18.3: Learning the Basics, and Learning Them in R

Okay, that was… long. And even that listing is massively incomplete. There really are a *lot* of big ideas in statistics that I haven't covered in this book. It can seem pretty depressing to finish a 600-page textbook only to be told that this only the beginning, especially when you start to suspect that half of the stuff you've been taught is wrong. For instance, there are a lot of people in the field who would strongly argue against the use of the classical ANOVA model, yet I've devote two whole chapters to it! Standard ANOVA can be attacked from a Bayesian perspective, or from a robust statistics perspective, or even from a "it's just plain wrong" perspective (people very frequently use ANOVA when they should actually be using mixed models). So why learn it at all?

As I see it, there are two key arguments. Firstly, there's the pure pragmatism argument. Rightly or wrongly, ANOVA is widely used. If you want to understand the scientific literature, you need to understand ANOVA. And secondly, there's the "incremental knowledge" argument. In the same way that it was handy to have seen one-way ANOVA before trying to learn factorial ANOVA, understanding ANOVA is helpful for understanding more advanced tools, because a lot of those tools extend on or modify the basic ANOVA setup in some way. For instance, although mixed models are way more useful than ANOVA and regression, I've never heard of anyone learning how mixed models work without first having worked through ANOVA and regression. You have to learn to crawl before you can climb a mountain.

Actually, I want to push this point a bit further. One thing that I've done a lot of in this book is talk about fundamentals. I spent a lot of time on probability theory. I talked about the theory of estimation and hypothesis tests in more detail than I needed to. When talking about R, I spent a lot of time talking about how the language works, and talking about things like writing your own scripts, functions and programs. I didn't just teach you how to draw a histogram using `hist()` , I tried to give a basic overview of how the graphics system works. Why did I do all this? Looking back, you might ask whether I really *needed* to spend all that time talking about what a probability distribution is, or why there was even a section on probability density. If the goal of the book was to teach you how to run a t-test or an ANOVA, was all that really necessary? Or, come to think of it, why bother with R at all? There are lots of free alternatives out there: PSPP, for instance, is an SPSS-like clone that is totally free, has simple "point and click" menus, and can (I think) do every single analysis that I've talked about in this book. And you can learn PSPP in about 5 minutes. Was this all just a huge waste of everyone's time???

The answer, I hope you'll agree, is no. The goal of an introductory stats is *not* to teach ANOVA. It's not to teach t-tests, or regressions, or histograms, or p-values. The goal is to start you on the path towards becoming a skilled data analyst. And in order for you to become a skilled data analyst, you need to be able to do more than ANOVA, more than t-tests, regressions and histograms. You need to be able to *think properly* about data. You need to be able to learn the more advanced statistical models that I talked about in the last section, and to understand the theory upon which they are based. And you need to have access to software that will let you use those advanced tools. And this is where – in my opinion at least – all that extra time I've spent on the fundamentals pays off. If you understand the graphics system in R, then you can draw the plots that *you* want, not just the canned plots that someone else has built into R for you. If you understand probability theory, you'll find it much easier to switch from frequentist analyses to Bayesian ones. If you understand the core mechanics of R, you'll find it much easier to generalise from linear regressions using `lm()` to using generalised linear models with `glm()` or linear mixed effects models using `lme()` and `lmer()` . You'll even find that a basic knowledge of R will go a long way towards teaching you how to use other statistical programming languages that are based on it. Bayesians frequently rely on tools like WinBUGS and JAGS, which have a number of similarities to R, and can in fact be called from within R. In fact, because R is the "lingua franca of statistics", what you'll find is that most ideas in the statistics literature has been implemented somewhere as a package that you can download from CRAN. The same cannot be said for PSPP, or even SPSS.

In short, I think that the big payoff for learning statistics this way is *extensibility*. For a book that only covers the very basics of data analysis, this book has a massive overhead in terms of learning R, probability theory and so on. There's a whole lot of other things that it pushes you to learn besides the specific analyses that the book covers. So if your goal had been to learn how to run an ANOVA in the minimum possible time, well, this book wasn't a good choice. But as I say, I don't think that is your goal. *I* think you want to learn how to do data analysis. And if that really is your goal, you want to make sure that the skills you learn in your introductory stats class are naturally and cleanly extensible to the more complicated models that you need in real world data analysis. You want to make sure that you learn to use the same tools that real data analysts use, so that you can learn to do what they do. And so yeah, okay, you're a beginner right now (or you were when you started this book), but that doesn't mean you should be given a dumbed-down story, a story in which I don't tell you about probability density, or a story where I don't tell you about the nightmare that is factorial ANOVA with unbalanced designs. And it doesn't mean that you should be given baby toys instead of proper data analysis tools. Beginners aren't dumb; they just lack knowledge. What you need is *not* to have the complexities of real world data analysis hidden from from you. What you need are the skills and tools that will let you handle those complexities when they inevitably ambush you in the real world.

And what I hope is that this book – or the finished book that this will one day turn into – is able to help you with that.

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