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Abstract: In this paper, we propose a multi-agent recommender system based on the Belief-Desire-Intention (BDI) model applied to multi-context systems. First, we extend the BDI model with additional contexts to deal with sociality and information uncertainty. Second, we propose an ontological representation of planning and intention contexts in order to reason about plans and intentions. Moreover, we show a simple real-world scenario in healthcare in order to illustrate the overall reasoning process of our model.

1 INTRODUCTION

Human activities take place in particular locations at specific times. The increasing use of wearable devices enables the collection of information about these activities from a diverse population varying in physical, cultural, and socioeconomic characteristics. Generally, the places you have been and spent regularly or occasionally time on, reflect your lifestyle, which is strongly associated to your socioeconomic features. This amount of information about people, their relations, and their activities are valuable elements to personalize healthcare being sensitive to medical, social, and personal characteristics of individuals. Besides, the decision-making process in human beings uses not only logical elements, but also emotional components that are typically extra-logical. As a result, behavior can also be explained by other approaches, which additionally consider emotions, intentions, beliefs, motives, cultural and social constraints, impulsive actions, and even the simple willingness to try. Hence, building recommender systems that take user behavior into account requires a step toward personalization.

To the best of our knowledge, there are no recommender systems that combine all these features at the same time. The following is a motivating example that had driven this research. Bob, a 40 year-old adult, wants to get back to a regular physical activity (*pa*). Bob believes that a regular physical activity reduces the risk of developing a non-insulin dependant diabetes mellitus (*rd*). Mechanisms that are responsible for this are weight reduction (*wr*), increased insulin sensitivity, and improved glucose metabolism. Due to his busy schedule (*bs*), Bob is available only on weekends (*av*). Hence, he would be happy if he can do his exercises only on weekends (*w*). Bob prefers also not to change his eating habits (*eh*). Besides all the aforementioned preferences, Bob should take into account his medical concerns (*c*) and certainly refer to a healthcare provider for monitoring. This scenario exposes the following problem: how can we help Bob to select the best plan to achieve his goal based on his current preferences and restrictions? This problem raises differents challenges. First, the proposed solution should take into account Bob's preferences and restrictions (e.g. medical and physical concerns) in the recommendation process. Second, information about the environment in which Bob acts and people that might be in relationship with him may have impact in his decision-making process. Third, the system should be able to keep a trace of Bob's activities in order to adapt the recommendation according to his progress. Finally, the information or data about Bob's activities is distributed geographically and temporarily.

In order to address these challenges, multi-agent systems stand as a promising way to understand, manage and use distributed, large-scale, dynamic, and heterogeneous information. The idea is to develop recommender systems to help users confronted with situations in which they have too many options to choose from with the aim of assisting them to explore and to filter out their preferences from a number of different possibilities. Based on this real-world application scenario, we propose in this paper a multi-agent-based recommender system where agents are described using the BDI model as a multi-context system. The system's goal is to recommend a list of activities according to user preferences. We propose also an extension of the BDI model to deal with sociality and uncertainty in dynamic environments.

The originality of what we are proposing with respect to existing works is the combination of an extended possibilistic BDI approach with multi-context systems. The resulting framework is then used as a healthcare recommender system.

There are several advantages of such combination. First, the use of a multi-context architecture allows us to have different syntaxes, e.g. ontology to represent and reason about plans and intentions. Besides, we believe that extending the classical BDI model with goals and social contexts better reflects humans behavior. The proposed approach deals with goal-belief consistency and proposes also a a belief revision process. The idea of extending the BDI model with social contexts is not novel. Different works explored trust or reputation (Koster et al., 2012; Pinyol et al., 2012) while in our approach we consider trust measures between two agents only if they are similar.

The rest of this paper is organized as follows. Section 2 includes a literature overview on the related work. In Section 3 we summarize the main concepts on which is based this work. We introduce after, in Section 4, the multi-context BDI agent framework. In order to give a view of how the model works, we show in Section 5 a real-world scenario in healthcare domain. Conclusions end the paper.

2 RELATED WORK

Recommender systems (RS) are information-filtering systems that help users to deal with the problem of information overload by recommending only relevant items. (Bobadilla et al., 2013) undertook a literature review and classification of recommender systems. They came up with the conclusion that approaches reviewed still require further improvements to make recommendation methods more effective in a broader range of applications. For example, in order to exploit information coming from various sensors and devices on the Internet of things and the acquisition and integration of trends related to the habits, consumption and tastes of individual users in the recommendation process. The main recommendation algorithms can be divided into four categories: content-based (CB), collaborative filtering (CF), Knowledge-based (KB) and hybrid recommendation (HR). The CB method recommends objects that are similar to the ones the user showed to prefer in the past. However, this method has a tendency to produce recommendations with a limited degree of novelty (serendipity). CF has been the most successful recommendation system technology. In CF, we make recommendations according to the assumption that users who share similar preferences choose similar items. However, the performance of CF is significantly limited by data sparsity. Knowledge-based recommender approaches (Trewin, 2000) appear to be more promising to tackle those challenges by exploiting explicit user requirements and specific domain knowledge. There are two approaches to knowledge-based recommendation: case-based (Bridge et al., 2005) and constraint-based recommendation (Felfernig et al., 2015). Case-based recommenders determine recommendations on the basis of similarity metrics while constraint-based recommenders exploit a predifined knowledge base that contains explicit rules to rely user requirements with item features. Finally, HR is currently the most popular approach. As its name suggests, it combines at least two recommendation algorithms to determine a recommendation. New trends of recommender system appeared with the abundance of smart devices like smartphones. This trend of recommender systems is called context-aware RS. Context-aware recommender systems (Adomavicius and Tuzhilin, 2011) focus on additional contextual information, such as time, location, and wireless sensor networks (Gavalas and Kenteris, 2011). However, those traditionnal recommendation approaches are not well-suited for the recommendation of complex products and services.

