Data Tidying

> "Tidy datasets are all alike but every messy dataset is messy in its own way." – Hadley Wickham

Data science, at its heart, is a computer programming exercise. Data scientists use computers to store, transform, visualize, and model their data. As a result, every data science project begins with the same task: you must prepare your data to use it with a computer. In the wild, data sets come in many different formats, but each computer program expects your data to be organized in a predetermined way, which may vary from program to program.

In this book, we will use R to do data science. R is an excellent language for data science because with R you can do everything from collect your data (from the web or a database), to transform it, visualize it, explore it, model it, and run statistical tests on it. You can also use R to report your results when you are finished, and you can run R interactively, as if you were operating a calculator and not writing computer code. Best of all, R is free.

In this chapter, you will learn the best way to organize your data for R, a task that I call data tidying. This may seem like an odd place to start, but tidying data is the most fruitful skill you can learn as a data scientist. It will save you hours of time and make your data much easier to visualize, manipulate, and model with R.

Note that this chapter explains how to change the format, or layout, of tabular data. To learn how to use different file formats with R, see Appendix B: Data Sources.

Outline

In *Section 2.1*, you will learn how the features of R determine the best way to layout your data. This section introduces "tidy data," a way to organize your data that works particularly well with R.

Section 2.2 teaches the basic method for making untidy data tidy. In this section, you will learn how to reorganize the values in your data set with the the `spread()` and `gather()` functions of the `tidyr` package.

Section 2.3 explains how to split apart and combine values in your data set to make them easier to access with R.

Section 2.4 concludes the chapter, combining everything you've learned about `tidyr` to tidy a real data set on tuberculosis epidemiology collected by the *World Health Organization*.

Prerequisites

You will need to have R installed on your computer to run the code in this chapter, as well as the RStudio IDE, a free program that makes it easier to use R. You can learn how to install both in *Appendix A: Getting Started*.

You will also need to install the `tidyr`, `devtools`, and `DSR` packages. To install, `tidyr` and `devtools`, open RStudio and run the command

```
install.packages(c("tidyr", "devtools"))
```

`DSR` is a collection of data sets that I have assembled for this book and saved online as a github repository (github.com/garrettgman/DSR). To install `DSR`, run the command

```
devtools::install_github("garrettgman/DSR")
```

2.1 Tidy data

You can organize tabular data in many ways. For example, the data sets below show the same data organized in four different ways. Each data set shows the same values of four variables *country*, *year*, *population*, and *cases*, but each data set organizes the values into a different layout . You can access the data sets in the `DSR` package.

```
library(DSR)

# Data set one
table1

## Source: local data frame [6 x 4]
##
##       country year  cases population
## 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

# Data set two
table2

## Source: local data frame [12 x 4]
##
##        country year        key      value
## 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

# Data set three
table3

## Source: local data frame [6 x 3]
##
##       country year              rate
## 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
```

The last data set is a collection of two tables.

```
# Data set four
table4  # cases

## Source: local data frame [3 x 3]
##
##       country   1999   2000
## 1 Afghanistan    745   2666
## 2      Brazil  37737  80488
## 3       China 212258 213766

table5  # population

## Source: local data frame [3 x 3]
##
##       country       1999       2000
## 1 Afghanistan   19987071   20595360
## 2      Brazil  172006362  174504898
## 3       China 1272915272 1280428583
```

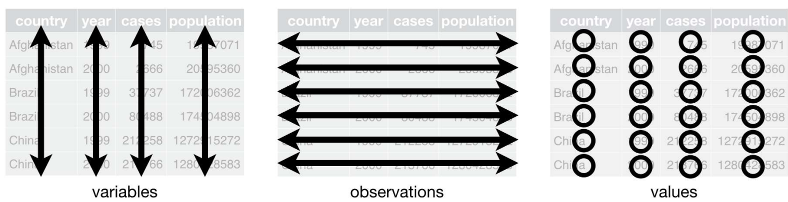
You might think that these data sets are interchangeable since they display the same information, but one data set will be much easier to work with in R than the others.

Why should that be?

