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Neural Information Processing

1 Part I

ICONIP
2010

Kok Wai Wong
B. Sumudu U. Mendis
Abdesselam Bouzerdoum (Eds.)

Neural Information Processing

Theory and Algorithms

17th International Conference, ICONIP 2010
Sydney, Australia, November 2010
Proceedings, Part I

1 Part I

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Preface

Welcome to the 17th International Conference on Neural Information Processing (ICONIP 2010) held in Sydney, 22–25 November 2010. In this volume you will find papers presented at this conference. ICONIP is the annual conference of the Asia Pacific Neural Network Assembly (APNNA, http://www.apnna.net). The aim of the Asia Pacific Neural Network Assembly is to promote the interaction of researchers, scientists, and industry professionals who are working in the neural network and related fields in the Asia Pacific region, primarily via the ICONIP conference. This year's theme was hybrid / human centred neural systems.

ICONIP 2010 received 470 excellent submissions. Of these, 146 regular session and 23 special session papers appear in these proceedings by Springer. Many outstanding papers do not appear here due to space limitations. Each paper was assessed by at least three reviewers. The conference will be followed by two associated workshops, the ICONIP International Workshop on Data Mining for Cybersecurity, held in November at the University of Auckland, New Zealand, and the ICONIP International Workshop on Bio-inspired Computing for Intelligent Environments and Logistic Systems, held in March at the Australian National University in Canberra, Australia.

I am very pleased to acknowledge the support of the conference Advisory Board, the APNNA Governing Board and Past Presidents, who gave their advice, assistance and promotion of ICONIP 2010. I gratefully acknowledge the technical sponsorship of the International Neural Network Society (INNS), the Japanese Neural Network Society (JNNS), the European Neural Network Society (ENNS), and the Australian Research Council Network in Human Communication Science (HCSNet).

A special thanks to Kevin Wong, Sumudu Mendis and Sukanya Manna without whom the conference organisation would have been much less smooth.

For the many reviewers who worked hard on giving thorough, tough but fair referee reports, thank you! Finally I would like to thank all the authors of papers, the speakers and panelists, volunteers and audience. With your support ICONIP 2010 will continue the tradition of being an uplifting, educational and enjoyable conference.

October 2010 Tom Gedeon

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Application Rough Sets Theory to Ordinal Scale Data for Discovering Knowledge

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Abstract. Rough set theory has been applied in many areas such as knowledge discovery and has the ability to deal with incomplete, imprecise or inconsistent information. The traditional association rule which should be fixed in order to avoid both that only trivial rules are retained and also that interesting rules are not discarded. In this paper, the new data mining techniques applied to ordinal scale data, which has the ability to handle the uncertainty in the classing process. The aim of the research is to provide a new association rule concept, which is using ordinal scale data.

Keywords: Knowledge discovery, Rough set, Data mining, Association rule.

1 Introduction

Rough set theory has been successfully applied in selecting attributes to improve the effectiveness in deriving decision trees/rules for decisions and classification problems. When decisions involve ordinal classes, the rough set reduction process should try to preserve the order relation generated by the decision classes [6]. And rough set theory, it has found practical applications in many areas such as knowledge discovery, multi-attribute choices, machine learning, approximate classification and data mining [7]. The previous research in mining association rules has two deficiencies. First, it pays no attention to finding rules from ordinal data. Second, it pays no attention to finding rules from imprecise data [4].Therefore, this study improved [4], and then proposed the concept of algorithm which combines with the rough set theory, so that it can more effectively solve the problem of uncertainty information in ordinal scale data.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature correlate with the research and problem statement. Section 3 Mathematical models for new algorithm. Closing remarks and future work are presented in Sect. 4.

2 Literature Review and Problem Statement

While there have been recent advances in algorithms for clustering categorical data, some are unable to handle uncertainty in the clustering process while others have stability

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issues. This research proposes a new algorithm for clustering categorical data, termed Min-Min-Roughness, based on rough set theory, which has the ability to handle the uncertainty in the clustering process [1]. Of the various data mining algorithms, this analysis uses the rough set algorithm due to its ability to deal with incomplete, imprecise or inconsistent information, which is typical in credit assessment analyses [2, 5].

Furthermore, in this research, we incorporate association rules with Rough sets, and promote a novel point of view in applications. In fact, there is no rule for the choice of the "right" connective, so this choice is always arbitrary to some extent.

3 Incorporation of Rough Set for Classification Processing

The traditional association rule which pays no attention to finding rules from ordinal data. Furthermore, in this research, we incorporate association rules with Rough sets, and promote a novel point of view in ordinal scale data applications. The data processing of ordinal scale data is described as below.

3.1 First: Data Processing

Definition 1. Transform the questionnaire answers into information system $IS=(U,A)$, where $U=\{x_1,x_2,\cdots x_n\}$ is a finite set of objects, $A=\{a_1,a_2,\cdots a_m\}$ is a finite set of general attributes/criteria. $f_a=U\times A\to V_a$ called the information function, V_a is the domain of the attribute/ criterion a, and f_a is a ordinal function set such that $f(x,a)\in V_a$ for each $x_i\in U$.

