A FRAMEWORK TO INCORPORATE DOMAIN KNOWLEDGE MODELING IN AN EDUCATION SYSTEM

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Abstract: This paper strives to present a solution for modeling the domain knowledge of a University Consortium instructional environment. This model determines the learners' prior knowledge on a particular subject based on the learners' background. The calculated prior knowledge of learners is used to select appropriate learning material for a particular type of learner. This framework may help a University Consortium Education System to sequence appropriate learning materials for a particular type of learner.

Keywords: Domain knowledge, e-learning, University Consortium.

Introduction : Learners of pursuing courses can have same educational background, significant differences are observed in them concerning their level of knowledge on the topics which they have already learnt. In particular, in case of interdisciplinary courses, learners may have diverse educational background and training on varying subjects. Subjects that such learners have studied may or may not relate to those of a course now being pursued.

A requirement, therefore, arises to ascertain the level of understanding that the learners' have acquired respectively in their chosen subjects. In an e-learning environment, learners could then segregate in groups so that the appropriate learning material can be delivered to each of the learners.

To build an intelligent system, a number of universities from diverse geographical locations together forming a University Consortium learning system [18], need an infusion of an effective active learning methodology supporting student-centric, self-paced and highly interactive learning environment.

In other words, to support customized learning processes, the University Consortium learning system would use selection, organizing and presenting the learning materials to individual students based on the needs of individual students i.e., learning styles, pedagogical rules, and background knowledge.

University Consortium would offer courses by providing common portal [15]. Online learning courses shall be used by learners who differ widely in terms of prior knowledge of the domain. Especially, in higher education and learning on interdisciplinary courses, some learners may have a background consisting of portions of knowledge of the course, while others could well be complete beginners.

However, regardless of the level and extent of prior knowledge, all the learners would need to have the same knowledge after completion of the course. On the one hand, users might lose active interest if they have to work on topics that they are already familiar with. On the other hand, they may not be in a position to estimate whether they do really know everything about a topic of a course without having gone through the chapters. Thus, letting users themselves decide whether they have enough knowledge or not, might result in an incomplete knowledge acquisition. Moreover, prior knowledge has an impact on the learning gain [11].

People learn by building on prior knowledge and abilities. This suggests it is important to design educational activities that are relevant to learners' prior knowledge so they can treat lessons meaningfully [12]. By the same token, learners need the appropriate prior knowledge to start with. If learners do not have useful prior knowledge, then there is a risk and high probability that they will build new knowledge on a faulty foundation. They might develop misconceptions or brittle behavioral routines, too.

In this paper, we will introduce a teaching methodology which gives the prior knowledge of the learners on the subjects of pursuing courses. The background and relatedworksare presented in the next two sections. Sections after that, analyzes the methodology (theoretical model) of determining the learners' prior knowledge, subsequent to the mathematical model for representing the domain knowledge has been proposed and this model has been executed with a complete set of data.

Background and Related Works

The popularity of the Internet, and recent developments in education technology, has created new possibilities for online learning. However, the problem of the "one-size-fits-all" may result in high dropout rates, and instill low levels of motivation and satisfaction. Human beings are different and as such they learn and process information in different ways. Past experience, prior knowledge, skills, learning style and interests are among the factors that may affect the individuals' requirements for effective learning. Instead of delivering the same content to all users, e-learning systems should be able to adapt to each individual's characteristics in order to increase the relevance and appropriateness of the learning material. The prior knowledge assessment and the learning style questionnaire proved to be simple but useful tools to gather necessary information about the user in order to deliver personalized e-learning experience. Based on the learners' feedback concerning the respective learner's prior knowledge and the learning style, selection of the LOs (introductory, intermediate or advanced) is made, and then the organization of the LOs is framed [14]. The process of personalized course construction starts with collecting information about the user's existing knowledge. This information is then used to match the level of LOs. The interoperability andreusability of developed learning materials are other aims of e-learning. The instructors may face a large number of the learning objects that may make them recombine a new teaching material laboriously, and the instructors might have to take in more than one factor or criterion into account when they organize a well structured teaching material. Bearing this in mind, an approach - particle swarm optimization (PSO) is used to generate particular teaching materials automatically [9]. But instructors have to specify multiple criterion that are scaled according to the degrees of difficulty of selected learning objects, range of expected lecture time, and relationship between selected learning objects and specified topics. Schedulingmodel for learning content organization has also developed based on pre-test, knowledge points learning (the granularity of learning object as a knowledge point), post-test and evaluation of learners [7]. The current SCORM content aggregation model uses a rule-driven approach that defines the intended sequencing and ordering of learning activities inside of a tree-structured content organization, but a process driven approach can be used to the SCORM content aggregation model [10]. The approach intends to replace the tree-structured content organization scheme, which is clearly evident in SCORM, by the concept of a process-driven content organization scheme to realize the learning activities' sequencing and ordering functionality, The process-driven e-Learning content organization model is based on a mathematical formalism and also aims to specify and analyze learning activity flows and processes for e-Learning instructions. So the learning process designer is able to easily build a process-driven content organization model through the graphical notation. To enable a learner to pursue a course which is fitting and relevant, as well as being appropriate, on the basis of his / her background knowledge, we have discussed and introduced a teaching methodology for learners. This methodology aims at providing an insight into a subject of a course being pursued by each and every learner in advance based on prior subject knowledge. The proposed method consists of the following steps: building a relation among "pursuing subjects", and union of the "pursuing subjects" and course related subjects; collect the information about the background knowledge on pursuing subjects and course related subjects.