R follows a set of conventions that makes one layout of tabular data much easier to work with than others. Your data will be easier to work with in R if it follows three rules

1. Each variable in the data set is placed in its own column
2. Each observation is placed in its own row
3. Each value is placed in its own cell*

Data that satisfies these rules is known as *tidy data*. Notice that `table1` is tidy data.



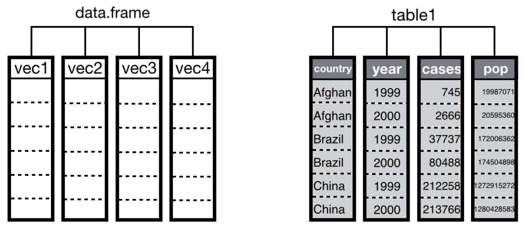
In `table1`, each variable is placed in its own column, each observation in its own row, and each value in its own cell.

Tidy data builds on a premise of data science that data sets contain *both values and relationships*. Tidy data displays the relationships in a data set as consistently as it displays the values in a data set.

At this point, you might think that tidy data is so obvious that it is trivial. Surely, most data sets come in a tidy format, right? Wrong. In practice, raw data is rarely tidy and is much harder to work with as a result. *Section 2.4* provides a realistic example of data collected in the wild.

Tidy data works well with R because R is a vectorized programming language. Data structures in R are built from vectors and R's operations are optimized to work with vectors. Tidy data takes advantage of both of these traits.

R stores tabular data as a data frame, a list of atomic vectors arranged to look like a table. Each column in the table is an atomic vector in the list.



A data frame is a list of vectors that R displays as a table. When your data is tidy, the values of each variable fall in their own column vector.

Tidy data arranges values so that the relationships in the data parallel the structure of the data frame. Recall that each data set is a collection of values associated with a variable and an observation. In tidy data, each variable is assigned to its own column, i.e., its own vector in the data frame. As a result, you can extract easily the values of a variable in a tidy data set with R's list syntax,

```
table1$cases

## [1]    745   2666  37737  80488 212258 213766
```

R will return the values as an atomic vector, one of the most versatile data structures in R. Many functions in R are written to take atomic vectors as input, as are R's mathematical operators. This adds up to an easy user experience; you can extract and manipulate the values of variables in tidy data with concise, simple code, e.g.,

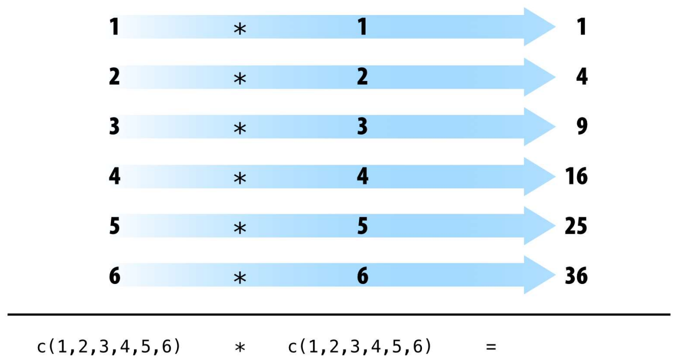
```
mean(table1$cases)

## [1] 91276.67

table1$cases / table1$population * 10000

## [1] 0.372741 1.294466 2.193930 4.612363 1.6674
95 1.669488
```

Tidy data also takes advantage of R's vectorized operations. In R, it is common to supply one or more vectors of values to a function or mathematical operator as input, and to receive a vector of values as output. To create the output, R applies the function in element-wise fashion: R first applies the function (or operation) to the first elements of each vector involved. Then R applies the function (or operation) to the second elements of each vector involved, and so on until R reaches the end of the vectors. If one vector is shorter than the others, R will recycle its values as needed (according to a set of recycling rules).



If your data is tidy, element-wise execution will ensure that observations are preserved across functions and operations. Each value will only be paired with other values that appear in the same row of the data frame.

