A Logic-based Approach for Recognizing Textual Entailment Supported by Ontological Background Knowledge

Andreas Wotzlaw
Institut für Informatik, Universität zu Köln
Weyertal 121, 50931 Köln, Germany
wotzlaw@informatik.uni-koeln.de

Ravi Coote
Fraunhofer-Institut FKIE
Fraunhoferstr. 20, 53343 Wachtberg, Germany
ravi.coote@fkie.fraunhofer.de

Abstract

We present the architecture and the evaluation of a new system for recognizing textual entailment (RTE). In RTE we want to identify automatically the type of a logical relation between two input texts. In particular, we are interested in proving the existence of an entailment between them. We conceive our system as a modular environment allowing for a high-coverage syntactic and semantic text analysis combined with logical inference. For the syntactic and semantic analysis we combine a deep semantic analysis with a shallow one supported by statistical models in order to increase the quality and the accuracy of results. For RTE we use logical inference of first-order employing model-theoretic techniques and automated reasoning tools. The inference is supported with problem-relevant background knowledge extracted automatically and on demand from external sources like, e.g., WordNet, YAGO, and OpenCyc, or other, more experimental sources with, e.g., manually defined presupposition resolutions, or with axiomatized general and common sense knowledge. The results show that fine-grained and consistent knowledge coming from diverse sources is a necessary condition determining the correctness and traceability of results.

1. Introduction

In this paper we present a new, logic-based system for recognizing textual entailment (RTE). Our aim is to provide it as a robust, modular, and highly adaptable environment for a linguistically motivated large-scale semantic text analysis. In RTE (see Dagan, Dolan, Magnini, & Roth, 2009, for a good introduction) we want to identify automatically the type of a logical relation between two written texts. In particular, we are interested in proving the existence of an entailment between them. The concept of textual entailment indicates the state in which the semantics of a natural language written text can be inferred from the semantics of another one. RTE requires a processing at the lexical, as well as at the semantic and discourse levels with an access to vast amounts of problem-relevant background knowledge. RTE is one of the greatest challenges for any natural language processing (NLP) system. If it succeeds with reasonable accuracy, it is a clear indication for some thorough understanding of how language works (Bos & Markert, 2005b). As a generic problem it has many useful applications in NLP (Giampiccolo, Magnini, Dagan, & Dolan, 2007). Interestingly, many application settings like, e.g., information retrieval,
paraphrase acquisition, question answering, or machine translation can fully or partly be modeled as RTE (Bentivogli, Dagan, Dang, Giampiccolo, & Magnini, 2009). Entailment problems between natural language texts have been studied extensively in the last few years, either as independent applications or as a part of more complex systems (e.g., RTE Challenges, see Bentivogli et al., 2009).

We try to solve a given RTE problem by applying a model-theoretic approach where a formal semantic representation of the RTE problem is computed and used in the subsequent logical analysis. In our setting, we try to recognize the type of the logical relation between two English input texts, i.e., between the text $T$ (usually several sentences) and the hypothesis $H$ (one short sentence). The following definition specifies more formally the inference problems we consider in RTE (see Van der Sandt, 1992, for a similar definition).

**Definition 1.** Let $T$ be a text consisting of several sentences and $H$ a hypothesis expressed by a sentence. Given a pair \{T,H\}, find answers to the following, mutually exclusive conjectures with respect to the background knowledge relevant both for $T$ and $H$:

1. $T$ entails $H$,

2. $T \land H$ is inconsistent, i.e., $T \land H$ contains some contradiction, or

3. $H$ is informative with respect to $T$, i.e., $T$ does not entail $H$ and $T \land H$ is consistent (contains no contradiction). This holds, e.g., when $H$ and $T$ are completely unrelated.

However, in contrast to automated deduction systems (e.g., presented in Akhmatova, 2005), which compare the atomic propositions obtained from text $T$ and hypothesis $H$ in order to determine the existence of entailment, we apply logical inference of first-order, similar to (Bos & Markert, 2005b). To compute adequate semantic representations for input problems, we build on a combination of deep and shallow techniques for semantic analysis. The main problem with approaches processing the text in a shallow fashion is that they can be tricked easily, e.g., by negation, or systematically replacing quantifiers. Also an analysis solely relying on some deep approach may be jeopardized by a lack of fault tolerance or robustness when trying to formalize some erroneous text (e.g., with grammatical or orthographical errors) or a shorthand note. The main advantage when integrating deep and shallow NLP components is the increased robustness of deep parsing by exploiting information for words that are not contained in the deep lexicon. The type of unknown words can then be guessed, e.g., by usage of statistical models.

