Challenges and Opportunities of Using Recommendation Systems in Academic Digital Libraries
Abstract
In the wake of recent advances in educational technologies and the rapid growth of data collection in modern digital libraries, learners have access to self-directed learning opportunities that are more adaptive, personalized, and accessible. Such learning opportunities are more important than ever before in an era of accelerating change and increasing competition. Meanwhile, the Big Data that is being generated provides valuable insights into library services and has the potential to reshape the future of library work. Earlier research and applications of library science have not paid enough attention to the role of affordances such as automated recommendation systems made possible by Big Data techniques. While there has been considerable discussion of commercial recommendation systems, such attention has not typically focused on educational applications. In this paper, we discuss recommendation systems and the role that they might play in education. To illustrate, we present a case study of a hybrid recommendation system on an open library online publication and discuss the challenges and opportunities of using such systems to support self-directed learning.

Keywords: Recommendation System, Self-directed Learning, Digital Library, Big Data
Challenges and Opportunities of Using Recommendation Systems in Academic Digital Libraries

Introduction

Attempts to understand, apply, and develop data science techniques in education have developed over several decades. However, practical efforts to close the gap between advances in data science and the experiences of learners are still limited outside of specialized applications. The development of network technologies and electronic communications that undergirds the digital revolution in education has created new opportunities for autonomous, customized, and adaptive learning in more general educational settings such as libraries. The current generation of library patrons utilizes electronic technologies and has more choices than ever before when it comes to accessing digital resources inside or outside of traditional learning environments. Moreover, with the growth of so-called “non-traditional” students in higher education, academic library patrons are more likely to be self-directed learners (Knowles, 1980). As a result, the application of new techniques (e.g., artificial intelligence and machine learning) are attracting increasing attention in library communities. Examples include search and recommendation systems, large-scale semantic analysis, integrated speech recognition, real-time multilingual translation, and cloud services for complex multivariate web content.

However, these new educational technologies are not "silver bullets" that address long-standing dilemmas in the field. Instead, they bring more challenges and indeterminacy to this Information Age. Will the resources help learners to remediate the gaps in their learning, or leave more unsolved issues? Will their choices help them to achieve more successful futures, or lure them into quick-hit, superficial, and highly suggestible learning experiences? Will learners find a better way to develop their personal or career interests, or instead become more confused and uninterested in learning? The fundamental problems we face are nothing new; students may still
lack the background, ability, and support to make use of self-directed learning opportunities. Despite the availability of many useful educational resources, the task of identifying relevant ones can be very difficult for self-directed learners.

Researchers developing recommendation systems have tried to address the problem of information overload for decades. Recommendation systems provide an adaptive, flexible, and effective dose selected from massive information stores based on learner behavior and a personal profile. Recommendation systems incorporate ideas in stages parallel to those developed by analysts of self-directed learning (Caffarella, 2000; Hiemstra, 2000; Merriam & Caffarella 1999):

1. Setting the goal. Defining the measurable metrics which the algorithm aims to optimize;
2. Searching the resource. Searching, ranking, and updating the available learning resource;
3. Designing, carrying out, and adjusting the study plan. Capturing more personalized information (e.g., behavior or user background data) and updating the content information system regularly.
4. Evaluating the study project. Measuring the performance of the recommendation and adapting to the new data.

However, most prior studies of recommendation systems have not paid enough attention to what we know about education. Meanwhile, most studies of education or academic libraries view recommendation systems only as tools for searching resources, without considering their full educational potential.
To address this gap, we will discuss the challenges and opportunities of using recommendation systems in an educational context. We will begin with a brief review of work on self-directed learning, followed by an overview of recommendation systems in digital libraries. From there we will proceed to a case study of the application of recommendation systems in an online library publication in a graduate school in education and conclude with a discussion of the potential for further research and development.

**Self-directed Learning**

In an era of abundant information resources that can be almost instantly available, some (Duderstadt, 2009; Chen, Xiang, Chae, & Natriello, 2019) have argued that academic libraries could be the most critical venue for studying how students learn. Work on self-directed learning precedes the digital revolution. However, in light of recent advances in communications and computing technologies, self-directed learning has become more central in our thinking about education in the Information Age.

