Linking FrameNet to the Suggested Upper Merged Ontology

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Abstract

Deductive reasoning with natural language requires combining lexical resources with the world knowledge provided by ontologies. In this paper we describe the connection of FrameNet – a lexicon for English – to the Suggested Upper Merged Ontology (SUMO). We express general-domain links between FrameNet Semantic Types (ST) and SUMO classes in SUO-KIF, the language of SUMO. Based on these links, we have developed a semi-automatic, domain-specific approach for linking FrameNet Frame Elements (FE) to SUMO classes that is based on typical fillers of an FE in a particular domain. We thus provide restricted, ontology-based types on the fillers of FEs. Our work will enable several lines of experimentation for semantic parsing and ontology lexicalization.

1. Introduction

Deductive reasoning with natural language requires combining semantically rich lexical resources with world knowledge provided by ontologies and databases. Concrete applications include semantic parsing and question answering. While great progress has been made in natural-language retrieval tasks, using natural language to support deep, automatic reasoning has progressed more slowly. The lack of large lexicons, large formal ontologies and linguistic frames, and most importantly, interrelationships among these products is a major obstacle. Ontologies like the Suggested Upper Merged Ontology[1] (SUMO) (Niles and Pease, 2001) or Cyc (Lenat, 1995) can be used for reasoning but do not have adequate linguistic components. Linguistic resources like WordNet (Fellbaum, 1998) or FrameNet[2] (Ruppenhofer et al., 2005) provide means for syntactic and semantic analysis of natural language but are not intended for general reasoning. Given the maturity of these resources, combining them should result in significant benefits to natural-language applications.

The primary goal of this work is to improve language understanding technology, e.g., semantic parsing and ontology lexicalization. We proceed by combining lexical frame semantics (Fillmore, 1976) (as provided by FrameNet) and formal world knowledge (as provided by SUMO). FrameNet is a large lexical resource based on frame semantics, which encodes language as interrelated semantic Frames (types of predication) with Frame Element (FE) arguments. SUMO is a large formal ontology coded in first order logic. A secondary goal is the improvement of both resources as a result of comparing and linking them.

SUMO, WordNet, and FrameNet all have their inherent weaknesses and strengths: SUMO lacks lexical information but formally defines concepts in the world. WordNet lacks formal definitions of concepts but has very good lexical coverage. FrameNet has lower lexical coverage than WordNet but has a uniquely rich level of semantic detail, e.g., predicate-argument structure. Part of the semantics of FrameNet is defined in OWL DL (Scheffczyk et al., 2006), but lacks the axiomatization of SUMO.

In this paper, we report on the first steps toward our goals. We expressed the FrameNet Semantic Types (STs) and their relations in the first-order logic language of SUO-KIF (Genesereth, 1991; Pease, 2004), the language of SUMO. We linked STs to SUMO classes, thus asserting SUMO axioms on STs for free. Each ST is linked to equivalent SUMO classes without restricting the links to any particular domain. Based on these links, we have developed a semi-automatic approach to link FrameNet Frame Elements (FE) to SUMO classes, taking advantage of pre-existing mappings from WordNet to SUMO (Niles and Pease, 2003). This allows us to develop domain-specific links from FEs to SUMO by examining annotated examples from a particular domain (e.g., Weapons of Mass Destruction). We thus provide restricted, ontology-based

[1]For more information and downloads see http://www.ontologyportal.org.

[2]For more information and downloads see http://framenet.icsi.berkeley.edu.

types on the fillers of FEs, which should help semantic parsers both with word sense disambiguation of predicators and identifying which pieces of a sentence fill FEs.

This paper proceeds as follows: We introduce FrameNet in Sect. 2. and SUMO in Sect. 3. We present our design decisions for linking FrameNet to SUMO in Sect. 4. Sect. 5. shows how we linked the FrameNet STs to SUMO for the general domain. In Sect. 6. we illustrate our semi-automatic approach to linking FrameNet FEs to SUMO in a domain-specific way. In Sect. 7. we show how SUMO and FrameNet themselves have benefited from our work. Sect. 8. sketches directions for future research.

