Content Recommendation Based on Education-Contextualized Browsing Events for Web-based Personalized Learning

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ABSTRACT

The WWW is now in widespread use for delivering on-line learning content in many large-scale education settings. Given such widespread usage, it is feasible to accumulate data concerning the most useful learning experiences of past students and share them with future students. Browsing events that depict how past students utilized the learning content to accomplish higher levels of achievement are especially valuable. This paper presents a new method for identifying potentially effective browsing events based on a contextualized browsing model built through association mining and statistical techniques. The model annotates browsing events with several contextual factors, including educational ones (group relevance and performance relevance) and non-educational ones (support and confidence). Based on this model, a personalized content recommender was implemented in a Web-based learning content management system, called IDEAL, to deliver personalized learning content based on a student's browsing history. An experiment was conducted to compare the user feedback concerning the recommendations provided through different recommendation models. The results show that students with different levels of achievement prefer different types of contextualization information. Finally, another performance experiment demonstrated that the contextualized browsing model is more effective in improving learning performance than the pure association mining model.

Keywords

Web-based learning, Personalized learning, Content annotation, Association mining, Content recommendation

Introduction

The WWW contains a huge amount of learning content and is now in widespread use for delivering on-line learning content in many large-scale education settings. However, the huge amount of learning content has presented a problem to on-line students. Students are apt to get lost in the huge content space. Therefore, personalized learning becomes an important mechanism of a learning system that can guide students by automatically recommending learning content to their needs in a just-in-time manner (Zaiane, 2001).

The target of personalized learning varies with the types of learning needs it is designed to (McNaught, Kennedy & Majoor, 2002). For example, for just-in-time training, the main focus is on delivering appropriate information that workers need to solve problems, perform specific tasks or update their knowledge and skills. To perform such a type of personalized learning, specific knowledge about the task structure is required, such as in AIMS (Aroyo & Dicheva, 2001). On the other hand, for Web-based learning where students build the domain knowledge by studying learning content and navigating through a rich set of learning resources, personalized recommendation focuses on providing the next-step browsing suggestions so that students can build knowledge effectively with no disorientation in the learning environment (Kinshuk & Lin, 2003). This type of personalized content recommendation is the main focus of this research.

As to the design of personalized content delivery platforms, a new eLearning application, called Learning Content Management System (LCMS) (Brennan, Funke & Anderson, 2001), has been developed as a critical component of the personalized learning paradigm in which the emphasis is shifted from the knowledge of the instructor to the knowledge inherent in the content. Besides, a significant change is taking place in the way on-line learning is going in recent years. This change is the advocacy of learning objects to support personal learning needs. The concept of learning objects features the reusability of learning resources in whatever contexts they can be applied (Mohan, 2004; Mphan & Greer, 2003). Based on the key idea of LCMS that it will deliver what is needed at the time when it is needed, personalized content recommendation has become a very important learning support in LCMS (Brusilovsky & Vassileva, 2003; Denaux, Dimitrova & Aroyo, 2004).
One approach to personalized content recommendation is knowledge-oriented, which is based on three types of knowledge: domain ontology, content knowledge and student models (Papanikolaou & Grigoriadou, 2003; Sampson, Karagiannidis & Cardinali, 2002; Mittal, Krishnan & Altman, 2006). Domain ontology plays a shared language base for representing content knowledge and student models. A knowledge-based recommender could give highly individualized content recommendations. However, this approach incurs the cost of developing knowledge bases and is limited by the extent to which the student model is accurate.

Another approach to personalized content recommendation is to acquire knowledge about effective learning experiences and then share the knowledge with future users (Mulvenna, Anand & Buchner, 2000). As far as content recommendation is concerned, the ability of a web-based learning system to keep traces of students’ browsing behavior can be exploited to promote the learning paradigm of learning by other’s learning experiences (Najjar, Wolper & Duval, 2006). For those online courses that operate in a yearly cycle, which are common in most universities, the browsing traces can be accumulated and enriched year by year. With an appropriate analysis of these traces, navigation patterns can be discovered and shared with future students (Liang & Leifer, 2000; Najjar, Wolper & Duval, 2006).

There have been several research efforts to clarify the relationship among student cognitive characteristics, navigation patterns and learning performance. Several research results show that student cognitive characteristics seem to have a great effect on the strategies of how they learn, navigate and search learning resources (Liu & Reed, 1995; Ford & Chen, 2000; Chen & Macredie, 2002). However, there is little evidence showing that the differences in cognitive characteristics have a great impact on learning performance. Some research results show there is a positive relationship between cognitive styles and learning performance in hypermedia environments (Andris, 1996; Parkinson & Redmond, 2002); while others failed to find a connection between them (Liu & Reed, 1994; Calcatera, Antonietti & Underwood, 2005). In particular, Calcatera et al (2005) showed that stylistic differences were not associated with navigation patterns, and specific browsing behavior induced a better learning outcome. In short, they found that specific browsing behavior did have an effect on learning performance, but such behavior is not influenced by student cognitive styles. While there is evidence that individual factors do affect hypermedia navigation, their impact on learning performance is not simple. Based on the findings of Calcatera et al (2005), it is assumed in this paper that sharing good browsing behavior is beneficial to students regardless of their cognitive characteristics.

