A Method of Imprecise Query Solving

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SUMMARY
In this paper the authors propose a new method of intelligent search called Neutrosophic-search to find the most suitable match for the predicates to answer any imprecise query made by the database users. The method is based on the theory of Neutrosophic sets introduced by Samrandech[7]. It is also to be mentioned that the Neutrosophic-search method could be easily incorporated in the existing commercial query languages of DBMS to serve the lay users better. So in this Paper Authors are suggesting a new method called Neutrosophic Relations and their operators to solve the imprecise query based on α-Neutrosophic-equality Search ,Neutrosophic Proximity search and combination of above two searches into single neutrosophic search with ranks.

KEYWORDS
Neutrosophic Search, α-Neutrosophic-equality Search , Neutrosophic Search, β-value of an interval, , Neutrosophic proximity search, Neutrosophic relation.

1. INTRODUCTION

Today Databases are Deterministic. An item is either in the database or not , either the query answer is available in the database or not is a very serious matter .An item belongs to the database" is a probabilistic event,or a tuple is an answer to the query" is a probabilistic event, and it Can be extended to all data models; here we discuss probabilistic *relational* data. Two Types of Probabilistic relational Data are there, *Database is deterministic and Query answers are probabilistic* or *Database is probabilistic and Query answers are probabilistic*.
Probabilistic relational databases have been studied from the late 80's until today.But today Application Need to manage imprecision's in data. Imprecision can be of many types: non-matching data values, imprecise queries, inconsistent data, misaligned schemas, etc, etc.

The quest to manage imprecisions is equal to major driving force in the database community is the Ultimate cause for many research areas: data mining, semistructured data, schema matching, nearest neighbor. Processing probabilistic data is fundamentally more complex than other data models .Some previous approaches sidestepped complexity .Now our implementation includes Ranking query answers. Since our Database is deterministic ,The query returns a *ranked list of tuples But our* User interested in top-k answers. Sometimes we get the empty answers for the user queries in the deterministic database.For eg.
For example, consider a database of personal Computers with 8GB memory. and the database is given in Table 1 as

Model	CPU	Clock_ Rate	Disk_ Size	Access_ Time	Price
A	8086	20(MHz)	40	40	1500
B	8086	25	80	28	2000
C	8086	25	75	26	2000
D	8086	25	80	24	3000
E	8086	25	85	28	2500

Table 1:Database for PCs

Now ,Consider the query as

```
SELECT * FROM PC
WHERE CPU = '8086'
AND MEMORY = 8
RANK_BY CLOCK_RATE >= 25
        DISK_SIZE >= 80
        ACCESS_TIME <25
        PRICE = LOW
```

.Now Suppose a User may seek for the PC with an 8086 Processor with a clock rate of at least 25 MHz, 8 GB of Main Memory ,an 80 GB of Hard Disk with an access time of less than 25 ms. And Of course he is interested in cheap offer. Now seeing at the above database only Model D fulfills the criteria But on the other hand Models (B, C,E) which do not fully meet the requirement but cheaper than Model D. So to Answer this probabilistic query we have to consider different neutrosophic predicates like " about " , " at most ", " High" , "Low" ," Some". Which our existing standard query languages will fail to answer .
This failure is because of the presence of imprecise constraints in the query predicate which can not be tackled due to the limitation of the grammar in standard query languages which work on crisp environment only. But this type of queries are very common in todays e-commerce world. To deal with uncertainties in searching match for such queries, fuzzy logic ,Vague Logic or Neutrosophic Logic will be the appropriate tool. And to deal with this imprecision we are using a Ranking method based on Neutrosophic Logic. So in the papers,

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Authors are describing the neutrosophic relations and its operators then implementing these relation to their search methods.

