Comment

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We agree wholeheartedly with Brown and Kass that something has indeed gone wrong with the way in which we attract and educate students in statistics. The problems begin with the standard unappealing and outdated introductory undergraduate course and persist through many, if not most, graduate programs. Our undergraduate courses focus on an exquisitely narrow set of topics that has changed little in 30 or more years. At the graduate level, we still persist with the increasingly untenable notion that there should be a core (and rather large) body of knowledge that *all* statistics students should know.

We see parallels with the discipline of engineering. Specialization into subdisciplines, such as civil engineering and chemical engineering, has existed for over a century, and while all engineers may share a certain mode of thinking, specific technical knowledge and skills divide along subdisciplinary lines. It is surely premature for statistics to subdivide into hard and fast subdisciplines, but we believe that some degree of specialization is in order. However, we also believe that specialization along applied versus theoretical lines is precisely the *wrong* type of specialization; this particular distinction reinforces the notion of the theoretical statistician developing mathematical artifacts without reference to any scientific enquiry while the applied statistician conducts the intellectually less challenging task of implementing the theory. The compleat statistician must span both aspects.

We believe that the characterization of statistics as a branch of mathematics also underlies many of the problems Brown and Kass describe. According to the Wikipedia entry for "statistician," the core work of a statistician is "to measure, interpret, and describe the world and human activity patterns within it." This seems about right to us—so how is it then that statistics came to be seen as a branch of mathematics? It makes no more sense to us than considering chemical engineering as a branch of mathematics. Both are highly quantitative subjects, and both use mathematics extensively. But in statistics, a purely mathematical agenda is often at the forefront. A statistics department attempting to go against these forces may meet resistance. (A story: We know of a top statistics department that had an interesting applicant with a math GRE of 650 (out of a possible 800). The dean tried to talk the department out of admitting this student. The department stuck to its guns, and the student is doing well.) Statistics departments often recruit mathematically adept students without regard to, for example, their potential to take leading roles in scientific teams. The net result is that our discipline has many outstanding mathematicians but few scientists in the mold of Fred Mosteller.

An example of the new style of statistical thinking described by Brown and Kass appears in the formula $y = f(x) + \varepsilon$. What is appealing about this expression is that the focus is on the deterministic model $f(x)$, rather than (as is traditional in statistics) the error distribution. Recall that in standard statistical notation, the notation f (generic mathematical notation for "function") has the privileged meaning of "probability density function." We believe that it is generally more important to model the mean than the error function, and moving to the generic "f" is a good start.

Statistics faculty recruiting provides another opportunity to effect change. Departments that kick-start the discipline out of its current rut will have many faculty deeply engaged in *different* interdisciplinary endeavors. Skilled "statistical thinking" cannot derive from experience in just one area. Indeed, one of the difficulties in our occasional efforts within statistics to discuss the future of our discipline is the often-narrow perspective that each of us brings to the table. Brown and Kass have done an outstanding job of generalizing from their neuroscience perspective, but nonetheless, the perspective of a social science statistician or a clinical trials biostatistician, to pick two examples, inevitably would be different and no less important.

Finally, as statisticians we should show some humility when recommending methods to others. For example, education researchers have long accepted the importance of randomization and other methods for facilitating "evidence-based" inference. But when devising our own educational plans, we resort to the usual mixture of introspection and anecdote that we deplore in others. We know of no easy way around this incoherence, but it should at least make us wary about over-certainty in our recommendations.

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Comment

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We want to congratulate Emory Brown and Rob Kass on an important, timely, and compelling article. They challenge each of us to think very seriously about the future of statistics education and practice, and our role in that evolution. Along with Brown & Kass, we too believe it essential for the health of the field to make significant changes and additions to the content and focus of statistics training at all levels to attract, retain, excite and inspire students to become statisticians. To us, it seems "obvious" that we should broaden our view of statistics education to incorporate, alongside existing mathematical content, the process of real-world data analysis, skills in computing and data technologies, and statistical experience in scientific contexts. Based on our experience, we believe that statistical programs need to:

- Focus on statistical experience, reasoning, and applications *throughout* statistical training
- Recognize computing as an essential building block for statistical learning, creativity, exploration, and practice
- Design new courses and curricula to attract bright, motivated students to the field
- Change the culture of statistics training to engage students in active, participatory "effortful learning" in addition to critical study.

We continue this comment by providing some details and our thoughts on these four important aspects of statistics education. We then describe some of the activities that we have pursued in our research and our teaching on these topics, and suggest how these might provide possible practical solutions to some aspects of the significant challenges enumerated by Brown and Kass.

