

# Fuzzy expert systems

## *Synlogy*

Project

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begin

# Plan of the project:

- Introduction to expert systems (*ES*)
- Basic architecture of rule-based *ES*
- Introduction to fuzzy mathematics
- Fuzzy inference
- Fuzzy expert systems (*FES*) - *Synlogy*
- Conclusions

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# Introduction to expert systems

## Motivation

- **Expert systems** - computer programs, software:
  - available some of the skills of an expert to nonexperts;
  - emulate the reasoning, thinking patterns of an expert;
  - handle uncertainty, vagueness, incompleteness, impreciseness, and inconsistency.
- **Human reasoning** - not a static process:
  - data - gathered;
  - hypotheses - advanced, tested, rejected;
  - conclusions - reached.
  - **The emulation of reasoning must proceed similarly.**
- **Human knowledge**:
  - **declarative**, facts stored in memory;
  - **procedural**, skills in utilising declarative knowledge.

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# Introduction to expert systems

## History

- Approaches to the emulation of expert (human) reasoning:
  - rule-based systems [Anderson, 1993];
  - semantic or associative nets [Quillian, 1968];
  - frames [Minsky, 1975];
  - neural nets [Haykin, 1994].
  - Dominant - the complementary rule-based systems and neural net approaches [Jackson, 1999].
- Important expert systems since the middle 1960's:
  - DENDRAL (1965) - determining molecular structure from mass spectrometer data [Feigenbaum, Buchanan, 1993];
  - MYCIN (1976) - medical diagnosis [Shortliffe, 1976];
  - R1 (1980) - computer configurations [McDermott, 1980];
- ES - in fields ranging from space shuttle operations, through hospital intensive-care-unit patient monitoring, geology to financial decision making.

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### PRODUCTION RULES

- A significant part of human (verbal) reasoning - expressed in **production rules** [Newell, 1972], [Anderson, 1993]:

*IF* the data available meet certain specified conditions,  
*THEN* take these specified **actions**.

- **Actions** - in a wide context, including drawing conclusions, firm or tentative, defeasible.
- *IF* part of a rule - the *antecedent*,  
*THEN* part of a rule - the *consequent*.

*IF* the car engine will not turn over when attempting to start  
*THEN* check if the battery is discharged

# Introduction to expert systems

## Rule-based (production) systems

### KNOWLEDGE

- **Declarative, factual knowledge** - represented by stored data.  
**Procedural knowledge** - represented by production rules.
- The two primary sources of knowledge:
  - the skills of an expert in the field,
  - available historical data.
- Rule-based expert systems:
  - much on the skills of an expert in the problem domain,
  - little on historical data.
- Rule-based systems acquire
  - knowledge by adding new facts,
  - skills by adding new rules.
  - **Both the learning techniques necessary.**

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# Basic architecture of rule-based *ES* - Plan:

- Production system
- Rule-based expert system
- Facts in *ES*
- Production rules in *ES*
- Inference performed by *ES*
- Forward chaining
- Backward chaining
- Simulation of recursion
- Agenda
- Conflict resolution strategies

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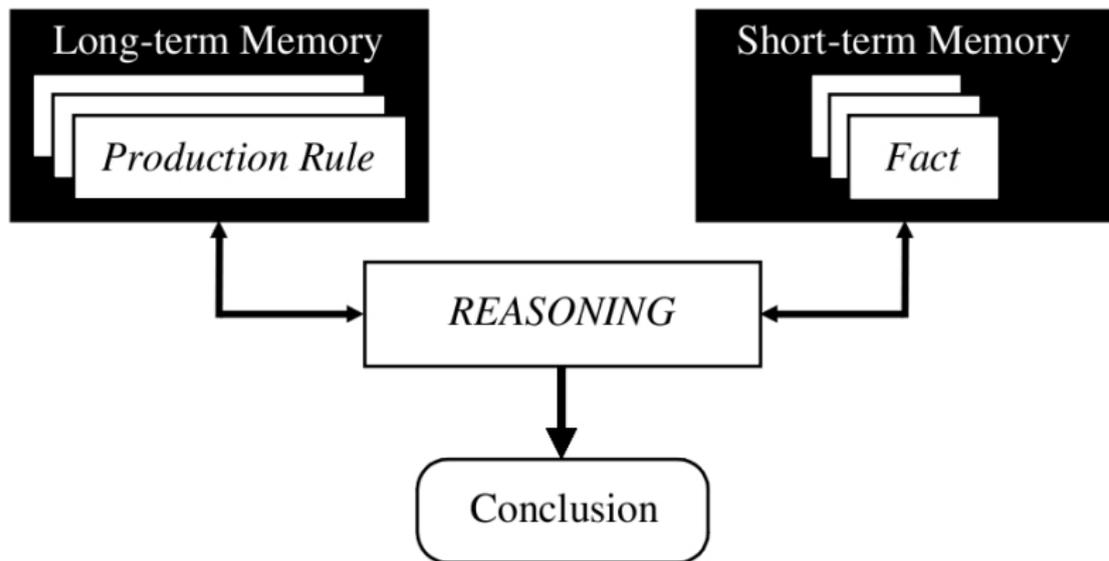
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# Basic architecture of rule-based ES

## Production system

### Basic architecture of a production system:



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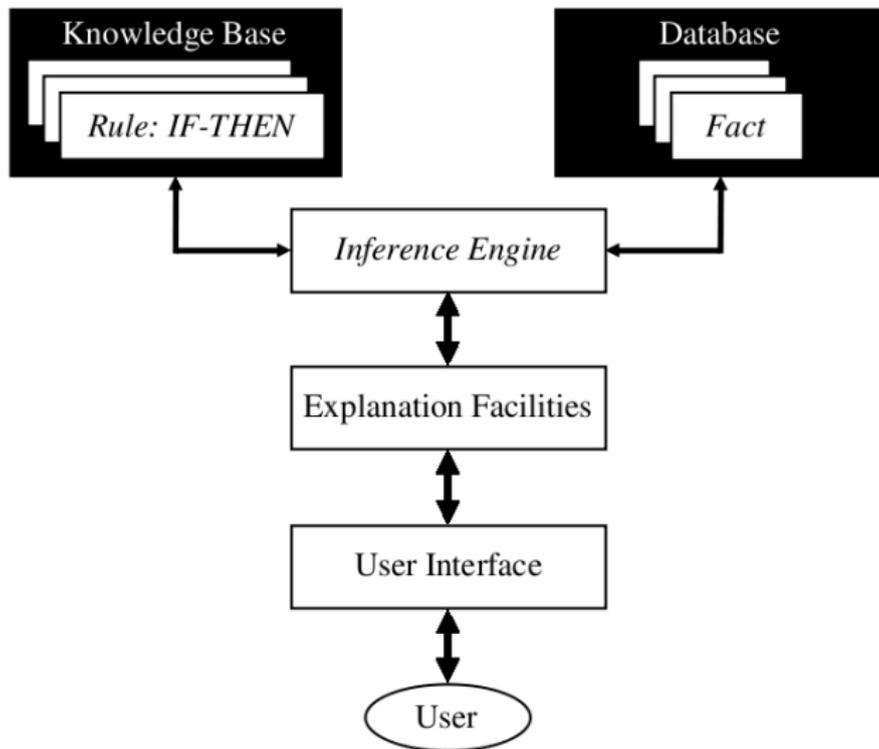
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## Rule-based expert system

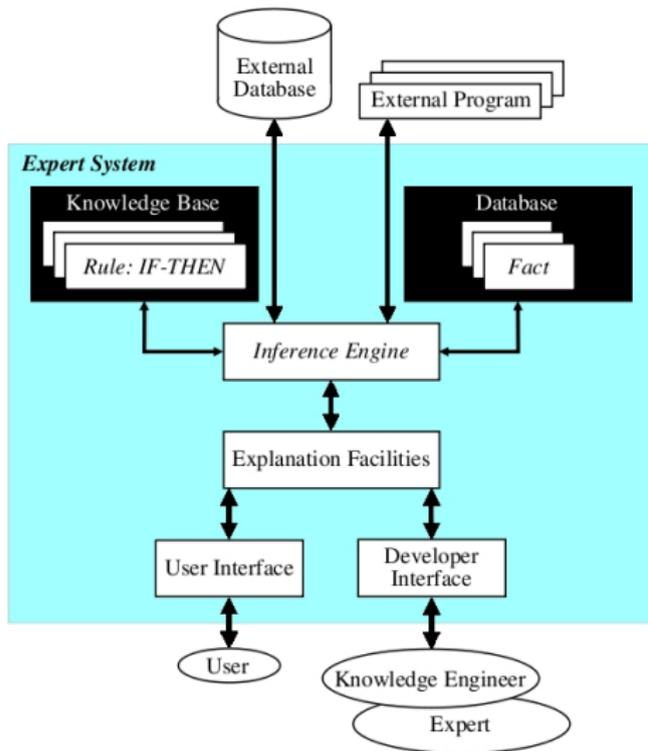
### Basic architecture of a rule-based expert system:



# Basic architecture of rule-based ES

## Rule-based expert system

### Complete architecture of a rule-based expert system:



# Basic architecture of rule-based ES

## Facts in ES

- **Data types:** integer, float, symbol, string, fact index.
- **"Ordered" facts (tuples):** (**the\_pump** is on)  
(**altitude** is 10000 feet)  
(**grocery-list** bread milk eggs)

- **"Template" facts:**

```
(deftemplate car (car
  (slot identifier (identifier car01)
  (slot brand) (brand VW)
  (slot model) (model Golf)
  (slot engine) (engine 1.4_TSI)
  (slot transmission) (transmission 6speed_manual)
  (multislot accessories)) (accessories Air_conditioner
                             Dusk_sensor
                             Hill_hold
                             Park_assist))
```

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## Production rules in ES

- **IF** part (*antecedent*) - built up from conditional elements (*patterns*) using the *and*, *or*, *not* connectives.
- **THEN** part (*consequent*) - a sequence of actions:
  - creation of new data, modifying, deletion of old data and their truth values;
  - input and output of data;
  - instructions for controlling the rule-firing process itself.

**IF** (speed is fast) *and* (it is raining) *and not* (windshield wipers on)  
**THEN** turn on windshield wipers, reduce speed

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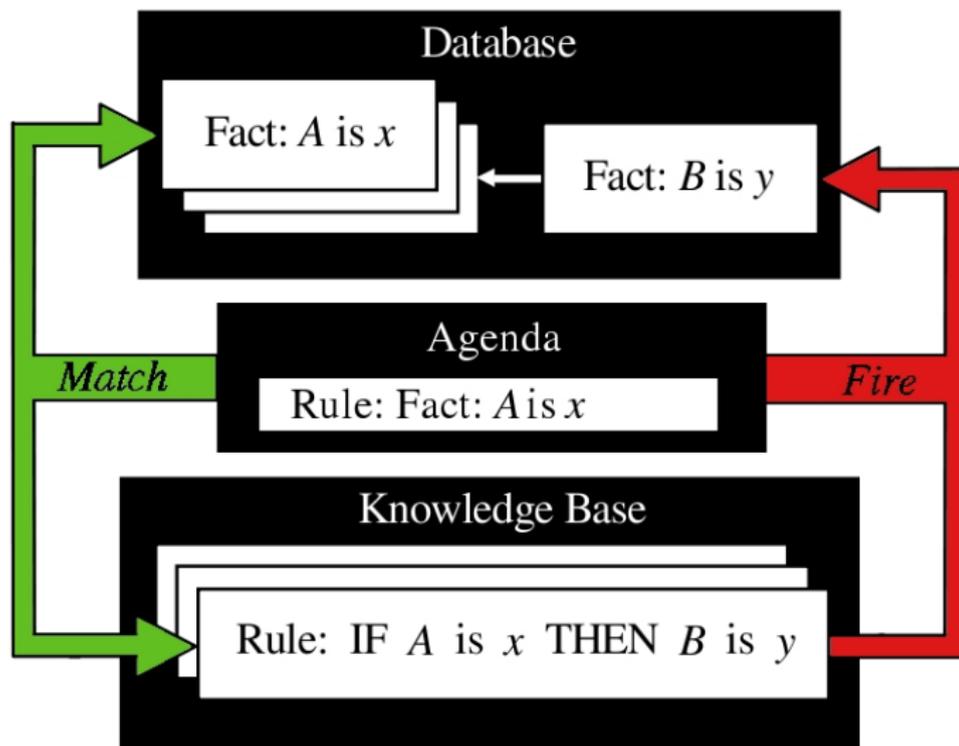
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Inference performed by ES

An inference cycle:



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Inference performed by ES

## AN INFERENCE CYCLE

- 1 If there are no rules on the **agenda**, then execution is **halted**.
- 2 The top rule on the **agenda** is **selected** for execution.
- 3 The **consequent** actions of the selected rule are **executed**.
- 4 Deactivated rules are **removed** from the **agenda**.
- 5 Activated rules are **placed** on the **agenda**.  
**Pattern matching** - performed using the **Rete algorithm** [Forgy, 1982].
- 6 The **placement** on the **agenda** is determined by the **salience** of the rule and the current **conflict resolution strategy**.
- 7 **Dynamic salience** values for all rules on the **agenda** are re-evaluated.
- 8 **Repeat** the cycle beginning with step (1).

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### CHARACTERISTICS

- Non-procedural, data-driven.
- A technique for gathering information and then inferring from it whatever can be inferred.
- Many rules may be executed that have nothing to do with the established goal.
- If our goal is to infer only one particular fact, the forward chaining inference technique would not be efficient.

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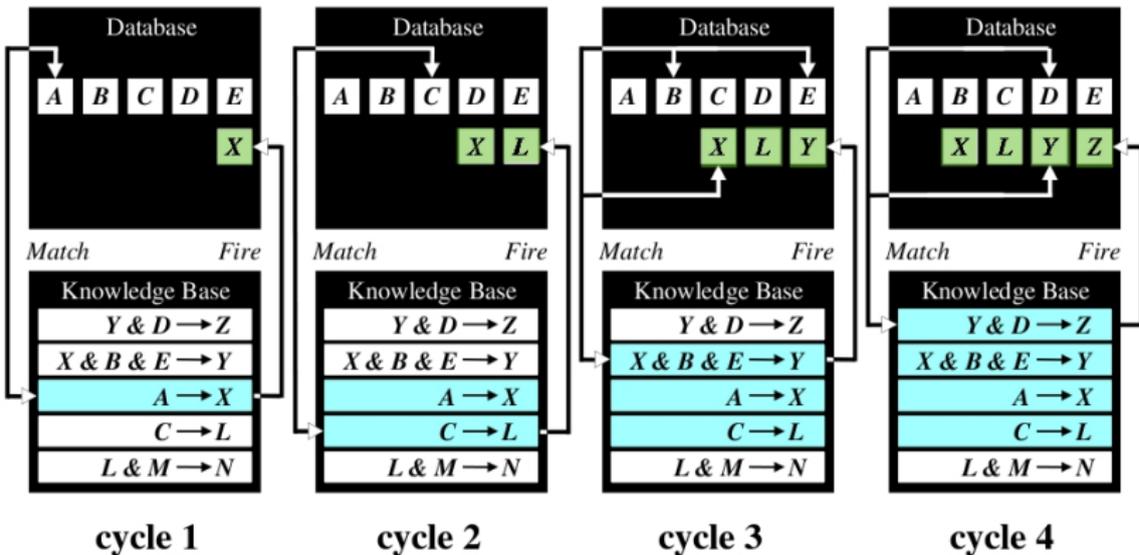
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## Forward chaining

### A forward chaining inference:



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# Basic architecture of rule-based ES

## Backward chaining

### CHARACTERISTICS

- Non-procedural, goal-driven.
- For a goal (a hypothetical solution) - the inference engine **attempts to prove** it (find an evidence).
- The knowledge base is **searched** to find rules that **might have** the desired goal in their **THEN** parts. They are **put** on the stack.
- Conditions in their **IF** parts are **new sub-goals**.
- If such a rule is **found** that its **IF** part **matches** data in the database, then the rule is **fired** and **removed** from the stack.
- Inference is **performed** until either the desired goal is **proved** or the stack is **empty**.

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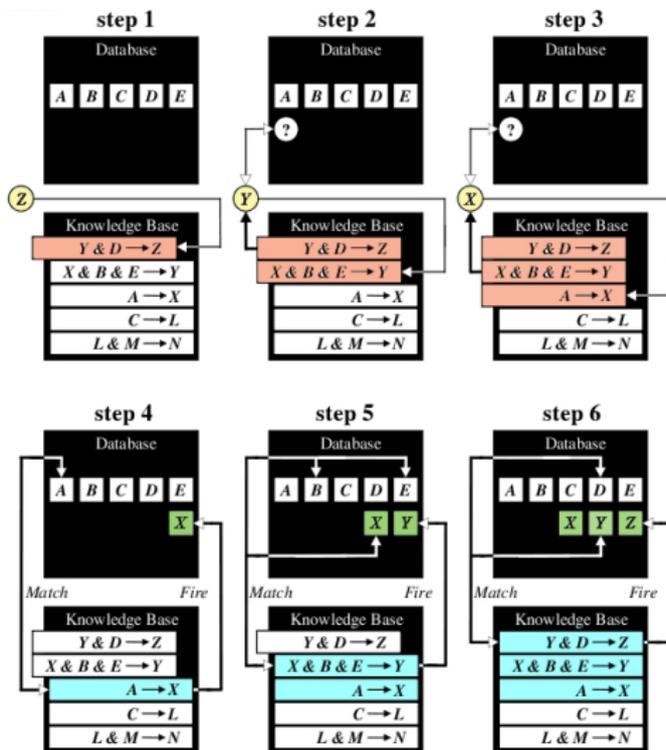
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## Backward chaining

A backward chaining inference:



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# Basic architecture of rule-based ES

## Basic inference techniques

### USAGE

- **Forward chaining** - if the expert first needs to gather some information and then tries to infer from it whatever can be inferred.
- **Backward chaining** - if the expert begins with a hypothetical solution and then attempts to find facts to prove it.
- Most *ES*, *FES* exploit **forward chaining**.
- **Forward chaining** much more advanced, especially in *FES*.
- **Backward chaining** can be simulated by **forward chaining** and vice-versa.

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# Basic architecture of rule-based ES

## Simulation of recursion

### Hanoi towers - an example of simulation in CLIPS

#### Decomposition rules:

```
(defrule r1
  (hanoi ?N ?A ?B ?C)
  =>
  (assert (run ?N ?N ?A ?B ?C)))

(defrule r2
  (run ?M ?N ?A ?B ?C)
  (test (> ?M 1))
  =>
  (assert (run (- ?M 1) ?N ?A ?C ?B))
  (assert (run (- ?M 1) ?N ?C ?B ?A)))
```

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## Simulation of recursion

### Hanoi towers - an example of simulation in CLIPS

#### Composition rules:

```
(defrule r3
  (run 1 ?N ?A ?B ?C)
=>
  (assert (sol 1 ?N ?A ?B ?C ?A "->" ?B)))

(defrule r4
  (sol ?M ?N ?A ?C ?B $?Mv1)
  (test (< ?M ?N))
  (sol ?M ?N ?C ?B ?A $?Mv2)
=>
  (assert (sol (+ ?M 1) ?N ?A ?B ?C $?Mv1 ?A "->" ?B $?Mv2)))

(defrule r5
  (hanoi ?N ?A ?B ?C)
  (sol ?N ?N ?A ?B ?C $?Mv)
=>
  (assert (hanoi_sol ?N ?A ?B ?C $?Mv)))
```

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## Conflict resolution strategies

### AGENDA

- The agenda - the list of all rules which have their conditions satisfied and have not yet been executed, **fired**.
- The agenda - similar to a stack; the top rule on the agenda is the first one to be executed.
- The placement of a newly activated rule:
  - Newly activated rules - above all rules of lower salience and below all rules of higher salience.
  - The **conflict resolution strategies** are used to determine the placement among rules of equal salience.

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## Conflict resolution strategies

- **Depth strategy:** newly activated rules - placed above all rules of the same salience.

rule-1: f-1, f-2	⇒	rule-2: f-3, f-1
rule-2: f-3, f-1		rule-4: f-3, f-2
rule-3: f-2		rule-3: f-2
rule-4: f-3, f-2		rule-1: f-1, f-2

- **Breadth strategy:** newly activated rules - placed below all rules of the same salience.

rule-1: f-1, f-2	⇒	rule-1: f-1, f-2
rule-2: f-3, f-1		rule-3: f-2
rule-3: f-2		rule-4: f-3, f-2
rule-4: f-3, f-2		rule-2: f-3, f-1

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## Conflict resolution strategies

- **The specificity of a rule** - the number of comparisons that must be performed on the *IF* part of the rule;
  - a comparison to a constant or previously bound variable **+1**;
  - a function call as part of a test conditional element **+1**;
  - the boolean functions *and*, *or*, *not* do not add, but their arguments do.

(defrule example

(item ?x ?y ?x)

(test (and (numberp ?x) (> ?x (+ 10 ?y)) (< ?x 100)))  
=>)

has a specificity of 5.

- **Simplicity strategy**: newly activated rules - placed above all activations of rules with equal or higher specificity.
- **Complexity strategy**: newly activated rules - placed above all activations of rules with equal or lower specificity.

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## Conflict resolution strategies

- *LEX* strategy:

- the time tag of a fact - its relative recency with respect to every other fact;
- the pattern entities associated with a rule activation - sorted in descending order;
- an activation with more recent pattern entities - placed above activations with less recent pattern entities using the lexicographical order;
- an activation with more pattern entities than the other activation and the compared time tags - all identical - placed above the other activation;
- for two activations with the exact same recency, the activation with the higher specificity - placed above the activation with the lower specificity.

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## Conflict resolution strategies

- *LEX* strategy:

- the time tag of *not*  $CE_1$
- less than the time tag of a pattern entity,
- greater than the time tag of *not*  $CE_2$  instantiated after *not*  $CE_1$ .

rule-6: f-1, f-4

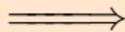
rule-5: f-1, f-2, f-3

rule-1: f-2, f-3

rule-2: f-3, f-1

rule-4: f-1, f-2

rule-3: f-2



rule-6: f-4, f-1

rule-5: f-3, f-2, f-1

rule-1: f-3, f-2

rule-2: f-3, f-1

rule-4: f-2, f-1

rule-3: f-2

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## Conflict resolution strategies

- *MEA* (Means-end analysis) strategy:
  - an activation with the **greater** time tag of the fact **associated** with the **first** pattern entity than the first pattern entity's time tag of another activation - **placed above** the other activation;
  - for activations with the **same** time tag associated with their **first** pattern entities, the *LEX* strategy used.

rule-6:	f-1, f-4	rule-2:	f-3, f-1
rule-5:	f-1, f-2, f-3	rule-1:	f-2, f-3
rule-1:	f-2, f-3	rule-3:	f-2
rule-2:	f-3, f-1	rule-6:	f-1, f-4
rule-4:	f-1, f-2	rule-5:	f-1, f-3, f-2
rule-3:	f-2	rule-4:	f-1, f-2

# Introduction to fuzzy mathematics - Plan:

- Fuzzy *and* operator
- Fuzzy *or* operator
- Fuzzy *implication* (*residuum*) operator
- Fuzzy sets
- Fuzzy numbers
- Fuzzy arithmetic
- Comparing fuzzy numbers
- Interval arithmetic
- Linguistic variables
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# Introduction to fuzzy mathematics

## Fuzzy *and* operator

A *t*-norm  $T$  is a function  $T : [0, 1] \times [0, 1] \rightarrow [0, 1]$ :

$$T(a, 1) = a; \quad (1 \text{ is a neutral element})$$

$$T(a, b) = T(b, a); \quad (\text{commutativity})$$

$$\text{if } a_1 \leq a_2, \text{ then } T(a_1, b) \leq T(a_2, b); \quad (\text{monotonicity})$$

$$T(a, T(b, c)) = T(T(a, b), c); \quad (\text{associativity})$$

- denoted in infix notation as  $*$ .

- Gödel, Zadeh operator:  $a *_{m} b = \min(a, b)$ ;
- the product, probabilistic operator:  $a *_{p} b = a \cdot b$ ;
- Łukasiewicz, the bounded difference operator:

$$a *_{\text{Ł}} b = \max(0, a + b - 1);$$

- the drastic intersection operator:

$$a *_{d} b = \begin{cases} a & \text{if } b = 1, \\ b & \text{if } a = 1, \\ 0 & \text{else.} \end{cases}$$

$$*_{d} \leq *_{\text{Ł}} \leq *_{p} \leq *_{m}$$

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# Introduction to fuzzy mathematics

## Fuzzy or operator

A  $t$ -conorm  $C$  is a function  $C : [0, 1] \times [0, 1] \rightarrow [0, 1]$ :

$$C(a, 0) = a; \quad (0 \text{ is a neutral element})$$

$$C(a, b) = C(b, a); \quad (\text{commutativity})$$

$$\text{if } a_1 \leq a_2, \text{ then } C(a_1, b) \leq C(a_2, b); \quad (\text{monotonicity})$$

$$C(a, C(b, c)) = C(C(a, b), c); \quad (\text{associativity})$$

- denoted in infix notation as  $\oplus$ .