Nevertheless, the tremendous amount of browsing traces arouses the need of an automatic pattern extraction method. As to acquiring access patterns from historical traces, association mining (Agrawal, Imielinski & Swami, 1993; Agrawal & Srikant, 1994; Chen, Han & Yu, 1996) has been applied successfully in commercial applications. Furthermore, there is also research in reusing browsing patterns in the educational context (Mobasher, Cooley & Srivastava, 2000; Wang & Shao, 2004), where association mining is adopted as well.

The rationale behind association mining is that frequent association events can be used to anticipate the potential needs of users. However, several problems arise when a pure association mining approach is applied in the educational context. For example, in many researches, only the frequency and confidence of association events are considered to support a user’s decisions on taking which recommendations. Besides, the 0/1 transactional model of association mining does not distinguish between browsing events with different amounts of efforts that past students have made in pursuing their learning goals; nor does it care about who have generated these events. It is our belief that past browsing patterns need to be contextualized appropriately in an educational setting before they can be used effectively by future students.

This paper presents a new approach to reusing past browsing patterns based on a contextualized browsing model. Specifically, a model is proposed to contextualize browsing events with two more educational factors: group relevance and achievement relevance, in addition to the support and confidence factors adopted in pure association mining. The group-relevance factor is concerned with the relation between browsing events and student groups of different achievements, while the achievement-relevance factor has to do with the correlation between browsing events and learning performance. By contextualizing the browsing events based on this model, browsing patterns can be shared with the students by providing them with the different educational perspectives which they can use to make a decision on what to study next.
Based on the contextualized browsing model, a content recommender was implemented in a Web-based learning content management system (LCMS), called IDEAL (Integration and Dissemination of Electronic Assessment and Learning). Finally, an experiment was conducted to compare the user feedback concerning the recommendations provided through different recommendation models. The results show that students with different levels of achievement prefer different types of contextualization information. Furthermore, another performance experiment demonstrated that the contextualized browsing model is more effective in improving learning performance than the pure association mining model.

Organization of the paper

The rest of this paper is organized as follows. The second section depicts the connection between association mining and personalized learning. The third one introduces the contextualization process for browsing patterns. Next, a brief introduction of how the recommender interacts with the IDEAL system is given, followed by a description of the evaluation of the system as well as a discussion on the experimental results. At last, a summary and future research is given.

Association Mining and Personalized Learning

Association mining is one of the most well studied methods in data mining (Agrawal, Imielinski & Swami, 1993; Agrawal & Srikant, 1994; Chen, Han & Yu, 1996). It has served as a useful tool for discovering correlated items in a large transaction database. It explores the probability of the event that when certain items are present in a transaction, what other items would also present themselves in the same one. In effect, an association rule is a statement of the form X → Y, where X and Y are two disjoint item sets. An interpretation of such an association rule in a business context is that if a customer has bought the items in X, he/she would like to buy the items in Y in the same transaction.

When it comes to measurement of effectiveness of association rules, support and confidence are the most adopted. The support value indicates the occurrence frequency of an item set in a transaction database. It is defined as the ratio of the occurrences of an item set over the total database size. For example, suppose there are x transactions containing items in an item set X, and the database has a total of y transactions, then the support of the item set X would be denoted by sup(X) = (x/y). Furthermore, in the minimum support approach, a set of items X is called a large itemset if the support rate of X meets a minimum support requirement. Association rules are generated only by a large itemset that has a support value greater than or equal to the minimum support. For an association rule X → Y, the support of the associated pattern XUY is used to check whether the rule is significant or not, implying that it is a frequent transaction pattern. On the other hand, confidence of an association rule X → Y represents the strength of the implication of the rule. It is defined as an estimation of the conditional probability computed by sup(XUY)/sup(X). An association rule is said to be more reliable if it has a higher confidence.

From the educational perspective, frequent itemsets can be browsing events consisting of learning objects often browsed together in a learning environment. The association rule corresponding to a browsing pattern can be used to generate personalized recommendations as follows. For example, let’s consider a browsing pattern (LO1, LO2, LO3, LO4) with support 0.05, and an association rule (LO1, LO2, LO3)→(LO4) with confidence 0.95, saying that 95% of the browsing transactions containing LO1, LO2 and LO3 would also contain the learning objects LO4. According to this rule, once a student has browsed learning objects LO1, LO2 and LO3, it would be anticipated that the student would like to browse LO4 as well (with confidence 0.95). Once the student adopt the recommendation, it can be said that s/he is following the past browsing pattern (LO1, LO2, LO3, LO4).

