Discussions of George Cobb's *"Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum from the Ground Up"*,
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- Cobb, 2015 preprint: *Mere renovation is too little too late: we need to rethink our undergraduate curriculum from the ground up*

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- **Rejoinder** by George Cobb

Attracting Undergraduates to Statistics Through Data Science

Jim ALBERT and Mark GLICKMAN

We agree with George Cobb that statisticians need to rebuild their undergraduate curricula in statistics in the wake of big data and the many opportunities for employment in Data Science. As Cobb notes, our statistics curricula are currently facing several threats such as big data in computer science and analytics in business, and we agree that it is high time for statisticians to seriously rethink our undergraduate curriculum.

In particular, we believe the one-year sequence in probability and mathematical statistics, the standard introduction to statisticians for the past 50 years, is no longer a suitable foundation for training for a modern applied statistician. At Bowling Green, one of us has been fortunate to participate in the creation of a new major in Data Science within a department of mathematics and statistics. At Harvard, where one of us has been visiting faculty for 10 years, a new Data Science track for the statistics concentration is actively under development. Here we focus on what we believe are the important components of a data science program/track that can attract majors and provide a good foundation for employment as a data scientist.

Introduce Statistics Through Exploratory and Visualization Methods

For students with minimal statistics prerequisites, a good foundation course in a data science major focuses on computation with data. A version of this course is already in existence at Harvard, and Baumer (2015) and Hardin et al. (2014) describe similar data science courses. The student learns basic methods for importing, manipulating, and exploring data using a scripting language such as R or python. Particular data wrangling tools such as the use of regular expressions for textual data play an important role since text data is representative of modern data with a different structure from the traditional "data frame" rectangular grid. This course provides a good opportunity to learn about categorical and quantitative variables, as well as data management that aids in accessing elements of large data sets. Many of the themes of Tukey's exploratory data analysis can be introduced in this computing with data course. Additionally, such a course can emphasize communication of results through visualization and interpretable summaries, including generation of hypotheses by simple data explorations.

Statistical Programming

Much of the work of a data scientist consists of the process of data collection and data wrangling and it seems clear that the student needs sufficient training in a statistics programming language. One required course in the new Bowling Green data science program is "Statistical Programming". This course is an in-depth look at data types and containers, and the students get experience writing scripts and functions for different data science tasks. The tools for collecting, managing, and visualizing data are changing quite rapidly and the student with a solid foundation in a statistics language such as R will likely be able to adapt to these new data science tools.

The Importance of Context

The computing with data course uses several interesting big data applications to demonstrate the value of statistical thinking. Nolan and Lang (2015) describe a number of real-life data science projects, and ideas from these projects can help the instructor in building interesting homework assignments and projects. Ideally, a curriculum in data science can prepare the student to work on an extended data science project in collaboration with a faculty member from an applied discipline. Each undergraduate program needs to develop a network of internships, advisers and summer programs that can help in the development of these capstone projects.

From Statistical Inference to a Broad View of Statistical Algorithms

We agree with Cobb that the statistics curriculum needs to move away from traditional statistical inference courses with their emphasis on testing hypotheses and normal error and independence assumptions. But what should a modern statistical inference course look like? One possibility is to offer a statistical learning course. One of the required courses in the Bowling Green data science program is a course based on James et al (2013) that gives an applied overview of various statistical learning algorithms together with lab exercises on interesting datasets. Another alternative would be one based on generalized linear models (GLM), but this would require the students to have knowledge of a variety of probability distributions. In the Harvard GLM course that one of us teaches, which assumes students have had exposure to basic probability but not mathematical statistics, we have incorporated a data prediction competition on Kaggle as a course project. This type of exercise provides students an opportunity not only to engage in model criticism and refinement, but also to explore machine learning prediction algorithms. Students are exposed through this project both to stochastic and algorithmic cultures that Breiman (2001) identified. Given the increasing popularity of Bayesian methods, we think the time is right for the development of an applied Bayesian course. Link and Barker (2009) is one example of an applied Bayesian text that illustrates basic concepts within the

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Jim Albert is Professor of Statistics, Bowling Green State University, Bowling Green, OH (Email: albert@bgnet.bgsu.edu). Mark Glickman is Research Professor of Health Law, Policy and Management, Boston University, Boston, MA.

context of interesting examples from a particular discipline.

The Intro Statistics Course?

We believe the most challenging task is to redesign the introductory statistics class. Too many classes focus on learning recipes and the student leaves the course with a distaste for the subject, and more troublesome a lack of appreciation of the discipline of statistics. One of us has incorporated magic tricks (Lesser and Glickman 2009) and class-participatory demonstrations (Gelman and Glickman 2000) as ways to enhance interest in introductory statistics concepts. One of us has had fun experimenting (Albert 2003) with a baseball version of our introductory class. The course arguably succeeds in part since the students are genuinely interested in the sports application and the statistics concepts make more sense when discussed in this context. Generally, any type of project in which the students get to implement all of the steps of a statistics investigation is one of the best ways of making the discipline real for the students.

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Response to: "Mere Renovation Is Too Little Too Late: We Need To Rethink Our Undergraduate Curriculum From The Ground Up"

Roxy PECK, Beth CHANCE, and Allan ROSSMAN

First, we thank and congratulate George for a thought-provoking article. We whole-heartedly agree that implementation of the new guidelines will require considerable holistic thinking about the undergraduate curriculum for statistics majors. Rather than tweaking existing courses, departments should embrace the challenge to rethink everything from the first course, to progression and scaffolding through the curriculum, to assessment of learning objectives. For example, rather than continuing to compartmentalize computing, theory, and applications, courses should address the junction of all three areas. Algorithmic thinking needs to be explicitly taught, though not at the complete expense of mathematical underpinnings. We believe that Breiman's two cultures can complement and reinforce each other.

The tricky trade-off is of course in practice. What is feasible for departments to do in the near term? Continuing George's "tear-down" metaphor, which requires an expensive and time-consuming process, a key question is where to live in the meantime? Statistics departments cannot simply suspend their programs for a few years and then admit students once their new programs are established, so is it realistic to pursue drastic innovations such as attempting to break down departmental barriers and abandon teaching "subjects" entirely?

Other questions abound, such as: How will we know our new structure is feasible? Do we test and evaluate before we tear down and build, or do we just tear down, build, and hope for the best? Do we need to reach consensus within and among our departments first? How do we prepare current faculty, the vast majority of whom were taught in the probabilistic culture, to develop courses that teach skills from both cultures?

Perhaps we should begin with more modest renovations. For example, at Cal Poly, we have introduced a 4-unit "orientation" course for entering first-quarter students that begins our majors' discussions of historical roots of the discipline, ethics, future directions, "big data," computing in R, communication skills, and collaboration strategies.. This is followed by an applied introductory two-course sequence that focuses on the statistical investigation process as a whole, working with messy data and using simulation to motivate mathematical theory of statistical inference. We want our statistics majors to immediately apply their knowledge to genuine research studies, rather than waiting to finish courses in calculus and probability first. This sequence is followed by an applied regression course, where we are currently adding more topics on predictive modeling, but in a manner that complements the modelling culture while focusing on overarching principles of statistical thinking. We are still collectively revising and hope to go further (especially as more course materials and texts become available), but what topics can/should now be omitted and just how far and should we go?

We hope the ASA will continue to provide resources and support for such changes. We are encouraged by the special issue's focus on rethinking the undergraduate curriculum in a collaborative manner, sharing resources and lessons learned, and learning from how individual institutions uniquely balance between cultures. Only by changing how undergraduate statistics majors are taught now will we be able to positively impact the discipline in the future.

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69, DOI: 10.1080/00031305.2015.10930. Roxy Peck is Professor Emerita, California Polytechnic State University–Statistics P.O. Box 7088, Los Osos, CA 93412. Beth Chance is Professor, Cal Poly, 1 Grand Ave, Department of Statistics, San Luis Obispo, CA 93047. Allan J. Rossman is Professor and Chair, Department of Statistics, Cal Poly San Luis Obispo, CA 93407.

Who, What, When and How: Changing the Undergraduate Statistics Curriculum: A Discussion of "Mere Renovation is Too Little Too Late"

Thomas J. FISHER and A. John BAILER

First, and foremost, we largely agree with the underlying themes presented by Professor Cobb: the need for a curriculum that attracts, inspires and engages students preparing them for the data and analysis questions they will face in their future; that the curriculum of statistics needs to evolve to include more modern tools; our profession (and discipline) is in danger of being superseded by computer science, business analytics and bioinformatics; and the need for a curriculum that is dynamic in the face of the evolving role of data science, mathematics and computing.

The manuscript is a provocative and interesting piece that generated a good conversation between us and we expect that it will do the same for our colleagues. The four threads outlined are particularly noteworthy and the analogy to the fast food industry is chillingly accurate. With all that said, the manuscript raised several intertwined questions about the implications of such a dramatic shift to the curriculum. These can be summarized in three main discussion points. The first is on the role of curriculum, the second is a question of scale and the third is on the topic of competition and collaboration.

As described by Professor Cobb, historically intro courses were based on sampling distribution theory and required some mathematical chops to grasp the probabilistic and statistical rationale. Applications with real data were a secondary consideration and many statistical results were taught as a mathematical recipe for different types of theoretical data. Although the standard intro course has evolved to a more data driven approach and to include various computing techniques, the same build up from probability through inference is typically taught. Before we can completely abandon this approach, we need to address a fundamental question: What is the role of introductory statistics classes in the curriculum? From our perspective, our introductory courses serve three distinct clientele: all students (think the general public), statistical doers (majors requiring skills with data and analysis—the sciences) and proto-statisticians (those majoring in statistics, mathematics or computer science or who may get an advanced degree in the area). The teaching goals for each of these groups can be quite different and can be summarized as literacy, rationale and comprehension, respectively. The discussed revolution of the curriculum appears to largely concentrate on the rationale of statistics, moving to a more intuitive algorithmic approach, which in our mind largely serves the 'statistical doers.' How will this affect our other students? That is, what are the repercussions for the general public and the proto-statistician with such a dramatic change in teaching. Even with the 'statistical doers', the methods courses taught in their home departments often still expect a certain level of established tools (the two-sample t-test for instance). The issue is not merely in a change of *our* curriculum, but an entire shift in thinking with our client departments, the general public and our graduate programs as well.

Although the curriculum shift should benefit many aspects of statistical literacy (understanding the statistical comparison of groups using a randomization or a classification tree type approach, for instance), we potentially lose several important components in the traditional curriculum. The redesign efforts abandon much of formal probability for the sake of flattening the prerequisites. Even if this has an overall benefit and makes the subject matter more attainable, we must not lose sight of some of the key goals in statistical literacy such as a general understanding of uncertainty, randomness, chance and (shall we say) luck. For instance, in her 7 topics for the Educated Citizens, Jessica Utts highlights an understanding of natural variability (what is *normal* versus what is *the average*) as a fundamental element in statistical literacy (Utts 2003). Although we believe such topics can be discussed even with the flattening of prerequisites, the discipline needs to decide how to include such pertinent elements and how much time to dedicate to such topics.

Our second point is largely an issue with scale but does connect to the role of curriculum. We commend Professor Cobb and colleagues at the liberal arts colleges for providing numerous innovations in the statistics curriculum; but such changes create a set of challenges that need to be discussed. At many large research universities, more than 1000 students may take the intro stat course every semester, with many of these classes taught by adjunct faculty to large lecture sessions ($\sim$100 students). There have been many calls for more active learning experiences in introductory classes in the recent past. Consider Project INGenIOuS or the MAA/ASA/SIAM/AMS Common Vision Project, for instance. When faculty currently teaching intro stat are more comfortable with the traditional format, how do we convince them to use different pedagogical methods? How do we create space for faculty to innovate in a climate where we are already being asked to do more with fewer resources? At universities with undergraduate statistics programs, changes to the foundational courses will require major changes in upper level courses as well. Many of our students enter universities with AP credit; how do we incorporate those trained through a more traditional model at the high school level? Will a need for the traditional first course in statistics, as currently formulated, exist in the near

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future? How will the change in curriculum translate with other universities and graduate programs that build off the traditional model? And, although a good problem, are we ready for the additional demand a more attractive curriculum may create?

The last point we would like to make is our disagreement with the assertion regarding self-interest and the dangers to our field. Although we agree that other disciplines are infringing on traditional statistics material (the so-called *fast food*), where Professor Cobb appears to suggest the need to protect our field against external threats, we believe the current climate is one of opportunity rather than turmoil. At Miami University, the Department of Statistics partnered with the Farmer School of Business in developing a Co-Major in Analytics: students pick up data management proficiency, statistical methods for predictive modeling, data visualization, communication and teamwork skills, all with an eye towards application. This program has grown substantially since its creation in 2013 with roughly 70 current students. Recently, the Department partnered with the Department of Information Systems & Analytics, Computer Science and Marketing to form the Center for Analytics and Data Science as an interdisciplinary effort to address the analytics skills gap in the current workforce and foster collaborations in the areas of analytics and data science. Rather than going on the defensive, we encourage cooperation with other disciplines to build stronger programs. If implemented correctly, these associations can foster interdisciplinary research, strengthen the importance of computing, disseminate the skills our students need, and will secure and preserve statistics place as a major partner with other data-oriented disciplines.

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We Need to Rethink the Way We Teach Statistics at K–12

Response to "Mere Renovation is Too Little Too Late: We Need to Rethink the Undergraduate Curriculum from the Ground Up"

Christine FRANKLIN

Kudos to George Cobb for again writing an elegant, visionary, and timely article about teaching our field of Statistics as we move forward in the 21st century—I support George's core beliefs as to where we need to advance as statistics educators. I would like to offer the following thoughts coming from two perspectives: one as faculty in a large university statistics department and as one involved with promoting the integration of statistics at the K–12 school level.

One statement stood out for me in this article: "In our profession as we practice it, we wait to learn what we need to know until we need to know it, and we focus our learning on what we need to know. Why shouldn't the ways we teach our subject follow the approach we use in practice?" At UGA, from my perspective as undergraduate coordinator, I have observed the legitimacy of this quote with the success of our two semester Capstone course for statistics undergraduate majors. You can read more about this course in *The American Statistician* article, "A Capstone Course for Undergraduate Statistics Major" (Lazar et al., 2011). During the exit interviews with our graduating students, it is this one course that students most often identify as having the biggest impact on their learning of statistics. They spend a year practicing statistics with a client. They learn such attributes as how to deal with messy data, new computing and database skills, new statistical techniques not in the standard statistics courses, soft skills of writing reports, conversing with clients who don't necessarily have a statistics background, and presenting their projects as posters to the statistics faculty. After graduating, the students frequently communicate with the department that the Capstone course has helped them most with their careers. This is not to say the students don't need understanding of core statistical concepts taught in standard classroom courses—our goal as statisticians needs to be identifying those concepts for helping students develop sound statistical reasoning skills. This development should begin at the school level, not post secondary. This leads me to my second perspective.

With the implementation of the Common Core Mathematics State Standards in the U.S. that includes statistics at grades 6–12, we are at a crossroads where we have the opportunity to embrace letting young students explore and take ownership of the wealth of data that surrounds them and that they help generate—with technology young students can explore data visually, learn at an early age database management skills, utilize programming skills, use simulation for modeling, and appreciate the way data impacts their lives. With the accessibility of data, formal inference is often not applicable although much emphasis is still placed on inference in our current teaching. There is so much to be learned from simply exploring the data and telling a story. I would like to advocate that we work toward implementing many of George's suggestions at the school level and not waiting until the university level. The field of Computer Science is showing innovation with the new Advanced Placement Course, Computer Science Principles—a course that introduces students to such topics as programming, abstractions, algorithms, and large data sets to address real-world problems. We as statisticians need to follow the lead of Computer Science. I observed first hand the first 6 months of 2015 how New Zealand is attempting to implement a school level curriculum where students explore real world data using technology to carry out the statistical investigative process and letting the data tell an informative story.

