

The Plain Person's Guide

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to Plain Text
Social Science

Kieran Healy

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1

Introduction

As a beginning graduate student in the social sciences, what sort of software should you use to do your work?¹ More importantly, what principles should guide your choices? I offer some general considerations and specific answers. The short version is: you should use tools that give you *more control* over the process of data analysis and writing. I recommend you write prose and code using a good text editor; analyze quantitative data with [R](#) and [RStudio](#), or use [Stata](#); minimize error by storing your work in a simple format (plain text is best), and make a habit of documenting what you've done. For data analysis, consider using a format like [RMarkdown](#) and tools like [Knitr](#) to make your work more easily reproducible for your future self. Use [Pandoc](#) to turn your plain-text documents into PDF, HTML, or Word files to share with others. Keep your projects in a [version control system](#). Back everything up regularly. Make your computer work for you by automating as many of these steps as you can.

To help you get started, I provide a drop-in set of useful defaults to get started with [Emacs](#) (a powerful, free text-editor). I share some templates and style files that can get you quickly from plain text to various output formats. But I emphasize that this is one viable choice amongst many. I discuss several alternatives because no humane person should recommend Emacs without presenting some other options as well.

To being, I discuss why you should care about having better control over your work materials. Rather than dive straight in to a list of tools or a recapitulation of their manuals, I want to encourage you to begin thinking about this issue in a way that will lead you to some solution that works well for you. Perhaps that will mean using the tools described here, but perhaps not.

¹ This website guide is available [as a single PDF file](#). Change the `.html` extension to `.Rmd` to see the plain-text source of any page. You can also take a look at the [github repository](#) for the project.

1.1 Motivation

You can do productive, maintainable and reproducible work with all kinds of different software set-ups. This is the main reason I don't go around encouraging everyone to convert to the applications I use. (My rule is that I don't try to persuade anyone to switch if I can't commit to offering them technical support during and after their move.) So this discussion is not geared toward convincing you there is One True Way to organize things. I do think, however, that if you're in the early phase of your career as a graduate student in, say, Sociology, or Economics, or Political Science, you should give some thought to how you're going to organize and manage your work.² This is so for two reasons. First, the transition to graduate school is a good time to make changes. Early on, there's less inertia and cost associated with switching things around than there will be later. Second, in the social sciences, text and data management skills are usually not taught to students explicitly. This means that you may end up adopting the practices of your advisor or mentor, continue to use what you are taught in your methods classes, or just copy whatever your peers are doing. Following these paths may lead you to an arrangement that you will be happy with. But maybe not. It's worth looking at the options.

² This may also be true if you are about to move from being a graduate student to starting as a faculty member, though perhaps the rationale is less compelling given the costs.

Two remarks at the outset. First, because this discussion is aimed at beginning students, some readers may find much with which they are already familiar. Second, although in what follows I advocate you take a look at several applications in particular, it's not really about the gadgets or utilities. The Zen of Organization is not to be found in Fancy Software. Nor shall the true path of Getting Things Done be revealed to you through the purchase of a nice [Moleskine Notebook](#). Instead, it lies within—unfortunately.

1.2 Two Revolutions in Computing

When talking to undergraduates or graduate students on this topic, and when teaching classes that use these tools, I increasingly run into the problem that it's hard to get started without backing up a bit first in order to talk about how the computer they are using works. I think the reason for this is the rise of the flat-screen, touch-based model of computing, most obviously

on phones and then very secondarily on things like Apple's iPad or Microsoft's Surface tablet. Now, most people who need to write long documents (like papers or dissertations) or work in an involved way with data do not use a tablet as their primary device. But it does seem clear that some kind of touch-screen interaction is the future of computing for most people. Indeed, once you consider phones properly you realize it's the *present* of computing for most people.

While it is not strictly impossible, it remains very difficult to do your academic, social-science work on a device of this sort. This is likely to be the case for some time. The tools we have are not designed for them. I think there is an underappreciated tension here. Two ongoing computing revolutions are tending to pull in opposite directions. On one side, the mobile, cloud-centered, touch-screen, phone-or-tablet model has brought powerful computing to more people than ever before. This revolution is the one everyone is talking about, because it is happening on a huge scale and is where all the money is. It puts single-purpose applications in the foreground. It hides the workings of the operating system from the user, and it goes out of its way to simplify or completely hide the structure of the file system where items are stored and moved around.

On the other side, open-source tools for plain-text coding, data analysis, and writing are also better and more accessible than they have ever been. This has happened on a smaller scale than the first revolution, of course. But still, these tools really have revolutionized the availability and practice of data analysis and scientific computing generally. They continue to do so, too, as people work to make them better at everything from slurping up data on the web to presenting results there. These tools mostly work by joining separate, specialized widgets into a reproducible workflow. They are "bitty" or granular because the process of data analysis is that way, too. These tools do much less to hide the operating system layer—instead they often directly mesh with it—and they often presuppose a working knowledge of the file system underpinning the organization of the things the researcher is using, from data files to code to figures and final papers.

The tension is that, increasingly, people who enter the world of social science excited to work with data will also tend to have little or no prior experience with text-based, command-

³ As opposed to multi-tasking in the less-interesting sense of trying to pay attention to a number of discrete tasks (writing, email, calendar, web-browsing), each controlled by a separate application.

line, file-system-dependent tools. In many cases, they will not have much experience making effective use of a multi-tasking windowing environment, either, in the sense of knowing how to make applications work together in the service of a single goal.³ To be clear, this is not something to blame users for. Neither is it some misguided nostalgia on my part for the command line. Rather, it is an aspect of how computer use is changing at a very large scale. The coding and data analysis tools we have are powerful and for the most part meant to allow research products to be opened up and inspected. But the way they work runs against the grain of everyday, end-use computing, which hides implementation details and focuses on single-purpose tasks. The net result for the social sciences in the short to medium term is that we will have a suite of powerful and very useful tools, developed in the open, supported by helpful communities, and mostly available for free. But it will get harder to teach people how to use them when they are just starting out, and perhaps even to convince people to try them in the first place.

1.3 What's the Problem?

The problem is that doing scholarly work is intrinsically a mess. There's the annoying business of getting ideas and writing them down, of course, but also everything before, during, and around it: data analysis and all that comes with it, and the tedious but unavoidable machinery of scholarly papers—especially citations and references. There is a lot of keep track of, a lot to get right, and a lot to draw together at the time of writing. Academic papers are by no means the only form of writing subject to constraints of this sort. Consider [this sensible discussion](#) by Dr. Drang, a (pseudonymous) consulting engineer:

[T]he type of writing I typically do . . . is loaded with facts. I am constantly referring to photographs, drawings, experimental test results, calculations, reports written by others, textbooks, journal articles, and so on. These are not distractions; they are essential to the writing process.

And it's not just reference material. Quite often I need to make my own graphs and drawings to include in a report. Because the text and the graphics are all part of a coherent whole, I need to go back and forth between the two; the words inform the pictures and the pictures inform the words. This is not the Platonic ideal of a clean writing environment—a cup of coffee on an empty desk in a white room—that you see in videos for distraction-free editors.

Some of the popularity of these editors is part of the backlash against multitasking, but people are confusing themselves with their computers. When I'm writing a report, that is my single task, and I bring to bear whatever tools are necessary to complete it. That my computer is multitasking by running many programs simultaneously isn't a source of confusion or distraction, it's the natural and efficient way for me to get my one task done.

A lot of academic writing is just like this. It can be tricky to manage. It's even worse when you have collaborators and other contributors. So, what to do?

1.4 The Office Model and the Engineering Model

Let me make a crude distinction. There are “Office Type” solutions to this problem, and there are “Engineering Type” solutions. Don't get hung up on the distinction or the labels. Office solutions tend towards a cluster of tools where something like Microsoft Word is at the center of your work. A Word file or set of files is the most “real” thing in your project. Changes to your work are tracked *inside* that file or files. Citation and reference managers plug into those files. The outputs of data analyses—tables, figures—get cut and pasted in as well, or are kept alongside them. The master document may be passed around from person to person to be edited and updated.⁴ The final output is exported from it, perhaps to PDF or to HTML, but maybe most often the final output just is the `.docx` file, cleaned up and with the track changes feature turned off.

⁴ If collaboration is paramount the work might get done in a Google Doc, at the cost of much of the traditional power of a word processor.

In the Engineering model, meanwhile, plain text files are at the center of your work. The most “real” thing in your project will either be those files or, more likely, the version control repository that stores the project. Changes are tracked outside of files, again using a version control system. Data analysis is managed in code that produces outputs in (ideally) a known and reproducible manner. Citation and reference management will likely also be done in plain text, as with a BibTeX `.bib` file. Final outputs are assembled from the plain text and turned to `.tex`, `.html`, or `.pdf` using some kind of typesetting or conversion tool. Very often, because of some unavoidable facts about the world, the final output of this kind of solution is also a `.docx` file.

This distinction is meant to capture a tendency in organization, not a rigid divide—still less a sort of personality. Obviously it is possible organize things on the Office model. (Indeed, it's

the dominant way.) Applications like [Scrivener](#), meanwhile, combine elements of the two approaches. Scrivener embraces the “bittyness” of large writing projects in an effective way, and can spit out clean copy in a variety of formats. Scrivener is built for people writing lengthy fiction (or qualitative non-fiction) rather than anything with quantitative data analysis, so I have never used it extensively. Microsoft Word, meanwhile, still rules large swathes of the Humanities and the Social Sciences, and the production process of many publishers. So even if you prefer plain text for other reasons—especially in connection with project management and data analysis—the routine need or obligation to provide a Word document to someone is one of the main reasons to want to be able to easily convert things. HTML is a great lingua franca.

I mostly focus on the Engineering model. But many people use the Office model, and you may end up working with (or for) some of them. In those cases, it is generally easier for you to use their software than *vice versa*, if only because you are likely have a copy of Word on your computer already. In these circumstances you might also collaborate using Google Docs or some other service that allows for simultaneously editing the master copy of a document. This may not be ideal, but it is better than not collaborating. There is little to be gained from plain-text dogmatism in a .docx world.

2

Keep a Record

2.1 Make Sure You Know What You Did

For any kind of formal data analysis that leads to a scholarly paper, whichever model you tend to favor, there are some basic principles to adhere to. Perhaps the most important thing is to do your work in a way that leaves a coherent record of your actions. Instead of doing a bit of statistical work and then just keeping the resulting table of results or graphic that you produced, for instance, write down what you did as a documented piece of code. Rather than figuring out but not recording a solution to a problem you might have again, write down the answer as an explicit procedure. Instead of copying out some archival material without much context, file the source properly, or at least a precise reference to it.

A second principle is that a document, file or folder should always be able to tell you what it is. Beyond making your work reproducible, you will also need some method for organizing and documenting your draft papers, code, field notes, datasets, output files or whatever it is you're working with. In a world of easily searchable files, this may mean little more than keeping your work in plain text and giving it a descriptive name. It should generally *not* mean investing time creating some elaborate classification scheme or catalog that becomes an end in itself to maintain.

A third principle is that repetitive and error-prone processes should be automated if possible. (Software developers call this “DRY”, or [Don't Repeat Yourself](#).) This makes it easier to check for and correct mistakes. Rather than copying and pasting code over and over to do basically the same thing to different parts of your data, write a general function that can be called

whenever it's needed. Instead of retyping and reformatting the bibliography for each of your papers as you send it out to a journal, use software that can manage this for you automatically.

