Formalizing Cognitive Acceptance of Arguments: Durum Wheat Selection Interdisciplinary Study

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Abstract

In this paper we present an interdisciplinary approach that concerns the problem of argument acceptance in an agronomy setting. We propose a computational cognitive model for argument acceptance based on the dual model system in cognitive psychology. We apply it in an agronomy setting within a french national project on durum wheat.
Keywords: Cognitive Model Argument Evaluation Substantive Irrationality

1 Introduction

A lot of research has been done in domains such as philosophy, psychology and computer science in order to study individual or collective decision-making behaviors in humans [30]. One of the fascinating aspects that makes the human reasoning such an impressive and flexible tool (but constitutes as well its greatest danger) is the coupling of a deductive logical reasoning with intuitive reasoning. This has been studied in the so called dual systems [23][18][19] and it has been used for practical benefits such as biased reasoning prediction [31].

In this paper we take inspiration from the previously cited literature on dual systems and propose a dual system for artificial agents with the benefit of flexibility on the use of associations alongside logical reasoning for expanding the notion of argument evaluation. A deductive reasoning, based on logical rules of thought, ensures the quality and the rationality of the decision taken, while an intuitive reasoning, based on associations between concepts, allows to be fast and to apply old knowledge to new domains. But each of these is not without its own pitfalls: a deductive logical reasoning might be too complex to handle or might lead to an impasse, and an intuitive reasoning might produce judgment mistakes, known as cognitive biases. Note that even very clever people can behave dysrationally (as defined by Stanovich see [29]), because of gaps or limitations in their education or experience or through heuristic trust or fallacious reasoning.

Our contribution is the definition of a new formal model of flexible argument evaluation. More precisely we show how such flexibility allows for generalization of current techniques of argument evaluation and their suitability in practical applications. We consider that, when it is not possible for an agent to make a logical inference (since it requires too much cognitive effort or she has insufficient knowledge), she might replace certain parts of the logical reasoning with mere associations. Using associations may alleviate the reasoning effort needed for argument evaluation and subsequently affect the argument acceptance. Moreover our long term aim is to be able to quantify the quality of the argument acceptance decision, in terms of cognitive effort spent and number of association rules used. These elements may allow an agent to evaluate the risk to have been biased in her reasoning.

We apply our work on an agronomy scenario. Agronomy is a particularly suitable field to this context of work because it involves many domain experts with very different backgrounds (economists, sociologists, mathematicians, computer scientists, transformation experts, agronomy experts, biologists, chemists). We investigate the Durum Wheat variety selection in the context of the French National Agency (ANR) DURDUR project[1]. The DURDUR project suggests developing a systematic approach to investigate issues related to the management of the nitrogen, energy and contaminants, to guarantee a global quality of products throughout the production and the processing chain of Durum Wheat with regards to pasta making. Started in 2014 and planned over 4 years, this multi-factorial approach aims at integrating the 3 dimensions of the sustainability (environmental, economic, and social) and proposing technical itineraries for Durum Wheat production. A task of integration by multi-criteria analyses and knowledge engineering aims at identifying the efficient levers to improve and guarantee the sustainability of the durum wheat agri-food chain. This project is dealing mainly with symbolic knowledge (since the different technical itineraries for Durum Wheat are represented in terms of logical rules or associations). The practical scenario considered in this paper will allow us to highlight if some decisions and reasoning were based on mere associations rules (i.e. non-pure logical reasoning). For instance we could explain why the argument of *considering bio-fertilizers for Durum Wheat* is potentially accepted for the "wrong" reasons, i.e. by using associations coming from experts not specialists of agronomy since the "bio" concept is associated with "sustainable agriculture" and they subsequently neglect the extensive damage to the soil done by such bio-fertilizers. In this case non-experts (or experts on complementary domains – economy, sociology, computing science) are more prone to biases than agronomy experts.

[1] `http://www.agence-nationale-recherche.fr/?Projet=ANR-13-ALID-0002`

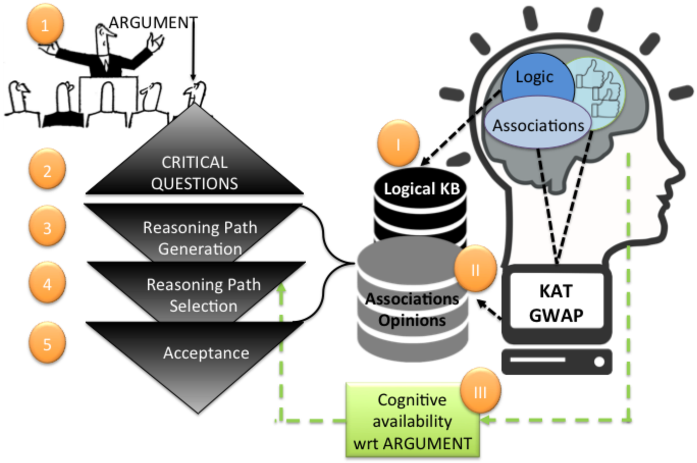

Figure 1: The proposed computational cognitive model

We extend upon previous work [9, 8, 22] by the expressivity of the logical language considered as well as the natural transition between the two systems of reasoning: logic based and association based and provide a *proof of concept of a true multidisciplinary application of cognitive science and artificial intelligence to the service of agronomy technical innovation (Durum Wheat selection).*

2 Paper in a Nutshell

In this section we present the different conceptual bricks that underlay the foundation of our work.

Figure 1 shows the overall process that we propose. First let us clearly define the purpose of the cognitive computational model. Please note that we do not aim to model the human reasoning in all its complexity. The long term aim of the computational cognitive model is to be able to function as a predictive model for argument acceptance by domain experts. The argument acceptance will be based on the expert profile (knowledge base, association rules, interest, attention etc.) and its reasoning process. Our research hypothesis, based on the dual process theory, assumes that the reasoning is done on two levels: on one hand we have the crisp logical based reasoning and on the other the less crisp association based reasoning.

The main contribution of the current work is to put in place such a computational cognitive model and its composing bricks for reasoning (logical or association based).

