Reasoning about abductive inferences in BDI agents

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Abstract

The capability of a computational system to deal with unexpected, changing situations and limited perception of the environment is becoming more a more relevant, in oder to make systems flexible and more reliable. Multi-agent Systems offer a computing paradigm where properties such as autonomy, adaptability or flexibility are basic in the construction of agent-based solutions. However most of current implementations are not flexible enough to cope with important changes in the environment or information loss. In this paper we propose to introduce abductive reasoning mechanisms in BDI agents and show how such agents are able to operate with partial models of the environment.

1 Introduction

For over a decade, Software agents have been proposed as a software engineering paradigm which eases the creation of flexible autonomous computational entities specially capable to operate in complex situations. Motivated by the inability of existing manufacturing systems (i) to deal with the evolution of products and (ii) to maintain a satisfying performance outside normal operation, agent-based technology is more and more used on industrial setups. But abnormal situation handling in industrial plants is often a challenging application area even for agent-based solutions. The main agent paradigm, BDI agents, is based on a mentalistic approach which tends to rely on a supra believe defining its knowledge as complete and consistent, even if there is missing information or imprecision on the expected observations.

In this work we want to investigate ways to improve BDI agents to operate in dynamic domains where information about the environment may be incomplete and agents need to establish some hypothesis in order to unblock a given reasoning process. Our approach is that agents, when faced with a hypothesis or a new piece of uncertain information, would try to seek an explanation or justification for the new hypothesis/information. After doing so, it could incorporate the explanation into its epistemic state together with the new information. We model this strategy through the use of abductive reasoning. This allows us to then investigate the role of abductive inference within a belief revision framework. In this paper we not only cover the incorporation of new information but also the removal of information.

Abduction, as opposed to *deduction* and *induction*[1], is based on the inference of ϕ (*explanans*[2]) from knowledge of the rule $\phi \rightarrow \psi$ and the observation ψ (*explanandum*). This means that abduction is not an analytic form of inference, but rather based on the Affirming the Consequent fallacy. Like induction, abduction is defeasible: the arrival of new observations might invalidate prior abductive inferences.

The conditions which define when a fact ϕ qualifies as a valid abductive explanation for an observed fact ψ, with a background theory Θ, are [Sindlar *et al.*, 2009]:

- $\Theta \cup \phi \models \psi$
- $\Theta \cup \phi \not\models \perp$
- $\Theta \not\models \psi$
- $\phi \not\models \psi$

In this paper we do not focus on the abductive logic explanation, as it is based on the work by [Sindlar *et al.*, 2009]. Our main concern is to infer some abductive logic conclusions at a lower level, and then construct a knowledge model that can be used for believes and desires reasoning approach to the human knowledge retrieval.

The structure of the paper is as follows: in §2 we describe the industrial use case scenario that will be used in the rest of the paper. Then in §3 we propose an architecture for a BDI agent capable of abduction-driven reasoning. In §4 we show a concrete example where abductive reasoning is applied. In §5 we discuss how BDI agents can process the results of abduction at the level of their practical reasoning. In §6 we compare our work to other approaches. Finally in §7 we present our conclusions and advance some of our future lines of work.

2 Use case example: industrial process

Nowadays industries are facing a profound change towards a wide-ranging awareness of the environmental impact of their inner processes. In order to identify specific ways to improve the production sustainability, industrial engineers more

[1]Deduction is based on the *modus ponens* syllogism ($\{\phi, \phi \rightarrow \psi\} \models \psi$), while induction is based on the inference of $\phi \rightarrow \psi$ as a rule from the observation of ϕ followed by ψ

[2]Some authors call this *explanantia*.

