Transform Data with

In R4DS

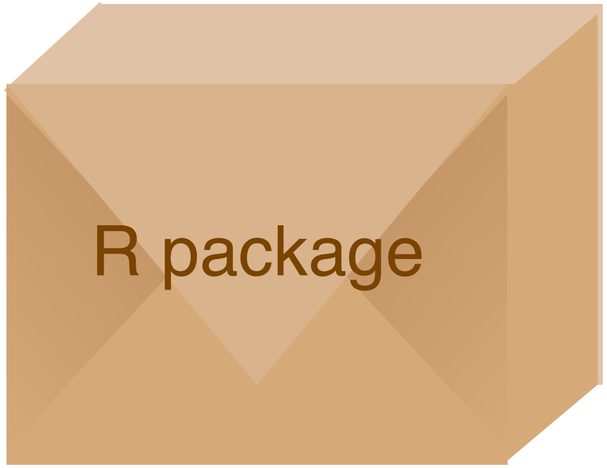
Transforming Data

Your Turn 0

Open **02-Transform.Rmd**.

Run the setup chunk

babynames



Names of male and female babies born in the US from 1880 to 2015. 1.8M rows.

```
library(babynames)
```

babynames

year <dbl>	sex <chr>	name <chr>	n <int>	prop <dbl>
1880	F	Mary	7065	7.238433e-02
1880	F	Anna	2604	2.667923e-02
1880	F	Emma	2003	2.052170e-02
1880	F	Elizabeth	1939	1.986599e-02
1880	F	Minnie	1746	1.788861e-02
1880	F	Margaret	1578	1.616737e-02
1880	F	Ida	1472	1.508135e-02
1880	F	Alice	1414	1.448711e-02
1880	F	Bertha	1320	1.352404e-02
1880	F	Sarah	1288	1.319618e-02

skim(babynames)

```
Skim summary statistics
 n obs: 1924665
 n variables: 5

── Variable type:character ─────────────────────────────────────────────────────────────────────────────────────────────
 variable missing complete       n min max empty n_unique
     name       0  1924665 1924665   2  15     0    97310
      sex       0  1924665 1924665   1   1     0        2

── Variable type:integer ───────────────────────────────────────────────────────────────────────────────────────────────
 variable missing complete       n   mean      sd p0 p25 p50 p75  p100     hist
        n       0  1924665 1924665 180.87 1533.34  5   7  12  32 99686 ▇▁▁▁▁▁▁▁▁▁

── Variable type:numeric ───────────────────────────────────────────────────────────────────────────────────────────────
 variable missing complete       n       mean      sd         p0        p25        p50        p75     p100     hist
     prop       0  1924665 1924665    0.00014  0.0012    2.3e-06    3.9e-06    7.3e-06    2.3e-05    0.082 ▇▁▁▁▁▁▁▁▁
     year       0  1924665 1924665 1974.85    34.03   1880       1951       1985       2003       2017     ▁▁▂▃▅▆▇▇
```

Sometimes, you don't want all the summary statistics skimr gives you. You can use `skim_with()` to remove them

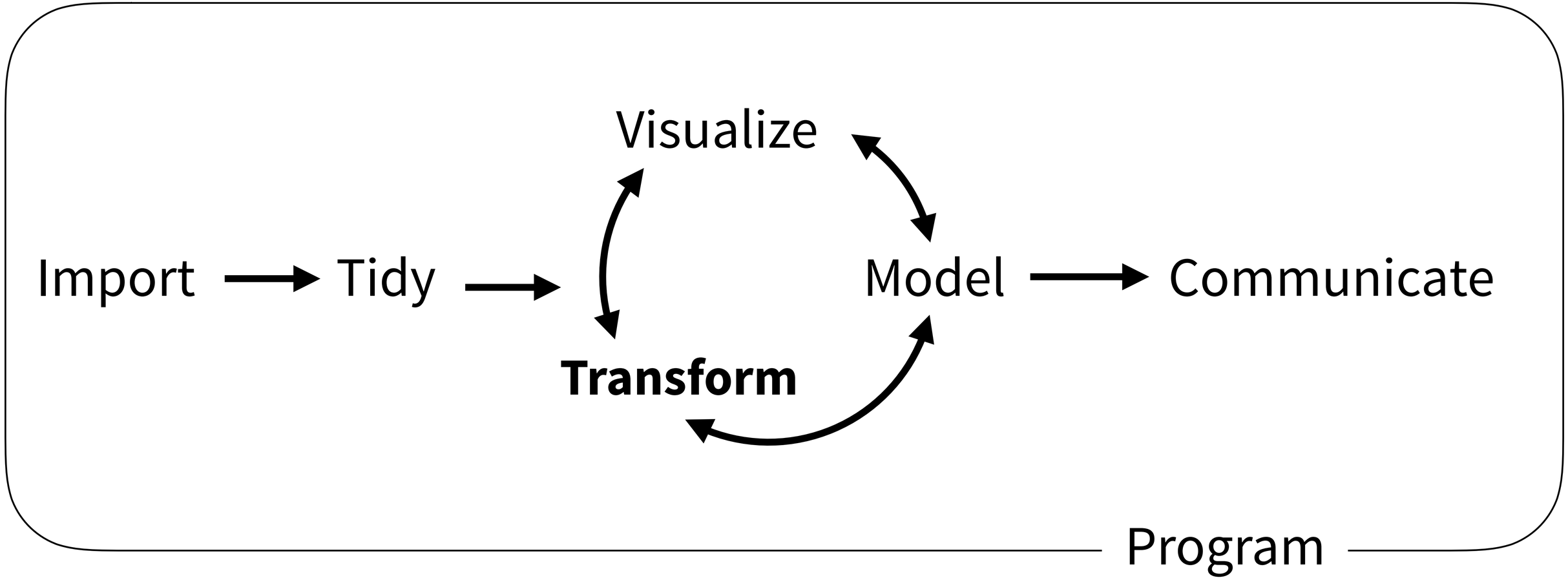
```
my_skim <- skim_with(numeric = sfl(p25 = NULL, p75=NULL))
my_skim()
```

`skim_with()` can also be used to add additional summary statistics (e.g. a trimmed mean) but we won't discuss this

Your turn 1

Run the `skim_with()` command, and then try skimming `babynames` again to see how the output is different

(Applied) **Data Science**



dplyr

dplyr

A package that transforms data.

dplyr implements a *grammar* for transforming tabular data.

Isolating data

Extract variables with **select()**

Extract cases with **filter()**

Arrange cases, with **arrange()**.

select()

select()

Extract columns by name.

```
select(.data, …)
```

data frame to transform

name(s) of columns to extract
(or a select helper function)

select()

Extract columns by name.

```
select(babynames, name, prop)
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

name	prop
John	0.0815
William	0.0805
James	0.0501
Charles	0.0451
Garrett	0.0001
John	0.081

Your Turn 2

Alter the code to select just the **n** column:

```
select(babynames, name, prop)
```

```
select(babynames, n)
#       n
#   <int>
# 1  7065
# 2  2604
# 3  2003
# 4  1939
# 5  1746
# …    …
```

select() helpers

: - Select range of columns

```
select(storms, storm:pressure)
```

- - Select every column but

```
select(storms, -c(storm, pressure))
```

starts_with() - Select columns that start with…

```
select(storms, starts_with("w"))
```

ends_with() - Select columns that end with…

```
select(storms, ends_with("e"))
```

select() helpers

contains() - Select columns whose names contain...

```
select(storms, contains("d"))
```

matches() - Select columns whose names match regular expression

```
select(storms, matches("^.{4}$"))
```

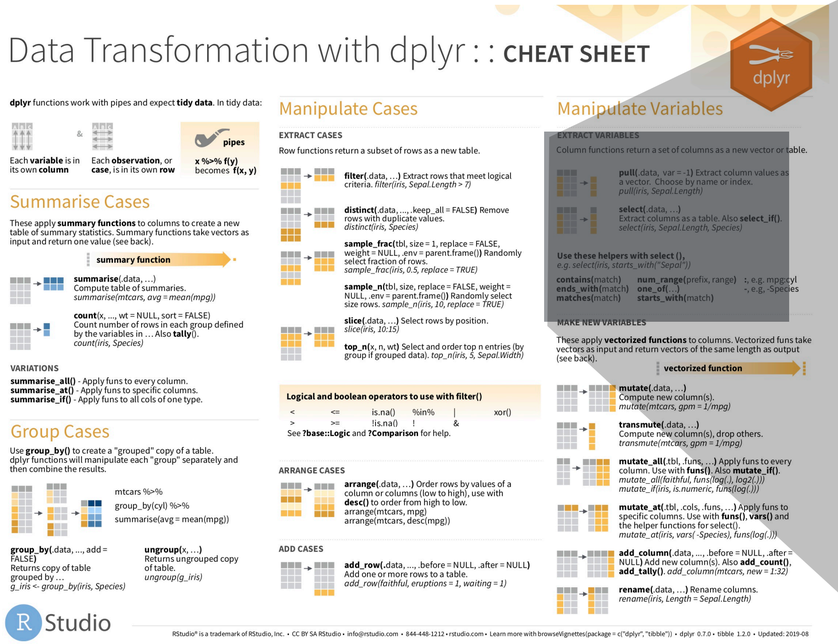
one_of() - Select columns whose names are one of a set

```
select(storms, one_of(c("storm", "storms", "Storm")))
```

num_range() - Select columns named in prefix, number style

```
select(storms, num_range("x", 1:5))
```

select() helpers



Data Transformation with dplyr : : **CHEAT SHEET**

dplyr

dplyr functions work with pipes and expect **tidy data**. In tidy data:

Each **variable** is in its own **column** & Each **observation**, or **case**, is in its own **row**

pipes
x %>% f(y) becomes **f(x, y)**

Summarise Cases

These apply **summary functions** to columns to create a new table of summary statistics. Summary functions take vectors as input and return one value (see back).

summary function

summarise(.data, …)
Compute table of summaries.
summarise(mtcars, avg = mean(mpg))

count(x, …, wt = NULL, sort = FALSE)
Count number of rows in each group defined by the variables in … Also **tally**().
count(iris, Species)

VARIATIONS

summarise_all() - Apply funs to every column.
summarise_at() - Apply funs to specific columns.
summarise_if() - Apply funs to all cols of one type.

Group Cases

Use **group_by()** to create a "grouped" copy of a table. dplyr functions will manipulate each "group" separately and then combine the results.

mtcars %>%
group_by(cyl) %>%
summarise(avg = mean(mpg))

group_by(.data, ..., add = FALSE)
Returns copy of table grouped by …
g_iris <- group_by(iris, Species)

ungroup(x, …)
Returns ungrouped copy of table.
ungroup(g_iris)

Manipulate Cases

EXTRACT CASES

Row functions return a subset of rows as a new table.

filter(.data, …) Extract rows that meet logical criteria. *filter(iris, Sepal.Length > 7)*

distinct(.data, ..., .keep_all = FALSE) Remove rows with duplicate values.
distinct(iris, Species)

sample_frac(tbl, size = 1, replace = FALSE, weight = NULL, .env = parent.frame()) Randomly select fraction of rows.
sample_frac(iris, 0.5, replace = TRUE)

sample_n(tbl, size, replace = FALSE, weight = NULL, .env = parent.frame()) Randomly select size rows. *sample_n(iris, 10, replace = TRUE)*

slice(.data, …) Select rows by position.
slice(iris, 10:15)

top_n(x, n, wt) Select and order top n entries (by group if grouped data). *top_n(iris, 5, Sepal.Width)*

Logical and boolean operators to use with filter()

<	<=	is.na()	%in%	|	xor()
>	>=	!is.na()	!	&	

See **?base::Logic** and **?Comparison** for help.

ARRANGE CASES

arrange(.data, …) Order rows by values of a column or columns (low to high), use with **desc()** to order from high to low.
arrange(mtcars, mpg)
arrange(mtcars, desc(mpg))

ADD CASES

add_row(.data, ..., .before = NULL, .after = NULL) Add one or more rows to a table.
add_row(faithful, eruptions = 1, waiting = 1)

Manipulate Variables

EXTRACT VARIABLES

Column functions return a set of columns as a new vector or table.

pull(.data, var = -1) Extract column values as a vector. Choose by name or index.
pull(iris, Sepal.Length)

select(.data, …)
Extract columns as a table. Also **select_if()**.
select(iris, Sepal.Length, Species)

Use these helpers with select ( ),
e.g. select(iris, starts_with("Sepal"))

contains(match)	**num_range**(prefix, range)	:, e.g. mpg:cyl
ends_with(match)	**one_of**(…)	-, e.g, -Species
matches(match)	**starts_with**(match)	

MAKE NEW VARIABLES

These apply **vectorized functions** to columns. Vectorized funs take vectors as input and return vectors of the same length as output (see back).

vectorized function

mutate(.data, …)
Compute new column(s).
mutate(mtcars, gpm = 1/mpg)

transmute(.data, …)
Compute new column(s), drop others.
transmute(mtcars, gpm = 1/mpg)

mutate_all(.tbl, .funs, …) Apply funs to every column. Use with **funs()**. Also **mutate_if()**.
mutate_all(faithful, funs(log(.), log2(.)))
mutate_if(iris, is.numeric, funs(log(.)))

mutate_at(.tbl, .cols, .funs, …) Apply funs to specific columns. Use with **funs()**, **vars()** and the helper functions for select().
mutate_at(iris, vars(-Species), funs(log(.)))

add_column(.data, ..., .before = NULL, .after = NULL) Add new column(s). Also **add_count()**, **add_tally()**. *add_column(mtcars, new = 1:32)*

rename(.data, …) Rename columns.
rename(iris, Length = Sepal.Length)

RStudio

EXTRACT VARIABLES

Column functions return a set of columns as a new vector or table.

pull(.data, var = -1**)** Extract column values as a vector. Choose by name or index.
pull(iris, Sepal.Length)

select(.data, …**)**
Extract columns as a table. Also **select_if()**.
select(iris, Sepal.Length, Species)

Use these helpers with select ( ),
e.g. select(iris, starts_with("Sepal"))

contains(match)	**num_range**(prefix, range)	:, e.g. mpg:cyl
ends_with(match)	**one_of**(…)	-, e.g, -Species
matches(match)	**starts_with**(match)	

dplyr

Consider

Which of these is NOT a way to select the **name** and **n** columns together?

