# Data Science for Business Analytics

*Data Wrangling – 1*

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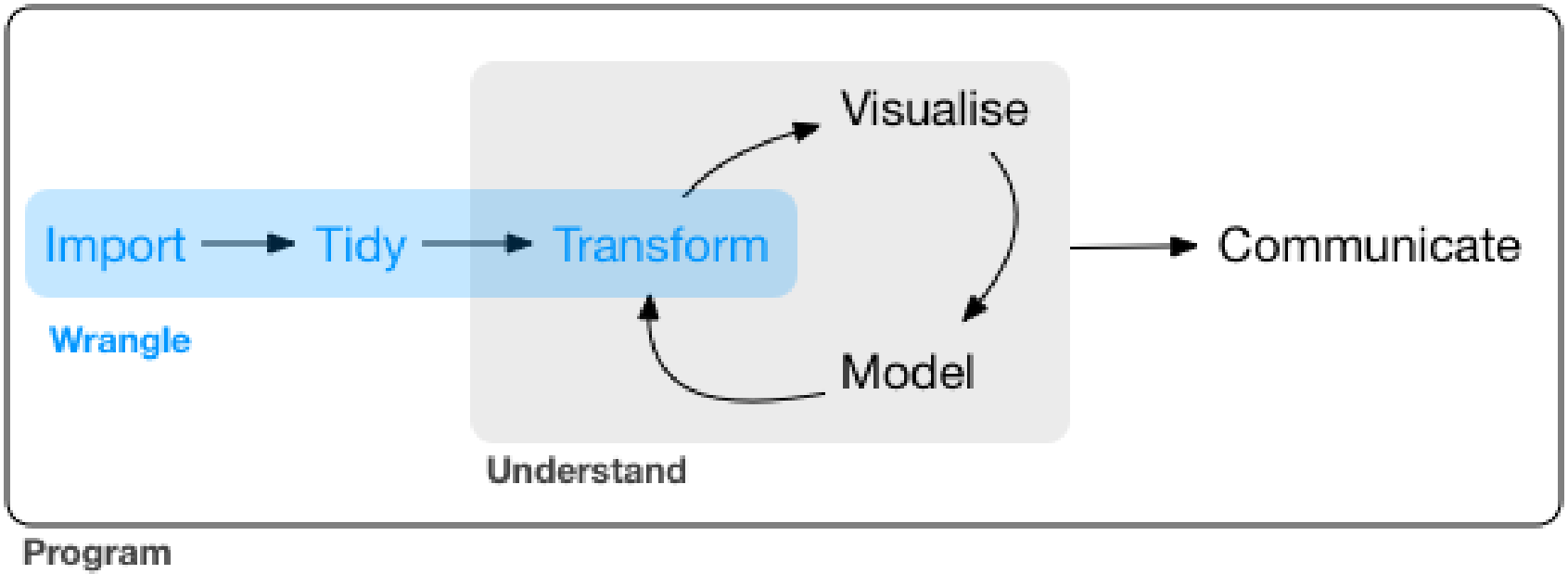
# Outline

# 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 it 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 group-wise.
  - Verbs work similarly...
    1. First argument: a `tibble` or a `data.frame`.
    2. Other arguments: what to do with it using variable names.
    3. Result: a new `tibble` or a `data.frame`.

# The dplyr package examples

Some examples using dplyr package on mtcars data set.

- Select rows with filter() where cyl is equal to 8.

```
filter(mtcars, cyl == 8)
```

- Arrange rows with arrange() by mpg.

```
arrange(mtcars, mpg)
```

- Select columns with select() where mpg and cyl are present.

```
select(mtcars, mpg, cyl)
```

- Add a new column with mutate() that is the ratio of hp to wt.

```
mutate(mtcars, hp_per_wt = hp / wt)
```

- Summarize the data with summarize() by calculating the mean of mpg.

```
summarize(mtcars, mean_mpg = mean(mpg))
```

# nycflights13 package

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
#> # i 336,766 more rows
#> # i 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
#> # i 39 more rows
```

1. **Group** flights by year, month, and day.
2. **Select** arrival and departure delays.
3. **Calculate** the mean arrival and departure delays.
4. **Filter** for days with average arrival or departure delays greater than 30 minutes.

# 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
#> # i 39 more rows
```

# Use the pipe operator |> or %>%

```
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
#> # i 39 more rows
```

**Advantages:**

- Focus on the **high-level composition** of functions.
- Focus on **what's being done**, not on what's being modified.
- Makes your code **more readable** by:
  - **Structuring** sequences of data operations left-to-right.
  - **Minimizing** the need for local variables and function definitions.
  - Making it easy to **add steps** anywhere in the sequence.

