Title: Combating anti-statistical thinking through the use of simulation-based methods throughout the undergraduate curriculum

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Abstract: Radical changes to the content and pedagogy of introductory statistics courses are providing students a stronger and more logical foundation on which to build future coursework in statistics, a clearer picture of statistical thinking, and a large and growing pool of students from which to draw for upper level courses in statistics. One key driver of these changes is the increased use of simulation-based methods for introducing inference, which may improve student's abilities to think statistically. These approaches directly combat pervasive anti-statistical thinking (e.g., statistics is like mathematics; statistics is an irrelevant black box). Although these changes have direct impact on students taking algebra-based introductory statistics courses, we contend that they also have the potential to impact the entire statistics curriculum by serving as a model for introductory statistics courses for more quantitatively mature students—students who've taken calculus or AP statistics. We also need to develop innovative programs that leverage the rapid growth of algebra-based statistics courses using simulation-based methods, as an entry point to an undergraduate statistics degree. Achieving these goals will require breaking free of historical forces tying undergraduate statistics curricula to mathematics, trying radical and innovative new approaches, and implementing assessment-driven innovation.

1. Introduction

For far too long, far too much of our effort in statistics education has been blinkered by a narrow focus on the introductory course. For the most part, that beginning course has been regarded as a terminal service course, and, unlike first courses in other STEM subjects, has offered neither an introduction to the undergraduate major, nor even a clear path to an existing second applied course in support of some other major. In short, neither a wing nor a prayer could be expected to impel a student to travel the invisible path from an applied introductory statistics course to a graduate program in statistics.

Accordingly, in the context of the insular nature of the introductory course, this special issue of *TAS* is a welcome acknowledgement that it is high time for those of us who care about undergraduate statistics to turn our attention to courses in statistics beyond the first one. In particular, considering goals and choices for a second or third applied course and identifying good models for undergraduate courses in programs for minors and majors.

Despite the importance of courses beyond the first one, we also regard it as important not to sever our thinking about the introductory course for future majors from the rest of the statistics curriculum. Within the last decade, the algebra-based introductory course has been the focus of significant pedagogical and content reform efforts. In that spirit, this article describes the rationale behind the growing reform effort incorporating simulation-based methods in the introductory statistics course, with an eye towards the implications of this curricular reform throughout the undergraduate statistics curriculum. Simulation-based introductory courses are one way to help improve students' ability to think statistically instead of encouraging "anti-statistical thinking" (e.g., statistics = mathematics or statistics = magic).

Promoting statistical thinking should not only be a goal only of introductory, applied statistics courses for non-majors and quantitatively less mature students. This should be a primary directive of the entire undergraduate statistics curriculum, instead of assuming that students will figure things out on their own. In this paper we will discuss how the use of simulation-based methods has the potential to radically improve statistical thinking in introductory statistics courses for more quantitatively mature students. Furthermore, we will explore how these ideas can act as a strong bridge to courses throughout the undergraduate statistics program. These approaches facilitate statistical thinking as opposed to mathematical thinking, and a focus on the entire research process, emphases of the new undergraduate program guidelines (Horton et al. 2014). Importantly, by better connecting with the rapidly growing audience of students in algebra-based introductory students, these approaches have the potential to significantly impact the numbers of students pursuing additional coursework in statistics.

We argue that the use of simulation-based methods in the introductory course and the entire undergraduate statistics curriculum is essential to the forward flow of our subject, that the soundness and vitality of a program beyond the first course is shaped by its starting point and that the reform efforts there should have myriad reverberations throughout the undergraduate statistics curriculum.

2. Anti-statistical thinking in traditional statistics courses

There is an increasing societal dependence upon data for informed decision making. No longer is it sufficient to make corporate, and even many personal, decisions based merely on intuition. Instead societal shifts are placing an increased emphasis on data-driven decision making. These shifts are now pervasive across disciplines and market sectors (Manyika et al. 2011).

Long the norm in science, this increased societal emphasis has moved statistical thinking to the forefront of daily life. Statistical thinking has been described as the need to understand data, the importance of data production, the omnipresence of variability, and the quantification and explanation of variability (Cobb 1992). However, most students in introductory statistics courses fail to develop the statistical thinking needed to utilize data effectively in decision making. In a macro-sense, students tend to enter and leave most introductory statistics courses thinking of statistics in one of at least two incorrect ways:

1. Students believe that statistics and mathematics are similar in that statistical problems have a single correct answer; an answer that tells us indisputable facts about the world we live in (Bog #1: *overconfidence*).

2. Students believe that statistics can be ‘made to say anything,’ like ‘magic,’ and so cannot be trusted. Thus, statistics is viewed as disconnected and useless for scientific research and society (Bog #2: *disbelief*).

