



## Fuzzy Logic using t-Norm

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# Fuzzy Logic using t-Norm

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**Abstract**— Mathematics is not only computing with numbers, variables and functions but also compute with words and sentences. Zadeh proposed fuzzy logic with membership function, disjunction, conjunction and implication for compute sets and words with uncertainty. In this paper fuzzy logic is studied differently using t-norms. Fuzzy logical operations and Fuzzy conditional inference is studied using t-norm.

**Keywords**— fuzzy logic, fuzzy conditional inference, t-norm, fuzzy t-norm

## I. INTRODUCTION

Zadeh defined fuzzy set as variable over interval [0,1]. Fuzzy sets are used to computes sets and words with uncertainty[8]. Zadeh[6] studied fuzzy logical operations and fuzzy conditional inference and it is universally not accepted.. Mamdani[3] TSK[5] and Reddy[7] are studied fuzzy conditional inference differently. It is also possible to study fuzzy logic differently using algebra. Fuzzy sets may be taken as variable. The variables may be combined for logical operations and inference. Using t-norm the computation with fuzzy variable may be studied using Algebra concepts additive, multiplicative of t-norm.

## II. A BRIEF REVIEW OF FUZZYLOGIC

The use of the fuzzy set theory for is now accepted because it is very convenient and believable... Zadeh [9] introduced fuzzy set by defining its mapping from a set in to unit interval. Goguen [2] extended fuzzy set in to functions from a set in to lattice. Fuzzy logic may be providing means of mathematically described by t-norm.

**Definition:** Given some universe of discourse X, a fuzzy set A of X is defined by its membership function  $\mu_A$  taking values on the unit interval[0,1] i.e.  $\mu_A: \subseteq [0,1]$

Suppose X is a finite set. The fuzzy set A of X may be represented as

$$A = \mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n$$

Goguen extended fuzzy set in to functions from a set in to lattice.

**Definition:** fuzzy set A of X is defined by fuzzy lattice which has lower bound and upper bound on the unit interval[0,1] ,  $0 \leq A \leq 1$

Fuzzy logic is non-statistical in nature. Let A and B be the fuzzy sets, and the operations on fuzzy sets are given below

.Fuzzy set is defined alternation functions of lattice theory

**Definition:** Fuzzy set A of X is defined by lattice which has lower bound and upper bound on the unit interval[0,1] ,  $0 \leq A \leq 1$

### Negation:

If x is not A

$$A' = 1 - \mu_A(x)$$

### Containment:

$A \subseteq B$  or A is smaller than or equal to B if and only if  $\mu_A(x) \leq \mu_B(x)$

**Conjunction:** x is A and y is B

$$A \cap B = \min(\mu_A(x), \mu_B(x))$$

$$A \wedge B = \min(\mu_A(x), \mu_B(y))$$

**Disjunction:** x is A or y is B

$$A \cup B = \max(\mu_A(x), \mu_B(x))$$

$$A \vee B = \max(\mu_A(x), \mu_B(y))$$

### implication

if x is A then y is B

$$A \Rightarrow B = A \oplus B = \min\{1, 1 - \mu_A(x) + \mu_B(y)\} / (x,y) \text{ Zadeh}$$

$$A \rightarrow B = A \times B = \min\{\mu_A(x), \mu_B(y)\} \text{ Mamdani}$$

The fuzzy quantifiers may be eliminated as

### A. Concentration

$$\mu_{\text{very } A}(x) = \mu_A(x)^2$$

### B. Diffusion

$$\mu_{\text{more or less } A}(x) = \mu_A(x)^{0.5}$$

## III. SOME METHODS OF FUZZY CONDITIONAL INFERENCE

Zadeh[7] and Mamdani[3] are proposed fuzzy conditional inference. Zadeh and Mamdani fuzzy inferences need prior information for consequent part in “if ... then ...”

