

## Basic notions of a fuzzy controller

Rule database:

**if**  $X$  is  $A_1$  **then**  $Y$  is  $C_1$  **and**

...

**if**  $X$  is  $A_n$  **then**  $Y$  is  $C_n$

where

$X \in \mathcal{F}(\mathcal{X})$  is a fuzzy input

$Y = \Phi(X) \in \mathcal{F}(\mathcal{Y})$  is the corresponding fuzzy output

$A_i \in \mathcal{F}(\mathcal{X})$ ,  $i = 1, \dots, n$ , are **antecedents (premises)** which can be interpreted as

- ◆ assumptions,
- ◆ domains of applicability, or
- ◆ typical fuzzy inputs

$C_i \in \mathcal{F}(\mathcal{Y})$ ,  $i = 1, \dots, n$ , are **consequents (conclusions)** expressing the desired outputs

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# Dimensionality

Antecedents are subsets of multi-dimensional spaces

They carry information about several variables (and so do the consequents)

Usually they are decomposed to conjunctions (cylindric extensions) of one-dimensional fuzzy sets

Then the rules attain the form

**if**  $A_1$  is  $A_{i1}$   
**and** ...  
**and**  $A_\mu$  is  $A_{i\mu}$   
**then**  $C_1$  is  $C_{i1}$   
**and** ...  
**and**  $C_\nu$  is  $C_{i\nu}$

$i = 1, \dots, n$

If an antecedent has a more complex shape (non-convex), we may cover it approximately by several rules of the above form

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## Simplifying assumptions

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  2. We decompose the output to single variables considered independently. Without loss of generality, we restrict attention to MISO (Multiple Input Single Output) systems
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## Compositional rule of inference

The rule base is represented by a fuzzy relation  $R \in \mathcal{F}(\mathcal{X} \times \mathcal{Y})$

The output,  $Y$ , is obtained by a composition of  $R$  with the input,  $X$ :

$$Y = \Phi(X) = X \circ R$$

$$Y(y) = \sup_{x \in \mathcal{X}} (R(x, y) \wedge X(x))$$

where  $\wedge$  is a t-norm (fuzzy conjunction); different choices are possible, but we shall restrict to **continuous t-norms**

The supremum is the standard t-conorm; it should not be replaced by another t-conorm (because it may have uncountably many arguments)

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## How to derive the fuzzy relation $R$ from the rule base

The most natural idea: **Residuum-based fuzzy controller:**

$$R_{\text{RES}}(x, y) = \min_i (A_i(x) \rightarrow C_i(y))$$

where  $\rightarrow$  is a **fuzzy implication**, usually the **residuum (R-implication)** of  $\wedge$ ,

$$\alpha \rightarrow \beta = \sup\{\gamma \in [0, 1] \mid \gamma \wedge \alpha \leq \beta\}$$

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Properties of residua of continuous t-norms:

- ◆  $\alpha \rightarrow \beta = 1$  iff  $\alpha \leq \beta$
  - ◆  $1 \rightarrow \beta = \beta$
  - ◆ non-increasing in the first and non-decreasing in the second variable
  - ◆ continuous iff the t-norm  $\wedge$  is nilpotent
  - ◆ **adjointness**:  $a \wedge b \leq c$  iff  $a \leq b \rightarrow c$
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## How to derive the fuzzy relation $R$ from the rule base 2

**Mamdani–Assilian fuzzy controller:**

$$R_{\text{MA}}(x, y) = \max_i (A_i(x) \wedge C_i(y))$$

Logically this is a **disjunction of conjunctions**, not a conjunction of implications



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These expressions are not totally different; if **crisp** sets  $A_i$ ,  $i = 1, \dots, n$ , form a partition of  $\mathcal{X}$  (i.e., they are mutually disjoint and  $\bigcup_i A_i = \mathcal{X}$ ), then  $R_{\text{MA}} = R_{\text{RES}}$

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However, this usually is not the case

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# Comparison of residuum-based and Mamdani–Assilian controllers