# 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)`

```
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 placeholder

- When `f` doesn't take the LHS as the first argument, use the `_` placeholder.
  - In general, **try to avoid this usage**.
- `x |> f(y, z = _)` is equivalent to `f(y, z = x)`
- The placeholder can only be used with *named* arguments

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

x |> f(y, b = _)
#>  [1] 2 2 2 2 2 2 2 2 2 2
x |> f(y, a = _)
#>  [1] 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5 0.5
```

# 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).
    - Arguments can get spread out over long distances.
  - 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.
    - Only for linear sequences transforming a single object.
- Most code use a combination of all three styles, but
  - **piping '|>' is more common in data analysis code.**

# Agenda

1. Tidy data
2. Filter, arrange select
3. Mutate
4. Summarize
5. Grouping

# 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?

```
tidyr::table1
#> # A tibble: 6 x 4
#>   country      year  cases population
#>   <chr>       <dbl>  <dbl>      <dbl>
#> 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?

```
tidyr::table2
#> # A tibble: 12 x 4
#>    country      year type            count
#>    <chr>       <dbl> <chr>           <dbl>
#>  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?

```
tidyr::table3
#> # A tibble: 6 x 3
#>   country      year rate
#>   <chr>       <dbl> <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
```

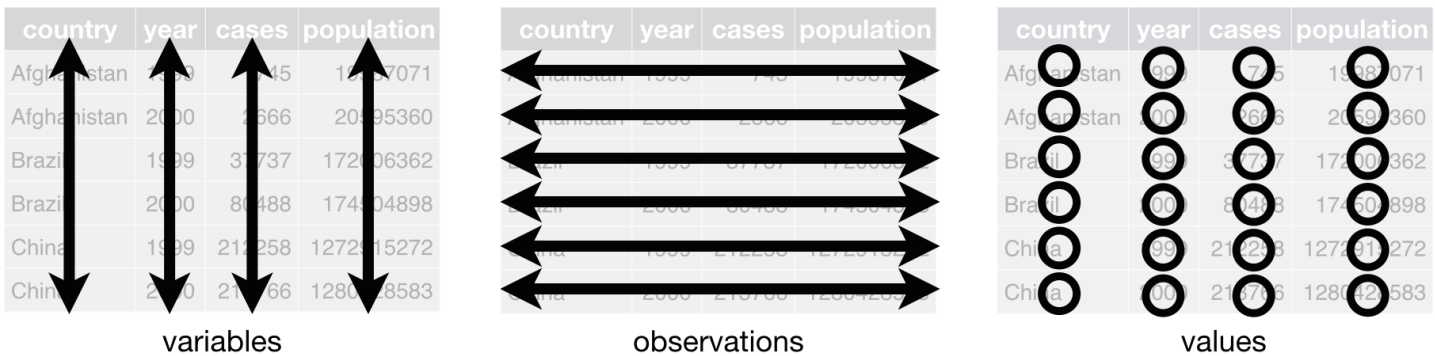
- Fourth representation?

```
tidyr::table4a  # cases
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#>   <chr>        <dbl>  <dbl>
#> 1 Afghanistan    745   2666
#> 2 Brazil       37737  80488
#> 3 China       212258 213766
tidyr::table4b  # population
#> # A tibble: 3 x 3
#>   country         `1999`     `2000`
#>   <chr>            <dbl>      <dbl>
#> 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.




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.

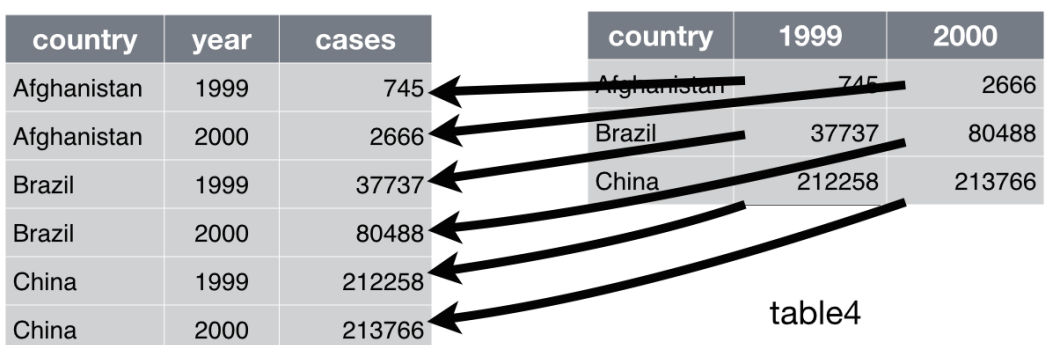
To fix these problems, you'll need to use:

- `tidyr::pivot_longer()`: "lengthens" data by increasing the number of rows and decreasing the number of columns.
- `tidyr::pivot_wider()`: "widens" data by increasing the number of columns and decreasing the number of rows.

# Longer with `pivot_longer()`

