Rough Set Theory Based Reasoning of Learning Style in e-Learning

Hemant Rana[1*], Manohar Lal[2]

[1] UCMS, Delhi, India.

[2] SOCIS, IGNOU, New Delhi, India.

* Corresponding author. Tel.: 9891679866; email: hemant.mca08@yahoo.in

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Abstract: The growth of e-learning is expanding tremendously. In this context, LMS is software for handling various management related activities in respect of learning and its delivery in online mode. The proposed system provides the learning content according to learner's learning style using the extracted rule. Rough sets may be seen as an emerging tool & technique for extracting knowledge from a large set of data. Rough set theory is particularly useful for discovering relationships and used to deal with imprecise or incomplete data. This is a case study in which we suggest an effective way to extract rule which can decide learner's learning style in e-learning environments through RSES software. In this study, we used concept of reducts to extract appropriate knowledge from large datasets and calculate confidence factor for conflicting rules. Rough Set Theory in e-learning environment can bring immense potential and will make E-learning procedure more interesting, decision friendly, and user friendly. The proposed system will be able to increase efficiency of learning as providing learning contents based on learner's style.

Key words: Decision support system, DSS, e-learning, learning style, LMS, rough set theory.

1. Introduction

In recent years, educational institutions and universities from all over the world are offering online services such as for admission, conduct classes, attendance, content creation and virtual learning services in order to facilitate the lifelong learning. To facilitate online services in e-learning system requires information on learners and learning [1], [2]. Stored data of learners provide useful information for effective learning to learners. The amount of learner's data successively increased day by day. However, such situations decrease the efficiency of e-learning systems and arises difficulties in extracting adaptable rules from the data. In this case study we suggest an approach of rough set theory to extract appropriate knowledge from huge amount of data in e-learning system. In rough set theory, we used concept of reducts to extract appropriate knowledge from large datasets.

To facilitate quality education, the identification & selection of learning contents that may influence learners and, hence, academic performance is very important. Working positively on the learning style may improve the performance of the student [1], [3]. Learning style is one of the important factors in learning [4], [5]. Learning styles provides environments and situations to the learners in an e-learning system. Knowing and understanding the types of learning styles is important for students of any age. It is advantageous for students to understand their type of learning style early on so that learning may become easier and less stressful in the future. According to this, rough set theory plays an important role to efficiently extract rules for providing learning and deciding learner's learning styles on the basis of learner's data. Rough Set Theory in e-learning environment can bring immense potential and will make e-learning procedure more interesting, decision friendly, and user friendly.

In this study, we extracted rules of learning style by using LMS system. We have used Rough set extensively in our approach of decision support system (DSS) to suggest the learning contents by using extracted rules based on learning styles to the learner. By offering such approach, education system could play much better for student centric operation towards positive improvement of his performance.

2. Background

2.1. Rough Set Theory

Rough Set (RS) theory is a mathematical formalism developed by Zdzislaw Pawlak, Warsaw University of Technology, in the early 1980s to analyze data tables [6], [7]. Rough set theory is particularly useful for discovering relationships in data. This process is commonly called knowledge discovery or data mining. It is also suited to reasoning about imprecise or incomplete data [8], [9]. The main objective of RS data analysis is to reduce data size [10]. It can be used for reduction of data sets, finding hidden data patterns, generation of decision rules [11], [12]. 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 [10].

Fuzzy set and rough set deals with the concept of vagueness in the information but unlike fuzzy set, rough set theory does not require degree of membership in dealing with vagueness. Rough set uses concepts of upper and lower approximation defined on the basis of the set.

2.2. Related Terms and Definitions

Rough set theory deals with data expressed in two-dimensional or matrix form of tables, called information tables or decision table. A Decision table is tabular representation of real world data. In Decision table, each row of the table represents an individual object. The input of Decision table contains condition attributes and decision attributes. Table 1 represents a decision table containing condition attribute and decision attribute.

Table 1. Sample Decision Table

Objects	Condition Attribute	Decision Attribute
O:1	C1	D1
O:2	C2	D2
O:3	C3	D3
O:4	C4	D4

Definition 1: A decision system is any system of the form A = <U, A, d>, where U is a non-empty finite set of objects called the universe, A is a non-empty set of objects and $d \notin A$ is the decision attribute [13], [14].

