International Society of
the Learning Sciences

Automated Tracking of Student Activities in a Makerspace Using Motion Sensor Data

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Abstract: Learning inside makerspaces can be difficult to track and support. Using Kinect data collected from students enrolled in a course for making, we explore ways to track student learning trajectories in an automated way. Namely, by transforming our data into a set of action sequences that span a semester, we are able to find that discouraged students display a statistically distinct type of activity pattern already in the first two weeks. Generating metrics on makerspace use, we also find that time spent alone and the number of transitions between stations are significant indicators for discouragement and motivation levels. We argue that high-frequency location data could provide an accessible, meaningful overview of student learning in a makerspace to all stakeholders, and conclude with limitations and future directions.

Makerspaces are collaborative learning environments that have the potential to promote key 21st century skills such as creativity, curiosity, and problem solving for participants (OECD, 2018). One challenge however is that it can be difficult to track and support students working on various open-ended projects in and outside supervised hours. Further, students who need the most help are often the ones most hesitant to seek it, causing them to fall behind and eventually give up on future making experiences. A pressing need in makerspace education therefore is to help instructors and facilitators track and support dispersed student experiences inside the makerspace.

Using sensor data to track learner actions inside the makerspace could provide a way to automate part of this task, as well as a way for researchers to quantitatively investigate the connection between different student trajectories and targeted outcomes. Cooke and Charnas (2019) suggest gate counters and sign-in systems as ways to generate useful information. We believe that this approach could be taken a step further by collecting fine-grained location data. Indeed, as a precursor to this study, Chng et al. (2020) has shown how location data from a multi-sensor Kinect system can provide insights into the social interactions inside a makerspace.

Generally, however, very few papers to date have used location data to explore makerspaces. One cause of the slow uptake may be that location data from physical learning environments tend to be large and complex, requiring extra cleaning and feature engineering steps. Thus, a pipeline to extract meaningful metrics and action sequences is an outstanding challenge for the widespread use of location data in research and practice. Our paper presents the preprocessing and analysis steps carried out on location data from 24 students enrolled in a maker course. Generating metrics and action sequences from location data, our paper 1) creates proof-of-concept visualizations of student trajectories in makerspaces; 2) tests if different student groups show distinct action sequences; and 3) tests if there are location-based indicators for student outcomes of interest.

Methods

Our setting is a maker course for education graduate students in a private northeastern U.S. university. Students worked freely in the makerspace on weekly tool-specific assignments as well as on a final project that asked students to create a digital fabrication product for educational purposes. The bulk of student making was done independently, with office hours and individual consultations providing instructional support.

The survey data comes from weekly surveys administered after every class. Surveys were crafted via a literature review of surveys that measure student states, namely self-efficacy and motivation (Pintrich & DeGroot, 1990; Williams & Deci, 1996), maker mindset (Clapp et al., 2016), and affective attitude (Watson et al., 1988). After adapting questions for our context, we validated the survey with input from students from a previous iteration of the course. Later, to address correlation between question responses and to improve interpretability of results, we conducted factor analysis on the survey data prior to final analysis. Following the recommendations of Costello and Osborne (2005), we used a scree plot to select the number of factors and affirmed that no items had less than a 0.4 loading. We were thus able to summarize 14 survey items into four factors: motivation, self-efficacy, help perceptions, and discouragement, where factors have by design a mean of 0 and variance near 1.

Student location data was continuously collected with six Microsoft Kinect v2 sensors placed around the walls. We began preprocessing the data by generating student ID labels with OpenFace. Then, using Cv2, data from all sensors was mapped onto a 2D coordinate system of the room. Next, we dropped all but one instance of an individual student observed by multiple sensors. Lastly, we gave each coordinate a location label (e.g., table, 3D printer, etc.), while filtering out transitions between stations and sparse data from the weekends. This facial recognition → homography → deduplication → labeling process gave us, per student, a series of location labels corresponding to their movements in the makerspace for the entire semester.

In making meaning of this data, we focused on hours and co-work as we were most interested in indicators that could help detect students in need of support. We hypothesized that spending relatively large portions of time alone and/or spending long hours working in the makerspace could be linked with high discouragement and low motivation. We were also interested in finding a proxy for iterative work, as it is well known that iterative processes are beneficial to problem-solving (Atman et al., 2007). In our data, we believed the number of times a student crosses location boundaries to work with different tools, or to return to tools after working on a non-tool task at the table (e.g., talk with people, look up information with personal laptop) could be one. Ultimately, we created and explored four metrics per student: *together time* versus *alone time* (i.e., time spent without OR with someone within 1 meter), *total time* in makerspace, and *number of transitions* made between stations. In figure 1, the dotted line in the left image shows a fictional student making 3 transitions (2-3, 3-4, 4-5). As no one else was in the space, 'alone time' equals 'total time' for this student.

