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# Bridging the Gap Between Tools for Learning and for Doing Statistics

A dissertation submitted in partial satisfaction
of the requirements for the degree
Doctor of Philosophy in Statistics

by

**Amelia Ahlers McNamara**

2015

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Abstract of the Dissertation

# Bridging the Gap Between Tools for Learning and for Doing Statistics

by

**Amelia Ahlers McNamara**

Doctor of Philosophy in Statistics

University of California, Los Angeles, 2015

Professor Robert L Gould, Co-chair

Professor Fredrick R Paik Schoenberg, Co-chair

Computers have changed the way we think about data and data analysis. While statistical programming tools have attempted to keep pace with these developments, there is room for improvement in interactivity, randomization methods, and reproducible research.

In addition, as in many disciplines, statistical novices tend to have a reduced experience of the true practice. This dissertation discusses the gap between tools for teaching statistics (like TinkerPlots, Fathom, and web applets) and tools for doing statistics (like SAS, SPSS, or R). We posit this gap should not exist, and provide some suggestions for bridging it. Methods for this bridge can be curricular or technological, although this work focuses primarily on the technological.

We provide a list of attributes for a modern data analysis tool to support novices through the entire learning-to-doing trajectory. These attributes include easy entry for novice users, data as a first-order persistent object, support for a cycle of exploratory and confirmatory analysis, flexible plot creation, support for randomization throughout, interactivity at every level, inherent visual documentation, simple support for narrative, publishing, and reproducibility, and flexibility to build extensions.

While this ideal data analysis tool is still a few years in the future, we describe several projects attempting to close the gap between tools for learning and tools for doing statistics. One is curricular, a high school level Introduction to Data Science curriculum. Others are technological, like the experimental LivelyR interface for interactive analysis, the **MobilizeSimple** R package, and **Shiny** microworlds.

Much of this work was inspired by Biehler (1997), which describes the attributes necessary for a software package for learning statistics. Biehler's vision has largely come to light, but advancements in computing and 'data science' have moved the goalposts, and there is more to learning statistics than before. This work envisions a tool not only encompassing these advancements, but providing an extensible system capable of growing with the times.

The dissertation of Amelia Ahlers McNamara is approved.

Alan Curtis Kay

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2015

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This work owes a debt of gratitude to Rolf Biehler. I have been wrestling with these issues for several years, and after coming across Biehler's 1997 paper "Software for Learning and for Doing Statistics," things started to click into place.

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Lunzer, A. and McNamara, A. (2014). It ain't necessarily so: Checking charts for robustness. In *IEEE Vis 2014*

Lunzer, A., McNamara, A., and Krahn, R. (2014). LivelyR: Making R charts livelier. In *useR! Conference*

McNamara, A. (2013a). Mobilize wiki: RStudio. `http://wiki.mobilizingcs.org/rstudio`

McNamara, A. and Hansen, M. (2014). Teaching data science to teenagers. In *ICOTS-9*

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The LivelyR work was done jointly with Aran Lunzer, who deserves most of the credit. Both Lunzer and I are associated with the Communications Design Group.

The bibliography is formatted in APA-like format, and programming languages and R packages are denoted using the styles prescribed by the Journal of Statistical Software.

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The sexy job in the next 10 years will be statisticians.

*Hal Varian, 2009*

# CHAPTER 1

# Introduction

We live in a world where the term "Big Data" is splashed across every media outlet. From the Large Hadron Collider to Twitter and Google Maps, we and our built world are creating data constantly. This data deluge has expanded society's view of data. No longer are we limited to spreadsheets filled with numbers, now almost anything can become data in statistical applications. Photos, maps, the text of books – the field is limitless. While there is no accepted definition of Big Data, it is often spoken of in terms of volume, velocity, and variety (Dumbill, 2012). That is, big data isn't just big in terms of storage space. It can also be big because it is streaming in at high velocity (as Twitter data does), or because of the extreme variety of data types (as in the use of photos and text as data). All of these features require new computational methods to address, and they can lead to new ethical issues as well (Crawford et al., 2013).

Because of the volume and variety of data now available, it is even easier to mash up or de-anonymize data. The vast majority of personal data can be uniquely identified using just zip code, gender, and date of birth, which has prompted work on new methods to keep data truly private (Sweeney, 2002). Having the power to merge data across many sources can expose facts about the world, create targeted advertisements, or provide arguments for new legislation.

‘Power’ is a crucial word here. For those with access to the data and tools to analyze it (corporations, newspapers, policy makers, scientists), data are power.

Data and data products, such as statistics, models, and visualization, are used to convey information, to argue, and to tell stories. Hal Varian thinks that being a statistician is a sexy job because Google has built their company on data – optimizing search results, doing machine translation, developing self-driving cars. Gone are the days where statisticians were only employed as academics or insurance agents. Today, every major corporation keeps data scientists on staff.

Outside of the corporate world, every scientific domain has recognized the value of data, and the humanities are not far behind. Whether it is a computational biologist sequencing genes or an English professor doing ‘far reading’ analysis on a corpus of text, practitioners have begun incorporating data everywhere. For the informed consumer of data, statistics and statistical graphics are as susceptible to biases and inaccuracies as journalistic accounts. But, without at least some statistical knowledge, citizens are highly unlikely to critique what they read and thus accept it as fact. So the ability to unpack data analysis and statistics is crucial to the informed citizen today.

This explosion of data and data analysis was wrought by computers. The volume, velocity, and variety of data are all made possible by computerized sensors, massive server space, the internet, and digital technologies of all kinds. Statistical methods to deal with these data have lagged behind, but data scientists are learning to compute on the data explosion and are gleaning insights that allow them to predict behavior, recommend movies, tailor advertisements, and uncover corruption in government.

Yet the average citizen does not have the opportunity to experience this type of data analysis. The current conception of statistics still echoes that of the 1970s – performing computations like mean and standard deviation on small, lifeless data sets presented in a textbook. However, with access to statistical software packages, computing summary statistics can become a small part of a much deeper analysis.

The word ‘access’ is crucial. Given the current state of computing, the practical reality is most citizens do not have access to statistical computing tools. They are either prohibitively expensive or prohibitively difficult to learn, and those tools that might be considered accessible to a large audience have not been kept up to date with the methods necessary for modern data analysis. These and other issues will be discussed in more detail in this dissertation, which identifies and begins to develop the most important aspects of software to promote statistical analysis and ‘data science’ as broadly as possible.

While the explosion of data and its accompanying challenges may sound like young problems, they are not. Much of the inspiration for this project has come from decades ago. John Tukey argued for more flexible tools for statistical programming in 1965, Jacques Bertin was developing matrix manipulation techniques by hand in 1967, and Seymour Papert was creating computer tools to better support users and learners in 1967. In other words, most of these ideas are almost 50 years old, and we are still struggling to see them implemented.

## 1.1 State of statistics knowledge

While statisticians have a vested interest in improving the statistical understanding of our society (Wild et al., 2011) and it is clear data skills are becoming more necessary and relevant, many people still find statistics boring, hard, or downright impossible (Gal et al., 1997).

Even teachers of statistics often have major misconceptions about statistical concepts or are unable to explain the reasoning behind them (Thompson et al., 2007; Hammerman and Rubin, 2004; Kennedy, 2001). So it is no surprise students often struggle to understand proportional groups (Rubin and Hammerman, 2006), use aggregates (Hancock et al., 1992), or find information from graphs (Vellom and Pape, 2000).

While some argue that attempting to incorporate computational methods into introductory statistics courses will only make this worse, research suggests the opposite. For example, teachers in professional development (even with a low baseline of knowledge) have more success when the training incorporates innovative practices and technology (Hall, 2008). Research shows similar findings among students, as active learning and exploratory analysis helps users integrate their knowledge (Garfield and Ben-Zvi, 2007). This suggests courses integrating computer technology into data analysis topics – even outside the statistics classroom – could be more successful in both engaging students and in teaching the material.

However, there is an important distinction to be made between statistical computation and computational statistics (Horton et al., 2014b). Statistical computation is using a computer to remove the need for pencil-and-paper calculations, while computational statistics takes the computer into the practice. This work discusses the development of computational statistics.

## 1.2 Relevancy at a variety of experience levels

Much of the research cited here refers specifically to high school education, but the problems discussed are more general. Introducing novices to new computer tools is a general problem in many disciplines (Deek and McHugh, 1998; Muller and Kidd, 2014), and when the tool requires broader contextual knowledge, the challenge can be even more complex. While secondary school students conform to standard ideas about what a novice looks like, there are novices at many ages and education levels. For example, masters students in data journalism are typically novices when it comes to statistical analysis and programming. Given the current state of statistics education at the secondary school level, most adults who have not specialized in statistics are also novices. Ideally, the statistical programming tools of the future will be useful to a broad variety of novices, regardless of age.

However, this work does not try to consider students below secondary school. At the primary school level, the necessity of a computational tool is less obvious, and students' reasoning is typically not to the level of abstract thinking required to grasp concepts like variation at a deep level. The Guidelines for Assessment and Instruction in Statistics Education (GAISE) outline three levels of statistical reasoning, A, B, and C, which build on one another (Franklin et al., 2005). The authors of the guidelines suggest pre-secondary school students should be exposed to levels A and B so they are prepared for level C (including randomization, comparing groups using measures of variability, and considering model fitting, including variability in model fitting) when they arrive in high school. The final reason for excluding younger students from this work is existing tools for teaching statistics seem to work well at this level (Biehler et al., 2013).

Going forward, the term 'novice' is used to refer to someone at the secondary school level or above, who does not have statistical or programming skills.

## 1.3 Technology as a component in the educational ecosystem

The problems and opportunities in statistics and statistics education are wide reaching. Certainly, access to statistics and data analysis will continue to broaden as material trickles down from innovations in academia and industry. However, for novices to learn statistics, there is a need for much more than technology. As has been the case in the evolution of all technology (e.g., moving pictures, radio, television, computers, and now hand-held devices like smartphones and tablets), just having the technology does not improve education.

The most crucial educational need is for good instructors. At the secondary school level, this appears to be particularly hard (the politics of education in the United States still have not resolved to a state where teachers are paid like other professionals) but even at the post-secondary level practitioners are valued more highly than educators.

However, simply having qualified teachers is still not enough. Teachers need training and curriculum in order to scaffold the material they are teaching. While modern statistical methods have begun to permeate courses at the college level, there has been limited trickledown to the high school level. The Introduction to Data Science course discussed in Section 5.1.3.3 is the only curriculum we are aware of focusing on computational statistics and data analysis at the high school level.

It is possible new methods of educational publishing will help remedy some of these problems. For example, Massive Open Online Courses (MOOCs) have been gaining traction, and Johns Hopkins University has developed a data science sequence on the Coursera platform, which introduces students to exploratory data analysis, R, reproducible research, statistical inference, and modeling, from simple linear modeling to machine learning (Caffo et al., 2015). Perhaps the availability of good computational statistics instruction on the web will reduce the need for teachers in other contexts, but it is likely to be an incremental shift rather than a large one.

The problems of good teachers, curriculum, and teacher training are all difficult. This work only touches on these problems briefly, although I acknowledge they are equally if not more important than the technological tool used. However, in the context of statistics and data analysis, a computational tool is necessary. There is simply no way to do data analysis without a computer, and the current tools leave a lot to be desired.

## 1.4 What is a tool?

One question I am often asked when discussing this work is why I use the term 'tool' to mean computer software or a programming language. Essentially, I am looking forward to a future where computers do more than just amplify human abilities – they enhance them (Pea, 1985). In the same way things we traditionally think of as tools (like hammers, levers, and sewing machines) allow us to do much more than we can do on our own, I believe computers are going to give us superpowers. Particularly in the context of data, where so much of it is high-dimensional, humans need some assistance 'seeing' the existing patterns.

## 1.5 The difference between users and creators

Throughout this work, I often reference the difference between being a 'user' of a tool and being a 'creator' of statistics. My use of these terms comes from the literature on equity in computer science education.

In her 2001 book "Unlocking the Clubhouse," Jane Margolis describes the difference between being a user of technology, which might include learning word processing software and typing skills, and being a creator of technology (Margolis and Fisher, 2001). In her book, she found women were less likely to be creators of technology than their male counterparts. Margolis followed this book by another, called "Stuck in the Shallow End," which presented similar results for minority students – minorities were less likely to have access to high school courses focused on creation (e.g., AP Computer Science) and more likely to take classes labeled as computer science but focused on using software (Margolis et al., 2008).

This distinction has continued to be forefronted in discussions of computer science education. In a 2014 article in Mother Jones, a National Science Foundation representative was quoted lamenting, "We teach our kids how to be consumers of technology, not creators of technology" (Raja, 2014).

In the realm of statistics education, there has been less explicit discussion of the difference between using statistics and statistical tools, and being a creator of statistical products. However, this distinction is crucial. Students are often taught statistics as a static set of formulas to be applied in particular situations. They may have a formal definition of a standard deviation memorized, and be able to apply a hypothesis test to some data, but they do not have deeper conceptual knowledge. With the recent focus on p-hacking (Head et al., 2015) and at least one journal banning the use of p-values (Trafimow and Marks, 2015), it is clear that even within the 'client disciplines' there is need for richer statistical understanding.

Being a 'creator' of statistics and statistical products requires a person to think creatively with data and to move through a cycle of exploration and confirmation with their data. In the context of a statistical tool, a creator of statistics should be able to build new methods and data visualizations based on existing functionality within the system.

## 1.6 Overview of the rest of the dissertation

This dissertation is a mash-up of case study, opinion piece, and provocative technology experiment.

Chapter 2 outlines the history of statistical programming, both for practitioners of statistics as well as for learners of statistics. Then it calls attention to the gap between tools for doing statistics and tools for learning statistics. The chapter ends with a call to action to close this gap by developing tools that can support a learning-to-doing trajectory.

Chapter 3 discusses existing tools and their success at spanning the gap, including Excel, R, TinkerPlots and Fathom, SAS, SPSS and STATA, as well as a number of bespoke data visualization tools.

Chapter 4 outlines requirements for future statistical programming tools, including the need for easy entry for novice users, interactivity at every level, and simple support for narrative, reproducibility, and publishing.

Chapter 5 discusses work I have done to close the gap between tools for teaching and learning statistics, and those for doing statistics. This chapter includes my work on the Mobilize project (the initial inspiration for this work), my joint work with Aran Lunzer of the Communications Design Group, called LivelyR, and two illustrative **Shiny** widgets I created to augment my teaching.

Chapter 6 brings these thoughts together, and outlines my vision for the future of this work. However, understanding this vision will take years to come to fruition, I also provide recommendations for best practices using currently-available tools.

We will be remiss in our duty to our students if we do not see that they learn to use the computer more easily, flexibly, and thoroughly than we ever have; we will be remiss in our duties to ourselves if we do not try to improve and broaden our own uses.

*John Tukey, 1965*

# CHAPTER 2

# The gap between tools for learning and for doing statistics

This chapter sets up the gap between tools for learning and tools for doing statistics. The current qualities of both types of tools were highly influenced by the time of their development and the specific goals the developers were considering. We begin by considering the history of tools for doing statistics, and follow with the history of tools for learning statistics. Looking at the diverging history makes it clear there is a gap between the two types of tools, so we consider the reasons (both educational and political) for the gap. Finally, I argue the gap should be eliminated in future tools.

## 2.1 History of tools for doing statistics

Many tools have been used for statistical computing over the years. It is not within the scope of this work to capture every one of them, but some of the largest stepping stones can be noted.

According to Jan De Leeuw, the history of statistical software packages began at UCLA in 1957 with the development of BMDP (De Leeuw, 2009). BDMP was part of the first generation of statistical software packages, the others being

SPSS and SAS, both introduced in 1968. The second generation includes Data Desk, JMP and STATA, all of which were developed in the 1980s (De Leeuw, 2009).

The next generation were the Lisp-inspired languages, S, LISP-STAT, and R (De Leeuw, 2009). Both S and LISP-STAT could be extended using Lisp, and R was based on Scheme, a dialect of Lisp. S was written by John Chambers in the 1970s when he grew frustrated with Fortran and developed S to provide more statistical power and flexibility (Becker, 1994).

The versions of S are often spoken of in terms of 'books' – the 'brown book' 'blue book' and 'white book' correspond with versions of S. The goal of S was initially to create an interactive functional programming language with a strong sense of data format (Becker, 1994). Initially, S was free to academics, but it was eventually sold to the Insightful corporation (De Leeuw, 2009) and now exists in the form of S-PLUS, sold by TIBCO Software, Inc.

However, R has essentially captured the former market of S and XLISP-STAT, at least in academia (De Leeuw, 2004). R was developed by Ross Ihaka and Robert Gentleman at the University of Auckland to provide an open-source alternative to S, incorporating features from both S and Scheme (De Leeuw, 2009; Ihaka and Gentleman, 1996). R is discussed in more detail in Section 3.8.

## 2.2 History of tools for learning statistics

Running parallel to the history of statistical programming tools is a trajectory of tools for making statistics easier for novices to understand. The history of tools for learning statistics is shorter than that of tools for doing statistics, in part because learning tools require more developed computer graphics, and also because there has been a long debate about whether computer tools are necessary for statistics education at all.

In 1997, Rolf Biehler described what he saw as the difference between tools for doing statistics and those for learning statistics (Biehler, 1997). Biehler distinguishes between tools (used for real statistical analysis), microworlds (interactive systems encouraging play), resources (including data and data documentation) and tutorial shells (he mentions Hypercard being used to create tutorial shells to interface with other software) (Biehler, 1997).

In the late 1990s, Minitab and Splus could provide functionality for creating microworlds, and were therefore commonly used in teaching. The other interfaces Bielher mentions are tutorial shells, including SUCROS, StatView, and Data Desk (Biehler, 1997). Interestingly, Data Desk is the one tool covered by both De Leeuw as a tool for statistical computing and by Biehler as a tool for teaching and learning statistics. It was developed in 1985, and has been maintained by its software publisher to this day (currently, the software is on version 7). The functionality is very inspiring in the context of the bridging I am considering, but the user interface looks antiquated compared to current tools.

In the context of the tools that existed in 1997, Biehler was arguing for a new type of software. He wanted a tool which would solve three problems: the complexity of tools for doing statistics, the challenge of closed microworlds, and the necessity of using many tools in order to cover a particular curricular trajectory (Biehler, 1997).

Biehler's paper expanded on the capabilities he believed were necessary for such a system, and his guidelines were used to develop TinkerPlots and Fathom in the early 2000s (Konold and Miller, 2005; Finzer, 2002a). Both tools are still in use today, and are discussed at more length in Section 3.4.

Since their development, TinkerPlots and Fathom have become extremely popular for teaching statistics in the K-12 context (Lehrer, 2007; Garfield and Ben-Zvi, 2008; Konold and Kazak, 2008; Watson and Fitzallen, 2010; Biehler et al., 2013; Finzer, 2013; Fitzallen, 2013; Mathews et al., 2013), at the introductory college level (Ben-Zvi, 2000; Garfield et al., 2002; Everson et al., 2008) and in training for teachers (Rubin, 2002; Biehler, 2003; Gould and Peck, 2004; Hammerman and Rubin, 2004; Rubin et al., 2006; Hall, 2008; Pfannkuch and Ben-Zvi, 2011).

The main alternatives to TinkerPlots and Fathom are browser applets (what Biehler might call microwords) like those by the five Locks (Morgan et al., 2014) or by Rossman and Chance (Chance and Rossman, 2006). Applets are described more fully in Section 3.5. In general, tools for learning statistics have not moved forward since the early 2000s, and have not kept up with modern statistical practice.

## 2.3 The gap between tools for learning and doing

Even the distinctions in the histories given by De Leeuw and Biehler suggest a dichotomy between tools for teaching and learning statistics, and those for legitimately doing statistics. De Leeuw explicitly states he is not concerned with "software for statistics"(De Leeuw, 2009) while Biehler is only interested in novices' ability to grasp a tool with minimal instruction (Biehler, 1997). Whatever your perspective, it is clear there is gap between these two types of tools. There are two main approaches taken with regard to the gap – either basing techniques for learning statistics on techniques for doing professional statistics, or using technology simply to illustrate statistical concepts (Biehler et al., 2013).

In fact, there are such distinct perspectives on this issue it is useful to have a visualization of their relationship, as seen in Figure 2.1. This figure shows the spectrum of opinions on the use of computers in education, from learning without a computer to learning with a tool specifically designed for students, to learning on a professional tool used by practitioners.

$$\begin{tikzcd}\text{No computer} \arrow[r] & \text{Tool for learning} \arrow[r] & \text{Professional tool}\end{tikzcd}$$

Figure 2.1: The spectrum of learning to doing

Interestingly, this spectrum is paralleled almost completely in the computer science education community, which has been studying novices' use of computers much longer than statisticians have. The question in computer science has been whether it is better for learners to begin on a simpler programming language or to start directly in a language used by experts.

In statistics, there are some educators who believe the mathematical underpinnings of statistics are sufficient to provide novices with an intuitive understanding of the discipline. Because of this, they do not find it imperative statistics education be accompanied by computation. In this paradigm, students learn basic concepts about sampling, distributions, and variability, and work through formulas by hand. At most, they use the computer to assist with their arithmetic calculations (statistical computation). This argument has two roots: one is some statisticians do not believe computers are necessary to do statistics, and the other is that even if doing real statistics requires a computer, students do not need to use one when they are first starting out. However, this is an unfortunate line of reasoning, because it prevents students from seeing real applications of statistics (i.e., the interesting stuff) until they have progressed to a second or third course.

One example to consider is the Advanced Placement Statistics course and associated exam. The AP Statistics teacher guide states "students are expected to use technological tools throughout the course," but goes on to say technological tools in this context are primarily graphing calculators (Legacy, 2008). Instead of building in computer work, the guide suggests exposing students to computer output so they can learn to interpret it.

Paralleling this argument in computer science, some experts believe students should begin learning about programming without a computer. For example, the website "CS Unplugged," promises "computer science ... without a computer!" (Bell et al., 2010). It provides lessons to get students working with physical materials to understand concepts of data representations, algorithms (e.g., sorting, ranking), and other basic topics. Even at more advanced levels there is argument for beginning programming projects outside the computer (Rongas et al., 2004). Computing great Edsger Dijkstra argues we should not teach students how to program in the current language de jour. Instead, we should require novices to write formal proofs of their programs so they understand the logic underpinning the computation (Dijkstra, 1989).

On the other side of the spectrum, much of the research on computer science education (particularly in the context of language acquisition) has been done on Java (Fincher and Utting, 2010; Kölling, 2010; Utting et al., 2010; Storey et al., 2003; Hsia et al., 2005). This is due to Java being the language of choice in AP Computer Science since 2003. The use of Java on the AP CS exam follows Pascal and C++, which were used previously. The choice to move from C++ to Java for the AP exam was based on the popularity of object-oriented languages (which both C++ and Java are) and the fact that Java is simpler to learn than C++.

All three of the languages that have been used for the AP exam are compiled, which means programmers write code and pass it through a 'compiler' to get a packaged piece of code that can be run by the computer. In contrast, 'interpreted' or 'scripting' languages allow dynamic work, typing code and running it piece-by-piece to see smaller results. These two paradigms (compiled and interpreted) can be used to describe nearly any programming language, and they are different in approach.

While both compiled and interpreted languages are 'real' programming languages, and the use of any real programming language in introductory computer science classes can be seen as an argument for the right end of the spectrum, compiled languages are generally considered to be tougher. So, it is interesting Java is used in AP Computer Science, while AP Statistics shies away from using a computer tool at all.

Additionally, recent efforts to increase diversity in computer science have found interpreted languages can be more accessible because they allow novices to get results more quickly (Alvarado et al., 2012). Almost all languages used for statistical computing are interpreted, which suggests they may be more accessible for learners than the alternative, but also makes it hard to apply the body of computer science education research (generally on compiled languages) to the problem.

The argument for teaching students a real programming language is that they will have a skill they can apply in the workforce or in college. This echoes the argument that students should learn to use statistical programming tools used by professionals.

Over time, there has been a movement toward students as true 'creators' of computational statistical work. Deb Nolan and Duncan Temple Lang argue well for this in their paper, "Computing in the statistics curriculum," where they suggest students should "compute with data in the practice of statistics" (Nolan and Temple Lang, 2010). They are promoting R, which is discussed in more detail in Section 3.8. Many universities and colleges are modifying their statistics courses to fall in line with Nolan and Temple Lang's recommendations, but to date, modifications have happened primarily at the graduate level and are still trickling down to the undergraduate level or below.

However, both in statistics and computer science, there is a middling perspective on the spectrum. This perspective holds students should be using computers to learn, but specialized tools should be developed specifically for learners.

In computer science, there is a field of programming languages developed particularly for novices. One of the earliest and most famous examples is Seymour Papert's LOGO language (Papert, 1979). Papert was a student of Piaget, the psychologist responsible for most current theories of childhood development. Using his knowledge of how children learn, Papert developed LOGO in the 1970s. It used 'turtle graphics,' so called because an icon of a turtle served as the cursor on the screen, and some implementations used a robotic turtle on the classroom floor. This was to allow students to 'see' themselves in the cursor, and all the directionality was in relation to the turtle (meaning 'up' wasn't necessarily the top of the screen, rather in the direction the turtle was pointed). This and many other features were carefully constructed based on child psychology.

More accessible and modern, Scratch has often been used as a first foray into programming (Resnick et al., 2009). It was implemented in Squeak, which is a dialect of Smalltalk. It is a blocks programming environment where students drag and drop elements together to create games, animations, or simple drawings. In the Exploring Computer Science curriculum (Section 5.1.3), Scratch is the most 'programming-like' element remaining.

After working with the language for a period of time, students will often find tasks they want to do that are not possible in Scratch. This realization can prompt them to dig further into the implementation in Squeak to modify things about the Scratch interface. However, this is not a natural transition, and something like the gap between tools for doing and teaching statistics can be seen here. The Scratch team is not interested in raising the ceiling of the tool. Instead, they are focused on lowering the threshold (making it easier to get started) and "widening the walls," providing more broad applications within the same simple framework (Resnick et al., 2009).

Another middling approach from computer science is the concept of language levels. In this paradigm, experts identify pieces of a programming language most crucial for beginners to understand, and fence off just those parts of the language. One version of this is called DrJava, and includes three levels (Elementary, Intermediate, Advanced) mimicking the Dreyfus and Dreyfus hierarchy of programming ability (novice, advanced beginner, competence, proficiency, expert) (Hsia et al., 2005). Students can move from one level to the next, learning additional features and concepts of the language. Usually, these levels are nested, meaning all the features learned in level one are also available in level two, and so on.

In the context of tools for learning statistics, a distinction is made between route-type and landscape-type tools (Bakker, 2002). Route-type tools drive the trajectory of learning, determining the tools available to students and the skills they should be using. Most applets are route-type tools, because they only allow for one concept to be explored. Landscape-type tools are less directive, and allow users to explore the field of possibilities themselves. TinkerPlots and Fathom are both landscape-type tools.

The route/landscape dichotomy is not paralleled well in computer science, as most programming tools are, by nature, landscape-type tools. However, while programming languages can be used to accomplish many tasks, they tend to obscure the range of tasks possible. Instead, users only consider the functions to which they have been exposed. Fathom and TinkerPlots make the landscape of possibilities more visible by arranging them in a palette of tools. While route-type tools for learning feel more restrictive, they can be appealing to teachers because they make it clear what students should be doing at any time, and limit the prior knowledge the teacher must bring to the classroom.

Novices who begin with a tool designed for learning – whether it is an applet or a full software package – encounter a lower barrier to entry, but there is still a cognitive task associated with learning how to use the interface. When they move on to additional statistical tasks, either in higher-level coursework or in the corporate world, they need more complex tools, and are forced to learn yet another interface. Unfortunately, because researchers have not studied this transition, at least in the context of statistics, there is little scaffolding to make the transition easier.

Instead, users are essentially returned to the novice state. Their experience with the learning tool presumably does not transfer well to their use of the tool for truly doing statistics. So in a sense, the effort to learn that initial tool is wasted. Alternatively, novices could be started immediately with a tool for doing statistics, which would allow them to skip the 'wasted' effort of learning to use an introductory tool, but would still incur the high startup costs of learning the tool. Whether beginning with a professional tool immediately or transitioning to it after a learning tool, the threshold for entry can be so high as to make users believe they are not capable of learning it.

There are many approaches that could be used to close this gap. For example, explicit curricular resources making reference to the prior tool and couching tasks in terminology from the previous system might make the transition easier. Likewise, providing some sort of 'ramping up' as users reach the end of the abilities of the learning tool and 'ramping down' at the beginning of the tool for doing could make the gap feel less abrupt.

## 2.4 Removing the gap

My argument is the gap between learning and doing statistics should be removed entirely by creating a new type of tool, bridging from a supportive tool for learning to an expressive tool for doing.

The belief there should be no gap between tools for learning and tools for doing statistics is not shared by everyone. In particular, Biehler's 1997 paper urges statisticians to take responsibility for developing appropriate tools for use in education, and Cliff Konold argues for the need for separate tools for these two cognitive tasks (Biehler, 1997; Konold, 2007). These arguments are summarized and expanded on by Susan Friel, who also believes students should not be using industry-standard tools (Friel, 2008). Instead, all three authors contend separate computer tools should be created with the specific goal of teaching students statistics.

I take issue with the idea of separate tools for teaching, as it removes novices from the experience of being true 'creators' of statistical products. As we will see in the more detailed analysis of tools, products like Fathom and TinkerPlots only allow users to work with data up to a certain size, and do not provide methods for sharing the results of analysis.

There are some aspects of the philosophies espoused by Biehler, Konold, and Friel I agree with. In particular, Konold says tools for learning statistics should not be stripped down versions of professional tools for doing statistics. Instead, they should be developed with a bottom-up perspective, thinking about what features novices need to build their understandings (Konold, 2007). In considering how to close the gap, it is important to keep in mind how tools can build novices' understanding from the ground up. Konold also emphasizes the importance of creating software that can grow beyond its initial static state (Konold, 2007). A tool that grows with users as they move from learning to doing is a large proposition, but I believe this goal can (and should) be met with a tool spanning the entire trajectory of experiences.

The rest of this work is concerned with methods for closing the gap. Next, we consider the existing tools on the market and how well they succeed at supporting the learning-to-doing trajectory.

Professional statistical systems are very complex and call for high cognitive entry cost. They are often not adequate for novices who need a tool that is designed from their bottom-up perspective of statistical novices and can develop in various ways into a full professional tool (not vice versa).

*Rolf Biehler, 1997*

# CHAPTER 3

# The current landscape of statistical tools

This chapter describes the landscape of currently-available statistical tools, from the prosaic (Excel) to the bespoke (Wrangler, Lyra). Keeping in mind the gap between tools for learning and tools for doing statistics, we consider the features of each tool most relevant to closing the gap. Many positive examples are shown (the bespoke tools provide particular inspiration) but negative examples are also examined.

The tools currently available for learning and doing statistics generally break along that particular divide: those good for an introductory learner are generally not good for actually performing data analysis, and vice versa. However, since any user of software for doing statistics must necessarily begin as a novice, it is logical there should be a coherent trajectory for learners to take.

My interest in the gap between tools for learning statistics and those for doing statistics grew out of my experience with the Mobilize project (Section 5.1) where we have iterated through a variety of tools over the years. The experience of trying many statistical programming tools with learners led me to research others that were available, in search of the ideal tool.

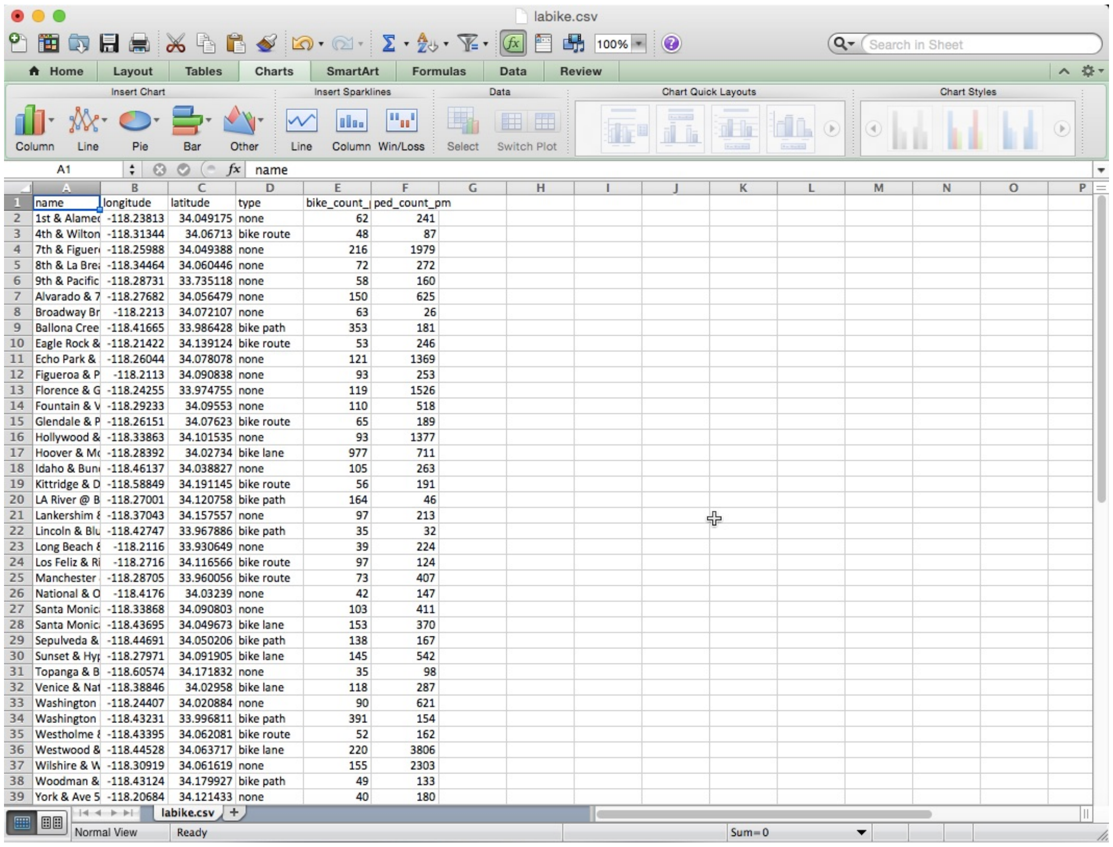
While there is rarely an ideal tool for anything, through examining the available software, programming languages, and packages, I began to see ways in which the gap could be filled.

## 3.1 Spreadsheets

Spreadsheet tools like Excel are probably the most commonly used to do data analysis by people across a broad swath of use-cases (see Figure 3.1 for a screenshot of Microsoft Excel for Mac 2011). Because of their common use, and the free availability of spreadsheet tools like Google Spreadsheets and the Open Office analogue of Excel, Sheets, they can be considered an accessible and equitable tool.

However, spreadsheets lack the functionality to be a true tool for statistical programming. They typically allow for only limited scripting, which means their capabilities are limited to those built in by the development company. The locked-in nature of the functionality means they are only able to provide a limited number of analysis and visualization methods, and cannot be flexible enough to allow for true creativity. The toolbar in Figure 3.1 shows the possible visualization methods available in this version of Excel. The categories can be counted on one hand, although each category does have further modifications that can be expanded using the disclosure widget located on the button.

Beyond this, several high profile cases of scientific paper retraction have been based on internal errors within Excel. Because the underlying code is closed-source, Excel does not allow users to view how methods are implemented, which means it is very difficult for an individual to assess the validity of the internal code. Some dedicated researchers have tested Excel's statistical validity over every software version Microsoft has released. Not only is every version flawed,



labike.csv

A1 name

| | A | B | C | D | E | F |
|---|---|---|---|---|---|---|
| 1 | name | longitude | latitude | type | bike_count_ | ped_count_pm |
| 2 | 1st & Alamec | -118.23813 | 34.049175 | none | 62 | 241 |
| 3 | 4th & Wilton | -118.31344 | 34.06713 | bike route | 48 | 87 |
| 4 | 7th & Figuer | -118.25988 | 34.049388 | none | 216 | 1979 |
| 5 | 8th & La Bre | -118.34464 | 34.060446 | none | 72 | 272 |
| 6 | 9th & Pacific | -118.28731 | 33.735118 | none | 58 | 160 |
| 7 | Alvarado & 7 | -118.27682 | 34.056479 | none | 150 | 625 |
| 8 | Broadway Br | -118.2213 | 34.072107 | none | 63 | 26 |
| 9 | Ballona Cree | -118.41665 | 33.986428 | bike path | 353 | 181 |
| 10 | Eagle Rock & | -118.21422 | 34.139124 | bike route | 53 | 246 |
| 11 | Echo Park & | -118.26044 | 34.078078 | none | 121 | 1369 |
| 12 | Figueroa & P | -118.2113 | 34.090838 | none | 93 | 253 |
| 13 | Florence & G | -118.24255 | 33.974755 | none | 119 | 1526 |
| 14 | Fountain & V | -118.29233 | 34.09553 | none | 110 | 518 |
| 15 | Glendale & P | -118.26151 | 34.07623 | bike route | 65 | 189 |
| 16 | Hollywood & | -118.33863 | 34.101535 | none | 93 | 1377 |
| 17 | Hoover & Mc | -118.28392 | 34.02734 | bike lane | 977 | 711 |
| 18 | Idaho & Bun | -118.46137 | 34.038827 | none | 105 | 263 |
| 19 | Kittridge & D | -118.58849 | 34.191145 | bike route | 56 | 191 |
| 20 | LA River @ B | -118.27001 | 34.120758 | bike path | 164 | 46 |
| 21 | Lankershim & | -118.37043 | 34.157557 | none | 97 | 213 |
| 22 | Lincoln & Blu | -118.42747 | 33.967886 | bike path | 35 | 32 |
| 23 | Long Beach & | -118.2116 | 33.930649 | none | 39 | 224 |
| 24 | Los Feliz & Ri | -118.2716 | 34.116566 | bike route | 97 | 124 |
| 25 | Manchester | -118.28705 | 33.960056 | bike route | 73 | 407 |
| 26 | National & O | -118.4176 | 34.03239 | none | 42 | 147 |
| 27 | Santa Monic | -118.33868 | 34.090803 | none | 103 | 411 |
| 28 | Santa Monic | -118.43695 | 34.049673 | bike lane | 153 | 370 |
| 29 | Sepulveda & | -118.44691 | 34.050206 | bike path | 138 | 167 |
| 30 | Sunset & Hyp | -118.27971 | 34.091905 | bike lane | 145 | 542 |
| 31 | Topanga & B | -118.60574 | 34.171832 | none | 35 | 98 |
| 32 | Venice & Nat | -118.38846 | 34.02958 | bike lane | 118 | 287 |
| 33 | Washington | -118.24407 | 34.020884 | none | 90 | 621 |
| 34 | Washington | -118.43231 | 33.996811 | bike path | 391 | 154 |
| 35 | Westholme & | -118.43395 | 34.062081 | bike route | 52 | 162 |
| 36 | Westwood & | -118.44528 | 34.063717 | bike lane | 220 | 3806 |
| 37 | Wilshire & W | -118.30919 | 34.061619 | none | 155 | 2303 |
| 38 | Woodman & | -118.43124 | 34.179927 | bike path | 49 | 133 |
| 39 | York & Ave 5 | -118.20684 | 34.121433 | none | 40 | 180 |

Figure 3.1: Microsoft Excel for Mac 2011

but even with specific attention shed on the problem, Microsoft often either fails to repair the problem, or makes a change to another flawed version (McCullough and Heiser, 2008).

Additionally, spreadsheets tend not to privilege data as a complete object. Once a data file is open, modification or deletion of data values is just a click away. In this paradigm, the sanctity of data is not preserved and original data can be lost forever. In contrast, most statistical tools discourage direct manipulation of original data. In tools used by practitioners to do statistical analysis (e.g., R, SAS), data is an almost sacred object, and users are only given a copy of the data to work with.

Data does not have structural integrity in a spreadsheet. Data values sit next to blocks of text and plots produced by data cover up data cells. Everything is included on one canvas. These pieces may be linked together, but there is no explicit visual connection. In a true statistical tool, results from the analysis are clearly separated from the data from which they were derived, and any data cleaning tasks performed in these tools can be easily documented.

This leads to the largest challenge with spreadsheets: their results are not reproducible. Data journalists have historically done analysis using tools like Excel (Plaue and Cook, 2015). Journalists must be careful about the analysis they publish, as it it must to be as verified as any other 'source' they might interview. Spreadsheets do not offer any inherent documentation. As a result, journalists developed their own reproducibility documentation, typically in the form of a document written in parallel with the analysis describing all the steps taken. This supplementary document is done separately, either by hand or in word processing software like Microsoft Word.

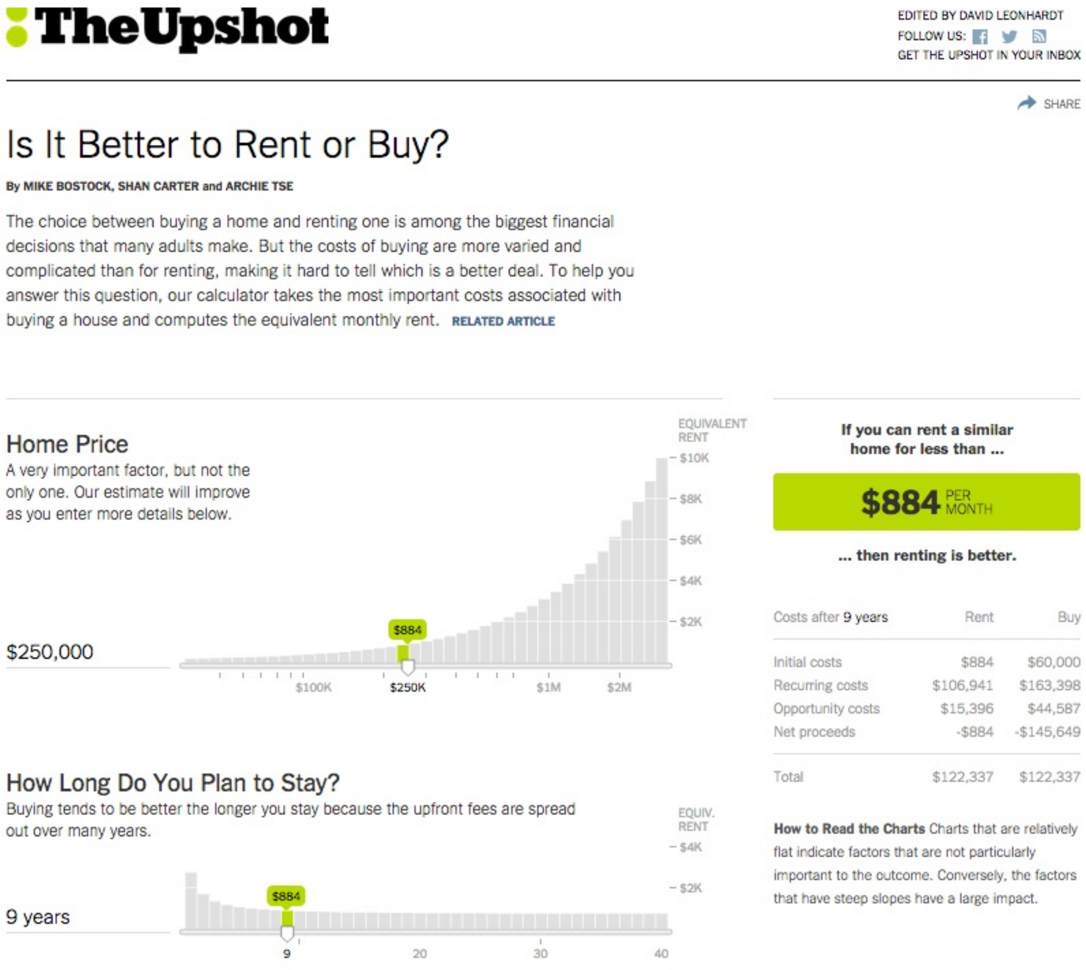
Because each stage of analysis in a spreadsheet is done by clicking and dragging, there is no way to fully record all the actions taken. Reproducibility is discussed more fully in Section 4.8, but one of its central tenets is it should be possible to perform the same analysis on slightly different data (e.g., from a different year). Spreadsheets do not make this possible, so they are not effective tools for data analysis.

However, the spreadsheet paradigm is not inherently troublesome. In fact, Alan Kay believes computer operating systems should essentially be spreadsheets, all the way down (Kay, 1984). The distinction is when Kay references spreadsheets, he is thinking of a reactive programming environment that can be built up into responsive tools to perform a wide variety of tasks. In this paradigm, objects can be linked together in a dependent structure, and whenever an input is changed, all the downstream elements are updated accordingly.

Of course, the reactive possibilities in spreadsheets can also lead to unintended consequences. In a study of spreadsheets used by Enron, researchers found 24% of spreadsheets with a formula included an error (Hermans and Murphy-Hill, 2015). This is likely because while spreadsheets allow for reactive linking of cells, they do not visualize the reactive connections, and it can be easy to double a formula or include unintended cells. The reactive programming environment **Shiny** (Section 3.8.2.3) showcases some of the capabilities of this paradigm in a more reproducible data analysis environment.