Definition 2: Given a decision system A = <U, A, d>, then with any $B \subseteq A$ there exists an equivalence or indiscernibility relation IA (B) such that

$IA(B) = \{(x, x') \in U x U \mid \forall a \in B\, [a(x) = a(x')]\}$.

Groups of similar objects are created based on the values of attributes [14].

Definition 3: Let A = <U, A, d> be a decision system, $B \subseteq A$, $X \subseteq U$ and $[x]B$ denote the equivalence class of IA(B). The B-lower approximation and B-upper approximation of X, denoted by bX and BX respectively, are defined by $bX = \{x \mid [x]\, B \subseteq X\}$ and $BX = \{x \mid [x]\, B \cap X \neq \emptyset\}$ [13], [14].

The definitions of approximations can be expressed in terms of granules of knowledge in the following Fig.1

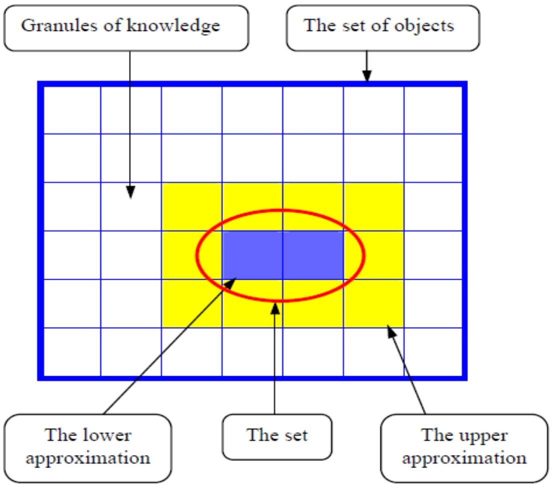

Fig. 1. Lower & upper approximations (Source: Zdzisław pawlak).

The lower approximation of a set is union of all granules which are entirely included in the set; the upper approximation − is union of all granules which have non-empty intersection with the set; the boundary region of a set is the difference between the upper and the lower approximation of the set [11].

Definition 4: Let A = <U, A, d> be a decision system and P, Q ⊆ A be sets of conditions, P ≠ Q. The set P is the reduct of set Q if P is minimal (i.e. no redundant attributes in P) and the equivalence relations defined by P and Q are the same [14].

In order to reduce redundant and insignificant attributes, concept of reduct is emerged in Rough Set Theory, a Reduct is the minimal set of attributes preserving classification power on original data set A [11]. Intersection of all reducts is called core. Decision rules are generated from reducts and used for classification of objects. These definitions & theories are being used in calculation of our results, as explained in this paper.

2.3. Learning Style

All learners have their own style of learning. The effectiveness of learning depends on the learning style of the learner's choice. In Learning Style research, our work is centered and focuses on how student prefer to learn. There are various researches on classification and determination of learning styles [15]-[17]. Few of them are Learning Style Inventory (Dunn, Dunn, & Price, 1979, 1989), the Grasha Riechmann Student Learning Style Scales (Riechmann & Grasha, 1974), and Kolb's (1976, 1985) Learning Styles Inventory. For non-native speakers of English, O'Brien's (1990) Learning Channel Preference Checklist, Oxford's (1993) Style Analysis Survey, and Reid's (1984) Perceptual Learning Style Preference Questionnaire have been developed [18].

We applied learning styles according to O'Brien's study in our study. O'Brien learning styles are categorized as Visual, Auditory and Hands on/Kinesthetic [19]. 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 [4], [20].

Nowadays, learning styles are decided by either tutors' or learners' own decision via questionnaire in e-learning systems. However, the studies on determining learning styles by analyzing data still leave much to be desired [19].

3. Rough Set Exploration System: A Research Tool

3.1. Overview of RSES

RSES stands for Rough Set Exploration System. RSES is a software system toolset is designed for data exploration, classification support and knowledge discovery [21]. The RSES software and underlying computational methods have been successfully applied in many studies and applications [12]. In RSES, the data is assumed in the form of information system or decision table. RSES make use of different classification algorithms from rough set theory, artificial neural networks and others.

