ROUGH TOPOLOGICAL STRUCTURE FOR INFORMATION-BASED REDUCTION FOR CHEMICAL APPLICATION

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In this study, digital information is regarded as fundamental to scientific growth and human knowledge. One of the challenges that scientists face is the enormous amount of digital information that exists nowadays. The rough is a significant topological strategy for reducing knowledge and arriving at decision rules. Furthermore, the research proposed a new methodology to reduce digital information uncertainty. This was clarified by the application provided in this study. In upcoming years, according to certain topological research, we see that it benefits all branches of science. For example, in electricity networks, pharmaceutical factories, patient treatment, and so on.

Key words*: rough set, knowledge reduction, topological space, decision making, neighborhoods*

Introduction

Information on our environment is often incomplete, inaccurate, or unclear. Dissecting data is essential to solving problems with people. Information about the surrounding world is sometimes imperfect, partial, or ambiguous [1-4]. The design and operation of intelligent systems are greatly impacted by the granulation of information, which is essential to human problem solving [5-7]. We will determine whether there is incompleteness or uncertainty, and in certain cases, new mathematical methods were used [1-4]. Pawlak proposed the concept of rough sets [8, 9]. One way to supporting the reasoning and analysis of information based on many levels of conceptualisation is the growing discipline of granular computing, a term coined by Lin *et al.* [10] and having its roots in Lin's study on neighbourhoods. The information may be certain or uncertain. It is a formal theory evolved from basic study into the logical features of information systems. It is obvious that there is another set, fuzzy theory, in which this theory and rough set theory are complimentary generalisations of classical sets. The rough set approach has many applications in process control, economics, medical diagnosis, biology, and so on. Rough set theory can be called a topological based method because it mainly depends on the partition formed by the equivalence relation and the topology generated by this partition. The success of rough sets in data analysis shifted the focus to topological methods for solving uncertainty problems. Pawlak's [11], the foundation of rough set theory is rooted in the concept of forest chaos, which results from insufficient and incomplete information systems. A filter-based approach can be used to extract knowledge efficiently from a domain while preserving information quality and

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minimizing the need for knowledge, which is made possible by rough set attribute reduction. The premise is that the set of reduced attributes is defined based on the standard of upholding the secure area, as defined by the complete range of characteristics.

This study presents a novel type of reduction-based rough set and topological space that generalises both lower and upper approximation operators as well as topological tools.

Preliminaries

Rough sets and approximations

Consider an equivalency relation R on a finite set Z. With $Y_1, Y_2,\ldots,Y_m$ as equivalency classes produced by R, this relation R will provide a partition $Z/R = \{Y_1, Y_2, \ldots, Y_m\}$ on Z. Tese classes of equivalence are often known as the elementary sets of R. The following two sets which are referred to as the lower and upper approximations of X, respectively, are used to characterize any $X \subset Z$, the elementary sets of R:

$$R^*(X) = \cup \{Y_i \in Z/R\text{: } \{Y_i\} \subseteq X\},\ R^*(X) = \cup \{Y_i \in Z/R\text{: } \{Y_i\} \cap X \neq \varnothing\}$$

Reduction and core

All concepts contained within the knowledge base [12] can only be articulated in terms of fundamental categories. However, each fundamental category is composed of a few elementary categories. In the context of qualities and knowledge, two key ideas of the rough sets theory are core and reduce [11]. The element shared by all reductions is called the core. The term *core* refers to the collection of all necessary qualities. New reduction may be supported by logical principles developed from experimental data. The dilemma of whether we may delete certain data while maintaining a data table's fundamental characteristics that is, whether the database contains any superfluous data occurs frequently. Indeterminacy is introduced by the suggested approach by the controlled removal of conditional qualities. The elements in the discernibility function are used to choose which attributes should be eliminated, eliminating the data required in the original information system to distinguish between classes [13-16].

Definition 1. [11] Given an information function $f\colon Z \to J$ where C is the collection of attributes, and is the domain J of the specific attributes where the values are real numbers, we can define (Z, C, J, f) as follows. For every attribute, the following relation R_{ci} is defined: if γ is established by a subject matter expert:

$$xR_{ci}y \text{ iff: } |c_i(x) - c_i(y)| \leq \gamma$$

When knowledge comes from the medical profession, for instance, the expert is someone who is engaged in medicine and solving problems. Because each $c_i \in C, O$ is a finite set, we may therefore, obtain a classification O/R_{ci}:

$$\{x R_{ci} : x \in O\},\ x R_{ci} = \{y : |c_i(x) - c_i(y)| \leq \gamma$$

Definition 2. [11] Let R be an equivalence family and $C \in R$. If IND(R) = IND(R – {C}), we can coclude that C is not necessary in R. Since IND(R) ≠ IND(R – {C}), we can conclude that C is necessary for R (Core).

