ASSOCIATION RULES AS WAY FOR BUILDING OPTIMAL LEARNING PATH

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Abstract

With huge number of learning materials distributed in the Internet, students are suffering finding the right materials. They spend a lot of time, firstly, in surveying and collecting such materials, and then, going through the documents to find the useful information. Furthermore, these materials may store in such way that make its reading is difficult. Thus, it will be great help if we guide students during their searching process. This paper presents a method that is based on well-known data mining technique for constructing browsing path. The proposed method combines two main approach, the learning path construction approach and the learning object (LO) recommendation approach. Firstly, we find a set of candidate LOs based on the well-known Apriori algorithm. Then, the learning path construction approach uses the extracted rules from the collected learning object to build a reading map.

Keywords: Adaptive and Intelligent Web-based Educational Systems (AIWBES); Association rules; Concept map; VSM; Prerequisite; Epistemological order

ملخص:

مع الانتشار الكبير في شبكة الانترنت للمواد التعليمية، يعاني المتعلمين الكثير في إيجاد المواد التعليمية المناسبة. لذا يقضون الكثير من الوقت لإيجاد تلك المواد ومن ثم يقومون بالبحث في تلك المواد للحصول على ما يفيدهم من معلومات. هذا بالإضافة إلى أن هذه المواد التعليمية قد خزنت بطريقة ما من ما يصعب القراءة فيها. لذا كان من المفيد إذا تم مساعدة المتعلمين من خلال عملية بحثهم على مثل تلك المواد. يقدم هذا البحث منهجية تعتمد على تقنية استخراج البيانات لبناء مسار التصفح.

وتحتوي المنهجية المقترحة على طريقتين طريقة بناء مسار التعلم و طريقة توصية وحدات التعلم. في البدء نقوم باختيار مجموعة من الباحثين بطريقة وحدات التعلم بالاعتماد على خوارزميات سابقة. ومن ثم طريقة بناء مسار التعلم باستخدام القواعد المستخلصة من وحدات التعلم المجمعة وذلك حتى يتسنى بناء خريطة القراءة.

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1. INTRODUCTION

As it is known that, most of the self-directed learners spend most of time in surveying and choosing the right learning materials collected from the Internet and most of those materials are imperfect and have no particular order in the content.

Adaptive and Intelligent Web-based Educational Systems (AIWBES) provide an alternative to the traditional "just-put-it-on-the-Web" approach in the development of Web-based educational courseware (Brusilovsky and Miller, 2001). This can be explained by the multitude of advantages that it offers. In particular, these systems accumulate a great deal of information which is very valuable in analyzing students' behavior and assisting them in the detection of possible errors, shortcomings and improvements of their learning process by building optimal pedagogical path (Samia Azough et al., 2010). According to (Romero and Ventura, 2006, 2007) the use of data mining is a promising area in the achievement of these objectives. In recent years, researchers have begun to investigate various data mining methods in order to help learners improve their programming learning process. Some of the most useful data mining tasks and methods are clustering, classification and association rule mining for example, in the National University of Singapore the data mining application have been used for classifying and selecting those students who need extra classes in a given subject. With the help of data mining they are able to select the targeted students much more precisely than by traditional methods (Ma et al., 2000). (Myller al., 2002) applied EM (Expectation-Maximization) – algorithm for clustering the students to construct homogeneous groups in terms of programming skills according to the students' skills, to predate exam results according to the skills shown in exercises. (Mostafavi and Barnes, 2010) suggested to use educational data mining methods as a way for creation a system that can judge a student's performance by the way he/she responds to questions (they gathered data from an introductory programming course teaching C++) for determining where the student needs to help. (Dominguez et al., 2010) integrated data mining into an e-learning system to generate dynamically tailored hints for students who are completing programming exercises during a national programming online tutorial and competition.