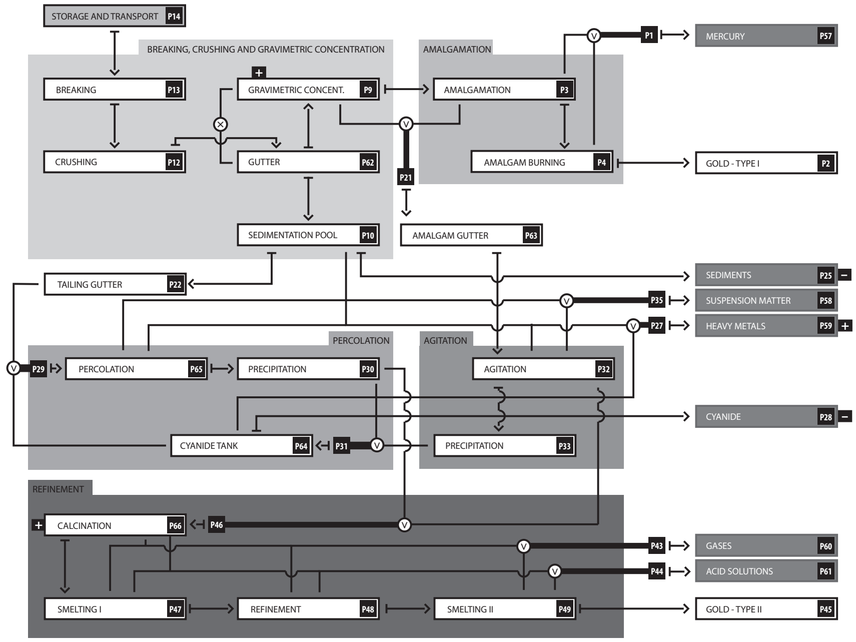

Figure 1: Example of flow diagram in a industrial process (premises).

and more employ a well-known framework described on ISO4000. This norm specifies a methodology that should be followed in order to model the industrial activity by the perspective of *matter as a flow* through an extensive knowledge about the relations between different individual processes, the matter that enters and the one that transits to another process. This general approach is called *Life-Cycle Analysis* and provides a useful way to achieve a horizontal conciseness of the industrial practices. However the world model is often incomplete mainly because industrial processes evolve over time leading, in most cases, to a built flow that only truly fully represents the activity on the short time span when the model was built. Figure 1 shows an example of a flow diagram for a gold-processing industry, with its inputs (top left and its outputs (right).

Another aspect of this model is that it usually is strongly goal oriented, meaning that it focuses on the global amount of matter produced and just specifies the quantifiable losses in a forward way, not proposing, directly at least, chains of events that could address a really systemic view over several independent processes. One can build some kind of deductive reasoning that contrasts specific consequences with the generalized description of a singular process. Also we can achieve a kind of induction based on the repetition of an independent variable so we can extract an inference rule not noticed on the initial model. However, some stochastic processes could be used to propagate a particular kind of property over a graph, and then obtain some time dependency probability model, such as Markov chains or Bayesian networks. Nevertheless these methods rely also on a finite space state and they are unable to provide solutions based on hypothetical correlations, essential to extract innovative knowledge that could be used to accomplish marked changes on the organization, even if the facing model is incomplete or inconsistent.

Also, the industry internal dynamics are very complex and the complete processes report, tracking each unit consumed until its transformation and final output, is an intricate task given the model's fuzziness. It usually involves extensive monitoring of the different steps of the process, and it is not uncommon that some information loss may happen due to, e.g. the failure of a sensor or its connection to the central control system. Computing over these process snapshots addresses an amount of useful knowledge that can easily be viewed on those cases that the control agent has to choose between different actions based on this limited information, conjecturing about what are the possible implicated outcomes of some particular process on a given moment.

3 A hybrid agent architecture supporting abduction

What we propose here is an extension of the traditional architecture for a BDI agent, adding the capability of abduction-driven reasoning. The formal logic used in our proposal is $\mathbf{LA}^r$, presented in [Meheus and Batens, 2006].

This logic represents *abductive steps* as formulas of the form:

$$B(\beta), (\forall\alpha)(A(\alpha) \supset B(\alpha))/A(\beta)$$

$\mathbf{LA}^r$ [Meheus, 2006] is a logic based on Classical Logic with a non-monotonic dynamical process in which deductive steps are combined with abductive steps. Abductive steps may be withdrawn if, via deductive steps, its negation is derived.

Also we may consider that even if the agent could monitor all the processes over time, also as the proceeding chain of past events, its access to computational resources often encounters limitations such as [Langley *et al.*, 2008; Magnani and Belli, 2006]:

- *bounded information:* sensor centric systems rely on partial information given by sensors refresh rate and also due to imprecise data acquisition or multiple failures,
- *lack of time:* decisions must be taken ön the go, meaning that since the world state is always changing so is its knowledge model. A theory is simply valid on a precise time-windowed constrain, and
- *limited computational capacity:* since the agent is strongly goal-oriented, the knowledge access and actualization is limited to the remaining computational capacity.

