Expanding the scope of statistical computing:
Training statisticians to be software engineers

Alex Reinhart and Christopher R. Genovese

February 28, 2022

Abstract

Traditionally, statistical computing courses have taught the syntax of a partic-
ular programming language or specific statistical computation methods. Since the
publication of [Nolan and Temple Lang [2010]], we have seen a greater emphasis on
data wrangling, reproducible research, and visualization. This shift better prepares
students for careers working with complex datasets and producing analyses for multiple
audiences. But, we argue, statisticians are now often called upon to develop statistical
software, not just analyses, such as R packages implementing new analysis methods or
machine learning systems integrated into commercial products. This demands different
skills.

We describe a graduate course that we developed to meet this need by focusing on
four themes: programming practices; software design; important algorithms and data
structures; and essential tools and methods. Through code review and revision, and a
semester-long software project, students practice all the skills of software engineering.
The course allows students to expand their understanding of computing as applied to
statistical problems while building expertise in the kind of software development that
is increasingly the province of the working statistician. We see this as a model for the
future evolution of the computing curriculum in statistics and data science.

1 Introduction

When [Nolan and Temple Lang [2010]] wrote their seminal paper on the role of computing
in statistics and statistics curricula, they noted the rapid change in the skills needed by
practicing statisticians. It would no longer be sufficient for statisticians to learn computing
only as a collection of numerical methods or specialized statistical algorithms, such as
Markov chain Monte Carlo or generating pseudo-random numbers. Statisticians now face
large quantities of data, often in new forms like text or networks, and this data must be obtained—such as from Web services or databases—then managed, wrangled in complex ways, and visualized. They argued that arming students with a solid computational base will prepare them to adapt to the wide range of problems they will see on the job—and that these computational skills will also give them new ways to explore and understand the statistical concepts. They suggested syllabi and curricula that would advance understanding of these skills in both undergraduate and graduate programs [Nolan and Temple Lang, 2009].

This premise has only become more true in the intervening years. As the conversation shifts to “data science” and organizations apply statistical thinking to an ever wider range of problems, statisticians must use their computational skills to acquire data from disparate sources, integrate it into a useful form, conduct exploratory analyses and visualizations to understand the data’s full complexity, and only then use statistical procedures to draw conclusions. To ensure these conclusions are reproducible, statisticians must also use computational tools like knitr [Xie, 2015] and the command line to automate a pipeline of scripts, analyses and results.

In this paper, we argue that though these computational skills are important, for some statisticians they are only a fraction of what is now needed. Many statisticians now find themselves delivering not analyses—in the form of reports or presentations on some statistical analysis—but products that are used continually. In academia, these products might be R packages implementing a newly developed statistical method, so that others can apply the same method to their own problems. In industry, these products could be new methods to detect fraud or improve advertising in a large online service, used continuously as new data arrives and new decisions have to be made. In either case, the product is often a large and complex piece of software with a codebase developed by a team over many months, and it’s never truly “done”: it must be maintained and updated as conditions change and new requirements are placed on it.

To build and maintain these products, statisticians need additional skills. Structuring a large and complex codebase so it can be easily understood requires principles from software engineering; writing code with a team requires version control systems and collaboration skills; applying new statistical methods to large and complicated data requires a firm understanding of algorithms and data structures so the resulting code will be efficient. And everything must be well-tested and debugged so colleagues, bosses, and users can have confidence in the results. These skills are less important for a one-off data analysis, but they are crucial for the tasks statisticians face as they put their expertise into practice as part of long-running systems and widely used products.

Beginning in 2015, we have developed a graduate-level course in statistical computing intended to teach software engineering skills. The course is now part of the required curriculum for both the Master’s in Statistical Practice and the Ph.D. in Statistics & Data
Science at Carnegie Mellon University, serving roughly 40–50 students per year. Most of these students have prior statistical programming experience from undergraduate courses, and our course is their only required graduate-level statistical computing course. The students have widely varied backgrounds, and though the master's program emphasizes professional skills [see Greenhouse and Seltman, 2018] while the Ph.D. program emphasizes theoretical and applied research, the course goals are shared: to prepare students to build complex statistical software.

In this paper, we set out the skills we aim to teach and the strategies we use to teach them. Our pedagogy has evolved every year as we have discovered that the course pedagogy is inextricable from its content. For students to learn complex computational skills, we must give them regular practice with these skills and rapid, targeted feedback on their performance. We argue that these skills are becoming increasingly important for graduate-level statisticians and cannot be left to others to fill in. Computation has only grown in importance in the ten years since Nolan and Temple Lang issued their call to action, and we expect it will only become more important in the ten years to come.

2 Role of Computing in Statistics and Data Science

Before we discuss the statistical computing course we developed, it will be useful to briefly trace the evolution of computing’s role in statistics and data science.

Since roughly 2000, a major focus of work and teaching in statistical computing has been “Literate Statistical Practice”, which “encourages the construction of documentation for data management and statistical analysis as the code for it is produced” [Rossini, 2001]. Tools such as Sweave [Leisch, 2002] began to allow statisticians to embed the code producing their analysis inside the text of the analysis report, so that a single command would run the analysis, produce the results, format tables and figures, and typeset the report for distribution. This had many practical advantages, making it easy to make small changes and then re-run analyses and reports from scratch, and has become even more important as reproducibility has become a major concern. Tools like knitr and R Markdown [Xie, 2015] have made reproducible reports easier to write and easier to use, contributing to their rapid spread.