• The standard union, Zadeh operator:  $a \oplus_m b = \max(a, b)$ ;

• the algebraic sum, probabilistic operator:

$$a \oplus_p b = a + b - a \cdot b;$$

• Łukasiewicz, the bounded sum operator:

$$a \oplus_{\text{Ł}} b = \min(1, a + b);$$

• the drastic union operator:

$$a \oplus_d b = \begin{cases} a & \text{if } b = 0, \\ b & \text{if } a = 0, \\ 1 & \text{else.} \end{cases}$$

$$\oplus_m \leq \oplus_p \leq \oplus_{\text{Ł}} \leq \oplus_d$$

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# Introduction to fuzzy mathematics

## Fuzzy *and*, *or* operators

$$T_m(a_1, \dots, a_n) = \min(a_1, \dots, a_n),$$

$$C_m(a_1, \dots, a_n) = \max(a_1, \dots, a_n);$$

$$T_{\perp}(a_1, \dots, a_n) = \max(0, (\sum_{i=1}^n a_i) - n + 1),$$

$$C_{\perp}(a_1, \dots, a_n) = \min(1, \sum_{i=1}^n a_i);$$

$$T_p(a_1, \dots, a_n) = a_1 \cdots a_n,$$

$$C_p(a_1, \dots, a_n) = \sum_{i=1}^n (-1)^{i-1} \sum_{\substack{J \subseteq \{1, \dots, n\}, \\ |J| = i}} \prod_{k \in J} a_k;$$

$$T_d(a_1, \dots, a_n) = \begin{cases} a_i & \text{if } \exists 1 \leq i \leq n \text{ and } \forall 1 \leq j \neq i \leq n a_j = 1, \\ 0 & \text{else,} \end{cases}$$

$$C_d(a_1, \dots, a_n) = \begin{cases} a_i & \text{if } \exists 1 \leq i \leq n \text{ and } \forall 1 \leq j \neq i \leq n a_j = 0, \\ 1 & \text{else.} \end{cases}$$

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# Introduction to fuzzy mathematics

## Fuzzy implication (residuum) operator

$$\mathbf{L} = ([0, 1], \leq, \vee, \wedge, *, \Rightarrow, \bar{\phantom{x}}, \oplus, 0, 1)$$

- a complete residuated lattice algebra,
  - $\leq$  - the linear order,
  - $\vee$  - the supremum,  $a \vee b = \max(a, b)$ ,
  - $\wedge$  - the infimum,  $a \wedge b = \min(a, b)$ ,
  - $*$  - a  $t$ -norm,  $\Rightarrow$  - its residuum,  $\oplus$  - its  $t$ -conorm,
  - $\bar{\phantom{x}}$  - the negation operator.

$$\textcircled{1} \quad a * b \leq c \iff a \leq b \Rightarrow c, \quad (\text{condition of residuation})$$

$$\textcircled{2} \quad \bar{a} = a \Rightarrow 0, \quad (\text{condition of negation})$$

$$\textcircled{3} \quad a \oplus b = \overline{\bar{a}^t * \bar{b}^t}, \quad (\text{condition of duality})$$

$$\textcircled{4} \quad a * (b \vee c) = a * b \vee a * c, \quad (\text{distributivity of } * \text{ over } \vee)$$

$$\textcircled{5} \quad a * b \leq a \wedge b,$$

$$\textcircled{6} \quad a \vee b \leq a \oplus b.$$

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## Fuzzy implication (residuum) operator

- Gödel residuum operator:

$$a \Rightarrow_G b = \begin{cases} 1 & \text{if } a \leq b, \\ b & \text{else;} \end{cases}$$

- the product, Goguen residuum operator:

$$a \Rightarrow_P b = \begin{cases} 1 & \text{if } a \leq b, \\ b/a & \text{else;} \end{cases}$$

- Łukasiewicz residuum operator:  $a \Rightarrow_L b = \max(0, 1 - a + b)$ ;

- the drastic residuum operator:

$$a \Rightarrow_D b = \begin{cases} b & \text{if } a = 1, \\ 1 & \text{else;} \end{cases}$$

- the crisp, Gaines-Rescher residuum operator:

$$a \Rightarrow_C b = \begin{cases} 1 & \text{if } a \leq b, \\ 0 & \text{else;} \end{cases}$$

- Zadeh residuum operator:  $a \Rightarrow_Z b = \max(1 - a, \min(a, b))$ .

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# Introduction to fuzzy mathematics

## Fuzzy sets

A fuzzy set  $F$  is a function  $F : U \rightarrow [0, 1]$  [Zadeh, 1965];

- $U \neq \emptyset$  - the universum;
- a fuzzy set - identified by its membership function;
- $F(x)$  - the **grade of membership** of  $x$  in  $F$ .

## BASIC OPERATIONS

Let  $A, B$  be fuzzy sets.

**Intersection:**  $A \cap B(x) = A(x) *_m B(x) = \min(A(x), B(x));$

**Union:**  $A \cup B(x) = A(x) \oplus_m B(x) = \max(A(x), B(x));$

**Algebraic product:**  $A *_p B(x) = A(x) *_p B(x);$

**Algebraic sum:**  $A \oplus_p B(x) = A(x) \oplus_p B(x);$

**Bounded product:**  $A *_l B(x) = A(x) *_l B(x);$

**Bounded sum:**  $A \oplus_l B(x) = A(x) \oplus_l B(x);$

**Complement:**  $\overline{A}(x) = \overline{A(x)}^l = 1 - A(x).$

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### BASIC NOTATION

Let  $A, B : U \rightarrow [0, 1]$  be fuzzy sets and  $\alpha \in [0, 1]$ .

$$A \subseteq B \iff \forall x \in U \ A(x) \leq B(x),$$

$$\text{support}(A) = \{x \mid A(x) > 0\},$$

$$\text{kernel}(A) = \{x \mid A(x) = 1\},$$

$$A[\alpha] = \{x \mid A(x) \geq \alpha\} \quad - \text{ } \alpha\text{-cut of } A,$$

$$A^\alpha = \{x \mid A(x) = \alpha\} \quad - \text{ } \alpha\text{-value of } A,$$

$$\text{height}(A) = \bigvee \{A(x) \mid x \in U\}.$$

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### SPECIAL CASES

- Discrete fuzzy sets:

$D : U \longrightarrow [0, 1]$ ,  $U$  - a finite set or only

a finite number of  $x_1, \dots, x_n \in U$  such that  $D(x_i) > 0$ ;

$$\left\{ \frac{D(x_1)}{x_1}, \dots, \frac{D(x_n)}{x_n} \right\};$$

- numerical - members describe a numeric quantity:

$$\text{Size} = \left\{ \frac{\mu_1}{\text{small}}, \frac{\mu_2}{\text{medium}}, \frac{\mu_3}{\text{large}} \right\};$$

- non-numerical - members describe a non-numeric quantity:

$$\text{Species} = \left\{ \frac{\mu_1}{\text{hamster}}, \frac{\mu_2}{\text{rabbit}}, \frac{\mu_3}{\text{hare}} \right\}.$$

### SPECIAL CASES

- Fuzzy numbers:

$\tilde{n} : \mathbb{R} \rightarrow [0, 1]$ , of whose value we are somewhat uncertain;

- $\tilde{n}$  - normal:  $\exists x \tilde{n}(x) = 1$ ;

- convex:

$$\forall \lambda \in [0, 1] \tilde{n}(\lambda \cdot x_1 + (1 - \lambda) \cdot x_2) \geq \min(\tilde{n}(x_1), \tilde{n}(x_2));$$

- continuous;

- shape: - triangular (piecewise linear),

- s-shape (piecewise quadratic),

- normal (bell-shaped, Gaussian);

- fuzzy intervals: - trapezoidal shape, a sub-interval of 1,

- linear, s-shape, normal tails,

- the increasing and decreasing slopes.

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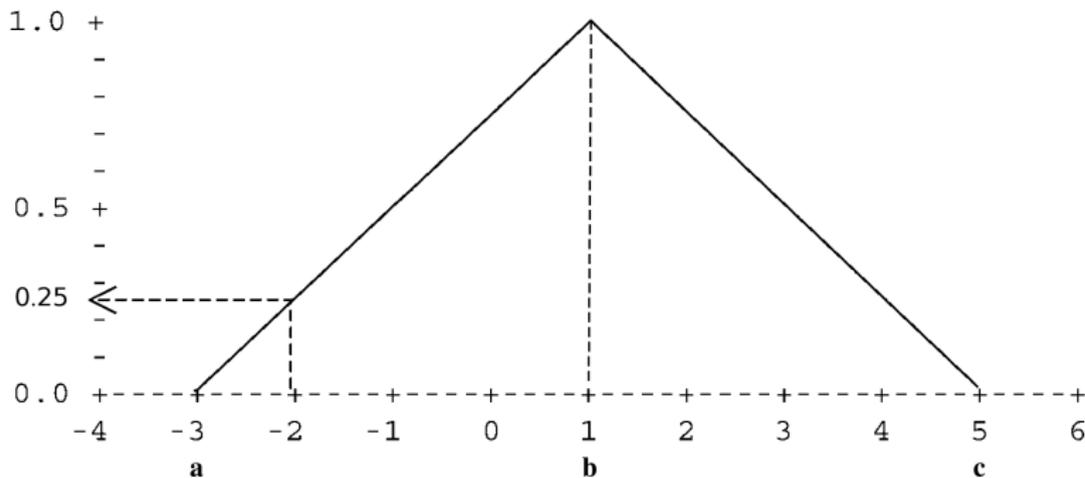
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# Introduction to fuzzy mathematics

## Fuzzy numbers

A triangular fuzzy number:



$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a, \\ \frac{x-a}{b-a} & \text{if } a < x \leq b, \\ \frac{c-x}{c-b} & \text{if } b < x \leq c, \\ 0 & \text{if } x > c. \end{cases}$$

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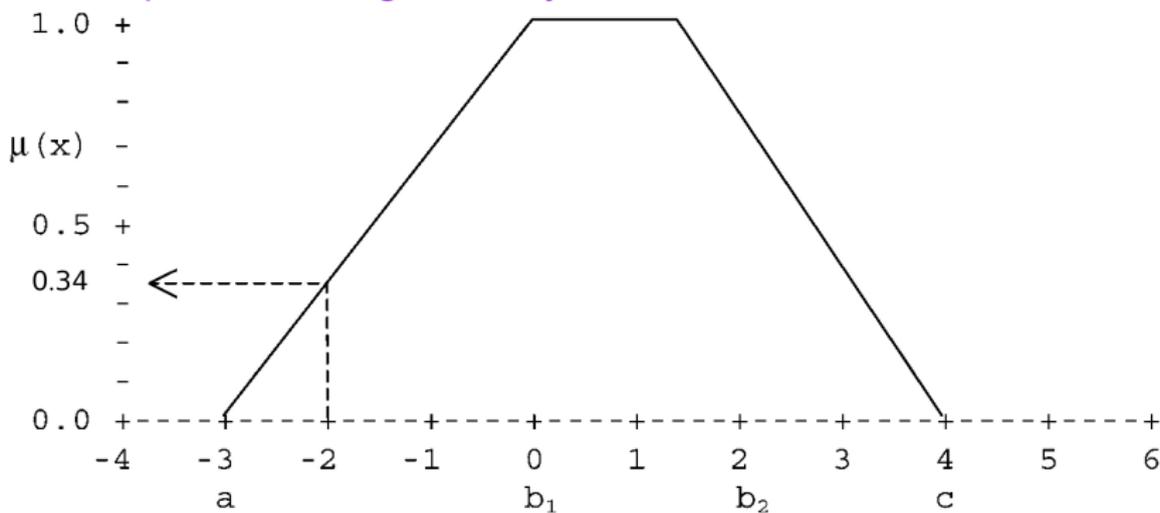
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### A trapezoidal triangular fuzzy number:

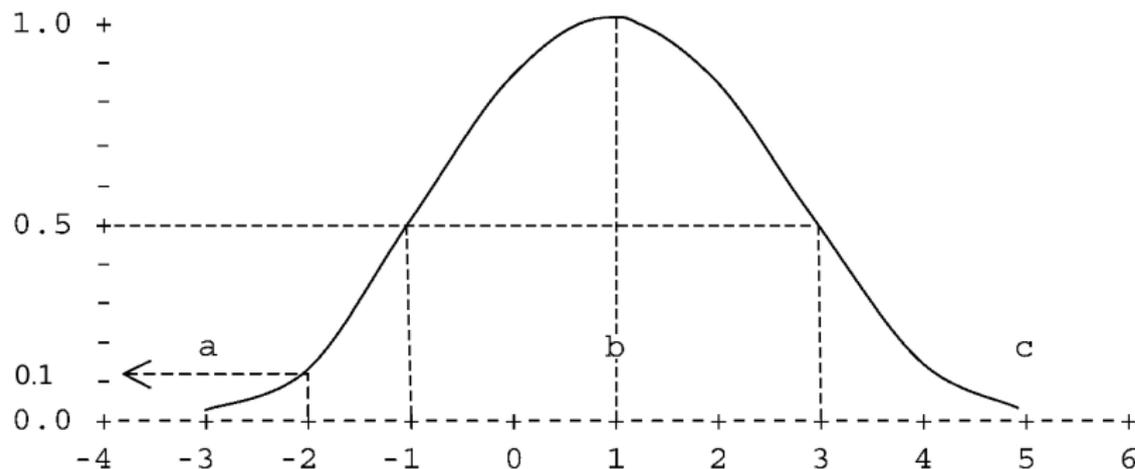


$$\mu(x) = \begin{cases} 0 & \text{if } x \leq a, \\ \frac{x-a}{b_1-a} & \text{if } a < x < b_1, \\ 1 & \text{if } b_1 \leq x \leq b_2, \\ \frac{c-x}{c-b_2} & \text{if } b_2 < x \leq c, \\ 0 & \text{if } x > c. \end{cases}$$

# Introduction to fuzzy mathematics

## Fuzzy numbers

### An s-shape fuzzy number:



$$\mu(x) = \begin{cases} k_1 \cdot (x - a)^2 & \text{if } a \leq x \leq \frac{a+b}{2}, \\ 1 - k_1 \cdot (b - x)^2 & \text{if } \frac{a+b}{2} < x \leq b, \\ 1 - k_2 \cdot (x - b)^2 & \text{if } b < x \leq \frac{b+c}{2}, \\ k_2 \cdot (c - x)^2 & \text{if } \frac{b+c}{2} < x \leq c, \end{cases}$$

$k_1, k_2$  - from  $\mu(x) = 1/2$  for  $x = \frac{a+b}{2}$  and  $x = \frac{b+c}{2}$ .

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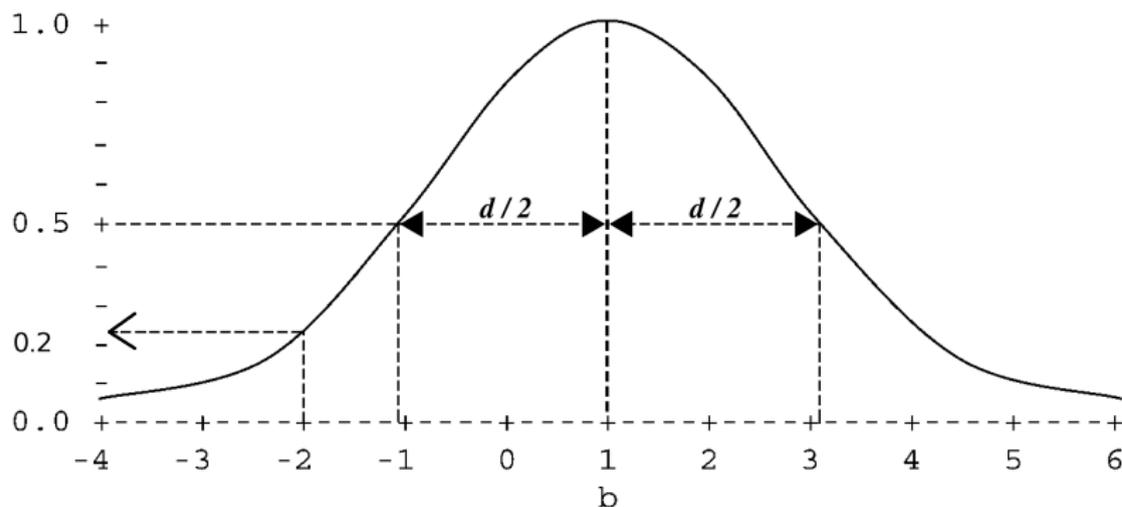
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## Fuzzy numbers

A normal (bell-shaped, Gaussian) fuzzy number:



$$\mu(x) = \exp\left(\ln\frac{1}{2}\right)\left(\frac{x-b}{d/2}\right)^2.$$

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### EXTENSION PRINCIPLE [Zadeh, 1975]

- A general tool used to fuzzify crisp operations (+, −, ·, /).

Let  $A$ ,  $B$  be fuzzy numbers, and  $*$  a crisp operation.

$$C(z) = \bigvee_{x * y = z} \{\min(A(x), B(y))\}.$$

- The procedure is computationally expensive.

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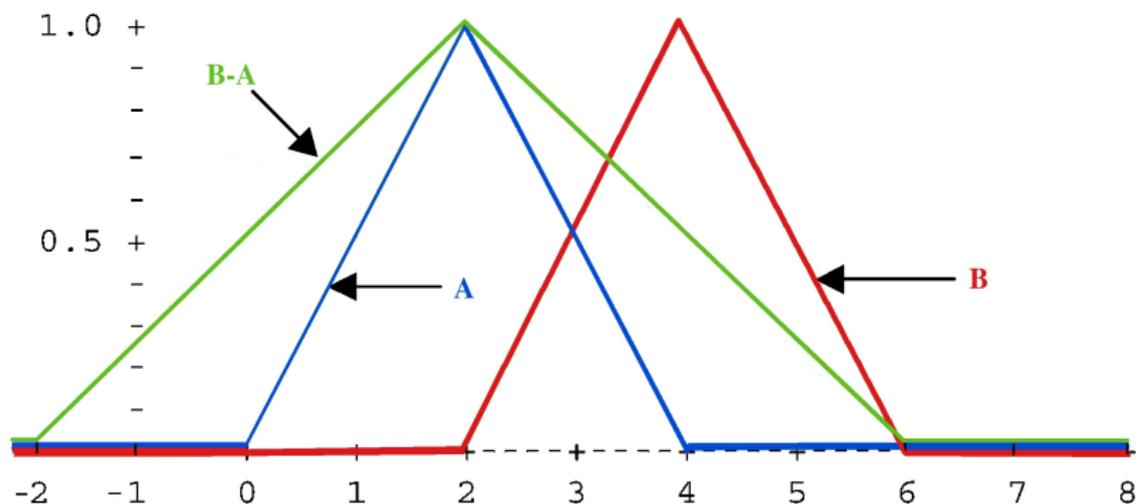
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## Fuzzy arithmetic

### Subtraction of fuzzy numbers:



$$B-A(z) = \bigvee_{x,y} \{ \min(A(x), B(y)) \mid y - x = z \}.$$

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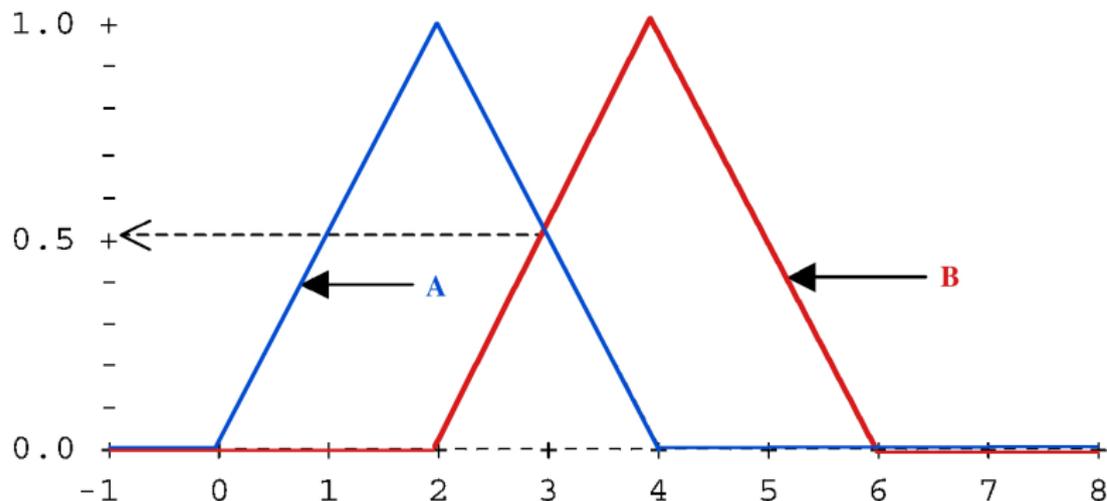
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# Introduction to fuzzy mathematics

## Comparing fuzzy numbers

Approximate equality  $\approx =$  :



$$A \approx B = \bigvee_x \{ \min(A(x), B(x)) \}.$$

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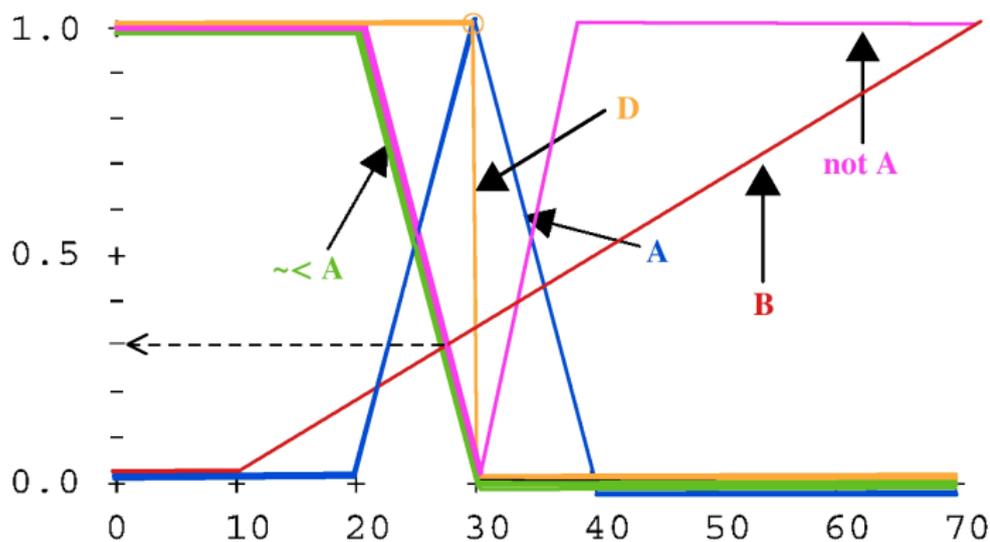
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# Introduction to fuzzy mathematics

## Comparing fuzzy numbers

### Approximate less $\sim <$ :



$$B \sim < A = \bigvee_x \{ \min(\bar{A} \cap D(x), B(x)) \},$$

$$D(z) = \begin{cases} 1 & \text{if } z < \min\{v \mid A(v) = 1\}, \\ 0 & \text{else.} \end{cases}$$

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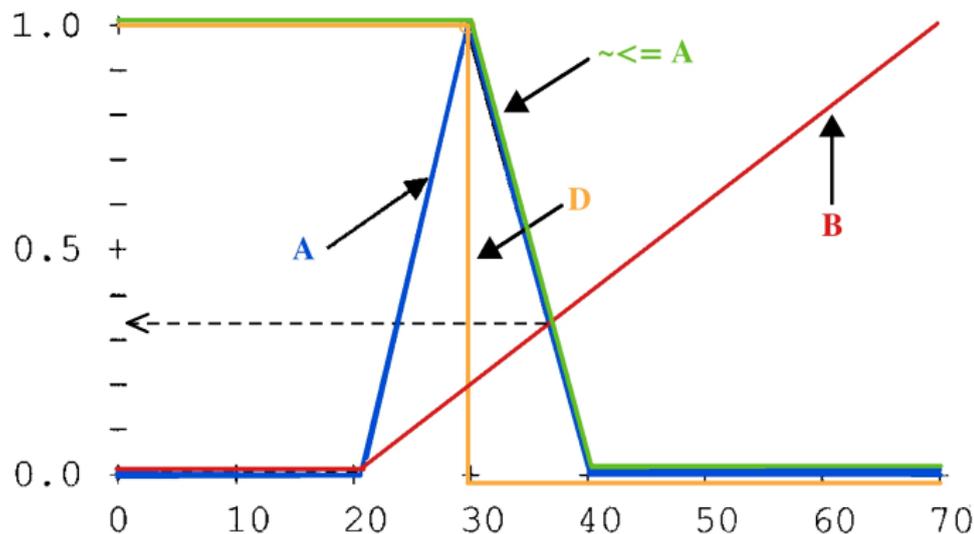
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# Introduction to fuzzy mathematics

## Comparing fuzzy numbers

### Approximate less or equal $\sim \leq$ :



$$B \sim \leq A = \bigvee_x \{ \min(A \cup D(x), B(x)) \},$$

$$D(z) = \begin{cases} 1 & \text{if } z < \min\{v \mid A(v) = 1\}, \\ 0 & \text{else.} \end{cases}$$

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## Comparing fuzzy numbers

### ALTERNATE METHOD [Klir, Yuan, 1995]

Let  $A$  be a fuzzy number and  $\text{kernel}(A) = [a, b]$ .

$$\delta = \frac{a + b}{2},$$

$$L(x) = \begin{cases} 1 & \text{if } x \leq \delta, \\ 0 & \text{else,} \end{cases} \quad R(x) = \begin{cases} 1 & \text{if } x \geq \delta, \\ 0 & \text{else,} \end{cases}$$

$$\sim < A = \bar{A} \cap L,$$

$$\sim \leq A = \sim < A \oplus_{\perp} L,$$

$$\sim > A = \bar{A} \cap R,$$

$$\sim \geq A = \sim > A \oplus_{\perp} R.$$

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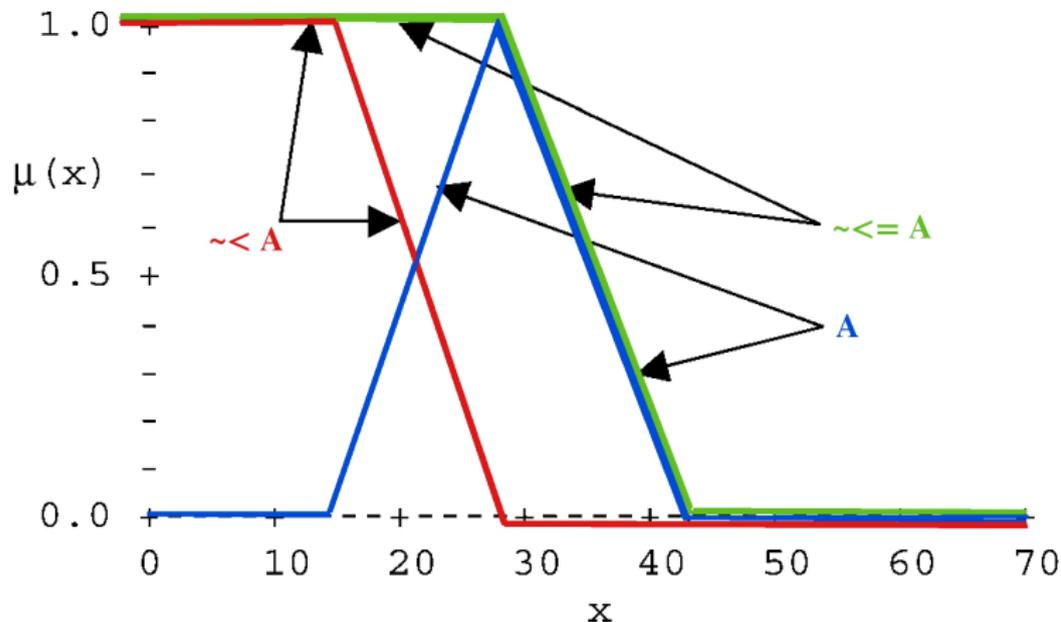
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# Introduction to fuzzy mathematics

## Comparing fuzzy numbers

### ALTERNATE METHOD

$\sim < A$  and  $\sim \leq A$ :



### BASE OF A FUZZY NUMBER

Let  $A$  be a fuzzy number and  $\alpha \in (0, 1]$ .