Figure 1 illustrates this dichotomy. The tendency is for students to get stuck in one of the two bogs of anti-statistical thinking instead of appropriately viewing statistical thinking as a primary tool to inform decision making. This black-and-white view of the world of statistics is common when first learning a new subject area, and reflects a tendency to focus on lower-order learning objectives (e.g., knowledge; comprehension) in introductory courses.

These broad, wrong-minded, ‘take home messages’ have been documented in different settings. For example, incorrectly concluding that the accuracy of the data depends solely on the size of the sample, fails to account for the impact of sampling design on potential bias (Bezzina & Saunders 2014). Students who have this misconception are tending towards *overconfidence*, in that they think that statistics is trying to provide a single correct answer (e.g., the underlying parameter value) and the bigger the sample the closer you will get to that true underlying parameter value. However, when trying to address this misconception, statistics educators may have a tendency to show many examples of how biased sampling, question wording, question order, and a variety of other possible sampling and measurement issues can impact results in a dramatic way, potentially leading students to believe that statistics are so sensitive to these issues that it is rare that results can be trusted (*disbelief*).

Misconceptions about descriptive statistics are not alone in feeding these two misconceptions. Students often have a misconception that a p-value less than 0.05 means that the null hypothesis is wrong, failing to account for the possibility of a type I error (*overconfidence*). However, when teaching about type I errors students are quick to latch onto the idea that 'we never know for sure' and wonder about the value of statistics in informing our understanding of populations, processes, and experimental interventions (*disbelief*).

These misconceptions are not limited to the introductory course. In fact, arguably, they are pervasive throughout many aspects of the typical undergraduate statistics curricula. Even statistics majors are often caught without good statistical intuition. For example, the traditional probability and mathematical statistics sequence is taught by some as applied calculus where the primary form of student assessment is how well a student can take integrals. Similarly, a course in regression topics may over-focus on having student perform matrix multiplication and partial derivatives. Both of these approaches focus on the mathematical aspects of statistics, at the expense of the applied (e.g., ignoring the impact of where the data came from on downstream inference).

Addressing student misconception about statistical reasoning and practice, and avoiding the two common ways of thinking 'anti-statistically' requires at least two broad curricular themes: (1) Students need to avoid concluding that statistical thinking is like mathematics, and (2) Students need to see statistics as informing the entire research process. To move students out of the bog of mathematical overconfidence in the undergraduate curriculum means overcoming the entirety of a student's traditional K-12 quantitative training which focuses on deductive reasoning with an eye towards a pinnacle of Calculus (Benjamin 2009). Moving students beyond thinking that statistics is disconnected from reality and acts like a magic black box means consistently helping students see how statistical thinking informs the entire scientific research process (Speed 2014; Horton et al. 2014).

The traditional undergraduate curriculum in statistics does little to address these two broad themes. However, there is reason to be optimistic. Recent innovations in the algebra-based, introductory statistics course, facilitated in large part through the use simulation-based inference methods throughout the course, directly address these two curricular themes. For example, to test a single proportion, flip coins or spin spinners and ask the question "How likely it is to occur by chance alone?" Furthermore, these new introductory courses serve as a model for future individual curricular innovation, while also offering greater continuity with the rest of the undergraduate curriculum: in statistics in particular, and all of the sciences in general.

Figure 1. Student and societal tendencies with regards to statistical thinking

Caption: Like a ball at the top of a steep incline, students and society have a tendency to quickly fall into one of the two bogs of 'Anti-statistical thinking' leading to a view that statistics is irrelevant to science and society. The undergraduate statistics curriculum tends to do little to bring students away from these bogs. If anything, the traditional curriculum encourages the decline by encouraging memorization and focusing on algorithms and algebraic manipulation (low order learning objectives), instead of emphasizing the scientific method and the entire statistical process: from hypothesis formulation through communication of results (high order learning objectives).

3. Leveraging simulation-based methods in introductory statistics to get out of the bogs

Moving beyond read data to real research

As advised by the Guidelines for Assessment and Instruction in Statistics Education (GAISE) a decade ago (Aliaga et al. 2004), and reiterated more recently in the guidelines on undergraduate programs in statistical sciences (Horton et al. 2014), best practices for statistics education mean that we must increasingly incorporate real data into our courses. A cursory examination of most applied statistics textbooks on the market today suggests that this is indeed the case. However, we need to go further. In many cases, the use of real data in applied statistics courses means using an interesting set of data to compute a mean, a confidence interval, or a *p*-value, with little emphasis on consequences of data production, or, more broadly, the context which initiated the research study, the broader implications of the conclusions and limitations of the study and next steps in the research. There are at least four major forces feeding this narrow approach to the integration of real data: (1) A focus on small, 'building block,' compartmentalized, learning objectives that reduce statistics to a single computation, (2) The belief that it isn't until late in a course, or late in the undergraduate statistics curriculum, that students are capable of making connections between statistics and the entire scientific method, (3) That students will make the connections between statistics and the entire scientific method automatically, and (4) That students necessarily have to explicitly learn a lot of probability theory before they are capable of understanding the broader context of statistical thinking. Conceptually, we can view these four negative forces as pulling students from the pinnacle of statistical thinking into the bog of disbelief or the bog of overconfidence (see Figure 1).