Note that such a mechanism for personalized learning is different from those knowledge-based ones (Papanikolaou & Grigoriadou, 2003; Sampson, Karagiannidis & Cardinali, 2002). The essence of this type of personalized learning is the herd mentality exploited through emphasizing the popularity of learning objects that are often browsed together. It is based on the assumption that students often feel like they have made the right choices when they are doing as those students having similar need did.
Furthermore, there are differences between applying association mining to the educational arena and to the commercial one. In the educational context, association rules resulting in patterns with high support values may represent learning trends, while those with low support values but high confidence values may represent “special” ones. Unlike those commercial applications that focus only on events with large support values, it appears that both event categories, either trends or special ones, might expose valuable information to instructors and students. Besides, there are limitations of the 0/1 transactional model of pure association mining. It does not distinguish between transactions containing different amounts of items; nor does it care about who have generated those transactions. It is our belief that experiences from past students need to be contextualized appropriately before they can be used effectively by future students. Therefore, some contextualization task is required to help students better understand the rationale behind the system’s recommendation and make a more cohesive decision.

The Contextualized Browsing Model

In this research, the browsing model that depicts past browsing behavior is developed based on frequent browsing events. In addition to the non-educational contextual information of support and confidence in pure association mining, browsing events are provided with more educational contextual information, that is, the group relevance and achievement relevance. Figure 1 shows the data analysis process that integrates association mining and statistical techniques to extract contextualized browsing patterns that are useful for personalized delivery of learning objects.

![Data Analysis Process Diagram](image)

**Figure 1**: A data analysis process for contextualizing browsing events through data mining and statistic techniques

**Data collection and preprocessing**

During the progression of an online course, the content access traces associated with each learning activity need to be collected so that we can identify what students have browsed to achieve the goal of the corresponding learning activity. The learning environment is equipped with content access tracking to facilitate the data collection task. A proper design of data tracking needs to select appropriate tracking attributes such as user ID, learning activity ID, content type and content ID, the date and session during which it was accessed, and so on. Table 1 shows the format of access traces that are saved in a database.
The collected data has to be cleaned up and transformed properly before it can be analyzed further. In situations where user sessions are not easy to identify, several heuristic methods have been explored to decide on user sessions from the logged access history (often logged in an http server) (Chen, Han & Yu, 1996). Nevertheless, in our situation where login actions are required from registered users, the problem of session determination is trivial. A number of preprocessing steps are performed to prepare the data for further analysis. For example, all browsing records are sorted in an ascending order with the user ID as the major key and the event time as a minor key. After this sorting step, it is easy to identify user sessions by packing contiguous records that follow a login record until the next one. Specifically, browsing records picked out between two successive login records are grouped into a browsing session. Notice that a web trail may be followed just because it seems attractive for students, and that doesn’t necessarily mean it is a right choice from a student’s perspective. To reduce the trail-attraction effect, this research adopts the minimum page-stay session-grouping approach (Wang and Shao, 2004) that filters out learning objects browsed by a student in less than a specified time (say 7 seconds).

Table 1: The format of access traces.

<table>
<thead>
<tr>
<th>Data Field</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>User ID</td>
<td>Identifier of students.</td>
</tr>
<tr>
<td>Activity ID</td>
<td>Identifier of a learning activity</td>
</tr>
<tr>
<td>LO ID</td>
<td>Identifier of the referenced learning objects (assets, SCOs).</td>
</tr>
<tr>
<td>Activity Type</td>
<td>Activity type such as login, browsing, and so on.</td>
</tr>
<tr>
<td>Stay Time</td>
<td>Stay time of the LO access.</td>
</tr>
</tbody>
</table>

Discovering browsing events through association mining

In this step, association mining is adopted to discover the set of browsing events consisting of learning objects frequently browsed together in a learning session. Recommendation rules can then be generated based on these browsing events. In this research, we adopt the one-page recommendation rule formation, in which a rule has multiple antecedents but only one consequent. The antecedents represent learning objects currently browsed, and the consequent represents the learning object for recommendation. Each recommendation rule is tagged with two labels representing a partitioned range of the support and confidence values, respectively. The label for support is assigned one of the five terms: very-infrequent, infrequent, moderately-frequent, frequent, very-frequent. Similarly, the confidence label is assigned one of the five terms: very-uncertain, uncertain, moderately-certain, certain, very-certain. The two labels are provided to help students understand the recommendations in terms of their frequency and certainty.

Contextualization of browsing events

Additional contextualization steps are performed on browsing events using the educational contextual information of group relevance and achievement relevance. The former is concerned with how a browsing event relates to student groups of different learning achievements. For example, while some browsing events may receive more attention from students who are high achievers, they might not receive as much attention from students who are low achievers. On the other hand, there might be some browsing events that receive attention from all students, regardless of their learning achievements. Knowing this kind of knowledge is helpful for personalized learning because it could uncover browsing patterns specific to different student groups.

The second contextualization step is concerning how a browsing event correlates with learning achievement. Though the correlation is not necessarily a causality that guarantees effective learning, it reveals a potential direction for utilizing learning objects effectively. As to those browsing events showing a positive correlation with learning achievement, they reveal the potentially significant learning objects that students should pay more attention to. On the other hand, for those browsing events showing a negative correlation with learning achievement, they might indicate a potential problem with students trying to learn from the learning objects of the browsing events. Finally,
for those browsing events showing no significant correlation with learning achievement, it can only be assured that those events do not play significant roles in making learning achievement different.

