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# Minimal solutions in Fuzzy Relation Equations. Application to Fuzzy Logic Programming

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### Outline

Introduction

Adjoint triples

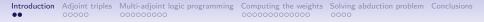
Multi-adjoint logic programming

Computing the weights of the rules of M.A.L. programs

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Solving the abduction problem

Conclusions and future work



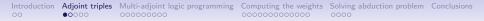
## Introduction I

- Multi-adjoint logic programming [Medina et al(2001)] is a general logical framework whose semantic structure is the multi-adjoint lattice
- Adjoint triples [Cornejo et al(2013), Medina et al(2004)] are a generalization of the t-norms and their residuated implications, which satisfy their main properties.
- They are used as the basic operators to make the calculus in several frameworks, which provides them more flexible.
- MALP, fuzzy concept lattices, fuzzy rough sets, fuzzy relation equations, etc.

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## Introduction II

- Fuzzy relation equations, introduced by E. Sanchez, are associated with the composition of fuzzy relations.
- FRE have been used to investigate theoretical and applicational aspects of fuzzy set theory, e.g., approximate reasoning, decision making, fuzzy control, etc.
- The multi-adjoint relation equations [Díaz and Medina(2013)] were presented as a generalization of the fuzzy relation equations.
- Two important problems in fuzzy logic programming is to find out the confidence factors of the rules in a program and abductive reasoning.
- This lecture describes and solves these problems in terms of multi-adjoint relation equation theory.



## Adjoint triples

Assuming non-commutativity on the conjunctor, directly provides two different residuated (adjoint) implications

### Definition

Let  $(P_1, \leq_1)$ ,  $(P_2, \leq_2)$ ,  $(P_3, \leq_3)$  be posets and  $\&: P_1 \times P_2 \to P_3$ ,  $\swarrow: P_3 \times P_2 \to P_1, \land: P_3 \times P_1 \to P_2$  be mappings, then  $(\&, \swarrow, \land)$  is an *adjoint triple* with respect to  $P_1, P_2, P_3$  if:

• Adjoint property:

$$x \leq_1 z \swarrow y$$
 iff  $x \& y \leq_3 z$  iff  $y \leq_2 z \land x$ 

where  $x \in P_1$ ,  $y \in P_2$  and  $z \in P_3$ .

## Main properties of adjoint triples

- We have three different general sorts, which also provides a more flexible language for a potential user. Furthermore, few conditions are required.
- The adjoint triples play an important role in several important environments: fuzzy logic, fuzzy relation equations, fuzzy concept lattices, etc.
- More properties must be assumed in order to assure the mechanism for the calculus needed to resolve problems.
- M. Cornejo, J. Medina, and E. Ramírez A comparative study of adjoint triples. Fuzzy Sets and Systems, 211:1-14, 2013.

### T-norm and its residuated implication

Product adjoint triple

 $\&_P: [0,1] \times [0,1] \to [0,1]$  defined as:

 $\&_P(x, y) = x \cdot y$ 

Residuated implications:  $\swarrow^P = \swarrow_P [0,1] \times [0,1] \rightarrow [0,1]$  are defined as:

$$z \swarrow^P y = \min\{1, z/y\}$$

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## Granular adjoint triples

### Granular product adjoint triple

Considering regular partitions of [0,1] into several pieces:  $[0,1]_5 = \{0,0.2,0.4,0.6,0.8,1\}$ .  $\&_P^*: [0,1]_5 \times [0,1]_3 \rightarrow [0,1]_4$ defined as:

$$\&_P^*(x,y) = \frac{\left\lceil 4 \cdot x \cdot y \right\rceil}{4}$$

where  $\lceil _{-} \rceil$  is the ceil function ( $\lceil 3.6 \rceil = 4$ ,  $\lceil 7.1 \rceil = 8$ ,  $\lceil 2 \rceil = 2, ...$ ). The residuated implications:  $\swarrow _{P}^{*} : [0,1]_{4} \times [0,1]_{3} \rightarrow [0,1]_{5}$  and  $\nwarrow _{P}^{*} : [0,1]_{4} \times [0,1]_{5} \rightarrow [0,1]_{3}$  are defined as:

$$z \swarrow_P^* y = \frac{\lfloor 5 \cdot \min\{1, z/y\} \rfloor}{5} \qquad z \nwarrow_P^* x = \frac{\lfloor 3 \cdot \min\{1, z/x\} \rfloor}{3}$$

where  $\lfloor \_ \rfloor$  is the floor function.

