Integrating Psychological Behaviors in the Rational Process of Conversational Assistant Agents

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Abstract

In this paper, we describe a framework dedicated to studies and experimentations upon the nature of the relationships between the rational reasoning process of an artificial agent and its psychological counterpart, namely its behavioral reasoning process. This study is focused on the domain of Conversational Assistant Agents, which are software tools providing various kinds of assistance to people of the general public interacting with computer-based applications or services. In this context, we show on some examples the need for the agents to be able to exhibit both a rational reasoning about the system functioning and a human-like believable dialogical interaction with the users.

Introduction

Adding psychological behaviors to rational agents

According to traditional definitions stemming from Artificial Intelligence and Multi-Agent Systems, Rational Agents are associated with programs capable of Practical Reasoning, i.e. building plans and choosing actions to be executed, in order to achieve their goals. For example, SOAR-based architectures are one of the first attempts at modeling the cognitive reasoning process of an agent (Laird, Newell, and Rosenbloom 1987) by means of explicit IF-THEN rules. More recently, the BDI approach of Bratman (1990), Rao and Georgeff (1995) is a theory of practical reasoning (deciding what to do next) directed towards situated reasoning about actions and plans (Allen et al. 1991). Recently, authors have proposed to integrate into rational agent architectures psychological notions, in order to propose: 1) a more complete model of agents capable of sustaining more human-like interactions with people, especially ordinary people involved in conversational activities with assistant agents. For example, Gratch and Marsella (2004) have proposed a model of emotions based on SOAR, with a significant impact upon the SOAR architecture. Using the agent creation platform JACK that implements the BDI theory, CoJACK (Norling and Ritter 2004; Evertsz et al. 2008) is an extension layer intended to simulate physiological human constraints like the duration taken for cognition, working memory limitations (e.g. “loosing a belief” if the activation is low or “forgetting the next step” of a procedure), fuzzy retrieval of beliefs, limited focus of attention or the use of moderators to alter cognition. Emotions have also been integrated to the BDI framework, for instance with eBDI (Jiang, Vidal, and Huhns 2007) or KARO (Steenbrink, Dastani, and Meyer 2007). All those works provide a good introduction about the history of the necessity to implement emotions, and more generally psychological notions, into rational agents. Although there has also been a lot of research works about the effect of personality on agents’ behaviors in the virtual agents community (one of the most recent one being the SEMAINE project (Bevacqua et al. 2010)), they generally focus more on their impact on the animated agent (e.g. gaze or facial expressions) than on the rational decision process.

Adding psychological behaviors to agents

Psychological behaviors can play a major part in Conversational Assistant Agents (CAA), at the crossroad between: Assistant Agents (Maes 1994), which are software tools designed to assist, in many ways, people involved in a computer-based or computer-mediated activity. The scope of application of assistant agents covers several roles such as: presenters, helpers, companions, teachers, coaches, etc. Research on assistant agents is based on artificial intelligence reasoning over symbolic representations and they focus on the notion of rational agent.

Conversational agents (Cassell et al. 2000), which are often embodied as virtual characters interacting with people through a dialogical session involving various modalities: textual or spoken natural language, body gestures, facial emotions, actions in the interface or environment, etc. Most conversational agents are given a personality and are hence supposed to interact with people according to the character they endorse: social role, personality traits, mental preferences, affects and moods. Research on conversational agents focuses on modeling human psychology (mental states, emotions, etc.) and its expression in conversational sessions.

Although presented above as separated notions, the rational and the psychological reasoning capacities of an agent actually work in quite an intricate manner (Ellsworth and Scherer 2003; Frijda 2006). Moreover, most studies mentioned in section focus on low-level/transitory psychological notions (such as emotions and moods, e.g. for natural language interaction (Allbeck and Kress-Gazit 2010)), while other notions associated with high-level/long-lasting
A framework dedicated to experimental case studies on rational & psychological agents

We believe necessary to study the nature of relationships between the rational and psychological reasoning capacities of a CAA. It requires a dedicated test bed that we describe in this paper: the Rational and Behavioral (R&B) ¹ architecture, where ‘behavioral’ here stands for ‘psychological behavior’². The R&B framework has been designed to meet two main requirements:

Genericity: in order to support various case studies, involving distinct viewpoints upon the rational/psychological interactions. Hence, languages and formats of the R&B architecture must act as a common layer upon which each case study can implement its particular strategies.

