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Constructing concept maps for adaptive learning systems based on data mining techniques

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ABSTRACT

In this paper, we propose a new method for automatically constructing concepts maps for adaptive learning systems based on data mining techniques. First, we calculate the counter values between any two questions, where the counter values indicate the answer-consistence between any two questions. Then, we consider four kinds of association rules between two questions to mine some information. Finally, we calculate the relevance degree between two concepts derived from the association rule to construct concept maps for adaptive learning systems. The proposed method can overcome the drawbacks of Chen and Bai's (2010) and Lee et al.'s method (2009). It provides us with a useful way to construct concept maps for adaptive learning systems based on data mining techniques.

1. Introduction

In recent years, some researchers focused on the research topic of adaptive learning systems (Bai & Chen, 2008a, 2008b, 2008c; Chen & Bai, 2010; Chen, Hsieh, & Hsu, 2007; Cheng, Lin, & Huang, 2009; Chen & Sue, 2010; Chen, Wei, & Chen, 2006; Gonida, Voulala, & Kiosseoglou, 2009; Heift & Schulze, 2003; Huang, Lin, & Cheng, 2009; Kelly & Tangney, 2006; Lee, Lee, & Leu, 2009; Shen, Yang, Wang, & Lin, 2012; Sue, Weng, Su, & Tseng, 2004; Wang, Tseng, & Liao, 2009). Bai and Chen (2008a) presented a method for evaluating students' learning achievement using fuzzy membership functions and fuzzy rules. Bai and Chen (2008b) presented a method for automatically constructing grade membership functions of fuzzy rules for students' evaluation. Bai and Chen (2008c) presented a method for automatically constructing grade membership functions of fuzzy rules for students' evaluation. Chen and Bai (2010) presented a method for automatically constructing concept maps based on fuzzy rules for adapting learning systems. Lee et al. (2009) presented a method to automatically construct concepts maps for conceptual diagnosis. However, it has some drawbacks that it constructs unnecessary concepts-relationships in concept map. Chen and Bai (2010) presented a method to automatically construct concept maps based on data mining techniques to overcome the drawbacks of Lee et al.'s method (2009). Chen et al. (2007) presented a remedy learning approach based on the discovered common learning misconceptions to promote the learning performance. Chen et al. (2006) applied text-mining techniques to automatically construct concept maps for the e-learning domain. Cheng et al. (2009) presented a dynamic question-generation system for web-based tests using particle swarm optimization techniques. Gonida et al. (2009) presented student modeling techniques for computer-assisted language learning. Heift and Schulze (2003) presented a method for student modeling and ab initio language learning. Huang et al. (2009) presented an adaptive testing system for supporting versatile educational assessments. Kelly and Tangney (2006) presented a system called EDUCE which explores the effect of using different adaptive presentation strategies and their impact on learning performance. Shen et al. (2012) presented a learning evaluation model based on a high-level fuzzy Petri net (HLFPN) model. Sue et al. (2004) presented a two-phase concept map construction (TPCMC) approach to automatically construct concept maps based on learners' historical testing record. Wang et al. (2009) presented a method for learning sequence in English language instruction based on data mining techniques.

In this paper, we propose a new method for automatically constructing concepts maps for adaptive learning systems based on data mining techniques. First, we calculate the counter values between any two questions, where the counter values indicate the answer-consistence between any two questions. Then, we consider four kinds of association rules between two questions to mine some information. Finally, we calculate the relevance degree

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between two concepts derived from the association rule to construct concept maps for adaptive learning systems. The proposed method can overcome the drawbacks of Chen and Bai's method (2010) and Lee et al's. method (2009). It provides us with a useful way to construct concept maps for adaptive learning systems based on data mining techniques.

