

# **Experiential Learning in Statistics: Expanding its role**

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## **Abstract**

Statistics has evolved to embrace a wide scope of tools and concepts. The answer to “What are the basics?” seems to expand as the years pass. The difficult task for curriculum planners is to design programs that reflect the dynamic nature of the discipline. A common approach is to start with mathematical simplicity and build a scaffold of general tools. One problem with this approach is the lack of motivation it implies for students with an interest in the real world. Another is the lack of intuition it imparts to students with a thirst for abstract concepts. In this talk I want to make the case for an expanded role of experiential learning in an academic setting. For students requiring the abstract scaffold of general tools, this can be provided after the experiential immersion. For students interested in the power of statistics for their particular applied interest, this experiential approach can provide context-specific examples that convey useful intuition and practical advice. The experiential approach has the additional advantage that it also adapts the course content to modern contexts, and helps to keep pace with changes in statistical practice. I will provide some examples of this approach from my teaching experience at SFU.

## **Experiential Learning in Statistics: Expanding its role**

**Outline:** Math Roots and Course Taxonomy  
Calls for change: 1986 and 2009  
Examples of Experiential Teaching  
Features of Experiential Teaching & Learning  
Implementation Issues

### **Math Roots and Course Taxonomy**

When I was at U of T in the early 60s, statistics was taught in the “Mathematics” department, and this was the pattern across Canada. Today, almost all statistics courses in Canadian universities are taught in departments of “Mathematics and Statistics” or “Statistics”. There has slowly emerged a recognition that Statistics is a separate discipline from Mathematics. The difference is multifaceted but one feature is the attitude to context. Mathematics champions the abstraction out of context, while statistics tries to incorporate context into its processes. To teach statistics as a body of abstractions would be to leave the student unable to use the discipline in the real world. Some would say real-world statistics is “applied statistics”, but statistical theory is the

body of generally useful tools and concepts, and so this theory necessarily involves the real world for relevance.

In the early 20<sup>th</sup> century, mathematicians developed methods useful for statistical work. This led to the assumption that statistics was a branch of applied mathematics. However, the computation and communication revolutions have vastly expanded the scope of the discipline of statistics. While mathematics is still a key technology for statistical research, the culture of statistics has diverged from the culture of mathematics. Mathematics is no longer the sole basis of statistics. Mathematics shares this role with natural, life and social science and computing science. Statistics might be called the science of evidence-based information abstraction. Statistics education has to adapt to this new basis.

One result of the role of math in the history of statistics education is the taxonomy of undergraduate courses based on mathematical complexity. Statistics appreciation courses have almost no mathematics, service courses have some formulas but usually no calculus, undergraduate courses for science use calculus but not much linear algebra, and graduate courses in statistics use advanced linear algebra. However, the criteria for sequencing statistics courses should be based on the utility of the course content for statistical work, and the ease with which it can be absorbed. This is quite different. Consider, for example, the topics of time series, simulation, graphics, and smoothing. Many techniques in these areas are often both very useful and easy-to-understand. But these techniques are not given much emphasis in undergraduate courses.

Brown and Kass (2009) have criticized the prevailing taxonomy of statistics courses:

“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.”

If we add the fairly uncommon category of statistics appreciation courses, there seem to be three types of course that lead the student in different directions:

Appreciation courses: discuss the impact of statistics on the real world without insisting on methodological practice

Service courses: these show students how to do some common statistical methods, such as descriptive display and parametric inference. These courses are often required by user programs.

Mainstream courses: these focus on the mathematical framework of the common statistical methods. These tend to be for statistics majors or majors involving a lot of mathematics.

The premise underlying this taxonomy is that different careers require a different brand of statistics. But do math majors not require appreciation of the discipline and a knowledge of the methods? And do users of the methods not require an appreciation of the discipline? A better model for curriculum design might be

Appreciation -> Service -> Mainstream

In other words, statistics experts do not need different, but rather more.

In fact, considering that the vast majority of students studying statistics will not be statistics majors, the “mainstream” could be redefined as the students allotted to “service courses”. Then the education sequence would look like this:

Appreciation -> Mainstream -> Expert

The major goal of each level would be to answer the following questions:

Appreciation: What is statistics and why is it useful?

Mainstream: What are the basic tools and concepts in the discipline, and how can I benefit from them?

