Intro: Why we wrote this

It seems like everywhere we look now, people are using data in beautiful and surprising ways to present their positions or shed light on new topics. We remember the first time we saw the impact data can have on storytelling. Hans Rosling, the Swedish physician/statistician, gave a talk displaying the gapminder dataset. Rosling perfectly his paired enthusiasm with a brilliant display on the screen. As he spoke, over a dozen colorful circles slid across the protection. His Ted profile description is perfect, "In Hans Rosling's hands, data sings."

Today, most primary sources of media use data as part of their evidence base. Check out the interactive data visualizations on the UpShot at the New York Times, the visual journalism data projects at the BBC, or the daily graphs in the Economist.

The massive amounts of data available have spawned new forms of media. Nate Silver's blog covering elections and politics has grown into multiple projects on fivethirtyeight. The Pudding is an example of an online data journalism site that covers non-conventional sources of data. Vox recently won an award for producing a graph that communicates a topic that pundits could've debated endlessly.

Now that we've shown you all this cool stuff, we want to tell you why we wrote this book,

"You've found something cool on the internet, but you have no idea what it took to make it."

There are a ton of really great resources on the internet right now for learning data science (see here, here, and here). Many of these courses are fantastic–they can teach you programming languages, website design, database management, statistics, and machine learning. But we sometimes found the sheer volume of these courses can be overwhelming for audiences who are wanting to understand how these technologies fit together.

We decided to take a step back and write a book that describes a data science workflow, or *shows how these tools work together*. We'll show you how R, RStudio, Git, & Github can be used to create elegant yet durable data analysis projects.

We chose to center this book around a particular use case, so there will be code files and tools we'll use that are specific to this project. But we've chosen not to spend too much time on the content of these files (we've documented them you want to look into the details). Instead, We're going to focus more on the "high level" ideas because these are topics you can take with you to your next project. We also encourage you to consult the articles and resource we've recommended throughout each chapter for more materials on each topic.

Our goal for anyone reading this book

We want to show you how to 1) take something neat you found on the internet, 2) figure out what went into making it, and 3) see if you can reproduce the result.

We plan to include enough information to get you up and running and at the same time, not overwhelm you. If you've already Googled "Getting started in data science," you know there are a *ton* of resources. Figuring out where to start can feel like trying to get a drink of water from a fire hose.

Along the way, we will also cover some practical principles of programming, command-line tools, project file organization, and a few computer science topics.

Who this book is for

We've tried to keep the materials accessible to a broad audience, but we understand there are few useful data analysis texts written for everyone. Data tends to be very specific to the field they come from, and it's hard to find data that gets everyone excited. To try and help address this issue, we use data from multiple sources (Google trends, Twitter, Wikipedia, and Googlesheets).

We focus on the workflow and tools.

The next chapters outline a 'one-stop-shop' toolset that you can learn quickly and readily re-use (because we know your time is limited).

Technical assumptions

The reader we had in mind while writing this book was someone who,

1. Uses a computer every day at work
2. Understands how to navigate a web browser (Chrome, Safari, Firefox, etc.)
3. Has worked with a word processor (like Microsoft Word, Google Docs, or Apple Papers)

If you're an accountant, scientist, analyst, journalist, grad student, product manager, or decision-maker, this book is for you.

What this book covers

We will be covering R, RStudio, Git, and Github. We use these tools daily now, but we began our careers in other statistical programs (SPSS, Stata, SAS). We abandoned those tools (we know your pain) because of the sheer number of tasks we can accomplish, and that's what makes us recommend this toolkit to you. We've also reached out to our colleagues and included their lessons and insights.

What this book doesn't cover

We also understand there are alternative approaches to accomplishing the same goal, and we will try to mention these examples wherever possible. Jupyter Lab and Jupyter Notebooks, for example, offer reproducible scientific programming environments that can accomplish many of the same objectives we'll tackle in this book. However, we still think there are reasons you should use RStudio + Github instead, and we will outline these in the following chapters.

How this book is structured

We structured this book somewhat like an Army Field Manual, which means each topic was chosen using the following criteria:

- (a) *Relative importance*. Which activities contribute most to successful training?

    *This book contains **brief descriptions** of the tools we recommend, with **diagrams and figures** outlining how they work, and **examples** for using them.*

- (b) *Need*. Which training activities will benefit the most from guidance? Which activities have received little attention in the past or which have previously required improvement?

    We'll expand on a few tools we felt are harder to grasp (Git and version control). We will also go over topics typical college courses overlook or neglect (file naming, project organization).

- (c) *Time*. How much time is available? Which activities can be effectively taught in that time?

    Time is the real enemy of any data project. All computational work comes down to keystrokes and neurons. This book is trying to narrow the gap between 1) seeing a data product (neurons) and 2) translating what you see into commands on a computer that can be used to recreate that product.

- (d) *Personnel*. What are the known or suspected levels of expertise among individuals receiving training?

    We assume everyone reading this text has very little exposure to the tools we'll be covering (R, RStudio, Git, or Github). We do expect you are comfortable using a computer.

The secret to the Army's training abilities is the Field Manual (FM). Army FMs are amazing–they cover almost any topic you can imagine and are well illustrated. For example, watch this video of the drill and ceremony movement called the "counter column".

Now, look at the same thing in a figure.

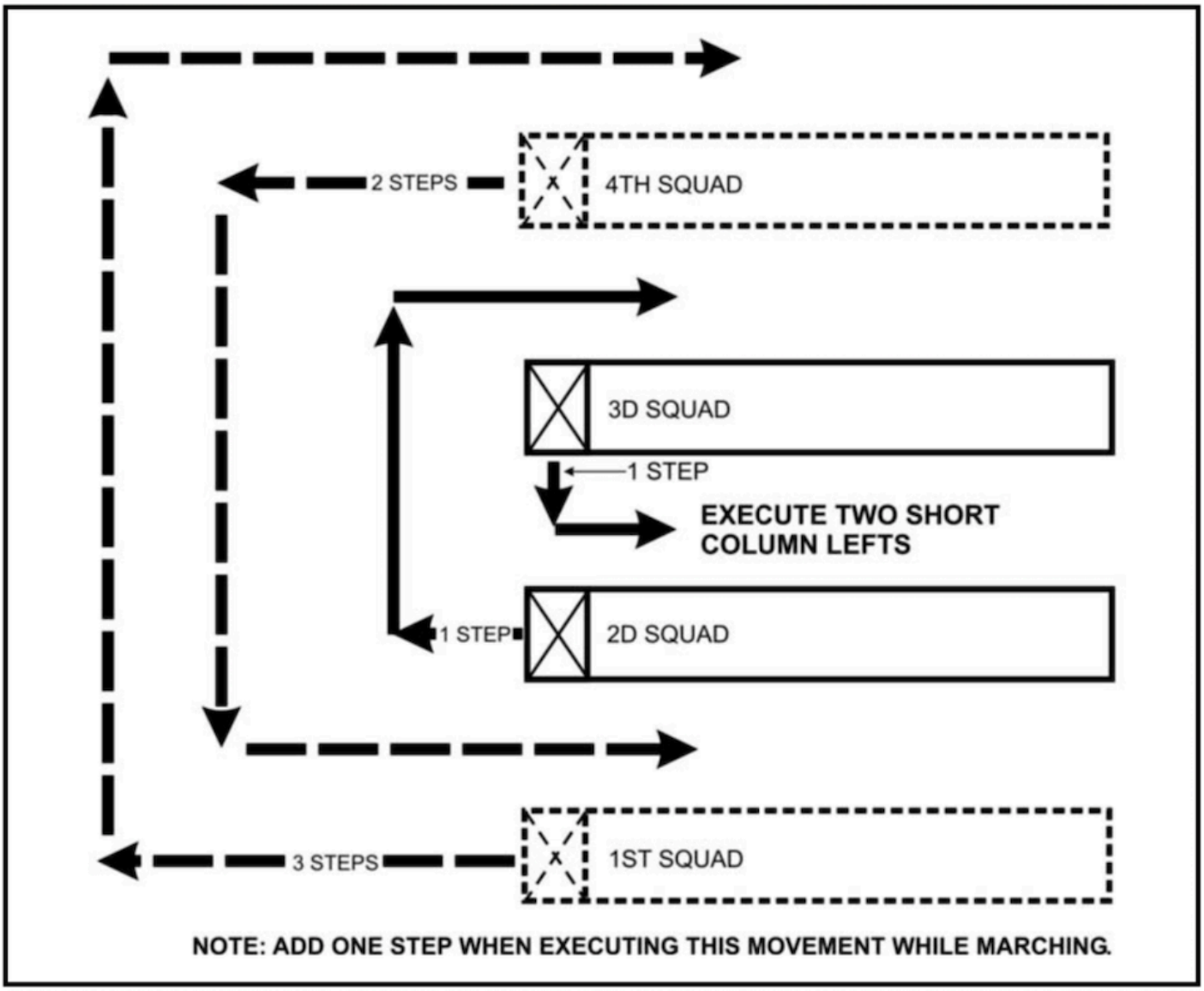


Figure 7-2. Counter-Column March at the Halt.

As you can see, executing a counter column is complicated. But the Army has taught hundreds of thousands of soldiers on this movement for decades. How? They give soldiers a field manual (FM 22–5) to read and dedicated time to practice.

The strength of the FMs is how they present information: they gave the material in everyday language (usually between a 6th–8th-grade reading level) with an emphasis on diagrams, pictures, and simple drawings.

We've found so much data science and statistical information on the internet has a ton of acronyms, jargon, and equations. We've actively avoided using technical verbiage, and focused on using figures and graphics.

> *"…there are lots of other books that explain what things are called. This book explains what they do."*

The quote above comes from Randall Munroe, author of the xkcd comic. In his book "Thing Explainer", Munroe uses pictures and plain language to describe multiple complex systems (rocket ships, the periodic table, laptops, etc.).

The subtitle of "*Thing Explainer*" is *Complicated stuff in simple words*, which is what we're trying to replicate here. Wherever possible, we've dropped unnecessary technical jargon and spelled out any acronyms.

What you'll walk away with

You will have a working project (cool visualizations, lots of code, data) a ton of resources, and a book for reproducing this process again.

Language and style guide

We use the plural 'we' throughout the book based on the excellent advice from Donald Knuth, Tracy Larabee, and Paul Roberts, "*think of a dialog between author and reader.*."

As with most written works, the topics in this book are the result of many conversations, emails, comment threads, and communications that could not have happened in isolation. We want to thank everyone who's contributed to these ideas over the years.

The text uses the following style guide:

`this is code.`

```
# this a code chunk
```

> *some quoted text*

click on hyperlinks

plain text for our thoughts

Learn more

- Practical Data Science for Stats is a resource you should bookmark in your browser. The articles in this collection will come up again in future sections, but we found we use these resources so much it's nice to have them somewhere handy.
- The R for data science community and R for Data Science book are excellent resources to help you started.
- **Collaboration and reproducibility** - there's a direct connection between collaboration and reproducibility. The better your collaborators can reproduce your work, the better they'll understand your results.
- Our text is an *opinionated technical manual*, modeled after Hilary Parker's excellent paper (check out quote),
"*Statisticians have long shied away from teaching process, with the complaint that it might limit the creativity necessary to tackle different analytical problems. However, by not teaching opinionated analysis development, we subject fledgling data to each individually spin their wheels in coming up with process for avoiding common and generalized problems*."
- We recommend RStudio and Github for anyone looking to get started with data science, visualization, reproducible reporting, dashboards development, or website/blog creation. By suggesting these particular tools, we're not saying there aren't other ways or workflows capable of accomplishing the same activities. These are the tools we've found success with, so they're what we recommend.

Part 2: “Have a workflow.”

Working with data **workbench** is a place to keep and organize tools, and a **workflow** is how you combine these tools to get things done. This chapter will cover the workbench we use and the three guiding principles of the workflow we recommend.

1. Use free open source software
2. Write code
3. Document everything in plain text

Principle 1: Use open-source software

All of the tools in this book are available open-source and available free of charge. Just as a point of reference, the cost of a subscription to SPSS at the time of this writing is $99.00 per user per month. Stata is $595 per year or $1,595 for a perpetual license. There are educational discounts available, but this cost is not offset by much when you take into account the rising price of tuition.

A more important reason we recommend open source tools are the communities that you’ll get access to when you start using them. By entering the universe of open source software, you get to take advantage of seeing problems solved in the open. You’ll also find people like you, grappling with the same issues, and it’s hard to overstate the benefit of this shared camaraderie.

The final reason is philosophical: we all benefit from using open source tools and sharing improvements on them together. The ‘four freedoms’ of open source software captures this sentiment below.

Freedom 0: The freedom to run the program as you wish, for any purpose.

Freedom 1: The freedom to study how the program works, and change it, so it does your computing as you wish.

Freedom 2: The freedom to redistribute copies so you can help your neighbor.

Freedom 3: The freedom to distribute copies of your modified versions to others. By doing this, you can give the whole community a chance to benefit from your changes.

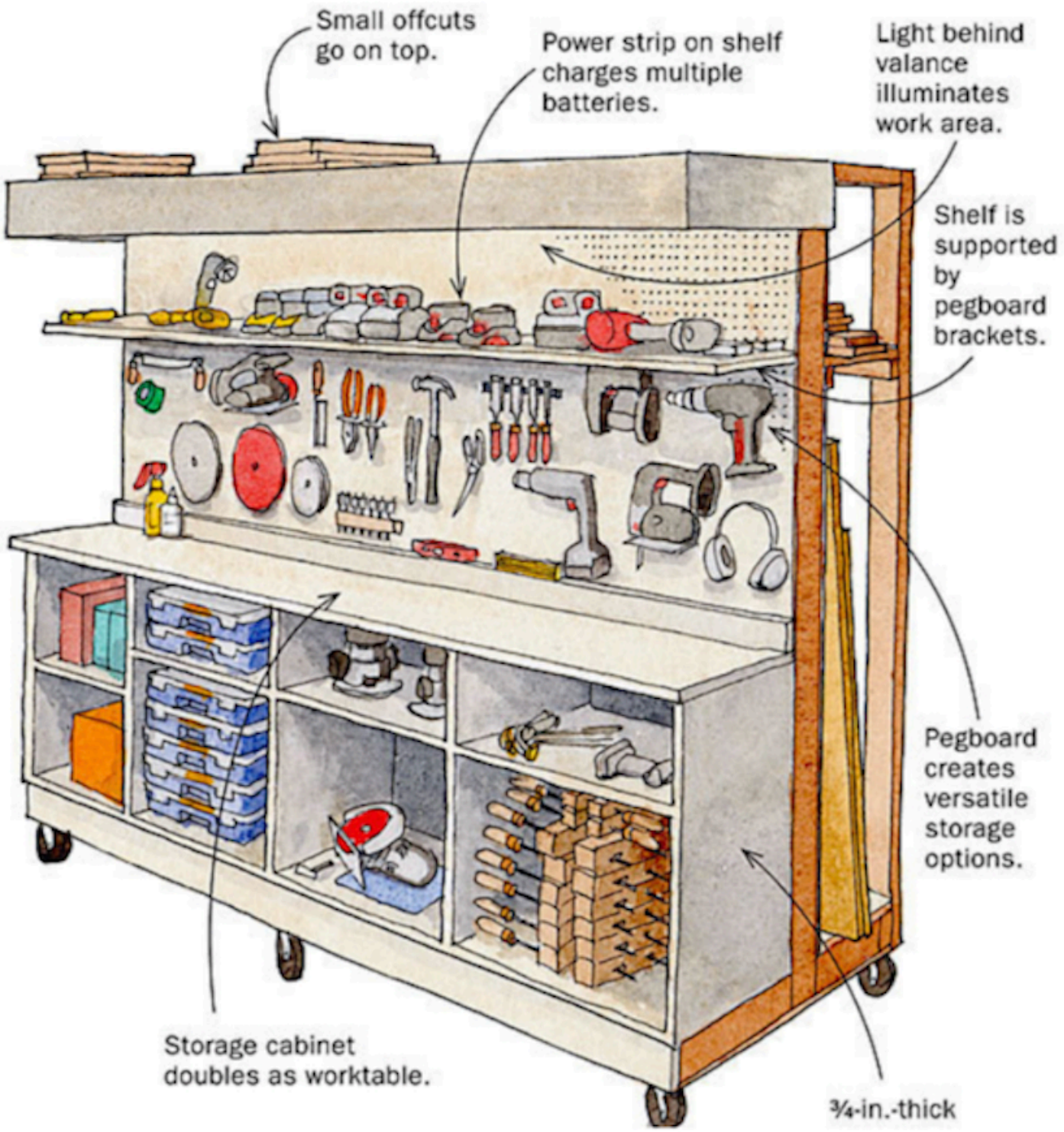
We’ve displayed some examples of open source tools for data management, statistics, and communication in the image below:

Follow the links below to learn more.