Self-directed learning is learning in which the learner directs the conceptualization, design, conduct, and evaluation of a learning project (Brookfield, 2006). Knowles (1978) initially advanced theoretical work on self-directed learning as a critical element in his concept of andragogy. Self-directed learning is viewed not only as a special type of education but also a basic human competence (Knowles, 1978), where learners are in control of deciding what to learn and how to learn it. Self-directed learning aligns easily with Western notions of libertarian individualism (Brookfield, 2006). Academic libraries can support self-directed learning by providing the resources, tools, and services to support learners to execute their study plans with a high degree of autonomy. Furthermore, rapidly evolving information and communication
technologies (ICTs) have significantly enhanced how knowledge and skills are searched, accessed, and acquired, especially in the digital environment.

Empirical studies of self-directed learning initially became popular among educational researchers in the 1970s and 1980s. According to Tough (1971), 90% of all adults were claimed to conduct at least one self-directed learning project each year, spending an average of 100 hours on this effort. The influence of peer-networks (Brookfield, 2006), human resources (Candy, 2013; Brockett & Hiemstra, 2019), and learning communities (Abdullah & Hayati, 2001) on self-directed learning have been studied over decades. Hawk (2011) concluded that personality type, the learner’s previous experience, the availability of relevant resources, and perceived cultural constraints or enhancers are critical variables that strongly influence self-directed learning.

Recently, self-directed learning has become even more prevalent in libraries with the expansion of library services via knowledge or research commons, the proliferation of social media, and the explosive growth of the use of mobile devices, tablets, and related applications (Raju, 2014). This trend poses more challenges and opportunities for library staff to understand, assist, and support learners in more dimensions.

Work on self-directed learning is facing new challenges in the digital environment. From a methodological perspective, the self-reported nature of research on self-directed learning has attracted many critiques (Brookfield, 2006). Brookfield (2006) suggests that research on self-directed learning requires revitalization through the use of more efficient and accurate technologies to report and synthesize findings.

Furthermore, as necessary as the construct is to self-directed learning, little attention has been directed to the learning process itself (Garrison, 1997). For example, one of the main challenges self-directed learners face today is finding relevant educational resources that are
constructive, appropriate, and engaging. However, the educational information space on the Internet is enormous, and it is leading to an information overload problem that threatens to overwhelm or derail efforts at self-directed learning. The growth of information and knowledge is indeterminable, and learners need special skills or additional support to survive and adapt to it (Saks & Leijen, 2014).

Fortunately, advances in the architecture of digital learning service infrastructure enable the collection of various types of data related to learning behavior. Consequently, understanding the learning process of self-directed learners and supporting them in filtering the overwhelming information becomes possible.

**Recommendation System**

We can frame the operation of the recommendation system from the perspective of self-directed learning. A recommendation system seeks to predict the "rating" or "preference" a self-directed learner will have for a learning resource. Work in data science has led to advances in both the theory and application of recommendation systems. Our primary goal in this section is to delineate the data, algorithms, and evaluations of recommendation systems in a coherent and structured way. Additional details about recommendation systems are beyond the scope of this paper. Ricci, Rokach, and Shapira (2011) provide a more general introduction.

**Data**

Recommendation systems evaluate a potentially overwhelming number of available items based on learner personal experience or competence. In terms of learning resources, an item can be a book, an article, a video, a (digital) course, and many other types of content in a modern library system. Since inappropriate recommendations can be interest-killers and potentially lead
to self-doubt and emotional insecurity, multidimensional data sources are preferred to capture more comprehensive information to support more targeted resources. Some recommendation techniques are more knowledge dependent, and so they require more sophisticated data like social relations, learner activity (learning processes), domain knowledge, and ontological descriptions of learners and items. Furthermore, we need to consider the complexity, utility, and even time-dependence of the item. For instance, selecting an online MOOC typically requires much more complex decision making and higher cost compared with finding an online article.

Generally, there are three types of data:

1. Item data: Item data refers to a range of properties and features of items, such as title, description, author (ROCID), subjects (categories), and identifiers (e.g., DOI, ISBN, and ISSN). However, the metadata of academic library resources (both digital and physical) can be plagued by human-made mistakes, insufficient information, and a failure to apply standards. The availability of data and data consistency across different vendor-managed systems is also challenging.