These methods uncover new, interesting and useful knowledge based on students' usage data. Some of the mains e-learning problems or subjects to which data mining techniques have been applied (Castro et al., in press) are provide course adaptation and learning recommendations based on the students' learning behaviour, dealing with the evaluation of learning material and educational web-based courses, provide feedback to both teachers and students of e-learning courses, and detection of atypical student's learning behaviour. This knowledge,

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however, can be useful not only to the providers (educators) but also to the users themselves (students), as it can be oriented towards different ends for different partakers in the process (Zorrilla et al., 2005). It could be oriented towards students in order to recommend learners'activities, resources, suggest path or simply links that would favor and improve their learning. In this paper, we propose an approach to build the suitable pedagogical path based on the association rules. The remainder of the paper is organized as follows. In section 2, we discuss the related work. Proposed approach is given in Section 3.In Section 4 we use an example to illustrate the process of constructing concept maps based on the proposed method. Section 5 concludes the whole paper and discusses the future work.

2- RELATED WORK.

The e-learning systems act as an adaptive system if they select the path of learning that meet the learner's requirements and needs and discard those paths, which are not in accordance with these needs (Alian and Jabri, 2009), to achieve this goal, learner model and domain model are two of the key problems. A human behavior based learner model can be learned by observing the learner's actions therefore learner model can be built based on learner's behavior during solving task. (Tsai et al., 2001) used two-phase fuzzy mining and learning algorithm. They integrated an association rule mining algorithm, called Apriori, with fuzzy set theory to find embedded information that could be fed back to teachers for refining or reorganizing the teaching materials and tests. In a second phase, they used an inductive learning algorithm of the AQ family: AQR, to find the concept descriptions indicating the missing concepts during students' learning. The results of this phase could also be fed back to teachers for refining or reorganizing the learning path. (Chen et al., 2005) used association rule learning to discover common learning misconception of learning. According to that, the obtained rules can be applied to tune courseware structure through modifying the difficulty parameters of courseware in the courseware database. (Carchiolo et al., 2002) proposed an adaptive system for e-learning, which provides students with all paths from an initial knowledge to a desired one. The paths are retrieved and optimized based on student profile and teacher profile. Thus discarding those paths, which are not in accordance with the student's needs and the remaining paths are presented to the student to select one path and learn its course units. (Chen et al., 2006) presented a Personalized Web-based Instruction System (PWIS) to construct suitable learning pathway based on a modified item response theory for helping learning. (Colace et al., 2005) also presented an approach, which can obtain the learning style and capabilities of each learner to arrange the learning path

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adaptively with most suitable teaching contents. (Zhang et al., 2007) proposed an assessment model based on Bayesian Networks, which assesses learning status by knowledge map after absorbing and analyzing test results and creates learning guidance. (Hsieh and Wang, 2010) presented a web-based learning support system that uses both the preference-based and the correlation-based algorithms for recommending the most suitable learning objects or documents for each unit of the courses in order to facilitate more efficient learning for the learner. (Lee et al., 2009) proposed to apply the algorithm of Apriori for Concept Map to develop an intelligent concept diagnostic system (ICDS). This system provides teachers with constructed concept maps of learners rapidly, and enables them to diagnose the learning barriers and misconception of learners instantly. (Azough et al., 2010) proposed an adaptive system in order to generate pedagogical paths which are adapted to the learner profile and to the current formation pedagogical objective. They have studied the problem as an "Optimization Problem". Using Genetic Algorithms, the system seeks an optimal path starting from the learner profile to the pedagogic objective passing by intermediate courses. (Huang et al., 2007) also used genetic algorithm and case-based reasoning to construct a near-optimal learning path. In this paper we present an algorithm for building adaptive learning system that finds the suitable learning path based on the Concept Map and Good Learners Average Rating (GLAR).

3- RESEARCH APPROACH

In a learning activity, each step has a learning focus, which was called ‘‘concept”. The learning of these concepts should be done in a proper sequence. This kind of learning sequence called epistemological order (Chen et al., 1999). ‘‘Epistemological order” is used to standardize the learning order of different concepts. Let's present the epistemological order in the Fig. 1, C_i and C_{i+1} represent two concepts. The connecting line between them represents that there is a correlation of a certain epistemological order in between.