2. The FrameNet Lexicon

FrameNet (Ruppenhofer et al., 2005) is a lexical resource for English, based on Frame semantics (Fillmore, 1976). A semantic Frame (hereafter simply Frame) represents a set of concepts associated with an event or a state, ranging from simple (Arriving, Placing) to complex (Revenge, Criminal_process). For each Frame, a set of roles (or arguments), called Frame Elements (FEs), is defined, about 10 per Frame. We say that a word can evoke a Frame, and its syntactic dependents can fill the FE slots. Semantic relations between Frames are captured in Frame relations, each with corresponding FE-to-FE mappings. FrameNet currently contains more than 780 Frames, covering roughly 10,000 Lexical Units (LUs) = word senses; these are supported by more than 135,000 FrameNet-annotated example sentences used as training data for Frame and FE recognizing systems (Litkowski, 2004; Erk and Padó, 2006).[3]

Fig. 1 shows a portion of the Attack Frame, which *inherits* from the more general Frame Intentionally_affect (which in turn inherits from the Frame Transitive_action). In addition, Attack has a *using* relation to the Frame Hostile_encounter. The FEs of the Attack Frame are mapped to the corresponding FEs in the related Frames. For example, the FE Assailant in the Attack Frame is mapped to the FE Agent in the Intentionally_act Frame.

3. The Suggested Upper Merged Ontology

SUMO (Niles and Pease, 2001) is an open source, formal ontology of about 1000 terms and 4000 definitional statements. It is provided in first-order logic (SUO-KIF), and also translated into DAML. It is now in its 75th version, having undergone five years of development, review by a community of hundreds of people, and application in expert reasoning and linguistics. The ontology has been subjected to formal verification with an automated theorem prover and has been extended with a number of domain ontologies, also open-source, that together number some 20,000 terms and 60,000 axioms. SUMO has also been mapped to the WordNet lexicon of 100,000 noun, verb, adjective and adverb word senses (Niles and Pease, 2003), which not only acts as a check on coverage and completeness, but also provides a basis for application to natural language understanding tasks. It covers areas of knowledge such as temporal and spatial representation, units and measures, processes, events, actions, and obligations. Most importantly, SUMO employs *rules*. These formal descriptions make explicit the meaning of each of the terms in the ontology, unlike a simple taxonomy, or controlled keyword list.

There are associated natural-language generation templates and a multi-lingual lexicon that allows statements in KIF and SUMO to be expressed in multiple natural languages. SUMO has an open-source ontology management system called Sigma (Pease, 2003), which incorporates a version of the Vampire theorem prover (Riazanov and Voronkov, 2002).

4. Toward Linking FrameNet to SUMO

FrameNet and SUMO are both relatively mature resources, but their strengths must be combined in order to reach their full potential for natural-language processing (NLP). In particular, NLP applications using FrameNet require knowledge about the possible fillers for FEs. For example, a semantic Frame parser needs to know whether a certain piece of text (or a named entity) might be a proper filler for an FE – so it will check whether the *filler type* of the FE is compatible with the type of the named entity. Therefore, we want to provide Semantic Types (ST) as constraints on fillers of FEs.

FrameNet has defined about 40 STs that are ordered by a type hierarchy. For example, the Assailant FE in the Attack Frame has the ST Sentient. FrameNet STs are similar to classes in SUMO, but in a *lexicographic* project like FrameNet, STs play only a minor role. Compared to SUMO classes STs are much shallower, have fewer relations between them (only have subtyping), and lack axiomatization. Thus, STs only provide a shallow taxonomy.

Therefore, we want to use SUMO classes as STs, thereby realizing a number of advantages almost for free:

- AI applications can use the knowledge provided by SUMO.

[3]For further information on FrameNet see http://Framenet.icsi.berkeley.edu.

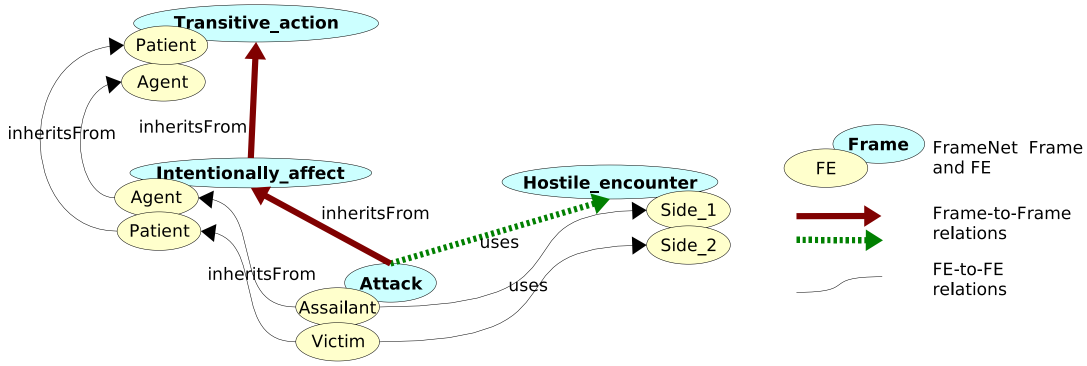

Figure 1: Abridged example Frame Attack and some connected Frames.

