On Learning to Use Statistical Theory

K. Laurence Weldon
Dept. of Math & Stats, Simon Fraser Univ., Burnaby, B.C., Canada. V5A 1S6

Students of statistical theory need to learn the general concepts, and simultaneously how to use these concepts. To achieve a useful knowledge of statistical theory, students must have the proper motivation, the opportunity to learn the tools and concepts and when to use them, and a chance to gain the depth of understanding required to balance the dogma with common sense. In this paper, we explore the implications of these simple requirements for instruction in statistical theory and practice.

Introduction:

Statistical theory is the body of concepts and tools that enables a person to collect informative data, and to extract information from the data. The essence of statistical theory is that it enables people to get information from data: the theory is essentially utilitarian.

There seems to me to be a widespread confusion about "theory" and "practice" in discussions of statistical education. Current curricula in universities suggest there is a dichotomy of things to learn -- some courses teach theory, occasionally called "mathematical statistics", while some teach practice, the latter being called "service" or "application" courses. But this dichotomy has had very unfortunate consequences for the learning of statistics. The "theory" courses teach how to mathematize statistical problems without teaching how to recognize a statistical problem in the real world, or how to get rid of the mathematics from the result when the mathematics is done, and turn the result into something scientifically meaningful. On the other hand, the "practice" courses teach how to answer questions that real scientists do not ask. Without a deeper understanding of the theory, students will not be able to adapt the statistician's questions to a real scientific context. In other words, the theory and practice of statistics are inseparable, because the theory is about the practice, and the practice should be according to the theory. So the pedagogic separation of theory and practice is unwise.

Most teachers are aware of this problem, but the radical remedies that have been proposed for it are not widely prescribed. My contention is that we should banish this dichotomy from the curriculum. The more useful dichotomy, between users and teachers of statistics, is a valid one, but the teachers should take more courses, not different courses, than the users. There are arguments for segregating various groups of users by discipline, but this does not imply that these users need no theory.

The traditions of our discipline were established in a pre-computer age in which the mathematicians were the only ones able to provide a rational approach to data analysis. The tendency of the mathematical statisticians to focus on the tractability of the mathematics rather than the utility of the procedures was harmless at a time when these statisticians were out of the mainstream of science and social science. But the situation today is very different. Statistics and Statisticians are becoming an integral part of the modern research and development process in almost all disciplines, and statisticians are expected to know how to relate statistical ideas to the objectives of other disciplines. See

Kettenring(1994) for a supporting argument from the industrial sector. The utility of statistical theory for applications has become a more important focus for statistical research than the mathematics of statistical theory. Computers have opened up the field of statistics to users from many disciplines, and this has changed the content of statistics courses as well as the way this content should be learned.

The changes in teaching statistics that are needed apply equally well to universities, secondary school, and elementary school. If statistics is thought of as a component of mathematics, the statistics that is taught in the schools will continue to be limited to combinatorics and histograms. The wider role of statistics, as an essential tool in a wide variety of data-based investigations, will be missed. The developing field of computerized data display will be thought of as computer science rather than statistics. The charm of exploratory data analysis via computer graphics will not be recognized as a key part of the discipline of statistics. Those interested in scientific method will study science rather than statistics. It may not be possible to change attitudes to statistics once students reach the university level.

In this paper, we go "back to basics" by considering what is needed for a student to become an effective user of statistics. We consider the components necessary for a student to learn the "theory of statistics" -- the generally applicable tools and concepts:

I the proper motivation
II the opportunity to learn the tools and concepts,
III the opportunity to learn when to use these tools and concepts, and
IV a chance to gain understanding required to balance the dogma with common sense

These components are needed by anyone using or teaching statistics -- each component is detailed in the sections that follow.