Adjoint triples 0000

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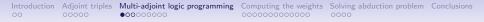
### Non-commutative adjoint triple

&:  $[0,1] \times [0,1] \rightarrow [0,1]$  defined as:

$$\&(x,y)=x^2y$$

The residuated implications:  $\checkmark: [0,1] \times [0,1] \rightarrow [0,1]$  and  $\nwarrow: [0,1] \times [0,1] \rightarrow [0,1]$  are defined as:

$$z \swarrow y = \min\{1, \sqrt{z/y}\}$$
  
 $z \nwarrow x = \min\{1, z/x\}$ 



## Fuzzy logic

- There exists a big interest in the development of logics for dealing with information which might be either vague or uncertain.
- Several different approaches to the so-called inexact or fuzzy or approximate reasoning have been proposed, such that fuzzy, annotated, probabilistic and similarity-based logic programming.

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### Logic programming

Standard Logic Programming Rule [Kowalski and van Emden]:

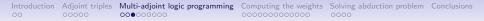
 $paper\_accepted \leftarrow good\_work, good\_referees$ 

Quantitative Deduction Rule [van Emden]:

 $paper\_accepted \xleftarrow{0.9} good\_work \& good\_referees$ 

Fuzzy Logic Programming [Vojtáš and Paulík]:

 $paper\_accepted \leftarrow \stackrel{0.9}{\_product} min(good\_work, good\_referees)$ 



### Logic programming

Probabilistic Deductive Databases [Lakshmanan and Sadri]:

 $\left( paper\_accepted \xleftarrow{([0.7,0.95],[0.03,0.2])} good\_work, good\_referees; ind, pc \right)$ 

Hybrid Probabilistic Logic Programs [Dekhtyar and Subrahmanian]:

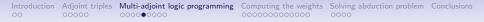
 $(paper\_accepted \lor_{pc} go\_conference): [0.85, 0.98] \leftarrow (good\_work \land_{ind} good\_referees): [0.7, 0.9] & have\_money: [0.9, 1.0]$ 

## Multi-Adjoint Logic Programming

Multi-adjoint logic programming was introduced by J. Medina, M. Ojeda-Aciego and P. Vojtáš (2001) as a generalization of the previous frameworks. Among its distinctive features we emphasize:

• It is possible to use a number of different type of connectives in the rules of the programs.

- The requirements on the lattice of truth-values and on the connectives are weaker than those on other approaches.
- Sufficient conditions for continuity of the consequence operator are known.
- Completeness theorem for the computational model.



### Language

A language  $\mathcal{L}$  is considered, which contains propositional variables, constants, and a set of logical connectives (adjoint triples and a number of aggregators).

The language  $\mathcal{L}$  is interpreted on a *(biresiduated) multi-adjoint lattice*,  $(L_1, L_2, L_3, \&_1, \swarrow^1, \nwarrow_1, \ldots, \&_n, \swarrow^n, \nwarrow_n)$ , where  $(L_1, \preceq_1), (L_2, \preceq_2), (L_3, \preceq_3)$  are complete lattices and  $(\&_i, \swarrow^i, \nwarrow_i)$ is a collection of adjoint triples.

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## Multi-adjoint logic program

A *rule* is a formula  $A \swarrow^i \mathcal{B}$  or  $A \nwarrow_i \mathcal{B}$ , where A is a propositional symbol (the *head*) and  $\mathcal{B}$  (the *body*) is a formula built from propositional symbols  $B_1, \ldots, B_n$ , and conjunctions, disjunctions and aggregations of  $\mathcal{L}$ .

