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On Neutrosophic Vague Measure Using Python

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Abstract. Many scientists wish to obtain appropriate solutions to some mathematical problems that cannot be solved by traditional methods. For representing and manipulating uncertain, incomplete, inconsistent or imprecise, Neutrosophic relation database model is a more general platform, in the human decision-making process. In this paper, we study and examine about Neutrosophic vague Measure utilizing Python and furthermore Various Measure in Neutrosophic Vague Sets with some example. in this paper, we utilized example to study about the Various Measure in Neutrosophic Vague Sets and Python programming labguage.

INTRODUCTION

In our day to day life, the most as often as possible experienced encountered uncertainty is uniqueness. Zadeh's fuzzy set theory revolutionized the systems, accomplished with uncertainty[1]. Various specialists extended the origination of Zadeh and displayed various theories regarding uncertainty. Atanassov [15] introduced fuzzy intuitionistic set in which every element of a nonempty set has a degree of membership and a degree of non membership ,which has been intrigued by many researchers . The theory of vague sets was first proposed by Gau and Buehrer as an extension of fuzzy set theory and vague sets are regarded as a special case of context-dependent fuzzy sets[2]. It is such a branch of philosophy which examines the origin, nature, and extent of neutralities just as their connections with various ideational spectra. In 1995 neutrosophic set theory has been presents by Smarandache[5,7,9] as another scientific devices for giving issue and solution. A new mathematical tool for managing issues including deficient, indeterminacy and inconsistent knowledge. In NS, the indeterminacy is quantified explicitly and truth-membership, indeterminacy membership, and false-membership are totally free. In 2015 , Shawkat Alkhazaleh[12] has presents the Neotrosophic Vage set as a blend of neutrosophic set and vague set . In 1997 Szmidt and Kacprzyk [11]characterized various sorts of distance between intuitionistic fuzzy sets.In 1989, Python has been created by Guido van Rossum it is a programming language used to deal with the issue[16]. Manhattan distance is a measurement wherein distance between two points is the sum of the absolute differences of their Cartesian coordinates. While Euclidean distance is the most widely recognized utilization of distance. In most cases when people said about distance, they will refer to Euclidean distance, which is also known as simple distance. The Euclidean distance between two points is the length of the way interfacing them[14]. The motivation behind this paper is to present the measuring distance between neutrosophic vague set and connection among them and furthermore we utilized python in distance measure between neutrosophic vague sets.

PRELIMINARIES

Definition .1 [2] *A Vague set V on the universe of discourse X written as* $A=\{ <x, t_A(x), 1\text{-}f_A(x)> \mid x \in X \}$. *is characterized by a true membership function* t_v *, and a false membership function* f_v*, as follows:*
$t_v : U \to [0, 1]$, $f_v: U \to [0, 1]$, *and* $t_v+f_v \leq 1$

Definition .2 [2] *Let A and B be vague sets of the form* $A=\{ <x, t_A(x), 1\text{-}f_A(x)> \mid x \in X \}$ *and* $B=\{ <x, t_B(x), 1\text{-}f_B(x)> \mid x \in X\}$*.Then*
$A \subseteq$ *if and only if* $t_A(x) \leq t_B(x)$ *And* $1\text{-}f_A(x) \leq 1\text{-}f_B(x)$.
$A=B$ *if and only if* $A \subseteq B$ *and* $B \subseteq A$.
$A^c =\{ <x, 1\text{-}f_A(x), t_A(x)> \mid x \in X\}$.
$A \cup B = \{ <x, \max(t_A(x), t_B(x)), \max(1\text{-}f_A(x), 1\text{-}f_B(x))> \mid x \in X \}$.
$A \cap B = \{ <x, \min(t_A(x), t_B(x)), \min(1\text{-}f_A(x), 1\text{-}f_B(x))> \mid x \in X \}$.

