Crowdsourcing and Education: Towards a Theory and Praxis of Learnersourcing

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Abstract: Due to the scale of online environments, large numbers of learners interact with the exact same resources, such as online math homework problems and videos. It is therefore essential these are of the highest quality to help learners. Ideally, online educational resources would constantly improve based on data and input from each learner, giving a better outcome for the next. This symposium explores issues around the use of crowdsourcing to harness learners' interactions with resources like online problems and videos in order to improve these resources for the next learner. We hope to explore the benefits and limitations of thinking about learners through the lens of crowdsourcing, to imagine *learner*sourcing. We will discuss four ways in which researchers have leveraged crowdsourcing to help students learn in a variety of educational contexts, and in doing so we will also discuss ways in which educational theory can guide the future of learnersourcing.

Introduction

Due to the scale of online environments, large numbers of learners interact with the exact same resources, such as online math homework problems and videos. It is therefore essential these are of the highest quality to help learners, but it is difficult to know how best to design these before deploying them 'in the wild'. Ideally, online educational resources would constantly improve based on data and input from each learner, giving a better outcome for the next. This symposium explores issues around the use of crowdsourcing to harness learners' interactions with educational resources in order to improve these resources for the next learner.

Crowdsourcing is the outsourcing of jobs or tasks to a large number of (amateur or novice) people, typically through the use of technology, rather than relying on a single expert (Saxton et al., 2009). Crowdsourcing (especially when referred to as "human computation") can be viewed from the perspective of using humans to do something that state of the art artificial intelligence is not capable of doing (Law & von Ahn, 2011). Unfortunately, crowdsourcing does not always have the reputation of being human-centered; for example, using crowdsourcing to harness the "computational power" of people to complete microtasks, as is often done on websites such as Amazon Mechanical Turk and Crowdflower, does not evoke the image of a technology we want to use with our students. But recently, researchers have been exploring many ways in which crowdsourcing can be used in more human-centered applications (Bigham et al., 2010; Lasceki et al. 2014; Andolina et al. 2017) as well as finding ways to value the people behind crowdwork (Kittur et al. 2014; Salehi et al. 2015; Gaikwad et al. 2015). Moreover, with the growth of crowdsourcing, researchers and educators are beginning to realize how students can interact with resources generated and improved by their peers in meaningful ways for a more enriched learning experience (Weld et al. 2012; Heffernan et al. 2016; Paulin & Haythornthwaite, 2016). In this symposium, we explore various ways to tap into that potential of crowdsourcing to help learners in a variety of settings, from massive open online courses (MOOCs) to online learning platforms used in K-12 classrooms to instructors using crowdsourcing in their own classrooms. We will look at not only practical ways that several researchers have used crowdsourcing in these settings, but also the theoretical insights from the learning sciences and broader educational theory that motivate their approaches. We hope to explore the benefits and limitations of thinking about learners through the lens of crowdsourcing, to imagine ***learner*sourcing** (a term originally coined by Juho Kim (2015)).

This symposium explores in depth some of the different ways that researchers might understand and approach various conceptions of learnersourcing. We will discuss the similarities and differences in ways that four research groups have used crowdsourcing to impact learners in different settings. Despite the different settings and various approaches to crowdsourcing, one theme that exists across the four presentations in this symposium is that crowdsourcing can help both the learners involved in generating new content, as well as the learners who then engage with the crowdsourced content. This vision of how crowdsourcing can impact students, is nicely described by Duffy and Cunningham (1996) in a metaphor for their account of constructivist instruction:

> In his popular novel *The Name of the Rose*, Umberto Eco (1983) describes a medieval library, a labyrinth of passages, stairways, and chambers filled with books...learning is illustrated by Brother William, the main character of the novel, feeling and groping his way through the library. As Brother William constructs a path (or pattern of connections) through the library, one of only many possible paths, he is transforming his means of participating in the community of scholars, both those using the library (constructing their own paths) and those who have written manuscripts contained therein."

