

INTERACTIVE SIMULATIONS IN THE TEACHING OF STATISTICS: PROMISE AND PITFALLS

David M. Lane
Rice University, United States
S. Camille Peres
University of Houston - Clear Lake, United States
peresc@uhcl.edu

Research on discovery learning and simulation training are reviewed with the focus on principles relevant to the teaching of statistics. Research indicates that even a well-designed simulation is unlikely to be an effective teaching tool unless students' interaction with it is carefully structured. Asking students to anticipate the results of a simulation before interacting with it appears to be an effective instructional technique. Examples of simulations using this technique from the project Online Statistics Education: An Interactive Multimedia Course of Study (http://psych.rice.edu/online_stat/) are presented.

INTRODUCTION

Statistical education has made great strides toward making the student a more active learner. Over a decade ago, Cobb (1994) noted that teaching laboratories are increasingly incorporating computer simulations to illustrate important statistical concepts and to allow students to discover important principles themselves. Since the publication of Cobb's article, the widespread availability of the World Wide Web and interactive technologies such as Java and Flash have lead to an explosion in the development of simulations; most of these simulations are easily and freely accessible. A few examples are given below.

EXAMPLES OF SIMULATIONS

The Rice Virtual Lab in Statistics (RVLS) developed by David Lane (2000) has over 20 Java applets that simulate various statistical concepts (<http://www.ruf.rice.edu/~lane/rvls.html>). The sampling distribution simulation estimates and plots the sampling distribution of various statistics (http://www.ruf.rice.edu/~lane/stat_sim/sampling_dist/index.html). The student specifies the population distribution, sample size, and statistic. Then an animated sample from the population is shown and the statistic is plotted. The student can then repeat the process many times to estimate the sampling distribution.

The simulation on the effects of range restriction (Figure 1) shows how the correlation between two variables is affected by the range of the variable plotted on the X-axis (http://www.ruf.rice.edu/~lane/stat_sim/restricted_range/index.html). The top portion of Figure 1 shows the entire dataset and allows the student to "restrict the range" by sliding the vertical bars toward the left and/or right. Also shown are the statistics for the entire dataset. The bottom portion of Figure 1 shows the scatter plot without the excluded data and the statistics for these data. By sliding the bars on the top scatter plot, the student can interactively explore the effects of restricting the range.

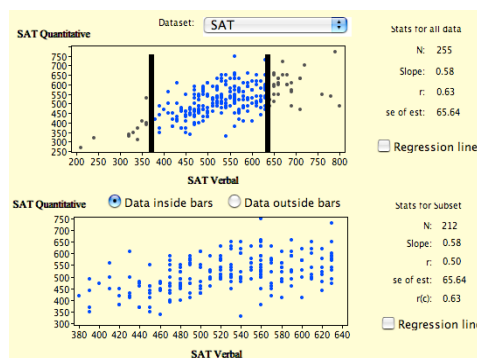


Figure 1: Simulation of the effects of range restriction

A popular statistical concept to present with a simulation is the “Let’s make a deal paradox.” R. Webster West developed a simulation that lets students explore this paradox interactively (<http://www.stat.sc.edu/~west/javahtml/LetsMakeaDeal.html>). Figure 2 (a, b, c) shows how the simulation takes the student through the game and illustrates the concept that there is a 2/3 chance of winning when the switching strategy is used. The student picks a door by clicking on it. Figure 2a shows the simulation before the student has picked a door. Figure 2b occurred after the student chose door 2 and instructs the student that s/he can either stay with door 2 or switch to door 1. Figure 2c occurred after the student did not switch and indicates the results. At this point the student can see how many games were won and/or lost by switching or not.