Separability: in order to prevent confusions between rational and behavioral concepts, and also to separate the competences of the designers, the design of the rational heuristics is separated from the design of the behavioral ones. Moreover, the execution of the two classes of heuristics is performed concurrently on two separate engines. Subsequently, the R&B framework makes it possible to experiment various kinds of agents personalities by combining, within a given agent, rational and behavioral heuristics, which were once elaborated separately.

Outline of the paper: The next section describes the general architecture of the R&B framework. Then we present the notations and languages working as a generic layer to support experimental case studies. In the final section, we present the implementation of agent’s heuristics, illustrated by two distinct case studies showing the principles of genericity and separability of the R&B approach.

The R&B framework

Conversational Architecture

A typical R&B architecture, as illustrated in Figure 1, involves the following entities:

- the User U, who is an ordinary person who desires to use the system in the presence of a CAA,
- the System S, which can be for example a standalone application or an Internet service,
- the Agent A, which is a software tool endorsing a role in a given instance of given conversational situation.

The Graphical User Interface GUI is the traditional way for the user to interact with the system. However, when the user needs help, the Conversational User Interface CUI captures the multimodal interactions of the user with the agent and displays the reactions of the agent. The modalities handled by the the Dialogue manager D are classified into two main categories: 1) textual or oral Natural Language utterances (NL), that play a major part in assisting situations to ordinary people; and 2) other Non Verbal Interactions (NVI). Finally, the Control/Command Interface CCI links dynamically the symbolic model of the agent M to the system, so that the current state of the model and the current state of the system’s runtime remain synchronized.

Internal structure of the agent

A typical agent, instantiated in the R&B framework, is made of five processing modules:

D: the Dialogue manager takes analyzed utterances from the CUI Natural Language Processing-chain (NLP-chain). It performs pragmatic reasoning heuristics (written in the so-called Heuristic Description Language, HDL) to produce formal requests expressed in the Formal Request Language (FRL).

M: the Model handles the symbolic representations of the agent \( M = (A, U, T, S) \) where:
- \( U \) is the model of the user as a conversational character, containing data like its name, age, gender, etc.
- \( A \) is the mental model of the agent (cf. next section),
- \( T \) is the model of the the assisted application S,
- \( S \) is the model of the current dialogue session with U.

The symbolic structures in M are represented in the Model Description Language (MDL), they can be accessed in read/write mode by queries written in the Model Query Language (MQL). \( M \) is a dynamic structure evolving when updated by the agent reasoning engines (internal changes) or by the system via the CCI (external updates).

R: the rational reasoning engine of the agent implements the rational part of the role endorsed by the agent.

B: the behavioral reasoning engine of the agent implements the behavioral part of the role endorsed by the agent.

W: the engines D, M, R and B are considered as independent processing engines that work in parallel and communicate through a shared workspace \( \mathcal{W} \) containing Query objects \( Q_i \) in Query Description Language (QDL).

¹http://www.limsi.fr/~jps/research/rnb/rnb.htm
²The word ‘behavioral’ here is hence opposed to ‘rational’ - as such, we acknowledge it differs from the usual cognitive science terminology where rational behavior is just a subclass of behaviors.
The model of the agent

Structure: Basically, the model $\mathcal{M}$ is an evolving tree structure (as in evolving algebra for abstract state machines (Gurevich 1995)). Given a new session, the model $\mathcal{M}_0$ starts at $t_0$: $\mathcal{M}_0 = (A_0, \emptyset, T_0, \emptyset)$, where $A_0$ is the submodel of a given agent and $T_0$ is the submodel of a given application. $\mathcal{M}$ non terminal nodes are labelled by concepts (a concept is a symbol or an index) and terminal nodes are conventional values (Symbols, Numbers, Booleans, Strings).

