

Intelligent Systems

Susana M. Vieira

Universidade de Lisboa, Instituto Superior Técnico IS4, Center of Intelligent Systems, IDMEC, LAETA, Portugal {susana.vieira}@tecnico.ulisboa.pt



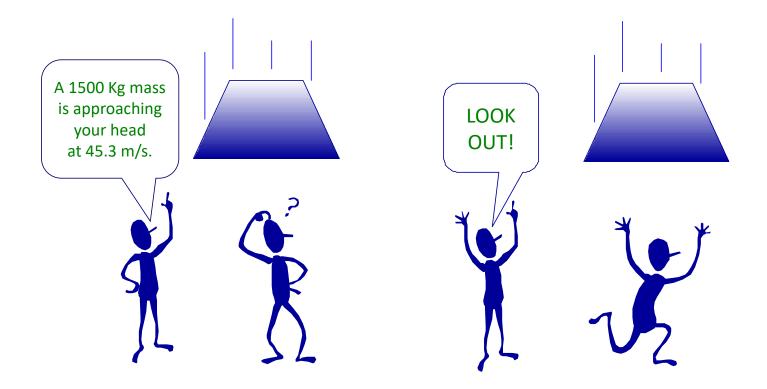
FUZZY SETS

SI2 – Introduction to Fuzzy Sets

Reading: Part I Fuzzy Set Theory: Chapter 2 Fuzzy Sets

J.-S. Jang, C.-T. Sun and E. Mizutani. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence.* Prentice Hall, New Jersey, 1997.

Precision vs. Relevancy





Introduction

- How to simplify very complex systems?
 - Allow some degree of imprecision in their description!
- How to deal mathematically with uncertainty?
 - Using probabilistic theory (stochastic).
 - Using the theory of fuzzy sets (non-stochastic).
- Proposed in 1965 by Lotfi Zadeh (Fuzzy Sets, *Information Control*, 8, pp. 338-353).
- Imprecision or vagueness in natural language does not imply a loss of accuracy or meaningfulness!



Examples

- Give travel directions in terms of city blocks OR in meters?
- The day is sunny OR the sky is covered by 5% of clouds?
 - If the sky is covered by 10% of clouds is still sunny?
 - And 25%?
 - And 50%?
 - Where to draw the line from sunny to not sunny?
 - Member and not member or membership degree?



Probability vs. Possibility

- Event *u*: Hans ate *X* eggs for breakfast.
- Probability distribution: $P_X(u)$
- Possibility distribution: $\pi_X(u)$

| u | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|------------|-----|-----|-----|---|---|---|---|---|
| $P_X(u)$ | 0.1 | 0.8 | 0.1 | 0 | 0 | 0 | 0 | 0 |
| $\pi_X(u)$ | 1 | 1 | 1 | | | | | |



You're lost in the outback; dying of thirst



"Honestly, the water hole is back that way... Why would I lie?"



You come upon two bottles containing liquid





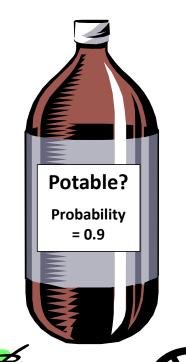
• Which one will you choose?

How will you process the information?



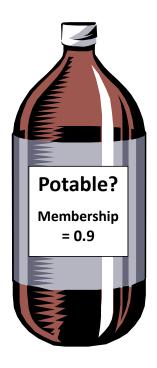


0.9 probability of belonging to the **set of non-poisonous liquid**



OR OR

1 out of 10



0.9 degree of membership to the set of non-poisonous liquid

Might taste funky, but shouldn't kill you



Why would anyone want to fuzzify logic?

- Isn't "fuzzy logic" an inherent contradiction? Why would anyone want to fuzzify logic?
- Fuzzy sets and logic must be viewed as a formal mathematical theory for the representation of uncertainty. Uncertainty is crucial for the management of real systems: if you had to park your car PRECISELY in one place, it would not be possible. Instead, you work within, say, 10 cm tolerances. The presence of uncertainty is the price you pay for handling a complex system.



Why would anyone want to fuzzify logic?

- Isn't "fuzzy logic" an inherent contradiction? Why would anyone want to fuzzify logic?
- Nevertheless, fuzzy logic is a mathematical formalism, and a membership grade is a precise number. What's crucial to realize is that fuzzy logic is a logic OF fuzziness, not a logic which is ITSELF fuzzy. But that's OK: just as the laws of probability are not random, so the laws of fuzziness are not vague.



Applications of fuzzy sets

- Fuzzy sets belong to "conventional" mathematics (measures, relations, topology, etc.)
- Fuzzy logic and AI (approximate reasoning, expert systems, etc.)
- Fuzzy systems
 - Fuzzy modeling
 - Fuzzy control, etc.
- Fuzzy decision making
 - Multi-criteria optimization
 - Optimization techniques

• ...



Classical set theory

- Set: collection of objects with a common property.
- Examples:
 - Set of basic colors:

$$A = \{\text{red, green, blue}\}$$

• Set of positive integers:

$$A = \{ x \in \mathbf{Z} | x \ge 0 \}$$

• A line in **R**³:

$$A = \{(x,y,z) \mid ax + by + cz + d = 0\}$$

Representation of sets

- Enumeration of elements: $A = \{x_1, x_2, ..., x_n\}$
- Definition by property $P: A = \{x \in X \mid P(x)\}$
- Characteristic function $\mu_{A(x)}: X \to \{0,1\}$

$$\mu_A(x) = \begin{cases} 1, & \text{if } x \text{ is member of } A \\ 0, & \text{if } x \text{ is not member of } A \end{cases}$$

Example:

Set of odd numbers: $\mu_A(x) = x \mod 2$

Set operations

- Intersection: $C = A \cap B$
 - C contains elements that belong to A and B
 - Characteristic function: $\mu_C = \min(\mu_A, \mu_B) = \mu_A \cdot \mu_B$
- Union: $C = A \cup B$
 - C contains elements that belong to A or to B
 - Characteristic function: $\mu_C = \max(\mu_A, \mu_B)$
- Complement: $C = \bar{A}$
 - ullet C contains elements that do not belong to A
 - Characteristic function: $\mu_C = 1 \mu_A$

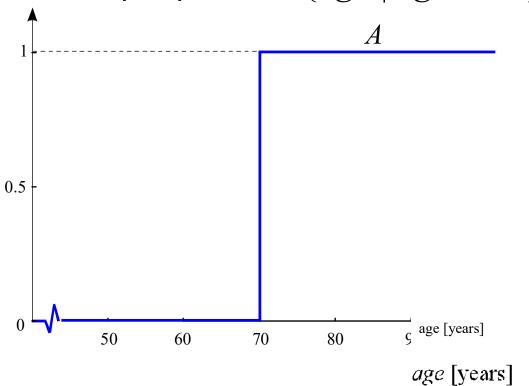
Fuzzy sets

- Represent uncertain (vague, ambiguous, etc.) knowledge in the form of propositions, rules, etc.
- Propositions:
 - expensive cars,
 - cloudy sky,...
- Rules (decisions):
 - Want to buy a big and new house for a low price.
 - If the temperature is *low*, then *increase* the heating.
 - ...



Classical set

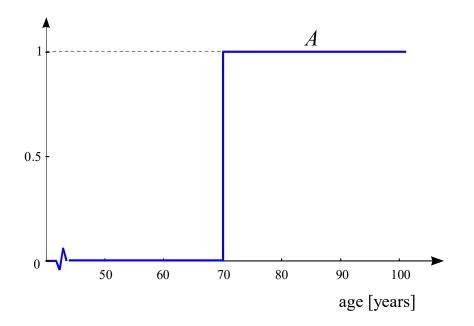
• Example: set of old people $A = \{age \mid age \ge 70\}$





Logic propositions

- "Nick is old" ... true or false
- Nick's age:
 - $age_{Nick} = 70$, $\mu_A(70) = 1$ (true)
 - age_{Nick} = 69.9, μ_A (69.9) = 0 (false)

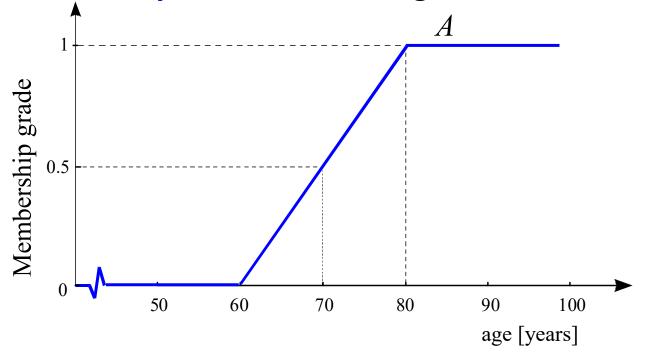




Fuzzy set

• Graded membership, element belongs to a set to a certain

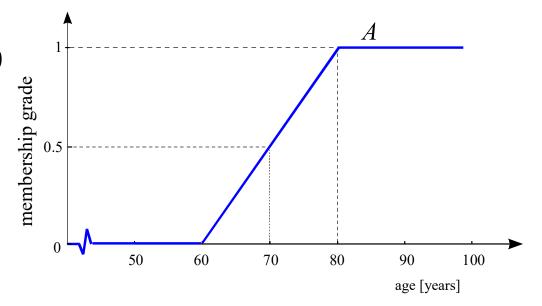
degree.





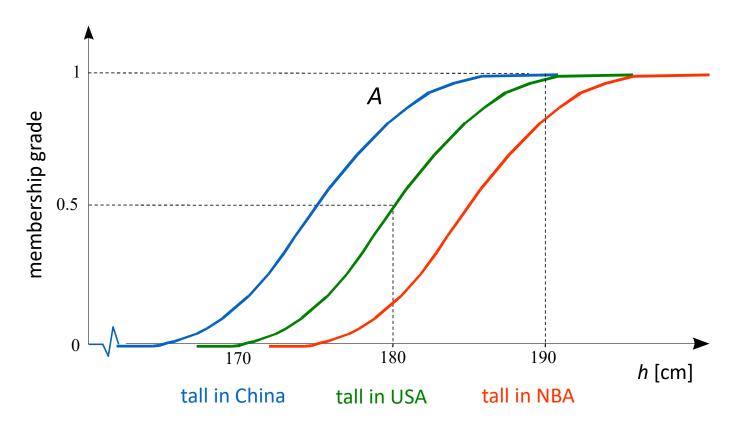
Fuzzy proposition

- "Nick is old"... degree of truth
 - $age_{Nick} = 70$, $\mu_A(70) = 0.5$
 - $age_{Nick} = 69.9$, $\mu_A(69.9) = 0.49$
 - $age_{Nick} = 90$, $\mu_A(90) = 1$