On the right hand side of the Figure 1 we consider a human agent having its logical knowledge base (with factual observations about the world and generic statements such as *Miradoux is a wheat variety*, *wheat contains proteins*), its own associations (*proteins are related to nutrition*) and its opinions (*I like Mi-*

radoux, I don't like spoiled wheat). The structure associated to an agent, called the computational cognitive model, proposed in this paper is explained in Section 3.

In the next section, we explain how we "fill in" the proposed cognitive model. In our approach, the logical knowledge is stored as a logical knowledge base (I, in Figure 1) expressed in Datalog+/- [12] (for re-utilisability purpose). In practice, as detailed in Section 4.1, this base has been built from existing written knowledge, namely ontologies about wheat.

The associations (II) (that can relate two pieces of information as well as a piece of information to an appreciation - in that case it is called opinion) are more difficult to elicit and are not often handled in the literature. One of the main difficulties is that the associations depend on the profile of the person (expert in wheat selection, non-expert, etc.).

To this end we devised a game with a purpose to elicit the associations of the different people according to their profile. This is represented on the right hand side of the image as the "neck" of the profile depicting the expert. It is an original building block of our approach and it is detailed in Section 4.2.

A third parameter is also required by our model, namely, the cognitive availability (abbreviated *ca*) of the agent (III) which depends on the agent's interest about the particular argument and on the amount of attention he has to spent (its precise definition is not studied here, it may be based on the agent mood, her knowledge, sometimes on the speaker, on the topic of the argument, etc.). This cognitive availability is a parameter that we use to filter the possible reasoning the agent is able to do, see Section 5.

More precisely, on the left hand side of Figure 1, we show the proposed process of argument acceptance using the cognitive model detailed in Section 5. When the agent hears a new argument (step (1)), a number of critical questions are fired (*"is the premise of the argument correct?"*, *"do I agree with the conclusion?"*, *"can I infer the conclusion from the premise based on what I know?"* - step (2)).

Thanks to the proposed cognitive model, it will then be possible to compute reasoning paths (i.e. sequences of logical rules and association rules constituting a chain of inferences that leads to a desired conclusion) for each critical question (step (3)). For a reasoning path we introduce the notion of effort (cognitive effort to use the rules of the reasoning path) which is confronted to the cognitive availability of the agent. An association is usually effortless while logical reasoning is considered as more expensive. The cognitive availability of the agent allows us to have an upper bound of the effort the agent is able to put into her reasoning paths. The reasoning paths will be selected based on the effort needed to carry on (step (4)). Based on this selection we can accept or reject an argument. Please note that the reasoning paths will be constructed starting from the logical knowledge base and the associations that computationally represent the knowledge of the expert.

3 Agent Cognitive Model Definition

In this paper we want to cope with several kinds of reasoning mechanisms, this is why we define the cognitive model of an agent to contain beliefs, associations and opinions. These three kinds of inputs are used together in a first attempt to incorporate Kahneman's System 1 [31] ideas in a formal language. Roughly speaking, System 1 is a human reasoning system dealing with quick, instinctive and heuristic thoughts. By doing so, the aim is to have a framework allowing to mix deductive and purely logical reasoning with System 1 reasoning.

The beliefs, opinions and associations are represented in a finite set of formulas written in a Datalog+/-[12] language $\mathcal{L}$. The language $\mathcal{L}$ is based on a set of user-defined *predicates* $\mathcal{P}$, a finite set of *variables* $\mathcal{V}$ (written in capital letters) and a finite set of *constants* $\mathcal{C}$. A *term* is a variable or a constant, an *atom* has the form p or $p(t_1, \ldots, t_n)$ where p is a predicate and for all $i \in [1 \ldots n]$, t_i is a term. In particular $\bot$ is the predicate of arity 0 (hence an atom) representing the contradiction. Formulas of $\mathcal{L}$ are atoms or *rules*[2] i.e., expressions of the form $\varphi(\vec{X}, \vec{Y}) \rightarrow \exists \vec{Z}\ \psi(\vec{X}, \vec{Z})$ where φ and ψ are conjunctions of atoms and $\vec{X}$, $\vec{Y}$ and $\vec{Z}$ are (possibly empty) vectors of variables representing respectively the variables occurring in φ and also ψ, the variables occurring only in φ and the variables occurring only in ψ. An *opinion* about a variable or a constant $\alpha \in \mathcal{C} \cup \mathcal{V}$ is encoded by the use of the predicates *like*, *dislike* and *dontcare*, those predicates being mutually exclusive. Hence we assume that $\{like, dislike, dontcare\} \subseteq \mathcal{P}$ and that the three clauses $like(X) \wedge dislike(X) \rightarrow \bot$, $like(X) \wedge dontcare(X) \rightarrow \bot$ and $dislike(X) \wedge dontcare(X) \rightarrow \bot$ are present in any Datalog+/- base. Rules ending in $\bot$ are called *negative constraints*. In the following, we call *proper rules* a set of rules not including any negative constraints.

A given agent cognitive model contains a finite set of beliefs $B \subseteq \mathcal{L}$ that contains formulas that do not use the predicates $\{like, dislike, dontcare\}$, a set of opinions $O \in \mathcal{L}$ of formulas that contains at least one predicate $\{like, dislike, dontcare\}$ and a set of non-atomic clauses $A \in \mathcal{L}$ called *association rules*. The set A is supposed to come from a manually translation of pairs of concepts that are given by human people, this implies a certain degree of flexibility. For instance, the association (buy_sheba, cat_owner) (associating someone who buys the common cat food *Sheba* to a *cat_owner*), could be translated as follows: $buys(Y, Z) \wedge sheba(Z) \rightarrow \exists X cat(X) \wedge own(Y, X)$.

We define the notion of "reasoning" as the process of inferring a formula φ using a sequence R of formulas from $B \cup O \cup A$ on an initial set of pieces of information K, denoted $K \vdash_R \varphi$.