2. A review of Chen and Bai's method for constructing concept maps based on data mining techniques

Chen and Bai (2010) presented a method for automatically constructing concept maps based on data mining techniques. In the following, we briefly review Chen and Bai's method (2010). Assume that there are n learners $S_1, S_2, \ldots, S_n$, m questions $Q_1, Q_2, \ldots, Q_m$, and p concepts $C_1, C_2, \ldots, C_p$, then we can transform the test portfolio of the learners and the degree of relevance between test questions and concepts into the grade matrix G and the questions-concepts matrix QC, respectively. Let Q_i denote the ith question, where $1 \leqslant i \leqslant m$, and let S_j denote the jth learner, where $1 \leqslant j \leqslant n$. Then, we can get the grade matrix G, shown as follows:

$$G = \begin{array}{c} \\ Q_1 \\ Q_2 \\ \vdots \\ Q_m \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & \cdots & S_n \end{array} \\ \begin{bmatrix} g_{11} & g_{12} & \cdots & g_{1n} \\ g_{21} & g_{22} & \cdots & g_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ g_{m1} & g_{m2} & \cdots & g_{mn} \end{bmatrix} \end{array},$$

where $g_{ij} \in \{0,1\}$, $g_{ij} = 1$ denotes the learner S_j gets the right answer in question Q_i, $g_{ij} = 0$ denotes the learner S_j has a wrong answer in question Q_i, where $1 \leqslant i \leqslant m$ and $1 \leqslant j \leqslant n$. In the same way, we can construct the questions-concepts matrix QC, shown as follows:

$$QC = \begin{array}{c} \\ Q_1 \\ Q_2 \\ \vdots \\ Q_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_p \end{array} \\ \begin{bmatrix} qc_{11} & qc_{12} & \cdots & qc_{1p} \\ qc_{21} & qc_{22} & \cdots & qc_{2p} \\ \vdots & \vdots & \ddots & \vdots \\ qc_{m1} & qc_{m2} & \cdots & qc_{mp} \end{bmatrix} \end{array},$$

where qc_{ij} denotes the degree of relevance of question Q_i with respect to concept C_j and $0 \leqslant qc_{ij} \leqslant 1$. In the following, we briefly review Chen and Bai's (2010) as follows:

Step 1: Based on the grade matrix G and the Apriori algorithm (Agrawal & Srikant, 1994), mining two kinds of association rules between questions:

(1) if question Q_i is correctly learned by the learner, then question Q_j is also correctly learned by the learner,
(2) if question Q_i is incorrectly learned by the learner, then question Q_j is also incorrectly learned by the learner.

Construct the association rules from the large 1-itemset with respect to the other questions and calculate the confidence of the rules, where the confidence "conf($Q_i \to Q_j$)" of an association rule "$Q_i \to Q_j$" is calculated as follows:

$$\mathrm{conf}(Q_i \to Q_j) = \frac{\sup(Q_i,\ Q_j)}{\sup(Q_i)}, \tag{1}$$

where Q_i is a question in the large 1-itemset, Q_j is a question in the test paper, "$Q_i \to Q_j$" denotes the association rule from Q_i to Q_j, "conf ($Q_i \to Q_j$)" denotes the confidence of the association rule "$Q_i \to Q_j$", "sup(Q_i, Q_j)" denotes the support of the 2-itemset (Q_i, Q_j), "sup(Q_i)" denotes the support of the large 1-itemset Q_i, where $1 \leqslant i \leqslant m$, $1 \leqslant j \leqslant m$ and $i \neq j$.

Step 2 : Based on the association rules obtained in Step 1, construct two kinds of questions-relationship maps. For the association rules that question Q_i is correctly learned by the learner and question Q_j is also correctly learned by the learner, build the relationship from question Q_j to question Q_i in the "correct-to-correct questions-relationship map" associated with the confidence. For the association rules that the learner failed question Q_i and failed question Q_j, build the relationship from question Q_i to question Q_j in the "failure-to-failure questions-relationship map" associated with the confidence.