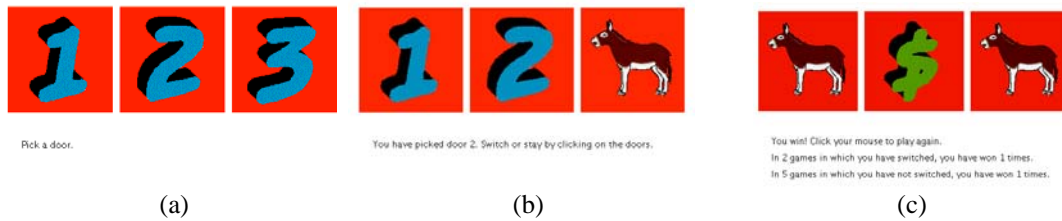


Figure 2: Three stages of the “Let’s make a deal” simulation by R. Webster West

A simulation developed at Texas A&M University by James Hardin (2001) helps a student visualize the correlation coefficient associated with different scatter plots (<https://www.stat.tamu.edu/~jhardin/applets/signed/Corr.html>). The student varies the sample size and the correlation and a randomly selected scatter plot from a population with that parameter is presented. This allows the student to see how the correlation communicates the variability of the relationship between the two variables (Figure 3).

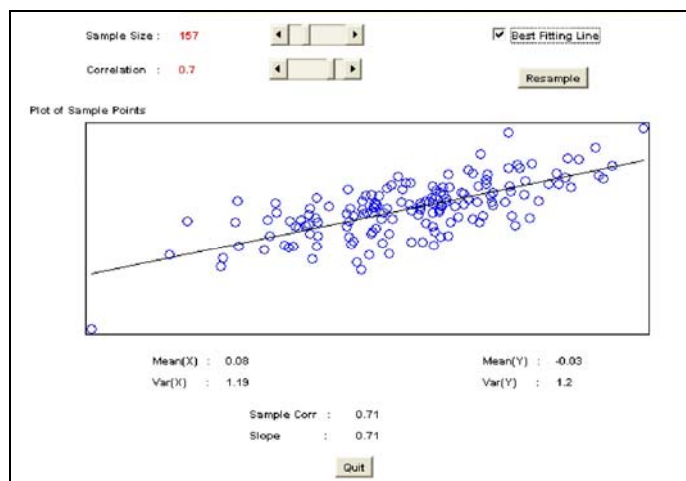


Figure 3: Simulation providing a visualization of the correlation coefficient. The student can vary the sample size and the correlation by moving the “Correlation” and “Sample size” sliders to the left or right.

SIMULATIONS CAN LEAD TO PASSIVE LEARNING

One common way to use a simulation is as a demonstration in class. For example, one might use a simulation to demonstrate characteristics of a sampling distribution such as the relationship between sample size and the standard error of the mean. Unfortunately, using a simulation in this way does not ensure active learning since students can be passive observers. As might therefore be expected, this use of simulations can lead to poor learning. An informal study at Rice University bears this out. One of the school’s award winning instructors (unfortunately not one of the authors) presented a lecture and a simulation covering various properties of

sampling distributions. Although both the instructor and the students felt the class was excellent, one third of the students at this highly selective university produced the wrong answer to a simple question about the effect of sample size on the standard error of the mean. Similarly, delMas, Garfield, and Chance (1999, Experiment 1) found that students taught with a well-designed simulation of sampling distributions missed over 50% of the items on a posttest. The authors concluded, “good software and clear directions that point students to important features will not ensure understanding.”

The key point is that using simulations in a way that spoon feeds students by providing them with knowledge without requiring that they actively pursue that knowledge is relatively ineffective. This is consistent with the considerable evidence that training methods that are too easy on the learner are relatively ineffective, especially regarding long-term retention (Schmidt and Bjork, 1992). A good example of this principle is the use of animation for teaching people how to use computer software. Several studies have found that using animation to demonstrate how to operate computer software allows the user to adopt a passive learning style which results in good immediate performance but poor performance a week later (Atlas, Cornett, Lane, and Napier, 1996; Palmiter and Elkerton, 1991). Instructions presented in text are more difficult and lead to poorer immediate performance but better performance later.

DISCOVERY LEARNING

In contrast to passively watching a demonstration, there is considerable evidence for the salutary effects of active learning. An early advocate of active learning, Bruner (1961) hypothesized that the act of discovery leads to acquiring information in a way that makes it readily available for problem solving. Hermann (1969) reviewed the literature on the efficacy of discovery learning and concluded that discovery learning leads to better transfer and long-term retention than does the more traditional “rule-example” learning. Hirsch (1977) found that a class taught algebra by “guided discovery” outperformed classes taught by exposition or programmed learning on transfer to more advanced problems and transfer to different types of problems. In an impressive demonstration of how active learning can lead to excellent long-term retention, Conway, Cohen, and Stanhope (1991) found that memory for research methods taught by having students design and conduct experiments did not decline over a period of 12 years.