Definition 1 (Rule application and Dependency) *Given a set of formulas $K \subseteq \mathcal{L}$, and a rule $r = \varphi(\vec{X}, \vec{Y}) \rightarrow \exists \vec{Z}\ \psi(\vec{X}, \vec{Z})$ in $\mathcal{L}$, r is* applicable *in the context K iff there exists a substitution σ that unifies a conjunction of formulas of K with $\varphi(\vec{X}, \vec{Y})$. In that case, the result of the application of r to K with substitution σ is $\exists \vec{Z}\ \psi(\sigma\vec{X}, \vec{Z})$.*

A rule r is dependent *on a set of rules $\mathcal{R}$ in a context K if r is not applicable in the context K but r is applicable in the context resulting from one or several applications of rules of $\mathcal{R}$ to K.*

We call the successive application of rules depending on their predecessors a "reasoning path". Please note that our definition of rule dependency implies the equivalent use of "$\wedge$" and "," when handling conjunctions (resp. sets) of formulas.

[2] In [12] they are called "Tuple Generating Dependencies" (TGD) clauses.

Definition 2 (Reasoning path) *A reasoning path is a member of*

$$\mathcal{R} = \bigcup_{p \in \mathbb{N}} (B \cup O \cup A)^p$$

A reasoning path R of length p in the context $K \subseteq \mathcal{L}$ is denoted by the sequence of its formulas $R = \langle r_1, r_2, \ldots r_p \rangle$ and is such that r_1 is applicable in the context K and any r_i with $i > 1$ is dependent on $\{r_1, \ldots, r_{i-1}\}$ and $\{r_1, \ldots, r_{p-1}\}$ is only composed of proper rules.

Inside this reasoning path we differentiate the use of logical inference formulas from the use of an association rule. A reasoning on a formula can be achieved using different reasoning paths, each path has a cost depending on the cognitive effort needed to use its formulas. Intuitively it is less costly to use association rules (that are not far fetched) than using logical inference formulas.

The fact that some associations may be more or less far fetched is encoded by a function e that associates a number which is higher if the association is less immediate. More generally, the cognitive effort that the agent must do to use an inference is a function e that associates to each rule a number, the more it is difficult for the agent to use it the higher is this number. Note that we do not consider the effort of exploration that is required for the agent in order to obtain these reasoning paths.[3] Moreover, we allow for the fact that an agent may not know some formulas, it can be encoded by an infinite effort to use them. The same convention is done for associations, if an association is not known by an agent it has an infinite far fetched degree.

Now we are in position to define the cognitive model of an agent based on the previous notions.

Definition 3 (Cognitive model) *A* cognitive model *is a tuple*

$$\kappa = (B, O, A, e)$$

- *$B \subseteq \mathcal{L}$ is a set of Datalog+/- wffs not using $\{like, dislike, dontcare\}$ representing beliefs*
- *$O \subseteq \mathcal{L}$ is a set of Datalog+/- wffs that use at least one predicate $\{like,$ $dislike,$ $dontcare\}$ representing opinions,*
- *$A \subseteq \mathcal{L}$ is a set of non-atomic clauses representing the associations,*
- *e is a function $B \cup O \cup A \to \mathbb{N} \cup \{+\infty\}$ that represents the effort required to use each Datalog+/- expression.*

Before focusing on the cognitive evaluation of an argument, in the next section we explain how it is possible to construct the knowledge bases for beliefs, opinions and associations of the cognitive model.

[3] We assume here that the effort of exploration is somewhat included in the cognitive effort associated to the rule, but in further research a statistical approach could be used: in a reasoning path the cost of exploration could take into account the number of all the possible formulas (with their different possible instantiations) that could apply at each step.

4 Model Construction

In this section we detail how we constructed the model defined in the previous section with regards to the DURDUR application. In face of the current issues (climate change, price volatility, regulation changes, and environmental impact decrease), the sustainability of the French durum wheat agri-food chain lies on its capacities of organization, innovation and adaptation. The DURDUR project integrates the knowledge base of the three kinds of actors of corresponding profiles (environmental, economic and social). This is performed by formalizing the technical itineraries provided by each actor group. The expressivity of the language needed to represent and reason about such itineraries includes logical inference (*all durum wheat culture needs a precedence culture*), opinions (*I like nitrogen reduction*) and associations (*Miradoux variety of durum is associated to nitrogen fertilization*). However, when an actor needs to evaluate the argument of another actor (and agree upon its inclusion in the integrated knowledge base) this evaluation is not always done in a fully logical way. It is important to be able to predict how this evaluation is done in order to be able to correct it and to explain the potential risks taken by using some dangerous associations rules during a decision process.

Before we detail the evaluation of arguments let us first show how we constructed the logical formulas, opinions and associations of the various actors involved. In Section 4.1, we present a knowledge base built specifically for the Durum Wheat domain. In Section 4.2, we present a game introduced in order to collect associations specific to stereotypical types of agents. Please note that we will pay particular attention to the association rules capitalization as the logical belief base construction is not an innovative process as such and done using classical knowledge engineering methods [13].

4.1 Model Construction: Belief Base

The durum wheat belief base has been constructed within the DURDUR project. The goal of this base, among others, is to integrate a part of the scientific knowledge acquired during the project to redesign the durum wheat chain. The base is used in many computational tasks, notably analyzing and comparing the alternative innovative technical itineraries proposed in the project to reduce the dependence to chemical inputs (nitrogen fertilizers and pesticides).[4]

The base represents domain-specific knowledge and it is composed of the vocabulary, facts, rules and negative constraints. It is represented using existential rules (Datalog+/-) [12], a prominent knowledge representation language that is generalizing some fragments of Description Logics. The vocabulary contains 533 concepts and 200 relations. The rule base contains 30 rules while the factual part has about 865 atoms e.g. the rule stating that if the durum wheat is cultivated on soil which has a Colza precedent then the quality of this durum wheat will improve. This can be formalized in Datalog+/- as

$$durumWheat(X) \wedge cultivatedOnSoil(X,Y) \wedge \; precedent(Y, colza) \\ \rightarrow improvedQuality(X)$$

[4]All details about the Durum wheat base, as well as ways of downloading and using it can be found at `http://www.lirmm.fr/~arioua/dkb/`.

We will not insist on the rules and facts in the belief base, more details can be found in [1].