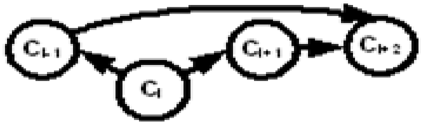

Fig.1. Epistemological order of concept

The arrow of the connected line represents the learning order. Therefore, Fig. 1 indicates that concept C_i precedes concept C_{i+1} in terms of the epistemological order. In addition, we can presume that the learner will have difficulty if he/she decided to read concept C_{i+1} before concept C_i. In general, the learner’s learning

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difficulty of concept C_{i+1} is caused by incomplete learning of concept C_i. Therefore, If C_i is a prerequisite to concept C_{i+1}, then teachers could identify the learning problems of students by tracing the relationship between concepts (Cheng et al., 2005; Hwang, 2003; Hwang et al., 2008), furthermore, it can be used to demonstrate how the learning status of a concept can possibly be influenced by learning status of other concepts and give learners adaptive learning guidance, therefore to provide learning suggestions to individual students, we firstly construct the concept map, then we suggest a personalized material according to social learning theory (Bandura, 1977) that strongly supports idea that people can learn by observing the behavior of others and outcome of behavior of good learner can increase their performance.

Therefore, the proposed approach uses the algorithm of Apriori for providing the learning guidance and Good Learners Average Rating to guide learners in selecting good learning resources in order to improve their learning process.

Phase 1: *The construction of concept map*

Phase 2: *Generate the suitable learning path*

Phase 3: *Suggestion of adaptive materials*

Phase 1: *The construction of concept map*

Assuming that there are n learning objects $LO_1, LO_2, \dots, LO_n$ in learning objects repository and let each learning object LO contains a m set of concepts: LO=$\langle C_1, C_2, C_3, \dots, C_m \rangle$.

The construction of concept map procedure includes five steps.

Step 1: *Determining the learner's goal*

Let's after analysis the learner's testing, found that the problem lies in the lack of understanding of a concrete concept and suppose that learner intends to learn more about this concept.

Step 2: *This step consists of 2 sub steps, shown as follows:*

Step 2a: *Identify the candidate Learning Objects*

Based on the learner's goal, the learning object repository (LOR) will search to find n learning objects that contained m related concepts. For simplicity, assume that the LOR found five learning object that are associated with the learner's goal and contain contents for among C_1, C_2 ,C_3,C_4 and C_5 concepts respectively where C_2 is a learner's goal as shown in Table 1.

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Table 1.*Learning objects that associated with the learner's goal*

Learning Objects	Related Concepts
LO_1	C_1, C_2, C_3, C_4 and C_5
LO_2	C_2, C_3 and C_5
LO_3	C_1, C_2, C_3 and C_5
LO_4	C_2 and C_5
LO_5	C_2 and C_4

Applying the Apriori algorithm (Agrawal and Srikant, 1994), we identify the largest item set by extract association rules among all collected LO, where an itemset is called a large-itemset if its support value is greater or equal to the user-specified support threshold (called minSupport) and an association rule is an expression $X \rightarrow Y$ where X and Y are disjoint itemsets, which represents possibility when X appears that Y will also appear. The support of an association rule is the support of X⋃Y, and the confidence of such a rule is the fraction of all transactions containing X that also contain Y (Hidber, 1999). The following is the detail of the Apriori algorithm.

Apriori algorithm

Input: Learning objects (**LO**), Threshold of minimum support value (**minSupport**).

Output: Large item sets in learning objects (**LI**).

Procedure:

1: LI_1 = find large 1-itemsets in **LO**.