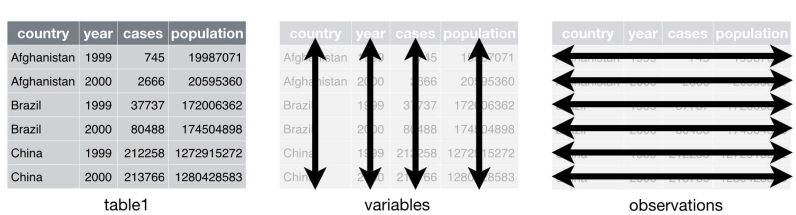
Do these small advantages matter in the long run? Yes. Consider what it would be like to do a simple calculation with each of the data sets from the start of the section.

Assume that in these data sets, `cases` refers to the number of people diagnosed with TB per country per year. To calculate the *rate* of TB cases per country per year (i.e, the number of people per 10,000 diagnosed with TB), you will need to do four operations with the data. You will need to:

1. Extract the number of TB cases per country per year
2. Extract the population per country per year (in the same order as above)
3. Divide cases by population
4. Multiply by 10000

If you use basic R syntax, your calculations will look like the code below. If you'd like to brush up on basic R syntax, see Appendix A: Getting Started.

Data set one



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

Since `table1` is organized in a tidy fashion, you can calculate the rate like this,

```
# Data set one
table1$cases / table1$population * 10000
```

Data set two

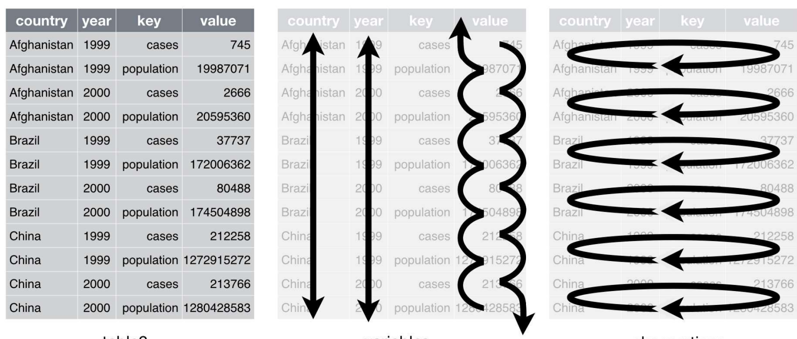


table2 variables observations

Data set two intermingles the values of *population* and *cases* in the same columns. As a result, you will need to untangle the values whenever you want to work with each variable separately.

You'll need to perform an extra step to calculate the rate.

```
# Data set two
case_rows <- c(1, 3, 5, 7, 9, 11, 13, 15, 17)
pop_rows <- c(2, 4, 6, 8, 10, 12, 14, 16, 18)
table2$value[case_rows] / table2$value[pop_rows]
 * 10000
```

Data set three

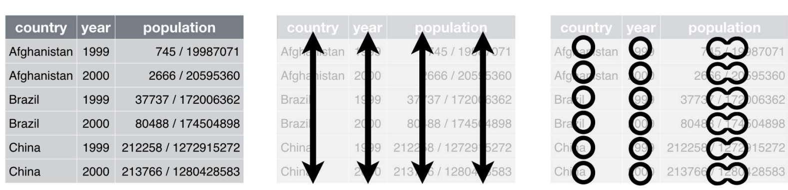
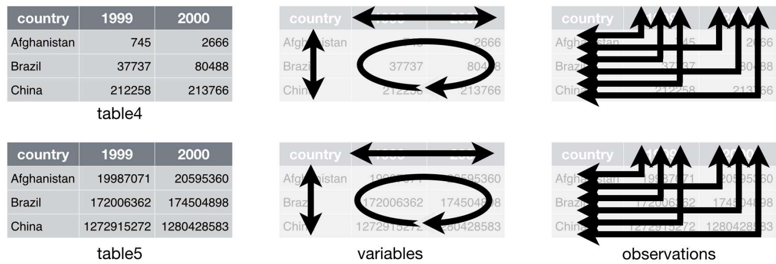


table3 variables values

Data set three combines the values of cases and population into the same cells. It may seem that this would help you calculate the rate, but that is not so. You will need to separate the population values from the cases values if you wish to do math with them. This can be done, but not with "basic" R syntax.

```
# Data set three
# No basic solution
```

Data set four



Data set four stores each variable in a different format: as a column, a set of column names, or a field of cells. As a result, you will need to work with each variable differently. This makes code written for data set four hard to generalize. The code that extracts the values of *year*, `names(table4)[-1]` , cannot be generalized to extract the values of population, `c(table5$1999, table5$2000, table5$2001)` . Compare this to data set one. With `table1` , you can use the same code to extract the values of year, `table1$year` , that you use to extract the values of population. To do so, you only need to change the name of the variable that you will access: `table1$population` .

