Social Learning Networks: A Brief Survey

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***Abstract*—Social Learning Network (SLN) is a type of social network among students, instructors, and modules of learning. It consists of the dynamics of learning behavior over a variety of graphs representing the relationships among the people and processes involved in learning. Recent innovations in online education, including open online courses at various scales, in flipped classroom instruction, and in professional and corporate training have presented interesting questions about SLN. Collecting, analyzing, and leveraging data about SLN lead to potential answers to these questions, with help from a convergence of modeling languages and design methods, such as social network theory, science of learning, and education information technology. This survey article overviews some of these topics, including prediction, recommendation, and personalization, in this emergent research area.**

I. Introduction

Social Learning Network (SLN) encapsulates a wide variety of scenarios, in which a number of people learn from one another through interaction. An SLN model consists of functionality models and graph-theoretic models. Typically, the *nodes* in an SLN will represent the learners, learning concepts, or both learners and concepts. The *links* will represent connections between these nodes, and can be undirected to denote a similarity, or directed to indicate the flow of information. The links can also be *weighted* to give magnitude to these meanings, which are typically extracted from some network measurement.

A. Motivation and Applications

1) MOOC: The rapid deployment of Massive Open Online Courses (MOOCs) [1] has created a surge in the global connectivity among students for educational purposes. Platforms like Coursera, edX, and Udacity, which emerged in late/early 2011/2012 have become the subject of debates as people explore the future of higher education.

There are now over a dozen MOOC platforms in higher education, and common across all of them are these features: online, free, open content consumption, very large numbers of enrolled students, very low completion rates, lecture videos with quizzes, and, most notably for SLN, *discussion forums*, which are the primary means for student-to-student and instructor-to-student interaction.

MOOC discussion forums are structurally similar to Q&A sites, but with different terminology. Typically, each course's forum consists of a number of *threads*, which are comprised of *posts*; the first post is written by the creator of the thread. Posts may in turn contain a number of *comments*, which makes a three-level hierarchy. A user in a forum has the option to create a thread, make a post, or comment on an existing post. When creating a thread, each course has a number of forum categories that can be applied, but these are often inconsistent since there is no effective mechanism to force learners to abide by them consistently [2]. Posts and comments on MOOC forums can also receive up-votes and down-votes from users and staff.

Our MOOC experience. We have instructed two MOOCs over four offerings. In 2012, our undergraduate course *Networks: Friends, Money, and Bytes* (N:FMB) was one of the six piloted by Princeton on Coursera in 2012. Almost 150K students enrolled in N:FMB on Coursera between 2012 and 2013. We also created a second course, *Networks Illustrated: Principles Without Calculus* (NI), which explains the underlying concepts in N:FMB but with much simpler mathematics.

2) FLIP: Blended learning, the technique of combining elements of online and traditional instruction, is increasingly being explored across K12 and higher education. Pioneered by Salman Khan, the result in many cases has been a flipped classroom (FLIP) [3], where watching the lectures online becomes homework, and class time is instead used for discussion.

The interaction of the students on a flip classroom discussion forum allows us to extract the SLN. The structure of posts and comments here is likely similar to that for MOOC, but we expect the resulting network to have a number of differences:

(a) *Size and sparsity.* FLIP will have a much smaller number of learners, but the connectivity among them will be much denser. This is due to the fact that the learners on MOOC form a heterogeneous background and tend to have less in common, and also that participation will not benefit a learner's performance in a MOOC course. In FLIP, the students have a much higher chance of meeting one another and may interact out of compulsion.

(b) *Informational vs. conversational discussions* [4]. In addition to course-relevant, informational discussions, MOOC forums tend to contain a significant portion of conversational discussions, where learners engage in "small-talk" [2]. In FLIP, the SLN would not typically contain conversational discussion for two reasons: first, students can readily interact informally either in person or on other media, and second, the close monitor of the instructor may discourage such behavior.