There are many ways of implementing these principles. You could use Microsoft Word, Endnote and SPSS. Or Textpad and Stata. Or a pile of legal pads, a calculator, a pair of scissors and a box of file folders. But software applications are not all created equal, and some make it easier than others to do the Right Thing. For instance, it is *possible* to produce well-structured, easily-maintainable documents using Microsoft Word. But you have to use its styling and outlining features strictly and responsibly, and most people don't bother. You can maintain reproducible analyses in SPSS, but the application isn't set up to do this automatically or efficiently, nor does its design encourage good habits. So, it is probably a good idea to invest some time learning about the alternatives. Many of them are free to use or try out, and you are at a point in your career where you can afford to play with different setups without too much trouble.

The dissertation, book, or articles you write will generally consist of the main text, the results of data analysis (perhaps presented in tables or figures) and the scholarly apparatus of notes and references. Thus, as you put a paper or an entire dissertation together you will want to be able to easily *keep a record of your actions* as you *edit text*, *analyze data* and *present results*, in a *reproducible way*. In the next section I describe some applications and tools designed to let you do all of this. I focus on tools that fit together well (by design) and that are all freely available for Windows, Linux and Mac OS X. They are not perfect, by any means—in fact, some of them can be awkward to learn. But graduate-level research and writing can also be awkward to learn. Specialized tasks need specialized tools and, unfortunately, although they are very good at what they do, these tools don't always go out of their way to be friendly.

2.2 Use Version Control

Writing involves a lot of editing and revision. Data analysis involves cleaning files, visualizing information, running models, and repeatedly re-checking your code for mistakes. You need to keep track of this work. As projects grow and change, and as you explore different ideas or lines of inquiry, the task of document-

ing your work at the level of particular pieces of code or edits to paragraphs in individual files can become more involved over time. The best thing to do is to institute some kind of *version control* to keep a complete record of changes to a single file, a folder of material, or a whole project. A good version control system allows you to “rewind the tape” to earlier incarnations of your notes, drafts, papers and code. It lets you keep explore different aspects or branches of a project. In its more developed forms it provides you with some powerful tools for collaborating with other people. And it helps stop you from having directories full of files with confusingly similar names like `Paper-1.doc`, `Paper-2.doc`, `Paper-conferenceversion.doc`, `Paper-Final-revised-DONE-lastedits.doc`.

In the social sciences and humanities, you are most likely to have come across the idea of systematic version control by way of the “Track Changes” feature in Microsoft Word, which lets you see the edits you and your collaborators have made to a document. Collaborative editing of a single document is also possible through platforms like Google Docs or [Quip](#). True version control is a way to do these things for whole projects, not just individual documents, in a comprehensive and transparent fashion. Modern version control systems such as [Mercurial](#) and [Git](#) can, if needed, manage very large projects with many branches spread across multiple users. Git has become the *de facto* standard, and [GitHub](#) is a place where software developers and social scientists make their work available, and where you can contribute to ongoing projects or make public your own.

Modern version control requires getting used to some new concepts related to tracking your files, and learning how your version control system implements these concepts. There are some [good resources](#) for learning them. Because of their power, these tools might seem like overkill for individual users. (Again, though, many people find Word’s “Track Changes” feature indispensable once they begin using it.) But version control systems can be used quite straightforwardly in a basic fashion, and they can often be easily integrated with your text editor, or used via a friendlier application interface that keeps you away from the command line. The core idea is shown in Figure 2.1. You keep your work in a *repository*. This can be kept locally, or on a remote server. As you work, you periodically *stage* your changes and then *commit* them to the repository, along with a little note about what you did. Repositories can be copied, cloned, merged,

and contributed to by you or other people.

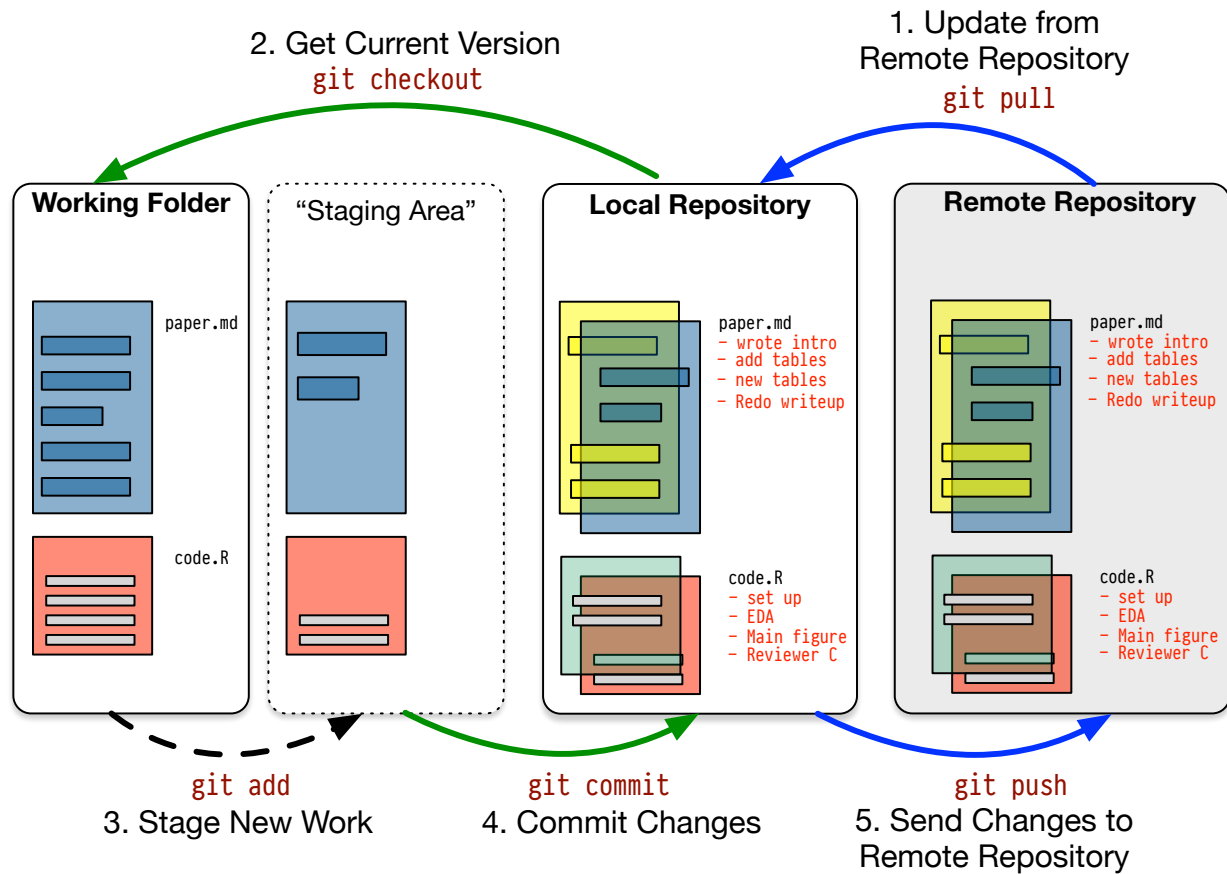


Figure 2.1: A schematic git workflow.

Figure 2.1 describes a schematic git workflow. You get the most recent version of your project from a remote repository (such as GitHub), and then “check-out” the project to work on, writing your code or text. You work on your files as usual in a folder on your computer. But it is the repository that is “real” as far as the project is concerned. Once you are happy with the changes you have made to your documents you *stage* these changes. Behind the scenes, this means the changes are added to an index that Git uses to keep track of things. But these changes are not yet permanently recorded. To make them permanent, you *commit* the changes to the repository, along with a note about what you did. You now have a firm record of your actions. You then “push” the changes up to the remote repository, which

in effect also functions as a backup of your work. Over time, the repository comes to contain a complete record of the project, any step of which can be revisited as needed. In the simplest case there is no remote repository, only a local one you check out and commit changes to. You can do all this from the command line, or use one of several front-end applications designed to help you manage things.

Revision control has significant benefits. A tool like Git combines the virtues of “track changes” with those of backups. Every repository is a complete, self-contained, cryptographically signed copy of the project, with a log of every recorded step in its development by all of its participants. It puts you in the habit of committing changes to a file or project piecemeal as you work on it, and (briefly) documenting those changes as you go. It allows you to easily test out alternative lines of development or thinking by creating “branches” of a project. It allows collaborators to work on a project at the same time without sending endless versions of the “master” copy back and forth via email. And it provides powerful tools that allow you to automatically merge or (when necessary) manually compare changes that you or others have made. Perhaps most importantly, it lets you revisit any stage of a project’s development at will and reconstruct what it was you were doing. This can be useful whether you are writing code for a quantitative analysis, managing field notes, or writing a paper. While you will probably not need to control everything in this way, I *strongly* suggest you consider managing at least the core set of text files that make up your project (e.g., the code that does the analysis and generates your tables and figures; the dataset itself; your notes and working papers, the chapters of your dissertation, etc). As time goes by you will generate an extensive, annotated record of your actions that is also a backup of your project at every stage of its development. Services such as [GitHub](#) allow you to store public or (for a fee) private project repositories and so can be a way to back up work offsite as well as a platform for collaboration and documentation of your work.

After you download and install Git—e.g., by installing Apple’s developer tools—the easiest way to get up and running with it is to create a GitHub account and then [configure git and GitHub](#). While git is free software; GitHub is a commercial service with a free tier.

Why should you bother to do any of this? Because the main

person you are doing it for is *you*. Papers take a long time to write. When you inevitably return to your table or figure or quotation nine months down the line, your future self will have been saved hours spent wondering what it was you thought you were doing and where you got it from.

2.3 Back Up Your Work

Regardless of whether you choose to use a formal revision control system, you should nevertheless have *some* kind of systematic method for keeping track of versions of your files. Version-controlled projects are backed-up to some degree if you keep your repository somewhere other than your work computer. But this is not nearly enough. Apple's Time Machine software, for example, backs up and versions your files on your disk, or to a local hard drive, allowing you to step back to particular instances of the file you want. This still isn't enough, though. You need regular, redundant, automatic, off-site backups of your work. Because you are lazy and prone to magical thinking, you will not do this responsibly by yourself. This is why the most useful backup systems are the ones that require a minimum amount of work to set up and, once organized, back up everything automatically without you having to remember to do anything. This means paying for a secure, offsite backup service like [Crashplan](#), or [Backblaze](#). Offsite backup means that in the event (unlikely, but not unheard of) that your computer *and* your local backups are stolen or destroyed, you will still have copies of your files. I know of someone whose office building was hit by a tornado. She returned to find her files and computer sitting in a foot of water. You never know. Less dramatically, but no less catastrophic from the point of view of one's work, I know people who have lost months or even years of work as a result of dropping a laptop, or having it stolen, or simply having their computer (or "backup drive") fail for no apparent reason. Like seat belts, you don't need backups until you really, really need them. As Jamie Zawinski [has remarked](#), when it comes to losing your data "The universe tends toward maximum irony. Don't push it."