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Definition .3 [5] *A neutrosophic set A on the universe of discourse X is defined as* $A = \{ < x, T_A(x), I_A(x), F_A(x) >, x \in X \}$ *where T, I, F:* $X \to]^{-}0, 1^{+}[$ *and*

$$^{-}0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3^{+}.$$

NEUTROSOPHIC VAGUE SET

Definition .4 [12] *A neutrosophic vague set* A_{NV} *(NVS in short) on the universe of discourse X written as* $A_{NV} = \{ <x; T_{A_{NV}}(x); I_{A_{NV}}(x); F_{A_{NV}}(x)>; x \in X \}$ *whose truth membership, indeterminacy membership and false membership functions is defined as:*
$T_{A_{NV}}(x) = [T^{-}, T^{+}]$, $I_{A_{NV}}(x) = [I^{-}, I^{+}]$, $F_{A_{NV}} = [F^{-}, F^{+}]$
where
1) $T^{+} = 1 - F^{-}$
2) $F^{+} = 1 - T^{-}$ *and*
3) $^{-}0 \leq T^{-} + I^{-} + F^{-} \leq 2^{+}$.

Definition .5 [12] *Let* A_{NV} *and* B_{NV} *be two NVSs of the universe U . If* $\forall\, u_i \in U$, $T_{A_{NV}}(u_i) = T_{B_{NV}}(u_i)$, $I_{A_{NV}}(u_i) = I_{B_{NV}}(u_i)$, $F_{A_{NV}}(u_i) = F_{B_{NV}}(u_i)$, *then the NVS* A_{NV} *and* B_{NV}, *are called equal, where* $1 \leq i \leq n$.

Example .1 *let* A_{NV} *and* B_{NV} *be the NVS and* $U = \{u_1, u_2, u_3\}$ *be the universe define as follows:*

$$A_{NV} = \left\{ \frac{u_1}{<[0.4,0.8],[0.4,0.4],[0.4,0.7]>}, \frac{u_2}{<[0.5,0.6],[0.5,0.5],[0.5,0.6]>}, \frac{u_3}{<[0.2,0.5],[0.6,0.6],[0.5,0.7]>}, \right\}.$$

$$B_{NV} = \left\{ \frac{u_1}{<[0.2,0.5],[0.7,0.7],[0.2,0.6]>}, \frac{u_2}{<[0.6,0.4],[0.5,0.5],[0.3,0.4]>}, \frac{u_3}{<[0.5,0.3],[0.4,0.4],[0.3,0.4]>}, \right\}.$$

then we have by the Union definition[12] *of NVS* $C_{NV} = A_{NV} \cup B_{NV}$

$$C_{NV} = \left\{ \frac{u_1}{<[0.4,0.8],[0.7,0.7],[0.4,0.7]>}, \frac{u_2}{<[0.5,0.4],[0.5,0.5],[0.3,0.4]>}, \frac{u_3}{<[0.2,0.3],[0.4,0.4],[0.3,0.4]>}, \right\}.$$

then we have by the intersection definition[12] *of NVS* $C_{NV} = A_{NV} \cap B_{NV}$

$$C_{NV} = \left\{ \frac{u_1}{<[0.2,0.5],[0.4,0.4],[0.2,0.6]>}, \frac{u_2}{<[0.6,0.6],[0.5,0.5],[0.5,0.6]>}, \frac{u_3}{<[0.5,0.5],[0.6,0.6],[0.5,0.7]>}, \right\}.$$

DISTANCE FOR NEUTROSOPHIC VAGUE SETS

Definition .6 [13] *Let* $A_{NV} = \{ <x; T_{A_{NV}}(x); I_{A_{NV}}(x); F_{A_{NV}}(x)>; x \in X \}$ *and* $B_{NV} = \{ <x; T_{B_{NV}}(x); I_{B_{NV}}(x); F_{B_{NV}}(x)>; x \in X \}$ *Neutrosophic Vague Set in X*