2. Learner data: learner data makes personalized recommendations possible. It includes socio-demographic information, such as gender, age, and profession. Sometimes, we also use learners’ relationships and interactions in social networks to identify their interests.

3. Transaction data: Transactions are data logs that store essential information generated during the human-computer interactions and are useful for measuring learners’ preferences (Ricci, et al., 2011). Their preferences are either explicitly expressed as ratings of items (through feedback or a simple thumbs-up/down), or implicitly inferred from learner behavior (e.g., reading history, search pattern, or even mouse movements).
The application of recommendation systems currently faces a significant problem posed by the enormous increase in the volume and complexity of available data (Hoang, Long, & Jung, 2015). Consequently, methods such as distance measurement (e.g., Minkowski Distance and Pearson correlation), sampling (e.g., random sampling and stratified sampling), and dimensional reduction (e.g., Principal Component Analysis) might be necessary as part of data preparation. Similar to any other data science project, the recommendation system relies on an appropriate data source, which further requires multiple techniques for collecting, maintaining, and cleaning the data.

**Algorithm**

There are many types of recommendation systems in terms of addressed domains, the knowledge used, the data collected, and the mathematical design. Here we will briefly introduce the most popular and high potential recommendation systems.

1. **Content-based:** Content-based recommendation systems calculate the similarity of items based on the item data (usually metadata features). Based on the current visited resource or profile of learner’s preferences, the system selects similar items as recommendations (Kembellec, Chartron, & Saleh, 2014). The complete process of content-based recommendation systems involves content analysis, profile learning, and component filtering (Lops, de Gemmis, & Semeraro, 2011). Natural language processing and other text mining techniques (e.g., topic modeling) are typically used to extract the essential features of the content.

   Content-based recommendation systems support learner independence (exploit the item information), and can be capable of recommending new items. Nonetheless, content analysis is often limited to certain types of features and cannot successfully handle items with no or poor
metadata (Miller, Beckwith, Fellbaum, Gross, & Miller, 1990). Additionally, content-based recommendation systems have over-specialization issues (Billsus & Pazzani, 2000).

2. Collaborative filtering: Collaborative filtering recommendation systems calculate the similarity in the taste of two learners based on the similarity of learner preferences. The underlying assumption is that learners would like the items that other learners with similar tastes reached in the past.

Collaborative filtering employs the learners’ data, which typically involves more flexible, larger-scale, and real-life databases. Such learner data also tends to provide more serendipitous suggestions, captures more nuances around items, and contains information on the different types of item content (Koren & Bell, 2015). However, collaborative filtering also faces challenges, including data sparsity (Popescul, Pennock, & Lawrence, 2001), data scalability (Sarwar, Karypis, Konstan, & Riedl, 2002), synonyms (the tendency of a number of the same or very similar items to have different names or entries; Su & Khoshgoftaar, 2009), and the long tail (difficulty in handling new items and learners with limited historical data; Celma, 2010).

To capture more features about learners, researchers have used ideas similar to collaborative filtering in many other dimensions. For example, demographic information is leveraged to train a classifier that can map specific learner preferences (Vozalis & Margaritis, 2004). Community-based recommendation systems employ the preferences of learners’ friends with the help of social network analysis (Walter, Battiston, & Schweitzer, 2008).

3. Knowledge-based: Knowledge-based recommendation systems rely on explicit knowledge about the item assortment, learner preferences, and recommendation criteria. Such systems use knowledge about learners and items to generate a recommendation, reasoning about what items meet the learners’ needs. Given the complexity of specific domains (e.g., education),
feedback from the learners through conversations (conversational systems; Felfernig, Friedrich, Jannach, & Zanker, 2011), questions (search-based systems; Bridge, GÖker, McGinty, & Smyth, 2005), or critiques (navigation-based systems; McGinty & Reilly, 2011) are helpful. The additional information provides more timely and accurate constraints that we can use to make recommendations. However, knowledge-based systems typically require learners to specify what they want explicitly.

4. Hybrid recommendation systems: These recommendation systems combine the techniques mentioned above. Hybrid systems usually utilize a wider variety of data and have the flexibility of using different recommendation approaches (Burke, 2002). The challenges are how to mix and weigh different recommendation components.