I: The Proper Motivation

Students will be guided in their approach to a course by the style of the assignments and tests, and especially by any old exams set by the instructor. It is very important that these instruments provide the right signals to the students. (See Garfield (1994) for a broader discussion of assessment methods). Clever students may not attempt the deeper conceptual understanding if there is no reward at exam time for the extra time spent. For example, if exam questions do not include any jargon-free questions, the student will consider the problem-formulation stage of statistical analysis to be a frill to be left to work-experience, and will not pay much attention to it. This is not simply a detail. The ability to recognize the need for a statistical strategy in a non-jargon question requires conceptual understanding, and this conceptual understanding is not easily learned from unsupervised work-experience. Examination questions in a course for statistics "users" must examine whether the student knows how to use the subject in a real world context. The best way to do this is with jargon-free questions.

Another aspect of examination questions is that the answers need to be expressible in ordinary language. Now "$P < .05$, Reject Ho: $\mu=10$" is not ordinary language. We need to insist that students can relate what they are doing to their real world, and one test of this is whether they can express their calculation results in ordinary language. In fact, it is also very useful to use exam questions that request verbal explanations of statistical theory, in some real context. One can easily tell if a student understands a tool like a "confidence interval" or a concept like "frequency distribution" by using theory questions that call for verbal answers. For example, a question describing context and data from an agricultural experiment might include the query "How would you describe the effect of the new fertilizer relative to the standard?" A good answer should include not only an estimate of the difference in yield but also an indication of the precision with which it is estimated. The student who needs to be told a confidence level before thinking of using a confidence interval will be stuck, just as he would be in practice. Multiple-choice questions have many nice properties, such as ease and objectivity of marking, but they are very bad at encouraging students to internalize statistical ideas. This requires verbal questions and responses, in jargon-free language.

Another motivational factor in statistics courses is whether the student perceives the material to be relavant to their major field. Even compulsory courses in statistics will be viewed with more enthusiasm if the student feels it is relevant to his or her career. Students of science or social science must see that what they learn in statistics has some relevance to their own discipline, whether business, psychology, or biology. But the questions in these fields that are of interest to a student are not questions that involve statistical jargon. The instructor must show that statistics can help find answers to scientific questions that are free of statistical jargon. For example, a Psychology student will be far more interested in the question "Does the grasp of the dominant hand have a higher or lower reaction time than the grasp of the non-dominant hand?", than in the question "Is there a statistically significance difference between dominant and non-dominant hands based on this grasp reaction time data?". The instructor must start with the general question and move to the jargon as necessary. The point is that we should remember that while jargon helps to reduce ambiguity for a statistical expert, it is not the starting point for most "users" of statistics. For users, the motivation comes from an interest in their particular subject matter.

Now let us consider the math major whose main interest is mathematics. In a course with a lot of words, how do we keep the math major motivated? If everyone is to take the same basic course in statistics, with a minimum of mathematics, then the motivation of the math student is a natural concern. But we should consider what sort of student is best suited to a career in statistics. Is the math major really the prime target? Don't we want students who are capable in mathematics but whose primary interest is science (or social science) and research method? A student who is bored with a good course in basic statistics, but one that has minimal mathematics, is probably not suited to the modern discipline of statistics. As a parallel, would math-oriented students be bored with a strength of materials course that had only the simplest mathematics? If they have a narrow interest in mathematics, they may well find "strength-of-materials" boring, but if so, they should probably not be mechanical engineers. The point is that in introducing students to statistics, we should tell them what the discipline is in its broadest perspective, not merely the role that mathematics has in codifying the theory. Mathematics is still an important tool for statistics, but its role is diminishing in relative terms, and we must realize the importance of other capabilities and interests in attracting students to our discipline. The "statistics for math majors" should be a very small segment of our teaching, whereas the "statistics for math-capable students" will continue to grow, as long as we teach what is necessary to use statistics, and not merely the portion of the theory that is mathematics.

