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Credibility Coefficients for Objects of Rough Sets

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Abstract. In this paper focus is set on data reliability. We propose a few methods, which calculate credibility coefficients for objects stored in decision tables. Credibility coefficient of object is a measure of its similarity with respect to the rest of the objects in the considered decision table. It can be very useful in detecting either corrupted data or abnormal and distinctive situations. It is assumed that the proper data appear in majority and can be separated from improper data by exploring mutual resemblance. The proposed methods take advantage of well known and widely used data mining technique - rough sets.

Keywords. Data reliability, credibility coefficient, information system, decision table, rough sets, artificial intelligence

1 Introduction

Improper data in the information system can be blamed for corrupting relationships between the other objects. Such a situation can be revealed, when elimination of the improper data results in improving the outcome of the data analysis denoted by better quality of generated rules and/or uncovering some new ones. For large sets of data the process of identifying improper data has to be automatic. The process has no prior information about the data and all suppositions on correctness features of data have to be gained only from the data.

Credibility coefficient of object is a measure of its similarity with respect to the rest of the objects in the considered decision table. Credibility coefficients can be very useful in detecting either corrupted data or abnormal and distinctive situations. Such functionality can be valuable in different fields of science, including medicine, where exceptional cases have to be often considered with a special care. In medical applications credibility coefficients enable recognizing data not adequate enough to rules applicable to the other cases. These exceptions may entail a special treatment [1] [2] [11] and automatic detection of such anomalies cannot be overestimated in many situations. The exceptions can be very interesting for investigation in many applications of natural sciences as an expected item corresponding to the rules. On the other hand, it may be interesting to perform data analysis on the set of objects without the uncertain cases and compare the results. The quality of knowledge gained without objects with low values of credibility coefficients should be enhanced.

There is no common way to define the relation of similarity between objects in information system, so it is strictly connected with the implemented method. Credibility coefficients calculations were implemented in ARES Rough Set Exploration System [3] [4] [5] [12], which is a tool for versatile data analysis exploiting the rough set theory. In this paper we present three different heuristic methods of calculating credibility coefficients for objects from a decision table:

- algorithm based on frequency/statistical analysis – very fast and intuitive method
- algorithm based on class approximation – uses rough set approximation concept
- hybrid algorithm – combination of the two methods

The paper provides a short description of the rough set theory. This introduction is required for following presentation of formulas for calculating the proposed credibility coefficients.

2 Rough Set Theory Basics

The rough set theory [6] [7] [8] [9] is used for analyzing data in an information system. The information system S can be defined as:

$$S=<U,Q,V,\rho> \quad (\mathbf{1})$$

where:

U is finite set of object,

Q is a finite set of attributes,

$V = \sum_{q \in Q} V_q$, where V_q is a domain of the attribute q,

$\rho : U \times Q \to V$ is a function that $\rho(x,q) \in V_q$ for every $x \in U$, $q \in Q$.

An information system is very often expressed by a table, where rows represent objects and columns represent attributes. Every cell holds a value of a given attribute for a particular object (the values of function ρ are kept in the table cells).

Let $S =< U,Q,V,\rho >$ be an information system and $P \subseteq Q$, and $x, y \in U$. Objects x and y are indiscernible by set of attributes P (denoted by $x \tilde{P} y$) in S if $\rho(x, q) = \rho(y, q)$ for every $q \in P$. The indiscernibility relation $\tilde{P}$ is an equivalence relation on set of objects U.

Let P^* denotes family of all equivalence classes of relation $\tilde{P}$ on U. Equivalence classes of $\tilde{P}$ on U are called P-elementary sets in information system S. $Des_P(X)$ denotes a description of P-elementary set $X \in P^*$.

$$Des_P(X) = \{(q, v): \rho(x, q) = v, \text{ for all } x \in X \text{ and all } q \in P\} \qquad \textbf{(2)}$$

For any set of objects $Y \subseteq U$ and any set of attributes $P \subseteq Q$ it is possible to define P-lower approximation ($\underline{PY}$) and P-upper approximation ($\overline{PY}$) of Y in information system S as follows:

$$\begin{aligned} \underline{PY} &= \bigcup_{X \in P^* \wedge X \subseteq Y} X \\ \overline{PY} &= \bigcup_{X \in P^* \wedge X \cap Y \neq \varnothing} X \end{aligned} \qquad \textbf{(3)}$$

P-boundary, P-positive area and P-negative area of Y are defined respectively as in (4).

$$\begin{aligned} BN_P(Y) &= \overline{PY} - \underline{PY} \\ POS_P(Y) &= \underline{PY} \\ NEG_P(Y) &= U - \overline{PY} \end{aligned} \qquad \textbf{(4)}$$

The accuracy of approximation of set Y by set of attributes P in information system S can be defined as:

$$\mu_P(Y) = \frac{card(\underline{PY})}{card(\overline{PY})} \qquad \textbf{(5)}$$

where *card* is cardinality of a set.