Model Query Language (MQL) The model is accessed by the agent or by the application using the Model Query Language (MQL). The main access functions, used in the examples of the last section, are described in Table 1, where $\text{path}$ stands for a tree path expression $\mathcal{M}.s_1.s_2...s_n$ ($s_i$ being node labelling symbols), $n$ is the node referred to by $\text{path}$ and $\text{expr}$ is a terminal value or a subtree. The replies are of the form $\text{OK}[\text{result}]$, or $\text{FAIL}[\text{report}]$ if it fails.

The mental model of the agent

Of the four submodels of $\mathcal{M}$, the most specific to this paper is $\mathcal{A}$ that supports the representations of the agent’s mind. The R&B framework can support various mental models, defining various agents, provided they are expressed in the formalism of the model $\mathcal{M}$. As an example, we define here a specific mind model supporting the case studies presented in the last section. It covers most significant notions discussed in the mental states modeling literature (Ortony 2003) de-
spite some simplifications (e.g., we consider traits and roles are static during a dialogue session). This model distinguishes four types of states according to their dynamicity and to their arity, as summarized in Table 2. Each of them is associated with a value in \([-1, 0, 1]\), where 1.0 denotes the maximum intensity of the concept, -1.0 is the maximum intensity of the antonym of the concept and 0 stands for the “neutral” position (neither the concept nor its antonym stand).

**Unary categories:** The agent is viewed as autonomous:
- **Traits** (\(\Psi_T\)) correspond to typical personality attributes that can be considered as stable during the agent’s lifetime, implemented using the classical “Five Factors Model” of personality traits (Goldberg 1981):
  - **Openness:** appreciation for adventure and curiosity,
  - **Conscientiousness:** self-discipline, will to achieve goals,
  - **Extraversion:** energy, strength of positive emotions and tendency to seek company of others,
  - **Agreeableness:** being compassionate and cooperative,
  - **Neuroticism:** tendency to feel negative emotions.

- **Moods** (\(\Psi_m\)) are agent’s factors varying with time thanks to heuristics and according to previous state of the agent and to the current state of the world. We define:
  - **Happiness:** physical contentment wrt current situation,
  - **Satisfaction:** cognitive contentment wrt current situation,
  - **Energy:** agent’s physical strength,
  - **Confidence:** agent’s cognitive strength.

**Binary categories:** (also called interpersonal categories) the agent A interacts with another actor, called B.
- **Roles** (\(\Psi_R\)) represent a static relationship between the agent and B. We define two main categories of roles:
  - **Authority:** the right the agent feels to be directive and reciprocally not to accept directives from others. This role is often antisymmetric, i.e.,
    
    \[
    \text{Authority}(X,Y) = -\text{Authority}(Y,X)
    \]
    
  - **Familiarity:** the right the agent feels to use informal behaviors towards B. This role is often symmetric.

- **Affects** (\(\Psi_a\)) denote, in this particular model, dynamic relationships between the agent and B. We define three kinds of affects:
  - **Dominance:** the agent feels powerful relatively to B. This relationship is often antisymmetric.
  - **Cooperation:** the agent tends to be nice, and helpful with B. It is not necessarily symmetric.
  - **Trust:** the agent feels it can rely on B. It is not necessarily symmetric.