- The base of a fuzzy number:

triangular:  $A[0] = [a, b],$

trapezoidal:  $A[0] = [a, c],$

s-shape:  $A[0] = [a, c],$

normal:  $A[0] = [a - 3\delta, a + 3\delta].$

- $A[\alpha] = [a_1(\alpha), a_2(\alpha)]$  - a closed, bounded, interval.

# Introduction to fuzzy mathematics

## Interval arithmetic

### INTERVAL EXTENSION

Let  $[a, b]$ ,  $[c, d]$  be closed, bounded, intervals;  
\* denote  $+$ ,  $-$ ,  $\cdot$ ,  $/$  on  $\mathbb{R}$ .

- The interval extension:

$$[a, b] * [c, d] = \{x * y \mid x \in [a, b], y \in [c, d]\},$$

$$[a, b] + [c, d] = [a + c, b + d],$$

$$[a, b] - [c, d] = [a - d, b - c],$$

$$[a, b] \cdot [c, d] = [\min\{a \cdot c, a \cdot d, b \cdot c, b \cdot d\}, \\ \max\{a \cdot c, a \cdot d, b \cdot c, b \cdot d\}],$$

$$[a, b] / [c, d] = [a, b] \cdot \left[\frac{1}{d}, \frac{1}{c}\right], \quad 0 \notin [c, d],$$

$$A * B[\alpha] = A[\alpha] * B[\alpha] = [a_1(\alpha), a_2(\alpha)] * [b_1(\alpha), b_2(\alpha)].$$

Both the methods - the same results for  $+$ ,  $-$ ,  $\cdot$ ,  $/$ ; not e.g. for  $\frac{A+B}{A}$ .

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### LINGUISTIC VARIABLE - A MODIFIED VERSION

[Zadeh, 1974], [Zadeh, 1975]

- The linguistic type of a linguistic variable - determined by
  - a finite set  $T$  of linguistic terms (slow, medium, ...);
  - the universum  $U - \mathbb{R}$  (an interval);
  - for each linguistic term  $t \in T$  - a fuzzy set (fuzzy number)  
 $F_t : U \rightarrow [0, 1]$ .
- A value of a linguistic variable is a numerical discrete fuzzy set  
 $D : T \rightarrow [0, 1]$ ;

$$\text{Speed} = \left\{ \frac{\mu_1}{\text{slow}}, \frac{\mu_2}{\text{medium}}, \frac{\mu_3}{\text{fast}} \right\}.$$

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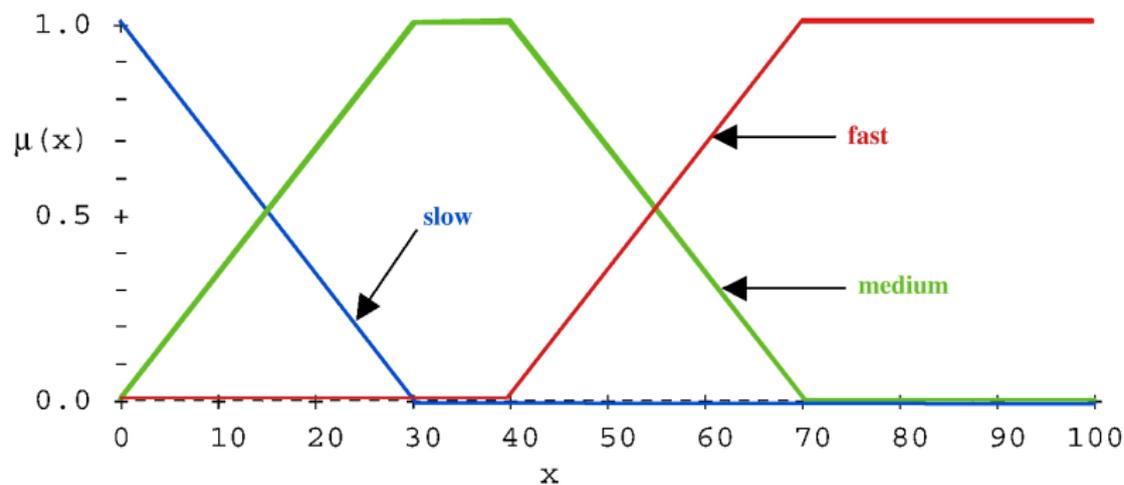
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## Linguistic variables

Linguistic terms of a linguistic variable **Speed** and their fuzzy sets:



$$\text{Speed} = \left\{ \frac{0.4}{\text{slow}}, \frac{0.6}{\text{medium}}, \frac{0.1}{\text{fast}} \right\}.$$

# Introduction to fuzzy mathematics

## Hedges

**HEDGES** [Zadeh, 1972], [Cox, 1999]

Hedges - modifiers, adjectives, or adverbs, which change truth values;

- about, nearly, roughly, extremely;
- several types of hedges.

Dispersion hedges for triangular fuzzy numbers:

Hedge	Spread: $[z \cdot (1 - \frac{x}{100}), z \cdot (1 + \frac{x}{100})]$ of the central value $z$ at a membership of 0.5
nearly	5%
approximately	10%
about	15%
roughly	25%
crudely	50%

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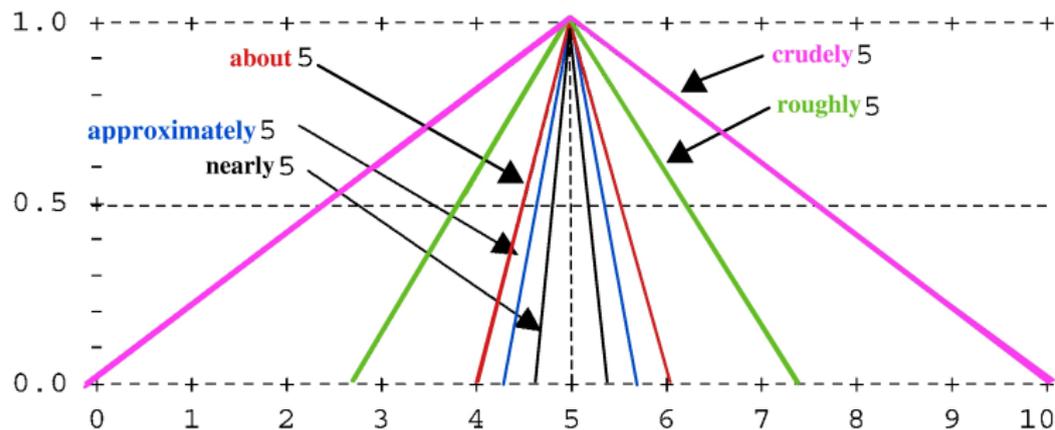
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## Hedges

Triangular fuzzy numbers of 5 created by various dispersion hedges:



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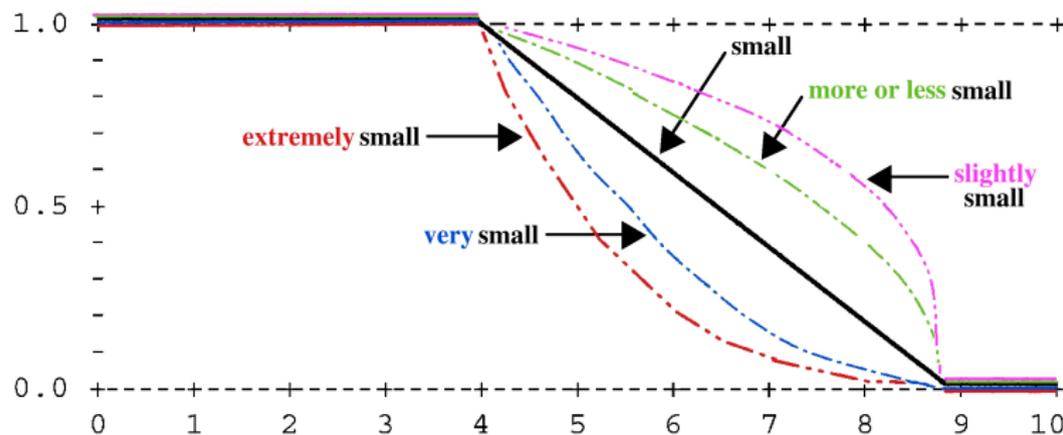
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# Introduction to fuzzy mathematics

## Hedges

### Powering hedges:

Hedge	Power
slightly	$F(x)^{\frac{1}{3}}$
more or less	$F(x)^{\frac{1}{2}}$
very	$F(x)^2$
extremely	$F(x)^3$

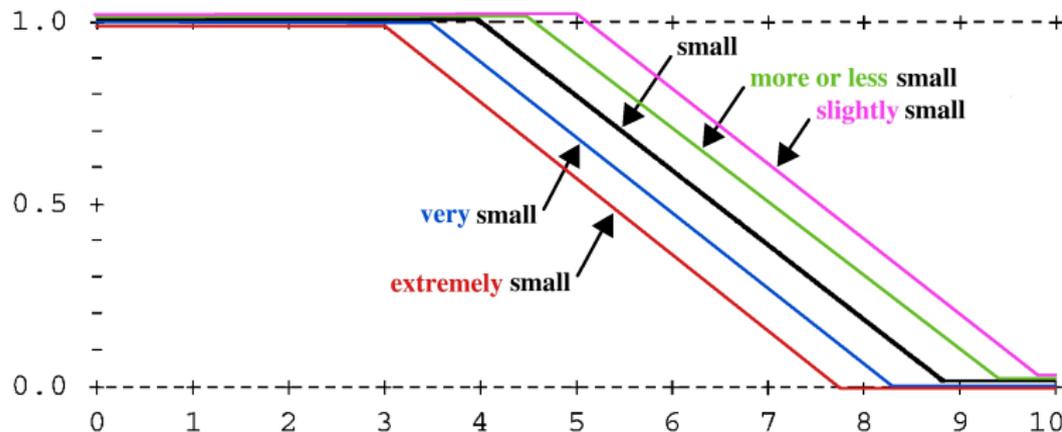


# Introduction to fuzzy mathematics

## Hedges

Shifting hedges for decreasing fuzzy sets:

Hedge	Shift
slightly	$F(x - 1)$
more or less	$F(x - \frac{1}{2})$
very	$F(x + \frac{1}{2})$
extremely	$F(x + 1)$



# Fuzzy inference - Plan:

- Fuzzification
- Defuzzification
- Fuzzy rule (Mamdani type)
- Fuzzy rule (Sugeno-Takagi type)
- Fuzzy inference systems (*FIS*)

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# Fuzzy inference

## Fuzzification

### BASICS

Fuzzification means

- 1 to find the fuzzy version of a crisp concept;
- 2 to find the degrees of membership of linguistic terms of a linguistic variable for an input (scalar, fuzzy) number.

- A fuzzy number  $t$  with the universum  $[0, 100]$  ( $^{\circ}\text{C}$ ) of temperature;
- a linguistic variable **Temperature** with linguistic terms **low**, **medium**, **high** on  $[0, 100]$ .
- **Fuzzification** - the degree of membership of each linguistic term:

$$\mu(\text{low}) = t \sim \text{low},$$

$$\mu(\text{medium}) = t \sim \text{medium},$$

$$\mu(\text{high}) = t \sim \text{high}.$$

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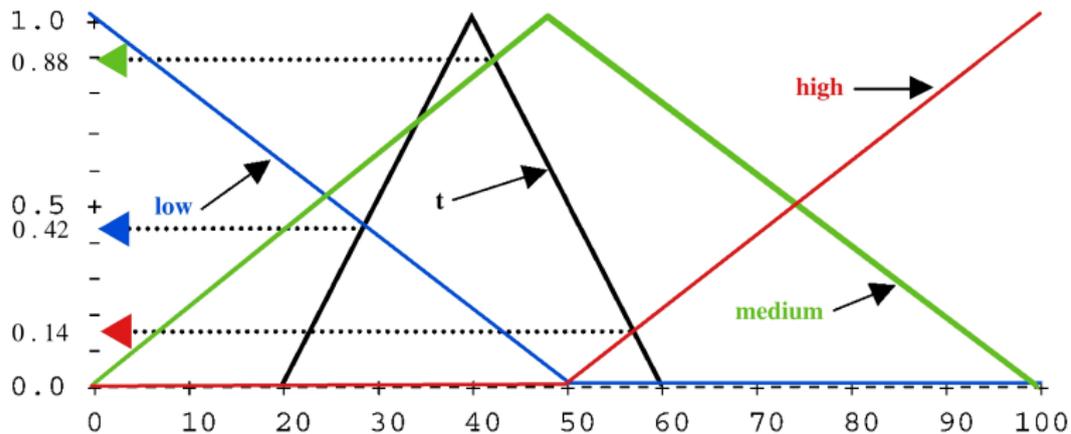
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# Fuzzy inference

## Fuzzification

Fuzzification of  $t$  into the linguistic variable **Temperature**:



$$\text{Temperature} = \left\{ \frac{0.42}{\text{low}}, \frac{0.88}{\text{medium}}, \frac{0.14}{\text{high}} \right\}.$$

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### OVERVIEW

Defuzzification is the conversion of a fuzzy set to a crisp set.

- Defuzzification to a point:
  - maxima methods,
  - distribution methods,
  - area methods.
- Defuzzification to a set:
  - averaging procedures,
  - average  $\alpha$ -cuts.
- An example of defuzzification methods.
- Recovering the crisp original value.

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### Defuzzification to a point

#### Maxima methods:

- The computation (selection) of an element on the basis of the maxima (local, global) of a fuzzy set as the defuzzification value - simplicity.

- *RCOM* - a random choice of maximum;

- *FOM* - the first of maxima;

- *LOM* - the last of maxima;

- *MiOM* - the middle of maxima;

- *MOM* - the mean of maxima:

$$MOM(F) = \frac{\sum_{i=1}^n x_{max_i}}{n};$$

- *WAOM* - the weighted average of maxima:

$$WAOM(F) = \frac{\sum_{i=1}^n x_{loc\_max_i} \cdot F(x_{loc\_max_i})}{\sum_{i=1}^n F(x_{loc\_max_i})}.$$

### Defuzzification to a point

#### Distribution methods:

- The conversion of a fuzzy set  $F$  into a probability distribution, the computation of the expected value.

- *COG* - the center of gravity:

$$COG(F) = \frac{\sum_{i=1}^n loc\_center_i \cdot loc\_area_i}{\sum_{i=1}^n loc\_area_i}, \quad COG(F) = \frac{\sum_{i=1}^n x_i \cdot F(x_i)}{\sum_{i=1}^n F(x_i)};$$

- *BADD* - the basic defuzzification distribution:

$$BADD(F, \gamma) = \frac{\sum_{i=1}^n loc\_center_i \cdot loc\_area_i^\gamma}{\sum_{i=1}^n loc\_area_i^\gamma}, \quad \gamma \in [0, \infty) - \text{the confidence};$$

- *GLSD* - the generalized level set defuzzification:

$$GLSD(F, \gamma) = \frac{\sum_{i=1}^n \mu_i \cdot |F[\alpha_i]| \cdot \gamma^i}{\sum_{i=1}^n |F[\alpha_i]| \cdot \gamma^i}, \quad \gamma \in (0, \infty), \quad \mu_i - \text{the average of } F[\alpha_i].$$

# Fuzzy inference

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### Defuzzification to a point

#### Area methods:

- COA - the center of area:

$$COA(F) = z \text{ such that } \left| \sum_{x=\min U}^z F(x) - \sum_{x=z}^{\max U} F(x) \right| - \text{least.}$$

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### Defuzzification to a set

#### Averaging procedures:

- The arithmetic mean of two sets:

$$\frac{1}{2}(A + B) = \{\frac{1}{2}(x + y) \mid x \in A, y \in B\};$$

- $A'$  - an averaging procedure:

$$A'(F, \alpha) = \frac{1}{2}(F[\alpha] + F[1 - \alpha]);$$

- $M$  - an averaging procedure:

$$M(F) = \frac{1}{2}(F[1] + F[\frac{1}{2}]).$$

#### Average $\alpha$ -cuts:

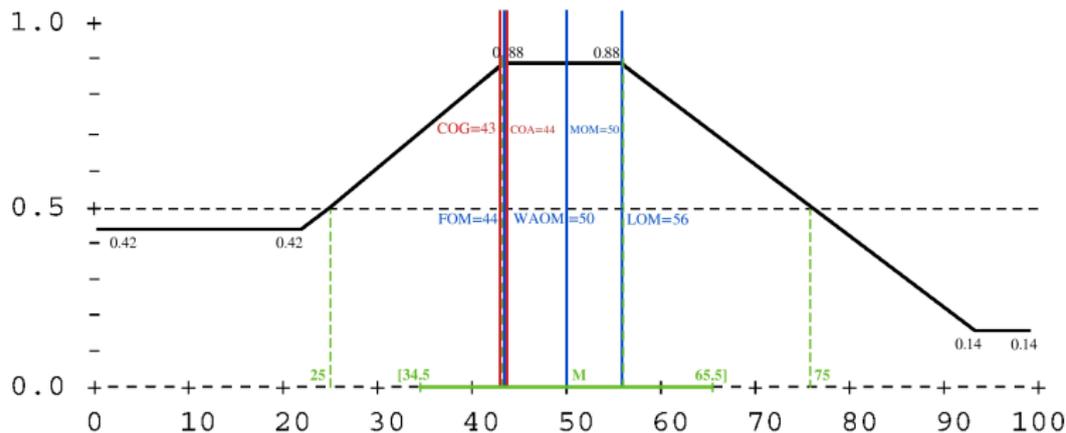
- $A$  - the average  $\alpha$ -cut:

$$A(F) = [\int_{[0,1]} \min F[\alpha] d\alpha, \int_{[0,1]} \max F[\alpha] d\alpha].$$

# Fuzzy inference

## Defuzzification

An example of defuzzification methods:



$$\text{Temperature} = \left\{ \frac{0.42}{\text{low}}, \frac{0.88}{\text{medium}}, \frac{0.14}{\text{high}} \right\}.$$

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### Defuzzification recovering the crisp original value

- A value  $y \in \mathbb{R}$  is fuzzified;
- a vector  $\mathbf{v}$  of membership degrees of all used linguistic terms - known;
- $y$  - recovered from  $\mathbf{v}$ .
- Suitable for fuzzy reasoning.

- *HeM* - the height method:

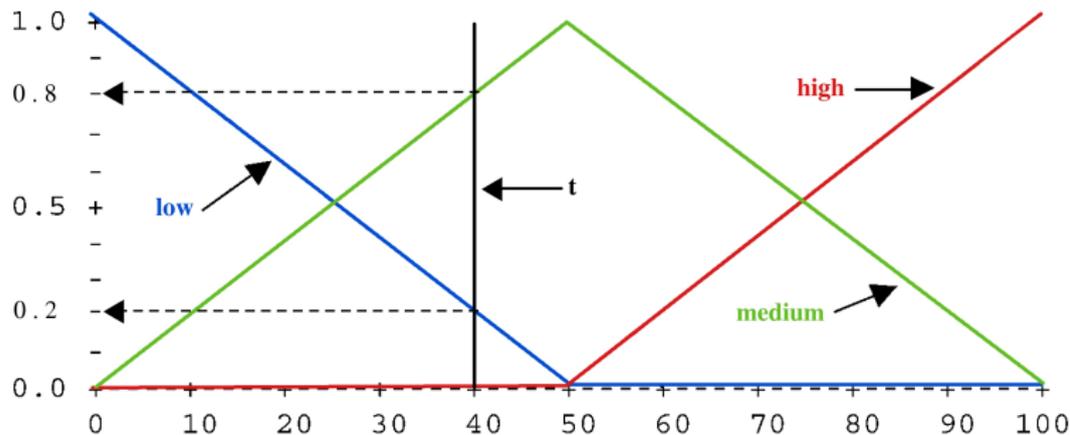
$$\text{HeM}(\mathbf{v}) = \frac{\sum_{i=1}^n v_i \cdot B_i}{\sum_{i=1}^n v_i},$$

- $f_i$  - a triangular fuzzy set with the barycenter  $B_i$ ;
- $\mathbf{v} = (v_1, \dots, v_n)$  - a vector of membership degrees of  $y$  in  $f_i$ ;
- for every  $v_i$  there is some  $y_i$  such that  $v_i = f_i(y_i)$ .

# Fuzzy inference

## Defuzzification

### Defuzzification using the height method:



$$\text{low}(t) = 0.2 \quad B_1 = 0$$

$$\text{medium}(t) = 0.8 \quad B_2 = 50$$

$$\text{high}(t) = 0 \quad B_3 = 100$$

$$\mathbf{v} = (0.2, 0.8, 0)$$

$$\text{HeM}(\mathbf{v}) = \frac{\sum_{i=1}^3 v_i \cdot B_i}{\sum_{i=1}^3 v_i} = \frac{0.2 \cdot 0 + 0.8 \cdot 50 + 0 \cdot 100}{0.2 + 0.8 + 0} = 40 = t.$$

# Fuzzy inference

## Fuzzy rule (Mamdani type)

- Definition of a fuzzy rule (Mamdani type)
- Fuzzy relations
- Compositional rule of inference (*CRI*)
- *CRI*'s using *t*-norms
- Mamdani-Assilian method
- A simplified scheme of *CRI*
- Larsen method
- Drastic product method
- Bounded product method
- Tsukamoto method

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# Fuzzy inference

## Fuzzy relations

### BASICS

Let  $X$ ,  $Y$ ,  $Z$  be sets.

A fuzzy relation  $R$  is a function  $R : X \times Y \rightarrow [0, 1]$ ;

- a special case of fuzzy set, with the universum  $X \times Y$ ;
- given analytically or as matrices if the sets involved - finite.

Let  $R$  be a fuzzy relation on  $X \times Y$  and  $S$  on  $Y \times Z$ .

The composition  $R \circ S : X \times Z \rightarrow [0, 1]$ :

$$R \circ S(x, z) = \bigvee_y \{R(x, y) * S(y, z)\};$$

- for  $X = \{x_i \mid 1 \leq i \leq m\}$ ,  $Y = \{y_j \mid 1 \leq j \leq n\}$ ,  
 $Z = \{z_k \mid 1 \leq k \leq p\}$ , being finite non-empty sets,

$$R \circ S(x_i, z_k) = \bigoplus_{y_j} \{R(x_i, y_j) * S(y_j, z_k)\}.$$

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### COMPOSITION OF A FUZZY SET AND A RELATION

Let  $A$  be a fuzzy set on  $X$  and  $R$  a fuzzy relation on  $X \times Y$ .

For  $y \in Y$  - a fuzzy set  $R[y] : X \rightarrow [0, 1] : R[y](x) = R(x, y)$ .

The composition  $A \circ_* R : Y \rightarrow [0, 1]$ :

$$A \circ_* R(y) = \bigvee_x \{A(x) * R(x, y)\} = \bigvee_x \{A * R[y](x)\};$$

- for  $X = \{x_i \mid 1 \leq i \leq m\}$ ,  $Y = \{y_j \mid 1 \leq j \leq n\}$ ,  
being finite non-empty sets,

$$A \circ_* R(y_j) = \bigoplus_{x_i} \{A(x_i) * R(x_i, y_j)\} = \bigoplus_{x_i} \{A * R[y_j](x_i)\}.$$

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## Fuzzy relations

### MATRICES

- the multiplication of the matrices of membership degrees:

$$\begin{bmatrix} R \circ S(x_1, z_1) \cdots R \circ S(x_1, z_p) \\ \vdots \quad \dots \quad \vdots \\ R \circ S(x_m, z_1) \cdots R \circ S(x_m, z_p) \end{bmatrix} = \begin{bmatrix} R(x_1, y_1) \cdots R(x_1, y_n) \\ \vdots \quad \dots \quad \vdots \\ R(x_m, y_1) \cdots R(x_m, y_n) \end{bmatrix} \circ \begin{bmatrix} S(y_1, z_1) \cdots S(y_1, z_p) \\ \vdots \quad \dots \quad \vdots \\ S(y_n, z_1) \cdots S(y_n, z_p) \end{bmatrix}$$

$m \times p$                        $m \times n$                        $n \times p$

For  $* = \min = *_m$ ,  $\oplus = \max = \oplus_m$ :

$$\begin{bmatrix} 0.6 & 0.4 \\ 0.9 & 0.5 \end{bmatrix} = \begin{bmatrix} 0.2 & 0.4 & 0.6 \\ 0.3 & 0.6 & 0.9 \end{bmatrix} \circ \begin{bmatrix} 0.5 & 1 \\ 0.7 & 0.5 \\ 1 & 0 \end{bmatrix}$$

$$B = A \circ_{*_m} R$$

$$\begin{bmatrix} 0.6 & 0.4 \end{bmatrix} = \begin{bmatrix} 0.2 & 0.4 & 0.6 \end{bmatrix} \circ_{*_m} \begin{bmatrix} 0.5 & 1 \\ 0.7 & 0.5 \\ 1 & 0 \end{bmatrix}$$

-  $A$  on  $X = \{x_1, x_2, x_3\}$ ,  $B$  on  $Y = \{y_1, y_2\}$ ,  $R$  on  $X \times Y$ .

