Artificial Intelligence, the Missing Piece of Online Education?

—PO-HSUAN LIN
MobLab Data Science Unit, Pasadena, CA 91107, USA
Department of Economics, National Taiwan University, Taipei, 10617, Taiwan

—ANDREW WOODERS
MobLab Data Science Unit, Pasadena, CA 91107, USA

—JOSEPH TAO-YI WANG
Department of Economics, National Taiwan University, Taipei, 10617, Taiwan
MobLab Visiting Senior Economist

—WALTER M. YUAN
MobLab Data Science Unit, Pasadena, CA 91107, USA

(Corresponding author: Walter M. Yuan.)

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Abstract—*Despite the recent explosive growth of online education, it still suffers from suboptimal learning efficacy, as evidenced by low student completion rates. This deficiency can be attributed to the lack of facetime between teachers and students, and amongst students themselves. In this article, we use the teaching and learning of economics as a case study to illustrate the application of artificial intelligence (AI) based robotic players to help engage students in online, asynchronous environments, therefore, potentially improving student learning outcomes. In particular, students could learn about competitive markets by joining a market full of automated trading robots who find every chance to arbitrage. Alternatively, students could learn to play against other humans by playing against robotic players trained to mimic human behavior, such as anticipating spiteful rejections to unfair offers in the Ultimatum Game where a proposer offers a particular way to split the pot that the responder can only accept or reject. By training robotic players with past data, possibly coming from different country and regions, students can experience and learn how players in different cultures might make decisions under the same scenario. AI can thus help online educators bridge the last mile, incorporating the benefit of both online and in-person learning.*

Key words: Online education, classroom experiments, games, robotic strategy, artificial intelligence

BACKGROUND

WITH the exponential advancement of Internet technology in recent decades and its subsequent impact on content consumption, online education has profoundly changed how we teach and learn [1]. The emergence of Massive Open Online Courses, or MOOCs, popularized by platforms such as Khan Academy, Coursera, edX, and Udemy in the last several years, enables educators to reach an audience orders of magnitude more than they would have through traditional face-to-face classrooms. At the same time, millions of students and adult learners from around the world now have opportunities to learn countless subjects on-demand, often taught by world-class instructors [2].

SIGNIFICANCE

There is also a growing trend for traditional post-secondary institutions, community colleges, and four-year universities alike, to invest significantly more in online programs in order to expand their student bodies without the confinement of their physical campuses. Over 60% of liberal arts college presidents and close to 80% of research university presidents report that their institutions offer classes that are taught exclusively online. Over 65% of college students have taken at least one class online per academic year [3].

CHALLENGES

Despite its disruptive potential to traditional classrooms, online education's realized impact has been much more unclear than expected largely due to students' low completion rates. Intuitively, one of the crucial factors to engaging students is to facilitate the right teacher-to-student and peer-to-peer interactions. In online education, we gain on scalability but often give up on interpersonal connectivity [4], even though the opportunity for connectivity is intrinsically present. Unlike in brick-and-mortar classrooms, students *have* to be online to be part of this new frontier of learning. How can we bring together the best features of both online and in-person learning?

Can AI Help?

In this brief discussion, we focus on economics, one of the most popular undergraduate subjects, to demonstrate how the latest AI methods can help improve interactivity in an online learning environment and empower students to reach their expected learning objectives.

Recent developments in the pedagogy of economics have introduced experiments in the form of interactive social and economic games. Students learn abstract concepts and theories through firsthand experiences, just like the way they learn experientially in the natural sciences. A concrete example is teaching the concepts of supply and demand and market equilibrium by having students join a virtual market where they learn to trade, maximize profit, and explore the inner workings of market structure [5]. With Internet-connected mobile devices reaching saturation among students, running such synchronous online experiments in classrooms has become feasible in recent years [6]. But how can we leverage such interactive technology in online classes to help augment student engagement and connectivity even when students are spread across different time zones? Part of the solution may lie in the engineering of robotic players who can learn from human plays to realistically interact with students in asynchronous activities.

Approach

We should only start programming after two key questions are addressed: What is the goal of the AI players, and what do we want the students to learn? For example, one of the most important educational objectives of economics is to let the students learn to maximize their payoff by correctly responding to an opponent's strategy. To this end, the programming challenge becomes how to make the robots play like real human players [7].

