COLUMBIA UNIVERSITY
IN THE CITY OF NEW YORK

DSFBA: Data Wrangling

Data Science for Business Analytics

Thibault Vatter

Department of Statistics, Columbia University

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Outline

1 Tidy data

2 Filter

3 Arrange

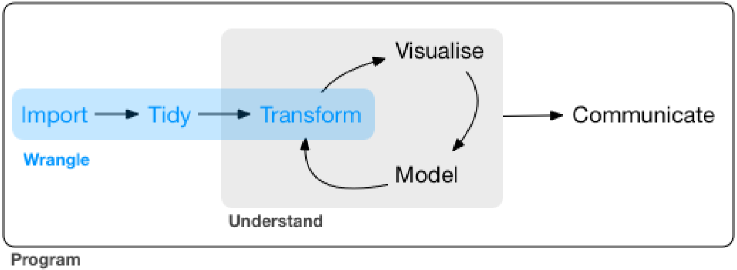
4 Select

5 Mutate

6 Summarize

7 Relational data

Today



Most of the material (e.g., the picture above) is borrowed from

R for data science

A grammar of data manipulation

- When working with data you must:
  - Figure out what you want to do.
  - Describe those tasks as a computer program.
  - Execute the program.
- The `dplyr` package makes this fast and easy with 5 verbs!
  - `filter()`: select observations based on their values.
  - `arrange()`: reorder the observations.
  - `select()`: select variables based on their names.
  - `mutate()`: add variables as functions of existing variables.
  - `summarize()`: collapse many values down to a single summary.
- Two important features:
  - Verbs can be used with `group_by()` to operate groupwise.
  - Verbs work similarly...
    1. First argument: a data frame.
    2. Other arguments: what to do with it using variable names.
    3. Result: a new data frame.

nycflights13

All 336,776 flights that departed from NYC in 2013 (US BTS):

```
nycflights13::flights
#> # A tibble: 336,776 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      517            515         2      830
#>  2  2013     1     1      533            529         4      850
#>  3  2013     1     1      542            540         2      923
#>  4  2013     1     1      544            545        -1     1004
#>  5  2013     1     1      554            600        -6      812
#>  6  2013     1     1      554            558        -4      740
#>  7  2013     1     1      555            600        -5      913
#>  8  2013     1     1      557            600        -3      709
#>  9  2013     1     1      557            600        -3      838
#> 10  2013     1     1      558            600        -2      753
#> # ... with 336,766 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

What is this code doing?

```
a1 <- group_by(flights, year, month, day)
a2 <- select(a1, arr_delay, dep_delay)
a3 <- summarize(a2,
                arr = mean(arr_delay, na.rm = TRUE),
                dep = mean(dep_delay, na.rm = TRUE))
filter(a3, arr > 30 | dep > 30)
#> # A tibble: 49 x 5
#> # Groups:   year, month [11]
#>     year month   day   arr   dep
#>    <int> <int> <int> <dbl> <dbl>
#>  1  2013     1    16  34.2  24.6
#>  2  2013     1    31  32.6  28.7
#>  3  2013     2    11  36.3  39.1
#>  4  2013     2    27  31.3  37.8
#>  5  2013     3     8  85.9  83.5
#>  6  2013     3    18  41.3  30.1
#>  7  2013     4    10  38.4  33.0
#>  8  2013     4    12  36.0  34.8
#>  9  2013     4    18  36.0  34.9
#> 10  2013     4    19  47.9  46.1
#> # ... with 39 more rows
```

Same code (no unnecessary objects)

```
filter(summarize(select(group_by(flights, year, month, day),
           arr_delay, dep_delay),
    arr = mean(arr_delay, na.rm = TRUE),
    dep = mean(dep_delay, na.rm = TRUE)),
    arr > 30 | dep > 30)
#> # A tibble: 49 x 5
#> # Groups:   year, month [11]
#>     year month   day   arr   dep
#>    <int> <int> <int> <dbl> <dbl>
#>  1  2013     1    16  34.2  24.6
#>  2  2013     1    31  32.6  28.7
#>  3  2013     2    11  36.3  39.1
#>  4  2013     2    27  31.3  37.8
#>  5  2013     3     8  85.9  83.5
#>  6  2013     3    18  41.3  30.1
#>  7  2013     4    10  38.4  33.0
#>  8  2013     4    12  36.0  34.8
#>  9  2013     4    18  36.0  34.9
#> 10  2013     4    19  47.9  46.1
#> # ... with 39 more rows
```

. . . Or use %>%

```
flights %>%
  group_by(year, month, day) %>%
  select(arr_delay, dep_delay) %>%
  summarize(arr = mean(arr_delay, na.rm = TRUE),
            dep = mean(dep_delay, na.rm = TRUE)) %>%
  filter(arr > 30 | dep > 30)
#> # A tibble: 49 x 5
#> # Groups:   year, month [11]
#>     year month   day   arr   dep
#>    <int> <int> <int> <dbl> <dbl>
#>  1  2013     1    16  34.2  24.6
#>  2  2013     1    31  32.6  28.7
#>  3  2013     2    11  36.3  39.1
#>  4  2013     2    27  31.3  37.8
#>  5  2013     3     8  85.9  83.5
#>  6  2013     3    18  41.3  30.1
#>  7  2013     4    10  38.4  33.0
#>  8  2013     4    12  36.0  34.8
#>  9  2013     4    18  36.0  34.9
#> 10  2013     4    19  47.9  46.1
#> # ... with 39 more rows
```

Basic piping

- `x %>% f` is equivalent to `f(x)`
- `x %>% f(y)` is equivalent to `f(x, y)`
- `x %>% f(y) %>% g(z)` is equivalent to `g(f(x, y), z)`

```r
x <- 1:10
y <- x + 1
z <- y + 1
f <- function(x, y) x + y

x %>% sum
#> [1] 55
x %>% f(y)
#>  [1]  3  5  7  9 11 13 15 17 19 21
x %>% f(y) %>% f(z)
#>  [1]  6  9 12 15 18 21 24 27 30 33
```

The argument (“dot”) placeholder

- `x %>% f(y, .)` is equivalent to `f(y, x)`
- `x %>% f(y, z = .)` is equivalent to `f(y, z = x)`

```
x <- 1:10
y <- 2 * x
f <- function(z, y) y / z

x %>% f(y, .)
#>  [1] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
x %>% f(y, z = .)
#>  [1] 2 2 2 2 2 2 2 2 2 2
```

Function composition

- Each of the three options has its own strengths and weaknesses:
  - Nesting, `f(g(x))`:
    - Concise, and well suited for short sequences.
    - Longer sequences harder to read (inside out & right to left).
    - Arguments can get spread out over long distances (see Dagwood sandwich).
  - Intermediate objects, `y <- f(x); g(y)`:
    - Requires you to name intermediate objects.
    - A strength when objects are important, but a weakness when values are truly intermediate.
  - Piping, `x %>% f() %>% g()`:
    - Allows to read code in straightforward left-to-right fashion.
    - Doesn't require to name intermediate objects.
    - Only for linear sequences of transformations of a single object.
- Most code use a combination of all three styles, but. . .
- **Piping is more common in data analysis code!**

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Tidy data

> *"Happy families are all alike; every unhappy family is unhappy in its own way." —- Leo Tolstoy*

> *"Tidy datasets are all alike, but every messy dataset is messy in its own way." —- Hadley Wickham*

To learn more about the underlying theory, see the Tidy Data paper.

Which representation is “best”?

- First representation?

```
table1
#> # A tibble: 6 x 4
#>   country      year  cases population
#>   <chr>       <int>  <int>      <int>
#> 1 Afghanistan  1999    745   19987071
#> 2 Afghanistan  2000   2666   20595360
#> 3 Brazil       1999  37737  172006362
#> 4 Brazil       2000  80488  174504898
#> 5 China        1999 212258 1272915272
#> 6 China        2000 213766 1280428583
```

- Second representation?

```
table2
#> # A tibble: 12 x 4
#>    country      year type            count
#>    <chr>       <int> <chr>           <int>
#>  1 Afghanistan  1999 cases             745
#>  2 Afghanistan  1999 population   19987071
#>  3 Afghanistan  2000 cases            2666
#>  4 Afghanistan  2000 population   20595360
#>  5 Brazil       1999 cases           37737
#>  6 Brazil       1999 population  172006362
#>  7 Brazil       2000 cases           80488
#>  8 Brazil       2000 population  174504898
#>  9 China        1999 cases          212258
#> 10 China        1999 population 1272915272
#> 11 China        2000 cases          213766
#> 12 China        2000 population 1280428583
```

- Third representation?

```
table3
#> # A tibble: 6 x 3
#>   country      year rate
#> * <chr>       <int> <chr>
#> 1 Afghanistan  1999 745/19987071
#> 2 Afghanistan  2000 2666/20595360
#> 3 Brazil       1999 37737/172006362
#> 4 Brazil       2000 80488/174504898
#> 5 China        1999 212258/1272915272
#> 6 China        2000 213766/1280428583
```

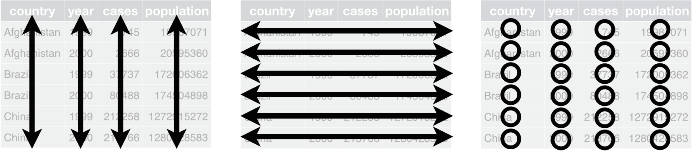
- Fourth representation?

