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Zdzisław Pawlak

Rough classification

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INSTYTUT PODSTAW INFORMATYKI POLSKIEJ AKADEMII NAUK
INSTITUTE OF COMPUTER SCIENCE POLISH ACADEMY OF SCIENCES
00-901 WARSAW, P.O. Box 22, POLAND

Zdzisław Pawlak

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Pracę zgłosił Witold Lipski

Mailing address: Zdzisław Pawlak
Institute of Computer Science
of the Polish Academy of Sciences
P.O. Box 22
00-901 Warszawa, PKiN

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Abstract . Содержание . Streszczenie

The paper contains a new concept of approximate analysis of data, based on the idea of "rough" set. The notion of approximate (rough) description of set is introduced and investigated. The application to medical data analysis is shown as an example.

Приближенная классификация

Работа содержит новую концепцию приближенного анализа данных на основе идеи приближенных множеств. Приведено и исследовано понятие приближенного описания множества. Применение вышеуказанных понятий проиллюстрировано на примере медицинских данных.

Klasyfikacja przybliżona

Praca zawiera nową koncepcję przybliżonej analizy danych w oparciu o ideę zbiorów przybliżonych. Podano i zbadano pojęcie przybliżonego opisu zbioru. Zastosowanie powyższych pojęć zilustrowano przykładem analizy danych medycznych.

1. INTRODUCTION

The paper is concerned with "approximate" classification of objects, based on the concept of a "rough" set introduced in Pawlak (1982). The idea of approximate classification was introduced in Pawlak (1983), where an algorithm for approximate classification was outlined.

This paper discusses in more detail the concept of "rough" classification. A program for approximate classification - based on the rough set concept - has been developed (see Fila & Wilk 1983) and applied for computer - assisted medical diagnosing. Results of computation are briefly discussed.

We used standard mathematical notation throughout this paper and we assume that the reader is familiar with basic notions of set theory and topology.

2. BASIC NOTIONS

2.1. Sets and their approximations

In this section we recall after Pawlak (1982a) the notion of an upper and a lower approximation of a set, wchich are basic concepts in our approach to approximate (rough) classification.

By an approximation space A we measn an ordered pair $A = (U,R)$, where U is a set called the universe and R is a binary relation over U, called an indiscernibility relation. We assume that R is an equivalence relation. If $(x,y) \in R$ we say that x and y are indiscernibable in A. Equivalence classes of the relation R are called elementary sets, or atoms, in A. We assume that the empty set is also elementary for every approximation space A.

Any finite union of elementary sets in A will be called definable set in A. The family of an definable sets in A will be denoted by Def(A).

Let $X \subseteq U$. By an upper approximation of X in A, in symbols $\overline{A}X$, we mean the least definable set in A containing set X; by a lower approximation of set X in A, in symbols $\underline{A}X$, we mean the greatest definable set in A, contained in X; Set $Bn_A(X) = \overline{A}X - \underline{A}X$ will be called a boundary of X in A.

2.2. Properties of approximations

Approximation space $A = (U,R)$ defines uniquely the topological space $T_A = (U, Def(A))$, where Def(A) is topology for U, and it is the family of open and closed sets in T_A. The family of an elementary sets in A is a base for T_a.

The lower and upper approximation of X in A are interior and closure operations respectively in the topological space T_A.

Thus $\underline{A}X$ and $\overline{A}X$ have the following properties:

(A1) $\underline{A}X \subset X \subset \overline{A}X$

(A2) $\underline{A}U = \overline{A}U = U$

(A3) $\underline{A}\phi = \overline{A}\phi = \phi$

(A4) $\overline{A}(X \cup Y) = \overline{A}X \cup \overline{A}Y$

(A5) $\underline{A}(X \cup Y) \supset \underline{A}X \cup \underline{A}Y$

(A6) $\overline{A}(X \cap Y) = \underline{A}X \cap \underline{A}Y$

(A7) $\underline{A}(X \cap Y) \subset \underline{A}X \cap \underline{A}Y$

(A8) $\overline{A}(-X) = -\underline{A}X$

(A9) $\underline{A}(-X) = -\overline{A}X$

Moreover in topological space T_A we have the following properties:

(A10) $\underline{A}\,\underline{A}X = \overline{A}\,\underline{A}X = \underline{A}X$

(A11) $\overline{A}\,\overline{A}X = \underline{A}\,\overline{A}X = \overline{A}X$

2.3 Undefinable sets

Let us notice that set X is definable in A iff $\underline{A}X = \overline{A}X$; otherwise set X is undefinable in A.

