Eduard Bartl: Minimal Solutions of Fuzzy Relational Eq.: Probabilistic Algorithm

Introduction

- :: generalized fuzzy relational equations (FREs) are equations of the form $R \square S = T$, where R, S, and Tare binary fuzzy relations, and <a>o denotes a general composition introduced by Radim Belohlavek in [3]
- :: problem: given two of the relations, determine the third one for which the equality $R \square S = T$ holds
- :: the aim of the current research: extension of the previous work on generalized FREs by developing a method for constructing all minimal solutions and, consequently, for determining the whole solution set

Preliminaries

:: an aggregation structure (L_1, L_2, L_3, \Box) , where L_i are complete lattices and $\Box: L_1 \times L_2 \rightarrow L_3$ is a function which commutes with suprema in both arguments; define operations:

 $\circ_{\Box} : L_1 \times L_3 \to L_2, \ a_1 \circ_{\Box} a_3 = \bigvee_2 \{a_2 \mid a_1 \Box a_2 \leq_3 a_3\}$ $\Box \circ : L_3 \times L_2 \to L_1, \quad a_3 \Box \circ a_2 = \bigvee_1 \{a_1 \mid a_1 \Box a_2 \leq_3 a_3\}$ ${}^{\text{op}}_{\Box} \circ : L_3 \times L_2 \to L_1, \ a_3 {}^{\text{op}}_{\Box} \circ a_2 = \bigwedge_1 \{ a_1 \, | \, a_1 \Box a_2 \ge_3 a_3 \}$

:: consider two important examples of aggreg. struct.; in both cases, $(L, \wedge, \vee, \otimes, \rightarrow, 0, 1)$ is a complete residuated lattice; $L_i = L$ and \leq_i is either \leq or the dual of \leq

1.
$$\mathbf{L}_1 = \langle L, \leq \rangle, \ \mathbf{L}_2 = \langle L, \leq \rangle, \ \mathbf{L}_3 = \langle L, \leq \rangle, \ \Box = \otimes$$
:
 $a_1 \circ_{\Box} a_3 = \bigvee \{a_2 \mid a_1 \otimes a_2 \leq a_3\} = a_1 \to a_3$

 $a_3 \Box \circ a_2 = \bigvee \{a_1 \mid a_1 \otimes a_2 \le a_3\} = a_2 \to a_3$

- **2.** $\mathbf{L}_1 = \langle L, \leq \rangle$, $\mathbf{L}_2 = \langle L, \leq^{-1} \rangle$, $\mathbf{L}_3 = \langle L, \leq^{-1} \rangle$, $\Box = \rightarrow$: $a_1 \circ_{\Box} a_3 = \bigwedge \{a_2 \,|\, a_1 \to a_2 \ge a_3\} = a_1 \otimes a_3$ $a_3 \Box \circ a_2 = \bigvee \{a_1 \mid a_1 \to a_2 \ge a_3\} = a_3 \to a_2$
- :: for fuzzy relations $R \in L_1^{X \times Y}$, $S \in L_2^{Y \times Z}$, let a fuzzy relation $R \square S \in L_3^{X \times Z}$ be defined by

$$(R \square S)(x,z) = \bigvee_{3 y \in Y} (R(x,y) \square S(y,z))$$

- : product <a>e generalizes both sup-t-norm product ((and inf-residuum product (\triangleleft): for the setting of Example 1: $R \square S = R \circ S$ for the setting of Example 2: $R \square S = R \triangleleft S$
- :: for $R \in L_1^{X \times Y}$ and $S \in L_3^{Y \times Z}$, let $R \triangleleft_{\Box} S \in L_2^{X \times Z}$ and $R \square \triangleleft S \in L_1^{X \times Z}$ be defined by

 $(R \triangleleft_{\Box} S)(x,z) = \bigwedge_{2 \ y \in Y} (R(x,y) \circ_{\Box} S(y,z))$ $(R_{\Box} \triangleleft S)(x,z) = \bigwedge_{1 \ y \in Y} (R(x,y)_{\Box} \circ S(y,z))$



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Minimal Solutions

- :: assumption: (L_1, L_2, L_3, \Box) be an aggreg. struct. such that \Box commutes with infima in the first arg.
- :: scalar-by-scalar equation is expression

$$u \square s = t, \tag{1}$$

where $u \in L_1$, $s \in L_2$, $t \in L_3$

Theorem 1 If equation (1) is solvable then for each solution $r \in L_1$ we have $r \in [t \square^{\text{op}} \circ s, t \square^{\circ} s]$.