- Git
- Github
- Linux
- MySQL
- Netlify
- Python
- R
- RStudio

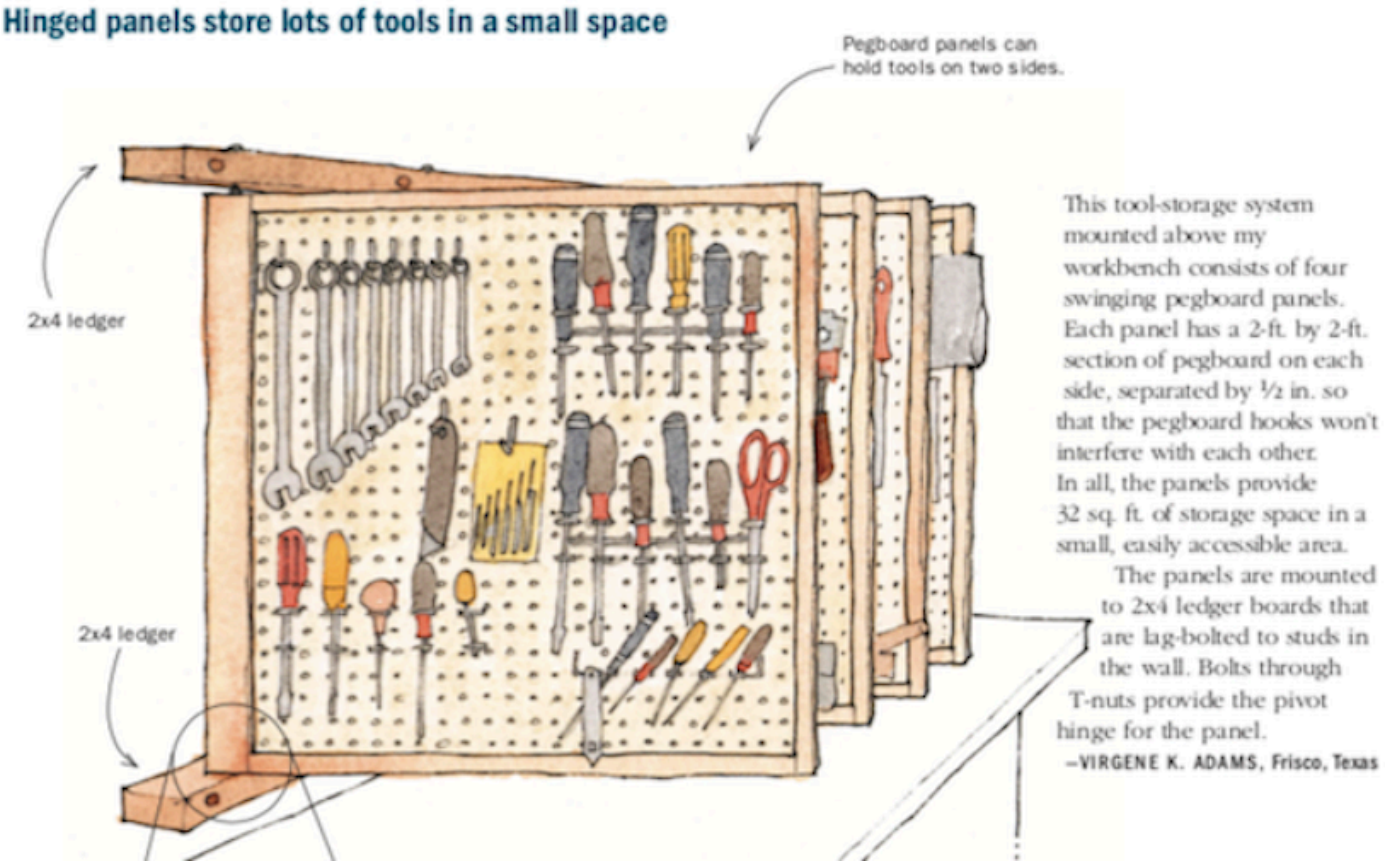
The integrated development environment (aka data science workbench)

An integrated development environment (IDE) is an application typically used by programmers to build and test software. We find it helpful to think of a woodworkers workbench as an analogy. The image below is an example of a workbench with a simple rolling cart design (for people with minimal garage space).



source: https://www.finewoodworking.com/2008/12/11/lighted-storage-cart-for-tools-and-lumber

As we can see, this workbench is efficiently designed to keep essential tools for the job within arms reach, and it uses storage space efficiently. IDE design follows these same principles. However, we also know some models are better than others. For example, consider the design of a different workbench below.



source: https://www.finewoodworking.com/2010/11/12/free-plan-space-saving-tool-rack

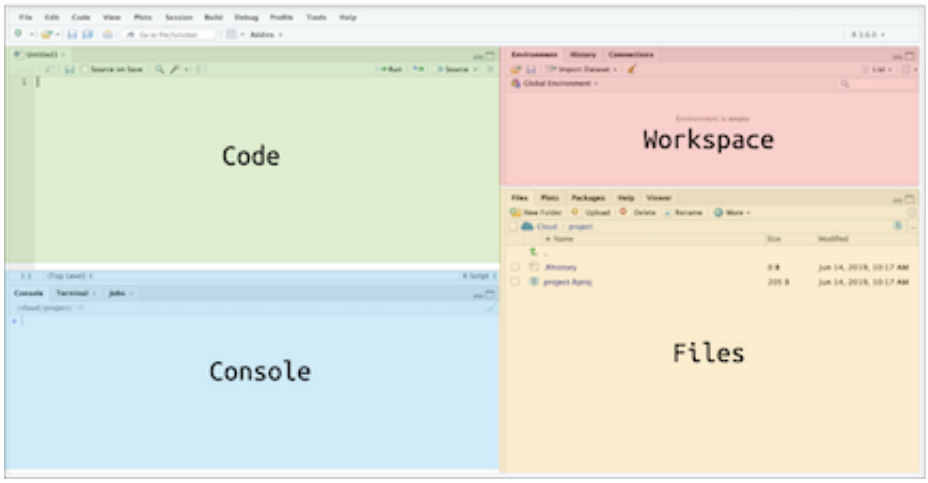
By making the panel positions adjustable, the workbench allows for easier access to more tools. Depending on the job, woodworkers can customize the panel arrangements with "*the simple pin that allows the rack's various faces to swing left/right for access to either side.*."

These examples illustrate how differences in the design of a workbench can have a meaningful impact on levels of productivity. Well-designed workbenches give us access to more tools without making these tools more difficult to find.

Our workbench

We recommend choosing a workbench that minimizes the number of additional applications you'll need to have open to get work done. We've found we can use RStudio for ~90% of our daily work (*they're not paying us to say this*). RStudio gives us access to all the tools we need in the same place.

RStudio Integrated Development Environment



RStudio has four primary panes, each serving a specific function.

- the **Code** or **Source** pane is where we can document both human-readable and computer-readable text
- the **Workspace** holds the data, functions, and other data analysis objects
- the **Console** displays the results from our written code (and allows us to enter commands directly)
- the **Files** gives us access to the happenings outside the RStudio environment (imported raw data, exported results, etc.)

Just like any workbench, we need to fill RStudio with tools we need for the job (and RStudio plays well with many open-source software tools!). For now, we are just going to focus on R and Git.

What is R?

R is a free statistical modeling software application and language. If you are using the desktop application, follow the links below to install R.

Installing R & RStudio

1. First, you'll need to download and install R from CRAN.
2. Second, download and install RStudio, the integrated development environment (IDE) for R

Use RStudio in the browser

An alternative to downloading and installing R and RStudio is using RStudio.Cloud which operates entirely in your browser. You'll need to sign up for RStudio.cloud for free using your Google account or email address, but we recommend using a Github account. You can create a Github account here.

What is Git?

Git is a version control system (VCS). VCSs are used to track changes to projects with code. You can read more about Git in their online text here.

What is Github?

Github is the web-based hosting service for Git. You should set up a free an account with Github here.

What do Git/Github do?

We will cover more on Git/Github in later sections, but for now, know these tools will allow you to keep track of changes to your project over time.

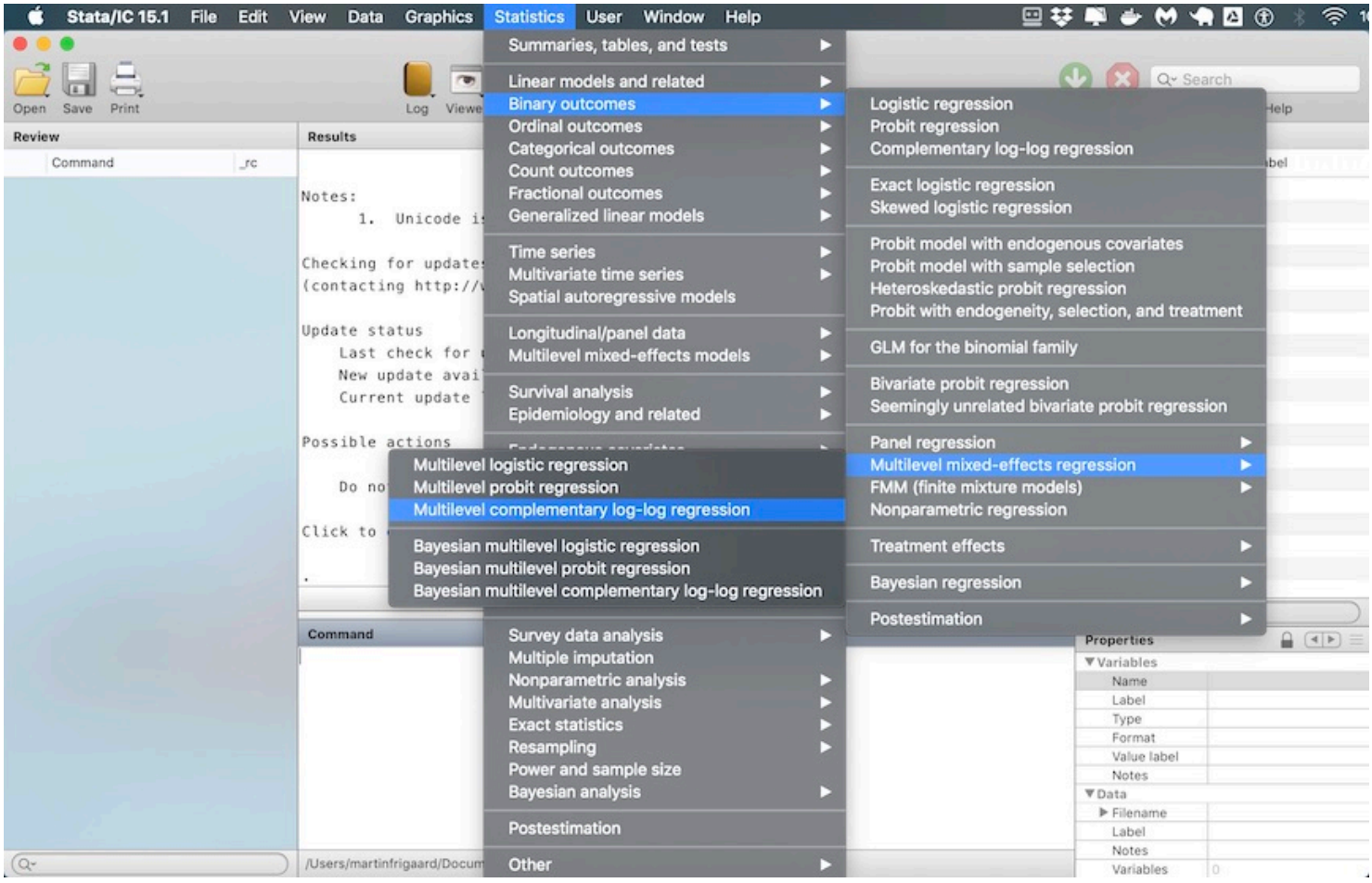
Note: *You should explore different IDE's on your own– you'll see there are many options, both paid and unpaid. We're confident you'll see RStudio is well suited to handle more than most of the things you'll want to accomplish.*

Open-source software bonus: *As mentioned previously, you'll also find a massive network of support on Stackoverflow, RStudio Community, and Google Groups.*

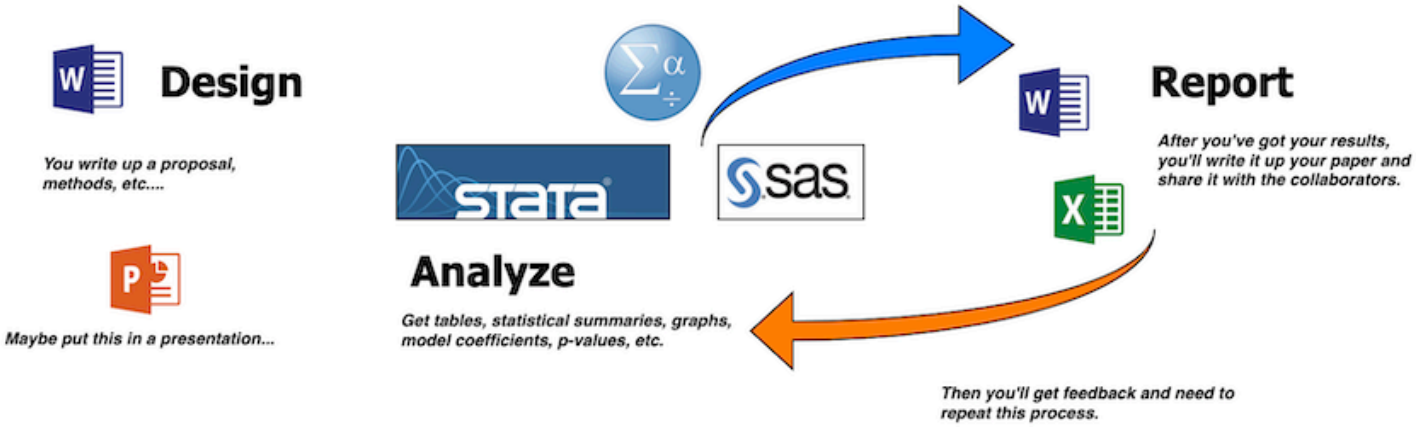
Principle 2: Write code

Usually, people interact with their computers using point-and-click graphical user interfaces or GUIs (pronounced 'gooey'). GUIs are quick and easy to learn because their design environment usually mimics an actual physical space (i.e., desktops, folders, or documents). GUIs are a mostly positive development because designing software with a more user-centered design is one of the main reasons technology adoption has been on the rise for the past 20+ years.

User-centered-designed software includes most of the point-and-click operating systems and applications. These programs give the user the ability to click through a predetermined list of options and procedures using their mouse or track-pad.



However, we think there are times when we should resist the temptation to abstract away some of life's complexity, and data science is one of them. Using applications like these encourage a copy + paste workflow like the one below.



As you can see from the image, you'll be required to go back through the same elaborate workflow whenever you receive feedback or input to your project. Each time will take just as long as the first.

We recommend an alternative to the copy + paste workflow based on the activities of a modern scientist from Jeff Leek we outlined in Chapter 1:

1. Develop code in the open
2. Publish data and code open source
3. Post preprints of your work
4. Submit and review for traditional journals
5. Blog or use social media to critique published work

Two things should stand out from the list above: First, modern science is mostly writing. Second, some of that writing is code (i.e., programming). It's, for this reason, we recommend adopting a workflow based on "*writing code*" wherever possible. We are aware that 'writing code' means being able to type, which might be daunting for people who struggle on a keyboard. We recommend practicing this skill (there are plenty of great apps out there to help!) because typing is an unavoidable necessity for using a computer.

Software as a tool, not a solution

We think of data science software as the tools that help us gain a deeper understanding of the world. We don't think of software as an alternative to thinking or expect a software tool to do our thinking for us. We also prefer tools that we can reuse on future projects.

As we stated in chapter 1, the scientific method is a process. Software is a tool to help move that process along faster. Tools that improve our understanding shorten the distance between questions and answers, but doesn't leave out any crucial details.

For this reason, we don't recommend relying too heavily on point-and-click proprietary software applications (SPSS, Stata, SAS, etc.). These GUI's make it hard to keep track of what you've clicked on, the order of you clicked on them in, and can oversimplify or obfuscate what's going on.

What do we mean by 'a workflow'?

A workflow is a set of steps that can be used repeatedly to answer any question you might encounter in your work.

The quote below is from an interview with Andrew Gelman, a statistician from Cornell, who is an author on the excellent blog Statistical Modeling, Causal Inference, and Social Science.

> ***Question:*** *"I'm wondering how you, as an educator and statistician, would like to see statistical and data literacy change in general for a general population?"*
>
> ***Answer:*** *"… I've come to realize that a lot of people don't even know what they did. People don't have a workflow, they have a bunch of numbers, and they start screwing around with the numbers and putting calculations in different places on their spreadsheet, and then at the end, they pull a number out and write it down and type it into their report." - Andrew Gelman*

As the quote above illustrates, how you got an answer is just as relevant as the answer you got. The tools we provide in this text give you a start-to-finish chain of documentation from question to solutions.

Data science jobs need a particular set of tools, and a workbench to organize these tools. To manage your data science projects, you'll need a workflow that gives you the ability to 1) document your intentions and, 2) write code that can translate your plans into something a computer can execute. These two points bring us to our next topic: plain text. As you'll discover, plain text files are a great way to accomplish these tasks.

Principle 3: Document everything in plain text

In The Pragmatic Programmer, authors Hunt and Thomas advise *'Keep[ing] Knowledge in Plain Text'*. This sentiment has been repeated here, here, and here.

We recommend you keep your files, notes, and any pertinent documentation about your project in plain text files. The reasons for this will become more apparent as we move through the example, but I wanted to outline a few here:

- plain text lasts forever (files written 40 years ago are still readable today)
- plain text can be *converted* to any other kind of document
- plain text is searchable (`ctrl+F` or `cmd+F` allows us to find keywords or phrases)

We'll also cover why you might want switch over to a plain text editor if you're currently using Google Docs, Apple Papers, or Microsoft Word.

Wait–why would I change what I'm doing if it works?

We get it–change is difficult, and if you have a working ecosystem of software that keeps you productive, don't abandon it. However, you should be aware of these technologies and recognize that people using them will be adapting *their* workflows to collaborate with you.

We covered the problems with a copy+paste workflow previously, but there are additional reasons to avoid this toolset:

1. It's not reproducible
2. It's not logical or necessarily honest to separate computation from the analysis or presentation
3. It's error-prone

If we've sold you on using this flexible and adaptable tool, but you're still wondering what makes a file 'plain text,' we'll cover that next. But first, we need to talk about what *isn't* a plain text file.

What *isn't* plain text

Non-plain text files are usually called binary (i.e., files with binary-level compatibility) need special software to run on your computer. The language below is a handy way to think about these files:

> *"Binary files are computer-readable but not human-readable"*

What *is* plain text

So if binary files aren't plain text, what is a plain text file? The language from the Wikipedia description is helpful here:

> *When opened in a text editor, plain text files display computer and human-readable content.*

The last bit is the most crucial distinction–**human-readable vs. computer-readable**. In this manual, we'll point out which files are binary and which are plain text. Generally speaking, plain text files can be opened using a text editor or viewed with a command-line tool. Examples of text editors include Atom, Sublime Text, and Notepad++.