Expert: What is needed to adapt basic tools and concepts to be able to use them in novel situations?

This cumulative model of statistics education refocuses attention on the subject instead of the student. We are teaching the same discipline to all students, but some students need more detail than others. We need not “dumb down” the material for students only taking one course. And we do not have to make the courses for experts so difficult mathematically that only a few can pass these courses. One method of instruction that could work for all levels is experiential learning. Combining the cumulative model of course sequencing with this single method of presentation could simplify the variety of statistics offerings and provide more faculty time for interactive teaching. In the following we introduce the motivation for experiential learning, its implementation in current university contexts, and suggestions for overcoming difficulties.

### **Calls for change: 1986 and 2009**

The inadequacy of undergraduate statistics education has been a recurring theme for many years. The quadrennial series of conferences called ICOTS (International Conference on Teaching Statistics) were created in 1982 to draw attention to this problem. These conferences do provide useful advice for curriculum planners. Here are some examples from ICOTS2 in 1986:

"The development of statistical skills needs what is no longer feasible, and that is a great deal of one-to-one student-faculty interaction ..." (Zidek 1986)

"The interplay between questions, answers and statistics seems to me to be something which should interest teachers of statistics, for if students have a good appreciation of this interplay, they will have learned some statistical thinking, not just some statistical methods." (Speed 1986)

"Using the practical model [of teaching statistics] means aiming to teach statistics by addressing such problems in contexts in which they arise. At present this model is not widely used." (Taffe 1986)

"To take advantage of these developments, one must recognize that, while most statistics professors like statistics for its own sake, most students become interested in statistics mainly if the subject promises to do useful things for them. I believe that even the seemingly limited goal of developing "intelligent consumers of statistics" is best attained if students try to produce statistics on a modest scale. Only then do most students seem to become sufficiently intrigued with statistics to want to learn about statistical theory." (Roberts 1986)

These ideas span different parts of the problem: the need for interaction of students with experts in statistics, the need for students to learn the whole process of statistics from verbal questions to verbal answers, the need to incorporate context into students' experiences in statistical analysis, and the need to excite students about applications before presenting the theory. As an index of the extent to which these suggestions have been adopted, consider their impact on current textbooks. I suggest that the impact has been very slight.

How can it be that decades of concentrated study of the undergraduate curriculum has produced very little change? Its true that we are putting more emphasis on applications, more use of software, and more emphasis on study design and data collection, but the sequence of topics presented to students has not changed very much. The textbooks that guide our courses have changed in minor ways (more examples, more exercises, more student aids, more use of software) but they still present the same sequence of topics. Of course, the textbook publishers do not favor radical change for fear of missing the existing market. In a world of static textbook content, students and faculty are easily induced to avoid radical change in course content.

A shift to experiential learning can provide a way around these difficulties. Imagine a course based on a series of data-based studies rather than a series of techniques. The context of the studies would provide interest for students (sports, medicine or social science rather than means, distributions and estimators). The students would be motivated to invent primitive procedures which the instructor could improve upon, and this would help students appreciate the improvements. Students would be building on what they know rather than adding a foreign object to their domestic files. Students would see examples of information extraction from data instead of applications of techniques barely understood. Students learn to verbalize what they are doing with statistical strategies rather than merely thinking in terms of symbols and formulas. Finally, and importantly, the techniques students will learn will be those actually required to extract information from data, in the context of today's resources, rather than those techniques that a textbook writer decides constitute the basics of the discipline: sometimes this is called "authentic learning". *The generation of authentic material for statistics courses via actual statistics practice is what can keep our course content current, and avoid the inertia of content that has plagued statistics education in the past.*

Experiential learning satisfies the implied criticisms in the quotes from ICOTS2:

Zidek's call for more student-instructor interaction is provided for when the role of the instructor is to guide discussion rather than transfer knowledge. Speed's questions and answers are embodied directly in experiential learning. Taffe's and Roberts' call for teaching in context are also an essential part of an experiential learning environment. These researchers had good ideas in 1986. But the suggestions were not simply the fad of the day. Consider these more recent quotes:

Nolan and Lang (2009) "It is unclear that we are achieving the goals of basic statistical literacy by focusing on formulae or even by concentrating almost exclusively on methodology. Instead, we believe the field and students would be significantly better served by showing the challenges and applicability of statistics to everyday life, policy, and scientific decision making in many contexts, and by teaching students how to think statistically and creatively."

