

Explainable and Contextual Preferences based Decision Making with Assumption-based Argumentation for Diagnostics and Prognostics of Alzheimer’s Disease

Extended Abstract

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ABSTRACT

We present an argumentation-based approach to decision making that can support context-based defeasible preferences and offer dialogical explanations for the decisions made. The proposed approach makes and explains a decision as follows: (1) construct a *Contextual Preference Decision Framework (CPDF)* to model the problem, (2) use Assumption-based Argumentation as a sound and complete computational mechanism for identifying most-contextual-preferred decisions in the CPDF, and (3) construct *explaining dialogues* to provide dialogical explanations for identified decisions. We have implemented our approach for two tasks, diagnostics and prognostics of Alzheimer’s Disease (AD), and evaluated the performance of our models on the two tasks with real-world datasets.

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1 INTRODUCTION

Argumentation-based decision making has gained an increasing amount of research interest recently due to its explanatory power [4, 4, 6]. The key components of a general decision framework [4], which is used to model agents’ knowledge base, include *decisions*, *goals*, and *attributes*. *Preferences* can be specified for decision information, such as attributes or goals, to prioritize and order them. In real-life applications, preferences do not always remain the same but may vary in different contexts. For example, in the problem of determining whether a patient is at high risk for Alzheimer’s Disease (AD), although the APOE4 allele is a genetic risk factor for both men and women, its magnitude and effect appear to differ between genders. Medical research suggests that the effect of APOE4 is far more pronounced in women than in men [1, 5]. Considering the patient being a man or a woman as the context for this decision problem, we may arrive at the following two different preferences:

- $APOE4 > ADASQ4 \text{ test results}^1$ (patient is a female)

¹ADASQ4 stands for the Alzheimer’s Disease Assessment Scale Question 4

- $ADASQ4 \text{ test results} > APOE4$ (patient is a male)

In this paper, we propose a formal decision making approach that can handle the problem mentioned above and at the same time provide selected and focused dialogical explanations. We first formalize contextual preferences in decision making by proposing Contextual Preference Decision Frameworks (CPDFs). Then, we rely on Assumption-based Argumentation (ABA) frameworks to compute most-contextual-preferred decisions in CPDFs. We select ABAs to support reasoning in our approach since they provide underlying structures that can facilitate the generation of explanations. We have implemented the proposed approach as an AD diagnosis agent (ADDA) for two tasks, the diagnosis of AD and the prediction of progression to AD in the future (prognosis). Rather than relying on expert knowledge which can be hard to obtain, the contextual preferences are learned from data directly. We choose three types of contexts based on medical research, namely gender, education, and age. The highest accuracy for the diagnosis and the prognosis task is achieved by our model that considers the education context and the gender context, respectively. All our models also outperform the argumentation model that considers preferences without contexts.

2 CONTEXTUAL PREFERENCE BASED DECISION MAKING

We propose *Contextual Preference Decision Frameworks (CPDFs)* which can model decision problems involving contextual preferences over goals. CPDFs model decisions (D), goals (G), attributes (A), the relationships among them (T_{DA} , T_{GA}), as well as contexts (C) and preferences (P). C is a set of defeasible contexts. P is a set of contextual preference rules that represents the contextual preference orderings of different combinations of goals. We first present formal definitions for contexts (C) and preferences (P).

Definition 2.1. Let G be a set of goal, the **preference relation** \succsim is a partial preorder (a reflexive and transitive relation) over 2^G . We use $s > s'$ to denote $s \succsim s'$ and $s' \not\succeq s$, where $s, s' \in 2^G$.

Definition 2.2. The **context terms** T is a set of distinct atoms representing granular contexts in the concerned domains.

Definition 2.3. The **defeasible context** C is a set of context sentences, in which each sentence $c \in C$ is of the form $t_n \wedge \dots \wedge t_1 \rightarrow t_0$ where $n \geq 0$ and $t_0, t_1, \dots, t_n \in T$.

Definition 2.4. A **defeasible contextual preference rule** is an expression of the form $s_i > s_j \mid T$ where $T \subseteq T$ is a set of context terms, $s_i, s_j \in 2^G$ are two sets of goals.

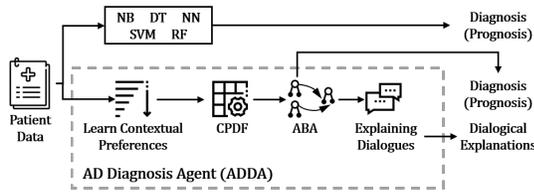


Figure 1: An overview of the AD Diagnosis Agent

Definition 2.5. The **contextual preference** P is a set of defeasible contextual preference rules. For each rule $s_i > s_j \mid T$ in P , s_i and s_j belong to a set of **comparables** $S \subseteq 2^G$ such that

- for every $s \in S$, there is a set $s' \in S$ and a set of context terms $T \subseteq T$, such that either $s > s' \mid T \in P$ or $s' > s \mid T \in P$;
- for all $s' \in 2^G$, if there is a $T \subseteq T$ and some $s \in 2^G$ with $s' > s \mid T \in P$ or $s > s' \mid T \in P$, then $s' \in S$.

