Effective Reasoning of Learning Styles using Rough Set Theory in e-Learning

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Abstract: - This study suggests an effective way to extract knowledge which can decide learners' learning styles in e-learning environments. The proposed system provides the adaptive learning contents to the leaner using the extracted rule. Rough Set theory is efficient in extracting the needful knowledge from enormous and various amounts of data. Accordingly, we show the method that extracts rules. The system can decide learners' learning styles using the rules from amounts of data in e-learning system. It is possible by rough set theory. The proposed system will be able to increase efficiency of learning as providing learning contests based on learner's style. In short, this study proposes a plan that distinguishes learning style to increase an efficiency of learner and applies to e-learning environment.

Key-Words: - Rough Set Theory, Learning Style, e-Learning

1. Introduction

There are various kinds of data including information on learners and learning in e-learning systems. Stored data provides useful clues for effective learning to learners. The amounts of these data are successively increased as processing of learning. The increment of data, however, decrease efficiency of systems and has difficulty in extracting adaptable data from users (learners, tutors and managers). In this reason, we suggest the application plan of rough set theory in order to extract appropriate knowledge from enormous amounts of data in e-learning systems.

Learning style is an important factor in learning [7][4]. Especially, learning methods in online learning are suitably given according to learners' situation and environments. From this point of view, rough set theory can be efficiently used to extract rules for providing learning and to decide learners' learning styles on the basis of data referring to learners. In this study, we extracted rules of learning style by using LMS system data that was operated with elementary school students in Korea. Also, basing on this, we suggested the design of system that selects learning contents by rules of learning style and gives to the learner.

2. Background

2.1 Rough Set

Rough Set (RS) theory is a mathematical formalism developed by Zdzislaw Pawlak to analyze data tables [10] [6]. Its peculiarity is a well understood formal model, which allows finding several kinds of information, such as relevant features or classification rules, using minimal model assumptions.

In RS data model information is stored in a table, where each row (tuple) represents a fact or an object. All we know about a real world object is the corresponding tuple in the table. Interesting data tables are usually difficult to analyze. They store a huge quantity of data, which is hard to manage from a computational point of view.

Moreover, it is possible for some facts not to be consistent to each other. One of the main objectives of RS data analysis is to reduce data size [6]. It can be used for reduction of data sets, finding hidden data patterns, generation of decision rules [11][2].

Since Rough Set has an advantage of its simplification and usefulness in the mathematical aspect, it could deal with problems, such as, maximizing of decision tables, rules generative for expert systems, symbolic learning from examples, dissimilarity analysis, and design of switching circuits [6].

2.2 Learning Style

All learners have their favorite learning styles. The effectiveness of learning can be decided by whether or not providing adaptable learning styles according to learners' preferences. There are various researches on classification and determination of learning styles [3][5][8].

This study applied learning styles according to O'Brien's study. The types of learning styles by O'Brien are categorized as Visual, Auditory and Hands on/Kinesthetic. In order to determine learning styles by sensory preference, Learning Channel Preference Checklist, Perceptual Learning Style Preference Questionnaire and Perceptual Learning Preference Survey are used [7][9].

Nowadays, learning styles in e-learning systems are decided by tutors' or learners' own judgment via question. However, the studies on determining learning styles by analyzing data still leave much to be desired.

3. The definition of rough set for deciding learning styles

3.1 Overview of e-Learning System

A structure of the proposed system is as Fig 1. LMS system accumulates a various data about the learner's learning on a learner DB. LMS system extracts the data of connection frequency, participation rate and learning time from the learner DB. LMS system decides a learning style of learner using the extracted data with Rough Set-based Reasoning Engine. LMS system requires adaptive contents on the learning style of the learner. Finally, the system provides the adaptive contents on learning style to the learner.

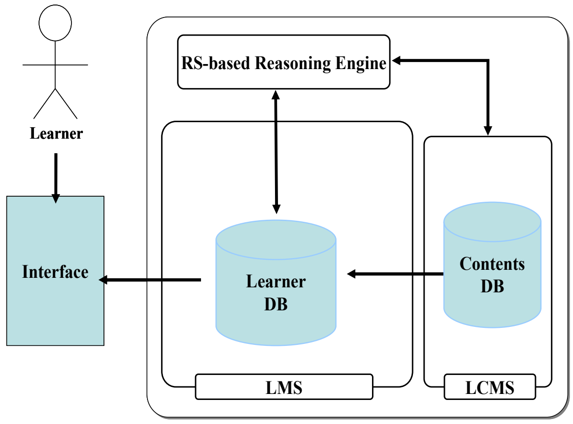

Fig. 1 The Overview of System

3.2 Decision Table Learning Style

Within the framework of mathematics, the knowledge representation system can be shown as follows.