Theoretical Model for Representing the Domain Knowledge

In this section, we describe a learning methodology for the learners of pursuing courses. Though, the learners of pursuing courses can have same educational background (in case of interdisciplinary courses, learners have the diverse educational background and training on varying subjects), significant differences are observed in them concerning their level of knowledge on the topics which they have already learnt. Also, their subjects may or may not relate to those of a course now being pursued**.** Therefore, considering the learners' previous knowledge and, further, considering a relation between the subjects which can be found in common to the one that a learner may have already studied, and those in the curriculum of the pursuing course, we propose the following approach:

● Relate all the "pursuing subjects" to the "union of the pursuing subjects and their related subjects (list of subjects which helps to learn the pursuing subjects)" on the basis of whether each constituent portion of the union helps to learn the pursuing subjects or not.

On the basis of the amount of subject matter/content related with the pursuing subject, points are selected from a numerical scale graded from 0 to 3, where 3 indicates strong relation while 0 represents the least strength or no relation at all. The details of the ranking, through this scale, have been described below:

3 → the "pursuing subjects" and the "union of the pursuing subjects and their related subjects"are strongly related (very large portions of subject matter are related).

2 → the "pursuing subjects" and the "union of the pursuing subjects and their related subjects"are related (large portions of subject matter are related).

1 → the "pursuing subjects" and the "union of the pursuing subjects and their related subjects"are weakly related (scattered amounts of subject matter are related).

0 → the "pursuing subjects" and the "union of the pursuing subjects and their related subjects"are not related.

● Relate all learners with the pursuing subjects and their related subjects on the basis of their knowledge on those subjects.

Again, a numerical scale graded from 0 to 2 is used to determine the level of the knowledge of a particular learner, on pursuing and related subjects.

On this scale, grade 2 indicates that the particular learner has an educational background with prior knowledge on the subjects. Grade 1 denotes the learner's lack of educational background despite knowledge in those subjects. The total lack of educational background and knowledge base of the learner in the pursuing and related subjects, are denoted by grade 0.

2 → the learners of pursuing courses have educational background with pursuing subjects or related subjects.

1 → the learners of pursuing courses do not have educational background with pursuing subjects or related subjects and but have knowledge on those subjects.

0 → the learners of pursuing courses do not have educational background with pursuing course or related subjects but do not have knowledge on those subjects.

- Using the above two relations, construct a data table which provides previous / prior knowledge on the pursuing subjects.

MathematicalModel for Representing the Domain Knowledge

Let X be the set of all learners pursuing a particular course, Y be the set of all subjects of pursuing course, and $Y^{'}$ be the set of pursuing subjects together with their related subjects. Let R be a binary relation between Y and $Y^{'}$, where R is defined by $s \in Y$ is related to $s^{'} \in Y^{'}$ - if, "to learn s, knowledge of $s^{'}$ is essential" (help to learn). Similarly, let R' be a binary relation between X and $Y^{'}$, where $x \in X$ is related to $s^{'} \in Y'$ - if, $x \in X$ has knowledge on $s^{'} \in Y'$.

For the learner $x \in X$ and having the previous knowledge on some of the subjects of $s_i \in Y'$, we define the truth degree of the fact "the student $x \in X$ has knowledge on the subject $s_k \in Y$" as

$$I(x,s_k) = \frac{\sum_i \min_i \{w(x;s_i), w(s_k;s_i)\}}{\sum_i w(s_k;s_i)},$$

where $w(s_k;s_i)$ is the weight given on the subject $s_i \in Y'$ considering if $(s_k,s_i) \in R$ and $w(x;s_i)$ is the weight given on the subject $s_i \in Y'$ and if $(x,s_i) \in R'$. We denote this truth value by $I(x,s_k)$. This truth value $I(x_i,s_j)$ expresses the degree to which the learner x_i carries the knowledge on s_j.

Example: Consider $Y = \{s_1, s_2, s_3, s_4, s_5\}$ as a set of pursuing subjects and $Y^{'} = \{s_1, s_2, s_3, s_4, s_5, s_6, s_7, s_8\}$ as a set of pursuing subjects, together with their related subjects and $X = \{x_1, x_2, x_3, x_4, x_5\}$ as a set of learners. We also consider the following two relations given in Table 1 and Table 2, respectively. Using the above-described transformation, we obtain a fuzzy context given in Table 3.

