Tidy Data and Tidying Data

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Learning Objectives

- Identify tidy and non-tidy data
- Learn to make your data tidy:
  - "Pivotting" which converts between long and wide forms with `pivot_longer()`, `pivot_wider()`
  - Splitting and combining character columns:
    - Use `separate()` and `extract()` to pull a single character column into multiple columns;
    - use `unite()` to combine multiple columns into a single character column.
  - Make implicit missing values explicit with complete()
  - Make explicit missing values implicit with values_drop_na()
  - Replace missing values with next/previous value with fill(), or a known value with replace_na()

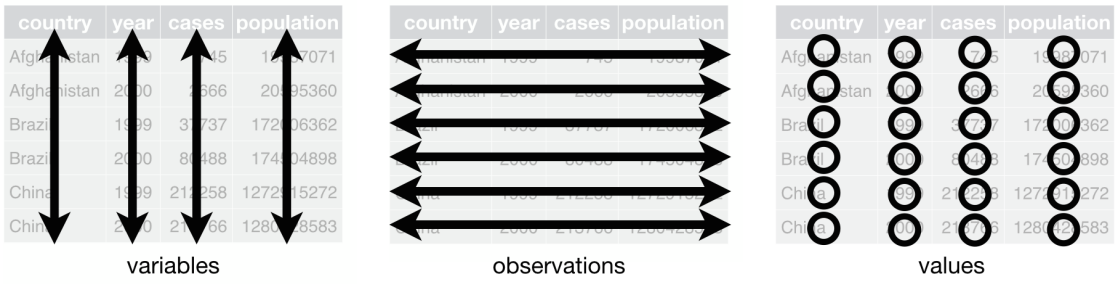
Resources

- Chapter 12 of RDS
- Data Import Cheat Sheet
- Article by Hadley Wickham
- Tidyr Vignette
- Pivot Vignette
- Separate Vignette
- Unite Vignette

Tidy Data

- Recall:
  - Observations/units/subjects/individuals/cases: objects described by a set of data (e.g. cars, people, countries).
  - Variable: describes some characteristic of the units (e.g. mpg, age, GDP).
  - Each unit has a single value of each variable (e.g. 20 mpg, 31 years old, $20,513,000 US$million).
- Tidy Data:
  - One observation per row.
  - One variable per column.
  - One value per cell.

- Hadley's visualization:



- We will use the tidyr package (a member of the tidyverse) to make data tidy.

```
library(tidyverse)
```

- Frequent Characteristics of "Nontidy" Data
  - Column headers are values, not variable names.
  - Multiple variables are stored in one column.
  - Variables are stored in both rows and columns.
  - Multiple types of observational units are stored in the same table.
  - A single observational unit is stored in multiple tables.

Look at table1, table2, table3, table4a, table4b. Which one is tidy? Why?

It is easy to analyze and plot your data with tidy data .... is why it is called the tidyverse.

```r
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
```

```r
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
```

```r
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
```

```r
table4a
```

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

```r
table4b
```

```
## # A tibble: 3 x 3
##   country         `1999`     `2000`
## * <chr>            <int>      <int>
## 1 Afghanistan   19987071   20595360
## 2 Brazil       172006362  174504898
## 3 China       1272915272 1280428583
```

```r
```

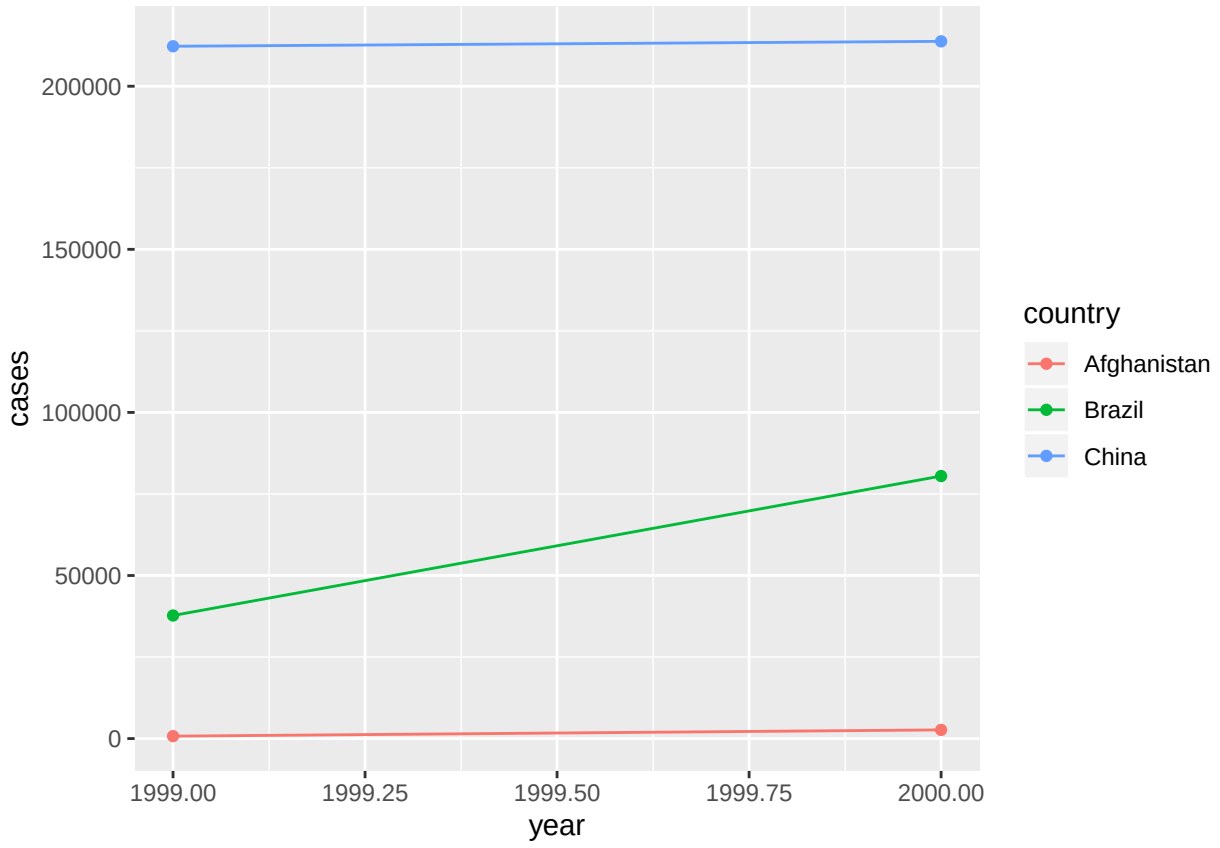
```
# rate per 10,000
table1 %>%
  mutate(rate = cases/population*10000)
```

```
## # A tibble: 6 x 5
##   country      year  cases population  rate
##   <chr>       <int>  <int>      <int> <dbl>
## 1 Afghanistan  1999    745   19987071 0.373
## 2 Afghanistan  2000   2666   20595360 1.29
## 3 Brazil       1999  37737  172006362 2.19
## 4 Brazil       2000  80488  174504898 4.61
## 5 China        1999 212258 1272915272 1.67
## 6 China        2000 213766 1280428583 1.67
```

```r
# cases per year
table1 %>%
  count(year, wt=cases)
```

```
## # A tibble: 2 x 2
##    year      n
## * <int>  <int>
## 1  1999 250740
## 2  2000 296920
```

```r
table1 %>% ggplot(aes(x = year, y = cases, color = country)) +
  geom_line() +
  geom_point()
```



