TEACHIT: TURNING THE CLASSROOM INTO A RESEARCH LABORATORY VIA INTERACTIVE E-LEARNING TOOLS

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This paper introduces ISLE (Interactive Statistics Learning Environment), an authoring framework for building interactive statistics lessons that supplement classroom instruction. Using a case study of two university courses at Carnegie Mellon University ("R Programming for Analytics" for graduate students, "Reasoning with Data" for undergraduates) we show how ISLE helps to blend off-line and on-line instruction. Features that facilitate ISLE's blended learning approach include 1) a hint, assessment, and feedback system 2), on-the-fly data collection from students e.g. through surveys, and 3) real-time peer-to-peer communication and monitoring of student actions. ISLE also allows collection of all user interactions, including mouse clicks and text inputs along with their associated timestamps. It is our hope that this will give instructors new insights into patterns of student learning.

INTRODUCTION

Online learning platforms provide one key advantage that sets them apart from classroom instruction, namely the fact that one can monitor, store, and analyze student interactions, which can be used to improve instruction. We developed the ISLE (*Interactive Statistics Learning* Environment) framework to allow instructors to create and deploy hands-on e-learning modules for classes in data analytics, statistics, and statistical computing.

A main goal of the ISLE project is to build up a research laboratory that allows instructors to better monitor their classes and understand how students interact with class material. All user interactions are monitored when students interact with ISLE lessons and can be analyzed through an accompanying dashboard. We hypothesize that a system of feedback and monitoring of user actions can reveal issues students are facing and uncover what material they find interesting or uninteresting. To test this hypothesis, we are gathering data on the time spent in the lessons, all mouse clicks, inputs to text fields, interactions, and feedback provided through an integrated feedback submission system.

ISLE takes advantage of visualizations, simulations, and real-world data sets, prompting students to engage with data in a goal-oriented way. There is ample evidence that interactive activities can have a much higher impact on student learning than video lectures or reading materials alone (Koedinger et al., 2015). The research also suggests that exercises which allow students to manipulate experimental factors can improve learning outcomes (Tobin et al., 1999). ISLE activities can be made to more closely mimic guided real world statistical and data analytic tasks, and are therefore much more closely connected to statistical practice. Drawing upon the research on Intelligent Tutoring Systems, which have been shown to have a positive effect on student's understanding and retention of subject material (Ma et al., 2014), ISLE provides facilities for personalized feedback. Moreover, we can use the user activity logs to learn whether students are interacting with the modules in the manner intended, and to run A/B tests to identify module changes that help to improve engagement.

In its first two years, ISLE has been used in classes for Master's students enrolled in the Heinz College, the Public Policy and Information Systems School at Carnegie Mellon University. It has also been incorporated into a new undergraduate introductory data reasoning class at the Department of Statistics & Data Science that is aimed at a broad audience spanning a wide range of majors. Combining online learning with classroom instruction in a blended learning context allows that the two spheres (online/offline) may complement each other instead of being treated as mutually exclusive.

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DATA

In class 94-842: Programming in R for Analytics taught by A.C. at the Heinz College, we deployed ISLE lessons in the first and second mini (half-semester) of the Fall 2016 semester as well as the first mini of Spring 2017. Students were exposed to twelve interactive labs. The labs consist of a mix of interactive, explorable simulations explaining the underlying statistical concepts, R exercises with accompanying hints to practice programming, and multiple-choice and free-text questions for students to test their understanding.

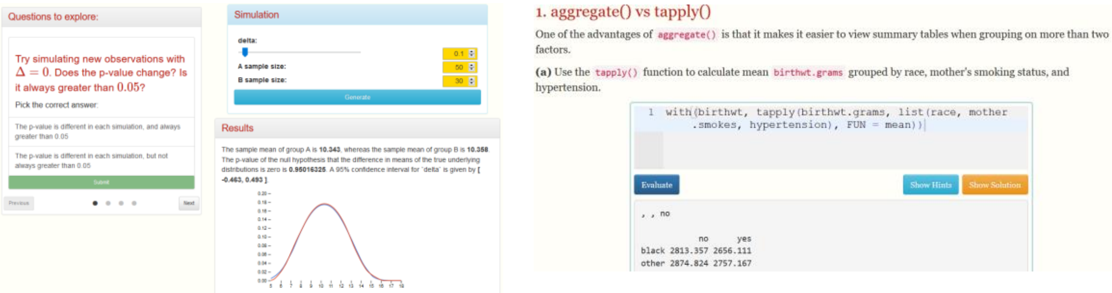

Figure 1. Simulation study for a comparison of means on the left, screenshot of an R exercise, where students can execute R commands, access hints, and compare their answer with the solution, on the right.

