

MPI - Lecture 8

Fuzzy logic

Motivation

Introduction

Consider having a pot of water having temperature of x degrees Celsius.

Is the water **hot**? Is the water **cold**?

Sometimes we want to describe systems by properties which are not evaluated as **true** or **false** (and we do not have the exact value of x).

Fuzzy logic / fuzzy control systems allow such description: truth and falsehood notions are graded and allow to state, for instance, that the water is “**tepid**”.

Basic definitions

Let U denote the **universe**, that is, our playground containing every set that we may consider.

A set $A \subset U$ can be given by its **characteristic function**:

$$\chi_A : U \rightarrow \{0, 1\}, \quad \chi_A(x) = \begin{cases} 1 & \text{if } x \in A \\ 0 & \text{if } x \notin A \end{cases}$$

There is a bijection between sets and characteristic functions, so we identify each set with its characteristic function.

A is a set in the ordinary sense, sometimes called a **crisp** set.

Fuzzy sets generalize this concept and allow elements to belong to a given set with a certain *degree*.

We replace the characteristic function by a **membership function**

$$\mu_A : U \rightarrow [0, 1].$$

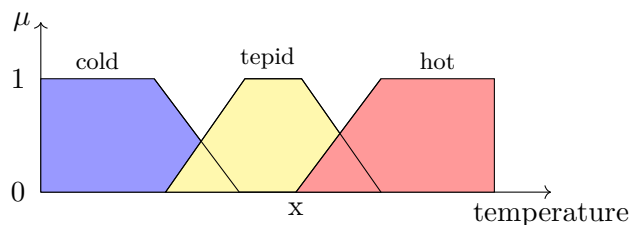
A **fuzzy subset** A of a set X is a function $\mu_A : X \rightarrow [0, 1]$.

For every element $x \in X$, the **degree of membership** of x to A is given by $\mu_A(x) \in [0, 1]$.

Let $X = [0, 100]$ be the set of temperatures of water in our pot.

We consider three fuzzy subsets of X to describe **cold**, **tepid** and **hot** temperatures.

The membership functions may be given as follows:



Given a set X and its power set $\mathcal{P}(X)$ (the set of all subsets of X), the operations of **union**, **intersection**, and **complement** are given as follows (for usual sets):

$$\begin{aligned} A \cup B &= \{x : x \in A \text{ or } x \in B\}, \\ A \cap B &= \{x : x \in A \text{ and } x \in B\}, \\ A^c &= X \setminus A = \{x \in X : x \notin A\}. \end{aligned}$$

How do these operations translate to characteristic functions?

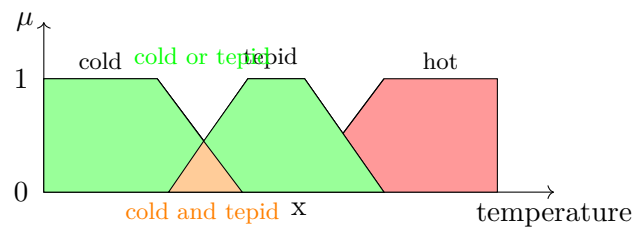
$$\begin{aligned} \chi_{A \cup B} &= \max\{\chi_A, \chi_B\}, \\ \chi_{A \cap B} &= \min\{\chi_A, \chi_B\}, \\ \chi_{A^c} &= 1 - \chi_A. \end{aligned}$$

For fuzzy sets, we can define the membership function of a union, intersection, or a complement in the same way.

Let A and B be two *fuzzy* subsets of X .

We set

$$\begin{aligned} \mu_{A \cup B} &= \max\{\mu_A, \mu_B\}, \\ \mu_{A \cap B} &= \min\{\mu_A, \mu_B\}, \\ \mu_{A^c} &= 1 - \mu_A. \end{aligned}$$



Our choice for fuzzy set operation was fast.
Let A and B be two subsets of X . We have

$$\begin{aligned}\chi_{A \cap B}(x) &= \min\{\chi_A(x), \chi_B(x)\} \\ &= \chi_A(x) \cdot \chi_B(x) \\ &= \max\{0, \chi_A(x) + \chi_B(x) - 1\}.\end{aligned}$$

We can extend the second definition to membership functions and obtain another definition of union and intersection of fuzzy sets.

We shall do this in a more general fashion.