Our FLIP experience. As N:FMB went online and became available to everyone in the world including Princeton's own undergrads, it became difficult to justify the use of classroom time to repeat an identical version of the same lectures. As such, we started using classroom time for three purposes: question and answer sessions, guest lecturers from industry, and real-time demonstrations and experiments.

3) Q&A Sites: A number of popular social question and answer (Q&A) portals have emerged which compliment search engines by allowing users to enter questions in natural language form [5]. Today, sites like Yahoo! Answers, WikiAnswers, and Stack Overflow each receive thousands of questions daily, with material from diverse subject areas. For example,

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since its inception in 2008, Stack Overflow has amassed 2.8M registered users and 6.7M total questions.

As with most online forums, Q&A sites typically allow users a few key functions: post question, answer question, comment on answer, and up/down-vote post. Additionally, they usually allow the asker to choose choose a single "best" or "acceptable" answer. Also, as a mechanism for quality assurance and incentivization, Q&A portals typically allocate points to users for receiving up-votes, and likewise detract for down-votes.

We can identify several differences between the SLN here and those forming in educational settings:

(a) *Incentive structure.* Q&A sites have a well-defined, automated set of incentives to encourage participation. With MOOC and FLIP, the instructor can choose to design these on his/her own, but this may not be a scalable process. Platforms like Coursera have started to provide a forum rank of students, but it is not tied to student performance.

(b) *Broader concept list.* Information propagated in an SLN for a course will be limited to material pertaining to the course. Each course has only one forum, and only students enrolled can participate. Though some Q&A forums have some focal specificity, we expect the number of concepts emerging in these SLN to be much broader.

(c) *Single learning modality.* With a Q&A forum SLN is the only means of learning, as opposed to an educational setting where it is only one of four modalities: there are also lecture videos, assessments, and textual resources.

Previous studies. There have been a number of studies focused on Q&A forums, focused in two main areas of SLN: (1) identifying authority users and quality posts (*e.g.,* [4], [6], [7]), and (2) designing methods to incentivize participation [8], [9]. MOOC forum studies have started emerging, *e.g.,* [2], [10].

B. Graph Types

1) Undirected graph among learners: If we consider the learners in an SLN as the nodes, we can use undirected links to indicate the presence or absence of some characteristic(s) between them. These properties could be age, geographic location, education level, whether or not they have interacted, and so on. Then, for nodes i and j, we can say for example that

$$(i, j) \in G \Leftrightarrow \sum_{k \in \mathcal{K}} \text{prop}_k(i, j) \geq P, \qquad (1)$$

where $\text{prop}_k(i, j)$ is a binary variable that is 1 iff i and j satisfy property k (*e.g.,* both between the ages of 18 and 24) in the set of properties $\mathcal{K}$, and $P \leq |\mathcal{K}|$ is a threshold constant. In other words, nodes i and j are connected if and only if they both satisfy at least P criteria specified in $\mathcal{K}$.

2) Directed graph among learners: We may instead want to measure the flow of information in the SLN. To do this, we can turn to the interaction forums and analyze the relationships between the learners. Through this, we can for example include a directional link from i to j whenever j answers a question posted by i. This could further be restricted to only the "best answer" for a given question, and could be a multigraph [6] where there is more than one link from i to j since learners can ask and answer more than one question.

3) Undirected graph among learners and concepts: We may also be interested in representing the information itself as a second type of node. Key concepts can be extracted in a number of ways, such as running textual analysis to find keywords in discussions or using a syllabus specified by an instructor, and then we can define a bipartite graph between learners and concepts. To specify this,we could again use (1) but this time have each property k represent a condition on the participation of user i in concept j (*e.g.,* having asked or answered at least 3 questions pertaining to the concept).