Definition 1.1 Ranking

Compute a similarity score between a tuple and the query,

Consider the query

```
Q = SELECT *
    FROM  R
    WHERE A1=v1 AND … AND Am=vm
```

Query is a vector given as Q = (v1, …, vm)

Tuple is a vector given as T = (u1, …, um)

Consider the applications: personalized search engines, shopping agents, logical user profiles, "soft catalogs"

To answer the queries realated with the above application Two approaches are given:

- Qualitative → Pare to semantics (deterministic)
- Quantitative→ alter the query ranking

Definition 1.2

An imprecise attribute value $t_m(a_i)$must be specified as a discrete probability distribution

over Di, that is $t_m(a_i) = \{(z_j,P_j)\backslash z_j \in D_i$and $P_j \in [O, 1]\}$ with $\sum P_j = \alpha_{im}, 0 <= \alpha_{im} <= 1$.

$(z_j,P_j) \in f_{vn}(a;)$

This definition covers both interpretations of null values as well as the usual interpretation of imprecise data: If $a_{im} = 1$, we certainly know that an attribute value exists, and with $a_{im} = 0$, we represent the fact that no value exists for this attribute. In the case of $0 < o_i, < 1$, o_i, gives the probability that an attribute value exists: For example, someone who isgoing to have a telephone soon gave us his number,but we are not sure if this number is valid already.With imprecise values specified this way, their probabilistic indexing weight can be derived easily.

Definition 1. 3 Probabilistic Relation

A *probabilistic relation r* of the scheme *R*(*A*) is a finite set of probabilistic tuples of *R*(*A*). By *domr*(*A*) we will denote the set of all values of the attribute A_i in the relation *r*.

Now, the failure of the RDBMS is due to the presence of imprecise constraints in the query predicate which can not be tackled due to the limitation of the grammar in standard query languages which work on crisp environment only. But this type of queries are very common in business world and in fact more frequent than grammatical-queries, because the users are not always expected to have knowledge of DBMS and the query languages.

Consequently, there is a genuine necessity for the different large size organizations, specially for the industries, companies having world wide business, to develop such a system which should be able to answer the users queries posed in natural language, irrespective of the QLs and their grammar, without giving much botheration to the users. Most of these type of queries are not crisp in nature, and involve predicates with fuzzy (or rather vague) data, fuzzy/vague hedges (with concentration or dilation). Thus, this type of queries are not strictly confined within the domains always. The corresponding predicates are not hard as in crisp predicates. Some predicates are soft because of vague/fuzzy nature and thus to answer a query a hard match is not always found from the databases by search, although the query is nice and very real, and should not be ignored or replaced according to the business policy of the industry. To deal with uncertainties in searching match for such queries, fuzzy logic and rather vague logic [1] and Neutrosophic logic by Smarandache [7]will be the appropriate tool.

In this paper we propose two things .A neutrosophic relation and based on this relation they are suggesting a new type of searching techniques using Neutrosophic set theory of to meet the predicates posed in natural language in order to answer imprecise queries of the users. Thus it is a kind of an intelligent search for match in order to answer imprecise queries of the lay users. We call this method by

α-Neutrosophic-equality search and,

Neutrosophic proximity search

Our method, being an intelligent soft-computing method, will support the users to make and find the answers to their queries without iteratively refining them by trial and error which is really boring and sometimes it seriously effects the interest (mission and vision) of the organization, be it an industry, or a company or a hospital or a private academic institution etc. to list a few only out of many. Very often the innocent (having a lack of DBMS knowledge) users go on refining their queries in order to get an answer. The users are from different corner of the academic world or business world or any busy world. For databases to support imprecise queries, our intelligent system will produce answers that closely match the queries constraints, if des not exactly. This important issue of closeness can not be addressed with the crisp mathematics. That is why we have used the Neutrosophic tools .

