The Use of Recommendation in Learning Analytics

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Abstract

In recent years, the massification of tertiary education has dramatically changed the teaching-learning landscape. A key aspect of the change has been the use of technologies to disrupt traditional teaching paradigms and pedagogies. Technologies now play different teaching-learning roles, one of them being the personalisation of the individual's learning experience to compensate against the high teacher to student ratio. In this paper, we investigate the use of recommendation technologies (within an e-Learning environment) as a candidate solution to 'individualising' the learning experience. We will first review the various recommendation technologies, and then a discussion of how the technology could be applied is presented.

1. Introduction

As the world continues to undertake more activities online, the amount of data generated is skyrocketing. For many commercial entities, the data generated has been used to drive improvements in revenue, services, product offerings, and so on. For example, it is now well-known that commercial entities use consumer data to identify what they may like, and then use the insight to promote new products. The data can be used to recommend new social networks, suggest videos of interest and also detect if an email is a spam. Collectively, this set of technology is called data mining or data analytics – a technique where computer algorithms are developed to identify patterns, rules, or other forms of insights from the massive amount of data collected.

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In the arena of education, institutions have long embraced some form online presence represented primarily by learning management systems (LMS) such as Moodle, WebCT, Desire2Learn, and Knewton, to name a few. Interestingly, these environments have only served as a host for content and provided student management facilities for instructors and administrators. While these environments actually generate massive volume data from the student activities, there has been very little interest in finding ways to make use of the insights it might present.

However, the recent massification of online learning is renewing interest to transform "learning management systems" into "online learning environments" [1, 2]. With instructors teaching a large class from thousands to several thousands of students in massive online courses, the instructors can no longer provide the same teaching-learning experience of a small physical classroom. With more students in a single classroom, the variation of individual's learning capability, understanding and grasp of the subject will require different approaches, pace and material from the instructor. Clearly without the assistance of technology, the lone instructor will find delivering such individualised experience to many thousands of students is difficult and, impossible.

In fact, the factors that are driving disruption in learning are rapidly consolidating. We now have access to student data and activity logs. The multiple modes of interaction are available between the instructor and the students. The most important of all, we need a more productive way to deliver a learning experience is to individualise the student's learning needs. These factors would motivate researchers taking a page out of commercial entities that have long used the technology to deliver the personalised experience. The same in education [3], we foresee that personalisation will become a common place in learning; especially in an online learning environment where the class size is large and accessing to the lone instructor is limited (or reduced).

In this paper, we investigate the use of recommendation technologies (within an e-Learning environment) as a candidate solution to 'individualising' the learning experience. We will first review the various recommendation technologies in Section 2, and then a discussion of how the technology could be applied is presented in Section 3. Finally, we present a survey of various online learning environments that use recommendation technologies in Section 4 before we conclude in Section 5.

2. Recommendation Technologies

Before we begin our discussion of different recommendation technologies, it is first important to understand what the technology achieves.

The goal of recommendation technologies is to automatically present users with relevant options that are of interest to them or to the activity that they are carrying out. The most well known examples are Amazon and Netflix, where products are suggested to customers. These suggestions are however different between individuals. That is, they are personalised according to data about their customers such as their profile and purchase histories. This 'individualised' suggestions, when provided at the right moment, tend to deliver a number of positive outcomes including

1). an increased in sales and consequently profit;
2). the ability to cross-sell items leading to better inventory turnover;
3). increased user satisfaction and loyalty (fidelity) as a result of the 'concierge' experience; and
4). a better understanding of their consumers that inform future business decisions.

2.1 Content-based Recommenders

Content-based recommenders [4, 8] are the most straightforward recommendation technology. The idea is to suggest products that are similar to the ones that the user has purchased or positively rated. There are two major approaches in this category: (i) case-based reasoning and (ii) attribute-based techniques.

In case-based reasoning [5, 6], the technology learns about the past histories (cases) of the user and recommends are new but similar products. This approach is robust across different domains and the accuracy of recommendation tends to improve over time for "repeat customers". However, the technology is incapable of recommending products to new users; hence, it faces the cold-start problem. Also it faces problems of making a recommendation. Therefore, the recommendation tends to be 'over-specialised' over time since similar products are repeatedly recommended.

