Tips & tRicks in R

Amanda D. Perez, PhD

Table of contents

Welcome

This website contains the living documentation of R Tips & tRicks.

1 Introduction

This is a resource created from markdown and executable code. The github repo containing all of the code can be found here. These are pieces of code that I regularly use in my work and have created this site to create one cohesive location to easily search and find relevant code.

Part I

Data Exploration

Our goal in this part of the book is to give you a rapid overview of the main tools of data science: **importing**, **tidying**, **transforming**, and **visualizing data**….

We want to show you the "whole game" of data science giving you just enough of all the major pieces so that you can tackle real, if simple, data sets. The later parts of the book, will hit each of these topics in more depth, increasing the range of data science challenges that you can tackle.

Five chapters focus on the tools of data science:

- Visualisation is a great place to start with R programming, because the payoff is so clear: you get to make elegant and informative plots that help you understand data. In … so in **?@sec-basics**, you'll learn the key verbs th
- Visualisation alone is typically not enough, so in Chapter 2, you'll learn the key verbs that allow you to select important variables, filter out key observations, create new variables, and compute summaries.
- In Chapter 3, you'll learn about tidy data, a consistent way of storing your data that makes transformation, visualization, and modelling easier. You'll learn the underlying principles, and how to get your data into a tidy form.

2 The psych package

2.1 Introduction

In this chapter, I will focus exclusively on the `psych` package. I will cover all of the functions that I regularly use.

2.1.1 Prerequisites

If you do not already have the `psych` package downloaded, you will first need to run `install.packages("psych")`

Then, you will be able to load the library and use its functions.

```
library(psych)
```

We will be using the `bfi` dataset that is included in the `psych` package. It is described as follows:

> *25 personality self report items taken from the International Personality Item Pool (ipip.ori.org) were included as part of the Synthetic Aperture Personality Assessment (SAPA) web based personality assessment project. The data from 2800 subjects are included here as a demonstration set for scale construction, factor analysis, and Item Response Theory analysis. Three additional demographic variables (sex, education, and age) are also included.*

The code `data(bfi)` will take the `bfi` dataset from the `psych` package and add it to your R Environment.

```
data(bfi)
```

2.2 Describing Data

The `describe()` function will return the following for any numeric variable: number of valid cases, mean, standard deviation, trimmed mean (with trim defaulting to .1) , median (standard or interpolated, mad: median absolute deviation (from the median), minimum, maximum, skew, kurtosis, standard error.

Below I am `describing` the `A2` variable which has responses to the Agreeableness statement: `Inquire about others' well-being`.

```
describe(bfi$A2)
```

```
   vars    n mean   sd median trimmed  mad min max range  skew kurtosis   se
X1    1 2773  4.8 1.17      5    4.98 1.48   1   6     5 -1.12     1.05 0.02
```

You can also describe by `groups` which will return descriptive statistics by groups. Below I am describing the `A2` variable by gender. Males = 1, Females =2.

```
describeBy(A2 ~ gender, data = bfi)
```

```

 Descriptive statistics by group 
gender: 1
   vars   n mean   sd median trimmed  mad min max range  skew kurtosis   se
X1    1 908  4.5 1.26      5    4.65 1.48   1   6     5 -0.89     0.34 0.04
------------------------------------------------------------ 
gender: 2
   vars    n mean   sd median trimmed  mad min max range  skew kurtosis   se
X1    1 1865 4.95 1.09      5    5.12 1.48   1   6     5 -1.24     1.55 0.03
```

Another useful function is `headTail` which will show the first and last couple of lines of a dataset.

```
headTail(bfi)
```

