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Information Measures of Roughness of Knowledge and Rough Sets for Incomplete Information Systems

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Abstract: In this paper we address information measures of roughness of knowledge and rough sets for incomplete information systems. The definition of rough entropy of knowledge and its important properties are given. In particular, the relationship between rough entropy of knowledge and the Hartley measure of uncertainty is established. We show that rough entropy of knowledge decreases monotonously as granularity of information become smaller. This gives an information interpretation for roughness of knowledge. Based on rough entropy of knowledge and roughness of rough set, a definition of rough entropy of rough set is proposed, and we show that rough entropy of rough set decreases monotonously as granularity of information become smaller. This gives more accurate measure for roughness of rough set.

Keywords: rough sets; knowledge; roughness; rough entropy; incomplete information systems

1 Introduction

Rough set theory, introduced by Pawlak [1], is a relatively new soft computing tool to deal with vagueness and uncertainty. It has been applied to many areas successfully including machine learning, data analysis, pattern recognition, decision support, data mining, process control and predictive modeling [1—6].

Rough set theory gives a formal definition of knowledge and provides a series of tools to deal with knowledge by set algebra. In rough set theory, knowledge can be regarded as partition of the universe, this makes knowledge have granularity. However, in the set algebra representation of this theory, it is difficult to understand the essence of rough set theory. [7, 8] discuss information interpretation of rough set theory, [9] addresses information measures of uncertainty for rough sets and rough relation databases.

We know that the concept of rough sets has proved to be an effective method for analysis of information systems describing a set of objects by a set of multi-valued attributes. However, in many practical cases, incomplete information systems is often exist. Hence, it is important to study information interpretation of rough set theory for incomplete information systems.

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In this paper, a concept of rough entropy is introduced into incomplete information systems, and its several important properties are given. In particular, the relationship between rough entropy of knowledge and the Hartley measure of uncertainty is established. We show that rough entropy of knowledge decreases monotonously as granularity of information become smaller. This gives an information interpretation for roughness of knowledge. Based on rough entropy of knowledge and roughness of rough set, a definition of rough entropy of rough set is proposed, and we show that rough entropy of rough set decreases monotonously as granularity of information become smaller. This gives more accurate measure for roughness of rough sets.

2 Incomplete Information Systems

Information system is a pair $S = (U, A)$, where:

1) U is a non-empty finite set of objects;

2) A is a non-empty finite set of attributes;

3) for every $a \in A$, there is a mapping a, $a: U \to V_a$, where V_a is called the value set of a.

Each subset of attributes $P \subseteq A$ determines a binary indistinguishable relation $IND(P)$ as follows:

$$IND(P) = \{(x,y) \in U \times U \mid \forall\, a \in P,\ a(x) = a(y)\}$$

It can be easily shown that $IND(P)$ is an equivalence relation on the set U.

The relation $IND(P)$, $P \subseteq A$, constitutes a partition of U, which is denoted by $U/IND(P)$.

It may happen that some of attribute values for an object are missing. For example, in medical information systems there may exist a group of patients for which it is impossible to perform all the required tests [10]. These missing values can be represented by the set of all possible values for the attribute or by the domain of the attribute. To indicate such a situation, a so-called null value is usually assigned to those attributes.

If V_a contains a null value for at least one attribute $a \in A$, then S is called an incomplete information system [11,12], otherwise it is complete. Further on, we will denote a null value by $*$.

Let $P \subseteq A$. We define tolerance relation:

$$SIM(P) = \{(x,y) \in U \times U \mid \forall\, a \in P,\ a(x) = a(y) \text{ or } a(x) = * \text{ or } a(y) = *\}$$

It can be easily shown that

$$SIM(P) = \bigcap_{a \in P} SIM(\{a\})$$

Let $S_P(x)$ denote the object set $\{y \in U \mid (x,y) \in SIM(P)\}$. $S_P(x)$ is the maximal set of objects which are possibly indistinguishable by P with x.

Let $U/SIM(P)$ denote classification, which is the family set $\{S_P(x) \mid x \in U\}$. Any element from $U/SIM(P)$ will be called a tolerance class or granularity of information. Tolerance classes in $U/SIM(P)$ do not constitute a partition of U in general. They constitute a covering of U, i.e., for every $x \in U$, we have that $S_P(x) \neq \varnothing$ and $\bigcup_{x \in U} S_P(x) = U$.

Let $P, Q \subseteq A$.