Zadeh fuzzy conditional inference (if(Antecedent) then (Consequent) ) “if A then B is  $R: A \sqsubseteq B$  and the relationship on A and B is known is given by

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B = \min(1, (1 - \mu_A(x) + \mu_B(y)))$$

If  $(A_1 \text{ and } A_2 \dots A_n)$  then y is B

$$= \min\{1, (1 - \min(\mu_{A_1}(x), \mu_{A_2}(x), \dots, \mu_{A_n}(x)) + \mu_B(y))\} \quad (3.1)$$

Mamdani fuzzy conditional inference (if(Antecedent) then (Consequent) ) “if A then B is  $R: A \sqsubseteq B$  and the relationship on A and B is given by

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B = A \times B = \min(\mu_A(x), \mu_B(y))$$

If  $(A_1 \text{ and } A_2 \dots A_n)$  then y is B

$$= \min(\mu_{A_1}(x), \mu_{A_2}(x), \dots, \mu_{A_n}(x), \mu_B(x)) \quad (3.3)$$

TSK fuzzy conditional inference (if(Antecedent) then (Consequent) ) “if A then B is  $R: A \sqsubseteq B$  and the relationship on A and B is given by

$$\text{if } x \text{ is } A \text{ then } y = f(x) \text{ is } B$$

if  $x_1$  is  $A_1$  and  $x_2$  is  $A_2 \dots$  and  $x_n$  is  $A_n$  then  $y = f(x_1, x_2, \dots, x_n)$  is B

Fuzzy conditional inference (if(Antecedent) then (Consequent) ) “if A then B is  $R: A \sqsubseteq B$  and the relationship on A and B and when consequent part is derived from precedent part is given by

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B = A$$

fuzzy conditional inference using Mamdani fuzzy

conditional inference is given by

$$\text{if } x \text{ is } A \text{ then } y \text{ is } B = A \times A = \{\mu_A(x)\}$$

If  $(A_1 \text{ and } A_2 \dots A_n)$  then y is B

$$= A_1 \times A_2 \times \dots \times A_n \times B$$

$$= A_1 \times A_2 \times \dots \times A_n \times A_1 \times A_2 \times \dots \times A_n$$

$$= A_1 \times A_2 \times \dots \times A_n$$

$$= \min(\mu_{A_1}(x), \mu_{A_2}(x), \dots, \mu_{A_n}(x), \mu_B(x)) \quad (3.3)$$

Mamdani[3] has studied for nested fuzzy conditional inference of the type “if x is A then if x is B then y is C”  
i.e.,  $A \sqsubseteq B \sqsubseteq C = A \times B \times C = \min\{A, B, C\}$

Mamdani nested fuzzy conditional inference is given by  
if  $x_1$  is  $A_1$  then if  $x_2$  is  $A_2$  then y is B

i.e.,  $A_1 \dot{\sqsubseteq} A_2 \dot{\sqsubseteq} A_3$

fuzzy conditional inference is by using (3,3)

if  $x_1$  is  $A_1$  then (if  $x_2$  is  $A_2$  then y is B)

= if  $x_1$  is  $A_1$  then  $x_2$  is  $A_2$

=  $x_1$  is  $A_1$

i.e.,  $A \dot{\sqsubseteq} B \dot{\sqsubseteq} C = A$

#### IV. ALGEBRA T-NORM

Fuzzy logic is studied differently using t-norms.

Suppose a and b are numbers, t-norm is given by

**Definition 4.1:** The algebra set mapping  $t:R \sqsubseteq R$  is called derivation

$$t(x) = x$$

**Definition 4.2:** The algebra containment mapping

$t:R \times R \sqsubseteq R$  is called derivation

$$t(x \sqsubseteq y) = t(x \leq y) = x \leq y$$

**Definition 4.3:** The algebra additive mapping  $t:R \times R \sqsubseteq R$  is derivation

$$t(x+y) = t(x) + t(y)$$

**Definition 4.4:** The algebra multiplicative mapping

$t:R \times R \sqsubseteq R$  is derivation

$$t(x*y) = t(x)*t(y)$$

**Definition 4.5:** The algebra composition mapping

$t:R \times R \sqsubseteq R$  is derivation

$$t(x.y) = t(x).t(y)$$

**Definition 4.6:** The algebra implication mapping

$t:R \times R \sqsubseteq R$  is derivation

$$t(x \sqsubseteq y) = t(x \sqsubseteq y) = t(x \times y) = t((x) \times t(y))$$

**Definition 4.7:** The algebra nested implication mapping

$t:R \times R \times R \sqsubseteq R$  is derivation

$$t(x \sqsubseteq y \sqsubseteq z) = t(x \sqsubseteq y) \sqsubseteq z = t(x \times y \times z) = t((x) \times t(y) \times t(z))$$