Definition 3. [12] A family of sets, $F = \{z_1, z_2, \ldots, z_n\}$, is defined $i = 1, 2, 3, \ldots, n$. The set $z_i \subseteq Z$. In F, we consider the set zi to be indispensable if $(F - z_i) = F$, and otherwise dispensable otherwise. Families F are dependent on each other unless every member of the family is indispensable in F. If $H = F$ and H is independent, the the family $H \subseteq F$ is a reduct of F. To be considered the core of F, it is the family of all indispensable sets in F.

Information data

Data

We present a novel reduction on information technology in this work, as well as how topology is applied in contemporary rough set theory employing data and information about a problem. We begin by converting the values of the decision attribute $\{d\}$ and the characteristics $\{c_1, c_2, \ldots, c_7\}$ into qualitative words in order to establish an acceptable information system for the application. The modelling of a protein's unfolding energy, involving 19 coded amino acids (AA) [13], is the topic of discussion with this data. The AA are described in terms of seven attributes: c_1 = PIE, c_2 = PIF, c_3 = DGR of transfer from the protein interior to water, c_4 = MR = molecular refractivity, c_5 = SAC = surface area, c_6 = LAM = the side chain polarity and c_7 = Vol. = molecular volume compare this results with the new reduction. The application starts by translating the values of the attributes $\{c_1, c_2, \ldots, c_7\}$ and the value of the decision attribute $\{d\}$ into qualitative terms. We need to make a reduction of information system tables by using neighborhood. The definitions of the next determine the new method. Let us illustrate a part of tab. 1.

Table 1. Decisions made with the information

Objects	Attributes							Decision
	c_1	c_2	c_3	c_4	c_5	c_6	c_7	d
Z_1	0.23	0.31	–0.55	254.2	2.126	–0.020	82.20	8.5
Z_2	–0.48	–0.60	0.51	303.6	2.994	–1.24	112.3	8.2
Z_3	–0.61	–0.77	1.20	287.9	2.994	–1.08	103.7	8.5
Z_4	0.45	1.45	–1.4	282.9	2.933	–0.110	99.10	11.0
Z_5	–0.11	–0.22	0.29	335.0	3.458	–1.19	127.5	6.3
Z_6	–0.51	–0.64	0.76	311.6	3.243	–1.43	120.5	8.8
Z_7	0.00	0.00	0.00	224.9	1.662	0.030	65.00	7.1
Z_8	0.15	0.13	–0.25	337.2	3.856	–1.06	140.6	10.1
Z_9	1.20	1.80	–2.1	322.6	3.350	0.040	131.7	16.8
Z_{10}	1.28	1.70	–2.0	324.0	3.518	0.120	131.5	15.0
Z_{11}	–0.77	–0.99	0.78	336.6	2.933	–2.26	144.3	7.9
Z_{12}	0.90	1.23	–1.6	336.3	3.860	–0.330	132.3	13.3
Z_{13}	1.56	1.79	–2.6	336.1	4.638	–0.050	155.8	11.2
Z_{14}	0.38	0.490	–1.5	228.5	2.876	–0.310	106.7	8.2
Z_{15}	0.00	–0.04	0.09	266.7	2.279	–0.400	88.50	7.4
Z_{16}	0.17	0.26	–0.58	282.9	2.743	–0.530	105.3	8.8
Z_{17}	1.85	2.25	–2.7	401.8	5.755	–0.310	185.9	9.9
Z_{18}	0.89	0.96	–1.7	377.8	4.791	–0.840	162.7	8.8
Z_{19}	0.71	1.22	–1.6	295.1	3.054	–0.130	115.6	12.0

Whereas the choice attribute is coded into three qualitative terms (low, medium, and high), the condition characteristics are coded into four terms (very low, low, high, and very high). Next, natural numbers are used to code each attribute's qualitative words. The coded information system and ele- mentary set are given in tab. 2.

