Fuzzy Systems
Fuzzy Arithmetic

Prof. Dr. Rudolf Kruse   Christoph Doell
{kruse,cmoewes}@iws.cs.uni-magdeburg.de
Otto-von-Guericke University of Magdeburg
Faculty of Computer Science
Department of Knowledge Processing and Language Engineering
Outline

1. The Extension Principle
   - Truth Values
   - Extensions to Sets and Fuzzy Sets

2. Fuzzy Arithmetic
Motivation I

How to extend $\phi : X^n \rightarrow Y$ to $\hat{\phi} : \mathcal{F}(X)^n \rightarrow \mathcal{F}(Y)$?

Let $\mu \in \mathcal{F}(\mathbb{R})$ be a fuzzy set of the imprecise concept “about 2”.

Then the degree of membership $\mu(2.2)$ can be seen as truth value of the statement “2.2 is about equal to 2”.

Let $\mu' \in \mathcal{F}(\mathbb{R})$ be a fuzzy set of the imprecise concept “old”.

Then the truth value of “2.2 is about equal 2 and 2.2 is old” can be seen as membership degree of 2.2 w.r.t. imprecise concept “about 2 and old”.
Any $\top$ ($\bot$) can be used to represent conjunction (disjunction). However, now only $T_{\text{min}}$ and $\bot_{\text{max}}$ shall be used.

Let $\mathcal{P}$ be set of imprecise statements that can be combined by \textit{and}, \textit{or}. \textit{truth} : $\mathcal{P} \rightarrow [0, 1]$ assigns truth value $\text{truth}(a)$ to every $a \in \mathcal{P}$.

$\text{truth}(a) = 0$ means $a$ is definitely false.

$\text{truth}(a) = 1$ means $a$ is definitely true.

If $0 < \text{truth}(a) < 1$, then only gradual truth of statement $a$. 
Motivation III – Extension Principle

Combination of two statements \( a, b \in P \):

\[
\text{truth}(a \text{ and } b) = \text{truth}(a \land b) = \min\{\text{truth}(a), \text{truth}(b)\},
\]
\[
\text{truth}(a \text{ or } b) = \text{truth}(a \lor b) = \max\{\text{truth}(a), \text{truth}(b)\}
\]

For infinite number of statements \( a_i, i \in I \):

\[
\text{truth}(\forall i \in I : a_i) = \inf \{\text{truth}(a_i) \mid i \in I\},
\]
\[
\text{truth}(\exists i \in I : a_i) = \sup \{\text{truth}(a_i) \mid i \in I\}
\]

This concept helps to extend \( \phi : X^n \rightarrow Y \) to \( \hat{\phi} : \mathcal{F}(X)^n \rightarrow \mathcal{F}(Y) \).

- Crisp tuple \((x_1, \ldots, x_n)\) is mapped to crisp value \(\phi(x_1, \ldots, x_n)\).
- Imprecise descriptions \((\mu_1, \ldots, \mu_n)\) of \((x_1, \ldots, x_n)\) are mapped to fuzzy value \(\hat{\phi}(\mu_1, \ldots, \mu_n)\).
Example – How to extend the addition?

\[ + : \mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}, \quad (a, b) \mapsto a + b \]

Extensions to sets:

\[ + : 2^{\mathbb{R}} \times 2^{\mathbb{R}} \rightarrow 2^{\mathbb{R}} \]

\[ (A, B) \mapsto A + B = \{ y \mid (\exists a)(\exists b)y = a + b \land a \in A \land b \in B \} \]

Extensions to fuzzy sets:

\[ + : \mathcal{F}(\mathbb{R}) \times \mathcal{F}(\mathbb{R}) \rightarrow \mathcal{F}(\mathbb{R}), \quad (\mu_1, \mu_2) \mapsto \mu_1 \oplus \mu_2 \]

\[
\text{truth}(y \in \mu_1 \oplus \mu_2) = \text{truth}((\exists a)(\exists b) : y = a + b \land a \in \mu_1 \land b \in \mu_2)
\]

\[
= \sup \{ \text{truth}(y = a + b) \land \text{truth}(a \in \mu_1) \land \text{truth}(b \in \mu_2) \}
\]

\[
= \sup \{ \min(\mu_1(a), \mu_2(b)) \}
\]
Example – How to extend the addition?

