

Fuzzy Orders for Solving MOLP Problems

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January 30 - February 03, 2012

FSTA2012

Problem formulation

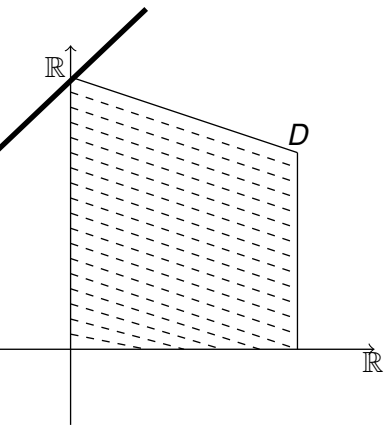
In our work we observe a multi-objective linear programming problem, which can be represented as follows:

MAX Z , where $Z = (z_1, \dots, z_k)$ is a vector of objectives,

$$z_i = \sum_{j=1}^n c_{ij} x_j \text{ where } i = 1, \dots, k,$$

subject to $\sum_{j=1}^n a_{ij} x_j \leq b_i, i = 1, \dots, m.$

That is we should find a vector $x^o = (x_1^o, \dots, x_n^o)$ which maximizes k objective functions with n variables, and m constraints.

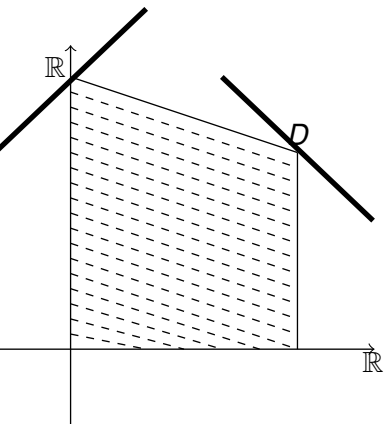


MAX z

$$z = \sum_{j=1}^n c_j x_j$$

subject to $\sum_{j=1}^n a_{ij} x_j \leq b_i,$

$i = 1, \dots, m.$



$$\text{MAX } (z_1, z_2)$$

$$z_i = \sum_{j=1}^n c_{ij} x_j \text{ where } i = 1, 2$$

$$\text{subject to } \sum_{j=1}^n a_{ij} x_j \leq b_i,$$

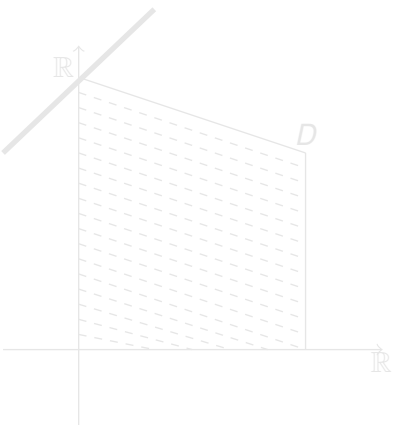
$$i = 1, \dots, m.$$

Fuzzy approach

Membership functions:

$$\mu_i(x) = \begin{cases} 0, & z_i(x) < z_i^{\min}, \\ \frac{z_i(x) - z_i^{\min}}{z_i^{\max} - z_i^{\min}}, & z_i^{\min} \leq z_i(x) \leq z_i^{\max}, \\ 1, & z_i(x) > z_i^{\max}. \end{cases}$$

$$\max_x \min_i \mu_i(x)$$

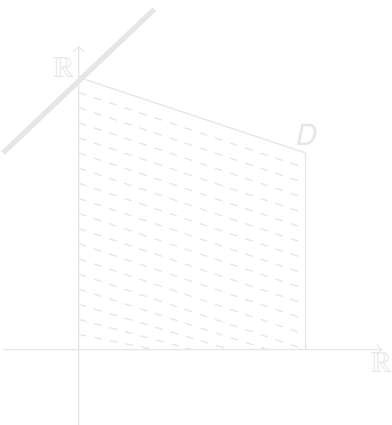


$$\begin{aligned} & \text{MAX } z \\ & z = \sum_{j=1}^n c_j x_j \\ & \text{subject to } \sum_{j=1}^n a_{ij} x_j \leq b_i, \\ & i = 1, \dots, m. \end{aligned}$$