- Example of tidy data:

```
tidyr::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
```

  - Variables: Country, Year, Cases, Population
  - Units: location×time

- Untidy data: Each observational unit is spread across multiple rows

```
print(tidyr::table2, n = 12)
```

```
## # 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
```

- Untidy data: Two variables are in one column

```
tidyr::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
```

- Untidy data: Data are spread across two data frames. Within each data frame, multiple observations are in one row.

```
tidyr::table4a
```

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

```
tidyr::table4b
```

```
## # A tibble: 3 x 3
##   country         `1999`     `2000`
## * <chr>            <int>      <int>
## 1 Afghanistan   19987071   20595360
## 2 Brazil       172006362  174504898
## 3 China       1272915272 1280428583
```

- Sometimes it is easy to determine the units and the variables.
- Sometimes it is very hard and you need to talk to the data collectors to find out.
- We want tidy data because R easily manipulates vectors. So in the long run it will make your life easier to first make data tidy.
- **Exercise 1** The following built-in datasets are not tidy. For each one, describe why it is not tidy and write out what the first five entries would look like once it is in a tidy format.

  a. relig_income
  b. billboard
  c. us_rent_income

---

intro to pivot_longer and pivot_wider

When one variable spread across multiple columns, use `pivot_longer()`

- Column names are actually *values* of a variable
- `table4a` and `table4b`
- Solution: `pivot_longer()`
- Hadley's visualization:

- Specify
  i. The columns that are values, not variables,
  ii. The name of the variable that will take the values of the column names (`names_to`), and
  iii. The name of the variable that will take the values spread in the cells (`values_to`).

```
table4a
```

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

```
tidy4a <- table4a %>%
  pivot_longer(cols = c(`1999`,`2000`), names_to = "year",
               values_to = "cases")
```

- **Exercise 2** Try on your own to do the same thing to table4b. We will learn next class how to join these two data frames next week. But the code is

```
full_join(tidy4a, tidy4b)
```

```
## Joining, by = c("country", "year")
```

```
## # A tibble: 6 x 4
##   country     year   cases population
## * <chr>       <chr>  <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
```

- **Exercise 3**: Tidy built-in dataset relig_income

```
## # 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
```

- **Exercise 4**: gather the `monkeymem` data frame (also available at https://dcgerard.github.io/stat_412_612/data/monkeymem.csv). The cell values represent identification accuracy of some objects (in percent of 20 trials).

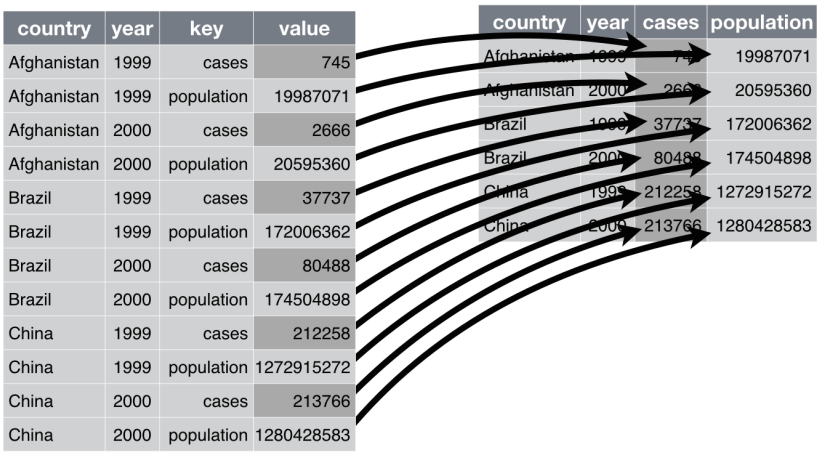
```
## Parsed with column specification:
## cols(
##   Monkey = col_character(),
##   Treatment = col_character(),
##   Week2 = col_double(),
##   Week4 = col_double(),
##   Week8 = col_double(),
##   Week12 = col_double(),
##   Week16 = col_double()
## )
```

```
## # A tibble: 90 x 4
##    Monkey Treatment Week   Percent
##    <chr>  <chr>     <chr>    <dbl>
##  1 Spank  Control   Week2       95
##  2 Spank  Control   Week4       75
##  3 Spank  Control   Week8       80
##  4 Spank  Control   Week12      65
##  5 Spank  Control   Week16      70
##  6 Chim   Control   Week2       85
##  7 Chim   Control   Week4       75
##  8 Chim   Control   Week8       55
##  9 Chim   Control   Week12      75
## 10 Chim   Control   Week16      85
## # ... with 80 more rows
```