The semantic representation language we use in our RTE system for the results of the deep-shallow analysis is a first-order fragment of Minimal Recursion Semantics (MRS, see Copestake, Flickinger, Pollard, & Sag, 2005). However, for their further usage in the logical inference, the MRS expressions are translated into another, semantic equivalent representation of First-Order Logic with Equality (FOLE). This logical form with a well-defined model-theoretic semantics was successfully applied for RTE by Bos & Markert, 2005b.

An adequate representation of a natural language semantics requires access to vast amounts of common sense and domain-specific world knowledge. Many applications in modern information technology utilize ontological knowledge to increase their performance.

---

2. In this paper we mean by ontology any set of facts and/or axioms comprising potentially both individuals (e.g., London) and concepts (e.g., city).
and to improve the quality of results. This applies in particular to the applications from the Semantic Web, but also to other domains. For instance, machine translation exploits lexical knowledge (Chatterjee, Goyal, & Naithani, 2005), document classification uses ontologies (Ifrim & Weikum, 2006), whereas question answering (Hunt, Lita, & Nyberg, 2004), information retrieval (Bentivogli et al., 2009), and textual entailment (Bos & Markert, 2006) rely strongly on background knowledge. There are also emerging trends towards entity- and fact-oriented Web search which can build on rich knowledge bases (Cafarella, Re, Suciu, & Etzioni, 2007; Milne, Witten, & Nichols, 2007). Furthermore, ontological knowledge structures play an important role in information integration in general (Noy, Doan, & Halevy, 2005).

Unfortunately, the existing applications today use typically only one source of background knowledge, e.g., WordNet (Fellbaum, 1998) or Wikipedia. They could boost their performance if a huge ontology with knowledge from several sources was available. Such a knowledge base would have to be of high quality and accuracy comparable with that of an encyclopedia. It should include not only ontological concepts and lexical hierarchies like those of WordNet, but also a great number of named entities (here also referred to as individuals) like, e.g., people, geographical locations, organizations, events, etc. Also other semantic relations between them, e.g., who-was-born-when, which-language-is-spoken-in, etc. should be comprised.

RTE systems need problem-relevant background knowledge to support their proofs. The logical inference in our system is supported by external background knowledge integrated automatically and only as needed into the input problem in form of additional first-order axioms. In contrast to already existing applications (see, e.g., Curran, Clark, & Bos, 2007; Bentivogli et al., 2009), our system enables flexible integration of background knowledge from more than one external source (see Section 4.1 for details). In its current implementation, our system supports RTE, but can also be used for other NLP tasks like, e.g., large-scale syntactic and semantic analysis of English texts, or multilingual information extraction.

The rest of the paper is organized as follows. In Section 2, we review some related works and compare our method with the existing ones. In Section 3, we introduce the architecture of our system for RTE. In Section 4, we show how the quality of the logic-based inference process of our system can further be improved. Finally in Section 5, we discuss the evaluation results and conclude the paper.

2. Related Work.

As a generic problem RTE has many applications in NLP which have been studied extensively in the last few years. We refer the reader to Dagan et al. (2009), Bentivogli et al. (2009), and Androutsopoulos and Malakasiotis (2010) for good overviews. Our work was mostly inspired by the ideas given by Blackburn and Bos (2005), and Bos and Markert (2005b), where a similar model-theoretic approach was used for the semantic text analysis with logical inference. However, in contrast to our logic-based approach, they applied another, more discourse-oriented semantic formalism, Discourse Representation Theory (Kamp & Reyle, 1993), for the computation of full semantic representations. Furthermore, in our system the framework Heart of Gold by Schäfer (2007) was used as a basis
for the semantic analysis. For a good overview on a combined application of deep and shallow NLP methods for RTE, we refer to Schäfer (2007), and Bos and Markert (2005a). The application of logical inference techniques for RTE was already elaborately presented in Blackburn, Bos, Kohlhase, and De Nivelle (1998), Bos and Markert (2005b), and Bos and Markert (2006). Moreover, an interesting discussion on the importance of WordNet as a source of background knowledge for RTE can be found in Bos (2005), and Bos and Markert (2006). Tatu and Moldovan (2006) proposed for RTE a new knowledge representation model and a logic proving setting with axioms on demand. A detailed discussion on formal methods for the analysis of the meaning of natural language expressions can be found in Bos (2008). Furthermore, a new approach for RTE using natural logics was given by MacCartney and Manning (2009). The authors propose a promising, annotation-based model of natural language inference which identifies valid inferences by their lexical and syntactic features, without full semantic interpretation. Note that in the system presented in this paper we aim at computing a full semantic representation of the input texts.

