

# Acquiring Commonsense Knowledge for a Cognitive Agent

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## Abstract

A critical prerequisite for human-level cognitive systems is having a rich conceptual understanding of the world. We describe a system that learns conceptual knowledge by deep understanding of WordNet glosses. While WordNet is often criticized for having a too fine-grained approach to word senses, the set of glosses do generally capture useful knowledge about the world and encode a substantial knowledge base about everyday concepts. Unlike previous approaches that have built ontologies of atomic concepts from the provided WordNet hierarchies, we construct complex concepts compositionally using description logic and perform reasoning to derive the best classification of knowledge. We view this work as simultaneously accomplishing two goals: building a rich semantic lexicon useful for natural language processing, and building a knowledge base that encodes common-sense knowledge.

## Introduction

When researchers talk about learning by reading, they often are talking about different types of knowledge that is acquired. To us, there are three main classes of knowledge that need to be acquired to enable a human-level cognitive agent:

1. Learning facts about the world (e.g., Chicago is a city, Chicago is in the USA, ...)
2. Learning complex structured information using existing concepts (e.g., how to get to a restaurant)
3. Learning new concepts that extend our ontology (e.g., learning about plumbing)

This paper describes work addressing the third problem: how to acquire new concepts and learn the meanings of new words. It is motivated by our long-standing interest in building deep language understanding systems that provide a high-fidelity mapping of language to an underlying knowledge representation (KR). Rather than trying to build the entire target ontology by hand, however, we want to build the ontology and its associated common-sense knowledge by reading existing textual sources. We believe this is the only way we may be able to build truly broad-coverage deep understanding systems, which then would enable the acquisitions of much more complex common-sense knowledge by reading further texts (e.g., Wikipedia).

As an initial exploration of the feasibility of this enterprise, we are building an ontology by reading the definitions that are present in WordNet glosses. Learning concepts from machine readable dictionaries has a long history. Ide & Veronis, (1994) is an excellent survey of

early work, and lays out key problems in understanding dictionary definitions. First, definitions tend to be quite complex, both in structure and in the conceptualizations used; and second, they are vague, imprecise, and incomplete. However, while glosses may not capture word meaning precisely, they can capture significant amounts of common-sense knowledge.

We believe we can overcome the difficulties others have found by bringing several key ideas to bear. First, we bootstrap the whole process with a hand-built upper-level ontology that works in conjunction with a deep understanding system, namely the TRIPS system (Allen et al, 2008). This provides a capability to interpret many of the complexities in the glosses, and seeds the development of the ontology inherent in the glosses. Second, we define concepts compositionally using description logic (specifically OWL-DL) and then use off-the-shelf reasoning systems to develop the ontology using efficient subsumption algorithms. The result is a multiple-inheritance structure supporting complex composition concepts, including disjunctive and conjunctive concepts, much better suited to the definitions present in WordNet (Miller, 1995). Third, in order to produce a useful common-sense knowledge base, we hand-axiomatize key abstract concepts that people would learn from direct experience with the world, and are difficult to capture in language definitions. These are concepts like START, STOP, CHANGE, and the like. With fairly rudimentary axiomatization of such core concepts, the learned knowledge is “activated” and can produce significant entailments and common-sense models from the data. And finally, though not discussed in this paper, we use similarity and abstraction techniques to clean up the conceptual hierarchy, merging redundant and/or overly specific concepts, producing an ontology better suited for both reasoning and language processing.

## The Approach and an Example

A major stumbling block in learning conceptual knowledge from text has been the differences between the semantics inherent in natural language and the knowledge representations that have been developed for reasoning. One key problem is the issue of granularity. Linguistic representations primarily encode meaning at the word level, whereas knowledge representations deal with more complex conceptualization. As an example, note that KRs often have a top-level distinction that subdivides events into *processes* (*perdurants* in DOLCE (Gangemi et al. 2002)) such as *I'm laughing* and

accomplishments (*endurants in DOLCE*) such as *It broke*. But when we try to define the meaning of the verb *climb*, where does it fit? The sentence *I climbed all day* describes a process, whereas *I climbed the hill* describes an accomplishment. Is the verb *climb* ambiguous? If not, how can we classify it? The problem is that many concepts in ontologies correspond to *phrasal meanings* rather than word meanings, whereas linguistic ontologies stay focused on the words. This is one reason why WordNet has so many senses for each word, it tries to pack meanings of phrases into meanings of single words (typically the verb).