**Definition 4.8:** The modified algebra nested implication

mapping  $t:R \times R \times R \sqsubseteq R$  is derivation

$$t(x \sqsubseteq y \sqsubseteq z) = t(x \sqsubseteq y) \sqsubseteq z = t(x \sqsubseteq z) = t((x))$$

where  $t(x \sqsubseteq y) = t(x)$  and  $t(x \sqsubseteq z) = t(x)$

**Definition 4.8** The algebra quantifier mapping  $t:Q \sqsubseteq R$  is derivation

$$t(Qx) = Q(t(x))$$

t-norm is used in several fuzzy classification systems.

$$t(x+y) \leq \max(t(x), t(y))$$

$$t(x*y) \leq \min(t(x), t(y))$$

$$t(x.y) \leq \min(t(x), t(y))$$

$$t(x \times y) \leq \min(t(x), t(y))$$

An algebra set in X is characterized by a membership function  $f_a(x)$  which associated with each point in X a real number in the interval [0,1]

i.e.,  $f_a(x): X \dot{\sqsubseteq} [0, 1], x \in X$

$$a = f_a(x)$$

$$a \subset b \iff f_a(x) \leq f_b(x)$$

a disjunction b

$$f_c(x) = \max\{f_a(x), f_b(x)\}$$

a conjunction b

$$f_c(x) = \min\{f_a(x), f_b(x)\}$$

For instance, x is small number

$$f(0)=0, f(10)=.2, f(20)=0.4, f(30)=0.6, f(40)=.7$$

let a and b are algebra fuzzy sets

$$t(a) = a$$

$$t(a') = a' = 1 - a$$

$$t(a \sqsubseteq b) = t(a) \leq t(b)$$

$$t(a+b) = \max(a, b)$$

$$t(a.b) = \min(a, b)$$

$$t(a \times b) = \min(a, b)$$

$$t(a \times b) = \min(a, b)$$

$$t(qa) = qt(a), \text{ where } q \text{ is constant.}$$

#### V. ALGEBRA LOGIC USING T-NORM

We apply t-norms on sets. The algebraic set may be taken as fuzzy set.

Algebraic Set A in X is characterized by a membership function  $f_A(x)$  which associated with each point in X a real number in the interval [0,1]

i.e.,  $f_A(x): X \dot{\sqsubseteq} [0, 1], x \in X$

$$A \subset B \iff f_A(x) \leq f_B(x)$$

A union B

$$f_c(x) = \max\{f_A(x), f_B(x)\}$$

A intersection B

$$f_c(x) = \min\{f_A(x), f_B(x)\}$$

For instance, x is small number

$$f(0)=1, f(10)=.2, f(20)=0.4, f(30)=0.6, f(40)=.7$$

**Definition 5.1:** The algebra fuzzy set mapping  $t:R \sqsubseteq R$  is called derivation

$$t(a) = a, \text{ where } 0 \leq a \leq 1$$

The logical operator are ' (negation), + (disjunction) and \* (Conjunction),  $\sqsubseteq$  (implication) and , (composition)

$$t(a) = a$$

A. Negation

$$a' = 1 - a$$

$$t(a) = a' = 1 - a$$

B. Disjunction

$$a + b = \max(a, b)$$

$$t(a + b) = a + b = \max(a, b)$$

C. Conjunction

$$t(a * b) = a * b = \min(a, b)$$

D. Implication

The fuzzy conditional inference for “if a then if b then c” is given by

is given by

$$t(a \sqsubseteq b) = t(a * b) = a * b = \min(a, b)$$

The modified fuzzy conditional inference for “if a then if b then c” is given by

is given by

$$t(a \sqsubseteq b) = t(a) = a * b = a$$

The nested fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(a \sqsupset (b \sqsupset c)) &= t(a * b * c) = t(a) * t(b) * t(c) \\ &= \min(a, b, c) \end{aligned}$$

