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Evaluating the Combination of Relaxation and Argumentation in Ontology Matching Negotiation

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Resumo

No decorrer dos últimos anos, os agentes (inteligentes) de *software* foram empregues como um método para colmatar as dificuldades associadas com a gestão, partilha e reutilização de um crescente volume de informação, enquanto as ontologias foram utilizadas para modelar essa mesma informação num formato semanticamente explícito e rico. À medida que a popularidade da Web Semântica aumenta e cada vez informação é partilhada sob a forma de ontologias, o problema de integração desta informação amplifica-se. Em semelhante contexto, não é expectável que dois agentes que pretendam cooperar utilizem a mesma ontologia para descrever a sua conceptualização do mundo. Inclusive pode revelar-se necessário que agentes interajam sem terem conhecimento prévio das ontologias utilizadas pelos restantes, sendo necessário que as conciliem em tempo de execução num processo comummente designado por Mapeamento de Ontologias [1].

O processo de mapeamento de ontologias é normalmente oferecido como um serviço aos agentes de negócio, podendo ser requisitado sempre que seja necessário produzir um alinhamento. No entanto, tendo em conta que cada agente tem as suas próprias necessidades e objetivos, assim como a própria natureza subjetiva das ontologias que utilizam, é possível que tenham diferentes interesses relativamente ao processo de alinhamento e que, inclusive, recorram aos serviços de mapeamento que considerem mais convenientes [1]. Diferentes *matchers* podem produzir resultados distintos e até mesmo contraditórios, criando-se assim conflitos entre os agentes. É necessário que se proceda então a uma tentativa de resolução dos conflitos existentes através de um processo de negociação, de tal forma que os agentes possam chegar a um consenso relativamente às correspondências que devem ser utilizadas na tradução de mensagens a trocar. A resolução de conflitos é considerada uma métrica de grande importância no que diz respeito ao processo de negociação [2]: considera-se que existe uma maior confiança associada a um alinhamento quanto menor o número de conflitos por resolver no processo de negociação que o gerou. Desta forma, um alinhamento com um número elevado de conflitos por resolver apresenta uma confiança menor que o mesmo alinhamento associado a um número elevado de conflitos resolvidos. O processo de negociação para que dois ou mais agentes gerem e concordem com um alinhamento é denominado de Negociação de Mapeamentos de Ontologias. À data existem duas abordagens propostas na literatura: (i) baseadas em Argumentação (e.g. [3] [4]) e (ii) baseadas em Relaxamento [5] [6].

Cada uma das propostas expostas apresenta um número de vantagens e limitações. Foram propostas várias formas de combinação das duas técnicas [2], com o objetivo de beneficiar das vantagens oferecidas e colmatar as suas limitações. No entanto, à data, não são conhecidas experiências documentadas que possam provar tal afirmação e, como tal, não é possível atestar que tais combinações tragam, de facto, o benefício que pretendem. O trabalho aqui apresentado pretende providenciar tais experiências e verificar se a afirmação de melhorias em relação aos resultados das técnicas individuais se mantém.

Com o objetivo de permitir a combinação e de colmatar as falhas identificadas, foi proposta uma nova abordagem baseada em Relaxamento, que é posteriormente combinada com as abordagens baseadas em Argumentação. Os seus resultados, juntamente com os da combinação, são aqui apresentados e discutidos, sendo possível identificar diferenças nos resultados gerados por combinações diferentes e possíveis contextos de utilização.

Palavras-chave: Negociação de Mapeamentos de Ontologias; Argumentação; Relaxamento; Agentes; Sistemas Multi-Agente; Mapeamento de Ontologias;

Abstract

Agent-based Ontology Alignment Negotiation process aims to generate an alignment through the interaction of two or more agents. When these agents exploit different matching services they can reach incompatible alignments, giving rise to conflicts. In such cases it is necessary that they engage in a negotiation process in order to achieve consensus. Two different types of ontology matching negotiation approaches can be found in literature: (i) Relaxation-based and (ii) Argumentation-based. Each of these approaches has its advantages and limitations. To benefit from both techniques' advantages and overcome their limitations, several ways of combining them have been proposed.

To the best of our knowledge however, no experiments have been described and no results regarding these combinations have been reported in literature. This work aims to provide such results by implementing and comparing different combinations of Relaxation-based and Argumentation-based approaches. After carefully analyzing these approaches, we concluded that the state of the art Relaxation-based approach needed improvement before it could be combined with Argumentation-based approaches.

In this context, a new proposal for the Relaxation-based approach is described and a thorough analysis of the results achieved through two of the proposed combinations.

The presented results allow identifying the different benefits of each combination, thus making it possible for developers to choose which one fits their requirements for the generated alignment.

Keywords: Ontology Alignment Negotiation; Argumentation; Relaxation; Agents; Multi-Agent Systems; Ontology Matching;

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Acronyms and Nomenclature

List of Acronyms

AF	**A**rgumentation **F**ramework
AI	**A**rtificial **I**ntelligence
ANP	**A**rgumentation-based **N**egotiation **P**rocess
API	**A**pplication **P**rogramming **I**nterface
BAF	**B**ipolar **A**rgumentation **F**ramework
CMS	**C**ROSI **M**apping **S**ystem
FCT	Science and Technology Foundation (***F**undação para a **C**iência e a **T**ecnologia*)
FDO	**F**lexible approach for **D**etermining agents' **O**rientation on ontology matching
GECAD	Knowledge Engineering and Decision Support Research Centre *(**G**rupo de investigação em **E**ngenharia do **C**onhecimento e **A**poio à **D**ecisão)*
GOAlS	**G**ECAD **O**ntology **Al**ignment **S**ystem
MAS	**M**ulti-**A**gent **S**ystem
MbA	**M**eaning-**b**ased **A**rgumentation
OAEI	**O**ntology **A**lignment **E**valuation **I**nitiative
OMN	**O**ntology **M**atching **N**egotiation
OMR	**O**ntology **M**atching **R**epository
TLAF	**T**hree-**L**ayer **A**rgumentation **F**ramework
VAF	**V**alue-based **A**rgumentation **F**ramework

Nomenclature

a	An argument
$\neg a$	An argument's *a* negation
a_1	Negotiating agent
a_2	Negotiating agent
balance	Global difference between profits and efforts achieved by a agent through Relaxation
c	A correspondence, or match
c_1	A match
c_2	Another match
c_n	Confidence value of a match
conf	Initial confidence value of a agent in a match
dir	Direction of the relaxation effort
e	Source entity in a match
e'	Target entity in a match
eff	Effort done by an agent through Relaxation
effp	Power applied to the effort function
G	Justification for *pos*
$Max(P)$	Maximum value of *P*
minP	Minimum profit required to accept relaxing a match
O_s	Source Ontology
O_t	Target Ontology
pos	Belief of an agent concerning the validity of a match
profit	Profit or benefit an agent achieves through Relaxation
R_{att}	Attack relationships between two arguments
$Ref(e)$	Number of references of a entity in a ontology

relax(c,dir)	Function determining whether it is possible or not to relax in the *dir* direction
R_{sup}	Support relationship between two arguments
Somf	References of the most referred entity in a ontology
step(dir)	Function determining the intended confidence value
Tg	Profit achieved in previous relaxations
t_m	Mandatory Threshold
t_n	Negotiation Threshold
tomf	References of the most referred entity in a ontology
t_p	Proposition Threshold
t_r	Rejection Threshold
U	Utility Function
U	Meta-Utility Function

1 Introduction

Over the last few years, agents have been introduced as a way to overcome the difficulties associated with managing and sharing the increasing amount of data available in information systems, while ontologies have been used to model this data in a semantically rich way. As the popularity of the Semantic Web increases and more data is being shared in the form of different ontologies, the integration problem escalates. In such a world, it is not reasonable to expect that two agents, interacting on behalf of users and willing to communicate, will be using the same ontology to describe their universe of discourse. Agents may be required to interact without previous knowledge of the ontologies the others are using – it is necessary that agents can reconcile their ontologies in real-time, in a process usually referred to as Ontology Matching [1].

The ontology matching process is usually available as a service provided to the business agent so it can be requested when an alignment is necessary. However, considering that each agent has its own needs and objectives and the subjective nature of ontologies, agents may have different preferences concerning the matching process; they can also exploit the matching services they find more convenient [1]. Different matchers can produce different and even contradictory candidate alignments, giving rise to conflicts between the agents. These conflicts must be addressed and tentatively resolved in some negotiation process, such that the agents may reach an agreement concerning each and every correspondence they will use in the conversation. Conflict resolution can be seen as an important metric in the negotiation process [2]: by taking it into account, it is possible to argue whether an agreed alignment is more or less sound than other. An alignment with a low number of unresolved conflicts can be taken with more confidence than the same alignment with more remaining conflicts. The process of reaching an agreement is commonly addressed as Ontology Matching Negotiation (OMN) and two approaches have been addressed in literature: (i) Argumentation-based (e.g. [3] [4]) and (ii) Relaxation-based [5] [6].

Each of these approaches has its advantages and limitations. To benefit from both techniques' advantages and overcome their limitations, several ways of combining them have been proposed [2]. Nevertheless, no experiments have been described and no results regarding these combinations have been reported in literature and, as such, it is not known if the combinations proposed actually generate the benefit they intend to. This work aims to provide and discuss said results.

The available results allow identifying the different benefits of each combination, thus making it possible for developers to choose which one fits their requirements for the generated alignment.

1.1 Main Goals

The work developed and described in this document intends to implement different combinations of Argumentation-based and Relaxation-based Ontology Matching Negotiation approaches. Several different ways of combining these approaches have been proposed in literature. Yet, no implementation or documented experiments are available to date, which is considered a major flaw. By providing an implementation and documenting the results obtained through different combinations, we wish to prove the hypothesis that combining techniques provides results which are better than those obtained via the basic approaches.

In short, the work presented in this documented aims to:

- Understand if combining Argumentation and Relaxation-based approaches does generate alignments which are better than those obtained via each approach individually.
- Identify how the different combinations impact the metrics chosen to evaluate the alignment's quality and
- Assess the differences between the results achieved via different combinations and if different combinations can be exploited more profitably according to the utilization context of the generated alignment.

1.2 Main Contributions

This document provides the missing documented experiments concerning different combinations of Argumentation-based and Relaxation-based Ontology Matching Negotiation approaches which are not present anywhere in literature. These experiments are then explored in order to demonstrate how the combination produces alignments which are better than those obtained via the basic approaches.

As such, this work contributes with:

- Implementation of two of the combinations described in literature;
- Experiments concerning these two combinations;

- Comparison between the results obtained via the two different approaches in order to assess which of them is better and under which circumstances.

In order to reach the objectives stated above, it was required to:

- Analyze the state-of-the-art Argumentation-based and Relaxation-based approaches in order to choose which specific methods to combine;
- Improve the state-of-the-art Relaxation-based approach in order to reach the full-automatism required for being used in the combinations. As such, the new Relaxation proposal is an independent and automatic Ontology-Matching Algorithm. An implementation of the new proposal is also provided. The new Relaxation proposal includes:
    - Specification of Utility and Meta-Utility functions, which have been described in literature but not specified or implemented;
    - Gain functions, to compute how much the agents are winning or losing through the inclusion or exclusion of a single match in the alignment;
    - Effort functions to compute if the relaxation is profitable to an individual agent;
    - Balancing mechanisms such that agents can achieve an agreement which is advantageous both locally and globally.

Additionally, through analysis of the experimentation's results, it is possible to see that the combinations do, in fact, provide better results than the basic approaches. This is considered a strong evidence for the validity of the combination of Argumentation-based and Relaxation-based approaches as a new form of Ontology Matching Negotiation.

The experiments also show that the results obtained through the new and improved Relaxation-based approach produces alignments with a quality comparable with those obtained via other state-of-the-art Ontology Matching Algorithms and reach a quality comparable to those obtained via Argumentation-based approaches.

The documented experiments concerning the new Relaxation approach have been published in a scientific paper:

- Alda Canito, Paulo Maio, Nuno Silva, ”Improved Relaxation-based Ontology Matching Negotiation”, 15th International Conference on Information Integration and Web-based Applications & Services (iiWAS2013), Vienna, Austria, 2-4 December 2013, ACM.

1.3 Document Structure

This thesis is comprised of 6 chapters which are organized as follows:

This current chapter, the first, which presents a description of the work developed, including the motivations, main goals and contributions.

Chapter 2 presents the background relevant for understanding of this work. This chapter introduces the nomenclature that will be used in the remaining of the document while presenting relevant concepts for understanding the work developed.

Chapter 3 presents and analyses the possible combinations of Argumentation and Relaxation-based approaches and explores how these combinations *per se* can be developed.

Chapter 4 presents a new and improved Relaxation-based approach that can be used in the combinations with detail.

Chapter 5 presents the experiments and results. A detailed explanation of the settings and datasets utilized in the experiments is provided. The results are presented and discussed in comparison with other state-of-the-art Ontology Matching Algorithms.

Finally, Chapter 6 presents the conclusions which can be taken from this work and the open issues. It also presents a description of possible future work to further improve the techniques described.

2 Background

2.1 Ontologies

One of the most common definitions for the term ontology is provided in [7], which states: "Ontology is an explicit specification of a conceptualization". Despite the simplicity, this is the definition most used in the Artificial Intelligence (AI) field and the one most agreed upon. The relevant terms have been further described by [8]:

- Conceptualization – meaning a rational and abstract model of a certain domain, including the identification and description of concepts, properties and relations between them;
- Specification – the detailed, accurate, consistent, solid and meaningful description of the domain;
- Explicit – representation of the conceptualization in a way that intelligent agents can understand and reason upon.

A modification to the initial definition has been proposed by [9] which is also widely accepted. Two more concepts would be added, namely "formal" and "shared", thus resulting in "Ontology is a formal and shared specification of a conceptualization". The definition is thus improved with:

- Formal – either humans or machines (i.e. intelligent agents) must be able to read, understand and process the ontology;
- Shared – the ontology is accepted in consensus by a group and not only by an individual.

2.2 Agent-Based Systems

In AI, "Agent" is commonly seen as a computer system (i.e. software) which can act upon an environment, either on behalf of a user or an organization, with a set of goals or objectives [10][11] [12]. While there is no unanimous agreement on the definition of the agent concept, there is a consensus over some of the characteristics an agent should possess. Among these are [13]:

- Sensorial capability – the agent must have sensor which allow it to capture information about the environment it figures in;
- Reactivity – the agent must react to ever-changing environment;
- Autonomy – the agent decides and controls its actions;
- Pro-Activity – the agent goes beyond reacting to the environment, taking initiative in order to achieve its goals;
- Persistency – the agent exists for long periods of time;
- Social Skills – the agent must be able to communicate and cooperate with other agents or even people;
- Learning – the agent is able to change its behavior according to previous experiences;
- Mobility – the agent is able to move from one machine to other;
- Flexibility – there's no need for pre-determining the agent's tasks;
- Agility - the agent has the ability to take advantage of unforeseen opportunities;
- Character – the agent has a credible personality and emotional behavior;
- Intelligence – the agent must be able to reason autonomously, plan its actions and correct its mistakes, react and adapt to unforeseen situations.

Stand-alone agents are useful for performing some tasks delegated by a user [14], alleviating their workload. Nonetheless, it is more common to find agents in environments where they can interact with other agents, comprising a Multi-Agent System (MAS).

Multi-Agent Systems are a division of Distributed Artificial Intelligence consisting on a community of agents which cooperate, coordinate and negotiate with each other in order to achieve their goals. These provide several advantages to the use of isolated agents such as reliability, robustness, modularity, scalability, adaptability, concurrency, parallelism and dynamism [15].

Much like a community of people, individual agents may have unique goals and describe their world of discourse in a heterogeneous way. With the use of ontologies, agents can specify their knowledge through an explicit conceptualization [7].

As the popularity of the Semantic Web increases and more data is being shared in the form of ontologies, it is not reasonable to expect that two agents willing to communicate will be using the same ontology. In fact, agents may have to interact without previous knowledge of the ontologies the others are using. In this scenario, it is necessary that agents are able to reconcile their ontologies in real-time, in a process usually referred to as Ontology Matching [1].

2.3 Ontology Matching

Ontology Matching is seen as the process of discovering, (semi-) automatically, the correspondences between semantically related entities of two different but overlapping ontologies. Thus, as stated in [1], the matching process is formally defined as a function $f: (O_s, O_t, p, res, A) \rightarrow A'$ which, from a pair of ontologies to match – O_s and O_t – a set of parameters p, a set of oracles and resources res and an input alignment A, it returns an alignment A' between the matched ontologies. Ontologies O_s and O_t are often denominated as source and target ontologies respectively. An alignment is a set of correspondences expressed according to:

- Two entity languages Q_{L_1} and Q_{L_2} associated with the ontologies languages L_1 and L_2 of matching ontologies (respectively) defining the matchable entities (e.g. classes, object properties, data properties, individuals);
- A set of relations R that is used to express the relation held between the entities (e.g. equivalence, subsumption, disjoint, concatenation, split);
- A confidence structure φ that is used to assign a degree of confidence in a correspondence. It has a greatest element $\top$ and a smallest element $\bot$. The most common structure are the real numbers in the interval $[0\text{-}1]$, where 0 represents the lowest confidence and 1 represents the highest confidence.