These tools are now widely used in statistics education and in practice. Baumer et al. [2014], for example, use knitr in introductory statistics courses to “develop the basic capacity to undertake modern data analysis and communicate their results,” and Çetinkaya-Rundel and Rundel [2018] described its coordinated use in an undergraduate course sequence designed to develop statistical computing skills in students from the introductory level onward. In industry, Bion et al. [2018] describe the widespread adoption of knitr among
the data science team at Airbnb, who use it routinely to share their analyses and business experiments with each other, with management, and even publicly as blog posts and academic publications.

The other main emphasis of statistical computing work has been on tools to make wrangling, restructuring, summarizing, and aggregating data much easier. There is a growing emphasis on “tidy data” [Wickham, 2014], and the R community has developed many new packages [e.g. the Tidyverse, Wickham et al., 2019] that make it easy for statisticians to express the operations they need to wrangle their data into the most convenient form. Other packages facilitate interactive visualizations or make it easy to present statistical results in written reports. Statistical computing curricula have adapted to include these tools and to give students authentic practice wrangling messy data.

But we should not narrow our focus too quickly. Not every statistical task fits into the framework of “receive a question, wrangle the data, conduct an analysis, and write a report on the results.” No longer relegated to roles as consultants or analysts brought in to answer specific questions, statisticians and data scientists increasingly hold roles as integral parts of teams developing products and delivering services. They need “data acumen,” which includes facility with a much wider range of tools and the ability to collaborate with software engineering teams and other disciplines [National Academies of Sciences, Engineering, and Medicine, 2018, Chapter 2].

Bion et al. [2018] provided an insightful example of this shift. At Airbnb, a service allowing property owners to list spaces for short-term rentals, the data science team might build “a machine learning algorithm that takes into account a variety of points of information” to suggest a fair price for a host to charge for guests. But the outcome of this work is not a report to be submitted to management describing the results of their modeling efforts—after developing a prototype model, they “worked with engineers to bring the prototype into production,” where hosts now use its recommendations every day. That is, the final outcome was the deployment of a piece of statistical software, which now continually operates as a part of Airbnb’s core business.

We can also look beyond industry to see statistical software used for purposes other than writing analytical reports. Consider a Ph.D. student conducting theoretical work on new models for some complex type of data. This work may involve thousands of lines of code: code to simulate data with known parameters, code to estimate the model from data, code to run simulation studies that verify theoretical results, code to calculate diagnostics or measure goodness of fit, code to fit benchmark models and run comparisons, etc. Much of the code forms a product that an ambitious graduate student might release as an R package submitted to CRAN or a Python package on PyPI, allowing other researchers to benefit from their theoretical labor and use the newly developed methods for their own practical purposes. And the wide availability of these statistical products has been a boon for the
field, allowing new statistical methods to be quickly adopted in industry [Bion et al., 2018]. The broader impact of this statistical software ecosystem is hard to overstate.

The shift in statistical computing is noticeable in the work done by statisticians in academia, but also by the jobs they take in industry. For example, of 91 total graduates of Carnegie Mellon University’s Bachelor’s in Statistics & Data Science program in 2018, 56 reported being employed at the time of a survey of their career outcomes, and of these, 14 (25%) reported a job title implying a software development role, such as “Software Engineer” [CMU Career & Professional Development Center 2018]. It has been our experience that many industry roles titled “Data Scientist” or “Data Analyst” also heavily involve software development.

3 Course Content

In the next sections, we discuss what it would mean for a statistical computing curriculum to prepare students for these roles, and discuss a course we developed to do so. We focus on four themes—four sets of skills students must learn to effectively develop statistical products and not just statistical reports. These themes are covered in lectures, but it is also vital that the course give students repeated practice with all these skills, and the necessary assignments and pedagogy will be discussed in Section 4.

3.1 Four Themes for Statistical Product Development

3.1.1 Effective Programming Practices

Students must learn practices that make software more reliable, more usable, and easier to maintain. Such practices include testing, code review, clear naming, and effective documentation.

Unit testing, for example, is often adopted in professional software development to ensure code is correct and defects are not accidentally introduced. A unit test isolates a specific “unit” of code, such as a function or class, and runs that unit with specific inputs, then verifies that the unit’s output matches the expected output. Unit tests are written using a package designed to organize test cases, run all tests automatically with a single command, and report summary results indicating which test cases failed and giving descriptions of the failure. The testthat package is widely used for R [Wickham 2011], and similar packages are available for almost every common programming language.

Unit testing is an essential part of software engineering for several reasons. Most obviously, it helps ensure correctness of software. If each function or method has detailed test cases, and these test cases can easily be checked every time the code is changed, mistakes
can be detected immediately. Software engineering research shows that while writing unit tests takes extra time, this time can in some settings be made up in the time saved fixing problems and debugging errors [Williams et al., 2003; Bissi et al., 2016]. There have been notable cases of errors in statistical and scientific software going undetected for years, even as the software was used routinely for scientific research, underscoring the importance of effective testing [Eklund et al., 2016]. Less obviously, dividing up complex tasks into simple pieces—so they can be easily tested—also encourages software to be composed of small, easily understood pieces, which is a key software design recommendation (see Section 3.1.2).

Code review is another essential programming practice. In collaborative software projects, such as software developed by a team in a large company or an open-source package developed by a group of volunteers, collaborators often practice peer code review [Rigby and Bird, 2013; Sadowski et al., 2018]. Each proposed change to the software, such as a new feature or fix for a problem, is submitted for review by a coworker or collaborator. The peer gives line-by-line feedback on the code, enforcing project style guidelines, looking for flawed reasoning and bugs, and giving feedback so the code can be improved. Only after the proposed change has passed peer review is it merged into the product or package.