:: vector-by-vector equation is expression

$$\begin{pmatrix} u_1 \dots u_n \end{pmatrix} \boxdot \begin{pmatrix} s_1 \\ \vdots \\ s_n \end{pmatrix} = t, \tag{2}$$

where
$$(u_j) \in L_1^Y$$
, $(s_j)^{-1} \in L_2^Y$, $t \in L_3$, $j \in J$

Theorem 2 If there is $j' \in J$ such that $u_{j'} \Box s_{j'} = t$ is solvable then equation (2) has a minimal solution $R = (r_1 \dots r_n)$ such that

$$r_j = \begin{cases} t \stackrel{\text{op}}{\Box} \circ s_j & \text{for } j = j', \\ 0_1 & \text{otherwise.} \end{cases}$$

:: vector-by-matrix equation is expression

$$\begin{pmatrix} u_1 \dots u_n \end{pmatrix} \boxdot \begin{pmatrix} s_{11} \dots s_{1p} \\ \vdots \dots \vdots \\ s_{n1} \dots s_{np} \end{pmatrix} = \begin{pmatrix} t_1 \dots t_p \end{pmatrix}, \quad (3)$$

where
$$(u_j) \in L_1^Y$$
, $(s_{jk}) \in L_2^{Y \times Z}$, $(t_k) \in L_3^Z$, $j \in J$, $k \in K$

:: equation (3) can be rewritten using the table \mathfrak{T} :

$$\mathfrak{T}_{jk} = \begin{cases} u_j \square s_{jk} & \text{for } j \in J \\ t_k & \text{for } j = n+1 \end{cases}$$

- : now, we need to suppose L_1 is a chain and $\Box^{\circ} = \Box^{\circ}$
- :: important result: when we put the greatest solution into the equation (3), the k-th column of \mathfrak{T} consists of the values equal to t_k or the values that are strictly smaller than t_k ; this allows us to binarize table $\mathfrak{T}: \mathfrak{B}_{jk} = 1$ if $\mathfrak{T}_{jk} = t_k$, $\mathfrak{B}_{jk} = 0$ if $\mathfrak{T}_{jk} <_3 t_k$
- :: we say that $J_{COV} \subseteq J$ is a covering of the last row of \mathfrak{B} if $\max_{i \in J_{cov}} \mathfrak{B}_{ik} = 1$ for all $k \in K$; we say that $J_{\text{COV}} \subseteq J$ is a minimal covering of the last row of \mathfrak{B} if there is no covering J'_{COV} such that $J'_{COV} \subset J_{COV}$

Theorem 3 Let $\hat{R} = (\hat{r}_1 \dots \hat{r}_n)$ be the greatest solution of a solvable equation (3). Then every minimal solution $\breve{R} = (\breve{r}_1 \ldots \breve{r}_n)$ of (3) is of the form:

$$\breve{r}_j = \begin{cases} \hat{r}_j & \text{for } j \in J_{\text{cov}}, \\ 0_1 & \text{otherwise}, \end{cases}$$

where J_{cov} is a minimal covering of the last row of \mathfrak{B} .

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:: algorithm requires the table \mathfrak{B} and returns a family of (almost) minimal coverings of the last row in \mathfrak{B}

$\mathcal{C} \leftarrow \emptyset$

Algorithm

:: let $J_{COV} \subseteq J$ denote a set of row-indices in table \mathfrak{B} representing an (almost) minimal covering, let $K_{\text{unc}} \subseteq K$ denote a set of uncovered column-indices of the last row in table \mathfrak{B} , and let $\mathfrak{B}_i \subseteq K$ denote a set of column-indices representing the *j*-th row in table *B*, i.e.

$$k \in \mathfrak{B}_{j_{-}}$$
iff $\mathfrak{B}_{jk} = 1$

for all $k \in K$

:: the crucial part of algorithm is calculating a minimal covering: in a given step of computation, the problem of finding a minimal covering can be identified with the set cover problem

:: since the set cover problem is NP-hard optimization problem, we apply the greedy approach

:: such approach guarantees a known approximation ratio of the algorithm (note, the approximation ratio tells us how far the obtained solution is from a minimal solution in the worst case)

Probabilistic algorithm for computing all minimal solutions based on greedy approach:

Require: binary table \mathfrak{B} of dimension $(n+1) \times p$, last row of \mathfrak{B} is full of 1s