Consider now the students who are comfortable with mathematics but not focused on it for a career -- students in engineering or management science come to mind, but there are others in all majors. What kind of course should these students have, as an introduction to statistics? Should they involve procedures for confidence intervals and hypothesis testing, or data-based projects aimed at answering questions of interest to the students? Should they focus on the different approaches to hypothesis testing according to whether the population variance is known or unknown, or should they observe through simulation and graphical displays how a small sample will provide a poor estimate of the population variance. Although these students are capable in mathematics, the purely mathematical approach will rarely be successful in exposing the important concepts, or be as interesting, as an approach that deals with the conceptual issues in a non-mathematical way. Data-based projects provide the best introduction to the questions that the discipline of statistics tries to answer, and this is as true for the mathematically inclined as for others. Moreover, understanding the scientific questions will allow a student to assess statistical dogma with more sophistication, to judge its strengths and weaknesses. This is a fine objective for the first courses in statistics.

Basic Statistics courses are required of students in fields like Criminology and Archeology, where students often have very little affinity for mathematics. In serving these students, we have too often mounted courses that might be called "statistics-for-dummies". The arrogance of the mathematical statistician is manifest in the assumption that a "mathematically challenged" student must lack normal intelligence! Our courses for these students should limit the sophistication of mathematics, but not the sophistication of the concepts. A serious first course in statistics need not include any but the simplest mathematics: percentages, summation formulas, and the equation of a line, are about all that is needed. We can still deal with tough ideas like randomization, confounding, levels of measurement, roles of variables (predictor, predicted, nuisance, covariate), measures of variability and covariability, comparisons of whole distributions, etc., within a framework of minimal mathematics. We should not give condescending treatments of statistics, with emphases on rote memory and calculation rituals, to those who do not find mathematics helpful.

There are many introductory statistics courses taught by departments other than the statistics department. Many departments argue that their students need familiar examples in order to relate to statistical material. The psychology department may talk about normal distributions with reference to IQs, the biology department with reference to water quality studies, and the criminology department with reference to the weekly arrests for vagrancy. As long as the instructors in these departments are properly trained in statistics per se, this does seem like a reasonable scheme. It would be hard to argue that a general statistician would be able to relate to psychology, biology, and criminology as effectively as a statistician specializing in one of these areas. On the other hand, maintaining competence in statistics as a discipline at the same time as specializing in applications to one area, will be difficult for most faculty. Depending on the size of the university and the heterogeneity of the statistics faculty, some joint teaching arrangements between the statistics department and the applications departments may be the optimal route.

To summarize the argument so far:

1. Students will be more motivated to study statistics if they see its relevance to their own field, so applicability of the course material must be demonstrated.
2. Application of statistics requires the ability to identify opportunities for the various tools and concepts of "the theory of statistics".
3. Examinations and tests must reward students who have developed the necessary understanding of the tools and concepts that allows them to apply these tools and concepts in a jargon-free framework of scientific questions.
4. Math-capable students should not be distracted from learning to relate the statistical tools and concepts to the real world by receiving the material in mathematical form only.
5. All students need the same style of introduction to statistics, although the examples used should probably relate to the student's own discipline if possible. All students need to learn to verbalize their understanding of statistical concepts, and to verbalize the outcome of statistical calculations or graphs.

II: Opportunity to learn tools and concepts

The student must have clear and unambiguous descriptions of the most useful tools and concepts of statistics. This is what many textbooks do well. Textbooks are usually technique-based, and this is appropriate. A problem-based textbook might be very interesting, but it would be a frustrating book to use as a reference by a student who is trying to sort out terminology and procedures. The traditional textbooks, either mathematically based or not, will continue to have an important role in statistical education.