2. THEORY OF NEUTROSOPHIC SET

In the real world there are vaguely specified data values in many applications, such as sensor information,Robotics etc. Fuzzy set theory has been proposed to handle such vagueness by generalizing the notion of membership in a set. Essentially, in a Fuzzy Set (FS) each element is associated with a point-value selected from the unit interval [0,1], which is termed the grade of membership in the set. A Vague Set (VS), as well as an Intuitionistic Fuzzy Set (IFS), is a further generalization of an FS. Now take an example, when we ask the opinion of an expert about certain statement, he or she may say that the possibility that the statement is true is between 0.5 and 0.7, and the statement is false is between 0.2 and 0.4, and the degree that he or she is not sure is between 0.1 and 0.3. Here is another example, suppose there are 10 voters during a voting process. In time t1, three vote "yes", two vote "no" and five are undecided, using neutrosophic notation, it can be expressed as x(0.3,0.5,0.2); in time t2, three vote "yes", two vote "no", two give up and three are undecided, it then can be expressed as x(0.3,0.3,0.2). That is beyond the scope of the intuitionistic fuzzy set. So, the notion of neutrosophic set is more general and overcomes the aforementioned issues. In neutrosophic set, indeterminacy is quantified explicitly and truth membership, indeterminacy-membership and falsity-membership are independent. This assumption is very important in many applications such as information fusion in which we try to combine the data from different sensors. Neutrosophy was introduced by Smarandache [7].

Neutrosophic set is a powerful general formal framework which generalizes the concept of the classic set, fuzzy set [2], Vague set [1] etc.

A neutrosophic set A defined on universe U. x = x(T,I,F) ε A with T,I and F being the real standard or non-standard subsets of]0-,1+[, T is the degree of truth-membership of A, I is the degree of indeterminacy membership of A and F is the degree of falsity-membership of A.

Definition 2.1

A Neutrosophic set A of a set U with $t_A(u)$, $f_A(u)$ and $I_A(u)$, $\forall u \in U$ is called the α- Neutrosophic set of U, where $\alpha \in [0,1]$.

Definition 2.2

A Neutrosophic number (NN) is a Neutrosophic set of the set R of real numbers.

3 .OPERATIONS WITH NEUTROSOPHIC SETS

We need to present these set operations in order to be able to introduce the neutrosophic connectors.

Let S1 and S2 be two (unidimensional) real standard or non-standard subsets, then one defines:

3.1 ADDITION OF SETS:

S1 ⊕ S2 = {x|x=s1+s2, where s1 ∈ S1 and s2 ∈ S2},

with inf S1 ⊕ S2 = inf S1 + inf S2, sup S1 ⊕ S2 = sup S1 + sup S2;

and, as some particular cases, we have

{a} ⊕ S2 = {x|x=a+s2, where s2 ∈ S2}

with inf {a} ⊕ S2 = a + inf S2, sup {a} ⊕ S2 = a + sup S2.

3.2 SUBTARCTION OF SETS:

S1ϴS2 = {x|x=s1-s2, where s1 ∈ S1 and s2 ∈ S2}.

For real positive subsets (most of the cases will fall in this range) one gets

inf S1ϴS2 = inf S1 - sup S2, sup S1ϴS2 = sup S1 - inf S2;

and, as some particular cases, we have

{a}ϴS2 = {x|x=a-s2, where s2 ∈ S2},

with inf {a}ϴS2 = a - sup S2, sup {a}ϴS2 = a - inf S2;

3.3 MULTIPLICTAION OF SETS:

S1 ⊗ S2 = {x|x=s1.s2, where s1 ∈ S1 and s2 ∈ S2}.

For real positive subsets (most of the cases will fall in this range) one gets

inf S1 ⊗ S2 = inf S1 . inf S2, sup S1 ⊗ S2 = sup S1 ⊗ sup S2;

and, as some particular cases, we have

{a} ⊗ S2 = {x|x=a ⊗ s2, where s2 ∈ S2},

with inf {a} ⊗ S2 = a * inf S2, sup {a} ⊗ S2 = a ⊗ sup S2;

3.4 DIVISION OF SETS BY A NUMBER:

Let k ∈ R* then S1/k = {x|x=s1/k, where s1 ∈ S1}.

