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INTRODUCTORY ARTICLE

# Learning at Scale

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**Abstract** Learning at Scale is a fast growing field that affects formal, informal, and workplace education. Highly interdisciplinary, it builds on solid foundations in the learning sciences, computer science, education, and the social sciences. We define learning at scale as the study of the technologies, pedagogies, analyses, and theories of learning and teaching that take place with a large number of learners and a high ratio of learners to facilitators. The scale of these environments often changes the very nature of the interaction and learning experiences. We identify three types of technologies that support scale in education: dedicated content-agnostic platforms, such as MOOCs; dedicated tools, such as Intelligent Tutoring Systems; and repurposed platforms, such as social networks. We further identify five areas that scale affects: learners, research and data, adaptation, space and time, and pedagogy. Introducing the papers in this special issue on the topic, we discuss the characteristics, affordances, and promise of learning at scale.

**Keywords** Learning at scale · MOOCs · Learning analytics · Intelligent tutoring systems

Online learning has undergone a sharp growth over the last decade. After a fashionable delay, the transformative changes that have taken place in service areas such as commerce and entertainment have reached education, in both formal and informal settings. With its unique affordances and constraints, the prevalence of online learning changes much more than the delivery method - it changes the very nature the educational experience at both micro- and macro-levels. For example, online learning makes learning available anywhere and anytime; it produces big data that supports mass customization and insights about the learning process; and it connects a large number of learners across diverse backgrounds and expertise.

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This growth is facilitated by a wide range of online environments that have recently come into existence. Content-agnostic *Dedicated platforms* for online learning have received the most attention in the public media and in conferences. One type of dedicated platforms facilitates Massive Open Online Courses (MOOCs). MOOCs gained increased popularity (and attention) in the late 2000's (Chuang and Ho 2016; Pappano 2012). While not replacing higher education, it becomes increasingly clear that MOOCs fulfill a wide range of instructional functions: providing professional workplace education, improving scientific and technological literacies, offering leisure activities, and increasing and diversifying reach to online resources. MOOCs have facilitated changes in the way people consume and engage with instructional resources. For example, they offer global access to education offered by top universities in a way that was not available before; they also support grassroots organization around open resources, such as the Peer to Peer University project (p2pu.org). However, MOOCs are not the only type of dedicated platforms for learning at scale. Another example of dedicated platforms is *Citizen Science* services, in which community members collect and analyze data of scientific value (Bonney et al. 2014). Citizen Science exemplifies the impact of online learning on other fundamental fields such as the very scientific endeavor. Other dedicated platforms are community-based discussion forums such as Stack Overflow. These facilitate just-in-time support and learning around specific topics or fields.

Notably, the above examples are content-agnostic platforms and are extremely popular by both students and practitioners. The educational content itself is generated by universities and companies (as is the case with MOOCs) or learners themselves (as is the case with community tools). The content in these platforms is often open to some degree - whether free to use, or in the more complete sense of open, to modify and reuse. These platforms also offer different network models. Most current MOOCs follow the xMOOC model (Fidalgo-Blanco et al. 2016). These are MOOCs that are centralized around the instructional team and use traditional eLearning tools and approaches. In these MOOCs, the instructional team creates the learning materials and evaluates the quality of the work. More importantly, the learning goals are defined by the instructional team. In contrast, the role of instructors in connectivist MOOCs (cMOOCs; Siemens 2014; Fidalgo-Blanco et al. 2016) and Citizen Science platforms is much more limited. There, the instructional team functions more as a facilitator or a guide. The resources themselves are provided by the community. Different social media offer an even more distributed model, where the questions and topics are created by the community. In the case of forums, learners define their own goals and pursue these when engaging with the learning platform to a greater degree. Thus, the more distributed the learning, the greater the impact of "scale". For example, Q&A websites such as Stack Overflow or eHow succeed because they have a large user population with a diverse set of backgrounds and skills.

A second kind of online learning environments are *dedicated tools*. Unlike the content-agnostic environments described above, dedicated tools facilitate specific types of learning activities on specific topics. In such environments, the learning activity cannot be decoupled from the tool in which it occurs or from the domain in which it occurs. One example of a learning tool is virtual labs and simulations that support science learning. For instance, PhET simulations allow learners to conduct scientific experiments in over 100 topics, and have over 80 million runs a year (Wieman et al.

