

Matching Law Ontologies using an Extended Argumentation Framework based on Confidence Degrees

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Abstract. Law information retrieval systems use law ontologies to represent semantic objects, to associate them with law documents and to make inferences about them. A number of law ontologies have been proposed in the literature, what shows the variety of approaches pointing to the need of matching systems. We present a proposal based on argumentation to match law ontologies, as an approach to be considered for this problem. Argumentation is used to combine different techniques for ontology matching. Such approaches are encapsulated by agents that apply individual matching algorithms and cooperate in order to exchange their local results (arguments). Next, based on their preferences and confidence, the agents compute their preferred matching sets. The arguments in such preferred sets are viewed as the set of globally acceptable arguments. We show the applicability of our model matching two legal core ontologies: LKIF and CLO.

Keywords. Ontology matching, law ontologies, argumentation framework

Introduction

Law ontologies provide a formal description of the objects and their relations in the legal domain. Law information retrieval systems, such as question answering systems, use this knowledge to represent semantic objects, to associate them with law documents and to make inferences about them. Law ontologies covering different aspects of the law domain have been proposed in the literature.

Regarding the fact that overlapping ontologies cover complementary aspects of the law domain, a primary problem to solve in order to obtain interoperability between the systems is the ontology matching. The matching process takes two ontologies as input and determines as output correspondences between the semantically related entities of those ontologies. There are many different approaches to the matching problem. Whereas lexical approaches consider measures of lexical similarity; semantic ones consider semantic relations usually on the basis of semantic oriented linguistic resources. Other approaches consider term positions in the ontology hierarchy. Indeed, taxonomies of

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the different matching approaches have been proposed in the literature, see for example [18][19] and [20]. However, the use of a single technique for a large variety of schemes is unlikely to be successful[6]. Since these approaches are complementary to each other their combination should lead to high matching accuracies than those provided by each one individually.

This paper presents a proposal based on argumentation to combine ontology matching approaches. We use the abstract argumentation framework[7] to combine matching approaches. In previous work [25] we extended a state of art argumentation framework, namely Value-based Argumentation Framework (VAF)[3], in order to represent arguments with confidence degrees. The VAF allows to determine which arguments are acceptable, with respect to the different *audiences* represented by different agents. We then associate to each argument a confidence degree, representing how confident an agent is in the similarity of two ontology terms. Our agents apply different matching approaches and cooperate in order to exchange their local results (arguments). Next, based on their preferences and confidence of the arguments, the agents compute their preferred matching sets. The arguments in such preferred sets are viewed as the set of globally acceptable arguments. The idea is not to provide an improved matching technique, but allowing all techniques to compete, as there are many different matching situations, a competing (complementary) approach is evaluated as a way to select the right strategy to apply in each situation.

We show the applicability of our model in a law match case using two legal core ontologies, LKIF and CLO.

This paper is structured as follows. Section 1 introduces the ontology matching approaches. Section 3 comments on argumentation framework. Section 4 presents our argumentation model. Section 5 presents the law matching case. Section 6 presents the main related work. Finally, section 7 presents the final remarks and future work.

1. Ontology Matching

Ontology matching is the process of finding relationships or correspondences between entities of different ontologies [9]. If two concepts correspond, they mean the same thing, or closely related things. The approaches for ontology matching vary from lexical (see [23][17]) to semantic and structural levels (see [11]). In the lexical level, metrics to compare string similarity are adopted. One well-known measure is the Levenshtein distance or edit distance [14], which is given by the minimum number of operations (insertion, deletion, or substitution of a single character) needed to transform one string into another. Other common metrics can be found in [17], [22], and [8].