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# Fuzzy inference

## Compositional rule of inference

### DEFINITION

- The classical (crisp) modus ponens:  $\frac{A, \text{ IF } A \text{ THEN } B}{B}$ .

Let  $*$  be a  $t$ -norm,  $\Rightarrow$  a residuum operator.

Let  $A, A'$  be fuzzy sets on  $X$ ,  $B$  on  $Y$ .

- The generalized (fuzzy) modus ponens: [Zadeh, 1973]

$$\frac{x = A', \text{ IF } x = A \text{ THEN } y = B}{y = B'}$$

A compositional rule of inference:

$$\begin{aligned} B'(y) &= A' \circ_* [A \Rightarrow B](y) = \bigvee_x \{A'(x) * [A \Rightarrow B](x, y)\} \\ &= \bigvee_x \{A'(x) * (A(x) \Rightarrow B(y))\}, \end{aligned}$$

$$[A \Rightarrow B](x, y) = A(x) \Rightarrow B(y) \text{ on } X \times Y.$$

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## Compositional rule of inference

For  $* = *_t, \Rightarrow = \Rightarrow_t$ :

$$a *_t b = \max(0, a + b - 1),$$

$$[A \Rightarrow B](x_i, y_j) = A(x_i) \Rightarrow_t B(y_j) = \min(1, 1 - A(x_i) + B(y_j)).$$

$$\text{Let } A = \left\{ \frac{0.8}{x_1}, \frac{0.7}{x_2}, \frac{1}{x_3} \right\}, B = \left\{ \frac{0.5}{y_1}, \frac{1}{y_2}, \frac{0.6}{y_3} \right\}, A' = \left\{ \frac{0.5}{x_1}, \frac{0.2}{x_2}, \frac{0.3}{x_3} \right\}.$$

$$[A \Rightarrow B] = \begin{bmatrix} 0.7 & 1 & 0.8 \\ 0.8 & 1 & 0.9 \\ 0.5 & 1 & 0.6 \end{bmatrix}$$

$$B' = A' \circ_{*_t} [A \Rightarrow B]$$

$$\begin{bmatrix} 0.2 & 0.5 & 0.3 \end{bmatrix} = \begin{bmatrix} 0.5 & 0.2 & 0.3 \end{bmatrix} \circ_{*_t} \begin{bmatrix} 0.7 & 1 & 0.8 \\ 0.8 & 1 & 0.9 \\ 0.5 & 1 & 0.6 \end{bmatrix}$$

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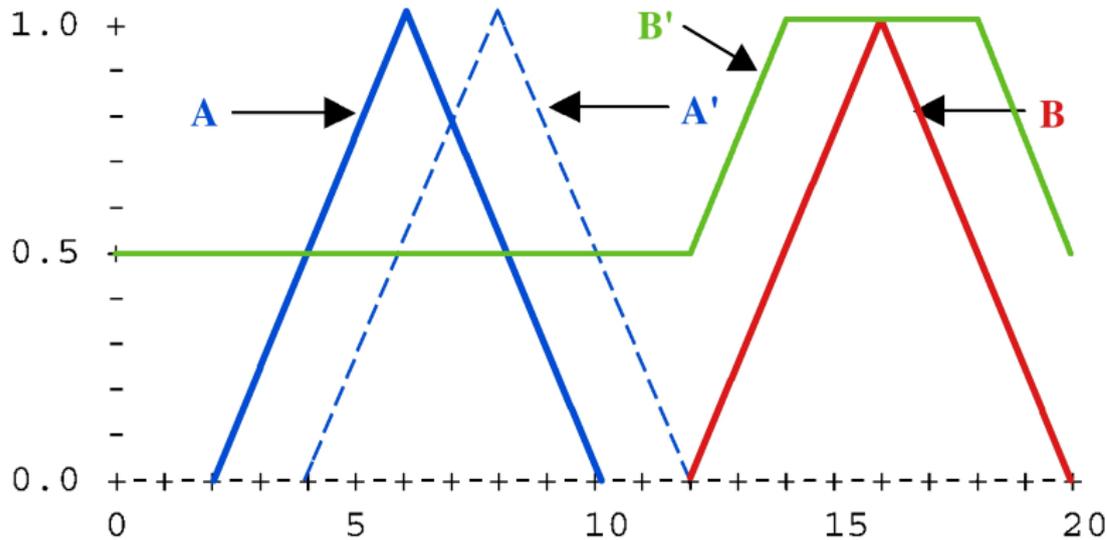
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## Compositional rule of inference

For  $* = *_{m}, \Rightarrow = \Rightarrow_G$ :



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# Fuzzy inference

CRI's using  $t$ -norms

## DEFINITION

Let  $*$  be a  $t$ -norm. Let  $A, A'$  be fuzzy sets on  $X$ ,  $B$  on  $Y$ .  
A compositional rule of inference using a  $t$ -norm:

$$\begin{aligned} B'(y) &= A' \circ_{*m} [A * B](y) = \bigvee_x \min(A'(x), [A * B](x, y)) \\ &= \bigvee_x \min(A'(x), (A(x) * B(y))), \\ [A * B](x, y) &= A(x) * B(y) \text{ on } X \times Y. \end{aligned}$$

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# Fuzzy inference

CRI's using  $t$ -norms

## MAMDANI-ASSILIAN METHOD [Mamdani, Assilian, 1975]

Let  $\mathbb{RB}$  be a rule base.

$$B^{i'}(y) = \min_{j=1}^m \bigvee_x \min(A_j^i(x), A_j^i(x), B^i(y))$$

$\alpha^j$  - the firing strength

$$= \min \left( \underbrace{\min_{j=1}^m \bigvee_x \min(A_j^i(x), A_j^i(x))}_{\alpha_j^i - \text{the matching degree}}, B^i(y) \right),$$

$$B' = \bigcup_{i=1}^n B^{i'} \text{ - the aggregation.}$$

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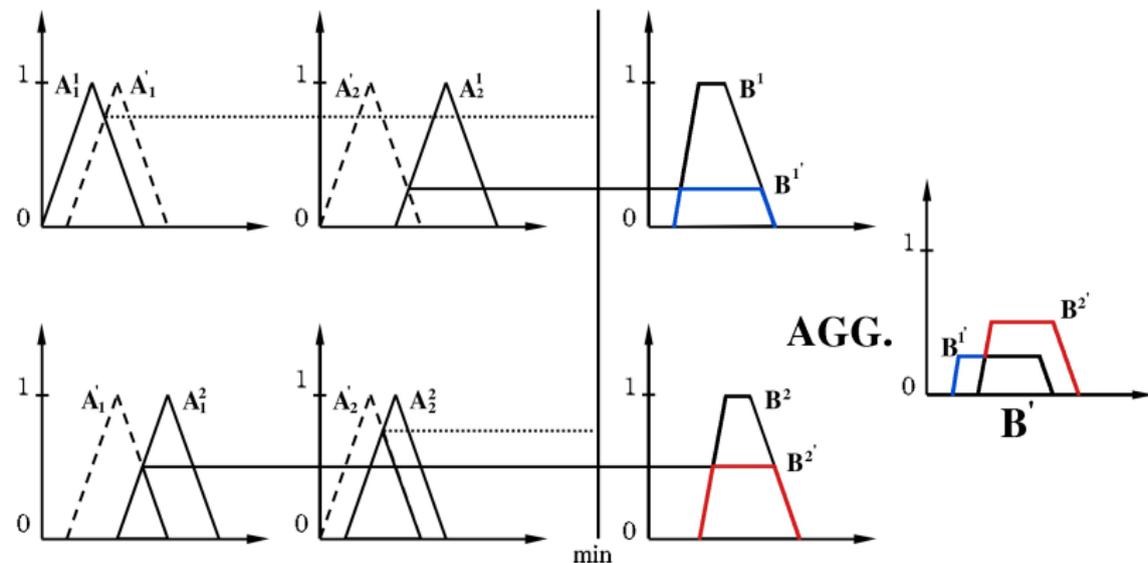
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An example of Mamdani-Assilian method:



IF  $a_1$  is  $A_1^1$  and  $a_2$  is  $A_2^1$  THEN  $b$  is  $B^1$

IF  $a_1$  is  $A_1^2$  and  $a_2$  is  $A_2^2$  THEN  $b$  is  $B^2$

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# Fuzzy inference

CRI's using  $t$ -norms

## DEFINITION

Let  $*$  be a  $t$ -norm. Let  $\mathbb{RB}$  be a rule base.

A simplified compositional rule of inference using a  $t$ -norm:

$$B^{i'}(y) = \left( \underbrace{\min_{j=1}^m \bigvee_x \min(A_j^i(x), A_j^i(x))}_{\alpha_j^i - \text{the matching degree}} \right) * B^i(y),$$

$\alpha^i$  - the firing strength

$$B' = \bigcup_{i=1}^n B^{i'} - \text{the aggregation.}$$

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## LARSEN METHOD [Larsen, 1980]

Let  $\mathbb{R}\mathbb{B}$  be a rule base.

$$B^{i'}(y) = \left( \min_{j=1}^m \bigvee_x \min(A_j'(x), A_j^i(x)) \right) \cdot B^i(y),$$

$$B' = \bigcup_{i=1}^n B^{i'} - \text{the aggregation.}$$

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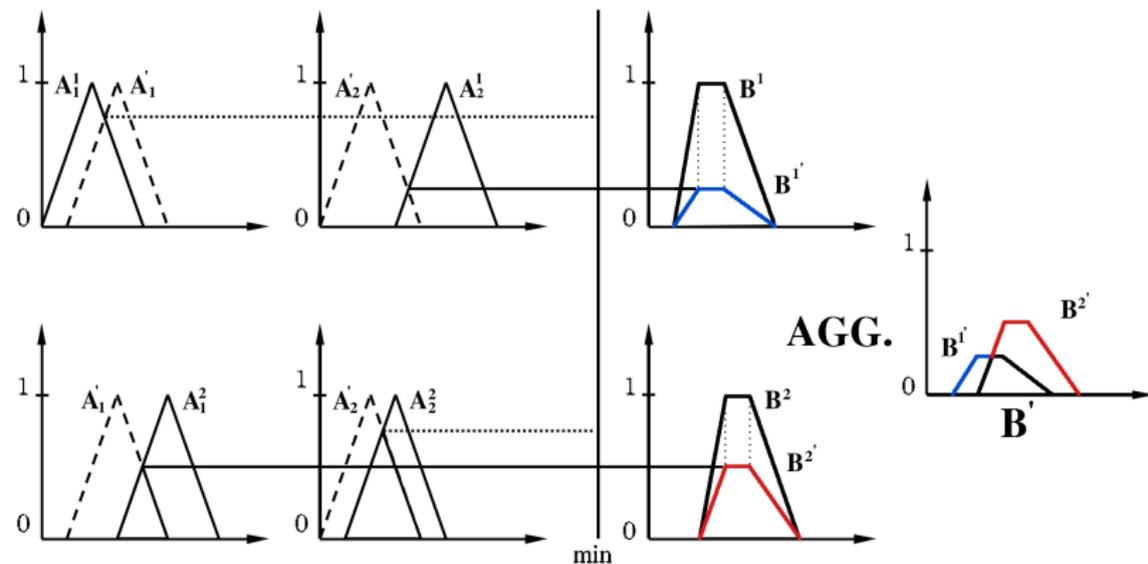
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An example of Larsen method:



IF  $a_1$  is  $A_1^1$  and  $a_2$  is  $A_2^1$  THEN  $b$  is  $B^1$

IF  $a_1$  is  $A_1^2$  and  $a_2$  is  $A_2^2$  THEN  $b$  is  $B^2$

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## DRASTIC PRODUCT METHOD [Larsen, 1980]

Let  $\mathbb{R}\mathbb{B}$  be a rule base.

$$B^{i'}(y) = \left( \min_{j=1}^m \bigvee_x \min(A_j'(x), A_j^i(x)) \right) *_d B^i(y),$$

$$B' = \bigcup_{i=1}^n B^{i'} - \text{the aggregation.}$$

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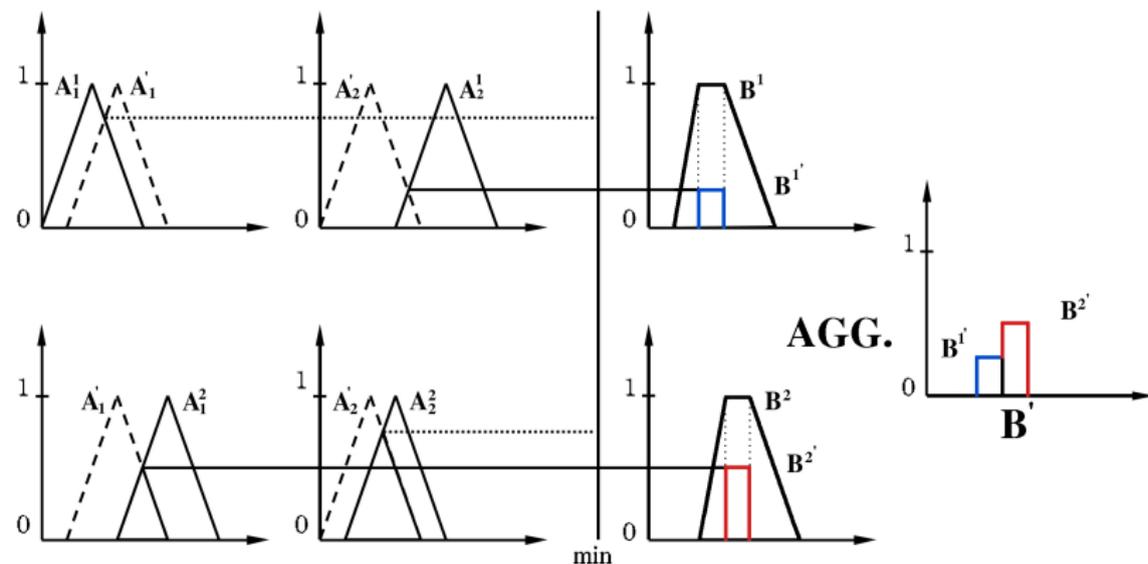
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An example of the drastic product method:



IF  $a_1$  is  $A_1^1$  and  $a_2$  is  $A_2^1$  THEN  $b$  is  $B^1$

IF  $a_1$  is  $A_1^2$  and  $a_2$  is  $A_2^2$  THEN  $b$  is  $B^2$

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## BOUNDED PRODUCT METHOD [Larsen, 1980]

Let  $\mathbb{R}\mathbb{B}$  be a rule base.

$$B^{i'}(y) = \left( \min_{j=1}^m \bigvee_x \min(A_j'(x), A_j^i(x)) \right) *_t B^i(y),$$

$$B' = \bigcup_{i=1}^n B^{i'} \text{ - the aggregation.}$$

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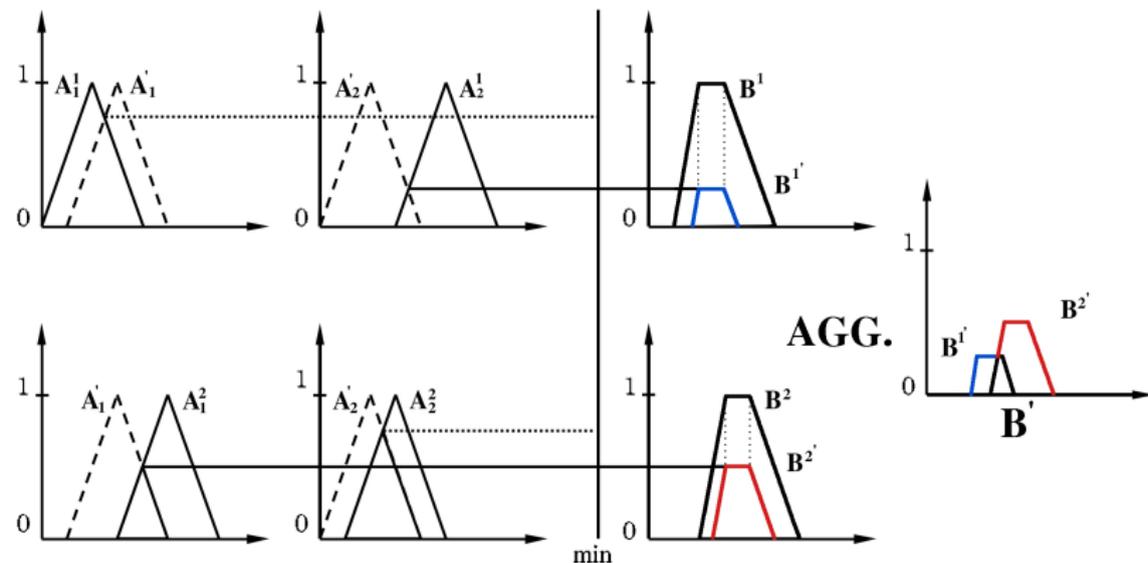
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An example of the bounded product method:



IF  $a_1$  is  $A_1^1$  and  $a_2$  is  $A_2^1$  THEN  $b$  is  $B^1$

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## TSUKAMOTO METHOD [Larsen, 1980]

Let  $\mathbb{RB}$  be a rule base. Let  $B^i$  are monotonic.

$$\alpha^i = \min_{j=1}^m \bigvee_x \underbrace{\min(A_j^i(x), A_j^i(x))}_{\alpha_j^i \text{ - the matching degree}}$$

$$\alpha = \sum_{i=1}^n \alpha^i,$$

$$B^{i'}(y) = \begin{cases} \alpha^i & \text{if } y = B^{i-1}(\alpha^i), \\ 0 & \text{else,} \end{cases}$$

$$B'(y) = \begin{cases} 1 & \text{if } y = \frac{\sum_{i=1}^n \alpha^i \cdot B^{i-1}(\alpha^i)}{\alpha}, \\ 0 & \text{else} \end{cases}, \quad \text{- the aggregation.}$$

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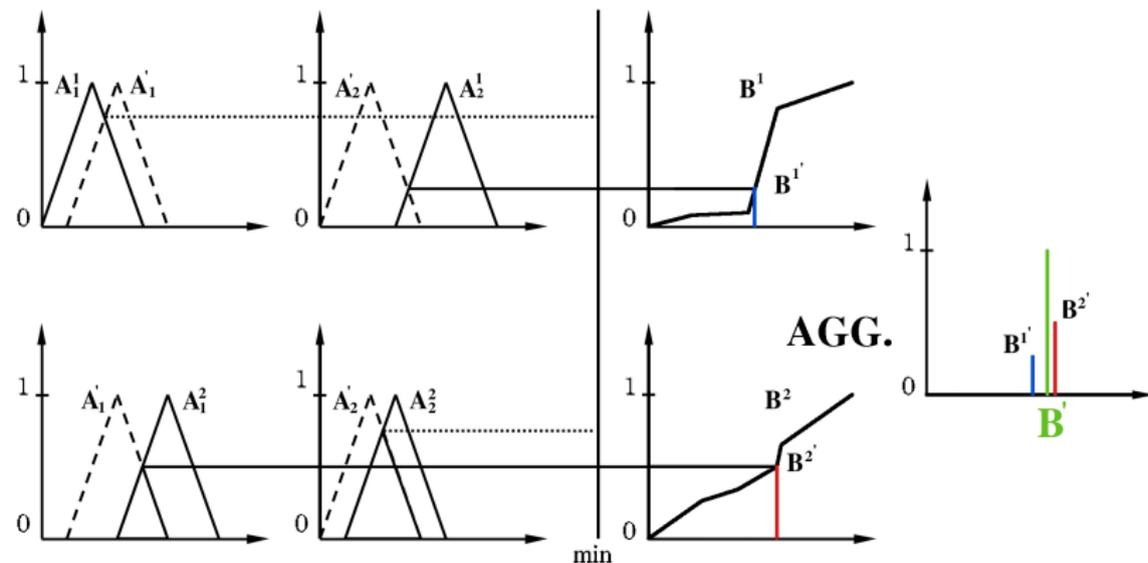
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An example of Tsukamoto method:



IF  $a_1$  is  $A_1^1$  and  $a_2$  is  $A_2^1$  THEN  $b$  is  $B^1$

IF  $a_1$  is  $A_1^2$  and  $a_2$  is  $A_2^2$  THEN  $b$  is  $B^2$

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## Fuzzy rule (Sugeno-Takagi type)

### DEFINITION

Let  $A_i$  be fuzzy sets on  $\mathbb{R}$ ,  $q_i \in \mathbb{R}$ .

A fuzzy rule of the Sugeno-Takagi type is of the form

$$\text{IF } \tilde{a}_1 \text{ is } A_1 \text{ and } \dots \text{ and } \tilde{a}_m \text{ is } A_m \text{ THEN } z = q_0 + \sum_{j=1}^m q_j \cdot a_j$$

$a_j$  - input crisp variables;  $z$  - an output crisp variable;

$\tilde{a}_j$  - the corresponding fuzzy variables to  $a_j$ .

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## Sugeno-Takagi-Kang method

### SUGENO-TAKAGI-KANG METHOD [Takagi, Sugeno, 1985]

Let  $\mathbb{RB}$  be a rule base.

$$\alpha^i = \min_{j=1}^m \underbrace{\bigvee_x \min(A_j^i(x), A_j^i(x))}_{\alpha_j^i - \text{the matching degree}}$$

$$\alpha = \sum_{i=1}^n \alpha^i,$$

$$z^i = q_0^i + \sum_{j=1}^m q_j^i \cdot a_j,$$

$$z = \frac{\sum_{i=1}^n \alpha^i \cdot z^i}{\alpha} - \text{the aggregation.}$$

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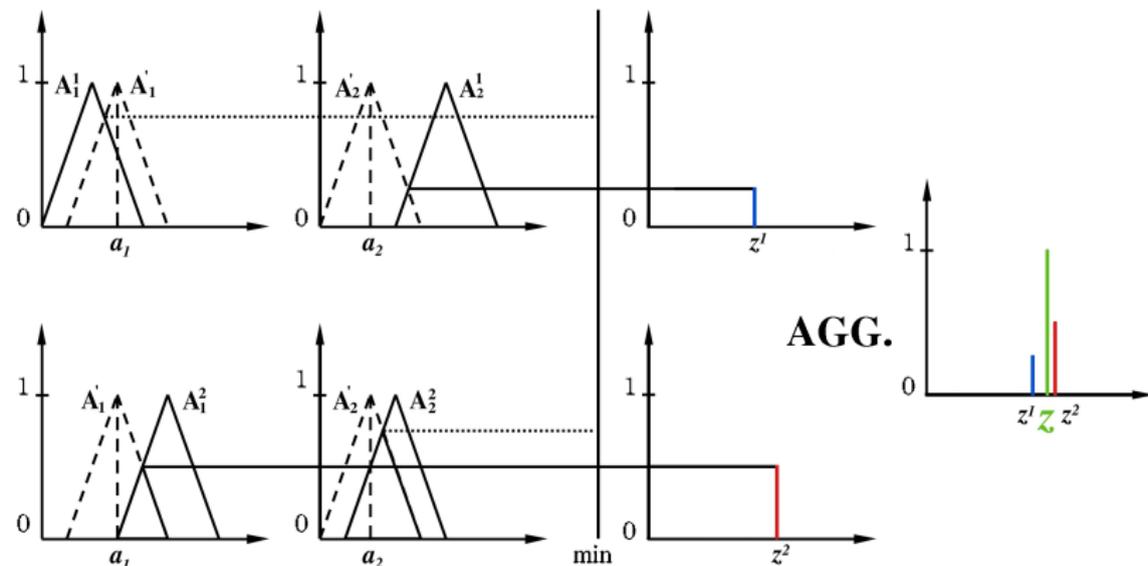
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## Sugeno-Takagi-Kang method

An example of Sugeno-Takagi-Kang method:



$$\text{IF } \tilde{a}_1 \text{ is } A_1^1 \text{ and } \tilde{a}_2 \text{ is } A_2^1 \text{ THEN } z^1 = q_0^1 + q_1^1 \cdot a_1 + q_2^1 \cdot a_2$$

$$\text{IF } \tilde{a}_1 \text{ is } A_1^2 \text{ and } \tilde{a}_2 \text{ is } A_2^2 \text{ THEN } z^2 = q_0^2 + q_1^2 \cdot a_1 + q_2^2 \cdot a_2$$

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  - Input/output variables and fuzzy sets
  - Rule base
  - Aggregation and defuzzification
  - Control surface for  $* = \min$
  - Control surface for  $* = \cdot$

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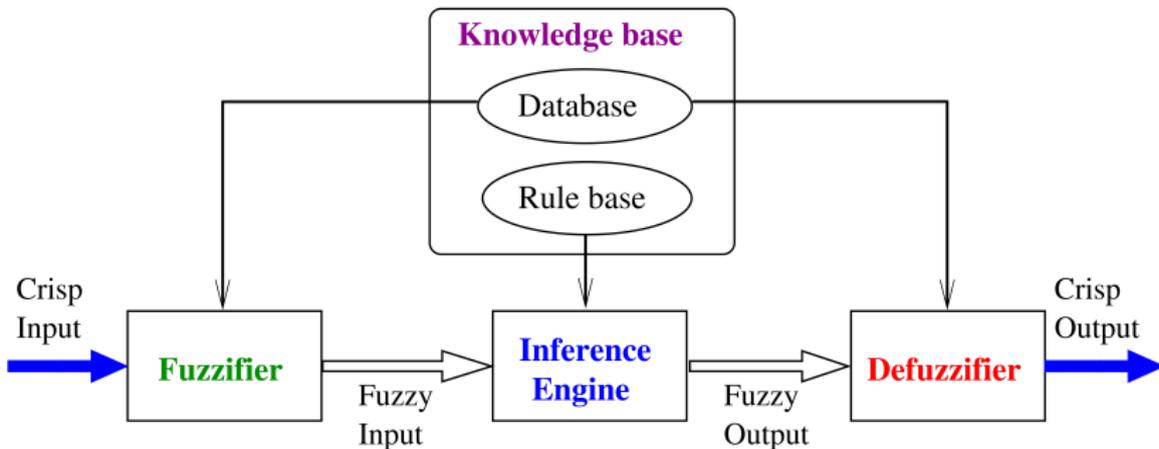
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### DESIGN OF A *FIS*

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- 2 The definition of input/output crisp/fuzzy variables.
- 3 The definition of fuzzy sets.
- 4 The definition of fuzzy rules.
- 5 Building (coding) a fuzzy expert system in some expert system tool (*FuzzyCLIPS*, *FuzzyShell*, *FuzzyJess*, *OPS5*, *FRIL*, *FLOPS*).
- 6 Testing the system.
- 7 Tuning the rules and fuzzy sets.