Participation credit was given to the students for attempting the labs, but completion of them was completely voluntary. The courses concluded with a final project that spanned the whole curriculum and had the students analyze a data set and write up a report. Out of a total of 45 points, students obtained an average grade of 36.3 points. Over a period of two years, we have collected 24,500 student interactions with the platform, belonging to 172 unique students enrolled. We define student interactions as mouse clicks, inputs to text fields, answers to R exercises etc. Each action is associated with a time stamp. Overall, the mean number of actions performed by students in a single session was 22.2.

METHODS

Trajectory Analysis: Group-based trajectory models (GBTMs) allow to identify groups of individuals who share a common trajectory of some outcome over time. Originally devised by Nagin and colleagues as a quantitative method to identify different trajectories in criminal careers, they can be used as well to track the behavior and progress of students in an educational setting (Nagin, 1999). GBTMs are semi-parametric mixture models, in which for each one of a finite number of latent groups a response variable is modeled as a function of time and potentially other covariates. For the present analysis, we have decided to focus on the proportion of exercises inside the labs that were attempted by the students as our variable of interest. This stands as a proxy for how well students engage with the material. Other possible metrics for measuring student engagement, such as the amount of time spent inside the labs or the number of user actions, were considered but ultimately discarded as they were either hard to measure accurately or not comparable enough across students due to different usage patterns.

RESULTS

Completion Rates: Due to the limited number of students present in our data set, we have fitted a model with just two latent groups, which should allow us to uncover in broad strokes the main archetypical trajectories. The results of this alongside the original data are displayed in Figure 2.

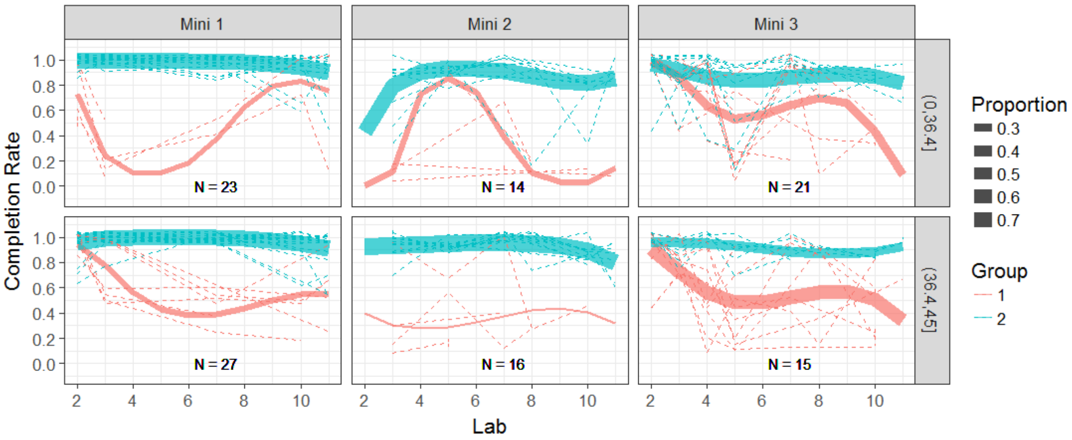

Figure 2. Trajectories for the completion rates of each lab, split by class section (mini) and whether students performed below average (36.4) on the final project. The solid lines represent the fitted trajectories of a group-based trajectory model with two latent groups. Each trajectory is modeled as a cubic spline, with line thickness indicating the proportion of students from the respective categories who were assigned to the given group. Dotted lines show the observed, jittered individual student trajectories.

The solid lines representing the fitted trajectories reveal differences both across the different minis, i.e. half-semester class, as well as the final grades of the students. For the most part, students assigned to the blue group completed all the questions inside the labs, although there are some differences across the different sections of the course: Whereas the line appears to be straight for the first mini when students took the labs inside the class room, there is a slight trend in both the second and third minis. And indeed: the interaction terms of the mini and grade indicator variables with the trajectories are significant at the 1\% level. In contrast to the students assigned to the blue group, the red line shows the fitted trajectory for those who completed only a smaller amount of the exercises in each lab.

Click Rates: One finding of our preliminary investigation into the data is that students approach the exercises of the lessons in a non-linear manner. The lab sessions for the R Programming class were designed as single-page applications unrolling as a sequence of individual exercises, frequently building on top of each other. Considering this, one might expect that students would follow the pre-determined path and approach the questions one after the other.

