Autonomous adaptation of software agents in the support of human activities

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Abstract. This paper is aimed at formalize the interplay among a person to be assisted, an assistive agent-based software, and a caregiver. We propose principles that agents should follow in such interplay, this principles may have impact in different agent-based assistive technology. We propose a mechanism to integrate individual's information into the final decision-making process of an agent. Moreover, we endow agents with mechanisms for evaluating the distance between independent and supported activity execution, the so called zone of proximal development (ZPD) in four scenarios: I) independent activity execution; II) ZPD_H activity performance of a person when is supported by another person (*e.g.* a therapist); III) the ZPD_S representing a potential activities when a person is supported by a software agent; and IV) the ZPD_{H+S} when a person is supported by a caregiver and a software agent. Formal argumentation theory is used as foundation. Our formal models were tested using a prototype using augmented reality as assistive software. A pilot study with older adults and health-care personnel was performed and formal and empirical results are presented.

Keywords: Argumentation theory · Rational agents · Assistive technology · Human activity · Activity theory.

1 Introduction

This paper is aimed at investigate assistive technology using argumentation-based agents and the interplay with individuals that require physical assistance and their caregivers.

We present formal and empirical results on how *intelligent* software adapts to support activities of individuals including, those who need assistance and care givers. The focus of the paper is on the provision of *human-like* characteristics to software agents in order to provide adaptable support, namely *common-sense* and reflection on action decision. The proposed agent model is oriented to reason about human activities, *i.e.*, identify, interpret and support individuals during the execution of physical activities. To this end, representations of complex activities from Activity Theory [14] were utilized to characterize the knowledge of software agents and model their decision-making process. Formal argumentation theory is used to provide non-monotonic reasoning to the agents. Moreover, we present a novel information model oriented at how an agent[3] may *reflect* on their actions. In human learning literature, reflection enables a person to correct distortions in her/his beliefs and errors in problem-solving [16]. We contribute with a first step on how rational software agents may reflect during the support of human activities.

Finally, as core of our research, we propose a model of adaptation of a support level for agents, based on a computation version of the so-called *zone of proximal development* (ZPD) [22]. Our model of adaptation is formally presented and empirically tested.

The research questions (RQ) addressed in this paper are the following:

– **RQ1**: how an agent may infer potential activities that an individual needs and performs with and without its assistance?
– **RQ2**: in a smart environment scenarios, where individuals require support from others to execute an activity, how an agent-based software may adapt autonomously to team-up with humans to enhance such support?
– **RQ3**: how rational agents can "reflect" on decision to make when a human is in the loop?

2 Material and methods

In this paper, the human perspective is investigated using Activity Theory [14], which is a social sciences framework oriented to understand human complex activities. On the other hand, formal argumentation theory is used to characterize precisely the internal reasoning of agent software.

2.1 Activity theory

In this paper, activity theory is used with two purposes: 1) for structuring the knowledge of an agent following a hierarchical model; and 2) to understand the potential level of activity achievement of a person.

Activity as structure. An activity consists of a set of *actions*. At the lowest level, an action consists of a set of *operations*. Actions are oriented to goals and are executed by the actor at a conscious level, in contrast with operations which do not have a goal of their own and which are executed at the lowest level as automated, unconscious processes. An *activity model* (AT) (see Definition 1) corresponds to information of a person that an agent uses to reason about an activity. In artificial intelligence literature, this hierarchical structure has been used as framework to represent knowledge of software agents, *e.g.* in [8,10,11,17].

Potential level of activity achievement. Vygotsky in [22] proposed to measure the level of development not through the level of current performance, but through the difference ("the distance") between two performance indicators: 1)

[3] Hereinafter we will identify a rational software agent as just an agent.

an indicator of independent problem solving, and 2) an indicator of problem solving in a situation in which the individual is provided with support from other people [13]. This indicator was coined as a zone of proximal development ZPD and it has been used extensively in social sciences (see [2,5,12,20]) to understand changes of individuals during assisted learning processes.