The semantic level considers the semantic relations between concepts to measure the similarity between them, usually on the basis of semantic oriented linguistic resources. The well-known WordNet² database, a large repository of English semantically related items, has been used to provide these relations. This kind of matching is complementary to the pure string similarity metrics. It is common that string metrics yield high similarity between strings that represent completely different concepts (i.e, the words "score" and "store"). Moreover, semantic-structural approaches have been explored [4][11]. In this

²<http://www.wordnet.princeton.edu>

case, the positions of the terms in the ontology hierarchy are considered, i.e, terms more general and terms more specific are also considered as input to the matching process.

It is assumed that the approaches are complementary to each other and combining different ones reflect better solutions when compared to the solutions of the individual approaches. Heuristics to combine different approaches for ontology matching have been proposed in the literature (see, for example, [15], [6], [10]). Our proposal is to use argumentation to combine such approaches. Different approaches are encapsulated by agents that cooperate in order to exchange their local results (arguments). Based on their preferences and confidence of the arguments, the agents compute their preferred matching sets. The arguments in such preferred sets are viewed as the set of arguments globally acceptable (objectively or subjectively).

2. Argumentation Framework

Our argumentation model is based on the Value-based Argumentation Frameworks (VAF)[3], a development of the classical argument system of Dung [7]. First, we present the Dung's framework, upon which the VAF rely. Next, we present the VAF and our extended framework.

2.1. Classical argumentation framework

Dung [7] defines an argumentation framework as follows.

Definition 2.1.1 An Argumentation Framework is a pair $AF = (AR, attacks)$, where AR is a set of arguments and $attacks$ is a binary relation on AR , i.e., $attacks \subseteq AR \times AR$. An $attack(A,B)$ means that the argument A attacks the argument B . A set of arguments S attacks an argument B if B is attacked by an argument in S .

The key question about the framework is whether a given argument A , $A \in AR$, should be accepted. One reasonable view is that an argument should be accepted only if every attack on it is rebutted by an accepted argument [7]. This notion produces the following definitions:

Definition 2.1.2 An argument $A \in AR$ is *acceptable* with respect to set arguments $S(acceptable(A,S))$, if $(\forall x)(x \in AR) \ \& \ (attacks(x,A)) \longrightarrow (\exists y)(y \in S) \ \& \ attacks(y,x)$

Definition 2.1.3 A set S of arguments is *conflict-free* if $\neg(\exists x)(\exists y)((x \in S) \ \& \ (y \in S) \ \& \ attacks(x,y))$

Definition 2.1.4 A conflict-free set of arguments S is *admissible* if $(\forall x)(x \in S) \longrightarrow acceptable(x,S)$

Definition 2.1.5 A set of arguments S is a *preferred extension* if it is a maximal (with respect to inclusion set) admissible set of AR .

A *preferred extension* represent a consistent position within AF , which can defend itself against all attacks and which cannot be further extended without introducing a conflict.

The purpose of [3] in extending the AF is to allow associate arguments with the social values they advance. Then, the attack of one argument on another is evaluated to say whether or not it succeeds by comparing the strengths of the values advanced by the arguments concerned.

2.2. Value-based argumentation framework

In Dung's frameworks, attacks always succeed. However, in many domains, including the one under consideration, arguments lack this coercive force: they provide reasons which may be more or less persuasive [13]. Moreover, their persuasiveness may vary according to their audience.

The VAF is able to distinguish attacks from successful attacks, those which defeat the attacked argument, with respect to an ordering on the values that are associated with the arguments. It allows to accommodate different audiences with different interests and preferences.

Definition 2.2.1 A Value-based Argumentation Framework (VAF) is a 5-tuple $VAF = (AR, attacks, V, val, P)$ where $(AR, attacks)$ is an argumentation framework, V is a nonempty set of values, val is a function which maps from elements of AR to elements of V and P is a set of possible audiences. For each $A \in AR$, $val(A) \in V$.

If V contains a single value, or no preference between the values has been defined, the AVAF becomes a standard AF. If each argument can map to a different value, a Preference Based Argumentation Framework is obtained [1].