## 3.2 Interactive data visualizations

If the average person has interacted with interesting data sets, it was likely in the context of an interactive data visualization. The New York Times produces some especially salient examples. The Times makes a point to create visualizations for the web that are much more than electronic versions of print graphics. Instead of static graphics, their visualizations allow readers to manipulate representations of data themselves. For example, the Times has produced graphics allowing readers to balance the federal budget, predict which way states will vote in the presidential election, or assess whether they would save more money by buying or renting their housing (Carter et al., 2010; New York Times, 2012; Bostock et al., 2014). The graphic companion to the article on buying versus renting, Figure 3.2, allows users to drag sliders on a variety of graphs to determine whether it is better for them to rent or buy, given the particular set of parameters.



TheUpshot

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Is It Better to Rent or Buy?

By MIKE BOSTOCK, SHAN CARTER and ARCHIE TSE

The choice between buying a home and renting one is among the biggest financial decisions that many adults make. But the costs of buying are more varied and complicated than for renting, making it hard to tell which is a better deal. To help you answer this question, our calculator takes the most important costs associated with buying a house and computes the equivalent monthly rent. RELATED ARTICLE

Home Price
A very important factor, but not the only one. Our estimate will improve as you enter more details below.

$250,000

How Long Do You Plan to Stay?
Buying tends to be better the longer you stay because the upfront fees are spread out over many years.

9 years

If you can rent a similar home for less than ...

$884 PER MONTH

... then renting is better.

| Costs after 9 years | Rent | Buy |
|---|---|---|
| Initial costs | $884 | $60,000 |
| Recurring costs | $106,941 | $163,398 |
| Opportunity costs | $15,396 | $44,587 |
| Net proceeds | -$884 | -$145,649 |
| Total | $122,337 | $122,337 |

**How to Read the Charts** Charts that are relatively flat indicate factors that are not particularly important to the outcome. Conversely, the factors that have steep slopes have a large impact.

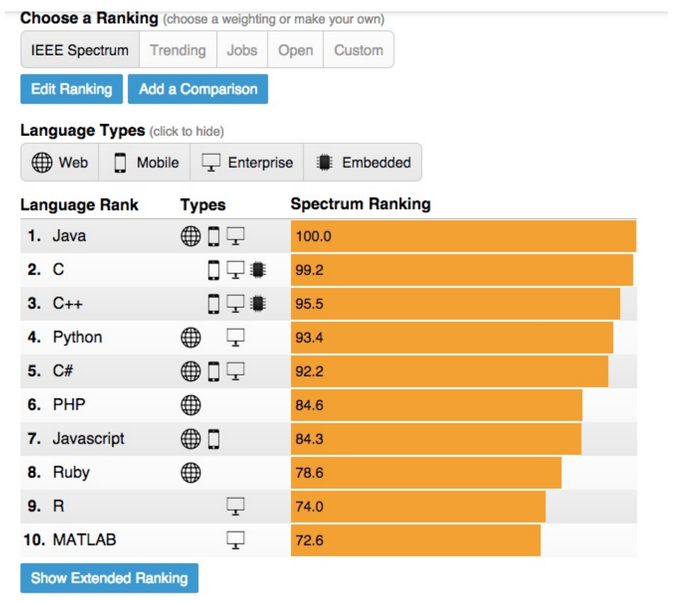
Figure 3.2: “Is it better to rent or buy?” from The Upshot

The paradigm of interactive data visualizations on the web is beginning to approach the concept of the “active essay” (Yamamiya et al., 2009). Like active essays, interactive articles on the web can be updated dynamically depending on parameter manipulations, and some news outlets have begun including contextual information in their articles. Rather than hyperlinks taking the user away from the page they were reading, New York Magazine includes ephemeral popovers, and Medium has instituted in-context comments linked to a particular paragraph or sentence.

Interactive data visualizations of the type done by the Times are helping us move toward broader statistical literacy, but they are lacking on a number of levels. First, many people do not have the quantitative skills to interpret statistical graphics, despite this literacy becoming more crucial (Meirelles, 2011).

Then, even if a reader is able to interpret the graphics, visualizations tend to be highly scripted. This scripted quality is actually valued in data visualization, because visualizations should provide some context and storytelling for the data, rather than simply leaving users to explore (Cairo, 2013). But the script can also be limiting. If a reader is looking at a graphic about renting and buying in the United States, she cannot easily compare the data in other countries. She also cannot access the demographic data to determine how many people fell into her particular demographic category. And there is no way to explicitly validate the authors' analysis, other than completely reproducing it. In short, a reader is limited to exploring the story the journalists have provided. For true democratic data access, citizens need to be able to analyze raw data sources.

Some interactive data visualizations have been opening the hood on the analysis process, allowing readers to critique the creation process or algorithmic decisions. One notable example is the 2014 IEEE Spectrum rating of programming languages, shown in Figure 3.3. The article provides a default ranking (shown in Figure 3.3a), but it allows readers to create a custom ranking by adjusting the weights of all the data inputs (Figure 3.3b) (Cass et al., 2014). It is possible to imagine a future where all journalistic products based on data are accompanied by this type of auditable representation of the process used to create them.



**Choose a Ranking** (choose a weighting or make your own)

IEEE Spectrum | Trending | Jobs | Open | Custom

Edit Ranking | Add a Comparison

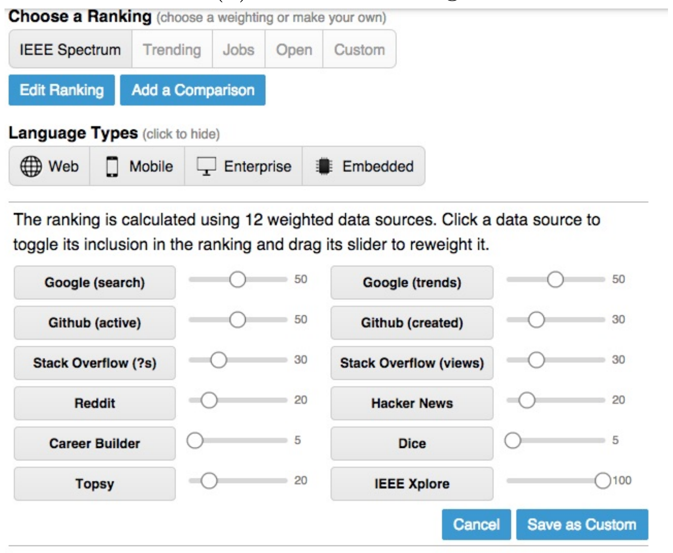
**Language Types** (click to hide)

🌐 Web | 📱 Mobile | 🖥 Enterprise | ▪ Embedded

| Language Rank | Types | Spectrum Ranking |
|---|---|---|
| 1. Java | 🌐 📱 🖥 | 100.0 |
| 2. C | 📱 🖥 ▪ | 99.2 |
| 3. C++ | 📱 🖥 ▪ | 95.5 |
| 4. Python | 🌐 🖥 | 93.4 |
| 5. C# | 🌐 📱 🖥 | 92.2 |
| 6. PHP | 🌐 | 84.6 |
| 7. Javascript | 🌐 📱 | 84.3 |
| 8. Ruby | 🌐 | 78.6 |
| 9. R | 🖥 | 74.0 |
| 10. MATLAB | 🖥 | 72.6 |

Show Extended Ranking

(a) Default ranking



**Choose a Ranking** (choose a weighting or make your own)

IEEE Spectrum | Trending | Jobs | Open | Custom

Edit Ranking | Add a Comparison

**Language Types** (click to hide)

🌐 Web | 📱 Mobile | 🖥 Enterprise | ▪ Embedded

The ranking is calculated using 12 weighted data sources. Click a data source to toggle its inclusion in the ranking and drag its slider to reweight it.

| | | | |
|---|---|---|---|
| Google (search) | 50 | Google (trends) | 50 |
| Github (active) | 50 | Github (created) | 30 |
| Stack Overflow (?s) | 30 | Stack Overflow (views) | 30 |
| Reddit | 20 | Hacker News | 20 |
| Career Builder | 5 | Dice | 5 |
| Topsy | 20 | IEEE Xplore | 100 |

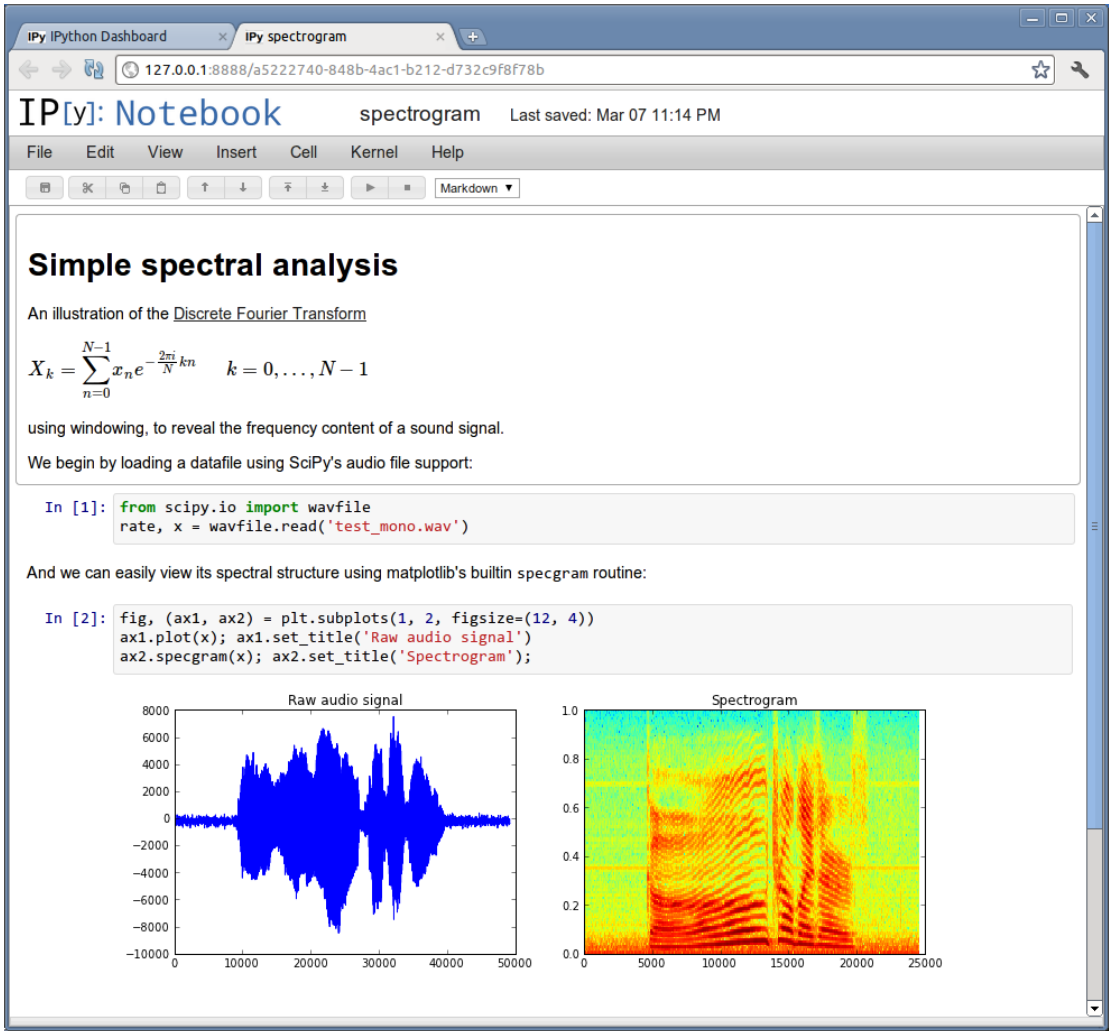
Cancel | Save as Custom

(b) Ranking editor

Figure 3.3: IEEE Spectrum ranking of programming languages

## 3.3 iPython notebook/Project Jupyter

The iPython notebook is a movement toward both more reproducible research and interactive analysis output. The iPython notebook environment (Figure 3.4) allows a user to combine text and Python code, and to immediately see the output from the code chunks (Pérez and Granger, 2007).



Simple spectral analysis

An illustration of the Discrete Fourier Transform

$$X_k = \sum_{n=0}^{N-1} x_n e^{-\frac{2\pi i}{N} kn} \qquad k = 0, \dots, N-1$$

using windowing, to reveal the frequency content of a sound signal.

We begin by loading a datafile using SciPy's audio file support:

```
In [1]: from scipy.io import wavfile
        rate, x = wavfile.read('test_mono.wav')
```

And we can easily view its spectral structure using matplotlib's builtin `specgram` routine:

```
In [2]: fig, (ax1, ax2) = plt.subplots(1, 2, figsize=(12, 4))
        ax1.plot(x); ax1.set_title('Raw audio signal')
        ax2.specgram(x); ax2.set_title('Spectrogram');
```

Figure 3.4: iPython notebook

When authoring an iPython notebook, it is possible to execute each of the code chunks separately, allowing the author to perform interactive manipulation during the creation process. The system also provides the capability to create interactive graphics, so if the author has decided to include them readers can interact with selected graphics.

However, once the notebook is published or shared, the ability to execute code is removed, and the only interactive elements are those programmed in by the author. Instead, all code and output is presented as a static file, which prevents readers from manipulating it. If a reader wants to modify the code, they must download the source code, edit it, and then re-share the results.

The iPython notebook project is currently under transition to become part of Project Jupyter, a larger umbrella project focused on scientific computation more generally. Just recently, GitHub[1] announced that Jupyter notebooks will render directly on their site. This frees notebook authors from the necessity of hosting their notebooks elsewhere in order to share them.

The iPython notebook and Project Jupyter represent some movement toward the goals of interactive and reproducible analysis (like the scenarios discussed in Sections 3.2 and 4.8), but will require more work toward fully interactive notebooks that can be manipulated by readers.

## 3.4 TinkerPlots and Fathom

Specifically designed for learning statistics, TinkerPlots and Fathom are essentially sibling software packages. The two have similar functionality and slightly different intended users. TinkerPlots is described as being appropriate for students from 4th grade up to university, and Fathom is directed at secondary school and introductory college levels.

Both TinkerPlots and Fathom are excellent tools for novices to use when learning statistics. They comply with nearly all the specifications outlined by

[1]A code sharing website supporting collaborative coding projects and the version control software `git`.

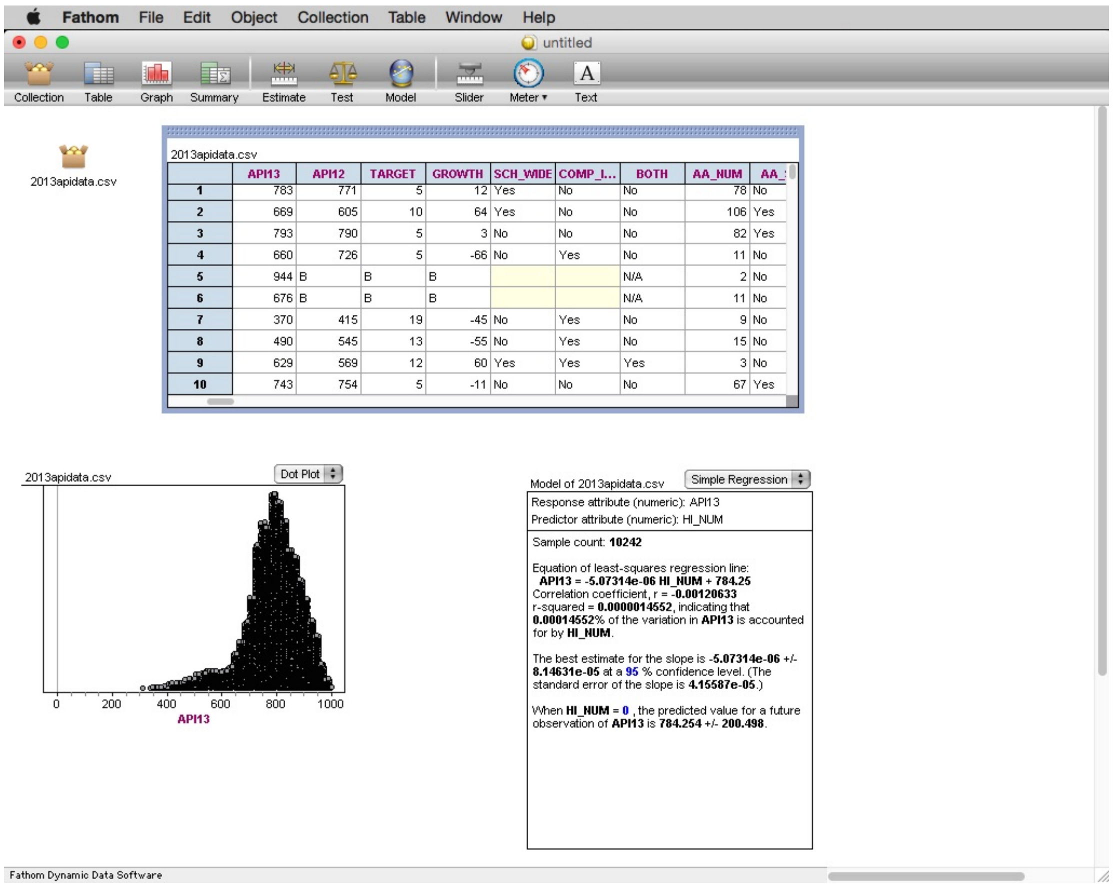
Biehler (1997), allowing for flexible plotting, providing a low threshold, and encouraging play and re-randomization. They allow students to jump right in, to perform exploratory data analysis and to move through a data analytic cycle (e.g., asking questions, trying to answer them, re-forming questions), and have been shown to enhance student understanding (Watson and Donne, 2009).

TinkerPlots and Fathom are both standalone software, which means they must be installed directly on a user's computer. They both offer versions for Macintosh and Windows computers. Clicking on the application icon will launch a blank canvas, with buttons and menus to support loading data, plotting, resampling, and more.

Fathom (Figure 3.5) was developed by William Finzer as tool for learning statistics (Finzer, 2002a). It was based on principles from Biehler (1997), and intended to allow students play with statistical concepts in a more creative way. Like Seymour Papert and his LOGO language, discussed in Section 2.3, the authors of Fathom and TinkerPlots wanted to design tools relevant to the way students think. Because Fathom is intended for slightly older users, it includes more features than TinkerPlots does.

Finzer was working from the perspective of a designer of education software rather than an education researcher. Therefore, he was solving a design problem rather than a research problem (Finzer, 2002b). He notes the development process could have benefited from more input from education researchers, but the resulting software has been reasonably useful regardless (Finzer, 2002b). He also mentions one of the largest challenges with developing education software (or software in general)– how to know if it 'works' (Finzer, 2002b).

The design specs upon which Fathom is based include a focus on resampling, a belief there should be no modal dialog boxes, the location of controls outside the document proper, and animations to illustrate what is happening (Finzer, 2002b). Many of these ideas are also brought forward in Chapter 4.



2013apidata.csv

| | API13 | API12 | TARGET | GROWTH | SCH_WIDE | COMP_I... | BOTH | AA_NUM | AA_ |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 783 | 771 | 5 | 12 | Yes | No | No | 78 | No |
| 2 | 669 | 605 | 10 | 64 | Yes | No | No | 106 | Yes |
| 3 | 793 | 790 | 5 | 3 | No | No | No | 82 | Yes |
| 4 | 660 | 726 | 5 | -66 | No | Yes | No | 11 | No |
| 5 | 944 | B | B | B | | | N/A | 2 | No |
| 6 | 676 | B | B | B | | | N/A | 11 | No |
| 7 | 370 | 415 | 19 | -45 | No | Yes | No | 9 | No |
| 8 | 490 | 545 | 13 | -55 | No | Yes | No | 15 | No |
| 9 | 629 | 569 | 12 | 60 | Yes | Yes | Yes | 3 | No |
| 10 | 743 | 754 | 5 | -11 | No | No | No | 67 | Yes |

Model of 2013apidata.csv

Response attribute (numeric): API13
Predictor attribute (numeric): HI_NUM

Sample count: **10242**

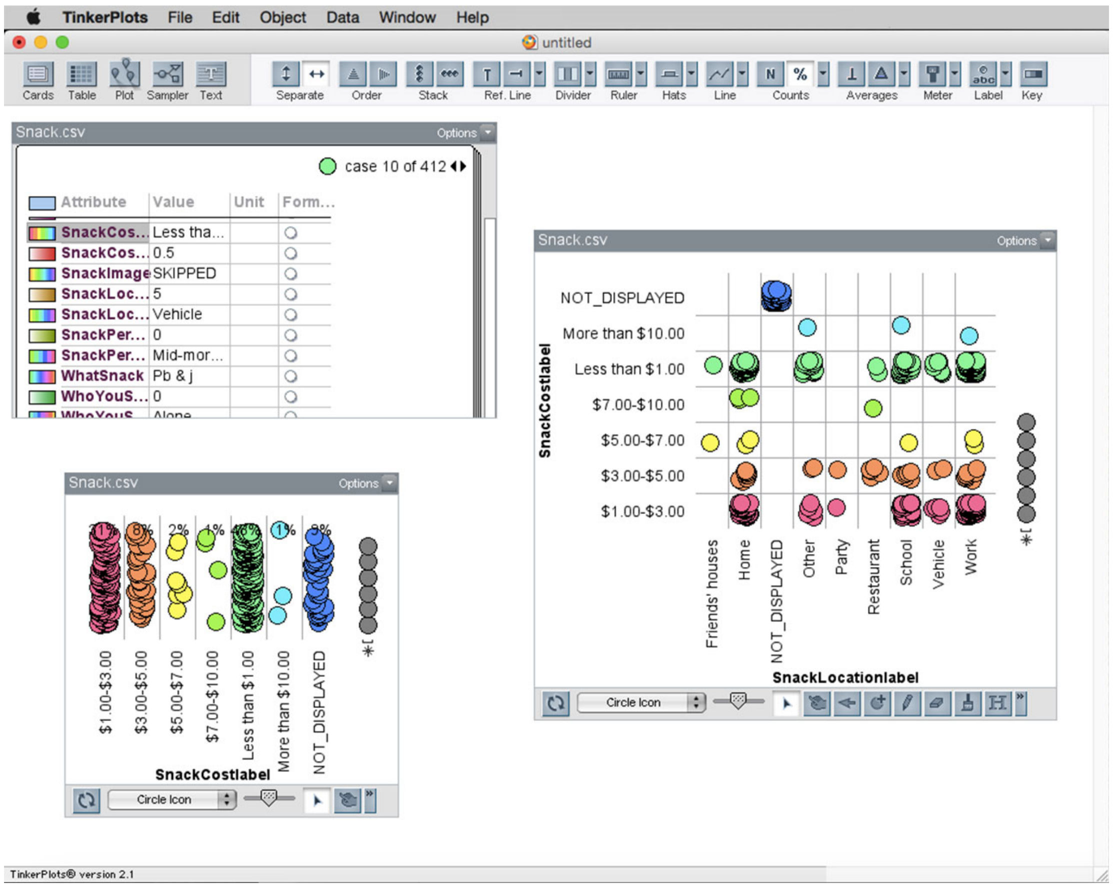
Equation of least-squares regression line:
**API13 = -5.07314e-06 HI_NUM + 784.25**
Correlation coefficient, r = **-0.00120633**
r-squared = **0.0000014552**, indicating that **0.00014552**% of the variation in **API13** is accounted for by **HI_NUM**.

The best estimate for the slope is **-5.07314e-06** +/- **8.14631e-05** at a **95** % confidence level. (The standard error of the slope is **4.15587e-05**.)

When **HI_NUM** = **0** , the predicted value for a future observation of **API13** is **784.254** +/- **200.498**.

Figure 3.5: Fathom version 2.13

The TinkerPlots graphical user interface (Figure 3.6) was designed by a team led by Clifford Konold, a psychologist focused on statistics education (Konold and Miller, 2005). TinkerPlots was built on Fathom's infrastructure, but designed for younger students. TinkerPlots was developed the same year as the GAISE guidelines (Franklin et al., 2005), and the connection between the cognitive tasks TinkerPlots makes possible and the A and B levels of the guidelines is clear. TinkerPlots includes probability modeling, but no standard statistical models (e.g. linear regression). It supports students through the development of more abstract representations of data (discussed further in Section 4.4). Users can develop their own simulations and link components together to see how changing elements in one area will impact the outcome somewhere else.



| Attribute | Value | Unit | Form... |
|---|---|---|---|
| SnackCos... | Less tha... | | ○ |
| SnackCos... | 0.5 | | ○ |
| SnackImage | SKIPPED | | ○ |
| SnackLoc... | 5 | | ○ |
| SnackLoc... | Vehicle | | ○ |
| SnackPer... | 0 | | ○ |
| SnackPer... | Mid-mor... | | ○ |
| WhatSnack | Pb & j | | ○ |
| WhoYouS... | 0 | | ○ |
| WhoYouS... | Alone | | ○ |

Figure 3.6: TinkerPlots version 2.0

As mentioned in Section 2.2, TinkerPlots and Fathom have a large market share when it comes to teaching introductory statistics, both at the K-12 and university levels (Lehrer, 2007; Garfield and Ben-Zvi, 2008; Konold and Kazak, 2008; Watson and Fitzallen, 2010; Biehler et al., 2013; Finzer, 2013; Fitzallen, 2013; Mathews et al., 2013; Ben-Zvi, 2000; Garfield et al., 2002; Everson et al., 2008). Past their design principles, both tools were popular for their reasonable pricing strategy, which made it possible for schools to afford licenses. However, while they are commonly used by forward-thinking educators, their market saturation cannot begin to compare with the TI calculators, which are familiar to every high school student, particularly those taking the AP Statistics exam.

For educators who want to teach concepts like randomization and data-driven inference, the primary competitors at this level are applets. TinkerPlots and Fathom have a number of advantages over applets. Most importantly, TinkerPlots and Fathom allow students to use whatever data they want, rather than demonstrating data on one locked-in data set. The systems come with pre-loaded data sets, but it is easy to open other data and use it in the same way.

However, even with the popularity of TinkerPlots and Fathom in the statistics education community, their future was not always certain. McGraw Hill Education, the publishing company which owned and distributed TinkerPlots and Fathom, decided in 2013 to discontinue carrying the software products. After discontinuing their corporate support, McGraw Hill returned the licensing to the tools' original creators, Konold and Finzer. Konold and Finzer provided temporary versions free of charge, and as of 2015 have found new publishers. TinkerPlots will be distributed by Learn Troop, and Fathom by the Concord Consortium (the research group with which Finzer is associated).

While both TinkerPlots and Fathom provide good support for novices, there are drawbacks to using them, even in an educational context. All the arguments discussed in Section 2.3 about the gap between tools for learning and tools for doing apply. In particular, even though using these tools requires the use of a computer, they do not necessarily require students to be producers of statistics. Instead, users can become focused on learning the interface to the software and the language surrounding the various buttons. Users may learn statistical concepts, but they are not developing any “computational thinking” or programming proficiency.

Fathom was developed in 2002, and TinkerPlots in 2005. In the 10 years since their respective releases, statistical programming has moved forward in ways these software have not. For example, while few would expect novices to be working with ‘big data’ in the truest sense of the term, TinkerPlots can only deal with data up to a certain size. A trial using a dataset with 12,000 observations and 20 variables caused considerable slowing, while larger datasets caused the program to hang indefinitely. Fathom dealt with the same data much more easily, but still had a noticeable delay loading and manipulating the data.

While both software packages allow for the inclusion of text in the workspace, there is no way to develop a data analysis narrative. The more free-form workspace can feel creative, but it makes it nearly impossible to reproduce analysis, even using an existing file. There is no easy way to publish results from these programs. The proprietary file types (.tp for TinkerPlots and .ftm for Fathom) need the associated software in order to be run interactively, and the only way to produce something viewable without the application is to ‘print’ the screen.

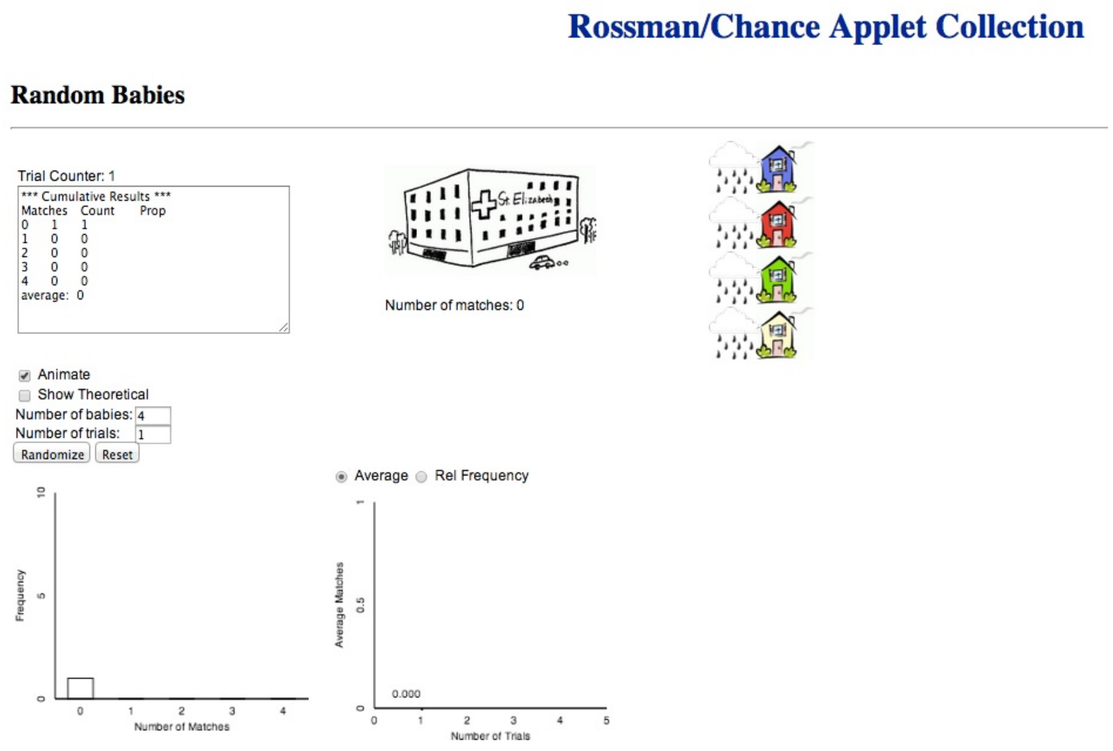
Again, because the software is closed-source, neither TinkerPlots nor Fathom are extendable in any way. What you see is what you get. This becomes particularly problematic when it comes to modern modeling techniques. For example, in the Introduction to Data Science class developed for high school students through the Mobilize grant (discussed in Section 5.1), students use classification and regression trees, and perform k-means classification. Those methods are not available in either software package, and cannot be added. In fact, TinkerPlots has no standard statistical models, which means it cannot be used for real data analysis tasks. It is truly only a tool for learning. Fathom, which is designed for slightly older students, does provide limited modeling functionality in the form of simple linear regression and multiple regression.

In the context of Clifford Konold's argument that tools for learning should be completely separate from tools for doing (Konold, 2007), it makes sense there are limits to these tools. They were consciously designed to be separate. However, given the capabilities of modern computing, it should be possible to provide this ground-up entry while still supporting more extensibility. Through the attributes listed in Chapter 4, we will explore how this balance could be met.

## 3.5 Applets

Applets pose the most direct competition to TinkerPlots and Fathom in introductory statistics courses. Statistics applets will illustrate one concept through the use of a specialized interactive web tool. They are highly accessible because they are hosted online, and they are free to use.

Some of the best applets were designed by statistics educators Alan Rossman and Beth Chance (Chance and Rossman, 2006). One of their applets (Figure 3.7) allows students to discover randomization by working through a scenario about randomly assigning babies at the hospital. The applet asks the question, if we randomly assign four babies to four homes, how often do they end up in the home to which they belong? The user can watch the randomization happen once, as a stork flies across the screen to deliver the babies to their color-coded homes, and then accelerate the illustration to see what the distribution would look like if one tried the same experiment many times. Students can use checkboxes to turn the animation on or off, or to see the theoretical probabilities. They can also try again with a different number of babies or a different number of trials.


Rossman/Chance Applet Collection

Random Babies

Trial Counter: 1

```
*** Cumulative Results ***
Matches  Count   Prop
0    1    1
1    0    0
2    0    0
3    0    0
4    0    0
average:  0
```

Number of matches: 0

[✓] Animate
[ ] Show Theoretical
Number of babies: 4
Number of trials: 1

Figure 3.7: A Rossman Chance applet demonstrating randomization

Another popular applet set was developed by the Lock5 group. This set of applets is called StatKey and accompanies the textbook the Locks have authored (Lock et al., 2012; Morgan et al., 2014).

In Figure 3.8, a StatKey applet for a bootstrap confidence interval for a mean is shown. This example does not include an animation like the stork featured in the Rossman Chance example, but users can still specify how many samples they want to take, stepping through one sample at a time, or accelerating the process by clicking the "generate 1000 samples" button.

Applets can be useful for students to learn distinct concepts like randomization, but they can also be frustrating when students want to do things just outside the scope of the applet. The Rossman and Chance applets include many concepts, but very few of them let users import their own data. The

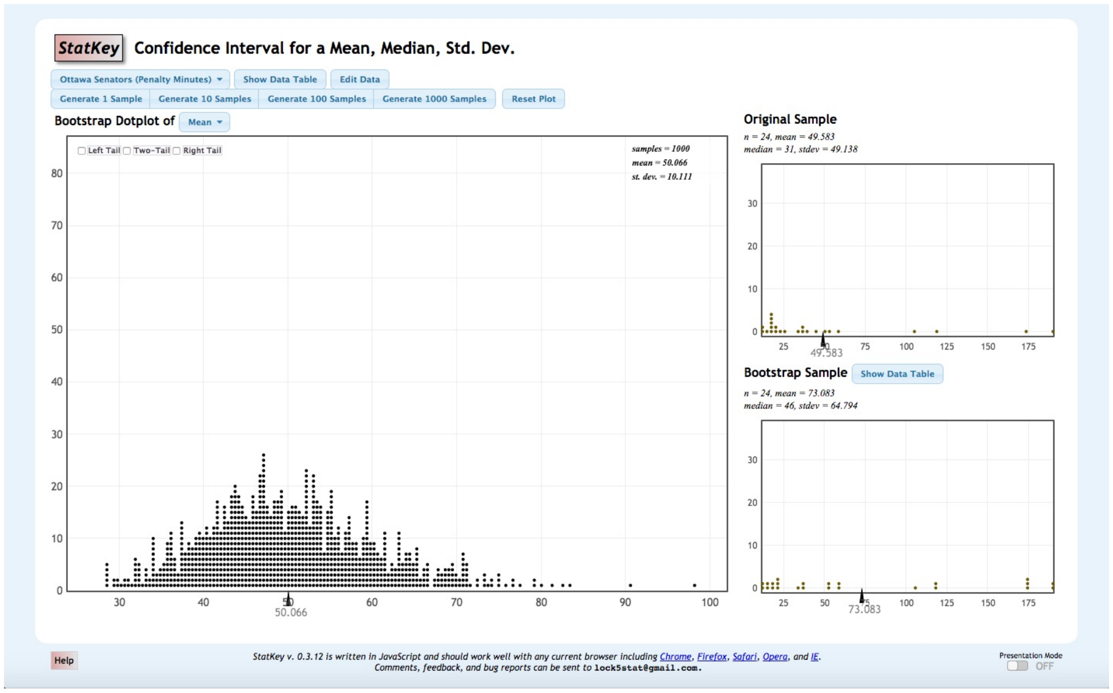

StatKey
Confidence Interval for a Mean, Median, Std. Dev.
Ottawa Senators (Penalty Minutes)
Show Data Table
Edit Data
Generate 1 Sample
Generate 10 Samples
Generate 100 Samples
Generate 1000 Samples
Reset Plot
Bootstrap Dotplot of
Mean
Left Tail
Two-Tail
Right Tail
samples = 1000
mean = 50.066
st. dev. = 10.111
50.066
Original Sample
n = 24, mean = 49.583
median = 31, stdev = 49.138
49.583
Bootstrap Sample
n = 24, mean = 73.083
median = 46, stdev = 64.794
73.083
Help
StatKey v. 0.3.12 is written in JavaScript and should work well with any current browser including Chrome, Firefox, Safari, Opera, and IE.
Comments, feedback, and bug reports can be sent to lock5stat@gmail.com.
Presentation Mode
OFF

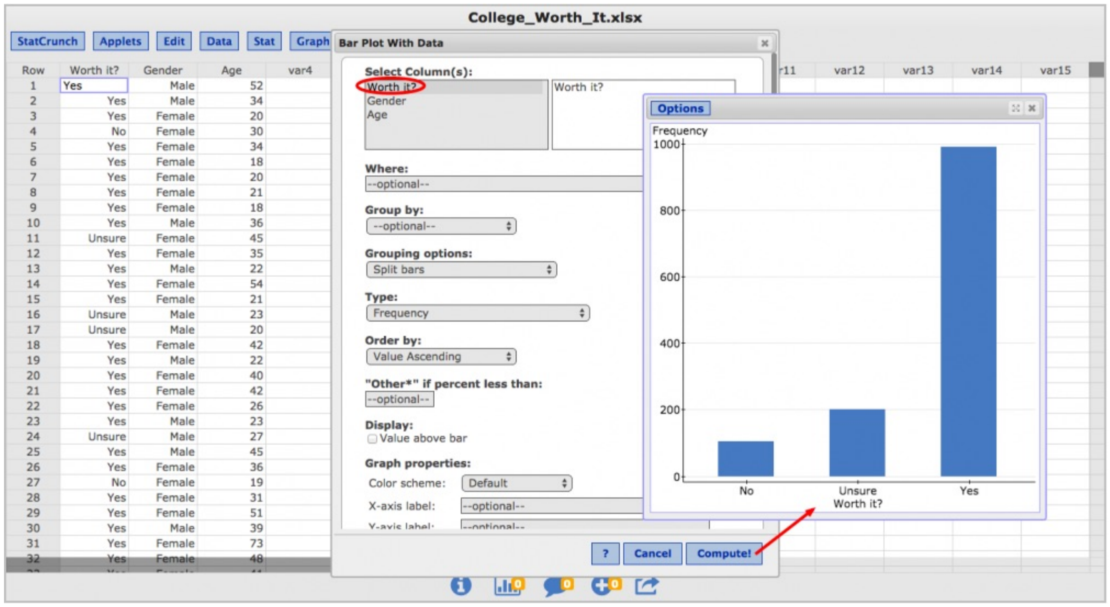
Figure 3.8: StatKey applet demonstrating a bootstrap confidence interval

StatKey applets do allow users to edit the example data sets or upload entirely new data, but they are necessarily limited to what they were programmed to do.

## 3.6 StatCrunch

StatCrunch is another popular tool used by educators. It was developed by Webster West, and it combines features from software packages like TinkerPlots and Fathom alongside spreadsheet-like functionality and “microworld”-style applets. A screen shot is shown in Figure 3.9. StatCrunch is inexpensive and available through the web browser. It was initially developed in the late 1990s as a Java applet (West et al., 2004), but has since been reworked into a modern web tool (likely using JavaScript) distributed by Pearson Education.

Unfortunately, while StatCrunch does collect a lot of the best features of the tools it amalgamates, it also accumulates many of the negatives. For example,



| Row | Worth it? | Gender | Age | var4 |
|---|---|---|---|---|
| 1 | Yes | Male | 52 | |
| 2 | Yes | Male | 34 | |
| 3 | Yes | Female | 20 | |
| 4 | No | Female | 30 | |
| 5 | Yes | Female | 34 | |
| 6 | Yes | Female | 18 | |
| 7 | Yes | Female | 20 | |
| 8 | Yes | Female | 21 | |
| 9 | Yes | Female | 18 | |
| 10 | Yes | Male | 36 | |
| 11 | Unsure | Female | 45 | |
| 12 | Yes | Female | 35 | |
| 13 | Yes | Male | 22 | |
| 14 | Yes | Female | 54 | |
| 15 | Yes | Female | 21 | |
| 16 | Unsure | Male | 23 | |
| 17 | Unsure | Male | 20 | |
| 18 | Yes | Female | 42 | |
| 19 | Yes | Male | 22 | |
| 20 | Yes | Female | 40 | |
| 21 | Yes | Female | 42 | |
| 22 | Yes | Female | 26 | |
| 23 | Yes | Male | 23 | |
| 24 | Unsure | Male | 27 | |
| 25 | Yes | Male | 45 | |
| 26 | Yes | Female | 36 | |
| 27 | No | Female | 19 | |
| 28 | Yes | Female | 31 | |
| 29 | Yes | Female | 51 | |
| 30 | Yes | Male | 39 | |
| 31 | Yes | Female | 73 | |
| 32 | Yes | Female | 48 | |

Select Column(s): [✓ Worth it?] Gender Age — Worth it?

Where: --optional--

Group by: --optional--

Grouping options: Split bars

Type: Frequency

Order by: Value Ascending

"Other*" if percent less than: --optional--

Display: ☐ Value above bar

Graph properties:

Color scheme: Default

X-axis label: --optional--

Y-axis label: --optional--

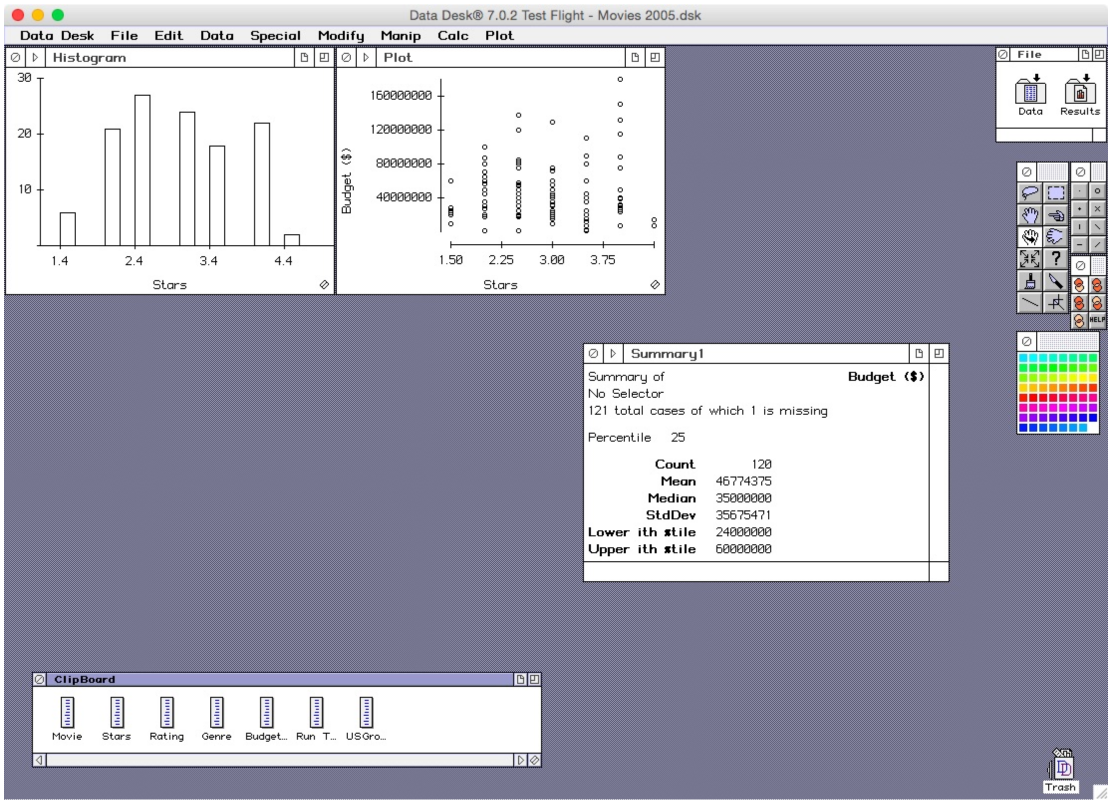
Figure 3.9: StatCrunch instructions for creating a bar plot

the lack of data sanctity mentioned in the spreadsheets section is certainly true here, as is the messy canvas associated with both spreadsheets and software like TinkerPlots and Fathom.

## 3.7 DataDesk

As mentioned in the introduction, Data Desk is the one tool that was considered by DeLeeuw to be a statistical programming tool (De Leeuw, 2009) and by Biehler to be software for learning statistics (Biehler, 1997). Data Desk (Figure 3.10) was introduced in 1985 and a current version exists to this day (Velleman, 1989). The program was developed to facilitate John Tukey's exploratory data analysis, and represents one of the first uses of linked visualization (Wills, 2008).

The interface was clearly the inspiration for TinkerPlots and Fathom, and features a palette of tools as well as menu bars. However, Data Desk provides much richer functionality than either TinkerPlots or Fathom, including linear



```
Summary1
Summary of                        Budget ($)
No Selector
121 total cases of which 1 is missing

Percentile    25

          Count        120
           Mean   46774375
         Median   35000000
         StdDev   35675471
Lower ith %tile   24000000
Upper ith %tile   60000000
```

Figure 3.10: DataDesk version 7

and nonlinear models, cluster analysis, and principal component analysis.

The drawbacks of Data Desk are slight, and similar to those of TinkerPlots and Fathom. The interface looks outdated, only static versions of analysis can be shared, and it does not promote the inclusion of text supporting the data 'story.' However, all these drawbacks notwithstanding, it is very inspirational.

## 3.8 R

R is a programming language for statistical computing (R Core Team, 2014). It is the tool of choice of academic statisticians, and has a growing market outside academia (Vance, 2009). Analysts at companies like Google routinely use R to perform exploratory data analysis and make models.