```
table4a  # cases
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#> * <chr>        <int>  <int>
#> 1 Afghanistan    745   2666
#> 2 Brazil       37737  80488
#> 3 China       212258 213766
table4b  # population
#> # A tibble: 3 x 3
#>   country         `1999`     `2000`
#> * <chr>            <int>      <int>
#> 1 Afghanistan   19987071   20595360
#> 2 Brazil       172006362  174504898
#> 3 China       1272915272 1280428583
```

What makes a dataset tidy?

Three interrelated rules:

- Each variable must have its own column.
- Each observation must have its own row.
- Each value must have its own cell.



variables observations values

Because it's impossible to only satisfy two of the three:

- Put each dataset in a tibble.
- Put each variable in a column.

Why ensure that your data is tidy?

- Why?
  - With consistent data structure, it's easier to learn the tools that work with it because they have an underlying uniformity.
  - Placing variables in columns allows R's vectorized nature to shine.
- Tidy data principles seem obvious, BUT:
  - Most people aren't familiar with them.
  - Data often organized to facilitate something different than analysis.
- Hence, you'll most likely need to do some tidying.

The two steps of tidying

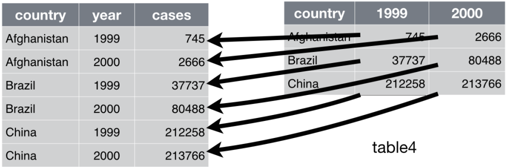
- Figure out what the variables and observations are.
- Resolve one of two common problems:
  - One variable might be spread across multiple columns.
  - One observation might be scattered across multiple rows.

... To fix these problems, you'll need `pivot_longer()` and `pivot_wider()`.

Longer with `pivot_wider()`

```
table4a
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#> * <chr>        <int>  <int>
#> 1 Afghanistan    745   2666
#> 2 Brazil       37737  80488
#> 3 China       212258 213766
```

```
table4a %>%
  pivot_longer(c(`1999`, `2000`),
               names_to = "year",
               values_to = "cases")
#> # A tibble: 6 x 3
#>   country     year   cases
#>   <chr>       <chr>  <int>
#> 1 Afghanistan 1999     745
#> 2 Afghanistan 2000    2666
#> 3 Brazil      1999   37737
#> 4 Brazil      2000   80488
#> 5 China       1999  212258
#> 6 China       2000  213766
```



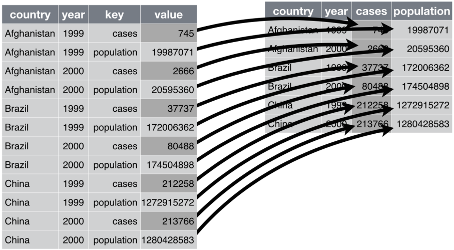
country	year	cases
Afghanistan	1999	745
Afghanistan	2000	2666
Brazil	1999	37737
Brazil	2000	80488
China	1999	212258
China	2000	213766

country	1999	2000
Afghanistan	745	2666
Brazil	37737	80488
China	212258	213766

Wider with `pivot_wider()`

```
table2
#> # A tibble: 12 x 4
#>    country      year type            count
#>    <chr>       <int> <chr>           <int>
#>  1 Afghanistan  1999 cases             745
#>  2 Afghanistan  1999 population   19987071
#>  3 Afghanistan  2000 cases            2666
#>  4 Afghanistan  2000 population   20595360
#>  5 Brazil       1999 cases           37737
#>  6 Brazil       1999 population  172006362
#>  7 Brazil       2000 cases           80488
#>  8 Brazil       2000 population  174504898
#>  9 China        1999 cases          212258
#> 10 China        1999 population 1272915272
#> 11 China        2000 cases          213766
#> 12 China        2000 population 1280428583
```

```
table2 %>%
    pivot_wider(names_from = type,
                values_from = count)
#> # A tibble: 6 x 4
#>   country      year  cases population
#>   <chr>       <int>  <int>      <int>
#> 1 Afghanistan  1999    745   19987071
#> 2 Afghanistan  2000   2666   20595360
#> 3 Brazil       1999  37737  172006362
#> 4 Brazil       2000  80488  174504898
#> 5 China        1999 212258 1272915272
#> 6 China        2000 213766 1280428583
```



country	year	key	value
Afghanistan	1999	cases	745
Afghanistan	1999	population	19987071
Afghanistan	2000	cases	2666
Afghanistan	2000	population	20595360
Brazil	1999	cases	37737
Brazil	1999	population	172006362
Brazil	2000	cases	80488
Brazil	2000	population	174504898
China	1999	cases	212258
China	1999	population	1272915272
China	2000	cases	213766
China	2000	population	1280428583

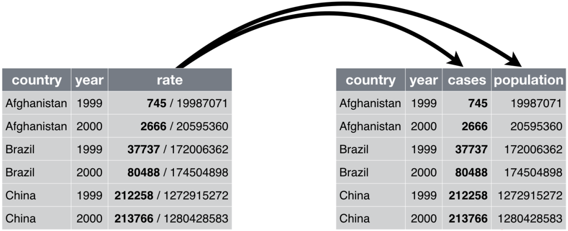
country	year	cases	population
Afghanistan	1999	745	19987071
Afghanistan	2000	2666	20595360
Brazil	1999	37737	172006362
Brazil	2000	80488	174504898
China	1999	212258	1272915272
China	2000	213766	1280428583

table2

Separate a column with separate()

```
table3
#> # A tibble: 6 x 3
#>   country      year rate
#> * <chr>       <int> <chr>
#> 1 Afghanistan  1999 745/19987071
#> 2 Afghanistan  2000 2666/20595360
#> 3 Brazil       1999 37737/172006362
#> 4 Brazil       2000 80488/174504898
#> 5 China        1999 212258/1272915272
#> 6 China        2000 213766/1280428583
```

```
table3 %>% separate(rate,
                    into = c("cases",
                             "population"))
#> # A tibble: 6 x 4
#>   country      year cases  population
#>   <chr>       <int> <chr>  <chr>
#> 1 Afghanistan  1999 745    19987071
#> 2 Afghanistan  2000 2666   20595360
#> 3 Brazil       1999 37737  172006362
#> 4 Brazil       2000 80488  174504898
#> 5 China        1999 212258 1272915272
#> 6 China        2000 213766 1280428583
```



country	year	rate
Afghanistan	1999	**745** / 19987071
Afghanistan	2000	**2666** / 20595360
Brazil	1999	**37737** / 172006362
Brazil	2000	**80488** / 174504898
China	1999	**212258** / 1272915272
China	2000	**213766** / 1280428583

table3

country	year	cases	population
Afghanistan	1999	**745**	19987071
Afghanistan	2000	**2666**	20595360
Brazil	1999	**37737**	172006362
Brazil	2000	**80488**	174504898
China	1999	**212258**	1272915272
China	2000	**213766**	1280428583

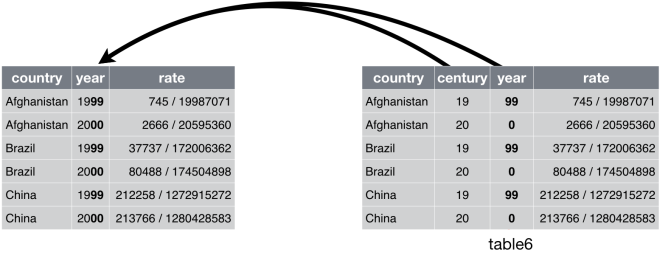
separate() using convert = TRUE

```
table3 %>%
  separate(rate, into = c("cases", "population"), convert = TRUE)
#> # A tibble: 6 x 4
#>   country      year  cases population
#>   <chr>       <int>  <int>      <int>
#> 1 Afghanistan  1999    745   19987071
#> 2 Afghanistan  2000   2666   20595360
#> 3 Brazil       1999  37737  172006362
#> 4 Brazil       2000  80488  174504898
#> 5 China        1999 212258 1272915272
#> 6 China        2000 213766 1280428583
```

Unite two columns with `unite()`

```
table5
#> # A tibble: 6 x 4
#>   country     century year  rate
#> * <chr>       <chr>   <chr> <chr>
#> 1 Afghanistan 19      99    745/19987071
#> 2 Afghanistan 20      00    2666/20595360
#> 3 Brazil      19      99    37737/172006362
#> 4 Brazil      20      00    80488/174504898
#> 5 China       19      99    212258/1272915272
#> 6 China       20      00    213766/1280428583
```

```
table5 %>%
  unite(new, century, year, sep = "")
#> # A tibble: 6 x 3
#>   country     new   rate
#>   <chr>       <chr> <chr>
#> 1 Afghanistan 1999  745/19987071
#> 2 Afghanistan 2000  2666/20595360
#> 3 Brazil      1999  37737/172006362
#> 4 Brazil      2000  80488/174504898
#> 5 China       1999  212258/1272915272
#> 6 China       2000  213766/1280428583
```



country	year	rate
Afghanistan	1999	745 / 19987071
Afghanistan	2000	2666 / 20595360
Brazil	1999	37737 / 172006362
Brazil	2000	80488 / 174504898
China	1999	212258 / 1272915272
China	2000	213766 / 1280428583

country	century	year	rate
Afghanistan	19	99	745 / 19987071
Afghanistan	20	0	2666 / 20595360
Brazil	19	99	37737 / 172006362
Brazil	20	0	80488 / 174504898
China	19	99	212258 / 1272915272
China	20	0	213766 / 1280428583

table6

Missing values and tidy data

- A value can be missing in one of two possible ways:
    - **Explicitly**, i.e. flagged with `NA`.
    - **Implicitly**, i.e. simply not present in the data.

"An explicit missing value is the presence of an absence; an implicit missing value is the absence of a presence." Hadley Wickham

- Are there missing values in this dataset?