Definition 2.2.2 An Audience-specific Value Based Argumentation Framework (AVAF) is a 5-tuple $VAF_a = (AR, attacks, V, val, valpref_a)$ where $AR, attacks, V$ and val are as for a VAF, a is an audience and $valpref_a$ is a preference relation (transitive, irreflexive and asymmetric) $valpref_a \subseteq V \times V$, reflecting the value preferences of audience a . $valpref(v_1, v_2)$ means v_1 is preferred to v_2 .

Definition 2.2.3 An argument $A \in AR$ defeats _{a} (or *successful attacks*) an argument $B \in AR$ for audience a if and only if both $attacks(A, B)$ and not $valpref(val(B), val(A))$.

An attack succeeds if both arguments relate to the same value, or if no preference value between the values has been defined.

Definition 2.2.4 An argument $A \in AR$ is *acceptable* to audience a ($acceptable_a$) with respect to set of arguments S , $acceptable_a(A, S)$ if $(\forall x)((x \in AR \ \& \ defeats_a(x, A)) \longrightarrow (\exists y)((y \in S) \ \& \ defeats_a(y, x)))$.

Definition 2.2.5 A set S of arguments is *conflict-free* for audience a if $(\forall x)(\forall y)((x \in S \ \& \ y \in S) \longrightarrow (\neg attacks(x, y) \vee valpref(val(y), val(x)) \in valpref_a))$.

Definition 2.2.6 A *conflict-free* set of arguments S for audience a is *admissible* for an audience a if $(\forall x)(x \in S \longrightarrow acceptable_a(x, S))$.

Definition 2.2.7 A set of arguments S in the VAF is a *preferred extension* for audience a ($preferred_a$) if it is a maximal (with respect to set inclusion) *admissible* for audience a of AR.

In order to determine the preferred extension with respect to a value ordering promoted by distinct audiences, [3] introduces the notion of *objective* and *subjective* acceptance.

Definition 2.2.8 An argument $x \in AR$ is *subjectively* acceptable if and only if x appears in the preferred extension for some specific audiences but not all. An argument $x \in AR$ is *objectively* acceptable if and only if, x appears in the preferred extension for every specific audience. An argument which is neither objectively nor subjectively acceptable is said to be *indefensible*.

2.3. An extended value-based argumentation framework (E-VAF)

We extend the VAF in order to represent arguments with confidence degrees. Two elements have been added to the VAF: a set with confidence degrees and a function which maps from arguments to confidence degrees. The confidence value represents the confidence that an individual agent has in some argument. Any matching tools actually output mappings with a confidence that reflects the confidence degree they have in the similarity of the entities involved in the correspondence. These confidence degrees are usually derived from the similarity assessments made during the ontology matching process, *e.g.* from an edit distance measure between labels, or a overlap measure between instance sets. So, the confidence degrees is a criteria which must be considered when combining matching approaches.

Definition 2.3.1 An Extended Value-based Argumentation Framework (E-VAF) is a 7-tuple $E-VAF = (AR, attacks, V, val, P, C, valC)$ where $(AR, attacks, V, val, P)$ is a value-based argumentation framework, C is a nonempty set of values representing the confidence degrees, $valC$ is a function which maps from elements of AR to elements of C . $valC \subseteq C \times C$ and $valprefC(c_1, c_2)$ means c_1 is preferred to c_2 .

Definition 2.3.2 An argument $x \in AR$ defeats _{a} (or *successful attacks*) an argument $y \in AR$ for audience a if and only if $attacks(x, y) \wedge (valprefC(valC(x), valC(y)) \vee (\neg valpref(val(y), val(x)) \wedge \neg valprefC(valC(y), valC(x))))$.

An attack succeeds if (a) the confidence degree of the attacking argument is greater than the confidence degree of the argument being attacked; or if (b) the argument being attacked does not have greater preference value than attacking argument (or if both arguments relate to the same preference values) and the confidence degree of the argument being attacked is not greater than the attacking argument.