ICF qualifiers. The notion of *qualifier* to specify the extent of the functioning or disability of an individual was introduced by the International Classification of Functioning, Disability and Health (ICF)[4] [18] proposing two main quantifiers: *performance* and *capacity*. In general, a qualifier specifies information about functioning status: the magnitude, the location and the nature of any activity-related problem [19].

2.2 Formal argumentation theory

Argumentation-based systems, have become influential in artificial intelligence particularly in multi-agent systems design (see [4] for a systematic review).

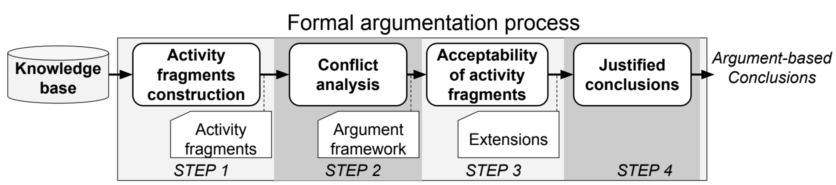

Fig. 1. Inference of an argument-based conclusion using a formal argumentation process

Formal argumentation can be seen as a process consisting of the following steps (see Figure 1): 1) Constructing *arguments* (in favor of _ against a "statement") from a knowledge base; 2) Determining the different *conflicts* among the arguments; 3) Evaluating the *acceptability* of the different arguments; and 4) Concluding, or defining the *justified conclusions*. From artificial intelligence perspective, the important and distinctive characteristics of this process are: 1) their *non-monotonic* behavior, *i.e.,* changing the conclusion when more knowledge is added, and 2) their *traceability*, providing explanations in every step of the reasoning process. In Appendix A, underlying theory is presented summarizing formal processes (STEP1-4) in Figure 1. Formal results presented in Section 3.1 rely upon of that underlying theory. In Figure 2, an argumentation process over an activity is presented as example.

3 Results

In this section, we report formal and empirical results. A pilot evaluation study was performed using a prototype that we developed. The evaluation setting and some results are briefly described in the end of this section.

[4] http://www.who.int/classifications/icf/en/

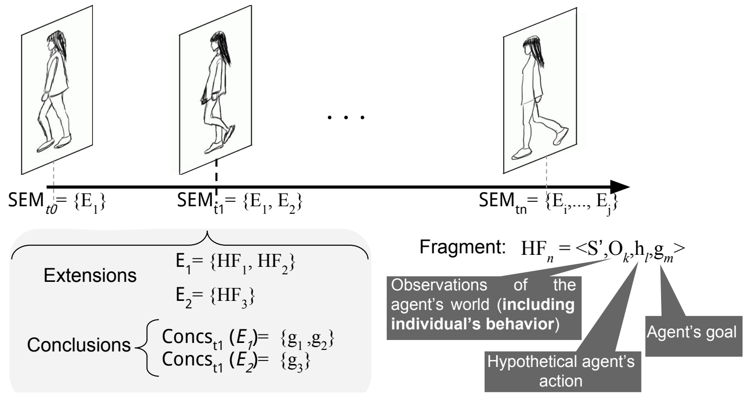

Fig. 2. Goal oriented decision-making using an argument-based reasoning. An activity model AT, describes a person executing an activity: walking. At time *t1* SEM is calculated. Two extensions are obtained with two sets o available goals: g_1, g_2 and g_3.

3.1 Formal results

Two main formal results are presented in this section: 1) a mechanism for agent's decision-making based on the individual's information analyzing consequences of hypothetical actions a mechanism that we called *reflection*; and 2) a formalism to determine the potential of activity performance in four different cases: independence, supported by another person, supported by a software agent and supported by a team person-agent.

3.1.1. Reflection on decisions about human activity Conclusions of an argument-based process (Appendix A Definition 9, see also Figure 2) about an activity, may contain sets of goal-based conclusions sets, indicating that the agent has different available decision alternatives which are consistent. We propose add a mechanism for selecting an appropriate decision but considering those agent's actions that maximize humans' goals (Go) in an *activity model* (AT model Definition 1). An AT model captures all the information necessary to define a human activity. We condensed this process in Algorithm 1.