3

Write and Edit

3.1 Use a Text Editor

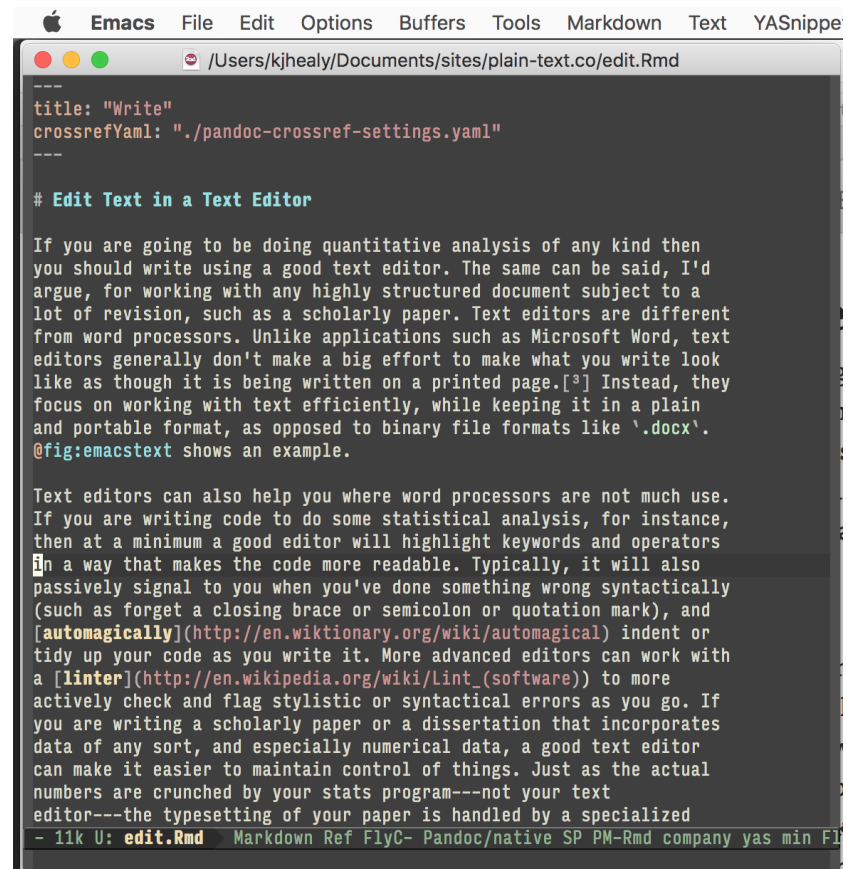
If you are going to be doing quantitative analysis of any kind then you should write using a good text editor. The same can be said, I'd argue, for working with any highly structured document subject to a lot of revision, such as a scholarly paper. Text editors are different from word processors. Unlike applications such as Microsoft Word, text editors generally don't make a big effort to make what you write look like as though it is being written on a printed page.¹ Instead, they focus on working with text efficiently, while keeping it in a plain and portable format, as opposed to binary file formats like `.docx`. Figure 3.1 shows an example.

Text editors can also help you where word processors are not much use. If you are writing code to do some statistical analysis, for instance, then at a minimum a good editor will highlight keywords and operators in a way that makes the code more readable. Typically, it will also passively signal to you when you've done something wrong syntactically (such as forget a closing brace or semicolon or quotation mark), and **automagically** indent or tidy up your code as you write it. More advanced editors can work with a **linter** to more actively check and flag stylistic or syntactical errors as you go. If you are writing a scholarly paper or a dissertation that incorporates data of any sort, and especially numerical data, a good text editor can make it easier to maintain control of things. Just as the actual numbers are crunched by your stats program—not your text editor—the typesetting of your paper is handled by a specialized application, too. That tool should automatically take care of things like entries in your bibliography, the labelling of tables and figures, and cross-

¹ For further argument about the advantages of text-editors over word processors see Allin Cottrell's polemic, "[Word Processors: Stupid and Inefficient](#)".

references and other paraphernalia. The best editors can closely integrate with the tools you use to do the various pieces of your work.

Figure 3.1: Working on part of this document in Emacs.



Emacs is a text editor, in the same way the blue whale is a mammal. It does the things I have just described, and rather more besides, if you want it to. Combining Emacs with some other applications and add-ons allows you to manage writing and data-analysis effectively. If it seems odd to do a bunch of different tasks inside an editor, the blogger Rekado makes a [useful analogy](#) to the way people use web browsers:

Just like a browser is used by many as a platform for running applications operating on some HTML document, Emacs is a platform for anything that can “reasonably” (this is up for interpretation) be mapped to buffers of text. Applications in browsers are written in JavaScript, applications in Emacs are written in EmacsLisp (also called “elisp”). . . . If you have used your web browser (or have observed someone use their web browser) to play games, listen to music, watch videos, read and compose email, edit text (e.g. by contributing to the Wikipedia),

chat with friends (or chat about foes), read documentation, installed an extension—well, then the notion of a generic tool as a platform should not be a foreign concept to you. Emacs can be understood as such a generic tool providing a text interface (one of which may be a file editor).

While very powerful and flexible, Emacs can be annoying. Indeed, to many people encountering it for the first time—especially those used to standard applications on Windows or Mac OS—its conventions seem bizarre and byzantine. As applications go, Emacs is quite ancient. The first version was written by Richard Stallman in the 1970s. Because it evolved in a much earlier era of computing (before the development of decent graphical displays, for instance, and window managers, and possibly also fire), it doesn't share many of the conventions of modern applications. Like most powerful text editors, Emacs offers many opportunities to waste your time learning its particular conventions, tweaking its settings, and generally customizing it. There are several good alternatives on each major platform.

Given all that, why mention it in the first place? Partly because it's the editor I use. Partly because it is available for all of the main desktop and laptop computing platforms. And partly because it is very, *very* good at doing what I want it to do. There are many good reasons to use something like [TextMate](#), or [Sublime Text](#) instead of Emacs. Similarly, when doing data analysis with R, you may just want to use the [RStudio environment](#). You will do fine if you go with these alternatives.

3.2 Use Markdown

When you write papers in plain text, how do you manage the formatting, sectioning, and other related aspects of your document? [Markdown](#) is a loosely-standardized way of writing plain text that includes information about the formatting of your document. It was originally developed by John Gruber, with input from Aaron Swartz. The aim was to make a simple format that could incorporate structural information about the document (such as headings and subheadings, *emphasis*, [hyperlinks](#), lists, footnotes, and so on), with minimal loss of readability. Formats like HTML or TeX are much more extensive markup languages, but Markdown was meant to be simple. Over the years it has become a *de facto* standard. Text editors and note-taking appli-

cations support it, and tools exist to convert Markdown not just into HTML (its original target output format) but many other document types as well. listing 3.1 shows the markdown source for part of this document.

Listing 3.1: The Markdown source for a nearby part of this document.

```
# Use Markdown

When you write papers in plain text, how do you manage the formatting,
sectioning, and other related aspects of your document?
[Markdown](http://en.wikipedia.org/wiki/Markdown) is a
loosely-standardized way. It was originally developed by John Gruber,
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that could incorporate structural information about the document
(such as headings and subheadings, *emphasis*,
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and so on), with minimal loss of readability. Formats like HTML or TeX
are much more extensive markup languages, but Markdown was meant to be
simple. Over the years it has become a *de facto* standard. Text
editors and note-taking applications support it, and tools exist to
convert Markdown not just into HTML (its original target output
format) but many other document types as well. @lst:markdown-example shows
the markdown source for this paragraph and its subheading.
```

The excerpt shown in listing 3.1 shows a few of the most common Markdown conventions, most notably how it represents headings and subheadings (a # symbol for a top-level header, with ## for the next level down, and so on), how it represents hyperlinks, and how it emphasizes text. Once your text is marked up in this format, you need a bit of software to get from there to a properly readable HTML, PDF, or Word file. This is what [pandoc](#) is for—more on that [later on](#).

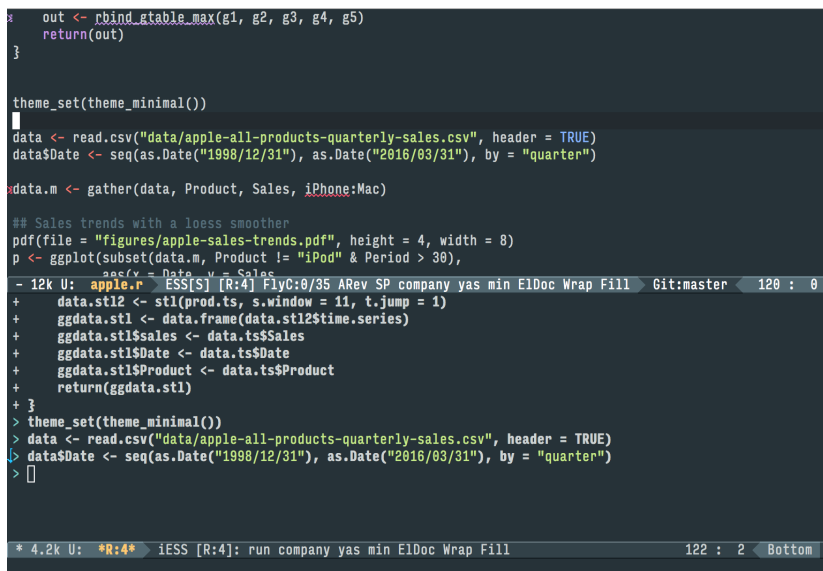
There are a number of Markdown variants, or “flavors”, that have extended it to manage things like cross-references and labels, citations, and other textual elements. I recommend using [Pandoc’s markdown](#), which can handle all of these. This means you can use Markdown to write in plain text, while not having to worry whether your reference list is complete, or whether cross-references (to ‘Figure 3’ for example) remain correct after you move things around in your text.

3.3 Use R with ESS or RStudio

You will probably be doing some—perhaps a great deal—of quantitative data analysis. R is an environment for statistical

computing. It's well-supported, continually improving, and has a very active expert-user community. The documentation that comes with the software is complete, if somewhat terse, but there are a large number of excellent reference and teaching texts that illustrate its use. These include Dalgaard (2008), Venables and Ripley (2002), Maindonald and Braun (2003), Fox (2002), Harrell (2016), Matloff (2011), and Gelman and Hill (2007). Although it is a command-line tool at its core, it can easily be used in conjunction with the [RStudio IDE](#). You can download R from [The R Project Homepage](#).

R can be used directly within Emacs by way of a package called ESS (for “Emacs Speaks Statistics”). As shown in Figure 3.2, it allows you to work with your code in one Emacs frame and a live R session in another right beside it. Because everything is inside Emacs, it is easy to do things like send a chunk of your code over to R using a keystroke. This is a very efficient way of doing interactive data analysis while building up code you can use again in future.



```

x out <- rbind_gtable_max(g1, g2, g3, g4, g5)
  return(out)
}

theme_set(theme_minimal())

data <- read.csv("data/apple-all-products-quarterly-sales.csv", header = TRUE)
data$date <- seq(as.Date("1998/12/31"), as.Date("2016/03/31"), by = "quarter")

data.m <- gather(data, Product, Sales, `iPhone:Mac`)

## Sales trends with a loess smoother
pdf(file = "figures/apple-sales-trends.pdf", height = 4, width = 8)
p <- ggplot(subset(data.m, Product != "iPod" & Period > 30),
  aes(x = Date, y = Sales))
+ data.stl2 <- stl(prod.ts, s.window = 11, t.jump = 1)
+ ggdata.stl <- data.frame(data.stl2$time.series)
+ ggdata.stl$Sales <- data.ts$Sales
+ ggdata.stl$date <- data.ts$date
+ ggdata.stl$Product <- data.ts$Product
+ return(ggdata.stl)
+ }
> theme_set(theme_minimal())
> data <- read.csv("data/apple-all-products-quarterly-sales.csv", header = TRUE)
> data$date <- seq(as.Date("1998/12/31"), as.Date("2016/03/31"), by = "quarter")
>

```

The bottom pane shows the R session output: `* 4.2k U: *R:4* iESS [R:4]: run company yas min ElDoc Wrap Fill 122 : 2 Bottom`

Figure 3.2: Working with R in Emacs using ESS. A document containing R code is open in the top half of the screen. Below the divider, an R session is running, also inside Emacs. Code from the top pane is sent to the bottom with a keyboard shortcut, where it is evaluated by R. We can also jump down to the bottom pane and do work there. Small details like a lint checker, active line highlighting, and revision-control information are also visible.