```
select(babynames, -c(year, sex, prop))
```

```
select(babynames, name:n)
```

```
select(babynames, starts_with("n"))
```

```
select(babynames, ends_with("n"))
```

Consider

Which of these is NOT a way to select the **name** and **n** columns together?

```
select(babynames, -c(year, sex, prop))
```

```
select(babynames, name:n)
```

```
select(babynames, starts_with("n"))
```

```
select(babynames, ends_with("n"))
```

filter()

filter()

Extract rows that meet logical criteria.

```
filter(.data, … )
```

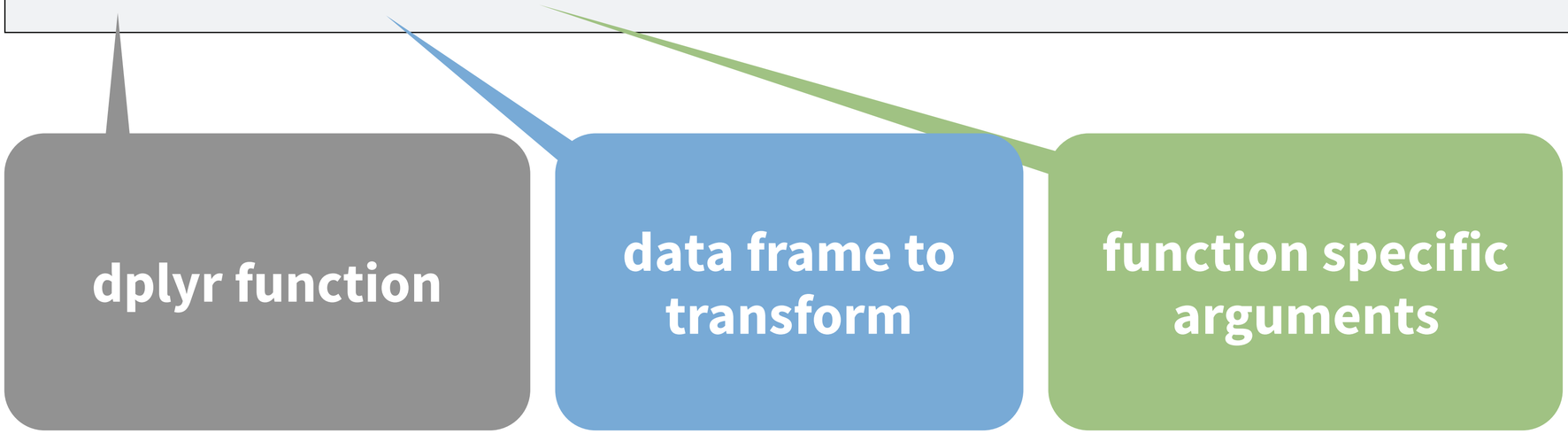
data frame to transform

one or more logical tests (filter returns each row for which the test is TRUE)

common syntax

Each function takes a data frame / tibble as its first argument and returns a data frame / tibble.

```
filter(.data, … )
```



filter()

Extract rows that meet logical criteria.

```
filter(babynames, name == "Amelia")
```

babynames

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135

year	sex	name	n	prop
1880	F	Amelia	221	0.00226
1881	F	Amelia	225	0.00238
…	…	Amelia	…	…

filter()

Extract rows that meet logical criteria.

```
filter(babynames, name == "Amelia")
```

babynames

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135

= sets
(returns nothing)

== tests if equal
(returns TRUE or FALSE)

Logical tests

?Comparison

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

Your Turn 3

See if you can use the logical operators to manipulate our code below to show:

- All of the names where **prop** is greater than or equal to 0.08
- All of the children named “Sea”
- All of the names that have a missing value for **n**
  (Hint: this should return an empty data set).

```
filter(babynames, prop >= 0.08)
#    year   sex    name      n       prop
# 1  1880     M    John  9655 0.08154630
# 2  1880     M William  9531 0.08049899
# 3  1881     M    John  8769 0.08098299
```

```
filter(babynames, name == "Sea")
#    year   sex  name      n         prop
# 1  1982     F   Sea     5 2.756771e-06
# 2  1985     M   Sea     6 3.119547e-06
# 3  1986     M   Sea     5 2.603512e-06
# 4  1998     F   Sea     5 2.580377e-06
```

```
filter(babynames, is.na(n))
#  0 rows
```

Two common mistakes

1. Using `=` instead of `==`

```
filter(babynames, name = "Sea")
filter(babynames, name == "Sea")
```

2. Forgetting quotes

```
filter(babynames, name == Sea)
filter(babynames, name == "Sea")
```

filter()

Extract rows that meet *every* logical criteria.

```
filter(babynames, name == "Amelia", year == 1880)
```

babynames

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135

year	sex	name	n	prop
1880	F	Amelia	221	0.00226

Boolean operators

?base::Logic

`a & b`	and
`a | b`	or
`xor(a,b)`	exactly or
`!a`	not
`a %in% c(a, b)`	one of (in)

Your Turn 4

Use Boolean operators to alter the code below to return only the rows that contain:

- Girls named Sea
- Names that were used by exactly 5 or 6 children in 1880
- Names that are one of Acura, Lexus, or Yugo

```
filter(babynames, name == "Sea" | name == "Anemone")
```

```
filter(babynames, name == "Sea", sex == "F")
#    year   sex  name      n          prop
# 1  1982     F   Sea      5 2.756771e-06
# 2  1998     F   Sea      5 2.580377e-06
```

```
filter(babynames, n == 5 | n == 6, year == 1880)
#    year   sex    name      n          prop
# 1  1880     F    Abby      6 6.147289e-05
# 2  1880     F  Aileen      6 6.147289e-05
# …     …      …       …      …             …
```

```
filter(babynames, name == "Acura" | name =="Lexus" |name =="Yugo"))
#    year   sex  name     n          prop
# 1  1990     F Lexus    36 1.752932e-05
# 2  1990     M Lexus    12 5.579156e-06
# …     …      …     …     …             …
```

Two more common mistakes

3. Collapsing multiple tests into one

```
filter(babynames, 10 < n < 20)
filter(babynames, 10 < n, n < 20)
```

4. Stringing together many tests (when you could use %in%)

```
filter(babynames, n == 5 | n == 6 | n == 7 | n == 8)
filter(babynames, n %in% c(5, 6, 7, 8))
```

```
filter(babynames, name == "Sea", sex == "F")
#    year   sex  name      n          prop
# 1  1982     F   Sea      5 2.756771e-06
# 2  1998     F   Sea      5 2.580377e-06
```

```
filter(babynames, n == 5 | n == 6, year == 1880)
#    year   sex    name      n          prop
# 1  1880     F    Abby      6 6.147289e-05
# 2  1880     F  Aileen      6 6.147289e-05
# …     …     …       …      …             …
```

```
filter(babynames, name %in% c("Acura", "Lexus", "Yugo"))
#    year   sex  name      n          prop
# 1  1990     F Lexus    36 1.752932e-05
# 2  1990     M Lexus    12 5.579156e-06
# …     …     …      …      …             …
```

arrange()

arrange()

Order rows from smallest to largest values.

```
arrange(.data, …)
```

data frame to transform

one or more columns to order by (additional columns will be used as tie breakers)

arrange()

Order rows from smallest to largest values.

```
arrange(babynames, n)
```

babynames

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135

year	sex	name	n	prop
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135
1880	F	Elizabeth	1939	0.0199
1880	F	Emma	2003	0.0205
1880	F	Anna	2604	0.0267
1880	F	Mary	7065	0.0724

Your Turn 5

Arrange babynames by **n**. Add **prop** as a second (tie breaking) variable to arrange by.

Can you tell what the smallest value of **n** is?

```
arrange(babynames, n, prop)
#     year   sex         name     n          prop
#  1  2007     M        Aaban     5 2.259872e-06
#  2  2007     M      Aareon      5 2.259872e-06
#  3  2007     M       Aaris      5 2.259872e-06
#  4  2007     M         Abd      5 2.259872e-06
#  5  2007     M  Abdulazeez      5 2.259872e-06
#  6  2007     M   Abdulhadi      5 2.259872e-06
#  7  2007     M  Abdulhamid      5 2.259872e-06
#  8  2007     M  Abdulkadir      5 2.259872e-06
#  9  2007     M Abdulraheem      5 2.259872e-06
# 10  2007     M  Abdulrahim      5 2.259872e-06
# ... with 1,858,679 more rows
```

desc()

Changes ordering to largest to smallest.

```
arrange(babynames, desc(n))
```

babynames

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Amelia	221	0.00226
1880	F	Bertha	1320	0.0135

year	sex	name	n	prop
1880	F	Mary	7065	0.0724
1880	F	Anna	2604	0.0267
1880	F	Emma	2003	0.0205
1880	F	Elizabeth	1939	0.0199
1880	F	Bertha	1320	0.0135
1880	F	Amelia	221	0.00226

Your Turn 6

Use **desc()** to find the names with the highest **prop**.

Then, use **desc()** to find the names with the highest **n**.

```
arrange(babynames, desc(prop))
#      year   sex     name      n       prop
#  1   1880     M     John   9655 0.08154630
#  2   1881     M     John   8769 0.08098299
#  3   1880     M  William   9531 0.08049899
#  4   1883     M     John   8894 0.07907324
#  5   1881     M  William   8524 0.07872038
#  6   1882     M     John   9557 0.07831617
#  7   1884     M     John   9388 0.07648751
#  8   1882     M  William   9298 0.07619375
#  9   1886     M     John   9026 0.07582198
# 10   1885     M     John   8756 0.07551791
# ... with 1,858,679 more rows
```

```
arrange(babynames, desc(n))
#      year   sex     name     n       prop
#  1   1947     F    Linda 99680 0.05483609
#  2   1948     F    Linda 96211 0.05521159
#  3   1947     M    James 94763 0.05102057
#  4   1957     M  Michael 92726 0.04238659
#  5   1947     M   Robert 91646 0.04934237
#  6   1949     F    Linda 91010 0.05184281
#  7   1956     M  Michael 90623 0.04225479
#  8   1958     M  Michael 90517 0.04203881
#  9   1948     M    James 88588 0.04969679
# 10   1954     M  Michael 88493 0.04279403
# ... with 1,858,679 more rows
```

%>%

Steps

```
boys_2015 <- filter(babynames, year == 2015, sex == "M")
boys_2015 <- select(boys_2015, name, n)
boys_2015 <- arrange(boys_2015, desc(n))
boys_2015
```

1. Filter babynames to just boys born in 2015
2. Select the name and n columns from the result
3. Arrange those columns so that the most popular names appear near the top.

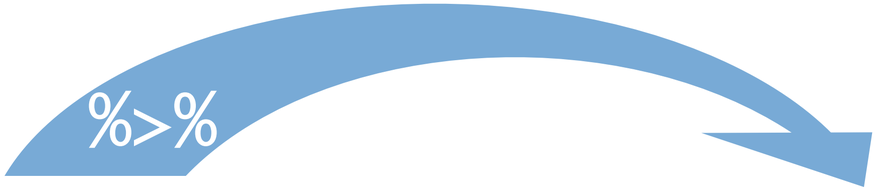
Steps

```
boys_2015 <- filter(babynames, year == 2015, sex == "M")
boys_2015 <- select(boys_2015, name, n)
boys_2015 <- arrange(boys_2015, desc(n))
boys_2015
```

Steps

```
arrange(select(filter(babynames, year == 2015,
  sex == "M"), name, n), desc(n))
```

The pipe operator %>%




```
babynames          filter(_____, n == 99680)
```

Passes result on left into first argument of function on right.
So, for example, these do the same thing. Try it.