```
stocks <- tibble(
  year   = c(2015, 2015, 2015, 2015, 2016, 2016, 2016),
  qtr    = c(   1,    2,    3,    4,    2,    3,    4),
  return = c(1.88, 0.59, 0.35,   NA, 0.92, 0.17, 2.66)
)
```

Implicit to explicit and conversly

- Implicit to explicit by pivoting:

```
stocks %>%
  pivot_wider(names_from = year,
              values_from = return)
#> # A tibble: 4 x 3
#>     qtr `2015` `2016`
#>   <dbl>  <dbl>  <dbl>
#> 1     1   1.88  NA
#> 2     2   0.59   0.92
#> 3     3   0.35   0.17
#> 4     4  NA      2.66
```

- Implicit to explicit using `complete`:

```
stocks %>% complete(year, qtr)
#> # A tibble: 8 x 3
#>    year   qtr return
#>   <dbl> <dbl>  <dbl>
#> 1  2015     1   1.88
#> 2  2015     2   0.59
#> 3  2015     3   0.35
#> 4  2015     4  NA
#> 5  2016     1  NA
#> 6  2016     2   0.92
#> 7  2016     3   0.17
#> 8  2016     4   2.66
```

- Explicit to implicit via `drop_na()`.

Fill in missing values with `fill()`

```
treatment <- tribble(
  ~ person,             ~ treatment, ~response,
  "Derrick Whitmore", 1,           7,
  NA,                 2,           10,
  NA,                 3,           9,
  "Katherine Burke",  1,           4
)
treatment %>%
  fill(person)
#> # A tibble: 4 x 3
#>   person           treatment response
#>   <chr>                <dbl>    <dbl>
#> 1 Derrick Whitmore         1        7
#> 2 Derrick Whitmore         2       10
#> 3 Derrick Whitmore         3        9
#> 4 Katherine Burke          1        4
```

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Filter rows with `filter()`

```
filter(flights, month == 1, day == 1)
#> # A tibble: 842 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      517            515         2      830
#>  2  2013     1     1      533            529         4      850
#>  3  2013     1     1      542            540         2      923
#>  4  2013     1     1      544            545        -1     1004
#>  5  2013     1     1      554            600        -6      812
#>  6  2013     1     1      554            558        -4      740
#>  7  2013     1     1      555            600        -5      913
#>  8  2013     1     1      557            600        -3      709
#>  9  2013     1     1      557            600        -3      838
#> 10  2013     1     1      558            600        -2      753
#> # ... with 832 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

Comparisons

- The standard suite: >, >=, <, <=, !=, and ==.
- Most common mistake:

```
filter(flights, month = 1)
```

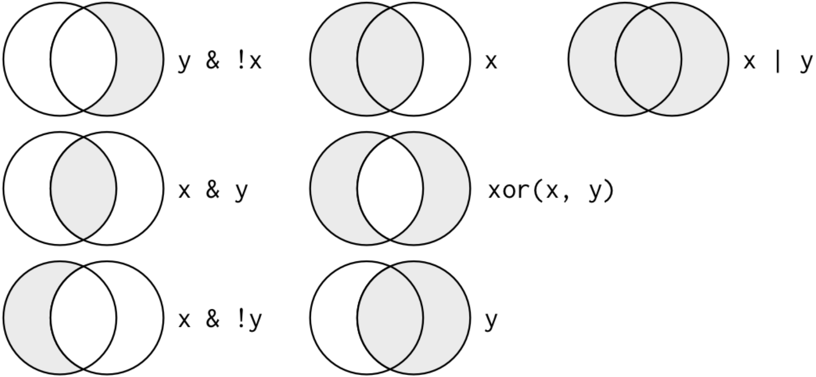
- What happens in the following?

```
sqrt(2) ^ 2 == 2
#> [1] FALSE
1/49 * 49 == 1
#> [1] FALSE
near(sqrt(2) ^ 2,  2)
#> [1] TRUE
near(1 / 49 * 49, 1)
#> [1] TRUE
```

Logical operators

Multiple arguments to `filter()` are combined with:

- & for "and"
- | for "or"
- `!` for "not"



What is this code doing?

```
filter(flights, month == 11 | month == 12)
```

What is this code doing?

```
filter(flights, month == 11 | month == 12)
```

- Literally “finds all flights that departed in November or December”.
- ... `filter(flights, month == 11 | 12)` ?

What is this code doing?

```
filter(flights, month == 11 | month == 12)
```

- Literally “finds all flights that departed in November or December”.
- ... `filter(flights, month == 11 | 12)` ?
- No, but a solution:

```
filter(flights, month %in% c(11, 12))
```

De Morgan's law

- `!(x & y)` is the same as `!x | !y`
- `!(x | y)` is the same as `!x & !y`

```
all.equal(
  filter(flights, !(arr_delay > 120 | dep_delay > 120)),
  filter(flights, arr_delay <= 120, dep_delay <= 120)
  )
#> [1] TRUE
```

Missing values and `filter()`

```
df <- tibble(x = c(1, NA, 3))
filter(df, x > 1)
#> # A tibble: 1 x 1
#>       x
#>   <dbl>
#> 1     3
filter(df, is.na(x) | x > 1)
#> # A tibble: 2 x 1
#>       x
#>   <dbl>
#> 1    NA
#> 2     3
```

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Arrange rows with arrange()

```
arrange(flights, year, month, day)
#> # A tibble: 336,776 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      517            515         2      830
#>  2  2013     1     1      533            529         4      850
#>  3  2013     1     1      542            540         2      923
#>  4  2013     1     1      544            545        -1     1004
#>  5  2013     1     1      554            600        -6      812
#>  6  2013     1     1      554            558        -4      740
#>  7  2013     1     1      555            600        -5      913
#>  8  2013     1     1      557            600        -3      709
#>  9  2013     1     1      557            600        -3      838
#> 10  2013     1     1      558            600        -2      753
#> # ... with 336,766 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

arrange() and desc()

```
arrange(flights, desc(arr_delay))
#> # A tibble: 336,776 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     9      641            900      1301     1242
#>  2  2013     6    15     1432           1935      1137     1607
#>  3  2013     1    10     1121           1635      1126     1239
#>  4  2013     9    20     1139           1845      1014     1457
#>  5  2013     7    22      845           1600      1005     1044
#>  6  2013     4    10     1100           1900       960     1342
#>  7  2013     3    17     2321            810       911      135
#>  8  2013     7    22     2257            759       898      121
#>  9  2013    12     5      756           1700       896     1058
#> 10  2013     5     3     1133           2055       878     1250
#> # ... with 336,766 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

arrange() and missing values

```
df <- tibble(x = c(5, NA, 2))
arrange(df, x)
#> # A tibble: 3 x 1
#>       x
#>   <dbl>
#> 1     2
#> 2     5
#> 3    NA
arrange(df, desc(x))
#> # A tibble: 3 x 1
#>       x
#>   <dbl>
#> 1     5
#> 2     2
#> 3    NA
```

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Select columns with `select()`

```
select(flights, year, month, day)
#> # A tibble: 336,776 x 3
#>     year month   day
#>    <int> <int> <int>
#>  1  2013     1     1
#>  2  2013     1     1
#>  3  2013     1     1
#>  4  2013     1     1
#>  5  2013     1     1
#>  6  2013     1     1
#>  7  2013     1     1
#>  8  2013     1     1
#>  9  2013     1     1
#> 10  2013     1     1
#> # ... with 336,766 more rows
```

All columns between year and day

```
select(flights, year:day)
#> # A tibble: 336,776 x 3
#>     year month   day
#>    <int> <int> <int>
#>  1  2013     1     1
#>  2  2013     1     1
#>  3  2013     1     1
#>  4  2013     1     1
#>  5  2013     1     1
#>  6  2013     1     1
#>  7  2013     1     1
#>  8  2013     1     1
#>  9  2013     1     1
#> 10  2013     1     1
#> # ... with 336,766 more rows
```