The two biggest challenges I see regarding George's suggestions are building a culture that advocates this as the direction we should travel and the teacher preparation needed (both at the school level and the post secondary level). Even well respected statisticians don't necessarily want to change the way they teach or what has always been the traditional mathematical based curriculum. Moving the teachers to empower a new culture of teaching statistics has been advocated for at least 50 years, since the championing of exploratory data analysis by John Tukey. We are still struggling to simply teach statistical topics that are more real world and conceptually based versus the more procedural mathematical statistics. Fortunately, the American Statistical Association has one of its priorities teacher preparation at K–16.

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Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Christine Franklin, University of Georgia, Athens GA (Email: codycory@uga.edu).

Moving Forward in Statistics Education While Avoiding Overconfidence

Andrew GELMAN and Eric LOKEN

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 naive 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-

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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.

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Augmenting the Vocabulary Used to Describe Data

Robert GOULD

This is one of the most exciting papers I have read in a while. George Cobb has, as he has before, clearly identified a challenge to our statistics community that many of us have been aware was lurking somewhere on the margins, but have not seen so clearly until now. There's much to comment on here, and I expect there will be years of discussion, but I'd like to emphasize two topics mentioned in this paper – data and curricula.

Here was my very first introduction to data as an undergraduate math major: "Let $X_1, X_2, \ldots, X_n$ denote n random variables that have the joint p.d.f. $f(x_1, x_2, \ldots, x_n)$." (Hogg and Craig, 1978, p. 122). Some of you who enjoyed a similar introduction to data are probably marveling that Hogg and Craig were so far-sighted as to introduce the topic as early as page 122. Today, most data used in examples and homework problems in introductory courses—while represented less abstractly than in my course and possessing, thank goodness, some level of "realness"—are derived from random samples or studies that applied random assignment. When they are not, homework questions often begin "Assume that these are from a random sample" because without that assumption there's not much we can ask students to do. These probabilistic-culture data, I suggest, represent a very small fraction of data that our students encounter in life and maybe in their careers. This attention to only one type of data in our classrooms risks making our profession insignificant.

Despite being the "science of data," the statistics classroom has a narrow vocabulary for describing data. Let me expand this vocabulary by two terms. The first, "opportunistic data," was coined, to the best of my knowledge, by Amy Braverman, a statistician at Jet Propulsion Labs. The second is my own: "algorithmic data." Algorithmic data are data collected through an algorithm. Sensors collect data algorithmically, for example. The algorithmic trigger might be an occasional event, such as when a sensor detects motion, or might be a semi-continuous event, such as when sensors on a satellite are programmed to collect a stream of measurements. Opportunistic data are often collected by sensors, but more generally are data sets that are collected and await an opportunity for analysis. This category includes large, national databases which continue to foster research for purposes not originally foreseen by those who collected the data. (Think of the NHANES dataset.)

Opportunistic and algorithmic data challenge educators because they do not fit into the inference box; these approaches usually do not produce random samples, and a naive approach can lead to philosophical and scientific mistakes. (For example, see "The Parable of Google Flu: Traps in Big Data Analysis," Lazer. D et . al. 2014). And yet these data provide a pivotal role in students' lives and so provide a platform in which the science of data analysis can be introduced to a very wide audience.

When designing curricula, we should keep in mind this motto: Data First. We should design curricula that help *all* students understand *all* data, including algorithmic and opportunistic data. As George recommends, we should order topics in the order that best helps them understand data and not because we are supporting a "beautiful structure." We should exclude topics that do not help students understand data.

I would like to depart from George's recommendations, though, and urge us to think, when designing curricula, not in terms of semesters, but years. How should students learn about data from Kindergarten through retirement? This question had an easy answer when learning statistics meant learning mathematics. (Answer: wait until they've learned calculus.) However, as George points out, many useful and important tools can be understood through algorithms, and are more accessible at younger ages. In addition, educational technology can provide students with experiential access to abstractions such as random samples or repeated sampling, and so many topics now taught in graduate school or in the last months of a bachelor of science program can be introduced much earlier.

I have some experience with this first-hand. As the principal investigator of Mobilize, an NSF-funded project dedicated to bringing a "data science" curriculum to high schools, I've been struggling with the challenges of helping high school teachers teach their students to find meaning in data that do not belong to the probability culture. Our students use their cell-phones to engage in "participatory sensing campaigns," a form of algorithmic data collection in which they strive to gain insight into their lives and their communities. The data they collect are rich. They include geocoded locations, dates, photos, text, as well as answers to survey questions that fall into the more mundane categories of categorical and numerical.

From the Mobilize project, I've learned a few lessons about designing curricula. The most important: emphasize the statistical investigation process, as outlined in the GAISE K-12 report (Franklin et al. 2007). This consists of four stages: Ask Questions, Examine/Collect data, Analyze, Interpret. Most statistics curricula I've seen emphasize only the last two stages. Most high school science curricula emphasize the first two stages. Future citizens need all four stages. This investigation process works well in either of Breiman's two cultures and it keeps us focused on what matters: understanding of our lives, community, world.

The second important lesson I've learned is that engaging students in this cycle is not easy and requires considerable professional development for teachers. Our community needs to engage seriously in the preparation of teachers, not just through hosting workshops, but through changing teacher preparation at the undergraduate, graduate, and credentialing levels. Both science and math teachers are, with some exceptions, frightfully

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Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Robert Gould, UCLA, Department of Statistics, Math Sciences Building, Los Angeles, CA 90095-1554 (Email: rgould@stat.ucla.edu).

unprepared to teach students to engage meaningfully with data.

"Big Data" and the algorithmic data culture provide a way for us to move forward to reach more students and to reach them through engagement in authentic analysis of data. George is to be applauded for shoving us in the right direction.

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Seeking the Niche for Traditional Mathematics within Undergraduate Statistics and Data Science Curricula

John P. Holcomb, Linda Quinn, and Thomas Short

George Cobb's wonderful paper stimulates thought regarding the undergraduate statistics curriculum. The historical insights and the use of metaphor are illuminating. The list of references provides an entire seminar course curriculum on seminal work in statistics and how it can be taught.

In our commentary, we focus on the complex role mathematics plays in the undergraduate curriculum as it relates to the teaching of statistical science. In Section 3 of his paper, Cobb presents his case for "How we got stuck: the evolving role of mathematics." Our experiences in departments of mathematics at Cleveland State University (a comprehensive urban state university of approximately 12,000 undergraduates) and John Carroll University (a private university of approximately 3,000 undergraduates) indicate that many students get "stuck" in their quests to learn more statistics because they are limited by deficient knowledge of traditional mathematics.

At Cleveland State University, we have structured an undergraduate minor in statistics with access points for students from a variety of majors, including psychology and business. Our minor consists of a general introductory course, a second course, and separate courses in regression, design, and consulting. When non-mathematics majors become excited about statistics and wish to take additional coursework, they run into the mathematical wall. The minor at John Carroll University is similar, but differs in that students can count up to two quantitative methods courses within their home major. The statistics minor for students outside of the mathematics major does not include enough mathematical content to support graduate work in most traditional statistics programs. By this we mean programs that need students to have understanding of multivariable calculus or linear algebra in required courses at the masters or Ph.D. level.

For many students who do not take college algebra or calculus in their first year (most likely because they took a more appropriate introductory statistics course as their general education mathematics course), Cobb's summary of access to statistical ideas becomes a much longer chain of courses:

$$\text{College Algebra} \rightarrow \text{Trigonometry} \rightarrow \text{Calc I} \rightarrow \text{Calc II} \rightarrow \text{Calc III} \rightarrow \text{Probability} \rightarrow \text{Math Stat}$$

We propose a thought experiment, inspired by Cobb's three-part triage in Section 2.2 on how we work with data and clients. Whom should we allow to major in statistics (per the "Curriculum Guidelines for Undergraduate Programs in Statistical Science") or go on to graduate school in statistics?

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. John P. Holcomb, Cleveland State University 2121 Euclid Avenue, Cleveland, OH 44115 (Email: j.p.holcomb@csuohio.edu). Linda Quinn, Cleveland State University - Mathematics 2121 Euclid Avenue RT 1515 Cleveland, Cleveland, OH 44115. Thomas Short, John Carroll University.

1. Are you a third-year college student who has already taken up through multivariable calculus and linear algebra? If not, go away.

2. Are you ready, are you willing, and do you have the time before graduation to take calculus, linear algebra, real analysis, and Markov chain probability (and all the perquisites for those courses)? If not, go away.

3. Do you have the written and oral communication skills that employers repeatedly say that they really want in their employees? If not, that is okay because it is really only mathematical aptitude that matters for admittance into our programs (even though we will do little to help you acquire those needed communication skills).

To embrace Cobb's use of metaphor, we wonder if the mathematical jewels worn on the necklace around the statistician's neck have turned that jewelry into a noose that is choking access to our field.

We argue that the budget crises facing both state and private colleges and universities should make faculty aware of enrollment figures in their programs. A data-informed culture of higher education administrators is looking very closely at student enrollment data and the numbers of majors in programs. "Program prioritization" is being used across the country to help to determine where resources should flow for growth and where programs should be cut. Even state legislatures are demanding to know how established and successful universities are preparing students for immediate employment upon graduation. Statistics as a program has a tremendous opportunity to attract a great many students. Word is reaching both traditional-age and non-traditional students that there is an abundance of high-paying jobs available for those who possess data skills. Mathematics, statistics, and data science departments cannot afford to turn potential majors away. We believe that there are talented undergraduates who want to explore statistical science, but find their lack of mathematical training a hurdle that cannot be overcome in time to graduate within a reasonable window. Thus, we agree with Cobb's contention to "flatten prerequisites" at the undergraduate level, but worry that students in these courses will still be too mathematically deficient to enroll in graduate programs in statistics.

On the other hand, undergraduate mathematics programs are stocked with large numbers of mathematically talented students who need to find employment upon graduation. Inviting these students to take more statistics courses in order to broaden their skill sets will provide them with an easier path to employment and is one way to help to meet the high demand for data workers. We believe that we need to caution our mathematical colleagues that encouraging their students to go on to graduate school in mathematics might be a disservice. The popular goals of becoming a community college instructor with a master's degree in pure mathematics or earning a tenure-track position at a college or university with a Ph. D. in pure mathematics are very difficult to attain. Recently, John Carroll University had approximately 500 applications for a single tenure-track position in mathematics where the area of specialization was not specified.

Statistics has the potential to help bridge this mismatch of highly talented students and employment needs in government, industry, and academia. We in statistics should advocate to our mathematical colleagues that advising students to pursue a double major in mathematics and statistics (or some major/minor combination in mathematics, statistics, and computer science) ultimately serves the students better than earning graduate degrees in mathematics. This will not be easy, as so much of personal identification is tied in up in an individual's focus of study.

We leave it to others to debate whether the undergraduate curriculum needs to be a "tear down" as Cobb suggests, but we would argue that at the very least, our statistical house needs an additional wing. We need coursework and curricula that invite students who begin in other majors (including mathematics!) to acquire data analysis skills that in turn provide an avenue to high-paying and satisfying careers.

The Gap Between Statistics Education and Statistical Practice

Robert E. KASS

As I write this response to George Cobb's call to rebuild the statistics curriculum, I am returning from a symposium, "Statistics in the 21st Century," aimed at helping to define goals of a new center for statistics at MIT (which has been an outlier among premier U.S. universities in not having a statistics department). To me, the most striking aspect of the symposium was the consistency among its speakers in their admiration for the discipline of statistics, which focuses on the foundation of science and engineering: the use of data to provide information about the world. Maintaining this foundation as technology advances is a noble endeavor and, in the past few years, partly due to the advent of Data Science and Big Data, the importance of statistics has become much more widely appreciated.

The teaching of statistics has evolved more slowly than statistical practice. In diagnosing the problem with undergraduate statistics education, Cobb returns to Leo Breiman's "two cultures" article and makes some important points. I completely agree with him when, consistently with Breiman's earlier sentiment, Cobb warns against ceding to others "all methods of analysis that do not rely on a probability model." Tukey's profoundly important emphasis on the distinction between exploratory and confirmatory (inferential) methods, including the corruption of operating characteristics due to exploratory preprocessing, remains central to modern statistics. Furthermore, Cobb rightly suggests that computation should play a big role throughout the curriculum.

In Brown and Kass (2009, B&K hereafter), after criticizing our profession's lag in adapting training programs to contemporary statistical sensibility, we tried to move things forward by focusing on the highest level goal: to help students think more like expert statisticians. Our understanding of the way statisticians think was based on our experience in neuroscience. We said, "In the course of perusing many, many articles over the years . . . we have found ourselves critical of much published work [in neuroscience]. Starting with vague intuitions, particular algorithms are concocted and applied, from which strong scientific statements are made. Our reaction is too frequently negative: we are dubious of the value of the approach, believing alternatives to be much preferable; or we may concede that a particular method might possibly be a good one, but the authors have done nothing to indicate that it performs well. In specific settings, we often come to the opinion that the science would advance more quickly if the problems were formulated differently, formulated in a manner more familiar to trained statisticians." We asked ourselves, What is it that differentiates expert statisticians from other mathematically and computationally sophisticated data analysts? Our conclusion was that, roughly speaking, "statistical thinking uses probabilistic descriptions of variability in (1) inductive reasoning and (2) analysis of procedures for data collection, prediction, and scientific inference." It was not our intention to confine statistical education to those topics that involve statistical models, and I again agree with Cobb (as we argued also in B&K) that there is too much emphasis on the subtleties of mathematics-based statistical logic in many statistics courses. However, I would not back off the B&K formulation of what differentiates statistical approaches to data analysis, and I continue to advocate it as an overarching guide when considering what curricula can accomplish. In fact, my continuing experience as an active member of the Machine Learning Department in Carnegie Mellon's School of Computer Science has only strengthened my conviction on this point, and deepened my feeling about Breiman's article: Breiman coupled some valid concerns with the bad advice that we should all think much more like 20th century practitioners of artificial intelligence.

An anecdote may be helpful. Some years ago, in the process leading up to Carnegie Mellon's creation of its Machine Learning Department, from the outset a joint enterprise of statistics and computer science, we held a retreat to explore shared interests and develop a vision. At one point, a computer science colleague said, "I've figured out the difference between statisticians and computer scientists: statisticians attack problems with 10 parameters and want to get it right; computer scientists attack problems with 10 million parameters and want to get an answer." This was a telling remark. Yet, in the intervening time, the two perspectives have largely merged, as we are all trying to do the best job we can with very large data sets, and complex models; in fact, the statistical perspective has been largely victorious in the sense of being fully integrated into every major machine learning conference and journal. At Carnegie Mellon, our Department of Statistics has incorporated computation extensively across our undergraduate offerings, as well as requiring students to engage with real, complex data sets, and we have just started a new major in statistical machine learning. I will urge my colleagues to distribute details about their laudable efforts.