4) Directed graph among learners and concepts: Finally, we may want to depict the structure of interactions in more detail. To do this, we can again incorporate concept nodes, except here we will view each question or post by a learner as a separate one. In this way, we define two sets of links for each post: $(i_0, j) \in G$ for learner i_0 who makes the initial post, and $(j, i_l) \in G$ for each learner i_l who commented on j. In a forum where users can up and down-vote posts/comments, we can weight these links with the net votes obtained.

These four examples are meant to illustrate a few useful graphs that can be defined on an SLN, and are not comprehensive. Furthermore, dynamic functionalities on top of the graph structures will be an integral part of the model too.

II. Research Questions

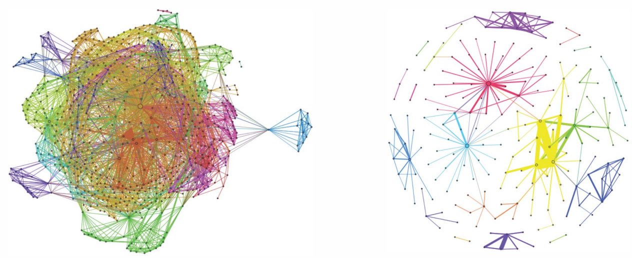
A. Prediction

1) Performance: The ability to predict performance on assessments – meaning homework, quiz, or exam questions – a student has not taken is an important research area. A natural way to attack this problem is to employ a classification model in which each observation represents a user's grade on an assessment. Factor analysis techniques have been recently developed to extract question-concept relations and user proficiency, using data from traditional classrooms [11], [12].

In a MOOC setting, we have access to data from a much larger set of users, but in general the amount of questions each student answers will be less, leading to the issue of sparsity. For example, in our N:FMB MOOC, the average fraction of questions answered among students who answered at least one was only 9%. At the same time, on MOOC we have access to a wide set of SLN data, and analysis of this might increase the accuracy of what is possible using traditional techniques.

2) Drop-off rate: Another application, especially in online courses, is to predict drop-off rates. This could be for an individual student, or for the volume of participation in the course as a whole. The metrics of interest could be completion of certain assignments, lecture videos, or a given rate of involvement in discussions. Recently, [13] focused on predicting assignment completion in a MOOC by incorporating a custom interface in each assignment for different groups of learners.

SLN data could be helpful in detecting student drop-off, and subsequently in modifying courses to increase retention. For instance, if a student is normally active in asking or answering questions, then if the rate of her participation declines, this could be an indication in advance that she will not complete a given assignment. Even for learners who are not active on the forums, the use of SLN information of similar users could help make predictions.



(a) Forum discussion. (b) More useful visualization.

Fig. 1: Depicted in (a) is the directed graph of forum discussion from our N:FMB MOOC in 2012, with 713 active participants (nodes) and 4353 replies (edges). (b) is a more useful visualization, obtained from weighting each link by the number of replies and only showing those above 2. This highlights a large number of clusters, and a disconnected graph.

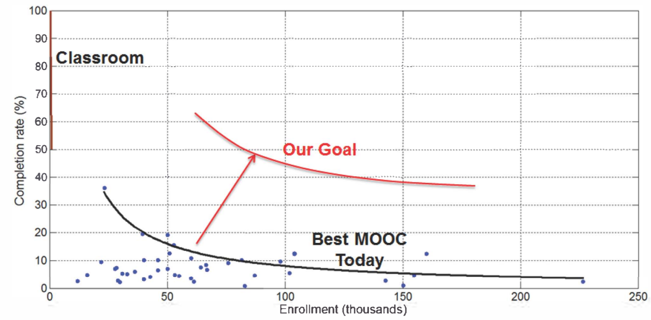


Fig. 2: Traditional classrooms have high completion rates but small enrollment numbers. Empirical data for MOOCs in spring 2013 [15], where each dot is a course, shows how they operate on the other end of the scale-efficacy tradeoff: high enrollment but small completion rates.

B. Recommendation

Recommendation methods leveraging SLN will also be useful in a number of scenarios. This is especially true for MOOC, with its information overflow and a massive number of learners.