The organization of data set four is inefficient in a second way as well. Data set four separates the values of some variables across two separate tables. This is inconvenient because you will need to extract information from two different places whenever you want to work with the data.

After you collect your input, you can calculate the rate.

```
# Data set four
cases <- c(table4$1999, table4$2000, table4$2001)

population <- c(table5$1999, table5$2000, table5
$2001)
cases / population * 10000
```

Data set one is much easier to work with than with data sets two, three, or four. To work with data sets two, three, and four, you need to take extra steps, which makes your code harder to write, harder to understand, and harder to debug.

Keep in mind that this is a trivial calculation with a trivial data set. The energy you must expend to manage a poor layout will increase with the size of your data. Extra steps will accumulate over the course of an analysis and allow errors to creep into your work. You can avoid these difficulties by converting your data into a tidy format at the start of your analysis.

The next sections will show you how to transform untidy data sets into tidy data sets.

Tidy data was popularized by Hadley Wickham, and it serves as the basis for many R packages and functions. You can learn more about tidy data by reading *Tidy Data* a paper written by Hadley Wickham and published in the Journal of Statistical Software. *Tidy Data* is available online at www.jstatsoft.org/v59/i10/paper.

2.2 `spread()` and `gather()`

The `tidyr` package by Hadley Wickham is designed to help you tidy your data. It contains four functions that alter the layout of tabular data sets, while preserving the values and relationships contained in the data sets.

The two most important functions in `tidyr` are `gather()` and `spread()`. Each relies on the idea of a key value pair.

2.2.1 key value pairs

A key value pair is a simple way to record information. A pair contains two parts: a *key* that explains what the information describes, and a *value* that contains the actual information. So for example,

```
Password: 0123456789
```

would be a key value pair. `0123456789` is the value, and it is associated with the key `Password`.

Data values form natural key value pairs. The value is the value of the pair and the variable that the value describes is the key. So for example, you could decompose `table1` into a group of key value pairs, but it would cease to be a useful data set because you no longer know which values belong to the same observation.

```
Country: Afghanistan
Country: Brazil
Country: China
Year: 1999
Year: 2000
Year: 2001
Population:   19987071
Population:   20595360
Population:  172006362
Population:  174504898
Population: 1272915272
Population: 1280428583
Cases:    745
Cases:   2666
Cases:  37737
Cases:  80488
Cases: 212258
Cases: 213766
```

Every cell in a table of data contains one half of a key value pair, as does every column name. In tidy data, each cell will contain a value and each column name will contain a key, but this doesn't need to be the case for untidy data. Consider `table2` .

```
table2

## Source: local data frame [12 x 4]
##
##         country year        key      value
## 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
```

In `table2` , the `key` column contains only keys (and not just because the column is labelled `key`). Conveniently, the `value` column contains the values associated with those keys.

You can use the `spread()` function to tidy this layout.

2.2.2 `spread()`

`spread()` turns a pair of key:value columns into a set of tidy columns. To use `spread()` , pass it the name of a data frame, then the name of the key column in the data frame, and then the name of the value column. Pass the column names as they are; do not use quotes.

To tidy `table2` , you would pass `spread()` the `key` column and then the `value` column.

