Cyber Mentoring in an Online Introductory Statistics Course

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Students in an online statistics course were prone to become increasingly disengaged as the semester progressed. In Spring 2015, we took a proactive measure to retain student engagement by introducing a cyber mentoring session. We describe the framework, operation and effectiveness of cyber mentoring in improving students' learning experience and performance. With the implementation of cyber mentoring, the percentage of online students passing the class increased from 76% to 94%, and the mean score of online students increased from 74.6 to 83.2 (out of 100), while the corresponding parameters did not change significantly for students in the face-to-face classes.

Introduction

At Indiana University-Purdue University Indianapolis (IUPUI), the Department of Mathematical Sciences has been teaching a multi-section STAT 30100 Elementary Statistical Methods course for over twenty years. It is a non-Calculus based introduction to statistical methods course offered to undergraduate students mostly at the junior/senior level. This course introduces statistical methods with applications to diverse fields of study. The emphasis is on understanding and interpreting standard techniques, and effectively writing down the findings. The goal is to help students develop statistical thinking necessary to formulate research questions, to collect or identify appropriate data, to select suitable statistical methods, to process the data to gain insight for making informed decisions, and to communicate the findings in a meaningful way.

Huge advances in instructional technology have taken place in the last decade (West et al., 1998; Brian, 2005; Mills & Raju, 2011). Following such advancement in technology, colleges and universities are offering not only online courses, but also a wide variety of online degrees (Council for Higher Education Accreditation, 2002). Introductory statistics courses that require examination of large data sets have become progressively dependent on web-based resources (West & Ogden, 1998). However, Pan (2003) and Grandzol (2004), among others, mention that teaching statistics online is especially challenging. To address this challenge, several educators have documented their efforts, which highlight both the advantages and the disadvantages of teaching online statistics courses (Eversion & Garfield, 2008; Mills & Raju, 2011).

The Department of Mathematical Sciences at IUPUI is committed to utilizing the most advanced technological tools to present the STAT 30100 course content through the worldwide web, while maintaining a high quality of instruction and promoting a deeper understanding of statistical concepts. As part of the Indiana University (IU) Online Initiative (IUPUI is an integral part of the IU system), an online version of the course has been developed during Fall 2013, and one of the sections was converted to online delivery in Spring 2014 for the first time, and a similar set up was repeated in Fall 2014. The instructor who taught the online section in Fall 2014 also taught another face-to-face section. We will compare the performance of students in these two sections, and other pairs of sections, taught by the same instructor.

We must highlight that ours is not a designed experiment since we were not at liberty to assign students to the different sections. The students self-selected themselves into the two types of sections. However, this drawback does not invalidate our findings because such self-selection can be assumed to have operated in the same way for both the Fall 2014 students and the Spring 2015 students.

All sections took the same ten sets of homework, a quiz following each homework, three projects, and a comprehensive final examination (worth 25% of the course grade) at the end of the semester. But the online section took only one on-campus midterm exam, whereas the face-to-face section took three exams during the semester. The development and delivery of such an online section was supported through a Special Focus Curriculum Enhancement Grant (CEG) administered by the Center for Teaching and Learning (CTL) at IUPUI.

The paper is organized as follows: In Section 2, we compare the odds of passing for students in the face-to-face section and those in the online section in Fall 2014 before there was cyber mentoring. In Section 3, we reason why we were motivated to introduce cyber mentoring. In Section 4, we describe the framework and operation of the cyber mentoring sessions implemented at IUPUI in Spring 2015. We compare the online delivery without cyber mentoring and online delivery with cyber mentoring by presenting the data and the results in Section 5. In Section 6, we compare online sections without and with cyber mentoring against the face-to-face classes during the corresponding semesters. We also compare the face-to-face classes across the two semesters. We close the paper with some concluding remarks in Section 7, including student comments on cyber mentoring.

Face-to-face Versus Online (Before There Was Cyber Mentoring)

Based on the composite scores, in Spring 2014 semester, 36 students in face-to-face section passed and 8 did not pass (those who earned letter grades D+ or below, including F, are henceforth referred to as "failed"); while 18 online students passed and 6 failed. Thus, the odds of passing the course (with a grade of C- or better) for students who enrolled in face-to-face class was 1.50 times higher than those enrolled in the online class (P-value=.5415). Throughout this paper, we calculate the P-value of odds ratio based on a 2×2 table using Fisher's Exact test. See help file ?fisher.test on statistical freeware R for details.