1) Courses and topics: A much broader market than just MOOC, the general market of online education offers a large number of courses, and each typically has a rich amount of teaching material and a large volume of student activity in the forums. Students often have trouble locating the most relevant information to their individual learning desires and needs.

This presents an opportunity to improve the educational experience by designing intelligent algorithms to assist student navigation. On a given platform, a student would be presented with a list of courses of potential interest that she was likely unaware existed. Within a given course, a student would be given an indication as to which lecture videos were of utmost importance (considering his/her prerequisites), and would be redirected to the most relevant/interesting discussion threads.

2) Study-buddies: Collaboration with study partners is an essential aspect of engagement for many learners, whether the course is online or not. In the case of any MOOC, there are tens of thousands of students from a multitude of backgrounds, so for any given student there are likely a number of others who would be a good "match" for her to study with. At the same time, these massive numbers – further complicated by the asynchronous nature of learning and the lack of face-to-face interaction – make it very difficult for students to locate and form these optimal groupings on their own. For example, take Figure 1, which depicts the SLN from the discussion forums of our N:FMB MOOC. As one can see from (b), the graph is highly disconnected, indicating the students have not explored many potential connections in their SLN.

Recommendation algorithms could focus on similarities or, perhaps more importantly, *dissimilarities* between users. For example, one student who actively engages on the forums on certain topics could be paired with another who is struggling on those topics.

3) Peer-grading: In a massively-scaled online course, the teacher-to-student ratio is extremely small, often fractions of one percent (*e.g.,* we observed an average ratio of 0.0035 over 73 courses, considering those who posted on the forums at least once [2]). As a result, it is infeasible for a teaching staff to manually grade each student's submissions. One way this is obviated currently is by assigning machine gradeable homework and exams, such as multiple choice. But this often compromises the quality of the questions that can be asked.

In many instances, MOOC instructors have turned to another alternative, requiring students to grade each other. So far, this grading system has lacked efficacy, for two main reasons. First is that different students have different grading quality: as in any class, students on MOOC understand the material at different levels. Second is the time commitment required for grading: an instructor typically wants each participant to grade at least a few homeworks, and some students may not be able or willing to make the necessary time commitment.

Using data from two Coursera offerings, [14] recently developed a method to determine which submissions in a MOOC need to be allocated additional graders, through statistical estimates of learner properties. But the question as to *which learners* should be allocated to given submissions is still unexplored. One may be able to use the structures of SLN to discover quality-graders for each assignment's scope of topics. Additionally, it is desirable to design a system to offset grading bias and to use statistical estimation to reduce the total volume of jobs required for each student.

C. Personalization

One of the fundamental debates about online education is the tradeoff between efficacy and scale in learning. As evident in Figure 2, which shows empirical enrollment–completion data pairs for a variety of MOOCs, it is rare to see more than 10% of students complete one of these courses.

There are many reasons why MOOC is not yet effective: teacher-to-student ratios are very small, learning is done asynchronously, and the student population is very diverse. Needed is advanced technology for course individualization, to lift this tradeoff curve and enable effective learning at massive

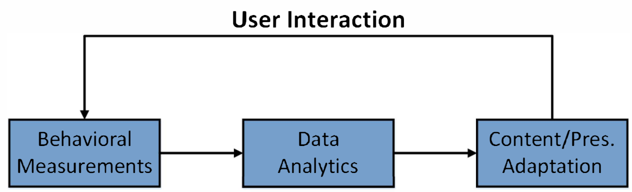


Fig. 3: A typical flowchart of individualization. Each block constitutes a substantial engineering challenge in its own right.

scale. Rather than having a one-size-fits-all (OSFA) online course, an instructor should be able to author and deliver an adaptive versions that change the content in real-time to fit each student's desires and needs.