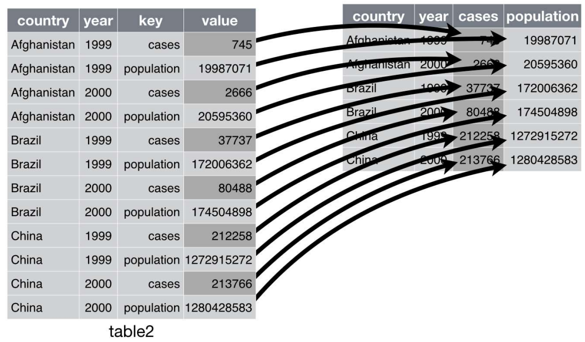
```
table2

## Source: local data frame [12 x 4]
##
##        country year        key      value
## 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

library(tidyr)
spread(table2, key, value)

## Source: local data frame [6 x 4]
##
##       country year  cases population
## 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
```

`spread()` returns a copy of your data set that has had the key and value columns removed. In their place, `spread()` adds a new column for each unique value of the key column. These unique values will form the column names of the new columns. `spread()` distributes the cells of the former value column across the cells of the new columns and truncates any non-key, non-value columns in a way that prevents duplication.



`spread()` distributes a pair of key:value columns into a field of cells. The unique values of the key column become the column names of the field of cells.

You can see that `spread()` maintains each of the relationships expressed in the original data set. The output contains the four original variables, *country*, *year*, *population*, and *cases*.

And the values of these variables are grouped according to the orginal observations, but now the layout of these relationships is tidy.

`spread()` takes three optional arguments in addition to `data`, `key`, and `value`:

- **`fill`** - If the tidy structure creates combinations of variables that do not exist in the original data set, `spread()` will place an `NA` in the resulting cells. `NA` is R's missing value symbol. You can change this behaviour by passing `fill` an alternative value to use.

- **`convert`** - If a value column contains multiple types of data, its elements will be saved as a single type, usually character strings. As a result, the new columns created by `spread()` will also contain character strings. If you set `convert = TRUE`, `spread()` will run `type.convert()` on each new column, which will convert strings to doubles (numerics), integers, logicals, complexes, or factors.

- **`drop`** - The `drop` argument controls how `spread()` handles factors in the key column. If you set `drop = FALSE`, spread will keep factor levels that do not appear in the key column, filling in the missing combinations with the value of `fill`.

2.2.3 `gather()`

`gather()` does the reverse of `spread()`. `gather()` collects a set of column names and places them into a single "key" column. It also collects the cells of those columns and places them into a single value column. You can use `gather()` to tidy `table4`.

```
table4  # cases

## Source: local data frame [3 x 3]
##
##       country   1999   2000
## 1 Afghanistan    745   2666
## 2      Brazil  37737  80488
## 3       China 212258 213766
```

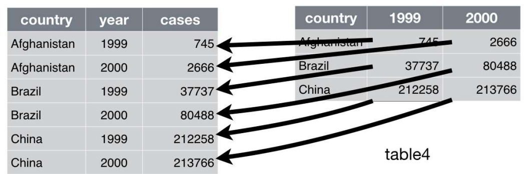
To use `gather()`, pass it the name of a data frame to reshape. Then pass `gather()` a character string to use for the name of the "key" column that it will make, as well as a character string to use as the name of the value column that it will make. Finally, specify which columns `gather()` should collapse into the key value pair (here with integer notation).

```
gather(table4, "year", "cases", 2:3)

## Source: local data frame [6 x 3]
##
##       country year  cases
## 1 Afghanistan 1999    745
## 2      Brazil 1999  37737
## 3       China 1999 212258
## 4 Afghanistan 2000   2666
## 5      Brazil 2000  80488
## 6       China 2000 213766
```

`gather()` returns a copy of the data frame with the specified columns removed. To this data frame, `gather()` has added two new columns: a "key" column that contains the former column names of the removed columns, and a value column that contains the former values of the removed columns. `gather()` repeats each of the former column names (as well as each of the original columns) to maintain each combination of values that appeared in the original data set. `gather()` uses the first string that you supplied as the name of the new "key" column, and it uses the second string as the name of the new value column.

I've placed "key" in quotation marks because you will usually use `gather()` to create tidy data. In this case, the "key" column will contain values, not keys. The values will only be keys in the sense that they were formally in the column names, a place where keys belong.



