Three Principles for Modernizing an Undergraduate Regression Analysis Course

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ABSTRACT
As data have become more prevalent in academia, industry, and daily life, it is imperative that undergraduate students are equipped with the skills needed to analyze data in the modern environment. In recent years there has been a lot of work innovating introductory statistics courses and developing introductory data science courses; however, there has been less work beyond the first course. This article describes innovations to Regression Analysis taught at Duke University, a course focused on application that serves a diverse undergraduate student population of statistics and data science majors along with nonmajors. Three principles guiding the modernization of the course are presented with details about how these principles align with the necessary skills of practice outlined in recent statistics and data science curriculum guidelines. The article includes pedagogical strategies, motivated by the innovations in introductory courses, that make it feasible to implement skills for the practice of modern statistics and data science alongside fundamental statistical concepts. The article concludes with the impact of these changes, challenges, and next steps for the course. Portions of in-class activities and assignments are included in the article, with full sample assignments and resources for finding data in the supplemental materials. Supplementary materials for this article are available online.

1. Introduction
In recent years there has been a lot of innovation in introductory statistics courses; however, there has been less work on innovating subsequent courses for the modern student and data environment. It is important that courses beyond the first one are modernized as well, so students can continue developing the necessary skills to analyze data and effectively communicate results as they progress through the statistics curriculum. This article focuses on modernizing the undergraduate regression analysis course at Duke University aimed at a broad audience of quantitatively-minded students from majors across the university. As the Statistical Science major has grown substantially and as more students from across the university conduct more data-driven work in and outside of the classroom, it is imperative to offer a second course that can prepare nonmajors to use statistical methods in research and internships while also preparing majors for the statistical and computational rigor of upper-level courses. The 2018 report by the National Academies of Sciences, Engineering, and Medicine emphasizes the imperative to equip all undergraduate students with such skills in the recommendation that “academic institutions should encourage the development of a basic understanding of data science in all undergraduates.” (National Academies of Sciences, Engineering, and Medicine and others 2018). This understanding includes many of the knowledge and skills in the second course, such as statistical modeling, model assessment, and model interpretation, among others.

Taking into account the skills students need in the modern data-driven environment, three principles have motivated the innovations to the pedagogy in the regression analysis course at Duke University.

1. Regularly engage with complex [and relevant] real-world data and applications
2. Develop the skills and computational proficiency for a reproducible data analysis workflow
3. Develop important nontechnical skills, specifically written communication and teamwork

These principles are largely inspired by innovations in introductory statistics courses and the creation of introductory data science courses. They are also driven by the skills students need as they apply for graduate school, internships, and careers. For example, a recent ad for the position Staff Editor - Statistical Modeling at the New York Times asked applicants to “describe or link to an example of a statistical model you’ve created…describe any reporting, development or data visualization skills you may have.” (Staff Editor - Statistical Modeling 2020). The ad also listed expertise with R and statistical modeling as requirements for the position.

The remainder of the article focuses on the implementation of these three principles in the undergraduate regression analysis course. Section 2 provides a summary of similar second
courses at other institutions and a brief overview of statistics guidelines for instruction. The course structure and pedagogy are detailed in Section 3, and Section 4 expands on the guiding principles used for modernizing the courses and the pedagogy of implementing these changes. Section 5 concludes with a discussion of the impact of the changes, challenges, and next steps for the course.

2. Background

2.1. The Course in the Statistics Curriculum

STA 210: Regression Analysis is the second statistics course for many students who have taken an introductory statistics, data science, or probability course. Taking one of these introductory courses is a prerequisite requirement for the class, so most students have some prior experience conducting exploratory data analysis, statistical inference, and simple linear regression using R. Students who have taken the introduction to data science course also have prior experience writing reproducible reports using R Markdown and implementing version control using git and GitHub. Students who take probability as a first course generally have less prior experience with data analysis and computing; however, they have more in-depth prior study of the mathematics of probability and statistics. This regression course has a few important roles in the undergraduate statistics curriculum. It is a core requirement of the undergraduate Statistical Science major and minor, and a prerequisite for most of the upper-level courses in the Department of Statistical Science. It is also the earliest course taken by all students in the major and minor, so it is their first shared experience in the statistics curriculum. Therefore, it is one of the first opportunities to teach fundamental skills that are part of the learning outcomes for the statistics undergraduate curriculum (Student Learning Outcomes 2022), in particular

- Students will demonstrate ability in computational methods— including basic statistical programming, data analysis, and reproducibility—necessary to do applied data analysis.
- Students will demonstrate the ability to use appropriate statistical methodologies for real-world data analysis settings.
- Students who take only one or two courses from the department will demonstrate understanding of the usefulness, importance, and power of statistical thinking and methodologies.

In addition to the course’s role in the statistics curriculum, it is also a service course that is taken by students with a variety of academic interests. The student population includes students who are or intend to be Statistical Science majors and students in majors from other disciplines who are interested in developing their analysis skills in preparation for data-driven research, graduate school, or internships. Thus, the course content, learning goals, and instructional design are developed to serve the diverse student population with competing learning objectives.