Markdown & Rmarkdown

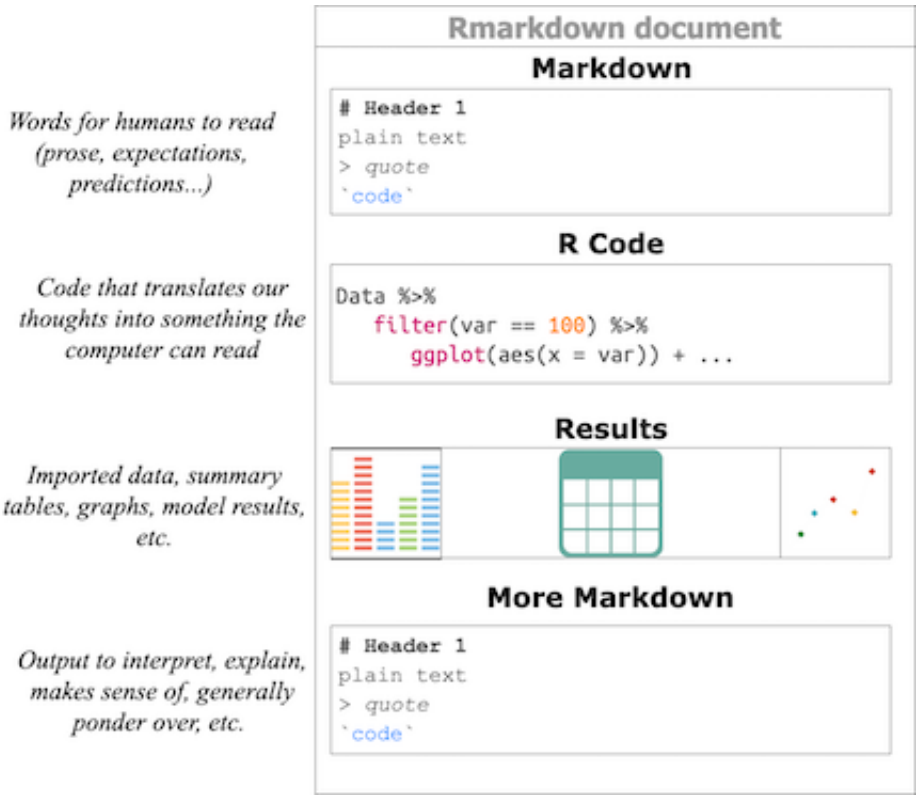
Markdown files (`.md`) are common type of plain text files. Markdown is a 'lightweight markup language,' which means it's easy for humans to read, and computers can convert it to HyperText Markup Language (HTML). Markdown allows for some formatting options to aid with communication (see below)

```
<!-- comments -->

normal text

*italic*

**bold**

> quote

`code`

# h1
## h2
### h3
#### h4
##### h5
###### h6
```

To learn more, see Markdown Syntax Documentation on John Gruber's site).

We recommend learning markdown before any other programming language because it's the lingua franca for asking questions. Stackoverflow, RStudio community, Reddit, Github, and many other sites use markdown to post questions and answers. We recommend experimenting with StackEdit, a browser-based markdown editor that gives you the ability to write in markdown and see the syntax rendered as HTML.

RStudio has an extension of markdown, RMarkdown. Using RMarkdown in RStudio allows for a genuinely reproducible workflow: you're able to write your thoughts, code, display results, and then share everything in multiple outputs.



I recommend reading up on R and RMarkdown because of how many different outputs this combination can be used to produce (.pdf, .docx, and .html). Consult the R Markdown: The Definitive Guide for more information. The image below is an output from an `.Rmd` document in RStudio.

Rmarkdown Document

R Markdown

This is an R Markdown document. Markdown is a simple formatting syntax for authoring HTML, PDF, and MS Word documents. For more details on using R Markdown see http://rmarkdown.rstudio.com.

Load the `tidyverse`.

```
## ● __  _     __    .    ○         ●  .
##  / /_(_)__/ /_ ___  _____ _______ ___
## / __/ / _  / // / |/ / -_) __(_-</ -_)
## \__/_/\_,_/\_, /|___/\__/_/ /___/\__/
##      ●  . /___/      ○      .      ●
```

When you click the **Knit** button a document will be generated that includes both content as well as the output of any embedded R code chunks within the document. You can embed an R code chunk like this:

```
ggplot2::diamonds %>% glimpse(78)
```

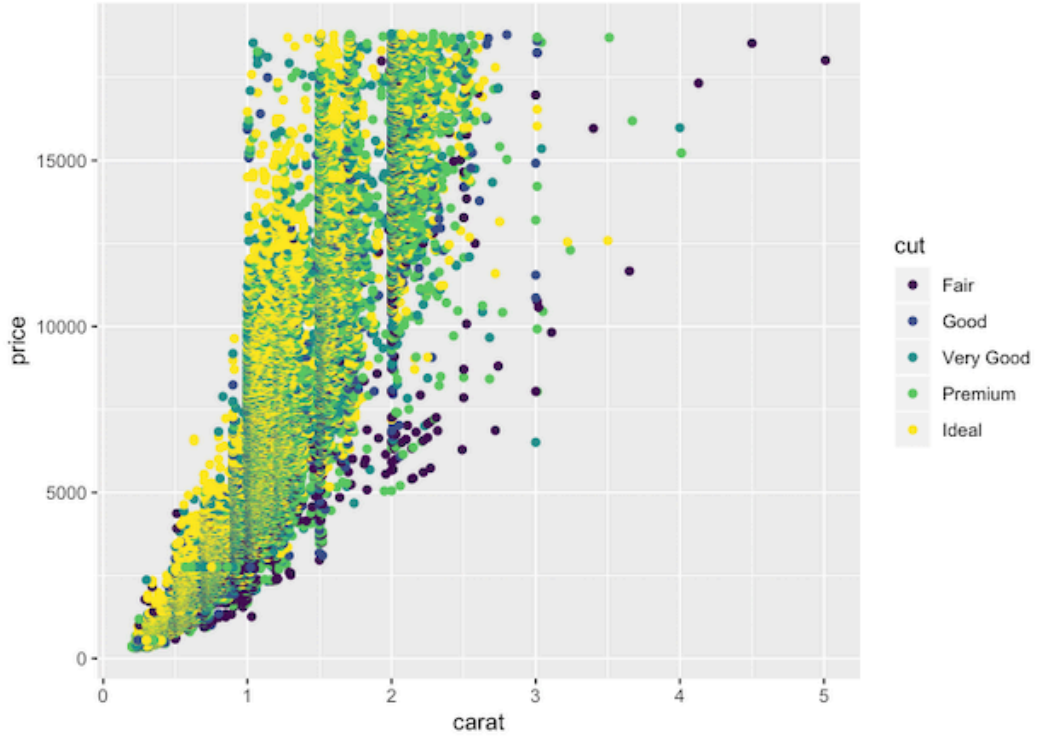
```
## Observations: 53,940
## Variables: 10
## $ carat   <dbl> 0.23, 0.21, 0.23, 0.29, 0.31, 0.24, 0.24, 0.26, 0.22, 0.23,…
## $ cut     <ord> Ideal, Premium, Good, Premium, Good, Very Good, Very Good, …
## $ color   <ord> E, E, E, I, J, J, I, H, E, H, J, J, F, J, E, E, I, J, J, J
```

```
## $ color   <ord> E, E, E, I, J, J, I, H, E, H, J, J, F, J, E, E, I, J, J, J,…
## $ clarity <ord> SI2, SI1, VS1, VS2, SI2, VVS2, VVS1, SI1, VS2, VS1, SI1, VS…
## $ depth   <dbl> 61.5, 59.8, 56.9, 62.4, 63.3, 62.8, 62.3, 61.9, 65.1, 59.4,…
## $ table   <dbl> 55, 61, 65, 58, 58, 57, 57, 55, 61, 61, 55, 56, 61, 54, 62,…
## $ price   <int> 326, 326, 327, 334, 335, 336, 336, 337, 337, 338, 339, 340,…
## $ x       <dbl> 3.95, 3.89, 4.05, 4.20, 4.34, 3.94, 3.95, 4.07, 3.87, 4.00,…
## $ y       <dbl> 3.98, 3.84, 4.07, 4.23, 4.35, 3.96, 3.98, 4.11, 3.78, 4.05,…
## $ z       <dbl> 2.43, 2.31, 2.31, 2.63, 2.75, 2.48, 2.47, 2.53, 2.49, 2.39,…
```

Including Plots

You can also embed plots, for example:

```
diamonds %>%
    ggplot(aes(x = carat,
               y = price,
               color = cut)) + geom_point()
```



Python vs. RStudio

Python is a neat language and a great tool to combine with R.

It's also helpful to know a little Python even if you're primarily working in R, because the benefits of being multilingual extend beyond just spoken languages, too.

We recommend R/RStudio because we wrote this book for people who have a data file and specific questions (or general curiosity). Thus, the entry point for our audience into data science is *with data they need to analyze*, and this is what R was made to do.

Additional reasons for using R/RStudio

Below are a few more reasons you should consider using R/RStudio in case you're still on the fence.

You can focus on your work

> *'The only factor becoming scarce in a world of abundance is human attention" – Kevin Kelly in Wired*

We recommend R/RStudio because of the time saved by switching between software applications. For example, when I was in graduate school, I'd have *a minimum of five applications open* to do data analysis. I would be using Word to write, Stata for statistics, Excel to create tables, the browser for internet research, and Adobe Acrobat for reading PDFs. That means I needed to learn five different GUIs, each with their design characteristics.

Each software application cost me valuable neurons whenever I had to switch between them (read more about attentional residue in the footnotes). With R/RStudio, I cut this number to two (RStudio and the browser).

RStudio gives you a better mental model for data analysis

The third reason is the design of the IDE itself. RStudio is a complementary cognitive artifact, something described in this article from David Krakauer,

> *"[complementary cognitive artifacts are] certainly amplifiers, but in many cases, they're much, much more. They're also teachers and coaches…Expert users of the abacus are not users of the physical abacus—they use a mental model in their brain. And expert users of slide rules can cast the ruler aside having internalized its mechanics. Cartographers memorize maps, and Edwin Hutchins has shown us how expert navigators form near symbiotic relationships with their analog instruments."*

These are in contrast to competitive cognitive artifacts, which is what a GUI does.

> *"In the case of competitive artifacts, when we are deprived of their use, we are no better than when we started. They're not coaches and teachers—they are serfs."*

RStudio does not remove the complexity of doing data analysis, writing blog posts, building applications, debugging code, etc. Instead, it creates an environment where you can do each of these tasks without having them abstracted away from you into drop-down menus, dialogue boxes, and point-and-click options.

There have been considerable efforts from the scientists at RStudio to create an environment and ecosystem of tools (called `packages`) to make data analysis less painful (and even fun). We're confident you'll find it helps you think about the inputs and outputs of your work in productive and creative ways.

FOOTNOTES

- The Ford Foundation report, "Roads and Bridges", outlines some other reason you should be using open-source software.
- Read these articles on attentional residue and multitasking (then try to stop doing it):
  1) Why is it so hard to do my work? The challenge of attention residue when switching between work tasks
  2) Information, Attention, and Decision Making
  3) Causes, effects, and practicalities of everyday multitasking
- See Baumer et al. for an in-depth summary of why you should abandon a copy + paste workflow

Part 3: Setting up your data science project

"*If you can't describe what you are doing as a process, you don't know what you're doing*." - W. Edwards Deming

In the last chapter, we recommended a workbench (RStudio) and a set of tools (R, Git, Github). Now we'll use an example project to show how combining these tools create a durable and adaptive workflow. We want to get started with an example early because having a job to do allows us to cover project organization.

Our statistical coursework never covered the details of setting up a project (and we often marvel at how much time we wasted trying to find our files). The way we set our projects up–how we organize files and folders–will directly contribute to our ability to be productive. You've probably discovered it's hard to get things done in a messy office? Well, it will be hard to do data science if we don't organize our files in a logical way that helps us get things done.

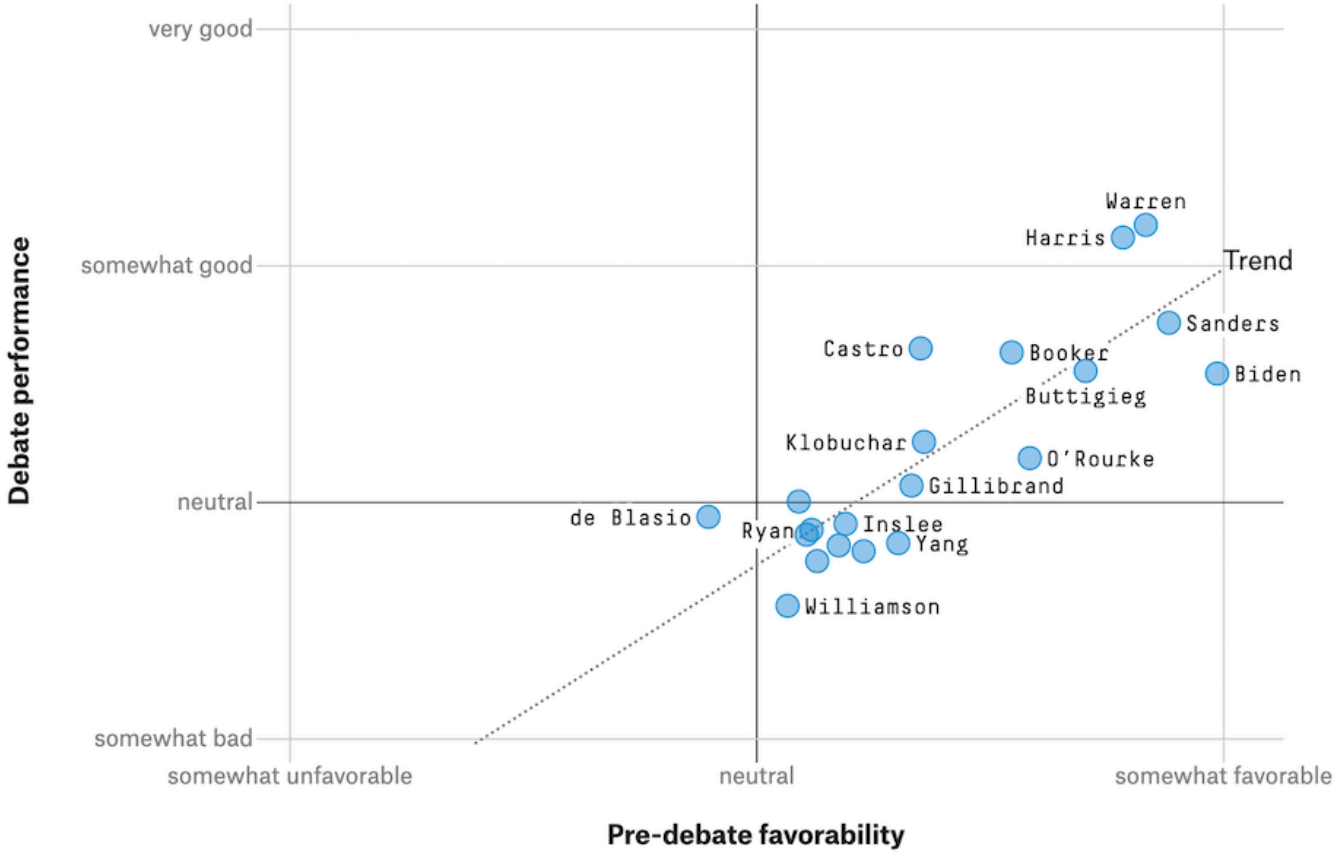
Example: FiveThirtyEight's 2019 Presidential debate project

I read something on the internet, got curious, and decided I wanted to dig a little deeper.

The scenario we've described above might seem vague, but we want to show the power of these tools. We've also found some of the most exciting data projects are born from basic curiosity.

In this case, let's imagine we read something about the first round of the 2019 Democratic Presidential Debates, but we missed all the news coverage.

We stumbled across an article on the data journalism website `fivethirtyeight`, and it displayed an image showing the relationship between how voters felt about the candidates before the debates, and how the candidates did in the debate.



source: https://projects.fivethirtyeight.com/democratic-debate-poll/

Wanting to be informed citizens–and knowing how to collect and analyze data–we decide to investigate how each candidate performed using various sources of data.

Data journalism

Journalists are a bit like statisticians in the sense that both get to "play in everyone's backyard". Data journalists explicitly combine analysis and communication skills. Marrying these two skills makes data journalism an extraordinary place to look for tools and methods to adapt to different projects.

The best data journalism projects combine the rigor of numbers and math with an ability to **write something people want to read**. Data journalists like Aleszu Bajak, Andrew Flowers, and Andrew Ba Tran have been hugely influential in introducing R as a tool in the newsroom.

Another reason journalism is an excellent resource for sharing your work is that journalists are trained to view the world differently than typical scientists or analysts. As the NBC investigative reporter Andy Lehren describes in the text Digital Investigative Journalism,

> *"Journalists can approach data differently than those more trained in computer sciences. Take, for instance, matching databases. Traditional IT managers compare data sets that were designed to talk with each other. Journalists may wonder if the payroll list of school teachers includes registered sex offenders."*

Journalists can communicate *why something matters*, which is a great skill to hone. Explaining a data project to someone with zero domain expertise (or data science knowledge) is a great way to practice your communication skills. It's also a great way to make sure you're thinking about an audience for the project.

A collection of modern data sources

To demonstrate how powerful R/RStudio can be, we are going to combine data from four different sources. Each source represents a different way to access data in using R + RStudio.

1) The `gtrendsR` package for R gives us access to Google search terms and trends. We're going to import data from Google searches before and after the night of the debates.

2) `rtweet` package in R can be used to download Twitter data but takes a few steps to get set up. Fortunately, we've written a tutorial here and the package has excellent documentation (see here and here).