Just like `spread()` , gather maintains each of the relationships in the original data set. This time `table3` only contained three variables, *country*, *year* and *cases*. Each of these appears in the output of `gather()` in a tidy fashion.

`gather()` also maintains each of the observations in the original data set, organizing them in a tidy fashion.

We can use `gather()` to tidy `table4` in a similar fashion.

```
table5  # population

## Source: local data frame [3 x 3]
##
##       country       1999       2000
## 1 Afghanistan   19987071   20595360
## 2      Brazil  172006362  174504898
## 3       China 1272915272 1280428583

gather(table5, "year", "population", 2:3)

## Source: local data frame [6 x 3]
##
##       country year population
## 1 Afghanistan 1999   19987071
## 2      Brazil 1999  172006362
## 3       China 1999 1272915272
## 4 Afghanistan 2000   20595360
## 5      Brazil 2000  174504898
## 6       China 2000 1280428583
```

In this code, I identified the columns to collapse with a series of integers. `2:3` describes the second and third columns of the data frame. You can identify the same columns with each of the commands below.

```
gather(table5, "year", "population", c(2, 3))
gather(table5, "year", "population", -1)
```

You can also identify columns by name with the notation introduced by the `select` function in `dplyr`, see Section 3.1.

In *Section 3.6*, you will learn how to combine two data frames, like the tidy versions of `table4` and `table5` into a single data frame.

2.3 `separate()` and `unite()`

`spread()` and `gather()` help you reshape the layout of your data to place variables in columns and observations in rows. `separate()` and `unite()` help you split and combine cells to place a single, complete value in each cell.

2.3.1 `separate()`

`separate()` turns a single character column into multiple columns by splitting the values of the column wherever a separator character appears.

[SEPARATE DIAGRAM]

So, for example, we can use `separate()` to tidy `table3`, which combines values of *cases* and *population* in the same column.

```
separate(table3, rate, into = c("cases", "populat
ion"))

## Source: local data frame [6 x 4]
##
##       country year  cases population
## 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
```

To use `separate()` pass separate the name of a data frame to reshape and the name of a column to separate. Also give `separate()` an `into` argument, which should be a vector of character strings to use as new column names. `separate()` will return a copy of the data frame with the column removed. The previous values of the column will be split across several columns, one for each name in `into`.

By default, `separate()` will split values wherever a non-alphanumeric character appears. Non-alphanumeric characters are characters that are neither a number nor a letter. For example, in the code above, `separate()` split the values of `rate` at the forward slash characters.

If you wish to use a specific character to separate a column, you can pass the character to the `sep` argument of `separate()`. For example, we could rewrite the code above as

```
separate(table3, rate, into = c("cases", "populat
ion"), sep = "/")
```

See Appendix E to learn more about regular expressions in R.

You can also pass an integer or vector of integers to `sep`. `separate()` will interpret the integers as positions to split at. Positive values start at 1 at the far-left of the strings; negative value start at -1 at the far-right of the strings. The length of `sep` should be one less than the number of names in `into`. You can use this arrangement to separate the last two digits of each year.

```
separate(table3, year, into = c("century", "yea
r"), sep = 2)

## Source: local data frame [6 x 4]
##
##       country century year              rate
## 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
```

You can futher customize `separate()` with the `remove`, `convert`, and `extra` arguments:

- **`remove`** - Set `remove = FALSE` to retain the column of values that were separated in the final data frame.
- **`convert`** - By default, `separate()` will return new columns as character columns. Set `convert = TRUE` to convert new columns to double (numeric), integer, logical, complex, and factor columns with `type.convert()`.
- **`extra`** - `extra` controls what happens when the number of new values in a cell does not match the number of new columns in `into`. If `extra = error` (the default), `separate()` to return an error. If `extra = drop`, `separate()` will drop new values and supply `NA` s as

necessary to fill the new columns. If `extra = merge`, `separate()` will split at most `length(into)` times.

2.3.2 `unite()`

`unite()` does the opposite of `separate()`: it combines multiple columns into a single column.

