On the Pedagogically Guided Paper Recommendation for an Evolving Web-Based Learning System

Tiffany Y. Tang[1,2] and Gordon I. McCalla[2]

[1]Dept. of Computing
The Hong Kong Polytechnic University, Hong Kong
[2]Dept. of Computer Science
University of Saskatchewan, Saskatoon, SK S7N5A9, CANADA
cstiffany@comp.polyu.edu.hk, mccalla@cs.usask.ca

Abstract

In this paper we discuss the mechanism of a recommender system recommending papers for an evolving web-based learning system. Our system is unique in three aspects. The first is that our learning environment can evolve based on the system's observance of learners and their behaviors. Therefore, the fittest papers will survive the natural selections by learners: papers liked by learners will survive. The second is that we introduce a pedagogically layered similarity between items that have been read by learners and candidate items for recommendation, which is different and desirable, since we argue that papers that match a learner's interest might not be pedagogically suitable for him/her. The third significance is that we propose to annotate each paper with temporal sequences of learners' learning behaviors. By doing it, we can maintain the objectivity as well as integrity of the papers. In addition the accumulated sequences of learners can play a key role for a deeper understanding of their knowledge levels/states, which, in turn, provide 'just-in-time' recommendations to support and encourage e-learning.

Introduction

Recommender systems have been explored mostly in applications other than e-learning. Generally, the recommendation techniques are based on the following information:

- observations of like-minded consumers (Resnick et al. 1994; Shardanand and Maes 1995),
- analysis of the past purchasing or browsing behaviors of a consumer (Fu et al. 2000), and
- analysis of the contents of the items a consumer has found interesting (Billsus and Pazzani 1999).

In e-commerce, it is imperative to provide personalized experiences for consumers involved, which has proved to be effective for cross-selling, up-selling, and mass marketing (Schafer et al. 2001). In e-learning, however, we want to recommend items such as papers, and other items where learners' (consumers') pedagogical characteristics should be considered. To maximize the utility of learning, the recommending mechanism should consider not only learners' *interest* towards the items like most other recommender systems do, but also their *knowledge of domain concepts*, for instance, not to recommend highly technical papers to a first-year-undergraduate student or popular-magazine articles to a senior-graduate student. In addition, items contained in recommendation list might not be entirely interesting to learners. Therefore, making recommendations in a pedagogically ordered list is very important, which is quite different from recommendation in e-commerce, where site managers prefer to leave the list unordered to avoid leaving the impression that a specific recommendation is the best choice (Schafer et al. 2001).

To address these issues, in this paper we will discuss our work on recommending papers for learners engaged in an evolving web-based learning system. Several contributions of our on-going work include: a). propose a new evolvable web-based learning environment; b). identify the uniqueness of making recommendations for e-learning system; c). propose a way of annotating a paper using the time-stamped sequences of learners' learning behaviors.

The rest of the paper is organized as follows. In the next section, we will present some related work. We will then discuss in detail a survey we conducted as part of our study, which raises some interesting issues for the design of our system. After that, we will propose the formal problem statement for our system and present some formal definitions of pedagogical similarity. We then explore the notion of annotating papers with temporal sequences of learners. We conclude this paper by pointing to some interesting issues we will explore in our future work.

Related Work

Due to the characteristics of the system, related works are grouped into two main categories:

Curriculum Sequencing and Adaptive Hypermdia

ELM-ART (Weber and Brusilovsky 2001) is an adaptive on-line textbook for LISP programming, which supports several key features such as adaptive navigation, curriculum sequencing, and personalized diagnosis of student solutions for learners with different prior knowledge. In order to assess individual learners' skills and progress, a series of tests and exercises are used to trace learner knowledge during the learning process. (Stern and Woolf 1998) is another similar study. In contrast to the model tracing approach in ELM-ART, (Tang and Chan 2002) use both active assessment (tests, exercises, and questionnaire) and passive assessment (learners' browsing behavior) to construct the learner model. In addition, as far as we know, the majority of current web-based learning systems are *adaptive* e-learning system where the delivery of learning item is personalized while the items inside the system are a *priori* determined by the system designer/tutor. In our open evolving e-learning system, learning items are automatically found on the web and integrated into the system based on users' interactions with the system. Therefore, the fittest papers survive. Figure 1 compares the differences with respect to these two types of e-learning systems.