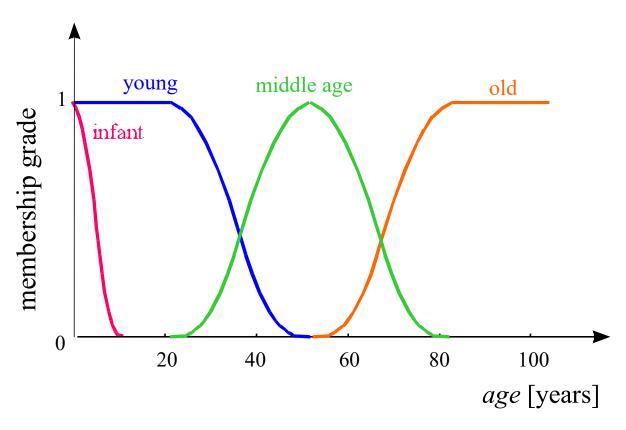


Context dependent



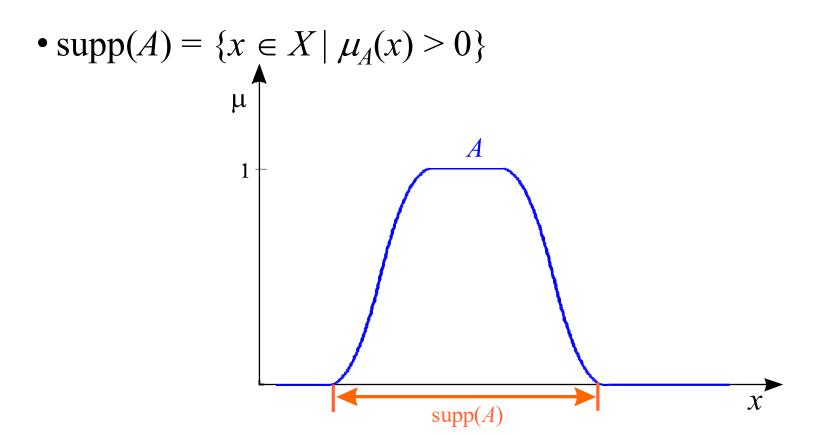


Typical linguistic values



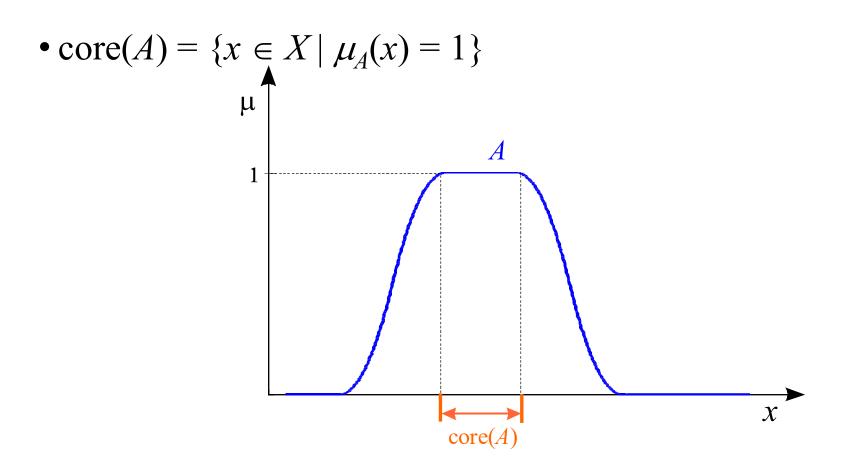


Support of a fuzzy set





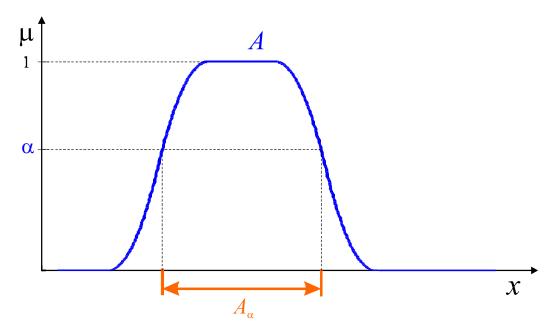
Core (nucleous, kernel)





α -cut of a fuzzy set

- α -cut is the crisp set: $A_{\alpha} = \{ x \in X \mid \mu_{A}(x) \geq \alpha \}$
- Strong α -cut: $A_{\alpha} = \{ x \in X \mid \mu_A(x) > \alpha \}$





Resolution principle

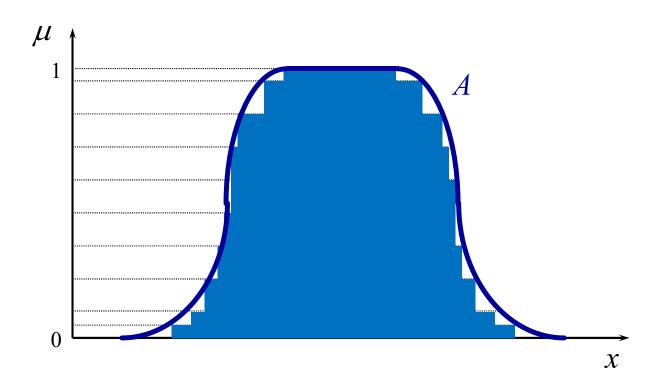
• Every fuzzy set A can be uniquely represented as a collection of α -level sets according to

$$\mu_A(x) = \sup_{\alpha \in [0,1]} \{ \alpha \in [0,1] \mid x \in A_\alpha \}$$

• Resolution principle implies that fuzzy set theory is a generalization of classical set theory, and that its results can be represented in terms of classical set theory.



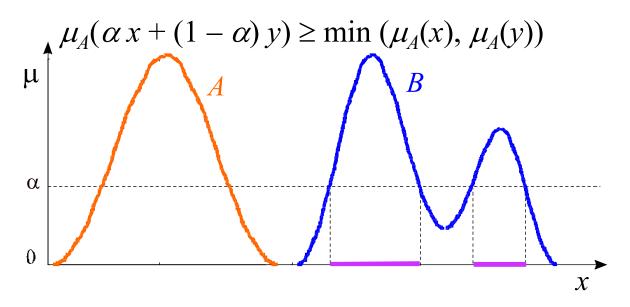
Resolution principle





Other properties

- **Height** of a fuzzy set: hgt $(A) = \sup \mu_A(x), x \in X$
- Fuzzy set is **normal(ized)** when hgt(A) = 1.
- A fuzzy set A is **convex** iff $\forall x,y \in X$ and $\alpha \in [0,1]$:





Other properties (2)

- Fuzzy singleton: single point $x \in X$ where $\mu_A(x) = 1$.
- Fuzzy number: fuzzy set in R that is normal and convex.
- Two fuzzy sets are **equal** (A = B) iff:

$$\forall x \in X, \ \mu_A(x) = \mu_B(x)$$

• A is a **subset** of B iff:

$$\forall x \in X, \ \mu_A(x) \leq \mu_B(x)$$



Other properties (3)

• Bandwith (or width): of *normal* and *convex* fuzzy sets is defined as the distance between two unique crossover points:

width(A) =
$$|x_2 - x_1|$$
, where $\mu_A(x_1) = \mu_A(x_2) = 0.5$.

• **Symmetry**: a fuzzy set A is symmetric if its μ_A is symmetric around a certain point x = c:

$$\mu_A(\mathbf{c} + x) = \mu_A(x + c), \forall x \in X,$$

Open left, open right, closed:

$$\lim x \to -\infty \ \mu_A(x) = 1 \text{ and } \lim x \to +\infty \ \mu_A(x) = 0$$

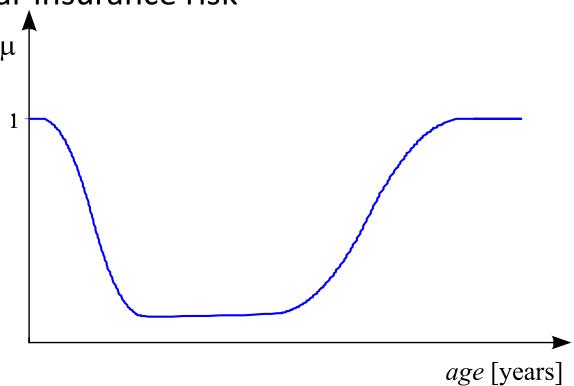
$$\lim x \to -\infty \ \mu_A(x) = 0 \text{ and } \lim x \to +\infty \ \mu_A(x) = 1$$

$$\lim x \to -\infty \ \mu_A(x) = \lim x \to +\infty \ \mu_A(x) = 0$$



Non-convex fuzzy sets

• Example: car insurance risk





Representation of fuzzy sets

Discrete Universe of Discourse:

Point-wise as a list of membership/element pairs:

•
$$A = \mu_A(x_1)/x_1 + ... + \mu_A(x_n)/x_n = \sum_i \mu_A(x_i)/x_i$$

•
$$A = \{\mu_A(x_1)/x_1, \dots, \mu_A(x_n)/x_n\} = \{\mu_A(x_i)/x_i \mid x_i \in X\}$$

• As a list of α -level/ α -cut pairs:

•
$$A = \{\alpha_1/A_{\alpha_1}, ..., \alpha_n/A_{\alpha_n}\} = \{\alpha_i/A_{\alpha_i} | \alpha_i \in [0,1]\}$$



Representation of fuzzy sets

Continuous Universe of Discourse:

$$\bullet \ A = \int_X \mu_A(x)/x$$

- Analytical formula: $\mu_A(x) = \frac{1}{1+x^2}, x \in \mathbb{R}$
- Various possible notations:
 - $\mu_A(x)$, A(x), A, a, etc.



Examples

Discrete universe

- Fuzzy set A = "sensible number of children".
 - number of children: $X = \{0, 1, 2, 3, 4, 5, 6\}$
 - A = 0.1/0 + 0.3/1 + 0.7/2 + 1/3 + 0.6/4 + 0.2/5 + 0.1/6
- Fuzzy set C = "desirable city to live in"
 - $X = \{SF, Boston, LA\}$ (discrete and non-ordered)
 - $C = \{(SF, 0.9), (Boston, 0.8), (LA, 0.6)\}$



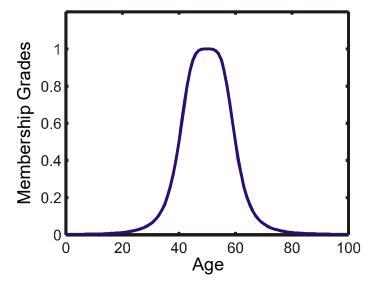
Examples

Continuous universe

- Fuzzy set B = "about 50 years old"
 - $X = R^+$ (set of positive real numbers)

$$\bullet B = \{(x, \mu_B(x)) \mid x \in X\}$$

$$\mu_B(x) = \frac{1}{1 + \left(\frac{x - 50}{10}\right)^4}$$





Complement of a fuzzy set

$$c: [0,1] \to [0,1]; \qquad \mu_A(x) \to c(\mu_A(x))$$

- Fundamental axioms
- Boundary conditions c behaves as the ordinary complement

$$c(0) = 1;$$
 $c(1) = 0$

2. Monotonic non-increasing

$$\forall a,b \in [0,1]$$
, if $a < b$, then $c(a) \ge c(b)$



Complement of a fuzzy set

Other axioms:

- c is a **continuous** function.
- c is *involutive*, which means that

$$c(c(a)) = a, \forall a \in [0,1]$$



Complement of a fuzzy set

Equilibrium point

$$c(a) = a = e_c, \ \forall a \in [0,1]$$

- Each complement has at most one equilibrium.
- If c is a continuous fuzzy complement, it has one equilibrium point.