```
filter(babynames, n == 99680)
babynames %>% filter(n == 99680)
```

Pipes

```
babynames
boys_2015 <- filter(babynames, year == 2015, sex == "M")
boys_2015 <- select(boys_2015, name, n)
boys_2015 <- arrange(boys_2015, desc(n))
boys_2015
```

```
babynames %>%
  filter(year == 2015, sex == "M") %>%
  select(name, n) %>%
  arrange(desc(n))
```

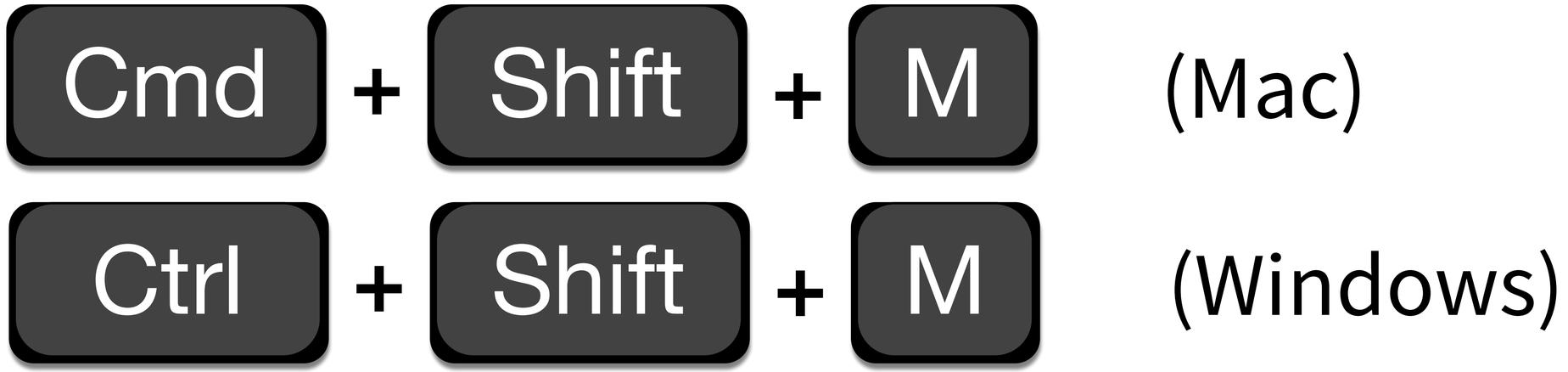
```
foo_foo <- little_bunny()
```

```
foo_foo %>%
  hop_through(forest) %>%
  scoop_up(field_mouse) %>%
  bop_on(head)
```

VS.

```
foo_foo2 <- hop_through(foo_foo, forest)
foo_foo3 <- scoop_up(foo_foo2, field_mouse)
bop_on(foo_foo3,  head)
```

Shortcut to type %>%



Your Turn 7

Use **%>%** to write a sequence of functions that:

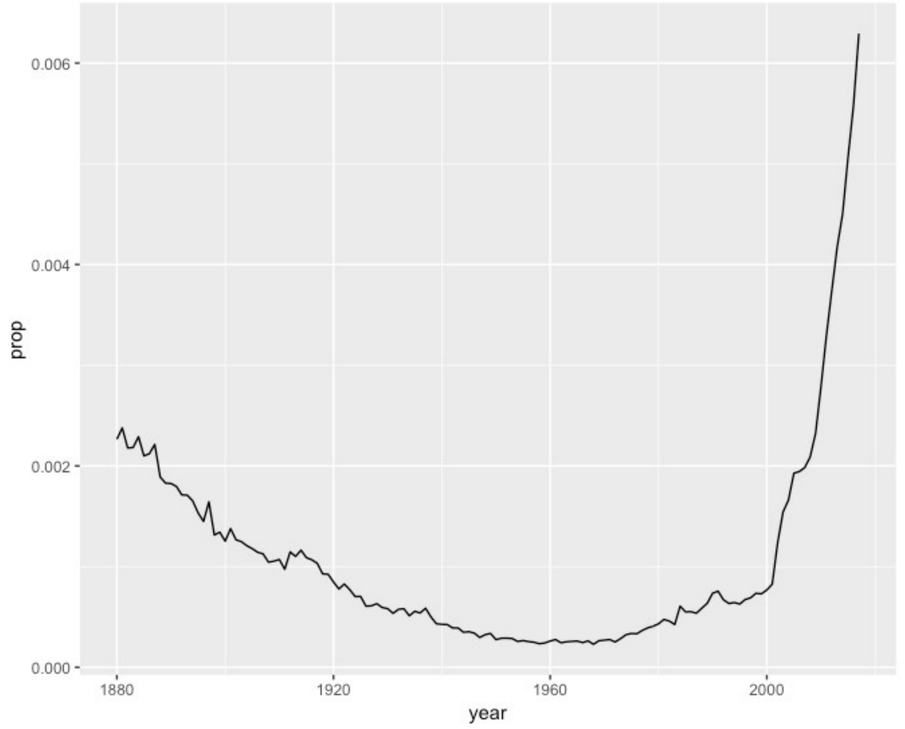
1. Filter babynames to just the girls that were born in 2015
2. Select the **name** and **n** columns
3. Arrange the results so that the most popular names are near the top.

```
babynames %>%
  filter(year == 2015, sex == "F") %>%
  select(name, n) %>%
  arrange(desc(n))
#          name     n
#  1       Emma 20355
#  2     Olivia 19553
#  3     Sophia 17327
#  4        Ava 16286
#  5   Isabella 15504
#  6        Mia 14820
#  7    Abigail 12311
#  8      Emily 11727
#  9 Charlotte 11332
# 10     Harper 10241
# ... with 18,983 more rows
```

Your Turn 8

1. Trim babynames to just the rows that contain your **name** and your **sex**
2. Trim the result to just the columns that will appear in your graph (not strictly necessary, but useful practice)
3. Plot the results as a line graph with **year** on the x axis and **prop** on the y axis

```
babynames %>%
  filter(name == "Amelia", sex == "F") %>%
  select(year, prop) %>%
  ggplot() +
    geom_line(mapping = aes(year, prop))
```



What are the most popular names?

How should we define popularity?

A name is popular if:

How should we define popularity?

A name is popular if:

1. **Sums** - a large number of children have the name when you sum across years

How should we define popularity?

A name is popular if:

1. **Sums** - a large number of children have the name when you sum across years
2. **Ranks** - it consistently ranks among the top names from year to year.

Consider

Do we have enough information to:

1. Calculate the total number of children with each name?
2. Rank names within each year?

Deriving information

Make tables of summaries with **summarise()**.

Make new variables, with **mutate()**.

summarise()

/

British and American spellings recognized! Apologies for my (inevitable) inconsistency

summarize()

summarise()

Compute table of summaries.

```
babynames %>% summarise(total = sum(n), max = max(n))
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

total	max
127538	99680

Your Turn 9

Use summarise() to compute three statistics *about the data*:

1. The first (minimum) year in the dataset
2. The last (maximum) year in the dataset
3. The total number of children represented in the data

```
babynames %>%
   summarise(first = min(year),
             last = max(year),
             total = sum(n))
#   first  last     total
# 1  1880  2015 340851912
```

Your Turn 10

Extract the rows where **name == "Khaleesi"**. Then use summarise() and a summary functions to find:

1. The total number of children named Khaleesi
2. The first **year** Khaleesi appeared in the data

```
babynames %>%
  filter(name == "Khaleesi") %>%
  summarise(total = sum(n), first = min(year))
#   total first
# 1  1127  2011
```

Summary functions

Take a vector as input.

Return a single value as output.

Summarise Cases

These apply **summary functions** to columns to create a new table of summary statistics. Summary functions take vectors as input and return one value (see back).

summary function

summarise(.data, …)
Compute table of summaries.
summarise(mtcars, avg = mean(mpg))

count(x, ..., wt = NULL, sort = FALSE)
Count number of rows in each group defined by the variables in … Also **tally**().
count(iris, Species)

VARIATIONS

summarise_all() - Apply funs to every column.
summarise_at() - Apply funs to specific columns.
summarise_if() - Apply funs to all cols of one type.

Data Transformation with dplyr : : CHEAT SHEET

dplyr functions work with pipes and expect **tidy data**. In tidy data:

Each **variable** is in its own **column** & Each **observation**, or **case**, is in its own **row**

pipes
x %>% f(y) becomes **f(x, y)**

Summarise Cases

These apply **summary functions** to columns to create a new table of summary statistics. Summary functions take vectors as input and return one value (see back).

summary function

summarise(.data, …)
Compute table of summaries.
summarise(mtcars, avg = mean(mpg))

count(x, ..., wt = NULL, sort = FALSE)
Count number of rows in each group defined by the variables in … Also **tally**().
count(iris, Species)

VARIATIONS

summarise_all() - Apply funs to every column.
summarise_at() - Apply funs to specific columns.
summarise_if() - Apply funs to all cols of one type.

Group Cases

Use **group_by()** to create a "grouped" copy of a table. dplyr functions will manipulate each "group" separately and then combine the results.

mtcars %>%
group_by(cyl) %>%
summarise(avg = mean(mpg))

group_by(.data, ..., add = FALSE)
Returns copy of table grouped by …
g_iris <- group_by(iris, Species)

ungroup(x, …)
Returns ungrouped copy of table.
ungroup(g_iris)

Manipulate Cases

EXTRACT CASES

Row functions return a subset of rows as a new table.

filter(.data, …) Extract rows that meet logical criteria. *filter(iris, Sepal.Length > 7)*

distinct(.data, ..., .keep_all = FALSE) Remove rows with duplicate values. *distinct(iris, Species)*

sample_frac(tbl, size = 1, replace = FALSE, weight = NULL, .env = parent.frame()) Randomly select fraction of rows. *sample_frac(iris, 0.5, replace = TRUE)*

sample_n(tbl, size, replace = FALSE, weight = NULL, .env = parent.frame()) Randomly select size rows. *sample_n(iris, 10, replace = TRUE)*

slice(.data, …) Select rows by position. *slice(iris, 10:15)*

top_n(x, n, wt) Select and order top n entries (by group if grouped data). *top_n(iris, 5, Sepal.Width)*

Logical and boolean operators to use with filter()

<	<=	is.na()	%in%	|	xor()
>	>=	!is.na()	!	&	

See **?base::Logic** and **?Comparison** for help.

ARRANGE CASES

arrange(.data, …) Order rows by values of a column or columns (low to high), use with **desc()** to order from high to low.
arrange(mtcars, mpg)
arrange(mtcars, desc(mpg))

ADD CASES

add_row(.data, …, .before = NULL, .after = NULL) Add one or more rows to a table.
add_row(faithful, eruptions = 1, waiting = 1)

Manipulate Variables

EXTRACT VARIABLES

Column functions return a set of columns as a new vector or table.

pull(.data, var = -1) Extract column values as a vector. Choose by name or index.
pull(iris, Sepal.Length)

select(.data, …) Extract columns as a table. Also **select_if()**.
select(iris, Sepal.Length, Species)

Use these helpers with select (),
e.g. select(iris, starts_with("Sepal"))

contains(match) **num_range**(prefix, range) **:**, e.g. mpg:cyl
ends_with(match) **one_of**(…) **-**, e.g, -Species
matches(match) **starts_with**(match)

MAKE NEW VARIABLES

These apply **vectorized functions** to columns. Vectorized funs take vectors as input and return vectors of the same length as output (see back).

vectorized function

mutate(.data, …) Compute new column(s). *mutate(mtcars, gpm = 1/mpg)*

transmute(.data, …) Compute new column(s), drop others. *transmute(mtcars, gpm = 1/mpg)*

mutate_all(.tbl, .funs, …) Apply funs to every column. Use with **funs()**. Also **mutate_if()**. *mutate_all(faithful, funs(log(.), log2(.)))* *mutate_if(iris, is.numeric, funs(log(.)))*

mutate_at(.tbl, .cols, .funs, …) Apply funs to specific columns. Use with **funs()**, **vars()** and the helper functions for select(). *mutate_at(iris, vars(-Species), funs(log(.)))*

add_column(.data, …, .before = NULL, .after = NULL) Add new column(s). Also **add_count()**, **add_tally()**. *add_column(mtcars, new = 1:32)*

rename(.data, …) Rename columns. *rename(iris, Length = Sepal.Length)*

RStudio® is a trademark of RStudio, Inc. • CC BY SA RStudio • info@rstudio.com • 844-448-1212 • rstudio.com • Learn more with browseVignettes(package = c("dplyr", "tibble")) • dplyr 0.7.0 • tibble 1.2.0 • Updated: 2019-08

n()

The number of rows in a dataset/group

```
babynames %>% summarise(n = n())
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

n
1858689

n_distinct()

The number of distinct values in a variable