A multi-adjoint logic program is a set of pairs  $\langle \mathcal{R}, \alpha \rangle$ , where  $\mathcal{R}$  is a rule and  $\alpha$  is a value, which may express the confidence which the user of the system has in the truth of the rule  $\mathcal{R}_{-}$ 

# Example: behavior of a motor

### Example

The set of variables (propositional symbols)

$$\Pi = \{\texttt{rm}, \texttt{nb}, \texttt{oh}, \texttt{hfc}, \texttt{lo}, \texttt{lw}\}$$

The multi-adjoint lattice

 $([0,1]_{100},[0,1]_8,[0,1]_{20},\&_{\mathrm{G}}^*,\swarrow_{\mathrm{G}}^*,\bigvee_{\mathrm{G}}^*,\&_{\mathrm{P}}^*,\swarrow_{\mathrm{P}}^*,\bigwedge_{\mathrm{P}}^*,\wedge_{\mathrm{L}})$ 

The multi-adjoint program:

$$\begin{array}{lll} \langle \texttt{hfc} & \nwarrow_{\mathrm{G}}^{*} & \texttt{rm} \wedge_{\mathrm{L}} \texttt{lo}, 0.75 \rangle \\ \langle \texttt{oh} & \nwarrow_{\mathrm{G}}^{*} & \texttt{lo}, 0.5 \rangle \\ \langle \texttt{nb} & \nwarrow_{\mathrm{P}}^{*} & \texttt{rm}, 0.75 \rangle \\ \langle \texttt{oh} & \nwarrow_{\mathrm{P}}^{*} & \texttt{lw}, 1 \rangle \\ \langle \texttt{nb} & \nwarrow_{\mathrm{G}}^{*} & \texttt{lo}, 1 \rangle \end{array}$$

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### Example: behavior of a motor

#### Example

The usual procedure is to measure the levels of "oil", "water" and "mixture" of a specific motor, after that the values for low\_oil, low\_water and rich\_mixture are obtained, which are represented in the program as:

$$\langle lo, 0.20 \rangle \quad \langle lw, 0.20 \rangle \quad \langle rm, 0.50 \rangle$$

Finally, the values for the rest of variables are computed. For instance, in order to attain the value for overheating(o, w), for a level of oil, o, and water, w, the rules  $\langle oh \nwarrow_{\mathrm{G}}^* lo, \vartheta_1 \rangle$  and  $\langle oh \nwarrow_{\mathrm{P}}^* lw, \vartheta_2 \rangle$  are considered and its value is obtained as:

$$\operatorname{oh}(o,w) = (\operatorname{lo}(o) \&^*_{\mathrm{G}} \vartheta_1) \vee (\operatorname{lw}(w) \&^*_{\mathrm{P}} \vartheta_2)$$

## Example: behavior of a motor

### Example

From another point of view, the problem could be: given the levels of oil,  $o_1, \ldots, o_n$ , the levels of water,  $w_1, \ldots, w_n$ , and the measures of mixture,  $r_1, \ldots, r_n$ , and the values of the variables:  $nb(r_i, o_i)$ ,  $hfc(r_i, o_i)$  and oh $(o_i, w_i)$ , for all  $i \in \{1, ..., n\}$ ; to look for the values of  $\vartheta_1$  and  $\vartheta_2$ , which solve the following system obtained after assuming the experimental data for the propositional symbols,  $ov_1, o_1, w_1, \ldots, ov_n, o_n, w_n$ .

$$\begin{array}{rcl} \operatorname{oh}(ov_1) &=& (\operatorname{lo}(o_1) \,\&_{\mathrm{G}}^* \,\vartheta_1) \vee (\operatorname{lw}(w_1) \,\&_{\mathrm{P}}^* \,\vartheta_2) \\ \vdots & \vdots & \vdots & \vdots \\ \operatorname{oh}(ov_n) &=& (\operatorname{lo}(o_n) \,\&_{\mathrm{G}}^* \,\vartheta_1) \vee (\operatorname{lw}(w_n) \,\&_{\mathrm{P}}^* \,\vartheta_2) \end{array}$$

## Multi-adjoint relation equations

Multi-adjoint relation equations arise as a generalization of the usual fuzzy relation equations, following the philosophy of multi-adjoint framework.