- We can provide different STs suitable for particular applications by bindings to SUMO domain ontologies.
- From the SUMO axioms, parts of FrameNet gain axiomatization.
- SUMO benefits from FrameNet, supplementing its ontological knowledge with a proper lexicon and annotated example sentences.

Compared to other lexicon-ontology bindings (Niles and Pease, 2003; Burns and Davis, 1999), our bindings offer a range of advantages due to specific characteristics of FrameNet and SUMO: FrameNet, in contrast to WordNet, models semantic and syntactic valences and exemplifies them with many high-quality annotations. Frame semantics naturally provides cross-linguistic abstraction and normalization of paraphrases. We have chosen SUMO as the formal ontology to map to for a number of reasons. Unlike Cyc and DOLCE (Gangemi and others, 2002), SUMO has been mapped to all of WordNet. SUMO is much larger than DOLCE. Unlike Cyc, all of SUMO and its domain ontologies are open source.

We express all bindings from FrameNet to SUMO in SUO-KIF, which permits the use of SUMO tools without any intermediate steps. Also, we use SUO-KIF to define axioms and ad-hoc classes if no exactly corresponding class can be found in SUMO. In our experience this occurs often because FrameNet is driven by lexicographic concerns rather than the knowledge engineering concerns that drive ontologies. The SUMO-WordNet mappings include only instance, equivalent, and subsuming relations to SUMO classes (or their complements). They do not support arbitrary SUO-KIF expressions.

In order to simplify the linking of FEs and to preserve the hierarchy of FEs, we have taken the following approach:

1. We express STs in SUO-KIF, along with their hierarchy from FrameNet and also additional axioms that are not formally expressible in FrameNet (Sect. 5.).
2. We link STs to SUMO classes by hand, which asserts SUMO axioms on STs. Moreover, we gain an initial indication of how FEs that have STs associated should be linked in a hierarchy-preserving way (Sect. 5.).
3. We have developed a semi-automatic approach to link FEs to SUMO classes. For an FE f, we take into account how f was annotated in a particular domain, how the STs of f were linked to SUMO, and how other FEs that are connected to f (and their STs) were linked to SUMO (Sect. 6.).

For each ST we want to find high-level SUMO classes that express its meaning across all domains. For FEs, however, our links should express the most specific meaning possible for a particular domain, so that we get a very constrained meaning, which is most useful for semantic parsing. Moreover, our links to SUMO express the literal meaning of FE fillers. In natural language almost everything can be construed as something completely different.[4]

5. Linking Semantic Types to SUMO

The lower part of Fig. 2 shows a portion of the FrameNet ST hierarchy,[5] the design of which is based on by linguistic principles. We chose STs which

[4]The obvious cases involve metaphor and metonymy (Lakoff and Johnson, 1980), but many other more subtle cases exist. For example, almost everything is interpretable as a literal container – people, houses, planets, most artifacts – since they are physically existent, three-dimensional entities with an interior that can be filled.

[5]Other STs – including Event and State – are linked straightforwardly to SUMO.