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### APPLICATIONS OF *FIS*

- Control engineering.
- Modelling of complex systems.
- Pattern recognition.
- Operation research.
- Decision analysis support systems.

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### A SIMPLE FUZZY CONTROLLER

- 1 Design a motor speed controller for an air conditioner.
- 2 Input crisp variables and fuzzy sets:
  - Temperature - COOL, WARM, HOT ( $^{\circ}\text{C}$ );
  - Humidity - DRY, MOIST, WET (%).
- 3 An output crisp variable and fuzzy sets:
  - Speed - LOW, MEDIUM, HIGH (%).

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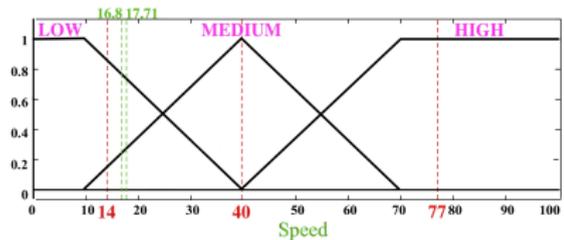
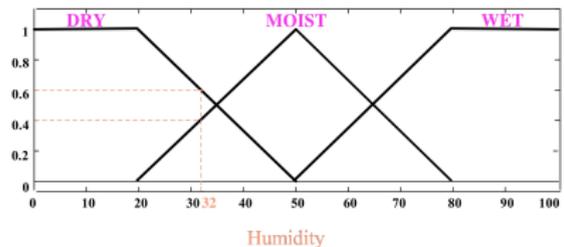
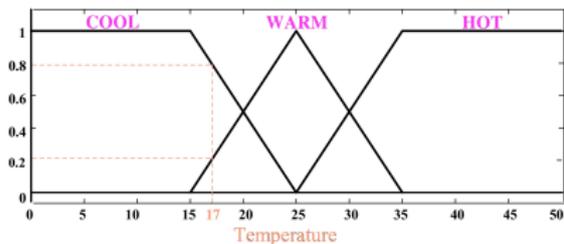
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### Input/output crisp variables and fuzzy sets:



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## A SIMPLE FUZZY CONTROLLER

(4) The rule base  $\mathbb{R}\mathbb{B}$ :

*IF* Temperature *is* COOL *and* Humidity *is* DRY *THEN* Speed *is* LOW

*IF* Temperature *is* COOL *and* Humidity *is* MOIST *THEN* Speed *is* LOW

*IF* Temperature *is* COOL *and* Humidity *is* WET *THEN* Speed *is* MEDIUM

*IF* Temperature *is* WARM *and* Humidity *is* DRY *THEN* Speed *is* LOW

*IF* Temperature *is* WARM *and* Humidity *is* MOIST *THEN* Speed *is* MEDIUM

*IF* Temperature *is* WARM *and* Humidity *is* WET *THEN* Speed *is* HIGH

*IF* Temperature *is* HOT *and* Humidity *is* DRY *THEN* Speed *is* MEDIUM

*IF* Temperature *is* HOT *and* Humidity *is* MOIST *THEN* Speed *is* HIGH

*IF* Temperature *is* HOT *and* Humidity *is* WET *THEN* Speed *is* HIGH

## A SIMPLE FUZZY CONTROLLER

### (5) Aggregation and defuzzification by WAF:

Let  $\mathbb{R}B$  consist of  $n$  rules of the form

*IF  $x$  is  $A_i$  and  $y$  is  $B_i$  THEN  $z$  is  $C_i$ .*

Let  $\mu_i = A_i(x) * B_i(y)$  - the firing strength;  $*$  is either  $\min$  or  $\cdot$ .

Let  $c_i$  be the center of gravity of  $C_i$ .

The crisp output  $z$ :

$$\mu = \sum_{i=1}^n \mu_i,$$
$$z = \frac{\sum_{i=1}^n \mu_i \cdot c_i}{\mu}.$$

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## A SIMPLE FUZZY CONTROLLER

(6) Aggregation and defuzzification by *WAF* (an example):

Let **Temperature** = 17°C ( $x$ ), **Humidity** = 32% ( $y$ ).

**COOL**(17) = 0.8, **WARM**(17) = 0.2, **HOT**(17) = 0.

**DRY**(32) = 0.6, **MOIST**(32) = 0.4, **WET**(32) = 0.

$c_{\text{LOW}}$  = 14,  $c_{\text{MEDIUM}}$  = 40,  $c_{\text{HIGH}}$  = 77.

**Speed** = ??% ( $z$ ).

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### A SIMPLE FUZZY CONTROLLER

#### (6) Aggregation and defuzzification by *WAF* (an example):

For  $*$  = min,

$$\begin{aligned}\mu &= \sum_{i=1}^9 \mu_i = \min(0.8, 0.6) + \min(0.8, 0.4) + \min(0.8, 0) + \\ &\quad \min(0.2, 0.6) + \min(0.2, 0.4) + \min(0.2, 0) + \\ &\quad \min(0, 0.6) + \min(0, 0.4) + \min(0, 0) \\ &= 0.6 + 0.4 + 0 + 0.2 + 0.2 + 0 + 0 + 0 + 0 \\ &= 1.4,\end{aligned}$$

$$\begin{aligned}\text{Speed} &= \frac{\sum_{i=1}^9 \mu_i \cdot c_i}{\mu} = \frac{0.6 \cdot 14 + 0.4 \cdot 14 + 0 \cdot 40 + \\ &\quad 0.2 \cdot 14 + 0.2 \cdot 40 + 0 \cdot 77 + \\ &\quad 0 \cdot 40 + 0 \cdot 77 + 0 \cdot 77}{1.4} = \frac{24.8}{1.4} \\ &= 17.714285714\%.\end{aligned}$$

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### A SIMPLE FUZZY CONTROLLER

#### (6) Aggregation and defuzzification by *WAF* (an example):

For  $* = \cdot$ ,

$$\begin{aligned}\mu &= \sum_{i=1}^9 \mu_i = 0.8 \cdot 0.6 + 0.8 \cdot 0.4 + 0.8 \cdot 0 + \\ &\quad 0.2 \cdot 0.6 + 0.2 \cdot 0.4 + 0.2 \cdot 0 + \\ &\quad 0 \cdot 0.6 + 0 \cdot 0.4 + 0 \cdot 0 \\ &= 0.48 + 0.32 + 0 + 0.12 + 0.08 + 0 + 0 + 0 + 0 \\ &= 1,\end{aligned}$$

$$\begin{aligned}\text{Speed} &= \frac{\sum_{i=1}^9 \mu_i \cdot c_i}{\mu} = \frac{0.48 \cdot 14 + 0.32 \cdot 14 + 0 \cdot 40 + \\ &\quad 0.12 \cdot 14 + 0.08 \cdot 40 + 0 \cdot 77 + \\ &\quad 0 \cdot 40 + 0 \cdot 77 + 0 \cdot 77}{1} = \frac{16.8}{1} \\ &= 16.8\%.\end{aligned}$$

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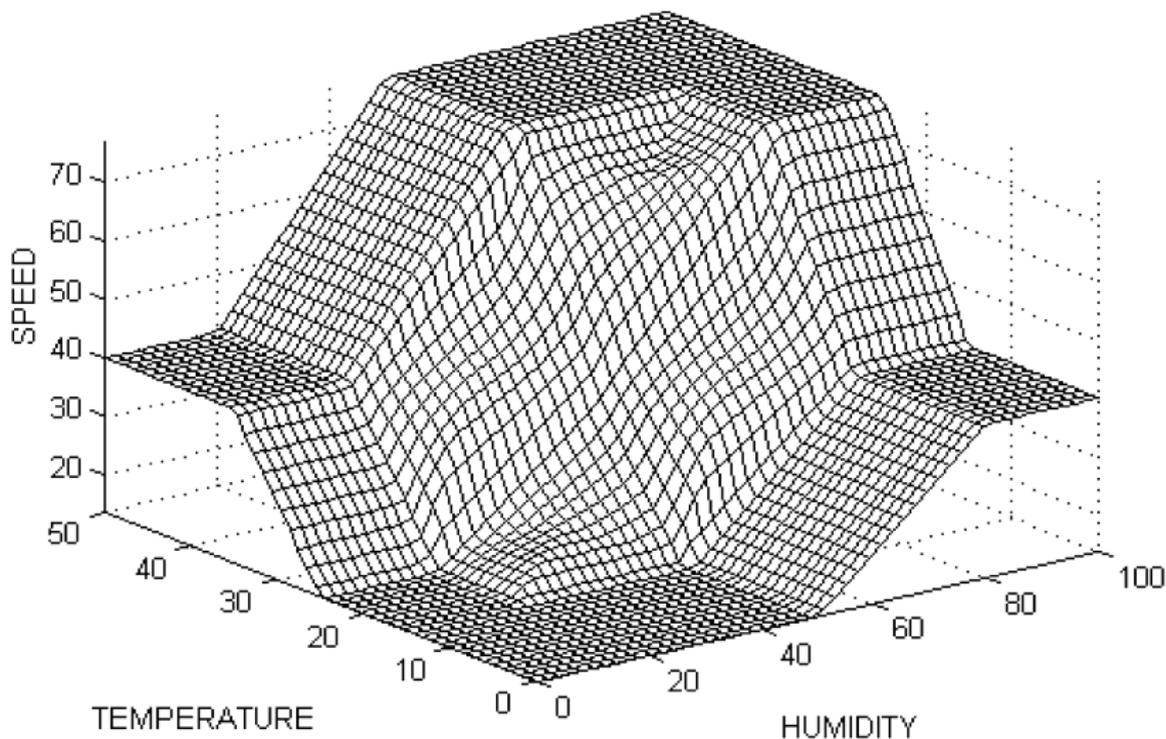
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Control surface for  $* = \min$ :



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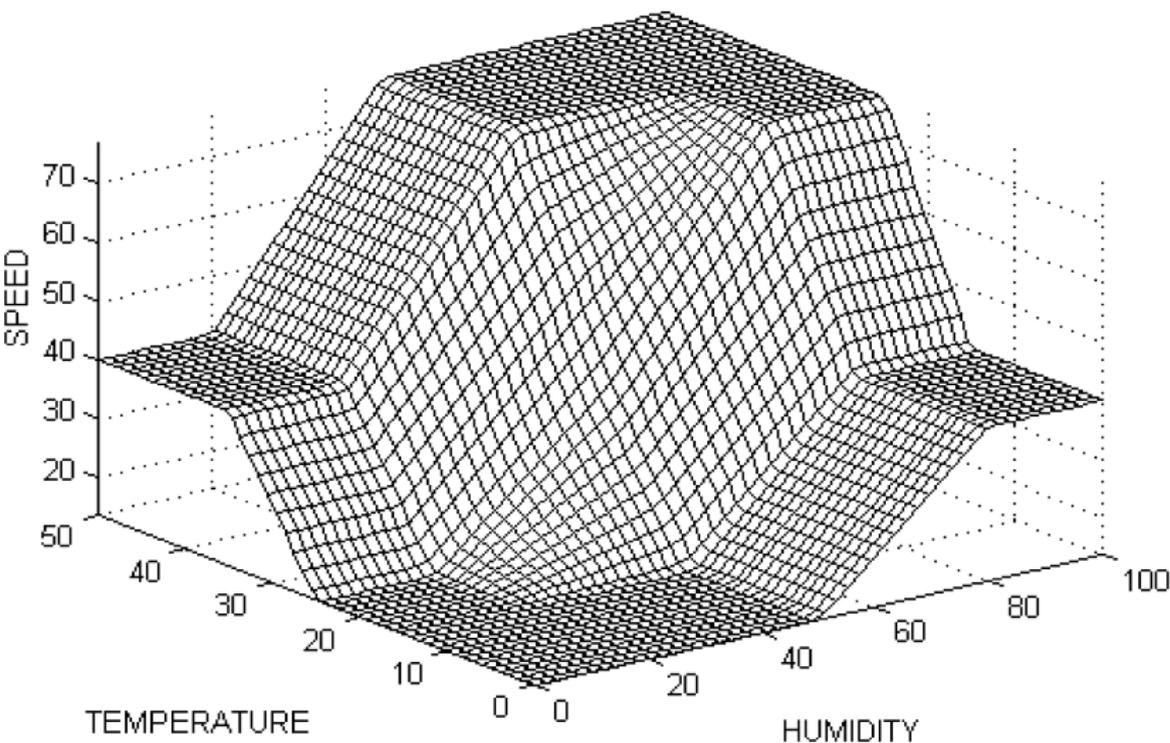
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## A bilattice approach

**BILATTICES** [Fitting, 1988], [Ginsberg, 1988]

$$\mathcal{R} = ([0, 1] \times [0, 1], \leq_k, \vee_k, \wedge_k, 0|0, 1|1, \leq_t, \vee_t, \wedge_t, 0|1, 1|0),$$
$$a|b \equiv (a, b),$$

$$a|b \leq_k c|d \Leftrightarrow a \leq c, b \leq d, \quad (\text{knowledge order})$$

$$a|b \vee_k c|d = \max(a, c)|\max(b, d), \quad (\text{knowledge supremum})$$

$$a|b \wedge_k c|d = \min(a, c)|\min(b, d), \quad (\text{knowledge infimum})$$

$$a|b \leq_t c|d \Leftrightarrow a \leq c, b \geq d, \quad (\text{truth order})$$

$$a|b \vee_t c|d = \max(a, c)|\min(b, d), \quad (\text{truth supremum})$$

$$a|b \wedge_t c|d = \min(a, c)|\max(b, d). \quad (\text{truth infimum})$$

- The data type:  $\text{truth\_value} \equiv [0, 1] \text{ float} | [0, 1] \text{ float}$ ;
- the constructor:  $a|b$ ;
- the selectors:  $\text{for}(a|b) = a$ ,  $\text{against}(a|b) = b$ .

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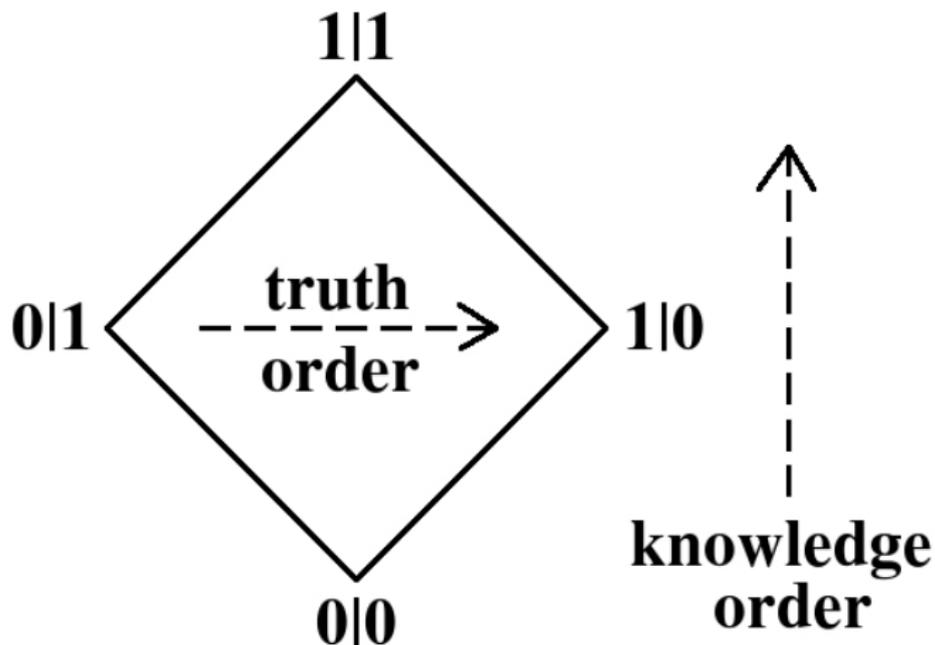
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Bilattice  $\mathcal{B}$ :



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## A bilattice approach

### OTHER BASIC OPERATORS

$$a|b * c|d = (a * c)|(b * d), \quad (\text{knowledge } t\text{-norm})$$

$$a|b \diamond c|d = (a * c)|(b \oplus d), \quad (\text{truth } t\text{-norm})$$

$$a|b \oplus c|d = (a \oplus c)|(b \oplus d), \quad (\text{knowledge } t\text{-conorm})$$

$$a|b \square c|d = (a \oplus c)|(b * d), \quad (\text{truth } t\text{-conorm})$$

$$\neg a|b = b|a, \quad (\text{negation})$$

$$\Leftrightarrow a|b = (1 - b)|(1 - a). \quad (\text{conflation, possibility})$$

- The certainty factor  $a|b$  - attached to a datum;  
 $a$  - an extent for the datum,  $b$  - an extent against the datum;  
accessed by  $datum.cf$ .

- An expression  $exp$  of  $truth\_value$  is well-formed  
from atoms:  $exp_1|exp_2, datum.cf$   
 $float \quad float$

using the operators:  $\vee_k, \wedge_k, \vee_t, \wedge_t, *, \diamond, \oplus, \square, \neg, \Leftrightarrow$ .

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## A bilattice approach

### PARACONSISTENCY

- $a|b$  - consistent iff  $a + b \leq 1$ ;
- $a|b$  - exact iff  $a + b = 1$ ;
- $a|b$  - inconsistent iff  $a + b > 1$ .
  
- $a|b$  - consistent iff  $a|b \leq_k \Leftrightarrow a|b$ ;
- $a|b$  - exact iff  $a|b = \Leftrightarrow a|b$ ;
- $a|b$  - inconsistent iff  $a|b >_k \Leftrightarrow a|b$ .

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## A bilattice approach

### BASIC PROPERTIES

$$a|b \leq_k c|d \Leftrightarrow \neg a|b \leq_k \neg c|d,$$

$$a|b \leq_t c|d \Leftrightarrow \neg a|b \geq_t \neg c|d,$$

$$\neg \neg a|b = a|b,$$

$$a|b \leq_k c|d \Leftrightarrow \Leftrightarrow a|b \geq_k \Leftrightarrow c|d,$$

$$a|b \leq_t c|d \Leftrightarrow \Leftrightarrow a|b \leq_t \Leftrightarrow c|d,$$

$$\Leftrightarrow \Leftrightarrow a|b = a|b,$$

$$\neg \Leftrightarrow a|b = \Leftrightarrow \neg a|b = (1 - a)|(1 - b), \quad (\text{default negation})$$

$$\neg(a|b * c|d) = \neg a|b * \neg c|d,$$

$$\neg(a|b \oplus c|d) = \neg a|b \oplus \neg c|d,$$

$$\neg(a|b \diamond c|d) = \neg a|b \square \neg c|d,$$

$$\neg(a|b \square c|d) = \neg a|b \diamond \neg c|d,$$

$$\Leftrightarrow(a|b \vee_k c|d) = \Leftrightarrow a|b \wedge_k \Leftrightarrow c|d,$$

$$\Leftrightarrow(a|b \wedge_k c|d) = \Leftrightarrow a|b \vee_k \Leftrightarrow c|d,$$

$$\Leftrightarrow(a|b \vee_t c|d) = \Leftrightarrow a|b \vee_t \Leftrightarrow c|d,$$

$$\Leftrightarrow(a|b \wedge_t c|d) = \Leftrightarrow a|b \wedge_t \Leftrightarrow c|d.$$

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# Fuzzy expert systems

## Data types in *FES*

### BASIC DATA TYPES AND THEIR TRUTH VALUES

- **Scalars:** integers, floats, chars, strings;

- *literal.cf* = 1|0.

```
declare x integer
```

```
x := 5 x.cf := 0.8|0.1
```

```
7.cf = 1|0.
```

- **Fuzzy numbers:**

- *fnum.cf* = 1|0;

- approximate **comparison** and **arithmetic** operators.

```
declare x triang_fnum
```

```
x := create_triang_fnum(5, 0.5);  $\tilde{5}$  with a dispersion of 0.5
```

```
x.cf = 1|0.
```

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# Fuzzy expert systems

## Data types in *FES*

### BASIC DATA TYPES AND THEIR TRUTH VALUES

- Membership functions:

- *memf.cf* = 1|0;
- basic fuzzy set operators.

```
defmemftype rotation shape : polygon domain : 0 9000
declare memf rotation
memf := create_polygon_memf(0 0 1000 0.8 5000 1 9000 0)
memf.cf = 1|0.
```

- Discrete fuzzy sets:

- a value - a vector of the membership degrees for|against of the members of a discrete fuzzy set,
- accessed by *name.member.cf* = *name(member)*.

```
defdisfstype Species members : hamster rabbit hare
declare species1 Species
species1 :=
    create_disfs(hamster 0.3|0.4 rabbit 0.6|0.2 hare 0.8|0.2)
species1.rabbit.cf = 0.6|0.2.
```

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## Data types in FES

### BASIC DATA TYPES AND THEIR TRUTH VALUES

- Numerical discrete fuzzy sets:
  - membership functions - attached to the members, accessed by *name.member*;
  - linguistic terms - members of a numerical discrete fuzzy set;
  - a value of a linguistic variable - a vector of the membership degrees for|against of the linguistic terms, accessed by *name.member.cf = name(member)*.

```
defmemftype H_Length shape : polygon domain : 0 250
defnumfstype Hum_Length members : small medium tall
                memftype : H_Length
Hum_Length.small := create_polygon_memf(0 1 160 0 250 0)
Hum_Length.medium := create_polygon_memf(0 0 170 1 250 0)
Hum_Length.tall := create_polygon_memf(0 0 170 0 250 1)
declare length1 Hum_Length
length1 := create_numfs(small 0.2|0.5 medium 0.6|0.2 tall 0|0.9)
length1.medium.cf = 0.6|0.2 length1.medium = (0 0 170 1 250 0).
```

# Antecedents of fuzzy rules in *FES*

## Basic conditional elements (*CE*)

- $assigned(x)$   
*variable*
- $exp_1 | exp_2$  *datum.cf*  
*float float*
- $exp_1$  *crisp\_comparison*  $exp_2$   
*scalar<sub>1</sub> scalar<sub>2</sub>*
- $exp_1$  *comparison*  $exp_2$   
*fnumtype<sub>1</sub> fnumtype<sub>2</sub>*
- $exp_1$  *comparison*  $exp_2$   
*memftype<sub>1</sub> memftype<sub>2</sub>*
- $x$  *is member*  
*fstype*
- $x$  *is member*  
*numfstype*
- $exp_1$  *is*  $exp_2$   
*float memftype*
- $exp$   $exp_1$  *crisp\_comparison*  $exp_2$   
*truth\_value truth\_value truth\_value*

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## Antecedents of fuzzy rules in FES

### BASIC CONDITIONAL ELEMENTS (CE)

Let  $P$  be a proposition.  $\nu(P)$  - the truth value  $a|b$  of  $P$ .

Let  $exp$  be an expression. We shall identify  $exp$  with its value.

- $P$  : *assigned*( $\underset{\text{variable}}{x}$ )

-  $x$  - a variable:

$$\nu(P) = \begin{cases} x.cf & \text{if } x \text{ has assigned a value,} \\ 0|0 & \text{else} \end{cases}$$

```
declare x y integer  x := 35  x.cf := 0.8|0.1
```

```
declare fnum1 fnum2 triang_fnum  
fnum1 := create_triang_fnum(5, 0.5)
```

```
P1 : assigned(x)  P2 : assigned(y)
```

```
P3 : assigned(fnum1)  P4 : assigned(fnum2)
```

```
 $\nu(P_1) = 0.8|0.1$    $\nu(P_2) = 0|0$    $\nu(P_3) = 1|0$    $\nu(P_4) = 0|0$ .
```

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## Antecedents of fuzzy rules in FES

### BASIC CONDITIONAL ELEMENTS (CE)

Let  $exp$  be an expression.

The certainty factor  $\xi(exp)$  of  $exp$ :

$$\xi(exp) = \begin{cases} x.cf & \text{if } exp \equiv x - \text{a variable of scalar,} \\ 1|0 & \text{if } exp - \text{a literal,} \\ 1|0 & \text{if } exp - \text{of a fuzzy number or} \\ & \text{membership function type,} \\ 1|0 & \text{if } exp \equiv datum.cf, \\ 1|0 & \text{if } exp \equiv assigned(x), \\ \prod_{i=1}^n \xi(exp_i) & \text{if } exp \equiv \gamma(exp_1, \dots, exp_n), n \geq 1, \\ & \gamma \neq assigned - \text{an operator.} \end{cases}$$

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### BASIC CONDITIONAL ELEMENTS (*CE*)

$$\bullet P_1 : \begin{array}{c} \text{exp}_1 | \text{exp}_2 \\ \text{float} \quad \text{float} \end{array} \qquad P_2 : \text{datum.cf}$$

-  $\text{exp}_i$  - an expression of *float*:

$$\nu(P_1) = \xi(\text{exp}_1) \diamond \text{exp}_1 | \text{exp}_2 \diamond \xi(\text{exp}_2),$$

$$\nu(P_2) = \text{datum.cf}.$$

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### BASIC CONDITIONAL ELEMENTS (CE)

*declare x y float*

*x := 0.5 x.cf := 0.8|0.1 y := 0.4 y.cf := 0.7|0.2*

*species<sub>1</sub> :=*

*create\_disfs(hamster 0.3|0.6 rabbit 0.6|0.2 hare 0.8|0.2)*

*length<sub>1</sub> := create\_numfs(small 0.2|0.8 medium 0.7|0.3 tall 0|0)*

*P<sub>1</sub> : x|y*

*P<sub>2</sub> : x.cf*

*P<sub>3</sub> : species<sub>1</sub>.rabbit.cf*

*P<sub>4</sub> : length<sub>1</sub>.medium.cf*

$\nu(P_1) = x.cf \diamond x|y \diamond y.cf = 0.8|0.1 \diamond 0.5|0.4 \diamond 0.7|0.2$

$\nu(P_2) = x.cf = 0.8|0.1$

$\nu(P_3) = species_1.rabbit.cf = 0.6|0.2$

$\nu(P_4) = length_1.medium.cf = 0.7|0.3$

for  $*$  = min,  $\oplus$  = max,  $\diamond = \diamond_m$  :  $\nu(P_1) = 0.5|0.4$ .

