Application of Credibility Coefficients Based on Decision Rules

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Abstract. Credibility coefficients reflect similarity of objects in respect to other ones in information systems. For decision tables we can use credibility coefficients based on decision rules. Knowledge discovery methods can extract rules from an information system. The knowledge represented by the rules may be not exact due to improper data. Calculation of credibility coefficients is based on an assumption that majority of data is correct and only a minor part may be improper. The main purpose of using credibility coefficients is to indicate to which group a particular object probably belongs. A main focus of the paper is set on an algorithm of calculating credibility coefficients and a presentation how credibility coefficients can be used. The algorithm of presented credibility coefficients is based on decision rules, which are generated using the rough set theory. Some remarks on practical results of identifying improper data by credibility coefficients are inserted in the paper as well.

Keywords. Credibility coefficients, information system, decision tables, decision rules, rough set theory.

1 Introduction

Credibility coefficients [1] [2] [3] [4] [5] [6] were invented to discover objects, which do not match to the other ones in information systems or decision tables. A credibility coefficient is just a heuristically calculated value ranging from 0 to 1. The values closer to the lower bound stand for low credibility and values near to the upper bound represent high credibility. The whole concept has been worked out with an assumption that majority of data is correct and only minority of them can be treated as improper or unusual. Calculations of credibility coefficients are aimed to discover similarities between objects using different approaches. The ARES Rough Set Exploration System [3] [7] exploits the rough set theory concepts [8] [9] [10] for providing data analysis. A functionality of the ARES System covers all phases of rough sets theory aimed to discovering rules by choosing different algorithms. A unique feature of the ARES System is a capability of evaluating credibility coefficients for objects from decision tables. Some algorithms were already published [1] [2] [3] [5] [6] and this paper present results of calculations of one particular credibility coefficient (based on decision rules) for a significantly large decision table.

Although the ARES Rough Set Exploration System is a general data analysis tool, its primary destination was medicine [10] [11]. In medicine and other natural sciences exceptions to rules very often are more interesting and inspiring than the rules themselves. For instance, in medicine it is a challenge to identify a disease even when the symptoms are not typical, when, in general terms, a case does not fit to the rules. A good physician can be distinguished by his/her intuition in solving exceptional cases. The goal of introducing credibility coefficients was to provide an automatic aid in expert systems for identifying exceptional cases to draw a special attention of specialists to these cases.

The paper comprises a very short description of rough set theory to enable expressing mathematical descriptions of credibility coefficients based on decision rules. An intuitive description and explanation of the algorithm is given as well. Then follows chapters presenting an example of a tiny decision table, for which the credibility coefficients were computed, and a proposal of developing the algorithm. Then potentials of ARES System are presented in an example with a significant volume of data. The paper is completed with some conclusions and suggestions how credibility coefficients can be applied in practice.

2 Rough Set Concepts

The information system S can be defined as $S = \langle U, Q, V, f \rangle$**,** where U is a finite set of objects, Q is a finite set of attributes, $V = \sum_{q \in Q} V_q$ and V_q is a domain of the attribute q and $f: U \times Q \to V$ is a function that $f(x, q) \in V_q$ for every $x \in U$, $q \in Q$.

An information system can be represented by a table, where rows correspond to objects and columns correspond to attributes. Every cell stores a value of the given attribute for a particular object.

An information system is a decision table if the set of all attributes is split into condition attributes C and decision attributes D ($Q = C \cup D$ and $C \cap D = \varnothing$). Information system $S = \langle U, C \cup D, V, f \rangle$ is deterministic iff $C \to D$; otherwise is non-deterministic.

For further consideration we assume that number of decision attributes is limited to one. This restriction is often met in practical data analysis tools and in the ARES Rough Set Exploration System as well.

Elementary condition is a pair of attribute-value. Every object satisfies a set of elementary conditions represented by cells of information system (or decision table). Set of all elementary conditions of object $t \in U$ is denoted as $Inf(t)$.

Coverage of set of elementary conditions P (denoted as $\langle P \rangle$) in a given information system is a set of objects satisfying all conditions represented by P.

Support of set of elementary conditions P (denoted as $sup(P)$) in a given information system is a cardinality of set $\langle P \rangle$, which is a number of objects satisfying all conditions represented by P. A set of elementary conditions is called frequent set if its support is greater (or greater-equal) than a given value.

