Uncertain Query on Neutrosophic Database and Compare the Result with Other Imprecise Data Set

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Abstract
Objective of this paper is to process uncertain query using neutrosophic set to obtain better outcome compare to vague set. Processing uncertain query using neutrosophic set has been explained through architectural view. In the architecture, at first we have taken an uncertain query as input. Next, an algorithm using similarity measures formula for neutrosophic set has been developed to find similarity measures of each database tuple corresponding to the given uncertain query. Finally, a threshold (α-cut) value will be supplied by the decision maker for selecting appropriate resultant tuples from the database. In the present work, we have considered a patient database to process few uncertain queries using neutrosophic as well as vague set and shown neutrosophic set gives better output.
Keywords: Neutrosophic Set; Similarity Measures; Uncertain Data.

1. Introduction

In reality, imprecise data are often used in different applications such as medical sciences, decision analysis, and engineering. We are using vague, fuzzy and neutrosophic set for imprecise data. In fuzzy set membership value of each data is [0, 1]. Vague set is more restricted and provides better outcome compare to fuzzy because in vague set two membership values truth and false are associated for each element. Vague set satisfies following condition ie., (truth_membership + false_membership) ≤ 1 and the portion 1- (truth_membership + false_membership) will remain indeterminacy. But in neutrosophic set, a membership value for this indeterminacy part is also assigned [0, 1] along with truthness and falseness values for each element. This is reason for which neutrosophic set is more acceptable compare to other two.

Since 1970, we have studied relational database which is proposed by Codd [20] and several commercial relational data model based on precise and unambiguous data are available [7, 9, 19]. The classical relational data model doesn’t resolve the problem when data are imprecise, for example, find rooms of floor length around 18 ft or simply the floor is large.

Other example on imprecise data “employees having almost equal experiences earn more or less same salary". Zadeh [21] has been extended classical database for imprecise data in 1965. Several authors have been contributed for fuzzy database model in their literature [12, 15, 16, 17]. The Gau et al. [18] in 1993 have been proposed imprecise information based vague set. The notion of vague sets has also been included into relation database model to process uncertain query in [8]. Smarandache has introduced neutrosophic set [11], in the year 2001 for handling imprecise data. With this new notion of neutrosophic set, authors have developed theoretical concept Neutrosophic Database Model in the literature [1, 2, 3, 4, 5]. In this paper our objective is to show uncertain query processing using neutrosophic set provides better result compare to fuzzy or vague set. Here, we have focused to perform a logic based comparison among different imprecise data set to process imprecise queries and established that imprecise query on neutrosophic data is more accurate to take the decision rather than fuzzy and vague data. Here, we have chosen a PATIENT database to process uncertain queries and we have seen that the neutrosophic set gives better result compare to vague and fuzzy sets.

This paper is organized as follows: some basic definitions in Section 2. Similarity measures between imprecise data are also defined here. In Section 3, processing of uncertain queries is explained in details through architecture. Similarity measures between uncertain data and domain value for each tuple of the database is calculated by an algorithm using fuzzy or vague or neutrosophic set is discussed in section 4. In section 5 we have explained that a neutrosophic set is generated better result than vague and fuzzy set. We have drawn a conclusion in section 6.

2. Basic Definitions

Here, we have discussed preliminary concepts of fuzzy, vague and neutrosophic sets along with similarity measure of the corresponding imprecise data sets.

2.1 Fuzzy Set

A Fuzzy set (F_1) in the U^1 is characterized by $\mu F_1 : U^1 \rightarrow [0, 1]$ and is defined as an ordered pairs set $F_1 = \{\langle u_1, \mu F_1 (u_1)\rangle : u_1 \in U^1\}$ where $\mu F_1 (u_1)$ for each $u_1 \in U^1$ denotes the membership grades of u_1 in the fuzzy set F_1.