In short, Algorithm 1 takes as input the AT model and the set of extensions from a previous common-sense reasoning output. In lines 8-15 of Algorithm 1 a qualifier is calculated (line 12) over sets of sets of fragments (the so-called *extensions* in argumentation theory, see Appendix A). This qualifier calculation is based on computing a similarity function between the current achievement of human goals in AT ($\mathcal{O}_{\mathsf{Go}}$) *w.r.t.* a set of goal reference ($\mathsf{Ref}_{\mathsf{Go}}$ line 12). The $\mathcal{Q}$ function depicted in line 12, follows the qualifier idea presented in previous approaches [10,11], returning a numerical value ($0 \leq \alpha \leq 4$).

The importance of Algorithm 1 lies on the mechanism for associating a human activity quantification with the internal action decision of an agent. From a computational complexity perspective, this algorithm may be $O(N^2)$ in the worst case, however the number of extensions *numExt* (line 4) depends on the utilized

Algorithm 1: Goal-based action reflection

input : $\mathcal{E}$, AT
output : $h \in \mathcal{H}_A$

$H \longleftarrow \emptyset$ // list of agent's decisions
$\mathsf{Go} \longleftarrow \emptyset$ // list of human's goals
$\mathsf{Ref} \longleftarrow \emptyset$ // list of human's reference goals
$numExt = |\mathcal{E}|$ // number of extensions
$numArg = |\mathcal{A}|$ // number of arguments per extension
$\alpha \longleftarrow 0$ // numeric value of a qualifier $(0 \leq \alpha \leq 4)$
$decisionLat < \alpha, h >=$ // lattice of decisions
for $i \leftarrow 0$ **to** $numExt$ **do**
  for $j \longleftarrow 0$ **to** $numArg$ **do**
    $h \longleftarrow$ `Act` (hf_j)
    $\mathcal{O} \longleftarrow$ `Obs` (hf_j)
    $\alpha \longleftarrow \mathcal{Q}(\mathcal{O}_{\mathsf{Go}}, \mathsf{Ref}_{\mathsf{Go}})$ // Qualifier function considering observations and a reference value *w.r.t.* person goals Go
    $decisionLat \longleftarrow (\alpha, h)_{hf_j}$ // decision tuple is qualifier and an agent's decision *w.r.t* the current fragment
  end
end
return $max(\alpha, h)$

argumentation semantic. In fact, algorithm output depends entirely of previous extensions computation. Proposition 1 and Proposition 2 present two special cases of agent's behavior when Algorithm 1 is used[5]. One is the possibility to have a conclusion with no action, and the second expresses an inconclusive behavior given that stable semantics may return $\emptyset$ as output.

Proposition 1. *An agent calculating th goal-based action reflection Algorithm 1 using a skeptic semantics, grounded or ideal, may result in a conclusive empty decision.*[6]

Proposition 2. *An agent calculating th goal-based action reflection Algorithm 1 using the credulous semantics: stable, may result in a inconclusive decision.*[7]

3.1.2. Zone of proximal development using formal argumentation In this section, based on the common-sense reasoning of activities using argumentation theory, we propose a theory to calculate the following four scenarios in assistive agent-based technology:

I. Independent activity execution This scenario describes an *observer agent* which takes a decision which is purposefully do nothing to support a person, or the decision is empty. More formally, the type of fragments (Definition

[5] We refrain of describing fully the proofs of these propositions due the lack of paper space
[6] Proof sketch: output of grounded and ideal may include $\{\emptyset\}$. See [6]
[7] Proof sketch: output of stable semantics may include $\emptyset$. See [6]

3) generated by the agents are with the form $HF = \langle S, O^{'}, h^*,\ g\rangle$ such that $h^* \in \mathcal{H}_A = \{\emptyset, do\_Nothing\}$. In this setting, all the extensions generated by $SEM(AF_P) = \mathcal{E}$ during a period of time will create an activity structure. In other words, the cumulative effect of generating fragments, re-construct an activity in a bottom-up manner. Moreover, Algorithm 1 returns only values of α, *i.e.* the current value of a qualifier when the agent does not take any support action. This context defines the baseline of activity execution independence of a person.

