

# 02\_Fuzzy Systems and Fuzzy Clustering

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## 1. Fuzzy Systems

### 1.1. Linguistic (Mamdani) fuzzy model

if  $x$  is  $A$  then  $y$  is  $B$   
 $x$  is  $A \rightarrow$  antecedent(fuzzy proposition)  
 $y$  is  $B \rightarrow$  consequent(fuzzy proposition)

### 1.2. Fuzzy Relational Model

if  $x$  is  $A$  then  $y$  is  $B_1(0.1), B_2(0.8)$

### 1.3. Takagi-sugeno Fuzz model

if  $x$  is  $A$  then  $y = f(x)$

## 2. Mandani Fuzzy Systems

Given the if-then **rules** and an **input** fuzzy set, deduce the **corresponding output fuzzy set**

## 2.1. Fuzzy implication and Conjunctions

$$R : [0, 1] \times [0, 1] \rightarrow [0, 1]$$

$$\mu_R(x, y) = I(\mu_A(x), \mu_B(y))$$

"classical"	Kleene–Dienes	$I(a, b) = \max(1 - a, b)$	} implication
	Łukasiewicz	$I(a, b) = \min(1, 1 - a + b)$	
T-norms	Mamdani	$I(a, b) = \min(a, b)$	} conjunctions
	Larsen	$I(a, b) = a \cdot b$	

Same value as classical

## 2.2. Normal Inference

### Inference with One Rule

1. construct implication relation

$$\mu_R(x, y) = I(\mu_A(x), \mu_B(y))$$

2. use relational composition to derive  $B'$  from  $A'$

$$B' = A' \circ R$$

### Inference with Several Rules

1. Construct implication relation for each rule  $i$

$$\mu_{R_i}(x, y) = I(\mu_{A_i}(x), \mu_{B_i}(y))$$

2. Aggregate relations  $R_i$  into one

$$\mu_R(x, y) = \text{aggr}(\mu_{R_i}(x, y))$$

The aggr operator is the minimum for implications and the maximum for conjunctions

3. Use relational composition to derive  $B' \square$  from  $A' \square$

$$B' = A' \circ R$$

## 2.3. A simpler way: Mamdani Inference

1. **Compute the match** between the input and the antecedent membership functions (degree of fulfillment)
2. **Clip** the corresponding output fuzzy set for each rule by using the degree of fulfillment.
3. **Aggregate** output fuzzy sets of all the rules into one fuzzy set.

It can be seen as :

1. first finding the highest point (maximum fulfillment)
2. Then all inference result should less than the result of maximum fulfillment and at the same time meet the property of initial result.

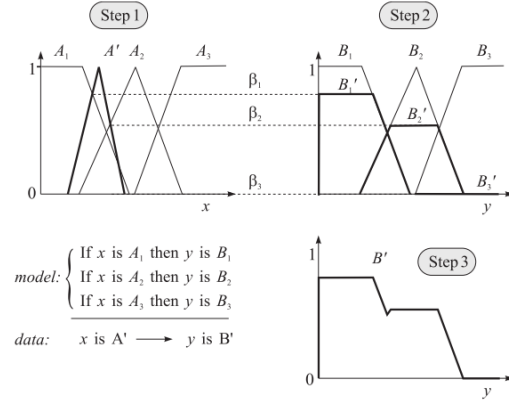


Figure 3.8.: A schematic representation of the Mamdani inference algorithm.

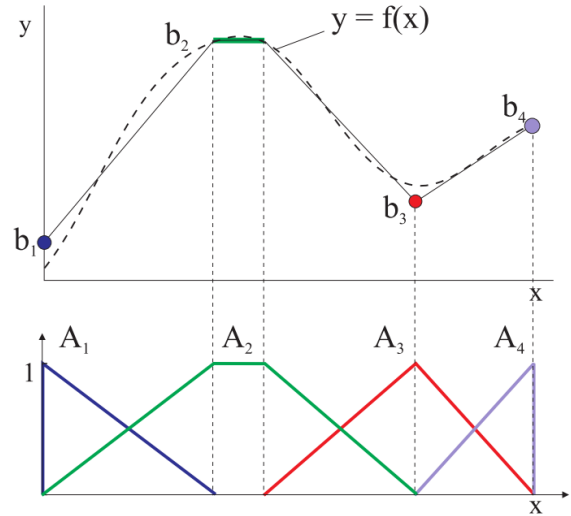
## 3. Singleton and Takagi-Sugeno Fuzzy System