4. NEUTROSOPHIC LOGIC CONNECTORS

One uses the definitions of neutrosophic probability and neutrosophic set operations.

Similarly, there are many ways to construct such connectives according to each particular problem to solve; here we present the easiest ones:

One notes the neutrosophic logic values of the propositions A1 and A2 by

NL(A1) = (T1, I1, F1) and NL(A2) = (T2, I2, F2) respectively.

For all neutrosophic logic values below: if, after calculations, one obtains numbers < 0 or > 1, one replaces them $^-0$ or 1^+ respectively.

4.1 NEGATION:

NL(¬ A1) = ($\{1^+\}$ϴT1, $\{1^+\}$ϴI1, {1+}ϴF1)

4.2 .CONJUNCTION:

NL(A1 ∧ A2) = (T1 ⊗ T2, I1 ⊗ I2, F1 ⊗ F2).

(And, in a similar way, generalized for n propositions.)

4.3 IMPLICATION*:*

NL(A1 ↔ A2) = ($\{1^+\}$ϴT1 ⊕ T1 ⊗ T2, $\{1^+\}$ϴI1 ⊕ I1 ⊗ I2, $\{1^+\}$ϴF1 ⊕ F1 ⊗ F2).

5. NEUTROSOPHIC RELATION

In this section, we will define the Neutrosophic relation. A tuple in a neutrosophic relation is assigned a measure. will be referred to as the *truth* factor and will be referred to as the *false* factor. The interpretation of this measure is that we believe with confidence and doubt with confidence that the tuple is in the relation. The truth and false confidence factors for a tuple need not add to exactly 1. This allows for incompleteness and inconsistency to be represented. If the truth and false factors add up to less than 1, we have incomplete information regarding the tuple's status in the relation and if the truth and false factors add up to more than 1, we have inconsistent information regarding the tuple's status in the relation.

In contrast to vague relations where the grade of membership of a tuple is fixed, neutrosophic relations bound the grade of membership of a tuple to a subinterval $[\alpha, 1-\beta]$ for the case, $\alpha+\beta \leq 1$.. The operators on fuzzy relations can also be generalized for neutrosophic relations. However, any such generalization of operators should maintain the belief system intuition behind neutrosophic relations.

Definition 5.1 A neutrosophic relation on scheme R on $\sum$ is any subset of

$\tau(\sum) \times [0,1] \times [0,1]$, Where $\tau(\sum)$ denotes the set of all tuples on any scheme $\sum$.

For any $t \in \tau(\sum)$, we shall denote an element of R as $\langle t, R(t)^+, R(t)^- \rangle$, where, $R(t)^+$ is the truth factorr assigned to t by R and $R(t)^-$ is the false factor assigned to t by R.Let V($\sum$) be the set of all neutrosophic relation on $\sum$.

Definition 5.2 A neutrosophic relationon scheme R on $\sum$ is consistent if $R(t)^+ + R(t)^- \leq 1$, for all $t \in \tau(\sum)$ .Let C($\sum$)be the set of all consistent neutrosophic relations on $\sum$.R is said to be complete if $R(t)^+ + R(t)^- \geq 1$, for all $t \in \tau(\sum)$. If R is both consistent and complete*, i.e.* $R(t)^+ + R(t)^- = 1$, for all $t \in \tau(\sum)$. then it is a *total* neutrosophic relation, and let T($\sum$) be the set of total neutrosophic relation on $\sum$.

5.1 Operator Generalizations

It is easily seen that neutrosophic relations are a generalization of vague relations, in that for each vague relation there is a neutrosophic relation with the same information content, but not *vice versa*. It is thus natural to think of generalizing the operations on vague relations such as union, join, and projection etc. to neutrosophic relations. However, any such generalization should be intuitive with respect to the belief system model of neutrosophic relations. We now construct a framework for operators on both kinds of relations and introduce two different notions of the generalization relationship among their operators.