We introduce four classes of undefinable sets in A.

Let X be undefinable set in A.

(B1) If $\underline{A}X \neq \phi$ and $\overline{A}X \neq U$, X will be called roughly definable in A

(B2) If $\underline{A}X \neq \phi$ and $\overline{A}X = U$, X will be called externally undefinable in A

(B3) If $\underline{A}X = \emptyset$ and $\overline{A}X \neq U$, X will be called <u>internally undefinable</u> in A

(B4) If $\underline{A}X = \emptyset$ and $\overline{A}X = U$, X will be called <u>totally undefinable</u> in A.

Let us give some intuitive meaning of the above - introduced definitions.

If set X is roughly definable in A it is to mean that we can define set X with some "approximation", i.e. define its lower and upper approximations in A.

If set X is externally undefinable in A it means that we are unable to exclude any element $x \in U$ being possibly member of X.

If set X is internally undefinable in A it means that we are unable to say for sure that any $x \in U$ is a member of X.

If set X is totally undefinable it means that we are unable to define even its approximations (both approximations in this case are trivial, i.e. $\underline{A}X = \emptyset$, and $\overline{A}X = U$).

2.4. <u>Accuracy of approximation</u>

In this section we introduce a measure of accuracy of an approximation of a set in the approximation space A. The measure is defined for finite sets only.

An accuracy measure of set X in the approximation space $A = (U,R)$ is defined as

$$\mu_A(X) = \frac{\underline{\mu}_A(X)}{\overline{\mu}_A(X)} = \frac{card(\underline{A}X)}{card(\overline{A}X)}$$

Instead of $\mu_A(X)$ we shall also write $\mu_R(X)$.

Notice that $0 \leq \mu_A(X) \leq 1$, and $\mu_A(X) = 1$ if X is definable in A; if X is undefinable in A, then $\mu_A(X) < 1$.

2.5. <u>Approximation of families of sets</u>

Let $A = (U,R)$ be an approximation space and let $F = \{X_1, X_2, \ldots, X_n\}$, $X_i \subset U$, be a family of subsets of the universe U.

By lower (upper) approximation of F in A, in symbols $\underline{A}F(\overline{A}F)$ we understand the family

$$\underline{A}F = \{\underline{A}X_1, \underline{A}X_2, \ldots, \underline{A}X_n\}$$

and

$$\overline{A}F = \{\overline{A}X_1, \overline{A}X_2, \ldots, \overline{A}X_n\}$$

respectively.

If F is a partition of o U, i.e.

$$X_i \cap X_j = \emptyset \text{ for every } i, j, 1 \leq i, j \leq n$$

$$\bigcup_{i=1}^{n} X_i = U$$

we call then F a <u>classification</u> of U and X_i are called <u>classes</u> or <u>blocks</u> of F.

If F is a classification of U we shall write C(U) instead of F, and the corresponding approximations of C(U) in A are denoted by $\overline{A}(C(U))$ and $\underline{A}(C(U))$ or in short $\overline{C}(U)$ and $\underline{C}(U)$ when A is understood.

The number

$$\eta_A C(U) = \frac{card(\bigcup_{i=1}^{n} \underline{A}X_i)}{card\ U}$$

will be called the <u>quality</u> of the classification C(U) =

$=\{x_1,\ldots,x_n\}$ in A and the number

$$\beta_A C(U) = \frac{\operatorname{card}\left(\bigcup_{i=1}^{n} \underline{A}X_i\right)}{\operatorname{card}\left(\bigcup_{i=1}^{n} \overline{A}X_i\right)}$$

will be called the <u>accuracy</u> of the classification $C(U)$ in A. Instead of $\eta_A\, C(U)$ and $\beta_A\, C(U)$ we shall also write $\eta_R\, C(U)$ and $\beta_R\, C(U)$ respectively.