```
babynames %>% summarise(n = n(), nname = n_distinct(name))
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

n	nname
1858689	95025

Grouping cases

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
```

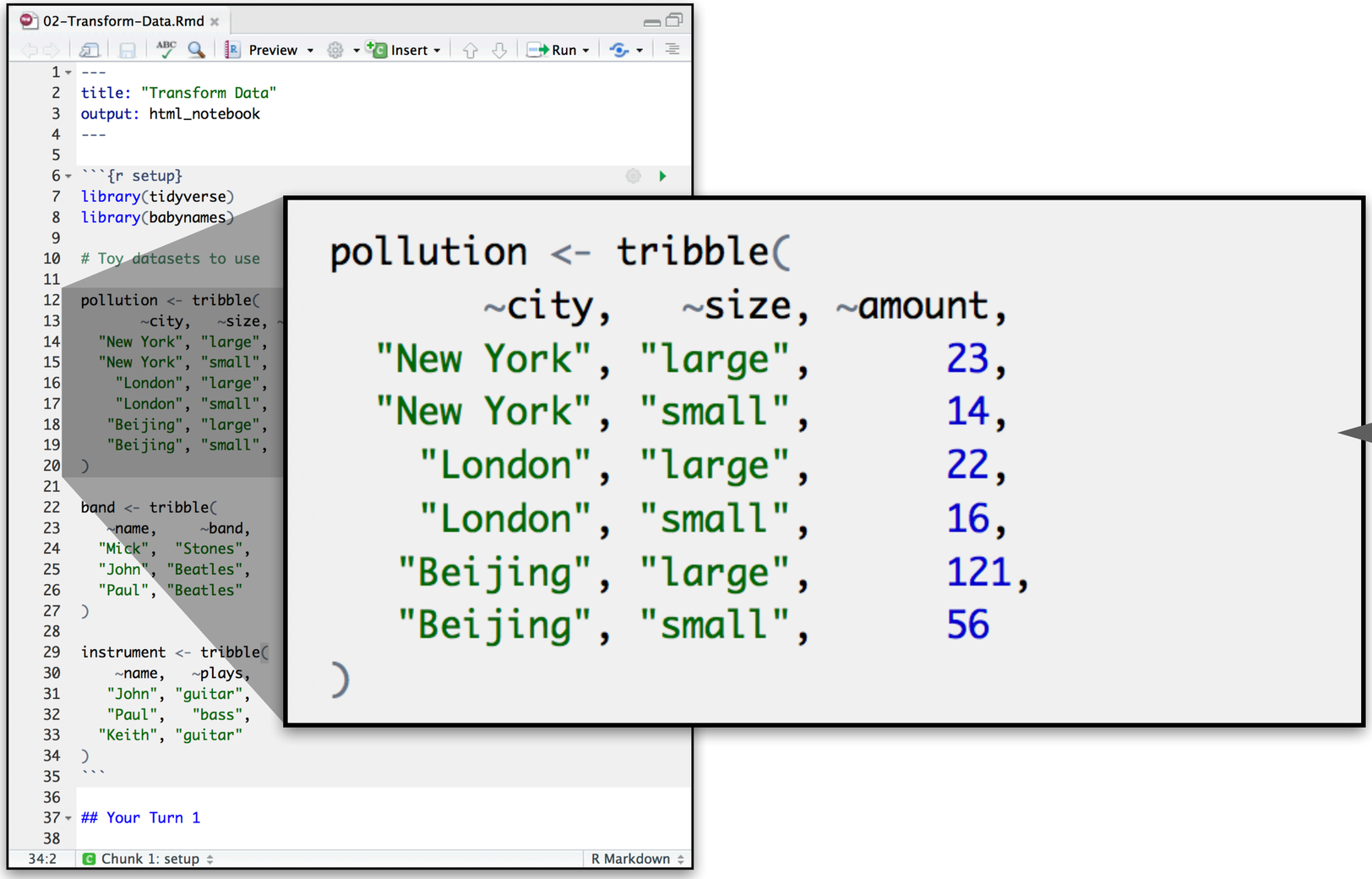
group_by()

Groups cases by common values.

```
babynames %>%
  group_by(sex) %>%
  summarise(total = sum(n))
```

sex	total
F	167070477
M	170064949

Transform Data Notebook



Toy data sets to practice with

dplyr

```
pollution <- tribble(
       ~city,   ~size, ~amount,
  "New York", "large",      23,
  "New York", "small",      14,
    "London", "large",      22,
    "London", "small",      16,
   "Beijing", "large",      121,
   "Beijing", "small",      56
)
```

pollution

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

city	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

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

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

mean	sum	n
42	252	6

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

mean	sum	n
42	252	6

city	particle size	amount ($\mu g/m^3$)
New York	large	23
New York	small	14

mean	sum	n
18.5	37	2

London	large	22
London	small	16

19.0	38	2

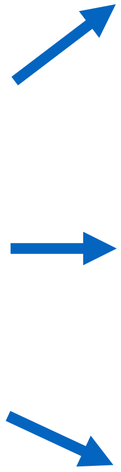
Beijing	large	121
Beijing	small	56

88.5	177	2

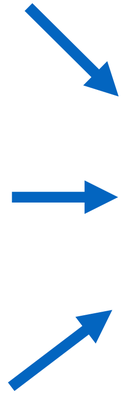
group_by() + summarise()

group_by()

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



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

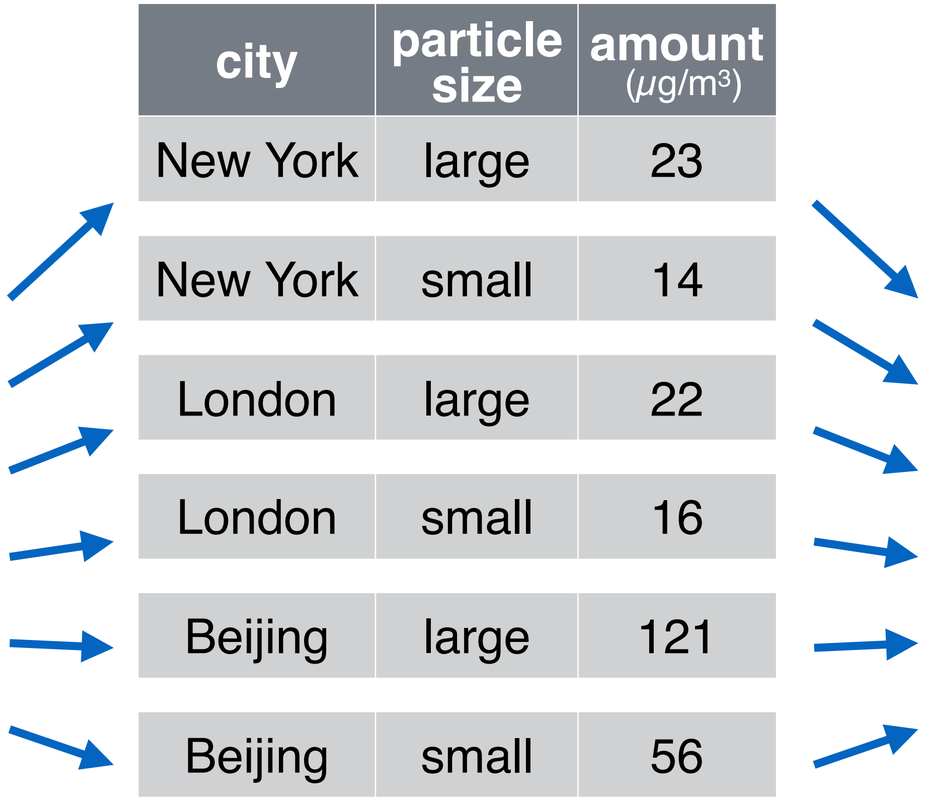


city	mean	sum	n
New York	18.5	37	2
London	19.0	38	2
Beijing	88.5	177	2

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

group_by()

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



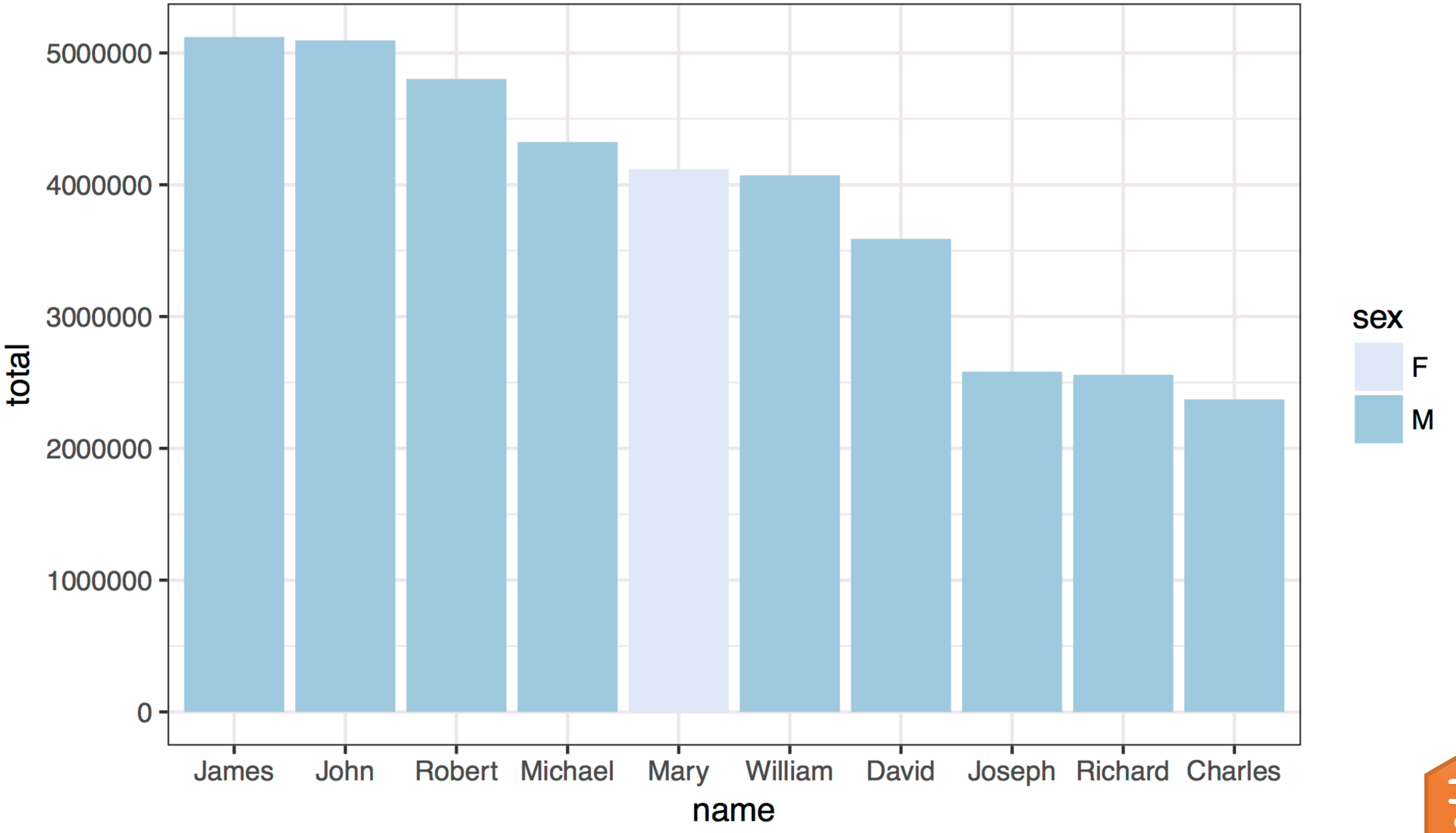
city	particle size	mean	sum	n
New York	large	23	23	1
New York	small	14	14	1
London	large	22	22	1
London	small	16	16	1
Beijing	large	121	121	1
Beijing	small	56	56	1

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

Your Turn 11

Use **group_by()**, **summarise()**, and **arrange()** to display the ten most popular baby names. Compute popularity as the total number of children of a single gender given a name.