**Shortened notation:** The actual value of a mind attribute like “happiness” can be accessed by its full path in the model tree (\(\text{\texttt{'M,$\cdot$A.mind.mood.happiness.val'}}\)) or by using a short-}

**Query Description Language (QDL)**
A query is an element of \(\mathbb{N}\) that wraps a request written in FRL or MQL and provides extra attributes. It has the following structure and shortened notation:

\[
Q_i = [\text{val}([r_1], \text{history}([D,R,\ldots]), \text{to}([n]), \text{status}([+]])
\]

Where:
- \(i \in \mathbb{N}^+\) absolute identifier of a query
- \(\text{val}\) contains one or a sequence of FRL/MQL requests
- \(\text{history} \in \{D,R,B,M\}^*\) stack of engines that handled \(Q_i\)
- \(\text{to} \in \{D,R,B,M\}\) next engine meant to treat \(Q_i\)
- \(\text{status} \in \{0, -1, +\}\) success status of \(Q_i\)

Note that although a query \(Q_i\) can be given a destination (field ‘to’), it doesn’t prevent other engines to access \(Q_i\) while it is in the workspace \(\mathbb{W}\) and to possibly alter it.

**Implementation of the heuristics**

**Heuristic Description Language (HDL)**
HDLC makes it possible for both rational and psychological designers to handcraft rules. The main reason for this choice is that the R&B framework is dedicated to experimental studies: designers will have to share and read heuristics from others (e.g., see examples proposed below); besides we are not at the stage where a rule-learning process (inductive or other) can be easily implemented.

**Syntax** A heuristic defines a rational or behavioral reaction to a class of formal requests expressed in QDL (defined by a pattern matching expression). Its general form is:

\[
\text{H: id}[QDL\text{]}::=\{\text{GuardedScript}_1, \ldots, \text{GuardedScript}_n\}
\]

Where:
- \(\text{GuardedScript} \equiv \{\text{Guard}_1 \rightarrow \text{Script}_1, \ldots, \text{Guard}_n \rightarrow \text{Script}_n\}\)
- \(\text{Guard}\) \equiv Logical expr \(\theta\) \(\theta = \text{True}\)
- \(\text{Script}\) \equiv Instruction \{Instruction_1, \ldots, Instruction_n\}
- \(\text{Instruction}\) \equiv Basic operation | Query call | GuardedScript |
- \(\text{Query call} \equiv Q[\text{Query id}, \{\text{FRL req}, \text{MQL req}\}]\)

Note that instructions can recursively be guarded scripts.

**Dynamics** In the R&B framework, for a given case study, a set of heuristics can be defined and associated with any of the four engines D, M, R and B (here, we only discuss those associated with R and B). Their execution is performed by the Heuristic Scheduler (HS) which ensures their coroutines and achieves its control at two levels:
- within a given heuristic \(H\), it decides when instructions (guard \(\rightarrow\) script) should be executed,
- within a given R&B case study, it decides when engines and heuristics should take a turn.

As guards in heuristics can overlap, several execution policies can be selected (e.g., first-hit-exit, execute-all, random-choice...), and as a guard can remain active (true)
after the execution of its script, several repetition policies can also be selected (e.g. execute-once, loop-over). Moreover, since in the same engine or in distinct ones, several heuristics can match one query or several queries situated into \( \mathcal{W} \), again, several heuristic policies (behavior-first, rational-first, alternate-M/B) and query policies (FIFO-based, random choice...) are possible.

The principle of genericity, stated in the first section, compels the R&B scheduler to be parametrizable to enable various simulations. For the case studies presented below, we will use a single scheduling policy, such that:

- **Within heuristics**: all instructions with active guards (true) are executed; when several guards are simultaneously active, a random choice is performed; instructions are only executed once; a heuristic is terminated when all its instructions are executed (which may never happen – hence, \( \mathcal{W} \) is cleared after each request handling).
- **Between heuristics**: all heuristics that match a query object in \( \mathcal{W} \) are launched (i.e. coroutines with the already launched ones). When a heuristic is terminated, it can be launched again (but no reentrance is available). When several heuristics (even associated with different engines) are eligible, a random choice is performed, thus resulting in various R&B interleaved executions (cf. last example).

**Case study 1: Asking for information**

Assume the user puts the question “What is your age?”, resulting in the addition to the workspace of \( Q_1 = \{ \text{ASK}_a[\text{agent.age}] \} \).