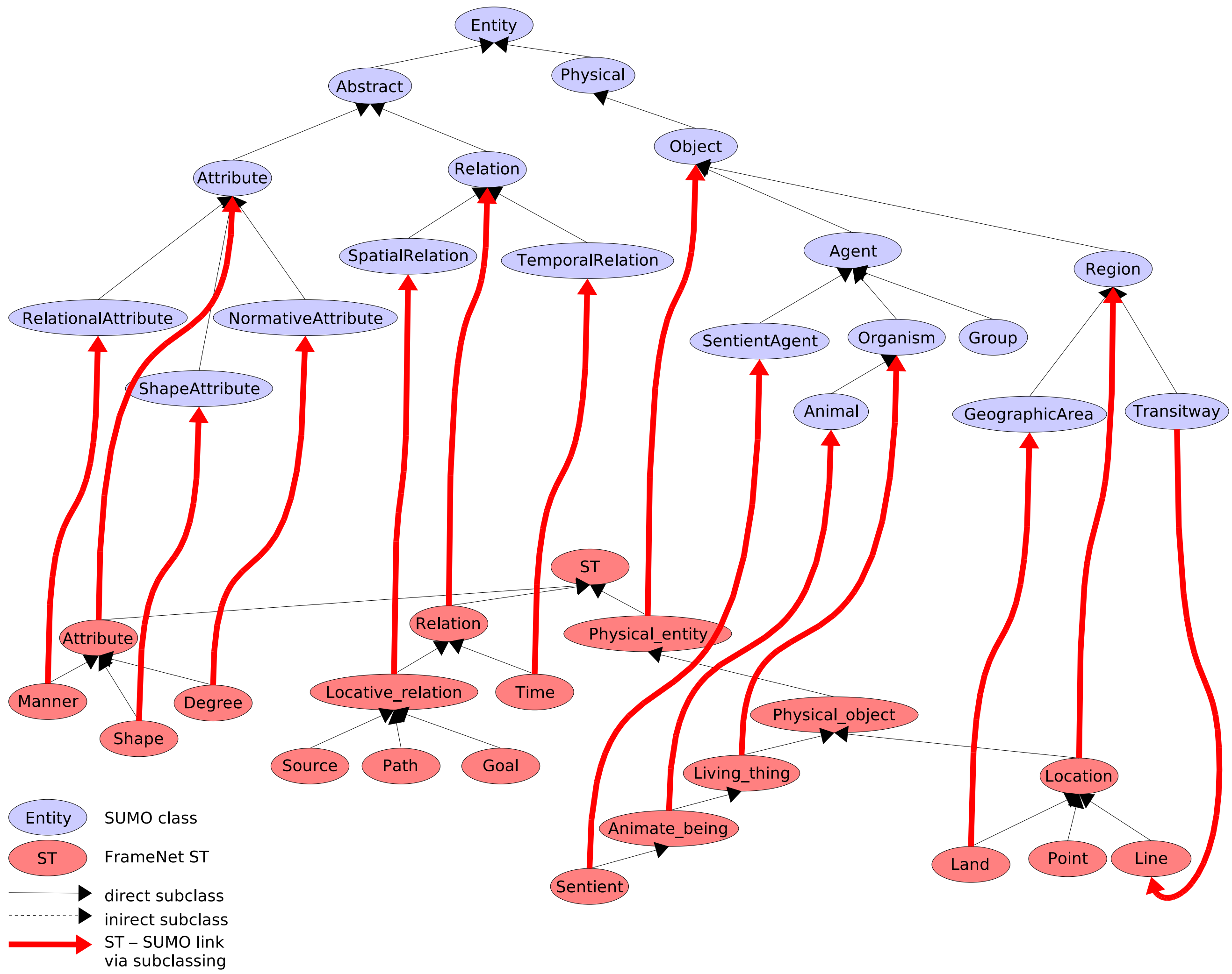

Figure 2: Bindings of a portion of the FrameNet STs to SUMO

best cover our most general and common FE fillers. We did not intend to produce STs corresponding to WordNet synsets or SUMO classes, but many of the STs we formed in fact do correspond naturally. The most important STs that do *not* correspond to SUMO classes are Source, Path, and Goal. We use Source to mark FEs whose fillers relate processes to their origins. Similarly, Goal relates to destination relations and Path to path relations. We distinguish between Locative_relations and Locations; Locations are often used as the range of Locative_relations. Relations in the Source and Goal class have Point as their range. Relations in the Path class have Line as their range. Point and Line do *not* mean geometric figures but locations (which may be construed as geometric figures).

The upper part of Fig. 2 includes part of the SUMO class hierarchy, which is slightly different from the ST hierarchy because it follows knowledge engineering principles rather than linguistic principles. For example, SUMO distinguishes between physical and abstract entities. Also, the level of detail is different between SUMO classes and STs.

We have developed the bindings based on our definitions of STs and the SUMO class documentation. This manual approach is feasible for our 40 STs. Linking FrameNet's thousands of FEs is, however, a large project, which should be partly automatized (see Sect. 6.).

In Fig. 2 thick arrows indicate subclass relationships between STs and SUMO classes. Our bindings preserve the hierarchies of both SUMO and STs. The bindings are, however, of various kinds:

- Some STs have one corresponding SUMO class, such as Shape, Time, Animate_being, or Location. In such cases, we make the ST a subclass of its corresponding SUMO concept without further axioms.

- Some STs, e.g., Sentient, correspond to the intersection of multiple SUMO classes. A Sentient being is something alive that is able to reason. In SUMO a SentientAgent does not need to be alive; e.g., organizations are also SentientAgents. So we define a mapping with multiple inheritance to SentientAgent and Animal.

- Some STs, such as Line, have a broader meaning than the corresponding SUMO classes. Line is an arbitrary linear region, whereas Transitway is used for transportation. Therefore, we make Transitway a subclass of Line.