Finally, the inference process of our system applies ontological knowledge coming from different external sources like, e.g., WordNet or YAGO (Suchanek, Kasneci, & Weikum, 2008). In the last few years we have been observing a reasonable growth of interest in huge ontologies and their applications. There exists also a number of huge ontology integration projects like, e.g., YAGO together with the Suggested Upper Model Ontology (SUMO, see de Melo, Suchanek, & Pease, 2008), DBpedia (Auer, Bizer, Kobilarov, Lehmann, Cyganiak, & Ives, 2007), or the Linking Open Data Project (Bizer, Heath, & Berners-Lee, 2008) which aim is to extract and to combine ontological data from many sources. Since YAGO is a part of those ontology projects, it should be possible to integrate them (at least partly) into the RTE application by applying the integration procedure from Section 4.

3. System Architecture

Our system for RTE provides the user with a number of essential functionalities for syntactic, semantic, and logical textual analysis which can selectively be overridden or specialized in order to provide new or more specific ones, e.g., for anaphora resolution or word sense disambiguation. In its initial form, the application supplies, among other things, flexible software interfaces and transformation components, allows for execution of a deep-shallow syntactic and semantic analysis, integrates external inference machines and background knowledge, maintains and controls the semantic analysis and the inference process, and provides the user with a graphical interface for control and presentation purposes.

In the following we describe our system for RTE in more detail. It consists of three main modules (see Figure 1):

1. **Syntactic and Semantic Analysis**, where the combined deep-shallow semantic analysis of the input texts is performed;

2. **Logical Inference**, where the logical deduction process is implemented (it is supported by two external components integrating external knowledge and inference machines);

3. **Graphical User Interface**, where the analytical process is supervised and its results are presented to the user.
In the following we describe the way the particular modules of the system work. To make our description as comprehensible as possible, we make use of a small RTE problem. More specifically, with its help we show some crucial aspects of how our system proceeds while solving some RTE problem. We want to identify the logical relation between text $T$:

$T$: *Tower Bridge is one of the most recognizable bridges in the world. Many falcons inhabit its old roof nowadays.*

and hypothesis $H$:

$H$: *Birds live in London.*

To prove the entailment automatically, among other things, a precise semantic representation of the problem must be computed, the anaphoric reference in $T$ must be resolved, and world knowledge (e.g., *Tower Bridge* is in *London*) and ontological relations between the concepts (e.g., that *falcons* are *birds*) must be provided to the logical inference. In the following we show how our system proceeds while computing the first-order semantic representation of the input texts above.

### 3.1 Syntactic and Semantic Analysis

The texts of the input RTE problem after entering the system via the user interface (see Figure 1) go first through the syntactic processing and semantic construction of the first system module. To this end, they are analyzed by components of an XML-based middleware architecture *Heart of Gold* (see Figure 2). It allows for a flexible integration of various shallow and deep linguistics-based and semantics-oriented NLP components, and thus constitutes a sufficiently complex research instrument for experimenting with novel processing strategies. Here, we use its slightly modified standard configuration for English centered around the English Resource HPSG Grammar (ERG, see Flickinger, 2000). The shallow processing is performed through statistical or simple rule-based, typically finite-state methods, possessing sufficient precision and recall. The particular tasks are as follows: tokenization with the Java tool JTok, part-of-speech tagging with a statistical tagger TnT of Brants (2000)
Figure 2: Syntactic and semantic analysis

trained for English on the Penn Treebank (Marcus, Marcinkiewicz, & Santorini, 1993), and named entity recognition with SProUT (Drozdzyński, Krieger, Piskorski, Schäfer, & Xu, 2004). The last one, by combining finite state and typed feature structure technology, plays an important role for the deep-shallow integration, i.e., it prepares the generic named entity lexical entries for the deep HPSG parser PET of Callmeier (2000). This makes sharing of linguistic knowledge among deep and shallow grammars natural and easy. PET is a highly efficient runtime parser for unification-based grammars (like, e.g., ERG) and constitutes the core of the rule-based, fine-grained deep semantic analysis. The integration of NLP components is done either by means of an XSLT-based transformation, or with the help of Robust Minimal Recursion Semantics (RMRS, see Copestake, 2003), provided a given NLP component supports it natively. RMRS is a generalization of MRS. It can not only be underspecified for scope as MRS, but also partially specified, e.g., when some parts of the text cannot be resolved by a given NLP component. Thus, RMRS is well suited for representing output also from shallow NLP components. This can be seen as a clear advantage over approaches based strictly on some specified semantic representation like those presented in, e.g., Blackburn et al. (1998), or Bos and Markert (2005b).