We have been thinking about and working on making changes in these directions for many years. We believe strongly that the field of statistics is at a crucial tipping point, and that bold measures of reform in statistics curricula are called for. The changes are necessary both to attract and prepare future statisticians and to keep pace with the rapidly changing "big science" fields. Our experiences over the last 10 years have shaped our views on the subject. These experiences include:

- Organizing a summer school that engages students in applied research projects of statisticians, with an aim of encouraging undergraduates to apply to statistics graduate programs
- Designing and teaching new courses in statistical computing and data technologies
- Teaching faculty how to teach computing
- Revamping a graduate program to broaden the curriculum and the graduate student population
- Exploring how to make research activities and results available through dynamic, reproducible, interactive documents.

Before continuing, it behooves us to make explicit a few parameters in this discussion. When considering statistics training programs, there are several different levels and career goals to take into account: undergraduate preparation for the workforce, undergraduate preparation for graduate school, Masters preparation for the workforce, and Ph.D. preparation for academia and careers outside of academia. With one exception related to an introductory course to attract freshmen into the major, our discussion focuses primarily on advanced undergraduate and graduate students, not the service-oriented introductory statistics class. Commonalities and differences can be found across these different levels of training. One important commonality is teaching data analysis. The collective perspective is that data analysis is taught in all statistics programs; however, the phrase "data analysis" has many connotations, and we believe that it is often the case that "data analysis" experience is simply illustrating a particular statistical method by applying it to a pedagogically chosen data set. We use the term quite differently, to refer to formulating a statistically oriented approach to a scientific question, which involves much more than just applying one or more statistical methods. Also, when we refer to "computing," we mean not simply programming or numerical algorithms, but rather the broader notions of computational concepts, ideas, and skills for statistical inquiry and working with data. Both of these concepts are core elements of statistical thinking.

Statistical Experience. For those learning statistics, the intuition and experience required for good statistical practice are the hardest things to learn (Wild and Pfannkuch 1999) and to teach. They involve very different types of concepts and a new *dimension* of thinking than in mathematics. After years of studying mathematics and statistics from textbooks, statistics students have learned a toolbox of methods, but not necessarily how to frame a question in a meaningful way, for example, balancing constraints, resources, and context. Students may know how to use one or more of these tools but are not masters of the tools, and often use them with trepidation. They need training and practice in mapping a scientific question into a statistical approach and developing understanding, experience, and intuition of when and how to use statistical methodology in the scientific context. These are essential skills in statistical thinking that involve many aspects beyond selecting and applying statistical methods to data. However, most courses focus explicitly on statistical methodology, either the theory or the "application," and very few address the essential larger context. A result of this

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focus on techniques is to train students as confirmatory consultants rather than engaged scientific collaborators. To add this important dimension to statistics programs, we advocate regularly teaching statistics at all levels from the standpoint of statistical concepts flowing from contextual problem solving with data. We realize that this is challenging, but that does not excuse us from avoiding it.

Computing. Traditionally, education and research in statistics have relied primarily on mathematics. However, the enormous increase in computational power over the past 20 years provides numerous opportunities for the field for both statistical practice and statistical education. Computing represents an alternative, complementary medium to help students understand and explore statistical concepts and methods. The ability to simulate and compute gives students and researchers a tangible laboratory for exploring statistical concepts to concretize mathematical abstraction, and provides a forum for gaining insight and intuition about potential new methodologies. Through computing, students actively engage in constructively framing instructions to do a particular task, for example, designing experiments to explore or confirm understanding of concepts. This is quite different from mathematical exposure to statistical concepts, where the student is passively accepting the results of theorems or cautiously manipulating symbols to prove a concept known to be true. If students had as much background in computing as they do in algebra and calculus, we would be able to exploit this additional medium much more effectively.

Besides leveraging the computer for pedagogical purposes, computing in its own right is an essential part of statistical training. Statisticians use computers almost exclusively to access data; filter, process, and explore data; iteratively model the data; and report findings about the data. Each of these steps requires a computer, and in fact each requires very different computational skills. Computing also provides a source of new research problems, such as stochastic algorithms, understanding computer networks, and software reliability. Furthermore, it has changed the nature of other scientific problems by providing a medium for acquiring and exchanging both data and statistical methods in such areas as computational biology, astrophysics, aeronautics, transportation engineering, and medicine. Without computational skills, one simply cannot engage in the application and practice of statistics, regardless of one's knowledge of the concepts. In addition, a good foundation in concepts of scientific and statistical computing and data technologies is essential to the ability to continue to adapt to rapid technological changes. Because most statistics students go on to apply statistics rather than study it academically, computational skills are vital, but as with data analysis, it is a dimension omitted from many statistical curricula.