Learnersourcing and the Learning Sciences

Learning scientists can benefit learnersourcing in a number of ways by (1) bringing theories to bear on pedagogically valuable ways of approaching learnersourcing, (2) studying how teachers and researchers can effectively use learnersourcing to help learners, (3) studying how learners can effectively engage with learnersourced resources, and (4) creating systems that can support effective forms of learnersourcing. In doing so, the learning sciences can benefit from better theoretical insights on how students learn and interact in ways mediated by learnersourcing. These insights might transcend beyond learnersourcing into other areas of the learning sciences, such as computer-supported collaborative learning. Moreover, this symposium will discuss how effectively integrating crowdsourcing and education requires bridging insights from psychology and education with systems and algorithms from computer science. Our hope is to show the promise of forming new collaborations between learning scientists and computer scientists. Such collaborations can have a long-lasting impact on the future of the learning sciences. Finally, this symposium is particularly relevant this year, as crowdsourcing is also a topic of interest to the Learning @ Scale and Artificial Intelligence in Education communities, both of which are having co-located conferences with ICLS this year. Our hope is to bring together researchers from these fields.

Symposium Synopsis

The symposium will include four presentations. Juho Kim will present work on learnersourcing for helping learners more effectively navigate and use online instructional videos, such as those in MOOCs. Joseph Jay Williams will then report on a system that prompts learners to self-explain, presents those explanations to future learners, and then discovers which explanations future learners find most helpful by using machine learning to conduct dynamic experiments. The ASSISTments group will report on their work on deploying a platform used in many K-12 classrooms that allows students to provide their work as assistance for other students. The group will also describe an instance of *teachersourcing* in their platform, broadening the scope of how crowdsourcing can impact educational practice. Finally, Thomas Hills discusses how he used crowdsourcing in his undergraduate level course on the psychology of persuasion in order to allow students to create content that influenced the course by bringing their own interests to the table. As the discussant, Carolyn Rosé will share her insights on the similarities and differences in the approaches taken by the four presenters, how approaches to learnersourcing relate to the learning sciences and computer-supported collaborative learning, and what are some of the limitations of learnersourcing as currently envisioned.

A goal of this symposium is to see how theoretical insights from the learning sciences, psychology, and broader educational theory can guide the application of ideas from crowdsourcing. For example, Joseph Jay Williams' considers how crowdsourcing explanations from students can be of pedagogical value to those students by building upon the literature on self-explanation. Similarly, Thomas Hills describes how his use of crowdsourcing is guided by theories of learner-centered education such as constructivism and related principles coming from cognitive psychology.

Given that the symposium is about crowdsourcing, the session will also include two interactive crowdsourced components. First, we will ask attendees at the beginning of the session to tell us (through a Google form) their first impression of applying crowdsourcing to education (whether that is a thought, idea, question, or concern). We will then ask them the same question at the end of the session. Our goal is to have attendees reflect on what they think about crowdsourcing and give us a sense of the attendees' prior background and opinions and how our session might have changed their opinions. Second, we will have a crowdsourced Q&A session, where attendees can "upvote" and comment on questions, both so that questions that are of greatest interest will get answers by participants, but also so that online discussions can start and continue among attendees. We will now describe the contributions of each of the four presentations.

Learnersourcing: Improving Learning with Collective Learner Activity

Juho Kim

My research has focused on improving the video learning experience online. My primary approach has been learnersourcing, in which learners collectively generate novel content and interfaces for future learners while engaging in a meaningful learning experience themselves. Millions of learners today use educational videos from online platforms such as YouTube, Khan Academy, Coursera, or edX. Learnersourcing can improve the content and interfaces in a way neither experts, nor computers, nor existing crowdsourcing methods can achieve at scale. My research demonstrates that interfaces powered by learnersourcing can enhance content navigation, create a sense of learning with others, and ultimately improve learning.