Hence, a correspondence (or a match) is a 4-tuple $c = (s, t, r, conf)$ where $s \,\epsilon\, Q_{L_1}(O_s)$ and $t \,\epsilon\, Q_{L_2}(O_t)$ are the entities between which a relation $r \in R$ is asserted and $conf \in \varphi$ is the degree of confidence in the correspondence.

Over recent years, research initiatives in ontology matching have developed many systems (e.g. [16]) that rely on the combination of several basic algorithms yielding different and complementary competencies to achieve better results. A basic algorithm generates correspondences based on a single matching criterion [17]. These algorithms can be multiple classified as proposed in [1] [18] (e.g. terminological, structural, semantic). Yet, systems make use of a variety of functions such as:

- Aggregation functions whose purpose is to aggregate two or more sets of correspondences into a single one (e.g. min, max, linear average);
- Alignment Extraction functions whose purpose is to select from a set of correspondences those that will be part of the resulting alignment. The selection method may rely on the simplest methods such as the ones based on threshold-

values (summarized in [1]) or more complex methods based on, for example, local and global optimizations (e.g.[19] [20]).

The selection of the most suitable algorithms/system is still an open issue as they should not be chosen exclusively with respect to the given data but also adapted to the problem that is to be solved [1]. However, this question has already been dealt with in [21] [22] [23]. Despite all the existing (conceptual and practical) differences between matching systems and algorithms, we will refer to both as matchers as all of them have a set of (candidate) correspondences as output.

2.4 Ontology Matching Negotiation

As previously stated, when two agents using different ontologies wish to interact, they may have to reconcile their ontologies in run-time. These agents can exploit matching services available in their environment in order to obtain an alignment they may use to translate the exchanged messages.

Each agent has its individual needs, objectives and preferences. Agents may have different preferences concerning the matching process and even make use of different matching services. Different matchers can produce diverse and even contradictory candidate alignments, giving rise to conflicts between the agents. These conflicts must be addressed and tentatively resolved in some negotiation process, such that the agents may reach an agreement concerning each and every correspondence they will use in the conversation. The process of reaching an agreement is commonly referred as Ontology Matching Negotiation (OMN).

Not all Ontology Matching Negotiation processes are the same, but for the sake of simplicity and to state the nomenclature used in this document concerning OMN, a very brief and informal description of a negotiation process is provided below.

Each agent generates or requests a set of matches. Then, the agent can apply its preferences to the set, e.g. by applying a method or a threshold to obtain only the matches over a certain level of confidence or having certain characteristics. These are the matches the agent is confident in and constitute the agent's Initial Proposal. The importance and impact of engaging in a negotiation process may be measured by comparing the agents' initial proposals with the alignment they generate through negotiation.

When engaging in a negotiation process with another agent, both parties present their Initial Proposals. All the matches which are included in both the proposals (i.e. their intersection) are immediately accepted – this set of matches will be referred to as Agreements from now on. The remaining matches will be the object of the rest of the negotiation process, named Negotiable matches.

Since agents did not agree about whether to include or exclude the matches on this set, they will either try to change their opinion on the match or require that the other agent does so. Three outcomes are possible:

- Both agents now agree about including the match, and the match is moved from Negotiable to the Agreements;
- Both agents agree to exclude the match. The match will not figure in the alignment and the conflict is resolved by having both agents removing the match from the negotiation;
- Agents still disagree about including or not including the match. The agents either engage further in negotiation, trying again to change its or the other's opinions, or the match is added to a set referred to as Disagreements.

The negotiation process may end when all matches have been processed or run for another iteration, where the remaining conflicts will be addressed again and again until no changes are reported between two iterations or a stop decision occurs. The matches contained in the Agreements set will form the agreed alignment, while those in the Disagreements are the remaining conflicts.

Two OMN approaches have been presented in literature: (i) Argumentation-based (e.g. [3] [4]) and (ii) Relaxation-based [5] [6]. These will be subsequently addressed.

2.4.1 Relaxation-based Ontology Matching Negotiation

The Relaxation-based approach presented in literature [5] [6] suggests that each of the negotiating parties generates an alignment between O_s and O_t. Each party assigns a confidence value c_n to each match through the use of a utility function (u), normally in the range [0-1]. This confidence value is used to classify the match as one of "rejected", "negotiable", "proposed" or "mandatory" classes. These classes are defined based on a multi-threshold approach (also seen in Figure 1, below):

- Mandatory Threshold (t_m), such that $t_m < c_n < 1$, determines that the agent is so confident about the match's relevance such that it is fundamental that the match is accepted by the other agent.
- Proposition Threshold (t_p), such that $t_p < c_n < t_m$, above which the confidence in the match is enough for it to be proposed to the other agent, but not such that an agreement cannot be reached without it.
- Negotiation Threshold, (t_n), such that $t_n < c_n < t_p$, above which the match is considered negotiable, meaning that the agent is not confident enough to propose the match to the other agent, but is willing to revise/relax its confidence if prompted.
- Rejection Threshold (t_r), above which match is considered rejected and below which eliminated.

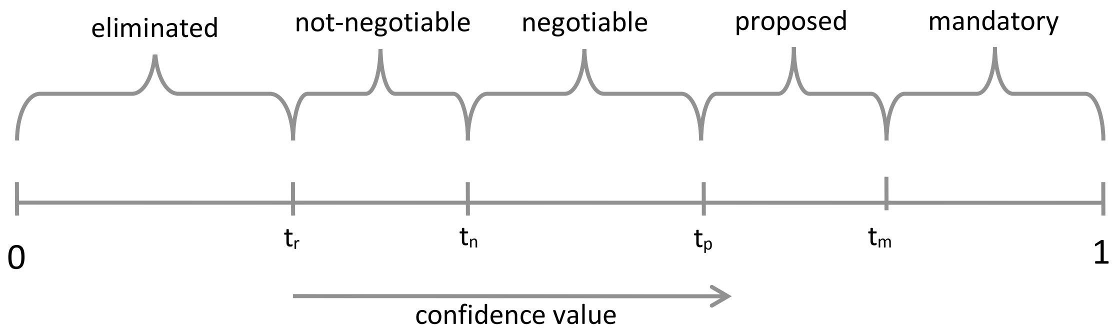

Figure 1 – Relationship between Relaxation's thresholds and categories

The confidence value can be updated through the use of a Meta-Utility function (U), allowing the re-categorization of matches from one category to another. This function is responsible for (i) identifying the parameter variation possibilities, (ii) the priorities over parameter variation and (iii) the conditions under which the variation may occur. It is possible that the Meta-Utility function cannot update the confidence value in order to achieve the intended re-categorization. On the other hand, when an agent re-categorizes a match, it makes a convergence effort (eff) that must measured and balanced against the profit ($profit$) the agent achieves with said effort.

The negotiation process unfolds in two main phases: Mandatory Correspondences Processing phase and Proposed Correspondences Processing phase. During the former phase, each agent shows the other the matches it considers mandatory. If no agreement is achieved in this phase, the negotiation fails and no alignment is generated. Otherwise, it proceeds to the Proposed Correspondences Processing phase.

In this phase, each agent shows their proposed matches to the other agent. In this scenario, three situations may occur:

- The match is also proposed by the other agent and is thus accepted;
- The match is considered "negotiable" by the other agent. In this case, the negotiable match is re-evaluated with the Meta-Utility function and it may either be accepted or considered remain as a conflict;
- The match is considered not negotiable by the other agent and is therefore rejected.

An illustration of the possible outcomes when negotiating about a match is provided in Table 1:

Table 1 – Possible Relaxation conflict scenarios and their outcomes [2]

Agent 2 / Agent 1	Mandatory	Proposed	Negotiable	Not Negotiable
Mandatory	accept	Accept	accept/ terminate negotiation	terminate negotiation
Proposed	accept	Accept	accept/ disagreement	rejected
Negotiable	accept/ terminate negotiation	accept/ disagreement	user	rejected
Not Negotiable	terminate negotiation	Rejected	rejected	rejected

Despite the simplicity, this approach has some limitations.

In this proposal, it is considered that a match's confidence value can only be increased. This means that existing disagreements can only be resolved via including the matches in the alignment, and there is no scenario where the parties can agree to exclude a match after it being deemed at least "negotiable". Two relevant scenarios must be analyzed:

(i) When the party holding the "negotiable" position will not relax its match's confidence value to "proposed" no further negotiation concerning it occurs, resulting in an unresolved conflict.

(ii) It gets worse when the disagreement is between "proposed" and "not negotiable" stances. In this case, the disagreement is so pronounced that the protocol does not even consider it worth of relaxation efforts. From this follows that the match is automatically excluded from the alignment, and thus the "not negotiable" stance automatically wins the conflict, while the "proposed" stance has no say on the matter.

Furthermore, the proposal provides no mechanism to calculate how much the agents are winning/losing under these conditions.

This approach also considers scenarios where human intervention is required, namely when both agents consider a match "negotiable". This can be seen as a limitation when compared to some argumentation approaches, which are generally able to run in fully automatic mode [24][25] [26].

2.4.2 Argumentation-based Ontology Matching Negotiation

Argumentation-based Negotiation occurs in a community of agents. For these to properly interact and understand each other's arguments, they must accept a shared Argumentation Model, which is an artifact that defines the vocabulary used to form arguments, the arguments' structure and semantics, i.e. the way they affect each other, either through attack or support.

Frameworks such as AF [27], BAF [28] and VAF [26] provide abstract models that can be adopted regardless of the negotiation's context. While this abstract nature facilitates the study of properties independent from any specific argumentation context, it also limits the expressiveness which can be achieved in specific application contexts [29]. In order to overcome this, it is generally considered that argumentation systems can adopt an abstract framework and extend it to properly suit their needs regarding the negotiation's context, namely concerning argument generation, possible kinds of arguments, the structure of the arguments themselves and their semantics, i.e. the way these affect each other in the negotiation process. However, these argumentation frameworks do not provide mechanisms to facilitate how applications should instantiate the framework. This results in a significant gap between abstract argumentation frameworks and applications [30]. The Argumentation Model is public and all the agents must be able to reason over it. It is also considered that each agent must be able to internally generate and re-evaluate its arguments [11]. For this, the agent could adopt a personal Argumentation Model, or privately extend the public one. This would represent the agent's individual perception or knowledge concerning the domain, resulting in possible different interpretations and conceptualizations of the same information.

Next, we'll be presenting two different approaches on Argumentation-based Negotiation when applied to the Ontology Matching context. The first, the Meaning-based Argumentation, provides only a public yet implicit Argumentation Model for all agents to follow. The latter, the Three-Layer Argumentation Framework, is an approach that specifies an explicit public Argumentation Model that can be privately extend by each agent.

2.4.2.1 Meaning-based Argumentation

Meaning-based Argumentation (MbA) [3], further improved in [4] into a more flexible approach (FDO), adopts the Value-based Argumentation Framework (VAF) [26].

Agents can express their matching preferences according to the classification of the matching algorithms:

- Terminological (T): comparing the names, labels and comments related to ontological entities;
- Internal Structural (IS): exploiting the internal features of entities (such as domain and range of their properties, cardinalities of attributes);
- External Structural (ES): exploiting the external relations between the entities in the ontology (such as super-entity, sub-entity or sibling);

- Semantic (S): using theoretical models to determine if there is a match between two entities;
- Extensional (E): comparing the set of instances under evaluation.

In MbA, arguments are represented as 3-uples, $t = \{G, c, pos\}$ where:

- c is a match;
- pos is one of $\{-, +\}$, depending on the agent's belief that the correspondence does or does not hold, and
- G is the grounds justifying pos.

Agents negotiate through the exchange of arguments in order to decide whether or not to include the match in the alignment. A match is accepted if all agents participating in the negotiation have a positive opinion of it.

MbA/FDO has a series of relevant limitations in comparison with the Relaxation approach, namely:

- Symmetric attacks. An argument (a) can only be attacked by its negation ($\neg a$), or counter-argument;
- The MbA/FDO approach exploits only rebuttal arguments. As such, agents must reject the entire argument and not the individual premises. Since the agents cannot argue about the reasons that lead them to a specific opinion, they cannot be argued into changing their stance;
- This approach requires that all agents use the same ontology matching repository (OMR). This means that, apart from preferences and thresholds which are unique to each agent, all agents have the same perception about the set of matches. As a consequence, the outcome of the negotiation process corresponds to the intersection of the alignments proposed by the agents.

While there are more limitations addressed in literature [30], these are the most relevant when in comparison to the previously presented Relaxation-based approach. These show that is very unlikely for agents to be able to revise their initial stances, which is the opposite of what the core point of the Relaxation-based approach.

2.4.2.2 The Three-Layer Argumentation Framework

The Three-Layer Argumentation Framework (ANP-TLAF) [31] is an argumentation framework whose main purpose is to reduce the gaps between abstract argumentation frameworks and argumentation systems. Its three layers are: (i) the Meta-Model Layer, (ii) the Model Layer and (iii) the Instance Layer. A visual interpretation of the three layers and the relationships between them is presented in Figure 2.

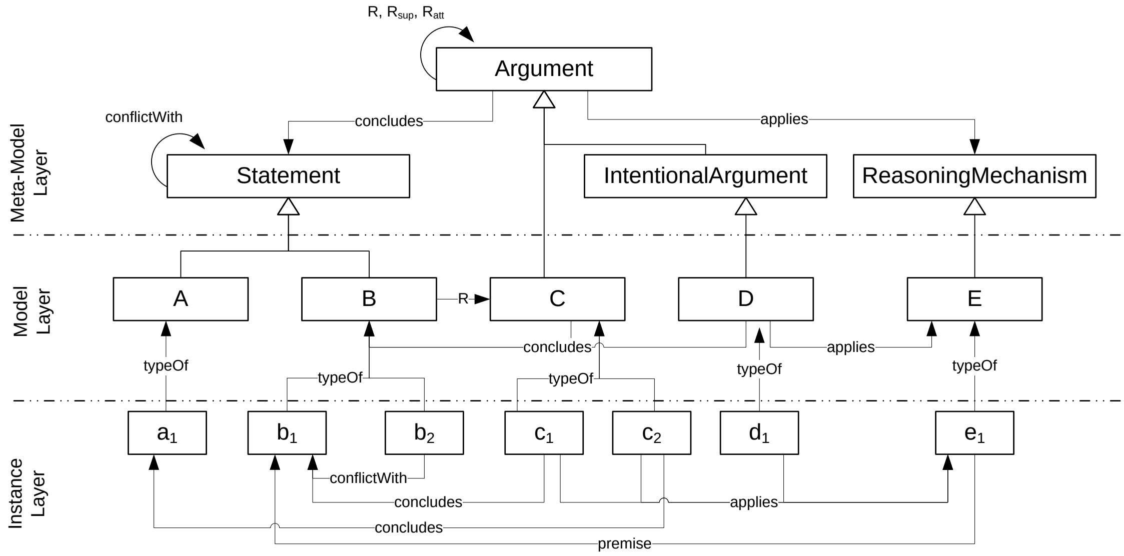

Figure 2 – The Three layers of TLAF, as captured by the ANP-TLAF's OWL ontology

The Meta-Model Layer defines the notion of argument. An argument, following the minimal definition presented in [30], consists of three parts:

(i) a set of premise-statements;

(ii) a conclusion-statement;

(iii) an inference from premises to conclusion achieved through a reasoning mechanism.

Additionally, following the notions presented in [32] and [33], the ANP-TLAF's Meta-Model Layer adopts the following concepts:

- *Intentional Argument*, which corresponds to the type of arguments whose content corresponds to an intention;
- *Statements*, which capture domain data and its meaning, including domain intentions, desires and beliefs of an agent;
- *Reasoning Mechanism*, capturing the rules, methods and processes applied by arguments.

By separating the notions of *Statement* and *Argument*, it is possible for agents to interpret the same domain's data differently and using it in different contexts.

The ANP-TLAF's Model Layer aims to capture the different argument types and the way they relate to each other in a specific domain (in this case, Ontology Matching). The model specifies the perception the agents have about the domain, making it an important artifact for knowledge sharing and reuse. In order to negotiate, agents must agree to use a vocabulary consistent with that specified in the model.

An argument type is described by:

- the statement type it concludes,
- the reasoning mechanism applied
- the set of affectation relationships it has (represented in Figure 2 as *R*). These relationships are either of attack (R_{att}) or support (R_{sup}). They define how the instances in the Instance Layer affect, positively or negatively, instances of other argument types.