Recommending Technical Papers

There are several related works concerning tracking and recommending technical papers. Basu et al. (2001) define the paper recommendation problem as: "*Given a representation of my interests, find me relevant papers.*" They studied this issue in the context of assigning conference paper submissions to reviewing committee members. Bollacker *et al*. (1999) refine CiteSeer, NEC's digital library for scientific literature, through an automatic personalized paper tracking module which retrieves each user's interests from well-maintained heterogeneous user profiles. (Woodruff et al. 2000) discuss an enhanced digital book with a spreading-activation-geared mechanism to make customized recommendations for readers with different types of background and knowledge. (McNee et al.2002) investigate the adoption of collaborative filtering techniques to recommend papers for researchers; the paper did not address the issue of how to recommend a research paper, however, but rather how to recommend *additional* references for a target research paper. In the context of an e-learning system, we believe that additional readings cannot be recommended purely through an analysis of the citation matrix of a target paper. Indeed in some cases pedagogically valuable papers might not be interesting and papers with significant influence on the research community might not be pedagogically suitable for learners. Therefore, we cannot simply present all highly relevant papers to learners; instead, in order to prevent them from being frustrated, a recommending mechanism is adopted to stimulate their motivation to read through those papers.

In this paper, we will not consider the issue of finding related papers using various citation techniques described in []; instead, we assume that a well-selected collection of papers is maintained by the system. In order to keep up with the most up-to-date research on the subject, the system carries a paper-updating mechanism powered by an imbedded web crawler, responsible for accommodating new papers and removing some older papers (Tang and McCalla 2003).

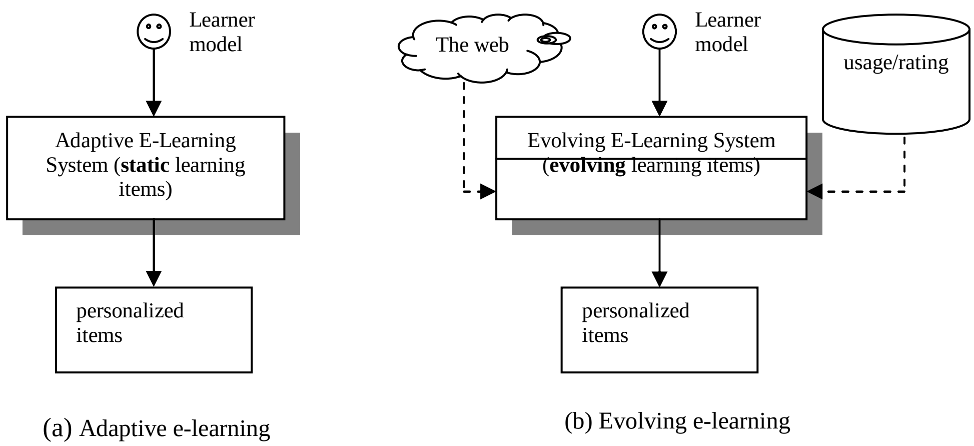

Figure 1. Adaptive e-learning system versus evolving e-learning system

A Survey

Research on recommender systems for adaptive web-based environments has proliferated due to the information overload on the Internet. Unfortunately, research on recommending learning items to e-learners has been largely ignored. To make matters worse, as we discussed previously, making recommendations in the context of an e-learning system can be strikingly different from that for e-commerce. The main goal of recommending items is to provide learners with necessary knowledge of a given topic and personalize the learning environment which motivates them to explore more. This is a goal of learner-centered education (Soloway et al.,1994).

We carried out a survey in order to understand what average learners actually want from the system, we sent a questionnaire to 28 people and received 26 responses.