We have the following requirements of a mapping

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

that would interpret intersection of two fuzzy sets.

1. $1 \star x = x$ for all $x \in [0, 1]$,
2. $0 \star x = 0$ for all $x \in [0, 1]$,
3. $x \star y = y \star x$ for all $x, y \in [0, 1]$ (*commutativity*),
4. $(x \star y) \star z = x \star (y \star z)$ for all $x, y, z \in [0, 1]$ (*associativity*),
5. $x \leq y$ and $w \leq z$ implies $x \star w \leq y \star z$ (*monotonicity*).

The following t-norms are usually considered.

Let $x, y \in [0, 1]$.

- (i) **Gödel** t-norm: $x \star y = \min\{x, y\}$,
- (ii) **product** t-norm: $x \star y = x \cdot y$,
- (iii) **Lukasiewicz** t-norm: $x \star y = \max\{0, x + y - 1\}$,

- (iv) **Hamacher product** t-norm: $x \star y = \begin{cases} 0 & \text{if } x = y = 0 \\ \frac{xy}{x + y - xy} & \text{otherwise} \end{cases}$,
- (v) ...

The distinct t-norms give us distinct strategies on how to interpret intersection of fuzzy sets.

If we have intersection and complement, we define union by $A \cup B = (A^c \cap B^c)^c$ (De Morgan's laws).

Fuzzy control systems

Reasoning in
fuzzy logic

In classical logic we can have the following statements:

If “the water is cold” is **true**, then “my shower is bad” is **true**.

An implication is in fact a mapping

$$\{0, 1\} \times \{0, 1\} \rightarrow \{0, 1\}.$$

In fuzzy logic, to interpret such implications, we consider “the water is cold” and “my shower is bad” as fuzzy sets and we decide using an **implication** function

$$[0, 1] \times [0, 1] \rightarrow [0, 1].$$

This is sometimes called **approximate reasoning**.

Implication

An **implication** is a function $I : [0, 1] \times [0, 1] \rightarrow [0, 1]$ satisfying the following conditions for all $x, y, z \in [0, 1]$:

1. If $x \leq z$, then $I(x, y) \geq I(z, y)$;
2. if $y \leq z$, then $I(x, y) \leq I(x, z)$;
3. $I(0, y) = 1$;
4. $I(x, 1) = x$;
5. $I(1, 0) = 0$.

Examples:

- (i) **Mamdani**: $I(x, y) = \min\{x, y\}$ (this fails item 3, but usually in knowledge systems we are not interested in rules where the antecedent part is false),
- (ii) **Willmott**: $I(x, y) = \max\{1 - x, \min\{x, y\}\}$,
- (iii) ...

A **controller** measures some inputs and gives an output following some rules.

For instance, we have the following set of rules:

- r1. If “water is cold”, then “shower is bad”.
- r2. If “water is tepid”, then “shower is good”.
- r3. If “water is hot”, then “shower is bad”.

The fuzzy sets “shower is bad” and “shower is good” are subsets of $Y = [0, 100]$, measuring how good a shower is.

1. Measure the input variables, i.e., the temperature $x_0 \in X$.
2. Transform the measured values into fuzzy sets: we have fuzzy sets with constant membership functions $\mu_{cold}(x_0)$, $\mu_{tepid}(x_0)$, and $\mu_{hot}(x_0)$.
3. Apply all the rules: we obtain 3 *control* fuzzy sets
 - $\mu_{r_1}(y) = I(\mu_{cold}(x_0), \mu_{bad}(y))$,
 - $\mu_{r_2}(y) = I(\mu_{tepid}(x_0), \mu_{good}(y))$,
 - $\mu_{r_3}(y) = I(\mu_{hot}(x_0), \mu_{bad}(y))$.
4. Aggregate the control fuzzy sets into one fuzzy set C .
5. Defuzzify C to obtain the output value $c \in Y$.

For each step, there are many possible choices:

- transformation to fuzzy sets (and application of operators to construct the antecedent of all implications in the rules);
- implication itself;
- aggregation;
- defuzzification.

A usual choice is Gödel t-norm and Mamdani for implication, union for aggregation, and a defuzzification by center of gravity:

$$y_0 = \frac{\int_Y y \mu_C(y) dy}{\int_Y \mu_C(y) dy}$$

(or replace by sums if Y is discrete).