Moving Forward in Statistics Education While Avoiding Overconfidence

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As demonstrated in his provocative article, George Cobb has strong views about statistics education and would like to see big changes. In these respects he is typical—indeed, we don’t know if we’ve ever met anyone who feels satisfied with how statistics is taught at most colleges, whether in statistics departments or elsewhere. What makes Cobb’s thinking worth engaging with, are his decades of experience working on these problems as a textbook writer, a committed teacher, and a participant in many committees on the teaching and learning of statistics.

We begin our discussion by emphasizing the parts of Cobb’s article we can unequivocally stand behind: we also recommend the substitution of computing in the place of mathematics, and we are moving this way in our own teaching: not just having students learn a statistics package, but having them do real (if simple) programming to manipulate, graph, and analyze data, and to simulate random processes.

And we also agree that introductory statistics should better match good statistical practice rather than the current standard focus on null hypothesis significance testing and toy math problems such as the sampling distribution of the sample mean, which we have long felt is an unnecessary stumbling block in the standard curriculum.

That said, developing a forward-thinking approach to teaching is not so easy, given the diversity of modern statistical approaches and the diversity of application areas. On one hand, Cobb supports the teaching of regression models while making no assumptions about probability models; on the other hand, he notes the increasing popularity of Bayesian methods, which of course are all about probability models. Should an introductory course gain some coherence by covering just one of these approaches, or would it be better to have a little of each?

One place we disagree with Cobb is in his linking of algorithmic thinking—which we support—with a particular anti-probability-modeling ideology espoused by Breiman in his 2001 article. Probability modeling is just as algorithmic as any other approach to statistics, and it seems to us naïve to think that data manipulations are somehow cleaner if they are expressed without reference to generative models for data. Of course, that’s just our perspective based on our teaching and applied research, just as Cobb is offering his own perspective. The challenge for all of us is to decide what to make of all of our personal views on these matters, and to decide where and how we want to teach in a huge and evolving market.

One challenge in dealing with Cobb’s recommendations, and others of this sort, is figuring out who the “we” is. With metaphors ranging from the California real estate market to the fast food industry, Cobb worries about defending “our turf” and the incursion of “others” who teach statistics in unhealthy “Happy Meals.” Cobb seems to be concerned with the future of traditional statistics departments with their undergraduate and graduate curricula. But at many universities undergraduate statistics programs are flourishing, indicating that students are attracted to the current system, or at least to the statistics label. Beyond this, there are much bigger forces in play redefining the traditional notions of student and university, and so Cobb’s Reformation analogy might apply more to higher education in general than to the state of one particular discipline.

As teachers, statisticians have the opportunity to serve broad and evolving populations, including adult workers returning for online masters programs, students taking online courses, and traditional undergraduate and graduate students from across the current university structure. At the undergraduate level, non-statistics majors outnumber statistics majors by a huge factor in introductory courses at many universities. At the graduate level, statisticians again are generally only a small fraction of students taking a reasonably in-depth sequence of statistics courses when one accounts for psychology, political science, sociology, education, nutrition, kinesiology, engineering and so many other departments. It makes sense that training programs will rise up to meet the demand. Penn State’s Department of Human Development and Family Studies, for instance, offers about a dozen courses in linear modeling, experimental design, longitudinal methods, Bayesian methods, data mining, and dynamic systems analysis—and we don’t think the content and teaching of these courses should be described as unhealthy fare, relative to what might be offered in a pure statistics program.

At Harvard, Columbia, and Penn State (to take the three institutions where we teach), undergraduate statistics programs are growing, and the influx is already forcing adaptation and rethinking of curricula. With the process of change well under way, statistics departments will find new ways to serve their own growing student bodies, and also the exponentially larger external market. And this will be achieved by balancing different instructional strategies to meet different demands.

We have the impression that attitudes on statistics education come much more from views about statistics, and personal experiences in the classroom, than from systematic studies of what works and in what context. We admit this regarding our own views (Gelman and Loken, 2012), and we think it’s the case for Cobb as well, given that his article has over 100 references, only one of which addresses empirical research in educational effectiveness.

From a psychological point of view, we can think of our general tendency to understate uncertainty and to discount alterna-
tive views; or, from a statistical perspective, we can recognize that effects vary. A teaching style that works well for George Cobb’s students at Mount Holyoke College might not be so effective in the hands of other instructors teaching working adults, or nurses, or MBA students, or sociologists, or political scientists.

References