\[ \mu(2) = 1 \quad \text{because} \quad \mu_1(1) = 1 \quad \text{and} \quad \mu_2(1) = 1 \]

\[ \mu(5) = 0 \quad \text{because if} \quad a + b = 5, \quad \text{then} \quad \min\{\mu_1(a), \mu_2(b)\} = 0 \]

\[ \mu(1) = 0.5 \quad \text{because it is the result of an optimization task with optimum at, e.g.} \quad a = 0.5 \quad \text{and} \quad b = 0.5 \]
Extension to Sets

Definition

Let $\phi : X^n \to Y$ be a mapping. The extension $\hat{\phi}$ of $\phi$ is given by

$$\hat{\phi} : [2^X]^n \to 2^Y$$

with

$$\hat{\phi}(A_1, \ldots, A_n) = \{ y \in Y \mid \exists (x_1, \ldots, x_n) \in A_1 \times \cdots \times A_n : \phi(x_1, \ldots, x_n) = y \}.$$
Extension to Fuzzy Sets

Definition

Let $\phi : X^n \to Y$ be a mapping. The extension $\hat{\phi}$ of $\phi$ is given by

$$\hat{\phi} : [\mathcal{F}(X)]^n \to \mathcal{F}(Y) \quad \text{with}$$

$$\hat{\phi}(\mu_1, \ldots, \mu_n)(y) = \sup \{ \min \{ \mu_1(x_1), \ldots, \mu_n(x_n) \} \mid (x_1, \ldots, x_n) \in X^n \land \phi(x_1, \ldots, x_n) = y \}$$

assuming that $\sup \emptyset = 0$. 
Example 1

Let fuzzy set “approximately 2” be defined as

\[
\mu(x) = \begin{cases} 
  x - 1, & \text{if } 1 \leq x \leq 2 \\
  3 - x, & \text{if } 2 \leq x \leq 3 \\
  0, & \text{otherwise.}
\end{cases}
\]

The extension of \( \phi : \mathbb{IR} \to \mathbb{IR}, x \mapsto x^2 \) to fuzzy sets on \( \mathbb{IR} \) is

\[
\hat{\phi}(\mu)(y) = \sup \left\{ \mu(x) \ \bigg| \ x \in \mathbb{IR} \land x^2 = y \right\} = \begin{cases} 
  \sqrt{y} - 1, & \text{if } 1 \leq y \leq 4 \\
  3 - \sqrt{y}, & \text{if } 4 \leq y \leq 9 \\
  0, & \text{otherwise.}
\end{cases}
\]
The extension principle is taken as basis for “fuzzifying” whole theories. Now, it will be applied to arithmetic operations on fuzzy intervals.
Outline

1. The Extension Principle

2. Fuzzy Arithmetic
   - Linguistic Variables
   - Analysis of Linguistic Data
   - Efficient Operations on Fuzzy Sets
   - Interval Arithmetic
Fuzzy Sets on the Real Numbers

There are many different types of fuzzy sets. Very interesting are fuzzy sets defined on set $\mathbb{R}$ of real numbers. Membership functions of such sets, i.e.

$$
\mu : \mathbb{R} \rightarrow [0, 1],
$$

clearly indicate quantitative meaning.

Such concepts may essentially characterize states of fuzzy variables. They play important role in many applications, e.g. fuzzy control, decision making, approximate reasoning, optimization, and statistics with imprecise probabilities.
Some Special Fuzzy Sets I

Here, we only consider special classes $\mathcal{F}(\mathbb{R})$ of fuzzy sets $\mu$ on $\mathbb{R}$.