Cobb is concerned exclusively with the undergraduate curriculum. But the biggest challenge in statistics education arises from the difficulty humans have in accepting ambiguity and acting reasonably in the presence of uncertainty. Together with cognitive psychologists, we should devise educational strategies for helping people grapple with this predicament, beginning at an early age. In addition, we should recognize the extraordinary expectations we place on those who teach elementary statistics, especially in high school. To teach the process of "thinking with data," one must not only comprehend the basics of statistical reasoning (which is notoriously difficult) but also have some experience with the way such reasoning is used in drawing con-

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Robert E. Kass is Professor, Carnegie Mellon University, Department of Statistics, Machine Learning Department, and Center for the Neural Basis of Cognition, 5000 Forbes Ave., Pittsburgh, PA 15213. Support for this work was provided by NIMH grant R01 064537 (Email: kass@stat.cmu.edu).

clusions from data analysis. I fear we have not penetrated far into schools of education, where teachers are trained, and I hope we can find creative ways to do better in the future.

I presume this special issue will offer many constructive suggestions for advancing statistics education, which is a very good way for committed teachers to share ideas. I am less clear about the impact of the hand-wringing by both B&K and Cobb: we wrote, "The concerns we have articulated above are not minor matters to be addressed by incremental improvement. Rather, they represent deep deficiencies requiring immediate attention." And Cobb frames his plea for reform with the "tear-down" metaphor. My guess is that, despite our undeniably compelling arguments, which undoubtedly convinced the vast readership of these articles, change across the country as a whole will continue to evolve incrementally, and often more slowly than at institutions such as Carnegie Mellon (where our Department of Statistics has a pretty unified view of our teaching mission, a substantial campus presence, and a great deal of autonomy within our institution). I strongly endorse efforts to create modern, forward-looking online materials that can be used by statistics teachers everywhere. Meanwhile, those of us in Ph.D.-granting departments must remain vigilant as we train the students who will populate diverse environments, and will shape statistics education in the future.

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Training the Next Generation of Statistical Scientists

Eileen C. KING

George Cobb presents a provocative paper titled "Mere Renovation is Too Little Too Late: We Need to Rethink our Undergraduate Curriculum From the Ground Up." He discusses the need for a total revamp to the undergraduate program. Essentials to this renovation of the curriculum include the following: "exploit context, embrace computation, seek depth, flatten prerequisites, and teach through research."

I have been a statistician involved in team science since the early 1980's and have seen a major evolution of our profession. As a manager in industry, I determined the correct mix of educational training for our employees which included BS/BA, MS, and PhD prepared statisticians. At any point in time, approximately 30% of our employees were BS/BA prepared, many of whom continued their education while still working. The BS/BA statisticians would be very active and highly regarded members of multi-functional project teams and collaborated with data managers, physicians, senior statisticians and other team members on study design, data collection and cleaning, data analysis, and data presentation and interpretation.

In order to prepare our undergraduates to contribute to their maximum potential, a new approach to the educational process needs to be undertaken. In the sections that follow, I propose one method for preparing undergraduate students for a rewarding career as a statistical scientist that incorporates the imperatives laid out by Dr. Cobb and is in close alignment with the recently issued "ASA Guidelines for Undergraduate Programs in Statistical Sciences" (*http://www.amstat.org/education/curriculumguidelines.cfm*. I also discuss the need for providing opportunities for undergraduates to advance their educational training throughout their career by having access to top statistics programs without the need to relocate or leave their current position.

Training the BS/BA Statistical Scientists

Recruitment of top talent needs to happen at the high school level and within the AP calculus, statistics, computer science, and science classes. These students enter their post-high school educational process well prepared to become successful statistical scientists. Students expressing an interest in statistical science as an undergraduate major should be required to identify 1–2 areas of collaboration by the end of their first semester, e.g. biology, psychology, medicine, business. To facilitate this requirement, the following two-step process is recommended: 1) each student would be required to attend a seminar series with speakers from other divisions who present on their research so the student can identify a collaborating division, and 2) each student would write a proposal and make a presentation on his/her interest in working with the specified division. This requirement provides the first of many opportunities for the development of effective writing and presentation skills.

At the beginning of the second semester, students would then be paired with an allied department for their collaboration experience whereby they will be involved in working on projects with researchers in those areas for their entire undergraduate program (Cobb: "Exploit context—use research as a vehicle for teaching statistics"). Students could have the opportunity to change areas after their first two years but it is important that students learn the scientific area in which they consult so that they can be effective. A faculty member and/or advanced MS or PhD student within the statistics department must provide technical oversight and training to the undergraduate student. Based on this initial assignment, the curriculum for the student can be developed; hence, "context dictates content" [Cobb]. For example, if the collaboration requires knowledge of approaches for analyzing "big data" such as in the business world or informatics, then courses specific to this area can be taken (e.g. multivariate statistics, exploratory data analysis, data visualization).

Of course, all students will need to take a set of core courses including statistical theory. However, the method, prerequisites and timing of these courses within the curriculum should take into account the individual student's progression through the research experience [Cobb: flatten prerequisites]. This approach will provide the context for learning [Cobb: "practice usually leads and theory follows."] Technology today allows for intuitive ways of learning important theoretical concepts through simulation and algorithmic methods as opposed to "formulas that you can easily compute by hand" [Cobb: Embrace computation]. For example, concepts of p-values and confidence intervals are still necessary for making inferences, especially since our scientific colleagues rely on them (although I often question if they understand them) but the approach for constructing and interpreting can be made more intuitive [Cobb: Seek depth]. Sample size calculations through simulations should be a mainstay. Undergraduates must know statistical programming languages very well (e.g. SAS, R, etc) to be marketable. Structured programming skills and the importance of producing well-documented and validated programs that lead to reproducible results is imperative. Undergraduate students must also master the "soft skills" such as good oral and written communication skills, effective teamwork and collaboration, and the capability of making effective presentations. The proposed program will provide ample opportunities for development of these skills.

Internships after the sophomore and junior years should be available and strongly encouraged for the students pursuing a BS/BA in statistics. The proposed program structure provides early opportunities to develop the skills required for effective collaboration within multi-functional teams. As a result, they will be prepared for these internships and will add value for the

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sponsoring organizations.

Challenges to Implementation

I recognize there will be many challenges to this approach. First, in order to provide the opportunity for students to pair with a department upon entry into the program, the college and/or university must have access to active research programs within or external to their institution. Another challenge is the availability of faculty within the statistics departments to provide oversight to these undergraduate students. The faculty member must be proficient in collaborative research with other departments in order to be an effective mentor for these students. The biggest challenge will be the willingness of other departments to provide research opportunities for undergraduate statistics students. These departments must see the reward of participation through effective and value added statistical collaborations that lead to publication and increased funding.

Attracting top talent that can develop into highly effective statistical collaborators is a barrier. It is my perception that students typically enter their undergraduate programs with the desire to "change the world." It is important that these students see the impact they can make as a statistical scientist on producing high quality research that can, in fact, "change the world" for the better. They must experience "team science" from the beginning of their educational program.

Supporting the Career of the BS/BA Trained Statistical Scientist

Part of the renovation should also include consideration of the entire professional career for BS/BA trained statistical scientists including opportunities for obtaining advanced degrees from highly regarded programs. It is common that these individuals will, after a few years, want to further their education without leaving a position that is fulfilling, provides a good income, and oftentimes provides money for advanced education. There are many opportunities through distance learning for students to obtain a MS degree. However, there are few, if any, options available for students who wish to continue the educational process by obtaining a PhD degree from a top program without relocating to the specific university. Today's technology allows for synchronous and asynchronous learning and effective collaborations with thesis advisors at all levels of the educational process.

Conclusion

The curriculum for undergraduates in statistical science must be renovated. I have proposed one approach that augments Dr. Cobb's discussion with the aim of attracting top talent into our programs and produces well-prepared and "in demand" BS/BA graduates.

Stirring the Curricular Pot Once Again

Sharon J. Lane-Getaz

A Look Back, Then Forward

Rethinking the Introductory Course

I had high hopes of a major upheaval in statistics education after George Cobb's 2005 USCOTS talk and paper (Cobb, 2007). I naively believed that statistics educators would find new insights for teaching statistical concepts as they integrated technology more routinely into their teaching. I believed that introductory students would embrace a randomization-based curriculum to deepen inferential understanding. I believed that teaching and learning randomization-based inference would promote statistical thinking and would be an impetus to transform our overall approach to introductory statistics education. It would just take some time.

What I see a decade later is that a dedicated minority of statistics educators embraced the development and teaching of randomization-based inference and simulation (e.g., Chance and Rossman, 2006; Lock, Lock, Morgan, Lock, and Lock, 2013; Tintle, Chance, Cobb, Rossman, Roy, Swanson, VanderStoep, 2015; West, 2009). However, the vast majority of statistics educators seem skeptical. Some teachers report having tried a randomization or simulation demonstration or two. Others inserted a few class activities as well. Such minor changes are not likely to produce a lasting, measureable change in students' inferential reasoning. And the research comparing learning outcomes from randomization-based courses to the normal-based status-quo has enough limitations and confounding factors that the skeptic can remain unconvinced.

Rethinking the Entire Undergraduate Curriculum

Having been a proponent of randomization-based methods, I was at first taken aback by Cobb's newest "shaking of his finger." I took a deep breath. I reread one of Cobb's recent papers (Cobb, 2011) and reminded myself that he has been calling for curricular change on a regular basis (Cobb, 2011, 2007, 2000, 1992; Cobb and Moore, 1997). He has proposed that we teach inference using the randomization test (Cobb, 2007) for some and start with statistical modeling for the more mathematically minded student (a la Kaplan, 2012). He seems to periodically stir the pot to challenge us to better teaching and learning of statistics. "We can advance the cause of statistics teaching and learning by identifying and questioning unexamined assumptions about what we do, why we do it, and when we do it" (Cobb, 2011, p. 31).

Cobb now asks statistics educators to take a more dramatic step, to think outside of our comfortable curricular box. Think creatively about how we can better prepare our students to wrangle the truth from data. Rethink our curriculum in order to make room for:

- algorithmic and computational techniques,
- data science methods,
- Bayesian inference, and an
- authentic research experience.

Cobb is challenging us to admit that not all probabilities are equiprobable; many statistical questions cannot be modeled with a known reference distribution; and all probabilities are conditional. And to do something about it!

One Alternate Path

At St. Olaf we have experimented with teaching topics outside the more traditional sequence (i.e., outside of z-tests, t-tests, multiple regression, logistic regression, etc.). Our intermediate course for social science research includes topics that students might encounter in graduate school (Lane-Getaz, 2012). The course is designed to meet the preparedness of students who have only taken our statistical literacy service course. The syllabus includes four weeks of ANOVA and ANCOVA methods (one-way, two-way and interaction), two weeks of measurement topics (scale development, reliability, validity, bias and discrimination) and six weeks of dimension reduction analyses: principal components analysis (PCA) and exploratory factor analysis (EFA). During the final three weeks students choose, develop and present an activity-based lesson to the class. After the inaugural course offering, one student wrote, her favorite aspect of the course was "learning PCA and EFA. I had never done anything like this before, and I was really excited to learn it because it is so applicable in psychology research! I think we learned it in a way that made it comprehensible at the undergraduate level" (Lane-Getaz, 2012).

Fall of 2015 is the third scheduled offering of the course. After reading Cobb's article, I ask "Was I bold enough?"

I am reminded of a bright student in Statistical Modeling, the foundational course for statistics concentrators. This student proposed to do his final project using decision tree classification. I was hesitant. The course topics were multiple and logistic regression. Besides, how would I evaluate his work? Despite my misgivings, his final presentation to the class was sound, easy to follow and quite extensive—including animated colorful graphics. Regretfully, his final exam was less than stellar. He hadn't attended to learning the intended course topics. To this day I feel that he deserved a better grade than he earned, mathematically. The student had followed his curiosity, taught himself a new procedure, and introduced the class to classification. The topic was an accessible, useful alternative to logistic regression for his dataset.

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This story points out how we, as statistics educators, need to join our students in the dance of curiosity and experiment. We need to let go of our fear of change and the unknown. We need to remind ourselves that teaching and learning is a never-ending process for the students and for us. If we get stuck in a rut of teaching the same things we learned, the same way we learned them, and assess the same way we always have, then we—and the field of statistics—will be left behind.

Cobb's Five Imperatives

With that in mind, I wish to applaud Cobb's five summative imperatives that might guide our re-thinking of undergraduate statistics curricula:

1. *Flatten the pre-requisites.* Mathematics prerequisites serve as a barrier to entry to non-mathematical but bright thinkers. Many of the students in our introductory level service course are good critical thinkers but are not well-prepared mathematically. Of these students, a small number do choose to take a second course in statistics, our intermediate level statistics course for social science research (Lane-Getaz, 2012.) These students have an avenue to deepen their statistical thinking and gain confidence in their statistical ability. The course is a step up for those who plan to attend graduate school in statistics or a related field.

2. *Embrace algorithmic/computational thinking.* My ambitious statistical modeling student serves as an example to me to be fearless. A logical, step-by-step, computational approach to a problem is valid when the data do not conform to our standard paradigm: (1) same data source, (2) row and column format, (3) probability model fits. Our data-driven society demands that we grapple with these new types of data and that we make this new content accessible to a broader array of student interests and needs (Horton, 2015). [Flashing back to my story and my new course, could I find a place in my new course for decision tree classification?]

3. *Seek depth.* In the tradeoff between depth and breadth, we teachers tend to cling to breadth. But students may better remember the deeper experiences. For example, we teach ANOVA designs and analysis using data that students have collected from a day of launching gummy bears (adapted from Cobb and Miao, 1998). The first day of class is dedicated to time-consuming data collection. It is well worth it. Students are actively engaged, rolling up their sleeves in teams, and discussing design issues to the degree they can, from day one. For homework they are asked to start organizing their data to compare launch distances for the various conditions. They are primed to learn two-way ANOVA, blocking, main effects and interaction. They remember.

4. *Exploit context.* As a mathematics undergraduate, I saw context as ancillary to the problem, even bothersome. Cobb (2015) reminds us "in applied data analysis context provides meaning." This statement is blatantly obvious to my social science students. In fact, they are more comfortable dealing with issues related to the context of our case studies than they are with the statistical issues. Students in our introductory level service course tend to take on big, controversial questions for their final class projects. They typically analyze data from the General Social Survey and Youth Risk Behavior Survey, among others. Recent topics explored relationships between: Gender, Alcohol and Depression; Mental Health, Drugs and Physical Activity; Racial Discrimination in Employment, and Drugs, Mental Health and Sexual Behavior. Context motivates.

5. *Teach through research.* Similarly, authentic research experiences motivate and teach students what statisticians really do. The expanded Center for Interdisciplinary Research (eCIR) has proved to be a great maturation ground for our statistics concentrators (Legler, Roback, Zieglar-Graham, Scott, Lane-Getaz, and Richey, 2010). The eCIR lab promotes creative approaches to data analysis, in collaboration with faculty from across the college. These research collaborations foster closer relationships among the eCIR fellows (our students), between the fellows and faculty, and among the faculty as well. Most importantly, the eCIR fellows are inspired to pursue additional statistical studies.

Conclusion

"For every action there is an equal and opposite reaction." If Newton's law applies, we can expect a big reaction to Cobb's call for curricular change. We need to temper this reaction and heed the call to rethink our content and our teaching. We need to promote the statistical thinking required to analyze today's data. The modern students sitting in our classrooms now have dramatically different data-related experiences than in years past (Gould, 2010). With the heightened expectations of the modern student, our traditional courses are sure to disappoint. Rethinking the undergraduate curriculum is imperative. Cobb has laid out some essential ingredients for our consideration as we stir the curricular pot once again.

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Authentic Data Analysis Experience

Duncan TEMPLE LANG

I'd like to applaud and thank George for a very stimulating and entertaining paper, and the challenge to reinvent the statistics undergraduate curriculum. I am very hopeful that it will lead to real discussions, experimentation and, importantly, significant changes.