3. INFORMATION SYSTEMS AND CLASSIFICATION

3.1. <u>Information systems</u>

In this section we shall consider special kind of approximation spaces needed when classifying objects on basis of their properties, and we identify properties with some attributes characteristic for those objects. With each attribute a set of values is associated. Description of an object is given when one value for each attribute is chosen.

The above idea can be expressed more precisely by means of the notion of an information system introduced in Pawlak (1981).

By an information system S we mean an ordered quadruple

$S = (U, Q, V, \rho)$, where:

U - is a set called the <u>universe</u> of S; elements of U are called <u>objects</u>

Q - is a set of <u>attributes</u>

$V = \bigcup_{q\in Q} V_q$ - is a set of <u>values</u> of attributes; V_q will be called the <u>domain</u> of q

$\rho : U \times Q \to V$ is a <u>description function</u>, such that $\rho(x,q) \in V_q$ for every $q \in Q$ and $x \in U$.

We introduce function $\rho_x : Q \to V$ such that $\rho_x(q) = \rho(x,q)$ for every $q \in Q$ and $x \in U$; ρ_x will be called <u>description</u> of x in S.

For the sake of simplicity function ρ_x will be written as a sequence of attribute values $v_{i_1}, v_{i_2}, \ldots, v_{i_n}$ assumming that $v_{i_j} \in V_{q_j}$. Of course, order of values in this sequence is immaterial.

We say that objects $x, y \in U$ are <u>indiscernibable</u> with respect to $q \in Q$ in A, iff $\rho_x(q) = \rho_y(q)$, and we shall write $x \tilde{q}\, y$; certainly $\tilde{q}$ is an equivalence relation. Objects $x, y \in U$ are indiscernibable with respect to $P \subset Q$ in S, in symbols $x \tilde{P}\, y$, iff $\tilde{P} = \bigcap_{p\in P} \tilde{p}$.

In particular if $P = Q$ we say that x and y are indiscernibable in S and write $x \tilde{S}\, y$ instead of $x \tilde{Q}\, y$.

Obviously P is an equivalence relation, thus each information system $S = (U, Q, V, \rho)$ defines uniquely an approximation space $A_S = (U, \tilde{S})$, where $\tilde{S}$ is the indiscernibility relation generated by the information system S.

If $x \in U$ and ρ_x is the description of x in S, then we assume that ρ_x is also the description of the equivalence class of the relation $\tilde{S}$ containing x.

We say that subset $X \subset U$ is describable in S iff X is definable in A_S; if X is undefinable in A_S, X will be called <u>nondescribable</u> in S. description of a describable set in S consists of QU descriptions of its elementary sets. Description of an empty set is denoted by λ.

Example 1

Suppose we are given information system $S = (U, Q, V, \rho)$ where

$U = \{x_1, x_2, \ldots, x_{10}\}$

$Q = \{p, q, r\}$

$V_p = \{0, 1, 2\}$

$V_q = \{0, 1\}$

$V_r = \{0, 1, 2, 3\}$

and information function ρ is given by the table below

U	p	q	r
x_1	1	0	3
x_2	0	1	1
x_3	0	1	1
x_4	1	1	0
x_5	1	1	0
x_6	2	0	1
x_7	0	1	1
x_8	2	0	1
x_9	2	0	2
x_{10}	1	0	3

These are the following elementary sets in the system

$E_1 = \{x_1, x_{10}\}$

$E_2 = \{x_2, x_3, x_7\}$

$E_3 = \{x_4, x_5\}$

$E_4 = \{x_6, x_8\}$

$E_5 = \{x_9\}$

For example sets

$X_1 = \{x_1, x_2, x_3, x_9, x_{10}\} = E_1 \cup E_2$

$X_2 = \{x_2, x_3, x_4, x_5, x_6, x_7, x_8\} = E_2 \cup E_3 \cup E_4$

are describable in S, and sets

$X_3 = \{x_1, x_2, x_3, x_7, x_8\}$

$X_4 = \{x_1, x_3, x_9\}$

are nondescribable in S.

We can introduce the following four classes of nondescribable sets in a information system S.