3 Credibility Coefficients Based on Decision Rules

3.1 Notations for Algorithm

The following notation is used in describing the algorithm of calculating credibility coefficients based on decision rules:

- *W[]* – vector *W*, which index domain may be any set of data, in particular for object $t \in DT$, *W[t]* denotes value of vector element, which is associated with object t (e.g. vectors *counts[]*, *decCount[]*, *CFS[]*),
- *Inf(t)* – set of elementary conditions based on values of successive attributes of object t
- $(X \rightarrow Y).conf$ – confidence of rule $X \rightarrow Y$

3.2 Algorithm

Input data:

- *AR* – set of decision rules
- *DT* – decision table

Output data:

- *CR[]* – vector of credibility coefficients for all objects

```
1   counts[] = New counts[]
2   C_R'[] = New C_R'[]
3   Forall (X→Y)∈AR Do
4          Forall t∈DT Do
5                 If X ⊂ Inf(t) And Y ∉ Inf(t) Then
6                        counts[t] := counts[t] + 1
7                        C_R'[t] := C_R'[t] + (X→Y).conf
8   Forall t∈DT Do
9          C_R[t] := 1
10         If (count[t] <> 0) Then
11                C_R[t] := C_R[t] – C_R'[t]/counts[t]
```

For all rules the algorithm investigates all objects form the decision table (lines 3-7). For objects, which satisfy an antecedent of the analyzed rule and at the same time have decision values different than the decision of the rule, an auxiliary value of credibility coefficient (CR[t]) is incremented by a confidence of the rule (not supported by the object) and a counter for the object is incremented by one.

The last part of the algorithm (lines 8-11) sets initial values of the credibility coefficients to maximum (1). If a counter of a particular object is not zero (it means, there was at least one rule, which antecedent was satisfied by the object and decision values of the objects and the rule were different) the value of the credibility coefficient is decremented by the quotient of the auxiliary value and the counter.

The idea of the algorithm is to punish such objects, which do not fit to the rules of the system. The objects exposed by the algorithm (by assigning lower values of credibility coefficients) satisfy only antecedents of rules (one or more), but have their decisions set not in accordance to the rules. The penalty to the maximal value of the credibility coefficient is an average confidence of the violated rules.

3.3 Formulas

Formula for credibility coefficient C_R [1] [2] for object $u \epsilon U$ from a decision table $TD = <U, C \cup \{d\}, V, f>$ and set of rules AR can be presented as

$$C_R(u) = \begin{cases} 1 & for \quad S(u) = \phi \\ 1 - \dfrac{C_R^{'}(u)}{|S(u)|} & for \quad S(u) \neq \phi \end{cases}$$

$$S(u) = \left\{ \quad (X \rightarrow Y) \in AR : u \in \left\langle X \right\rangle \ \wedge \ u \notin \left\langle \{Y\} \right\rangle \ \right\}$$

$$C_R^{'}(u) = \sum_{(X \rightarrow Y) \in S(u)} (X \rightarrow Y).conf$$

where $(X \rightarrow Y).conf$ denotes confidence of rule $X \rightarrow Y$

The idea of the algorithm is to discover such objects, which do not fit to the decision rules (emerging from the decision table). The improper objects identified by the algorithm (by assigning lower values of credibility coefficients) satisfy antecedents of rules (one or more), but have their consequents different that these in the rules. The penalty decreasing value of the credibility coefficient is an average confidence of the violated rules.

The presented algorithm can be modified by applying only possible rules (and not all rules). The modification of the algorithm results in a slight change in its meaning. A specific feature of possible rules (but not certain ones) is used in the algorithm. If an object covers antecedent of the rule and have a different value of the decision it means that there are some other objects which are indiscernible with this one (from the point of view of the condition attributers) and have the decision equal to the consequent of the rule. Such object is “different” then others in respect to the considered rules and this is the reason why its credibility coefficient is decremented (by average confidence of the rules).

3.4 Example

Credibility coefficient based on decision rules can be found in an example of six objects representing a group of patients (Table 1). Three condition attributes (headache, myalgia and temperature) and one decision attribute (flue) create the original decision table. Values in cells of the decision tables are presented in text form (for legibility) and corresponding integer number used by the ARES System (number in parentheses). The decision table is augmented by two columns with values of credibility coefficients based on decision rules:

- $\mathbf{C_{AR}}$ denotes credibility coefficient evaluated from all rules,
- $\mathbf{C_{PR}}$ denotes credibility coefficient evaluated from possible rules.