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## Antecedents of fuzzy rules in *FES*

### BASIC CONDITIONAL ELEMENTS (*CE*)

•  $P$  :  $exp_1$  *crisp\_comparison*  $exp_2$   
 $scalar_1$   $scalar_2$

- $exp_i$  - an expression of  $scalar_i$ ;
- *crisp\_comparison* - =, <, >, ...:

$$\nu(P) = \begin{cases} \xi(exp_1) \diamond \xi(exp_2) & \text{if } exp_1 \text{ } \textit{crisp\_comparison} \textit{ } exp_2, \\ \neg(\xi(exp_1) \diamond \xi(exp_2)) & \text{else.} \end{cases}$$

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### BASIC CONDITIONAL ELEMENTS (*CE*)

*declare*  $x$   $y$   $z$  *integer*

$x := 35$   $x.cf := 0.8|0.1$   $y := 35$   $y.cf := 0.6|0.2$

$z := 33$   $z.cf := 0.7|0.1$

$P_1 : x = y$

$P_2 : x < z$

$P_3 : x + y > y + z$

$$\nu(P_1) = 0.8|0.1 \diamond 0.6|0.2$$

$$\nu(P_2) = \neg(0.8|0.1 \diamond 0.7|0.1)$$

$$\nu(P_3) = \underbrace{(0.8|0.1 \diamond 0.6|0.2)}_{\xi(x+y)} \diamond \underbrace{(0.6|0.2 \diamond 0.7|0.1)}_{\xi(y+z)}$$

for  $*$  =  $\cdot$ ,  $\oplus = \oplus_p$ ,  $\diamond = \diamond_p$  :  $\nu(P_1) = 0.48|0.28$

$$\nu(P_2) = 0.19|0.56$$

$$\nu(P_3) = 0.2016|0.4816.$$

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### BASIC CONDITIONAL ELEMENTS (CE)

•  $P$  :  $\underset{fnumtype_1}{exp_1}$   $comparison$   $\underset{fnumtype_2}{exp_2}$

-  $exp_i$  - an expression of  $fnumtype_i$ ;

-  $comparison$  -  $\sim=$ ,  $\sim<$ ,  $\sim\leq$ :

$$\nu(P) = cmp | (1 - cmp),$$

$$cmp = fnum_1 \text{ comparison } fnum_2$$

```
declare x y z triang_fnum
```

```
x := create_triang_fnum(5, 2)
```

```
y := create_triang_fnum(7, 2)
```

```
z := create_triang_fnum(10, 2)
```

```
P1 : x  $\sim=$  y P2 : x  $\sim=$  z P3 : x  $\sim<$  y P4 : z  $\sim\leq$  y
```

```
 $\nu(P_1) = 0.5|0.5$   $\nu(P_2) = 0|1$   $\nu(P_3) = 1|0$   $\nu(P_4) = 0.25|0.75$ .
```

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### BASIC CONDITIONAL ELEMENTS (CE)

- $P$  :  $exp_1$  comparison  $exp_2$   
 $memftype_1$   $memftype_2$

- $exp_i$  - an expression of  $memftype_i$ ;
- comparison -  $\subset$ ,  $\subseteq$ ,  $is$  :

$$\nu(P) = cmp | (1 - cmp),$$

$$cmp = exp_1 \text{ comparison } exp_2,$$

$$exp_1 \text{ is } exp_2 = height(exp_1 \cap exp_2)$$

declare  $memf_1$   $memf_2$  rotation

$memf_1 := create\_polygon\_memf(0 \ 0 \ 1000 \ 0 \ 5000 \ 1 \ 9000 \ 1)$

$memf_2 := create\_polygon\_memf(0 \ 1 \ 500 \ 1 \ 2500 \ 0 \ 9000 \ 0)$

$P_1$  :  $memf_1$  is  $memf_2$   $P_2$  :  $memf_1 \subset memf_2$

$\nu(P_1) = 0.25 | 0.75$   $\nu(P_2) = 0 | 1.$

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### BASIC CONDITIONAL ELEMENTS (CE)

•  $P$  :  $x$  is member  
*fstype*

-  $x$  - a variable of *fstype*;

- *member* - a member of a (numerical) discrete fuzzy set of *fstype*:

$$\nu(P) = x.\text{member.cf}$$

```
declare species1 Species
```

```
species1 :=
```

```
    create_disfs(hamster 0.3|0.6 rabbit 0.6|0.2 hare 0.8|0.1)
```

```
declare length1 H_Length
```

```
length1 := create_numfs(small 0.2|0.7 medium 0.6|0.2 tall 0|1)
```

```
P1 : species1 is hamster P2 : length1 is small
```

```
 $\nu(P_1) = 0.3|0.6$   $\nu(P_2) = 0.2|0.7$ .
```

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### BASIC CONDITIONAL ELEMENTS (CE)

•  $P$  :  $x$  is member  
*numfstype*

- $x$  - a variable of *numfstype*;
- *member* - a member of a numerical discrete fuzzy set of *numfstype*:

$$\nu(P) = \text{cmp} | (1 - \text{cmp}),$$

$$\text{cmp} = (x.\text{member}.cf * x.\text{member}) \text{ is } \text{numfstype}.\text{member},$$

$$a|b * A(u) = \begin{cases} \frac{a * A(u) * \gamma + b * (1 - A(u)) * \delta}{a + b} & \text{if } a + b > 0, \\ \frac{1}{2} & \text{else,} \end{cases}$$

$A$  - a fuzzy set,  $\gamma, \delta \in [0, 1]$ .

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### BASIC CONDITIONAL ELEMENTS (CE)

$\text{Hum\_Length.small} := \text{create\_polygon\_memf}(0 \ 1 \ 160 \ 0 \ 250 \ 0)$

$\text{declare length}_1 \ \text{Hum\_Length}$

$\text{length}_1 := \text{create\_numfs}(\text{small} \ 0.2|0.7 \ \text{medium} \ 0.6|0.2 \ \text{tall} \ 0|1)$

$\text{length}_1.\text{small} := \text{create\_polygon\_memf}(0 \ 1 \ 160 \ 0.3 \ 250 \ 0)$

$P_1 : \text{length}_1 \text{ is small} \quad P_2 : \text{length}_1 \text{ is small}$

$$\nu(P_1) = 0.2|0.7$$

$$\begin{aligned} \text{cmp} &= (\text{length}_1.\text{small.cf} * \text{length}_1.\text{small}) \text{ is Hum\_Length.small} \\ &= (0.2|0.7 * \text{length}_1.\text{small}) \text{ is Hum\_Length.small} \end{aligned}$$

$$\nu(P_2) = \text{cmp} | (1 - \text{cmp})$$

$$\text{for } * = \cdot, \gamma = \delta = 1 : \quad 0.2|0.7 \cdot \text{length}_1.\text{small} = (0 \ \frac{2}{9} \ 160 \ \frac{5.5}{9} \ 250 \ \frac{7}{9})$$

$$\begin{aligned} \text{cmp} &= (0 \ \frac{2}{9} \ 160 \ \frac{5.5}{9} \ 250 \ \frac{7}{9}) \text{ is } (0 \ 1 \ 160 \ 0 \ 250 \ 0) \\ &= 1 - \frac{7}{12.5} = 1 - 0.56 = 0.44 \end{aligned}$$

$$\nu(P_2) = 0.44|0.56.$$

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### BASIC CONDITIONAL ELEMENTS (CE)

•  $P$  :  $exp_1$  is  $exp_2$   
float memftype

- $exp_1$  - an expression of *float*;
- $exp_2$  - an expression of *memftype*:

$$\nu(P) = \xi(exp_1) \diamond exp_2(exp_1) | (1 - exp_2(exp_1))$$

*declare* x y z float

x := 500 x.cf := 0.8|0.1 y := 6 y.cf := 0.3|0.5 z := 120 z.cf := 0.6|0.1

*declare* memf rotation

memf := create\_polygon\_memf(0 0 1000 0.8 5000 1 9000 0)

*declare* fnum triang\_fnum fnum := create\_triang\_fnum(5, 2)

Hum\_Length.small := create\_polygon\_memf(0 1 160 0 250 0)

$P_1$  : x is memf  $P_2$  : y is fnum  $P_3$  : z is Hum\_Length.small

$\nu(P_1) = 0.8|0.1 \diamond 0.4|0.6$   $\nu(P_2) = 0.3|0.5 \diamond 0.5|0.5$

$\nu(P_3) = 0.6|0.1 \diamond 0.25|0.75$

for  $\diamond = \diamond_p$  :  $\nu(P_1) = 0.32|0.64$   $\nu(P_2) = 0.15|0.75$   $\nu(P_3) = 0.15|0.775$ .

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### BASIC CONDITIONAL ELEMENTS (*CE*)

•  $P^*$  :  $exp_1$  is  $p\_modifier$   $exp_2$   
*float* *memftype*

$P^+$  :  $exp_1$  is  $s\_modifier$   $exp_2$   
*float* *memftype*

- $exp_1$  - an expression of *float*;
- $exp_2$  - an expression of *memftype*:

$$\nu(P^*) = \xi(exp_1) \diamond exp_2(exp_1)^p | (1 - exp_2(exp_1)^p),$$

$$\nu(P^+) = \xi(exp_1) \diamond exp_2(exp_1 + s) | (1 - exp_2(exp_1 + s)).$$

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### BASIC CONDITIONAL ELEMENTS (CE)

$x := 500$   $x.cf := 0.8|0.1$   $y := 120$   $y.cf := 0.6|0.3$

$memf := create\_polygon\_memf(0\ 0\ 1000\ 0.8\ 5000\ 1\ 9000\ 0)$

$Hum\_Length.small := create\_polygon\_memf(0\ 1\ 160\ 0\ 250\ 0)$

$P_1$ :  $x$  is very\*  $memf$

$P_2$ :  $y$  is slightly\*  $Hum\_Length.small$

$P_3$ :  $x$  is very+  $memf$

$P_4$ :  $y$  is slightly+  $Hum\_Length.small$

$$\nu(P_1) = 0.8|0.1 \diamond 0.4^2|(1 - 0.4^2)$$

$$\nu(P_2) = 0.6|0.3 \diamond 0.25^{\frac{1}{3}}|(1 - 0.25^{\frac{1}{3}})$$

$$\begin{aligned}\nu(P_3) &= 0.8|0.1 \diamond memf(500 - 100)|(1 - memf(500 - 100)) \\ &= 0.8|0.1 \diamond 0.32|(1 - 0.32)\end{aligned}$$

$$\mu = Hum\_Length.small(120 - 20)$$

$$\nu(P_4) = 0.6|0.3 \diamond \mu|(1 - \mu) = 0.6|0.3 \diamond 0.375|0.625$$

$$\text{for } \diamond = \diamond_p : \quad \nu(P_1) = 0.128|0.856 \quad \nu(P_2) \doteq 0.378|0.5590$$

$$\nu(P_3) = 0.256|0.712 \quad \nu(P_4) = 0.225|0.7375.$$

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### BASIC CONDITIONAL ELEMENTS (CE)

- $P$  :  $exp_1$  is  $d\_modifier$   $exp_2$   
float float

-  $exp_i$  - an expression of *float*:

$$\mu = create\_fnum(exp_2, d)(exp_1),$$
$$\nu(P) = \xi(exp_1) \diamond \mu | (1 - \mu) \diamond \xi(exp_2)$$

$x := 97.5$   $x.cf := 0.8|0.1$   $y := 100$   $y.cf := 0.7|0.2$

$P_1$  :  $x$  is nearly  $y$   $P_2$  :  $x$  is approximately  $y$

$$\mu_1 = create\_triang\_fnum(y, 5)(x) = 0.5|0.5$$
$$\nu(P_1) = 0.8|0.1 \diamond \mu_1 | (1 - \mu_1) \diamond 0.7|0.2 = 0.8|0.1 \diamond 0.5|0.5 \diamond 0.7|0.2$$

$$\mu_2 = create\_triang\_fnum(y, 10)(x) = 0.75|0.25$$
$$\nu(P_2) = 0.8|0.1 \diamond \mu_2 | (1 - \mu_2) \diamond 0.7|0.2 = 0.8|0.1 \diamond 0.75|0.25 \diamond 0.7|0.2$$

for  $\diamond = \diamond_p$  :  $\nu(P_1) = 0.28|0.64$   $\nu(P_2) = 0.42|0.46$ .

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### BASIC CONDITIONAL ELEMENTS (CE)

$$\bullet P_1 : \begin{array}{l} \text{exp} \\ \text{truth\_value} \end{array}$$

$$P_2 : \begin{array}{l} \text{exp}_1 \quad \text{crisp\_comparison} \quad \text{exp}_2 \\ \text{truth\_value} \qquad \qquad \qquad \text{truth\_value} \end{array}$$

- $\text{exp}$ ,  $\text{exp}_i$  - an expression of  $\text{truth\_value}$ ;
- $\text{crisp\_comparison}$  -  $=$ ,  $\leq_k$ ,  $<_k$ ,  $\leq_t$ ,  $<_t$ :

$$\nu(P_1) = \text{exp} \diamond \xi(\text{exp}),$$

$$\nu(P_2) = \begin{cases} \xi(\text{exp}_1) \diamond \xi(\text{exp}_2) & \text{if } \text{exp}_1 \text{ crisp\_comparison } \text{exp}_2, \\ \neg(\xi(\text{exp}_1) \diamond \xi(\text{exp}_2)) & \text{else.} \end{cases}$$

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### BASIC CONDITIONAL ELEMENTS (CE)

$x := 0.5$   $x.cf := 0.9|0.1$   $y := 0.4$   $y.cf := 0.8|0.2$

$species_1 :=$

$create\_disfs(hamster\ 0.3|0.6\ rabbit\ 0.6|0.2\ hare\ 0.8|0.2)$

$length_1 := create\_numfs(small\ 0.2|0.8\ medium\ 0.6|0.2\ tall\ 0|0)$

$P_1 : species_1.hamster.cf \leq_k x|y$

$P_2 : species_1.rabbit.cf >_t 0.5|0.3$

$P_3 : x|y >_k \Leftrightarrow x|y$

$P_4 : species_1.rabbit.cf = length_1.tall.cf$

$\nu(P_1) = \neg(0.9|0.1 \diamond 0.8|0.2); 0.3|0.6 \not\leq_k 0.5|0.4$

$\nu(P_2) = 1|0 \diamond 1|0 = 1|0; 0.6|0.2 >_t 0.5|0.3$

$\nu(P_3) = \neg((0.9|0.1 \diamond 0.8|0.2) \diamond (0.9|0.1 \diamond 0.8|0.2)); 0.5|0.4 \not>_k 0.6|0.5$

$\nu(P_4) = \neg(1|0 \diamond 1|0) = 0|1; 0.6|0.2 \neq 0|0$

for  $\diamond = \diamond_p$  :  $\nu(P_1) = 0.28|0.72$   $\nu(P_3) = 0.4816|0.5184$ .

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## Fuzzy rules in *FES*

### ANTECEDENT OF A FUZZY RULE

- Basic connectives and their interpretation:

<i>and</i>		*		<i>t_and</i>		◇		<i>not</i>		¬
<i>or</i>		⊕		<i>t_or</i>		□		<i>pos</i>		⇔

- A literal  $l$  is either a  $CE$  or  $cn_1 CE$  or  $cn_1 cn_2 CE$  where  $cn_i \in \{not, pos\}$ .
- A clause  $Cl$  is an expression well-formed from literals using  $or, t_or$ .
- An antecedent  $Ant$  is an expression well-formed from clauses using  $and, t_and$ .
- $\nu(l), \nu(Cl), \nu(Ant)$  - the truth value of  $l, Cl, Ant$ 
  - defined on the structure of the respective formula.

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### BASIC FUZZY RULE STRUCTURE

A fuzzy rule is of the form

*IF antecedent THEN<sup>cf</sup><sub>th</sub> consequent*

- *antecedent* - an antecedent;
- $cf = a|b$  - the certainty (necessity) factor of the fuzzy rule;
- $pos = \Leftrightarrow a|b$  - the possibility of the fuzzy rule;
- $th = c|d$  - the threshold of the fuzzy rule;
- *consequent* - the consequent of a fuzzy rule - a sequence of actions: *BCA* and other program instructions (control, I/O,...);
- $\nu(\textit{antecedent})$  - the matching degree of the fuzzy rule;
- $fs = \nu(\textit{antecedent}) \diamond cf$  - the firing strength of the fuzzy rule.
- If  $fs \geq_t th$  - the fuzzy rule **fires**.

*IF distance is short and speed is high THEN<sup>0.8|0.1</sup><sub>0.6|0.4</sub> braking := hard*

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# Consequents of fuzzy rules in *FES*

## Basic consequent actions (*BCA*)

•  $x := exp_1$        $y.cf := exp_2$   
variable    scalar      variable      truth\_value

•  $x := exp$   
variable    memftype

•  $x := create\_disfs(.), create\_numfs(.)$   
fstype

$y$  is member<sub>1</sub>  
fstype

$z$  is member<sub>2</sub>  
numfstype

•  $x := fuzzify(u)$   
numfstype      float

$y := fuzzify(v)$   
numfstype      fnumtype

$z := defuzzify(w, method)$   
float      numfstype

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### BASIC CONSEQUENT ACTIONS (*BCA*)

- Crisp assignments:

$$A_1 : \quad \underset{\text{variable}}{x} := \underset{\text{scalar}}{\text{exp}_1} \quad A_2 : \quad \underset{\text{variable}}{y}.cf := \underset{\text{truth\_value}}{\text{exp}_2}$$

- $x$  - a variable of *scalar*;
- $y$  - a variable of *truth\_value*;
- $\text{exp}_1$  - an expression of *scalar*;
- $\text{exp}_2$  - an expression of *truth\_value*:

$$fs : \text{ IF antecedent THEN}_{th}^{cf} A_1, A_2$$

$$A_1 : \quad x = \text{exp}_1, \\ x.cf = \xi(\text{exp}_1),$$

$$A_2 : \quad y.cf = \text{exp}_2 \diamond \xi(\text{exp}_2).$$

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## BASIC CONSEQUENT ACTIONS (*BCA*)

*declare*  $x$   $y$   $w$   $z$  *integer*

$x := 5$   $x.cf := 0.8|0.1$   $y := 4$   $y.cf := 0.7|0.2$

$A_1$ :  $w := x + y$

$A_2$ :  $z.cf := \frac{x}{10} | \frac{y}{10}$

$A_1$ :  $w = 5 + 4 = 9$   $w.cf = (0.8|0.1 \diamond 0.7|0.2)$

$A_2$ :  $z.cf = \frac{5}{10} | \frac{4}{10} \diamond (0.8|0.1 \diamond 0.7|0.2)$

for  $\diamond = \diamond_p$ :

$w.cf = 0.56|0.28$

$z.cf = 0.5|0.4 \diamond 0.56|0.28 = 0.28|0.568.$

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## Consequents of fuzzy rules in FES

### BASIC CONSEQUENT ACTIONS (BCA)

- Fuzzy assignments:

$$F : \quad \underset{\text{variable}}{x} := \underset{\text{memftype}}{\text{exp}}$$

- $x$  - a variable of *memftype*;
- $\text{exp}$  - an expression of *memftype*:

$$fs : \text{IF antecedent THEN}_{th}^{cf} F_1$$
$$F : \quad \begin{aligned} x &= \text{exp}, \\ x.cf &= 1|0. \end{aligned}$$

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Consequents of fuzzy rules in *FES*

## BASIC CONSEQUENT ACTIONS (*BCA*)

```
defmemftype rotation shape : polygon domain : 0 9000
```

```
defnumfstype Motor_Speed members : slow medium fast  
memftype : rotation
```

```
declare memf1 memf2 memf3 rotation
```

```
declare speed1 Motor_Speed
```

```
memf1 := create_polygon_memf(0 0 2000 0 4000 1 9000 1)
```

```
memf2 := create_polygon_memf(0 0 2500 0 3500 1 9000 1)
```

```
F1 : memf3 := memf1 ∪ memf2
```

```
F2 : speed1.fast := very memf3
```

```
F1 : memf3 = (0 0 2500 0 3000 0.5 3500 1 9000 1)  
memf3.cf = 1|0
```

```
F2 : speed1.fast = (0 0 2500 0 3000 0.25 3500 1 9000 1)  
speed1.fast.cf = 1|0.
```

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## Consequents of fuzzy rules in *FES*

### BASIC CONSEQUENT ACTIONS (BCA)

- Fuzzy assignments:

$F_1$  :  $x$  := *create\_disfs*(.), *create\_numfs*(.)  
*fstype*

$F_2$  :  $y$  *is member*<sub>1</sub>  
*fstype*

$F_3$  :  $z$  *is member*<sub>2</sub>  
*numfstype*

- $x, y$  - variables of *fstype*;
- $z$  - a variable of *numfstype*;
- *member*<sub>1</sub> - a member of a (numerical) discrete fuzzy set of *fstype*;
- *member*<sub>2</sub> - a member of a numerical discrete fuzzy set of *numfstype*.

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## Consequents of fuzzy rules in FES

### BASIC CONSEQUENT ACTIONS (BCA)

$fs$  : IF antecedent THEN<sub>th</sub><sup>cf</sup>  $F_1, F_2, F_3$

$F_1$  :  $x = \text{create\_disfs}(\cdot), \text{create\_numfs}(\cdot),$   
 $x.cf = 1|0,$

$F_2$  :  $y.\text{member}_1.cf = fs,$   
 $y.cf = 1|0,$

$F_3$  :  $z.\text{member}_2 = \nu(\text{antecedent}) * \text{numfstype}.\text{member}_2,$   
 $z.\text{member}_2.cf = cf,$   
 $z.cf = 1|0.$

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## Consequents of fuzzy rules in *FES*

### BASIC CONSEQUENT ACTIONS (*BCA*)

*declare species<sub>1</sub> species<sub>2</sub> Species*

*declare length<sub>1</sub> length<sub>2</sub> Hum\_Length*

*Hum\_Length.small := create\_polygon\_memf(0 1 160 0.5 250 0)*

*F<sub>1</sub> : species<sub>1</sub> species<sub>2</sub> :=  
create\_disfs(hamster 0.3|0.6 rabbit 0.6|0.2 hare 0.8|0.1)*

*F<sub>2</sub> : length<sub>1</sub> length<sub>2</sub> :=  
create\_numfs(small 0.2|0.7 medium 0.6|0.2 tall 0|0.9)*

*F<sub>3</sub> : species<sub>2</sub> is hamster*

*F<sub>4</sub> : length<sub>2</sub> is small*

*F<sub>1</sub> : species<sub>1</sub> species<sub>2</sub> =  
(hamster 0.3|0.6 rabbit 0.6|0.2 hare 0.8|0.1)*

*F<sub>1</sub> : species<sub>1</sub>.cf = 1|0 species<sub>2</sub>.cf = 1|0*

*F<sub>2</sub> : length<sub>1</sub> length<sub>2</sub> = (small 0.2|0.7 medium 0.6|0.2 tall 0|0.9)*

*F<sub>2</sub> : length<sub>1</sub>.cf = 1|0 length<sub>2</sub>.cf = 1|0.*

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### BASIC CONSEQUENT ACTIONS (BCA)

$$F_3 : \text{species}_2.\text{hamster}.cf = fs = \nu(\text{antecedent}) \diamond cf$$

$$F_3 : \text{species}_2.cf = 1|0$$

$$F_4 : \text{length}_2.\text{small} = \nu(\text{antecedent}) * \text{Hum\_Length.small}$$

$$F_4 : \text{length}_2.\text{small}.cf = cf$$

$$F_4 : \text{length}_2.cf = 1|0$$

for  $\nu(\text{antecedent}) = 0.7|0.2$ ,  $cf = 0.9|0.1$ ,  $*$  =  $\cdot$ ,  $\gamma = \delta = 1$ ,  $\diamond = \diamond_p$ :

$$F_3 : \text{species}_2.\text{hamster}.cf = 0.7|0.2 \diamond 0.9|0.1 = 0.63|0.28$$

$$F_4 : \text{length}_2.\text{small} = 0.7|0.2 \cdot (0 \ 1 \ 160 \ \frac{1}{2} \ 250 \ 0) \\ = (0 \ \frac{7}{9} \ 160 \ \frac{1}{2} \ 250 \ \frac{2}{9})$$

$$F_4 : \text{length}_2.\text{small}.cf = 0.9|0.1.$$

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# Fuzzy expert systems

## Consequents of fuzzy rules in *FES*

### BASIC CONSEQUENT ACTIONS (*BCA*)

- Fuzzification, defuzzification:

$$F_1 : \quad \underset{\text{numfstype}}{x} := \text{fuzzify}(\underset{\text{float}}{u})$$

$$F_2 : \quad \underset{\text{numfstype}}{y} := \text{fuzzify}(\underset{\text{fnumtype}}{v})$$

$$A : \quad \underset{\text{float}}{z} := \text{defuzzify}(\underset{\text{numfstype}}{w}, \text{method})$$

- $x, y, w$  - variables of *numfstype*;
- $u, z$  - variables of *float*;
- $v$  - a variable of *fnumtype*;
- *method* - a method of defuzzification (*COG, MOM, ...*).

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## Consequents of fuzzy rules in FES

### BASIC CONSEQUENT ACTIONS (BCA)

$fs$  : IF antecedent THEN<sup>cf</sup><sub>th</sub>  $F_1, F_2, A$

$F_1$  :  $x = \text{fuzzify}(u) \diamond u.cf$ ,

$[A \diamond a|b](m) = A(m) \diamond a|b$ ;  $A$  - a discrete fuzzy set,

$x.cf = 1|0$ ,

$F_2$  :  $y = \text{fuzzify}(v)$ ,

$y.cf = 1|0$ ,

$F_3$  :  $z = \text{defuzzify}(w)$ ; the defuzzification of  $\bigcup_{m \in w} w.m.cf * w.m$ ,

$z.cf = fs$ .