Definition 2.3.3 A set S of arguments is *conflict-free* for audience a if $(\forall x)(\forall y) ((x \in S \ \& \ y \in S) \longrightarrow (\neg attacks(x, y) \vee (\neg valprefC(valC(x), valC(y)) \wedge (valpref(val(y), val(x)) \vee valprefC(valC(y), valC(x)))))$.

It is important to distinguish the difference between *values* and *confidence*. There are different types of agents representing different matching approaches. Each approach represent a *value* and each agent represents an audience, with preferences between the *values*. The *values* are used to determine the preference between the different agents. Moreover, each agent generates arguments with a *confidence*, based on the confidence returned by the matching technique. So, we extended the VAF in order to define a new notion of argument acceptability which combines *values* (related with the agent's preference) and *confidence* (confidence degree of an argument). If our criterion was based only on the *confidence* of the arguments, a Preference Based Argumentation Framework could be used [1].

3. E-VAF for Ontology Matching

In our model, dedicated agents encapsulate different matching approaches. In this paper we consider three *values*: lexical (L), semantic (S), and structural (E) (i.e. $V = \{L, S, E\}$, where $V \in \text{E-VAF}$). These values represent the matching approach used by the agent. Each audience has an ordering preference between the *values*. For instance, the lexical agent represents an audience where the value *L* is preferred to the values *S* and *E*. Our idea is not to have an individual audience with preference between the agents (i.e., semantic agent is preferred to the other agents), but it is to try accommodate different audiences (agents) and their preferences. So, using only the strengths is not sufficient to the problem. The idea is to obtain a consensus when using different matching techniques, which are represented by different preference between values.

3.1. Argumentation generation

First, the agents work in an independent manner, applying the matching approaches and generating matching sets. The matching result will consist of a set of all possible correspondences between terms of two ontologies. A matching m can be described as a 5-tuple $m = (t_1, t_2, h, R, c)$, where t_1 corresponds to a term in the ontology 1, t_2 corresponds to a term in the ontology 2, h is one of $\{-, +\}$ depending on whether the matching does or does not hold, R is the mapping relation resulting from the matching between these two terms, and $c \in C$ is the confidence degree associated to that matching (*certainty* or *uncertainty*, as it will be commented below). In an initial setting, the agents are able to return *equivalence* value to R . Each mapping m is encapsulated in an argument. The arguments can be defined as follows:

Definition 4.1 An *argument* $\in AR$ is a 2-tuple $x = (m, a)$, where m is a mapping; $a \in V$ is the value of the argument, depending of the agent generating that argument (i.e., lexical, semantic or structural);

The confidence degree is defined by the agent when applying the specific matching approach. Here, we assumed $C = \{\text{certainty}, \text{uncertainty}\}$, where $C \in \text{E-VAF}$. Table 1 shows the possible values to h and c , according to the agent's value. The agents generate their arguments based on rules from Table 1.

Table 1. h and c to values.

h	c	Values	
		Lexical	Semantic
+	certainty	1	synonym
+	uncertainty	$1 > r > t$	related
-	certainty	$0 < r \leq t$	unknown
-	uncertainty	0	unknown

3.1.1. Lexical agent

The output of lexical agents (r) is a value from the interval $[0,1]$, where 1 indicates high similarity between two terms. This way, if the output is 1, the lexical agent generates an argument $x = (m,L)$, where $m = (t_1,t_2,+,equivalence,certainty)$. If the output is 0, the agent generates an argument $x = (m,L)$, where $m = (t_1,t_2,-,equivalence,certainty)$. A threshold (t) is used to classify the output in uncertain categories. The threshold value can be specified by the user.