Both coefficients were calculated using rules extracted with minimal support equal to 33% and minimal confidence equal to 50%.

Table 1. Credibility coefficients based on decision rules for a set of patients

No.	Headache	Myalgia	Temperature	Flue	C_{AR}	C_{PR}
1	No (0)	Yes (1)	High (0)	Yes (1)	1.00	1.00
2	Yes (1)	No (0)	High (0)	Yes (1)	1.00	1.00
3	Yes (1)	Yes (1)	Very High (1)	Yes (1)	1.00	1.00
4	No (0)	Yes (1)	Very High (1)	Yes (1)	1.00	1.00
5	Yes (1)	No (0)	High (0)	No (0)	0.34	0.34
6	No (0)	Yes (1)	Normal (2)	No (0)	0.31	1.00

Only for objects 5 and 6 credibility coefficients are reduced. Value of credibility coefficient $\mathbf{C_{PR}}$ for object 5 indicates that this is the only object for which there is at least one possible rule, which has antecedent covered by the object and consequent different than decision of the object. In general, values of both credibility coefficients result form a small number of rules applicable to the objects.

The similar tests were performed for the following rule parameters:

- Minimal support (in number of objects): {1, 2, 3}
- Minimal confidence (in %): {25, 50, 75, 100}

The results are presented in Table 2, which contains as well number of rules applicable in each case. Every combination of two values of the support and the confidence is labeled by a variant for further discussion of the results.

For minimal support set to 3 (variants v3, v6 and v9) coefficient CAR has non-maximal value. There were no possible rules for these cases and hence values of coefficient CPR were evaluated to 1. For minimal confidence equal to 100% all rules were possible and certain, so no objects could be punished by algorithm evaluating the credibility coefficients. For minimal support set to 75% (variants v7, v8, v9) only object 6 has non-maximal value for coefficient CPR and all other coefficient values are highest. For variants v1 and v4 objects 2 and 5 get non-maximal value. The better discrimination of objects in these cases (characterized by small support and small confidence for rules involved) is caused by more significant number of the rules and then more precise evaluation of each object.

Table 2a. Series of credibility coefficients based on decision rules with confidence values equal to 25% and 50% for set of patients from Table 1.

Conf.		25						50					
Supp.		1		2		3		1		2		3	
Var.		v1		v2		v3		v4		v5		v6	
|AR|		34		7		1		29		7		1	
|PR|		26		4		0		26		4		0	
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}
Patients	1	0,7	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	2	0,5	0,5	1,0	1,0	1,0	1,0	0,5	0,5	1,0	1,0	1,0	1,0
	3	0,7	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	4	0,7	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	5	0,5	0,5	0,3	0,3	1,0	1,0	0,5	0,5	0,3	0,3	1,0	1,0
	6	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0

Table 2b. Series of credibility coefficients based on decision rules with confidence values equal to 75% and 100% for set of patients from Table 1

Conf.		75						100	
Supp.		1		2		3		1	2
Var.		v7		v8		v9		v10	v11
|AR|		15		3		1		14	2
|PR|		14		2		0		14	2
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{PR}	C_{PR}
Patients	1	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	2	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	3	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	4	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	5	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	6	0,3	1,0	0,3	1,0	0,3	1,0	1,0	1,0

The next table (Table 3) presents the same series of credibility coefficients when object 5 was removed from the decision table. This object was indicated the "worst" one by relatively low values of credibility coefficients based on decision rules. If it is the exception to the rules we are curious how works the same algorithm on data without the exception.

Table 3a. Series of credibility coefficients based on decision rules with confidence values equal to 25% and 50% for set of patients from Table 1 without object 5

Conf.		25						50					
Supp.		1		2		3		1		2		3	
Var.		v1		v2		v3		v4		v5		v6	
|AR|		27		7		1		24		7		1	
|PR|		21		4		0		21		4		0	
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}
Patients	1	0,7	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	2	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	3	0,8	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	4	0,7	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	6	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0	0,3	1,0

Table 3b. Series of credibility coefficients based on decision rules with confidence values equal to 75% and 100% for set of patients from Table 1 without object 5