Brown and Kass (2009) "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 appears to be extraneous to the compelling scientific problems students are interested in solving."

Meng (2009) In discussing the curriculum for users, Meng says

"Equally important, and time consuming, is to design general introductory courses that would truly inspire students to learn – and learn *happily* – statistics as a way of scientific thinking for whatever they do, not a collection of tools that they may or may not need some day.

In discussing his new course STAT 105 at Harvard, he says

"The central feature of this course is that the materials are organized by real-life topics instead of statistical ones.... The statistical topics are covered whenever they are needed by a module, which means that they may be "out-of-sequence" or appear multiple times."

Nolan and Temple Lang (2007)

"We advocate broadening and increasing this effort to all levels of students and, importantly, using topical, interesting, substantive problems that come from the actual practice of statistics. We want students to understand the thought process of the "masters" in context, seeing their choices, different approaches and explorations."

Our courses have always aimed to have students "experience" statistical work. However, the nature of scope of those experiences can be greatly enlarged to help to address some of the criticisms implicit in the quotations above. We will now explore experiential learning in more detail.

## Examples of Experiential Teaching

It is impossible to recreate in print the detail of an episode of experiential learning. However, the outline below may give some rough idea of how it might work. These particular examples are not offered as paragons of the type, but rather are examples I happen to be familiar with. However the choice is guided by diversity of context: sports, medicine, and business.

### Example 1: Sports Leagues

The current standings in a sports league of interest to some students is presented. Students are asked if they think the ranking reflects the underlying quality of the team? How would “underlying quality” be defined? (Ans: For a team A playing a team B, the probability that A wins in a match against B).  
Is it possible that all teams have the same quality? (Ans: simulate league for  $P(\text{Win})=0.5$ )  
How can we measure the degree to which a team departs from the assumption  $P(\text{Win})=0.5$ ? Might this be an alternate measure of “team quality”?  
Do the best teams get into the playoffs? How good does a team have to be to have a high probability of winning the playoffs?  
How would a gambler use the information about the equal-quality team analysis?

Many students would have a sport league that they find interesting and would be motivated to participate in this discussion.

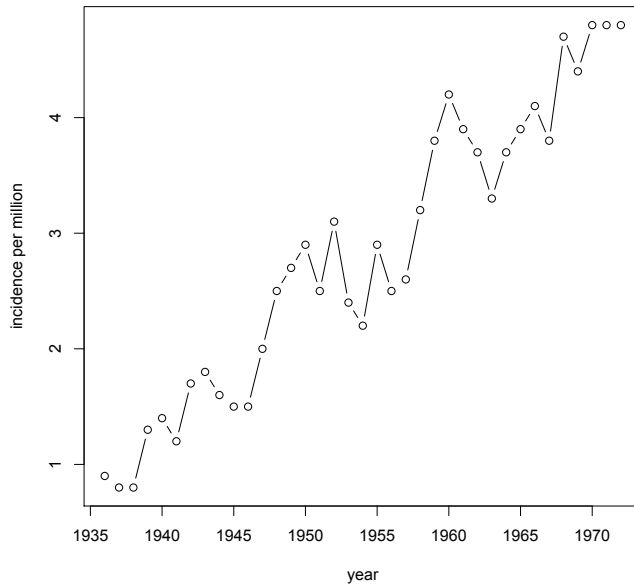
What do students learn from this discussion?

- Randomness can create illusions
- Probability can be useful in studying events that have occurred
- Simulation can be done simply via software
- Some hypotheses can be tested via simulation
- Construction of Measures of Interest is a creative challenge
- The results of simulations can have practical use