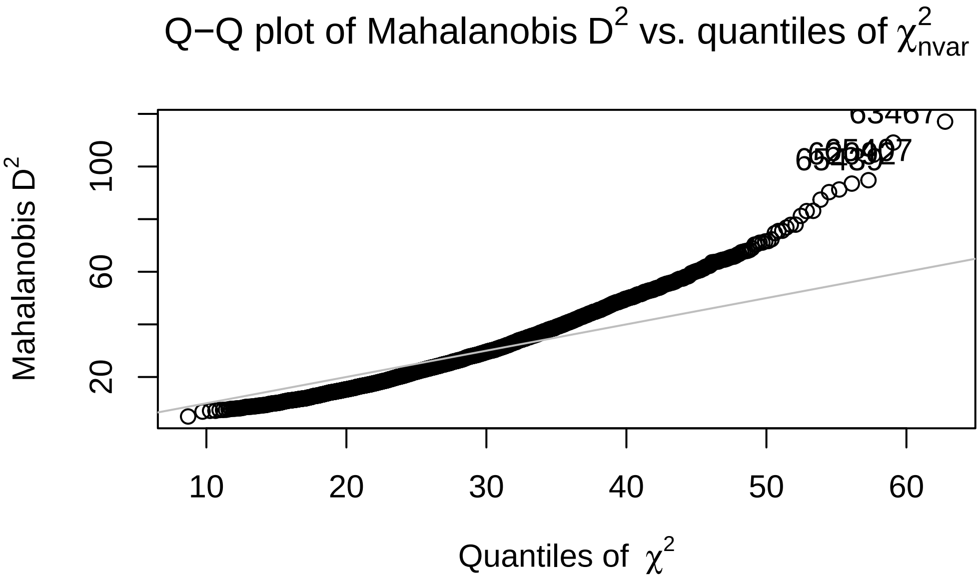
```
       A1  A2  A3  A4  A5  C1  C2  C3  C4  C5  E1  E2  E3  E4  E5   N1  N2  N3
61617   2   4   3   4   4   2   3   3   4   4   3   3   3   4   4    3   4   2
61618   2   4   5   2   5   5   4   4   3   4   1   1   6   4   3    3   3   3
61620   5   4   5   4   4   4   5   4   2   5   2   4   4   4   5    4   5   4
61621   4   4   6   5   5   4   4   3   5   5   5   3   4   4   4    2   5   2
```

```
...    ... ... ... ... ... ... ... ... ... ... ... ... ... ... ...  ... ... ...
67552    2   4   4   3   5   2   3   4   4   3   2   2   4   4   3 <NA>   3   2
67556    2   3   5   2   5   5   5   5   1   1   2   2   6   3   6    3   4   3
67559    5   2   2   4   4   5   5   5   2   6   2   2   4   5   4    5   5   6
67560    2   3   1   4   2   5   5   3   3   3   3   3   1   2   2    1   2   2
        N4  N5  O1  O2  O3  O4  O5 gender education age
61617    2   3   3   6   3   4   3      1      <NA>  16
61618    5   5   4   2   4   3   3      2      <NA>  18
61620    2   3   4   2   5   5   2      2      <NA>  17
61621    4   1   3   3   4   3   5      2      <NA>  17
...    ... ... ... ... ... ... ...    ...       ... ...
67552    3   3   6   3   5   4   2      1         4  27
67556    3   1   5   1   6   4   3      2         4  29
67559    4   1   5   2   5   5   1      1         4  31
67560    1   1   3   1   3   5   1      2         4  50
```

2.3 Outlier Detection

Find and graph Mahalanobis squared distances to detect outliers using the `outlier` function. The Mahalanobis distance is D^2 = (x-)' Σ^-1 (x-) where Σ is the covariance of the x matrix. D2 may be used as a way of detecting outliers in distribution. Large D2 values, compared to the expected Chi Square values indicate an unusual response pattern. The outlier values are in the vector d2.The mahalanobis function in stats does not handle missing data, therefore I always add in `na.rm = TRUE` so that NA values are removed.

```
d2 <- outlier(bfi, plot= TRUE, na.rm = TRUE)
```



2.4 Scoring Scales

My biggest use of the **psych** package is scale scoring. This example will score the BFI (Big Five Inventory) personality scale.

2.4.1 Make a list of keys

First, we need to create a list that will tell R how to score our scale. In the `bfi` dataset, the Openness items begin with O, the Conscientiousness items begin with C, the Extraversion items begin with E, the Agreeableness items begin with A, and the Nueroticism items begin with N. We will also need to account for any reverse score items by adding a '-' sign to the variable names that need to be reversed.

```
ocean.key <- list(Open = c("O1",  "-O2", "O3",  "O4",  "-O5"),
                  Cons = c("C1",  "C2",  "C3",  "-C4", "-C5"),
                  Extra = c("-E1", "-E2", "E3",  "E4",  "E5" ),
  Agree = c("-A1", "A2",  "A3",  "A4",  "A5"),
  Neuro = c("N1", "N2", "N3", "N4", "N5")
  )
```

