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A Rank Neutrosophic Technique for Effective Decision Making Problems

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Abstract

Only a part of uncertain problems can be solved with present theories of dealing with imprecise information and knowledge existing in the real world. A neutrosophic ranking approach algorithm based on correlation coefficients and weighted correlation coefficient is introduced in this paper which can effectively deal with decision making problems in regard of uncertain and incomplete information which exist commonly in real world situation. This data mining approach depending on concept of similarity gives a presentation of data analysis common to all applications.

Keywords: Rank Neutrosophic set; Soft cosine measure; Rank neutrosophic Relatio; Unit rank neutrosophic set

INTRODUCTION

Data mining[1] that is "knowledge mining" is an essential process where intelligent methods are applied to extract data patterns [2]. Data is analyzed from different perspectives and summarized into some useful information. Association, classification, clustering and sequential patterns are the three different types of data mining techniques[3]. Fuzzy methods are proposed by E Hullermeier [4] in data mining.

Real-world problems can be easily handled by Neutrosophic sets. In this paper, an algorithm is proposed for decision making and an example is illustrated to demonstrate the application of the proposed model.

Uncertainty from statistical variations or randomness that arises (or is assumed to arise) in the natural world can be handled by all data mining existing techniques. The two main elements on which data mining depends are, machine learning framework and the concept of similarity and it covers the domains namely mathematical, chemical, multimedia, medical, educational, etc. Indeterminacy components may arise in real world problem for data mining. Neutrosophic logic can handle this situation. In this paper, the role neutrosophic set logic in data mining is discussed.

The decision-making for incomplete, indeterminate and inconsistent information which exist usually in real situations the proposed cross entropy measures is very efficient. In decision making methods, Through the weighted cross entropy measure between each alternative one can obtain the ideal alternative, via ranking order of all alternatives

PRELIMANARIES

Neutrosophic logic uses three-valued logics that use an indeterminate value is an extension/combination of the fuzzy logic and was created by Florentin Smarandache (1995) .

Definition 2.1 Neutrosophic Logic **(Smarandache 1998) [5].** A logic in which each proposition is estimated to have the percentage of truth in a subset T, the percentage of indeterminacy in a subset I, and the percentage of falsity in a subset F, where T, I, F are defined below, is called *Neutrosophic Logic*. Constants: (T, I, F) truth-values, where T, I, F are standard or non-standard subsets of the nonstandard interval $]^-0, 1^+[$, where n_{inf} = inf T + inf I + inf F≥ $^-0$, and n_{sup} = sup T + sup I + sup F≤ 3^+.

Neutrosophic Set

A Neutrosophic set consists of three membership functions (truth-membership function, indeterminacy membership function and falsity-membership function), where every function value is a real standard or non-standard subset of the nonstandard unit interval $]0^-,1^+[$.

Definition 2.1.1 (Neutrosophic Set): Let X be a space of points (objects), with a generic element in X denoted by x. A neutrosophic set A in X is characterized by a truth-membership function T_A, an indeterminacy-membership function I_A and a falsity-membership function F_A. $T_A(x)$, $I_A(x)$ and $F_A(x)$ are real standard or non-standard subsets of $]^-0, 1^+[$. That is

$$T_A : X \rightarrow]^-0, 1^+[\quad , \qquad (1)$$

$$I_A : X \rightarrow]^-0, 1^+[\quad , \qquad (2)$$

$$F_A : X \rightarrow]^-0, 1^+[\quad . \qquad (3)$$

There is no restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$ so $^-0 \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.

In many cases it is difficult to determine exact percentages of truth and of falsity , so instead of numbers we use or approximate them as a subset of truth (or indeterminacy, or falsity), instead of a number only. Subsets may be discrete, continuous, open or closed or half open/half-closed interval, intersections or unions of the previous sets, etc : for example a proposition is between 20-80% true and between 80-20% false, or: between 30-70% or 40-50% true (according to various analyzers), and 70% or between 60-50% false.

Ranking:

Computing a similarity score is termed as Ranking between a query and a tuple e.g.

Consider the query Q = SELECT* From R Where $X_1 = p_1$ and … and $X_m = p_m$

Tuple is a vector: T = $(p_1,…, p_m)$; Query is a vector: Q = $(q_1,…, q_m)$

Consider applications such as :, shopping agents, personalized search engines , logical user profiles etc. Two approaches can be used for the above said applications

a) Quantitative → alteration of query ranking

b) Qualitative → Deterministic - Pare to semantics

2.3 Rank Neutrosophic Set

In this section Rank Neutrosophic sets[6] in an approximation space (*U; R*) is defined and set theoretic operations are applied on them. In engineering applications and real scientific problems, RNS an instance of neutrosophic set can be used

Zero Rank Neutrosophic set of U is defined as A Rank Neutrosophic set A of a set U with $t_A(u) = 0$ and $f_A(u) = 1$ ∀u Є U .