An n-ary operator on fuzzy relations with signature $\langle \sum_{1,\ldots\ldots\ldots,} \sum_{n+1} \rangle$ is a function Θ :F($\sum_1$) $\times \ldots \times$ F($\sum_n$)→ $\sum_{n+1}$,where $\sum_{1,\ldots,} \sum_{n+1}$ are any schemes. Similarly An n-ary operator on neutrosophic relations with signature $\langle \sum_{1,\ldots\ldots\ldots,} \sum_{n+1} \rangle$ is a function Ψ :V($\sum_1$) $\times \ldots \times$ V($\sum_n$)→V($\sum_{n+1}$).

Definition 5.3

An operator Ψ on neutrosophic relations with signature $\langle \sum_{1,\ldots\ldots\ldots,} \sum_{n+1} \rangle$ is *totality preserving* if for any total neutrosophic relations $R_{1,\ldots}R_n$ on schemes $\sum_{1,\ldots,} \sum_{n+1}$, respectively. Ψ ($R_{1,\ldots}R_n$) is also total.

Definition 5.4

A totality preserving operator Ψ on neutrosophic relations with signature $\langle \sum_{1,\ldots\ldots\ldots,} \sum_{n+1} \rangle$ is a *weak generalization* of an operator Θ on fuzzy relations with the same signature, if for any total neutrosophic relations $R_{1,\ldots}R_n$ on schemes $\sum_{1,\ldots,} \sum_n$, respectively ,we have

$\lambda_{\sum_{n+1}}(\Psi(R_{1,\ldots}R_n)) = \Theta(\lambda_{\sum_1}(R_1),\ldots.., \lambda_{\sum_n}(R_n))$.

The above definition essentially requires Ψ to coincide with Θ on total neutrosophic realtions (which are in One-one correspondence with the vague relations). In general, there may be many operators on neutrosophic relations that are weak generalizations of a given operator Θ on fuzzy relations. The behavior of the weak generalizations of Θ on even just the consistent neutrosophic relations may in general vary. We require a stronger notion of operator generalization under which, at least when restricted to consistent neutrosophic relations, the behavior of all the generalized operators is the same. Before we can develop such a notion, we need that of 'representation' of a neutrosophic relation.

We associate with a consistent neutrosophic relation R the set of all (vague relations corresponding to) total neutrosophic relations obtainable from R by filling the gaps between the truth and false factors for each tuple. Let the map be $reps_{\sum}$:C($\sum$)→$2^{F(\sum)}$.is given by ,

$$reps_{\sum}(R) = \{Q \in F(\sum) \mid \bigwedge_{t_i \in \tau(\sum)} (R(t_i)^+ \leq Q(t_i) \leq 1 - R(t_i)^-)\}.$$

The set $reps_{\sum}$ (R) contains all fuzzy relations that are 'completions' of the consistent neutrosophic relation R .Observe that $reps_{\sum}$ is defined only for consistent neutrosophic relations and produces sets of fuzzy relations. Then we have following observation.

Proposition 5.1 For any consistent neutrosophic relation R on scheme $\sum$, reps$_{\sum}$ (R) is the singleton {$\lambda_{\sum}$ (R)}, iff R is total.

Proposition 5.2 If Ψ is a strong generalization of Θ, then Ψ is also a weak generalization of Θ.

6. Generalized Algebra on Neutrosophic Relations

In this section, we present one strong generalization each for the vague relation operators such as union, join, and projection. To reflect generalization, a hat is placed over a vague relation operator to obtain the corresponding neutrosophic relation operator. For example, ∞ denotes the natural join mong fuzzy relations, and $\hat{\infty}$ denotes natural join on neutrosophic relations. These generalized operators maintain the truth system intuition behind neutrosophic relations.

6.1 Set-Theoretic Operators

We first generalize the two fundamental set-theoretic operators, union and complement.

