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Efficient Coalition Formation for Web Services

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Abstract

Web services are loosely-coupled business applications willing to cooperate in distributed settings within different groups called communities. Communities aim to provide better visibility, efficiency, market share and total payoff. There are a number of proposed mechanisms and models on aggregating web services and making them cooperate within their communities. However, forming optimal and stable communities as coalitions to maximize individual and group efficiency and income has not been addressed yet. In this paper, we propose an efficient coalition formation mechanism using cooperative game-theoretic techniques. We propose a mechanism for community membership requests and selections of web services in the scenarios where there is interaction between one community and many web services and scenarios where web services can join multiple established communities. The ultimate objective is to develop a mechanism for web services to form stable groups allowing them to maximize their efficiency and generate near-optimal (welfare-maximizing) communities. The theoretical and extensive simulation results show that our algorithms provide web services and community owners, in real-world like environments, with applicable and near-optimal decision making mechanisms.

Chapter 2

Introduction

In this chapter we introduce the context of this research, which is about argumentation-based negotiation dialogue games. We also present the motivations behind this work and the research questions. Also, we discuss the objective of this research and our preliminary contributions. Proposal organization is presented in the last section.

2.0.1 Context of the research

Autonomous agents and multiagent systems (MAS) provide a technology offering an alternative for the design of intelligent and cooperative systems. Recently, efforts have been made to develop novel tools, methods, and frameworks to establish the necessary standards for wider use of MAS as an emerging paradigm [14]. An increasing interest within this paradigm is on modeling interactions and dialogue systems. In fact, several dialogue systems have been proposed in the literature for modeling *information seeking* dialogues (e.g., [33]), *inquiry* dialogues (e.g., [10, 11]), *deliberation* dialogues (e.g., [42]), *persuasion* dialogues (e.g., [3]), and *negotiation* dialogues (e.g., [40]), which are our concern in this paper. Negotiation is a form of interaction in which a group of agents, with conflicting interests, but a desire to cooperate, try to come to a mutually acceptable agreement on the division of scarce resources [35, 8]. It is worth noting that in all types of dialogue systems mentioned above, a dialogue game is a normative model of dialogue, which mainly consists of: i) a set of moves (e.g., challenge, assertion, question, etc.); ii) one commitment store for each conversant where the advanced moves are stored; iii) a communication language specifying the locution that will be used by agents during a dialogue for exchanging moves; iv) a protocol specifying the set of rules governing the dialogues; and v) agents' strategies, which are the different tactics used by agents for selecting their moves at each step in the dialogue [1]. A dialogue correctly proceeds as long as the participants conform to the dialogue rules and eventually ends when some termination rules are achieved [1, 30, 34].

In the recent years, argumentation theory has been widely investigated and used to model and analyze dialogue games [9, 6, 37, 28]. Argumentation provides a powerful tool to represent, model, and reason about dialogue moves, strategies, and dialogue outcomes. The core idea is the ability to support moves with justifications and explanations, which play a key role in persuasion and negotiation settings [20]. In this paper, we will focus on the exchanged moves in a dialogue game (i.e., the dialogue itself) and the agents playing these moves when supporting arguments are used. The main issue we are investigating is the uncertainty index of selecting the right moves during the dialogue, the certainty index that the selected move will be accepted by the addressee, and the uncertainty index of the whole dialogue. Uncertainty can be thought of as being the inverse of information. Information about a particular engineering or scientific problem may be incomplete, imprecise, fragmentary, unreliable, vague, contradictory, or even deficient [41]. Uncertainty about values of given variables (e.g., the disease affecting a patient in medical applications) can result from some errors and hence from unreliability (in the case of sensors) or from different background knowledge (in the case of agents). As a result, it is possible to obtain different uncertain pieces of information about a given value from different sources [24]. Our aim is to investigate the uncertainty issues that the agent faces when choosing an argument to play in argumentation-based negotiations. In the literature, many efforts have been deployed to model negotiation. A brief description of those efforts is given in the following subsection.

A multiagent system is a system where agents (software autonomous entities) are allowed to freely enter and leave the system, thus making the environment continuously changing. These agents need to communicate with each other, with individual or collective tasks, with different resources, and different skills. As a result, these agent societies are becoming more and more similar to the human ones [16].

An attractive characteristic of MAS is that agents can act more effectively in groups. Agents are designed to autonomously collaborate with each other in order to satisfy both their internal goals and the shared external demands generated by virtue of their participation in agent societies.

The languages used by agents to communicate are called Agent Communication Languages (ACLs). The main objective of an ACL is to model a suitable framework that allows heterogeneous agents to interact and to communicate with meaningful statements that convey information about their environment or knowledge [27]. Two main ACLs have been proposed: the Knowledge Query and Manipulation Language (KQML) [18], and the Foundation for Intelligent Physical Agents' Agent Communication Language (FIPA-ACL) [19]. Furthermore, there is an increasing interest on modeling interactions and dialogue systems.

Indeed, several dialogue systems have been proposed in the literature for modeling information seeking dialogues (e.g. [33]), inquiry dialogues (e.g., [10]), persuasion dialogues (e.g., [3]) and finally negotiation dialogues (e.g., [40]).

Evaluating multiagent systems and the dialogues taking place between the participants is a very important issue in the recent developments of multiagent systems. The existing approaches on evaluating these systems are focusing on one aspect at a time, such as evaluating persuasion dialogues ([3]), and measuring the impact of argumentation ([23]). They are more concerned with proposing dialogue strategies and analyzing dialogues. However, nothing is said about the agents' certainty about their dialogues and the goodness degree of the agents in the dialogues. In this thesis, we are interested particularly in negotiation dialogue games. In fact, negotiation is a form of interaction in which a group of agents, with conflicting interests, but a desire to cooperate, try to come to a mutually acceptable agreement on the division of scarce resources [35, 8]. Dialogue games are a set of rules governing the dialogue. such rules specify the allowed communicative acts agents can perform when participating in a dialogue. Precisely, we focus in this work on quantitative negotiation dialogue games such as bargaining. We will focus first on the exchanged moves (i.e. the dialogue itself) in terms of the certainty index of selecting the right moves during the dialogue, and the certainty index of the whole dialogue. Uncertainty about values of given variables (e.g. the disease affecting a patient in medical applications) can result from some errors and hence from non-reliability (in the case of sensors) or from different background knowledge (in the case of agents). As a result, it is possible to obtain different uncertain pieces of information about a given value from different sources [24]. The second focus of this thesis is on the agents' strategies in terms of goodness degree of the agents in the real dialogue (i.e. the dialogue that effectively happened between the participants) and the farness degree of the agents from the right dialogue (i.e. the best dialogue that can be produced by two agents if they know the knowledge bases of each other). For example in negotiation setting, the best dialogue is the one in which with a minimum number of moves, two agents can achieve the best agreement for both of them, if such an agreement exists considering the knowledge bases of these two agents.

2.0.2 Motivations and research questions

Multiagent systems are widely used in everyday life, and to add more value to these systems in the field of software engineering, they supposed to be measurable. Our motivation is to find a way to measure these systems from different aspects such as measuring the dialogues, the performance of the participants in the dialogues, and the protocols governing the dialogues, etc. In order to evaluate dialogues in multiagent systems, we define a new set of measurements from an external agent's point of view. Defining measures for the participants in the dialogues is another motivation in this thesis. The aim behind developing such measurements is to help engineers and developers of agent-based systems in evaluating these systems and their performances.

When monitoring a dialogue between two or more agents, there are many question that should be answered. In this thesis, we are interested in answering the following questions:

- How much are agents certain about selecting a move at each dialogue step?
- How much are agents certain about their dialogues?

- How good are agents in the real dialogue (i.e. the effective dialogue)?
- How far are agents from the right dialogue (i.e. the best dialogue given the knowledge bases of the participants)?

Answering these questions is undoubtedly complex. Therefore, we do not expect a comprehensive answer to all these questions.

2.0.3 Research objectives and contributions

The main objective of this thesis is to develop a new set of measurements for negotiation dialogue games to help in evaluating and comparing different negotiation dialogues with different participants for the same topic. The importance of introducing measures for negotiation dialogue games at each step of the dialogue such as measuring how much the agent is certain about its move is to help in developing intelligent multiagent systems (MAS) and to help evaluating different agents provided by different developers.

Our research aims to ensure that the agents' certainty about their dialogue is fairly represented at each step during the dialogue by making sure that the agent's certainty about selecting the right move is kept in mind and considered as a property of multiagent systems.

The main contribution of this thesis is the proposition of a new set of measures for dialogue games from an external agent's point of view. In particular, we introduce two sets of measurements. In the first set we use Shannon entropy to measure the certainty index of the dialogue. This involves i) using Shannon entropy to measure the agent's certainty about each move during the dialogue; and ii) using Shannon entropy to measure the certainty of the agents about the whole dialogue with two different ways. The first way is by taking the average of the certainty index of all moves, and the second way is by determining all possible dialogues and applying the general formula of Shannon entropy. In the second set, we are measuring how good are agents in the real dialogue *(Goodness Degree)*, and measuring how far are agents from the right dialogue *(Farness Degree)* [**?**].

As mentioned earlier, there exist several proposals on the argumentation-based negotiation. Most of them are concerned with proposing protocols to show how agents can interact with each other, and how arguments and offers can be generated, evaluated and exchanged during the negotiation process. However, none of them has investigated the agents' uncertainty about the exchanged arguments and how such an uncertainty could be measured at each dialogue step to assist the agents make a better decision. The uncertainty is generally defined as "that which is not precisely known". This definition permits the identification of different kinds of uncertainty arising from different sources and activities, most of which go unnoticed in analysis. To the best of our knowledge, this work is the first of it's kind in dealing with the agent's uncertainty while making a decision at each dialogue step in order to achieve an agreement. In this paper, we define a new set of uncertainty measures for dialogue games from an external agent's point of view. In particular, we distinguish two types of uncertainty: **Type I** and **Type II**.

Type I is about the uncertainty of playing the right move (i.e., advancing the right argument) at each dialogue step. For this type, we use Shannon entropy to measure: i) the uncertainty index of the agent that he is selecting the right move at each step during the dialogue; and ii) the uncertainty index of both agents participating in the dialogue about the whole dialogue. The latter measurement will be conducted in two different ways. The first way is by taking the average of the uncertainty index of all moves, and the second is by determining all possible dialogues based on the union of the agents' knowledge bases and applying the general formula of Shannon entropy.

Type II is about the uncertainty of the agent that the selected move (argument) will be accepted by the addressee (from now on we will call this second type of uncertainty by *uncertainty degree*). In this context, we introduce a new classification of arguments based on their certainty index. These measures are of great importance since they can be used as guidelines for a protocol in order to generate the best dialogue between autonomous intelligent agents.

Figure 1 summarizes the whole proposed approach where the certainty index (CI) and weighted certainty index (W_CI) of the moves and the whole dialogue are measured for Type I. For Type II, different cases are considered depending on how many arguments are in use.

2.0.4 Research outline

The rest of the paper is organized as follows: In Section 4.1, we present a brief theoretical background on the argumentation system and agent's theory, strategic reasoning, tactic reasoning and risk of failure notions are also discussed in this section. In Section 4.2, we present the agent's uncertainty measures using Shannon entropy, which include type I (measuring the uncertainty of the agent about selecting the right move) and type II (measuring the uncertainty degree that the selected move will be accepted). Argument classification is also presented in this section. Related work is discussed in Section **??**. Finally, conclusion and future work are presented in Section 5.1.

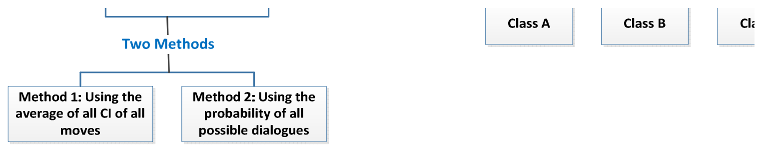

Figure 1: General overview of the approach

Chapter 3

Introduction to Multiagent Systems

3.1 Types of Dialogue Games

3.2 Negotiation Dialogue Games

Negotiation is a form of interaction in which a group of self-interested agents with conflicting interests and a desire to cooperate attempt to reach a mutual acceptable agreement on the division of scarce resources.

3.2.1 Negotiation Component

3.2.2 Approaches to Automated Negotiation

Three types of approaches have been discussed in MAS literature as the authors argued in [25]. These approaches are: the *game-theoretic* approach, the *heuristic-based* approach, and the *argumentation-based* negotiation (ABN) approach.

The Game-theoretic approach is based on studying and developing strategic negotiation models based on game-theoretic precedents [32, 38]. The basic idea of this approach is to see the negotiation process as a game in which each participant tries to maximize his own utility. While this approach is very promising in terms of results analysis, it suffers from some drawbacks as the authors argued in [5], due to the assumptions upon which it is built. The most important ones are (i) the approach allows agents to exchange offers only, but not reasons or justifications, and (ii) the preference relation $\succeq$ on offers is fixed during a negotiation for an agent. These assumptions are not realistic since in everyday life, other information than offers may be exchanged. Moreover, it is very common that preferences on offers may change [5].

The second approach is heuristic-based. This approach came to overcome some limitations of the game-theoretic approach (e.g., [17, 25]). Heuristics are ad hoc rules that aim to achieve a good solution, but not necessarily an optimal one. That is why some strong assumptions made in the game-theoretic approach such as the notion of rationality of agents as well as their resources are relaxed. Even though this approach came to cope with the game-theoretic approach limitations, it does not solve the problem of the preference relation, i.e., the relation $\succeq$ remains the same during the negotiation [5].

The third approach, which is our focus in this paper, is the argumentation-based negotiation approach (ABN). Plenty of research has been done on this approach as witnessed by many publications, such as [4, 23, 31, 2, 5, 12]. The basic idea behind this approach is to allow the participants of the negotiation dialogue not only to exchange offers, but also reasons and justifications that support these offers in order to mutually influence their preference relation on the set of offers, and consequently to the out come of the dialogue. In [36], the authors have introduced a particular style of argument-based negotiation, namely interest-based negotiation (IBN), which is a form of ABN in which agents explore and discuss their underlying interests.

Chapter 4

Contribution and Research Activities

In this chapter we will introduce the important notions in argumentation-based negotiation,

4.1 Argumentation System and Agent Theory

Let us recall some basic definitions in the argumentation-based negotiation.

Definition 1. [Move]. *Let* $Ag = \{Ag_1, Ag_2, \ldots\}$ *be a set of symbols representing agent names that may be involved in a negotiation dialogue* D*. A move* $M_i \in D$ *consists of the agent that utters the move:* $Speaker(M_i) \in Ag$*; the set of agents to which the move is addressed:* $Hearer(M_i) \subseteq Ag$*; and the content of the move:* $Content(M_i)$*.*

For simplification reasons, we will consider bilateral negotiation (i.e., only two agents involved in the dialogue Ag_1 and Ag_2). Multi-party dialogues is an important issue that we plan to investigate in future work. During a dialogue, several moves may be uttered. Those moves constitute a dialogue D, which is a sequence of moves denoted by $[M_0,M_1,\ldots,M_n]$, where M_0 is the initial move, M_n is the final one, and $|D|$ is the length of the dialogue (i.e., $|D| = |[M_0,M_1,\ldots,M_n]| = n + 1$).

In what follows, we assume that the agents exchange the content of the moves during the dialogue as arguments because our approach is argumentation-based. In argumentation systems the logical language $\pounds$ is essential, we will recall the definition of the argument concept, a definition of the attack relation between arguments, and the definition of acceptability from [3], then we will use these definitions in our approach. Here Γ indicates a possibly inconsistent knowledge base with no deductive closure, and $\vdash$ stands for classical inference.

Definition 2. [Argument]. *An argument Arg is a pair* (H, h) *where* h *is a formula of* $\pounds$ *and* H *a subset of* Γ *such that: i)* H *is consistent, ii)* $H \vdash h$ *and iii)* H *is minimal, so that no subset of* H *satisfying both i and ii exists.* H *is called the support of the argument and* h *its conclusion.*

Definition 3. [Attack]. *Let* (H, h), (H', h') *be two arguments.* (H', h') *attacks* (H, h) *iff* $H' \vdash \neg h$. *In other words, an argument is attacked iff there is an argument for the negation of its conclusion.*

Our dialogue architecture also involves general knowledge, such as knowledge about the dialogue subject. Agents can also reason about their preferences in relation to beliefs. The idea is to capture the fact that some facts are believed more than others. For this reason, we assume, like in [31], that any set of facts has a preference order over it. We suppose that this ordering derives from the fact that the agent's knowledge base (Γ) is stratified into non-overlapping sets $\Gamma_1, \cdots, \Gamma_n$ such that facts in Γ_i are all equally preferred and are more preferred than those in Γ_j where $i < j$. The preference level of a subset of Γ whose elements belong to different non-overlapping sets is defined as follows.

Definition 4. [Preference Level]. *The preference level of a nonempty subset γ of Γ denoted by level (γ) is the number of the highest numbered layer which has a member in γ.*

Example 1. *Let $\Gamma = \Gamma_1 \bigcup \Gamma_2$ with $\Gamma_1 = \{a, b\}$ and $\Gamma_2 = \{c, d\}$ and $\gamma = \{a\}$ and $\gamma\prime = \{a, d\}$. We have: level$(\gamma) = 1$ and level$(\gamma\prime) = 2$.*

4.1.1 Strategic and Tactic Reasoning

A preliminary framework for strategic and tactic reasoning for agent communication was proposed in [31]. This reasoning framework is specified using argumentation theory combined to a relevance theory. Strategic reasoning enables agents to decide about the global communication plan in terms of the macro-actions to perform in order to achieve the main dialogue goal. Tactic reasoning, on the other hand, allows agents to locally select, at each dialogue step the most appropriate argument according to the adopted strategy.

In this paper, we refine, and use the notion of strategic and tactic reasoning. The agent uses his tactic reasoning at each dialogue step to measure his uncertainty about selecting the right move to achieve some sub goals of the global goal (i.e., the agreement in our case). In other words, how agent can select the right argument from a set of possible choices at certain dialogue step depends on his tactic by assigning different probability values to the different arguments and select the one with higher probability to be accepted by his opponent. On the other hand, this tactic is based on the adapted strategy that the agent built before starting the negotiation to achieve the agreement. Moreover, we study the relationship between these two types of uncertainty not only when a unique move is considered, but also when the whole dialogue is being analyzed.

Strategic Reasoning

Before engaging in a negotiation, agents must build a global strategy on the sub-goals to achieve. Sub-goals determine the general steps to follow so that the global goal can be realized. Strategy is subject to the agent's current beliefs and constraints, such as the agent's budget and negotiation time limit. To achieve the same negotiation goal, an agent can have several alternative strategies reflected by different sets of subgoals. The dialogue goal, sub-goals, and constraints can be expressed using propositional logic. The set of constraints can be inconsistent, but the sub-set of those constraints and the sub-set of beliefs the agent decides to consider should be consistent. We define the strategy as a function that associates to a goal and a sub-set of consistent beliefs and constraints a sub-set of alternatives, each of which is a set of sub goals, which means an element of the set $2^{2^{\mathbb{B}}}$, where $\mathbb{B}$ is the set of goals.

Definition 5. [Strategy][1]. *Let $\mathbb{B}$ be a set of goals, $\mathbb{C}$ a set of constraints and Γ the agent's knowledge base. A strategy is a function:*

$$\mathcal{S} : \mathbb{B} \times 2^{\mathbb{C}} \times 2^{\Gamma} \rightarrow 2^{2^{\mathbb{B}}} \tag{1}$$

Tactic Reasoning

Tactics allow agents to select one action (i.e., the content of the move or the argument) from a set of possible actions (i.e., set of arguments) in order to achieve a sub-goal as computed

[1] This definition is different than the one proposed in [31], in the sense that this function associates a set of sub-goals to a sub-set of agent's knowledge base and constraints instead of associating a set of goals to a set of operational constraint and a set of conversational criterions.

by the adapted strategy. The purpose of this theory is to ensure that the selected argument is the most appropriate one according to the current context i.e., the less risk of failure, the more favorable and the more preferable one, which means the move with the higher probability. Our aim is to investigate the uncertainty issues associated with the agent while taking decision and selecting the arguments. By refining some definition in the work presented in [31] such as the definition of strategy, context, tactic, and risk of failure. We will advocate some criteria that help to compute and analyze the agents' uncertainty at each negotiation step i.e., at the tactic level. and based on these criteria we classify the set of possible arguments into three different classes "*Arguments Classification*", which will be introduced later on in section 4.2.3.1. This also will help the agents to assign the probability to each possible argument and use it in measuring the uncertainty using Shannon Entropy as it will be explained in section 4.2.2.1. Arguments classification is based on the relevance of arguments, risk of failure, favorite and preference relations. In the following we will discuss the definitions of these notions.

Relevance of Argument.

We define the relevance of argument as in [31] according to the conversation context. This will allow the participants in the dialogue to select the most relevant argument from the set of possible arguments at certain dialogue step by taking into account the last communicative act as well as the previous ones. This will give the agents the ability of backtracking in case the choice is shown to be incorrect because the selected argument is not accepted by the addressee. The arguments are ordered based on their relevance, and the process of selecting arguments is called *Arguments Selection Mechanism.*

Arguments Selection Mechanism.

Let $\pounds$ be a logical language. We define the conversation context for an agent Ag_1 committed in a conversation with another agent Ag_2 as follows:

Definition 6. [Context]. *The conversation context for an agent Ag_1 (the speaker) committed in a conversation with an agent Ag_2 (the addressee) is a 7-tuple $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ where:*

- *$\mathcal{S}$ is the speaker's strategy;*
- *$\mathcal{T}$ is the current speaker's tactic, which we will define after introducing all the context elements;*
- *T is a formula of $\pounds$ representing the negotiation topic that corresponds to the global goal;*
- *s is a formula of $\pounds$ representing the argument on which the speaker should act;*
- *P_{Ag_1,Ag_2} is the set of $Ag_1's$ beliefs about $Ag_2's$ beliefs $P^{bel}_{Ag_1,Ag_2}$ and about $Ag_2's$ preferences $P^{pref}_{Ag_1,Ag_2}$. Thus $P_{Ag_1,Ag_2} = P^{bel}_{Ag_1,Ag_2} \cup P^{pref}_{Ag_1,Ag_2}$;*
- *CK is the common knowledge that the two agents share about the conversation.*

In this definition we refine the context definition proposed in [31] by adding the speaker strategy, the current speaker tactic and the negotiation topic that corresponds to the global goal.

During negotiation, CK is constantly updated by adding all the information on which the two agents agree, including the accepted arguments. We also assume that $CK \cap P_{Ag_1,Ag_2} = \emptyset$. In the context C_{Ag_1,Ag_2}, the influence of the strategy on the tactic is reflected through the link between the topic T, the current argument s and the strategy $\mathcal{S}$.

Let $\mathbb{T}$ be the set of topics ($T \in \mathbb{T}$), g the current goal ($g \in \mathbb{B}$), C the sub-set of current constraints ($C \in \mathbb{C}$), γ the sub-set of beliefs the agent is currently considering ($\gamma \in \Gamma$), and $\mathbb{A}$ the set of arguments ($s \in \mathbb{A}$), we define the tactic as follows:

Definition 7. [Tactic]. *A tactic is a function:*

$$\mathcal{T} : \mathbb{T} \times \mathcal{S}(g, C, \gamma) \times \mathbb{A} \rightarrow \mathbb{B} \tag{2}$$

The key idea is that the current action (at the tactic level) is related to a sub-goal, which is determined by the strategy. From the operational perspective, the current argument s can attack or support the formula representing the sub-goal T. In order to define the logical relation between T and s, the authors in [31] introduced the notion of argumentation tree and the notion of path that are defined as follow.

Definition 8. [Argumentation Tree]. *Let Ag be the set of participating agents and $Arg \subseteq \mathbb{A}$ be the set of arguments used by the agents in the dialogue. An argumentation tree Tr is a 2-tuple $Tr = \langle N, \rightarrow \rangle$ where:*

- $N = \{(Ag_i, (H, h)) \mid Ag_i \in Ag, (H, h) \in Arg\}$ *is the set of nodes. Each node is described as a pair $(Ag_i, (H, h))$, which indicates that the argument (H, h) is used by the agent Ag_i.*
- $\rightarrow \subseteq N \times N$ *is a relation between nodes. We write $n_0 \rightarrow n_1$ instead of $(n_0, n_1) \in \rightarrow$ where $\{n_0, n_1\} \subseteq N$. The relation $\rightarrow$ is defined as follows: $(Ag_1, (H, h)) \rightarrow (Ag_2, (H', h'))$ iff $Ag_1 \neq Ag_2$ and (H', h') attacks (H, h).*

Definition 9. [Path]. *Let $Tr = \langle N, \rightarrow \rangle$ be an argumentation tree. A path in Tr is a* *finite sequence of nodes* $n_0, n_1, \cdots, n_m$ *such that* $\forall i\ , 0 \leq i < m : n_i \to n_{i+1}$.

In order to distinguish between relevant and irrelevant arguments in a given context let us recall the definition of irrelevant arguments:

Definition 10. [Irrelevant Argument]. *Let* $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ *be a conversation context, Ag be the set of participating agents,* $Tr = \langle N, \to \rangle$ *be the argumentation tree associated to the conversation, and* $(Ag_i, (H, h))$ *be a node in* Tr *where* $i \in \{1, 2\}$. (H, h) *is irrelevant in the context* C_{Ag_1,Ag_2} *iff:*

1. *There is no path between the node* $(Ag_i, (H, h))$ *and the root of* Tr *or;*

2. $\exists x \in CK : H \vdash \neg x$.

The distinction between relevant and irrelevant arguments allows agents to eliminate irrelevant arguments at each dialogue step before ordering the relevant arguments in order to select the most relevant one. Agents also have private preferences about different knowledge. Therefore, they may have private preferences about arguments. This preference relation denoted by $(H, h) \ll^{Ag_i}_{pref} (H', h')$ means that agent Ag_i prefers the argument (H', h') to the argument (H, h).

Definition 11. [Preference]. *Let* (H, h) *and* (H', h') *be two arguments.* $(H, h) \ll^{Ag_i}_{pref} (H', h')$ *iff level* $(H') \leq$ *level* (H).

Because $\leq$ is an ordering relation, the preference relation $\ll^{Ag_i}_{pref}$ is reflexive, antisymmetric, and transitive. Agents may also have favorites among their arguments. How an agent favors an argument over others depends on the dialogue type. For example, in a persuasive dialogue, an agent can favor arguments having more chances to be accepted by the addressee. In order to characterize this notion, we introduce the notion of weight of an argument. The weight of an argument (H, h) compared to another argument (H', h') in the context $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ is denoted by $W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')}$ and is evaluated according to the following algorithm:

***Algorithm** 1.*

Step 1: $W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')} = 0$.

Step 2: $(\forall x \in H), (\forall x' \in H') : (pref(x, x') \in P^{pref}_{Ag_1,Ag_2}) \Rightarrow W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')} = W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')} + 1$

$pref(x, x') \in P^{pref}_{Ag_1,Ag_2}$ means that Ag_1 believes that Ag_2 prefers x to x'. According to this algorithm, the weight of an argument (H, h) compared to another argument (H', h') is incremented by 1 each time Ag_1 believes that Ag_2 prefers a knowledge in H to a knowledge in H'. Indeed, each element of H is compered once to each element of H' according to the preference relation. Consequently, the computation algorithm of the weight of an argument is finite because H and H' are finite sets. The favorite relation is denoted by $\preceq^{P_{Ag_1,Ag_2}}_{fav}$ and the strict favorite relation is denoted by $\prec^{P_{Ag_1,Ag_2}}_{fav}$. $(H, h) \preceq^{P_{Ag_1,Ag_2}}_{fav} (H', h')$ means that agent Ag_1 favors the argument (H', h') over the argument (H, h) according to P_{Ag_1,Ag_2}. This relation is defined as follows.

Definition 12. [Favorite Argument]. *Let $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ be a conversation context and (H, h) and (H', h') be two arguments in the context C_{Ag_1,Ag_2}. We have:*

- $(H, h) \preceq^{P_{Ag_1,Ag_2}}_{fav} (H', h')$ *iff* $W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')} \leq W^{P_{Ag_1,Ag_2}}_{(H',h')/(H,h)}$,

- $(H, h) \preceq^{P_{Ag_1,Ag_2}}_{fav} (H', h')$ *iff* $W^{P_{Ag_1,Ag_2}}_{(H,h)/(H',h')} < W^{P_{Ag_1,Ag_2}}_{(H',h')/(H,h)}$.

In order to allow agents to select the most relevant argument in a conversation context, an ordering relation between relevant arguments is used. This ordering relation depends on the adopted strategy and is based on the notion of the risk of failure of an argument. This notion of risk is subjective and there are several heuristics to evaluate it. In this paper, we use a heuristic based on the fact that CK contains certain knowledge and P_{Ag_1,Ag_2} contains uncertain beliefs. To define this notion formally, let $|H|_\emptyset$ be the number of formulas in H that are not in $CK \cup P_{Ag_1,Ag_2}$, $|H|_{CK}$ be the number of formulas in H that are in CK, and $|H|_{P_{Ag_1,Ag_2}}$ be the number of formulas in H that are in P_{Ag_1,Ag_2}.

Definition 13. [Risk of Failure of an Argument]. *Let $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ be a conversation context and (H,h) and (H',h') be two relevant arguments in the context C_{Ag_1,Ag_2}. The risk of failure $risk(H,h)$ of an argument (H,h) is a function mapping an argument to a natural number that satisfies the following property: $risk(H,h) \geq risk(H',h')$ iff:*

- $|H|_\emptyset \geq |H'|_\emptyset$; *or*
- $|H|_\emptyset = |H'|_\emptyset$ *and* $|H|_{CK} \leq |H'|_{CK}$; *or*
- $|H|_\emptyset = |H'|_\emptyset$, $|H|_{CK} = |H'|_{CK}$, *and* $|H|_{P_{Ag_1,Ag_2}} \leq |H'|_{P_{Ag_1,Ag_2}}$.

Other approaches like those used in fuzzy systems to reason with uncertainty (using for example probabilities and possibilities) can also be used to evaluate the risk of an argument. The advantages of our approach are its straightforward implementation and additivity over uncertain hypotheses, which means adding uncertain hypotheses increases the risk of failure of an argument. The relevance ordering relation denoted by $\preceq_r$ is defined as follows.

Definition 14. [Relevance Ordering Relation]. *Let* $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ *be a conversation context and* (H, h) *and* (H', h') *be two relevant arguments in the context* C_{Ag_1,Ag_2}*.* (H', h') *is more relevant than* (H, h) *denoted by* $(H, h) \preceq_r (H', h')$ *iff:*

- $risk(H', h') < risk(H, h)$*; or*
- $risk(H', h') = risk(H, h)$ *and* $(H, h) \prec_{fav}^{P_{Ag_1,Ag_2}} (H', h')$*; or*
- $risk(H', h') = risk(H, h)$ *and* $(H, h) \preceq_{fav}^{P_{Ag_1,Ag_2}} (H', h')$ *and* $(H', h') \preceq_{fav}^{P_{Ag_1,Ag_2}} (H, h)$ *and* $(H, h) \ll_{pref}^{Ag_1} (H', h')$*.*

According to this definition, (H', h') is more relevant than (H, h) if the risk of (H, h) is greater than the risk of (H', h'). If the two arguments have the same risk, the more relevant argument is the more favorable one according to the favorite relation. If the two arguments have the same risk and they are equal according to the favorite relation, the more relevant argument is the more preferable one according to the preference relation. The two arguments have the same relevance if in addition they are equal according to the reference relation.

4.1.1.1 Computational complexity of the Selection Mechanism

Computationally speaking, the arguments selection mechanism is based on :

1. The elimination of irrelevant arguments;
2. The construction of new relevant arguments;
3. The ordering of the relevant arguments using the relevance ordering relation; and

4. The selection of one of the most relevant arguments.

This process is executed by each participating agent at each dialogue step at the tactical level. The relevant arguments that are not selected at a step t_i, are recorded and added to the set of potential arguments PA because they can be used at a subsequent step. The set of potential arguments can be viewed as a stack in which the higher level argument is the most relevant one. A relevant argument constructed at a step t_i and used latter at a step t_j simulates the backtracking towards a previous node in the argumentation tree and the construction of a new path.

Here we prove that our selection mechanism is tractable if arguments are represented using propositional Horn clauses. propositional Horn clauses is a restricted language that has been proved to be sufficient to represent and reason about knowledge in many concrete applications [7]. A propositional Horn clause is a disjunction of literals, which are atomic propositions (called positive literals) or their negations (called negative literals), with at most one positive literal. Formally, a propositional Horn clause has the form $\neg p_1 \vee \neg p_2 \vee \cdots \vee \neg p_n \vee c$ or also $p_1 \wedge p_2 \wedge \cdots \wedge p_n \rightarrow c$, which is simply an implication. A propositional Horn formula is a conjunction of propositional Horn clauses. We focus on a further restriction called propositional definite Horn clauses, where each clause has exactly one positive literal. A propositional definite Horn formula is a conjunction of propositional definite Horn clauses. This restriction is of particular interest in modeling argumentation reasoning for negotiation, because formulas of the type $p_1 \wedge p_2 \wedge \ldots p_n \rightarrow c$ are adequate to describe interrelationships between premises (i.e., reasons or justifications) and conclusions (i.e., offers). Thus, agents could support their offers (the part c) as positive literals using the support $p_1 \wedge p_2 \wedge \ldots p_n$.

Theorem 1. *If arguments are represented in proportional definite Horn clauses, the arguments selection mechanism runs in polynomial time.*

Proof. *It is known from Bentahar et al. [7], that given a Horn knowledge base* Γ*, a subset* $H \subseteq \Gamma$*, and a formula* h*; checking whether* (H, h) *is an argument is polynomial. To decide if an argument is irrelevant, we have to check if 1)* $H \vdash \neg x$ *for an* $x \in CK$*, which can be done in polynomial time since* H *is a definite Horn formula; or 2) there is a path from the root to* (H, h)*, which is a graph reachability problem, and it is known by Jones [26] that the problem is in NLOGSPACE. Since NLOGSPACE* $\subseteq$ *P, the problem can be solved in polynomial time. To decide about the preference, we only need to compute the level of an argument from the level of a subset of* Γ*, which is a simple procedure that is obviously polynomial. Computing the favorite argument given two arguments needs the computation of the arguments' weight, which is again a polynomial procedure as shown by Algorithm 1. To compere two given arguments using the risk, we only need to compute the number of formulas in* H *and check if they are part of different sets, which is a polynomial procedure. Finally, the relevance ordering relation is simply based on comparing risks and favorites, which are both polynomial, so we are done.* ■

4.2 Agent's Uncertainty

4.2.1 Generalities and Overview

The process of selecting arguments is always associated with a degree of uncertainty. Despite the agent will select the most relevant argument at each dialogue step using his theory and tactic reasoning, however, there still be a doubt that the selected argument is the right one and it will be accepted by the addressee. To measure this uncertainty, we use Shannon entropy as we did in our pervious work [29], a well-known technique that defines and quantifies the information. The idea behind Shannon entropy in information theory is based on the amount of randomness that exists in a random event. In dialogue games, we assume that at each dialogue step, the agent has different choices of arguments (i.e., the set of potential arguments PA at that step) and he will select one of them. The selection is based on the speaker's knowledge base and characterized by an amount of uncertainty over this base and an amount of randomness over the addressee's knowledge, beliefs, and preferences. Indeed, Shannon entropy is a measure of the uncertainty associated with a random variable (i.e., in our case, the selected argument). The more uncertain we are about the content of the message, the more informative it is [13].

Definition 15. [Shannon entropy]. *Shannon entropy for a discrete random variable X taking its values from a set of values S (sample space), with probability mass function $P(x)$ is given by Equation 3:*

$$H(X) = -\sum_{x \in S} P(x) Log P(x) \tag{3}$$

Shannon entropy $H(X)$ depends on the probability distribution of X rather than the actual values of X. The logarithm in Equation 3 is considered to be of base 2 in the computations. The value of $H(X)$ varies from zero to $Log(|S|)$, where zero means that there is no uncertainty, while $Log(|S|)$ is the maximum value of uncertainty. In this paper, we aim to investigate to what extent we can use Shannon entropy in the evaluation of the agent's uncertainty in the dialogue. We place ourselves in the role of an external observer trying to evaluate the uncertainty of the participants to the dialogue i.e., how certain/uncertain each agent is about the selected move, how certain/uncertain he is that the selected move will be accepted by the addressee and the distinction between these tow types of uncertainty. The basic idea is to measure how much the agent is uncertain about selecting the right move M_i at each step t_i in dialogue D by assuming that there is a set S_i of choices facing the agent at each dialogue step. Throughout the paper, we will measure the agent's uncertainty using Shannon entropy, then we normalize it to have a value between zero and one and subtracting it from one to get the agent's certainty for selecting the right move at that step. We call this measure the *certainty index* "$CI(M_i)$" of that move, and then we calculate how much the agents are certain about the whole dialogue using what we call the *certainty index of the dialogue* "$CI(D)$" by taking the average of the certainty index of all moves in this dialogue (taking the minimum is another choice that we also discuss). Furthermore, we measure the certainty index of the whole dialogue by computing all possible dialogues, using the Cartesian product of all possible moves, and determining the probability of each dialogue, and then applying the general formula of Shannon entropy for the whole dialogue (exactly as what we do in the case of calculating the certainty of the moves). Moreover, we differentiate between to types of uncertainty; namely Type 1, and Type 2, and for the first time we classify the arguments into three classes based on three criteria that we will introduce later on.

To allow agents to refer to their dialogue history, a data structure called commitment store "CS" is used to restore utterances that agents utter during the dialogue [21]. Let Ag_1 and Ag_2 be two agents $Ag_1 \neq Ag_2$. Also, let Γ_{Ag_x} be $Ag_x's$ knowledge base ($x \in \{1, 2\}$). $CS^{t_i}_{Ag_x}$ is the commitment store of agent Ag_x at step t_i of the dialogue. Suppose that at step t_{i-1}, agent Ag_2 uttered a move. To utter a move at the next step t_i, agent Ag_1 should consider his knowledge base and the content of $Ag_2's$ commitment store. Let m_i^j be the j^{th} move among the possible moves an agent has at the step t_i and $P(m_i^j)$ the associated probability such that the relationship between the move M_i and m_i^j is as follows:

$$\forall i\ \exists j : M_i = m_i^j \tag{4}$$

where M_i is the selected move the agent utters at the step t_i, and the production of moves for Ag_1 along with their probabilities is a function of Γ_{Ag_1} and $CS_{Ag_2}^{t_i}$:

$$\zeta(\Gamma_{Ag_1} \cup CS_{Ag_2}^{t_i}) = \{(m_i^j, P(m_i^j)) | m_i^j \in S_i\} \tag{5}$$

where S_i is the set of choices facing the agent at the dialogue step t_i.

We belief that such measures can help the participants to the dialogue make a better decisions for playing the most appropriate argument at each moment (i.e., at the tactical level) to achieve their agreements based on the adapted strategy, and it will help evaluate dialogues and strategies of the participants to these dialogues. In what follows we introduce the two types of agent's uncertainty.

4.2.2 Agent's Uncertainty: Type I

In this section, we will discuss to what extent we can use Shannon entropy in dialogue games to measure the uncertainty/certainty index of the agents about their dialogue. To do so, we measure the uncertainty index of the agents about their moves and then we compute the uncertainty index about the whole dialogue. The following two subsections illustrate these measures.

4.2.2.1 Measuring How Certain the Agent is about his Move

To measure the uncertainty index of the agent about his move, we calculate Shannon entropy of that move, which means the agent's uncertainty about selecting the right move at a given dialogue step. Here we consider only possible moves, which are moves whose the associated probability is in $[0, 1]$. Then we normalize this value by dividing it by the logarithm of the number of all possible moves at that step. By subtracting the normalized value from one; we get the agent's certainty index about selecting the right move at this step.

Definition 16. [Move's entropy]. *Let $D = [M_0, M_1, \ldots, M_n]$ be a negotiation dialogue, and suppose that at each dialogue step t_i a set S_i of moves $\{m_i^1, m_i^2, \ldots, m_i^k\}$ are possible, and each one of them is associated with a given probability $P(m_i^j) = 1 - risk(m_i^j)$, such that $\sum_{m_i^j \in S_i} P(m_i^j) = 1$. Shannon entropy for a random move M_i taking its values from the set of moves S_i is defined by:*

$$H(M_i) = -\sum_{m_i^j \in S_i} P(m_i^j) Log P(m_i^j) \tag{6}$$

The value of $H(M_i)$ varies from zero to $Log(|S_i|)$, where zero means that there is no uncertainty (i.e., there is only one choice), while $Log(|S_i|)$ means that the uncertainty is at its maximum value (i.e., all moves have the same probability). We further normalize $H(M_i)$ to have a metric that ranges from 0 to 1. This can be achieved by dividing $H(M_i)$ by $Log(|S_i|)$. So, the uncertainty about selecting the right move is given by:

$$\mu(M_i) = \begin{cases} 0 & iff \quad Log(|S_i|) = 0 \\ H(M_i)/Log(|S_i|) & otherwise \end{cases} \tag{7}$$

Proposition 1. *The uncertainty of a move M_i at a certain step t_i during the dialogue is equal to zero (i.e., $\mu(M_i) = 0$) iff at that step the agent has only one choice.*

Proof.

$\mu(M_i) = 0 \Leftrightarrow Log(|S_i|) = 0$

$\Leftrightarrow |S_i| = 1.$ ■

So, there is only one move in S_i available to the agent at step t_i. Intuitively, at the beginning steps of a dialogue, the uncertainty is expected to be high as all possible moves have close probabilities, then gradually the uncertainty decreases, because agents are rational and they learn from each other when advancing in the dialogue.

Proposition 2. *The uncertainty of a move M_i at a certain step t_i during the dialogue is equal to one ($i.e.$, $\mu(M_i) = 1$) iff at that step, all the moves in S_i have the same probability.*

Proof.

Let us first prove the direct implication $\Rightarrow$. We assume that all the moves at a certain step t_i have the same probability, and prove that the uncertainty is equal to one. Without loss of generality, we assume that $|S_i| = k_i$. So we have:

$\mu(M_i) = H(M_i)/Log(k_i)$

$= -\sum_{m_i^j \in S_i, j=1}^{k_i} P(m_i^j) Log P(m_i^j)/Log(k_i)$

$= -k_i[(1/k_i)Log(1/k_i)]/Log(k_i)$

$= -[Log(1/k_i)]/Log(k_i)$

$= Log(k_i)/Log(k_i)$

$= 1$

Let us now prove the inverse implication $\Leftarrow$. *We assume that the uncertainty is equal to one, and prove that all moves have the same probability. So we have:*

$\mu(M_i) = 1$

$\Rightarrow 1 = H(M_i)/Log(k_i)$

$\Rightarrow 1 = -\sum_{m_i^j \in S_i, j=1}^{k_i} P(m_i^j)LogP(m_i^j)/Log(k_i)$

$\Rightarrow -Log(k_i) = \sum_{m_i^j \in S_i, j=1}^{k_i} P(m_i^j)LogP(m_i^j)$

$\Rightarrow Log(1/k_i) = \sum_{m_i^j \in S_i, j=1}^{k_i} P(m_i^j)LogP(m_i^j)$

$\Rightarrow Log(1/k_i) = P(m_i^1)LogP(m_i^1) + P(m_i^2)LogP(m_i^2) + \ldots + P(m_i^{k_i})LogP(m_i^{k_i})$

By taking the exponential of both sides of the equation, we obtain:

$$\exp^{Log(1/k_i)} = \exp^{P(m_i^1)LogP(m_i^1)+P(m_i^2)LogP(m_i^2)+\ldots+P(m_i^{k_i})LogP(m_i^{k_i})}$$

$$\Rightarrow 1/k_i = \exp^{P(m_i^1)LogP(m_i^1)} * \exp^{P(m_i^2)LogP(m_i^2)} * \ldots * \exp^{P(m_i^{k_i})LogP(m_i^{k_i})}$$

$$\Rightarrow 1/k_i = \exp^{LogP(m_i^1)^{P(m_i^1)}} * \exp^{LogP(m_i^2)^{P(m_i^2)}} * \ldots * \exp^{LogP(m_i^{k_i})^{P(m_i^{k_i})}}$$

$$\Rightarrow 1/k_i = P(m_i^1)^{P(m_i^1)} * P(m_i^2)^{P(m_i^2)} * \ldots * P(m_i^{k_i})^{P(m_i^{k_i})}$$

$$\Rightarrow 1/k_i = \Pi_{m_i^j \in S_i, j=1}^{k_i} \; P(m_i^j)^{P(m_i^j)}$$

Because 1 *is the maximum uncertainty, the solution of this equation can be obtained by resolving the following optimization problem:*

$$Max[\Pi_{m_i^j \in S_i, j=1}^{k_i} \; P(m_i^j)^{P(m_i^j)}]$$

$$subject\ to:$$

$$\begin{cases} \sum_{m_i^j \in S_i, j=1}^{k_i} \; P(m_i^j) = 1 \\ 0 < P(m_i^j) \leq 1 \qquad \forall\ 1 \leq j \leq k_i \end{cases}$$

Using the nonlinear programming techniques, we can easily find the solution of this problem, *which is:* $\forall\ 1 \leq j \leq k\ P(m_i^j) = 1/k_i$. ■

Definition 17. [Move's Certainty Index] *Let* $D = [M_0, M_1, \ldots, M_n]$ *be a negotiation dialogue, and suppose that at each dialogue step* t_i *a set* S_i *of moves* m_i^j *are possible, and each one of them is associated with a given probability* $P(m_i^j)$ *such that* $\sum_{m_i^j \in S_i} P(m_i^j) = 1$. *If Shannon entropy of the move* M_i *at step* t_i *is* $H(M_i)$, *we define the certainty index of the move as follows:*

$$CI(M_i) = \begin{cases} 1 & iff \quad Log(|S_i|) = 0 \\ 1 - H(M_i)/Log(|S_i|) & otherwise \end{cases} \tag{8}$$

Using the certainty index, we can determine at each dialogue step how much the agent is certain about the move he can play at that time. The following lemmas are straightforward from Propositions 1 and 2.

Lemma 1. *The certainty index of a move* M_i *at a given step* t_i *in the dialogue is at its maximum value "1" iff the agent has only one choice at that step.*

Lemma 2. *The certainty index of a move* M_i *at a given step* t_i *in the dialogue is at its minimum value "0" iff the agent has more than one move at the same step with equal probabilities.*

By considering the uncertainty and certainty index of dialogue moves, agents should resolve at each dialogue step t_i one of the following equivalent optimization problems.

1. At each dialogue step the agent should minimize the uncertainty index.

$$M_i^* = \underset{M_i}{\operatorname{argmin}}\, \mu(M_i) \tag{9}$$

2. At each dialogue step the agent should maximize the certainty index.

$$M_i^* = \underset{M_i}{\operatorname{argmax}}\, CI(M_i) \tag{10}$$

Theorem 2. *There is an algorithm for solving these optimization problems in a polynomial time.*

Proof. *Because these problems are equivalent, we consider only one of them, for example the maximization one. Without loss of generality, we assume that agent Ag_1 should solve this problem. The algorithm is as follows:*

1) Ag_1 should calculate the probability of each possible move m_i^j $(1 \leq j \leq k)$ using the moves probability function*: $\zeta(\Gamma_{Ag_1} \cup CS_{Ag_2}^{t_i})$ considering his knowledge base Γ_{Ag_1} and $Ag_2's$ commitment store $CS_{Ag_2}^{t_i}$;*

2) take the move with the highest probability. Because Γ_{Ag_1} and $CS_{Ag_2}^{t_i}$ are bounded at each step t_i, this calculation is clearly polynomial and searching the maximum probability is polynomial, so we are done. ■

This theorem is compatible with the intuition that by adding new information in $CS_{Ag_2}^{t_i}$, the number of possible choices decreases. However, this is only true when we consider just the next move. When we consider the whole dialogue, the complexity is much higher.

Example 2. *Let us consider a negotiation dialogue D between two agents Ag_1 and Ag_2 such that $D = [M_0, M_1, M_2]$, and the number of possible moves at each dialogue step is $|S_i| = 3$. In the following we explain how to measure the certainty index of the move M_0.*

Using Equation 8, we obtain:

$$CI(M_0) = 1 - H(M_0)/Log(|S_0|)$$

$$CI(M_0) = 1 - [(-\sum_{j=1}^{3} P(m_0^j)LogP(m_0^j))/Log(3)]$$

$$CI(M_0) = 1 + [(P(m_0^1)LogP(m_0^1) + P(m_0^2)LogP(m_0^2) + P(m_0^3)LogP(m_0^3))/Log(3)]$$

From Table 1, we have:

$$CI(M_0) = 1 + [((0.33 * -1.599) + (0.33 * -1.599) + (0.34 * -1.556))/Log(3)]$$

$$CI(M_0) = 1 - 1 = 0$$

Table 1 shows the possible choices of the moves that facing agent Ag_1 at step t_0 to play his first move M_0 in the first column, and their associated probabilities in the second column. From the above calculations, we notice that the certainty index of agent Ag_1 about selecting the right move at this step is at its minimum value "0" because agent Ag_1 had different choices of moves with equal probabilities of acceptance from the addressee agent Ag_2. This means that agent Ag_1 was uncertain 100% about which move he should play.

The above calculations and Table 1 are just for the first move M_0, and to obtain the certainty index of the other two moves M_1 and M_2, we use the same procedure as for M_0.

Table 1: Measuring the certainty index of the move M_0 in Example 2.

Possible Moves	$P(m_0^j)$	***Log*** $\boldsymbol{P(m_0^j)}$	$\boldsymbol{P(m_0^j)}$***Log*** $\boldsymbol{P(m_0^j)}$
m_0^1	*0.33*	*-1.599*	*-0.528*
m_0^2	*0.33*	*-1.599*	*-0.528*
m_0^3	*0.34*	*-1.556*	*-0.529*
	$H(M_0)$=*1.58*	$\mu(M_0) = 1$	$CI(M_0) = 0$

At step t_1, agent Ag_2 to play his move M_1 as a reply to agent Ag_1, he had three different choices of moves with different values of probabilities $(0.05, 0.12, 0.83)$, *such that the sum is equal to one. From the calculation we find that agent Ag_2 was certain about* 0.50%, $(i.e., CI(M_1) = 0.50\%)$ *that he will select the move with higher probability* (0.83) *of acceptance from agent Ag_1. The other two choices that agent Ag_2 had were with lower probabilities and he was uncertain about them.*

At step t_2, agent Ag_1 to reply to agent Ag_2 with his move M_2, he had different choices of moves with different values of probabilities $(0.9999, 1E-8, 1E-8)$, *such that the sum is equal to one. Agent Ag_1 was then certain almost* 100%, *and the certainty index is at its maximum value "1". This is because all choices that he had are with very low probabilities except one of them was with very high probability.*

In order to highlight the quality of information involved in the selected move in terms of its certainty index, we assign a weight to this move. We suppose that the selected moves have different weights reflecting the importance degree of the moves. For example, in some negotiation dialogues, the last moves could be more important than the first moves as they lead to an agreement. Let $\mathcal{M}$ be the set of all moves. The weight of the move is calculated based on algorithm 1 and assigned to the move using the following function:

$$W : \mathcal{M} \rightarrow \mathbb{N}^* \tag{11}$$

Definition 18. [Weighted Certainty Index of the Move]. *Let* $D = [M_0, M_1, \ldots, M_n]$ *be a negotiation dialogue, and* $CI(M_i)$ *the certainty index of the move* M_i *at a step* t_i *and* $W(M_i)$ *the weight of that move at that step. We define the weighted certainty index as follows:*

$$W\_CI(M_i) = W(M_i) * CI(M_i) \tag{12}$$

4.2.2.2 Measuring how Certain the Agents are about the Dialogue

In section 4.2.2.1, we discussed how to measure the agent's uncertainty/certainty about his move at each dialogue step. In this section, we will discuss how to measure the uncertainty/certainty index of the agents about the whole dialogue. We will present this in two different methods. The first method is by using the average of the calculated uncertainty/certainty index of all moves in the dialogue. The second one is by calculating the possible number of dialogues and the probability of each one, and then we apply Shannon entropy in the same way as for the moves. Measuring the certainty of the dialogue by considering the minimum certainty over all the moves is another way if the agent is very conservative. In this paper, we only focus on the first two methods.

Method 1: Using the Average of CI for all Moves.

The basic idea is to measure how much each agent is uncertain/certain about his move at each dialogue step. Then we calculate how much the two agents are uncertain/certain about the "whole dialogue" by taking the average of the uncertainty/certainty index of all the moves in the dialogue.

Definition 19. [Agents' Certainty about the Dialogue]. *Let* $D = [M_0, M_1, \ldots, M_n]$ *be a negotiation dialogue with length* $|D| = n + 1$*.* Ag_1 *and* Ag_2 *are the two agents participating* *to the dialogue, where Ag_1 utters the even moves and Ag_2 utters the odd ones. $CI(M_i)$ is the certainty index of the move M_i at the step t_i. The certainty index of the dialogue "$CI(D)$" is given by:*

$$CI(D) = \sum_{M_i \in D} CI(M_i)/(|D|) \tag{13}$$

Example 3. *Let us consider that we have three negotiation dialogues D_1, D_2 and D_3, such that $D_k = [M_0, M_1, \ldots, M_9]$, $(1 \leq k \leq 3)$. Table 2 shows the dialogue moves and the certainty index of each move in the dialogue. We suppose that it is given that at each dialogue step each agent has different choices with their associated probabilities (i.e., complement of risk), and we calculate the certainty index of each possible move based on Equation 8 as we did in Example 2. Then we compute the certainty index of each dialogue by applying Equation 13. We will calculate the certainty index of D_1, and in the same way we calculate it for D_2 and D_3.*

Using Equation 8, we have:

$CI(D_1) = \sum_{M_i \in D_1} CI(M_i)/(|D_1|)$

From Table 2, we obtain:

$CI(D_1) = [0.01 + 0.20 + 0.15 + 0.05 + 0.22 + 0.02 + 0.11 + 0.21 + 0.10 + 0.05]/10$

$CI(D_1) = 0.112$

Table 2: The certainty index of the dialogues of Example 3

Dialogue Moves	***CI(***M_i***) of*** D_1	***CI(***M_i***) of*** D_2	***CI(***M_i***) of*** D_3
M_0	*0.01*	*0.01*	*0.99*
M_1	*0.20*	*0.99*	*0.98*
M_2	*0.15*	*0.15*	*0.95*
M_3	*0.05*	*0.95*	*0.99*
M_4	*0.22*	*0.22*	*0.90*
M_5	*0.02*	*0.80*	*0.90*
M_6	*0.11*	*0.11*	*0.80*
M_7	*0.21*	*0.75*	*0.95*
M_8	*0.10*	*0.05*	*0.90*
M_9	*0.05*	*1*	*1*
	CI(D_1*)=0.112*	*CI(*D_2*)=0.503*	*CI(*D_3*)=0.936*

In the same way we can find that:

$CI(D_2) = 0.503$, *and*

$CI(D_3) = 0.936$

We notice that for the dialogue D_1*, the certainty index is low. This is because the certainty indexes of all the moves in this dialogue are low as they range between* 0.01 *and* 0.22*. This means that the participants were not certain about the dialogue, and even if they achieve an agreement, they do not know whether it is a good agreement or not.*

The certainty index of the dialogue D_2 *is medium, and that is because of the low certainty of the agent* Ag_1 *about his moves during the dialogue, and the high certainty of the agent* Ag_2 *about his moves in the same dialogue. So, when we take the average of the certainty indexes of all the moves, we get a medium certainty index for the whole dialogue.*

In the third dialogue D_3*, the certainty index is very high. This means the participants* *were very certain about their moves at each step during the dialogue.*

Taking the average of the certainty indexes of all moves gives us an indicator about how certain the agents are about their dialogue. However, it does not allow us to compare different dialogues with the same certainty index. To do so, we define another metric called the *weighted certainty index* of the dialogue by giving weights to the moves and taking the average of the weighted certainty indexes of all the moves.

Definition 20. [Weighted Certainty Index of the Dialogue]. *Let $D = [M_0, M_1, \ldots, M_n]$ be a negotiation dialogue. Ag_1 and Ag_2 are the two agents participating to the dialogue, where Ag_1 utters the even moves and Ag_2 utters the odd moves. $CI(M_i)$ is the certainty index of the move M_i at the step t_i, and $W(M_i)$ the weight of M_i. The weighted certainty index of the dialogue is given by:*

$$W\_CI(D) = \sum_{M_i \in D} W(M_i) * CI(M_i) / \sum_{M_i \in D} W(M_i) \tag{14}$$

This will help us compare dialogues with the same certainty index. This is because the average of weighted certainty index of all moves can be different than the average of certainty index of the moves without weights "$CI(D)$".

Example 4. *let us consider the following three negotiation dialogues D_1, D_2 and D_3 (that are different from the dialogues considered in example 3), such that $D_k = [M_0, M_1, \ldots, M_5]$, $(1 \leq k \leq 3)$. Table 3 shows the certainty index and weight of each move. The certainty index of each move is calculated as in example 2, and the certainty index of each dialogue is calculated based on Equation 13, as in Example 3. By applying Equation 14, we obtain*

Table 3: Weighted certainty index of the dialogues of Example 4

Dialogue Moves	***CI***(M_i) ***of*** D_1	***CI***(M_i) ***of*** D_2	***CI***(M_i) ***of*** D_3	***W***(M_i)
M_0	*0.50*	*0.10*	*0.90*	*1*
M_1	*0.50*	*0.25*	*0.75*	*2*
M_2	*0.50*	*0.40*	*0.60*	*3*
M_3	*0.50*	*0.60*	*0.40*	*4*
M_4	*0.50*	*0.75*	*0.25*	*5*
M_5	*0.50*	*0.90*	*0.10*	*6*
	CI(D_1)=*0.50*	*CI*(D_2)=*0.50*	*CI*(D_3)=*0.50*	
	W_CI(D_1)=*0.50*	*W_CI*(D_2)=*0.64*	*W_CI*(D_3)=*0.36*	

the weighted certainty index of each dialogue. In the following we explain how we calculate the weighted certainty index for D_1*, and in the same way we calculate it for* D_2 *and* D_3*.*

Using Equation 14:

$$W\_CI(D_1) = \sum_{M_i \in D_1} W(M_i) * CI(M_i) / \sum_{M_i \in D_1} W(M_i)$$

From Table 3, we have:

$$W\_CI(D_1) = [(0.5 * 1) + (0.5 * 2) + (0.5 * 3) + (0.5 * 4) + (0.5 * 5) + (0.5 * 6)]/21$$

$$W\_CI(D_1) = 0.50$$

and in the same way we can find that:

$$W\_CI(D_2) = 0.64$$

$$W\_CI(D_3) = 0.36$$

From the calculations and Table 3, we see that in D_1 the agents have the same CI from the first move till the last one, and it is medium so the certainty index of the whole dialogue is medium too. In D_2, the agents were uncertain about their moves (i.e. CI very low) in the very early stages of the dialogue, and then the CI of their moves started increasing to reach 0.90, which is a very good certainty index to guarantee a good agreement. While in D_3, we notice the opposite situation of D_2, where the agents have started very certain about their moves then their certainty started decreasing, which might result in not achieving an agreement. In this example, if we look at W_CI of each dialogue, we see that D_2 is the best dialogue, because its weighted certainty index is greater than that of D_1 and D_3, followed by D_1 and then D_3. We notice in the case of D_2 that both agents have started with low certainty about their moves, then they have started learning from each other till they become more certain, especially in the last two moves. Also, we notice that the three different dialogues have the same certainty index, so by calculating just the certainty index of the dialogue we cannot compare such dialogues except if we look at the performance of the participants during the dialogue. However, we can do so by calculating the weighted certainty index of each dialogue, which gives us a good indicator about the goodness of dialogues.

Figure 2 shows the weighted certainty indexes of the moves for the three dialogues, and here we can see the difference between the three dialogues after giving weights to the moves as we discussed before.

Method 2: Using the Probability of all Possible Dialogues

In this method, we measure the certainty index of the dialogue by calculating the number of all possible dialogues using the Cartesian product of all possible moves m_i^j at each step t_i in the dialogue. Thus, by knowing the probability of each possible move, we can calculate

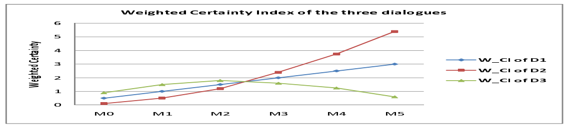

Figure 2: The weighted certainty indexes of the three dialogues of example 4

the probability of each possible dialogue, and then we apply the general formula of Shannon entropy.

Definition 21. [Number of Possible Dialogues]. *Let $D = [M_0, M_1, \ldots, M_n]$ be a negotiation dialogue and Ag_1 and Ag_1 are the two agents participating to it. Suppose that at each dialogue step t_i, the move M_i has a set S_i of possible moves $S_i = \{m_i^1, m_i^2, \ldots, m_i^{k_i}\}$, each one with probability $P(m_i^j)$. The number of all possible moves is equal to $\sum_{i=0}^{n} k_i$. The union of all sets of the moves is $\Omega = S_1 \cup S_2 \cup \ldots \cup S_n$, such that there is no intersection between the sets of moves: $S_1 \cap S_2 \cap \ldots \cap S_n = \emptyset$. So, the number of possible dialogues is $N_D = |S_0 \times S_1 \times \ldots \times S_n|$.*

As explained in Equation 4, each move M_i in a possible dialogue D_l is equal to a possible move m_i^j for a given j. Thus, $P(M_i) = P(m_i^j)$. Knowing this probability, we can calculate the probability of a dialogue D_l as follows:

$$P(D_l) = P(M_0) \times P(M_1) \times \ldots \times P(M_n) \tag{15}$$

Because $\forall i \sum_{j=1}^{k_i} P(m_i^j) = 1$, the sum of the probabilities of all possible dialogues is equal to one (i.e., $\sum_{l=1}^{N_D} P(D_l) = 1$). Now we can define the certainty index of the dialogue as we did for the move in Section 4.2.2.1.

First, we measure the uncertainty of the dialogue by the general formula of Shannon entropy:

$$H(D) = -\sum_{l=1}^{N_D} P(D_l)Log(D_l) \tag{16}$$

Then, we normalize it by dividing it by $Log(N_D)$ to have a metric between 0 and 1, and finally, we measure the certainty index of the dialogue by subtracting the normalized value from one. So, the certainty index of the dialogue is given by:

$$CI(D) = 1 - H(D)/Log(N_D) \tag{17}$$

Example 5. *Let us consider the negotiation dialogue in example 2, where* $n = k_i = 3$, $1 \leq i \leq 3$. *The number of all possible dialogues is (*$N_D = 27$ *dialogues) and the probability of each possible dialogue is computed by the product of probability of its moves. For example for* D_1*, we take the first possible choice of the moves (*m_0^1, m_1^1, m_2^1*) with their respective probabilities (*$0.33, 0.05, 1$*). So, the probability of* D_1 *is equal to* 0.02*, and in the same way we compute the probability of all possible dialogues. By applying Equation 16, we get the entropy of the dialogue* $H(D) = 2.39$*, and by applying Equation 17, we get the certainty index of the dialogue* $CI(D) = 0.497$*. Here we notice that the certainty index of the dialogue is medium, and if we compare the result in this method with the result in the previous one, which uses the average of certainty index of all moves, and applying it on the same example (Example 2), we notice that the result is almost the same.*

4.2.3 Agent's Uncertainty: Type II

In Section 4.2.2, we assumed that the probability of each possible argument is given through the risk value of the move, but we did not elaborate in details on how it can be assigned. Furthermore, the addressee is not considered in Type I uncertainty. In this section, these two issues will be addressed. We will explain in more details how probabilities can be assigned based on three main criteria involving the addressee as discussed in Section 4.1.1, which are as follows:

1. $Cr1$: Risk of failure;

2. $Cr2$: Favorite relation; and

3. $Cr3$: Preference relation.

These criteria have precedence relation over each other. This means the order of examining these criteria is important in order to assign probabilities to the different arguments available at certain step. First, we check ($Cr1$) to examine the risk of failure of each possible argument in the move and assign the probability so that the less move's risk of failure, the more likely to be accepted by the addressee. Second, if there is more than one argument with the same risk of failure, then we check the second criterion ($Cr2$), which examines the favorite relation and we assign higher probability to the more favorable argument. Third, if arguments have the same risk and are equally favorable, then we check the third criterion ($Cr3$), which examines the preference relation. This process follows the argument selection mechanism and it depends on the agent's tactic and the adapted strategy presented in Section 4.1.1, The notion of argument's probability is subjective and different heuristic approaches to evaluate it can be proposed. In this paper, we use a heuristic similar to the one used to evaluate the risk of failure. Probabilities are based on the fact that the knowledge base CK contains certain knowledge and the set of agent's beliefs and preferences P_{Ag_1,Ag_2} contains uncertain beliefs. Therefore, the probability of an argument that belongs to CK to be accepted by the addressee is higher than the probability of another argument that belongs to the set P_{Ag_1,Ag_2}. Consequently, the risk of failure of an argument belonging to CK is less than another argument belonging to P_{Ag_1,Ag_2}. In fact, in negotiation dialogues, the probability of a move at a given step t_i depends on the knowledge the agent has at that step (i.e., the content of the agent's knowledge base at that step), the favorite relation, and the preference relation.

Definition 22. [Move's Probability Function]. *Let CK be the set of common agents' knowledge, P_{Ag_1,Ag_2} the set of $Ag_1's$ beliefs about $Ag_2's$ beliefs, f_r the set of favorable arguments, p_r the set of preferred arguments, and $\mathcal{M}$ the set of all possible moves, we define Δ as a function associating a set of knowledge and preferences and favorites to a set of possible moves and their probabilities. We call this function the move's probability function.*

$$\Delta : 2^{k_n \times f_r \times p_r} \to 2^{\mathcal{M} \times [0,1]} \tag{18}$$

where:

$k_n = CK \times P_{Ag_1,Ag_2}$;

$f_r = \{(Arg_i, Arg_j) \in \mathbb{A} \times \mathbb{A} | Arg_i \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_j\}$; *and*

$p_r = \{(Arg_i, Arg_j) \in \mathbb{A} \times \mathbb{A} | Arg_i \ll_{pref}^{Ag_1} Arg_j\}$.

The function Δ should satisfy the following properties:

- Minimality: $\forall I, I' \in 2^{k_n \times f_r \times p_r}$ if $I \subseteq I'$ and no relevant argument can be generated from $I' - I$, then $\Delta(I) = \Delta(I')$.

- Uniqueness: $\forall I \in 2^{k_n \times f_r \times p_r}$ and $\forall i, j$ s.t. $\{(M_i, P(M_i)), (M_j, P(M_j))\} \subseteq \Delta(I)$, if $i \neq j$, then $M_i \neq M_j$.

- Universality: $\forall I \in 2^{k_n \times f_r \times p_r}$ if $I = \{(M_1, P(M_1)), \cdots, (M_n, P(M_n))\}$, then $\sum_{i=1}^{n} P(M_i) = 1$.

The procedure is as follows. First, we calculate the risk of failure of each possible move based on the argument supporting it, then we order them ascending based on the risk of failure. Second, if there is more than one move with the same risk of failure, then we check the favorite relation for the equivalent arguments in terms of risk of failure and reorder them descending based on the favorite relation. Third, if there is more than one argument equally favorable then we check the preference relation and reorder them descending based on the preference relation. We assume that each of the three resulting classes c $(1 \leq c \leq 3)$ is associated with a given probability P_c $(P_1 < P_2 < P_3)$ (this aspect will be addressed in the next section). The agents have to perform this procedure at each dialogue step in order to be able to assign the probability based on the order of arguments. After that, the uncertainty can be measured based on these probabilities following the method we advocated in Section 4.2.2. The only difference is that unlike the procedure of Section 4.2.2, here the probability that the addressee accepts the move is being considered since probability computation is based on the agent's common knowledge and the beliefs of the speaker agent about the beliefs of the addressee and his preferences using the following probability ordering relation.

Definition 23. [Probability Ordering Relation]. *Let* $C_{Ag_1,Ag_2} = \langle \mathcal{S}, \mathcal{T}, T, s, P_{Ag_1,Ag_2}, CK \rangle$ *be a conversation context and* Arg_i *and* Arg_j *be two relevant arguments in the context* C_{Ag_1,Ag_2}*. The probability of argument* Arg_i *is greater than the probability of argument* Arg_j*:* $P(Arg_j) \leq P(Arg_i)$ *iff* $(Arg_j) \preceq_r (Arg_i)$*.*

Theorem 3. *If arguments are represented in proportional definite Horn clauses, the probability assignment procedure runs in polynomial time.*

Proof. *the result is straightforward from Definition 23 and Theorem 1.* ∎

Based on uncertainty Type II, we introduce a new classification of arguments for negotiation based on their risk of failure, which means on their probabilities.

4.2.3.1 Arguments Classification

There are three main classes of arguments in our framework: Class A of arguments (and consequently of moves supported by those arguments) having low risk of failure (certain arguments); Class B of arguments having medium risk of failure (medium certain arguments); and Class C of arguments having high risk of failure (uncertain arguments). The three classes A, B, and C are disjoint, i.e., $A \cap B = A \cap C = B \cap C = \emptyset$. Each class is divided into three subclasses. In what follows, we explain these classes in details.