$U/SIM(P) = U/SIM(Q)$ denote $S_P(x) = S_Q(x)$ for every $x \in U$

$U/SIM(P) \subseteq U/SIM(Q)$ denote $S_P(x) \subseteq S_Q(x)$ for every $x \in U$

$U/SIM(P) \subset U/SIM(Q)$ denote $S_P(x) \subseteq S_Q(x)$ for every $x \in U$ and $S_P(x) \neq S_Q(x)$ for some $x \in U$.

In this paper, incomplete information systems $S = (U, A)$ be regarded as knowledge representation system $U/SIM(A)$ or knowledge A.

3 Roughness of Knowledge and Rough Entropy

Now we introduce rough entropy of knowledge [13], and establish the relationship between roughness of knowledge and rough entropy for incomplete information systems.

Definition 1 Let $S = (U, A)$ be an incomplete information system, and $P \subseteq A$. The rough entropy of knowledge P is

$$E(P) = -\sum_{i=1}^{|U|} \frac{|S_P(x_i)|}{|U|} \log \frac{1}{|S_P(x_i)|} \tag{1}$$

where $U = \{x_1, x_2, \cdots, x_{|U|}\}$, $|U|$ is cardinality of set U and $\log x$ denotes $\log_2 x$; $\frac{|S_P(x_i)|}{|U|}$ represents the ratio of tolerance class $S_P(x_i)$ within the universe U, $\frac{1}{|S_P(x_i)|}$ denotes the probability of one of the values in tolerance class $S_P(x_i)$.

Property 1 (Cardinality) Let $S = (U, A)$ be an incomplete information system and P, $Q \subseteq A$. If there exists a one-to-one, onto function $h: U/SIM(P) \to U/SIM(Q)$ such that

$$|h(S_P(x_i))| = |S_P(x_i)|, \quad i = 1, 2, \cdots, |U|$$

then

$$E(P) = E(Q)$$

Property 1 states that the rough entropy of knowledge be invariant with respect to difference the set of tolerance classes that are size-isomorphic.

Property 2 (Monotonicity) Let $S = (U, A)$ be an incomplete information system and P, $Q \subseteq A$. If $U/SIM(Q) \subset U/SIM(P)$, then $E(Q) < E(P)$.

Proof Since $U/SIM(Q) \subset U/SIM(P)$, we have that $S_Q(x_i) \subseteq S_P(x_i)$ for every $x_i \in U$ and $S_Q(x_j) \subset S_P(x_j)$ for at least one $x_j \in U$ (where $|S_P(x_i)| \geq 1$ and $|S_Q(x_i)| \geq 1$ for every $x_i \in U$). Hence,

$$\frac{1}{|U|} \sum_{i=1}^{|U|} |S_Q(x_i)| \log |S_Q(x_i)| < \frac{1}{|U|} \sum_{i=1}^{|U|} |S_P(x_i)| \log |S_P(x_i)|$$

i.e.

$$-\sum_{i=1}^{|U|} \frac{|S_Q(x_i)|}{|U|} \log \frac{1}{|S_Q(x_i)|} < -\sum_{i=1}^{|U|} \frac{|S_P(x_i)|}{|U|} \log \frac{1}{|S_P(x_i)|}$$

Thus, $E(Q) < E(P)$.

Property 2 states that rough entropy of knowledge decreases monotonously as granularity of information become smaller.

Corollary 1 Let $S = (U, A)$ be an incomplete information system, and P, $Q \subseteq A$. If $P \subseteq Q$, then $E(Q) < E(P)$.

From property 2 we can obtain immediately the following properties.

Property 3 (Equivalence) Let $S_1 = (U, P)$ and $S_2 = (U, Q)$ be two incomplete information systems, and $U/SIM(P) \subseteq U/SIM(Q)$. Then $E(P) = E(Q)$ if and only if $U/SIM(P) = U/SIM(Q)$.

Property 3 states that if two knowledge representation systems exist inclusion relation, then their rough entropies are equal, if and only if, two knowledge representation systems are equivalent.

Property 4 (Maximum) Let $S = (U, A)$ be an incomplete information system, $P \subseteq A$. The maximum of rough entropy of knowledge P is $|U|\log|U|$. This value is achieved only by the $U/SIM(P) = \{S_P(x) = U | x \in U\}$.

Property 5 (Minimum) Let $S = (U, A)$ be an incomplete information system, $P \subseteq A$. The minimum of rough entropy of knowledge P is 0. This value is achieved only by the $U/SIM(P) = \{S_P(x) = \{x\} | x \in U\}$.