2.2 Vague Set

A vague set (V_1) in the U^1 is represented by the functions of two memberships given by:
a function of truthness $tV_1 : U^1 \rightarrow [0, 1]$ and
a function of falseness $fV_1 : U^1 \rightarrow [0, 1]$,
where $tV_1 (u_1)$ is the positive 'evidence for u_1', and $fV_1 (u_1)$ is the negation 'evidence against u_1' , and $tV_1 (u_1) + fV_1 (u_1) \leq 1$. Thus the vague set V_1 is bounded by $[tV_1 (u_1), 1-fV_1 (u_1)]$ of [0, 1], i.e., $tV_1 (u_1) \leq \mu V_1 (u_1) \leq 1-fV_1 (u_1)$ as subintervals. Then, V_1 is written as $V_1 = \{\langle u_1, [tV_1 (u_1), 1 - fV_1 (u_1)]\rangle : u_1 \in U_1\}$ as a vague set. Here, the interval $[tV_1 (u_1), 1 - fV_1 (u_1)]$ is represent by $VV_1 (u_1)$.

For example, in biomedical diagnosis system, this representation [0.3, 0.6] indicates "the positive report of disease is 30%, evidence against disease is 40% and rest 30% is unpredictable". But this indeterminable cannot be solved by vague set. It has been used in neutrosophic set and gives better outcome than vague set. The knowledge about u_1 is characterized by $(1-fV_1(u_1) - tV_1(u_1))$. If $tV_1(u_1)$ is equal to $(1- fV_1 (u_1))$, then the knowledge of u_1 is precise, and vague set reverts back to fuzzy . If $tV_1 (u_1)$ and $(1 - fV_1 (u_1))$ are both equal to 1 or 0, then the knowledge is exact and the theory goes back to an ordinary set.

2.3 Neutrosophic Set

U_1 is used for the universe and one of the elements is m. Z is a neutrosophic set on U_1 , represented by the membership functions such as:

i) Membership of truthness function $t_z : U_1 \rightarrow [0,1]$,

ii) Membership of falseness function $f_z : U_1 \rightarrow [0,1]$,

iii) Membership of indeterminate function $i_z : U_1 \rightarrow [0,1]$ with $t_z(m) + f_z(m) \leq 1$ because in real situation, summation of truthness & falseness value never exceeds 1 and some indeterminacy value also be there .So we can make the equation $t_z(m) + f_z(m) + i_z(m) \leq 2$, written as $Z = \left\{\left\langle m, \left[t_z(m), i_z(m), f_z(m)\right]\right\rangle, m \in U_1\right\}$.

Let two neutrosophic values of p and q represented as $p = [t_p, i_p, f_p]$ and $q = [t_q, i_q, f_q]$ where $0 \leq t_p \leq 1$, $0 \leq i_p \leq 1$, $0 \leq f_p \leq 1$ and $0 \leq t_q \leq 1, 0 \leq i_q \leq 1, 0 \leq f_q \leq 1$ with $0 \leq t_p + f_p \leq 1$, $0 \leq t_q + f_q \leq 1$, $0 \leq t_p + i_p + f_p \leq 2$, $0 \leq t_q + i_q + f_q \leq 2$.

2.4 Measure of Similarity

There some studies of vague sets similarity also discussed in [6, 10, 13, 14].
Let x_1 and y_1 be any two vague values such that $x_1 = [tx_1, 1 - fx_1]$ and $y_1 = [ty_1, 1 - fy_1]$,

then $SM\ (x_1, y_1) = \sqrt{1 - \frac{\left|(t_{x_1} - t_{y_1}) - (f_{x_1} - f_{y_1})\right|}{2}\left(1 - \left|(t_{x_1} - t_{y_1}) + (f_{x_1} - f_{y_1})\right|\right)}$

Next, similarities between two neutrosophic data.
Here, x and y are the two neutrosophic values such that $x = [t_x, i_x, f_x]$ and $y = [t_y, i_y, f_y]$
Then,

$$SM\ (x, y) = \sqrt{\left(1 - \frac{\left|(t_x - t_y) - (i_x - i_y) - (f_x - f_y)\right|}{3}\right)\left(1 - \left|(t_x - t_y) + (i_x - i_y) + (f_x - f_y)\right|\right)}$$