When an observation is scattered over multiple rows, use `pivot_wider()`

- `pivot_wider()` makes a dataset wider by increasing the number of columns and decreasing the number of rows.
- One of the columns contains the *names* of the variables
- `table2`
- Solution: `pivot_wider()`

- Hadley's visualization:



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

- Specify

  i. The column from which to pull the variable names (`names_from`),
  ii. The column from which to get the associated values of the variables.

```
table2
```

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

```
table2 %>% pivot_wider(names_from = type, values_from = count)
```

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

- **Exercise 5**: Tidy the fish_encounters dataset of fish spotting by monitoring stations. Make the NA into 0 using the option values_fill = list(seen = 0)

```
## # A tibble: 19 x 12
##    fish  Release I80_1 Lisbon  Rstr Base_TD   BCE   BCW  BCE2  BCW2   MAE   MAW
##    <fct>   <int> <int>  <int> <int>   <int> <int> <int> <int> <int> <int> <int>
##  1 4842        1     1      1     1       1     1     1     1     1     1     1
##  2 4843        1     1      1     1       1     1     1     1     1     1     1
##  3 4844        1     1      1     1       1     1     1     1     1     1     1
##  4 4845        1     1      1     1       1     0     0     0     0     0     0
##  5 4847        1     1      1     0       0     0     0     0     0     0     0
##  6 4848        1     1      1     1       0     0     0     0     0     0     0
##  7 4849        1     1      0     0       0     0     0     0     0     0     0
##  8 4850        1     1      0     1       1     1     1     0     0     0     0
##  9 4851        1     1      0     0       0     0     0     0     0     0     0
## 10 4854        1     1      0     0       0     0     0     0     0     0     0
## 11 4855        1     1      1     1       1     0     0     0     0     0     0
## 12 4857        1     1      1     1       1     1     1     1     1     0     0
## 13 4858        1     1      1     1       1     1     1     1     1     1     1
## 14 4859        1     1      1     1       1     0     0     0     0     0     0
## 15 4861        1     1      1     1       1     1     1     1     1     1     1
## 16 4862        1     1      1     1       1     1     1     1     1     0     0
## 17 4863        1     1      0     0       0     0     0     0     0     0     0
## 18 4864        1     1      0     0       0     0     0     0     0     0     0
## 19 4865        1     1      1     0       0     0     0     0     0     0     0
```

- **Exercise 6**: Spread the `flowers1` data frame (also available at https://dcgerard.github.io/stat_412_612/data/flowers1.csv). Hint: use `read_csv2()` to read in the dataset.

```
## Using ',' as decimal and '.' as grouping mark. Use read_delim() for more control.
```

```
## Parsed with column specification:
## cols(
##   Time = col_double(),
##   replication = col_double(),
##   Variable = col_character(),
##   Value = col_double()
## )
```

```
## # A tibble: 24 x 4
##     Time replication Flowers Intensity
##    <dbl>       <dbl>   <dbl>     <dbl>
##  1     1           1    62.3       150
##  2     1           2    77.4       150
##  3     1           3    55.3       300
##  4     1           4    54.2       300
##  5     1           5    49.6       450
##  6     1           6    61.9       450
##  7     1           7    39.4       600
##  8     1           8    45.7       600
##  9     1           9    31.3       750
## 10     1          10    44.9       750
## # ... with 14 more rows
```

separate and unite functions

`separate()` splits a column into multiple columns.

- Problem: One column contains two (or more) variables.
- `table3`
- Solution: `separate()`
- Hadley's visualization:

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	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

table3

- Specify:
  i. The column that contains two (or more) variables,
  ii. A character vector of the new names of the variables, and
  iii. The character that separates variables (or the position that separates variables) The default is the first non-numeric character.

```
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
```

```
table3 %>%
  separate(rate, into = c("cases","population"), sep="/")
```

```
## # 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
```

```
table3 %>%
  separate(
    rate,
     into = c("cases","population"),
     convert = TRUE  # to convert to numeric if desired
   )
```

```
## # 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
```

```
table5 <- table3 %>%
  separate(year, into=c("century", "year"), sep=2)
```

- **Exercise 7:** Tidy the dataset flowers2.csv (also available at https://dcgerard.github.io/stat_412_612/data/flowers2.csv) by turning the one column into 3 separate columns.

```
## Parsed with column specification:
## cols(
##   `Flowers/Intensity;Time` = col_character()
## )
```

```
## # A tibble: 24 x 3
##    Flowers Intensity Time
##    <chr>   <chr>     <chr>
##  1 62.3    150       1
##  2 77.4    150       1
##  3 55.3    300       1
##  4 54.2    300       1
##  5 49.6    450       1
##  6 61.9    450       1
##  7 39.4    600       1
##  8 45.7    600       1
```

```
##  9 31.3    750       1
## 10 44.9    750       1
## # ... with 14 more rows
```

unite is the inverse of separate()

- Problem: One variable spread across multiple columns.
- Solution: `unite()`
- Hadley's visualization:

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

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

table6

- Much less common problem.

```
table5 %>% unite(new, century, year)
```

```
## # A tibble: 6 x 3
##   country     new   rate
##   <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
```

- **Exercise 8**: Re-unite the data frame you separated from the `flowers2` exercise. Use a comma for the separator.

```
## # A tibble: 24 x 2
##    `Flowers,Intensity` Time
##    <chr>               <chr>
##  1 62.3,150            1
##  2 77.4,150            1
##  3 55.3,300            1
##  4 54.2,300            1
##  5 49.6,450            1
##  6 61.9,450            1
##  7 39.4,600            1
##  8 45.7,600            1
##  9 31.3,750            1
## 10 44.9,750            1
## # ... with 14 more rows
```

Dealing with Missing Values

Two types of missing values:

- explicitly missing (NA)
- implicitly missing (just row missing)

Make NA's explicit using `complete()`

First we will look at ways to make a missing row explicit The `complete()` function fills in NA's where needed so each combination of columns is in the output

```r
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)
)
stocks
```

```
## # A tibble: 7 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     2   0.92
## 6  2016     3   0.17
## 7  2016     4   2.66
```

```r
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
```