1.Manhattan Distance

$$M_{NV}(A_{NV}, B_{NV}) = \sum_{i=1}^{n} | T^{+}_{A_{NV}}(u_i) - T^{+}_{B_{NV}}(u_i)| + |T^{-}_{A_{NV}}(u_i) - T^{-}_{B_{NV}}(u_i)| + | I^{+}_{A_{NV}}(u_i) - I^{+}_{B_{NV}}(u_i)| + |I^{-}_{A_{NV}}(u_i) - I^{-}_{B_{NV}}(u_i)| + | F^{+}_{A_{NV}}(u_i) - F^{+}_{B_{NV}}(u_i)| + |F^{-}_{A_{NV}}(u_i) - F^{-}_{B_{NV}}(u_i)|$$

2.Normalized Manhattan Distance

$$MN_{NV}(A_{NV}, B_{NV}) = \sum_{i=1}^{n} \frac{1}{n} \left(| T^{+}_{A_{NV}}(u_i) - T^{+}_{B_{NV}}(u_i)| + |T^{-}_{A_{NV}}(u_i) - T^{-}_{B_{NV}}(u_i)| + | I^{+}_{A_{NV}}(u_i) - I^{+}_{B_{NV}}(u_i)| + |I^{-}_{A_{NV}}(u_i) - I^{-}_{B_{NV}}(u_i)| + | F^{+}_{A_{NV}}(u_i) - F^{+}_{B_{NV}}(u_i)| + |F^{-}_{A_{NV}}(u_i) - F^{-}_{B_{NV}}(u_i)| \right)$$

3.Euclidean distance

$$E_{NV}(A_{NV}, B_{NV}) = \left(\sum_{i=1}^{n} \left(| T^{+}_{A_{NV}}(u_i) - T^{+}_{B_{NV}}(u_i)|^2 + |T^{-}_{A_{NV}}(u_i) - T^{-}_{B_{NV}}(u_i)|^2 + | I^{+}_{A_{NV}}(u_i) - I^{+}_{B_{NV}}(u_i)|^2 + |I^{-}_{A_{NV}}(u_i) - I^{-}_{B_{NV}}(u_i)|^2 + | F^{+}_{A_{NV}}(u_i) - F^{+}_{B_{NV}}(u_i)|^2 + |F^{-}_{A_{NV}}(u_i) - F^{-}_{B_{NV}}(u_i)|^2 \right) \right)^{\frac{1}{2}}$$

4.Normalized Euclidean distance

$$EN_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\frac{1}{n}\ \big(\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^2 + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^2 + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^2 + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^2 + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^2 + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^2\ \big)\Big)^{\frac{1}{2}}$$

5. Minkowski distance

$$K_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\ \big(\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^p + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^p + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^p + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^p + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^{\ p} + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^p\ \big)\Big)^{\frac{1}{p}}$$

6.Normalized Minkowski distance

$$KN_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\frac{1}{n}\ \big(\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^p + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^p + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^p + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^p + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^{\ p} + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^p\ \big)\Big)^{\frac{1}{p}}$$

Distance measures satisfies the following conditions:

$0 \leq \mathrm{M}_{NV}(A_{NV},B_{NV}) \leq 2\mathrm{n}$

$0 \leq \mathrm{MN}_{NV}(A_{NV},B_{NV}) \leq 2$

$0 \leq \mathrm{E}_{NV}(A_{NV},B_{NV}) \leq \sqrt{2n}$

$0 \leq \mathrm{EN}_{NV}(A_{NV},B_{NV}) \leq \sqrt{2}$

$0 \leq \mathrm{K}_{NV}(A_{NV},B_{NV}) \leq (2\mathrm{n})^{\frac{1}{p}}$

$0\leq \mathrm{K}_{NV}(A_{NV},B_{NV}) \leq (2)^{\frac{1}{p}}$

Relationship Between These Measure

- In Minkowski Distance, if p= 1 then it become as Manhattan distance.
- In Minkowski distance , if p=2 then it become as Euclidean distance.
- In Minkowski Distance, if p= ∞ then it become as Chebyshev distance
- The Minkowski Distance is generalized metric Euclidean distance and Manhattan distance.