The model

In summary, the two-dimensional contextualization model can be depicted as shown in Figure 2. The group-relevance dimension is concerned with the browsing characteristics specific to student groups, while the achievement-relevance dimension concerns the correlation between browsing events and learning achievement.

According to Figure 2, there are five types of browsing events. For type I events, they are not characteristic of any student group, but they have positive correlation with learning achievement. These events are significant because students who pay more attention to them are apt to perform better.

As to type II events, they are characteristic of some student group and have a positive correlation with learning achievement. These events are significant because a specific group of students paying more attention to them are apt to learn better. Therefore, the corresponding learning objects are good recommendation candidates for future students of that group.

For type III events, they are characteristic of some student group, but they have a negative correlation with learning achievement. These events are significant because students of that group are apt to perform worse when they pay more attention to the events. One possible reason for this might be that students of that specific group have problems learning from the corresponding learning objects. Therefore, more remedial instruction based on those learning objects should be given to the students in that group.

For type IV events, they are not characteristic of any student group, and they have a negative correlation with learning achievement. These events are significant because students who pay more attention to them are apt to perform worse. Therefore, more remedial instruction based on those learning objects should be given to all students in the class.

Finally, type V events, as marked in the shaded area of Figure 2, are not achievement-correlated. They are less significant in terms of the contextual factors considered in this paper. Nevertheless, this does not mean that the corresponding learning objects are not effective for learning. Instead, they still provide some information of past browsing behavior, and this type of information should also be referenced by future students for a general learning purpose.
The method

To cope with the 0/1 transaction problem of pure association mining, the degree of attention paid by students to browsing events needs to be quantified in some way. This research introduces a concept of session browsing effort (SBE) that a student has made with respect to a browsing event \( e \) in a learning session \( s \). Specifically, it is defined as a summation of occurrences of each learning object of \( e \) in session \( s \). Note that the browsing effort of an event \( e \) in a session \( s \) is meaningful only if the session \( s \) contains the pattern \( e \). For example, given a browsing event \( e = \{LO_1, LO_2, LO_3\} \), and a session \( s_1 = \langle LO_1, LO_4, LO_1, LO_2, LO_5 \rangle \), the browsing effort with respect to event \( e \) in session \( s_1 \) is \( 2+1+1=4 \), because there are two visits of LO_1, one visit of LO_2, and one visit of LO_3 in session \( s_1 \). On the other hand, in a session \( s_2 = \langle LO_1, LO_4, LO_2, LO_3, LO_5 \rangle \), the browsing effort with respect to event \( e \) in session \( s_2 \) would be 0 since session \( s_2 \) does not contain LO_3 in event \( e \). Finally, the total browsing effort (TBE) of a student with respect to an event \( e \) is defined as the total summation of all session browsing efforts (SBEs) of the student with respect to the event \( e \). The quantification of browsing events by a measure of object visits is in line with Yin (2001) and Calcaterra et al (2005), who showed that higher performance was associated with re-visiting learning objects.

Now, we define the “mean browsing effort” (MBE) of a student group with respect to a browsing event as the average TBE of all students in that group. Those events that have significant difference in MBE among different student groups are called “group-relevant” browsing events; otherwise they are called “group-irrelevant” ones.

To identify group-relevant browsing events, students are first divided into three groups according to their learning achievements (often measured by their post-test scores) after a learning activity. The first group consists of the top 25% students, which is called the “high-achievement” group. The second consists of the next 50% students, which is called the “middle-achievement” group. The last one is called the “low-achievement” group that covers the bottom 25% students. The relevance of a browsing event to student groups is then tested by conducting a one-way ANOVA F test on the mean browsing efforts (MBEs) among the three student groups. However, when the data does not meet the normality assumption of an ANOVA, the non-parametric Kruskal-Wallis Test (Siegel & Castellan, 1988) is performed instead. When a group-relevant event is identified, the t-test is performed on each pair of the student groups to identify the group relevant to the event.

Figure 3: A screenshot (English-translated) of the association mining tool for discovering frequent browsing events and generating contextualized recommendation rules
As to the correlation between browsing events and learning achievement, it is computed by conducting a linear association test on the population correlation coefficient \( \rho \), \(-1 \leq \rho \leq 1\), between the total browsing effort (TBE) and learning achievement of each student. The null hypothesis is \( H_0: \rho = 0 \), which shows no linear correlation in the population, and the alternate hypothesis is \( H_a: \rho \neq 0 \), which means there exists a linear correlation (either positive or negative) in the population. The test statistic is

\[
t = \frac{r \sqrt{n - 2}}{\sqrt{1 - r^2}},
\]

where \( r \) is the Pearson correlation coefficient and \( n \) is the number of students.

**The tool**

We have implemented a mining tool, as shown in Figure 3, to discover frequent browsing events and generate recommendation rules based on the contextualized browsing model.