R has a number of benefits over the other tools we have discussed. First, it is free. When members of the open source community use the word "free" they often distinguish between "free as in speech" and "free as in beer." These phrases indicate the difference between software that costs no money (e.g., most Google products) and software that is completely unrestricted and available for anyone to modify and edit. R is free in both ways.

R is an interpreted language, as are all the other languages commonly used for statistical computing. The interpreted paradigm means a user can type a piece of code, say `mean(height)` and see the results immediately. A program in an interpreted language gets executed in the same way as a single line of code. That is, the computer looks directly at the code, not a compiled version of it. So, while the education research on the acquisition of Java can be useful as inspiration, it cannot be used directly in a statistical computing context, due to the differences between compiled and interpreted languages.

R can be a very slow language to work with, as it reads all data into the computer's working memory. Because of its lack of speed and a few other language features (the result of R being developed by statistical practitioners rather than computer scientists) it is often criticized by programming language experts. Even the author of R admits that there are drawbacks to R and suggests that a better language could be created if they started over (Ihaka, 2010).

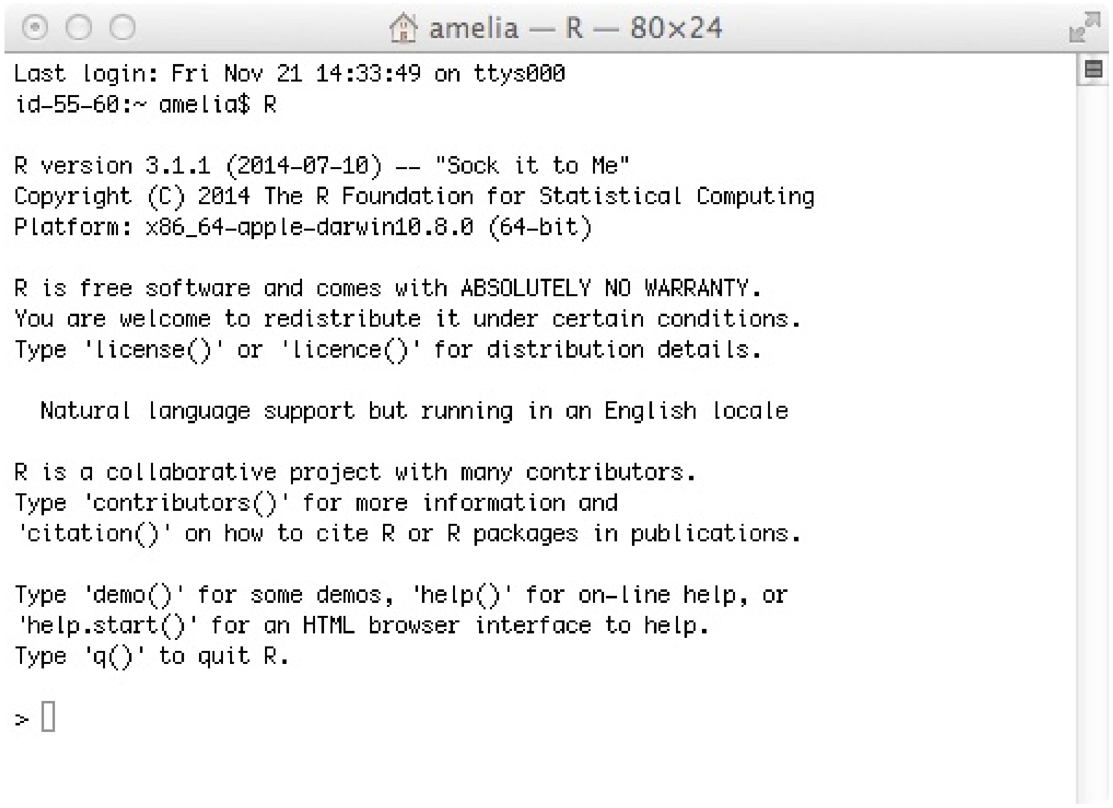
But, R provides such a flexible framework for statistical computing it has virtually taken over statistical computing in academia and is making inroads in the corporate world (Vance, 2009). And even programming language researchers admit it has interesting and unique language features (Morandat et al., 2012). In particular, its lazy evaluation and lexical scoping are often pointed to.

Lazy evaluation describes the fact that code is not evaluated until its results are asked for, either by another function or by the user. Since R is a functional language, there are often chained functional statements equivalent to a set of nested functions, `f(g(h(x,y)))`, and functions `g()` and `h()` will not be evaluated until the result of `f()` is asked for.

Lexical scoping is a quality either lauded or critiqued in R. In general, the term means variables are only available in particular environments, but in R, lexical scoping means the language looks within local environments first (for example, within the function being used) but if it cannot find a particular variable it will continue to look outside to the next highest environment (the next highest function) until it reaches the global scope. Again, this type of scoping can be good or bad. It means R is less restrictive than some other languages, but it can also lead to unintended side effects.

R work typically takes place at a command-line interface (CLI). In fact, R can be used directly at the command line, as seen in Figure 3.11. A slightly friendlier interface is the regular R graphical user interface (GUI) that comes with the language when it is downloaded (Figure 3.12). GUIs are discussed in more depth in Section 3.8.5, but essentially the GUI allows a user to move some tasks from command line typing tasks to more menu-oriented tasks. The regular

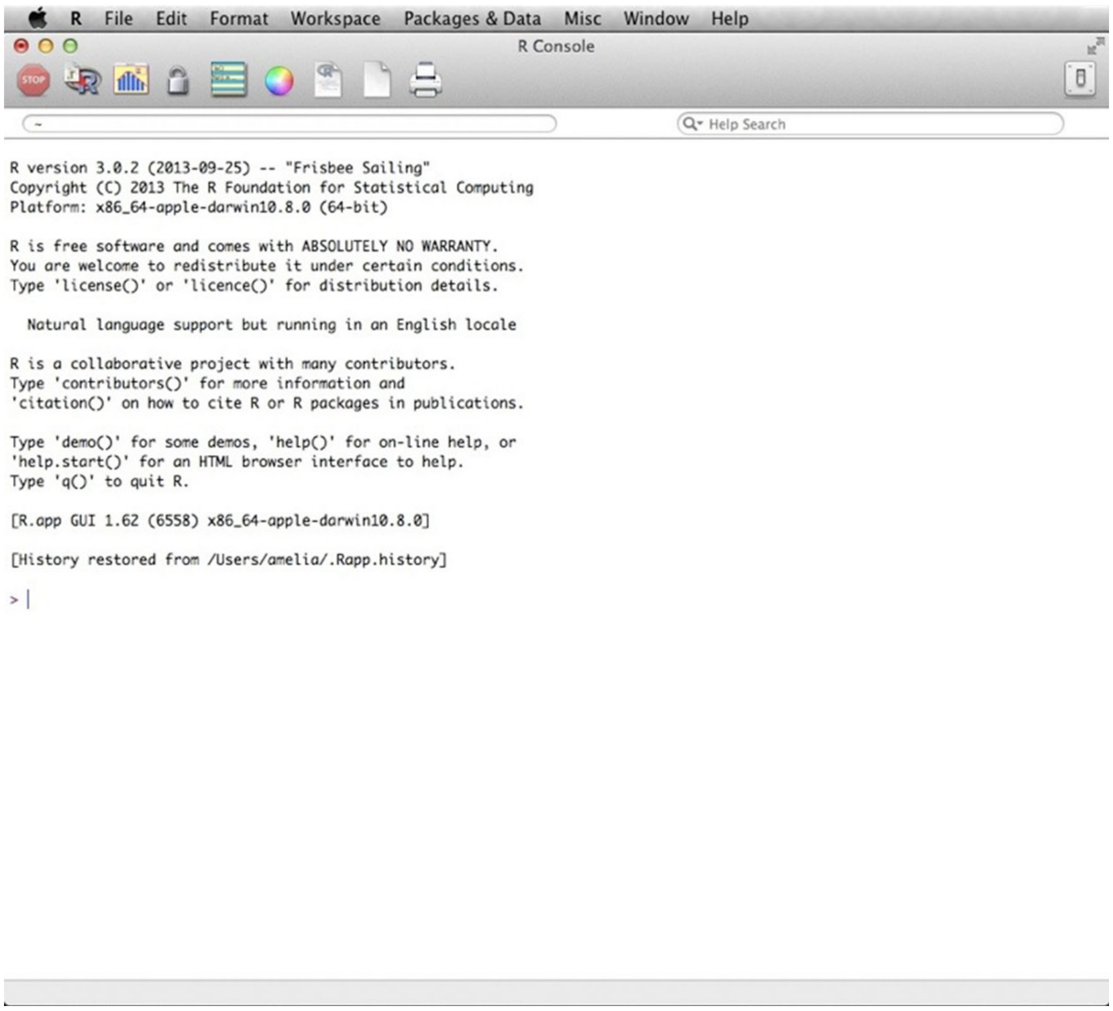
R GUI provides a file menu, a red stop button for when code gets out of hand, and not much else. Section 3.8.5 examines more advanced GUIs for R as well as the integrated development environment RStudio. All these approaches add support for users, but still require syntactic knowledge.



```
Last login: Fri Nov 21 14:33:49 on ttys000
id-55-60:~ amelia$ R

R version 3.1.1 (2014-07-10) -- "Sock it to Me"
Copyright (C) 2014 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin10.8.0 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> 
```

Figure 3.11: R at the command line

Like many programming languages, R has both a language base and additional libraries, allowing users to extend its functionality. The additional libraries are called ‘packages’ and most are hosted on a centralized server called the Comprehensive R Archive Network (CRAN) (R Core Team, 2015). Having CRAN makes it simple for users to install new packages, as they do not have to go hunting for where a particular package is hosted. Additionally, R provides great library management support. By using the command `install.packages()`, a particular package can be pulled from CRAN, unpacked, and installed in precisely the right location. This simplifies the installation process and makes it



```
R version 3.0.2 (2013-09-25) -- "Frisbee Sailing"
Copyright (C) 2013 The R Foundation for Statistical Computing
Platform: x86_64-apple-darwin10.8.0 (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

  Natural language support but running in an English locale

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

[R.app GUI 1.62 (6558) x86_64-apple-darwin10.8.0]

[History restored from /Users/amelia/.Rapp.history]

> |
```

Figure 3.12: Regular R graphical user interface

much more straightforward than library management in Python, for example.

Because R has the statistical community invested in it, and because it is open-source and easy to modify, there are many additional packages for R. As of this writing, CRAN hosts over 6,500 packages. However, there has been a recent movement away from hosting packages on CRAN toward hosting them on GitHub. Using Hadley Wickham's **devtools** package, package installation from GitHub is as seamless as from CRAN, although there are fewer checks on packages prior to their installation. The reduced checks could allow unscrupulous package writers to distribute packages with nefarious aims (a worst case scenario would be some type of trojan horse virus). However, because of the high bar packages must pass to be included on CRAN, the relaxed checking also promotes more creative packages and allows users to try out packages still in development. The flexibility of being able to install packages from GitHub has outweighed the risks for many users.

One good affordance of R is it makes it very difficult to modify original data. Instead, R loads a copy of the data into the work session and the user works with the copy. Once it is loaded, it is possible to 'clean' the data, i.e., standardize some of the fields so labels are consistent, convert 0s to NAs, etc. None of these actions are taken on the data itself. Instead, they take place on the copy of the data you have loaded. Because R is a language, it is possible to follow the trail of actions taking the original data file to the cleaned version. Code can be saved and verified by another party if there are questions of reproducibility. Of course, it is still possible to save the modified data file over the original, but the process of making changes to a local copy makes it much less likely.

There are many other affordances of data analysis systems that shape the way users think about and work with data. For example, while many languages rely on constructs like 'for' loops and 'while' statements (often called control statements), other languages, like R, support vectorized operations. Instead of having to explicitly state an operation should be done for every entry in a list, R allows for the operation to be applied to the list itself, and the program's inherent paradigm will know to do it in vectorized format. R includes control statements like 'for' loops, but they are used less often than in other similar languages.

As with any tool, R has its shortcomings as well. The main drawback of R is its status as a programming language. Many of the other tools discussed here are much more toward graphical user interfaces, while R is a language, meaning users need to provide the correct function calls with appropriate syntax and arguments. Adding to this is R's inconsistent syntax, which makes it hard to learn for novices and programming experts alike. This is discussed below in Section 3.8.1.

There have been efforts to simplify the coding aspects of R over the years. Some of these efforts are curricular, reducing the number of commands to which novices are exposed, or providing more consistent syntax (Verzani, 2005; Kaplan and Shoop, 2013). Other efforts are Graphical User Interfaces (GUIs) like Deducer (Fellows, 2012) and RCommander (Fox, 2004), discussed further in Section 3.8.5. However, none of these efforts have truly solved the problem.

### 3.8.1 R syntaxes

One complex aspect of R is the multitude of syntaxes it supports. Where most programming languages would have one standard syntax, R has many.

The two main syntaxes most users encounter are the dollar sign syntax and the formula syntax. The dollar sign syntax uses the `$` operator to denote when an object is within another object. For example `mtcars$wt` indicates the `wt` variable within the `mtcars` dataset. The formula syntax is so named because it is most commonly found in functions performing modeling, which use a formula specification. This syntax uses a ~ operator, but the entire syntax is different. Instead of referring to variables within datasets, the user refers to the variables directly and then notes the dataset later.

For a more thorough example, see below. In this example, a set of three plots are made to compare the weight (`wt`) and miles per gallon (`mpg`) of cars with different numbers of cylinders (`cyl`).

First, the dollar sign syntax:

```
par(mfrow=c(1,3))
plot(mtcars$wt[mtcars$cyl == 4], mtcars$mpg[mtcars$cyl == 4])
plot(mtcars$wt[mtcars$cyl == 6], mtcars$mpg[mtcars$cyl == 6])
plot(mtcars$wt[mtcars$cyl == 8], mtcars$mpg[mtcars$cyl == 8])
```

Then, the formula syntax:

```
xyplot(mpg~wt | as.factor(cyl), data=mtcars)
```

The plot from the dollar sign example is seen in Figure 3.13 and the plot from the formula example is seen in Figure 3.14. Perhaps the most obvious observation of these two plots is they do not appear to be 'the same.' This is because the formula syntax example standardizes the axes automatically, while the dollar sign syntax example generates the best axes for each plot.

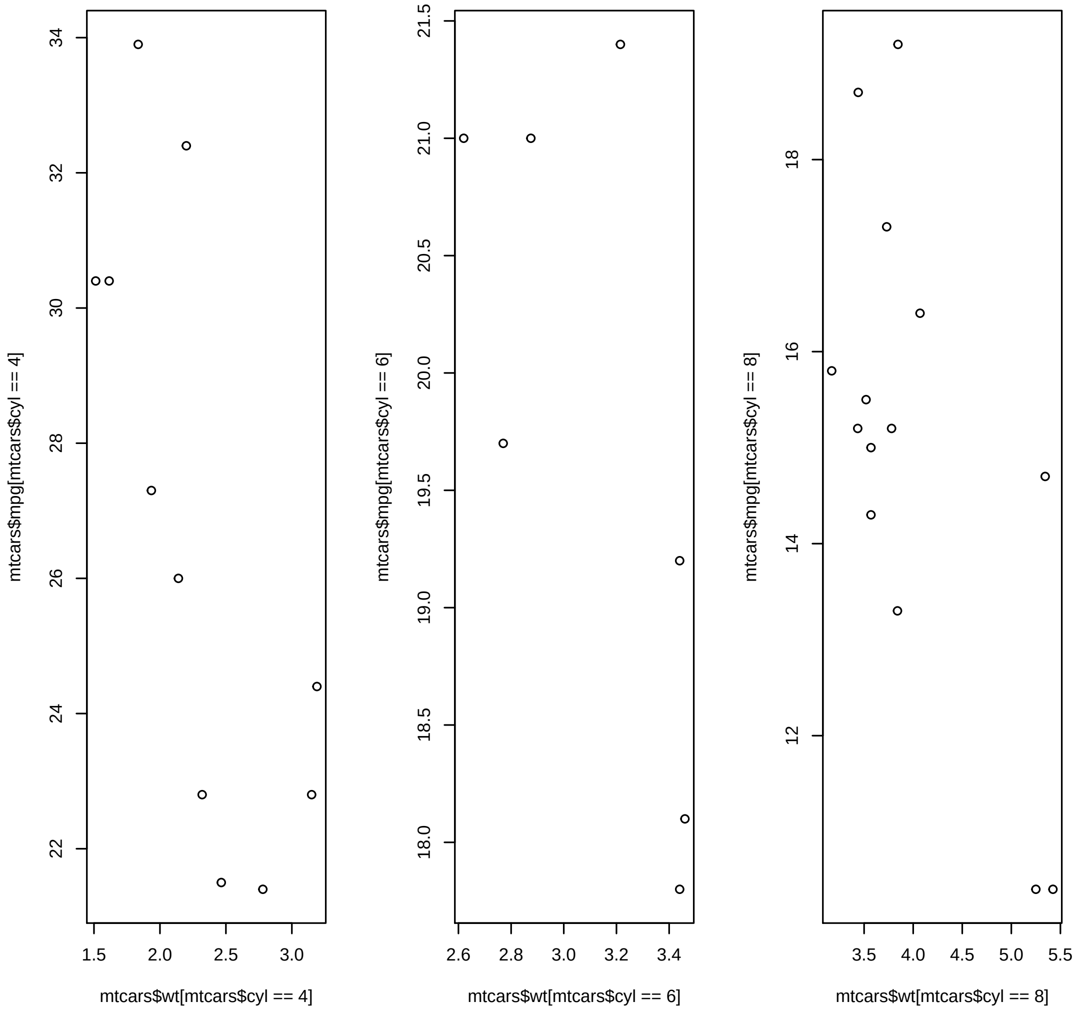


Figure 3.13: Plot using dollar sign syntax

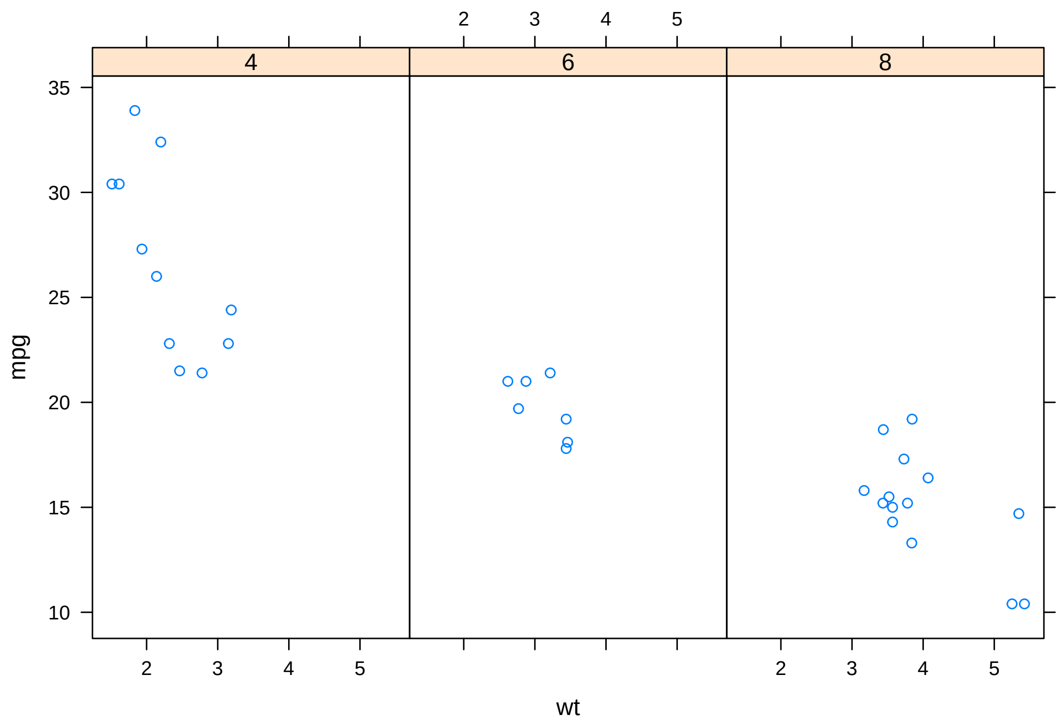


Figure 3.14: Plot using formula syntax

The plotting example makes the formula syntax appear far superior, but there are tasks that are much easier in the dollar sign syntax as well. For example, creating a new variable in the formula syntax requires something like

```r
mtcars = mutate(mtcars, avgWT = mean(wt))
```

rather than

```r
mtcars$avgWT = mean(mtcars$wt)
```

in the dollar sign syntax.

One method for simplifying R for novices is to expose them to only one syntax. In projects limiting exposure to only one syntax (Project MOSAIC and Mobilize), the choice has been made to use the formula syntax (Pruim et al., 2015a; Gould et al., 2015), although either choice would have been effective. In order to focus on the formula syntax, graphics are made using the **lattice** package (Sarkar, 2008), summary statistics are computed with the **mosaic** package (Pruim et al., 2015b), and modeling can continue to be done in **base** R.

### 3.8.2 R packages

Again, one of the strengths of R is the large quantity of additional packages available to extend its functionality.

#### 3.8.2.1 mosaic

Project MOSAIC and its associated R package, **mosaic**, have advanced the state of R for education (Pruim et al., 2015a,b). By making summary statistics available in the formula-based R syntax, the **mosaic** package allows for a standardization within the introductory curricula. By using the **mosaic** package, along with **lattice** graphics (Sarkar, 2008), students can stay firmly within the formula-based syntax for an entire introductory statistics course.

In addition, the project has been improving RMarkdown templates (discussed further in Section 3.8.3), and creating interactive widgets – what Bieher might call microworlds – to allow users to interact with R more dynamically (Biehler, 1997). However, even with these advantages, students still need to type syntactically correct code and cannot easily create their own interactive graphics.

#### 3.8.2.2 The Hadleyverse

In recent years, simpler and more flexible R packages have become more plentiful. A main driver of this trend is Hadley Wickham, the Chief Scientist at RStudio (RStudio is discussed more in Section 3.8.5.3). Wickham developed the flexible graphics package **ggplot2** as his doctoral dissertation (Wickham, 2009). **ggplot2** is an implementation of The Grammar of Graphics (Wilkinson, 2005), which means it supports the creation of novel plot types within a structured syntax.

Wickham has also developed packages to help users deal with data manipulation, such as **plyr**, **reshape2** and **dplyr** (Wickham, 2011, 2007; Wickham and Francois, 2015). Wickham has said he wants to build tools that allow users to easily express 90% of what they want to be able to do, while only losing 10% of the flexibility. He acknowledges there will always be edge cases falling outside the capabilities of his packages. But, he is not trying to create a complete language, simply domain-specific languages for data analysis tasks.

#### 3.8.2.3 Shiny and manipulate

**Shiny** is an R package developed by the RStudio team enabling R programmers to create interactive visualizations for the web (Chang et al., 2015).

In order to develop a **Shiny** app, an author must create two R files, one called `ui.R` and one called `server.R`. These two files must be developed in parallel, taking particular care to match variable names between the processes happening on the back end (in the server file) and those visible in the app (in the UI file). In the server file, authors can define reactive expressions. The reactive expressions can be used to build a system that responds to user input, updating only those values that depend on the modifications made by the user.

**Shiny** supports interface features like sliders, radio buttons, check boxes, even text input. Typically, though, the resulting visualizations are themselves static. The user cannot zoom into them naturally in the way they would with a d3 web graphic. Instead, the designer would have to incorporate sliders for the x- and y-ranges, and the user would manipulate those to impact the zoom. **Shiny** also supports simple publishing, as local **Shiny** apps can be ported to RStudio's `shinyapps.io` hosting site with one button click.

However, authoring **Shiny** apps is not a task for novices. In order to create an interactive graphic, the user first needs to understand R syntax and which parameters she wants to manipulate. The user must also have a basic understanding of reactive programming, and must be able to match up variable names and outputs in the paired server/UI paradigm **Shiny** uses. Much more useful would be a tool where users could create interactive graphics using direct manipulation of objects on the screen, without needing to know R syntax.

Its challenges notwithstanding, **Shiny** is a very powerful tool, and it has been enabling R programmers to build interactive tools that have gained viral success, such as the dialect map (Katz and Andrews, 2013) published on the New York Times that eventually received more views than any article in the history of the paper (Leonhardt, D. (@DLeonhardt), 2014).

As it stands, **Shiny** can be useful as what Biehler calls a “meta-tool,” enabling teachers to “adapt and modify material and software for their students” (Biehler, 1997). There are many nice examples of these types of tools, including the gallery being curated by Mine Çetinkaya-Rundel (Çetinkaya Rundel, 2014) and tools for exploring database joins (Ribeiro, 2014). Two **Shiny** apps I developed are discussed in Section **??**.

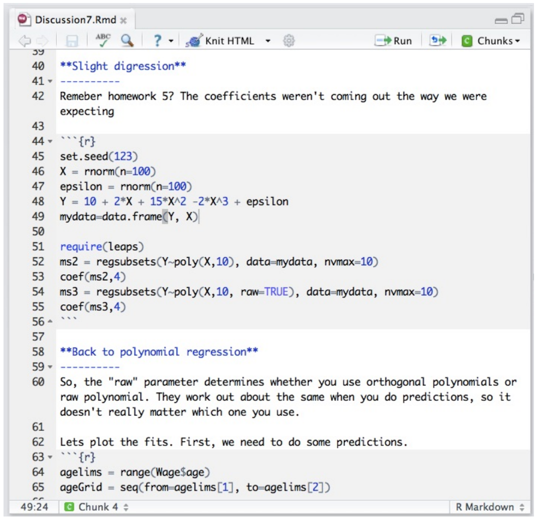
A simpler package with a similar idea is the **manipulate** package, which was also developed at RStudio (Allaire, 2014). **manipulate** is easier for novices to use, although it still requires some knowledge of R. However, instead of requiring the server/UI paradigm **Shiny** requires (which is useful for publishable web documents), **manipulate** works directly at the command-line to produce interaction that cannot be published but can be used for educational purposes.

### 3.8.3 knitr/RMarkdown

While not specifically for doing statistical analysis, several projects by Yihui Xie are extending the capabilities for reproducible research, both with R and more generally.

During his doctoral dissertation, Xie wrote the **knitr** package, which expanded the capabilities of previous functionality called `Sweave` from **base** R (Xie, 2013). **knitr** makes it possible to combine text, code, and the results from the code. This is much like the iPython notebooks discussed in Section 3.3, but is more flexible in terms of languages and output formats. The most canonical examples are including R code in LaTeX or Markdown text, but the package is much more flexible (Xie, 2013). In fact, **knitr** allows users to combine any type of code (Python, C++, etc) with any textual format.

Users write text and code (delimited as such by particular syntax depending on the textual format they are using), then ‘knit’ the source document to create

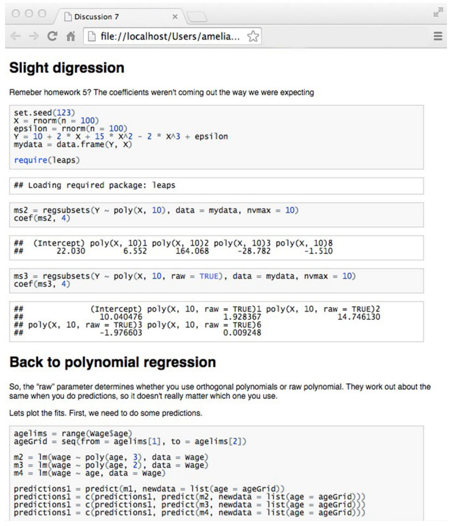


~~~
**Slight digression**
----------
Remeber homework 5? The coefficients weren't coming out the way we were
expecting

```{r}
set.seed(123)
X = rnorm(n=100)
epsilon = rnorm(n=100)
Y = 10 + 2*X + 15*X^2 -2*X^3 + epsilon
mydata=data.frame(Y, X)

require(leaps)
ms2 = regsubsets(Y~poly(X,10), data=mydata, nvmax=10)
coef(ms2,4)
ms3 = regsubsets(Y~poly(X,10, raw=TRUE), data=mydata, nvmax=10)
coef(ms3,4)
~~~

**Back to polynomial regression**
----------
So, the "raw" parameter determines whether you use orthogonal polynomials or
raw polynomial. They work out about the same when you do predictions, so it
doesn't really matter which one you use.

Lets plot the fits. First, we need to do some predictions.
```{r}
agelims = range(Wage$age)
ageGrid = seq(from=agelims[1], to=agelims[2])
```

(a) Code



**Slight digression**

Remeber homework 5? The coefficients weren't coming out the way we were expecting

```
set.seed(123)
X = rnorm(n = 100)
epsilon = rnorm(n = 100)
Y = 10 + 2 * X + 15 * X^2 - 2 * X^3 + epsilon
mydata = data.frame(Y, X)

require(leaps)
```

```
## Loading required package: leaps
```

```
ms2 = regsubsets(Y ~ poly(X, 10), data = mydata, nvmax = 10)
coef(ms2, 4)
```

```
##  (Intercept) poly(X, 10)1 poly(X, 10)2 poly(X, 10)3 poly(X, 10)8
##       22.030        6.552      164.068      -28.782       -1.510
```

```
ms3 = regsubsets(Y ~ poly(X, 10, raw = TRUE), data = mydata, nvmax = 10)
coef(ms3, 4)
```

```
##              (Intercept) poly(X, 10, raw = TRUE)1 poly(X, 10, raw = TRUE)2
##                10.040476                 1.928367                14.746130
## poly(X, 10, raw = TRUE)3 poly(X, 10, raw = TRUE)6
##                -1.976603                 0.009248
```

**Back to polynomial regression**

So, the "raw" parameter determines whether you use orthogonal polynomials or raw polynomial. They work out about the same when you do predictions, so it doesn't really matter which one you use.

Lets plot the fits. First, we need to do some predictions.

```
agelims = range(Wage$age)
ageGrid = seq(from = agelims[1], to = agelims[2])

m2 = lm(wage ~ poly(age, 3), data = Wage)
m3 = lm(wage ~ poly(age, 2), data = Wage)
m4 = lm(wage ~ age, data = Wage)

predictions1 = predict(m1, newdata = list(age = ageGrid))
predictions1 = c(predictions1, predict(m2, newdata = list(age = ageGrid)))
predictions1 = c(predictions1, predict(m3, newdata = list(age = ageGrid)))
predictions1 = c(predictions1, predict(m4, newdata = list(age = ageGrid)))
```

(b) Output

Figure 3.15: Code and associated output from RMarkdown

a fully formatted HTML or PDF document. The output document has nicely formatted text, code with syntax highlighting, and all the results from the code, including numeric summaries and plots. If the user changes something in the source document, they have only to re-knit the document to see the updated results in their output document. For an example of the RMarkdown code and corresponding HTML output, see Figure 3.15.

This paradigm supports reproducible research. It makes it very simple to share analysis results in such a way that the reader can easily audit them, and the same analysis can be easily run on new data, changing only one line in the source code and re-knitting the report to see the results.

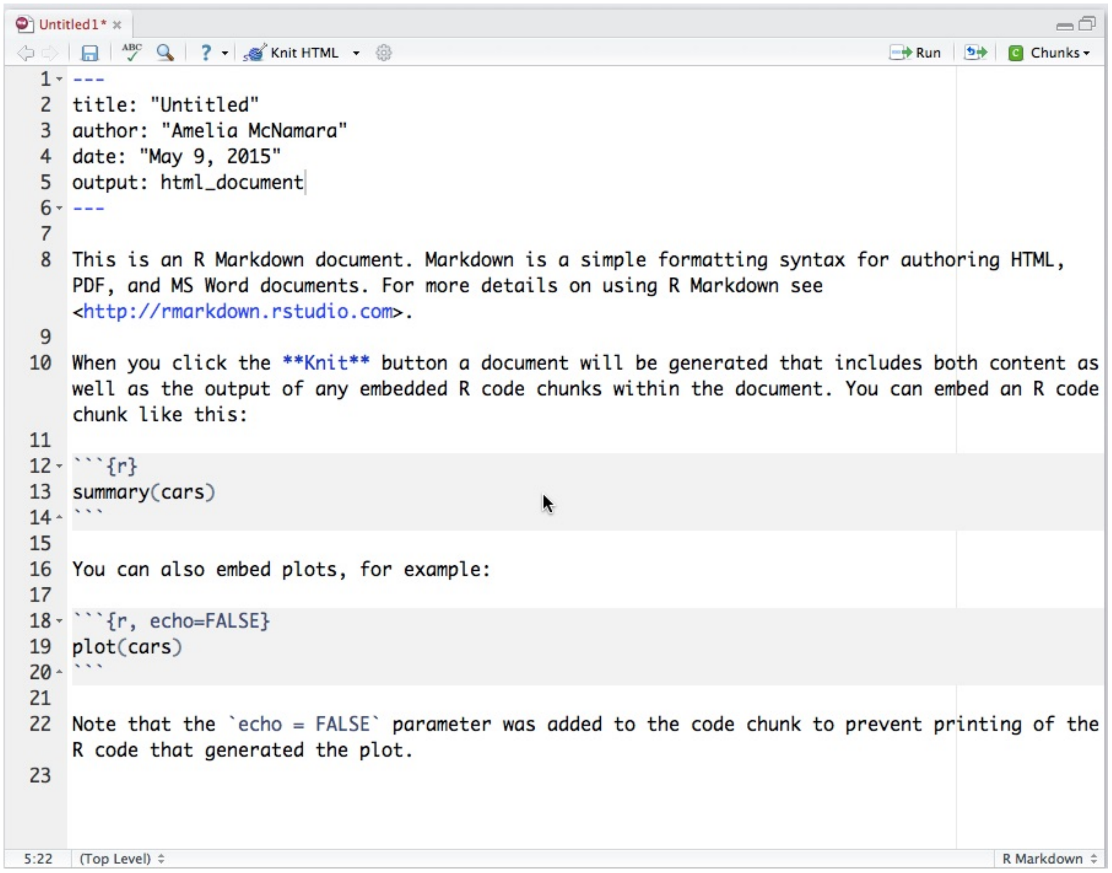
**knitr** functionality is available through any R session, but the most embedded support is through RStudio, where the file menu of gives users the choice of RMarkdown document and R Sweave (LaTeX), among others. Users can also choose the output format they would like from their RMarkdown code. For a document, the choices are HTML, PDF, or Word.

Once a document type has been chosen, RStudio provides a new document, as shown in Figure 3.16. However, rather than presenting the user with a blank page (as might be seen in word processing software, for example), there is some minimal code already there. This template demonstrates the most important features of the syntax, and it provides a working example using sample datasets that should run on any system.

Providing a minimal working example has been shown to support novices, particularly through research on the acquisition of Java. Michael Kölling calls this the "recipe" format (Kölling, 2010), and suggests a student should never start with a blank page. Instead, they should always be presented with something that 'works' (meaning it either either runs or compiles, depending on the type of language) that they can modify. In Java, sometimes these recipes are in the form of the layout for a function, and other times more like a documentation scheme.

In the realm of statistical computing, RStudio provides document templates for all of their document types. Starting with a recipe provides two supports for learners. First, it is always easier to edit than it is to write (the "just put something down" philosophy), and second, when given a working example, students can verify their system is set up correctly. If the minimal example does not run, they know they need to get more help from their instructor in terms of installation.

Because of all the support they provides for reproducible research, RMarkdown and **knitr** are clearly moving toward the future of statistical programming. However, the re-knitting step that must take place between every change and its appearance in the compiled document is a stumbling block. And because of its connection to textual languages, it is not clear how **knitr** could extend in a visual setting.



~~~
---
title: "Untitled"
author: "Amelia McNamara"
date: "May 9, 2015"
output: html_document
---

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>.

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:

```{r}
summary(cars)
~~~

You can also embed plots, for example:

```{r, echo=FALSE}
plot(cars)
```

Note that the `echo = FALSE` parameter was added to the code chunk to prevent printing of the R code that generated the plot.
```

Figure 3.16: New RMarkdown document with template
```

### 3.8.4 Tools for learning R

There have been efforts to provide tools specifically to guide students through the process of learning R. Two of the most promising are **swirl** and DataCamp.

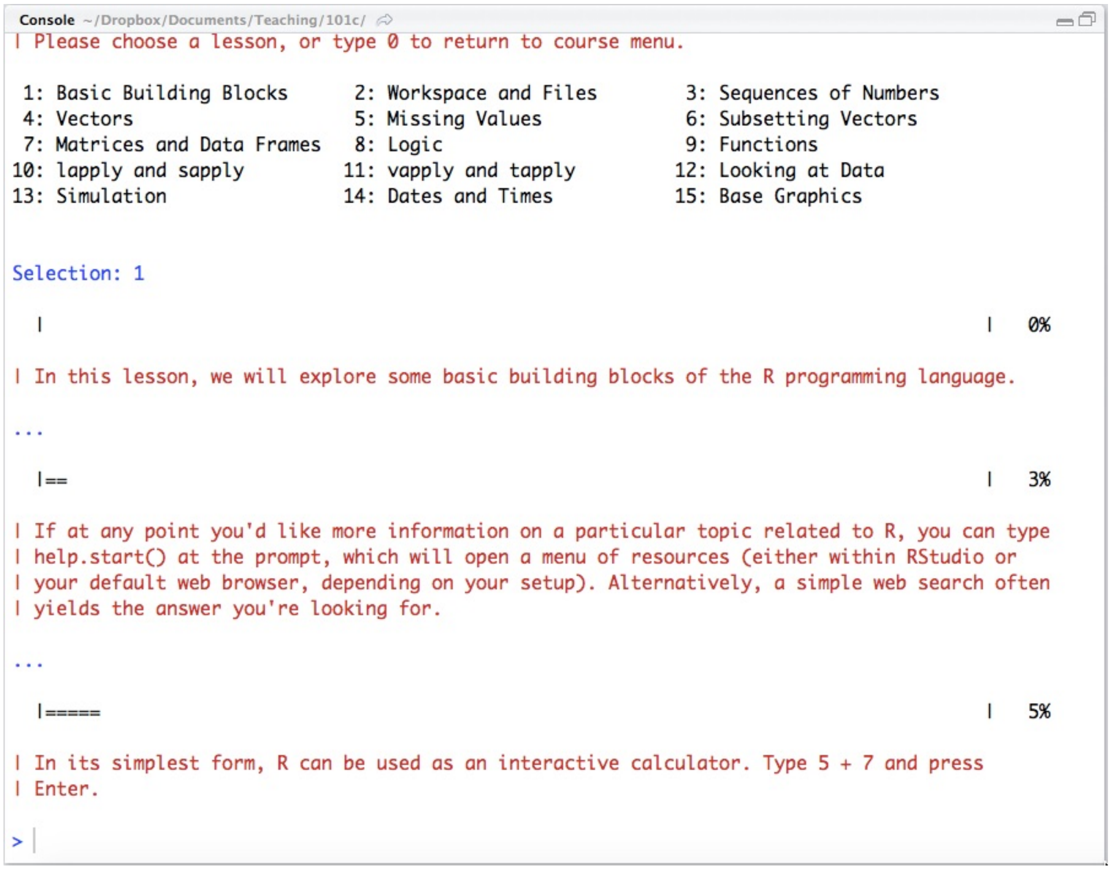
#### 3.8.4.1 swirl

**swirl** is an R package intended to teach R at the command line (Carchedi et al., 2015). It was developed by Nick Carchedi, a graduate student at Johns Hopkins University.

**swirl** has a number of advantages, the biggest being that students do not need to leave their R environment to see the curricular materials to which they are referring. Compared to other approaches for learning R, which might include looking at a book next to a computer and then trying exercises on the screen, or switching back and forth between a browser window with some documentation and an R session, **swirl** does have the advantage. By combining everything into one window, it makes the experience of learning R more focused and less likely to be sidelined by other issues (e.g., the book falling closed, losing the browser window).

Another advantage of **swirl** is its status as an open-source R package. The code is hosted on GitHub, and any instructor can develop their own **swirl** 'module' to cover a particular lesson or set of lessons. These modules are available on GitHub and can be easily loaded in through the **swirl** interface, so students can pull in modules on whichever topic they want to learn. Currently, there are very few modules, which makes it hard to assess the usefulness of the platform. However, as more R experts port their material to **swirl** modules it will become easier to assess.

The authors of **swirl** suggest using it within RStudio, which means users can see their plots in the plot pane and the items they add to their workspace in the environment pane. These features are discussed more extensively in Section 3.8.5.3. However, beyond encouraging students to use RStudio, the authors have not taken full advantage of the features available in RStudio (e.g., presentations, markdown documents, etc).



```
Console ~/Dropbox/Documents/Teaching/101c/
| Please choose a lesson, or type 0 to return to course menu.

 1: Basic Building Blocks      2: Workspace and Files        3: Sequences of Numbers
 4: Vectors                    5: Missing Values             6: Subsetting Vectors
 7: Matrices and Data Frames   8: Logic                      9: Functions
10: lapply and sapply         11: vapply and tapply         12: Looking at Data
13: Simulation                14: Dates and Times           15: Base Graphics


Selection: 1

  |                                                                                 |   0%

| In this lesson, we will explore some basic building blocks of the R programming language.

...

  |==                                                                               |   3%

| If at any point you'd like more information on a particular topic related to R, you can type
| help.start() at the prompt, which will open a menu of resources (either within RStudio or
| your default web browser, depending on your setup). Alternatively, a simple web search often
| yields the answer you're looking for.

...

  |=====                                                                            |   5%

| In its simplest form, R can be used as an interactive calculator. Type 5 + 7 and press
| Enter.

>
```

Figure 3.17: **swirl** introducing R

A view of a **swirl** session is shown in Figure 3.17. Much like the Mobilize labs discussed in Section 5.1.3.3, **swirl** will prompt the user to try running a piece of code to see what it does. Once the task is completed, **swirl** will give more information and then ask another question. Because the system is set up to wait for a correct response, it is a very directed form of learning. Unlike the inquiry-based model upon which Mobilize was based, **swirl** is a linear trajectory of learning. Of course, this form of learning was determined by the format the authors chose to use for **swirl**. Because it uses a command-line tool and does not have any fancy machine learning behind it, support of very fluid learning trajectories could not be expected.

In the first version of **swirl**, the questions were quite vague and the required answers were very specific. The authors had not built in an escape function, so if a user got stuck, their only recourse was to close their `R` session. Additionally, if a user wanted to play around with a function to see what it did, they had to endure endless error messages from the system. There was no capability to go back, which made it feel limiting. The user could only enter code in one particular instance, and once they did it right the system would move on completely.

However, the second version has corrected for all these problems and more. The questions have been simplified and it is much easier to escape. For example, if a user is in a code prompt and types `info()`, they will be shown a list of other commands they can use for utility functions, like `skip()` to skip the question, `play()` to try things out without **swirl** interpreting the code as an answer to a question, or `bye()` to end the swirl session.

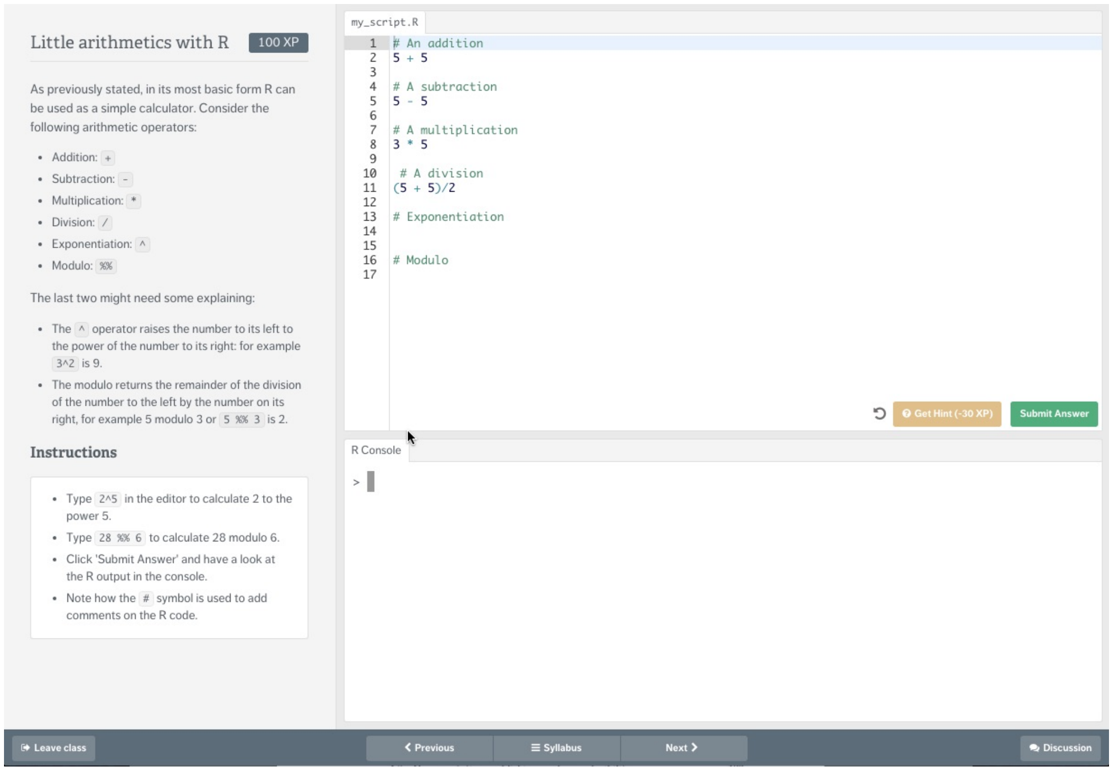
The `info()` command helps ease frustration, but still requires the cognitive load of remembering the command. A quick reference of some sort would be very useful – taking advantage of RStudio's support of presentations open in the viewer pane throughout an entire session, or providing custom documentation files to be loaded in the help pane. Again, the authors have not taken advantage of all the capabilities of RStudio yet.