Let $P \subseteq Q$ be a set of attributes and $Y = \{Y_1, Y_2, \dots Y_n\}$ be family of sets where $Y_i \cap Y_j = \varnothing$ for all $i, j \leq n$ and $\bigcup_{i=1}^{n} Y_i = U$.

P-lower and P-upper approximations of family of sets Y in information system S are respectively the sets:

$$\begin{aligned} \underline{PY} &= \{\underline{PY_1}, \underline{PY_2}, \dots, \underline{PY_n}\} \\ \overline{PY} &= \{\overline{PY_1}, \overline{PY_2}, \dots, \overline{PY_n}\} \end{aligned} \qquad \textbf{(6)}$$

The quality of approximation of partitioning of Y by a set of attributes $P \subseteq Q$ is:

$$\chi_P(Y)=\frac{\sum_{i=1}^{n} card(\underline{PY_i})}{card(U)} \quad (7)$$

An information system can be regarded as decision table, if the set of all attributes is split into condition attributes C and decision attributes D: $Q = C \cup D$ and $C \cap D = \emptyset$.

Decision class is an element from V_d , where $\rho(x, d) \in V_d$ for every $x \in U$, $d \in D$.

Decision table $S = <U, C \cup D, V, \rho>$ is deterministic if $C \rightarrow D$ (the same values of all condition attributes of any pair of objects from decision table imply equality of values of all their decision attributes respectively); otherwise is non-deterministic.

3 Credibility Coefficients

3.1 Introduction

In this section we present our proposals of methods for calculating credibility coefficients of objects from decision tables.

In this and subsequent chapters we concentrate on decision tables which have only one decision attribute ($D = \{d\}$). The aim of this assumption is to simplify formulas. They can be easily generalized on decision tables containing more then one decision attribute.

Presented methods differ from each other significantly in applied methodology, but they have one common feature. All presented credibility coefficients are normalized to range <0, 1>. Value 0 represents the least level of credibility of a given object, while value 1 is the maximum representing perfect relationship of similarity to other objects in the information system. This normalization is very useful especially when we want to compare results returned by different algorithms.

3.2 Algorithm based on Statistical/Frequency Analysis

This is a very simple and fast algorithm. It is based on frequency analysis of values of certain attributes from a decision table. Each object is compared with objects which belong to the same decision class (or alternatively speaking - have the same value of the decision attribute). The credibility coefficient for each object is proportional to the number of objects having the same values for given attributes. The credibility coefficient has higher value if more objects with the same values of condition attributes are in decision table. It is worth noticing that in this method each object is treated exactly in the same way (fairly). Influence of each object on values of the credibility coefficient of the other objects in the decision table is the same.

Credibility coefficient $C_{SF}(u,d)$ for object $u \in U$ of decision table $S = <U, C \cup \{d\}, V, \rho>$ using frequency based method is calculated according to the following formula:

$$C_{SF}(u,d) = \frac{\sum_{a \in C} \frac{card(W_{u,d,a})}{card(K_{u,d})}}{card(C)} \qquad \textbf{(8)}$$

where:

$$K_{u,d} = \{y \in U : \rho(y,d) = \rho(u,d)\}$$

$$W_{u,d,a} = \{y \in U : \rho(y,d) = \rho(u,d) \wedge \rho(y,a) = \rho(u,a)\}$$

3.3 Algorithm based on Class Approximation

Let $S = <U, C \cup \{d\}, V, \rho>$ be a decision table. We say that object $u \in U$ is:

- non-conflicting one with decision class *h*, if:
  $u \in \{POS_C(X) \cap NEG_C(X)\}$ where $X=\{y \in U: \rho(y, d)=h\}$
- conflicting one with decision class *h*, if:
  $u \in \{BN_C(X)\}$ where $X=\{y \in U: \rho(y, d)=h\}$

The main idea of this algorithm is based on the assumption, that the non-conflicting objects should have higher values of credibility coefficients than the conflicting ones. To introduce more variety for a conflicting object, the algorithm additionally performs frequency analysis of particular attributes in respect to positive and negative areas of a given decision class.