I draw on several fields to design learnersourcing applications: crowdsourcing to aggregate small contributions into meaningful artifacts; social computing to motivate participation and build a sense of community among learners; content-based video analysis techniques such as computer vision and natural language processing to complement learner input; and the learning sciences to inform the design of learnersourcing tasks that are pedagogically meaningful. I explore two types of learnersourcing: **passive learnersourcing** uses data generated by learners' natural interaction with the learning platform, and **active learnersourcing** prompts learners to provide specific information.

Passive Learnersourcing: Natural learner interactions improve video learning

In traditional classrooms, teachers adapt their instruction to students based on their level of engagement and confusion. While online videos enable access for a wide audience, instructors and learners are disconnected; it is as if instructors are talking to a wall without feedback from learners watching the video. I created a thread of research that leverages natural learning interaction data to better understand and improve video learning, specifically using thousands of learners' second-by-second video player interaction traces (e.g., clicking the play button in the video player).

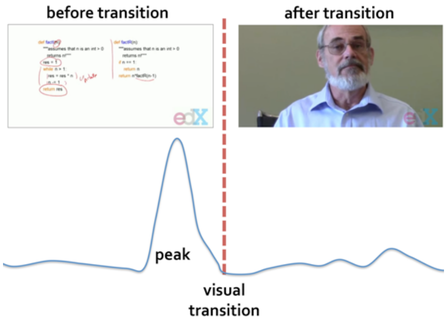

Figure 1: An example interaction peak

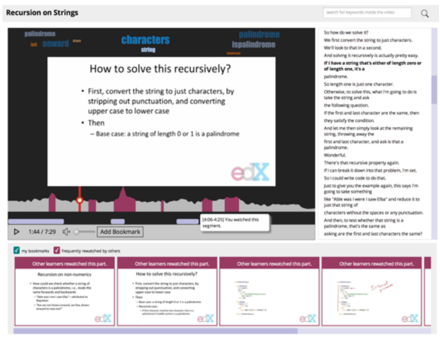

Figure 2: LectureScape: lecture video player powered by interaction data.

Data analysis of 39 million MOOC video clicks

Exploratory data analyses of four massive open online courses (MOOCs) on the edX platform investigated 39 million video events and 6.9 million watching sessions from over 120,000 learners. Analyzing collective in-video interaction traces revealed video interaction patterns, one of which is interaction peaks**,** a burst of play button clicks around a point in a video indicating points of interest and confusion for many learners. Figure 1 shows one such interaction peak; notice that the peak occurs just before the video transitions visually from showing the instructor walking through code and showing the instructor speaking. I identified student activity patterns that can explain peaks, including playing from the beginning of new material, returning to missed content, and replaying a brief segment (Kim et al., 2014b). These analyses have implications for video authoring, editing, and interface design, and provide a richer understanding of video learning on MOOCs.

Video interface that evolves with data

LectureScape (Kim et al., 2014a; see Figure 2) is an enhanced video player for educational content online, powered by data on learners' collective video watching behavior. LectureScape dynamically adapts to thousands of learners' interaction patterns to make it easier to rewatch, skim, search, and review. LectureScape introduces a set of data-driven interaction techniques that augment existing video interface widgets: a 2D video timeline with an embedded visualization of collective navigation traces; dynamic and non-linear timeline dragging; data-enhanced transcript search and keyword summary; automatic display of relevant still frames next to the video; and a visual summary representing points with high learner activity.

Active Learnersourcing: Learner prompts contribute to new learning materials

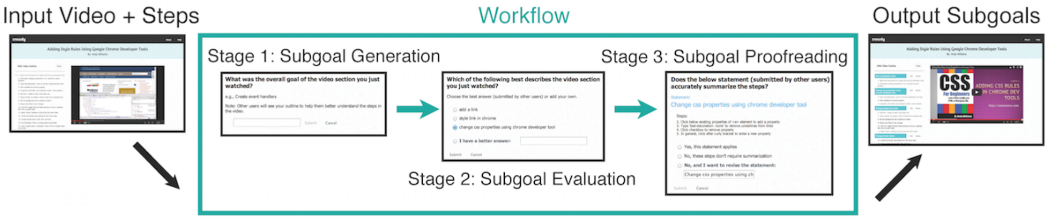

Figure 4: Crowdy: Learnersourcing workflow for summarizing steps in a how-to video.