At the Instance Layer, an argument applies a specific reasoning mechanism to achieve a conclusion from a set of premises. Here, all instances follow the modeling of one of the types declared in the Model Layer.

3 Combining Relaxation and Argumentation approaches

It has been hypothesized in [2] that the limitations presented in the Relaxation-based and Argumentation-based approaches can be minimized if they are combined, all while taking advantage of each approach's strong points. For the approaches to be combined, three main dimensions must be considered beforehand:

- **Composition** – referring to the way the approaches are combined. There are three possibilities:
  - Sequential, meaning that the outcome of one negotiation approach is the input of the next. Since the order of the approaches is relevant to the outcome, two alternatives are available: (i) the Argumentation-based approach followed by the Relaxation-based approach and (ii) vice-versa;
  - Parallel, where both approaches run at the same time and independently from each other. Two results emerge, which then have to be aggregated through means of some function into a single result;
  - Merged, in which one of the approaches is diluted into the other. Again, two options are available: (i) Argumentation-driven, where the Relaxation-based approach is diluted into the Argumentation-based approach and (ii) vice-versa;
- **Process Granularity** – refers to the moment in the negotiation process where one approach passes control onto the other approach. This can occur at:
  - The end of the negotiation: the outcome is an agreement along with the remaining conflicts;
  - The end of each iteration: the outcome is an intermediary result comprised of the (i) accepted matches, (ii) tentatively accepted matches or disagreements and (iii) remaining conflicts;

- **Object of Negotiation** – refers to the kind of object the agents are negotiating. The possibilities are: (i) match (correspondence, in Figure 3), (ii) alignment and (iii) both.

These dimensions can be combined in several ways, which are illustrated in Figure 3, below:

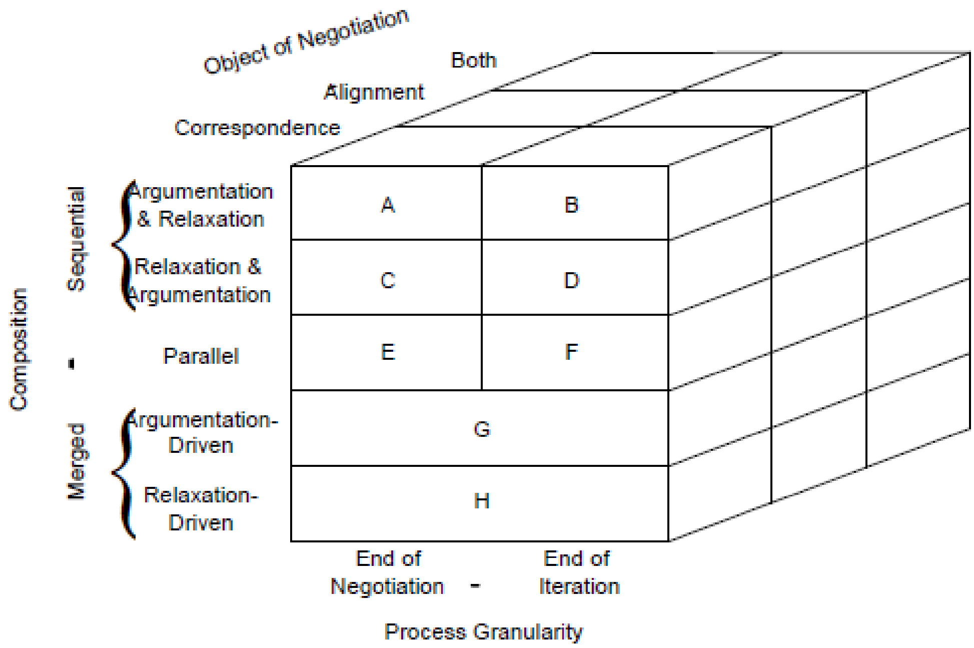

Figure 3 – Possible combinations of the three identified dimensions [2]

3.1 Combinations A and C

Combinations A and C combine the approaches sequentially at the end of the negotiation process. The output of the first approach is used as input for the next, which is responsible for generating a new and hopefully improved outcome. This way, the basics of each approach are preserved and the only modification required is that the second approach is able to understand and work upon the results of the first.

Combination A runs the Argumentation-based approach first. The Relaxation-based approach attempts to solve any conflicts the Argumentation could not and is thus responsible for improving the results of the first approach (Figure 4).

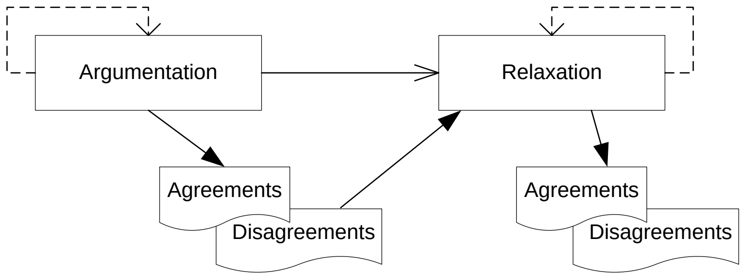

Figure 4 – Combination A

Combination C inverts the order and has the Relaxation-based approach running first than the Argumentation-based approach (Figure 5).

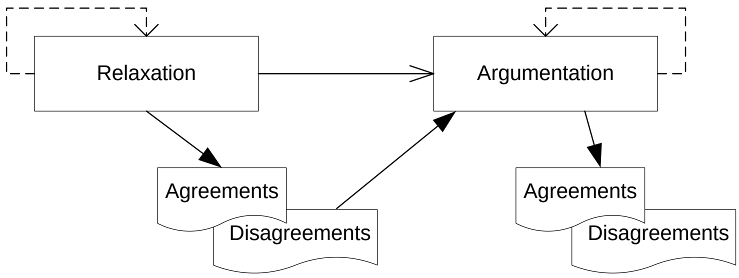

Figure 5 – Combination C

The first approach (either Relaxation or Argumentation) generates a set of matches which represent an intermediary alignment (the Agreements) and a set of conflicts it could not resolve (the Disagreements) (cf. Section 2.4).

The second approach (either Argumentation or Relaxation respectively) uses these two sets as input. Each set has a different purpose: agents will negotiate only about the matches included in the Disagreements set in order to decide if the matches will (i) be added to the Agreements and thus included in the final alignment, (ii) rejected and thus removed from both Agreements and Disagreements, such that they will no longer be considered or (iii) remain in the Disagreements.

3.2 Combinations B and D

Combinations B and D combine the approaches sequentially, but at the iteration level. Here, each iteration exploits both the Argumentation-based and Relaxation-based approaches.

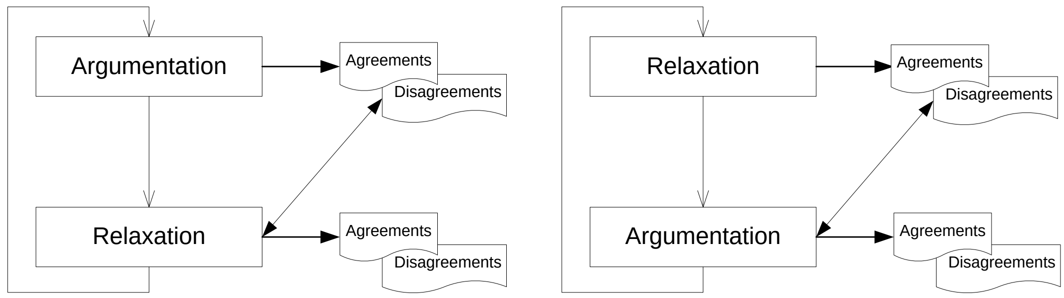

Figure 6 – Combinations B and D, respectively

The Argumentation-based approach will try to decide whether or not to include a certain match in the alignment. If the agents cannot agree as to include it or not, the agents engage in a Relaxation-based approach and will try, once again, to resolve the conflict. This means that the second approach is only exploited when the first is unsuccessful. The latter approach is responsible for deciding if the iteration ends – either successfully, by reaching an agreement or unsuccessfully, by remaining at conflict – or if it runs for another iteration.

While it may sound like these combinations will not generate results distinct from those of Combinations A and C, it is important to consider some questions concerning the fact that both approaches are being exploited at iteration level. The Relaxation-based approach does not account for possible relationships between the matches in the agents' initial proposals. On the other hand, the Argumentation-based approach, according to the configuration used, can exploit these relationships and this may be an issue when combined with the Relaxation-based approach.

Consider, for instance, two matches, c_1 and c_2. There is a dependency between them, such that the match c_1 can only be accepted if c_2 is accepted as well. This dependency is illustrated in Figure 7, below:

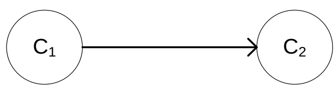

Figure 7 – Dependency between matches c_1 and c_2

The Argumentation phase, which considers dependencies between matches, could consider the acceptance of c_2 as an important argument in favor of including c_1. However, by negotiating c_2 after c_1, it is possible for the Relaxation phase, which is oblivious to dependencies between matches being considered by the Argumentation phase, to decide to exclude the match c_2. The Argumentation is now forced to revise its arguments in order to keep inner consistency: since c_2 has not been accepted, c_1 must not be accepted either. However, the agents have already agreed to accept it previously, thus resulting in an inconsistency.

One way to overcome this problem would be by having the Argumentation-based approach drop the exploitation of relationships between matches by using only configurations which do not require it. This is, however, merely restricting the Argumentation-based approach's potential.

3.3 Combinations E and F

As for Combinations E and F, the individual approaches run in parallel and are afterwards aggregated by an external process (or function). Like Combinations A and C, the approaches do not need to communicate with each other and their internal mechanisms remain the same. The core focus of this scenario is actually the aggregator, which must convert the two agreements into a single one. In Combination E, the totality of the alignment has to be aggregated at the end of the process, as shown in Figure 8.

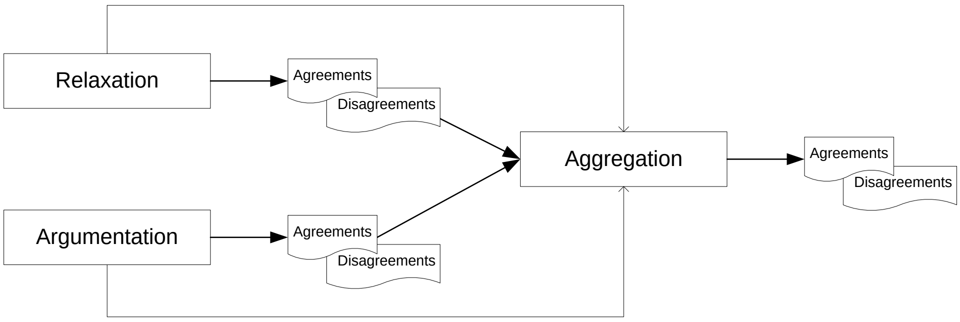

Figure 8 – Combination E

The aggregation process has the responsibility of aggregating the two outcomes of the different approaches into a single one. In Combination F, the aggregation occurs at the end of each iteration. The aggregation function also bears responsibility about deciding if the result will be used as input for another iteration or if the negotiation process ends.

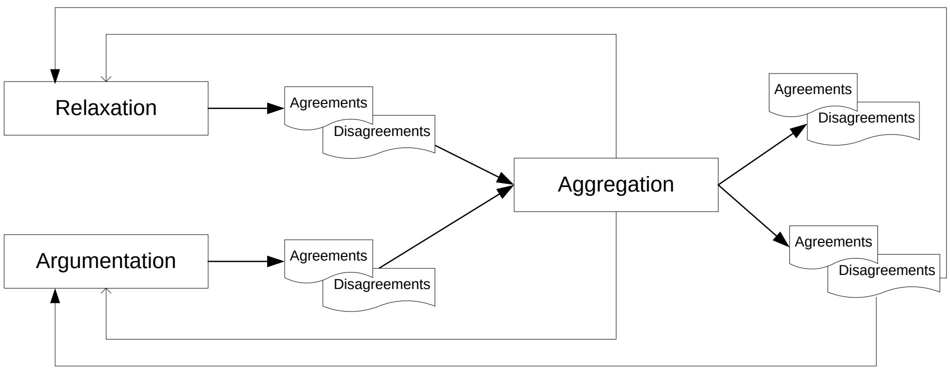

Figure 9 – Combination F

As presented in Figure 9, both approaches generate an intermediary result for each match. These are combined in an aggregation process into a single result. If the result is positive, the match is added to the agreement. Otherwise, it is considered a conflict and the aggregation process has the responsibility to decide if the negotiation of this match continues, by feeding the conflict back to the Relaxation and Argumentation processes, or if the iteration ends and the match remains a conflict.

3.4 Combinations G and H

In Combinations G and H, the process is either driven by the Argumentation or the Relaxation-based approach, respectively. One approach is diluted seamlessly into the other, such that its features become intrinsic.

Combination G, presented in Figure 10, adds new kinds of arguments to the Argumentation Model, in order to grant it Relaxation features, which could be an effective strategy for persuasion purposes.

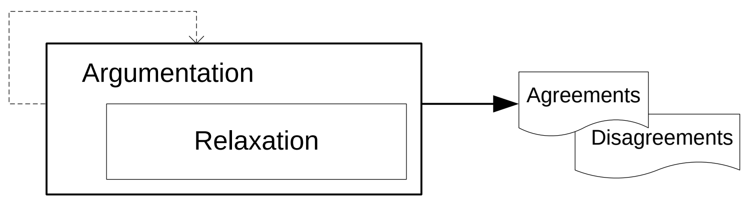

Figure 10 – Combination G

Furthermore, Relaxation features could also be used for evaluating arguments, both internally and received from other agents.

In Combination H, the Relaxation-based approach includes features seen in the Argument-based approach, as depicted in Figure 11, abaixo:

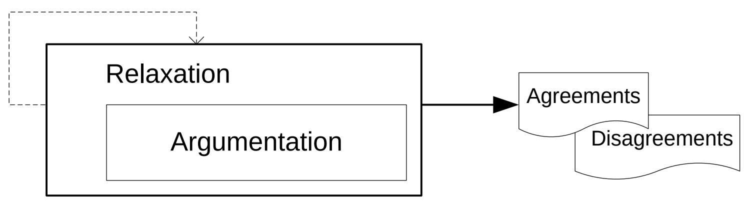

Figure 11 – Combination H

Internal arguments can be exploited in the Relaxation-based approach when an agent is trying to make a decision concerning a match. This argumentation feature can thus be exploited and included in both Utility and Meta-Utility functions.

One possible use of Argumentation features in the Relaxation-based approach would be by allowing an agent to have an internal argumentation process when prompted to relax its confidence value in a given match, e.g. by adding arguments to the parameters of the Meta-Utility function. This could exploit existing argument types while adding new ones for dealing with effort and profit computations.

As in the Argumentation-based approach, the agent can have an internal negotiation process in order to decide which matches to propose, the same can happen when the agent is assigning a confidence value to a match in the Relaxation-based approach.

3.5 Final Remarks/Considerations about the combinations

After analyzing all possible combinations, it has been decided to implement and evaluate Combinations A and C because these maintain a set of desirable characteristics, namely (i) sequential composition and (ii) process granularity being at the end of the negotiation. This is especially due to:

- The reuse of the existing implementations of both approaches, as no modifications to the inner mechanisms of the basic approaches are required.
- The independence of the Relaxation and Argumentation approaches, any improvements the second approach makes on the first's results are more evident and can easily be quantified by comparing them with those obtained via the first approach alone.

These characteristics make Combinations A and C stand out over the other considered combinations when concerning implementation, evaluation and result analysis, therefore making them the best choice for the first efforts.

But before implementing any of the proposed combinations, it is necessary to analyze the individual approaches and deal with possible limitations found.

As suggested in [2], one of the most relevant Argumentation-based approaches limitations is the fact that these approaches do not provide means to change or revise their opinions in favor of a bigger goal, such as interoperability or reaching an agreement. Since this is exactly the focus of relaxation mechanism, the limitation can be overcome simply through the combination of Argumentation-based approaches with Relaxation-based approaches.

As for the Relaxation-based approach, a set of limitations has been identified (cf. Section 2.4.1) and must be addressed before any combination can be implemented. For that, a new and improved Relaxation-based approach is proposed, which will be described in Section 4. For the remainder of this document, all references to the Relaxation-based approach concern the new proposal, unless stated otherwise.

4 Improving the Relaxation approach

In this chapter the previously proposed Relaxation–based ontology matching negotiation approach [5] is improved in order to overcome the identified limitations (cf. Section 2.4.1):

- Agents can only revise their initial stances on a match's categorization in order to promote its inclusion in the alignment. If the negotiating agents cannot both agree to include a match, it will be added to the Disagreements;
- Whenever a match is considered "not-negotiable" by any of the parties, it is automatically excluded from the negotiation process, even if the other party deemed it "proposed";
- Conflicts between two "negotiable" stances require user intervention.