```
babynames %>%
  group_by(name, sex) %>%
  summarise(total = sum(n)) %>%
  arrange(desc(total))
#       name   sex   total
#  1   James     M 5120990
#  2    John     M 5095674
#  3  Robert     M 4803068
#  4 Michael     M 4323928
#  5    Mary     F 4118058
#  6 William     M 4071645
#  7   David     M 3589754
#  8  Joseph     M 2581785
#  9 Richard     M 2558165
# 10 Charles     M 2371621
# ... with 105,376 more rows
```


5000000
4000000
3000000
2000000
1000000
0
total
James
John
Robert
Michael
Mary
William
David
Joseph
Richard
Charles
name
sex
F
M

```
babynames %>%
  group_by(name, sex) %>%
  summarise(total = sum(n)) %>%
  arrange(desc(total)) %>%
  ungroup() %>%
  slice(1:10) %>%
  ggplot() +
    geom_col(mapping = aes(x = fct_reorder(name,
      desc(total)), y = total, fill = sex)) +
    theme_bw() +
    scale_fill_brewer() +
    labs(x = "name")
```

Your Turn 12

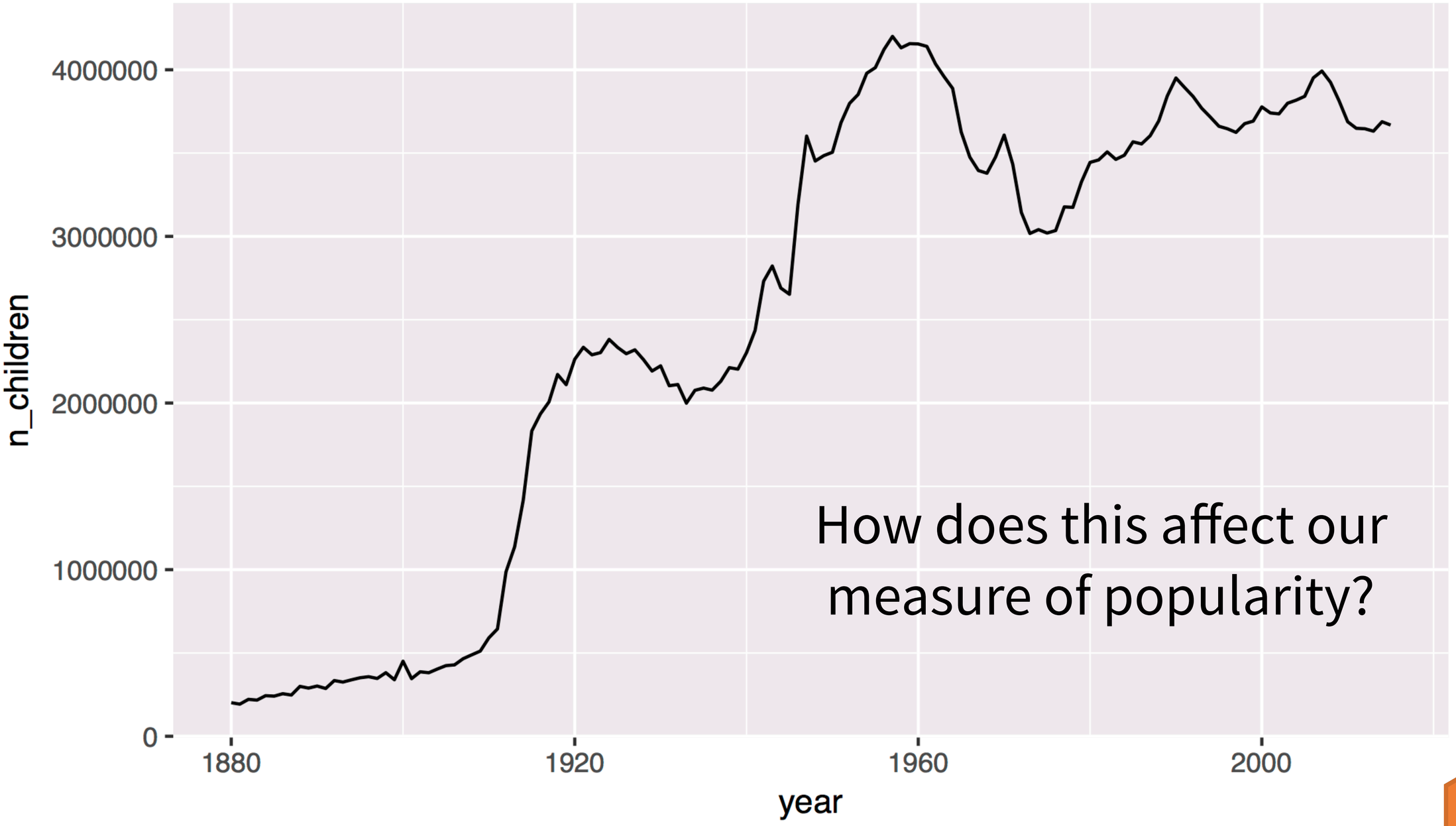
recall

```
babynames %>%
  group_by(name, sex) %>%
  summarise(total = sum(n)) %>%
  arrange(desc(total)) %>%
  ungroup() %>%
  slice(1:10) %>%
  ggplot() +
    geom_col(mapping = aes(x = fct_reorder(name,
      desc(total)), y = total, fill = sex)) +
    theme_bw() +
    scale_fill_brewer() +
    labs(x = "name")
```

Use grouping to calculate **number of children born each year**.

Plot the results as a line graph.

```
babynames %>%
  group_by(year) %>%
  summarise(n_children = sum(n)) %>%
  ggplot() +
    geom_line(mapping = aes(x = year, y = n_children))
```


4000000
3000000
2000000
1000000
0
n_children
1880
1920
1960
2000
year
How does this affect our measure of popularity?

ungroup()

Removes grouping criteria from a data frame.

```
babynames %>%
  group_by(name, sex) %>%
  summarise(total = sum(n)) %>%
  arrange(desc(total))
#       name   sex   total
#  1   James     M 5120990
#  2    John     M 5095674
#  3  Robert     M 4803068
#  4 Michael     M 4323928
#  5    Mary     F 4118058
```

ungroup()

Removes grouping criteria from a data frame.

```
babynames %>%
  group_by(name, sex) %>%
  ungroup() %>%
  summarise(total = sum(n)) %>%
  arrange(desc(total))
#       total
# 1 340851912
```

mutate()

mutate()

Create new columns.

```
babynames %>%
  mutate(percent = round(prop*100, 2))
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

year	sex	name	n	prop	percent
1880	M	John	9655	0.0815	8.15
1880	M	William	9532	0.0805	8.05
1880	M	James	5927	0.0501	5.01
1880	M	Charles	5348	0.0451	4.51
1880	M	Garrett	13	0.0001	0.01
1881	M	John	8769	0.081	8.1

mutate()

Create new columns.

```
babynames %>%
  mutate(percent = round(prop*100, 2), nper = round(percent))
```

babynames

year	sex	name	n	prop
1880	M	John	9655	0.0815
1880	M	William	9532	0.0805
1880	M	James	5927	0.0501
1880	M	Charles	5348	0.0451
1880	M	Garrett	13	0.0001
1881	M	John	8769	0.081

year	sex	name	n	prop	percent	nper
1880	M	John	9655	0.0815	8.15	8
1880	M	William	9532	0.0805	8.05	8
1880	M	James	5927	0.0501	5.01	5
1880	M	Charles	5348	0.0451	4.51	5
1880	M	Garrett	13	0.0001	0.01	0
1881	M	John	8769	0.081	8.1	8

Vector functions

Take a vector as input.

Return a vector of the same length as output.

Vector Functions

TO USE WITH MUTATE ()

mutate() and **transmute()** apply vectorized functions to columns to create new columns. Vectorized functions take vectors as input and return vectors of the same length as output.

vectorized function

OFFSETS

dplyr::**lag()** - Offset elements by 1
dplyr::**lead()** - Offset elements by -1

CUMULATIVE AGGREGATES

dplyr::**cumall()** - Cumulative all()
dplyr::**cumany()** - Cumulative any()
cummax() - Cumulative max()
dplyr::**cummean()** - Cumulative mean()
cummin() - Cumulative min()
cumprod() - Cumulative prod()
cumsum() - Cumulative sum()

RANKINGS

dplyr::**cume_dist()** - Proportion of all values <=
dplyr::**dense_rank()** - rank w ties = min, no gaps
dplyr::**min_rank()** - rank with ties = min
dplyr::**ntile()** - bins into n bins
dplyr::**percent_rank()** - min_rank scaled to [0,1]
dplyr::**row_number()** - rank with ties = "first"

MATH

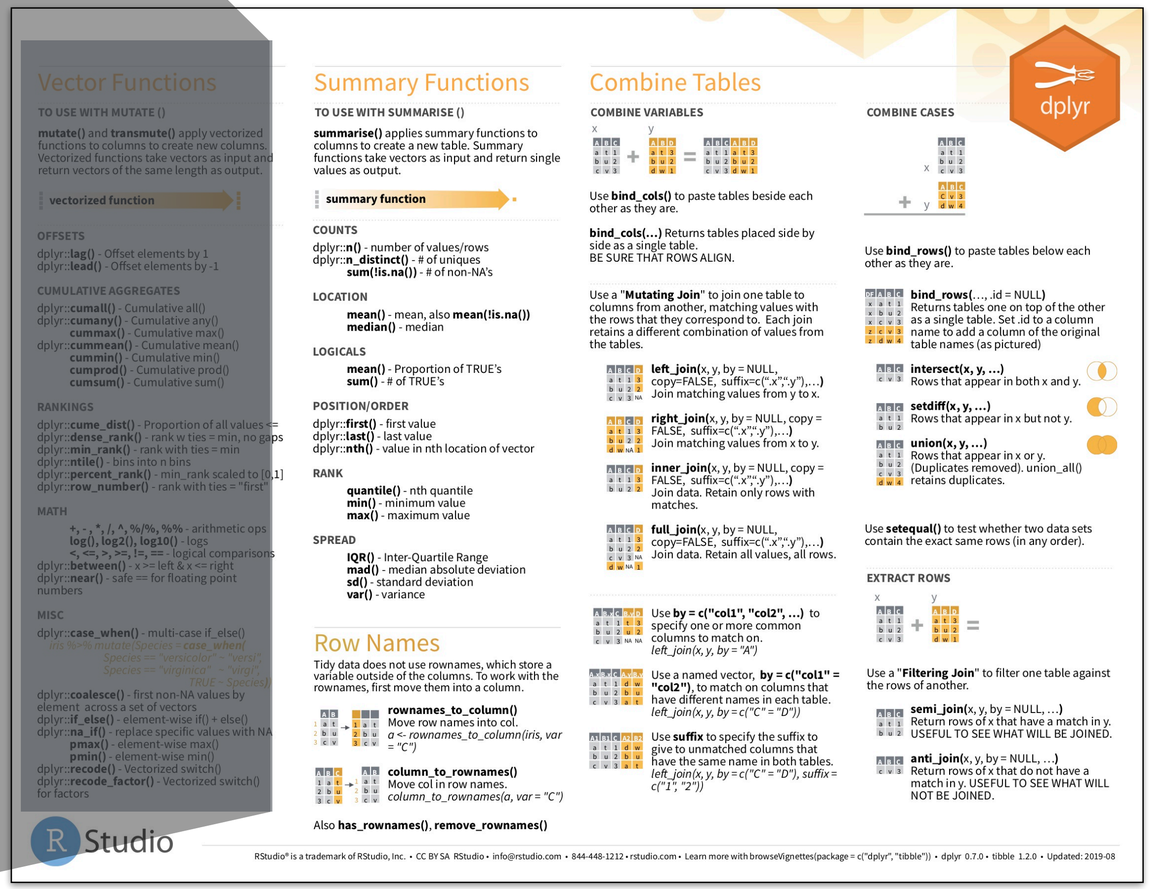
+, - , *, /, ^, %/%, %% - arithmetic ops
log(), log2(), log10() - logs
<, <=, >, >=, !=, == - logical comparisons
dplyr::**between()** - x >= left & x <= right
dplyr::**near()** - safe == for floating point numbers

MISC

dplyr::**case_when()** - multi-case if_else()

```
iris %>% mutate(Species = case_when(
            Species == "versicolor" ~ "versi",
            Species == "virginica"  ~ "virgi",
                          TRUE ~ Species))
```

dplyr::**coalesce()** - first non-NA values by element across a set of vectors
dplyr::**if_else()** - element-wise if() + else()
dplyr::**na_if()** - replace specific values with NA
pmax() - element-wise max()
pmin() - element-wise min()
dplyr::**recode()** - Vectorized switch()
dplyr::**recode_factor()** - Vectorized switch() for factors



Summary Functions

TO USE WITH SUMMARISE ()

summarise() applies summary functions to columns to create a new table. Summary functions take vectors as input and return single values as output.

summary function

COUNTS

dplyr::**n()** - number of values/rows
dplyr::**n_distinct()** - # of uniques
sum(!is.na()) - # of non-NA's

LOCATION

mean() - mean, also **mean(!is.na())**
median() - median

LOGICALS

mean() - Proportion of TRUE's
sum() - # of TRUE's

POSITION/ORDER

dplyr::**first()** - first value
dplyr::**last()** - last value
dplyr::**nth()** - value in nth location of vector

RANK

quantile() - nth quantile
min() - minimum value
max() - maximum value

SPREAD

IQR() - Inter-Quartile Range
mad() - median absolute deviation
sd() - standard deviation
var() - variance

Row Names

Tidy data does not use rownames, which store a variable outside of the columns. To work with the rownames, first move them into a column.

rownames_to_column()
Move row names into col.
a <- rownames_to_column(iris, var = "C")

column_to_rownames()
Move col in row names.
column_to_rownames(a, var = "C")

Also **has_rownames()**, **remove_rownames()**

Combine Tables

COMBINE VARIABLES

Use **bind_cols()** to paste tables beside each other as they are.

bind_cols(…) Returns tables placed side by side as a single table.
BE SURE THAT ROWS ALIGN.