II. ZPD_H: activities supported by another person Similarly to previous scenario, the role of the software agent is being an observer. However, built fragments have the form $HF = \langle S, O^*, h^*,\ g\rangle$ such that $h^* \in \mathcal{H}_A = \{\emptyset, do\_Nothing\}$ and $O^* = O^{'} \cup O^{''}$, where O^* is the set of joint observations from the agent's perspective about the individual supported ($O^{'}$) and the supporter $O^{''}$. We have that $O^{'} \subseteq O^{''}$, and $O^{'}, O^{''} \neq \emptyset$. In this scenario, $O^{''}$ is considered a reference set of observations (Ref lines 3 and 12 in Algorithm 1). Algorithm 1 will return a value of α which measures in what extent an individual follows the guide provided by another person.

When multiple extensions are collected during the period of time that the individual is supported, then a different set of activities than individual activity execution may be re-generated in a bottom-up manner.

III. ZPD_S: activities supported by an agent In this scenario, an *assistive agent* takes a decision oriented to uphold human interests. This is a straightforward scenario where $h \in \mathcal{H}_A \neq \{\emptyset, do\_Nothing\}$.

IV. ZPD_{H+S}: human-agent supporting In this scenario, the main challenge for the agent perspective is detect: 1) actions that an assistant person executes, and 2) observations of both, the person assisted and the person who attends. This is similar to ZPD_H but with fragments built from $\mathcal{H}_A \neq \{\emptyset, do\_Nothing\}$. In this case, the level of ZPD_{H+S} is given by Algorithm 1, and the set of extensions $\mathcal{E}$ with *aligned* goals between agent and human assistant.

Proposition 3. *Let $\mathcal{O}_{\mathsf{Go}}$ be a set of observations about human goals (Go) and actions (Ax) framed on an activity, captured by an agent using an activity model AT. Let $\mathcal{G}$ and $\mathcal{H}_A$ be agent's goals and its hypothetical actions. In order to provide non-conflicting assistance two properties have to be fulfilled:*

- *PROP1:* $\mathcal{O}_{\mathsf{Go}} \cap \mathcal{G} \neq \emptyset$
- *PROP2:* $\mathcal{O}_{\mathsf{Ax}} \cap \mathcal{H}_A \neq \emptyset$

PROP1 and PROP2 provides coherence among human-agents actions and goals. This two properties may define a first attempt to establish consistency principles of agent-based assistance. This is a future work in our research.

3.2 Empirical results

3.2.1. Prototype and pilot evaluation The scenario selected to test our approach was framed on supporting an older adult in the activity: *medication management* using a *smart medicines cabinet*. In a smart environment[8] devel-

[8] 360 degrees view of the lab: `https://goo.gl/maps/rq3YiF1c5An`

oped at the *user, interaction and knowledge management* research group[9], we setup the smart cabinet [10] (see Figure 3).

