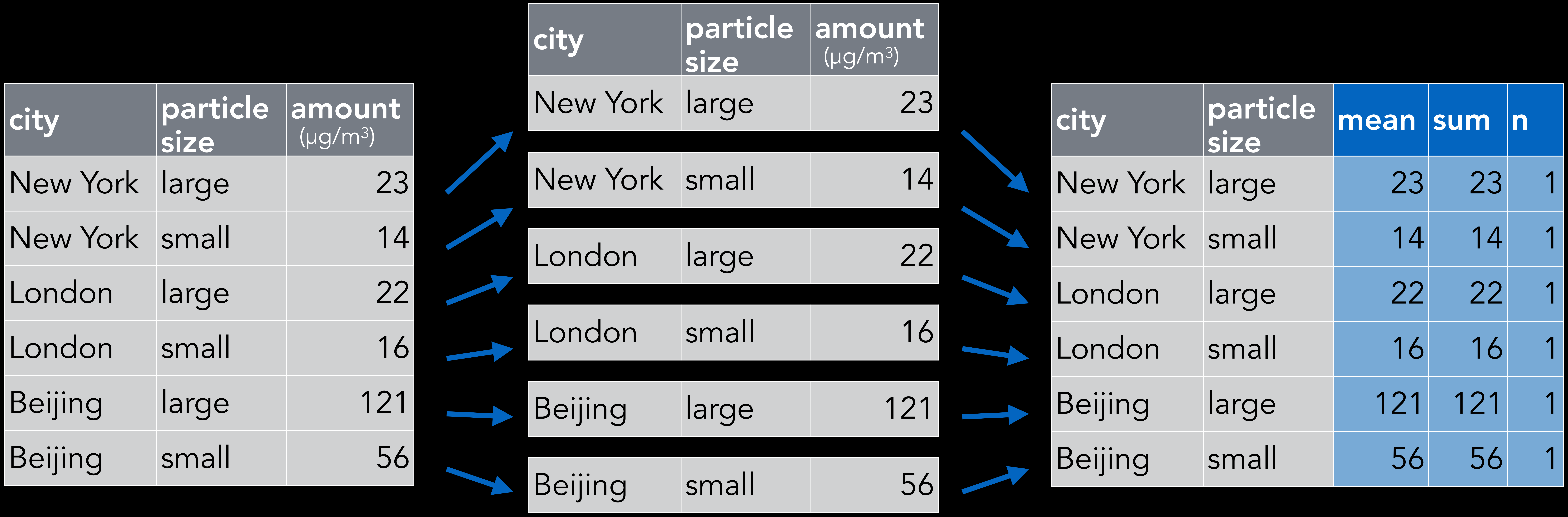
city	particle size	amount (µg/m^3)
New York	large	23
New York	small	14

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

```
pollution |>
  group_by(city) |>
  summarize(mean = mean(amount), sum = sum(amount), n = n())
```



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

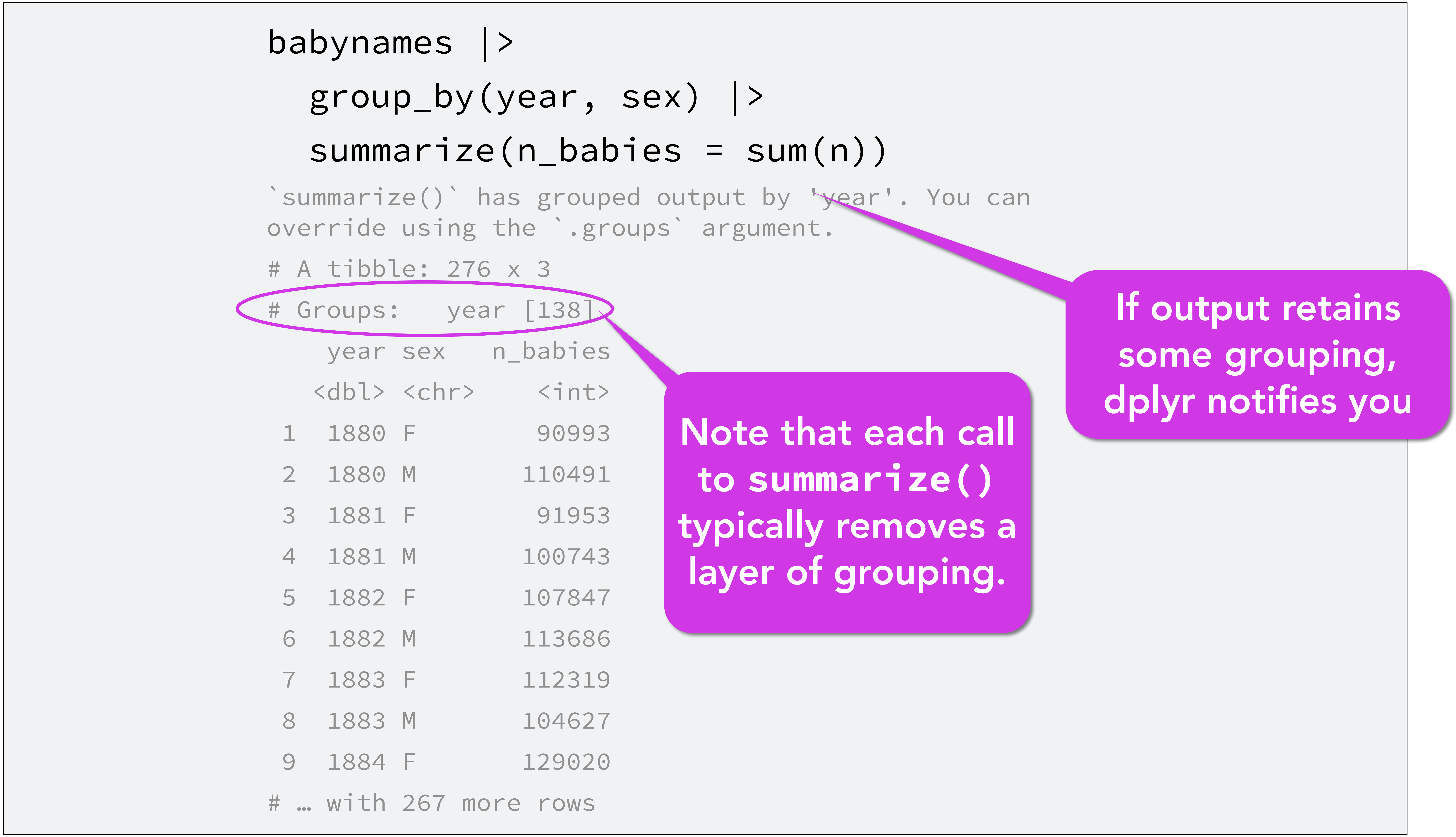
city	particle size	amount (µg/m3)
New York	large	23
New York	small	14
London	large	22
London	small	16
Beijing	large	121
Beijing	small	56

