

# GR5206: lecture 5

*Computational Statistics  
And Introduction to Data Science*

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1 Data wrangling

2 Filter

3 Arrange

4 Select

5 Mutate

6 Summarize

7 Tidy data

1 Data wrangling

2 Filter

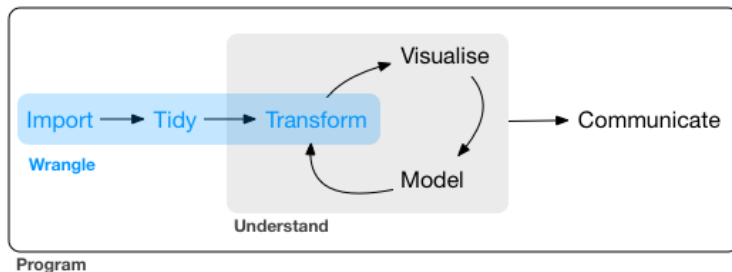
3 Arrange

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

**R for data science**

- When working with data you must:
  - ▶ Figure out what you want to do.
  - ▶ Describe those tasks in the form of a computer program.
  - ▶ Execute the program.
- The dplyr package makes these steps fast and easy:
  - ▶ By constraining your options, it helps you think about your data manipulation challenges.
  - ▶ It provides simple “verbs”, functions that correspond to the most common data manipulation tasks, to help you translate your thoughts into code.
  - ▶ It uses efficient backends, so you spend less time waiting for the computer.

- 5 verbs to solve common data manipulation challenges:
  - ▶ `filter()` to select observations based on their values.
  - ▶ `arrange()` to reorder the observations.
  - ▶ `select()` to select variables based on their names.
  - ▶ `mutate()` to add variables as functions of existing variables.
  - ▶ `summarize()` to 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 is a data frame.
    2. Other arguments describe what to do with it using variable names.
    3. Result is a new data frame.

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 <dtm>
```

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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 <dtm>
```

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

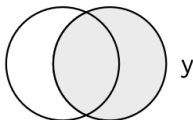
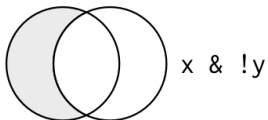
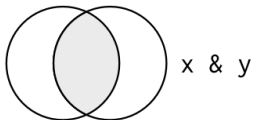
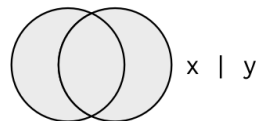
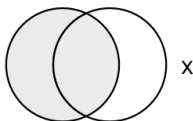
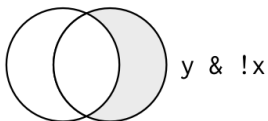
```
filter(flights, month = 1)
```

- 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
```

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))
```

- $!(x \ \& \ y)$  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 <dtm>
```

# 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 <dtm>
```

# 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 <dtm>
```



# 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
#>   <dtm>            <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>
```

- 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,  
  year:day,  
  ends_with("delay"),  
  distance,  
  air_time))
```

