

## DEVELOPING STATISTICAL LITERACY ACROSS SOCIAL, ECONOMIC AND GEOGRAPHICAL BARRIERS USING A “STAND-ALONE” ONLINE COURSE

Oded Meyer and Candace Thille  
Carnegie Mellon University, United States  
meyer@stat.cmu.edu

*Carnegie Mellon University was funded to develop a “stand-alone” web-based introductory statistics course, openly and freely available to individual learners online. The goal of this project is to develop statistical literacy among people who do not have access to academic institutions because of remote locations, financial difficulties or social barriers. In order to achieve this goal, the design of the course has been a collaboration among statistics faculty, cognitive scientists and experts in human computer interaction. This paper discusses the challenges in developing such a learning environment and ways in which the course tries to address them. We also describe the design and results of a pilot study where the degree to which the course is successful in developing statistical literacy has been examined.*

### INTRODUCTION

As part of the Open Learning Initiative (OLI) project, Carnegie Mellon University has been funded by The William and Flora Hewlett Foundation to develop an online introductory statistics course. The Foundation’s interest is in providing open access to high-quality post-secondary education and educational materials to those who otherwise would be excluded due to geographic, economic or time constraints (Smith and Thille, 2004), as well as for those who due to social barriers are not encouraged to pursue higher education. In other words, we were asked to develop a web-based introductory statistics course that will be openly and freely available to individual learners online. The use of web-based instruction can take many forms. According to Utts *et al.* (2005), the options range from using web-based applications in a traditional course to full-blown online courses in which there is no face-to-face contact with an instructor. The latter, as we understand it, refers to distance learning where an instructor exists and his/her interaction with the students is mediated “electronically.” An online course that meets the Foundation’s goal adds a new “end-point” to this continuum; a complete “stand-alone,” or self-sufficient online course which *does not require an instructor* in the background. Such a course can, of course, be used in any form on the “web-based instruction continuum,” and in fact, using the course in “hybrid” forms is aligned with one of The Hewlett Foundation’s other priorities – “California Reform” - supporting California’s community colleges in providing high-quality education to all students even as the state experiences a vast increase in enrollment known as “Tidal Wave II” (CPEC, 1999). In addition, in their research on the market for online statistics courses, Griffiths and Rascoff (2005) reported that two-year colleges *in general*, due to their limited ability to innovate, are good candidates for a new online statistics course which will bring their statistics curriculum up to date in substance and teaching methodology. Even though the course can support introductory statistics instruction in a variety of ways, its design and development processes was guided by The Hewlett Foundation’s primary interest - the needs of the individual learner using the course to develop statistical literacy as a complete stand-alone course.

### THE COURSE DESIGN

Our general approach to the task of developing a stand-alone web-based course was to create a course that would be as close to a *fully online enactment of instruction* as possible. The course design used the wealth of experience and knowledge of statistics faculty members and is informed by general cognitive theory and by learning principles that are specific to statistics. The course design was also informed by earlier research conducted at Carnegie Mellon into how students learn statistical reasoning. In this section we’ll present some of the challenges we confronted when making the transition from the classroom to an online format, and demonstrate how teaching experience and learning principles helped us address them.

### Course Organization and Structure

Students often view what they learn as a set of isolated facts (Schoenfeld, 1987). As statistics instructors we can definitely relate to this, as students often view statistics as a “bag of tools and methods” and our role as instructors is to promote coherence by teaching students how the discrete skills they are learning fit together in a meaningful bigger picture. This also helps students organize their knowledge which is particularly important in an introductory course where students do not have an existing organization in which to fit the new knowledge. Maintaining a very clear structure and a high level of organization is especially important in a stand-alone online course since in addition, it creates a “clearly marked path” for the students as they go through the course on their own and thus reduces the chance of their feeling lost. Our course is organized around the “big picture” of statistics - the process of (1) producing data (choosing a sample and collecting data) (2) Exploratory data analysis (EDA) and (3) making inferences from the sample back to the population of interest. (See Figure 1).