- For some STs we find classes in SUMO with a broader meaning, but instances of them that correspond nicely. For example, for the ST *classes* Source, Path, and Goal, we only find relation *instances* like origin, path, and destination. Therefore, we make the relation origin an instance of Source, path an instance of Path, and destination an instance of Goal:

$$\begin{array}{lcl} \texttt{origin} & : & \texttt{Source} \\ \texttt{path} & : & \texttt{Path} \\ \texttt{destination} & : & \texttt{Goal} \end{array}$$

Particularly for those cases where we do not find corresponding SUMO classes, we refine the semantics of STs, i.e., we express in SUO-KIF what distinguishes them from their superclass in SUMO. Also, we define relations between STs themselves; we give some examples below.
We define the semantics of the ST Source as follows: If some relation $?rel$ is an instance of Source and $?rel$ holds between some process $?p$ and some source $?src$ then we know that the origin of the process $?p$ is the Point $?src$.[6]

$$\begin{array}{lcl} ?rel : \texttt{Source} \wedge & & \texttt{origin}(?p, ?src) \wedge \\ ?rel(?p, ?src) & \Rightarrow & ?src : \texttt{Point} \end{array}$$

We express the semantics of Goal and Path similarly:

$$\begin{array}{lcl} ?rel : \texttt{Goal} \wedge & & \texttt{destination}(?p, ?gl) \wedge \\ ?rel(?p, ?gl) & \Rightarrow & ?gl : \texttt{Point} \\ ?rel : \texttt{Path} \wedge & & \texttt{path}(?p, ?pth) \wedge \\ ?rel(?p, ?pth) & \Rightarrow & ?pth : \texttt{Line} \end{array}$$

The ST Manner describes the manner attribute of a process. Therefore, given such an attribute for some process, the manner of the process must be defined:

$$\begin{array}{lcl} ?attr : \texttt{Manner} \wedge & & \exists ?m \bullet \\ \texttt{attribute}(?attr, ?pr) & \Rightarrow & \quad \texttt{manner}(?pr, ?m) \end{array}$$

[6]The second order formula $?rel(?p, ?src)$ is expressed as $\texttt{holds}(?rel, ?p, ?src)$ in SUO-KIF.

In FrameNet we distinguish countable entities (Physical_object) from non-countable entities (Material). Therefore, for every Physical_object, a Counting process has the capability to count the Physical_object and vice versa. Similarly, for every Material, a Measuring process has the capability to measure the Material and vice versa.

$$\begin{array}{lcl} & & \texttt{capability} \\ ?o : \texttt{Physical\_object} & \Leftrightarrow & \quad (\texttt{Counting}, \\ & & \quad \texttt{patient}, ?o) \\ & & \texttt{capability} \\ ?m : \texttt{Material} & \Leftrightarrow & \quad (\texttt{Measuring}, \\ & & \quad \texttt{patient}, ?m) \end{array}$$

6. Linking Frame Elements to SUMO

In this section we introduce and demonstrate our semi-automatic approach to linking FEs to SUMO classes. Since the links from FEs to SUMO are highly domain-specific we will end up with many different bindings. Therefore, we want to automatize the linking process as much as possible.

6.1. A Semi-automatic Approach

Our approach finds candidate classes in SUMO (or any of its domain ontologies) that a particular FE can be linked to, respecting both hierarchy preservation and the use of the FE in a particular domain. The filler type of an FE is represented as a SUMO class. For restricting the possible SUMO superclasses, we use the following automated procedure:

1. Determine all fillers of the FE from annotations of a particular domain.

2. Look up all WordNet synsets of the headword[7] of each filler.

3. Determine SUMO classes associated with the WordNet synsets from the SUMO-WordNet mappings.

Our approach is similar to the WordNet detour to FrameNet (Burchardt et al., 2005). Finally, we manually analyze *frequency* (how often a SUMO class is evoked by the fillers) and *coverage* (how many fillers a SUMO class covers), both of which should be high for “good” candidate classes.
We subject these candidate classes to the following conditions in order to preserve the associations of FEs to STs and the hierarchy of FE mappings in FrameNet:

[7]For this we employ the minipar parser, which claims to have a 88% precision and 80% recall. See http://www.cs.umanitoba.ca/~lindek/minipar.htm.