Use a "**Mutating Join**" to join one table to columns from another, matching values with the rows that they correspond to. Each join retains a different combination of values from the tables.

left_join(x, y, by = NULL, copy=FALSE, suffix=c(".x",".y"),…)
Join matching values from y to x.

right_join(x, y, by = NULL, copy = FALSE, suffix=c(".x",".y"),…)
Join matching values from x to y.

inner_join(x, y, by = NULL, copy = FALSE, suffix=c(".x",".y"),…)
Join data. Retain only rows with matches.

full_join(x, y, by = NULL, copy=FALSE, suffix=c(".x",".y"),…)
Join data. Retain all values, all rows.

Use **by = c("col1", "col2", …)** to specify one or more common columns to match on.
left_join(x, y, by = "A")

Use a named vector, **by = c("col1" = "col2")**, to match on columns that have different names in each table.
left_join(x, y, by = c("C" = "D"))

Use **suffix** to specify the suffix to give to unmatched columns that have the same name in both tables.
left_join(x, y, by = c("C" = "D"), suffix = c("1", "2"))

COMBINE CASES

Use **bind_rows()** to paste tables below each other as they are.

bind_rows(…, .id = NULL)
Returns tables one on top of the other as a single table. Set .id to a column name to add a column of the original table names (as pictured)

intersect(x, y, …)
Rows that appear in both x and y.

setdiff(x, y, …)
Rows that appear in x but not y.

union(x, y, …)
Rows that appear in x or y. (Duplicates removed). union_all() retains duplicates.

Use **setequal()** to test whether two data sets contain the exact same rows (in any order).

EXTRACT ROWS

Use a "**Filtering Join**" to filter one table against the rows of another.

semi_join(x, y, by = NULL, …)
Return rows of x that have a match in y.
USEFUL TO SEE WHAT WILL BE JOINED.

anti_join(x, y, by = NULL, …)
Return rows of x that do not have a match in y. USEFUL TO SEE WHAT WILL NOT BE JOINED.

RStudio® is a trademark of RStudio, Inc. • CC BY SA RStudio • info@rstudio.com • 844-448-1212 • rstudio.com • Learn more with browseVignettes(package = c("dplyr", "tibble")) • dplyr 0.7.0 • tibble 1.2.0 • Updated: 2019-08

dplyr

min_rank()

A go to ranking function (ties share the lowest rank)

```
min_rank(c(50, 100, 1000))
# [1] 1 2 3
```

```
min_rank(desc(c(50, 100, 1000)))
# [1] 3 2 1
```

Your Turn 13

Use **min_rank()** and **mutate()** to rank each row in babynames from largest **n** to lowest **n**.

```
babynames %>%
  mutate(rank = min_rank(desc(prop)))
#      year   sex       name     n       prop  rank
#   1  1880     F       Mary  7065 0.07238433    14
#   2  1880     F       Anna  2604 0.02667923   709
#   3  1880     F       Emma  2003 0.02052170  1131
#   4  1880     F  Elizabeth  1939 0.01986599  1192
#   5  1880     F     Minnie  1746 0.01788861  1427
#   6  1880     F   Margaret  1578 0.01616737  1683
#   7  1880     F        Ida  1472 0.01508135  1897
#   8  1880     F      Alice  1414 0.01448711  2040
#   9  1880     F     Bertha  1320 0.01352404  2279
# 10  1880     F      Sarah  1288 0.01319618  2387
# ... with 1,858,679 more rows
```

```
babynames %>%
  group_by(year, sex) %>%
  mutate(rank = min_rank(desc(prop)))
```

```
babynames %>%
  group_by(year, sex) %>%
  mutate(rank = min_rank(desc(prop)))
#      year sex   name           n   prop  rank
#   1  1880 F     Mary        7065 0.0724     1
#   2  1880 F     Anna        2604 0.0267     2
#   3  1880 F     Emma        2003 0.0205     3
#   4  1880 F     Elizabeth   1939 0.0199     4
#   5  1880 F     Minnie      1746 0.0179     5
#   6  1880 F     Margaret    1578 0.0162     6
#   7  1880 F     Ida         1472 0.0151     7
#   8  1880 F     Alice       1414 0.0145     8
#    ... with 1,858,681 more rows
```

Your Turn 14

recall

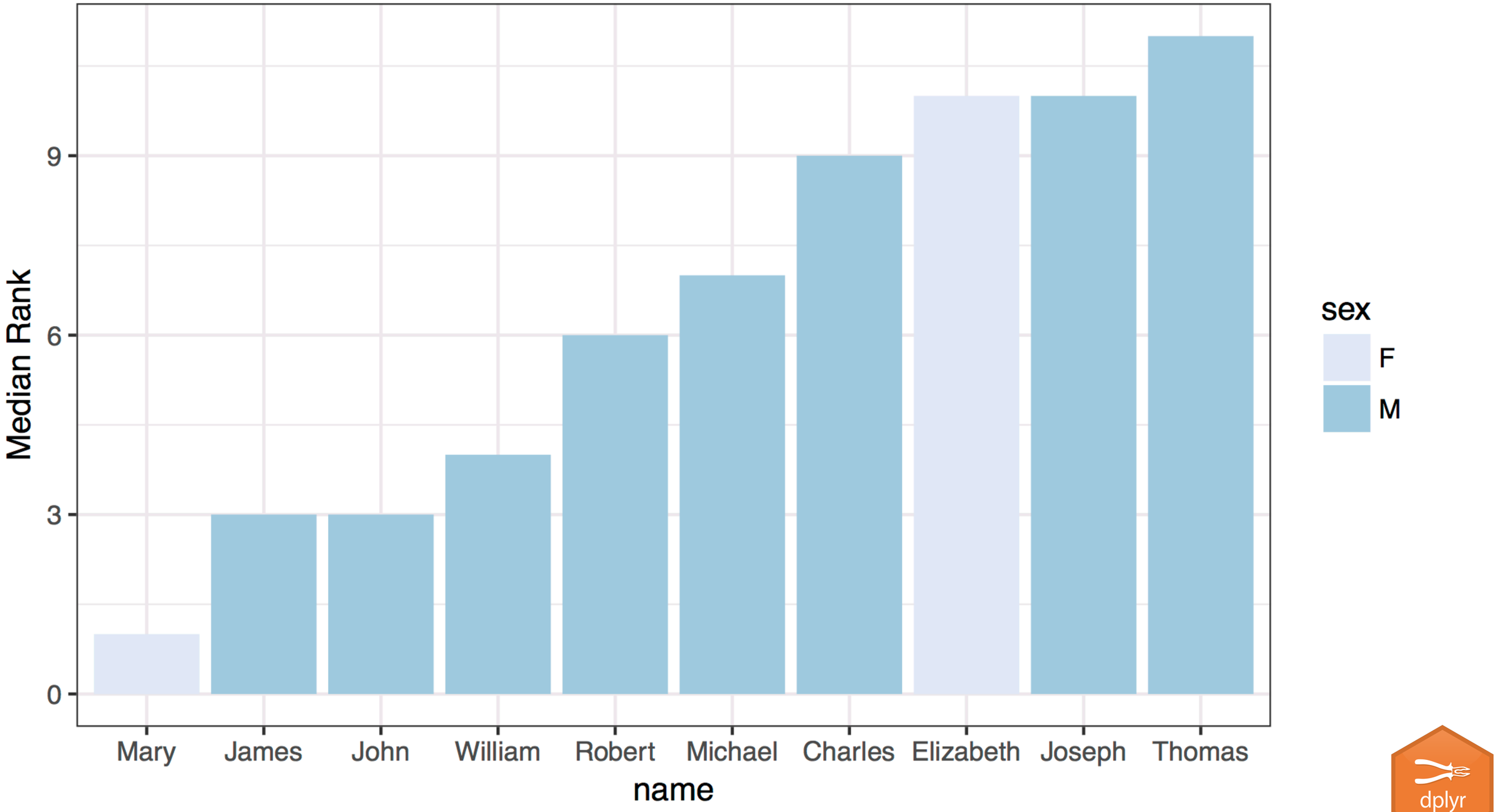
```
babynames %>%
  group_by(year, sex) %>%
  mutate(rank = min_rank(desc(prop)))
```

What was each name's median rank?

i.e., compute each name's rank *within its year and sex*.

Then compute the median rank for each combination of *name and sex*, and arrange the results from highest median rank to lowest.

```
babynames %>%
  group_by(year, sex) %>%
  mutate(rank = min_rank(desc(prop))) %>%
  group_by(name, sex) %>%
  summarise(score = median(rank)) %>%
  arrange(score)
#         name   sex score
#  1      Mary     F     1
#  2     James     M     3
#  3      John     M     3
#  4   William     M     4
#  5    Robert     M     6
# ... with 105,381 more rows
```


Median Rank
0
3
6
9
Mary
James
John
William
Robert
Michael
Charles
Elizabeth
Joseph
Thomas
name
sex
F
M

```
babynames %>%
  group_by(year, sex) %>%
  mutate(rank = min_rank(desc(prop))) %>%
  group_by(name, sex) %>%
  summarise(score = median(rank)) %>%
  ungroup() %>%
  arrange(score) %>%
  slice(1:10) %>%
  ggplot() +
    geom_col(mapping = aes(x = fct_reorder(name, score), y = score,
      fill = sex)) +
    theme_bw() +
    scale_fill_brewer() +
    labs(x = "name", y = "Median Rank")
```

Recap: Single table verbs

Extract variables with **select()**

Extract cases with **filter()**

Arrange cases, with **arrange()**.

Make tables of summaries with **summarise()**.

Make new variables, with **mutate()**.

Joining Datasets

In R4DS

Relational Data

nycflights13

Data about every flight that departed La Guardia, JFK, or Newark airports in 2013

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

Flights

```
View(flights)
```

year	month	day	dep_time	sched_dep_time	dep_delay	arr_time	sched_arr_time	arr_delay	carrier	flight	tailnum	origin	dest	air_time	distance	hour	minute	time_hour
2013	1	1	517	515	2	830	819	11	UA	1545	N14228	EWR	IAH	227	1400	5	15	2013-01-01 05:00:00
2013	1	1	533	529	4	850	830	20	UA	1714	N24211	LGA	IAH	227	1416	5	29	2013-01-01 05:00:00
2013	1	1	542	540	2	923	850	33	AA	1141	N619AA	JFK	MIA	160	1089	5	40	2013-01-01 05:00:00
2013	1	1	544	545	-1	1004	1022	-18	B6	725	N804JB	JFK	BQN	183	1576	5	45	2013-01-01 05:00:00
2013	1	1	554	600	-6	812	837	-25	DL	461	N668DN	LGA	ATL	116	762	6	0	2013-01-01 06:00:00
2013	1	1	554	558	-4	740	728	12	UA	1696	N39463	EWR	ORD	150	719	5	58	2013-01-01 05:00:00
2013	1	1	555	600	-5	913	854	19	B6	507	N516JB	EWR	FLL	158	1065	6	0	2013-01-01 06:00:00
2013	1	1	557	600	-3	709	723	-14	EV	5708	N829AS	LGA	IAD	53	229	6	0	2013-01-01 06:00:00
2013	1	1	557	600	-3	838	846	-8	B6	79	N593JB	JFK	MCO	140	944	6	0	2013-01-01 06:00:00
2013	1	1	558	600	-2	753	745	8	AA	301	N3ALAA	LGA	ORD	138	733	6	0	2013-01-01 06:00:00
2013	1	1	558	600	-2	849	851	-2	B6	49	N793JB	JFK	PBI	149	1028	6	0	2013-01-01 06:00:00
2013	1	1	558	600	-2	853	856	-3	B6	71	N657JB	JFK	TPA	158	1005	6	0	2013-01-01 06:00:00
2013	1	1	558	600	-2	924	917	7	UA	194	N29129	JFK	LAX	345	2475	6	0	2013-01-01 06:00:00
2013	1	1	558	600	-2	923	937	-14	UA	1124	N53441	EWR	SFO	361	2565	6	0	2013-01-01 06:00:00
2013	1	1	559	600	-1	941	910	31	AA	707	N3DUAA	LGA	DFW	257	1389	6	0	2013-01-01 06:00:00
2013	1	1	559	559	0	702	706	-4	B6	1806	N708JB	JFK	BOS	44	187	5	59	2013-01-01 05:00:00
2013	1	1	559	600	-1	854	902	-8	UA	1187	N76515	EWR	LAS	337	2227	6	0	2013-01-01 06:00:00
2013	1	1	600	600	0	851	858	-7	B6	371	N595JB	LGA	FLL	152	1076	6	0	2013-01-01 06:00:00