## Continuity:

$R_{\text{RES}}$  only for  $\wedge$  nilpotent

$R_{\text{MA}}$  always

## Computational efficiency:

$$\Phi_{\text{RES}}(X)(y) = \sup_x \left( X(x) \wedge \min_i (A_i(x) \rightarrow C_i(y)) \right)$$

requires **three** nested cycles (over  $\mathcal{X}$  and  $\mathcal{Y}$  and over the number of rules)

$$\Phi_{\text{MA}}(X)(y) = \sup_x \left( X(x) \wedge \max_i (A_i(x) \wedge C_i(y)) \right)$$

$$= \max_i \sup_x \left( X(x) \wedge A_i(x) \wedge C_i(y) \right)$$

$$= \max_i (\mathcal{D}(X, A_i) \wedge C_i(y))$$

$\mathcal{D}(X, A_i) = \sup_x (X(x) \wedge A_i(x))$  ... the **degree of overlapping (non-disjointness)**

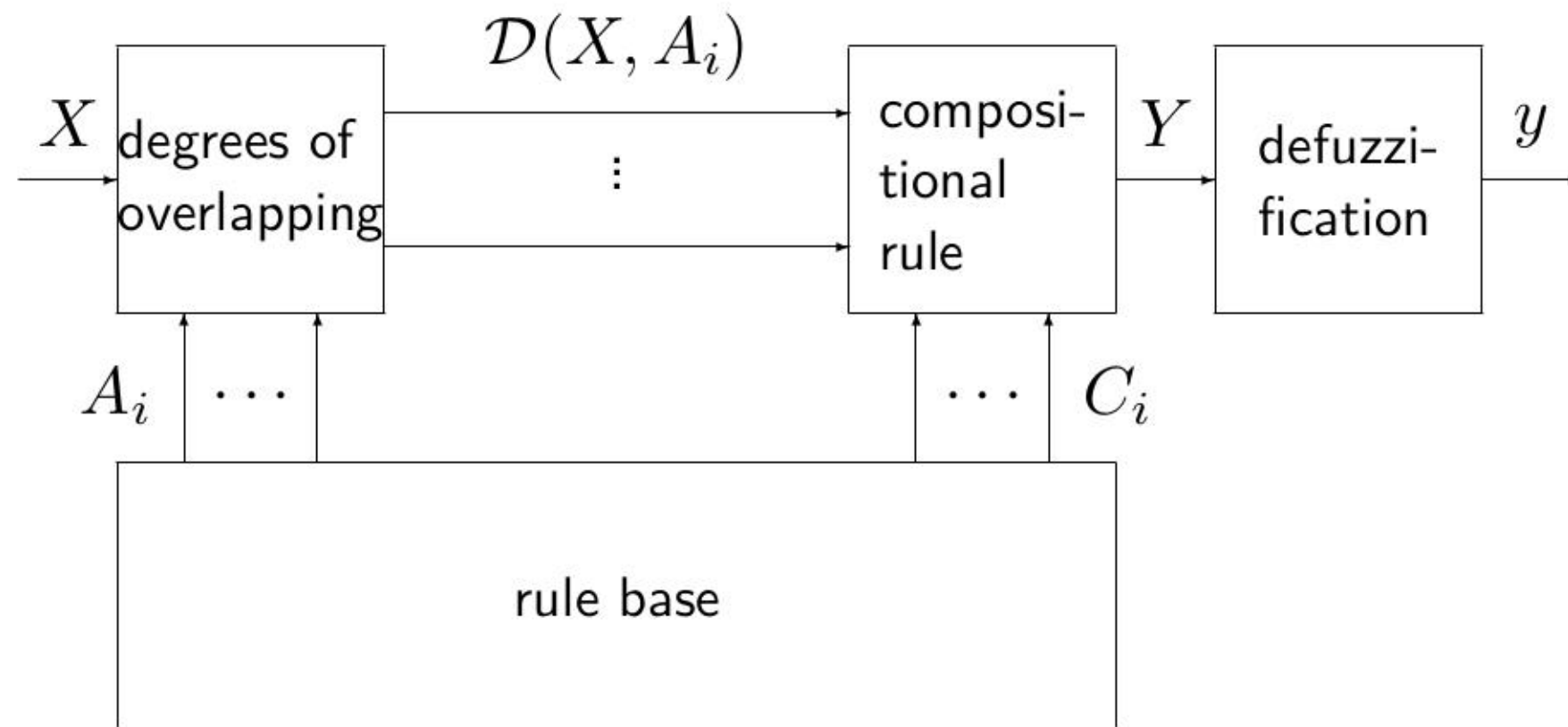
here equal to the **degree of firing (applicability)**