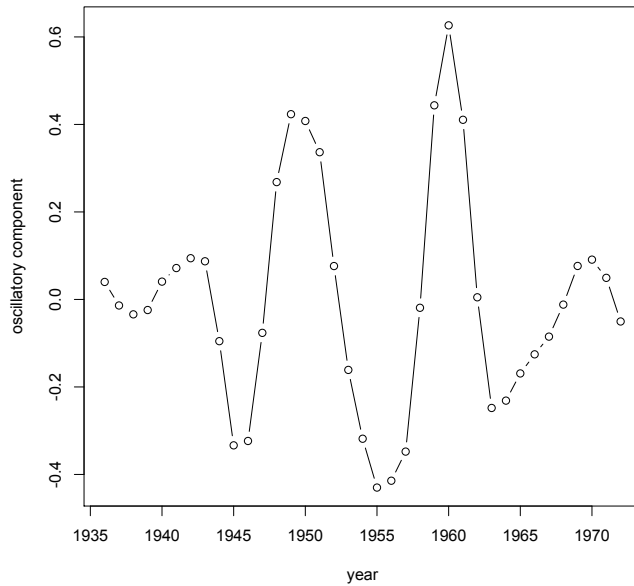
### Example 2: Melanoma Incidence

This example appears in the textbook *Visualizing Data* by Cleveland (1993), pp 152-158. The basic data is shown in the figure below:

**Melanoma Incidence, Connecticut, 1936-1972**



**smoothed loess residual from trend removal**



The analysis reveals an oscillatory component that is not obvious from the raw data. It turns out to have a lagged phase (about 3 years) and same wavelength as the sunspot cycle. Several lessons can be learned by leading students through this analysis:

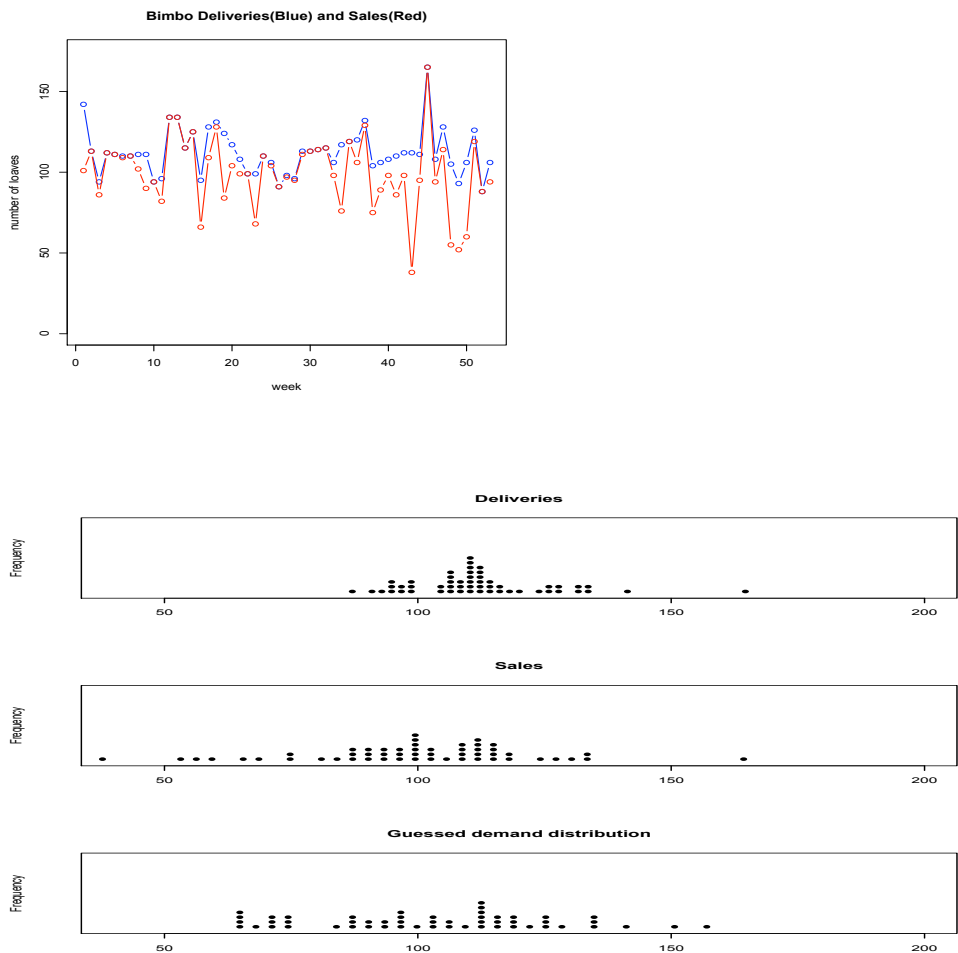
- de-trending of time series
- role of residual plots that have patterns
- iterative nature of curve-fitting, choice of smoothing level

value of general knowledge for data analysis  
the importance of aspect ratio in graphical displays  
comparison of two time series  
the value of exploratory data analysis  
convenience of loess as a smoothing method  
the use of timing in relating causation to correlation