2.2. Related Courses at Other Institutions

This article is about innovations to the undergraduate regression analysis course taught at Duke University; however, there are undergraduate regression analysis courses at other institutions that are similarly focused on application and are implementing some of the pedagogical approaches described in the text. A few of these courses are

- STA 212: Statistical Models at Wake Forest University
- STAT 272: Statistical Modeling at St. Olaf College
- STA 363: Intro to Statistical Modeling at Miami University
- STA 324: Applied Regression Analysis at California Polytechnic State University

Based on a review of available course descriptions, syllabi, and websites, these courses are similar to the regression analysis course discussed in the article in that most occur earlier in the statistics curriculum and generally emphasize application over mathematical theory. Focusing on application helps better serve both nonmajors and majors, as it prepares students who may not take additional statistics courses while also motivating the theory majors encounter in advanced courses.

2.3. Curriculum Guidelines and Related Work

The Guidelines for Assessment and Instruction in Statistics Education (GAISE) College Report (Carver et al. 2016) gives guidance on the skills students should develop in their introductory course and pedagogy recommendations to help students achieve these aims. Though the report is specifically focused on the introductory course, the authors of the report state that their recommendations extend beyond the introductory course and could be applied throughout the undergraduate curriculum. They encourage statistics instructors to “emphasize the practical problem-solving skills that are necessary to answer statistical questions.” (p. 12) They also emphasize the use of real-world data with context in classes, as using “real datasets of interest to students is a good way to engage students in thinking about the data and relevant statistical concepts.” (p. 17), and as part of that, exposing students to the messiness that often arises when working with real data.

The American Statistical Association’s 2014 Curriculum Guidelines for Undergraduate Programs in Statistical Science (ASA Undergraduate Guidelines Workgroup 2014) provides recommendations about the skills that are important for an undergraduate statistics major. In addition to the knowledge of statistical methods and theory, the report emphasizes skills in statistical practice that are critical for students as they prepare for careers in statistics and data science. Some of the skills it highlights are key drivers for the principles guiding the modernization of the regression course. The report states that courses should focus on the use of “authentic data” and that the curriculum should include “concepts and approaches for working with complex data…and analyzing non-textbook data” (Principle 1). Additionally, the report states that students should be “facile with professional statistical software” and that students’ analyses “should be undertaken in a well-documented and reproducible way” (Principle 2). Finally, the report discusses the importance of teaching students skills in “statistical practice” including being able to “write clearly, speak fluently, and construct effective visual displays and compelling written summaries” and “demonstrate ability to collaborate in teams and to organize and manage projects” (Principle 3).
While there is no expectation students would demonstrate mastery of these skills by the end of the second course, emphasizing them earlier in the curriculum allows time to better equip statistics majors with the full suite of skills needed to use statistics and data science in practice. Much of this philosophy has been incorporated in the introductory courses. In recent years there has been a wealth of literature on innovations in introductory statistics and data science courses (e.g., Baumer 2015; Hardin et al. 2015; Farmus et al. 2020; Adams et al. 2021; Çetinkaya-Rundel and Ellison 2021). Many of these innovations, have been motivated by the need to help students gain the conceptual knowledge and computing skills required to analyze authentic complex and nonstandard data, such as analyzing text and spatial data. Additionally these newly revised courses have put more emphasis on visualizing and interpreting multivariable relationships (Adams et al. 2021) in line with GAISE recommendations to "give students experience with multivariable thinking." (p. 6)

Despite the abundance of literature on introductory statistics and data science courses, there has been less published work about subsequent undergraduate courses, especially the "second" statistics course. Love (1998) and Roback (2003) describe courses primarily focused on linear and logistic regression aimed at a broad student audience, with Love (1998) presenting a project-based approach for teaching this content. blades et al. (2015) makes the point that even though linear regression has been taught in most second statistics courses, given the relative recent development of many of these courses there isn’t a consensus about the content that should be covered. In fact they propose focusing on the design and analysis of experiments rather than regression analysis as the next course in statistics.

Taking the curriculum guidelines and previous work into account, much of the innovation in the course has been in regard to skills important for modern data analysis and pedagogical strategies for teaching these skills. As seen in the next section, many of the statistical topics align with those more traditionally taught in an undergraduate regression or second statistics course.

3. Pedagogy

3.1. Learning Objectives and Topics

Below are the primary learning objectives for the course:

By the end of the semester students will be able to...

- analyze real-world data to answer questions about multivariable relationships.
- fit and evaluate linear and logistic regression models.
- assess whether a proposed model is appropriate and describe its limitations.
- use R Markdown to write reproducible reports and GitHub for version control and collaboration.
- communicate results from statistical analyses to a general audience.

The course is divided into three units: linear regression, logistic regression, looking ahead.