You'll present your results in papers, but also in talks where you will likely use some kind of presentation software. You can use Microsoft PowerPoint or Apple's [Keynote](#). Or, you can produce HTML or PDF slides [directly](#) from plain text documents.²

² The actual business of giving talks based on your work is beyond the scope of this discussion. Suffice to say that there is plenty of good advice available via Google, and you should pay attention to it.

4

Reproduce Work

4.1 Minimize Error

We have already seen how the right set of tools can save you time by automatically highlighting the syntax of your code, ensuring everything you cite ends up in your bibliography, picking out mistakes in syntax, and providing templates for commonly-used methods or functions. Your time is saved twice over: you don't repeat yourself, and you make fewer errors you'd otherwise have to fix. When it comes to managing ongoing projects, minimizing error means addressing two related problems. The first is to find ways to further reduce the opportunity for errors to creep in without you noticing. This is especially important when it comes to coding and analyzing data. The second is to find a way to figure out, retrospectively, what it was you did to generate a particular result. Using a revision control system gets us a good distance down this road. But there is more we can do at the level of particular reports or papers.

When you write code it is often in the process of doing some analysis on the fly. Ideas occur to you, you have a few things you want to look at, one thing leads to another. As a rule, you should try to document your work as you go. If you are writing an R script, then this usually means adding (brief, but useful) comments to your work to explain what it is a piece of code is meant to do. It should also mean trying to write your code so that is readable. Code is like prose in this respect. Hadley Wickham's [R Style Guide](#) provides some useful guidelines about writing readable code. The R package [lintr](#) implements these principles—it acts like a copy-editor for your code. In Emacs you can use `lintr` automatically through a tool called [flycheck](#).

You should also try not to repeat yourself when you write

your code. A good rule is that if you find yourself copying and pasting chunks of code (for example, to draw the same sort of plot or run the same kind of model for a bunch of different variables) then you should pause and see if you can write a quick convenience function instead to automate things more effectively. That way, your code can be shorter and also less prone to the errors and inconsistencies that creep in through repeated copy-and-paste.

4.2 From Server Farm to Data Table

Errors in data analysis often well up out of the gap that typically exists between the procedure used to produce a figure or table in a paper and the subsequent use of that output later. In the ordinary way of doing things, you have the code for your data analysis in one file, the output it produced in another, and the text of your paper in a third file. You do the analysis, collect the output and copy the relevant results into your paper, often manually reformatting them on the way. Each of these transitions introduces the opportunity for error. In particular, it is easy for a table of results to get detached from the sequence of steps that produced it. Almost everyone who has written a quantitative paper has been confronted with the problem of reading an old draft containing results or figures that need to be revisited or reproduced (as a result of peer-review, say) but which lack any information about the circumstances of their creation. Academic papers take a long time to get through the cycle of writing, review, revision, and publication, even when you're working hard the whole time. It is not uncommon to have to return to something you did two years previously in order to answer some question or other from a reviewer. You do not want to have to do everything over from scratch in order to get the right answer. I am not exaggerating when I say that, whatever the challenges of replicating the results of someone else's quantitative analysis, after a fairly short period of time authors themselves find it hard to replicate their *own* work. Computer Science people have a term of art for the inevitable process of decay that overtakes a project simply in virtue of its being left alone on the hard drive for six months or more: bit-rot.

4.3 Use RMarkdown and knitr

An important way to caulk this gap is to use [RMarkdown](#) and [knitr](#) when doing quantitative analysis in R. We’ve already seen how to write plain-text documents in Markdown’s lightweight format. RMarkdown allows you to incorporate code into this process. It is designed to integrate the plain-text documentation or writeup of a data analysis and its execution. You write the text of your paper (or, more often, your report documenting a data analysis) as normal. Whenever you want to run a model, produce a table or display a figure, rather than paste in the results of your work from elsewhere, you write down the R code that will produce the output you want. These “chunks” of code can be interspersed throughout the document. They are distinguished from the regular text by a special delimiter at the beginning and end of the block.

When you’re ready, you `knit` the document (Xie 2015). That is, you feed your `.Rmd` file to R, which processes the code chunks, and produces a new `.md` where the code chunks have been replaced by their output. You can then turn that Markdown file into a PDF or HTML document. Relatedly, the [rmarkdown library](#) in R provides a `render()` function that takes you from `.Rmd` to HTML or PDF in a single step. This is what RStudio uses to produce your documents. Conversely, if you just want to extract the code you’ve written from the surrounding text, then you “tangle” the file, which results in an `.R` file. It’s pretty straightforward in practice. The strength of this approach is that it makes it much easier to document your work properly. There is just one file for both the data analysis and the writeup. The output of the analysis is created on the fly, and the code to do it is embedded in the paper. If you need to do multiple but identical (or very similar) analyses of different bits of data, RMarkdown and `knitr` can make generating consistent and reliable reports much easier.

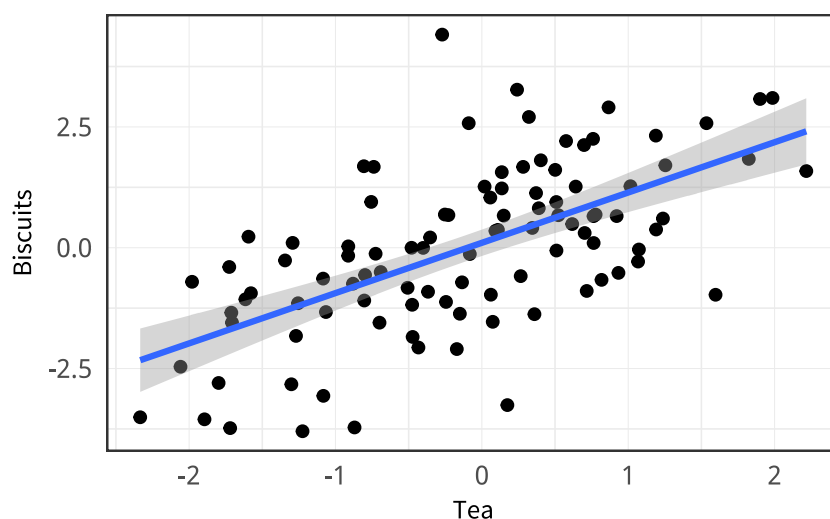
RMarkdown is one of several “literate programming” formats. The idea goes back to Donald Knuth, the pioneering theorist of computer science who developed the TeX typesetting system in his spare time. Although his focus was on documenting computer programs, in retrospect Knuth anticipated many of the main ideas—and developed several of the initial tools—for reproducible data analysis.

Figure [4.1](#), for instance, could be generated on the fly from

source-code blocks included in the `.Rmd` source for this article. Sometimes we will want to only show the results produced by the code—in this case, Figure 4.1. But at other times we will want to display the code as well, as here.

```
library(ggplot2)
tea <- rnorm(100)
biscuits <- tea + rnorm(100, 0, 1.3)
data <- data.frame(tea, biscuits)
p <- ggplot(data, aes(x = tea, y = biscuits)) +
  geom_point() + geom_smooth(method = "lm") +
  labs(x = "Tea", y = "Biscuits") + theme_bw()
print(p)
```

Figure 4.1: R code for a figure.



The `knitr` library and RMarkdown make it easy to produce HTML output, too. This makes for easy portability, conversion, and quick previewing while editing. You can work with RMarkdown files in any text editor, and Emacs has strong support for them. RStudio also comes with built-in support for `.Rmd` files and makes it very easy to produce HTML and PDF output, and to publish your reports to the web via its [Rpubs](#) service.¹

The [knitr website](#) has [numerous examples](#) showing how it works. These range from [the basic setup](#) to [more developed examples](#).

The literate programming approach has its limits. For large or complex analyses it can still make more sense to produce the final result in pieces rather than all at once in a single `.Rmd` file. This is one of the reasons it remains important to manage your

¹ RStudio's Rmarkdown support uses all the same tools described here—i.e. `knitr`, `pandoc`, and so on. Writing RMarkdown documents via RStudio is the easiest way to get used to producing finished papers and reports using plain-text sources and R.

projects using some kind of version control, so you can keep track of work that is needed but might not fit inside a single `.Rmd` document.

5

Pull it Together

We write papers. Those papers cite books and articles. They often incorporate tables and figures created in [R](#). What we want to do is quickly turn a Markdown file containing things like that into a properly formatted scholarly paper, without giving up any of the necessary scholarly apparatus (on the output side) or the convenience and convertibility of Markdown (on the input side). We want to easily get good-looking output from the same source in HTML, PDF, and DOCX formats. And we want to do that with an absolute minimum of—ideally, *no*—post-processing of the output beyond the basic conversion step. This is within our reach.

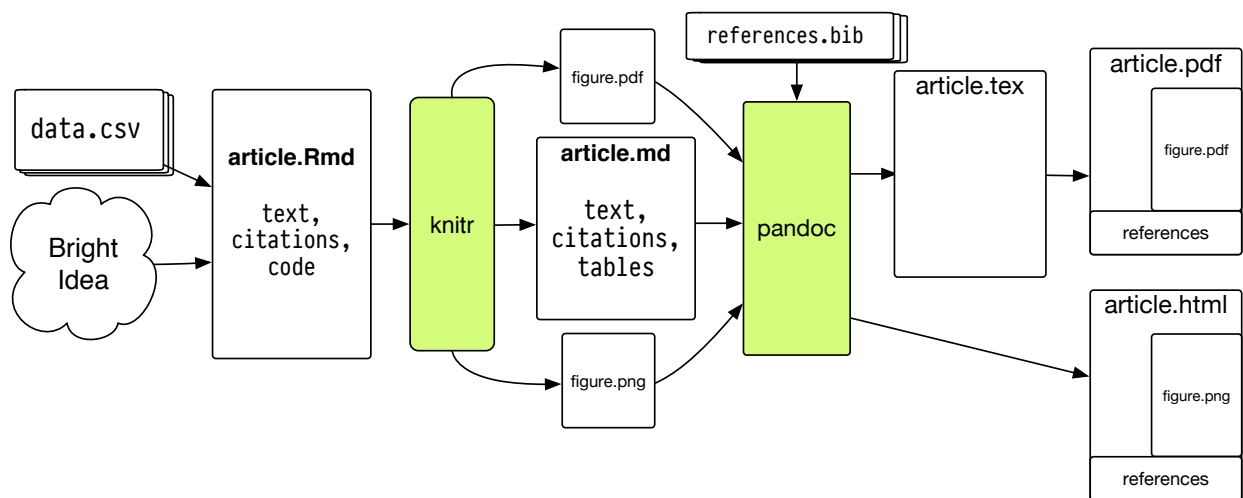


Figure 5.1: A plain-text document toolchain.

A sample document flow is shown in [Figure 5.1](#). I promise it is less insane than it appears. Describing it all at once might make it sound a little crazy. But, at bottom, there are just two

¹ Here's how. Open a terminal window and type `xcode-select --install`. You can install pandoc and many other tools using the [Homebrew package manager](#).

separable pieces. First, `knitr` converts `.Rmd` files to `.md` files. Second, John MacFarlane's superb [Pandoc](#) converts `.md` files to HTML, `.tex`, PDF, or Word formats. In both cases we use a few switches, templates and configuration files to do that nicely and with a minimum of fuss. You should install a standard set of Unix developer tools, which on OS X can conveniently be installed [directly from the command line](#).¹ along with R, `knitr`, `pandoc`, and a [TeX distribution](#). Note that the default set-ups for `knitr` and `pandoc`—the two key pieces of the process—will do most of what we want with no further tweaking. What I will you here are just the relevant options to use and switches to set for these tools, together with some templates and document samples showing how nice-looking output can be produced in practice.