Do we need such radical changes to our undergraduate curriculum? To answer this, I hope every instructor will seriously reflect on whether their graduates have the capabilities to perform good data analyses? and whether we could be doing substantially better in this regard? My focus here is on data analysis, broader than statistics, as that is what the majority will do with what they have learned, and is increasingly in high demand.

In my opinion, most of our students are not prepared for data analysis after their statistics major. My explanation is simple—they have done very little actual data analysis. Instead, they have learned methods, solved homework problems corresponding to the method taught that week, and perhaps done a project or a single capstone course. They think there is "one correct answer" and that the data analysis process starts by being told to fit a model or perform a hypothesis test, and ends by reporting the parameter estimates or a p-value. For a model, they may have generated the expected diagnostic plots, but not necessarily have really interpreted them.

Many students enjoy the mathematics, and others lose sight of the "why" of the methods due to the mathematical and computational details. Many see only the deterministic aspects of the methods, and not the variability in the data and the approximations and rough precision needed for the insights and qualitatively solving real problems. They get drawn into the details of a test, only to forget to ask if the observations form the population or a sample, or are dependent. The statistical methods are important elements of data analysis, but there is so much more to the data analysis process than these methods and we don't spend much time teaching these other components. Exploring data is something they may feel compelled to do because that is "recommended", but is an obligation before the "real statistics" are done. Indeed, George says we teach EDA in a first course, but typically, this is labeled "Graphical Summaries" or "Descriptive Statistics" in textbooks. Unfortunately, the very important steps of cleaning and exploring of both the data and the problem are not emphasized as being essential parts of the data analysis process.

While a laudable goal is statistical reasoning, students need to develop, *at least*, a sense of intelligent data analysis, the ability to frame a data analysis question and identify the goals, and the skills to express the necessary computations and create graphical displays. They develop these by repeating the process multiple times, not just once in a capstone course. They must learn the process by first watching how data analysts actually work, via guided case studies. The ideas and motivation of common methods can be introduced at this point without the details. This is, as many have written, quite a different learning experience from presenting a long list of methods and their underpinnings that we typically teach in courses without the actual data analysis context and connecting the thinking to the question. The NSF-funded Explorations in Statistical Research (ESR) workshops (Nolan and Temple Lang 2015) that Deborah Nolan (UC Berkeley) and I organized exposed students to the data analysis process. While very short, they illustrate the need and potential for quarter/semester–long immersion with real data analysis.

Students enjoy exploring data when they understand what is being measured (e.g., cost of apartments in different cities, car traffic patterns, airline delays, climate change, social network patterns.) Students can acquire reasonable computational skills by exploring data. These are the skills they will need to process and analyze data. Given these computational skills, they can then simulate data and explore the characteristics of statistical methods. This can augment, or substitute for, the mathematical understanding for different students.

On reading George's paper, I was led to Friedman's 1997 article on Data Mining and Statistics (Friedman 1997), which led me back to Tukey's "The Future of Data Analysis" (Tukey 1962), and of course to Brown and Kass (2009), and other historical calls for changes to the curriculum. We should reflect on these papers and see how much has changed. Indeed, George writes about adoption of Bayesian statistics: "Statisticians read the arguments, followed the proofs, nodded in agreement, and continued in their pursuit of incoherence." All of these calls for change are important, and I believe statistics education is slowly changing. However, it is too slow and there are many other fields that are providing alternatives, and for teaching the actual practice of data analysis, this may be a good thing.

I recently became the director of the Data Sciences Initiative at University of California, Davis. While there are many logistical challenges, I feel liberated and less constrained. We have an opportunity to develop programs from the ground up, as George is encouraging. There are many constituents hungry for Data Sciences education and research skills that span the entire data pipeline, including data identification, acquisition, cleaning, exploration, visualization, analysis and dissemination of insights. This demand for data pipeline knowledge is something we should embrace. We should work with various different fields (both consumers and producers of data sciences methods) to create students with the essential fundamentals and problem solving capabilities needed in data science. Data science requires data analysis, computational reasoning, and actual experience and practice.

Deciding if and how we should change the curriculum in-

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Duncan Temple Lang, University of California, Davis (Email: dtemplelang@ucdavis.edu)

volves clearly articulating and prioritizing our goals. For me, the ability to be creative, independent, problem solve, work in a team, be able to map ideas into computations and results, and, most importantly, to make sense of data are important for the majority of our students. Whether this involves more or less mathematics, computing, methods, . . . is up for debate and, importantly, experimentation and evaluation. Learning “just-in-time” or “on-demand” is an important skill for problem solving, and can help the students escape the “multiple-choice/one-correct-answer” mindset into which they are led from high-school through college. A mode of teaching that leads students to “discover” traditional statistical methods, rather than just being told them, will be much richer.

George’s suggestions of a “Teacher’s corner” that present innovations and experiences in teaching is a good idea. Facilitating instructors to develop and share case studies and projects would also be very useful. Having these recognized as scholarly contributions could help. While change in the curriculum is hopefully proceeding, we can act more quickly by having students participate in data analysis challenges. These might be as short as the weekend-long DataFest™ that has emerged through UCLA, the ASA, and others, or 6–7 week long ongoing problem solving activities centered around real problems (e.g., extra-curricular team-based data analysis competitions).

Let’s embrace the new opportunities that data science presents and include Statistics in the next generation of data analysis.

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Vision or Bad Dream?

William I. NOTZ

And afterward, I will pour out my Spirit on all people. Your sons and daughters will prophesy, your old men will dream dreams, your young men will see visions. (Joel 2:28)

I thank George Cobb for a thought-provoking and prophetic paper. The following are a few thoughts that occurred to me as I read the paper.

To begin, by the undergraduate curriculum I mean the entire body of courses and programs we offer for undergraduates, from introductory service courses to programs for majors. By statistics department I mean any department that employs faculty with advanced degrees in statistics to teach courses and offer programs in statistics. I will use "the science of data" (a phrase used by Moore (1992)) to include bioinformatics, data mining, data analytics, data science, and big data. Not everyone agrees that these are part of statistics and I use the terms "statistics" and "the science of data" to emphasize this discrepancy.

1. Arguments Concerning Change

1.1 Arguments Against Rethinking our Curriculum from the Ground Up?

- Most departments already periodically rethink (and even formally assess) their curriculum. Are we really in dire straits?
- Graduate programs and employers expect a basic level of competency, but prefer to provide training in additional skills. Perhaps all we need do is provide a basic level of competency, something far less ambitious than what George Cobb proposes.
- We teach (but do not always practice) that extrapolation from the present into the future is dangerous. Will changes we make now be outdated tomorrow?

If statisticians taught all courses in the science of data, George Cobb's case might be less compelling. Unfortunately, the growing popularity of the science of data and the increase in courses taught by faculty not trained as statisticians, makes this both the best of times and the worst of times for statistics departments.

1.2 The Best of Times?

Reports about the science of data appear regularly in the media. Success stories abound. The "internet of everything" will generate massive amounts of data to be mined. The science of data is suddenly "sexy." Students are flocking to our courses and majors. STEM initiatives and employers seeking people with skills in the science of data, increase the chances of funding for statistics departments. Responding to this growing interest in and demand for people who can extract information from data will force us to reexamine our undergraduate curriculum.

1.3 The Worst of Times?

There is a great deal of confusion about exactly what is the science of data. Researchers in many disciplines claim expertise, and hence the right to offer courses and programs in the science of data. Has Breiman's stochastic culture dominated the way we teach and practice statistics, so that Breiman's algorithmic culture is not regarded by outsiders as statistics? If so, it is not surprising that others do not believe they are encroaching on our turf. To quote George Cobb, "do we really want to cede to them all methods that do not rely on a probability model?" To address this, we need to seriously rethink our undergraduate curriculum.

Others have noted that this is both the best and worst of times in statistics. See, for example, Wasserstein (2015), who provides a more thorough discussion of why it is a great time to be a statistician, as well as challenges facing our profession.

2. Miscellaneous Thoughts

2.1 All Curriculum is Local

No department can be all things to all people. Graduate programs vary from one department to another, reflecting the strengths and interests of the faculty. Should the undergraduate curriculum exhibit similar flexibility? For example, in spite of claims that Bayesian inference is an advanced topic, Bayes methods are discussed in all the introductory service courses at Duke University. Dalene Stangl offers a short course in teaching Bayesian methods for teachers in secondary education. Descriptions of courses taught by Mine Çetinkaya-Rundel can be found at *https://stat.duke.edu/~mc301/teaching*. Not all departments will want to emulate Duke, but I hope we avoid overprescribing what the undergraduate curriculum should look like.

2.2 Practice What We Preach

Many of my colleagues insist that all, or nearly all, courses about statistical methods should be taught by faculty in a statistics department. However, in an era of scarce resources, we cannot meet demands for new courses while accommodating growing enrollments in existing courses.

We preach the interdisciplinary nature of statistics, but do we practice it in our curriculum? Should we pursue collabo-

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rative teaching with faculty in other departments, or more radically, encourage faculty in other departments to teach courses in the science of data? Such a suggestion is controversial, and if George Cobb is to be identified with Martin Luther, I may be regarded as an Anabaptist, despised by Catholics, Lutherans, and Reformed. A more cooperative approach to the undergraduate curriculum could involve the following.

- At The Ohio State University, general education courses in data analysis must be approved by a committee. Any department can propose to teach a general education course in data analysis, but must meet guidelines (developed by the Department of Statistics) regarding the content (see *https://asccas.osu.edu/files/ASC_CurrAssess_Operations_Manual.pdf*). At institutions where there is a process for approving new courses, faculty in statistics departments could suggest basic standards that all courses in the science of data must meet to insure some level of quality (see the GAISE guidelines for introductory courses at *http://www.amstat.org/education/gaise/GaiseCollege_Full.pdf* and the ASA/MAA statement on qualifications for teaching statistics at *http://www.amstat.org/education/pdfs/TeachingIntroStats-Qualifications.pdf*). With the growing emphasis on assessing courses and curriculum, statistics faculty could develop the rubrics for assessing courses in the science of data.

  Faculty in statistics departments could provide workshops for or informal gatherings with faculty in other departments to discuss the teaching of courses in the science of data, share ideas, syllabi, resources, or provide training in the use of statistical software. One of my colleagues in the Department of History told me that such workshops were held annually at Grinnell College when he was a faculty member there.

  Faculty in statistics departments could offer to mentor those wishing to teach a course in the science of data. This might involve helping draft a proposal for a course, guiding such a proposal through the approval process, suggesting resources, helping develop a syllabus, or even providing evaluations for the faculty member.

  Faculty in statistics departments could offer to team-teach courses. This would bring together statistical and subject matter expertise.

- Should we consider dual majors and minors for which we share responsibility? For example, at Miami University one can major in statistics as well as in data analytics (the latter is a co-major shared by Information Systems and Analytics, and Statistics).

- What about multiple programs? Rather than a single major, departments could offer multiple majors with different prerequisites, different core competencies, and different objectives.

2.3 Challenges

- Can our faculty agree on what is fundamental? Not too long ago undergraduate majors in statistics were rare. Requirements for acceptance into a graduate program are much less stringent than the requirements for an undergraduate major. What is essential for an undergraduate planning to pursue a PhD is different than what is essential for a student seeking a job upon graduation.

  Even for introductory service courses, what is essential is not clear. One recommendation has been to minimize the discussion of probability. However, to introduce Bayes thinking, students need to know something about probability distributions, conditional probability, and Bayes theorem.

- Most introductory courses in statistics are taught by people without advanced degrees in statistics (for example, instructors in secondary schools and community colleges). We must train such teachers how to incorporate the changes we propose in their teaching. Failure to do so will be a failure to institutionalize change.

  As an example of potential problems, many introductory statistics textbooks begin with exploratory data analysis. One reason is to expose students from the outset to the experience of exploring data in order to learn what the data are saying (see Moore (1992)). This motivates later discussions about the pitfalls that can occur when drawing conclusions from data and how these pitfalls might be avoided. Unfortunately, many instructors teach the sections on data analysis as descriptive statistics, perhaps because this is what they experienced in their first course. They emphasize the process of calculating numerical summaries and making graphical displays, rather than using these as tools to explore what the data are saying. How many instructors expose their students to exploratory tools such as brushing and slicing or linked displays? Introducing algorithmic methods could suffer a similar fate without training others to teach these methods.

  What resources are needed for teachers to teach effectively? Can one introduce students to computationally intensive methods when one is unable or reluctant to require students to use computers? Can one simply rely on graphing calculators? How do we examine students on computer intensive methods when we fear the use of computers on exams will encourage cheating? Shouldn't our methods of assessment match the material we emphasize in class?

- I like George Cobb's suggestions for disseminating changes. Publication of innovations (new courses, new teaching methods, new curricula) in journals, exposing innovations to testing and refinement by the larger statistical community, and eventually institutionalizing change is an excellent strategy. The challenge is finding journals willing to publish such papers. As a former editor of the *Journal* *of Statistic Education*, I suspect that the journal would be receptive to a teachers' corner section.

3. Conclusions

Do we need to rethink our curriculum from the ground up? I believe we do. This will be challenging, but there are both faculty and programs already thinking about and engaged in this exercise who can serve as resources for the rest of us. I again thank George Cobb for his call to arms. Others will decide whether his is a vision for the future or just a bad dream.

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A Response to “Mere Innovation is Too Late”: Data Cowboys and Statistical Indians

Jim RIDGWAY

“Mere Innovation is Too Late” is an important paper calling for reflection and constructive discussions about the future of statistics education. George Cobb offers a metaphor from California real estate, namely that serviceable properties are often rebuilt by their owners to bring them up to date. However, I fear that he has mapped out the most positive scenario for the future of statistics. A “middle ground” metaphor is that of Indian tribes being moved from their reservations to less desirable and less fertile ground—here, statisticians being displaced by data scientists from their sacred territory; a darker metaphor is the fate of the Indian tribes in California in the Mission and post-Mission eras—condemned to servitude, and random acts of genocide. Data cowboys are unlikely to shoot statisticians—but then they don’t need to, because they seem to take over core territory, with rather little effort. Data science is seen to be sexy; it uses data that everyone actually generates (twitter streams, purchasing data, mobile phone locations), and creates applications that are really useful and part of everyday life in developed countries—fingerprint access, speech recognition, weather forecasts, shopping and vacation advice. So there is an existential crisis for statistics—if you can ride the data revolution, who needs a statistician? Well, some statisticians think you do.

“Most real life statistical problems have one or more nonstandard features. There are no routine statistical questions; only questionable statistical routines” (Cox, quoted in Chatfield, 1991, p. 240). “All models are wrong, but some are useful” (Box and Draper, 1987, p. 424).

Statistics has its origins in solving novel, practical problems. Both the Royal Statistical Society and the American Statistical Association were established by heterogeneous collections of individuals united by a common goal to tackle exciting problems by inventing methods and mathematics (see Pullinger, 2014). A problem for statistics education is that the curriculum devotes too much time to modeling well-understood problems with traditional (1920s) methods, and too little time modeling unfamiliar ones—thereby ignoring the raison d’etre of the discipline. Here, I consider introductory statistics courses.

Many introductory courses focus on one- and two-variable problems, work with small samples, and use made-up data. This runs real risks, pedagogically, namely reinforcing the common notion that every sample is representative of the population from which it is drawn, and that small samples are as representative as large ones (i.e. Tversky and Kahneman’s (1974) “representativeness” heuristic). Starting from one- and two-sample problems makes the leap to understanding multivariate data, and notions of interaction, rather difficult. Similarly, the emphasis on correlation and linear relationships makes the idea of nonlinear relationships hard. The range of applications of this approach is narrow (assuming additivity and linearity even in school science would be a big mistake). Some positive alternative approaches can be found in Ridgway (2015).