Simulation-based methods

A major recent reform effort in algebra-based, introductory statistics courses (e.g., N. Tintle et al. 2014; Chance & Rossman 2015; Lock et al. 2012) involves the emphasis of simulation-based inference methods. A few examples of the use of simulation-based methods in the introductory course include:

(1) Simulating null distributions for a single proportion using coins and spinners,
(2) Generating confidence intervals using (a) the bootstrap, (b) inversions of many tests of significance and/or (c) estimated standard error from simulated null distributions, and
(3) Simulating null distributions for two variable inference using permutation of the response variable

Simulation-based methods have demonstrated themselves to be a key to helping students see the entire scientific research process, and prioritizing statistical thinking over mathematical thinking. Before we explain how (section 4), we highlight four key lessons from the use of simulation-based methods in the introductory, algebra-based statistics course for non-majors.

1. Explicit, integrated connections between curriculum and scientific research process The GAISE guidelines list five parts of the statistical process through which statistics works to answer research questions:

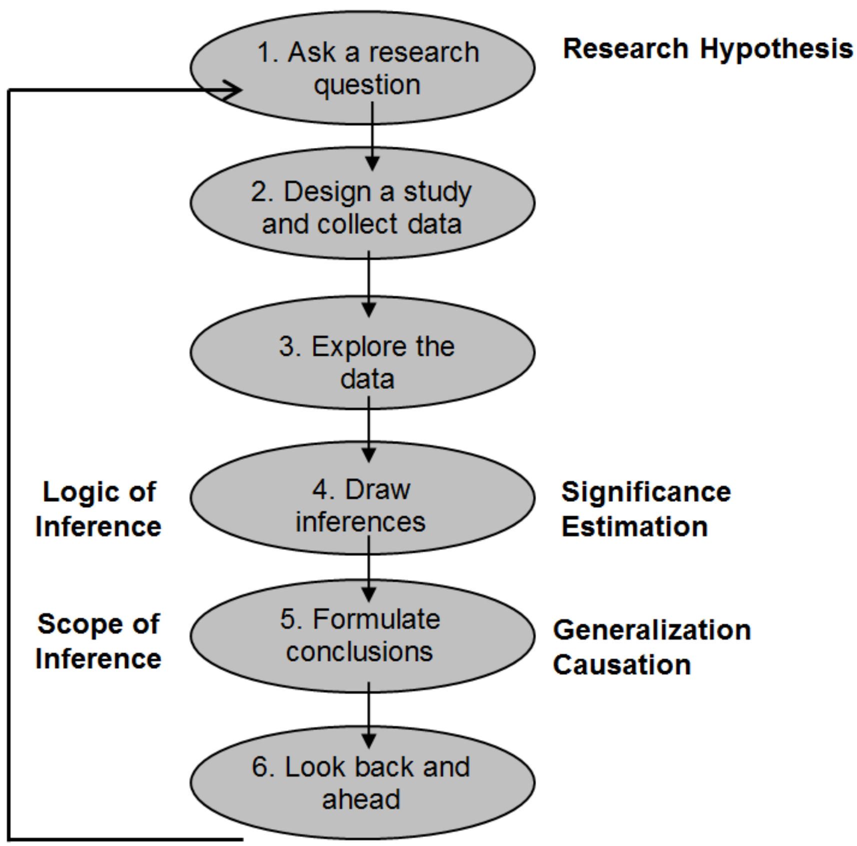
1. How to obtain or generate data,
2. How to graph the data as a first step in analyzing data, and how to know when that's enough to answer the question of interest,
3. How to interpret numerical summaries and graphical displays of data- both to answer questions and to check conditions,
4. How to make appropriate use of statistical inference, and
5. How to communicate the results of a statistical analysis.

