Using an Extended Argumentation Framework based on Confidence Degrees for Legal Core Ontology Mapping

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ABSTRACT

Web legal information retrieval systems use legal ontologies to represent semantic objects, to associate them with legal documents and to make inferences about them. The quality of the output of these systems can be improved with the ontology completeness, which can be obtained by the ontology merging process. The first step in this process is the ontology mapping. This paper proposes to use abstract argumentation frameworks to combine ontology mapping approaches. We extend the Value-based Argumentation Framework (VAF)[1], in order to represent arguments with confidence degrees. Our agents apply individual mapping algorithms 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 mapping sets. The arguments in such preferred sets are viewed as the set of globally acceptable arguments. We applied our model to map two legal core ontologies, LRI-Core and DOLCE-Lite, and to map LRI-Core with SUMO generic core ontology.

Keywords

argumentation, legal ontologies, ontology mapping

1. INTRODUCTION

Legal ontologies provide a formal description of the objects and their relations in the legal domain. Web legal information retrieval systems, such as question answering systems, use this knowledge to represent semantic objects, to associate them with legal documents and to make inferences about them. The quality of the output of these systems can be improved with the ontology completeness, which can be obtained by merging ontologies from different sources. The first step in this process is the ontology mapping, which takes two ontologies as input and determines as output correspondences between the semantically related entities of those ontologies.

In this paper, we propose to use an argumentation model to map legal ontologies. Different ontology mapping approaches are combined, as terms may be mapped by a measure of lexical similarity ([14][12]), or they can be evaluated semantically, usually on the basis of semantic oriented linguistic resources, or considering the term positions in the ontology hierarchy ([8]). 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.

We use the abstract argumentation frameworks[5] to combine mapping approaches. We extend a state of art argumentation framework, namely Value-based Argumentation Framework (VAF)[1], 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 mapping 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 mapping sets. The arguments in such preferred sets are viewed as the set of globally acceptable arguments. Our approach is able to give a formal motivation for the composite mapping approaches. We applied our model to map two legal core ontologies, LRI-Core (see [2]) and DOLCE-Lite[1], and to map LRI-Core with SUMO [2] generic core ontology.

This paper is structured as follows. Section 2 comments on argumentation framework. Section 3 introduces the ontology mapping approaches. Section 4 presents our agent argumentation model. Section 5 presents two walk through examples. Finally, section 6 presents the final remarks and the future work.

2. ARGUMENTATION FRAMEWORK

Our argumentation model is based on the Value-based Argumentation Frameworks (VAF)[1], a development of the classical argument system of Dung [5]. First, we present the Dung's framework, upon which the VAF rely. Next, we present the VAF and our extended framework.

[1] http://www.loa-cnr.it/DOLCE.html (version 2.1)
[2] http://ontology.teknowledge.com

2.1 Classical argumentation framework

Dung [5] defines an argumentation framework as follows.

Definition 2.1.1 An Argumentation Framework is a pair $AF = (AR, \textit{attacks})$, 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 [5]. 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 [1] 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 [10]. 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 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 $A \in AR$, $val(A) \in V$.

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 argument 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 argument 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, [1] 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

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. We assumed that the confidence degrees is a criteria which is necessary to represent the ontology mapping domain.

Definition 2.3.1 An Extended Value-based Argumentation Framework (E-VAF) is a 7-tuple $E\text{-}VAF = (AR, attacks, V, val, P, C, valC)$ 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 $(\forall x)(\forall y)$ $((x \in S \,\&\, y \in S) \longrightarrow (\neg attacks(x, y) \vee (\neg valprefC(valC(x), valC(y)) \wedge (valpref(val(y), val(x)) \vee valprefC(valC(y), valC(x)))))$.

3. ONTOLOGY MAPPING

The approaches for ontology mapping vary from lexical (see [14][12]) to semantic and structural levels (see [8]). In the lexical level, metrics to compare string similarity are adopted. One well-known measure is the Levenshtein distance or edit distance [11], 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 [12], [13], and [6].

