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# Explainable and Argumentation-based Decision Making with Qualitative Preferences for Diagnostics and Prognostics of Alzheimer's Disease

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## Abstract

Argumentation has gained traction as a formalism to make more transparent decisions and provide formal explanations recently. In this paper, we present an argumentation-based approach to decision making that can support modelling and automated reasoning about complex qualitative preferences and offer dialogical explanations for the decisions made. We first propose *Qualitative Preference Decision Frameworks (QPDFs)*. In a QPDF, we use contextual priority to represent the relative importance of combinations of goals in different contexts and define associated strategies for deriving decision preferences based on prioritized goal combinations. To automate the decision computation, we map QPDFs to *Assumption-based Argumentation (ABA)* frameworks so that we can utilize existing ABA argumentative engines for our implementation. We implemented our approach for two tasks, diagnostics and prognostics of Alzheimer's Disease (AD), and evaluated it with real-world datasets. For each task, one of our models achieves the highest accuracy and good precision and recall for all classes compared to common machine learning models. Moreover, we study how to formalize argumentation dialogues that give contrastive, focused and selected explanations for the most preferred decisions selected in given contexts.

## 1 Introduction

Argumentation-based decision making has gained an increasing amount of research interest recently due to its explanatory power (Amgoud and Prade 2006; Zeng et al. 2018). The key components of a general decision framework (Fan and Toni 2013), which is used to model agents' knowledge base, include *decisions*, *goals*, and *attributes*. *Qualitative preferences* over decisions are often derived from the relative importance of some decision properties, such as goals and attributes. In real-life applications, the relative importance of these properties does 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 (Altmann et al. 2014; Sampedro et al. 2015). Considering the patient being a man or a woman as the context for this decision problem, we may arrive at the following two different priority rules:

- $APOE4 > ADASQ4\, test\, results$[1] (patient is a female)
- $ADASQ4\, test\, results > APOE4$ (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 propose *Qualitative Preference Decision Framework*, in which preferences over decisions depend on which decisions can meet which goals and the priority of these goals. In a QPDF, the relative importance of goal combinations is conditioned on the decision contexts hence different sets of priority orderings are applicable in different contexts. We also present strategies for deriving decision preferences from such contextual priority of goal combinations. Instead of using an aggregation method to derive the entire preference relation for pairwise decision comparison, we take a more holistic strategy and directly compute all the most preferred decisions in given contexts. To enable automated decision reasoning, we employ Assumption-based Argumentation (ABA) frameworks. We choose ABA for two reasons: (1) it has existing argumentative engines which can ease our implementation, and (2) it provides underlying structures that can facilitate the generation of explanations.

Dementia is one of the major causes of disability and dependency among older people and is affecting 50 million people worldwide[2]. Alzheimer's disease (AD) is the most common form of dementia and may contribute to 60–70% of cases[2]. We have implemented the proposed approach for two tasks, the diagnosis of AD and the prediction of progression to AD in the future (prognosis). Rather than relying on

[*]For the ADNI: data used in preparation of this article were obtained from the ADNI database (adni.loni.ucla.edu). As such, the investigators within the ADNI contributed to the design and implementation of ADNI and/or provided data but did not participate in analysis or writing of this report. A complete listing of ADNI investigators can be found at: http://adni.loni.ucla.edu/wp-content/uploads/how_to_apply/ADNI_Acknowledgement_List.pdf

[1]ADASQ4 stands for the Alzheimer's Disease Assessment Scale Question 4 Delayed Word Recall (a short-term memory test)

[2]WHO dementia fact sheet: https://www.who.int/en/news-room/fact-sheets/detail/dementia

expert knowledge which can be hard to obtain, the contextual priority of goal combinations are learned from patient 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.

In previous works on argumentative explanations, explanations are often given as various forms of argumentative trees, which are essentially subgraphs of an argument graph and model the process of argument evaluation in the form of disputes (Rago, Cocarascu, and Toni 2018; García et al. 2013; Čyras et al. 2019). Most of these explanations are generated based on the entire dispute process. However, as the size of the agent knowledge base increases and the reasoning process becomes more complex, the size and complexity of such unselected explanations may become unmanageable. The explanations may also become very hard for users to gauge and hard to implement in interactive applications. As an attempt to tackle this issue, we propose the notion of *explaining dialogue* and study its properties. By referring only to the parts requiring explanations in the dispute process, explaining dialogues can provide focused dialogical explanations that contain selective information pertaining to users' doubts and inquiries, rather than all the information involved in evaluating the decision.

## 2 Preliminaries

This paper relies upon Assumption-based Argumentation (ABA) and Dispute Tree, as summarized below.

**Assumption-based Argumentation (ABA)** *frameworks* (Toni 2014) are tuples $\langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C} \rangle$ where

- $\langle \mathcal{L}, \mathcal{R} \rangle$ is a deductive system, with a *language* $\mathcal{L}$ and a rule set $\mathcal{R}$ of the form $\beta_0 \leftarrow \beta_1, \ldots, \beta_m (m \geq 0, \beta_i \in \mathcal{L})$;
- $\mathcal{A} \subseteq \mathcal{L}$ is a non-empty set, referred to as *assumptions*;
- $\mathcal{C}$ is a total mapping from $\mathcal{A}$ into $2^{\mathcal{L}}$, where each $c \in \mathcal{C}(\alpha)$ is a *contrary* of $\alpha$.

In ABA frameworks, for all rules $\rho = \beta_0 \leftarrow \beta_1, \ldots, \beta_m$, $\beta_0$ cannot be assumptions. *Arguments* are deductions of claims with sets of rules and supported by sets of assumptions. Attacks against arguments are directed at the assumptions in the support of arguments. Formally, adapted from (Toni 2014; Dung, Kowalski, and Toni 2009):

- An *argument for* $\beta \in \mathcal{L}$ supported by $\Delta \subseteq \mathcal{A}$ with $R \subseteq \mathcal{R}$ (denoted $\Delta \vdash_R \beta$) is a finite tree with nodes labelled by sentences in $\mathcal{L}$ or by $\tau$[3], the root labelled by $\beta$, leaves either $\tau$ or assumptions in $\Delta$, and non-leaves $\beta'$ with the items of the body of some rule in $R$ with head $\beta'$ as children, and $R$ contains only the rules in the tree.
- An argument $\Delta_1 \vdash_{R_1} \beta_1$ *attacks* an argument $\Delta_2 \vdash_{R_2} \beta_2$ iff $\beta_1$ is a contrary of one of the assumptions in $\Delta_2$.

$\Delta \vdash \beta$ is used as the shorthand form for $\Delta \vdash_R \beta$. A set of assumptions $A$ attacks a set of assumptions $A'$ iff an argument supported by a subset of $A$ attacks an argument supported by a subset of $A'$.

[3] $\tau \notin \mathcal{L}$ represents"true" and stands for the empty body of rules

A set of assumptions is *admissible* in $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C} \rangle$ iff it does not attack itself and it attacks all $\Delta \subseteq \mathcal{A}$ that attack it. We say that an argument $\Delta \vdash \beta$ is *admissible* in $ABF$ iff there is an admissible set $\Delta' \subseteq \mathcal{A}$ for which $\Delta \subseteq \Delta'$. We also say that an argument $\Delta \vdash_R \beta$ is in $ABF$ iff $R \subseteq \mathcal{R}$ and $\Delta \subseteq \mathcal{A}$.

Definition of **Dispute Trees** is adapted from (Dung, Mancarella, and Toni 2007). Given an ABA framework $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C} \rangle$, a *dispute tree for* $\mathcal{X} \in \mathcal{L}$ is a tree $\mathcal{T}$, such that: (1) every node $n$ of $\mathcal{T}$ is of the form $[\mathtt{S} : X]$, labelled by a status $\mathtt{S} \in \{\mathtt{P}, \mathtt{O}\}$ and an argument $X$ in $ABF$, where the status can be either *proponent* (P) or *opponent* (O) but not both; (2) the root of $\mathcal{T}$ is a node of the form $[\mathtt{P} : \Delta \vdash \mathcal{X}]$; (3) for every P node $n$ labelled by an argument $B$, and for every argument $C$ that attacks $B$, there exists a child of $n$, which is an O node labelled by $C$; (4) for every O node $n$ labelled by an argument $C$, there exists at most one child of $n$ which is a P node labelled by an argument that attacks $C$; (5) no other nodes in $\mathcal{T}$ except the ones listed above.

A dispute tree $\mathcal{T}$ is an *admissible dispute tree* iff: (1) every O node in $\mathcal{T}$ has a child, i.e. all attackers are defended against; (2) no argument in $\mathcal{T}$ labels both P and O nodes, i.e. conflict-free.

## 3 Decision Making with Qualitative Preferences

In this section, we propose *Qualitative Preference Decision Frameworks (QPDFs)* which can model qualitative preferences over decisions based on an ordered goal base. The goal base contains sets of goals which are ordered according to a set of contextual priority rules. These rules specify the relative importance of the goal sets in different contexts. We first formalize contextual priority orderings of goal sets. Then, we introduce QPDFs and associated strategies for deriving preferences over decisions from QPDFs.

**Definition 1.** Let G be a set of goals, the **priority relation** $\geqslant_g$ is a partial preorder (a reflexive and transitive relation) over $2^{\mathtt{G}}$, representing relative importance of sets of goals.