city	particle size	mean	sum	n
New York	large	23	23	1
New York	small	14	14	1
London	large	22	22	1
London	small	16	16	1
Beijing	large	121	121	1
Beijing	small	56	56	1

```
pollution |>
  group_by(city, size) |>
  summarize(mean = mean(amount), sum = sum(amount), n = n())
```

ACTIVITY 3

- Use `group_by()` and `summarize()` to calculate the number of male and female babies born in each year.



```
babynames |>
  group_by(year, sex) |>
  summarize(n_babies = sum(n))
`summarize()` has grouped output by 'year'. You can
override using the `.groups` argument.
# A tibble: 276 x 3
# Groups:   year [138]
    year sex   n_babies
   <dbl> <chr>    <int>
 1  1880 F        90993
 2  1880 M       110491
 3  1881 F        91953
 4  1881 M       100743
 5  1882 F       107847
 6  1882 M       113686
 7  1883 F       112319
 8  1883 M       104627
 9  1884 F       129020
# … with 267 more rows
```

If output retains some grouping, dplyr notifies you

Note that each call to `summarize()` typically removes a layer of grouping.

```
babynames |>
  group_by(year, sex) |>
  summarize(n_babies = sum(n), .groups = "drop")
# A tibble: 276 x 3
    year sex   n_babies
   <dbl> <chr>    <int>
 1  1880 F        90993
 2  1880 M       110491
 3  1881 F        91953
 4  1881 M       100743
 5  1882 F       107847
 6  1882 M       113686
 7  1883 F       112319
 8  1883 M       104627
 9  1884 F       129020
10  1884 M       114442
# … with 266 more rows
```

Change this behavior with the optional `.groups` argument.

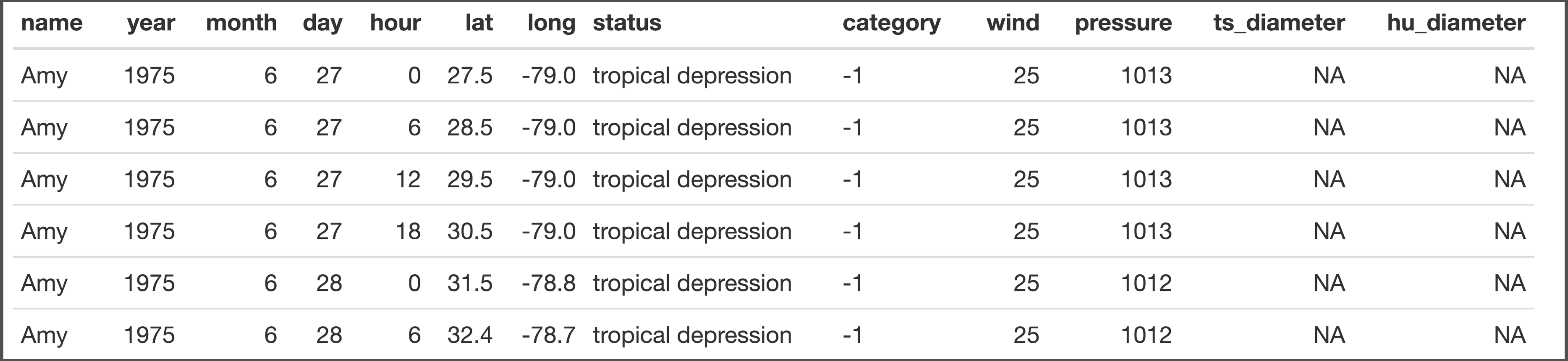
```
babynames |>
  group_by(year, sex) |>
  summarize(n_babies = sum(n), .groups = "keep")
```

```
# A tibble: 276 x 3
# Groups:   year, sex [276]
    year sex   n_babies
   <dbl> <chr>    <int>
 1  1880 F        90993
 2  1880 M       110491
 3  1881 F        91953
 4  1881 M       100743
 5  1882 F       107847
 6  1882 M       113686
 7  1883 F       112319
 8  1883 M       104627
 9  1884 F       129020
# … with 267 more rows
```

Change this behavior with the optional `.groups` argument.

ACTIVITY 4

- On the storms data set, calculate the maximum wind speed and minimum pressure for each **hurricane** in each year, and arrange the summary in descending order of wind speed (hint: filter first).



name	year	month	day	hour	lat	long	status	category	wind	pressure	ts_diameter	hu_diameter
Amy	1975	6	27	0	27.5	-79.0	tropical depression	-1	25	1013	NA	NA
Amy	1975	6	27	6	28.5	-79.0	tropical depression	-1	25	1013	NA	NA
Amy	1975	6	27	12	29.5	-79.0	tropical depression	-1	25	1013	NA	NA
Amy	1975	6	27	18	30.5	-79.0	tropical depression	-1	25	1013	NA	NA
Amy	1975	6	28	0	31.5	-78.8	tropical depression	-1	25	1012	NA	NA
Amy	1975	6	28	6	32.4	-78.7	tropical depression	-1	25	1012	NA	NA

```
storms |>
  filter(status == "hurricane") |>
  group_by(year, name) |>
  summarize(wind_max = max(wind),
            pressure_min = min(pressure)) |>
  arrange(desc(wind_max))
```

```
# Groups:   year [47]
    year name     wind_max pressure_min
   <dbl> <chr>       <int>        <int>
 1  1980 Allen         165          899
 2  1988 Gilbert       160          888
 3  2005 Wilma         160          882
 4  2019 Dorian        160          910
 5  1998 Mitch         155          905
 6  2005 Rita          155          895
 7  2017 Irma          155          914
 8  1977 Anita         150          926
# ℹ 302 more rows
```