2: For (k=2; $LI_{K-1} \neq \phi$;k++){

C_k = apriori-gen(LI_{K-1}); // New candidates

3: for all of records r $\in$ **LO** {

C_t = subset(C_k, r) // Candidates contained in r

for all of candidates c $\in C_t$

c.count++;}

LI_k ={c $\in C_K$ | c.count $\geqslant$ minSupport}}

4: **Return** LI= $\bigcup_k LI_k$;

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After the operation of the Apriori algorithm, the large item set is$\{C_2, C_3, C_5\}$ and the confidence of an association rule "$C_i \rightarrow C_j$" is calculated as follows:

$\mathrm{conf}(c_i \rightarrow c_j)=\frac{\mathrm{Sup}(c_i,c_j)}{\mathrm{Sup}(c_i)}$, where C_i is a concept in the large 1-itemset, C_j is a concept in the learning object, "$C_i \rightarrow C_j$" denotes the association rule from C_i to C_j , "$\mathrm{conf}(C_i \rightarrow C_j)$" denotes the confidence of the association rule "$C_i \rightarrow C_j$", "$\mathrm{Sup}(C_i, C_j)$" denotes the support of the 2-itemset "(C_i, C_j)" , "$\mathrm{Sup}(C_i)$" denotes the support of the large 1-itemset C_i ; $i \neq j$; $1 \leq i \leq n$ and $1 \leq j \leq n$.

In Table 2 shown the confidence of an association rule "$C_i \rightarrow C_j$"

Step 2b: *Find out all of the learning objects which are designated for the candidate concepts*

Table2.The confidence of an association rule"$C_i \rightarrow C_j$"

Rules	Confidence
$C_1 \rightarrow C_2$	1
$C_1 \rightarrow C_3$	1
$C_1 \rightarrow C_4$	0.5
$C_1 \rightarrow C_5$	1
$C_2 \rightarrow C_1$	0.4
$C_2 \rightarrow C_3$	0.6
$C_2 \rightarrow C_4$	0.4
$C_2 \rightarrow C_5$	0.8
$C_3 \rightarrow C_1$	0.667
$C_3 \rightarrow C_2$	1
$C_3 \rightarrow C_4$	0.33
$C_3 \rightarrow C_5$	1
$C_4 \rightarrow C_1$	0.5
$C_4 \rightarrow C_2$	1
$C_4 \rightarrow C_3$	0.5
$C_4 \rightarrow C_5$	0.5
$C_5 \rightarrow C_1$	0.5
$C_5 \rightarrow C_2$	1
$C_5 \rightarrow C_3$	0.75
$C_5 \rightarrow C_4$	0.25

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Step 3: *Presetting the relevance between concepts and learning objects by a teacher*

Assume that r_{ij} denotes the ratio of concept C_i contained in learning object LO_j that indicates the weight of the concept contained in the learning object. Then, we can get the Concept-Learning object matrix R, shown as follows:

$$R = \begin{array}{c} \\ C_1 \\ C_2 \\ \vdots \\ C_m \end{array} \begin{array}{c} \begin{array}{cccc} LO_1 & LO_2 & \cdots & LO_n \end{array} \\ \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ r_{m1} & r_{m1} & \cdots & r_{mn} \end{bmatrix} \end{array},$$

where $r_{ij} \in [0,1]$, $r_{ij} = 0$ denotes that the concept C_i doesn't appear in learning object LO_j, $r_{ij} = 1$ otherwise, $0 \le i \le m$ and $0 \le j \le n$. As shown in Table 3, five LOs contain these related concepts C_1, C_2, C_3, C_4 and C_5.Each $r_{C_iLO_j}$ is set by teacher.

Table3. *Concept-Learning Object relevance mapping table*

Concept	Learning Objects						
	LO_1	LO_2	LO_3	LO_4	LO_5	LO_6	LO_7
C_1	0.2	0.0	0.3	0.0	0.0	0.0	0.0
C_2	0.3	0.3	0.3	0.8	0.7	0.0	0.0
C_3	0.1	0.2	0.3	0.0	0.0	0.1	0.7
C_4	0.2	0.0	0.0	0.0	0.3	0.0	0.0
C_5	0.2	0.5	0.1	0.2	0.0	0.4	0.0
C_6	0.0	0.0	0.0	0.0	0.0	0.0	0.3
C_7	0.0	0.0	0.0	0.0	0.0	0.5	0.0

Step 4: Calculate the relevance degree between LOs.