Furthermore, RMRS is a common semantic formalism for HPSG grammars within the context of the LinGO Grammar Matrix (Bender, Flickinger, & Oepen, 2002). Besides ERG, which we use for English, there are also grammars for other languages like, e.g., the Japanese HPSG grammar JaCY (Siegel & Bender, 2002), the Korean Resource Grammar (Jong-Bok & Jaehyung, 2005), the Spanish Resource Grammar (SRG, see Marimon, 2002), or the proprietary German grammar (Cramer & Zhang, 2009). Since all of those grammars can
be used to generate semantic representations in form of RMRS, a replacement of ERG with another grammar in our system can be considered and thus a higher degree of multilinguality achieved.

The combined results of the deep-shallow analysis in the RMRS form are transformed into MRS and resolved with Utool 3.1 of Koller and Thater (2005). Utool translates first the input from MRS into dominance constraints (Thater, 2007), a closely related scope underspecification formalism, and then enumerates all readings represented by the dominance graph. In the current implementation one of the most reasonable readings is chosen manually by the analyst for the further processing in the logical inference. For more detail on the production of first-order expressions from a broad coverage HPSG grammar ERG we refer to Coote and Wotzlaw (2010).

For our small RTE example from the beginning of the section, the result of the combined syntactic and semantic analysis for \( H \) in form of RMRS, given as attribute value matrix, is presented in Figure 3. The results from the shallow analysis (marked bold) describe the named entities from \( H \). As described above, in the next step the structure is transformed into MRS and resolved by Utool. The resulting first-order MRS for the hypothesis \( H \) from our example is given below (in Prolog notation). The predicates with \( \text{q} \), \( \text{n} \), \( \text{v} \), and \( \text{p} \) in their names represent quantifiers, nouns, verbs, and prepositions, respectively.

```prolog
undef_q_rel(X6),
bird_n_1_rel(X6),
proper_q_rel(X9, and(
named_rel(X9, london), and(
locname_rel(london, X9),
loctype_rel(city, X9))), and(
live_v_1_rel(E2, X6),
in_p_dir_rel(E10, E2, X9))).
```

Figure 3: RMRS as attribute value matrix for hypothesis \( H \) from the example
3.2 Logical Inference

The results of the semantic analysis in form of specified MRS combining deep-shallow predicates are translated into another, logical equivalent semantic representation FOLE (see Figure 4). The rule-based transformation conveys argument structure with a neo-Davidsonian analysis with semantic roles (Dowty, 1989). A definite article is translated according to the theory of definite description of Russell (1905). Temporal relations are modeled by adding additional predicates similar to Bos and Markert (2005b), and Curran et al. (2007), i.e., without explicit usage of time operators. Furthermore, it is possible to extend the translation mechanism to cover plural and modal forms. Appropriate ideas can be found in Curran et al. (2007) and Lohnstein (1996). In this case, however, the complexity and amount of the resulting FOLE formulas will grow rapidly, making the problem much harder to solve with the currently available inference machines (see Section 3.3).

The translated FOLE formulas are stored locally and can be used for the further analysis. Furthermore, such formally expressed input text can and should be extended with additional knowledge in form of background knowledge axioms. In our system, the additional axioms are formulated in FOLE and integrated into the input problem. The integration of background knowledge will be discussed in detail in Section 4.
As an example here, the translation of the specified MRS into FOLE for the hypothesis \( H \) from our example given earlier produces the following formula with a neo-Davidsonian event representation:

\[
\text{some}(X6, \text{and}(
\text{bird}_n_1(X6),
\text{some}(X9, \text{and}(\text{named}_r_1(X9), \text{and}(
\text{location}_n_1(X9), \text{and}(
\text{location}_n_1(X9), \\
\text{city}_n_1(X9)))))),
\text{some}(E2, \text{and}(\text{event}_n_1(E2), \text{and}(\text{live}_v_1(E2),
\text{agent}_r_1(E2, X6)),
\text{in}_r_1(E2, X9))))).
\]