**A simple rational reaction**: A possible rational heuristic that can handle questions about the agent’s attributes is:

1: \( \text{HR}_1 : \text{ask-agent-attribute}(\{ \text{ASK}_a[\text{agent.x}] \}) \rightarrow \{ \}
2: \quad \rightarrow Q[i, \text{GET}[x_i]]
3: \quad Q_i^+ \rightarrow Q[j, \text{TELL}_a[\text{agent.x}, Q_i, \text{val}]]
4: \quad Q_i^- \rightarrow Q[j, \{ \text{UNKNOWN}_a[\text{agent.x}],
\quad \text{TELL}_a[Q_i, \text{val}]]
5: \quad Q_i^0 \rightarrow Q_i^{\text{this}}
6: \}

Explanations:

1: \( x_i \) is a pattern variable matching any symbol like age, gender...
2: The empty guard prompts the script to be executed immediately. In \( Q_1 \), \( x_i \) being ‘age’ (shortcut for full path \( M_a.\text{age}.\text{val} \)), it creates a new query \( Q_i \) to retrieve this value from the model.
3: If the request in \( Q_i \) has been successful \( (Q_i.\text{status} = +) \), FRL request \( \text{TELL}_a[\text{agent.x}, Q_i, \text{val}] \) is wrapped into a new query \( Q_j \), and \( Q_i, \text{val} \) contains a MQL request \( \text{OK} \) [retrieved-val].
4: If the request in \( Q_i \) has been unsuccessful \( (Q_i.\text{status} = -) \), a FRL answer in two parts is wrapped into a new query \( Q_i \) and \( Q_i, \text{val} \) contains \( \text{FAIL} \) [report].
5: Once \( Q_i \) has been handled, the current query \( Q_i^{\text{this}} \) is declared to have been successfully handled as well. In any case, the request in \( Q_j \) is then retrieved by \( \mathcal{D} \) to be sent to \( U \).

**Handling user’s repetitions**: If the same request (in FRL) is issued several times during the same dialogical session, since a new wrapping query will be created for each of them, \( \text{HR}_1 \) will generate exactly the same formal answer. But lack of handling of repetitions has been identified as a major cause of the lack of human-likeness (Xuetao, Bouchet, and Sanssonet 2009) in CAA: rationality isn’t enough. A solution consists in using a simple rational heuristic to actually store the interaction with the user, like:

\[
\text{HR}_2 : \text{interact-mem} \{ (x_a, y_i) \} := \{
\quad \rightarrow Q[i, \text{ADD} \{ S, x_i.\text{y}_j \}]
\}
\]

And a behavioral one generating additional FRL and MQL queries, such as:

1: \( \text{HR}_1 : \text{repetition} \{ (x_a, y_i) \} := \{
2: \quad \rightarrow Q[i, \text{COUNT}[S, x_i.\text{y}_j]]
3: \quad Q_i^+ \wedge Q_i.\text{val} > 1 \rightarrow Q[j, \text{TELL}_a[\text{repetition}]]
4: \quad Q_i^+ \wedge Q_i.\text{val} > 2 \rightarrow Q[k, \text{MAP}[\text{coop}, \lambda x.x.\text{val} * 0.9]]
5: \quad Q_i^+ \wedge Q_i.\text{val} > 4 \rightarrow Q[j, \text{DISLIKE}_a[\text{repetition}]]
6: \}

Explanations:

2: Retrieval of the number of similar requests previous issued.
3 & 5: Extra information to the user reveals increasing boredom.
4: The agent modifies its mind state in an appraisal-like reaction (coop \( \equiv M_a.\text{mind}.\text{mood}.\text{cooperation}.\text{val} \)) with \( \lambda x.x.\text{val} * 0.9 \) being a \( \lambda \)-expression decrementing its argument by 10%.

**Case study 2: Handling user’s feelings**

Assume that the user hasn’t been satisfied by the agent previous reaction(s) and now expresses only her/his feelings about it with a force that can range on a scale from “I am not satisfied” to “I hate you!”. It results in the same class of FRL request, generating the query: \( Q_2 = \{ \text{DISLIKE}_a[\text{agent}] \} \).