One particularly ill-advised design choice is the use of red font for all instructions. As we found when implementing Deducer (Section 3.8.5.2) with teenage users in the Mobilize project, users associate red with errors, so red text can be very anxiety-producing (McNamara and Hansen, 2014; Ellior et al., 2007).

Overall, **swirl**'s main drawback is its rigidity. Even with the improvements in version two, the material feels linear and the question and answer format does not seem structured to provide for long-lasting learning.

#### 3.8.4.2 DataCamp

A competitor to **swirl** is the website DataCamp (Figure 3.18) (Cornelissen et al., 2014). DataCamp uses the format seen on popular sites such as CodeAcademy and applies it to R. Each element of learning R is defined as a module, and as a user moves through the modules they earn points. The interface asks questions that the user must supply an answer to in order to move on, although it will also provide hints.



Little arithmetics with R

As previously stated, in its most basic form R can be used as a simple calculator. Consider the following arithmetic operators:

- Addition: `+`
- Subtraction: `-`
- Multiplication: `*`
- Division: `/`
- Exponentiation: `^`
- Modulo: `%%`

The last two might need some explaining:

- The `^` operator raises the number to its left to the power of the number to its right: for example `3^2` is 9.
- The modulo returns the remainder of the division of the number to the left by the number on its right, for example 5 modulo 3 or `5 %% 3` is 2.

**Instructions**

- Type `2^5` in the editor to calculate 2 to the power 5.
- Type `28 %% 6` to calculate 28 modulo 6.
- Click 'Submit Answer' and have a look at the R output in the console.
- Note how the `#` symbol is used to add comments on the R code.

```
# An addition
5 + 5

# A subtraction
5 - 5

# A multiplication
3 * 5

 # A division
(5 + 5)/2

# Exponentiation


# Modulo

```

```
>
```

Figure 3.18: DataCamp introducing R

DataCamp sidesteps some of the issues from **swirl** by situating the learning on the web. Users do not have to install R, RStudio, or any supporting packages on their computer. Instead, everything takes place in the browser. However, working in the browser is a somewhat artificial experience, as real R work will take place in another interface. The other disadvantage to Data Camp is that it is not free. The site allows users access to some introductory material without a subscription, but to see all the modules in their entirety, users must pay $25 per month or $50 per year.

### 3.8.5 GUIs and IDEs for R

In contrast to the Command Line Interface (CLI) that characterizes much of programming, Graphical User Interfaces (GUIs) and Integrated Development Environments (IDEs) are used by programmers to reduce cognitive load in a variety of languages. IDEs are support tools for textual coding, which often provide a source code editor with debugging support, code completion, and sometimes automated code refactoring. A common example is Eclipse, which is used by Java programmers. There have been efforts to simplify Eclipse for novices, like the Gild project (Storey et al., 2003).

The term GUI can be used more broadly. In computer science, the term was initially used to suggest a graphical system allowing a user to interact with a (typically text-only) programming language without having to understand the underlying syntax. However, as personal computers have become more graphical, the term GUI has begun to be used more broadly to mean any computer interface using menus and buttons for interaction. Under this definition, Word, Skype, and Google Chrome are all GUIs.

Both GUIs and IDEs are attempts at simplifying the use of computers, and there have been efforts to use them to simplify and improve R. As with the history of statistical programming languages, there are too many to exhaustively mention, so we will consider a small selection.

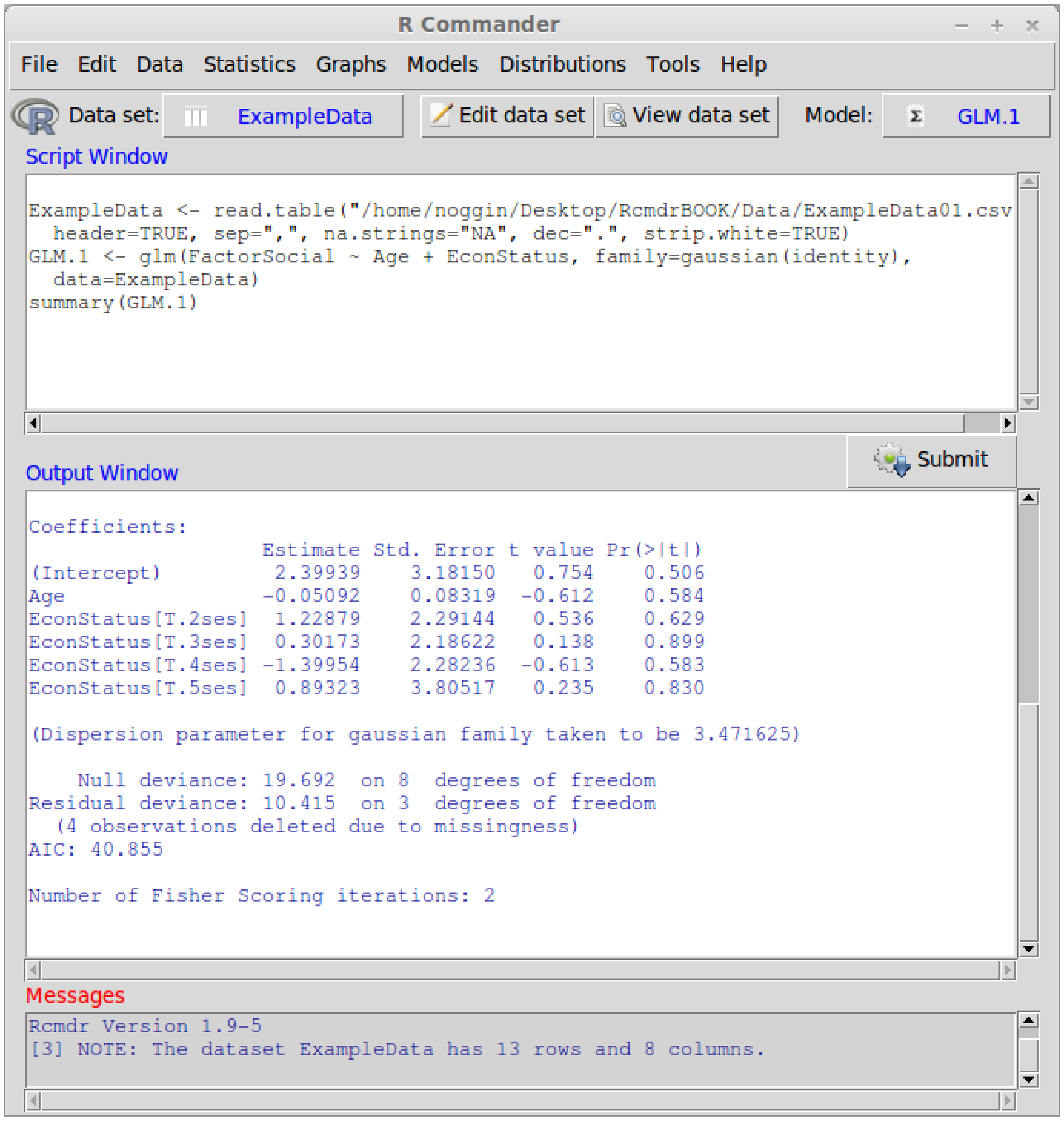
#### 3.8.5.1 R Commander

R Commander (Figure 3.19) is a GUI for R. It was developed by John Fox as a way to use R in introductory statistics classes without students having to learn syntax (Fox, 2004). Much like the tools for learning discussed in Section 3.4, R Commander provides a limited set of possible tasks and provides a graphical user interface. While the interface is much more route-type than the landscape-type TinkerPlots and Fathom (Bakker, 2002), R Commander also makes it possible to do summary statistics, graphics, and simple models.

R Commander is a button- and menu-driven GUI for R, and any action taken in the GUI results in the corresponding R code appearing in the Script Window (top pane) and output appearing in the Output Window (bottom pane). Any messages appear at the bottom of the GUI.

While this method allows students to use the tool for introductory statistics courses, it does not facilitate play (as Fathom does) or develop computational thinking (as learning R does). The connection between actions taken with the menus and the resulting code is implicit rather than explicit, and there is little reason for users to manipulate the code.

R Commander offers one of the same benefits as Fathom and TinkerPlots (namely, the user does not need to know how to code in order to use it) but does not take the rest of them (flexible and creative exploration). It is not clear R Commander would help bridge the gap better than other tools for learning, so there is little incentive to use it.



```
ExampleData <- read.table("/home/noggin/Desktop/RcmdrBOOK/Data/ExampleData01.csv
  header=TRUE, sep=",", na.strings="NA", dec=".", strip.white=TRUE)
GLM.1 <- glm(FactorSocial ~ Age + EconStatus, family=gaussian(identity),
  data=ExampleData)
summary(GLM.1)
```

```
Coefficients:
                   Estimate Std. Error t value Pr(>|t|)
(Intercept)         2.39939    3.18150   0.754    0.506
Age                -0.05092    0.08319  -0.612    0.584
EconStatus[T.2ses]  1.22879    2.29144   0.536    0.629
EconStatus[T.3ses]  0.30173    2.18622   0.138    0.899
EconStatus[T.4ses] -1.39954    2.28236  -0.613    0.583
EconStatus[T.5ses]  0.89323    3.80517   0.235    0.830

(Dispersion parameter for gaussian family taken to be 3.471625)

    Null deviance: 19.692  on 8  degrees of freedom
Residual deviance: 10.415  on 3  degrees of freedom
  (4 observations deleted due to missingness)
AIC: 40.855

Number of Fisher Scoring iterations: 2
```

```
Rcmdr Version 1.9-5
[3] NOTE: The dataset ExampleData has 13 rows and 8 columns.
```

Figure 3.19: R Commander GUI

#### 3.8.5.2 Deducer

Deducer is another GUI for R which, much like R Commander, provides access to some of R's functionality through menus and wizards[2].

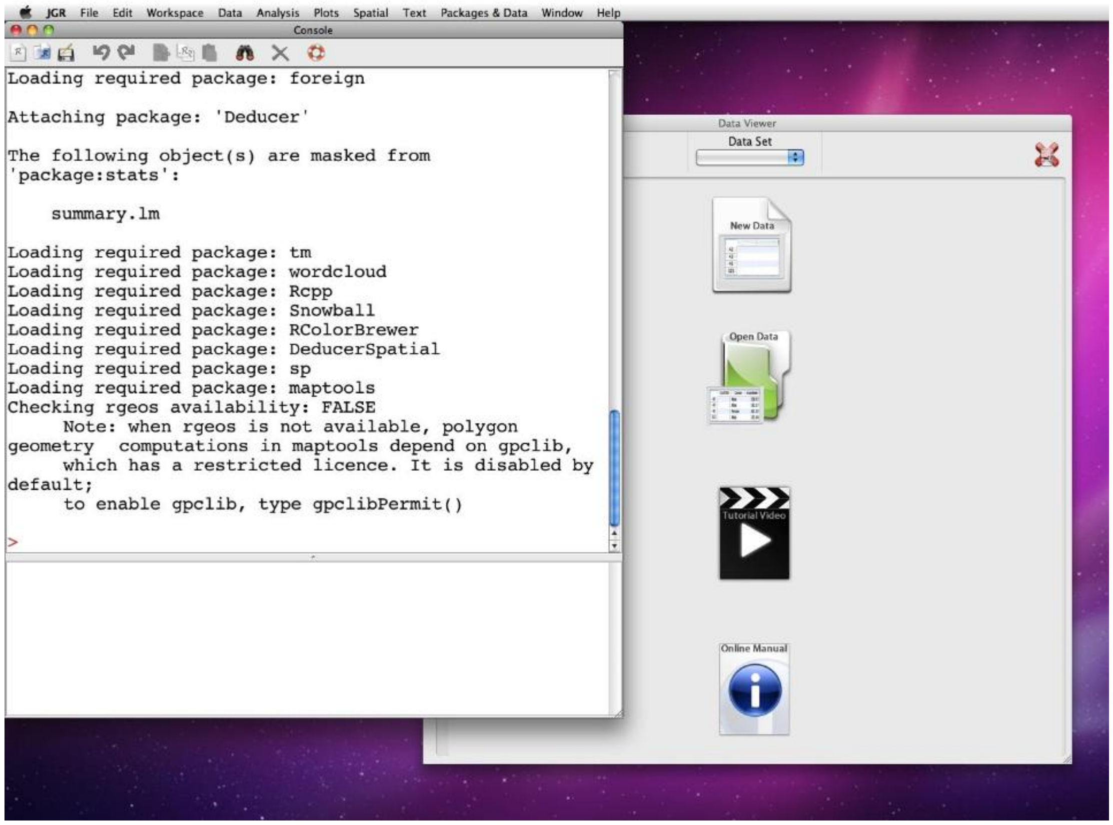
Deducer also preserves command-line access to R's full potential and displays source code as the result of each action in the GUI. It allows novices to perform basic data analyses and produce exploratory plots, maps, and word clouds.

Deducer was developed by a graduate student named Ian Fellows, who saw a disconnect between the way psychologists at UCSD worked with data and the possibilities available in R (Ohri, 2013; Fellows, 2012). Fellows continued work on Deducer at the Center for Embedded Network Sensing (CENS) at UCLA, specifically considering the Mobilize project (Section 5.1) as a use-case. Deducer's primary advantage is that it is free, which makes it possible to use in educational settings where funding is tight. It was used in a live educational setting during the second year of the Mobilize project. While Deducer was slightly easier for teachers to learn than R, the disadvantages of the system easily outweighed this slight advantage. See Section 5.1.4 for more on Deducer in the Mobilize project.

Deducer suffers from one of the same problems as the standard R GUI: there are many free-floating windows, and it is easy to lose one.

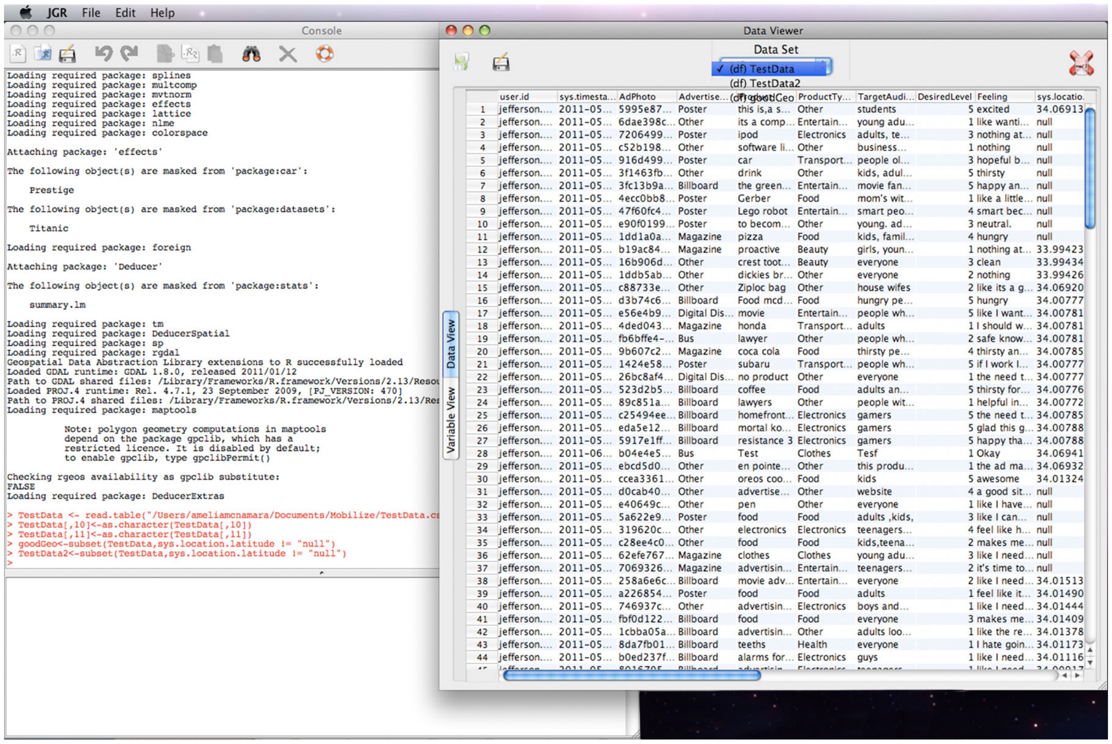
Another detail is the automatically-created R code, which should be non-threatening if we want users to make the association between the actions they take in wizards (for example, the plot-creation wizard) and the resulting code, is bright red. In many users' minds, red signifies 'error,' (Ellior et al., 2007) so many users initially believed they had done something wrong.

[2]The term wizard refers to pop-up windows guiding the user through particular tasks. One commonly-encountered wizard is the letter writing wizard in Microsoft Word, which guides users through the salutation and closing of a formal letter. In Deducer, the wizards were for tasks like graph creation or modeling.


JGR File Edit Workspace Data Analysis Plots Spatial Text Packages & Data Window Help
Console
Data Viewer
Data Set
New Data
Open Data
Tutorial Video
Online Manual

```
Loading required package: foreign

Attaching package: 'Deducer'

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

    summary.lm

Loading required package: tm
Loading required package: wordcloud
Loading required package: Rcpp
Loading required package: Snowball
Loading required package: RColorBrewer
Loading required package: DeducerSpatial
Loading required package: sp
Loading required package: maptools
Checking rgeos availability: FALSE
     Note: when rgeos is not available, polygon
geometry  computations in maptools depend on gpclib,
     which has a restricted licence. It is disabled by
default;
     to enable gpclib, type gpclibPermit()

>
```

Figure 3.20: The initial Deducer screen



```
Loading required package: splines
Loading required package: multcomp
Loading required package: mvtnorm
Loading required package: effects
Loading required package: lattice
Loading required package: nlme
Loading required package: colorspace

Attaching package: 'effects'

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

    Prestige

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

    Titanic

Loading required package: foreign

Attaching package: 'Deducer'

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

    summary.lm

Loading required package: tm
Loading required package: DeducerSpatial
Loading required package: sp
Loading required package: rgdal
Geospatial Data Abstraction Library extensions to R successfully loaded
Loaded GDAL runtime: GDAL 1.8.0, released 2011/01/12
Path to GDAL shared files: /Library/Frameworks/R.framework/Versions/2.13/Resou
Loaded PROJ.4 runtime: Rel. 4.7.1, 23 September 2009, [PJ_VERSION: 470]
Path to PROJ.4 shared files: /Library/Frameworks/R.framework/Versions/2.13/Res
Loading required package: maptools

          Note: polygon geometry computations in maptools
          depend on the package gpclib, which has a
          restricted licence. It is disabled by default;
          to enable gpclib, type gpclibPermit()

Checking rgeos availability as gpclib substitute:
FALSE
Loading required package: DeducerExtras

> TestData <- read.table("/Users/ameliamcnamara/Documents/Mobilize/TestData.cs
> TestData[,10]<-as.character(TestData[,10])
> TestData[,11]<-as.character(TestData[,11])
> goodGeo<-subset(TestData,sys.location.latitude != "null")
> TestData2<-subset(TestData,sys.location.latitude != "null")
>
```

| | user.id | sys.timesta... | AdPhoto | Advertise... | Product | ProductTy... | TargetAudi... | DesiredLevel | Feeling | sys.locatio. |
|---|---|---|---|---|---|---|---|---|---|---|
| 1 | jefferson.... | 2011-05... | 5995e87... | Poster | this is,a s... | Other | students | 5 | excited | 34.06913 |
| 2 | jefferson.... | 2011-05... | 6dae398c... | Other | its a comp... | Entertain... | young adu... | 1 | like wanti... | null |
| 3 | jefferson.... | 2011-05... | 7206499... | Poster | ipod | Electronics | adults, te... | 3 | nothing at... | null |
| 4 | jefferson.... | 2011-05... | c52b198... | Other | software li... | Other | business... | 1 | nothing | null |
| 5 | jefferson.... | 2011-05... | 916d499... | Poster | car | Transport... | people ol... | 3 | hopeful b... | null |
| 6 | jefferson.... | 2011-05... | 3f1463fb... | Other | drink | Other | kids, adul... | 5 | thirsty | null |
| 7 | jefferson.... | 2011-05... | 3fc13b9a... | Billboard | the green... | Entertain... | movie fan... | 5 | happy an... | null |
| 8 | jefferson.... | 2011-05... | 4ecc0bb8... | Poster | Gerber | Food | mom's wit... | 1 | like a little... | null |
| 9 | jefferson.... | 2011-05... | 47f60fc4... | Poster | Lego robot | Entertain... | smart peo... | 4 | smart bec... | null |
| 10 | jefferson.... | 2011-05... | e90f0199... | Poster | to becom... | Other | young. ad... | 3 | neutral. | null |
| 11 | jefferson.... | 2011-05... | 1dd1a0a... | Magazine | pizza | Food | kids, famil... | 4 | hungry | null |
| 12 | jefferson.... | 2011-05... | b19ac84... | Magazine | proactive | Beauty | girls, youn... | 1 | nothing at... | 33.99423 |
| 13 | jefferson.... | 2011-05... | 16b906d... | Other | crest toot... | Beauty | everyone | 3 | clean | 33.99434 |
| 14 | jefferson.... | 2011-05... | 1ddb5ab... | Other | dickies br... | Other | everyone | 2 | nothing | 33.99426 |
| 15 | jefferson.... | 2011-05... | c88733e... | Other | Ziploc bag | Other | house wifes | 2 | like its a g... | 34.06920 |
| 16 | jefferson.... | 2011-05... | d3b74c6... | Billboard | Food mcd... | Food | hungry pe... | 5 | hungry | 34.00777 |
| 17 | jefferson.... | 2011-05... | e56e4b9... | Digital Dis... | movie | Entertain... | people wh... | 5 | like I want... | 34.00781 |
| 18 | jefferson.... | 2011-05... | 4ded043... | Magazine | honda | Transport... | adults | 1 | I should w... | 34.00781 |
| 19 | jefferson.... | 2011-05... | fb6bffe4-... | Bus | lawyer | Other | people wh... | 2 | safe know... | 34.00781 |
| 20 | jefferson.... | 2011-05... | 9b607c2... | Magazine | coca cola | Food | thirsty pe... | 4 | thirsty an... | 34.00785 |
| 21 | jefferson.... | 2011-05... | 1424e58... | Poster | subaru | Transport... | people wh... | 5 | if I work I... | 34.00777 |
| 22 | jefferson.... | 2011-05... | 26bc8af4... | Digital Dis... | no product | Other | everyone | 1 | the need t... | 34.00777 |
| 23 | jefferson.... | 2011-05... | 523d2b5... | Billboard | coffee | Food | adults an... | 5 | thirsty for... | 34.00776 |
| 24 | jefferson.... | 2011-05... | 89c851a... | Billboard | lawyers | Other | people wit... | 1 | helpful in... | 34.00772 |
| 25 | jefferson.... | 2011-05... | c25494ee... | Billboard | homefront... | Electronics | gamers | 5 | the need t... | 34.00785 |
| 26 | jefferson.... | 2011-05... | eda5e12... | Billboard | mortal ko... | Electronics | gamers | 5 | glad this g... | 34.00788 |
| 27 | jefferson.... | 2011-05... | 5917e1ff... | Billboard | resistance 3 | Electronics | gamers | 5 | happy tha... | 34.00788 |
| 28 | jefferson.... | 2011-06... | b04e4e5... | Bus | Test | Clothes | Tesf | 1 | Okay | 34.06941 |
| 29 | jefferson.... | 2011-05... | ebcd5d0... | Other | en pointe... | Other | this produ... | 1 | the ad ma... | 34.06932 |
| 30 | jefferson.... | 2011-05... | ccea3361... | Other | oreos coo... | Food | kids | 5 | awesome | 34.01324 |
| 31 | jefferson.... | 2011-05... | d0cab40... | Other | advertise... | Other | website | 4 | a good sit... | null |
| 32 | jefferson.... | 2011-05... | e40649c... | Other | pen | Other | everyone | 1 | like I have... | null |
| 33 | jefferson.... | 2011-05... | 5a622e9... | Poster | food | Food | adults ,kids, | 3 | like I can... | null |
| 34 | jefferson.... | 2011-05... | 319620c... | Other | electronics | Electronics | teenagers... | 4 | feel like h... | null |
| 35 | jefferson.... | 2011-05... | c28ee4c0... | Other | food | Food | kids,teena... | 2 | makes me... | null |
| 36 | jefferson.... | 2011-05... | 62efe767... | Magazine | clothes | Clothes | young adu... | 3 | like I need... | null |
| 37 | jefferson.... | 2011-05... | 7069326... | Magazine | advertisin... | Entertain... | teenagers... | 2 | it's time to... | null |
| 38 | jefferson.... | 2011-05... | 258a6e6c... | Billboard | movie adv... | Entertain... | everyone | 2 | like I need... | 34.01513 |
| 39 | jefferson.... | 2011-05... | a226854... | Poster | food | Food | adults | 1 | feel like it... | 34.01490 |
| 40 | jefferson.... | 2011-05... | 746937c... | Other | advertisin... | Electronics | boys and... | 1 | like I need... | 34.01444 |
| 41 | jefferson.... | 2011-05... | fbf0d122... | Billboard | food | Food | everyone | 3 | makes me... | 34.01409 |
| 42 | jefferson.... | 2011-05... | 1cbba05a... | Billboard | advertisin... | Other | adults loo... | 1 | like the re... | 34.01378 |
| 43 | jefferson.... | 2011-05... | 8da7fb01... | Billboard | teeths | Health | everyone | 1 | I hate goin... | 34.01173 |
| 44 | jefferson.... | 2011-05... | b0ed237f... | Billboard | alarms for... | Electronics | guys | 1 | like I need... | 34.01116 |

Figure 3.21: Deducer data preview

Additionally, the plot menus produce beautiful **ggplot2** graphics (Wickham, 2009), which is ideal for users because they are inclined to feel pride for having created something appealing. Unfortunately, the resulting **ggplot2** code printed into the console is much too difficult for users to parse. It is the difficulty discussed with R Commander taken to the extreme. It is highly unlikely a novice will make the implicit connection between their actions and the code. Much like R Commander, the simplicity of the system is not coupled with any inherent playfulness, and it does not seem to actually teach R.

### 3.8.5.3 RStudio

On the other hand, RStudio is an Integrated Development Environments (IDE) for R (RStudio Team, 2014). It was initially developed by J.J. Allaire, who is now supported by a team of expert R programmers, including several who have been mentioned previously in this document (Yihui Xie and Hadley Wickham in particular).

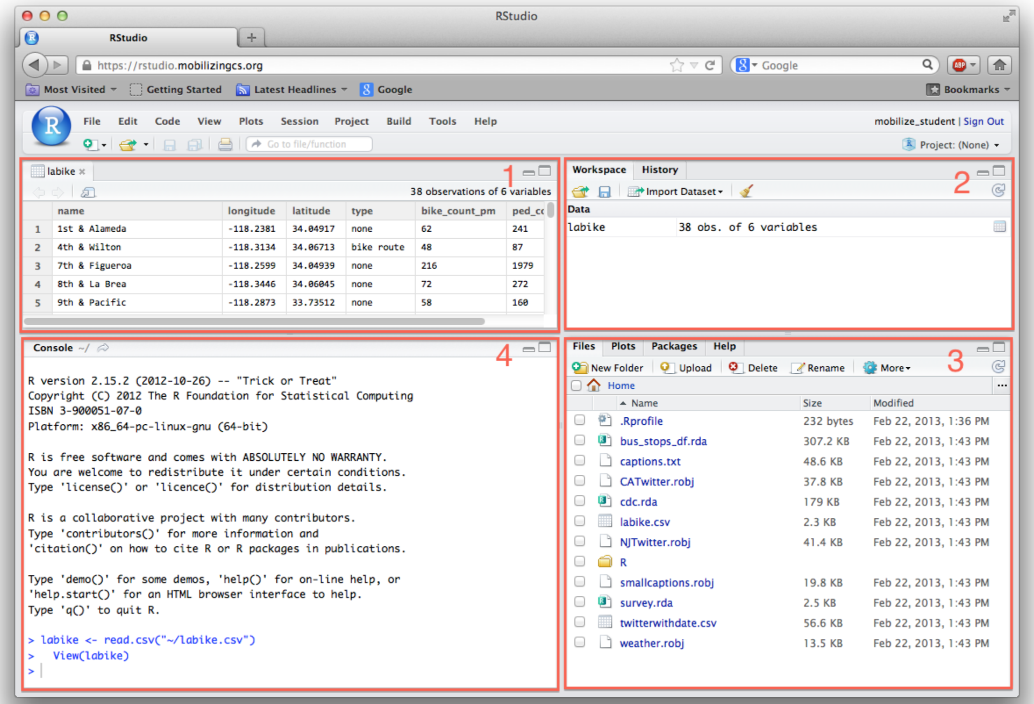
RStudio offers many useful features, such as code completion, file management, and comprehensive code history. For introductory college users, many professors have found the support RStudio provides makes it much easier to pick up R (Baumer et al., 2014; Muller and Kidd, 2014; Pruim et al., 2014; Horton et al., 2014a). It is also easier for high school teachers and students, as discovered during the Mobilize project and in McNamara and Hansen (2014).

RStudio can be run as a desktop application for Mac, Windows, or Linux, but it is also available as a server install. By using a server version, instructors can manage package installations from a central location and provide quick bug fixes to all students at once. Users go to a particular web address, log in, and find their R session just how they left it. All files can be hosted on a central server, which means students can do their work from any computer without having to worry about moving data from place to place.

Because of how simple it makes access, many colleges use RStudio servers for their students. In particular, Smith College, Mount Holyoke College, Duke University, and Macalester College all use this arrangement. For Mobilize, a server version was used for our high school teachers and students (discussed further in Section 5.1).

When a user opens RStudio, whether in the desktop version of the application or through a server, the initial screen will look much like what is seen in Figure 3.22. In fact, in the book "Start Teaching with R," the authors warn the server version and desktop version "look so similar that if you run them both, you will have to pay attention to make sure you are working in the one you intend to be working in." (Pruim et al., 2014).

The RStudio screen has four panes, which are shown in their default arrangement in Figure 3.22[3]. RStudio does allow the user to move panes in the options menu, but this layout is the default when a user first launches the program, so we will act as though it is standard.



38 observations of 6 variables

|  | name | longitude | latitude | type | bike_count_pm | ped_cc |
|---|---|---|---|---|---|---|
| 1 | 1st & Alameda | -118.2381 | 34.04917 | none | 62 | 241 |
| 2 | 4th & Wilton | -118.3134 | 34.06713 | bike route | 48 | 87 |
| 3 | 7th & Figueroa | -118.2599 | 34.04939 | none | 216 | 1979 |
| 4 | 8th & La Brea | -118.3446 | 34.06045 | none | 72 | 272 |
| 5 | 9th & Pacific | -118.2873 | 33.73512 | none | 58 | 160 |

Data

| | |
|---|---|
| labike | 38 obs. of 6 variables |

```
R version 2.15.2 (2012-10-26) -- "Trick or Treat"
Copyright (C) 2012 The R Foundation for Statistical Computing
ISBN 3-900051-07-0
Platform: x86_64-pc-linux-gnu (64-bit)

R is free software and comes with ABSOLUTELY NO WARRANTY.
You are welcome to redistribute it under certain conditions.
Type 'license()' or 'licence()' for distribution details.

R is a collaborative project with many contributors.
Type 'contributors()' for more information and
'citation()' on how to cite R or R packages in publications.

Type 'demo()' for some demos, 'help()' for on-line help, or
'help.start()' for an HTML browser interface to help.
Type 'q()' to quit R.

> labike <- read.csv("~/labike.csv")
>   View(labike)
> 
```

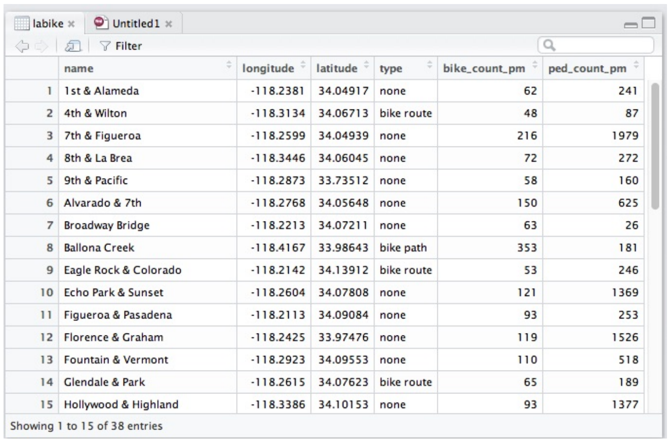
| Name | Size | Modified |
|---|---|---|
| .Rprofile | 232 bytes | Feb 22, 2013, 1:36 PM |
| bus_stops_df.rda | 307.2 KB | Feb 22, 2013, 1:43 PM |
| captions.txt | 48.6 KB | Feb 22, 2013, 1:43 PM |
| CATwitter.robj | 37.8 KB | Feb 22, 2013, 1:43 PM |
| cdc.rda | 179 KB | Feb 22, 2013, 1:43 PM |
| labike.csv | 2.3 KB | Feb 22, 2013, 1:43 PM |
| NJTwitter.robj | 41.4 KB | Feb 22, 2013, 1:43 PM |
| R | | |
| smallcaptions.robj | 19.8 KB | Feb 22, 2013, 1:43 PM |
| survey.rda | 2.5 KB | Feb 22, 2013, 1:43 PM |
| twitterwithdate.csv | 56.6 KB | Feb 22, 2013, 1:43 PM |
| weather.robj | 13.5 KB | Feb 22, 2013, 1:43 PM |

Figure 3.22: Panes in RStudio

The first pane allows users to view files and data. This is a useful feature because it allows users to view a spreadsheet-like representation of their data, which they can scroll through (Figure 3.23). In standard R, views of data are much more piecemeal, and users must type commands like `head(data)` and `tail(data)` to view the first (or last) few rows. In contrast, RStudio helps smooth the transition from a spreadsheet tool. This is also the pane where documentation can be written by users, such as .R files or RMarkdown documents (discussed at more length in Section 3.8.3).

The second pane allows users to view a list of all the objects loaded into the

[3]The following text has been modified from McNamara (2013a)

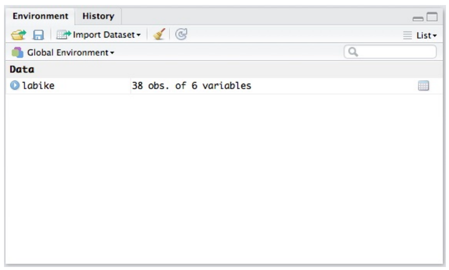


| | name | longitude | latitude | type | bike_count_pm | ped_count_pm |
|---|---|---|---|---|---|---|
| 1 | 1st & Alameda | -118.2381 | 34.04917 | none | 62 | 241 |
| 2 | 4th & Wilton | -118.3134 | 34.06713 | bike route | 48 | 87 |
| 3 | 7th & Figueroa | -118.2599 | 34.04939 | none | 216 | 1979 |
| 4 | 8th & La Brea | -118.3446 | 34.06045 | none | 72 | 272 |
| 5 | 9th & Pacific | -118.2873 | 33.73512 | none | 58 | 160 |
| 6 | Alvarado & 7th | -118.2768 | 34.05648 | none | 150 | 625 |
| 7 | Broadway Bridge | -118.2213 | 34.07211 | none | 63 | 26 |
| 8 | Ballona Creek | -118.4167 | 33.98643 | bike path | 353 | 181 |
| 9 | Eagle Rock & Colorado | -118.2142 | 34.13912 | bike route | 53 | 246 |
| 10 | Echo Park & Sunset | -118.2604 | 34.07808 | none | 121 | 1369 |
| 11 | Figueroa & Pasadena | -118.2113 | 34.09084 | none | 93 | 253 |
| 12 | Florence & Graham | -118.2425 | 33.97476 | none | 119 | 1526 |
| 13 | Fountain & Vermont | -118.2923 | 34.09553 | none | 110 | 518 |
| 14 | Glendale & Park | -118.2615 | 34.07623 | bike route | 65 | 189 |
| 15 | Hollywood & Highland | -118.3386 | 34.10153 | none | 93 | 1377 |

Showing 1 to 15 of 38 entries

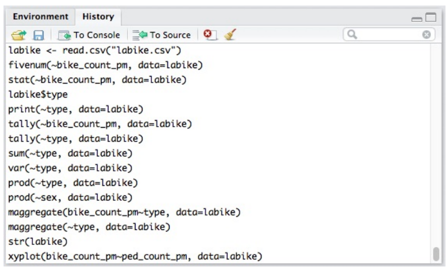
Figure 3.23: Preview pane, showing data and files

working environment, as in Figure 3.24a. For example, all datasets loaded will appear here, along with any other objects that have been created (special text or spatial formats, vectors, etc). Again, this helps make using R more concrete. Every time a user creates a new variable, they see its name appear in the environment tab, and can click on its name to inspect it more closely. The other tab in the second pane is a code history, which includes the complete history of all code typed, over all R sessions, as in Figure 3.24b. The history is searchable, so the user can use the search box at the upper right of the pane to search through their code history.



```
labike          38 obs. of 6 variables
```

(a) Environment



```
labike <- read.csv("labike.csv")
fivenum(~bike_count_pm, data=labike)
stat(~bike_count_pm, data=labike)
labike$type
print(~type, data=labike)
tally(~bike_count_pm, data=labike)
tally(~type, data=labike)
sum(~type, data=labike)
var(~type, data=labike)
prod(~type, data=labike)
prod(~sex, data=labike)
maggregate(bike_count_pm~type, data=labike)
maggregate(~type, data=labike)
str(labike)
xyplot(bike_count_pm~ped_count_pm, data=labike)
```

(b) History

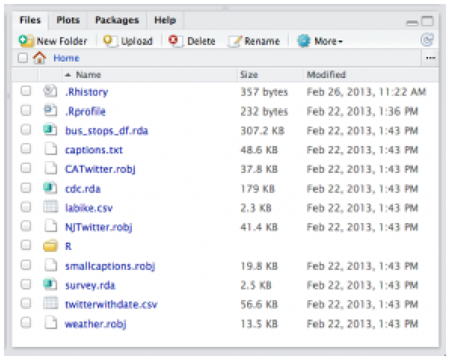
Figure 3.24: Second pane in RStudio: environment and history

The third pane provides integrated views of files, plots, packages and help. When a user runs code in the Console creating a plot, the Plots tab will be automatically selected, as in Figure 3.25b. The automatic plot tab selection makes it very simple for users to know when the code they have run created a plot. In contrast with the standard R GUI, which has a floating window for plots that can easily get 'lost,' this integrated tab keeps everything cohesively together.

The packages tab (Figure 3.25c) gives a visual summary of all the packages the user has installed and which are loaded into the current working session. Again, the ability to visually keep track of packages supports users. In the standard R GUI, users have to type `installed.packages()` to see the list of packages they have installed, and this command is often not taught. By making it simple to see the list of packages, RStudio is encouraging users, even novices, to view their installed packages. Similar to the plots tab, the help tab will be automatically selected whenever the user runs help code in the Console, like `help(plot)` or `?plot`.

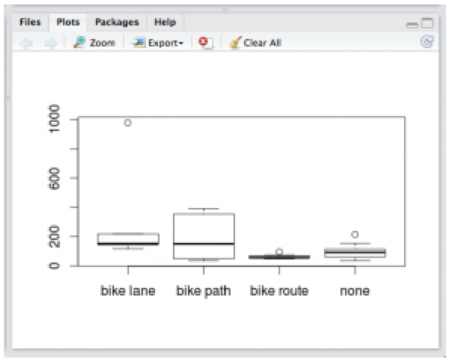
The fourth pane is the console, and provides the command line for users to enter R code. The console pane is where the majority of work takes place – the other panes provide support for the user, but no code interpretation. The console looks similar to the standard R GUI, but it also provides support for users. For example, if a user begins to type a function and then hits the 'tab' key on their keyboard, RStudio will do code completion and provide a hovering hint of the documentation of the function (Figure 3.26).

RStudio provides many support features, in particular a unified interface where windows cannot get 'lost.' It also provides visual cues; to objects in the working environment, to installed packages, and to files in the working directory. The data preview functionality helps ease the transition from spreadsheet programs. And even in the most programming-oriented area, the Console, RStudio provides coding support features like tab completion and code hints. RStudio has been used successfully in many introductory college statistics classes (Baumer et al., 2014; Muller and Kidd, 2014; Pruim et al., 2014; Horton et al.,

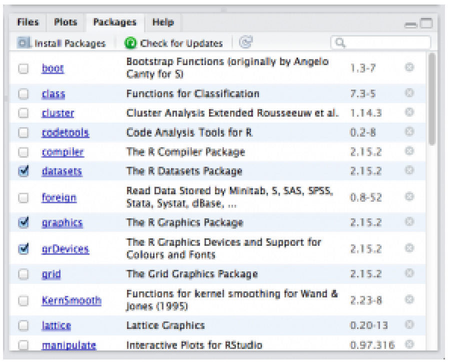


| | Name | Size | Modified |
|---|---|---|---|
| | .Rhistory | 357 bytes | Feb 26, 2013, 11:22 AM |
| | .Rprofile | 232 bytes | Feb 22, 2013, 1:36 PM |
| | bus_stops_df.rda | 307.2 KB | Feb 22, 2013, 1:43 PM |
| | captions.txt | 48.6 KB | Feb 22, 2013, 1:43 PM |
| | CATwitter.robj | 37.8 KB | Feb 22, 2013, 1:43 PM |
| | cdc.rda | 179 KB | Feb 22, 2013, 1:43 PM |
| | labike.csv | 2.3 KB | Feb 22, 2013, 1:43 PM |
| | NJTwitter.robj | 41.4 KB | Feb 22, 2013, 1:43 PM |
| | R | | |
| | smallcaptions.robj | 19.8 KB | Feb 22, 2013, 1:43 PM |
| | survey.rda | 2.5 KB | Feb 22, 2013, 1:43 PM |
| | twitterwithdate.csv | 56.6 KB | Feb 22, 2013, 1:43 PM |
| | weather.robj | 13.5 KB | Feb 22, 2013, 1:43 PM |

(a) Files

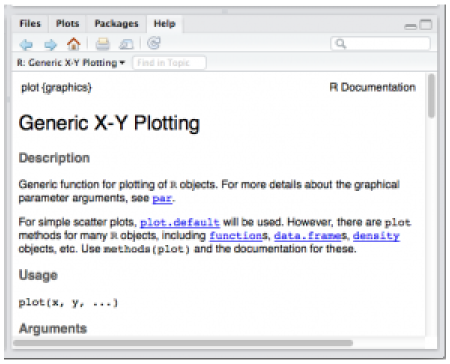


(b) Plots



| | | | |
|---|---|---|---|
| ☐ | boot | Bootstrap Functions (originally by Angelo Canty for S) | 1.3-7 |
| ☐ | class | Functions for Classification | 7.3-5 |
| ☐ | cluster | Cluster Analysis Extended Rousseeuw et al. | 1.14.3 |
| ☐ | codetools | Code Analysis Tools for R | 0.2-8 |
| ☐ | compiler | The R Compiler Package | 2.15.2 |
| ✓ | datasets | The R Datasets Package | 2.15.2 |
| ☐ | foreign | Read Data Stored by Minitab, S, SAS, SPSS, Stata, Systat, dBase, ... | 0.8-52 |
| ✓ | graphics | The R Graphics Package | 2.15.2 |
| ✓ | grDevices | The R Graphics Devices and Support for Colours and Fonts | 2.15.2 |
| ☐ | grid | The Grid Graphics Package | 2.15.2 |
| ☐ | KernSmooth | Functions for kernel smoothing for Wand & Jones (1995) | 2.23-8 |
| ☐ | lattice | Lattice Graphics | 0.20-13 |
| ☐ | manipulate | Interactive Plots for RStudio | 0.97.316 |

(c) Packages



plot {graphics} R Documentation

Generic X-Y Plotting

Description

Generic function for plotting of R objects. For more details about the graphical parameter arguments, see par.

For simple scatter plots, plot.default will be used. However, there are plot methods for many R objects, including functions, data.frames, density objects, etc. Use methods(plot) and the documentation for these.

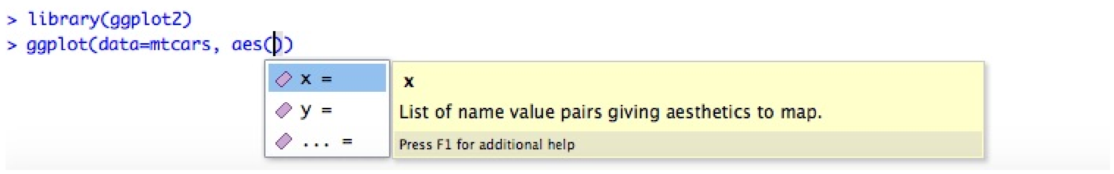
Usage

```
plot(x, y, ...)
```

Arguments

(d) Help

Figure 3.25: Third pane in RStudio: file viewing, plots, packages, and help



```
> library(ggplot2)
> ggplot(data=mtcars, aes())
```

x

List of name value pairs giving aesthetics to map.

Press F1 for additional help

Figure 3.26: Tab completion in RStudio

2014a) and with high school teachers and students through the Mobilize Project (Section 5.1). However, even though it lowers the barrier to entry for R, RStudio still requires users to code, so there is a startup cost associated with using it.