2.4.2 Scoring the scale

```r
bfi.scores <- scoreItems(keys = ocean.key, items = bfi, min = 1, max = 6)

bfi.scores
```

```
Call: scoreItems(keys = ocean.key, items = bfi, min = 1, max = 6)

(Unstandardized) Alpha:
      Open Cons Extra Agree Neuro
alpha  0.6 0.72  0.76   0.7  0.81

Standard errors of unstandardized Alpha:
       Open  Cons Extra Agree Neuro
ASE   0.017 0.014 0.013 0.014 0.011

Average item correlation:
          Open Cons Extra Agree Neuro
average.r 0.23 0.34  0.39  0.32  0.46

Median item correlation:
 Open  Cons Extra Agree Neuro
 0.22  0.34  0.38  0.34  0.41

 Guttman 6* reliability:
         Open Cons Extra Agree Neuro
Lambda.6  0.6 0.72  0.76   0.7  0.81

Signal/Noise based upon av.r :
             Open Cons Extra Agree Neuro
Signal/Noise  1.5  2.6   3.2   2.3   4.3

Scale intercorrelations corrected for attenuation
 raw correlations below the diagonal, alpha on the diagonal
 corrected correlations above the diagonal:
        Open  Cons Extra Agree Neuro
Open    0.597  0.30  0.32  0.23 -0.12
Cons    0.194  0.72  0.35  0.36 -0.30
Extra   0.215  0.26  0.76  0.63 -0.28
Agree   0.147  0.26  0.46  0.70 -0.24
Neuro  -0.086 -0.23 -0.22 -0.18  0.81
```

```
In order to see the item by scale loadings and frequency counts of the data
print with the short option = FALSE
```

```r
print(bfi.scores, short = F)
```

```
Call: scoreItems(keys = ocean.key, items = bfi, min = 1, max = 6)

(Unstandardized) Alpha:
      Open Cons Extra Agree Neuro
alpha  0.6 0.72  0.76   0.7  0.81

Standard errors of unstandardized Alpha:
       Open  Cons Extra Agree Neuro
ASE   0.017 0.014 0.013 0.014 0.011

Average item correlation:
          Open Cons Extra Agree Neuro
average.r 0.23 0.34  0.39  0.32  0.46

Median item correlation:
 Open  Cons Extra Agree Neuro
 0.22  0.34  0.38  0.34  0.41

 Guttman 6* reliability:
         Open Cons Extra Agree Neuro
Lambda.6  0.6 0.72  0.76   0.7  0.81

Signal/Noise based upon av.r :
             Open Cons Extra Agree Neuro
Signal/Noise  1.5  2.6   3.2   2.3   4.3

Scale intercorrelations corrected for attenuation
 raw correlations below the diagonal, alpha on the diagonal
 corrected correlations above the diagonal:
        Open  Cons Extra Agree Neuro
Open   0.597  0.30  0.32  0.23 -0.12
Cons   0.194  0.72  0.35  0.36 -0.30
Extra  0.215  0.26  0.76  0.63 -0.28
Agree  0.147  0.26  0.46  0.70 -0.24
Neuro -0.086 -0.23 -0.22 -0.18  0.81