Despite all these advances, the current generation of recommender systems still requires further improvements to make recommendation methods more effective and applicable to broader range of real-life applications, including recommending holidays plans (flight, places, and accommodation), certain types of financial services to investors, and workout plans for healthcare purpose. These improvements include better methods for representing user behavior and the information about the items to be recommended, more advanced recommendation modeling methods, incorporation of contextual information into the recommendation process, utilization of multi-criteria ratings, development of less intrusive and more flexible recommendation methods that also reason beyond user preferences.

A solution to this research problem can be provided by the use of recommender agents, which are agent-based recommender systems that take into account users preferences to generate relevant recommendations. Agents are also well suited for autonomous applications operating in a dynamic environment. Building systems based on agents gives a more natural way to simulate complex real-world situations (Jennings, 2000). A complete taxonomy of this kind of recommendation systems can be found in (Adomavicius and Tuzhilin, 2005). They are widely used in the tourism domain as (Casali et al., 2011; Batet et al., 2012; Gavalas et al., 2014), healthcare applications (Amir et al., 2013), and traffic ones aiming at improving the travel efficiency and mobility (Chen and Cheng, 2010).

3 BACKGROUND

In this section, we summarize the main insights and notions, which the present contribution is based on.

An agent in a BDI architecture is defined by its beliefs, desires and intentions. Beliefs encode the agent's understanding of the environment, desires are those states of affairs that an agent would like to accomplish and intentions those desires that the agent has chosen to act upon. Many approaches tried to formalize such mental attitudes (e.g. (Cohen and Levesque, 1990), (Rao et al., 1995), (Wooldridge et al., 2000) and (Singh, 1998)). However, all these works concentrated on the human decision-making process as a single approach without considering social influences. They did not take the gradual nature of beliefs, desires, and intentions into account. Incorporating uncertainty and different degrees of attitudes will help the agent in the decision-making process. In order to represent and reason about uncertainty and graded notions of beliefs, desires, and intentions, we follow the approach proposed by (da Costa Pereira and Tettamanzi, 2010) where uncertainty reasoning is dealt with by possibility theory. Possibility theory is an uncertainty theory dedicated to handle incomplete information. It was introduced by (Negoita et al., 1978) as an extension to fuzzy sets which are sets that have degrees of membership in [0, 1]. Possibility theory differs from probability theory by the use of dual set functions (possibility and necessity measures) instead of only one. Possibility distribution assigns to each element ω in a set Ω of interpretations a degree of possibility $\pi(\omega) \in [0,1]$ of being the right description of a state of affairs. It represents a flexible restriction on what is the actual state with the following conventions:

- $\pi(\omega) = 0$ means that state ω is rejected as impossible;
- $\pi(\omega) = 1$ means that state ω is totally possible (plausible).

While we chose to adopt a possibilistic BDI model to include gradual mental attitudes, unlike (da Costa Pereira and Tettamanzi, 2010), to represent our BDI agents we use multi-context systems (MCS) (Parsons et al., 2002). According to this approach, a BDI model is defined as a group of interconnected units $\{C_i\}, i \in I, \Delta_{br}$, where:

- For each $i \in I$, $C_i = \langle L_i, A_i, \Delta_i \rangle$ is an axiomatic formal system where L_i, A_i and Δ_i are the language, axioms, and inference rules respectively. They define the logic for context C_i whose basic behavior is constrained by the axioms.
- Δ_{br} is a set of bridge rules; i.e. rules of inference, which relate formulas in different units.

The way we use these components to model BDI agents is to have separate units for belief B, desires D and intentions I, each with their own logic. The theories in each unit encode the beliefs, desires, and intentions of specific agents and the bridge rules (Δ_{br}) encode the relationships between beliefs, desires and intentions. We also have two functional units C and P, which handle communication among agents and allow to choose plans that satisfy users desires. To summarize, using the multi-context approach, a BDI model is defined as follows:

$$Ag = (\{BC, DC, IC, PC, CC\}, \Delta_{br})$$

where BC, DC, IC represent respectively the Belief Context, the Desire Context and the Intention Context. PC and CC are two functional contexts corresponding to Planning and Communication Contexts.

The use of MCS offers several advantages when modeling agent architectures. It gives a neat modular way of defining agents, which allows from a software perspective to support modular architectures and encapsulation.

4 THE MULTI-CONTEXT BDI FRAMEWORK

The BDI agent architecture we are proposing in this paper extends Rao and Georgeffs well-known BDI architecture (Rao et al., 1995). We define a BDI agent as a multi-context system being inspired by the work

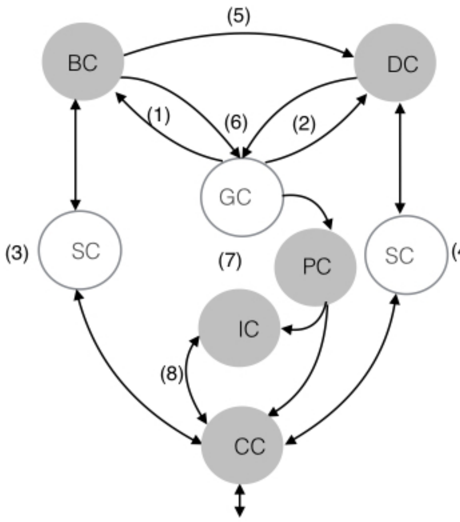

Figure 1: Extended Multi-context BDI Agent Model

of (Parsons et al., 2002). Following this approach, our BDI agent model visualized in Figure 1 is defined as follows:

$$Ag = (\{BC, DC, GC, SC, PC, IC, CC\}, \Delta_{br})$$

where GC and SC represent respectively the Goal Context and the Social Context.