As demonstrated by some recent introductory curricula, simulation-based methods make it possible to discuss inferential methods (confidence intervals; tests of significance) earlier in the course, meaning that students more quickly have all of the tools needed to talk about the entire research process. For example, the *Introduction to Statistical Investigations* curriculum (N. Tintle et al. 2014) makes it a point to start the entire course by framing statistics in light of the "six steps of the statistical method" (Figure 2) and walking students through all six steps in virtually every study presented throughout the book. This allows students to consistently be engaged with the entire scientific process, while allowing a spiral approach to key concepts throughout the curriculum, with deeper exploration each time. Importantly, it ensures that connections between data production and analysis (Cobb 2007) can be explored and help reinforce student learning. Furthermore, the presentation and exploration of new statistical techniques are always motivated by a genuine research study, so that students start by thinking about a research question, not a mathematical 'what if?' question.

2. Developing the curriculum with research questions in mind, not mathematical topics Historically, statistics curricula, like mathematics curricula presented material in a deductive manner (e.g., probability theory, then sampling theory, then confidence intervals and tests of significance). In some newer curricula, it is research questions and data structures that motivate new sections and concepts. One way to do this is by having the chapters of a curriculum focused on a type of data/research question (e.g., Chance & Rossman 2015; N. Tintle et al. 2014; Malone et al. 2010). For example, a chapter theme could be the comparison of two groups on a binary response variable, introducing both the descriptive and inferential components of the analysis. Going further, this approach has the advantage of more clearly being able to highlight the distinctions between observational studies and randomized experiments and their impact on inference (e.g., Step 5 in Figure 2) (N. Tintle et al. 2014; Ramsey & Schafer 2013) in an integrated manner.

3. Creating a sandbox for advanced statistical thinking Traditional introductory statistics courses have tended to promote a laundry list approach to teaching data analysis procedures (e.g., if you have a binary explanatory variable and a quantitative response variable, use a two-sample *t*-test). However, when using genuine research studies and simulation-based methods, students are more easily and readily able to engage with the types of messy data problems that are more often the case in real research. For example, simulation-based methods have less need for large samples and symmetric variable distributions. Furthermore, these methods are flexible and allow for student experimentation about summary statistics (e.g., how best to summarize the data from a $R \times C$ contingency table into one statistic before doing a permutation test?) keeping students engaged in real, applied data analysis, while foreshadowing ideas typically reserved only for upper-level undergraduate statistics students: the focus can be on the logic of inference, standardization, variability, and strength of evidence. In short, students can see how these themes and standard data analysis questions are pervasive across research questions and data structures.

Figure 2. An example of how the scientific method can be presented to statistics students



Caption: The Introduction to Statistical Investigations textbook (N. Tintle et al. 2014) emphasizes the 6-

steps to students for nearly every example presented, an emphasis facilitated through the use of simulation-based methods which moves ideas of inference and conclusions earlier in the course. This curricular emphasis includes asking questions to students about steps 1, 2, 5 and 6 for a study, even when main learning objectives for the section are related to steps 3 and/or 4.

4. Not ignoring other best practices The use of simulation-based methods does not in any way preclude the full integration of other best practices that help students experience the fullness of statistics and the entire research process. For example, statistics courses should include a student-directed applied statistics research project which provides students the tremendous opportunity to experience the scientific method first-hand (Singer & Willett 1990). It is possible, however, to fail to fully realize all of the potential benefits of a project in an introductory course. However, because students often have a deeper and better understanding of data exploration and inference techniques in a simulation-based course, student projects have the potential to be deeper and richer student learning experiences. Furthermore, because of the natural connections between active learning activities (e.g., coin flipping, card shuffling) and simulation-based methods, it has been argued that simulation-based methods are naturally conducive to pedagogical best practices for statistics education (Tintle et al. 2011) as presented in the GAISE guidelines (Aliaga et al. 2004).

Preliminary quantitative evidence on student performance

Growing evidence suggests that the use of simulation-based methods is working to improve statistical thinking. For example, Tintle et al. (2011) showed better post-course performance on the CAOS test, with particular gains in areas related to inference and study design compared to the traditional curriculum. Furthermore, Tintle et al. (2012) demonstrated better retention of these concepts post-course. More recently, Tintle et al. (2014), found improved performance among students at a variety of institutions, though additional data is needed to demonstrate that this performance is better than standard curricula.

Using a different simulation-based inference curriculum, Maurer and Lock (Maurer & Lock 2015) found improvement on questions related to confidence intervals in an introductory course utilizing the bootstrap.

4. Impact of simulation-based approaches throughout the curriculum

Despite promising experimentation in the introductory algebra-based course, we contend that the potential impact of simulation-based methods as key component of improved statistical thinking has not been realized in the undergraduate statistics curriculum. Instead, students who are more quantitatively trained (e.g., prior training in statistics; calculus) before taking their first statistics course tend to see more of the mathematical foundations of statistics, instead of focusing on growing students' ability to think statistically. Instead, the success of the integration of simulation-based methods in algebra-based introductory statistics courses should act as a catalyst for the development of alternative, introductory level statistics courses for students with a stronger mathematical background. Furthermore, additional coursework in statistics should connect to simulation-based methods in first courses. In fact, we argue that simulation-based methods and the thinking they promote should be a pervasive theme throughout the undergraduate statistics curriculum.