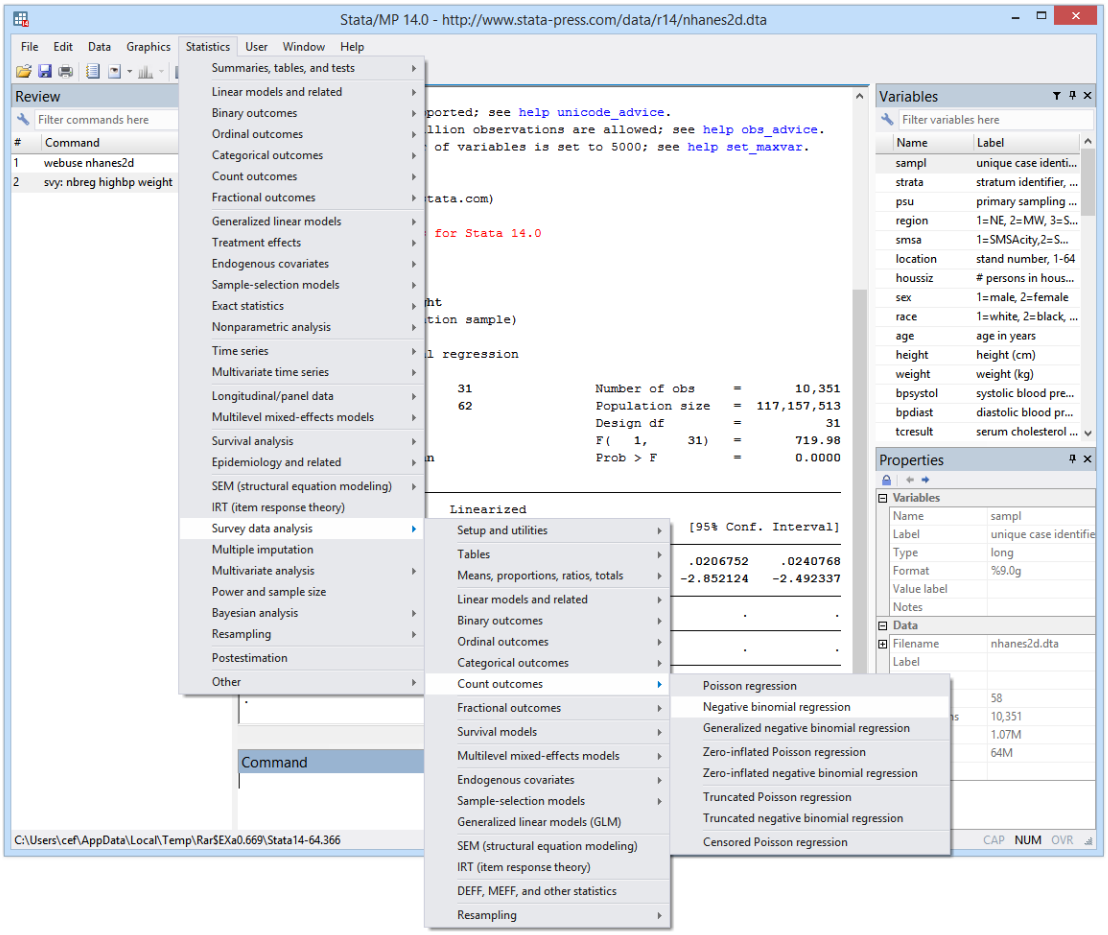
## 3.9 Stata, SAS, and SPSS

Other commonly used tools for doing statistical analysis are Stata, SAS, and SPSS. All three tools are stand-alone software, and all combine elements of graphical user interfaces with command-line tools. They are used in a variety of disciplinary contexts, so the argument for teaching them is 'students will need to use this in the future.' They are often popular in industry, because they come with guarantees of validity and technical support.

Stata (Figure 3.27) is often the tool of choice for introductory statistics courses taught in an economics department, as it is used routinely by economists. Stata does support users writing their own routines, so it is extensible. It also includes a command-line language, so it can be used to create reproducible research, in the sense that analyses can be re-run to get the same results.

However, Stata does not integrate with tools like the iPython notebook or **knitr**, so there is no easy way to produce reproducible reports (Rising, 2014). Another major drawback to Stata is its price. As of 2015, educational pricing was $445 for an annual license or $895 for a perpetual license. A single business license costs $845 per year or $1,695 for a perpetual license. The company does offer group discounts, but these are also expensive (for example, a 10-user lab costs $1,850 plus $160 each, unless purchasing the "small" version which only deals with data up to 1,200 observations).

SAS has similar benefits and drawbacks to Stata. It is often used in pharmaceutical and business applications because it comes with a guarantee of ac-



| # | Command |
|---|---|
| 1 | webuse nhanes2d |
| 2 | svy: nbreg highbp weight |

```
ported; see help unicode_advice.
llion observations are allowed; see help obs_advice.
 of variables is set to 5000; see help set_maxvar.

tata.com)

 for Stata 14.0

ht
tion sample)

l regression

  31                   Number of obs     =      10,351
  62                   Population size   = 117,157,513
                       Design df         =          31
                       F(    1,      31) =      719.98
n                      Prob > F          =      0.0000

   Linearized
                          [95% Conf. Interval]

                           .0206752    .0240768
                          -2.852124   -2.492337

                                  .           .

                                  .           .
```

| Name | Label |
|---|---|
| sampl | unique case identi... |
| strata | stratum identifier, ... |
| psu | primary sampling ... |
| region | 1=NE, 2=MW, 3=S... |
| smsa | 1=SMSAcity,2=S... |
| location | stand number, 1-64 |
| houssiz | # persons in hous... |
| sex | 1=male, 2=female |
| race | 1=white, 2=black, ... |
| age | age in years |
| height | height (cm) |
| weight | weight (kg) |
| bpsystol | systolic blood pre... |
| bpdiast | diastolic blood pr... |
| tcresult | serum cholesterol ... |

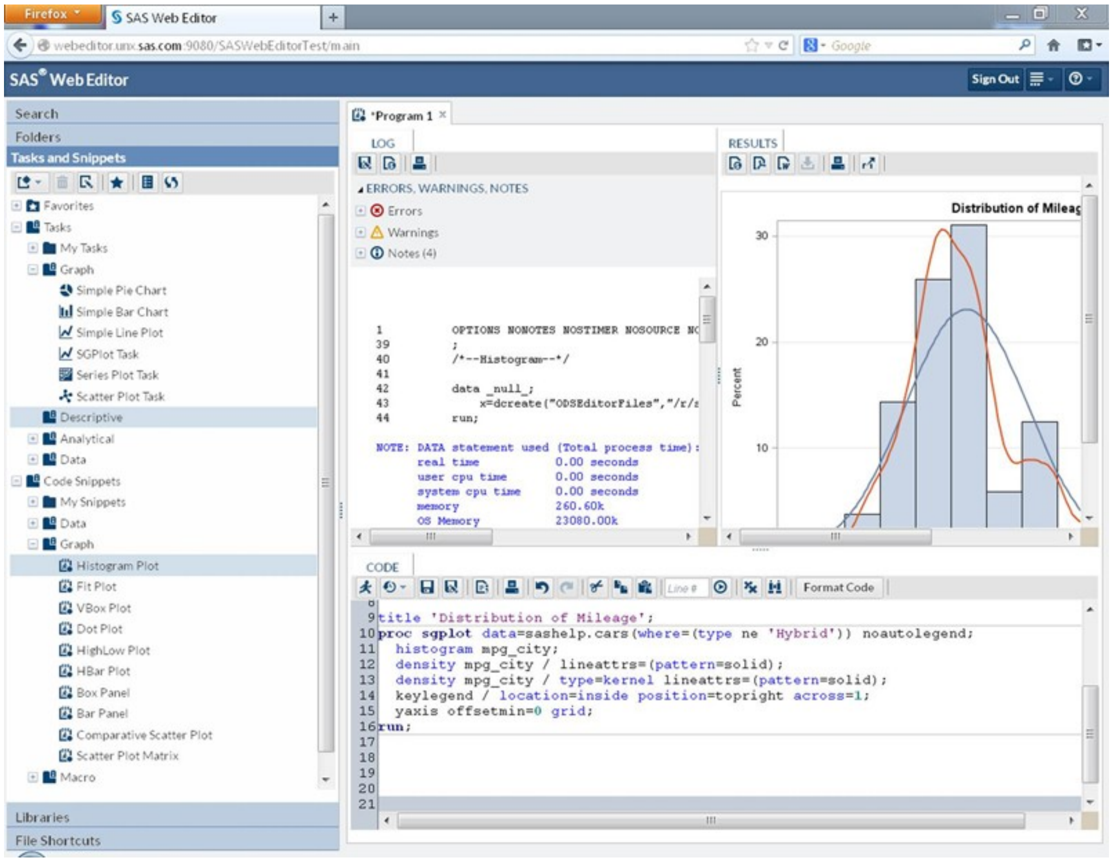
| Variables | |
|---|---|
| Name | sampl |
| Label | unique case identifie |
| Type | long |
| Format | %9.0g |
| Value label | |
| Notes | |
| **Data** | |
| Filename | nhanes2d.dta |
| Label | |
| | |
| | 58 |
| s | 10,351 |
| | 1.07M |
| | 64M |

C:\Users\cef\AppData\Local\Temp\Rar$EXa0.669\Stata14-64.366

Figure 3.27: Stata interface

curacy. SAS is also hugely expensive for corporate use, in part because of the guarantee of accuracy and included support. For an individual it costs $9,000, and enterprise and government licenses require users to submit a request for a quote.

However, the company makes the software free for educational use, both as desktop software and via the cloud, so students can access it via a web browser, much like RStudio. This is a shrewd business decision, because it grooms students to become experts at their software. A screenshot of SAS is shown in Figure 3.28.



```
1          OPTIONS NONOTES NOSTIMER NOSOURCE NO
39         ;
40         /*--Histogram--*/
41
42         data _null_;
43             x=dcreate("ODSEditorFiles","/r/s
44         run;

NOTE: DATA statement used (Total process time):
      real time           0.00 seconds
      user cpu time       0.00 seconds
      system cpu time     0.00 seconds
      memory              260.60k
      OS Memory           23080.00k
```

```
title 'Distribution of Mileage';
proc sgplot data=sashelp.cars(where=(type ne 'Hybrid')) noautolegend;
  histogram mpg_city;
  density mpg_city / lineattrs=(pattern=solid);
  density mpg_city / type=kernel lineattrs=(pattern=solid);
  keylegend / location=inside position=topright across=1;
  yaxis offsetmin=0 grid;
run;
```

Figure 3.28: SAS 9.4 interface

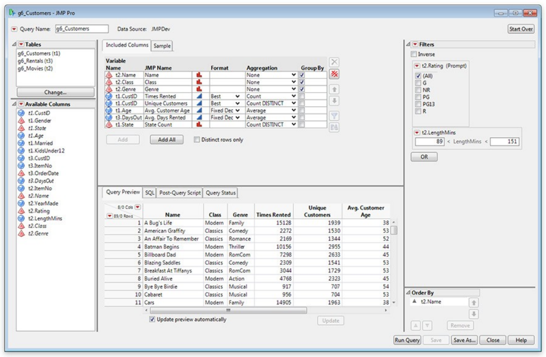
The other product from SAS often used in an educational setting is JMP. JMP is a drag-and-drop, menu-driven graphical user interface. Some features of JMP are shown in Figure 3.29. The backbone of JMP is SAS, but JMP provides a simple visual interface. Again, JMP is expensive ($1,540 for an individual) but they offer academic discounts: $50 for a yearly license for undergraduate and graduate students.

JMP provides many features useful for novices, like interactive brushing and linking, generalizable data cleaning, and visual model support.

Like TinkerPlots and Fathom, while JMP does produce interactive graphics within an individual session, these interactive results cannot be exported. Instead, a work session can be printed or pasted into a document. The student version of JMP does not support exporting graphics, but individual licenses do.

SPSS (Figure 3.30) is typically used by social scientists and is focused on a menu-driven interface, although it does have a proprietary command-line syntax allowing for reproducibility. However, the syntax is hard to understand and code is generally only created by copying and pasting, versus users generating code themselves (Academic Technology Services, 2013). SPSS is also very expensive– $5,760 for a 12-month individual license, or $95.75 for a one-year student license.

Although Stata, SAS, and SPSS are commonly used in industry, none of them seem to be supportive of learners. They all provide specific types of graphics, and most work is done using menus and wizards, so they do not make clear what the tool is actually doing. Using these tools creates 'users' not 'creators' of statistics (see Section 1.5 for more on the distinction). All three tools obscure the underlying computational processes and reduce statistical procedures to button clicks. Although they all provide some capability of extending the software with scripting, none of them have the community of statisticians sharing work that R has. Further, they all suffer from a lack of transparency about how internal routines were coded, they do not produce reproducible reports, and their pricing is prohibitive for the secondary school use-case.



g6_Customers - JMP Pro

Query Name: g6_Customers    Data Source: JMPDev    Start Over

**Tables**

- g6_Customers (t1)
- g6_Rentals (t3)
- g6_Movies (t2)

Change...

**Available Columns**

- t1.CustID
- t1.Gender
- t1.State
- t1.Age
- t1.Married
- t1.KidsUnder12
- t3.CustID
- t3.ItemNo
- t3.OrderDate
- t3.DaysOut
- t2.ItemNo
- t2.Name
- t2.YearMade
- t2.Rating
- t2.LengthMins
- t2.Class
- t2.Genre

Included Columns | Sample

| Variable Name | JMP Name | Format | Aggregation | Group By |
|---|---|---|---|---|
| t2.Name | Name | | None | ✓ |
| t2.Class | Class | | None | ✓ |
| t2.Genre | Genre | | None | ✓ |
| t1.CustID | Times Rented | Best | Count | |
| t1.CustID | Unique Customers | Best | Count DISTINCT | |
| t1.Age | Avg. Customer Age | Fixed Dec | Average | |
| t3.DaysOut | Avg. Days Rented | Fixed Dec | Average | |
| t1.State | State Count | | Count DISTINCT | |

Add    Add All    ☐ Distinct rows only

Query Preview | SQL | Post-Query Script | Query Status

8/0 Cols    89/0 Rows

| | Name | Class | Genre | Times Rented | Unique Customers | Avg. Customer Age |
|---|---|---|---|---|---|---|
| 1 | A Bug's Life | Modern | Family | 15128 | 1939 | 38 |
| 2 | American Graffity | Classics | Comedy | 2272 | 1530 | 53 |
| 3 | An Affair To Remember | Classics | Romance | 2169 | 1344 | 52 |
| 4 | Batman Begins | Modern | Thriller | 10156 | 2955 | 44 |
| 5 | Billboard Dad | Modern | RomCom | 7298 | 2633 | 45 |
| 6 | Blazing Saddles | Classics | Comedy | 2309 | 1541 | 53 |
| 7 | Breakfast At Tiffanys | Classics | RomCom | 3044 | 1729 | 53 |
| 8 | Buried Alive | Modern | Action | 4768 | 2323 | 45 |
| 9 | Bye Bye Birdie | Classics | Musical | 917 | 707 | 54 |
| 10 | Cabaret | Classics | Musical | 956 | 704 | 53 |
| 11 | Cars | Modern | Family | 14905 | 1963 | 38 |

☑ Update preview automatically    Update

**Filters**

☐ Inverse

t2.Rating (Prompt)

- ☑ (All)
- ☐ G
- ☐ NR
- ☐ PG
- ☐ PG13
- ☐ R

t2.LengthMins: 89 < LengthMins < 151

OR

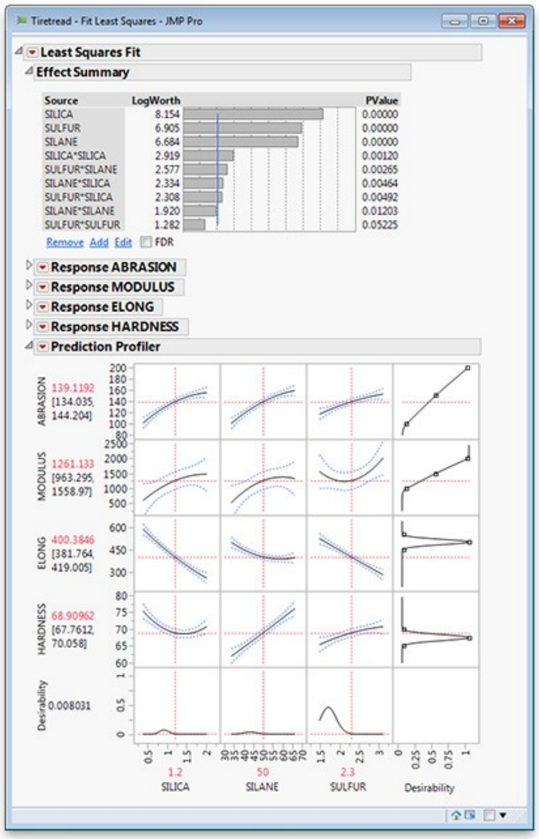
**Order By**

t2.Name

Remove

Run Query    Save    Save As...    Close    Help

(a) JMP dynamic querying



Tiretread - Fit Least Squares - JMP Pro

**Least Squares Fit**

**Effect Summary**

| Source | LogWorth | PValue |
|---|---|---|
| SILICA | 8.154 | 0.00000 |
| SULFUR | 6.905 | 0.00000 |
| SILANE | 6.684 | 0.00000 |
| SILICA*SILICA | 2.919 | 0.00120 |
| SULFUR*SILANE | 2.577 | 0.00265 |
| SILANE*SILICA | 2.334 | 0.00464 |
| SULFUR*SILICA | 2.308 | 0.00492 |
| SILANE*SILANE | 1.920 | 0.01203 |
| SULFUR*SULFUR | 1.282 | 0.05225 |

Remove    Add    Edit    ☐ FDR

**Response ABRASION**

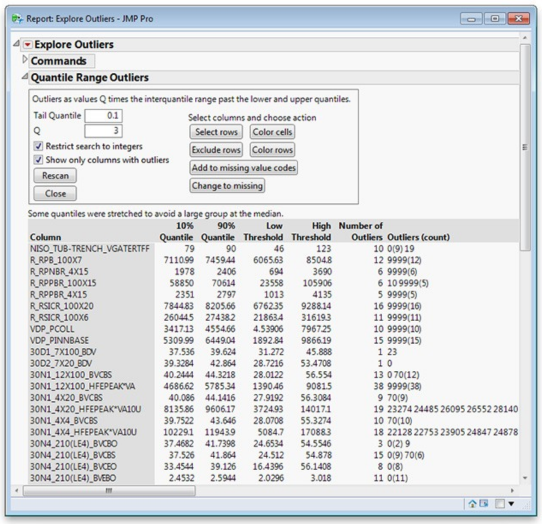
**Response MODULUS**

**Response ELONG**

**Response HARDNESS**

**Prediction Profiler**

(b) JMP modeling



Report: Explore Outliers - JMP Pro

**Explore Outliers**

**Commands**

**Quantile Range Outliers**

Outliers as values Q times the interquantile range past the lower and upper quantiles.

Tail Quantile: 0.1

Q: 3

☑ Restrict search to integers

☑ Show only columns with outliers

Rescan    Close

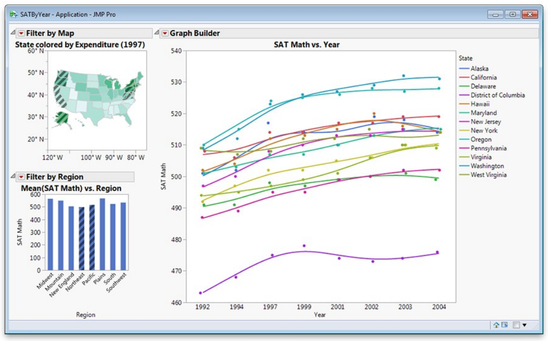
Select columns and choose action

Select rows    Color cells    Exclude rows    Color rows    Add to missing value codes    Change to missing

Some quantiles were stretched to avoid a large group at the median.

| Column | 10% Quantile | 90% Quantile | Low Threshold | High Threshold | Number of Outliers | Outliers (count) |
|---|---|---|---|---|---|---|
| NISO_TUB-TRENCH_VGATERTFF | 79 | 90 | 46 | 123 | 10 | 0(9) 19 |
| R_RPB_100X7 | 7110.99 | 7459.44 | 6065.63 | 8504.8 | 12 | 9999(12) |
| R_RPNBR_4X15 | 1978 | 2406 | 694 | 3690 | 6 | 9999(6) |
| R_RPPBR_100X15 | 58850 | 70614 | 23558 | 105906 | 6 | 10 9999(5) |
| R_RPPBR_4X15 | 2351 | 2797 | 1013 | 4135 | 5 | 9999(5) |
| R_RSICR_100X20 | 7844.83 | 8205.66 | 6762.35 | 9288.14 | 16 | 9999(16) |
| R_RSICR_100X6 | 26044.5 | 27438.2 | 21863.4 | 31619.3 | 11 | 9999(11) |
| VDP_PCOLL | 3417.13 | 4554.66 | 4.53906 | 7967.25 | 10 | 9999(10) |
| VDP_PINNBASE | 5309.99 | 6449.04 | 1892.84 | 9866.19 | 15 | 9999(15) |
| 30D1_7X100_BDV | 37.536 | 39.624 | 31.272 | 45.888 | 1 | 23 |
| 30D2_7X20_BDV | 39.3284 | 42.864 | 28.7216 | 53.4708 | 1 | 0 |
| 30N1_12X100_BVCBS | 40.2444 | 44.3218 | 28.0122 | 56.554 | 13 | 0 70(12) |
| 30N1_12X100_HFEPEAK*VA | 4686.62 | 5785.34 | 1390.46 | 9081.5 | 38 | 9999(38) |
| 30N1_4X20_BVCBS | 40.086 | 44.1416 | 27.9192 | 56.3084 | 9 | 70(9) |
| 30N1_4X20_HFEPEAK*VA10U | 8135.86 | 9606.17 | 3724.93 | 14017.1 | 19 | 23274 24485 26095 26552 28140 |
| 30N1_4X4_BVCBS | 39.7522 | 43.646 | 28.0708 | 55.3274 | 10 | 70(10) |
| 30N1_4X4_HFEPEAK*VA10U | 10229.1 | 11943.9 | 5084.7 | 17088.3 | 18 | 22128 22753 23905 24847 24878 |
| 30N4_210(LE4)_BVCBO | 37.4682 | 41.7398 | 24.6534 | 54.5546 | 3 | 0(2) 9 |
| 30N4_210(LE4)_BVCBS | 37.526 | 41.864 | 24.512 | 54.878 | 15 | 0(9) 70(6) |
| 30N4_210(LE4)_BVCEO | 33.4544 | 39.126 | 16.4396 | 56.1408 | 8 | 0(8) |
| 30N4_210(LE4)_BVEBO | 2.4532 | 2.5944 | 2.0296 | 3.018 | 11 | 0(11) |

(c) JMP model diagnostics



(d) JMP graphing

Figure 3.29: JMP

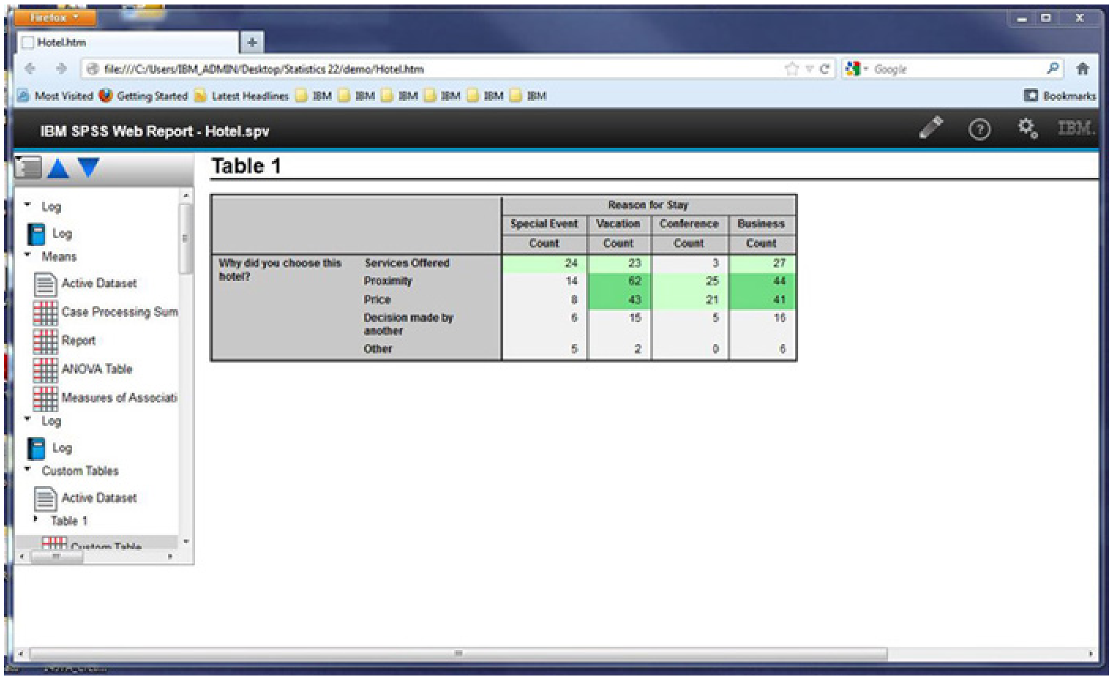


Table 1

| | | Reason for Stay | | | |
|---|---|---|---|---|---|
| | | Special Event | Vacation | Conference | Business |
| | | Count | Count | Count | Count |
| Why did you choose this hotel? | Services Offered | 24 | 23 | 3 | 27 |
| | Proximity | 14 | 62 | 25 | 44 |
| | Price | 8 | 43 | 21 | 41 |
| | Decision made by another | 6 | 15 | 5 | 16 |
| | Other | 5 | 2 | 0 | 6 |

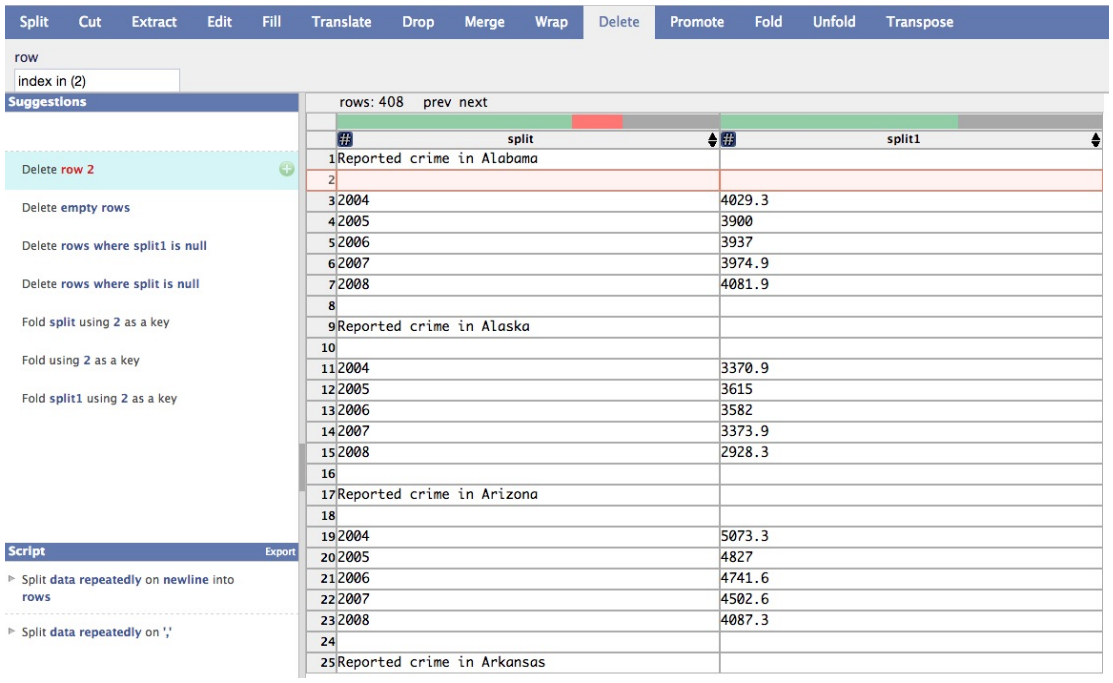
Figure 3.30: SPSS Standard Edition

The most inspirational is JMP (Figure 3.29), which makes data analysis visual and interactive, providing many of the features of software for learning statistics with the power of a tool for really doing statistics.

## 3.10 Bespoke tools

In addition to the tools discussed above, there are a number of 'bespoke' tools for doing particular things with data. The most salient examples are Data Wrangler, Open Refine, Tableau, and Lyra.

Data Wrangler (Figure 3.31) began as a project from the Stanford Visualization Group in 2011 (Kandel et al., 2011b). Their goal was to provide a visual representation of data transforms, as well as a reproducible history of those transforms. For example, a user could select an empty row and indicate it should be deleted, at which point the Wrangler interface would suggest a variety of generalizable transformations that could be built from that one 'rule' (e.g., delete all empty rows, or always delete the 7th row). Once the user specifies a transform, it is applied to the data and added to the interaction history. The interaction history can be exported as a data transformation script in a variety of languages.



row
index in (2)

Delete row 2
Delete empty rows
Delete rows where split1 is null
Delete rows where split is null
Fold split using 2 as a key
Fold using 2 as a key
Fold split1 using 2 as a key

Split data repeatedly on newline into rows
Split data repeatedly on ','

rows: 408

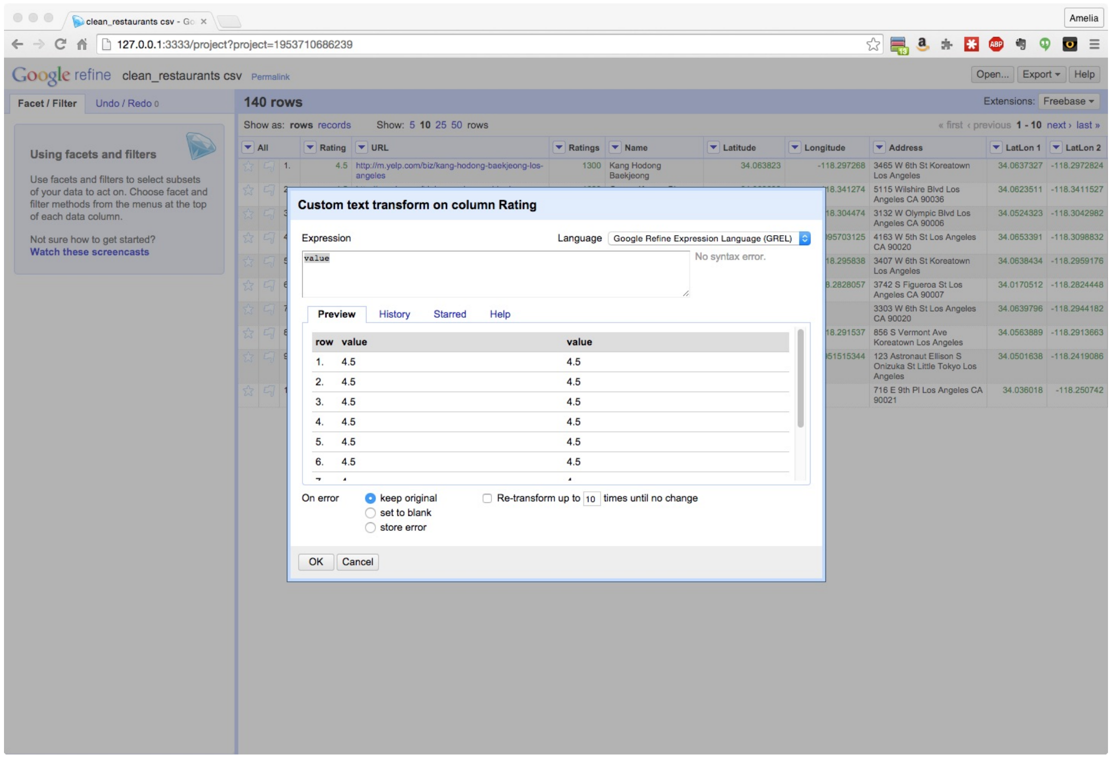
| | split | split1 |
|---|---|---|
| 1 | Reported crime in Alabama | |
| 2 | | |
| 3 | 2004 | 4029.3 |
| 4 | 2005 | 3900 |
| 5 | 2006 | 3937 |
| 6 | 2007 | 3974.9 |
| 7 | 2008 | 4081.9 |
| 8 | | |
| 9 | Reported crime in Alaska | |
| 10 | | |
| 11 | 2004 | 3370.9 |
| 12 | 2005 | 3615 |
| 13 | 2006 | 3582 |
| 14 | 2007 | 3373.9 |
| 15 | 2008 | 2928.3 |
| 16 | | |
| 17 | Reported crime in Arizona | |
| 18 | | |
| 19 | 2004 | 5073.3 |
| 20 | 2005 | 4827 |
| 21 | 2006 | 4741.6 |
| 22 | 2007 | 4502.6 |
| 23 | 2008 | 4087.3 |
| 24 | | |
| 25 | Reported crime in Arkansas | |

Figure 3.31: Data Wrangler

Wrangler can also perform simple database manipulations, in the same way **dplyr** manipulates data in R. The tools Wrangler provided were so useful the authors were able to convert their academic research project into a corporate venture, which is now known as Trifacta.

Very similar to Data Wrangler is Open Refine (Verborgh and Wilde, 2013). The project was initially called Google Refine, but has since been turned into an open source package. Like Wrangler, Open Refine can help clean data and document the data cleaning process. It can also be used for data exploration and data matching, including geooding. Open Refine is shown in Figure 3.32. Again, the results of the refining process are available as a re-useable script.

Both Data Wrangler and Open Refine provide great alternatives to the



Custom text transform on column Rating

Expression: `value` — No syntax error.

Language: Google Refine Expression Language (GREL)

| row | value | value |
|---|---|---|
| 1. | 4.5 | 4.5 |
| 2. | 4.5 | 4.5 |
| 3. | 4.5 | 4.5 |
| 4. | 4.5 | 4.5 |
| 5. | 4.5 | 4.5 |
| 6. | 4.5 | 4.5 |

On error: [✓ keep original] set to blank store error

Re-transform up to 10 times until no change

Figure 3.32: Open Refine

spreadsheet paradigm. They privilege data as a complete object, and document all modifications. By suggesting methods of generalizing data transformations, they remove much of the grunge work of spreadsheet analysis. The other benefit of generalized data transformations is they encourage the user to think computationally. Instead of just doing 'whatever works,' there is user incentive to find a way to describe the data cleaning rule in a way that works generally.

Tableau (Figure 3.33[4]) is a bespoke system for data visualization. As such, it does not provide much support for data cleaning. Tableau makes it simple for users to create interactive graphics that can be easily published on the web. Tableau will suggest the 'best' plot for particular data, which is both a blessing and a curse (Mackinlay et al., 2007). It can lead to much more appropriate uses of standard plots, but it also does not support novices' learning trajectory. A user can make a plot without having any idea of what it means. Similarly,

[4] Screenshot from Lin (2012).

Tableau makes it possible to fit models to data, but again does not make it clear what these models mean or how appropriate they may be. Like the tools discussed in Section 3.9, Tableau is expensive– $999 for an individual license or $1,999 for an individual professional license. However, as with SAS, they make the tool free to students.

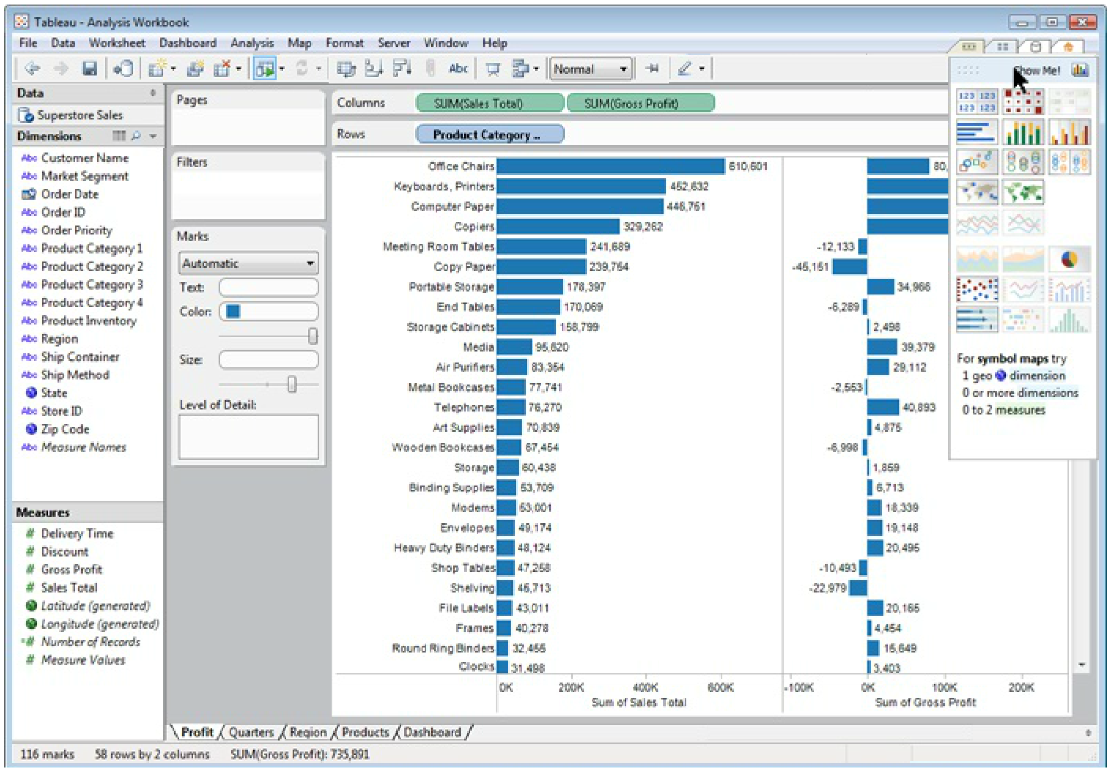


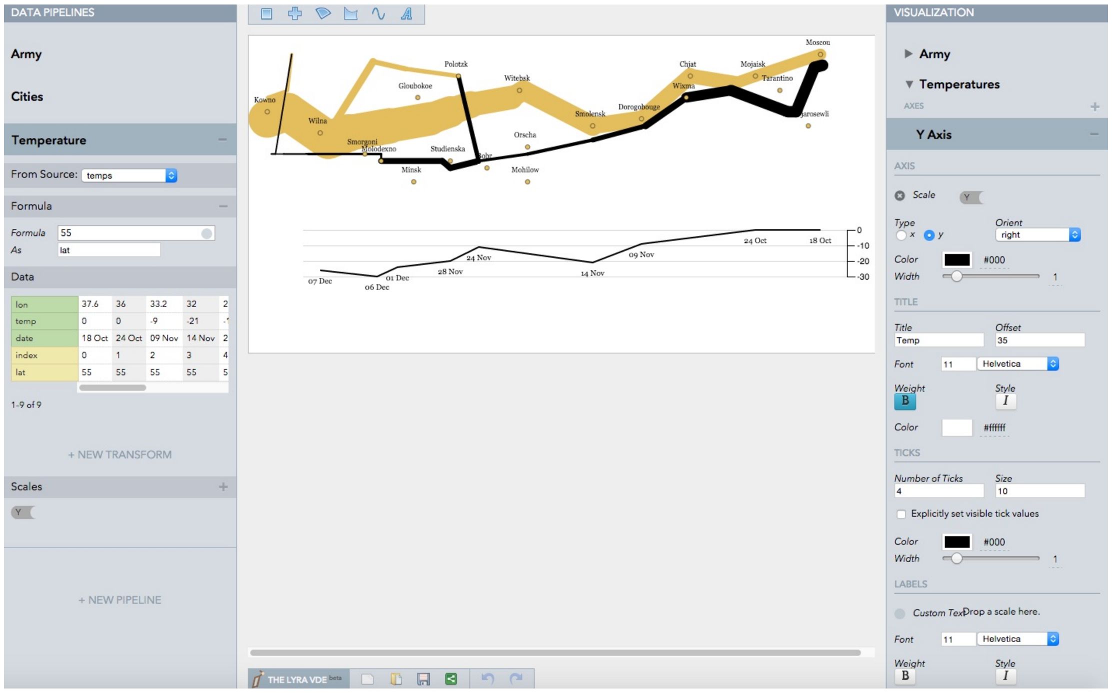
Figure 3.33: Tableau

Another bespoke data visualization system is Lyra, which makes it easy for novices to create graphics in a drag-and-drop matter (Satyanarayan and Heer, 2014). Lyra was developed at the University of Washington Interactive Data Lab. Interestingly, Jeffrey Heer was a member of the Stanford Visualization Group that created Data Wrangler, and is now one of the founders of Trifacta. He has since moved to the University of Washington and is a member of the Interactive Data Lab. Lyra is built on top of vega, an abstraction layer on top of d3, a JavaScript library.

`d3` is a library for "manipulating documents based on data," where here 'documents' refers to the document object model (DOM) of the web (Bostock et al., 2011; Bostock, 2013). It is commonly used to create interactive web visualizations. `d3` is generally considered to be the work of Mike Bostock, but the paper introducing the library also lists Vadim Ogievetsky and Jeffrey Heer. `d3` is a very general library, and cannot be considered to be a plotting library at all. It does not provide primitives like bar, box, axes, etc., like standard visualization systems. Instead, it binds data to the DOM of a web page. Many of the pieces by the New York Times mentioned in Section 3.2 are based on `d3`, and are co-authored by Mike Bostock himself. Bostock has created a site where users can share 'blocks' they have created in `d3`, and he has contributed many of them (Bostock, 2015). While the sharing of code examples helps users get started, `d3` is generally considered to be quite difficult to get started using.

`Vega` is an attempt to make it easier for novices to create the beautiful interactive graphics associated with `d3` (Heer, 2014). It provides the sorts of graphical primitives more typically associated with data visualization tools: `rect`, `area`, and `line`. However, even with these primitives, `Vega` can be difficult for novices in the same way all textual programming languages can be.

Enter Lyra, a tool to make the creation of `Vega` graphics very simple. It supports simple data transformation, like grouping based on a variable, but generally should only be considered to be a visualization tool, because it does not provide functionality for data cleaning, modeling, etc. It is a reproducible tool, because the resulting graphics are `Vega` graphics and can therefore be interrogated in the way standard `Vega` graphics can be (i.e., by looking at the code). Lyra does not support interactive graphics creation, but it is likely the group will soon go in that direction. Figure 3.34 shows how the tool can be used to reproduce the famous Minard visualization of Napoleon's march to Moscow (Satyanarayan and Heer, 2014).



From Source: temps

Formula

Formula: 55
As: lat

Data

| | | | | | |
|---|---|---|---|---|---|
| lon | 37.6 | 36 | 33.2 | 32 | 2 |
| temp | 0 | 0 | -9 | -21 | - |
| date | 18 Oct | 24 Oct | 09 Nov | 14 Nov | 2 |
| index | 0 | 1 | 2 | 3 | 4 |
| lat | 55 | 55 | 55 | 55 | 5 |

1-9 of 9

Scale: Y
Type: x [✓ y]
Orient: right
Color: #000
Width: 1
Title: Temp
Offset: 35
Font: 11 Helvetica
Weight: B
Style: I
Color: #ffffff
Number of Ticks: 4
Size: 10
Explicitly set visible tick values
Color: #000
Width: 1
Custom TexDrop a scale here.
Font: 11 Helvetica
Weight: B
Style: I

Figure 3.34: Lyra

Bespoke data tools like these are great sources for inspiration about new ways to visualize and improve data cleaning, modeling, and visualization. Many of these projects are open-source, so while they do not cover the entire analysis trajectory, they show promise as tools for particular data needs.

## 3.11 Summary of currently available tools

As is probably clear, my preference for doing statistical analysis is R, for its status as a free and open source project, as well as its flexibility, extensibility, and community of users. However, I acknowledge that R is a very difficult tool to begin learning. There have been attempts to ease the transition to R at a variety of levels. The attempts including GUIs and IDEs for R, pedagogical frameworks like **swirl** and Data Desk, and fencing attempts including **mosaic** and the **MobilizeSimple** package discussed further in Section 5.1.4.2. However, none of these attempts have been able to fully remove the barrier to entry for R. On the learning end of the spectrum, tools like TinkerPlots and Fathom provide flexible and creative ways to explore data. They offer little barrier to entry, but do not support reproducible analysis or the sharing of results.

Many of the tools we have examined are inspirational. TinkerPlots and Fathom in particular, but also the bespoke tools Data Wrangler, Open Refine, Tableau, and Lyra. All of these tools forefront methods to increase the visual representation of analysis and to simplify it for novices. However, none of the tools we have seen are ideal. In the next chapter, we look to the future of statistical programming.

This idea—that programming will provide exercise for the highest mental faculties, and that the cognitive development thus assured for programming will generalize or transfer to other content areas in the child's life—is a great hope. Many elegant analyses offer reasons for this hope, although there is an important sense in which the arguments ring like the overzealous prescriptions for studying Latin in Victorian times.

*Roy Pea, 1983*

# CHAPTER 4

# Attributes

Given the capabilities of current tools, it is possible to imagine a new system which combines the strengths of existing tools with some of the abilities not yet possible. Considering these strengths and weaknesses, we can develop a list of requirements for the statistical programming tools of the future. The remainder of this chapter describes these requirements.