Modern textbooks include lots of examples to demonstrate the use of the definitions and formulas. These examples can be simple *applications*, more extensive *case studies*, or *projects* to be carried out by the student. Now an *application* can have some explanatory value, but ironically, it usually does not tell the student how to apply the technique. For example, after defining the correlation coefficient, we may show how high school and university grades of class members have a positive correlation. But this is not going to tell students when a correlation coefficient is a good thing to calculate, or how to describe a situation in which the correlation has a certain value. *Case studies* are a step in the right direction: these are applications with enough context to explain what the investigator wanted to find out, and how certain statistical strategies helped to answer the investigator's questions. For example, a university admissions committee may wish to know how reliable the high school Algebra 12 grade is as an indicator of future success in the university. This might be an opportunity to suggest that regression is a predictive technique. But even "case studies" are not rich enough in context. The student needs experience in bridging the gap between scientific questions and the statistical strategies that may help in arriving at an answer to the questions. *Projects* are studies where only the broad scientific question is posed, and the student has to think through the whole process of data collection, analysis and interpretation, and be able to focus on the aspects that are important in answering the original question. Typically, a project will involve the student coming up with a scientific question that might be answered by a fairly simple data-collection process, and also the actual collection of the data, and, after the analysis, the writing of a report which answers the scientific question posed. The scientific significance of these projects is of little concern - it is the process of question->data-analysis->synthesis->answer that is important in this kind of exercise. See Bentley(1992) and McKenzie (1992) for interesting examples of this approach.

Students need *applications* to grasp definitions and the components of formulas; they need *case studies* to demonstrate how certain strategies are used in applications, and they need *projects* to give them experience in connecting statistical theory with scientific questions.

Until 1965 or so, statistics students used to be subjected to “labs” in which hours on end were spent computing sums of squares formulas column by column, on mechanical or electro-mechanical calculating machines. The advent of the computer changed all that, to the relief of many. The tradition of experiencing the numbers in order to learn the theory is still alive today, but the way numbers are experienced has changed. For example, instead of requiring students to compute sums of squares and F statistics, we ask students to use statistical programs to compute multiple regression fits, to examine the residual plots, and to study empirically the influence of suspected outliers. There is clearly more theoretical learning going on with these more modern exercises.

One negative aspect of the tradition of hand calculation is the belief today that it is important to know how to use the calculation formulas, even though the computer software is doing all the calculations. For wise use of formulas, one has to know the criteria that led to the formula, not really the formula itself. For example, a student will not learn much about the standard deviation by computing it many times. Better to consider what deviations are being summarized, and what the resulting number represents. Note that the “hand-calculation” formula for the standard deviation completely obscures the rationale of this variability measure.

One aspect of modern statistics that a student learns by doing computer-based data analysis is that modeling is a trial-and-error process. In pre-computer days, there was much more emphasis on optimal procedures, the idea being that one wanted to choose the most efficient procedure that was suited to the situation at hand. For example, means were preferred to medians for estimating population means in populations that were assumed to be approximately normal. But every optimal procedure had assumptions on which the optimality depended, and the computer age brought a tradition of “look at the data first, and try some ad hoc fits as a preliminary assessment”. More emphasis began to be put on the exploratory phase of the analysis, and less on the more formal tests. The reality that complex data sets did not have an optimal procedure became less of a concern. The exploratory methods for these complex data sets became the only analysis, with graphical methods playing a prominent role. Data analysis has become a more subjective process, however disturbing this is to those proud of the mathematical roots of statistics.

The main points in this section are:

1. Traditional textbooks are a good source of definitions and technique-based explanations.

2. *Applications* demonstrate a technique, *case-studies* show how the technique relates to the realities of scientific inquiry, and *projects* show how to select what techniques to use, and how to assess the importance of methodological imperfections in the interpretation of results. 3. Computer software relieves students of the necessity of learning calculation formulas, but experience in data analysis using computer is still needed.
4. Students must learn to use a trial-and-error approach to data analysis, using graphical displays for guidance along the way.

III: Opportunity to learn identification skills

Textbooks teach techniques and definitions -- a table of contents will include things like “Contingency Tables," “Confidence Intervals”, or “Scatter Diagrams” but scientific questions rarely mention these words. A student has to learn how scientific questions relate to statistical questions, and how to identify which statistical tools and techniques to call upon in a given scientific inquiry. Until fairly recently, statistical educators have assumed that this step is learned following the period of formal education; but there has been quite severe criticism of this assumption recently, and it now appears that this process of identifying opportunities for statistical theory in answering scientific questions must be taught more deliberately. See Yilmaz(1996).