4.1. A model for alternative introductory statistics courses to emphasize statistical thinking

Students who've had AP statistics and/or any calculus course typically will not take an introductory, algebra-based introductory statistics course: AP statistics students will place out of the course and students who have taken calculus will typically take a different introductory course (e.g., calculus-based introductory statistics or a probability-mathematical statistics sequence). With these paths, they tend to miss out on the active-learning, real-data focus, technology-enhanced introductions to statistics posited by the GAISE guidelines. These students often fail to see the role of statistics in the larger scientific practice and may have a weaker understanding of statistical inference than students leaving a simulation-based algebra level course. Instead, we feel use of simulation-based methods, and the statistical thinking they promote, can and should be an integral part of introductory courses for all students regardless of background. Few course such courses currently exist (ISCAM (Chance & Rossman 2015) is one such exception). When considering the development of such courses, there are at least four main principles that should be kept in mind.

Cover some topics more quickly

Students who have taken more advanced mathematics courses or have taken AP statistics have a stronger mathematical and statistical foundation, thus many topics in the algebra-based introductory statistics course can be covered more quickly. Arguably, this means even more time can be spent on learning objectives emphasizing statistical thinking, as opposed to lower-order learning objectives that emphasize computation. Unfortunately, there is a tendency when working with more mathematically sophisticated students to leverage their mathematical sophistication into more sophisticated mathematical tasks, heading towards a learning goal of applied calculus or algebra instead of statistical thinking. For example, if introductory statistics students know calculus, then focus them on the connections between test statistic choice, resulting null distributional shape and, ultimately, statistical power, instead of emphasizing how to take integrals of probability density functions.

Cover topics not covered in AP Statistics

While the simulation-based introductory statistics course for students who've taken algebra already covers topics not in AP statistics (e.g., permutation tests, non-traditional test statistics for comparing groups, etc.), even more additional non-traditional topics can be added to an introductory undergraduate course for students who've had AP statistics. For example, the inclusion of multivariable methods, an emphasis on more complex study designs, and statistical power are all easily incorporated in a simulation-based introductory statistics course for students with a stronger background. Another example is to use simulation of the null hypothesis for a study design with blocking to simultaneously underscore the details of the blocked design while reinforcing advantages to unblocked designs by comparing simulated null distributions with and without blocking. Numerous other examples exist

Make explicit connections with mathematical and probabilistic concepts

For students who have additional mathematical training, an introductory undergraduate statistics course can be used as a place to make connections to mathematical and probability concepts. These connections must be made, however, with an eye towards enhanced statistical thinking, instead of demonstrating interesting mathematical ideas. For example, a permutation test comparing two independent groups on a binary response generates a null distribution that can be modelled exactly using Fisher's Exact Test. Thus, there is a natural segue into a discussion of the hypergeometric distribution and summing the tails of the resulting density function to yield *p*-values. We feel that when presenting this topic that students can be kept focused on statistical concepts by discussing issues like computational challenges in getting exact *p*-values for Fisher's exact test vs. increasing the number of permutations, and how best to define a two-sided p-value for an asymmetric distribution, instead of on the derivation of the hypergeometric density.

General principles from algebra-based introductory statistics

Finally, best-practices pedagogy, as summarized in the GAISE guidelines, should be kept at the forefront of any curriculum development for more quantitatively mature, introductory students. We have argued before that best-practices pedagogy is inextricably linked to simulation-based approaches (Tintle et al. 2012; Tintle et al. 2011) so this should not be challenging. Furthermore, as described earlier (see *Section 3 Leveraging*), any introductory statistics curriculum should make explicit, integrated connections with the scientific research process, be driven by research questions not mathematical topics and be a sandbox for advanced statistical thinking. These principles should be at the heart of any statistics course in the undergraduate curriculum.

4.2. Bridging to additional coursework in statistics

The traditional view of the introductory applied statistics course (especially the algebra-based course) is that it is a terminal course: students who take this course rarely, if ever, end up being a statistics major or minor. In fact, these students rarely, if ever, take any additional coursework in statistics outside of courses in their major. However, while the numbers of students taking Calculus are stagnant, the numbers of students taking statistics in high school (e.g., via AP statistics, Common Core) or via an introductory college-level course continue to rise. Thus, a key area of focus when considering ways to dramatically increase the number of statistics majors or minors should be building bridges to introductory applied statistics courses.