Generally, there are five types of data mining techniques which underlie these recommendation system designs: neighborhood-based models (e.g., K-Nearest Neighbor classification), latent factor models (e.g., Singular Value Decomposition), decision trees, neural networks, and association rules.

Evaluation

A variety of methods have been used to assess recommendation systems, including offline experiments, learner studies (e.g., questionnaires), and online evaluations. Recommendation systems have a variety of properties that may affect learner experience: accuracy, robustness, scalability, adaptivity, novelty, privacy, and many others. The most important property for most investigators is prediction accuracy.

In practice, analysts use the AB test (split testing) for measuring the impact of incorporating a particular recommendation system. AB testing is an experiment where two or more variants of recommendations are shown to learners at random, and statistical analysis is
applied to determine which variation performs better for a given conversion goal (e.g., increasing the prediction accuracy of rating, increasing the duration, and reducing bounce rate).

**Recommendation System to Support Self-directed Learning**

Despite the great success of recommendation systems in business (e.g., Amazon), social media (e.g., Facebook and Twitter), and entertainment (e.g., Netflix and YouTube), relatively little attention has been paid to recommendation systems in educational contexts.

**Applications**

Educational data mining (EDM) is an emerging area of study that deals with educational data and applies statistical methods to understand students and their learning environments better (Romero & Ventura, 2013). Some studies have applied recommendation systems in conventional education settings. For traditional face-to-face learning environments, Thai-Nghe, Drumond, Krohn-Grimberge, and Schmidt-Thieme (2010) used matrix factorization to generate recommendations and predict student academic performance. Vialardi, Bravo, Shafti, and Ortigosa (2009) used collaborative recommendation systems with students’ educational background information (e.g., department, previous courses, and academic performance) to recommend university curriculums. Al-Badarenah and Alsakran (2016) created an automated recommendation system for course selection with association rules. For digital learning environments, Mei-Hua Hsu and Jui-Hua Chang (2009) used collaborative filtering and content-based models for a personalized English learning recommendation system. Santos and Boticario (2011) created a semantic educational recommendation system with e-Learning scenarios. Dwivedi and Roshni (2017) summarized the application of educational recommendation systems and discussed models using Big Data tools in educational data mining.
Opportunities

The primary goal of introducing recommendation systems in the context of self-directed learning is to help the learners find a suitable resource for learning with less cognitive, time, and monetary cost. Learners today are facing a dilemma of searching through an ever-growing body of information. 90% of the published papers in academic journals are never cited, and half of published papers are never read by anyone beyond authors, journal editors, and referees (Meho, 2007). Meanwhile, many learners still encounter unpleasant and time-consuming searching experiences and often end up with irrelevant or useless resources. Recommendation systems mimic the cognitive process of information seeking, knowledge acquisition, and problem-solving in advance before the learners begin to search, and before they lose interest and become discouraged. Providing more powerful recommendation systems could enhance learner motivation and lead to better learning.

The fundamental problem of self-directed learners is to know about themselves and to know what to learn. Learners need help identifying their learning patterns, exploring the potential learning opportunities, finding encouragement to persist, searching for useful learning resources, and even tracking their learning process. In the face of the contemporary information explosion, these tasks will be overwhelmingly difficult without the support of techniques like recommendation systems.

A sound recommendation system may be thought of like a virtual mentor. It can help to identify students’ interests and to learn patterns directly based on the behavior data in the system. In addition, it can analyze a massive amount of data from learning resources much faster and efficiently than humans can. Meanwhile, it can capture the new data from items and learners, and adapt to the new learning data in real-time. It identifies students with problems and weaknesses
(Hsu, 2008), detects student misconceptions (Berkes & Davidson–Hunt, 2007), and helps students to navigate through knowledge hyperspace, and secure high-quality information (Prieto, Menéndez, Segura, & Vidal, 2008). These interactions are essential for improving the motivation of learners since learners are more likely to experience some distress in the common isolated digital learning environment. (Bonk & Dennen, 2003; Cornell & Martin, 1997; Keller, 1999, Essex & Cagiltay, 2001; Hara & Kling, 2000).