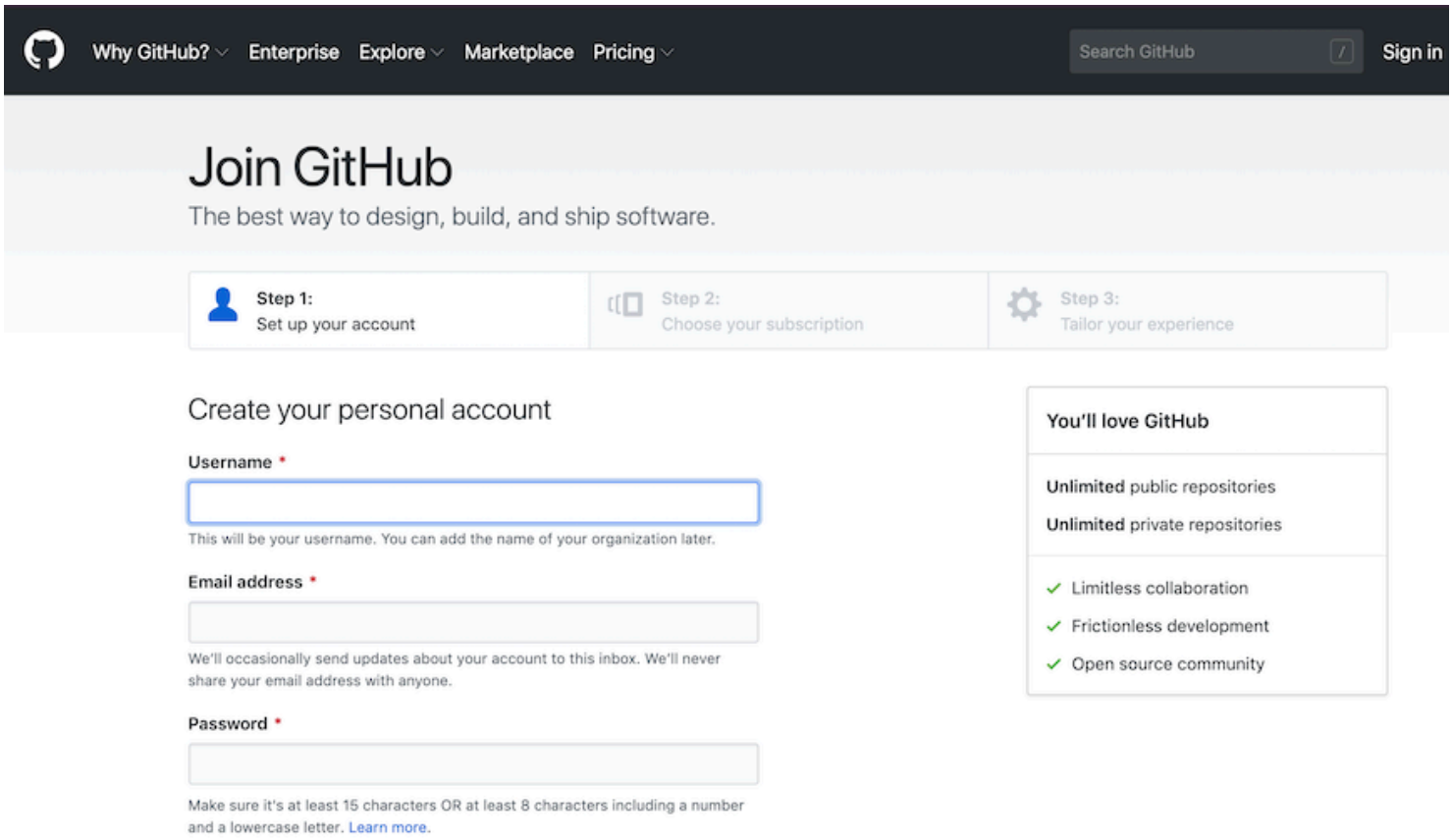
3) There is a Wikipedia page dedicated to the debates. We'll be scraping the tables with airtime for a candidate using the `xml2` and `rvest` packages.

4) Finally, we also have some data from voters on how they felt about each democratic candidate going into the debates. These data are in a Google Sheet, and we've used the `datapasta` package and copy + paste these data into R. Another option is the `googlesheets4` package in R (*you will need to copy this sheet into your Google drive to get this data set*).

Step 1: Github

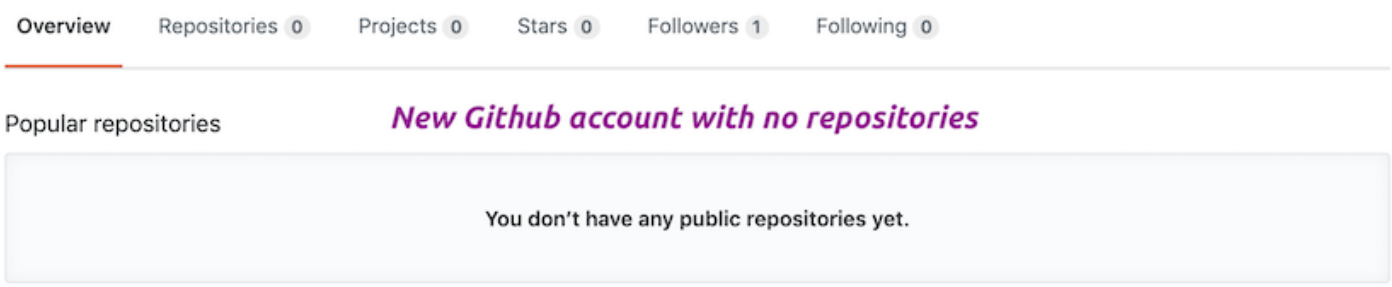
In this example, we will be using an RStudio.Cloud environment to perform the analyses. All of these steps can be accomplished using the RStudio IDE on your local desktop, too.

Head over to Github and sign up for a free account.



Join Github

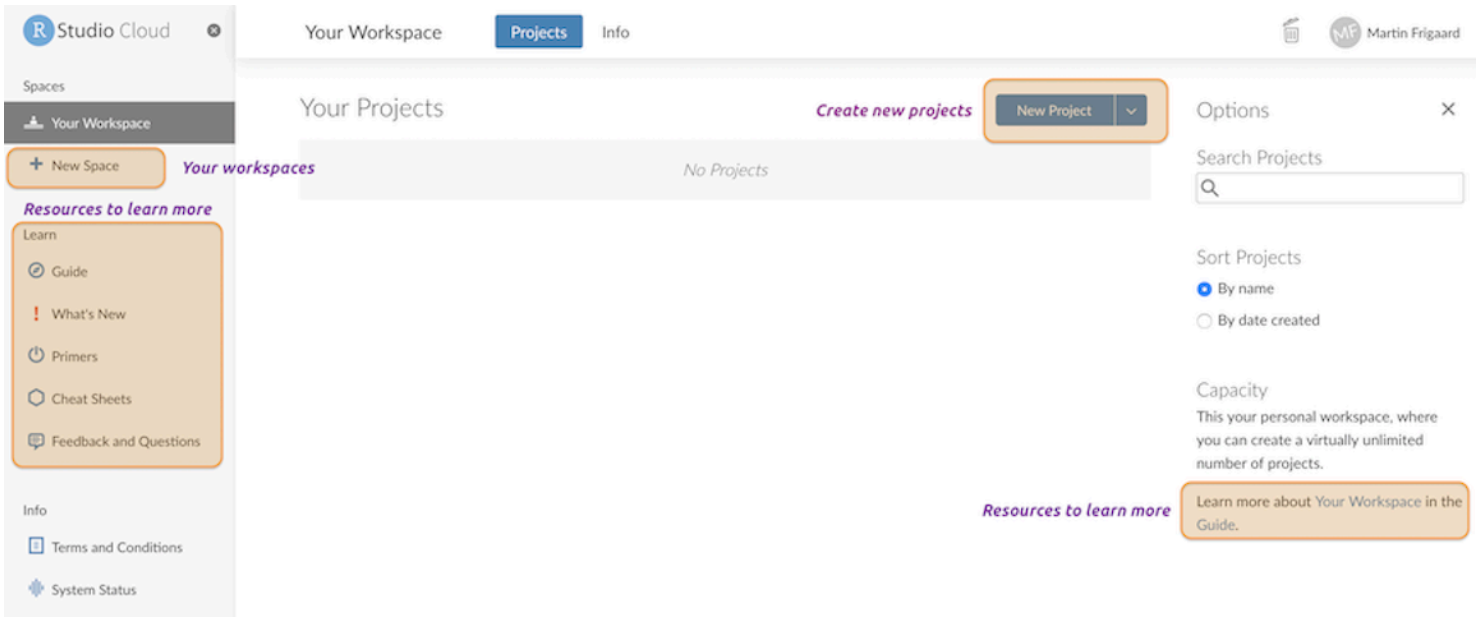
After you've completed the necessary forms (*remember you only need a free account!*), you should see a page with a message telling you "**You don't have any public repositories yet**".



Github profile overview

Step 2: RStudio.Cloud

We will eventually create our repositories, but for now, let's head over and use our Github account to sign in to RStudio.Cloud. After we're all signed in, we will see the screen below:

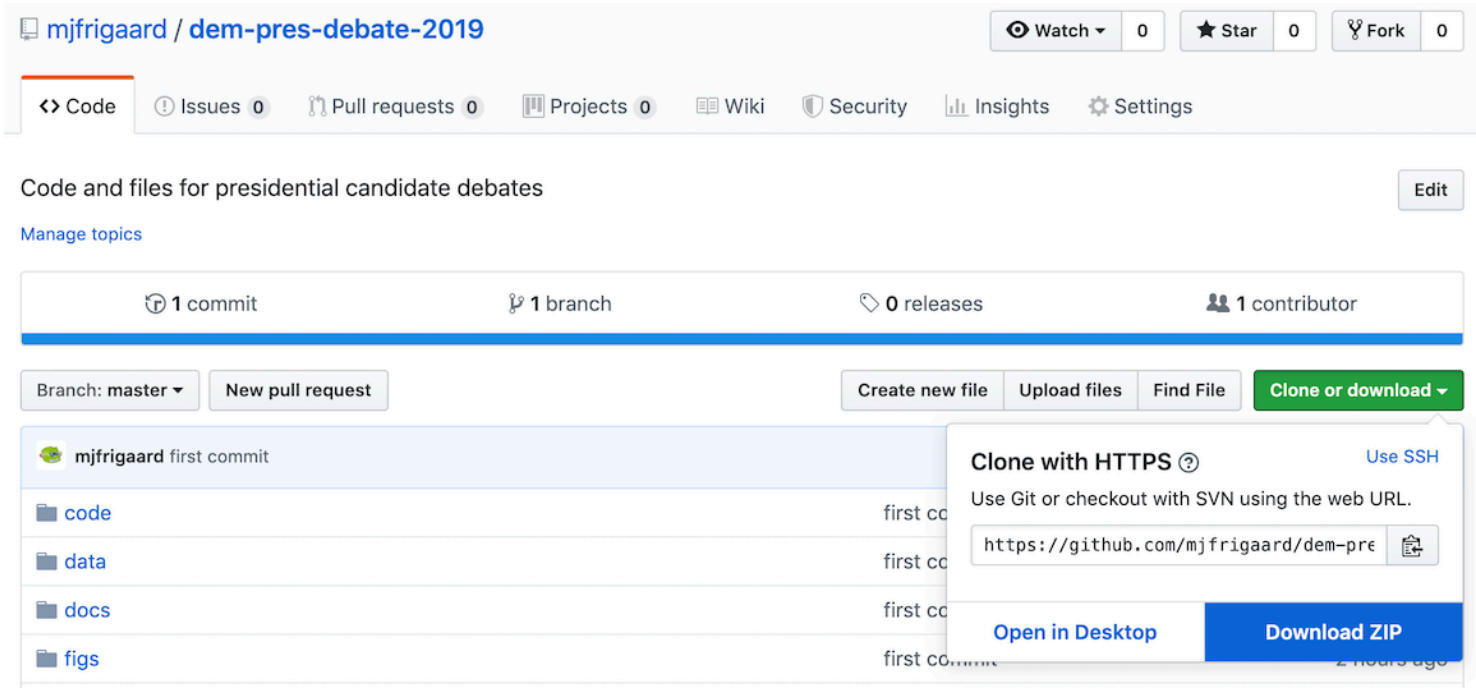


RStudio.Cloud environment

We've outlined the various resources, projects, and workspaces in the image above (we will go over each in more detail in a later section). For now, we are going to download a repository from Github and open it in RStudio.Cloud.

Step 3: Download a repository from Github

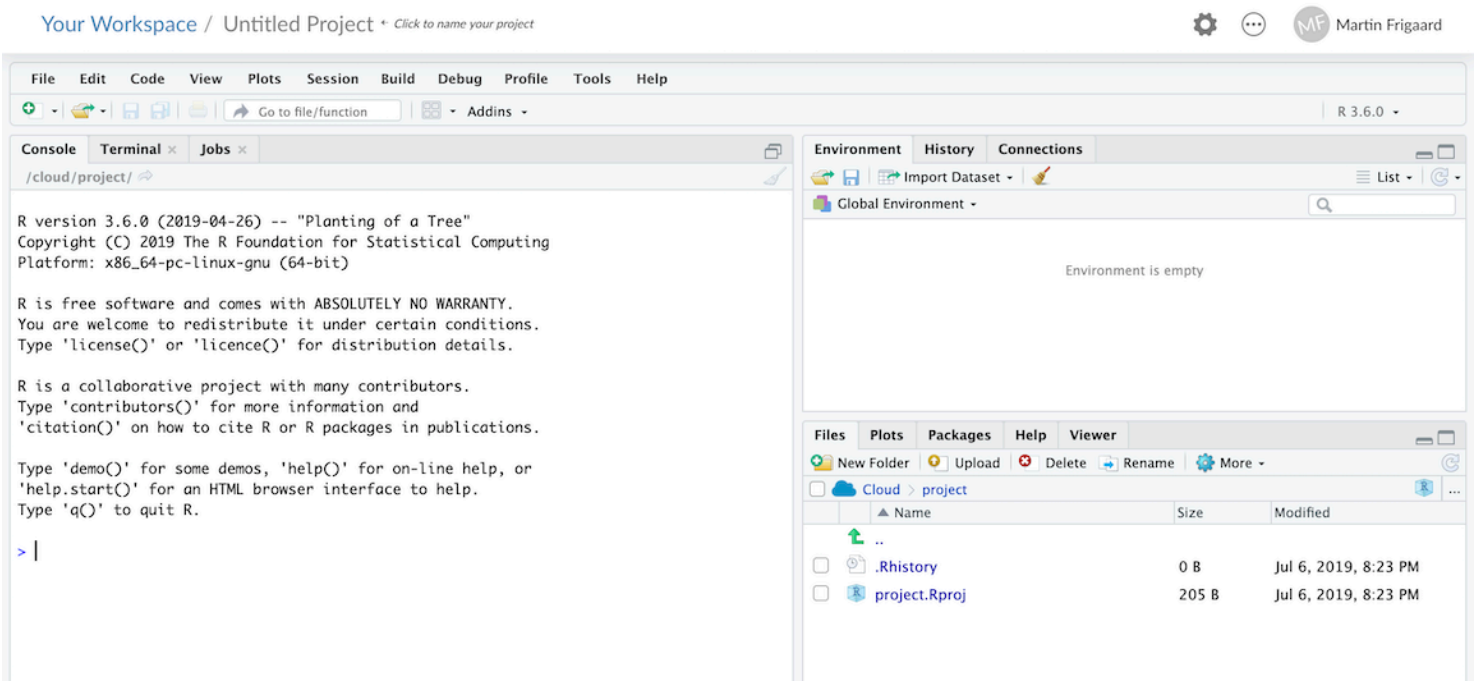
Most of the repos on Github are free for us to download and use. We can do this by clicking on the green **Clone or download** button and click **Download ZIP**.



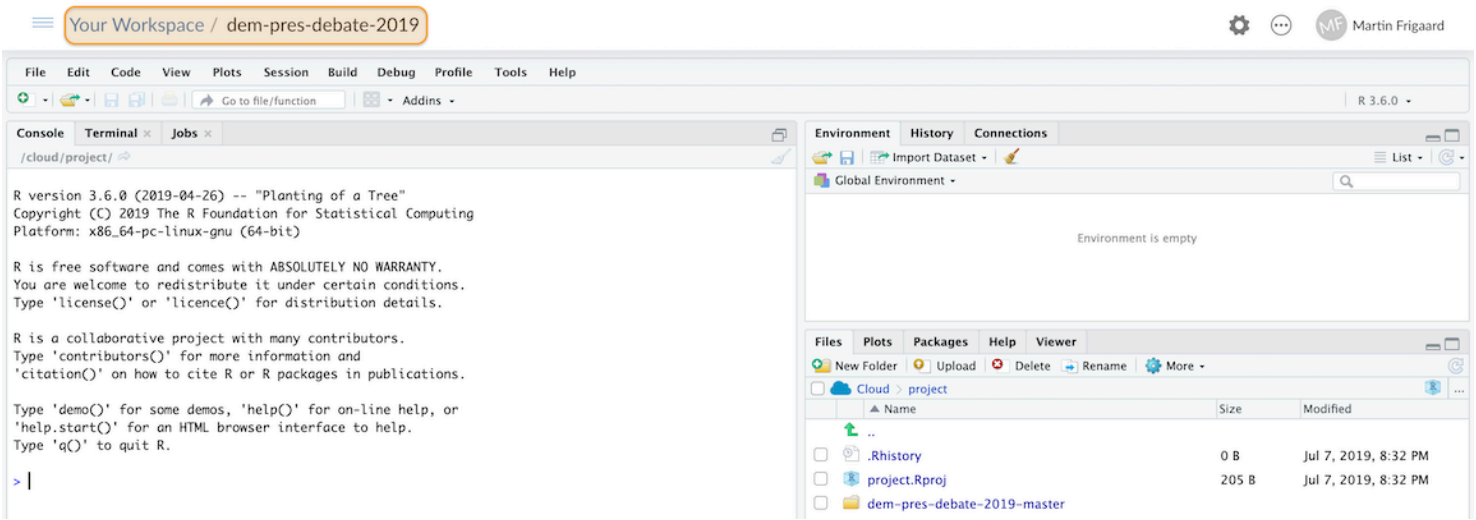
Pick a location on your computer to put your project and download the zipped Github folder.