3.1.2. Semantic agent

The semantic agents consider semantic relations between terms, such as synonym, antonym, holonym, meronym, hyponym, and hypernym (i.e., such as in WordNet database). When the terms being mapped are synonymous, the agent generates an argument $x = (m,S)$, where $m = (t_1,t_2,+,equivalence,certainty)$. The terms related by holonym, meronym, hyponym, or hypernym are considered related and an argument $x = (m,S)$ is generated, where $m = (t_1,t_2,+,equivalence,uncertainty)$ (the terms have some degree of equivalence); when the terms can not be related by the WordNet (the terms are unknown for the WordNet database), an argument $x = (m,S)$, where $m = (t_1,t_2,-,uncertainty,equivalence)$, is then generated.

3.1.3. Structural agent

The structural agents consider the super-classes (or sub-classes) intuition to verify if the terms can be mapped. First, it is verified if the super-classes of the compared terms are lexically similar. If not, the semantic similarity between them is used. If the super-classes of the terms are lexically or semantically similar, the terms are considered equivalent to each other. The argument is generated according to the lexical or semantic comparison. For instance, if the super-classes of the terms are not lexically similar, but they are synonymous (semantic similarity), an argument $x = (m,E)$, where $m = (t_1,t_2,+,equivalence,uncertainty)$, is generated. If the structural agent finds similarity between the super-classes of the compared terms, it is because they can be mapped, but it does not mean that the terms have lexical or semantic similarity, then the *confidence* for the mapping is *uncertainty*. For instance, for the terms “Publication/Topic” and “Publication/Proceedings”, the structural agent indicates that the terms can be mapped because they have the same super-class, but not with *certainty* because it is not able to indicate that the terms are equivalent at all.

Moreover, it is pointed out that the semantic agent does not explore any kind of hierarchical propriety, as done by the structural agent. The semantic agent is based on the analysis of synsets and it does not use the structural information available on WordNet.



Figure 1. SUMO partial ontology.

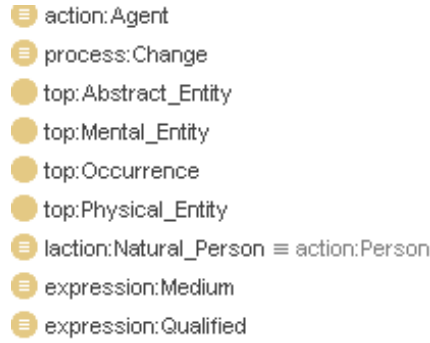


Figure 2. LKIF partial ontology.

3.2. Preferred extension generation

After generating their set of arguments, the agents exchange with each other their arguments. When all agents have received the set of arguments of the each other, they generate their *attacks* set. An *attack* (or counter-argument) will arise when we have arguments for the mapping between the same terms, but with conflicting values of h . For instance, an argument $x = (m_1, L)$, where $m_1 = (t_1, t_2, +, \text{certainty}, \text{equivalence})$, have as an *attack* an argument $y = (m_2, E)$, where $m_2 = (t_1, t_2, -, \text{uncertainty}, \text{equivalence})$. m_1 and m_2 refer to the same terms in the ontologies. The argument y also represents an *attack* to the argument x .

As an example, consider the mapping between terms “Abstract” (from generic core ontology SUMO - Figure 1) and “Abstract-Entity” (from the LKIF ontology - Figure 2), and the lexical and structural agents.

The lexical agent generates an argument $x = (m, L)$, where $m = (\text{Abstract}, \text{Abstract-Entity}, +, \text{certainty}, \text{equivalence})$; and the structural agent generates an argument $y = (m, E)$, where $m = (\text{Abstract}, \text{Abstract-Entity}, -, \text{uncertainty}, \text{equivalence})$. For both lexical and structural agents, the set of arguments is $AR = \{x, y\}$ and the *attacks* = $\{(x, y), (y, x)\}$. However, the relations of *successful attacks* will be defined according to specific audience (see *Definition 2.3.2*). The argument x *successfully* attacks the argument y , because x has greater confidence than y .