3. Uncertain Query Based Architecture

This **Figure 1** represents the processing an imprecise query

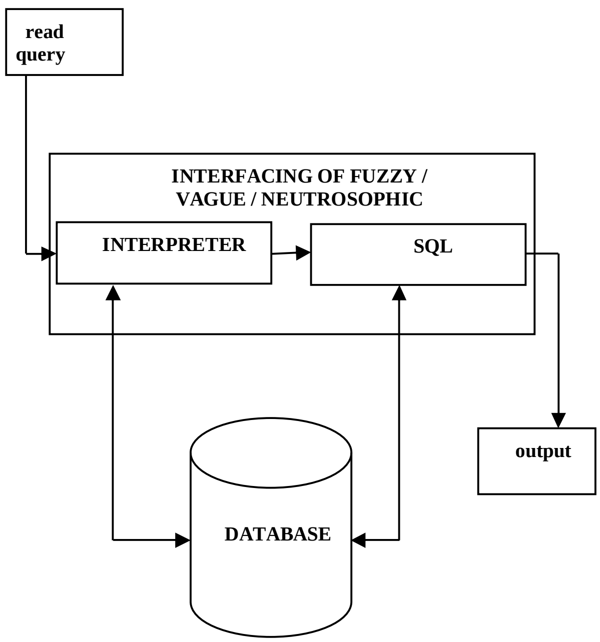

Fig.1. Architecture of Imprecise Query Processing.

Working principle is given below:
Input: Fuzzy or vague or neutrosophic attributes base relational database, imprecise query, α-tolerance for threshold value.
Interface:
It consists of Interpreter and imprecise data based SQL.
Interpreter: The interpreter is representing the domain values of an attributes. **Algorithm 1** is described section 4 and it is used to determine imprecise data oriented membership values of an attributes as per imprecise data set.
Fuzzy/Neutrosophic/ Vague SQL: Here, decision maker is responsible to provide a threshold or α-cut value as per SQL statement for the given imprecise query.
Output: At last, the SQL will generate the desired result with the help of corresponding database.

4. Algorithm for Membership Value

This algorithm will work on domain value of attributes with respect to imprecise data given in the uncertain query.
Calculation of Membership using Algorithm 1
Input: Attributes of imprecise data based on imprecise query.

Output: The interval [0, 1] for fuzzy or vague data and interval value [0, 2] for neutrosophic data.
Method: Firstly we have focused on attributes of imprecise data of fuzzy or vague or neutrosophic for the query.
for each attribute **do**
start
$f_{data} \leftarrow$ imprecise data based on fuzzy attribute of the uncertain query

$RANGE_{value} = MAX_{Dvalue} - MIN_{Dvalue}$
$VALUE_{avg} \leftarrow$ mean value of imprecise attribute
$A \leftarrow VALUE_{avg}$
while($VALUE_{avg} \leq RANGE_{value}$) **do**
start
$VALUE_{avg} = VALUE_{avg} + A$
end while loop
for each row of the table **do**
start
$ROW_{value} \leftarrow$ row value from the fuzzy or neutrosophic or vague attribute domain
$MSHIP_{value} = 1-(|f_{data} - ROW_{value}| / VALUE_{avg})$
end for loop of row
end for loop

5. Real Problem Based Uncertain Query

In this section, we have shown that neutrosophic set is produced better results than vague and fuzzy sets. We have chosen database of PATIENT relation in **Table 1**.

PName	**PAge(yrs)**	**Fever (centigrade)**	**FSugar (mg/dl)**	**Pulse (bpm)**
Amit Das	28	100	80	85
Bikas Samanta	51	99	98	83
Pitar Joseph	37	98	112	90
Kamal Hasan	41	101.5	100	95
Biju Mahato	38	99.5	102	98
Rinku Sasmal	40	101	99	80
Sumita Panja	44	102	97	88
Pintu Hasda	39	98.4	90	92
Gitika Mudi	47	99.7	103	87
Nita Agarwal	53	98.5	101	86

Table 1. PATIENT Relation.

Next we consider imprecise queries for vague sets and compare to fuzzy set that vague set will produce better result.