The influential “constructivist” theoretical framework maintains that students learn best when they actively construct their own knowledge. According to this perspective, learning occurs through hands-on interaction rather than through direct instruction in which the student passively receives knowledge (Cobb, 1994; Mills, 2003). Although most educational researchers accept the notion that active learning is better than passive learning (Bransford, Brown, and Cocking, 1999; Bruer, 1993; Lambert and McCombs, 1998; Mayer, 2004), and that teaching and training methods that provide direct instruction without engaging the learner can lead to good immediate performance but poor long-term retention (Schmidt and Bjork, 1992), other constructivist notions are less well accepted. Anderson, Reder, and Simon (2000) argued convincingly that the following claims of “radical constructivism” are inconsistent with existing data: (1) Knowledge cannot be transmitted by a teacher, it can only be constructed by the learner, (2) Knowledge cannot be represented symbolically, (3) Knowledge can only be communicated in complex learning situations, and (4) It is not possible to apply standard evaluations to assess learning.

The research showing the benefits of active learning suggests that a good way to use simulations would be to allow learners to discover the principles themselves by interacting with the simulation. It would seem that despite the likelihood that it would take longer to learn concepts through discovery learning than by direct instruction, once learned, these concepts should be better understood and better remembered. Unfortunately, studies of the effectiveness of pure discovery learning have produced disappointing results (de Jong *et al.*, 1999; de Jong and van Joolingen, 1998; Klahr and Nigam, 2004; Mayer, 2004). When asked to discover concepts on their own, students often fail to approach the problem systematically and thus may have difficulty discovering the concept. de Jong and van Joolingen (1998) described problems students have with discovery learning including their inability to be proficient at (a) generating hypotheses, (b) designing experiments, and (c) interpreting data.

Much more positive results have been observed with guided discovery learning. Mayer (2004) reviewed three important paradigms in which the effectiveness of discovery learning has been tested: (1) discovery of problem-solving rules, (2) discovery of Piagetian conservation strategies, and (3) discovery of programming concepts. In each case, guided discovery was more effective than pure discovery learning. Similarly, learning from simulations appears to be most effective when it is structured (de Jong and van Joolingen, 1998). One method of structuring shown to be effective is asking students to use a simulation to ascertain answers to specific questions posed beforehand (de Jong, Hartel, Swaak, and van Joolingen 1996). This method requires intellectual activity on the part of the student as opposed to the passive mode adopted when being spoon fed information via text or animations. An instructional approach similar to that of de Jong *et al.* (1996) was developed for statistics by delMas, Garfield, and Chance (1999) who gave students a pretest on concepts that could be demonstrated by a simulation. The students then used the simulation to evaluate their responses. Students learned more with this method than from simply viewing a demonstration of the simulation. A likely reason for the success of this technique is that it forces students to confront discrepancies between what they expect and what occurs. Confronting such discrepancies has been shown to be a potent avenue to conceptual change (Posner, Strike, Hewson, and Gertzog, 1982). Moreover, it keeps the student focused on the relevant questions and guides the exploratory learning. This technique, which we call “query first,” appears to be effective in additional contexts such as lectures. For example, Weiman (2005) found that asking students to commit to an answer to a non-obvious physics question greatly increased their learning and memory: A non-obvious fact presented in a lecture was retained by only 10% of the students after 15 minutes. In contrast, the retention rate was increased to 90% after one week when students were forced to commit to answering a question about the non-obvious fact. However, the use of the query first method does not mean simulations are unnecessary. For example, Ziemer and Lane (2000) found that the use of the query first method in a lecture was not as effective as the query first method used in conjunction with a simulation. One section of a statistics course was taught about sampling distributions using a simulation in the context of the “query-first” strategy whereas a second class, comparable in every respect that we could feasibly measure, was taught using a similar “query-first” strategy but without benefit of the simulations. Students taught with the simulations performed better on all questions and reported greater enjoyment of the class. Their mean rating of enjoyment was 6.4 on a 7-point rating scale, compared to 4.0 for the group taught without the simulations.