On the other hand, attribute-based techniques make recommendations [7] by looking at what other similar users (i.e., users with similar attributes to the user getting the recommendation) would buy and then recommends those that the current user hasn't yet purchased. Therefore, this approach is more "outward looking" as it looks at what others are doing rather than just the user's own activities. As a result, it doesn't face the cold-start problem in the presence of a new customer. This technique can also become 'over-specialised' if the other users buy within a limited range of goods. Nevertheless, when we compare this approach to case-based reasoning, there is opportunity for greater diversity of recommendations since items recommended are drawn from the purchases of other users instead.

2.2 Collaborative Filtering

The simplest of collaborative filtering is to recommend items that other similar users have liked in the past. In some sense, this is an extension of attribute-based techniques, where (i) items are selected based on what the users have rated well and (ii) similar users are identified as those who share similar 'likes' or 'taste'. The first extension [9, 14, 15, 16] ensures a recommendation is sounded as it only recommends items that are positively rated by other users. The second extension broadens the user-base by assuming that people with different attributes can have similar 'likes'/'tastes'. Consequently, the items drawn for recommendation become potentially more diverse. The downside of this user-based collaborative filtering is that it is often computationally expensive [9, 12, 13], i.e., the algorithm has to find neighbours among a large user population of potential neighbours.

The user-based collaborative filtering focus on first finding like-minded users, and then suggest top rated items among them. This alternative is to focus on the items first where they are similar if (i) they share the same kind of ratings and (ii) they appear highly correlated. This item-based approach [9, 11, 17] focuses on evaluating the similarity of the items first rather than the users. And because the relationships between items are often relatively static, a great deal of online computation is avoided. Consequently, the one-off compute allows the search space of each recommendation to be dramatically reduced. This leads to an improvement in runtime performance. Many studies show that an item-based approach also produces higher-quality recommendations [9].

The last approach, demographics collaborative filtering, involves finding users who have similar attributes and recommending items that are preferred among them. Compared to the two collaborative filtering techniques [10] this approach tend not to have the cold start problem. The recommendation can get rather limited as only popular items are considered. If the range of popular items for a particular group is small, the technology may appear to fail.

2.3 Constraint-based Recommenders

While content-based recommenders (Section 2.1) and collaborative filtering (Section 2.2) are ideal for recommending products such as books, movies, or new items, these techniques do not perform well in recommending infrequently purchased items such as a car, a house or an appliance. For example, the same house cannot be easily rated by a large number of users and so the techniques discussed so far will not perform well as most of them determined recommendations on the basis of some similarity metrics. In contrast, constraint-based recommenders exploit predefined recommender knowledge is based on explicit rules about how to relate customer requirements with product features.

A constraint-based recommender [18, 19, 20] derives its knowledge base from two sets of properties and three sets of constraints. The properties are common against the other recommenders, i.e., customer and product properties. The constraints including restrictions to recommendation is based on a customer's properties, which filter conditions represent the customer's given requirements and the available products fulfil the properties and constraints. An example of a restriction may be a first home buyer will have a highly limited budget and a small deposit. Therefore it is incompatible with homes in established markets. An example of a filter condition may be said customer "does not want double storey homes". Therefore the fulfillment will have to be the homes,which are affordable and can be financed on a small deposit and single story".

Of course a situation that can easily arise is when fulfillment cannot be met against the filter conditions and restrictions, or that there are just too many possible candidates in the fulfillment. In the former, we can continue to recommend by relaxing [20, 21, 22] the filter conditions, restrictions, or both. Another method is to suggest alternatives as recommendations. In the latter, there are too many fulfillment candidates, the opposite can occur by tightening either the filter conditions or restrictions.

2.4 Context-Aware Recommenders

Compared to other recommenders, context-aware recommendation [23, 25] is a relatively new technique. This method can be thought of as a hybrid recommender, which one of the above techniques is used but with the added constraints of taking context into account. The context is then specified as a filter condition to the candidate list of recommendations. The most common and well-understood examples of context are location and time.

For example, a context-aware recommender on a travel site may first identify holidays that match the traveler's profile. It may impose a filter condition based on the time context if currently it is the winter season in summer packages, it is then excluded from recommendation. This recommendation paradigm is called contextual post-filtering. Another example could be that when a smartphone user is within a vicinity of a shop that sells products of interest, the location context is used to make a recommendation, i.e., location-based services [24]. For example, the recommendation paradigm is called *contextual pre-filtering*.