```

```
Item by scale correlations:
 corrected for item overlap and scale reliability
    Open  Cons Extra Agree Neuro
O1  0.52  0.20  0.31  0.17 -0.09
O2 -0.45 -0.18 -0.07 -0.01  0.19
O3  0.61  0.20  0.42  0.26 -0.07
O4  0.32 -0.02 -0.10  0.06  0.21
O5 -0.53 -0.14 -0.11 -0.09  0.11
C1  0.28  0.53  0.19  0.13 -0.08
C2  0.20  0.61  0.17  0.22  0.00
C3  0.08  0.54  0.14  0.21 -0.09
C4 -0.23 -0.66 -0.23 -0.24  0.31
C5 -0.10 -0.59 -0.29 -0.26  0.36
E1 -0.16 -0.06 -0.59 -0.30  0.11
E2 -0.15 -0.25 -0.70 -0.39  0.34
E3  0.37  0.20  0.60  0.44 -0.10
E4  0.04  0.23  0.68  0.51 -0.22
E5  0.31  0.40  0.55  0.34 -0.10
A1 -0.14 -0.06 -0.11 -0.39  0.14
A2  0.17  0.23  0.40  0.67 -0.07
A3  0.17  0.22  0.48  0.70 -0.11
A4  0.01  0.29  0.30  0.49 -0.14
A5  0.18  0.23  0.55  0.62 -0.23
N1 -0.12 -0.21 -0.11 -0.22  0.76
N2 -0.06 -0.19 -0.12 -0.22  0.74
N3 -0.03 -0.20 -0.14 -0.14  0.74
N4 -0.02 -0.31 -0.39 -0.22  0.62
N5 -0.18 -0.14 -0.19 -0.04  0.54

Non missing response frequency for each item
      1    2    3    4    5    6 miss
O1 0.01 0.04 0.08 0.22 0.33 0.33 0.01
O2 0.29 0.26 0.14 0.16 0.10 0.06 0.00
O3 0.03 0.05 0.11 0.28 0.34 0.20 0.01
O4 0.02 0.04 0.06 0.17 0.32 0.39 0.01
O5 0.27 0.32 0.19 0.13 0.07 0.03 0.01
C1 0.03 0.06 0.10 0.24 0.37 0.21 0.01
C2 0.03 0.09 0.11 0.23 0.35 0.20 0.01
C3 0.03 0.09 0.11 0.27 0.34 0.17 0.01
C4 0.28 0.29 0.17 0.16 0.08 0.02 0.01
C5 0.18 0.20 0.12 0.22 0.17 0.10 0.01
E1 0.24 0.23 0.15 0.16 0.13 0.09 0.01
E2 0.19 0.24 0.12 0.22 0.14 0.09 0.01
```

```
E3 0.05 0.11 0.15 0.30 0.27 0.13 0.01
E4 0.05 0.09 0.10 0.16 0.34 0.26 0.00
E5 0.03 0.08 0.10 0.22 0.34 0.22 0.01
A1 0.33 0.29 0.14 0.12 0.08 0.03 0.01
A2 0.02 0.05 0.05 0.20 0.37 0.31 0.01
A3 0.03 0.06 0.07 0.20 0.36 0.27 0.01
A4 0.05 0.08 0.07 0.16 0.24 0.41 0.01
A5 0.02 0.07 0.09 0.22 0.35 0.25 0.01
N1 0.24 0.24 0.15 0.19 0.12 0.07 0.01
N2 0.12 0.19 0.15 0.26 0.18 0.10 0.01
N3 0.18 0.23 0.13 0.21 0.16 0.09 0.00
N4 0.17 0.24 0.15 0.22 0.14 0.09 0.01
N5 0.24 0.24 0.14 0.18 0.12 0.09 0.01
```

```
headTail(bfi.scores$scores)
```

```
      Open Cons Extra Agree Neuro
61617    3  2.8   3.8     4   2.8
61618    4    4     5   4.2   3.8
61620  4.8    4   4.2   3.8   3.6
61621  3.2    3   3.6   4.6   2.8
...    ...  ...   ...   ...   ...
67552  4.8  3.2   4.2   4.2   2.8
67556    5  5.4     5     4   2.8
67559  5.2  4.2   4.6   2.8   4.2
67560  4.6  4.2   2.6     3   1.4
```