The role of data-based projects has already been mentioned: when students start with a question like “How can I build a paper airplane that will stay aloft for a long time?”, they must think hard about how the data is going to be collected and analyzed before actually taking any observations. Moreover, they will realize that the statistical work is not complete until the data has been summarized in a simple form (usually graphically) and the conclusions have been expressed in ordinary language -- these steps requires a good understanding of the logic of the techniques used.

The role of words in statistical instruction is often under-rated. A typical student arrives at a course with 18 years of experience in using words to describe the real world, and unless the student can use words to describe statistical strategies, the strategies and the real world will never be in contact within the students mind! For example, suppose a student learns that the correlation between muscle mass and maximum weight lifted is .75. In reporting this result the student must state what this means about the relationship between muscle mass and maximum lift: a minimum would be to say that, as expected, the higher lift weights were accomplished by the lifters with the larger muscle mass. A more detailed explanation might discuss the degree of linearity of the relationship, the difference between frame size and muscle added through training, the possibility that the apparent positive association was an illusion of randomness, and possible biases in the selection of the lifters. The “r=0.75” is a very small part of the result. The verbal description of the outcome encourages a consideration of the real meaning of the calculation. In doing so, it brings up issues that are key components of statistical theory: in this example, the issues of linearity assumptions of models, the correlation vs. causation distinction, the issue of reproducibility (statistical significance), and sampling bias.

When a student considers a data-based question, there must be a few salient points in mind that a statistics course has emphasized as important for all statistics work. Do courses put enough emphasis on these "big ideas" so that students will not purge them from memory the moment the exam is written? Here are some suggestions for "big ideas" that need emphasis:

- No statistical model is perfect in the sense that it mimics reality perfectly, and we must assess models by how useful they are in simplifying the analysis of the data.
- Inference procedures depend on an assumption of random sampling from a population of interest, and one must always consider how badly this assumption is violated in generalizing results to the population.
- Words are the best way to summarize data-based results -- Graphs are the next best way to summarize results, and graphs have an additional feature that they are able to convey more detail than words, for a given amount of a reader's time.
- Findings based on small samples, or those that are very sensitive to small subsets of a sample, may turn out to be illusions of randomness, and not reproducible.
- To prove causality in the presence of unexplained error, one needs a true experiment in which the investigator controls the assignment of treatments to experimental units.
- Comparisons with observational studies must attempt to adjust for known covariates before concluding whether or not apparent differences can be attributed to the variable of interest. This applies to variables of all kinds (in particular, measurement variables and categorical variables).
- Some data-based studies have parameter estimation as a goal, some are for testing hypotheses about parameters, and some are for descriptions of whole distributions rather than particular parameters -- we must distinguish between these goals in choosing statistical methods of analysis.

Of course there are other big ideas involving probability, likelihood, prior information, serial correlation, variance reduction strategies, etc. The above list is just a beginning, but it is intended to indicate some things that practitioners take for granted, and yet are essential for proper use of statistical theory, but which get scant mention in our basic courses. Moreover, just because an idea is easy to convey, and does not take much time in a statistics course, does not mean that it is unimportant. If we spend half the course telling students how to do hypothesis tests, we should not be surprised if the student gets the idea that this is the most important part of the course. We need to convey appropriate levels of usefulness, especially when this does not match the time spent on the concept.

The basic course in Statistics often restricts attention to statistical theory developed about fifty years ago. The rationale seems to be that the historical sequence of statistical research is also the current logical sequence. New developments like resampling methods, nonparametric smoothing of graphs, three-dimensional scatterplot rotation, and anything having to do with time series or Bayesian methods, are assumed to be advanced topics unsuited for the basic course. But these ideas are not more difficult than the ones traditionally included, and are arguably more useful. The conservative forces in an institution that prevent a basic course content from changing must be counteracted by the need to integrate useful developments into the basic courses as these novelties are developed. Those students that only take one or two or three statistics courses, which surely is the majority of students taking any statistics courses, should not be left with an anachronistic introduction to the subject.