Curricular barriers The curricular barriers for students taking courses beyond the introductory applied statistics course are large and imposing. First, at most institutions almost all upper-level coursework in statistics requires that at least two semesters of calculus be taken first. In fact, sometimes more than two semesters are needed, with the possible addition of coursework in linear algebra or real analysis. Second, after taking calculus, the entry level course to upper-level coursework in statistics is typically a 1-2 semester course in probability and mathematical statistics, which typically has little connection whatsoever to an applied introductory statistics course. In particular, data analysis is not part of the course, and any possible connections to an applied introductory course involve abstract mathematical notions of probability density functions and theorems. Third, even if a student was ambitious enough to begin the major undertaking of additional coursework (e.g., courses like calculus, linear algebra, probability) to get the chance to learn and do more applied statistics, there is little reward for these students along the way. The courses typically do nothing to reinforce statistical thinking, instead driving home the already pervasive misconception that statistics is, in fact, mathematics.

Current reform There is, however, some reason to be optimistic. Recent curricular efforts have developed materials for post-introductory students who have not had calculus, so that immediately after their first applied course in statistics, students can take a second or third applied course (Cannon et al. 2013; Kuiper & Sklar 2013; Ramsey & Schafer 2013; Tintle et al. 2013; Legler & Roback 2015). These courses have debunked the ages old notion that calculus is needed before more advanced statistics courses are possible. With one exception (Tintle et al. 2013) these courses do not necessarily build on the simulation-based introductory statistics course. However, we argue that the simulation-based introductory statistics course provides a stronger foundation on which to build future course material.

As outlined earlier, (*3. Leveraging*), we argue that students in a simulation-based introductory course have a greater opportunity to grow in statistical thinking than in a traditional course. Second courses in statistics can leverage this strong foundation in a number of ways. First, this stronger foundation means that students retain concepts longer (Tintle et al. 2012) meaning less time is needed for review and reinforcement of key Stat 101 concepts. For example, deeper student understanding and retention about both the logic and scope of inference means that second courses can begin with multivariable study design and analysis strategies, instead of spending more time reviewing introductory approaches for one and two variables.

Second, a more global view of statistical thinking, manifested by viewing statistics as part of the scientific research process in introductory coursework can continue to be reinforced in second courses. This approach helps students to transition to the advanced design and analysis strategies covered in post-introductory courses. For example, students can quickly learn that a multiple regression model on observational data is simply an alternative way to yield a statement about statistical significance and an “effect” estimate, which adjusts for potential confounding variable explanations for bivariate relationships. Thus, a multiple regression model can be presented as a way to narrow the scope of potential explanations for the observed bivariate relationship and further limit the field of potentially needed follow-up studies. These concepts are natural and straightforward for students to consider immediately after learning bivariate methods in an introductory course focusing on the scientific research process.

Third, students who have taken simulation-based introductory courses have already begun bumping up against advanced statistical topics. For example, the simulation-based first course makes it natural to consider non-parametric statistical approaches (for example, compare quantiles of two distributions), the power and robustness of different summary statistics (e.g., consider different statistics to summarize strength of evidence in a contingency table), or expanding the approach to compare two standard deviations. Relatedly, simulation-based first courses make it easier to recognize that the overarching logic of statistical inference is the same regardless of how complicated the data analysis scheme is (e.g., interpreting confidence intervals and *p*-values is the same). For example, it is reasonable to ask students to interpret the implications of a *p*-value (e.g., likelihood of data given chance alone explanation) in a peer-reviewed research article even if they are unfamiliar with the method of how it was calculated. Another example is using a simulation-based *p*-value to confirm a theoretical *p*-value when validity questions are questionable.

While many of the examples presented above discuss the impact on second courses in applied statistics, the potential impact of simulation-based methods and improved statistical thinking are pervasive throughout the undergraduate curriculum. See, for example, a recent effort to use simulation-based methods in teaching mathematical statistics (Chihara & Hesterberg 2011).

Increasing the pipeline The impact of a simulation-first introductory course on subsequent statistics courses goes even further than content carry-over and a stronger conceptual foundation on which to build. Because a simulation-based first course better reflects statistical thinking, and not mathematical thinking, it may be more appealing to a broader and more diverse set of students. Impacting even a small percentage of this large group of students (nearly 500,000 at four year and two-year colleges and universities alone in 2010 (Blair et al. 2010)) to take additional coursework in statistics, potentially leading to a minor or major, could have a substantive impact on the number of individuals with statistical training. In the past, the algebra-based introductory course has been ignored as a potential source of student's interested majors/minors.