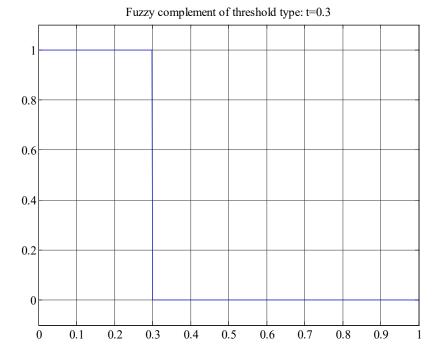


Examples of fuzzy complements

Standard complement:

Satisfying only fundamental axioms:

$$c(a) = \begin{cases} 1, & \text{if } a \le t \\ 0, & \text{if } a > t \end{cases}$$



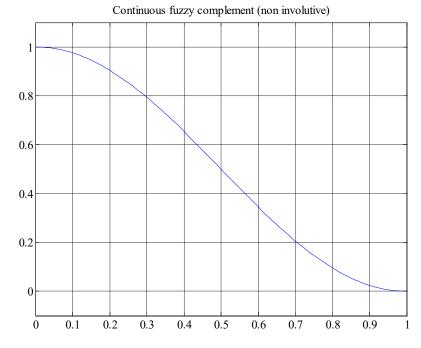


Examples of fuzzy complements

Cosine complement:

$$c(a) = \frac{1}{2} (1 + \cos \pi a)$$

Satisfying fundamental axioms and continuity:

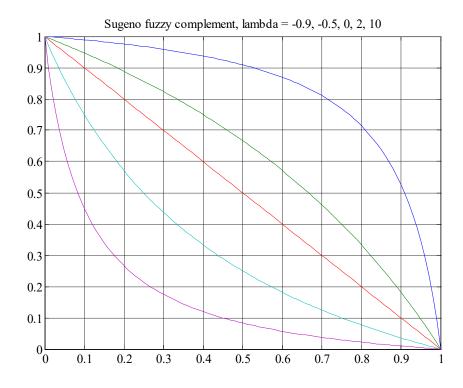




Examples of fuzzy complements

Sugeno complement:

$$c_{\lambda}(a) = \frac{1-a}{1+\lambda a}, \ \lambda \in]-1,\infty]$$

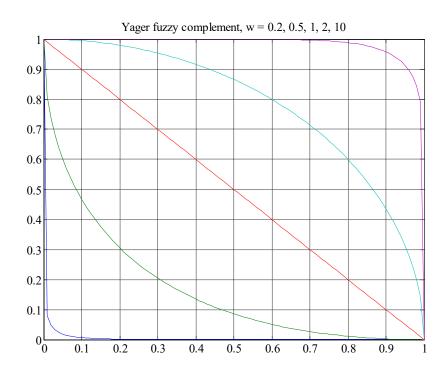




Examples of fuzzy complement

Yager complement:

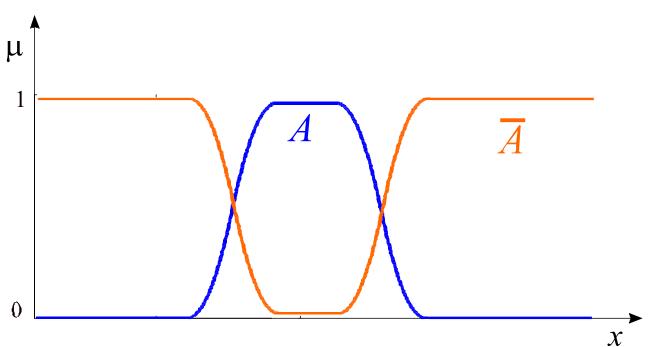
$$c_w(a) = \left(1 - a^w\right)^{1/w}, \quad w \in]0, \infty]$$





Representation of complement

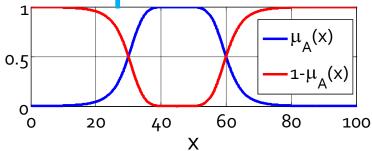
$$\bullet \ \mu_{\bar{A}}(x) = 1 - \mu_{A}(x)$$





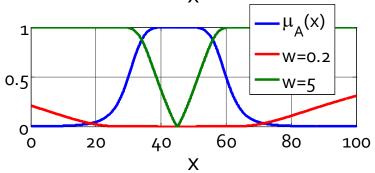
Representation of complement

Standard complement



Sugeno complement

Yager complement





Intersection of fuzzy sets

i:
$$[0,1] \times [0,1] \to [0,1];$$

 $\mu_{A \cap B}(x) \to i(\mu_A(x), \mu_B(x))$

- Fundamental axioms: triangular norm or t-norm
- 1. Boundary conditions i behaves as the classical intersection

$$i(1,1) = 1;$$

 $i(0,1) = i(1,0) = i(0,0) = 0$

2. Commutativity

$$i(a,b) = i(b,a)$$



Intersection of fuzzy sets

3. Monotonicity

If
$$a \le a$$
 and $b \le b$, then $i(a,b) \le i(a',b')$

4. Associativity

$$i(i(a,b),c) = i(a,i(b,c))$$

Other axioms:

- *i* is a *continuous* function.
- i(a,a) = a (idempotent).



Examples of fuzzy conjunctions

Zadeh

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

Probabilistic (or algebraic product)

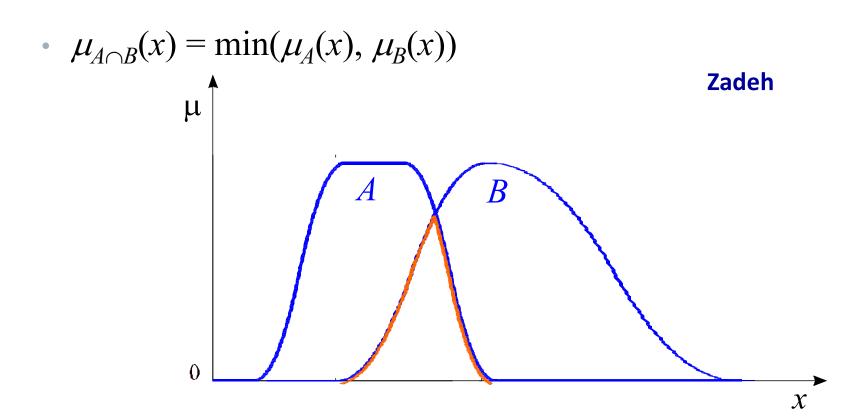
$$\mu_{A \cap B}(x) = \mu_A(x) \cdot \mu_B(x)$$

Łukaziewicz

$$\mu_{A \cap B}(x) = \max(0, \mu_A(x) + \mu_B(x) - 1)$$

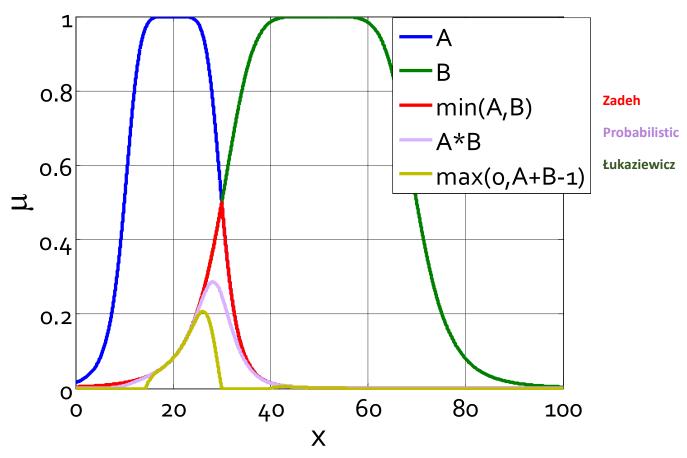


Intersection of fuzzy sets





Intersection of fuzzy sets



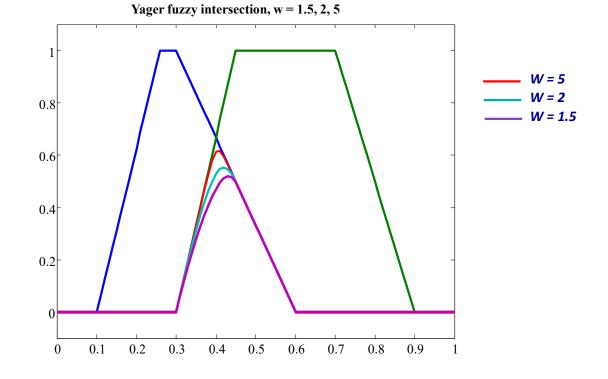


Yager *t*-norm

$$i_w(a,b) = 1 - \min \left[1, \left((1-a)^w + (1-b)^w \right)^{1/w} \right], \ w \in]0,\infty]$$

Example of weak and strong intersections:

Parametric t-norm





Union of fuzzy sets

$$u: [0,1] \times [0,1] \to [0,1];$$

 $\mu_{A \cup B}(x) \to u(\mu_A(x), \mu_B(x))$

- Fundamental axioms: triangular co-norm or s-norm
- 1. Boundary conditions u behaves as the classical union

$$u(0,0) = 0;$$

 $u(0,1) = u(1,0) = u(1,1) = 1$

2. Commutativity

$$u(a,b) = u(b,a)$$



Union of fuzzy sets

3. Monotonicity

If
$$a \le a$$
 and $b \le b$, then $u(a,b) \le u(a',b')$

4. Associativity

$$u(u(a,b),c) = u(a,u(b,c))$$

Other axioms:

- *u* is a *continuous* function.
- u(a,a) = a (idempotent).



Examples of fuzzy disjunctions

Zadeh

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

Probabilistic (algebraic sum)

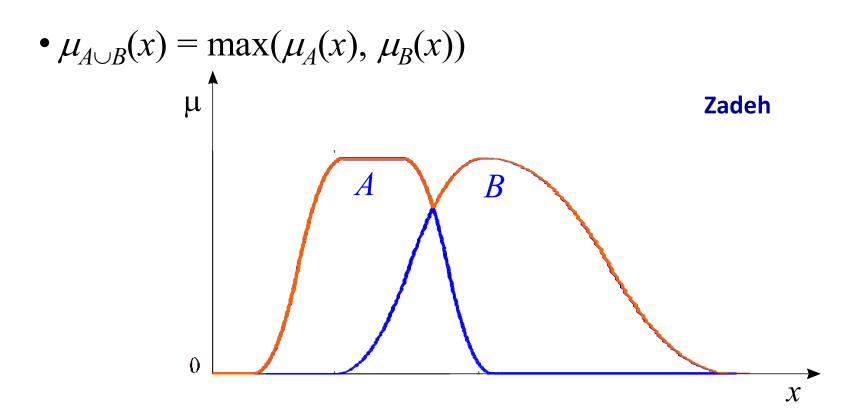
$$\mu_{A \cup B}(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x)$$