Unit Rank Neutrosophic set of U is defined as a Rank Neutrosophic set A of a set U with $t_A(u) = 1$ and $f_A(u) = 0$ ∀u Є U.

Rank Neutrosophic relation(RNR) are the relations based on rank neutrosophic set.

COSTRUCTIVE APPROACH OF RNS

There is no restriction on the sum of $T_A(x)$, $I_A(x)$ and $F_A(x)$, thus $0^- \leq \sup T_A(x) + \sup I_A(x) + \sup F_A(x) \leq 3^+$.

Definition 3.1 Let U be a space of points (objects), with a generic element in U denoted by x. Let P and Q be two NSs in U. If for any x ∈ U, $T_P(x) \leq T_Q(x)$, $I_P(x) \geq I_Q(x)$ and $F_P(x) \geq F_Q(x)$, then we call it as P is contained in Q, i.e., P □Q. If P□ Q and Q□ P, then we call P is equal to Q.

1) The union of P and Q is denoted by L = P UQ, where ∀x ∈U,

$T_L(x) = T_P(x) \vee T_Q(x)$, $I_L(x) = I_P(x) \wedge I_Q(x)$ and $F_L(x) = F_P(x) \wedge F_Q(x)$;

(2) The intersection of □ P and Q is a RNS denoted by M = P∩Q, where ∀x ∈ U, $T_M(x) = T_P(x) \wedge T_Q(x)$, $I_M(x) = I_P(x) \vee I_Q(x)$, and $F_M(x) = F_P(x) \vee F_Q(x)$, where "∨" and "∧" denote maximum and minimum, respectively.

Definition 3.2 A Rank neutrosophic Relation in U, denoted by R ={(x,y), $T_R(x,y)$, $I_R(x,y)$, $F_R(x,y)$| (x, y) ∈ U ×U}, where denote the truth-membership function, indeterminacy membership function, and falsity-membership function of R are denoted by T_R : U ×U −→[0,1], I_R :U ×U →[0,1], and F_R :U ×U → [0,1] , respectively.

Let R be a RNR in U, the complement R^c of R is defined as,

R^c={(x,y), $T_R^c(x,y)$, $F_R^c(x,y)$, $I_R^c(x,y)$ | (x, y) ∈U ×U}, where ∀(x, y) ∈ U×U, $T_R^c(x, y) = F_R(x, y)$, $F_R^c(x, y) = T_R(x, y)$ an $I_R^c(x, y) = 1 - I_R(x, y)$.

The lower and upper approximations of P with respect to (U, R), denoted by R(P) and R̂ (P), are two RNSs whose membership functions are defined as : ∀x ∈U,

$T_{R(P)}(x) = \text{Min}_{y \in U} (F_{R(x, y)} \vee T_{A(y)})$,

$I_{R(P)}(x) = \text{Max}_{y \in U}((1 - I_{R(x, y)}) \wedge I_{A(y)})$,

$F_{R(P)}(x) = \text{Max}_{y \in U}(T_{R(x, y)} \wedge F_{A(y)})$;

$T_{\hat{R}(P)}(x) = \text{Max}_{y \in U} (T_{R(x, y)} \wedge T_{A(y)})$,

$I_{\hat{R}(P)}(x) = \text{Min}_{y \in U} (I_{R(x, y)} \vee I_{A(y)})$,

$F_{\hat{R}(P)}(x) = \text{Min}_{y \in U} (F_{R(x, y)} \vee F_{A(y)})$.

Neutrosophic lower and upper approximation operators are denoted as R and R̂ complement .

Definition 3.3 The operations on two neutrosophic numbers m1 & m2, let m1 = (T_{m1}, I_{m1}, F_{m1}) amd m2 = (T_{m2}, I_{m2}, F_{m2}) be can be defined as follows:

$m_1 \oplus m_2 = (T_{m1} + T_{m2} - T_{m1} \cdot T_{m2}, I_{m1} \cdot I_{m2}, F_{m1} \cdot F_{m2})$;

$m_1 \Theta\, m = (T_{m1} \cdot T_{m2}, I_{m1} + I_{m2} - I_{m1} \cdot I_{m2}, F_{m1} + F_{m2} - F_{m1} \cdot F_{m2})$.

Definition 3.4 We define the sum of two neutrosophic sets P and Q in U as

P+Q ={a, P(a)⊕ Q(a) | a ∈U}.