**A simple behavioral reaction**: Dealing with an emotional reaction can’t be rational and “objective”, and a possible behavioral reactions could be given by a heuristic like:

1: \( \text{HR}_3 : \text{dislike-agent}[\text{DISLIKE}_a[\text{agent}] := \{
2: \quad \rightarrow \{ Q[i, \text{MAP}[\text{energy}, \lambda x.x.\text{val} * 0.9]],
3: \quad Q[j, \text{MAP}[\text{confidence}, \lambda x.x.\text{val} * 0.9]],
4: \quad Q[k, \text{MAP}[\text{cooperation}, \lambda x.x.\text{val} * 0.9]] \}
5: \quad Q_i^+ \wedge Q_i.\text{val} < -0.5 \rightarrow Q[i, \text{TELL}_a[\text{energy}, “tired”]]
6: \quad Q_i^+ \wedge Q_j.\text{val} < -0.5 \rightarrow Q[i, \text{TELL}_a[\text{confidence, “depressed”}]]
7: \}

Explanations:

2 & 4: Executes a sequence of queries to modify agent’s mind state.
6: If its energy is very low, a query with a FRL request to say “I feel tired” is generated.
7: A second FRL request can be added to that query (if it already exists, to a new one if not).

**Taking mood into account**: Despite the purely emotional aspect of \( Q_2 \), some rationality is still necessary, at least to remember user’s negative opinion of the agent with a heuristic like \( \text{HR}_3 \), we have:

\[
\text{HR}_3 : \text{dislike-mem} \{ \text{DISLIKE}_a[\text{agent}] := \{
\quad \rightarrow Q[i, \text{ADD} \{ U, \text{dislikes}, x_i \}]
\}
\]

However, a basic rational reaction like that can be put into question by the agent’s current mind state. For instance, if the agent is currently in a high level of satisfaction and not neurotic \( M_a^+ \wedge T_a^- \), it would tend to be in denial when
facing negativity into user’s utterances. A behavioral alteration upon this query put in \( w \) then could be:

1. \( H_{B3} : \text{good-mood} \{ \text{ADD}((A \rightarrow \text{x dislikes}, \text{x}_{n}) \} \}

2. \( M \rightarrow T_{n} \rightarrow Q_{i}^{+} \rightarrow Q_{this}.val=\text{VOID}() \)

3. \( ... \)

Explanations:
1. The agent refuses a MQL query adding a dislike into \( M \).
2. So it replaces it by a MQL request \( \text{VOID}() \) and declares the query as successfully handled.

Note that, depending on the order in which the heuristics are applied, several sequences can be produced: \(<H_{R3}, H_{B3}, H_{B2}>\) or \(<H_{B2}, H_{R3}, H_{B3}>,\) thus resulting in a variety of reactions that in turn can be perceived by the users from simple variants to drastically different behaviors.

**Implementation and conclusion**

In previous works, a full CAA architecture has been implemented\(^1\), which encompasses the components of the R&B architecture defined in Figure 1. Moreover, it has enabled us to collect a corpus of assistance-based natural language utterances that resulted in the grounding of the FRL language (Bouchet 2009). Recently, a first toolkit to experiment R&B agents has been implemented (Bouchet and Sansonnet 2009a) in Mathematica. This toolkit can be freely accessed at the Web page of the R&B project (cf. footnote 1).

We have proposed a framework dedicated to the support of experimental case studies about the R&B problem: the nature of the relationships between rational and psychological reasoning. The particular context of the conversational assistant agents was chosen because this issue is central to the acceptability factor of those systems, hence providing good test field. In future work, more case studies must be performed to confirm that the R&B framework actually provides a generic layer to experiment various strategies for integrating psychological behaviors into rational agents, as well as a validation using human subjects to evaluate the identification of implemented behaviors.

**References**


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1. http://www.limsi.fr/~jps/research/daft