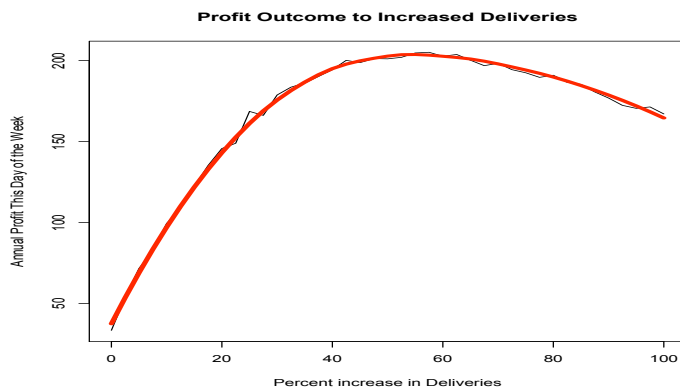
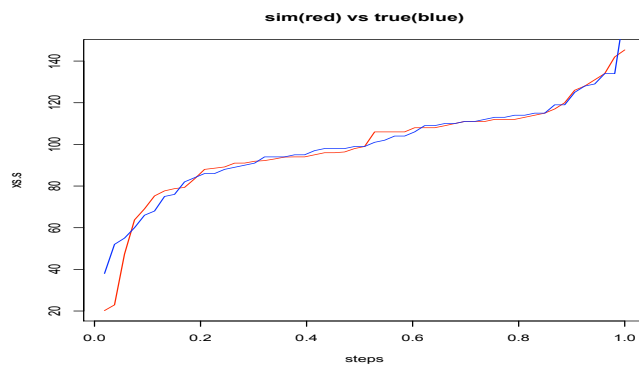
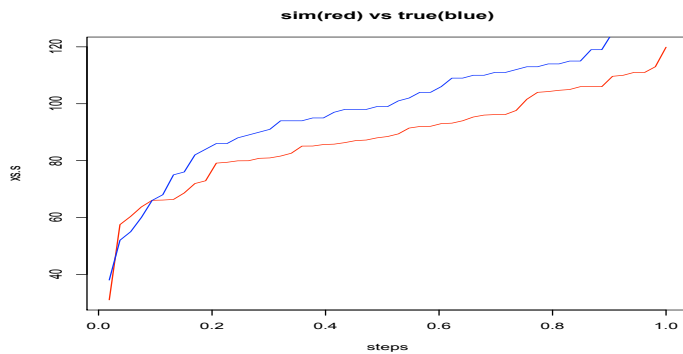
In introducing this example, the deadly nature of malignant melanoma should intensify interest.

### Example 3: Bimbo Bakery

Bimbo Bakery is a Mexican Bakery with dozens of products and thousands of employees worldwide. One generic problem Bimbo has is to supply retail outlets with enough product (e.g. fresh loaves of bread) to satisfy daily demand while taking account of the unwanted cost of excess deliveries (e.g. bread that is no longer fresh on day 2). As an example of available data, the bakery supplies data on actual sales for a particular product at a particular retail outlet every day for one year. What analysis could be done to advise the bakery on altering its delivery amounts?







The data consists of 53 values of “deliveries” and “sales” for each of six days of the week (not Sunday). Typically about 100 loaves of bread are delivered to the retail outlet each day and at the end of the day there are either no loaves left, or some positive number of loaves remain unsold. However, both the delivered quantities and the sold quantities vary quite a lot from day to day. Of course, the sales cannot exceed the deliveries, and this makes the problem interesting.

A series of activities can result from a consideration of this problem, from the simplest descriptive computations and graphs of the data as presented, to a consideration of how to

deal with the missing data, to an optimization of profit by varying the delivery amounts by a certain percentage for each day of the week. One way to deal with the missing data is to guess the demand distribution, and simulate a run through the year's deliveries to try to match the actual sales experience. The seasonal trends need to be removed first however. Once the demand distribution for each day of the week is estimated, an input of economic parameter values can allow maximization of annual profit relative to the percentage changes in deliveries.