4.2 Model Construction: Opinions and Associations

In order to represent associations in our model we use Associative Networks. Associative Networks have been investigated as a way of representing human memory. Starting from the PhD of Quillian 1966 [24] they have been used as a way to provide intelligent machines with a working memory. In order to elicit associative networks from humans, different knowledge acquisition and elicitation techniques have been used [35]. Such techniques range from direct interviews and questionnaires to Games With A Purpose (GWAPs). The main idea in GWAPs is to integrate tasks (such as image tagging, video annotation, knowledge acquisition etc.) into games [33]. This technique is cheaper to implement than other knowledge acquisition methods because it relies on entertainment rather than material compensation while at the same time it yields similar or better results as shown in [32].

In our model, we need to extract association lists for different profiles, each profile representing a specific type of agents. This type of profile-based association lists cannot be extracted using existing GWAP due to two main limits. First, existing GWAPs do not take into account any information regarding the agents themselves as their main purpose is to extract objective information (information that is shared by all agent), and second, these GWAPs only elicit associative networks for concepts that come from a predefined list (dictionaries, etc.). This poses problems since the game itself is not easily configurable to focus on particular domains (e.g. a product or a process in DURDUR.) or on particular kinds of complex concepts (e.g. "Pasta" vs "Pasta Quality" vs "Good Pasta Quality"). While questionnaires can be used to extract the type of associative networks we need, they inherently lack scalability which greatly limits the predictive capabilities of our model.

Therefore, and in order to make use of the scalability of GWAPs and the subjective information extraction of questionnaires, we proposed in [22] a method to build an associative network using a GWAP that takes into account the profiles of the players to make explicit the differences in terms of associations between stereotypical types of agents. Here, the associations creation task is transformed into elements of a game where profile-teamed players construct and validate associations as a consequence of playing the game, rather than by performing a more traditional direct questions-answering task.

In order to make sure we can extract profile-based associative networks, we conducted an experiments in the domain of the DURDUR project in which we were interested in the changes in associations between experts in transformation, experts in Life Cycle Analysis (LCA) and non-experts. We built profiles implicitly using their expertise, and conducted game sessions on 15 concepts specific to the DURDUR domain across two experiments. A first experimentation was carried out with 9 experts of the DURDUR project (7 of them were transformation experts while the rest were LCA experts). A second experimentation was carried out with 15 undergraduate students in computer science from the University Institute of Technology (IUT) in Montpelier. All 24 participants played 15 game sessions that they successfully completed.

Concretely, the participants played a game session where they were shown the concept name in English, a description in French and optionally a photo representing the concept, (e.g. For "Pasta Quality", the game displayed "Pasta Quality" as concept name, "Qualité des pates" as a description, and an image of pasta). Each participant was then asked to give associations in English, organize them from most relevant to least relevant and, optionally, give an opinion for each association (⊕ like, ⊙ dontcare, ⊖ dislike).

In this game, the aim of the players was to produce common associations (or what they thought is common) for their particular profile. More precisely, the participants were earning points when they gave associations already given by other participants within the same profile. In our case, the students knew that their profiles were corresponding to non-experts in agronomy, and as such they tried to give general associations in order to maximize their points. In contrast, the agronomy experts gave associations emphasizing technical associations that are relevant to their domain of expertise.

An important aspect to highlight is that participants are encouraged to give associations they think are typical for their group because we want to obtain a rather stereotypical profile of particular classes of people (we consider experts and non-experts in the remainder of the paper, but it could be anything else, for instance "man aged between 20 and 30"). By playing, participants will by themselves reason about the type of players they are associated with and elicit obvious associations relating to this group (even if the participant himself does not use these associations).

The participants gave a total of 1623 associations (along with their opinion on each association) for 15 concepts. Here we will only present 3 concepts, of which we show the full results for the concepts "Pasta Quality" and the partial results for "Protein content" and "Couscous Processing" (shown in Tables 1, 2 and 3; please note that associations are ordered from most relevant on top to least relevant at the end of the tables).

If we take for example the association list for *Couscous Processing*, we can see how certain information surfaces when we take profiles into account. By aggregating associations based on profile we can expose valuable associations of the experts (e.g. *Semolina* and *Rolling* and *Durum Wheat*) that have been drowned in the associations of the entire group of participants (like *Arab*, *Tajine*). Also please note that the associations of IUT students are similar to the associations of the whole group due to the higher number of students. This clearly shows how not considering profile information suppressed the associations of under-represented types of agents. We can also see in the association list for *Pasta Quality* that based on the granularity of the profiles taken into account we can generate different associations, for example, the associations for expert and non-expert, and for specific types of experts, at each level of granularity more subjective information is exposed, thus for the purpose of our model, we tend to seek association lists with the finest granularity in profile construction as they are more representative of the agent associations.

Using both the knowledge base and the association base, it is now possible to study how an argument may be evaluated thanks to the cognitive model.

Table 1: Association Lists for "Pasta Quality"

All Participants		Experts		Non-Experts	
Italy	$\oplus$	Yellowness	$\oplus$	Italy	$\oplus$
Cooking time	$\odot$	Color	$\odot$	Cooking time	$\odot$
Taste	$\odot$	Protein Content	$\oplus$	Price	$\odot$
Protein Content	$\oplus$	Texture	$\oplus$	Taste	$\odot$
Yellowness	$\oplus$	Stickiness	$\oplus$	Brand	$\odot$
Nutrition	$\oplus$	Starch	$\odot$	Nutrition	$\oplus$
Price	$\odot$	Cooking loss	$\ominus$	Slow Sugar	$\oplus$
Color	$\odot$	Taste	$\odot$	Gluten	$\odot$
Gluten	$\oplus$	Drying Temperature	$\oplus$	Tomato Sauce	$\oplus$
Brand	$\odot$	Hydration	$\oplus$	Panzanni	$\oplus$
Average relevance: 0.08		Average relevance: 0.22			