**Challenges**

Applying recommendation systems to support self-directed learning is challenging. Activities in almost all phases of the data science life cycle (acquisition, preparation, modeling, evaluation, deployment, operation, optimization, and interpretation) can present problems. For example, the goal of a recommendation system is typically predicting the items that will be preferred by a learner so that the learner will engage with the material to extend their learning. Clearly defined and measurable targets are the best foundations for creating rules for algorithms. However, learning cannot be measured simply by engagement indicators (e.g., duration time goes up by 30 mins, or visiting time increases by 30%). The usefulness of the resource in terms of personal development, persistence and efficiency of learning, and the improvement of the whole learner community is also important. Thus, the complexity of goals for self-directed learning requires us to design and evaluate recommendation systems along more dimensions.

Recommendation systems require reliable, complete, accurate, and standardized data. Collecting and managing learners’ data can be difficult since learners usually engage in different e-Learning platforms and even use multiple accounts. Given the complexity of different data sources, combining the data and detecting the useful features from the data is a formidable task. In terms of learning items, they are usually in multiple formats (e.g., text, image, and video).
Many items do not have complete or updated metadata. Moreover, specific domain knowledge and specific data (both for items and learners) are usually required. Incorporating professional knowledge and experiences into the recommendation system can present additional hurdles.

A recommendation system that employs Big Data techniques also elicits Big Data’s brand of problems. On the one hand, the techniques for Big Data are still under development. For example, the transactional or feedback data sometimes can be sparse and insufficient to identify the genuine interest of a learner. The learner’s behaviors data can be full of noise (e.g., a click can represent a certain degree of preference or just random behavior). On the other hand, privacy and confidentiality are significant concerns as more and more personalized information is captured. Rubel and Zhang (2015) note, resolving the "trade-off’s between patron privacy and access" to digital resources has proved challenging. To cast light on the mystery of patrons’ learning processes, more personalized information about the learner is needed. Consequently, most web-based e-Learning systems require learners to "log in" and provide personal information. However, seeking access to learners’ data degrades patron privacy, a special concern in the case of library applications.

Finally, building a "perfect" recommendation system is not only impossible but a naive venture. It would be misleading for researchers to focus on capturing "all" the data from learners and items to create a recommendation system as a "final" solution for all self-directed learning issues. Different types of recommendation systems serve different purposes. For example, a content-based recommendation system is usually an excellent choice for a current visiting page because these recommendations are directly related to the current reading materials. Consequently, the recommended additional materials can enhance the persistence of learning on a specific topic. In contrast, collaborative filtering recommendation systems may work better for
a learner’s profile page since such systems summarize historical behaviors and give learners a big picture of their learning interests. A recommendation system for curriculum selection may require more educational background information and a knowledge base for a specific content area, while a recommendation system for a newsletter can be more random and flexible to encourage learners to explore more possibilities.

The acknowledged limitations of even the best current recommendation systems highlight the importance of information searching as an essential skill for all contemporary learners. Information processing requires substantial individual mental processing, including identification of correct terminology and development of an effective search strategy (e.g., reform queries, break down, link, and synthesis of information). A recommendation system is a supplementary tool that cannot and should not replace such learner information searching. Information searching is also an essential part of self-directed learning. After all, recommendation systems should encourage us to develop the skills to become smarter and more diligent learners; they should not displace these essential skills.

Case Study

To illustrate the potential of library developed recommendation systems for locally produced resources in this first instance, we present a case study of a recommendation system application in an online publication produced at the Gottesman Libraries at Teachers College, Columbia University. The editorial mission of the publication, New Learning Times (NLT), is to provide "daily coverage of the transformation of learning opportunities in the information age for those shaping the future of education." As a free web-based e-learning resource focusing on education with over 6,000 articles available, NLT has an impact both within the Teachers College
community and beyond it. From August 2017 to May 2019, there have been approximately 120,000 visits (about 180 visits per day). Meanwhile, massive data on learner behavior is being generated, and reliable metadata about items are available.

Data

The metadata for the items in NLT includes author, keywords (manually created), submission date, review date, publication date, title, sections (which section an article belongs to), and article content. There are eight sections: (1) EdLab Review, a review of a learning application; (2) High Five, the top five most interesting articles of the day from around the web; (3) NL Sector, articles on innovative educational organizations; (4) Profile, an interview with an educational technology leader; (5) Research Digest, a precise of a research article on new learning technologies; (6) Seen in New York, a video story on educational innovations in the New York City area; (7) Vialogues, a video and accompanying discussion on a new development in learning; and (8) VisualizED, a cartoon poking fun at some aspect of the new learning era. Every article in New Learning Times belongs to one and only one of the sections. Thus, the sections are also categories of the article.