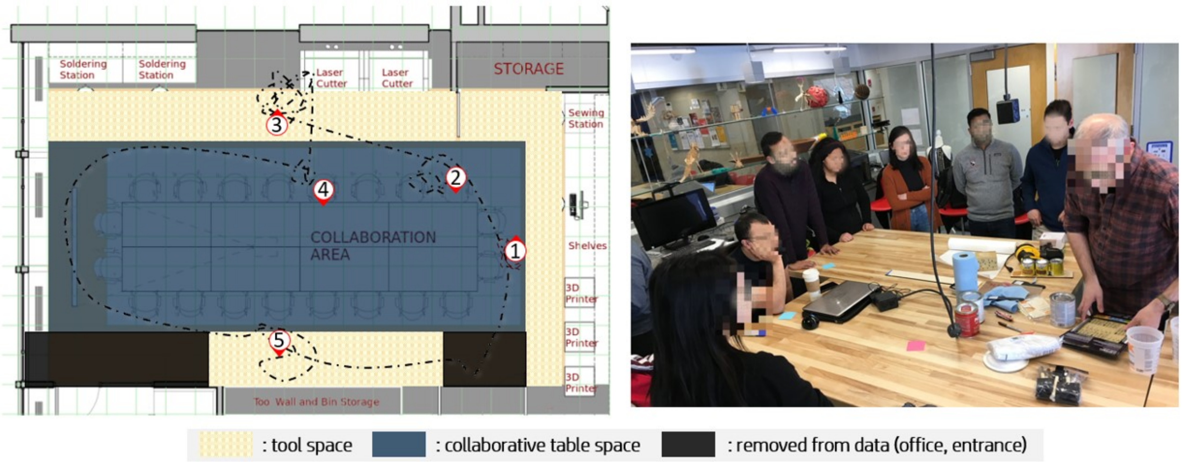

Figure 1. Makerspace layout and photo of actual learners in the space.

In addition to weekly summative metrics, we also generated daily action sequences for each student from the data and investigated whether there are patterns connected to student outcomes. Looking again at total time and co-work proportions, we gave each day of a student one out of five labels: a long day spent alone at the makerspace, a short day spent alone, a long day spent together, a short day spent together, and absence. Long/short and alone/together thresholds were median values for the entire semester. As a result, each student had an action sequence of length 57, the number of days data was collected during the semester excluding the weekends.

For sequence visualization and analysis, we utilized R's TraMiner package (Gabadinho et al., 2011). For analysis on summative metrics, we used R to regress weekly survey outcomes on the weekly summative metrics while controlling for idiosyncratic week and student effects, as both were seen to affect survey outcomes. Data for statistical analysis consisted of 11 weeks' worth of survey and Kinect-derived metrics from 24 students. As we dropped 7 rows from the data due to missing student survey responses, the final dataset had 257 rows (11 x 24 – 7), where each row corresponds to a week of a student.

Results

We first provide an overview of student activities in the makerspace, derived from the Kinect data. Students spent an average of around 5 hours a week in the makerspace (316 minutes), and time spent in the space grew about 8 minutes on average per week ($b = 7.89$, $se = 3.81$, $p = 0.04$). Students tended to underreport the time spent in the makerspace by 3 hours a week (179 minutes, $sd = 391$) on average, likely due to the fact that we asked students to only estimate the time spent in the makerspace working on assignments. A point increase in reported frustration (7-point scale) was linked to an average student's reporting error (reported time – Kinect time for a week) being 70 minutes larger, controlling for student effects ($b = 70.49$, $se = 17.14$, $p < 0.001$). That is, students who reported higher frustration tended to feel they spent more time in the makerspace. Students only spent about 9% of the total time at tool stations. Among the tools, laser cutters were used most frequently and sewing machines the least, which aligns with instructor observations on how students used the space.

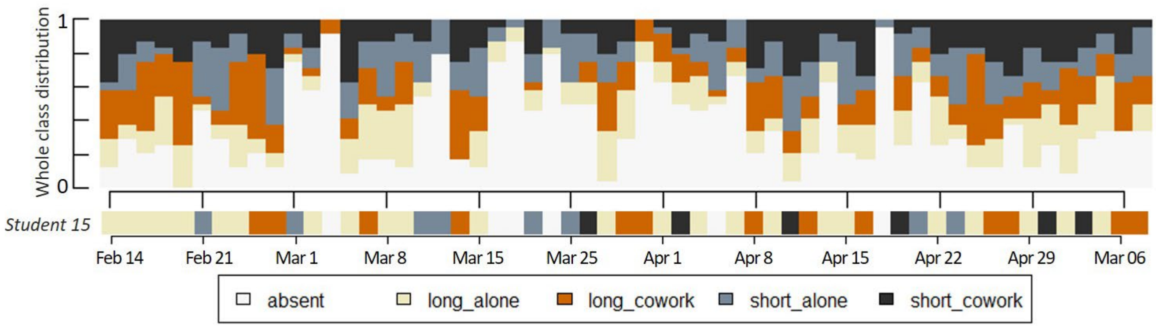

Figure 2. Whole class and individual student trajectories.