$$x \doteq y \Leftrightarrow z(x) = z(y)$$

$$x \preceq y \Leftrightarrow z(x) \leq z(y)$$

$$\max(D, \preceq)$$

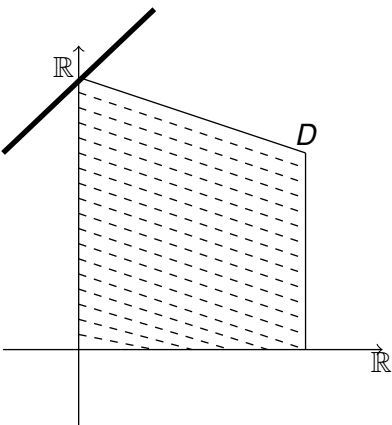


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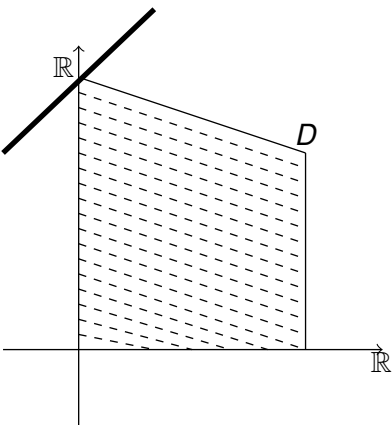


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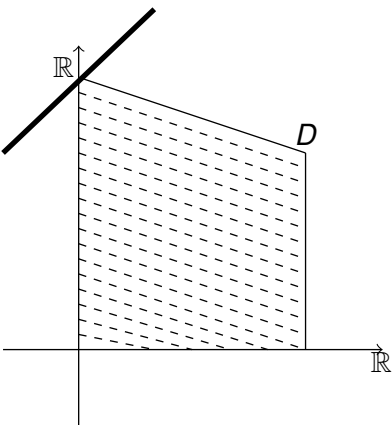


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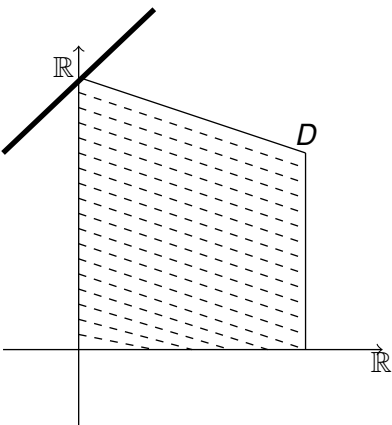


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Fuzzy order approach

1. We define fuzzy order relations P_i which generalize the following crisp order relations
 $x \preceq_i y \Leftrightarrow z_i(x) \leq z_i(y)$, $i = 1, \dots, k$. Thus each fuzzy order relation describes corresponding objective function z_i .
2. We aggregate fuzzy orders using an aggregation function A which preserves the properties of initial fuzzy orders.

$$P(x, y) = A(P_1(x, y), \dots, P_k(x, y)).$$

Thus the aggregated fuzzy order relation P provides the information about all objective functions.

3. We maximize aggregated fuzzy order relation.

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Definition of a fuzzy equivalence relation

Definition

A fuzzy binary relation $E : X \times X \rightarrow [0, 1]$ on a set X is called fuzzy equivalence relation with respect to a t-norm T , for brevity T -equivalence, if and only if the following three axioms are fulfilled for all $x, y, z \in X$:

1. $E(x, x) = 1$ reflexivity;
2. $E(x, y) = E(y, x)$ symmetry;
3. $T(E(x, y), E(y, z)) \leq E(x, z)$ T -transitivity.

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Fuzzy equivalence relation

Theorem

Let T be a continuous Archimedean t -norm with an additive generator t . For any pseudo-metric d , the mapping

$$E_d(x, y) = t^{(-1)}(\min(d(x, y), t(0)))$$

is a T -equivalence.