ACTIVITY 5

- Building on the previous code, calculate the average hurricane wind_max for each year. Which year had the most intense hurricanes, on average?

```
storms |>
  filter(status == "hurricane") |>
  group_by(year, name) |>
  summarize(wind_max = max(wind)) |>
  summarize(avg_wind_max = mean(wind_max)) |>
  arrange(desc(avg_wind_max))
    year avg_wind_max
   <dbl>        <dbl>
 1  1999         114.
 2  2017         110.
 3  1988         109
 4  2004         107.
 5  2019         106.
 6  2008         106.
 7  1992         104.
 8  2009         103.
# ℹ 39 more rows
```

Second call to **`summarize()`** uses the year grouping only.

You might want to make the groupings explicit for readability.

```
storms |>
  filter(status == "hurricane") |>
  group_by(year, name) |>
  summarize(wind_max = max(wind), .groups = "drop_last") |>
  summarize(avg_wind_max = mean(wind_max)) |>
  arrange(desc(avg_wind_max))
    year avg_wind_max
   <dbl>        <dbl>
 1  1999         114.
 2  2017         110.
 3  1988         109
 4  2004         107.
 5  2019         106.
 6  2008         106.
 7  1992         104.
 8  2009         103.
# …
```

```
storms |>
  filter(status == "hurricane") |>
  group_by(year, name) |>
  summarize(wind_max = max(wind)) |>
  ungroup() |>
  group_by(year) |>
  summarize(avg_wind_max = mean(wind_max)) |>
  arrange(desc(avg_wind_max))
     year avg_wind_max
    <dbl>        <dbl>
 1   1999         114.
 2   2017         110.
 3   1988         109
 4   2004         107.
 5   2019         106.
 6   2008         106.
 7   1992         104.
 8   2009         103.
# …
```

THINGS TO WATCH OUT FOR

- Many summary functions will return NA if there are any missing values
- Fortunately, many summary functions have an `na.rm = TRUE` argument to avoid this problem.

THINGS TO WATCH OUT FOR

- Once grouped, the tibble will remain that way unless grouping layers are removed. Be careful carrying out futher operations and summaries!

- It's good practice to use `ungroup()` after finishing your grouped operations.

ACTIVITY 6

- What is the average diameter of the area experiencing hurricane strength winds (`hurricane_force_diameter`) for each category of hurricane (`category`)?

```
storms |>
  group_by(category) |>
  summarize(mean_diameter = mean(hurricane_force_diameter))
  category mean_diameter
     <dbl>         <dbl>
1        1            NA
2        2            NA
3        3            NA
4        4            NA
5        5            NA
6       NA            NA
```

Many of these values are missing

This causes the means to be NA

```
storms |>
  group_by(category) |>
  summarize(mean_diameter = mean(hurricane_force_diameter,
                                 na.rm = TRUE)))

  category mean_diameter
     <dbl>         <dbl>
1        1          50.0
2        2          71.4
3        3          75.6
4        4          80.6
5        5          90.9
6       NA           1.56
```

Remove missing values before calculating means

COLUMN-WISE SUMMARIES

- Often you may need to perform the same summary or other operation across *multiple columns*.

- This can be accomplished by writing each column operation, but a more efficient and less error-prone approach is provided by the `across()` function.

Limited

```
df |>
  group_by(g1, g2) |>
  summarize(a = mean(a), b = mean(b), c = mean(c), d = mean(d))
```

Better

```
df |>
  group_by(g1, g2) |>
  summarize(across(a:d, mean))
```

COLUMN-WISE SUMMARIES

- Often you may need to perform the same summary or other operation across *multiple columns*.

- This can be accomplished by writing each column operation, but a more efficient and less error-prone approach is provided by the `across()` function.

Limited

```
df |>
  group_by(g1, g2) |>
  summarize(a = mean(a), b = m
```

Better

```
df |>
  group_by(g1, g2) |>
  summarize(across(a:d, mean))
```

Inside of `across()`, the first argument is a `select()`-style expression of columns to summarize.

COLUMN-WISE SUMMARIES

- Often you may need to perform the same summary or other operation across *multiple columns*.

- This can be accomplished by writing each column operation, but a more efficient and less error-prone approach is provided by the `across()` function.

Limited

```
df |>
  group_by(g1, g2) |>
  summarize(a = mean(a), b = m
```

Better

```
df |>
  group_by(g1, g2) |>
  summarize(across(a:d, mean))
```

Second argument is the summary function (or a list of multiple functions)

COLUMN-WISE SUMMARIES

- Often you may need to perform the same summary or other operation across *multiple columns*.

- This can be accomplished by writing each column operation, but a more efficient and less error-prone approach is provided by the `across()` function.

