

Chapter 4. Fuzzy Logic and Approximate Reasoning

- *Linguistic variable:*

~ A variable whose values are words or sentences in a natural or artificial language.

Ex: "speed", values: slow, fast, very fast.

~ providing a means of approximate characterization of phenomena that are too complex or too ill-defined to be amenable to description in conventional quantitative terms.

- *Fuzzy variable:*

A fuzzy variable is characterized by a triple $(X, U, R(x))$

X : the name of the variable.

U : universe of discourse.

$R(x)$: a fuzzy subset of U which represents a fuzzy restriction imposed by X .

Ex: $X = \text{"old"}$.

$U = \{10, 20, \dots, 80\}$

$R(x) = 0.1/20 + 0.2/30 + 0.4/40 + 0.5/50 + 0.8/60 + 1/70 + 1/80$

- A linguistic variable is a variable of higher order than a fuzzy variable, and it takes fuzzy variable as its values. A linguistic variable is characterized by a quintuple $(x, T(x), U, G, M)$.

x : name of the variable.

$T(x)$: a term set of x , i.e. the set of names of linguistic values of x with each value being a fuzzy variable defined on U .

G : a syntactic rule for generating the name of values of x .

M : a semantic rule for associating each value of x with its meaning.

Ex 6.1:

$x = \text{"speed"}$

$T(\text{speed}) = \{\text{very slow, slow, Moderate, Fast, ...}\}$

G: intuitive.

M(slow): the fuzzy set for "a speed below about 40 miles per hour (mph)"

with μ_{slow}

M(Moderate): the fuzzy set for "a speed close to 55mph" with μ_{Moderate}

- A linguistic variable x is said to be *structured* if its term set $T(x)$ and its semantic rule M can be characterized such that they can be viewed as algorithmic procedures for generating the elements of $T(x)$ and computing the meaning of each term in $T(x)$.

- **Linguistic hedge (or modifier) h :**

An operator for modifying the meaning of its operator or, more generally, of a fuzzy set A to create a new fuzzy set $h(A)$.

- The following fuzzy set operations are used in defining a linguistic hedge:

~ Concentration : $\text{con}(A)$

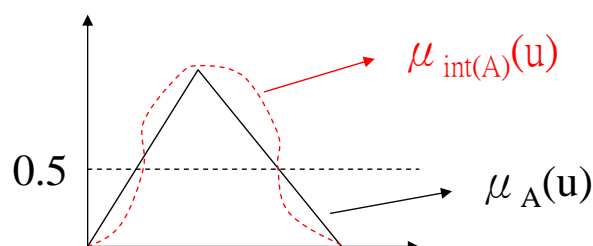
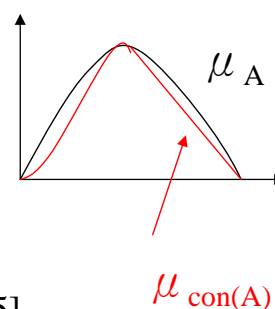
$$\mu_{\text{CON}(A)}(u) = (\mu_A(u))^2$$

~ Dilation : $\text{dil}(A)$

$$\mu_{\text{dil}(A)}(u) = (\mu_A(u))^{\frac{1}{2}}$$

~ Intensification : $\text{int}(A)$.

$$\mu_{\text{int}(A)}(u) = \begin{cases} 2(\mu_A(u))^2 & , \mu_A(u) \in [0, 0.5] \\ 1 - 2(1 - \mu_A(u))^2 & , \text{otherwise} \end{cases}$$



- some popular linguistic hedges are :

$$\text{Very}(A) = \text{con}(A): (\mu_A(u))^2$$

$$\text{highly}(A): (\mu_A(u))^3$$

$$\text{fairly(more or less)}(A) = \text{dil}(A): (\mu_A(u))^{\frac{1}{2}}$$

$$\text{roughly}(A) = \text{dil}(\text{dil}(A))$$

$$\text{plus}(A): (\mu_A(u))^{1.25}$$

$$\text{minus}(A) = (\mu_A(u))^{0.75}$$

$$\text{rather}(A) = \text{int}(\text{con}(A)) \text{ AND NOT}[\text{con}(A)].$$

where AND and NOT are the fuzzy conjunction and complement.