When the set of arguments and attacks have been produced, the agents need to define which of them must be accepted. To do this, the agents compute their preferred extension, according to the audiences and confidence degrees. A set of arguments is *globally subjectively acceptable* if each element appears in the preferred extension for some agent. A set of arguments is *globally objectively acceptable* if each element appears in

the preferred extension for every agent. The arguments which are neither objectively nor subjectively acceptable are considered *indefensible*.

In the example above, considering the lexical (L) and structural (E) audiences, where $L \succ E$ and $E \succ L$, respectively, for the lexical audience, the argument y successfully attacks the argument x , while the argument x does not successfully attack the argument y for the structural audience. Then, the preferred extension of both lexical and structural agents is composed by the argument y , which can be seen as globally *objectively* acceptable.

4. Experiments and Evaluation

Let us consider that three agents need to obtain a consensus about mappings that link corresponding class names in two different ontologies. We had used two legal core ontologies: LKIF and CLO. Table 2 shows the number of classes and attributes of the two ontologies.

Table 2. Number of classes and attributes of the ontologies.

Ontology	Classes	Attributes
LKIF-Core	154	84
CLO	107	69

Three agents were considered: lexical (L), semantic (S), and structural (E). The agents were implemented in Java 5.0, and the experiments ran on Pentium(R) 4, UCP 3.20GHz, 512MB.

The lexical agent was implemented using the edit distance measure (Levenshtein measure). We used the algorithm available in the API for ontology alignment (INRIA)³ (EditDistNameAlignment). The semantic agent has used the JWordNet API⁴, which is an interface to the WordNet database. For each WordNet synset, we retrieved the synonymous terms and considered the hypernym, hyponym, member-holonym, member-meronym, part-holonym, and part-meronym as related terms. The structural agent was based on super-classes similarity.

The threshold used to classify the matcher agents output was 0.8. This value was defined based on previous analysis of the edit distance values between the terms of the ontologies used in the experiments. The terms with edit distance values greater than 0.8 have presented lexical similarity.

The evaluation of law ontology matching lacks well established benchmarks. Therefore our choices on evaluation were based on the manual analysis of the positive mapping ($h = +$) returned by our model, when using the ontologies described above. So, we compute the precision of the automatic positive mappings. Table 3 shows the number of correct and incorrect mappings, together the precision, when considering the *mappings with certainty* and the *mappings with uncertainty*.

As shown in Table 3, the results are better when considering only the *mapping with certainty*. This setting is specially useful when the matching system is used without user feedback (i.e., communication between agents where the mappings are computed on the fly). In the cases where the systems is used to help users in a manual matching

³<http://alignapi.gforce.inria.fr>

⁴<http://jwn.sourceforge.net> (using WordNet 2.1)

Table 3. Matching results.

Ontology entity	Mapping	Total	Correct	Incorrect	Precision
Attribute	<i>certainty</i>	9	7	2	0.77
	<i>uncertainty</i>	245	29	216	0.11
Class	<i>certainty</i>	20	14	6	0.70
	<i>uncertainty</i>	929	59	870	0.06

process, could be interesting to retrieval a larger set of mapping, i.e., considering also the *mappings with uncertainty*.

Although further evaluation is needed, the values of precision are promising, for both mappings with classes and instances.

5. Related Work

In the field of ontology argumentation few approaches are being proposed. Basically, the closer proposal is from [13][12], where an argument framework is used to deal with arguments that support or oppose candidate correspondences between ontologies. The candidate mappings are obtained from an Ontology Mapping Repository (OMR) – the focus is not how the mappings are computed – and argumentation is used to accommodate different agent’s preferences. In our approach mappings are computed by the specialized agents described in this paper, and argumentation is used to solve conflicts between the individual results.