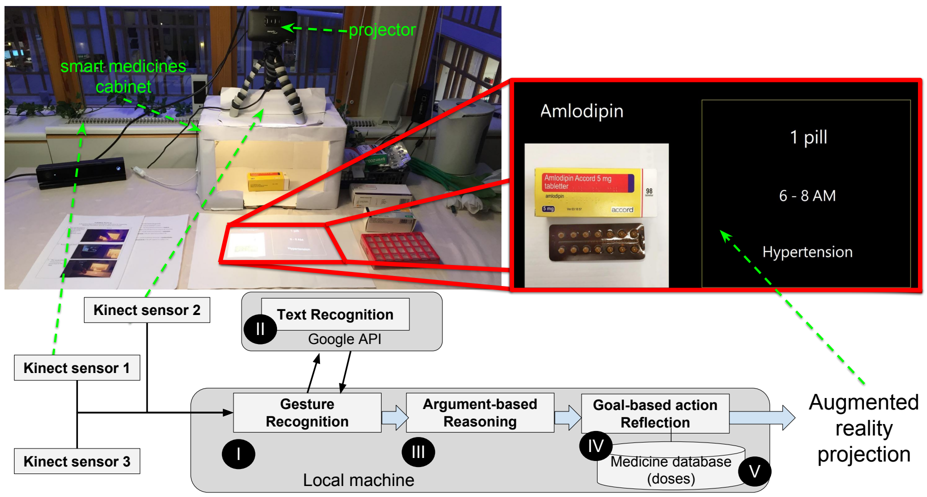

Fig. 3. Smart medicines cabinet using argument-based reasoning and an augmented reality projection. I) Gesture recognition using three Kinect cameras, one for client body capture, another for assistant personal gesture recognition, last one (Kinect sensor 2) on the top of the cabinet to recognize text from medicines boxes; II) Google API for text recognition; III) common-sense reasoning; IV) goal-based action reflection to consider human side; V) database containing doses and timing of pill intake.

Architecture summary: Our prototype consists of five main parts: 1) gestures recognition: obtaining observations from individuals using Kinect cameras; 2) text recognition using anotjer Kinect camera with Google API text recognition (`https://cloud.google.com/vision`); 3) argument-based reasoning: the main agent-based mechanism of common sense reasoning; 4) goal-based action reflection generating an augmented reality feedback: a module to generate support indications as projections in the smart environment; and 5) a database of medicine doses to obtain appropriate messages[11]. We use three 3D cameras to capture: 1) observations of an individual that needs help in a physical activity; 2) observations of the smart environment, including a supporting person; and 3) information of the handle gestures of medicine manipulation. A central computer was connected to the cameras, processing the information in real-time analyzing gestures of individuals as observations for the agent. The agent platform (JaCaMo) was used to build the agent. An argumentation process was used

[9] Computing Science department Umeå University- Sweden
[10] Due the lack of space, we briefly describe the smart cabinet prototype which is connected to our agent-based platform
[11] Sources and documentation of the prototype can be found in `https://github.com/esteban-g`

using an argumentation library previously developed (see [9]). An agent try to update/trigger its plan every frame time that a pre-defined gesture of the 3D camera. Those pre-defined gestures were defined in Stage 1 and Stage 2 with users and experts.

Pilot evaluation setting summary: This pilot study recruited five participants comprised of three target users (TA-1, TA-2, TA-3; mean = 65, SD = 7.21) and two health-care professionals (S-1, S-2). All of the participants had technology experience using computers . The procedure comprised three stages: 1) baseline interview (subjects: TA-1, TA-2, TA-3 + S-1, S-2); 2) interview with a nurse (S-2); and 3) prototype evaluation (subjects: TA-1, TA-2 + S-2). For a lack of space we only describe the third stage in which participants interact the smart platform. In the third stage, TA-1 participated the evaluation in his home and the other two participates evaluated the system. They were asked to read the instruction message from the augmented reality projection and then, distribute three medications with different prescriptions by using the system. The Assessment of Autonomy in Internet-Mediated Activity protocol (AAIMA) [15] was used to evaluate ZPD. A comparison between our agent ZPD and AAIMA results were obtained. In Table 1 results of ZPD-S and ZPD-H were obtained.