I write everything in Emacs, but as I hope is clear by now, that doesn't matter. Use whatever text editor you like and just learn the hell out of it. The [custom LaTeX style files](#) were originally put together to let me write nice-looking `.tex` files directly, but now they just do their work in the background. Pandoc will use them when it converts things to PDF. The heavy lifting is done by the [org-preamble-pdflatex.sty](#) and [memoir-article-styles](#) files. If you install these files where LaTeX can find them—i.e., if you can compile a LaTeX document [based on this example](#)—then you are good to go. My [BibTeX master file](#) is also available, but you will probably want to use your own, changing references to it in the templates as appropriate. Second, we have the custom pandoc stuff. [Here is the repository for that](#). Much of the material there is designed to go in the `~/pandoc/` directory, which is where pandoc expects to find its configuration files. I have also set up a sample [md-starter project](#) and an [rmd-starter project](#). These are the skeletons of project folders for a paper written in Markdown (just an `.md` file, with no R) and a paper beginning life as an `.Rmd` file. The sample projects contain the basic starter file and a `Makefile` to produce `.html`, `.tex`, `.pdf` and `.docx` files.

Listing 5.1: Markdown file with document metadata

```
---
title: "A Pandoc Markdown Article Starter"
author:
- name: Kieran Healy
  affiliation: Duke University
  email: kjhealy@soc.duke.edu
- name: Joe Bloggs
  affiliation: University of North Carolina, Chapel Hill
  email: joebloggs@unc.edu
```



```

date: January 2014
abstract: "Lorem ipsum dolor sit amet."
...

# Introduction
Lorem ipsum dolor sit amet, consectetur adipisicing elit,
sed do eiusmod tempor incididunt ut labore et dolore magna
aliqua [@fourcade13classssituat]. Notice that citation.

# Theory
Lorem ipsum dolor sit amet, consectetur adipisicing
elit, sed do eiusmod tempor incididunt ut labore et
dolore magna aliqua [@fourcade13classssituat].

```

Let's start with a straightforward markdown file—no R code yet, so nothing to the left of `article.md` line in Figure 5.1. The start of the sample `article-markdown.md` file is shown in listing 5.1. The bit at the top is metadata, which pandoc understands. The HTML and LaTeX templates in the [pandoc-templates repository](#) are set up to use this metadata properly.

For scholarly work, efficient management of citations is particularly important. The `pandoc-citeproc` filter is an add-on that handles these. It can be installed alongside `pandoc`. Your bibliography can be stored in one of a variety of formats (such as BibTeX, or EndNote). Within your `.md` document, cites are referred to by their key, such as `[@healy14datavisualsociol]`. When `pandoc` converts your document, the cite key is replaced with the reference information, like this (Healy and Moody 2014), and the full bibliographic entry is included in an automatically-generated list of references. Read [Pandoc's documentation for more details](#) about citations. Pandoc can also handle in-text labels and cross-references. A filter named `pandoc-crossref` extends the `@label` convention to deal to things like figures, tables, equations, theorems, code listings and so on.

There is more than one way to have pandoc manage citations, but here we just use the most self-contained route. Simple documents can be contained in a single `.md` file. Documents including data analysis start life as `.Rmd` files which are then knitted into `.md` files and converted to PDF or HTML. At its simplest, a `mypaper.md` document can be converted to `mypaper.pdf` file by opening a terminal window and typing a command like the one in listing 5.2.

Listing 5.2: The simplest way to convert a Markdown file to PDF with pandoc

```

pandoc mypaper.md -o mypaper.pdf

```

5.1 Automation with make

Because we will probably run commands like this a lot, it's convenient to automate them a little bit, and to add some extra bells and whistles to accommodate things we will routinely add to files, such as author information and other metadata, together with the ability to process bibliographic information and cross-references. These are handled by `pandoc` by turning on various switches in the command, and by ensuring a couple of external “filters” are present to manage the bibliographies and cross-references. Rather than type long commands out repeatedly, we will automate the process. This kind of automation is especially useful when our final output file might have a number of prerequisites before it can be properly produced, and we would like the computer to be a little bit smart about what needs to be re-processed and under what conditions. That way, for example, if a Figure has not changed we will not re-run the (possibly time-consuming) R script to create it again, unless we have to.

We manage this process using a tool called `make`. Inside our project folder we put a plain-text `Makefile` that contains some rules governing how to produce a *target* file that might have a number of *prerequisites*. In this case, a PDF or HTML file is the target, and the various figures and data tables are the prerequisites—if the code that produces the prerequisites changes, the final document will change too. `make` starts from the final document and works backwards along the chain of prerequisites, re-compiling or re-creating them as needed. It's a powerful tool. For a good basic introduction, take a look at Karl Broman's “[Minimal Make](#)”. (Incidentally, Karl Broman has [a number of tutorials and guides](#) providing accurate and concise tours of many of the tools and topics described here, including [getting started with reproducible research](#), [using git and GitHub](#), and [working with knitr](#).)

Following Karl Broman's example, let's imagine that you have a paper, `paper.md` written in Markdown, that incorporates references to a figure, `fig1.pdf` generated by an R script, `fig1.r`. You could of course have an `.Rmd` file that produces the output, but there are situations where that isn't ideal. The end-point or target is the full article in PDF form. When the text of the paper changes in `paper.md`, then `paper.pdf` will have to be re-created. In

the same way, when we change the content of `fig1.r` then `fig1.pdf` will need to be updated, and thus also `paper.pdf` will need to be re-created as well. Using `make` we can take care of the process.

Here is what a basic `Makefile` for our example would look like:

Listing 5.3: A simple `Makefile`

```
## Read as "mypaper.pdf depends on mypaper.md and fig1.pdf"
mypaper.pdf: mypaper.md fig1.pdf
    pandoc mypaper.md -o mypaper.pdf

## Read as "fig1.pdf depends on fig1.r"
fig1.pdf: fig1.r
    R CMD BATCH fig1.r
```

The big gotcha for `Makefiles` is that for no good reason they use the `<TAB>` key rather than spaces to indent the commands associated with rules. If you use spaces, `make` will not work. With the `Makefile` in listing 5.3, typing `make` at the command line will have `make` check the state of the final target (`makefile.pdf`) and all its dependencies. If the target isn't present, `make` will create it in accordance with the rules specified. If the target is present, `make` will check to see if any of its prerequisites have changed since it was last created. If so, it will recreate the file. The chain of prerequisites propagates backwards, so that if you change `fig1.r`, then `make` will notice and re-run it to create `fig1.pdf` before running the commands in the rule to create `mypaper.pdf`. You can also choose to just invoke single rules from the `makefile`, e.g. by typing `make fig1.pdf` instead of `make` at the command line. This will evaluate just the `fig1.pdf` rule and any associated prerequisites.

For a simple example like this, `make` is mostly a minor convenience, saving you the trouble of typing a sequence of commands over and over to create your paper. However, it becomes very useful once you have projects with many documents and dependencies—for example, a dissertation consisting of separate chapters, each of which contains figures and tables, which in turn depend on various R scripts to set up and clean data. In those cases, `make` becomes a very powerful and helpful way of ensuring your final output really is up to date.

To deal with more complex projects and chains of prerequisites, `make` can make use of a number of variables to save you from (for example) typing out the name of every `figure-x.pdf` in your directory.

The `Makefile` in the sample `md-starter` project will convert any

markdown files in the working directory to HTML, .tex, .pdf, or .docx files as requested. Typing `make html` at the command line will produce .html files from any .md files in the directory, for example. The PDF output (from `make pdf`) will look like [this article](#), more or less. The different pieces of the Makefile define a few variables that specify the relationship between the different file types. In essence the rules say, for example, that all the PDF files in the directory depend on changes to an .md file with the same name; that the same is true of the HTML files in the directory, and so on. Then the show the `pandoc` commands that generate the output files from the markdown input. The Makefile itself is shown in Listing listing 5.4 makes use of a few variables as shorthand, as well as special variables like `$(` and `$(`, which mean “the name of the current target” and “the name of the current prerequisite”, respectively.

Listing 5.4: A more complicated Makefile

```
## What extension (e.g. md, markdown, mdown) is being used
## for markdown files MEXT = md

## Expands to a list of all markdown files in the working directory
SRC = $(wildcard *.$(MEXT))

## Location of Pandoc support files.
PREFIX = /Users/kjhealy/.pandoc

## Location of your working bibliography file
BIB = /Users/kjhealy/Documents/bibs/socbib-pandoc.bib

## CSL stylesheet (located in the csl folder of the PREFIX directory).
CSL = apsa

## x.pdf depends on x.md, x.html depends on x.md, etc
PDFS=$(SRC:.md=.pdf)
HTML=$(SRC:.md=.html)
TEX=$(SRC:.md=.tex)
DOCX=$(SRC:.md=.docx)

## Rules -- make all, make pdf, make html. The 'clean' rule is below.
all: $(PDFS) $(HTML) $(TEX) $(DOCX)
pdf: clean $(PDFS)
html: clean $(HTML)
tex: clean $(TEX)
docx: clean $(DOCX)

## The commands associated with each rule. The first one is run with
## 'make html'. Read the rule as "When making the html file, run
## this pandoc command if the .md file has changed."
%.html: %.md
    pandoc -r markdown+simple_tables+table_captions+yaml_metadata_block \
    -w html -S --template=$(PREFIX)/templates/html.template \
    --css=$(PREFIX)/marked/kultiad-serif.css --filter pandoc-crossref \
    --filter pandoc-citeproc --csl=$(PREFIX)/csl/$(CSL).csl \
```

```

--bibliography=$(BIB) -o $$ $<

## Same goes for the other file types.
## Watch out for the TAB before 'pandoc'
%.tex: %.md
    pandoc -r markdown+simple_tables+table_captions+yaml_metadata_block \
    --listings -w latex -s -S --latex-engine=pdflatex \
    --template=$(PREFIX)/templates/latex.template \
    --filter pandoc-crossref --filter pandoc-citeproc \
    --csl=$(PREFIX)/csl/ajps.csl --filter pandoc-citeproc-preamble \
    --bibliography=$(BIB) -o $$ $<

%.pdf: %.md
    pandoc -r markdown+simple_tables+table_captions+yaml_metadata_block \
    --listings -s -S --latex-engine=pdflatex \
    --template=$(PREFIX)/templates/latex.template \
    --filter pandoc-crossref --filter pandoc-citeproc \
    --csl=$(PREFIX)/csl/$(CSL).csl --filter pandoc-citeproc-preamble \
    --bibliography=$(BIB) -o $$ $<

%.docx: %.md
    pandoc -r markdown+simple_tables+table_captions+yaml_metadata_block \
    -s -S --filter pandoc-crossref --csl=$(PREFIX)/csl/$(CSL).csl \
    --bibliography=$(BIB) -o $$ $<

clean:
    rm -f *.html *.pdf *.tex *.aux *.log *.docx

.PHONY: clean

```

Note that the `pandoc` commands are interpreted single lines of text, not several lines separated by the `<return>` key. But you can use the `\` symbol to tell `make` to continue to the next line without a break. With this Makefile, typing `make pdf` would take all the `.md` files in the directory one at a time and run the `pandoc` command to turn each one into a PDF, using the [APSR](#) reference style, my latex template, and a `.bib` file called `socbib-pandoc.bib`.

You shouldn't use this Makefile blindly. Take the time to learn how `make` works and how it can help your project. The [official manual](#) is pretty clear. Make's backward-looking chain of pre-requisites can make it tricky to write rules for complex projects. When writing or inspecting a Makefile and its specific rules, it can be helpful to use the `--dry-run` switch, as in `make --dry-run`. This will print out the sequence of commands `make` would run, but without actually executing them. You can try this with the Makefile in listing 5.4 in a directory with at least one `.md` file in it. For example, look at the commands produced by `make pdf --dry-run` or `make docx --dry-run` OR `make clean --dry-run`.