3.2. Aim and Capabilities of RSES

The following are some of the capabilities and features [21] of the RSES system:

- Import of data from text files.
- Visualization and pre-processing of data including, among others, methods for discretization and missing value completion.
- Construction and application of classifiers for both smaller and vast data sets, together with methods for classifier evaluation.

The RSES system is a software tool features a bunch of method that can perform compound, non-trivial experiments in data exploration with use of Rough Set methods [21].

3.3. Data Analysis Process of RSES

In RSES, the construction of classifier is usually require several initial steps; First, the import of raw data (data for analysis) to be loaded/imported into RSES software. The RSES can accept several input formats of data. After import of data, user may perform & examine visualization and statistics tools available with the RSES software. The process of data analysis [22] is shown below in the following Fig. 2.

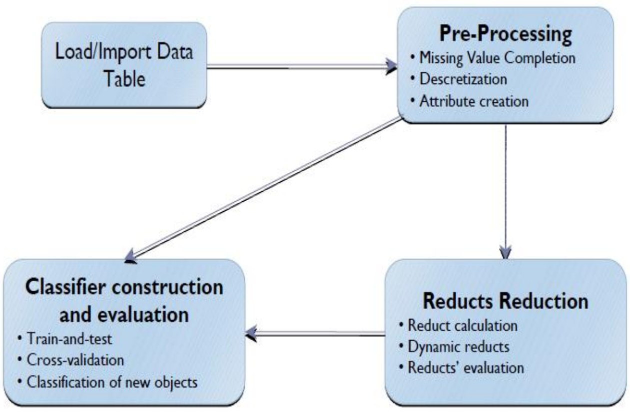

Fig. 2. RSES data analysis process.

4. The Process of Extracting Rule

Extracting rules can be done by using simplified techniques of decision table to decide a learner's effective learning style. In order to generate decision rules, we propose the following steps as shown in Fig. 3. In this study we use rough set theory to create reducts and on the basis of reducts we induced rules for learning style. For generating reducts, we used RSES software inbuilt exhaustive algorithm.

The very first step in generation of rules is to select a proper dataset and identifies the condition attributes and decision attributes. After that we create a text file containing condition attributes, decision attribute and objects in the form of tab file. After selection of dataset and creation of tab file, the second step is data preprocessing, third is reduct generation, and last step is rule generation and rule validation. In the first step, problem should identify clearly, and then create a tab file containing objects, condition attributes and decision attributes. After finalizing the input, we need to preprocess the data by using data discretization process of RSES software. In third step, we generate reducts on the basis of RSES inbuilt exhaustive algorithms, an analysis tool for rough set. In next step, we generate rules based on reducts generated by system. In final step, generated rule should be validated by rule set technique of RSES and generate confusion matrix for system accuracy and coverage.

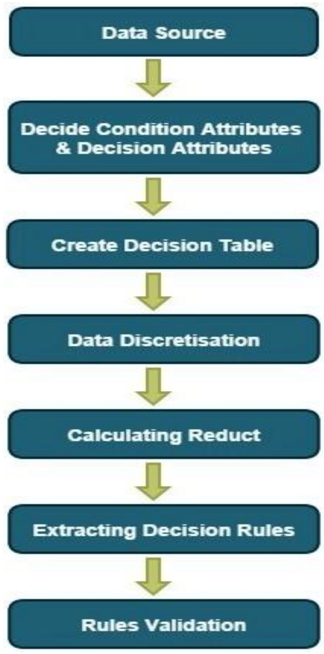

Fig. 3. Rule extraction process.

5. Rules Extraction Experiment on RSES

5.1. Representation of Decision Table

Within the framework of mathematics, the knowledge representation system can be shown as Table 2

A decision system is represented in the form A = <U, A, d>, where U is a non-empty finite set of objects called the universe, A is a non-empty set of objects and d ∉ A is the decision attribute.

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

U = {Learners' Data}

S = {INTERNET_SPD}

F = {ONLINE_FREQ_STUDY}

T = {ONLINE_TIME_STUDY}

D = {{LEARNING_STYLE}}

In order to generate decision rules, we propose the following steps as shown in Fig. 3.

In this study, we decide to choose three attributes that was treated significantly of stored learners' data and extract available rules. Also, in this system, we extracted rules by using data of 20 students of distance learning program.