Here is a tibble where the item_id and item_name go together and we need to have all items showing for each group.

```r
df <- tibble(
  group = c(1:2, 1),
  item_id = c(1:2, 2),
  item_name = c("a", "b", "b"),
  value1 = 1:3,
  value2 = 4:6
)
df
```

```
## # A tibble: 3 x 5
##   group item_id item_name value1 value2
##   <dbl>   <dbl> <chr>      <int>  <int>
## 1     1       1 a              1      4
## 2     2       2 b              2      5
## 3     1       2 b              3      6
```

Note that there is no row for group 2 with item_id = 1, item_name = a. We specify that we want to expand the group to accomodate the patterns present in item_id and item_name. In this case, those are sort of equivalent in that the item_name goes with the item_id. Since they are equivalent, we use the nesting to tell the code to group those together. We also used the fill option to specify that missing value1's should be given a 0 rather than an NA.

```r
df %>% complete(group, nesting(item_id, item_name),
                fill = list(value1 = 0))
```

```
## # A tibble: 4 x 5
##   group item_id item_name value1 value2
##   <dbl>   <dbl> <chr>      <dbl>  <int>
## 1     1       1 a              1      4
## 2     1       2 b              3      6
## 3     2       1 a              0     NA
```

```
## 4     2       2 b               2      5
```

- **Exercise 9** In the following dataset, turn the implicit missing values to explicit.

```r
output <- tibble(
  treatment   = c("a", "b", "a", "c", "b"),
  gender   = factor(c("M", "F", "F", "M", "M"), levels = c("M", "F", "O")),
  return = c(1.5, 0.75,  0.5,  1.8,  NA)
)
output
```

```
## # A tibble: 5 x 3
##   treatment gender return
##   <chr>     <fct>   <dbl>
## 1 a         M        1.5
## 2 b         F        0.75
## 3 a         F        0.5
## 4 c         M        1.8
## 5 b         M       NA
```

```
## # A tibble: 9 x 3
##   treatment gender return
##   <chr>     <fct>   <dbl>
## 1 a         M        1.5
## 2 a         F        0.5
## 3 a         O       NA
## 4 b         M       NA
## 5 b         F        0.75
## 6 b         O       NA
## 7 c         M        1.8
## 8 c         F       NA
## 9 c         O       NA
```

Make explicit NA's implicit using `values_drop_na`

To turn explicit missing values to implicit missing values, you can use values_drop_na = TRUE as an option to `pivot_longer()`

```r
stocks %>%
  pivot_wider(
    names_from = year,
    values_from = return) %>%
  pivot_longer(
    cols = c(`2015`, `2016`),
    names_to = "year",
    values_to = "return",
    values_drop_na = TRUE)
```

```
## # A tibble: 6 x 3
##     qtr year  return
##   <dbl> <chr>  <dbl>
## 1     1 2015    1.88
```

```
## 2     2 2015    0.59
## 3     2 2016    0.92
## 4     3 2015    0.35
## 5     3 2016    0.17
## 6     4 2016    2.66
```

fill()

A similar option uses fill to carry forward the previous value to any missing spots.

```r
stocks %>%
 fill(return)
```

```
## # A tibble: 7 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   0.35
## 5  2016     2   0.92
## 6  2016     3   0.17
## 7  2016     4   2.66
```

replace_na()

We can also use the `replace_na()` function to replace the NA values in our tibble with other things.

```r
df2 <- df %>% complete(group, nesting(item_id, item_name))
df2 %>% replace_na(list(value1 = 0, value2 = "unknown"))
```

```
## # A tibble: 4 x 5
##   group item_id item_name value1 value2
##   <dbl>   <dbl> <chr>      <dbl> <chr>
## 1     1       1 a              1 4
## 2     1       2 b              3 6
## 3     2       1 a              0 unknown
## 4     2       2 b              2 5
```

---

names_pattern()

- Problem: The value of the variable is part of the column name.
- Solution: `names_pattern()` option of `pivot_longer()`

```r
preg <- read_csv("./Data/preg.csv")

## Parsed with column specification:
## cols(
##   name = col_character(),
##   treatmenta = col_double(),
##   treatmentb = col_double()
## )
preg

## # A tibble: 3 x 3
##   name         treatmenta treatmentb
##   <chr>             <dbl>      <dbl>
## 1 John Smith           NA         18
## 2 Jane Doe              4          1
## 3 Mary Johnson          6          7
```

tidy preg

```r
preg2 <- preg %>% pivot_longer(
  cols = starts_with("treatment"),
  names_to = "treatment",
  values_to = "result",
  names_pattern = "treatment(.)")

preg2
```

```
## # A tibble: 6 x 3
##   name         treatment result
##   <chr>        <chr>      <dbl>
## 1 John Smith   a             NA
## 2 John Smith   b             18
## 3 Jane Doe     a              4
## 4 Jane Doe     b              1
## 5 Mary Johnson a              6
## 6 Mary Johnson b              7
```