Limited

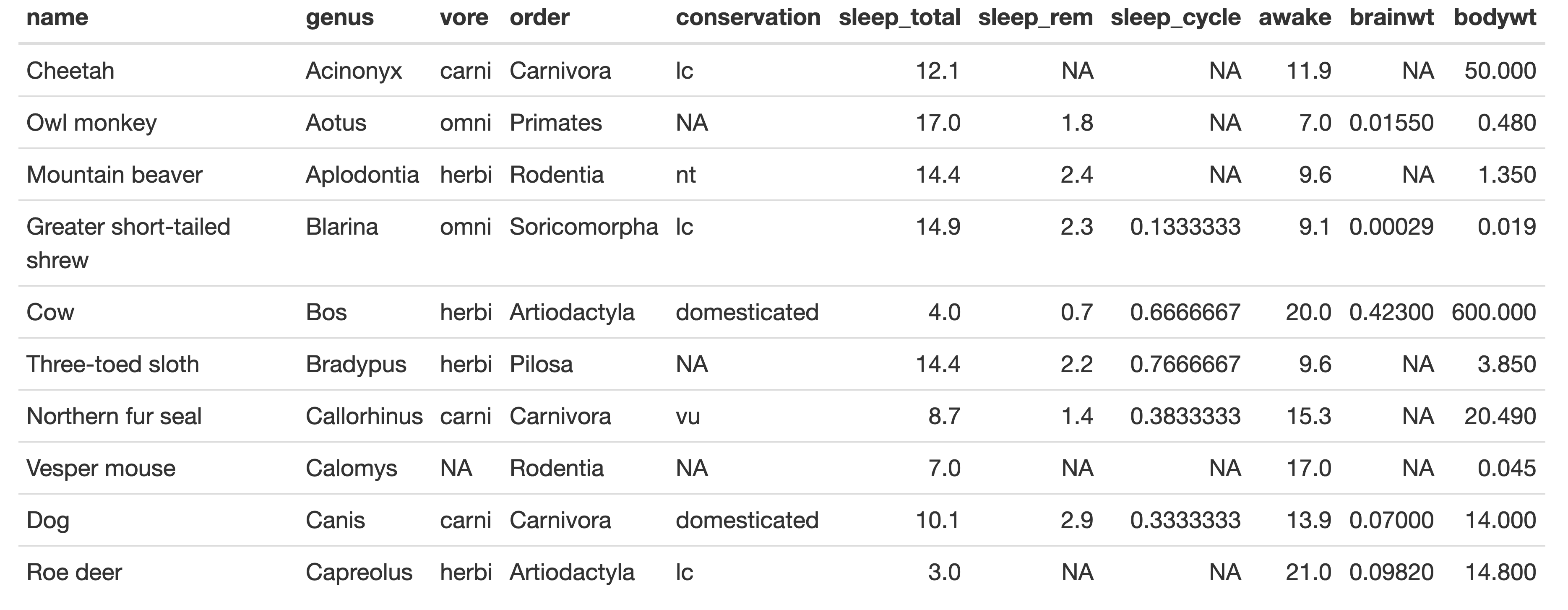
```
df |>
  group_by(g1, g2) |>
  summarize(a = mean(a), b = m
```

Better

```
df |>
  group_by(g1, g2) |>
  summarize(across(a:d, ~ mean(.x, na.rm = TRUE)))
```

If needed, additional arguments for the summary function can be provided using a special "`~` and `.x`" syntax.

msleep (lots of missing values)



name	genus	vore	order	conservation	sleep_total	sleep_rem	sleep_cycle	awake	brainwt	bodywt
Cheetah	Acinonyx	carni	Carnivora	lc	12.1	NA	NA	11.9	NA	50.000
Owl monkey	Aotus	omni	Primates	NA	17.0	1.8	NA	7.0	0.01550	0.480
Mountain beaver	Aplodontia	herbi	Rodentia	nt	14.4	2.4	NA	9.6	NA	1.350
Greater short-tailed shrew	Blarina	omni	Soricomorpha	lc	14.9	2.3	0.1333333	9.1	0.00029	0.019
Cow	Bos	herbi	Artiodactyla	domesticated	4.0	0.7	0.6666667	20.0	0.42300	600.000
Three-toed sloth	Bradypus	herbi	Pilosa	NA	14.4	2.2	0.7666667	9.6	NA	3.850
Northern fur seal	Callorhinus	carni	Carnivora	vu	8.7	1.4	0.3833333	15.3	NA	20.490
Vesper mouse	Calomys	NA	Rodentia	NA	7.0	NA	NA	17.0	NA	0.045
Dog	Canis	carni	Carnivora	domesticated	10.1	2.9	0.3333333	13.9	0.07000	14.000
Roe deer	Capreolus	herbi	Artiodactyla	lc	3.0	NA	NA	21.0	0.09820	14.800

ACTIVITY 7A

- For each vore, calculate the average of *only the columns that start with "sleep"* in the msleep data set.
  - Hint: use a `select()` helper (see Week 11 slides) inside `across()`, and use `na.rm = TRUE`

```r
msleep |>
  group_by(vore) |>
  summarize(across(starts_with("sleep"),
                   ~ mean(.x, na.rm = TRUE)))
```

```
  vore    sleep_total sleep_rem sleep_cycle
  <chr>         <dbl>     <dbl>       <dbl>
1 carni         10.4       2.29       0.373
2 herbi          9.51      1.37       0.418
3 insecti       14.9       3.52       0.161
4 omni          10.9       1.96       0.592
5 NA            10.2       1.88       0.183
```

Equivalent to…

```
msleep |>
  group_by(vore) |>
  summarize(sleep_total = mean(sleep_total, na.rm = TRUE),
            sleep_rem = mean(sleep_rem, na.rm = TRUE),
            sleep_cycle = mean(sleep_cycle, na.rm = TRUE))
```

```
  vore    sleep_total sleep_rem sleep_cycle
  <chr>         <dbl>     <dbl>       <dbl>
1 carni         10.4       2.29       0.373
2 herbi          9.51      1.37       0.418
3 insecti       14.9       3.52       0.161
4 omni          10.9       1.96       0.592
5 NA            10.2       1.88       0.183
```

ACTIVITY 7B

- For each vore, calculate the average of *only the numeric columns* in the msleep data set.
  - Hint: use a `select()` helper (see Week 11 slides) inside `across()`, and use `na.rm = TRUE`

```
msleep |>
  group_by(vore) |>
  summarize(across(where(is.numeric),
                   ~ mean(.x, na.rm = TRUE)))
  vore    sleep_total sleep_rem sleep_cycle awake brainwt  bodywt
  <chr>         <dbl>     <dbl>       <dbl> <dbl>   <dbl>   <dbl>
1 carni         10.4       2.29       0.373 13.6  0.0793   90.8
2 herbi          9.51      1.37       0.418 14.5  0.622   367.
3 insecti       14.9       3.52       0.161  9.06 0.0216   12.9
4 omni          10.9       1.96       0.592 13.1  0.146    12.7
5 NA            10.2       1.88       0.183 13.8  0.00763   0.858
```

Grouping variable isn't numeric, but it still appears in the summary.