2.4.3 Adding score to dataset

```
bfi$OPEN <- bfi.scores$scores[,1]
bfi$CONS <- bfi.scores$scores[,2]
bfi$EXTRA <- bfi.scores$scores[,3]
bfi$AGREE <- bfi.scores$scores[,4]
bfi$NEURO <- bfi.scores$scores[,5]
```

Males = 1, Females =2.

```
describeBy(OPEN + CONS + EXTRA + AGREE + NEURO ~ gender, data = bfi)
```

```
 Descriptive statistics by group
gender: 1
      vars   n mean   sd median trimmed  mad min max range  skew kurtosis   se
OPEN     1 919 4.66 0.81    4.8    4.69 0.89 1.2   6   4.8 -0.36    -0.37 0.03
CONS     2 919 4.14 0.96    4.2    4.17 1.19 1.0   6   5.0 -0.24    -0.31 0.03
EXTRA    3 919 3.99 1.11    4.0    4.03 1.19 1.0   6   5.0 -0.36    -0.36 0.04
AGREE    4 919 4.39 0.93    4.4    4.45 0.89 1.2   6   4.8 -0.57     0.04 0.03
NEURO    5 919 2.95 1.14    2.8    2.91 1.19 1.0   6   5.0  0.26    -0.64 0.04
------------------------------------------------------------
gender: 2
      vars    n mean   sd median trimmed  mad min max range  skew kurtosis   se
OPEN     1 1881 4.56 0.80    4.6    4.59 0.89 1.4   6   4.6 -0.34    -0.23 0.02
CONS     2 1881 4.33 0.93    4.4    4.38 0.89 1.0   6   5.0 -0.50    -0.03 0.02
EXTRA    3 1881 4.22 1.02    4.4    4.28 1.19 1.0   6   5.0 -0.52    -0.11 0.02
AGREE    4 1881 4.78 0.85    5.0    4.86 0.89 1.0   6   5.0 -0.89     0.80 0.02
NEURO    5 1881 3.27 1.20    3.2    3.23 1.19 1.0   6   5.0  0.18    -0.68 0.03
```

3 The tidyverse

3.1 Introduction

> "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

In this chapter, you will learn a consistent way to organize your data in R using a system called **tidy data**. Getting your data into this format requires some work up front, but that work pays off in the long term. Once you have tidy data and the tidy tools provided by packages in the tidyverse, you will spend much less time munging data from one representation to another, allowing you to spend more time on the data questions you care about.

In this chapter, you'll first learn the definition of tidy data and see it applied to simple toy dataset. Then we'll dive into the main tool you'll use for tidying data: pivoting. Pivoting allows you to change the form of your data, without changing any of the values. We'll finish up with a discussion of usefully untidy data, and how you can create it if needed.

3.1.1 Prerequisites

In this chapter we'll focus on tidyr, a package that provides a bunch of tools to help tidy up your messy datasets. tidyr is a member of the core tidyverse.

```
library(tidyverse)
```

```
Warning: package 'ggplot2' was built under R version 4.1.2
```

```
Warning: package 'readr' was built under R version 4.1.2
```

From this chapter on, we'll suppress the loading message from `library(tidyverse)`.

3.2 Tidy data

You can represent the same underlying data in multiple ways. The example below shows the same data organised in four different ways. Each dataset shows the same values of four variables: *country*, *year*, *population*, and *cases* of TB (tuberculosis), but each dataset organizes the values in a different way.

```
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
```

```
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
```

```
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
```

```
# Spread across two tibbles
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
```

These are all representations of the same underlying data, but they are not equally easy to use. One of them, `table1`, will be much easier to work with inside the tidyverse because it's tidy.

There are three interrelated rules that make a dataset tidy:

1. Each variable is a column; each column is a variable.
2. Each observation is row; each row is an observation.
3. Each value is a cell; each cell is a single value.

?@fig-tidy-structure shows the rules visually.

Why ensure that your data is tidy? There are two main advantages:

1. There's a general advantage to picking one consistent way of storing data. If you have a consistent data structure, it's easier to learn the tools that work with it because they have an underlying uniformity.

2. There's a specific advantage to placing variables in columns because it allows R's vectorised nature to shine. As you learned in **?@sec-mutate** and **?@sec-summarize**, most built-in R functions work with vectors of values. That makes transforming tidy data feel particularly natural.

dplyr, ggplot2, and all the other packages in the tidyverse are designed to work with tidy data. Here are a couple of small examples showing how you might work with `table1`.