Definition

(a) $\mathcal{F}_N(\mathbb{R}) \overset{\text{def}}{=} \{ \mu \in \mathcal{F}(\mathbb{R}) \mid \exists x \in \mathbb{R} : \mu(x) = 1 \}$,

(b) $\mathcal{F}_C(\mathbb{R}) \overset{\text{def}}{=} \{ \mu \in \mathcal{F}_N(\mathbb{R}) \mid \forall \alpha \in (0, 1] : [\mu]_\alpha \text{ is compact} \}$,

(c) $\mathcal{F}_I(\mathbb{R}) \overset{\text{def}}{=} \{ \mu \in \mathcal{F}_N(\mathbb{R}) \mid \forall a, b, c \in \mathbb{R} : c \in [a, b] \Rightarrow 
\mu(c) \geq \min\{\mu(a), \mu(b)\} \}$. 
Some Special Fuzzy Sets II

An element in $\mathcal{F}_N(\mathbb{IR})$ is called **normal fuzzy set**:
- It’s meaningful if $\mu \in \mathcal{F}_N(\mathbb{IR})$ is used as *imprecise description* of an existing (but not precisely measurable) variable $\subseteq \mathbb{IR}$.
- In such cases it would not be plausible to assign maximum membership degree of 1 to no single real number.

Sets in $\mathcal{F}_C(\mathbb{IR})$ are **upper semi-continuous**:
- Function $f$ is upper semi-continuous at point $x_0$ if values near $x_0$ are either close to $f(x_0)$ or less than $f(x_0)$
  $\Rightarrow \lim_{x \to x_0} \sup f(x) \leq f(x_0)$.
- This simplifies arithmetic operations applied to them.

Fuzzy sets in $\mathcal{F}_l(\mathbb{IR})$ are called **fuzzy intervals**:
- They are *normal* and *fuzzy convex*.
- Their core is a classical interval.
- $\mu \in \mathcal{F}_l(\mathbb{IR})$ for real numbers are called *fuzzy numbers*. 
Comparison of Crisp Sets and Fuzzy Sets on $\mathbb{R}$

- "exactly 1.3"

- "close to 1.3"

- crisp interval

- fuzzy interval
Basic Types of Fuzzy Numbers

- Symmetric bell-shaped: "around $r$"
- Asymmetric bell-shaped: "around $r$"
- Right-open sigmoid: "large number"
- Left-open sigmoid: "small number"
Quantitative Fuzzy Variables

The concept of a fuzzy number plays fundamental role in formulating quantitative fuzzy variables.

These are variables whose states are fuzzy numbers.

When the fuzzy numbers represent linguistic concepts, e.g. very small, small, medium, etc.

then final constructs are called linguistic variables.

Each linguistic variable is defined in terms of base variable which is a variable in classical sense, e.g. temperature, pressure, age.

Linguistic terms representing approximate values of base variable are captured by appropriate fuzzy numbers.
Each linguistic variable is defined by quintuple \((\nu, T, X, g, m)\).

- **name** \(\nu\) of the variable
- **set** \(T\) of **linguistic terms** of \(\nu\)
- **base variable** \(X \subseteq \mathbb{R}\)
- **syntactic rule** \(g\) (grammar) for generating linguistic terms
- **semantic rule** \(m\) that assigns **meaning** \(m(t)\) to every \(t \in T\),
  i.e. \(m : T \rightarrow \mathcal{F}(X)\)
Operations on Linguistic Variables

To deal with linguistic variables, consider

- not only set-theoretic operations
- but also arithmetic operations on fuzzy numbers (i.e. interval arithmetic).

e.g. statistics:

- Given a sample = (small, medium, small, large, ...).
- How to define mean value or standard deviation?
Analysis of Linguistic Data

Linguistic Data

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>large</td>
<td>very large</td>
<td>medium</td>
</tr>
<tr>
<td>2</td>
<td>2.5</td>
<td>medium</td>
<td>about 7</td>
</tr>
<tr>
<td>3</td>
<td>[3, 4]</td>
<td>small</td>
<td>[7, 8]</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Fuzzy Data

<table>
<thead>
<tr>
<th></th>
<th>A</th>
<th>B</th>
<th>C</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td><img src="image1" alt="Graph" /></td>
<td><img src="image2" alt="Graph" /></td>
<td><img src="image3" alt="Graph" /></td>
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<td><img src="image4" alt="Graph" /></td>
<td><img src="image5" alt="Graph" /></td>
<td><img src="image6" alt="Graph" /></td>
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<tr>
<td>3</td>
<td><img src="image7" alt="Graph" /></td>
<td><img src="image8" alt="Graph" /></td>
<td><img src="image9" alt="Graph" /></td>
</tr>
</tbody>
</table>

- **computing with words**
  - “The mean w.r.t. A is approximately 4.”