Therefore this hybrid architecture must balance between the immediate efficiency and hypothesis retrieval mechanics. We also know that in a large time span, if the abductive knowledge base is boosted so as the actions effectiveness increase, therefore the real cost of abduction may just be considered on future steps and not on the strict time it occurs, as we consider that as an investment.

4 Applying abduction in the use case example

Let us take a look to the forward example of a mineral extraction industry. The production diagram is shown in Figure 1 and we can then set the rules that define this scope [Stylios *et al.*,].

Note that the arrows on the diagram represent the matter flow, not the entailment between predicates. In order to use the architecture presented in §3, each relation $A \mapsto B$ in the diagram is translated into two entailment rules:

$$(\forall x)(B(x) \supset A(x))$$

$$(\forall x)(\neg A(x) \supset \neg B(x))$$

For example, the arrow between $P14$ and $P13$ in the diagram is translated into two rules: $(\forall x)(P14(x) \supset P13(x))$ (i.e., in all cases if there is a *BREAKING* process then it is true that there is also a *STORAGE AND TRANSPORT* one); and $(\forall x)(\neg P13(x) \supset \neg P14(x))$ (i.e., in all cases if there is not a *STORAGE AND TRANSPORT* process then there is not also a *BREAKING* one). Please note also that we have some non-restrictive conjunctive clauses, which lead to a general premise that just represent the co-occurrence of two or more conditions.

As explained before, in this example context, we can just observe some of the processes that are occurring in the industry on a given moment. Based on the agents' observations, we build a table (see Figure 2) were we identify the observed events and also the ones that we know that have not happened. We leave in white the events which we do not know if they have happened or not.

Let us now start explaining the abduction process in case $C01$ for the predicates $P9$ and $P28$ in this order, meaning that we will try to extract the larger amount of information from this subset of the observed experience. The set of *explanans* thus is defined as $W^e = \{P9(1), P28(1)\}$. The "+" signs at row $C01$ state that $P9(1)$ and $P59(1)$ hold, while the "−" sign states that $\neg P25(1)$ and $\neg P28(1)$ hold. Formally:

$$C01 \equiv P9(1) \wedge \neg P(25) \wedge \neg P(28) \wedge P59 \wedge \neg P(66)$$

The first abduction is easily observed; from rule $(\forall x)(P3(x) \supset P9(x))$ (which comes from the $P9 \mapsto P3$ in Figure 1) we can abduce an explanatory hypothesis for $P9(C01)$ (defined by the premise R85 on our arguments list). We can represent RC (conditional rule), allowing for adding abductive hypotheses to the proof, but only on a certain condition, called *abnormality*. This condition is represented by the last element of the line:

1	$P3(1)$	*RC*	$R85, C01$	$\{[[P9(1), \neg P3(1)]]\}$

We can read this step as: $P3(1)$ could be derived from $P9(1)$ until the proof condition keeps being undefeatable (meaning that in this $C01$ we do not find that $\neg P3(1)$). If, at a later stage of the proof, it turns out that the abnormality condition holds, then this line will be *marked* and the formula that occurs on it will no longer be considered to be inferred. We continue this process for:

2	$P4(1)$	*RC*	$R79, 1$	$\{[[P3(1), \neg P4(1)]]\}$
3	$P2(1)$	*RC*	$R80, 2$	$\{[[P4(1), P2(1)]]\}$
...				
5	$P21(1)$	*RU*	$R86, C01$	$\emptyset$

As we can see on the condition on 5 we apply RU, an unconditional rule that, unlike RC, does not lead to the introduction of new conditions. If we continue this process we will find these cases:

15	$P64(1)$	*RC*	$R164, 12$	$\{[[P31(1), \neg P64(1)]]\}$
...				
17	$P29(1)$	*RU*	$R109, 15$	$\emptyset$
...				
24	$P65(1)$	*RU*	$R111, 17$	$\{[[P29(1), \neg P65(1)]]\}$
25	$P30(1)$	*RU*	$R110, 24$	$\{[[P65(1), \neg P30(1)]]\}$
...				