Example 1. According to Table 1, ranking the non-alcoholic beverages brand recall from the first to eighth by x_1 named Tea, Packaged-waters, Sports, Juice, Soda, Others, Coffee and Energy.

Table 1. Information system

U	A Ordinal Scale Data Sets							
	Tea a_1	Soda a_2	Coffee a_3	Juice a_4	Sports a_5	Packaged -waters a_6	Energy a_7	Others a_8
x_1	1	5	7	4	3	2	8	6
x_2	1	4	3	7	6	5	4	2
x_3	1	7	2	4	6	5	3	8
x_4	1	2	3	5	7	6	4	8
x_5	1	3	6	6	5	4	8	7

Then: $f_{a_1}=\{1\}$ $f_{a_3}=\{2,3,6,7\}$ $f_{a_5}=\{3,5,6,7\}$ $f_{a_7}=\{3,4,8\}$

$f_{a_2}=\{2,3,4,5,7\}$ $f_{a_4}=\{4,5,6,7\}$ $f_{a_6}=\{2,4,5,6\}$ $f_{a_8}=\{2,6,7\}$

Definition 2. According to specific universe of discourse classification, a similarity relation of the general attributes $a \in A$, denoted by $U/_A$. All of the similarity relation, denoted by $K = (U, R_1, R_2 \cdots R_{m-1})$.

$$U|A = \{[x_i]_A | x_i \in U\}$$

Example 2.

$$R(a_3) = \frac{U}{a_3} = \{\{x_1\}, \{x_2, x_4\}, \{x_3\}, \{x_5\}\} \qquad R(a_6) = \frac{U}{a_6} = \{\{x_1\}, \{x_2, x_3\}, \{x_4\}, \{x_5\}\}$$

$$R(a_5) = \frac{U}{a_5} = \{\{x_1\}, \{x_2, x_3\}, \{x_4\}, \{x_5\}\} \qquad R(a_7) = \frac{U}{a_7} = \{\{x_1, x_5\}, \{x_2, x_4\}, \{x_3\}\}$$

Definition 3. The Information system is an ordinal scale data, therefore between the two attributes will have the ordinal response, where B is called the relation between a_i under $U/_a$ condition.

$$D_a^+ = \left\{ x_i \middle| \frac{U}{a}, V_{f_{a_i}} > V_{f_{a_j}} \right\} \qquad D_a^- = \left\{ x_i \middle| \frac{U}{a}, V_{f_{a_i}} < V_{f_{a_j}} \right\} \qquad D_a^0 = \left\{ x_i \middle| \frac{U}{a}, V_{f_{a_i}} = V_{f_{a_j}} \right\}$$

When the two random objects both belong to the same fundamental set, $\forall : D_a^+ \equiv D_a^<$ or $\forall : D_a^- \equiv D_a^>$, is mean a core attribute value of ordinal scale data between a_i and a_j. As $V_{f_{a_i}} = V_{f_{a_j}}$, then will be ignored. And $ind(B) = [f_a]_{ind(B)} = \bigcap_{B \in U} [U/_a]_U$.

Example 3. According to the similarity relation, and then finding that $R(a_5) = U/_{a_5} = \{\{x_1\}, \{x_2, x_3\}, \{x_4\}, \{x_5\}\}$ and $R(a_6) = U/_{a_6} = \{\{x_1\}, \{x_2, x_3\}, \{x_4\}, \{x_5\}\}$ are both belong to the same fundamental set, and the ranking of $V_{f_{a5}}$ is place front $V_{f_{a6}}$, that denoted $D_a^<$, as shown in table2. In other words, Sports and Packaged-waters are both the core attribute value of ordinal scale data of non-alcoholic beverages, and Sports always places after Packaged-waters.

$$ind(B) = [\text{Sports, Packaged - waters}]$$

Table 2. The core attribute value of ordinal scale data of non-alcoholic beverages

R	f_{a_5}	f_{a_6}	D_a
$\{x_1\}$	3	2	D_a^+
$\{x_2, x_3\}$	6	5	D_a^+
$\{x_4\}$	7	6	D_a^+
$\{x_5\}$	5	4	D_a^+

3.2 Second: Generated Rough Associational Rule

Definition 1. The first step in this study, we have found the core attribute value of ordinal scale data, hence in the step, the object is to generated rough associational rule. To consider other attributes into and the core attribute of ordinal scale data as the highest decision-making attributes is hereby to establish the decision table, ease to generate rules, shown as Table 3.

$DT = (U, Q)$, where $U = \{x_1, x_2, \cdots x_n\}$ is a finite set of objects, Q is usually divides into two parts, $G = \{g_1, g_2, \cdots g_m\}$ is a finite set of general attributes/criteria, $D = \{d_1, d_2, \cdots d_l\}$ is a set of decision attributes. $f_g = U \times G \rightarrow V_g$ called the information function, V_g is the domain of the attribute/ criterion g, and f_g is a total function such that $f(x, g) \in V_g$ for each $g \in Q$; $x \in U$. $f_d = U \times D \rightarrow V_d$ called the sorting decision-making information function, V_d is the domain of the decision attributes / criterion d, and f_d is a total function such that $f(x, d) \in V_d$ for each $d \in Q$; $x \in U$.