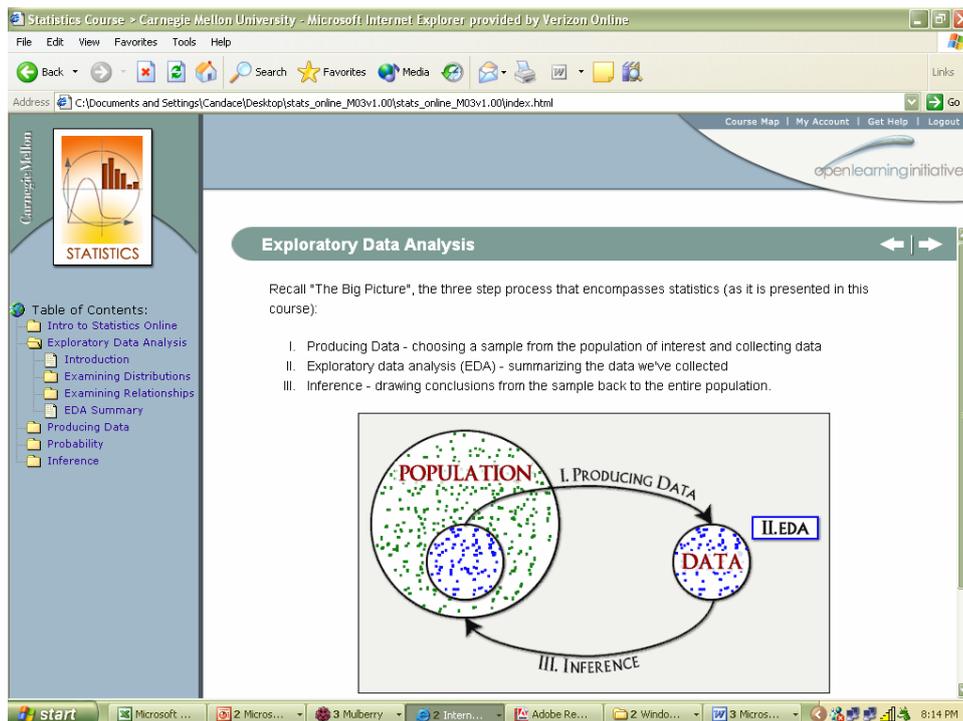


Figure 1: The big picture of statistics as it is presented in the course

A rigid structure is also maintained in lower levels of the material hierarchy. The EDA section is broken down into two modules – examining distributions and examining relationships (which you can see in the navigation panel in figure 1), and the latter is further broken down into 4 cases according to the “role-type classification table” (see Figure 2). Whenever the learning experience shifts cases (for example, from case I to case II), the narrative refers back to this table, reminding learners where they have been (check-mark), what they are going to do next (“Now”), and how each piece fits into a larger whole. Designing the course as a clear and smooth path makes it easier for the individual learner to go through it when no human guidance is available

### Providing Immediate and Targeted Feedback

Studies have shown that immediate feedback leads to significant reductions in time taken by students to achieve a desired level of performance (Anderson, Conrad and Corbett, 1989). When moving to a fully online enactment of instruction we must compensate for the absence of immediate feedback loops between instructor and students, and so in any problem-solving context throughout the course immediate and tailored feedback is given. This includes frequent “*Did I get this*” activities which are multiple choice comprehension checks where the wrong choices

<i>Explanatory</i>	<i>Response</i>	
	Categorical	quantitative
Categorical	Now: Case II	✓ Case I
Quantitative	Case IV	Case III

Figure 2: The role-type classification table that appears in the transition from case I to case II

were carefully chosen by an experienced instructor who is aware of students’ common mistakes and misconceptions. The course also features cognitive tutors such as *StatTutor* (Meyer and Lovett, 2002) which presents students with data analysis problems and guides them through the solution, and “mini-tutors” which focus on just one skill. In addition to providing feedback on answers, cognitive tutors and “mini-tutors” can provide *assistance during problem solving* in a form of a hint. Figure 3 is an example of a “mini-tutor” focusing on understanding the boxplot:

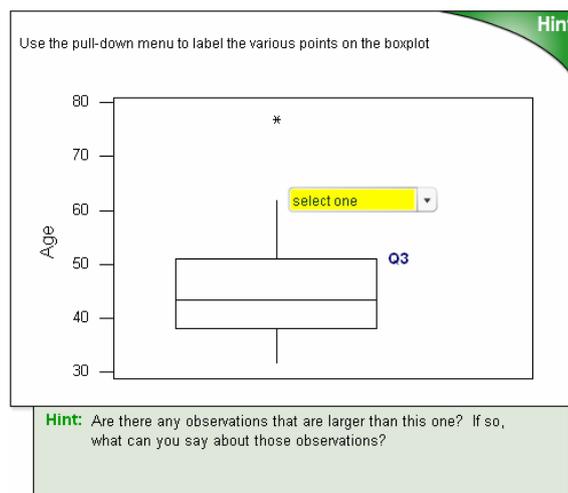


Figure 3: A “mini-tutor” about labeling boxplots

Other activities which are worth mentioning are multiple choice questions which are inserted in and are part of the content and where the immediate feedback forces students to confront their misconceptions (such as in Figure 4) or helps students root out common mistakes. One of the principles of learning statistics in Garfield (1995) is that such activities enhance learning.