Step 4: Upload files into RStudio.Cloud

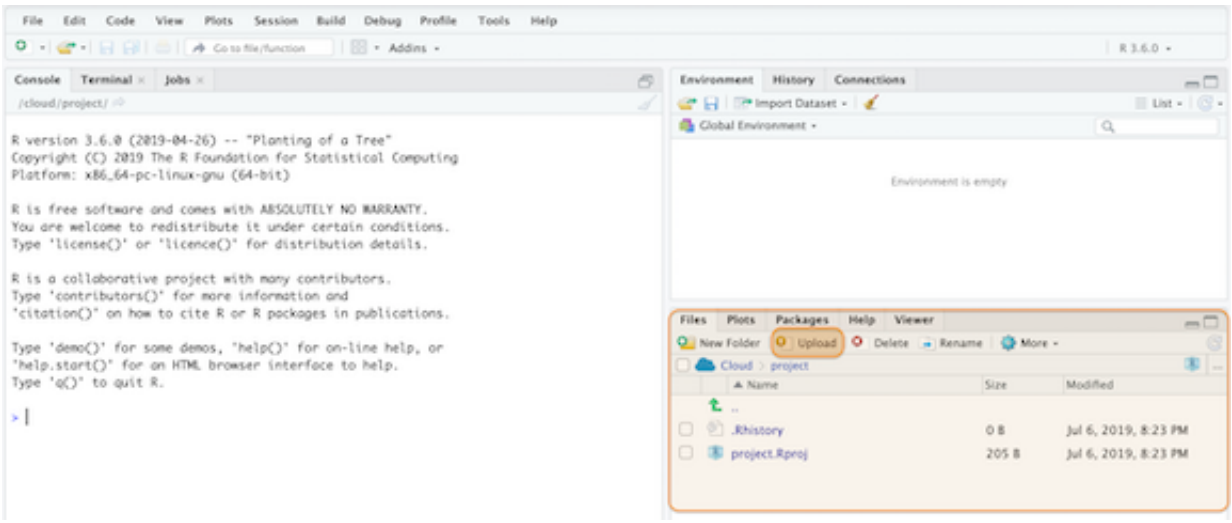
Back in the RStudio.Cloud browser, we're going to click on the **New Project** button. It should display the RStudio IDE in the browser like the image below:



We are going to change the name of this **Untitled** project to **dem-pres-debate–2019**. The results should look like the image below:



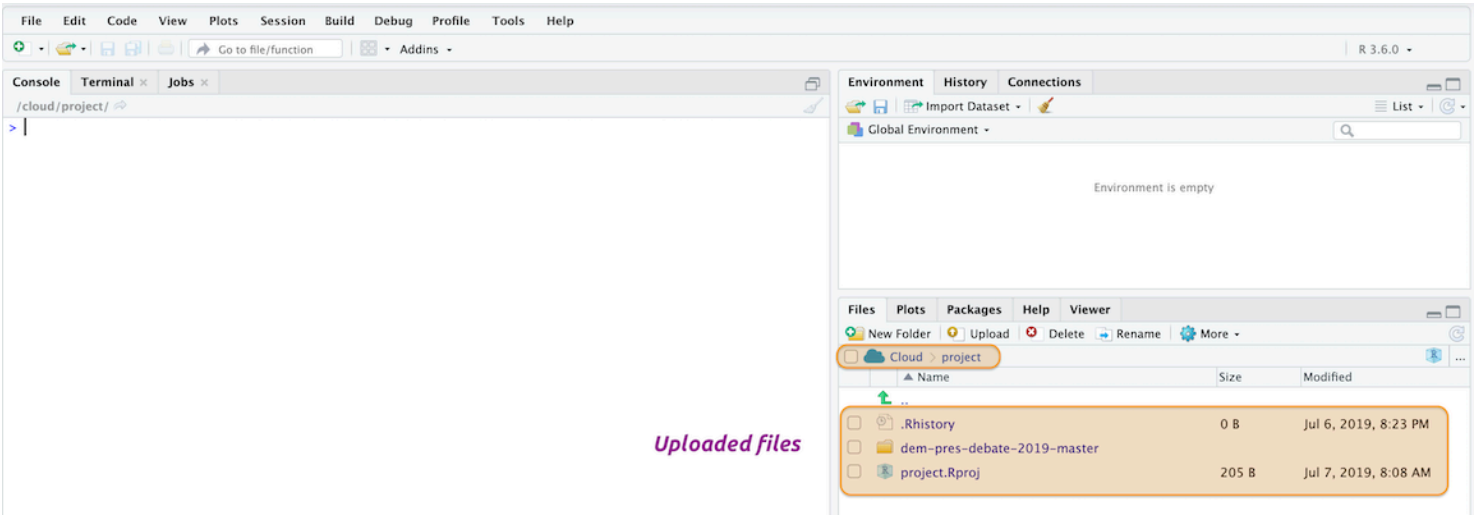
Look at the **Files** pane in the lower right corner and click on the **Upload** button, then click on **Choose files** and locate the recently downloaded zipped Github folder. Upload this file into the RStudio.Cloud project workspace.



upload button

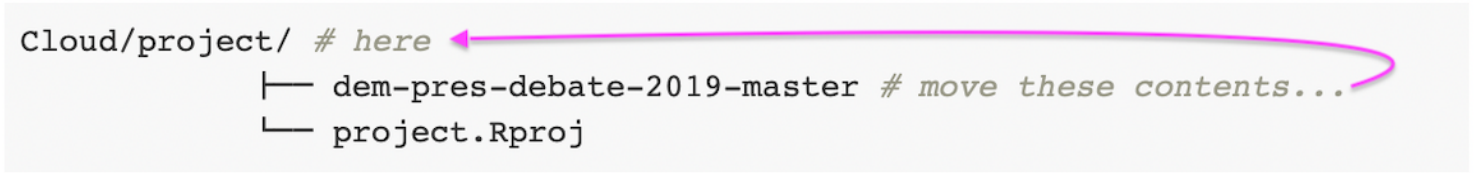
Accessing files in RStudio.Cloud

Uploading these files might take some time, but when everything is in RStudio.Cloud, we'll see the `dem-pres-debate-2019-master` folder in the **Files** pane.



the newly uploaded files

The unzipped the file we uploaded and created a folder called `dem-pres-debate-2019-master`. Unfortunately, it put this folder *inside* the `cloud/project` folder. We wanted to upload the *contents* of the `dem-pres-debate-2019-master` file into the `cloud/project` folder (and not the folder itself).



We are going to use this opportunity to introduce a few command-line tools. To do this, we'll be working from the **Terminal** pane in RStudio.Cloud. The next session will be a quick 'crash course' on operating systems, some **Terminal** commands, and how they work together.

The Command line: Unix and Windows

In 2007, Apple released its Leopard operating system that was the first to adhere to the Single Unix Specification. I only introduce this bit of history to help keep the terminology straight. macOS and Linux are both Unix systems, so they have a similar underlying architecture (and philosophy). Most Linux commands also work on macOS.

Windows has a command-line tool called Powershell, but this is not the same as the Unix shells discussed above. The differences between these tools reflect the differences in design between the two operating systems. However, if you're a Windows 10 user, you can install a bash shell command-line tool.

Command-line interfaces

The command line interface (CLI) was the predecessor to a GUI, and there is a reason these tools haven't gone away. CLI is a text-based screen where users interact with their computer's programs, files, and operating system using a combination of commands and parameters. This basic design might make the CLI sound inferior to a trackpad or touchscreen, but after a few examples of what's possible from on the command-line and you'll see the power of using these tools.

"What am I getting out of this?"

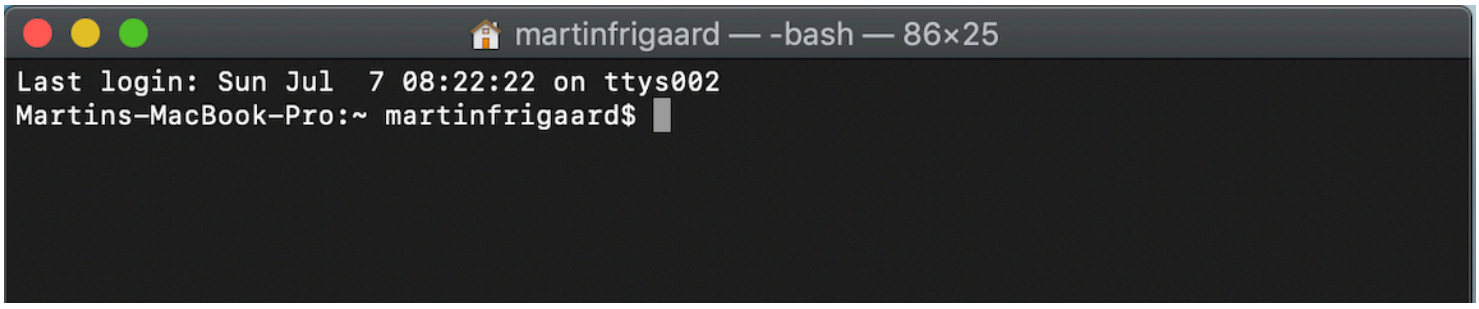
That's a fair question–being able to use the command line gives us more 'under-the-hood' access to any computer. We can use the command line to navigate a computer's directories (folders), install new programs or libraries, and track changes to files. It might seem clunky and ancient, but people keep this technology around because of it's 1) specificity and 2) modularity (also the two features that make Unix programs so powerful). What do we mean by this?

- Specificity means each Unix command or tool does one thing very well (or DOTADIW)
- Modularity is the ability to mix and match these tools together with 'pipes,' a kind of grammatical glue that allows users to expand these tools in seemingly endless combinations

Having these skills have also made us more comfortable when we've had to interact with remote machines or different operating systems (Linux, per se). We will work through an example to demonstrate some of these features.

The Terminal (mac0S)

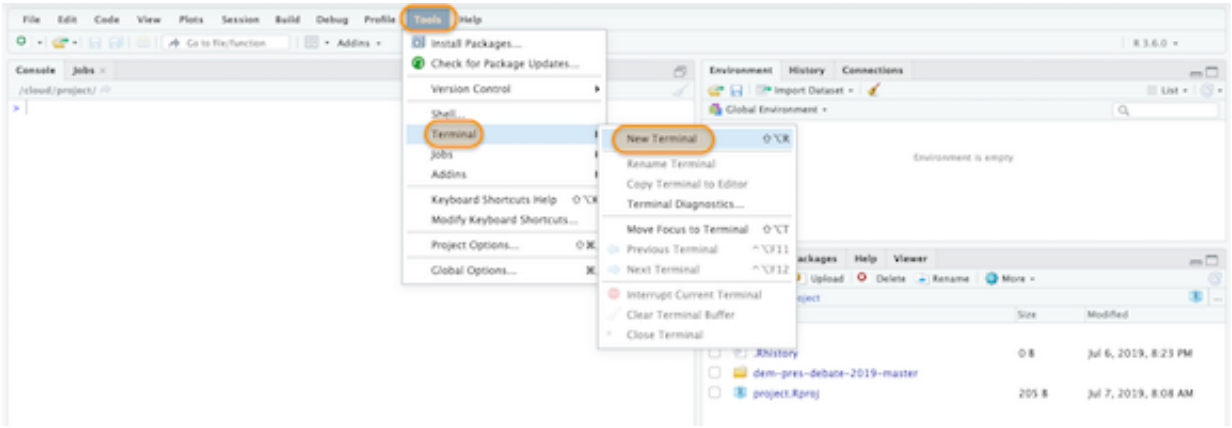
Below is an image of what the terminal application looks like on macOS. On Macs, the Terminal application runs a bash shell, which is why you can see the `bash -- 86x25` on the top of the window. Bash is a commonly-used shell, but there are other options too (see Zsh, tcsh, and sh). *Fun fact: `bash` is a pun for the `sh` shell: bourne-again `shell`.*



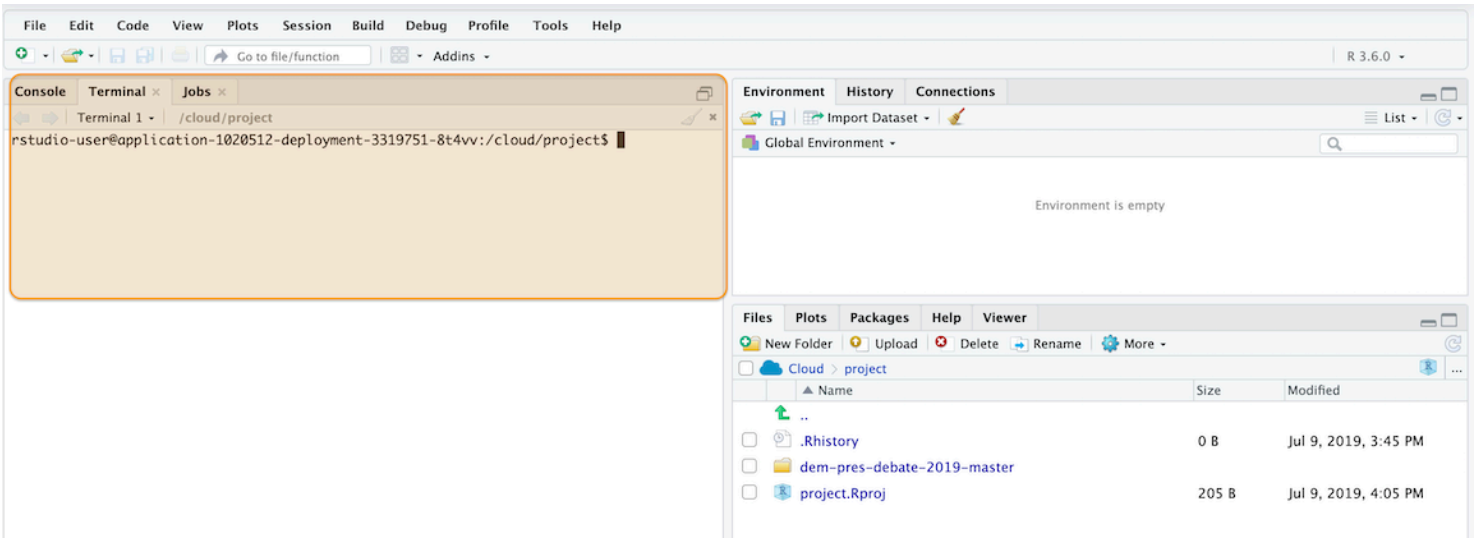
The Terminal is an emulator application for Mac users. Terminal is available as an application under the **Applications** > **Utilities** > **Terminal**.

The Terminal (RStudio)

The Terminal pane is also available in RStudio under **Tools** > **Terminal** > **New Terminal**.



The **Terminal pane** will open in the same window as the **Console pane**.



Now we will get some practice organizing our data science project using the command line.

Good enough command-line tools

FAIR WARNING–command-line interfaces can be frustrating. Computers don't behave in ways that are easy to understand (that's why GUIs exist). Switching from a GUI to a CLI seems like a step backward at first, but the initial headaches pay off because of the gains we'll have in control, flexibility, automation, and reproducibility.

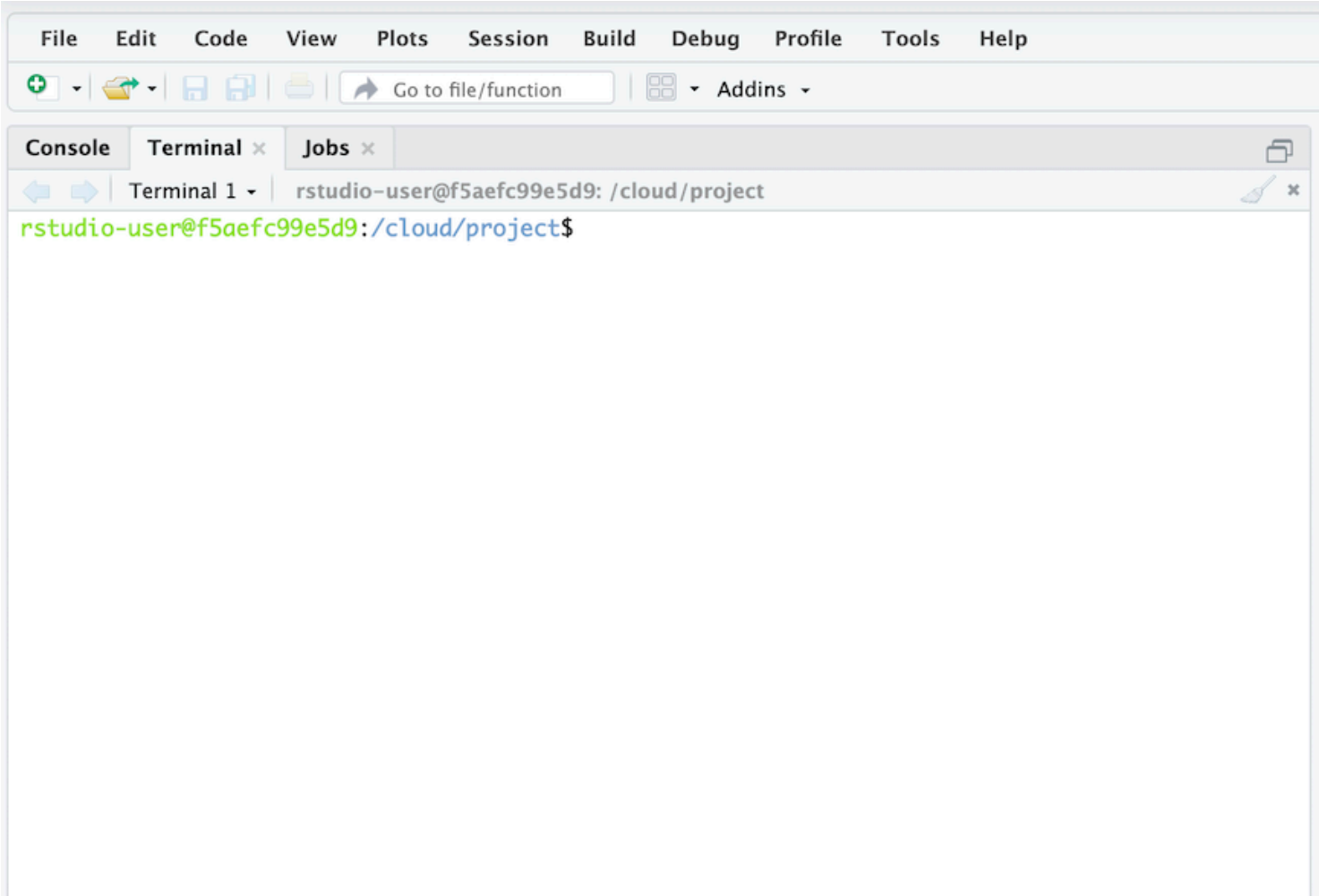
Here is a quick list of commonly used Terminal commands.

- **`pwd`** - print working directory
- **`cd`** - change directories
- **`cp`** - copy files from one directory to another
- **`ls`** - list all files
- **`ls -la`** - list all files, including hidden ones
- **`mkdir`** - make directory
- **`rmdir`** - remove a directory
- **`cat`** - display a text file in Terminal screen
- **`echo`** - outputs text as arguments, prints to Terminal screen, file, or in a pipeline
- **`touch`** - create a few files
- **`grep`** - "globally search a regular expression and print"
- **`>>`** and **`>`** - redirect output of program to a file (don't display on Terminal screen)

- **`sudo`** and **`sudo -s`** (**BE CAREFUL!!**) performing commands as **`root`** user can carry some heavy consequences.

Command-line skill #1: who is using what?

After downloading the files from Github, we've uploaded the zipped folder into the `Cloud/project`. In the RStudio.Cloud **Terminal** pane, we should see something like this:



Cloud terminal prompt

The figure above might look like gobbledygook at first, but command-line interfaces have a recognizable pattern if we know what we're looking for:

- First, we can almost always expect some `user@machine` identifier to tell us who we're signed is as and on what machine
- Second, there's usually some way of displaying the **`home`** directory. In this case, it's the stuff between the colon (`:`) and the dollar sign `$` (**`/cloud/project`**)

Let's check a few things to help figure out what's going on.

```
rstudio-user@f5aefc99e5d9:/cloud/project$ whoami
rstudio-user
```

We are the `rstudio-user` on this machine `f5aefc99e5d9`. The same information on a local MacBook laptop might look like this:

```
Martins-MacBook-Pro:~ martinfrigaard$ whoami
martinfrigaard
```

In this case, the machine information would be `Martins-MacBook-Pro` and the location to be the **`home`** directory ~ (the top-level folder) for the user `martinfrigaard`.

Command-line skill #2: where am I?