Table 3. Decision-making table of the drinking habits of "non-alcoholic beverages"

Q / U	General attributes				Decision attributes	
	Product Features g_1	Product Information Source g_2	Consumer Behavior g_3	Channels g_4	Rank	Products
x_1	Price	Seen on shelves	purchase by promotions	Convenience Stores	3	Sports
x_2	Price	Advertising	purchase by promotions	Hypermarkets	6	Sports
x_3	Brand	Seen on shelves	will not purchase by promotions	Convenience Stores	6	Sports
x_4	Brand	Seen on shelves	will not purchase by promotions	Convenience Stores	7	Sports
x_5	Price	Advertising	purchase by promotions	Hypermarkets	5	Sports

Then: $f_{g_1} = \{\text{Price, Brand}\}$ $\quad f_{g_2} = \{\text{Seen on shelves, Advertising}\}$

$f_{g_3} = \{\text{purchase by promotions, will not purchase by promotions}\}$

$f_{g_4} = \{\text{Convenience Stores, Hypermarkets}\}$

Definition 2. According to specific universe of discourse classification, a similarity relation of the general attributes, denoted by $U/_G$. All of the similarity relation, denoted by $K = (U, R_1, R_2 \cdots R_{m-1})$.

$$U|G = \{[x_i]_G | x_i \in U\}$$

Example 2.

$$R_1 = \frac{U}{g_1} = \{\{x_1, x_2, x_5\}, \{x_3, x_4\}\} \qquad R_6 = \frac{U}{g_2 g_4} = \{\{x_1, x_3, x_4\}, \{x_2, x_5\}\}$$

$$\vdots \qquad \vdots$$

$$R_5 = \frac{U}{g_1 g_3} = \{\{x_1, x_2, x_5\}, \{x_3, x_4\}\} \qquad R_{m-1} = \frac{U}{G} = \{\{x_1\}, \{x_2, x_5\}, \{x_3, x_4\}\}$$

Definition 3. According to the similarity relation, and then finding the reduct and core. The attribute g which were ignored form G and the set G will not affect, thereby g is the unnecessary attribute, we can reduct it. $R \subseteq G$ and $\forall_g \in R$. A similarity relation of the general attributes from decision table, denoted by $ind(G)$. If $ind(G) = ind(G - g_1)$ then g_1 is the reduct attribute, and if $ind(G) \neq ind(G - g_1)$ then g_1 is the core attribute.

Example: $$U|ind(G) = \{\{x_1\}, \{x_2, x_5\}, \{x_3, x_4\}\}$$

$$U|ind(G - g_1) = U|(\{g_2, g_3, g_4\}) = \{\{x_1\}, \{x_2, x_5\}, \{x_3, x_4\}\} = U|ind(G)$$

$$U|ind(G - g_1 g_3) = U|(\{g_2, g_4\}) = \{\{x_1, x_3, x_4\}, \{x_2, x_5\}\} \neq U|ind(G)$$

When considers g_1 alone, g_1 is the reduct attribute, but when considers g_1 and g_3 simultaneously, g_1 and g_3 are the core attributes. A similarity relation and the relational attribute value as shown in Table 4.

Definition 4. The lower approximation, denoted as $\underline{G}(X)$, is defined as the union of all these elementary sets which are contained in $[x_i]_G$. More formally:

$$\underline{G}(X) = \cup\left\{[x_i]_G \in \frac{U}{G} \middle| [x_i]_G \subseteq X\right\}$$

The upper approximation, denoted as $\overline{G}(X)$, is the union of these elementary sets, which have a non-empty intersection with $[x_i]_G$. More formally:

$$\overline{G}(X) = \cup\left\{[x_i]_G \subseteq \frac{U}{G} \middle| [x_i]_G \cap X \neq \phi\right\}$$

The difference: $Bn_G(X) = \overline{G}(X) - \underline{G}(X)$ is called a boundary of $[x_i]_G$.

Example 4. $\{x_1, x_2, x_4\}$ are those customers that we are interested in, thereby $\underline{G}(X) = \{x_1\}$, $\overline{G}(X) = \{x_1, x_2, x_3, x_4, x_5\}$ and $Bn_G(X) = \{x_2, x_3, x_4, x_5\}$.