Conf.		75						100	
Supp.		1		2		3		1	2
Var.		v7		v8		v9		v10	v11
|AR|		22		5		1		21	2
|PR|		21		4		0		21	2
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{PR}	C_{PR}
Patients	1	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	2	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	3	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	4	1,0	1,0	1,0	1,0	1,0	1,0	1,0	1,0
	6	0,3	1,0	0,3	1,0	0,3	1,0	1,0	1,0

For all variants, values of coefficient C_{PR} are utmost, because the new decision table (without object 5) is deterministic one, so all rules are certain. For variants v2-v9 coefficients C_{AR} have non-maximal values only for object 6, which is the only one having decision different than the other objects. For variant v1 all objects but object 2 have non-maximal value of credibility coefficient C_{AR}. The objects were "punished" by rules generated from object 6 (in variant v1 minimal support is 1).

3.5 Modification of the Algorithm

The proposed algorithm for evaluating credibility coefficients based on decision rules has a very important drawback. Initial value of the credibility coefficient for every object is set to one. Only such objects which cover antecedents of the rules can have their initial value of credibility coefficients modified (in minus). Some objects may do not fit to any rules, because their set is limited by values of minimal support and minimal confidence of the rules. Such objects were not involved in calculations, and pretended to be perfectly appropriate in the decision table, which is obviously not true. The objects will be called uncertain and modification of the algorithm is aimed to point them out.

Let us have the modification of the algorithm presented in chapter 3.2.

```
counts[] = New counts[]
visited[] = New visited[]
CR'[] = New CR'[]
Forall (X→Y)∈AR Do
      Forall t∈DT Do
            If X ⊂ Inf(t) Then
                  visited[t] := TRUE
                  If Y ⊄ Inf(t) Then
                        counts[t] := counts[t]+1
                        CR'[t]:=CR'[t]+(X→Y).conf
Forall t∈DT Do
      If visited[t] = TRUE Then
            CMR [t] := 1
      Else
            CMR [t] := -1
      If (count[t] <> 0) Then
            CMR [t] := CMR [t] – CR'[t]/counts[t]
```

More formally, the modified credibility coefficient C^M_R for object $u \in U$ from decision table $TD = (U, C \cup \{d\}, V, f)$ and set of rules AR can be expressed as below.

$$C_R^M(u) = \begin{cases} -1 & \text{for } W(u) = \phi \\ 1 & \text{for } W(u) \neq \phi \ \wedge \ S(u) = \phi \\ 1 - \dfrac{C'_R(u)}{|S(u)|} & \text{for } S(u) \neq \phi \end{cases}$$

$$W(u) = \{ (X \to Y) \in AR : \ u \in \langle X \rangle \}$$

$$S(u) = \{ (X \to Y) \in AR : \ u \in \langle X \rangle \ \wedge \ u \notin \langle \{Y\} \rangle \}$$

$$C'_R(u) = \sum_{(X \to Y) \in S(u)} (X \to Y).conf$$

Value -1 is a special one for denoting the uncertain objects. It does not belong to the domain of the credibility coefficient and is used only for objects for which the algorithm cannot be properly applied. Such objects may be interested as a different kind of exceptions (in contradiction do exceptions pointed out by the credibility coefficients.

Table 4 presents the impact of the modification on values of credibility coefficients evaluated with the same assumptions as for Table 2. The uncertain object is denoted by ‘?’ when the algorithm fails in classifying the credibility of the object.

Table 4a. Series of modified credibility coefficients based on decision rules with confidence values equal to 25% and 50% for set of patients from Table 1

Conf.		25						50					
Supp.		1		2		3		1		2		3	
Var.		v1		v2		v3		v4		v5		v6	
$\lvert AR \rvert$		34		7		1		29		7		1	
$\lvert PR \rvert$		26		4		0		26		4		0	
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}
Patients	1	0,7	1,0	1,0	1,0	1,0	?	1,0	1,0	1,0	1,0	1,0	?
	2	0,5	0,5	1,0	1,0	?	?	0,5	0,5	1,0	1,0	?	?
	3	0,7	1,0	1,0	1,0	1,0	?	1,0	1,0	1,0	1,0	1,0	?
	4	0,7	1,0	1,0	1,0	1,0	?	1,0	1,0	1,0	1,0	1,0	?
	5	0,5	0,5	0,3	0,3	?	?	0,5	0,5	0,3	0,3	?	?
	6	0,3	1,0	0,3	?	0,3	?	0,3	1,0	0,3	?	0,3	?