Example .2 *let* $X = \{\ u_1,u_2,u_3\ \}$ *be the universe and let*

$A_{NV} = \Big\{< \frac{u_1}{(0.1,0.2),(0.2,0.2),(0.2,0.3)} >,< \frac{u_2}{0.2,0.4),(0.1,0.3),(0.2,0.1)} > ,< \frac{u_3}{(0.2,0.1),(0.4,0.3),(0.1,0.2)} >\Big\}$ *and*

$B_{NV} = \Big\{\ < \frac{u_1}{(0.3,0.1),(0.1,0.1),(0.3,0.1)} >,\ < \frac{u_2}{(0.3,0.1),(0.1,0.2),(0.3,0.1)} > ,< \frac{u_3}{(0.3,0.2),(0.1,0.1),(0.2,0.1)} >\Big\}$

1.Manhattan Distance

$$M_{NV}(A_{NV},B_{NV}) = \sum_{i=1}^{3}\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)| + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)| + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)| + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)| + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)| + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|$$

$= |0.1\text{-}0.3|+|0.2\text{-}0.1|+|0.2\text{-}0.3|+|0.4\text{-}0.1|+|0.2\text{-}0.3|+|0.1\text{-}0.2|+|0.2\text{-}0.1|+|0.2\text{-}0.1|+|0.1\text{-}0.1|+|0.3\text{-}0.2|+|0.4\text{-}0.1|+|0.3\text{-}0.1|+|0.2\text{-}0.3|+|0.3\text{-}0.1|+|0.2\text{-}0.3|+|0.1\text{-}0.1|+|0.1\text{-}0.2|+|0.2\text{-}0.1|$

$=2.3$

2.Normalized Manhattan Distance

$$MN_{NV}(A_{NV},B_{NV}) = \sum_{i=1}^{3}\frac{1}{3}\ \big(\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)| + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)| + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)| + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)| + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)| + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|\ \big)$$

$=\frac{1}{3}\ \big(|0.1\text{-}0.3|+|0.2\text{-}0.1|+|0.2\text{-}0.3|+|0.4\text{-}0.1|+|0.2\text{-}0.3|+|0.1\text{-}0.2|+|0.2\text{-}0.1|+|0.2\text{-}0.1|+|0.1\text{-}0.1|+|0.3\text{-}0.2|+|0.4\text{-}0.1|+|0.3\text{-}0.1|+|0.2\text{-}0.3|+|0.3\text{-}0.1|+|0.2\text{-}0.3|+|0.1\text{-}0.1|+|0.1\text{-}0.2|+|0.2\text{-}0.1|\big)$

$=\frac{2.3}{3} = 0.766$

3.Euclidean distance

$$E_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\ \big(\ |\ T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^2 + |T^{-}_{A_{NV}}\ (u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^2 + |\ I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^2 + |I^{-}_{A_{NV}}\ (u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^2 + |\ F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^2 + |F^{-}_{A_{NV}}\ (u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^2\ \big)\Big)^{\frac{1}{2}}$$

$=\Big(\ |0.1\text{-}0.3|^2+|0.2\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.4\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.1\text{-}0.2|^2+|0.2\text{-}0.1|^2+|0.2\text{-}0.1|^2$

$+|0.1\text{-}0.1|^2+|0.3\text{-}0.2|^2+|0.4\text{-}0.1|^2+|0.3\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.3\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.1\text{-}0.1|^2+|0.1\text{-}0.2|^2$
$+|0.2\text{-}0.1|^2 \Big)^{\frac{1}{2}}$
$=0.64031$

4.Normalized Euclidean distance

$$EN_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\frac{1}{n}\Big(|T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^2 + |T^{-}_{A_{NV}}(u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^2 + |I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^2 + |I^{-}_{A_{NV}}(u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^2 + |F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^2 + |F^{-}_{A_{NV}}(u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^2\Big)\Big)^{\frac{1}{2}}$$

$$=\Big(\frac{1}{3}\Big(|0.1\text{-}0.3|^2+|0.2\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.4\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.1\text{-}0.2|^2+|0.2\text{-}0.1|^2+|0.2\text{-}0.1|^2+|0.1\text{-}0.1|^2 +|0.3\text{-}0.2|^2+|0.4\text{-}0.1|^2+|0.3\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.3\text{-}0.1|^2+|0.2\text{-}0.3|^2+|0.1\text{-}0.1|^2+|0.1\text{-}0.2|^2 +|0.2\text{-}0.1|^2\Big)\Big)^{\frac{1}{2}}$$