Given the universes U, V and W, the fuzzy relations  $K: W \times U \rightarrow P$ , and  $D: W \times V \rightarrow L_1$ , an unknown fuzzy relation  $R: U \times V \rightarrow L_2$ , and a mapping that relates each element in U to one adjoint triple,  $\sigma: U \rightarrow \{1, \ldots, I\}$ , a multi-adjoint relation equation is

$$\bigvee_{u \in U} (\mathcal{K}(w, u) \&_{\sigma(u)} \mathcal{R}(u, v)) = D(w, v), \quad w \in W, v \in V$$
(1)

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## Example: behavior of a motor

#### Example

 $U = \{ \text{rm}, \text{lo}, \text{lw}, \text{rm} \land_L \text{lo} \}, V = \{ \text{hfc}, \text{nb}, \text{oh} \}, W = \{ 1, 2, 3 \};$ the mapping  $\sigma$  that relates the elements 10, rm  $\wedge_{\rm L}$  10 to the Gödel triple, and rm, lw to the product triple; and the relations  $K: W \times U \rightarrow [0,1]_{100}$ , and  $D: W \times V \rightarrow [0,1]_{20}$ . The unknown fuzzy relation  $R: U \times V \rightarrow [0,1]_8$  is formed by the weights of the rules in the program. For instance, for v = oh,

$$\begin{array}{lll} \operatorname{oh}(ov_1) &=& (\operatorname{lo}(o_1) \&_{\mathrm{G}}^* \vartheta_{1\mathrm{o}}^{\mathrm{oh}}) \vee (\operatorname{lw}(w_1) \&_{\mathrm{P}}^* \vartheta_{1\mathrm{w}}^{\mathrm{oh}}) \\ \operatorname{oh}(ov_2) &=& (\operatorname{lo}(o_2) \&_{\mathrm{G}}^* \vartheta_{1\mathrm{o}}^{\mathrm{oh}}) \vee (\operatorname{lw}(w_2) \&_{\mathrm{P}}^* \vartheta_{1\mathrm{w}}^{\mathrm{oh}}) \\ \operatorname{oh}(ov_3) &=& (\operatorname{lo}(o_3) \&_{\mathrm{G}}^* \vartheta_{1\mathrm{o}}^{\mathrm{oh}}) \vee (\operatorname{lw}(w_3) \&_{\mathrm{P}}^* \vartheta_{1\mathrm{w}}^{\mathrm{oh}}) \end{array}$$

where  $\vartheta_{10}^{oh}$  and  $\vartheta_{1w}^{oh}$  are the weights associated with the rules with head oh.

### The greatest solution of MARE

Given a multi-adjoint relation equation, its associated multi-adjoint property-oriented context is  $(W, U, K, \sigma)$ , and the concept lattice associated with this context will be called  $\mathcal{M}_{\Pi N}(K)$ .

#### Theorem

Let  $v \in V$  and the fuzzy subset  $f_v \in L_1^W$ , defined as  $f_v(w) = D(w, v)$ , for all  $w \in W$ . Then the corresponding System can be solved if and only if  $\langle f_v^{\downarrow^N}, f_v \rangle$  is a concept of  $\mathcal{M}_{\Pi N}(K)$ . In this case,  $f_v^{\downarrow^N}$  is the greatest solution.

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## Concept-forming operators

Given a frame  $(L_1, L_2, P, \&_1, \dots, \&_I)$  and context  $(A, B, R, \sigma)$ , we consider  $\uparrow_{\pi} : L_2^B \to L_1^A, \downarrow^{N} : L_2^A \to L_1^B$ :

$$g^{\uparrow \pi}(a) = \sup\{R(a,b) \&_{\sigma(b)} g(b) \mid b \in B\}$$
  
$$f^{\downarrow^{N}}(b) = \inf\{f(a) \nwarrow_{\sigma(b)} R(a,b) \mid a \in A\}$$

These definitions are generalizations of the classical and fuzzy possibility and necessity operators by Düntsch, Gediga, Georgescu, Popescu, Lai, etc.

The pair  $(\uparrow^{\pi},\downarrow^{N})$  is an isotone Galois connection, that is  $\uparrow^{\pi}$  and  $\downarrow^{N}$  are order-preserving; and they satisfy that  $f^{\downarrow^{N}\uparrow_{\pi}} \leq_{1} f$ , for all  $f \in L_{1}^{A}$ , and that  $g \leq_{2} g^{\uparrow_{\pi}\downarrow^{N}}$ , for all  $g \in L_{2}^{B}$ .

## Multi-adjoint property-oriented concept lattice

#### Concept

A pair of fuzzy sets  $\langle g, f \rangle$ , with  $g \in L_2^B$ ,  $f \in L_1^A$ , such that  $g^{\uparrow_{\pi}} = f$ and  $f^{\downarrow^N} = g$ , is called *multi-adjoint property-oriented concept*. g is called the *extension* and f, the *intension* of the concept.