LCA Experts		Transformation Experts		Non-Experts	
Yellowness	$\oplus$	Color	$\odot$	Italy	$\oplus$
Texture	$\oplus$	Protein Content	$\oplus$	Cooking time	$\odot$
Strach	$\oplus$	Yellowness	$\oplus$	Price	$\odot$
Nutrition	$\oplus$	Stickiness	$\oplus$	Taste	$\odot$
Protein Nature	$\odot$	Drying Temperature	$\oplus$	Brand	$\odot$
Network	$\odot$	Overcooking resistance	$\oplus$	Nutrition	$\oplus$
Cropping system	$\oplus$	Gluten	$\oplus$	Slow Sugar	$\oplus$
Quantity	$\oplus$	cooking loss	$\ominus$	Gluten	$\odot$
Brightness	$\oplus$	Texture	$\oplus$	Tomato Sauce	$\oplus$
Color Imperfection	$\ominus$	Viscoelasticity	$\oplus$	Panzanni	$\oplus$
Average relevance: 0.38					

5 Argument Evaluation

Generally speaking, argumentation is a reasoning model based on the construction and the evaluation of interacting arguments. Those arguments are intended to support / explain / attack statements that can be decisions, opinions etc. Argumentation has been used in Artificial Intelligence for different purposes. The main purpose is non-monotonic reasoning ([15]) where several frameworks have been developed for handling inconsistency in knowledge bases (e.g. [7]). Moreover, it has been shown that argumentation is generally enough to capture different existing approaches for non-monotonic reasoning [15]. Argumentation has also been extensively used for modeling different kinds of dialogues, in particular persuasion (e.g. [2]) and negotiation (e.g. [25]). Indeed, an argumentation-based approach for negotiation has the advantage of exchanging reasons that support these offers. The explanation dialogues were marginally investigated [5, 4, 3].

In this paper and from the Argumentation theory we solely use two main notions: the fact that information is structured into two parts (a premise and a conclusion) and the three ways to attack an argument. We propose a new way to evaluate their acceptance based on three critical questions related to those three ways.

Usually, different agents will differently accept arguments according to their

Table 2: Association List for “Protein Content”

All Participants		Experts		Non-Experts	
Meat	$\oplus$	Quality	$\oplus$	Meat	$\oplus$
Muscle	$\oplus$	Gluten	$\oplus$	Muscle	$\oplus$
Nutrition	$\oplus$	Gliadine	$\oplus$	Eggs	$\oplus$
Quality	$\oplus$	Nutrition	$\oplus$	Nutrition	$\oplus$
Eggs	$\oplus$	Network	$\oplus$	Chicken	$\oplus$
...	...	...	...	...	...
Average relevance: 0.04		Average relevance: 0.23			

Table 3: Association List for “Couscous Processing”

All Participants		Experts		Non-Experts	
Semolina	$\oplus$	Semolina	$\oplus$	Arab	$\odot$
Arab	$\odot$	Rolling	$\oplus$	Tajine	$\oplus$
Water	$\oplus$	Durum Wheat	$\odot$	Semolina	$\odot$
Tajine	$\oplus$	Agglomeration	$\oplus$	Water	$\oplus$
Rolling	$\oplus$	Water	$\oplus$	Maghreb	$\odot$
...	...	...	...	...	...
Average relevance: 0.04		Average relevance: 0.19			

associations and knowledge base. Since in DURDUR all actors do not have the same level of expertise (according to their profile) sometimes argument evaluation combines logical reasoning with ill-founded associations of ideas that people made during their exposure to other domains. Such biased reasoning needs to be detected in order to be corrected. With the long term purpose of building a decision support system that predicts argument evaluation by domain experts we need to start by investigating the problem of argument evaluation in presence of logic-based and association-based reasoning.

Before going any further, it is mandatory to define the notion of argument. We consider a simple definition for an argument given below. Note that we are not requiring a link between the premise and the conclusion of the argument, this allows us to consider arguments that are ill-formed on their warrant part (the link in itself), be it because the argumentative agent is wrong and considers a “bad” rule, or because she is actually trying to manipulate her audience. Moreover there is no requirement for the argument to be related to some particular cognitive model, because it will be evaluated as it is, by a given agent with its own cognitive model. The only requirement is that it is expressed in the logical language $\mathcal{L}$.

Definition 4 (Argument) *Considering the language of beliefs and opinions $\mathcal{L}$, an argument is a pair $(\varphi \in \mathcal{L}, \alpha \in \mathcal{L})$ stating that having some beliefs and opinions described by φ leads to concluding α.*

Example 1 *Let us consider an argument expressing that* Miradoux is a very good wheat variety since it contains proteins. *This argument could be encoded by: ($has\_protein(miradoux)$, $like(miradoux)$).*

In some work (such at [34]), whether or not an argument is acceptable depends on critical questions. For the sake of generality, we propose to consider the classical notions that are used in argumentation in order to define attacks on arguments. Classically three notions are used, called *rebuttal*, *undermine* and *undercut*. More precisely an argument (φ, α) can be attacked either on its conclusion (α) directly or on a part of its premises (φ) or on the link between the premises and the conclusion.

Definition 5 (Critical Questions) *Given an argument (φ, α), we define:*

- $CQ_1(\varphi, \alpha) \stackrel{def}{=}$ *there exists* $R \in \mathcal{R}$, $B \cup O \cup A \cup \{\alpha\} \vdash_R \perp$
- $CQ_2(\varphi, \alpha) \stackrel{def}{=}$ *there exists* $R \in \mathcal{R}$, $B \cup O \cup A \cup \{\varphi\} \vdash_R \perp$
- $CQ_3(\varphi, \alpha) \stackrel{def}{=}$ *there exists* $R \in \mathcal{R}$, $B \cup O \cup A \cup \{\varphi\} \vdash_R \alpha$

Example 2 *Let us consider a LCA expert on Pasta Quality as described in Table 1 with the following cognitive state described below. Please note that the expert will consider two types of Durum Wheat: miradoux and a spoiled version of miradoux hereby denoted miradoux2. Also, please note that the set of formulas in this example is not exhaustive; this choice being done for illustrative reasons.*

B	1. $wheat(miradoux)$ 2. $spoiled\_wheat(miradoux2)$ 3. $spoiled\_wheat(X) \rightarrow low\_protein(X)$ 4. $low\_protein(X) \wedge has\_protein(X) \rightarrow \perp$ 5. $wheat(X) \rightarrow has\_protein(X)$ 6. $has\_protein(X) \rightarrow nutrient(X)$
O	1. $dislike(miradoux2)$ 2. $like(X) \wedge dislike(X) \rightarrow \perp$ 3. $like(X) \wedge dontcare(X) \rightarrow \perp$ 4. $dislike(X) \wedge dontcare(X) \rightarrow \perp$
A	1. $nutrient(X) \rightarrow like(X)$ 2. $has\_protein(X) \rightarrow dontcare(X)$