We use $s >_g s'$ to denote $s \geqslant_g s'$ and $s' \not\geqslant_g s$, where $s, s' \in 2^{\mathtt{G}}$. $s \geqslant_g s'$ means that $s$ is at least as important as $s'$. $s >_g s'$ means that $s$ is strictly more important than $s'$.

**Definition 2.** The **context terms** T is a set of distinct atoms representing granular contexts in the concerned domains.

**Definition 3.** A **defeasible context** C is a set of context sentences, in which each sentence $c \in \mathtt{C}$ is of the form $t_n \wedge \ldots \wedge t_1 \rightarrow t_0$ where $n \geq 0$ and $t_0, t_1, \ldots, t_n \in \mathtt{T}$.

**Definition 4.** A **defeasible contextual priority rule** is an expression of the form $s_i \geqslant_g s_j \mid T$ where $T \subseteq \mathtt{T}$ is a set of context terms, $s_i, s_j \in 2^{\mathtt{G}}$ are two sets of goals.

The left-hand side of a defeasible contextual priority rule specifies the relative importance of two sets of goals while the right-hand side represents the context in which this priority order holds.

**Definition 5.** The **contextual priority** P is a set of defeasible contextual priority rules. For each rule $s_i \geqslant_g s_j \mid T$ in P, $s_i$ and $s_j$ belong to a goal base $\mathtt{S} \subseteq 2^{\mathtt{G}}$ containing all comparable sets of goals such that

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

**Definition 6.** A **Qualitative Preference Decision Framework (QPDF)** is a tuple $\langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$ such that:

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

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

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

The contextual priority $\mathtt{P}$ contains priority rules in all possible contexts. The set of applicable priority rules changes with the defeasible context $\mathtt{C}$. Formally, we define *applicable priority* as follows.

**Definition 7.** Given a QPDF $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, the **applicable priority** in context $\mathtt{C}$ is formally defined as:

$$P_a = \{s_i \geqslant_g s_j : s_i \geqslant_g s_j \mid T \in \mathtt{P},\ T \subseteq EC(\mathtt{C})\}$$

where $EC(\mathtt{C})$ stands for the epistemic closure of $\mathtt{C}$[4].

**Example 1.** *Let* $\mathtt{G}$ *be* $\{g_1, g_2, g_3\}$, *let* $\mathtt{C}$ *be* $\{t_1 \wedge t_2 \rightarrow t_3\}$, *and let* $\mathtt{P}$ *be:*

$$\begin{array}{lll} \{ & \{g_1\} >_g \{g_2\} \mid \{t_1\}, & \{g_2\} >_g \{g_3\} \mid \{t_1\}, \\ & \{g_2\} >_g \{g_1\} \mid \{t_4\}, & \{g_1, g_2\} >_g \{g_1\} \mid \{t_2\}, \\ & \{g_3\} >_g \{g_2\} \mid \{t_4\}, & \{g_2, g_3\} >_g \{g_1, g_2\} \mid \{t_3, t_5\} \quad \} \end{array}$$

*With the given context* $\mathtt{C}$, *no priority rules are applicable and* $P_a = \varnothing$. *However, when the context changes,* $P_a$ *changes accordingly. Table 1 shows the content in* $P_a$ *when different context information is added.*

In Example 1, we illustrate that a qualitative preference decision framework (QPDF) not only describes the relationships among decisions, attributes, and goals, but also captures changing relative importance of goal sets in different contexts. We then define a preference relation over decisions and present our strategies for deriving decision preferences based on contextual priority of goal sets.

[4]The epistemic closure of $\mathtt{C}$, $EC(\mathtt{C})$, is derived by repeatedly applying the modus ponens inference rule to $\mathtt{C}$ until the elements of $EC(\mathtt{C})$ do not change anymore, where modus ponens amounts to deriving $b$ either from $\rightarrow b$ or from $a \rightarrow b$ and $a$.

| Additional Contexts | Applicable Priority $P_a$ |
|---|---|
| $\{\rightarrow t_1\}$ | $\{g_1\} >_g \{g_2\} >_g \{g_3\}$ |
| $\{\rightarrow t_2\}$ | $\{g_1, g_2\} >_g \{g_1\}$ |
| $\{\rightarrow t_4\}$ | $\{g_3\} >_g \{g_2\} >_g \{g_1\}$ |
| $\{\rightarrow t_1, \rightarrow t_2\}$ | $\{g_1, g_2\} >_g \{g_1\} >_g \{g_2\} >_g \{g_3\}$ |
| $\{\rightarrow t_1, \rightarrow t_2, \rightarrow t_5\}$ | $\{g_2, g_3\} >_g \{g_1, g_2\} >_g \{g_1\} >_g \{g_2\} >_g \{g_3\}$ |

Table 1: Illustration of varying context $\mathtt{C}$ and the corresponding applicable priority $P_a$ in different contexts

| $\mathtt{T_{DA}}$ | | | | $\mathtt{T_{GA}}$ | | | | $\mathtt{T_{DG}}$ | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | $a_1$ | $a_2$ | $a_3$ | | $a_1$ | $a_2$ | $a_3$ | | $g_1$ | $g_2$ | $g_3$ |
| $d_1$ | 1 | 1 | 0 | $g_1$ | 1 | 0 | 0 | $d_1$ | 1 | 1 | 0 |
| $d_2$ | 1 | 0 | 1 | $g_2$ | 0 | 1 | 0 | $d_2$ | 1 | 0 | 1 |
| $d_3$ | 0 | 1 | 1 | $g_3$ | 0 | 0 | 1 | $d_3$ | 0 | 1 | 1 |

Table 2: Illustration of most-contextual-preferred decision function

**Definition 8.** A **preference relation** is a preorder $\succsim$ on $\mathtt{D}$.

Similarly, we use $d \succ d'$ to denote $d \succsim d'$ and $d' \not\succsim d$. We say that $d$ is at least as preferred as $d'$ given $d \succsim d'$, and $d$ is strictly preferred than $d'$ given $d \succ d'$,

Given the information captured in a decision framework, a *decision function* for the framework returns a set of "good" decisions in the framework (Fan and Toni 2013). Decision functions can be viewed as mappings between decision frameworks and sets of decisions, according to certain decision criteria. We define the general form of *decision functions* for QPDFs formally as follows.

**Definition 9.** Given a QPDF $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, a **decision function** for $F_{qp}$ is a mapping $\psi_{qp} \colon \mathcal{F_{QP}} \longmapsto \mathcal{DEC}$, such that: (1) $\psi_{qp}(F_{qp}) \subseteq \mathtt{D}$; (2) for any $d, d' \in \mathtt{D}$, if $\Gamma(d) = \Gamma(d')$ and $d \in \psi_{qp}(F_{qp})$, then $d' \in \psi_{qp}(F_{qp})$.

We use $\Psi_{qp}$ to denote the set of all decision functions for QPDFs.

From the general form of decision functions given in Definition 9, we then instantiate the *most-contextual-preferred decision function*.

**Definition 10.** Given a QPDF $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, let $\mathtt{S}$ be the goal base of $F_{qp}$, let $P_a$ be the applicable priority in context $\mathtt{C}$, a **most-contextual-preferred decision function** $\psi_{qp} \in \Psi_{qp}$ is a mapping such that, for every $d \in \mathtt{D}$, $d \in \psi_{qp}(F_{qp})$ iff

- for all $d' \in \mathtt{D}$ and $d' \neq d$, $d \succsim d'$, i.e. the following holds:
  - for all $s \in \mathtt{S}$, if $s \not\subseteq \Gamma(d)$ and $s \subseteq \Gamma(d')$, then there exists $s' \in \mathtt{S}$, such that: (1) $s' \geqslant_g s \in P_a$, (2) $s' \subseteq \Gamma(d)$, (3) $s' \not\subseteq \Gamma(d')$.

The decision strategy enforced by the most-contextual-preferred decision function is similar to the *discrimin* ordering described in (Coste-Marquis et al. 2004). For each decision selected by $\psi_{qp}$ in given contexts, if it does not meet a set of goals that is met by some other decisions, it must meet a more important or at least as important set of goals than the one it does not meet. As the relative importance of goal sets may vary with contexts, the decisions selected by $\psi_{qp}$ can be different depending on the contexts, as in Example 2.