skim(flights)

```
Skim summary statistics
 n obs: 336776
 n variables: 19

── Variable type:character ─────────────────────────────────────────────────────
 variable missing complete      n min max empty n_unique
  carrier       0   336776 336776   2   2     0       16
     dest       0   336776 336776   3   3     0      105
   origin       0   336776 336776   3   3     0        3
  tailnum    2512   334264 336776   5   6     0     4043

── Variable type:integer ───────────────────────────────────────────────────────
       variable missing complete      n    mean      sd   p0  p25  p50  p75 p100     hist
       arr_time    8713   328063 336776 1502.05  533.26    1 1104 1535 1940 2400 ▁▂▆▇▇▇▇▅
            day       0   336776 336776   15.71    8.77    1    8   16   23   31 ▇▇▇▇▆▇▇▇
       dep_time    8255   328521 336776 1349.11  488.28    1  907 1401 1744 2400 ▁▃▇▇▇▇▅▂
         flight       0   336776 336776 1971.92 1632.47    1  553 1496 3465 8500 ▇▃▂▁▂▁▁▁
          month       0   336776 336776    6.55    3.41    1    4    7   10   12 ▇▅▆▃▅▆▅▇
 sched_arr_time       0   336776 336776 1536.38  497.46    1 1124 1556 1945 2359 ▁▂▆▅▇▇▇▇
 sched_dep_time       0   336776 336776 1344.25  467.34  106  906 1359 1729 2359 ▁▃▆▇▇▇▇▃
           year       0   336776 336776 2013       0    2013 2013 2013 2013 2013 ▁▁▁▇▁▁▁▁

── Variable type:numeric ───────────────────────────────────────────────────────
  variable missing complete      n    mean     sd  p0 p25 p50  p75 p100     hist
  air_time    9430   327346 336776  150.69  93.69  20  82 129  192  695 ▇▆▂▂▁▁▁▁
 arr_delay    9430   327346 336776    6.9   44.63 -86 -17  -5   14 1272 ▇▁▁▁▁▁▁▁
 dep_delay    8255   328521 336776   12.64  40.21 -43  -5  -2   11 1301 ▇▁▁▁▁▁▁▁
  distance       0   336776 336776 1039.91 733.23  17 382 872 1389 4983 ▇▃▂▂▁▁▁▁
      hour       0   336776 336776   13.18   4.66   1   9  13   17   23 ▂▆▇▇▆▆▃▁
    minute       0   336776 336776   26.23  19.3    0   8  29   44   59 ▇▃▅▃▅▃▅▃
```

Details

⚠ The class of service you searched may not be available on one or more flights

BNA - ORD
Flight 1 of 2

ORD - YVR
Flight 2 of 2

Nashville, TN to Chicago, IL

Thursday, July 26, 2018

4:10 PM → 6:03 PM

AA 3246 ▪ CR7-Canadair RJ 700

Operated by SkyWest Airlines As American Eagle

Travel info

Travel time: **1h 53m**
Connection time: **2h 33m**

Performanc

On time: **52**
Late: **43%**

Main Cabin

Meals: Beverage service
Booking code: V
Class: Economy

Business

Meals: Beverage service
Booking code: I
Class: First

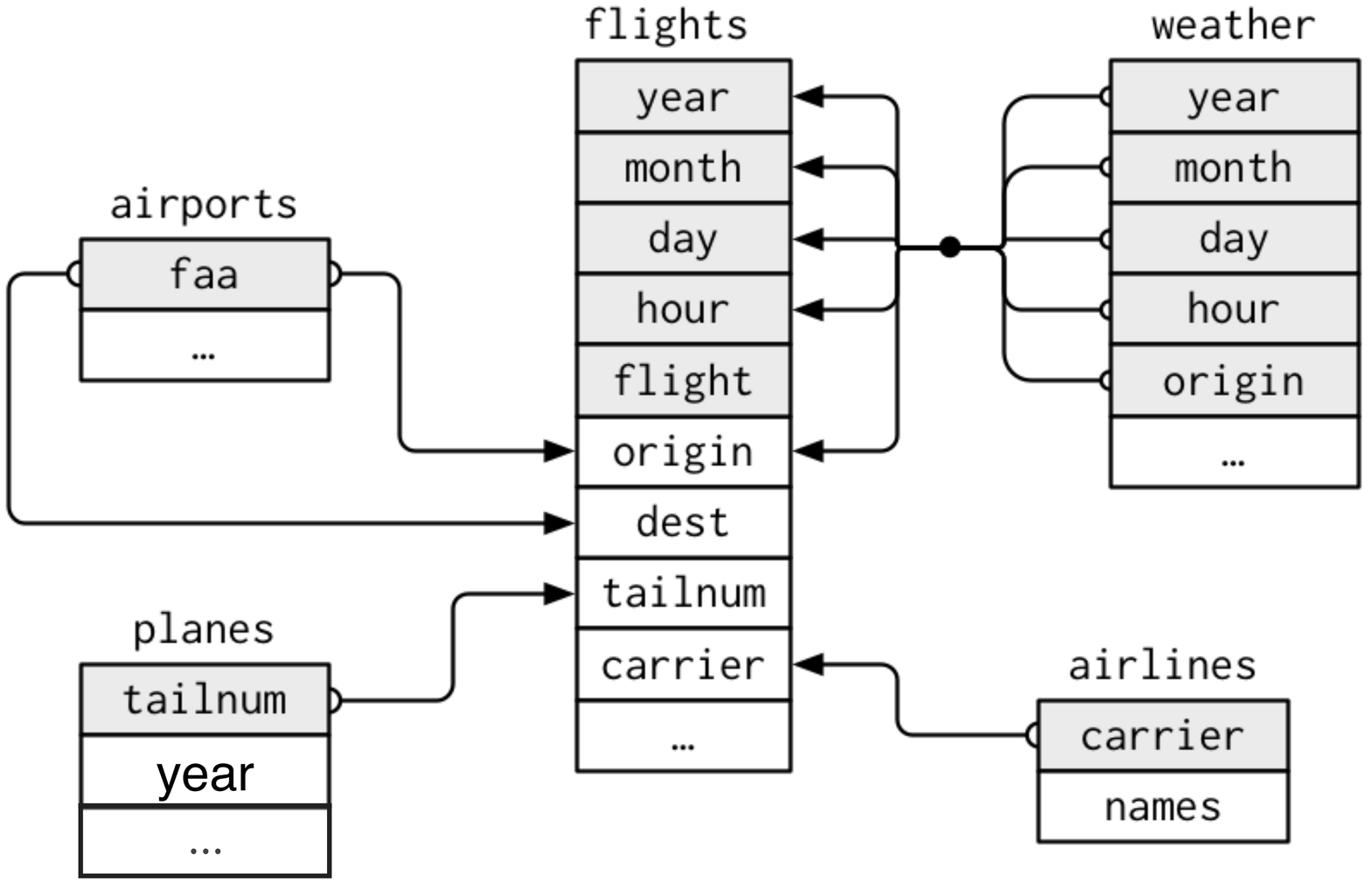
* This is based on information from the month of May 2018
** The on-time arrival percentage for the selected flight is based on arrival within 14 minutes after

Performance*

On time: **52%****
Late: **43%**

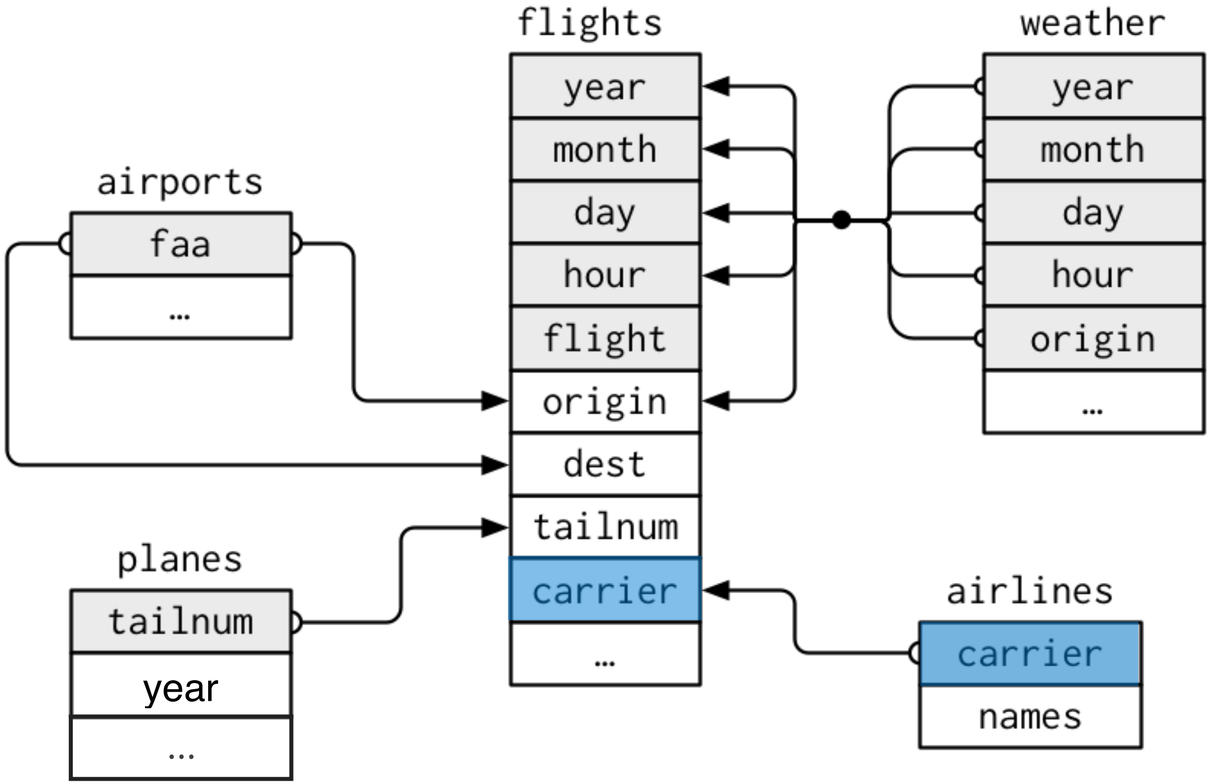
** The on-time arrival percentage for the selected flight is based on arrival within 14 minutes after the scheduled arrival as reported monthly to the U.S. Department of Transportation.

nycflights13



nycflights13

What airline had the longest delays?



Airline names

```
View(flights["carrier"])
```

	carrier
1	UA
2	UA
3	AA
4	B6
5	DL
6	UA
7	B6

```
View(airlines)
```

	carrier	name
1	9E	Endeavor Air Inc.
2	AA	American Airlines Inc.
3	AS	Alaska Airlines Inc.
4	B6	JetBlue Airways
5	DL	Delta Air Lines Inc.
6	EV	ExpressJet Airlines Inc.
7	F9	Frontier Airlines Inc.

types of joins

Mutating joins use information from one data set **to add variables** to another data set (like **mutate()**)

Filtering joins use information from one data set **to extract cases** from another data set (like **filter()**)

mutating joins

common syntax

Each join function returns a data frame / tibble.

```
left_join(x, y, by = NULL, … )
```

join function

data frames to join

names of columns to join on

Toy data

```
band <- tribble(
   ~name,     ~band,
  "Mick",  "Stones",
  "John", "Beatles",
  "Paul", "Beatles"
)
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

```
instrument <- tribble(
    ~name,   ~plays,
   "John", "guitar",
   "Paul",   "bass",
  "Keith", "guitar"
)
```

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

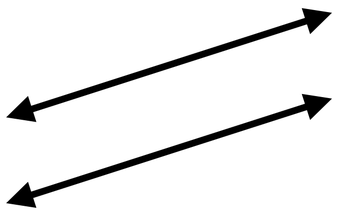
Toy data

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar



left

```
band %>% left_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass

right

```
band %>% right_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
John	Beatles	guitar
Paul	Beatles	bass
Keith	<NA>	guitar

full

```
band %>% full_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass
Keith	<NA>	guitar

inner

```
band %>% inner_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
John	Beatles	guitar
Paul	Beatles	bass

Airline names

```
View(flights["carrier"])
```

	carrier
1	UA
2	UA
3	AA
4	B6
5	DL
6	UA
7	B6

```
View(airlines)
```

	carrier	name
1	9E	Endeavor Air Inc.
2	AA	American Airlines Inc.
3	AS	Alaska Airlines Inc.
4	B6	JetBlue Airways
5	DL	Delta Air Lines Inc.
6	EV	ExpressJet Airlines Inc.
7	F9	Frontier Airlines Inc.

Your Turn 15

Which airlines had the largest arrival delays? Work in groups to complete the code below.