This algorithm analyses all objects from a decision table. For each object all decision classes are considered. Each decision class for which object is non-conflicting increases credibility coefficient of the object by one. If examined object *u* is in conflict with decision class *h* then credibility of such object is increased by value of additional coefficient *addCoef*, which value is positive and smaller than one. The additional coefficient is calculated according to the following rules:

- Create empty set *K*
- If a current object belongs to decision class *h*, than add all objects which belong to positive area of decision class *h* to set *K*
- If current object does not belong to decision class *h*, than add all objects which belong to negative area of decision class *h* to set *K*
- For each condition attribute *a*, create set *W* containing all objects which belong to set *K* and which have the same value of attribute *a* as object *u*. In each step add to *addCoef* value equal to: *card(K)/card(W)*. At the end normalize *addCoef* by dividing it by value *card(C)* (*addCoef = addCoef / card(C)*).

The aim of the next step is the normalization of the value to range <0, 1>. Value of credibility coefficient of each object is divided by number of decision classes (*card*(V_d)).

It should be underlined that this algorithm will be giving very imperfect results if most of the objects belong to the boundary of particular decision classes.

Credibility coefficient $C_{CA}(u,d)$ for object $u \in U$ of decision table $S = <U, C \cup \{d\}, V, \rho>$ using method based on class approximation is calculated according to the following formula:

$$C_{CA}(u,d) = \frac{\sum_{h \in H} def(u,d,h)}{card(H)} \qquad \textbf{(9)}$$

Where functions *def(u, d, h)* and *addCoef(u, d, h, a)* are defined as follows:

$$def(u,d,h) = \begin{cases} 1 & for \quad u \in \{ POS_C(X) \cup NEC_C(X) \} \\ \dfrac{\sum_{a \in A} addCoef(u,d,h,a)}{card(C)} & for \quad u \in BN_C(X) \end{cases}$$

$$addCoef(u,d,h,a) = \begin{cases} \dfrac{card(Wpos_{u,a})}{card(Kpos)} & for \quad \rho(u,d) = h \\ \dfrac{card(Wneg_{u,a})}{card(Kneg)} & for \quad \rho(u,d) \neq h \end{cases}$$

and:

$$H = \{ v \in V_d \}$$

$$X_{d,h} = \{ u \in U : \rho(u,d) = h \}$$

$$Kpos = \{ u \in U : u \in POS_C(X) \}$$

$$Kneg = \{ u \in U : u \in NEG_C(X) \}$$

$$Wpos_{u,a} = \{ y \in U : y \in POS_C(X) \wedge \rho(y,a) = \rho(u,a) \}$$

$$Wneg_{u,a} = \{ y \in U : y \in NEG_C(X) \wedge \rho(y,a) = \rho(u,a) \}$$

3.4 Hybrid algorithm

This method combines features of two previously presented algorithms. Its execution is very similar to the approximation based method. The only difference is the way to cope with objects which are in conflict with the decision class. In such cases the credibility coefficient is calculated similarly to the frequency method and it depends on number of appearances of value of given attribute for objects belonging to the same decision class (it does not consider whether the particular object belongs to the positive or the negative area of decision class).

Credibility coefficient $C_{HM}(u,d)$ for object $u \in U$ of decision table $S = <U, C \cup \{d\}, V, \rho>$ using the hybrid method is calculated according to the following formula:

$$C_{HM(u,d)} = \frac{\sum_{h \in H} def(u,d,h)}{card(H)} \qquad \mathbf{(10)}$$

where function *def(u, d, h)* is defined as follows:

$$def(u,d,h) = \begin{cases} 1 & for \quad u \in \{POS_C(X) \cup NEG_C(X)\} \\ \dfrac{\sum\limits_{a \in C} \dfrac{card(W_{u,d,a})}{card(K_{u,d})}}{card(C)} & for \quad u \in BN_C(X) \end{cases}$$

$$K_{u,d} = \{y \in U{:}\rho{:}\rho(y, = \rho(u,d)\}$$

$$W_{u,d,a} = \{y \in U{:}\rho{:}\rho(y, = \rho(u,d) \wedge \rho(y,a) = \rho(u,a)\}$$

3.5 Example

Let us consider a decision table presented in Table 3.5.1 ($S = <U, C \cup \{d\}, V, \rho>$, where we have set of objects $U=\{1, 2, 3, 4, 5, 6\}$, set of condition attributes $C=\{c1, c2, c3\}$ and decision attribute $d=dec$) [4]. The table contains the values of three credibility coefficients C_{SF}, C_{CA} and C_{HM}. For every object of this decision the credibility coefficients were calculated using the method based on statistical/frequency analysis, the method based on class approximation and the hybrid method respectively. An object with number 5 has the lowest value of credibility coefficient averaged over all three analyzed methods. We consider the object with number 5 as the least credible (the least typical) and we would like to observe changes in the rough set analysis of the objects without the “worst” one. Table 3.5.2 presents the modified decision table (after removing object 5).