![Figure 4: Some contextualized recommendation rules](image)

The recommendation model is stored as a set of recommendation rules in Jena Triple format. Each rule contains at least one antecedent and a unique decision consequent. A variety of information, such as the author ID of learning objects, object type, object ID, and all the contextual information, are encoded and concatenated together with the separator character '*' as shown below:

```jena
[RuleName: (?c browse fhwang*score*8629)
 - (?c sug_browse fhwang*score*8664), (fhwang*score*8664 cf 0.81081*0.18072*0.1)]

CPP951: (?c browse fhwang*score*8664)
 - (?c sug_browse fhwang*score*8629), (fhwang*score*8629 cf 0.64516*0.18072*0.1)

CPP952: (?c browse fhwang*score*17416)
 - (?c sug_browse fhwang*score*8629), (fhwang*score*8629 cf 0.4*0.01205*0.1)

CPP953: (?c browse fhwang*score*8629)
 - (?c sug_browse fhwang*score*8677), (fhwang*score*8677 cf 0.7027*0.15663*0.1)

CPP954: (?c browse fhwang*score*8677)
 - (?c sug_browse fhwang*score*8629), (fhwang*score*8629 cf 0.71233*0.15663*0.1)]
```

where \( ?c \) denotes a variable representing some student.

For example, the following recommendation rule,

[r0:}
(\texttt{?c browse fhwang*scoref*5197}), (\texttt{?c browse fhwang*scoref*6061}), (\texttt{?c browse fhwang*scoref*6056}) \\
\rightarrow \\
(\texttt{?c sug_browse fhwang*scoref*6058}), (\texttt{fhwang*scoref*6058 cf 0.8*0.05545*0*0}) ]

says that if a student has browsed the SCO object of ID=5197 (authored by ‘fhwang’), the SCO object of ID=6061 (authored by ‘fhwang’) and the SCO object of ID=6056 (authored by ‘fhwang’), then the rule will recommend the SCO object of ID=6058 (authored by ‘fhwang’) with confidence=0.8. By SCO here we mean Sharable Content Object, which is a concept derived from SCORM. Furthermore, the browsing event is group-independent and achievement-irrelevant, with support=0.05545 and confidence=0.8. Figure 4 lists some contextualized recommendation rules discovered by the mining tool.

The Learning Environment

The IDEAL system

IDEAL is a standard-conformant and Web-based learning content management system that was developed to help instructors design and deliver reusable learning objects conformant to modern eLearning standards like IEEE LOM, ADL’s SCORM, IMS QTI, and IMS RS. The motivation of developing IDEAL is to integrate three kinds of learning resources, including learning content, test items and learning design, conformant to currently popular e-Learning standards. In particular, IEEE LOM is the main metadata-tagging scheme adopted in IDEAL. Through the LOM metadata tagging, learning objects in IDEAL can carry educational contextual information that is helpful to their applications in personalized learning. Besides, IDEAL provides several educational facilities like course management, on-line testing and reporting services, resource access tracking, and statistical report of user feedbacks on learning objects. Through the IDEAL system, students can take on-line courses, access learning objects and engage themselves in on-line testing. Therefore, IDEAL can be deployed as a computer-assisted learning environment on the Web. Currently, IDEAL is running on Tomcat 5.0 with a native XML database X-Hive 6.0.

Search Result List

Totally 16 records found

1—10 (Page 1/2)

[Private Resources]

1. XPATH Package (manifest)
   Classification: (/SimpleResourceType/Theory) (/SimpleResourceType/Exercise)
   Description: This package contains slides and an online exercise for the XPATH topic
   Difficulty: moderate
   Producer (citer): fhwang (fhwang@mcu.edu.tw)
   Popularity: unavailable

2. XPATH Sample Collections (manifest)
   Classification: (/SimpleResourceType/Example)
   Description: This learning objects contains a set of XPATH samples
   Difficulty: moderate
   Producer (citer): fhwang (fhwang@mcu.edu.tw)
   Popularity: unavailable

Figure 5: A screenshot (English-translated) for searching learning objects in the IDEAL system

In this research, IDEAL serves as a Web-based repository and a deliver of learning objects. IDEAL provides two channels for students to access learning objects. One is through the index list of learning packages, which are pre-
designed by instructors packing relevant learning objects together for specific topics. The second is through a search component in IDEAL. Figure 5 shows a screenshot of a list of learning objects returned by the search component in IDEAL. Specifically, the search component is a flexible search engine that could search learning resources at different levels of granularity. A search criterion in IDEAL is described by three categories of query constraints: (1) the LOM metadata constraint, (2) the document-space constraint indicating the resources created by specific authors, and (3) the access-control constraint. The LOM constraints are described in terms of IEEE LOM entries, such as the title, keyword, learning resource type and so on. The document-space constraint describes where the resources could be located, either in public or private user spaces. The last constraint describes the access control criterion, which in the current implementation says that students have to enroll in a course before they can access the resources authorized to the course.

The recommender

A recommendation server was designed based on the Web-service technology to provide open recommendation services. An automatic reasoning system written in Jena performs the inference task based on the contextualized rules and the current browsing history of a student. The recommendation list is passed back to IDEAL in XML format, and then IDEAL transforms the recommendations from XML format into HTML pages using the XSL technique. The XSL technique was adopted to implement different recommendation modules. For each recommendation module, one XSL program is coded to display the recommendations showing different types of contextual information.