```
table4a
#> # A tibble: 3 x 3
#>   country     `1999` `2000`
#>   <chr>        <dbl>  <dbl>
#> 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>  <dbl>
#> 1 Afghanistan 1999     745
#> 2 Afghanistan 2000    2666
#> 3 Brazil      1999   37737
#> 4 Brazil      2000   80488
#> 5 China       1999  212258
#> 6 China       2000  213766
```



# Wider with `pivot_wider()`

```
table2
#> # A tibble: 12 x 4
#>    country      year type            count
#>    <chr>       <dbl> <chr>           <dbl>
#>  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>       <dbl>  <dbl>      <dbl>
#> 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
```

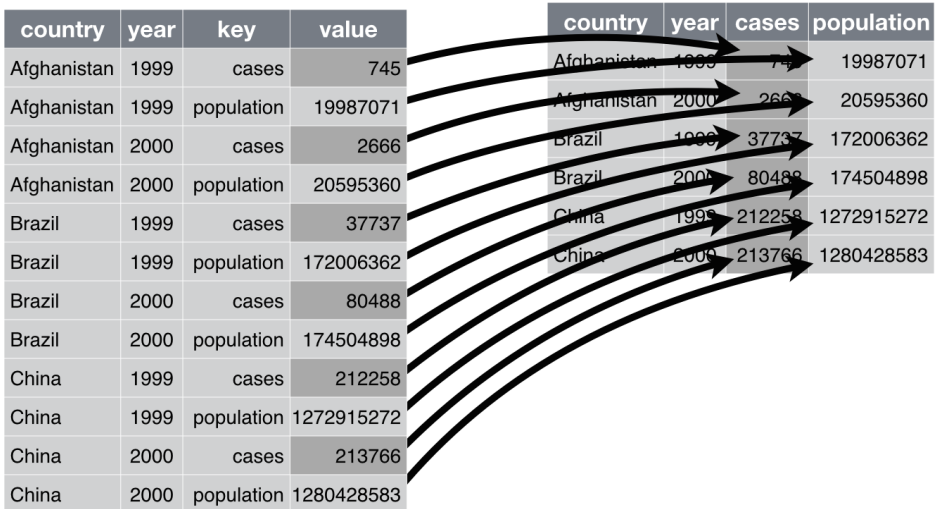


table2

# Separate a column with `tidyr::separate`

```
table3
#> # A tibble: 6 x 3
#>   country      year rate
#>   <chr>       <dbl> <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_wider_delim(
    rate,
    delim = "/", names = c("cases", "population")
  )
#> # A tibble: 6 x 4
#>   country      year cases  population
#>   <chr>       <dbl> <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 |

# 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 using `tidyr::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()`.

```
stocks |> drop_na()
#> # A tibble: 6 x 3
#>    year   qtr return
#>   <dbl> <dbl>  <dbl>
#> 1  2015     1   1.88
#> 2  2015     2   0.59
#> 3  2015     3   0.35
#> 4  2016     2   0.92
#> 5  2016     3   0.17
#> 6  2016     4   2.66
```