Student behaviors on SLN is an under-studied yet potentially key input to this adaptation. In turn, individualization will provide an effective way for students to form connections with those on the same or similar learning paths. We will outline how individualization engines in learning systems can interact with SLN research.

There are a number of existing adaptive educational systems in literature. Most of these are restricted to web browsers and are built to support content that acts as a supplement to in-class lectures. Regardless of the application, most individualization frameworks will incorporate three sequential components in a feedback loop, as in Figure 3. What remains challenging is to design, implement, and deploy such feedback systems, and how to incorporate SLN into the architecture. We sketch some of the key elements in the design below.

Behavioral measurements. This functional module includes measurements of user behavior while interacting with the course material. For example, a user's video watching trajectory (with pauses and jumps) can be captured, as can her answers on quizzes and other assessments. And most notably for our purposes here, the information a user enters in discussion forums while interacting with her SLN can also be collected. Such a rich set of information can be used to generate data analytics that are necessary for adaptation, and also enables numerous research paths in machine learning, data mining, and social network analysis.

Data analytics. This module uses machine learning techniques to generate a low-dimensional model for the high-dimensional process of learning. The latent space can either be (a) discovered through data mining or (b) defined in advance in terms of author-specified learning features. For (a), it represents a major step toward a goal that has remained elusive so far: structured understanding of the process of learning. For (b), the instructor has flexibility in deciding the number and designation of the features. As defined in [16], they can represent user "goals, knowledge, background, hyperspace experience and preferences." The instructor will tag segments of content with the features they are associated with, and with this each student's model in each of the feature-dimensions can be updated.

Adaptive learning systems today rely mostly on responses to assessments to update the user model. New algorithms are necessary to translate different types of behavior to some indication of "performance." In particular, one must consider characteristics of a user within her SLN, such as level of discussion activity, quality of comments, timing of sharing private notes with friends, and similarity to others on the same learning path.

Content/presentation adaptation. The user's updated profile will be mapped into decisions on *what* content will be presented next and *how* it will be presented. Different versions of the text and video may be chosen. For example, those struggling at the current level of instruction will see reinforcement material before moving forward, whereas those bored will be challenged with advanced material. The author can specify the transition logic, and a tree of "parallel universes" of learning will branch out. Furthermore, students on different learning paths can still interact through the SLN and discuss the material from the various angles they have witnessed.

III. Research Methodologies

A. Data Collection

In order to collect data about SLN, a research team has two options, each with pros and cons:

1) Use existing data: Over the past few years, there have been a substantial number of open online course offerings. Some of these remain open even after the session ends, which gives one access to the discussion forums and other basic information about each class. Additionally, all SLN data from Q&A portals is accessible through the respective websites.

MOOC forum: data crawling. As an example, we refer to our summer 2013 large-scale statistical analysis of MOOC [2], where we focused on all 80 courses that were available on Coursera in the middle of July and that ended before a given date. As part of our data collection, we crawled the forum content from Coursera's server using Python and the Selenium library, and subsequently used Beautifulsoup to parse the HTML into text files. In total, our dataset consisted of approximately 830K posts and 115K distinct users. We will discuss our subsequent analysis more in Section III-B.

2) Generate new data: There are also disadvantages to using existing data. First, there is no opportunity to excite the state of SLN formation for subsequent data analysis. Second, only data on open courses are available. Third – and perhaps most importantly – data is only publicly accessible up to a certain measurement granularity. Measurements of video-watching behavior, student performance, and other forms of input valuable in studying SLN are rarely available to anyone except the course instructor and platform provider.

A second option then is collaboration between educators and data scientists. Or alternatively, a team could invest resources in creating a brand new online education platform to host courses for a number of instructors.

3ND. As an example, we created a non-profit, free online education platform in 2013 called "3 Nights and Done" (3ND). It uses one weekend (1 hour per night) as the time unit of learning. 3ND content is made-to-order, and starts with 15 "3-nighters," each given by a prominent leader in a field who donated his or her time to this "education charity" on different topics. The video lectures are supplemented by multiple choice questions, discussion forums, and note-taking/sharing boxes next to the videos. Data on user interaction with these learning modalities is captured at fine granularity.