Likewise, in Fall 2014 semester, 74 students in face-to-face sections passed and 10 failed; while 29 online students passed and 9 failed. Thus, the odds of passing the course for students in the face-to-face class was 2.30 times higher than those in the online class (P-value=.1111).

Although the results in Spring 2014 and Fall 2014 are not statistically significant, the student success rate tended to be higher in the face-to-face class compared to the online class, and with time the disparity seemed to have increased. However, as we will see later in Section 6 of this paper, with the implementation of cyber mentoring in Spring 2015, this trend is not only stopped but also reversed.

Motivation for Introducing Cyber Mentoring

Disengagement seems to be a major problem in online math courses (Petty and Farinde, 2013). Another study conducted by Zhang (2002) described the disadvantages with delivery of their online elementary statistics course. Two major disadvantages were: (a) lack of face-to-face interaction, and (b) inability to motivate students and/or identify students needing help immediately. The author recommended, among others, a plan to be available to students via telephone, email, and chat. Following this recommendation and to ensure a systematic adherence to remaining available to the students, we at IUPUI employed a cyber mentor in Spring 2015. The mentor's role was to engage the students in the learning process and to maximize the students' learning outcomes in an online environment. The purpose of this paper is to discuss the framework and operation of the cyber mentoring sessions, and to demonstrate the effectiveness of cyber mentoring through statistical analyses.

Cyber Mentoring and its Framework

In Spring 2015, a cyber mentor for STAT 30100 online course was selected from among students who had taken this course previously and had passed the course with an excellent grade, and who had demonstrated confidence and commitment to teaching his/her peers as evidenced by their service at the Math Assistance Center (MAC) at IUPUI. The mentor was trained by the CTL office for about a week to learn how to use Adobe Connect, how to set up IPEVO camera, how to create a poll question, and other related topics. The mentor was supervised by an assistant manager of the MAC.

We structured the cyber mentoring session in the following way:

i. We created ten workbooks on topics students were supposed to learn week by week. The cyber mentor solved the problems herself before receiving a solution key from the instructor. A sample cyber mentoring workbook solution key is given in the Appendix.

ii. We asked the students to work on the workbook on their own before they would meet the cyber mentor online for that week's session. Students could choose to meet with the cyber mentor during any one of the three sessions offered each week. But they did not have to commit to the same session week after week. Rather, to accommodate their schedules, they were allowed to change the session week by week. For example, in Spring 2015 the sessions were: (i) Friday 7:00 PM–8:30 PM; (ii) Saturday 11:00 AM–12:30 PM; and (iii) Sunday 7:00 PM–8:30 PM.

iii. We asked the students to log into Adobe Connect using their university ID and password to connect with the cyber mentor.
iv. During the mentoring session, the cyber mentor worked out the solutions to the workbook problems, demonstrated proper writing styles, and answered all related questions.
v. The cyber mentor recorded students' attendance by taking screenshots at the beginning, the middle and the end of each session to make sure of their presence throughout the session. The cyber mentor also called out students' names at random times during the session to make sure they were paying attention to the mentor.
vi. Students were required to attend the entire mentoring session to be eligible to earn 10 points for each session.
vii. Students were required to turn in a hard copy of their workbooks when they would come to campus to take the on-campus midterm and the final exams. Based on the work shown in the hard copy, students earned all or part of the promised 10 points.

Online Without Cyber Mentoring Versus Online With Cyber Mentoring

Composite course scores (which were used to determine students' final letter grades) were extracted from the same instructor who taught the online course in Fall 2014 (without cyber mentoring sessions) and Spring 2015 (with cyber mentoring sessions). This instructor also taught one face-to-face class each semester. In this Section, we compare the scores of the two online classes in Fall 2014 (without cyber mentoring) and Spring 2015 (with cyber mentoring). Specifically, we carry out the following hypothesis testing problem:

H_0: $\mu_{Spring2015} = \mu_{Fall2014}$, the mean scores in Spring 2015 and Fall 2014 are the same;

H_a: $\mu_{Spring2015} > \mu_{Fall2014}$, the mean score in Spring 2015 is higher than that in Fall 2014.