*Providing Frequent Learning Opportunities Through Practice*

One of the principles of learning statistics is that students learn to do well only what they practice doing (Garfield, 1995). In a typical introductory statistics course students get to practice through in-class-activities, weekly homework assignment and through hands-on activities in lab sessions. In the absence of these opportunities in our course, we implement this principle using expository text interspersed with frequent opportunities for learners to practice. An example is the two screens that cover measures of center. Within this short section, the student is introduced to the concepts of the mean and the median, shown an example and given a comprehension check for each concept, and is given an opportunity to apply the concepts to analyze a real life situation. The student is also asked to answer three answer-reflective-questions which contrast the strengths of each type of measure, work with a “mini-tutor” on the processes of calculating the median, work with an applet to experiment with the changes to the mean and median when changing the distribution of points in a dataset, and finally, given four questions that support him/her to reflect on in which sorts of situations each measure is most appropriate. In addition to providing multiple opportunities to learn through practice, the activities are designed so that students experience applying ideas in *different* situations, which leads to better learning (Garfield, 1995).

A fair coin is tossed 10 times. Which of the following two outcomes is more likely?

(a) HHHHHHHHHH

(b) HTTHHTTTH

Before we solve this, what does your intuition tell you?

(a) is more likely

(b) is more likely

(a) and (b) are both equally likely

⊗ This is not quite right. Read on to see why.

Figure 4: An activity which requires students to confront their misconceptions about chance

### *Applying Principles of Effective Use of Media Elements*

Cognitive theory tells us that the capacity of working memory to process information is limited. The amount of information that needs to be simultaneously processed in working memory to achieve a current learning goal can be thought of as the “cognitive load.” In designing the course, we adhered closely to well-researched principles of effective use of media elements to minimize extraneous cognitive load, i.e., that is imposed by the learning design. For example throughout the course we present short *flash animations with spoken narration* that are based on a cognitive design principle that tells us that students will learn best if we give them complementary and mutually reinforcing information over both their auditory and visual channels (Clark and Mayer, 2003). In these demonstrations, as the audio stream continues, the various points being discussed are highlighted to help the learner focus attention on the specific parts of the visual image to which the audio stream is referring.

### COURSE EVALUATION

Soon after the completion of the first iteration of the course, during the Fall 2005 semester, we conducted a pilot study in order to test whether the course is successful in achieving its goal. In other words, we wanted to know whether a motivated learner who goes thoroughly through the course and completes all the activities is able to achieve a satisfactory level of statistical literacy. In addition, we wanted to observe students as they attempt to learn the material and collect data traces of their learning processes to inform the next iteration of the course. Our general approach to the study was to see whether we were successful in “approximating” our traditional Introductory Statistics course, the design of which was informed by extensive research conducted at Carnegie Mellon about how students learn statistical reasoning (see for example Lovett and Greenhouse, 2000). More specifically, we wanted to test whether students who go through our online course on their own can achieve a similar performance level to that of students who take the traditional course where, we believe, students *do* gain a satisfactory level of statistical literacy. It should be stressed that we were not trying to test which of the two courses is more effective (since the target audience of the online course do not have the option of choosing between the two forms of learning), but rather treat our traditional course as a benchmark against which to measure the efficacy of our “enactment of instruction” online. In this section we will describe the study design, report results, and discuss their implications.

### *The Study Design*

The traditional Introductory Statistics at Carnegie Mellon (36-201) is a semester-long course (approximately 15 weeks) that meets three times a week for a 50 minutes lecture (200-240 students). In addition, students meet once a week in smaller groups (up to 40) in a computer lab where they have a chance to apply the material “hands-on” in a guided environment of approximately one teaching assistant per 10 students. Students are assigned weekly homework assignments, and have three midterm exams and a comprehensive final. During the Fall 2005 semester, the fifth edition of *Introduction to the Practice of Statistics* has accompanied the course.

