What is Statistics?

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Abstract

Abstract: We use our experience in neuroscience as a source of defining issues for the discipline of statistics. We argue that to remain vibrant the field must open up by taking a less restrictive view of what constitutes statistical training.

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Short Supply

Our field faces fundamental challenges. The statistical needs of science, technology, business, and government are huge, and growing rapidly, producing a shortfall in statistical workforce production. In their summary of an NSF workshop, *The Future of Statistics*, Lindsay, Kettenring, and Siegmund (2004) reported that

> Workshop participants pointed repeatedly to shortages in the pipeline of students and unmet demand from key industries and government laboratories and agencies. ... The shortage may prove quite damaging to the nation's infrastructure.

The growth in demand for data analysis may be attributed, in large part, to the exponential increase in computing power and data collection capabilities. At the same time, there is a worrisome tendency for quantitative investigators or technical staff to attack problems using blunt instruments and naive attitudes. Our discipline as a whole has been gloriously productive, making available a wide variety of tools. But we have been less successful in producing easy-to-master operating instructions and training programs. We have, effectively, created a supply side of the problem: statistical education has not been sufficiently accessible. Curricula in statistics have been based on a now-outdated notion of an educated statistician as someone knowledgeable about existing approaches to handling nearly every kind of data. Degrees in statistics have emphasized a large suite of techniques, and introductory courses too often remain unappetizing. The net result is that, at every level of study, gaining statistical expertise has required extensive coursework, much of which has appeared extraneous to the compelling scientific problems students are interested in solving.

We must also acknowledge that some of the most innovative and important new techniques in data analysis have come from researchers who would not identify themselves as statisticians. Computer scientists have been especially influential in the past decade or so. The influx of methodology from outside the discipline is not new; indeed, the field of statistics itself is relatively young, with much foundational achievement pre-dating the advent of departments of statistics. But an undeniable fear lurks in the hearts of many statistics professors: as others leap daringly into the fray, attempting to tackle the most difficult problems, might statistics as we know it become obsolete?

The two of us recently co-organized the fourth international workshop on statistical analysis of neural data. This series of conferences has brought together quantitatively-oriented experimenters and cutting-edge data analysts working in the field of neuroscience, offering new challenges for statistical science in the process. We and others have found the high quality of statistical application gratifying, and the articulation of new ideas very stimulating. One of the reactions from readers of our grant proposal to the National Science Foundation, however, took us by surprise. Only a relatively small minority of our speakers and participants came from departments of statistics and, as a result, some reviewers questioned whether the Division of Mathematical Sciences should be supporting this activity. Luckily, the program officers handled this issue adeptly, in part by getting co-sponsorship from Computational Neuroscience. But the issue is an aspect of the existential identity crisis: the reviewers were grappling with the vexing question, raised by institutional structures, of who should be counted as a statistician.

The participation in neuroscientific research of many non-statisticians doing sophisticated data analysis is not surprising. The brain is considered a great scientific frontier. Studying it creates many technological challenges and, because neuronal networks form electrical circuits, fundamental contributions to neurophysiology have been made by physical arguments, in the form of differential equations. Furthermore, brain science is where artificial neural network models arose, not as machines for nonparametric multiple regression, but as descriptors of cognitive mechanism. For these reasons neuroscience has attracted many researchers trained in quantitative disciplines, especially physics and engineering. While their activities might make some statisticians nervous when it comes to federal grants and other resources, a more serious threat is a disciplinary attitude that contrasts strikingly with what we see among many statisticians. Physicists and engineers very often become immersed in the subject matter. In particular, they work hand-in-hand with neuroscients, and often become experimentalists themselves. Furthermore, physicists and engineers (and likewise, computer scientists) are ambitious: when faced with problems, they tend to attack, sweeping aside impediments stemming from limited knowledge about the procedures they apply. In seeing this we often shudder, and we will criticize this cavalier attitude in our remarks below. But there is a flip side to our reaction: in contrast, we find graduate students in statistics often reticent to the point of inaction. Somehow, in emphasizing the logic of data manipulation, teachers of statistics are instilling excessive cautiousness. Students seem to develop an extreme risk-aversion, apparently fearing that the inevitable flaws in their analysis will be discovered and pounced upon by statistically-trained colleagues. Along with communicating great ideas and fostering valuable introspective care, our discipline has managed to create a culture that is often detrimental to the very efforts it aims to advance.