There are many other recommenders that we have not investigated in this paper. Many of them are hybrids in the above, mentioned or that they are variations in the underlying algorithm or metric. Nevertheless, the purpose of this paper's theme and the discussion in this section provide the recommender technology that we can apply to an e-Learning environment, which is discuss in next. The curious reader can refer to [26] a detailed discussion of recommender systems and its recent state of the art.

3. Applications within an e-Learning Environment

Until recently, many of the previous works are related to e-Learning and recommendation technologies have focused on proof of concept systems. For example, in [30, 31, 32] a recommendation system centred on recommending similar learning material within an e-Learning environment was proposed. The focus the underlying technology to identify documents with similar topics, and suggested the ones that hasn't been seen by the learner.

In [27], Budalakotiet. al. developed a model to capture expertise in recommendations to answers for questions posted within an online forum. And in [28, 29], Shishehchiet. al. has explored rule-based and ontology based techniques as methods of making recommendations for learners online. In essence, the focus of research earlier has been underlying the technology and exploring the possibilities of applying the technologies for e-Learning.

In this paper, we believe the term 'learning analytics' signifies a number of changes that is forthcoming for online learning, digital education, or e-Learning. First, the term suggests the maturing state of the technologies can now be used to improve learning outcomes. Second, as online learning reaches critical mass and acceptance, the paradigm has to shift towards dependence on technology providing the individualised learning experience. Of course, learning analytics became the suite of technologies to fill this need. Rather than explore the various technologies with coming under the 'learning analytics' umbrella, our discussion here be focuses on what recommendation technologies can achieved, i.e., the applications.

3.1 The e-Learning Model

Before discussing the applications, the technology can bring about to e-Learning. We first establish the components of a typical online learning environment that many of us are familiar with. In many established learning institutions, the provision of online learning is largely achieved through a learning management system (LMS) such as Desire2Learn, WebCT, or Moodle. These LMS presents a learning portal to learners, where each course (or a unit/subject) is made up of

1).the primary course material (e.g., PowerPoint slides, PDF reading material, worksheets, tutorials and links to external resources)
2).secondary course material (e.g., lecture recordings and alternative formats of the primary course material already available)
3).interactive tools to support the learners (e.g., online discussion forums, social networks for peer to peer support, and online Webinars or live chat sessions)

In a setting such as the above, the learner can usually access the primary course material for self-learning. However, there is an augment that secondary course material reflects or reinforces learning from the primary material. Where questions arise, the learner may then take to the interactive tools for support. The support to a learner is received is success in two ways: first from peer-to-peer support and second from the instructor. In a peer-to-peer setting, other learners may discuss or provide answers to a learner's question on discussion forums or a private social network. From the instructor, the support is delivered via the online forum, online Webinars, or live chat sessions.

Clearly, the use of recommendation technologies fit into the unmentioned category of 'self-learning'. Consequently, the load on the instructor is lighten with less questions and the effectiveness of peer-to-peer support will be improved which more answers are put up to discussion. In the next two sections, we present how recommendation technologies can be weaved into such an e-Learning model.

3.2 Recommendation Technologies for Learning

We explicate the differences between learning and upskilling, where the former is about gaining a new skill and the latteris about developing, extending or refreshing the acquired skill to stay relevant into the future. For the learning component, we identified six areas where recommendation technologies can have an impact on 'self-learning'. We discuss each of them as below:

3.2.1. Social Networking

The concept of using social networks within an e-Learning environment is an interesting one. Since social networks are the basis of peer-support, this can be an avenue where students can share their learning problems, discuss a given topic, or even share learning material that they discover. While in similar setting as FaceBook, the social network will have to be private, secure and integrated with other student systems. Yammer, for example, could be a candidate to create such a social-network like learning environment.

Recommendation technologies can be useful here by connecting students to their seniors. For example, a first year psychology student could connect to a second year student who has done the same subject, or is currently studying advanced psychology. In this the students are cast as customers in a recommender scenario with subjects as items. The goal of recommendation is then cast as finding similar user profiles, matching relevant units, and then providing a suggestion that the two individuals connect to form a peer supported study group.