All columns except from year to day

```
select(flights, -(year:day))
#> # A tibble: 336,776 x 16
#>    dep_time sched_dep_time dep_delay arr_time sched_arr_time
#>       <int>          <int>     <dbl>    <int>          <int>
#>  1      517            515         2      830            819
#>  2      533            529         4      850            830
#>  3      542            540         2      923            850
#>  4      544            545        -1     1004           1022
#>  5      554            600        -6      812            837
#>  6      554            558        -4      740            728
#>  7      555            600        -5      913            854
#>  8      557            600        -3      709            723
#>  9      557            600        -3      838            846
#> 10      558            600        -2      753            745
#> # ... with 336,766 more rows, and 11 more variables:
#> #   arr_delay <dbl>, carrier <chr>, flight <int>, tailnum <chr>,
#> #   origin <chr>, dest <chr>, air_time <dbl>, distance <dbl>,
#> #   hour <dbl>, minute <dbl>, time_hour <dttm>
```

select() and everything()

```
select(flights, time_hour, air_time, everything())
#> # A tibble: 336,776 x 19
#>    time_hour           air_time  year month   day dep_time
#>    <dttm>                 <dbl> <int> <int> <int>    <int>
#>  1 2013-01-01 05:00:00      227  2013     1     1      517
#>  2 2013-01-01 05:00:00      227  2013     1     1      533
#>  3 2013-01-01 05:00:00      160  2013     1     1      542
#>  4 2013-01-01 05:00:00      183  2013     1     1      544
#>  5 2013-01-01 06:00:00      116  2013     1     1      554
#>  6 2013-01-01 05:00:00      150  2013     1     1      554
#>  7 2013-01-01 06:00:00      158  2013     1     1      555
#>  8 2013-01-01 06:00:00       53  2013     1     1      557
#>  9 2013-01-01 06:00:00      140  2013     1     1      557
#> 10 2013-01-01 06:00:00      138  2013     1     1      558
#> # ... with 336,766 more rows, and 13 more variables:
#> #   sched_dep_time <int>, dep_delay <dbl>, arr_time <int>,
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   distance <dbl>, hour <dbl>, minute <dbl>
```

More on select

- Helper functions you can use within `select()`:
  - `starts_with("abc")`: matches names that begin with "abc".
  - `ends_with("xyz")`: matches names that end with "xyz".
  - `contains("ijk")`: matches names that contain "ijk".
  - `matches("(.)\\1")`: selects variables that match a regular expression (this one matches any variables that contain repeated characters).
  - `num_range("x", 1:3)` matches `x1`, `x2` and `x3`.
- `select()` can be used to rename variables, but it drops all of the variables not explicitly mentioned. Instead, use `rename()`
- See `?select` for more details.

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Create a narrower dataset

```
(flights_sml <- select(flights,
  ends_with("delay"),
  distance,
  air_time))
#> # A tibble: 336,776 x 4
#>    dep_delay arr_delay distance air_time
#>        <dbl>     <dbl>    <dbl>    <dbl>
#>  1         2        11     1400      227
#>  2         4        20     1416      227
#>  3         2        33     1089      160
#>  4        -1       -18     1576      183
#>  5        -6       -25      762      116
#>  6        -4        12      719      150
#>  7        -5        19     1065      158
#>  8        -3       -14      229       53
#>  9        -3        -8      944      140
#> 10        -2         8      733      138
#> # ... with 336,766 more rows
```

Add new variables with mutate()

```
mutate(flights_sml,
  gain = arr_delay - dep_delay,
  speed = distance / air_time * 60)
#> # A tibble: 336,776 x 6
#>    dep_delay arr_delay distance air_time  gain speed
#>        <dbl>     <dbl>    <dbl>    <dbl> <dbl> <dbl>
#>  1         2        11     1400      227     9  370.
#>  2         4        20     1416      227    16  374.
#>  3         2        33     1089      160    31  408.
#>  4        -1       -18     1576      183   -17  517.
#>  5        -6       -25      762      116   -19  394.
#>  6        -4        12      719      150    16  288.
#>  7        -5        19     1065      158    24  404.
#>  8        -3       -14      229       53   -11  259.
#>  9        -3        -8      944      140    -5  405.
#> 10        -2         8      733      138    10  319.
#> # ... with 336,766 more rows
```

Refer to columns just created

```
mutate(flights_sml,
  gain = arr_delay - dep_delay,
  hours = air_time / 60,
  gain_per_hour = gain / hours)
#> # A tibble: 336,776 x 7
#>    dep_delay arr_delay distance air_time  gain hours gain_per_hour
#>        <dbl>     <dbl>    <dbl>    <dbl> <dbl> <dbl>         <dbl>
#>  1         2        11     1400      227     9 3.78           2.38
#>  2         4        20     1416      227    16 3.78           4.23
#>  3         2        33     1089      160    31 2.67          11.6
#>  4        -1       -18     1576      183   -17 3.05          -5.57
#>  5        -6       -25      762      116   -19 1.93          -9.83
#>  6        -4        12      719      150    16 2.5            6.4
#>  7        -5        19     1065      158    24 2.63           9.11
#>  8        -3       -14      229       53   -11 0.883        -12.5
#>  9        -3        -8      944      140    -5 2.33          -2.14
#> 10        -2         8      733      138    10 2.3            4.35
#> # ... with 336,766 more rows
```

transmute()

```
transmute(flights,
  gain = arr_delay - dep_delay,
  hours = air_time / 60,
  gain_per_hour = gain / hours)
#> # A tibble: 336,776 x 3
#>     gain hours gain_per_hour
#>    <dbl> <dbl>         <dbl>
#>  1     9 3.78           2.38
#>  2    16 3.78           4.23
#>  3    31 2.67          11.6 
#>  4   -17 3.05          -5.57
#>  5   -19 1.93          -9.83
#>  6    16 2.5            6.4 
#>  7    24 2.63           9.11
#>  8   -11 0.883        -12.5 
#>  9    -5 2.33          -2.14
#> 10    10 2.3            4.35
#> # ... with 336,766 more rows
```

Useful creation functions I

Any vectorized function would work, but frequently useful are:

- Arithmetic operators: +, −, ∗, /, ˆ.
  - Vectorized with "recycling rules" (e.g., `air_time / 60`).
  - Useful in conjunction with aggregate functions (e.g., `x / sum(x)` or `y - mean(y)`).
- Modular arithmetic: %/% (integer division) and %% (remainder), where `x == y * (x %/% y) + (x %% y)`.
  - Allows you to break integers up into pieces (e.g., `hour = dep_time %/% 100` and `minute = dep_time %% 100`)
- Logs: `log()`, `log2()`, `log10()`.
  - Useful for data ranging across multiple orders of magnitude.
  - Convert multiplicative relationships to additive.

Useful creation functions II

- Offsets: `lead()` and `lag()`:
  - Refer to lead-/lagging values (e.g., compute running differences `x - lag(x)` or find values change `x != lag(x)`).

```
x <- 1:10
lag(x)
#>  [1] NA  1  2  3  4  5  6  7  8  9
lead(x)
#>  [1]  2  3  4  5  6  7  8  9 10 NA
```

- Cumulative aggregates: `cumsum()`, `cumprod()`, `cummin()`, `cummax()`, `cummean()`.

```
cumsum(x)
#>  [1]  1  3  6 10 15 21 28 36 45 55
cummean(x)
#>  [1] 1.0 1.5 2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5
```

Useful creation functions III

- Logical comparisons, <, <=, >, >=, !=
- Ranking functions: `min_rank()`, `row_number()`, `dense_rank()`, `percent_rank()`, `cume_dist()`, `ntile()`

```r
y <- c(1, 2, 2, NA, 3, 4)
min_rank(y)
#> [1]  1  2  2 NA  4  5
min_rank(desc(y))
#> [1]  5  3  3 NA  2  1
row_number(y)
#> [1]  1  2  3 NA  4  5
dense_rank(y)
#> [1]  1  2  2 NA  3  4
percent_rank(y)
#> [1] 0.00 0.25 0.25   NA 0.75 1.00
cume_dist(y)
#> [1] 0.2 0.6 0.6  NA 0.8 1.0
```

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IN THE CITY OF NEW YORK

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Collapse values with `summarize()`

```
summarize(flights, delay = mean(dep_delay, na.rm = TRUE))
#> # A tibble: 1 x 1
#>   delay
#>   <dbl>
#> 1  12.6
```

summarize() paired with group_by()

```
by_day <- group_by(flights, year, month, day)
summarize(by_day, delay = mean(dep_delay, na.rm = TRUE))
#> `summarise()` has grouped output by 'year', 'month'. You can override using t
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>     year month   day delay
#>    <int> <int> <int> <dbl>
#>  1  2013     1     1 11.5
#>  2  2013     1     2 13.9
#>  3  2013     1     3 11.0
#>  4  2013     1     4  8.95
#>  5  2013     1     5  5.73
#>  6  2013     1     6  7.15
#>  7  2013     1     7  5.42
#>  8  2013     1     8  2.55
#>  9  2013     1     9  2.28
#> 10  2013     1    10  2.84
#> # ... with 355 more rows
```

- To suppress the summarize info

```
options(dplyr.summarise.inform = FALSE)
```

An alternative to na.rm: pre-filter

```
not_cancelled <- flights %>% filter(!is.na(dep_delay))
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(mean = mean(dep_delay))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>     year month   day  mean
#>    <int> <int> <int> <dbl>
#>  1  2013     1     1 11.5
#>  2  2013     1     2 13.9
#>  3  2013     1     3 11.0
#>  4  2013     1     4  8.95
#>  5  2013     1     5  5.73
#>  6  2013     1     6  7.15
#>  7  2013     1     7  5.42
#>  8  2013     1     8  2.55
#>  9  2013     1     9  2.28
#> 10  2013     1    10  2.84
#> # ... with 355 more rows
```

Useful summary functions I

- Measures of location: `mean()`, `median()`.
- Measures of spread: `sd()`, `IQR()`, `mad()`.
- Measures of rank: `min(x)`, `quantile(x, 0.25)`, `max(x)`.