Attracting Students. We agree entirely with Brown & Kass that statistical thinking and interdisciplinary interaction (or better, immersion) is key for a statistics student to learn. Brown & Kass also recommend presenting statistics as a deep subject, with serious content. Again, we wholeheartedly agree, and also add that we must present it as vibrant and relevant in the modern world as well as for the future. The repeated focus throughout undergraduate and graduate courses on the same concepts at different levels of mathematical rigor presents the view that the important statistical ideas have all been developed. Indeed, many students, even graduate students, do not encounter methods developed within the last decade or two within their courses. Also, the repetition of the classical material is not a compelling approach to attracting good students to the major. Similarly, in our experience at the graduate level, this approach does not attract students to advanced study or prepare them for research. The traditional statistics curriculum is based on the need to first present an intellectual infrastructure for understanding the statistical method. But instead, statisticians need to lead with real and interesting scientific questions and show how statistics "saves the day." Early and continued exposure to statistics in this form we believe will excite and interest students. They will be eager to learn about the statistical theory and take the more traditional classes on the fundamentals that we offer.

Changing the Culture. As Brown & Kass note, the culture of statistics is more one of confirming other people's work, and often criticizing it. A culture of changing the world, attacking the very hard problems, and "dreaming big" is associated more with physics, computer science, and engineering and seems to be quite removed from our field. Perhaps this "caution" is the nature of statistics and a good thing. However, being cautious and circumspect is quite different from a "can't do" attitude. As Brown & Kass note, we must instill in our students the self-confidence to immerse themselves in the subject matter discipline and work alongside the content experts. In our view, statistics students equipped with the unique skills of computing and experience with data can gain this confidence and be welcomed into scientific teams because they have something unique to contribute.

1. CHALLENGES, EXPERIENCES, AND SOLUTIONS

The Role of Introductory Courses. Over the last decade, many educators have focused attention on improving introductory statistics courses. These courses service thousands of students who take only one statistics course, typically to fulfill some general education requirement of the university or their degree program. However, the introductory course can be viewed as a recruitment opportunity rather than solely a vehicle for providing basic statistical literacy to the masses. We believe the field and the students would be significantly better off if this course showed the challenges and applicability of statistics to important policy and scientific decision making in many contexts, and taught students how to think statistically and creatively in these contexts. How can we present the role of statistics in addressing "big science" problems in introductory courses? One possibility is to develop an "honors course" for a small group of students that is creative and bold in the research-like experiences it provides.

Our experience in developing and running a summer program in statistics with Mark Hansen (Hansen, Nolan, and Temple Lang 2006) provides ideas on how such a course might work. In the summer program, undergraduates with limited backgrounds in statistics and computing are exposed to important, topical scientific research problems presented by statisticians working on a scientific team. The program was held at UCLA in 2005 and 2006, and was funded primarily by the Institute for Pure and Applied Mathematics. Recently the NSF awarded a grant to continue this program for four summers, beginning in 2009 at UC Berkeley and then moving to the National Center for Atmospheric Research (NCAR), Columbia University, and UCLA.

The core of the program consists of three data analysis projects spread over 6 days. Each project is lead by a research statistician, who organizes 2 days of activities around an applied project. The researcher presents the scientific problem and explains its importance, provides data, and prepares short talks and computer investigations that introduce the students to the material in stages. At each stage, the instructor guides a discussion in which the students come up with with different approaches for the subproblem, work in groups to follow up on one or more of these approaches, and return to discuss their findings. Students use R (R Development Core Team 2006) to explore and visualize the data. The aim is to keep the interaction fluid and make it easy to move from individual and small group activities to a short presentation on a topic by the speaker to informal class discussion and group presentations. Overall, we found that the students were captivated and engaged by their interactions with the researcher. With the help of numerous instructors and teaching assistants, they quickly mastered the computing tools and were excited about using them to uncover the basic structure of the data, get to the statistical problems that the data present, and gain a sense of how statisticians approach large, complex problems. The program has been successful in attracting a broad spectrum of students; for example, in 2005 & 2006, half of the participants were female (24/49) and one fifth (11/49) were from underrepresented minority groups.