The set of the concepts

$$\mathcal{M}_{\pi N} = \{ \langle g, f \rangle \mid g \in L_2^B, f \in L_1^A \text{ and } g^{\uparrow_{\pi}} = f, f^{\downarrow^N} = g \}$$

together with the ordering  $\leq$  defined by  $\langle g_1, f_1 \rangle \leq \langle g_2, f_2 \rangle$  iff  $g_1 \leq_2 g_2$  (or  $f_1 \leq_1 f_2$ ) forms a complete lattice,  $(\mathcal{M}_{\pi N}, \leq)$ , which is called *multi-adjoint property-oriented concept lattice*.

## Example: behavior of a motor

#### Example

For example, the experimental data could be:

$$\begin{array}{ll} \operatorname{oh}(ov_1) = 0.3 & \operatorname{oh}(ov_2) = 0.6 & \operatorname{oh}(ov_3) = 0.5 \\ \operatorname{lo}(o_1) = 0.3 & \operatorname{lo}(o_2) = 0.6 & \operatorname{lo}(o_3) = 0.5 \\ \operatorname{lw}(w_1) = 0.3 & \operatorname{lw}(w_2) = 0.8 & \operatorname{lw}(w_3) = 0.2 \end{array}$$

The multi-adjoint property-oriented context is  $(W, U, K, \sigma)$ , where the relation  $K: W \times U \rightarrow [0,1]_{100}$  is defined by

Table: Relation <i>H</i>	<	
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	lo	lw	
1	0.3	0.3	
2	0.6	0.8	
3	0.5	0.2	

### Example: behavior of a motor

#### Example

The fuzzy subset  $f_{oh}$ :  $W \rightarrow [0, 1]_{20}$  associated with oh is defined by  $f_{oh}(1) = 0.3$ ,  $f_{oh}(2) = 0.6$ , and  $f_{oh}(3) = 0.5$ . First of all, we compute  $(f_{oh})^{\downarrow^N}$ .

$$(f_{\rm oh})^{\downarrow^N}(lo) = 1.00 \ (f_{\rm oh})^{\downarrow^N}(lw) = 0.75$$

And then, the fuzzy subset  $(f_{oh})^{\downarrow^N\uparrow_{\pi}}$  is obtained.

Thus, the largest values to  $\vartheta_{1o}^{oh}$ ,  $\vartheta_{1w}^{oh}$  are 1.00, 0.75, respectively.

## Computing the complete set of solutions

The set of solutions Fuzzy Relation Equations can be characterized, providing a useful mechanism to obtain the whole set of solutions. This characterization is given by the equivalence classes  $\downarrow_{M}^{-1}(f_{v})$ .

### Theorem

The whole set of solutions of System (1) is

$$\mathrm{SS}_{\&}(f_{v})=(f_{v}^{\downarrow^{N}}]\setminus\bigcup\{(f_{v}^{\downarrow^{N}-}]\mid\langle f_{v}^{\downarrow^{N}-},f_{v}^{-}\rangle\in\mathrm{Pre}(\langle f_{v}^{\downarrow^{N}},f_{v}\rangle)\}$$

### Example

The considered equation can be solved and  $f_v^{\downarrow N} = (1.000, 0.750)$  is the greatest solution.

Now, we apply Theorem 9 to obtain the set of solutions. First of all, we compute the predecessors concepts of  $\langle f_v^{\downarrow^N}, f_v \rangle$  in the lattice  $\mathcal{M}_{\Pi N}(K)$ .