I agree with George Cobb that a focus on mathematical technique hides statistical ideas, and with his assertion that accessible ideas (e.g. Bayesian inference) are made obscure by dressing them up in heavy mathematics. Rakow et al. (2015) reported presenting funnel plots on outcomes from child heart surgery to 172 participants (a quarter of whom had no education beyond compulsory schooling) who (predominantly) were related to a child under the care of a specialist cardiac unit. The researchers asked questions which required an understanding of the funnel plot, and questions about which hospital or surgeon to choose. Around 90% of the responses were correct. They concluded that “. . . funnel plots can be readily understood. . . ” (p.327). Our own work supports the assertion that formal mathematics is not necessary for the understanding of important statistical ideas. We used Rasch scaling to show that computer-based problems involving three variables can be easier (in psychometric terms) than one and two variable problems presented on paper (Ridgway, McCusker and Nicholson, 2003). We have also shown that statistically naíve students aged 16 years can express sophisticated ideas such as interaction, nonlinear functions, and piecewise functions when asked to describe patterns in data presented in interactive displays (here, on alcohol use by young people, sexually transmitted diseases, and photosynthesis). Data visualisation makes it possible for students to explore large, authentic data sets and to reason about complex situations using these data. For example, we created the *constituency explorer* in collaboration with the House of Commons Library. This presents data on 150+ variables (demographics, health, voting patterns in two national elections etc.) relevant to every constituency in the UK in a visualization that runs on desktops and mobile devices. The primary target audience was politicians and their aides, but the resource has been used in the teaching of political science, social history, and geography, as well in school statistics classes. Is this approach strong on short term gratification and weak on long-term need? It *is* strong on short-term “wow”, but it can also bring core statistical ideas into introductory courses (data provenance, metadata descriptions, nonlinearity, discontinuities, and effect size, as well as means, medians and spread).

The range of phenomena that need to be modeled has expanded, and students know it. Linear additive models are not the only game in town. For example, analysis of Wikipedia use has been used to predict stock exchange movements (Moat et al. 2013). The key words associated with upward and downward movements are in the public domain. Should you use these

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keywords when making investment decisions? Students have created imaginary traffic jams on Satnavs (see Bilton, 2104). These examples illustrate situations where agents can "game" important systems for their own purposes. Modeling systems is hard; modeling systems undergoing change is harder; now students are familiar with systems undergoing change that are "self aware". Should we be teaching students 1920s mathematics, or introducing big statistical ideas relevant to their own lives? Can we cede all algorithmic thinking to data science? A modest set of targets for statistics education is: use data visualisations of big open data sets to teach big statistical ideas; teach about the statistics that underpin the lived experiences of technology-savvy students (notably pattern recognition in its many applications); introduce modeling, early. And make friends with the data cowboys.

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Challenges, Changes and Choices in the Undergraduate Statistics Curriculum

Jessica UTTS

George Cobb has (yet again) written a thought-provoking and entertaining article that should be required reading for anyone involved in the training of statisticians. My reactions when reading the article ranged from agreement with the main ideas to pessimism about the viability of implementing them. My pessimistic side predicts that the recommendations will meet the fate Cobb describes for Bayesian methods before computing made them tractable, namely "Statisticians read the arguments, followed the proofs, nodded in agreement, and continued in their pursuit of incoherence."

What changed the landscape for Bayesian methods was not only that computers made them tractable, but that a few innovative leaders made it easy for others to implement and teach them by writing textbooks and computer programs that could be used in the classroom and the consulting room. We need those innovators if we are to implement the widespread changes recommended in Cobb's article.

My optimistic side kicked in when I realized how much and how quickly things have changed during my academic career. It's hard to remember that it wasn't until at least 10 years after I started teaching that faculty members were given individual computers, rather than relying on single mainframe computers that served the whole campus! And in 1987 when I took a one year leave of absence to work at SRI International I became one of the first in my academic circle to have an email address. Commercial email providers didn't become popular until the mid-1990s. We have come a very long way in a very short time. And the pace is quickening.

In the remainder of this commentary I address a variety of unrelated issues brought to mind when reading Cobb's article. The first is a reminiscence of the workshop and article that led to my first published commentary (Utts, 1986), in Volume 1 of *Statistical Science*, in response to an article titled "Computers in Statistical Research" (Eddy, 1986). Next is an exploration of why undergraduate degrees in statistics should be offered at all. And third is a discussion of what happens after graduation, and indeed, to those who have graduated already.

The aforementioned *Statistical Science* paper was a commentary on an article (Eddy, 1986) about how academic statistics departments were beginning to acquire their own computers, and speculating on how this would affect the future of research in statistics. The article was the culmination of a workshop on the topic, and should be required reading for anyone who thinks the statistics profession has not changed in the past 30 years! The relevance of my 1986 commentary to the Cobb article is that I outlined a science fiction story then that I feared would be upon us 30 to 40 years hence, in other words, just about now. The essence of the story was that statisticians were no longer needed because the "black box" was able to do everything automatically: spitting out p-values, confidence intervals and conclusions without any need for the thoughtful input of a human. But eventually someone realized that results were being generated that made no sense. When they tried to figure out what was in the black box it was impossible to do so, until they located some ancient statisticians who actually remembered the reasoning that used to be part of the decision-making that accompanied the algorithms. Let's make sure we don't go there!

Any discussion of what should be covered in the undergraduate curriculum needs to take into account the fact that the reason for having an undergraduate degree in statistics is changing rapidly. What will become of our undergraduates? A small percentage of them are likely to attend graduate school, but the rest are likely to get jobs that involve working with data. What do they need to know to be hired, what do we want them to know once they start working, and are those the same? We need information on what kinds of jobs our bachelors' level graduates are getting, but anecdotal evidence indicates that the jobs they are getting require more computing skills than high-level statistical thinking. I agree with Cobb's view that we need to train our students to combine algorithmic thinking with probabilistic thinking, even if it is not immediately obvious that they need the latter for these data-crunching jobs. Otherwise, it is too likely that my science fiction story will become reality.

The biggest challenge our graduates will face (eventually) is the same one that probably faces most professionals in this era, and that is keeping current with changing technology and methodology. As a profession, I think we need to vastly increase our continuing education offerings. I've restricted my comments to the undergraduate level because that's the focus of Cobb's article, but I think we need more continuing education at all levels. I agree with Brown and Kass (2009) that no one can be expected to know all areas of statistics anymore—there are simply too many specialties, and effective statisticians need to learn a good deal about the disciplines in which they collaborate in addition to keeping current with developments in statistics. As a profession we need to develop mechanisms for offering continuing education in addition to the ones currently available (such as short courses and webinars).

One final note is that I think the emergence of undergraduate programs in data science is a good step forward. It is easier to think about implementing change when it's viewed as part of a new major than a revision of a current one. But even within existing statistics majors, I don't think radical change is needed to implement the ideas put forth by Cobb. Changes to existing courses could easily be made that would accomplish much of what Cobb recommends. And it is only on this final point that

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Jessica Utts, University of California, Irvine (Email: jutts@uci.edu).

I disagree with Cobb. I think an appropriate amount of "mere" renovation would be sufficient to create the effect he wants. But we need innovators to make it happen.

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Teaching Statistics Algorithmically or Stochastically Misses the Point: Why not Teach Holistically?

Richard De Veaux and Paul F. Velleman

"It takes judgment, brains, and maturity to score in a balk-line game, but I say that any fool can take and shove a ball in a pocket... you've got Trouble..."
—"Professor" Harold Hill (*The Music Man*)

We agree with Professor Cobb on the need to reconstruct the undergraduate statistics curriculum. But if we are to "preach what we practice," we must first examine what we practice. Viewed as a whole, the practice of statistics hasn't really changed, although methods continually evolve. We should not allow debates about methods, whether algorithmic or stochastic, to distract us from teaching a holistic understanding of what statisticians actually do. The challenge of sound statistical practice has been discussed for decades, but apparently with less impact on statistics education than we might hope for. Consider, for example, these two wise comments, each decades old.

Feinstein (quoted by Zahn 1985) said nearly 50 years ago:

> A clinician is taught to identify and formulate patients' problems in a carefully structured manner; but he is then left to develop diverse tactics of "judgment" for managing the outlined problems. A statistician is taught a carefully organized set of mathematical structures for managing an outlined problem; but he is left to develop diverse judgmental methods for identifying and formulating the problem. The clinician may emerge able to express the right questions but unable to find the answers; the statistician may emerge with the right answers but unable to select the questions.

William Hunter (1981) advocated a solution to this challenge: Statisticians should work as *colleagues* with scientists and others with whom we consult. In that role, we must comprehend the entire enterprise. Hunter pointed out that the first step in collaboration is for the statistical consultant to work with the client to formulate the best question.

> Therefore, it is of the utmost importance that in each new situation the consultant try to discover what the real problem is. To avoid the mistake of solving the wrong problem ... (p. 73)

Kimball (1957) called finding the right answer to the wrong problem a Type III error. We must teach our students to avoid such errors.

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Richard De Veaux, Department of Mathematics and Statistics, Williams College. Paul F. Velleman, Department of Statistical Sciences, Cornell University (Email: pfv2@cornell.edu).

Undergraduate statistics education often focuses too much on methods rather than taking this holistic view. It matters little whether the analysis tests the equality of two means with a classical t-test or with a resampling approach if the conclusions of the test are invalid from the beginning. Rather than debating the choice of t-test versus a decision tree, shouldn't we first ensure that the comparison is a scientifically valid one?

To follow Hunter's advice we must ask questions such as whether the data allow generalization to a larger population, whether their structure can be meaningfully described with the models we wish to fit, and whether important subgroups or individuals were excluded from the data. In the decades since Hunter's article, we have seen the development of graphical and diagnostic tools that make it even easier for the statistician probe data to see whether a model is appropriate and to identify unusual or influential groups and cases.

The answers to these questions (or, of greater concern, the violations of the naíve assumptions our methods have been making) often emerge *during* a careful statistical analysis. Because of this *it is essential that the statistician participate in the analysis*. It is statistical malpractice to turn the data over to an automated algorithm, to, as Professor Hill would say, simply shove the data into the pocket of a particular analysis.

Exceptions, anomalies, outliers, and subgroups are best recognized and understood in the context of the question being addressed. That is why the statistician must be, as Feinstein would want, fully conversant with both the right question and the statistical methods being applied. And that is why fully automated methods cannot be trusted to produce statistical analyses on their own; computers don't (yet?) understand the real world sufficiently to take a holistic view of the analysis. But the trained human mind and eye are remarkably effective tools for spotting unanticipated patterns and exceptions and understanding what they might mean in the context of the question being investigated. So that training is essential.

Rather than focus on the methods used to solve the problem, we must teach the entire process by which the statistician probes for the correct problem formulation, translates that problem into a statistical question, finds an appropriate method to solve that problem, and then communicates the result back to the scientist. The methods themselves are important. Indeed, as the American Dental Association Seal of Acceptance says (to paraphrase), they "have been shown to be of significant value when used in a conscientiously applied program of [data] hygiene and regular professional care." But conscientious application is the requisite element. Simply replacing a stochastic method by an algorithmic one will not help. We believe that the current statistics curriculum focuses too much on the method rather than on the conscientious application of methods in the context of the question to be addressed, and that "data science" exacerbates this trend.

It is certainly wise to provide our students with a full quiver of methodological arrows. But (to mix our sports metaphors a bit) we must not ignore the target. We must teach the entire process of developing a question that can be addressed with the available data and examining the data before, during, and after an analysis in nearly every undergraduate course we offer. By the time statistics majors come to the capstone course, typically during their final year, the approach should be second nature, not something they see for the first time.

This process requires "judgment, brains, and maturity." Perhaps that is why after decades, our statistics courses still have not moved sufficiently in this direction. We should try to teach judgment, and our students certainly have fine brains, but maturity comes only with experience. We must take the time to give students practical experience in data analysis.

Ignoring the more difficult parts of this process and concentrating only on the algorithmic part (as the worst practices of data science do) is an abdication of our responsibility as statisticians and educators.

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Learning Communities and the Undergraduate Statistics Curriculum: A Response to “Mere Renovation Is Too Little Too Late”

Mark Daniel WARD

George Cobb urges the Statistics discipline to “rethink” the entire undergraduate curriculum. As I was reading his excellent, thought provoking article, I was asking myself, “Why do students continue learning Statistics on college campuses at all?” After all, Cobb points out many excellent books, which treat Statistics and Probability from broad points of view. Students can also fall in love with Statistics through data driven projects, many of which can be explored on the Internet, during internships, or in research opportunities related to data analysis. So what distinguishes the undergraduate academic experience in Statistics on a college campus from what a well-motivated student could learn on her/his own, from the excellent books, journal articles, and online resources, including those that Cobb cites in his paper? Answer: A sense of community. Learning communities are sometimes called “communities of practice” (see Lave and Wenger, 1991, p. 49). They provide an excellent environment for students to practice what they are learning (e.g., to apply statistical methods) at a much earlier point in their studies, much as Cobb urges. Although Cobb also points out that “all curriculum is local” (p. 34), nonetheless, I believe that some of the initiatives we recently began at Purdue could be implemented much more broadly, in Statistics departments nationwide. The Purdue Statistics Living-Learning Community blends the academic, research, residential, and professional development experiences of 20 sophomore students per year. We briefly discuss Purdue’s new initiative here, but we also refer interested readers to visit *http://llc.stat.purdue.edu* and to contact me directly.

Students in a learning community have a sense of comfort and confidence that is often missing from the undergraduate STEM experience. This comfort promotes retention. Cobb does not explicitly mention retention in his article, but if we are completely revamping the undergraduate program, we are obligated to keep retention in mind. If learning communities were implemented more broadly in Statistics undergraduate programs, our discipline could potentially increase the numbers of women, minorities, and persons with disabilities, who are pursuing (and completing) undergraduate degrees in Statistics. This would yield a broader and more diverse pipeline of students into graduate programs in Statistics. Project INGenIOuS (Zorn et al., 2014) has a great vision for broadening the pipeline in the mathematical and statistical sciences. Our discipline could also benefit from best practices learned in Computer Science about attrition and students’ comfort levels; Margolis and Fisher (2002) give a helping starting point to this literature.

Cobb states, “statistics suffers from the difficulty of its challenge to integrate abstract deductive thinking with interpretation in context.” To address this, faculty can offer pairs of Statistics courses in block-scheduled patterns, such as theoretical probability paired with data analysis. When students take multiple courses together as a cohort, they have more opportunities to discuss complementary ideas, outside the classroom. Residential life staff members can work with faculty on ways to supplement the academic learning experience. Professional development helps too, and it can consist of simply a series of weekly seminars. Also, faculty who take the time to dine with students in the residence hall cafeterias are richly rewarded with good discussions and increased insight into the student experience in Statistics. These are just a few extracurricular ideas; many others are possible.

Cobb celebrates diverse means of presenting the material to students. Such innovations, such as “flipped” classroom experiences in Statistics, can help us to better engage with students. At Purdue, I use video content and online modules in both my probability and my data analysis courses. Instead of lectures, the students spend class periods working on problems in probability or projects in data analysis. So that our questions are appealing to students, Ellen Gundlach and I asked undergraduate students to design the majority of the examples that we included in our recent textbook, Ward and Gundlach (2015).