Teaching Computing. While statistics students must learn practical details of computing such as programming language syntax and the names of useful functions, we must strive to teach higher-level concepts of computational thinking that enable students to approach computational tasks intelligently. This includes the ability to discuss and reason about computational problems precisely and clearly. Furthermore, as computing and data technologies continue to evolve rapidly and as we enter the era of mainstream parallel and distributed computing for scientific computing, it is essential that statistics students be in a position to continue to learn new aspects of computation based on a good foundation, rather than a thin memorization of specifics and ad hoc tricks. Statistics programs must prepare the student for the future, which undoubtedly involves computing.

Since 2004, we have been developing and teaching an upper-division course in our respective departments. The two courses are similar and have been developed in close collaboration. The overarching topics are data technologies and statistical and scientific programming. Although the course has no statistics prerequisites, students work with topical and relatively large data sets, performing exploratory data analyses using advanced data technologies and "modern" computationally intensive statistical methods that they typically do not encounter in other classes. These methods (e.g., CART, kth nearest-neighbor methods, naive Bayes classifiers, hierarchical clustering, spline smoothers) are intuitive and relatively easy to describe, and give students a sense of the power of modern statistics. We have observed amazing transformations in our classes as students who initially were unsure of their abilities in computing or otherwise reluctant to work with the computer gain the confidence and skills to tackle a wide variety of data problems. It is empowering because they are involved, active participants. The students find it interesting because the data are available for compelling topical questions, and many find it refreshingly different than more traditional classes. We also have found that the course attracts many students from other majors and graduate students from other disciplines; for example, at UC Berkeley the course is now taught every semester, with an enrollment of about 75 students.

Faculty Experience. For many faculty, there is a large divide between their computational training and what today's students are expected to do. Some faculty have kept up and learned how to "compute," but many have not, and many have done so in an ad hoc manner, which conveys to students that computing is not important. This is very unfortunate, because it means that new students do not get the opportunity to learn it either. So they are in the same position as previous generations, left to learn computing by themselves, and the results typically are quite poor, resulting in students with significant misconceptions, limited abilities, and lack of confidence. How do we break this cycle and provide the opportunity for students to learn this material? One approach that we have pursued is to develop workshops specifically to teach faculty and foster Internet discussion groups for instructors.

Besides developing new computing courses, we also have worked to develop expertise among faculty and graduate students at other institutions so that they can teach this important material to the current and next generation of students. To do this, we (along with M. Hansen of UCLA and R. Peng of Johns Hopkins) are organizing workshops to help faculty acquire knowledge, skills to acquire additional knowledge, and teaching practices in these new areas. The NSF provided us with funds for a series of three workshops. The first, held in 2007, brought together computing specialists and industry consultants (people who have employees in statistical roles) to advise us on preparing material for course and curriculum development plans. Two additional workshops (one held in 2008 and another scheduled for summer 2009) focus on providing the necessary background and skills for instructors who want to teach statistical computing courses, along with examples of how to include modern data analyses projects in their courses. The materials produced for these workshops and resources from our classes are available on the Web (Nolan, Temple Lang, and Hansen 2007). We also have created electronic mailing lists, discussion boards, and a wiki for continued discussion and assistance. Overall, we aim to build a community of educators interested in incorporating computing into the statistics curriculum and sharing course materials.

Course Materials. Finding interesting and topical scientific problems with accompanying data in a form accessible to instructors who want to teach in this experiential manner can be difficult. The Internet provides a great resource for data but often falls short in supplying analysis and context. Articles that present applications are plentiful in research journals, but the analysis is typically presented as a completed work, with the pedagogically important thought process that led to the conclusions and approaches omitted. Where will educators find a wealth of materials suited to this approach to teaching statistics? Vehicles for transferring the experience with data from working statisticians to students are needed.

A project that we are experimenting with (Nolan and Temple Lang 2007) offers a novel approach to providing students with statistical experience. The idea is to enable researchers to document all of their computations and analysis process so that they can be reproduced in their entirety for both themselves and their peers (Gentleman and Temple Lang 2007) (e.g., reviewers, editors, bosses). Researchers would work in an environment that captures their writings, computations, and thought processes in an electronic notebook. In essence, this "lab notebook" would be a database of all of the activities involved in the data analysis or simulation study, and could be projected into different "views" (e.g., code, the final paper, various "dead ends") to make the information available for different audiences. An important consequence of this approach is that these rich documents will provide a flow of materials from statistics researchers involved in scientific applications to the education community. These documents will provide resources to instructors to assist teaching in new ways by opening up the thought process and experiences involved in data analysis to both instructors and students. Moreover, these documents can be displayed with interactive controls, allowing the reader to explore different analysis choices (e.g., changing the values of nuisance parameters, discarding outliers). This technological approach will support a model for passive cooperation between statisticians active in research and consulting and the community of statistics educators. Instructors will then have libraries of real case studies that include data analysis projects and current research methodologies that show how statisticians think and work.