The modified nested fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(a \sqsupset (b \sqsupset c)) &= t(a \sqsupset c) = t(a) = a \end{aligned}$$

#### E. Quantifiers

The fuzzy propositions may contain quantifiers like “very”, “more or less”. These fuzzy quantifiers may be eliminated as

$$t(qa) = qt(a) = q(a), \text{ where } Qq \text{ is quantifier}$$

#### Concentration

$$\begin{aligned} & \text{very } a \\ t(\text{very } a) &= \text{very } t(a) = \text{very } t(a) \end{aligned}$$

#### Diffusion

$$\begin{aligned} & \text{more or less } a \\ t(\text{more or less } a) &= \text{more or less } t(a) = \text{more or less } t(a) \end{aligned}$$

#### F. Composition

$$\begin{aligned} t(a \sqsupset b) &= t(aXb) = aXb = \min(a, b) \\ t(a1.r) &= a, r = \min(a1, r) \\ \text{where } r &= a \sqsupset b = axb \end{aligned}$$

### VI. FUZZY LOGIC USING T-NORM

We apply t-norms on fuzzy logic for words

The fuzzy logical operators are ' (negation), V (disjunction) and  $\wedge$  (Conjunction) and 0 (composition)

#### A. Fuzzy set

$$\begin{aligned} A \\ t(A) &= A \\ t(\text{tall}) &= \text{tall} \end{aligned}$$

#### B. Negation

$$\begin{aligned} A' &= 1 - A \\ t(A) &= A' = 1 - A \\ t(\text{not tall}) &= \text{not tall} = 1 - \text{tall} \end{aligned}$$

#### C. Disjunction

$$\begin{aligned} t(A \vee B) &= A \vee B = \max(A, B) \\ t(\text{tall} \vee \text{weight}) &= \text{tall} \vee \text{weight} = \max(\text{tall}, \text{weight}) \end{aligned}$$

#### D. Conjunction

$$\begin{aligned} t(A \wedge B) &= A \wedge B = \min(A, B) \\ t(\text{tall} \wedge \text{weight}) &= \text{tall} \wedge \text{weight} = \min(\text{tall}, \text{weight}) \end{aligned}$$

#### E. Implication

The fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(A \sqsupset B) &= t(A * B) = A * B = \min(A, B) \end{aligned}$$

The modified fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(A \sqsupset B) &= t(A * B) = A * B = A \end{aligned}$$

The nested fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(A \sqsupset (B \sqsupset C)) &= t(A * B * C) = t(A) * t(B) * t(C) \\ &= \min(A, B, C) \end{aligned}$$

The modified nested fuzzy conditional inference for “if a then if b then c” is given by

$$\begin{aligned} & \text{is given by} \\ t(A \sqsupset (B \sqsupset C)) &= t(A \sqsupset C) = t(A) = A \end{aligned}$$

#### F. Quantifiers

The fuzzy propositions may contain quantifiers like “very”, “more or less”. These fuzzy quantifiers may be eliminated as

$$t(qA) = qt(A) = q(A), \text{ where } q \text{ is quantifier}$$

#### Concentration

$$\begin{aligned} & \text{very } A \\ t(\text{very } A) &= \text{very } t(A) = \text{very } t(A) \end{aligned}$$

#### Diffusion

$$\begin{aligned} & \text{more or less } a \\ t(\text{more or less } A) &= \text{more or less } t(A) = \text{more or less } t(A) \end{aligned}$$

#### G. Composition

$$\begin{aligned} t(A \sqsupset b) &= t(AXb) = AXb = \min(A, b) \\ t(A1.r) &= a, r = \min(A1, r) \\ \text{where } r &= A \sqsupset b = A.B \end{aligned}$$

$$\begin{aligned} t(\text{tall} \sqsupset \text{weight}) &= t(\text{tall} . \text{weight}) = \min(\text{tall} * \text{weight}) \\ t(\text{very tall} . \text{tall} \sqsupset \text{weight}) &= t(\text{very tall}) . t(\text{tall} * \text{weight}) \\ &= \text{very tall} . \text{tall} * \text{weight}. \end{aligned}$$

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