In order to reason about beliefs, desires, goals and social contexts we follow the approach developed by (da Costa Pereira and Tettamanzi, 2010; da Costa Pereira and Tettamanzi, 2014) where they adopt a classical propositional language for representation and possibility theory to deal with uncertainty.

Let $\mathcal{A}$ be a finite set of atomic propositions and $\mathcal{L}$ be the propositional language such that $\mathcal{A} \cup \{\top, \bot\} \subseteq \mathcal{L}$ and $\forall \phi, \psi \in \mathcal{L}, \neg\phi \in \mathcal{L}, \phi \vee \psi \in \mathcal{L}, \phi \wedge \psi \in \mathcal{L}$. These propositions can contain temporal elements that are left as future work. As in (da Costa Pereira and Tettamanzi, 2010), $\mathcal{L}$ is extended and we will denote with $\Omega = \{0,1\}^{\mathcal{A}}$ the set of all interpretations on $\mathcal{A}$. An interpretation $\omega \in \Omega$ is a function $\omega : \mathcal{A} \to \{0,1\}$ assigning a truth value p^{ω} to every atomic proposition $p \in \mathcal{A}$ and, by extension, a truth value ϕ^{ω} to all formula $\phi \in \mathcal{L}$. $[\phi]$ denotes the set of all interpretations satisfying ϕ. (i.e., $[\phi] = \omega \in \Omega : \omega \models \phi$).

In the planning and intentions contexts, we propose an ontological representation for plans and intentions in order to offer to agents a computer-interpretable description of the services they offer and the information they have access to (workout plans in our case). In the following subsections, we will outline the different theories defined for each context in order to complete the specification of our multi-context agent model.

4.1 Belief Context

4.1.1 The BC language and semantics

In order to represent beliefs, we use the classical propositional language with additional connectives, following (da Costa Pereira and Tettamanzi, 2010). We introduce also a fuzzy operator B over this logic to represent agents beliefs. The belief of an agent is then represented as a possibility distribution π. A possibility distribution π can represent a complete preorder on the set of possible interpretations $\omega \in \Omega$. This is the reason why, intuitively, at a semantic level, a possibility distribution can represent the available knowledge (or beliefs) of an agent. When representing knowledge, $\pi(\omega)$ acts as a restriction on possible interpretations and represents the degree of compatibility of interpretation ω with the available knowledge about the real world. As in (da Costa Pereira and Tettamanzi, 2010), a graded belief is regarded as a necessity degree induced by a normalized possibility distribution π on the possible worlds ω. The degree to which an agent believes that a formula Φ is true is given by:

$$B(\phi) = N([\phi]) = 1 - \max_{\omega \not\models \phi}\{\pi(\omega)\} \tag{1}$$

An agent's belief can change over time because new information arrives from the environment or from other agents. A belief change operator is proposed in (da Costa Pereira and Tettamanzi, 2010), which allows to update the possibility distribution π according to new trusted information. This possibility distribution π' which induces the new belief set B' after receiving information ϕ is computed from the possibility distribution π with respect to the previous belief set B ($B' = B * \frac{\tau}{\Phi}, \pi' = \pi * \frac{\tau}{\Phi}$) as follows: for all interpretation ω,

$$\pi'(\omega) = \begin{cases} \frac{\pi(\omega)}{\Pi([\phi])} & \text{if} \quad \omega \models \phi \textit{ and } B(\neg\phi) < 1; \\ 1 & \text{if} \quad \omega \models \phi \textit{ and } B(\neg\phi) = 1; \\ \min\{\pi(\omega), (1-\tau)\} & \text{if} \quad \omega \not\models \phi. \end{cases} \tag{2}$$

where τ is the trust degree toward a source about an incoming information ϕ.

4.1.2 BC Axioms and Rules

Belief context axioms include all axioms from classical propositional logics with weight 1 as in (Dubois and Prade, 2006). Since a belief is defined as a necessity measure, all the properties of necessity measures are applicable in this context. Hence, the belief modality in our approach is taken to satisfy these properties that can be regarded as axioms. The following axiom is then added to the belief unit:

$$BC: B(\phi) > 0 \rightarrow B(\neg\phi) = 0$$

This axiom is a straightforward consequence of the properties of possibility and necessity measures. It means that if an agent believes ϕ to a degree then it cannot believe $\neg\phi$ at all. Other consequences are:

$$B(\phi \wedge \psi) \equiv \min\{B(\phi), B(\psi)\}$$
$$B(\phi \vee \psi) \geq \max\{B(\phi), B(\psi)\}$$

The inference rules are:

- $B(\neg p \vee q) \geq \alpha, B(p) \geq \beta \vdash B(q) \geq \min(\alpha, \beta)$ (modus ponens)
- $\beta \leq \alpha$, $B(p) \geq \alpha \vdash B(p) \geq \beta$(weight weakening)

where $\vdash$ denote the syntactic inference of possibilistic logic.