![Diagram of the interaction among the recommender, IDEAL and a user](image)

*Figure 6: The interaction among the recommender, IDEAL and a user*

The interaction among the recommender, IDEAL and a student is depicted as shown in Figure 6. A student first selects an item from the search list. This will trigger a learning object request (LO request) to the LO Fetcher in IDEAL, and the LO Fetcher will then retrieve the requested learning object from the LO repository and send it to the learning object player (LO Player). The LO Player is aimed to display the content of a learning object while providing interactions between the learning object and the student through several embedded buttons in the screen. The interactive buttons include those for posting/reviewing comments concerning the learning object, and those for
making recommendation requests. Figure 7 shows a screenshot of browsing a learning object in IDEAL, where students can post comments and/or browse comments given by other students about the learning object. Besides, students can ask for item recommendations from the two buttons in the top-right part of the screen.

Figure 7 A screenshot (English-translated) for browsing learning objects in the IDEAL system

Figure 8: A screenshot (English-translated) for recommendation module of pure association mining showing only support and confidence in the IDEAL system
The recommender currently provides two recommendation modules. The first one displays only support, confidence and object description for each recommendation item. Figure 8 shows a screenshot of the recommendation list displayed by the first module. In the left window, the recommendations are given in a descendant order of confidence, which is classified into five categories ranged from “least-certain” to “very-certain”. Students can select recommendations based on support, confidence, and/or object descriptions. Furthermore, a student can ask for a totally new recommendation list by switching on/off the items listed in the browsing history window on the right, in which the items are sorted in a descendant order based on recency of the browsing time. This is especially helpful when students want the system to focus on more recent browsing events that reflect their most recent interests.

The second module displays recommendations according to the educationally contextualized event model. In addition to support, confidence and object descriptions, a variety of educational contextual information like group relevance and achievement relevance are also displayed. Figure 9 shows a screenshot of the recommendation list rendered by the second module. Students are provided with links associated with different types of recommended items. Therefore, they can make a decision on which recommendations to take based on their preference for contextual information. By selecting one of the links, the recommendation window below the Link one will display a list of recommended items. Again, students can ask for a totally new recommendation by switching on/off the items listed in the browsing history window on the right.

![Figure 9: A screenshot (English-translated) for recommendation module of contextualized browsing model showing more educational contextual information in the IDEAL system](image_url)

**Evaluations and Results**

A prototype evaluation of the system by a few experts had been conducted so that feedback on the system design and quality of the recommendation services can be collected (Wang, 2007). Problems exposed through the feedback have been corrected. To further assess the revised system, another evaluation with a larger number of students was conducted. Furthermore, an evaluation was conducted to compare the performance of the recommender based on pure association mining with that of the one based on the contextualized browsing model. At last, suggestions and insights gained from the research into personalized learning are also presented.
Model construction

To build a test recommendation model, a course named “XML Programming” was first conducted from February 2006 to July 2006. A total of 65 students enrolled in the course. Given the free network access to on-line resources in IDEAL, all fetched learning objects during each learning session are tracked and stored in a log database. For each learning activity in the course, the learning achievement of each student was measured by a post test and stored in a database for further analysis. Table 2 shows a summary of the mining results obtained from these access traces. As shown in Table 2, a total of 477 browsing events were discovered.

Table 3 lists the contextualization results over the 477 browsing events, with support ≥ 0.02, under the F distribution with (2, 62) degrees of freedom, and the t distribution with 60 degrees of freedom, and P-value ≤ 0.05. It can be seen that only 8.81% of the browsing events are group-relevant ones, all of which happened to be characteristic of high-achievement students. Though just only a small percentage, these events represent special browsing behavior of the high-achievement students. Besides, it is shown in Table 3 that 10.06% of the browsing events are achievement-relevant, all of which are positively relevant. Furthermore, it is interesting to find that none of the browsing events are negatively related to learning achievement.

Student Evaluation

The recommender was then evaluated by another 36 undergraduate students who enrolled in the XML programming course in 2007 spring semester. Among the 36 students, four students claimed themselves as experts, and the other thirty-two students as novices. After a brief introduction to the system operation, these students were given three hours to study the course using the recommender system. After the self-study hours, they were asked to fill out a questionnaire, and a post test was administered to them. The questionnaire contains thirteen 7-point Likert scale items, the same as those used in the prototype evaluation (Wang, 2007). Table 4 shows the questionnaire evaluation results.

From Table 4, it can be seen that students were satisfied with the efficiency (with mean = 5.06) and accuracy (with mean = 5.08) of the system. Besides, as to the accuracy of the recommendations based on different types of contextual information, it is interesting to find that students were satisfied with the recommendations based on the information of achievement relevance (with mean = 5.08), group-relevance (with mean = 5.0) and confidence (with mean = 5.0). Finally, students agreed the system, as a whole, is beneficial to their learning (with mean = 5.0).
As to the preference, sufficiency and usefulness of the contextual information, students felt moderately positive toward them. Since only moderately positive attitudes toward the aforementioned items are revealed, further investigation into the decision styles of different student groups will be made and discussed later.