**Example 2.** *Given a QPDF $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, let $\mathtt{D} = \{d_1, d_2, d_3\}$, let $\mathtt{C} = \{t_1 \wedge t_2 \rightarrow t_3\}$, let $\mathtt{G}$ and $\mathtt{P}$ be the same as in Example 1. The content of the two tables $\mathtt{T_{DA}}$ and $\mathtt{T_{GA}}$ are shown in Table 2. From $\mathtt{T_{DA}}$ and $\mathtt{T_{GA}}$, we can derive the contents in $\mathtt{T_{DG}}$. We analyze the most-contextual-preferred decision in three different contexts:*

1. *With additional context $\{\rightarrow t_1\}$, as in Table 1, the applicable priority $P_a$ in the current contexts are $\{g_1\} >_g \{g_2\} >_g \{g_3\}$. It is trivial to see that $d_1$ is more preferred than $d_2$ since $d_1$ meets $g_2$ which is not met by $d_2$ and $\{g_2\} >_g \{g_3\}$. Similarly, both $d_1$ and $d_2$ are more preferred than $d_3$. Hence, we have $\psi_{qp}(F_{qp}) = \{d_1\}$ and $d_1 \succ d_2 \succ d_3$.*
2. *With additional context $\{\rightarrow t_4\}$, $P_a$ in the current contexts are $\{g_3\} >_g \{g_2\} >_g \{g_1\}$. In this case, we have $\psi_{qp}(F_{qp}) = \{d_3\}$ and $d_3 \succ d_2 \succ d_1$.*
3. *With additional contexts $\{\rightarrow t_1, \rightarrow t_2, \rightarrow t_5\}$, $P_a$ in given contexts are $\{g_2, g_3\} >_g \{g_1, g_2\} >_g \{g_1\} >_g \{g_2\}$. We have $\psi_{qp}(F_{qp}) = \{d_3\}$, but $d_3 \succ d_1 \succ d_2$.*

A decision function defines the strategy for choosing "good" decisions but does not specify how such "good" decisions can be computed. Hence, we translate QPDFs and their decision functions into *Assumption-Based Argumentation (ABA)* frameworks which have established semantics and computational support. ABA frameworks can be used to compute most-contextual-preferred decisions directly, rather than aggregating the contextual priority of goal sets to derive the preference order between each pair of decisions.

The contextual priority $\mathtt{P}$ and defeasible contexts $\mathtt{C}$ are encoded within existing ABA components, e.g. rules and assumptions, avoiding the needs to modify the semantics of ABA. In Definition 11, we show how to construct an ABA counterpart for a QPDF.

**Definition 11.** Given a QPDF $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, let $\mathtt{S}$ be the goal base in $F_{qp}$, the **most-contextual-preferred ABA framework counterpart** for $F_{qp}$ is $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C} \rangle$, where:

- $\mathcal{R}$ is such that:
  - for all $d \in \mathtt{D}, a \in \mathtt{A}$, if $\mathtt{T_{DA}}[d, a] = 1$: $hasAttr(d, a) \leftarrow$;
  - for all $g \in \mathtt{G}, a \in \mathtt{A}$, if $\mathtt{T_{GA}}[g, a] = 1$: $satBy(g, a) \leftarrow$;
  - for all $t_n \wedge \ldots \wedge t_1 \rightarrow t_0 \in \mathtt{C}$: $con(t_0) \leftarrow con(t_1), \ldots, con(t_n)$;
  - for all $s_i, s_j \in \mathtt{S}$, if $s_i \geqslant_g s_j \mid T \in \mathtt{P}$, then for every $t_k \in T$: $notImp(s_i, s_j) \leftarrow notCon(t_k)$;
  - $met(d, g) \leftarrow hasAttr(d, a), satBy(g, a)$;
  - for all $d \in \mathtt{D}, s \in \mathtt{S}, s = \{g_1, \cdots, g_m\}$: $metS(d, s) \leftarrow met(d, g_1), \cdots, met(d, g_m)$;
  - $notCPre(d) \leftarrow notMetS(d, s), metS(d', s), noBetter(d, d', s)$;
  - $better(d, d', s) \leftarrow metS(d, s'), notMetS(d', s'), dImp(s', s)$;
  - nothing else is in $\mathcal{R}$.
- $\mathcal{A}$ is such that:
  - for all $d \in \mathtt{D}$: $cPre(d)$;
  - for all $t_n \wedge \ldots \wedge t_1 \rightarrow t_0 \in \mathtt{C}$: $notCon(t_0)$;
  - for all $s_i \geqslant_g s_j \mid T \in \mathtt{P}$: $dImp(s_i, s_j)$;
  - for all $d \in \mathtt{D}, s \in \mathtt{S}$: $notMetS(d, s)$;
  - for all $d, d' \in \mathtt{D}, d \neq d'$ and $s \in \mathtt{S}$: $noBetter(d, d', s)$;
  - nothing else is in $\mathcal{A}$.
- $\mathcal{C}$ is such that:
  - $\mathcal{C}(cPre(d)) = \{notCPre(d)\}$;
  - $\mathcal{C}(notCon(t)) = \{con(t)\}$;
  - $\mathcal{C}(dImp(s_i, s_j)) = \{notImp(s_i, s_j)\}$;
  - $\mathcal{C}(notMetS(d, s)) = \{metS(d, s)\}$;
  - $\mathcal{C}(noBetter(d, d', s)) = \{better(d, d', s)\}$;
  - nothing else in $\mathcal{C}$.

It is not hard to observe the correspondence between the most-contextual-preferred decision function in the QPDF and the component $\mathcal{R}$ in its ABA framework counterpart. For example, the following two rules are defined in the same spirit as Definition 10.

$$notCPre(d) \leftarrow notMetS(d, s), metS(d', s), noBetter(d, d', s) \quad (1)$$

$$better(d, d', s) \leftarrow metS(d, s'), notMetS(d', s'), dImp(s', s) \quad (2)$$

An intuitive reading of rule (1) is: decision $d$ is not a most-contextual-preferred decision, if it does not meet the set of goals $s$, while some other decision $d'$ meets $s$ and there is no way $d$ can be better (preferred) than $d'$. Rule (2) further specifies that a decision $d$ can still be better (preferred) than $d'$, given that $d'$ meets $s$ while $d$ does not, if $d$ meets $s'$ which is more important than $s$ and $d'$ does not meet $s'$. Assumption $dImp(s', s)$ indicates that the priority order $s' \geqslant_g s$ is defeasible, i.e. may not hold depending on the contexts. Once the favourable context applies, i.e. $\{\} \vdash con(t)$ exists, it defends the defeasible priority $dImp(s', s)$ from $notCon(t)$.

We then prove the sound and complete result to establish the connection between QPDFs and their ABA counterparts: the most-contextual-preferred decisions, i.e. decisions selected by $\psi_{qp}$ in a QPDF correspond to the claims of admissible arguments in their ABA counterparts and vice versa.

**Theorem 1.** *Given a qualitative preference decision framework $F_{qp} = \langle \mathtt{D}, \mathtt{A}, \mathtt{G}, \mathtt{T_{DA}}, \mathtt{T_{GA}}, \mathtt{C}, \mathtt{P} \rangle$, let $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C} \rangle$ be the most-contextual-preferred ABA framework counterpart for $F_{qp}$. Then, for all $d \in \mathtt{D}$, $d \in \psi_{qp}(F_{qp})$ iff argument $\{cPre(d)\} \vdash cPre(d)$ is admissible in $ABF$.*

*Proof.* (*Sketch*) First, we prove if $d_i \in \psi_{qp}(F_{qp})$, then $\{cPre(d_i)\} \vdash cPre(d_i)$ is an admissible argument in $ABF$. We need to show two things: all attackers of $\{cPre(d_i)\} \vdash cPre(d_i)$ can be defended against by a set of assumptions $\Delta \subset \mathcal{A}$, and $\{cPre(d_i)\} \cup \Delta$ is conflict-free. Since $d_i$ is most-contextual-preferred, for each goal set $s \in \mathtt{S}$, either (1) $d_i$ meets goal set $s$, therefore argument $\{\} \vdash metS(d_i, s)$ exists and is not attacked; or (2) $d_i$ does not meet $s$, but for every $d_j \in \mathtt{D}$ and $d_j \neq d_i$, there exists some $s'$, such that $d_i$ meets $s'$ while $d_j$ does not and $s' \geqslant_g s \in P_a$ in the current context $\mathtt{C}$. Hence, the argument $A = \{notMetS(d_j, s'), dImp(s', s)\} \vdash better(d_i, d_j, s)$ exists. However, for each $t_k \in T$ where $s' \geqslant_g s \mid T \in \mathtt{P}$, there exists an argument $B = notImp(s', s) \vdash notCon(t_k)$ that attacks $A$. Since $s' \geqslant_g s \in P_a$, there exists an argument $\{\} \vdash con(t_k)$ for each $t_k \in T$ that counter-attacks argument $B$. In both cases, the attackers of argument $\{cPre(d_i)\} \vdash cPre(d_i)$, i.e. $\{notMetS(d_i, s), noBetter(d_i, d_j, s)\} \vdash notCPre(d_i)$, are always counter attacked. Thus, $\{cPre(d_i)\} \vdash cPre(d_i)$ withstands all attacks. Since the set $\Delta$ includes all assumptions defending $\{cPre(d_i)\} \vdash cPre(d_i)$, it contains assumptions of the following forms: $notMetS(d_j, s')$, $dImp(s', s)$

(in case (2)), while $\{\} \vdash con(t_k)$ (in case (2)) and $\{\} \vdash metS(d_i, s)$ (in case (1)) are arguments with empty supports. Since $i \neq j$ and $s \neq s'$, $\{cPre(d_i)\} \cup \Delta$ is conflict-free. Since the support of $\{cPre(d_i)\} \vdash cPre(d_i)$, $cPre(d_i)$, is in a conflict-free set that withstands all attacks, it is admissible.