```
flights %>%
  drop_na(arr_delay) %>%
  _____________________ %>%
  group_by(_____________) %>%
  _____________________ %>%
  arrange(_____)
```

1. Join airlines to flights

2. Compute and order the average arrival delays by airline. Display full names, no codes.

```
flights %>%
  drop_na(arr_delay) %>%
  left_join(airlines, by = "carrier") %>%
  group_by(name) %>%
  summarise(delay = mean(arr_delay)) %>%
  arrange(delay)
```

```
## # A tibble: 16 × 2
##                          name       delay
##                         <chr>       <dbl>
## 1   Alaska Airlines Inc. -9.9308886
## 2   Hawaiian Airlines Inc. -6.9152047
## 3   American Airlines Inc.  0.3642909
## 4   Delta Air Lines Inc.  1.6443409
## 5   Virgin America  1.7644644
```

Toy data

```
band <- tribble(
   ~name,     ~band,
  "Mick",  "Stones",
  "John", "Beatles",
  "Paul", "Beatles"
)
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

```
instrument2 <- tribble(
    ~artist,   ~plays,
   "John", "guitar",
   "Paul",   "bass",
  "Keith", "guitar"
)
```

instrument2

artist	plays
John	guitar
Paul	bass
Keith	guitar

What if the names do not match?

Use a named vector to match on variables with different names.

```
band %>% left_join(instrument2, by = c("name" = "artist"))
```

A named vector

The name of the element = the column name in the first data set

The value of the element = the column name in the second data set

common syntax - matching names

```
band %>% left_join(instrument2, by = c("name" = "artist"))
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument2

artist	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band	plays
Mick	Stones	<NA>
John	Beatles	guitar
Paul	Beatles	bass

Airport names

```
View(flights["dest"])
```

	dest
1	IAH
2	IAH
3	MIA
4	BQN
5	ATL
6	ORD

```
View(airports)
```

faa	name
04G	Lansdowne Airport
06A	Moton Field Municipal Airport
06C	Schaumburg Regional
06N	Randall Airport
09J	Jekyll Island Airport
0A9	Elizabethton Municipal Airport

Airport names

```
airports %>% select(1:3)
```

faa <chr>	name <chr>
04G	Lansdowne Airport
06A	Moton Field Municipal Airport
06C	Schaumburg Regional
06N	Randall Airport
09J	Jekyll Island Airport
0A9	Elizabethton Municipal Airport
0G6	Williams County Airport
0G7	Finger Lakes Regional Airport

```
flights %>% select(14:15)
```

dest <chr>	air_time <dbl>
IAH	227
IAH	227
MIA	160
BQN	183
ATL	116
ORD	150
FLL	158
IAD	53

common syntax - matching names

```
airports %>% left_join(flights, by = c("faa" = "dest"))
```

faa <chr>	name <chr>
04G	Lansdowne Airport
06A	Moton Field Municipal Airport
06C	Schaumburg Regional
06N	Randall Airport
09J	Jekyll Island Airport
0A9	Elizabethton Municipal Airport
0G6	Williams County Airport
0G7	Finger Lakes Regional Airport

dest <chr>	air_time <dbl>
IAH	227
IAH	227
MIA	160
BQN	183
ATL	116
ORD	150
FLL	158
IAD	53

filtering joins

filtering joins

Mutating joins use information from one data set **to add variables** to another data set (like **mutate()**)

Filtering joins use information from one data set **to extract cases** from another data set (like **filter()**)

semi

```
band %>% semi_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band
John	Beatles
Paul	Beatles

anti

```
band %>% anti_join(instrument, by = "name")
```

band

name	band
Mick	Stones
John	Beatles
Paul	Beatles

+

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

=

name	band
Mick	Stones

Airport names

```
airports %>% select(1:3)
```

faa <chr>	name <chr>
04G	Lansdowne Airport
06A	Moton Field Municipal Airport
06C	Schaumburg Regional
06N	Randall Airport
09J	Jekyll Island Airport
0A9	Elizabethton Municipal Airport
0G6	Williams County Airport
0G7	Finger Lakes Regional Airport

```
flights %>% select(14:15)
```

dest <chr>	air_time <dbl>
IAH	227
IAH	227
MIA	160
BQN	183
ATL	116
ORD	150
FLL	158
IAD	53

Your Turn 16

How many airports in **airports** are serviced by flights originating in New York (i.e. flights in our dataset?)

Notice that the column to join on is named **faa** in the **airports** dataset and **dest** in the **flights** dataset.

```
airports %>%
  semi_join(flights, by = c("faa" = "dest")) %>%
  distinct(faa)
```

faa <chr>
IAH
MIA
ATL
ORD
FLL
IAD
MCO
PBI
TPA
LAX

1–10 of 101 rows

distinct()

Removes rows with duplicate values (in a column).

```
distinct(instrument, plays)
```

instrument

name	plays
John	guitar
Paul	bass
Keith	guitar

plays
guitar
bass

Recap: Two table verbs

left_join() retains all cases in **left** data set

right_join() retains all cases in **right** data set

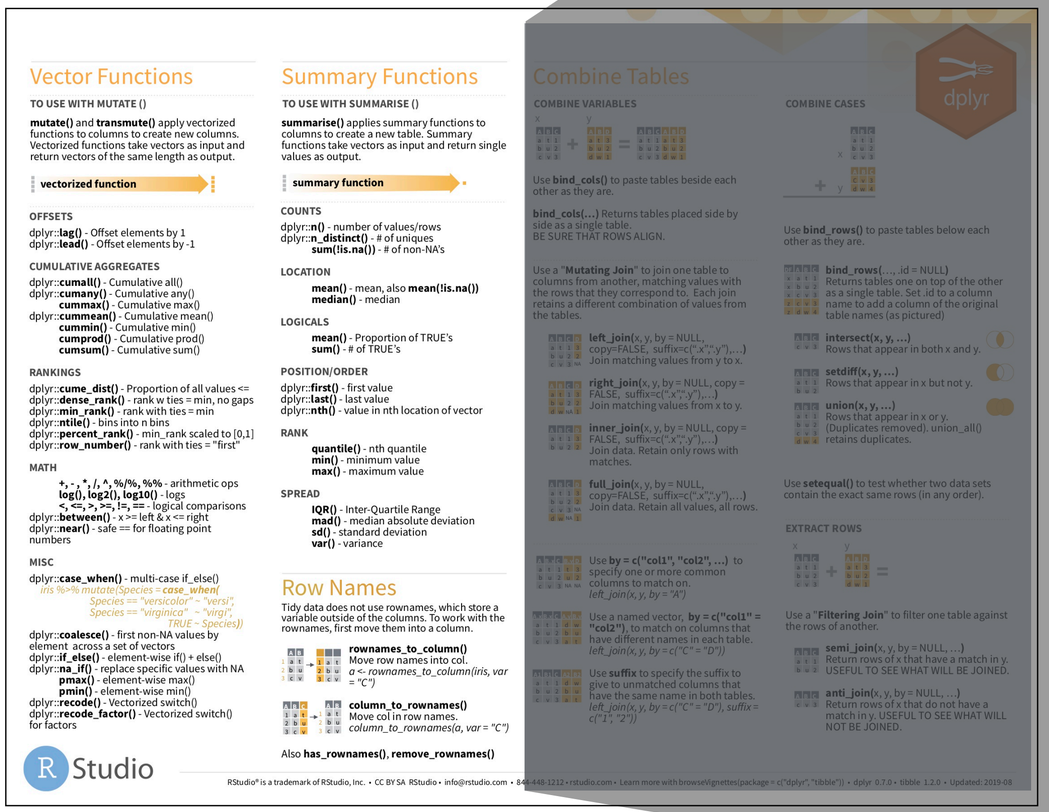
full_join() retains all cases in **either** data set

inner_join() retains only cases in **both** data sets

semi_join() extracts cases that **have a match**

anti_join() extracts cases that **do not have a match**

Two table verbs



Vector Functions

TO USE WITH MUTATE ()

mutate() and **transmute()** apply vectorized functions to columns to create new columns. Vectorized functions take vectors as input and return vectors of the same length as output.

vectorized function

OFFSETS

dplyr::**lag()** - Offset elements by 1
dplyr::**lead()** - Offset elements by -1

CUMULATIVE AGGREGATES

dplyr::**cumall()** - Cumulative all()
dplyr::**cumany()** - Cumulative any()
cummax() - Cumulative max()
dplyr::**cummean()** - Cumulative mean()
cummin() - Cumulative min()
cumprod() - Cumulative prod()
cumsum() - Cumulative sum()

RANKINGS

dplyr::**cume_dist()** - Proportion of all values <=
dplyr::**dense_rank()** - rank w ties = min, no gaps
dplyr::**min_rank()** - rank with ties = min
dplyr::**ntile()** - bins into n bins
dplyr::**percent_rank()** - min_rank scaled to [0,1]
dplyr::**row_number()** - rank with ties = "first"

MATH

+, - , * , /, ^, %/%, %% - arithmetic ops
log(), log2(), log10() - logs
<, <=, >, >=, !=, == - logical comparisons
dplyr::**between()** - x >= left & x <= right
dplyr::**near()** - safe == for floating point numbers

MISC

dplyr::**case_when()** - multi-case if_else()

```
iris %>% mutate(Species = case_when(
                Species == "versicolor" ~ "versi",
                Species == "virginica"  ~ "virgi",
                TRUE ~ Species))
```

dplyr::**coalesce()** - first non-NA values by element across a set of vectors
dplyr::**if_else()** - element-wise if() + else()
dplyr::**na_if()** - replace specific values with NA
pmax() - element-wise max()
pmin() - element-wise min()
dplyr::**recode()** - Vectorized switch()
dplyr::**recode_factor()** - Vectorized switch() for factors

Summary Functions

TO USE WITH SUMMARISE ()

summarise() applies summary functions to columns to create a new table. Summary functions take vectors as input and return single values as output.

summary function

COUNTS

dplyr::**n()** - number of values/rows
dplyr::**n_distinct()** - # of uniques
sum(!is.na()) - # of non-NA's

LOCATION

mean() - mean, also **mean(!is.na())**
median() - median

LOGICALS

mean() - Proportion of TRUE's
sum() - # of TRUE's

POSITION/ORDER

dplyr::**first()** - first value
dplyr::**last()** - last value
dplyr::**nth()** - value in nth location of vector

RANK

quantile() - nth quantile
min() - minimum value
max() - maximum value

SPREAD

IQR() - Inter-Quartile Range
mad() - median absolute deviation
sd() - standard deviation
var() - variance

Row Names

Tidy data does not use rownames, which store a variable outside of the columns. To work with the rownames, first move them into a column.

rownames_to_column()
Move row names into col.
a <- rownames_to_column(iris, var = "C")

column_to_rownames()
Move col in row names.
column_to_rownames(a, var = "C")

Also **has_rownames()**, **remove_rownames()**

Combine Tables

COMBINE VARIABLES

Use **bind_cols()** to paste tables beside each other as they are.

bind_cols(...) Returns tables placed side by side as a single table.
BE SURE THAT ROWS ALIGN.

Use a "**Mutating Join**" to join one table to columns from another, matching values with the rows that they correspond to. Each join retains a different combination of values from the tables.

left_join(x, y, by = NULL, copy=FALSE, suffix=c(".x",".y"),...)
Join matching values from y to x.

right_join(x, y, by = NULL, copy = FALSE, suffix=c(".x",".y"),...)
Join matching values from x to y.

inner_join(x, y, by = NULL, copy = FALSE, suffix=c(".x",".y"),...)
Join data. Retain only rows with matches.

full_join(x, y, by = NULL, copy=FALSE, suffix=c(".x",".y"),...)
Join data. Retain all values, all rows.

Use **by = c("col1", "col2", ...)** to specify one or more common columns to match on.
left_join(x, y, by = "A")

Use a named vector, **by = c("col1" = "col2")**, to match on columns that have different names in each table.
left_join(x, y, by = c("C" = "D"))

Use **suffix** to specify the suffix to give to unmatched columns that have the same name in both tables.
left_join(x, y, by = c("C" = "D"), suffix = c("1", "2"))

COMBINE CASES

Use **bind_rows()** to paste tables below each other as they are.

bind_rows(..., .id = NULL)
Returns tables one on top of the other as a single table. Set .id to a column name to add a column of the original table names (as pictured)

intersect(x, y, ...)
Rows that appear in both x and y.

setdiff(x, y, ...)
Rows that appear in x but not y.

union(x, y, ...)
Rows that appear in x or y. (Duplicates removed). union_all() retains duplicates.

Use **setequal()** to test whether two data sets contain the exact same rows (in any order).

EXTRACT ROWS

Use a "**Filtering Join**" to filter one table against the rows of another.

semi_join(x, y, by = NULL, ...)
Return rows of x that have a match in y. USEFUL TO SEE WHAT WILL BE JOINED.

anti_join(x, y, by = NULL, ...)
Return rows of x that do not have a match in y. USEFUL TO SEE WHAT WILL NOT BE JOINED.

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Transform Data with