In Table 2, the three attributes are represented as follows.

INTERNET_SPD stands for Internet Speed

{S |1 = 1 ~ 10Mbps, 2 = 100Mbps, 3 = 3G, 4 = 2G}

S= {1, 4} Low Speed

S= {2, 3} High Speed

ONLINE_FREQ_STUDY stands for frequency of internet used for study

{F |1=1-3 times, 2 = 4-6 times, 3= 7-9 times, 4 = more than 9 times}

F= {1, 2} Low

F= {3} Medium

F= {4} High

ONLINE_TIME_STUDY stands for learning time

{T |1= 1-4 hours, 2 = 5-8 hours,3 = 9-12 hours, 4 = more than 12 hours }

T= {1} Low

T= {2} Medium

T= {3, 4} High

LEARNING_STYLE stands for Learning Style

{L |1 = Visual, 2 = Auditory, 3 = Hands− on/ kinesthetic}

Table 2. Decision Table with Condition and Decision Attributes

20/4	INTERNET_SPD	ONLINE_FREQ_STUDY	ONLINE_TIME_STUDY	LEARNINIG_STYLE
O:1	3	2	1	1
O:2	4	4	4	2
O:3	3	4	1	1
O:4	2	1	1	1
O:5	3	1	1	1
O:6	3	1	1	1
O:7	3	1	1	1
O:8	4	4	2	1
O:9	3	2	1	1
O:10	3	1	1	1
O:11	3	2	1	1
O:12	3	2	1	1
O:13	4	2	2	1
O:14	2	4	1	2
O:15	4	1	1	2
O:16	2	4	2	3
O:17	3	4	3	2
O:18	3	1	1	1
O:19	4	2	1	2
O:20	2	1	1	1

5.2. Rule Extraction Using the RSES

In order to induce relevant rules on the data, we make use of RSES software according to the process defined in Fig. 3. By using RSES Software, we implement an algorithm which is shown in Fig. 3. After implementing the algorithms in RSES Software, we generate decision rules and show the number of matched objects for each rule. The following Fig. 4 depicts the implementation of algorithm in RSES environment which is required to induce rules according to the algorithm.

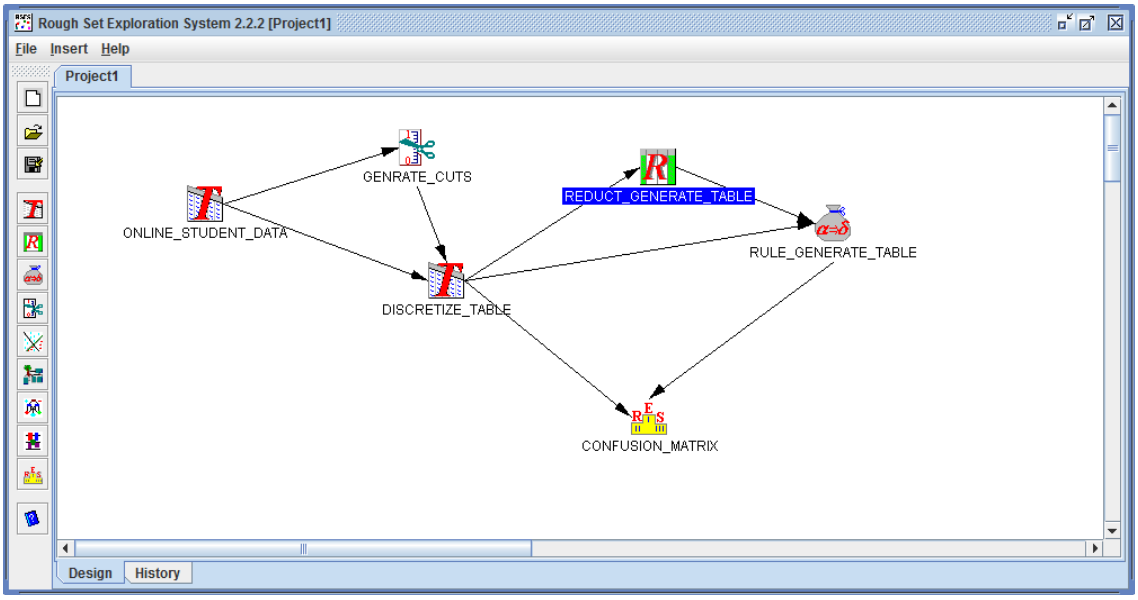

Fig. 4. Experiment setup in RSES software.