Let X U be nondescribable set in S. Then

(C1) If X is roughly definable in A_S then X is called <u>roughly describable</u> in S,

(C2) If X is externally undefinable in A_S, then X is called <u>externally nondescribable</u> in S,

(C3) If X is internally undefinable in A_S, then X is called <u>internally nondescribable</u> in S,

(C4) If X is totally undefinable in A_S, then X is called <u>totally nondescribable</u> in S.

The meaning of these definitions is abvious. They simply say that there are several grades of nondescribability, from approximate describability to total nondescribability. In other words if we are given some properties (attributes) of object, and we want to characterize subset of objects by means of these properties, the task can end in failure, because only describable sets can be uniquely characterized by given set of attributes.

Example 2

Let us consider information system as in example 1.

Then set

$$Y_1 = \{x_1, x_2, x_4, x_5\}$$

is roughly describable in S;

Set

$$Y_2 = \{x_1, x_2, x_3, x_4, x_6, x_9\}$$

is externally nondescribable in S;

Set

$$Y_3 = \{x_1, x_2, x_5, x_8\}$$

is internally nondescribable in S.

There are no totally nondescribable sets in this system.

3.2. Attribute dependenciesand reduced information systems

By means of the indescernibility relation we can easily define some important features of information systems, first of all the most important one - dependency at attributes.

Let $S = (U, Q, V, \varrho)$ be an information system and let $p, q \in Q$.

(a) Attribute p is said to be dependent on attribute q in S, $(q \rightarrow p)$ iff $\tilde{q} \subset \tilde{b}$.

(b) Attributes p, q are called independent in S iff neither $p \rightarrow q$ nor $q \rightarrow p$ hold.

The meaning of these two definitions is obvious. For more details see Pawlak (1981).

Example 3

Consider the information system $S = (U, Q, V, \varrho)$ such that $U = \{x_1, x_2, x_3, x_4, x_5\}$, $Q = \{q_1, q_2, q_3, q_4\}$, $V_{q_1} = \{0, 1\}$, $V_{q_2} = \{0, 1\}$, $V_{q_3} = \{0, 1\}$, $V_{q_4} = \{0, 1, 2\}$, and function ϱ given by the table below:

U	q_1	q_2	q_3	q_4
x_1	0	0	0	0
x_2	0	1	0	2
x_3	1	1	0	1
x_4	1	1	0	1
x_5	0	1	1	2

It is easy to see that $q_4 \rightarrow q_2$ and $q_4 \rightarrow q_1$ because $\tilde{q}_4 \subset \tilde{q}_2$ and $\tilde{q}_4 \subset \tilde{q}_1$.

For later purpose we introduce some new definitions.

(c) A subset $P \subset Q$ is said to be independent in S iff for every $P' \subset P$, $\tilde{P'} \supset \tilde{P}$.

(d) A subset $P \subset Q$ is said to be dependent in S iff there exists a $P' \subset P$ such that $\widetilde{P'} = \widetilde{P}$.

(e) A subset $P' \subset P$ is said to be superfluous in P iff $\widetilde{P - P'} = \widetilde{P}$.

(f) A subset $P \subset Q$ is called reduct of Q in S iff Q - P is superfluous in Q and P is independent in S; the corresponding system $S' = (U, P, V, \varrho')$ is called reduced system (ϱ' is the restriction of ϱ to set UxP).

Example 4

In the information system considered in example 3 set of attributes Q is dependent in S and sets $\{q_1, q_2, q_3\}$, $\{q_3, q_4\}$ are reducts of Q.

Note the a system can have more than one reduct!

Now we give some properties of attributes, which enable us to simplify the decision procedure whether set of attributes is dependent or not, and the procedure for finding reducts of the set of attributes. The proofs are by simple computation.

Fact 1. If set of attributes Q is independent in S then all its different attributes are pairwise independent in S.

Fact 2. Subset $P \subset Q$ is dependent in S iff there exists $P' \subset P$ such that P' is superfluous in P.

Fact 3. If $P \subset Q$ is independent in S then every $P' \subset P$ is also independent in S.

Fact 4. If $P \subset Q$ is dependent in S, then for every $P' \supset P$ and $P' \subset Q$, P' is dependent in S.