ACTIVITY 7C

- For each vore, calculate the average of *all* columns in the msleep data set.
  - Hint: use a `select()` helper (see Week 11 slides) inside `across()`, and use `na.rm = TRUE`

```
msleep |>
  group_by(vore) |>
  summarize(across(everything(),
                   ~ mean(.x, na.rm = TRUE)))
```

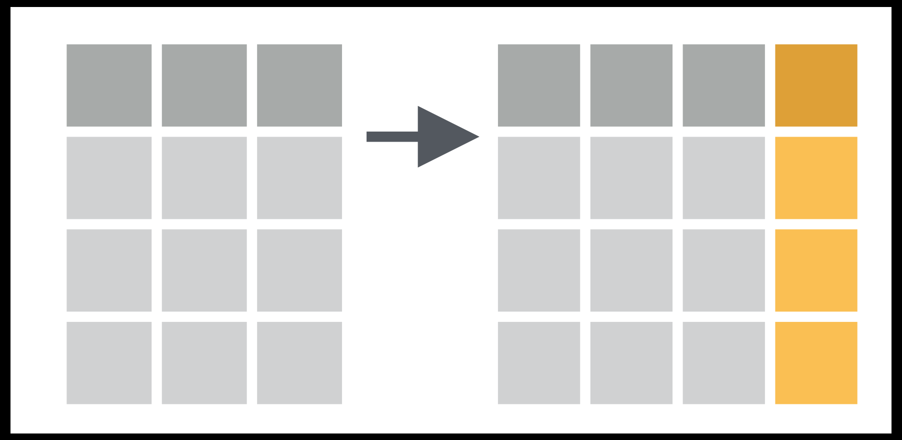
```
  vore     name genus order conservation sleep_total sleep_rem sleep_cycle awake brainwt
  <chr>   <dbl> <dbl> <dbl>        <dbl>       <dbl>     <dbl>       <dbl> <dbl>   <dbl>
1 carni      NA    NA    NA           NA       10.4       2.29       0.373 13.6  0.0793
2 herbi      NA    NA    NA           NA        9.51      1.37       0.418 14.5  0.622
3 insecti    NA    NA    NA           NA       14.9       3.52       0.161  9.06 0.0216
4 omni       NA    NA    NA           NA       10.9       1.96       0.592 13.1  0.146
5 NA         NA    NA    NA           NA       10.2       1.88       0.183 13.8  0.00763
```

Note that `mean()` doesn't make sense for the text variables, hence the warnings.

OTHER GROUPED OPERATIONS

- `group_by()` can also be used with `mutate()` and `filter()` to do some interesting things.

- Reminder: `mutate()` creates a new variable of the same length as the original data.



ACTIVITY 8

- In babynames, try to recreate the `prop` column using a grouped mutate (call it "`new_prop`"). Specifically, divide each row's n by the total number of n for that sex and year.

- Why are the values slightly different?

```
babynames |>
  group_by(sex, year) |>
  mutate(grp_sum = sum(n),
         new_prop = n  / grp_sum)
 # Groups:   sex, year [276]
    year sex   name          n   prop grp_sum new_prop
   <dbl> <chr> <chr>     <int>  <dbl>   <int>    <dbl>
 1  1880 F     Mary       7065 0.0724   90993   0.0776
 2  1880 F     Anna       2604 0.0267   90993   0.0286
 3  1880 F     Emma       2003 0.0205   90993   0.0220
 4  1880 F     Elizabeth  1939 0.0199   90993   0.0213
 5  1880 F     Minnie     1746 0.0179   90993   0.0192
 6  1880 F     Margaret   1578 0.0162   90993   0.0173
 7  1880 F     Ida        1472 0.0151   90993   0.0162
 8  1880 F     Alice      1414 0.0145   90993   0.0155
 9  1880 F     Bertha     1320 0.0135   90993   0.0145
10  1880 F     Sarah      1288 0.0132   90993   0.0142
# … with 1,924,655 more rows
```

Current ***group's*** total n

Current row's new_prop

Note that the result has as many rows as the original data (it's not a summary)

More concisely…

```
babynames |>
  group_by(sex, year) |>
  mutate(new_prop = n / sum(n))
# Groups:   sex, year [276]
    year sex   name          n   prop new_p
   <dbl> <chr> <chr>     <int>  <dbl>    <dbl>
 1  1880 F     Mary       7065 0.0724   0.0776
 2  1880 F     Anna       2604 0.0267   0.0286
 3  1880 F     Emma       2003 0.0205   0.0220
 4  1880 F     Elizabeth  1939 0.0199   0.0213
 5  1880 F     Minnie     1746 0.0179   0.0192
 6  1880 F     Margaret   1578 0.0162   0.0173
 7  1880 F     Ida        1472 0.0151   0.0162
 8  1880 F     Alice      1414 0.0145   0.0155
 9  1880 F     Bertha     1320 0.0135   0.0145
10  1880 F     Sarah      1288 0.0132   0.0142
# … with 1,924,655 more rows
```