We performed a two-sample t-test under the assumptions that the two samples are independent, and the two samples are drawn randomly from normal distributions with possibly different means but the same variance (which is unknown *a priori*). For example, in R use the following code:

```
> t.test(sp2015onl, fa2014onl, var.equal=TRUE,
alternative="g")
```

The numerical and graphical summaries are as follows:

Table 1. Summary statistics of Fall 2014 and Spring 2015 online classes

Online class	Sample Size	Mean	Standard Deviation
Fall 2014 online (no cyber mentoring)	38	74.58	13.48
Spring 2015 online (with mentoring)	34	83.21	10.73

The two-sample t-test yielded a calculated value $t_{cal} = \frac{\bar{y}-\bar{x}}{s_p\sqrt{\frac{1}{n_x}+\frac{1}{n_y}}} = 2.98$, and a right-sided P-value=.0019. The results indicate that the population mean score in Spring 2015 is statistically significantly higher than that in Fall 2014. Since the sample sizes are very close to each other and also the sample standard deviations are close to each other, the effect size for the t-test is given by Cohen's $d = \frac{\bar{y}-\bar{x}}{s_p} = 0.704$, which indicates that there is a medium differential effect between the mean scores during the two semesters.

Furthermore, an observed mean difference of $\bar{y} - \bar{x} = 8.63$, which in our particular application causes a grade of D or a D+ to become a C- or C respectively, is practically significant as well. Hence, we conclude that the implementation of cyber mentoring improved the students' performance. However, in the absence of a designed experiment these statistical findings are suggestive at best.

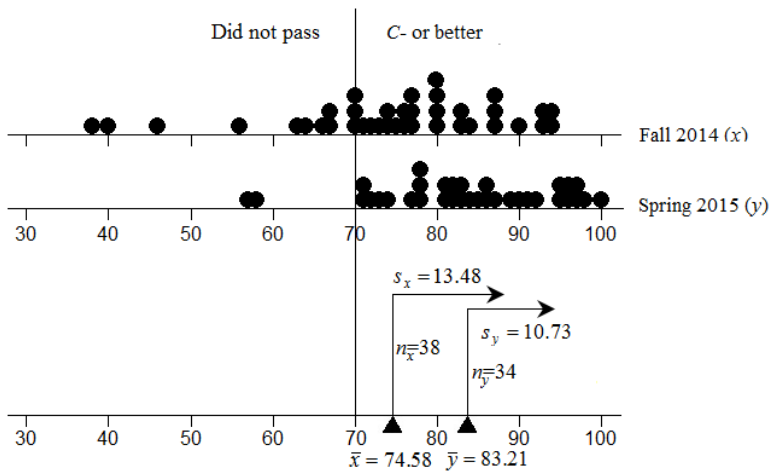

Fig. 1. The dot plots, sample sizes, means and standard deviations of final exam scores in Fall 2014 online and Spring 2015 online classes

Furthermore, Fig. 1 indicates that cyber mentoring helps the weakest group of students by raising their scores. In particular, the standard deviation of scores in the Spring 2015 online class is lower (though not statistically significantly) than that in Fall 2014. Also, the scores do have a hard upper bound of 100, making the assumption of normality a suspect. Consequently, the two-sample t-test may be called to question. To preempt these possible criticisms, we also performed the nonparametric Kolmogorov-Smirnov two-sample test:

```
>ks.test(sp2015onl, fa2014onl, alternative="g")
```

and the two-sample t-test with possibly unequal population variances:

```
>t.test(sp2015onl, fa2014onl, var.equal=FALSE, alternative="g")
```

The results of the more robust nonparametric Kolmogorov-Smirnov test (D^+=.387, P-value=.0046), as well as those of the two-sample t-test with unequal population variances (t=3.020, right-sided P-value=.0018), lead to the same conclusion as the parametric t-test with equal population variance; that is, we conclude that the population mean score for Spring 2015 online class is significantly higher than that of Fall 2014 online class. Therefore, in the rest of this paper, we continue to use the two-sample t-test (permitting unequal population variances by using the default option var.equal=FALSE) for comparing mean scores of two groups.