3.2.2. Discussion Forums

Evidences from [27, 33, 34] suggest that discussion forums can motivate learners to use online learning environments in two ways. First every time a new question is posted, the question will motivate learner to reflect on his or her own knowledge. If the learner responds with an answer, the response will be engaged with other learners. Second, the interactions that result will become a thread that in itselfcould become a "lesson snippet" on a given topic. In other words, a properly managed forum could become a rich resource for a course, where a new learner with a question could find answers on the discussion forum. However, as anarguement in [34], the normal search to finds answers to a question on a discussion forum is often difficult. This is the areathat recommendation technology can assist.

As a user enters a question, recommendation technologies such as QSIA [41, 42], collaborative filtering, or case-based reasoning could be used to automatically suggest the discussion thread that a student should read. So instead of having to filter through unrelated threads that appear because of a keyword being mentioned, recommendation technology will enable a learner to be more willing to engage in online. More importantly, the discussion forum will act as an alternative to a direct discussion with the instructor. For "shy" learners who prefer a less confrontational approach, a proactive discussion forum might be preferred.

3.2.3. Video Learning

Video learning has experienced rapid growth in recent years as user-generated content and sharing services such as YouTube and Vimeo became popular. As a matter of fact, the sharing phenomenon has resulted in the creation of online education sites such as Khan Academy, Kaplan and Agile Mind. Of course, these sites have also gone on to become interactive learning environment as a result, are increasing parts of an open learning resource for e-Learning environments to tap into.

Videos contain motion, sound, text, images, objects, and speech. This multi-sensory learning approach has been touted to be better than pure text-based learning [35]. However, as noted in [36], the large volume of videos now are available to become a case of information overload. While videos may teach a particular topic, but not all would be suitable or that they cover the topic as a depth and breadth that is appropriate for the learner. Again, this is where recommendation technologies can play a significant role. A possible solution that we envisioned is to utilise the ratings of learners on the open learning resources and to build a learning profile based on user comments. The word terms in user comments are used as the basis for building a profile that is attached to a learning video. A learner interested in finding a video on a given topic would then specify the video as a constraint-based search such that the search will attempt to recommend videos according to the video attributes deduced from the word terms. The idea is to improve recall and precision [37] so that learners are not disengaged as a result of a series of inappropriate learning resource.

The video learning is important and will not be completely replaced text-based material especially when a rigor theory is properly formulated. There also remains a massive volume of text-based material archived in the digital libraries and on e-Learning environment. Many of the research systems are reviewed and discussed how the technology is used. Thus, the discussion of text-based learning is deferred to Section 4.

3.2.4. Audio Learning

Although the merits of video learning have been discussed, it is not said that audio-based learning does not have merits of its own. In particular, audio versions of lecture have been found and popular with learners whilethey are walking, jogging or driving. A good audio could influence on the subconscious state of the learner [38] to reinforce concepts or introduce new ideas while he or she is doing something else.

Here context-aware recommendations, in particular, location-based services, could be an ideal candidate for audiolearning. When a student is driving to home, the smartphone detects its movement along traffic; and an App automatically logs-on to their online e-Learning environment figure out a list of audios that relates to the student's progress; meanwhile asked if he or she wants a particular audio played. As more cars are provided better integration with smartphones, we envisioned that context-aware recommendation will become a significant technology going forward.

3.3 Recommendation Technologies for Upskilling

Many literature we came across does not differentiate learning into (i) learning a new skill and (ii) upgrading the skills once it's acquired. In this paper, we consider our discussion so far as solution to learning a new skill. In this section, we turn to discuss how recommendation technology may potentially assists a learner with upgraded skill, i.e., extending a given skill base by learning about new developments and identifying new opportunities.

Employers today expect more from their employees. Just having skills for the job is often insufficient for promotion. Therefore, it is important that any e-Learning environment provides additional value to learners besides imparting the hard skills. An aspect of constant upgrading is personal development. This can include topics such as time management, communications skills, managerial/leadership skills, etc. From time to time, one may need to acquire those skills or attend a refresher course to continue to be better at what they do. Many of these personal development courses are short and can be delivered via an e-Learning environment. For example, learning about a new Email tool or understanding occupational health and safety issues for a certain industry domain.

Here collaborative filtering recommenders and sequencing rules (or Markov chain) recommenders could be applied to identify prospective employees who might require upgradeskill. These employees would then sign up to become learners within the organisation's internal e-Learning environment, or with an external e-Learning institution.