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 WordNet[3] database, a large repository of English semantically related items, has been used to provide these relations. This kind of mapping 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 [3][8]. In this case, the positions of the terms in the ontology hierarchy are considered, i.e, terms more generals and terms more specifics are also considered as input to the mapping process.

Heuristics to combine different approaches for ontology mapping have been proposed in the literature (see, for example, [9], [4], [7]). 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.

We propose to use the E-VAF to combine such approaches. Our agents apply different mapping algorithms 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 mapping sets. The arguments in such preferred sets are viewed as the set of arguments globally acceptable (objectively or subjectively).

4. E-VAF FOR ONTOLOGY MAPPING

In our model, dedicated agents encapsulate different mapping approaches. Each approach represents a different audience in an E-VAF, i.e, the agents' preferences are based on specific approach used by the agent. In this paper we consider three audiences: lexical (L), semantic (S), and structural (E) (i.e. $P = \{L, S, E\}$, where $P \in$ E-VAF). We point out that our model is extensible to other audiences.

[3]http://www.wordnet.princeton.edu

Table 1: h and c to audiences.

		Audiences	
h	c	Lexical	Semantic
+	certainty	1	synonym
+	uncertainty	1 > r > t	related
-	certainty	0 < r <= t	
-	uncertainty	0	unknown

4.1 Argumentation generation

First, the agents work in an independent manner, applying the mapping approaches and generating mapping sets. The mapping result will consist of a set of all possible correspondences between terms of two ontologies. A mapping m can be described as a 3-tuple $m = (t_1, t_2, R)$, where t_1 corresponds to a term in the ontology 1, t_2 corresponds to a term in the ontology 2, and R is the mapping relation resulting from the mapping between these two terms. The lexical and semantic agents are able to return *equivalence* value to R, while the structural agents return *sub-class* or *super-class* values to R. Each mapping m is represented as a argument. Now, we can define arguments as follows:

Definition 4.1 An *argument* $\in AR$ is a 4-tuple $x = (m, a, c, h)$, where m is a mapping; $a \in P$ is the agent's audience generating that argument (agent's preference, i.e, lexical, semantic or structural); $c \in C$ is the confidence degree associated to that mapping (*certainty* or *uncertainty*, as it will be commented below); h is one of {-,+} depending on whether the argument is that m does or does not hold.

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

4.1.1 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,*certainty*,+), where m = (t_1,t_2,*equivalence*). If the output is 0, the agent generates an argument x = (m,L,*certainty*,-), where m = (t_1,t_2, *equivalence*). A threshold (t) is used to classify the output in uncertain categories. The threshold value can be specified by the user.

4.1.2 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,*certainty*,+), where m= (t_1,t_2, *equivalence*). The terms related by holonym, meronym, hyponym, or hypernym are considered related and an argument x = (m,S, *uncertainty*,+) is generated, where m =(t_1,t_2, *equivalence*); when the terms can not be related by the WordNet (the terms are unknown for the WordNet database), an argument x = (m,L,*uncertainty*, -), where m = (t_1,t_2,*equivalence*), is then generated.

4.1.3 Structural agent

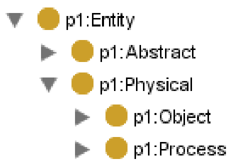

Figure 1: SUMO partial ontology.

Figure 2: LRI-Core partial ontology.

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 they 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,*certainty*,+), where m = (t_1,t_2, *super-class*), is generated.

4.2 Preferred extension generation

After generating their set of arguments, the agents exchange with each other their arguments. Following a specific protocol, an agent asks (*ask* sign) the others about their arguments. The other agents then, send their arguments to the first agent. An *ack* sign is then sent to requesting agents, in order to indicate that the arguments have been correctly received. Otherwise, an *error* sign is sent.