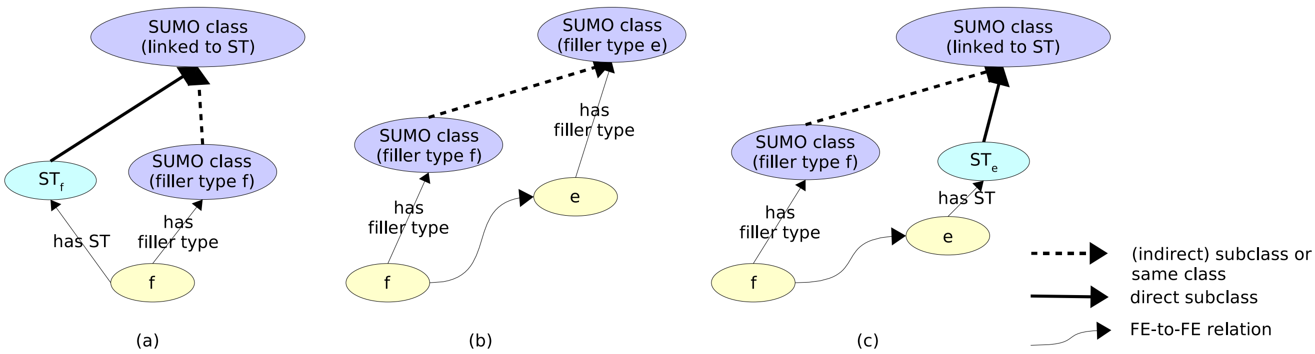

Figure 3: Conditions for linking FEs in a hierarchy-preserving way.

- If an FE has STs associated then the filler type should be a subclass[8] of each of the classes the STs are linked to (see Fig. 3a).
- If in FrameNet an FE f is a subtype of another FE e, then the SUMO classes associated with f should be subclasses of the SUMO classes associated with e; i.e., f is more restricted than e (see Fig. 3b).
- If in FrameNet an FE f is a subtype of another FE e, which has STs, linked to some SUMO classes cs then f should be linked to subclasses of cs (see Fig. 3c).

If there are conflicts (at least) one of the following conditions must hold: (1) There is a metonymic or metaphorical mapping from the typical fillers in this particular domain to a subclass of the FE's ST. (2) We have found an error in the FE annotations, the ST-SUMO links, the association of an FE to an ST, the FrameNet mappings between FEs, the SUMO-WordNet mapping, or WordNet itself.
For a particular domain, we suggest beginning by linking those FEs that are most frequently annotated.

6.2. Example

We exemplify our approach with the Assailant FE of the Attack Frame, comparing attestations in a special domain with those in the general domain. For the domain of Weapons of Mass Destruction and terrorism, we examine sentences from the Nuclear Threat Initiative Country Profiles[9] and a separate smaller corpus with 21 text annotations for the Assailant FE. For the general domain, we examine the main corpus of FrameNet examples, which come from the (open-domain) British National Corpus[10] with 27 annotations for the Assailant FE.
Fillers for the Assailant FE in the example domain-specific corpora, their headwords, and frequencies are shown below:

Filler	Headword	Frequency
it	it	3
its	its	3
Iraqi	Iraqi	2
Iran	Iran	2
terrorist	terrorist	2
the US	US	2
Iraq	Iraq	1
Al-Qaida	Al-Qaida	1
his forces	force	1
by Iraq	Iraq	1
US	US	1
U.S.	U.S.	1
Chadian forces	force	1

Lookup of the SUMO classes associated with WordNet synsets of these headwords results in:

SUMO Class or Instance	Frequency
Nation	4
UnitedStates : Nation	4
ViolentContest	4
SubjectiveAssessmentAttribute	4
GroupOfPeople	2
SocialRole	2
Human	2
Group	2
FunctionQuantity	2
NormativeAttribute	2
EthnicGroup	2
MilitaryUnit	2
Newton	2
TerroristOrganization	1

Some fuzziness results from the headword “terrorist” whose synset is mapped to SocialRole. For our ex-

[8]In this list, by “subclass” we mean the reflexive transitive closure of subclass relationships.
[9]See http://www.nti.org/e_research/profiles/.
[10]See http://www.natcorp.ox.ac.uk/.

periments we added SUMO-WordNet bindings from synsets like terrorist to the SUMO class Human. Additional fuzziness is introduced by words like “force” with many synsets.

Fig. 4 shows part of the SUMO class hierarchy for the Assailant FE, which we generate from the table above and the corresponding table for the general domain. Each SUMO class has two associated numbers, showing the percentage of fillers that are covered by this class and its subclasses: The first number is for our example domain; the second number is for the general domain. For example, the class Agent (and its subclasses) cover 71% of all fillers of the Assailant FE in our example domain and 52% of all fillers in the general domain.[11]