We then prove if $\{cPre(d_i)\} \vdash cPre(d_i)$ is admissible in $ABF$, i.e. there exists a set of assumptions $\Delta$ such that $\{cPre(d_i)\} \cup \Delta$ is admissible, then $d_i \in \psi_{qp}(F_{qp})$. Since $\{cPre(d_i)\} \vdash cPre(d_i)$ is admissible, all its attackers, i.e. $\{notMetS(d_i, s), noBetter(d_i, d_j, s)\} \vdash notCPre(d_i)$ for all $s \in \mathtt{S}$, must be counter attacked by arguments supported by $\Delta$. Each such attacker is counter attacked due to one of the following: (1) there exists an argument $\{\} \vdash metS(d_i, s)$ or (2) there exists an argument $\{notMetS(d_j, s'), dImp(s', s)\} \vdash better(d_i, d_j, s)$ that can withstand all its attackers. Hence, we have either $d_i$ meets $s$, implied by case (1), or $d_i$ does not meet $s$ while some other $d_j$ meets $s$, but $d_i$ meets some more important goal set $s'$ which $d_j$ does not meet, implied by case (2). By Definition 10, $d_i \in \psi_{qp}(F_{qp})$. □

With Theorem 1, we can utilize the semantics and computational tools of ABA to derive most-contextual-preferred decisions in QPDFs. ABA also provides underlying structures for generating dialogical explanations (see Section 5).

## 4 Diagnostics and Prognostics of AD

We implemented the proposed argumentation-based decision making approach for the 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.

Data used in the experiments of the two tasks were obtained from the Alzheimer's Disease Neuroimaging Initiative (ADNI) database (adni.loni.usc.edu). The ADNI is a long term project that collects a broad range of demographic, clinical, laboratory and neuroimaging data about patients with different cognitive impairments. For detailed information, see www.adni-info.org.

### 4.1 Implementation

Specific to the two tasks studied, we adopt a hybrid ABA-CBR (case-based reasoning) approach — the diagnosis (prognosis) of a new case is derived based on the diagnosis (prognosis) of past similar cases, where ABA yields the most similar past cases to the given new case. As in shown Figure 1, our model first learns contextual priority of goal sets from patient data. For each new case, it constructs a QPDF that encodes patient data, the case information, and the contextual priority of goal sets. It then creates an ABA counterpart for the QPDF, and uses it to identify a list of reference cases. The QPDF and its corresponding ABA framework are constructed in a way such that the most-contextual-preferred decision is the case most similar to the new case.

**Learn Contextual Priority of Goal Sets.** The relationship between demographic features and the prevalence of AD has been studied intensively in medical research. It has been observed in multiple large-scale studies that age, gender, and education can influence the prevalence of AD (Zhang et al. 1990; Gao et al. 1998). In our implementation, we consider age, gender and education as contexts and model priority of goal sets in different contexts. To determine contextual priority of features (modeled as goal sets in QPDF), we separate the patient cases according to their contexts, e.g. female and male for gender, and use an *Extra Trees Classifier* to rank the importance of features separately. Features with importance scores greater than 0.02 are selected. In the same context, the features with higher importance scores have higher priority than those with lower scores. Due to space constraint, only the priority orderings of the best performing context of each task, i.e. education for the diagnosis task and gender for the prognosis task, are presented in Table 3. For the full text descriptions of the feature acronyms, please refer to the data dictionary of ADNI at http://adni.loni.usc.edu.

| Diagnosis | Diagnosis Education | | Prognosis | Prognosis Gender | |
|---|---|---|---|---|---|
| All Data | $\leq$ 16 (350) | $>$ 16 (193) | All Data | Female (174) | Male (260) |
| LDELTOTAL | MMSE | LDELTOTAL | mPACCtrailsB | FAQ | ADASQ4 |
| CDRSB | LDELTOTAL | mPACCtrailsB | ADAS13 | RAVLT_imme | mPACCtrailsB |
| MMSE | CDRSB | CDRSB | FAQ | mPACCtrailsB | ADAS13 |
| mPACCtrailsB | mPACCdigit | mPACCdigit | mPACCdigit | mPACCdigit | mPACCdigit |
| mPACCdigit | FAQ | FAQ | RAVLT_imme | ADAS13 | RAVLT_imme |
| FAQ | mPACCtrailsB | MMSE | ADASQ4 | APOE4 | CDRSB |
| PTEDUCAT | ADAS13 | TRABSCOR | APOE4 | RAVLT_perc | FAQ |
| ADAS13 | RAVLT_learn | ADAS13 | RAVLT_perc | ADASQ4 | MMSE |
| Fusiform | RAVLT_perc | RAVLT_learn | DX_bl | DX_bl | APOE4 |

Table 3: Contextual priority orderings of the top 9 features (each modelled as a goal set) of the best performing context in each task

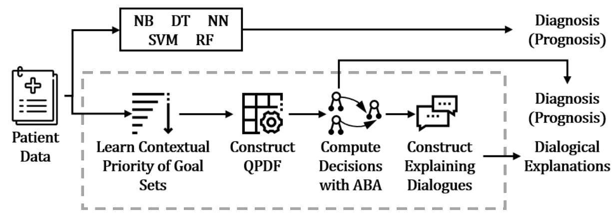


Figure 1: Implementing our approach for AD diagnosis (prognosis)

**Data Encoding.** Each selected feature is then discretized into two or three nominal values either according to clinically validated cut-off scores or according to the data distribution. For example, the feature $FAQ$, which stands for the score of Functional Activities Questionnaire, is discretized into three nominal values $FAQ$ $(\leq 1)$, $FAQ$ $(> 1, < 5)$, and $FAQ$ $(\geq 5)$ according to cut-off scores in (Teng et al. 2010). The feature $Fusiform$, which stands for the MRI fusiform gyrus volume, is discretized into three nominal values $Fusiform(< 14454)$, $Fusiform(\geq 14454, \leq 18090)$, and $Fusiform(> 18090)$ according to data distribution since no clear cut-offs are available. Then, all the nominal values are category encoded with one-hot encoding.

**Construct QPDF.** For each new case, a QPDF is constructed based on the case information, encoded patient data and the contextual priority derived previously. In our implementation, the decisions are choices to use the case of an existing patient as reference for diagnosis (prognosis), which can be represented by the patient ID. The features of past

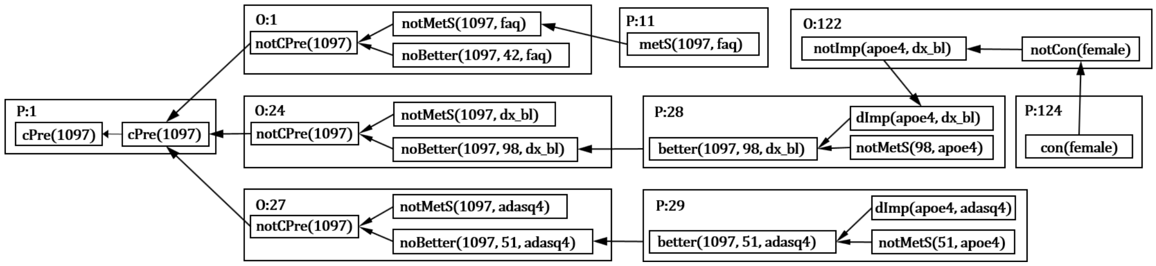


Figure 2: A fragment of an admissible dispute tree (also a partial dispute tree according to Definition 15) for decision 1097 being a most-contextual-preferred decision. Hence, patient 1097 is the case most similar to the patient of interest, case 675.

| | Diagnosis | | | | | | | Prognosis | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Accuracy | Precision | | | Recall | | | Accuracy | Precision | | Recall | |
| | | CN | MCI | AD | CN | MCI | AD | | Stay | Progress | Stay | Progress |
| Naive Bayes | 0.853 | 0.888 | **0.921** | 0.710 | 0.939 | 0.813 | **0.873** | 0.834 | **0.919** | 0.667 | 0.849 | **0.793** |
| Decision Tree | 0.884 | 0.941 | 0.899 | 0.795 | **0.957** | 0.897 | 0.779 | 0.811 | 0.857 | 0.679 | 0.893 | 0.585 |
| Multilayer Perceptron | 0.895 | 0.926 | 0.903 | 0.859 | 0.932 | 0.916 | 0.804 | 0.836 | 0.883 | 0.710 | 0.896 | 0.672 |
| Support Vector Machine | 0.897 | 0.973 | 0.858 | **0.979** | 0.871 | **0.984** | 0.693 | 0.836 | 0.881 | 0.719 | 0.899 | 0.664 |
| Random Forest | 0.911 | **0.982** | 0.894 | 0.905 | 0.930 | 0.965 | 0.750 | **0.839** | 0.878 | 0.719 | **0.906** | 0.656 |
| Our Model (context: gender) | 0.901 | 0.926 | 0.894 | 0.900 | 0.949 | 0.945 | 0.736 | **0.839** | 0.880 | **0.723** | 0.903 | 0.664 |
| Our Model (context: education) | **0.915** | 0.936 | 0.916 | 0.927 | 0.949 | 0.949 | 0.792 | 0.825 | 0.863 | 0.711 | **0.906** | 0.604 |
| Our Model (context: age) | 0.904 | 0.926 | 0.899 | 0.902 | 0.932 | 0.942 | 0.778 | 0.837 | 0.876 | **0.723** | **0.906** | 0.646 |

Table 4: Classification reports for the two tasks: (1) diagnosis (left): determine if the patient is cognitively normal (CN), MCI or AD; (2) prognosis (right): predict whether a patient will stay undemented (Stay) or progress to AD (Progress) in 3 years

patient cases are considered as attributes. For a new case of interest, its features are modelled as goal sets and goals — each feature is modeled as a goal set and the nominal values derived from it as the goals in the goal set[5].