Figure 2 demonstrates one way to visualize student learning trajectories over the course of a semester. With the stacked graph above, instructors and facilitators can see whole-class trends from February to May. We see spring break appearing as a spike in absences mid-March, and students spending longer hours for final project work in later weeks (less absent, short_alone, short_cowork days). The single line for student 15 demonstrates how we could zoom in on an individual student for check-in purposes and see e.g., a student spending long hours alone in the makerspace at the start of the semester. This could warrant a check-in based on our sequence analysis, where we found that groups with high and low discouragement levels show statistically significant differences in their action sequences in the first two weeks (discrepancy test on dissimilarity matrix; $F = 1.51$, $p = 0.048$). Visual inspection showed that those who report a level of discouragement lower than the mean have more co-work days in the early weeks. Regression analysis on the first two weeks also show that the discouragement factor is positively associated with alone time and negatively with together time, although these associations are not statistically significant.

The observation regarding the association of discouragement and co-work in the early weeks is contrasted by what we find in the regression analysis for the entire semester, where we regressed each of the four weekly outcome factors on each of the six metrics. Namely, we find that the discouragement factor was negatively associated with alone time, controlling for week and student effect ($\beta = -0.0008$, $se = 0.0003$, $p = 0.003$; note that small scale of effect is due to large X, minutes spent for entire semester, while Y has mean 0 and $sd \approx 1$). Also for the entire semester, we found that groups with low and high help perceptions differ in their sequences ($F = 1.592$, $p = 0.031$). Not surprisingly, students who felt they gave and received less help were characterized by shorter days at the makerspace and more absences. An additional finding is that the number of transitions between stations was positively associated with motivation ($\beta = 0.014$, $se = 0.005$, $p = 0.002$).

Discussion

Our results demonstrate different ways in which high-frequency location data from makerspaces could be used to track students. With sequences and metrics derived from Kinect data, we find that the activity patterns of students with lower discouragement tend to show higher levels of co-work in the early weeks compared to those feeling more discouraged, but that more solo work was indicative of low discouragement for the semester overall. This may imply that students benefit more from peer support in the earlier weeks when frustration is generally higher, but that investing more time working alone on a task becomes more important as the class advances.

We also find that transitions between stations are positively associated with the level of motivation throughout the semester. This aligns with prior research that finds that an iterative design process is important for creating effective solutions (Atman et al., 2007). Conversely, it could also mean that motivated students are more willing to undergo this effortful iterative process. This is a promising metric for a model to automatically detect students who are frustrated and lose motivation without asking for help in makerspaces.

Lastly, we contribute intuitive visualizations that could help instructors and facilitators monitor student activities inside the makerspace, including those carried out outside of supervised hours. While the proof-of-concept visualizations in the current paper only display total time and time spent alone, more sophisticated, interactive visualizations could integrate multiple layers of information inferable from location data. Immediate uses of such representations include learning what stations are underutilized or need additional resources, or getting an objective sense of the workload students are experiencing from a course week by week. This can offer benefits similar to teacher orchestration graphs (Prieto et al., 2018), which is posited to benefit teacher professional development and serve as a novel quantitative method to understand the process of learning in physical learning environments.

Conclusion: Future directions and Limitations

There are several limitations to our paper, the largest one being the coarseness of the labels we create for student states. Table time takes up around 92% of the total time. Co-work, which takes up around 60%, is also too broad as co-work can take many forms in a makerspace. While we generated more elaborate labels such as active building or working side-by-side based on skeletal joint data, we ultimately decided that we do not have a reliable way to validate these labels without ground truth data. Collecting short videos clips along with Kinect data for validation purposes seem essential to fully utilize the rich information latent in Kinect data.

We also note that the outcomes utilized in this study are limited to self-reported states. In future studies, we hope to generate researcher codes with protocols such as BROMP (Ocumpaugh, 2015), or seek input from instructors to triangulate student outcomes. With these improvements to the data, we hope to replicate findings, explore new metrics, and use new analysis methods such as frequent pattern mining or recurrent neural networks to advance our understanding of what action patterns in makerspaces can tell us of student states.

Our results show that location data from makerspaces can provide insights into student learning processes and help track student states. Data from makerspaces are especially well-suited for this approach as most student activities, in and outside of regular class hours, occur inside the makerspace. Additionally, distinct makerspace stations can be labelled in the data and provide contextual information. We believe it can be both feasible and impactful to equip makerspaces with location data-based learning dashboards that visualize student trajectories.

Moving beyond makerspaces, utilizing location data have the potential to yield generalizable information on student collaborations, or help track student states in any hands-on, physically active learning activities. Particularly with the maturation of algorithms that track people's movement in a space with low-cost camera systems (Mulloni et al., 2009), establishing an analysis pipeline for extracting pedagogically meaningful metrics and sequences from location data could offer a new means to understanding what goes on inside a wide variety of physical learning environments.

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