Definition 2.6. A **Contextual Preference Decision Framework (CPDF)** is a tuple $\langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$ such that:

- D is a finite set of decisions $D = \{d_1, \dots, d_n\}$, ($n > 0$),
- A is a finite set of attributes $A = \{a_1, \dots, a_m\}$, ($m > 0$),
- G a finite set of goals $G = \{g_1, \dots, g_l\}$, ($l > 0$), and
- T_{DA} (size $n \times m$), and T_{GA} (size $l \times m$), are two tables s.t.
 - for every $T_{DA}[i, j]$ ($1 \leq i \leq n, 1 \leq j \leq m$), $T_{DA}[i, j]$ is either 1, representing d_i has a_j , or 0, otherwise.
 - for every $T_{GA}[k, j]$ ($1 \leq k \leq l, 1 \leq j \leq m$), $T_{GA}[k, j]$ is either 1, representing g_k is satisfied by a_j , or 0, otherwise.
- C is a set of context sentences;
- P is a set of defeasible contextual preference rules, representing the preference ranking over goals in different contexts.

Given a CPDF $F_{cp} = \langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$, a decision $d_i \in D$ meets a goal $g_k \in G$, with respect to F_{cp} , iff there exists an attribute $a_j \in A$, such that $T_{DA}[i, j] = 1$ and $T_{GA}[k, j] = 1$.

We use $\Gamma(d) = S$, where $d \in D, S \subseteq G$, to denote the set of goals met by d , \mathcal{DEC} to denote the set of all possible decisions and \mathcal{F}_{CP} to denote the set of all possible CPDFs.

Definition 2.7. Given a CPDF $F_{cp} = \langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$, the **applicable preferences** in context C is formally defined as:

$$P_a = \{s_i > s_j : s_i > s_j \mid T \in P, \forall t \in T, C \vdash_{MP} t\}$$

where \vdash_{MP} stands for repeated applications of the modus ponens inference rule² to the set of defeasible context C until the elements of P_a do not change anymore.

Definition 2.8. Given a contextual preference decision framework $F_{cp} = \langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$, a **decision function** for F_{cp} is a mapping $\psi_{cp} : \mathcal{F}_{CP} \mapsto \mathcal{DEC}$, such that: (1) $\psi_{cp}(F_{cp}) \subseteq D$; (2) for any $d, d' \in D$, if $\Gamma(d) = \Gamma(d')$ and $d \in \psi_{cp}(F_{cp})$, then $d' \in \psi_{cp}(F_{cp})$.

Definition 2.9. Given a CPDF $F_{cp} = \langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$ where P is the contextual preference, let S be the set of comparables in F_{cp} , let P_a be the applicable preferences in context C , a **most-contextual-preferred decision function** $\psi_{cp} \in \Psi_{cp}$, where Ψ_{cp} denotes the set of all decision functions for CPDFs, is a mapping such that, for every $d \in D$, $d \in \psi_{cp}(F_{cp})$ iff for all $d' \in D \setminus \{d\}$ the following holds:

- for all $s \in S$, if $s \notin \Gamma(d)$ and $s \subseteq \Gamma(d')$, then there exists $s' \in S$, such that: (1) $s' > s \in P_a$, (2) $s' \subseteq \Gamma(d)$, (3) $s' \not\subseteq \Gamma(d')$.

We then map CPDFs and most-contextual-preferred decision functions to Assumption-Based Argumentation (ABA) frameworks which support semantics for computing decisions. ABA counterparts can be constructed for CPDFs in a way similar to [6]. Theorem 2.10 shows that decisions selected by ψ_{cp} in a CPDF correspond to the claims of admissible arguments in the ABA counterpart of the CPDF and vice versa. The contextual preferences P and defeasible contexts C are encoded within existing ABA components, e.g. rules and assumptions, avoiding the needs to modify the semantics of ABA. ABA also provides underlying structures for generating explanations from the reasoning process subsequently.

THEOREM 2.10. Given a CPDF $F_{cp} = \langle D, A, G, T_{DA}, T_{GA}, C, P \rangle$, let $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, C \rangle$ be the most-contextual-preferred ABA framework counterpart for F_{cp} . Then, for all $d \in D$, $d \in \psi_{cp}(F_{cp})$ iff argument $\{cPre(d)\} \vdash cPre(d)$ is admissible in ABF .

3 EXPERIMENT RESULTS

We implemented the proposed contextual preference based decision approach as an Alzheimer’s Disease Diagnosis Agent (ADDA) for diagnostics and prognostics of Alzheimer’s Disease (AD). We investigated two tasks: (1) diagnosis: to determine the clinical diagnosis, i.e. normal (CN), mild cognitive impairment (MCI), and AD, based on multiple sources of data, (2) prognosis: to predict whether a patient is to stay at undemented status (Stay) or progress to AD (Progress) in 3 years based on current data. Data used in the experiments were obtained from the ADNI database (adni.loni.usc.edu).

To evaluate the performance of our proposed approach and ADDA for the two tasks, five machine learning models were implemented in Python: Naive Bayes (NB), CART Decision Tree (DT), Multilayer Perceptron (MLP), Random Forest (RF), and SVM with RBF kernel type. An argumentation-based model that only considers preferences without contexts [3] was also implemented. For the diagnosis task, among the three types of contexts studied, the optimal result is achieved by the model that considers education. It yields an accuracy of 0.915, which is the highest among all models, and relatively high precision and recall values for all three classes. Our models that consider the other two contexts, gender and age, also achieve good accuracy results, which are higher than all comparison models except Random Forest. For the prognosis task, the best performance is achieved by the model that considers gender. It yields an accuracy of 0.839, which is the same as Random Forest. It is closely followed by the model that considers age, which achieves an accuracy of 0.837 and also the highest precision for the Progress class (0.723) and the highest recall for the Stay class (0.906).

Building upon the proposed approach, we also studied how to formalize dialogues that give contrastive, focused and selected explanations for most-contextual-preferred decisions in CPDF.

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²The modus ponens inference rule amounts to deriving c from either $\rightarrow c$ or $a \rightarrow c$ and a , for any set (conjunction) of sentences a and sentences c .

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