Experiments have shown that code review detects bugs and improves software quality, often by encouraging code to be clearer and easier to maintain [Mäntylä and Lassenius, 2009; Beller et al., 2014]. Popular software collaboration platforms like GitHub and GitLab support code review through “pull requests” or “merge requests.” We give students experience with code review in two ways. We first host an in-class activity in which students reviewed real code written (by a course instructor) to solve a specific problem. Students are given a code review checklist to follow, encouraging them to look at specific features of the code and comment on them as part of their review. Later in the semester, students conduct in-class peer code review of their Challenge projects (see Section 4.3) using GitHub’s code review features.

3.1.2 Fundamental Principles of Software Design

Throughout the semester, we emphasize a few key principles of design. This includes modularity and code organization, the way that the many features required of software are organized into files, functions, classes, scripts, and so on. Effective software design is a powerful means to manage complexity. In a poor design, functions may become large and complicated, and interact with each other in complicated ways, so that changing one small part of the code’s behavior requires intricate surgery on many separate functions. In an effective design, functions are small and modular, and features are clearly separated so that changing behavior only requires changing a few specific functions that are clearly
responsible for that behavior. Good design also facilitates code reuse and refinement.

This kind of design is not a major concern when writing a literate statistical report, which is mostly linear with a few helper functions. But when developing a software package that’s intended to be reusable, careful design is essential—a good design makes it easy to modify and extend the package, for example as a Ph.D. student explores new methods in a thesis, while a bad design can make changes excruciatingly difficult.

The semester-long Challenge project, described below in Section 4.3 is designed to give students practical design experience. Since the project requires students to build a complicated product over the entire semester, and later portions of the project require students to build on or modify earlier portions, they either experience the benefits of well-designed code or suffer the pain of modifying poorly designed code. The teaching assistants also provide extensive feedback on design, starting before students implement any features.

3.1.3 Important Algorithms, Data Structures, and Representations

In recent years, a large amount of statistical research has been focused on scaling statistical methods to enormous datasets without an extravagantly large computational budget. Commonly, statistical computing courses prepare students to work with large datasets by teaching them different tools. SQL database systems, for example, are designed to efficiently query massive datasets that do not fit in memory, while software like Hadoop and Apache Spark are designed to distribute calculations across multiple servers that each have their own chunk of data. Students might also learn to use tools like Rcpp, which allows users to write the most computationally intensive parts of their R packages in efficient C++ code that can be easily called from within R [Eddelbuettel and Francois, 2011]. (Cython [Behnel et al., 2011] serves a similar role in the Python world.) And students are often exposed to R programming folk wisdom: use built-in functions whenever possible, avoid for loops in favor of vectorization, and perhaps use packages like data.table instead of native data frames.

But this misses the ways that careful software design can make code efficient and scalable. First, the designer must select an algorithm appropriate to the task at hand, meaning the designer must be familiar with general strategies for designing algorithms. For example, the divide-and-conquer strategy is to reduce a large problem into several smaller problems whose solutions can be combined to yield the overall solution; by doing this recursively, a complex problem can be reduced to many small and trivial problems. The divide-and-conquer strategy is widely used in computer science to produce algorithms that scale well to large datasets (for example, mergesort is a divide-and-conquer sorting algorithm), and it has been recently explored as a tool for implementing statistical methods.
on large datasets [Jordan, 2013]. Dynamic programming is another widely used strategy to break problems into smaller problems whose solutions can be combined efficiently; for example, the fused lasso can be expressed as a dynamic programming problem, leading to a linear-time algorithm [Johnson, 2013].

Along with the appropriate algorithm, the designer must also select appropriate data structures to store the data needed for an algorithm in an efficient way. Students used to working in R for data analysis tend to think of data frames, lists, matrices, and vectors as the only available data structures, and often write algorithms that require repeatedly scanning through an entire dataset to find relevant elements—which scales poorly to large datasets. But data structures like hash tables (dictionaries), binary trees, stacks, and queues all have their uses in statistical algorithms.

In statistics, for example, the \( k \)-d tree can store \( n \) data points, each in \( k \) dimensions, and can find all data points in specific intervals or ranges in \( O(\log n) \) time, rather than requiring a loop through all \( n \) data points [Bentley, 1975]. This can also be used to solve \( k \)-nearest-neighbor problems efficiently, and has been adapted to perform fast approximate kernel density estimation [Gray and Moore, 2003]. Other tree data structures are widely used by SQL databases to efficiently process queries with complex joins and WHERE clauses.

Our Statistical Computing course covers basic algorithmic strategies such as divide-and-conquer and dynamic programming, as well as basic data structures. We emphasize to students that selecting the appropriate algorithm and data structure can be much more important than the ordinary R performance tips. An algorithm that uses repeated (but vectorized) scans through an entire data frame or vector is intrinsically less efficient than one that uses a tree to do the same operation in \( O(\log n) \) time, for example.

In the course, various homework assignments pose simple problems that can be solved in an obvious but tremendously inefficient way as well as a less-obvious but efficient way using an appropriate algorithm and data structure. (These can be challenging in R, which does not provide efficient data structures by default; for example, looking up an item by name in an R list requires an \( O(n) \) scan through all entries, and base R does not provide flexible collection data structures [Barry, 2018].) Along with the Challenge projects, these assignments teach students that fast code often requires careful thinking about the organization and use of data.

### 3.1.4 Essential Tools and Methods

There are many ways to produce good statistical software, but there are several core tools that are almost universally useful. Such tools include editors, integrated development environments, version control systems, debuggers and profilers, databases (relational and otherwise), and the command line. This theme focuses on giving students substantive experience with those tools to give them a foundation for building good practices and habits.
going forward.

We build experience with such tools into the structure of the course, providing support for a range of quality tools while giving students as much flexibility as possible. For instance, we cover using SQL in class and let students interact with SQL databases through their favorite programming language in assignments and class activities. Similarly, while it is possible to work completely through graphical user interfaces (GUIs), we believe that command line tools can add value for practitioners and be a powerful tool in many circumstances. We show students how to use these tools and build a set of practices for the effective design and use of such tools.