- The resulting fuzzy sets should be normalized if the height is not one.
- With the aid of linguistic hedges, we can define a term set of a linguistic variable, such as

$$T(\text{Age}) = \{\text{old}, \text{very old}, \text{very very old}, \dots\}$$

in which "old" is called the **primary term**, and the corresponding syntactic rule G which can generate the term set, T(Age), recursively, could be the following recursive algorithm :

$$T^{i+1} = \{\text{old}\} \cup \{\text{very } T^i\}. \quad i=0,1,2,\dots(*)$$

Ex: for $i = 0, 1, 2, 3$. we have

$$T^0 = \emptyset$$

$$T^1 = \{\text{old}\}.$$

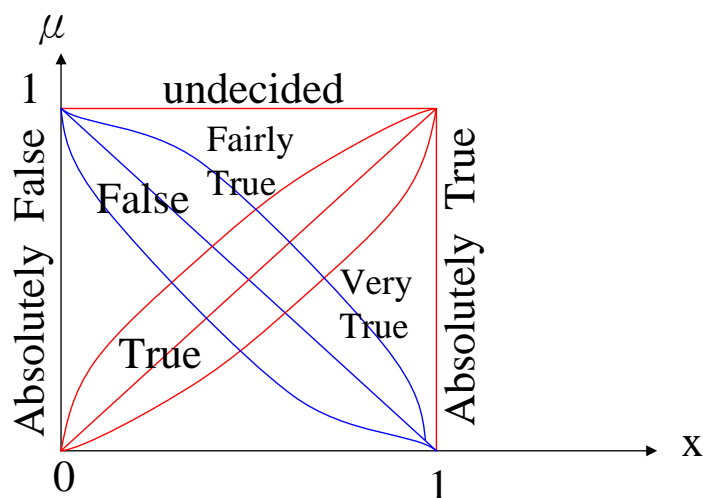
$$T^2 = \{\text{old}, \text{very old}\}.$$

$$T^3 = \{\text{old}, \text{very old}, \text{very very old}\}.$$

- The semantic rule M which can associate with each T^i a meaning could be the following recursive algorithm :

$$M(T^i) = \cup old^j, j = 1, 2, \dots, 2^{i-1}. \quad (**)$$

with Eqs. (*) and (**), "Age" is a **structured linguistic variable**.



• Linguistic Approximation

~ A procedure for solving the problem of how to find a term from the term set of a linguistic variable such that the meaning of this term is closest to a given fuzzy set.

~ To solve the linguistic approximation problem, one can base on the *similarity measure* of two fuzzy sets, $E(A, B)$, which indicates the degree of equality of two fuzzy sets A and B,

$$E(A, B) = \frac{|A \cap B|}{|A \cup B|}$$

where $0 \leq E(A, B) \leq 1$, and $|A| = \sum \mu_A(x)$.

~ The idea is that the linguistic approximation of a given fuzzy set A is the term $T_A \in T(x)$, which is most similar to A than the other terms in the term set $T(x)$, of a given linguistic variable, that is

$$E(A, T_A) = \max_{T^i \in T(x)} E(A, T^i)$$

Ex 6.2 :

Given $U = \{0, 0.1, 0.2, \dots, 1\}$, and the term set $\{A, B, C\}$ of the linguistic variable "Truth", where

$$A = \text{"True"} = 0.7/0.8+1/0.9+1/1$$

$$B = \text{"MORE OR LESS True"} = 0.5/0.6+0.7/0.7+1/0.8+1/0.9+1/1$$

$$C = \text{"ALMOST True"} = 0.6/0.8+1/0.9+0.6/1$$

find the linear approximation of the fuzzy set D defined by

$$D=0.6/0.8+1/0.9+1/1$$

$$\text{since } E(D,A) = \frac{|D \cap A|}{|D \cup A|} = \frac{0.6+1+1}{0.7+1+1} = \frac{2.6}{2.7} = 0.96$$

$$E(D,B) = \frac{|D \cap B|}{|D \cup B|} = \frac{0.6+1+1}{0.5+0.7+1+1+1} = \frac{2.6}{4.2} = 0.62$$

$$E(D,C) = \frac{|D \cap C|}{|D \cup C|} = \frac{0.6+1+0.6}{0.6+1+1} = \frac{2.2}{2.6} = 0.85$$

the linguistic approximation of the fuzzy set D is the term A "True".