One major inspiration for the qualities that follow is a paper in which Repenning et al outlined what they saw as the requirements for a "computational thinking tool" (Repenning et al., 2010). They posit a computational thinking tool must fulfill all the following conditions:

- "Has low threshold." The tool does not take much time to get up to speed with the software, and students can easily jump into really 'doing' whatever it is the tool helps them do (in this case, statistics).
- "Has high ceiling." The tool allows students to learn as much as they want and have access to the industry-standard methods.
- "Scaffolds flow." As related to the curriculum accompanying the tool, it allows for pieces to build on one another.
- "Enables transfer." The tool teaches skills useful in other contexts (generally, computer science contexts).

- "Supports equity."The tool should be easy to access for all types of students.
- "Systemic and sustainable." The tool can be used to teach students at a variety of levels, and aligns with standards.

Also inspiring was John Tukey's 1965 paper about the "technical tools of statistics," (Tukey, 1965), in which he describes his vision for the future of statistical programming tools. He argues statisticians should be looking for,

"(1) More of the essential erector-set character of data-analysis techniques, in which a kit of pieces are available for assembly into any of a multitude of analytical schemes,

(2) an increasing swing toward greater emphasis on graphicality and informality of inference,

(3) a greater and greater role for graphical techniques as aids to exploration and incisiveness

(4) steadily increasing emphasis on flexibility and on fluidity,,

(5) wider and deeper use of empirical inquiry, of actual trials on potentially interesting data, as a way to discover new analytic techniques

(6) greater emphasis on parsimony of representation and inquiry, on the focusing, in each individual analysis, of most of our attention on relatively specific questions, usually in combination with a broader spreading of the remainder of our attention to the exploration of more diverse possibilities." (Tukey, 1965)

Given these requirements for a computational thinking tool and the various positive qualities existing in current tools for doing and teaching statistics, we hold that a *statistical thinking tool* bridging the gap between learning and doing statistics must provide the following:

All these requirements will be discussed in more detail in their respective sections.

## 4.1 Easy entry for novice users

**Requirement 1** *Easy entry for novice users.*

This theory comes directly from Reppenning's work on tools for computational thinking (Repenning et al., 2010). Tools to be used by novices – and really, all tools – should make it easy to get started (Repenning et al., 2010). It should be clear what the tool does, how to use it, and what the most salient components are. The tools should provide immediate gratification, rather than a period of frustration eventually leading to success assuming the user perseveres.

Some systems that are supposedly easy to get started using have startup times around a week – in this context, we want novices to be examining data in a rich way within the first 10 or 15 minutes. With tools like TinkerPlots and Fathom, this is possible within the first minute, so 10-15 minutes should not be unreasonable. In fact, depending on the curricular structure, novices can begin making plots within their first hour of R, but typically the first lesson is unnecessarily hung up on installation issues.

In the context of statistical programming tools, users should be able to jump directly into 'doing' data analysis without having to think about the minutiae of a particular data import function or the name of a plot type. As Biehler says, "In secondary education, but also in introductory statistics in higher education, using a command language system is problematical. We are convinced that a host system with a graphical user interface offers a more adequate basis" (Biehler, 1997). Thus, by Biehler's definition, a system that provides easy entry for novices will likely have a visual component, either initially or throughout.

## 4.2 Data as a first-order persistent object

**Requirement 2** *Data as a first-order persistent object.*

Perhaps the most important component of any data analysis platform is how it deals with data, or, more specifically, the way data are formatted and represented within the system. The issue of data representation is important at a number of levels[1].

First, the system must find a balance between the sanctity of data and its fallibility. When novices begin engaging with data, they often perceive data as infallible (Hancock et al., 1992). In a pedagogical setting, it is important for students to move toward an awareness of data's subjectivity and to learn how to critique data and data products. However, the realization of the subjectivity of data can send students into a state of extreme skepticism, making arguments like "you can say anything with statistics!" In this nihilistic state, it can be hard to see the difference between the inherently subjective nature of data and the effects of intentional manipulation. However, it is vitally important to

[1]In this context, we are thinking most specifically of how the data appear to the user, not how they are stored within the computer's memory system

the scientific process that data are not modified in this way. We need to treat data sets as complete objects without room for modification, while also identifying the weaknesses and biases that may be present within them.

As discussed in Sections 3.1 and 3.8, data are given particular affordances in each analysis system. Excel does not privilege data as a complete object, because once a user has a spreadsheet of data open, modification is just a click away, and the original value is lost forever. In contrast, R, which uses data as its primary object, makes it very difficult to modify the original data file. This paradigm helps provide implicit valuing of maintaining original data.

A system privileging initial data should also have a commitment to providing data as the result of all actions. In systems like SAS and SPSS, results are often just text outputs that cannot be saved or incorporated into additional stages of the analysis. However, in R, almost every result is itself data that can be used again. This is a design decision on the part of the language authors, and could be implemented in other systems. The main exception to this rule in R are **base** plots, which are ephemeral. They cannot be saved, other than exporting them as image files. However, **ggplot2** plots remedy this. They can be saved into objects, which is in fact the suggested use case. In the tool of the future, all results should be re-useable data, even plots.

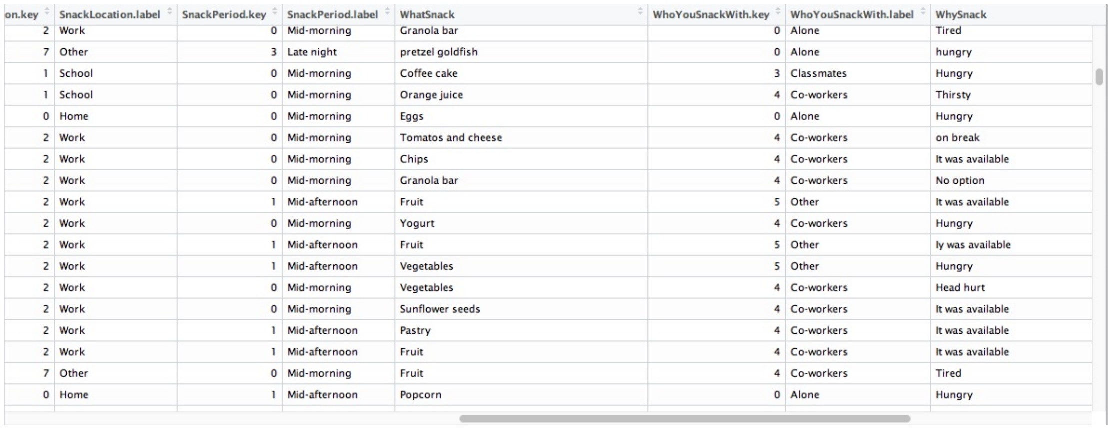
Another important consideration is how the data are represented. One of the most common data representations is a flat file or rectangular data set. This representation is composed of rows and columns – observations and variables – and can generally be visualized as a spreadsheet. The data most naturally used in R are rectangular, particularly those data that come stored as comma separated values (.csv files). Hadley Wickham wrote a paper on 'tidy' data which describes the way a rectangular or flat data file should be structured (Wickham, 2014b). It specifies that for a flat file, every row should represent one case (e.g., a person, gene expression, or experiment), and every column should be a variable (i.e., something measured or recorded about the case). Wickham's tidy requirements necessarily exclude hierarchical structures, but do lead to neat rectangular datasets that avoid many error sources.

However, novices who have not encountered data before often default to a list-based or hierarchical format for their data (Lehrer and Schauble, 2007; Finzer, 2014, 2013). This suggests that rectangular data may not be the most natural representation. Adults, particularly those who have taken a statistics class, will default to the format they were taught, typically a flat spreadsheet-like file, although they also tend to find the format challenging. So it is clear the affordances of a data analysis system have far-reaching implications for the people who learn on that system.

There are popular hierarchical and list-based formats, such as JSON and XML, but they are typically not introduced to novices. A more modern data analysis system might include these data types, and should attempt to find ways to represent them naturally.

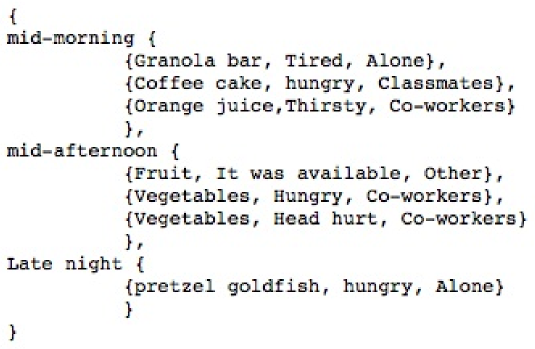
One reason rectangular formatting has been popular with statisticians is it allows us to think of many operations on data as matrix manipulations (e.g., take the inverse, do a multiplication, decompose the whole thing and take some pieces out, find eigenvalues, etc.). Hierarchical data will likely require new metaphors or operations to clarify how the pieces fit together.

In one data collection exercise from Mobilize, students collect data on their snacking habits, and data are aggregated by class on a centralized server. When they download the aggregated data, it is represented in a rectangular format (Figure 4.1). However, it could also be represented in a more hierarchical format, as shown in Figure 4.2. Considering the current curricular tasks we expect students to complete, some tasks seem difficult using this representation. For example, subsetting is less straightforward. Subsetting the data to select only the snacks where the reason given was "hungry" would be difficult, and would require removal of the matching pieces and creation of an entirely new data structure with the time of day attached.



| on.key | SnackLocation.label | SnackPeriod.key | SnackPeriod.label | WhatSnack | WhoYouSnackWith.key | WhoYouSnackWith.label | WhySnack |
|---|---|---|---|---|---|---|---|
| 2 | Work | 0 | Mid-morning | Granola bar | 0 | Alone | Tired |
| 7 | Other | 3 | Late night | pretzel goldfish | 0 | Alone | hungry |
| 1 | School | 0 | Mid-morning | Coffee cake | 3 | Classmates | Hungry |
| 1 | School | 0 | Mid-morning | Orange juice | 4 | Co-workers | Thirsty |
| 0 | Home | 0 | Mid-morning | Eggs | 0 | Alone | Hungry |
| 2 | Work | 0 | Mid-morning | Tomatos and cheese | 4 | Co-workers | on break |
| 2 | Work | 0 | Mid-morning | Chips | 4 | Co-workers | It was available |
| 2 | Work | 0 | Mid-morning | Granola bar | 4 | Co-workers | No option |
| 2 | Work | 1 | Mid-afternoon | Fruit | 5 | Other | It was available |
| 2 | Work | 0 | Mid-morning | Yogurt | 4 | Co-workers | Hungry |
| 2 | Work | 1 | Mid-afternoon | Fruit | 5 | Other | ly was available |
| 2 | Work | 1 | Mid-afternoon | Vegetables | 5 | Other | Hungry |
| 2 | Work | 0 | Mid-morning | Vegetables | 4 | Co-workers | Head hurt |
| 2 | Work | 0 | Mid-morning | Sunflower seeds | 4 | Co-workers | It was available |
| 2 | Work | 1 | Mid-afternoon | Pastry | 4 | Co-workers | It was available |
| 2 | Work | 1 | Mid-afternoon | Fruit | 4 | Co-workers | It was available |
| 7 | Other | 0 | Mid-morning | Fruit | 4 | Co-workers | Tired |
| 0 | Home | 1 | Mid-afternoon | Popcorn | 0 | Alone | Hungry |

Figure 4.1: Rectangular data



```
{
mid-morning {
          {Granola bar, Tired, Alone},
          {Coffee cake, hungry, Classmates},
          {Orange juice,Thirsty, Co-workers}
          },
mid-afternoon {
          {Fruit, It was available, Other},
          {Vegetables, Hungry, Co-workers},
          {Vegetables, Head hurt, Co-workers}
          },
Late night {
          {pretzel goldfish, hungry, Alone}
          }
}
```

Figure 4.2: Hierarchical data

Another common initial assumption is data should always be visualized in such a way that all of the values can immediately be read. In conversations with data journalists, they often cite reading data values in a spreadsheet as their first line of inquiry, so this practice may be useful. However, there are other possibilities for the highest level view of data. For example, Victor Powell's CSV Fingerprint project provides an extremely high-level view of data, and uses colors to indicate data types and missing data (Powell, 2014). See Figure 4.3 for an example of this visualization.

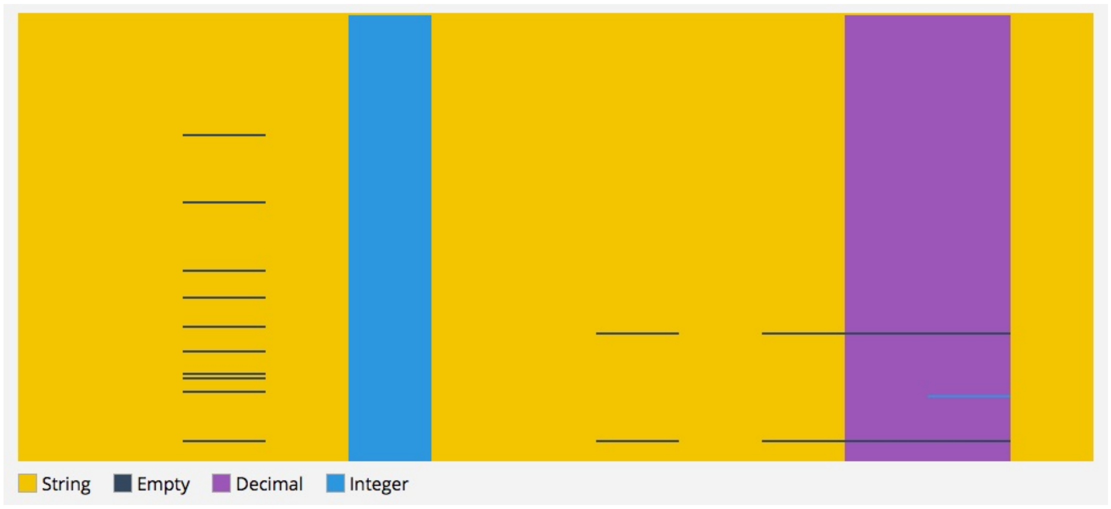


Figure 4.3: ‘CSV Fingerprint’ dataset visualization by Victor Powell

Because so much of the interesting data on the web are made available through application programming interfaces (APIs)[2], it is crucial to provide smooth integration with them. An API connection helps users quickly engage with interesting topics requiring little prior contextual knowledge (Gould, 2010). Several of the existing tools for statistical analysis provide API connections, Fathom being most notable on the statistical education side (Finzer, 2002a). However, the interfaces are often clunky.

Another open area of research focuses on how data could be surrounded by more inherent documentation. When using API data, a user will typically perform a direct call to the API, store the data locally during their work session, and save results. However, they often do not cache the API data. The next time the user runs the analysis, they make another API call and get the most current data. This workflow means the analysis must be very reproducible, as the data cleaning steps need to work for slight variations in the supplied data.

However, because APIs rely on internet services, there is the possibility the data provider could ‘go dark’ and stop providing data. To protect against this,

[2]In this context, APIs specifically refer to data access APIs. The term API is more general, and can be used to refer to any programming language specification, but statisticians do not use it this way.

there is a growing desire to provide functionality for caching API data calls so the most recent data can continue to be used in these cases (Ogden et al., 2015).

There is also a need for better metadata about API data, and about data in general. Ideally, API data would be accompanied with information about how it was retrieved and when, and perhaps more context about how it was collected initially. Fuller data documentation fits in with the idea of documentation as part of the process (discussed in Section 4.8), because the data would come with more of a story from the start.

## 4.3 Support for a cycle of exploratory and confirmatory analysis

**Requirement 3** *Support for a cycle of exploratory and confirmatory analysis.*

Statistical thinking tools should always promote exploratory analysis. Exploratory Data Analysis (EDA) was proposed by John Tukey in his 1977 book of the same name. Although it has its own acronym, EDA is not very complicated; it is simply the idea that we can glean important information about data by exploring it. Instead of starting with high-powered statistical models, Tukey proposes doing simple descriptive statistics and making many simple graphs – of one variable or several – in order to look for trends. Indeed, humans looking at graphs are often better than computers at identifying trends in data (Kandel et al., 2011a).

EDA is an engaging and empowering way to introduce novices to statistics, but introductory courses do not always include it, perhaps because it requires computational skills to achieve, or because it can seem to teachers as too ‘soft’ a skill to be truly useful. In particular, the math teachers we have trained as part of the Mobilize grant (Section 5.1) are often wary of situations where there is more than one possible answer.

Although EDA can appear as a ‘soft’ or subjective practice, there are situations where it is the best and richest method for analysis. For example, to make inference using formal statistical tests, data must be randomly collected. But in many situations (including the participatory sensing context discussed in Section 5.1.1) data are either non-random, or comprise a census. In these situations, EDA is the best method for finding patterns in the data and performing informal inference.

When Tukey wrote his book, computers were not in everyday use, so his text suggests using pencil and paper to produce descriptive statistics and simple plots. Today, the tasks listed in the book are even easier because of the many computer tools facilitating them, and the results are analogous to those made by hand (Curry, 1995; Friel, 2008). However, simply being able to implement the things Tukey did by hand in the 1970s is not enough; computers should be enabling even more powerful types of exploration (Pea, 1985).

Many tools for teaching statistics do support rapid exploration and prototyping. In fact, this is one area where tools for doing statistics fall short. In R, creating multiple graphs takes effort, as does playing with parameter values.

A sense of play is important to data analysis, which is never a linear process from beginning to end. Instead, data scientists repeatedly cycle back through questioning, exploration, and confirmation or inference.

There are many opinions as to what the cycle entails. In the Mobilize Introduction to Data Science course we use a cycle of statistical questions, collecting data, analyzing data, and interpretation, based on the GAISE guidelines discussed in Section 1.2 (Franklin et al., 2005). Because this is a cycle, interpreting leads back to questioning. Ben Fry suggests data analysis takes the shape of a cycle comprising the steps of acquiring, parsing, filtering, mining, representing, refining, and interacting (Fry, 2004). These cycles can be thought of as either exploratory or confirmatory, and the two complement each other. If users find something interesting in a cycle of exploratory analysis, they need to follow with confirmatory analysis.

The complementary exploratory and confirmatory cycles were suggested by Tukey, and have been re-emphasized by current educators (Biehler et al., 2013). There are several ways to bring the two cycles together. One method uses graphics to perform inference, discussed in Section 4.5, and thus brings exploratory and confirmatory analysis together. Andrew Gelman thinks modelers should be using simulation-based methods to check their models, and people doing exploratory data analysis should be fitting models and making graphs to show the patterns left behind (Gelman, 2004).

The difference between exploratory and confirmatory analysis (or informal and formal inference) is like the difference between sketching or taking notes and the act of writing an essay. One is more creative and expansive, and the other tries to pin down the particular information to be highlighted in the final product. A system supporting exploration and confirmation should provide a workflow connecting these two types of activities. Users need 'scratch paper,' or a place to play with things without them being set in stone. While data analysis needs to leave a clear trail of what was done so someone else can reproduce it, a scratch paper environment might allow a user to do things not 'allowed' in the final product, like moving data points around. This connects to Biehler's goal of easily modifiable draft results (Biehler, 1997).

Many current systems for teaching statistics provide simple sketching-like functionality (allowing users to manipulate data or play with graphic representations), but the transition to an essay-like format is more complex. An essay requires a solid line of reasoning strung through. The question then becomes, how do readers interact with it? We also want the user to be able to see the multiplicity of possibilities (the 'what-ifs'), while maintaining the ability to reset to reality.

If the system kept a transcript of all the actions taken in the sketching area, the resulting analysis possibilities would be analogous to a set of sketches an artist or designer does in the first stages of a project (a 'charrette'). The goal is produce and document many ideas, ideally all very different from one another. The charrette process is useful in art because it allows an artist to provide provocations instead of prototypes (Bardzell et al., 2012). Provocations drive thinking forward, while prototypes tend to lock in a particular direction. In order to support this, the system could provide a way to save many analyses and look through the collection.

In the context of art, once the charrette is complete, one sketch is converted into a finished product. In statistics, we want to support this same type of trajectory. Artists take one sketch and look back and forth between it and their in-progress painting as they complete it. With data, the user needs to make sure the trajectory of analysis is solid, so the relationship between a less-detailed sketch and a finished product is less clear.

The book "Infographic Designers' Sketchbooks" provides a glimpse into how designers of infographics and data visualizations work. Designers of infographics typically start with pen-and-paper sketches, and they use digital tools as digital paint (occasionally, they will speak about sketching in Photoshop or Illustrator). In contrast, designers of visualizations grounded in data (Mike Bostock, Tony Chu, Cooper Smith, Moritz Stefaer) begin by 'sketching' using code. They use a variety of computer tools to do this (e.g., Bostock's sketches look to be done in R, Smith sketches in Processing), but they are not explicitly mapping color to paper the way the infographic designers are (Heller and Landers, 2014).

While it is not precisely clear how these different styles of creation could be incorporated into one tool, the LivelyR work discussed in Section 5.2 shows some methods for allowing both in the same interface.

## 4.4 Flexible plot creation

**Requirement 4** *Flexible plot creation.*

To fully support exploratory data analysis, a tool needs to emphasize plotting. Computers make it possible to visually explore large datasets in a way not possible before. For example, Jacques Bertin developed a method for reordering matrices of unordered data in the 1960s. At the time, Bertin's method involved cutting up paper representations of matrices or creating custom physical representations, then reordering the rows and columns by hand (Bertin, 1983). Much like the graphical methods John Tukey developed by hand in the '60s, Bertin's methods are now easily accessible on the computer.

Providing easy plotting functionality is a goal of almost any tool, both for learning and doing statistics. However, there are two perspectives on plotting. One is to provide appropriate default plots based on data types, and the other is a system allowing for the flexible creation of any plot a user can think of.

The use of appropriate defaults is the perspective driving the **base** `R` graphics, which use similar defaults in the generic `plot()` function, producing different graph types depending on the data passed to it.

There are also efforts to provide default visualizations representing all variables in a particular data set, such as the generalized pairs plot, which can be

| Variable(s) | Default plot |
|---|---|
| one numeric | histogram |
| one categorical | bar chart |
| two numeric | scatterplot |
| two categorical | mosaic plot |
| one numeric and one categorical | pair of box plots |

Table 4.1: Typical default plots for common data types

used to automatically visualize all two-variable relationships (Emerson et al., 2013). There are also many bespoke data visualization systems (discussed further in Section 3.10) that automatically offer the ‘best’ plots for each variable in the data (Miller, 2014; Mackinlay et al., 2007). Some of the most common defaults are enumerated in Table 4.1.

The matching of plots to data is in line with most educational standards. When mathematical educational standards reference statistical graphics, they tend to do so in a rote way, suggesting students should learn how to pick the most appropriate standard plots for their data. Educators of this mindset will often critique students’ visualization choices, and emphasize students should be able to choose appropriate plots for their data or otherwise make, read, and interpret standard plots (e.g., scatterplots, bar charts, histograms) (National Governors Association Center for Best Practices and Council of Chief State School Officers, 2010). In other words, students should serve as the plot-choosing algorithm, and learn to make the mappings outlined in Table 4.1.

This is also the paradigm spreadsheet tools like Excel, or route-type tools (Bakker, 2002) implicitly expect, because they only offer standard visualization types. However, there is a growing body of research suggesting learning by rote, both in general and particularly with respect to statistical graphics, is not an effective way to embed knowledge. Instead, researchers suggest students should learn to develop their own representations of data.

The development of new data representations falls on the other end of the spectrum. In Leland Wilkinson's Grammar of Graphics, Hadley Wickham's **gg-plot2**, TinkerPlots, and Fathom, users can build up novel plots from any type of data encoding they find appropriate (Wilkinson, 2005; Wickham, 2008; Konold and Miller, 2005; Finzer, 2002a). While the Grammar of Graphics and **ggplot2** are intended for use by advanced data analysts, the inclusion of this type of flexible plotting in the learning tools TinkerPlots and Fathom points to the cognition research about visual encodings.

Learners tend to move through a standard sequence of levels of understanding as they begin to map data to visual representations. Typically, their first representations are idiosyncratic (Watson and Fitzallen, 2010). That is, they have some relation to the data at hand, but typically do not explicitly represent it. For example, when students are asked to represent a set of random draws from a collection, an idiosyncratic representation might be a drawing of a person taking a slip out of a bowl.

Students move on to a case-value plot. In case-value plots, every data value is explicitly shown on the plot. In other words, there is no abstraction away from the raw data, simply a visual encoding. Visualizations like dot plots and scatterplots are barely abstractions. They allow a reader to easily retrieve the exact values of the data. Studies show students start with case-value plots and gradually move toward more abstract representations (Kader and Mamer, 2008). Students will often initially think a graph representing speed is actually representing location, or a graph of growth is a graph of height. They have difficulty with the abstractions. Instead, they think the graph is representing the most 'real' thing possible (Shah and Hoeffner, 2002).

The next level of abstraction is classifying (e.g., stacking similar cases together and then abstracting them as a bar, as in bar charts and histograms) (Konold et al., 2014). These visualizations add a count abstraction. The original data are still retrievable, but the reader must understand the height of the bar has encoded how many times a particular value has been seen. Even more abstract is the histogram. A reader could generate data that would produce the histogram (randomly choosing $n$ values between $a$ and $a + x$ for all $y$ bins in the histogram, where $n$ is the height of the bar in the histogram, and $(a, a + x]$ is the range of the bin), but the resulting data would not necessarily be the same as the original. It would preserve some qualities of the data, but not necessarily even the true summary statistics of center and spread.

The final level of abstraction is where data are fully abstracted to summary values, as in a box plot (Konold et al., 2014). In these plots, there is no way to map back to the original data. The reader could generate data to would produce the same boxplot, but the data might have almost no correspondence to the original data. Modifications to the boxplot such as the violin and vase plots reduce the abstraction level slightly, but still often leave the size of the dataset abstract (Wickham and Stryjewski, 2011). Some examples of common data representations and their abstraction level are shown in Table 4.2.

By providing a tool that grows as a user learns, we can support learners on their path toward more abstraction. Rolf Biehler emphasized the importance of "co-evolution" of user and tool (Biehler, 1997). TinkerPlots intentionally supports the natural trajectory to build from less abstract plots, as its default plot of a single variable is just a set of dots set randomly displayed in the plot window. However, while TinkerPlots supports the natural sequence of building graph understandings, it is characterized as a landscape-type tool (Bakker, 2002), because it does not prescribe this particular trajectory. If a student had a different natural inclination, she could build representations that felt natural to her. However, even with a landscape-type tool, the affordances of a tool such as TinkerPlots impact the sorts of plots and reasoning users develop (Hammerman and Rubin, 2004).

Again, the standard (named) plot types mentioned in Table 4.2 do not rep-

| **Level of abstraction** | **Plot type** |
|---|---|
| Idiosyncratic | drawings of data collection methods |
| No abstraction (Case-value) | dot plot, scatter plot, map with points, complete text |
| Abstracted into categories | stem and leaf plot, bar chart, histogram, pie chart, donut chart, choropleth map, word counts or word clouds |
| Abstracted to summary values | box plot |

Table 4.2: Levels of abstraction in standard statistical plots

resent an exhaustive list of possible visualization methods, and users should have the opportunity to build their own encodings. In fact, being able to create unique visual data representations may help users to better understand non-standard visualizations they encounter in the wild. That is, learning to encode data visually will help them decode other visuals (Meirelles, 2011).

Most of the plot types described here are simple visualizations of one or two variables. But again, we want computational tools to do more than amplify human abilities (Pea, 1985). Methods like the Grand Tour (Cook et al., 1995; Buja and Asimov, 1986; Asimov, 1985), or the generalized pairs plot (Emerson et al., 2013) can allow humans to look for patterns in more dimensions.

Beyond providing an interface to flexibly create novel plot types, the tool should support graphs as an interface to the data (Biehler, 1997). Behaviors like brushing and linking should do dynamic subsetting (Few, 2010).

As Biehler suggests, the tool should provide functionality for formatting, as well as interacting with, and enhancing graphics (Biehler, 1997). Formatting consists of tasks like the zoom, scale, data symbols, and graph elements. Interaction should allow for actions like select, group, modify, and measure. Enhancing should allow for labeling, the inclusion of statistical information, and other variables (Biehler, 1997).

Some current tools for learning statistics allow users to draw pictures on top of their data, circling interesting features and providing annotations. Drawing functionality could be enhanced to become another method for interacting with the system. Researchers in the Communications Design Group are thinking about the ways in which drawing could become another level of vocabulary for humans to use as they interact with the computer. Ken Perlin has developed a tool he calls Chalktalk, which allows him to draw from a vocabulary of simple drawings to create the impression of interaction in his presentations (Perlin, 2015). For example, he might draw a crude pendulum and set it swinging. The behavior of these gestures has been coded behind the scenes, but they allow him to quickly and fluidly show examples almost like sketches. There is also work being done to add 'smart' drawing features to Lively Web (Section 5.2). This work is so new there is not yet a good pointer to it, but Calmez et al. (2013) describe the initial work making it possible.

The system should also make it possible to see multiple coordinated views of everything in the user's environment. Rolf Biehler suggests a multiple window environment to allow for easy comparisons (Biehler, 1997). The importance of a coordinated view is supported by researchers who suggest allowing for multiple views of the same data may help students gain a more intuitive understanding (Shah and Hoeffner, 2002; Bakker, 2002). In many systems, this is supported by brushing and linking (Wilkinson, 2005).

## 4.5 Support for randomization throughout

**Requirement 5** *Support for randomization throughout.*

Computers have made it possible to use randomization and bootstrap methods where approximating formulas would once have been the only recourse. These methods are not only more flexible than traditional statistical tests, but can also be more intuitive for novices to understand (Pfannkuch et al., 2014; Tintle et al., 2012).

Randomization and bootstrap methods can help make inferences from data, even if those data are from small sample sizes or non-random collection methods (Efron and Tibshirani, 1986; Lunneborg, 1999; Ernst, 2004). While these methods are not new, they have recently been extended into a field of visual inference. Statisticians at Iowa State University have been working on methods to use randomized or null data to provide graphical inference protocols (Wickham et al., 2010; Majumder et al., 2013; Buja et al., 2009).

Humans are very adept at finding visual patterns, whether the patterns are real or artifacts. Graphical inference helps people train their eyes to more accurately judge whether a pattern is real or not. In these protocols, one plot created with the original data is displayed in a matrix of $n$ decoy plots. If the user sets $n = 19$, the chance of randomly picking the true plot at random is $\frac{1}{20} = 0.05$, which is the traditional boundary for statistical significance (Wickham et al., 2010).

The method for generating the null plots can vary. Sometimes it is as simple as randomizing one of the variables to break any linear relationship that might have existed between the two. However, this does not work on data where the relationship is more complex, e.g., a quadratic relationship. In those cases, data are generated from the null model and compared to the true data.

Using the null data, plots analogous to the one filled with real data are generated. If the user creates a matrix of decoy plots with the true plot randomly placed within the matrix, identifying the true plot means it is somehow different from randomness. These methods have been extended for use in validating models (Majumder et al., 2013; Buja et al., 2009; Gelman, 2004).

Of course, protocols must be followed so as not to introduce bias. For example, if the user has been working with the data or doing exploratory data analysis, familiarity will make it easier to recognize the true plot in the matrix. However, even with prior knowledge, picking the real data out of a lineup of plots it is a very compelling exercise. I have introduced the idea to groups of high school teachers and students, and the 'game' of picking the right plot has proven to be very engaging. In fact, showing randomized plots can be a great extension to the 'making the call' activity of trying to determine the difference between groups – in this case, between real and randomized versions (Pfannkuch, 2006; Wild et al., 2011).

The application of randomization and the bootstrap is another place where tools for teaching statistics shine. All the popular applet collections provide functionality for simply randomizing or bootstrapping data (Chance and Rossman, 2006; Morgan et al., 2014). TinkerPlots and Fathom also provide interfaces for this (Finzer, 2002a; Konold and Miller, 2005). However, the tools for doing statistics have lagged behind. R provides the most complete functionality, but it has not been simple to use. Tim Hesterberg has prepared a document explaining how bootstrap methods could be integrated into the undergraduate curriculum (Hesterberg, 2014), as well as an R package called **resample** providing a simpler syntax.

Because of their intuitive nature and generalizability, randomization and bootstrap methods are ideal for novices. They can be used in a variety of contexts, including graphical inference methods bridging the gap between exploratory and confirmatory analysis.

## 4.6 Interactivity at every level

**Requirement 6** *Interactivity at every level.*

Interactivity is becoming the standard for the web, and data analysis should be no different. It should be possible for users to interactively develop an analysis, e.g., building up a plot by using drag-and-drop elements. The results of this analysis in the session should themselves be interactive. All graphs should be zoomable, it should be easy to change the data cleaning methods and see how that change is reflected in the analysis afterward, and parameters should be easily manipulable. This type of simple parameter manipulation will further support exploratory data analysis.

Finally, the product from the tool should also be interactive. Interactivity in published analysis would be of particular use for data journalism and academic publishing. As reproducibility becomes more valued in the academic community, data products are more often accompanied with fully reproducible code, and if the code were interactive, the audience – even if they do not know much about statistics – could play with the parameters and convince themselves the data were not doctored.

With a tool that made it simple to publish fully interactive results of data analysis, it would be easy to imagine data-driven newspaper articles accompanied by the reproducible code that produced them, allowing readers to audit the story. As noted in Chapter 3, bespoke projects such as the IEEE programming language ratings (Cass et al., 2014) provide readers access to the process used to create an analysis.

The draw of interactivity was also clear to Rolf Biehler, who inspirationally wrote,

> The concept of slider pushes the tool a step in the direction of a method construction tool where one can operate with general parameters. [...] It may be considered a weakness of systems like Data Desk that the linkage structure is not explicitly documented as it is the case with explicit programming or if we had written the list of commands in an editor. An improvement would be if a list of commands or another representation of the linkage structure would be generated automatically. (Biehler, 1997)

The implementation of this vision may require something akin to the **Shiny** reactive environment to allow the system to keep track of all the downstream elements depending on the one above.

The power and usefulness of this type of functionality is easy to imagine, and likely the possibilities are even greater than can be imagined at present. For example, if a user had used a cut point to create a categorical variable from a continuous variable, and then fed that categorical variable into a regression model, the system would allow them to manipulate the cut point to see the effect on regression parameters, interaction effects, etc. This example is examined further in Section 5.3.2.

Many other possibilities would be available in the world opened up by this type of functionality. All plots would be resizable, zoomable, and pan-able. Clicking on an element in a plot would highlight the associated element in the data representation, while clicking on a non-data element (e.g., an axis, tick line or model line) would offer information about the element, and that information would be manipulable as well.

For a histogram, the bin size and width would be draggable, providing an affordance for the user to manipulate these parameters, rather than encouraging them to keep the default, as R does. Similarly, spatial binning would be manipulable, again providing the user the capability of exploring and gaining intuition about the 'true' underlying spatial distribution. Essentially, every level of abstraction could be manipulated. A histogram is generalizing into bins, so the generalization (binning) can be manipulated. A box plot has a lot of abstraction, so the user could manipulate the various parameters there, by changing the mapping of center from median to mean, for example, or by redefining how outliers are determined.

Interaction is one of the weakest elements in R. The R programming paradigm means if a user wants to manipulate a parameter value they must modify the code and re-run it, making the comparison between states in their head. Comparing two states in this way may be possible, but comparing more than two is very difficult. Additionally, because of the static way code is saved, there is no user incentive to return to the beginning of the analysis to see how a code modification would trickle down.

The development of RMarkdown has improved this somewhat, as users can change elements in their code and re-knit the report to see the full scope of effects from the change. However, the edit/compile cycle is still quite clunky. As Biehler suggests, we want to encourage direct manipulation over modifying a script (Biehler, 1997). This concept has been given a lot of attention. One of the main tenants of Michael Kölling's Greenfoot (the integrated development environment designed for novices to learn Java) was shortening the feedback loop (Kölling, 2010). Bret Victor has made the shortening of the loop one of his driving design principles, to provide users with the ability to see the direct results of their actions without waiting for something to compile (Victor, 2012).

Deborah Nolan and Duncan Temple-Lang make the distinction between dynamic documents (those that are compiled and then automatically include the results of embedded code), and interactive documents (those that let a reader interact with components like graphics) (Nolan and Temple Lang, 2007). Given the goals of interactivity all the way down, and the importance of publishing, the system we are imagining should provide dynamic-interactive graphics. Users could interact with any component of the document and have the results re-run in real time.

R programmers have been wrestling with the issue of making interactive graphics from within R (Nolan and Temple Lang, 2012). Several efforts have been made, the most successful being the R packages **Shiny** and **ggvis**. However, these packages are not accessible for novices. While they allow expert users to create dynamic graphics, they are too complicated for a beginner. For that use case, **manipulate** is the closest to the functionality we are imagining.

Currently existing tools like the iPython notebook and RMarkdown provide some of this dynamic-interactive functionality. They can be used to create interactive documents that respond to user input, but the process is not dynamic for the author, Users must modify code and then re-run it in order to see results, so direct manipulation is not being achieved, and readers only have access to dynamic behavior programmed in by the author.

TinkerPlots and Fathom are dynamic and interactive, but they break down on this requirement when it comes to publishing interactive documents. TinkerPlots makes it easy to interactively develop analysis and play with it, but there is no way to share an interactive result.

## 4.7 Inherent visual documentation

**Requirement 7** *Inherent visual documentation.*

Each component of the system should show the user what it is going to do, versus simply telling them. Another version of this goal would be 'help that is helpful,' because most documentation in systems like R is unintelligible to novices. However, the idea of a self-articulating system goes one step further. The system should show the user what it is going to do, not just use textual labels. For example, if it is going to perform k-means clustering, instead of a box with the words "k-means" on it, the user should see a visual representation of the algorithm, and as it is applied to the data interim steps should be visualized (Mühlbacher et al., 2014). There also needs to be a nice model object and likely an associated visualization (not residual plots, etc.) to give the user a sense of the model in order to increase intuition.

This is similar to the idea of scented widgets, which are embedded visualizations providing hints to users about what all elements are capable of (Willett et al., 2007). Scented widgets are really a specific platform for implementing this idea, but the concept is generalizable.

## 4.8 Simple support for narrative, publishing, and reproducibility

**Requirement 8** *Simple support for narrative, publishing, and reproducibility.*

The products of the system should be as easy to understand as the process of creating them, and they should be simple to share with others.

### 4.8.1 Narrative

Many programming systems tend toward a paradigm of writing code in one document and narrative in another, such as performing analysis in Excel and writing about the results in Word. Code comments notwithstanding, narrative and analysis are usually kept separate. However, in order to create compelling reports, it must to be easier to combine the two. This means the system should encourage documentation alongside or mixed in with the code in order to facilitate the integration of storytelling with words and statistical products.

Data science is so much about storytelling that it should be built into the analysis process. Andrew Gelman and Thomas Basboll have written about how stories can be a way to develop hypotheses (Gelman and Basboll, 2013), which is one of the powers of data journalism. Where statisticians usually think of data as a pre-existing object, journalists are more likely to 'interview' their data source and research the contextual story surrounding it. This process should be integrated into the documentation and analysis.

In this sense, documentation does not refer to the indecipherable comments I am guilty of inserting into my code (e.g., "#Don't know what this does"), but rather a supporting narrative that surrounds the analysis when it is complete. Instead of encouraging a process where analysts create their data product first, then go back and try to interpret it, a good statistical programming tool should create major incentive to do the hard work of thinking as you go.

Students can learn how to write about their data analysis early on. While not ideal, RMarkdown and **knitr** are beginning to make it possible to integrate this into introductory courses (Baumer et al., 2014).

### 4.8.2 Publishing

Similarly, data analysis products should be easy to publish. Rather than having to translate the document to another format, it should be as simple as a button click to make the finished product available to an audience.

It should be easy for a journalist to create a data-driven website, or a citizen scientist to share the cool thing they found in the data they helped create. On top of this philosophy, the publishing format should allow for exploration. In fact, the ideal case would be a system that would look nearly identical to the person accessing the 'publication' as it did to the person producing it. In this way, users could continue to explore the data, modify the analysis, and perhaps move sliders to see the effects of changes in the analysis and visualizations.

Integrated documentation and one-click publishing will necessarily encourage reproducibility. Anyone who reads the published product will not only be able to see the code, but it will be easy to understand, given the integrated documentation.

Again, RStudio is working toward making this possible. Their RPubs website makes it possible, particularly for students, to write RMarkdown documents and then publish them to be viewable to their class or on the web at large.

### 4.8.3 Reproducibility

Most important in this requirement is the focus on reproducibility. While it has been a goal of research for some time, reproducibility is being more explicitly valued in the scientific publishing community (Buckheit and Donoho, 1995; Ince et al., 2012). Jan DeLeeuw ends his summary of statistical programming tools by making it clear reproducibility is the next frontier (De Leeuw, 2009).

People agree modern data analysis should be reproducible. However, there is some debate about what reproducibility really means. There are two main perspectives on this issue.

The first is the perspective that posits reproducibility means someone other than the author of the analysis should be able to take the data and code used by the author and get exactly the same result. The goal of reproducing an analysis using the same data and code seems like it should be simple to achieve, but there are many factors that can make it difficult. Namely, software versions can change, package dependencies can get broken, and most disruptive to the process, authors often do not manage to document their entire process. There may have been data cleaning steps that took place outside the main software package (e.g., the bulk of the analysis takes place in R but the author does some data cleaning in Excel before the analysis), or analysis steps run elsewhere and not added to the code. The provided code might not be the current version, or it might have bugs that need to be addressed before the code will run (and often, code is poorly documented, so it is hard to debug someone else's code). The R package **packrat** is attempting to fix some of these problems (Ushey et al., 2015).

The second view of reproducibility is an independent researcher should be able to replicate the results, either with new data and code, or at least with new code. In this framework, another researcher would replicate the study that produced the data or go about procuring it in the same way as the original researcher (e.g., making API calls to a service, or using FOIA requests to access government data). They would then attempt to perform the same analysis, writing the code from scratch or using a different analysis platform, to see if the results were the same.

As we are attempting to expose students to an authentic experience of data science, it is crucial they experience reproducibility. This aim has implications both pedagogically and technologically. Pedagogically, the aim of reproducibility needs to be written into the curriculum, and teachers need to be trained in order to understand the aim. Technologically, the tool students are using needs to support reproducibility. Supporting reproducibility means, first and foremost, the process that created a data product needs to be savable. Some teaching tools, like applets, are more for interaction than anything else, and the creation process can not be saved. Other tools, like TinkerPlots and Fathom, allow the user to save the environment that produced the product, but do not document the steps taken within the environment. An 'independent researcher' (in this context, another student) could potentially use this environment and manage to reproduce the steps required to produce the analysis product, but it would be much harder to do so.

The current tools for learning statistics fall quite short in this regard. In most systems, there is no encouragement of documentation, and analysis is not reproducible because it was all produced interactively. This tension is addressed in Section 5.2, where we attempt a method of tracking interactions. Tools like Excel also fail to meet this criteria, because they do not make it clear what modifications have been made on the data, not do they provide a method for reproducing the analysis with different data.

Even in courses where introductory college students are using R, they often document their data process in Microsoft Word, copying and pasting results into their final document. This can be a very frustrating experience, because if a student realizes they made a mistake early in their analysis they must replace all the dependent pieces of the analysis in their Word document. In introductory college statistics courses there is a movement toward students using tools like RMarkdown from the beginning in order to get them in the habit of reproducible research (Baumer et al., 2014). While RMarkdown takes some cognitive effort to learn, the payoffs are typically great enough students see the usefulness.

Much of the work of data analysis is gaining access to data and getting it into a format a tool can work with, which can take up to 80% of the time in data projects (Kandel et al., 2011a). This ties into reproducibility, as well. If, once a user has cleaned some data and neatened it into a 'tidy' format (Wickham, 2014b), they are given a new version of the data set, are they able to perform those same actions on these new data? Thus, another benchmark is to be able to reproduce wrangling steps and share them with others (Kandel et al., 2011a).

Once data have been wrangled, it should be clear what steps have been taken, and how to re-do them on another data set. 'Consumers' of the product should be able to look at the process and assess whether it was done in good faith. Again, this is a shortcoming of tools designed for learning statistics, as they make it difficult to share and reproduce research. Several products are working to address this problem, most notably Data Wrangler and Open Refine.

## 4.9 Flexibility to build extensions

**Requirement 9** *Flexibility to build extensions.*

Again, this requirement comes from the paper on computational thinking tools referenced in the introduction to this chapter. In the words of Repenning et al, the system should have a "high ceiling" (Repenning et al., 2010). This means users should not 'age out or 'experience out of the system. Instead, it should be possible to build almost anything from the components the system provides. As discussed in Section 4.4, it should be possible to develop new visualization types, building from a series of primitives. Similarly, it should be possible to build new data processes from other modular pieces.

Many of the tools currently used for teaching statistics are guilty of not providing a high enough ceiling. For example, TinkerPlots does not even provide simple statistical modeling functionality.

Most tools for doing statistics provide the ceiling, but not the low threshold. For example, in R it is easy to create new components of the system using old components, and then share them through a centralized repository where other users can easily find and import others' work.

Again, Konold argues a high ceiling is not necessary for a statistical tool for students (Konold, 2007), but in order to close the gap between tools for learning and tools for doing statistics, extensibility is a requirement. Even Biehler argues that "adaptability (including extensibility) is a central requirement for data analysis systems to cope with the variety of needs and users" (Biehler, 1997).