To unify the two styles of representation: we must ground out the representation in word meanings, because that is how the knowledge in language is delivered, and then capture entailments using complex concepts built compositionally from word meanings. We are exploring this by building a system that understands word definitions from different sources and builds the complex concept definitions that the definitions encode.

Specifically, we are employing the deep understanding capabilities of the TRIPS system, with its extensive grammar, lexicon and 2000+ concept upper ontology, to parse WordNet glosses. Like many other knowledge representation systems such as Cyc (Lenat & Guha 1990), KM (Clark & Porter 1996) and SUMO (Niles & Pease 2001), TRIPS includes a coarse grained mapping from WordNet synsets into its upper ontology. The allows an initial scaffolding with which to construct the much more detailed ontology based on the glosses.

The resulting knowledge is represented in OWL (Smith et al. 2004), for which there is a substantial technology base of efficient reasoning engines. Key to our effort, we use subsumption reasoning to organize and refine new concepts into a rich ontology. Also key is the ability of an OWL-based system to support complex compositional concepts, not just atomic concepts. This allows us to construct complete representations of many definitions, and reasonable approximations for the more complex definitions. Note that while many criticize WordNet for having too fine-grained a treatment of word senses, it's important to note that the glosses in WordNet are generally true statements about word/concept meaning, and thus encode common-sense knowledge as reflected in word meaning. By reasoning over the definitions of the different variants for a word, we can develop techniques to collapse similar senses/synsets in a systematic way.

Consider a simple example of our approach: the WordNet synset *wake\_up%2-29-00*, involving the verb “wake up,” is defined by the gloss *stop sleeping [1:09:00]*. Our processing is made simpler by the fact that about half the content words in WordNet glosses are already tagged with their WordNet sense. In this definition, we are given the sense of *sleeping* but must identify the appropriate sense of *stop*.

The relevant part of the logical form produced by the TRIPS parser for this definition is output as three terms:

(F v1 (:\* STOP stop%2:42:00) :affected v3 :process v2)  
 (F v2 (:\* BODILY-PROCESS sleep%1:09:00) :affected v3))  
 (IMPRO v3 LIVING)

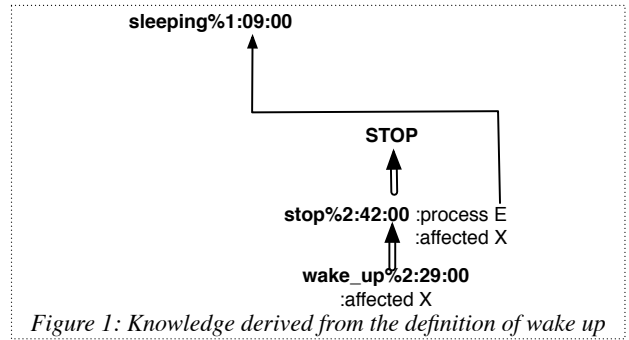


Figure 1: Knowledge derived from the definition of wake up

Interpreting these terms, there is an event, **V1**, which is of type STOP in the TRIPS ontology and **stop%2:38:00** in WordNet, which has a :process role filled with an event **V2**, which is of type BODILY-PROCESS in TRIPS and **sleep%1:09:00** in Wordnet. Finally, there is an implicit argument (the IMPRO form), which is an object of type LIVING and fills the :affected role of both the stopping and sleeping events. This type was derived from the selectional restrictions in the TRIPS ontology that only LIVING things can undergo bodily processes.

The TRIPS ontology gives an initial framework for conceptual classification but few specifics about actual word meaning for most words. For instance, TRIPS knows nothing about the action *sleeping%1-09-00*, except that it is some BODILY-PROCESS. Since we haven't read the definition of *sleeping%1-09-00* yet, we have no further information about it.

The other key thing we need to do to define a new concept is to identify the its arguments (i.e., roles). To identify the roles for new concepts, we take all the roles in the defining concept that are either missing in the definition (i.e., as a gap) or are filled by an indefinite pro-form (e.g., someone, somewhere, ...). In the current example, we infer that the new concept “wake up” has a *affected* role, derived from the role structure of STOP. Note another essential role in STOP, namely the *process* role, but this is not inherited to *wake\_up%2-29-00* because it was fully instantiated in the definition. To confirm the role hypotheses, we parse the examples attached to entries in wordnet and adjust the analysis if necessary.

Figure 1 shows the definition in human-readable form that the system constructs from the gloss. The double arrows relate an entire concept to it's superclass, and the single arrows relate an argument to its superclass (i.e., its restriction). The actual definition in OWL-DL would be:

$wake\_up\%2:29:00 \subseteq stop\%2:42:00 \cap$   
 $\exists process.sleeping\%1:09:00 \cap \exists affected.living$

i.e., a waking up event is a subset of stopping events whose affected role is an intentional agent and whose process is sleeping.

If we then reading the gloss for **sleeping%1:09:00** we can extend the knowledge base with additional information. The result of processing the definition *the state%1:03:00 of being asleep%4:02:00* is shown in Figure 2.

As mentioned above, a key part of our approach is that we treat concepts as complex objects, not atoms. This allows for compositional construction of new concepts as

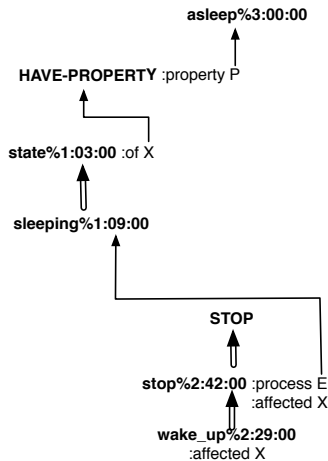


Figure 2: After processing *sleeping%1:09:00*

well as opening the door to using reasoning techniques such as the subsumption algorithm found in description logics. An ontology that treats all concepts as atoms inhibits learning, for there is no systematic mapping from phrases in language to new concepts. There is no structure to support non-trivial reasoning.

Before we consider how we and use such knowledge for reasoning, we will explore the construction of concepts from definitions in more detail.

### Constructing Definitions

This section provides a little more detail on how we build definitions from glosses. The first stage of processing involves parsing the definitions using TRIPS parser [Allen et al, 2008]. We use all the information present in the glosses, including part of speech tags and sense tags when available, in order to provide guidance to the parser. For words not in the TRIPS lexicon, or that do not have a sense corresponding to the WordNet sense tag, the TRIPS lexicon managers searches WordNet for words matching the provided information and automatically constructs an underspecified representation in the TRIPS lexical format. The WordNet sense tags are converted into TRIPS ontology concepts using hand-built mappings from high-level WordNet senses to the TRIPS ontology. To control ambiguity arising from multiple senses in WordNet, the parser prefers lexical entries corresponding to actual tagged senses when they are present in the glosses.

The output of the parser is a logical form graph, which encodes an unscoped modal logic with reified events and semantic roles as shown above.

The logical form graph is then translated into an OWL compositional class using a simple algorithm, which we illustrate using the LF term

(F v1 (\* STOP stop%2:42:00) :affected v3 :process v2)

1. We create a new concept for the class being defined using the type in the LF graph (e.g., **wake\_up %2:29:00**). Call this **C**.
2. Create (or identify in the ontology) a concept corresponding to the defining concept (e.g., **stop %2:42:00**). Call this **T**.
3. If the defining concept has roles  $r_1, \dots, r_n$  (e.g., :affected, :process), recursively build new concepts for each of the arguments. Call these concepts **R<sub>1</sub>, ..., R<sub>n</sub>**.
4. Define the class:  $C \subseteq T \cap \exists r_1.R_1 \cap \dots \cap \exists r_n.R_n$

There are a few special cases that complicate the algorithm. For example, many of the glosses involve disjunctive constructs, and these are handled by mapping the disjunctive in the logical form to a UNION of the two classes. Conjunctions are treated as intersections.

### Building a Micro-Theory of Sleeping

To explore the potential of this approach, we extracted a subset of WordNet consisting of all the concepts that involve the notion of sleeping in some way. This includes all the senses of sleep itself, words derivationally related to sleep, words that have some connection to sleep in their definitions, plus the definitions of all words used in the definitions of sleep (see Table 1). WordNet does encode some relationships between these words, but they are highly underspecified. The most common link is the “derivationally related” link, which indicates some morphological connection between words but nothing about their semantic relationship. More useful are the antonym relations, and we used these links when gathering related words. We did not, for this experiment, use the antonym information to define the KB. Thus one test of the worth of our approach is whether antonyms can be derived automatically.

The result of interpreting these glosses is shown in Figure 3. There are few things to note. First, while there is considerable variation in how definitions are phrased, in the end all the sense reduce down to the nominal

Synset Name	Gloss
wake_up%2:29:00	to stop%2:42:00 sleeping%1:09:00
sleeping%1:09:00	the state%1:03:00 of being asleep%4:02:00
asleep%4:02:00	into a sleeping state%1:03:00
fall_asleep%2:29:00	to change%2:30:00 from a waking%1:09:00 to a sleeping [sleep%2:29:00] state%1:03:00
waking%1:09:00	the state%1:03:00 of remaining awake
sleep%2:29:00	to be asleep%4:02:00
awake%3:00:00	not in a state%1:03:00 of sleep%1:26:00
asleep%3:00:00	in a state%1:03:00 of sleep%1:26:00
sleep%1:26:00	a natural and periodic state%1:03:00 of rest during which consciousness%1:09:00 of the world %1:09:00 is suspended [suspend%2:30:02]
keep_up%2:29:00	prevent%2:41:00 from going to bed [go_to_bed%2:29:00]
go_to_bed%2:29:00	to prepare for sleep%2:29:00
sleeper%1:18:00	a rester%1:18:00 who is sleeping [sleep%2:29:00]
rester%1:18:00	a person%1:03:00 who rests [rest%2:35:00,rest%2:32:00,rest%2:29:00]

Table 1: Glosses in WordNet directly related to sleeping, showing sense tags when provided

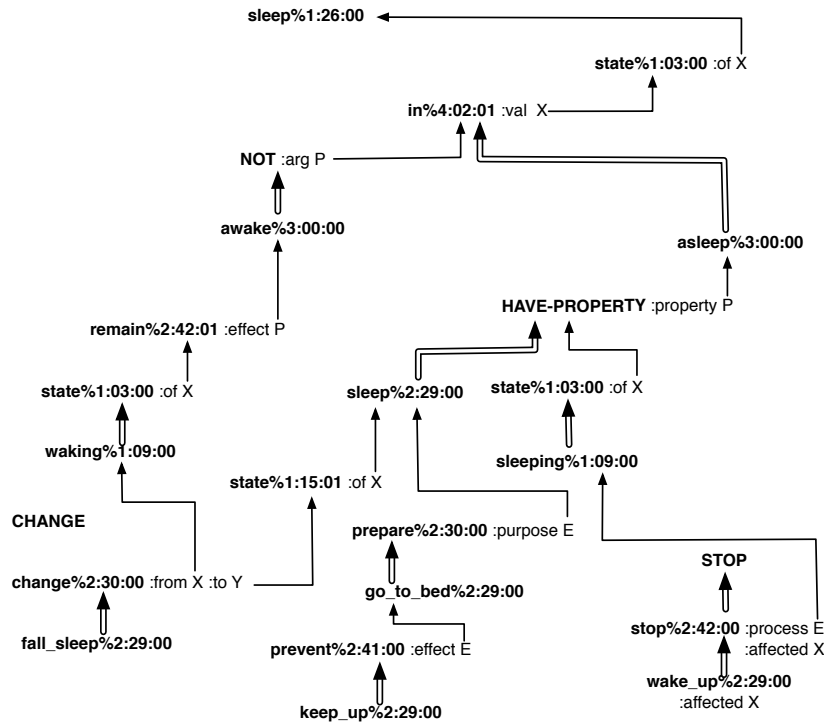


Figure 3: The micro-theory of sleeping constructed by the system

concept **sleep%1:26:00**. This concept is further defined (as *a natural and periodic state of rest during which consciousness of the world is suspended*), but we have suppressed this information as it does not affect our example. On the face of it, there seems great potential for reasoning over these concepts. We see, for instance, that being **awake%3:00:00** is “not being in state of **sleep%1:26:00**” while being **asleep%3:00:00** is “in a state of **sleep%1:26:00**”. With an appropriate handling of negation, we could infer that both this states cannot hold simultaneously. But other conclusions seem close but evade realization. For instance, we would like to be able to conclude that after one wakes up, one is awake. But this not not derivable from the current knowledge base as we don’t have appropriate knowledge about what it means to **stop%2:42:00**. And looking at the WordNet definitions doesn’t help. Here are the relevant definitions:

- Stop: come to a halt, stop moving*
- Halt: the event of something ending*
- Ending: be the end of*
- End: the point in time when something ends*

WordNet has the same problem that we find in all dictionaries, namely that some core concepts are simply impossible to reduce to other concepts and the definitions become circular. This leads us to the next key part of the work: defining an inferential model that can exploit the knowledge we have gained.

### Inference

Description logic supports inference about classes of objects, and provides efficient inference models for computing subsumption of classes in a multiple-inheritance representation. These definitions say nothing about any particular individuals. For instance, **wake\_up%2:29:00** was defined as the stopping of an event described by the nominalization **sleep%1:09:00**, which

is defined as “a state of **sleep%2:29:00**”, which is the verbal form of the event. Nothing in the description logic says that when you are in the state of some event occurring, that the event is actually occurring. To capture such relationships and use the knowledge we produce, we need to introduce some axioms for basic concepts.

We’ll define a representation for making assertions based on interval-based temporal logic (Allen, 1984). We have a predicate  $T$  that asserts that some concept (described by a OWL concept) holds/occurs over time  $t$ . While Allen distinguished between events occurring and properties holding, we will ignore such issues here. With this representation, we can now define some basic axioms that enable inference. To handle negation, we have the axiom (where all lower case letters are universally quantified variables)

$$T([\text{NOT :arg } p], t) \Leftrightarrow \neg T(p, t)$$

i.e., the concept of a situation not holding holds at  $t$  if and only if it’s not the case that the situation holds at  $t$ . With this axiom, we can now prove that the situations described by **awake%3:00:00** and **asleep%3:00:00** are mutually exclusive.

In order to derive much of the rest of the relationships we’d like, we need to axiomatize some key concepts like stopping, causing, preventing, and so on. As an example, here is one of the axioms for **stop%2:42:00** (all variables without quantifiers are assumed to be universally quantified):

$$T([\text{stop}\%2:42:00 \text{ :process } e], t) \supset \exists t' . \neg T(e, t') \wedge \text{meets}(t, t')$$

i.e., if event  $e$  stops at time  $t$ , then  $e$  is not occurring at time  $t'$  that immediately follows  $t$ , using the *meets* relation from Allen (1983).

Figure 4 shows a sampling of these core axioms, ones that are particularly relevant to the micro-theory of sleeping we have derived. A reader might complain that

#	Axiom	Example Entailment in the sleeping microtheory using the axiom i
1	$T([stop\%2:42:00 :effect\ e], t) \supset \exists t' . \neg T(e, t') \wedge meets(t, t')$	After stopping sleeping, you are not sleeping
2	$T([in\%4:02:01 :val\ [state\%1:03:00 :of\ e]], t) \supset T(e, t)$	If you are in a state of sleeping, you are sleeping
3	$T([state\%1:03:00 :of\ e], t) \supset T(e, t)$	If a state of sleeping holds now, then sleeping holds now.
4	$T([[[HAVE-PROPERTY :property\ p], t) \supset T(p, t)$	If you have the property 'you are sleeping', then 'you are sleeping'
5	$T([prevent\%2:41:00 :effect\ e], t) \supset \neg T(e, t)$	If you prevent E from happening, then it isn't happening
6	$T([remain\%2:42:01 :effect\ e], t) \supset T(e, t) \ \& \ \exists t' . Meets(t', t) \wedge T(e, t')$	If you remain sleeping, then you were sleeping before and are sleeping now.
7	$T([change\%2:30:02 :from\ e], t) \supset \exists t' . Meets(t', t) \wedge T(e, t') \ \& \ \neg T(e, t)$	If something changes from being in some situation, then it was in that situation before
8	$T([change\%2:30:02 :to\ e], t) \supset \neg T(E) \ \& \ \exists t' . Meets(t, t') \wedge T(e, t')$	If something changes to being in some situation, then it is in that situation next

Figure 4: Some common-sense axioms

we are hand-building the knowledge we need, but in fact, we believe the number of core concepts that will be axiomatized is relatively small, say on the order of 50 to 100 concepts, and that almost all the knowledge in the axioms is knowledge that a cognitive agent would generally learn by early experiences interacting with the world. So the hand-defined set of axioms replace the the need for an agent that can learn in situ before acquiring much language. With this base, then we can learn the meanings of all other words directly from the glosses.

Finally, in this logical framework we need an axiom schema that relates subsumption and inference. Essentially, if a concept describing a situation holds, then all superconcepts of that concept also hold. This rule is the inheritance rule:

#### Inheritance Rule

If concept A subsumes concept B, then  $T(B, t) \supset T(A, t)$

We now have everything we need to use the knowledge base to compute entailments. First, note we can derive the antonym relation between awake%3:00:00 and asleep%3:00:00 directly from the definitions. As a more complex example showing how the axioms work, consider the following proof of the statement *Before falling asleep (Fall\_asleep%2:29:00), the agent is awake%3:00:0:*

- a. Assume  $T(Fall\_asleep\%2:29:00, T)$
- b.  $[change\%2:30:02 :to\ [state\%1:03:00 :of\ sleep\%2:29:00]]$  holds at time T (inheritance, defn of *Fall\_asleep%2:29:00*)
- c. *sleep%1:09:00* holds at a time  $T_n$  which immediately follows time T (axiom 3)
- d.  $[state\%1:03:00 :of\ [HAVE-PROPERTY :property\ asleep\%3:00:00]]$  holds at the a time  $T_n$  ((inheritance, defn of *sleep%1:09:00*)
- e.  $[HAVE-PROPERTY :property\ asleep\%3:00:00]$  holds at  $T_n$  (axiom 8).
- f. *asleep%3:00:00* holds at  $T_n$  (axiom 4)
- g.  $[in\%4:02:01 :val\ [state\%1:03:00 :of\ sleep\%1:26:00]]$  holds at time  $T_n$  (inheritance, defn of *asleep%3:00:00*)
- h.  $[state\%1:03:00 :of\ sleep\%1:26:00]$  holds at time  $T_n$  (axiom 2)
- i. Thus, *sleep%1:26:00* holds at time  $T_n$  (axiom 3)

Note that while there are 8 inference steps to derive this conclusion from the definitions, the search space is very small and such inference can be performed rapidly using a simple forward inference chaining algorithm. It would be entirely possible to precompute many of these

conclusions (that seem obvious to us) in a post-processing phase of the learning in order to simplify the knowledge base.

## Implementation

We have implemented this reasoning framework using SWRL, a standard reasoning engine for OWL. Each of the axioms in Figure 4 have a direct translation into SWRL. We then can perform such inference in a forward chaining fashion when instances are added, pretty much following the proof just presented.

Using this, we can test what conclusions the agent can draw about sleeping given the derived knowledge from the glosses. Here are a few other statement it now believes

*Being awake%3:00:0 is mutually exclusive with being asleep%3:00:00*

*If an agent is Sleeping%2:29:00, then it is asleep, and thus not awake.*

*If an agent falls asleep (Fall\_asleep%2:29:00), then it is in a state of sleep afterwards, and is not awake.*

*If an agent wakes up, then it was sleeping and now is not.*

Note that there are other facts we would like to derive but cannot be obtained from the definitions. For instance, we learn that keeping someone up is preventing them from going to bed, which is defined as *preparing for sleep*. So we can conclude that keeping someone up prevents them from preparing for sleep, but not that they didn't fall asleep anyway without preparation! Either we need to find a better definition or, more practically, we need to develop a framework for default/probabilistic reasoning. Another solution is to gather information from many different sources and use reasoning processes to combine and reconcile differences.

## Can this really work?

Constructing the mini-theory of sleep was quite successful, so it leads to the question of whether we can use these techniques to construct a knowledge base containing all the information present in WordNet. In this section we discuss some of the challenges we face in accomplishing this task. There are two main challenges we face: getting accurately understanding of definitions, and cleaning up and organizing the knowledge that is produced.

## Challenges in Understanding

Regarding understanding the glosses, we first note that the glosses for the sleeping words are unusually clean and concise. Many other glosses are significantly more difficult to understand, which we discuss here.

### *Disjunction and Conjunction*

The first thing to note is that many glosses involve significant use of disjunctions and conjunctions. While it is not difficult to express such concepts in OWL-DL, getting the right parses is a considerable challenge. Consider the gloss for *bouillabaisse*:

*Highly seasoned Mediterranean soup or stew made of several kinds of fish and shellfish with tomatoes and onions or leeks and seasoned with saffron and garlic and herbs*

The TRIPS parser is unable to find a full spanning parse for this definition because of the complexity of the search space. It does however produce a partial understanding using its robustness mechanism and produces a definition equivalent to the fragment a *seasoned Mediterranean soup or stew*. While this correctly defines *bouillabaisse* as a soup/stew dish it misses much of the detail present in the gloss. We plan to explore some preprocessing techniques to bracket conjunctions using semantic similarity measures to improve conjunction handling.

### *Vague Semantic Relations*

We can use the same example to illustrate the next issue. The understander is currently unable to refine vague relations in the definitions. The most common source of such vagueness is in noun-noun modification, as in *Mediterranean soup*. The logical form for this fragment uses the very abstract relation *Assoc-with* (i.e., associated with), which could be *ownership*, *part-of*, *made-from*, and so on. We currently have no mechanism for refining this to a better relation. This may be a case where we attempt a bootstrapping approach. We first acquire information about the various relationships such as *partof* and *madeof* using text mining techniques. We then can use this knowledge to identify more specific relations when available. As an example, the gloss for the locomotive sense of *engine* starts with *a wheeled vehicle ...* which produces an LF with a vehicle *Assoc-with* wheels. If we already know that vehicles can have wheels, we could refine this semantic relation appropriately. Note that while WordNet does contain *part-of* information, it is very partial - in fact there is only one part identified for vehicles, namely the dashboard.

### *Word Sense Ambiguity*

In general word sense ambiguity remains an issue when learning by reading online sources. For WordNet, however, about half of the words in the the glosses have been hand-tagged with their senses, making this a very useful resource to start with. While there are some errors, as noted above, in some cases the parser is able to correct the problem as these tagged senses only come in as preferences, not absolute constraints. For the general problem when we move to other resources, we need to address better what are useful senses. It is widely acknowledged that WordNet uses far too fine a set of

senses to be useful as a knowledge base. This issue is revisited in the next section, under cleaning up and organizing knowledge.

## Challenges in Organizing Acquired Knowledge

Even if the glosses were understood perfectly, the resulting knowledge would be a jumble of idiosyncratic information based on the whims of the people writing the glosses. In this section we consider a few techniques that we pursuing to clean up the resulting knowledge.

### *Cleaning up Redundancies*

Note first that we do have a good start in using OWL-DL reasoners. If equivalent concepts are defined from the glosses, the subsumption algorithms should be able to identify them. There are a fair number of concepts in WordNet that are unnecessary and create spurious ambiguity issues. For instance, WordNet has a concept **young\_person%1:18:00** defined as *a young person!* To identify such issues, we parse the phrase *young person* that is associated with the sense and find that the compositional semantics is exactly equivalent to the gloss definition. In other words, there is no need for **young\_person%1:18:00** as a separate concept as it can be produced compositionally. Not all cases are so easy, but we believe similar techniques will identify likely candidates. For instance, **young\_woman%1:18:00** is defined as *a young female*, and **woman%1:18:01** is defined as *a female person*. Processing these definitions places **young\_woman%1:18:00** very close in the hierarchy go the compositional meaning of *young woman*. We need to identify effective heuristics for collapsing such cases.

### *Reducing Word Senses*

Related to this are techniques we are exploring for reducing the number of senses for words to an effective core. As an example, consider glosses for two of the 49 senses of the verb *make*:

*Cause to do*

*Compel or make someone to act in a certain way*

Now, *compel* is defined as *force somebody to do something*, and *force* is defined as *to cause to do ...* Thus *compel* and *cause* are closely related. Furthermore, the appropriate sense of *do* is defined as *perform an action*, and *act* is also defined as *perform an action*. By constructing all these concepts, we find these two senses of *make* are virtual synonyms of each other, and so we should construct a single sense that captures all the entailments of both.

This, again, is a simple example. We are exploring more general clustering techniques based on semantic similarity in the conceptual hierarchy to identify abstract senses that produce much cleaner knowledge.

### *Eliminating Meta-talk and Language Variants*

Language supports substantial variation in conceptualizing the same circumstances. This can be seen in the sleep mini-theory we constructed, where we see multiple nominalizations (**sleeping%1:09:00**, **sleep%1:26:00**), verbal forms (**sleep%1:26:00**), adjectival properties (**asleep%3:00:00**) and adverbials (**asleep%4:02:00**) all essentially referring to the same state of

affairs (i.e., being asleep).. One of the points of doing the sleeping mini-theory in detail was to show that we could inferentially connect all these concepts in a reasonable way. We could also use the same derived knowledge, however, to produce much more concise knowledge base that is abstracted one level away from language. The idea would be to use the forward chaining of the core axioms in order to produce simplified knowledge. As an example, consider the concept `wake_up%2:29:00` again. Rather than depending on inference every time we consider a waking up event, we could do forward chaining once in a preprocessing stage and then build a richer conceptual structure with the concept. Taking terminology from the event semantics, we might directly assert that the result of a *wake up* event is that the actor is *awake*, and that a necessary precondition on this event occurring is that the actor was *asleep*. By doing this, we could build an axiomatization of events similar to that proposed in Allen (1984).

### Related Work

While clearly a critical need in constructing human-level cognitive agents, automatic acquisition of linguistically-based knowledge has not been explored much in the cognitive systems literature. But there is a significant history trying to build lexical knowledge from dictionaries, and a substantial amount of new work on mining the web to learn facts. The latter work, however, does not focus on learning conceptual knowledge, so we will not consider it further here.

Research on automatically building knowledge bases from lexical resources has a long history. Early attempts used techniques such as hypertext extraction (e.g., Calozari 1984; Chodorow et al. 1985), pattern matching (e.g., Alshawi 1989; Vossen et al. 1989; Wilks et al. 1989) and co-occurrence data (e.g., Wilks et al. 1989).

In an evaluation, Ide & Véronis (1994) conclude that the limited results from these efforts show that understanding lexical definitions requires deeper processing than the techniques applied to date. They attribute lack of progress to lack of sophistication of the extraction techniques as well as source information that is inconsistent, circular, or missing crucial (often common sense) information.

Other work targets encoding WordNet glosses as axioms in first-order logic (Harabagiu et al. 1999; Rus 2005). The logical information is extracted from syntactically processed glosses using straightforward structural analysis (for example mapping the NP in a subject position to an AGENT role), which limits the depth of the semantic representation. In addition, the representation does not lend itself to using reasoning processes in order to clean up and refine the conceptual definitions.

Our approach addresses many of the shortcomings in previous work. TRIPS gives us a well developed core deep language understanding system that provides a substantial processing boost beyond what is available with other off-the-shelf tools. Furthermore, its ontology defines key concepts and their participant roles in a hierarchy. Each word is associated with a concept and

linking templates that align the semantic relations with syntactic structure during parsing. The TRIPS NL framework helps us overcome the bootstrapping problem that limits the depth of information extracted with earlier approaches.

### Concluding Remarks

A critical obstacle preventing the constructing of human-level cognitive agents is the lack of common-sense knowledge that it would need to understand language and reason about the world. We hope we have presented a convincing case that extraction of high quality knowledge from sources such as WordNet is a feasible goal to pursue.

While the example we presented in this paper is small, and based on a particularly suitable subset of WordNet, we are currently performing a significantly larger experiment based on approximately 7500 synsets that are likely to be related to cooking. In order to construct an effective knowledge base, we are working on a number of the challenges presented earlier. We plan to evaluate this cooking KB by having subjects pose queries about cooking (based on a provided set of templates) to both the system and to a human using a web-based system, and then scoring the resulting answers for degree of appropriateness and correctness.

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