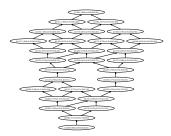


Figure: Concept lattice  $\mathcal{M}_{\Pi N}$ 

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### The whole set of solutions

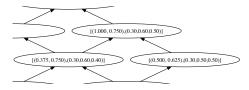


Figure: Concept lattice  $\mathcal{M}_{\Pi N}$ 

The set of the predecessors of the greatest solution is

 $\{\langle (0.375, 0.750), (0.30, 0.60, 0.40) \rangle, \langle (0.500, 0.625), (0.30, 0.50, 0.50) \rangle \}$ 

Solutions:  $((1.000, 0.750)] \setminus ((0.375, 0.750)] \cup ((0.500, 0.625)]$ 

$\{(1.000, 0.000),$	(1.000, 0.125),	(1.000, 0.250),	(1.000, 0.375),	(1.000, 0.500),
(1.000, 0.625),	(1.000, 0.750),	(0.875, 0.000),	(0.875, 0.125),	(0.875, 0.250),
(0.875, 0.375),	(0.875, 0.500),	(0.875,0625),	(0.875, 0.750),	(0.750, 0.000),
(0.750, 0.125),	(0.750, 0.250),	(0.750, 0.375),	(0.750, 0.500),	(0.750, 0.625),
(0.750, 0.750),	<b>(0.625</b> , <b>0.000</b> ),	(0.625, 0.125),	(0.625, 0.250),	(0.625, 0.375),
(0.625, 0.500),	(0.625, 0.625),	(0.625, 0.750),	(0.500, 0.750)}	

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## Example with no minimal solution

Frame:  $([0,1]_{10}, [0,1], [0,1], \&_{C}^{*})$ .

$\langle \texttt{oh}$	$\swarrow^*_{G}$	$\texttt{lo}, \vartheta_{\texttt{lo}}^{\texttt{oh}}  angle$
$\langle \texttt{oh}$	$\overline{\backslash}_{G}^{*}$	$\texttt{lw}, \vartheta_{\texttt{lw}}^{\texttt{oh}} \rangle$

Universes  $U = \{10, 1w\}, V = \{oh\}, W = \{1, 2\}$ , and the fuzzy relations K, D, defined by the matrices:

#### Table: Relations K and D.

	lo	lw			oh
1	0.2	0.3	1	L	0.1
2	0.5	0.7	2	2	0.1

the equation  $K \odot_{\sigma} R = D$  can be solved  $(\langle f_V^{\downarrow N}, f_V \rangle \in \mathcal{M}_{\Pi N}(K)).$ 

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### The greatest solution

Therefore, the greatest solution of the equation  $K \odot_{\sigma} R = D$ , which is equivalent to the system

$$\begin{array}{rcl} 0.2\,\&_G^*\,R(u_1,\,v)\lor 0.3\,\&_G^*\,R(u_2,\,v) &=& 0.1\\ 0.5\,\&_G^*\,R(u_1,\,v)\lor 0.7\,\&_G^*\,R(u_2,\,v) &=& 0.1 \end{array}$$

is the fuzzy relation  $R: U \times V \rightarrow [0,1]$ , defined by  $R(u_1, v) = 0.1$ ,  $R(u_2, v) = 0.1$ , which we can write as R = (0.1, 0.1).

In order to find out the rest of the solutions of the system, we need to obtain the predecessors of  $\langle f_v^{\downarrow N}, f_v \rangle = \langle (0.1, 0.1), (0.1, 0.1) \rangle$ .

The whole set of solutions has not minimal solutions

$$\operatorname{Pre}(\langle f_{v}^{\downarrow^{N}}, f_{v} \rangle) = \{\langle (0,0), (0,0) \rangle\}$$

Therefore, the complete set of solutions is

$$\begin{aligned} \mathrm{SS}_{\&}(f_{v}) &= (f_{v}^{\downarrow N}] \setminus \bigcup \{ (f_{v}^{\downarrow N-}] \mid \langle f_{v}^{\downarrow N-}, f_{v}^{-} \rangle \in \mathrm{Pre}(\langle f_{v}^{\downarrow N}, f_{v} \rangle) \} \\ &= \{ (x, y) \in [0, 1] \times [0, 1] \mid x \leq 0.1, y \leq 0.1 \} \setminus \{ (0, 0) \} \\ &= [0, 0.1] \times [0, 0.1] \setminus \{ (0, 0) \} \end{aligned}$$

The whole set of solutions is formed by  $R: U \times V \rightarrow [0,1]$ , defined as  $R(u_1, v) = x$ ,  $R(u_2, v) = y$ , with  $(x, y) \in [0, 0.1] \times [0, 0.1] \setminus \{(0, 0)\}$ , which clearly has no minimal elements.