We are worried. While we expect that in many institutions—perhaps most—there may exist specific courses and programs that are in certain respects exemplary, in the aggregate we are frustrated with the current state of affairs. The concerns we have articulated above are not minor matters to be addressed by incremental improvement. Rather, they represent deep deficiencies requiring immediate attention.

Changing Times

In making critical comments, we hope to stir discussion and debate. We do not wish to be misunderstood, however: our most fundamental loyalty is to the discipline of statistics. Not only do we appreciate its role in technical advances over the past century, we see even greater opportunities for essential contributions in the future, as scientific investigations rely on more massive and intricate data sets to examine increasingly complex phenomena. Furthermore, in addition to utility there is great beauty in the subject. We have spent considerable effort learning and trying to advance neuroscience. But even after substantial exposure to one of the most exciting and rapidly-developing areas of science, we still think that statistics, with its unique blend of real-world mathematics, epistemology, and computational technique, is the most deeply interesting and rewarding of all intellectual endeavors. There are strong arguments to suggest that much of cognition is based on pattern learning, and that humans have well-developed neural machinery for making inferences implicitly, without conscious recognition. Perhaps part of the pleasure we get from statistical reasoning comes from bringing a harmonious coherence to otherwise unappreciated brain processes. Regardless of its biological explanation, however, there is certainly an inspiring aesthetic of statistics driven in part by the emotional overlay of trying to tame uncertainty. The problem is not with the nature of the discipline. There are compelling reasons to love statistics, and to pass on to others both knowledge of its methods and appreciation of its powerful logic.

So where have things gone wrong? We think the primary source of the current difficulties is an anachronistic, yet pervasive conception of statistics. The problem is that departments of statistics often act as if they are preparing students to be short-term consultants, able to answer circumscribed methodological questions based on limited contemplation of the context. The short-term consultant model relegates the statistician to a subsidiary position, and suggests that applied statistics consists of handling well-formulated questions, so as to match an accepted method to nearly any kind of data. This notion may have developed partly because—at least in the United States—statistics evolved from mathematics with its lone investigator, and partly because a qualified statistician could know the entire field. The large majority of senior statisticians began their academic careers as math majors. Within statistics departments, mathematical thinking influenced both research and infrastructure while the mathematics involved was relatively limited, so that Ph.D. statisticians could master the technical details in diverse areas of statistics. Graduate programs thus emphasized mathematically thorough knowledge of multiple branches of the field. At one point in time this served useful purposes. But statistics has expanded, and deepened, so that individuals rarely have state-of-the-art, rigorous expertise in more than a few well-developed sub-domains. Furthermore, in today's dynamic and interdisciplinary world, success in confronting new analytical issues requires both substantial knowledge of a scientific or technological area and highly flexible problem-solving strategies. In neuroscience, for example, a statistician will have far more impact once he or she is able to generate ideas for scientific investigation. In other fields the situation is surely analogous. The discipline of statistics needs to recognize our new situation, and act accordingly. We would like to suggest two over-arching principles of curricular revision.

A Focus on Statistical Thinking

According to syllabi and lists of requirements, statistics courses and degree programs tend to emphasize mastery of technique. But statisticians with advanced training and experience do not think of statistics as simply a collection of methods. Like experts in any field, they consider their subject highly conceptual. This deserves emphasis, as it distinguishes a disciplinary approach from efforts that might be disparaged as the work of amateurs. In neuroscience, we have seen many highly quantitative researchers trained in physics and engineering, but not statistics, apply sophisticated techniques to analyze their data. These are often appropriate, and sometimes inventive and interesting. In the course of perusing many, many articles over the years, however, we have found ourselves critical of much published work. 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. As an example, neuroscientists developed the highly intuitive "spike-triggered average" to identify an association between a neural spike train, which may be considered a point process, and a continuous stimulus. Point process analysis by a member of Columbia's Department of Statistics (Paninski, 2003) has shown that spike-triggered averaging can be inconsistent in some realistic settings, but consistent estimators may be constructed using generalized linear (or nonlinear) regression models, an approach first championed by Brillinger (for related references and other examples see Brown, Kass, and Mitra, 2004, and Kass, Ventura, and Brown, 2005).