```
#> # A tibble: 336,776 x 7
```

```
#>   year month   day dep_delay arr_delay distance air_time  
#>   <int> <int> <int>    <dbl>    <dbl>    <dbl>    <dbl>  
#> 1  2013     1     1         2        11    1400      227  
#> 2  2013     1     1         4        20    1416      227  
#> 3  2013     1     1         2        33    1089      160  
#> 4  2013     1     1        -1       -18    1576      183  
#> 5  2013     1     1        -6       -25     762      116  
#> 6  2013     1     1        -4        12     719      150  
#> 7  2013     1     1        -5        19    1065      158  
#> 8  2013     1     1        -3       -14     229       53  
#> 9  2013     1     1        -3        -8     944      140  
#> 10 2013     1     1        -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 9
#>   year month   day dep_delay arr_delay distance air_time gain
#>   <int> <int> <int>     <dbl>     <dbl>     <dbl>   <dbl> <dbl>
#> 1  2013     1     1         2         11      1400     227     9
#> 2  2013     1     1         4         20      1416     227    16
#> 3  2013     1     1         2         33      1089     160    31
#> 4  2013     1     1        -1        -18      1576     183   -17
#> 5  2013     1     1        -6        -25       762     116  -19
#> 6  2013     1     1        -4         12       719     150    16
#> 7  2013     1     1        -5         19      1065     158    24
#> 8  2013     1     1        -3        -14       229      53   -11
#> 9  2013     1     1        -3         -8       944     140    -5
#> 10 2013     1     1        -2          8       733     138    10
#> # ... with 336,766 more rows, and 1 more variable: speed <dbl>
```

# 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 10
#>   year month   day dep_delay arr_delay distance air_time  gain
#>   <int> <int> <int>    <dbl>    <dbl>    <dbl>    <dbl> <dbl>
#> 1  2013     1     1         2        11      1400      227     9
#> 2  2013     1     1         4        20      1416      227    16
#> 3  2013     1     1         2        33      1089      160    31
#> 4  2013     1     1        -1       -18      1576      183   -17
#> 5  2013     1     1        -6       -25       762      116  -19
#> 6  2013     1     1        -4        12       719      150   16
#> 7  2013     1     1        -5        19      1065      158   24
#> 8  2013     1     1        -3       -14       229       53  -11
#> 9  2013     1     1        -3        -8       944      140   -5
#> 10 2013     1     1        -2         8       733      138   10
#> # ... with 336,766 more rows, and 2 more variables: hours <dbl>,
#> #   gain_per_hour <dbl>
```

```
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
```

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`)
- Logs: `log()`, `log2()`, `log10()`.
  - ▶ Useful for data ranging across multiple orders of magnitude.
  - ▶ Convert multiplicative relationships to additive.



- Offsets: `lead()` and `lag()`:
  - ▶ Refer to lead-/lagging values (e.g., compute running differences  $x - \text{lag}(x)$  or find values change  $x \neq \text{lag}(x)$ ).

```
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
```

- Logical comparisons, <, <=, >, >=, !=
- Ranking functions: 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
```

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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))
#> # 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
```

# 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
```



# What is happening here?

```
flights %>%  
  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    NA  
#> 2  2013     1     2    NA  
#> 3  2013     1     3    NA  
#> 4  2013     1     4    NA  
#> 5  2013     1     5    NA  
#> 6  2013     1     6    NA  
#> 7  2013     1     7    NA  
#> 8  2013     1     8    NA  
#> 9  2013     1     9    NA  
#> 10 2013     1    10    NA  
#> # ... with 355 more rows
```

# Use `na.rm = TRUE`

```
flights %>%  
  group_by(year, month, day) %>%  
  summarize(mean = mean(dep_delay, na.rm = TRUE))  
#> # 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
```

# Or pre-filter the dataset

```
not_cancelled <- flights %>%  
  filter(!is.na(dep_delay), !is.na(arr_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  11.4  
#> 2  2013     1     2  13.7  
#> 3  2013     1     3  10.9  
#> 4  2013     1     4   8.97  
#> 5  2013     1     5   5.73  
#> 6  2013     1     6   7.15  
#> 7  2013     1     7   5.42  
#> 8  2013     1     8   2.56  
#> 9  2013     1     9   2.30  
#> 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
```

- 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
```

- 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
```

## ■ A simple helper function for counts:

```
not_cancelled %>% count(dest)
```

```
#> # A tibble: 104 x 2
```

```
#>   dest      n
```

```
#>   <chr> <int>
```

```
#> 1 ABQ      254
```

```
#> 2 ACK      264
```

```
#> 3 ALB      418
```

```
#> 4 ANC        8
```

```
#> 5 ATL    16837
```

```
#> 6 AUS      2411
```

```
#> 7 AVL      261
```

```
#> 8 BDL      412
```

```
#> 9 BGR      358
```

```
#> 10 BHM     269
```

```
#> # ... with 94 more rows
```

## ■ 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 NOEGMQ 239143
```

```
#> 3 N10156 109664
```

```
#> 4 N102UW  25722
```

```
#> 5 N103US  24619
```

```
#> 6 N104UW  24616
```

```
#> 7 N10575 139903
```

```
#> 8 N105UW  23618
```

```
#> 9 N107US  21677
```

```
#> 10 N108UW 32070
```

```
#> # ... with 4,027 more rows
```



- 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
```

- 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  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  
#> # ... 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)))  
(per_year <- summarize(per_month, 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  
#> # A tibble: 1 x 2  
#>   year flights  
#>   <int>   <int>  
#> 1  2013  336776
```

```
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 <dtm>
```

```
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
```