The questionnaire also contains four open questions related to how students interact with the recommender. A summary of student answers to the four questions are listed in Table 5. The first question is about which type of information students considered the most important and the least important, respectively, for selecting recommendations. Table 5 shows that information of group independency is considered the most important by 22.2% students, while only 8.3% students considered it the least one. Furthermore, 13.9% students valued the information of confidence, while only 5.5% students disfavoring it. Therefore, information of confidence was the second welcome one. On the other hand, only 8.3% students considered the information of object description the most important, while 22.2% students considered it the least important. As some students had expressed in an interview that the object descriptions were a little bit rough, and hence they failed to provide useful information for making sensible decisions.

<table>
<thead>
<tr>
<th>Question Item Description</th>
<th>Mean</th>
<th>Std. Dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. The system is friendly to use. (friendliness)</td>
<td>4.72</td>
<td>1.23</td>
</tr>
<tr>
<td>2. The system is efficient in generating recommendations. (efficiency)</td>
<td>5.06</td>
<td>1.27</td>
</tr>
<tr>
<td>3. What I need can be found in the recommendation list. (recall)</td>
<td>4.72</td>
<td>0.97</td>
</tr>
<tr>
<td>4. Items in the recommendation list meet my needs. (accuracy)</td>
<td>5.08</td>
<td>0.94</td>
</tr>
<tr>
<td>5. I would like to use the various types of information to sort out what I need in the recommendation list. (preference)</td>
<td>4.78</td>
<td>1.07</td>
</tr>
<tr>
<td>6. The information is sufficient to help me sort out what I need in the recommendation list. (sufficiency)</td>
<td>4.58</td>
<td>1.00</td>
</tr>
<tr>
<td>7. The information is helpful in sorting out what I need in the recommendation list. (usefulness)</td>
<td>4.89</td>
<td>0.92</td>
</tr>
<tr>
<td>8. The recommendations given by group-dependent browsing events meet my needs.</td>
<td>5.00</td>
<td>0.99</td>
</tr>
<tr>
<td>9. The recommendations given by group-independent browsing events meet my needs.</td>
<td>4.53</td>
<td>0.84</td>
</tr>
<tr>
<td>10. The recommendations given by support meet my needs.</td>
<td>4.94</td>
<td>1.07</td>
</tr>
<tr>
<td>11. The recommendations given by confidence meet my needs.</td>
<td>5.00</td>
<td>0.93</td>
</tr>
<tr>
<td>12. The recommendations given by achievement-relevance meet my needs.</td>
<td>5.08</td>
<td>0.97</td>
</tr>
<tr>
<td>13. The contents recommended by the system are helpful to my learning. (effectiveness)</td>
<td>5.00</td>
<td>1.04</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Question</th>
<th>Answers</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Which information do you think is the most important for selecting recommended learning resources? Which is the least one?</td>
<td>1. Group Relevance 7 (19.4%) 6 (16.6%) 2. Group Independency 8 (22.2%) 3 (8.3%) 3. Learning Achievement Relevance 4 (11.1%) 5 (13.9%) 4. Support 4 (11.1%) 3 (8.3%) 5. Confidence 5 (13.9%) 2 (5.5%) 6. Object Description 3 (8.3%) 8 (22.2%)</td>
</tr>
<tr>
<td>2. What other types of information you think are needed to support the recommendation decision?</td>
<td>2-1. Average time spent for browsing a learning object 2-2. A significant index provided by peer students 2-3. Recommendations provided by high-achievement students 2-4. Recommendations for novices only</td>
</tr>
<tr>
<td>3. Do you have any suggestions for improving the system interface?</td>
<td>3-1. The interface design is too complex (too many sub-windows) 3-2. Relate the recommendations based on some semantic meanings.</td>
</tr>
<tr>
<td>4. Which recommendation model do you prefer?</td>
<td>4-1. Twenty two vote for pure association module (61.1%) 4-2. Thirteen vote for contextualization module (36.1%)</td>
</tr>
</tbody>
</table>
Roughly equal percentage of students favored and disfavored each of the remaining three types of information (group relevance, achievement relevance, and support). They seemed to be the most controversial ones. In particular, relatively high percentage students favor (with 19.4%) and disfavor (with 16.6%) the information of group relevance, respectively. Similar situations happened to the information of achievement relevance. It seemed that the students had shown a huge controversy over the preference for educational contextual information (group relevance and achievement relevance).

**Group comparison and results**

Students are divided into three groups according to their post test scores. The high-achievement group consists of the top 25% students, the middle-achievement group consists of the next 50% students, and the remaining 25% students are in the low-achievement group. To investigate further into the information preference specific to each student group, the ratios of students favoring and disfavoring the various information types for each student group are depicted in Figure 10, where G1 denotes the high-achievement group, G2 denotes the middle-achievement group, and G3 the low-achievement group.

![Figure 10: Ratios of students favoring and disfavoring the information types for each student group (A+: favor Group Relevance; A-: disfavor Group Relevance; B+: favor Group Independency; B-: disfavor Group Independency; C+: favor Achievement Relevance; C-: disfavor Achievement Relevance; D+: favor Support; D-: disfavor Support; E+: favor Confidence; E-: disfavor Confidence; F+: favor Object Description; F-: disfavor Object Description)](image)

For high-achievement students, they favored the group-relevance information most. Therefore, a large number of high-achievement students seemed to be highly motivated to visit what past high-achievement students had browsed. Besides, they seemed to have the profession to comprehend the short and concise object descriptions in order to select sensible recommendations. On the other hand, near 30% of high-achievement students disfavored the information of support, implying the tendency to ignore the frequency of past browsing events.