Making sure a system can be used to extend itself is crucial, because a system author can never think of all the features a priori.

## 4.10 Summary of attributes

Again, the overall structure of a tool complying with these requirements could take a variety of forms. Currently, I imagine a multi-layered system, with a visual drag-and-drop blocks programming environment providing easy entry for novices. Visual representations can help novices understand the underlying workings of a data system (Shneiderman, 1994), which suggests this is the appropriate direction. Once users have reached a certain point, they will likely want to extend their capabilities, and could move on to the next 'layer' down, a domain-specific programming language (DSL). The DSL would provide simple primitives, allowing users to develop their own elements to extend their analysis, and create their own visual blocks to add to the layer above. If users reached the limits of that layer, they could move down again, to the standard statistical programming tool (e.g., R) in which the DSL was implemented. The underlying domain-specific language could be implemented in any target language (e.g., R, Python or Julia), but because the community of statisticians is currently using R that is what I am currently imagining.

This falls in line with Biehler's belief that "a co-evolution of tool and user should be facilitated" (Biehler, 1997). In other words, as users top out in the capabilities of one aspect of the system, they can move on to a more complex version allowing for more functionality and flexibility. A solution Biehler proposes is "embedded microwords" (Biehler, 1997). In an embedded microworld, a larger system is used to make a microworld, which can then be extended in the larger system. However, Biehler warns embedding sometimes brings language artifacts from whatever the microworld is embedded in.

As Clifford Konold urges, the system should be built from the bottom up (Konold, 2007), so the first step is to consider the tasks a novice would need to accomplish and work from there. Some examples of tasks are discussed in the next chapter.

The best way to predict the future is to invent it.

*Alan Kay, 1971*

# CHAPTER 5

# First forays

Given the current state of tools for doing and teaching statistics (Chapter 3), and my vision of future statistical programming tools (Chapter 4), it is clear there is work to be done. Since 2011, I have produced a variety of initial attempts toward this vision of the future. Most of my work can be categorized either under the umbrella of Mobilize (described in Section 5.1) or the Communications Design Group (Section 5.2), although I also describe several **Shiny** widgets I created as microworlds for courses I taught (Section 5.3).

## 5.1 Mobilize

Mobilize is a six year, $12.5 million National Science Foundation grant focused on integrating data science and computational thinking into a multiplicity of STEM (science, technology, engineering and math) disciplines. The grant has eight "principal investigators" (PIs) and six institutional partners, the most important of which is the Los Angeles Unified School District (LAUSD). The LAUSD is the second-largest school district in the United States, after the City School District of the City of New York. For three years, I was a graduate student researcher on the grant, and the experience inspired and motivated my work on statistical programming tools for novices.

The Mobilize team has developed curriculum and supporting technology to allow high school teachers to integrate data science into their classes. In addition, we hold regular professional development[1] sessions for in-service teachers[2], and our research and evaluation teams study what makes elements of the curriculum work (or not work).

Currently, our data-centric curriculum exists as insertable units in computer science, math, and science, and as a stand-alone, year-long data science class, called Introduction to Data Science (IDS). IDS was piloted in the 2015-2016 school year in the LAUSD. For more detail about these courses, see Section 5.1.3.

All the curricula are based on the idea of engaging students with data through the process of participatory sensing, whereby they learn to collect data about themselves and their communities, often using mobile technology. By grounding the analysis in data with a direct contextual relationship with the students, we hope to make our lessons more compelling. Once data have been collected, students begin a process of Exploratory Data Analysis (EDA).

The Mobilize curricula all attempt to follow current best practices in statistics education. In particular, students participate in almost all the activities suggested by Biehler et al. (2013):

“1. Students can practise graphical and numerical data analysis by developing an exploratory working style.
2. Students can construct models for random experiments and use computer simulation to study them.
3. Students can participate in ‘research in statistics,’ that is to say they participate in constructing, analyzing and comparing statistical methods.
4. Students can use, modify and create ‘embedded’ microworlds in the software for exploring statistical concepts.” (Biehler et al., 2013)

[1]Professional development is additional training for teachers
[2]In-service teachers are those currently certified as teachers and actively teaching

All of these activities are woven throughout the Mobilize curricula, with the possible exception of 4. Students do not construct microworlds, but they do ask and answer questions using data. In IDS in particular, students learn to code in R within RStudio.

### 5.1.1 Participatory sensing

Participatory sensing is a data collection method in which people participate in data collection using sensors. The term was developed by researchers at UCLA's Center for Embedded Networked Sensing, an institutional partner and source of many PIs for both the Exploring Computer Science and Mobilize grants (Burke et al., 2006).

The term participatory sensing tends to defy definition, so it is most easily explained in terms of negative examples, or by its component parts, breaking it into its component words ('participatory' and 'sensing') for easier understanding.

'Sensing' means using sensors, and sensors could be anything from thermometers, scales, and pressure gauges to electronic sensors like the GPS and accelerometer in a modern smartphone. Often when we think of sensor data, we imagine it coming from electronic sensors programmed to collect data in a particular way (Kanhere, 2011), such as a water clarity sensor programmed to move along a trajectory in a pond, taking readings every 3 feet and storing the results. In the context of participatory sensing, sensors are not as autonomous, although there may be automatic data collection modes accompanying the human elements.

'Participatory' means humans participate in the data collection process. So, the water clarity sensor from above is not an example of participatory sensing. It is certainly sensing, and, like all data collection methods, does involve humans in some way, but does not directly involve participants in the act of data collection. The Audubon bird count, which has been taking place since 1900, is a participatory data collection exercise without sensors. Each year, thousands of participants across the country report the breeds of birds they have seen in their area (Silvertown, 2009).

Starting in 2002, the Audubon Society has supplemented their traditional Christmas Bird Count with a program called eBird, which "engages a vast network of human observers (citizen-scientists) to report bird observations using standardized protocols" (Sullivan et al., 2009). More than 500,000 users have visited the site and have gathered 21 million bird records (Sullivan et al., 2009). This activity is more closely approximating participatory sensing because it uses electronic data recording to standardize records, but it is still light on the sensing component.

For an example of both participatory as well as sensing, consider the Mobilize snack campaign. For this data collection exercise, students use a smartphone app to record information about every snack they eat. It is participatory because students are doing the data collection and are also the trigger for when data collection occurs. Unlike the sensor in the pond, programmed to record data every 3 feet, students are 'programmed' to record data every time they eat a snack. It is sensing because they are using smartphones to collect the data. Although they are entering reasonably qualitative survey data, the phone is recording precise GPS coordinates and time stamps.

Another element characteristic of participatory sensing is the idea data need to be collected regularly over space and time to get an idea of how the phenomena varies. So, for example, measuring the heights of students in a class does not count as participatory sensing, because although students are participating in the data collection, and the ruler/yardstick could count as a sensor, there is no variation over space or time. It would not make sense to continue taking repeated measurements of the students' heights throughout the week. If there was variation in the measurements, it would be due to random error rather than to some true variation.

Participatory sensing is an inherently democratic process. It involves people collecting data about themselves, for themselves. The data do not get sent to some higher authority and disappear. Instead, the participants should be able to see and participate in the data analysis process, or at the very least, receive information from the final analysis. It is an effort to give back access to data to those who create it, and balance the scales of information power, if only slightly.

#### 5.1.1.1 Teenagers and participatory sensing

In 1993, George Cobb exhorted instructors to expose students to real-world data and involve them in collecting data. If both could be achieved at once, he called it a "best of two worlds" situation (Cobb, 1993). Statistics courses have gradually moved toward using more relevant data to engage students (Friel, 2008; Hall, 2011). Particularly since the explosion of data on the internet, data are being collected about students constantly, whether they know it or not (Meirelles, 2011). Whether they are tracking runs with Nike+ or simply giving off their location by posting on Instagram with location services enabled, students – and people in general – are producing digital data streams constantly. Many statistics courses attempt to focus on data relevant to students' lives (particularly those which they may be aware of producing already), such as social media data from Facebook or Twitter, data about music, or physical activity data (Gould, 2010; Lee and DuMont, 2010). With the rise of the "data natives" (young people who have grown up in the big data era where services are continuously predicting what an individual will do next), there will only be more data to use (Rogati, 2014)

Involving students in participatory sensing is one more step along this trajectory. Teenagers are especially likely to be involved in participatory cultures (Jenkins et al., 2009). They are drawn to cultures with "relatively low barriers to artistic expression and civic engagement, strong support for creating and sharing one's creations, and some type of informal mentorship whereby what is known by the most experienced is passed along to novices." (Jenkins et al., 2009). Some examples of such cultures include blogs and Facebook. Obviously, there are access issues if participatory cultures are dependent on computer or internet access, and young adults often have trouble seeing the way media shape our culture. But, urban youth are actually more likely to be online content creators (Jenkins et al., 2009). Recognizing young adults as entrenched in participatory cultures suggests introducing data analysis within the context of participatory sensing may be highly appropriate.

In this context, the use of participatory sensing data in Mobilize is a natural next step. It is a "best of two worlds" situation, where students are handed back the power over their own data. The Mobilize technical team has developed an app making it easy for students to deploy 'campaigns' on issues they care about, and collect data directly on their phones (Tangmunarunkit et al., 2013). Each piece of Mobilize curriculum uses at least one participatory sensing campaign to ground the rest of the unit. So far, our campaigns have been less science-focused and more sociological (e.g., sleep patterns, advertising in neighborhoods, snacking habits).

#### 5.1.1.2 User rewards for participatory sensing

The eBird project has produced research suggesting data collection participants submitted more data to the project when the program instituted more user-rewards (Sullivan et al., 2009). For example, users have profiles on the site and there is a competitive component where prolific contributors are featured on a leaderboard. Users are also rewarded with data visualizations including the data they helped collect (Sullivan et al., 2009). Showing the results of the data collection process is an important piece of citizen science (Bonney et al., 2009). However, not all citizen science initiatives include this type of user incentive.

On the Mobilize project, we have done our best to provide satisfactory user rewards. In fact, being able to analyze their own data is one of the main payoffs students receive for participating in the collection exercise. The dashboards produced by the technical team (discussed in Section 5.1.4.1) help with this. But again, the tools we are using are falling short, as they encourage students to become users of a dashboard tool and not true producers of statistics. It is also clear other participatory projects could benefit from an easy-to-use data analysis platform as well.

#### 5.1.1.3 Analyzing participatory sensing data

While participatory sensing data has many benefits, in particular giving power back to data creators, it is always messy. It rarely represents a random sample, either in terms of people collecting data or their collection methods.

For example, classes involved in the Mobilize project have collected data on snacking habits every year since the grant began in 2010. If students are completely successful at collecting every snack they eat, the data represent a census rather than a sample, and it is hard to say what statistics should be used to analyze it. However, even the most conscientious of data collectors usually miss a few observations. It is unknown if those observations are missing at random or missing not at random, and even less clear what to do with the data.

Up to this point, the grant has side-stepped this issue by focusing on exploratory data analysis rather than formal inference. The IDS course has used randomization to make limited conclusions from the data. However, it is often unsatisfying for teachers, students, and even non-statistical PIs to learn we cannot make formal inference from these data.

Many of the examples of participatory sensing and dealing with missing data come from ornithology. The Cornell Laboratory of Ornithology has found data mining methods can be used to help deal with missing data (Caruana et al., 2006). Decision trees, bagging, and boosting can all be used to help fill in data where it is missing not at random. For example, bird data tends to be biased toward higher population areas, where more people exist to track bird sightings (Hochachka et al., 2010). Another approach is to do data augmentation, combining two datasets – one collected using a participatory method and one more rigorously collected (perhaps by paid researchers). Using these two data sets, data augmentation suggests researchers fit a model, one to each data set, and compare the predictions (Munson et al., 2010).

In environmental contexts, where the variable of interest is assumed to be smoothly distributed, researchers have used interpolation (Mendez et al., 2013). If this results in a model with high variability in certain areas, researchers can then try to incentivize data collectors to collect data in highly variable spatial areas (Mendez and Labrador, 2012). There are also examples predicting election outcomes using non-representative polls (Wang et al., 2014).

Finally, because many psychological researchers are using the Amazon Mechanical Turk[3], there is a growing field of research for dealing with those data. While Turkers do not represent a random sample of humanity, they do seem to represent the demographics of the internet well, although they tend to skew a bit young (Ipeirotis, 2010; Ross et al., 2010). One method for increasing the quality of data from Turkers is to do repeated labeling (i.e., have several Turkers answer the same question to see what the consensus is). But, too much re-

[3]The Amazon Mechanical Turk is an online forum to find humans to perform tasks difficult for computers. It was first developed to create reference data sets for image recognition research, as humans can easily identify a number shown in an image, for example.

peated labelling is costly. An alternative is to use the EM algorithm to convert 'hard' labels to 'soft' (probabilistic) labels (Ipeirotis et al., 2010). A simpler method is to determine some measure of trustworthiness for each data collector, and use weightings to put emphasis on the more trusted data (Welinder et al., 2010).

### 5.1.2 Computational and statistical thinking

"Computational thinking" is a term first described by Jeannette Wing, the head of the computer science department at Carnegie Mellon (Wing, 2006). Wing is concerned with access to computer science in the general population, and has developed the concept of computational thinking to describe the skills she believes are foundational. Computational thinking encompasses much more than the traditional view of computer science. Wing describes it as "a fundamental skill for everyone" (Wing, 2006). It includes many facets of thinking like a computer: problem solving, algorithmic thinking, recursive thinking, and abstraction. Computational thinking, therefore, is one of the crucial skills in today's economy. Not coincidentally, true statistical literacy requires many computational thinking skills.

'Statistical thinking' is a similarly general term, encompassing fundamental skills of thinking related to statistical concepts. For example, statistical thinking means considering the tendency of phenomena in a distribution or over time, as well as the variation within data or with repeated sampling. While these topics are included in introductory statistics curriculum, they are often presented as skills to be applied within class, not generally in life. Students presented with data visualizations often do not connect them to the context of the data from which they came (Meirelles, 2011; Wickham, 2010).

Statistical thinking also includes what Darrell Huff called "talking back to a statistic," or checking for bias in reporting on statistical issues, and asking if it makes sense when presented with a statistical argument (Huff, 1954). On a broader level, it can be argued that people should develop a "data habit of mind" and look for evidence to ground things in their life, even outside of a statistics class (Finzer, 2013; Pfannkuch et al., 2014).

Computational and statistical thinking tie together because computers are so necessary for statistics today. There is no 'data science' without computation, and statistics provides an excellent place to introduce computing because it is inherently contextualized. Traditional methods of motivating programming in the classroom (e.g., building a game) are often not as appealing to women (Kelleher and Pausch, 2005; Cooper and Cunningham, 2010). However, by couching statistics in data in which students are interested (particularly data in which they can see themselves, like participatory sensing data) makes the desire for inference natural (Wild et al., 2011). Speaking about the difference between mathematics and statistics, Cobb and Moore note, "in mathematics, context obscures structure. [...] In data analysis, context provides meaning" (Cobb and Moore, 1997).

### 5.1.3 Curriculum

As previously note, Mobilize has created curricular units across content areas. They are all grounded in participatory sensing, computational thinking, and statistical thinking. While the grant has units to insert into computer science, algebra, and biology courses, as well as a stand-alone, year-long Introduction to Data Science curriculum, my primary contributions were on the ECS and IDS material. The ECS and IDS curricula were also the two most computationally-based courses.

#### 5.1.3.1 Exploring Computer Science unit

The first Mobilize curriculum to be developed was a six-week-long unit on data analysis, written to fit within a year-long curriculum called Exploring Computer Science (ECS)[4]. ECS initially piloted in the LAUSD, but has now grown to include schools in Chicago, Oregon, Utah, Washington, D.C. and New York. Thousands of high school students are exposed to ECS annually. ECS includes 6-week-long units on human computer interaction, problem solving, HTML and web design, Scratch programming (animation and game design), LEGO Mindstorms robotics, and data analysis.

Members of the Mobilize team, including myself, helped developed the data analysis unit for ECS. In the unit, students engage in exploratory data analysis, creatively interacting with their own data.

The initial version of the curriculum involved students collecting data using one of two 'canonical' surveys provided: one for collecting data about advertising in the community, and one for collecting data about personal snacking habits. In the example of the advertising survey, a student would take a photo of an ad (e.g., a billboard), and then answer questions about the demographic they believe the ad is targeting, what product it is selling, how much they want the product, etc.

In keeping with participatory sensing, the survey is implemented on a smartphone, and the data are automatically uploaded to a server, along with information gathered by the phone. The unit incorporated student-collected data alongside previously-collected data from sources like the CDC to expose students to a variety of data analysis topics.

The curriculum and its implementation struggled with many issues. A major stumbling block for the teachers in professional development was learning the

[4]Mobilize is essentially a sibling grant to ECS, with many overlapping PIs.

data analysis tool. However, as we moved through the various technical tools discussed in Section 5.1.4, we realized that not only was our professional development too short to get the teachers up to speed, but the six-week unit really was not enough time for students to truly engage with R. Additionally, as ECS grew nationally, it became harder to support a particular data analysis tool. The curriculum was later re-written to be tool agnostic, and the need for smartphones for data collection was minimized. In the most current version, students decide what topic they want to study, collect data using pencil and paper, then analyze it using a tool of their teacher's choice.

This experience underscored the need for a longer data science curriculum, which formed the inspiration for the Introduction to Data Science curriculum.

#### 5.1.3.2 Math and science units

The Mobilize math and science curricula comprise shorter units, and were designed to be inserted into existing courses: Algebra I and Biology, respectively.

In math, students collect participatory sensing data on their snacking habits, and learn to connect linear modeling and predictions to the equation of the line, $y = mx + b$. In science, the participatory sensing campaign is related to trash–whether recyclables are being put into the incorrect container or not. This gets related to environmental concerns biology teachers are comfortable discussing.

The math and science units were loosely based on the ECS curriculum I helped develop. For more on the curricula, see (Board et al., 2015; Perez et al., 2015).

Because these curricula were on much shorter time scales, and because the teachers we trained were even less comfortable with statistics, neither the Algebra I nor the Biology unit include true computational statistics. Instead, students use bespoke dashboards to analyze their data. By using the dashboards, they are able to ask and answer questions with data, but the questions are somewhat limited by the abilities of the tool.

#### 5.1.3.3 Introduction to Data Science course

The most exciting curricular development in Mobilize is the year-long course, Introduction to Data Science (IDS). This course piloted in 10 schools in the 2014-2015 school year, and will be expanded to 25 teachers in 34 schools in 2015-2016. Unlike the previous curricula mentioned, the IDS course is a full, free standing course for high school students.

Historically, it has been difficult to schedule students into courses in statistics and computer science because these courses do not typically fulfill graduation requirements. The state of California adds an additional hitch, as all high school courses must be approved by the University of California Office of the President (UCOP) to be used for admission to college within the UC system, the Cal States, or the California community colleges. One boon to the IDS course is we were able to get it approved by the UCOP, so as of fall 2014, taking the IDS course counts for "C" credit.[5]

As a result of the UCOP approval, high school counselors are interested in scheduling students into the course, and students are interested in taking it.

I was involved in the overall planning for the curriculum, the UCOP application, and the detailed development of the first two units of the curriculum. However, I was not involved in the detailed development of the second two units. The rest of the IDS team includes Suyen Moncada-Machado, Robert Gould, Terri Johnson, and James Molyneux.

The topics covered by the class include visualizing data in one and multi-

[5]California has "A-G" requirements, which require high school students to take two years history, four years of English, three years of math, two years of science, two years of a foreign language, one year of visual or performing arts, and one year of an elective. "C" credit indicates the IDS course satisfies one of the three years of college preparatory math.

ple dimensions, statistical questioning, randomization methods, linear modeling, classification and regression trees, and k-means clustering. For the full curriculum, see (Gould et al., 2015).

The entire curriculum is based on R within RStudio, with regular labs for students to work through the techniques they are learning in class. There are also numerous 'hands-on' activities allowing students to enact data analysis physically, whether creating a human box plot as captured in (Menezes, 2015) or doing randomization activities with notecards.

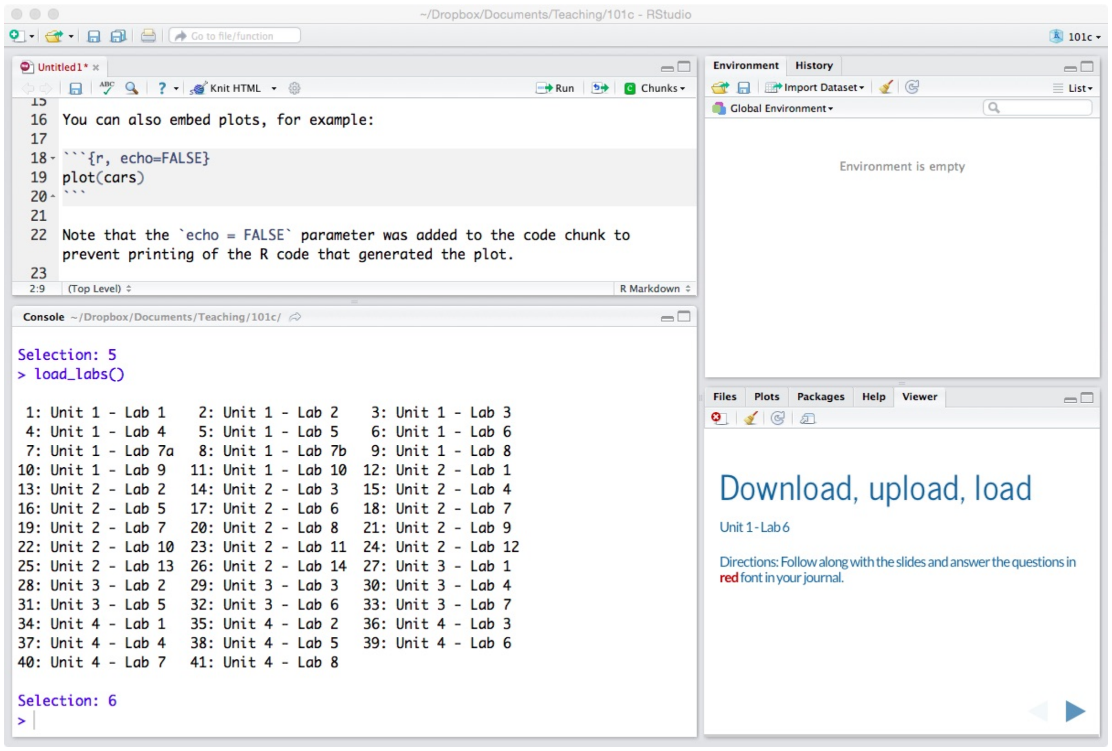
#### 5.1.3.4 Labs

All of the IDS coursework is grounded in computational labs (Figure 5.1), which take place in RStudio (Molyneux et al., 2014). The labs take advantage of the features of RStudio, and provide an integrated method for viewing lab prompts and accomplishing the associated tasks[6].

For students enrolled in IDS, the labs appear to be a coherent piece of the RStudio implementation. When students log in to the server version of RStudio, they can call up whichever lab they are completing by using the `load_labs()` function. Whichever lab they select is then displayed in the Viewer pane of RStudio (as described in Section 3.8.5.3). Because of the embedded slide viewing functionality in RStudio, students can page through the lab at their own speed and answer questions in their 'journal,' either on paper or in an RMarkdown document.

This essentially provides the type of functionality offered by **swirl** (Section 3.8.4.1), but without getting locked into answering questions. All the curricular materials are in the same browser window, so students do not need to flip back and forth between screens, but they are still free to play with code.

[6]To see the full text and installation instructions for all the labs, see `https://github.com/mobilizingcs/ids_labs`.



~~~
You can also embed plots, for example:

```{r, echo=FALSE}
plot(cars)
```

Note that the `echo = FALSE` parameter was added to the code chunk to
prevent printing of the R code that generated the plot.
~~~

```
Selection: 5
> load_labs()

 1: Unit 1 - Lab 1     2: Unit 1 - Lab 2     3: Unit 1 - Lab 3
 4: Unit 1 - Lab 4     5: Unit 1 - Lab 5     6: Unit 1 - Lab 6
 7: Unit 1 - Lab 7a    8: Unit 1 - Lab 7b    9: Unit 1 - Lab 8
10: Unit 1 - Lab 9    11: Unit 1 - Lab 10   12: Unit 2 - Lab 1
13: Unit 2 - Lab 2    14: Unit 2 - Lab 3    15: Unit 2 - Lab 4
16: Unit 2 - Lab 5    17: Unit 2 - Lab 6    18: Unit 2 - Lab 7
19: Unit 2 - Lab 7    20: Unit 2 - Lab 8    21: Unit 2 - Lab 9
22: Unit 2 - Lab 10   23: Unit 2 - Lab 11   24: Unit 2 - Lab 12
25: Unit 2 - Lab 13   26: Unit 2 - Lab 14   27: Unit 3 - Lab 1
28: Unit 3 - Lab 2    29: Unit 3 - Lab 3    30: Unit 3 - Lab 4
31: Unit 3 - Lab 5    32: Unit 3 - Lab 6    33: Unit 3 - Lab 7
34: Unit 4 - Lab 1    35: Unit 4 - Lab 2    36: Unit 4 - Lab 3
37: Unit 4 - Lab 4    38: Unit 4 - Lab 5    39: Unit 4 - Lab 6
40: Unit 4 - Lab 7    41: Unit 4 - Lab 8

Selection: 6
>
```

Download, upload, load

Unit 1 - Lab 6

Directions: Follow along with the slides and answer the questions in red font in your journal.

Figure 5.1: IDS lab in Viewer pane of RStudio

### 5.1.4 Technology

Over the years I was involved with the Mobilize project, we iterated through a variety of technological tools[7]. In the 'pre-pilot' stage of the grant, immediately preceding my appointment, the platform of choice was R, using the base R GUI, as described in Section 3.8. Although we were working with computer science teachers, this proved to be very difficult for them, as they had little prep time and struggled to pick up a new programming language on the fly.

Our next endeavor was Deducer, a graphical user interface (GUI) for R. For more information about Deducer, see Section 3.8.5.2. We used Deducer in the 2011-2012 school year. Deducer was slightly easier for the teachers to learn, but its status as a menu-driven standalone application presented a number of logistical challenges.

[7]This work is adapted from McNamara and Hansen (2014).

Because Deducer is completely menu driven, it is very hard to document, and thus difficult to use in an educational context, where supporting materials are always needed. Rather than providing a reproducible code example, each step of our documentation needed to be a screenshot of the particular configuration of the system.

Teachers often wanted features not available in the current version, and even though Deducer was a tool developed in conjunction with the grant, long development times prohibited this from happening. The development time was the result of Deducer being implemented in Java, which required the grant to hire an expert developer and pass them design specifications before changes could be made.

Finally, Deducer had to be installed on each computer individually. This was problematic for two reasons. First, any bugs present in the installed version are essentially set in stone until another version is available. Second, because many teachers lacked the time and resources to do installations themselves, we sent grant employees into the field to do installations. Sometimes this was very complicated, as installation required administrator passwords to which teachers did not have access, or which had been lost to time. As a result, some features did not work properly.

Learning from the experience of Deducer, we chose to move back toward R in the 2012-2013 school year. However, instead of using the standard R GUI as discussed in Section 3.8, we chose to deploy using the server-side version of RStudio. The use of the RStudio server version allowed us to sidestep the installation problems associated with Deducer. Because students could access RStudio through the browser, they could access the tool from any computer with internet access, and did not have to worry about user privileges. Files were stored on the server, so they could not be lost to nightly hard drive wipes.

Simply making the switch to RStudio made a huge difference. One of the challenges of the base R GUI and with Deducer is there are many disconnected windows that float seemingly at random on the screen. Users often minimize windows (e.g., the plot or help window), and then struggle the next time they make a plot because they cannot find their results. One of the simple solutions RStudio offers is it 'sticks' all windows together, so the plot window cannot be lost, since it is stuck to the others.

Another improvement to getting started using R was the development of an R package called **MobilizeSimple**. The aim of **MobilizeSimple** is to provide simplifying functions to reduce the number of lines of code necessary to perform tasks such as making maps and word clouds. I was the original author of **MobilizeSimple**, with subsequent revisions and iterations developed by James Molyneux. This package is discussed in more depth in Section 5.1.4.2.

Finally, we provided as much documentation as possible to support teachers as they began implementing the curriculum in their own classrooms. First, package documentation for the **MobilizeSimple** package and all the other packages used by the project are accessible through the standard R `help()` function and the Help tab in RStudio.

Teachers were also provided with a one-page summary, or 'cheatsheet,' of all functions necessary for completion of the unit, including minimal working examples, and a pdf document describing how to put together functions to accomplish tasks in the curriculum (e.g., text analysis and map creation).

The project's Youtube page hosted videos showing the basics of logging in to RStudio, the tabs and features of RStudio, and tasks like plotting, mapping, and working with text. A wiki containing the the same material as the pdf document and cheatsheet – updated on a daily basis as I received questions or comments from teachers – was accessible on the web. Finally, I offered – and the current team still offers – support via an email ticketing queue, answered within 24 hours (often, within 2-3 hours).

However, even with all these support materials, ECS teachers ran into snags. Without access to the research and evaluation results from the grant team it is impossible to make any formal statements. However, my anecdotal experience answering email and hearing from people who observed classroom behavior suggests many teachers, perhaps insecure about their skill in R, relied heavily on my videos and wiki as curricular materials. Although there is a full, day-by-day curriculum guide for ECS, replete with classroom activities and questions for the students to work through, teachers rarely used this. Instead, they had students work through examples I had posted on the wiki, copying and pasting commands into the console.

However, the modifications have helped R became usable enough that teachers were able to deploy successfully in IDS, and the project settled on R within RStudio for the remainder of the life of the grant.

Another interesting observation from the early years of Mobilize was that no matter which tool the teachers were first exposed to, they disliked changing away from it. Even if they acknowledged the new tool was objectively better, they were opposed to the change. This is supported by research in other areas. In a route-type software trajectory, Bakker observed participants were hesitant to make the switch to the next minitool (Bakker, 2002).

Running in parallel to our search for the right tool for data science at the high school level was a conversation about whether teachers and students needed to truly learn to code. Because there was still such a high startup cost to learning R, it became clear we could not expect teachers to try to introduce it into their class if students were only going to see it for a day or two. However, we still wanted those students to have the experience of asking and answering questions with data, so the technology team on the grant developed a few tools to allow students to view their data without having to code.

#### 5.1.4.1 Dashboard tools

Jeroen Ooms developed several tools for simple visualization of the student-collected data. The first is an embedded visualization tool (Figure 5.2) within our data access platform, ohmage (Tangmunarunkit et al., 2013). It allows students to select one or two variables to analyze, and then produces an appropriate type of plot.

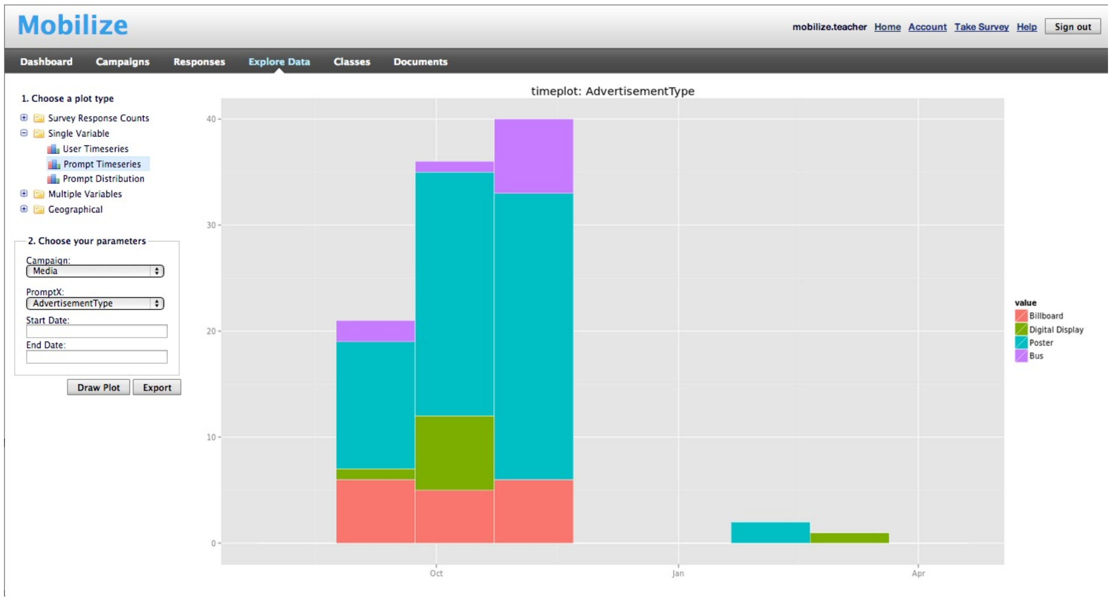


Figure 5.2: ohmage in-browser data visualization engine

Ooms has also produced a standalone data visualization tool (Figure 5.3) that is currently custom-tailored to the data students are producing.

These tools have been invaluable for teachers and students participating in the Mobilize project. They allow students to begin working with data without first having to learn a lot of computational skills. For this reason, they're an excellent first step into the world of data analysis, particularly in short curricular excursions like the math and science units. However, much like the visualizations from the New York Times, they prescribe what a person can do with them. There is limited support for subsetting, and the raw data cannot

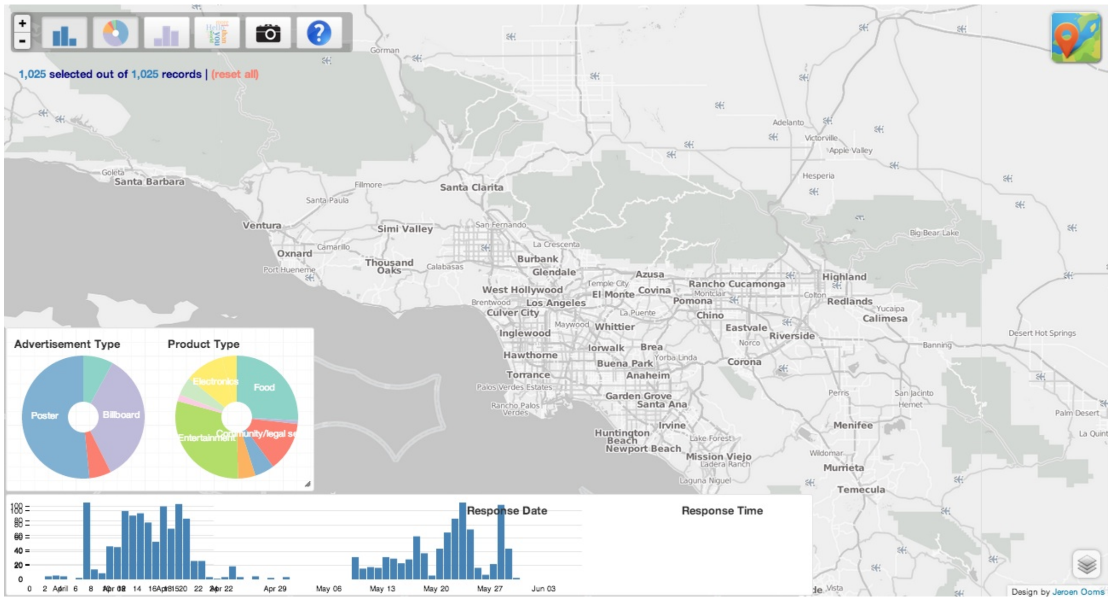


Figure 5.3: Standalone data visualization tool

be worked upon, only be browsed.

### 5.1.4.2 R package

The Mobilize project limits what learners see of R, particularly during their first semester of a course, to the formula syntax. In order to do this, we have used the **mosaic** package, pkglattice graphics, and a few additional functions in the **MobilizeSimple** package.

The motivation for the creation of **MobilizeSimple** was a one-day professional development session for ECS teachers in 2011, after which they were expected to be proficient enough with R to teach it to their students. California does not have a certification for computer science teachers (Lang et al., 2013), so most of the participating teachers has degrees in mathematics or business, and were only nominally computer scientists. As a result, they were novice programmers and novice statisticians.

Using the Exploring Computer Science Mobilize unit discussed in Section 5.1.3.1, I enumerated the tasks teachers needed to be able to accomplish in R, noting how many lines of code it would take to do them. My heuristic was if a task could be done using one function call or one line of code, I would leave the existing R functionality as it was. However, there were several tasks requiring many lines of code, such as:

- Creating a map, using as base map pulled from Google Maps or OpenStreetMaps.
- Plotting points on top of the map and adjusting the sizes of points.
- Creating a map with the same base map, but with points scaled by some other variable in the data set.
- Initializing and processing textual data, including removing stop words, making all words lowercase, and stemming common words.
- Creating and modifying a word cloud based on absolute frequencies of word appearance as well as by percentages (e.g., show only the top 1%).
- Creating and modify a bar chart showing the same types of frequencies and percentages.
- Performing basic regular expressions, like pulling `4` out of a string that says "`4 hours of sleep`."

For tasks requiring more than one line of code, I wrapped up the code into a helper function. For a concrete example, let us examine text analysis. It is possible to do text analysis in R using the package **tm** (Feinerer and Hornik, 2008). However, to get a basic word cloud (Figure 5.4) of some text data, the following code is necessary:

```
MobilizeSimple
library(tm)
library(RColorBrewer)
library(wordcloud)
twitter = read.csv("twitterwithdate.csv")
textCorpus = Corpus(VectorSource(twitter$message))
processedText = tm_map(textCorpus, tolower)
processedText = tm_map(processedText, removePunctuation)
```

```r
processedText = tm_map(processedText, removeNumbers)
processedText = tm_map(processedText, removeWords,
                stopwords("english"))
tdm = TermDocumentMatrix(processedText)
m = as.matrix(tdm)
v = sort(rowSums(m), decreasing = T)
d = data.frame(word =names(v), freq = v, row.names = NULL)
pal = brewer.pal(9, "BuGn")
pal = pal[-(1:4)]
wordcloud(d$word, d$freq, random.color = T, min.freq = 2,
          color = pal)
```

I did not want to completely hide the process when creating the wrapper function for **MobilizeSimple**, but the goal was to reduce the number of lines to code while maintaining the computational process. In **MobilizeSimple**, the same task is wrapped into three functions:

```r
text = InitializeText(twitter$message)
processedText = ProcessText(text, removestopwords = TRUE)
MakeWordCloud(processedText)
```

The plot is identical to the one seen in Figure 5.4. The simplified flow in **MobilizeSimple** still captures the workflow of the text analysis process. A user has to initialize the text to get it stored in the right format for R to consider a textual corpus, process it to standardize capitalization, remove stop words, and finally plot the word cloud. The package abstracts away the details students do not need to know. Note the `ProcessText` function defaults to making every word lowercase and removing numbers and punctuation, but if the user wants the function to remove stop words they must pass that argument. It was

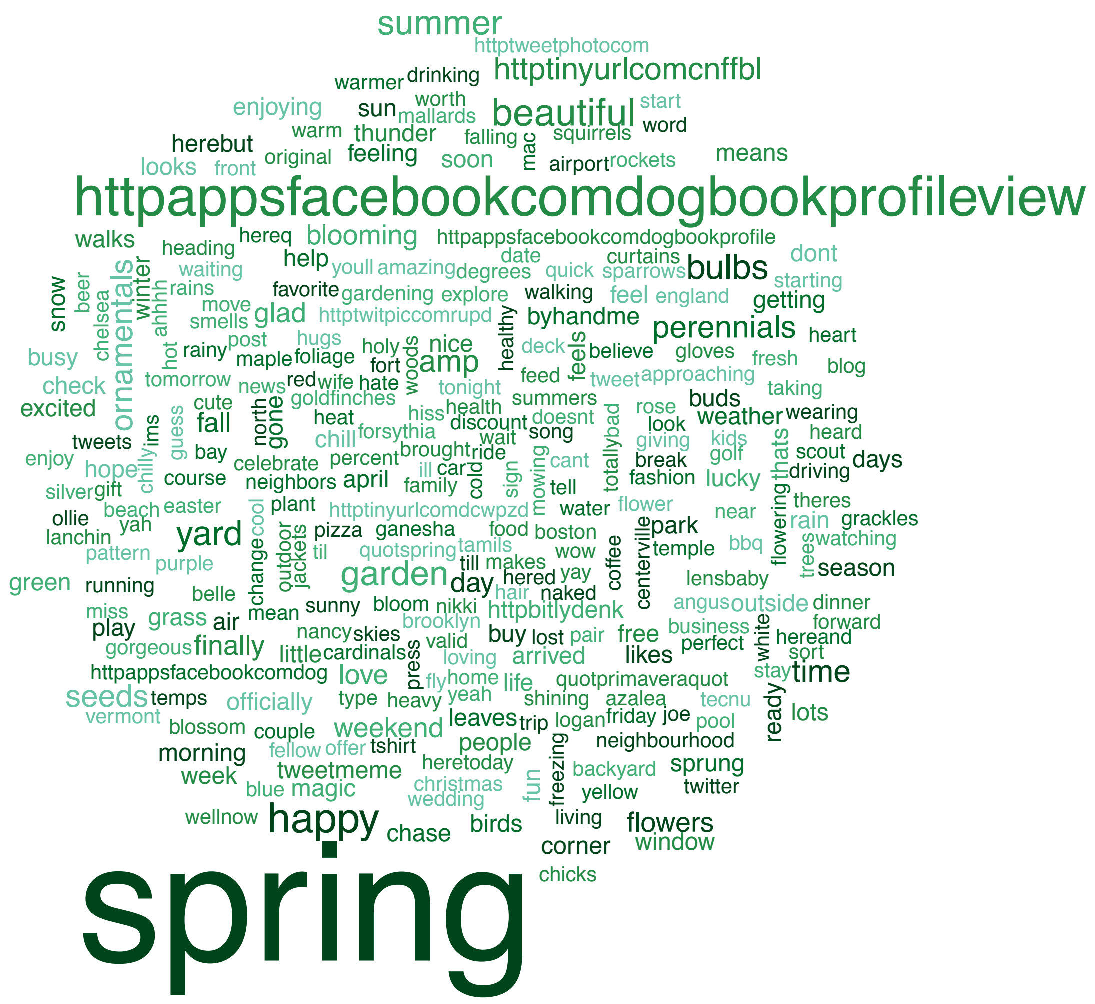


Figure 5.4: Output from **tm** code

a conscious decision to make the simplest processes standard, but require extra arguments to do other motivational tasks. For example, if a student is confused or frustrated when they see “the” as the largest word in their word cloud, they will hopefully be motivated to study the documentation to learn how to remove words like this.

This workflow provides a simple algorithm to getting word clouds to work, and requires users to pass arguments to functions. Thus, it is capturing some components of computational thinking, but it does not require the burden of many lines of code, like the **tm** package would, or totally remove the computational experience as GUIs so often do.

Critics of this package have cited its function naming and syntax, and as the package authors we think these concerns are legitimate. Future versions of **MobilizeSimple** will use more standard R naming conventions, such as using lowercase function names (Wickham, 2014a). It will also be modified to use the so-called ‘formula syntax’ discussed further in Section 3.8.1. While the **MobilizeSimple** package has not yet been added to CRAN, it can be installed from Github using the **devtools** package (McNamara, 2013b).

The experience of developing and deploying the **MobilizeSimple** package underscored my earlier understanding, which is that users need support as they learn a language. Exactly how to support people is the salient question.

## 5.2 LivelyR

Through my work with the Communications Design Group, I was able to collaborate with Aran Lunzer to develop a tool we are calling LivelyR. The Communications Design Group is an independent research lab headed by Alan Kay. It draws together researchers from Kay’s non-profit, Viewpoints Research Institute, as well as employees from SAP.

The product of this work is an interface we are calling LivelyR[8]. The interface is a bespoke system (see Section 3.10 for other examples of such systems). An R server is running in the background, either locally on a user's computer or on a centralized server. Results are much quicker (and therefore, interaction is smoother) when R is run locally, but of course that requires a local installation. As discussed in Section 5.1.4, relying on a local installation is a barrier to accessibility. However, because LivelyR is more provocation than prototype, we were not as concerned with the realities of use cases.

R interacts with a JavaScript programming environment called Lively Web. Lively is an open source tool making it easy to develop applications in the web browser (Ingalls et al., 2013). Each component of a Lively page is 'live,' so a user can give it behavior using code, modify the shape or size of it, move it, delete it, and copy it. The results can be shared as completely 'live' products (Ingalls et al., 2013). When a user goes to a page produced by LivelyWeb – even the project's main web page – every element is fully moveable, transformable, and programmable. In order to program the elements, the user does need to know JavaScript, but edits can be made on the fly without having to download source code and edit it 'offline.' This stands in direct contrast to projects like RMarkdown and the iPython notebook, where the results may be interactive (if the author made them that way), but in order to edit the user needs to move away from the live implementation.

The Lively team also maintains a "parts bin" where users can share components they have developed, either by dragging and dropping pieces together or writing code (Lincke et al., 2012). There was no existing connection between the Lively server and a server running R, but Robert Krahn created a web socket

[8]Lunzer is the primary author on this work, as he did the coding, but we worked through the conceptual ideas together. Our joint work has been supported by thoughtful input from many of our colleagues, most notably Robert Krahn, Dan Ingalls, Alan Kay, Bret Victor, Alex Warth, and Ted Kaehler. The written descriptions included here are based on Lunzer and McNamara (2014); Lunzer et al. (2014)

connection. Additionally, the interaction available off the shelf with Lively was not sufficient for the types of behavior we wanted to implement, so Lunzer wrote additional code hacking **Shiny** and **ggvis** to provide reactive behavior. In contrast to the standard **ggvis** functionality, LivelyR uses JavaScript to initiate and control all behavior. This work is discussed in more depth in Lunzer and McNamara (2014); Lunzer et al. (2014).