Definition 5. Using the traditional association rule to calculate the value of Support and Confidence, the formula is shown as follows:

$$Sup(ind(B)) = \left|\left\{ind(B) \middle| \underline{G}(X) \subseteq \overline{G}(X)\right\}\right| = \left|\frac{ind(B) | \underline{G}(X)}{\overline{G}(X)}\right|$$

$$Conf\left(ind(B) \to d_{g_m}\right) = \left|\left\{ind(B) \cap d_{g_m} \middle| Sup(ind(B))\right\}\right| = \left|\frac{Sup\left(ind(B) \cap d_{g_m}\right)}{Sup(ind(B))}\right|$$

Definition 6. Rough set-based association rules.

$$\frac{\{x_1\}}{g_1 g_3} : g_{1_1} \cap g_{3_1} \Rightarrow d_{d_1}^1 = 4 \qquad \frac{\{x_1\}}{g_1 g_2 g_3 g_4} : g_{1_1} \cap g_{2_1} \cap g_{3_1} \cap g_{4_1} \Rightarrow d_{d_1}^1 = 4$$

Table 4. A similarity relation and the relational attribute value

R	Product Features g_1	Product Information Source g_2	Consumer Behavior g_3	Channels g_4	Decision attributes D (Sports)
$\{x_1\}$	Price	Seen on shelves	Purchase by promotions	Convenience Stores	Third $d_{a_5}^1 = 3$
$\{x_2, x_5\}$	Price	Advertising	Purchase by promotions	Hypermarkets	Sixth $d_{a_5}^2 = 6$
					Fifth $d_{a_5}^5 = 5$
$\{x_3, x_4\}$	Brand	Seen on shelves	will not purchase by promotions	Convenience Stores	Sixth $d_{a_5}^3 = 6$
					Seventh $d_{a_5}^4 = 7$
$\{x_1, x_2, x_5\}$	Price	Seen on shelves	Purchase by promotions	Convenience Stores	Third $d_{a_5}^1 = 3$
		Advertising		Hypermarkets	Sixth $d_{a_5}^2 = 6$
		Advertising		Hypermarkets	Fifth $d_{a_5}^5 = 5$
$\{x_1, x_3, x_4\}$	Price	Seen on shelves	Purchase by promotions	Convenience Stores	Third $d_{a_5}^1 = 3$
	Brand		will not purchase by promotions		Sixth $d_{a_5}^3 = 6$
	Brand		will not purchase by promotions		Seventh $d_{a_5}^4 = 7$

Algorithm-Step1
Input:
Information System (IS);
Output:
{Core Attributes};
Method:
1. Begin
2. $IS = (U, A)$;
3. $x_1, x_2, \cdots, x_n \in U$; /* where $x_1, x_2, \cdots, x_n$ are the objects of set U */

4. $a_1, a_2, \cdots, a_m \in A$; /* where $a_1, a_2, \cdots, a_m$ are the elements of set A */
5. For each a_m do;
6. compute $f(x,a)$; /* compute the information function in IS as described in definition1*/
7. compute $R(a_m)$; /* compute the similarity relation in IS as described in definition2*/
8. compute D_a ; /* compute the V_a as condition attributes in $R(a_m)$ as described in definition3*/
9. Endfor;
10. Output {Core Attributes};
11. End;

Algorithm-Step2

Input:
Decision Table (DT);
Output:
{Classification Rules};
Method:
1. Begin
2. $DT = (U, Q)$;
3. $x_1, x_2, \cdots x_n \in U$; /* where $x_1, x_2, \cdots x_n$ are the objects of set U */
4. $Q = (G, D)$;
5. $g_1, g_2, \cdots, g_m \in G$; /* where $g_1, g_2, \cdots, g_m$ are the elements of set G */
6. $d_1, d_2, \cdots, d_l \in D$; /* where $d_1, d_2, \cdots, d_l$ are the "core attributes" generated in Step1*/
7. For each d_l do;
8. compute $f(x,g)$; /* compute the information function in DT as described in definition1*/
9. compute R_m ; /* compute the similarity relation in DT as described in definition2*/
10. compute $ind(G)$; /* compute the relative reduct of DT as described in definition3*/
11. compute $ind(G - g_m)$; /* compute the relative reduct of the elements for element m as described in definition3*/
12. compute $\underline{G}(X)$; /* compute the lower-approximation of DT as described in definition4*/
13. compute $\overline{G}(X)$; /* compute the upper-approximation of DT as described in definition4*/
14. compute $Bn_G(X)$; /* compute the bound of DT as described in definition4*/

```
15. compute Sup(ind(B)); /* compute the support as
              described in definition5*/
16. compute conf(ind(B) → d_{g_m}); /* compute the confidence
              as described in definition5*/
17. Endfor;
18. Output {Classification Rules};
19. End;
```

4 Conclusion and Future Works

The ordinal attributes which commonly occur in decision making problems, therefore in the research, we provide a new association rule concept, which is using ordinal scale data. Market segmentation is defined as a marketing technique that targets a group of customers with specific characteristics, and pursues the growth opportunities of further market. Every decision algorithm reveals some well-known probabilistic properties; in particular it satisfies the total probability theorem and Bayes' theorem. These properties give a new method of drawing conclusions from data, without referring to prior and posterior probabilities, inherently associated with Bayesian reasoning [3]. So, in the future, we try to incorporate the new association rules with Bayesian network, and promote a novel point of view in applications. The traditional association rules, the user must be trial and error for the association rules issued by explanatory power. The new association rule algorithm which try to combination with rough set theory to provide a more easily explained rules for user. For the convenience of users, to design a expert support system will help to improve the efficiency of the user.