For middle-achievement students, 22% students favored the information of group relevance; while there were also near 22% students disfavored that. Besides, another 22% of middle-achievement students favored the information of confidence and the same percentage of students disfavored the information of object descriptions. Therefore, middle-achievement students seemed not to be as motivated as high-achievement students in following the behavior of past high-achievement students. Nor did they have the same profession as high-achievement students to comprehend the concise object descriptions. Besides, they seemed to rely more on the information of confidence to select sensible recommendations.
For low-achievement students, 44% of them favored the group independency. On the other hand, there were near 44% students disfavored the information of object descriptions. Therefore, for low-achievement students, they are the least motivated to follow past high-achievement students, and have the least profession to comprehend the concise object descriptions.

**Performance Evaluation**

To evaluate the performance of the proposed recommendation model, 80 students from two “C Programming” courses joined the experiment. Among them, 40 students were randomly picked out and assigned to the control group, who used the recommender with the pure association mining model. The other 40 students were assigned to the experiment group, who used the recommender with the contextualized browsing model. Before the experiment started, all students took a pretest on the topics of “variables”, “flow-control” and “recursive programming”. After a brief introduction to the system operation, they were given three hours to study those topics. After the self-study hours, a post test was administered to them. Table 6 shows the results of both tests. The t-test was used to test the difference between the score means of the two experiment groups. As shown in Table 6, there is no significant difference between the pretest mean scores of both student groups. After the treatment was administered, it can be seen that the mean score of the experiment group was significantly higher than that of the control group.

<table>
<thead>
<tr>
<th>Test</th>
<th>Pretest</th>
<th>Post-Test</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>Std.</td>
</tr>
<tr>
<td>Control Group</td>
<td>56.95</td>
<td>15.31</td>
</tr>
<tr>
<td>Experiment Group</td>
<td>59.30</td>
<td>14.83</td>
</tr>
</tbody>
</table>

* P-value 0.244 \( * \) 0.013

As a summary, the main contributions of this research can be described from three perspectives. The first is concerned with how students react to the various types of contextual information. The second is concerning how well students think the system has done the jobs. Finally, the last is related to the performance of the new recommendation model. In this research, six types of contextual information were investigated, and three of them (group relevance, achievement relevance, object descriptions) are educational ones, and the other three (group independence, support, confidence) are non-educational.

**Perspective 1: How students react to the various types of contextual information**

As a whole, students react differently for different information types. Specifically, high-achievement students are more willing to follow the behavior of past high-achievement students, while low-achievement students show the least preference. Middle-achievement students seemed not to be as motivated as high-achievement students in following the behavior of past high-achievement students. Besides, they seemed to rely more on the information of confidence to make sensible decisions on adopting which recommendations. The difference in preference may also come from the different needs of learning control specific to different student groups. Low-achievement students are less willing to take on extra responsibility to make the learning decision, while high-achievement students tend to learn autonomously.

Therefore, as low-achievement students heavily rely on direct supports from the system, the recommendations given to them should be as useful and simple as possible (e.g., a complete package of learning objects). The complex decision model can therefore be hidden in the background from them. For high-achievement students, educational contextual information does help, especially the information of group relevance and object descriptions. Furthermore, they tend to ignore the non-educational information of support of past browsing events. Finally, for middle-achievement students, a controversy exists among the preferences for various information types. As a result,
there is a need of providing the support from multiple perspectives, including educational and non-educational ones, for middle-achievement students to make sensible decisions on taking recommendations.

**Perspective 2: How well students think the system has done the jobs**

As a whole, the efficiency of the recommender is acceptable to most students. However, the friendliness of the system is simply moderately acceptable. As aforementioned, different student groups have different needs for the decision model; therefore, the system interface should also be adaptable to different student groups. Furthermore, the accuracy of recommendation is more acceptable than the recall rate, especially for recommendations generated based on the educational contextual information.

**Perspective 3: The performance of the contextualized brewing recommendation model**

The preliminary experiment showed that students using the recommender with contextualized browsing model gained higher achievement than those using the recommendation model with pure association mining. It showed that contextualizing browsing events is a potential way to improve the performance of the recommender.

**Concluding Remarks**

In this paper, a new method for discovering contextualized browsing events based on association mining and statistical techniques is proposed. Also presented is a Web-based LCMS system, called IDEAL, which fulfills the idea of designing and disseminating personalized learning objects. As outlined in Perspective 2 of the previous section, the current data mining approach, though providing useful browsing experiences, fails to take care of each student’s individual needs. Therefore, more types of contextual information, such as the learning style, learning orientation (Martinez, 2001), and student learning states, could also be considered in order to mine out more personal learning patterns. As a result, it is worth acquiring the knowledge of more types of educational contextual information so that their effects on personalized learning can be investigated in future research.

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