Argumentation with Goals for Clinical Decision Support in Multimorbidity

Extended Abstract

Tiago Oliveira
National Institute of Informatics
Tokyo, Japan
toliveira@nii.ac.jp

Jérémie Dauphin
University of Luxembourg
Esch-sur-Alzette, Luxembourg
jeremie.dauphin@uni.lu

Ken Satoh
National Institute of Informatics
Tokyo, Japan
toliveira@nii.ac.jp

Shusaku Tsumoto
Department of Medical Informatics, Faculty of Medicine, Shimane University
Izumo, Japan
tsumoto@med.shimane-u.ac.jp

Paulo Novais
Department of Informatics/Algoritmi Research Centre, University of Minho
Braga, Portugal
pjon@di.uminho.pt

ABSTRACT

The present work proposes a computational argumentation system equipped with goal seeking to combine independently generated recommendations for handling multimorbidity.

KEYWORDS

Argumentation; Clinical Decision Support; Conflict Resolution;

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1 INTRODUCTION

Multimorbidity is the presence of two or more medical conditions [7, 9]. It poses challenges, namely in the use of multiple drugs, which brings risks related to the interaction of the different drugs among themselves (drug-drug interactions) and the effects their combination may have on the patient's body (drug-disease interactions). The few existing computational frameworks addressing this problem and aggregating recommendations produced from different sources [4, 10–12], present limitations at the level of the number of Computer-Interpretable Guidelines (CIGs) they are able to combine and the dimensions of multimorbidity considered in their reasoning models. Regarding this last aspect, these works do not include the representation of human-centric aspects of decision-making in multimorbidity, namely those that are related to preferences expressed by the physicians and patients regarding the treatment.To answer these challenges, we present a structured argumentation framework called ASPIC-G and provide the following contributions in this paper: (i) representation and reasoning mechanisms for aggregating CIG recommendations from multiple agents; (ii) an argumentation system called ASPIC-G that provides an explicit and explanatory representation of the different conflicts in a decision-making situation; (iii) an extension to the ASPIC+ argumentation system by including goals in the argumentation process.

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2 CASE EXAMPLE

The case example to be used throughout the paper [7, 9], is the following.

Example 2.1. Patient A is a 69-year-old man with a 5-year history of type 2 diabetes. Upon consultation and the completion of medical exams, it was possible to conclude that the patient has uncontrolled type 2 diabetes, obesity, and severe chronic kidney disease. The latter is a common condition characterized by the progressive loss of kidney function over a period of months or years.

The example describes the current state of a patient that has three health conditions. The case is run in a system with CIG agents that handle each one of these conditions separately, with the following recommendations and explanations.

CIG Agent 1 (for obesity): Define weight loss (*w_loss*) as a therapy goal. In order to reduce weight, the patient should practice diet and exercise (*diet_ex*).

CIG Agent 2 (for diabetes): Define blood glucose lowering (*gluc_low*) as a therapy goal. Sulfonylurea (*sulf*) or meglitinide (*meg*) can reduce blood glucose elevations, but they are also associated with weight gain (*w_gain*). Metformin (*met*) can lower blood glucose by reducing hepatic glucose. The patient should only take one of the drugs.

CIG Agent 3 (for kidney disease): Define delay kidney disease (*delay_kid*) as a therapy goal. To that effect, the patient is advised to take angiotensin converting enzyme inhibitors (*ang_conv_enz*), as they have been found to slow the progression of chronic kidney disease to kidney failure. In severe chronic kidney disease, the use of metformin should be avoided as the drug generates large amounts of lactic acid, which may cause the kidneys to overwork ant thus deteriorate faster (*acc_kid*).

In essence, following the three CIG Agents separately would generate conflicts at the level of treatment effects/ treatment goals.

In real practice, this type of case is handled by establishing a priority of therapy goals, and thus addressing the goals by order of importance. This reflects the emerging trend in health care of collaborative goal setting [1, 8], with the involvement of patients in their own treatment process.

3 THE ASPIC-G ARGUMENTATION SYSTEM

We define the ASPIC-G argumentation system as follows.

Definition 3.1. An argumentation theory in ASPIC-G is a tuple $\langle \mathcal{L}, \mathcal{R}, n, \mathcal{G}, \leqslant \rangle$, where:

- $\mathcal{L}$ is a logical language closed under negation ($\neg$).
- $\mathcal{R} = \mathcal{R}_s \cup \mathcal{R}_d$ is a set of strict ($\mathcal{R}_s$) and defeasible ($\mathcal{R}_d$) rules of the form $\phi_1, ..., \phi_n \rightarrow \phi$ and $\phi_1, ..., \phi_n \Rightarrow \phi$ respectively, where $n \geq 0$ and $\phi_i, \phi \in \mathcal{L}$.
- n is a partial function such that $n : \mathcal{R} \rightarrow \mathcal{L}$.
- $\mathcal{G} \subseteq \mathcal{L}$ is a set of goals that the arguments will try to fulfil such that $\forall\ \theta \in \mathcal{G}$, there exists a rule $\phi_1, ..., \phi_n \rightarrow \phi$ in $\mathcal{R}_s$ or $\phi_1, ..., \phi_n \Rightarrow \phi$ in $\mathcal{R}_d$ such that $\phi = \theta$.
- $\leqslant$ is a total relation transitive and reflexive over $\mathcal{G}$ which represents preference of the goals, with $a < b$ iff $a \leqslant b$ and $b \nleqslant a$.