Table 1. Example week in the course.

| Day       | Activity                                    |
|-----------|---------------------------------------------|
| Monday    | Complete prepare assignment                 |
| Tuesday   | In-class lecture                            |
| Wednesday | Complete prepare assignment                 |
|           | Tuesday’s in-class exercises due            |
| Thursday  | In-class lecture                            |
| Friday    | In-class lab                                |
|           | Thursday’s in-class exercises due           |

Linear regression (Weeks 01–09): The unit includes a review of statistical inference, simple and multiple linear regression, and ANOVA. Topics include the interpretation of the model coefficients, inference for coefficients and predictions, assessing model conditions and diagnostics, categorical predictors, interactions and polynomial predictors, log-transformations on the response and predictor variables, and model selection.

Logistic regression (Weeks 10–12): The unit primarily focuses on logistic regression with a brief introduction to multinomial logistic regression. Topics include the interpretation and inference of model coefficients, model conditions, selection, and using the ROC curve to assess model fit and prediction.

Looking ahead (Weeks 13–15): The unit is a collection of special topics that may vary each semester. The purpose of the special topics is to introduce students to models and related methods that extend beyond the scope of the course. Recent topics have included dealing with missing data, models for correlated data, time series, and model validation. There is also one lecture in the last week of classes dedicated to advanced skills to write reports using R Markdown (e.g., including citations, figure captions, etc.).

A more detailed outline of the course topics and schedule is available in the supplemental materials in Section 5.4

3.2. Course Structure and Assessments

About 90–100 students take the course each semester, and students attend two full-class 75-minute lectures and one smaller 75-minute lab each week. The lectures are primarily focused on the introduction of new statistical concepts, and the labs are focused on computing and application. Before each lecture, students complete a prepare assignment that includes a combination of videos and readings. The prepare assignments introduce students to new definitions, concepts and brief mathematical details, and an example demonstrating how the concept is applied. Students have access to the slides presented in the videos, so the prepare assignment primarily replaces the presentation of slides that is common in more traditional lecture formats. The lecture sessions follow a flipped format with hands-on exercises and applications. The flipped lectures are detailed in Section 3.3. A typical week in the course is outlined in Table 1.

In a given semester there are usually three or four lab sections, with 25–30 students in each. Each lab is led by a graduate teaching assistant with another graduate or undergraduate teaching assistant to help answer questions. During lab sessions students work primarily in teams of three or four on
case studies involving real-world data and analysis questions. These lab assignments account for 15% of the final course grade. The structure and assessment of teamwork is detailed in Section 4.3.

In addition to weekly labs, students are assessed through individual homework assignments, assigned about every three weeks, that account for 30% of the final course grade. There are five assignments, four that directly assess the content and one for a “statistics experience.” Students have a week to complete the four content-based assignments, which are used to assess their ability to combine the statistical concepts and computing skills by completing short conceptual exercises and open-ended data analyses.

The statistics experience is introduced early in the semester and is due the last week of classes. The purpose of the assignment is for students to intentionally engage with statistics outside of the classroom by attending a talk, interviewing a statistician, listening to relevant podcast, reading a relevant book, or participating in a data analysis competition. They submit a slide briefly summarizing the experience and discussing how it connects to the course content. Given the size of the course, students submit a PDF of the slides for grading; however, in a smaller setting it may be valuable to have students present their experiences to the class.

The larger summative assessments in the course are periodic quizzes (three or four per semester; 30% of the course grade) that assess conceptual understanding and proficiency in applying the methods on real-world data, and a final group project (15% of the course grade).

Over the past few years different textbooks have been used for the course in an effort to identify an applied regression analysis text with rich data examples that is not cost prohibitive for students. Texts such as Stat2: Modeling and Regression with ANOVA (Cannon et al. 2018) and The Statistical Sleuth: A Course in Methods of Data Analysis (Ramsey and Schafer 2012) have been used in the course in previous semesters. In the most recent semesters readings have come from Introduction to Modern Statistics (Çetinkaya Rundel and Hardin 2021) and Handbook of Regression Analysis (Chatterjee and Simonoff 2013).

3.3. “Flipped” Lectures

The lectures follow a modified flipped classroom structure. Though they do not follow the full structure in Bergmann and Sams (2012), they are “flipped” in term of what students do synchronously during class versus what they do asynchronously outside of class. This format is best described by Farmus et al. (2020) as students engaging in passive content learning prior to class, allowing the in-class time to be dedicated to active learning of content.

Each class begins with a 5–10 min review of the material from the prepare assignment, then the rest of the lecture session is used for a combination of individual and small group exercises where students apply the new concepts. Through these exercises, students engage with conceptual ideas, computational skills, interpretations, and inference, and how these components combine to answer an analysis question. There are multiple ways for students to participate in a given class session, as students can work with peers, submit responses and questions using the course discussion forum, and participate in large class discussions. The students submit their responses to the in-class exercises at the end of class through the GitHub repository assigned to them for that lecture (more about the use of GitHub repositories in Section 4.2). The responses are graded for completion, with the grading merely serving as a measure that student are keeping on pace with the course content. The completion grade was particularly important during remote learning in 2020–2021 when some students participated fully asynchronously.