Table 2. Elementary set induced by IND (C)

Z/C \ C	Attributes						
	c_1	c_2	c_3	c_4	c_5	c_6	c_7
$X_1 = \{Z_1, Z_7, Z_{15}\}$	2	2	3	1	1	4	1
$X_2 = \{Z_2, Z_3, Z_6\}$	1	1	4	2	2	2	2
$X_3 = \{Z_9, Z_{10}\}$	4	4	1	3	2	4	3
$X_4 = \{Z_4\}$	2	4	2	2	2	4	2
$X_5 = \{Z_5\}$	2	1	4	3	2	2	3
$X_6 = \{Z_8\}$	2	2	3	3	3	3	3
$X_7 = \{Z_{11}\}$	1	1	4	3	2	1	3
$X_8 = \{Z_{12}\}$	3	3	2	3	3	4	3
$X_9 = \{Z_{13}\}$	4	4	1	4	3	4	4
$X_{10} = \{Z_{14}\}$	2	2	2	2	2	4	2
$X_{11} = \{Z_{16}\}$	2	2	3	2	2	3	2
$X_{12} = \{Z_{17}\}$	4	4	1	4	4	4	4
$X_{13} = \{Z_{18}\}$	3	3	2	4	4	3	4
$X_{14} = \{Z_{19}\}$	3	3	2	2	2	4	2

By leaving out the attribute c_2 in tab. 3.

Table 3. Removing attribute c_2 from tab. 2

Z/C – $\{c_2\}$ \ $C - \{c_2\}$	Attributes					
	c_1	c_3	c_4	c_5	c_6	c_7
$X_1 = \{Z_1, Z_7, Z_{15}\}$	2	3	1	1	4	1
$X_2 = \{Z_2, Z_3, Z_6\}$	1	4	2	2	2	2
$X_3 = \{Z_9, Z_{10}\}$	4	1	3	2	4	3
$X_4 = \{Z_4, Z_{14}\}$	2	2	2	2	4	2
X5 = $\{Z_5\}$	1	4	3	2	2	3
$X_6 = \{Z_8\}$	2	3	3	3	3	3
$X_7 = \{Z_{11}\}$	1	4	3	2	1	3
$X_8 = \{Z_{12}\}$	3	2	3	3	4	3
$X_9 = \{Z_{13}\}$	4	1	4	3	4	4
$X_{10} = \{Z_{16}\}$	2	3	2	2	3	2
$X_{11} = \{Z_{17}\}$	4	1	4	4	4	4
$X_{12} = \{Z_{18}\}$	3	2	4	4	3	4
$X_{13} = \{Z_{19}\}$	3	2	2	2	4	2

Similar results occur when we remove c_2 and c_5, respectively, yielding the objects X_4 and X_{10} are equals and X_9 and X_{12} are equals when remove c_5. We observe that, in addition IND(C) ≠ IND(C – $\{c_2\}$), IND(C) ≠ IND(C – $\{c_5\}$). The c_2 and c_5 are hence essential. As an obtain tab. 4 by excluding c_1.

Table 4. Removing attribute c_1 from tab. 2

$Z/C - \{c_1\}$ \ $C - \{c_1\}$	Attributes					
	c_2	c_3	c_4	c_5	c_6	c_7
$X_1 = \{Z_1, Z_7, Z_{15}\}$	2	3	1	1	4	1
$X_2 = \{Z_2, Z_3, Z_6\}$	1	4	2	2	2	2
$X_3 = \{Z_9, Z_{10}\}$	4	1	3	2	4	3
$X_4 = \{Z_4\}$	4	2	2	2	4	2
$X_5 = \{Z_5\}$	1	4	3	2	2	3
$X_6 = \{Z_8\}$	2	3	3	3	3	3
$X_7 = \{Z_{11}\}$	1	4	3	2	1	3
$X_8 = \{Z_{12}\}$	3	2	3	3	4	3
$X_9 = \{Z_{13}\}$	4	1	4	3	4	4
$X_{10} = \{Z_{14}\}$	2	2	2	2	4	2
$X_{11} = \{Z_{16}\}$	2	3	2	2	3	2
$X_{12} = \{Z_{17}\}$	4	1	4	4	4	4
$X_{13} = \{Z_{18}\}$	3	2	4	4	3	4
$X_{14} = \{Z_{19}\}$	3	2	2	2	4	2

As similar, when removing c_3, c_4, c_6, and c_7, we get IND(C) = IND($C - \{c_1\}$), IND(C) = IND($C - \{c_3\}$), IND(C) = IND($C - \{c_4\}$), IND(C) = IND($C - \{c_6\}$), and IND(C) = IND($C - \{c_7\}$), Then c_1, c_3, c_4, c6, and c_7 are superfluous, tab. 5.