Such improvements rely on the premise of increasing the number of scenarios where conflict resolution can occur. For that it is considered that it is necessary to obtain an agreement not only concerning the correspondences to include in the final alignment, but also concerning those to remove.

The initial proposal only provided one way to solve conflicts: the party holding the "negotiable" position had to change it to "proposed". If that could not be done, the match would be added to the Disagreements. However, this does not correspond to the only possible way of resolving this conflict: if the agent holding the "proposed" stance was able to revise it to a lower one, such as "negotiable" or "not negotiable", the conflict would be solved as well. This suggests that more conflicts could be resolved if the agents were allowed to relax their stances weather to promote the inclusion (rising their confidence value) or the exclusion (lowering their confidence value) of a given match. A match should only be added to the Disagreements if the conflict cannot be resolved through any of these ways.

Allowing agents to relax their confidence both ways proposal provides a way to resolve the second identified limitation as well. Consider a match deemed "proposed" by one of the agents and "not negotiable" by the other. The original approach would not consider this as a conflict and the match would be automatically excluded from the negotiation (i.e. defined as excluded) and from the agreement. This would happen with no engagement in a negotiation process, even when considering one of the parties was confident enough to propose the match to the other. The party holding the "not negotiable" stance automatically wins the round. Nonetheless, this scenario could also be seen as a conflict to be resolved. The "not negotiable" party may not be changing its position, but the proposing party may be willing to change theirs by trying to lower their confidence value so they no longer consider the match "proposed". Only when the proposing party cannot lower its confidence value should the match is added to the Disagreements.

Summarily, it is possible to overcome the limitations of the original Relaxation approach if:

- More scenarios for conflict resolution are created by allowing agents to either move the match to a higher or a lower category;
- A match is not automatically excluded just because one of the parties holds a "not negotiable" stance. The other party should have a say on the negotiation and be allowed to move the match to a lower category, if it finds that possible;
- No user intervention is required.

The following section will describe how to improve the Relaxation approach with the inclusion of these measures.

4.1 Full relaxation and no user intervention

This means that two relaxing ways are now possible:

(i) rising the match's confidence value in order to include the match in the Agreements. This action can be done over matches deemed "negotiable", thus corresponding to "relax a negotiable match" in Table 2;

(ii) lowering the confidence value in order to exclude the match from the negotiation. This action can be done over matches deemed "proposed", thus corresponding to "relax a proposed match" in Table 2.

In order to reach agreements about excluding matches, it is necessary to consider the possibility of relaxing a negotiable correspondence not only to "proposed" (effort for including), but also for "not negotiable" (effort for rejecting).

Based on this approach, an update to the conflict resolution Table 1 is presented in Table 2:

Table 2 – Possible Conflict Resolution Scenarios for the proposed Relaxation approach

Agent 2 / Agent 1	Mandatory	Proposed	Negotiable	Not-Negotiable
Mandatory	accept	accept	relax negotiable ↑ terminate negotiation	terminate negotiation
Proposed	accept	accept	relax negotiable ↑ relax proposed ↓	relax proposed ↓
Negotiable	relax negotiable ↑ terminate negotiation	relax negotiable ↑ relax proposed ↓	reject	reject
Not-Negotiable	terminate negotiation	relax proposed ↓	reject	reject

From this it follows that the agents can now make an effort to include matches or to exclude them, since both are important for conflict resolution. Consequently, it is necessary to devise a method to deal with these contradictory approaches:

- precedence is given to inclusion of new matches in the alignment, so agents will first negotiate for inclusion and only if they fail at this they will negotiate for exclusion;
- precedence is given to exclusion of new matches in the alignment, so agents will first negotiate for inclusion and only if they fail at this they will negotiate for inclusion;
- no precedence is given to any of the methods, thus evaluating both approaches. In case the two choices relaxations are possible, a further negotiation step is necessary. This can be delegated to a posterior iteration of the Relaxation process, where agents could try to relax their positions further. If the Relaxation process is combined with the Argumentation process, this decision can be addressed by the Argumentation.

Also consider that in this situation, if none of the scenarios produces a consensus, the match will remain as a conflict and will be added to the Disagreements.

Unlike the state of the art relaxation approach and as seen in Table 2, when a match is deemed "negotiable" by both parties, it is considered rejected. This is devised so user intervention is not required for the completion of the negotiation process, making it completely automatic. The decision of excluding the match relies on the grounds that it was not proposed by any of the parties and there is no use negotiating about a match none of the parties feels confident about. This further helps on resolving cases when a match considered "proposed" is relaxed down to "negotiable": since, once again, the match is no longer considered proposed by any of the parties, it means they agree to reject it.

4.2 Deciding on the Relaxation action

The goal of the negotiation process is to reach an agreement concerning which matches must be included in the ontology alignment. It is important that agents are willing to relax their positions locally in favor of a global agreement [6].

Whenever a conflict occurs, one or both parties can try to relax their matches' confidence values with the use of a Meta-Utility function. It is relevant that the Meta-Utility function knows which direction the relaxation effort must take, since now it is possible to either rise or lower the value. The function is devised as:

$$relax(c, dir) = \begin{cases} true\colon \begin{cases} profit(c) - eff(c, dir) \geq 0 & : \mathrm{dir} = 1 \\ -profit(c) - eff(c, dir) \geq -1 & : \mathrm{dir} = 0 \end{cases} \\ \qquad\qquad false\colon otherwise \end{cases}$$

where:

- c is a match;
- $profit(c)$ is the function that yields the agent's gain with the match;
- $eff(c, dir)$ is the function that yields the effort associated with changing the match's current confidence value;
- dir is one of $[0,1]$, stating whether the agent is trying to obtain a higher (1) or a lower confidence value (0), and
- $relax$ is one of $\{true, false\}$, stating whether it is possible or not to relax to the desired value.

The function $profit$ returns a value in the range $[0\text{-}1]$. Because the relaxation effort can occur both for including and for excluding the match, it is necessary to consider when relaxing for exclusion the agent is actually losing the value associated with the match, thus resulting in a negative profit.

The function eff follows the notion that the relaxation attempts do not come for free, meaning that agents will not always be willing to change their initial positions. It is important to compute how much effort the relaxation entails and how much the agent is willing to relax. For that, the following formula is proposed:

$$eff(c, dir) = \left| \left(1 + (|step(dir) - conf|)\right)^{effp} - 1) \right|$$

where:

- $conf$ is the confidence value ($[0\text{-}1]$) of c;
- $step(dir)$ is the function giving the minimum value the match should have if changing category in the intended direction (given by dir). It corresponds to one of the thresholds previously introduced, and

- $effp$ is the power applied to determine how fast the effort grows with the increasing distance between $step(dir)$ and $conf$.

However, this function measures only local profits and efforts, but common sense suggests that one agent is willing to relax its confidence in a match by a certain amount if it figures the match (local perspective) and the alignment (global perspective) worth that effort. In order to have a global evaluation of the generated alignment, it is necessary to introduce yet another function, which should be able to assess if the agreement is globally beneficial to both agents. One way to do this would be by calculating a balance between the totality of benefits and of efforts, such as:

$$balance = \begin{cases} +\colon \sum \pm profit(c) - \sum eff(c, dir) \geq 0 \\ -\colon otherwise \end{cases}$$

where $balance$ is one of $\{+, -\}$, stating weather the alignment is globally beneficial to the agent (+) or not (-). Depending on the value for each agent, they may decide to:

- Agree upon the alignment, so it becomes definitive and the negotiation process ends successfully;
- End the negotiation process without reaching an agreement;
- Propose a revision to the alignment in order to maximize their local and global benefits. The negotiation process runs for another iteration.

If they decide to revise the alignment, it is required that the negotiation process generates new alignments until the agents reach one that is advantageous to for both. Because this may be a long process, heuristic approaches have been suggested in [6]. In order to introduce a more agile process, an approach that allows combining local and global benefit is provided next.

It is possible to revise the relaxation function itself in order to include a measure concerning previous relaxation efforts and obtained profits. Instead of revising the entirety of the alignment, agents would maintain a stack of profits previously obtained, allowing them to execute bigger efforts as the total gain with relaxation increases. This approach would thus combine local and global evaluations in a single function, such as:

$$relax(c, dir) = \begin{cases} true\colon tg + profit(c, dir) - eff(c, dir) \geq minP \\ false\colon\ otherwise \end{cases}$$

where:

- c is a match;
- dir is as described above;
- tg is the sum of the gain ($[0\text{-}1]$) achieved throughout the previous relaxation efforts (i.e. matches' relaxations). It results of the accumulation of previous profits obtained from the difference between $profit$ and eff. Accordingly, even if the agent may not

achieve gain with a specific match, it may have accumulated enough gain with previously accepted ones, thus keeping a positive value overall. In order to manage this value in respect to $minP$, it is considered that agents can only accumulate gain up to 1 (i.e. otherwise it will grow indefinitely);

- $minP$ is the minimum profit value the agent must still have after all computation in order to accept the match's re-categorization;
- $eff(c, dir)$ is the function as described above;
- The $profit(c)$ function has been is re-defined as $profit(c, dir)$ in order to accommodate the introduced requirements:

$$profit(c, dir) = \begin{cases} profit(c) & : dir = 1 \\ 1 - profit(c) & : dir = 0 \end{cases}$$

4.3 Example

For a better understanding of the relaxation process, an example will be provided.

Consider a match between a source entity "Color" (a Class from the source ontology) and a target entity "Hue" (a Class from the target ontology), as depicted in Figure 12 and two negotiating agents, a_1 and a_2. Agent a_1 evaluated this match as having a confidence value of 0.87 while a_2 attributed it 0.91.

Figure 12 – Match between source entity "Color" and target entity "Hue"

As depicted in Figure 13, the different confidence values attributed by the agents have these sorting the match in different categories. To make this example simpler, let's consider that both agents apply the same thresholds (depicted in Figure 13) and $effp = 8$. The profit associated with this match will also be the same for both agents: $profit = 0.20$. Further, let's consider that precedence is given to inclusion of new matches in the alignment.

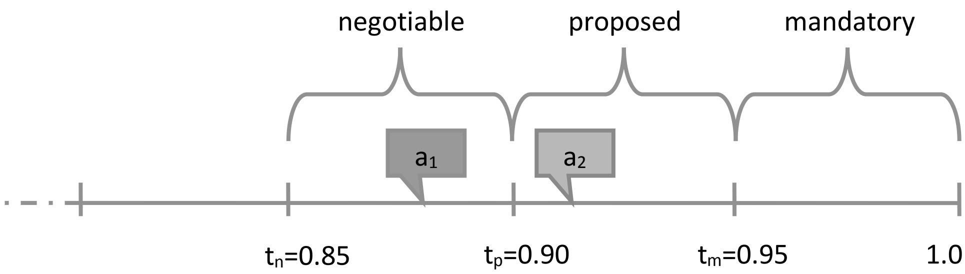

Figure 13 – Graphical representation of the categories assigned to the match by each agent

Because agent a_1 holds the position with the lowest confidence value, it must be the first trying to relax its position. For that, it must measure:

- how much the confidence value must be relaxed;
- how much effort such action entails;
- how much it will profit by engaging in the effort.

The amount of relaxation required is provided by the difference between the current confidence value and the closest threshold that would resolve the conflict. Because $dir = 1$, meaning the agent wishes to raise its confidence value, the closest threshold in such direction is given by $step(1) = tp = 0.90$.

The effort associated with changing the confidence value can now be calculated:

$$eff(c, dir) = \left|\left(1 + (|0.90 - 0.87|)\right)^{8} - 1)\right| \cong 0.267$$

Now all information required has been gathered and the relax function can be computed.

$$relax(c, dir) = \begin{cases} true: 0.20 - 0.267 \geq 0 \\ false: \quad otherwise \end{cases}$$

Because the difference between profits and efforts results in a negative number, -0.067, the agent a_1 decides that it will not revise its initial position.

In the original Relaxation proposal, the negotiation concerning this match would end here, as a disagreement. However, because the new proposal allows for relaxing the confidence value both up and down, it is possible for agent a_2 to try to resolve the conflict as well, this time by trying to lower its confidence value so the match is excluded. The process is very similar to that executed by agent a_1. Now $dir = 0$, making $step(0) = tp = 0.90$. The effort function is now computable through:

$$eff(c, dir) = \left|\left(1 + (|0.90 - 0.91|)\right)^{8} - 1)\right| \cong 0.083$$

Once the effort is computed, the process proceeds to the relaxation function:

$$relax(c, dir) = \begin{cases} true: -\ 0.2 - 0.083 \geq -1 \\ false: \quad otherwise \end{cases}$$

Because the sum of all loses is still below the minimum value permitted, -1, the agent a_2 can relax its position. The revised agent stances are now "negotiable" for a_1 and "negotiable" for a_2. According to the possible conflict resolution scenarios described in Table 2, this conflict is resolved through the exclusion of this match.

4.4 Gain Functions

Concerning the computation of the gain associated with each match, three different gain functions are proposed: (i) Ontological Type, (ii) Ontology Usage and (iii) Hybrid.

4.4.1 Ontological Type

The Ontological Type function allows an agent to assign different gain values to different kinds of matches depending on their types of entities. As a result an agent can decide if a match between two Object Properties is more or less valuable than one between two Classes.

Figure 14 illustrates the three possible cases. In particular, the figure states that a match between two Classes (Color-Hue) is considered more valuable than one between two Properties (colorOf-HasHue) and this more valuable than one between a Class and an ObjectProperty (colorOf-Hue).

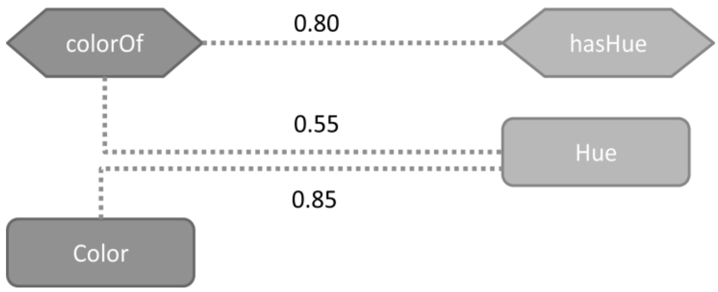

Figure 14 – Assigning different gain values to different kinds of matches

This means that an agent may consider that a match between two Classes is more relevant to the alignment than a match between a Class and an Property, simply by stating, e.g. that it considers a match's gain is 0.75 when it is between Properties, while different ontological entities have an intrinsic gain of 0.35. Because Class, Object Property and Datatype Property are considered, 3^2 configurations are possible, as represented in Table 3:

Table 3 – Possible configuration values for the Ontological Type Function

Target / Source	Class	ObjectProperty	DatatypeProperty
Class	typeWeight(c,c)	typeWeight(c,o)	typeWeight(c,d)
Object Property	typeWeight(o,c)	typeWeight(o,o)	typeWeight(o,d)
Datatype Property	typeWeight(d,c)	typeWeight(d,o)	typeWeight(d,d)

4.4.2 Ontology Usage

The Ontology Usage function pertains to relate the value of an entity presented in an ontology with the number of times it is referred in the ontology. Consider "reference" as the presence of an entity in a triple.

Having a $triple = \{S, P, O\}$, the number of references corresponds to the number of references of the entity as either S, P, or O, both in the ABox and TBox. In the context of this function, it is considered that an entity is more relevant to the ontology as more times it is used. The more the importance of a certain entity, the more gain it brings to the alignment.

Therefore, the Ontology Gain function compares how often the entity is referred with the most mentioned entity. This is computed as follows:

$$profit(c) = \frac{\frac{ref(e)}{somf} + \frac{ref(e')}{tomf}}{2}$$

where:

- $ref(e)$ yields the number of references of a certain entity (e) in an ontology;
- $somf$ is the number of references of the most referred entity in the source ontology and corresponds to $somf = Max\big(ref(e)\big) : e \in O_s$, and
- $tomf$ is the number of references of the most referred entity in the target ontology and corresponds to $tomf = Max\big(ref(e')\big) : e' \in O_t$.

To better understand how the Ontology Usage Function works, an example is presented next. Consider a match between two entities: “Color” (a Class from the source ontology) and “Hue” (a Class from the target ontology) as depicted in Figure 15:

Figure 15 – Match between source entity “Color” and target entity “Hue”

Now let’s assume that the entity “Color” is referred 4 (four) times in the source ontology. Similarly, the entity “Hue” is referred 6 (six) times. Knowing this, we must compare their frequencies with those of the most referred entities in their respective ontologies. Consider that the most referred entity in the source ontology has 8 (eight) references and that of the target ontology is actually the entity “Hue”, which has 6 (six). I.e.:

- $ref(Color) = 4$
- $ref(Hue) = 6$
- $somf = 8$
- $tomf = 6$

The gain associated with including this match would then be computed as follows:

$$profit(Color, Hue) = \frac{\frac{4}{8} + \frac{6}{6}}{2} = 0{,}75$$

Therefore, the match between “Color” and “Hue” brings a profit of 0,75 if included in the alignment.

4.4.3 Hybrid

The Hybrid gain function is actually a combination of the values obtained with the two Gain Functions, Ontological Type and Ontology Use, described previously. Figure 16 depicts a metaphor for the process:

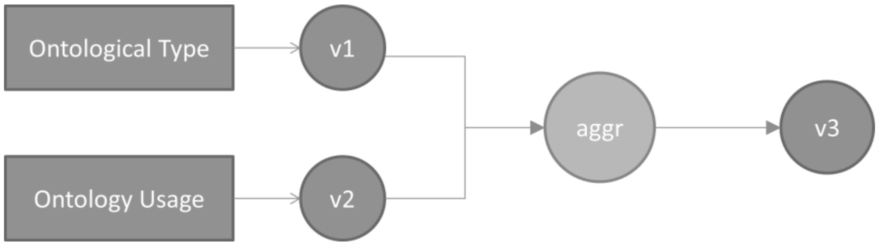

Figure 16 – Process of combining the gain values obtained in Ontological Type and Ontology Usage Functions

The values outputted by the Ontology Type and Ontology Usage functions are combined via some aggregation process to generate a new value, e.g. average, min, max, weighted average.

4.5 Final Remarks

When it comes to the Relaxation process *per se*, it was implemented in such a way that it can be used independently from the Argumentation process. It can simply use any two sets of matches as input for the agents to negotiate, whether these have been generated from another Ontology Matching Negotiation mechanism or not. From this it follows that it can be treated as any other Ontology Matching Algorithm and the Experiments section (cf. Section 5.2) will reflect this.

5 Experiments

The following experiments were elaborated with two goals:

- to assess the validity of the Relaxation approach as a Ontology Matching Negotiation mechanism
- to verify how combining it with Argumentation-based approaches affects the quality of the generated alignments. While it has been hypothesized that combining the two approaches leads to better results, no documented experiments are available.

Two metrics will be considered of importance in these experiments: the alignment's accuracy , which here will correspond to the alignment's F-Measure, and the number of conflicts resolved via the negotiation. The higher the values in these two metrics, the better the alignment's quality. Nonetheless, according to the scenario the alignment will be used in, one of them may be of bigger importance than the other.

For assessing the alignment's accuracy, we will compare the results of the Relaxation-approach with the results of the OAEI 2011 participants and those obtained with the Three-Layer Argumentation Framework with two different configurations (one of them mimicking the MbA/FDO approach). This will allow us to assess the Relaxation-based approach in comparison with other Ontology Matching Algorithms.

Because conflict resolution is a metric relevant only when evaluating Ontology Matching Negotiation approaches' generated alignments, the results of the OAEI 2011 participants will not be considered when discussing this metric's results.

Further, we will be comparing the results obtained with the Combinations A and C described in Section 3, in order to assess the improvements over each of the individual approaches.

5.1 Set-up

This section describes the set-up process of the experiments which includes:

- the description and preparation of the adopted dataset;
- configuration of the agents in respect to:
    - the adopted matchers;
    - the relaxation process, namely considering the parameters introduced in the previous section;
    - the argumentation processes, namely considering the argumentation models and respective configuration.

These topics will be addressed in the following sections.

Additionally, keep in mind that several assumptions were made when developing the prototype which generated the results seen in this section. Specifically:

- The Relaxation approach only runs one iteration, at the end of which the generated alignment is presented;
- The negotiation process must always generate an alignment, even if it is one the agents would not consider advantageous;
- No heuristic methods of modifying the generated alignment are implemented.

5.1.1 Dataset

Concerning the data set, several ontologies of overlapping domains were used, taken from the OAEI 2011 Conference Track repository [16], along with 21 reference alignments. For the sake of simplicity, these are grouped and treated as one big alignment, with 305 correspondences as suggested by the gold standard alignments provided. As a comparison metric, we present the matching results of the OAEI 2011 participants for the same dataset in Table 4 (adapted from [34]).

Table 4 – OAEI 2011 participants' results for the considered dataset

Matching System	Precision %	Recall %	F-Measure %
YAM++	78	56	65
CODI	74	57	64
LogMap	84	50	63
AgreementMaker	65	59	62
MaasMatcher	83	42	56
CSA	50	60	55
CIDER	64	45	53

Matching System	Precision %	Recall %	F-Measure %
MapSSS	55	47	51
Lily	36	47	41
AROMA	35	46	40
Optima	25	57	35
MapPSO	21	25	23
LDOA	10	56	17
MapEVO	15	2	4
Average	49,64%	46,36%	44,93%

5.1.2 Agents

Three negotiation agents have been devised – A, B and C. To ensure that the results observed are in fact representatives of the matching and negotiation capabilities of the agents, these have been sorted in two different pairs: (i) agents A and B and (ii) A and C . The matches used by the agents in the negotiation process are generated using the GECAD Ontology Alignment system (GOAlS) [23]. The specific matching algorithms and the ways these were combined for each agent are described below.

Agent A uses the following matching algorithms:

- M_{a1}: WNMatcher, the standard WordNet-based matching algorithm, available in the CROSI Mapping System (CMS) [35] ;
- M_{a2}: A string-based matching algorithm available in the FALCON-AO system [36];
- M_{a3}: V-Doc [37], a matching algorithm available in the FALCON-AO, which discovers matches by exploring the context of domain entities presented in the ontologies;
- M_{a4}: corresponds to the aggregation of M_{a1} and M_{a2} by means of a maximum function;
- M_{a5}: GMO [38], also available in the FALCON-AO system, discovers matches by measuring the structural similarity of the ontologies' entities;
- M_{a6} : corresponds to the aggregation of the alignments generated by the algorithms M_{a1}, M_{a2} and M_{a3} through means of a maximum function.

Agent B uses the following matching algorithms:

- M_{b1}: the string-based matching algorithm presented in the SimMetrics[1] project, exploiting the phonetic Soundex algorithm [39] [40];
- M_{b2}: an improved WordNet-based matching algorithm (WNPlusMatcher), available in CMS [35];
- M_{b3}: is the aggregation of the alignments generated with M_{b1}, M_{b2} and M_{b6}, which is a string-based algorithm available in SimPack [41] that exploits the frequency of sub-strings with length 2 in a given string (BiGram). The alignments are aggregated with an OWA operator [42];
- M_{b4}: is the standard structure-based matching algorithm, the StructureMatcher, available in CMS [35];
- M_{b5}: is the aggregation of the alignments generated through M_{b2} and M_{b7}, which is the string distance matching algorithm SMOA [43], available through the Alignment API[2];

Finally, Agent C uses the following matching algorithms:

- M_{c1} is the Levenshtein string distance matching algorithm [44], available on the SimMetrics project;
- M_{c2} is the matching algorithm M_{b2}, the WNPlusMatcher, which has been previously described;
- M_{c3} corresponds to the aggregation of the alignments generated by M_{c1}, M_{c2} and M_{c6}, which is the SMOA algorithm previously described for M_{b7}, through means of an average function;
- M_{c4} is the aggregation of the alignments generated by M_{c6} and M_{c7}, which is the output of an improved structure-based algorithm, the StructurePlusMatcher, available in CMS [35] and filtered through the Hungarian method [45] (M_{c8}). The resultant alignment is then aggregated with the results of the aggregation of the alignments generated through M_{c6} and M_{c7} via a linear average function;
- M_{c5} is the aggregation of the alignments generated through M_{c2}, M_{c6} and M_{c7} via the maximum function. The result is then globally optimized by applying the Hungarian method [45].

[1] This project is available at http://sourceforge.net/projects/simmetrics/
[2] The Alignment API is Java-based and is available at http://alignapi.gforge.inria.fr/

5.1.3 Argumentation's Configurations

5.1.3.1 Mimicking the MbA/FDO approach

The ANP-TLAF can mimic the results obtained through the MbA/FDO approach. However, in order to do so, several assumptions and constraints have to be made. Namely:

- All agents must adopt the community's argumentation model, but should not extend it privately;
- Each agent exploits two matching algorithms: one for generating terminological arguments and another for generating external structural arguments;
- Intentional Arguments are instantiated according to the most preferred argument-type of the agent;
- *TerminologicalArg* and *ExtStructuralArg* are evaluated by a function returning a value k stating whether the argument does or does not hold;
- Intentional arguments are evaluated by a function which mimics the MbA/FDO's evaluation process, where the agents express their preferences concerning argument-types (or values, in the VAF terminology);

The ANP-TLAF will mimic the MbA/FDO approach with a configuration such that:

- Agent A prefers terminological arguments (T) to external structural arguments (ES). This is stated in MbA/FDO through $\mathrm{P} = \{\mathrm{T}, \mathrm{ES}\}$;
- Agents B and C prefer external structural arguments to terminological arguments, i.e. $\mathrm{P} = \{\mathrm{ES}, \mathrm{T}\}$.

5.1.3.2 Exploiting the ANP-TLAF-based approach

The other configuration-set aims to exploit the features of ANP-TLAF-based approach and corresponds to Scenario 9 of [34]. To do so, agents adopt the common argumentation model, while each agent has its own private extension.

The argumentation models for each agent are depicted in Figure 17, Figure 18 and Figure 19. The grey colored components are the common argumentation model while the white ones are the private extensions made by each agent. Dashed line squares represent Statements and solid line square represent Non-Intentional Arguments. The oval-shaped entities represent Intentional Arguments.

The terminological argument is considered defeasible in these three argumentation models and, as such, each agent introduces new arguments affecting it. These new arguments, however, are themselves indefeasible. The new arguments must be interpreted as follows:

- *LabelArg* is an argument stating the similarity between the labels associated with the two ontological entities;
- *SyntaticLabelArg* is a specialization of the *LabelArg* argument which considers the application of a syntactic technique to evaluate the similarity of the labels;

- *LexicalLabelArg* is another specialization of the *LabelArg* which exploits lexical resources, such as the WordNet [46];
- *WNLabelArg* is an argument similar to *LexicalLabelArg* but which has been named differently by Agent C. This happens because each agent has its own private conceptualization and thus two agents may regard the same kind of argument differently;
- *SoundexLabelArg* is an argument stating the similarity of labels considering the sound of these when pronounced [39] [40].

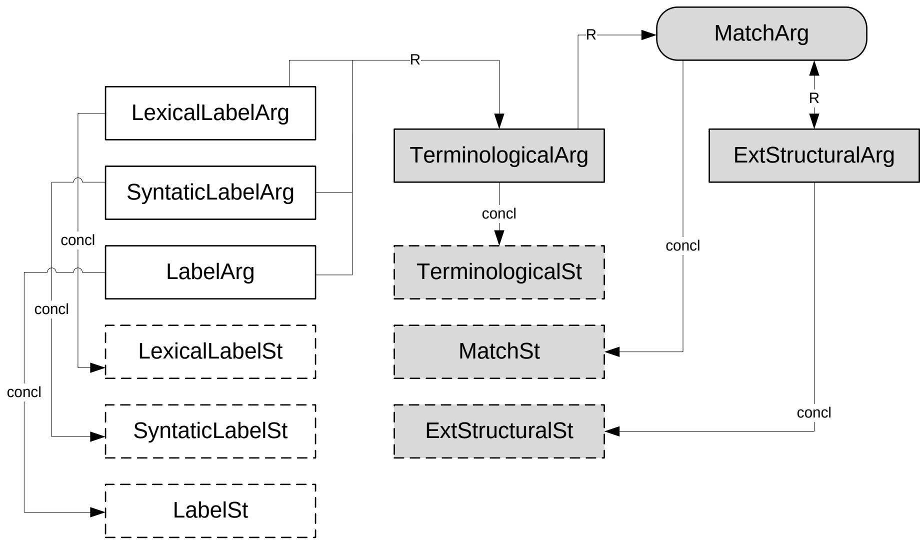

Figure 17 – The internal argumentation model adopted by Agent A (EAF_A)

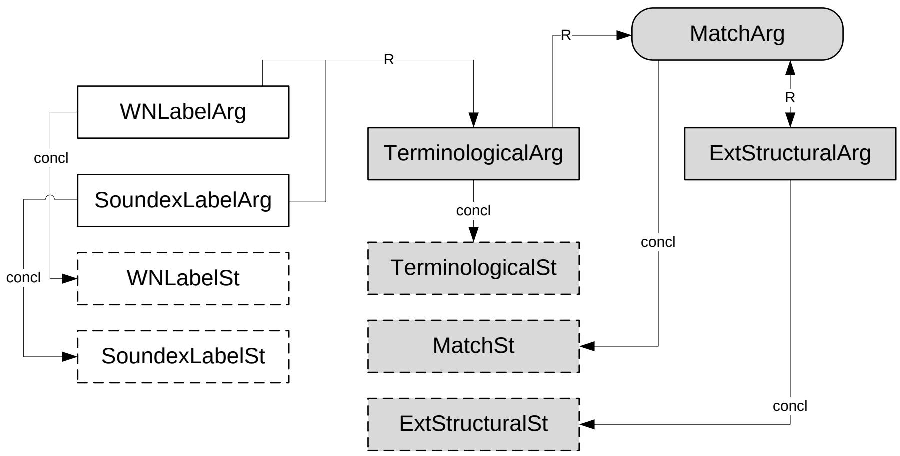

Figure 18 – The internal argumentation model adopted by Agent B (EAF_B)

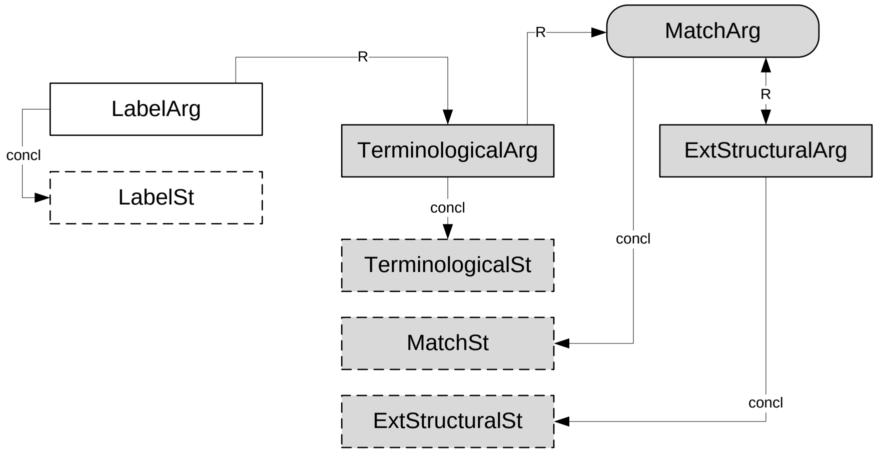

Figure 19 – The internal argumentation model adopted by Agent C (EAF_C)

5.1.4 Relaxation's Configurations

In order to perform the experiments and evaluations of the new Relaxation approach, several configuration parameters must be decided. After a thorough and careful analysis of the impact of each variable in the generated alignment, it was decided to use the Relaxation's Parameters as presented in the Table 5, Table 6 and Table 7. Based on such analysis, these are those that produce an alignment with a better ratio of accuracy and conflict resolution. For a more detailed explanation of how these configurations were achieved, cf. Annex A – Relaxation's Configurations. The agents' threshold parameters are presented in Table 5:

Table 5 - Relaxation Thresholds

Agent	tr	tn	tp	tm
Agent A	0.60	0.85	0.93	1.0
Agent B	0.60	0.85	0.99	1.0
Agent C	0.60	0.85	0.95	1.0

The agents' effort and gain functions' parameters are presented in Table 6:

Table 6 - Effort and Gain calculation parameters

Agent	*effP*	Function[3]
Agent A	8	Usage
Agent B	8	Type
Agent C	8	Usage

[3] "Type" and "Usage" descriptors correspond, respectively, to the Ontological Type and the Ontology Usage functions mentioned in Section 4.4 - Gain Functions.

Agent B is using the Ontological Type function, with the following parameters:

Table 7 - Ontology Usage function parameters for Agent B

Source \ Target	Class	Object Property	Datatype Property
Class	0.20	0.15	0.15
Object Property	0.15	0.20	0.15
Datatype Property	0.15	0.15	0.20

5.2 Relaxation-based negotiation

In the following experiments we compare the Relaxation-based approach results with those obtained with the Argumentation-based approaches. The MbA/FDO method's results were obtained using the Three-Layer Argumentation Framework, as described in [31], Scenario 1. The results described as ANP-TLAF are those obtained while running the configurations seen in Scenario 9 of [31], as previously described.

With these experiments, we want to assess not only the benefits in terms of conflict resolution but also the consequences in terms of the accuracy of the alignments. The Relaxation-based negotiation approach is divided twofold, according to the two proposals previously presented: (i) considering local benefit only and (ii) combining local and global benefits.

5.2.1 Relaxation-Based negotiation benefits

In order to assess if agents are profiting from the negotiation process, it is relevant to know the accuracy of the alignment they have initially proposed and compare it to the accuracy of the final agreement. Table 8 compares the agents' initial proposals with the alignment they reach after consensus.

Table 8 – Comparing Agents' Initial Proposals with the Agreements achieved

	# of Matches	# of which are correct	Precision	Recall	F-Measure
Agent A's Initial Proposal	313	159	50,80%	52,13%	51,46%
Agent B's Initial Proposal	833	177	21,25%	58,03%	31,11%
Agent C's Initial Proposal	329	165	50,15%	54,10%	52,05%
Relaxation – local benefit					
A&B's Agreement	201	149	74,13%	48,85%	58,89%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
Relaxation – global and local benefit					
A&B's Agreement	230	156	67,83%	51,15%	58,32%
A&C's Agreement	210	155	73,81%	50,82%	60,19%

The results of Table 8 are graphically depicted in Figure 20 and Figure 21:

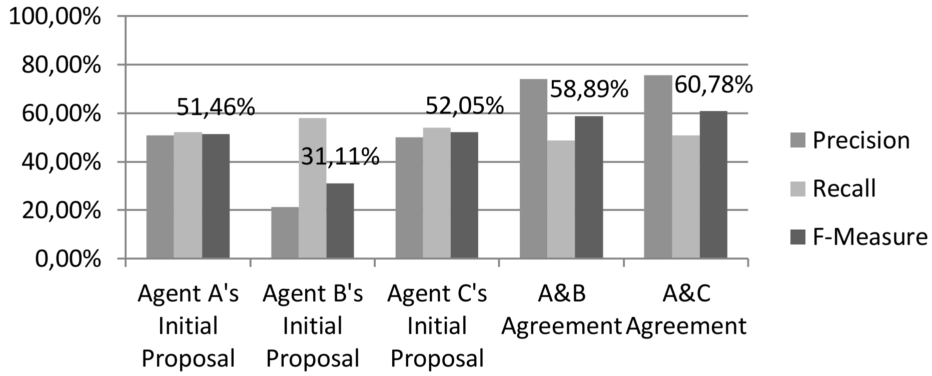

Figure 20 – Comparing Agents Initial Proposals with the Agreements achieved through Relaxation, considering only local benefit

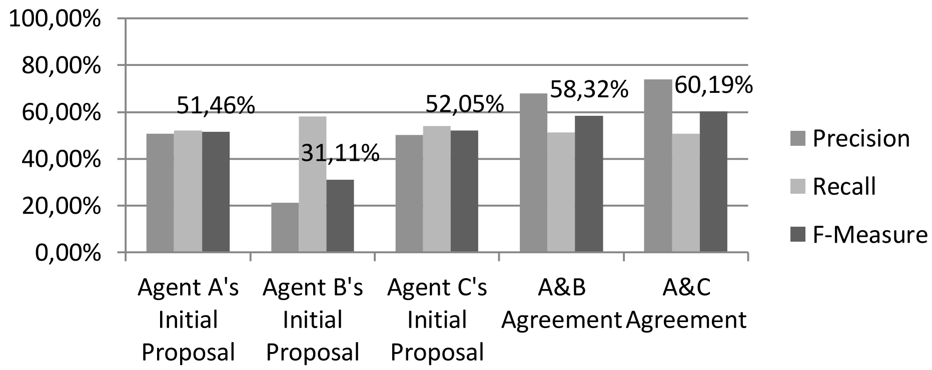

Figure 21 - Comparing Agents Initial Proposals with the Agreements achieved through Relaxation, combining local and global benefit

In both cases, agents clearly benefit from engaging in a Relaxation-based negotiation process since the agreement's accuracy is higher than their initial proposals, both in terms of precision and F-Measure. This benefit, however, seems to be slightly superior when considering only a local perspective.

The number of correct matches is lower on the agreements than on the initial proposals since some of the matches are only known to one of the agents. These are therefore excluded from the process, since agents can only negotiate about what they both know. From this follows a slight decrease on the recall, which in turns affects the F-Measure.

5.2.2 Alignment Accuracy

The Relaxation approach will be compared to the argumentation approaches MbA/FDO and ANP-TLAF in order to assess if it can achieve results comparable in terms of quality.

Furthermore, since the Relaxation-based process was modified to become completely automatic, it is relevant to compare its results with other automatic matchers too. For that, it will be compared as well to the results of the OAEI 2011 participants for the same dataset. Concerning these, an average of the results is presented, along with the best and worse values of Precision, Recall and F-Measure. The comparison of results is presented in Table 9.

Table 9 - Comparing MbA/FDO, Relaxation, ANP-TLAF and the OAEI 2011 results

	# of Matches	# of which are correct	Precision	Recall	F-Measure
Maximum from OAEI	-	-	84,00%	60,00%	65,00%
Minimum from OAEI	-	-	10,00%	2,00%	4,00%
OAEI 2011 Average Results	-	-	49,64%	46,36%	44,93%
	MbA/FDO				
A&B's Agreement	218	149	68,35%	48,85%	56,98%
A&C's Agreement	257	167	64,98%	54,75%	59,43%
	ANP-TLAF				
A&B's Agreement	276	176	63,77%	57,70%	60,59%
A&C's Agreement	237	159	67,09%	52,13%	58,67%
	Relaxation – local benefit				
A&B's Agreement	201	149	74,13%	48,85%	58,89%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
	Relaxation – local and global benefit				
A&B's Agreement	230	156	67,83%	51,15%	58,32%
A&C's Agreement	210	155	73,81%	50,82%	60,19%

The results presented in Table 9 are graphically depicted in Figure 22, for agents A and B, and Figure 23 for agents A and C.

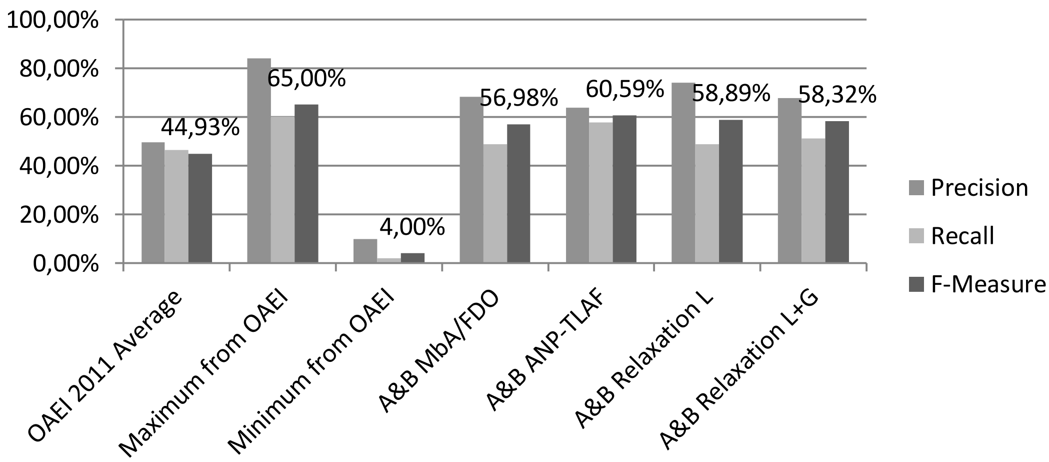

Figure 22 – Comparing Relaxation's alignment accuracy values with those of other OMNs for agents A and B

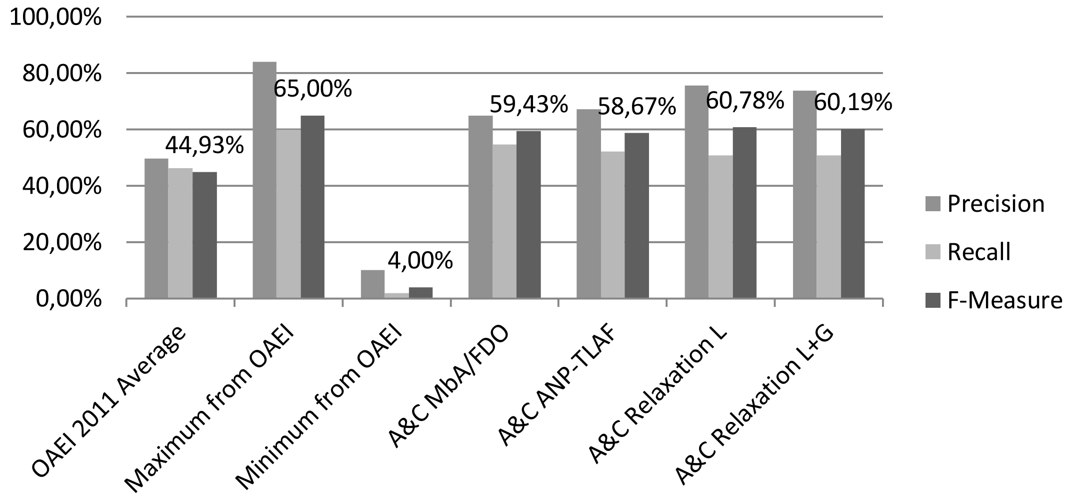

Figure 23 – Comparing Relaxation's alignment accuracy values with those of other OMNs for agents A and C

In both scenarios, both Relaxation results are shown to be better than the average results of the OAEI 2011 participants for this dataset, but inferior to the best. The results are also slightly superior to those of the MbA/FDO approach, but only for a very small margin (in the best scenario, the increase was only slightly above 1%). As for comparing with the ANP-ANP-TLAF's results, the Relaxation-based approach generates a more accurate alignment for agents A and C, but not for agents A and B.

5.2.3 Conflict Resolution

We consider that the more conflicts are correctly resolved the better and more significant the agreement is. The ideal scenario would be having all conflicts correctly resolved, i.e. when agents agree about including all the correct matches and excluding all the incorrect ones. It is possible to evaluate the impact of resolving conflicts by comparing the intersection of both agents' proposals with the final agreement. Table 10 depicts the obtained results.

Table 10 - Comparing Intersections with Agreements

	# of Matches	# of which are correct	Precision	Recall	F-Measure
A&B's Intersection	199	149	74,87%	48,85%	59,13%
A&C's Intersection	204	154	75,49%	50,49%	60,51%
	Relaxation – local benefit				
A&B's Agreement	201	149	74,13%	48,85%	58,89%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
	Relaxation – local and global benefit				
A&B's Agreement	230	156	67,83%	51,15%	58,32%
A&C's Agreement	210	155	73,81%	50,82%	60,19%

The results presented in Table 10 are graphically depicted in Figure 24 and Figure 25:

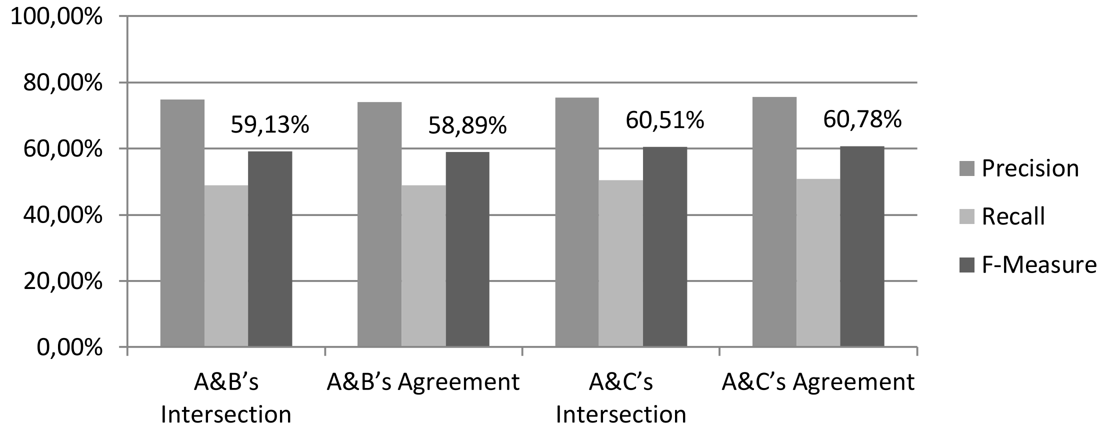

Figure 24 – Comparing alignments' intersection with the agreements achieved through Relaxation, considering only local benefit

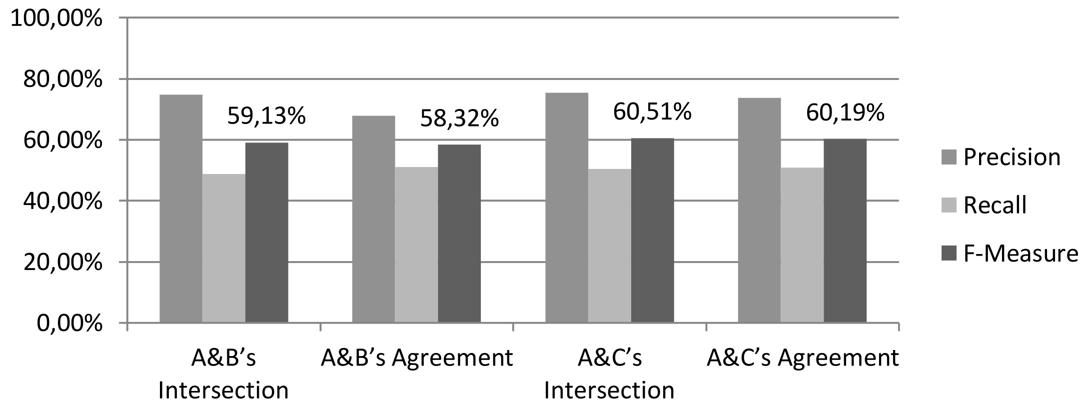

Figure 25 – Comparing alignments' intersection with the agreements achieved through Relaxation, considering local and global benefit

Through the analysis of Table 10, it is possible to see that there is a slight decrease on F-Measure in both scenarios. This happens because some of the conflicts were incorrectly resolved, thus reducing the precision. The decrease observed in F-Measure is, however, below 1% on both cases. One can argue that this is almost statistically insignificant and also comes with an increase on the alignment's soundness, since the number of resolved conflicts is very high in both scenarios. In fact, the observations concerning the accuracy of the conflicts resolved are presented in Table 11:

Table 11 - Resolved conflicts and their accuracy for the Relaxation approach

Relaxation – local benefit				
Agents	# Matches		% Conflicts	
	Initial	Remain	Resolved	Correctly
A vs B	748	35	95,32%	94,53%
A vs C	234	44	81,20%	92,63%
	Relaxation – local and global benefit			
Agents	# Matches		% Conflicts	
	Initial	Remain	Resolved	Correctly
A vs B	748	39	94,79%	92,24%
A vs C	234	45	80,77%	89,95%

While the results obtained by combining local and global benefits are slightly inferior to those obtained when considering only local benefits, the difference is, nonetheless, small (between 1% and 3%). Both scenarios show, however, the same tendency: it is evident that the number of conflicts resolved is very high and the percentage of these which are correctly done is very high as well. With such a low number of matches remaining in conflict, one can question if properly resolving those remaining conflicts would improve the alignment's accuracy. It is possible to argue that this is due to the initial proposal's intersections, since matches are only being added to it, and not removed from it. This means that if an agent has an initial proposal with very low accuracy, it is likely to generate bad alignments, unless it is willing to relax its position when engaging in the negotiation with a persuasive partner with a very good proposal, such that the newly added matches will dilute the impact of those which were incorrectly added before.

5.2.4 Final Remarks

Experiments show that results with similar tendencies can be achieved with both of the devised relaxation functions. Both functions provide good results, both in terms of alignment accuracy and conflict resolution. However, since those obtained by considering only local profit achieve better results both in terms of conflict resolution and in alignment's accuracy, this approach is the one considered in the rest of the document. The combination of global and local profits will no longer be considered in the following experiments.

Yet, it is worth to notice that with such decision it is possible that agents are agreeing to an alignment that might not be globally beneficial to them, even if it is one with high accuracy or a low number of remaining conflicts. This alignment is not globally evaluated and thus might not be beneficial to one or both the individual agents.

5.3 Combination A

This section presents the experiments and evaluation of Combination A, which runs the Argumentation-based approach first and the Relaxation-based second.

5.3.1 Alignment's Accuracy

Because Combination A has the Argumentation phase running first and only then the Relaxation phase, it is important to compare the results of the Combination with those attained with the Argumentation approaches only. This way, we can see how much the Relaxation phase is improving or not on the Argumentation phase.

Table 12 –Alignment Accuracy of Combination A with MbA/FDO and ANP-TLAF

	# of Matches	# of which are correct	Precision	Recall	F-Measure
		MbA/FDO			
A&B's Agreement	218	149	68,35%	48,85%	56,98%
A&C's Agreement	257	167	64,98%	54,75%	59,43%
		ANP-TLAF			
A&B's Agreement	276	176	63,77%	57,70%	60,59%
A&C's Agreement	237	159	67,09%	52,13%	58,67%
		Relaxation			
A&B's Agreement	201	149	74,13%	48,85%	58,89%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
		MbA/FDO + Relaxation			
A&B's Agreement	218	149	68,35%	48,85%	56,98%
A&C's Agreement	257	167	64,98%	54,75%	59,43%
		ANP-TLAF + Relaxation			
A&B's Agreement	276	176	63,77%	57,70%	60,59%
A&C's Agreement	237	159	67,09%	52,13%	58,67%

These results are graphically depicted in Figure 26 for agents A and B and in Figure 27 for agents A and C.

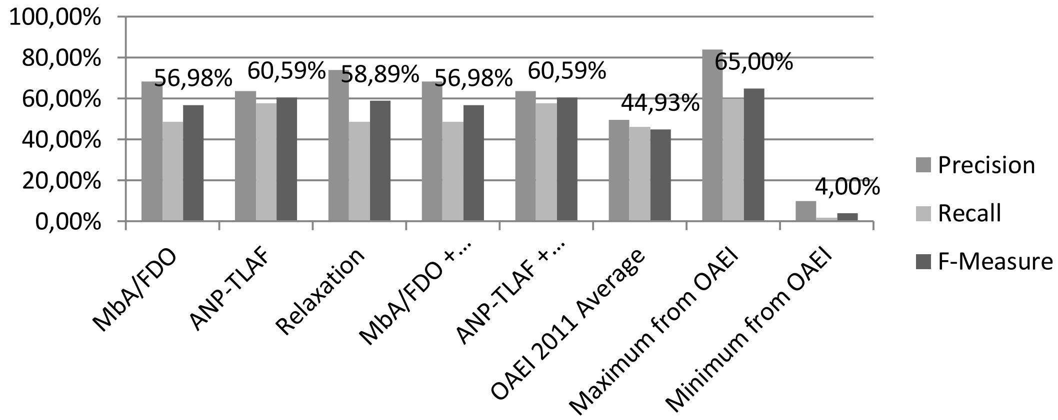

Figure 26 – Alignment Accuracy of Combination A with MbA/FDO and ANP-TLAF for agents A and B

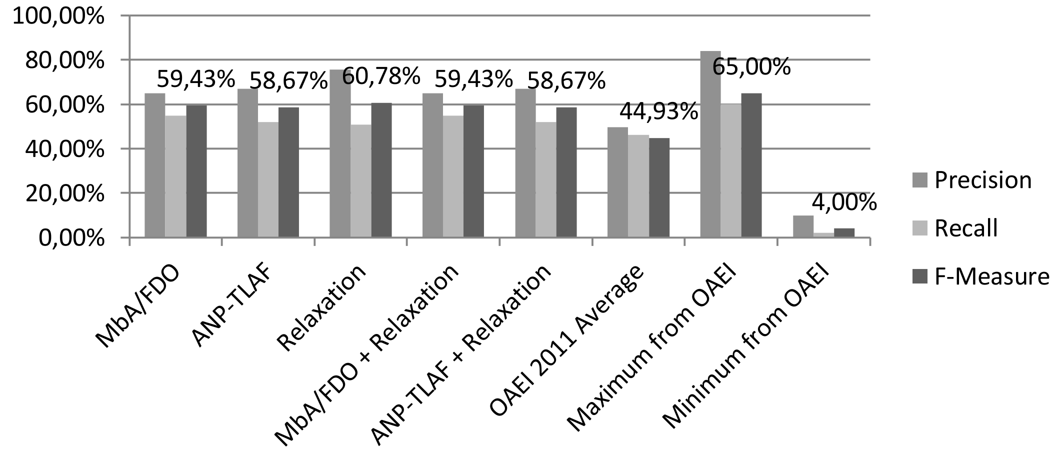

Figure 27 – Alignment Accuracy of Combination A with MbA/FDO and ANP-TLAF for agents A and C

It is possible to see that applying the Relaxation process after the Argumentation's does not show any difference in terms of the reached agreement's accuracy, meaning that no matches are being removed from the Disagreements in order to be added to the Agreements. This may be because the matches in conflict have such low confidence values that they are not considered "proposed", thus meaning the previous Argumentation phase has dealt with all the matches the Relaxation phase could possible re-evaluate for inclusion.

5.3.2 Conflict Resolution

Since the agreed alignments show the same values of Precision, Recall and F-Measure, it is important to know if these alignments are more or less sound than those achieved without the Relaxation phase. For that, the number of correctly solved conflicts is once again considered. Table 13 shows the results of the ANP-TLAF approach as well for a comparative measure:

Table 13 - Resolved conflicts and their accuracy for the Combination A and those of ANP-TLAF and MbA/FDO

Agents	# Matches		Conflicts	
	Initial	Remain	Resolved	Correctly
	ANP-TLAF			
A vs B	995	238	76,08%	94,06%
A vs C	356	137	61,52%	93,15%
	Relaxation			
A vs B	748	35	95,32%	94,53%
A vs C	234	44	81,20%	92,63%
	MbA/FDO + Relaxation			
A vs B	1319	50	94,62%	96,47%
A vs C	493	35	92,90%	94,10%
	ANP-TLAF + Relaxation			
A vs B	995	62	97,19%	93,28%
A vs C	356	55	96,07%	88,60%

The results presented in Table 13 are graphically described in Figure 28 for agents A and B and Figure 29 for agents A and C.

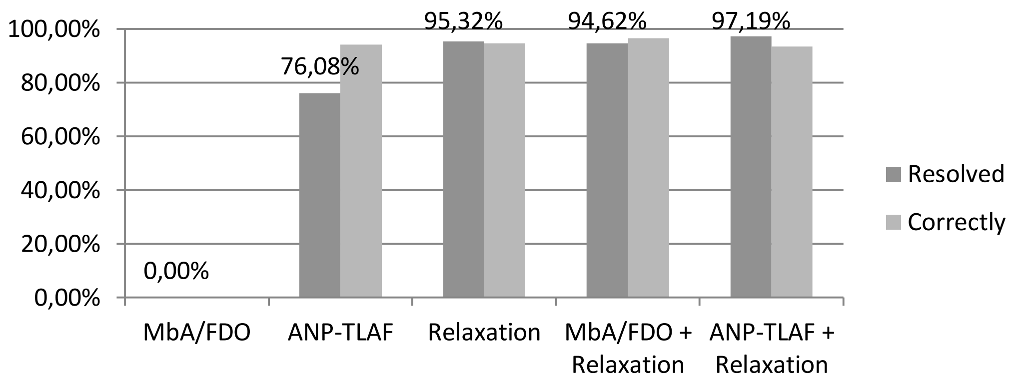

Figure 28 – Combination A's percentage of conflicts resolved and their accuracy for agents A and B

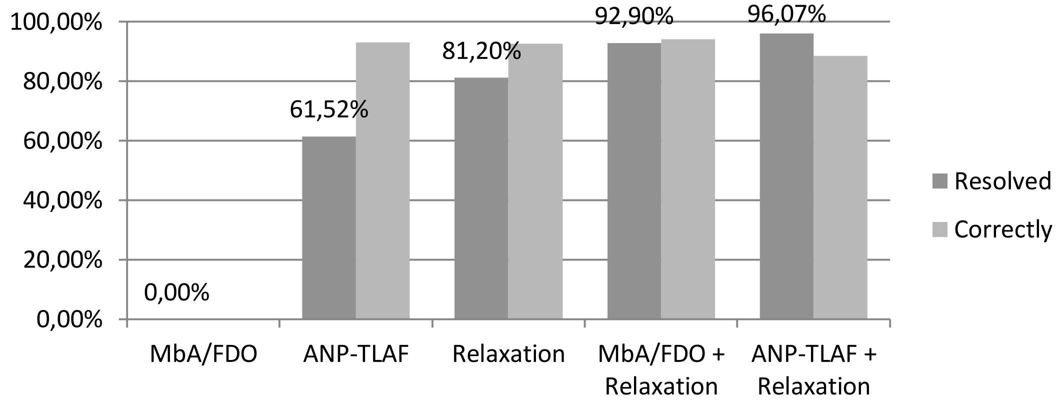

Figure 29 – Combination A's percentage of conflicts resolved and their accuracy for agents A and C

When reading Table 13 it is important to notice that the MbA/FDO approach does not solve any conflicts. Accordingly, all the solved conflicts are an improvement upon the reached agreement. When the Relaxation phase takes places, the amount of resolved conflicts centers around 93%, with an equally high amount of those correctly solved.

On the combination of ANP-TLAF with Relaxation it is possible to see that there are more solved conflicts but a lower accuracy; although more conflicts are being resolved, the percentage of these which are correctly resolved is lower. However, one can argue about the relevance of this decrease in accuracy – it is only around 4% and can be weighed against the number of resolved conflicts, which shows an improvement between 20% and 30%.

We must also consider that the alignments' accuracy, as previously seen, is not decreasing with the usage of relaxation efforts. This means that although the Relaxation phase is solving a lot more conflicts, it is discarding some correct matches in the process and thus not including them on the generated alignment. On the other hand, it is not adding any incorrect matches either. It is worth to note that the matches excluded by the Relaxation phase were not part of the reached alignment on the ANP-TLAF, and thus the alignment's accuracy is not affected.

5.4 Combination C

This section presents the experiments and evaluation of Combination C, which runs the Relaxation-based approach first and then the Argumentation-based approach.

5.4.1 Alignment's Accuracy

Combination C runs the Relaxation phase first and then feeds its results into the Argumentation phase. Therefore, if we want to assess how the Argumentation phase is improving – or not – on the Relaxation phase, it is necessary to compare the results of the combination with those obtained when running the Relaxation process only. Table 14, below, presents the results obtained through Combination C:

Table 14 – Alignment Accuracy of Combination C when combined with MbA/FDO and ANP-TLAF

	# of Matches	# of which are correct	Precision	Recall	F-Measure
		MbA/FDO			
A&B's Agreement	218	149	68,35%	48,85%	56,98%
A&C's Agreement	257	167	64,98%	54,75%	59,43%
		ANP-TLAF			
A&B's Agreement	276	176	63,77%	57,70%	60,59%
A&C's Agreement	237	159	67,09%	52,13%	58,67%
		Relaxation			
A&B's Agreement	201	149	74,13%	48,85%	58,89%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
		Relaxation + Mba/FDO			
A&B's Agreement	206	149	72,33%	48,85%	58,32%
A&C's Agreement	205	155	75,61%	50,82%	60,78%
		Relaxation + ANP-TLAF			
A&B's Agreement	216	151	69,91%	49,51%	57,97%
A&C's Agreement	207	156	75,36%	51,15%	60,94%

The results presented in Table 14 are graphically depicted in Figure 30 for agents A and B and in Figure 31 for agents A and C.

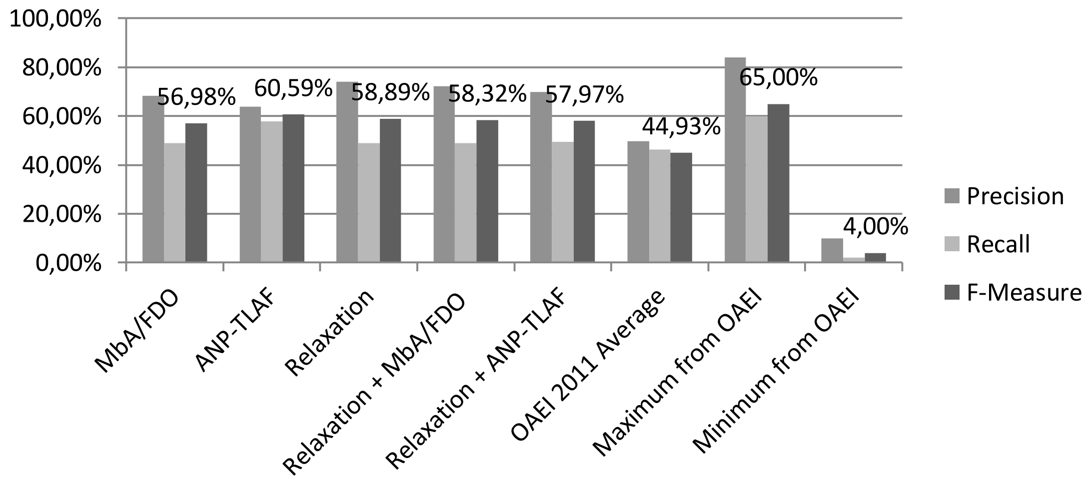

Figure 30 – Alignment Accuracy of Combination C when combined with MbA/FDO and ANP-TLAF for agents A and B

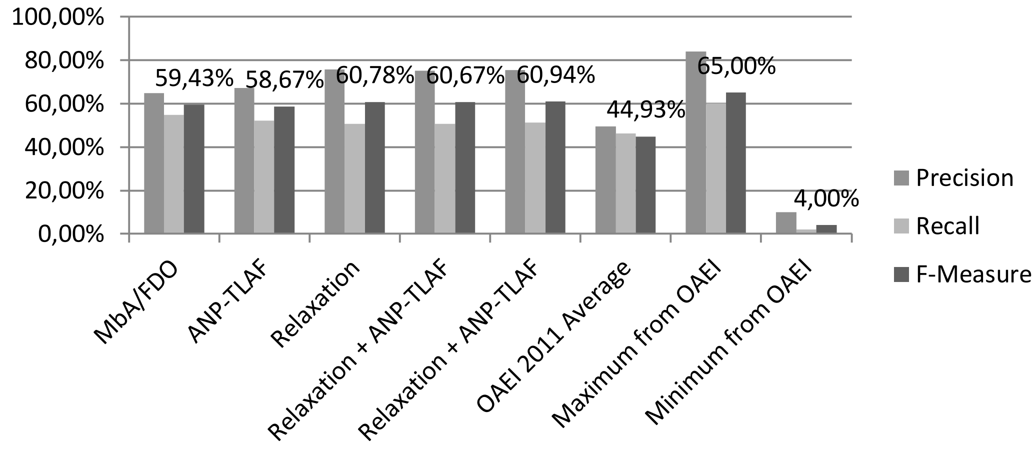

Figure 31 - Alignment Accuracy of Combination C when combined with MbA/FDO and ANP-TLAF for agents A and C

Because Combination C runs the Relaxation phase first, we can assess how the ANP-TLAF phase affects the results by comparing these with those obtained through the Relaxation approach only.

Agents A and B show better results when using the Relaxation-approach only than when combined with both the Argumentation-based approaches. The difference, however, is at most around 1%. The same does not happen for agents A and C, where the alignment's F-Measure is maintained or improved in a statistically insignificant value.

It is possible that this slight variance is happening because the Relaxation-based approach already had a high number of resolved conflicts (95% and 80%), meaning that the Argumentation-based approaches that follows have a very small number of remaining conflicts to deal with. Such a low number may mean that even though they may be resolving the conflicts properly and even introducing more correct matches to the alignment, the alignment's accuracy will not suffer significant changes.

5.4.2 Conflict Resolution

Once again, it is relevant to compare the results of Combination C with those obtained with the Relaxation approach only. The results on conflict resolution are presented in Table 15:

Table 15 - Resolved conflicts and their accuracy for Combination C

Agents	# Matches		Conflicts	
	Initial	Remain	Resolved	Correctly
	Relaxation			
A vs B	748	35	95,32%	94,53%
A vs C	234	44	81,20%	92,63%
	Relaxation + MbA/FDO			
A vs B	748	1	99,87%	94,31%
A vs C	234	3	98,72%	93,67%
	Relaxation + ANP-TLAF			
A vs B	748	1	99,87%	93,17%
A vs C	234	9	96,15%	93,78%

The results presented in Table 15 is graphically represented in Figure 32 for agents A and B and in Figure 33 for agents A and C.