IMPRECISE QUERY1 (IQ-1):"Find whole details of the Patients whose PAge is near to 40".
i) **Fuzzy set based solution:** In this imprecise query 1, Page consists of fuzzy data which is around 40. Now, applied an algorithm 1 to each domain fuzzy value of attribute PAge for membership value.
Input: PAge attribute with fuzziness and fuzzy data around 40.
Method: Membership value calculation for each row value of PAge based on fuzzy data around 40.
dom (PAge) = *{* 28, 51, 37, 41, 38, 40, 43, 39, 47, 53*}*
given f_{data}= 40
$RANGE_{value}$ = 53 - 28 = 25
$VALUE_{avg}$ = 41.7
A = 41.7
$VALUE_{avg} \geq RANGE_{value}$, then $VALUE_{avg}$ is same i.e., $VALUE_{avg}$ = 41.7
Next, using algorithm 1 to find membership value :

Membership value = 1 − (|fdata − rowValue|/Avg)
for 1st row : Membership value = 1 − (|40 − 28|/41.7) = 0.71
for 2nd row Membership value = 1 − (|40 − 51|/41.7) = 0.73
for 3rd row: Membership value = 1 − (|40 − 35|/41.7) = 0.88
for 4th row: Membership value = 1 − (|40 − 41|/41.7) = 0.98
for 5th row: Membership value = 1 − (|40 − 38|/41.7) = 0.95
for 6th row: Membership value = 1 − (|40 − 40|/41.7) = 1
for 7th row: Membership value = 1 − (|40 − 44|/41.7) = 0.90
for 8th row: Membership value = 1 − (|40 − 39|/41.7) = 0.98
for 9th row: Membership value = 1 − (|40 − 47|/41.7) = 0.83
for 10th row: Membership value = 1 − (|40 − 53|/41.7) = 0.69

The PATIENT relation with fuzzy representation using IQ-1 is in Table 2. Now, third attribute PAge appears in fuzzy representation.

ii) Vague set based solution: Next, IQ-1 is also used here.
Consider the vague data is near to 40.
The attribute PAge into vague form and it is 4th column of Table 2 .To find the similarities of vague data around 40 and its representation in vague < 40, [1, 1] >. The similarity value was evaluated using section 2.4 and it is shown in Table 2 of 5th column.
For example
Here p= <40,[1,1]> and q= <28,[.71,.71]> . Here $t_p = 1$, $f_p = 0$, $t_q = .71$, $f_q = .29$

$$SM\ (p,q) = \sqrt{\left(1 - \frac{|(1-.71)-(0-.29)|}{2}\right)\left(1-|(1-.71)+(0-.29)|\right)}$$
$$= \sqrt{1-.29} = \sqrt{.71} = 0.84$$

Next vague values p = 40[1,1] and q = <51,[.73,.73]> . Here $t_p = 1$, $f_p = 0$, $t_q = .73$, $f_q = .27$
$$SM\ (p,q) = \sqrt{\left(1 - \frac{|(1-.73)-(0-.27)|}{2}\right)\left(1-|(1-.73)+(0-.27)|\right)}$$
$$= \sqrt{1 - \times 0.27} = \sqrt{0.73} = 0.85$$

and so on.

iii) Neutrosophic set based solution: Here neutrosophic data is close to 40.

In Table 2 , we have shown PAge attribute into neutrosophic form in the 6th column and we found the neutrosophic similarity using section 2.4 with fuzzy data close to 40 and its neutrosophic representation is < 40, [1, 0, 0] and it was shown in 7th column of Table 2. For example:

Here p= <40,[1,0,0]> and q= <28,[.71,.8,.24]> . Here $t_p = 1$, $i_p = 0$, $f_p = 0$, $t_q = .71$, $i_p = .8$, $f_q = .24$

$$SM(p,q) = \sqrt{\left(1 - \frac{|(1-.71)-(0-.8)-(0-.24)|}{3}\right)\left(1 - |(1-.71)+(0-.8)+(0-.24)|\right)}$$
$$= \sqrt{.556 \times .25} = \sqrt{.139} = 0.32$$

Next neutrosophic values p = 40[1,0,0] and q = <51,[.73,.72,.25]> . Here $t_p = 1$, $i_p = 0$, $f_p = 0$, $t_q = .73$, $i_p = .72$, $f_q = .25$

$$SM(p,q) = \sqrt{\left(1 - \frac{|(1-.73)-(0-.72)-(0-.25)|}{3}\right)\left(1 - |(1-.73)+(0-.72)+(0-.25)|\right)}$$
$$= \sqrt{.586 \times 0.3} = \sqrt{0.1758} = 0.42$$

and continue.