Example

Let us consider the set of real numbers $X = \mathbb{R}$ and metric $d(x, y) = |x - y|$ on it. Taking into account that $t_L(x) = 1 - x$ is an additive generator of T_L (Łukasiewicz t -norm) and that $t_P(x) = -\ln(x)$ is an additive generator of T_P (product t -norm), we obtain two fuzzy equivalence relations:

$$E_L(x, y) = \max(1 - |x - y|, 0);$$

$$E_P(x, y) = e^{-|x-y|}.$$

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Definition

Let X be a set. By a fuzzy order relation with respect to a t -norm T and T -equivalence E we call a fuzzy relation $P : X \times X \rightarrow [0, 1]$ such that

1. $P(x, x) = 1 \forall x \in X$ reflexivity;
2. $T(P(x, y), P(y, z)) \leq P(x, z) \forall x, y, z \in X$ T -transitivity;
3. $T(P(x, y), P(y, x)) \leq E(x, y) \forall x, y \in X$ T - E -antisymmetry.

A pair (X, P) is called a fuzzy ordered set.

A fuzzy ordering P is called strongly linear if and only if

$$\forall x, y \in X : \max(P(x, y), P(y, x)) = 1.$$

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Construction of fuzzy orderings (U.Bodenhofer)

Let X be a set.

Linear ordering \leq + T -equivalence E (compatible with \leq) =

$$P(x, y) = \begin{cases} 1, & \text{if } x \leq y \\ E(x, y), & \text{otherwise} \end{cases}$$

a strongly linear T - E -ordering on X .

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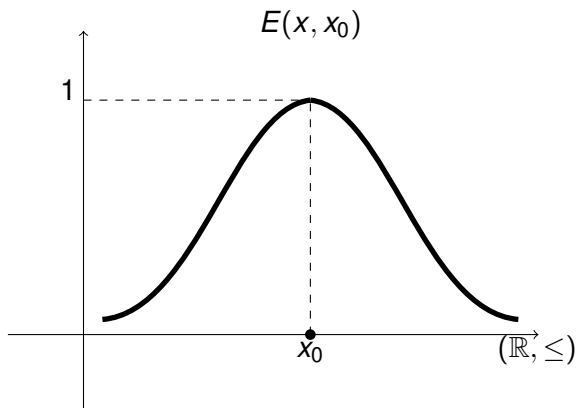
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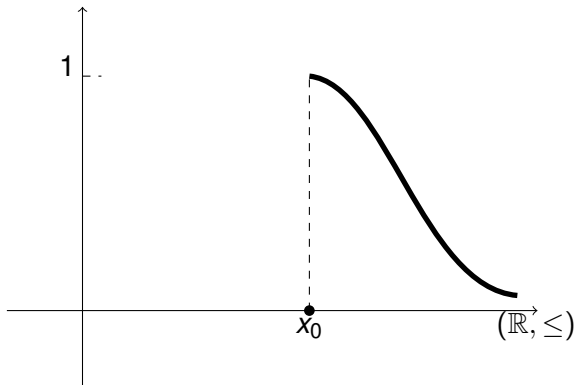
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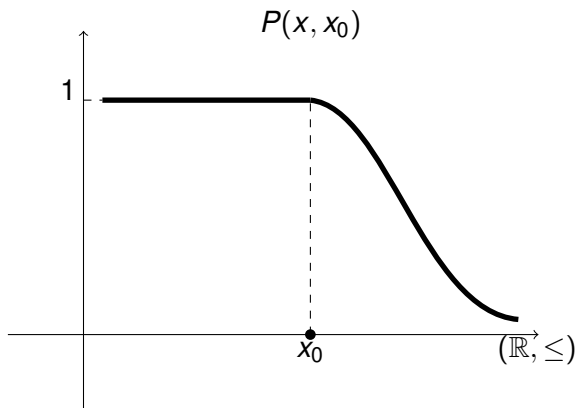
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1. $d_i(x, y) = \frac{|z_i(x) - z_i(y)|}{z_i^{\max} - z_i^{\min}}$ are pseudo-metrics
2. $E_i(x, y) = t^{(-1)}(\min(\frac{|z_i(x) - z_i(y)|}{z_i^{\max} - z_i^{\min}}, t(0)))$ are fuzzy T -equivalence relations
3. we build fuzzy order relations (T - E -orders) by the following way:

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1. $d_i(x, y) = \frac{|z_i(x) - z_i(y)|}{z_i^{\max} - z_i^{\min}}$ are pseudo-metrics
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Aggregation of fuzzy relations

We aggregate fuzzy orders P_i $i \in \{1, \dots, k\}$ using an aggregation function A which preserves the properties of initial fuzzy orders:

$$P(x, y) = A(P_1(x, y), \dots, P_k(x, y))$$

Definition

Consider an n -argument aggregation function $A^n : [0, 1]^n \rightarrow [0, 1]$ and an m -argument aggregation function $B^m : [0, 1]^m \rightarrow [0, 1]$. We say that A^n dominates B^m if for all $x_{i,j} \in [0, 1]$ with $i \in \{1, \dots, m\}$ and $j \in \{1, \dots, n\}$ the following property holds:

$$\begin{aligned} & B^m(A^n(x_{1,1}, \dots, x_{1,n}), \dots, A^n(x_{m,1}, \dots, x_{m,n})) \leq \\ & \leq A^n(B^m(x_{1,1}, \dots, x_{m,1}), \dots, B^m(x_{1,n}, \dots, x_{m,n})). \end{aligned}$$

Theorem

Let $|X| > 3$ and let T be a t -norm. An aggregation function A preserves T -transitivity of fuzzy relations on X if and only if A belongs to the class of aggregation functions which dominate T .

Example

For any $k > 2$ and any $p = (p_1, \dots, p_k)$ with $\sum_{i=1}^k p_i \geq 1$ and $p_i \in [0, \infty]$ k -ary aggregation function

$$A_p(x_1, \dots, x_k) = \prod_{i=1}^k x_i^{p_i}$$

dominates the product t -norm T_P .

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$$A_p(x_1, \dots, x_k) = \max\left(\sum_{i=1}^k x_i \cdot p_i + 1 - \sum_{i=1}^k p_i, 0\right)$$

dominates the Łukasiewicz t -norm T_L .

Theorem

Let $|X| > 3$ and let T be a t -norm. If E_i for all $i \in \{1, \dots, n\}$ are fuzzy equivalence relations (T -equivalences) then

$$E(x, y) = A(E_1(x, y), \dots, E_n(x, y))$$

is also a T -equivalence relation if A belongs to the class of aggregation functions which dominate T .

Theorem

Let $|X| > 3$ and let T be a t -norm. If E_i for all $i \in \{1, \dots, n\}$ are fuzzy equivalence relations (T -equivalences); P_i for all $i \in \{1, \dots, n\}$ are fuzzy order relations (T - E_i -orders) then

$$P(x, y) = A(P_1(x, y), \dots, P_n(x, y))$$

is a T - E -order relation if A belongs to the class of aggregation functions which dominate T and

$$E(x, y) = A(E_1(x, y), \dots, E_n(x, y)).$$

Further the multi-objective linear programming problem comes to the following problem:

$$\max_y \min_x P(x, y) \quad (P)$$

Definition

x^* is called Pareto optimal solution if and only if there does not exist another $x \in D$ such that $z_i(x) \leq z_i(x^*)$ for all i and $z_j(x) \neq z_j(x^*)$ for at least one j .