# Agenda

1 Tidy data

2 Filter, arrange select

3 Mutate

4 Summarize

5 Grouping

# Filter rows with `dplyr::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
#> # i 832 more rows
#> # i 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)
```

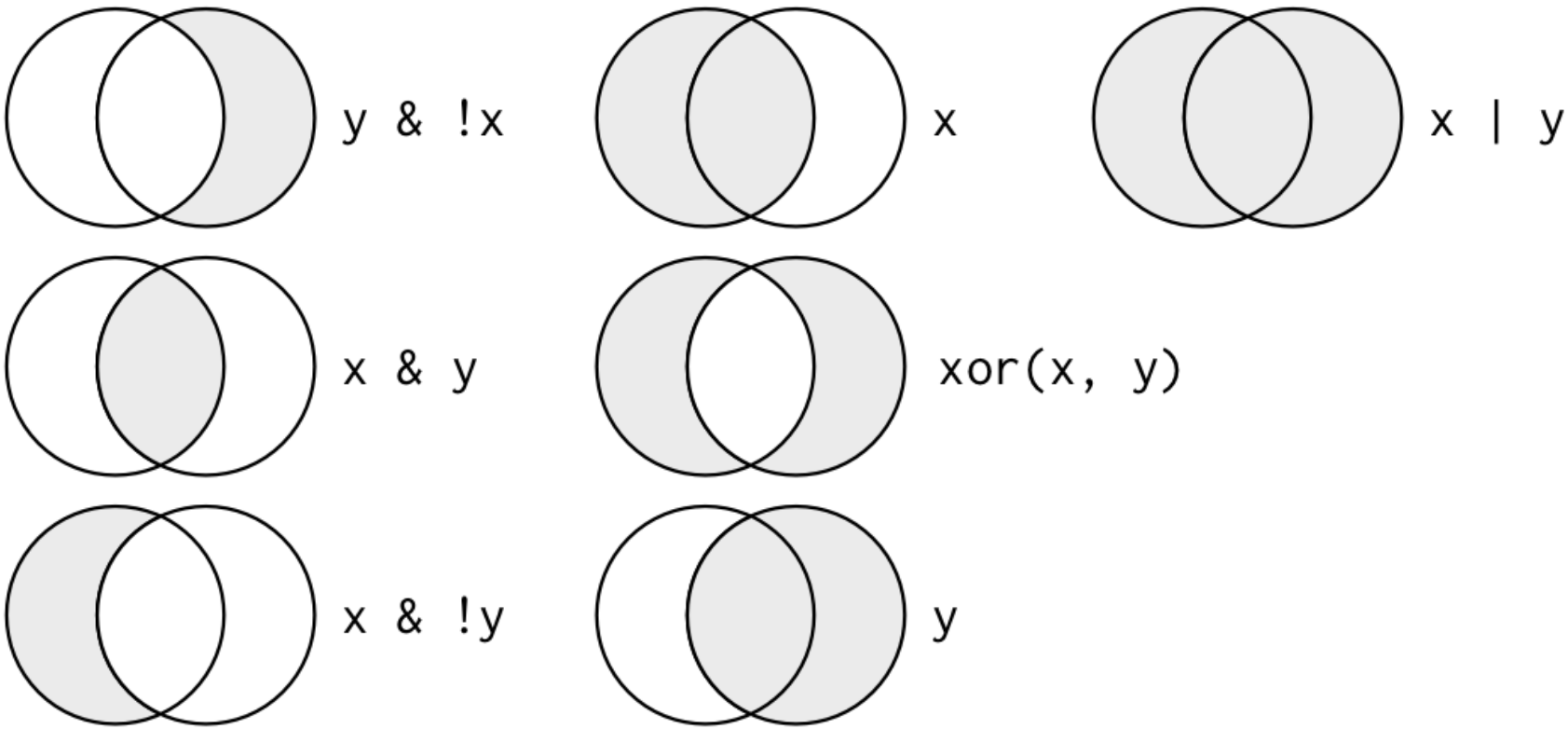
- What happens in the following?

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

# Logical operators

Multiple arguments to `dplyr::filter()` are usually combined with element-wise (vectorised) logical operations:

- `&`: vectorised "and"
- `|`: vectorised "or"
- `!`: vectorised "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)
```

- Reasoning:
  - `month == 11` is interpreted as `TRUE` or `FALSE` depending on the `month`.
  - `12` is interpreted as `TRUE` because it's not `0` or `NA`.
  - Result: (`TRUE` or `FALSE`) or `TRUE` = `TRUE`.
  - Therefore, **all flights** are returned.

# 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)
```

- Reasoning:
  - `month == 11` is interpreted as `TRUE` or `FALSE` depending on the `month`.
  - `12` is interpreted as `TRUE` because it's not `0` or `NA`.
  - Result: (`TRUE` or `FALSE`) or `TRUE` = `TRUE`.
  - Therefore, **all flights** are returned.

- A concise way to write the same code using `%in%`:

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

# 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
```

# Arrange rows with `arrange()`

```
arrange(flights, dep_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    12     7     2040           2123       -43       40
#>  2  2013     2     3     2022           2055       -33     2240
#>  3  2013    11    10     1408           1440       -32     1549
#>  4  2013     1    11     1900           1930       -30     2233
#>  5  2013     1    29     1703           1730       -27     1947
#>  6  2013     8     9      729            755       -26     1002
#>  7  2013    10    23     1907           1932       -25     2143
#>  8  2013     3    30     2030           2055       -25     2213
#>  9  2013     3     2     1431           1455       -24     1601
#> 10  2013     5     5      934            958       -24     1225
#> # i 336,766 more rows
#> # i 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(dep_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     6    27      959           1900       899     1236
#>  9  2013     7    22     2257            759       898      121
#> 10  2013    12     5      756           1700       896     1058
#> # i 336,766 more rows
#> # i 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
```