2008; Roll et al. 2018). Another example is Intelligent Tutoring Systems that adapt the learning experience to individual students' knowledge and performance (cf. Cognitive Tutors and AssistMENTS; Koedinger and Corbett 2006; Heffernan and Heffernan 2014). Other examples include games (e.g., FoldIT; Cooper et al. 2010) and language learning platforms (e.g., Duolingo; von Ahn 2013). In dedicated tools such as these, the platform, the instructor role, and the content, are typically bundled. The benefits of such an approach are rich and relevant interactions, in which affordances match content. The downside is high development effort per instructional content (Aleven et al. 2015; Sottilare et al. 2015). The scale in these environments is not necessarily in the number of learners. Rather, as defined below, it is other dimensions of scale (such as availability of big data) that allows these to engage in a cycle of improvement.

Finally, a third type of learning at scale environments are *repurposed platforms*. These are general platforms that have been repurposed to support learning. An obvious example is YouTube with its many educational channels, and the birth of Khan Academy from the YouTube platform (Thompson 2011). Other examples are Facebook groups that are created for most university courses as a place for open discussion about the course material (Escobar-Rodrguez et al. 2014; Hurt et al. 2012). Notably, the adoption to educational purposes is done by the users, rather than the platforms themselves, and exists in parallel with the original uses of the platforms.

## What Is Learning at Scale?

While the concept of Learning at Scale is frequently referred to, and is the focus and name of a series of successful ACM conferences, it is often use descriptively, and we are unaware of a definition of the term. Thus, we define Learning at Scale as the study of the technologies, pedagogies, analyses, and theories of learning and teaching that take place with a large number of learners and a high ratio of learners to facilitators. The scale of these environments changes the very nature of the interaction and learning experiences.

The impact of scale can be seen in different areas:

1. *Learners* at scale. Current online learning sees an unprecedented number of learners who engage with content. Often, this is more than a multiplier, as it gives way to emergent phenomena. For example, citizen science requires a large number of community numbers who witness, share, and analyze a large number of observations, and thus requires scale to be successful. This area of scale also means diversity at scale. Learners come from diverse contexts and bring with them diverse experiences, goals, beliefs, and ways of engaging with content (Chuang and Ho 2016). It is this diversity that supports distributed learning, as the knowledge is no longer owned only by the instructional team. In this way, learning at scale gives room for multiple perspectives and contributes to democratizing education (Yeomans et al. 2017).
2. *Research and data* at scale. Many of these online learning environments provide detailed trace data about learner engagement and performance. This big data allows us to better understand how learning unfolds and to experiment with different

technologies, approaches, and content with rapid design and evaluation cycles (Joksimović et al. 2017; Gašević et al. 2014). This has led to a significant growth in fields such as learning analytics and educational data mining (Baker 2016; Lang et al. 2017; Siemens 2013), and impacts a broad range of fields from computer science to the social sciences.

3. *Adaptation* at scale. The large number of learners and the magnitude of data support the clustering of learners to groups of related profiles, thus enabling mass personalization (Schuwer and Kusters 2014; Roll and Wylie 2016). The large diversity of learners means that we know more about how learners with different attributes engage and learn, and thus are able to offer diversified educational experiences that match learners' goals and background (Kizilcec and Cohen 2017; Roll and Winne 2015).
4. *Time and space* at scale. The availability of smart and connected devices provides learning opportunities anytime, anywhere. Thus, the scale of learning facilitates the shift from rigid to fluid online learning. Rather than long periods of learning, decoupled from life, as done in residential universities, online learning supports just-in-time modular learning that is goal-focused and embedded in context of actual practice and use (Roll and Wylie 2016). Thus, learning at scale, in its very nature, supports life-long (and life-wide) learning. The prevalence of learning opportunities contributes to changing the economy around education. Not surprisingly, one market that has seen a major shift due to learning at scale is workplace education. This impact is seen also in traditional educational system. For example, universities now offer shorter and more modular degrees and programs (Ehrenberg 2015).
5. *Pedagogy* at scale. All of the above has a profound impact on pedagogies. Traditional ways of teaching do not scale well, and new opportunities require new ways of thinking. Thus, the field of learning at scale pushes us to understand how learner diversity can be leveraged to enhance educational experiences, what forms of adaptation are effective, and most of all, what the goals of education in the digital age should be (Collins and Halverson 2009; Roll and Wylie 2016).

## This Special Issue

In this issue, we have six papers that capture many of the current developments in the field of Learning at Scale. Here is a summary of each of the papers in this issue:

In their paper ***Going global: Understanding English Language Learners Student Motivation in English-Language MOOCs,*** the authors link several of the dimensions above, to study the motivations and needs of English language learners in MOOCs (Uchidiuno et al. 2017b). Via a combination of interviews and surveys, the authors identify common goals among these learners. Students who are English language learners seek to achieve long-term goals of economic, social, and geographic mobility, to practice their English, and also to interact with other learners - a goal that at present is often unmet. MOOC developers, designers, and instructors should support these learners in achieving their goals.