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Rough-Set-Based Association Rules Applied to Brand Trust Evaluation Model

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Abstract. Of the consumers who often patronize retail stores, 87 of 100 respondents visited a convenience store in the past three months. The superstore/hypermarket and the supermarket came in second and third, respectively. This demonstrates that retail channels are essential to the day-to-day life of the common populace. With the social and economic evolution, not only have product sales and shopping habits changed, but the current marketing concepts have also changed from being product-oriented to being consumer-oriented. In this research, we first provide new algorithms modified from the Apriori algorithm. The new approach can be applied in finding association rules, which can handle an uncertainty, combined with the rough set theory, and then to find the influence degree of the consumer preferences variables for the marketing decision-makers used.

Keywords: Data mining, Rough set, Association rule, Retailing industry, Brand trust.

1 Introduction

We can judge consumer decisions on the basis of certain rules of thumb when the consumer choice factors taken into account are simple. However, when we have a variety of choices as well as an increasing number of factors to consider, it is important to determine how a simple analysis and consumer rule of thumb can help to determine the shopping behavior of consumers. In such a case, we may need a more rigorous approach to help us determine future consumer decision making and to find a complex combination of factors that affect the decision making irrespective of whether the effects of these factors are tangible. The rest of this paper is organized as follows. Section 2 reviews relevant literature related to the research and the problem statement. Section 3 presents the data processing for the new algorithm. Closing remarks and a discussion of future work are presented in Section 4.

2 Literature Review and Problem Statement

Data mining (DM), sometimes referred to as knowledge discovery in a database, is a systematic approach used for finding underlying patterns, trends, and relationships

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buried in data. DM has drawn serious attention from both researchers and practitioners because of its wide applications in crucial business decisions [7]. The related applications using these methodologies can be summarized as classification, prediction, clustering, summarization, dependency modeling, linkage analysis, and sequential analysis [8]. The rough set theory is different from the fuzzy theory and neural networks. Further, a majority of scholars have mentioned the use of association rules that are required for dealing with uncertainties or inaccurate information. In this research, we further explore the use of the rough set theory to improve the use of association rules.

"If the gender is Male, age is 30 years, and income is more than 35,000, then the favorite milk brand is Lin-Feng-Ying." In the case of R2, the decision-making rule is "If the gender is Male, age is 45 years, and income is more than 80,000, then the favorite milk brand is Wei-Chuan." From the information given above, we observe that the attributes of "age" and "income" affect the preference for a certain milk brand. Further, we may want to know whether "a male whose favorite milk brand is Lin-Feng-Ying would relatively like the Wei-Chuan brand of milk" or whether "a male whose favorite milk brand is Lin-Feng-Ying would absolutely like the Wei-Chuan brand of milk." That is, we may wish to know the relationships between attributes that are substitutes or complements and so on. However, without further information of rules, generated by the traditional rules, we cannot derive the necessary information. Therefore, when the rules have a hierarchical or ordinal structure, provided by the application of knowledge is very meaningful. If "age (A) is 30 years (a1) and revenue (R) is 35,000 or more (r1)," certain conditions of $a_1 \le A \le a_2$ and $r_1 \le R \le r_2$, where a1 and a2 and r1 and r2 correspond respectively to A and R, are satisfied.

3 Methodology—Algorithm Concept and Data Processing

We hope to figure out the consumer's subjective or objective point of view and preferences by using ratio-scale algorithms combined with the rough set theory, and then find the influence degree of the consumer preferences variables for the marketing decision-makers used. Fig. 1 presents the algorithm concept and data processing.