Multiple variables stored in one column

Look at the built-in dataset who.

```r
who
```

```
## # A tibble: 7,240 x 60
##    country iso2  iso3   year new_sp_m014 new_sp_m1524 new_sp_m2534 new_sp_m3544
##    <chr>   <chr> <chr> <int>       <int>        <int>        <int>        <int>
##  1 Afghan~ AF    AFG    1980          NA           NA           NA           NA
##  2 Afghan~ AF    AFG    1981          NA           NA           NA           NA
```

```
##  3 Afghan~ AF    AFG    1982          NA           NA           NA           NA
##  4 Afghan~ AF    AFG    1983          NA           NA           NA           NA
##  5 Afghan~ AF    AFG    1984          NA           NA           NA           NA
##  6 Afghan~ AF    AFG    1985          NA           NA           NA           NA
##  7 Afghan~ AF    AFG    1986          NA           NA           NA           NA
##  8 Afghan~ AF    AFG    1987          NA           NA           NA           NA
##  9 Afghan~ AF    AFG    1988          NA           NA           NA           NA
## 10 Afghan~ AF    AFG    1989          NA           NA           NA           NA
## # ... with 7,230 more rows, and 52 more variables: new_sp_m4554 <int>,
## #   new_sp_m5564 <int>, new_sp_m65 <int>, new_sp_f014 <int>,
## #   new_sp_f1524 <int>, new_sp_f2534 <int>, new_sp_f3544 <int>,
## #   new_sp_f4554 <int>, new_sp_f5564 <int>, new_sp_f65 <int>,
## #   new_sn_m014 <int>, new_sn_m1524 <int>, new_sn_m2534 <int>,
## #   new_sn_m3544 <int>, new_sn_m4554 <int>, new_sn_m5564 <int>,
## #   new_sn_m65 <int>, new_sn_f014 <int>, new_sn_f1524 <int>,
## #   new_sn_f2534 <int>, new_sn_f3544 <int>, new_sn_f4554 <int>,
## #   new_sn_f5564 <int>, new_sn_f65 <int>, new_ep_m014 <int>,
## #   new_ep_m1524 <int>, new_ep_m2534 <int>, new_ep_m3544 <int>,
## #   new_ep_m4554 <int>, new_ep_m5564 <int>, new_ep_m65 <int>,
## #   new_ep_f014 <int>, new_ep_f1524 <int>, new_ep_f2534 <int>,
## #   new_ep_f3544 <int>, new_ep_f4554 <int>, new_ep_f5564 <int>,
## #   new_ep_f65 <int>, newrel_m014 <int>, newrel_m1524 <int>,
## #   newrel_m2534 <int>, newrel_m3544 <int>, newrel_m4554 <int>,
## #   newrel_m5564 <int>, newrel_m65 <int>, newrel_f014 <int>,
## #   newrel_f1524 <int>, newrel_f2534 <int>, newrel_f3544 <int>,
## #   newrel_f4554 <int>, newrel_f5564 <int>, newrel_f65 <int>
```

Note that country, iso2, iso3, and year are already variables, so they can be left as is. But the columns from new_sp_m014 to newrel_f65 encode four variables in their names:

1. The new_/new prefix indicates these are counts of new cases. This dataset only contains new cases, so we'll ignore it here because it's constant.

2. The next two letters describe the type of TB:

   - `rel` stands for cases of relapse
   - `ep` stands for cases of extrapulmonary TB
   - `sn` stands for cases of pulmonary TB that could not be diagnosed by a pulmonary smear (smear negative)
   - `sp` stands for cases of pulmonary TB that could be diagnosed be a pulmonary smear (smear positive)

3. The sixth letter gives the sex of TB patients. The dataset groups cases by males (`m`) and females (`f`).

4. The remaining numbers gives the age group. The dataset groups cases into seven age groups:

   - `014` = 0 – 14 years old
   - `1524` = 15 – 24 years old
   - `2534` = 25 – 34 years old
   - `3544` = 35 – 44 years old
   - `4554` = 45 – 54 years old
   - `5564` = 55 – 64 years old
   - `65` = 65 or older

We can break these variables up by specifying multiple column names in names_to, and then either providing names_sep or names_pattern. Here names_pattern is the most natural fit. It has a similar interface to extract: you give it a regular expression containing groups (defined by ()) and it puts each group in a column.

```r
# separate using regular expression
who_tidy <- who %>% pivot_longer(
  cols = new_sp_m014:newrel_f65,
  names_to = c("diagnosis", "gender", "age"),
  names_pattern = "new_?(.*)_(.)(.*)", # or use names_sep for separator
  values_to = "count"
)
head(who_tidy)
```

```
## # A tibble: 6 x 8
##   country     iso2  iso3   year diagnosis gender age   count
##   <chr>       <chr> <chr> <int> <chr>     <chr>  <chr> <int>
## 1 Afghanistan AF    AFG    1980 sp        m      014      NA
## 2 Afghanistan AF    AFG    1980 sp        m      1524     NA
## 3 Afghanistan AF    AFG    1980 sp        m      2534     NA
## 4 Afghanistan AF    AFG    1980 sp        m      3544     NA
## 5 Afghanistan AF    AFG    1980 sp        m      4554     NA
## 6 Afghanistan AF    AFG    1980 sp        m      5564     NA
```

We could go one step further and specify the types of the gender and age columns. This is good practice when you have categorical variables with a known set of values. Let's also get rid of all the NA counts.

```r
# separate using regular expression and add types for gender and ordered type for age
who_tidy <- who %>% pivot_longer(
  cols = new_sp_m014:newrel_f65,
  names_to = c("diagnosis", "gender", "age"),
  names_pattern = "new_?(.*)_(.)(.*)", # or use names_sep for separator
  values_to = "count",
  values_drop_na = TRUE,
  names_ptypes = list(
    gender = factor(levels = c("f", "m")),
    age = factor(
      levels = c("014", "1524", "2534", "3544", "4554", "5564", "65"),
      ordered = TRUE)
    )
)
head(who_tidy)
```

```
## # A tibble: 6 x 8
##   country     iso2  iso3   year diagnosis gender age   count
##   <chr>       <chr> <chr> <int> <chr>     <fct>  <ord> <int>
## 1 Afghanistan AF    AFG    1997 sp        m      014       0
## 2 Afghanistan AF    AFG    1997 sp        m      1524     10
## 3 Afghanistan AF    AFG    1997 sp        m      2534      6
## 4 Afghanistan AF    AFG    1997 sp        m      3544      3
## 5 Afghanistan AF    AFG    1997 sp        m      4554      5
## 6 Afghanistan AF    AFG    1997 sp        m      5564      2
```