B. Analysis

Once SLN data is collected, the next step is to perform analysis. There are many ways to approach this depending on the research question of interest; most would involve large-scale machine learning methods. For exemplary purposes, we summarize two case studies from our recent work.

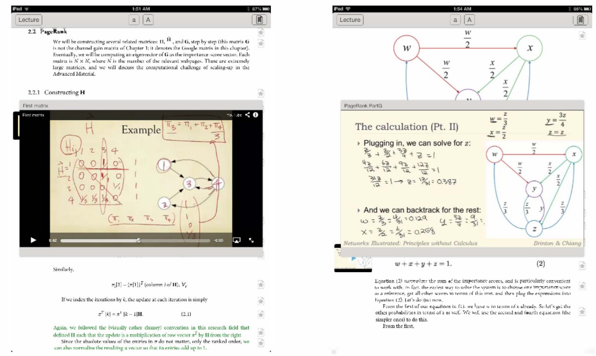
MOOC forum: analysis. Referring again to our MOOC study [2], after crawling we turned to analyze the forum characteristics. Through examination, we quickly discovered that both high dropout rate and information overload are ubiquitous on Coursera. As a result, we broke our subsequent analysis into two main parts.

First, we used linear regression models to determine which course properties were correlated with student participation in the forums, which we quantified as the number of posts (or users) that appeared each day for each course in our dataset. Some of our preliminary findings here included the following. For one, teaching staff active participation in forums was correlated with an increased volume of discussion, but also with higher decline rates in the long run. Similarly, when a course was peer-graded, there tended to be an increased volume of discussion in the short run but a higher decline rate in the long run. In the future, we plan to revisit this analysis by incorporating SLN graph properties such as clustering coefficient and homophily into the models.

Second, we extracted the amount of small-talk present in each course's discussion, both (1) overall and (2) over time. We relied on Amazon Mechanical Turk (AMT) labeling in both cases. For (1), we randomly chose 30 threads from each course and had each thread labeled by AMT as small-talk or not; we found that a substantial portion of the course forums had more than 10%. For (2), we trained a support vector machine classifier from the AMT data across all courses within a given category, and used it to classify the threads within the first 35 days. We found that in the first few days, each category had over 40% small-talk. SLN information that factors in the structure of the forums could potentially improve the accuracy over what is possible using only text classifiers.

Performance prediction. We have also applied some standard prediction algorithms to our MOOC data. Procedurally, for each of two course offerings we extracted all user–quiz pairs available and collected them into a matrix, where an entry took one of three values: 0 if the student answered the question incorrectly, 1 if correctly, and `NA` if he/she did not answer the question. For N:FMB, this yielded 2,229 students and 90 quizzes, with 8.9% of the entries filled; for NI, we had 3,196 students and 69 quizzes, with 23% filled. Then, using 70% of the available data, we trained two algorithms: (1) a baseline predictor, which solves least squares optimization to minimize error in terms of student and quiz biases, and (2) a neighborhood predictor, which extends the baseline to leverage student-student and quiz-quiz similarities. The remaining 30% of the data was used to test the performance of the trained algorithm.

To obtain the performance, in each case we computed the percent accuracy after rounding the predictions to 0 or 1. This was compared to a naive average which simply predicts the average value of all elements in each dataset partition. We obtained close to 75% accuracy in N:FMB, 9.2% higher than the average, and close to 80% for NI, 3.6% higher than the average. These results are promising, but they only consider structure within the performance data itself. Again, incorporating SLN data into these models could increase the accuracy of what is obtained here.



(a) Linear algebra (b) Basic algebra

Fig. 4: Shown here are pages from two different learning paths in a MIIC course. (a) is one which uses only basic algebra to explain the fundamentals, and (b) is a more in-depth treatment of the subject, requiring knowledge of linear algebra.