$=0.4527$

5. Minkowski distance

$$K_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\Big(|T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^p + |T^{-}_{A_{NV}}(u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^p + |I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^p + |I^{-}_{A_{NV}}(u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^p + |F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^p + |F^{-}_{A_{NV}}(u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^p\Big)\Big)^{\frac{1}{p}}$$

$$=\Big(\Big(|0.1\text{-}0.3|^P+|0.2\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.4\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.1\text{-}0.2|^P+|0.2\text{-}0.1|^P+|0.2\text{-}0.1|+^P|0.1 \text{-}0.1|+^P|0.3\text{-}0.2|^P+|0.4\text{-}0.1|^P+|0.3\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.3\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.1\text{-}0.1|^P+|0.1\text{-}0.2|^P +|0.2\text{-}0.1|^P\Big)\Big)^{\frac{1}{p}}$$

$=(0.0221)^{\frac{1}{4}} =0.3855$

6.Normalized Minkowski distance

$$KN_{NV}(A_{NV},B_{NV}) = \Big(\sum_{i=1}^{n}\frac{1}{n}\Big(|T^{+}_{A_{NV}}(u_i)\text{-}T^{+}_{B_{NV}}(u_i)|^p + |T^{-}_{A_{NV}}(u_i)\text{-}T^{-}_{B_{NV}}(u_i)|^p + |I^{+}_{A_{NV}}(u_i)\text{-}I^{+}_{B_{NV}}(u_i)|^p + |I^{-}_{A_{NV}}(u_i)\text{-}I^{-}_{B_{NV}}(u_i)|^p + |F^{+}_{A_{NV}}(u_i)\text{-}F^{+}_{B_{NV}}(u_i)|^p + |F^{-}_{A_{NV}}(u_i)\text{-}F^{-}_{B_{NV}}(u_i)|^p\Big)\Big)^{\frac{1}{p}}$$

$$=\Big(\frac{1}{3}\Big(|0.1\text{-}0.3|^P+|0.2\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.4\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.1\text{-}0.2|^P+|0.2\text{-}0.1|^P+|0.2\text{-}0.1|^P+ |0.1\text{-}0.1|^P+|0.3\text{-}0.2|^P+|0.4\text{-}0.1|^P+|0.3\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.3\text{-}0.1|^P+|0.2\text{-}0.3|^P+|0.1\text{-}0.1|^P+|0.1\text{-}0.2|^P+ |0.2\text{-}0.1|^P\Big)\Big)^{\frac{1}{P}}$$

$=(0.0073)^{\frac{1}{4}}=0.2929$

Distance in Neutrosophic vague sets should be calculated by taking truth membership, indeterminacy membership and false membership function and it also satisfies the following conditions.

$0 \leq 2.3 \leq 6$
$0 \leq 0.766 \leq 2$
$0 \leq 0.64031 \leq 2.44$
$0 \leq 0.4527 \leq 1.414$
$0 \leq 0.3855 \leq 1.5650$
$0 \leq 0.2929 \leq 1.1892$

DISTANCE FOR NEUTROSOPIC VAGUE SETS USING PYTHON

For the above example we use python software to get the solution let X ={ u_1,u_2,u_3 } be the universe and let
$A_{NV} = \Big\{<\frac{u_1}{(0.1,0.2),(0.2,0.2),(0.2,0.3)}>,<\frac{u_2}{(0.2,0.4),(0.1,0.3),(0.2,0.1)}>,<\frac{u_3}{(0.2,0.1),(0.4,0.3),(0.1,0.2)}>\Big\}$ and
$B_{NV} = \Big\{<\frac{u_1}{(0.3,0.1),(0.1,0.1),(0.3,0.1)}>,<\frac{u_2}{(0.3,0.1),(0.1,0.2),(0.3,0.1)}>,<\frac{u_3}{(0.3,0.2),(0.1,0.1),(0.2,0.1)}>\Big\}$