4. Shaping the Course to Prepare the Modern Student

As described thus far, the statistical topics in the course have been similar to those often covered in a traditional regression analysis or second statistics course, so much of the most recent innovation has been in the pedagogical approach and content beyond the regression concepts. The goal is to prepare students with a full suite of skills that includes the necessary statistical knowledge, computing proficiency required to implement the statistical methods, experience gained from working with a variety of complex real-world datasets, skills in effectively communicating results, and experience collaborating on data analysis projects. As demonstrated by the work in modernizing introductory courses discussed in Section 2, these skills can be successfully implemented in a course without distracting from the fundamental statistical content. Implementation has been done by considering ways to integrate these other skills into the curriculum alongside the statistical content, providing opportunities for practice through in-class activities and assignments, and focusing on application rather than mathematical theory. A half-credit course on the mathematics of regression has been implemented in the statistics curriculum; students have the option to take the course alongside or after completing the regression analysis course.

Though some of these skills are introduced in the introductory course, we seek to emphasize them in this second course for a few key reasons. The first reason, as stated earlier, is this is the first shared course experience among all students in the major and minor. Next, though students are introduced to the data analysis workflow, collaboration, and written communication in the introductory course, focusing too much on these skills could result in cognitive overload as students are also being introduced to statistical thinking and many new concepts. Students come into the second course with some exposure and experience with these skills and concepts, so there is less cognitive load as they continue honing the skills related to workflow and collaboration alongside learning the new statistical content. Finally, it is important that the skills students start building in the introductory course continue to be reinforced and further developed as they progress through the statistics curriculum.

4.1. Principle 1: Regularly Engage with Complex [and Relevant] Real-World Data and Applications

GAISE emphasizes the importance of using real-world data in the classroom. Though many textbooks use relevant real-world
data in their examples and exercises, the datasets often do not represent the messiness and complexity of modern data. Therefore, the “real-world” data referred to here are the messy data that often require cleaning and other pre-processing before they are suitable for analysis. In previous semesters, some students had difficulty dealing with the data cleaning required for the final project where they analyzed a dataset of their choice. With this in mind, the datasets used in the regression course are chosen to give students some exposure to the data cleaning and wrangling required before doing most regression analyses, and to demonstrate how regression can be used in a wide variety of interesting and relevant contexts.

Working with complex and messy datasets provides some continuity as students progress through the curriculum, as students are continuing to hone the data wrangling skills they’ve learned in their introductory courses. They are learning how to use visualizations and descriptive statistics to explore data and make data preparation decisions, such as how to handle missing data and outliers and the implications their decisions have on the scope of their conclusions or potential biases in the results. In the past they may have only dealt with issues in the final project. While there are components of working with data that are based on content knowledge, there are other skills that are derived from experience and being exposed to a lot of different datasets and contexts. By having students engage with complex data throughout the semester, they are getting that exposure and continually honing these skills, better preparing them as they address these questions as they work with data outside of the classroom.

Complex real-world datasets are used in every component of the courses: lecture slides, in-class activities, and lab and homework assignments. Depending on the context, students will engage with more or less of the data cleaning and pre-processing. For example, the in-class activities mostly use cleaned datasets so that the class time can be focused on the new regression concepts. Sometimes, however, there will be a short, guided data cleaning exercise incorporated into the in-class activity so we can discuss strategies to approach such tasks as a class.

One aspect that has been emphasized through the use of these data are the importance of exploratory data analysis and how visualizations can help inform the data cleaning and preparation process. Examples of how this idea has been implemented in an in-class activity and in a homework assignment are below.

The LEGO brick dataset and exercises modified from Peterson and Ziegler (2021) is used for an in-class activity about categorical predictors and indicator variables. The dataset contains price and various characteristics of LEGO sets sold on the website brickset.com. On variable in the dataset theme (the theme of the LEGO set) has 32 levels, many with very few observations. Students can make this observation when they create a bar chart of the distribution of the variable theme as shown in Figure 1 and discuss some of the potential issues with including such a variable as is in a regression model.

Studentsthenconsiderdifferentstrategies to collapse the variable into a few categories that would be more feasible and informative in the model. They consider what information they want to learn by having the variable in the model, how to collapse the variable to be able to answer their analysis question, and potential advantages and limitations to the approach. Example strategies for collapsing the variable are in Figure 2. Once they have talked about it in small groups, there is a whole class discussion about the advantages and disadvantages of a few of the proposed strategies and the importance of documenting the process of creating the collapsed variable from the original data.

![Figure 1. Distribution of theme in the LEGO brick dataset.](image-url)
After discussing different strategies, one is chosen and that collapsed variable theme_new is used in the regression models for the remainder of the in-class exercises. Some example questions related to the regression models are as follows:

- **Fit the model using pieces, size, and theme_new, where theme_new is the newly collapsed variable.**
  - What is the baseline level of theme_new?
  - What is the interpretation of the coefficient for Star Wars?
  - What is the difference in the predicted Amazon.com price between a Friends set with 500 pieces and a Star Wars set with 100 pieces, each with small pieces?