The behavior of LivelyR was based on my commitment to interactive statistical programming tools, and Lunzer's longstanding work on subjunctive interfaces (Lunzer and Hornbæk, 2008). For an overview of the functionality of LivelyR as of May 2014, see Lunzer (2014)[9].

### 5.2.1 Histogram cloud

One feature that has garnered a lot of attention when we have shown this work is what I call the 'histogram cloud.' The data used in the example shown in Figure 5.5 is from the R sample dataset `mtcars`.

In the screenshot, a scatterplot of weight (`wt`) versus miles per gallon (`mpg`) is shown in the center of the plot window. At the top of the image, a few simple summary statistics are displayed: the number of data points currently in use (which changes as subsets are applied), the mean and standard deviation of both variables, and the Pearson correlation coefficient. Green arrows indicate the range of the data included. The arrows can modified interactively to subset the data, but the view shown is using the complete data set.

At the bottom of the screen is a rectangular display of the data set, with the x- and y-variables noted, and ranges for each of the variables. The 0 and 100 indicate 100% of the data are included for each variable. Again, this could be interactively modified to only include a particular percentile of the data.

[9]https://vimeo.com/93535802

For this version of LivelyR, we made it possible to plot several different types of plot in the same plotting window. Therefore, the left vertical axis is the `wt` axis, but the right vertical axis is the count for the histogram(s) of `mpg`. Researchers have found this type of layering of multiple plots is difficult for users to understand, so this functionality would ideally not be included in a production tool (Isenberg et al., 2011; Few, 2008). However, providing histograms along the margins of scatterplots (typically outside the plot region, rather than inside as shown here) is a common visualization feature (Emerson et al., 2013).

Typically, statistical packages provide default bin widths and bin offsets, and the affordances of the system provide a disincentive to modify the parameters. For example, in **base** R, the `hist()` command uses a default bin width based on the Sturges algorithm (Sturges, 1926). The `geom_bar()` command in the R package **ggplot2** uses *range*/30 and though it does provide a warning,

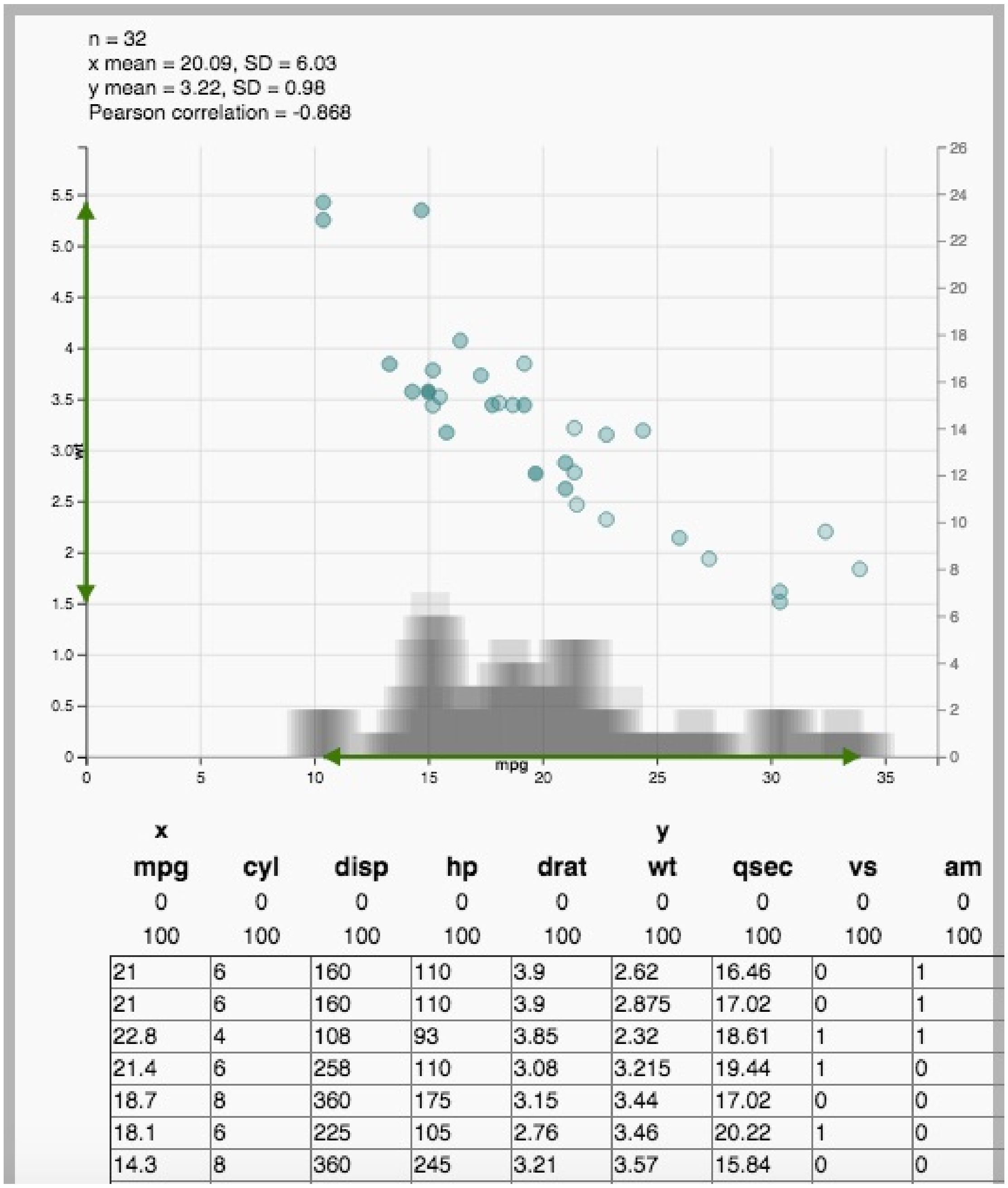
```
stat_bin: binwidth defaulted to range/30.
Use ‘binwidth = x’ to adjust this.
```

many people stick with what is given.

There are several other accepted algorithms for choosing optimal histogram bin width (Wand, 1997), but generally the parameters should be tuned to a particular data set. Choosing appropriate bin widths is one of the pieces of data science that ends up being more of an art.

Therefore, we sought to make it so easy to modify the defaults there would be no reason not to. This is in line with Biehler's idea of a "stretchy" histogram, allowing users to pull the height of bars up or down (Biehler, 1997). In this interface, the bars cannot be directly manipulated, but the parameters are easily manipulable.

Outside the scope of the screenshot in Figure 5.5 but visible in Figure 5.7 are the slider controls for bin width and bin offset. Users can interactively ma-



n = 32
x mean = 20.09, SD = 6.03
y mean = 3.22, SD = 0.98
Pearson correlation = -0.868

| x |  |  |  |  | y |  |  |  |
|---|---|---|---|---|---|---|---|---|
| mpg | cyl | disp | hp | drat | wt | qsec | vs | am |
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 21 | 6 | 160 | 110 | 3.9 | 2.62 | 16.46 | 0 | 1 |
| 21 | 6 | 160 | 110 | 3.9 | 2.875 | 17.02 | 0 | 1 |
| 22.8 | 4 | 108 | 93 | 3.85 | 2.32 | 18.61 | 1 | 1 |
| 21.4 | 6 | 258 | 110 | 3.08 | 3.215 | 19.44 | 1 | 0 |
| 18.7 | 8 | 360 | 175 | 3.15 | 3.44 | 17.02 | 0 | 0 |
| 18.1 | 6 | 225 | 105 | 2.76 | 3.46 | 20.22 | 1 | 0 |
| 14.3 | 8 | 360 | 245 | 3.21 | 3.57 | 15.84 | 0 | 0 |

Figure 5.5: LivelyR interface showing a histogram cloud of miles per gallon

nipulate these sliders independently, to see a series of static histograms with the particular parameter value. However, Lunzer's work often gives users the ability to modify several parameters together, in order to see more 'what if?' possibilities. In this case, it is possible to make a 'sweep' of one of the parameters. In Figure 5.5 the sweep is of the bin offset parameter. Therefore, each histogram in the cloud has the same bin width, but they all have slightly different bin offsets, where the bin begins. Once this sweep is in place, the user can use the slider to modify the bin width of the cloud, which will produce a new set of histograms with the same (new) bin width, but a variety of bin offsets.

When people are presented with the histogram cloud for the first time, they typically express a sense of wonder. Because the full range of possible histograms for a particular data set has never been accessible to them, they find it fascinating how many variations are possible. The cloud also gives a sense of the 'true' shape of the distribution. Obviously, kernel density estimation can provide similar information about the true distribution of the data, but understanding kernel densities requires another layer of abstraction. Understanding histograms is a complicated task for novices (Watson and Fitzallen, 2010; Friel, 2008), but the histogram cloud only requires an additional small cognitive step in order to be understood.

Inspired by the popularity of the histogram cloud when showing LivelyR, I have begun to think about how the concept could be extended to a 2-D setting. Mapmaking is often appealing to novices because it is very grounded in reality. As Tom MacWright noted, "The problem with maps is that the world looks like a map. We don't have that problem with other visualizations." One of the challenges with map-making, particularly of choropleth maps, is the areal units used do not have much meaning in terms of the variable being mapped. For example, mapping incidences of traffic accidents by zipcode or Census block is typically not useful, because traffic accidents tend to happen along streets. Because data are often measured in standard areal units, there is typically not much that can be done.

In geography, this is called the Modifiable Areal Unit Problem (MAUP). Geographers and geostatisticians have developed some methods for dealing with these data. The methods are usually spoken of in terms of 'scaling.' Upscaling is the easiest task, and it involves making a map at a less detailed spatial resolution than the data collection method (e.g., taking a map aggregated at the county level and turning it into one aggregated at the state level). Side-scaling is somewhat more complex, as it involves taking two similarly-sized areal units and translating between them (e.g., moving from zipcodes to Census tracts). The most complex is down-scaling, which involves taking data at a less-detailed level down to a more detailed level (Atkinson, 2013).

There are a variety of methods to deal with this problem, including data fusion and area-to-point kriging. Also relevant are efforts using data augmentation, much like what was discussed in Section 5.1.1, which will use auxiliary information to help with disagreggation. For example, the Disser project helps disaggregate Census data by bringing in information about zoning to determine housing density (Martin-Anderson, 2014).

Again, because viewers found the ability to move bins in the histogram cloud and see the resulting changes in distribution in 1-D, it seemed likely an analogous action would be appealing in 2-D. However, this extension is still a work in progress.

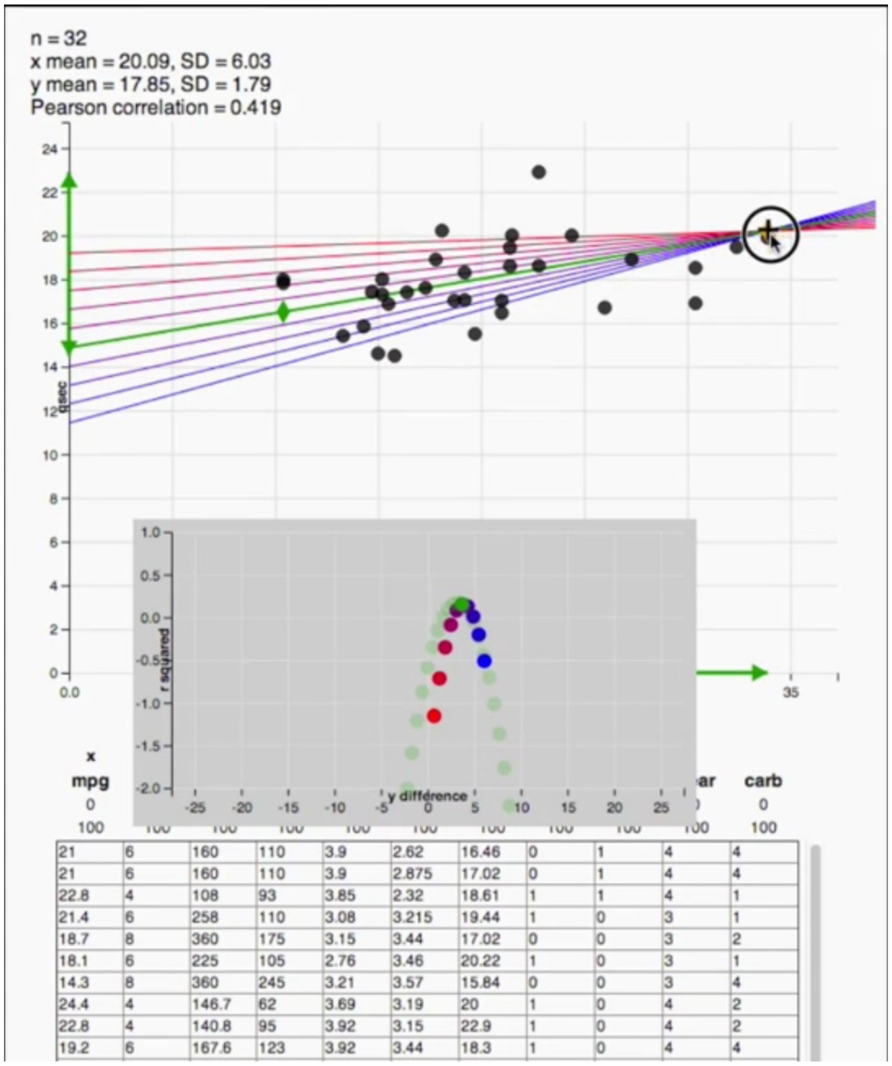
### 5.2.2 Regression guess line

Another feature built into LivelyR is the ability to create a 'regression guess' line. This is another feature suggested by Biehler, who suggests, "eye-fitted lines with residual analysis should precede the method of least squares" (Biehler, 1997). As in the previous section, a video of the interaction is available to more clearly display the functionality (Lunzer, 2014).

Similar to the histogram cloud discussed above, this feature allows users to manipulate one or multiple parameters in order to find the best fit line. In this case, the parameters are the start and end points of the line the user is guessing. Choosing the best line can be done by eye by modifying first one end of the line and then the other, then judging how well the line fits the scatterplot of points. The interface provides additional information in the form of the residual sum of squares (RSS) value, which a user can also use as a guide, manually attempting to optimize RSS.

Because LivelyR complies with Lunzer's conception of a subjunctive interface (Lunzer and Hornbæk, 2008), it also allows users to try a 'sweep' of parameter values. In this case, the user defines a sweep of point locations on one end of the line, then moves the other end by hand. This allows the user to visually compare a selection of lines with a more dynamic set of end points. Additionally, the interface provides an ephemeral plot of the RSS value, which allows the user to more directly attempt to optimize the value by aiming for the local maximum on the plot. A screenshot of this functionality is shown in Figure 5.6. Again, this falls into the category of allowing learners to discover things by themselves, as Biehler suggests.

Of course, even the LivelyR implementation does not do the most superb job of supporting discoverability. The interface provides RSS as a measure to optimize without ever explaining why one might want to optimize it, and there is no visual support to suggest why the movement of the line is increasing or decreasing the RSS. A second generation of this type of tool should include a more self-articulating version of this, where the residuals or the squares are visually represented on the screen. More work should be done to study how novices conceptualize the sum of squares, and to determine the most effective way of conveying the concept visually.


n = 32
x mean = 20.09, SD = 6.03
y mean = 17.85, SD = 1.79
Pearson correlation = 0.419

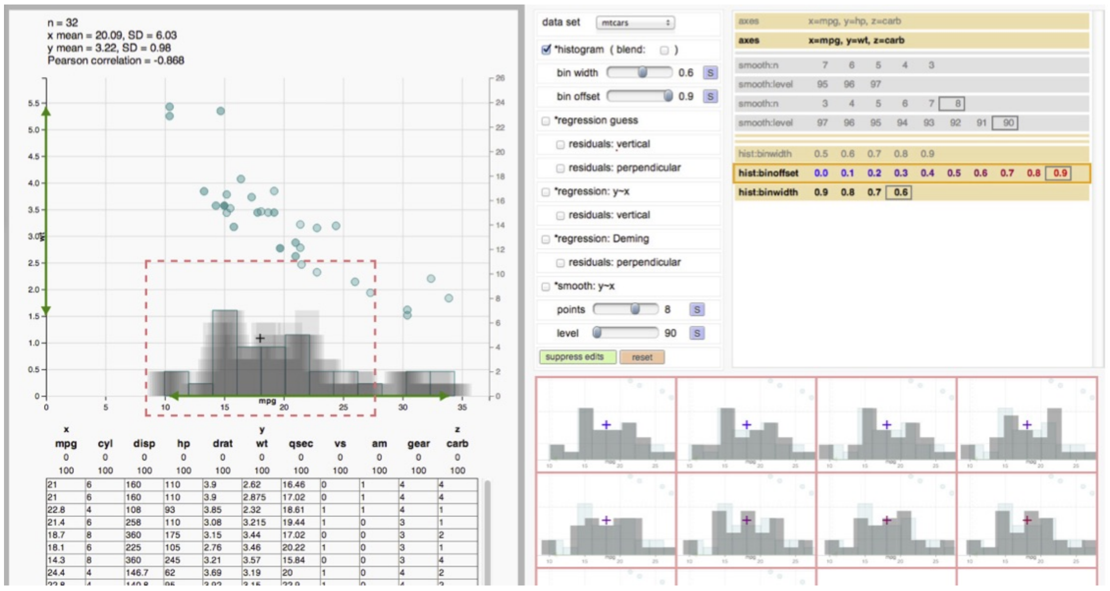
| mpg | | | | | | | | | ar | carb |
|---|---|---|---|---|---|---|---|---|---|---|
| 21 | 6 | 160 | 110 | 3.9 | 2.62 | 16.46 | 0 | 1 | 4 | 4 |
| 21 | 6 | 160 | 110 | 3.9 | 2.875 | 17.02 | 0 | 1 | 4 | 4 |
| 22.8 | 4 | 108 | 93 | 3.85 | 2.32 | 18.61 | 1 | 1 | 4 | 1 |
| 21.4 | 6 | 258 | 110 | 3.08 | 3.215 | 19.44 | 1 | 0 | 3 | 1 |
| 18.7 | 8 | 360 | 175 | 3.15 | 3.44 | 17.02 | 0 | 0 | 3 | 2 |
| 18.1 | 6 | 225 | 105 | 2.76 | 3.46 | 20.22 | 1 | 0 | 3 | 1 |
| 14.3 | 8 | 360 | 245 | 3.21 | 3.57 | 15.84 | 0 | 0 | 3 | 4 |
| 24.4 | 4 | 146.7 | 62 | 3.69 | 3.19 | 20 | 1 | 0 | 4 | 2 |
| 22.8 | 4 | 140.8 | 95 | 3.92 | 3.15 | 22.9 | 1 | 0 | 4 | 2 |
| 19.2 | 6 | 167.6 | 123 | 3.92 | 3.44 | 18.3 | 1 | 0 | 4 | 4 |

Figure 5.6: Regression guess functionality in LivelyR

### 5.2.3 Small multiple callout plots

In all the plot scenarios involving sweeps of parameters, LivelyR makes it possible to see each of the possible scenarios broken out into small multiple plots (Tufte, 2001). An example of this is shown in Figure 5.7, where each of the histograms from the histogram cloud in section 5.2.1 is broken out into an individual plot.

Once again, this feature allows for exploration over multiple parameters. In


n = 32
x mean = 20.09, SD = 6.03
y mean = 3.22, SD = 0.98
Pearson correlation = -0.868

| x mpg | cyl | disp | hp | drat | y wt | qsec | vs | am | gear | z carb |
|---|---|---|---|---|---|---|---|---|---|---|
| 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 | 100 |
| 21 | 6 | 160 | 110 | 3.9 | 2.62 | 16.46 | 0 | 1 | 4 | 4 |
| 21 | 6 | 160 | 110 | 3.9 | 2.875 | 17.02 | 0 | 1 | 4 | 4 |
| 22.8 | 4 | 108 | 93 | 3.85 | 2.32 | 18.61 | 1 | 1 | 4 | 1 |
| 21.4 | 6 | 258 | 110 | 3.08 | 3.215 | 19.44 | 1 | 0 | 3 | 1 |
| 18.7 | 8 | 360 | 175 | 3.15 | 3.44 | 17.02 | 0 | 0 | 3 | 2 |
| 18.1 | 6 | 225 | 105 | 2.76 | 3.46 | 20.22 | 1 | 0 | 3 | 1 |
| 14.3 | 8 | 360 | 245 | 3.21 | 3.57 | 15.84 | 0 | 0 | 3 | 4 |
| 24.4 | 4 | 146.7 | 62 | 3.69 | 3.19 | 20 | 1 | 0 | 4 | 2 |

data set: mtcars
*histogram ( blend: ☐ ) ✓
bin width 0.6
bin offset 0.9
☐ *regression guess
☐ residuals: vertical
☐ residuals: perpendicular
☐ *regression: y~x
☐ residuals: vertical
☐ *regression: Deming
☐ residuals: perpendicular
☐ *smooth: y~x
points 8
level 90

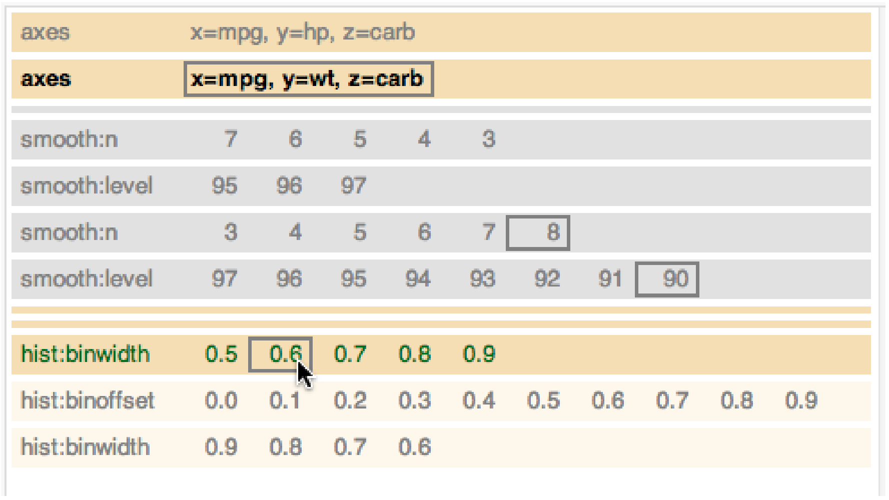
| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| axes | x=mpg, y=hp, z=carb | | | | | | | | | |
| axes | x=mpg, y=wt, z=carb | | | | | | | | | |
| smooth:n | 7 | 6 | 5 | 4 | 3 | | | | | |
| smooth:level | 95 | 96 | 97 | | | | | | | |
| smooth:n | 3 | 4 | 5 | 6 | 7 | 8 | | | | |
| smooth:level | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 90 | | |
| hist:binwidth | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | | | | | |
| hist:binoffset | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| hist:binwidth | 0.9 | 0.8 | 0.7 | 0.6 | | | | | | |

Figure 5.7: Small multiples in LivelyR

this case, although the small multiples each display one of the set of histograms from the histogram cloud, the user can use a second input device (in Lunzer's experiments, an iPad configured for use as a lefthand input) to select a histogram they want to compare with all others. In Figure 5.7, there is a light ghosted histogram shown in the background of all the small multiples. This is the histogram being used for comparison. In this example, the histogram being used for comparison is the beginning of the sweep (notice the small multiple in the upper left does not have a ghost histogram), but the tool is more generic.

### 5.2.4 Documentation of interaction history

Many of the features discussed above are available in other software packages, particularly those for learning statistics (see Section 2.2 for more on these tools). However, LivelyR offers a feature we have not witnessed in any common interactive tools: a history. Each time a user performs an action in the LivelyR interface, whether changing the subset of the data, modifying the histogram bin width, or sweeping values for a regression line guess, a line is added to the history list. The history list is visible on the right side of the screenshot in Figure 5.7 and is shown in more detail in Figure 5.8.



| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| axes | x=mpg, y=hp, z=carb | | | | | | | | | |
| **axes** | **x=mpg, y=wt, z=carb** | | | | | | | | | |
| smooth:n | 7 | 6 | 5 | 4 | 3 | | | | | |
| smooth:level | 95 | 96 | 97 | | | | | | | |
| smooth:n | 3 | 4 | 5 | 6 | 7 | 8 | | | | |
| smooth:level | 97 | 96 | 95 | 94 | 93 | 92 | 91 | 90 | | |
| hist:binwidth | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 | | | | | |
| hist:binoffset | 0.0 | 0.1 | 0.2 | 0.3 | 0.4 | 0.5 | 0.6 | 0.7 | 0.8 | 0.9 |
| hist:binwidth | 0.9 | 0.8 | 0.7 | 0.6 | | | | | | |

Figure 5.8: History transcript in LivelyR

The history not only makes the interactive system reproducible (see Section 4.8 for more about this requirement), it allows users to move forward and backward through their history. In Figure 5.8, the cursor is indicating a move 'back in time' to the way the interface was when the bin width was set to 0.6. The interface also allows the user to rewrite history and see what the situation in the past would have looked like with a slight parameter tweak. There are obviously open issues surrounding how to deal with those alternate histories, but other researchers in the Communications Design Group are experimenting with novel methods to address those problems (Warth et al., 2011).

## 5.3 Additional Shiny experiments

The goal of 'interaction all the way down' (Section 4.6) in a statistical programming tool does not always immediately present itself as a useful feature. However, given my experience teaching high school students, professional development for high school teachers, and undergraduates, I am able to see many possible use cases. Because of the effort it took to create LivelyR (again, mostly on the part of Lunzer), it was clear we needed a simpler solution to mocking up interface possibilities.

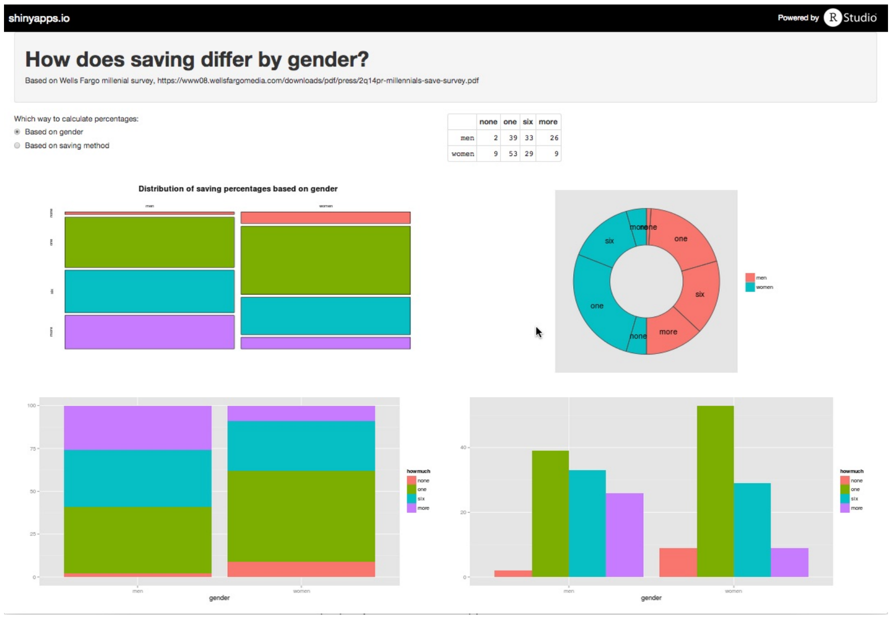
As a result, I have been creating a few experiments in **Shiny** to show some of the features that could be available in a full system complying with the requirements listed in Chapter 4.

### 5.3.1 Conditional visualizations

A very simple **Shiny** app I developed for a data visualization course I taught is shown in Figure 5.9[10]. In the class, we were looking at a visualization about the saving habits of men and women, made by Wells Fargo (Harris Poll, 2014). In the original visualization, a donut chart is broken down into overall percentages of the surveyed population who saved a particular percent of their savings. For example, 18% of those surveyed saved more then 10% of their income. However, in addition, conditional percentages were given by gender. For that same slice of the donut, it said “men - 26%” and “women - 9%” Obviously, those numbers are for those groups individually, but upon first glance it seemed like the graphic was suggesting that 26% of the 18% were men and 9% women.

In order to help my students understand the difference between the two breakdowns, I created a series of graphics: one with the data broken first into saving categories, and then gender (5.9b), and the other breaking on gender first (5.9a). While this app will not win any awards for visualization style, it conveyed the point easily, and allowed my students to flip back and forth between the versions.

[10]Interactive version available at `https://ameliamn.shinyapps.io/ConditionalPercens`


shinyapps.io

Powered by R Studio

## How does saving differ by gender?

Based on Wells Fargo millenial survey, https://www08.wellsfargomedia.com/downloads/pdf/press/2q14pr-millennials-save-survey.pdf

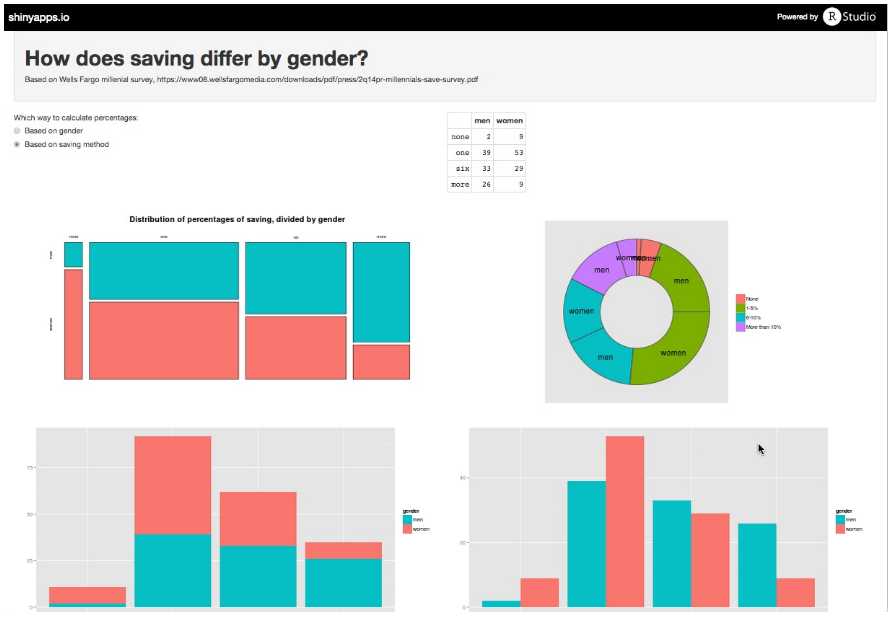
Which way to calculate percentages:

[✓ Based on gender]

Based on saving method

|  | none | one | six | more |
|---|---|---|---|---|
| men | 2 | 39 | 33 | 26 |
| women | 9 | 53 | 29 | 9 |

(a) Split on gender first


shinyapps.io

Powered by R Studio

## How does saving differ by gender?

Based on Wells Fargo millenial survey, https://www08.wellsfargomedia.com/downloads/pdf/press/2q14pr-millennials-save-survey.pdf

Which way to calculate percentages:

Based on gender

[✓ Based on saving method]

|  | men | women |
|---|---|---|
| none | 2 | 9 |
| one | 39 | 53 |
| six | 33 | 29 |
| more | 26 | 9 |

(b) Split on saving method first

Figure 5.9: Conditional percentages

### 5.3.2 Interaction plot with manipulable data cut point

Another example stuck out from a modeling course for which I was the teaching assistant. In the course, students were asked to prepare a linear model to predict API scores[11] from a number of other factors about schools. The assignment asked students to discuss interaction effects in their final paper.

Because the data had many numeric variables and the students preferred the clarity of studying interaction plots when both variables were categorical, many groups chose to split a numeric variable into a categorical variable with two classes. Of course, the choice of cut point was somewhat arbitrary. Some groups chose the mean of their variable, others the median, while others chose a cutoff that they believed to be significant given some contextual knowledge. However, because they were programming in R and the choice of cut point was so early in their analysis, many groups did not realize how sensitive their analysis was to their earlier parameter choice.

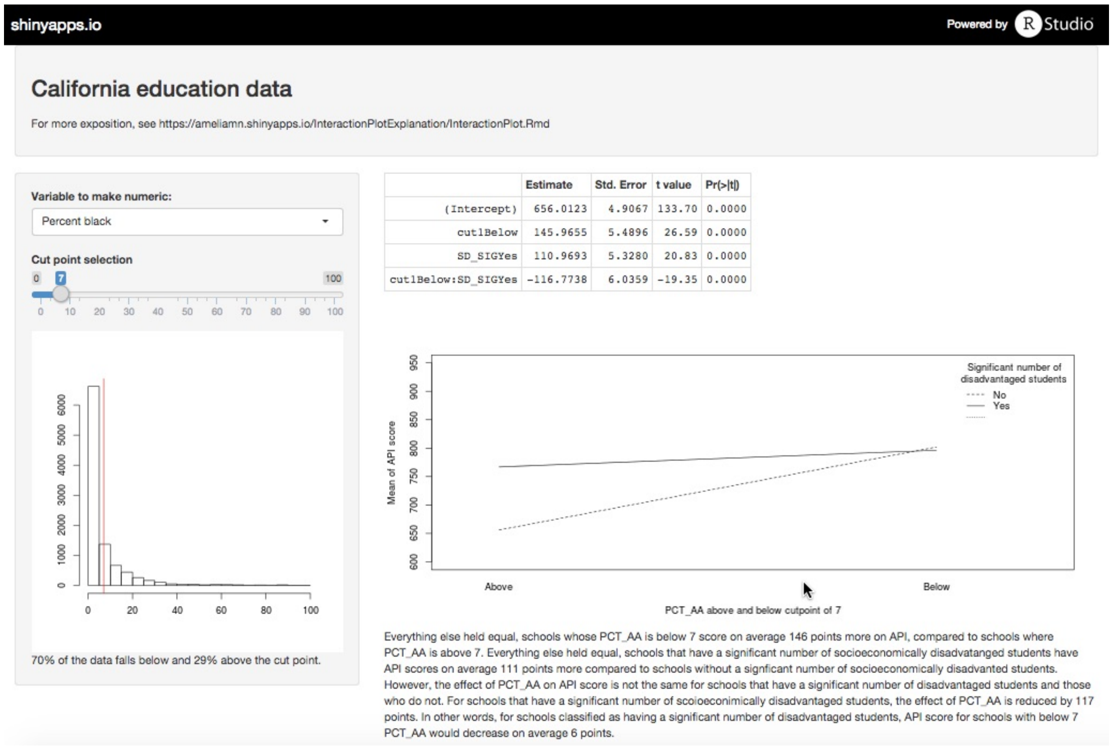
Difficulty understanding the impact of cut points is not unique to my students. Other researchers have observed similar behavior in students and teachers (Hammerman and Rubin, 2004; Rubin and Hammerman, 2006).

In order to display how a completely interactive system could help even intermediate and advanced analysts, I created a **Shiny** app which allows a user to pick a variable in the dataset to convert to a categorical variable, and then allows them to manipulate the cut point. Because **Shiny** uses a reactive framework, even time the cut point is manipulated the model output, interaction plot, and coefficient interpretation change. A view of this **Shiny** app is shown in Figure 5.10[12].

The app makes it very simple to see where the choice of cutpoint makes the

[11]In this context, API means Academic Performance Index, not to be confused with Application Programming Interfaces.

[12]Interactive version available at `https://ameliamn.shinyapps.io/InteractionPlot/`



shinyapps.io

Powered by RStudio

California education data

For more exposition, see https://ameliamn.shinyapps.io/InteractionPlotExplanation/InteractionPlot.Rmd

Variable to make numeric: Percent black

Cut point selection: 7

|  | Estimate | Std. Error | t value | Pr(>\|t\|) |
|---|---|---|---|---|
| (Intercept) | 656.0123 | 4.9067 | 133.70 | 0.0000 |
| cut1Below | 145.9655 | 5.4896 | 26.59 | 0.0000 |
| SD_SIGYes | 110.9693 | 5.3280 | 20.83 | 0.0000 |
| cut1Below:SD_SIGYes | -116.7738 | 6.0359 | -19.35 | 0.0000 |

70% of the data falls below and 29% above the cut point.

Everything else held equal, schools whose PCT_AA is below 7 score on average 146 points more on API, compared to schools where PCT_AA is above 7. Everything else held equal, schools that have a significant number of socioeconomically disadvatanged students have API scores on average 111 points more compared to schools without a signficant number of socioeconomically disadvanted students. However, the effect of PCT_AA on API score is not the same for schools that have a significant number of disadvantaged students and those who do not. For schools that have a significant number of scoioeconimically disadvantaged students, the effect of PCT_AA is reduced by 117 points. In other words, for schools classified as having a significant number of disadvantaged students, API score for schools with below 7 PCT_AA would decrease on average 6 points.

0
10
20
30
40
50
60
70
80
90
100
Mean of API score
Significant number of disadvantaged students
No
Yes
Above
Below
PCT_AA above and below cutpoint of 7

Figure 5.10: Shiny app demonstrating fragility of interaction based on cutpoint

interaction effect flip, and even provides a visual cue as to why that might be happening– the vastly different sizes of data in the two groups. However, this app had to be hand-coded by me, using the **Shiny** server/UI framework, so it is not something an introductory student could develop on their own.

## 5.4 Discussion of first forays

The work discussed in this chapter has helped to ease some of the transition between learning and doing, particularly for high school students associated with the Mobilize Project. However, the tools developed only hint at the richer interfaces that are possible. The experience of creating LivelyR prompted Lunzer and myself to reconsider our choice of target technology, because the combination of R and Lively Web caused us to get locked in to particular interface choices too early. Instead, we should be attempting to create as many distinct possibilities as possible (as in a charrette) and using user studies to learn which are most successful. These experiences motivate my future work.

# CHAPTER 6

# Conclusions, recommendations, and future work

Nearly 20 years after Rolf Biehler's 1997 paper, "Software for learning and for doing statistics," much of Biehler's vision has been realized through the development of TinkerPlots and Fathom. These landscape-type tools for learning statistics and data analysis allow novices to jump into 'doing' statistics and experience the playful nature of the cycle of exploratory analysis, moving from questioning to analysis and back to questioning. However, new developments in computation and data analysis are beginning to trickle down into introductory material, and need better support. In particular, the drive for reproducible research has trickled down from science (Buckheit and Donoho, 1995) to introductory statistics (Baumer et al., 2014), and needs to be supported by tools for learning.

However, the movement of best practices is not simply from professional tools to tools for learning. In fact, tools like Fathom and TinkerPlots have strengths professional tools are sorely lacking, like support for interactive graphics, parameter manipulation, building new plot types, and integrated randomization. We can imagine a tool combining the strengths of both paradigms, eliminating the gap between tools for learning and tools for doing statistics.

In Chapter 3 we considered the strengths and weaknesses of tools currently on the market. While R has been gaining followers because of its strengths, like its status as a free and open source programming language, the R programming paradigm is very stilted and does not support exploratory analysis as well as it could. Projects like **Shiny**, RMarkdown and the iPython notebook are making it possible to combine textual programming languages with interactive and publishable results, but they typically provide either dynamic or interactive graphics, never dynamic-interactive.

Conversely, TinkerPlots and Fathom make it simple for everyone, including novices, to interact with their data. However, this interactivity comes with tradeoffs, particularly in terms of sharing results (proprietary file formats make it hard to share interactive results with others) and reproducibility (as there is no linear documentation of the analysis process).

In Chapter 4, we discussed the attributes necessary for a modern statistical programming tool bridging the gap between being a tool for learning and a tool for doing. These attributes include easy entry for novice users, data as a first-order persistent object, support for a cycle of exploratory and confirmatory analysis, flexible plot creation, full support for randomization, interactivity at every level, inherent visual documentation, simple support for narrative, publishing, and reproducibility, and the flexibility to build extensions. While there are efforts to move toward this ideal tool, no existing products satisfy all the requirements.

Chapter 5 describes a set of experiments I have undertaken in the space of closing the gap between tools for learning and tools for doing statistics. One component of this is curricular: high school level material developed through the NSF grant Mobilize, including data science units to be added to courses in computer science, Algebra I and Biology, and a freestanding course called Introduction to Data Science. As part of the Mobilize project I have also considered appropriate computational tools (R, Deducer, and R within RStudio), and developed additional functionality in the **MobilizeSimple** package.

In joint work with Aran Lunzer, we considered ways in which interactive tools would provide capabilities not possible using pen-and-paper, including an interaction history to make using an interface more reproducible. Finally, I created a few illustrative **Shiny** apps, to demonstrate the microworld capabilities of the system.

## 6.1 Current best practices

Because there are currently no tools containing all the attributes discussed in Chapter 4, it makes sense to consider the best practices using existing technology. As we have seen repeatedly throughout this work, there is a contrast between tools for learning and tools for doing. On the tools for learning side, Fathom appears to have the most features complying with the requirements. It has a low threshold, provides plenty of interactivity for analysis authors, and has a low price point. However, if Fathom is to be used in an introductory class, efforts must be taken to scaffold its use toward the next tool. For example, the end of the semester could include a basic exploratory data analysis project in R.

For those more interested in starting students on a professional tool, but providing better 'on-ramping' to the tool, the use of R within RStudio is recommended. In addition, scoping decisions should be made to only introduce students to a small set of R commands and one unified syntax. In the Mobilize project, we have followed the lead of Project MOSAIC and have used the formula syntax, using **mosaic**, **lattice** graphics, and the additional tools available from the **MobilizeSimple** package. This package includes the integrated lab exercises described in Section 5.1.3.4, which allow students to move through structured activities without leaving the RStudio interface. This approach is similar to that taken by tools like **swirl** and DataCamp, but the Mobilize labs offer more space for creativity and inquiry by not locking students into a particular trajectory. R is a landscape-type tool, which does not specify any particular trajectory. The Mobilize labs provide more of a route through the material, while allowing for exploration around the edges.

As shown in Section 5.3, **Shiny** has potential as a tool for creating microworlds or minitools, allowing novices to explore within an environment built in a target language. However, while **Shiny** apps allow users to interact with data, they still suffer from a hard gap between using the interactive tool and using the target language (i.e., R).

## 6.2 Future work

None of the work presented in this dissertation is ‘the’ system, so my goal for the future is to begin building larger experimental prototypes in order to explore the possibilities. At present, I imagine a blocks-programming environment along the lines of Scratch, allowing novices to begin doing statistics and data analysis. However, underlying this environment would be a textual programming environment more like the target language (e.g., R).

The challenge is there should be a tight coupling between the visual representation in the block and the language underneath it. And, it should be possible to build up additional visual blocks to add to the system, and share with others. In other words, we want a bijection between visual blocks and textual programming, rather than an injection. If the blocks programming system is fixed and the only way to move forward is to write in the textual language, then the language becomes injective.

There are several components to be developed in order for this sort of system to work properly. The first is the domain-specific language to underly the visual component. The challenge with developing these primitives is to make them descriptive enough to capture all the basic tasks necessary, while still providing the possibility to create new functionality. The language should be expressive enough to be used in many circumstances, but limited enough it can be captured by the (small) working memory of humans – either $7 \pm 2$ or 4, depending on who you consult (Miller, 1955; Cowan, 2000; Shah and Hoeffner, 2002).

The second is the visual system itself. The interfaces of tools like TinkerPlots, Fathom, Data Desk, and JMP provide some inspiration, but as they do not capture a reproducible workflow or encourage integrated narrative, there are changes to be made. My future work will focus on paper prototyping in order to "get the design right and the right design" as Bill Buxton says (Buxton, 2007).

Once the design has been solidified, and the underlying language is clear, there is a challenge of implementation. As reactive programming in R gets more support through **Shiny**, I am hopeful implementation in R will be possible. However, it is likely additional computational components will need to be included to support all the functionality. For example, research and anecdotal experience suggest packages used through the browser are best for novices, because they remove many technical difficulties. However, in-browser support for data is very limited, and running on a centralized server can lead to delays.

## 6.3 Final words

As noted in the introduction, there is much more to education than technology tools. In order for novices to have an authentic experience of data, they need to work with real data to answer questions, but that experience requires guidance. It is not clear how to develop more instructors capable of guiding this experience. In the United States, the answer is often to develop a new teacher certification. Computer scientists are currently working toward a certification for K-12 teachers to teach computer science in schools. However, the road to certification is long and fraught with politics. And, given the way statistics is often taught even at the post-secondary level, not all certifications would be equal.

There is also an important consideration about the affordances of tools we use. In 1995, Michael Curry wrote a piece about the implications associated with the rise of Geographic Information Systems (GIS) (Curry, 1995). In it, he talks about how difficult it is for a software user to take responsibility for the actions of the software. Just like GIS products, statistical and data analysis products are used to make decisions about real people. While scholars are bringing attention to the algorithmic and data-driven processes governing our everyday lives (Diakopoulos, 2014; boyd and Crawford, 2012), creators and users of software need to bring more awareness to the process. While technological tools can appear neutral, they shape the way we think, and thus should be created with care.

Finally, while the subject of this inquiry has been statistical programming tools, there is a noticeable lack of rigorous research in the field. There is a need for more and better data about just what interface features and design decisions support thinking, and which promote misconceptions.

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