Version control is a more challenging example. It is a critical tool for successfully developing large-scale software in collaboration with others, allowing team members to track the history of every source file. It allows changes to be systematically recorded and reverted if necessary, and allows collaborators working independently to make changes to code without interfering with each other’s work. Version control software is now widely used by companies and by collaborative open-source software projects. The R system itself, for example, is developed using the Subversion version control system.

There are many version control systems available, with non-trivial differences in use and details. We focus particularly on Git, which is perhaps the most widely used modern version control system, particularly with the growth of web-based collaboration services such as GitHub, GitLab, and Bitbucket that enhance Git with online tools for filing bug reports, reviewing proposed changes to code, and tracking project timelines and milestones. Students who are familiar with Git will be prepared to work at organizations that use Git or similar systems, or to collaborate on any of the thousands of open source data science packages that organize their development with Git. [Bryan 2018] has also persuasively argued that Git is valuable for managing the data, code, and figures involved in a literate statistical analysis, such as data analysis reports, further enhancing their reproducibility by making the history of changes visible.

Unfortunately, Git is not known for being user-friendly. Its primary interface is through the command line shell, and its documentation can be almost impenetrable to new users. We have found that simply teaching the concepts to students in a lecture is not sufficient; students need extensive practice using Git throughout the semester to begin to grasp its concepts. Hence students use Git and GitHub to submit all homework assignments and course projects, starting with an in-class tutorial during the first week.

Readers interested in using Git in their own courses may benefit from the experiences of [Çetinkaya-Rundel and Rundel 2018] and [Fiksel et al. 2019], who discuss how to use Git in statistics courses and describe common student experiences, many of which match what we have seen in our course.
3.2 Anti-Themes

It would perhaps be most accurate to say that our course teaches a problem-solving philosophy, encompassed in the four themes presented above, rather than simply a collection of tools suited for specific problems. This is reflected by several topics we choose not to cover in the course.

For example, our course does not teach a programming language. We assume that our students have already had some exposure to programming, such as in an undergraduate statistical computing course or through practical experience conducting data analyses, and so we do not spend class time covering syntax or programming constructs. We do not require students to use any specific programming language for their work, and examples in our lectures are often given in R, Python, C++, Clojure, Racket, and other languages.

As the concepts, practices, and skills covered in the course are widely relevant, this design decision makes the course accessible to students from a range of programming backgrounds. We believe an even bigger benefit of this approach is the perspective it offers. A focus on a single language tends to conflate approaches to problems with the way their solutions can be expressed in that language. Instead, we often show examples in multiple languages so that students can see both the commonalities that are conserved across most languages as well as some contrast across other possible design choices and idioms. Students quickly find that, even excepting a few syntactic details, they can understand the approach taken in a wide range of languages and that this affects how they approach problems even in their chosen language.

We encourage students to get some experience in a new language, even if only on simple problems. Some students use this opportunity to explore languages they expect to use in practice (such as Python, or C++ for use with Rcpp), while others explore more widely and pick up functional or strongly typed languages.

Similarly, the Statistical Computing course does not cover specific packages, such as the Tidyverse [Wickham et al., 2019] or tools to obtain and wrangle data (such as Web scraping systems). Such tools are important in practice, but we feel it is more important for the course to cover fundamental computing concepts that will enable students to effectively use whatever tools may appear.

4 Pedagogy

One might suspect that a computing course emphasizing concepts without teaching any specific programming languages or tools—as our does—can’t teach the practical skills they need. But in a course intended to teach students a complex skill, such as engineering statistical software, the only way for students to learn the skill—and not just the prerequisite
knowledge for that skill—is regular practice with targeted feedback. Regular practice gives students the opportunity to practice the skills we teach, while targeted feedback ensures they learn those skills and learn from their mistakes.

Hence the content of the Statistical Computing course cannot be separated from its pedagogy. In this section, we describe a course design that ensures students gain regular hands-on practice and detailed feedback, and the practical considerations that went into it. Many of these pedagogical features were developed through experience with each iteration of the course, and so the course has changed significantly over time; these changes are summarized in Table 1 and discussed in the subsections that follow.

### 4.1 Active Learning

In-class active learning has been repeatedly shown to improve student learning in a variety of STEM fields [Freeman et al., 2014]. Most of our course lectures incorporate active learning activities in various forms. For example, early in the semester we cover unit testing; we have found that students often struggle to think of test cases for code they write, so a large portion of the unit-testing class is spent having the students work in small groups to think of test cases for a few example functions.

Our experience has been that much of the student learning in a lecture seems to come from these activities. We frequently discover that after spending 30 minutes lecturing on a particular topic and feeling that the lecture is going well, an in-class activity reveals that some students are still deeply confused and have misinterpreted much of the lecture. Without these activities, the confusion could only be detected (and corrected) much later.

For key concepts that all students must master to succeed in the course, we have

| Semester     | Changes                                                                 |
|--------------|-------------------------------------------------------------------------|
| Spring 2015  | Pilot version (half-semester)                                           |
| Fall 2015    | Challenge project introduced (one short project)                        |
| Fall 2016    | Pull request & revision system; Master’s students join; 2 Challenge projects |
| Fall 2017    | Various small content & activity improvements                          |
| Fall 2018    | Switch to one four-part challenge                                      |
| Fall 2019    | Recommended homework schedule provided                                 |
| Fall 2020    | Problem bank rotation; Master’s students in separate course            |

Table 1: A summary of revisions and changes made to the Statistical Computing course during each iteration, as discussed in Section 4. The course structure has undergone many adjustments in response to experience.
gradually shifted from long lectures to in-class group activities that students can later turn in individually for homework credit, ensuring that all students practice the necessary skills before completing other assignments or the Challenge project.