[UNITE DESCRIPTION]

We can use `unite()` to rejoin the *century* and *year* columns that we created in the last example. That data is saved in the `DSR` package as `table6`.

```
table6

## Source: local data frame [6 x 4]
##
##       country century year              rate
## 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

unite(table6, "new", century, year, sep = "")

## Source: local data frame [6 x 3]
##
##       country  new              rate
## 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
```

Give `unite()` the name of the data frame to reshape, the name of the new column to create (as a character string), and the names of the columns to unite. `unite()` will place an underscore (_) between values from separate columns. If you would like to use a different separator, or no separator at all, pass the separator as a character string to `sep`.

`unite()` returns a copy of the data frame that includes the new column, but not the columns used to build the new column. If you would like to retain these columns, add the argument `remove = FALSE`.

You can also use integers or the syntax of the `dplyr::select` to specify columns to unite in a more concise way. We'll learn about `select` in Section 3.1.

2.4 Case Study

The `who` data set in the `DSR` package contains cases of tuberculosis (TB) reported between 1995 and 2013 sorted by country, age, and gender. The data comes in the *2014 World Health Organization Global Tuberculosis Report*, available for download at www.who.int/tb/country/data/download/en/. The data provides a wealth of epidemiological information, but it would be difficult to work with the data as it is.

To see the data in its raw form, load `DSR` with `library(DSR)` then run

```
View(who)
```

Filter

	country	iso2	iso3	year	new_sp_m014	new_sp_m1524	new_sp_m2534	new_sp_m3544	new_sp_
1	Afghanistan	AF	AFG	1980	NA	NA	NA	NA	
2	Afghanistan	AF	AFG	1981	NA	NA	NA	NA	
3	Afghanistan	AF	AFG	1982	NA	NA	NA	NA	
4	Afghanistan	AF	AFG	1983	NA	NA	NA	NA	
5	Afghanistan	AF	AFG	1984	NA	NA	NA	NA	
6	Afghanistan	AF	AFG	1985	NA	NA	NA	NA	
7	Afghanistan	AF	AFG	1986	NA	NA	NA	NA	
8	Afghanistan	AF	AFG	1987	NA	NA	NA	NA	
9	Afghanistan	AF	AFG	1988	NA	NA	NA	NA	
10	Afghanistan	AF	AFG	1989	NA	NA	NA	NA	

Showing 1 to 10 of 7,240 entries

A subset of the `who` data frame displayed with `View()`.

`who` provides a realistic example of tabular data in the wild. It contains redundant columns, odd variable codes, and many missing values. In short, `who` is messy.

TIP

The `View()` function opens a data viewer in the RStudio IDE. Here you can examine the data set, search for values, and filter the display based on logical conditions. Notice that the `View()` function begins with a capital V.

The most unique feature of `who` is its coding system. Columns five through sixty encode four separate pieces of information in their column names:

1. The first three letters of each column denote whether the column contains new or old cases of TB. In this data set, each column contains new cases.

2. The next two letters describe the type of case being counted. We will treat each of these as a separate variable.
   - `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 describes the sex of TB patients. The data set groups cases by males (`m`) and females (`f`).

4. The remaining numbers describe the age group of TB patients. The data set groups cases into seven age groups:
   - `014` stands for patients that are 0 to 14 years old
   - `1524` stands for patients that are 15 to 24 years old
   - `2534` stands for patients that are 25 to 34 years old
   - `3544` stands for patients that are 35 to 44 years old
   - `4554` stands for patients that are 45 to 54 years old
   - `5564` stands for patients that are 55 to 64 years old
   - `65` stands for patients that are 65 years old or older

Notice that the `who` data set is untidy in multiple ways. First, the data appears to contain values in its column names. We can move the values into their own column with `gather()` . This will make it easy to separate the values combined in each code.

```
who <- gather(who, "code", "value", 5:60)
```