Definition 6.1 Let R and S be neutrosophic relations on scheme $\sum$. Then,

The union of R and S ,denoted R $\hat{\cup}$ S , is a neutrosophic relation on scheme $\sum$,given by

$$R \hat{\cup} S = \left\langle \max\{R(t)^{+}, S(t)^{+}\}, \min\{R(t)^{-}, S(t)^{-}\} \right\rangle$$

for any t $\in \tau(\sum)$.

(a) The complement of R ,denoted by $\hat{-}$ R,is a neutrosophic relation on scheme $\sum$,given by

$(\hat{-}R)(t)=\langle R(t)^{+},R(t)^{-}\rangle$,for any t $\in \tau(\sum)$.

An intuitive appreciation of the union operator can be obtained as follows: Given a tuple *t*, since we believed that it is present in the relation *R* with confidence *R(t)*$^{+}$ and that it is present in the relation *S* with confidence *S(t)*$^{+}$, we can now believe that the tuple *t* is present in the "either -*R* or - *S* " relation with confidence which is equal to the larger of $R(t)^{+}$ and $S(t)^{+}$. Using the same logic, we can now believe in the absence of the tuple *t* from the "either - *R* - or - *S* " relation with confidence which is equal to the smaller (because *t* must be absent from both *R* and *S* for it to be absent from the union) of *R(t)*$^{-}$ and S(t)$^{-}$.

Proposition 6.1 : The operator $\hat{\cup}$ and $\hat{-}$ on neutrosophic relation are strong generalization of the operators $\cup$ and unary – on vague relations.

Definition 6.2 Let R and S be neutrosophic relations on scheme $\sum$. Then, The intersection of R and S denoted as $\hat{\cap}$, is a neutrosophic relation on scheme $\sum$,given by

$$R \hat{\cap} S(t)=\langle \min\{R(t)^{+},S(t)^{+}\},\max\{R(t)^{-},S(t)^{-}\}\rangle,$$ for any t $\in \tau(\sum)$ .The difference of R and S denoted as R $\hat{-}$ S,is a neutrosophic relation on scheme $\sum$,given by

$$(R \hat{-} S)(t) =\langle \min\{R(t)^{+},S(t)^{-}\},\max\{R(t)^{-},S(t)^{+}\}\rangle,$$

for any t $\in \tau(\sum)$.

The following proposition relates the intersection and difference operators in terms of the more fundamental set-theoretic operators union and complement.

Proposition 6.2 : For any neutrosophic relation on the same scheme

$$R \hat{\cap} S = \hat{-}(\hat{-}R \hat{\cup} \hat{-}S) \text{ and}$$
$$R \hat{-} S = \hat{-}(\hat{-}R \hat{\cup} S).$$

7.A NOTE ON INTERVAL MATHEMATICS

Dealing with the mathematics of Neutrosphic set theory, the crisp theory of interval mathematics is sometimes useful. In this section, we recollect some basic notions of interval mathematics. For our purpose in this paper, we need to consider intervals of non-negative real numbers only.

Let I_1 = [a,b] and I_2 = [c,d] be two intervals of non-negative real numbers. A point valued non-negative real number r also can be viewed, for the sake of arithmetic, as an interval [r,r].

7.1 SOME ALGEBRAIC OPERATIONS

(i) Interval Addition : $I_1 + I_2$ = [a+c,b+d]
(ii) Interval Subtraction : $I_1 - I_2$ = [a-c,b-d]
(iii) Interval Multiplication : $I_1 * I_2$ = [ac,bd]
(iv) Interval Division : $I_1 \div I_2$ = [a/d,b/c] , when c, d $\neq$ 0.
(v) Scalar Multiplication : k . I_1 = [ka, kb].