Łukasiewicz

$$\mu_{A \cup B}(x) = \min(1, \mu_A(x) + \mu_B(x))$$

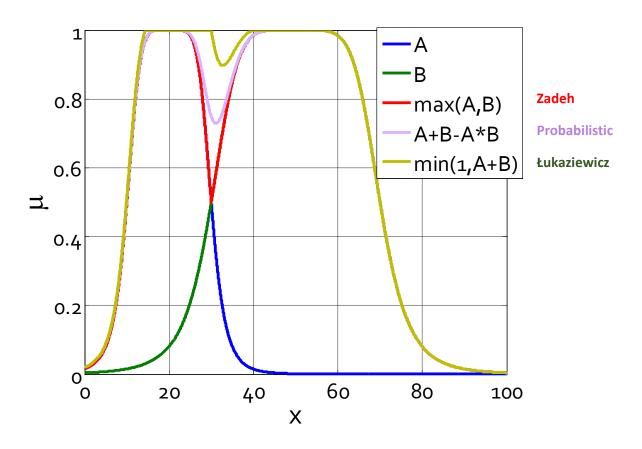


Union of fuzzy sets





Union of fuzzy sets

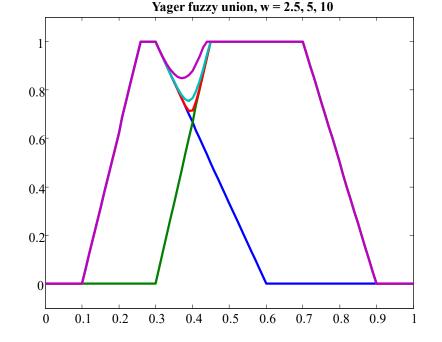




Yager *t*-conorm (s-norm)
$$u_{w}(a,b) = \min\left[1,\left(a^{w}+b^{w}\right)^{1/w}\right], \ w \in]0,\infty]$$

Example of weak and strong disjunctions:

Parametric t-conorm







General aggregation operations

$$h: [0,1]^n \to [0,1];$$

 $\mu_A(x) \to h(\mu_{A_1}(x),...,\mu_{A_n}(x))$

- Axioms
- 1. Boundary conditions

$$h(0,...,0) = 0$$

 $h(1,...,1) = 1$

2. Monotonic non-decreasing

For any pair
$$a_i, b_i \in [0,1], i \in \mathbb{N}$$

If $a_i \ge b_i$ then $h(a_i) \ge h(b_i)$



General aggregation operations

- Other axioms:
 - h is a *continuous* function.
 - h is a **symmetric** function in all its arguments:

$$h(a_i) = h(a_{p(i)})$$

for any permutation p on \mathbf{N}



Averaging operations

• When all the four axioms hold:

$$\min(a_1,...,a_n) \le h(a_1,...,a_n) \le \max(a_1,...,a_n)$$

Operator covering this range: Generalized mean

$$h_{\alpha}(a_1,\ldots,a_n) = \left(\frac{\left(a_1^{\alpha} + \ldots + a_n^{\alpha}\right)}{n}\right)^{1/\alpha}$$



Generalized mean

- Typical cases:
 - Lower bound:
 - Geometric mean:
 - Harmonic mean:

- Arithmetic mean:
- Upper bound:

$$h_{-\infty} = \min(a_1, \dots, a_n)$$

$$h_0 = (a_1 \cdot a_2 \cdot \ldots \cdot a_n)^{1/n}$$

$$h_{-1} = \frac{n}{\frac{1}{a_1} + \ldots + \frac{1}{a_n}}$$

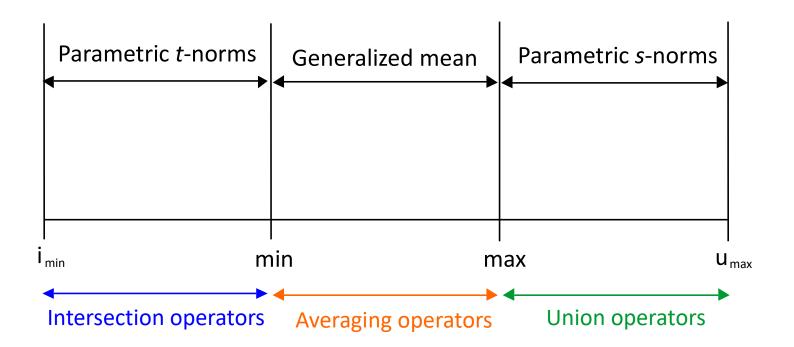
$$h_1 = \frac{a_1 + \dots + a_n}{n}$$

$$h_{\infty} = \max(a_1, \dots, a_n)$$

$$h_{\infty} = \max(a_1, \dots, a_n)$$



Fuzzy aggregation operations





Membership functions (MF)

• Triangular MF:
$$Tr(x;a,b,c) = \max \left(\min \left(\frac{x-a}{b-a}, \frac{c-x}{c-b} \right), 0 \right)$$

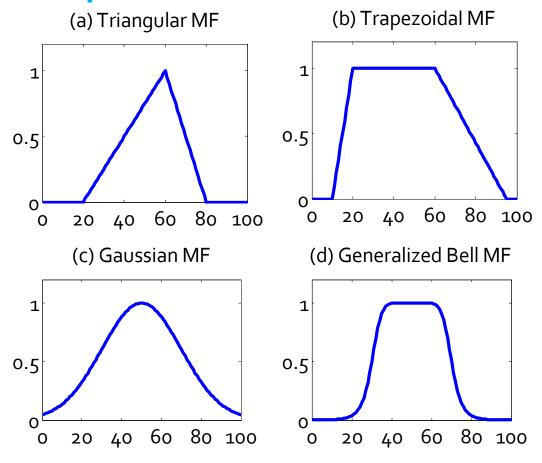
• Trapezoidal MF:
$$Tp(x;a,b,c,d) = \max\left(\min\left(\frac{x-a}{b-a},1,\frac{d-x}{d-c}\right),0\right)$$

• Gaussian MF:
$$Gs(x;a,b,c) = e^{-\frac{1}{2}\left(\frac{x-c}{\sigma}\right)^2}$$

• Generalized bell MF:
$$Bell(x;a,b,c) = \frac{1}{1 + \left| \frac{x-c}{b} \right|^{2a}}$$



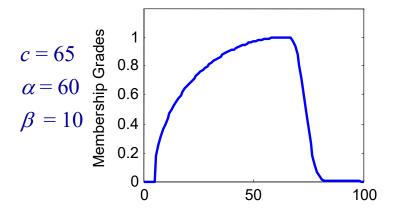
Membership functions

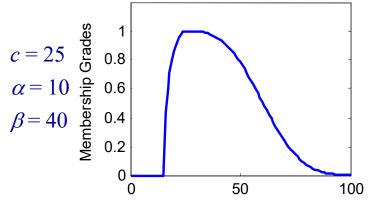




Left-right MF

$$LR(x;c,\alpha,\beta) = \begin{cases} F_L\left(\frac{c-x}{\alpha}\right), x < c \\ F_R\left(\frac{x-c}{\beta}\right), x \ge c \end{cases}$$

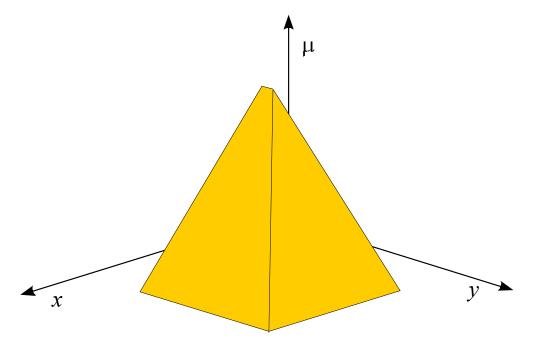






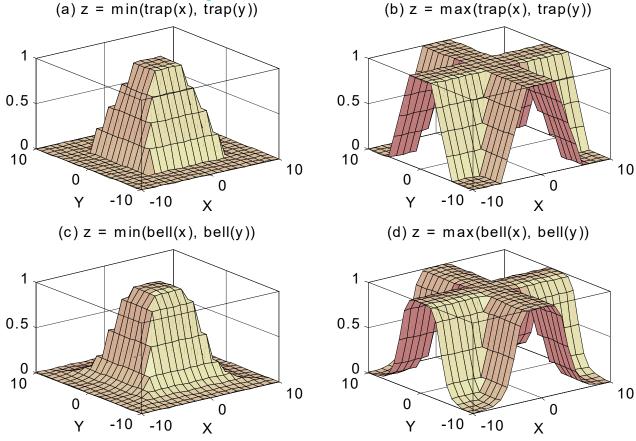
Two-dimensional fuzzy sets

$$A = \int_{X \times Y} \mu_A(x, y) = \left\{ \mu_A(x, y) \middle| (x, y) \in X \times Y \right\}$$





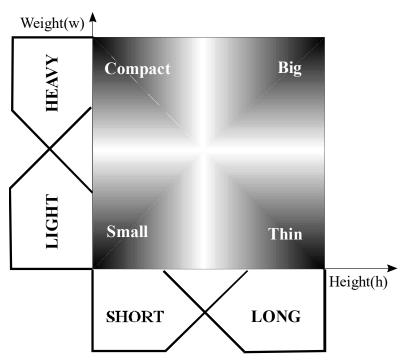
2-D membership functions (a) z = min(trap(x), trap(y)) (b) z = max





Compound fuzzy propositions

• Small = Short and Light (conjunction) $\mu_{Small}(h, w) = \mu_{Short}(h) \cap \mu_{Light}(w)$

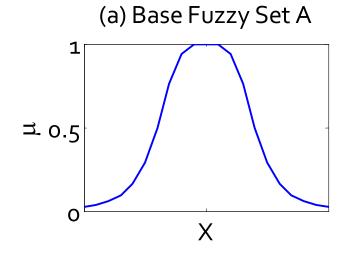


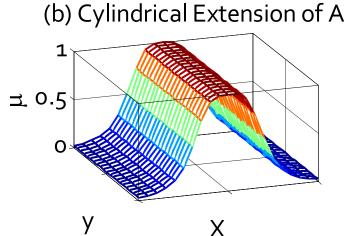


Cylindrical extension

• Cylindrical extension of fuzzy set A in X into Y results in a two-dimensional fuzzy set in $X \times Y$, given by

$$\operatorname{cext}_{y}(A) = \int_{X \times Y} \mu_{A}(x) / (x, y) = \{ \mu_{A}(x) / (x, y) | (x, y) \in X \times Y \}$$







Example

• Premise: Fuzzy set $\mu(x)$ that represents 'Young people' in the domain X representing age:

```
• X = \{18, 20, 22, 25, 30\} [years] \mu_{Young}(x) x \qquad 18 \quad 20 \quad 22 \quad 25 \quad 30 \mu_{Young}(x) \qquad 1 \quad 1 \quad 0.8 \quad 0.5 \quad 0.2
```

• Consider the set of 'duration of mobile calls' $Y = \{1, 3, 5, 7, 10, 20\}$ [min/call]