Another example is a homework assignment that asks students to carefully consider the model conditions for linear regression. There are a lot of datasets in which there is spatial dependence between observations, thus, violating the independence assumption for regression. Though students are taught to consider potential spatial dependence, they are often unsure about how to do so in practice. Therefore, in this homework assignment, students consider the scenario in which they are tasked with building a regression model that predicts the percentage of votes in a county that were cast in-person in the 2020 election based on the percentage of votes for Donald Trump in the 2016 election (serving as a proxy for the political leanings of that county).

In addition to visualizing the distribution of the response variable, they are asked to visualize the distribution of the response variable on a map and discuss what features are apparent in a plot such as a histogram that are not easily apparent in the map and vice versa. They are provided some starter code to produce the map, because spatial visualization is not specifically taught in the course. Figure 3 shows examples of the visualizations students may create.

They are asked to fit a model and visualize the residuals on a map as shown in Figure 4. They are then asked to assess the independence condition using the map by answering the following questions:

- Briefly explain why we may want to view the residuals on a map to assess independence.
- Briefly explain what pattern (if any) we would expect to observe on the map if the independence condition is satisfied.
- Is the independence condition satisfied? Briefly explain based on what you observe from the map.

The full in-class activity using the LEGO data and assignment using the North Carolina county data, along with resources used to find data are available in the supplementary materials. Additionally, Adrian et al. (2020) provides extensive examples on using maps to provide context for interpretations and conclusions drawn from linear regression.

### 4.2. Principle 2: Develop the Skills and Computational Proficiency for a Reproducible Data Analysis Workflow

Many have called for the incorporation of computing as a core part of the statistics curriculum (e.g., Nolan and Temple Lang 2010, 2021 *Journal of Statistics and Data Science Education* special issue “Computing in the Statistics and Data Science Curriculum,” among others). Developing computing skills is integrated as a key learning objective in the course, since it is important that students have proficiency with the computing tools that make it feasible to work with the messy real-world data described in Section 4.1. Much more than that, it is also in service of another one of the driving principles of the course to equip students with the skills necessary to work with data.
using a reproducible analysis workflow. While proficiency using statistical technology or software is required to achieve the learning objectives in Section 4.1, these skills do not extend to the entire data analysis workflow. Therefore, in addition to proficiency in computing, there is a more holistic approach to the data analysis workflow, specifically writing reproducible reports using R Markdown and using git and GitHub for version control and collaboration.

There has been increased emphasis in recent years on open science and being able to reproduce published analysis results. Using a reproducible workflow is also good practice in industry, as it is important to write analyses in a transparent way that can be fully replicated. By incorporating these skills early in the statistics curriculum, students learn practices for reproducibility as part of their analysis workflow from the beginning, rather than having to adjust their workflow if they learn these skills in later courses.

4.2.1. Computing Toolkit and Infrastructure

The computing toolkit includes RStudio and GitHub, which were chosen for a few key reasons. The undergraduate statistics courses are all taught using R and many using GitHub; therefore, many students will have been introduced to R in their introductory courses, and all students will need proficiency using these tools as they progress to the upper-level courses. Students who have taken introductory data science have also learned the basics of version control using git and GitHub. Next, R and GitHub are commonly used in academic labs and industry, so teaching with these tools equips a broad group of students with relevant skills that will make them more competitive as they apply for future opportunities. Lastly, RStudio and GitHub are freely available, so all students will have access to both platforms after they complete the course.

The computing infrastructure is modeled on the server-based system described in Çetinkaya-Rundel and Rundel
(2018). RStudio is made available through Docker containers that are set up and maintained by the Duke University’s Office of Information Technology. Instructors are granted back-end access, so they have the ability to update or install packages, if needed. An alternative to this set up is using RStudio Cloud (rstudio.cloud), a cloud-based platform set up and maintained by RStudio.

There are a few advantages to the server-based set up. First, students access RStudio through a web browser, so they are able to use the software from any device with access to the internet such as laptops, tablets, or Chromebooks. The next advantage is that computing support for students is streamlined, because all students are using the same version of R and RStudio and have the same git configurations regardless of computer type. Third, because git is already configured in the RStudio containers, students are immediately able to share work between the platforms. Lastly, the infrastructure is flexible enough to easily accommodate in-person, hybrid, and online learning.

The main limitation to using the server-based set up is that by the end of the course, students have only used RStudio through the web browser rather than a version installed on their local machine. This limitation is partially mitigated by the fact that the interface in the university’s server-based RStudio is the same as the interface in a local installation. The largest potential hurdle for students moving from the server to a local installation is configuring git and GitHub. At the end of the semester, students are given instructions that direct them to the relevant sections of the book Happy Git and GitHub for the useR (Bryan 2018) for detailed step-by-step instructions on setting up R, RStudio, and git. Duke University’s Office of Information Technology provides access to a server-based RStudio for all students at the university, so students also have the option to continue using RStudio through the web browser.

Overall the advantages of the server-based set up outweigh the limitations, and these advantages are not limited to RStudio. This set up reduces many of the challenges of computing in statistics courses; however, it is still feasible to successfully incorporate computing and a reproducible workflow as a learning objective in a regression course using a different computing set up and infrastructure.