Step 3 : Convert the two kinds of question-relationship maps obtained in Step 2 into the concept-relationship table. Calculate the relevance degree $\mathrm{rev}(C_i \to C_j)_{Q_xQ_y}$ between concepts C_i and C_j from the relationship $Q_x \to Q_y$, shown as follows:

$$\mathrm{rev}(C_i \to C_j)_{Q_xQ_y} = \mathrm{Min}(W_{Q_xC_i}, W_{Q_yC_j}) \times \mathrm{conf}(Q_x \to Q_y), \tag{2}$$

where "$\mathrm{rev}(C_i \to C_j)_{Q_xQ_y}$" denotes the relevance degree of the relationship "$C_i \to C_j$" derived from the relationship "$Q_x \to Q_y$", $\mathrm{rev}(C_i \to C_j)_{Q_xQ_y} \in [0,\ 1]$, C_i denotes a concept appearing in the question Q_x, C_j denotes a concept appearing in the question Q_y, $W_{Q_xC_i}$ denotes the weight of concept C_i in question Q_x, $W_{Q_yC_j}$ denotes the weight of concept C_j in question Q_y, "conf ($Q_x \to Q_y$)" denotes the confidence of the relationship "$Q_x \to Q_y$", $1 \leqslant i \leqslant p$, $1 \leqslant j \leqslant p$, $i \neq j$, $1 \leqslant x \leqslant m$, $1 \leqslant y \leqslant m$ and $x \neq y$. If there are more than one relationship between any two concepts, then choose the relationship which has the maximum relevance degree between them.

Step 4 : Combine the concepts-relationship tables obtained in Step 3 into the combined concepts-relationship table, described as follows:

(1) If the relationship "$C_i \to C_j$" only exists in one of concepts-relationship tables, then put it to the combined concepts-relationship table.
(2) If the relationship "$C_i \to C_j$" exists in both concepts-relationship tables, then calculate the difference degree $\frac{|\mathrm{rev}(C_i \to C_j)^* - \mathrm{rev}(C_i \to C_j)^{**}|}{\mathrm{Max}\left(\mathrm{rev}(C_i \to C_j)^*,\ \mathrm{rev}(C_i \to C_j)^{**}\right)}$, where "$\mathrm{rev}(C_i \to C_j)^*$" denotes the relevance degree of the relationship $C_i \to C_j$ in the "correct-to-correct concepts-relationship table", "$\mathrm{rev}(C_i \to C_j)^{**}$" denotes the relevance degree of the relationship $C_i \to C_j$ in the "failure-to-failure concepts-relationship table", $1 \leqslant i \leqslant p$ and $1 \leqslant j \leqslant p$. If the difference degree is larger than the threshold value λ, where $0 \leqslant \lambda \leqslant 1$, then delete the relationship $C_i \to C_j$. Otherwise, choose the relationship which has the largest relevance degree between the concepts C_i and C_j.

However, Chen and Bai's method (2010) has the drawback that it does not correctly construct concept maps in some situations. In the following, we use an example to show the drawback of Chen and Bai's method. Assume that there are four learners S_1, S_2, S_3, S_4, three questions Q_1, Q_2, Q_3 and two concepts C_1, C_2. Assume that the test portfolio of the learners is represented by a matrix A, shown as follows:

$$A = \begin{array}{c} \\ Q_1 \\ Q_2 \\ Q_3 \end{array} \begin{array}{c} \begin{array}{cccc} S_1 & S_2 & S_3 & S_4 \end{array} \\ \begin{bmatrix} 1 & 1 & 0 & 0 \\ 1 & 1 & 1 & 1 \\ 1 & 1 & 0 & 0 \end{bmatrix} \end{array},$$

where $A[i,j] \in \{0,1\}$, $A[i,j] = 1$ denotes learner S_j gets the right answer in question Q_i, $A[i,j] = 0$ denotes learner S_j does not get the right answer in question Q_i, $1 \leqslant i \leqslant 3$ and $1 \leqslant j \leqslant 4$. Assume that the degree of relevance between test questions and concepts is represented by the matrix B, shown as follows: