Linking FrameNet to the Suggested Upper Merged Ontology

Jan SCHEFFCZYK a, 1 Adam PEASE b Michael ELLSWORTH a

a International Computer Science Institute
1947 Center St., Suite 600, Berkeley, CA, 94704
{jan,infinity}@icsi.berkeley.edu
b Articulate Software
420 College Ave., Angwin, CA 94508
apease@articulatesoftware.com

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 align FrameNet Semantic Types (ST) with SUMO classes, which we express in SUO-KIF, the language of SUMO. Based on this general-domain alignment, 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 FEs in a particular domain. We thus provide restricted, ontology-based types on the fillers of FEs. We are confident that our basic work can improve semantic parsing and ontology lexicalization.

Keywords. FrameNet, SUMO, Ontologies, Lexicons

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 Ontology2 (SUMO) [1] or Cyc [2] can be used for reasoning but do not have adequate linguistic components. Linguistic resources like WordNet [3] or FrameNet3 [4] 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 processing (NLP).

1 Part of this work was supported by the German Academic Exchange Service.
2 For more information and downloads see http://www.ontologyportal.org.
3 For more information and downloads see http://framenet.icsi.berkeley.edu.
There have not, to our knowledge, been other mapping efforts like ours to integrate SUMO with FrameNet and WordNet. Other efforts have combined formal ontologies with linguistic resources (mainly WordNet) but in each case lose some of the power of the ontology or linguistic resource. For Omega [5] – a lightweight lexical merging effort – the authors state ‘Omega contains no formal concept definitions . . .’. Cyc [2] has been mapped to a small portion of WordNet and has not released their results. DOLCE [6] has also mapped to an even smaller portion of WordNet.

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, especially predicate-argument structure. Part of the semantics of FrameNet is defined in OWL DL [7], but lacks the axiomatization of SUMO. Although this is beyond the scope of this paper, a promising next step would be the integration of all three products.

Our primary goal is to provide an improved foundation for NLP tasks, e.g., semantic parsing and ontology lexicalization. We proceed by combining lexical Frame semantics [8] (as provided by FrameNet) and formal world knowledge (as provided by SUMO). Frame semantics 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.

Compared to other lexicon-ontology bindings [9,10], 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 [6], 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.

In this paper, we report on the first steps toward our goals. We aligned the FrameNet Semantic Types (STs) with SUMO, thus asserting SUMO axioms on STs for free. Based on this general-domain alignment, we have developed a semi-automatic approach to link FrameNet Frame Elements (FEs) to SUMO classes, taking advantage of pre-existing mappings from WordNet to SUMO [9]. This allows us to develop restricted, domain-specific, and ontology-based types on the fillers of FEs, which should help semantic parsers.

This paper proceeds as follows: We introduce FrameNet in Sect. 1 and SUMO in Sect. 2. We present our design decisions for linking FrameNet to SUMO in Sect. 3. Sect. 4 shows how we aligned the FrameNet STs with SUMO for the general domain. In Sect. 5 we illustrate our semi-automatic approach to linking FrameNet FEs to SUMO in a domain-specific way. In Sect. 6 we show how SUMO and FrameNet themselves have benefited and discuss further impacts of our work. Sect. 7 concludes.

1. The FrameNet Lexicon

FrameNet [4] is a lexical resource for English, based on Frame semantics [8]. A semantic Frame (hereafter simply Frame) represents a set of concepts associated with an event or
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 790 Frames, covering more than 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 [11,12].

Fig. 1 shows a portion of the Attack Frame, which inherits from the more general Frame Intentionally_affect. In addition, Attack has a perspectiveOn 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.

2. The Suggested Upper Merged Ontology

SUMO [1] 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 OWL. 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 [9], which not only acts as a check on coverage and completeness, but also provides a basis for its use in NLP tasks. Most importantly, SUMO employs rules. These formal descriptions make explicit the meaning of terms in the ontology, unlike a simple taxonomy, or controlled keyword list. SUMO has an open-source ontology management system called Sigma [13], which incorporates a version of the Vampire theorem prover [14].

3. 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 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 (STs) 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. Compared to SUMO classes, STs are much shallower, have fewer relations between them (only subtyping), and lack axiomatization. Therefore, we want FrameNet to refer to SUMO classes directly as STs, thereby realizing a number of advantages almost for free:

- AI applications can use the knowledge provided by SUMO.
- We can provide domain-specific STs by bindings to SUMO domain ontologies.
- From the SUMO axioms, parts of FrameNet gain axiomatization.
- FrameNet supplements SUMO’s ontological knowledge with a Frame-based lexicon and annotated sentences.

We have expressed all bindings from FrameNet to SUMO in SUO-KIF, permitting the use of SUMO tools without any intermediate steps. Also, we have used SUO-KIF to define axioms and ad-hoc classes if no equivalent class could be found in SUMO. In our experience this is often needed because FrameNet STs are motivated by lexicographic concerns, rather than the knowledge engineering concerns that drive ontologies. Thus, our bindings are more flexible than the SUMO-WordNet mappings, which include only instance, equivalent, and subsuming relations to SUMO classes (or their complements).

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

1. We have aligned STs with 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. 4).
2. We have developed a semi-automatic approach to linking 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. 5).

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.\(^4\)

### 4. Linking Semantic Types to SUMO

Fig. 2 shows the alignment of a portion of the FrameNet ST hierarchy to SUMO.\(^5\) The SUMO class hierarchy is slightly different from the ST hierarchy because it follows knowledge engineering principles rather than linguistic principles. For example, SUMO

\(^4\)The obvious cases involve metaphor and metonymy [15], 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

distinguishes between physical and abstract entities. Also, the level of detail is different between SUMO classes and STs.

FrameNet has defined STs that best cover the most general and common FE fillers. STs are not intended to correspond to WordNet synsets or SUMO classes, but many of the STs we formed do, in fact, 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 themes of 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 construable as geometric figures.

Our alignment preserves the hierarchies of both SUMO and STs. The bindings are, however, of various kinds:

- Some STs have equivalent SUMO classes, such as Shape, Time, Relation, or Physical_entity. In such cases, we identify the ST with its corresponding SUMO class.
- 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 use multiple inheritance to SentientAgent and Organism.
- 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 are closely related. For example, for the ST classes Source, Path, and Goal, we find closely related relation instances like origin, path, and destination. (We show axiomatization of these facts below.)
If we do not find an equivalent SUMO class for an ST, we refine its semantics, i.e., we express in SUO-KIF what distinguishes the ST from its SUMO superclass. Also, we define relations between STs themselves.

For example, a Locative_relation \( r \) is a SpatialRelation relating at least two physical objects:

\[
\begin{align*}
  r: & \text{Locative\_relation} \Rightarrow \text{domain}(r,1,\text{Physical}) \land \text{domain}(r,2,\text{Physical})
\end{align*}
\]

Given a Goal relation \( rel \) as filler of an FE of some process \( p \), we can conclude the following: The relation \( rel \) relates some patient \( thm \) of the Motion process \( p \) to its destination \( dest \), which also is a filler of \( rel \). The destination \( dest \) itself will be of type Point. Finally, \( rel \) invokes a Locative_relation \( lr \) at the end of \( p \):

\[
\begin{align*}
  \exists \text{dest,thm,lr} & \bullet \\
  p: & \text{Motion} \land \text{dest:Point} \land \text{lr:Locative\_relation} \land \\
  \text{feFiller}(lr,dest) & \land \text{feFiller}(lr,thm) \land \\
  lr(thm,dest,(\text{EndFn}(\text{WhenFn} p))) & \land \\
  \text{rel}(\text{thm,dest,p}) & \land \\
  \text{patient}(p,thm) & \land \text{destination}(p,dest) \land \\
\end{align*}
\]

The semantics of Source and Path relations are expressed similarly. Notice that these fairly complex alignments between FrameNet and SUMO do not point out flaws or errors. Rather, they reveal modeling choices taken due to different methodologies.

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:

\[
\begin{align*}
  \text{attr}: & \text{Manner} \land \text{attribute}(\text{attr,pr}) \Rightarrow \exists \text{m} \bullet \text{manner}(\text{pr,m})
\end{align*}
\]

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.

\[
\begin{align*}
  \text{o: Physical\_object} & \leftrightarrow \text{capability(Counting,patient,o)} \\
  \text{m: Material} & \leftrightarrow \text{capability(Measuring,patient,m)}
\end{align*}
\]

5. Linking Frame Elements to SUMO

In this section we introduce and demonstrate our semi-automatic approach to linking FEs to SUMO classes, which is based on our general-domain alignment of STs with SUMO. 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.
5.1. 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, which is similar to the WordNet detour to FrameNet [16]:

1. Determine all fillers of the FE from annotations of a particular domain.
2. Look up all WordNet synsets of the headword6 of each filler.
3. Determine SUMO classes associated with the WordNet synsets from the SUMO-WordNet mappings.

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:

- If an FE has associated STs then the filler type should be a subclass7 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 alignment, 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.

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6For 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.

7By “subclass” we mean the reflexive transitive closure of the subclass relation.
5.2. 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 (WMD) and terrorism, we examine sentences from the Nuclear Threat Initiative Country Profiles and a separate smaller corpus with 21 text annotations overall 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 with 27 annotations for the Assailant FE.

Fillers for the Assailant FE in the example domain-specific corpora, their headwords, and frequencies are shown in Tab. 1a. Tab. 1b shows the SUMO classes associated with WordNet synsets of these headwords. Some fuzziness results from the headword “terrorist” whose synset is mapped to SocialRole. For our experiments we added SUMO-WordNet bindings from synsets like terrorist to the SUMO class Human to reflect the intended interpretation of SocialRole in SUMO. Additional fuzziness is introduced by words like “force” with many synsets. Note, e.g., “Newton” as a unit of measure in Tab. 1b.

Fig. 4 shows part of the SUMO class hierarchy for the Assailant FE, which we generate from Tab. 1b 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.

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

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Table 1. (a) Fillers of the Assailant FE; (b) SUMO classes associated to corresponding WordNet synsets.

<table>
<thead>
<tr>
<th>Filler</th>
<th>Headword</th>
<th>Frequency</th>
<th>SUMO Class or Instance</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>it</td>
<td>it</td>
<td>3</td>
<td>Nation</td>
<td>4</td>
</tr>
<tr>
<td>its</td>
<td>its</td>
<td>3</td>
<td>UnitedStates : Nation</td>
<td>4</td>
</tr>
<tr>
<td>Iraqi</td>
<td>Iraqi</td>
<td>2</td>
<td>ViolentContest</td>
<td>4</td>
</tr>
<tr>
<td>Iran</td>
<td>Iran</td>
<td>2</td>
<td>SubjectiveAssessmentAttribute</td>
<td>4</td>
</tr>
<tr>
<td>terrorist</td>
<td>terrorist</td>
<td>2</td>
<td>GroupOfPeople</td>
<td>2</td>
</tr>
<tr>
<td>the US</td>
<td>US</td>
<td>2</td>
<td>SocialRole</td>
<td>2</td>
</tr>
<tr>
<td>Iraq</td>
<td>Iraq</td>
<td>1</td>
<td>Human</td>
<td>2</td>
</tr>
<tr>
<td>Al-Qaida</td>
<td>Al-Qaida</td>
<td>1</td>
<td>Group</td>
<td>2</td>
</tr>
<tr>
<td>his forces</td>
<td>force</td>
<td>1</td>
<td>FunctionQuantity</td>
<td>2</td>
</tr>
<tr>
<td>by Iraq</td>
<td>Iraq</td>
<td>1</td>
<td>NormativeAttribute</td>
<td>2</td>
</tr>
<tr>
<td>US</td>
<td>US</td>
<td>1</td>
<td>EthnicGroup</td>
<td>2</td>
</tr>
<tr>
<td>U.S.</td>
<td>U.S.</td>
<td>1</td>
<td>MilitaryUnit</td>
<td>2</td>
</tr>
<tr>
<td>Chadian forces</td>
<td>force</td>
<td>1</td>
<td>Newton</td>
<td>2</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>TerroristOrganization</td>
<td>1</td>
</tr>
</tbody>
</table>

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8See http://www.nti.org/e_research/profiles/.
9See http://www.natcorp.ox.ac.uk/.
10Due to pronouns and parsing errors we do not find SUMO classes for all FE fillers.
Figure 4. Generated partial SUMO class hierarchy for the Assailant FE

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. Nation, e.g., is a one of the best candidates – 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. Another good candidate is PoliticalOrganization because it only has subclasses MilitaryForce and TerroristOrganization. GovernmentOrganization is a mixed candidate – it has ill-fitting subclasses like PublicLibrary and PublicSchool but also the fitting subclass MilitaryOrganization. Agent covers all mapped fillers. It has, however, many ill-fitting subclasses and is, therefore, not preferred. In summary, we link the Assailant FE to the union of the SUMO classes Nation, PoliticalOrganization, Government, MilitaryOrganization, and EthnicGroup:

\[
\text{Assailant} \subseteq \text{Nation} \cup \text{Government} \cup \text{PoliticalOrganization} \cup \\
\text{EthnicGroup} \cup \text{MilitaryOrganization}
\]

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. 5.1). 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.\footnote{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.}

For the general-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
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 WMD and terrorism 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,
- determining sources of error or abstracting from errors (like eliminating the class Abstract although it covers 44% of the fillers in the general domain).