We asked if learners, both an intrinsically motivated and uncompensated crowd, can generate summaries of individual steps at scale. This research question resulted in a learnersourcing workflow that periodically prompts learners who are watching the video to answer one of the pre-populated questions, such as "what was the overall goal of the video section you just watched?" (Figure 4) (Weir et al. 2015). Learners' answers help generate, evaluate, and proofread subgoal labels, so that future learners can navigate the video with the solution summary. We deployed Crowdy, a live website with the learnersourcing workflow implemented on a set of introductory web programming videos. The 25-day deployment attracted more than 1,200 learners who contributed hundreds of subgoal labels and votes. A majority of learner-generated subgoals were comparable in quality to expert-generated ones, and learners commented that the system helped them grasp the material. A controlled experiment with 300 crowd workers on Amazon Mechanical Turk showed that participants' retention of knowledge in statistics covered in video was higher with Crowdy than with a baseline video interface, and comparable to seeing expert-generated subgoals.

Generating Explanations using Crowdsourcing and Machine Learning for Dynamic Experimentation

Joseph Jay Williams

To help students learn from solving online problems and receiving feedback, it can be beneficial to provide explanations for how to solve these problems after student make their attempts. However, instructors have limited time and resources to generate quality explanations for all the problems they create, and many MOOCs or online resources only provide correct answers. We developed the Adaptive eXplanation Improvement System (AXIS, Williams et al, 2016) to investigate how to crowdsource explanations from learners by prompting learners to generate self-explanations (Chi et al, 1989; Williams & Lombrozo, 2010). We then used machine learning to guide a dynamic experiment that discovered which explanations learners rated as being helpful, and analyzed that data in real-time in order to present the highest rated explanations more frequently to future learners.

Learners attempted to solve four mathematics word problems (in algebra and probability), and were provided the correct answer after entering their own. In addition, they would be assigned one of the explanations from the current AXIS pool (the first few learners did not receive any explanations), and asked to rate how helpful the explanation was for their learning, on a scale from 0 (not at all helpful) to 10 (extremely helpful). They were also prompted to explain in their own words why they thought the answer was correct, as it would help them learn. If a learner's explanation was longer than 60 characters and the learner rated their explanation as likely to help others, the explanation would be added to the pool to be presented to future students.

Assignment of explanations to learners was initially done with equal probability, but as learners provided ratings of explanations, higher rated explanations were presented more frequently than lower rated explanations, using weighted randomization. More precisely, we used a statistical machine learning algorithm to calculate the probability that an explanation was higher rated than all the others in the pool (based on a Beta-Binomial model & algorithm commonly used to optimize websites, Chappelle & Li, 2013) and used those probabilities to set the weights for randomization (e.g. transitioning from 50/50 to 60/40 to 80/20). The output was therefore a probability distribution over a constantly increasing pool of explanations (as learners generated new self-explanations). The probability distribution was updated every time a learner rated an explanation, so that the probability of future learners receiving an explanation was proportion to the evidence that this was the highest rated explanation.

Benefits of Explanations for Learning

To evaluate whether the explanations that emerged also led to benefits for learning, we conducted an additional experiment. Participants were randomly assigned to receive: No explanation (original problems), learner explanations from AXIS explanations, learner explanations that AXIS gave low probability to (got low ratings), and as a gold standard, explanations written by an instructional designer. The second experiment recruited 564 new participants.