Theorem

An optimal solution x^ to the problem (P) is a Pareto optimal solution if it is unique optimal solution.*

Theorem

An optimal solution x^ to the problem (P) is a Pareto optimal solution if for all x and y $z_i(x) > z_i(y) \Rightarrow P_i(x, y) < 1$, A is a strictly monotone function and set D is linearly connected.*

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An optimal solution x^ to the problem (P) is a Pareto optimal solution if for all x and y $z_i(x) > z_i(y) \Rightarrow P_i(x, y) < 1$, A is a strictly monotone function and set D is linearly connected.*

Further the multi-objective linear programming problem comes to the following problem:

$$\max_y \min_x P(x, y) \quad (P)$$

Definition

x^* is called Pareto optimal solution if and only if there does not exist another $x \in D$ such that $z_i(x) \leq z_i(x^*)$ for all i and $z_j(x) \neq z_j(x^*)$ for at least one j .

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Numerical example

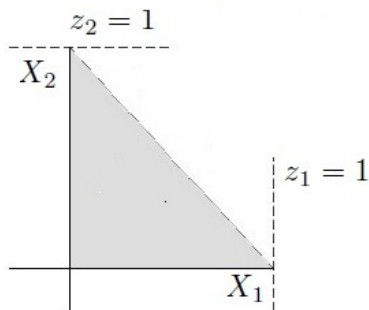
Let us observe the following linear programming problem:

$$\max z_1 = x_1,$$

$$\max z_2 = x_2,$$

$$\text{s.t. } x_1 + x_2 \leq 1,$$

$$x_1, x_2 \geq 0.$$



Numerical example

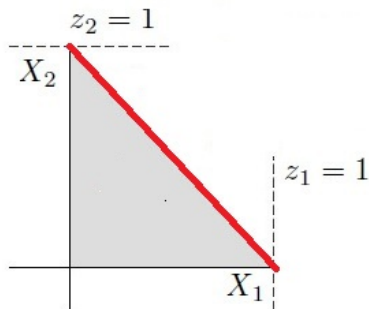
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Numerical example (Łukasiewicz t-norm)

We solve the following problem: $\max_{y \in D} \min_{x \in D} P(x, y)$.

$$f(y) = \min_{x \in B} P(x, y) :$$

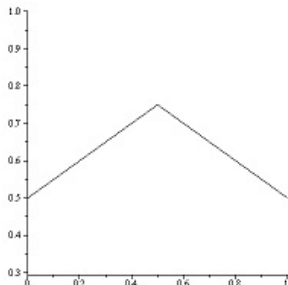


Figure:

$$P(x, y) = \frac{P_1(x, y) + P_2(x, y)}{2}$$

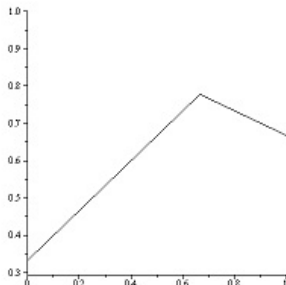


Figure:

$$P(x, y) = \frac{2P_1(x, y) + P_2(x, y)}{3}$$

Numerical example(Product t-norm)

We solve the following problem: $\max_{y \in D} \min_{x \in D} P(x, y)$.

$$f(y) = \min_{x \in B} P(x, y) :$$

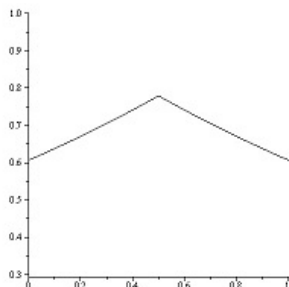


Figure:

$$P(x, y) = P_1(x, y)^{\frac{1}{2}} \cdot P_2(x, y)^{\frac{1}{2}}$$

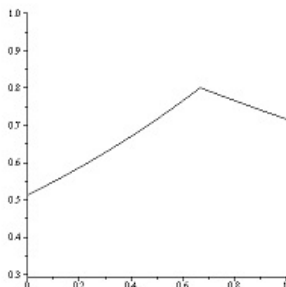


Figure:

$$P(x, y) = P_1(x, y)^{\frac{2}{3}} \cdot P_2(x, y)^{\frac{1}{3}}$$

Thank you for attention!