6. Lessons Learned and Impact of Our Work

We found that the hierarchies of SUMO and the FrameNet STs can be aligned. Therefore, we can confirm that the SUMO ontology relates well to natural language, a fact already indicated by the SUMO-WordNet mappings. For specifying the alignment of the two hierarchies, we need, however, a fairly complex formal language like first-order logic. This is due to fundamental differences in methodology between ontological and linguistic resources.

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 some deficiencies with the FrameNet STs:

- 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 Locative_relation the new supertype of Source, Path, and Goal.
- Some STs like Aktionsarten and Animate_being described meta information or were indistinguishable and never used. So we removed these STs from FrameNet and put their subtypes elsewhere.

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

- Some SUMO relations like ξνωσε relate a CognitiveAgent and a Formula. Formula is, however, the representation of knowledge and not the knowledge itself. So we will change ξνωσε 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.
Other additions to SUMO are the creation of a Line class, which would cover linear regions such as the earth’s equator, and LivingThing which would be SUMO Organisms that have the AnimacyAttribute of Living.

We conjecture that our work has immediate impact on semantic parsing and reasoning about natural language.

A Frame parser [11,12] that analyzes a sentence like “Iraq attacked Kuwait” could use a named entity recognizer, which asserts that “Iraq” invokes an instance of the SUMO class Nation. In order for “Iraq” to be a proper Assailant, the Nation class must be a subclass of the SUMO class, the Assailant FE is linked to for the domain of discourse. A more sophisticated approach could involve reasoning in order to figure out proper FE fillers.

Through our work, FrameNet data receive a greater level of ontologization. For example, in the Placing frame, we have annotation such as the following:

\[ \text{AGENT She} \text{PUT [THEME two pieces] [GOAL under the grill] [PURPOSE to toast].} \]

Leaving aside the Agent, Theme, and Purpose FEs, the ST on the Goal FE is specified as Goal. By definitions of the FrameNet concepts we can conclude w.r.t. a Putting process P and a Goal relation rel:

\[ \text{rel:Goal} \land \text{feFiller}(P, \text{rel}) \land P: \text{Putting} \]

Our axiom for Goal relations yields:

\[
\exists \text{dest,thm,lr} \bullet \text{dest:Point} \land \text{lr:Locative}_\text{relation} \land \\
\text{feFiller}(lr,dest) \land \text{feFiller}(lr,thm) \land \\
\text{lr}(\text{thm,dest,\text{EndFn(WhenFn P)})} \land \text{rel}(\text{thm,dest,P}) \land \\
\text{patient}(P,\text{thm}) \land \text{destination}(P,\text{dest})
\]

Thus there must be a Locative Relation lr in the context that relates thm and dest, which should be given as a second annotation. Given such an annotation, the existentially quantified variables lr, thm, and dest can be instantiated with the locative relation, theme, and destination mentioned in the sentence thus concluding that “two pieces” were located “under the grill” after the Putting P. Otherwise, this should instruct a Frame parser to create a proper Locative relation annotation. Even without this annotation for the Locative relation lr, one could instantiate the filler for thm via the patient(P, thm) assertion above, given a link from the Motion Frame (which the Putting Frame uses) to the Translocation Process in SUMO.

7. Conclusion and Outlook

Our goal has been to link FrameNet to SUMO in order to provide a foundation for further experimentation in NLP, e.g., semantic parsing and ontology lexicalization. A particularly important subgoal is to constrain the filler types of FEs for specific domains. This work relies on our manual alignment of FrameNet STs with SUMO classes for the general domain. We use SUO-KIF to specify this alignment, which allows us to express complex, axiom-based, formal interrelations and gives us a homogeneous representation featuring good tool support. Based on our alignment, 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 for a particular domain, (2) FE-to-FE relations in FrameNet, and (3) STs associated with FEs. We thus provide restricted, domain-specific, ontology-based types on the fillers of FEs, which we anticipate will help semantic parsers.

We are currently investigating ways to use SUMO classes directly as STs. In the future, we will put forward our axiomatization of FrameNet STs like the Degree attributes, which calls for an ontological treatment of gradable attributes. Also, bindings from Frames to Processes in SUMO are crucial for reasoning about natural language as well as a proper ontological treatment of metonymy and metaphor. We plan further to continue to link FEs to SUMO and refine our semi-automatic approach by including additional heuristics. Finally, we envision further integration of WordNet, FrameNet, and SUMO in order to foster reasoning over natural language resources.

References