Among the respondents (graduate students or alumni from computer science and engineering departments), 92% have more than a year fulltime working experience; 65% are graduate students; 15% are active researchers in their area; 19% have experiences as either tutors or lecturers; and more than 35% already had their master degree. The results can be regarded as the basis of our design. A learning scenario is introduced in the questionnaire: "*Assume that you are taking a graduate-level class where you need to read several papers (as what we usually did). For each topic taught in the class, you are required to read 2 or more items (journal paper, workshop paper, etc.) recommended by the professor or your classmates.*" Then, 10 questions are asked which can be categorized into three groups, i.e. learner preferences about different items, contents, and delivery methods. The results of the survey are tabulated into four diagrams shown in figure 2. The two left-side diagrams of figure 2 show the learners' preferences over different items. The upper-left diagram shows the results if the learner is interested in the topic being taught, while the lower-left diagram shows the results if the learner is not interested in the topic. The vertical axis represents the number of respondents. And the solid /shading bar represents the number of respondents like/dislike most on the type of item shown below the horizontal axis. The results show that magazine articles are the least popular items for learners who are interested in the topic being taught. Moreover, most of them avoid reading journal papers if they are not interested in the topic, and they rely heavily on lecture notes as shown in the lower-left diagram.

The upper-right diagram shows learners' preferences over the presentation of the paper. The results show that most learners prefer graphical representations, and dislike papers with formal models or algorithms only. And most of them prefer papers by well-known authors (92%), from reputable conference (96%), and with up-to-dated results or latest version (92%) as shown in the first three bars of the lower-right diagram. On the delivery issue, all respondents prefer to know more about various approaches to solving a similar problem rather than to learn a single approach repetitively, which indicates their enthusiasm to explore in breadth. And most of them prefer up-to-dated works (84%) rather than earlier versions (16%). Respondents who prefer to compare earlier-version work believe that earlier-version work is less completed thus easier to read (even though we explicitly state in the question that both earlier and later-versions have similar technical level). But they will read the up-to-date version as well if they found the topic interesting enough to pursue.

69% of respondents prefer to read an interesting but unimportant paper before they proceed to read an important but uninteresting one. However, 80% of respondents are still willing to eventually read that important, yet uninteresting, paper. This finding substantiates our previous claims that uninteresting, yet pedagogically valuable papers should be recommended. These pedagogically useful, yet uninteresting papers (items) are not *false positives* (Sarwar et al., 2000), because they could be helpful in one way or another to fulfill learners' learning expectations. But strategically recommend item becomes very important as shown that 69% of them prefer to read unimportant yet interesting paper before read uninteresting one. Moreover, the ratio of learners who prefer deep review paper(s) (with many technical aspects) to shallow review paper(s) (with many interesting presentations/application descriptions) is 50:50. At least three respondents (12%) said that they are willing to read both papers if they are interested in the topic being reviewed and two of them stated that they would skim the shallow review paper first before going deep into the other one. At last, when they are recommended to follow a rich research resources link maintained by well-known researchers or research groups, 50% of respondents prefer the recommender system to provide more specific information rather than search by themselves from it. A solution to this problem is to provide additional annotations so as to keep the recommendation to be more personalized and specific.

From the above analysis, it is obvious that personalized recommendation is very important in order to accommodate learner needs, knowledge levels and expectations. And the delivery of recommendations serves

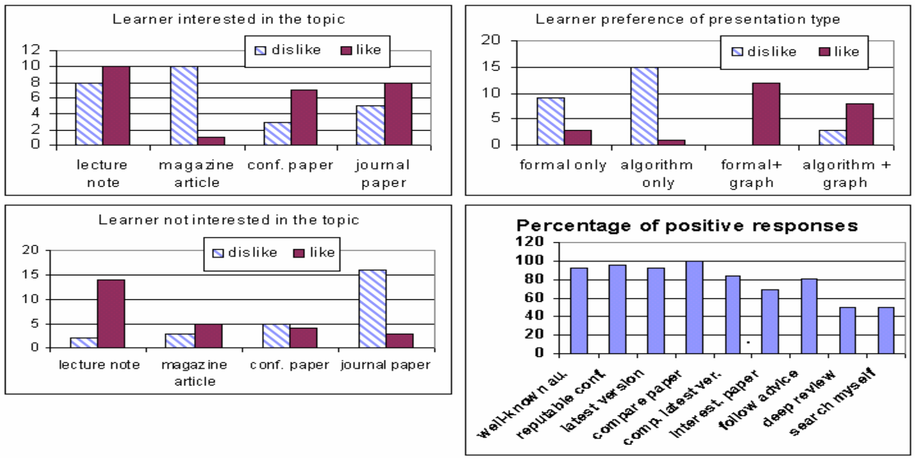

Figure 2. Result of the survey

to keep learners engaged and motivated. In the next section we will present a detailed description of our approach and also introduce some important definitions for our proposed approach.