If X is a finite set then the Hartley measure [14] of uncertainty is

$$H(X) = \log|X|$$

We will now show the relationship between the rough entropy of knowledge and the Hartley measure.

$$E(P) = -\sum_{i=1}^{|U|} \frac{|S_P(x_i)|}{|U|} \log \frac{1}{|S_P(x_i)|} = \sum_{i=1}^{|U|} \frac{|S_P(x_i)|}{|U|} \log |S_P(x_i)|$$

$$= \sum_{i=1}^{|U|} \frac{|S_P(x_i)|}{|U|} H(S_P(x_i))$$

Thus rough entropy of knowledge P is the sum of the weighted Hartley measures of the elements of $U/SIM(P)$.

4 Roughness of Rough Sets and Rough Entropy

Let $S = (U, A)$ be an incomplete information system, $P \subseteq A$, and $X \subseteq U$. $\underline{P}X$ is lower approximation of X, iff

$$\underline{P}X = \{x \in U | S_P(x) \subseteq X\} = \{x \in X | S_P(x) \subseteq X\}$$

$\overline{P}X$ is upper approximation of X, iff

$$\overline{P}X = \{x \in U | S_P(x) \cap X \neq \varnothing\} = \bigcup \{S_P(x) | x \in X\}$$

Of course, $\underline{P}X \subseteq X \subseteq \overline{P}X$ for every $X \subseteq U$.

The accuracy measure of rough set X with respect to P is defined as

$$\alpha_P(X) = \frac{|\underline{P}X|}{|\overline{P}X|}$$

where $X \neq \varnothing$, $0 \leq \alpha_P(X) \leq 1$.

The roughness of rough set X with respect to P is defined as

$$\rho_P(X) = 1 - \alpha_P(X)$$

Property 6 Let $S=(U,A)$ be an incomplete information system. Let $P,Q \subseteq A$, $X \neq \varnothing$, $X \subseteq U$, and $U/SIM(Q) \subseteq U/SIM(P)$. Then the following properties hold

$$\underline{P}X \subseteq \underline{Q}X, \qquad \overline{P}X \supseteq \overline{Q}X$$

$$\alpha_P(X) \leq \alpha_Q(X), \quad \rho_P(X) \geq \rho_Q(X)$$

Example 1 Consider descriptions of several cars in Table 1.

Table 1 An incomplete information system

Car	Price	Mileage	Size	Max-Speed
1	High	High	Full	Low
2	Low	*	Full	Low
3	*	*	Compact	High
4	High	*	Full	High
5	*	*	Full	High
6	Low	High	Full	*

This is an incomplete information system, where $U=\{1,2,3,4,5,6\}$, $A=\{p, m,s,x\}$, and p,m,s,x denote Price, Mileage, Size, Max-Speed.

We obtain by computing

$U/SIM(A) = \{S_A(1),\ S_A(2),\ S_A(3),\ S_A(4),\ S_A(5),\ S_A(6)\}$, where $S_A(1)=\{1\}$, $S_A(2)=\{2,6\}$, $S_A(3)=\{3\}$, $S_A(4)=\{4,5\}$, $S_A(5)=\{4,5,6\}$, $S_A(6)=\{2,5,6\}$.

$U/SIM(P) = \{S_P(1),\ S_P(2),\ S_P(3),\ S_P(4),\ S_P(5),\ S_P(6)\}$, where $P=\{s,x\}$, $S_P(1)=S_P(2)=\{1,2,6\}$, $S_P(3)=\{3\}$, $S_P(4)=S_P(5)=\{4,5,6\}$, $S_P(6)=\{1,2,4,5,6\}$.

It can be also observed easily that

$$U/SIM(A) \subset U/SIM(P)$$

For $Y=\{1,2,4,6\}$, we have that

$$\underline{A}Y=\{1,2\}, \qquad \overline{A}Y=\{1,2,4,5,6\}$$

$$\underline{P}Y=\{1,2\}, \qquad \overline{P}Y=\{1,2,4,5,6\}$$

and

$$\alpha_A(Y)=\alpha_P(Y)=2/5$$

$$\rho_A(Y)=\rho_P(Y)=3/5$$

Let us note that two knowledge representation systems $U/SIM(A)$ and $U/SIM(P)$ exist inclusion relation, but the same accuracy or roughness can be obtained for rough set Y. So it is necessary for us to give more accurate measure for rough set.