Variables stored in both rows and columns

Get the data and look at it

```r
weather <- read_csv("./Data/weather.csv")
```

```
## Parsed with column specification:
## cols(
##   .default = col_double(),
##   id = col_character(),
##   element = col_character(),
##   d9 = col_logical(),
##   d12 = col_logical(),
##   d18 = col_logical(),
##   d19 = col_logical(),
##   d20 = col_logical(),
##   d21 = col_logical(),
##   d22 = col_logical(),
##   d24 = col_logical()
## )
```

```
## See spec(...) for full column specifications.
```

```r
head(weather)
```

```
## # A tibble: 6 x 35
##   id     year month element    d1    d2    d3    d4    d5    d6    d7    d8
##   <chr> <dbl> <dbl> <chr>   <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
## 1 MX17~  2010     1 tmax       NA  NA    NA      NA  NA      NA    NA    NA
## 2 MX17~  2010     1 tmin       NA  NA    NA      NA  NA      NA    NA    NA
## 3 MX17~  2010     2 tmax       NA  27.3  24.1    NA  NA      NA    NA    NA
## 4 MX17~  2010     2 tmin       NA  14.4  14.4    NA  NA      NA    NA    NA
## 5 MX17~  2010     3 tmax       NA  NA    NA      NA  32.1    NA    NA    NA
## 6 MX17~  2010     3 tmin       NA  NA    NA      NA  14.2    NA    NA    NA
## # ... with 23 more variables: d9 <lgl>, d10 <dbl>, d11 <dbl>, d12 <lgl>,
## #   d13 <dbl>, d14 <dbl>, d15 <dbl>, d16 <dbl>, d17 <dbl>, d18 <lgl>,
## #   d19 <lgl>, d20 <lgl>, d21 <lgl>, d22 <lgl>, d23 <dbl>, d24 <lgl>,
## #   d25 <dbl>, d26 <dbl>, d27 <dbl>, d28 <dbl>, d29 <dbl>, d30 <dbl>, d31 <dbl>
```

- daily weather data from the Global Historical Climatology Network
- one weather station (MX17004) in Mexico for five months in 2010.
- variables in columns for id, year and month, spread across columns for days of month
- variables spread across rows for minimum and maximum temperatures
- months with fewer than 31 days have structural missing values

Use `pivot_longer()` to put the days all in one column

```r
weather2 <- weather %>% pivot_longer(
  cols = starts_with("d"),
  names_to = "day",
  values_to = "value",
  names_prefix = "d", # removes the prefix specified
  names_ptypes = list(day = integer()), #sets the value left to be an integer
  values_drop_na = TRUE
)
```

Rearrange the data

```r
weather3 <- weather2 %>%
  select(id,year, month, day, element, value) %>%
  arrange(id, year, month, day)
weather3
```

```
## # A tibble: 66 x 6
##    id       year month   day element value
##    <chr>   <dbl> <dbl> <int> <chr>   <dbl>
##  1 MX17004  2010     1    30 tmax     27.8
##  2 MX17004  2010     1    30 tmin     14.5
##  3 MX17004  2010     2     2 tmax     27.3
##  4 MX17004  2010     2     2 tmin     14.4
##  5 MX17004  2010     2     3 tmax     24.1
##  6 MX17004  2010     2     3 tmin     14.4
##  7 MX17004  2010     2    11 tmax     29.7
##  8 MX17004  2010     2    11 tmin     13.4
##  9 MX17004  2010     2    23 tmax     29.9
## 10 MX17004  2010     2    23 tmin     10.7
## # ... with 56 more rows
```

Use pivot_wider to separate tmax and tmin into separate columns

```r
weather4 <- weather3 %>% pivot_wider(
  names_from = element,
  values_from = value
)
head(weather4)
```

```
## # A tibble: 6 x 6
##   id       year month   day  tmax  tmin
##   <chr>   <dbl> <dbl> <int> <dbl> <dbl>
## 1 MX17004  2010     1    30  27.8  14.5
## 2 MX17004  2010     2     2  27.3  14.4
## 3 MX17004  2010     2     3  24.1  14.4
## 4 MX17004  2010     2    11  29.7  13.4
## 5 MX17004  2010     2    23  29.9  10.7
```

```
## 6 MX17004  2010     3     5  32.1  14.2
```

Look at resulting dataframe

```r
summary(weather4)
```

```
##       id                 year          month             day
##  Length:33          Min.   :2010   Min.   : 1.000   Min.   : 1.00
##  Class :character   1st Qu.:2010   1st Qu.: 4.000   1st Qu.: 5.00
##  Mode  :character   Median :2010   Median : 8.000   Median :14.00
##                     Mean   :2010   Mean   : 7.212   Mean   :14.88
##                     3rd Qu.:2010   3rd Qu.:10.000   3rd Qu.:26.00
##                     Max.   :2010   Max.   :12.000   Max.   :31.00
##       tmax            tmin
##  Min.   :24.10   Min.   : 7.90
##  1st Qu.:27.80   1st Qu.:13.40
##  Median :29.00   Median :15.00
##  Mean   :29.19   Mean   :14.65
##  3rd Qu.:29.90   3rd Qu.:16.50
##  Max.   :36.30   Max.   :18.20
```

- **Exercise 10:**

Tidy the billboard dataset (built-in)