6. Results and Discussion

The results related to experiment are shown in Fig. 4.

Reduct: The concept of reduct originate from rough set theory, which is used to reduce redundant and insignificant attributes. A reduct is the minimal set of attributes preserving classification power on original data set. The reducts are generated by RSES software using exhaustive algorithm. Decision rules are generated from reducts and used for classification of objects. The total numbers of reducts formed in this experiment are 5 with their positive region value respectively. The table depicting reducts is shown in the Fig. 5.

Reduct set: ONLINE_STUDENT_DATA

(1-5)	Size	Pos.Reg.	SC	Reducts
1	2	0.35	1	{ INTERNET_SPD, ONLINE_FREQ_STUDY }
2	1	0.1	1	{ ONLINE_TIME_STUDY }
3	3	0.75	1	{ INTERNET_SPD, ONLINE_FREQ_STUDY, ONLINE_TIME_STUDY }
4	2	0.35	1	{ INTERNET_SPD, ONLINE_TIME_STUDY }
5	2	0.15	1	{ ONLINE_FREQ_STUDY, ONLINE_TIME_STUDY }

Fig. 5. Reduct generated by the RSES software.

Rules Induced: After reduct generation, we generate rules on the basis of reduct formed in this experiment. The total number of rules generated by RSES is 38 without shortening technique as shown in Fig. 6 and 12 with shortening technique as shown in Fig. 7. The decision rules supported with more matched objects would be consider as the process result.

Rules Formation: We shorten the rules formed by the above process with shortening ratio 0.9 using inbuilt function for shorten reduct provided in RSES software. As a result of that, a learners' learning style can be interpreted as follows.

IF (Internet Speed is high and study frequency is low) OR (Internet Speed is low and study time is medium) OR (study frequency is low and study time is medium) OR (Internet Speed is high and study time is low) OR

(Internet Speed is high and study frequency is high and study time is low) THEN (learning style is visual).

IF (Internet Speed is low and study time is low) OR (study time is high) OR (Internet Speed is low and study frequency is low) OR (Internet Speed is high and study frequency is high and study time is low) THEN (learning style is auditory).

(1-38)	Match	Decision rules
1	4	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=2)=>(LEARNINIG_STYLE={1[4]})
2	2	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=4)=>(LEARNINIG_STYLE={2[1],1[1]})
3	2	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=4)=>(LEARNINIG_STYLE={1[1],2[1]})
4	2	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=1)=>(LEARNINIG_STYLE={1[2]})
5	5	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=1)=>(LEARNINIG_STYLE={1[4],2[1]})
6	2	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=2)=>(LEARNINIG_STYLE={1[1],2[1]})
7	2	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=4)=>(LEARNINIG_STYLE={2[1],3[1]})
8	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
9	15	(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[11],2[4]})
10	1	(ONLINE_TIME_STUDY=4)=>(LEARNINIG_STYLE={2[1]})
11	3	(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[2],3[1]})
12	1	(ONLINE_TIME_STUDY=3)=>(LEARNINIG_STYLE={2[1]})
13	4	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[4]})
14	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=4)=>(LEARNINIG_STYLE={2[1]})
15	1	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[1]})
16	2	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=1)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[2]})
17	5	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=1)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[4],2[1]})
18	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[1]})
19	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[1]})
20	1	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
21	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=1)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
22	1	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={3[1]})
23	1	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=3)=>(LEARNINIG_STYLE={2[1]})
24	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
25	10	(INTERNET_SPD=3)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[9],2[1]})
26	1	(INTERNET_SPD=4)&(ONLINE_TIME_STUDY=4)=>(LEARNINIG_STYLE={2[1]})
27	3	(INTERNET_SPD=2)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[2],2[1]})
28	2	(INTERNET_SPD=4)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[2]})
29	2	(INTERNET_SPD=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[2]})
30	1	(INTERNET_SPD=2)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={3[1]})
31	1	(INTERNET_SPD=3)&(ONLINE_TIME_STUDY=3)=>(LEARNINIG_STYLE={2[1]})
32	5	(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[4],2[1]})
33	1	(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=4)=>(LEARNINIG_STYLE={2[1]})
34	2	(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[1],2[1]})
35	8	(ONLINE_FREQ_STUDY=1)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[6],2[2]})
36	2	(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[1],3[1]})
37	1	(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[1]})
38	1	(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=3)=>(LEARNINIG_STYLE={2[1]})

Fig. 6. Extracted rule set without shortening.