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(first = min(dep_time), last = max(dep_time))
#> # A tibble: 365 x 5
#> # Groups:   year, month [12]
#>     year month   day first  last
#>    <int> <int> <int> <int> <int>
#>  1  2013     1     1   517  2356
#>  2  2013     1     2    42  2354
#>  3  2013     1     3    32  2349
#>  4  2013     1     4    25  2358
#>  5  2013     1     5    14  2357
#>  6  2013     1     6    16  2355
#>  7  2013     1     7    49  2359
#>  8  2013     1     8   454  2351
#>  9  2013     1     9     2  2252
#> 10  2013     1    10     3  2320
#> # ... with 355 more rows
```

Useful summary functions II

- Measures of position: `first(x)`, `nth(x, 2)`, `last(x)`.

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(first_dep = first(dep_time), last_dep = last(dep_time))
#> # A tibble: 365 x 5
#> # Groups:   year, month [12]
#>     year month   day first_dep last_dep
#>    <int> <int> <int>     <int>    <int>
#>  1  2013     1     1       517     2356
#>  2  2013     1     2        42     2354
#>  3  2013     1     3        32     2349
#>  4  2013     1     4        25     2358
#>  5  2013     1     5        14     2357
#>  6  2013     1     6        16     2355
#>  7  2013     1     7        49     2359
#>  8  2013     1     8       454     2351
#>  9  2013     1     9         2     2252
#> 10  2013     1    10         3     2320
#> # ... with 355 more rows
```

Useful summary functions III

- Counts: `n(x)`, `sum(!is.na(x))`, `n_distinct(x)`.

```
not_cancelled %>%
  group_by(dest) %>%
  summarize(carriers = n_distinct(carrier)) %>%
  arrange(desc(carriers))
#> # A tibble: 104 x 2
#>    dest  carriers
#>    <chr>    <int>
#>  1 ATL          7
#>  2 BOS          7
#>  3 CLT          7
#>  4 ORD          7
#>  5 TPA          7
#>  6 AUS          6
#>  7 DCA          6
#>  8 DTW          6
#>  9 IAD          6
#> 10 MSP          6
#> # ... with 94 more rows
```

Useful summary functions IV

- A simple helper function for counts:

```
not_cancelled %>% count(dest)
#> # A tibble: 104 x 2
#>    dest      n
#>    <chr> <int>
#>  1 ABQ     254
#>  2 ACK     265
#>  3 ALB     419
#>  4 ANC       8
#>  5 ATL   16898
#>  6 AUS    2418
#>  7 AVL     263
#>  8 BDL     412
#>  9 BGR     360
#> 10 BHM     272
#> # ... with 94 more rows
```

Useful summary functions V

- Counts with an optional weight variable:

```
not_cancelled %>% count(tailnum, wt = distance)
#> # A tibble: 4,037 x 2
#>    tailnum      n
#>    <chr>    <dbl>
#>  1 D942DN    3418
#>  2 N0EGMQ  240626
#>  3 N10156  110389
#>  4 N102UW   25722
#>  5 N103US   24619
#>  6 N104UW   25157
#>  7 N10575  141475
#>  8 N105UW   23618
#>  9 N107US   21677
#> 10 N108UW   32070
#> # ... with 4,027 more rows
```

Useful summary functions VI

- Counts of logical values: e.g., `sum(x > 10)`.

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(n_early = sum(dep_time < 500))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>     year month   day n_early
#>    <int> <int> <int>   <int>
#>  1  2013     1     1       0
#>  2  2013     1     2       3
#>  3  2013     1     3       4
#>  4  2013     1     4       3
#>  5  2013     1     5       3
#>  6  2013     1     6       2
#>  7  2013     1     7       2
#>  8  2013     1     8       1
#>  9  2013     1     9       3
#> 10  2013     1    10       3
#> # ... with 355 more rows
```

Useful summary functions VII

- Proportions of logical values: e.g., `mean(y == 0)`.

```
not_cancelled %>%
  group_by(year, month, day) %>%
  summarize(hour_perc = mean(arr_delay > 60))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>      year month   day hour_perc
#>     <int> <int> <int>     <dbl>
#>  1  2013     1     1    NA
#>  2  2013     1     2    NA
#>  3  2013     1     3    NA
#>  4  2013     1     4    NA
#>  5  2013     1     5     0.0349
#>  6  2013     1     6    NA
#>  7  2013     1     7     0.0333
#>  8  2013     1     8    NA
#>  9  2013     1     9    NA
#> 10  2013     1    10     0.0183
#> # ... with 355 more rows
```

Grouping by multiple variables I

```
daily <- group_by(flights, year, month, day)
(per_day   <- summarize(daily, flights = n()))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>     year month   day flights
#>    <int> <int> <int>   <int>
#>  1  2013     1     1     842
#>  2  2013     1     2     943
#>  3  2013     1     3     914
#>  4  2013     1     4     915
#>  5  2013     1     5     720
#>  6  2013     1     6     832
#>  7  2013     1     7     933
#>  8  2013     1     8     899
#>  9  2013     1     9     902
#> 10  2013     1    10     932
#> # ... with 355 more rows
```

Grouping by multiple variables II

```
(per_month <- summarize(per_day, flights = sum(flights)))
#> # A tibble: 12 x 3
#> # Groups:   year [1]
#>      year month flights
#>     <int> <int>   <int>
#>  1  2013     1   27004
#>  2  2013     2   24951
#>  3  2013     3   28834
#>  4  2013     4   28330
#>  5  2013     5   28796
#>  6  2013     6   28243
#>  7  2013     7   29425
#>  8  2013     8   29327
#>  9  2013     9   27574
#> 10  2013    10   28889
#> 11  2013    11   27268
#> 12  2013    12   28135
(per_year  <- summarize(per_month, flights = sum(flights)))
#> # A tibble: 1 x 2
#>     year flights
#>    <int>   <int>
#> 1  2013  336776
```

Ungrouping

```
daily %>%
  ungroup() %>%                # no longer grouped by date
  summarize(flights = n())  # all flights
#> # A tibble: 1 x 1
#>   flights
#>     <int>
#> 1  336776
```

Grouped filters

```
(popular_dests <- flights %>%
   group_by(dest) %>%
   filter(n() > 365))
#> # A tibble: 332,577 x 19
#> # Groups:   dest [77]
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      517            515         2      830
#>  2  2013     1     1      533            529         4      850
#>  3  2013     1     1      542            540         2      923
#>  4  2013     1     1      544            545        -1     1004
#>  5  2013     1     1      554            600        -6      812
#>  6  2013     1     1      554            558        -4      740
#>  7  2013     1     1      555            600        -5      913
#>  8  2013     1     1      557            600        -3      709
#>  9  2013     1     1      557            600        -3      838
#> 10  2013     1     1      558            600        -2      753
#> # ... with 332,567 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

Grouped mutates

```
popular_dests %>%
  filter(arr_delay > 0) %>%
  mutate(prop_delay = arr_delay / sum(arr_delay)) %>%
  select(year:day, dest, arr_delay, prop_delay)
#> # A tibble: 131,106 x 6
#> # Groups:   dest [77]
#>     year month   day dest  arr_delay prop_delay
#>    <int> <int> <int> <chr>     <dbl>      <dbl>
#>  1  2013     1     1 IAH          11  0.000111
#>  2  2013     1     1 IAH          20  0.000201
#>  3  2013     1     1 MIA          33  0.000235
#>  4  2013     1     1 ORD          12  0.0000424
#>  5  2013     1     1 FLL          19  0.0000938
#>  6  2013     1     1 ORD           8  0.0000283
#>  7  2013     1     1 LAX           7  0.0000344
#>  8  2013     1     1 DFW          31  0.000282
#>  9  2013     1     1 ATL          12  0.0000400
#> 10  2013     1     1 DTW          16  0.000116
#> # ... with 131,096 more rows
```

Outline

1 Tidy data

2 Filter

3 Arrange

4 Select

5 Mutate

6 Summarize

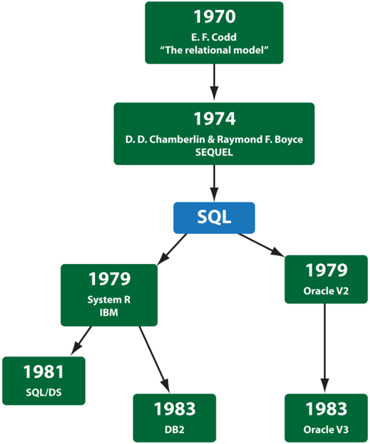
7 Relational data

Relational data

- Until now: analysis of a single table of data.
- Typically: multiple tables of data to be combined.
  - Called **relational data**:
    - Because relations, not just the individual datasets, are important.
    - Relations are always defined for a pair of tables.
    - Relations of three or more tables are built from the relations between pairs.