	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
s_1	1(3)	0(0)	0(0)	0(0)	0(0)	1(2)	0(0)	0(0)
s_2	1(1)	1(3)	0(0)	0(0)	0(0)	0(0)	1(1)	0(0)
s_3	1(0)	1(1)	1(3)	0(0)	0(0)	0(0)	0(0)	1(1)
s_4	0(0)	0(0)	0(0)	1(3)	0(0)	1(1)	1(1)	0(0)
s_5	1(1)	0(0)	0(0)	0(0)	1(3)	1(1)	0(0)	0(0)

Table 1. A binaryrelation between the set of 'pursuing subjects' and the union of 'pursuing subjects and its related subjects'

	s_1	s_2	s_3	s_4	s_5	s_6	s_7	s_8
x_1	1(2)	0(0)	0(0)	1(1)	1(2)	1(2)	1(1)	0(0)
x_2	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)	1(1)	0(0)
x_3	1(2)	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)	0(0)
x_4	1(2)	1(2)	1(1)	0(0)	0(0)	1(2)	0(0)	1(1)
x_5	0(0)	0(0)	0(0)	1(1)	0(0)	1(2)	1(1)	0(0)

Table 2.A binaryrelation between the set of 'learners' and the union of 'pursuing subjects and its related subjects'

Here Table 1 describes the relation between Y and Y', where table entries $r_{ij} = 1$ denote that "to learn the subject $s_i \in Y$, knowledge of $s_j \in Y'$ is required", and $r_{ij} = 0$ otherwise. In Table 1, the weights $w(s_i; s_j)$ on the subjects $s_j \in Y'(j = 1,2,.....8)$ for $s_i \in Y(i = 1,2,.....5)$ are shown within brackets in the table entries. Similarly, Table 2 describes the relation between Y and Y', where table entries $r'_{ij} = 1$ denote that the learners $x_i \in X(i = 1,2,.....5)$ have knowledge on $s_j \in Y'(i = 1,2,.....8)$, and $r'_{ij} = 0$ if the learner $x_i \in X$ do not have knowledge on $s_j \in Y'$. In Table 2, the weights $w(x_i; s_i)(i = 1,2,....8)$ on the subjects $s_i (i = 1,2,.....8)$ for the learners $x_i \in X(i = 1,2,.....5)$ are shown within brackets in the table entries.

Next, using the above-described transformation, we obtain the following Table 3 as fuzzy context which provides the knowledge information on the pursuing subjects for each learner.

	s_1	s_2	s_3	s_4	s_5
x_1	0.8	0.4	0.0	0.6	0.8
x_2	0.0	0.2	0.0	0.2	0.0
x_3	0.4	0.2	0.0	0.0	0.2
x_4	0.8	0.6	0.6	0.2	0.4
x_5	0.4	0.2	0.0	0.6	0.2

Table 3. Fuzzy context

It may appear from the Table 2 that learners x_2 and x_5 are inappropriate candidates for pursuing the above course and they may be discouraged to pursue it. But on the basis of their previous knowledge, we are able to infer from the Table 3 that both learners have knowledge on some subjects of pursuing course. Especially, we can say that the learner x_5 could well be one of best learners for this course.

Conclusion : In this paper, we have introduced a teaching methodology for the learners on the basis of their background knowledge. This method aims at providing an insight into a subject of a pursuing course of each learner in advance, and also helps a learner to pursue a course which is fitting and appropriate in the context of his/her background knowledge.

The proposed method consists of the following steps: building a relation among "pursuing subjects", and union of the "pursuing subjects" and course related subjects; collect the information about the background knowledge of the learner on pursuing subjects and course related subjects. In this paper, we have also discussed proposed model with an example. In future, we will analysis the data table of background knowledge using Fuzzy Formal Concept Analysis. The data table of background knowledge is a concrete example of fuzzy formal context. Students representobjects, subjects represent attributes and corresponding valuations represent values assigned to every object–attribute pair by fuzzy binary relation over the set [0,1]. Therefore using Fuzzy Formal Concept Analysis, we can find clusters of students similar by their studying results of all subjects, or to find clusters of subjects similar by knowledge of all students. In other words to find pairs of classical subset of objects or attributes and fuzzy subset of attributes or objects. Similarity is determined by fuzzy subsets. Moreover based on their prior knowledge on the pursuing subjects, we will also divide all learners into three groups of clusters of students, so that cluster of students belonging to the first group may learn the subjects starting with basic of the subjects; the cluster of students classified under the second group may learn the subjects starting with intermediate level of knowledge on the subjects; and the cluster of students who belong to the third group may learn the subjects starting with advance level of the subjects. Our future works will build blocks of the framework which ultimately help in selecting and sequencing the appropriate, and consequently, the most effective learning materials for a given type of a learner.

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