The critical questions concerning the argument $arg =$ *(has_protein(miradoux), like(miradoux)) are:*

- $CQ_1(arg) =$ *there exists* $R \in \mathcal{R}$ *s.t.* $B \cup O \cup A \cup \{\ like(miradoux)\} \vdash_R \perp$
- $CQ_2(arg) =$ *there exists* $R \in \mathcal{R}$ *s.t.* $B \cup O \cup A \cup \{has\_protein(miradoux)\} \vdash_R \perp$
- $CQ_3(arg) =$ *there exists* $R \in \mathcal{R}$ *s.t.* $B \cup O \cup A \cup \{has\_protein(miradoux)\} \vdash_R like(miradoux)$

Intuitively, in order to determine if an argument is *acceptable*, we are going to check if the agent can find a negative answer to CQ_1 and CQ_2 and a positive answer to CQ_3. The argument will be *rejectable* if the agent can find a positive answer to one of the two first questions or a negative one to CQ_3. The argument will be *undecidable* otherwise. Reasoning paths will allow us to define the answers to critical questions. However, it is important to note that an agent might not always be able to compute every possible answer to a critical question (she might be tired or busy thinking about something else, for instance).

Some works are addressing this issue. For instance, the ELM model [11] defines two "routes" that govern the reception of persuasive communications: the *central route*, that involves a large amount of cognition and that has the tendency to be more rational concerning the logical quality of the received argument, and the *peripheral route*, that involves little cognition and where arguments are more likely to be evaluated thanks to simple cues such as the political view on the advocated position, the liking of the speaker, etc. The determination of the route is made thanks to two main factors: the interest in processing the message and the ability (wrt. knowledge and cognitive availability) to process it.

Hence, we assume here that each agent has a cognitive availability that represents the maximum cognitive effort she is willing to make in order to reason on an argument. The reader can refer to [10] for a more detailed study of four extreme kinds of cognitive availability profiles, namely, *engaged*, *quiescent*, *unconcerned* and *enthusiastic* representing respectively an exclusively logical reasoning, an exclusively association-based reasoning, a disinterest and a superficial evaluation of an already convinced agent.

The cognitive availability will determine if the agent has the possibility to be perfectly rational (which is reminiscent of Kahneman's S2 reasoning) or if she needs some heuristic in the form of associations in order to reason (leaning towards Kahneman's S1 reasoning). In our model, the current cognitive availability of an agent is denoted *ca*. Note that this current cognitive availability may depend, among others, on the interest of the agent towards the argument, her self-perceived proficiency on the considered topic, etc.

Example 3 *Let us assume that all the formulas of $B \cup O$ are associated with a cognitive effort of* 10 *for a given agent and that the formulas of A with an effort of* 1*. Considering the formula $like(miradoux)$, the reasoning path to infer it is $\langle B1, B5, B6, A1\rangle$ and requires a cognitive ability of at least* 31*. But with a $ca \in [21, 31[$, the agent will also be able to compute $dontcare(miradoux)$ with the reasoning path $\langle B1, B5, A2\rangle$.*

Given an argument, we compute reasoning paths wrt an effort c. A negative answer with an effort c to a critical question corresponds to the non-existence of a reasoning path inferring the conclusion that requires a cognitive effort less or equal to c. A positive answer to a question is associated with the minimum effort required to answer to the critical question (i.e., the effort required by the minimum reasoning path inferring the conclusion).

Definition 6 (Positive/negative answers) *Given an agent with a cognitive model κ, a question $CQ =$ (there exists $R \in \mathcal{R}$, $\varphi \vdash_R \psi$) and an integer c, we say that:*

- *CQ is* answered negatively with effort c, *denoted* $negative_{\kappa,c}(CQ)$, *iff there exists no* $R \in \mathcal{R}$ *with* $Eff(R) \leq c$ *s.t.* $\varphi \vdash_R \psi$.

- *CQ is* answered positively with effort c, *denoted* $positive_{\kappa,c}(CQ)$, *iff there exists* $R \in \mathcal{R}$ *with* $Eff(R) = c$ *s.t.* $\varphi \vdash_R \psi$ *and for all* $c' < c$, $negative_{\kappa,c'}(CQ)$.

where $Eff(R) \stackrel{def}{=} \sum_{r \in R} e(r)$.

In the following, when not ambiguous, we simply denote $negative_{\kappa,c}(CQ)$ (resp. $positive_{\kappa,c}(CQ)$) by $negative_c(CQ)$ (resp. $positive_c(CQ)$).

Note that this definition implies that a question will be answered by the minimum effort path (this idea is in accordance with Kahneman theory and was a starting point of our research).

Example 4 *Considering the argument* $arg = (has\_protein(miradoux), like(miradoux))$ *and the* (B, O, A, e) *described in Example 2 and 3, it holds that* $positive_{31}(CQ_1(arg))$ *since* $\langle B1, B5, A2\rangle$ *allows to infer* $dont\_care(miradoux)$ *and* $O3$ *with* $like(miradoux)$ *leads to* $\perp$. *It also holds that* $positive_{22}(CQ_2(arg))$ *with the reasoning path* $\langle B6, A1, A2, O3\rangle$, *and that* $positive_{11}(CQ_3(arg))$ *with the reasoning path* $\langle B6, A1\rangle$.