The statistician's perspective, missing from much analysis of neural data, is the most important thing we can provide. Once students have it, they will be empowered in diverse situations. We therefore suggest that the primary goal of statistical training, at all levels, should be to help students develop *statistical thinking.*

What, exactly, do we mean? Different statisticians would use somewhat different words to say what defines the essential elements of our discipline's approach, but we believe there is general consensus about the substance, which can be stated quite concisely: statistical thinking uses probabilistic descriptions of variability in (1) inductive reasoning and (2) analysis of procedures for data collection, prediction, and scientific inference. For instance, a prototypical description of variability among data pairs $(x_1, y_1), \ldots, (x_n, y_n)$ is the nonparametric regression model

$$Y_i = f(x_i) + \varepsilon_i,$$

in which each ε_i is a random variable. This may be used to suggest methods of smoothing the data and to express uncertainty about the result (both of which are part of item (1)) and also to evaluate the behavior of alternative smoothing procedures (item (2)). One can dream up a smoothing method, and apply it, without ever referencing a model—indeed this is the sort of thing we witness and complain about in neuroscience. Meanwhile, among statisticians there is no end of disagreement about the details of a model and the choice among methods (what space of functions should be considered? should the ε_i random variables enter additively? independently? what class of probability distributions should be used? should decision-theoretic criteria be introduced? or prior probabilities?). The essential component that characterizes the discipline is the introduction of probability to describe variation in order to provide a good solution to a problem involving the reduction of data for a specified purpose. This is not the only thing statisticians do or teach, but it is the part that characterizes the way they think.

Currently, statistical thinking is internalized as a by-product of extensive statistical training. Elevating it to an over-arching goal allows curricula to be assessed according to the way statistical thinking is engendered.

Flexible Cross-Disciplinarity

Contemporary students see before them a world dominated by "big science," with a host of exciting paths to participate in progress. Many students recognize a fundamental role for statistics, and most see great value in learning statistical methods, but they are increasingly motivated by a desire to solve important problems. In this context, the very best quantitatively-oriented students often come from other quantitative disciplines, including computer science, physics, and engineering, and they have many options.

Here is an example. Due to involvement in computational neuroscience at Carnegie Mellon, one of us (Kass) became aware of an outstanding senior undergraduate: a young woman majoring in computer science at one of the top liberal arts colleges, with nearly perfect GPA and GREs. She was very interested in computational aspects of neuroimaging, and wanted to pursue a Ph.D. However, she had never taken a statistics course and had, in fact, taken only one math course beyond calculus. It had not occurred to her that statistics might be a good option and, from the point of view of admission to a graduate program in statistics, she presented logistical complications: it was not clear exactly what she would study, nor how many years it would take to complete her degree. We must make room for students like this, and recruit them.

To attract students with "non-traditional" quantitative backgrounds, statistics programs must guide them toward making important contributions in a timely manner. Cross-disciplinary projects will have to play a major role. Once a department accepts as its primary mission to help students develop an ability to think like statisticians, it becomes freed from the constraints of excessive content and able to recognize alternative ways that students can demonstrate their abilities and achievements. On the one hand, we see cross-disciplinary work to be essential for anyone having any kind of statistical credential—and, therefore, to statistical training at every level. On the other hand, we view cross-disciplinary research as an opening to students of varied backgrounds: a way of welcoming them into the fold, and a mechanism to streamline training, making programs more manageable and the discipline more inviting.

To satisfy different kinds of students, programs must also allow multiple pathways toward degrees. Increasing the emphasis on cross-disciplinarity goes hand-in-hand with reducing the importance of particular courses, and thereby decreases programmatic rigidity. Flexibility is paramount: we do not wish to remove theoreticians from our midst; indeed, many non-mathematicians will blossom in theoretical directions. Rather, our aim is to allow a broader notion of who counts as a statistician.

Implications

If someone is able to (i) appreciate the role of probabilistic reasoning in describing variation and evaluating alternative procedures, and (ii) produce a cutting-edge cross-disciplinary analysis of some data, should we feel comfortable calling that person a statistician? We think so, and we would like to see our profession broaden its perspective enough to make this possible.