To mimic human behavior, one natural robotic candidate is the "equilibrium player" who attempts to play the equilibrium strategy. This can be a good approximation for a human player in many cases. It's also an interactive way for students to learn about the abstract models presented in their textbooks. For instance, the idea of a competitive market is clearly illustrated when one joins a market full of automated trading robots who find every chance to arbitrage.

However, sometimes the assumption of rationality makes the equilibrium-player robot behave different than a human player. Consider the Ultimatum Game, where a proposer makes an offer to split a sum of money that the responder can only accept or reject. If the responder rejects, both players earn nothing. If the robot precisely follows the prediction of the subgame perfect Nash equilibrium, the proposer robot would always offer at the lowest positive unit and the responder would always accept any positive offer. However, well-established literature shows that, on average, human proposers would offer 30 to 40% of the pot to the responder. One explanation for this "generosity" is that players care not only about their own payoffs but also their payoff relative to others. In this case, playing the equilibrium strategy doesn't mimic a typical human player [8], and students would miss the point of how economic theories don't always capture the complexities of human behavior.

To mitigate this problem and better meet our teaching objectives, we should make our robot incorporate and respond to human players' non-equilibrium behavior. In other words, the robot should be able to form beliefs about how human players would play, and best respond to that. For example, the robot could form the belief that it is facing an average human player. In the Ultimatum Game, the robot proposer should anticipate spiteful rejections from the average human and act accordingly, something not all humans can do. In this case, we can borrow the techniques from machine learning and train the robot with past data in our dataset [9]. This dataset could even come from several different cultures to capture the significant between-country heterogeneity in the proposal offers. This approach not only gives students a chance to play the game asynchronously but also enables them to experience and learn how players in different cultures might make decisions under the same scenario. Furthermore, the demographic variation also allows us to build robots with different "personalities," which can absolutely broaden the students' understanding about the games and the strategies.

Summary

Thanks to its unprecedented convenience, breadth, flexibility, and accessibility, online education is cemented as a new pedagogical frontier for learners across all ages. However, we have yet to fully optimize our instructional and learning models. Identifying where and why students drop off or lose interest is a crucial step for incremental improvement. Here, we demonstrate the power of applying the latest AI methods, using teaching and learning economics as a concrete example, to help better engage and connect students with each other and their instructors in asynchronous online environments that break through spatiotemporal barriers to learning.

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Po-Hsuan Lin (po.lin@moblab.com) received the B.A. degree in economics with minor in mathematics from National Taiwan University, Taipei, Taiwan, in 2016. He is currently working toward the Master's degree with the Department of Economics, National Taiwan University. He is also a data analyst intern with MobLab, Pasadena, CA, USA.

Andrew Wooders (andrew.wooders@moblab.com) joined MobLab, Pasadena, CA, USA, as robotic strategy intern in 2018 and will begin his Bachelor's studies at The University of Chicago in Fall 2018.

Joseph Tao-Yi Wang (josephw@ntu.edu.tw) received the B.S. degree in mathematics with minors in foreign languages (English) and economics from National Taiwan University, Taipei, Taiwan, in 1998, and the M.A. and Ph.D. degrees in economics from the University of California, Los Angeles (UCLA), Los Angeles, CA, USA, in 2003 and 2005, respectively. He was a Postdoctoral Scholar in economics with the Division of Humanities and Social Sciences, California Institute of Technology, from 2004 to 2007. In 2007, he joined the Department of Economics, National Taiwan University, as an Assistant Professor, became an Associate Professor in 2010, and a Professor in 2014. He has been a visiting Senior Economist with MobLab, Pasadena, CA, USA, since 2018. His current research interests include experimental economics that tests theory, economic theory inspired by experiments, and the human reasoning process that leads to economic decisions.

Walter M. Yuan (walter.yuan@moblab.com) studied microbiology at Peking University, Beijing, China, from 1988 to 1991. He received the B.S. and M.S. degrees in microbiology and molecular biology from the University of Idaho, Moscow, Russia, and the Ph.D. degree in bioinformatics from the University of Wisconsin-Madison, Madison, WI, USA, in 2000. He was the Technical Lead and then Manager with the California Social Science Experimental Laboratories, Division of Humanities and Social Sciences, California Institute of Technology, and the Department of Economics, UCLA, from 2000 to 2011. In late 2011, he founded MobLab, Pasadena, CA, USA, with Stephanie Wang, a behavioral economist, and has since been serving as its CEO.