# 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
#> # i 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
#> # i 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
#> # i 336,766 more rows
#> # i 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 `tidyselect::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
#> # i 336,766 more rows
#> # i 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>
```

- This is similar to rearranging columns. Alternatively, you can use `dplyr::rellocate()`.

# `select()` and `tidyselect` helpers

- Helper functions you can use within `dplyr::select()` are available in the `tidyselect` package:
  - `starts_with()`: starts with an exact prefix.
  - `ends_with()`: ends with an exact suffix.
  - `contains()`: contains a literal string.
  - `matches()`: matches a regular expression.
  - `num_range()` matches a numerical range like `x01`, `x02`, `x03`.

```
select(flights, starts_with("arr"))
select(flights, contains("delay"))
select(flights, matches("^(dep|arr)"))
```

# Agenda

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# Create a narrower dataset

```
flights_sml <- flights %>%
  select(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
#> # i 336,766 more rows
```

# Add new variables with `mutate()`

```
flights_sml %>%
  mutate(
    net_delay = arr_delay - dep_delay,
    avg_speed = distance / air_time * 60
  )
#> # A tibble: 336,776 x 6
#>    dep_delay arr_delay distance air_time net_delay avg_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.
#> # i 336,766 more rows
```

# Refer to columns just created

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

# Useful creation functions I

Any vectorized function would work, but frequently useful are:

- Arithmetic operators: `+`, `-`, `*`, `/`, `^`.
  - 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`)
- Logarithms: `log()`, `log2()`, `log10()`.
  - Useful for data ranging across multiple orders of magnitude.
  - Convert multiplicative relationships to additive.

# Useful creation functions II

- Offsets: `dplyr::lead()` and `dplyr::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 from dplyr: `min_rank()`, `row_number()`, `dense_rank()`, `percent_rank()`, `cume_dist()`, `ntile()`

```
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
```

# Agenda

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# Collapse values with `summarize()`

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

# `summarize()` paired with `group_by()`

`group_by()` returns a **grouped tibble**, where the result is sorted by the grouping variables.

```
flights |>
    group_by(year, month, day) |>
    summarize(
      delay = mean(dep_delay, na.rm = TRUE)
    )
#> # 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
#> # i 355 more rows
```

`.by` returns an **ungroupped tibble**, where the order of the original data is preserved.

```
flights %>%
  summarise(
    delay = mean(dep_delay, na.rm = TRUE),
    .by = c(year, month, day)
  )
#> # A tibble: 365 x 4
#>     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
#> # i 355 more rows
```

- See more about groupping in *Per-operation grouping with .by/by*.

# 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
#> # i 355 more rows
```

# Useful summary functions I

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

```
not_cancelled |>
  group_by(year, month, day) |>
  summarize(first_dep = min(dep_time), last_dep = max(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
#> # i 355 more rows
```

# Useful summary functions II

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

```
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
#> # i 355 more rows
```

# Useful summary functions III

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

```
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
#> # i 94 more rows
```

# Useful summary functions IV

- `count()`: 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
#> # i 94 more rows
```

# Useful summary functions V

- `count(data, ..., wt = NULL)`: 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
#> # i 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
#> # i 355 more rows
```

# Useful summary functions VII

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

```
not_cancelled |>
  group_by(year, month, day) |>
  summarize(late_flights_ratio = mean(arr_delay > 60, na.rm = TRUE))
#> # A tibble: 365 x 4
#> # Groups:   year, month [12]
#>     year month   day late_flights_ratio
#>    <int> <int> <int>               <dbl>
#>  1  2013     1     1              0.0722
#>  2  2013     1     2              0.0851
#>  3  2013     1     3              0.0567
#>  4  2013     1     4              0.0396
#>  5  2013     1     5              0.0349
#>  6  2013     1     6              0.0470
#>  7  2013     1     7              0.0333
#>  8  2013     1     8              0.0213
#>  9  2013     1     9              0.0202
#> 10  2013     1    10              0.0183
#> # i 355 more rows
```

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# Grouping by multiple variables I

```
daily <- group_by(flights, year, month, day)
(flights_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
#> # i 355 more rows
```

# Grouping by multiple variables II

```
(flights_per_month <- summarize(flights_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
(flights_per_year  <- summarize(flights_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
#> # i 332,567 more rows
#> # i 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
#> # i 131,096 more rows
```