### 3.1. Singleton Fuzzy model

If  $x$  is  $A_i$  then  $y = b_i$

- Defuzzication/Inference:

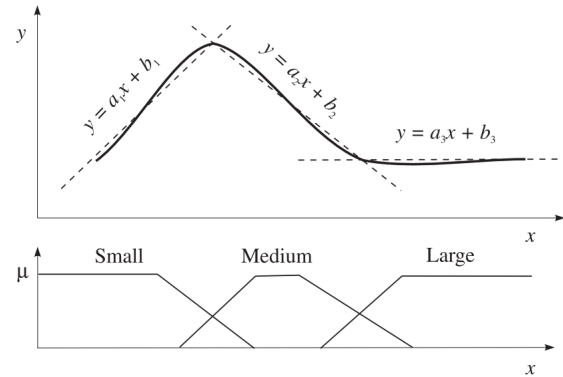
$$y = \frac{\sum_{i=1}^K \mu_{A_i}(x) b_i}{\sum_{i=1}^K \mu_{A_i}(x)}$$



### 3.2. Takagi-Sugeno (TS) Fuzzy model

If  $x$  is  $A_i$  then  $y_i = a_i x + b_i$

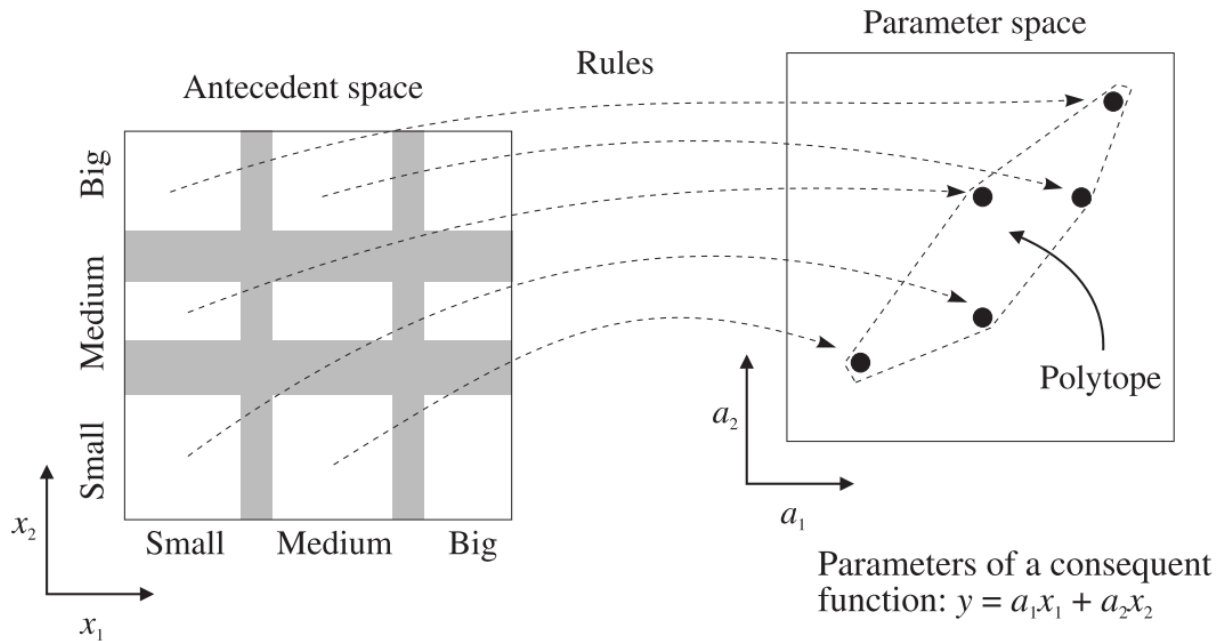
$$y = \frac{\sum_{i=1}^K \mu_{A_i}(x) y_i}{\sum_{i=1}^K \mu_{A_i}(x)} = \frac{\sum_{i=1}^K \mu_{A_i}(x) (a_i x + b_i)}{\sum_{i=1}^K \mu_{A_i}(x)}$$