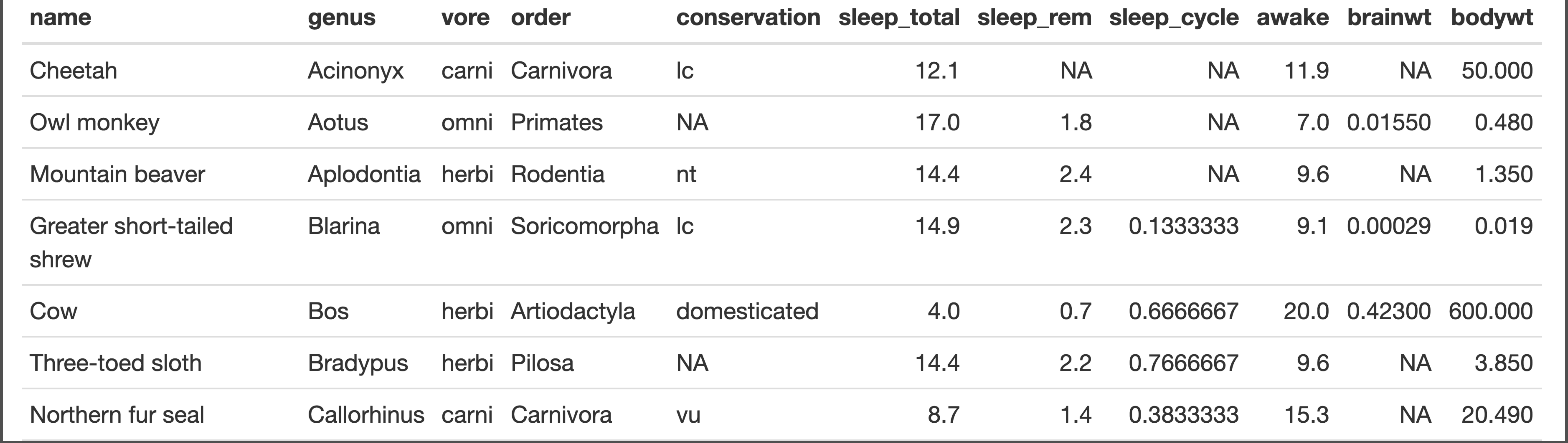
Group denominator calculated for each for each row

MORE ON GROUPED MUTATES

- Grouped mutates are useful for calculating deviations, ranks, and other row-level values within groups.

ACTIVITY 9A

- Using msleep, determine how much each species' log body weight differs from the average log body weight for its order.



name	genus	vore	order	conservation	sleep_total	sleep_rem	sleep_cycle	awake	brainwt	bodywt
Cheetah	Acinonyx	carni	Carnivora	lc	12.1	NA	NA	11.9	NA	50.000
Owl monkey	Aotus	omni	Primates	NA	17.0	1.8	NA	7.0	0.01550	0.480
Mountain beaver	Aplodontia	herbi	Rodentia	nt	14.4	2.4	NA	9.6	NA	1.350
Greater short-tailed shrew	Blarina	omni	Soricomorpha	lc	14.9	2.3	0.1333333	9.1	0.00029	0.019
Cow	Bos	herbi	Artiodactyla	domesticated	4.0	0.7	0.6666667	20.0	0.42300	600.000
Three-toed sloth	Bradypus	herbi	Pilosa	NA	14.4	2.2	0.7666667	9.6	NA	3.850
Northern fur seal	Callorhinus	carni	Carnivora	vu	8.7	1.4	0.3833333	15.3	NA	20.490

```
msleep |>
  group_by(order) |>
  mutate(log_bodywt = log(bodywt),
         order_mean = mean(log_bodywt, na.rm = TRUE),
         bodywt_dev = log_bodywt - order_mean)
```

```
# Groups:   order [19]
   name            genus    vore  order    conservation sleep_total sleep_rem sleep_cycle awake  brainwt  bodywt log_bodywt order_m
   <chr>           <chr>    <chr> <chr>    <chr>              <dbl>     <dbl>       <dbl> <dbl>    <dbl>   <dbl>      <dbl>     <d
 1 Cheetah         Acinon… carni Carniv… lc                  12.1      NA        NA      11.9 NA        50          3.91       3
 2 Owl monkey      Aotus    omni  Primat… NA                  17         1.8      NA       7    0.0155   0.48     -0.734      1.
 3 Mountain beav… Aplodo… herbi Rodent… nt                  14.4       2.4      NA       9.6 NA         1.35      0.300     -1.98     2.28
 4 Greater short… Blarina omni  Sorico… lc                  14.9       2.3       0.133   9.1  0.00029  0.019    -3.96      -3.54     -0.423
 5 Cow             Bos      herbi Artiod… domesticated         4         0.7       0.667  20    0.423  600          6.40       4.65      1.75
 6 Three-toed sl… Bradyp… herbi Pilosa   NA                  14.4       2.2       0.767   9.6 NA         3.85      1.35       1.35      0
 7 Northern fur … Callor… carni Carniv… vu                   8.7       1.4       0.383  15.3 NA        20.5       3.02       3.15     -0.130
 8 Vesper mouse    Calomys NA    Rodent… NA                   7        NA        NA      17    NA         0.045    -3.10      -1.98     -1.12
 9 Dog             Canis    carni Carniv… domesticated        10.1       2.9       0.333  13.9  0.07     14          2.64       3.15     -0.511
10 Roe deer        Capreo… herbi Artiod… lc                   3        NA        NA      21     0.0982  14.8        2.69       4.65     -1.95
```

Each row's log bodywt

Current order's mean bodywt

Current row's deviation from mean of current order

ACTIVITY 9B

- Using baby names, add a rank column to each name *for each year and sex*. What were the top 1 and 2 ranked boys names for years 2012 to 2017 (which is the end of the data set)?

```
babynames |>
  group_by(year, sex) |>
  mutate(rank = min_rank(desc(prop))) |>
  filter(year >= 2012 & year <= 2017 & sex == "M" & rank <= 2)
# Groups:   year, sex [1]
    year sex   name       n    prop  rank
   <dbl> <chr> <chr> <int>   <dbl> <int>
 1  2012 M     Jacob 19069 0.00941     1
 2  2012 M     Mason 18964 0.00936     2
 3  2013 M     Noah  18241 0.00904     1
 4  2013 M     Jacob 18148 0.00900     2
 5  2014 M     Noah  19286 0.00943     1
 6  2014 M     Liam  18451 0.00903     2
 7  2015 M     Noah  19613 0.00962     1
 8  2015 M     Liam  18355 0.00900     2
 9  2016 M     Noah  19082 0.00946     1
10  2016 M     Liam  18198 0.00902     2
11  2017 M     Liam  18728 0.00954     1
12  2017 M     Noah  18326 0.00933     2
```