7.2 RANKING OF INTERVALS

Intervals are not ordered. Owing to this major weakness, there is no universal method of ranking a finite (or infinite) number of intervals. But in real life problems dealing with intervals, we need to have some tactic to rank them in order to arrive at some conclusion. We will now present a method of ranking of intervals, which we shall use in our work here in subsequent sections. We consider a decision maker (or any intelligent agent like a company manager, a factory supervisor, an intelligent robot, an intelligent network, etc) who makes a pre-choice of a decision parameter $\beta \in$ [0,1]. The intervals are to be ranked once the decision-parameter β is fixed. But ranking may differ if the pre-choice β is renewed.

Definition 7.1 ***β-value of an interval***

Let J = [a,b] be an interval. The β-value of the interval J is a non-negative real number J_β, given by $J_\beta = (1-\beta).a + \beta.b$.

Clearly, $0 \le J_\beta \le 1$, and for $\beta = 0$ $J_\beta = a$ which signifies that the decision-maker is pessimistic, and also for $\beta = 1$ $J_\beta = b$ which signifies that the decision-maker is optimistic. For $\beta = .5$ it is the arithmetic-mean to be choosen usually for a moderate decision.

Comparison of two or more intervals we will do here on the basis of β-values of them. If the value of β is renewed, the comparison-results may change. The following definition will make it clear. Now Author is proposing α-Neutrosophic-equality search.

8. α-NEUTROSOPHIC EQUALITY SEARCH

Consider a normal type of query like

PROJECT (EMPLOYEE_NAME)
WHERE AGE = "approximately 20" .

The standard SQL is unable to provide any answer to this query as the search for an exact match for the predicate will fail. The value "approximately 20" is not a precise data. Any data of type "approximately x", "little more than x", "slightly less than x", much greater than x" etc. are not precise or crisp, but they are neutrosophic numbers(NN) which are a special case of vague numbers. Denote any one of them , say the vague number "approximately x" by the notation I(x). We know that a Neutrosophic number is a Neutrosophic Set of the real numbers. Clearly for every member $a \in$ dom(AGE), there is a membership value $t_{I(x)}(a)$ proposing the degree of equality of this crisp number a with the quantity "approximately x", and a non-membership value $f_{I(x)}(a)$ proposing the degree of non-equality . Thus, in neutrosophic philosophy of samarandache, every element of dom(AGE) satisfies the predicate AGE = "approximately 20" upto certain extent and does not satisfy too, upto certain extent. But we will restrict ourselves to those members of dom(AGE) which are α-neutrosophic-equal, the concept of which we will define below. Any imprecise predicate of type AGE = "approximately 20", or of type AGE = "young" (where the attribute value "young" is not a member of the dom(AGE)), is to be called by Neutrosophic-predicate, and a query involving Neutrosophic-predicate is called to be a Neutrosophic-query.

Definition 8.1

Consider a choice-parameter $\alpha \in [0,1]$. A member of a of dom(AGE) is said to be α-Neutrosophic-equal to the quantity "approximate x" if $a \in I_\alpha(x)$, where $I_\alpha(x)$ is the α-cut of the Neutrosophic number I(x). The degree or amount of this equality is measured by the interval $m_{I(x)}(a) = [t_{I(x)}(a), 1\text{-}f_{I(x)}(a)]$. Denote the collection of all such α-neutrosophic-equal members from dom(AGE) by the notation $AGE_\alpha(x)$, which is a subset of dom(AGE). If $AGE_\alpha(x)$ is not a null-set or singleton, then the members can be ranked by ranking their corresponding degrees of equality.

Definition 8.2

Consider a choice value $\beta \in [0,1]$. At β level of choice, for every element a of $AGE_\alpha(x)$, the truth-value $t(p_1,p_2)$ of the matching of the predicate p_1: given by AGE = "approximately x" with the predicate p_2: AGE = a is equal to the β-value of the interval $m_{I(x)}(a)$.