Table 5. Removing attributes

	Eliminating features							
Quantity of basic sets	None	c_1	c_2	c_3	c_4	c_5	c_6	c_7
	14	14	13	14	14	13	14	14

As shown in tab. 6, the set of all partitions induced by IND(A') was introduced.

Table 6. The set of all partitions induced by IND (C')

Z/C' \ C'	Attributes	
	c_2	c_5
$T_1 = \{Z_1, Z_7, Z_{15}\}$	2	1
$T_2 = \{Z_2, Z_3, Z_5, Z_6, Z_{11}\}$	1	2
$T_3 = \{Z_4, Z_9, Z_{10}\}$	4	2
$T_4 = \{Z_{14}, Z_{16}\}$	2	2
$T_5 = \{Z_8\}$	2	3
$T_6 = \{Z_{12}\}$	3	3
$T_7 = \{Z_{13}\}$	4	3
$T_8 = \{Z_{17}\}$	4	4
$T_9 = \{Z_{18}\}$	3	4
$T_{10} = \{Z_{19}\}$	3	2

Pawlak method and neighborhood method

Pawlak method

We illustrate the reduction of Pawlak in the decision of the following tab. 7, contains four attributes $\{c_1, c_2, c_3, c_5\}$ and one decision $\{d\}$ describes the belongingness of eight objects. In the next, we have to reduce superfluous values of condition in every decision rule. Also, we compute the core values of condition attribute by using *Definition 2*.

Table 7. Decision table of some objects

Objects	Attributes			
	c_1	c_2	c_3	c_5
h_1	2	2	3	1
h_2	1	1	4	2
h_3	1	1	4	2
h_4	2	4	2	2
h_5	2	1	4	2
h_6	1	1	4	2
h_7	2	2	3	1
h_8	2	2	3	3

Consider the families of sets $F_1, \ldots, F_8$, where

$$F_1 = \{[\mathbf{1}]c_1, [\mathbf{1}]c_2, [\mathbf{1}]c_3, [\mathbf{1}]c_5\} = \{\{h_1, h_4, h_5, h_7, h_8\}, \{h_1, h_7, h_8\}, \{h_1, h_7\}\}.$$

The $\cup F_1 = \{h_1, h_4, h_5, h_7, h_8\}$, since $c_1(1) = 2$, $c_2(\mathbf{1}) = 2$, $c_3(\mathbf{1}) = 3$, $c_5(\mathbf{1}) = 1$.

In order to find dispensable,

$$\cup(F_1 - [\mathbf{1}]c_1) = \{h_1, h_7, h_8\} \neq \cup F_1,\ \cup(F_1 - [\mathbf{1}]c_2) = \{h_1, h_4, h_5, h_7, h_8\} =$$
$$= \cup F_1,\ \cup(F_1 - [\mathbf{1}]c_3) = \{h_1, h_4, h_5, h_{7,} h_8\} = \cup F_1,\ \cup(F_1 - [\mathbf{1}]c_5) =$$
$$= \{h_1, h_4, h_5, h_7, h_8\} = \cup F_1.$$

This means that the core value is $c_1(\mathbf{1}) = 2$, and also, we find that,

$$F_2 = \{[\mathbf{2}]a_1, [\mathbf{2}]a_2, [\mathbf{2}]a_3, [\mathbf{2}]a_5\} = \{h_2, h_3, h_6\}, \{h_2, h_3, h_5, h_6\}, \{h_2, h_3, h_4, h_5, h_6\}\},$$
$$\cup F_2 = \{h_2, h_3, h_4, h_5, h_6\}, \text{ since } c_1(\mathbf{2}) = 1,\ c_2(\mathbf{2}) = 1,\ c_3(\mathbf{2}) = 4,\ c_5(\mathbf{2}) = 2.$$
$$\cup(F_2 - [\mathbf{2}]c_1) = \{h_2, h_3, h_4, h5, h_6\} = \cup F_2,\ \cup(F2 - [\mathbf{2}]c_2) = \{h_2, h_3, h_4, h_5, h_6\} = \cup F_2,$$
$$\cup(F2 - [\mathbf{2}]c_3) = \{h_2, h_3, h_4, h_5, h_6\} = \cup F_2,\ \cup(F_2 - [\mathbf{2}]c_5) = \{h_2, h_3, h_5, h_6\} = F_2.$$

This means that the core value is $c_4(\mathbf{2}) = 2$ and we find by similar $F_3, F_4, \ldots, F_8$. The final decision is given in tab. 8.