1 Data wrangling

2 Filter

3 Arrange

4 Select

5 Mutate

6 Summarize

**7 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
```

## ■ 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
```

## ■ 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
```

## ■ 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.

country	year	cases	population
Afghanistan	1999	1845	19400071
Afghanistan	2000	1866	20000360
Brazil	1999	30737	172006362
Brazil	2000	80088	174004898
China	1999	210258	1272005272
China	2000	210066	128000583

variables

country	year	cases	population
Afghanistan	1999	1845	19400071
Afghanistan	2000	1866	20000360
Brazil	1999	30737	172006362
Brazil	2000	80088	174004898
China	1999	210258	1272005272
China	2000	210066	128000583

observations

country	year	cases	population
Afghanistan	1999	1845	19400071
Afghanistan	2000	1866	20000360
Brazil	1999	30737	172006362
Brazil	2000	80088	174004898
China	1999	210258	1272005272
China	2000	210066	128000583

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?
  - ▶ 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.

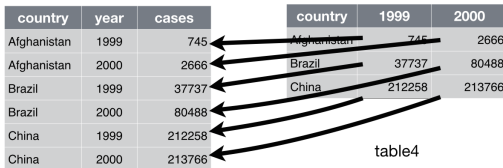
- Figure out what the variables and observations are.
- Resolve one of two common problems:
  - ▶ One variable might be spread across multiple columns.
  - ▶ One observation might be scattered across multiple rows.

... To fix these problems, you'll need `gather()` and `spread()`.

# Gathering with gather()

```
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 %>%
  gather(`1999`, `2000`,
         key = "year", value = "cases")
#> # A tibble: 6 x 3
#>   country    year    cases
#>   <chr>      <chr>   <int>
#> 1 Afghanistan 1999      745
#> 2 Brazil      1999    37737
#> 3 China       1999   212258
#> 4 Afghanistan 2000     2666
#> 5 Brazil      2000    80488
#> 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

# Spreading with spread()

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 %>% spread(key = type,
                  value = 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

table2

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 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	00	2666 / 20595360
Brazil	19	99	37737 / 172006362
Brazil	20	00	80488 / 174504898
China	19	99	212258 / 1272915272
China	20	00	213766 / 1280428583

table6

- 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:

```
stocks %>%  
  spread(year, 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
```

## ■ Explicit to implicit:

```
stocks %>%  
  spread(year, return) %>%  
  gather(year, return,  
         `2015`:`2016`, na.rm = TRUE)  
#> # A tibble: 6 x 3  
#>   qtr year return  
#>   <dbl> <chr> <dbl>  
#> 1     1  2015     1.88  
#> 2     2  2015     0.59  
#> 3     3  2015     0.35  
#> 4     2  2016     0.92  
#> 5     3  2016     0.17  
#> 6     4  2016     2.66
```

# Implicit to explicit with 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
```

# 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
```

- Since `tidyr` 1.0:
  - ▶ `pivot_longer()` and `pivot_wider()` to convert between long and wide forms
- The goal:
  - ▶ Improve on `spread()` and `gather()`!
- `vignette("pivot")` for more details

- Makes datasets **longer** by increasing the number of rows and decreasing the number of columns.
- Commonly needed to tidy datasets optimized for ease of data entry or ease of comparison rather than ease of analysis.

```
relig_income %>% print(n = 10)
#> # A tibble: 18 x 11
#>   religion `<$10k` ` $10-20k` ` $20-30k` ` $30-40k` ` $40-50k` ` $50-75k`
#>   <chr>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>      <dbl>
#> 1 Agnostic      27        34        60        81        76       137
#> 2 Atheist       12        27        37        52        35        70
#> 3 Buddhist      27        21        30        34        33        58
#> 4 Catholic     418       617       732       670       638      1116
#> 5 Don't k~      15        14        15        11        10        35
#> 6 Evangel~     575      869     1064     982     881     1486
#> 7 Hindu         1         9         7         9        11        34
#> 8 Histori~     228      244      236      238     197      223
#> 9 Jehovah~      20       27       24       24       21       30
#> 10 Jewish       19       19       25       25       30       95
#> # ... with 8 more rows, and 4 more variables: ` $75-100k` <dbl>,
#> #   ` $100-150k` <dbl>, ` >150k` <dbl>, `Don't know/refused` <dbl>
```