• *Fuzzy Logic* :

- Logic is a basis for reasoning.
- Classical bivalence logic deals with propositions that are required to be either true (with a logical value of 1) or false (with a logical value of 0), which are called truth value of the propositions.
- Propositions are sentences expressed in some language and can be expressed, in general, in the canonical form

$$x \text{ is } P,$$

where x is a symbol of a subject, and P designates a predicate which characterizes a property of the subject.

- For example, "Taipei is in Taiwan", is a proposition in which "Taipei" is a subject and "in Taiwan" is a predicate that specifies a property of "Taipei", namely, its geographical position in Taiwan.
- Each proposition A has an opposite called *negation* of the proposition and is denoted as \bar{A}

- A proposition and its negation are required to assume opposite truth values.
- We shall consider two major topics in logic:
logic operations and *logic reasoning*.

- *Logic operations*

- ~ Logic operations are (logic) functions of two propositions.
- ~ The logic operations are defined via truth tables.
- ~ Consider two propositions A and B, either of which can be true ("1") or false ("0").
- ~ The four basic logic operations are "*conjunction*(\wedge)", "*disjunction*(\vee)", "*implication* (or *conditional*)(\Rightarrow)", and "*equivalence* (or *bi-directional*)(\Leftrightarrow)" and are interpreted as "A and B", "A or B", "if A then B", and "A if and only if B," respectively.

- Truth table

Propositions		Conjunction	Disjunction	Implication	Equivalence
A	B	$A \wedge B$	$A \vee B$	$A \Rightarrow B$	$A \Leftrightarrow B$
1	1	1	1	1	1
1	0	0	1	0	0
0	1	0	1	1	0
0	0	0	0	1	1

- *Logic reasoning*

- ~ Another main concern of logic system is the reasoning procedure which is performed through some *inference rules*.
- ~ Some important inference rules are :
 - $(A \wedge (A \Rightarrow B)) \Rightarrow B$ (modus ponens)
 - (*) $(\bar{B} \wedge (A \Rightarrow B)) \Rightarrow \bar{A}$ (modus tollens)
 - $((A \Rightarrow B) \wedge (B \Rightarrow C)) \Rightarrow (A \Rightarrow C)$ (hypothetical syllogism)

- ~ The resulting propositions in Eq(*) are always true no matter what the truth values of propositions A and B are. These are called **tautologies**.
- ~ We interpret the modus ponens as: If A is true and if the proposition “If A is true then B is true” is also true then proposition B is true.
- ~ The modus ponens is closely related to the forward data-driven inference which, when extended to fuzzy logic, is particularly useful for fuzzy logic control.
- Unlike two-valued logic, the truth values of propositions in fuzzy logic are allowed to range over the fuzzy subsets of unit interval [0, 1], or more simply, a point in the interval.
- For example, a truth value in fuzzy logic "very true" may be interpreted as a fuzzy set in [0, 1].
- Def : The *truth-value* of the proposition "x is A," or simply truth value of A, which is denoted by $V(A)$ is defined to be a point in [0, 1] (called *numerical truth-value*) or possibly a fuzzy set in [0, 1] (called *linguistic truth-value*).

- Let us see how to get the truth value of a proposition which comes from the logic operations (that is, negation, conjunction, disjunction, and implication) of other propositions whose truth values are known.

- Def :

If $V(A)$ and $V(B)$ are numerical truth values of propositions A and B, respectively, then

$$V(\text{NOT } A) \triangleq 1 - V(A)$$

$$V(A \text{ AND } B) \triangleq V(A) \wedge V(B) = \min\{V(A), V(B)\}$$

$$V(A \text{ OR } B) \triangleq V(A) \vee V(B) = \max\{V(A), V(B)\}$$

$$V(A \Rightarrow B) \triangleq V(A) \Rightarrow V(B) = \max\{1 - V(A), \min(V(A), V(B))\}.$$

(other definitions of implications can also be applied (See Table 7.1)).

- Using the extension principle, we have the following definition.