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

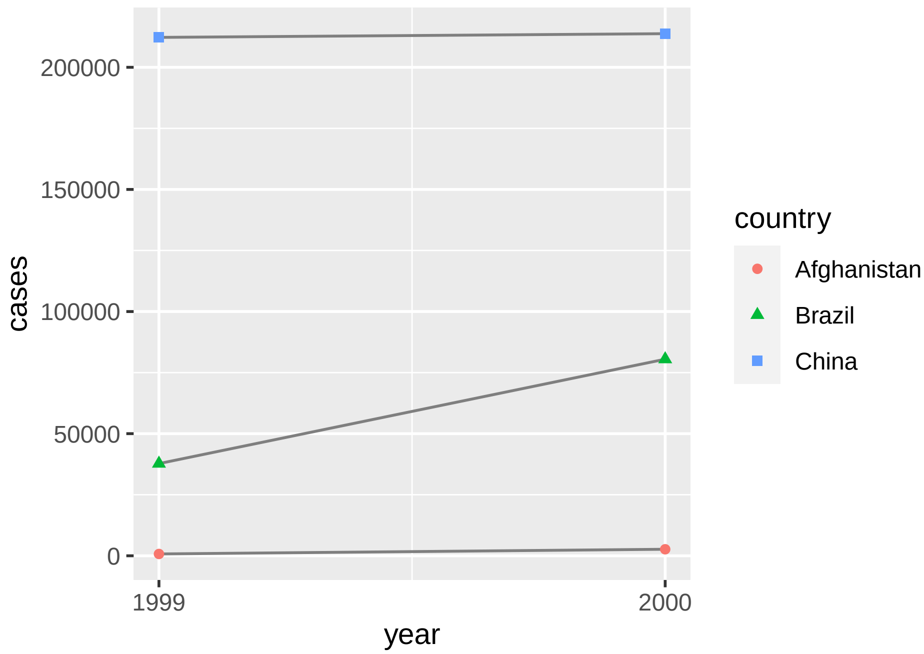
```
# A tibble: 6 x 5
  country      year  cases population  rate
  <chr>       <int>  <int>      <int> <dbl>
1 Afghanistan  1999    745   19987071 0.373
2 Afghanistan  2000   2666   20595360 1.29
3 Brazil       1999  37737  172006362 2.19
4 Brazil       2000  80488  174504898 4.61
5 China        1999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

```
# Compute cases per year
table1 |>
  count(year, wt = cases)
```

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

```
# Visualise changes over time
ggplot(table1, aes(year, cases)) +
  geom_line(aes(group = country), color = "grey50") +
```

```
geom_point(aes(color = country, shape = country)) +
scale_x_continuous(breaks = c(1999, 2000))
```



3.2.1 Exercises

1. Using prose, describe how the variables and observations are organised in each of the sample tables.
2. Sketch out the process you'd use to calculate the `rate` for `table2` and `table4a` + `table4b`. You will need to perform four operations:

    a. Extract the number of TB cases per country per year.
    b. Extract the matching population per country per year.
    c. Divide cases by population, and multiply by 10000.
    d. Store back in the appropriate place.

    You haven't yet learned all the functions you'd need to actually perform these operations, but you should still be able to think through the transformations you'd need.
3. Recreate the plot showing change in cases over time using `table2` instead of `table1`. What do you need to do first?

3.3 Pivoting

The principles of tidy data might seem so obvious that you wonder if you'll ever encounter a dataset that isn't tidy. Unfortunately, however, most real data is untidy. There are two main reasons:

1. Data is often organised to facilitate some goal other than analysis. For example, it's common for data to be structured to make data entry, not analysis, easy.
2. Most people aren't familiar with the principles of tidy data, and it's hard to derive them yourself unless you spend a lot of time working with data.

This means that most real analyses will require at least a little tidying. You'll begin by figuring out what the underlying variables and observations are. Sometimes this is easy; other times you'll need to consult with the people who originally generated the data. Next, you'll **pivot** your data into a tidy form, with variables in the columns and observations in the rows.

tidyr provides two functions for pivoting data: `pivot_longer()`, which makes datasets **longer** by increasing rows and reducing columns, and `pivot_wider()` which makes datasets **wider** by increasing columns and reducing rows. The following sections work through the use of `pivot_longer()` and `pivot_wider()` to tackle a wide range of realistic datasets. These examples are drawn from `vignette("pivot", package = "tidyr")`, which you should check out if you want to see more variations and more challenging problems.

Let's dive in.

3.3.1 Data in column names

The `billboard` dataset records the billboard rank of songs in the year 2000:

```
billboard
```

```
# A tibble: 317 x 79
   artist   track   date.entered   wk1   wk2   wk3   wk4   wk5   wk6   wk7   wk8
   <chr>    <chr>   <date>       <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl> <dbl>
 1 2 Pac    Baby D~ 2000-02-26      87    82    72    77    87    94    99    NA
 2 2Ge+her  The Ha~ 2000-09-02      91    87    92    NA    NA    NA    NA    NA
 3 3 Doors~ Krypto~ 2000-04-08      81    70    68    67    66    57    54    53
 4 3 Doors~ Loser   2000-10-21      76    76    72    69    67    65    55    59
 5 504 Boyz Wobble~ 2000-04-15      57    34    25    17    17    31    36    49
 6 98^0     Give M~ 2000-08-19      51    39    34    26    26    19     2     2
 7 A*Teens  Dancin~ 2000-07-08      97    97    96    95   100    NA    NA    NA
 8 Aaliyah  I Don'~ 2000-01-29      84    62    51    41    38    35    35    38
```

```
 9 Aaliyah  Try Ag~ 2000-03-18      59    53    38    28    21    18    16    14
10 Adams, ~ Open M~ 2000-08-26      76    76    74    69    68    67    61    58
# ... with 307 more rows, and 68 more variables: 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>, ...
```

In this dataset, each observation is a song. The first three columns (`artist`, `track` and `date.entered`) are variables that describe the song. Then we have 76 columns (`wk1-wk76`) that describe the rank of the song in each week. Here, the column names are one variable (the `week`) and the cell values are another (the `rank`).

To tidy this data, we'll use `pivot_longer()`. After the data, there are three key arguments:

- `cols` specifies which columns need to be pivoted, i.e. which columns aren't variables. This argument uses the same syntax as `select()` so here we could use `!c(artist, track, date.entered)` or `starts_with("wk")`.
- `names_to` names of the variable stored in the column names, here `"week"`.
- `values_to` names the variable stored in the cell values, here `"rank"`.

That gives the following call:

```
billboard |>
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank"
  )
```

```
# A tibble: 24,092 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 2 Pac  Baby Don't Cry (Keep... 2000-02-26   wk8      NA
```

```
 9 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk9      NA
10 2 Pac   Baby Don't Cry (Keep... 2000-02-26   wk10     NA
# ... with 24,082 more rows
```

What happens if a song is in the top 100 for less than 76 weeks? Take 2 Pac's "Baby Don't Cry", for example. The above output suggests that it was only the top 100 for 7 weeks, and all the remaining weeks are filled in with missing values. These `NA`s don't really represent unknown observations; they're forced to exist by the structure of the dataset[1], so we can ask `pivot_longer()` to get rid of them by setting `values_drop_na = TRUE`:

```
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
```

You might also wonder what happens if a song is in the top 100 for more than 76 weeks? We can't tell from this data, but you might guess that additional columns `wk77`, `wk78`, … would be added to the dataset.

This data is now tidy, but we could make future computation a bit easier by converting `week` into a number using `mutate()` and `parse_number()`. You'll learn more about `parse_number()` and friends in **?@sec-data-import**.

[1] We'll come back to this idea in **?@sec-missing-values**.

```r
billboard_tidy <- billboard |>
  pivot_longer(
    cols = starts_with("wk"),
    names_to = "week",
    values_to = "rank",
    values_drop_na = TRUE
  ) |>
  mutate(
    week = parse_number(week)
  )
billboard_tidy
```

```
# A tibble: 5,307 x 5
   artist  track                   date.entered  week  rank
   <chr>   <chr>                   <date>       <dbl> <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
```

Now we're in a good position to look at how song ranks vary over time by drawing a plot. The code is shown below and the result is Figure 3.1.