The learners’ profile and behavior data include IP address, location, device type, browser, visiting date-time, referrer URLs, URLs and URL type (e.g., read, download, share, out-link, and search). Many web analytics applications (e.g., Google Analytics and Matomo) can capture these log data. Based on the URL links, we can determine the item or section that learners have accessed. The dynamic item and learner data are saved and used by the recommendation system. We only take learner information from those learners who “login” to NLT when visiting. This data allows us to consider the history of behavior across different visits to NLT. Such data is not available for learners who visit without logging into NLT.
Recommendation Framework

For a recommendation framework, we selected Apache PredictionIO. Apache PredictionIO is an open-source Machine Learning Server for building, evaluating, and developing Big Data engines across different platforms (Chan, Stone, Szeto, & Chan, 2013). One of the most significant advantages of using Apache PredictionIO lies in its ability to build and deploy with customized templates (sometimes together) dynamically. There are several helpful Big Data components used in Apache PredictionIO: HBase (an open-source, non-relational, distributed database), Spark (an open-source distributed general-purpose cluster-computing framework), and Elasticsearch (a search engine based on a free and open-source information retrieval software library: Lucene).
Within Apache PredictionIO, we selected the Universal recommendation (UR) engine template. The Universal recommendation template offers a new type of hybrid recommendation based on the Correlated Cross-Occurrence algorithm (CCO) that can use data from a wide variety of learner taste indicators. CCO algorithm can ingest different learner actions (clickstream data), profile data, contextual information (location, device), and some types of content information (Ferrel, 2016). CCO provides a scalable solution to handle different types of data in the same way as collaborative filtering. It can also implement flexible filters and learning rules. For example, we can put more weight on "share" than "download" and "read." The UR recommendation template thus provides the flexibility for both our current case and for the addition of other library resource collections in the future.

To maximize flexibility moving forward, we deployed the UR recommendation template in the context of the DakGalBi Framework proposed by Nam and Jung (2018). The DakGalBi framework is used in this case study since it can deal with multi-domain databases.

**Proof of Concept**

As a proof of concept of our overall approach, we conducted a small experiment with the recommendation system applied to NLT content and readers. This allowed us to test the approach, including its speed and acceptability to library patrons, as well as to assess the quality of the recommendations for learners. Because we intended to move directly from the experimental stage to implementation into library service, it was important to understand both the usability and the impact of the recommendation system.

**Sample**

We identified a purposive sample of 22 library patrons willing to try out the new recommendation system. Among these patrons, 12 were termed “loyal learners” who visited
NLT twice a week on average with login, 8 “ordinary learners” who visited NLT more than once a month, and 2 “inactive/new” learners who visited NLT less than once a month.

Method

To examine the impact on learning of the NLT recommendation system we compared recommendations generated by Apache PredictionIO’s Universal recommendation engine with recommendations generated at random from the latest NLT articles, using the same pool of approximately 6,100 content items for each participant. For the comparison, we selected the top 5 recommendations for each participant generated by the Universal recommendation engine (personalized recommendations) and recommendations based on a random pick from the latest articles. The source of the recommendations was not known to the participants.

During the test session, participants had 20 mins (2 mins per article) to explore all the recommendations independently. Participants were asked to rate each item as either “a good recommendation” or “not a good recommendation.” Because we wanted each patron to apply their criteria of judgement, we supplied no additional rating guidance. Our only direction was that patrons use the same criteria to judge each item. This direction prompted patrons to make each recommendation decision independently and not relative to decisions about other items.

Results

Our examination of the results proceeded in four stages. First, we observed the implementation of the recommendation system as library patrons used it. We were interested in knowing if the system operated quickly and smoothly enough to be used by regular library patrons who were accustomed to commercially produced library search engines as well as internet search engines. Second, we were interested in knowing how library patrons would rate results produced by our locally developed recommendation system based on the Universal
recommendation template. Third, we examined the actual recommendation results returned to patrons as a check on the patron ratings. Fourth, we examined patron decision making patterns as a follow-up to their ratings of the recommended resources.