Cobb calls for students to get involved in research at an earlier stage in their studies. For large data analysis projects, students can benefit from having immersion into a yearlong project with a research mentor from another discipline. Students learn not only about the data set to be studied, but more broadly, they learn about the terminology, customs, literature, and traditions in the applied discipline. Such an interdisciplinary view gives the students a renewed appreciation of the concepts that they learn in their Statistics classes. I believe that these research projects exemplify what Cobb is mentioning, when he discusses the crucial role of “context as a source of understanding” (p. 21).

Immersive research experiences will require improved computational facilities dedicated for student use. Cobb alludes to this need. Some departments will require a strong push—for internal or external funding—to secure sufficient computational resources.

Academic advisors should be invited to the discussion about the kind of curricular overhaul that Cobb is advocating in Statistics departments. Academic advisors are often uniquely positioned to guide students who are pursuing double (or triple) major programs of study, or minor programs that complement their main areas of interest. Students in Statistics can naturally be encouraged to pursue double majors, since Statistics complements many applied areas of study. Cobb discusses the need to minimize prerequisites. This goal is accomplished more easily

Online discussion of “Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up,” by George Cobb, *The American Statistician*, 69. Mark Daniel Ward, Department of Statistics, Purdue University (Email: mdw@purdue.edu). This material is based upon work supported by the National Science Foundation under Grant No. 1246818.

when academic advisors are able to give direct input to the curriculum design. They understand a student's view of the overall curricular structure at the university or college.

The ASA DataFest is emerging as a way that the American Statistical Association is working with faculty on several campuses, to give students a very exciting annual data analysis experience. Among the many activities in Statistics at Purdue this year, the students cited the ASA DataFest as one of the most rewarding and enjoyable events. I encourage the ASA to continue recruiting more departments to host ASA DataFest events for undergraduate students.

I applaud George Cobb for his vision about the entire undergraduate curriculum in Statistics. His paper is full of insights and innovative ideas! I also thank Cobb for pointing out several very recent innovations in the undergraduate Statistics curriculum, including Kuiper and Sklar (2013) and Wagaman (2013). Finally, I heartily thank Nolan and Temple Lang for their workshops on "Integrating Computing into the Statistics Curricula"; see Nolan and Temple Lang (2010) for an overview of their efforts to implement changes. My participation in their workshops inspired me to start Purdue's Statistics Living-Learning Community, with large research projects for sophomores as a unifying element. Cobb is urging all of us to do more, to try new things, and to continue the dialogue about how innovations can support our students.

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Teaching Safe-Stats, Not Statistical Abstinence

Hadley WICKHAM

I thoroughly agree with George Cobb that it is time to rethink the statistics curriculum. We are at grave risk of becoming irrelevant, not because we are useless, but because we have focussed too much on doing the right thing, rather than doing something that works. As a field, statistics tends to lean towards abstinence based outreach: you should only do statistics if you're in a committed long-term relationship with a professional statistician. If you experiment on your own (or with friends), you will hurt yourself and others. Abstinence based approaches don't work because people will take the risk anyway, and most of the time they will safely enjoy themselves. Abstinence based statistics is particularly problematic as there are simply not enough professional statisticians to go around.

Rather than stigmatizing amateur statistics, we should be doing out best to provide tools to make it safer. We can't force people to use our tools (as much as we'd like to!), so those tools must be more fun and more empowering than the alternatives. The undergraduate statistics curriculum is a vital place to develop and promulgate these tools. As statistics grows ever more popular, we must be able to provide a curriculum that give students the skills they need to practice safe-stats for the rest of their lives.

To me, one of the keys to teaching safe-stats is to develop grammars of data analysis. A grammar is a framework that lays out the minimal set of independent components and a means of composing them to solve a wide range of problems within a domain. Much of my own work has been in this area: How can we provide an accessible grammar of graphics (Wilkinson 2005) that makes it easy to create graphics tailored to the problem at hand (Wickham 2009)? What are the verbs of data manipulation that allow us to solve 95% of problems (Horton, Baumer, and Wickham 2015)? What are the key components of tidy data, and how can we tidy messy data (Wickham 2014)?

The best grammars are both flexible and constraining. Once you've seen the grammar used to solve two problems, you should be able to recombine the pieces to solve a third, new, problem. But a grammar also needs to be constraining: unmitigated freedom is both overwhelming and potentially dangerous. Constraints can guide users towards better outcomes, but can not guarantee them. A system that prevents the user from doing the wrong thing must necessarily prevent many right things. (A personal example is the use of rather elegant ggplot2 graphics in the paper discussed by Singal 2015.)

To have that needed flexibility, a grammar must be embedded in a programming language. This offers an escape clause: each grammar need solve only the 90% of most common problems, leaving the long-tailed 10% to other parts of the language. This implies that statistics students must be taught to program.

Teaching programming even in the first statistics course is eminently achievable, as Baumer et al. (2014) and others have shown. The key is to focus on immediate pay-offs. You don't need to study the foundations of programming before you can start to program data analyses. Students can start with recipes, code snippets that students can use and adapt, to show immediately useful (and interesting) tools. Over the length of the course, students can grow from simple duplication to creative rearrangement of entire components.

We must give statistics students the skills to dive into the data ocean. Yes, there are sharks and jellyfish and rip tides, but we can not be paralyzed by all the potential dangers. Students will go swimming with or without us, and all we can do is prepare them as best we are able.

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Further, Faster, Wider

Chris J. WILD

Cobb (2015) is right on the money when he says, "For our profession, the valuable territory is the science of data," It is a territory we once had largely to ourselves but, as it expands rapidly and becomes more densely populated, we are sharing it with waves of immigrants and are in danger of becoming just one more indigenous people subsisting invisibly in the shadows of their homeland. Our competition, Cobb says, "takes place in the marketplace of ideas." It also takes place in the marketplace of credibility, in the marketplace of influence, in the marketplace of great jobs for graduates, in the marketplace of access to the best and brightest young minds, and in the marketplace of educational curriculum share. When business and organisations, as well as science, need to gain valuable insights from data, "Who you gonna call?"

As I have been reading Cobb (2015) I have also been reading the ASA Curriculum Guidelines (2014) and Diggle (2015), Peter Diggle's Royal Statistical Society Presidential Address paper. In stark contrast to the expansive vision of undergraduate statistics in Cobb (2015) and the ASA Curriculum Guidelines, Diggle says, "I would like to see less statistics in undergraduate mathematics degrees," This matters because in the UK, "most academic statistics groups now sit within departments or schools of mathematics or mathematical sciences." He did go on to talk about less statistics in undergraduate degrees being "counterbalanced by a radical expansion of postgraduate statistics teaching." But this is our old model, the conversion model whereby one obtains students to fund the discipline and replace its aging research-academics by attracting people into the fold who thought they were heading someplace else—generally into mathematics. It has been a long time since statistics graduate-programmes in western countries have been able to attract sufficient of their own nationals to be sustainable. They have been saved from withering only by an influx of students from poorer countries, mainly in Asia. Is this forever sustainable? Is this what "success" looks like?

This clash of viewpoints is a manifestation of big-tent versus small-tent statistics; see Rodriguez (2013); the "wider view" of Marquardt (1987; see also Wild, 1994, 2015) versus his narrower views; the "greater statistics" of Chambers (1993) versus his "lesser statistics," and the "wider field" of Bartholomew (1995). Big-tent statistics is increasingly favoured by the ASA as both its strategic and its service-to-society stance. It also underpins whether you see your role as educating a small number of great scientists in a fairly narrow if pure tradition, or education on a much grander scale to build a statistically capable society—as building a narrow tower or a broad-based pyramid, a select priesthood or a mass movement.

Online discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum From the Ground Up," by George Cobb, *The American Statistician*, 69. Chris J. Wild, University of Auckland (Email: c.wild@auckland.ac.nz).

Does this really matter? It matters because statistics has an ancestry of great thinkers whose wisdom needs to be preserved and passed on. It matters because statistics has important messages for all of society, not just a few scientists. It matters because, "Those who ignore statistics are condemned to reinvent it" (attributed to Brad Efron by Friedman, 2001) and their ignorance can do real damage in the meantime. It matters because statistics is in a bad position to promulgate those messages because of the pitifully small market share it has in the educational curriculums of almost all countries. It matters because data is currently seen as exciting and valuable, and the people who know how to gain value from it are highly sought after. It matters because there has never been a better time for getting attention and market share for teaching a modern, accessible, data-centric statistics than there is right now.

Statistics education has an opportunity to help a wide cross-section of students come to a much broader appreciation of what data is and what it can do for them and society. It has an opportunity to help all students to make better sense of their world using data, to be not-easily-misled, and to prepare for a burgeoning job market. It has an opportunity to harness the power of visualization to greatly enhance the statistical understanding of a much wider spectrum of society. We can do so much more than just passive "statistical literacy," we can build significant statistical capability.

Where are most of the innovations fostering big-tent statistics education coming from? Mainly from elite U.S. liberal arts colleges like George Cobb's. They are a distinctive U.S. national treasure. With a few rare exceptions, research-universities are reactionary forces. They slow down any expansion of statistical vision because they are squeezed between the pincers of ranking systems, research assessment frameworks and research funding systems that favor traditional areas of strength and a narrow range of journals. To get promoted or funded, it is much safer to stick to your (predominantly mathematical) knitting. At this time of heightened opportunity, the needs of the wider society and the employment marketplace (more data, more accessibility to statistical capability) and the short-term health of many research-university academic units (more mathematics) seem to be pulling in opposing directions.

As with all of Cobb's writings, this paper is a joy to read both for the vividness of his imagery and his provocative messages. We have just started to settle down and get comfortable after his last onslaught when along comes George Cobb again, poking us once more with a sharpened stick. So we will pick ourselves up and lurch forward, making a little more progress.

I agree entirely with Cobb's thesis of a radical re-thinking of the curriculum from the ground up, particularly for intro and early applied statistics courses. The standard intro course has passed its use-by date. It reveals far too little of the exploding world of data and does it far too slowly. In the early stages of statistical education, I favor actually outdoing the fast-food competition by providing even faster food. The early stage relationship should have more in common with "courtship" than "eat-it-because-its-good-for-you" gruel. To summon up a phrase I use in talks, "Don't make students crawl over broken glass—until a desire has been aroused for what's on the other side."

I am all for the ambitious experimentation Cobb praises and advocates to push the limits of what we can do without (or with very few) pre-requisites. Where students will take many of these courses it may, fittingly in this big-data age, enable educational timespans to be shortened by massive parallelization using divide and recombine (see Cleveland and Hafen, 2014)!

But the end aim should not be a smorgasbord of choose-one intro courses each covering a small number of "advanced" topics at an intro level. The data world is exploding in scope and potential and we need to efficiently convey as much as possible of the scale and excitement of this in intro courses as well as providing personal empowerment—to create a sense of possibility and potential "for me in my life," not just something for some high-powered PhDs somewhere. We should target "What I can do with data and what data can do for me" to build a desire to learn more. Beginning experiences of data analysis should feel like driving a shiny sports car at breakneck speed along the Riviera, sliding around hairpin bends overlooking thrilling vistas. We spend too much time in working in windowless workshops with our heads stuck under the hood. This is not fanciful reverie. I have done enough prototyping with my iNZight (*http://www.stat.auckland.ac.nz/~wild/iNZight/*) and VIT (*http://www.stat.auckland.ac.nz/~wild/VIT/*) software projects and "Data to Insight" MOOC (*http://www.stat.auckland.ac.nz/~wild/d2i/4StatEducators/*) to believe that this is within our grasp. If struggling to get the right stuff out of software chews up a significant proportion of intro students' time then its the wrong software.

And let's stand some common practices on their heads. Let's excite students about what can go right before moderating that with "keep yourself safe" messages about what can go wrong. Let's distinguish between the fundamental statistical messages and enabling skills. Where time is short, let's concentrate on fundamentals and strive for the fastest ways to convey them. I fully favor the expanded curriculum that empowers students to speak the enabling languages used by statisticians (computing/algorithmic, graphics/visualisation, and mathematics). But they are not the fundamentals. They are great enabling skills for helping people on their way once they know where they are going. Visualisation, stands out from the others because it can provide a fast track to understanding fundamentals.

I applaud the more "data-science" agenda for those making a serious commitment to statistics. Integrity (Section 2.2) also demands that undergraduate statistics programmes provide good employment skills for the majority who will not go on to further study. There are more of these in the "data science" aspects of statistics than in most of what we have traditionally stressed. But we have to consider the striptease of what to reveal and when. Not everything we newly think is important has to be revealed straight away.

I worry about starting too early with wrangling messy data. Yes we need to teach statistics majors to deal with messy data. But extracting jewels from gloop is not something most people do because they love messing around in gloop. They want the jewels. But first they have to know (i) that jewels exist, and (ii) they might be in there. So lets first have them discover jewels in places where they are easier to find. Also coming into vogue for intro courses is working in "reproducible-research" modes. Yes statisticians should work like this, and yes, there is a stage in a program where it should become the standard way of operating. But all these things slow down what you can see and how fast you can see it. There should be a sniff test. Is this an enticing element of courtship? Or do I feel the skin-pricks of glass shards? So should we save it for after marriage? Or at least till after moving in?

Can statistics secure a central position in the new data world? Is there a will to find a way? Sadly I think statisticians in the best liberal arts colleges and Bob Hoggs BIG (Business, Industry, and Government) offer more hope than most research universities. The former want it. As to the latter, Im not so sure.

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Teardowns, Historical Renovation, and Paint-and-Patch: Curricular Changes and Faculty Development

Andrew ZIEFFLER and Nicola JUSTICE

When Nicola and I agreed to write a discussion for George Cobb's paper, "Mere Renovation is too Little too Late: We Need to Rethink Our Undergraduate Curriculum from the Ground Up," we knew that one of the more difficult tasks would be to respond in under 1000 words. The first thoughts we had after reading Cobb's paper were… "we agree that the current consensus undergraduate curriculum George refers to is out-of-date and needs to be up-dated." The second thought, almost instantaneously thereafter, was, "how will such a change happen, particularly given all of the potentially affected stakeholders?" (faculty, students, alumni, administration, client disciplines, etc.) And the third, much more cynical thought, after several minutes of discussion was, "this may be impossible."

As we cogitated over Cobb's vision, we kept returning to the seemingly difficult question of how to get stakeholders to buy-in to the immense amount of work involved in curricular revision. Curriculum of any kind is a statement about the values and cultural norms of a discipline. It is the educational process through which aspiring members of the profession gain knowledge, skills, values, habits, and attitudes. Curricular revision is at its best difficult, and can be quite controversial due to the conflicting views that inevitably emerge, and in some cases may even be divisive (e.g., the reading and mathematics wars; see Schoenfeld and Pearson, 2009). All that being said, George has an uncanny ability to illuminate the large problems that need solving in the discipline and motivate others to rise to the challenge of making the "impossible" possible.

We envision that realistically, any kind of lasting change of the type Cobb is proposing will occur, initially, at the local level. If so, then perhaps it is fitting to ask: (1) does my institution's curriculum need changing; and (2) if it does, what level of curricular revision is palatable to local stakeholders?

In answering the first question, ASA's *Curriculum Guidelines for Undergraduate Programs in Statistical Science* (Horton et al., 2014) and Cobb both offer compelling reasons that most institutions' statistics curricula need revision. But, we hope it is also in the nature of any particular statistics program to collect the evidence needed to evaluate their own situation; as Reagan said, "trust… but verify." There are several questions that can guide the collection of data, depending on what the local stakeholders value. For example (adapted from Preskill and Catsambas, 2006, pp. 101–103),

- What are the objectives for the curriculum, and is it achieving those objectives?
- What are the needs of those closest to the program (e.g., students, faculty, etc.), and is the current curriculum meeting those needs?
- What are all the effects of the current curriculum on students, including any side effects?
- What are the local and more global arguments for and against the current curriculum (cost–benefit)?
- Would an educated consumer (student) choose to study under the current curriculum?