## pivot\_longer() cont'd

```
relig_income %>%  
  pivot_longer(-religion, names_to = "income", values_to = "count")  
#> # A tibble: 180 x 3  
#>   religion income      count  
#>   <chr>    <chr>    <dbl>  
#> 1 Agnostic <$10k      27  
#> 2 Agnostic $10-20k    34  
#> 3 Agnostic $20-30k    60  
#> 4 Agnostic $30-40k    81  
#> 5 Agnostic $40-50k    76  
#> 6 Agnostic $50-75k   137  
#> 7 Agnostic $75-100k  122  
#> 8 Agnostic $100-150k 109  
#> 9 Agnostic >150k     84  
#> 10 Agnostic Don't know/refused 96  
#> # ... with 170 more rows
```

- First argument: the dataset to reshape
- Second argument: which columns need to be reshaped.
- names\_to/values\_to: the name of the variable created from the data stored in the column names/cell value.

# Numeric data in column names

```
billboard
```

```
#> # A tibble: 317 x 79
#>   artist track date.entered wk1 wk2 wk3 wk4 wk5 wk6
#>   <chr> <chr> <date>      <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
#> 1 2 Pac Baby- 2000-02-26      87 82 72 77 87 94
#> 2 2Geth- The ~ 2000-09-02      91 87 92 NA NA NA
#> 3 3 Doo- Kryp- 2000-04-08      81 70 68 67 66 57
#> 4 3 Doo- Loser 2000-10-21      76 76 72 69 67 65
#> 5 504 B- Wobb- 2000-04-15      57 34 25 17 17 31
#> 6 98 0 Give- 2000-08-19      51 39 34 26 26 19
#> 7 A*Tee- Danc- 2000-07-08      97 97 96 95 100 NA
#> 8 Aaliy- I Do- 2000-01-29      84 62 51 41 38 35
#> 9 Aaliy- Try ~ 2000-03-18      59 53 38 28 21 18
#> 10 Adams- Open- 2000-08-26      76 76 74 69 68 67
#> # ... with 307 more rows, and 70 more variables: wk7 <dbl>,
#> # wk8 <dbl>, wk9 <dbl>, wk10 <dbl>, wk11 <dbl>, wk12 <dbl>,
#> # wk13 <dbl>, wk14 <dbl>, wk15 <dbl>, wk16 <dbl>, wk17 <dbl>,
#> # wk18 <dbl>, wk19 <dbl>, wk20 <dbl>, wk21 <dbl>, wk22 <dbl>,
#> # wk23 <dbl>, wk24 <dbl>, wk25 <dbl>, wk26 <dbl>, wk27 <dbl>,
#> # wk28 <dbl>, wk29 <dbl>, wk30 <dbl>, wk31 <dbl>, wk32 <dbl>,
#> # wk33 <dbl>, wk34 <dbl>, wk35 <dbl>, wk36 <dbl>, wk37 <dbl>,
#> # wk38 <dbl>, wk39 <dbl>, wk40 <dbl>, wk41 <dbl>, wk42 <dbl>,
#> # wk43 <dbl>, wk44 <dbl>, wk45 <dbl>, wk46 <dbl>, wk47 <dbl>,
#> # wk48 <dbl>, wk49 <dbl>, wk50 <dbl>, wk51 <dbl>, wk52 <dbl>,
#> # wk53 <dbl>, wk54 <dbl>, wk55 <dbl>, wk56 <dbl>, wk57 <dbl>,
#> # wk58 <dbl>, wk59 <dbl>, wk60 <dbl>, wk61 <dbl>, wk62 <dbl>,
#> # wk63 <dbl>, wk64 <dbl>, wk65 <dbl>, wk66 <lg1>, wk67 <lg1>,
#> # wk68 <lg1>, wk69 <lg1>, wk70 <lg1>, wk71 <lg1>, wk72 <lg1>,
#> # wk73 <lg1>, wk74 <lg1>, wk75 <lg1>, wk76 <lg1>
```

```
billboard %>%
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank",
    values_drop_na = TRUE
  )
#> # A tibble: 5,307 x 5
#>   artist track date.entered week rank
#>   <chr> <chr> <date> <chr> <dbl>
#> 1 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk1 87
#> 2 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk2 82
#> 3 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk3 72
#> 4 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk4 77
#> 5 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk5 87
#> 6 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk6 94
#> 7 2 Pac Baby Don't Cry (Keep... 2000-02-26 wk7 99
#> 8 2Ge+her The Hardest Part Of ... 2000-09-02 wk1 91
#> 9 2Ge+her The Hardest Part Of ... 2000-09-02 wk2 87
#> 10 2Ge+her The Hardest Part Of ... 2000-09-02 wk3 92
#> # ... with 5,297 more rows
```



```
billboard %>%
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    names_prefix = "wk",
    names_ptypes = list(week = integer()),
    values_to = "rank",
    values_drop_na = TRUE,
  )
#> # A tibble: 5,307 x 5
#>   artist      track      date.entered week rank
#>   <chr>      <chr>      <date>      <int> <dbl>
#> 1 2 Pac      Baby Don't Cry (Keep... 2000-02-26     1    87
#> 2 2 Pac      Baby Don't Cry (Keep... 2000-02-26     2    82
#> 3 2 Pac      Baby Don't Cry (Keep... 2000-02-26     3    72
#> 4 2 Pac      Baby Don't Cry (Keep... 2000-02-26     4    77
#> 5 2 Pac      Baby Don't Cry (Keep... 2000-02-26     5    87
#> 6 2 Pac      Baby Don't Cry (Keep... 2000-02-26     6    94
#> 7 2 Pac      Baby Don't Cry (Keep... 2000-02-26     7    99
#> 8 2Ge+her The Hardest Part Of ... 2000-09-02     1    91
#> 9 2Ge+her The Hardest Part Of ... 2000-09-02     2    87
#> 10 2Ge+her The Hardest Part Of ... 2000-09-02     3    92
#> # ... with 5,297 more rows
```