4.2.2. Activities and Assessment

Students write responses to all in-class activities and assignments in an R Markdown document, which facilitates writing up results in a reproducible way. About 6%–10% of the total points on each assignment (typically three to five points out of 50) are dedicated to document formatting and implementing a reproducible workflow, which includes using version control through regular commits and informative commit messages. The commit history is assessed by the instructor or a graduate teaching assistants using functions from ghclass, an R package that is “designed to enable instructors to efficiently manage their courses on GitHub” (Rundel and Cetinkaya-Rundel 2022). For team assignments, students are expected to use GitHub for collaboration, mimicking the collaborative workflow is commonly used in academia and industry. The git commit history is used as part of the assessment of each students’ contribution to the team assignment, as each team member is required to have at least one commit on these assignments.

More details about the way version control is introduced to students, how its incorporated into assignments and assessed, and the assignment workflow for students and the instructor in this regression course and other courses at multiple levels of the undergraduate and graduate curriculum are available in Beckman et al. (2021).

4.3. Principle 3: Develop Important Nontechnical Skills, Specifically Written Communication and Teamwork

The final principle for modernizing the course is the emphasis on nontechnical skills, specifically written communication and teamwork. It is important that students are also equipped with the nontechnical skills that will make them more effective collaborators as they prepare to conduct statistical analyses outside of the classroom.

4.3.1. Written Communication

There has been a breadth of work on writing in undergraduate statistics, both as a way to assess students’ understanding of statistical concepts (e.g., Woodard et al. 2020) and with the specific purpose of developing students’ communication skills (e.g., Cline 2008). Additionally there are texts such as the book Communicating with Data: The Art of Writing for Data Science (Nolan and Stoudt 2021) dedicated to the “how” of communicating statistical results. The latter idea of effectively communicating statistical results to a general audience is the focus of the writing in this course.

For each assignment, points are dedicated to the quality of the formatting and presentation of the document. The formatting and presentation criteria include writing all responses as a cohesive narrative in full sentences and having a document with formatting suitable for a professional setting. It also means using informative titles and axis labels on graphs and neatly formatted tables and output. Students see examples of these formatting elements in R Markdown documents for in-class activities. Students are also provided R Markdown templates for assignments. The templates are scaffolded, so those for early assignments provide a lot of guidance on formatting and structuring the responses. As the semester progresses, the scaffolding in the templates is reduced, and by the final project students are expected to format their document given a fairly sparse template. Because students come from one of several introductory courses, providing the templates at the beginning of the semester helps establish a consistent set of formatting guidelines for the course. It also ensures students have the code required to properly format their work without spending much time on it in class.

In addition to formatting, points on each assignment are dedicated to writing interpretations and conclusions that are meaningful in practice. Therefore, students receive full credit for interpretations that are conceptually correct and written at a meaningful scale. A rubric is used that differentiates the accuracy of the interpretations from the effectiveness of how the results are communicated. For example, in a homework assignment on multiple linear regression, students are asked to visualize and interpret interaction terms between two variables in a dataset of the price and characteristics of
houses in King County, Washington (Kaggle 2018). They are first asked a series of questions that assess their conceptual understanding:

- **We are interested in fitting a model using the square footage, whether the house has a waterfront view, and the interaction between the two variables to help explain variability in the price. Make a visualization of the price versus square footage with the points differentiated by waterfront. Interpret the visualization.**

- **Fit a model with the log-transformed price (see the previous lab to see why we use log-transformed price!) as the response and sqft, waterfront, and their interaction as the predictors.**

- **Interpret the effect of square footage on the price of a house for**
  - houses with no waterfront view
  - houses with a waterfront view

Then students are asked the following prompt to assess their ability to synthesize and communicate the results:

*Use the results from the previous questions to write a short paragraph (~3–5 sentences) about the relationship between square footage and the price of houses in King County, WA, and how (if at all) the relationship differs based on whether the house has a waterfront view. The paragraph should be written in a way that is practical and can be easily understood by a general audience of home buyers.*

In the first set of exercises, students are assessed on the accuracy of their visualizations and interpretations. In the second exercise, the assessment is focused on the ability to summarize the information to derive general conclusions (not just write a list of interpretations) and write the results using a meaningful scale. Given these criteria, a student would not receive full credit for an technically correct interpretation written in terms of a one square foot increase in the size of a house, as this interpretation would not be meaningful in practice and given the range of square feet values in the data.

In the final group project, students work in teams of three or four to answer a research question of their choice using the methods they’ve learned in the course. As part of the final project, students submit a draft with an introduction to the data and research question, a description of their regression modeling approach, and preliminary conclusions. Teams peer review each other’s work with a peer review rubric that asks them to comment on specific aspects of the analysis, including the writing and presentation. By going through the process, students not only receive feedback on their work but they have the opportunity to see each other’s writing and garner ideas from another on effectively communicating results. Students also receive feedback from a member of the teaching team at this point, either from the instructor or a graduate teaching assistant, with some feedback focusing on elements of the writing and presentation in addition to the statistical results.