Our Approach: Pedagogy-Oriented Paper Recommendation

Problem Statement

Our goal is the following:
Given a collection of items and a learner's profile, recommend and deliver a set of items in a pedagogically appropriate sequence, so as to meet both the learner's pedagogical needs and interest.

To be precise, *items* include any online item which can help learners understand the topic being taught, such as technical papers, review papers, book chapters, magazine articles, abstracts, white papers, presentation slides, and tutorial notes. In our current research, we will not include presentation slides and tutorial notes.

A Formal Notation of Paper Recommendations. For a learner model **U**, find a group of similar learners, **N**(**U**). Given content **C**, find a group of relevant papers **P**(**C**). Find a subset of learners **N'** $\subseteq$ **N**(**U**), who have read/rated any paper in **P**(**C**); denoted by $\boldsymbol{f}$: **N**(**U**) $\times$ **P**(**C**) $\rightarrow$ **N'.** Based on the ratings given by **N'**, use collaborative filtering to find a set of recommended papers **P'**$\subseteq$ **P(C).** In the following section, we are going to introduce the notion of pedagogically layered similarity for paper recommendations.

Basic Model of Recommendation in E-learning

We present a model of our *recommendation system* starting with some basic definitions.

Definition 1. A item in the domain being learned, denoted by r, is called commonly well selected if it is pedagogically suitable for all learners $\boldsymbol{L}$ *under common learning constraints (time, prior knowledge, availability, etc.). The same definition applies for a set of all item, denoted by* $\boldsymbol{R^C}$*, i.e. it is commonly well selected if all items* $r \in \boldsymbol{R^C}$ *is commonly well selected.*

Definition 2. An item in the domain being learned is individually well selected if it is pedagogically suitable for a specific learner $j \in L$*, under his/her individual learning constraints (common learning constraints plus individual learner characteristics, such as learning style, prior knowledge, preference, etc.). The same definition applies for all individually well selected item, denoted by* $\boldsymbol{R^I}$*, i.e. it is individually well selected if all items* $r \in \boldsymbol{R^I}$ *is individually well selected.*

Definition 3. The set of all individually well selected items is called the aggregate well selected item, denoted by $\boldsymbol{R}$*.*

Thus, we get $\boldsymbol{R^C} = \bigcap_{j \in L} \boldsymbol{R^I_j}$ and $\boldsymbol{R} = \bigcup_{j \in L} \boldsymbol{R^I_j}$. Additional item beyond $\boldsymbol{R}$ is unnecessary. However, deciding $\boldsymbol{R^I}$ is a non-trivial task, because in an ideal case, the tutor needs to decide proper pedagogical criteria in recommending the item. This issue is beyond the scope of this paper, so we continue with the definition of similarity between two items in the following part.

Definition 4. Similarity of two items r_1 *and* $r_2 \in \boldsymbol{R}$*.*

1. *v-similarity (version-based):* r_1 *and* r_2 *share the same topic, might be written by same authors, but one is a refined/updated version of another.*
2. *c-similarity (comparison-based):* r_1 *and* r_2 *discuss the same topic, with different approach.*
3. *t-similarity (technique-based):* r_1 *and* r_2 *use the same technique to solve two different problems.*
4. *s-similarity (simplicity-based):* r_1 *and* r_2 *concern the same topic and have the same level of simplicity in order to be understood.*

Definition 5. Ordering of a set of item $\boldsymbol{R^S}$*, where* $\boldsymbol{R^S} \subseteq \boldsymbol{R}$ *and* $|\boldsymbol{R^S}| > 1$.