In the RStudio.Cloud **Terminal** pane, enter the print working directory (`pwd`) command:

I've omitted everything preceding the prompt ($) for easier printing

```
$ pwd
/cloud/project
```

`pwd` tells us where we are, otherwise known as the current working directory. Imagine the current working directory as the spot we're standing, and file path `/cloud/project` as the way back to our **`root`** folder.

To get a sense of our surroundings lets list the files in `/cloud/project` using `ls`

```
$ ls
dem-pres-debate-2019-master  project.Rproj
```

We can see the folder (`dem-pres-debate-2019-master`) and the RStudio project file (`project.Rproj`). On a side note, it's always a good idea to pay attention to file extensions (`.Rproj`, `.R`, `.md`, etc.), because different files interact with the **Terminal** in different ways.

Command-line skill #3: moving around

Now that we know where we are, and what files and folders are in here with us, we can start to stretch our legs and move around. Let's start by changing directories `cd` to the `dem-pres-debate-2019-master` folder, then check with `pwd`.

```
$ cd dem-pres-debate-2019-master
$ pwd
/cloud/project/dem-pres-debate-2019-master
```

Now we can check the files in this new directory with `ls`

```
$ ls
01-import.Rmd  02-wrangle.Rmd    README.Rmd  code
01-import.md   03-visualize.Rmd  README.md   data  figs
dem-pres-debate-2019.Rproj
```

The output from `ls` shows me there are three sub-folders in the `dem-pres-debate-2019-master` folder (`code`, `data`, `figs`), three `.Rmd` files, one `README.md` file, and one `.Rproj` file.

Now that we've moved into this folder and looked around let's climb back out of it. We can always move up one folder by executing the `cd ..` command.

```
$ cd ..
$ pwd
cloud/project
```

Let's move back into `dem-pres-debate-2019-master` using `cd` again, but this time, we will move up one folder using `cd /cloud/project`.

```
$ cd /cloud/project
$ ls
dem-pres-debate-2019-master  project.Rproj
```

We can also check the files in `dem-pres-debate-2019-master` using `ls` and the folder name.

```
$ ls dem-pres-debate-2019-master
01-import.Rmd     README.Rmd  data
```

```
02-wrangle.Rmd    README.md   dem-pres-debate-2019.Rproj
03-visualize.Rmd  code        figs
```

We can add the `-F` option to the end of the command to tell **Terminal** to list the files in the folder at the end of the file path.

```
ls dem-pres-debate-2019-master -F
01-import.Rmd  02-wrangle.Rmd    README.Rmd  code/
01-import.md   03-visualize.Rmd  README.md   data/  figs/
dem-pres-debate-2019.Rproj
```

Now we can see the folders have a `/` forward slash at the end of their name to separate them from the other files.

Absolute vs. relative file paths

An **absolute file path** starts at the root directory (~ or \) and follows along the path, folder by folder, until it lands on the last folder or file.

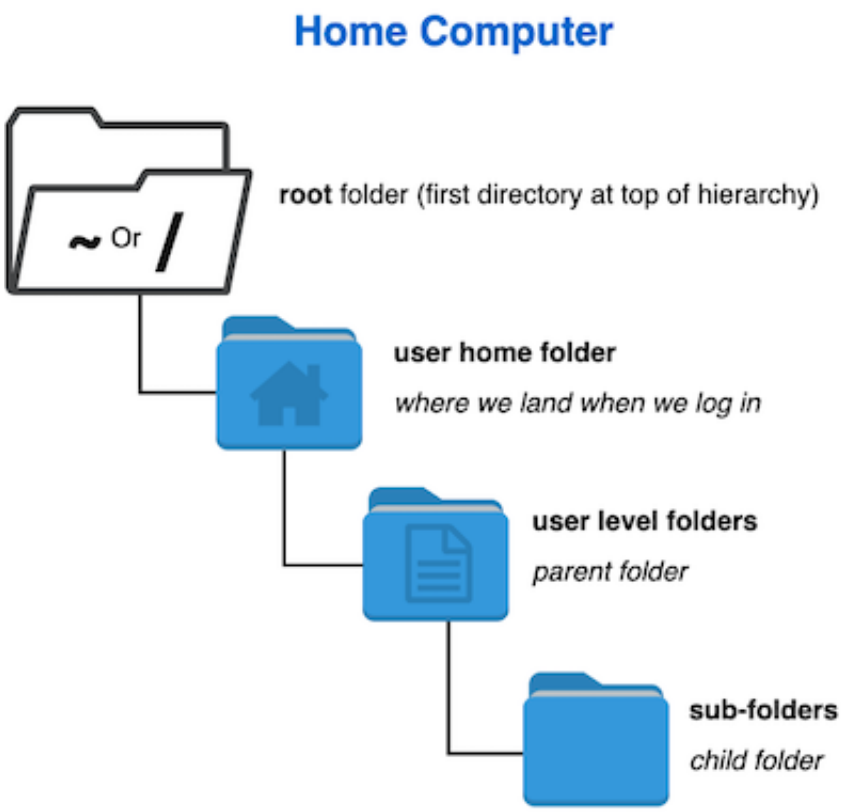
`/start/from/absolutely/where/i/tell/us`

A **relative file path** starts at a folder but leaves the rest 'relative' to wherever that folder is located.

`start/from/wherever/we/put/me`

Folder trees

Below is an example folder tree structure on a macOS.



The **`root`** folder is the "uppermost" location of this machine's folders and files. In macOS, `root` is represented with a tilde (~). In Windows, the `root` folder is located with the forward-slash (`/`). If we have the right privileges, we can log in as the `root` user, and the prompt will change from `$` to `#` (be careful here!)

When we log into a computer, we start in a **`home`** folder (usually with a shorter version of that user's full name they used to set up their operating system). The `home` folder is the typical "starting point" for that `user`'s folders and files. If we are working on macOS, this is the folder with a little house on it.

Depending on the operating system, this location starts with some standard default folders (`Desktop`, `Documents`, `Downloads`, and `Applications`)

Special case: Windows machines

On Windows machines, the file path to `dem-pres-debate-2019-master` might look like this:

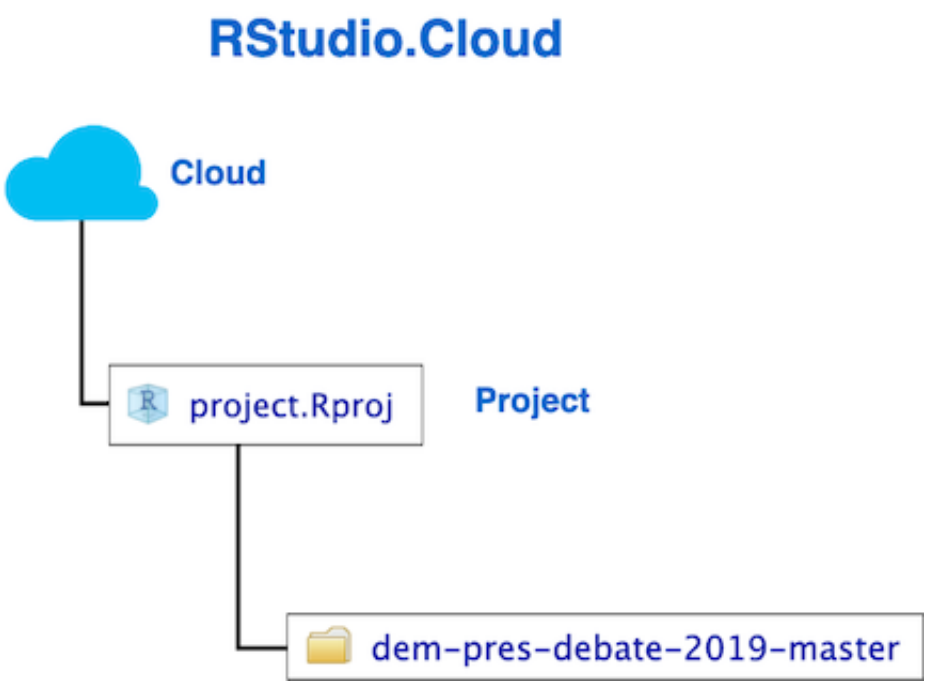
```
C:\Users\martinfrigaard\Documents\dem-pres-debate-2019-master
```

But we would need to write it like this:

```
C:\\Users\\martinfrigaard\\Documents\\dem-pres-debate-2019-master
```

This odd way of writing file paths is because, in R, the `\` is called an escape character, so to navigate through folders we will have to use two backslashes `\\`.

Below is the folder tree on RStudio.Cloud:



Now, this image might be about as clear as mud, but it'll make more sense when we start moving things around.

Command-line skill #4: moving things around

We're working in RStudio.Cloud, but the GUI representation of our folder structure won't be much different if we were working on our local laptop.

Remember, we want to move the contents of `dem-pres-debate-2019-master` into `cloud/project`. The command for moving files from one place to another is `mv`, but we are going to add two options, `-v` and `*`. There are many other options for using `mv`, read about them here.

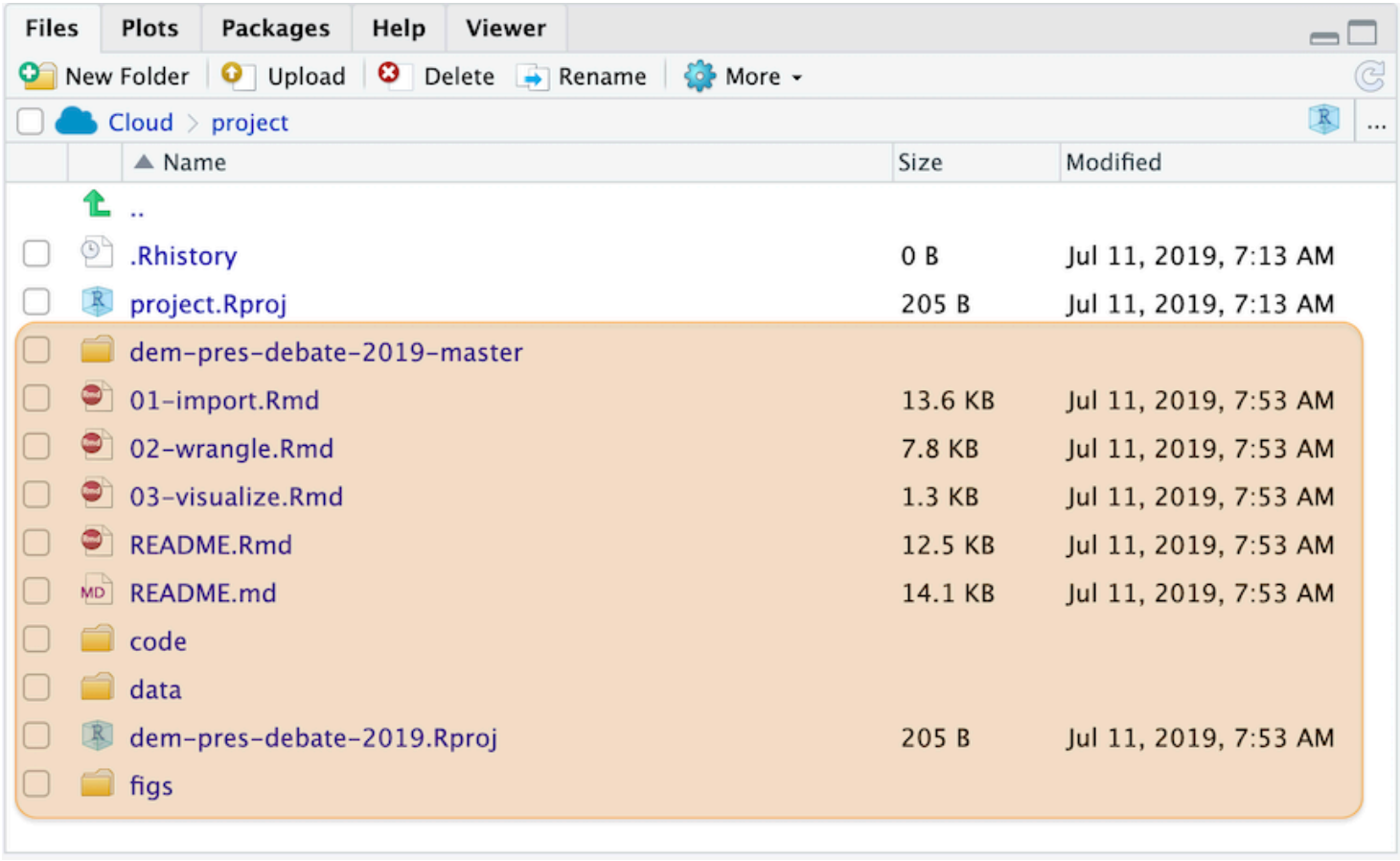
The sequence of commands we'll enter in the RStudio.Cloud Terminal are below:

```
$ mv -v dem-pres-debate-2019-master/* /cloud/project
```

You will see the following changes in **Terminal**:

```
'dem-pres-debate-2019-master/01-import.Rmd' -> '/cloud/project/01-import.Rmd'
'dem-pres-debate-2019-master/02-wrangle.Rmd' -> '/cloud/project/02-wrangle.Rmd'
'dem-pres-debate-2019-master/03-visualize.Rmd' -> '/cloud/project/03-visualize.Rmd'
'dem-pres-debate-2019-master/README.Rmd' -> '/cloud/project/README.Rmd'
'dem-pres-debate-2019-master/README.md' -> '/cloud/project/README.md'
'dem-pres-debate-2019-master/code' -> '/cloud/project/code'
'dem-pres-debate-2019-master/data' -> '/cloud/project/data'
'dem-pres-debate-2019-master/dem-pres-debate-2019.Rproj' -> '/cloud/project/dem-pres-debate-2019.Rproj'
'dem-pres-debate-2019-master/figs' -> '/cloud/project/figs'
```

And the following changes in the **Files** pane:



mv-ed files

Now we know we've successfully moved all of the files. But we will want to get rid of the old folder, `dem-pres-debate-2019-master`.

Command-line skill #5: Deleting things

To delete a folder, we can either use `rmdir` or `rm -Ri`.

```
$ rm dem-pres-debate-2019-master -Ri
rm: descend into directory 'dem-pres-debate-2019-master'?
```

This command is helpful because the `i` option tells **Terminal** to check with us before doing anything. Go ahead and enter `n` and try using `rmdir` to delete the `dem-pres-debate-2019-master` folder.

```
$ rmdir dem-pres-debate-2019-master
```

```
rmdir: failed to remove 'dem-pres-debate-2019-master': Directory not empty
```

Terminal does it's best to save us from ourselves, but that's not always possible. As Doug Gwyn said,

> *"Unix was not designed to stop its users from doing stupid things, as that would also stop them from doing clever things."*

Well, what does `rmdir` actually do then? We can figure this out with `rmdir --help`

```
$  rmdir --help
```

This command will print some useful information about the `rmdir` command:

```
$  rmdir --help
Usage: rmdir [OPTION]... DIRECTORY...
Remove the DIRECTORY(ies), if they are empty.
# else omitted...
```

Now we know this is not the right tool for the job (the folder isn't empty), so we will use `rm -Ri dem-pres-debate-2019-master`. Each folder and file will prompt a question that needs a response before **Terminal** can delete anything.

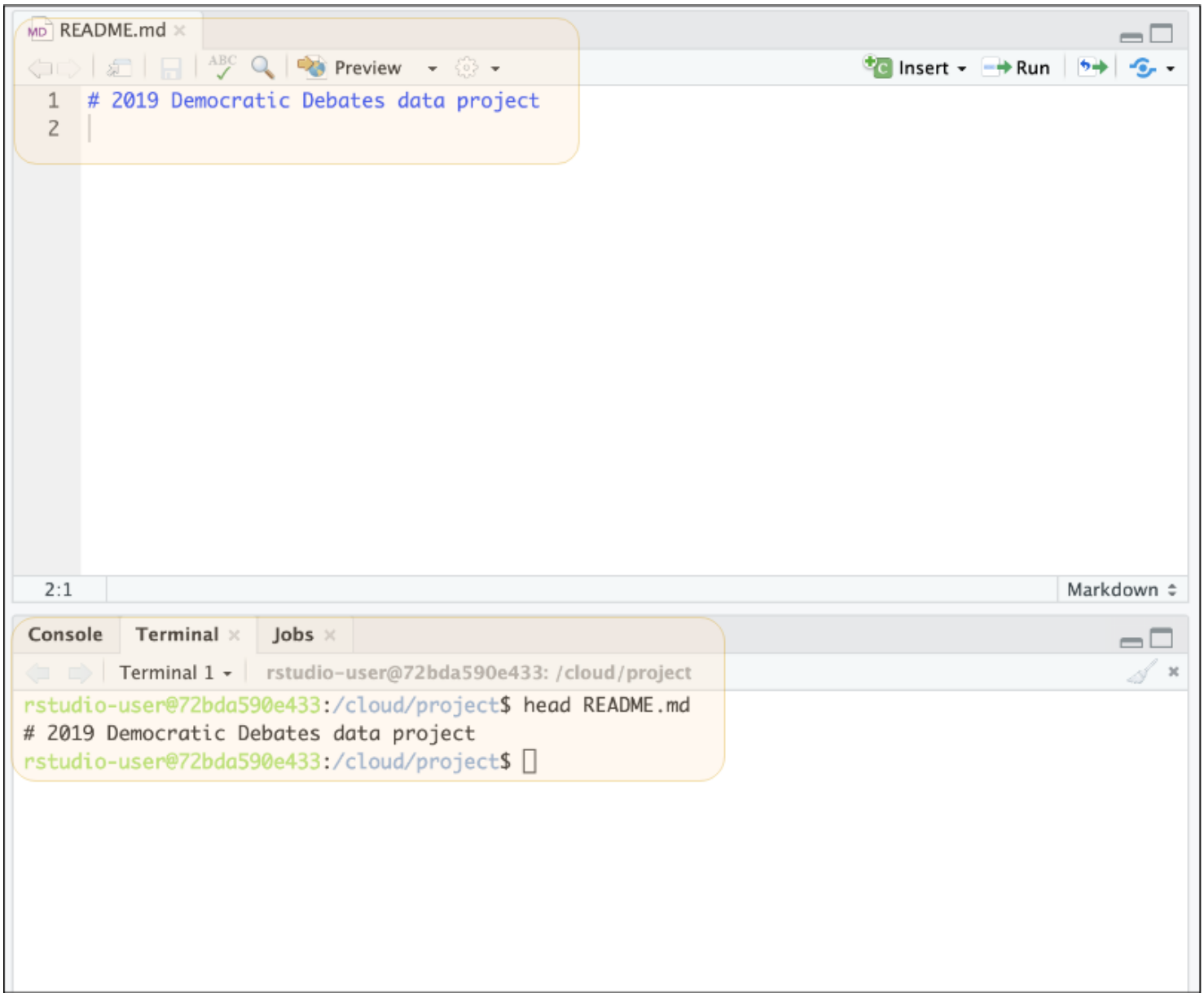
The **Terminal** pane should have the following contents when we're finished:

```
$ rm -Ri dem-pres-debate-2019-master
rm: descend into directory 'dem-pres-debate-2019-master'? y
rm: remove regular file 'dem-pres-debate-2019-master/.DS_Store'? y
rm: remove regular file 'dem-pres-debate-2019-master/.gitignore'? y
rm: remove directory 'dem-pres-debate-2019-master'? y
```

Command-line skill #6: Printing things

Terminal works very well with plain text format. For example, I can use `head` and the name of a file I want to see.

```
$ head README.md
```



As we can see, this is the first few lines of the `README.md`. Markdown is a plain text format so that it will print clearly to the **Terminal** window. In addition to `head`, we can also use the `tail` command to view the bottom of the `README.md` file.