RDBMS

- Common place to find relational data.
- Oracle, MySQL, Microsoft SQL Server, PostgreSQL, IBM DB2, Microsoft Access, SQLite, and others.



nycflights13::flights

- All 336,776 flights that departed from NYC in 2013 (US BTS):

```
flights
#> # A tibble: 336,776 x 19
#>      year month   day dep_time sched_dep_time dep_delay arr_time
#>     <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>   1  2013     1     1      517            515         2      830
#>   2  2013     1     1      533            529         4      850
#>   3  2013     1     1      542            540         2      923
#>   4  2013     1     1      544            545        -1     1004
#>   5  2013     1     1      554            600        -6      812
#>   6  2013     1     1      554            558        -4      740
#>   7  2013     1     1      555            600        -5      913
#>   8  2013     1     1      557            600        -3      709
#>   9  2013     1     1      557            600        -3      838
#>  10  2013     1     1      558            600        -2      753
#> # ... with 336,766 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

nycflights13::airlines

```
airlines
#> # A tibble: 16 x 2
#>    carrier name
#>    <chr>   <chr>
#>  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.
#>  8 FL      AirTran Airways Corporation
#>  9 HA      Hawaiian Airlines Inc.
#> 10 MQ      Envoy Air
#> 11 OO      SkyWest Airlines Inc.
#> 12 UA      United Air Lines Inc.
#> 13 US      US Airways Inc.
#> 14 VX      Virgin America
#> 15 WN      Southwest Airlines Co.
#> 16 YV      Mesa Airlines Inc.
```

nycflights13::airports

```
airports
#> # A tibble: 1,458 x 8
#>    faa   name                  lat    lon   alt    tz dst   tzone
#>    <chr> <chr>               <dbl>  <dbl> <dbl> <dbl> <chr> <chr>
#>  1 04G   Lansdowne Airport    41.1  -80.6  1044    -5 A     America/Ne~
#>  2 06A   Moton Field Muni~    32.5  -85.7   264    -6 A     America/Ch~
#>  3 06C   Schaumburg Regio~    42.0  -88.1   801    -6 A     America/Ch~
#>  4 06N   Randall Airport      41.4  -74.4   523    -5 A     America/Ne~
#>  5 09J   Jekyll Island Ai~    31.1  -81.4    11    -5 A     America/Ne~
#>  6 0A9   Elizabethton Mun~    36.4  -82.2  1593    -5 A     America/Ne~
#>  7 0G6   Williams County ~    41.5  -84.5   730    -5 A     America/Ne~
#>  8 0G7   Finger Lakes Reg~    42.9  -76.8   492    -5 A     America/Ne~
#>  9 0P2   Shoestring Aviat~    39.8  -76.6  1000    -5 U     America/Ne~
#> 10 0S9   Jefferson County~    48.1 -123.    108    -8 A     America/Lo~
#> # ... with 1,448 more rows
```

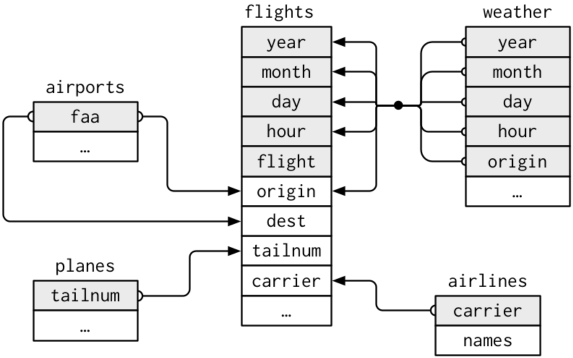
nycflights13::planes

```
planes
#> # A tibble: 3,322 x 9
#>    tailnum  year type   manufacturer model engines seats speed engine
#>    <chr>   <int> <chr>  <chr>        <chr>   <int> <int> <int> <chr>
#>  1 N10156   2004 Fixed~ EMBRAER      EMB-~       2    55    NA Turbo~
#>  2 N102UW   1998 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  3 N103US   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  4 N104UW   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  5 N10575   2002 Fixed~ EMBRAER      EMB-~       2    55    NA Turbo~
#>  6 N105UW   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  7 N107US   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  8 N108UW   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#>  9 N109UW   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#> 10 N110UW   1999 Fixed~ AIRBUS INDU~ A320~       2   182    NA Turbo~
#> # ... with 3,312 more rows
```

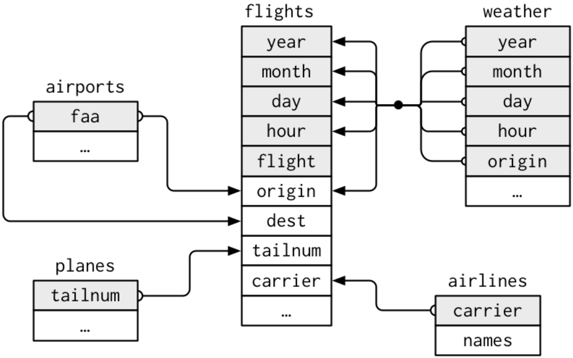
nycflights13::weather

```
weather
#> # A tibble: 26,115 x 15
#>    origin  year month   day  hour  temp  dewp humid wind_dir
#>    <chr>  <int> <int> <int> <int> <dbl> <dbl> <dbl>    <dbl>
#>  1 EWR     2013     1     1     1  39.0  26.1  59.4      270
#>  2 EWR     2013     1     1     2  39.0  27.0  61.6      250
#>  3 EWR     2013     1     1     3  39.0  28.0  64.4      240
#>  4 EWR     2013     1     1     4  39.9  28.0  62.2      250
#>  5 EWR     2013     1     1     5  39.0  28.0  64.4      260
#>  6 EWR     2013     1     1     6  37.9  28.0  67.2      240
#>  7 EWR     2013     1     1     7  39.0  28.0  64.4      240
#>  8 EWR     2013     1     1     8  39.9  28.0  62.2      250
#>  9 EWR     2013     1     1     9  39.9  28.0  62.2      260
#> 10 EWR     2013     1     1    10  41    28.0  59.6      260
#> # ... with 26,105 more rows, and 6 more variables: wind_speed <dbl>,
#> #   wind_gust <dbl>, precip <dbl>, pressure <dbl>, visib <dbl>,
#> #   time_hour <dttm>
```

nycflights13

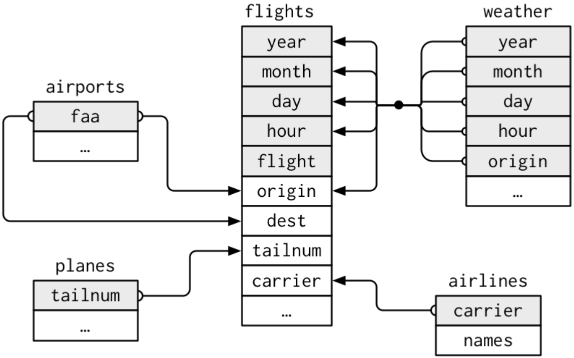


Exercise 1



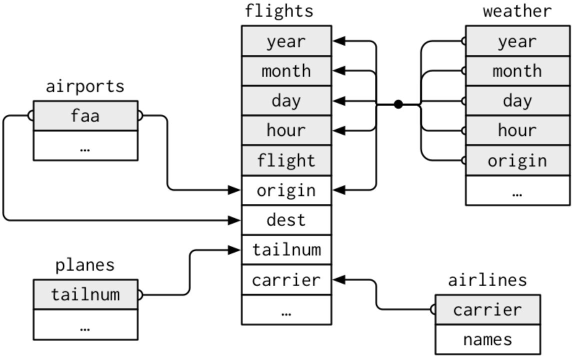
- Imagine you wanted to draw (approximately) the route each plane flies from its origin to its destination.
  - What variables would you need?
  - What tables would you need to combine?

Exercise 2



- I forgot to draw the relationship between `weather` and `airports`.
    - What is the relationship and how should it appear in the diagram?

Exercise 3



- `weather` only contains information for the origin (NYC) airports.
    - If it contained weather records for all airports in the USA, what additional relation would it define with `flights`?

Keys

- Keys:
  - Variables used to connect pair of tables.
  - Uniquely identifies an observation.
  - Can be:
    - A single variable (e.g., `tailnum` for `planes`).
    - Multiple variables (e.g., `year`, `month`, `day`, `hour`, and `origin` for `weather`).
- Two types of **keys**:
  - **Primary:** uniquely identifies an observation **in its own table.**
    - E.g., `planes$tailnum`.
  - **Foreign:** uniquely identifies an observation **in another table.**
    - E.g., `flights$tailnum`.
- Note that:
  - A variable can be both a primary key *and* a foreign key.
  - A primary key and the corresponding foreign key in another table form a **relation**.
  - Relations are typically one-to-many (e.g., flights and planes).

Is a given key primary?

```
planes %>%
  count(tailnum) %>%
  filter(n > 1)
#> # A tibble: 0 x 2
#> # ... with 2 variables: tailnum <chr>, n <int>

weather %>%
  count(year, month, day, hour, origin) %>%
  filter(n > 1)
#> # A tibble: 3 x 6
#>    year month   day  hour origin     n
#>   <int> <int> <int> <int> <chr>  <int>
#> 1  2013    11     3     1 EWR        2
#> 2  2013    11     3     1 JFK        2
#> 3  2013    11     3     1 LGA        2
```

No explicit primary key?