Explanations from the system led to improved learning over the default practice, where learners simply solved problems and received answers. Participants were significantly more likely to solve future problems after receiving AXIS explanations, when compared to practicing problems that did not have explanations. A pairwise comparison within a mixed-effect model revealed a significant increase in accuracy from the initial problems to the assessment problems (M = 12% versus just 2.7%, $SE = 0.027$, $p < 0.05$). It might seem obvious in hindsight that providing any explanation will increase learning and success on future problems. However, the learnersourced explanations that AXIS discarded did not provide any learning benefits beyond normal practice of math problems (M = 2% vs 3%, $p = 0.86$) and were significantly less beneficial for learning than explanations delivered by the AXIS policy (M = 12% vs. 2%, $SE = 0.04$, $p < 0.029$). The AXIS explanations also increased success in solving novel transfer problems that required going beyond the explicit information in the explanation (differences of 9-12%, SE = 0.03, 0.04, $p < 0.01$).

Finally, there were no significant differences in learning between learnersourced explanations curated by AXIS, and the explanations written by the instructional designer themself (all *p*s > 0.30). Overall, this illustrates how we can rely on *self-explanation* to make the learnersourcing experience pedagogically meaningful for the learner, as well as using machine learning for dynamic experimentation to identify and then present learnersourced content that is helpful for future learners.

Crowdsourcing in ASSISTments: PeerASSIST and TeacherASSIST

Thanaporn Patikorn, Korinn S. Ostrow, Douglas Selent, Neil T. Heffernan

ASSISTments is an online learning platform that is being used by over 600 teachers and 50,000 students worldwide (Heffernan & Heffernan, 2014 & Heffernan et al., 2016). The platform is built on the idea that it *assist*s students in learning while providing formative assess*ments* to teachers. As such, ASSISTments values the role of both students and teachers in how the platform is used. Three years ago, we ran a large-scale randomized controlled trial on ASSISTments in the state of Maine. We discovered that one teacher participating in the study, Mr. Chris LeSiege, wrote tutoring messages for every problem in his textbook so that he could better assist his students when they were doing their homework. After meeting with Mr. LeSiege and discussing his vast content creation, we realized the potential of crowdsourcing for ASSISTments, including how it could allow teachers to create and share content, expanding and improving the ASSISTments system, while strengthening the relationship between the system and its users as well as amongst users. As a result of this revelation, we have developed two features that utilize crowdsourcing: PeerASSIST and TeacherASSIST.

PeerASSIST

As its name suggests, PeerASSIST allows students to help their struggling peers by sharing solutions to their homework as worked examples. When a student is struggling, PeerASSIST will automatically select and show them a correct solution submitted by one of their classmates. The goal is not to have higher-performing students completing homework for lower-performing students, but rather to have moments of struggle turn into moments of learning. A peer's worked solution might provide the necessary "Aha!" moments that an automated answer or hint provided by ASSISTments may fail to ignite. As with the AXIS system (see above), PeerASSIST is driven by multi-armed bandit algorithms that aim to select peer work that will maximize the likelihood that a struggling student will correctly answer the next question in their assignment. Teachers can also designate some of their students as "star students," whose contributions will be more heavily weighted for prioritization in PeerASSIST's selection process. Over a seven month period, PeerASSIST distributed worked examples for over 250,000 problem instances (from around 12,000 unique problems) to over 1,000 students.

TeacherASSIST

While this symposium primarily focuses on learnersourcing, we are also exploring *teacher*sourcing in ASSISTments through TeacherASSIST. This feature will allow teachers like Mr. LeSiege to easily create tutoring feedback messages for not only their own problems, but also for problems sourced from textbooks or written by the ASSISTments Team. We are currently allowing beta teachers who are testing the system to share tutoring messages they have created with other teachers. For example, other teachers in Mr. LeSiege's school or district who use the same textbook and problems will be able to also access the tutoring messages that he created for his students. In future versions of TeacherASSIST, we hope to refine our model into a platform that not only allows teachers within the same school or district to create and share with each other, but to broaden sharing capacities across the United States, and perhaps the world, allowing teachers to communicate and build upon each other's content and thereby improve student learning. It is our vision for the future that TeacherASSIST and PeerASSIST will work in parallel to serve as valuable crowdsourcing tactics to strengthen the feedback available within ASSISTments while simultaneously working to simplify platform usage for teachers and provide robust, collaborative learning opportunities for students.