Level of activity	Activity description	Level of independence		
Activity	**Distribute Medication**	TA-1	TA-3	S-2
Level 0	Understands the purpose of the activity but does not participate	A	A	A
Level 1	Contributes with operation information	ZPD-S	ZPD-S	ZPD-S
Level 2	Contributes with medication information	ZPD-S	ZPD-S	ZPD-S
Level 3	Completes the medication distribution	ZPD-H	ZPD-S	ZPD-S
Action	**Understand Medication Instruction**			
Level 0	Able to trigger the projection of medication instruction	ZPD-S	ZPD-S	ZPD-S
Level 1	Understands the different contents of medication instruction	ZPD-S	ZPD-S	ZPD-S
Level 2	Able to use the instruction to distribute medication	ZPD-S	ZPD-S	ZPD-S
Level 3	Full understanding of the function of the system and its role in medication distribution	ZPD-S	ZPD-S	ZPD-S
Operation	**Interact with interaction devices**			
Level 0	Basic tasks have a goal in itself, i.e., executed as activities	A	A	A
Level 1	Basic tasks have partly been integrated in activity as actions among other actions	A	A	A
Level 2	Basic tasks are partly operationalized, causes breakdowns but is handled by the individual	ZPD-H	ZPD-H	ZPD-H
Level 3	Basic tasks are operationalised	ZPD-S	ZPD-S	ZPD-S

Table 1. AAIMA Protocol for assessing medication management

4 Discussion and conclusions

Our main contribution in this paper is in general, a formal understanding of the interplay among an assistive agent-based software, a person to be assisted and a caregiver. Moreover, as far as we know, this is a first attempt to formalize the behavior of rational agents using formal argumentation theory, in four scenarios (see Section 16). We propose two properties (Proposition 3) that software agents should follow if their goals are linked to human goals. The relevance and impact of these properties not only covers agents based on formal argumentation theory, but other approaches, such as those based on the Belief Desire Intention model [3].

We propose an algorithm to integrate individual's information (the AT model Definition 1) into the final decision-making process of an agent. This mechanism captured in Algorithm 1, resembles a process of "reflection" which in humans is a re-consideration of actions and goals given some other parameters. In fact, our reflection mechanism maybe seen as an action-filtering process with the human-in-the-loop[12]. We also analyze different outputs of Algorithm 1 considering two groups of argumentation semantics (Propositions 1 and 2).

We evaluate our approach in a three stages pilot study using a scenario of medication management as a complex activity. In this regard, we conducted an experiment with older adults and practitioners to evaluate such activity. We developed a prototype platform using augmented reality projecting assistive messages about medication when a person required some support. For lack of space, we did not fully report in this paper, the full functioning of the platform neither the process of co-design and expert feedback.

A Formal argumentation background

We use a propositional logic with a syntax language constituted by propositional symbols: $p_0, p_1, \ldots$; connectives: $\wedge, \leftarrow, \neg$, *not*, $\top$; and auxiliary symbols: (,), in which $\wedge, \leftarrow$ are 2-place connectives, $\neg$, *not* are 1-place connectives and $\top$ is a 0-place connective. Propositional symbol $\top$ and symbols of the form $\neg p_i (i \geq 0)$ stand for indecomposable propositions which we call *atoms*, or *atomic propositions*. Atoms of the form $\neg a$ are called *extended atoms* in the literature. An *extended normal clause*, C, is denoted: $a \leftarrow b_1, \ldots, b_j,\ not\ b_{j+1}, \ldots, not\ b_{j+n}$ where $j+n \geq 0$, a is an atom and each $b_i (1 \leq i \leq j+n)$ is an atom. When $j+n=0$ the clause is an abbreviation of $a \leftarrow \top$ such that $\top$ always evaluates true.

Definition 1 (Activity model). *Let P be a logic program capturing the behavior rules of an activity. $\mathcal{L}_P$ denotes the set of atoms which appear in a program P. An **AT model** is a tuple of the form $\langle \mathsf{Ax}, \mathsf{Go}, \mathsf{Op} \rangle$ in which:*
- *$\mathsf{Ax} = \{ax_1, \ldots, ax_j\} (j > 0)$ is a set of atoms such that $\mathsf{Ax} \subseteq \mathcal{L}_P$. Ax denotes the set of actions in an AT model.*
- *$\mathsf{Go} = \{g_1, \ldots, g_k\} (k > 0)$ is a set of atoms such that $\mathsf{Go} \subseteq \mathcal{L}_P$. Go denotes the set of goals in an AT model.*
- *$\mathsf{Op} = \{o_1, \ldots, o_l\} (l > 0)$ is a set of atoms such that $\mathsf{Op} \subseteq \mathcal{L}_P$. Op denotes the set of goals in an AT model.*

An activity framework corresponds to the goals, observations and actions of an agent oriented to assist a human during the execution of an activity, which in turn is represented by the AT model.