```r
billboard_tidy |>
  ggplot(aes(week, rank, group = track)) +
  geom_line(alpha = 1/3) +
  scale_y_reverse()
```

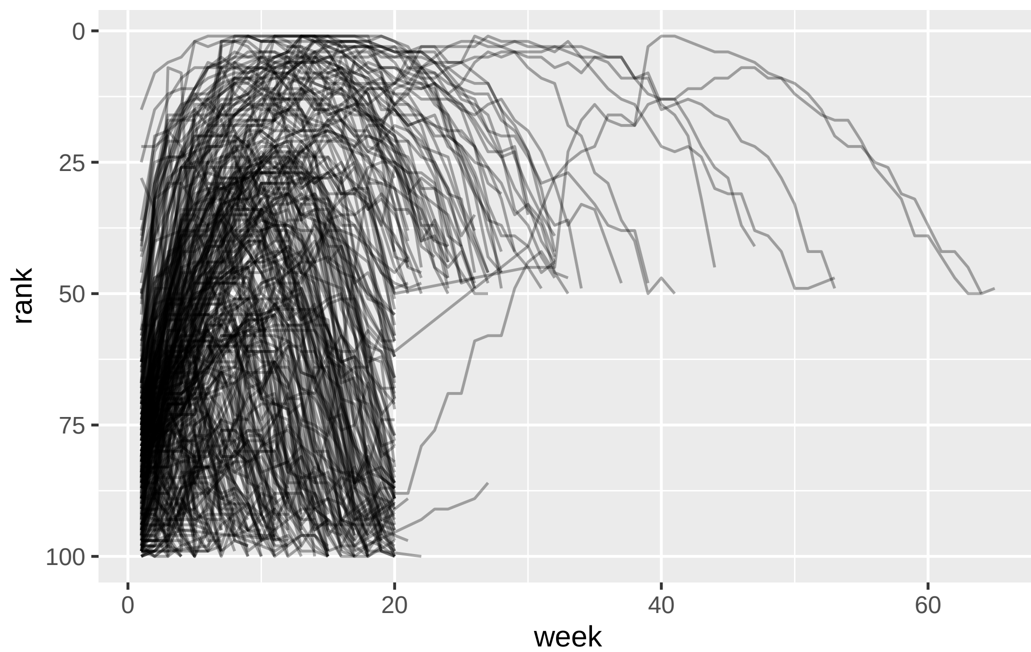


Figure 3.1: A line plot showing how the rank of a song changes over time.

3.3.2 How does pivoting work?

Now that you've seen what pivoting can do for you, it's worth taking a little time to gain some intuition about what it does to the data. Let's start with a very simple dataset to make it easier to see what's happening:

```
df <- tribble(
  ~var, ~col1, ~col2,
   "A",     1,     2,
   "B",     3,     4,
   "C",     5,     6
)
```

Here we'll say there are three variables: `var` (already in a variable), `name` (the column names in the column names), and `value` (the cell values). So we can tidy it with:

```
df |>
  pivot_longer(
    cols = col1:col2,
    names_to = "names",
```

```
    values_to = "values"
  )
```

```
# A tibble: 6 x 3
  var   names values
  <chr> <chr>  <dbl>
1 A     col1       1
2 A     col2       2
3 B     col1       3
4 B     col2       4
5 C     col1       5
6 C     col2       6
```

How does this transformation take place? It's easier to see if we take it component by component. Columns that are already variables need to be repeated, once for each column in `cols`, as shown in **?@fig-pivot-variables**.

The column names become values in a new variable, whose name is given by `names_to`, as shown in **?@fig-pivot-names**. They need to be repeated once for each row in the original dataset.

The cell values also become values in a new variable, with a name given by `values_to`. They are unwound row by row. **?@fig-pivot-values** illustrates the process.

3.3.3 Many variables in column names

A more challenging situation occurs when you have multiple variables crammed into the column names. For example, take the `who2` dataset:

This dataset records information about tuberculosis data collected by the WHO. There are two columns that are already variables and are easy to interpret: `country` and `year`. They are followed by 56 columns like `sp_m_014`, `ep_m_4554`, and `rel_m_3544`. If you stare at these columns for long enough, you'll notice there's a pattern. Each column name is made up of three pieces separated by `_`. The first piece, `sp`/`rel`/`ep`, describes the method used for the `diagnosis`, the second piece, `m`/`f` is the `gender`, and the third piece, `014`/`1524`/`2535`/`3544`/`4554`/`65` is the `age` range.

So in this case we have six variables: two variables are already columns, three variables are contained in the column name, and one variable is in the cell name. This requires two changes to our call to `pivot_longer()`: `names_to` gets a vector of column names and `names_sep` describes how to split the variable name up into pieces:

Of course, tidy data can't solve every problem so we also showed you some places were you might want to deliberately untidy your data into order to present to humans, feed into statistical models, or just pragmatically get shit done. If you particularly enjoyed this chapter and want to learn more about the underlying theory, you can learn more about the history and theoretical underpinnings in the Tidy Data paper published in the Journal of Statistical Software.

In the next chapter, we'll pivot back to workflow to discuss the importance of code style, keeping your code "tidy" (ha!) in order to make it easy for you and others to read and understand your code.