- First gather up all the week entries into a row for each week for each song (where there is an entry)
- Then, convert the week variable to a number and figure out the date corresponding to each week on the chart
- Sort the data by artist, track and week. Here are what your first entries should be (formatting can be different):

```
#>  A tibble: 5,307 x 5
#   artist  track                   date.entered  week  rank   date
 #    <chr>   <chr>                   <date>       <int> <dbl>   <date>
 #  1 2 Pac   Baby Don't Cry (Keep... 2000-02-26       1    87 2000-02-26
 #  2 2 Pac   Baby Don't Cry (Keep... 2000-02-26       2    82 2000-03-04
 #  3 2 Pac   Baby Don't Cry (Keep... 2000-02-26       3    72 2000-03-11
 #  4 2 Pac   Baby Don't Cry (Keep... 2000-02-26       4    77 2000-03-18
 #  5 2 Pac   Baby Don't Cry (Keep... 2000-02-26       5    87 2000-03-25
 #  6 2 Pac   Baby Don't Cry (Keep... 2000-02-26       6    94 2000-04-01
 #  7 2 Pac   Baby Don't Cry (Keep... 2000-02-26       7    99 2000-04-08
 #  8 2Ge+her The Hardest Part Of ... 2000-09-02       1    91 2000-09-02
 #  9 2Ge+her The Hardest Part Of ... 2000-09-02       2    87 2000-09-09
 # 10 2Ge+her The Hardest Part Of ... 2000-09-02       3    92 2000-09-16
 # ... with 5,297 more rows
```

```
## # A tibble: 5,307 x 5
##    artist  track                    week  rank date
##    <chr>   <chr>                   <int> <dbl> <date>
##  1 2 Pac   Baby Don't Cry (Keep...     1    87 2000-02-26
##  2 2 Pac   Baby Don't Cry (Keep...     2    82 2000-03-04
```

```
##  3 2 Pac   Baby Don't Cry (Keep...     3    72 2000-03-11
##  4 2 Pac   Baby Don't Cry (Keep...     4    77 2000-03-18
##  5 2 Pac   Baby Don't Cry (Keep...     5    87 2000-03-25
##  6 2 Pac   Baby Don't Cry (Keep...     6    94 2000-04-01
##  7 2 Pac   Baby Don't Cry (Keep...     7    99 2000-04-08
##  8 2Ge+her The Hardest Part Of ...     1    91 2000-09-02
##  9 2Ge+her The Hardest Part Of ...     2    87 2000-09-09
## 10 2Ge+her The Hardest Part Of ...     3    92 2000-09-16
## # ... with 5,297 more rows
```

Multiple observations per row

You can usually recognise this case because the name of the column that you want to appear in the output is part of the column name in the input.

```
family <- tribble(
  ~family,  ~dob_child1,  ~dob_child2, ~gender_child1, ~gender_child2,
       1L, "1998-11-26", "2000-01-29",             1L,             2L,
       2L, "1996-06-22",           NA,             2L,             NA,
       3L, "2002-07-11", "2004-04-05",             2L,             2L,
       4L, "2004-10-10", "2009-08-27",             1L,             1L,
       5L, "2000-12-05", "2005-02-28",             2L,             1L,
)
family <- family %>% mutate_at(vars(starts_with("dob")), parse_date)
family
```

```
## # A tibble: 5 x 5
##   family dob_child1 dob_child2 gender_child1 gender_child2
##    <int> <date>     <date>             <int>         <int>
## 1      1 1998-11-26 2000-01-29             1             2
## 2      2 1996-06-22 NA                     2            NA
## 3      3 2002-07-11 2004-04-05             2             2
## 4      4 2004-10-10 2009-08-27             1             1
## 5      5 2000-12-05 2005-02-28             2             1
```

Note that we have two pieces of information (or values) for each child: their gender and their dob (date of birth). These need to go into separate columns in the result. Again we supply multiple variables to names_to, using names_sep to split up each variable name. Note the special name .value: this tells pivot_longer() that that part of the column name specifies the "value" being measured (which will become a variable in the output).

```
family %>%
  pivot_longer(
    -family,
    names_to = c(".value", "child"),
    names_sep = "_",
    values_drop_na = TRUE
  )
```

```
## # A tibble: 9 x 4
##   family child  dob        gender
##    <int> <chr>  <date>      <int>
## 1      1 child1 1998-11-26      1
## 2      1 child2 2000-01-29      2
```

```
## 3      2 child1 1996-06-22      2
## 4      3 child1 2002-07-11      2
## 5      3 child2 2004-04-05      2
## 6      4 child1 2004-10-10      1
## 7      4 child2 2009-08-27      1
## 8      5 child1 2000-12-05      2
## 9      5 child2 2005-02-28      1
```

- **Exercise 11:** Do the same with the built-in dataset anscombe

```
##    x1 x2 x3 x4    y1   y2    y3    y4
## 1  10 10 10  8  8.04 9.14  7.46  6.58
## 2   8  8  8  8  6.95 8.14  6.77  5.76
## 3  13 13 13  8  7.58 8.74 12.74  7.71
## 4   9  9  9  8  8.81 8.77  7.11  8.84
## 5  11 11 11  8  8.33 9.26  7.81  8.47
## 6  14 14 14  8  9.96 8.10  8.84  7.04
## 7   6  6  6  8  7.24 6.13  6.08  5.25
## 8   4  4  4 19  4.26 3.10  5.39 12.50
## 9  12 12 12  8 10.84 9.13  8.15  5.56
## 10  7  7  7  8  4.82 7.26  6.42  7.91
## 11  5  5  5  8  5.68 4.74  5.73  6.89
```

```
## # A tibble: 44 x 3
##    set       x     y
##    <chr> <dbl> <dbl>
##  1 1        10  8.04
##  2 1         8  6.95
##  3 1        13  7.58
##  4 1         9  8.81
##  5 1        11  8.33
##  6 1        14  9.96
##  7 1         6  7.24
##  8 1         4  4.26
##  9 1        12 10.8
## 10 1         7  4.82
## # ... with 34 more rows
```