In this section we have made the following points:

1. Statistical Jargon is not used for scientific questions, and students must learn how to identify opportunities for their jargon-based statistical knowledge.
2. Verbalization of statistical concepts and formulas is a useful exercise for improving understanding of statistical theory and for making proper use of the theory.
3. Instructors of statistics must make clear the big ideas that students are sure to run into in their professional lives, even though these ideas may not be the ones requiring the most time to learn.
4. In revising course content, we should be careful to distinguish between those topics that are truly advanced, and those that are merely recently developed. Some recently developed techniques belong in the basic course.

All these points arise naturally when students are exposed to real scientific questions, and asked to apply what they have learned about statistical theory to these scientific questions. Data-based projects are ideal for this.

IV: Learning to Balance Dogma with Common Sense

The idealized situations described by statistics texts are seldom met exactly in practice. Samples are seldom selected at random from a population of interest, and there is usually no way to really validate the assumption of randomness in a measurement model. Critical P-values and confidence levels are seldom chosen based on any exact analysis of the requirements of a situation. There is no rigorous theory of the identification of outliers. Models which assume normality or some other distribution are used even when the model assumptions cannot be checked. In fact the inevitable shortcomings of models are simply ignored as long as they do not show up in a residual plot. Scientific judgment is needed at every step of a statistical analysis. These points suggest that to take statistical theory as applied mathematics is a extremely unrealistic.

In fact the theory of statistics as it is taught in modern courses is not a well-worked out theory at all - it is more a jumble of ad hoc techniques suited to rather special situations.

It may be unfair to expect a neat theory that embodies all approaches to dealing with unexplained variation; but we can at least highlight the particular aspects of statistics that arise again and again in applications. At the present state of theoretical development of statistics, it is necessary to prepare students to adapt what they learn to the needs of particular applications, and to be skeptical of dogma that says “you must always ...”. The message for the student should be “Don’t take the dogma too seriously!”. Most instructors have observed a certain behaviour of students in which they slavishly accept the dogma without question. Surely this is prompted by a lack of understanding of the rationale behind the methods presented in the course. If we are going to recommend that students reject our teachings on occasion, we must emphasize the necessity of understanding the concepts, so such rejections can be appropriate. An example is the familiar Hypothesis Test when applied to a huge sample. In this case the student must understand that the hypothesis may be rejected when it is, except for a negligible difference, true. Another example of dangerous hypothesis testing dogma is to use the traditional $\alpha = 0.05$ when the test is exploratory in nature. In these situations a large α such as .20 or even .30 may be appropriate in determining which options should be investigated further. Yet another example is to use procedures for parameter estimation when the entire distribution is the focus of interest, and the functional form of the distribution is uncertain. These strategic errors can be avoided with a good understanding of the basic concepts.

To learn the fallibility of the basic strategies requires experience with applications of the theory. Mastery of basic statistics allows the student to reject the rules when the circumstances warrant it. But unless students can see this being done without shame under the supervision of an expert (an instructor), they may not have the courage to try it when they are on their own. Guided experience with live data-based investigations is needed to demonstrate this activity.

Computers have shaken the foundations of our statistical traditions. One of the main reasons for this, although there are others, is that computers make data visualization easy. Consider the following quotation from Cleveland (1993) in his book "Visualizing Data":

> Probabilistic inference is the classical paradigm for data analysis in science and technology. It rests on a foundation of randomness; variation in data is ascribed to a random process in which nature generates data according to some probability distribution. This leads to a codification of uncertainty by confidence intervals and hypothesis tests. ....
> Visualization ...is a different paradigm for learning from data. It stresses a penetrating look at the structure of data. What is learned from the look is guided by knowledge of the subject under study. Sometimes visualization can fully replace the need for probabilistic inference.