- **linguistic modeling**

- **linguistic approximation**

- **statistics with fuzzy sets**
  - mean of attribute A
Example – Application of Linguistic Data

Consider the problem to model the climatic conditions of several towns.

A tourist may want information about tourist attractions.

Assume that linguistic random samples are based on subjective observations of selected people, e.g.

- climatic attribute *clouding*
- linguistic values *cloudless, clear, fair, cloudy, ...*
Example – Linguistic Modeling by an Expert

The attribute *clouding* is modeled by elementary linguistic values, *e.g.*

\[
\begin{align*}
\text{cloudless} & \mapsto \text{sigmoid}(0, -0.07) \\
\text{clear} & \mapsto \text{Gauss}(25, 15) \\
\text{fair} & \mapsto \text{Gauss}(50, 20) \\
\text{cloudy} & \mapsto \text{Gauss}(75, 15) \\
\text{overcast} & \mapsto \text{sigmoid}(100, 0.07) \\
\text{exactly}(x) & \mapsto \text{exact}(x) \\
\text{approx}(x) & \mapsto \text{Gauss}(x, 3) \\
\text{between}(x, y) & \mapsto \text{rectangle}(x, y) \\
\text{approx\_between}(x, y) & \mapsto \text{trapezoid}(x - 20, x, y, y + 20)
\end{align*}
\]

where \(x, y \in [0, 100] \subset \mathbb{R}\).
Example

Gauss\((a, b)\) is, e.g. a function defined by

\[
f(x) = \exp \left( - \left( \frac{x - a}{b} \right)^2 \right), \quad x, a, b \in \mathbb{R}, \quad b > 0
\]

induced language of expressions:

\[
<\text{expression}> := <\text{elementary linguistic value}> | ( <\text{expression}> ) | \{ \text{not} | \text{dil} | \text{con} | \text{int} \} <\text{expression}> | <\text{expression}> \{ \text{and} | \text{or} \} <\text{expression}>,
\]

\(\text{e.g.}\ \text{approx}(x)\ \text{and cloudy}\) is represented by function

\[
\text{min} \{ \text{Gauss}(x, 3), \text{Gauss}(75, 15) \}.
\]
Example – Linguistic Random Sample

<table>
<thead>
<tr>
<th>Attribute</th>
<th>Observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Clouding</td>
<td>Limassol, Cyprus</td>
</tr>
<tr>
<td>2009/10/23</td>
<td>cloudy</td>
</tr>
<tr>
<td>2009/10/24</td>
<td>dil approx_between(50,70)</td>
</tr>
<tr>
<td>2009/10/25</td>
<td>fair or cloudy</td>
</tr>
<tr>
<td>2009/10/26</td>
<td>approx(75)</td>
</tr>
<tr>
<td>2009/10/27</td>
<td>dil(clear or fair)</td>
</tr>
<tr>
<td>2009/10/28</td>
<td>int cloudy</td>
</tr>
<tr>
<td>2009/10/29</td>
<td>con fair</td>
</tr>
<tr>
<td>2009/11/30</td>
<td>approx(0)</td>
</tr>
<tr>
<td>2009/11/31</td>
<td>cloudless</td>
</tr>
<tr>
<td>2009/11/01</td>
<td>cloudless or dil clear</td>
</tr>
<tr>
<td>2009/11/02</td>
<td>overcast</td>
</tr>
<tr>
<td>2009/11/03</td>
<td>cloudy and between(70,80)</td>
</tr>
<tr>
<td>...</td>
<td>...</td>
</tr>
<tr>
<td>2009/11/10</td>
<td>clear</td>
</tr>
</tbody>
</table>

Statistics with fuzzy sets are necessary to analyze linguistic data.
Example – Ling. Random Sample of 3 People