The method of Soft cosine measure between neutrosophic numbers is proposed to rank the neutrosophic numbers in the decision-making process

SIMILARITY APPROACH METHODOLOGY

Definition 4.1 Let m = (T_m, I_m, F_m) be a neutrosophic number, m∗ = (T_{m*}, I_{m*}, F_{m*}) = (1,0,0) be an ideal neutrosophic number, then the Soft cosine measure between m and m∗ is defined as follows:

$S(m,m*) = [\,(T_m \cdot T_{m*} + I_m \cdot I_{m*} + F_m \cdot F_{m*})] \,/\, [(\text{sqrt}(T^2{}_m + I^2{}_m + F^2{}_m)) \cdot (\,\text{sqrt}(\,(T_{m*})^2 + (I_{m*})^2 + (F_{m*})^2)]$.

The characteristics of the alternatives x_i(i = 1,2,...,n) are represented by single valued neutrosophic numbers m_{xi} for the multi-attribute decision-making problem .

The the alternative xi will be better when the value of the Soft cosine measure $S(m_{xi}, m^*)$ is bigger, because the alternative x_i then is close to the ideal alternative x∗.

The ranking of all alternatives can be determined by comparing the Soft cosine measure value and the optimal alternative can be obtained.

ALGORITHM

Step1. Check whether the set is rank neutrosophic set or not.

Step 2. Read its $T_A(x)$, $I_A(x)$ and $F_A(x)$ values.

Step 3. Calculate The lower and upper approximations of P with respect to (U, R), denoted by R(P) and R̂ (P), are two RNSs whose membership functions are defined as : ∀x ∈U,

Step 4. Calculate R(X) + R^c (X) by using P+Q ={a, P(a)⊕ Q(a) | a ∈U}.

Step 5. Compute $S(m_{xi}, m^*) = [(T_m \cdot T_{m*} + I_m \cdot I_{m*} + F_m \cdot F_{m*})] / [(sqrt(T^2{}_m + I^2{}_m + F^2{}_m)) \cdot (sqrt((T_{m*})^2 + (I_{m*})^2 + (F_{m*})^2)]$ where (i =1 ,2,...,n),

Step 6. Select the optimal decision a_k such as $S(m_{ak}, m^*) = \max_{i\in\{1,2,...,n\}}(S(m_{xi}, m^*))$ if k is a multi valued attribute.

A numerical example given below illustrates the application of rank valued neutrosophic sets on two-universes by use of the algorithm above.

Example 4.1 There is an investment company, which wants to invest the money with optimal option: Let U ={ a1,a2,a3,a4,a5} be set of five companies , where ai(i = 1,2,3,4,5) stand for “cloth company,” “flat management company”, “Oil company,”“Steel company” and “Finance company,” respectively.

V ={ b1, b2, b3, b4, b5, b6, b7} be seven attributes, where yj(j = 1,2,3,4,5,6,7) stand for “cost” , "Risk", “man power,” "enviormental impact", “schemes” ,"growth" and “Demand,” respectively. R is a knowledge statistic data of the relationship of the company ai (ai ∈ U) and the attributes bj(bj ∈ V), and R is actually a neutrosophic relation from U to V (given in Table 4).

Suppose the attributes of a company A are described by a NS in the universe V, and

By Definition 3.1 we calculate the lower and upper approximations R(A) and R̂(A)

By Definition, 3.4 we compute R(A) + R̂(A)

Then, by Definition 4.1 , we can compute the Soft cosine measure between the neutrosophic number n ai corresponding to ai and the ideal neutrosophic number m∗ as follows: $S(m_{x1},m^*)$,$S(m_{x2},m^*)$, $S(m_{x3},m^*)$, $S(m_{x4},m^*)$, $S(m_{x5},m^*)$.

Then, if we have

$S(m_{x1},m^*)>S(m_{x4},m^*)>S(m_{x2},m^*)>S(m_{x5},m^*) > S(m_{x3},m^*)$.

So, the optimal and best decision is to select a1. That is, alternative 5 is the best choice among the all given choices.

Thus, the application domain of the proposed method is wider than previous ones.

CONCLUSION AND FUTURE SCOPE

An algorithm of decision making based on rank neutrosophic sets on two-universes is presented in this paper. An example is also given to show the usefulness of rank valued neutrosophic sets on two-universes. The proposed method have been applied to multiple attribute decision-making problems under neutrosophic environments Ranking order of all alternatives and the best alternative can be obtained through this method of decision making.

The problems with the incomplete and inconsistent information which exist commonly can be effectively dealt with the proposed method in real situations .

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