Ensure: family C of (almost) minimal coverings of the last row in table \mathfrak{B}

```
J \leftarrow \{1, 2, \dots, n\}
repeat
      J_{\text{COV}} \leftarrow \emptyset
      K_{\text{unc}} \leftarrow \{1, 2, \dots, p\}
      while (K_{unc} \neq \emptyset) and (J_{cov} \neq J) do
             select j \in J for which |\mathfrak{B}_{j_{-}} \cap K_{unc}| is largest
             J_{\text{COV}} \leftarrow J_{\text{COV}} \cup \{j\}
             K_{\text{unc}} \leftarrow K_{\text{unc}} \setminus \mathfrak{B}_{j}
      end while
      if K_{\text{unc}} = \emptyset then
             \mathcal{C} \leftarrow \mathcal{C} \cup \{J_{\rm COV}\}
             randomly choose j \in J_{COV}
             remove j-th row from table \mathfrak{B}
             J \leftarrow J \setminus \{j\}
      end if
until K_{\text{unc}} \neq \emptyset
return C
```

Example

:: we assume a five-element Gödel chain and a vector-by-matrix sup-t-norm eq. $U \circ S = T$, where

$$S = \begin{pmatrix} 0.50\\ 1.00\\ 1.00\\ 0.25\\ 0.75\\ 0.25 \end{pmatrix}$$

being

: tables \mathfrak{T} and \mathfrak{B} , respectively:

```
r_1 \otimes s_{11} = 0.50
r_2 \otimes s_{21} = 0.75
r_3 \otimes s_{31} = 0.75
r_4 \otimes s_{41} = 0.25
r_5 \otimes s_{51} = 0.25
r_6 \otimes s_{61} = 0.25
    t_1 \!=\! \mathbf{0.75}
```

	minimal c
::	minimal s
	\breve{R}_{1}
	\breve{R}_{ϵ}

Future Research

References



0	0.50	0.25	0.50	
0	1.00	0.00	0.25	
0	0.50	0.00	0.00	$, T = (0.75 \ 0.75 \ 0.25 \ 0.50)$
5	0.75	0.00	0.25	$, I = (0.75 \ 0.75 \ 0.25 \ 0.50)$
5	0.00	0.75	0.75	
5	0.50	0.00	1.00	

:: the equation is solvable with the greatest solution

 $\hat{R} = (1.00 \ 0.75 \ 0.75 \ 1.00 \ 0.25 \ 0.50)$

0	$r_1 \otimes s_1$	2 = ().50	r_{1}	$_1 \otimes s_{13}$ =	=0.25	$r_1 \otimes s_{14} = 0.50$)
5	$r_2 \otimes s_{22}$	2 = 0	0.75	$r_{ m c}$	$_2 \otimes s_{23}$ =	=0.00	$r_2 \otimes s_{24} = 0.25$	5
5	$r_3 \otimes s_3$	2 = ().50	r_{i}	$_3 \otimes s_{33}$ =	=0.00	$r_3 \otimes s_{34} = 0.00$)
5	$r_4 \otimes s_{42}$	2 = 0	0.75	r_{\cdot}	$_4 \otimes s_{43}$ =	=0.00	$r_4 \otimes s_{44} = 0.25$	5
5	$r_5 \otimes s_5$	2 = ().00	rį	$_5 \otimes s_{53}$ =	= 0.25	$r_5 \otimes s_{54} = 0.25$	5
5	$r_6 \otimes s_{62}$	2 = ().50	r	$_6 \otimes s_{63}$ =	=0.00	$r_6 \otimes s_{64} = 0.50$)
	$t_2 \!=\! 0.75$				$t_3 \!=\! 0$.25	$t_4\!=\!{f 0.50}$	
		0	0	1	1			
		1	1	0	0			
		1	0	0	0			
		0	1	0	0			
		0	0	1	0			
		0	0	0	1			
		1	1	1	1			
coverings: {1,2}, {1,3,4}, {2,5,6}, {3,4,5,6}								

 $\text{OVERINGS:} \{1, 2\}, \{1, 3, 4\}, \{2, 5, 0\}, \{3, 4, 5, 0\}$

solutions of $U \circ S = T$:

$\tilde{R}_1 = (1.00)$	0.75	0.00	0.00	0.00	(0.00)
$\tilde{R}_2 = (1.00)$	0.00	0.75	1.00	0.00	0.00)
$\tilde{R}_3 = (0.00)$	0.75	0.00	0.00	0.25	0.50)
$\tilde{R}_4 = (0.00)$	0.00	0.75	1.00	0.25	0.50)

:: complexity issues, efficient computation of all solutions (removing duplicities)

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