It is indicated as a pair S=(U,A), here, U is not a empty set but a finite set and is called "Universe". Also A is not a empty set but a finite set of primitive attributes. Every origin attributes $a \in A$ is a function, $a: V \rightarrow V_a$, at this time, V_a is a's set of attribute value and is called "domain".

In this study, condition attributes and decision attributes can be represented as follows.

$$U = \{Learner'sDB\}$$
$$a_1 = \{connection\_frequency\},$$
$$a_2 = \{participation\_rate\}$$
$$a_3 = \{learning\_time\} \ldots$$
$$\mathrm{Va} = \{\{Learning\_Style\}\}$$

If we represent it as decision table, it is as follows, table 1.

Table 1 The example of Decision table

Object	a_1	a_2	a_3	V_a
1	1	1	1	1
2	2	1	2	2
3	1	2	2	1
4	2	2	2	1
5	2	1	2	2

3.3 The Process of Extracting Rules

Extracting rules can be done by using simplified techniques of decision table to decide a learner's effective learning style.

According to a general decision table simplified method[11], in this study, we progressed the process of extracting rules like Fig 2.

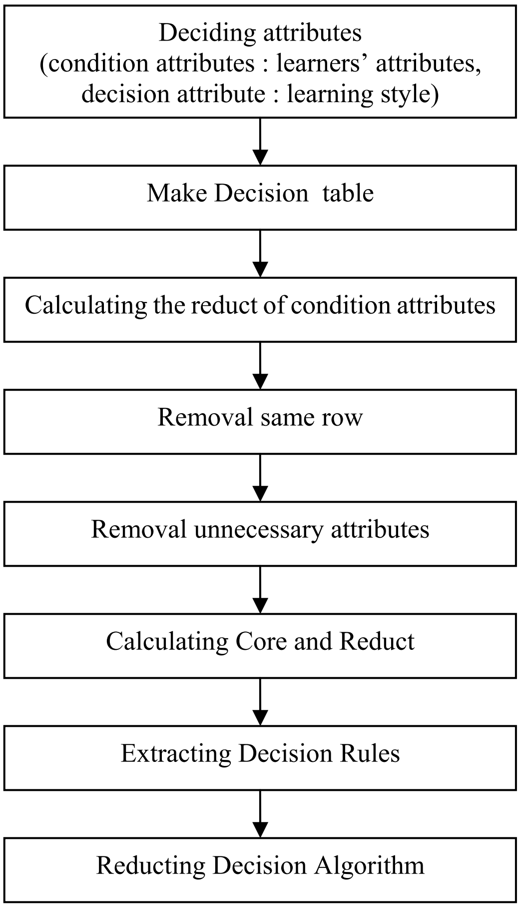

Fig. 2 The Process of Extraction Rules

Classification using rough set is to select the rule that correspond learning styles to rules generated by data. There is no fixed algorithm to be used for classification in rough set. For that reason, we used Standard Voter algorithm, an analysis tool for rough set, which is provided by Rosetta™ [10].

In Standard Voter algorithms, when the given results conflict with each other, it selects rules for decision by measuring rate certainty $certainty(x,\beta)$ for a rule. The definition of rate certainty is as follows.

$$R_\beta = \{r \in RUL(x) r \ \ predicts \ \ \beta\}$$
$$Votes(\beta) = \sum_{r \in R\beta} votes(r)$$
$$certainty(x,\beta) = votes(\beta)/norm(x)$$

Rate certainty in this formula is defined that if there is a certain Rule r and a predicted result β by this Rule, then the number of $x \in$ supported by the Rule is $votes(\beta)$ and the number of $x \in U$ holding Rule r is defined as $norm(x)$ [10]. Suppose we apply above method to this study,

$IF\ Rule\ A\ is\ [2]_{connection\ frequency}[1]_{participation\ rate}[2]_{learning\ time} \rightarrow [2]_{learning\ style}$
$and\ Rule\ B\ [2]_{connection\ frequency}[1]_{participation\ rate}[2]_{learning\ time} \rightarrow [3]_{learning\ style}$

Then the object holding Rule A is five, the object applied is three, and then rate certainty is 3/5. And the object holding Rule B is four, the applied object is two, and then rate certainty is 2/5. In this case, therefore, Rule *A* is selected because rate certainty of Rule *A* is higher than Rule *B*.

4. Extraction rules for decision learning styles

4.1 Representation of Decision Table

Since data stored in LMS system is enormous and various, it is difficult to extract learning styles by applying every single attribute.

In this study, we decide to choose three attributes that was treated significantly of stored learners' dates and extract available rules. Also, in this system, we extracted rules by using data of 34 students of fifth grade in a class.