We find similar proposals in the field of ontology negotiation. [24] presents an ontology to serve as the basis for agent negotiation, the ontology itself is not the object being negotiated. A similar approach is proposed by [5], where agents agree on a common ontology in a decentralized way. Rather than being the goal of each agent, the ontology mapping is a common goal for every agent in the system. [2] presents an ontology negotiation model which aims to arrive at a common ontology which the agents can use in their particular interaction. We, on the other hand, are concerned with delivering mapping pairs found by a group of agents using argumentation. [21] describes an approach for ontology mapping negotiation, where the mapping is composed by a set of semantic bridges and their inter-relations, as proposed in [16]. The agents are able to achieve a consensus about the mapping through the evaluation of a confidence value that is obtained by utility functions. According to the confidence value the mapping rule is accepted, rejected or negotiated. Differently from [21], we do not use utility functions. Our model is based on cooperation and argumentation, where the agents change their arguments and by argumentation they select the preferred mapping.

6. Final Remarks and Future Work

This paper presented a composite matching approach based on the argumentation formalism to map legal core ontologies. The matching process, takes two ontologies as input and determines as output correspondences between the semantically related entities of those ontologies. It can help users to reuse and compare information from different sources.

We extended a state of art argumentation framework, namely Value-based Argumentation Framework (VAF), in order to represent arguments with confidence degrees. The VAF allows to determine which arguments are acceptable, with respect to the different preferences represented by different agents. Our extension associates to each argument a confidence degree, representing the confidence that a specific agent has in that argument. We assumed that the confidence degrees is a criteria which is necessary to represent the ontology matching domain.

We have used different agents' output which use distinct matching algorithms in order to verify the behavior of our model.

We had applied our model to map two legal core ontologies: LKIF and CLO.

We point out that our approach is not restrict to legal domain. The proposed argumentation model seems to be useful for general ontology matching (see, for example [25][26], where we applied our model for other domains).

In the future, we intend to develop further tests considering also agents using constraint-based matching approaches (i.e., the similarity between two terms can be based on the equivalence of data types and domains, of key characteristics, or relationship cardinality); use the ontology's application context in our matching approach (i.e, how the ontology entities are used in some external context, which is especially interesting, for instance, to identify WordNet senses that must be considered to specific terms); and test our approach for less high-level ontologies. Moreover, we plan to extend our model to multilingual ontology matching. Next, we will use the matching result as input to an ontology merge process in a question answering system for the law domain.

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References

- [1] L. Amgoud and C. Cayrol. On the acceptability of arguments in preference-based argumentation . In *14th Conference on Uncertainty in Artificial Intelligence (UAI'98)* , Madison, Wisconsin, , pages 1–7, San Francisco, California, juillet 1998. Morgan Kaufmann. Dates de conférence : juillet 1998 1998.
- [2] S. Bailin and W. Truszkowski. Ontology negotiation between intelligent information agents. *The Knowledge Engineering Review*, 17(1):7–19, 2002.
- [3] T. Bench-Capon. Persuasion in practical argument using value-based argumentation frameworks. *Journal of Logic and Computation*, 13:429–448, 2003.
- [4] M. Chaves. Mapeamento e comparacao de similaridade entre estruturas ontologicas. Master's thesis, Pontificia Universidade Catolica do Rio Grande do Sul, 2002.
- [5] J. v. Diggelen, R. Beun, F. Dignum, v. R. Eijk, and J. C. Meyer. Anemone: An effective minimal ontology negotiation environment. In *Proceedings of the V International Conference on Autonomous Agents and Multi-Agent Systems*, pages 899–906, 2006.
- [6] H. H. Do and E. Rahm. Coma - a system for flexible combination of schema matching approaches. In *Proceedings of the 28th Conference on Very Large Databases (VLDB)*, 2002.
- [7] P. Dung. On the acceptability of arguments and its fundamental role in nonmonotonic reasoning, logic programming and n-person games. *Artificial Intelligence*, 77:321–358, 1995.
- [8] J. Euzenat, T. Le Bach, J. Barrasa, P. Bouquet, J. De Bo, R. Dieng-Kuntz, M. Ehrig, M. Hauswirth, M. Jarrar, R. Lara, D. Maynard, A. Napoli, G. Stamou, H. Stuckenschmidt, P. Shvaiko, S. Tessaris, S. Van Acker, and I. Zaihrayeu. State of the art on ontology alignment. Technical report, 2004.