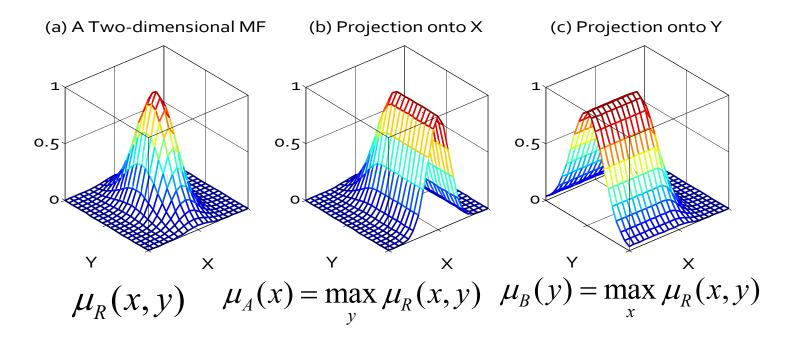
Example

• Compute the cylindrical extension of $\mu(x)$ in to Y:

```
[years]
            20
                22
                     25
                         30
\mu_{Young}(x) 1 1 0.8 0.5
                                         \mu_{Young}(x) into X x Y
  Y = \{1, 3, 5, 7, 10, 20\} [min/call]
                                    \mu_{Young}(x)_1 3 5 7
                                 X
                                       1 1 1 1 1 1
                                 18
                                       1 1 1 1 1
                                 20
                                 22
                                       0.8 0.8 0.8 0.8 0.8
                                                           8.0
                                      0.5 0.5 0.5 0.5 0.5 0.5
                                 25
                                 30
                                       0.2 0.2 0.2 0.2 0.2 0.2 0.2
```



Projection





Cartesian product and co-product

• Cartesian product of fuzzy sets A and B is a fuzzy set in the product space $X \times Y$ with membership

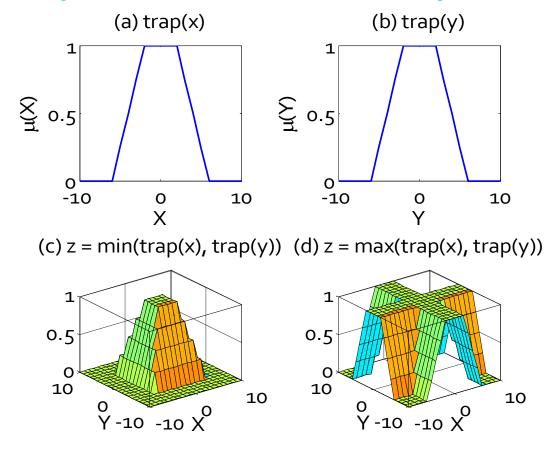
$$\mu_{A\times B}(x,y) = \min(\mu_A(x), \mu_B(y))$$

• Cartesian co-product of fuzzy sets A and B is a fuzzy set in the product space $X \times Y$ with membership

$$\mu_{A+B}(x,y) = \max(\mu_A(x), \mu_B(y))$$



Cartesian product and co-product







FUZZY RELATIONS

SI3 – Fuzzy Relations

Reading: Part I Fuzzy Set Theory: Chapter 3 Fuzzy Rules and Fuzzy Reasoning

J.-S. Jang, C.-T. Sun and E. Mizutani. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence.* Prentice Hall, New Jersey, 1997.

Motivation

- A Crisp relation represents presence or absence of association, interaction or interconnection between elements of ≥ 2 sets.
 - This concept can be generalized to various degrees or strengths of association or interaction between elements.
- A fuzzy relation generalizes these degrees to membership grades. So, a crisp relation is a restricted case of a fuzzy relation.



Classical relations

• Classical relation $\Re(X_1, X_2, ..., X_n)$ is a subset of the Cartesian product:

$$\mathcal{R}(X_1, X_2, \dots, X_n) \subset X_1 \times X_2 \times \dots \times X_n$$

Characteristic function:

$$\mu_{\mathcal{R}}(x_1, x_2, \dots, x_n) = \begin{cases} 1, & \text{iff } (x_1, x_2, \dots, x_n) \in \mathcal{R} \\ 0, & \text{otherwise} \end{cases}$$



Example

```
• X = {English, French}
```

- Y = {dollar, pound, euro}
- Z = {USA, France, Canada, Britain, Germany}
- R(X, Y, Z) = {(English, dollar, USA),
 (French, euro, France), (English, dollar, Canada),
 (French, dollar, Canada), (English, pound, Britain)}



Matrix representation

| | USA | Fra | a Can Brit Ger | | | USA | Fra | Can | Brit | Ger | |
|--------|----------|-----|----------------|---|----|--------|-----|-----|------|-----|---|
| Dollar | 1 | 0 | 1 | 0 | 0 | Dollar | 0 | 0 | 1 | 0 | 0 |
| Pound | 0 | 0 | 0 | 1 | 0 | Pound | 0 | 0 | 0 | 0 | 0 |
| Euro | 0 | 0 | 0 | 0 | 0] | Euro | 0 | 1 | 0 | 0 | 0 |
| | | | French | | | | | | | | |



Fuzzy relation

• Fuzzy relation:

$$\mathcal{R}: X_1 \times X_2 \times ... \times X_n \rightarrow [0,1]$$

- Each tuple $(x_1, x_2, ..., x_n)$ has a **degree of membership**.
- Fuzzy relation can be represented by an n-dimensional membership function (continuous space) or a matrix (discrete space).
- Examples:
 - *x* is close to *y*
 - x and y are similar
 - x and y are related (dependent)



Discrete examples

• Relation \mathcal{R} "very far" between $X = \{\text{New York, Lisbon}\}$ and $Y = \{\text{New York, Beijing, London}\}$:

```
\Re(x,y) = O/(NY,NY) + 1/(NY,Beijing) + 0.6/(NY,London) + 0.5/(Lisbon,NY) + 0.8/(Lisbon,Beijing) + 0.1/(Lisbon,London)
```



Discrete examples

• Relation: "is an important trade partner of"

| | Holland | Germany | USA | Japan |
|---------|---------|---------|-----|-------|
| Holland | 1 | 0,9 | 0,5 | 0,2 |
| Germany | 0,3 | 1 | 0,4 | 0,2 |
| USA | 0,3 | 0,4 | 1 | 0,7 |
| Japan | 0,6 | 0,8 | 0,9 | 1 |

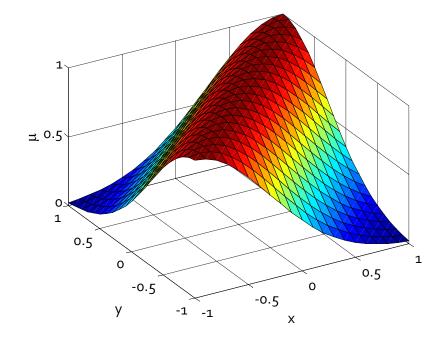
X = {New York, Lisbon}
and Y = {New York, Beijing, London}



Continuous example

• \Re : $x \approx y$ ("x is approximately equal to y")

$$\mu_{\Re}(x,y) = e^{-(x-y)^2}$$





Composition of relations

• $\mathcal{R}(X,Z) = \mathcal{P}(X,Y) \circ \mathcal{Q}(Y,Z)$

Conditions:

- $(x,z) \in \mathcal{R}$ iff exists $y \in Y$ such that
- $(x,y) \in \mathcal{P}$ and $(y,z) \in \mathcal{Q}$. $\mu_{\mathcal{P} \circ \mathcal{Q}}(x,z) = \max_{y \in Y} \min \left[\mu_{\mathcal{P}}(x,y), \mu_{\mathcal{Q}}(y,z) \right]$
- Max-min composition



Properties

• Associativity: $\Re \circ (S \circ \mathcal{F}) = (\Re \circ S) \circ \mathcal{F}$

- Distributivity over union: $\Re \circ (S \cup \mathcal{F}) = (\Re \circ S) \cup (\Re \circ \mathcal{F})$
- Weak distributivity over intersection: $\Re \circ (S \cap \mathcal{F}) \subseteq (\Re \circ S) \cap (\Re \circ \mathcal{F})$
- Monotonicity: $S \subseteq \mathcal{F} \Rightarrow (\mathcal{R} \circ S) \subseteq (\mathcal{R} \circ \mathcal{F})$



Other compositions

Max-prod composition

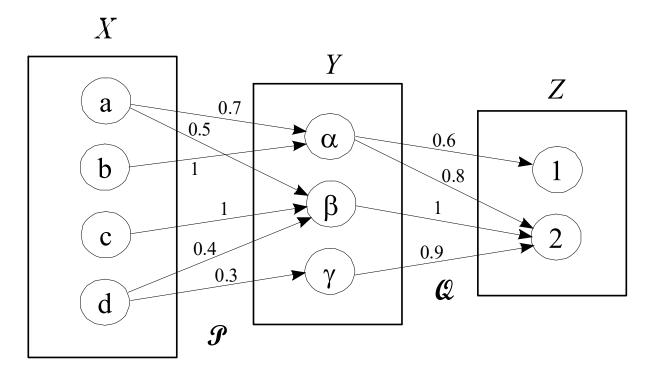
$$\mu_{\mathscr{P} \circ \mathscr{Q}}(x, z) = \max_{y \in Y} \left(\mu_{\mathscr{P}}(x, y) \cdot \mu_{\mathscr{Q}}(y, z) \right)$$

Max-t composition

$$\mu_{\mathcal{P} \circ \mathcal{Q}}(x, z) = \max_{y \in Y} t(\mu_{\mathcal{P}}(x, y), \mu_{\mathcal{Q}}(y, z))$$



Example





Example

• Composition $\mathcal{R} = \mathcal{F} \circ \mathcal{Q}$ Max-min composition

• Composition $\mathcal{R} = \mathcal{P} \otimes \mathcal{Q}$?

Max-prod composition

| X | Z | $\mu_R(x,z)$ |
|---|---|--------------|
| а | 1 | 0.6 |
| а | 2 | 0.7 |
| b | 1 | 0.6 |
| b | 2 | 0.8 |
| С | 2 | 1 |
| d | 2 | 0.4 |



Matrix notation examples

Max-min composition: max(min(0.3,0.9),min(0.5,0.3),min(0.8,1.0)) =

 $\begin{bmatrix} 0.3 & 0.5 & 0.8 \\ 0 & 0.7 & 1 \\ 0.4 & 0.6 & 0.5 \end{bmatrix} \circ \begin{bmatrix} 0.9 & 0.5 & 0.7 & 0.7 \\ 0.3 & 0.2 & 0 & 0.9 \\ 1 & 0 & 0.5 & 0.5 \end{bmatrix} = \begin{bmatrix} 0.9 & 0.5 & 0.7 & 0.7 \\ 0.3 & 0.2 & 0 & 0.9 \\ 1 & 0 & 0.5 & 0.5 \end{bmatrix} = \begin{bmatrix} 0.9 & 0.5 & 0.7 & 0.7 \\ 0.3 & 0.2 & 0 & 0.9 \\ 1 & 0 & 0.5 & 0.5 \end{bmatrix}$



Matrix notation examples

$$\begin{bmatrix} 0.3 & 0.5 & 0.8 \\ 0 & 0.7 & 1 \\ 0.4 & 0.6 & 0.5 \end{bmatrix} \circ \begin{bmatrix} 0.9 & 0.5 & 0.7 & 0.7 \\ 0.3 & 0.2 & 0 & 0.9 \\ 1 & 0 & 0.5 & 0.5 \end{bmatrix} = \begin{bmatrix} 0.8 & 0.3 & 0.5 & 0.5 \\ 1 & 0.2 & 0.5 & 0.7 \\ 0.5 & 0.4 & 0.5 & 0.6 \end{bmatrix}$$

$$\begin{bmatrix} 0.3 & 0.5 & 0.8 \\ 0 & 0.7 & 1 \\ 0.4 & 0.6 & 0.5 \end{bmatrix} \otimes \begin{bmatrix} 0.9 & 0.5 & 0.7 & 0.7 \\ 0.3 & 0.2 & 0 & 0.9 \\ 1 & 0 & 0.5 & 0.5 \end{bmatrix} = \begin{bmatrix} 0.8 & 0.15 & 0.4 & 0.45 \\ 1 & 0.14 & 0.5 & 0.63 \\ 0.5 & 0.2 & 0.28 & 0.54 \end{bmatrix}$$



Relations on the same universe

- Let \mathcal{R} be a relation defined on $U \times U$, then it is called:
- **Reflexive**, if $\forall u \in U$, the pair $(u,u) \in \mathcal{R}$
- Anti-reflexive, if $\forall u \in U, (u,u) \notin \mathcal{R}$
- Symmetric, if $\forall u,v \in U$, if $(u,v) \in \mathcal{R}$, then $(v,u) \in \mathcal{R}$ too
- Anti-symmetric, if $\forall u,v \in U$, if (u,v) and $(v,u) \in \mathcal{R}$, then u = v
- **Transitive**, if $\forall u,v,w \in U$, if (u,v) and $(v,w) \in \mathcal{R}$, then $(u,w) \in \mathcal{R}$ too.