Definition 2 Let $S=(U,\ A)$ be an incomplete information system, $P \subseteq A$. The rough entropy $E_P(X)$ of a rough set $X(X \neq \varnothing,\ X \subseteq U)$ with respect to P is defined as

$$E_P(X) = \rho_P(X)E(P) \tag{2}$$

For example 1, we obtain by computing

$$\begin{aligned} E(A) = &-[(1/6)\log(1/1) + (2/6)\log(1/2) + (1/6)\log(1/1) \\ &+ (2/6)\log(1/2) + (3/6)\log(1/3) + (3/6)\log(1/3)] \\ =&\ 1.9183 \end{aligned}$$

and

$$\begin{aligned} E(P) = &-[(3/6)\log(1/3) + (3/6)\log(1/3) + (1/6)\log(1/1) \\ &+ (3/6)\log(1/3) + (3/6)\log(1/3) + (5/6)\log(1/5)] \end{aligned}$$

$$=5.1049$$

Hence,

$$E_A(Y) = \rho_A(Y)E(A) = (3/5) \times 1.9183 = 1.15098$$

and

$$E_P(Y) = \rho_P(Y)E(P) = (3/5) \times 5.1049 = 3.06294$$

Therefore,

$$E_A(Y) < E_P(Y)$$

In fact, we have the following by using property 2 and property 6.

Theorem 1 Let $S = (U, A)$ be an incomplete information system. Let $P, Q \subseteq A$, and $X \subseteq U$. If $U/SIM(Q) \subseteq U/SIM(P)$, then $E_Q(X) \leq E_P(X)$.

Theorem 1 states that rough entropy of rough set decreases monotonously as granularity of information become smaller.

Corollary 2 Let $S = (U, A)$ be an incomplete information system. Let $P, Q \subseteq A$, and $X \subseteq U$. If $P \subseteq Q$, then $E_Q(X) \leq E_P(X)$.

5 Conclusion

Information measures again prove to be an useful metric for quantifying information content. In this paper, the given information measures of roughness of knowledge and rough sets are helpful for people to understand the essence of rough sets and essential to seek new efficient algorithm of knowledge reduction for incomplete information systems.

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相似文献(10条)

network framework for knowledge discovery

An important task in knowledge discovery is feature selection. This paper describes a practical approach to feature subset selection proposed as part of a hybrid rough sets/neural network framework for knowledge discovery for decision support. In this framework neural networks and rough sets are combined and used cooperatively during the system life cycle. The reason for combining rough sets with neural networks in the proposed framework is twofold. Firstly, rough sets based systems provide domain knowledge expressed in the form of If-then rules as well as tools for data analysis. Secondly, rough sets are used in this framework in the task of feature selection for neural network models. This paper examines the feature selection aspect of the framework. An empirical study that tested the approach on artificial datasets and real-world datasets was carried out. Experimental results indicate that the proposed approach can improve the performance of neural network models. The framework was also applied in the development of a real-world decision support system. The experience with this application has shown that the approach can support the users in the task of feature selection.

4.期刊论文 S-rough sets and the discovery of F-hiding knowledge -系统工程与电子技术(英文版)

2008,19(6)

Singular rough sets (S-rough sets) have three classes of forms: one-directional S-rough sets, dual of one-directional S-rough sets, and two-directional S-rough sets. Dynamic, hereditary, mnemonic, and hiding properties are the basic characteristics of S-rough sets. By using the S-rough sets, the concepts of f-hiding knowledge, F-hiding knowledge, hiding degree, and hiding dependence degree are given. Then, both the hiding theorem and the hiding dependence theorem of hiding knowledge are proposed. Finally, an application of hiding knowledge is discussed.

5.期刊论文 Guoyin Wang Domain-Oriented Data-Driven Data Mining Based on Rough Sets -南昌工程学院学报

2006,25(2)

Data mining (also known as Knowledge Discovery in Databases - KDD) is defined as the nontrivial extraction of implicit, previously unknown, and potentially useful information from data. The aims and objectives of data mining are to discover knowledge of interest to user needs. Data mining is really a useful tool in many domains such as marketing, decision making, etc. However, some basic issues of data mining are ignored. What is data mining? What is the product of a data mining process? What are we doing in a data mining process? Is there any rule we should obey in a data mining process? In order to discover patterns and knowledge really interesting and actionable to the real world Zhang et al proposed a domain-driven human-machine-cooperated data mining process. Zhao and Yao proposed an interactive user-driven classification method using the granule network. In our work, we find that data mining is a kind of knowledge transforming process to transform knowledge from data format into symbol format. Thus, no new knowledge could be generated (born) in a data mining process. In a data mining process, knowledge is just transformed from data format, which is not understandable for human, into symbol format, which is understandable for human and easy to be used. It is similar to the process of translating a book from Chinese into English. In this translating process, the knowledge itself in the book should remain unchanged.What will be changed is the format of the knowledge only. That is, the knowledge in the English book should be kept the same as the knowledge in the Chinese one. Otherwise, there must be some mistakes in the translating proces, that is, we are transforming knowledge from one format into another format while not producing new knowledge in a data mining process. The knowledge is originally stored in data (data is a representation format of knowledge). Unfortunately, we can not read, understand, or use it, since we can not understand data. With this understanding of data mining, we proposed a data-driven knowledge acquisition method based on rough sets. It also improved the performance of classical knowledge acquisition methods. In fact, we also find that the domain-driven data mining and user-driven data mining do not conflict with our data-driven data mining. They could be integrated into domain-oriented data-driven data mining. It is just like the views of data base. Users with different views could look at different partial data of a data base. Thus, users with different tasks or objectives wish, or could discover different knowledge (partial knowledge) from the same data base. However, all these partial knowledge should be originally existed in the data base. So, a domain-oriented data-driven data mining method would help us to extract the knowledge which is really existed in a data base, and really interesting and actionable to the real world.

