Providing Instructional Support for Makerspaces: Examining the Type and Diversity of Student Social Interactions

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Abstract: Open-ended learning environments such as makerspaces present a unique challenge for instructors in monitoring student progress. While it is expected that students are given free rein to work on their projects, instructors are left with the uncertainty of whether students are in need of assistance. Instructors have to strike a difficult balance between micromanaging students and simply leaving them without any form of instructional support. Here we propose the use of Kinect sensors to consistently and continuously monitor students' social interactions within makerspaces so that instructors can gain a more comprehensive view of their progress. Overall, the examination of type and diversity of social interactions affords instructors an early opportunity to identify struggling students.

Introduction

Makerspaces are open-ended learning environments with little pockets of instructional time when instructors explicitly lead and teach students. Students are often left to explore on their own when it comes to working on their design projects in makerspaces. With removed contact from the students, it is difficult for instructors to gauge the amount of instructional support that must be rendered in the space. The use of minimally invasive sensors such as Kinect can provide instructors with an advantage in quietly monitoring student progress without affecting their natural workflow (Blikstein & Worsley, 2016). Therefore, the goal of this paper is to examine the type and diversity of student social interactions within makerspaces using Kinect sensors. This is done in order to provide instructional support for identifying students who are in need of assistance without disrupting their natural workflow.

Literature review

Makerspaces embody learning under the long tradition of constructionism. In such a learning environment, instructors play the role of facilitators while students are given free rein to explore the space as they construct knowledge for themselves. However, as students are still novices, they may encounter barriers to learning within makerspaces and have unknown struggles. In this respect, researchers like Berland et al. (2014) have proposed the use of technology-enabled learning analytics to derive rich inference about learning and learners. The question of what data should our sensors be collecting is answered when we consider Lave's (1991) call for situating learning in communities of practice. In his seminal paper, Lave (1991) states that 'learning is recognized as a social phenomenon' (p. 64). Therefore, when viewed through the lens of communities of practice, students' social interactions become natural targets for data collection to apprise instructors of students' state of learning.

Overview

Over the course of fifteen weeks, the research team collected motion sensor data and survey responses of 16 graduate students enrolled in a hands-on digital fabrication course. The goal of the course was to teach students the usage of modern fabrication technologies such as 3D printers and laser cutters, and their application in educational contexts.

Research question

Can examining the types and diversity of social interactions (as detected by Kinect sensors) provide meaningful and accurate information about students' performance in the makerspace?

Methods

The data used in this study was collected around the clock for the duration of the semester by two Kinect sensors situated at opposing ends of the makerspace. After collection, the data was cleaned and processed to obtain the type and diversity of student social interactions within the space. Three types of social interactions were identified, namely working alone, working with instructors and working with others. In addition, two senior instructors were tasked to assign each student a final technical score. A score of 1 on any dimension indicates weak, 2 indicates average, and 3 indicates strong. We then compared the Kinect-derived students' social interactions with the instructors' average ratings to address our research questions.

Results

We correlated the time spent by students in each interaction category (individual: working alone; instructor: working with an instructor; and student: working with others) with the scores assigned by the instructors. We found most statistically significant results during the final project phase of the course. Both spending more time working individually and spending more time working with other students were found to significantly positively correlate to receiving a higher technical score ($r = 0.54$, $p<0.05$ and $r = 0.64$, $p<0.01$ respectively). Figure 1 shows generated heatmaps indicating the diversity of student social interactions. The heatmap on the left includes student interactions with their assigned partners while the heatmap on the right leaves out all student interactions with their assigned partners. By comparing the two heatmaps, we witness a stark difference between the time spent among partners compared to non-partners: a lot more time is spent with assigned partners as compared to the rest of the student population. The heatmaps also allow instructors to directly identify pairs of students who work closely together.

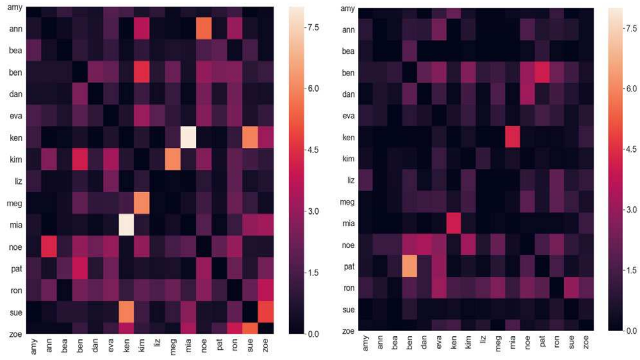

Figure 1. Heatmaps indicating diversity of student interactions.

Discussion

The results of our analyses were most significant in the final project phase of the course. This might indicate that the nature of the final projects necessitates both individual and group efforts to produce an outcome that meets instructor expectations on the technical dimension. The heatmaps generated allow instructors to visualize student behavior. This is a task that is challenging for an instructor to accomplish based solely on personal observations or interactions with students. Ultimately, the information and data made available by the Kinect sensor system, paired with analysis techniques and methodologies to understand and interpret the data, opens new doors for both teachers, as classroom facilitators, and students for making (un)productive behaviors salient.

Conclusion

While makerspaces hold much promise in providing training grounds for students to develop 21st century skills such as collaboration, communication, critical thinking and creativity, instructors face the constant tension in deciding when and how to intervene in the pedagogical process. Our findings suggest that multimodal sensors have a role to play in aiding instructors in harnessing the full potential of makerspaces and represent initial steps towards the development of a semi-automated teacher dashboard to provide instructional support for makerspaces.

References

Berland, M., Baker, R. S. & Blikstein, P. (2014). Educational Data Mining and Learning Analytics: Applications to Constructionist Research. *Technology, Knowledge and Learning, 19*(1-2), 205-220.

Blikstein, P., & Worsley, M. (2016). Multimodal Learning Analytics and Education Data Mining: Using computational technologies to measure complex learning tasks. *Journal of Learning Analytics, 3*(2), 220 – 238.

Lave, J. (1991). Chapter 4: Situating learning in communities of practice. In L. B. Resnick, J. M. Levine., & S. Teasley (Eds.), *Perspectives on Socially Shared Cognition* (pp. 63-82). Washington, DC: American Psychological Association.