Examples

- ${\mathcal R}$ is an *equivalence relation* if it is reflexive, symmetric and transitive.
- \mathcal{R} is a partial order relation if it is reflexive, anti-symmetric and transitive.
- \mathcal{R} is a total order relation if \mathcal{R} is a partial order relation, and \forall $u, v \in U$, either (u,v) or $(v,u) \in \mathcal{R}$.

Examples:

- The subset relation on sets (\subseteq) is a partial order relation.
- The relation \leq on N is a total order relation.





FUZZY SYSTEMS

SI3 – Fuzzy Systems

Reading: Part I Fuzzy Set Theory: Chapter 4 Fuzzy Inference Systems

J.-S. Jang, C.-T. Sun and E. Mizutani. *Neuro-Fuzzy and Soft Computing: A Computational Approach to Learning and Machine Intelligence.* Prentice Hall, New Jersey, 1997.

Extension Principle

- General procedure to extend crisp mathematical expressions to fuzzy domains.
- Generalizes a point-to-point mapping into a mapping between fuzzy sets.
- Given a function f mapping points in set X to points in set Y:

$$f: X_1 \times X_2 \times ... \times X_n \to Y, \ y = f(x_1, x_2, ..., x_n)$$

And a fuzzy set A where:

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



Extension Principle

the extension principle states that:

$$f(A) = f(\mu_A(x_1)/x_1 + \mu_A(x_2)/x_2 + \dots + \mu_A(x_n)/x_n)$$
$$+ \mu_A(x_1)/y_1 + \mu_A(x_2)/y_2 + \dots + \mu_A(x_n)/y_n$$

- If f is a many-to-one mapping, then $\mu_B(y) = \max_{x=f^{-1}(y)} \mu_A(x)$
- Fuzzy set B is the image of A in Y using f, and is given by:

$$\mu_{B}(y) = \begin{cases} \max_{\mathbf{x} = f^{-1}(y)} \left[\min_{i} \left(\mu_{A_{i}}(x_{i}) \right) \right], & \text{if } f^{-1}(y) \neq \emptyset \\ 0, & \text{if } f^{-1}(y) = \emptyset \end{cases}$$



Example

Let

$$A = 0.1/-2 + 0.4/-1 + 0.8/0 + 0.9/1 + 0.3/2$$

and

$$f(x) = x^2 - 3$$

Applying the extension principle:

$$B = 0.1/1 + 0.4/-2 + 0.8/-3 + 0.9/-2 + 0.3/1$$
$$= 0.8/-3 + (0.4 \lor 0.9)/-2 + (0.1 \lor 0.3)/1$$
$$= 0.8/-3 + 0.9/-2 + 0.3/1$$



Example

•
$$X_1 = \{a,b,c\}, X_2 = \{x,y\}, Y = \{p,q,r\}$$

•
$$f: X_1 \times X_2 \to Y$$

$$\begin{array}{ccc}
x & y \\
a & p & p \\
b & q & r \\
c & r & p
\end{array}$$

•
$$A_1 = .3/a + .9/b + .5/c$$
, $A_2 = .5/x + 1/y$

•
$$\mu_B(p) = \max[\min(.3,.5), \min(.3,1), \min(.5,1)] = .5$$

 $\mu_B(q) = \max[\min(.9,.5)] = .5$
 $\mu_B(r) = \max[\min(.5,.5), \min(.9,1)] = .9$

•
$$f(A_1, A_2) = .5/p + .5/q + .9/r$$



Extension Principle Example

Example for a continuous function

$$[f(A)](y) = \sup_{x|y=f(x)} A(x)$$
for all $A \in \mathcal{F}(X)$ and
$$[f^{-1}(B)](x) = B(f(x))$$
for all $B \in \mathcal{F}(Y)$.

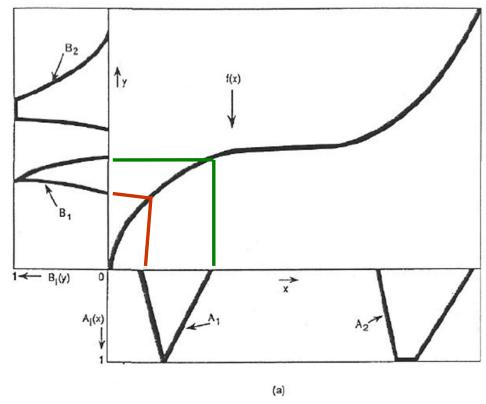


Figure 2.5 Illustration of the extension principle when f is continuous.



Linguistic variable

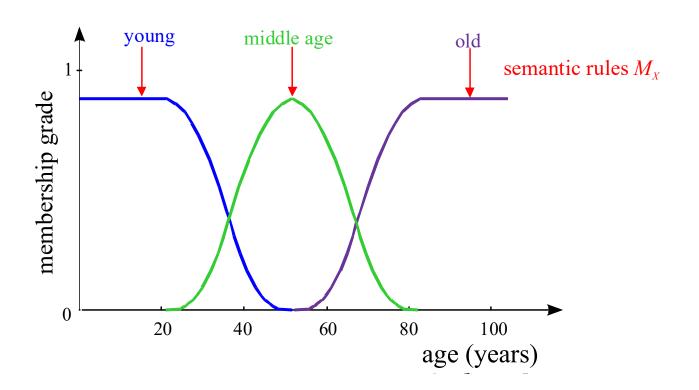
$$\{x, \mathsf{LX}, \mathsf{X}, M_X\}$$

- Where:
- x -name of the linguistic variable
- LX linguistic values (terms)
- X Universe of discourse
- $ullet M_X$ semantic rule that associates each linguistic value to a membership function.



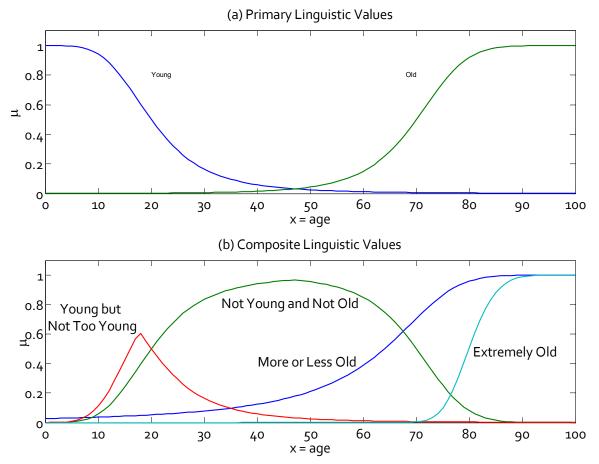
Example

• x is age and LX = {young, middle age, old}





Linguistic values (terms)





Linguistic hedges (modifiers)

- More common modifiers: likely, almost, very, more or less, fairly, rather, too, extremely, etc.
- Typical concentration operator: very

$$CON(\mu_A(x)) = \mu_A^2(x)$$

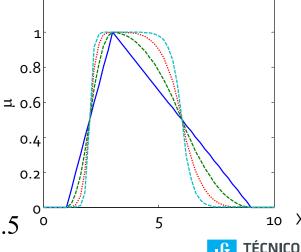
Typical dilation operator: more or less

$$DIL(\mu_A(x)) = \mu_A^{0.5}(x)$$

Contrast intensification operator:

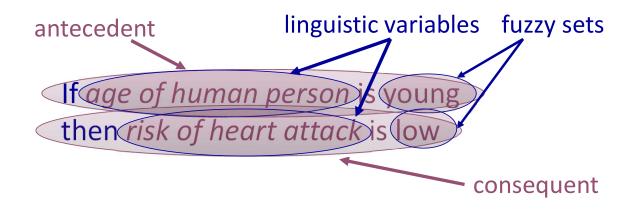
INT
$$(\mu_A(x)) = \begin{cases} 2\mu_A^2(x), & 0 \le \mu_A(x) \le 0.5 \end{cases}$$

$$\overline{2}(\overline{\mu}_A^2(x)), & 0.5 \le \mu_A(x) \le 1$$



Fuzzy systems

- Fuzzy systems manipulate fuzzy sets to model the world.
- Most fuzzy systems are rule based.



Consequent can be a fuzzy set or a crisp function



Fuzzy if-then rules

- Linguistic (Mamdani) fuzzy if-then rule
 - **If** *x* is *A* **then** *y* is *B*
- Rule is represented by a *fuzzy relation* defined on $X \times Y$

Examples:

- If the road is slippery then brake softly.
- If a tomato is red then the tomato is ripe.
- If the temperature is high then reduce the heat.
- If the valve is closed then the pressure is high.



Fuzzy inference

The rule If x is A then y is B can be interpreted as A entails B

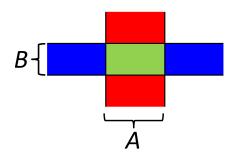
(fuzzy implication) where

$$\mathcal{R} = \overline{A} \cup B$$

• or that A is coupled with B, resulting in the following relation:

$$\mathcal{R} = \operatorname{cext}_{Y}(A) \cap \operatorname{cext}_{X}(B)$$

$$\mu_{\mathcal{R}}(x,y) = \min(\mu_{A}(x), \mu_{B}(x))$$



B +



Fuzzy implications

• Fuzzy implications: $\mu_{\mathcal{R}}(x,y) = I(\mu_{A}(x),\mu_{B}(y))$

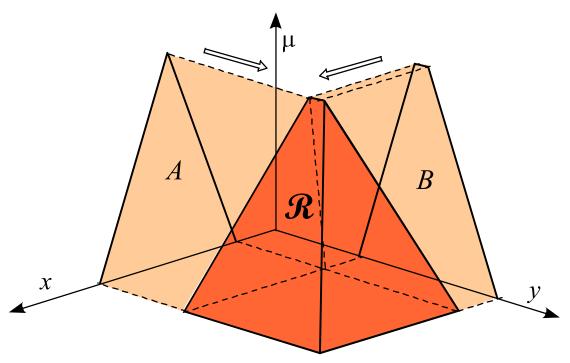
Examples of implications:

| Kleene-Dienes | $I(\mu_A(x), \mu_B(x)) = \max(1 - \mu_A(x), \mu_B(x))$ |
|---------------|--|
| Lukasiewicz | $I(\mu_A(x), \mu_B(x)) = \min(1, 1 - \mu_A(x) + \mu_B(x))$ |
| Mamdani | $I(\mu_A(x), \mu_B(x)) = \min(\mu_A(x), \mu_B(x))$ |



Example of Mamdani inference

• If x is A then y is B using the min.