Most traditional theorists would consider this last statement a dangerous heresy, and yet it certainly has some validity, a point well demonstrated by the content of Cleveland's book. The point for the learner of statistical theory is that graphical methods are increasingly important for statistical work, both for analysis and for display of results. The fact that traditional statistical methods tend to ignore graphical tools should not be taken as a guideline for current practice.

Of course, the increase in the use of graphical methods is not the only feature of the computer's impact on statistical theory. There is the obvious impact of the calculation power of the computer, bringing multiple regression in all its forms into the mainstream of statistical practice, as just one example. More subtle but important impacts stimulated by computerization include trial-and-error methods, resampling techniques including the bootstrap, algorithmic optimizations, simulation demonstrations, and the dimensionality reduction of multivariate data. The "resampling" school of statistics is very dependent on computer availability, and has been advocated fairly recently. (Simon 1994). This school advocates a completely non-traditional approach to statistical analysis. Another impact of the computerization of statistics is the shift from parametric to non-parametric methods. Instead of starting with a parametric model for "errors", and using data to estimate parameters, we now tend to smooth data with general smoothing kernels, and examine it graphically. These items are mentioned to make the point that the theory of statistics is in flux, and we should inform the student of the instability of the theory, even if it tends to reduce full faith in the traditional theory we are teaching.

To summarize this section:

1. Statistical theory is not a unified body of principles that applies to all situations - it is a disjointed collection of tools and concepts that need sophistication for their proper application.
2. The computerization of Statistics has destabilized the theory that existed in the sixties and earlier, so that the theory is in rapid flux now.
3. Students must be aware of the need to use common or even uncommon sense in adapting the various prescriptions of statistical theory to particular applications.

Conclusions

1. We should design basic statistics courses to appeal to those expecting to be users of statistics, and require both users and potential teachers to take them. All students need to learn to verbalize their understanding of statistical concepts, and to verbalize the outcome of statistical calculations or graphs.
2. Examinations in statistics must motivate students to learn the theory well enough that they can apply it to answer scientific questions, even when these questions are expressed without statistical jargon or traditional statistical formulation.
3. Students need guided experience with live data-based projects in order to learn how to identify the opportunities for statistical tools and concepts.
4. Statistical Theory consists of "big ideas", that may or may not have a convenient mathematical formulation, but that are useful in a wide variety of data-based studies.
5. In revising course content, we should be careful to distinguish between those topics that are truly advanced, and those that are merely recently developed. Some recently developed techniques belong in the basic courses.
6. With statistical theory in flux, students will have to forgo the luxury of having a unified theory to apply, and instead will have to adapt their formal learning to the practical contexts of data-based scientific problems.

References

Bentley, D. L. (1992), Investigational Statistics: A Data Driven Course, Proceedings of the Section on Statistical Education, American Statistical Association, pp. 119-122.

Cleveland, William S. (1993) Visualizing Data. Hobart Press, P.O. Box 1473, Summit NJ USA 07902-8473.

Garfield, J. B. (1994), Beyond Testing and Grading: Using Assessment to Improve Student Learning. Journal of Statistics Education: v.2, n.1

Kettenring, J.(1994) What Industry Needs: Proceedings of a Symposium: Modern Interdisciplinary University Statistics Education. National Research Council, Washington D.C.

McKenzie, J. D., Jr. (1992), The Use of Projects in Applied Statistics Courses, in Proceedings of the Section on Statistical Education, American Statistical Association, pp. 142-146.

Simon, Julian (1994) What Some Puzzling Problems Teach About the Theory of Simulation and the Use of Resampling. The American Statistician 48:290-293.

Yilmaz, Mustafa R. (1996) The challenge of teaching statistics to non-specialists, Journal of Statistics Education: v.4, n.1