4.2 Desire Context

Desires represent a BDI agent's motivational state regardless its perception of the environment. Desires may not always be consistent. For example, an agent may desire to be healthy, but also to smoke; the two desires may lead to a contradiction. Furthermore, an agent may have unrealizable desires; that is, desires that conflict with what it believes possible.

4.2.1 The DC language and semantics

In this context, we make a difference between desires and goals. Desires are used to generate a list of coherent goals regardless to the agent's perception of the environment and its beliefs. Inspired from (da Costa Pereira and Tettamanzi, 2014), the language of DC (L_{DC}) is defined as an extension of a classical propositional language. We define a fuzzy operator D^+, which is associated with a satisfaction degree ($D^+(\phi)$ means that the agent positively desires ϕ) in contrast with a negative desire, which reflects what is rejected as unsatisfactory. For sake of simplicity, we will only consider the positive side of desires in this work and the introduction of negative desire is left as future work.
In this theory, (da Costa Pereira and Tettamanzi, 2010) use possibility measures to express the degree of positive desires. Let $u(\omega)$ be a possibility distribution called also qualitative utility (e.g. $u(\omega) = 1$, means that ω is fully satisfactory). Given a qualitative utility assignment u (formally a possibility distribution), the degree to which the agent desires $\phi \in L_{DC}$ is given by:

$$D(\phi) = \Delta([\phi]) = \min_{\omega \models \phi}\{u(\omega)\} \tag{3}$$

where Δ is a guaranteed possibility measure that, given a possibility distribution π, is defined as follows, for all set $S \subseteq \Omega$:

$$\Delta(S) = \min_{\omega \in S}\{\pi(\omega)\}. \tag{4}$$

4.2.2 DC Axioms and Rules

The axioms consist of all properties of possibility measures such as $D(\phi \vee \psi) \equiv \min\{D(\phi), D(\psi)\}$. The basic inference rules, in the propositional case, associated with Δ are:

- $[D(\neg p \wedge q) \geq \alpha], [D(p \wedge r) \geq \beta] \vdash [D(q \wedge r) \geq min(\alpha, \beta)]$(resolution rule)
- if p entails q classically, $[D(p) \geq \alpha] \vdash [D(q) \geq \alpha]$(formula weakening)
- for $\beta \leq \alpha$, $[D(p) \geq \alpha] \vdash [D(p) \geq \beta]$ (weight weakening)
- $[D(p) \geq \alpha]; [D(p) \geq \beta] \vdash [D(p) \geq max(\alpha, \beta)]$ (weight fusion).

4.3 Goal Context

Goals are sets of desires that, besides being logically "consistent", are also maximally desirable, i.e., maximally justified. Even though an agent may choose some of its goals among its desires, nonetheless there may be desires that are not necessarily goals. The desires that are also goals represent those states of the world that the agent might be expected to bring about precisely because they reflect what the agent wishes to achieve. In this case, the agent's selection of goals among its desires is constrained by three conditions. First, since goals must be consistent and desires may be inconsistent, only the subsets of consistent desires can be the potential candidates for being promoted to goal-status, and also the selected subsets of consistent desires must be consistent with each other. Second, since desires may be unrealizable whereas goals must be consistent with beliefs (justified desires), only a set of feasible (and consistent) desires can be potentially transformed into goals. Third, desires that might be potential candidates to be goals should be desired at least to a degree α. Then only the most desirable, consistent, and possible desires can be considered as goals.
Example: Let us consider one agent representing Alice. Alice believes that her usual road to work is congested and that there are other alternative routes that she probably did not know. She would like to be at her office at time without leaving earlier. She also prefers a route without stops. Some of Alice desires can not be moved to goal status such as desiring a route without stops because Alice's agent does not believe that a route without stops is possible.

4.3.1 The GC language and semantics

The language L_{GC} to represent the Goal context is defined over the propositional language L extended by a fuzzy operator G having the same syntactic restrictions as D^+. $G(\phi)$ means that the agent has goal ϕ. As explained above, goals are a subset of consistent and possible desires. Desires are adopted as goals because they are justified and achievable. A desire is justified because the world is in a particular state that warrants its adoption. For example, one might desire to go for a walk because he believes it is a sunny day and may drop that desire if it starts raining. A desire is achievable, on the other hand, if the agent has a plan that allows it to achieve that desire.

4.3.2 GC Axioms and Rules

Unlike desires, goals should be consistent, meaning that they can be expressed by the D_G axiom (D from the KD45 axioms (Rao et al., 1995)) as follows:

$$D_G \quad GC : G(\phi) > 0 \rightarrow G(\neg\phi) = 0$$

Furthermore, since goals are a set of desires ,we use the same axioms and deduction rules as in DC. Goals-beliefs and goals-desires consistency will be expressed with bridge rules as we will discuss later on the paper.

4.4 Social Context

One of the benefits of the BDI model is to consider the mental attitude in the decision-making process, which makes it a more realistic than a purely logical model. However, this architecture overlooks an important factor that influences this attitude, namely the sociality of an agent. There are a number of ways in which agents can influence one another's mental states such as authority where an agent may be influenced by another to adopt a mental attitude whenever the latter has the power to guide the behavior of the former, trust where an agent may be influenced by another to adopt a mental attitude merely on the strength of its confidence in the latter or persuasion where an agent may be influenced to adopt another agents mental state via a process of argumentation or negotiation. In this work we will only consider trust as a way by which agents can influence each others.