- Def : If $V(A)$ and $V(B)$ are linguistic truth-values of propositions A and B, respectively, and are expressed as

$$v(A) = \alpha_1/v_1 + \alpha_2/v_2 + \dots + \alpha_n/v_n.$$

$$v(B) = \beta_1/w_1 + \beta_2/w_2 + \dots + \beta_m/w_m.$$

where

$\alpha_i, \beta_i, v_i, w_i \in [0, 1]$, then we have

$$v(\text{NOT } A) = \alpha_1/(1-v_1) + \alpha_2/(1-v_2) + \dots + \alpha_n/(1-v_n)$$

$$v(A \text{ AND } B) = v(A) \wedge v(B) = \sum_{ij} \min(\alpha_i, \beta_j) / \min(v_i, w_j).$$

$$v(A \text{ OR } B) = v(A) \vee v(B) = \sum_{ij} \min(\alpha_i, \beta_j) / \max(v_i, w_j).$$

$$v(A \Rightarrow B) = v(A) \Rightarrow v(B)$$

$$= \sum_{ij} \min(\alpha_i, \beta_j) / \max\{1 - v_i, \min(v_i, w_j)\} \dots (*)$$

Remark : Various definitions of implication can be applied to Eq (*).

Ex6.3 : $V(P)$ ="MORE OR LESS True", $V(Q)$ ="ALMOST True", are

linguistic values of propositions P and Q, and are defined in Ex 6.2.

$$V(\text{NOT } P) = V(\text{NOT MORE OR LESS True})$$

$$= 0.5/0.4 + 0.7/0.3 + 1/0.2 + 1/0.1 + 1/0$$

$$V(P \text{ AND } Q) = V(P) \wedge V(Q)$$

$$= 0.5/0.6 + 0.7/0.7 + 1/0.8 + 1/0.9 + 0.6/1$$

$$\text{"MORE OR LESS True"} = 0.5/0.6 + 0.7/0.7 + 1/0.8 + 1/0.9 + 1/1$$

$$\text{"ALMOST True"} = 0.6/0.8 + 1/0.9 + 0.6/1$$

- *Approximate Reasoning*

- ~ As in any other logic, the rule of inference in fuzzy logic governs the deduction of a proposition, q , from set of premises $\{p_1, p_2, \dots, p_n\}$
- ~ In fuzzy logic both the premises and the conclusion are allowed to be a fuzzy proposition.
- ~ Since the inferred results usually must be translated into more meaningful terms (fuzzy sets) by the use of linguistic approximation, the final conclusion drawn from the premises p_1, p_2, \dots, p_n is, in general, an approximate rather than exact consequences of p_1, p_2, \dots, p_n .
- ~ There are four principal modes of fuzzy reasoning (or approximate reasoning) in fuzzy logic. *categorical reasoning, qualitative reasoning, syllogistic reasoning* and *dispositional reasoning*.

- ~ We shall only discuss categorical reasoning and qualitative reasoning which are used in FLCs.
- *Categorical reasoning:*
 - ~ In this mode of reasoning, the premises are assumed to be in the canonical form " X is A " or in the conditional canonical form , "If X is A then Y is B", where A and B are fuzzy predicates.
 - ~ Notations :
 - X, Y, Z, = (fuzzy) variables taking values in the universes U,V, W.
 - A, B, C, = fuzzy predicates.
 - ~ *Projection rule of inference:*

$$\frac{(X, Y) \text{ is } R}{X \text{ is } [R \downarrow X]}$$

where $[R \downarrow X]$ denotes the projection of fuzzy relation R on X .