Thanks to the previous definitions, we are now in position to formally define the problem of argument evaluation wrt an agent cognitive model and its cognitive availability. Intuitively, an argument is *acceptable* by the agent if she can establish the link between the premises and the conclusion (i.e., answer positively to CQ_3) and the agent has not enough cognitive ability to find a counter-example for either the conclusion (i.e., she would answer negatively to CQ_1) or the premises (negative answer to CQ_2). An argument is *rejectable* if the agent is able to find a counter-example corresponding to one of the two first critical questions (CQ_1 and CQ_2). An argument which is both rejectable and acceptable is called *undecidable*, this may occur when the agent is able to find a proof for CQ_3 or for CQ_1 independently but has not enough cognitive availability to compute both proof together (see Proposition 7.1). Note that given an argument (φ, α), when the agent's cognitive availability doesn't allow her to establish the connection between ϕ and α, she may not be convinced that α is not a consequence of the given premises. Hence we have defined the *weakly_acceptable* arguments for which the agent has no counter-argument and the *weakly_rejectable* arguments for with the agent is not able to find the link between premise and conclusion. A *conflicting* argument is a particular case of rejectable argument such that the agent has enough cognitive availability both to prove that the link between premise and conclusion holds and to either prove that the premise does not hold or that the conclusion does not hold. A *confusing* argument is an argument for which the agent cannot prove anything (neither the logical link nor the premise nor the conclusion).

Definition 7 (Potential status of arguments) *Given an agent with a cognitive model* κ, *a cognitive availability* ca *and an argument* arg. *We define:*

- $acceptable_{\kappa,ca}(arg) \stackrel{def}{=}$ *there exists* $c \leq ca$ *s.t.* $positive_c(CQ_3(arg))$ *and* $negative_{ca-c}(CQ_1(arg))$ *and* $negative_{ca-c}(CQ_2(arg))$

- $rejectable_{\kappa,ca}(arg) \stackrel{def}{=}$ *there exists* $c \leq ca$ *s.t.* $positive_c(CQ_1(arg))$ *or* $positive_c(CQ_2(arg))$

- $undecidable_{\kappa,ca}(arg) \stackrel{def}{=} acceptable_{\kappa,ca}(arg)$ *and* $rejectable_{\kappa,ca}(arg)$

- $weakly\_acceptable_{\kappa,ca}(arg) \stackrel{def}{=}$ *there exists* $c \leq ca$ *s.t.* $negative_c(CQ_1(arg))$ *and* $negative_{ca-c}(CQ_2(arg))$

- $weakly\_rejectable_{\kappa,ca}(arg) \stackrel{def}{=} negative_{ca}(CQ_3(arg))$

- $conflicting_{\kappa,ca}(arg) \stackrel{def}{=}$ *there exists* $c+c' \leq ca$ *s.t.* $positive_c(CQ_3(arg))$ *and* $(positive_{c'}(CQ_1(arg))$ *or* $positive_{c'}(CQ_2(arg)))$.

- $confusing_{\kappa,ca}(arg) \stackrel{def}{=} negative_{ca}(CQ_1(arg))$ *and* $negative_{ca}(CQ_2(arg))$ *and* $negative_{ca}(CQ_3(arg))$

Please note that the acceptability (resp. rejectability) does not mean that the agent accepts (resp. rejects) the argument but rather that it is potentially acceptable (resp rejectable) for her. Hence the notion of "potential status". Indeed, as we do not define the way the agent will allocate her cognitive availability, the notion of acceptable argument is somehow credulous. She might for instance exhaust her cognitive availability using a reasoning path for $positive_{ca}(CQ_3(arg))$ even if she has a reasoning path for $positive_{ca}(CQ_1(arg))$. Besides our definition of acceptable is a compact way to express that the cognitive availability is parted into three efforts, one for each critical question, as it is stated more explicitly in the following proposition.

Proposition 1 *Given an agent with a cognitive model* κ *and a cognitive availability* ca*, for any argument* arg*, it holds that:* $acceptable_{\kappa,ca}(arg)$ *iff there exists* $c_3 \leq ca$ *s.t.* $positive_{c_3}(CQ_3(arg))$ *and for all* c_1, c_2 *with* $c_1 + c_2 + c_3 = ca$, $negative_{c_1}(CQ_1(arg))$ *and* $negative_{c_2}(CQ_2(arg))$.

Proof 1 *If there exists* $c_3 \leq ca$ *s.t.* $positive_{c_3}(CQ_3(arg))$ *and for all* c_1, c_2 *with* $c_1 + c_2 + c_3 = ca$, $negative_{c_1}(CQ_1(arg))$ *and* $negative_{c2}(CQ_2(arg))$*, then it holds for* $c_1 = ca - c_3$ *hence* $negative_{ca-c_3}(CQ_1(arg))$ *and it also holds for* $c_1 = 0$*, i.e.,* $c_2 = ca - c_3$*, hence* $negative_{ca-c_3}(CQ_2(arg))$.

Conversely, if for any $i \in \{1, 2\}$, $negative_{ca-c}(CQ_i(arg))$ *then it holds for any* $c_i \leq ca - c$.

The statuses have the following relations:

Proposition 2 *Given an agent with a cognitive model* κ*, a cognitive availability* ca *and an argument* arg*:*

1. $positive_c(CQ_3(arg))$ *and* $(positive_{c'}(CQ_1(arg))$ *or* $positive_{c'}(CQ_2(arg)))$ *with* $c + c' > ca$ *implies* $undecidable_{\kappa,ca}(arg)$

2. $conflicting_{\kappa,ca}(arg)$ *implies* $rejectable_{\kappa,ca}(arg)$

3. $confusing_{\kappa,ca}(arg)$ *implies* $(weakly\_acceptable_{\kappa,ca}(arg)$ *and* $weakly\_rejectable_{\kappa,ca}(arg))$

Proof 2

1. *If (positive$_c(CQ_1(arg))$ or positive$_c(CQ_2(arg)))$ and positive$_{c'}(CQ_3(arg))$ with $c + c' > ca$ then acceptable$_{\kappa,ca}(arg)$ and rejectable$_{\kappa,ca}(arg)$.*

2. *Due to the definition.*

3. *If negative$_{ca}(CQ_1(arg))$ then it also holds for a given $c \leq ca$, similarly, negative$_{ca}(CQ_2(arg))$ also holds for $ca - c$ hence arg is weakly_acceptable. Moreover, confusing$_{\kappa,ca}(arg)$ implies negative$_{ca}(CQ_3(arg))$ which characterizes a weakly_rejectable argument.*

Example 5 *We have seen in Example 4 several possible reasoning paths for answering the critical questions associated with the argument arg = (has_protein(miradoux), like(miradoux)) that are requiring different cognitive efforts from the agent. Hence, it holds that:*