4.4.1 The SC language and semantics

In our model, we consider a multi-agent system MAS consisting of a set of N agents $\{a_1, .., a_i, ..a_N\}$. The idea is that those agents are connected in a social network such as agents with the same goal. Each agent has links to a number of other agents (neighbors) that change over time. In this paper, we do not consider dynamic changes in the social network, but we assume to deal with the network in a specific time instant. Between neighbors, we consider a trust relationship. The trustworthiness of an agent a_i toward an agent a_j about an information ϕ is interpreted as a necessity measure $\tau \in [0, 1]$ as in (Paglieri et al., 2014) and is expressed by the following equation:

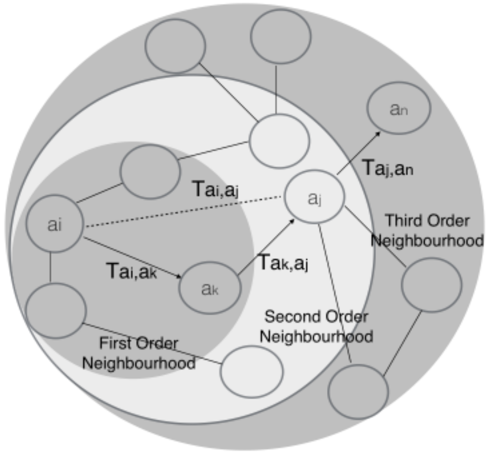

Figure 2: An example of a social multi-agent trust network

$$T_{a_i,a_j}(\phi) = \tau \tag{5}$$

where $a_i, a_j \in MAS = \{a_1, .., a_i, .., a_N\}$. Trust is transitive in our model, which means that, trust is not only considered between agents having a direct link to each others but, as showed in Figure 2, indirect links are also considered. Namely if agent a_i trusts agent a_k to a degree τ_1 which trusts agent a_j with a trust degree τ_2 then a_i can infer its trust to agent a_j and $T_{a_i,a_j}(\phi) = min\{\tau_1, \tau_2\}$. We only consider first and second order neighbors in our work e.g. agent a_i can be influenced by agent a_k and agent a_j.

4.4.2 SC Axioms and Rules

As sociality is expressed as a trust measure, which is interpreted as a necessity measure, SC axioms include properties of necessity measures as in BC (e.g. $N(\phi \wedge \psi) \equiv \min\{N(\phi), N(\psi)\}$).

When an agent is socially influenced to change its mental attitude, by adopting a set of beliefs and/or desires, the latter should maintain a degree of consistency. Those rules will be expressed with bridge rules that link the social context to the belief and the desire contexts.

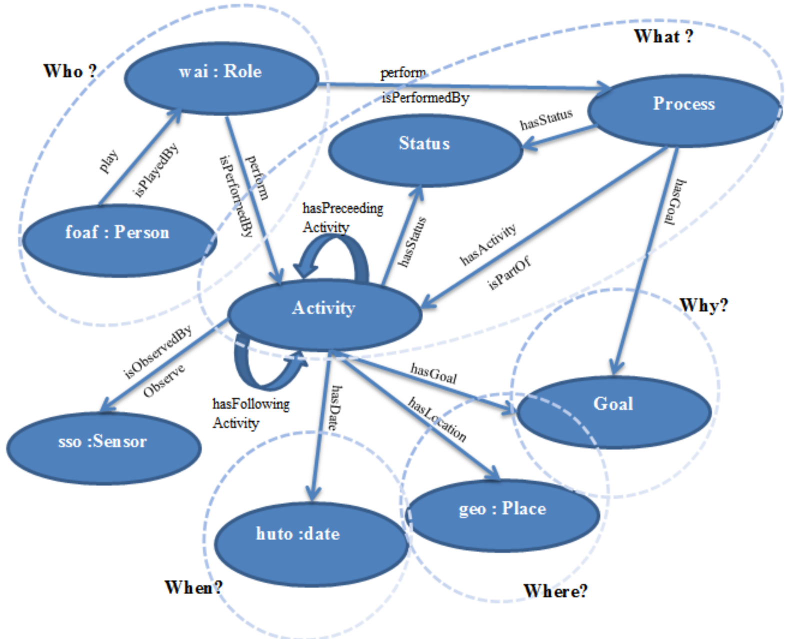

Figure 3: Main Concepts and relationships in the 5W ontology

4.5 Planning and Intention Contexts

The aim of this functional context is to extend the BDI architecture in order to represent plans available to agents and provide a way to reason over them. In this context, we were inspired from (Batet et al., 2012) to represent and reason about plans and intentions.

Plans are described using ontologies. (Gruber, 1993) defines an ontology as 'the specification of conceptualizations, used to help programs and humans share knowledge'. According to the World Wide Web Consortium[1] (W3C), ontologies or vocabularies define the concepts and relationships used to describe and represent an area of concern. We use the 5W[2] (Who, What, Where, When, Why) vocabulary which is relevant for describing different concepts and constraints in our scenario. The main concepts and relationships of this ontology are illustrated by Figure 3.

The main task of this context is to select plans that satisfy maximally the agents goals. To go from the abstract notions of desires and beliefs to the more concrete concepts of goals and plans, as illustrated by Figure 4, the following steps are considered: (1) new information arrives and updates beliefs or/and desires which trigger goals update; (2) these goal changes invoke the Plan Library.