Ex:

$$\frac{(X, Y) \text{ is Close to } (3, 2)}{X \text{ is Close to } 3.}$$

~ Conjunction or particularization rule of inference:

$$\frac{\begin{array}{l} X \text{ is } A \\ X \text{ is } B \end{array}}{X \text{ is } A \cap B} \qquad \frac{\begin{array}{l} (X, Y) \text{ is } A \\ X \text{ is } B \end{array}}{(X, Y) \text{ is } A \cap (B \times V)}$$

$$\frac{\begin{array}{l} (X, Y) \text{ is } A \\ (Y, Z) \text{ is } B \end{array}}{(X, Y, Z) = (A \times W) \cap (U \times B)}$$

Ex :

$$\frac{\begin{array}{l} \text{pressure is NOT VERY High} \\ \text{pressure is NOT VERY Low} \end{array}}{\text{pressure is NOT VERY High AND NOT VERY Low}}$$

$$\frac{\begin{array}{l} X \text{ and } Y \text{ are APPROXIMATELY Equal} \\ X \text{ is small} \end{array}}{X \text{ and } Y \text{ are (APPROXIMATELY Equal } \cap (\text{small } \times V)).}$$

- Disjunction or Cartesian product rule of inference:

$$\frac{\begin{array}{c} X \text{ is } A \\ \text{OR } X \text{ is } B \end{array}}{X \text{ is } A \cup B} \qquad \frac{\begin{array}{c} X \text{ is } A \\ Y \text{ is } B \end{array}}{(X,Y) \text{ is } A \times B}$$

- Negation rule:

$$\frac{\text{NOT}(X \text{ is } A)}{X \text{ is } \overline{A}} \qquad \frac{\text{NOT}(\text{John is Tall})}{\text{John is NOT Tall}}$$

- Entailment rule of inference (entailment principle):

$$\frac{\begin{array}{c} X \text{ is } A \\ A \subset B \end{array}}{X \text{ is } B}$$

Ex :

$$\frac{\begin{array}{c} \text{Mary is VERY Young} \\ \text{VERY Young} \subset \text{Young} \end{array}}{\text{Mary is Young}}$$

- Compositional rule of inference:

$$\frac{\begin{array}{c} X \text{ is } A \\ (X,Y) \text{ is } R \end{array}}{Y \text{ is } A \circ R}$$

$$\mu_{A \circ R}(v) = \max_u \min(\mu_A(u), \mu_R(u,v)).$$

The compositional rule of inference may be viewed as combination of the conjunction and projection rules. 4-23

By conjunction rule: $(X, Y) \text{ is } R \cap (A \times V)$

By projection rule: $Y \text{ is } [(R \cap (A \times V)) \downarrow Y]$

• **Generalized modes ponens:**

$X \text{ is } A$	Material implication(1-38):
$\frac{\text{If } X \text{ is } B, \text{ THEN } Y \text{ is } C}{Y \text{ is } A \circ (\bar{B} \oplus C)}$	$B \rightarrow C = s(\bar{B}, C) = (\bar{B} \oplus C)$
	s : bounded sum

where $\mu_{\bar{B} \oplus C}(u, v) = \min(1, 1 - \mu_B(u) + \mu_C(v))$.

~ Actually, the generalized modus ponens is a special case of the compositional rule of inference.

~ Unlike the modus ponens in classical logic, the generalized modus ponens does not require that the precondition "X is B" be identical to the premise "X is A".

4-24

~ The generalized modus ponens is related to the interpolation rule for solving the important problem of "partial" matching of preconditions of rules that arises in the operation of any rule-based system.

~ The generalized modus poems plays a very important role in fuzzy control and fuzzy expert systems.

• **Extension principle:**

$$\frac{X \text{ is } A}{f(X) \text{ is } f(A)}$$

where f is a mapping from U to V so that X is mapped into $f(X)$. By extension principle,

$$\mu_{f(A)}(v) = \sup_{v=f(u)} \mu_A(u), \quad u \in U, v \in V.$$

The extension principle can answer a question like, assuming that X taking values in U is constrained by the proposition "X is A," what is the constraint on f(x) that is induced by the constraint on X ? For example.

X is Small

$$X^2 \text{ is small}^2, \text{ where } \mu_{\text{small}^2}(v) = \sup_{v=u^2} \mu_{\text{small}}(u).$$

Ex : Consider the premises

$p_1 = \text{John is VERY Big.}$

$p_2 = \text{John is VERY Tall.}$

where "Big" is a given fuzzy subset of $U \times V$ (i.e. values of Height \times values of Weight) and "Tall" is a given fuzzy subset of U (values of Height).

How heavy is John?