Our first task was to determine if the recommendation system operated quickly and smoothly enough to be used by regular library patrons. Although for our proof of concept, we enlisted patron volunteers who were willing to try the new system, we wanted to be sure that the experience was consistent with their experiences accessing other library resources. Accordingly, we observed each of the 22 patron volunteers throughout the trial. The observations were made unobtrusively by library team members working nearby the trials.

In each case, the patrons were able to move quickly from the initial introduction of the new recommendation system to begin accessing content for their learning. Patrons moved easily from one item to the next, and rated the accompanying recommendations. The overall patron experience, aside from the need to rate recommendations, was indistinguishable from other library services, as we had intended.

We next examined the ratings applied to the recommended resources by the patrons using their criteria related to their learning. We began by conducting a chi-square test to determine if the source of the recommendation (Universal recommendation template vs. random picks), made a difference in the patron resource rating. We tested the hypothesis that the rated quality of the recommendation is independent of the source of the recommendation. Based on the test data, the chi-square statistic is 9.249, with a p-value of 0.02. Thus, we can conclude that the source of the recommendation does make a difference in the patron resource rating.

We next used logistic regression to measure the effect of the recommendation source quantitatively. In the model, \( y = 1 \) if participants think it is a good recommendation, otherwise 0.
Similarly, $x = 1$ if the recommendation is from UR, otherwise 0. The estimated coefficient for the source of the recommendation was 0.52. In other words, based on data from the 22 patrons in the trial, we expect a 0.52 increase in the log-odds of getting a "good recommendation" from the Universal recommendation compared to a random pick on average.

To unpack the ratings a bit more, we examined the ratings by source for the three types of patrons in the trial: loyal learners, ordinary learners, and inactive/new learners. We anticipated that the loyal learners might benefit the most from the historical visiting data, which provides information about their learning interests. We anticipated that the ordinary learners would benefit less because the system had less information on their interests as a basis for recommendations. We included the two inactive/new learners in this analysis for completeness. However, these patrons generally received the most popular items as their recommendations since the UR engine had insufficient data to make data-based recommendations.

For the loyal learners, the odds ratio of designating an item as a "good recommendation" between the Universal recommendation and random picks is 1.51 (82% of the recommendations from the Universal recommendation and 54% from random picks were deemed a "good recommendation"). For ordinary learners, the odds ratio is 1.183 (71% from the Universal recommendation, and 60% from random picks are designated as a "good recommendation"). For the inactive learners, the odds ratio is 1.75 (70% from the Universal recommendation, and 40% from random picks are classified as a "good recommendation"). As we anticipated, the loyal learners benefit most from the historical visiting data, which provides information about their interests.

The results for our analysis of the ratings of recommended resources show that the Universal recommendation template can allow the library to provide better support for self-
directed learners. Even with our modest sample of patrons, the results showed that the Universal recommendation template was more likely to generate recommendations deemed suitable.

Take one loyal user, J, as an example. This user has 191 article reading records (visit duration longer than two seconds), 186 section page visit records, 45 search records, and 1,051 other records related to location, device type, and browser. Author S writes 37.69% of the articles that J read. Three out of five articles provided by the Universal recommendation engine are also written by author S. Among all sections, “Vialogues” (19.89% traffic) and “EdLab Review” (15.64% traffic) are J’s favorite sections. Based on what we recommended, two articles are from “Vialogues,” and two articles are from “EdLab Review.” We selected the top five articles that J visited most often; all of these articles are about the application of modern technologies (e.g., mobile app, video game, and interactive environment design) in traditional teaching and learning practices. For example, J’s favorite article (written by S) is a product review of how a video game (“Variant: Limits”) is developed for teaching Calculus. Similar patterns can also be found in the recommendations. The first recommendation (written by S) is a product review of how a gaming-style learning platform (“EI Games”) can be used for training the emotional intelligence skills to become a successful businessperson. Another recommendation is about the comparison of three different feedback methods (pen and paper, oral survey, and digital response) in terms of the empowerment of students’ voices. Two articles are talking about how to redesign the classroom (through data-driven technique or arts and music). Moreover, the last recommendation is about introducing a community-built online class platform for all kinds of maker activities, including workshops, technology, and food creations. As we review these results, we find that the same keywords (e.g., online, digital, classroom, community, technology, game, and video) appear in both J’s favorite articles and our
recommendations. In J’s search records, we also find keywords under the same topic: video, game, discovery, self-direct, boot camp, school, and open lab. The recommendations support J in building on prior interests and knowledge and extend the learning path.