- The opposite of `pivot_longer()`
- Makes a dataset **wider** by increasing the number of columns and decreasing the number of rows.
- Rare to need it to tidy data, useful to create summary tables for presentation, or data in a format needed by other tools.

```
fish_encounters
#> # A tibble: 114 x 3
#>   fish station seen
#>   <fct> <fct>   <int>
#> 1 4842 Release     1
#> 2 4842 I80_1       1
#> 3 4842 Lisbon      1
#> 4 4842 Rstr        1
#> 5 4842 Base_TD     1
#> 6 4842 BCE         1
#> 7 4842 BCW         1
#> 8 4842 BCE2        1
#> 9 4842 BCW2        1
#> 10 4842 MAE        1
#> # ... with 104 more rows
```

# pivot\_wider() cont'd

```
fish_encounters %>%
  pivot_wider(names_from = station, values_from = seen) %>%
  print(n = 10)

#> # A tibble: 19 x 12
#>   fish Release ISO_1 Lisbon Rstr Base_TD BCE BCW BCE2 BCW2
#>   <fct>   <int> <int>   <int> <int>   <int> <int> <int> <int> <int>
#> 1 4842         1     1       1     1       1     1     1     1     1
#> 2 4843         1     1       1     1       1     1     1     1     1
#> 3 4844         1     1       1     1       1     1     1     1     1
#> 4 4845         1     1       1     1       1    NA    NA    NA    NA
#> 5 4847         1     1       1    NA    NA    NA    NA    NA    NA
#> 6 4848         1     1       1     1    NA    NA    NA    NA    NA
#> 7 4849         1     1    NA    NA    NA    NA    NA    NA    NA
#> 8 4850         1     1    NA     1     1     1     1    NA    NA
#> 9 4851         1     1    NA    NA    NA    NA    NA    NA    NA
#> 10 4854         1     1    NA    NA    NA    NA    NA    NA    NA
#> # ... with 9 more rows, and 2 more variables: MAE <int>, MAW <int>
```

# pivot\_wider()

```
fish_encounters %>%
  pivot_wider(
    names_from = station,
    values_from = seen,
    values_fill = list(seen = 0)
  ) %>%
  print(n = 10)
```