Table 3.5.3 shows approximation accuracy and quality of decision classes of the original decision table and the modified one. After removing the object with number 5, the qualitative indicators of the decision table were enhanced to the maximum level. Applying the credibility coefficients to objects successfully identified the improper data. Omitting it can result in a better knowledge induced from the modified decision table. This is the main goal of introducing the credibility coefficients – identification of exceptional, non-typical or unusual information. The improved values of accuracy and quality of approximation without the improper data do not involve neglecting it in analysis – it strongly depends on an approach. The observations just confirm suppositions demonstrated by the credibility coefficients.

Table 3.5.1. Sample decision table with values of credibility coefficients for every object

Object Id	*c1*	*c2*	*c3*	*dec*	C_{SF}	C_{CA}	C_{HM}
1	0	1	0	1	0.58	1.00	1.00
2	1	0	0	1	0.42	0.22	0.21
3	1	1	1	1	0.58	1.00	1.00
4	0	1	1	1	0.58	1.00	1.00
5	1	0	0	0	0.50	0.00	0.25
6	0	1	2	0	0.50	1.00	1.00
Average					0.53	0.70	0.74

Table 3.5.2. Sample decision table, after removing the least reliable object, and values of credibility coefficients for every object

Object Id	*c1*	*c2*	*c3*	*dec*	C_{SF}	C_{CA}	C_{HM}
1	0	1	0	1	0.58	1.00	1.00
2	1	0	0	1	0.42	1.00	1.00
3	1	1	1	1	0.58	1.00	1.00
4	0	1	1	1	0.58	1.00	1.00
6	0	1	2	0	1.00	1.00	1.00
Average					0.63	1.00	1.00

Table 3.5.3. Accuracy and quality of approximation of decision classes from the analysed decision tables

Type of measure	Table 3.5.1	Table 3.5.2
Accuracy of approximation	0.50	1.00
Quality of approximation	0.67	1.00

Table 3.5.4 shows another decision table ($S = <U, C\cup\{d\}, V, \rho>$, where $U=\{1, 2, \ldots, m\text{-}1, m\}$, $C=\{c1, c2, c3\}$ and $d=dec$) [1] with values of credibility coefficients for every object. All attributes have binary values (0 and 1). In the decision table there are *n-1* objects with all attributes set to 0 (including the decision), *m-n-2* objects with all attributes set to 1 (including the decision) and two "corrupted" objects (with numbers *n* and *n+1*), which have all condition attributes with value 0, but the decision attribute set to 1 and all condition attributes with value 1 and the decision attribute set to 0, respectively. For such a decision table both qualitative measures have value zero. It means that the "corrupted" data blurred the obvious relationships between the "correct" objects putting them all into the boundary of the rough set identified by the condition attributes. It is interesting how well the credibility coefficients can detect this obvious (and trivial) case. In the table values of the three credibility coefficients are presented for two sets of parameters (*n=20, m=40* and *n=10, m=25*, respectively for symmetric and asymmetric partitioning of the "correct" objects).

Table 3.5.4. Sample decision table and values of credibility coefficients for every object

Object Id	*c1*	*c2*	*c3*	*dec*	C_{SF}	C_{CA}	C_{HM}	C_{SF}	C_{CA}	C_{HM}
					n=20, m=40			*n=10, m=25*		
1	0	0	0	0	0.95	0.00	0.48	0.89	0.00	0.45
2	0	0	0	0	0.95	0.00	0.48	0.89	0.00	0.45
...	0	0	0	0	0.95	0.00	0.48	0.89	0.00	0.45
n-1	0	0	0	0	0.95	0.00	0.48	0.89	0.00	0.45
n	0	0	0	1	0.00	0.00	0.03	0.00	0.00	0.03
n+1	1	1	1	0	0.00	0.00	0.03	0.00	0.00	0.05
n+2	1	1	1	1	0.95	0.00	0.48	0.93	0.00	0.47
...	1	1	1	1	0.95	0.00	0.48	0.93	0.00	0.47
m-1	1	1	1	1	0.95	0.00	0.48	0.93	0.00	0.47
m	1	1	1	1	0.95	0.00	0.48	0.93	0.00	0.47
Average					0.90	0.00	0.45	0.84	0.00	0.43