1. *t-order: sequence of* $\boldsymbol{R^S}$ *according to their technical difficulty.*
2. *l-order: sequence of* $\boldsymbol{R^S}$ *according to their length.*
3. *p-order: sequence of* $\boldsymbol{R^S}$ *according to the abstraction of their presentation.*
4. *r-order: sequence of* $\boldsymbol{R^S}$ *according to the prestige of their publications.*
5. *c-order: sequence of* $\boldsymbol{R^S}$ *according to the chronology of their publications.*
6. *d-order: sequence of* $\boldsymbol{R^S}$ *according to their pedagogical value.*

Before we define some concepts of the delivery of recommended item, we will define *curriculum DAG* and *recommendation mapping* as follows:

Definition 6. The curriculum DAG (directed acyclic graph) is a weighted DAG with its nodes representing learning items and its link/arcs representing the 'prerequisite' relationship, e.g. the source node(s) are the prerequisite item for the destination node (target item). The weight represents the importance of corresponding prerequisite item in understanding target item.

Generally, a curriculum DAG can be formalized as a tuple $<\boldsymbol{Q}, \boldsymbol{W}, \boldsymbol{S}>$ where $\boldsymbol{Q}$ is the set of nodes, $\boldsymbol{W}$ is the adjacency matrix representing the weight and direction of links/arcs connecting pair of nodes, $\boldsymbol{S}$ represents the label matrix of logical relation (AND/OR) among nodes as the pre-requisite of other node. An example of curriculum DAG is the AND/OR graph (McCalla 1992).

Definition 7. Recommendation-Curriculum mapping (R-C mapping) is a mapping of $\boldsymbol{R}$ *to each node in the curriculum DAG under following constraints:*

1. learners can (to some degree) understand the item in R if they already understand the item covered in the node and/or some/all prerequisite node(s) given they possess some prior (basic) knowledge before they learn;

2. the learning item is useful to help learner understand a topic or motivate learner to learn more.

Formally, for each node q in curriculum DAG, the result of R-C mapping is the *candidate set* $\boldsymbol{R}^q = \{r_q \mid r_q \in \boldsymbol{R}$ and $r_q \oplus q > T$ and $(\forall k \in r_q)\ k \in p^0 \cup q \cup q^-\}$, where $\boldsymbol{R}^q \subseteq \boldsymbol{R}$ is all items stemmed from node q, $\oplus$ is a binary relation $\boldsymbol{R} \times \boldsymbol{Q} \rightarrow \mathbb{R}^+$ representing the degree of usefulness to know r_q after learning q, T is a threshold set by designer/tutor, k is a core knowledge contained in r_q which is crucial to understand r_q, p^0 is the estimation of learners' prior knowledge and q^- is the set of prerequisite nodes of q. The selection process mainly follows the tutor's subjective beliefs, because tutors may not know precisely learners' *recommendation arcs/links*, representing the relationship between these items in a candidate set, are based on the similarity measurement and ordering defined in definition 4 and definition 5. Since there are different orderings and similarity criteria, the arcs will have various weights and the DAG ($\boldsymbol{R}^q$) can be represented as $<\boldsymbol{R}^q, \boldsymbol{W}_1, \boldsymbol{W}_2, \ldots, \boldsymbol{W}_n, \boldsymbol{F}_q>$ where $\boldsymbol{R}^q$ is the set of nodes (candidate set), $\boldsymbol{W}_i$ is the adjacency matrix representing the weight and the direction of arcs connecting pairs of nodes based on criterion i, and $\boldsymbol{F}_q$ is the adjacency matrix representing the frequency of a link accessed by learners.

Now we are ready with the last definitions of *delivery sequence* and the *sequencing procedure*, i.e. how to select an item from each candidate set.

Definition 8. The delivery sequence of item, $\boldsymbol{S}_D$, is the sequence of item recommended to the learner, i.e. the partial topological order of DAG($\boldsymbol{R}^q$), according to