Let $P = \{p_1, p_2, \ldots, p_n\}$, $P \subset Q$ and let $P_i = P - \{p_i\}$, $1 \leq i \leq n$.

Fact 5. Set $P \subset Q$ is independent in S iff for every i $(1 \leq i \leq n)$ $\widetilde{P_i} \supset \widetilde{P}$.

Fact 6. Set $P \subset Q$ is independent in S iff for every i $(1 \leq i \leq n)$ $card(U/\widetilde{P_i}) < card(U/\widetilde{P})$.

By Facts 5 and 6 in order to check whether set $P \subset Q$ is independent or not in S it is enough to check for every attribute whether removing of this attribute increases the number of elementary sets or not in the system. This leads to very simple algorithm.

If set of attributes is dependent we can be interested in finding all reduced systems.

The reduction algorithm can be based on the following property:

Fact 7. If $P \subset Q$ is superfluous in Q and $\{p\}$ is superfluous in Q - P, then $P \cup \{p\}$ is superfluous in Q.

By this property we can eliminate superfluous attributes step by step from the system; after exhausting all possible patterns of reduction we get all reducts of Q in S.

In order to explain the above ideas in more detail let us first define the notion of representation of an information system.

Let $S = (U, Q, V, \rho)$ be an information system. The system $S^* = (U/\tilde{S}, Q, V, \rho^*)$ will be called representation of S where

$$\rho^* : U/\tilde{S} \times Q \to V$$

and

$$\rho^*(X,q) = v, \quad X \in U/\tilde{S}, \ q \in Q$$

iff

$$\rho(x, q) = v$$

for all $x \in X$.

In other words, if we omit all duplicate rows in the table of function ρ and replace objects by elementary sets containing these objects so we obtain representation of the system.

Example 5

Let us consider information system in example 3, i.e

U	q_1	q_2	q_3	q_4
x_1	0	0	0	0
x_2	0	1	0	2
x_3	1	1	0	1
x_4	1	1	0	1
x_5	0	1	1	2

For the sake of simplicity throughout the remainder of this paper we will identify the notion of the information system with the table of the information function.

The representation of this system has the form

$U/\tilde{S}$	q_1	q_2	q_3	q_4
$\{x_1\}$	0	0	0	0
$\{x_2\}$	0	1	0	2
$\{x_3, x_4\}$	1	1	0	1
$\{x_5\}$	0	1	1	2

Thus each row in the table is the description of an elementary set, and we can treat the whole table as the description of the whole information system.

In order to simplify the notation the above table will be also presented as follows:

1	2	3	4
0	0	0	0
0	1	0	2
1	1	0	1
0	1	1	2

The set of attributes in this system is dependent because by removing attribute 4 we obtain system

1	2	3
0	0	0
0	1	0
1	1	0
0	1	1

with the same number of elementary sets as the original system.

After removing attribute 3 from the last system we obtain system

1	2
0	0
0	1
1	1
0	1

in which the second and the fourth rows are the same, which is to mean that the second and the fourth elementary sets are "glued" together and in this way we get smaller number of elementary sets so attribute 3 is not superfluous. Proceeding in this way we get that 1, 2, 3 and 3, 4 are the only reducts of set of attributes 1, 2, 3, 4 .

The corresponding reduced systems are the following

1	2	3
0	0	0
0	1	0
1	1	0
0	1	1

3	4
0	0
0	2
0	1
1	2

One can easily see that each elementary set in these systems has different description and that removing any attribute (column) from the system changes this property.

If a set of attributes Q is independent in S and we remove subset P from Q, than we obtain independent set of attributes Q - P in S again. If the relations $\tilde{Q}$ and $\widetilde{Q-P}$ differ "a litle", we can say that set P is roughly superfluous in S.

More exactly, we say that set $P \subset Q$ is ε - <u>superfluous</u> in S iff

$$\mu_{\tilde{Q}}(X) - \mu_{\widetilde{Q-P}}(X) \leq \varepsilon$$

for every $X \subset U$, and consequently we say that $P \subset Q$ is ε -<u>reduct</u> of Q in S iff

$$\mu_{\tilde{Q}}(X) - \mu_{\tilde{P}}(X) \leq \varepsilon$$

for every $X \subset U$.