- **Exercise 12:** Tidy the world_bank_pop dataset

```
## # A tibble: 1,056 x 20
##    country indicator `2000` `2001` `2002` `2003`  `2004`  `2005`   `2006`
##    <chr>   <chr>      <dbl>  <dbl>  <dbl>  <dbl>   <dbl>   <dbl>    <dbl>
##  1 ABW     SP.URB.T~ 4.24e4 4.30e4 4.37e4 4.42e4 4.47e+4 4.49e+4  4.49e+4
##  2 ABW     SP.URB.G~ 1.18e0 1.41e0 1.43e0 1.31e0 9.51e-1 4.91e-1 -1.78e-2
##  3 ABW     SP.POP.T~ 9.09e4 9.29e4 9.50e4 9.70e4 9.87e+4 1.00e+5  1.01e+5
##  4 ABW     SP.POP.G~ 2.06e0 2.23e0 2.23e0 2.11e0 1.76e+0 1.30e+0  7.98e-1
##  5 AFG     SP.URB.T~ 4.44e6 4.65e6 4.89e6 5.16e6 5.43e+6 5.69e+6  5.93e+6
##  6 AFG     SP.URB.G~ 3.91e0 4.66e0 5.13e0 5.23e0 5.12e+0 4.77e+0  4.12e+0
##  7 AFG     SP.POP.T~ 2.01e7 2.10e7 2.20e7 2.31e7 2.41e+7 2.51e+7  2.59e+7
##  8 AFG     SP.POP.G~ 3.49e0 4.25e0 4.72e0 4.82e0 4.47e+0 3.87e+0  3.23e+0
##  9 AGO     SP.URB.T~ 8.23e6 8.71e6 9.22e6 9.77e6 1.03e+7 1.09e+7  1.15e+7
## 10 AGO     SP.URB.G~ 5.44e0 5.59e0 5.70e0 5.76e0 5.75e+0 5.69e+0  4.92e+0
## # ... with 1,046 more rows, and 11 more variables: `2007` <dbl>, `2008` <dbl>,
## #   `2009` <dbl>, `2010` <dbl>, `2011` <dbl>, `2012` <dbl>, `2013` <dbl>,
## #   `2014` <dbl>, `2015` <dbl>, `2016` <dbl>, `2017` <dbl>
```

```
## # A tibble: 19,008 x 4
##    country indicator   year  value
##    <chr>   <chr>       <chr> <dbl>
##  1 ABW     SP.URB.TOTL 2000  42444
##  2 ABW     SP.URB.TOTL 2001  43048
##  3 ABW     SP.URB.TOTL 2002  43670
##  4 ABW     SP.URB.TOTL 2003  44246
##  5 ABW     SP.URB.TOTL 2004  44669
##  6 ABW     SP.URB.TOTL 2005  44889
##  7 ABW     SP.URB.TOTL 2006  44881
##  8 ABW     SP.URB.TOTL 2007  44686
##  9 ABW     SP.URB.TOTL 2008  44375
## 10 ABW     SP.URB.TOTL 2009  44052
## # ... with 18,998 more rows
```

```
## # A tibble: 4 x 2
##   indicator       n
## * <chr>       <int>
## 1 SP.POP.GROW  4752
## 2 SP.POP.TOTL  4752
## 3 SP.URB.GROW  4752
## 4 SP.URB.TOTL  4752
```

```
## # A tibble: 19,008 x 5
##    country area  variable year  value
##    <chr>   <chr> <chr>    <chr> <dbl>
##  1 ABW     URB   TOTL     2000  42444
##  2 ABW     URB   TOTL     2001  43048
##  3 ABW     URB   TOTL     2002  43670
##  4 ABW     URB   TOTL     2003  44246
##  5 ABW     URB   TOTL     2004  44669
##  6 ABW     URB   TOTL     2005  44889
##  7 ABW     URB   TOTL     2006  44881
##  8 ABW     URB   TOTL     2007  44686
##  9 ABW     URB   TOTL     2008  44375
## 10 ABW     URB   TOTL     2009  44052
## # ... with 18,998 more rows
```

```
## # A tibble: 9,504 x 5
##    country area  year   TOTL    GROW
##    <chr>   <chr> <chr> <dbl>   <dbl>
##  1 ABW     URB   2000  42444  1.18
##  2 ABW     URB   2001  43048  1.41
##  3 ABW     URB   2002  43670  1.43
##  4 ABW     URB   2003  44246  1.31
##  5 ABW     URB   2004  44669  0.951
##  6 ABW     URB   2005  44889  0.491
##  7 ABW     URB   2006  44881 -0.0178
##  8 ABW     URB   2007  44686 -0.435
##  9 ABW     URB   2008  44375 -0.698
## 10 ABW     URB   2009  44052 -0.731
## # ... with 9,494 more rows
```

Specification by hand

Sometimes we want to be more specific in our tidying format than the standard inputs provide. Look at the built-in construction dataset.

```
construction
```

```
## # A tibble: 9 x 9
##    Year Month `1 unit` `2 to 4 units` `5 units or mor~ Northeast Midwest South
##   <dbl> <chr>    <dbl> <lgl>                    <dbl>     <dbl>   <dbl> <dbl>
## 1  2018 Janu~      859 NA                         348       114     169   596
## 2  2018 Febr~      882 NA                         400       138     160   655
## 3  2018 March      862 NA                         356       150     154   595
## 4  2018 April      797 NA                         447       144     196   613
## 5  2018 May        875 NA                         364        90     169   673
## 6  2018 June       867 NA                         342        76     170   610
## 7  2018 July       829 NA                         360       108     183   594
## 8  2018 Augu~      939 NA                         286        90     205   649
## 9  2018 Sept~      835 NA                         304       117     175   560
## # ... with 1 more variable: West <dbl>
```

We would like to have columns for units and one for region.

```
spec <- tribble(
  ~.name,            ~.value, ~units,  ~region,
  "1 unit",          "n",     "1",     NA,
  "2 to 4 units",    "n",     "2-4",   NA,
  "5 units or more", "n",     "5+",    NA,
  "Northeast",       "n",     NA,      "Northeast",
  "Midwest",         "n",     NA,      "Midwest",
  "South",           "n",     NA,      "South",
  "West",            "n",     NA,      "West",
)
pivot_longer_spec(construction, spec)
```

```
## # A tibble: 63 x 5
##     Year Month    units region        n
##    <dbl> <chr>    <chr> <chr>     <dbl>
##  1  2018 January  1     <NA>        859
##  2  2018 January  2-4   <NA>         NA
##  3  2018 January  5+    <NA>        348
##  4  2018 January  <NA>  Northeast   114
##  5  2018 January  <NA>  Midwest     169
##  6  2018 January  <NA>  South       596
##  7  2018 January  <NA>  West        339
##  8  2018 February 1     <NA>        882
##  9  2018 February 2-4   <NA>         NA
## 10  2018 February 5+    <NA>        400
## # ... with 53 more rows
```

The pivotting spec allows us to be more precise about exactly how pivot_longer(df, spec = spec) changes the shape of df: it will have nrow(df) * nrow(spec) rows, and ncol(df) - nrow(spec) + ncol(spec) - 2 columns.