Sol: Method1: conjunction rule of inference,

(height (John), weight(John))is Big²

(height(John)) is Tall²

(height(John), weight(John)) is Big² \cap (Tall² \times V)

projection rule of inference.

weigh (John) is [(Big² \cap (Tall² \times V)) \downarrow weight].

Method 2: compositional rule of inference

weigh (John) is Tall² \circ Big²

Ex : Consider the premises

$p_1 = X \text{ is small.}$

$p_2 = X \text{ and Y are APPROXIMATELY Equal.}$

in which X and Y range over the set $U = \{1,2,3,4\}$ and

Small = $1/1+0.6/2+0.2/3$

$$\text{APPROXIMATELY Equal: } X \begin{matrix} & \text{Y} \\ \begin{bmatrix} 1 & 0.5 & 0 & 0 \\ 0.5 & 1 & 0.5 & 0 \\ 0 & 0.5 & 1 & 0.5 \\ 0 & 0 & 0.5 & 1 \end{bmatrix} \end{matrix}$$

Y is ?

Sol:

Method 1:

$Y = X$ is small o APPROXIMATELY_ Equal.

$$= (1, 0.6, 0.5, 0.2).$$

$$Y = 1/1 + 0.6/2 + 0.5/3 + 0.2/4$$

Through the linguistic approximation, we can say, for example, “Y is MORE OR LESS Small,” which is inferred from propositions p_1 and p_2 .

Method 2: By conjunction and projection rules.

$$Y = [((\text{Small} \times U) \cap \text{APPROXIMATELY Equal}) \downarrow Y]$$

$$\text{Small} \times U = \begin{bmatrix} 1 & 1 & 1 & 1 \\ 0.6 & 0.6 & 0.6 & 0.6 \\ 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 1 & 1 & 1 \\ 0.6 & 0.6 & 0.6 & 0.6 \\ 0.2 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 \end{bmatrix} \cap \begin{bmatrix} 1 & 0.5 & 0 & 0 \\ 0.5 & 1 & 0.5 & 0 \\ 0 & 0.5 & 1 & 0.5 \\ 0 & 0 & 0.5 & 1 \end{bmatrix} = \begin{bmatrix} 1 & 0.5 & 0 & 0 \\ 0.5 & 0.6 & 0.5 & 0 \\ 0 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 \end{bmatrix}$$

$$\begin{bmatrix} 1 & 0.5 & 0 & 0 \\ 0.5 & 0.6 & 0.5 & 0 \\ 0 & 0.2 & 0.2 & 0.2 \\ 0 & 0 & 0 & 0 \end{bmatrix} \downarrow Y = (1, 0.6, 0.5, 0.2)$$

· *Qualitative Reasoning* :

- ~ A mode of reasoning in which the input-output relation of a system is expressed as a collection of fuzzy IF-THEN fuzzy or linguistic variables.
- ~ For example, if X and Y are input variables and Z is the output variable, the relation between X,Y,and Z may be expressed as

$$\begin{array}{l}
 \text{If } X \text{ is } A_1 \text{ and } Y \text{ is } B_1 \text{ then } Z \text{ is } C_1 . \\
 \text{If } X \text{ is } A_2 \text{ and } Y \text{ is } B_2 \text{ then } Z \text{ is } C_2 . \\
 \quad \quad \quad \vdots \\
 \text{If } X \text{ is } A_n \text{ and } Y \text{ is } B_n \text{ then } Z \text{ is } C_n .
 \end{array}
 \quad \left. \vphantom{\begin{array}{l} \\ \\ \\ \end{array}} \right\} (*)$$

where A_i, B_i and $C_i, i = 1, \dots, n$ are fuzzy subsets of their respective universe of discourse.

- ~ Given the dependence of Z on X and Y in the form of (*),we can employ the compositional rule of inference to compute the value of Z given the values of X and Y.

Ex : If pressure is High, Then volume is Small.

 If pressure is Low, Then volume is Large.

If pressure is Medium, Then volume is $\max \{w_1 \wedge \text{small}, w_2 \wedge \text{large}\}$

where $w_1 = \sup(\text{High} \wedge \text{Medium}), w_2 = \sup(\text{Low} \wedge \text{Medium})$, and can be considered as weighting coefficients that represent, respectively, the degrees to which the preconditions “High” and “Low” match the input “Medium.”