To this end let us remark that sometimes we are interested in removing superfluous (ε - superfluous) attributes not for the whole set of objects U, but for a certain subset X of U.

In such a case we can simply use the same methods as before assumming only that the universe of the system is not U but X.

4. EXAMPLE OF APPLICATION

4.1. <u>The program</u>

On the basis of the presented approach a program has been developed (see Fila & Wilk (1983)) which

(i) computes lower and upper approximations of sets

(ii) checks whether a set of attributes is dependent or independent

(iii) computes reducts of a set of attributes

(iv) computes accuracy of approximation

The program is very simple and contains about 200 lines in FORTRAN.

4.2. Medical diagnosis

As an example, the program has been used for medical data analysis.

A file of 150 patients suffering from heart disease seen in one of hospitals in Warsaw was used as a data base. All patients have been divided by experts into six classes corresponding to their health status.

With every patient seven items of information (attributes) were associated. For the sake of simplicity attributes were nembered 1, 2, 3, 4, 5, 6 and 7, and their domains were $V_1 = V_2 = V_3 = V_4 = V_5 = \{0, 1, 2\}$, $V_6 = \{0, 1, 2, 3, 4\}$ and $V_7 = \{0, 1, 2, 3\}$.

The problem was to find description of each class in terms of data available for each patient of this class, check whether the set of attributes is dependent or independent, find reducts for each class, and compute accuracy of descriptions.

4.3. Approximations and accuracy

There were 125 elementary sets in the system under consideration (104 - one element sets, 19 - two element sets, 1 - three element set and 1 - five element-set).

The table below showes the accuracy of description of each class:

Class Number	Number of patients	Lower Approx	Upper Approx	Accuracy
1	10	4	15	0,27
2	46	33	54	0,72
3	42	39	45	0,87
4	33	30	36	0,83
5	15	15	15	1,00
6	4	4	4	1,00

We see that classes 5 and 6 are describable in the system, and the remaining classes are <u>roughly</u> describable with the accuracy given in the least column. That is to say that data (symptoms) available from the patients characterize exactly classes 5 and 6 only, and the remaining classes not are characterized exactly by these data; especially class 1 has very low accuracy.

The quality of the whole classification is 0,87 and the accuracy of the whole classification is 0,95 (see section 2.5).

For the sake of simplicity we show only approximations for class 1.

Lower approximation

1	2	3	4	5	6	7
0	1	0	0	1	1	0
0	1	2	0	1	1	0
1	0	0	0	0	1	0
2	0	0	0	1	1	0

Upper approximation

1	2	3	4	5	6	7
0	0	0	0	0	1	0
0	0	0	0	1	1	0
0	0	0	0	1	0	0
0	0	0	0	1	1	1
0	1	0	0	1	1	0
0	1	2	0	1	1	0
1	0	0	0	0	1	0
2	0	0	0	1	1	0

The boundary

1	2	3	4	5	6	7
0	0	0	0	0	1	0
0	0	0	0	1	1	0
0	0	0	0	1	0	0
0	0	0	0	1	1	1

4.4. Independence of attributes

According to Fact 6 (section 3.2) in order to check whether the set of attributes is dependent or not we have to remove one attribute step-by-step and compute the number of elementary sets for each case.

The results of computation are given below:

Removed Attribute	non	1	2	3	4	5	6	7
Number of elementary sets	125	106	111	113	118	106	100	101

Because the number of elementary sets is always smaller than 125 that means that set of attributes is independent, and consequently all different attributes are pairwise independent.

In the next table we give accuracy of approximation for each class when removing one attribute

Class Number	non	1	2	3	4	5	6	7
				Removed Attribute				
1	0,27	0,06	0,19	0,12	0,27	0,19	0,18	0,25
2	0,72	0,59	0,59	0,58	0,65	0,57	0,54	0,59
3	0,87	0,65	0,67	0,65	0,69	0,59	0,55	0,55
4	0,83	0,60	0,60	0,72	0,78	0,62	0,68	0,46
5	1,00	0,68	0,76	1,00	0,88	0,82	0,55	0,63
6	1,00	0,40	1,00	1,00	1,00	1,00	0,00	0,17

It is easily seen from the table above how the attributes influence accuracy of description. For example removing attribute 4 gives the smallest changes in accuracy. The accuracy without attribute 4, differs at most about 0,18. So we can say that attribute 4 is ε- superfluous for the classification (ε= 0,18).