We are finished with $P9(1)$. The only available abduction for the second *explanans*, $\neg P28(1)$ is:

29	$\neg P64(1)$	*RC*	$R115, C01$	$\{[[\neg P28(1), P64(1)]]\}$

As we can see on condition 29, there is an abnormality with respect to condition 15, and as a consequence, the conclusion of line 29 is withdrawn from the proof 15. The withdrawal of a conclusion from the proof is recorded by marking the line on which the formula occurs and tracking all the conditionals identified on the same way, recursively.

We can conclude, on the presented limited set of observations, that there are correlated hypothesis in which all or some of the processes could occur except those ones involved on *PERCOLATION* processes. We may also conclude that *SEDIMENTATION POOL* and *TALLING GUTTER* probably

	P2	P3	P4	P9	P10	P12	P13	P14	P22	P25	P28	P30	P32	P33	P45	P47	P48	P49	P57	P58	P59	P60	P61	P62	P63	P64	P65	P66
C01				+						−	−										+							−
C02	+	+	+																−	+	+				+			
C03					−	+	+	+												+				+				
C04					−					−																+		
C05	−									+					+				−			+	+					
C06		+	+	+	−	+	+	+	−			−	−	−		−	−	−						+	−	−	−	−
C07		+	−					+		−	+														+			

Figure 2: Table of observations

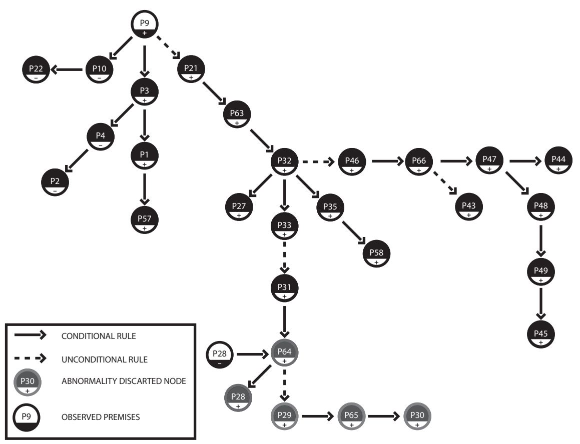

Figure 3: Abduction graph for the use case

were not used, leading us to also conclude that, based on the *xor* ($\otimes$) condition on *GUTTER*, that we are facing probably a flux of matter to *GRAVIMETRIC CONCENTRATION* instead of *SEDIMENTATION POOL*. This remarkable information, extracted with such few data sources, could hypothetically reconstruct the world model for this specific situation. This information could be inserted on the knowledge base for future inductions.

This example shows the viability of abduction in those cases where the agent has access to limited observations, because of, for example, a sensor fault, and it needs to maintain a certain degree of definition about the world state and therefore enduring discontinued operation. The knowledge extracted about correlations between distant entities can also be used to develop new production strategies based on hypothesis revision and test experiments suggested by the uncertainness of abduction explanation. For that reason, both creative and operation goal issues can be accomplished with abductive reasoning [Eco and Sebeok, 1983].

5 Knowledge creation strategies

As we discussed in 1, we aim at giving BDI agents the capability to process the results of abduction at the level of agent reasoning. In order to do this we need to give a higher level representation of the process that led to the whole set of *explanantium*. We define this structure as the *abduction graph* G of a proof U:

$$G(U) = < V, E >$$

where V is the set of stages s of the proof $U(\Gamma)$, and

E is the set of ordered pairs (u, v), being u the abductive hypothesis of $U_s(\Gamma)$ and v the *explanantium* of $U_s(\Gamma)$, $\forall s \in V$, plus the set of ordered pairs (u, v), being $u =$ and v an element of W^e, $\forall e \in W^e$.

Figure 3 depicts the *abduction graph* for our example use case.