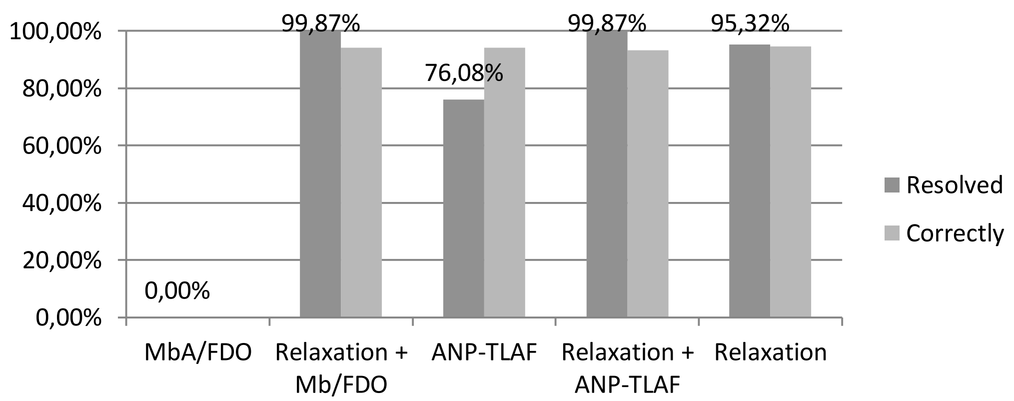

Figure 32 – Combination C's percentage of conflicts resolved and their accuracy for agents A and B

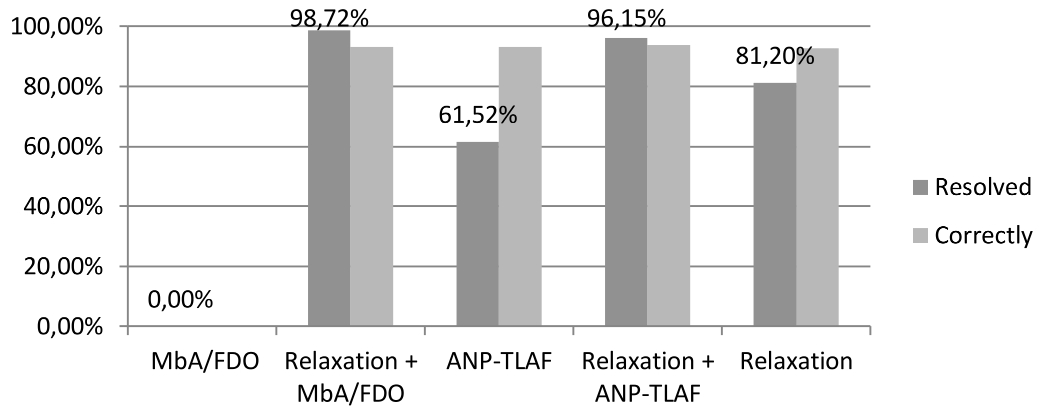

Figure 33 – Combination C's percentage of conflicts resolved and their accuracy for agents A and C

Both tests show that there's an improvement on the number of resolved conflicts, especially for agents A and C. Actually, these results show that Combination C can achieve high numbers of resolved conflicts, reaching almost 100% and having the lowest at 96%. It is possible that these results are being achieved because the Relaxation-based approach already resolves many of the existing conflicts. Analyzing Table 15, there are 35 conflicts remaining for agents A and B and 44 for agents A and C. The following Argumentation-based approach has a much smaller set of matches to work with. Coincidentally, it seems that these few conflicts are part of the set the Argumentation-based approach can resolve.

5.5 Discussion and Final Remarks

Experiments show that combining the Argumentation-based and Relaxation-based approaches in a sequential mode generates an alignment that is better than those generated by the individual approaches. This improvement, however, is different for each combination.

Combination A does not bring improvements over the Argumentation-based approaches in terms of alignment's accuracy, but does so when it comes to conflict resolution, providing a bigger number of properly solved conflicts. Since no modifications are being made to the intermediary alignment generated by the Argumentation-based approach, it is possible to conclude that the Relaxation-based approach is only deciding on the removal of conflicting matches and thus not introducing any new matches to the alignment.

As for Combination C, while the accuracy results are, in most cases, slightly inferior to those obtained with the Relaxation-based approach only, the difference is, however, negligible. When it comes to the number and quality of conflicts resolved, however, Combination C achieves great results, resolving almost 100% of the conflicts.

It is interesting to compare the results obtained via the two different combinations. A comparison of the results obtained concerning alignment accuracy and conflict resolution is presented next.

When comparing the alignments' accuracies obtained through Combination C (cf. Table 14) with those obtained via Combination A (cf. Table 12), it is visible that Combination C produces slightly better results. This trend reports on all test cases, with the exception of Agents A and B when using the ANF-TLAF approach.

Similarly, when comparing the number and quality of conflicts resolved by Combination C (cf. Table 15) and of Combination A (cf. Table 13), Combination C also scores a higher number, with an almost perfect scenario of conflict resolution.

Combination C, on the other hand, shows better results when compared to Combination A, and therefore, when compared to the individual Argumentation-based approaches as well. In this scenario, the Argumentation-based approach is actually adding more correct matches to the alignment, thus improving its quality. And it is doing so while removing undesired matches, and thus also improving the number and quality of the conflicts resolved.

This shows that it is more profitable to run the approach which produces the better result first and leave the remaining conflicts to the second, since the second will not greatly hamper the intermediary alignment's accuracy and might actually bring some profit when it comes to conflict resolution.

6 Conclusions and Future Work

6.1 Conclusions

In a multi-agent system populated by several different agents, it is not reasonable to expect them to use the same ontology to describe their universe. When and if these agents are willing to interact, they must first reconcile their ontologies. However, because of the ontology's very subjective nature and each agent's individual need and objectives, the generation of candidate alignments may lead to different and even conflicting results. These conflicts between the agents must be addressed and resolved in a negotiation process.

Two different Ontology Matching Negotiation approaches have been proposed in the literature, namely Argumentation-based and Relaxation-based approaches. It has been hypothesized that combining the two processes would result in a mechanism which overcomes each of the basic approach's limitations while exploiting its advantages. Consequently, the alignments generated would be better than those obtained with the basic approaches as well.

The work presented here explored and developed different combinations of Argumentation-based and Relaxation-based Ontology Matching Negotiation approaches which have been proposed in literature. For that, it analyzed the existing approaches and suggested modifications before the combination deployment. These reflect mainly on the Relaxation-based approach, which is now fully automatic and provides a means to increase the number and quality of conflicts resolved.

Two different possibilities have been devised on the improvement of the Relaxation-based approach, namely (i) considering only local gains and profit, balancing these values in the end and revising the agreement if it is not advantageous to both and (ii) combining local and global gains and profits and using them in each match's negotiation, allowing an agent to decide how much effort it can make considering the profits obtained in previous matches' negotiations. While both possibilities have their limitations, the combination of local and global values has the downside of relying on the order the matches are negotiated, hence needing strong revision before it can be properly used.

Combinations A and C have been chosen for implementation because of their composition and process granularity characteristics, which allow for easier comparison of the data obtained with that of the basic approaches while also allowing the reuse of existing implementations.

Through experimentation, it was possible to prove that combining the basic approaches produces better results than when using individual techniques. Specifically, Combination A improves the number and accuracy of resolved conflicts, while Combination C improves both on the alignment's accuracy and the number and correctness of the conflicts resolved. This means that running the approach with better results first produces better alignments – and it is possible to improve on the results obtained with Combination A if more of the possibilities provided by the ANF-TLAF platform are exploited.

When it comes to the combination of approaches sequentially, it is necessary to consider that once the second phase will feed only on the conflicts remaining from the first, it cannot verify if the matches already agreed include any wrong matches; in fact it will only verify if any matches on the Disagreements can be used to improve the final results or if these should be excluded. In the end, the improvements provided by the second phase rely on the amount and quality of the matches the agents could not agree upon on the first phase.

Hence, empirically, if the first phase achieves great results in terms of alignment accuracy, the second phase will not offer much improvement on the metric. It can, though, affect the amount of solved conflicts by attempting to resolve the existing disagreements, possibly leading to an agreement with a higher degree of confidence. This is particularly visible for Combination C, where the Relaxation-based approach already produces good results which are further improved by the Argumentation-based approach, but only very slightly in terms of accuracy and rather dramatic in terms of conflict resolution.

Parameter variation in the Relaxation-approach is very closely related to the quality of the alignment the agents can reach. The comparisons here presented show that improving the Initial Proposals of all agents is very beneficial to the agreement, while using high effort powers reduces the number of resolved conflicts, but improves their correctness.

6.2 Open Issues and Future Work

Even though the experiments provide positive results both for the Relaxation approach and for the two implemented combinations, the modified Relaxation-based approach proposed in this document can still be further improved.

While the improved Relaxation-based approach presents positive results, there's still the open issue of having an alignment which is advantageous to both agents. This approach only considers local profits and gains and it is possible that the alignments are not accepted by both parties. The usage of heuristic methods to modify the generated alignment until both agents have a positive balance is still an open issue.

Concerning the combination of local and global profit for the Relaxation-based approach, there are still several limitations. This approach is easily influenced by the order the matches are negotiated; this issue can be addressed if the process is iterative, such that matches previously added to the Disagreements may be reevaluated in the next iteration, where it is possible that agents have already achieved enough accumulated gain to be able to engage in a relaxation effort. The addiction of more iterations to the process leads to Combinations B and D and also provides a scenario where agents can use strategic behavior to get more of their proposed matches accepted.

It is also worth noting that, unlike the ANP-TLAF, the Relaxation approach does not consider dependencies between matches. Since the Argumentation-based approaches achieve better results when they weight the relationships between matches, it may be interesting to see how it would work out for the Relaxation approach.

Further, when allowing the relaxation to work both for including and excluding matches, it is important to decide if precedence is given to any of the possibilities. The experiments described here had precedence given to the inclusion, but it would be an interesting exercise to see the results provided through the other possibilities. Additionally, there's the situation when both parties try to relax their positions simultaneously, which needs to be addressed.

Gain functions are a major issue that needs to be addressed. Attempting to compute the gain of having an entity in an alignment without knowing the context this alignment will be used in is tricky to say the least. The proposed functions try to counter this problem by providing a way to compute a quantitative value on something that's inherently subjective and qualitative. The solution could be improved, however, if it was known to the agents, beforehand, which instances the alignment will be translating. This way, they could assign more relevance to the ontological entities the instances actually mention. This, obviously, means that different alignments can be generated when different instances are provided for translation.

Finally, more combinations of Argumentation and Relaxation-based approaches are possible and should be explored. The significant differences between the results of Combination A and C prove just that.

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7 References

8 Annex A – Relaxation's Configurations

The Relaxation-based approach depends on a multi-threshold configuration in order to properly categorize the matches. Furthermore, it also relies on other values concerning the effort and profit functions. Here, a study of the results achieved through different configurations is presented. The tests shown were devised in order to understand how the variation in the values affects the alignment generated and to find the configuration with the best results.

In order to do this, a base configuration is presented (Table 16). The following configurations are variations of a single parameter of the base and a small discussion of the results is provided.

Table 16 – Relaxation's base configuration

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	6	Ontology Usage	-	-	-	-

8.1 Testing variations in Negotiable and Proposed Thresholds

The following tests have been designed to understand how changing the proposed and negotiable thresholds affect the amount of resolved conflicts.

8.1.1 Configuration 1 – Increasing the Proposed threshold for agents B and C

Table 17 – configuration 1: increasing the proposed threshold for agents B and C

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.99	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.99	1	6	Ontology Usage	-	-	-	-

Agent C has an Initial Proposal with a higher accuracy (increasing F-Measure by 6%). The F-Measure of Agent B's Initial Proposal improves by 5%.

The agreement's accuracy for agent A and B is lowered in 2%. The same tendency is reported for agents A and C agreement. The percentage of conflicts resolved drops around 4% for agents A and C and 2% for agents A and B. Both pairs report a decrease in the number of correctly resolved conflicts, reaching around 5%.

It is important to notice that the difference between the thresholds of agents B and C is now bigger, thus making it harder to relax their positions. This means that agent A is the one doing the most relaxations to solve conflicts (though exclusion) and that seems to be an impacting factor on reported decrease in the agreements' accuracy.

8.1.2 Configuration 2 - Increasing the Proposed threshold for agent A

Table 18 – configuration 2: increasing the proposed threshold for agent A

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.90	0.99	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	6	Ontology Usage	-	-	-	-

Agent A proposes less matches and slightly lowers its Initial Proposal's accuracy. As a consequence, both pairs report a decrease in the agreement's accuracy. The number and quality of the resolved conflicts also drops.

8.1.3 Configuration 3 - Increasing the Negotiable threshold for agents B and C

Table 19 – configuration 3: increasing the negotiable threshold for agents B and C

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.90	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.90	0.95	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.90	0.95	1	6	Ontology Usage	-	-	-	-

Increasing the negotiable threshold has no effect on agent B's Initial Proposal. This may be due the fact that this has very high confidence values in most matches, meaning that no matches are being considered negotiable instead of proposed. The same seems to be happening with agent C. No changes are reported when compared to the base configuration.

However, since the difference in thresholds is lower in this scenario, it is safe to consider that the possibility of relaxing confidence values for exclusion is more likely to happen.

8.1.4 Configuration 4 - Increasing the Negotiable threshold for agent A

Table 20 – configuration 4: increasing the negotiable threshold for agent A

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.90	0.95	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.90	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.90	1	6	Ontology Usage	-	-	-	-

There's an increase in the number of correctly resolved conflicts for the two test cases. This is probably a result of agent A's thresholds being more close together, thus making it easier to relax the confidence value.

8.1.5 Discussion

Variations in the agent's Initial Proposals seem to have a great impact on the agreement's quality. For that, it is useful to use configurations which boost the accuracies of the Initial Proposals for all agents.

Agent B proposes a very high number of matches, reaching a very high recall, but very low F-Measure values when compared to the other agents. It seems reasonable that, in order to improve its F-Measure, that the proposed threshold must be increased as much as possible.

It seems important to allow agent A to relax some of its negotiable matches into proposed, as that shows improvements in the agreements' accuracies. This can be achieved by trying to reach a middle ground between a good Initial Proposal and a closer gap between the agent's thresholds.

8.2 Testing variations in the Effort Power

The Effort Power value ($effp$) affects mainly the agent's ability to relax their positions when trying to solve a conflict. A number of variations upon the initial number are provided to understand how they affect the result.

8.2.1 Configuration 5 – Increasing Agent A's Effort Power

Table 21 – configuration 5: increasing the effort power of agent A

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	7	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	7	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	6	Ontology Usage	-	-	-	-

Agents A and B report an insignificant increase in the number of correctly resolved conflicts (but not in the total number of resolved conflicts). The number of conflicts resolved for agents A and C is also lowered.

8.2.2 Configuration 6 – Increasing Agents B and C's Effort Power

Table 22 – configuration 6: increasing the effort power of agents B and C

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	8	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	8	Ontology Usage	-	-	-	-

The percentage of correctly resolved conflicts for agents A and B is improved in 2%, but no changes are reported in the total number of conflicts resolved. For agents A and C, there's seems to be less resolved conflicts, but more correctly resolved ones.

8.2.3 Configuration 7 – Agents B and C decrease Effort Power

Table 23 – configuration 7: decreasing the effort power of agents B and C

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	5	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	5	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	5	Ontology Usage	-	-	-	-

Decreasing effort powers has the same effect in all tests: the number of conflicts resolved increases by around 4%, but the quality of these is affected, lowering in around 2%. The quality of the alignment mirrors this by decreasing slightly.

8.2.4 Configuration 8 – Increasing all agents' Effort Power

Table 24 – configuration 8: increasing the effort power of all agents

Agent	tr	tn	tp	tm	effP	Gain Function	Ontological type values (gain)			
							d,d	o,o	c,c	All others
Agent A	0.60	0.85	0.95	1	8	Ontology Usage	-	-	-	-
Agent B	0.60	0.85	0.95	1	8	Ontological Type	0.20	0.20	0.20	0.15
Agent C	0.60	0.85	0.95	1	8	Ontology Usage	-	-	-	-

When all agents raise their effort powers, there seems to be a very slight decrease in the percentage of resolved conflicts (around 1-3%), but an increase in the quality of the resolution.

8.2.5 Discussion

Increasing the effort powers makes the agents less likely to revise their stances, thus resulting in a slight decrease of the number of resolved conflicts. However, there's a trend to have better results nonetheless, by having a higher number of correctly resolved conflicts.

8.3 Final Remarks

In order to have agent A increasing its Initial Proposal, it is required that it proposes more correct matches. To do so, it has to lower its proposed threshold. However, lower it too much and the agent will include many other matches which are not desirable. A middle ground for agent A's proposed threshold was found at around 0.93.

Agent B's Initial Proposal has the lowest of all accuracies. Its results present a very high recall, but a very low F-Measure, meaning that while it may be proposing most of the correct matches, it is also proposing many wrong matches. For that, it is important to reduce the number of matches it is proposing, by increasing its proposed threshold.

Further tests with the adjustments made in the thresholds shown that the results could be further improved by applying higher effort powers.

Agent C's Initial Proposal could be improved by around 5% by increasing its proposed threshold. However, the number of resolved conflicts and their correctness would substantially decrease. It seems more fitting, for this particular agent, to increase only the effort power, as it potentiates the quality of conflict resolution.

The study of variations in the gain functions was not presented here, for the base configuration proved to produce the best results. Previous tests had proven that, in order to potentiate agent B's will to relax, the values of the Ontological Type function should be low. The values considered in the Experiments section proved to produce the best results.