**Construct ABA Counterpart.** A corresponding ABA framework is constructed for the QPDF according to Definition 11. For example, the contextual priority rule $APOE4 >_g DX\_bl \mid \{female\}$ in the QPDF is converted to the rule, $notImp(apoe4, dx\_bl) \leftarrow notCon(female)$, in the corresponding ABA framework. Then, the most-contextual-preferred decision is computed using `proxdd`[6] and the resulting patient case can be used as a "good" reference case for the new case. Then, this resultant case is removed. The next most-contextual-preferred decision is computed in the same way until a specified number of cases are identified.

The diagnosis (prognosis) for the new case of interest is then determined based on the diagnosis (prognosis) of the reference cases using plurality voting, or weighted voting in case of a tie. Figure 2 illustrates a fragment of an admissible dispute tree for patient case 1097 being a most-contextual-preferred decision in the QPDF that considers features of the new case 675 (a female) as goals and goal sets and gender as contexts, i.e. case 1097 is chosen as one of the reference cases to determine the prognosis for patient 675.

[5]This means that the features in Table 3, e.g. $CDRSB$ and $MMSE$, are modelled as goal sets. Nominal values derived from them are modelled as goals. For example, $FAQ$ $(\leq 1)$, $FAQ$ $(> 1, < 5)$, and $FAQ$ $(\geq 5)$ are goals in goal set $FAQ$.

[6]http://robertcraven.org/proarg/proxdd.html

## 4.2 Experiment Results

To evaluate the performance of our proposed approach on the two tasks, three models were implemented based on the approach, each considering one of the three types of contexts that are selected based on medical research —gender, education, and age. Our models use six reference cases to determine the diagnosis of a new case. Five machine learning models were also implemented in Python: Naive Bayes (NB), CART Decision Tree (DT), Multilayer Perceptron (MLP), Random Forest (RF), and SVM with RBF kernel type. The hyperparameters in these models were optimized using Grid Search. 6-fold cross-validation was used for model evaluation and the results are shown in Table 4.

**Task 1: Diagnosis.** We choose to use data from the baseline visit in ADNI-1, which is the first phase of the project. After data preprocessing, 543 patient cases are selected, with 116 normal (CN) records, 310 MCI records, and 117 AD records. 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, 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, which are higher than all comparison models except Random Forest.

**Task 2: Prognosis.** For most ADNI patients, the progression from CN or MCI state to AD happens around the third year after their baseline visits. Hence, we use the data and diagnosis at the baseline visit to predict whether a progression to AD happens in the following 3 years. 434 patient cases are selected from the ADNI-1 participants who revisited 36 months after their baseline visits, with 116 patients stayed undemented and 318 patients progressed to AD in 3 years. 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). The model that considers education yields a lower accuracy. It achieves a high recall for the Stay class, but a relatively low recall for the Progress class.

## 5 Explaining Dialogues

Building upon the constructs of the decision making approach proposed in previous sections, we provide a new perspective on how to formalize dialogical explanations that are (1) focused: only present information pertaining to users' doubts and inquiries, and (2) contrastive: explain why a decision is chosen instead of another (Miller 2019).

We propose *explaining dialogue*, in which a proponent explains a decision to an opponent by uttering relevant arguments to defend attacks from the opponent. It can be constructed from a *partial dispute tree*, which represents a part of the debate process to evaluate the decision in need of explanation. An explaining dialogue has similar structures with an ABA-dialogue (Fan and Toni 2011). However, each of its utterances has a set of *unmarked assumptions* $S^{um}$, that can be used to determine whether the dialogue has been *successful*. We obtain sound and complete results that establish the equivalence among claims of successful explaining dialogues, topics of admissible partial dispute trees, and admissible arguments in ABA frameworks. With these results, we then illustrate how successful explaining dialogues can be used to give contrastive, focused and selected explanations for most-contextual-preferred decisions in QPDF.

**Definition 12.** An **explaining dialogue** is conducted between a proposing agent $\mathtt{P}$ and an opposing agent $\mathtt{O}$, and consists of *utterances* of the form $\langle a_1, a_2, T, C, S^{um}, ID\rangle$ where:

- $a_1, a_2 \in \{\mathtt{P}, \mathtt{O}\}$;
- $C$ is the content, and is one of: (1) a claim, **claim**($\beta$) for some $\beta \in \mathcal{L}$, (2) a rule, **rl**($\beta_0 \leftarrow \beta_1, \ldots, \beta_m$) for some $\beta_0, \cdots, \beta_m \in \mathcal{L}$, (3) an assumption, **asm**($\alpha$) for some $\alpha \in \mathcal{L}$, or (4) a contrary, **ctr**($\alpha, \beta$) for some $\alpha, \beta \in \mathcal{L}$;
- $S^{um}$ is a set of unmarked assumptions;
- $ID \in \mathbb{N}$ is the identifier;
- the target utterance $T \in \mathbb{N}_{>0}$ such that $T < ID$.

An utterance $\langle a_i, a_j, T, C, S^{um}, ID\rangle$ is from $a_i$ to $a_j$.

Given the notion of utterances, an explaining dialogue $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X})$ ($\mathtt{P}$ explains to $\mathtt{O}$ on $\mathcal{X} \in \mathcal{L}$) is a finite sequence $\delta = \langle u_1, \cdots, u_l\rangle$, $l \geq 0$, where each $u_k$, $k = 1, \cdots, l$, is an utterance from either $\mathtt{P}$ or $\mathtt{O}$. Given a dialogue $\delta_l = \langle u_1, \cdots, u_l\rangle$ and a sequence of utterances $U = \langle u_{l+1}, \cdots, u_{l+m}\rangle$, $\delta_l \oplus U = \langle u_1, \cdots, u_l, u_{l+1}, \cdots, u_{l+m}\rangle$. An explaining dialogue can be generated from a dispute tree as follows.

**Definition 13.** Given an ABA framework $ABF = \langle\mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C}\rangle$, and a dispute tree $\mathcal{T}$ for $\mathcal{X} \in \mathcal{L}$ in $ABF$, the explaining dialogue $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X})$ corresponding to $\mathcal{T}$ is a sequence $\delta_l = \langle u_1, \cdots, u_l\rangle$ (let $\delta_k$ denote the working $\delta_l$) s.t.:

- for the root node $[\mathtt{P} : \{\mathcal{X}\} \vdash \mathcal{X}]$ in $\mathcal{T}$, $\delta_k = \langle u_1, u_2\rangle$ where $u_1 = \langle \mathtt{P}, \mathtt{O}, 0, \mathbf{claim}(\mathcal{X}), \{\}, 1\rangle$, and $u_2 = \langle \mathtt{P}, \mathtt{O}, 1, \mathbf{asm}(\mathcal{X}), \{\}, 2\rangle$;
- for every node $[\mathtt{O} : \Delta_1 \vdash_{R_1} \beta]$ in $\mathcal{T}$, $R_1 = \{r_1, \cdots, r_n\}$, $\delta_k = \delta_k \oplus U$ where $U$ is a sequence $\langle u_{k+1}, \cdots, u_{k+m}\rangle$ consisting of:
  $u_{k+1} = \langle \mathtt{O}, \mathtt{P}, id, \mathbf{ctr}(\alpha_i, \beta), S^{um}_k, k+1\rangle$ where $\alpha_i$ is the assumption attacked by this opponent node, $id$ is the ID of the utterance with content $\mathbf{asm}(\alpha_i)$, and $S^{um}_k$ is the unmarked assumptions of the previous utterance $u_k$; for each $r_x \in R_1$, $u_{k+1+x} = \langle \mathtt{O}, \mathtt{P}, k+1, \mathbf{rl}(r_x), S^{um}_{k+x}, k+1+x\rangle$; for each $\beta_j \in \Delta_1$, $u_{k+1+n+j} = \langle \mathtt{O}, \mathtt{P}, k+1+x, \mathbf{asm}(\beta_j), S^{um}_{k+n+j} \cup \{\beta_j\}, k+1+n+j\rangle$ where $k+1+x$ is the ID of the utterance with the rule that contains $\beta_j$;
- for every node $[\mathtt{P} : \Delta_2 \vdash_{R_2} \alpha]$ in $\mathcal{T}$, $R_2 = \{r_1, \cdots, r_m\}$, $\delta_k = \delta_k \oplus U$ where $U$ is a sequence $\langle u_{k+1}, \cdots, u_{k+n}\rangle$ consisting of:
  $u_{k+1} = \langle \mathtt{P}, \mathtt{O}, id, \mathbf{ctr}(\beta_j, \alpha), S^{um}_k \setminus \Delta_1, k+1\rangle$ where $\Delta_1$ is the support of the argument attacked by this proponent node, $\beta_j \in \Delta_1$ is the assumption being attacked, and $id$ is the ID of the utterance with content $\mathbf{asm}(\beta_j)$; for each $r_y \in R_2$, $u_{k+1+y} = \langle \mathtt{P}, \mathtt{O}, k+1, \mathbf{rl}(r_y), S^{um}_{k+y}, k+1+y\rangle$; for each $\alpha_i \in \Delta_2$, $u_{k+1+m+i} = \langle \mathtt{P}, \mathtt{O}, k+1+y, \mathbf{asm}(\alpha_i), S^{um}_{k+m+i}, k+1+m+i\rangle$ where $k+1+y$ is the ID of the utterance with the rule that contains $\alpha_i$;

We use $F_\delta = \langle \mathcal{L}, \mathcal{R}_\delta, \mathcal{A}_\delta, \mathcal{C}_\delta\rangle$ to denote the *underlying framework* of the dialogue $\delta$ where $\mathcal{R}_\delta = \{r \mid \mathbf{rl}(r) \text{ is } C \text{ of some } u_i \text{ in } \delta\}$, $\mathcal{A}_\delta = \{\alpha \mid \mathbf{asm}(\alpha) \text{ is } C \text{ of some } u_i \text{ in } \delta\}$, $\mathcal{C}_\delta(\alpha) = \{\beta \mid \mathbf{ctr}(\alpha, \beta) \text{ is } C \text{ of some } u_i \text{ in } \delta\}$. $F_\delta$ is also the underlying framework of $\mathcal{T}$ from which $\delta$ is constructed.