Using abduction an agent can hypothesize using this restricted information and, if the *explanation* proves to be correct it saves time and resources [Peirce, 1995]. If it is not correct the agent can always compute a new hypothesis, based on the new observations and valid until inferring future ones. The world-model consistency is now improved with new knowledge that, if using another inference rule like induction, would take a larger amount of observations. The use of this tool for diagnosis problems is understandable because the implicit interaction act, in which the agent could test the resulted hypothesis contrasting it with the results of the test. In our example this could lead to new organizational challenges, bringing into being new paradigms that are now directed uncovered on the initial model.

In this sense, abduction has already been used and verified as a knowledge production mechanism [Subagdja *et al.*, 2006; Bracciali and Torroni, 2004; Niiniluoto, 1999]. However, in the literature, abduction is a process that is carried at the logic level. Our proposal is to improve the results of abduction from the higher level of agent reasoning, that is, to make some high-level interpretation of the background theory resulted from the logic abduction. Our agent reasoning cycle includes two knowledge creation strategical approaches: 1. the verification of sensitive abductions through intention revision, and 2. the selection of new *explanans*.

5.1 Verification of abductions through intention revision

Abduction, as we have seen, helps creating new knowledge, but this knowledge will always be tainted with a mark of uncertainty, that is, the permanent possibility that new facts or rules inserted into the background theory will arise abnormalities and thus removing knowledge that might have been used to arrive to wrong conclusions.

BDI agents are usually focused on actions rather than on the creation of new knowledge through learning [Rao and Georgeff, 1995; Meneguzzi, 2006]. The reason for this is that the fact agent is capable of maintaining a representation of the world that is good enough to carry the *desires* though deduction is taken as a fair assumption. However, it has been shown [Subagdja *et al.*, 2009; Herzig *et al.*, 2001] that abduction and intention can lead to better intention-based planning through non-analytic methods, namely induction and abduction.

We go a step further by creating new intentions. These intentions, rather than aiming at general actions, represent knowledge-driven actions. In other words, we want BDI agents to actively look for new knowledge that will help review the beliefs rather than the intentions. For this objective, suitable concepts representing learning ought to be defined and added to the ontologies used by BDI agents. The objective of this revision is to attack those critical abductions that, *a priori*, seem to be more prone to be refuted by an abnormality in a future state of the background theory.

From the strategical point of view of the agent, there is a variable of relevance in order to review the intention base, which we name *criticality*. We define the *criticality* of a stage s of the proof U over the theory Γ as the number of stages s' that *depend* on the stage s, and being $G(U) =< V, E >$ the *abduction graph* of the proof U:

$$criticality(s) = \sum^{\forall(s,u)\in E} 1 + criticality(u)$$

The *criticality* of a proof stage can be seen as a measure of how important that step in terms of the reliability of the posterior inferences not only of its abduction, but more notably, of the whole set of inferences recursively inferred from it. The higher the number of inferences depend on an abduction, the more dangerous it is to work with them and the more fragile the posterior inferences are.

Our BDI agents take *criticality* into account by putting emphasis on it from the *intentional* perspective. That is, the agent will actively look for possible attacks to the proof stage and thus reinforcing or finally discarding it by. Operationally, what the agent will do is to create an ordered set of actions $I(G)'$ of an *abduction graph* $G(U) =< V, E >$ such that:

$$I' = \{validate(s_1), validate(s_2), \ldots, validate(s_N)\}$$

where $\forall validate(s_i) \in I', s_i \in V$,
and $\forall validate(s_i), validate(s_j) \in I', i < j \rightarrow criticality(s_i) > criticality(s_j)$

Each of these actions will be part to the *intention base* of the BDI agent, prioritising their execution in the order defined by the set $I(G)'$. How the $validate()$ action will be carried out by an agent will depend on its implementation, its capabilities, and its own representation of the action, e.g. committing some resources to execute actions that may confirm the validity of the most critical abducted predicates.

5.2 Selection of new *explanans*

Section 5.1 describes a strategy for the reinforcement of successful abductions. However, a problem not tackled in the literature is how to find knowledge out of the contradictions. In the example presented in 4, there is a contradiction that arises because of the inference of a *disjunctive abnormality*: proof stages 15 and 64. Adaptive logics define several possible strategies to solve these contradictions, but the one used by $\mathbf{LA}^r$, *reliability*, is conservative and thus the conflictive proof stages and their posterior inferences are marked as removed. This is fine at the level of the logics, but this represents potential useful information that can be used from the agent reasoning level. In fact, what this kind of contradiction means is that either A or $\neg A$ can be abduced, but we are unsure of which one is the right inference path.