A PROJECT USING THE QUERY FIRST METHOD

Our project “Online Statistics Education: An Interactive Multimedia Course of Study” consists of an online textbook containing multimedia presentations, case studies, statistical analysis capabilities, and interactive simulations/demonstrations. The simulations and demonstrations available throughout this site implement the “query-first” method. Before viewing a simulation, students are presented with a short set of questions. Most of the questions are multiple choice, although some require numerical answers. Students are asked to answer each of the questions even if they have to guess. Feedback is not given initially to individual questions although the proportion correct is shown after the last question is answered. Students are then asked to answer the questions again, this time using the simulation to help them discover the answers. Since it may not be apparent to a student exactly how to best use the simulation to discover the answers, the simulation allows the student to view (a) general instructions, (b) step by step instructions, and (c) a summary. The general instructions provide information on how the simulation works and how to operate it, but do not instruct the student on how to use the simulation to discover the answers. Students for whom the general instructions are insufficient can choose to view the step-by-step instructions, which show exactly how the simulation can be used to discover the answers. The summary reviews the important principles the simulation demonstrates. When a student answers a question for a second time, detailed feedback is given about which response is correct and why.

The “Confidence Interval Simulation” begins by asking the following four questions:

1. What proportion of confidence intervals for the mean do not contain the population mean?

2. Which is wider, a 95% confidence interval or a 99% confidence interval?
3. Does sample size determine the probability the interval will contain the population mean?
4. Is it possible for the 95% confidence interval to contain the population mean while the 99% confidence interval does not?

We have found that students often get these questions wrong, especially question three.

Figure 4 shows the simulation used to discover the answers to these questions. After guided interaction with the simulation, students find it easy to determine that sample size does not affect the probability of containing the parameter but, instead, affects the widths of the intervals.

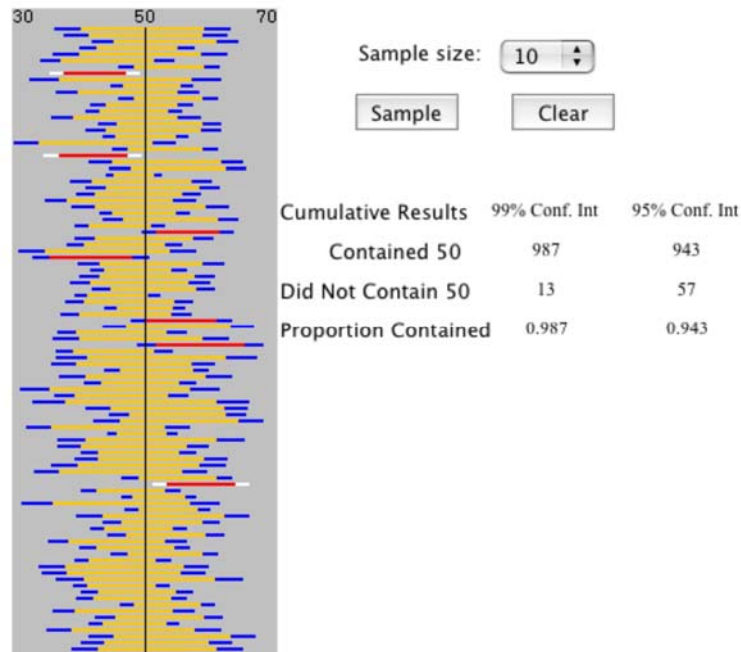


Figure 4: Simulation of confidence intervals. Horizontal lines show the 95% interval colored in gold and 99% intervals in blue. Intervals not crossing the vertical bar do not contain the population mean.

The website for this project can be found at http://psych.rice.edu/online_stat/. The project can be freely accessed as well as reproduced since it is in the public domain.

SUMMARY

Interactive simulations and demonstrations are now widely available on the web. Although these resources have the potential to make learning statistics easier and more fun, they should be used with care. One should avoid using simulations in a way that makes the students passive observers. One should also avoid giving students access to a simulation without providing enough structure for them to discover the important principles. Guided discovery learning in which students are asked questions before they interact with the simulation and then use the simulation to confirm or disconfirm their answers appears to be an effective technique.

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