We further believe it is consequential to declare (i) and (ii) to be defining goals for a training program. In applying this at the graduate level, however, we presume that in order do "cutting edge" work, along the way a trainee would have had to have learned something about classical techniques such as linear regression, some area of modern statistics (nonparametric regression; dimensionality reduction; graphical models; etc.), and also general inferential tools such as the bootstrap and Bayesian methods. Furthermore, appreciation of probabilistic reasoning comes from repeated exposure to it in varied contexts. And both of these require mathematical and computational skills. We are, therefore, proposing variations on what is already in place in training programs throughout the country: each training program formulates (explicitly or implicitly) a list of skills and units of knowledge that are truly essential, and figures out how those things are to be instructed and evaluated. What constitutes inculcation of statistical thinking may be in the eye of the beholder—in this case, the departmental training program. On the other hand, we have argued that the status quo is unacceptable. Here are four recommendations.

1. Minimize prerequisites to research. There are continual disagreements about the stage at which trainees should do research. We strongly favor making cross-disciplinary projects widely available, even to those with minimal backgrounds. While advanced trainees will have more tools at their disposal, talented, quantitatively-oriented students can learn quickly how to apply and interpret statistical techniques, without formal coursework—indeed, we witness this repeatedly in neuroscience. There has been a tendency in statistics to have students understand first, then do. But this sequence can be reversed, giving a statistical faculty supervisor the chance to demonstrate in practice the value of knowing the theoretical underpinnings of methodology. Perhaps most importantly, as we said above, students who want to solve real problems will be attracted to cross-disciplinary research. At both the graduate and undergraduate levels, exciting research opportunities are likely to be among the best recruitment tools.

2. Identify ways of fostering statistical thinking. How should we help our students internalize a principled approach to data collection, prediction, and scientific inference? Appreciation of statistical thinking should begin in introductory courses. Each instructor of a first course in statistics grapples with ideas behind reasoning from data, and much effort has gone into texts for such classes. While we recognize the many great strides taken by textbook authors, we are not entirely satisfied with the typical content of introductory courses. For example, in teaching young neurobiologists we have found it helpful to stress the value of probabilistic reasoning through propagation of uncertainty via simulation methods—as in bootstrap confidence intervals or Bayesian inference—and to emphasize "principles" by including explicit discussion of mean squared error. Both topics seem more advanced than what is usually found in elementary texts. To be attracted to the subject, however, the most gifted students must see it as deep, with serious theoretical content. Courses tend to be categorized as either theoretically-oriented for math/statistics majors or method-oriented "service courses" for other disciplines, and we find too little similarity between the two. The main point here is that the first college-level exposure to statistics matters. While, for pedagogical purposes, central ideas must remain simple and approachable, we think it important to represent the discipline as rich in profound concepts. More fundamentally, one goal of every first course in statistics for quantitatively-capable students should be to interest some of the participants in further study.

At the graduate level, existing curricula succeed in getting students to think like statisticians, but if programs are to be streamlined a focus on this goal will be necessary. Students will still need exposure to statistical reasoning in multiple diverse settings, together with emphasis on (a) the roles of heuristics, computational considerations, and/or generative models in producing procedures; and (b) theoretical performance, balanced by convenience, computational efficiency, and interpretability. Many excellent books on topics such as nonparametric regression, density estimation, time series analysis, or Bayesian methods offer very good comparative discussions combining both theoretical and practical concerns. The only problem we see is that they are designed for full-semester courses, and the modern student may, in many cases, wish to devote only a couple of weeks to each within formal coursework. We think there is an important place for courses, and texts, that give quick impressions while reinforcing underlying principles.

We also take it for granted, but think it nonetheless worth mentioning, that training programs—at every level—should include many opportunities for trainees to interact with experienced statisticians (in journal clubs, informal seminars, social events, etc.) partly to see how they think about problems, but also to have role models reinforce the joys and benefits of pursuing statistics.

3. Require real-world problem solving. Experienced statisticians spend much of their collaborative time trying to understand the nature of the data collection process, and its relationship to scientific or technological issues. Some students, especially those with backgrounds in experimental science, tend to be well prepared along this dimension, asking appropriate questions, digging up background material, and readily grasping the big picture. Many others, however, have difficulty making connections between scientific ideas, the resulting data, and appropriate analytic strategies. Having recognized this basic skill for applied statistics, we must help our students develop it. Several methods exist. Project courses, especially at the undergraduate level, can be helpful. Extended research projects—learning by doing—can of course be among the best ways to develop problem-solving skills. An important caveat, however, is that some projects are so well formulated that execution becomes straightforward and little effort toward big-picture comprehension is needed. We come across students who, in the course of doing statistical analyses, exhibit remarkably little curiosity about the material they are analyzing. Most likely this is because they have not been taught a systematic approach to problem solving, and have not appreciated the payoff from pursuing it.