The selection process is exressed by Algorithm 1

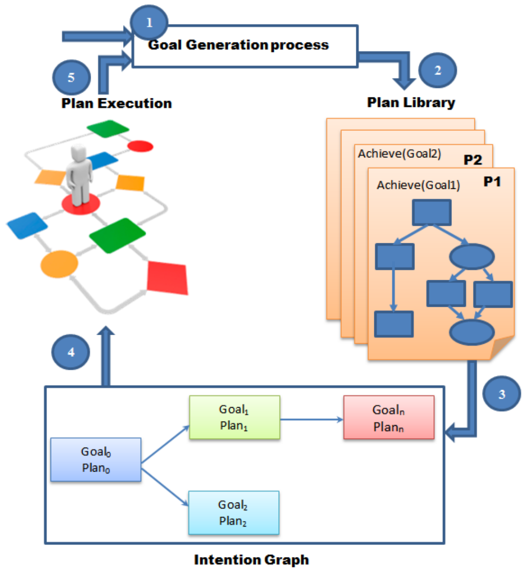

Figure 4: Planning and Intention Contexts

which looks in a knowledge base (KB) for all plans that satisfy maximally these goals; CB and/or CF techniques can be used in the selection process but will be investigated more thoroughly in further work. The algorithm complexity is significantly reduced since we discard from the beginning goals without plans. (3) one or more of these plans are then chosen and moved to the intention structure; finally (4) a task (intention) is selected for execution and once ex-

[1] http://www.w3.org/standards/semanticweb/ontology
[2] http://ns.inria.fr/huto/5w/

Data: G
Result: S //S is a list of plans
$G^* = \{\phi_1, \phi_2, .., \phi_n\}$
$m \leftarrow 0; S' \leftarrow \emptyset; G' \leftarrow \emptyset;$
for ***each*** ϕ_i *in* G^* **do**
    //Search in the KB for a plan satisfying ϕ_i
    $S_{\phi_i} \leftarrow SearchInKB(\phi_i);$
    if $S_{\phi_i} <> \emptyset$ **then**
        //Discard goals without plans
        $Append(G', S_{\phi_i});$
    end
end
for *i in* $1..Lenght(G')$ **do**
    //Combination of i elements in G'
    $S' \leftarrow Combination(G', i);$
    for *j in* $1..Length(S')$ **do**
        if $S'[j] <> \emptyset$ **then**
            //Compute the satisfaction degree of S'
            $\alpha_i = G(S'[j]);$
            //Select the maximum α_i
            if $\alpha_i > m$ **then**
                $m \leftarrow \alpha_i;$
                Initialize(S);
                Append(S, S');
            else
                if $\alpha_i = m$ **then**
                    Append(S,S');
                end
            end
        end
    end
end
Return S;

Algorithm 1: *RequestForPlan* Function

ecuted or failed this lead to the update of the agents beliefs (5).

Example (continued): Suppose that Alice's agent accepts to change its belief regarding 'the route without stops'. Then this desire will become a goal. So Alice's agent will look in its KB for alternatives routes without stops. Suppose that Algorithm 1 returns two plans (routes) A and B. If Alice chooses Route A then the first action a_1="Take Route Dolines" becomes the agent intention. Once done, Alice's agent updates its beliefs with information that a_1 is completed successfully.

4.6 Bridge Rules

There are a number of relationships between contexts that are captured by so-called bridge rules. A bridge rule is of the form:

$$u1 : \phi, u2 : \psi \rightarrow u3 : \theta$$

and it can be read as: if the formula ϕ can be deduced in context $u1$ and ψ in $u2$ then the formula θ is to be added to the theory of context $u3$. A bridge rule allows to relate formulae in one context to those in another one. In this section we present the most relevant rules illustrated by numbers in Figure 1.$\forall a_i \in MAS$, the first rule relating goals to beliefs can be expressed as follows:

$$(1) \vDash GC : G(a_i, \phi) > 0 \rightarrow BC : B(a_i, \neg\phi) = 0$$

which means that if agent a_i adopt a goal ϕ with a satisfaction degree equal to β_ϕ then ϕ is believed possible to a degree β_ϕ by a_i. Concerning rule (2) relating goal context to desire context, if ϕ is adopted as goal then it is positively desired with the same satisfaction degree.

$$(2) \vDash GC : G(a_i, \phi) = \delta_\phi \rightarrow DC : D^+(a_i, \phi) = \delta_\phi$$

An agent may be influenced to adopt new beliefs or desires. Beliefs coming from other agents are not necessarily consistent with agent's individual beliefs. This can be expressed by the following rule:

$$(3) \vDash BC : B(a_j, \phi) = \beta_\phi, SC : T_{a_i,a_j}(\phi) = t \rightarrow BC : B(a_i, \phi) = \beta'_\phi$$

where β'_ϕ is calculated using Equation 1 with $\tau = min\{\beta_\phi, t\}$ to compute the possibility distribution and Equation 1 to deduce the Belief degree.

Similarly to beliefs, desires coming from other agents need not to be consistent with agent's individual desires. For example, an agent may be influenced by another agent to adopt the desire to smoke, and at the same time having the desire to be healthy as shown by the following rule:

$$(4) \vDash DC : D^+(a_j, \psi) = \delta_\psi, SC : T_{a_i,a_j}(\psi) = \tau \rightarrow DC : D^+(a_i, \psi) = \delta'_\psi$$

where $\delta'_\psi = min\{\delta_\psi, \tau\}$. Desire-generation rules can be expressed by the following rule:

$$(5) \vDash BC : min\{B(\phi_1) \wedge ... \wedge B(\phi_n)\} = \beta, DC : min\{D^+(\psi_1) \wedge ... \wedge D^+(\psi_n))\} = \delta \rightarrow DC : D^+(\Psi) \geq min\{\beta, \delta\}$$

Namely, if an agent has the beliefs $B(\phi_1) \wedge ... \wedge B(\phi_n)$ with a degree β and positively desires $D^+(\psi_1) \wedge ... \wedge D^+(\psi_n)$ to a degree δ, then it positively desires Ψ to a degree greater or equal to $min\{\beta, \delta\}$.