4.5. Reduction of attributes

In this section we will show reducts of some classes, i.e. minimal sets of attributes necessary for description of these classes.

Let us first consider class 5 which is describable and has the following description

1	2	3	4	5	6	7
0	0	2	0	2	3	3
0	0	2	2	0	4	2
0	1	2	1	2	2	2
0	2	1	2	1	0	0
0	2	2	1	0	2	3
0	2	2	2	2	3	3
0	2	2	2	2	4	3
1	2	2	2	1	3	3
1	2	2	2	2	2	1
2	2	1	1	1	3	3

2	2	2	2	1	3	2
2	2	2	2	1	3	3
2	2	2	1	2	2	3
2	2	2	2	2	3	0
2	2	2	2	2	4	2

By Fact 7 (Section 3.2) we can compute that attributes 2, 3 and 5 are superfluous for class 5 in the system and we can have the following classification of class 5:

1	4	6	7
0	0	3	3
0	1	2	2
0	1	2	3
0	2	0	0
0	2	3	3
0	2	4	2
0	2	4	3
1	2	2	1
1	2	3	3
2	1	3	3
2	2	2	3
2	2	3	0
2	2	3	2
2	2	3	3
2	2	4	2

If we consider nondescribable class, for example class 1, then we get the following descriptions:

Lower approximation

1	2	3	4	5	6	7
0	1	0	0	1	1	0
0	1	2	0	1	1	0
1	0	0	0	0	1	0
2	0	0	0	1	1	0

Upper approximation

1	2	3	4	5	6	7
0	0	0	0	0	1	0
0	0	0	0	1	0	0
0	0	0	0	1	1	0
0	0	0	0	1	1	1
0	1	0	0	1	1	0
0	1	2	0	1	1	0
1	0	0	0	0	1	0
2	0	0	0	1	1	0

The boundary

1	2	3	4	5	6	7
0	0	0	0	0	1	0
0	0	0	0	1	0	0
0	0	0	0	1	1	0
0	0	0	0	1	1	1

Reducts of the lower approximation, upper approximation and the boundary are {1, 3}, {1, 2, 3, 5, 6, 7} and {5, 6, 7} respectively.

Consequently we have the following descriptions of these sets:

Lower approximation

1	3
0	2
2	0
0	0
1	0

Upper approximation

1	2	3	5	6	7
0	0	0	0	1	0
0	0	0	1	0	0
0	0	0	1	1	0
0	0	0	1	1	1
0	1	0	1	1	0
0	1	2	1	1	0
1	0	0	0	1	0
2	0	0	1	1	0

The boundary

5	6	7
0	1	0
1	0	0
1	1	0
1	1	1

4.6. <u>Combined case</u>

Sometimes we can be interested in combining same classes together, for example in our case classes 1 and 2, and 5 and 6.

In this case we obtain the following results:

Class Number	Number of Patients	Lower Approx	Upper Approx	Accuracy
1´	56	54	58	0,93
2´	42	39	45	0,87
3´	33	30	36	0,83
4´	19	19	19	1,00

We see that now the classification is much better described by the attributes, than in the previous example.

The quality and accuracy of this classification both are 0,95.

In the table below we give results of computation showing how the accuracy of class description changes when removing one attribute from the system.

Class	Removed Attribute							
Number	non	1	2	3	4	5	6	7
1´	0,93	0,85	0,82	0,84	0,85	0,80	0,74	0,81
2´	0,87	0,65	0,67	0,65	0,69	0,59	0,55	0,55
3´	0,83	0,60	0,60	0,72	0,78	0,62	0,68	0,46
4´	1,00	0,63	0,71	1,00	0,90	0,90	0,40	0,52

5. CONCLUSION

The proposed method can be viewed as a new approach to approximate data analysis, especially in approximate classification, approximate clustering, approximate learning algorithms, etc.

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