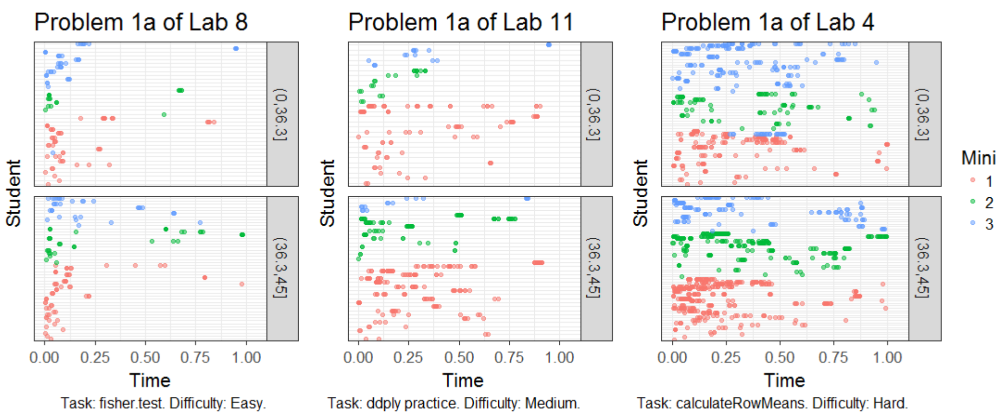

Figure 3. Student interactions with the R shells for the first problem from three of the labs (ordered by difficulty). Each dot represents a single action (Get Hint / Evaluate R Code / Show Solution), with the corresponding time in the session displayed on the x-axis, normalized to a number between zero and one. A line on the y-axis represents one student's click stream, where students with higher number of clicks overall appear at the top and vice versa.

However, as Figure 3 shows, this does not seem to be the case: The figure depicts the time stamps (normalized to the range [0,1] for each user) for the first R programming exercise of three of the labs, where the user is prompted to type in and evaluate R code to (labs in question are accessible under http://isle.heinz.cmu.edu/94-842/lab**/, where ** should be 04, 08, or 11). Although the distribution of the relative frequency of the time stamps allows us to situate the exercises correctly at the beginning of the labs, it is still noteworthy to that the students engaged with the task over the whole session. Some students revisited a problem after time has elapsed, while others started working on it at the end of the session. There is a great spread in the number of interactions by the individual students. One can further observe that a complex question (belonging to the plot on the right) results in a usage pattern characterized by students revisiting the problem over the entire session. In contrast, the two plots to the left display the user behavior with regards to a more basic question that may be solved with essentially a single interaction. To substantiate this, Figure 4 displays violin and box plots of the normalized times of all lab questions split by question difficulty. Questions of all difficulty levels were placed throughout the labs, such that question ordering cannot be the sole cause for these discrepancies. The integrated boxplots suggest an increase in the median as difficulty increases, while the shape of the violin plots may signal that harder questions were more likely to be re-visited at the end of a session.

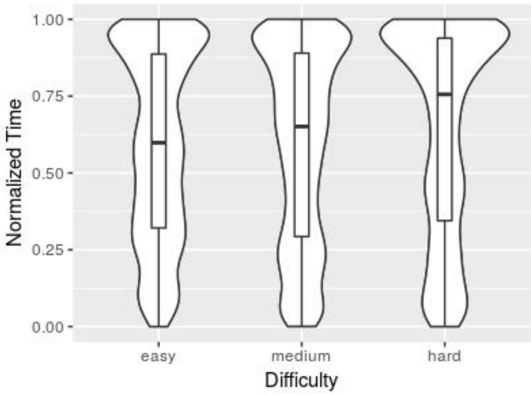

Figure 4. Violin plots and box plots showing time distribution for question interactions by difficulty level (classified by a human reviewer as either easy, medium, or hard).

CONCLUSION

ISLE (*Interactive Statistics Learning Environment*) provides a framework for building e-learning lessons for statistics and enables instructors to track the progress of their students. An analysis of click rates showed that students have completed labs in a non-linear manner, often delaying or revisiting problems during a session, an effect much more pronounced for harder questions. This demonstrates that students do not always act like one might expect. The analysis of student behavior confronts us with a plethora of unanticipated peculiarities that warrant further investigation. Analyses of user interactions with individual questions have demonstrated individualized engagement patterns that do not fit into the sequential order of the labs. A deeper understanding of this behavior might have implications for the structure of the lessons. Further research is needed to validate and elucidate these findings, which could impact the construction and design of e-learning lessons for statistics instruction.

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