Adjustments. Fundamental changes in the training of statisticians will not follow a prescribed, straight path. At most institutions, the training process has been running fairly smoothly for 20 years or longer. We cannot anticipate all that will happen to our programs as a result of such modifications. Even the question of where to begin is not easily answered. Changes of this magnitude will have repercussions, and it is important to make adjustments, continue on, and not turn back to the old system that supposedly "worked." How do we begin? How do we ensure that students on different pathways do not slip through the cracks? It takes a concerted effort, along with perseverance, to make significant changes to a program.

Over the past several years, the UC Berkeley Statistics Department has been making major changes in its Ph.D. program. A task force of faculty and graduate students reviewed the program, paying particular attention to the first 2 years and to whether students were being adequately prepared for research. The goals of broadening our graduate students' education and also broadening our graduate student population provided the impetus for this reform. The task force recommended that the program (1) broaden the traditional first-year course requirements of two year-long courses in two of the three areas of probability, theoretical statistics, and applied statistics to include other courses, such as the new course "Probability for Applications," as well as courses from other disciplines, and (2) require students to embark on a short-term research project, internship, or other research activity during the first summer of the program. To accomplish these recommendations, two additional key changes were needed: (3) Replace the preliminary exams, which were held in the summer between the first and second years in the Ph.D. program, with the requirement of satisfactory progress in the first 1–2 years of graduate course work, and (4) develop individual course plans for incoming students with the graduate advisor and a faculty mentor. The transition to this new program has not been without problems and has required much effort and resources. Naturally, not all of the effects of such significant changes to the program were anticipated at the start of the transition, and the program continues to evolve. Currently the general sentiment is that the program encourages increased cross-disciplinary research, and that the changes are attractive to graduate students.

2. CONCLUSION

Brown & Kass's discussion of statistical thinking is very important. The concept is what most of us recognize as the essence of statistical contributions. Yet too often, the educational focus remains on techniques and mathematical presentation of concepts because of their convenience and familiarity. Perhaps the problem is that most academic statisticians have not had the experience that Brown & Kass speak of, and the "anachronistic conception" is being passed on through the generations. At a time of great change for science and statistics, statistics education is not evolving at a sufficiently rapid rate. Educators are mostly doing the same things over and over again with minor extensions, and there are few forces to cause us to change in response to general changes in science. This is not any one individual's fault, and there are many truly vibrant and novel statistics educators in academia, but as Brown & Kass mention, this status quo is the result in the aggregate and has us concerned and frustrated. Can statisticians take on the challenge to find bold new ways to teach statistical thinking and practice? Where will the impetus come from? Senior statisticians can step up to this challenge and create a community that supports this change, including encouraging and enabling more junior statisticians who are in the midst of this sea change to take important roles in the process.

In summary, we agree wholeheartedly with most of the ideas that Brown & Kass espouse, and we are grateful that these two eminent statisticians have taken the time to write this article that challenges our field. Unfortunately, these types of articles often elicit tacit agreement but little or no action. Again, many individuals will be enthusiastic about the opportunity for change, but in the aggregate, change will be difficult. This is especially true if university programs must change, especially at a time when budgets are being squeezed. But this topic is clearly important, and vital for our field. We must find a way to effect change. Perhaps guidance should come from an organization such as the ASA. We must focus on changing the "anachronistic conception of statistics" of Ph.D. students and recent graduates, and encourage senior statisticians to seriously challenge their own perspectives and support junior faculty in designing new statistical programs that emphasize statistical thinking and reasoning. We should pool teaching resources, perhaps hold workshops to foster new ways of teaching, and develop case studies for teaching. We might even train graduate students nationally to teach important topics, such as computing, rapidly. Together, interdisciplinary science, computing, and the digital world present a change point for the field of statistics, requiring us to think about what a modern statistics curriculum would look like if we had both the freedom to change and the resources to implement such change. For too long, the field of statistics has acted more passively to such change points and responded by merely adding topics to classes, not by seeking, considering, and embracing new paradigms.

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