Students receive detailed comments along with grading based on a rubric for the final project. Because the final project occurs at the end of the semester, there are not opportunities for students to submitted a revised report. One improvement to the assignment would be to introduce the rubric for the final project early in the semester, so that students could use it as a guide for the various writing-focused in-class activities and assignments throughout the semester.

### 4.3.2. Teamwork and Collaboration

Another primary learning objective of the course is effective teamwork and collaboration. These are incorporated in the course through the nontechnical aspects of working with others and in technical skills such as using GitHub for collaborative work. Given much work in academia and industry is done on teams, it is important for students to develop these skills in the classroom, an environment designed for learning and growth. Working in teams also helps students learn and gain insight from their peers. Working collaboratively “provides students with the opportunity to use creative problem solving and to refine leadership skills…multidisciplinary teamwork also emphasizes inclusion and encourages diversity of thought in approaching data science problems.” (Vance 2021)

Students are assigned to teams of three or four based on the results of a “Get to Know You” survey at the beginning of the semester that asks about their previous statistics and computing experience, their major or academic interests (many students take the class before declaring a major), and their hobbies and interests outside of the classroom. Teams are assigned taking into account some considerations of the information from the survey. For example, seniors and first-year students are not put on the same team given they generally have very different motivations for taking the course (i.e., seniors are not taking the course to become a Statistical Science major but many first year students may be taking the course to consider the major), and teams are designed to reduce the possibility that a student is isolated on their team in terms of identity and background, academic interests, or previous experience. Students with different computing experience are put on the same team; however, if there is too much of a disparity in the computing experience, teams have a harder time working together, as the more experienced student takes on most of the computational tasks. Therefore, there is diversity in computing experience on the team to an extent, but, for example, a student with no previous experience using R would not be assigned to the same team as a student who rates themselves as being a “expert” in R.

Barring extenuating circumstances, students work on the same team throughout the semester on weekly computing lab assignments. By working on the same team they have time to establish and refine their team workflow and communication. The consistency also gives them the opportunity to get to know each other and develop productive team dynamics before working on the larger stakes final team project.

The first tasks for the teams are to come up with a fun team name and fill out a team agreement that is stored in a private “team-agreement” GitHub repo. The primary purpose of the team agreement is to establish a plan for communication outside of the lab sessions, including an agreed upon method of communication and weekly meeting time outside of the lab sessions. The work on the final project is primarily done outside of class, so scheduling a meeting time earlier in the semester helps make it easier to find time to collaborate on the final project. Finally, they choose a day in which all team members will have their portion of the assignment completed so the whole group can review the write up before submission. Particularly with the recent challenges from remote and hybrid collaboration, the team agreement has been helpful for students...
to discuss collaboration strategies, so they are better prepared if unexpected circumstances arise.

Students complete periodic team feedback, and the scores on feedback account for about 2.5% of the final course grade. The first team feedback is only graded for completion to encourage students to provide honest and constructive feedback without worrying about impacting their peers’ grades. It also alerts the instructor to teams that are having trouble and need follow up. Often the issues on teams are due to gaps in communication, therefore, it is helpful to have the team agreement available, so the team can be reminded of their collaboration plan and discuss any necessary adjustments.

5. Discussion
5.1. Impact of this Approach

Enrollment in the course has steadily increased, from 65 in Fall 2018 to about 100 in Fall 2021. The growth has been, in part, due to the increased popularity of the introductory courses that have encouraged more students to continue pursuing statistics beyond the first course. As enrollment has increased, the course has also gained a reputation for being one that prepares students to conduct statistical analysis in research and internships; there are regularly requests from students from a range of majors who want to take the course to develop skills they’ll need to conduct research in their discipline, and there are often some requests from graduate students interested in auditing the course to refresh their regression analysis skills. Students in the Statistical Science major have also expressed the value of the course in their work. Seniors in the class of 2021 were asked “Of all the courses you took in STA, which increased your understanding of the field the most or provided you the best future preparation?”

Regression Analysis was one of the top three courses mentioned in response to this question (noting the top course being the senior capstone course).

The course has been run in flipped format described in Section 3.3 since the transition to online and hybrid formats due to the onset of the COVID-19 pandemic. Even with the transition back to in-person learning in Fall 2021, it is still primarily taught in a flipped format given the pedagogical benefits. The format promotes “productive struggle,” the opportunity for meaningful learning as students struggle with various concepts and ideas (Hiebert and Wearne 2003; Lynch et al. 2018). Most class time is used for hands-on exercises, so students are able to talk with their peers and ask questions as they work through exercises. The flipped format has also allowed for more opportunity to have in-depth and nuanced discussions during class that encourage students to think beyond what is “technically correct” to what would be useful in practice such as those activities and exercises described in Sections 4.1 and 4.2.

Because of the emphasis on developing writing and computing skills in the course, students have a foundation as they move into upper level courses. Therefore, instructors in the upper-level courses don’t have to spend as much time teaching students how to conduct reproducible analyses beyond the usual content review at the beginning of the term. Students coming in with these skills also gives instructors in upper-level courses the opportunity to implement more of the advanced workflow skills that students may encounter in the workplace. For example, GitHub issues are more regularly used for feedback and conversation between the instructor and students on projects in an upper-level undergraduate elective. Additionally, there has been more focus on the details of writing in the elective course, such as effectively presenting a statistical argument to various audiences and crafting a research article, particularly when there are constraints on word count, tables, and figures.