In addition to personal development, a learner could be through ad-hoc opportunities. For example, a software developer can be upgradeskill by building an extensive portfolio of their works. This can be achieved in many ways, one of which is to engage in freelance projects. Currently, freelance sites carry projects but depend on interested parties to bid for them. A hybrid recommender made up of a user-based recommender and a constraint-based recommender could be used to identify projects of interest. Those matches can then be used to inform the individual to engage in the project andalso expand his or her portfolio.

Lastly, an e-Learning environment can continue to recommend relevant industry videos, news and other material (e.g., an important journal article) to graduated learners by sending the recommendation to their registered email accounts. For example, TED presentations where ideas, vision and inspiration talks are delivered are worthy videos that may be of interest to an alumnus. Such post-graduate learning resources are deserving material that a recommendation system could continue recommending after a learner has completed the required course.

Of course, the vision presented above will require consideration of many factors and will involve many stakeholders. Nevertheless, the key focus here is to envision how recommendation technology could be applied in an e-Learning environment. If the other factors do align, then the potential of what can be done as presented the above mentioned will deliver a different level of learning on the Internet. If massive online courses do indeed take off, existing institutions will have to differentiate either through high level of personalised learning, or they will have to the disruption ending up offering personalised learning of some form. Either way, we foresee that recommendation technologies will play a significant role in e-Learning environments.

4. Related Works

The use of recommendation technologies in an online learning environment is not new but most to date are largely experimental systems to confirm the benefits the technology provided.

The Altered Vista [30, 39] and RACOFI [32, 40] systems are two research prototypes that use collaborative filtering for recommending learning resources. In the Altered Vista, the ratings of learning resources by learners are collected and presented to other learners (with a similar learning profile) to help them evaluate the appropriateness of a learning resource. The RACOFI system went a step further by combining collaborative filtering with association rules. While collaborative filtering provided the insights about the learning resources, the rules inferred guides the system on what to recommend. Hence, the RACOFI is more proactive in suggesting what learning resource a learner should consider when the Altered Vista leaves the choice to the learner entirely. However, unlike the Altered Vista which has been evaluated [39] by users, the pedagogical value of RACOFI has not been reported.

The QSIA (Questions Sharing & Interactive Assignments) [41, 42] is a system that is used in the context of online communities. The system aims to harness peer-to-peer learning by promoting collaboration among a social groups to recommend learning resources to members in the group. Rather than automated systems like the ones above, QSIA uses a user-controlled recommendation process by allowing a user to make a recommendation, or let a collaborative filter complete the task.

Another approach to recommendation is suggested by [43], which recommendations are governed by a set of sequencing rules. Each sequence rule guides the learner through a series of concepts drawn from an ontology of topics. A sequence rule is fired when gap(s) in the competencies of a learner is identified.The appropriate learning resource to fill the gap is then suggested to the learner. A system similar to this was introduced by Huang et. al. [44]. Instead of being rule-based, Huang's system uses a Markov chain model to determine which of the possible path (in the Markov chain) to move through when a learning gap is identified. These approaches therefore work well when the topic has a clearly defined set of scaffolding.

For ad-hoc and expansive learning situations, the CoFind [45, 46] system may be more appropriate. Rather than limiting the learner to controlled resources, [45, 46]'s approach uses resources that are freely available on the Web. And rather than basing a recommendation through approaches like col-laborative filtering or preferences from similar users, the recommendation was done via tags associ-ated with resources that are publicly online. Other similar systems are used public resources including [47] and [48].

Besides the recommendation of learning resources, the technology was reportedly applied to recommending courses for students.TheCourseRank [49, 50] is one such example, and RPL [51] is an-other. Other research's works focused on the technology, where case-based reasoning, was evaluated in [52] and context-aware recommendation techniques was used in [53, 54] and [55].

5. Conclusions

This paper is penned at a time where educational data mining is emerging as a research base. Educational data mining refers to the development of methods by applying techniques in statistics, machine learning, data mining, toanalyze student-related data. The discussion undertaken in the related works, for example, can be classed as research work in educational data mining. As noted, most of these systems are either prototypes or have yet moved into production use.

However, we believe this may change as interest in learning analytics held. Learning analytics is the application of educational data mining tools while considering the pathology and psychology of learning in an online environment. Learning analytics thus has a direct bear at the educational practice. The discussion of application examples in Section 3 presents the ideas that learning analytics may have a potential impact upon. Each of the application will require further investigation, implementation and evaluation in order to assess its long term impact. Nevertheless, we can expect that some of them will form roots to drive the future of online learning.

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