Each row's rank within year and sex

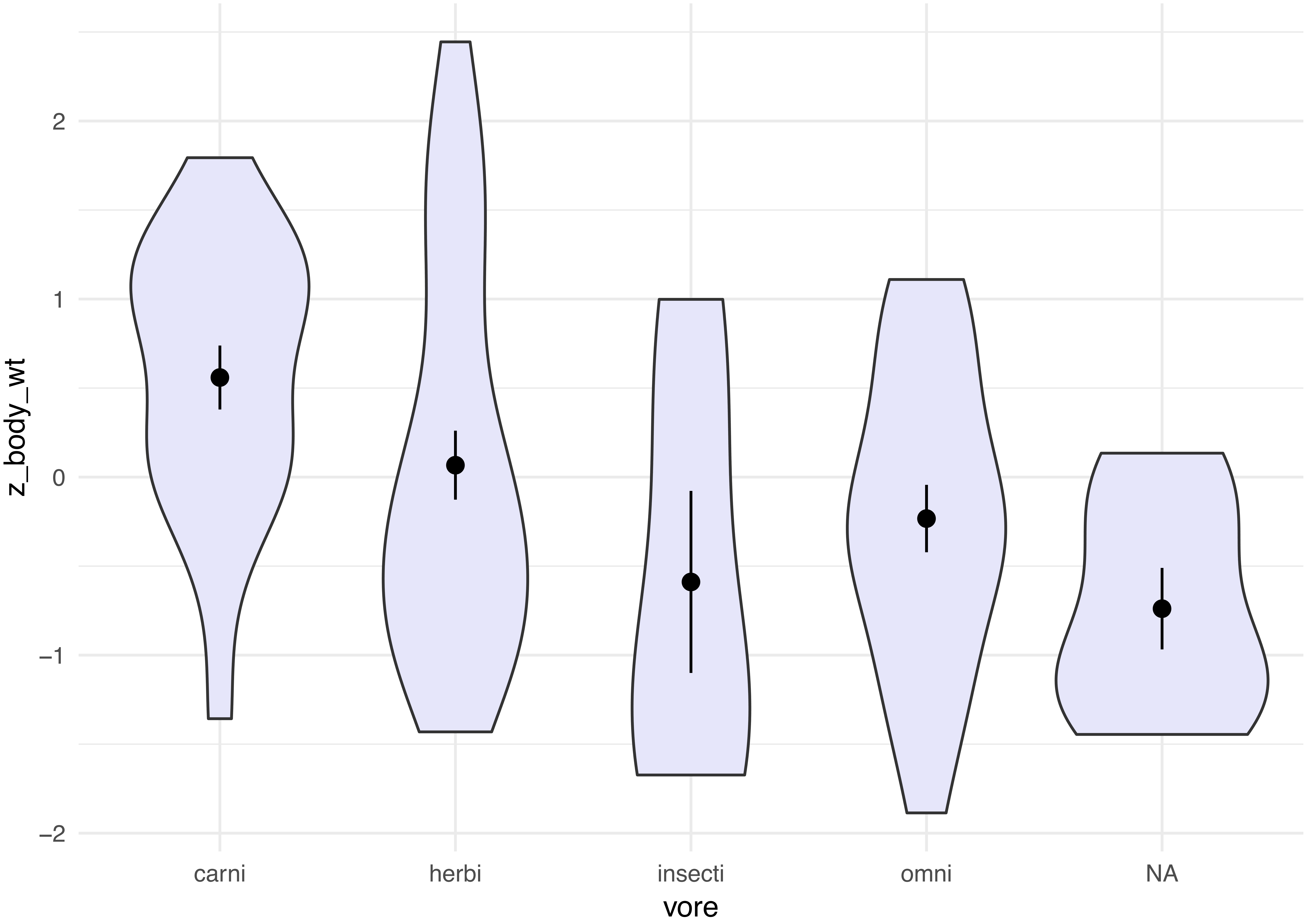
Get top 2 names for male babies for 2012 to 2017.

ACTIVITY 10A

- When building statistical models, it's often useful to standardize numeric variables by converting to z-scores:
  - z = (observed value - mean) / standard deviation
- Using msleep, use `mutate()` to calculate the z-score for log(`bodywt`) for each row in the data set.
- Plot the data using a violin plot and `stat_summary()`

```
ggplot(msleep, aes(x = vore, y = z_log_bodywt)) +
  geom_violin() +
  stat_summary(fun.data = "mean_se")
```

```r
msleep |>
  mutate(log_bodywt = log(bodywt),
         z_log_bodywt = (log_bodywt - mean(log_bodywt, na.rm = TRUE)) /
                        sd(log_bodywt, na.rm = TRUE)) |>
  ggplot(aes(x = vore, y = z_log_bodywt)) +
  geom_violin() +
  stat_summary(fun.data = "mean_se")
```