FD of PAge around 40	**VD of PAge**	**SM with VD <40,[1,1]>**	**ND of PAge**	**SM with ND <40,[1,0,0]>**
<28,.71>	<28,[.71,.71]>	0.84	<28,[.71,.8,.24]>	0.32
<51,.73>	<51,[.73,.73]>	0.85	<51,[.73,.7,.25]>	0.51
<35,.88>	<35,[.88,.88]>	0.93	<35,[.93,.35,.06]>	0.74
<41,.98>	<41,[.98,.98]>	0.99	<41,[.98,.02,.01]>	0.98
<38,.95>	<38,[.95,.95]>	0.97	<38,[.95,.15,.04]>	.89
<40,1>	<40,[1,1]>	1	<40,[1,0,0]>	1
<44,.90>	<44,[.90,.90]>	0.94	<44,[.90,.3,.07]>	0.78
<39,.98>	<39,[.98,.98]>	0.99	<39,[.98,.015,.01]>	0.99
<47,.83>	<47,[.83,.83]>	0.91	<47,[.83,.5,.15]>	0.61
<53,.69>	<53,[.69,.69]>	0.83	<53,[.69,.75,.25]>	0.42

Table 2. FD = Fuzzy Data, ND= Neutrosophic Data and VD = Vague Data.

Now, if the α-cut or threshold value is provided by the decision maker is 0.95 and the SQL statement is:

Select * from PATIENT where SM (row) ≥0.95
which fetch the resultant rows given in **Table 3** from the PATIENT relation.

PName	**PAge (yrs)**	**Fever (centigrade)**	**FSugar (mg/dl)**	**Pulse (bpm)**
Kamal Hasan	41	101.5	110	95
Biju	38	99.5	102	98

Mahato				
Rinku Sasmal	40	101	99	80
Pintu Hasda	39	98.4	90	92

Table 3. Result of Fuzzy Set using IQ-1.

PName	PAge (yrs)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)
Kamal Hasan	41	101.5	110	95
Biju Mahato	38	99.5	102	98
Rinku Sasmal	40	101	99	80
Pintu Hasda	39	98.4	90	92

Table 4. Result of Vague Set using IQ-1.

PName	PAge (yrs)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)
Kamal Hasan	41	101.5	110	95
Rinku Sasmal	40	101	99	80
Pintu Hasda	39	98.4	90	92

Table 5. Result of Neutrosophic Set using IQ-1.

We noted that IQ-1 based neutrosophic set gives more accurate solution than any other imprecise set.

IMPRECISE QUERY-2(IQ-2): Find out the details of patients from Patient relation whose PAge is near 40 and FSugar is close to 100.
i) Fuzzy set based solution: Second imprecise query has two fuzzy attributes, PAge and FSugar.
Here, μ_1 and μ_2 denotes the similarity measures of PAge and FSugar attributes and $\mu = \mu_1 \cap \mu_2$ denotes the tuples based similarity.
Then, query based outcome is checked for same α-cut value ($\alpha = 0.95$) given by the decision maker.

S.M with FD (μ_1) <40,[1,1]>	**S.M with FD (μ_2) <100,[1,1]>**	**$\mu = \mu_1 \cap \mu_2$**
0.84	0.80	0.80
0.85	0.98	0.85
0.88	0.78	0.78
0.99	1	0.99
0.97	0.95	0.95
1	0.99	0.99
0.90	0.96	0.90
0.99	0.89	0.89
0.91	0.96	0.91
0.83	0.99	0.83

Table 6. Imprecise Query 2 on Fuzzy based PATIENT Relation

The SQL statement "***Select * from PATIENT where α ≥0.95***" is now apply on Table 6 then IQ-2 based outcomes are store into Table 7.