As it could be expected the set of credibility coefficients properly and convincingly identified the "corrupted" items from the decision table. However the credibility coefficient based on class approximation cannot cope with this evident case. A striking outcome – values for all objects are 0.00 – is caused by the fact that the rough set has no positive and no negative regions. All objects belong to the boundary. Such a situation makes the algorithm based on class approximation useless because as a matter of fact the approximation cannot distinguish any relationships between data. One conclusion can be drawn from observation of the case. In general it is better to use a combined approach to detect exceptions in data relations. Candidates for the exceptions should be elected by a composite result, like an average value of all credibility coefficients. However detailed analysis of particular credibility coefficients can be surprising and hence interesting.

3.6 Summary

In this section we presented formulas for calculating the credibility coefficients for objects from decision table. Values of credibility coefficients are normalized to range <0, 1>, however they carry on only some descriptive information and are not an absolute measure of reliability. Comparison of values of credibility coefficients should be done with a caution. In general, values closed to one and close to zero denote respectively a high and a low reliability of a given element. If a credibility coefficient of one object is two times greater then a credibility coefficient of another object it does not mean that the first one is two times more reliable. Comparing values of credibility coefficients calculated with different algorithms has no sense.

Algorithms of the credibility coefficients are heuristic. It is difficult to state, whether any of them is superior in any sense. For a coarse recognition of improper data we can relay on an average of a bundle of credibility coefficients. To tune up the identification of non-typical data we can consider candidates with poor results of particular credibility coefficients.

All presented algorithms use all condition attributes while calculating credibility coefficients. These methods may be easily adapted to take into account only a limited set of condition attributes. Such a set could be for instance a relative reduct of a given decision table.

ARES Rough Set Exploration System [3] [4] [5] offers more algorithms of evaluation credibility of objects. They are based on frequent sets and decision rules generated from the decision table [5]. The limit of the space precludes possibility to present them in this paper.

4 Conclusions

In the paper the idea of credibility coefficients for objects from decision table was presented as well as three algorithms for calculating them. There are many purposes to use information, how well a given object from decision table suits to other data:

- The knowledge acquisition system can be supplemented with ability to recognize exceptions to the rules.
- Better knowledge can be inferred from an information system if improper data is removed form it. By better knowledge we can assume more precise classification (with better quality indicators) and maybe some new rules.
- Analysis of exceptions very often can enhance quality of data gaining, processing and storing (by avoiding errors).
- Exceptions to the rules are very often more interesting then the rules themselves, especially in natural sciences, including medical application for which ARES system was originally designed.

ARES Rough Set Exploration System provides a wide variety of algorithms calculating credibility coefficients. Methodology of handling improper data has to be worked out and ARES system seems to be a proper tool. Its multi-document architecture facilitates performing parallel analysis of decision tables with and without objects supposed to be improper.

Some preliminary tests on credibility coefficients were carried out and the gained results are promising. To the original data set [10] some randomly generated elements were added and it was possible to detect them by low values of credibility coefficients. The experiments performed show that the proposed credibility coefficients may be successfully used in detecting corrupted data or abnormal and distinctive situations.

The values of credibility coefficients can be regarded as rankings of objects in decision table. A predefined portion of objects with the lowest credibility coefficients can be “suspected to be unusual”. They can be discarded to improve the quality of the remaining data or can be inspected with special care to discover their peculiarities – the approach depends mainly from applications, however the both attitudes are interesting for a research.

In introducing and applying the credibility coefficients the main assumption is a belief that majority of data are proper and correct and appear more frequently then exceptional data. The repetition of the same data, maybe within some margins, should be reflected in formulas of credibility coefficients as a support for correctness. Then untypical objects appearing rarely can be spotted as not having enough backing from the other ones.

The methodology of dealing with credibility coefficients should be developed. New algorithms for credibility coefficients are being implemented and investigated. The practical effects of identifying improper data should be assessed by experts, whether such a feature is useful in knowledge acquisition. We do strongly believe that the rules can be fully recognized and understood if they have exceptions, which can be revealed by applying credibility coefficients.

In the paper only calculations based on rough set theory were presented. Some other concepts have been developed and implemented. The idea of assessing, how much a data object is typical one in respect to other objects in the set, is a general one. The concept may find its applications in data analyzing tools, expert systems, knowledge acquisition systems and many other information processing systems, where removing of improper data or exposing improper data is important.

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