When all agents have received the set of argument 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,*certainty*,+) have as an *attack* an argument y = (m_2,E, *certainty*,-), where 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 "Object" (from generic core ontology SUMO - Figure 1) and "Physical-Object" (from the LRI-Core ontology - Figure 2), and the lexical and semantic agents. The lexical agent generates an argument x = (m,L,*uncertainty*,-), where m = (Object,Physical-Object,*equivalence*); and the semantic agent generates an argument y = (m,E,*certainty*,+), where m = (Object,Physical-Object, *equivalence*). For both lexical and semantic audiences, 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*), as it is commented below.

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 semantic(S) audiences, where L $\succ$ S and S $\succ$ L, respectively, for the lexical audience, the argument y successful attacks the argument x, while the argument x does not successful attack the argument y for the semantic audience. Then, the preferred extension of both lexical and semantic agents is composed by the argument y, which can be seen as globally *objectively* acceptable. The mapping between the terms "Object" and "Physical-Object", indicated by y is correct.

5. WALK THROUGH EXAMPLES

Let us consider that three agents need to obtain a consensus about mappings that link corresponding class names in two different ontologies. First, we used our mode to map legal core ontologies, LRI-Core and DOLCE-Lite. Second, the LRI-Core ontology was mapped with SUMO generic core ontology. We point out that our approach is not restrict to legal domain. The proposed argumentation model seems to be useful for general ontology mapping (see, for example [15], where we applied our model for other domains).

We considered lexical (L), semantic (S), and structural (E) audiences (mapping approaches) in order to verify the behavior of our argumentation model. 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)[4] (EditDistNameAlignment). The semantic agent has used the JWordNet API[5], 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 0.7. 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 0.7 have presented lexical similarity.

5.1 LRI-Core and DOLCE-Lite Ontologies

We used a partial view of LRI-Core and DOLCE-Lite ontologies, which are shown in Figures 3 and 4.

We have selected a correct mapping returned by our model, in order to show the mapping process in details. The terms were "Abstract-Entity" (LRI-Core) and "Abstract" (DOLCE-Lite). Table 2 shows the arguments and attacks generated

[4]http://alignapi.gforce.inria.fr
[5]http://jwn.sourceforge.net (using WordNet 2.1)

Table 2: Arguments and attacks.

ID	Argument	Attacks
1	(Abstract-Entity,Abstract,*equivalence*,L,*uncertainty*,-)	2
2	(Abstract-Entity,Abstract,*equivalence*,S,*certainty*,+)	-
3	(Abstract-Entity,Abstract,*super-class*,E,*uncertainty*,-)	2

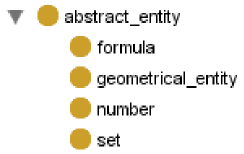

Figure 3: LRI-Core (partial two first layers).

Figure 4: DOLCE-Lite ontology (partial view).

for the agents. Each agent has as arguments AR = {1,2,3} and as relations of *attacks* = {(2,1), (2,3)}. These sets are generated by each agent, after receiving the arguments of other agents. Next, the arguments that defeat each other are computed, according to the agent's audience.

For the lexical audience, where L $\succ$ S and L $\succ$ E, the lexical agent returned a "not mapping with uncertainty" and this argument is attacked by the argument "2". For the semantic audience, where S $\succ$ L and S $\succ$ E, the semantic agent returned a "mapping with certainty" and there is no argument that successfully attacks this argument. As lexical audience, the structural agent returned a "not mapping with uncertainty", because the term "Abstract-Entity" does have a super-class to be compared with the corresponding super-class of "Abstract". Then the agent does not map the terms, but uncertainty.

The preferred extensions of the agents are composed by the arguments generated by the corresponding audience (i.e, the preferred extension of the lexical agent is {2}; the preferred extension of the semantic agent is {2}; and the preferred extension of the structural agent is {2}). The argument 2 indicate "a mapping" between the terms. Then, we can consider that the mapping is possible, what is correct according to a manual mapping.