To appreciate the impact of cyber mentoring on online delivery, we can focus on comparing the odds of passing (with a grade of C- or better) for online students in Spring 2015 (with cyber mentoring) against those in Fall 2014 (without cyber mentoring). The odds of passing in Spring 2015 was 4.97 times higher than that in Fall 2014 (P-value=.0499, using Fisher's Exact test). This is a statistically significant result that demonstrates the effectiveness of cyber mentoring for online students.

Face-to-face Versus Online: Cyber Mentoring Reverses the Trend

In Section 2, we mentioned that in Spring 2014 and in Fall 2014, before there was cyber mentoring, students in the face-to-face section performed slightly better than those in the online section. Also, the difference widened in the later semester, though neither difference was statistically significant. But this trend was reversed in Spring 2015, as shown in Table 2 below, where we compare passing rates of the online classes (with and without cyber mentoring) with those of the face-to-face classes in the respective semesters.

Table 2: Percentage of students passing in different classes during Fall 2014 and Spring 2015

Semester	Percentage of students passing	
	Face-to-face	On-line
Fall 2014	74/84 = 88%	29/38 = 76%
Spring 2015	34/38 = 89%	32/34 = 94%

Recall from Section 2 that in Fall 2014, the odds of passing the course (with a grade of C- or better) for students in the face-to-face class was 2.30 times higher than those in the online class (P-value=.1111). However, in Spring 2015, the odds of passing the course among students in the online class was 1.88 times higher than those in the face-to-face class (P-value=.6769). Although not statistically significant, the tendency has been reversed in Spring 2015 with the implementation of cyber mentoring from what it was in Fall 2014 and Spring 2014.

Next, going beyond the pass/fail indicators, let us compare the observed scores in all four classes simultaneously. Table 3 shows the summary statistics, and Fig. 2 depicts the raw scores as well as the summary statistics.

We use the two-sample t-test (with possibly unequal population variances) for comparing mean scores of different pairs of groups. For face-to-face classes, the population mean score in Spring 2015 is slightly higher than that in Fall 2014 (t=1.682, right-sided P-value=.0480). But for online classes,

Table 3: Summary statistics of Fall 2014 and Spring 2015 face-to-face and online classes

Class	Sample Size	Mean	Standard Deviation	Name of Variable
Fall 2014 face-to-face	84	80.85	12.57	u
Fall 2014 online (no cyber mentoring)	38	74.58	13.48	x
Spring 2015 online (with mentoring)	34	83.21	10.73	y
Spring 2015 face-to-face	38	84.37	9.74	v

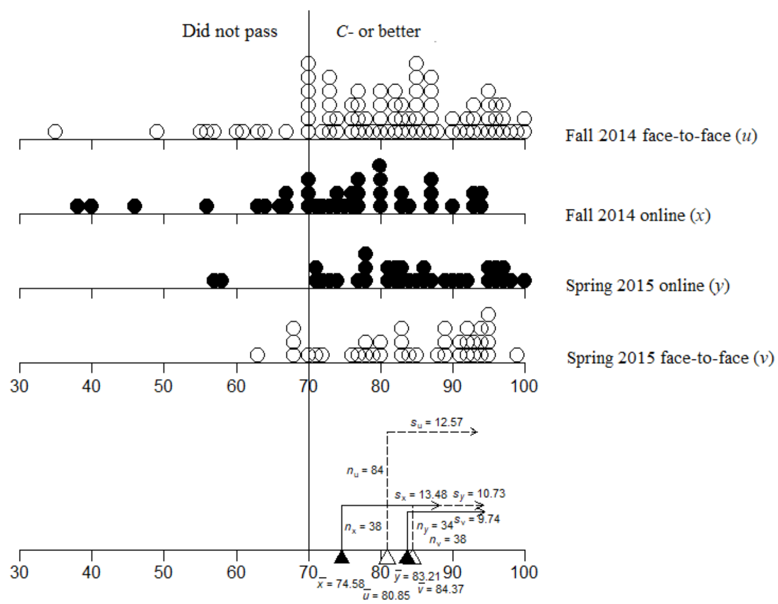

Fig. 2: The dot plots, sample sizes, means and standard deviations of Fall 2014 and Spring 2015 final exam scores for both face-to-face and online classes