Rule set: ONLINE_STUDENT_DATA_S

(1-12)	Match	Decision rules
1	4	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=2)=>(LEARNINIG_STYLE={1[4]})
2	2	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=1)=>(LEARNINIG_STYLE={1[2]})
3	1	(INTERNET_SPD=3)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[1]})
4	2	(INTERNET_SPD=4)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[2]})
5	1	(ONLINE_FREQ_STUDY=2)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={1[1]})
6	9	(INTERNET_SPD=3)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={1[9]})
7	1	(INTERNET_SPD=4)&(ONLINE_FREQ_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
8	1	(ONLINE_TIME_STUDY=4)=>(LEARNINIG_STYLE={2[1]})
9	1	(ONLINE_TIME_STUDY=3)=>(LEARNINIG_STYLE={2[1]})
10	1	(INTERNET_SPD=2)&(ONLINE_FREQ_STUDY=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[1]})
11	2	(INTERNET_SPD=4)&(ONLINE_TIME_STUDY=1)=>(LEARNINIG_STYLE={2[2]})
12	1	(INTERNET_SPD=2)&(ONLINE_TIME_STUDY=2)=>(LEARNINIG_STYLE={3[1]})

Fig. 7. Extracted rule set with shortening.

IF (Internet Speed is high and study time is medium) THEN (learning is hands-on/kinesthetic).

The last rule from both auditory and visual shows ambiguity in rule formation. These kind of conflicting cases inspire rough set concept. The uncertainty of such cases can be approximated by means of lower and upper approximation [23]. In rough set theory, we measure confidence factor (α) for a deciding rule with the help of lower approximation and upper approximation. The definition of confidence factor is as follows:

Let Xi be an elementary set in boundary region and Yj be a concept. For an uncertain rule, we can define Confidence Factor (α) from Xi and Yj [24].

$$\alpha = P \ |Xi \cap Yj| / |Xi| \tag{1}$$

The lower approximation of the Auditory style of learning are O:2, O:14, O:17 and upper approximation of the Auditory style of learning are O:2, O:8, O:14, O:15, O:17, O:19. On the basis of approximation, three distinct regions defined in rough set are Positive region, Negative Region and Boundary region. Positive Region of the Auditory style of learning is O:2, O:14, O:17 which is lower approximation of the set. Negative Region of the Auditory style of learning are O1, O:3, O:4, O:5,O:6, O7, O:9, O:10, O:11, O12, O:13, O:16, O:18, O:20 which is difference of universe and upper approximation of the set. Boundary Region of the Advanced level of students are O:8, O:15, O:19 which is difference between upper approximation and lower approximation of the set.

If the boundary region of the set is empty, then it is a crisp or precise set otherwise the set is rough set. The set of student shows in Table 2 is rough set.

Rule induced from its positive region are called certain rules, since they are certainly valid. On the other hand, rules induced from the boundary region are called uncertain rules.

For auditory learning style, the confidence factor will be:

Xi = O:8, O:15, O:19

Yj = O:2, O:14, O:15, O:17, O:19

Xi ∩ Yj = O:15, O:19

$$\alpha = |Xi \cap Yj| / |Xi| = 2/3 = 0.66$$

If Internet Speed is high and study frequency is high and study time is low THEN learning style is auditory with the confidence factor = 0.66

For visual learning style, the confidence factor will be:

Xi = O:8, O:15, O:19

Yj = O1, O:3, O:4, O:5,O:6, O7, O:8, O:9, O:10,O:11, O12, O:13, O:18, O:20

Xi ∩ Yj = O:8

$$\alpha = |Xi \cap Yj| / |Xi| = 1/3 = 0.33$$

If Internet Speed is high and study frequency is high and study time is low THEN learning style is visual with the confidence factor = 0.33

We can generate as many as rules according to their reducts formed by RSES 2.2. Rule formation plays an important role towards assessment of students, design course works, predict intelligence level of students etc.