For all association rules type"$C_i \to C_j$" obtained in Step 2, we calculate the relevant degree $rev(LO_i \to LO_j)_{C_xC_y}$between learning object LO_i and LO_j from the relationship"$C_x \to C_y$", shown as follows:

$$rev(LO_i \to LO_j)_{C_xC_y} = Min(W_{C_xLO_i}, W_{C_yLO_j}) * conf(C_x \to C_y)$$
(1)

where" $rev(LO_i \to LO_j)_{C_xC_y}$"denotes the relevance degree of the relationship "$LO_i \to LO_j$"converted from the relationship"$C_x \to C_y$", $rev(LO_i \to LO_j)_{C_xC_y} \in [0,1]$, $W_{C_xLO_i}$denotes the weight of the concept $C_x$in the learning object LO_i, $W_{C_yLO_j}$denotes the weight of the concept $C_j$in the Learning object LO_y, "$conf(C_x \to C_y)$"denotes the confidence of the relationship $C_x \to$

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C_y", $x \neq y$; $1 \leq x \leq m$, $1 \leq y \leq m$, $1 \leq i \leq n$ and $1 \leq j \leq n$. Furthermore, let $conf(LO_x \rightarrow LO_y)$ be the confidence of the relationship $LO_i \rightarrow LO_j$. If there is more than one relationship between any two constructed LOs, the relationship between them chooses as follows:

$rev(LO_i \rightarrow LO_j) = Max(rev(LO_i \rightarrow LO_j)_{C_x C_y})$ (2) Based on Eq. (1) mentioned above the relevance degree for the relationship $LO_1 \rightarrow LO_2$, calculated as follows:

$C_1 \rightarrow C_2$: Min (0.2, 0.3) ×1=0.2 (confidence=1)
$C_1 \rightarrow C_3$: Min (0.2, 0.2) ×1= 0.2(confidence=1)
$C_1 \rightarrow C_5$: Min (0.2, 0.5) ×1=0.2 (confidence=1)
$C_2 \rightarrow C_3$: Min (0.3, 0.2) ×0.6=0.12 (confidence=0.6)
$C_2 \rightarrow C_5$: Min (0.3, 0.5) ×0.8=0.24 (confidence=0.8)
$C_3 \rightarrow C_2$: Min (0.1, 0.3) ×1=0.1 (confidence=1)
$C_3 \rightarrow C_5$: Min (0.1, 0.5) ×1=0.1 (confidence=1)
$C_4 \rightarrow C_2$: Min (0.2, 0.3) ×1=0.2 (confidence=1)
$C_4 \rightarrow C_3$: Min (0.2, 0.2) ×0.5= 0.1 (confidence=0.5)
$C_4 \rightarrow C_5$: Min (0.2, 0.5) ×0.5=0.1 (confidence=0.5)
$C_5 \rightarrow C_2$: Min (0.2, 0.3) ×1=0.2 (confidence=1)
$C_5 \rightarrow C_3$: Min (0.2, 0.2) ×0.75= 0.15 (confidence=0.75)

And based on Eq. (2) the maximum value among these relevance degrees is:

$rev(LO_1 \rightarrow LO_2) = 0.24$

$conf(LO_1 \rightarrow LO_2) = conf(C_1 \rightarrow C_2) = 0.8$

By analogy, we calculate the relevance degree for all relationship $LO_i \rightarrow LO_j$ according to that we can get the learning objects-relationship table, as shown in ***Table 4.***

Learning Object-relationship	*Relevance degree*	*Confidence*
$LO_1 \rightarrow LO_2$	0.24	0.8
$LO_1 \rightarrow LO_3$	0.2	1
$LO_1 \rightarrow LO_4$	0.2	1
$LO_1 \rightarrow LO_5$	0.2	1
$LO_2 \rightarrow LO_1$	0.3	1
$LO_2 \rightarrow LO_3$	0.3	1
$LO_2 \rightarrow LO_4$	0.5	1
$LO_2 \rightarrow LO_5$	0.5	1
$LO_3 \rightarrow LO_1$	0.3	1

