R Without Statistics

David Keyes

Contents

About the Book

This is the in-progress version of *R Without Statistics*, a forthcoming book from No Starch Press.

Since R was invented in 1993, it has become a widely used programming language for statistical analysis. From academia to the tech world and beyond, R is used for a wide range of statistical analysis.

R's ubiquity in the world of statistics leads many to assume that it is only useful to those who do complex statistical work. But as R has grown in popularity, the number of ways it can be used has grown as well. Today, R is used for:

- Data visualization
- Map making
- Sharing results through reports, slides, and websites
- Automating processes
- And much more!

The idea that R is only for statistical analysis is outdated and inaccurate. But, without a single book that demonstrates the power of R for non-statistical purposes, this perception persists.

Enter R Without Statistics.

R Without Statistics will show ways that R can be used beyond complex statistical analysis. Readers will learn about a range of uses for R, many of which they have likely never even considered.

Each chapter will, using a consistent format, cover one novel way of using R.

1. Readers will first be introduced to an R user who has done something novel and learn how using R in this way transformed their work.
2. Following this, there will be code samples that demonstrate exactly how the R user did the thing they are being profiled for.

3. Finally, there will be a summary, with lessons learned from this novel way of using R.

Written by David Keyes, Founder and CEO of R for the Rest of Us, R Without Statistics will be published by No Starch Press.

```
library(tidyverse)
#> -- Attaching packages ------------------- tidyverse 1.3.1 --
#> v ggplot2 3.3.5     v purrr   0.3.4
#> v tibble  3.1.6     v dplyr   1.0.8
#> v tidyr   1.2.0     v stringr 1.4.0
#> v readr   2.1.2     v forcats 0.5.1
#> -- Conflicts ---------------------- tidyverse_conflicts() --
#> x dplyr::filter() masks stats::filter()
#> x dplyr::lag()    masks stats::lag()
library(readxl)
library(janitor)
#>
#> Attaching package: 'janitor'
#> The following objects are masked from 'package:stats':
#>
#>     chisq.test, fisher.test
library(knitr)
```

Introduction

Why R Without Statistics?

How New Zealand Used R to Fight COVID

TODO

How I Came to Use R

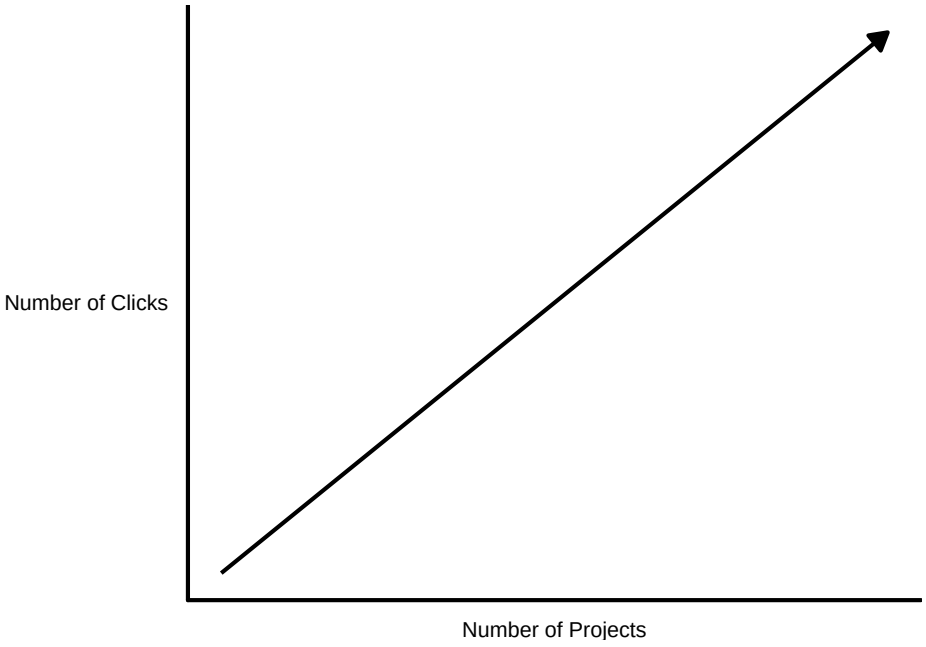
My own relationship with R goes back to 2016. At the time, I was a consultant, helping non-profits, government agencies, and educational institutions to measure the effectiveness of their work is (a field known as program evaluation). A lot of my work involved conducting surveys, analyzing the resulting the data, and sharing the results with clients.

The work itself was fine, but the tools I was using to do it were getting on my nerves. Well, one tool really: Excel.

Now look, this is not a place for an anti-Excel rant. Excel is a fine tool that has empowered millions to work with data in ways they would never have been able to otherwise.

But, for me, Excel was tedious. The amount of pointing and clicking I had to do when working with the amount of data I had got old fast. Each time I would conduct a survey, I'd know that it would yield an avalanche of data and that my wrists would end up exhausted from hours of pointing and clicking.