***How do English Language Learners Interact with Different Content Types in MOOCs?*** is another paper that addresses the diversity of learners (Uchidiuno et al. 2017a). By analyzing trace data from two very distinct MOOCs (one in Psychology and another one in Physics), the authors show that English language learners have distinct use patterns of different course resources. These patterns can be explained by looking at the affordances of the courses in terms of language support and demands. This paper has direct implications for design guidelines of courses that have global appeal.

The third paper in this collection addresses a different aspect of diversity among MOOC learners, and demonstrates the benefits of this mode of learning. In their paper, ***The Civic Mission of MOOCs: Engagement across Political Differences in Online Forums,*** the authors identify MOOC discussion forums as an opportunity for students with different political beliefs to engage with one another (Yeomans et al. 2017). Does this happen, or do different student perspectives just live in their own silos? The paper compares and contrasts two different politically-themed MOOCs, one on education policy and the other on American government. First, measuring the students' political perspectives, the authors observe student behavior in the course forum discussions. Surprisingly, they found that while students in these two political MOOCs hold diverse political beliefs, they participate equitably in online discussions, directly engaging with students holding opposing beliefs. They find that the students end up converging on a shared language and common ground, rather than merely talking past each other.

The paper titled ***Design Guidelines and Empirical Case Study for Scaling Authentic Inquiry-based Science Learning*** **via** ***Open Online Courses and Interactive Biology Cloud Labs*** reports on the design and large-scale deployment of an open online course with a biology cloud experimentation lab that supports actual live-biology lab work (Hossain et al. 2017). Developing a physical lab that can be operated remotely at scale is challenging, yet doable in certain contexts. This scalable, remote model of a working biology lab can engage remote learners in actual practices of experimentation, modeling and data analysis. The sample lab introduced in this paper shows how making this kind of capability available to online students both scales well, and offers students legitimate participation in real science, even though it's a wholly online experience. This study demonstrates that the platform and course content are suited for large-scale adoption in K-16 education. The paper concludes with recommendations for designing and building other inquiry-based science learning systems.

The next paper, ***Scaling Academic Writing Instruction: Evaluation of a Scaffolding Tool (Thesis Writer)***, uses a mixed-methods approach to understanding if the Thesis Writer system helps student create better academic prose (Rapp and Kauf 2018). Since academic writing poses multiple challenges to students learning to write in an appropriate academic style, such a system could scale to assist a very large number of students with its particular kind of structured, supportive instruction. Thesis Writer is a domain-specific, online learning environment for the scaffolding of student academic writing, combined with an online editor optimized for producing academic text. Compared to existing automated essay scoring and writing evaluation tools, the new tool offers different functionality and is based on a different genre (i.e., the research report) and a specific structure of introduction, methods, results and discussion.

The final paper in this collection, ***Automated Test Assembly using Determinant Point Processes for Handling Learner Cold-Start in Large-Scale Assessments***, confronts the large-scale learning problem of assessing the state of topic knowledge by students in MOOCs (Vie et al. 2018). In these large classes, a great deal of student performance data is available. Newcomers to an ongoing MOOC enter the course with a variety of different backgrounds and understanding of the content. Since they're new to the course, the MOOC knows almost nothing about their state of knowledge. So it is important to test their knowledge rapidly, in order to be able to personalize their learning experience. This problem has been called *learner cold-start.* The article describes an algorithm for sampling from a bank of diverse questions for a newcomer. This algorithm is based on a machine learning method known as *determinantal point processes*. In the paper, actual data taken from Trends in International Mathematics and Science Study (TIMSS), a large-scale assessment designed to inform policy, shows that this method outperforms existing techniques such as uncertainty sampling, and is able to provide useful feedback to the learner.

Taken together, these papers in the special issue provide a more complete understanding of the current state of Learning at Scale, with both its successes to date, and the challenges that we only begin to explore. These papers demonstrate the potential of learning at scale to offer a different kind of educational experiences. Not only have we shifted the time and place of learning, but also the social context of learning, as well as the chance for research to have a new and highly detailed look into how, when, and where students access educational materials, and how their behaviors map onto learning objectives. Learning at Scale can offer a new kind of education, and we have set ourselves the goal of understanding it. With the papers in this issue, we are on the right path.

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