On Partial Deduction and Conversational Agents

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Abstract. Agents are situated autonomous entities that perceive and act in their environment, and communicate with other agents. An agent usually starts a conversation by querying another agent because it needs to satisfy a specific goal. This process allocates a new goal to the agent receiving the initial query, starting new dialogs with other agents, generating a recursive interaction. The generation of this kind of dialog is interesting when the system has the possibility of generating conditional answers with uncertain values. We consider simple deliberative rule-based agents that proactively try to satisfy their goals. The mechanism to achieve this dialogs is based in the *specialization* of the mental state of agents, by means of the partial deduction of rule bases.

1 Introduction

Rule specialization has been used intensively in logic programming [6], but it has potential applications in other areas as multi-agent systems and particularly in communication among agents [15]. The proposal of this paper is not to explain the general advantages of an inference engine based on specialization [7, 9, 8], but to show that this mechanism is useful to drive the communication among agents, generating *reasonable* dialogs. We propose the use of this technique to model the communication behavior between agents, in an uncertain context, by allowing agents to use *conditional answers* [10].

In classical (boolean) rule bases, deduction is mainly based on the modus ponens inference rule: $a, a \rightarrow b \vdash b$. In the case that a denotes a conjunction of conditions $a_1 \wedge a_2$, the above inference rule is only applicable when every condition of the premise, i.e. a_1 and a_2, is satisfied, otherwise nothing can be inferred. However, if we only know that condition a_1 is satisfied, we can use *partial deduction* to extract the maximum information from incomplete knowledge in the sense of the following *specialization* inference rule: $a_1, a_1 \wedge a_2 \rightarrow b \vdash a_2 \rightarrow b$. The rule $a_2 \rightarrow b$ is called the *specialization* of $a_1 \wedge a_2 \rightarrow b$ with respect to the proposition a_1. The specialization of a *rule base* consists on the exhaustive specialization of its rules. Rules will be substituted by its specialized versions, and rules with no conditions will be eliminated and new propositions will be added.

In an approximate reasoning context the specialization is much more interesting. The above boolean specialization inference rule can be transformed in the following way: $(a_1, \alpha), (a_1 \wedge a_2 \rightarrow b, \rho) \vdash (a_2 \rightarrow b, \rho')$, meaning that if the proposition a_1 is known to be true at least to the degree α and the rule $a_1 \wedge a_2 \rightarrow b$ is true at least to the degree ρ, then the specialized rule $a_2 \rightarrow b$ is true at least to a degree $\rho' = f(\alpha, \rho)$, where f a suitable combination function.

Using conditional answers and the specialization mechanism, an agent is able to answer, when needed, with the information the questioner should know to come up with a value for the query, or it also may inform about other deductive paths that would be useful to improve the solution [7]. The difference with other approaches is that the agent will use external information to specialize its knowledge base, and incrementally build more precise answers.

In Section 2 we define both the agents mental state and the specialization process. In Section 3 both agents and their mental state cycle are described. Section 4 is devoted to the description of the protocols. Finally, some conclusions and future work are presented in Section 5.

2 Mental state and specialization

The state of our agents will be their mental state [17]. Below, a simplified version of our propositional language[1] and the inference mechanism will be described.

Definition 1. *(Language and inference)* $\mathcal{L} = \langle T_n, \Sigma, \mathcal{C}, \mathcal{S} \rangle$ *is defined by:*

- $T_n = \{t_0, t_1, \ldots, t_n\}$ *is an ordered set of truth-values, where* t_0 *and* t_n *are the booleans* True *(1) and* False *(0) respectively.*
- Σ *is a set of propositional variables (atoms or facts).*
- $\mathcal{C} = \{\wedge, \rightarrow\}$*, is the set of connectives.*
- $\mathcal{S}$ *are sentences composed by: atom pairs* (a, V)*, and rules of the form* $(p_1 \wedge p_2 \wedge \cdots \wedge p_n \rightarrow q, V)$*, where* $a, p_i, q \in \Sigma$*,* $V \in T_n$*, and* $\forall i, j (p_i \neq p_j, q \neq p_j)$

We will use the following inference rules:

- Parallel composition: from (φ, V_1) and (φ, V_2) infer $(\varphi, max(V_1, V_2))$
- Specialization: from (p_i, V) and $(p_1 \wedge \cdots \wedge p_n \rightarrow q, W)$ infer $(p_1 \wedge \cdots \wedge p_{i-1} \wedge p_{i+1} \wedge \cdots \wedge p_n \rightarrow q, min(V, W))$

The agents mental state contains a set of facts and rules. In our model, both facts and rules are weighted with truth-values in T_n, meaning that the fact or the rule is true at least to some degree. Rules are tuples $r = (m_r, c_r, \rho_r)$ where m_r is the premise (a set of atoms), c_r is the conclusion (an atom) and $\rho_r \in T_n$ is the rule truth-value. The representation consists of mapping each atom in Σ to its truth-value and the (possibly empty) set of rules that conclude it.