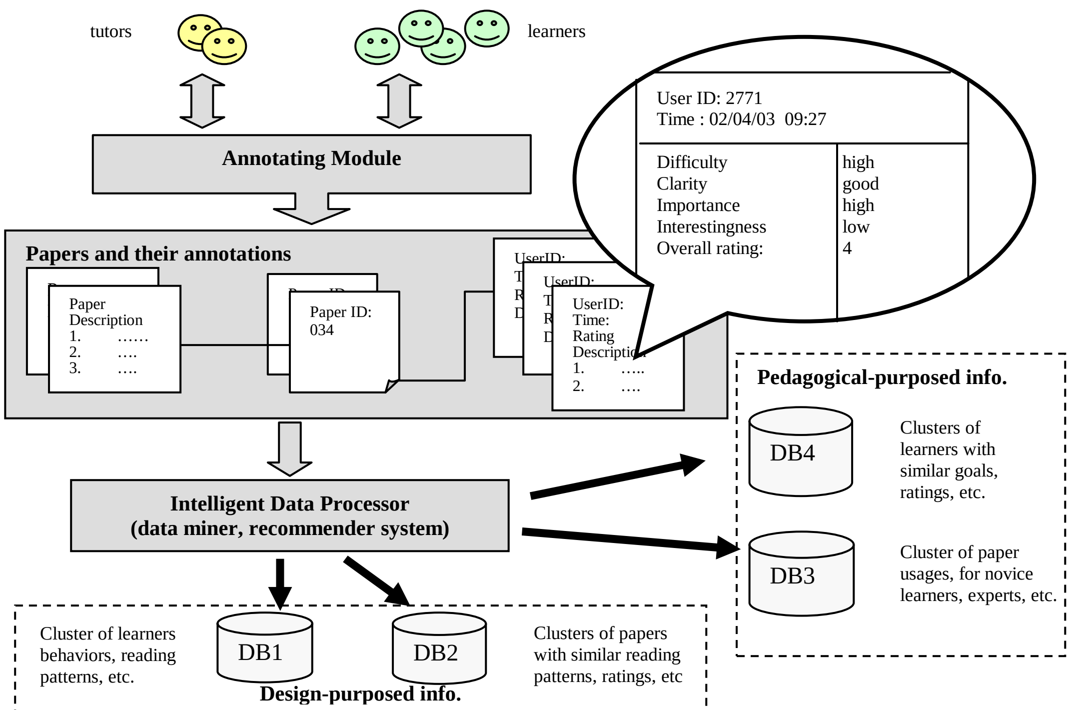

Figure 3. Annotating paper with sequence of learner models

exact prior knowledge at the time they are visiting node q, or tutors have different criteria deciding which item should be recommended. Moreover, the mapping must be *complete*, i.e. for all $r \in \boldsymbol{R}$ there are node(s) $q \in \boldsymbol{Q}$ such that $r \in \boldsymbol{R}^q$; otherwise we waste recommendation resources $\boldsymbol{R}$. Furthermore, the same item can be put into more than one candidate set. All ellipse nodes and their directed links/arcs constitute a curriculum DAG. And the set of all nodes in a small DAG (consisting of small black nodes) stemmed from each ellipse node is the candidate set. For instance, there are four item in candidate set $\boldsymbol{R}^{q5}$, which means that after a learner learns the topic in q_5 the system will recommend up to four additional items. The *observed learner characteristics, with the aim of maximizing the estimated utility of learning.*

Definition 9. The sequencing procedure of item, $\boldsymbol{\Sigma}$, is the procedure to produce $\boldsymbol{S}_D$ from $\boldsymbol{R}^q$ and learner model $\boldsymbol{M}_L$.

Annotating Papers with Temporal Sequences of Learner Models

It is obvious that as more and more learners have read and rated a paper, the number of user ratings with respect to the paper will be accumulated. These accumulated sequences of learner models reflected the temporal pedagogical knowledge state at the time when the learners accessed the paper. Figure 3 illustrates our idea of annotating papers with sequences of users.

The "Conflict of Understanding and Interest" Problem

For paper ***p***, and user ***U***, we might have the following learner sequences $\mathbf{U_i}^{\mathbf{t}}$, where t is the time when the user accessed the paper. Therefore, when a user reads a paper at different time, he/she might have different ratings toward it, i.e. his/her understanding towards the paper might change (either to the better or to the worse), due to his/her own increasing background knowledge on the subject. This will also lead to a so-called "conflict of understanding and interest" problem where a user might provide largely different ratings towards a paper. But from both learners' and tutors' perspective, this phenomena is natural given the increasing pedagogical ability of learners as time goes by, therefore, we will not make effort to "solve" this conflict; instead, these traces of living conflicts will be explored later to make a deep understanding of both the usage of a paper, and the learning curve of a learner.