4.2 Homework Problem Bank

Because our students have varied levels of programming experience and have varied goals for the course, we felt that an ordinary homework assignment structure, where each student completes the same assignments, would be inadequate. Some students may already be familiar with certain topics and require little practice, while others may be most interested in a specific topics they expect to use in their research or future job and desire specific practice for that topic.

To allow students to choose assignments that suit their needs, we developed a problem bank containing over 70 programming problems, categorized by topic and difficulty level. Some problems have direct connections to statistics, while others simply illustrate programming principles. Example assignments include:

- Implement a kernel smoothing procedure, but allow the user to pass in any kernel function and metric of their choice, not limited by any pre-specified list of kernels and metrics built in to the code.

- Implement graph search algorithms to solve mazes.

- Implement simple text tokenization to produce bag-of-words vectors for documents, then explore different distance metrics between documents of different types.

To give students constant practice the themes discussed in Section 3.1, students are required to write unit tests for every homework assignment, and must submit them for review using Git. An automated system runs the unit tests submitted with each homework assignment and verifies that all tests pass.

Throughout the semester, assignments from the problem bank are posted as the relevant topics are covered. Students can select from all the posted assignments those they believe are most interesting or relevant to their needs, and complete the assignments at their own pace. They may use any programming language that at least one of the course instructors or TAs is able to read, though most students choose Python or R. Our grading system (see Section 4.4) simply requires students to satisfactorily complete a certain number of assignments by the end of the semester.

To encourage effective time management by students, who may be tempted to abuse the flexibility of the homework system to put off submitting assignments until near the end of the semester, we have used two different strategies. Our first approach set a schedule by which
students are expected to complete certain numbers of homework points (see Section 4.4); our second approach provides a rotating selection of assignments and retires assignments from the problem bank after 2–3 weeks, so students must complete an assignment quickly before it becomes unavailable. This also ensures that in a given week, the TAs must only grade a few different types of assignment, allowing them to more efficiently grade.

### 4.3 Challenge Project

The homework problem bank allowed students to gain practice in many topics covered in the course, but small homework assignments do not cover a key learning goal of the course: learning effective strategies to design and develop large-scale software—with all the complexity it entails—over the course of months or years. To achieve this, the course includes a semester-long Challenge Project. Early in the semester, students choose between several Challenges on varying topics, and work on their chosen project for the rest of the semester.

For example, one Challenge asks students to implement an algorithm to build and prune classification trees, then use this code to build random forest classifiers [Breiman 2001]. They then extend this code to build classification trees using data stored in a SQL database without loading this data into memory, in principle allowing the construction of trees for very large datasets. Finally, they scrape abstracts from the arXiv preprint server and use their random forest code to try to classify abstracts by subject category using features extracted from the abstracts.

Initially the Challenge projects were designed to take several weeks and were due in one unit. But since Fall 2018, the Challenge projects are broken into four parts, due regularly throughout the semester. The entire project takes roughly three months. This allows the projects to be more detailed and ambitious, but also allows crucial scaffolding. In the first part, students consider the design of their code but do not actually implement it. Instead, they write function signatures but leave the bodies of the functions empty. The only code required to be submitted is extensive unit tests demonstrating what the code *should* do, encouraging students to think more deeply about their design before plunging in to implementation. The subsequent Challenge parts ask students to successively add features, following the requirements given in the assignment.

Besides the classification tree Challenge, other topics include applying the isolation forest method for anomaly detection [Liu et al. 2012] to videos, implementing fast data structures and algorithms for autocompletion [Wayne 2016], and using audio fingerprinting to match short snippets of audios to a database of recorded music [Li-chun Wang 2003]. All the Challenges are designed to produce a working piece of software that is usable in a relevant context, e.g., a package or library, a web or mobile app, or a command-line
tool. All the Challenges are also designed to integrate multiple skills: students must select appropriate data structures and algorithms for their code to work efficiently, while using software design principles to keep it simple and easy to maintain.

4.4 Specification-Based Grading and Revision

During the initial iteration of the course, homework grading was fairly conventional: the teaching assistant graded code submissions using a simple rubric, assigning a point value to each rubric category. However, we quickly found this system to be ineffective, as students were not reviewing the feedback or using it to improve their future submissions.

Beginning in Fall 2016, we switched to a new system. Students select assignments from the problem bank and submit their code through GitHub as pull requests. The teaching assistants then give detailed line-by-line feedback on the pull requests using GitHub’s code review features. The reviews point out bugs, critique difficult-to-read or poorly formatted code, suggest more appropriate algorithms or data structures, request additional unit test cases, and note design choices that make the code difficult to reuse or modify.

Crucially, there are only two possible outcomes of review: the assignment can be marked Mastered, indicating the student has successfully solved the problem, has used appropriate algorithms and data structures, and has written the code with good style and with unit tests that verified its correctness; or, if those criteria are not met, the assignment is marked “Changes requested” and the student is asked to revise it according to the feedback. Once revisions are complete, the student submits them for another review.

This system allows us to hold assignments to a very high standard. We expect that a large fraction of submissions will be revised. (We cut the required number of homework assignments in half at the same time as introducing the revision system; student workload has not appreciably dropped, showing that students are spending much more time on each assignment.) The revision process gives students practice with a constellation of skills that are often neglected in instruction and ensures they master the practical details of the concepts covered in the course. One could even consider the code reviews to be personalized tutoring provided by the teaching assistants, complementing the lectures and activities led by the instructors. This tutoring is what allows the course to cover topics at a high level and expect students to learn to implement them in their chosen programming languages.