```
flights %>%
  count(year, month, day, flight) %>%
  filter(n > 1)
#> # A tibble: 29,768 x 5
#>     year month   day flight     n
#>    <int> <int> <int>  <int> <int>
#>  1  2013     1     1      1     2
#>  2  2013     1     1      3     2
#>  3  2013     1     1      4     2
#>  4  2013     1     1     11     3
#>  5  2013     1     1     15     2
#>  6  2013     1     1     21     2
#>  7  2013     1     1     27     4
#>  8  2013     1     1     31     2
#>  9  2013     1     1     32     2
#> 10  2013     1     1     35     2
#> # ... with 29,758 more rows
```

- Solution: add one with `mutate()` and `row_number()`.
- This is called a **surrogate key**.

Combining tables

- Two families of verbs to work with relational data:
  - **Mutating joins**
    - Add new variables to one data frame from matching observations in another.
  - **Filtering joins**
    - Filter observations from one data frame based on whether or not they match an observation in the other table.

Create a narrower dataset

```
flights2 <- flights %>%
  select(year:day, hour, origin, dest, tailnum, carrier)

flights2
#> # A tibble: 336,776 x 8
#>     year month   day  hour origin dest  tailnum carrier
#>    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>
#>  1  2013     1     1     5 EWR    IAH   N14228  UA
#>  2  2013     1     1     5 LGA    IAH   N24211  UA
#>  3  2013     1     1     5 JFK    MIA   N619AA  AA
#>  4  2013     1     1     5 JFK    BQN   N804JB  B6
#>  5  2013     1     1     6 LGA    ATL   N668DN  DL
#>  6  2013     1     1     5 EWR    ORD   N39463  UA
#>  7  2013     1     1     6 EWR    FLL   N516JB  B6
#>  8  2013     1     1     6 LGA    IAD   N829AS  EV
#>  9  2013     1     1     6 JFK    MCO   N593JB  B6
#> 10  2013     1     1     6 LGA    ORD   N3ALAA  AA
#> # ... with 336,766 more rows
```

A simple example

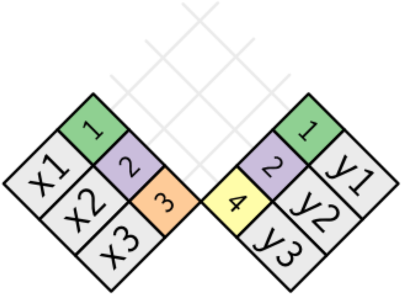
```
flights2 %>%
  select(-origin, -dest) %>%
  left_join(airlines, by = "carrier")
#> # A tibble: 336,776 x 7
#>     year month   day  hour tailnum carrier name
#>    <int> <int> <int> <dbl> <chr>   <chr>   <chr>
#>  1  2013     1     1     5 N14228  UA      United Air Lines Inc.
#>  2  2013     1     1     5 N24211  UA      United Air Lines Inc.
#>  3  2013     1     1     5 N619AA  AA      American Airlines Inc.
#>  4  2013     1     1     5 N804JB  B6      JetBlue Airways
#>  5  2013     1     1     6 N668DN  DL      Delta Air Lines Inc.
#>  6  2013     1     1     5 N39463  UA      United Air Lines Inc.
#>  7  2013     1     1     6 N516JB  B6      JetBlue Airways
#>  8  2013     1     1     6 N829AS  EV      ExpressJet Airlines Inc.
#>  9  2013     1     1     6 N593JB  B6      JetBlue Airways
#> 10  2013     1     1     6 N3ALAA  AA      American Airlines Inc.
#> # ... with 336,766 more rows
```

Why mutating join?

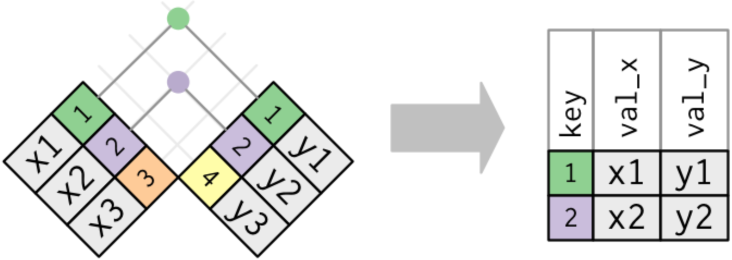
```
flights2 %>%
  select(-origin, -dest) %>%
  mutate(name = airlines$name[match(carrier, airlines$carrier)])
#> # A tibble: 336,776 x 7
#>     year month   day  hour tailnum carrier name
#>    <int> <int> <int> <dbl> <chr>   <chr>   <chr>
#>  1  2013     1     1     5 N14228  UA      United Air Lines Inc.
#>  2  2013     1     1     5 N24211  UA      United Air Lines Inc.
#>  3  2013     1     1     5 N619AA  AA      American Airlines Inc.
#>  4  2013     1     1     5 N804JB  B6      JetBlue Airways
#>  5  2013     1     1     6 N668DN  DL      Delta Air Lines Inc.
#>  6  2013     1     1     5 N39463  UA      United Air Lines Inc.
#>  7  2013     1     1     6 N516JB  B6      JetBlue Airways
#>  8  2013     1     1     6 N829AS  EV      ExpressJet Airlines Inc.
#>  9  2013     1     1     6 N593JB  B6      JetBlue Airways
#> 10  2013     1     1     6 N3ALAA  AA      American Airlines Inc.
#> # ... with 336,766 more rows
```

Understanding mutating joins

```
x <- tribble(~key, ~val_x,
             1, "x1",
             2, "x2",
             3, "x3")
y <- tribble(~key, ~val_y,
             1, "y1",
             2, "y2",
             4, "y3")
```



Inner join



key	val_x	val_y
1	x1	y1
2	x2	y2

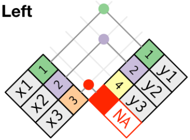
```
x %>%
  inner_join(y, by = "key")
#> # A tibble: 2 x 3
#>     key val_x val_y
#>   <dbl> <chr> <chr>
#> 1     1 x1    y1
#> 2     2 x2    y2
```

Outer joins

- **Outer joins** keep observations that appear in at least one of the tables:
  - **Left join:** keeps all observations in `x`.
  - **Right join:** keeps all observations in `y`.
  - **Full join:** keeps all observations in `x` and `y`
- They work by adding to each table an additional “virtual” observation which
  - has a key that always matches (if no other key matches),
  - and a value filled with `NA`.

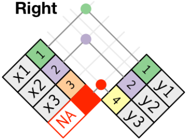
Outer joins II

Left



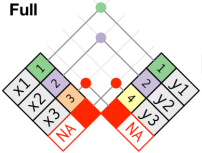
key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA

Right



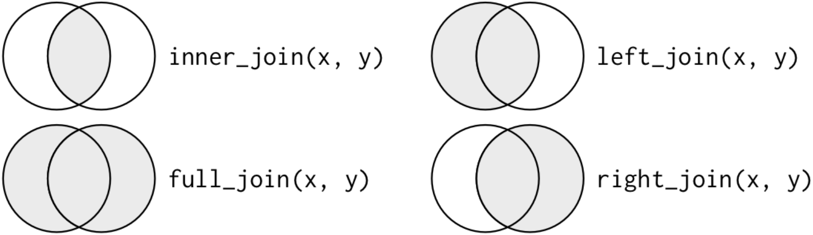
key	val_x	val_y
1	x1	y1
2	x2	y2
4	NA	y3

Full



key	val_x	val_y
1	x1	y1
2	x2	y2
3	x3	NA
4	NA	y3

A Venn diagram for joins



Duplicate keys

- Two possibilities:
  - One table has duplicate keys.
    - Useful to add in additional information as there is typically a one-to-many relationship.
  - Both tables have duplicate keys.
    - Usually an error because in neither table do the keys uniquely identify an observation.
    - When you join duplicated keys, you get all possible combinations (i.e., the Cartesian product).

One table has duplicate keys

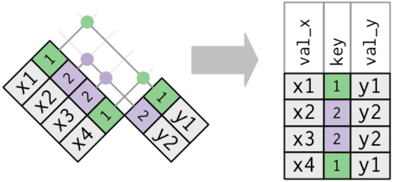
- Only x has duplicated keys:

```
x <- tribble(~key, ~val_x,
             1, "x1",
             2, "x2",
             2, "x3",
             1, "x4")
```

```
y <- tribble(~key, ~val_y,
             1, "y1",
             2, "y2")
```

- The join adds val_y to the matching rows:

```
left_join(x, y, by = "key")
#> # A tibble: 4 x 3
#>     key val_x val_y
#>   <dbl> <chr> <chr>
#> 1     1 x1    y1
#> 2     2 x2    y2
#> 3     2 x3    y2
#> 4     1 x4    y1
```



val_x	key	val_y
x1	1	y1
x2	2	y2
x3	2	y2
x4	1	y1

Both tables have duplicate keys

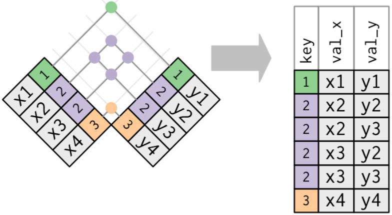
- Both x and y have duplicated keys:

```
x <- tribble(~key, ~val_x,
             1, "x1",
             2, "x2",
             2, "x3",
             3, "x4")
```

```
y <- tribble(~key, ~val_y,
             1, "y1",
             2, "y2",
             2, "y3",
             3, "y4")
```

- The joint creates all combinations:

```
left_join(x, y, by = "key")
#> # A tibble: 6 x 3
#>     key val_x val_y
#>   <dbl> <chr> <chr>
#> 1     1 x1    y1
#> 2     2 x2    y2
#> 3     2 x2    y3
#> 4     2 x3    y2
#> 5     2 x3    y3
#> 6     3 x4    y4
```



key	val_x	val_y
1	x1	y1
2	x2	y2
2	x2	y3
2	x3	y2
2	x3	y3
3	x4	y4

Defining the key columns

- Default uses all variables that appear in both tables.
- Called a **natural join.**