According to (da Costa Pereira and Tettamanzi, 2014), goals are a set of desires that, besides being logically 'consistent", are also maximally desirable, i.e., maximally justified and possible. This is expressed by the following bridge rule:

$$(6) \vDash BC : B(a_i, \phi) = \beta_\phi, DC : D^+(a_i, \psi) = \delta_\psi \rightarrow GC : G(\chi(\phi, \psi)) = \delta$$

Data: B,D
Result: G^*
1: $\gamma \leftarrow 0$;
2: Compute G_γ by Algorithm 3;
if $G_\gamma \neq \emptyset$ **then**
  terminate with $\gamma^* = 1-\gamma, G^* = G_\gamma$;
else
  //Move to the next more believed value in B

$$\gamma \leftarrow \begin{cases} \min\{\alpha \in Img(B)\} & if\ \alpha > \gamma \\ 1 & if\ \nexists\ \alpha \end{cases}$$

end
if $\gamma < 1$ **then**
  go back to Step 2;
end
terminate with $G^* = \emptyset$;*//No goal can be elected*

Algorithm 2: Goal Election Function

Data: B,D
Result: G_γ
//Img(D) is the degree of Desire
1: $\delta \leftarrow maxImg(D)$;
//Verify if ψ is believed possible
2: **if** $\min_{\psi \in D_\delta} B(\neg\psi) \leq \gamma$ **then**
  terminate with $G_\gamma = D_\delta$;
else
  //move to the next less desired value of D

$$\delta \leftarrow \begin{cases} \max\{\alpha \in Img(D)\} & if \alpha < \delta \\ 0 & if\ \nexists\ \alpha \end{cases}$$

end
if $\delta > 0$ **then**
  go back to Step 2;
end
terminate with $G_\gamma = \emptyset$;

Algorithm 3: Computation of G_γ

where $\chi(\phi,\psi) = ElectGoal(\phi,\psi)$, as specified in Algorithm 2, is a function that allows to elect the most desirable and possible desires as goals. If *ElectGoal* returns $\emptyset$ then $G(\emptyset) = 0$, i.e. no goal is elected.
As expressed by the bridge rule above, once goals are generated, our agent will look for plans satisfying goal ϕ by applying *RequestForPlan* function and intend to do the first action of the recommended plan.

$$(7) \vDash GC : G(a_i,\phi) = \delta, PC : RequestForPlan(\phi) \rightarrow IC : I(act_i, PostConditon(act_i))$$

where *RequestForPlan* is a function that looks for plans satisfying goal ϕ in the plan library as specified in Algorithm 1. Rule (8) means that if an agent has the intention of doing an action act_i with $PostCondition(act_i)$ then it passes this information to the communication unit and via it to other agents and to the user.

$$(8) \vDash IC : I(act_i, PostConditon(act_i)) \rightarrow CC : C(does(act_i, PostConditon(act_i)))$$

If the communication unit obtains some information that some action has been completed then the agent adds it to its beliefs set using rule (3) with $B(PostConditon(act_i)) = 1$.

5 A Running Example

To illustrate the reasoning process of our BDI architecture, we use the example introduced in Introduction and illustrated by Figure 5.

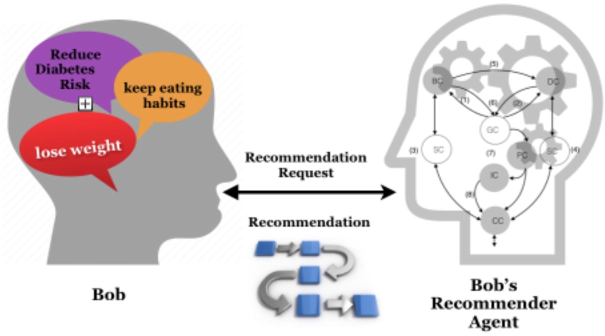

Figure 5: An Illustrating Example

To implement such a scenario using the BDI formalism, a recommender agent has a knowledge base (KB) like that shown in Table 1 initially specified by Bob.

Beliefs	Desires
$B(pa \rightarrow rd) = 0.75$	$D^+(pa) = 0.8$
$B(wr \rightarrow rd) = 0.8$	$D^+(wr) = 0.8$
$B(eh) = 0.4$	$D^+(\neg eh) = 0.9$
$B(bs) = 0.9$	$D^+(w) = 0.75$
	$D^+(wr \wedge \neg eh) = 0.95$

Table 1: Initial Knowledge Base of Bob's Recommender Agent

The belief set is represented by formulae describing the world (e.g. $B(\psi_1) = 1$, means that ψ_1 is necessary and totally possible). Desires are all possible states that the agent wishes to achieve. Notice that they can be conflicting like $D^+(wr)$ and $D^+(\neg eh)$ or unachievable like $D^+(wr \wedge \neg eh)$. $D^+(wr) = 0.8$, means that wr is desired to a degree equal to 0.8. Desire-generation rules from bridge rule (5) can be described as follows:

$$\begin{aligned} R_{5_1}: &\quad B(pa \rightarrow rd), D^+(rd) \rightarrow D^+(pa), \\ R_{5_2}: &\quad B(wr \rightarrow rd), D^+(rd) \rightarrow D^+(wr), \\ R_{5_3}: &\quad B(bs), D^+(pa) \rightarrow D^+(w), \\ R_{5_4}: &\quad B(pa \rightarrow wr), D^+(wr) \rightarrow D^+(\neg eh). \end{aligned}$$