If the data collected support curricular revision (and we sincerely believe it most often will), then it follows to consider the second question, regarding extent of the needed revision.

Using his real-estate metaphor, Cobb proposes a "tear-down" of the undergraduate curriculum—a complete gutting and rebuilding. Unfortunately, as Robin Lock reminded us in his 2005 discussion at the Joint Statistical Meetings, most attempts at curricular revision are not complete tear-downs, but rather, "paint-and-patch," fixing a few things that didn't work quite so well; mostly just sprucing things up. Cobb recognizes this, pleading that, "we do more than just graft a single new 'big data' unit onto an existing course." Of course, there is also something between these two extremes, a "remodel" akin to leaving the over-arching structure in place, while updating some things, rebuilding others. There is potential for "historical preservation"—trying to save structures and architecture, while at the same time updating and renovating, all while spending more resources than it would have taken to tear-down and rebuild. Granted, such an approach may be easier to navigate, politically.

When choosing a model of curricular change, it may be appropriate to revisit some of the evaluation questions listed above, but with more focused consideration on changes in the curriculum. For example,

- What are the needs of those closest to the program, and what scale of curriculum changes could meet those needs?
- What are all the potential effects of changing the curriculum on students (and faculty), including any side effects?

Other guiding questions may be:

- What can our faculty and staff afford in terms of time?
- Is there financial help available from the institution?
- Are there parts of the curriculum that can be saved or retained?
- What kind of construction debris are we willing to accept while we do the revision?

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- How will the changes eventually impact curricula to prepare students (high school) and to follow up (graduate studies)?

It is imperative in making and considering curricular changes that we also consider how those changes could affect the development of current and future teachers of statistics. There are many academics that are comfortable teaching the consensus curriculum. How will the community help them to teach potentially new courses that include content with which they are drastically less familiar? And, are those faculty members willing to engage in this preparation? It also may be that the changes in content may need to be accompanied by changes in pedagogy; faculty may need to transition from "let me, the expert, tell you" to an approach of "let's learn this together," an approach we acknowledge is far less comfortable for many instructors.

Finally, the rapid change we have observed in the discipline, especially in the last 10 years, make the curricular changes Cobb proposes more urgent, and at the same time, more difficult—it is easy to imagine that by the time a curricular revision is finished it could be almost immediately out of date. It may well be worthwhile to consider how to establish flexibility within the curricular structure to accommodate the inevitable changes that will continue to accompany the evolving discipline.

While the challenges Cobb lays out are numerous, the goal is admirable, and is worthy of deep thought and reflection. Using the tools of our discipline—data and analysis—we should be able to critically evaluate our current statistics curricula and make quality, informed improvement to them. How this occurs will no doubt be at the heart of many future conversations and scholarly debate, but with this paper, George has certainly begun that discussion.

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Rejoinder to Discussion of "Mere Renovation is Too Little Too Late: We Need to Rethink Our Undergraduate Curriculum from the Ground Up"

George W. Cobb

1. Introduction

What a failure! I worked so hard to be provocative only to have Gelman and Loken call me "typical," have DeVeaux and Velleman dismiss me as "beside the point," and have Notz fantasize that I might be only "a bad dream."[1] Wild, obliquely through his title, sneers at my challenges: not far enough, not fast enough, and not broad enough. Clearly my race is run. I was right to retire five years ago.

Of course my sample of characterizations is grossly biased, both by selection and by quotation out of context. In reality, I feel honored that so many colleagues whose work I have long admired have taken the time to read what I wrote, to think deeply in response, and to write such a variety of original comments. What a picnic! I won't go there, however; at least not in musteline clothing. But picnic, yes: I and all the respondents agree in wanting to make our blanket-buffet of statistics both more attractive and more substantive. In particular, we can agree with Fisher and Bailar that ours is a time of opportunity.

In what follows, rather than respond individually to the 19 sets of authors one at a time noting points of agreement and disagreement, I attempt to synthesize and respond by categories of topics. Accordingly, Section 2 summarizes and celebrates the variety of innovative courses and programs described in the responses. Then Sections 3 and 4 address two apparent misunderstandings and two major disappointments. Next, Section 5 offers a summary of the challenges and strategies for reform suggested by the respondents, and Section 6 follows with a call to redirect research in statistics education to help meet those challenges. Section 7 outlines a triangular tension: our subject, our university departments, and our U.S. liberal arts colleges. A valedictory Section 8 concludes on a note of constrained optimism.

2. Our Resplendent Picnic of New Programs

A disadvantage of the response/rejoinder format is that points of disagreement tend to get more space in the rejoinder than do points of agreement. There is far more to celebrate in the many innovations described in the responses than the length of this section might suggest. The academic levels of these innovations span the range from K–12 through graduate school (and beyond: Utts urges "continuing education" and Gould urges "K-retirement"). The institutions impacted include grade schools and high schools, all levels at four-year colleges, and graduate programs at universities. The scope ranges from single courses to entire programs, many of them interdisciplinary. The approaches are equally varied. Many could be seen as anticipations of the Horton report (ASA, 2015) in their emphasis on data science and/or their reliance on experience working with real data to address an applied challenge of genuine import.

To take space to summarize each of the innovations I applaud would duplicate what the respondents have already written, and so instead I urge any readers who have not read these responses to do so. Here, briefly, are summaries of five innovations, one that serves to illustrate the core recommendations of the Horton report, and four others that fall outside its convex hull. I list them from the one I consider most at the center to the one I consider extreme.

- *Chance/Peck/Rossman: A new kind of introductory course.* To paraphrase, California Polytechnic Institute at San Louis Obispo now offers a course for entering first quarter students that begins their majors' discussions of the historical roots of the discipline, of ethics, and of future directions, while introducing big data, computing in R, communication, and collaboration skills. Is it any wonder that for me the trio Chance/Peck/Rossman suggests "CPR" for our beginning course?

- *Gould: "bringing a 'data science' curriculum to high school."* Gould's project "Mobilize" is funded by the National Science Foundation. For me what stands out here is Gould's emphasis on teaching statistics within the context of the entire process of scientific investigation *at the high school level*. This goal resonates with the Horton report's attention to statistics as an integral part of the scientific enterprise, but also puts Gould's project in the vanguard of those who would challenge the entrenched Advanced Placement curriculum, its lingering obeisance to probability, and its tradition of mathematically oriented teachers.

- *King: A voice from industry*. The teaching of statistics has long been beneficiary of colleagues who work in business, industry and government, and who care also about education. I am happy to salute King for contributing to this important and valued tradition. I enthusiastically support what I see as her three main imperatives: (1) Recruit early, in high school, from students in Advanced Placement courses in calculus, statistics, and computer science; (2) encourage early, at the sophomore level in college, a

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[1] Here and after, when I cite invited comments, I omit the redundant 2015.

the challenges of implementation.

commitment to an applied subject, and (3) expect and face the challenges of implementation.

- *Ward: Learning communities.* Alone among the responses, Ward's focus is on sociology more than cognition, and describes a program already in place at Purdue University, one that anticipates my thesis in Section 6 that we need a new direction in our research on statistics education. Ward's learning community at Purdue "could be implemented nationwide. The Purdue Statistics Living Learning Community blends the academic, research, residential, and professional development experiences of 20 sophomore students per year." Clearly, there are issues of staffing and scale, but the Ward model is an inspiring example.

- *Wickham: A grammar of statistics.*[2] Wickham argues that our goal should be to develop a "grammar of statistics" as a framework that will allow us to broaden the "safe" use of statistics to a vast population of statistical "amateurs."

Modern theory of finance identifies a curve—the "efficient frontier"—that defines the tradeoff between the maximum expected return for a given level of risk. As one might anticipate, the higher the acceptable risk, the greater the expected return. I regard the efficient frontier as a metaphor that applies broadly to all human investments in our future, and applies in particular to our efforts in education reform. Thus I see a tradeoff between trying for a small change with a large chance of enlisting a major following, and, at the other extreme, trying for a much larger change with a correspondingly smaller chance of broad-based impact short term. In brief, attempts at reform are constrained: the bigger the step forward, the smaller the audience that will choose to follow.[3] In this context I regard Wickham's proposal for a "grammar of statistics" as the most ambitious of all the proposed innovations. It has the potential to revolutionize the way we think about data analysis and about how we teach it. At the same time, because it promises to be such a major step in a new direction, it may prove to be too far ahead of its time to gain traction short term. (See footnote 3.)

In choosing these previous five innovations to single out, I do not mean to downplay my admiration for any of the others. They may be closer to the mainstream of reform as set out in the Horton report, but for that very reason they may be more likely to attract followers in the short term, and thus more likely to have broader impact short-term.

I now turn to a pair of points where I wasn't clear enough, and another pair where I was disappointed.

[2]When it comes to statistics education, Christopher Wild advocates "courtship" and Hadley Wickham urges "safe sex." Exploring such metaphors is beyond the scope of this rejoinder, and so is left as an optional exercise for the reader.

[3]As a salient example, consider Peter Nemenyi, a Hungarian born mathematician who fled the Nazis and became a U.S. civil rights activist. Few teachers of statistics know his name, but in the 1960s he created and taught a randomization-based introduction to inference at the historically black Hampton Institute in Virginia, now Hampton University. Decades after Nemenyi, Gottfried Noether at University of Connecticut and Frederick Mosteller at Harvard wrote textbooks for courses in the same spirit. Only in the past decade, 50 years after Nemenyi, decades after Noether and Mosteller, has the idea of such a course begun to gain traction.

3. Two Failures to Communicate: "I Thought I Was"

Several comments brought to mind an old story about the notoriously taciturn Thomas Dewey, meeting the press as part of his 1948 run for President. "Smile, Governor," a photographer pleaded, to which the dour Dewey, taken aback, replied, "I thought I *was*." In a similar spirit, I was somewhat taken aback by two sets of comments I thought I had anticipated and addressed in response to helpful comments by reviewers of my initial draft. In short, "I thought I *was*."

- *The tear-down.* It is not our *curriculum* that is the tear-down, but rather, less drastically short term, but more ambitiously long term, it is our *thinking* about curriculum that needs to start from the ground up. Unless I misread, not one of the respondents wants us to continue to debride the skins of our noses on the same old curricular grindstone. We all want change. All the same, our thinking about change is too somnolent.

The distinction between *how we think* and *what we do* needs to be recognized more explicitly. What we *do* is constrained by reality. How we *think* is not, and should not be. To borrow from Robert Browning (1855), our reach should exceed our grasp. None of the respondents struck me as clear enough about this difference. Some accuse me of wanting to tear down our existing curriculum. I don't. What I do want is for us to seek out and question some lurking assumptions that shape the way we teach. As I see it, one of the biggest general issues in statistics education, one that may prove pivotal for our future, is the tension between mathematics and data, between abstraction and context, between theory and story. We statisticians have come mainly from mathematics: Mathematics has been our computational engine, our source of underlying theory, and in the undergraduate curricula since the 1950s, our path to respectability. By tradition, our allegiance is to mathematics. But mathematics insists that we understand, learn, and teach top down: Theory dominates, data merely illustrates. This too-often-unconscious hierarchy of priorities in our thinking about curriculum is the tear-down.

To recycle a simile, the tear-down is our mathematically driven tendency to treat topics and courses as structured like a pyramid: Knowledge comes in hard rectilinear blocks. You have to complete the first layer of blocks before you start the second one; you can't talk about *xyz* until you've talked about *rst* and *uvw*, all the way back to *abc*. Transferring this logic from the mathematics curriculum to, for example, how we learn to read exposes its flaws for teaching how we learn from data. We don't learn to read three letters at a time; rather, we learn the way De Veaux and Velleman want us to teach, holistically. In learning to read, once we get past the stage of what for my generation was "See Spot run. Oh, oh, look," we come to experience learning as a kind of archeological dig in which we put the pieces together as we gain depth. Different students learn different things in each of their courses, depending on their backgrounds, but for each student, the threads of new information and new ways of thinking get woven into a pre-existing and ever-evolving tapestry of understanding.

I've responded here to those for whom I failed to make clear my sense of what it is that needs to be reimagined from the ground up. Other respondents put their focus on obstacles and challenges. Although I agree with their concerns, I would be sorry to have the genuine boulders in our uphill path distract us from trying to anticipate the thrill of the long view from above tree line.

• *Breiman's dichotomy.* Of course De Veaux and Velleman are right to say that we should teach "holistically," but their "beside the point" is beside the point. To recognize a neglected polarity as Breiman has done is not to argue for a forced choice. As I read Breiman, his main point was not that we must choose one or the other, not that we should abandon probability-based analysis, but rather, that our current synthesis fails to recognize the importance of the kind of thinking he (unfortunately) named "algorithmic." Breiman was not arguing for either/or, but for balance, integration, and attention to the relationship between the available data and the goal of the analysis. So was I. So are De Veaux and Velleman.

I continue, as urged by Chance, Peck, and Rossman, to explore the fruitful tensions between Breiman and B&K: In thinking about curriculum, how can we best understand the role of probability? The comments of Kass help push this exploration forward, and I agree with his censure of authors who "have done nothing to indicate that [their method] performs well." Are there alternatives to probability-based models for this purpose? In this connection I also find it helpful to keep in mind, as I tried to point out myself but Loken and Gelman state more clearly, that "algorithmic" is not the same as "anti-probability." Finally, I wonder whether and how we can justify a probability model for what Gould calls "algorithmic data."

4. Two Disappointments: A Pier Into the Future?

In James Joyce's *Ulysses* Stephen Dedalus defines a pier as a "disappointed bridge," leaving implicit its failure to reach the intended destination (Joyce, 1922). Sadly, two of my more heartfelt attempts at a bridge to the future remain largely disappointed, short of the shore I had hoped to reach. They are: flattening prerequisites and teaching Bayes early.

• *Flattening prerequisites.* Few of the respondents commented directly and in substance on my argument that we can teach many core concepts and methods of our subject—applied Bayes, design and ANOVA, regression, and what is traditionally mislabeled "mathematical" statistics—*without* most of the traditional prerequisites.

I salute Lane-Getaz for being an exception. In her response, she describes a second statistics course at St. Olaf that teaches students of the social sciences much of the content they might otherwise learn in a graduate-level course in quantitative methods.

Even more radically, Ridgway encourages us to recognize that computers and visualization can engage students early and directly with multidimensional and nonlinear relationships. We should not *assume* that students can *only* understand multivariate data if they climb our familiar step-ladder, one dimension at a time. Step one, histograms. Step two, scatterplots. Step three, two-way additive models. Step four, interaction. And on and up. Ridgway shows us a different path.

We should all embrace the concern of Holcomb and Moreno that for many students across the country, as at their two institutions, mathematical expectations can be a major obstacle. Unless we flatten prerequisites, we bar the way to such students. But: If we do flatten prerequisites, where and when will students who aim for graduate school learn the mathematics they will need for admission? Finding answers to this question is critical. Here are three possibilities: (1) Change some of the ways we teach mathematics to students of statistics. (2) Change some of the expectations of graduate programs. (3) Recognize that more and more careers with data don't require a traditional graduate program. In more detail: (1) For some students, and at some institutions, it may work to teach applications first, and use that background to support the teaching of mathematics. For example, many teachers of mathematical statistics urge students to take Stat 101 first. More radically, as described in my article, it is possible to teach the concepts of mathematical statistics with only a prerequisite of a single semester of calculus. Probability can come later. (2) Many traditional PhD programs want incoming students to have learned mathematics through the level of a rigorous course in real analysis. The need for these students continues undiminished, but the need for other data-oriented graduate students without that background continues to grow. (3) As Utts points out, "the reason for having an undergraduate degree in statistics is changing rapidly," with more opportunities for jobs right after graduation, without the need for graduate courses.