For elementary classes, the discussion could be limited to the tabular and graphical description of the data. For intermediate classes, the use of a class of distributions in trial and error fitting of the demand distribution will inform students of the classes of distributions considered, and the way they can be simulated. For advanced classes, students learn the convenience of the ecdf for comparing empirical distributions, and the use of computer programs for producing what would otherwise be a very time-consuming simulation to determine the optimal percentage change of delivery amounts for profit maximization.

This is a project that uses elementary techniques to solve a very widely experienced business problem. Students with an eye on opportunities for a business career may well find this example useful. The exotic nature of the source and the titillating name of the company should arouse additional interest.

These three examples are simply three that I happen to know well. However, the features I look for in choosing an example to lead students through are:

1. Is the subject matter of interest to many students in this class?
2. Is the subject matter simple enough that the required background knowledge is known by students, or easily learned.
3. Are there known statistical techniques that are simple enough to explain to students, and that will provide some information from this data?

### **Features of Experiential Teaching and Learning in Statistics:**

What features of experiential projects make them good learning vehicles for statistics?

The choice of data context should match the interest of students. An unselected student group could be offered everyday examples such as sport, health, or social interaction. Classes with majors in a particular area provide an opportunity to choose examples from that area. The contextual material ideally should be of interest to many students to motivate the extraction of information from the data.

The techniques used in experiential exercises tend to involve software use, especially resampling, simulation and graphics. This mimics current practice. Undergraduate textbooks still do not include enough resampling, simulation and graphics. These

techniques are very useful for the practice of statistics. Note that the techniques that arise in such examples are often simple to understand. The inevitable difficulties of traditional inference are bound to arise, but not in every project.

Another feature that makes the projects interesting to students is the opportunity for creativity – in real data analysis problems, the blind alleys are as useful as the strokes of genius as teaching instruments.

A major potential pitfall of a project-based course is the possibility that key topics will be missed. This is the one advantage of a traditional technique-sequence course. However, if the important thing is to cover the topics that are most useful for analyzing data, a sequence of projects will likely produce these topics. And the fact that the discussion is based on a real data-based problem is very valuable for linking the practice to the theory.

### **Implementation Issues**

Experience-based teaching and learning raises several implementation issues. As with any innovation, difficulties will initially seem to overwhelm the advantages. What follows are suggestions for mediation of these difficulties.

#### **3hr/week lecture schedule**

Does experiential teaching of statistics fit into the traditional 3 hours per week lecture schedule? Although there are other schedules that would also work, the traditional 3 hours per week can also be made to work. Suppose a course has 13 weeks plus a 2 week exam period. Each week could involve a different topic. Lecture 1 would include an introduction to the topic by the instructor and a beginning of Socratic prodding of students. The students would be asked to prepare for lecture 2 by doing some data analysis and proposals or questions relating to further analysis. Lecture 2 would continue the discussion with perhaps some demonstrations by students or the instructor and the final hand-in would be required for lecture 3. The time in lecture 3 could be a review of results obtained by students and a discussion of pluses and minuses of each contribution. A class size too large for this model might be accommodated by using assignment teams. Tests and exams could relate to the general lessons from the projects covered.

#### **Fixed course content requires coverage**

The instructor can guide the extent to which a problem leads to the techniques required by the course syllabus. If there are a few techniques that, in spite of the instructor's guidance, do not arise, then it may be that they are the least important for the student. Of course the student can have the syllabus and be directed to any such material if necessary for subsequent courses. Usually, the techniques that arise will have a further description in a textbook and students can be directed to these as they arise. The mathematical structure of the techniques learned experientially can be outlined by the instructor towards the end of the course. Thus, mathematics will have a simplifying influence rather than seeming to require unnecessary abstraction as might be the case in a technique-oriented course.

### No textbook to follow

Attendance at class sessions should be compulsory. Missed classes will need student-to-student help, although some brief notes posted on the web by the instructor would be some help. Each project should result in textbook references provided by the instructor. If there is no one textbook required for the course then a list of technical terms could be provided so students can look up the material in whatever book or web resource they access. In preparing suggested analyses for the projects, students can use textbook examples and exercises to improve their understanding.

As this kind of course becomes more popular, software to support it will become available. An early version of this has been produced by Rodney Carr of Deakin University in Australia. The following display suggests how it might look. The case studies are linked to the techniques and concepts that a student is supposed to gather from the case study. This ensures that the student learns the abstractions as well as the particular application covered in class.