5. Conclusions and next steps

The statistical profession is at a crossroads. On the one hand, academia, society and industry are demanding more and more statistical literacy, increasingly counting on data for informed decisions. This means that informed citizens must have basic statistical literacy and that more and more data experts are needed to satisfy the insatiable demand for data-informed decision making (Manyika et al. 2011). For over a century, statisticians have been the primary individuals meeting this need. However, for far too long and far too shortsightedly, statisticians have kept their curriculum and courses tied to mathematics, simultaneously turning off generations of future statisticians to the profession and reinforcing misconceptions about statistics. Despite this substantial hurdle, refocusing the entire undergraduate statistics curriculum towards an emphasis on statistical thinking, an effort greatly enhanced through the use of simulation-based inference, may counteract the misconceptions about, and shortage of, statistically literate and trained individuals.

Threats

The undergraduate statistics curriculum continues to reinforce misconceptions about statistics even as the societal pendulum swings from distrust and under-appreciation of statistical concepts into overconfidence and over-trust in statistics to solve societal issues, compounded by a pervasive view of statistical thinking as deductive and mathematical. These misconceptions are further emphasized by growing numbers of individuals who draw conclusions from data (big or small) with little appreciation of variability and randomness. The development of complicated, multi-step, computationally intensive algorithms for big data underscores this threat. Results from such methods are often viewed as decisive and authoritative (overconfidence; mathematical) or completely unreliable and fickle (disbelief; magic).

Opportunities

Appropriate utilization of data in decision making requires the ability to think statistically. The way to counteract the negative forces driving students towards anti-statistical thinking is to reorient the entire undergraduate statistics curriculum towards statistical thinking. This requires an explicit and purposeful turning away from mathematical objectives in statistics courses, and embracing the role of statistical thinking throughout the entire research process. The combined widespread accessibility to big data and big computing power, along with societal demands for data-informed decision making, mean that we are optimally positioned to radically impact society towards greater statistical thinking.

Next steps

How then should we proceed? To take advantage of this unprecedented, and likely unrepeated, opportunity, the statistics profession must do at least three things with regards to the undergraduate curriculum to maximize its impact.

Recommendation #1. We must be willing to break out of a 'mathematical' mindset in our courses and programs. Most professional statisticians were mathematicians first. This trajectory is present today both in the broad structure of the undergraduate curriculum, as well as in the content and pedagogy of many statistics courses. As we consider radical overhauls to our courses and our pedagogy we must consistently ask "How will this promote statistical thinking?" Just because some students can do interesting mathematics, doesn't mean that they should do only interesting mathematics in statistics courses. A critically important step is to train K-12 and college level teachers to teach statistics as a way of thinking about data that is separate from mathematics. Simulation-based methods and experimental new courses are driving us to embrace statistical thinking---we need instructors to understand these approaches, why they are important and how to encourage statistical thinking in the classroom and throughout the curriculum.

Recommendation #2. We must be willing to radically experiment with new courses, sequences in programs in the undergraduate statistics curriculum. As we try to break 100-plus years of history in statistics education, we must remember that academia is notoriously slow moving. Hurdles to implementation at the individual, departmental, institutional and national level are significant. In an era of general fiscal restraint, institutional and funding agency willingness to gamble on high-risk, high-reward proposals for new courses, sequences and programs is waning. We must move away from traditional academic models that do more talking than action, and focus on the negatives before the positives of new ideas. We must recognize that society is changing (embracing data-informed decision making), and so is K-12 education (promoting more statistical exposure). Thus, we must embrace new ideas, as the only way to have a chance to ride the big data wave and promote statistical thinking at the undergraduate level. In this paper, we have only presented the tip of the iceberg with regards to ideas for promoting statistical thinking in the undergraduate statistics curriculum. Much more thinking and discussion is needed.

Recommendation #3. We must better understand what students do and don't learn in our statistics courses and use these assessments to drive curricular change. Finally, as we experiment and try new approaches, we must use assessment to drive curricular change. Unfortunately, few standardized assessments of student learning in the undergraduate statistics curriculum exist beyond the algebra-based introductory statistics course. Furthermore, assessments that focus on measures of statistical thinking in the introductory course tend to show poor student performance. The development and utilization of assessments of statistical thinking are needed to drive continuous improvement of courses and curricula and further expose the gaps in current courses and programs.

Conclusions

Despite the threats and the significant work that is needed, we remain optimistic. The momentum behind the use of simulation-based methods in introductory courses, the endorsement of modern pedagogical standards for statistics teaching (Aliaga et al. 2004) and the development of the recent undergraduate program guidelines (Horton et al. 2014) are all extremely encouraging signs of progress. Whereas the pessimist might point out that some of these arguments and approaches have been around for decades

(CATS 1994; Cobb 1992; Cobb 1993; Waldrop 1994; Higgins 1999), the persistent nature of these arguments and approaches keeps us encouraged. Although the integration of simulation-based methods is likely not a magic bullet in statistics education, it opens the door up to a variety of innovative pedagogy and content, enhancing students abilities to think statistically. Our positive outlook about the opportunities before the statistics community is perhaps best summarized by a quote from the new 'front door' of the statistical discipline (ASA 2014). Here you can read that "Statistics is a science. It involves asking questions about the world and finding answers to them in a scientific way." If we can build courses, curricula and instructors that embrace this philosophy the future of statistics is bright indeed.