9.Neutrosophic-Proximity Search

The notion of α-Neutrosophic-equality search as explained above is appropriate while there is an Neutrosophic-predicate in the query involving neutrosophic numbers. But there could be a variety of neutrosophic predicates existing in a neutrosophic query, many of them may involve neutrosophic fuzzy hedges (including concentration/dilation) like "good", "very good", "excellent", "too much tall", "young", "not old", etc. In this section we present another type of search for finding out a suitable match to answer imprecise queries. In this search we will use the theory of neutrosophic-proximity relation [4,5]. We know that a neutrosophic-proximity relation on a universe U is a neutrosophic relation on U which is both neutrosophic-reflexive and neutrosophic-symmetric.

Consider the EMPLOYEE database as described below and a query like

PROJECT (EMPLOYEE_NAME)
WHERE EYE-COLOR = "dark-brown".

The value/data "dark-brown" is not in the set dom(EYE-COLOR). Therefore a crisp search will fail to answer this. The objective of this research work is to overcome this
type of drawbacks of the classical SQL. For this we notice that there may be one or more members of the set dom(EYE-COLOR) which may closely match the eye-color of "brown" or "dark- brown".

Consider a new universe given by

$$W = \text{dom(EYE-COLOR)} \cup \{\text{dark-brown}\}.$$

Propose a neutrosophic-proximity relation R over W. Choose a decision-parameter $\alpha \in [0,1]$. We propose that search is to be made for the match $e \in$ dom(EYE-COLOR) such that

$$t_R(\text{dark-brown}, e) \ge \alpha.$$

(It may be mentioned here that the condition $t_R(\text{dark-brown},e) \ge \alpha$ does also imply the condition $f_R(\text{dark-brown},e) \le 1-\alpha$ **)**.

We say that e is a close match with "dark-brown" with the degree or amount of closeness being the interval $m_{dark\text{-}brown}(e)$ given by

$$m_{dark\text{-}brown}(e) = [\ t_R(\text{dark-brown},e),\ 1-f_R(\text{dark-brown},e)\ ].$$

At β level of choice, the truth-value $t(p_1,p_2)$ of the matching of the predicate p_1: given by EYE-COLOR = "dark-brown" with the predicate p_2: AGE = e is equal to the β-value of the interval $m_{dark\text{-}brown}(e)$.

10. Neutrosophic-search

In this section we will now present the most generalized method of search called by Neutrosophic-search. The neutrosophic-search of matching is actually a combined concept of α-neutrosophic-equality search, neutrosophic-proximity search and crisp search.

For example, consider a query like

PROJECT (EMPLOYEE_NAME)
WHERE (SEX = "M", EYE-COLOR = "dark-brown", AGE= "approximately 20") .

This is a neutrosophic-query.

To answer such a query, matching is to be searched for the three predicates p_1, p_2 and p_3 given by

(i) p_1: SEX = "M",
(ii) p_2: EYE-COLOR = "dark-brown" and
(iii) p_3 : AGE = "approximately 20",

where p_1 is crisp and p_2, p_3 are neutrosophic.

Clearly, to answer this query the proposed neutrosophic search method is to b applied, because in addition to crisp search, both of α-neutrosophic-equality search and neutrosophic-proximity search will be used to answer this query. The truth-value of the matching of the conjunction p of p_1, p_2 and p_3 will be the product of the individual truth values, (where it is needless to mention that for crisp match the truth-value will be exactly 1). There could be a multiple number of answers to this query, and the system will display all the results ordered or ranked according to the truth-values of p.

It is obvious that the neutrosophic-search technique for predicate-matching reduces to a new type of fuzzy-search technique as a special case.

CONCLUSION

In this paper, we have introduced a new method to answer imprecise queries of the lay users from the databases (details of the databases may not be known to the lay (users). We have adopted Neutrosophic set tool to solve the problem of searching an exact match or a close match (if an exact match is not available) of the predicates so that we will be able to get the answer of 'evidence for you'(i.e. exact/ truth match) and 'evidence against you'(i.e false match) and the 'undecidability'(i.e. indeterminacy) This is a complete new Method of Answering Queries based on Neutrosophic logic.

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