First: Data processing—Definition 1—Information system: Transform the questionnaire answers into information system $IS = (U, Q)$, where $U = \{x_1, x_2, \cdots x_n\}$ is a finite set of objects. Q is usually divided into two parts, $G = \{g_1, g_2, \cdots g_m\}$ is a finite set of general attributes/criteria, and $D = \{d_1, d_2, \cdots d_l\}$ is a set of decision attributes. $f_g = U \times G \to V_g$ is called the information function, V_g is the domain of the attribute/criterion g, and f_g is a total function such that $f(x, g) \in V_g$ for each $g \in Q$; $x \in U$. $f_d = U \times D \to V_d$ is called the sorting decision-making information function, V_d is the domain of the decision attributes/criterion d, and f_d is a total function such that $f(x, d) \in V_d$ for each $d \in Q$; $x \in U$.

```
Algorithm-Step1
     Input:
     Information System (IS);
     Output:
     {Trust Value};
     Method:
  1. Begin
  2.   IS = (U,Q);
  3.       x_1, x_2, ..., x_n ∈ U ; /* where x_1, x_2, ..., x_n are the objects of set U */
  4.       G,D ⊂ Q ; /* Q is divided into two parts G and D */
  5.           g_1, g_2, ..., g_m ∈ G ; /* where g_1, g_2, ..., g_m are the elements of set G */
  6.           d_1, d_2, ..., d_i ∈ D ; /* where d_1, d_2, ..., d_i are the elements of set D */
  7.       For each g_m and d_i do;
  8.           compute f(x,g) and f(x,d); /* compute the information function in IS as
                 described in definition1*/
  9.           compute R(g_m) and R(d_i); /* compute the similarity relation in IS as
                 described in definition2*/
  10.          compute F_p ; /* compute the V_g as condition attributes in R(g_m) as
                 described in definition3*/
  11.          compute F(g_ij°, d_i°); /* compute the P(d_i°) as condition attributes in R(d_i)
                 as described in definition4*/
  12.          compute E_c ; /* compute the brand image trust model as described in
                 definition5*/
  13.     Endfor;
  14.          Output { Trust Value };
  15. End;

Algorithm-Step2
Input:
Decision Table (DT);
Output:
{Classification Rules};
Method:
  1. Begin
  2.    DT = (U,Q);
  3.       x_1, x_2, ... x_n ∈ U ; /* where x_1, x_2, ... x_n are the objects of set U */
  4.       Q = (G,D);
  5.          g_1, g_2, ..., g_m ∈ G ; /* where g_1, g_2, ..., g_m are the elements of set G */
  6.          d_1, d_2, ..., d_i ∈ D ; /* where d_1, d_2, ..., d_i are the "trust value" generated in
              Step1*/
  7.    For each d_i do;
  8.       compute f(x,g); /* compute the information function in DT as described in
            definition1*/
  9.       compute R_m ; /* compute the similarity relation in DT as described in
            definition2*/
  10.      compute ind(G); /* compute the relative reduct of DT as described in
            definition3*/
  11.      compute ind(G - g_m); /* compute the relative reduct of the elements for element
            m as described in definition3*/
  12.      compute G_(X); /* compute the lower-approximation of DT as described in
            definition4*/
  13.      compute G¯(X); /* compute the upper-approximation of DT as described in
            definition4*/
  14.      compute Bn_G(X); /* compute the bound of DT as described in definition4*/
  15.      compute Sup(ind(B)); /* compute the support as described in definition5*/
  16.      compute Conf(ind(B) -> d_{g_m}); /* compute the confidence as described in
            definition5*/
  17.  Endfor;
  18.      Output {Classification Rules};
  19.End;
```

Fig. 1. Algorithm concept and data processing

Example: According to Tables 1 and 2, x_1 is a male who is thirty years old and has an income of 35,000. He ranks beer brands from one to eight as follows: Heineken, Miller, Taiwan light beer, Taiwan beer, Taiwan draft beer, Tsingtao, Kirin, and Budweiser.

Table 1. Information system

Q / U	General attributes G			Decision-making D
	Item1: Gender g_1	Item2: Age g_2	Item3: Income g_3	Item4: Beer brand recall
x_1	Male g_{1_1}	30 g_{2_1}	35,000 g_{3_1}	As shown in Table 4.
x_2	Male g_{1_1}	40 g_{2_2}	60,000 g_{3_2}	As shown in Table 4.
x_3	Male g_{1_1}	45 g_{2_3}	80,000 g_{3_4}	As shown in Table 4.
x_4	Female g_{1_2}	30 g_{2_1}	35,000 g_{3_1}	As shown in Table 4.
x_5	Male g_{1_1}	40 g_{2_2}	70,000 g_{3_3}	As shown in Table 4.

Table 2. Beer brand recall ranking table

U	D the sorting decision-making set of beer brand recall							
	Taiwan beer d_1	Heineken d_2	Taiwan light beer d_3	Miller d_4	Taiwan draft beer d_5	Tsingtao d_6	Kirin d_7	Budweiser d_8
x_1	4	1	3	2	5	6	7	8
x_2	1	2	3	7	5	6	4	8
x_3	1	4	3	2	5	6	7	8
x_4	3	1	6	2	5	4	8	7
x_5	1	3	6	2	5	4	8	7

Definition 2—Similarity relation: According to the specific universe of discourse classification, a similarity relation of the general attributes $g \in G$ is denoted as U/G, and a similarity relation of the decision attributes $d \in D$ is denoted as U/D

$$U|G = \{[x_i]_G | x_i \in U\} \qquad U|D = \{[x_i]_D | x_i \in U\}$$

Example:

$R(g_2) = U/g_2 = \{\{x_1, x_4\}, \{x_2, x_5\}, \{x_3\}\}$ $\qquad$ $R(d_1) = U/d_1 = \{\{x_1\}, \{x_2 x_3, x_5\}, \{x_4\}\}$

$R(g_3) = U/g_3 = \{\{x_1, x_4\}, \{x_2\}, \{x_5\}, \{x_3\}\}$ $\qquad$ $R(d_2) = U/d_2 = \{\{x_1, x_4\}, \{x_2\}, \{x_3, x_5\}\}$