Crowdsourcing Content Creation in the Classroom

Thomas Hills

This presentation will describe the Propaganda for Change Project, a case study for how crowdsourcing was successfully implemented in an undergraduate psychology course in 2013 with over 100 students (Hills, 2015). The course aimed to teach students about the psychology of persuasion and influence. Rather than taking an approach of direct instruction, the course was designed with a more learner-centered educational approach. Due to the large number of students in the course, traditional approaches to learner-centered education where the instructor would give individual attention to students would be difficult. Instead the course used crowdsourcing to scale the learner-centered approach in two ways by (a) having students find examples of content in the real world that were of interest to them and that highlighted various aspects of persuasion and influence and to write a blog post about it, and (b) having students create their own video as their final project that would utilize the principles of the course to create a persuasive prosocial message. All of the content created by students was shared on this blog: http://persuasion-and-influence.blogspot.co.uk/. The crowdsourced content had value in two distinct ways. First, it gave the instructor talking points in class to illustrate the course topics in ways that were meaningful to the students. By leveraging examples of advertisements that students found relevant to their own lives, the instructor could bring up pertinent examples that were shared on the blog in class. Additionally, the instructor could encounter many more examples (and perhaps better ones) that he himself could have curated. To further help the blog become an essential part of the course, the instructor created questions on the final exam where students had to describe the forms of persuasion used in images taken from the blog. Second, the content generated by students is publicly available on the course blog and so it can be read by (a) students currently in the course, (b) future students who can take inspiration from students who took the course previously, and (c) the general public. Indeed, the blog currently has over 700,000 views, with around 400 views per day from people around the world. The quality of student blog posts exceeded expectations. Many students were thankful (both in person and in evaluations) that the course dealt with real world content and they felt it prepared them for job interviews. Having described the course, we will now turn to discussing the types of crowdsourcing the course used, and the theoretical principles from psychology and educational theory that can help guide them.

Found Content and Produced Content

There are two types of crowdsourced content used in the course: *found content* and *produced content*. Asking students to find examples of persuasion in their lives and write a blog about it is an example of found content.

The concept of found content is similar to that of found objects in art (e.g., Marcel Duchamp's *Fountain*). By having students describe found content, students get experiences with detecting ideas from the course in the real world as well as finding ways to relate the content back to the principles taught in the course by explaining it (to themselves and to others). Having students create a persuasive video for positive change is an example of produced content. This is the type of crowdsourced content that typically comes to mind and that the other presentations in this symposium have focused on.

Educational Theory, Cognitive Psychology, and Content Creation

Having students find and produce content is supported by several educational theories and principles from cognitive psychology. Having students contribute content to the course builds on the idea of learner-centered education. Many learner-centered theories exist in the educational literature that support the idea of crowdsourced content generation. For example, we build on the recently developed idea of the student as producer (Neary and Winn, 2009), which posits that "undergraduate students working in collaboration with academics to create work of social importance that is full of academic content and value" (Neary and Winn, 2009). This approach also builds on a central idea in a variety of constructivist theories that students naturally try to make sense of their experiences by relying on their prior knowledge and experiences (Resnick, 1987; Raskin 2002), so it is our role as instructors to help students make sense of the world around them and learn to participate in a community of learners (Duffy and Cunningham, 1996).

Having students generate new content is also supported by principles from cognitive psychology (Dunlosky et al., 2013). For example, psychologists have shown a *generation effect* whereby students better recall and remember information they generated themselves rather than information given by others (Slamecka and Graf, 1978). Moreover, it has been shown that asking questions that relate to one's prior knowledge and experiences can help support complex learning beyond asking questions related to course content (King, 1994). Having students explain the relationship of found content to the ideas of the course also builds on the idea of *self-explanation*, a well-documented method for improving learning by elaborating on content information (Chi et al. 1989; Rittle-Johnson, 2006).

Understanding the relevant educational and psychological theories can help realize how to most effectively crowdsource the creation of new content, not just for the sake of creating content for others, but, perhaps more importantly, for enhancing the learning experience of the students engaged in generating new content.

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