In the spirit of Holcomb and Moreno, although I applaud Albert and Glickman's urging us to teach a course based on generalized linear models, I was disappointed to read that "this would require students to have knowledge of a variety of probability models." Why not teach those models, as needed, in the context of analyzing real data?

I agree with Wild that our aim should not be just to offer a "smorgasbord" of courses each covering "a small number of 'advanced' topics at an intro level." That aim, however, was not the point of my examples. In no way did I mean to suggest that we should revise our curriculum just by offering more flavors of Stat 101. Quite the contrary. My point was and is that if only we choose to, we can for many strong students skip Stat 101 altogether and offer instead courses that allow good students to learn important areas and real applications at the level of a second course, teaching the necessary Stat 101 concepts along the way. In short, we can, with modest effort and thought, revise existing intermediate courses to teach the same content without a statistics prerequisite. If we statisticians don't do it ourselves, others will do it for us. (I may be guilty of a manufactured disagreement here, a la reality TV. Anyone who knows inZight (Wild, 2015) knows that Wild wants to flatten prerequisites as much as I do.)

• *Teaching Bayes early.* I was doubly disappointed here. First and foremost, I was disappointed that only 3 responses out of 19 highlighted the importance of teaching Bayesian thinking. Surely the fraction 3/19 far under-represents the role of applied Bayes in our current practice. I agree emphatically with Albert and Glickman that "the time is right for the development of an applied Bayesian course," but why not a Bayesian version of Stat 101? Thus I was also disappointed that the few responses that did mention Bayes were heavy in their emphasis on prerequisites. I disagree with Notz that "to introduce Bayesian thinking students need to know something about probability distributions, conditional probability, and Bayes theorem." As I see it, this untested assumption (a call for education research!) bears substantial responsibility for the failure of past attempts to teach a Bayesian elementary course. As I have suggested, we can get by with far less formal probability than is usually assumed, and what little is truly essential can be taught along the way as needed in a Stat 101 course with a Bayesian orientation.

Albert and Glickman cite the textbook by Link and Barker (1999) as the basis for a "nice applied Bayesian course" and so, full of hope, I ordered a copy. Sure enough, it is a lovely book with an impressive collection of deep and interesting applications, but it implicitly requires three semesters of calculus and a semester of probability.

Utts is right that new textbooks can lead the way. Our profession urgently needs a new textbook for teaching applied Bayes at the introductory level. I hope for a book along the lines I have suggested, one that relies on Laplace's version of the likelihood principle to avoid the need for any of the usual formal mathematics. No marginal probabilities, no Bayes Theorem, and no calculus. Laplace's eighteenth century genius together with our twenty-first century computer simulations reduce the basic idea to a simple fraction $P(\theta|y) = \frac{\#(\theta|y)}{\#y}$. Adjustments for continuous distributions and prior probabilities are straightforward. (More research, please.)

I regard both of my two disappointments as strong support for my assertion that our *thinking* about curriculum is indeed a tear-down. We have the content already, but our thinking about how to make that content accessible to talented and motivated undergraduates remains immobilized in a spider web of old assumptions. Tear down that web!

5. Implementation: Principles, Obstacles, Challenges, and Strategies

My goal in what I wrote originally was to float high and take a long view, as a counterpoint to the Horton reports appropriately more practical and tethered emphasis. Many of those who wrote in response to my article have chosen to drop lead in my basket and drag my balloon back to earth. They emphasize obstacles to change and challenges to making change happen. Lane-Getaz reports on her own very real experience with resistance to change. Gelman and Loken are right that "developing a forward-thinking approach is not so easy" and I share with Utts her "pessimism about implementing" calls for change. Here again, however, we need to render unto reality that which is real, but only that much and no more. We should not let shadows of the short-term darken our vision of what we might accomplish with time and effort. Thus I am cheered that Utts, our ASA President elect, is no pessimist: " ...we have come a very long way in a very short time. And the pace is quickening." Franklin suggests, and I agree, that our "two biggest challenges" are "building a culture that advocates this" and "the teacher preparation needed."

Teacher preparation—this one of Franklin's (University of Georgia) two challenges is clearly a major issue, one that many other respondents echo. Fisher and Bailar (Miami University) raise the same concern in connection with issues of scale and teaching thousands of students at an institution that relies on adjunct faculty who are paid too little to learn to depart from their familiar traditional course. Although Fisher and Bailar focus their concern on the introductory course, I think their worry about implementing change in fact applies to faculty at all levels. For example, at the high school level, Gould (UCLA), in connection with his NSF-funded *Mobilize* project, which seeks to engage students with the role of statistics in the process of scientific investigation, cites the challenge of teacher preparation. At the graduate level, Kass (Carnegie Mellon University) notes that "we have not penetrated into schools of education." Notz (Ohio State) also identifies teacher preparation as a major issue. Although other respondents chose to focus on other issues, it is hard to imagine that any of them would disagree.

Changing the culture is closely tied to teacher preparation, in that teachers help shape the culture, and culture helps shape teacher preparation. Along with Franklin, several others champion the need to reshape the culture of statistics education. Fisher and Bailar point out the need to enlist client departments. Holcomb and Moreno urge us to publicize employment opportunities. Temple-Lang has found that "data analysis competitions" are effective in getting students actively engaged.

More broadly, Kass writes that "the biggest challenge in statistics education arises from the difficulty humans have in accepting ambiguity and acting reasonably in the presence of uncertainty." I agree wholeheartedly. At the same time, I can't resist a chance to re-engage: I find it useful to make a sharp distinction between uncertainty, which can be described using a probability model, and ambiguity, which cannot. Random samples and randomized experiments lead *without ambiguity to models for uncertainty*. For data from other sources, *the connection to any possible model for uncertainty is ambiguous*. Gould articulates the challenge to our profession: How can we "find meaning in data that do not belong to the probability culture"?

Also on a general level, Zieffler and Justice ask: "how to get stakeholders to buy into the immense amount of work involved in curricular revision." At the risk of appropriating their ideas for my own purposes, I suggest that they offer an answer to their own question: by "using the tools of our profession—data and analysis."

6. Research in Statistics Education: Time for a New Direction?

To start with my punch line, I suggest here that based on the available evidence, our profession would benefit from a shift in the direction of research in statistics education, away from the cognitive psychology of understanding probability and its discontents, toward the social psychology of institutional change and its resistances. Gelman and Loken note (using Zieffler and

Justice's "tools of our profession") that my article "has more than 100 references, only one of which addresses empirical research in educational effectiveness." As a matter of principle I try not to argue with data, and so I plead guilty as charged. This observation and its implications resonate with a question posed more explicitly by Chance, Peck, and Rossman, who ask, "Do we test and evaluate before we tear down and build, or do we just tear down, build, and hope for the best?" I regard the question as deliberately crafty in its phrasing, and my short answer is "Neither one," but I take the question seriously, and so I devote the rest of this section and much of the next one to a longer response.

In my experience research in educational effectiveness is useful in helping us to understand which of our existing practices are more effective, which ones are less effective, and why. But in my experience, also, such research, though important for evaluating what already exists, tends not to be a source of new courses. As an example, I borrow from Utts: "What changed the landscape for Bayesian methods" was "a few innovative leaders who made it easy for others" to implement and teach these methods "by writing textbooks and computer programs." As I recall, a certain Gelman was one of those innovative leaders and authors who helped ease the way to Bayes for the rest of us.

To pursue the point, I think the history of our subject supports Utts's thesis that innovative textbooks are our engines of change. Here, with apologies for many omissions, is a severely pruned list, offered more as a provocation than as data. For more detail, I refer readers to my original article. In this list, I choose one major innovation for each of the last several decades, and one influential textbook author for each.

- *1950s: Making the teaching of statistics legitimate at the elementary level.* Frederick Mosteller (1961).
- *1960s: Teaching us to teach with real data, before computers.* John Tukey (1977).
- *1970s: Interactive computing and data analysis.* Francis Anscombe (1981).
- *1980s: Real data in the first inference course.* Freedman, Pisani, and Purves (1978); Moore and McCabe (1984).
- *1990s: Activity-based statistics.* Richard Scheaffer, et al. (1996).
- *2000s: Randomization-based inference.* Peter Nemenyi and others. (Note here that Nemenyi developed and taught his randomization-based course in the 1960s. It has taken us 50 years to catch up. For more, see footnote 3.)

What stands out for me is that *none of these pivotal innovations originated from research in statistics education.* Such research does not ordinarily lead to directly to innovations; rather, it documents whether and in what ways existing approaches do or do not help students learn. At the same time, it is important to be clear. I do not mean to disparage the importance of this research, only to sharpen our sense of its role. Such research has been instrumental in advancing our profession. Although I assert that it has not been a direct source of innovative textbooks, I do credit that research as a source of new thinking that can lead to innovative textbooks. (A prime example is Chance and Rossman 2015.)

To conclude this section, I offer a four-point summary.

- *Salute: The importance (past and continuing) of research in statistics education.* This research has played an essential role both in supporting and in shaping our teaching. It has helped all of us who teach to choose approaches that help students understand, and to avoid approaches that reinforce misunderstanding. It has helped us to understand which approaches enlist student interest and enthusiasm. It has, I am convinced, pushed us in those directions that have powered our extraordinary growth in student enrollments. In addition, this research has been essential to the success of proposals to granting agencies for funding in statistics education, and helpful to those agencies in their decisions about which projects to fund. Looking to the future, it seems clear that our need for research continues.
- *Premise:* As fellow statisticians, our colleagues who specialize in research on the teaching and learning of statistics should, following Zieffler and Justice, rely on data to direct their talents and efforts. What are the important open questions?
- *Open questions: What do we need to know at this point in our development?* I think the responses to my original provocation offer a clear consensus. According to the two dozen statisticians in our admittedly biased sample, the main challenges to statistics education at this point are not matters of cognition, but matters of implementation, as set out in Section 5. This matches the concern of funding agencies with "dissemination."
- *A new direction?* Based on the available data, I suggest that where we most need research is in the area of implementation rather than cognition. I make this suggestion with diffidence, knowing that so many colleagues who do this research have come mainly from a background in cognitive psychology, in the tradition of Kahneman and Tversky. For many of them, the attraction of research is the challenge of trying to understand the way students learn the probability-based aspects of statistical thinking. Nevertheless, I think this vein of research offers a dwindling source of new nuggets, and that evidence supports my argument for change. Sadly, perhaps, a background in cognitive psychology is no longer the best preparation for research that will help shape the future of statistics education.

As I see it, the argument for change is even more compelling when it comes to university graduate programs in statistics.

7. A Triangular Tension: Our Subject, Our Graduate Departments, and Our U.S. Liberal Arts Colleges

Gelman and Loken observe that I seem "to be concerned with the future of traditional statistics departments. . . " and they are right: I failed to be clear about the difference between our subject and our graduate departments. Their comment is especially clarifying in the context of observations from Wild. Together, Gelman, Loken, and Wild suggest a tension involving our subject, our university departments, and our U.S. liberal arts colleges. In this section (1) I argue, with Gelman and Loken, that the future of our subject is assured, (2) I agree with Wild that many university departments are bastions of conservatism, under siege and at risk, and (3) I expand on Wild's hope that liberal arts colleges can help lead our way into the future.

Our subject. The success of our subject—learning from data—is no more in jeopardy than is the role of money in politics. *Data, like money, will always be in demand. You can't have too much of it unless you don't know what to do with it.*

University departments. As recently as two decades ago, our subject and our university departments were aliased. No longer. Our subject threatens to outgrow many of its graduate departments. Wild quotes from Peter Diggle's (2015) address as President of the Royal Statistical Society: "I would like to see less statistics in undergraduate mathematics degrees." In effect, our subject may be important, but graduate schools don't want you to study it. Diggle's declaration calls to mind the Shakers, a now-extinct New England sect that expected to advance its agenda despite a ban on sexual reproduction. Can university departments survive if they rely exclusively on students who major in mathematics, study little or no statistics, but nevertheless choose to pursue a PhD in a subject they barely know? If you apply to graduate school in molecular genetics, you are expected to know something about molecules and genes. If you apply in astrophysics, the more you know about galaxies and quantum theory the better. No so for statistics. Only in our subject, alone among the sciences, do we hear, "Please learn as little as possible." The future of our subject may be assured, but the future of university departments in our subject is a different matter. We can all take a lesson from mules, who are both stubborn and unable to propagate.

Liberal arts colleges. As Wild points out, these "elite" four-year colleges are unique to the U.S. They stand out in many ways:

- *Faculty tend to come from PhD programs at top research universities.*
- *Teaching load is comparatively light*, four to six courses per year, as opposed to as many as ten per year at U.S. two-year colleges.
- *Greater emphasis on teaching excellence*, in comparison with universities and two-year colleges.
- *Curricular development is recognized as a form of scholarship.*
- *Comparatively small programs offer flexibility and opportunities for change.* Our subject is changing rapidly. Large programs, like ocean liners, can respond only slowly. Liberal arts college programs, like kayaks, can turn quickly to take advantage of the currents.
- *Curricular emphasis remains tied to the ancient trivium and quadrivium, with an enduring commitment to process over content.*

As my former dean, now president of New College (Florida) used to say, US liberal arts colleges are the places where cutting edge research from universities is brought into the undergraduate curriculum. (O'Shea, 2005) Faculty at these colleges have the connections to colleagues at research universities, the time, and the institutional support to create new courses and programs.

But wait: There's more! The commitment of liberal arts colleges to putting critical thinking first—putting process ahead of content, skeptical reflection ahead of vocational training—creates a particular resonance with statistical thinking. Statistics is about how we learn from what we can observe, and how we communicate what we have learned, the two fundamental goals of the ancient liberal arts. This value of the liberal arts was recognized decades back when the school of business at the University of Chicago established a fellowship program based on a study that found that a disproportionate number of CEOs of the Fortune 500 companies came from liberal arts colleges. The fellowship program, which offered a summer internship and guaranteed admission, was open only to students at a select 50 liberal arts colleges, and only to students whose major was *not* in economics or business.

8. Conclusion

I look forward, with constrained optimism, based on the following four-point summary:

- Although the future of our university *departments* and their entrenched graduate programs may be uncertain, the future of our *subject* is assured.
- Education research can best serve our subject and its teaching by a shift in emphasis away from the old *cognitive* psychology of probability and its discontents toward the *social* psychology of institutional change and its resistances.
- Undergraduate programs at liberal arts colleges will likely be nimble enough to respond to trends in statistical practice and to relevant contributions from education research, regardless of what happens in university departments.
- Best of all, across the board and at all levels, our profession's shared commitment to reliance on data will keep us working together.

Finally, I am grateful to the cited authors whose thinking prompted me to write, especially to my fellow statisticians who devoted their time to help create the Horton report (ASA 2015); to the editor and associate editors who helped with my thinking and writing, and who arranged for the online discussion; to the many reviewers whose comments advanced my thinking

and clarified my understanding; and to the discussants who have joined with me and with those I have relied on in contributing to what I am sure will continue to be an ongoing discussion. I am confident that readers will agree: our profession can count on thoughtful efforts such as theirs. In the spirit of Fisher and Bailar, although our time may be one of turmoil, in good hands turmoil creates opportunity.

Additional References

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