the population mean score in Spring 2015 is highly statistically significantly higher than that in Fall 2014 (t=3.020, right-sided P-value=.0018). However, the statistically significant wide gap between the mean scores of face-to-face and online classes in Fall 2014 (t=2.4291, right-sided P-value=.0089) is no longer present in Spring 2015 (t=0.478, right-sided P-value=.3170).

Conclusion

This article explores the structure, operation and effectiveness of cyber mentoring in a non-Calculus based introductory statistics course. The cyber mentor effectively countered student disengagement in an online environment and added liveliness to the online class. This is evidenced by positive feedback received from the students in a semester end online survey conducted centrally by the School of Science. Here are some comments concerning the cyber mentoring sessions from students who took the class in Spring 2015.

> *"Cyber mentoring was very helpful in gaining an understanding of how to approach problems. In an online course, it is very helpful to have someone help the students with problems when they get stuck, especially in a mathematical science."*
>
> *"The workbooks and cyber mentoring were extremely beneficial, especially to students like myself who have a hard time learning and retaining information pertaining to math and science studies. It was really great to be able to see someone work out problems in front of you, as well as be available in real time to ask questions. Don't get rid of it!"*
>
> *"Cyber Mentoring was one of the best tools that I used in this course. It gave opportunity to really go over the questions and have rationale for the answers. Also, it was nice to have another person explain the same material maybe in a slight(ly) different way. I sincerely hope that cyber mentoring will continue in the future STAT online classes."*

The cyber mentoring sessions in STAT 30100 at IUPUI are continuing ever since Spring 2015. Students are performing reasonably well in an online environment compared to their peers in the face-to-face sections. They appreciate the tools and support that are available in this course. But mostly they relish the human touch provided by a peer who is only one or two years ahead of themselves in their pursuit of study.

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References

Council for Higher Education Accreditation (2002). *Accreditation and assuring quality in distance loearning*. CHEA Monograph Series, 1, 5.

Everson, M. G. & Garfield, J. (2008). An innovative approach to teaching online statistics courses. *Technology Innovations in Statistics Education, 2(1),* Retrieved from http://escholarship.org/uc/item/ 2v6124xr

Grandzol, J. R. (2004). Teaching MBA Statistics Online: A Pedagogically Sound Process Approach. *Journal of Education for Business*, 79, 237-244.

Mills, J. & Raju, D. (2011). Teaching statistics online: A decade's review of the literature about what works. *Journal of Statistics Education, 19(2),* Retrieved from https://www.amstat.org/publications/jse/v19n2/mills.pdf

Pan, W. S. (2003). The challenges of teaching statistics in the current technology environment. *The Journal of American Academy of Business, 3*, 351-354.

Petty, T. & Farinde, A. (2013). Investigating student engagement in an online mathematics course through Windows into Teaching and Learning. *Journal of Online Learning and Teaching, 9(*2*)*, 261-270.

R Core Team (2013). *R: A language and environment for statistical computing.* R Foundation for Statistical Computing, Vienna, Austria. Retrieved from http://www.R-project.org/

Sloboda, B. W. (2005*).* Improving the teaching of statistics online: A multi-faceted approach. *The Journal of Educators Online, 2(1),* Retrieved from thejeo.com/SlobodaFinal.pdf

West, R. W. & Ogden, R. T. (1998). Interactive demonstrations for statistics education on the World Wide Web. *Journal of Statistics Education, 6*(3), Retrieved from www.amstat.org/publications /jse/v6n3/ west.html

West, R. W., Ogden, R. T. & Rossini, A. J. (1998*).* Statistical tools on the World Wide Web. *The American Statistician, 52*(3), 257-262.

Zhang, J. (2002). Teaching statistics on-line: Our Experiences and Thoughts. *Proceedings of the Sixth International Conference on Teaching Statistics.* Editor B. Phillips, Voorburg, The Netherlands: International Statistical Institute.