```
flights2 %>%
  left_join(weather)
#> Joining, by = c("year", "month", "day", "hour", "origin")
#> # A tibble: 336,776 x 18
#>     year month   day  hour origin dest  tailnum carrier  temp  dewp
#>    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <dbl> <dbl>
#>  1  2013     1     1     5 EWR    IAH   N14228  UA       39.0  28.0
#>  2  2013     1     1     5 LGA    IAH   N24211  UA       39.9  25.0
#>  3  2013     1     1     5 JFK    MIA   N619AA  AA       39.0  27.0
#>  4  2013     1     1     5 JFK    BQN   N804JB  B6       39.0  27.0
#>  5  2013     1     1     6 LGA    ATL   N668DN  DL       39.9  25.0
#>  6  2013     1     1     5 EWR    ORD   N39463  UA       39.0  28.0
#>  7  2013     1     1     6 EWR    FLL   N516JB  B6       37.9  28.0
#>  8  2013     1     1     6 LGA    IAD   N829AS  EV       39.9  25.0
#>  9  2013     1     1     6 JFK    MCO   N593JB  B6       37.9  27.0
#> 10  2013     1     1     6 LGA    ORD   N3ALAA  AA       39.9  25.0
#> # ... with 336,766 more rows, and 8 more variables: humid <dbl>,
#> #   wind_dir <dbl>, wind_speed <dbl>, wind_gust <dbl>, precip <dbl>,
#> #   pressure <dbl>, visib <dbl>, time_hour <dttm>
```

Using a character vector

- Like a natural join, but uses only some of the common variables:

```
flights2 %>%
  left_join(planes, by = "tailnum")
#> # A tibble: 336,776 x 16
#>    year.x month   day  hour origin dest  tailnum carrier year.y type
#>     <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>    <int> <chr>
#>  1   2013     1     1     5 EWR    IAH   N14228  UA        1999 Fixe~
#>  2   2013     1     1     5 LGA    IAH   N24211  UA        1998 Fixe~
#>  3   2013     1     1     5 JFK    MIA   N619AA  AA        1990 Fixe~
#>  4   2013     1     1     5 JFK    BQN   N804JB  B6        2012 Fixe~
#>  5   2013     1     1     6 LGA    ATL   N668DN  DL        1991 Fixe~
#>  6   2013     1     1     5 EWR    ORD   N39463  UA        2012 Fixe~
#>  7   2013     1     1     6 EWR    FLL   N516JB  B6        2000 Fixe~
#>  8   2013     1     1     6 LGA    IAD   N829AS  EV        1998 Fixe~
#>  9   2013     1     1     6 JFK    MCO   N593JB  B6        2004 Fixe~
#> 10   2013     1     1     6 LGA    ORD   N3ALAA  AA          NA <NA>
#> # ... with 336,766 more rows, and 6 more variables:
#> #   manufacturer <chr>, model <chr>, engines <int>, seats <int>,
#> #   speed <int>, engine <chr>
```

Using a named character vector

- With `by = c("a" = "b")`, `left_join` matches variable a in table `x` to variable `b` in table `y`:

```
flights2 %>%
  left_join(airports, c("dest" = "faa"))
#> # A tibble: 336,776 x 15
#>     year month   day  hour origin dest  tailnum carrier name      lat
#>    <int> <int> <int> <dbl> <chr>  <chr> <chr>   <chr>   <chr>   <dbl>
#>  1  2013     1     1     5 EWR    IAH   N14228  UA      George~  30.0
#>  2  2013     1     1     5 LGA    IAH   N24211  UA      George~  30.0
#>  3  2013     1     1     5 JFK    MIA   N619AA  AA      Miami ~  25.8
#>  4  2013     1     1     5 JFK    BQN   N804JB  B6      <NA>     NA
#>  5  2013     1     1     6 LGA    ATL   N668DN  DL      Hartsf~  33.6
#>  6  2013     1     1     5 EWR    ORD   N39463  UA      Chicag~  42.0
#>  7  2013     1     1     6 EWR    FLL   N516JB  B6      Fort L~  26.1
#>  8  2013     1     1     6 LGA    IAD   N829AS  EV      Washin~  38.9
#>  9  2013     1     1     6 JFK    MCO   N593JB  B6      Orland~  28.4
#> 10  2013     1     1     6 LGA    ORD   N3ALAA  AA      Chicag~  42.0
#> # ... with 336,766 more rows, and 5 more variables: lon <dbl>,
#> #   alt <dbl>, tz <dbl>, dst <chr>, tzone <chr>
```

SQL is the inspiration

dplyr	SQL
`inner_join(x, y, by = "z")`	`SELECT * FROM x INNER JOIN y USING (z)`
`left_join(x, y, by = "z")`	`SELECT * FROM x LEFT OUTER JOIN y USING (z)`
`right_join(x, y, by = "z")`	`SELECT * FROM x RIGHT OUTER JOIN y USING (z)`
`full_join(x, y, by = "z")`	`SELECT * FROM x FULL OUTER JOIN y USING (z)`

- Note that:
  - "INNER" and "OUTER" are optional, and often omitted.
  - Joining different variables between the tables uses a slightly different syntax in SQL.
    - E.g. `inner_join(x, y, by = c("a" = "b"))` vs `SELECT * FROM x INNER JOIN y ON x.a = y.b`.

Filtering joins

- Similar to mutating joins, but affect the observations rather than the variables:
    - `semi_join(x, y)` **keeps** all observations in `x` that have a match in `y`.
        - Useful for matching filtered summary tables back to the original rows.
    - `anti_join(x, y)` **drops** all observations in `x` that have a match in `y`.
        - Useful for diagnosing join mismatches.

Flights that went to top destinations

```
top_dest <- flights %>%
  count(dest, sort = TRUE) %>%
  head(10)

flights %>%
  filter(dest %in% top_dest$dest) %>%
  print(n = 5)
#> # A tibble: 141,145 x 19
#>    year month   day dep_time sched_dep_time dep_delay arr_time
#>   <int> <int> <int>    <int>          <int>     <dbl>    <int>
#> 1  2013     1     1      542            540         2      923
#> 2  2013     1     1      554            600        -6      812
#> 3  2013     1     1      554            558        -4      740
#> 4  2013     1     1      555            600        -5      913
#> 5  2013     1     1      557            600        -3      838
#> # ... with 141,140 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

- How to extend to multiple variables?

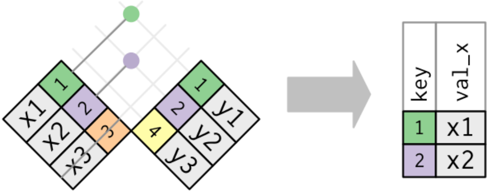
Semi-join

- Only keeps rows in x having a match in y:

```
flights %>%
  semi_join(top_dest)
#> Joining, by = "dest"
#> # A tibble: 141,145 x 19
#>     year month   day dep_time sched_dep_time dep_delay arr_time
#>    <int> <int> <int>    <int>          <int>     <dbl>    <int>
#>  1  2013     1     1      542            540         2      923
#>  2  2013     1     1      554            600        -6      812
#>  3  2013     1     1      554            558        -4      740
#>  4  2013     1     1      555            600        -5      913
#>  5  2013     1     1      557            600        -3      838
#>  6  2013     1     1      558            600        -2      753
#>  7  2013     1     1      558            600        -2      924
#>  8  2013     1     1      558            600        -2      923
#>  9  2013     1     1      559            559         0      702
#> 10  2013     1     1      600            600         0      851
#> # ... with 141,135 more rows, and 12 more variables:
#> #   sched_arr_time <int>, arr_delay <dbl>, carrier <chr>,
#> #   flight <int>, tailnum <chr>, origin <chr>, dest <chr>,
#> #   air_time <dbl>, distance <dbl>, hour <dbl>, minute <dbl>,
#> #   time_hour <dttm>
```

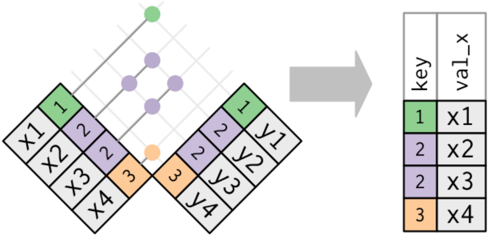
Visually understand the semi-join

- One-to-many:



key	val_x
1	x1
2	x2

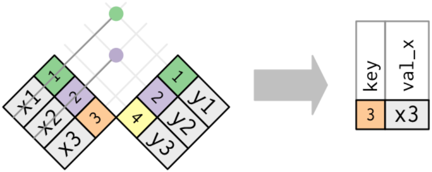
- Many-to-many:



key	val_x
1	x1
2	x2
2	x3
3	x4

flights without a match in planes

```
flights %>%
  anti_join(planes,
            by = "tailnum") %>%
  count(tailnum, sort = TRUE)
#> # A tibble: 722 x 2
#>    tailnum      n
#>    <chr>    <int>
#>  1 <NA>      2512
#>  2 N725MQ     575
#>  3 N722MQ     513
#>  4 N723MQ     507
#>  5 N713MQ     483
#>  6 N735MQ     396
#>  7 N0EGMQ     371
#>  8 N534MQ     364
#>  9 N542MQ     363
#> 10 N531MQ     349
#> # ... with 712 more rows
```


1
2
3
x1
x2
x3
1
2
4
y1
y2
y3
key
val_x
3
x3