[12] A concept to integrate human information in *cyber-physical systems* [21]

Definition 2 (Activity framework). *An activity framework ActF is a tuple of the form* $\langle P, \mathcal{H}_A, \mathcal{G}, \mathcal{O}, \mathsf{AT}\rangle$ *in which:*

- P *is a logic program.* $\mathcal{L}_P$ *denotes the set of atoms which appear in* P.
- $\mathcal{H}_A = \{h_1, \ldots, h_i\}$ *is a set of atoms such that* $\mathcal{H}_A \subseteq \mathcal{L}_P$. $\mathcal{H}_A$ *denotes the set of hypothetical actions which an agent can perform in a world.*
- $\mathcal{G} = \{g_1, \ldots, g_j\}$ *is a set of atoms such that* $\mathcal{G} \subseteq \mathcal{L}_P$. $\mathcal{G}$ *denotes a set of goals of an agent.*
- $\mathcal{O} = \{o_1, \ldots, o_k\}$ *is a set of atoms such that* $\mathcal{O} \subseteq \mathcal{L}_P$. $\mathcal{O}$ *denotes a set of world observations of an agent.*
- AT *is an activity model of the form:* $\langle \mathsf{Ax}, \mathsf{Go}, \mathsf{Op}\rangle$*, following Definition 1.*

ActF according to Definition 2 defines the space of knowledge of assistive agents without considering external assistance, for example from other assistive agents (human or software) actions. In this knowledge space, an argument-based process (see Figure 1) can be performed to obtain sets (or sets of sets) of explainable structures *support-conclusion* for what is the best assistive action to take. These structures can be seen as *fragments* of an activity and can be generated (STEP 1 in Figure 1) as follows:

Definition 3 (Hypothetical fragments). *Let* $ActF = \langle P,\ \mathcal{H}_A,\ \mathcal{G}, \mathcal{O},\ \mathsf{AT}\rangle$ *be an activity framework. A hypothetical fragment of an activity is of the form* $HF = \langle S, O^{'}, h,\ g\rangle$ *such that: 1)* $S \subseteq P,\ O^{'} \subseteq \mathcal{O},\ h \in \mathcal{H}_A,\ g \in \mathcal{G}$*; 2)* $S \cup O^{'} \cup \{h\}$ *is consistent; 3)* $g \in T$ *such that* $ASP(S \cup O^{'} \cup \{h\}) = \langle T,\ F\rangle$*; and 4)* S *and* $O^{'}$ *are minimal w.r.t. set inclusion.* $ASP(S)$ *is a function that returns an answer-set solution of an ELP program, i.e., it provides a common-sense reasoning process given a program as input.*

Definition 4 (Contradictory relationships among fragments). *Let* $ActF = \langle P, \mathcal{H}_A, \mathcal{G}, \mathcal{O}, Acts\rangle$ *be an activity framework. Let* $HF_1 = \langle S_1, O_1^{'}, a_1,\ g_1\rangle$, $HF_2 = \langle S_2, O_2^{'}, a_2,\ g_2\rangle$ *be two fragments such that* $HF_1, HF_2 \in \mathcal{HF}$. $ASP(\mathsf{Supp}(HF_1)) = \langle T_1, F_1\rangle$ *and* $ASP(\mathsf{Supp}(HF_2)) = \langle T_2, F_2\rangle$ *denote the semantic evaluation of the support, then* HF_1 *attacks* HF_2 *if one of the following conditions hold: 1)* $\alpha \in T_1$ *and* $\neg\alpha \in T_2$*.; 2)* $\alpha \in T_1$ *and* $\alpha \in F_2$.