The construction of arguments follows the structure defined in ASPIC+ [5]. Attacks are also defined as in ASPIC+, with the exception that only *rebuttal* and *undercutting* are allowed. *Undermining* attacks as a special case of rebuttal. The selection of arguments follows Dung's abstract argumentation framework [3]. Given the context in which ASPIC-G is applied, it is of interest to produce the *preferred extensions*, and thus maximal, self-defended sets of arguments. When using ASPIC-G for decision-making, the aim is to fulfil the preferred goals. Similar goal-driven mechanisms in argumentation have been proposed in [2] and [6]. As such, each preferred extension is lifted to a goal extension, containing the goals it fulfils. A **goal extension ordering** $GE_A \trianglelefteq_{GE} GE_B$ denotes that GE_A is less preferred than GE_B. This ordering is determined by several factors. However, the underlying principle is that the argumentation system will always try to fulfil the goals by their order of importance. As such, assuming a goal preference order $a < b < c$, the priority will always be fulfilling goal c. Therefore, if we have goal extensions $\{c\}$ and $\{a, b\}$, then $\{a, b\} \trianglelefteq_{GE} \{c\}$. Not fulfilling any goals is the least preferred alternative. Notice that every set is equally preferred to itself. The preferred set is the one with the most preferred goal, with respect to the maximal elements of each set. The ordering $\trianglelefteq_{GE}$ is placed over their respective preferred extensions to determine which hold the most suitable solutions for the argumentation.

4 MULTIMORBIDITY IN ASPIC-G

Assuming the goals given in Example 2.1, $\mathcal{G} = \{w\_loss, gluc\_low, delay\_kid\}$, and goal preference order, $w\_loss < delay\_kid < gluc\_low$, as well as the rules derived from the example, it is possible to build the following arguments:

$A_1 :\Rightarrow diet\_ex.$
$A_2 : A_1 \Rightarrow w\_loss.$
$B_1 :\Rightarrow sulf.$
$B_2 : B_1 \rightarrow gluc\_low.$
$B_2' : B_1 \rightarrow \neg met.$
$B_2'' : B_1 \rightarrow \neg meg.$
$B_2''' : B_1 \rightarrow w\_gain.$
$B_3 : B_2''' \rightarrow \neg r_1.$
$C_1 :\Rightarrow meg.$
$C_2 : C_1 \rightarrow gluc\_low.$
$C_2' : C_1 \rightarrow \neg met.$
$C_2'' : C_1 \rightarrow \neg sulf.$
$C_2''' : C_1 \rightarrow w\_gain.$
$C_3 : C_2''' \rightarrow \neg r_1.$
$D_1 :\Rightarrow met.$
$D_2 : D_1 \rightarrow gluc\_low.$
$D_2' : D_1 \rightarrow \neg meg.$
$D_2'' : D_1 \rightarrow \neg sulf.$
$E_1 :\Rightarrow ang\_conv\_enz.$
$E_1' :\rightarrow chron\_kid\_dis.$
$D_2''' : E_1', D_1 \rightarrow acc\_kid.$
$D_3 : D_2''' \rightarrow \neg delay\_kid.$
$D_4 : D_3 \rightarrow \neg ang\_conv\_enz.$
$E_2 : E_1, E_1' \rightarrow delay\_kid.$
$E_3 : E_2 \rightarrow \neg acc\_kid.$
$E_4 : E_1', E_3 \rightarrow \neg met.$
$G_1 : w\_loss.$
$G_2 : gluc\_low.$
$G_3 : delay\_kid.$

To reduce the complexity of the problem, we simplify the derived arguments by merging them with respect to their most relevant rule. Since, in this case, the elements of interest consist of treatments to apply to the patient, the defeasible rules denoting them become the most relevant rules. Following this principle, we obtain the following arguments: argument A_1 conveys that the patient should do diet and exercise; argument A_2 conveys that diet and exercise lead to weight loss; argument B conveys that the patient should take sulfonylurea; argument C conveys that the patient should take meglitinide; argument D conveys that the patient should take metformin; argument E conveys that the patient should take angiotensin converting enzyme. Based on this simplification step, we are able to calculate the preferred extensions (P_i) of the simplified argumentation theory. We also calculate their respective goal extensions (GE_{P_i}). The results are the following:

- $P_1 = \{A_1, B, E\}$, $GE_{P_1} = \{G_2, G_3\}$
- $P_2 = \{A_1, C, E\}$, $GE_{P_2} = \{G_2, G_3\}$
- $P_3 = \{A_1, A_2, D\}$, $GE_{P_3} = \{G_1, G_2\}$

So we have three possible solutions for the argumentation theory: S_1, S_2, and S_3. Each one fulfilling their respective goals. Considering the already established goal order of $G_1 < G_3 < G_2$, we calculate the goal extension ordering $\trianglelefteq_{GE}$ and then use it to calculate, the preferred extension ordering $\trianglelefteq_P$:

- $GE_{P_3} \trianglelefteq_{GE} GE_{P_1}, GE_{P_2}$
- $P_3 \trianglelefteq_P P_1, P_2$

Extensions P_1 and P_2 both fulfil the two top goals and are the top solutions to this argumentation theory in multimorbidity. This means that in Example 1, the patient should practice diet and exercise, take either sulfonylurea or meglitinide for his diabetes problem in order to reduce blood glucose, and take angiotensin converting enzyme to delay the progression of kidney disease. This is the consistent treatment. The ASPIC-G argumentation system ensures that the most important goals in the treatment process are achieved.

5 CONCLUSIONS

The purpose of ASPIC-G is to model discussions driven by goals, where it is not only important to have explanatory arguments in favour or against a position, but also to know where argumentation paths lead to. This is done by combining the recommendations of agents and deriving conflicts that arise from them.

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