4. Encourage deep cross-disciplinary knowledge. In neuroscience, as elsewhere, statistical training can shape the way data lead to useful knowledge. Once the information obtainable from an experiment is clearly understood, a new aspect of the scientific landscape may come into view. As a result, statisticians can make major contributions by redefining problems, and redirecting data-collection efforts.

In this regard we would like to distinguish two alternative roles. The first has been played by both of us: like other senior statisticians in varied domains, we have spent many years learning scientific principles and methods, and building collaborations with colleagues, so that our suggestions for research problems and approaches are taken seriously and often followed. The second, however, requires a deeper commitment to cross-disciplinary training. One of us, Brown, became a practicing anesthesiologist in addition to being a statistician. As a result of his extensive physiological knowledge and expertise, he has been able to create a laboratory and is undertaking a series of experiments on brain activity to describe the way anesthetic drugs produce the state of anesthesia. Many others in the profession play a similar "principal investigator" role. Two examples are John Quackenbush in the Biostatistics Department in the Harvard School of Public Health and the Dana Farber Cancer Institute, who formulates and executes experiments that use genomic and computational approaches to study networks and pathways in cancer development and progression; and Wing Wong in the Department of Statistics at Stanford University, who conducts experiments on developmental genomics and signal transduction that are informed by statistical considerations.

Faculty who run extra-disciplinary experiments, as well as contributing to disciplinary methodology, are becoming fairly common in engineering and physics but not in statistics. The change in attitude we advocate should, in time, produce more such people in departments of statistics. In addition to accepting the desirability of these appointments, however, more joint training programs are needed. As models in neuroscience we can point to our own institutions. The Harvard/MIT Health Sciences and Technology Ph.D. program trains students in quantitative subjects while also having them take substantial medical school courses and serve on rotations in the hospital as a medical student would. Carnegie Mellon's Ph.D. Program in Neural Computation is similar, requiring mastery of a technical discipline (such as computer science or statistics) together with multiple courses in the brain sciences, and rotation through experimental laboratories. Again, to attract large numbers of students, course requirements in interdisciplinary programs must be stripped to manageable essentials. We would like to see more such joint programs that offer credentials in statistics.

Discussion

The report by Lindsay, Kettenring, and Siegmund (2004) was aimed at the general community of mathematical scientists. Our discussion has been inward-looking, and critical. While there is much to be admired in statistical training programs throughout the world, we accuse them of harboring obsolete attitudes about the nature of statistics. Statistics is a wonderful field, but the way statisticians view it must evolve. We have suggested defining what our discipline brings to the table, and have used "statistical thinking" to label the perspective we find so fundamentally valuable. We have also advocated greater encouragement of cross-disciplinary training. Deepening cross-disciplinary involvement, and welcoming more experimentalists and other practitioners into the clan of statisticians, need not diminish the importance of the theoretical core. Quite the contrary: those with hands-on knowledge of context-driven issues can help identify methodological problems, prodding theory to advance in productive new directions.

Our call for reform echoes pleas by many others in the past. Snee (1990) noted that "Many of us talk about statistical thinking but rarely define it." Though the field is so broad that a single notion of statistical thinking can not possibly be universally applicable, we have provided a succinct definition coming from our own experience, and have claimed that it articulates a widely-held consensus. We are, at least, in line with Rubin (1993) when he said,

> The special training statisticians receive in mapping real problems into formal probability models, computing inferences from the data and models, and exploring the adequacy of these inferences, is not really part of any other formal discipline, yet is often crucial to the quality of empirical research.

Similarly, Mallows (1998) wrote that

> Statistical thinking concerns the relation of quantitative data to a real-world problem, often in the presence of variability and uncertainty. It attempts to make precise what the data has to say about the problem of interest.

In combining these points of view we wanted to recognize the centrality of probabilistic reasoning while distinguishing two roles for it: first, in moving, inductively, from description of variation to expressions of knowledge and uncertainty[1]; second, in evaluating procedures. We can elaborate our definition of statistical thinking slightly by saying it involves two principles:

1. Statistical models of regularity and variability in data may be used to express knowledge and uncertainty about a signal in the presence of noise, via inductive reasoning.
2. Statistical methods may be analyzed to determine how well they are likely to perform.