A similar revision system is used for the Challenge projects. Each part of the Challenge is submitted to the teaching assistants for review as it is completed, and the student must make satisfactory revisions before they can submit the next part of the Challenge. Once all parts of the Challenge are complete and meet the requirements, it can be graded either Mastered or Sophisticated. Sophisticated submissions are those that demonstrate exceptional software engineering skill, by being well-designed, clearly written, thoroughly
tested, unusually flexible and modular, and incorporating apt choices of methods/algorithms and data organization. Earning a Sophisticated grade on the Challenge increases the student’s course grade, as discussed below in Section 4.5.

Prior research on mastery learning systems suggests strategies like this can improve student learning [Kulik et al., 1990], though the additional flexibility in our system distinguishes it from the more widely used mastery grading systems.

4.5 Grading System

The course structure poses challenges for assigning final course grades. As described in Section 4.2, students select homework assignments from a bank of possible problems. Students can complete assignments in any order, and there are no fixed deadlines for submitting individual assignments, nor are there points to be averaged to give a final grade.

We base grades on the number of Mastered assignments. A simple table in the course syllabus specifies how many assignments must be Mastered to achieve a certain grade. The Challenge project is required, but achieving a Sophisticated on the Challenge can also move the final course grade up one grade level.

To account for the fact that individual homework assignments may involve different degrees of difficulty, we assigned each homework assignment a certain number of “points.” Typical assignments were 2 points, but difficult assignments were 3 points and trivial assignments 1 point. The only possible outcome is still either Mastered, meaning the student receives all the points, or revision, meaning the student does not yet receive any points for the assignment. There is no partial credit for submissions. The grade table is then based on the number of points Mastered, rather than the number of assignments, and accounts for assignment difficulty, preventing students from simply choosing the easiest assignments to complete.

We found that this grading system has several advantages. It is noticeably simpler than a normal points-based system to grade and administer, reducing workload on the TAs. It reduces uncertainty for students, who know that if they revise their submissions as instructed, they will obtain a certain number of points, and these points translate into grades. There is no concern over a final exam that heavily affects final grades—there is no final exam—and students know exactly how much work they must do for a certain grade. It also gives the students the flexibility to explore the problem bank to improve their skills and gives them incentive to tackle some of the more challenging problems.
5 Conclusion

The trends that motivated Nolan and Temple Lang’s call for a new focus on computing in statistics curricula have only accelerated. The scope and complexity of computing tasks expected of statisticians and data scientists require not only a detailed knowledge of statistical methods and numerical approaches but also skills related to data management, collaboration, and software engineering. Our Statistical Computing course is designed to give students a firm foundation—and authentic practice—in these skills. It is intended to serve as a base on which their programming experience can be built throughout their graduate career, and beyond. Novel features of our course include emphasis on the practice of software design, our multi-path problem bank, our grading system, integrated code review, regular revision, and a language-agnostic approach. The course has been successful in both our Ph.D. and Master’s program. Implementation, particularly at scale, is a continuing challenge, and we will continue to develop and refine the course.

Statistical computing is a broad topic, and students come with varied backgrounds and downstream needs. There are many reasonable approaches to teaching students the computing skills they will need in their careers. We believe, however, that working statisticians in industry and academia face increasingly stringent demands on the capabilities, usability, and maintenance of the software they produce, and that literate report-writing is only one component of the many computational skills a successful statistician will need. As the field’s computing curricula continue to evolve, we believe that this reality needs to be faced head on.

5.1 Student Feedback

Our university conducts anonymous course evaluation surveys at the end of each semester; student participation is voluntary and response rates can vary widely. Nonetheless, the quantitative data and comments from students can sometimes provide useful information about how a course is being received.

According to the survey results, students in our statistical computing course report working roughly 11 hours per week on the course, which is above the intended average of 9 for a course worth its number of credits. Student comments attributed this to the fast pace of the course: for example, one student wrote that “As the class was designed covers a lot of topics that would take a couple semesters in normal C.S. courses, this course is definitely conceptually difficult and has a quite heavy workload.” We do not think this is an unfair characterization, particularly for students with less prior programming experience, and continue to adjust the curriculum and pace based on student feedback.

Nonetheless, students enjoyed the pedagogy of the course and its flexibility. One student
noted that “My favorite parts were the interactive parts;” the interactive activities discussed in Section 4.1 “helped me feel more engaged and helped me understand the problems better.” Similarly, one student noted that “I could pick and choose easier and harder assignments, and get to explore new areas that interested me without being overwhelmed and stressed out constantly.” Though this flexibility was appreciated, it also has its drawbacks, as noted by the student who complained that “The homework system also really opened my eyes to how bad I am with time management.” With no homework deadlines during the semester, some students experienced a mad rush to get the required number of assignments completed in the last few weeks.

5.2 Future Improvements

The topics we emphasize have changed from year to year as our understanding of student needs have changed, and the prior skills of each student cohort have varied significantly from year to year. Also, the unconventional course structure, while giving students significant freedom to explore their interests, has required a great deal of experimentation to improve, and likely will continue to change each year as we learn what structure best teaches our intended skills.

Several challenges remain to be solved. Git has proven to be a major obstacle to students; they must use it to submit each homework assignment on GitHub for review by the TAs, but students who make mistakes often attempt to fix them with ad-hoc solutions found online, leading to tangled Git histories that must be carefully un-tangled by the instructors or TAs before assignments can be graded. The flexible homework system can sometimes be too flexible, and without formal deadlines, students can procrastinate and get into difficult situations, or skip assignments selected as in-class activities and miss important skills needed for the Challenge project. (This has been a bigger issue for Master’s students than for Ph.D. students.) The demands on course TAs to give high-quality feedback on assignments while also holding regular office hours can be stressful, requiring skilled TAs and large time commitments. We are working to streamline the course, automate some aspects of homework submission and review, and improve the student experience.