Filter

	country	iso2	iso3	year	code	value
1	Afghanistan	AF	AFG	1980	new_sp_m014	NA
2	Afghanistan	AF	AFG	1981	new_sp_m014	NA
3	Afghanistan	AF	AFG	1982	new_sp_m014	NA
4	Afghanistan	AF	AFG	1983	new_sp_m014	NA
5	Afghanistan	AF	AFG	1984	new_sp_m014	NA
6	Afghanistan	AF	AFG	1985	new_sp_m014	NA
7	Afghanistan	AF	AFG	1986	new_sp_m014	NA
8	Afghanistan	AF	AFG	1987	new_sp_m014	NA
9	Afghanistan	AF	AFG	1988	new_sp_m014	NA
10	Afghanistan	AF	AFG	1989	new_sp_m014	NA

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We can separate the values in each code with two passes of `separate()` . The first pass will split the codes at each underscore.

```
who <- separate(who, code, c("new", "var", "sexag
e"))
```

Filter

	country	iso2	iso3	year	new	var	sexage	value
1	Afghanistan	AF	AFG	1980	new	sp	m014	NA
2	Afghanistan	AF	AFG	1981	new	sp	m014	NA
3	Afghanistan	AF	AFG	1982	new	sp	m014	NA
4	Afghanistan	AF	AFG	1983	new	sp	m014	NA
5	Afghanistan	AF	AFG	1984	new	sp	m014	NA
6	Afghanistan	AF	AFG	1985	new	sp	m014	NA
7	Afghanistan	AF	AFG	1986	new	sp	m014	NA
8	Afghanistan	AF	AFG	1987	new	sp	m014	NA
9	Afghanistan	AF	AFG	1988	new	sp	m014	NA
10	Afghanistan	AF	AFG	1989	new	sp	m014	NA

Showing 1 to 10 of 405,440 entries

The second pass will split `sexage` after the first character to create a sex column and an age column.

```
who <- separate(who, sexage, c("sex", "age"), sep
 = 1)
```

Filter

	country	iso2	iso3	year	new	var	sex	age	value
1	Afghanistan	AF	AFG	1980	new	sp	m	014	NA
2	Afghanistan	AF	AFG	1981	new	sp	m	014	NA
3	Afghanistan	AF	AFG	1982	new	sp	m	014	NA
4	Afghanistan	AF	AFG	1983	new	sp	m	014	NA
5	Afghanistan	AF	AFG	1984	new	sp	m	014	NA
6	Afghanistan	AF	AFG	1985	new	sp	m	014	NA
7	Afghanistan	AF	AFG	1986	new	sp	m	014	NA
8	Afghanistan	AF	AFG	1987	new	sp	m	014	NA
9	Afghanistan	AF	AFG	1988	new	sp	m	014	NA
10	Afghanistan	AF	AFG	1989	new	sp	m	014	NA

Showing 1 to 10 of 405,440 entries

Finally, we can move the `rel` , `ep` , `sn` , and `sp` keys into their own column names with `spread()` .

```
who <- spread(who, var, value)
```

Filter

	country	iso2	iso3	year	new	sex	age	ep	rel	sn	sp
1	Afghanistan	AF	AFG	1980	new	m	014	NA	NA	NA	NA
2	Afghanistan	AF	AFG	1981	new	m	014	NA	NA	NA	NA
3	Afghanistan	AF	AFG	1982	new	m	014	NA	NA	NA	NA
4	Afghanistan	AF	AFG	1983	new	m	014	NA	NA	NA	NA
5	Afghanistan	AF	AFG	1984	new	m	014	NA	NA	NA	NA
6	Afghanistan	AF	AFG	1985	new	m	014	NA	NA	NA	NA
7	Afghanistan	AF	AFG	1986	new	m	014	NA	NA	NA	NA
8	Afghanistan	AF	AFG	1987	new	m	014	NA	NA	NA	NA
9	Afghanistan	AF	AFG	1988	new	m	014	NA	NA	NA	NA
10	Afghanistan	AF	AFG	1989	new	m	014	NA	NA	NA	NA

Showing 1 to 10 of 101,360 entries

The `who` data set is now tidy. It is far from sparkling (for example, it contains several redundant columns), but it will now be much easier to work with in R. We will continue to work with this tidy version of `who` in *Section 3.7*, where we will remove the redundant columns and calculate new variables.