Table 4b. Series of modified credibility coefficients based on decision rules with confidence values equal to 75% and 100% for set of patients from Table 1

Conf.		75						100	
Supp.		1		2		3		1	2
Var.		v7		v8		v9		v10	v11
$\lvert AR \rvert$		15		3		1		14	2
$\lvert PR \rvert$		14		2		0		14	2
Coeff.		C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{AR}	C_{PR}	C_{PR}	C_{PR}
Patients	1	1,0	1,0	1,0	?	1,0	?	1,0	1,0
	2	?	?	?	?	?	?	?	?
	3	1,0	1,0	1,0	1,0	1,0	?	1,0	1,0
	4	1,0	1,0	1,0	1,0	1,0	?	1,0	1,0
	5	?	?	?	?	?	?	?	?
	6	0,3	1,0	0,3	?	0,3	?	1,0	1,0

4 Applying the ARES System

The ARES Rough Set Exploration System is a versatile data analysis tool. Having an information system a user can decide to:

- calculate discernibility matrix,
- find reducts,
- find frequent sets,
- mine rules,
- calculate credibility coefficients.

The ARES System can analyze many information systems and their features can be compared with one another. In this section potentials of the ARES System associated with credibility coefficients based on decision rules are presented.

Credibility coefficients based on decision rules are useful only for such elements of a decision system, which is non-deterministic and we do not have such data set with large size. Most of data available in internet sources for classification testing are composed from exactly definable sets defined by the decision attributes and credibility coefficients based on decision rules produce only two values for all objects form such information system. The values are either 1.0 or '?' (not applicable).

To present methodology of applying the credibility coefficients we prepared the data set in an artificial way. We took a set of Letter Image Recognition Data [13], which has 20000 records (objects) and 17 integer attributes. Arbitrarily we chose the first attribute as a decision one. In Fig. 1 the properties of the initial information system are presented. Number of rules generated from the system was 733 – minimal support for the rules was set to 200 (1% of all objects) and minimal confidence was set to 50%. Then we got credibility coefficients based on decision rules for all objects.

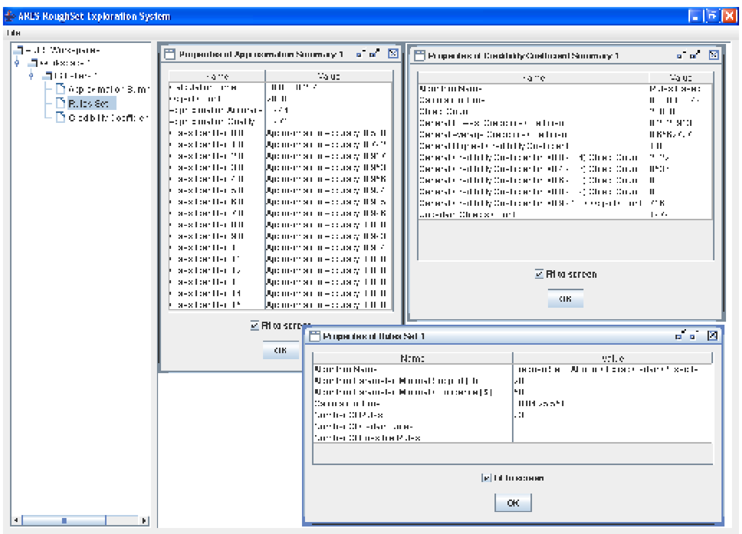

Figure 1. Properties of the initial version of information system

Then we arbitrarily decided to remove all objects which had credibility coefficients less than 0.3 (the lowest value of the credibility coefficient was 0.2024). There were 396 such objects, which is almost 2% of all objects. The process of object elimination is presented n Fig 2. After unchecking (to remove) a number of objects a new information system is may be created consisting only of objects, which remained checked. In general, it can be expected that an information system without some improper data should be better- more interesting knowledge should be available from such corrected system.

Properties of the information system without the “worst” objects are presented in Fig. 3. The average value of credibility coefficients increased very slightly, but it can be a result of removing objects with the lowest values of the coefficients. The lowest value of the credibility coefficients has decreased to 0.0665 – some objects became less credible in the final version of the information system. Two qualitative indicators of the information systems were very slightly incremented: approximation accuracy from 0.944 to 0.947 and approximation quality from 0.971 to 0.973. It is very difficult to assess these changes – the decision table data are artificial. Anyway we can observe positive changes, as we expected. Probably the most interesting outcome of the experiment can be observed in mining rules. From the initial version of the decision table we got 733 rules (with no possible or certain rules). Extracting the “improper” objects resulted in mining 723 rules with the same support (at least 200 objects) and confidence (at least 50%). Among the rules extracted from the final decision table there are two certain rules. This is a qualitative improvement of the knowledge discovered by the system.