First, we discuss the results for our example domain. Good candidate classes are low-level classes with coverage equal to the coverage of their superclasses. Whenever we hypothesize a superclass S of such a candidate class, we also take into account other subclasses of S, which may or may not be appropriate for the domain at hand. This results in a few restricted classes with high individual coverage. For example, Nation is a good candidate – it has the same coverage as its superclasses GeopoliticalArea, GeographicArea, and LandArea. We discard these superclasses because: (1) GeopoliticalArea also has subclasses like StateOrProvince and City, which are observed to be unlikely fillers of the Assailant FE in our domain, (2) LandArea has subclasses including ShoreArea, Field, or Campground and thus is an even worse candidate. GovernmentOrganization is a mixed candidate – it has ill-fitting subclasses like PublicLibrary and PublicSchool but also the fitting subclass MilitaryOrganization. PoliticalOrganization is a good candidate because it only has subclasses MilitaryForce and TerroristOrganization. Agent covers all mapped fillers. It has, however, many ill-fitting subclasses and is, therefore, not preferred. In summary, our algorithm proposes that we link the Assailant FE to the union of the SUMO classes Nation, PoliticalOrganization, Government, MilitaryOrganization, and EthnicGroup:

$$\texttt{Assailant} \subseteq \begin{array}{l}\texttt{Nation} \cup \texttt{Government} \cup \\ \texttt{PoliticalOrganization} \cup \\ \texttt{EthnicGroup} \cup \\ \texttt{MilitaryOrganization}\end{array}$$

Nation and EthnicGroup are *not* subclasses of SentientAgent, which is, however, a necessary condition because the Assailant FE has the ST Sentient, which in turn is linked to SentientAgent (see Sect. 6.1.). Strictly speaking, this would imply that they are impossible filler types. In our example domain, however, nations and ethnic groups are construed as sentient agents via a standard and commonly understood metonymy.[12]

For the general-domain annotations in FrameNet we get different results than for our example domain. Fuzziness increases as seen by the 44% coverage of abstract classes. Again, this is due to words like “soldier” (evoking the class Soldier – a subclass of SocialRole). 52% of the fillers are classified as SelfConnectedObject, resulting from fillers like “man” (evoking Human) and “tank” (evoking Device). The class Nation is not evoked at all in the general domain. Finally, SentientAgent covers a greater proportion of fillers than in the special domain (48% vs. 29%).

The main differences follow straightforwardly from the nature of the corpora: In the special domain Nations are valid Assailants because they are the major actors in this domain, whereas Humans are unlikely (and vice versa for the general domain).

Our semi-automatic approach points us to appropriate filler types, providing a constrained semantics of FEs in a particular domain. A lot of human judgment is still required, e.g., for

- deciding whether the superclass of an evoked class should be considered,
- determining proper candidate classes that are *not* evoked by the data (like MilitaryOrganization),
- determining sources of error or abstracting from errors (like eliminating the class Abstract although it covers 44% of the fillers in the general domain).

7. Lessons Learned

We found that the hierarchies of SUMO and the FrameNet STs are quite similar. Therefore, we can confirm that the SUMO ontology relates well to natural language, which was already indicated by the SUMO-WordNet mappings.

In addition, our research has helped us to find a number of issues both in FrameNet and SUMO and resolve them, as shown below:

Through our research we identified the following deficiencies with the FrameNet STs:

[11] Since we do not find SUMO classes for all FE fillers, no class has a coverage of 100%.

[12] We propose that metonymy be detected by the fact that a metonymic filler always implies the existence of a specific non-metonymic filler. For example, from a Nation filler, one can construe the actual SentientAgents who are the Assailants. This is, however, beyond the scope of this paper.