From the knowledge creation point of view, these contradictions are attractive, not only because there is a plausible explanation, but also because at the level of the logic we are pruning potentially good inferences. The strategy to follow in the case of found contradictions is simple: *investigate* about which is the correct inference path. To do so, we will follow a pure **CL** inference based on the main proof by adding as inference each one of the literals of the abnormality condition that is not the one related to the contradicted abduction.

Formally, if we have two proofs s_1 and s_2 such that s_1 has as abnormality condition $[[R_a, Q_a]]$ and s_2 has as abnormality condition $[[S_a, \neg Q_a]]$, we will test:
$\Gamma \wedge Q_a \neg \vdash_{\mathbf{CL}} \perp$ and $\Gamma \wedge \neg Q_a \neg \vdash_{\mathbf{CL}} \perp$

It might be the case that none of the tests arise a positive result. If that is the case, then the agent can assume that there is not enough knowledge of the world to make a proper decision. If one of both tests is positive, we can safely add the literal, Q_a in the first case and $\neg Q_a$ in the second case. We can then add this literal to the set W^e of *explananda* and continue abducing.

In the contradiction of our example, we have that:

$$[[P31(1), \neg P64(1)]] \vee [[\neg P28(1), P64(1)]]$$

The proof is trivial, as from the premises, $\neg P28(1)$ and by *modus ponens* we have $\neg P64(1)$. Therefore, the second case entails *false* from $P64(1) \wedge \neg P64(1)$. This allows us to add $\neg P64(1)$ to the theory and abduce explanations from this literal[3].

6 Discussion

Abduction is a powerful inference mechanism that generates conditional proofs, the conditions being assumptions. Both, together with a given knowledge base will enact the conclusion of the proof. However, the abduced conditions can be viewed as an answer, or as an explanation, in the context of the knowledge base, of the conclusion. The focus of [Ma *et al.*, 2008] is on distributed abduction where knowledge and constraints are distributed over a group of agents that cooperate to produce the proof. Each agent has its own knowledge base and consistency constraints. The abduced conditions for the collective proof may come from different agents but they must satisfy the relevant consistency constraints of all the agents who have contributed to the abductive proof. Our proposal condenses the task of consistency proof on inner logical steps that could recursively unfold the detected abnormality. The major difference resides on the objective of

[3]This seems to be an unnecessary check, as $\neg P64(1)$ can be directly inferred from the premises. However, $\mathbf{LA}^r$ is driven by the *explananda*, and this kind of cases can happen. Although the selection of new *explananda* is intended for more complex contradictions, it also helps in solving this kind of inferences that $\mathbf{LA}^r$ does not tackle directly.

abductive reasoning, in our case being not goal oriented but instead driven by a knowledge inference engine that models the mental state of the agent. This allows for detecting possible relevant correlations, optimizing the hierarchy of knowledge acquisition tasks.

Our proposal presented in this paper presents the idea of processing at a higher level of abstraction the results of the abduction. This is an approach that can be used to improve other approaches like [Chang *et al.*, 2005; Johnson and Zhang, 1995]. It would also be interesting to incorporate research done with respect to the improvement of ontologies via abduction [Elsenbroich *et al.*, ; Peraldi *et al.*, 2008]. However, our main focus will be on the definition and formalisation of new less conservative strategies.

The formalism chosen for the conceptual definition of our BDI architecture is $\mathbf{LA}^r$, although we are currently analysing how to adapt modal logics [Meheus and Batens, 2006] to our architecture. For a grounding to a real deployment, there are several possible implementations of an abductive-inductive logic, being the most notable HAIL and XHAIL [Ray, 2008]. However, it is not available right now, so we are carrying our proof of concept at the conceptual level for the moment.

7 Conclusions

In this paper we have presented an approach for agent reasoning with the use of abduction mechanisms. It has been shown with an example how this can be applied to a real industrial process setup.

We are currently working on verifying the proof of the concept and creating new high level reasoning strategies for the generation of new knowledge. Future work should focus on the consequences of induction after abduction in BDI agents, and to extend the idea to desires and intentions.

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