Definition 2. *(Mental State) Let* R *be a set of rules, we define an agent mental state* M *of an agent* A *as a mapping:* $M_A : \Sigma \rightarrow T_n \times 2^R$ *where, for each* $f \in \Sigma$*,* $M_A(f) = (\rho_f, R_f)$*, being* $R_f = \{(m_r, \rho_r) | (m_r, f, \rho_r) \in R\}$

[1] In the complete version of the language we consider negation and the values of facts and rules are intervals of truth values. For the sake of simplicity here we use *min* and *max* operations instead of general triangular norms. For more information please see [8].

The representation of an agent's mental state will evolve as deduction proceeds. We represent the initial mental state of an agent as a mapping from any atom into *unknown* and the set of rules deducing it.It means that atoms initially have the indeterminate value 0.

We consider that a proposition has a *definitive* value when there are no rules that can contribute to improve its value, producing a more precise one by means of applications of the parallel composition inference rule. We will use a proposition to specialize rules only when that proposition has a definitive value. This permits rules to be substituted by its specialized versions being the condition eliminated from its premise. When there are no conditions left in the premise of a rule the conclusion of the rule is generated.

Both, the description of the specialization algorithm and the specialization of a set of rules can be found in detail in [8].

Finally, to specialize a complete agent's mental state we will use each fact with definitive value in the mental state in turn to make specialization steps that possibly will generate definitive values for other atoms to be later used to specialize more the state.

3 Agents

In this Section we present the concept of agent considering that it is a goal driven entity. Apart from the passively information acquired by perception, agents proactively find new information that will be useful to satisfy their goals. Consider a multi-agent system with n agents $\mathcal{A}_n = \{A_1, \ldots, A_n\}$. Each agent has the following structure:

Definition 3. *(Agents) A deliberative agent is a tuple* $A_i = \langle M_i, G_i, I_i, O_i \rangle$ *where:*

- M_i *is the mental state of agent* A_i*.*
- G_i *are the set of goals of* A_i*. These are facts that* A_i *wants to solve because it has commitments with other agents—generated from communication—or self commitments. Goals are represented by tuples* $\langle x, A_j \rangle$*, where* $x \in \Sigma$ *and* $A_j \in \mathcal{A}$*.*
- I_i *is the input interface, the set of external facts that can be obtained querying other agents. They are tuples* $\langle x, A_j \rangle$*, where* $x \in \Sigma$*,* $A_j \in \mathcal{A}$ *and* $A_j \neq A_i$*.*
- O_i *is the output interface, this is, the set of facts that the agent can answer to other agents.*

Definition 4. *(Fact privacy) The mental state of an agent* A_i *contains two kinds of facts:*

- *A fact* $f \in O_i$ *is called* public*, then it can be answered to other agents.*
- *A fact* $f \notin O_i$ *is called* private*, then it can be revealed to no other agent.*

Definition 5. *(Fact state) The mental state of an agent* A_i *contains three kinds of facts:*

- *The facts* $f \in \{p \in \Sigma | M(p) = (V_p, \emptyset), V_p \neq 0\}$ *are called* definitive *or* totally specialized *because there is no more knowledge that could increase their precision.*

- *The facts* $f \in \{p \in \Sigma | M(p) = (V_p, R), V_p \neq 0, R \neq \emptyset\}$ *are called* provisional *or* partially specialized *and can be improved if there is enough information.*
- *The facts* $f \in \{p \in \Sigma | M(p) = (0, R)\}$ *are called* pending *and they are (provisionally)* unknown.