PName	PAge (yrs)	Fever (centigrade)	FSugar (mg/dl)	Pulse (bpm)

Kamal Hasan	41	101.5	100	95
Biju Mahato	38	99.5	102	98
Rinku Sasmal	40	101	99	80

Table 7. IQ-2 based outcome for Fuzzy Set.

ii) Vague set based solution:
Again, with the help of first algorithm and second definition, the vague data of FSugar is shown in Table 8. Now execute the query "***Select * from EMP where $\mu \geq 0.95$"*** *which* retrieves rows and are stored into Table 9.

S.M with VD (μ_1) <40,[1,1]>	**S.M with VD (μ_2) <100,[1,1]>**	**$\mu = \mu_1 \cap \mu_2$**
0.84	0.84	0.84
0.85	0.98	0.85
0.93	0.88	0.88
0.99	1	0.99
0.97	0.97	0.97
1	0.99	0.99
0.94	0.98	0.94
0.99	0.94	0.94
0.91	0.95	0.91
0.83	0.99	0.83

Table 8. IQ-2 based Vague Representation on PATIENT Relation.

PName	**PAge (yrs)**	**Fever (centigrade)**	**FSugar (mg/dl)**	**Pulse (bpm)**
Kamal Hasan	41	101.5	100	95
Biju Mahato	38	99.5	102	98
Rinku Sasmal	40	101	99	80

Table 9. Result using IQ-2 with Vague Set.

iii) Neutrosophic set based solution:
Again, finding the similarity between two neutrosophic data based attributes PAge and FSugar is shown in Table 10. The query statement "***Select * from PATIENT where $\mu \geq 0.95$***", retrieves some rows which are shown in Table 11.

S.M with ND (μ_1) <40,[1,0,0]>	**ND of FSugar Almost 100**	**S.M with ND (μ_2) <100,[1,0,0]>**	**$\mu = \mu_1 \cap \mu_2$**
0.32	<80,[.65,.25,.28]>	0.76	0.32
0.51	<98,[.97,.03,.02]>	0.97	0.51

0.74	<102,[.96,.1,.03]>	0.92	0.74
0.98	<100,[1,0,0]>	1	0.98
.89	<112,[.78,.3,.21]>	0.73	0.73
1	<99,[.98,.01,.01]>	0.99	0.99
0.78	<97,[.96,.04,.03]>	0.96	0.78
0.99	<95,[.88,.15,.10]>	0.87	0.87
0.61	<103,[.90,.15,.08]>	0.88	0.61
0.42	<101,[.98,.01,.02]>	0.95	0.42

Table 10. PATIENT Relation based Neutrosophic depiction of IQ-2.

PName	**PAge(yrs)**	**Fever (centigrade)**	**FSugar (mg/dl)**	**Pulse (bpm)**
Kamal Hasan	41	101.5	100	95
Rinku Sasmal	40	101	99	80

Table 11. Result of IQ-2 using Neutrosophic Set.

6. Conclusion

Imprecise query processing using fuzzy or vague or neutrosophic set is shown through architecture and it has been verified using a real life example. We have discussed an algorithm which is applicable to find closeness between two uncertain data with respect to fuzzy, vague and neutrosophic set. We have used PATIENT database to process uncertain queries and compare outcomes for different soft sets. In each uncertain query it has been observed that neutrosophic sets have produced more accurate result in comparison to fuzzy or vague sets. Hence neutrosophic database model is more accurate in solving our day to day conversation containing uncertain data compare to other conventional fuzzy models.

Future Scope

Further research work can also be aimed at applying neutrosophic set theory to develop a neutrosophic spatial database. Most naturally occurring spatial objects such as population density, pollution clouds, oil pouches contains certain parameters that are neutrosophic in nature. The neutrosophic data model can also serve as the database in various expert systems. For example, such a model may be used to diagnose medical conditions, predict future disease outbreaks.

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