In table 1, the three attributes are represented as follows.

$Connection\ frequency$
$= \{x \mid 1 = 1 \sim 10, 2 = 11 \sim 20, 3 = 21 \sim\}$
$Participation\ rate$
$= \{x \mid 1 = complete, 2 = incomplete\}$
$Learning\ time$
$= \{x \mid 1 = many, 2 = medium, 3 = less\}$

$$Learning\ styles = \{x \mid 1 = Auditory, 2 = Visual, 3 = Hands-on/kinesthetic\}$$

Table 2 Decision table

Learners	Connection frequency	Participation rate	Learning time	Learning styles
1	2	1	2	2
2	2	0	1	2
3	1	0	1	1
4	3	1	3	2
5	2	0	3	1
6	1	0	1	-
7	1	0	1	1
8	2	0	2	2
9	2	1	1	2
10	2	1	3	2
11	3	0	2	1
12	2	1	2	2
13	1	1	1	-
14	3	1	2	2
15	3	1	2	3
16	2	1	3	3
18	2	0	2	2
19	3	1	3	2
20	2	0	2	3
21	3	0	2	2
22	2	1	2	2
23	2	1	2	1
24	2	1	2	3
25	3	0	3	1
26	2	1	2	3
27	2	1	1	3
28	1	0	2	3
29	2	0	2	3
30	2	0	1	2
31	2	0	3	2
32	3	1	3	2
33	2	0	2	3
34	2	0	3	2

4.2 Extracting Decision Rules

In the table 1, we deleted a data contradicting each other, reduce equivalence relation data and then decreased decision table. Also, we applied Rosetta™ rule shown above part to extract Core and Reduct from each rules.

It is necessary to distinguish between Core and Reduct for extracting rules to decide learning styles. As extracting Core from Table 1, the result is like table 2. From here, extracting rules by finding Reduct is as below.

Table 3 Extracting Core

Learne-rs	Connection frequency(a)	Participation rate (b)	Learning time(c)	Learning style(D)
1	1	-	1	1
2	3	0	-	1
3	2	-	-	2
4	-	1	-	2
5	2	-	-	2
6	-	1	-	2
7	-	-	2	3
8	-	0	2	3

There are eight minimal solutions at least in this decision table that is used in this study. We take reduct according to each core. And we extract minimal rules through reducing equivalence relation rule. Result of analyzing datas in this study, we take below rules which are one of eight solutions.

$$a_1c_1 \rightarrow D_1 \qquad a_2c_3 \rightarrow D_2$$
$$a_3b_0 \rightarrow D_1 \qquad a_1c_2 \rightarrow D_3$$
$$a_2c_1 \rightarrow D_2 \qquad b_0c_2 \rightarrow D_3$$
$$b_1 \rightarrow D_2$$

The rules are presented as reduced algorithm, like this.

$$a_1c_1 \vee a_3b_0 \rightarrow D_1$$
$$a_2(c_1 \vee c_3) \vee b_1 \rightarrow D_2$$
$$c_2(a_1 \vee b_0) \rightarrow D_3$$

As a result of that, a learners' learning style can be interpreted as follows.

IF (connection frequency is less and learning time is less) OR (connection frequency is many and participation rate is less) THEN (learning style is auditory).

IF (connection frequency is medium and learning time is less) OR (connection frequency is medium and learning time is many) OR (participation rate is less) THEN (learning style is visual)

IF (connection frequency is less and learning time is medium) OR (participation rate is less and learning time is medium) THEN (learning is hands-on/kinesthetic).

Eventually, we need a simple rule as above for analyzing a learner's learning style, because using rough set facilitates to extract rules. By applying the rules, we can offer contents based on the learner's style.

5. Conclusions and Future Works

In this study, we showed the way to extract rules which can classify a learner's learning style using rough set theory. The extracted rules provide effective learning to each learner. The rules were extracted by using rough set decision table and analyzing appropriate attributes. Although the theory of rough set is used in many areas, it is not sufficiently used in learning systems. Therefore, this study has its significant meaning to who the possibility of using rough set theory in e-learning systems. Using rough set theory in e-learning systems is to show that it converts enormous amounts of data in stored at e-learning systems for usable and necessary data. Also, this method is an appropriate suggestion when amounts of data in e-learning systems are highly increased. We can implement the optimized system to learners, if we apply this study on e-learning systems. And if we apply this system to learning, it takes effective learning because of considering learning style.

Furthermore, it can be more sophisticated systems only we make up for the weak points of user modeling. A limitation of this study is that to select condition attributes which decide learners' learning styles would be somewhat arbitrary. Through analyzing user modeling, however, it can be overcome in respect of selecting condition attributes by system operation; selecting attributes added an extra weight and correction rate of rules.

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