Accuracy & coverage achieved: we measure accuracy and coverage factors of the study in the form of confusion matrix of RSES (Fig. 8). This setup has accuracy of 0.9 with coverage 1 for data of 20 distance learning students.

Comparison of results: We are comparing distribution of class support for rule set with shortening to distribution of class support for rule set without shortening. In Table 3, shows distribution of class support for rule set with shortening and distribution of class support for rule set without shortening. It shows size of classes with different learning style. The color representation in graphs are red color for visual learning style, blue color for auditory learning style and green for hands on/kinesthetic learning style.

We are comparing rule length for rule set with shortening to rule length for rule set without shortening. In Table 3, shows rule length for rule set with shortening and rule length for rule set without shortening. It shows size of rules formed with different learning style. The color representation in graphs are red color for visual learning style, blue color for auditory learning style and green for hands on/kinesthetic learning style.

Results of experiments by train&test method: ONLINE_STUDENT_DATA

	Predicted					
Actual	1	2	3	No. of obj.	Accuracy	Coverage
1	12	0	1	13	0.923	1
2	1	5	0	6	0.833	1
3	0	0	1	1	1	1
True positive rate	0.92	1	0.5			

Total number of tested objects: 20
Total accuracy: 0.9
Total coverage: 1

Fig. 8. Confusion matrix showing accuracy and coverage factors.

Table 3. Comparison of Results

	Visual	Auditory	Hands-on/kinesthetic
distribution of class support for rule set with shortening	6	5	1
distribution of class support for rule set without shortening	22	25	5
rule length for rule set with shortening	2	8	2
rule length for rule set without shortening	4	22	12

7. Conclusion

To facilitate quality education, the identification & selection of various factors that may influence a students' academic performance is very important. Working positively on these factors may improve the performance of the student. The proposed system may be seen as a helping hand to learner's to get content of their choice. In this study, we used rough set theory to extract rules which can classify a learner's learning style. The extracted rules provide effective learning to each learner. The rules were extracted by using RSES software reduct calculation and rule generation techniques. On the basis of reducts, we can calculate rules for learning styles. And finally we can verify results using RSES rule set technique and generate confusion matrix. The use of rough set theory in e-learning system is to handle efficiently enormous amount of data and extract knowledge from it. We recommend using this method when amounts of data increases and inconsistencies occur in e-learning systems. We can implement the optimized system to learners, if we apply this study on e-learning systems.

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Hemant Rana was born in Delhi on 6th May 1985. Hemant Rana received his BSc with honors in 2005 from Delhi University, Delhi, India and the MCA degree in 2008 from Guru Govind Singh Indraprastha University, Delhi, India.

He is pursuing his doctoral degree from School of Computer and Information Sciences, Indira Gandhi National Open University, New Delhi, India.

He is working as an STA (computer) at UCMS, Delhi, India. His earlier assignment includes Central Research Lab, BEL, Delhi and SOCIS, IGNOU, New Delhi, India. His research interests include artificial intelligence, e-learning, rough set theory, decision support system, web 3.0.

Manohar Lal is currently a professor in computer science in the University, and has teaching and research experience of more than 40 years, having taught at various universities including University of Delhi and JNU. He was a director in School of Computer & Information Sciences, Indira Gandhi National Open University, New Delhi. Earlier, he has been a professor and the head of Computer Science Department and the director in Computer Centre at M.D. University, Rohtak and at H.P. University, Shimla.

He completed his M. Tech in computer science and engineering from IIT Kanpur and pursued his second Ph.D. in computer science and engineering from IIT, Delhi. Earlier, he completed his master's and Ph. D. programmes in mathematics from University of Delhi. During 1982-1983, he visited North Carolina State University for post-doctoral work.

Prof. Lal has long research experience. Earlier, he worked in the area of 'error- correcting codes' (a branch of data communications). Currently, he is working in the areas of theoretical computer science, e-learning, 'automation of reasoning' (a branch of artificial intelligence) and computer networks.