Example

Premise: Young people make long Mobile calls

```
• X = \{18, 20, 22, 25, 30\} [years]
```

• $Y = \{1, 3, 5, 7, 10, 20\}$ [min/call]

| young(x) | | | | | | long(y | /) | | | | | |
|----------|----|----|-----|-----|-----|----------|----|-----|-----|-----|-----|----|
| X | 18 | 20 | 22 | 25 | 30 | у | 1 | 3 | 5 | 7 | 10 | 20 |
| $\mu(x)$ | 1 | 1 | 0.8 | 0.5 | 0.2 | $\mu(y)$ | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 |



Example

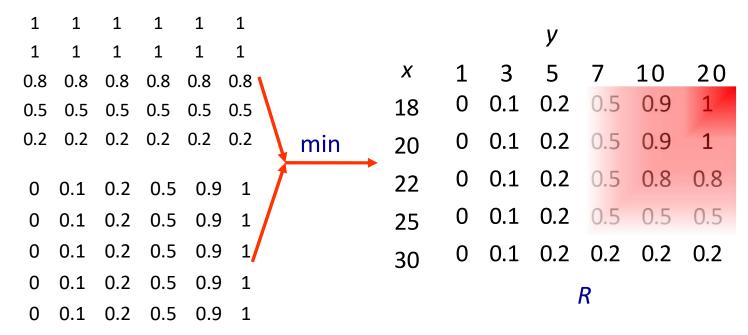
Compute cylindrical extensions

| | young(x) into X x Y | | | | | | | long(y) into X x Y | | | | | | | |
|----|---------------------|-----|-----|-----|-----|-----|-----|--------------------|---|-----|-----|-----|-----|----|---|
| | | | | у | | | | у | 1 | 3 | 5 | 7 | 10 | 20 | |
| X | $\mu(x)$ | 1 | 3 | 5 | 7 | 10 | 20 | $\mu(y)$ | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | |
| 18 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | |
| 20 | 1 | 1 | 1 | 1 | 1 | 1 | 1 | | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | , |
| 22 | 0.8 | 8.0 | 0.8 | 0.8 | 0.8 | 0.8 | 0.8 | | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | |
| 25 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 | | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | |
| 30 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | 0.2 | | 0 | 0.1 | 0.2 | 0.5 | 0.9 | 1 | |
| | | | | | | | | | | | | | | | |



Example

 Compute the aggregation of the two cylindrical extensions, using e.g conjunctive operator minimum.





Compositional rule of inference

• Let a fuzzy set A be defined on X, and \mathcal{R} be a fuzzy relation defined in $X \times Y$. The composition of A and \mathcal{R} results in fuzzy set B defined in Y:

$$B = A \circ \mathcal{R} = \operatorname{proj}_{X}(\operatorname{cext}_{Y}(A) \cap \mathcal{R})$$

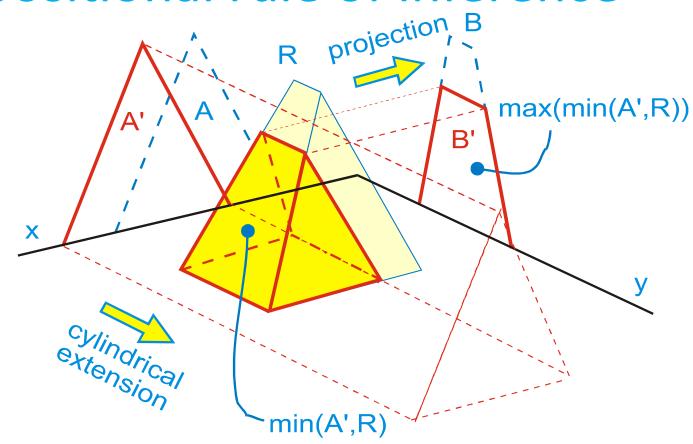
• If intersection is given by the **min** and the projection with the **max**, results in the **max-min composition**:

$$\mu_B(y) = \max_{x} \min \left[\mu_A(x), \mu_{\mathcal{R}}(x, y) \right]$$

• Returns the image of A transformed through the relation \mathcal{R} .



Compositional rule of inference





Example max-min composition

$$\mu_B(y) = \max_{x} \min \left[\mu_A(x), \mu_{\Re}(x, y) \right]$$



Example max-min composition

Young people make long Mobile calls (XxY)

People who make long Mobile calls give a lot of money to clothing (YxZ)

Young people give a lot of money to clothing (XxZ)

R

 $\begin{bmatrix} 0 & 0.5 & 1 \\ 0 & 0.5 & 1 \\ 0 & 0.5 & 0.8 \\ 0 & 0.5 & 0.5 \\ 0 & 0.2 & 0.2 \end{bmatrix}$

-G TÉCNICO

Fuzzy rules and fuzzy relations

- Fuzzy rules like $A \rightarrow B$ are represented as fuzzy relations.
- Often, minimum operator is used to compute the relation.
- The collection of all rules is represented as an aggregated relation using the union operator:

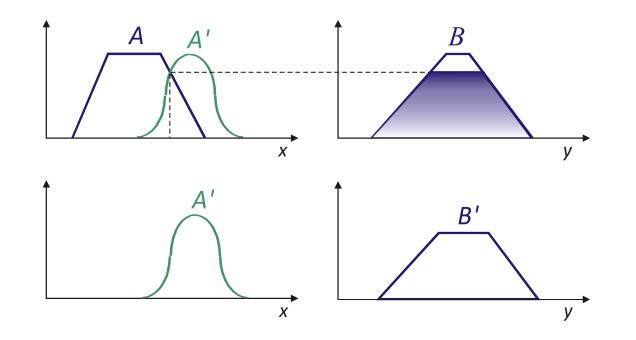
$$R_{\text{tot}} = \bigcup_{i=1}^{N} R_i = \bigvee_{i=1}^{N} R_i$$



Inference with one rule

If x is A then y is B

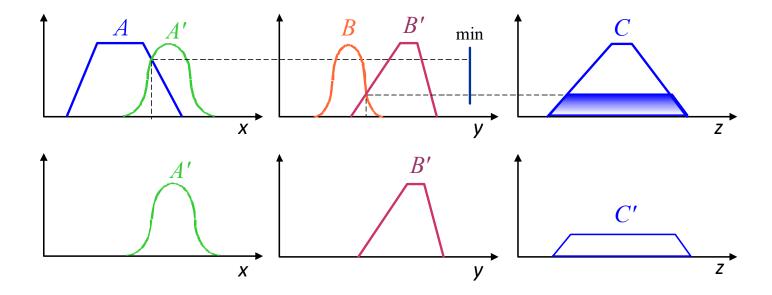
$$\mu_{\mathcal{R}}(x,y) = \min(\mu_{A}(x), \mu_{B}(y))$$





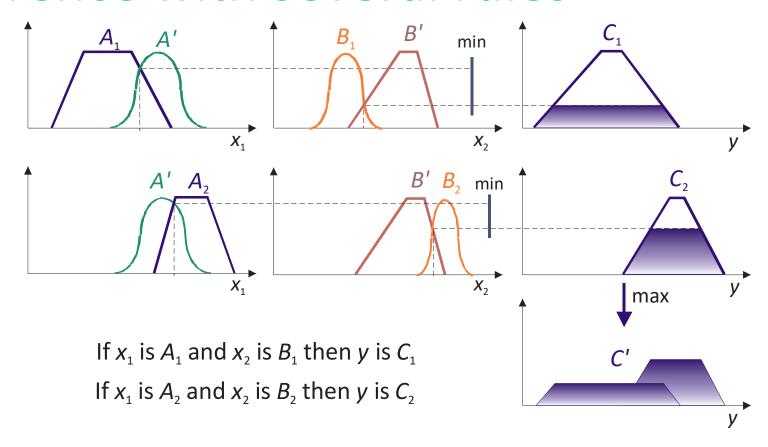
Inference with two antecedents

If x is A and y is B then z is C x is A' and y is B'. z is C'





Inference with several rules





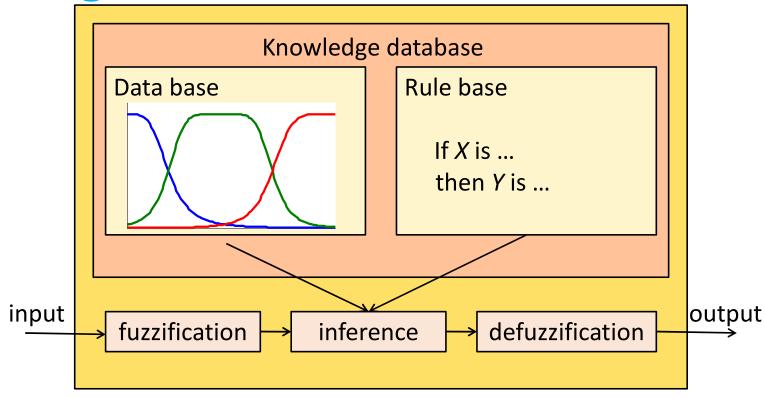
Fuzzy inference system

Multiple names:

- Fuzzy rule-based system
- Fuzzy expert system
- Fuzzy model
- Fuzzy associative memory
- Fuzzy logic controller
- Fuzzy system



Building blocks





Fuzzifier

- Interface between the inputs and the fuzzy system
- Determines the match between a given input and the linguistic terms
- For crisp inputs: computes the membership to linguistic terms
- For fuzzy inputs: computes the maximum membership of the fuzzy input in the linguistic terms



Knowledge base

- Encodes the general relation between the inputs and the outputs
- Rules can be examples, rules of thumb, encoded experience, qualitative relations between variables, etc.
- Rules are often represented as if-then statements



Inference engine

- The reasoning mechanism of the fuzzy system (to infer: to reason/deduce)
- Combines actual inputs with the information encoded in the rule base to compute the fuzzy output of the system
- Usually implements the *compositional rule of inference* or some equivalent computation
- Not as context-independent as the inference engine of an expert system



Defuzzifier

- Interface between the fuzzy systems and the output
- Needed when a crisp output is required (e.g. a final decision, a control action, a final advice, etc.)
- Computes a number/symbol that represents the output fuzzy set
- Enhances the interpolation properties of the fuzzy system



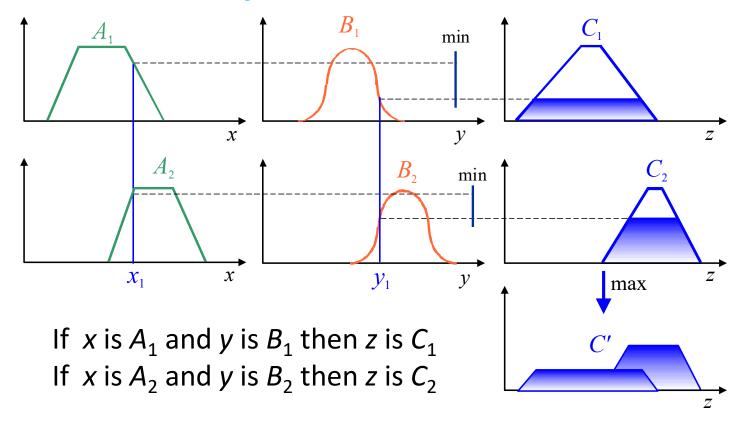
Mamdani fuzzy models

Five major steps:

- Fuzzification
- Degree of fulfillment
- Inference
- Aggregation
- Defuzzification
- Mamdani reasoning is mathematically equivalent to the compositional rule of inference.