- *rejectable$_{\kappa,ca}(arg)$ if $ca \geq 22$ since positive$_{22}(CQ_2(arg))$ (with the reasoning path $R = \langle B6,\ A1,\ A2,\ O3\rangle$),*
- *acceptable$_{\kappa,ca}(arg)$ if $ca \in [11, 33[$ since positive$_{11}(CQ_3(arg))$ and it requires at least 22 to prove $CQ_2(arg)$, and at least 31 to prove $CQ_1(arg)$.[5]*
- *confusing$_{\kappa,ca}(arg)$ if $ca < 11$, as the agent will not be able to use any path.*

The two previous Propositions may give a clearer idea on the mechanism of argument acceptance based on critical questions path evaluation. Moreover the definition of acceptability implies that the evaluation may be done from a restricted well chosen set of reasoning paths, hence they could be used to define efficient algorithms. For instance, since it is only necessary to compute a reasoning path that is minimal in terms of effort (for CQ_3), then a best-first search algorithm (such that the most promising node is the one minimizing the total cost of the path) can be used.

This, of course, requires to be able to compare reasoning paths. For example, the following definition provides a possible way of introducing comparison between reasoning paths according to their use of either logical formulas or associative rules.

Definition 8 (Reasoning path comparisons) *Let R_1,$R_2 \in \mathcal{R}$. We define respectively precise, fast and compact preference relations as:*

- *$R_1 \sqsubseteq_P R_2$ iff $a(R_1) \leq a(R_2)$,*
- *$R_1 \sqsubseteq_F R_2$ iff $l(R_1) \leq l(R_2)$,*
- *$R_1 \sqsubseteq_C R_2$ iff $a(R_1) + l(R_1) \leq a(R_2) + l(R_2)$,*

with $a(R) = \sum_{r \in R \cap A} e(r)$ and $l(R) = \sum_{r \in R \cap (B \cup O)} e(r)$.

In future work, this notion of comparison might allow us to introduce the notions of accepted and rejected arguments based on the agent's choice of reasoning paths. Note that it is also possible to define other preference relations, for instance preferring reasoning paths using the least possible amount of opinion formulas. Moreover, it would also be possible to combine them.

[5] Please note that for $ca \in [22, 33[$, we have both *acceptable$_{\kappa,ca}(arg)$* and *rejectable$_{\kappa,ca}(arg)$*.

6 Discussion and Related Work

The highly influential cognitive psychology work in dual systems ([31, 14, 18, 6, 17, 28]) is based on two reasoning systems: one system that is slow but logically precise and another system that is fast but logically sloppy. In this paper we consider the problem of argument evaluation and, based on critical questions satisfaction, extend the classical notions of argument acceptance statuses. We propose a dual system cognitive model and show its instantiation in an agronomy use-case.

As far as we know, our contribution is the first approach that formally defines and extends the problem of argument evaluation in a practical scenario. It is important to note that in this paper we do not define how a human being reasons but we try to obtain the preferred reasoning paths that a human could obtain. Hence, we do not simulate the agent reasoning but rather study the properties of the possible reasoning paths that an agent can follow. This is why in our proposal we assume that it is possible to compute a multiplicity of reasoning paths, while in real life it is probable that a human agent will not do so.

We plan to clarify this in future work where we will introduce the status of accepted (resp. rejected) argument for those arguments that are acceptable (resp. rejectable) and for which the cognitive availability was allocated to the "right" reasoning paths.

It should be noted that a guide to choose a path is the effort associated with association rules and formulas. It seems important to study this notion in future work as it might somehow represent the strength of an association. Indeed, a very low effort represents an association that is very easy to make, and as such using it does not depreciate the strength of the reasoning path too much.

Moreover our status definition can be enriched a lot, for instance it could be interesting to take into account the agent's self-assessment about her reasoning. Indeed, when the agent is not able to understand the link from premise to conclusion depending on her self-assessment she can decide to accept or reject the argument. Namely, if her cognitive availability is proportionally high relative to the complexity of the knowledge base, will she consider it to be a (defeasible) reason to reject the argument when she cannot establish a proof.

Furthermore, our idea to evaluate the acceptability based on critical question is very common, our originality is the use of reasoning paths. Note that some reasoning paths answering the three critical questions may intersect pairwise. So, once an agent has answered a critical question positively, she may already have established some facts useful for answering another question. Hence, she could save resources if she uses parts of already existing paths. Introducing the possibility to freely reuse parts of reasoning paths would have repercussions on the computation of arguments statuses. In that case the three computations of reasoning paths answering to the three critical questions should not be done independently anymore. In this paper, we did not try to account for overlapping reasoning paths since it may render the agent search strategic (with respect to the paths generated for one question and to the order the questions are considered) while we are interested in a more general setting that allows for irrationality at "all levels". This implies the ability to consider any possible reasoning path and any possible question answering order (neither of them being necessarily optimal).

Reasoning paths search can be related to the search for defeaters which is part of a classical more practical notion of acceptability. This pragmatic condition is evoked e.g. in [20] it specifies how much resources (time, etc.) are to be invested before deciding to accept an argument. Our model could be extended by considerations such as this by equipping agents with a threshold value that indicates how much time they need to spend on a search for defeaters if an argument is to be accepted. These thresholds could be defined with respect to the complexity of the knowledge base or to the possible cost of an error.

Finally and speaking about thresholds, it is important to clarify that in this paper we do not consider the so called bounded rationality agents. The notion of bounded rationality was introduced first by [26] and refers to the level of information and computational ability demanded by a theory. If this level is high then it will render impractical even straightforward applications of the theory. This notion corresponds to the procedural biases as introduced by [21] and [27] that is left for future work. However, it is interesting to mention that such approaches might pave the way to use any-time approximation algorithms (as already investigated in argumentation by [16]).

The main immediate perspective of work is the empirical evaluation of the predictive power of our model using real human data. The main difficulty of such evaluation is to make sure that the participants to the evaluation study do not use other knowledge than the one explicitly present in the knowledge base or the association rules. We are currently investigating different experimental settings that overcome such problem.

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