Table 8. Decision table by Pawlak definition

Objects	(*Definitio 2*) $\equiv \cup(F_i - c_k) = \cup F_i$			
	c_1	c_2	c_3	c_5
h_1	2	–	–	–
h_2	–	–	–	2
h_3	–	–	–	2
h_4	2	–	–	2
h_5	2	–	–	–
h_6	–	–	–	2
h_7	2	–	–	–
h_8	2	–	–	–

Neighborhood method

We notice that, the coded method convert some attributes are the same, as c_5, c_7, and some objectives are the same as objectives Z_2, Z_3, Z_6, and also, objectives Z_1, Z_7, Z_{15} are the same as shown in tab. 2. So, we thought for the other methods to solve the problems.

Table 9. Decision table of some objects original data

Objects	Attributes			
	c_1	c_2	c_3	c_5
h_1	0.23	0.31	–0.55	2.126
h_2	–0.48	–0.60	0.51	2.994
h_3	–0.61	–0.77	1.20	2.994
h_4	0.45	1.54	–1.40	2.933
h_5	–0.11	–0.22	0.29	3.458
h_6	–0.51	–0.64	0.76	3.243
h_7	0.00	0.00	0.00	1.662
h_8	0.15	0.13	–0.25	3.856

Look the attribute c_1 in the tab, 9: we take the neighborhoods between them:

$|x_i - x_j| \leq 0.6$, consider the families of sets $F_1, \ldots, F_8$,

where $F_1 = \{[\mathbf{1}]c_1, [\mathbf{1}]c_2, [\mathbf{1}]a_3, [\mathbf{1}]c_5\} = \{\{h_1, h_4, h_5, h_7, h_8\}, \{h_1, h_5, h_7, h_8\}, \{h_1, h_7, h_8\}, \{h_1, h_7\}\} \cup F_1 = \{h_1, h_4, h_5, h_7, \mathrm{h}_8\}$,

since $c_1(\mathbf{1}) = 0.23$, $c_2(\mathbf{1}) = 0.31$, $c_3(\mathbf{1}) = -0.55$, $c_5(\mathbf{1}) = 2.126$.

In order to find dispensable

$\cup (F_1 - [\mathbf{1}]c_1) = \{h_1, h_5, h_7, h_8\} \neq \cup F_1$, $\cup (F_1 - [\mathbf{1}]c_2) = \{h_1, h_4, h_5, h_7, h_8\} = \cup F_1$,
$(F_1 - [\mathbf{1}]c_3) = \{h_1, h_4, h_5, h_7, h_8\} = \cup F_1$, $\cup (F_1 - [\mathbf{1}]c_5) = \{h_1, h_4, h_5, h_7, h_8\} = \cup F_1$.

This means that the core value is $c_1(\mathbf{1}) = 0.23$, and also, we find that,

$F_2 = \{[\mathbf{2}]a_1, [\mathbf{2}]a_2, [\mathbf{2}]a_3, [\mathbf{2}]a_5\} = \{\{h_2, h_3, h_5, h_6, h_7\}, \{h_2, h_5, h_6, h_7\}, \{h_2, h_3, h_4, h_6\}\}$, $\cup F_2 = \{h_2, h_3, h_4, h_5, h_6, h_7\}$, since $a_1(\mathbf{2}) = -0.48$, $a_2(\mathbf{2}) = -0.6$, $a_3(\mathbf{2}) = 0.51$, $a_5(\mathbf{2}) = 2.994$.

$\cup (F_2 - [\mathbf{2}]a_1) = \{h_2, h_3, h_4, h_5, h_6, h_7\} = \cup F_2$,
$\cup (F_2 - [\mathbf{2}]a_2) = \{h_2, h_3, h_4, h_5, h_6, h_7\} = \cup F_2$,
$\cup (F_2 - [\mathbf{2}]a_3) = \{h_2, h_3, h_4, h_5, h_6, h_7\} = \cup F_2$, $\cup (F2 - [\mathbf{2}]a_5) = \{h_2, h_3, h_5, h_6, h_7\} \neq \cup F_2$.

This means that the core values is $a_5(\mathbf{2}) = 2.994$. By similar, we can find $F_3, F_4, \ldots, F_8$. The final decision is given in tab. 10 by the neighborhood method.