5.2. Challenges of Implementing these Innovations

There have been some challenges to incorporating these innovations in the course. The first is identifying interesting and complex datasets that are still accessible to new learners. Having to address model conditions can provide a learning experience and motivate concepts such as log transformations on the response and predictor variables. It can also be an opportunity to get students excited about later units in the course or future courses where they will learn how to deal with data that do not neatly fit the conditions for linear regression. For example, students see how log transformations can be used to model nonlinear relationships by examining the relationship between movie budgets and revenues based data from IDMB.com in the first week of class. There is not a lot of time spent on log transformation at the moment, but it gives students a glimpse of the type of data they’ll be able to analyze using techniques from the course.

As the course progresses, examples such as these can also be used to facilitate more nuanced discussions about statistical inference and model conditions, such as different approaches (simulation-based vs. mathematical models) and the robustness of these approaches to violations in conditions. These discussions expose students to a variety of realistic modeling scenarios and gives them practice developing the judgment and decision-making skills needed to use effectively use modeling in practice.

It is important, however, that students first have an understanding about what model conditions are and how they relate to inference for regression, so they understand the motivation for checking conditions even if inferential conclusions can be drawn from models with some violations.

The next challenge is having the ability to provide meaningful individual and iterative feedback to each student on writing exercises, particularly long-form writing where students must synthesize information from a full analysis to draw conclusions. As the course has increased in size, it has become not feasible to provide such detailed feedback to individuals regularly during the semester. There are some homework assignments in which students are asked to summarize results in one to two paragraphs as shown in Section 4.3 or where they are asked to conduct an abbreviated data analysis; however, the only assignment where students get iterative feedback on drafts of their writing with the opportunity to improve and resubmit is in the final group project.

The teaching team consists of undergraduate and graduate teaching assistants who help with grading assignments. It can be challenging to train teaching assistants, especially undergraduates who themselves are still relatively new learners, to accurately and effectively grade open-ended response. New
learners can still have difficulty differentiating responses that are incorrect versus those that are still correct but presented differently than what is in the instructor-provided solutions manual. This has been partially mitigated by using Gradescope, an online grading rubric platform (Gradescope 2020), and creating specific rubric items to identify key parts of an interpretation or analysis; however, without additional feedback to provide context to the rubric items, the very specific point system can seem more punitive to students rather than an indication of misunderstanding important concepts.

5.3. What’s Next for the Course and Curriculum

In recent semesters, innovations in the course have been more focused on modernizing the choice of topics and methods in the course. The most substantial change has been an emphasis on using regression models for prediction in addition to inference. Topics such as cross-validation were introduced early and carried as a theme throughout the semester. Other modern methods such as simulation-based inference were taught as core content in the course. The course also incorporated the use of tidymodels (tidymodels.org), a suite of modeling packages that aim to provide a more unified syntax and framework for modeling in R and more easily facilitate a regression workflow for both inference and prediction. The new content has created opportunities for more discussions about how the primary analysis objective (inference or prediction) is used to help inform the methodology, along with how to assess model conditions, model diagnostics, and their relative importance for different methods. To accommodate the addition of these topics there is less time in the course spent on ANOVA and simple linear regression, though a large portion of the course is still dedicated to multiple linear regression.

There is also ongoing work with faculty in Duke University’s writing center to develop more writing exercises that are feasible for the large classes, so students receive more individual and iterative feedback on writing throughout the semester.

5.4. Conclusion

As the ability to analyze data has become an increasingly important skill in academia, industry, and every day life, it is important that the statistics curriculum is designed to prepare students to responsibly work with modern data outside of the classroom. While there has been a lot of work on this front in the modernization of introductory statistics courses and the development of introductory data science courses, it is critical that the innovation extends beyond the introductory course. Three principles used to modernize an undergraduate regression analysis course, the second statistics course for many students, were presented. After implementing these innovations in the first and second courses, there has been increased student interest in the discipline and more opportunity to continue developing these skills in subsequent courses. While there are many benefits to this approach, instructors should keep in mind some of the cautions presented earlier, such as not discouraging students by consistently using data that requires methods beyond the scope of the course, being mindful of the student and instructor workload while at the same time finding opportunities for meaningful feedback, particularly on open-ended written work.

Though these principles were designed with the second course in mind, they are applicable and can benefit students throughout the curriculum. By incorporating a unified set of principles that influence the design of courses throughout the curriculum, students will have a more streamlined experience where they can continue developing their computing and communications alongside their statistical knowledge and literacy.

Supplementary Materials

Supplementary materials for the article including links to course websites, sample activities and assignments, and other resources are available at github.com/matackett/modernize-regression.

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Data Availability Statement

No new data were created or analyzed for this manuscript. Data used in the example in-class activity and assignment are available in the supplementary materials.

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