- [9] J. Euzenat and P. Shvaiko. *Ontology matching*. Springer-Verlag, Heidelberg (DE), 2007.
- [10] F. Giunchiglia, P. Shvaiko, and M. Yatskevich. S-match: An algorithm and an implementation of semantic matching. In *First European Semantic Web Symposium*, 2004.
- [11] F. Hakimpour and A. Geppert. Resolving semantic heterogeneity in schema integration: an ontology approach. In *Proceedings of the International Conference on Formal Ontology in Informational Systems*, 2001.
- [12] L. Laera, I. Blacoe, V. Tamma, T. Payne, J. Euzenat, and T. Bench-Capon. Argumentation over ontology correspondences in mas. In M. Durfee, E. H.; Yokoo, editor, *Proceedings of the Sixth International Joint Conference on Autonomous Agents and Multi-Agent Systems*, 2007.
- [13] L. Laera, V. Tamma, J. Euzenat, T. Bench-Capon, and T. R. Payne. Reaching agreement over ontology alignments. In *Proceedings of 5th International Semantic Web Conference (ISWC 2006)*, 2006.
- [14] I. Levenshtein. Binary codes capable of correcting deletions, insertions and reversals. In *Cybernetics and Control Theory*, 1966.
- [15] J. Madhavan, P. Bernstein, , and E. Rahm. Generic schema matching with cupid. In *Proceedings of the Very Large Data Bases Conference (VLDB)*, pages 49–58, 2001.
- [16] A. Maedche, B. Motik, N. Silva, and R. Volz. Mafra - a mapping framework for distributed ontologies. In *13th International Conference on Knowledge Engineering and Knowledge Management*, pages 235–250, 2002.
- [17] A. Maedche and S. Staab. Measuring similarity between ontologies. In *Proceedings of the European Conference on Knowledge Acquisition and Management*, pages 251–263, 2002.
- [18] E. Rahm and P. A. Bernstein. A survey of approaches to automatic schema matching. *VLDB*, 10:334–350, 2001.
- [19] P. Shvaiko. A classification of schema-based matching approaches. Technical report, Informatica e Telecomunicazioni, University of Trento, 2004.
- [20] P. Shvaiko and J. Euzenat. A survey of schema-based matching approaches. Technical report, Informatica e Telecomunicazioni, University of Trento, 2004.
- [21] N. Silva, P. Maio, and J. Rocha. An approach to ontology mapping negotiation. In *Proceedings of the K-CAP Workshop on Integrating Ontologies*, 2005.
- [22] T. Smith and M. Waterman. Identification of common molecular subsequences. *Journal of Molecular Biology*, 147:195–197, 1981.
- [23] G. Stoilos, G. Stamou, and S. Kollias. A string metric for ontology alignment. In *ISWC*, pages 624–637. 4th International Semantic Web Conference (ISWC 2005), 2005.
- [24] V. Tamma, M. Wooldridge, I. Blacoe, and I. Dickinson. An ontology based approach to automated negotiation. In *Proceedings of the IV Workshop on Agent Mediated Electronic Commerce*, pages 219–237, 2002.
- [25] C. Trojahn, P. Quaresma, and R. Vieira. A cooperative approach for composite ontology mapping. *LNCIS Journal of Data Semantic (to appear)*, 2007.
- [26] C. Trojahn, P. Quaresma, and R. Vieira. An extended value-based argumentation framework for ontology mapping with confidence degrees. In *Workshop of Argumentation, International Conference on Autonomous Agents and Multiagent Systems*, 2007.