Table 10. Decision table by neighborhood method

Objects	(*Definitio 2*) $\equiv \cup (F_i - c_k) = \cup F_i$			
	c_1	c_2	c_3	c_5
h_1	0.23	–	–	–
h_2	–	–	–	2.994
h_3	–	–	–	2.994
h_4	–0.45	–	–	2.933
h_5	–	–	–	–
h_6	–0.51	–	–	3.243
h_7	0	–	–	–
h_8	0.15	–	–	–

The final decision as showing in the tab. 11.

Table 11. Decision final table by neighborhood method

Objects		(*Definitio 2*) $\equiv\cup(F_i - c_k) = \cup F_i$	
		c_1	c_5
I.	h_1, h_7, h_8	2	–
II.	h_2, h_3	–	2
III.	h_5	–	–
IV.	h_4	2	2
V.	h_6	1	2

Let us assume that we intend to classify the following two sets of objects using the data of Pawlak method from tab. 12 and the data of neighborhood method from tab. 11,

$$Y_1 = \{x_1, x_2, x_3, x_5, x_6, x_7\} \text{ and } Y_2 = \{x_4, x_8\}.$$

Table 12. Decision final table by Pawlak method

Objects		(*Definitio 3*) $\equiv\cup(F_i - [c_k]) = \cup F_i$	
		c_1	c_5
I.	h_1, h_7, h_5, h_8	2	–
II.	h_2, h_3, h_6	–	2
III.	h_4	2	2

Lower and upper approximations of each class and the accuracy of their classification are presented in tab. 13.

Table 13. Accuracy of Pawlak and Neighborhood methods

Class number	Objects	Pawlak method			Neighborhood method		
		Lower	Upper	Accuracy	Lower	Upper	Accuracy
1	6	3	7	3 / 7	4	7	4 / 7
2	2	1	5	1 / 5	1	4	1 / 4

Comparing between tabs. 11 and 12, we find that the new work satisfy all aims from saving time and effort. The new method is best to deal with the fact information system. Table 8, obvious that Neighborhood method perfect from Pawlak method.

Removed attribute c_5: From using the data of Pawlak method from tab. 12 and the data of neighborhood method from tab. 11, $Y_1 = \{x_1, x_2, x_3, x_5, x_6, x_7\}$ and $Y_2 = \{x_4, x_8\}$. We get the results shown in tab. 14.

Table 14. Removed attribute c_5

Neighborhood method		Pawlak method	
$Z/C - \{c_5\}$	c_1	$Z/C - \{c_5\}$	c_1
$X_1 = \{Z_1, Z_4, Z_7, Z_8\}$	2	$X_1 = \{Z_1, Z_4, Z_5, Z_7, Z_8\}$	2
$X_2 = \{Z_2, Z_3, Z_5\}$	–	$X_2 = \{Z_2, Z_3, Z_6\}$	–
$X_3 = \{Z_6\}$	1		

From Neighborhood method, we find that:

The lower approximation is $L(Y_1) = 4 \neq \varphi$, the upper approximation is $U(Y_1) = 8 = Z$, then X is called externally undefinable in U. Accuracy of approximation $\mu(Y_1) = L(Y_1)/U(Y_1) = 1/2$.

From Pawlak method, we find that:

The lower approximation is $L(Y_1) = 3 \neq \varphi$ the upper approximation is $U(Y_1) = 8 = Z$, Then X is called externally undefinable in Z. Accuracy of approximation $\mu(Y_1) = L(Y_1)/U(Y_1) = 3/8$.

From the previous illustrate, we show that the new reduction is better than the method of Pawlak to find reduct.

Conclusions

The task of utilizing all the information obtained through an experimental measurement can be time-consuming. Eliminating extraneous attributes is crucial for saving time and effort. Topological methods (rough set) are significant and captivating when it comes to solving uncertain problems. According to the rough set methodology, the data pattern becomes more visible when the degree of precision is reduced. Knowledge is defined by the ability to categorize, which is the central premise of the rough set philosophy. Classification or decision criteria based on a set of instances are the products of the rough set technique. This work illuminates the challenge of attribute reduction in new ways. It suggests that further research should be done on additional semantic information preserved by attribute reduction. Knowledge reduction is the removal of redundant partitions (equivalence relations). This approach allows us to remove all extraneous knowledge from the knowledge base while retaining only the most useful information. The accuracy of the set was determined to be superior to the accuracy of Pawlak.

We discover a difference between the science of medicine practitioner and doctor consultative through experience, so this paper may help practitioners skills to handle their patients, as well as determine the proper medication in the treatment of disease.

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