- Quasi-Linear Property

$$y = \underbrace{\left( \sum_{i=1}^K \gamma_i(\mathbf{x}) \mathbf{a}_i^T \right)}_{\mathbf{a}(\mathbf{x})^T} \mathbf{x} + \underbrace{\sum_{i=1}^K \gamma_i(\mathbf{x}) b_i}_{b(\mathbf{x})}$$

linear in parameters  $a_i$  and  $b_i$ , pseudo-linear in  $x$  (LPV)

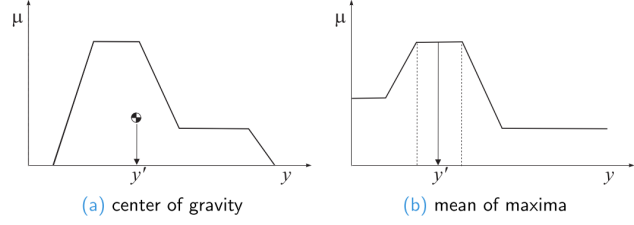


## 4. Defuzzification

Defuzzification convert a fuzzy set to a crisp value

- Center of Gravity Method:

$$y' = \frac{\sum_{j=1}^F \mu_{B'}(y_j) y_j}{\sum_{j=1}^F \mu_{B'}(y_j)}$$



## 5. Fuzzy Clustering

### 5.1. Problem Model

Given:

$$z_k = [z_{1k}, z_{2k}, \dots, z_{nk}]^T \in \mathbb{R}^n, \quad k = 1, \dots, N$$

Find:

- the fuzzy partition matrix

$$U = \begin{bmatrix} \mu_{11} & \dots & \mu_{1k} & \dots & \mu_{1N} \\ \vdots & \dots & \vdots & \dots & \vdots \\ \mu_{c1} & \dots & \mu_{ck} & \dots & \mu_{cN} \end{bmatrix}$$

- the cluster centers

$$V = \{v_1, v_2, \dots, v_c\}, \quad v_i \in \mathbb{R}^n$$

### 5.2. An optimization Approach

$$J(Z; V, U, A) = \sum_{i=1}^c \sum_{j=1}^N \mu_{i,j}^m d_{A_i}^2(z_j, v_i)$$

s.t.

$$0 \leq \mu_{i,j} \leq 1, \quad i = 1, \dots, c, j = 1, \dots, N \quad (\text{membership degree})$$

$$0 < \sum_{j=1}^N \mu_{i,j} < N, \quad i = 1, \dots, c \quad (\text{no cluster empty})$$

$$\sum_{i=1}^c \mu_{i,j} = 1, \quad j = 1, \dots, N \quad (\text{total membership})$$

#### Distance Matrices

- Euclidean norm

$$d^2(z_j, v_i) = (z_j - v_i)^T (z_j - v_i)$$

- Inner-product norm

$$d_{A_i}^2(z_j, v_i) = (z_j - v_i)^T A_i (z_j - v_i)$$

### 5.3. Fuzzy c-Means Algorithm

Repeat:

① Compute cluster prototypes (means):  $v_i = \frac{\sum_{k=1}^N \mu_{i,k}^m z_k}{\sum_{k=1}^N \mu_{i,k}^m}$

② Calculate distances:  $d_{ik} = (\mathbf{z}_k - \mathbf{v}_i)^T (\mathbf{z}_k - \mathbf{v}_i)$

③ Update partition matrix:  $\mu_{ik} = \frac{1}{\sum_{j=1}^c (d_{ik}/d_{jk})^{1/(m-1)}}$

until  $\|\Delta \mathbf{U}\| < \epsilon$