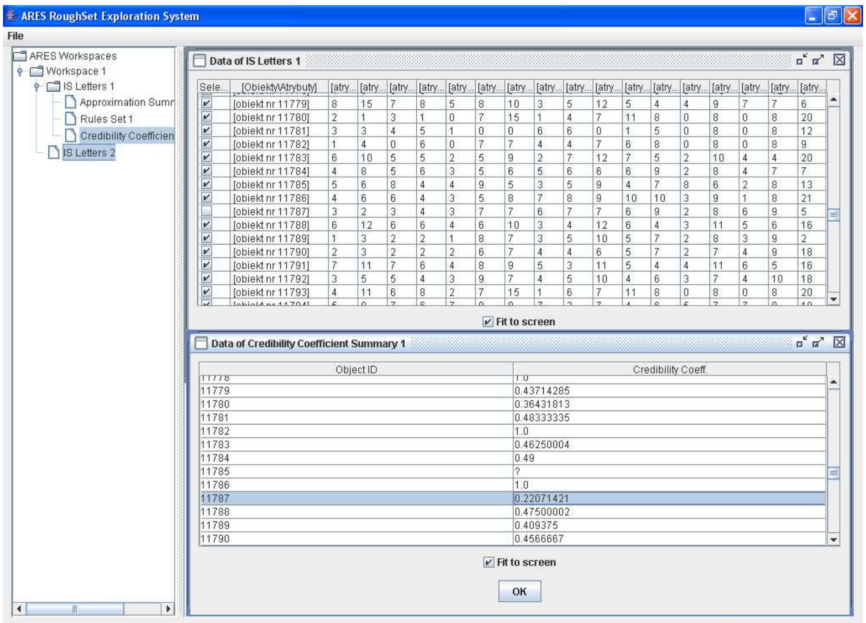

Figure 2. Removing (unchecking) objects with low values of credibility coefficients

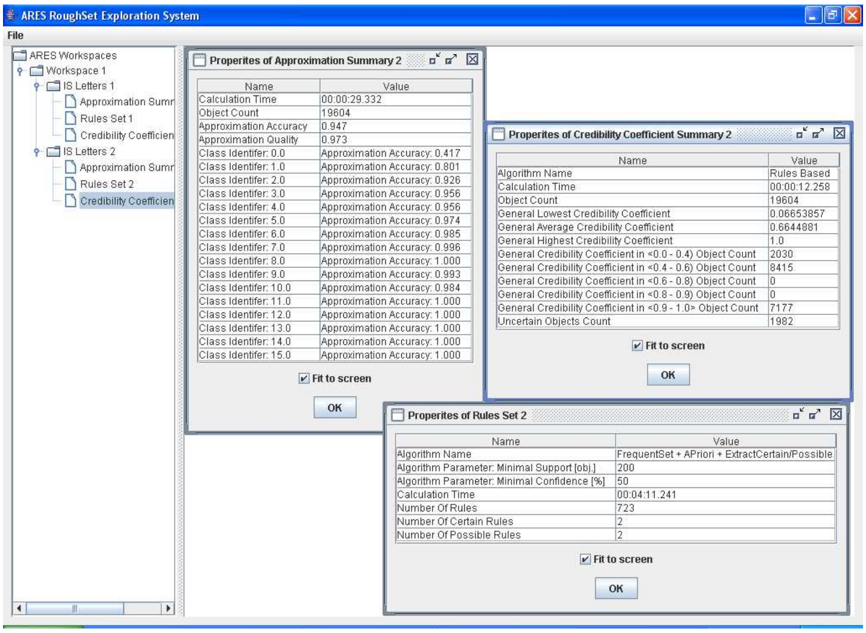

Figure 3. Properties of the final version information system

In this example it is very difficult to draw conclusions from the presented experiments. We do have no idea about meaning of the data, so our interpretation of the obtained results is very shallow. only the methodology of applying credibility coefficients was shown. A number of similar steps can be performed.

