Preface

Existing textbooks on regression typically have some mix of cookbook instruction and mathematical derivation. We wrote this book because we saw a new way forward, focusing on understanding regression models, applying them to real problems, and using simulations with fake data to understand how the models are fit. After reading this book and working through the exercises, you should be able to simulate regression models on the computer and build, critically evaluate, and use them for applied problems.

The other special feature of our book, in addition to its wide range of examples and its focus on computer simulation, is its broad coverage, including the basics of statistics and measurement, linear regression, multiple regression, Bayesian inference, logistic regression and generalized linear models, extrapolation from sample to population, and causal inference. Linear regression is the starting point, but it does not make sense to stop there: once you have the basic idea of statistical prediction, it can be best understood by applying it in many different ways and in many different contexts.

After completing Part 1 of this book, you should have access to the tools of mathematics, statistics, and computing that will allow you to work with regression models. These early chapters should serve as a bridge from the methods and ideas you may have learned in an introductory statistics course. Goals for Part 1 include displaying and exploring data, computing and graphing linear relations, understanding basic probability distributions and statistical inferences, and simulation of random processes to represent inferential and forecast uncertainty.

After completing Part 2, you should be able to build, fit, understand, use, and assess the fit of linear regression models. The chapters in this part of the book develop relevant statistical and computational tools in the context of several applied and simulated-data examples. After completing Part 3, you should be able to similarly work with logistic regression and other generalized linear models. Part 4 covers data collection and extrapolation from sample to population, and in Part 5 we cover causal inference, starting with basic methods using regression for controlled experiments and then considering more complicated approaches adjusting for imbalances in observational data or capitalizing on natural experiments. Part 6 introduces more advanced regression models, and the appendixes include some quick tips and an overview on software for model fitting.

What you should be able to do after reading and working through this book

This text is structured through models and examples, with the intention that after each chapter you should have certain skills in fitting, understanding, and displaying models:

• Part 1: Review key tools and concepts in mathematics, statistics, and computing.
  – Chapter 1: Have a sense of the goals and challenges of regression.
  – Chapter 2: Explore data and be aware of issues of measurement and adjustment.
  – Chapter 3: Graph a straight line and know some basic mathematical tools and probability distributions.
  – Chapter 4: Understand statistical estimation and uncertainty assessment, along with the problems of hypothesis testing in applied statistics.
  – Chapter 5: Simulate probability models and uncertainty about inferences and predictions.
After working through the book, you should be able to fit, graph, understand, and evaluate linear and generalized linear models and use these model fits to make predictions and inferences about quantities of interest, including causal effects of treatments and exposures.
Fun chapter titles

The chapter titles in the book are descriptive. Here are more dramatic titles intended to evoke some of the surprise you should feel when working through this material:

- **Part 1:**
  - *Chapter 1:* Prediction as a unifying theme in statistics and causal inference.
  - *Chapter 2:* Data collection and visualization are important.
  - *Chapter 3:* Here’s the math you actually need to know.
  - *Chapter 4:* Time to unlearn what you thought you knew about statistics.
  - *Chapter 5:* You don’t understand your model until you can simulate from it.

- **Part 2:**
  - *Chapter 6:* Let’s think deeply about regression.
  - *Chapter 7:* You can’t just *do* regression, you have to *understand* regression.
  - *Chapter 8:* Least squares and all that.
  - *Chapter 9:* Let’s be clear about our uncertainty and about our prior knowledge.
  - *Chapter 10:* You don’t just *fit* models, you *build* models.
  - *Chapter 11:* Can you convince me to trust your model?
  - *Chapter 12:* Only fools work on the raw scale.

- **Part 3:**
  - *Chapter 13:* Modeling probabilities.
  - *Chapter 14:* Logistic regression pro tips.
  - *Chapter 15:* Building models from the inside out.

- **Part 4:**
  - *Chapter 16:* To understand the past, you must first know the future.
  - *Chapter 17:* Enough about your data. Tell me about the population.

- **Part 5:**
  - *Chapter 18:* How can flipping a coin help you estimate causal effects?
  - *Chapter 19:* Using correlation and assumptions to infer causation.
  - *Chapter 20:* Causal inference is just a kind of prediction.
  - *Chapter 21:* More assumptions, more problems.

- **Part 6:**
  - *Chapter 22:* Who’s got next?

- **Appendixes:**
  - *Appendix A:* R quick start.
  - *Appendix B:* These are our favorite workflow tips; what are yours?

In this book we present many methods and illustrate their use in many applications; we also try to give a sense of where these methods can fail, and we try to convey the excitement the first time that we learned about these ideas and applied them to our own problems.

**Additional material for teaching and learning**

**Data for the examples and homework assignments; other teaching resources**

The website www.stat.columbia.edu/~gelman/regression contains pointers to data and code for the examples and homework problems in the book, along with some teaching materials.
Prerequisites

This book does not require advanced mathematics. To understand the linear model in regression, you will need the algebra of the intercept and slope of a straight line, but it will not be necessary to follow the matrix algebra in the derivation of least squares computations. You will use exponents and logarithms at different points, especially in Chapters 12–15 in the context of nonlinear transformations and generalized linear models.

Software

Previous knowledge of programming is not required. You will do a bit of programming in the general-purpose statistical environment R when fitting and using the models in this book, and some of these fits will be performed using the Bayesian inference program Stan, which, like R, is free and open source. Readers new to R or to programming should first work their way through Appendix A.

We fit regressions using the `stan_glm` function in the `rstanarm` package in R, performing Bayesian inference using simulation. This is a slight departure from usual treatments of regression (including our earlier book), which use least squares and maximum likelihood, for example using the `lm` and `glm` functions in R. We discuss differences between these different software options, and between these different modes of inference, in Sections 1.6, 8.4, and 9.5. From the user’s perspective, switching to `stan_glm` doesn’t matter much except in making it easier to obtain probabilistic predictions and to propagate inferential uncertainty, and in certain problems with collinearity or sparse data (in which case the Bayesian approach in `stan_glm` gives more stable estimates), and when we wish to include prior information in the analysis. For most of the computations done in this book, similar results could be obtained using classical regression software if so desired.

Suggested courses

The material in this book can be broken up in several ways for one-semester courses. Here are some examples:

* **Basic linear regression**: Chapters 1–5 for review, then Chapters 6–9 (linear regression with one predictor) and Chapters 10–12 (multiple regression, diagnostics, and model building).

* **Applied linear regression**: Chapters 1–5 for review, then Chapters 6–12 (linear regression), Chapters 16–17 (design and poststratification), and selected material from Chapters 18–21 (causal inference) and Chapter 22 (advanced regression).

* **Applied regression and causal inference**: Quick review of Chapters 1–5, then Chapters 6–12 (linear regression), Chapter 13 (logistic regression), Chapters 16–17 (design and poststratification), and selected material from Chapters 18–21 (causal inference).

* **Causal inference**: Chapters 1, 7, 10, 11, and 13 for review of linear and logistic regression, then Chapters 18–21 in detail.

* **Generalized linear models**: Some review of Chapters 1–12, then Chapters 13–15 (logistic regression and generalized linear models), followed by selected material from Chapters 16–21 (design, poststratification, and causal inference) and Chapter 22 (advanced regression).

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