The downside of spelling out a definition is that it would be easy to get side-tracked on the details. For starters, we intend "signal" to denote general underlying phenomena and relationships of interest, while "noise" refers to sources of variation that are being separated from the signal. We find these terms helpful partly because the nonparametric regression model, where they become explicit, is a useful archetype. Furthermore, we believe there is at least some modest historical evidence to support the importance of such a basic dichotomy. Stigler (1999) considered why psychology adopted statistical methods so much earlier than economics or sociology, and why astronomy did do so even earlier. His answer was that the theory of errors, arising in astronomy, was based on a conceptualization encapsulated by "observation = truth + error" and psychophysics was able to introduce this to psychology, via careful experimental design. Using our words, this suggests that the

[1]This is a move from what philosophers call "aleatory probability" to "epistemic probability." An example of aleatory probability (which we might instead call "descriptive probability") is, "The probability of rolling a 3 with a fair die is 1/6." An example of epistemic probability is "I'm 90% sure the capital of Wyoming is Cheyenne." Bayesians tend to merge these two kinds of probability by taking them to be equivalent, but in every form of statistical inference descriptive probability is used, somehow, to make epistemic statements.

idea of considering data to be generated by combining signal and noise was essential to the historical development of statistical thinking.

A related detail is that, just as there are disagreements about the subtleties of the nonparametric regression model and its application, there are important issues about the role of modeling in statistics. We intend to use "statistical model" very broadly, the only restriction being that probability is involved, so that the notion covers models with relatively weak assumptions, as in a two-sample permutation test, or strong ones, as in many Bayesian multi-level hierarchical models.[2] We are here also remaining agnostic about the extent to which a model may be "explanatory" or "empirical," as discussed by Cox (1990) and Lehmann (1990), recognizing that "[These descriptions] represent somewhat extreme points of a continuum" (Kruskal and Neyman, 1956). Rather, we believe that when Box (1979) said "All models are wrong, but some are useful," he was expressing a quintessential statistical attitude.

Regardless of these philosophical finepoints, our first main message is that training programs should have a clearer notion of what they intend to be doing. The second is that they need, in general, to strengthen and deepen their commitment to cross-disciplinary work. In the latter we again follow many others. We have emphasized the contrast between short-term consulting and deeper, long-term engagement because different attitudes and skills are needed. We are sympathetic to the promise made by Birnbaum (1971) that "each student of statistics working with me at any level shall also work systematically with another study adviser representing a scientific or technological research discipline of interest to the student" and we agree with Gnanedesikan (1990) that the focus in training should be less on defining the appropriate encompassing content than on instilling a relevant sense of cross-disciplinary curiosity: "We need a switch turned on, a value established, for impelling statisticians to be challenged intellectually and through a desire to contribute to solving major problems in other fields."

The worth of cross-disciplinary work, and its essential role in stimulating new statistical theory and methods, seems to be much more widely appreci-

[2]Our formulation can not accommodate the perspective of Breiman (2001), but we believe it is entirely consistent with the views given by discussants to that article by Cox (2001) and Efron (2001).

ated than it was in earlier years. We want to push harder, partly because we feel curricular ramifications have not been given sufficient attention, but also because the world needs more statistically-oriented scientific principal investigators. Such scientific leadership is, again, not only a recent development. As one example, in the mid 1970s Fred Mosteller, a master at initiating interdisciplinary collaborations on topics he deemed scientifically important, became interested in the benefits of surgical therapies, which are typically not studied using randomized controlled clinical trials. This led to his formulation of a large research effort involving statisticians, surgeons, anesthesiologists and public health specialists to investigate the costs, risks and benefits of surgery (Bunker et al., 1977). Mosteller was not trained in surgery, but he was clearly the intellectual leader of the project. Nor is this kind of leadership in any way limited to areas where "principal investigator" has a literal meaning in a biomedical context. As emphasized by Keller-McNulty (2007), many of today's big challenges throughout society are tackled by large teams, and they are in desperate need of statistical thinking at the very top levels of management. We would suggest a way forward begins with a focus on the fundamental goals of training combined with a broad vision of the discipline of statistics.

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