Students who registered for 36-201 in fall 2005 were invited on the first day of lecture to participate in our study and be in the “online section” in place of the traditional course. Of the students who volunteered to participate in the online section, we randomly chose a group of 20 students who resembled the entire class in terms of gender, race, and the level of exposure to statistics prior to taking the course. The students in the online section were only required to go through the course according to a specified schedule and complete all the course activities (except for self assessments which were optional). The students in the study were asked to refrain from attending the traditional lecture and labs and to not purchase the textbook. They had no other requirements except for attending a weekly 50 minute meeting to provide feedback about their learning experience for that week, and have an opportunity to ask questions. The assessment of the study group was similar to that of the students in the traditional group; three midterms and a comprehensive final, all of the tests were matched in level.

We are aware that the learning experience of the online section in our study is not a perfect simulation of the learning experience of an individual learner going through the course on his/her own; it differs in two significant ways. First, students in the study were not given complete freedom in their learning pace, but rather were given a schedule of weekly portions that they had to complete. We imposed the pacing on students to ensure that they covered the relevant material before midterms so that their performance would accurately reflect what they had learned from the course. Second, students in our study attended a weekly meeting with the instructor and even though the instructor did not prepare instruction for these meetings, students had the opportunity to ask questions. We conducted the weekly meeting both as a way to gather feedback from the students on the course as input to the design of the next iteration of the course and as a way of ensuring that participating in the study did not compromise student learning. As noted in the results section, while the meeting did prove useful for gathering feedback from the students, few students used the meeting to ask questions or seek additional instruction.

### *Results*

All but two students followed the course schedule (with up to two days of delay) and attended all the weekly meetings. There were only three instances during the semester when students asked for help with the material during the weekly meeting. The topics for which the students needed help were: least squares regression line, sampling distributions, and p-value. Beyond that, all the students’ questions did not reflect misunderstanding, but rather revealed some minor oversights on the part of the course developers such as critical typos that confused the students. During the entire semester, the only emails that we received were about administrative issues, and *none* were related to the course material. As Table 1 shows, the performance on exams of the students in the online section was very similar to that of the students in the traditional course, and obviously, no significant differences were found between the two groups on the four exams. At the end of the course, students in the online section were asked to fill out an “End of course survey” about their learning experience in which all reported at least some increase in their interest in statistics as a result of taking the course. On a four point Lickert scale, 75% of the students said that they would *definitely* recommend the online course to other students, 25% answered that they would *probably* recommend the online course and no students reported that would probably or definitely not recommend the online course.

### *Discussion*

Even though the study participants did not use the course as a complete “stand-alone,” with essentially only three interventions by an instructor for clarifications on three topics, their performance was similar to that of the students in the traditional course. Of the three topics for which students sought additional instruction, students performed well on the exams on two of the topics – the least squares regression line and p-value, so simply clearer explanations in the course might suffice. Sampling distributions was clearly a problematic topic for the students. Even after the instructor’s clarifications, students still had difficulties with this topic on the exams. In general, sampling distributions is one of the most challenging topics for students to learn in statistics (Larreamendy, Leinhardt and Corredor, 2005). Reworking the explanation and activities that teach sampling distributions will be a focus of our next iteration of the course design.

Table 1: Performance of traditional and online groups

Exam	Descriptive Statistics	Traditional	Online
First Midterm ( <i>EDA + Producing Data</i> )	Sample size	201	20
	Mean	90.17	88.75
	Standard deviation	8.59	6.23
Second Midterm ( <i>Probability</i> )	Sample size	202	20
	Mean	81.62	81.45
	Standard deviation	14.25	13.82
Third Midterm ( <i>All of inference</i> )	Sample size	201	20
	Mean	85.87	85.10
	Standard deviation	11.91	16.80
Final ( <i>Comprehensive</i> )	Sample size	204	20
	Mean	83.54	84.79
	Standard deviation	11.06	12.23

### FUTURE WORK

At the end of January 2006 we will begin analyzing the rich data we gathered during our study. As students engaged in activities in the on-line course, the system created a detailed data log file which recorded all student activities. We have the tests that the students completed outside of the online system and have linked these to the log data. In our next phase of analysis we will look for correlations between patterns of use of the online material with learning outcomes. As a result of this research, we hope to produce both design recommendations for future iterations of the online statistics course as well as guidelines for students and teachers regarding effective strategies for teaching and learning on-line. Such findings will help inform future students about productive learning strategies and contribute to research on learning.

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