Definition 3—Core value: We distinguish the hidden relation between the general attribute g_{i-1} and g_i, and then set the similarity relation of the quantity attribute as the top priority. $R^+(g_i)$ denotes the set of the general attribute objects as $g_{i_1} < g_{i_2} < \cdots < g_{i_n} \cap f(g_{i_1}) < f(g_{i_2}) < \cdots f(g_{i_n})$ for $\forall g_i \in G$, otherwise $R^-(g_i)$. $R^+(g_j)$ denotes the set of the general attribute objects as $g_{j_1} < g_{j_2} < \cdots < g_{j_n} \cap f(g_{j_1}) < f(g_{j_2}) < \cdots f(g_{j_n})$ for $\forall g_j \in G$, otherwise $R^-(g_j)$. $F_P(g_{i,} g_j)$ is the ratio relation between U/g_i and U/g_i. In the condition U/g, the set of x_i, is defined as follows:

$$F_P^+(g_i, g_j) = \{x_i | U/g, R^+(g_i) = R^+(g_j) \cup R^-(g_i) = R^-(g_j)\}$$
$$F_P^-(g_i, g_j) = \{x_i | U/g, R^+(g_i) = R^-(g_j) \cup R^-(g_i) = R^+(g_j)\}$$
$$F_P^0(g_i, g_j) = \{x_i | U/g, R^-(g_i) \neq R^+(g_j) \cup R^+(g_i) \neq R^-(g_j) \cup R^+(g_i) \neq R^+(g_j) \cup R^-(g_i) \neq R^-(g_j)\}$$

Example: According to Table 1, age and income are quantity attribute, and ratio relation between those two attributes is $F_P^+(g_2, g_3)$, that mean the income increases along with the age grows and are defined, respectively, as

$$R^+(g_2) = \{x_1, x_4, x_2, x_5, x_3\} \quad R^+(g_3) = \{x_1, x_4, x_2, x_5, x_3\} \quad F_P^+(g_2, g_3) = \{x_1, x_4, x_2, x_5, x_3\}$$

Definition 4—Similarity relation between general attribute and decision attributes: The decision attributes in the information system are an ordered set, therefore, the attribute values will have an ordinal relation defined as follows:

$$F(g_{ij}, d_l) = \begin{cases} P^+(d_l) : R(d_{1_1}) = F_P^+(1) \cap R(d_{1_i}) = F_P^+(i) \\ P^-(d_l) : R(d_{1_1}) = F_P^+(i) \cap R(d_{1_i}) = F_P^+(1) \\ P^0(d_l) : else \end{cases}$$

Example: The similarity relation between the general attribute and the decision attributes given in Tables 1 and 2 is presented in Table 3. For example, $R(d_1) = U/d_1 = \{\{x_1\}, \{x_2 x_3, x_5\}, \{x_4\}\}$ and $R(d_2) = U/d_2 = \{\{x_1, x_4\}, \{x_2\}, \{x_3, x_5\}\}$ show that the two decision attributes correspond to the quantity attribute, such as the quantity attribute value increased as the better ranking of Taiwan beer, but the quantity attribute value increased as the Worse ranking of Heineken. From this, we may conclude that Taiwan beer was well received by old people, and Heineken was well received by young people.

Table 3. Similarity relation between general attribute and decision attributes

d_l	$R(d_{l_1})$	$R(d_{l_i})$	$F_P^+(1)$	$F_P^+(i)$	$F(g_{ij}, d_l)$
d_1	$\{x_2, x_3, x_5\}$	$\{x_1\}$	x_1	x_3	$P^-(d_1)$
d_2	$\{x_1, x_4\}$	$\{x_3\}$	x_1	x_3	$P^+(d_2)$
		⋮			

Definition 5—Assessment model to establish brand trust: An assessment model for establishing brand trust, denoted by E_i, is defined as $E_c = \alpha \times (V_d)^{-1}$, $0 \leq E_c \leq 2$. Here, α represents the weight of the assessment model. When the similarity relation between the general attribute and the decision attributes is a positive

correlation or a negative correlation, such as $P^{+}(d_l)$ and $P^{-}(d_l)$, we obtain $E_c = \alpha \times (V_d)^{-1}$, where $\alpha = 2$, and the remainder $\alpha = 1$.

Example: By calculating the brand trust value shown in Table 4, we obtain the following: $E_1 = 2 \times 1/8 \times \text{Heineken}(d_2) == 1/4 = 0.25$, which indicates that the brand trust value of x_1 with respect to age and income is 0.25. $E_3 = 2 \times 1/5 \times \text{Heineken}(d_2) = 2/5 = 0.4$ indicates that the Heineken brand trust value of x_1 with respect to age and income is 0.4. The total brand trust value of Heineken is $(2+1+2/3+1+2/3) \div 5 = 16/15 = 1.067$.

Table 4. Brand trust value

U / D	$E_c^{x_2 x_3}$					Total brand trust value
	x_1	x_2	x_3	x_4	x_5	$\sum E_c / c$
Taiwan beer d_1	1/2	2	2	2/3	2	41/30 = 1.376
Heineken d_2	2	1	2/3	1	2/3	16/15 = 1.067

Second: Generated rough associational rule—Definition 1—Decision table: In the first step of this study, we found examples of the potential relationship between the attributes and calculated the degree of brand trust. Then, we generated rough association rules. To consider other attributes into, and to establish the decision table with the brand trust value as the highest decision-making attributes, shown as Table 5.