C. Design and Trial

Beyond SLN data analysis is the design of new learning systems. Subsequent data collection and analysis can help to incrementally improve these over time.

MIIC design. We have been developing a software system that we use as a test-bed for individualization, through a substantial effort with a team of software engineers and user interface designers. We call it the Mobile Integrated and Individualized Course (MIIC) because it contains the complimentary features of integration and individualization and is delivered as a mobile app.

There are many conjectures about course individualization that need to be tested through empirical studies, results of which can drive revisions of the technology. Using a prototype of MIIC in the form of an iOS mobile app, we carried out two trials recently, recruiting participants from a wide range of technical backgrounds on MOOC. In comparing individualization to a standard, OSFA presentation of the same material, promising results have already been witnessed.

Trial 1: Survey responses. The material for MIIC in this trial was based on two different explanations of Google PageRank. One was from N:FMB and the associated text *Networked Life: 20 Questions and Answers*, which requires a background in Linear Algebra. The other was from NI and *Networks Illustrated: 8 Principles Without Calculus*, which requires only simple additions and multiplications. Figure 4 shows two different parallel universes a user could be directed down.

We randomly divided the participants in this experiment into two groups. One was instructed to use MIIC and then

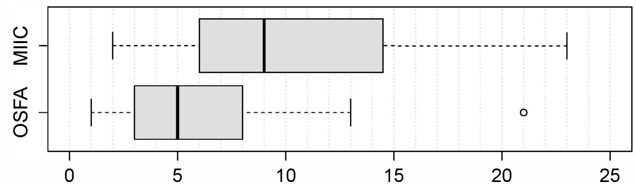


Fig. 5: Distribution of the pages accessed by students in the OSFA and MIIC groups. Testing of the difference between the groups yielded a p-value of 0.009.

OSFA, while the other was instructed to do the opposite. Each student was asked to fill out a post-experiment survey upon completion of these tasks, and 43 of them did so. Four questions in the post-experiment survey dealt with direct comparison between the two versions. For each of these, a trinomial test described in [17] was used to determine whether there was a statistically significant difference between the number of positive (in favor of MIIC) and negative (in favor of OSFA) responses. Questions inquiring about which version contained too much difficult material, which led to a better understanding, and which was preferred overall each led to significance in favor of MIIC, with two-sided p-values of 0.025, 0.008, and less than 0.001, respectively.

Trial 2: Retention rate. The setup for this trial was similar to the first, with the exception of three important details. First, the material used was a lecture on Cellular Power Control, rather than Google PageRank. Second, each participant was given only one of MIIC or OSFA, and they were unaware of which they received. Third, the objective here was to measure student engagement, rather than relying on survey responses. As a proxy for engagement, we chose *total page count* as one of the endpoints for statistical analysis. This is the total number of unique pages visited by each user. We expected that those using MIIC would have visited more material than those using OSFA, because of the ability of MIIC to cater to each user individually.

In our trial, 44 students engaged with the material long enough to be considered in our analysis. Figure 5 gives a boxplot of the total page counts for each group; the distribution for MIIC was clearly skewed to the right, suggesting a higher level of engagement. We then applied statistical tests to analyze the difference between the distributions. With departures from normality detected, we used the non-parametric Wilcoxon rank sum test, which produced a highly significant p-value of 0.009. Additionally, we computed a Hodges-Lehmann estimate of 5 pages, and a 95% confidence interval estimate of 1 to 8 pages, each in favor of MIIC. This verifies that students using MIIC tended to study more information than those with OSFA, which implies that adaptation has a positive influence on engagement.

IV. Conclusion

Recent innovations in online education have spawned an interest in SLN as a research area. In this paper, we have presented a brief survey of SLN, including applications, emerging research questions, and study methodology. Along the way, we also outlined a few of our recently completed steps in data collection, analysis, and system design.

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