References

Aliaga, M. et al., 2004. GAISE: college report. Available at: http://www.amstat.org/education/gaise/GaiseCollege_Full.pdf.

ASA, 2014. This is statistics. Available at: www.thisisstatistics.org [Accessed December 15, 2014].

Benjamin, A., 2009. Teach statistics before calculus! Available at: http://www.ted.com/talks/arthur_benjamin_s_formula_for_changing_math_education?language=en.

Bezzina, F. & Saunders, M., 2014. The Pervasiveness and Implications of Statistical Misconceptions Among Academics with a Special Interest in Business Research Methods. *Electronic Journal of Business Research Methods*, 12(2), pp.29–42.

Blair, R., Kirkman, E. & Maxwell, J., 2010. *CBMS report: Statistical abstract of undergraduate programs in the mathematical sciences in the United States*,

Cannon, A. et al., 2013. *Stat 2: Building models for a world of data*, WH Freeman.

CATS, (Committee on theoretical and applied statistics), 1994. *Modern Interdisciplinary University Statistics Education*, National Academies Press.

Chance, B. & Rossman, A., 2015. *Investigating statistical concepts, applications and methods*, Available at: http://www.rossmanchance.com/iscam2/index.html.

Chihara, L.M. & Hesterberg, T.C., 2011. *Mathematical statistics with resampling and R*, Wiley.

Cobb, G., 2007. A ptolemaic curriculum-fix entry. *Technology innovations in statistics education*.

Cobb, G., 1993. Reconsidering statistics education: A national science foundation conference. *Journal of statistics education*, 1(1).

Cobb, G., 1992. Teaching Statistics. In *Heeding the call for change: suggestions for curricular action (MAA Notes No. 22)*. pp. 3–43.

Higgins, J.J., 1999. Non-mathematical statistics: A new direction for the undergraduate curriculum. *The American statistician1*, 53(1), pp.1–6.

Horton, N. et al., 2014. Curriculum Guidelines for Undergraduate Programs in Statistical Science.

Kuiper, S. & Sklar, J., 2013. *Practicing Statistics: Guided investigations for the second course*, Pearson.

Legler, J. & Roback, P., 2015. *Broaden your statistical horizons: generalized linear models and multilevel models*,

Lock, R. et al., 2012. *Statistics: Unlocking the power of data* First., John Wiley and Sons.

Malone, C. et al., 2010. Resequencing topics in an introductory applied statistics course. *The American Statistician*, 64(1), pp.52–58.

Manyika, J. et al., 2011. *Big data: The next frontier for innovation, competition and productivity*, Available at: http://www.mckinsey.com/insights/business_technology/big_data_the_next_frontier_for_innovation.

Maurer, K. & Lock, E., 2015. Bootstrapping in the introductory statistics curriculum. *Technology innovations in statistics education*.

Ramsey, F. & Schafer, D., 2013. *The statistical sleuth: A course in methods of data analysis*, Duxbury.

Singer, J. & Willett, J., 1990. Improving the teaching of applied statistics: putting the data back into data analysis. *The american statistician*, 44(3), pp.223–230.

Speed, T., 2014. Statistics is more than a numbers game - it underpins all sciences. *The Epoch Times*. Available at: http://www.theepochtimes.com/n3/788791-statistics-is-more-than-a-numbers-game-it-underpins-all-sciences/.

Tintle, N. et al., 2011. Development and assessment of a preliminary randomization-based introductory statistics curriculum. *Journal of Statistics education*, 19(1), pp.1–25.

Tintle, N. et al., 2014. *Introduction to Statistical Investigations* Preliminar., John Wiley and Sons.

Tintle, N. et al., 2012. Retention of statistical concepts in a preliminary randomization-based introductory statistics curriculum. *Statistics education research journal*, 11(1), pp.21–40.

Tintle, N.L. et al., 2013. Challenging the state of the art in post-introductory statistics: preparation, concepts and pedagogy. *Proceedings of the international association on statistics education*.

Tintle, N.L. et al., 2014. Quantitative evidence for the use of simulation and randomization in the introductory statistics course. *Proceedings of the 9th International Conference on Teaching Statistics*.

Waldrop, R.L., 1994. *Statistics: Learning in the presence of variation* 1st ed., William C. Brown.