3.1 Agents mental state cycle

In the initial mental state of agent A_i, $G_i = \emptyset$ and all the facts have value *unknown* (0). We can summarize goal-driven work in the following steps:

1. When A_i receives a query q from an agent A_j, and $q \in O_i$, then $G_i := G_i \cup \{\langle q, A_j \rangle\}$
2. For each goal $\langle g, A_k \rangle \in G_i$: (i) if $A_k \neq A_i$ we generate a query g to the agent A_k or (ii) if $A_k = A_i$ it means that the goal is a self commitment and the agent starts a search process in order to find which is the information it needs.
3. Multiple specialization steps drives to reach goals. Given a goal $\langle g, A_i \rangle \in G_i$
   (a) If $M_i(g) = (V_g, \emptyset)$ and $V_g \neq 0$ then the agent generates a message for agent A_k with the contents $(g, V_g, \emptyset)$.
   (b) If $M_i(g) = (V_g, R)$ and $R \neq \emptyset$ and $\forall (m_r, c_r, \rho_r) \in R$, $m_r \subseteq O_i$ then the agent generates a message for agent A_k with (g, V_g, R).

   In both cases $G_i := G_i - \{\langle g, A_k \rangle\}$
4. When the agent receives answers from other agents, these are used to specialize the mental state. When the answer is (g, V'_g, R') and $M_i(g) = (V_g, R)$ then $M'_i(g) = (max(V_g, V'_g), R \cup R')$

The contents of answer messages are definitive facts or provisional facts with all the necessary rules to make it definitive. This does not mean that a fact with a provisional value will stop being a goal. This only means that a more precise value is reached. Stop criterion will be based on (i) goal value is found, (ii) goal is canceled or (iii) assigned time to find the goal is over (assigned time will depend on query priority and on priority agent A_i wants to give it). Different criterions to choose a rule or an atom are out of the scope of this paper, in a backward chaining style we will choose the rule with best truth-value and the first premise in order of writing.

4 Communication

Communication process between our agents is based on messages exchange in order to carry out one of these important actions: *querying* and *answering*. To give a semantic to these messages, we use speech act theory [4, 13] in form of performative verbs. Based on FIPA standard [1], a message is a tuple $C_i = \langle P, S, H, B \rangle$, where P is the performative that indicates the message type (we use `QUERY`, `ACCEPT`, `INFORM`, `REJECT` and `CANCEL`), S (sender) is the agent that sends the message, H (hearer) is the agent that receives the message, and B (body) is the message content.

The body of performatives `QUERY`, `ACCEPT`, `REJECT` and `CANCEL` is the name of one fact. The performative `INFORM` has a more complex format because it may contain facts and rules. For this performative, the body is a set of tuples $\langle M_x, V_x \rangle$ where, x is a fact, M_x is the mental state of x and V_x indicates if the value of x is *provisional* or *definitive*. Taking the example above as reference, let's see two possibilities:

– A_j knows the definitive value of f: `(INFORM,`A_j`,`A_i`,{(([1,1],`$\emptyset$`),definitive)})`
– Otherwise it decides to send to A_i one or a set of rules (which must not have any private fact): `(INFORM,`A_j`,`A_i`,{((`ρ_1`,{({a,b},`ρ_2`)}),provisional)})`

We define a dialog as a set of coherent messages: $D = \{C_1, \ldots, C_n\}$. We consider those which involve only two agents, which sequentially alternate dialogue moves. Protocols [12, 16] play a central role in agent communication to specify rules of interaction between communicating agents.

It is important to notice that performatives `ACCEPT` and `REJECT` allows agents to have social commitments [11]. A social commitment is defined as a structure indicating that there is a debtor committed to an action relative to a creditor [13]. In our case, when A_j accepts, it assumes a commitment with A_i, which is reflexed in its goals list.

5 Conclusions

This paper has showed how the specialization of rule-based knowledge bases can be the central mechanism to deliberate and also to produce *reasonable* dialogs among conversational agents [2]. We believe that this model makes sense when we manage imperfect information: vague, imprecise and incomplete. In this case the specialization mechanism gives new opportunities of richer conversations by using in each moment the more precise information to drive the questioning/answering protocols.

One important point not covered in this paper is related to the use of negation in the conclusions of rules. In a complete language, a fact a has the value $[\alpha, \beta]$ because rules concluding a are responsible of α (the minimum of the interval) and rules concluding $\neg a$ of β (the maximum). More certain rules produce more precision for the conclusion.

Another important issue is time. It may be reasonable to think in different strategies of specialization using provisional values, i.e. when a concrete timeout has been reached or when we need a value, we can use a less precise but useful result, similar to *anytime* algorithms.

What we need to do now is to carry out experiments to see which are the emergent conversations among agents; to study different strategies for obtaining information: in parallel, using provisional values, etc.; to study different kind of collaborative effort and delegation [14] and coordination [5]; and to extend our model by adding concepts related to the Electronic Institution model [3].

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