No matter what I did, analyzing data and creating charts in Excel just involved a lot of repetitive pointing and clicking. Kind of like this:



Endless pointing and clicking was just one problem I faced using Excel. Annoying though it was, it didn't affect the quality of my work. Or so I thought until I recalled a project I had worked on a few years earlier.

In this project, I was looking at which school districts in the state of Oregon have outdoor education programs known as Outdoor School. As part of this project, I had to download data on all school districts throughout Oregon, filter to only include relevant districts with fifth or sixth graders (the ages Outdoor School takes place), and then merge this with data that I collected as part of a survey I conducted.

I did the work in Excel, using a lot of (you guessed it!) pointing and clicking. The problem came when I was almost done with the project. I've blocked the details from my memory (as I've done with most things Excel-related), but what I do recall is that not being 100% certain I had done my filtering and joining correctly. And, to make it worse, I had no way to check my work. Why? Because all my pointing and clicking was ephemeral, gone in the ether as soon as I had completed it.

I finished the Outdoor School project and submitted my report. I think the work I did was *probably* accurate, but maybe it wasn't?

Now, you may be reading this thinking: why didn't you write down the steps you used in Excel so you could retrace them later? Sure, I could (and should) have done that. But let's be honest: most of us don't.

The reality is, we're human. We all make mistakes. And without a straightforward way to audit your work (and keeping a list of all of your Excel points

and clicks in a separate document is not, in my view, straightforward), mistakes will happen. If you've used Excel to work with data, I guarantee you've made a mistake, just like me.

The good news is that it's ok. There's a solution. And that solution is R.

If I were to redo that project on Outdoor School with R, here's what I'd do differently. Rather than watching points and clicks disappear into the ether, I'd write code that would serve as a record of everything I did. This code would:

Download data on all school districts:

```
# Download the data directly from the Oregon Department of Education website
download.file(url = "https://www.oregon.gov/ode/educator-resources/assessment/Documents/TestResul
              destfile = "data/pagr_schools_ela_tot_raceethnicity_1819.xlsx")

# Import the downloaded data and use the `clean_names()` function to make the variable names easy
oregon_schools <- read_excel("data/pagr_schools_ela_tot_raceethnicity_1819.xlsx") %>%
  clean_names()
```

Filter to only include districts with fifth or sixth graders:

```
# Start with the oregon_schools data from above
oregon_schools_fifth_sixth_grade <- oregon_schools %>%

  # Only keep schools with fifth or sixth graders
  filter(grade_level == "Grade 5" | grade_level == "Grade 6") %>%

  # Only keep the variables we need
  select(district_id:school) %>%

  # There are multiple observations of the same school, just keep one of each
  distinct()
```

Join the filtered data on school districts with my survey data:

```
# Use the school_id variable to join the survey data with the oregon_schools_fifth_sixth_grade fr
left_join(survey_data, oregon_schools_fifth_sixth_grade,
          by = "school_id")
```

Code can be scary. Having to write code is one of the reasons many people never learn R. But code is just a list of things you want to do to your data. It may be written in a hard-to-parse syntax (though it gets easier over time), but it's just a set of steps. The same steps that we should write out when we're working in Excel, but never do. Rather than having a separate document with my steps written down (the one that never gets written), I can see my steps in my code. See that line that says filter. Guess what it's doing? Yep, it's filtering!

If I had done things this way when working on the Outdoor School project, I could have looked back at any point to make sure what I thought was happening to my data was in fact happening. That nagging sensation I had near the end of the project that I may have made a mistake in one of my early points or clicks? It never would come up because I could just review my code to make sure it did what I thought it did. And if it didn't, I could rewrite and rerun my code to get updated results.

Using R won't mean you'll never make mistakes again (trust me, you will). But it will mean that you can easily spot your mistakes, make changes, and fix any issues.

I started learning R to avoid tedious pointing and clicking. But what I found was that R improved my work in ways I never expected. It's not just that my wrists are less tired. I now have more confidence that my work is accurate.

I used to feel ashamed about the way I use R.

I use R, a tool for statistical analysis, but I don't use it for complex statistical analysis. I don't do machine learning. I don't know what a random forest is. I've never even run a regression in R.

The only statistics I do in R are descriptive statistics. Counts, sums, averages: these are the statistics that I do in R.

For a long time, I felt like I wasn't a "real" R user. Real R users, in my mind, used R for hardcore stats. I "only" used R for descriptive stats.

I sometimes felt like I was using a souped up sports car to drive 20 miles an hour to the grocery store. What was the point in using a high-powered machine like R to do "simple" things?

Eventually, I realized that this framing misses the point. R started out as a tool created by statisticians for other statisticians. But, over a quarter century since its creation, R can do much more than statistical analysis.

My own use of R is an example of this. I think of my work with R in three buckets:

Illuminate through data visualization: making graphs, maps, and tables that look good and share results effectively.

TODO: Add examples

Communicate by doing reporting with RMarkdown: moving away from the inefficiency and error-prone workflow of using multiple tools to create reports by instead doing it all in the one tool that I think of as R's killer feature.

TODO: Add some image