**Definition 14.** An explaining dialogue $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X}) = \delta = \langle u_1, \cdots, u_l\rangle$ is **successful** if the unmarked assumptions $S^{um}$ of the last utterance $u_l$ in $\delta$ is an empty set.

An intuitive understanding of Definition 14 is that $\delta$ is *successful* if the supports of all opponent arguments in $\delta$ are attacked, or in other words, the proponent arguments in $\delta$ are sufficient and can counter-attack all opponent arguments.

An explaining dialogue $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X})$ can be viewed as a dialogical explanation for $\mathcal{X}$. However, an explanation for the entire debate process regarding $\mathcal{X}$ is not always necessary. The opponent may not challenge each and every assumption made by the proponent exhaustively. Hence, the proponent can choose to present only relevant arguments that can counter all attacks and make the dialogue successful. We define the notion of *partial dispute tree* to represent a partial debate process and study when an explaining dialogue constructed from a partial dispute tree is successful.

**Definition 15.** Given an ABA framework $ABF = \langle\mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C}\rangle$ and an admissible dispute tree $\mathcal{T}$ for $\mathcal{X} \in \mathcal{L}$ in $ABF$, a **partial dispute tree** $\mathcal{T}'$ for $\mathcal{X}$ constructed from $\mathcal{T}$ is a sub-tree of $\mathcal{T}$, such that: (1) every node $n$ in $\mathcal{T}'$ is also a node in $\mathcal{T}$; (2) if a node $[\mathtt{S} : x]$ is in $\mathcal{T}'$, then its parent $[\mathtt{S}' : y]$, $\mathtt{S}, \mathtt{S}' \in \{\mathtt{P}, \mathtt{O}\}$, $\mathtt{S} \neq \mathtt{S}'$, is also in $\mathcal{T}'$.

Given Definition 15, a partial dispute tree can be obtained by pruning branches of an admissible dispute tree. Explaining dialogues can also be constructed for partial dispute trees according to Definition 13.

| | |
|---|---|
| $\langle \mathtt{P}, \mathtt{O}, 0, \textbf{claim}(cPre(1097)), \{\}, 1\rangle$ | $\langle \mathtt{P}, \mathtt{O}, 1, \textbf{asm}(cPre(1097)), \{\}, 2\rangle$ |
| $\langle \mathtt{O}, \mathtt{P}, 2, \textbf{ctr}(cPre(1097), notCPre(1097)), \{\}, 3\rangle$ | |
| $\langle \mathtt{O}, \mathtt{P}, 3, \textbf{rl}(notCPre(1097) \leftarrow notMetS(1097, dx\_bl), metS(98, dx\_bl), noBetter(1097, 98, dx\_bl)), \{\}, 4\rangle$ | |
| $\langle \mathtt{O}, \mathtt{P}, 4, \textbf{asm}(notMetS(1097, dx\_bl)), \{notMetS(1097, dx\_bl)\}, 5\rangle$ | |
| $\langle \mathtt{O}, \mathtt{P}, 4, \textbf{asm}(noBetter(1097, 98, dx\_bl)), \{notMetS(1097, dx\_bl), noBetter(1097, 98, dx\_bl)\}, 6\rangle$ | |
| $\langle \mathtt{P}, \mathtt{O}, 6, \textbf{ctr}(noBetter(1097, 98, dx\_bl), better(1097, 98, dx\_bl)), \{\}, 7\rangle$ | |
| $\langle \mathtt{P}, \mathtt{O}, 7, \textbf{rl}(better(1097, 98, dx\_bl) \leftarrow metS(1097, apoe4), notMetS(98, apoe4), dImp(apoe4, dx\_bl)), \{\}, 8\rangle$ | |
| $\langle \mathtt{P}, \mathtt{O}, 8, \textbf{asm}(dImp(apoe4, dx\_bl)), \{\}, 9\rangle$ | $\langle \mathtt{P}, \mathtt{O}, 8, \textbf{asm}(notMetS(98, apoe4)), \{\}, 10\rangle$ |
| $\langle \mathtt{O}, \mathtt{P}, 9, \textbf{ctr}(dImp(apoe4, dx\_bl), notImp(apoe4, dx\_bl)), \{\}, 11\rangle$ | $\langle \mathtt{O}, \mathtt{P}, 11, \textbf{rl}(notImp(apoe4, dx\_bl) \leftarrow notCon(female)), \{\}, 12\rangle$ |
| $\langle \mathtt{O}, \mathtt{P}, 12, \textbf{asm}(notCon(female)), \{notCon(female)\}, 13\rangle$ | |
| $\langle \mathtt{P}, \mathtt{O}, 13, \textbf{ctr}(notCon(female), con(female)), \{\}, 14\rangle$ | $\langle \mathtt{P}, \mathtt{O}, 14, \textbf{rl}(con(female) \leftarrow), \{\}, 15\rangle$ |

Table 5: A successful explaining dialogue built from partial dispute tree $P\colon 1 \leftarrow O\colon 24 \leftarrow P\colon 28 \leftarrow O\colon 122 \leftarrow P\colon 124$ in Figure 2

**Theorem 2.** *Given an ABA framework $ABF = \langle \mathcal{L}, \mathcal{R}, \mathcal{A}, \mathcal{C}\rangle$ and an admissible dispute tree $\mathcal{T}$ for $\mathcal{X} \in \mathcal{L}$ in ABF, let $\mathcal{T}'$ be a partial dispute tree constructed from $\mathcal{T}$, let $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X}) = \delta$ be the explaining dialogue constructed from $\mathcal{T}'$ and $F_\delta = \langle \mathcal{L}, \mathcal{R}_\delta, \mathcal{A}_\delta, \mathcal{C}_\delta\rangle$ be the underlying framework of $\delta$ and $\mathcal{T}'$. Then, $\delta$ is successful iff $\mathcal{T}'$ is admissible in $F_\delta$.*

*Proof.* (*Sketch*) We first prove if $\mathcal{T}'$ is admissible in $F_\delta$, then $\delta$ constructed from $\mathcal{T}'$ is successful. Since $\mathcal{T}'$ is admissible in $F_\delta$, every O node in $\mathcal{T}'$ has a child. According to Definition 13, for every opponent node $[\mathtt{O} : \Delta_1 \vdash_{R_1} \beta]$ in $\mathcal{T}'$, all $\beta_j \in \Delta_1$ are added into $S^{um}$ by some utterance $u_n$ of the form $u_n = \langle \mathtt{O}, \mathtt{P}, id, \textbf{asm}(\beta_j), S^{um} \cup \{\beta_j\}, n\rangle$. Since every opponent has a child, then there exists a proponent node $[\mathtt{P} : \Delta_2 \vdash_{R_2} \alpha]$ such that $\Delta_2 \vdash_{R_2} \alpha$ attacks some $\beta_j \in \Delta_1$. Then, $\Delta_1$ is removed from $S^{um}$ by some utterance $u_m$ of the form $\langle \mathtt{P}, \mathtt{O}, n, \textbf{ctr}(\beta_j, \alpha), S^{um} \setminus \Delta_1, m\rangle$ from the proponent. Hence, for each O node, the assumptions added into $S^{um}$ by its utterances are removed by an utterance from its child P node. Since every O node has a child P node in $\mathcal{T}'$, for $\delta$ constructed from $\mathcal{T}'$, the $S^{um}$ in the last utterance of $\delta$ is empty and $\delta$ is successful.

