

Towards Fast Algorithms for Processing Type-2 Fuzzy Data: Extending Mendel's Algorithms From Interval-Valued to a More General Case

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Outline

Why Data Processing ...

From Probabilistic to ...

Main Problem of ...

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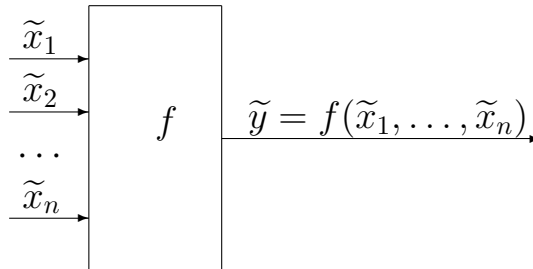
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1. Outline

- *Known*: processing (type-1) fuzzy data can be reduced to interval uncertainty:
 - Zadeh's extension principle is equivalent to
 - level-by-level interval computations on α -cuts.
- *More adequate description*: type-2 fuzzy sets.
- *Practical limitation*: transition to type-2 increases computational complexity.
- *Mendel's algorithm*: for interval-valued fuzzy sets, processing can also be reduced to interval computations.
- *In this talk*: we show that Mendel's ideas can be naturally extended to arbitrary type-2 fuzzy numbers.

2. Why Data Processing and Knowledge Processing Are Needed in the First Place

- *Problem:* some quantities y are difficult (or impossible) to measure or estimate directly.
- *Solution:* indirect measurements or estimates



- *Fact:* estimates \tilde{x}_i are approximate.
- *Question:* how approximation errors $\Delta x_i \stackrel{\text{def}}{=} \tilde{x}_i - x_i$ affect the resulting error $\Delta y = \tilde{y} - y$?

3. From Probabilistic to Interval Uncertainty

- Manufacturers of MI provide us with bounds Δ_i on measurement errors: $|\Delta x_i| \leq \Delta_i$.
- Thus, we know that $x_i \in [\tilde{x}_i - \Delta_i, \tilde{x}_i + \Delta_i]$.
- Often, we also know probabilities, but in 2 cases, we don't:

- cutting-edge measurements;
- cutting-cost manufacturing.

- In such situations:

- we know the intervals $[\underline{x}_i, \bar{x}_i] = [\tilde{x}_i - \Delta_i, \tilde{x}_i + \Delta_i]$ of possible values of x_i , and
- we want to find the range of possible values of y :

$$\underline{y} = [\underline{y}, \bar{y}] = \{f(x_1, \dots, x_n) : x_1 \in [\underline{x}_1, \bar{x}_1], \dots, [x_n, \bar{x}_n]\}.$$

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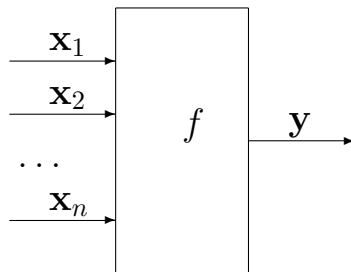
4. Main Problem of Interval Computations

We are given:

- an integer n ;
- n intervals $\mathbf{x}_1 = [\underline{x}_1, \bar{x}_1], \dots, \mathbf{x}_n = [\underline{x}_n, \bar{x}_n]$, and
- an algorithm $f(x_1, \dots, x_n)$ which transforms n real numbers into a real number $y = f(x_1, \dots, x_n)$.

We need to compute the endpoints \underline{y} and \bar{y} of the interval

$$\mathbf{y} = [\underline{y}, \bar{y}] = \{f(x_1, \dots, x_n) : x_1 \in [\underline{x}_1, \bar{x}_1], \dots, [x_n, \bar{x}_n]\}.$$



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5. Knowledge Processing and Fuzzy Uncertainty

- In many practical situations, we only have expert estimates for the inputs x_i like “around \tilde{x}_i ”.
- Such estimates are described by membership functions $m_i(x_i)$ or α -cuts $x_i(\alpha) = \{x : m_i(x) \geq \alpha\}$.
- Usually, each $m_i(x_i)$ is a *fuzzy number*: starts at 0, increases, then decreases to 0.
- For fuzzy numbers, α -cuts are intervals.
- The membership function for $y = f(x_1, \dots, x_n)$ is defined by Zadeh’s extension principle:

$$m(y) = \sup\{\min(m_1(x_1), \dots, m_n(x_n)) : y = f(x_1, \dots, x_n)\}.$$

- For fuzzy numbers, computations reduce to layer-by-layer interval computations:

$$\mathbf{y}(\alpha) = f(\mathbf{x}_1(\alpha), \dots, \mathbf{x}_n(\alpha)).$$

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6. Interval-Valued Fuzzy Sets: Mendel's Algorithm