<table>
<thead>
<tr>
<th>no.</th>
<th>age (linguistic data)</th>
<th>age (fuzzy data)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>approx. between 70 and 80 and definitely not older than 80</td>
<td>![μ1]</td>
</tr>
<tr>
<td>2</td>
<td>between 60 and 65</td>
<td>![μ2]</td>
</tr>
<tr>
<td>3</td>
<td>62</td>
<td>![μ3]</td>
</tr>
</tbody>
</table>
Example – Mean Value of Linguistic Random Sample

\[
\text{mean}(\mu_1, \mu_2, \mu_3) = \frac{1}{3} (\mu_1 \oplus \mu_2 \oplus \mu_3)
\]

\[
\text{mean}(\mu_1, \mu_2, \mu_3)
\]

\[
62 \quad 64 \quad 69
\]

i.e. approximately between 64 and 69 but not older than 69
Efficient Operations I

How to define arithmetic operations for calculating with $\mathcal{F}(\mathbb{R})$?

Using extension principle for sum $\mu \oplus \mu'$, product $\mu \odot \mu'$ and reciprocal value $\text{rec}(\mu)$ of arbitrary fuzzy sets $\mu, \mu' \in \mathcal{F}(\mathbb{R})$

$$(\mu \oplus \mu')(t) = \sup \left\{ \min\{\mu(x_1), \mu'(x_2)\} \mid x_1, x_2 \in \mathbb{R}, x_1 + x_2 = t \right\},$$

$$(\mu \odot \mu')(t) = \sup \left\{ \min\{\mu(x_1), \mu'(x_2)\} \mid x_1, x_2 \in \mathbb{R}, x_1 \cdot x_2 = t \right\},$$

$$\text{rec}(\mu)(t) = \sup \left\{ \mu(x) \mid x \in \mathbb{R} \setminus \{0\}, \frac{1}{x} = t \right\}.$$

In general, operations on fuzzy sets are much more complicated (especially if vertical instead of horizontal representation is applied).

It’s desirable to reduce fuzzy arithmetic to ordinary set arithmetic.

Then, we apply elementary operations of interval arithmetic.
Efficient Operations II

Definition
A family \((A_\alpha)_{\alpha \in (0,1)}\) of sets is called set representation of \(\mu \in \mathcal{F}_N(\mathbb{R})\) if

(a) \(0 < \alpha < \beta < 1 \implies A_\beta \subseteq A_\alpha \subseteq \mathbb{R}\) and

(b) \(\mu(t) = \sup \{\alpha \in [0, 1] \mid t \in A_\alpha\}\)

holds where \(\sup \emptyset = 0\).

Theorem
Let \(\mu \in F_N(\mathbb{R})\). The family \((A_\alpha)_{\alpha \in (0,1)}\) of sets is a set representation of \(\mu\) if and only if

\([\mu]_\alpha = \{t \in \mathbb{R} \mid \mu(t) > \alpha\} \subseteq A_\alpha \subseteq \{t \in \mathbb{R} \mid \mu(t) \geq \alpha\} = [\mu]_\alpha\)

is valid for all \(\alpha \in (0,1)\).
Efficient Operations III

Theorem

Let $\mu_1, \mu_2, \ldots, \mu_n$ be normal fuzzy sets of $\mathbb{R}$ and $\phi : \mathbb{R}^n \to \mathbb{R}$ be a mapping. Then the following holds:

(a) $\forall \alpha \in [0, 1) : [\hat{\phi}(\mu_1, \ldots, \mu_n)]_\alpha = \phi([\mu_1]_\alpha, \ldots, [\mu_n]_\alpha)$,

(b) $\forall \alpha \in (0, 1] : [\hat{\phi}(\mu_1, \ldots, \mu_n)]_\alpha \supseteq \phi([\mu_1]_\alpha, \ldots, [\mu_n]_\alpha)$,

(c) if $((A_i)_{\alpha} \in (0,1))$ is a set representation of $\mu_i$ for $1 \leq i \leq n$, then $\phi((A_1)_{\alpha}, \ldots, (A_n)_{\alpha}))_{\alpha \in (0,1)}$ is a set representation of $\hat{\phi}(\mu_1, \ldots, \mu_n)$.