What if we want to see all the contents in `README.md`? Well, before printing all the contents, we want to see how big the file is, and we can do that using `wc` (which stands for "word count").

```
$ wc README.md
# 1  6 39 README.md
```

The three numbers above are the number of lines (`1`), the number of words (`6`), and the number of characters (`39`).

`wc` is telling us that `README.md` won't be hard to read on the Terminal window. If it was, that's where the `less` command comes in.

```
$ less README.md
```

`less` will display the contents of `README.md` in a way that allows us to scroll through the file using the arrow keys. After we're done viewing the file, we can exit `less` using `q`.

Another option to print is `cat`, but this will print the entire contents to the **Terminal** window, so use `wc` first to see if that's the best choice.

Command-line skill #7: Create things

Sometimes we might need to create a new file and add some text to it. This skill is handy if we don't have to open any new applications.

The `touch` command will create a new file (`CHANGELOG.txt`), and `echo` will put the "some thoughts" on this file (which we can verify with `cat`).

```
$ touch CHANGELOG.txt
$ echo "some thoughts" > CHANGELOG.txt
$ cat CHANGELOG.txt
some thoughts
```

The > symbol tells **Terminal** to send `echo "some thoughts"` to `CHANGELOG.txt`. When we use `car`, we see these commands put "some thoughts" into the top lines of the new file, `CHANGELOG.txt`.

The `CHANGELOG.txt` file is for writing notes about changes to our project, but we should add a date to make sure they're listed chronologically. Unix has a `date` variable we can access using `$(date)` (which 'attaches' the output from the command date with "some thoughts"), so we will repeat the process above, but include today's date with `$(date)`.

```
$ echo $(date) "some thoughts" > CHANGELOG.txt
$ cat CHANGELOG.txt
```

In Unix systems, we can always access today's date with the `date` or `cal`.

```
$ cal
     July 2019
Su Mo Tu We Th Fr Sa
    1  2  3  4  5  6
 7  8  9 10 11 12 13
14 15 16 17 18 19 20
21 22 23 24 25 26 27
28 29 30 31
```

Command-line skill #8: Combine things

The commands above are great for creating new files and adding new text, but what if `CHANGELOG.txt` already exists and we wanted to add more thoughts to it? We can do this by changing the > symbol to >>.

```
$ echo $(date) "more thoughts" >> CHANGELOG.txt
$ cat CHANGELOG.txt
# Thu Jul 11 13:45:57 UTC 2019 some thoughts
# Thu Jul 11 13:49:42 UTC 2019 more thoughts
```

>> tells **Terminal** to append the output from `echo` to `CHANGELOG.txt` on a new line.

Another powerful tool in the Unix toolkit is the pipe (|). The pipe can be used to 'direct' outputs from one command to another. For example, if I wanted to see how many R script files are in the `code` folder, I could use the following:

```
$ ls code | grep ".R" | less
# 00-download-tweets.R
# 00-download-538.R
# 00-download-google.R
# 00-download-wikipedia.R
# 00-inst-packages.R
# 01-import.R
# 01.2-twitter-data.R
# 02-wrangle.R
# (END)
```

We will leave the `grep` command for you to investigate with `--help` to figure out what's happening here. Type `q` to leave this screen.

Other command line stuff: homebrew

The bash shell on macOS comes with a whole host of packages we can install with homebrew, the "The missing package manager for macOS (or Linux)".

(You won't be able to do this on RStudio Terminal, but there are other options we will list below)

After installing homebrew, we recommend installing the `tree` package.

```
$ # install tree with homebrew
$ brew install tree
$ # get a folder tree for this project
$ tree
```

The `tree` command gives us output like the folder tree below.

```
├── 01-import.Rmd
├── 02-wrangle.Rmd
├── 03-visualize.Rmd
├── README.Rmd
├── README.md
├── code
├── data
|   ├── processed
|   └── raw
└── dem-pres-debate-2019.Rproj
```

Folder trees come in handy for documenting the project files (and any changes to them).

Command line recap

We've covered eight command-line tools, and we hope you can see how these can be combined to create very efficient workflows and procedures. By tethering commands together, we can move inputs and outputs around with a lot of flexibility.

More on organizing your project files

As we saw above, the `tree` output gave us a printout of the project folder in a hierarchy (i.e. a tree with branches).

The thing to notice is the separation of files into folders titled, `data`, `docs`, and `src` or `code`. We didn't choose these folder names at random–there is a way to organize a data science project. We recommend starting with the structure outlined by Greg Wilson et al. in the paper, "Good Enough Practices for Scientific Computing". If you already have an organization scheme, we still recommend reading at least this section of the paper–it's full of great information and links to other resources.

Getting more help with command-line tools

This section has been a concise introduction to command-line tools, but hopefully, we've demystified some of the terminologies for you. The reason these technologies still exist is that they are powerful. Probably, you're starting to see the differences between these tools and the standard GUI software installed on most machines. Vince Buffalo, sums up the difference very well,

> *"the Unix shell does not care if commands are mistyped or if they will destroy files; the Unix shell is not designed to prevent you from doing unsafe things."*

The command line can seem intimidating because of its power and ability to destroy the world. But there are extensive resources available for safely using it and adding it to your wheelhouse.

- The Unix Workbench
- Data Science at the Command Line
- Software Carpentry Unix Workshop

Terminals vs. Shells: Sometimes you'll hear the term "shell" thrown around when researching command-line tools. Strictly speaking, the Terminal application is not a shell, but rather it *gives the user access to the shell*. Other terminal emulator options exist, depending on your operating system and age of your machine. Terminal.app is the default application installed on macOS, but you can download other options

(see iTerm2). For example, the GNOME is a desktop environment based on Linux which also has a Terminal emulator, but this gives users access to the Unix shell.

Part 4: Keep track of changes with version control

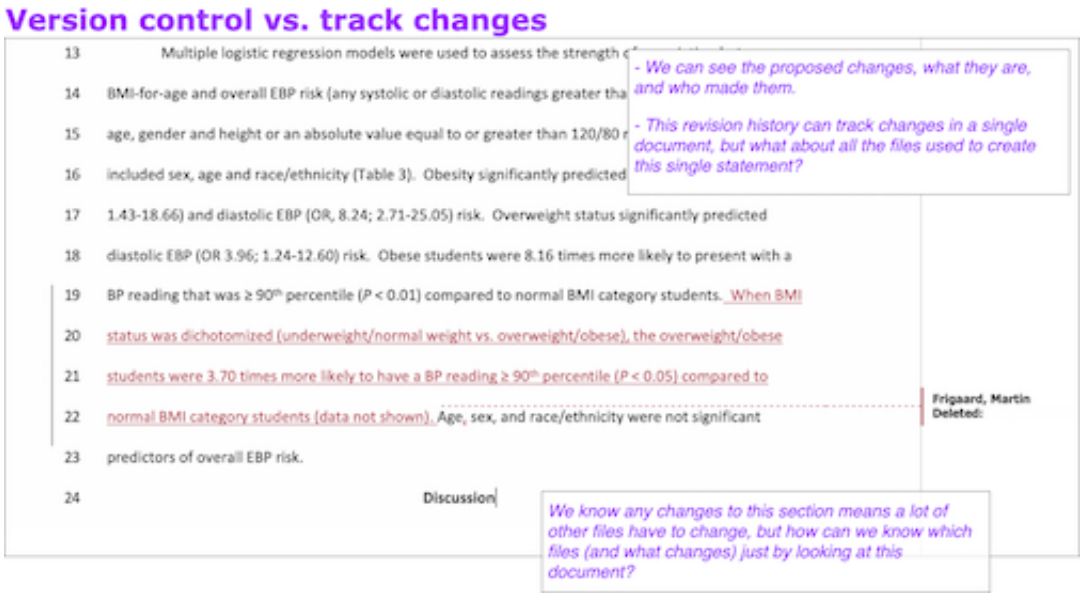
In the previous sections, we've covered using **Terminal** in the RStudio. If you're unfamiliar with these topics, please start there. This section will include tracking changes with version control, specifically Git, Github, and RStudio.

Tracing your steps

'Sharing your' can take a few forms. You can finish a project, then share your work for people to see and use in what they're doing. Another option is to share what you're currently working on in a way that allows other people can collaborate with you along the way.

To accomplish the second option, we need a means showing how our work has changed over time. For example, maybe you've used the 'Review' tools in Mircosoft Word, or you've collaborated in a Google sheet document. Both are types of version control because they're a formal system of managing changes to information over time.

Consider the image below of a .docx file:



The file is an earlier version of a manuscript. A coauthor has suggested changes to the results section. Sound version control systems let us see four aspects of changes:

1) what the differences are,
2) who recommended them,
3) the time/date of the proposed changes, and
4) any comments about the change

Unfortunately, tracked changes in Word only applies to a single document at a time. When you're working collaboratively (which is quite often), you know asking someone to change a single sentence can result in changes to dozens of files. That's why we need a way to track changes across a project's multiple files.

Git

Git is a version control system (VCS), which is somewhat like the **Tracked Changes** in Microsoft Word or the **Version History** in Google Docs, but extended to every file in a project. Git will help you keep track of your documents, datasets, code, images, and anything else you tell it to keep an eye on.

Why use Git?

You will eventually ask yourself, *why am I subjecting myself to this–is there another way?*

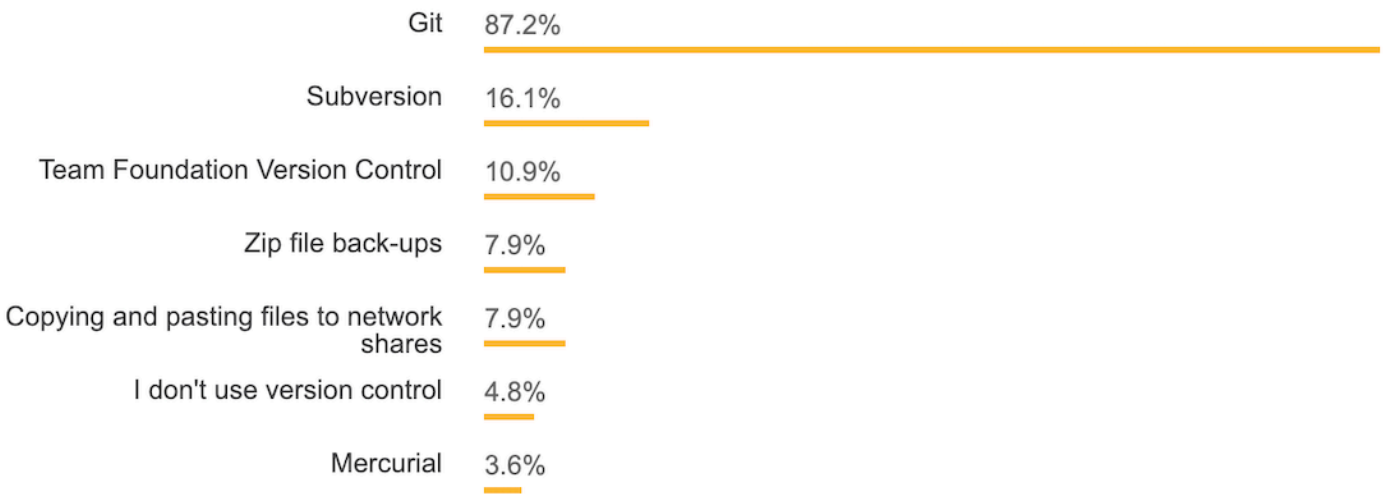
We've included these sections to remind you that you're making a sound choice.

Plain text + Git

Software developers keep track of their code with Git. We learned in the last chapter that most code files get kept in plain text, so Git plays well with plain text.

Everyone else is doing it

Git has become the most common version control system used by programmers.



74,298 responses; select all that apply

Git is the dominant choice for version control for developers today, with almost 90% of developers checking in their code via Git.

source: StackOverflow Developer Survey Results

Git is a useful way to think about making changes

Git is also a helpful way of thinking about the changes to your project. The terminology of Git is strange at first, but if you use Git long enough, you'll be thinking about your code in terms of 'commits,' 'pushes,' 'forks,' and 'repos.'

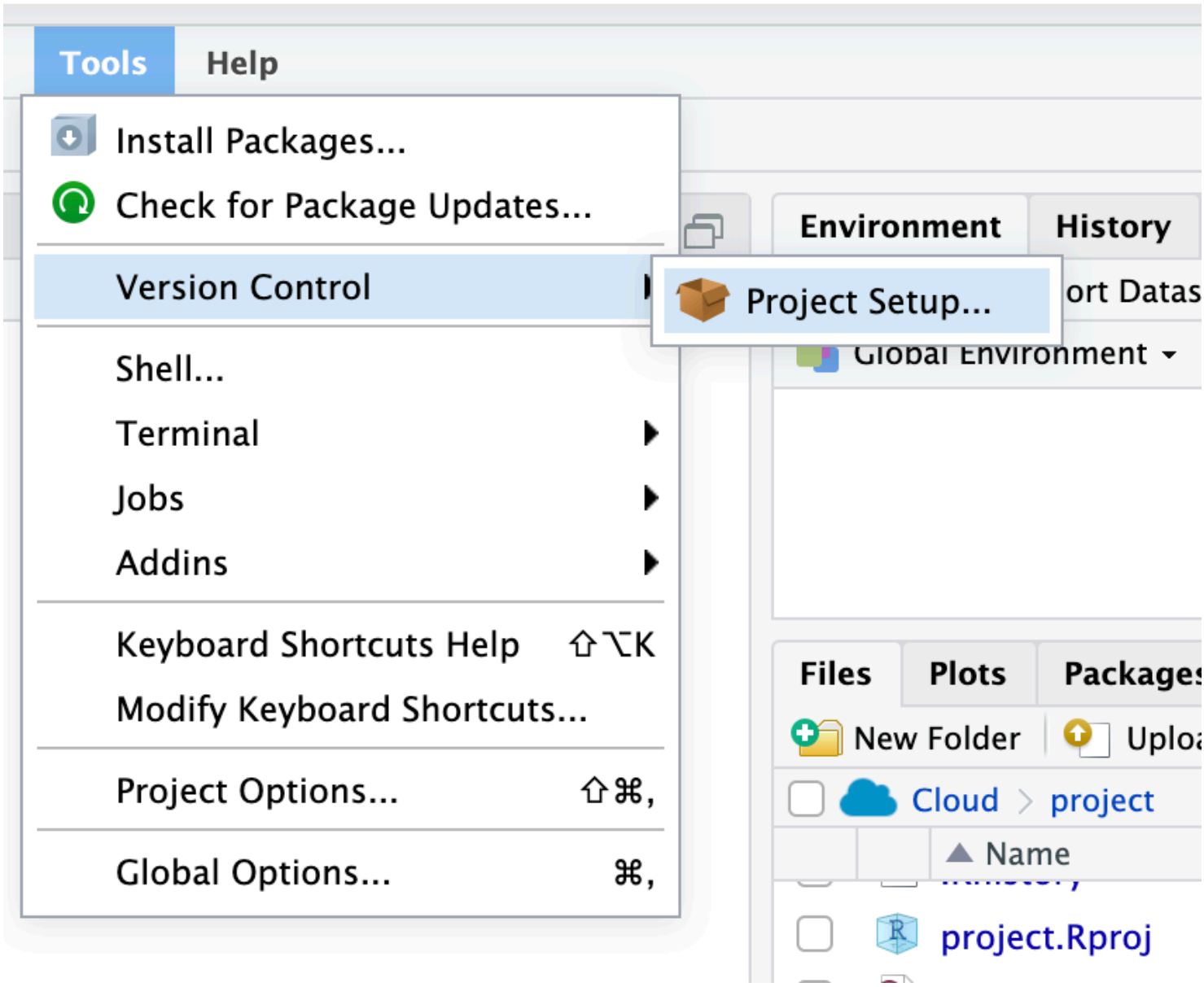
As someone who analyzes data regularly, these concepts are also countable, which means you can quantify change and work in more exciting ways.