We then prove the converse — if the dialogue $\delta$ constructed from a partial dispute tree $\mathcal{T}'$ is successful, then $\mathcal{T}'$ is admissible in $F_\delta$. Since $\delta$ is successful, the unmarked assumptions, $S^{um}$, in its last utterance is empty. For an opponent node $[\mathtt{O} : \Delta_1 \vdash_{R_1} \beta]$, all assumptions in $\Delta_1$ are added into $S^{um}$ by its utterances. Since $S^{um}$ in the last utterance of $\delta$ is empty, then there exists some utterance $u_m = \langle \mathtt{P}, \mathtt{O}, id, \textbf{ctr}(\beta_j, \alpha), S^{um} \setminus \Delta_1, m\rangle$, where $\beta_j \in \Delta_1$ and $id$ is the ID of the utterance with content $\textbf{asm}(\beta_j)$, that removes all assumptions in $\Delta_1$ from $S^{um}$. According to Definition 13, an utterance of such a form can only be constructed from a proponent node. Hence, this O node has a proponent child $[\mathtt{P} : \Delta_2 \vdash_{R_2} \alpha]$. In order for $S^{um}$ in the last utterance of $\delta$ to be empty, such P node must exist for every O node in $\mathcal{T}'$. Hence, $\mathcal{T}'$ is admissible in $F_\delta$. □

When $\mathcal{T}'$ for $\mathcal{X} \in \mathcal{L}$ is an admissible dispute tree in the underlying framework $F_\delta$, argument $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$. Hence, we have the following corollary.

**Corollary 2.1.** *Given an explaining dialogue $\mathcal{D}^{\mathtt{P}}_{\mathtt{O}}(\mathcal{X}) = \delta$, let $F_\delta = \langle \mathcal{L}, \mathcal{R}_\delta, \mathcal{A}_\delta, \mathcal{C}_\delta\rangle$ be the underlying framework of $\delta$. Then, $\delta$ is successful iff $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$.*

*Proof.* (*Sketch*) We first prove if $\delta$ is successful, then $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$. Let $\delta$ be constructed from a dispute tree $\mathcal{T}$ for $\mathcal{X}$. According to Theorem 2, if $\delta$ is successful, then $\mathcal{T}$ is admissible in $F_\delta$. This implies the following: (1) every node of the form $[\mathtt{O} : \Delta \vdash b]$ has a child in $\mathcal{T}$; (2) there exists no argument $\Delta \vdash x$ such that node $[\mathtt{P} : \Delta \vdash x]$ and node $[\mathtt{O} : \Delta \vdash x]$ both exist in $\mathcal{T}$. Let $[\mathtt{P} : \{\mathcal{X}\} \vdash \mathcal{X}]$ denote the root node of $\mathcal{T}$. Let $\mathcal{P}(\mathcal{T})$ denote the set of all assumptions in the supports of arguments labeling P nodes in $\mathcal{T}$. Item (1) implies that $\mathcal{P}(\mathcal{T})$ withstands attacks from the arguments embedded in all O nodes. Item (2) implies that $\mathcal{P}(\mathcal{T})$ is conflict-free. Hence, $\mathcal{P}(\mathcal{T})$ is admissible in $F_\delta$. Since $\mathcal{X} \in \mathcal{P}(\mathcal{T})$, $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$.

We then prove the converse — if $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$, then $\delta$ is successful. If $\{\mathcal{X}\} \vdash \mathcal{X}$ is admissible in $F_\delta$, then there exists a set of assumptions $\Delta$ such that $\Delta \cup \{\mathcal{X}\}$ is admissible in $F_\delta$. Hence, an admissible dispute tree $\mathcal{T}$ can be constructed from $\Delta \cup \{\mathcal{X}\}$, with $\{\mathcal{X}\} \vdash \mathcal{X}$ labeling the root node and each argument of the form $\Delta' \vdash x$, $\Delta' \subseteq \Delta$, labeling a P node in $\mathcal{T}$. Since $\delta$ can be constructed from $\mathcal{T}$ and $\mathcal{T}$ is admissible, $\delta$ is successful. □

Theorem 2 and Corollary 2.1 establish the connections among successful explaining dialogues, admissible partial dispute trees, and their underlying ABA frameworks. An explaining dialogue is successful when its claim corresponds to (1) the topic of an admissible partial dispute tree and (2) an admissible argument in the underlying ABA framework. Table 5 shows a successful explaining dialogue built from the partial dispute tree $P\colon 1 \leftarrow O\colon 24 \leftarrow P\colon 28 \leftarrow O\colon 122 \leftarrow P\colon 124$ in Figure 2.

The interaction between a user and our model can be characterized as an explaining dialogue, in which our model plays the role of a proponent and the user plays as an opponent. The user can challenge decisions made by our model by uttering contraries and rules with a set of sentences $\mathcal{U}(\mathcal{X}) \in \mathcal{L}$. Our model can offer explanations also by uttering contraries and rules with a set of sentences $\mathcal{M}(\mathcal{X}) \in \mathcal{L}$.

**Example 3.** *For the explaining dialogue in Table 5, with the mentioned sentences enclosed in the parentheses, a successful explaining dialogue between our model and the user may be as follows:*

***Model*** *(utterance 1): case 1097 is the most similar to ($cPre(1097)$) the case of interest 675.*

***User*** *(utterance 3, 4): case 1097 is not the most similar to ($notCPre(1097)$) case 675, since case 98 and case 675 share the same baseline diagnosis ($metS(98, dx\_bl)$) while 1097 does not ($notMetS(1097, dx\_bl)$).*

***Model*** *(utterance 7, 8): however, case 1097 and case 675 have similar APOE alleles ($metS(1097, apoe4)$), while case 98 does not ($notMetS(98, apoe4)$). APOE allele is a more important risk*

*factor than the baseline diagnosis ($dImp(apoe4, dx\_bl)$) for predicting progression to AD.*
***User*** *(utterance 11): APOE allele cannot be a more important risk factor than the baseline diagnosis ($notImp(apoe4, dx\_bl)$) because the context is not female ($notCon(female)$).*
***Model*** *(utterance 14, 15): Since patient 675 is a female ($con(female) \leftarrow$), APOE allele is a more important factor for predicting progression to AD.*

## 6 Related Works

The work presented in this paper shares some motivation with other works in the area of qualitative multi-attribute preferences, where preferences over decisions are defined based on a set of attributes or goals ranked by their priority (Visser, Hindriks, and Jonker 2012). More broadly, our work can also be viewed as a form of multiple criteria decision making (Amgoud and Prade 2009), with the criteria being the satisfaction of combinations of goals. Unlike most of the works in multi-attribute preferences that study different approaches to derive the global preference relation by aggregating goal or attribute priorities (Coste-Marquis et al. 2004; Bonnefon and Fargier 2006), we take a holistic approach and derive the most-contextual-preferred decisions directly without explicitly deriving the preference relation for each pair of decisions. Both our work and (Brewka 2004) model qualitative preference over decisions based on "multiple" priority orderings of goals. However, they model multiple priority orderings for different goal bases that co-exist in the same context, while we model contextual priority that can be viewed as multiple different priority orderings in different contexts. Moreover, they use ordinal ranks while we use a priority relation for representing the relative importance of goal sets, which allows us to easily approximate the priority relation with feature importance learned from training data.

The notions of our contextual priority may appear to be similar to the conditional preferences statements and CP-network proposed in (Boutilier et al. 1999). However, the two are quite different in nature. They model *ceteris paribus* preference, i.e. each preference statement is conditioned on certain value assignments of a subset of outcome variables (goals) and relates two outcomes that only differ in a single variable. Our contextual priority rule is conditioned on some defeasible contexts and relates two goal sets, which may differ in more than one variable (goal).

There has been extensive research on argumentation formalisms for modeling qualitative preferences (Modgil 2009; Modgil and Prakken 2014; García and Simari 2014; Besnard and Hunter 2014; Amgoud and Vesic 2014; Baroni et al. 2011). Most existing works account for defeasible preferences at the semantic level. Preferences are often used to modify existing (Amgoud, Dimopoulos, and Moraitis 2008; Modgil and Prakken 2014; Amgoud and Vesic 2014; Besnard and Hunter 2014) or construct new attack relations (Dung, Thang, and Son 2019), and hence refine the evaluation results of a framework. In value-based argumentation frameworks, values are assigned to arguments and preferences can then be specified over values to evaluate the acceptance of the competing arguments (Bench-Capon 2003). However, we choose to map QPDFs to ABAs and embed decision preferences at a "sub-semantic" level, similar to the approach in (Cyras and Toni 2016). Without modifying existing semantics, the implementation of our approach can be greatly eased as we can make use of existing ABA engines to support decision computation.

Recently, there are several emerging works on generating explanations based on argumentation constructs. Argumentative explanations for the acceptance of decisions are often given as various forms of subgraphs of an argument graph constructed from an argumentation framework. More often, argumentative trees, such as dispute trees (Fan and Toni 2014; Zeng et al. 2019; Čyras et al. 2019), and dialectical trees (García et al. 2013), are used to visualize the reasoning process and serve as computational constructs for generating explanations. Various forms of argumentation dialogues have also been explored for generating dialogical and interactive explanations (Fan et al. 2014; Caminada, Dvořák, and Vesic 2014; Cocarascu, Rago, and Toni 2019). Unlike previous works that produce explanations based on the entire reasoning process, e.g. using information from a complete argumentative tree or from several trees, our dialogical explanations can be derived from *partial dispute trees*. This enables focused dialogues to be generated with selected, rather than all, information involved in evaluating a decision.