Table 5. Table of degree-of-brand-trust-based decision-making

Q / U	General attributes				Decision attributes	
	Product features g_1	Product information source g_2	Consumer behavior g_3	Channels g_4	Total trust value	Product
x_1	Price	Seen on shelves	Purchase by promotions	Convenience stores	1/2	Taiwan beer
x_2	Price	Advertising	Purchase by promotions	Hypermarkets	2	Taiwan beer
x_3	Brand	Seen on shelves	Will not purchase by promotions	Convenience stores	2	Taiwan beer

Definition 2—Similarity relation: According to the specific universe of the discourse classification, the similarity relation of the general attributes $g \in G$ is denoted as U/G. All the similarity relations are denoted by $K = (U, R_1, R_2 \cdots R_{m-1})$.

$$U|G = \{[x_i]_G | x_i \in U\}$$

Example:
$R_1 = U/g_1 = \{\{x_1, x_2\}, \{x_3\}\}$ $R_5 = U/g_1\ g_3 = \{\{x_1, x_2\}, \{x_3\}\}$

Definition 3—Reduct and core: According to the similarity relation, and then finding the reduct and core. The attribute g, which was ignored from G, and the set G will not be affected, thereby g is the unnecessary attribute and we can reduct it. $R \subseteq G$ and $\forall_g \in R$. A similarity relation of the general attributes from the decision table are denoted as $ind(G)$. If $ind(G) = ind(G - g_1)$, then g_1 is the reduct attribute, and if $ind(G) \neq ind(G - g_1)$, then g_1 is the core attribute.

Example: $U|ind(G) = \{\{x_1\}, \{x_2\}, \{x_3\}\}$
$U|ind(G - g_1) = U|(\{g_2, g_3, g_4\}) = \{\{x_1\}, \{x_2\}, \{x_3\}\} = U|ind(G)$
$U|ind(G - g_1 g_3) = U|(\{g_2, g_4\}) = \{\{x_1, x_3\}, \{x_2\}\} \neq U|ind(G)$

When g_1 is considered alone, g_1 is the reduct attribute; however, when g_1 and g_3 are considered simultaneously, g_1 and g_3 are the core attributes.

Definition 4—Lower approximation and upper approximation: The lower approximation, denoted as $\underline{G}(X)$, is defined as the union of all the elementary sets that are contained in $[x_i]_G$. More formally:

$$\underline{G}(X) = \cup\{[x_i]_G \in U/G \,|\, [x_i]_G \subseteq X\}$$

The upper approximation, denoted as $\overline{G}(X)$, is the union of the elementary sets that have a non-empty intersection with $[x_i]_G$. More formally:

$$\overline{G}(X) = \cup\{[x_i]_G \subseteq U/G \,|\, [x_i]_G \cap X \neq \phi\}$$

The difference: $Bn_G(X) = \overline{G}(X) - \underline{G}(X)$ is called a boundary of $[x_i]_G$.

Example: $\{x_1, x_2, x_4\}$ are the customers that we are interested in; therefore, $\underline{G}(X) = \{x_1\}$, $\overline{G}(X) = \{x_1, x_2, x_3, x_4, x_5\}$, and $Bn_G(X) = \{x_2, x_3, x_4, x_5\}$.

Definition 5: By using the traditional association rule to calculate the value of Support and Confidence, we derive the formula as follows:

$$Sup(ind(B)) = \left|\{ind(B) | \underline{G}(X) \subseteq \overline{G}(X)\}\right| = \left|\frac{ind(B) | \underline{G}(X)}{\overline{G}(X)}\right|$$

$$Conf(ind(B) \rightarrow d_{g_m}) = \left|\{ind(B) \cap d_{g_m} | Sup(ind(B))\}\right| = \left|\frac{Sup(ind(B) \cap d_{g_m})}{Sup(ind(B))}\right|$$

Definition 6: Rough-set-based association rules.
$\{x_1\}/g_1 g_3 : g_{1_1} \cap g_{3_1} \Rightarrow d^1_{d_1} = 4$ $\{x_1\}/g_1 g_2 g_3 g_4 : g_{1_1} \cap g_{2_1} \cap g_{3_1} \cap g_{4_1} \Rightarrow d^1_{d_1} = 4$

4 Conclusion and Future Work

The traditional association rule should be fixed in order to avoid both the retention of only trivial rules and the discarding of interesting rules. In fact, using a relative comparison to express the association rule is more complete than those that use an absolute comparison. In this study, a new approach was applied to find association rules, which could handle the uncertainty in the classification process and was suitable for the ratio scale data. Private brands are increasingly finding their way into new product/market shares. Using the suggested methodology, a decision maker can make accurate decisions regarding the segmentation and assistance required for developing a new product. The system needs to re-calculate and find new rules when the conditions of the traditional association rules change. Thus, in this study, we extended the concept of a utility function used for establishing the demand for users to adjust the brand image with the brand-trust evaluation model.

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