## Chance and Data Analysis



The individual icons are live so that when clicked, they open up. The case studies have links to the related concepts and techniques, and the concepts and techniques have links

to the various case studies that involve them. For further information about this “Roadmap” software, contact [rodneyc@deakin.edu.au](mailto:rodneyc@deakin.edu.au).

### **Assessment**

Part of the assessment would have to involve participation in class discussions and students presentations in class, in order that attendance and participation is assured. One way to do this is to have student-based assessments of other student’s participation supplemented by the instructors own assessment.

As long as the student’s assessments agree closely to the instructor’s, it would be fair to use an average of these. In cases where there is marked disagreement, the instructor can either change his evaluation, or omit this component, or interview the student to discuss the situation.

Assessment by tests and exams can follow the usual style. However, there is an opportunity to ask students to explain why a certain strategy was used in one of the projects, or to suggest shortcomings of it. This encourages the acquisition by students of the ability to explain in words the techniques they are using, a very useful skill, and an aid to a lasting understanding.

### **Instructor Workload**

Preparing a case study for a class would take time, but it would be similar to the preparation of a traditional lecture. Moreover, the project would likely be discussed for more than one class. The keying of techniques and concepts to textbook jargon would require some time for each class. Class sessions would require full attention by the instructor but perhaps the sharing of presentations with students is easier than giving the entire lecture. Guidance for individual students could take time and might not be feasible for a large class. The instructors task changes from being primarily a “lecturer” to that of a “facilitator”, but the time required in preparation would not be much different.

### **Discussion with Large Classes**

Discussion classes such as are required in experiential learning cannot work well in classes greater than 30 students. This is probably the primary limitation of the experiential learning mode of instruction. However, the larger classes with the traditional technique-based presentation have not worked well, as evidenced by the decades of failed attempts to make statistics instruction effective. Useful learning of statistics requires interaction of students with experts. The exceptions to this are the few students who, having intelligence, initiative, and energy, would succeed even without formal instruction. The important cadre of statistics practitioners is very large and not so exceptional.

### **Experiential Preparation of Instructors**

Meng(2009) says that statistics material can be easy to learn but hard to teach: “Good statistical courses ...are not at all easy to teach. They are best taught by those who have

- (I) extensive statistical knowledge;
- (II) deep understanding of statistical foundations;

- (III) substantial experience in statistical practice;
- (IV) great communication skills;
- (V) profound pedagogical passion.

This is especially true of experiential teaching.

The experiential teaching mode definitely requires a more experienced instructor than teaching from a textbook. In initiating an experiential learning course, it would be important to use an instructor that has had a variety of consulting experiences. Less experienced instructors could be asked to attend the sessions in preparation for a future offering of the course. This time-consuming activity would need to be recognized as valuable “research-oriented” work for tenure and promotion considerations. Team teaching such a course would be another option, in which more experienced and less experienced instructors could collaborate on the course.

### **Choice of Appropriate Cases/Projects**

Almost any real data set can involve techniques and concepts unfamiliar to the student at that time. This is where the guidance of the instructor is crucial, so that the techniques introduced are neither too abstruse nor too familiar.

The Internet can be a good source of data and case studies. Of course, complete posted solutions are to be avoided, or else disguised by changing the naming of the data.

Students can collect data (reaction times, judgment games, internet searches, statcan sources) for discussion in class.

In time, the demand for assistance with project ideas might interest entrepreneurs in the academic world to produce aids.

### **Constraints from User Departments**

A typical situation is where the user department faculty want their senior students to be very familiar with statistical strategies used in the user-departments literature. “My students need to know Kruskal’s rank correlation coefficient”. Of course, once students understand the basis of estimation criteria and hypothesis tests, they can look up particular items as needed. A similar comment can apply to a user department’s preferred software (SAS, MINITAB, R, ...). This message has to be conveyed to the user departments. Perhaps the cooperation of a Dean is required. One possible strategy is to bring a high-profile psychologist or criminologist or engineer, who happens to be expert in statistics as well, to talk to the user department about the requirements of modern statistics in their field.

### **Conclusion**

Experiential Teaching and Learning has the potential to improve the effectiveness of undergraduate instruction in statistics, and to ultimately improve the image of statistics among non-experts. It aims to help students link together theory and application potential and if successful will improve the effectiveness of young statistical practitioners in their careers. Its implementation in today’s university environment is feasible and in fact has been implemented in some courses in Canada.

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