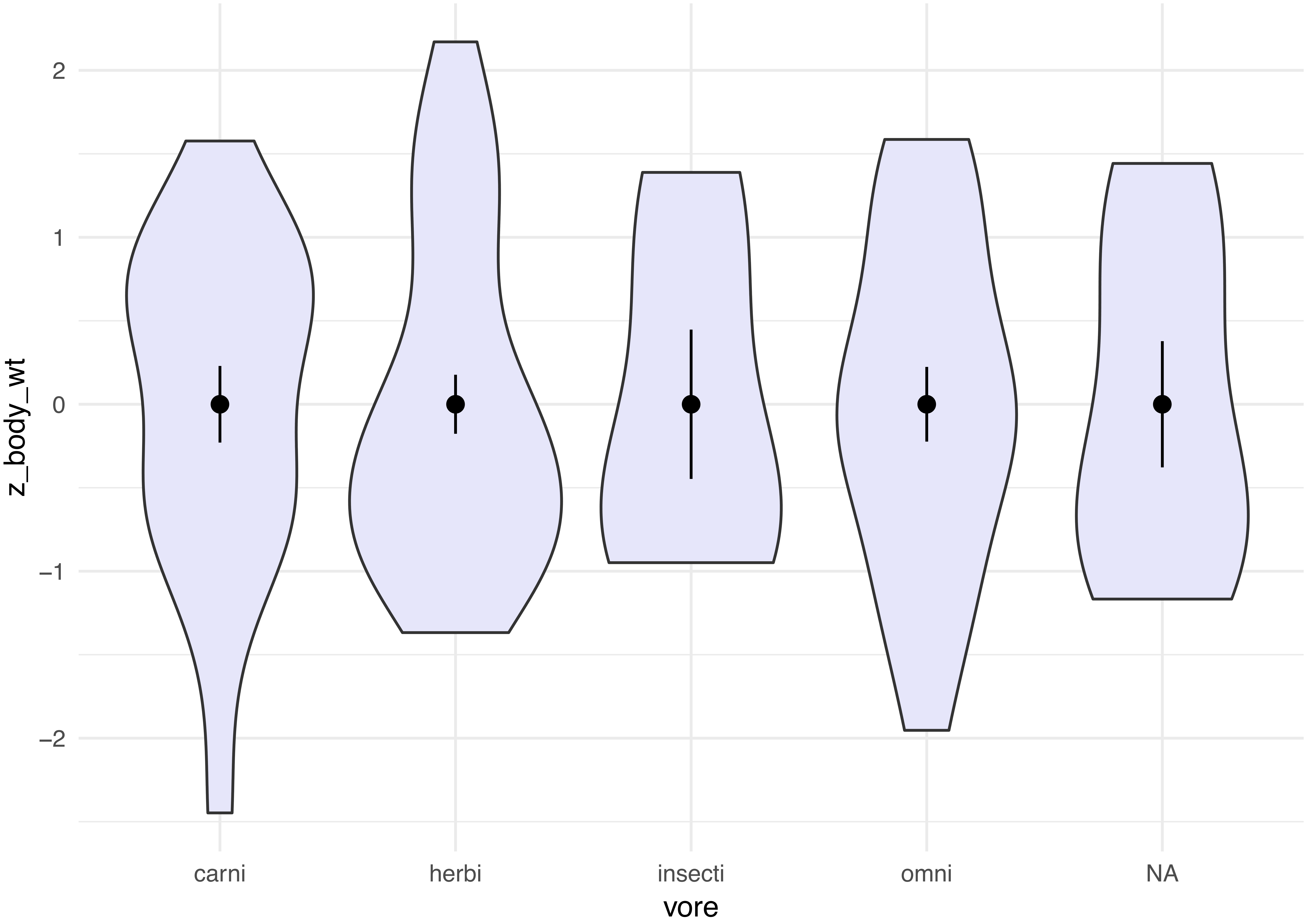

z_body_wt
2
1
0
−1
−2
carni
herbi
insecti
omni
NA
vore

ACTIVITY 10B

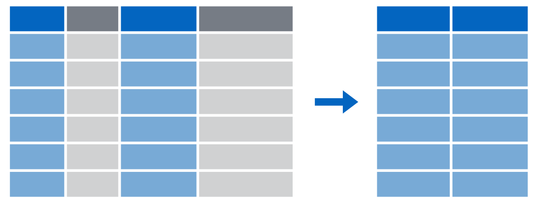
- Now do the same, but standardize *within groups* by using `group_by(vore)`.

```
ggplot(msleep, aes(x = vore, y = z_log_bodywt)) +
  geom_violin() +
  stat_summary(fun.data = "mean_se")
```

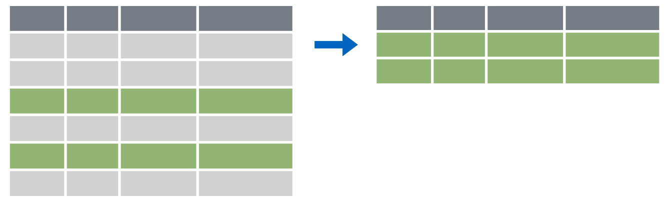
```
msleep |>
  mutate(log_bodywt = log(bodywt)) |>
  group_by(vore) |>
  mutate(z_log_bodywt = (log_bodywt - mean(log_bodywt, na.rm = TRUE)) /
                        sd(log_bodywt, na.rm = TRUE)) |>
  ggplot(aes(x = vore, y = z_log_bodywt)) +
  geom_violin() +
  stat_summary(fun.data = "mean_se")
```


2
1
0
−1
−2
z_body_wt
carni
herbi
insecti
omni
NA
vore

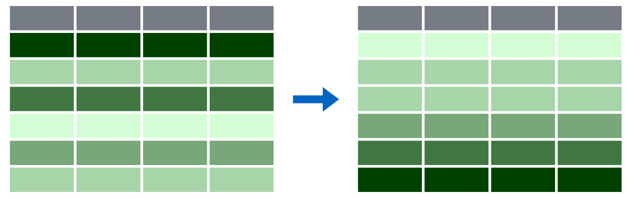
SINGLE TABLE VERBS



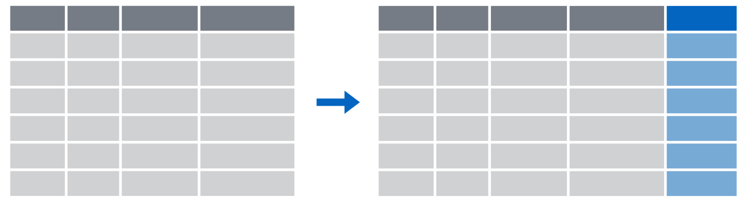
Extract variables with `select()`



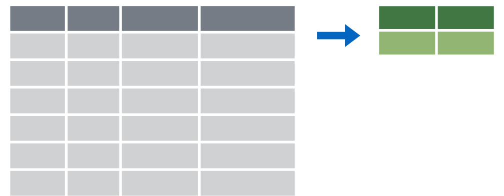
Extract cases with `filter()`



Arrange cases with `arrange()`



Make new variables with `mutate()`



Make tables of summaries with `summarize()`
along with `group_by()`