The particular steps needed for many projects may be quite simple, and not require the use of any variables or other frills.

If you find yourself repeatedly running the same sequence of commands to assemble a document (e.g. cleaning data; running preliminary code; producing figures; assembling a final document) then `make` can do a lot to automate the process. For further examples of `Makefiles` doing things relevant to data analysis, see [Lincoln Mullen's discussion](#) of the things he uses `make` to manage.

The examples directory [includes](#) a sample `.Rmd` file. The code chunks in the file provide examples of how to generate tables and figures in the document. In particular they show some useful options that can be passed to `knitr`. [Consult the `knitr` project page](#) for extensive documentation and many more examples. To produce output from the `article-knitr.Rmd` file, you could of course launch R in the working directory, load `knitr`, and process the file. This produces the `article-knitr.md` file, together with some graphics in the `figures/` folder (and some working files in the `cache/` folder). We set things up in the `.Rmd` file so that `knitr` produces both PNG and PDF versions of whatever figures are generated by R. That prepares the way for easy conversion to HTML and LaTeX. Once the `article-knitr.md` file is produced, HTML, `.tex`, and PDF versions of it can be produced as before, by typing `make` at the command line. But of course there's no reason `make` can't automate that first step, too. The [`rmd-starter` project](#) has a sample `Makefile` that begins with the `.Rmd` files in the directory and produces the outputs from there.

6

An Emacs Starter Kit

A step-by-step guide to downloading and installing every piece of software I've mentioned so far is beyond the scope of this discussion. But let's say you take the plunge and download Emacs, a TeX distribution, R, and maybe even Git. Now what? If you're going to work in Emacs, there are a variety of tweaks and add-ons that are very helpful but not set by default. To make things a little easier, I maintain an [Emacs Starter Kit for the Social Sciences](#). It's designed to smooth out Emacs' rough edges by giving you a drop-in collection of default settings, as well as automatically installing some important add-on packages. It will, I hope, help you skirt the abyss of Setting Things Up Forever.

What's the motivation for the starter kit? Emacs is a very powerful editor but it is less useful out-of-the-box than it might be, in part because many convenient settings and modes are not activated by default. The starter kit is a drop-in set of nice default settings. The idea is for you to be able to download GNU Emacs, put the starter kit into `~/.emacs.d/`, and get to work. If you already use Emacs and have a `.emacs` file or `~/.emacs.d` directory, the starter kit is designed to replace them, while leaving a place for you to easily append your own customizations.

The starter kit is designed to be used with GNU Emacs. Version 24.4 (released October 2014) or later is required. It will not work with [Aquamacs](#) without modification. More detailed commentary and documentation is provided inside the kit's `.org` files.

```

<boot-plot-06,results=hide,echo=FALSE>=
pdf(file="figures/rank-confboot.pdf",width=11,height=10,pointsize=12)
p <- ggplot(t25.06,aes(x=Name,
                      y=round(Mean,1),
                      ymin=Lower,
                      ymax=Upper)) + theme_bw() +
  scale_x_discrete(name=" ") + scale_y_continuous(name=" ") +
  opts(axis.text.y=theme_text(colour="#000000",hjust=1, size=14),
axis.text.x=theme_text(colour="#000000",hjust=1,angle=90, size=14))
p + geom_errorbar(size=1.1,width=0.2,colour=alpha("Grey30",0.9)) +
geom_point(size=4) + coord_flip()
dev.off()
@

\begin{figure}[h]
\centering
\includegraphics{figures/rank-confboot}
\caption{Top 25 Departments (2006) with bootstrapped 95 percent confidence
intervals.}
\label{fig:rank-confboot}
\end{figure}

Figure \ref{fig:rank-confboot} presents the top twenty five
departments from the 2006 survey by overall mean reputational score,
without distinguishing schools by country. New York University scores
highest with a 4.8. Rutgers and Oxford score 4.7, and Michigan and
Princeton 4.4 points, respectively. \footnote{I report PGR scores for
}

> vplayout <- function(x, y){
+   viewport(layout.pos.row = x, layout.pos.col = y)
+ }
> ###-----
> data <- read.csv("data/debt-income.csv", header=TRUE)
> colnames(data) <-
+   c("Percentile","1989","1992","1995","1998","2001","2004","2007")
> library(gdata)
data[,"Percentile"] <- reorder.factor(data[,"Percentile"],
new.order=c("90-100","80-89.9","60-79.9","40-59.9","20-39.9","0-20"))
gdata: read.xls support for 'XLS' (Excel 97-2004) files ENABLED.

gdata: read.xls support for 'XLSX' (Excel 2007+) files ENABLED.

Attaching package: 'gdata'

The following object(s) are masked from 'package:ggplot2':

  interpolate

The following object(s) are masked from 'package:utils':

  object.size

> > detach(package:gdata)
> dat.r <- melt(data)
Using Percentile as id variables
> colnames(dat.r) <- c("Percentile","Year","Percent")
> []

```

Figure 6.1: Emacs in Solarized colors.

6.1 Installation Instructions (Mac OS X)

Before you Begin

If you want to use the tools that the starter-kit works with—LaTeX, R, Git, Pandoc, and all the rest—then you will need to install them on your Mac. The ground floor is Apple’s own suite of Developer Tools, which allow you to compile software yourself and include things like Git. The most straightforward way to get these tools is to **install Xcode**. Xcode is what software developers use to write Mac and iOS applications. As such it comes with a bunch of things we are not so interested in, but it makes it easy to install what we do need. It’s available [for free via the Mac App Store](#). Once downloaded, launch Xcode, go to Xcode > Preferences > Downloads and install the **Command Line Tools for Xcode**. At that point you can quit Xcode and never use it again. Alternatively, go to [Apple’s Developer Site](#), login with your Apple ID and download the Command Line Tools for Xcode package by itself, without the Xcode application.

If you have used Emacs before and already have a `.emacs` file or `.emacs.d` directory, back them up and then delete them. See below

for details on how to add customizations to the kit.

Getting the Starter Kit

You have two choices. You can [download a .zip file of the kit](#). This will give you a static snapshot of the most recent version. But if you want to keep up with changes to the kit, you should clone the source code using git rather than simply copying a static version of it. You should be using version control on your plain-text documents anyway, so I recommend this second option.

Prerequisites

- **Get Emacs.** The starter kit requires Emacs 24.4 (released October 2014). [Download Emacs here](#). Alternatively, if you are comfortable with Homebrew, compile and install it.

- **Install a Modern TeX Distribution and the Skim PDF reader.** If you are using OS X, [download MacTeX here](#) and install it. The kit is set up to use the [Skim PDF reader](#) to display PDF files created from .tex files. You can use other readers, but will need to modify the setup in the `starter-kit-latex.org` file.

- **Install R and Pandoc.** These are not strictly required for the installation to work, and you can skip this step if you like. But you will probably be using them anyway, if you're not already. If you're doing statistical work you will probably want to use R or Stata.

- **Note your user name** or the name of your computer. If you don't know either, open the Terminal application and do

```
$ whoami
```

for your user name and

```
$ hostname
```

for the system name. You will need to know your login name to activate the final customization file properly. You can use the system name as well (or instead).

Setup

1. If you downloaded a `.zip` file of the kit, you must uncompress it, move the resulting folder to the top level of your home director and rename it `.emacs.d`. Assuming the downloaded zip file is in your `~/Downloads` folder, open a Terminal window and do this:

```
$ cd ~/Downloads
$ unzip emacs-starter-kit-master.zip
$ mv emacs-starter-kit-master ~/.emacs.d
```

Alternatively, if you are using git (the preferred method), then clone the starter kit from github. Open a Terminal window and do this:

```
$ git clone git://github.com/kjhealy/emacs-starter-kit ~/.emacs.d
```

2. Inside the file `kjhealy.org`, change the paths to any BibTeX databases as described at the top of that file.

3. Rename the starter kit's `kjhealy.org` file to that of `%your-username%.org` or `%your-systemname%.org`, based on the information you noted in 0.4 above. This is where you can add in any of your own further customizations to Emacs.

4. Launch Emacs.

When you first start Emacs after installing the starter-kit, it will try to contact several package repositories, so make sure you have an internet connection. The kit will download packages mainly from the official [GNU ELPA repository](#) and the [MELPA Repo](#). Each package will be fetched, compiled by Emacs, and stored in the `~/.emacs.d` directory. This process is sometimes prone to hiccups as packages are fetched from the servers, so please be patient with it. If it doesn't get everything first time around, quit and relaunch Emacs, and it will try again. If the problem persists—especially if you get a message saying “The package ‘auctex’ is not available for installation”—you can manually install packages as follows. Open Emacs, do `M-x list-packages` and in the resulting buffer search or scroll down the list to, e.g. Auc-tex, mark it for installation by pressing `i` and then install it (or them) by hitting `x`. With the packages in place, restart Emacs and the starter kit will finish setting itself up. Unfortunately, I can't control these intermittent installation errors. They seem to have something to do with the way Emacs talks to the GNU ELPA package server.

5. (Optional.) Once Emacs is up and running, do `M-x starter-kit-compile` to byte-compile the starter-kit's files, for slightly faster loading.

6.2 Using Marked

In everyday use, I find Brett Terpstra's application [Marked](#) to be a very useful way of previewing text while writing. Marked shows you your Markdown files as HTML, updating the preview on the fly whenever changes are saved in the Markdown file. It can render ordinary Markdown by default, and will work that way immediately for you. But it also supports `pandoc` as a custom processor. This means it can manage the various extra bells and whistles of scholarly formatting discussed so far. Essentially, you tell Marked run a `pandoc` command similar or identical the one shown above to generate its HTML previews. You do this in the "Advanced" tab of Marked's preferences. The "Path" field in the preferences dialog contains the full path to `pandoc`, and the "Args" field contains all the relevant command switches—in my case, the same as in the Makefile above.

When editing your markdown file in your favorite text editor, you point Marked at the file and get a live preview. You can add the [CSS files in the pandoc-templates repository](#) to the list of Custom CSS files Marked knows about, via the "Style" tab in the Preferences window. That way, Marked's preview will look the same as the HTML file that's produced. Figure 6.2 shows what this looks like in practice.

The upshot of all of this is powerful editing using Emacs, [ESS](#), R, and other tools; flexible conversion using `pandoc`; quick and easy previewing via HTML and Marked; and high-quality PDF typesetting at the same time (or whenever needed). All of it can be generated directly from plain text, and will include almost all of the machinery most scholarly papers need, most notably properly labeled Tables and Figures that can be cross-referenced in the text. While it all may seem quite complex when laid out in this way, in use it is quite straightforward, and doesn't require any thought when in use. I just live in my text editor. The various scripts and settings do their work quietly, and I get the formatted output I want.