6.外文会议 Yusheng Cheng.Yousheng Zhang.Xuegang Hu The Relationships Between Variable Precision Value and Knowledge Reduction Based on Variable Precision Rough Sets Model

The variable precision rough sets (VPRS) model is parametric and there are many types of knowledge reduction. Among the present various algorithms, β is introduced as prior knowledge. In some applications, it is not clear how to set the parameter. For that reason, it is necessary to seek an approach to realize the estimation of β from the decision table, avoiding the influence of β apriority upon the result. By studying relative discernibility in measurement of decision table, it puts forward algorithm of the threshold value of decision table’s relative discernibility: choosing β within the interval of threshold value as a substitute for prior knowledge can get knowledge reduction sets under certain level of error classification, thus finally realizing self-determining knowledge reduction from decision table based on VPRS.

7.外文会议 Qingxiang Wu.Jianyong Cai.Girijesh Prasad.T.M. McGinnity.David Bell.Jiwen Guan A Novel Discretizer for Knowledge Discovery Approaches Based on Rough Sets

Knowledge discovery approaches based on rough sets have successful application in machine learning and data mining. As these approaches are good at dealing with discrete values, a discretizer is required when the approaches are applied to continuous attributes. In this paper, a novel adaptive discretizer based on a statistical distribution index is proposed to preprocess continuous valued attributes in an instance information system, so that the knowledge discovery approaches based on rough sets can reach a high decision accuracy. The experimental results on benchmark data sets show that the proposed discretizer is able to improve the decision accuracy.

8.外文期刊 Guojun Zhang.Zheng Che.Peigen Li Application of rough sets theory in knowledge acquisition for the cold extrusion process

Cold extrusion is a process based on intensive knowledge and experience. Many knowledge based processing technologies have been used in this area. In this paper, we have attempted to apply rough sets theory to acquire and analyse the manufacturing knowledge in the cold extrusion process. An over view of the rough sets theory was given, and several reduction algorithms based on information theory and rough sets theory were presented. After defining the cost as decision attribute, some key condition attributes that influence the cost are studied in the cold extrusion process. The detailed procedures that utilise rough sets theory for knowledge acquisitions were introduced, including data preparation, core attributes calculation, attribute reduction, core values calculation and decision rules induction. The implementation of cold extrusion knowledge acquisition using rough sets theory was presented in this paper. The advantages and disadvantages of this method were also discussed in this paper.

9. 外文会议 Xiaoshu Hang. Zhen Yu Wang. Fanlun Xiong Constructing knowledge-based artificial neural network with rough sets

An approach of constructing knowledge-based artificial neural network based on rough sets is proposed. Crude domain knowledge is extracted from the 0-1 table produced from fuzzy information table of example data by a threshold. The extracted initial rules and their accuracy and coverage are used to configure the fuzzy multilayer perceptron-structure and initial weights. An algorithm of attribute-reduction based on information entropy is also proposed in this paper. Results on diagnosises of rice pests show that the performance of this fuzzy neural system is same with that of conventional multi-layer perceptron.

10. 外文会议 Xianzhong Zhou. Bing Huang. Jiabao Zhao Multi-Level Knowledge Reduction in Fuzzy Objective Information Systems

Knowledge reduction is one of the most important tasks in rough set theory. Aiming at fuzzy objective information systems (FOIS), several knowledge reductions, distribution reduction, maximum distribution reduction, assignment reduction and ordered assignment reduction, are defined under the condition of multi-level. The judgment theorem and discernibility matrix with respect to consistent set are obtained by means of the definitions. One method to extract the defined knowledge reductions is presented. This may aid to knowledge acquisition from fuzzy objective information systems.

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