Setting up Git

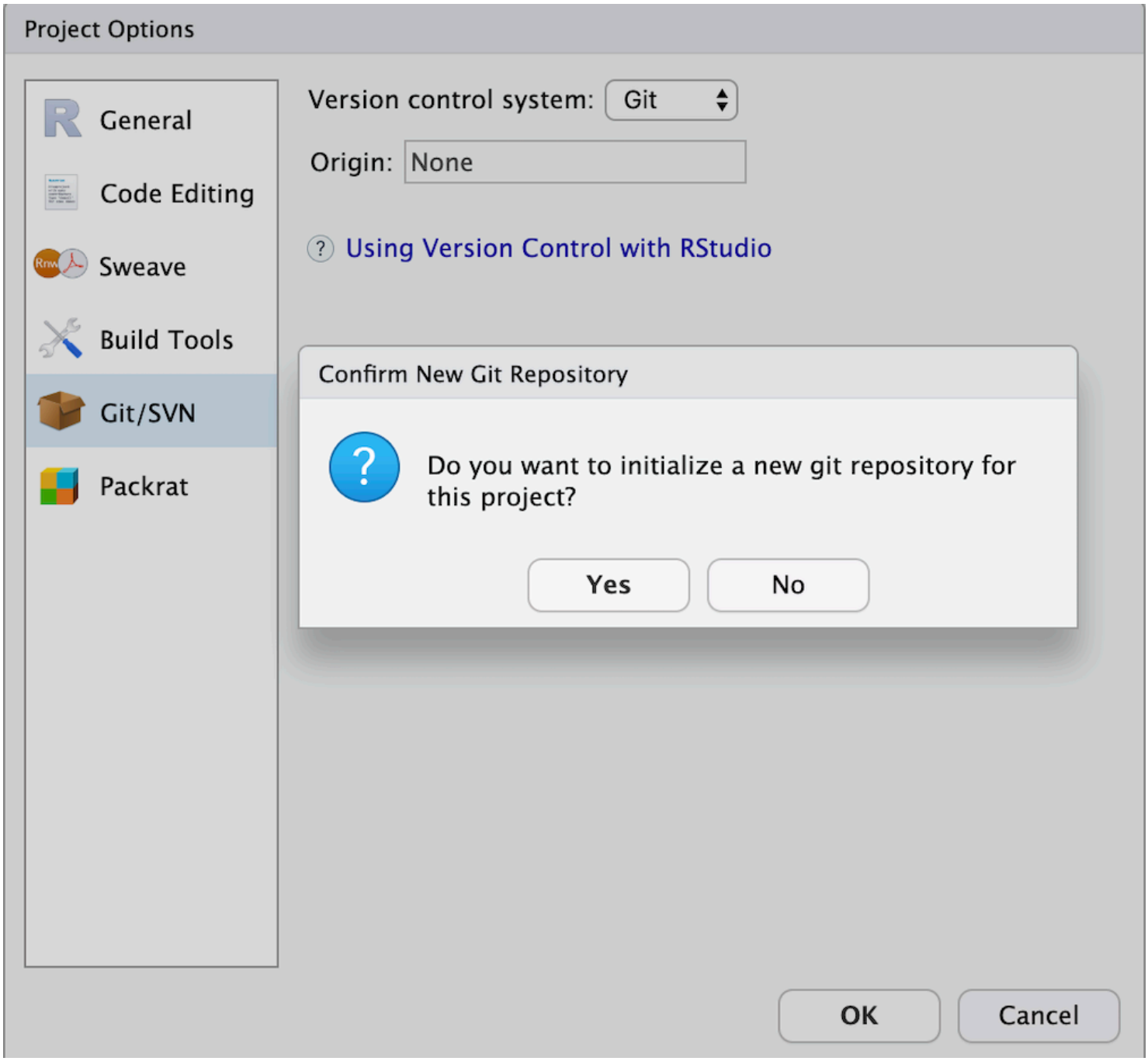
If you'd like to install Git on your local machine, you can do so following these two links:

1. Download and install Git.
2. Create a Github account.

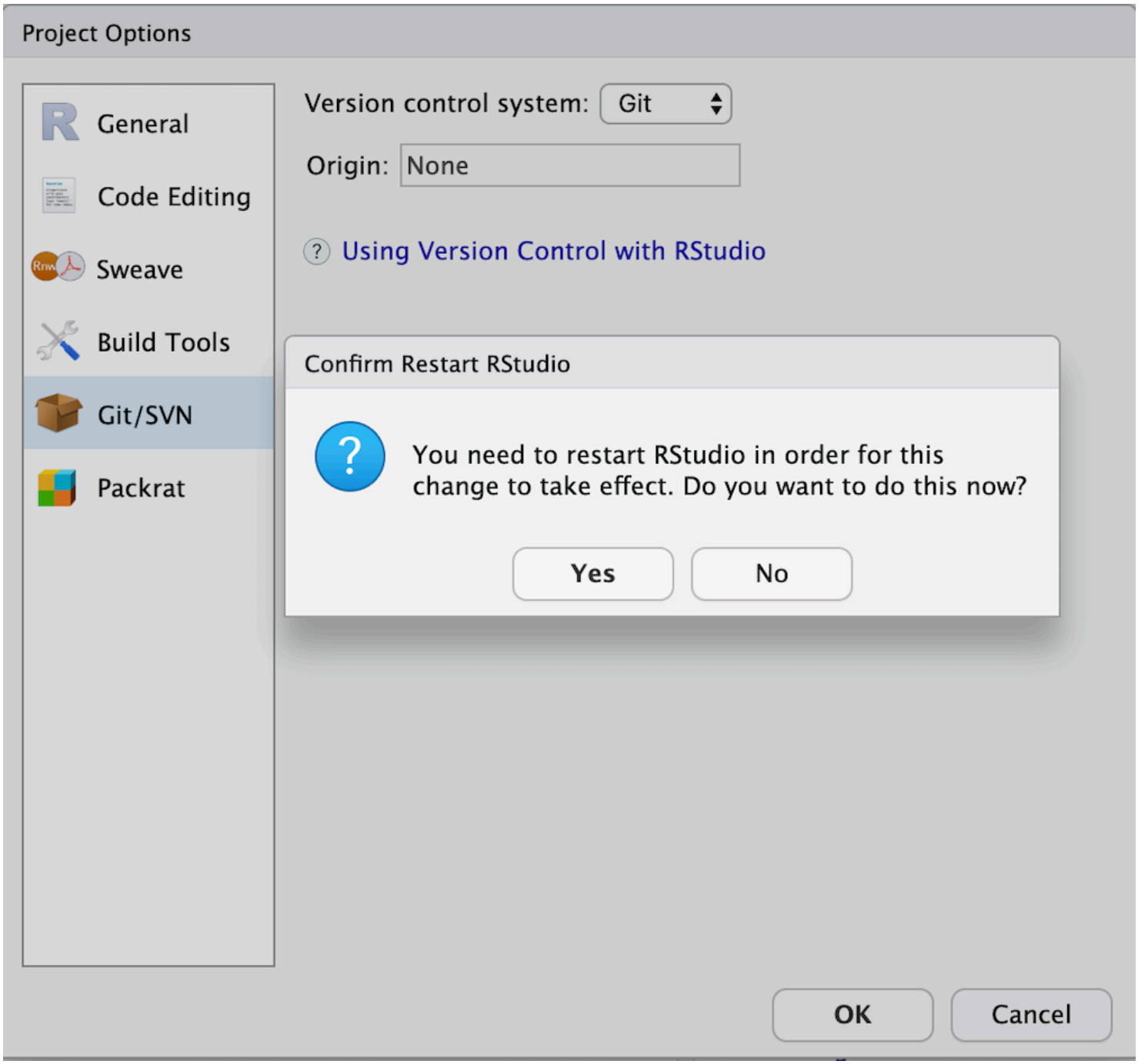
In RStudio.Cloud, we want to add version control to this project from *Tools* > *Version Control* > *Project Setup*



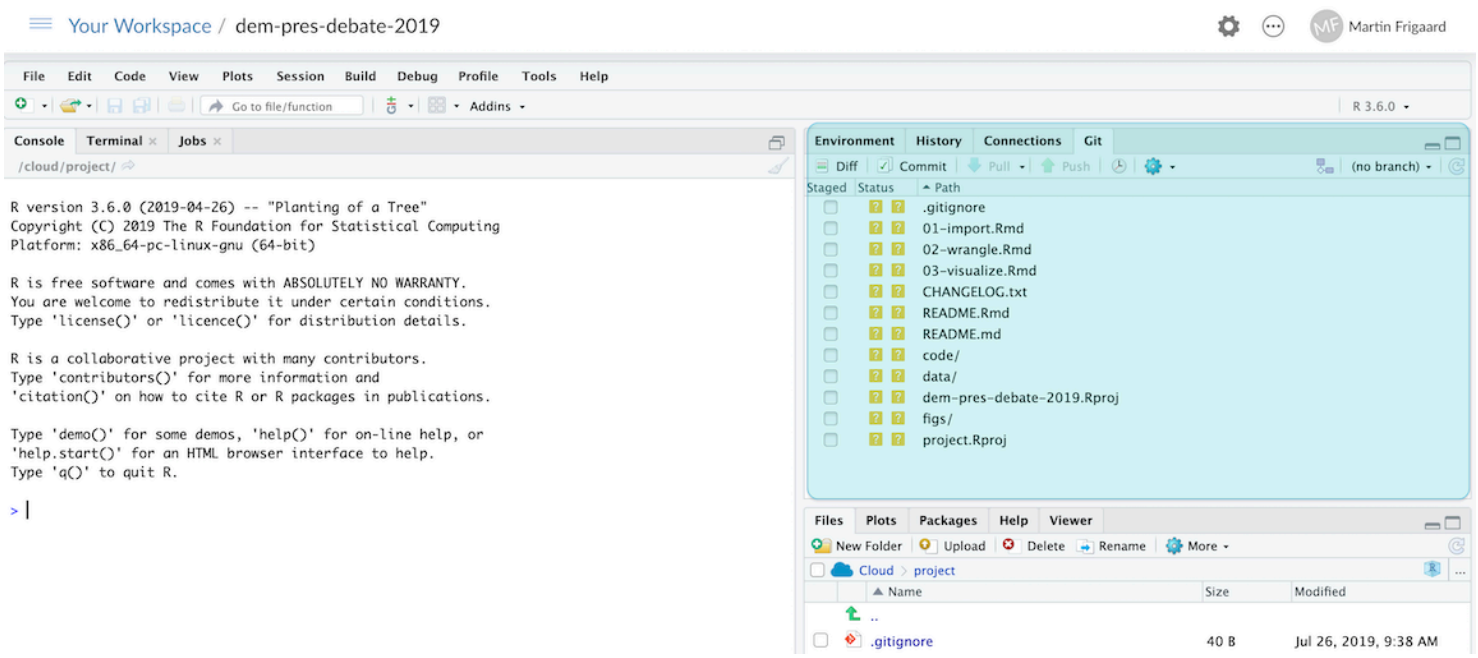
From here, you will see the *Git/SVN* option on the sidebar, where you will select *Git* from the dropdown list next to *Version control system*. After this, RStudio.Cloud will ask if you want to *initialize a new git repo*, which you do.



Then you will be asked if we are ok to restart RStudio (and we do).



After restarting the IDE, we should see the *Git* tab in one of the panes.



Configuring Git

Git needs a little configuration before we can start using it and linking it to Github. There are three levels of configuration within Git, `system`, `user`, and `project`.

1) For **system** level configuration use:
`git config --system`

2) For **user** level configuration, use:
`git config --global`

3) For **Project** level configuration use:
`git config`

We'll set our Git `user.name` and `user.email` with `git config --global` so these are configured for all projects.

```
$ git config --global user.name "Martin Frigaard"
$ git config --global user.email "mjfrigaard@gmail.com"
```

We can check what we've configured with `git config --list`.

```
$ git config --list
```

At the bottom of the output, we can see the changes.

```
user.name=Martin Frigaard
user.email=mjfrigaard@gmail.com
core.repositoryformatversion=0
core.filemode=true
core.bare=false
core.logallrefupdates=true
```

On our local machine, the `user.name` and `user.email` are in the `.gitconfig` file.

We can view this using:

```
$ cat .gitconfig
```

```
[user]
    name = Martin Frigaard
    email = mjfrigaard@gmail.com
```

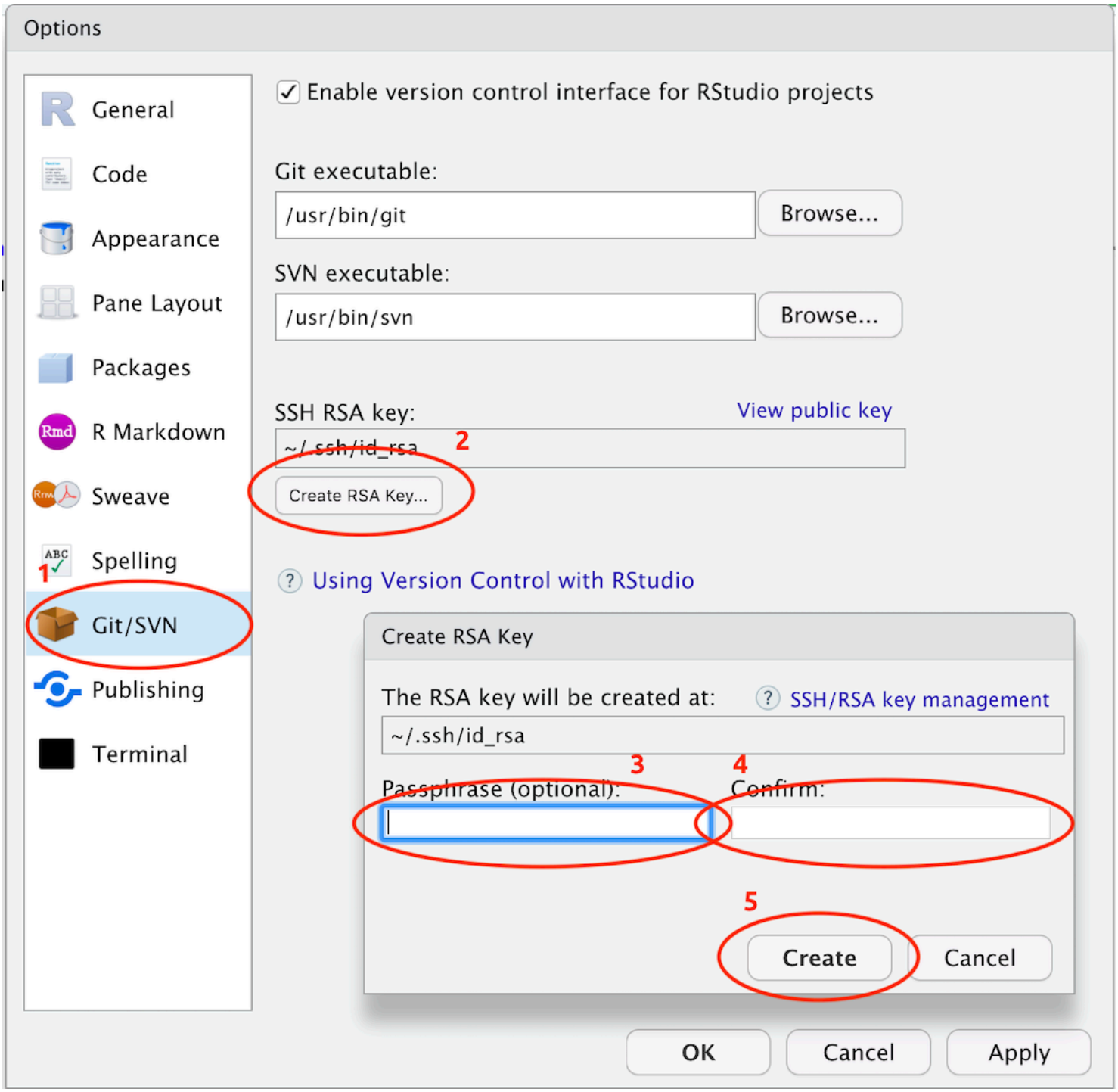
Synchronizing RStudio and Git/Github

Jenny Bryan has created the online resource Happy Git and GitHub for the useR has all in the information you will need for connecting RStudio and Git/Github. We echo a lot of this information below (with copious screenshots).

The first step is setting up the RSA Key and passphrase.

Go to *Tools* > *Global Options* > …

- 1. Click on *Git/SVN*
- 1. Then *Create RSA Key…*
- 3, 4, and 5. In the dialog box, enter a passphrase (and store it in a safe place), then click *Create*.



The result should look something like this:

```
Generating public/private rsa key pair.
Your identification has been saved in /home/rstudio-user/.ssh/id_rsa.
Your public key has been saved in /home/rstudio-user/.ssh/id_rsa.pub.
The key fingerprint is:
[redacted]
The key's randomart image is:
+---[RSA 2048]----+
|      .=0=..oOOo  |
|     ..=. o ++oo  |
|      o .o oo.ooo.|
|       .  Xoo.Eo..|
|     [redacted]   |
|                  |
|                  |
+----[SHA256]-----+
```

Or like this on your local machine.

```
whoeveryouare ~ $ ssh-keygen -t rsa -b 2891 -C "USEFUL-COMMENT"
Generating public/private rsa key pair.
Enter file in which to save the key (/Users/username/.ssh/id_rsa):
Enter passphrase (empty for no passphrase):
Enter same passphrase again:
Your identification has been saved in /Users/username/.ssh/id_rsa.
Your public key has been saved in /Users/username/.ssh/id_rsa.pub.
The key fingerprint is:
SHA483:g!bB3r!sHg!bB3r!sHg!bB3r!sH USEFUL-COMMENT
The key's randomart image is:
+---[RSA 2891]----+
|      o+   . .   |
|     .=.o . +    |
|     ..= + +     |
|      .+* E      |
|     .= So =     |
|    .  +. = +    |
|   o.. = ..* .   |
|  o ++=.o =o.    |
| ..o.++o.=+.     |
+----[SHA483]-----+
```

Great! We need to go back to Terminal and store this `SSH` from RStudio.

Adding a key SSH in Terminal

In the Terminal, we enter the following commands.

```
$ eval "$(ssh-agent -s)"
```

The response tells us we're an `Agent`.

```
Agent pid 007
```

Now we want to add the *SSH RSA* to the keychain. There are three elements in this command: the `ssh-add`, the `-K`, and `~/.ssh/id_rsa`.

- The `ssh-add` is the command to add the *SSH RSA*
- The `-K` stores the passphrase we generated, and
- `~/.ssh/id_rsa` is the location of the *SSH RSA*.

```
$ ssh-add -k /home/rstudio-user/.ssh/id_rsa
```

Enter the passphrase, and then git should tell us the identity has been added.

```
Enter passphrase for /home/rstudio-user/.ssh/id_rsa:
Identity added: /home/rstudio-user/.ssh/id_rsa (/home/rstudio-user/.ssh/id_rsa)
```

Create the `.ssh/config` file

Most operating systems require a `config` file. We can do this using the Terminal commands above.

First, I move into the `.ssh/` directory.

```
$ cd /home/rstudio-user/.ssh
```

Then we create this `config` file with `touch`

```
$ touch config
# verify
$ ls
config        id_rsa        id_rsa.pub
```

We use `echo` to add the following text to the `config` file.

```
Host *
 AddKeysToAgent yes
 UseKeychain yes
```

Recall the >> will send the text to the `config` file.

```
# add text
$ echo "Host *
>  AddKeysToAgent yes
>  UseKeychain yes" >> config
```

Finally, we can check `config` with `cat`

```
# verify
$ cat config
Host *
 AddKeysToAgent yes
 UseKeychain yes
```

Great! Now I am all set up to use Git with RStudio. In the next section, we'll extend our Github skills by moving the contents of a local folder to Github.

More on Git and Github and data organization

Fortunately, many articles have come out in the last few years with excellent, practical advice on organizing data analysis projects. I recommend reading these before getting started (you'd be surprised at the cacophony of files a single project can produce). We've listed a few 'must-reads' below:

- the importance of using version control

- sharing data with collaborators
- how to name your files