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$LO_3 \rightarrow LO_2$	0.3	1
$LO_3 \rightarrow LO_4$	0.3	1
$LO_3 \rightarrow LO_5$	0.3	1
$LO_4 \rightarrow LO_1$	0.2	1
$LO_4 \rightarrow LO_2$	0.4	0.8
$LO_4 \rightarrow LO_3$	0.2	1
$LO_4 \rightarrow LO_5$	0.24	0.8
$LO_5 \rightarrow LO_1$	0.16	0.8
$LO_5 \rightarrow LO_2$	0.4	0.8
$LO_5 \rightarrow LO_3$	0.3	1
$LO_5 \rightarrow LO_4$	0.3	1

Phase 2: *Generate the suitable learning path*

To fulfill a goal issued by a learner, learning objects must be arranged subsequently according to their weight and taught in the front side of the learning path, therefore for each relationship "$LO_i \rightarrow LO_j$" add an edge from LO_i to LO_j. The following algorithm briefs the learning path building procedure:

Learning Path Generation Algorithm

Input: Threshold value (θ), relevance degree matrix(REV), learning objects (LO) and total number of LOs (n).

Output: A suitable learning path (LP).

Procedure:

1: ***LP*** = {0}

2:While (length of LP < n){

if ($REV_{ij} < \theta$)

Set $rev_{ij} \leftarrow 0$

else

Arrange each LO_i according to their weight.

Add the $LO_i$to ***LP***

3: Return ***LP***.

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[Step 3b]: *Generate the optimal learning path*

Assume that, the threshold value given by learner is 0.75 then the previous figure will appear as follows:

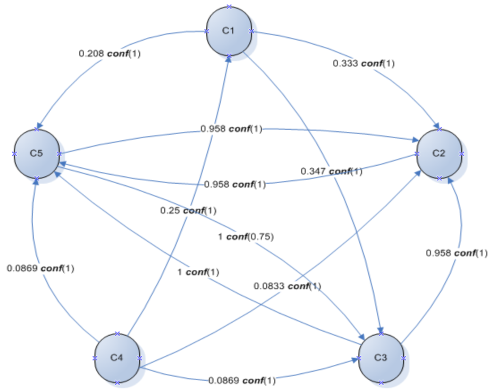

Fig3. *Concepts-relationship map according step3b*

[Step 3c]: *Generate the optimal learning path*

If a learner obtained to learn concept C_1 then the recommender concepts are C_3, C_2 and C_5, respectively , where $C_3 \in LO_3$, $C_2 \in LO_2$ and $C_5 \in LO_5$(for all other see Table 4.)

Table4.*Recommender learning path*

Learning Object	***Prerequisites LOs***	***Recommending LO***
C_1	C_4	C_3, C_2 and C_5
C_2	$(C_3, C_5), C_1$ and C_4	C_5
C_3	$C_5, C_1\, and\ C_4$	C_2
C_4	_	$C_1, (C_5, C_3) and\ C_2$
C_5	$C_1, C_2, C_1\, and\ C_4$	$C_3$and C_2

2. Future work and conclusion

In this paper, we have presented a new method for constructing learning path based on data mining techniques for adaptive learning systems. The proposed method combines two main approach, the learning path construction approach and the learning object recommendation approach. Firstly, we find a set of candidate LOs based on the well-known Apriority algorithm. Then, the learning path construction

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approach use the rules extracted from the collected learning object to build a Concept map, moreover, in order to assist a learner to study efficiently, the recommendation approach arranged the collected learning objects in the correct order to understand them efficiently.

In the future, we will try to integrate the proposed method with other efficient method. We also hope to study the user feedback and the impact on the profile of the learner.

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