#> # A tibble: 19 x 12

#>	fish	Release	I80_1	Lisbon	Rstr	Base_TD	BCE	BCW	BCE2	BCW2
#>	<fct>	<int>	<int>	<int>	<int>	<int>	<int>	<int>	<int>	<int>
#>	1 4842	1	1	1	1	1	1	1	1	1
#>	2 4843	1	1	1	1	1	1	1	1	1
#>	3 4844	1	1	1	1	1	1	1	1	1
#>	4 4845	1	1	1	1	1	0	0	0	0
#>	5 4847	1	1	1	0	0	0	0	0	0
#>	6 4848	1	1	1	1	0	0	0	0	0
#>	7 4849	1	1	0	0	0	0	0	0	0
#>	8 4850	1	1	0	1	1	1	1	0	0
#>	9 4851	1	1	0	0	0	0	0	0	0
#>	10 4854	1	1	0	0	0	0	0	0	0

#> # ... with 9 more rows, and 2 more variables: MAE <int>, MAW <int>

```
warpbreaks <- warpbreaks %>%  
  as_tibble() %>%  
  select(wool, tension, breaks)
```

warpbreaks

```
#> # A tibble: 54 x 3  
#>   wool tension breaks  
#>   <fct> <fct>   <dbl>  
#> 1 A     L       26  
#> 2 A     L       30  
#> 3 A     L       54  
#> 4 A     L       25  
#> 5 A     L       70  
#> 6 A     L       52  
#> 7 A     L       51  
#> 8 A     L       26  
#> 9 A     L       67  
#> 10 A    M       18  
#> # ... with 44 more rows
```

```
warpbreaks %>%  
  count(wool, tension)
```

```
#> # A tibble: 6 x 3  
#>   wool tension     n  
#>   <fct> <fct>   <int>  
#> 1 A     L       9  
#> 2 A     M       9  
#> 3 A     H       9  
#> 4 B     L       9  
#> 5 B     M       9  
#> 6 B     H       9
```



```
warpbreaks %>%  
  pivot_wider(  
    names_from = wool,  
    values_from = breaks,  
    values_fn = list(breaks = mean)  
  )  
#> # A tibble: 3 x 3  
#>   tension      A      B  
#>   <fct>    <dbl> <dbl>  
#> 1 L      44.6  28.2  
#> 2 M      24    28.8  
#> 3 H      24.6  18.8
```

# Generate column names

```
production <- expand_grid(
  product = c("A", "B"),
  country = c("AI", "EI"),
  year = 2000:2014
) %>%
  filter((product == "A" & country == "AI") | product == "B") %>%
  mutate(production = rnorm(nrow(.)))
production
#> # A tibble: 45 x 4
#>   product country  year production
#>   <chr>    <chr>  <int>      <dbl>
#> 1 A      AI      2000    -1.40
#> 2 A      AI      2001     0.255
#> 3 A      AI      2002    -2.44
#> 4 A      AI      2003   -0.00557
#> 5 A      AI      2004     0.622
#> 6 A      AI      2005     1.15
#> 7 A      AI      2006    -1.82
#> 8 A      AI      2007    -0.247
#> 9 A      AI      2008    -0.244
#> 10 A     AI      2009    -0.283
#> # ... with 35 more rows
```

# Generate column names cont'd

```
production %>% pivot_wider(  
  names_from = c(product, country),  
  values_from = production  
)  
#> # A tibble: 15 x 4  
#>   year      A_AI      B_AI      B_EI  
#>   <int>    <dbl>    <dbl>    <dbl>  
#> 1  2000 -1.40    -1.86    0.935  
#> 2  2001  0.255   -0.522   0.176  
#> 3  2002 -2.44    -0.0526  0.244  
#> 4  2003 -0.00557  0.543    1.62  
#> 5  2004  0.622   -0.914   0.112  
#> 6  2005  1.15     0.468  -0.134  
#> 7  2006 -1.82     0.363  -1.91  
#> 8  2007 -0.247   -1.30   -0.279  
#> 9  2008 -0.244    0.738  -0.313  
#> 10 2009 -0.283    1.89    1.07  
#> 11 2010 -0.554   -0.0974  0.0700  
#> 12 2011  0.629   -0.936  -0.639  
#> 13 2012  2.07    -0.0160 -0.0500  
#> 14 2013 -1.63    -0.827  -0.251  
#> 15 2014  0.512   -1.51    0.445
```