For arbitrary mapping $\phi$, set representation of its extension $\hat{\phi}$ can be obtained with help of set representation $((A_i)_{\alpha} \in (0,1), i = 1, 2, \ldots, n$.

It’s used to carry out arithmetic operations on fuzzy sets efficiently.
Example 1

For $\mu_1, \mu_2$, the set representations are

- $[\mu_1]_\alpha = [2\alpha - 1, 2 - \alpha]$, 
- $[\mu_2]_\alpha = [\alpha + 3, 5 - \alpha] \cup [\alpha + 5, 7 - \alpha]$.

Let $\text{add}(x, y) = x + y$, then $(A_\alpha)_{\alpha \in (0,1)}$ represents $\mu_1 \oplus \mu_2$

$$A_\alpha = \text{add}([\mu_1]_\alpha, [\mu_2]_\alpha) = [3\alpha + 2, 7 - 2\alpha] \cup [3\alpha + 4, 9 - 2\alpha]$$

$$= \begin{cases} 
[3\alpha + 2, 7 - 2\alpha] \cup [3\alpha + 4, 9 - 2\alpha], & \text{if } \alpha \geq 0.6 \\
[3\alpha + 2, 9 - 2\alpha], & \text{if } \alpha \leq 0.6.
\end{cases}$$
Example II

\[
(\mu_1 \oplus \mu_2)(x) = \begin{cases} 
\frac{x-2}{3}, & \text{if } 2 \leq x \leq 5 \\
\frac{7-x}{2}, & \text{if } 5 \leq x \leq 5.8 \\
\frac{x-4}{3}, & \text{if } 5.8 \leq x \leq 7 \\
\frac{9-x}{2}, & \text{if } 7 \leq x \leq 9 \\
0, & \text{otherwise}
\end{cases}
\]
Interval Arithmetic I

Determining the set representations of arbitrary combinations of fuzzy sets can be reduced very often to simple interval arithmetic.

Using fundamental operations of arithmetic leads to the following $(a, b, c, d \in \mathbb{R})$:

\[
[a, b] + [c, d] = [a + c, b + d] \\
[a, b] − [c, d] = [a − d, b − c]
\]

\[
[a, b] \cdot [c, d] = \begin{cases} 
[ac, bd], & \text{for } a \geq 0 \land c \geq 0 \\
[bd, ac], & \text{for } b < 0 \land d < 0 \\
[min\{ad, bc\}, max\{ad, bc\}], & \text{for } ab \geq 0 \land cd \geq 0 \land ac < 0 \\
[min\{ad, bc\}, max\{ac, bd\}], & \text{for } ab < 0 \lor cd < 0
\end{cases}
\]

\[
\frac{1}{[a, b]} = \begin{cases} 
\left[\frac{1}{b}, \frac{1}{a}\right], & \text{if } 0 \notin [a, b] \\
\left[\frac{1}{b}, \infty\right) \cup (-\infty, \frac{1}{a}], & \text{if } a < 0 \land b > 0 \\
\left[\frac{1}{b}, \infty\right), & \text{if } a = 0 \land b > 0 \\
\left(-\infty, \frac{1}{a}\right], & \text{if } a < 0 \land b = 0
\end{cases}
\]
Interval Arithmetic II

In general, set representation of $\alpha$-cuts of extensions $\hat{\phi}(\mu_1, \ldots, \mu_n)$ cannot be determined directly from $\alpha$-cuts.

It only works always for continuous $\phi$ and fuzzy sets in $\mathcal{F}_C(\mathbb{R})$.

**Theorem**

Let $\mu_1, \mu_2, \ldots, \mu_n \in \mathcal{F}_C(\mathbb{R})$ and $\phi : \mathbb{R}^n \to \mathbb{R}$ be a continuous mapping. Then

$$\forall \alpha \in (0, 1] : [\hat{\phi}(\mu_1, \ldots, \mu_n)]_\alpha = \phi([\mu_1]_\alpha, \ldots, [\mu_n]_\alpha).$$

So, a horizontal representation is better than a vertical one. Finding $\hat{\phi}$ values is easier than directly applying the extension principle. However, all $\alpha$-cuts cannot be stored in a computer. Only a finite number of $\alpha$-cuts can be stored.