It is obvious that as we can cluster users purely based on their browsing behaviors, we can also cluster the annotated user models with respect to a specific paper, or sequences of papers. Technically, the sequences of user models along with the collections of paper will provide rich information related to both users, user patterns, papers and paper usage patterns, which, in turn, can make more refined recommendations, provide both personalized and groupalized recommendations and form dynamic and collaborative groups based on clusters of learners with different interests, pedagogical backgrounds (Tang and Chan 2002).

Conclusions

In this paper we discuss the mechanism of a recommender system recommending papers for an evolving web-based learning system. Our system is unique in three aspects. The first is that it is evolvable, with the fittest papers survive. The second is that we introduce a pedagogically layered similarity between items read by learners and candidate items for recommendation. Finally, we propose to annotate each paper with temporal sequences of learners' learning behaviors. Currently, we are simulating artificial learners as a first step towards a deeper understanding of how the system works.

Acknowledgments. We would like to thank Canadian NSERC for the financial support.

References

Basu, C., Hirsh, H., Cohen, W. and Nevill-Manning, C. 2001. Technical paper recommendations: a study in combining multiple information sources. *JAIR* 1, 231-252.

Billsus, D.and Pazzani, M. 1999. A hybrid user model for news story classification, In *UM'99.*

Bollacker, K., Lawrence, S. and C. Lee Giles, C. L. 1999. A system for automatic personalized tracking of scientific literature on the web. In *ACM DL*, 105-113.

Fu, X., Buzdik, J. and Hammond, K.J. 2000. Mining navigation history for recommendation. In *ACM IUI'2000*, 106-112.

McCalla G. 1992. The search for adaptability, flexibility and individualization: approaches to curriculum in intelligent tutoring systems. *Adaptive Learning Environments.* NATO ASI Series, vol. F.85. Springer-Verlag. 91-121.

McNee, S, Albert, I., Cosley, D., Gopalkrishnan, P., Lam, S., Rashid, A., Konstan, J. and Riedl, J. 2002. On the Recommending of Citations for Research Papers. *ACM CSCW'02*. 116-125.

Pitkow, P., Schutze, H., Cass, T., Cooley, R. Turnbull, D., Edmonds, A., Adar, E. and Breuel, T. 2002. Personalized Search. *Communications of the ACM*, 45 (9): 50-55, Sept.

Resnick, P., Iacouvou, N., Suchak, M., Bergstrom, P. and Riedl, J. 1994. GroupLens: an open architecture for collaborative filtering of Netnews. In *ACM CSCW'94*, Chapel Hill. 175-186.

Sarwar, B., Karypis, G., Konstan, J. and Riedl, J. 2000. Analysis of recommendation algorithms for e-commerce. In *Proc. ACM EC'2000*, 158-167.

Schafer, J., Konstan, J. and Riedl, J. 2001. Electronic Commerce Recommender Applications. *Data Mining and Knowledge Discovery*, 5, (1/2, 2001), 115-152.

Shardanand, U., and Maes, P. 1995. Social information filtering: algorithms for automating 'word of mouth'. In *ACM CHI'1995*, 210-217. Denver.

Soloway, E., Guzdial, M., and Hay, K. 1994. Learner-centered design: the challenge for HCI in the 21st century. *ACM Interactions*, 1(2): 36-48, April.

Stern, M and Woolf, B. 1998. Curriculum Sequencing in a Web-based Tutor. In *ITS 98*. 574-583.

Tang, T.Y., and Chan, K.C.C. 2002. Feature construction for student group forming based on their browsing behaviors in an e-learning system. In *PRICAI 2002*. Springer LNCS 2417. 512-521.

Tang, T.Y and McCalla, G. 2003. Smart recommendations for an evolving e-learning system. In *Workshop on Technologies for Electronic Documents for Supporting Learning, AIED'2003,*. July Sydney, Australia. 2003.

Weber, G.,and Brusilovsky, P. 2001. ELM-ART: an adaptive versatile system for web-based instruction. *International Journal of AI in Education.* 12: 1-35.

Woodruff, A., Gossweiler, R., Pitkow, J., Chi, E. and Card, S. 2000. Enhancing a digital book with a reading recommender. In *ACM CHI 2000.*153-160.