Then the desire base of Bob, derived from desire-generation rules will be as follows:

$$D = \{(pa, 0.8), (wr, 0.8), (w, 0.75), (\neg eh, 0.9)\}$$

We may now apply rule (6) to elect Bob's goals, given his belief base and his desire base. This rule will apply the function *electGoal()* which will choose from the desire base the most desirable and possible desires. Then, $Img(B) = \{0.75, 0.8, 0.9, 0.4\}$ and $Img(D) = \{0.75, 0.8, 0.9\}$. We begin by calling Algorithm 2 with $\gamma = 0$; δ is set to $maxImg(D) = 0.9$ and the corresponding desire in D is $D_\delta = \{\neg eh\}$. Now if we verify $B(\neg(\neg eh)) = 0.4 > \gamma$ we move to the next less desired value which sets δ to $Img(D) = 0.8 < \delta = 0.9$. $\delta = 0.8 > 0$, then we go back to Step 2. In this case $D_\delta = \{(pa, wr\}$. Now $B(\neg pa) = B(pa) = 0$ because we ignore yet whether pa is possible or nor. Similarly, $B(\neg wr) = 0$ and Algorithm 2 will terminate with $G^* = G_\gamma = \{pa, wr\}$, i.e. Bob's recommender agent will elect as goal 'get back to a regular physical activity and reduce weight'.

Given these goals, Bob's agent (a_1) will look in the plan library for a plan satisfying them. As explained in rule (7), the agent will invoke function *RequestForPlan*, which will look for a plan satisfying pa and wr. Applying Algoritm 1, we have $G' = \{pa, wr\}$ and $S' = [pa, wr, \{pa, wr\}]$ with the same satisfaction degree $\alpha_1 = \alpha_2 = \alpha_3 = 0.8$. Suppose that it returns three plans p_1, p_2 and p_3 satisfying respectively goals pa, wr and $\{pa, wr\}$. Bob's recommender agent will propose plan p_3 to the user because it meets more Bob's requirements with the same satisfaction degree. We suppose that Bob chooses Plan p_3. Therefore, the first action (activity) in Plan p_3 will become the agent's intention. The intended action will be proposed to the user via the communication unit by applying rule (8). Finally, if Bob starts executing the activity, information such as speed, distance or heart rate are collected via sensors (i.e. smart watch) and transmitted to the communication unit in order to update the agent's beliefs. The revision mechanism of beliefs is the same as in (da Costa Pereira and Tettamanzi, 2010) defined by Equation 2. Once the activity is completed, rule(3) is triggered in order to update the belief set of Bob's agent with $B(postCondition(action1) = 1)$ which will permit to move to the next action in Plan α.

In order to illustrate the social influence between agents, we suppose that Bob's Doctor uses our application with the same goal as Bob i.e. reduce his diabete risk. Then, there is a direct link between agents a_1, a_2 representing respectively Bob and Bob's doctor with $T_{a_1,a_2}(\phi) = 0.9$ where ϕ represents any message coming from Bob's doctor (see (Paglieri et al., 2014) for more details). Now that Bob is executing his plan in order to get back to a physical activity, his recommender agent recieves the following information from $a_2 : B(\neg pa) = 1$ which means that Bob's doctor believes that physical activity is not possible (not recommended). This information will trigger bridge rule (3). Knowing the belief degree of a_2 about pa and given the trust degree of a_1 toward a_2 about information pa ($T_{a_1,a_2}(pa)$), a_1 decides to update its mental state according to Equation 2, and sets the new belief to $B'(pa) = 0$ according to Equation 1. This will trigger the goal generation process, which updates the elected goals. pa will be removed because $B(\neg pa) = 1$. Hence, a new plan is proposed to Bob.

6 CONCLUSIONS

We have presented in this paper a multi-context formalisation of the BDI architecture. We use a possibilistic approach, based on (da Costa Pereira and Tettamanzi, 2010), to deal with graded beliefs and desires which are used to determine agent's goals as suggested by (Casali et al., 2011) in their future works. We also take into account the social aspect of agents as a similarity-trust measure. The proposed model is conceived as a multi-context system where we define a mental context containing the beliefs, desires and intentions, a social context representing the social influence among agents in an implicit relationship, two functional contexts allowing to select a feasible plan among a list of precompiled plans, and a communication context that enables to communicate with other agents and with users. Short-term objectives of our research concern the realisation of a simulation of the MAS presented using Netlogo (Sakellariou et al., 2008). This simulation will help to have a testing of initial design ideas and choices and also to understand how the system will behave when it will be implemented. For the implementation of the proof-of-concept MCS framework, we have investigated the approaches of (Casali et al., 2008) and (Besold and Mandl, 2010). We will explore also approaches such as (Costabello et al., 2012) for multi-context access in RDF graph for our planning module. We consider that extending this model in order to handle temporal reasoning in dynamic environments (e.g. when executing recommended plan) will be more representative of real world applications. This includes a revision mechanism of the mental attitudes (beliefs, desires and intentions) and taking into account the evolution of the social relationship over time. Extending the social context in order to get into a communication process with agent via argumentation (Mazzotta et al., 2007) is also part of our future work.

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