## 7 Conclusion

We have proposed an argumentation-based decision making approach that can represent and reason with complex qualitative preferences and provide dialogical explanations for the decisions made. The main contributions of this paper are three-fold. Firstly, we extend the ability of decision frameworks to handle qualitative preferences based on contextual priority of goal combinations. This allows more complex goal priorities to be specified for different decision contexts. Secondly, the proposed *explaining dialogue* expands the explanation capabilities of argumentation-based decision making models. Different from previous explanation formalisms, it is able to generate dialogical explanations based on focused and selected information rather than all the disputes in the reasoning process. Lastly, we demonstrated the feasibility of our approach for AD diagnosis and prognosis using experiments on real-world datasets. Such applications in the healthcare domain could benefit greatly from the improved explainability offered by our approach.

As for future research directions, we hope to further develop and extend our proposed approach. Currently, the contextual priority of goal sets is approximated using feature importance learned from the data. This ensures that the resulting priority orderings are consistent and satisfiable. In the future, we will refine QPDF to include resolutions for inconsistent and unsatisfiable contextual priorities. We will also continue to study the relationship between QPDF and other preference-based formalisms. Due to the size of ADNI dataset, we were not able to illustrate all aspects of QPDF, such as complex contexts. We are looking to find and experiment with a larger dataset to better convey the full sophistication of our approach.

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## References

Altmann, A.; Tian, L.; Henderson, V. W.; Greicius, M. D.; and Investigators, A. D. N. I. 2014. Sex modifies the APOE-related risk of developing Alzheimer disease. *Annals of neurology* 75(4):563–573.

Amgoud, L., and Prade, H. 2006. Explaining qualitative decision under uncertainty by argumentation. In *Proceedings of the National Conference on Artificial Intelligence*, 219–224. Menlo Park, CA; Cambridge, MA; London; AAAI Press; MIT Press; 1999.

Amgoud, L., and Prade, H. 2009. Using arguments for making and explaining decisions. *Artificial Intelligence* 173(3-4):413–436.

Amgoud, L., and Vesic, S. 2014. Rich preference-based argumentation frameworks. *International Journal of Approximate Reasoning* 55(2):585–606.

Amgoud, L.; Dimopoulos, Y.; and Moraitis, P. 2008. Making decisions through preference-based argumentation. In *Proceedings of the Eleventh International Conference on Principles of Knowledge Representation and Reasoning (KR 2008)*, 963–970. AAAI Press.

Baroni, P.; Cerutti, F.; Giacomin, M.; and Guida, G. 2011. Afra: Argumentation framework with recursive attacks. *International Journal of Approximate Reasoning* 52(1):19–37.

Bench-Capon, T. J. 2003. Persuasion in practical argument using value-based argumentation frameworks. *Journal of Logic and Computation* 13(3):429–448.

Besnard, P., and Hunter, A. 2014. Constructing argument graphs with deductive arguments: a tutorial. *Argument & Computation* 5(1):5–30.

Bonnefon, J.-F., and Fargier, H. 2006. Comparing sets of positive and negative arguments: Empirical assessment of seven qualitative rules. *Frontiers in Artificial Intelligence and Applications* 141:16.

Boutilier, C.; Brafman, R. I.; Hoos, H. H.; and Poole, D. 1999. Reasoning with conditional Ceteris Paribus preference statements. In *Proceedings of the Fifteenth Conference on Uncertainty in Artificial Intelligence (UAI)*, volume 99, 71–80.

Brewka, G. 2004. A rank based description language for qualitative preferences. In *Proceedings of the 16th European Conference on Artificial Intelligence (ECAI)*, volume 16, 303–307.

Caminada, M. W.; Dvořák, W.; and Vesic, S. 2014. Preferred semantics as socratic discussion. *Journal of Logic and Computation* 26(4):1257–1292.

Cocarascu, O.; Rago, A.; and Toni, F. 2019. Extracting dialogical explanations for review aggregations with argumentative dialogical agents. In *Proceedings of the 18th International Conference on Autonomous Agents and MultiAgent Systems*, 1261–1269. International Foundation for Autonomous Agents and Multiagent Systems.

Coste-Marquis, S.; Lang, J.; Liberatore, P.; and Marquis, P. 2004. Expressive power and succinctness of propositional languages for preference representation. *Proceedings of the Ninth International Conference on the Principles of Knowledge Representation and Reasoning (KR 2004)* 203–212.

Cyras, K., and Toni, F. 2016. ABA+: assumption-based argumentation with preferences. In *Fifteenth International Conference on the Principles of Knowledge Representation and Reasoning (KR 2016)*, 553–556.

Čyras, K.; Birch, D.; Guo, Y.; Toni, F.; Dulay, R.; Turvey, S.; Greenberg, D.; and Hapuarachchi, T. 2019. Explanations by arbitrated argumentative dispute. *Expert Systems with Applications* 127:141–156.

Dung, P. M.; Kowalski, R. A.; and Toni, F. 2009.

Assumption-based argumentation. In *Argumentation in Artificial Intelligence*. Springer. 199–218.

Dung, P. M.; Mancarella, P.; and Toni, F. 2007. Computing ideal sceptical argumentation. *Artificial Intelligence* 171(10):642–674.

Dung, P. M.; Thang, P. M.; and Son, T. C. 2019. On structured argumentation with conditional preferences. In *Proceedings of the Thirty-Third AAAI Conference on Artificial Intelligence (AAAI-19)*, volume 33, 2792–2800.

Fan, X., and Toni, F. 2011. Assumption-based argumentation dialogues. In *Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence (IJCAI-11)*, 198–203.

Fan, X., and Toni, F. 2013. Decision making with assumption-based argumentation. In *Proceedings of the 2nd International Workshop on Theorie and Applications of Formal Argumentation (TAFA 2013)*, 127–142. Springer.

Fan, X., and Toni, F. 2014. On computing explanations in abstract argumentation. In *Proceedings of the Twenty-first European Conference on Artificial Intelligence (ECAI 2014)*, 1005–1006. IOS Press.

Fan, X.; Toni, F.; Mocanu, A.; and Williams, M. 2014. Dialogical two-agent decision making with assumption-based argumentation. In *Proceedings of the Thirteenth international conference on Autonomous agents and multi-agent systems (AAMAS 2014)*, 533–540. International Foundation for Autonomous Agents and Multiagent Systems.

Gao, S.; Hendrie, H. C.; Hall, K. S.; and Hui, S. 1998. The relationships between age, sex, and the incidence of dementia and alzheimer disease: a meta-analysis. *Archives of general psychiatry* 55(9):809–815.

García, A. J., and Simari, G. R. 2014. Defeasible logic programming: Delp-servers, contextual queries, and explanations for answers. *Argument & Computation* 5(1):63–88.

García, A. J.; ChesñEvar, C. I.; Rotstein, N. D.; and Simari, G. R. 2013. Formalizing dialectical explanation support for argument-based reasoning in knowledge-based systems. *Expert Systems with Applications* 40(8):3233–3247.

Miller, T. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial Intelligence* 267:1–38.

Modgil, S., and Prakken, H. 2014. The ASPIC+ framework for structured argumentation: a tutorial. *Argument & Computation* 5(1):31–62.

Modgil, S. 2009. Reasoning about preferences in argumentation frameworks. *Artificial intelligence* 173(9-10):901–934.

Rago, A.; Cocarascu, O.; and Toni, F. 2018. Argumentation-based recommendations: fantastic explanations and how to find them. In *Twenty-Seventh International Joint Conference on Artificial Intelligence*, 1949–1955.

Sampedro, F.; Vilaplana, E.; De Leon, M. J.; Alcolea, D.; Pegueroles, J.; Montal, V.; Carmona-Iragui, M.; Sala, I.; Sánchez-Saudinos, M.-B.; Antón-Aguirre, S.; et al. 2015. APOE-by-sex interactions on brain structure and metabolism in healthy elderly controls. *Oncotarget* 6(29):26663.

Teng, E.; Becker, B. W.; Woo, E.; Knopman, D. S.; Cummings, J. L.; and Lu, P. H. 2010. Utility of the functional activities questionnaire for distinguishing mild cognitive impairment from very mild Alzheimer's disease. *Alzheimer disease and associated disorders* 24(4):348.

Toni, F. 2014. A tutorial on assumption-based argumentation. *Argument & Computation* 5(1):89–117.

Visser, W.; Hindriks, K. V.; and Jonker, C. M. 2012. Argumentation-based qualitative preference modelling with incomplete and uncertain information. *Group Decision and Negotiation* 21(1):99–127.

Zeng, Z.; Fan, X.; Miao, C.; Leung, C.; Jih, C. J.; and Soon, O. Y. 2018. Context-based and explainable decision making with argumentation. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*, 1114–1122. International Foundation for Autonomous Agents and Multiagent Systems.

Zeng, Z.; Miao, C.; Leung, C.; Shen, Z.; and Chin, J. J. 2019. Computing argumentative explanations in bipolar argumentation frameworks. In *Proceedings of the AAAI Conference on Artificial Intelligence*, volume 33, 10079–10080.

Zhang, M.; Katzman, R.; Salmon, D.; Jin, H.; Cai, G.; Wang, Z.; Qu, G.; Grant, I.; Yu, E.; Levy, P.; et al. 1990. The prevalence of dementia and Alzheimer's disease in Shanghai, China: impact of age, gender, and education. *Annals of Neurology: Official Journal of the American Neurological Association and the Child Neurology Society* 27(4):428–437.