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## BASIC CONSEQUENT ACTIONS (*BCA*)

```
defmemftype Celsius shape : polygon domain : 0 100
```

```
defnumfstype Temperature members : low medium high  
memftype : Celsius
```

```
declare temp1 temp2 Temperature
```

```
Temperature.low := create_polygon_memf(0 1 50 0 100 0)
```

```
Temperature.medium := create_polygon_memf(0 0 50 1 100 0)
```

```
Temperature.high := create_polygon_memf(0 0 50 1 100 1).
```

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# Fuzzy expert systems

## Consequents of fuzzy rules in *FES*

### BASIC CONSEQUENT ACTIONS (*BCA*)

- Fuzzification:

```
declare x y float
```

```
x := 40 x.cf := 0.7|0.2
```

```
declare fnum triang_fnum
```

```
fnum := create_triang_fnum(40, 20)
```

```
F1 : temp1 := fuzzify(x)
```

```
F2 : temp2 := fuzzify(fnum)
```

```
F1 : temp1 = (low 0.2|0.8 medium 0.8|0.2 high 0|1)  $\diamond$  0.7|0.2
```

picture

```
F2 : temp2 = (low 0.42|0.58 medium 0.88|0.12 high 0.14|0.86)
```

picture

```
for  $\diamond$  =  $\diamond_p$ :
```

```
F1 : temp1 = (low 0.14|0.84 medium 0.56|0.36 high 0|1).
```

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# Fuzzy expert systems

## Consequents of fuzzy rules in FES

### BASIC CONSEQUENT ACTIONS (BCA)

- Defuzzification:

*declare*  $z_1 z_2$  float

$A_1$  :  $z_1 := \text{defuzzify}(\text{temp}_2, \text{COG})$

$A_2$  :  $z_2 := \text{defuzzify}(\text{temp}_2, \text{MOM})$

for  $fs = 0.9|0.1$ ,  $*$  = min,  $\gamma = 1$ ,  $\delta = 0$ :

$$\bigcup_{m \in \{\text{low}, \text{medium}, \text{high}\}} \text{temp}_2.m.cf * \text{temp}_2.m =$$
$$\min(0.42|0.58, (0 \ 1 \ 50 \ 0 \ 100 \ 0)) \cup \min(0.88|0.12, (0 \ 0 \ 50 \ 1 \ 100 \ 0)) \cup$$
$$\min(0.14|0.86, (0 \ 0 \ 50 \ 1 \ 100 \ 1)) =$$
$$(0 \ 0.42 \ 29 \ 0.42 \ 50 \ 0 \ 100 \ 0) \cup (0 \ 0 \ 44 \ 0.88 \ 56 \ 0.88 \ 100 \ 0) \cup (0 \ 0 \ 7 \ 0.14 \ 100 \ 0.14) =$$
$$(0 \ 0.42 \ 21 \ 0.42 \ 44 \ 0.88 \ 56 \ 0.88 \ 93 \ 0.14 \ 100 \ 0.14)$$

$A_1$  :  $z_1 = 43$   $z_1.cf = 0.9|0.1$

[picture](#)

$A_2$  :  $z_2 = 50$   $z_2.cf = 0.9|0.1$

[picture](#)

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# Fuzzy expert systems

## Template facts

### DEFINITION

*deftemplate* *name\_of\_fact\_template*

*slot* *name*<sub>1</sub> *scalar*<sub>1</sub>

*multislot* *name*<sub>2</sub> *scalar*<sub>2</sub>

*slot* *name*<sub>3</sub> *truth\_value*<sub>3</sub>

*multislot* *name*<sub>4</sub> *truth\_value*<sub>4</sub>

*slot* *name*<sub>5</sub> *fnumtype*<sub>5</sub>

*slot* *name*<sub>6</sub> *memftype*<sub>6</sub>

*slot* *name*<sub>7</sub> *disfstype*<sub>7</sub>

*slot* *name*<sub>8</sub> *numfstype*<sub>8</sub>

- *deftemplate* - the definition of a fact template;
- *slot* - a single field,
- *multislot* - a sequence of fields of *scalar*<sub>*i*</sub>, *truth\_value*<sub>*i*</sub>;
- *name\_of\_fact\_template.name*<sub>*i*</sub>.*cf* - the certainty factor  $a|b$  of the *slot* *name\_of\_fact\_template.name*<sub>*i*</sub> of *scalar*<sub>*i*</sub>.

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### ASSERTION AND RETRACTION

*assert* *name\_of\_fact\_template*

*name*<sub>1</sub> *exp*<sub>1</sub> (an expression of *scalar*<sub>1</sub>)

*name*<sub>2</sub> *seq*<sub>2</sub> (a sequence of expressions of *scalar*<sub>2</sub>)

*name*<sub>3</sub> *exp*<sub>3</sub> (an expression of *truth\_value*<sub>3</sub>)

*name*<sub>4</sub> *seq*<sub>4</sub> (a sequence of expressions of *truth\_value*<sub>4</sub>)

*name*<sub>5</sub> *exp*<sub>5</sub> (an expression of *fnumtype*<sub>5</sub>)

*name*<sub>6</sub> *exp*<sub>6</sub> (an expression of *memftype*<sub>6</sub>)

*name*<sub>7</sub> *x*<sub>7</sub> (a variable of *disfstype*<sub>7</sub>)

*name*<sub>8</sub> *x*<sub>8</sub> (a variable of *numfstype*<sub>8</sub>)

- *assert* - including an individual fact of a defined fact template to the fact list with the unique fact number *fn* (pointer);
- *x<sub>i</sub>* - a single field/value variable of *scalar<sub>i</sub>*/*truth\_value<sub>i</sub>*;
- *\$x<sub>i</sub>* - a sequence of fields/values variable of *scalar<sub>i</sub>*/*truth\_value<sub>i</sub>*;
- for a slot *name\_of\_fact\_template.name<sub>i</sub>* of *scalar<sub>i</sub>* and an expression *exp<sub>i</sub>* of *scalar<sub>i</sub>*,  
*name\_of\_fact\_template.name<sub>i</sub>.cf* =  $\xi(\text{exp}_i)$ .
- *retract(fn)* - retracting the individual fact with *fn*.

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### BASIC PATTERN ELEMENTS (*PE*) FOR MATCHING

$I \leftarrow /not$  *name\_of\_fact\_template*

*name*<sub>1</sub> *exp*<sub>1</sub> (an expression of *scalar*<sub>1</sub>)

*name*<sub>2</sub> *seq*<sub>2</sub> (a sequence of expressions of *scalar*<sub>2</sub>)

*name*<sub>3</sub> *exp*<sub>3</sub> (an expression of *truth\_value*<sub>3</sub>)

*name*<sub>4</sub> *seq*<sub>4</sub> (a sequence of expressions of *truth\_value*<sub>4</sub>)

*name*<sub>5</sub> *exp*<sub>5</sub> (an expression of *fnumtype*<sub>5</sub>)

*name*<sub>6</sub> *exp*<sub>6</sub> (an expression of *memftype*<sub>6</sub>)

*name*<sub>7</sub> *x*<sub>7</sub> (a variable of *disfstype*<sub>7</sub>)

*name*<sub>8</sub> *x*<sub>8</sub> (a variable of *numfstype*<sub>8</sub>)

- *I* - *fn* of a matched fact / *not* - all the variables in *PE* instantiated;
- for a single value variable *x*<sub>*i*</sub> of *scalar*<sub>*i*</sub>; and  
a slot *name\_of\_fact\_template.name*<sub>*i*</sub> of *scalar*<sub>*i*</sub>,  
*x*<sub>*i*</sub>.*cf* = *name\_of\_fact\_template.name*<sub>*i*</sub>.*cf*.
- The access to (multi)slots, their certainty factors - by *I.name*<sub>*i*</sub>(.cf).
- *retract*(*I*) - retracting the individual fact with *fn* = *I*.

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## Template facts

### DEFINITION AND ASSERTION

*deftemplate car*

*slot type string*  
*slot engine float*  
*slot age age\_of\_car*  
*slot condition condition\_of\_car*

*fn = 1: assert car*

*type golf 1|0*  
*engine 1.4 0.9|0.1*  
*age (new 0.9|0.1 medium 0.2|0.6 old 0|1)*  
*condition (good 0.7|0.1 medium 0.5|0.2 bad 0.1|0.8)*

*fn = 2: assert car*

*type passat 1|0*  
*engine 2.0 0.8|0.2*  
*age (new 0.6|0.3 medium 0.5|0.3 old 0|1)*  
*condition (good 0.5|0.1 medium 0.5|0.3 bad 0.1|0.9)*

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## Template facts

### PATTERN MATCHING AND RETRACTION

*declare* *x y float*

*declare* *age<sub>1</sub> age<sub>2</sub> age\_of\_car*

*declare* *cond<sub>1</sub> cond<sub>2</sub> condition\_of\_car*

**I** ← *car*

*type* *golf*

*engine* *x* (*x* = 1.4)

*age* *age<sub>1</sub>* (*age<sub>1</sub>* = (*new* 0.9|0.1 *medium* 0.2|0.6 *old* 0|1))

*condition* *cond<sub>1</sub>* (*cond<sub>1</sub>* = (*good* 0.7|0.1 *medium* 0.5|0.2 *bad* 0.1|0.8))

**I** = 1 *x.cf* = 0.9|0.1 **I.type** = *golf* **I.type.cf** = 1|0 *retract*(**I**)

**J** ← *car*

*type* *passat*

*engine* *y* (*y* = 2.0)

*age* *age<sub>2</sub>* (*age<sub>2</sub>* = (*new* 0.6|0.3 *medium* 0.5|0.3 *old* 0|1))

*condition* *cond<sub>2</sub>* (*cond<sub>2</sub>* = (*good* 0.5|0.1 *medium* 0.5|0.3 *bad* 0.1|0.9))

**J** = 2 *y.cf* = 0.8|0.2 **J.type** = *passat* **J.type.cf** = 1|0 *retract*(**J**).

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## Parallel computation in blocks

### BASIC BLOCK STRUCTURE

*block* *name\_of\_block* *priority* *P*

*definitions of types*

*declarations of variables*

*preamble instructions* (*variable assignments*)

⋮

*IF* *patern<sub>i</sub>* : *antecedent<sub>i</sub>* *THEN* <sup>*cf<sub>i</sub>*</sup><sub>*th<sub>i</sub>*</sub> *consequent<sub>i</sub>* ; *agg*  $\bar{x}_i$  : *assertion<sub>i</sub>* ;

⋮

*ending instructions* (*control, I/O, focus, ...*)

- $P \in [-10000, 10000]$ ;
- *patern<sub>i</sub>* - a sequence of *PE*'s;
- *consequent<sub>i</sub>* may contain *retract*'s of old facts;
- *assertion<sub>i</sub>* - a sequence of *assert*'s of new facts;
- $\bar{x}_i$  - the aggregated variables in *assertion<sub>i</sub>*.
- *FES* - a collection of blocks.

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### AN INFERENCE CYCLE

- (1) The execution of the *preamble instructions*.
- (2) Matching the rule *patterns* against the fact list; one rule may have several matches.
- (3) The evaluation of the rule *antecedents* for successful matches.
- (4) The execution of the rule *consequents* with respect to the evaluated *antecedents* with possible *retraction* of old facts from the fact list.
- (5) The *aggregation* of selected block variables.
- (6) The *assertion* of new facts with respect to aggregated block variables.
- (7) The execution of the *ending instructions*.

An example of parallel computation.

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## Parallel computation in blocks

### AN INFERENCE CYCLE

- $Vars$  - the set of all the variables in the block.
- $R$  - the set of all the rules in the block.

Let  $r \in R$ .

- $pattern\_vars(r)$  - the set of all the variables in the  $pattern(r)$ ;
- $antecedent\_vars(r)$  ..... in the  $antecedent(r)$ ;
- $consequent\_vars(r)$  ..... in the  $consequent(r)$ ;
- $assert\_vars(r)$  ..... in the  $assertion(r)$ ;
- $agg\_vars(r) = \bar{x}(r) \subseteq assert\_vars(r)$  where  $agg \bar{x}(r)$ ;
- $*\_vars(r) \subseteq Vars$ .

-  $\sigma : dom(\sigma) \longrightarrow \bigcup_{t \text{ is a type}} t$  - a variable assignment,

$dom(\sigma) \subseteq Vars$  - the domain of  $\sigma$ ;

if  $x \in dom(\sigma)$  is of  $scalar$ , then  $x.cf \in dom(\sigma)$ .

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### AN INFERENCE CYCLE

- 1 The output of the *preamble instructions*:  $\sigma_p$ .
- 2 The output of matching:  $\sigma_1, \dots, \sigma_n, R_1, \dots, R_n$ ,  
 $\sigma_i \supseteq \sigma_p$ ,  $dom(\sigma_i) = dom(\sigma_p) \cup \bigcup_{r \in R_i} pattern\_vars(r)$ ,  
 $\emptyset \neq R_i \subseteq R$ ;  
 $\sigma_i$  - an input variable assignment;  
 $R_i$  - the set of all the matched rules by  $\sigma_i$  against the fact list;  
 $\sigma_i, R_i$  - both maximal; there are no proper super sets of them satisfying some match.
- 3 The output of the evaluation of *antecedents*:  
 $\forall 1 \leq i \leq n, r \in R_i, \nu(antecedent(r))$  with respect to  $\sigma_i$ ;  
 $dom(\sigma_i) \supseteq antecedent\_vars(r)$ .

### AN INFERENCE CYCLE

- ④ The output of the evaluation of *consequents*:
- $\forall 1 \leq i \leq n, r \in R_i^A = \{r \mid r \in R_i, fs_r \geq_t th_r\}$  wrt.  $\sigma_i$ ,  
 $R_i^A \subseteq R_i$  - the subset of all activated rules;
- $$\rho_r^i, dom(\rho_r^i) = dom(\sigma_i) \cup consequent\_vars(r)$$
- $$\supseteq assert\_vars(r)$$
- an output variable assignment with respect to  $\sigma_i$ ,  
 $\nu(antecedent(r)), cf_r, fs_r$ .

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### AN INFERENCE CYCLE

5 The output of aggregation:

$$\forall 1 \leq i \leq n, r \in R_i^A,$$

$$\xi_r^i, \text{dom}(\xi_r^i) = \text{assert\_vars}(r) \supseteq \text{agg\_vars}(r)$$

- an aggregated output variable assignment with respect to  $\text{agg\_vars}(r)$  defined as follows:

$$\text{fixed\_vars}(r) = \text{assert\_vars}(r) - \text{agg\_vars}(r).$$

Let  $x \in \text{agg\_vars}(r) \subseteq \text{assert\_vars}(r) = \text{dom}(\xi_r^i) \subseteq \text{dom}(\rho_r^i)$ .

$$\text{aggregation}(\rho_r^i, x) = \{ \rho_s^j \mid 1 \leq j \leq n, s \in R_j^A, \\ \text{fixed\_vars}(r) \cup \{x\} \subseteq \text{dom}(\rho_s^j), \\ \rho_r^i|_{\text{fixed\_vars}(r)} = \rho_s^j|_{\text{fixed\_vars}(r)} \}.$$

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## Parallel computation in blocks

### AN INFERENCE CYCLE

5 For  $x \in \text{fixed\_vars}(r)$ ,

$$\xi_r^i(x) = \rho_r^i(x);$$

for  $x \in \text{agg\_vars}(r)$  of *scalar*,

$$\xi_r^i(x) = \rho_r^i(x),$$

$$\xi_r^i(x.cf) = \square\{\rho_s^j(x.cf) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x), \rho_s^j(x) = \rho_r^i(x)\};$$

for  $x \in \text{agg\_vars}(r)$  of *truth\_value*,

$$\xi_r^i(x) = \square\{\rho_s^j(x) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x)\};$$

for  $x \in \text{agg\_vars}(r)$  of *memftype*,

$$\xi_r^i(x) = \oplus\{\rho_s^j(x) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x)\};$$

for  $x \in \text{agg\_vars}(r)$  of *disfstype*,

$$\xi_r^i(x.m.cf) = \square\{\rho_s^j(x.m.cf) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x)\}, \min x;$$

for  $x \in \text{agg\_vars}(r)$  of *numfstype*,

$$\xi_r^i(x.m) = \oplus\{\rho_s^j(x.m) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x)\}, \min x,$$

$$\xi_r^i(x.m.cf) = \square\{\rho_s^j(x.m.cf) \mid \rho_s^j \in \text{aggregation}(\rho_r^i, x)\}, \min x.$$

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### AN INFERENCE CYCLE

- 6 The output of assertion:  
 $\forall 1 \leq i \leq n, r \in R_i^A$ , new facts asserted by *assertion*( $r$ ) with respect to  $\xi_r^i$ ;  $dom(\xi_r^i) = assert\_vars(r)$ .
- 7 The output of the *ending instructions*:  
e.g. control, I/O, focus actions.

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## AN INFERENCE CYCLE

```
defmemftype H_Age shape : polygon domain : 0 100
```

```
defnumfstype Hum_Age members : young medium old  
memftype : H_age
```

```
Hum_Age.young := create_polygon_memf(0 1 50 0 100 0)
```

```
Hum_Age.medium := create_polygon_memf(0 0 50 1 100 0)
```

```
Hum_Age.old := create_polygon_memf(0 0 50 1 100 1)
```

```
deftemplate person
```

```
slot name string
```

```
slot siblings integer
```

```
slot age Hum_Age
```

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## AN INFERENCE CYCLE

*block*  $b_1$  *priority* 0

*declare*  $x$  *string*  $s$  *integer*  $a$  *Hum\_Age*

$r_1$  *IF* *person* : 1|0

*name*  $x$

*siblings*  $s$

*age*  $a$

*THEN*  $^{0.9|0.1}$   
 $_{0.3|0.5}$  *agg*  $s, a$  : *assert* *conc\_of\_person*

*name*  $x$

*siblings*  $s$

*age*  $a$

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## AN INFERENCE CYCLE

*fn* = 1: *assert person*  
*name* John 1|0  
*siblings* 1 0.3|0.1  
*age* (*young* 0.3|0.4 *medium* 0.4|0.3 *old* 0.2|0.1)

*fn* = 2: *assert person*  
*name* John 1|0  
*siblings* 3 0.4|0.2  
*age* (*young* 0.5|0.4 *medium* 0.3|0.3 *old* 0.2|0.1)

*fn* = 3: *assert person*  
*name* John 1|0  
*siblings* 3 0.6|0.3  
*age* (*young* 0.6|0.2 *medium* 0.5|0.3 *old* 0.2|0.1)

*fn* = 4: *assert person*  
*name* Mary 1|0  
*siblings* 3 0.5|0.5  
*age* (*young* 0.2|0.4 *medium* 0.7|0.2 *old* 0.2|0.4)

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## AN INFERENCE CYCLE

① The output of the *preamble instructions*:  $\sigma_p = \emptyset$ .

② The output of matching:

$$\sigma_1 = \{x = \text{John}, x.cf = 1|0, s = 1, s.cf = 0.3|0.1, \\ a = (\text{young } 0.3|0.4 \text{ medium } 0.4|0.3 \text{ old } 0.2|0.1)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\sigma_2 = \{x = \text{John}, x.cf = 1|0, s = 3, s.cf = 0.4|0.2, \\ a = (\text{young } 0.5|0.4 \text{ medium } 0.3|0.3 \text{ old } 0.2|0.1)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\sigma_3 = \{x = \text{John}, x.cf = 1|0, s = 3, s.cf = 0.6|0.3, \\ a = (\text{young } 0.6|0.2 \text{ medium } 0.5|0.3 \text{ old } 0.2|0.1)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\sigma_4 = \{x = \text{Mary}, x.cf = 1|0, s = 3, s.cf = 0.5|0.5, \\ a = (\text{young } 0.2|0.4 \text{ medium } 0.7|0.2 \text{ old } 0.2|0.4)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$R_1 = R_2 = R_3 = R_4 = \{r_1\}.$$

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### AN INFERENCE CYCLE

- 3 The output of the evaluation of *antecedents*:  
 $\nu(\textit{antecedent}(r_1)) = 1|0$  with respect to  $\sigma_1, \sigma_2, \sigma_3, \sigma_4$ .
- 4 The output of the evaluation of *consequents*:  
for  $i = 1, \dots, 4$ ,  $\rho_{r_1}^i = \sigma_i$ ,  $R_i^A = R_i = \{r_1\}$ ;  
 $fs_{r_1} = \nu(\textit{antecedent}(r_1)) \diamond cf_{r_1} = 1|0 \diamond 0.9|0.1 = 0.9|0.1$   
 $\geq_t 0.3|0.5 = th_{r_1}$ .

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### AN INFERENCE CYCLE

5 The output of the aggregation  $agg\ s, a$ :

for  $*$  =  $\cdot$ ,  $\oplus$  =  $\oplus_p$ ,  $\square$  =  $\square_p$ :

$$\xi_{r_1}^1 = \{x = \text{John}, x.cf = 1|0, s = 1, s.cf = 0.3|0.1, \\ a = (\text{young } 0.86|0.032 \text{ medium } 0.79|0.027 \text{ old } 0.488|0.001)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\xi_{r_1}^2 = \{x = \text{John}, x.cf = 1|0, s = 3, s.cf = 0.76|0.06, \\ a = (\text{young } 0.86|0.032 \text{ medium } 0.79|0.027 \text{ old } 0.488|0.001)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\xi_{r_1}^3 = \{x = \text{John}, x.cf = 1|0, s = 3, s.cf = 0.76|0.06, \\ a = (\text{young } 0.86|0.032 \text{ medium } 0.79|0.027 \text{ old } 0.488|0.001)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\};$$

$$\xi_{r_1}^4 = \{x = \text{Mary}, x.cf = 1|0, s = 3, s.cf = 0.5|0.5, \\ a = (\text{young } 0.2|0.4 \text{ medium } 0.7|0.2 \text{ old } 0.2|0.4)\} \cup \\ \{a.m = \text{Hum\_Age.m} \mid m \text{ in } a\}.$$

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### AN INFERENCE CYCLE

- 6 The output of assertion:  
new facts asserted by  $assertion(r_1)$  with respect to  $\xi_n^1, \xi_n^2 = \xi_n^3, \xi_n^4$ :

$fn = 5$ :  $assert$  *conc\_of\_person*  
*name* John 1|0  
*siblings* 1 0.3|0.1  
*age* (*young* 0.86|0.032 *medium* 0.79|0.027 *old* 0.488|0.001)  
*age.m* *Hum\_Age.m, m in Hum\_Age*

$fn = 6$ :  $assert$  *conc\_of\_person*  
*name* John 1|0  
*siblings* 3 0.76|0.06  
*age* (*young* 0.86|0.032 *medium* 0.79|0.027 *old* 0.488|0.001)  
*age.m* *Hum\_Age.m, m in Hum\_Age*

$fn = 7$ :  $assert$  *conc\_of\_person*  
*name* Mary 1|0  
*siblings* 3 0.5|0.5  
*age* (*young* 0.2|0.4 *medium* 0.7|0.2 *old* 0.2|0.4)  
*age.m* *Hum\_Age.m, m in Hum\_Age*

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### INTRODUCTION

- Design a *FES* for tuning the hardware configuration of a *PC*.
- Evaluative criteria:
  - **Power** of a configured *PC* - subjective (*low*, *medium*, *high*),
  - **Temperature** of the *CPU* - objective (0 – 100°C)  
(measured e.g. by *BIOS*).
- Configuration factors:
  - **RAM** - the size of the operational memory (0 – 32GB),
  - **GAM** - the size of the memory of the graphic card  
(0 – 4GB),
  - **FCPU** - the frequency of the *CPU* (0 – 4GHz).

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## Hardware tuning of *PC*

### FUZZIFICATION

- Evaluative criteria:
  - *PC\_Power* - a discrete fuzzy set with members: *low, medium, high*.
  - *CPU\_Temperature* - a numerical discrete fuzzy set with members: *low, medium, high*.
- Configuration factors:
  - *Memory\_Size* - a numerical discrete fuzzy set with members: *small, medium, large*.
  - *Graphic\_Size* - a numerical discrete fuzzy set with members: *small, medium, large*.
  - *CPU\_Frequency* - a numerical discrete fuzzy set with members: *low, medium, high*.