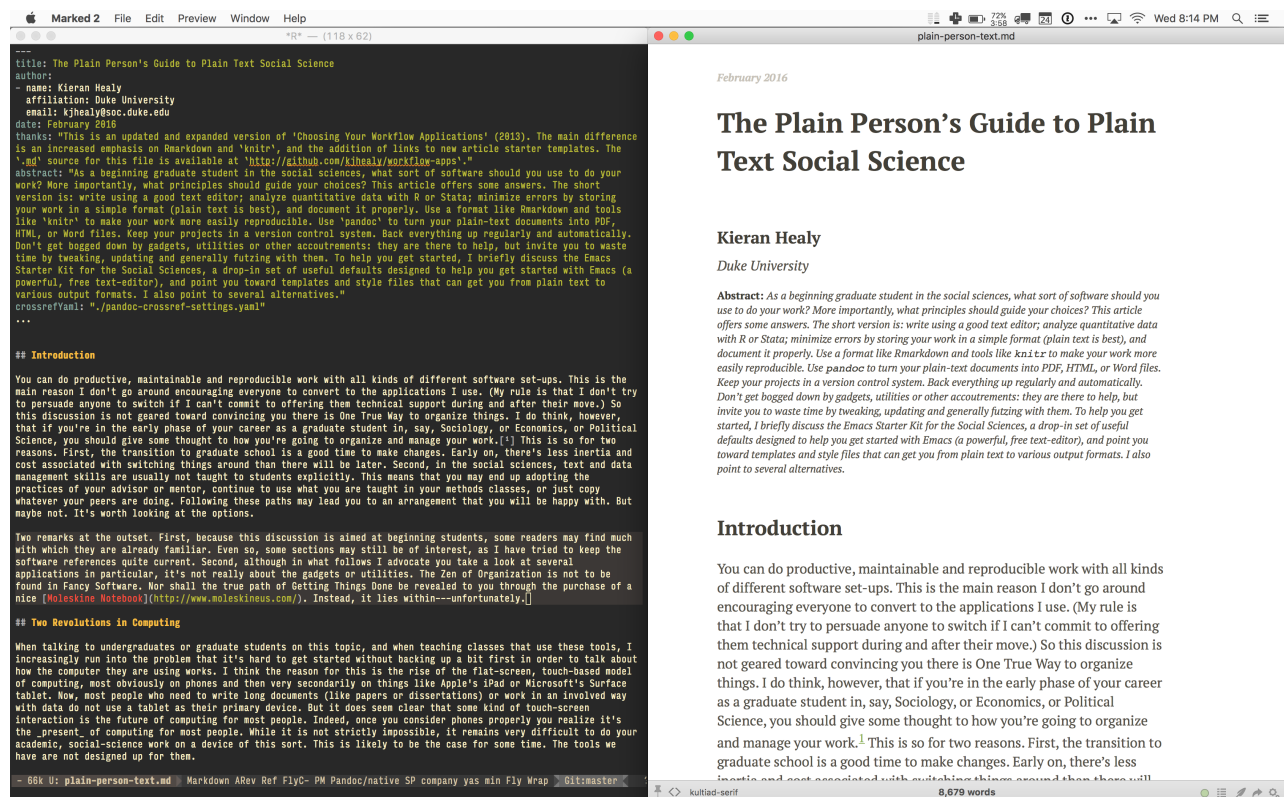


Figure 6.2: Working on this document in Emacs (left), with a live HTML version displayed in Marked (right).

7

Do I Have To Use This Stuff?

How to draw an owl

1.



2.



1. Draw some circles

2. Draw the rest of the fucking owl

Figure 7.1: How to Draw an Owl.

Installation/setup/whatever is always harder and much more poorly documented than mere usage — [Jenny's Law](#)

7.1 Why Bother, Again?

Running your data analysis in R, writing documents in Markdown or RMarkdown, doing both via Emacs or some other text editor, processing them with `pandoc`, tracking things with Git and using (behind the scenes) various Unix tools and LaTeX ... this all sounds rather complicated. It has four main advantages. First,

these formats, tools, and applications are all free. You can try them out without much in the way of monetary expense. (Your time may be a different matter, but although you don't believe me, you have more of that now than you will later.) Second, they are all open-source projects and are all available for Mac OS X, Linux and Windows. Portability is important, as is the long-term viability of the platform you choose to work with. If you change your computing system, your work can move with you easily. Third, they allow you to do your work in a portable, documented, and reproducible way. And fourth, the applications are closely integrated. Everything (including version control) can work inside Emacs. All of them can work directly with or take advantage of the others.

None of these tools is perfect. They can do very useful and important things for you, but they are not magic. There are bad habits associated with working in plain text, just as there are bad habits associated with writing everything in word. These tools are powerful, but they can be tedious to learn. However, you don't have to start out using all of them at once, or learn everything about them right away—the only thing you really, *really* need to start doing *immediately* is keeping good backups. There are a number of ways to try these tools out in whole or in part. You could try writing something in Markdown first, using any text editor. You could begin using R with [RStudio](#). Revision control is more beneficial when implemented at the beginning of projects, and best of all when committing changes to a project becomes a habit of work. But it can be added at any time.

You are not condemned to use these applications forever, either. RMarkdown and (especially) Markdown documents can be converted into many other formats. Your text files are editable in any other text editor and on any other computer. Statistical code is by nature much less portable, but the openness of R means that it is not likely to become obsolete or inaccessible any time soon. In everyday use, you may find that documents start life as plain-text, Markdown-formatted notes jotted down on your phone, or computer; then they become longer `.md` files that grow references and figures and so on; and eventually migrate to Word or Google Docs or something similar if you acquire a collaborator or the time comes to submit a manuscript to a journal.

A disadvantage of these particular applications is that you

might be in a minority with respect to other people in your field. This is less and less true in the case of R, and more recently with tools like Git as well. Writing papers in RMarkdown or Markdown is less common. Most people use Microsoft Word to write papers, and if you're collaborating with people (people you can't boss around, I mean) this can be an issue. It is usually easier to use applications like Word than convert people to a plain-text workflow. If you do, at least try and implement some of the principles discussed here when it comes to tracking changes to documents and managing the code and output of your data analysis.

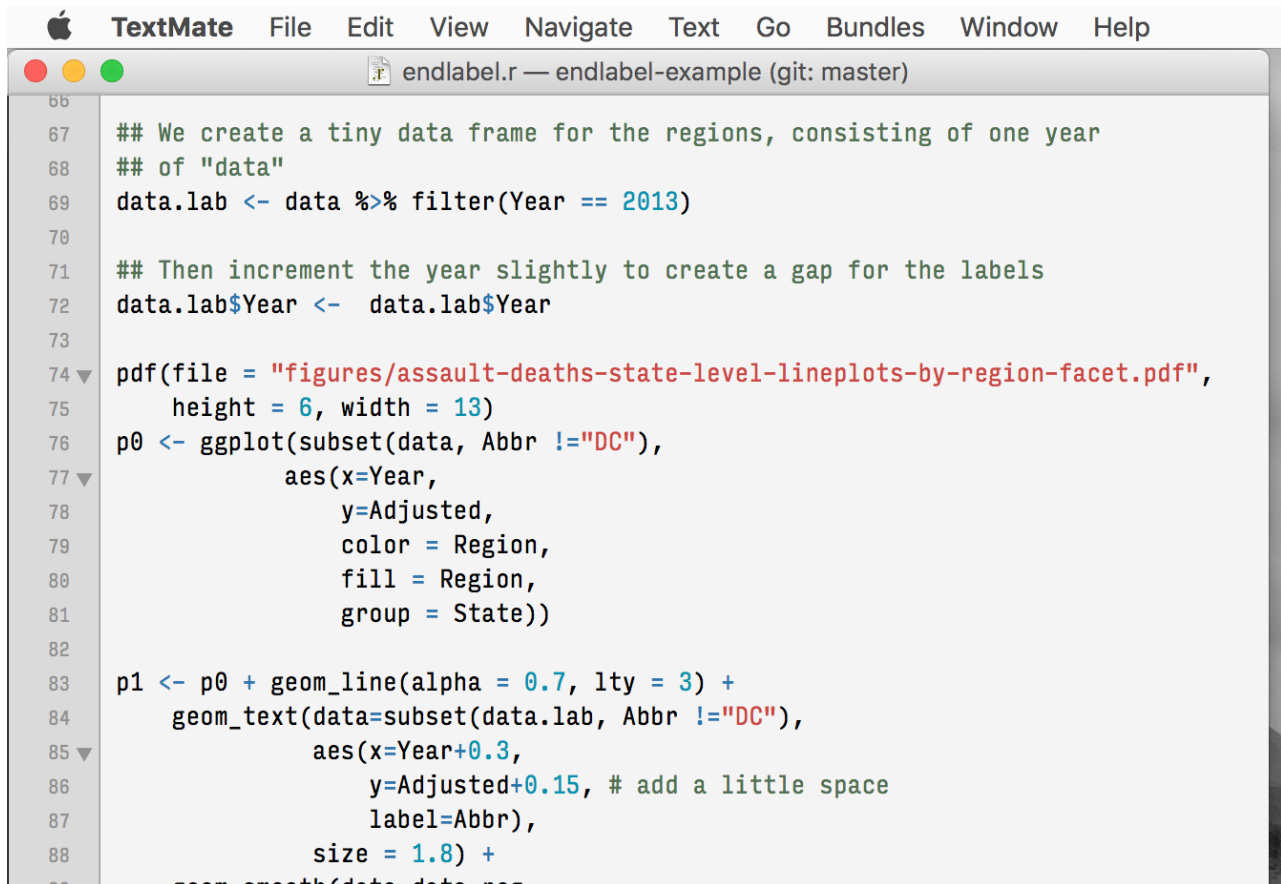
7.2 But Alternatives Might Be Better for You

There are many other applications you might put at the center of your workflow, depending on need, personal preference, willingness to pay some money, or desire to work on a specific platform. For text editing, especially, there is a plethora of choices. On the Mac, quality editors include [BBEdit](#) (beloved of many web developers, but with relatively little support for R beyond syntax highlighting), and [TextMate 2](#) (shown in Figure 7.2). On Linux, the standard alternative to Emacs is [vi](#) or [Vim](#), but there are many others. For Windows there is [Textpad](#), [WinEdt](#), [UltraEdit](#), and [Notepad++](#) amongst many others. Most of these applications have strong support for LaTeX and some also have good support for statistics programming.

[Sublime Text 3](#) is a cross-platform text editor under active development, and with an increasingly large user base. Sublime Text is fast, fluid, and contains a powerful plugin system based on the [Python](#) programming language. Uniquely amongst alternatives to Emacs and ESS, Sublime Text includes a well-developed [REPL](#) that allows R to be run easily inside the editor.¹ Sublime Text costs \$70.

For a different approach to working with R—and as repeatedly noted throughout this guide—you should consider [RStudio](#). A screenshot is shown in Figure 7.3. Although it appears quite late in this discussion, it might well be your first choice. I use it when teaching. It is not a text editor but rather an “IDE”, an integrated development environment. Your code and figures, together with an R console, documentation, and other output are all displayed in different panes and tabs of RStudio's application

¹ TextMate also has some support for this way of working, but it is conceived and accomplished a little differently.



```

66
67 ## We create a tiny data frame for the regions, consisting of one year
68 ## of "data"
69 data.lab <- data %>% filter(Year == 2013)
70
71 ## Then increment the year slightly to create a gap for the labels
72 data.lab$Year <- data.lab$Year
73
74 pdf(file = "figures/assault-deaths-state-level-lineplots-by-region-facet.pdf",
75     height = 6, width = 13)
76 p0 <- ggplot(subset(data, Abbr != "DC"),
77             aes(x=Year,
78                 y=Adjusted,
79                 color = Region,
80                 fill = Region,
81                 group = State))
82
83 p1 <- p0 + geom_line(alpha = 0.7, lty = 3) +
84     geom_text(data=subset(data.lab, Abbr != "DC"),
85             aes(x=Year+0.3,
86                 y=Adjusted+0.15, # add a little space
87                 label=Abbr),
88             size = 1.8) +
89     geom_smooth(data=data, aes(x=Year, y=Adjusted))

```

Figure 7.2: Part of an R file being edited in TextMate.

window. Data and script files are managed via various windows and menus. RStudio is available for Mac OS X, Windows, and Linux. It integrates nicely with R's help files. It understands `knitr` and `Git`. As discussed above, it has full support for Rmarkdown and generates HTML, PDF, and other formats for you very easily. It is the easiest way by far to get into using R, and provides a straightforward way to manage many of the tools already discussed here.