Finally, in the course of this case study, we interviewed the participants after their use of the recommendation system and collected information on how participants make their judgments. Digital self-directed learning is personalized, and the learning patterns are somewhat unique. However, we can generally categorize the learners, based on their interview feedback, into two types: specialists and generalists. Specialists were insistent on pursuing their established reading habits and personal preferences (e.g., topic, author, a section of the article, whether there is a video or external hyperlink in the article or even the length of the article). If the recommendation comes from an author or deals with a topic that they are not familiar with, they typically conclude that the recommendation is not good. The specialists focused on one specific learning area and wanted the recommendation system to provide a more in-depth and more relevant recommendation. In other words, they were more willing to take the recommendation as a tool to identify potential learning resources.

In contrast, generalists were more open to new learning opportunities as long as these learning opportunities triggered their learning interests. This pattern observed in the test case interview data suggests that personality and learning habits can also lead to differences in how learners receive and rate recommendation systems.

Discussion

With the advance of web-based e-Learning resources, the collection of various types of data to support self-directed learning behaviors is now more feasible. This growing availability
of data has the potential to reshape the future of the academic library with the addition of more sophisticated recommendation systems. As Artificial Intelligence is amplifying almost every aspect of human intelligence, learners in this generation need unprecedented support from techniques like recommendation systems for more efficient, sustained, and beneficial learning experiences. However, the complex processes of self-directed learning pose challenges to the appropriate application of recommendation systems. Furthermore, many recommendation systems currently in use have not begun to take the uniqueness of the educational context into account.

Encouraged by our experience with the Universal recommendation template discussed here, we are exploring additional avenues for further research to improve the current recommendation system in the *New Learning Times* and other library resources, both locally developed and vendor produced. We gathered valuable lessons along the way. For example, with about 70% of *New Learning Times* readers failing to "log in" to read, we are forced to ignore the data they are generating for specific analyses since we do not have individually identified data from these learners. However, the general user behavioral data still provides a "big picture" of the most common features of these learners.

In addition, because the *New learning Times* is designed to be part of a suite of learning applications offered by the Gottesman libraries, we can incorporate data on learner behavior across the set of learning applications to improve the recommendation system models. This is possible because the Universal recommendation template can ingest data from different types of sources. In the Gottesman libraries, other learning applications sharing the same learner account id system include Vialogues, an open and dynamic time-stamped video discussion platform; Rhizr, an open non-hierarchical content curation system; and PocketKnowledge, an open online
archive system. When patrons login, personalized data from these systems can be combined to provide recommendations more tailored to their learning needs.

Beyond institutionally specific systems, recommendation systems are also useful in generally available library applications. Publishers International Linking Association (PILA) and similar organizations, provide varied business models (both open access and subscription-based) to solve the problem of information mismatching, deficiency, and inaccuracy. Services, including open URL, DOI, and Crossref citations, provide efficient methodologies for checking, collecting, and updating item data. Meanwhile, behavioral data are available in library services platforms, or online library web proxy servers (e.g., EZProxy). Combining information on such resources with data on patron learning needs will allow libraries to enhance their support of self-directed learning.

Future studies might include drawing on learner behavior data and content access and creation patterns to augment the models supporting the recommendation systems used across library applications. Recommending learning resources across different applications in different formats (e.g., text, videos, images, and even codes) will provide learners with a broader set of options from which to draw and a set of recommendations that are more targeted to their learning goals. Such recommendations will ultimately contribute to building a more positive and interactive relationship between the library and learners.

Improved recommendation systems are not the entire solution for the challenges confronting those interested in improving opportunities for self-directed learning. However, better recommendation systems can play an essential role in supporting greater engagement and efficiency in the learning process. We hope that the present article will encourage researchers,
engineers, and librarians to study and apply recommendation systems in education. The result will be a more in-depth and more informative analysis of learning behaviors.
References


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