1.Manhattan Distance and Normalized Manhattan Distance

Here we use the Manhattan Distance and Normalized Manhattan Distance formula in the python software and get the solution as follows:

```
manhattan.py - C:/Python34/manhattan.py (3.4.1)
File  Edit  Format  Run  Options  Window  Help
def manhatan_dist(board,goal_stat):
    #Manhattan priority function. The sum of the Manhattan distances
    #(sum of the vertical and horizontal distance) from the blocks to t
    #plus the number of moves made so far to get to the search node.
   from math import
    b = board
    g = goal_stat

    manh_dist = 0
    for i in range (0,3,1):
        for j in range (0,3,1):
            bij = b[i][j]
            i_b = i
            j_b = j

            i_g, j_g = value_index(g,bij)

            manh_dist += (math.fabs(i_g - i_b) + math.fabs(j_g - j_b))

    return manh_dist
```

FIGURE 1. the coding for Manhattan distance

OUTPUT

```
==================== RESTART: C:/Python34/manhattan.py =
manhattan is 2.3
>>>
==================== RESTART: C:\Python34\manhattan.py =
normalized manhattan is 0.766
>>>
```

FIGURE 2. the output for Manhattan distance and normalized manhattan distance

2.Euclidean Distance and Normalized Euclidean Distance

Here we use the Euclidean Distance and Normalized Euclidean Distance formula in the python software and get the solution as follows:

```
File  Edit  Format  Run  Options  Window  Help
 from math import sqrt

distance = math.sqrt(sum([(a - b) ** 2 for a, b in zip(x, y)]))
print("Euclidean is ",distance)
```

FIGURE 3. the coding and solution for Euclidean distance

OUTPUT

```
==================== RESTART: C:/Python34/euclidean.py ===========
  Euclidean is 0.6403125
>>>
==================== RESTART: C:/Python34/euclidean.py ===========
 normalized Euclidean is 0.4527160
>>>
```

FIGURE 4. the output for Euclidean distance and normalized euclidean distance

3.Minkowski Distance and Normalized Minkowski Distanc

Here we use the Minkowski Distance and Normalized Minkowski Distance formula in the python software and get the solution as follows:

```
# import math library
from math import *
from decimal import Decimal

# Function distance between two points
# and calculate distance value to given
# root value(p is root value)
def p_root(value, root):

    root_value = 1 / float(root)
    return round (Decimal(value) **
             Decimal(root_value), 3)

def minkowski_distance(x, y, p_value):

    # pass the p_root function to calculate
    # all the value of vector parallely
    return (p_root(sum(pow(abs(a-b), p_valu
             for a, b in zip(x, y)), p_value
```

FIGURE 5. the coding and solution for Minkowski distance

OUTPUT

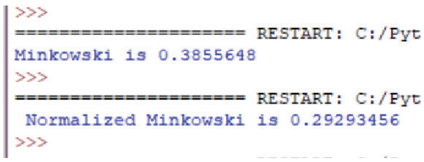

FIGURE 6. the output for Minkowski distance and normalized Minkowski distance.

Result and Discussion

Python has features like analyzing data and visualization, which helps in creating custom solutions without putting extra effort and time. While Python is a broadly useful language, Python is consistently getting all the more dominant by a quickly developing number of specific modules[16]. In this paper,we have done manual count and also use python programming language for distance measure in Neutrosophic vague set. From the procedure we can say that python is progressively compelling, than manual computation and furthermore the outcome we get from the python is increasingly viable .

CONCLUSION

In this paper we discuss about various distance measure in Neutrosophic vague set and also about the relationship between the distance measure and also we compare Neutrosophic vague measure in both manual computation and python software .

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