requires **two** nested cycles (over  $\mathcal{X}$  and the number of rules) resulting in real numbers  $\mathcal{D}(X, A_i)$ ,  $i = 1, \dots, n$ ; **then two** nested cycles (over  $\mathcal{Y}$  and the number of rules)

$\Phi_{\text{MA}}$  can be computed more efficiently (approx.  $\#Y/2$ -times faster)

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# Principle of Mamdani–Assilian controller — block diagram



## Generalized Compositional Rule of Inference

[Thiele 1995], [Lehmke, Reusch, Temme, Thiele 1998]

**FATI** principle (First Aggregation, Then Inference)

$$R_{\text{FATI}}(x, y) = \beta(\pi_1(A_1(x), C_1(y)), \dots, \pi_n(A_n(x), C_n(y)))$$

where  $\pi_i: [0, 1]^2 \rightarrow [0, 1]$ ,  $\beta: [0, 1]^n \rightarrow [0, 1]$

$$Y(y) = \Phi_{\text{FATI}}(X)(y) = Q\{\kappa(X(x), R_{\text{FATI}}(x, y)) \mid x \in \mathcal{X}\}$$

where  $\kappa: [0, 1]^2 \rightarrow [0, 1]$ ,  $Q: \mathcal{P}([0, 1]) \rightarrow [0, 1]$  (almost arbitrary operations)



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Particular cases:

Mamdani–Assilian controller:  $\pi_i = \wedge$ ,  $\beta = \max$ ,  $\kappa = \wedge$ ,  $Q = \sup$



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Residuum-based controller:  $\pi_i = \rightarrow$ ,  $\beta = \min$ ,  $\kappa = \wedge$ ,  $Q = \sup$

## Generalized Compositional Rule of Inference 2

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$$R_{\text{FITA}_i}(x, y) = \pi_i(A_i(x), C_i(y))$$

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*Handwritten red annotations:*  
 $\alpha_1 \dots \alpha_n$



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## Requirements on the rule base [Driankov et al. 1993]

1. **Completeness:**  $\bigcup_i \text{Supp } A_i = \mathcal{X}$ , where  $\text{Supp } A_i = \{x \in \mathcal{X} \mid A_i(x) > 0\}$

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usually weakened for **crisp inputs** to:

The output of the controller should be the fuzzy union of the outputs of separate rules (i.e., FATI=FITA;  
 this weaker form always holds for a Mamdani–Assilian controller;  
 see also [Lehmke, Reusch, Temme, Thiele 1998] for more general sufficient conditions for this equality)

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## Recommendations on the rule base [Driankov et al. 1993]

Antecedents (one-dimensional) should be

- ◆ **normal**,  $\forall i \exists x \in \mathcal{X} : A_i(x) = 1$
- ◆ continuous
- ◆ symmetric (when possible, usually not at the borders of the input space!)

The recommended degree of overlapping of neighbouring antecedents (computed using the standard t-norm,  $\min$ ) is 0.5

The recommended endpoints of the support of an antecedent are the peaks of the neighbouring antecedents

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  - ◆ **Weak interpolation property:**  $\Phi(X)$  is in the convex hull of all  $C_i$  with  $i$  such that  $\text{Supp } A_i \cap \text{Supp } X \neq \emptyset$
  - ◆ **Crisp correctness (crisp interaction):**  $(A_i(x) = 1) \Rightarrow (\Phi(x) = \Phi(\{x\}) = C_i)$  ("if there is a totally firing rule, it determines the output")
-