5.2 SUMO and LRI-Core Ontologies

We mapped a partial view of SUMO generic core and LRI-Core ontologies. Figures 4 and 5 show the hierarchical view of these ontologies. We considered the mappings returned as correct by our model ("mapping with certainty").

As shown in Table 3, the preferred extensions of the agents are composed by the arguments generated by the corresponding audience. The preferred extension of the lexical agents (for all mapped terms) is {2, 5, 8, 11, 14, 16, 19}; the preferred extension of the semantic agent is {2, 5, 8, 11, 14, 17, 20}; and the preferred extension of the structural agent is {2, 5, 8, 11, 14, 18, 21}).

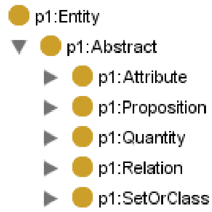

Figure 5: SUMO ontology (partial view).

Considering the arguments *"objectively acceptable"*, the arguments 2, 5, 8, 11 and 14 are considered as consensus, indicating the correct mapping between the corresponding terms. However, the arguments 18 and 19 indicate, for the terms "Quantity" and "Number" a "mapping with certainty", appearing in the 2/3 of the arguments, what indicates that they could be accepted. The same occurs with the terms "SetOrClass" and "Set".

6. FINAL REMARKS AND FUTURE WORK

This paper presented a composite mapping approach based on the argumentation formalism to map legal core ontologies. 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 mapping domain.

We have used different agents' output which use distinct mapping algorithms in order to verify the behavior of our model. Partial views of two legal core ontologies, LRI-Core and DOLCE-Lite, and the generic SUMO ontology were used.

In the future, we intend to develop further tests considering also agents using constraint-based mapping 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 mapping 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. Next, we will use the mapping result as input to an ontology merge process in a question answering domain for the law domain.

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Table 3: Arguments and attacks.

ID	Argument	Attacks
1	(Entity,Abstract-Entity,*equivalence*,L,*uncertainty*,-)	2
2	(Entity,Abstract-Entity,*equivalence*,S,*certainty*,+)	-
3	(Entity,Abstract-Entity,*super-class*,E,*uncertainty*,-)	2
4	(Entity,Geometrical-Entity,*equivalence*,L,*uncertainty*,-)	5
5	(Entity,Geometrical-Entity,*equivalence*,S,*certainty*,+)	-
6	(Entity,Geometrical-Entity,*super-class*,E,*uncertainty*,-)	5
7	(Entity,Mental-Entity,*equivalence*,L,*uncertainty*,-)	8
8	(Entity,Mental-Entity,*equivalence*,S,*certainty*,+)	-
9	(Entity,Mental-Entity,*super-class*,E,*uncertainty*,-)	8
10	(Entity,Physical-Entity,*equivalence*,L,*uncertainty*,-)	11
11	(Entity,Physical-Entity,*equivalence*,S,*certainty*,+)	-
12	(Entity,Physical-Entity,*super-class*,E,*uncertainty*,-)	11
13	(Abstract,Abstract-Entity,*equivalence*,L,*uncertainty*,-)	14
14	(Abstract,Abstract-Entity,*equivalence*,S,*certainty*,+)	-
15	(Abstract,Abstract-Entity,*super-class*,E,*uncertainty*,-)	14
16	(Quantity,Number,*equivalence*,L,*certainty*,-)	17, 18
17	(Quantity,Number,*equivalence*,S,*certainty*,+)	16
18	(Quantity,Number,*super-class*,E,*certainty*,+)	16
19	(SetOrClass,Set,*equivalence*,L,*certainty*,-)	20, 21
20	(SetOrClass,Set,*equivalence*,S,*certainty*,+)	-
21	(SetOrClass,Set,*super-class*,E,*certainty*,+)	-

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