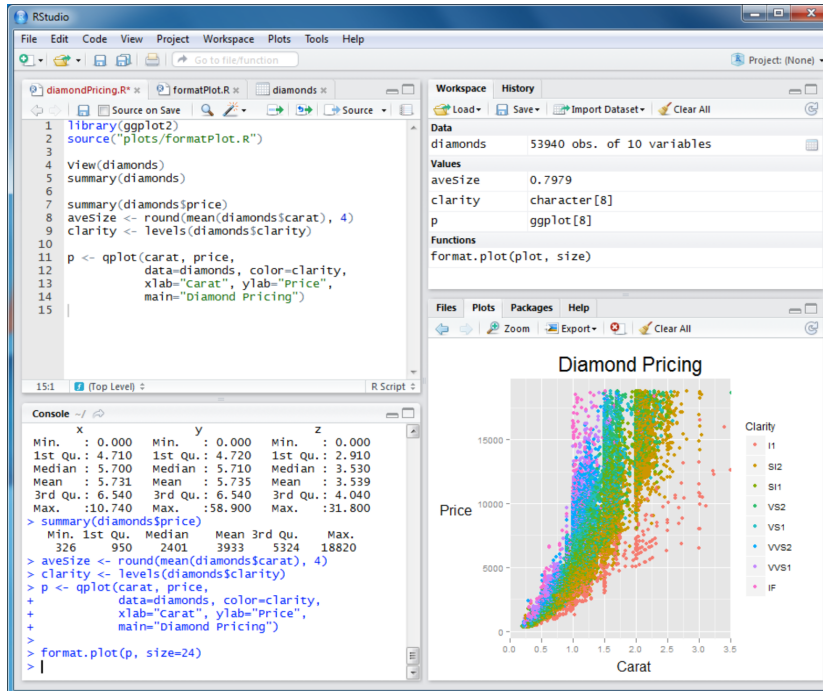


Figure 7.3: RStudio running on Windows.

For statistical analysis in the social sciences, the main alternative to R is [Stata](#). Stata is not free, but like R it is versatile, powerful, extensible and available for all the main computing platforms. It has a large body of user-contributed software. In recent versions its graphics capabilities have improved a great deal, as has its editor. ESS can highlight Stata `.do` files in the same way as it can do for R. Other editors can also be made to work with Stata. More recently, [Python](#) has been coming into frequent use in the social sciences. Python is a general-purpose computing language that is relatively straightforward to learn. It is often used for manipulating, cutting, and cleaning data prior to analysis in applications like R or Stata. But it is also increasingly a scientific computing platform in its own right. [SciPy](#) is a

useful place to begin learning about Python’s capabilities on this front. Like R and RMarkdown, it has good support for literate programming through tools like [iPython Notebooks](#). Naturally, Emacs has good support for working with Python.

Amongst social scientists, revision control is perhaps the least widely-used of the tools I have discussed. But I am convinced that it is the most important one over the long term. While tools like Git take a little getting used to both conceptually and in practice, the services they provide are extremely useful. It is already quite easy to use version control in conjunction with most of the text editors discussed above. There are also full-featured clients like [Tower](#) that allow you to administer git without having to use the command line. Taking a longer view, version control is likely to become more widely available through intermediary services or even as part of the basic functionality of operating systems.

7.3 A Broader Perspective

It would be nice if all you needed to do your work was a box of software tricks and shortcuts. But of course it’s a bit more complicated than that. In order to get to the point where you can write a paper, you need to be organized enough to have read the right literature, maybe collected some data, and most importantly asked an interesting question in the first place. No amount of software is going to solve those problems for you. Too much concern with the details of your setup hinders your work. Indeed—and I speak from experience here—this concern is itself a kind self-imposed distraction that placates work-related anxiety in the short term while storing up more of it for later.² On the hardware side, there’s the absurd productivity counterpart to the hedonic treadmill, where for some reason it’s hard to get through the to-do list even though the cafe you’re at contains more computing power than was available to the Pentagon in 1965. On the software side, the besetting vice of software is the tendency to waste a lot of your time installing, updating, and generally obsessing about it.³ Even more generally, efficient workflow habits are themselves just a means to the end of completing the projects you are really interested in, of making the things you want to make, of finding the answers to the questions that brought you to graduate school. The process of idea genera-

² See [Merlin Mann](#), amongst others, for more on this point.

³ Mike Hall’s brilliant “[Org-Mode in your Pocket is a GNU-Shaped Devil](#)” makes this point very well.

tion and project management can be run well, too, and perhaps even the business of choosing what the projects should be in the first place. But this is not the place—and I am not the person—to be giving advice about that.

All of which is just to reiterate two things. First, I am not advocating these tools on the grounds that they will make you more “productive”. Rather, they may help you stay in control of—and able to reproduce—your own prior work. That is an important difference. If you care about getting the right answer in your data analysis, or at least being able to repeatedly get the same probably wrong answer, then tools that enhance this sort of control should appeal to you. Second, even with that caveat it is still the *principles* of workflow management that are important. The software is just a means to an end. One of the [smartest, most productive people I’ve ever known](#) spent half of his career writing on a typewriter and the other half on an ancient [IBM Displaywriter](#). His backup solution for having hopelessly outdated hardware was to keep a spare Displaywriter in a nearby closet, in case the first one broke. It never did.

8

Links to Other Resources

8.1 Basic Tools

- [Apple's Developer Tools](#) Unix toolchain. Install directly with `xcode-select --install`, or just try to use e.g. `git` from the terminal and have OS X prompt you to install the tools.
- [Homebrew package manager](#). A convenient way to install several of the tools here, including Emacs and Pandoc.
- [Emacs](#). A powerful text editor. Ready-to-go Mac version at [Emacs for Mac OS X](#).
- [R](#). A platform for statistical computing.
- [knitr](#). Reproducible plain-text documents from within R.
- [Python](#) and [SciPy](#). Python is a general-purpose programming language increasingly used in data manipulation and analysis.
- [RStudio](#). An IDE for R. The most straightforward way to get into using R and RMarkdown.
- [TeX and LaTeX](#). A typesetting and document preparation system. You can write files in `.tex` format directly, or you can just have it available in the background for other tools to use. The [MacTeX Distribution](#) is the one to install for OS X.
- [Pandoc](#). Converts plain-text documents to and from a wide variety of formats. Can be installed with Homebrew. Be sure to also install `pandoc-citeproc` for processing citations and bibliographies, and `pandoc-crossref` for producing cross-references and labels.
- [Git](#). Version control system. Installs with Apple's Developer Tools, or get the latest version via Homebrew.
- [GNU Make](#). You tell `make` what the steps are to create the pieces of a document or program. As you edit and change the various pieces, it automatically figures out which pieces need to be updated and recompiled, and issues the commands to do that.

See Karl Broman's [Minimal Make](#) for a short introduction. Make will be installed automatically with Apple's developer tools.

- [lintr](#) and [flycheck](#). Tools that nudge you to write neater code.

8.2 Helpers and Templates

- [Emacs Starter Kit for the Social Sciences](#). Set Emacs up to use many of the tools described in this guide.
- [Pandoc Templates](#). LaTeX and HTML templates, together with Pandoc configuration files and other things needed to produce good-looking PDF, HTML, and Word documents from plain text sources using Pandoc.
- [md-starter project](#) and [rmd-starter project](#). Assuming you have the tools and Pandoc/LaTeX templates installed, these skeleton project folders contain a basic `.md` or `.rmd` starter file and a Makefile to produce `.html`, `.tex`, `.pdf` and `.docx` files as described in this guide.
- [RMarkdown Cheatsheet](#) An overview of Markdown and RMarkdown conventions.
- [RStudio Cheatsheets](#) Other quick guides, including a more comprehensive RMarkdown reference and a information about using RStudio's IDE, and some of the main tools in R.

8.3 Guides

- [R Style Guide](#). Write readable code.
- [Jenny Bryan's Stat 545](#). Notes and tutorials for a Data Analysis course taught by [Jennifer Bryan](#) at the University of British Columbia. Lots of useful material.
- [knitr demos](#) Documentation and examples for `knitr` by its author, Yihui Xie. There is also a [knitr book](#) covering the same ground in more detail.
- [Rmarkdown documentation](#) from the makers of RStudio. Lots of good examples.
- [Plain Person's Guide](#) The git repository for this project.
- [Karl Broman's Tutorials and Guides](#) Accurate and concise guides to many of the tools and topics described here, including [getting started with reproducible research](#), [using git and GitHub](#), and [working with knitr](#).
- [Makefiles for OCR and converting Shapefiles](#). Some further

examples of `Makefiles` in the data-analysis pipeline, by [Lincoln Mullen](#)

8.4 Paid Applications and Services

- [Backblaze](#). Secure off-site backup.
- [Crashplan](#). Secure off-site backup.
- [GitHub](#). Host public Git repositories for free. Pay to host private ones. Also a source for publicly available code (e.g. R packages and utilities) written by other people.
- [Marked 2](#). Live HTML previewing of Markdown documents. Mac OS X only.
- [Sublime Text](#). Python-based text editor.
- [Zotero](#), [Mendeley](#), and [Papers](#) are citation managers that incorporate PDF storage, annotation and other features. Zotero is free to use. Mendeley has a premium tier. Papers is a paid application after a trial period. I don't use these tools much, but that's not for any strong principled reason—mostly just inertia. If you use one and want to integrate with the material here, just make sure it can export to BibTeX/BibLaTeX files. Papers, which I've used most recently, can handily output citation keys in pandoc's format amongst several others.

References

- Dalgaard, Peter. 2008. *Introductory Statistics with R*. Second edition. New York: Springer.
- Fox, John. 2002. *An R and S-Plus Companion to Applied Regression*. Thousand Oaks: Sage.
- Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multi-level/Hierarchical Models*. New York: Cambridge University Press.
- Harrell, Frank. 2016. *Regression Modeling Strategies*. Second. New York: Springer.
- Healy, Kieran, and James Moody. 2014. "Data Visualization in Sociology." *Annual Review of Sociology* 40: 105–28.
- Maindonald, John, and John Braun. 2003. *Data Analysis and Graphics Using R: An Example-Based Approach*. New York: Cambridge University Press.
- Matloff, Norman. 2011. *The Art of R Programming*. San Francisco: No Starch Press.
- Venables, W.N., and B.D. Ripley. 2002. *Modern Applied Statistics with S*. Fourth. New York: Springer.
- Xie, Yihui. 2015. *Dynamic Documents with R and Knitr*. Second. New York: Chapman; Hall.
- Dalgaard, Peter. 2008. *Introductory Statistics with R*. Second edition. New York: Springer.
- Fox, John. 2002. *An R and S-Plus Companion to Applied Regression*. Thousand Oaks: Sage.
- Gelman, Andrew, and Jennifer Hill. 2007. *Data Analysis Using Regression and Multi-level/Hierarchical Models*. New York: Cambridge University Press.
- Harrell, Frank. 2016. *Regression Modeling Strategies*. Second. New York: Springer.
- Healy, Kieran, and James Moody. 2014. "Data Visualization in Sociology." *Annual Review of Sociology* 40: 105–28.
- Maindonald, John, and John Braun. 2003. *Data Analysis and Graphics Using R: An Example-Based Approach*. New York: Cambridge University Press.
- Matloff, Norman. 2011. *The Art of R Programming*. San Francisco: No Starch Press.
- Venables, W.N., and B.D. Ripley. 2002. *Modern Applied Statistics with S*. Fourth. New York: Springer.
- Xie, Yihui. 2015. *Dynamic Documents with R and Knitr*. Second. New York: Chapman; Hall.

Colophon

This book was made with open-source tools, principally R, ggplot2, knitr, bookdown, pandoc, and \LaTeX . The text is set in Bitstream Charter, Adobe Source Sans Pro, and Bera Mono.