- *Main idea behind type 2:* $m_i(x_i)$ is not a crisp number.
- *Interval-valued case:* instead of $m_i(x_i)$, we have an interval $\mathbf{m}_i(x_i) = [\underline{m}_i(x_i), \overline{m}_i(x_i)]$.
- Different $m_i(x_i) \in [\underline{m}_i(x_i), \overline{m}_i(x_i)]$ lead to different $m(y) = \sup\{\min(m_1(x_1), \dots, m_n(x_n)) : y = f(x_1, \dots, x_n)\}$.
- *Goal:* compute the range $[\underline{m}(y), \overline{m}(y)]$ of $m(y)$.
- *Idea:* the above expression is monotonic, so
$$\underline{m}(y) = \sup\{\min(\underline{m}_1(x_1), \dots, \underline{m}_n(x_n)) : y = f(x_1, \dots, x_n)\};$$
$$\overline{m}(y) = \sup\{\min(\overline{m}_1(x_1), \dots, \overline{m}_n(x_n)) : y = f(x_1, \dots, x_n)\}.$$
- Using the known relation with interval computations,
$$\underline{\mathbf{y}}(\alpha) = f(\underline{\mathbf{x}}_1(\alpha), \dots, \underline{\mathbf{x}}_n(\alpha)); \quad \overline{\mathbf{y}}(\alpha) = f(\overline{\mathbf{x}}_1(\alpha), \dots, \overline{\mathbf{x}}_n(\alpha)),$$
$$\underline{\mathbf{x}}_i \stackrel{\text{def}}{=} \{x_i : \underline{m}_i(x_i) \geq \alpha\} \quad \text{and} \quad \overline{\mathbf{x}}_i \stackrel{\text{def}}{=} \{x_i : \overline{m}_i(x_i) \geq \alpha\}.$$

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7. New Result: Extension of Mendel's Formulas to General Type-2 Fuzzy Numbers

- *Reminder:* Zadeh's extension principle

$$m(y) = \sup\{\min(m_1(x_1), m_2(x_2), \dots) : y = f(x_1, \dots, x_n)\}.$$

- *General type-2 case:* $m_i(x_i)$ are fuzzy numbers, with β -cuts $(m_i(x_i))(\beta) = [\underline{(m_i(x_i))(\beta)}, \overline{(m_i(x_i))(\beta)}]$.

- Due to known relation with interval computations:

$$(m(y))(\beta) = \sup\{\min((m_1(x_1))(\beta), \dots) : y = f(x_1, \dots, x_n)\}.$$

- Due to monotonicity:

$$\underline{(m(y))(\beta)} = \sup\{\min(\underline{(m_1(x_1))(\beta)}, \dots) : y = f(x_1, \dots, x_n)\};$$

$$\overline{(m(y))(\beta)} = \sup\{\min(\overline{(m_1(x_1))(\beta)}, \dots) : y = f(x_1, \dots, x_n)\}.$$

- Due to known relation with interval computations:

$$\underline{y}(\alpha, \beta) = f(\underline{\mathbf{x}}_1(\alpha, \beta), \dots); \quad \overline{y}(\alpha, \beta) = f(\overline{\mathbf{x}}_1(\alpha, \beta), \dots),$$

$$\underline{y}(\alpha, \beta) \stackrel{\text{def}}{=} \{x : \underline{y(\beta)} \geq \alpha\} \text{ and } \overline{y}(\alpha, \beta) \stackrel{\text{def}}{=} \{x : \overline{y(\beta)} \geq \alpha\}$$

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8. Conclusions

- Type-2 fuzzy sets more adequately describe expert's opinion than the more traditional type-1 fuzzy sets.
- The use of type-2 fuzzy sets has thus led to better quality control, better quality clustering, etc.
- *Main obstacle*: the computational time of data processing increases.
- *Mendel's result*: processing *interval-valued* fuzzy numbers can be reduced to interval computations.
- *Conclusion*: processing interval-valued fuzzy data is (almost) as fast as processing type-1 fuzzy data.
- In this talk, we showed that Mendel's algorithm can be extended to *general* type-2 fuzzy numbers.
- This will hopefully lead to more practical applications of type-2 fuzzy sets.

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