Mamdani fuzzy inference





Defuzzification methods

Main types:

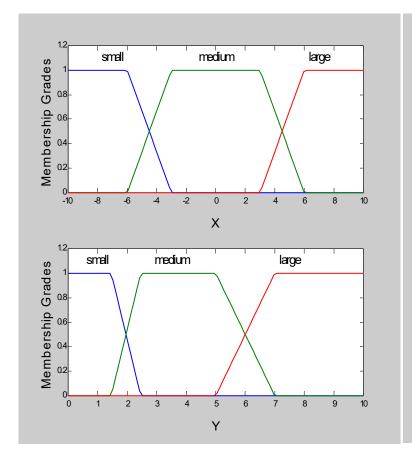
• Centroid of area (COA)
$$z_{\text{COA}} = \frac{\int_{z} \mu_{C'}(z) z \, dz}{\int_{z} \mu_{C'}(z) \, dz}$$

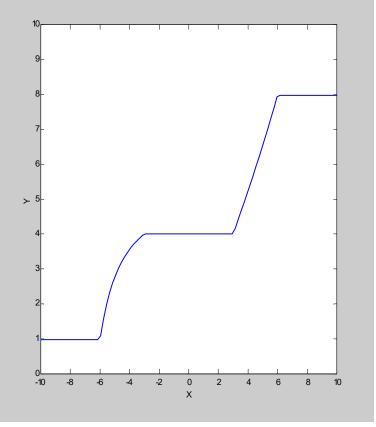
Mean of maxima (MOM)

$$z_{\text{MOM}} = \frac{\int_{z'} z \, dz}{\int_{z'} dz}, \quad Z' = \{z \mid \mu_{C'}(z) \text{ is maximum}\}$$



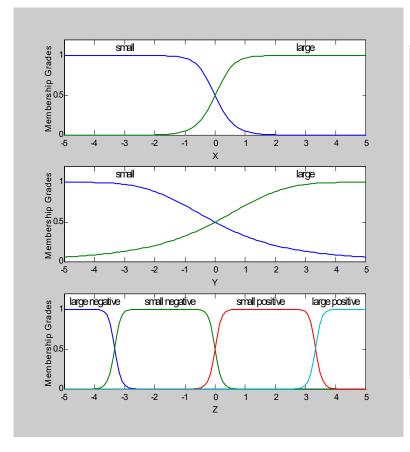
Mamdani – single input

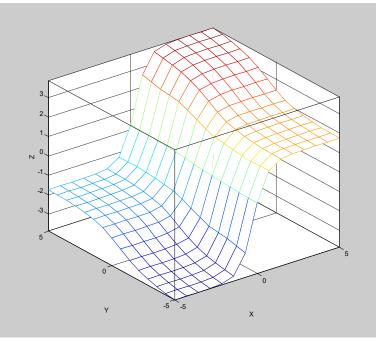






Mamdani – two inputs

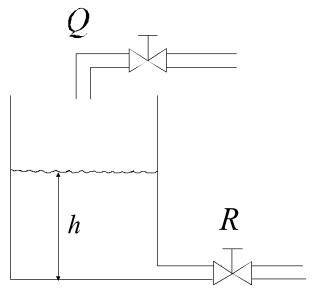






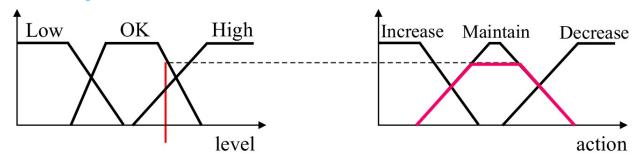
Example: control of liquid level

If level is low then increase valve openingIf level is OK then maintain valve openingIf level is high then decrease valve opening

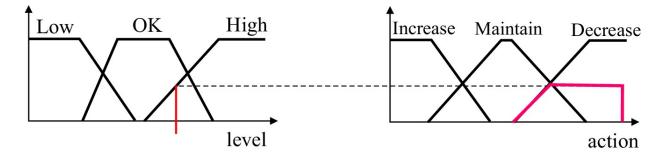




Fired fuzzy rules



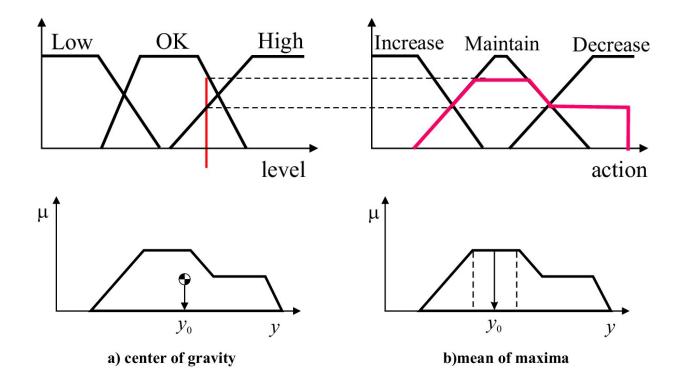
If level is OK then Maintain valve opening



If level is High then Decrease valve opening



Aggregation and defuzzifucation





Takagi-Sugeno fuzzy models

Fuzzy antecedents, crisp consequents

If
$$\mathbf{x}$$
 is A then $y = f(\mathbf{x})$

• Zero-order Sugeno: constant consequent

If
$$x$$
 is A then $y = b$

• First-order Sugeno: linear consequent

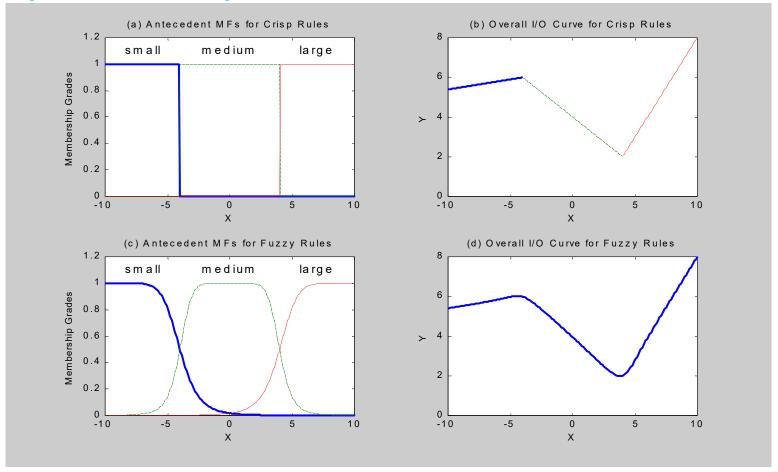
If
$$x$$
 is A then $y = ax + b$

Overall output is a weighted average of individual rule outputs:

$$\hat{y} = \frac{\sum_{k=1}^{K} w_k y_k}{\sum_{k=1}^{K} w_k}$$



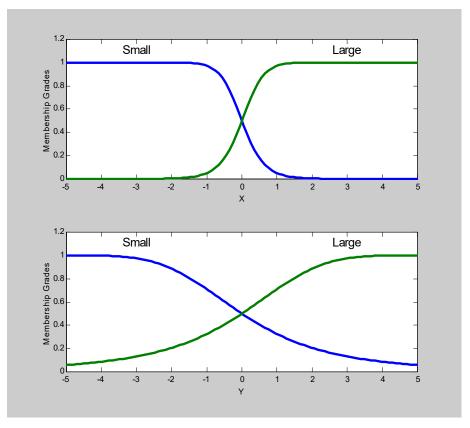
Fuzzy vs. crisp rule set



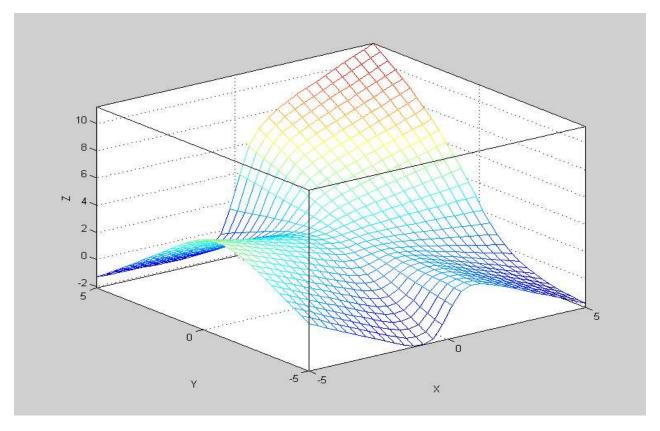


Sugeno – two inputs

- If x is Small and y is Small then z = -x + y + 1
- If x is Small and y is Large then z = -y + 3
- If x is Large and y is Small then z = -x + 3
- If x is Large and y is Large then z = x + y + 2



Sugeno – two inputs





Approximation capability

- Fuzzy systems are general function approximators (c.f. neural networks)
- Accuracy of a mapping augments by increasing the number of rules (examples) in the rule base
- Best results are obtained when the number of linguistic terms in the input and the output are increased (a finer partition)
- Using too many linguistic terms diminishes the transparency of fuzzy systems



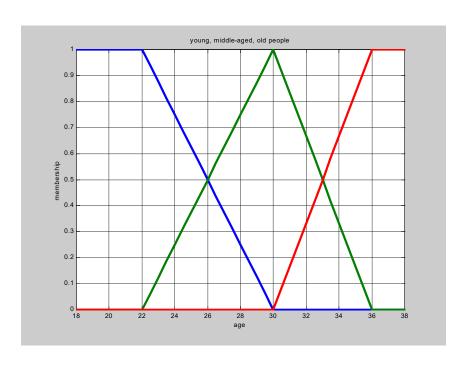
Interpolation properties

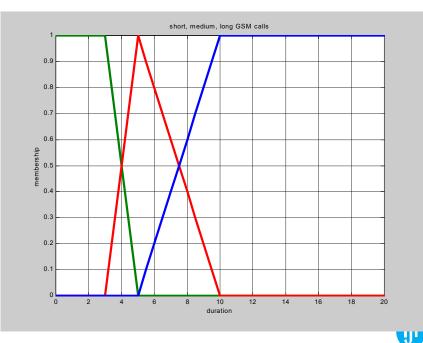
- Multiple rules in a fuzzy system may fire (become active) because fuzzy sets overlap
- Fuzzy rules represent typical cases or examples of the relation between two quantities
- The reasoning mechanism interpolates between the rules to determine the system output



Example

- 1. Young people make long Mobile calls
- 2. Middle aged people make short Mobile calls
- 3. Old people make medium-long Mobile calls





TÉCNICO

Exampl^a