5.3 Implementing a Similar Course

For those interested in teaching the core themes we describe in Section 3.1, comprehensive lecture notes are available at our course website, [https://36-750.github.io/](https://36-750.github.io/) (The website includes more than one semester worth of material: it includes notes on every topic that has been taught in the course, even as the selection of topics has changed from year to year.) The notes include in-class active learning activities, example programs, and notes that
were used during lectures. The homework problem bank (Section 4.2), including solutions to some problems, is kept privately by the authors and is available to instructors on request.

But so far, we have left one key question open: Who can effectively teach a statistical computing course on the topics we describe? The four core themes require faculty with experience designing and implementing complex software; while an introductory R programming class simply requires knowledge of syntax and some basic principles, our themes include principles of algorithms, data structures, and software design. To give effective feedback, the course teaching assistants must also be experienced programmers who can recognize inefficient algorithms or unnecessarily complex designs.

These constraints limit who can teach a course covering the skills we feel are most important, at least until such teaching becomes more widespread and faculty can be expected to have these skills. It may be practical, however, to co-teach the class. An instructor experienced in statistics and data science could cover those topics, while an instructor experienced in software engineering, perhaps from another department, provides the core computing content.

This raises a question: Why not have students take a computer science or software engineering course from another department? While a fair portion of the material we emphasize (including algorithms, data structures, testing, software design, and wide-ranging assignments) might seem more naturally obtained from a Computer Science department, we have found many reasons to prefer that material within a Statistics curriculum. First, we explicitly address these themes, with significant class time; these skills tend to be threaded more implicitly throughout a typical computer science curriculum. Second, we can focus the practice of our target skills with context and examples that are meaningful to Statistics and Data Science students. Third, having a single foundation course early in the Statistics graduate curriculum has been a significant downstream productivity enhancer for our students, who soon use the skills in their other courses and projects. Finally, we know of no other course, in Computer Science or elsewhere, that achieves our target balance on our themes and skill development.

Acknowledgments

We thank Peter Freeman for contributions to the course design and content during its first iteration. We are indebted to our excellent teaching assistants for their outstanding work in the class: Philipp Burckhardt, Niccolò Dalmasso, Sangwon Hyun, Nicolás Kim, Francis Kovacs, Taylor Pospisil, and Shamindra Shrotriya. Jerzy Wieczorek provided helpful insight on our mastery grading system. We thank the peer reviewers and guest editor for many suggestions that improved the manuscript.
References

Timothy Barry. Collections in R: Review and proposal. *The R Journal*, 10(1):455–471, 2018. doi: 10.32614/RJ-2018-037.

Benjamin S. Baumer, Mine Çetinkaya-Rundel, Andrew Bray, Linda Loi, and Nicholas J. Horton. R Markdown: Integrating a reproducible analysis tool into introductory statistics. *Technology Innovations in Statistics Education*, 8(1), 2014. URL https://escholarship.org/uc/item/90b2f5xh.

S. Behnel, R. Bradshaw, C. Citro, L. Dalcin, D.S. Seljebotn, and K. Smith. Cython: The best of both worlds. *Computing in Science Engineering*, 13(2):31 –39, 2011. ISSN 1521-9615. doi: 10.1109/MCSE.2010.118.

Moritz Beller, Alberto Bacchelli, Andy Zaidman, and Elmar Juergens. Modern code reviews in open-source projects: Which problems do they fix? In *Proceedings of the 11th Working Conference on Mining Software Repositories*, pages 202–211, 2014. doi: 10.1145/2597073.2597082.

Jon Louis Bentley. Multidimensional binary search trees used for associative searching. *Communications of the ACM*, 18(9):509–517, 1975. doi: 10.1145/361002.361007.

Ricardo Bion, Robert Chang, and Jason Goodman. How R helps Airbnb make the most of its data. *The American Statistician*, 72(1):46–52, 2018. doi: 10.1080/00031305.2017.1392362.

Wilson Bissi, Adolfo Gustavo Serra Seca Neto, and Maria Claudia Figueiredo Pereira Emer. The effects of test driven development on internal quality, external quality and productivity: A systematic review. *Information and Software Technology*, 74:45–54, 2016. doi: 10.1016/j.infsof.2016.02.004.

Leo Breiman. Random forests. *Machine Learning*, 45(1):5–32, 2001. doi: 10.1023/A:1010933404324.

Jennifer Bryan. Excuse me, do you have a moment to talk about version control? *The American Statistician*, 72(1):20–27, 2018. doi: 10.1080/00031305.2017.1399928.

Mine Çetinkaya-Rundel and Colin Rundel. Infrastructure and tools for teaching computing throughout the statistical curriculum. *The American Statistician*, 72(1):58–65, 2018. doi: 10.1080/00031305.2017.1397549.
Dirk Eddelbuettel and Romain Francois. Rcpp: Seamless R and C++ integration. *Journal of Statistical Software*, 40(8), 2011. doi: 10.18637/jss.v040.i08.

Anders Eklund, Thomas E Nichols, and Hans Knutsson. Cluster failure: Why fMRI inferences for spatial extent have inflated false-positive rates. *Proceedings of the National Academy of Sciences*, 113(28):7900–7905, 2016. doi: 10.1073/pnas.1602413113.

Jacob Fiksel, Leah R Jager, Johanna S Hardin, and Margaret A Taub. Using GitHub Classroom to teach statistics. *Journal of Statistics Education*, 27(2):110–119, 2019. doi: 10.1080/10691898.2019.1617089.