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### TEMPLATE FACTS

- *PC\_configuration\_crisp*

*variant* (X Y)

*RAM* 2 1|0

*GAM* 0.256 1|0

*FCPU* 1.2 1|0

- *PC\_configuration*

*variant* (X Y)

*RAM* (*small* 0.875|0.125 *medium* 0.125|0.875 *large* 0|1)

*GAM* (*small* 0.872|0.128 *medium* 0.128|0.872 *large* 0|1)

*FCPU* (*low* 0.4|0.6 *medium* 0.6|0.4 *high* 0|1)

- *PC\_test*

*variant* (X Y)

*power* (*low* 0.9|0 *medium* 0.2|0.8 *high* 0|1)

*TCPU* 25 1|0

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### HEURISTIC FUZZY RULES

$r_1$ : IF power is low t\_and RAM is small THEN  $\begin{matrix} 0.9|0.1 \\ 0.3|0.3 \end{matrix}$  RAM is large

$r_2$ : IF GAM is small t\_and possible RAM is medium  
THEN  $\begin{matrix} 0.7|0.2 \\ 0.5|0.5 \end{matrix}$  GAM is large

$r_3$ : IF TCPU is low t\_and not RAM is small  
THEN  $\begin{matrix} 0.6|0.3 \\ 0.5|0.5 \end{matrix}$  FCPU is high, aggregate FCPU

$r_4$ : IF possible not TCPU is high  
THEN  $\begin{matrix} 0.75|0.25 \\ 0.3|0.3 \end{matrix}$  FCPU is medium, aggregate FCPU

$r_5$ : IF PC\_configuration\_crisp  
THEN  $\begin{matrix} 1|0 \\ 1|0 \end{matrix}$  fuzzify PC\_configuration\_crisp

$r_6$ : IF PC\_configuration THEN  $\begin{matrix} 1|0 \\ 1|0 \end{matrix}$  defuzzify PC\_configuration

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```
defdisfstype PC_Power members : low medium high
```

```
defmemftype M_Size shape : polygon domain : 0 32 (GB)
```

```
defnumfstype Memory_Size members : small medium large  
memftype : M_Size
```

```
Memory_Size.small := create_polygon_memf(0 116 0 32 0)
```

```
Memory_Size.medium := create_polygon_memf(0 0 16 1 32 0)
```

```
Memory_Size.large := create_polygon_memf(0 0 16 0 32 1)
```

```
defmemftype G_Size shape : polygon domain : 0 4 (GB)
```

```
defnumfstype Graphic_Size members : small medium large  
memftype : G_Size
```

```
Graphic_Size.small := create_polygon_memf(0 1 2 0 4 0)
```

```
Graphic_Size.medium := create_polygon_memf(0 0 2 1 4 0)
```

```
Graphic_Size.large := create_polygon_memf(0 0 2 0 4 1)
```

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```
defmemftype C_Temperature shape : polygon domain : 0 100 (°C)
```

```
defnumfstype CPU_Temperature members : low medium high  
memftype : C_Temperature
```

```
CPU_Temperature.low := create_polygon_memf(0 1 50 0 100 0)
```

```
CPU_Temperature.medium := create_polygon_memf(0 0 50 1 100 0)
```

```
CPU_Temperature.high := create_polygon_memf(0 0 50 0 100 1)
```

```
defmemftype C_Frequency shape : polygon domain : 0 4 (GHz)
```

```
defnumfstype CPU_Frequency members : low medium high  
memftype : C_Frequency
```

```
CPU_Frequency.low := create_polygon_memf(0 1 2 0 4 0)
```

```
CPU_Frequency.medium := create_polygon_memf(0 0 2 1 4 0)
```

```
CPU_Frequency.high := create_polygon_memf(0 0 2 0 4 1)
```

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*deftemplate PC\_test*

*multislot variant char*

*slot power PC\_Power*

*slot TCPU float*

*deftemplate PC\_configuration*

*multislot variant char*

*slot RAM Memory\_Size*

*slot GAM Graphic\_Size*

*slot FCPU CPU\_Frequency*

*deftemplate PC\_configuration\_crisp*

*multislot variant char*

*slot RAM float*

*slot GAM float*

*slot FCPU float*

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## Hardware tuning of PC

block  $b_1$  priority 0

declare \$v char p PC\_Power t float r Memory\_Size  
g Graphic\_Size f CPU\_Frequency

$r_1$  IF PC\_test PC\_configuration : p is low t\_and r is small

variant \$v variant \$v

power p RAM r

TCPU t GAM g

FCPU f

THEN<sup>0.9|0.1</sup><sub>0.3|0.3</sub> r is large,  $r.small.cf := \neg r.large.cf$ ,

$r.medium.cf := \frac{for(r.small.cf) + for(r.large.cf)}{2} \Big| 0 :$

assert PC\_configuration

variant \$v A

RAM r

GAM g

FCPU f

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## Hardware tuning of PC

block  $b_1$  priority 0

$r_2$  IF  $PC\_test$   $PC\_configuration$  :  $g$  is small  $t\_and$   
variant \$v variant \$v pos  $r$  is medium  
power  $p$  RAM  $r$   
TCPU  $t$  GAM  $g$   
FCPU  $f$

THEN<sup>0.7|0.2</sup><sub>0.5|0.5</sub>  $g$  is large,  $g.small.cf := \neg g.large.cf$ ,  
 $g.medium.cf := \frac{for(g.small.cf) + for(g.large.cf)}{2} \Big| 0 :$

assert  $PC\_configuration$   
variant \$v B  
RAM  $r$   
GAM  $g$   
FCPU  $f$

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## Hardware tuning of PC

block  $b_1$  priority 0

$r_3$  IF PC\_test PC\_configuration :  $t$  is CPU\_Temperature.low

variant \$v variant \$v  $t\_and$  not  $r$  is small

power  $p$  RAM  $r$

TCPU  $t$  GAM  $g$

FCPU  $f$

THEN<sup>0.6|0.3</sup><sub>0.5|0.5</sub>  $f$  is high,  $f.low.cf := 0|1$ ,  $f.medium.cf := 0|1$  :

agg  $f$  : assert PC\_configuration

variant \$v C

RAM  $r$

GAM  $g$

FCPU  $f$

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## Hardware tuning of PC

block  $b_1$  priority 0

$r_4$  IF  $PC\_test$   $PC\_configuration$  : pos not  $t$  is  
variant \$ $v$  variant \$ $v$  CPU\_Temperature.high  
power  $p$  RAM  $r$   
TCPU  $t$  GAM  $g$   
FCPU  $f$

THEN<sup>0.75|0.25</sup><sub>0.3|0.3</sub>  $f$  is medium,

$$f.high.cf := \frac{for(v(antecedent)) + for(f.high.cf)}{2} \mid$$
$$\frac{against(v(antecedent)) + against(f.high.cf)}{2},$$

$$f.low.cf := \neg f.high.cf :$$

agg  $f$  : assert  $PC\_configuration$   
variant \$ $v$   $C$   
RAM  $r$   
GAM  $g$   
FCPU  $f$

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## Hardware tuning of PC

block  $b_2$  priority - 1

```
declare cr cg cf float $v char r Memory_Size
        g Graphic_Size f CPU_Frequency
```

```
r5 IF PC_configuration_crisp : 1|0 THEN1|01|0 assert PC_configuration
    variant ()
    RAM cr
    GAM cg
    FCPU cf
    RAM fuzzify(cr)
    GAM fuzzify(cg)
    FCPU fuzzify(cf)
```

```
r6 IF PC_configuration : $v ≠ () THEN1|01|0 assert
    variant $v
    RAM r
    GAM g
    FCPU f
    PC_configuration_crisp
    RAM defuzzify(r, MOM)
    GAM defuzzify(g, MOM)
    FCPU defuzzify(f, MOM)
```

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## Hardware tuning of *PC*: a computation

For  $*$  = min,  $\oplus$  = max,  $\diamond = \diamond_m$ ,  $\square = \square_m$ ,  $\gamma = \delta = 1$ :

0 : *PC\_configuration\_crisp* : user

variant	()
RAM	2 1 0
GAM	0.256 1 0
FCPU	1.2 1 0

Matching  $r_5, 0$ :

1 : *PC\_configuration* :  $r_5, 0$

variant	()
RAM	(small 0.875 0.125 medium 0.125 0.875 large 0 1)
GAM	(small 0.872 0.128 medium 0.128 0.872 large 0 1)
FCPU	(low 0.4 0.6 medium 0.6 0.4 high 0 1)

2 : *PC\_test* : user

variant	()
power	(low 0.9 0 medium 0.2 0.8 high 0 1)
TCPU	25 1 0

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Hardware tuning of *PC*: a computation

Matching  $r_1, 2, 1$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_1)) &= p.\textit{low}.cf \diamond_m r.\textit{small}.cf = 0.9|0 \diamond_m 0.875|0.125 \\ &= 0.875|0.125,\end{aligned}$$

$$\begin{aligned}fs_{r_1} &= \nu(\textit{antecedent}(r_1)) \diamond_m cf_{r_1} = 0.875|0.125 \diamond_m 0.9|0.1 \\ &= 0.875|0.125 \geq_t 0.3|0.3,\end{aligned}$$

$$\begin{aligned}r.\textit{large}.cf &= 0.875|0.125, \quad r.\textit{small}.cf = -0.875|0.125 = 0.125|0.875, \\ r.\textit{medium}.cf &= \frac{0.125+0.875}{2} | 0 = 0.5|0;\end{aligned}$$

3 : *PC\_configuration*

:  $r_1, 2, 1$

variant (A)

RAM (small 0.125|0.875 medium 0.5|0 large 0.875|0.125)

GAM (small 0.872|0.128 medium 0.128|0.872 large 0|1)

FCPU (low 0.4|0.6 medium 0.6|0.4 high 0|1)

Matching  $r_2, 2, 1$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_2)) &= g.\textit{small}.cf \diamond_m \Leftrightarrow r.\textit{medium}.cf \\ &= 0.872|0.128 \diamond_m \Leftrightarrow 0.125|0.875 = 0.125|0.875,\end{aligned}$$

$$\begin{aligned}fs_{r_2} &= \nu(\textit{antecedent}(r_2)) \diamond_m cf_{r_2} = 0.125|0.875 \diamond_m 0.7|0.2 \\ &= 0.125|0.875 \not\geq_t 0.5|0.5.\end{aligned}$$

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## Hardware tuning of PC: a computation

Matching  $r_3, 2, 1$ :

$$\begin{aligned} \nu(\text{antecedent}(r_3)) &= \nu(t = 25 \text{ is CPU\_Temperature.low}) \diamond_m \neg r.\text{small.cf} \\ &= 0.5|0.5 \diamond_m \neg 0.875|0.125 = 0.125|0.875, \end{aligned}$$

$$\begin{aligned} fs_{r_3} &= \nu(\text{antecedent}(r_3)) \diamond_m cf_{r_3} = 0.125|0.875 \diamond_m 0.6|0.3 \\ &= 0.125|0.875 \not\geq_t 0.5|0.5; \end{aligned}$$

Matching  $r_4, 2, 1$ :

$$\nu(\text{antecedent}(r_4)) = \Leftrightarrow \neg \nu(t = 25 \text{ is CPU\_Temperature.high}) = \Leftrightarrow \neg 0|1 = 1|0,$$

$$fs_{r_4} = \nu(\text{antecedent}(r_4)) \diamond_m cf_{r_4} = 1|0 \diamond_m 0.75|0.25 = 0.75|0.25 \geq_t 0.3|0.3,$$

$$f.\text{medium.cf} = 0.75|0.25, f.\text{high.cf} = \frac{1+0}{2} \Big| \frac{0+1}{2} = 0.5|0.5,$$

$$f.\text{low.cf} = \neg 0.5|0.5 = 0.5|0.5;$$

4 : PC\_configuration

:  $r_4, 2, 1$

variant (C)

RAM (small 0.875|0.125 medium 0.125|0.875 large 0|1)

GAM (small 0.872|0.128 medium 0.128|0.872 large 0|1)

FCPU (low 0.5|0.5 medium 0.75|0.25 high 0.5|0.5)

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## Hardware tuning of *PC*: a computation

Matching  $r_6, 3$ :

$$\nu(\textit{antecedent}(r_6)) = \nu((A) \neq ()) = 1|0,$$

$$fs_{r_6} = \nu(\textit{antecedent}(r_6)) \diamond_m cf_{r_6} = 1|0 \diamond_m 1|0 = 1|0 \geq_t 1|0,$$

$$s_v = (A),$$

$$r = (\textit{small} \ 0.125|0.875 \ \textit{medium} \ 0.5|0 \ \textit{large} \ 0.875|0.125),$$

$$\textit{defuzzify}(r, \textit{MOM}) = \frac{16+32}{2} = 24, \max_r = 0.875,$$

$$g = (\textit{small} \ 0.872|0.128 \ \textit{medium} \ 0.128|0.872 \ \textit{large} \ 0|1),$$

$$\textit{defuzzify}(g, \textit{MOM}) = \frac{0+2}{2} = 1, \max_g = 1,$$

$$f = (\textit{low} \ 0.4|0.6 \ \textit{medium} \ 0.6|0.4 \ \textit{high} \ 0|1),$$

$$\textit{defuzzify}(f, \textit{MOM}) = \frac{0+2}{2} = 1, \max_f = 1;$$

5 : *PC\_configuration\_crisp* :  $r_6, 3$

*variant* (A)

*RAM* 24 1|0

*GAM* 1 1|0

*FCPU* 1 1|0

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## Hardware tuning of *PC*: a computation

Matching  $r_6, 4$ :

$$\nu(\textit{antecedent}(r_6)) = \nu((A \neq ())) = 1|0,$$

$$fs_{r_6} = \nu(\textit{antecedent}(r_6)) \diamond_m cf_{r_6} = 1|0 \diamond_m 1|0 = 1|0 \geq_t 1|0,$$

$$s_v = (C),$$

$$r = (\textit{small} \ 0.875|0.125 \ \textit{medium} \ 0.125|0.875 \ \textit{large} \ 0|1),$$

$$\textit{defuzzify}(r, \textit{MOM}) = \frac{0+16}{2} = 8, \max_r = 1,$$

$$g = (\textit{small} \ 0.872|0.128 \ \textit{medium} \ 0.128|0.872 \ \textit{large} \ 0|1),$$

$$\textit{defuzzify}(g, \textit{MOM}) = \frac{0+2}{2} = 1, \max_g = 1,$$

$$f = (\textit{low} \ 0.5|0.5 \ \textit{medium} \ 0.75|0.25 \ \textit{high} \ 0.5|0.5),$$

$$\textit{defuzzify}(f, \textit{MOM}) = \frac{2}{1} = 2, \max_f = 0.75;$$

6 : *PC\_configuration\_crisp* :  $r_6, 4$

variant (C)

RAM 8 1|0

GAM 1 1|0

FCPU 2 1|0

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## Hardware tuning of *PC*: a computation

7 : *PC\_test* : *user*

*variant* (A)

*power* (*low* 0.5|0.5 *medium* 0.8|0.2 *high* 0|1)

*TCPU* 25 1|0

8 : *PC\_test* : *user*

*variant* (C)

*power* (*low* 0.6|0.4 *medium* 0.4|0.6 *high* 0|1)

*TCPU* 45 1|0

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## Hardware tuning of PC: a computation

Matching  $r_1, 7, 3$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_1)) &= p.\textit{low}.cf \diamond_m r.\textit{small}.cf = 0.5|0.5 \diamond_m 0.125|0.875 \\ &= 0.125|0.875,\end{aligned}$$

$$\begin{aligned}fs_{r_1} &= \nu(\textit{antecedent}(r_1)) \diamond_m cf_{r_1} = 0.125|0.875 \diamond_m 0.9|0.1 \\ &= 0.125|0.875 \not\geq_t 0.3|0.3;\end{aligned}$$

Matching  $r_2, 7, 3$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_2)) &= g.\textit{small}.cf \diamond_m \Leftrightarrow r.\textit{medium}.cf \\ &= 0.872|0.128 \diamond_m \Leftrightarrow 0.5|0 = 0.872|0.5,\end{aligned}$$

$$\begin{aligned}fs_{r_2} &= \nu(\textit{antecedent}(r_2)) \diamond_m cf_{r_2} = 0.872|0.5 \diamond_m 0.7|0.2 \\ &= 0.7|0.5 \geq_t 0.5|0.5,\end{aligned}$$

$$g.\textit{large}.cf = 0.7|0.5, \quad g.\textit{small}.cf = \neg 0.7|0.5 = 0.5|0.7,$$

$$g.\textit{medium}.cf = \frac{0.5+0.7}{2} | 0 = 0.6|0;$$

9 : *PC\_configuration*

:  $r_2, 7, 3$

variant (A B)

RAM (small 0.125|0.875 medium 0.5|0 large 0.875|0.125)

GAM (small 0.5|0.7 medium 0.6|0 large 0.7|0.5)

FCPU (low 0.4|0.6 medium 0.6|0.4 high 0|1)

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Matching  $r_3, 7, 3$ :

$$\begin{aligned}\nu(\text{antecedent}(r_3)) &= \nu(t = 25 \text{ is CPU\_Temperature.low}) \diamond_m \neg r.\text{small.cf} \\ &= 0.5|0.5 \diamond_m \neg 0.125|0.875 = 0.5|0.5,\end{aligned}$$

$$fs_{r_3} = \nu(\text{antecedent}(r_3)) \diamond_m cf_{r_3} = 0.5|0.5 \diamond_m 0.6|0.3 = 0.5|0.5 \geq_t 0.5|0.5,$$

$$f.\text{high.cf} = 0.5|0.5, f.\text{low.cf} = 0|1, f.\text{medium.cf} = 0|1;$$

Matching  $r_4, 7, 3$ :

$$\nu(\text{antecedent}(r_4)) = \Leftrightarrow \neg \nu(t = 25 \text{ is CPU\_Temperature.high}) = \Leftrightarrow \neg 0|1 = 1|0,$$

$$fs_{r_4} = \nu(\text{antecedent}(r_4)) \diamond_m cf_{r_4} = 1|0 \diamond_m 0.75|0.25 = 0.75|0.25 \geq_t 0.3|0.3,$$

$$f.\text{medium.cf} = 0.75|0.25, f.\text{high.cf} = \frac{1+0}{2} \Big| \frac{0+1}{2} = 0.5|0.5,$$

$$f.\text{low.cf} = \neg 0.5|0.5 = 0.5|0.5;$$

$$\text{agg } f: f.\text{low.cf} = 0|1 \square_m 0.5|0.5 = 0.5|0.5, f.\text{high.cf} = 0.5|0.5 \square_m 0.5|0.5 = 0.5|0.5,$$

$$f.\text{medium.cf} = 0|1 \square_m 0.75|0.25 = 0.75|0.25,$$

10 : PC\_configuration :  $r_3, r_4, 7, 3$

variant (A C)

RAM (small 0.125|0.875 medium 0.5|0 large 0.875|0.125)

GAM (small 0.872|0.128 medium 0.128|0.872 large 0|1)

FCPU (low 0.5|0.5 medium 0.75|0.25 high 0.5|0.5)

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Hardware tuning of *PC*: a computation

Matching  $r_1, 8, 4$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_1)) &= p.\textit{low}.cf \diamond_m r.\textit{small}.cf = 0.6|0.4 \diamond_m 0.875|0.125 \\ &= 0.6|0.4,\end{aligned}$$

$$fs_{r_1} = \nu(\textit{antecedent}(r_1)) \diamond_m cf_{r_1} = 0.6|0.4 \diamond_m 0.9|0.1 = 0.6|0.4 \not\leq_t 0.3|0.3;$$

Matching  $r_2, 8, 4$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_2)) &= g.\textit{small}.cf \diamond_m \Leftrightarrow r.\textit{medium}.cf \\ &= 0.872|0.128 \diamond_m \Leftrightarrow 0.125|0.875 = 0.125|0.875,\end{aligned}$$

$$\begin{aligned}fs_{r_2} &= \nu(\textit{antecedent}(r_2)) \diamond_m cf_{r_2} = 0.125|0.875 \diamond_m 0.7|0.2 \\ &= 0.125|0.875 \not\leq_t 0.5|0.5.\end{aligned}$$

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## Hardware tuning of PC: a computation

Matching  $r_3, 8, 4$ :

$$\begin{aligned}\nu(\textit{antecedent}(r_3)) &= \nu(t = 45 \textit{ is CPU\_Temperature.low}) \diamond_m \neg r.\textit{small.cf} \\ &= 0.1|0.9 \diamond_m \neg 0.875|0.125 = 0.1|0.9,\end{aligned}$$

$$f_{s_{r_3}} = \nu(\textit{antecedent}(r_3)) \diamond_m cf_{r_3} = 0.1|0.9 \diamond_m 0.6|0.3 = 0.1|0.9 \not\geq_t 0.5|0.5;$$

Matching  $r_4, 8, 4$ :

$$\nu(\textit{antecedent}(r_4)) = \Leftrightarrow \neg \nu(t = 45 \textit{ is CPU\_Temperature.high}) = \Leftrightarrow \neg 0|1 = 1|0,$$

$$f_{s_{r_4}} = \nu(\textit{antecedent}(r_4)) \diamond_m cf_{r_4} = 1|0 \diamond_m 0.75|0.25 = 0.75|0.25 \geq_t 0.3|0.3,$$

$$f.\textit{medium.cf} = 0.75|0.25, f.\textit{high.cf} = \frac{1+0.5}{2} \Big| \frac{0+0.5}{2} = 0.75|0.25,$$

$$f.\textit{low.cf} = \neg 0.75|0.25 = 0.25|0.75;$$

11 : *PC\_configuration*

:  $r_4, 8, 4$

*variant* (C C)

*RAM* (*small* 0.875|0.125 *medium* 0.125|0.875 *large* 0|1)

*GAM* (*small* 0.872|0.128 *medium* 0.128|0.872 *large* 0|1)

*FCPU* (*low* 0.25|0.75 *medium* 0.75|0.25 *high* 0.75|0.25)

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## Hardware tuning of PC: a computation

Matching  $r_6, 9$ :

$$\nu(\textit{antecedent}(r_6)) = \nu((A \neq ())) = 1|0,$$

$$fs_{r_6} = \nu(\textit{antecedent}(r_6)) \diamond_m cf_{r_6} = 1|0 \diamond_m 1|0 = 1|0 \geq_t 1|0,$$

$$s_v = (AB),$$

$$r = (\textit{small} 0.125|0.875 \textit{medium} 0.5|0 \textit{large} 0.875|0.125),$$

$$\textit{defuzzify}(r, \textit{MOM}) = \frac{16+32}{2} = 24, \max_r = 0.875,$$

$$g = (\textit{small} 0.5|0.7 \textit{medium} 0.6|0 \textit{large} 0.7|0.5),$$

$$\textit{defuzzify}(g, \textit{MOM}) = \frac{2+4}{2} = 3, \max_g = 0.7,$$

$$f = (\textit{low} 0.4|0.6 \textit{medium} 0.6|0.4 \textit{high} 0|1),$$

$$\textit{defuzzify}(f, \textit{MOM}) = \frac{0+2}{2} = 1, \max_f = 1;$$

12 : *PC\_configuration\_crisp* :  $r_6, 9$

*variant* (AB)

*RAM* 24 1|0

*GAM* 3 1|0

*FCPU* 1 1|0

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## Hardware tuning of PC: a computation

Matching  $r_6$ , 10:

$$\nu(\textit{antecedent}(r_6)) = \nu((A \neq ())) = 1|0,$$

$$fs_{r_6} = \nu(\textit{antecedent}(r_6)) \diamond_m cf_{r_6} = 1|0 \diamond_m 1|0 = 1|0 \geq_t 1|0,$$

$$s_v = (A C),$$

$$r = (\textit{small} 0.125|0.875 \textit{medium} 0.5|0 \textit{large} 0.875|0.125),$$

$$\textit{defuzzify}(r, \textit{MOM}) = \frac{16+32}{2} = 24, \max_r = 0.875,$$

$$g = (\textit{small} 0.872|0.128 \textit{medium} 0.128|0.872 \textit{large} 0|1),$$

$$\textit{defuzzify}(g, \textit{MOM}) = \frac{0+2}{2} = 1, \max_g = 1,$$

$$f = (\textit{low} 0.5|0.5 \textit{medium} 0.75|0.25 \textit{high} 0.5|0.5),$$

$$\textit{defuzzify}(f, \textit{MOM}) = \frac{2}{1} = 2, \max_f = 0.75;$$

13: *PC\_configuration\_crisp* :  $r_6$ , 10

*variant* (A C)

*RAM* 24 1|0

*GAM* 1 1|0

*FCPU* 2 1|0

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Matching  $r_6$ , 11:

$$\nu(\textit{antecedent}(r_6)) = \nu((A \neq ())) = 1|0,$$

$$fs_{r_6} = \nu(\textit{antecedent}(r_6)) \diamond_m cf_{r_6} = 1|0 \diamond_m 1|0 = 1|0 \geq_t 1|0,$$

$$s_v = (C C),$$

$$r = (\textit{small} 0.875|0.125 \textit{medium} 0.125|0.875 \textit{large} 0|1),$$

$$\textit{defuzzify}(r, \textit{MOM}) = \frac{0+16}{2} = 8, \max_r = 1,$$

$$g = (\textit{small} 0.872|0.128 \textit{medium} 0.128|0.872 \textit{large} 0|1),$$

$$\textit{defuzzify}(g, \textit{MOM}) = \frac{0+2}{2} = 1, \max_g = 1,$$

$$f = (\textit{low} 0.25|0.75 \textit{medium} 0.75|0.25 \textit{high} 0.75|0.25),$$

$$\textit{defuzzify}(f, \textit{MOM}) = \frac{2+4}{2} = 3, \max_f = 0.75;$$

14 : *PC\_configuration\_crisp* :  $r_6$ , 11

*variant* (C C)

*RAM* 8 1|0

*GAM* 1 1|0

*FCPU* 3 1|0

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0 : *PC\_configuration\_crisp*

variant ()  
RAM 2 1|0  
GAM 0.256 1|0  
FCPU 1.2 1|0

2 : *PC\_test*

variant ()  
power (low 0.9|0 medium 0.2|0.8 high 0|1)  
TCPU 25 1|0

5 : *PC\_configuration\_crisp*

variant (A)  
RAM 24 1|0  
GAM 1 1|0  
FCPU 1 1|0

7 : *PC\_test*

variant (A)  
power (low 0.5|0.5 medium 0.8|0.2 high 0|1)  
TCPU 25 1|0

12 : *PC\_configuration\_crisp*

variant (A B)  
RAM 24 1|0  
GAM 3 1|0  
FCPU 1 1|0

13 : *PC\_configuration\_crisp*

variant (A C)  
RAM 24 1|0  
GAM 1 1|0  
FCPU 2 1|0

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## Hardware tuning of *PC*: a computation - the summary

6 : *PC\_configuration\_crisp*    8 : *PC\_test*

variant (C)

RAM 8 1|0

GAM 1 1|0

FCPU 2 1|0

variant (C)

power (low 0.6|0.4 medium 0.4|0.6 high 0|1)

TCPU 45 1|0

14 : *PC\_configuration\_crisp*

variant (C C)

RAM 8 1|0

GAM 1 1|0

FCPU 3 1|0

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- *FES - Synlogy* - the next generation of *ES*:
  - the data-driven programming paradigm,
  - multi-step fuzzy inference,
  - parallel firing rules (in blocks),
  - combining uncertainty, vagueness, impreciseness,
  - mathematical foundations.
- **Future research:**
  - the development of formal semantics for *FES*,
  - the paraconsistent (e.g. bilattice) approach,
  - dealing with inconsistency in a reasonable manner,
  - an efficient implementation of large-scale pattern matching - the **Fuzzy rete algorithm**.

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