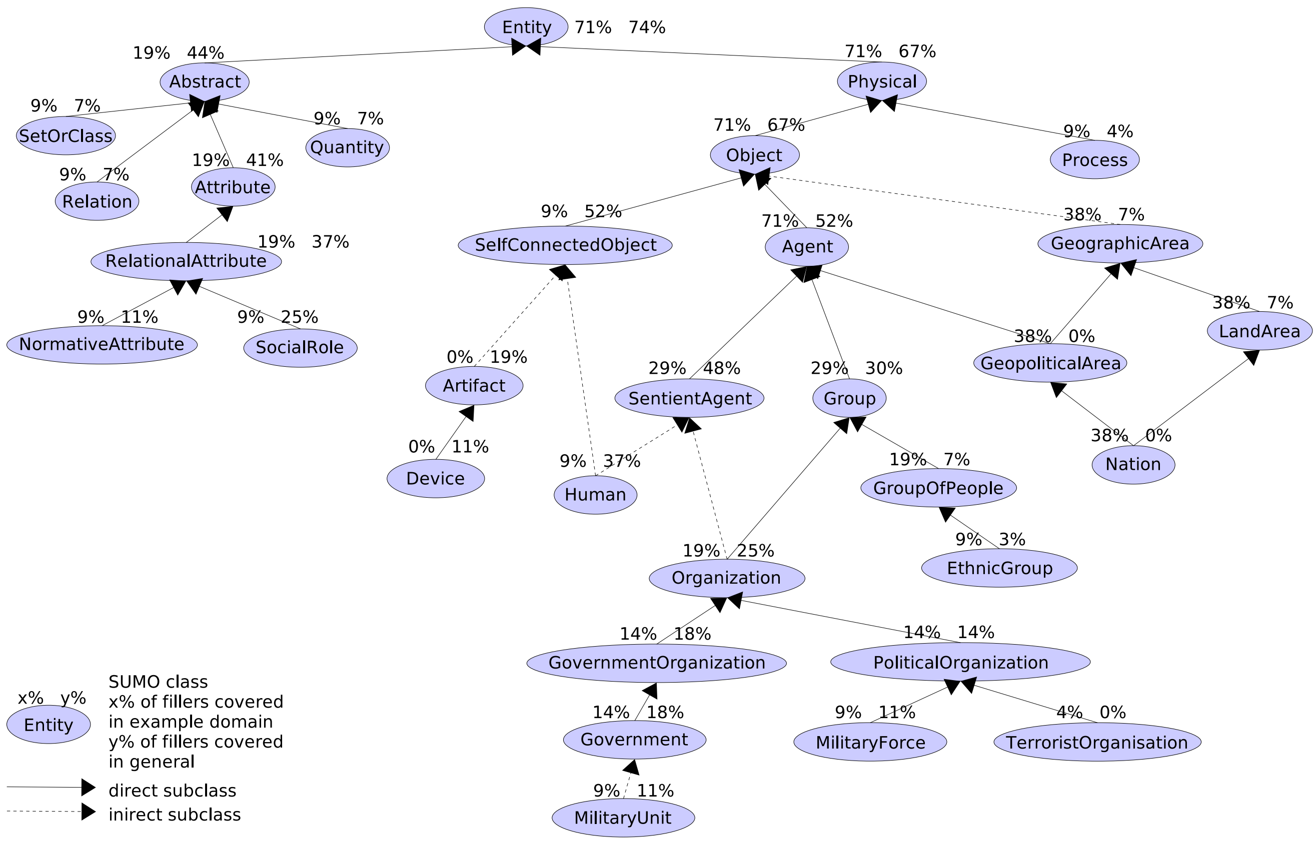

Figure 4: Generated partial SUMO class hierarchy for the Assailant FE

- STs were described by natural language, which was ambiguous. Now, we have a clear axiomatization of STs and improved formal definitions.

- The STs Source, Path, and Goal were subtypes of Location. We now have a clear distinction between Location and the newly introduced supertype of Source, Path, and Goal, Locative_relation.

- The ST Aktionsarten was included despite describing meta information. So we removed the ST Aktionsarten from FrameNet after discovering that all of its subtypes (including Event and State) were better put elsewhere.

We also identified some issues in SUMO version 75 (April 2006):

- Some SUMO relations like `knows` relate a CognitiveAgent and a Formula. Formula is, however, the *representation* of knowledge and not the knowledge itself. So we will change `knows` and similar relations to take a Proposition as range, which is an arbitrary bit of knowledge.

- The class CorpuscularObject should have an axiom stating that its instances are countable things. SUMO lacks this formal axiom, which will now be added.

- The relation `capacity` should not allow a TimePoint as an argument. TimePoint is a subclass of TimePosition, which in turn is a subclass of TimeMeasure and then ConstantQuantity. A point in time is, however, not a quantity.

8. Conclusion and Outlook

Our goal was to link FrameNet to SUMO to set the ground work for further experimentation in language understanding technology, e.g., semantic parsing and ontology lexicalization. A particularly important subgoal is to constrain the filler types of FEs for specific domains. This work relied on our manual linking of STs to SUMO classes for the general domain. We used SUO-KIF to express these links, which allows us to express complex, axiom-based, formal interrelations and gives us a homogeneous representation featuring good tool support. Using the ST-SUMO links to constrain the process, we have developed a semi-automatic approach that suggests SUMO classes as filler types for FEs. Suggestions are based on (1) typical fillers of FEs, (2) FE-to-FE relations in FrameNet, and (3) STs associated with FEs. We thus provide restricted, ontology-based types on the fillers of FEs, which we anticipate will help semantic parsers.

We plan to continue to link FEs to SUMO and refine our semi-automatic approach by including additional heuristics. We also envision further integration of WordNet, FrameNet, and SUMO in order to foster reasoning over natural language resources.

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