The other application of the credibility coefficients is identification of objects requiring a special examination. It may be interesting, why the objects are not typical (in comparison with other known objects). This task basically relies on interpretation of data and requires an expert experience.

The experiment of processing the decision table consisting of 20000 objects and 17 attributes took several minutes (above 4). The longest time was spent on mining rules. Time of generating approximation summary and calculating values of credibility coefficients was counted in seconds. User-friendly and intuitive interface makes the ARES System an interesting tool to be used for data analysis.

5 Conclusions

Rough set theory can be applied in knowledge discovery. Credibility coefficients can extend this approach by identifying exceptions to the rules. Probably more accurate knowledge can be detected if improper data are removed from it. In evaluating credibility coefficients we should identify a credible majority of data and a small portion of exceptions. In practice, objects in decision table are sorted according to their credibility coefficients. An arbitrary small part of objects (with the lowest credibility) can be possibly unusual. They can be deleted to improve the quality of the credible data or can be inspected as special cases – both approaches are attractive for research and can find many reasonable applications.

The methodology of utilization credibility coefficients requires a lot of further experience and only practical results can confirm whether credibility coefficients are useful in data analysis. We do believe that knowledge includes rules and exceptions and the latter ones should not be neglected.

The ARES Rough Set Exploration System can be applied to analyze relatively large information systems using rough set theory concept. Credibility coefficients introduce a new quality to data analysis. The idea of credibility coefficients is a general one. The concept of classifying the data by some measures of credibility or typicality may be exploited in many different data analyzing tools, expert systems, knowledge acquisition systems and other information processing systems, where revealing exceptional data can be significant or at least useful.

References

1. Podraza R., Walkiewicz M., Dominik A., (2006). Credibility Coefficients Based on Decision Rules, *Proc. of AAIA Conference*, Wisła, Poland.
2. Podraza R., Walkiewicz M., Dominik A., (2007). Application of Credibility Coefficients Based on Decision Rules, *Proc. IX Intl Conf. on Artificial Intelligence AI-22'2007*, Artificial Intelligence Studies, Vol. 2(27)/2007, 119-126.
3. Podraza R., Walkiewicz M., Dominik A., (2005). Credibility Coefficients in ARES Rough Set Exploration system, *Proc. 10th Intl Conference on Rough Sets, Fuzzy Sets, Data Mining, and Granular Computing, RSFDGrC 2005*, Regina, Canada, LNAI 3642, Part II, Springer-Verlag, 2005, 29-38.
4. Podraza R., Tomaszewski K., (2006). KTDA: Emerging Patterns Based Data Analysis System, *Annales Universitatis Mariae Curie-Skłodowska, Informatica*, AI, Vol.4, Lublin, Poland, 279-290.
5. Podraza R., Dominik A., (2005). Credibility Coefficients for Objects of Rough Sets, *Proc. of VII Intl Conf. on Artificial Intelligence AI-20'2005*, Artificial Intelligence Studies, Special Issue, Vol. 2, 25, 2005, 205-210.
6. Podraza R., Walkiewicz M., Dominik A., (2006). Credibility Coefficients Based on Frequent Sets, to appear in *Annales Universitatis Mariae Curie-Skłodowska, Sectio AI Informatica*.
7. Podraza R., Dominik A., Walkiewicz M., (2005). Application of ARES Rough Set Exploration System for Data Analysis, *Annales Universitatis Mariae Curie-Skłodowska, Sectio AI Informatica*, vol. III.
8. Pawlak Z. (1991). *Rough Sets. Theoretical Aspects of Reasoning about Data*, Kluwer, Dordrecht.
9. Pawlak Z. (1982). Rough Sets, *Intl J. of Computer Information Sciences*, 11.
10. Skowron A. (1995). Extracting Laws from Decision Tables: A Rough Set Approach, *Computational Intelligence*, 11.
11. Podraza R., Dominik A., Walkiewicz M., (2003). Decision Support System for Medical Applications, *Proc. of the IASTED Intl Conf. on Applied Simulations and Modeling*, Marbella, Spain, 329-334.
12. Podraza R., Podraza W., (2002). Rough Set System with Data Elimination, *Proc. of the 2002 Intl Conf. on Mathematics and Eng. Techniques in Medicine and Biological Sciences (METMBS'2002)*, Las Vegas, Nevada, USA, 493-499.
13. UCI Repository of Machine Learning Databases and Domain Theories (http://WWW.ics.uci.edu).