An argumentation framework is a pair $\langle Args, att\rangle$ in which $Args$ is a finite set of arguments and $att \subseteq Args \times Args$. In [10] an argumentation-based activity framework for reasoning about activities was proposed, by considering argumentation as inference method:

Definition 5 (Activity argumentation framework). *Let ActF be an activity framework of the form* $\langle P, \mathcal{H}_A, \mathcal{G}, \mathcal{O}, Acts\rangle$*; let* $\mathcal{HF}$ *be the set of fragments w.r.t. ActF and* $Att_{\mathcal{HF}}$ *or simply Att the set of all the attacks among* $\mathcal{HF}$*. An activity argumentation framework AAF with respect to ActF is of the form:* $AAF = \langle ActF, \mathcal{HF}, Att\rangle$

Dung in his seminal work [7] introduced a set of *patterns of selection* of arguments called *argumentation semantics*. Intuitively, an argumentation semantics SEM is a formal method to identify conflict outcomes from argumentation frameworks (AF).

Definition 6. *Let $AAF = \langle ActF, \mathcal{HF}, Att \rangle$ be an activity argumentation framework AAF with respect to $ActF = \langle P, \mathcal{H}_A, \mathcal{G}, \mathcal{O}, Acts \rangle$ An admissible set of fragments $S \subseteq \mathcal{HF}$ is stable extension if and only if S attacks each argument which does not belong to S. preferred extension if and only if S is a maximal (w.r.t. inclusion) admissible set of AAF. complete extension if and only if each argument, which is acceptable with respect to S, belongs to S. grounded extension if and only if it is a minimal (w.r.t. inclusion) complete extension. ideal extension if and only if it is contained in every preferred set of AAF.*

The sets of arguments suggested by an argumentation semantics are called *extensions*. Let $SEM()$ be a function returning a set of extensions, given an AF such as an AAF. In this sense, we can denote $SEM(AAF) = \{Ext_1, \ldots, Ext_k\}$ as the set of k extensions generated by an argumentation semantics *w.r.t.* an activity argumentation framework AAF.

Definition 7. *1) An fragment $HF_A \in \mathcal{HF}$ is acceptable w.r.t. a set S of fragments iff for each fragment $HF_B \in \mathcal{HF}$: if HF_B attacks HF_A, then HF_B is attacked by S. 2) conflict-free set of fragments S in an activity is admissible iff each fragment in S is acceptable w.r.t. S.*

Using these notions of fragment admissibility, different argumentation semantics can draw given an activity argumentation framework:

Definition 8. *Let $AAF = \langle ActF, \mathcal{HF}, Att \rangle$ be an activity argumentation framework following Definition 5. An admissible set of fragments $S \subseteq \mathcal{HF}$ is: 1)* stable *if and only if S attacks each fragment which does not belong to S; 2)* preferred *if and only if S is a maximal (*w.r.t. *inclusion) admissible set of AAF; 3)* complete *if and only if each fragment, which is acceptable with respect to S, belongs to S; and 4) the* grounded *extension of AAF if and only if S is the minimal (*w.r.t. *inclusion) complete extension of AAF.*

Conclusions of an argument-based reasoning about an activity (see STEP 4 in Figure 1) may be obtained using a *skeptical* perspective, *i.e.,* accepting only irrefutable conclusions as follows:

Definition 9 (Justified conclusions). *Let P be an extended logic program, $AF_P = \langle \mathcal{A}rg_P, At(\mathcal{A}rg_P) \rangle$ be the resulting argumentation framework from P and SEM_{Arg} be an argumentation semantics. If $SEM_{Arg}(AF_P) = \{E_1, \ldots, E_n\} (n \geq 1)$, then $\mathsf{Concs}(E_i) = \{\mathsf{Conc}(A) \mid A \in E_i\} (1 \leq i \leq n)$. $\mathsf{Output} = \bigcap_{i=1\ldots n} \mathsf{Concs}(E_i)$.*

Where E_i are sets of fragments called extensions. The set of all the extensions generated by $SEM_{Arg}(AF_P)$ are denoted as $\mathcal{E}$

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