S. Freeman, S. L. Eddy, M. McDonough, M. K. Smith, N. Okoroafor, H. Jordt, and M. P. Wenderoth. Active learning increases student performance in science, engineering, and mathematics. *Proceedings of the National Academy of Sciences*, 111(23):8410–8415, May 2014. doi: 10.1073/pnas.1319030111.

Alexander G. Gray and Andrew W. Moore. Nonparametric density estimation: Toward computational tractability. In *Proceedings of the 2003 SIAM International Conference on Data Mining*, pages 203–211, 2003. doi: 10.1137/1.9781611972733.19.

Joel B Greenhouse and Howard J Seltman. On teaching statistical practice: From novice to expert. *The American Statistician*, 72(2):147–154, 2018. doi: 10.1080/00031305.2016.1270230.

Nicholas A Johnson. A dynamic programming algorithm for the fused lasso and L0-segmentation. *Journal of Computational and Graphical Statistics*, 22(2):246–260, 2013. doi: 10.1080/10618600.2012.681238.

Michael I Jordan. On statistics, computation and scalability. *Bernoulli*, 19(4):1378–1390, 2013. doi: 10.3150/12-BEJSP17.

Chen-Lin C Kulik, James A Kulik, and Robert L Bangert-Drowns. Effectiveness of mastery learning programs: A meta-analysis. *Review of Educational Research*, 60(2):265–299, 1990. doi: 10.3102/00346543060002265.

Friedrich Leisch. Sweave: Dynamic generation of statistical reports using literate data analysis. In Wolfgang Härdle and Bernd Rönz, editors, *Compstat 2002 — Proceedings*
Avery Li-chun Wang. An industrial-strength audio search algorithm. In *Proceedings of the 4th International Conference on Music Information Retrieval*, 2003.

Fei Tony Liu, Kai Ming Ting, and Zhi-Hua Zhou. Isolation-based anomaly detection. *ACM Transactions on Knowledge Discovery from Data*, 6(1):3:1–3:39, March 2012. doi: 10.1145/2133360.2133363.

M. V. Mäntylä and C. Lassenius. What types of defects are really discovered in code reviews? *IEEE Transactions on Software Engineering*, 35(3):430–448, May 2009. ISSN 2326-3881. doi: 10.1109/TSE.2008.71.

National Academies of Sciences, Engineering, and Medicine. *Data Science for Undergraduates: Opportunities and Options*. The National Academies Press, Washington, DC, 2018. doi: 10.17226/25104.

Deborah Nolan and Duncan Temple Lang. Integrating computing into the statistics curricula, 2009. URL [https://www.stat.berkeley.edu/~statcur/](https://www.stat.berkeley.edu/~statcur/).

Deborah Nolan and Duncan Temple Lang. Computing in the statistics curricula. *The American Statistician*, 64(2):97–107, 2010. doi: 10.1198/tast.2010.09132.

Peter C Rigby and Christian Bird. Convergent contemporary software peer review practices. In *Proceedings of the 9th Joint Meeting on Foundations of Software Engineering*, pages 202–212, 2013. doi: 10.1145/2491411.2491444.

A J Rossini. Literate statistical practice. In K Hornik and F Leisch, editors, *Proceedings of the 2nd International Workshop on Distributed Statistical Computing*, 2001.

Caitlin Sadowski, Emma Söderberg, Luke Church, Michal Sipko, and Alberto Bacchelli. Modern code review: A case study at Google. In *Proceedings of the 40th International Conference on Software Engineering: Software Engineering in Practice*, pages 181–190, 2018. doi: 10.1145/3183519.3183525.

Kevin Wayne. Autocomplete-me. In *SIGCSE Nifty Assignments*, 2016. URL [http://nifty.stanford.edu/2016/wayne-autocomplete-me/](http://nifty.stanford.edu/2016/wayne-autocomplete-me/).

Hadley Wickham. testthat: Get started with testing. *The R Journal*, 3(1):5–10, 2011. URL [https://journal.r-project.org/archive/2011-1/RJournal_2011-1_Wickham.pdf](https://journal.r-project.org/archive/2011-1/RJournal_2011-1_Wickham.pdf).
Hadley Wickham. Tidy data. *Journal of Statistical Software*, 59(10), 2014. doi: 10.18637/jss.v059.i10.

Hadley Wickham, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Grolemund, Alex Hayes, Lionel Henry, Jim Hester, Max Kuhn, Thomas Lin Pedersen, Evan Miller, Stephan Milton Bache, Kirill Müller, Jeroen Ooms, David Robinson, Dana Paige Seidel, Vitalie Spinu, Kohske Takahashi, Davis Vaughan, Claus Wilke, Kara Woo, and Hiroaki Yutani. Welcome to the tidyverse. *Journal of Open Source Software*, 4(43):1686, Nov 2019. doi: 10.21105/joss.01686.

L. Williams, E. M. Maximilien, and M. Vouk. Test-driven development as a defect-reduction practice. In *14th International Symposium on Software Reliability Engineering*, pages 34–45, Nov 2003. doi: 10.1109/ISSRE.2003.1251029.

Yihui Xie. *Dynamic Documents with R and knitr*. Chapman and Hall/CRC, Boca Raton, Florida, 2nd edition, 2015. URL [https://yihui.name/knitr/](https://yihui.name/knitr/) ISBN 978-1498716963.

Yihui Xie, J.J. Allaire, and Garrett Grolemund. *R Markdown: The Definitive Guide*. Chapman and Hall/CRC, Boca Raton, Florida, 2018. URL [https://bookdown.org/yihui/rmarkdown](https://bookdown.org/yihui/rmarkdown) ISBN 9781138359338.