## The abduction problem

The abduction problem considers two subsets of variables, the *observed variables*, *OV*, and the *hypotheses*, *H*,

and consists in find out the values of the hypotheses in order to explain the given values of the observed variables.

## Solving the abduction problem

#### Example

We consider as observed variables the propositional symbols:

$$\mathit{OV}~=~\{\texttt{nb},\texttt{oh}\}$$

and as hypotheses:  $H = {rm, lo, lw}$ .

Hence, we know the weights of the rules and the values of their heads for an observation  $ov_1$ ,  $nb_i$  and we need to find out the values of the propositional symbols in the body of each rule. Therefore, we must solve the system of multi-adjoint relation equations:

$$\begin{split} & \mathsf{oh}(ov_i) = (\mathsf{lo}(o_i) \,\&_{\mathrm{G}}^* \,\vartheta_{\mathsf{lo}}^{\mathsf{oh}}) \lor (\mathsf{lw}(w_i) \,\&_{\mathrm{P}}^* \,\vartheta_{\mathsf{lw}}^{\mathsf{oh}}) \lor (\mathsf{rm}(r_i) \,\&_{\mathrm{P}}^* \,0) \\ & \mathsf{nb}(nb_i) = (\mathsf{lo}(o_i) \,\&_{\mathrm{G}}^* \,\vartheta_{\mathsf{lo}}^{\mathsf{nb}}) \lor (\mathsf{lw}(w_i) \,\&_{\mathrm{P}}^* \,0) \lor (\mathsf{rm}(r_i) \,\&_{\mathrm{P}}^* \,\vartheta_{\mathsf{rm}}^{\mathsf{nb}}) \end{split}$$

the values of  $lo(o_i)$ ,  $lw(w_i)$ ,  $rm(r_i)$  are unknown.

### Example abduction reasoning

Frame:  $([0,1]_{10},[0,1],[0,1],\&_{\mathrm{G}}^*)$ .

 $\begin{array}{lll} \langle \text{oh} & \swarrow_{\mathrm{G}}^{*} & \text{lo}, 0, 2 \rangle & & \langle \text{oh} & \swarrow_{\mathrm{G}}^{*} & \text{lw}, 0.3 \rangle \\ \langle \text{nb} & \swarrow_{\mathrm{G}}^{*} & \text{rm}, 0.5 \rangle & & \langle \text{nb} & \swarrow_{\mathrm{G}}^{*} & \text{lo}, 0.7 \rangle \end{array}$ 

Universes  $U = \{\vartheta_{lo}, \vartheta_{lw}\}, V = \{1\}, W = \{oh, nb\}$ , and the fuzzy relations K, D, defined by the matrices:

#### Table: Relations K and D.

	$\vartheta_{\texttt{lo}}$	$\vartheta_{\mathtt{lw}}$		1
oh	0.2	0.3	oh	0.1
nb	0.5	0.7	nb	0.1

the equation  $K \odot_{\sigma} R = D$  can be solved.

### Papers

Jesús Medina and Juan Carlos Díaz-Moreno Multi-adjoint relation equations: Definition, properties and solutions using concept lattices. *Information Sciences*, 253: 100–109, 2013.

Jesús Medina and Juan Carlos Díaz-Moreno Using concept lattice theory to obtain the set of solutions of multi-adjoint relation equations. *Information Sciences*, 266: 218–225, 2014.

Jesús Medina, Esko Turunen and Juan Carlos Díaz-Moreno An algebraic characterization to compute minimal solutions of general fuzzy relation equations on linear carriers. Submitted.

## Conclusions and future work

- Multi-adjoint logic programming is a general framework of fuzzy logic programming.
- Multi-adjoint relation equations are the most flexible relation equation that can be solved, at the moment.
- Two important problems in fuzzy logic programming have been considered, find out the weights of the rules of a multi-adjoint logic program and the abduction problem, which have been solved using fuzzy relation equations.
- In the future, more problems will be considered. Moreover, the comparison of other mechanism to solve the adductive reasoning will be studied.

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 Computing the weights
 Solving abduction problem
 Conclusions

- Cornejo ME, Medina J, Ramírez-Poussa E (2013) A comparative study of adjoint triples. Fuzzy Sets and Systems 211:1–14, DOI 10.1016/j.fss.2012.05.004
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# THANK YOU FOR YOUR ATTENTION

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