Class A: Low risk (Highly certain arguments)

Arguments of this class have equal risk, which is less than the risk of any other argument

Figure 3: Argument classification

not part of that class. Formally:

$$Arg_i \in A \text{ iff} : \begin{cases} risk(Arg_i) = risk(Arg_j) \quad \forall Arg_j \in A \\ \\ risk(Arg_i) < risk(Arg_j) \quad \forall Arg_j \notin A \end{cases} \tag{19}$$

This class is composed of three disjoint subclasses: A_a, A_b, and A_c, i.e., $A_a \cap A_b = A_a \cap A_c = A_b \cap A_c = \emptyset$. Let $=_{fav}^{P_{Ag_1,Ag_2}}$ be the favorite equality relation defined as follows: for two arguments Arg_i and Arg_j, $Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j$ iff $Arg_i \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_j$ and $Arg_j \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_i$. The preference equality relation $=_{pref}^{Ag_1}$ is defined from $\ll_{pref}^{Ag_1}$ in the same way. A_a is defined as follows:

$$Arg_i \in A_a \text{ iff : } \begin{cases} Arg_i \in A \\ Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \quad \forall Arg_j \in A_a \\ Arg_j \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_i \quad \forall Arg_j \in A - A_a \\ Arg_i =_{pref}^{Ag_1} Arg_j \qquad \forall Arg_j \in A_a \\ Arg_j \prec_{pref}^{Ag_1} Arg_i \qquad \forall Arg_j \in A - A_a \text{ s.t. } Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \end{cases} \tag{20}$$

This means, arguments in A_a are equality favorable and preferable, more favorable than any other argument which is not part of A_a, and more preferable than any other favorably equally argument.

In the sam way, the second class A_b is defined as follows:

$$Arg_i \in A_b \text{ iff : } \begin{cases} Arg_i \in A - A_a \\ Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \quad \forall Arg_j \in A_b \\ Arg_j \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_i \quad \forall Arg_j \in (A - A_a) - A_b \\ Arg_i =_{pref}^{Ag_1} Arg_j \qquad \forall Arg_j \in A_b \\ Arg_j \prec_{pref}^{Ag_1} Arg_i \qquad \forall Arg_j \in (A - A_a) - A_b \text{ s.t. } Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \end{cases} \tag{21}$$

Finally, the third class A_c is defined as follows:

$$A_c = (A - A_a) - A_b = A - (A_a \cup A_b) \tag{22}$$

Class B: Medium risk (Medium certain arguments)

Arguments of this class have equal risk, which is less than the risk of any other argument not part of the union of that class and Class A. Formally:

$$Arg_i \in B \text{ iff : } \begin{cases} risk(Arg_i) = risk(Arg_j) & \forall Arg_j \in B \\ risk(Arg_i) < risk(Arg_j) & \forall Arg_j \notin A \cup B \end{cases} \tag{23}$$

As for Class A, this class is composed of three disjoint subclasses: B_a, B_b, and B_c. B_a is defined as follows:

$$Arg_i \in B_a \text{ iff : } \begin{cases} Arg_i \in B \\ Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j & \forall Arg_j \in B_a \\ Arg_j \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_i & \forall Arg_j \in B - B_a \\ Arg_i =_{pref}^{Ag_1} Arg_j & \forall Arg_j \in B_a \\ Arg_j \prec_{pref}^{Ag_1} Arg_i & \forall Arg_j \in B - B_a \text{ s.t. } Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \end{cases} \tag{24}$$

In the sam way, the second class B_b is defined as follows:

$$Arg_i \in B_b \text{ iff} : \begin{cases} Arg_i \in B - B_a \\ Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \quad \forall Arg_j \in B_b \\ Arg_j \preceq_{fav}^{P_{Ag_1,Ag_2}} Arg_i \quad \forall Arg_j \in (B - B_a) - B_b \\ Arg_i =_{pref}^{Ag_1} Arg_j \qquad \forall Arg_j \in B_b \\ Arg_j \prec_{pref}^{Ag_1} Arg_i \qquad \forall Arg_j \in (B - B_a) - B_b \text{ s.t. } Arg_i =_{fav}^{P_{Ag_1,Ag_2}} Arg_j \end{cases} \tag{25}$$

Finally, the third class B_c is defined as follows:

$$B_c = (B - B_a) - B_b = B - (B_a \cup B_b) \tag{26}$$

Class C: High risk (Uncertain arguments)

This class is simply defined from the two other classes where $\mathbb{A}_{C_{Ag_1,Ag_2}}$ is the set of arguments in the context C_{Ag_1,Ag_2} as follows:

$$C = \mathbb{A}_{C_{Ag_1,Ag_2}} - (A \cup B) \tag{27}$$

The subclasses C_a, C_b, and C_c are defined in the same way as the subclasses of A and B.

The following theorem is straightforward from the above equations and Definition 23.

Theorem 4. *Arguments in Class A have higher probability to be accepted than arguments in Class B and arguments in class B have higher probability to be accepted than arguments* *in Class C.*

Chapter 5

Conclusion and Future Work

5.1 Conclusion

In this paper, we proposed a new set of uncertainty measures for the agents in argumentation-based negotiation dialogues from an external agent's point of view. Specifically, we introduced two types of uncertainty measures: 1) Type I, the uncertainty index of playing the right move at each dialogue step; and 2) Type II, the uncertainty degree of the agent that the move will be accepted by the addressee. For uncertainty Type I, we used Shannon entropy to assess the agents' uncertainty/certainty about their moves in the negotiation dialogues. We supposed that an external agent is monitoring the dialogue, and he wants to evaluate this dialogue in terms of the agent's uncertainty/certainty about selecting the right move at each step. In fact, at each step, the agent is supposed to have different choices, each choice is associated with a probability of being the right one, this probability reflects the importance of information included in that move, where the higher the probability is, the more certain the agent becomes (lower uncertainty). So we analyzed the fact that negotiating agents are rational, and they always try to perform the actions that will result in the optimal outcome for themselves. We used Shannon entropy to measure: i) the uncertainty/certainty index and the weighted uncertainty/certainty index of the agent that he is playing the right move at each step during the dialogue; and ii) the uncertainty/certainty index and the weighted uncertainty/certainty index of both agents participating in the dialogue about the whole dialogue. This was done in two different ways. The first is by taking the average of the uncertainty index of all moves, and the second is by determining all possible dialogues and applying the general formula of Shannon entropy.

For uncertainty Type II, we formalized the probability association to the arguments and the uncertainty that the move will be accepted by the addressee. In this context, we introduced a new classification of arguments based on the notion of risk of failure and showed that this classification is compatible with the probability that the moves supported by those arguments will be accepted by the address. An important result of this paper is that the selection and probability ordering mechanisms of arguments are tractable as they can be performed in polynomial time if arguments are represented in propositional definite Horn logic.

In our proposed measures, the move with the higher certainty (lower uncertainty) index is considered as the best move. We analyzed the fact that negotiating agents are rational, and they always try to perform the actions that will result in the optimal outcome for themselves. We started our work with measuring the uncertainty/certainty index of each move at each dialogue step, and in order to distinguish between two moves with the same certainty index, we assigned weight to each move, which reflects the importance of the move. Then, we proceeded to the whole dialogue and we measured the uncertainty/certainty index for the dialogue in two different ways, and we proved that the two ways give the same result. Also, assigning weight to the moves allowed us to compare two different dialogues. We believe that such measures are very significant and helpful in evaluating the dialogue and the agent's strategies, especially when they are making a decision and selecting the best moves to achieve an agreement (if one exists) in a timely manner.

5.2 Future Work

In this paper, we mainly focused on the classical (i.e., precise) probability theory, particularly the classical Shannonian information theory to measure the uncertainty. As pointed out in [22], there are other approaches of measuring uncertainty in the theories of imprecise probabilities, particularly the Dempster-Shafer theory (also known as the theory of belief functions) [39] and the possibility theory [15]. As future work, we will study key measurements in these two theories such as *nonspecificity*, *confusion*, *dissonance*, *discord*, and *strife*, and we will adapt, define and integrate them in our framework. Combining and aggregating those measurements to finally measure the total uncertainty will be investigated as well. The requirements of those new metrics as reported in [22] will be analyzed. Those requirements are: 1) generalization, meaning that the new uncertainty measures should generalize the uncertainty measures already established in the classical probability theory; 2) subadditivity, meaning that when the problem is broken into two orthogonal subproblems, the uncertainty of the original problem should be less than or equal to the sum of uncertainties of the subproblems; and 3) additivity, meaning that under the assumption of no interaction and no dependency between the subproblems, the uncertainty of the original problem is equal to the sum of uncertainties of the subproblems.

Another plan for future work is to extend the proposed metrics for other dialogue game types such as persuasion, deliberation, inquiry and information seeking. We also plan to analyze argumentation-based dialogues to evaluate agent strategies and analyze them from the optimization perspective. Analyzing the computational complexity of such optimization problems is another direction for future work. Finally, we plan to analyze multi-party dialogues to which many agents can participate. Extending the proposed metrics to this type of dialogues is not straightforward. For example, defining the rules of a multi-party negotiation is much more complicated than two-party dialogues. In fact, multi-party dialogues cannot be simply reduced to many two-party dialogues.

Chapter 6

Milestones

In this chapter, we describe the phases of our plan for exploring the research challenges and investigating the research issues identified in Chapter 4. This chapter also includes research methodology and future publication plan.

6.1 Research Methodology and Time Line

The goal of the research project of my Ph.D program is to propose a technically and economically feasible architecture for path stability in MANETs environment.

The time duration of each task includes the modeling of the proposed solution, its implementation, validation, performance evaluation and publication of its outcome.

6.2 Publication Plan

2014	January	Ph.D. seminar	Extend our framework by introducing new negotiation strategies and concession strategies that facilitate achieving an agreement		Submit a Paper to the 13th IEEE Internat Conference on Intelligent Software Method Tools and Techniques (SoMeT 2014)
	February				
	March				
	April				
	May			Analyze argumentation-based negotiation to evaluate agent strategies and analyze them from the optimization perspective	
	June				Submit a Journal Paper to the KBS Knowled Systems
	July				
	August				
	September	Thesis writing and defense			
	October				
	November				
	December				

Work done · Work in progress · Work to be done

Figure 4: Research milestones and time line

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