### 3.3 Inference Process

The goal here is to identify and to prove the logical relation between two input texts, represented formally as FOLE formulas, with respect to the problem-relevant background knowledge. We are interested in answering the question whether the relation is an entailment, a contradiction, or whether maybe hypothesis \( H \) provides just new information with respect to text \( T \), i.e., is informative (see Definition 1). As proposed by Bos & Markert, 2005b, in order to give a clear answer to these questions, it is sufficient to perform sequentially the following three tests on text \( T \), hypothesis \( H \), and background knowledge \( BK \), all given as FOLE formulas:

1. **Consistency Test:** Check whether \( T, H, \) and \( BK \) are mutually consistent in terms of first-order logic, i.e., if

   \[
   T \land H \land BK
   \]

   is satisfiable (i.e., there exists some first-order model for it).

2. **Informativity Test:** Check whether \( H \) contains new information (first-order assertions) which cannot be entailed from \( T \) and \( BK \), i.e., if

   \[
   T \land BK \rightarrow H
   \]

   is not valid, or put another way, if

   \[
   \neg(T \land BK \rightarrow H) \equiv T \land BK \land \neg H
   \]

   is satisfiable.

3. **Entailment Test:** Check whether \( H \) is a semantic consequence of \( T \) and \( BK \), i.e., if

   \[
   \{T, BK\} \models H
   \]
holds. Since in the first-order logic, \( \{T, BK\} \models H \) holds if and only if \( T \land BK \rightarrow H \) is valid and \( T \land BK \rightarrow \neg H \) is not valid (according to the semantic version of the deduction theorem, see, e.g., Boolos, Burgess, & Jeffrey, 2002), it suffices to show that

\[
T \land BK \land \neg H \quad \text{and} \quad T \land BK \land H
\]

are unsatisfiable and satisfiable, respectively.

Observe that the three logical relations between \( T, H, \) and \( BK \) we are considering here are mutually exclusive and partly complementary. Therefore the testing can be reduced to the first two tests, i.e., we need to perform only the consistency and the informativity tests. Figure 5 shows how a given RTE problem is solved by applying only these two tests.

It is a well-known fact that our tests are within the first-order logic undecidable. Thus, in order to check efficiently which type of a logical relation for the input problem holds, we use two kinds of automated reasoning tools:

- **Finite model builders**: Mace 2.2 by McCune (2001), Paradox 3.0 by Claessen and Sörensson (2003), and Mace4 by McCune (2003a), and

- **First-order provers**: Bliksem 1.12 by de Nivelle (2003), Otter 3.3 by McCune (2003b), Vampire 8.1 by Riazanov and Voronkov (2002), and Prover9 by McCune (2009).

While theorem provers are designed to prove that a formula is valid (i.e., the formula is true for any admissible interpretation), they are generally not good at deciding that a formula is not valid. On the contrary, model builders are designed to show that a formula is true for at least one interpretation. The experiments with different inference machines show that solely relying on theorem proving is in most cases insufficient due to low recall. Indeed, our inference process incorporates model building as a central part of the inference process. Similar to Bos (2003), Bos and Markert (2005b), and Curran et al. (2007), we exploit

Figure 5: Decision diagram for logical inference
the complementarity of model builders and theorem provers by applying them in parallel
to the first-order formulas specified by the first two tests given above in order to tackle
with its undecidability more efficiently. More specifically, for a given test, the theorem
prover attempts to prove whether the input formula $F$ is valid whereas the model builder
simultaneously tries to find a finite, first-order model for the negation of the input formula
$F$. For more clarity, in the decision nodes in Figure 5, the input formula is depicted only
in the form the model builder becomes it, i.e., in negated form as satisfiability problem.

All reasoning machines were developed to deal with inference problems stated in FOLE.
They are successfully integrated into our system for RTE. To this end, we use a translation
from FOLE into the formats required by the inference tools. Furthermore, the user can
specify via the user interface which inference machines (i.e., which theorem prover and
which model builder) should be used by the inference process. The tests have shown that
the efficiency and the success of solving a given RTE problem depend much on the inference
machines chosen for it. Thus, it is advisable to run simultaneously on the same RTE problem
more than one theorem prover and more than one model builder.

3.4 User Interface

The results of the syntactic processing, semantic construction, and logical inference like,
e.g., HPSG and MRS structures, FOLE formulas, first-order models and proofs, integrated
background knowledge, and other detailed information are presented to the user within a
dedicated GUI. With its help, one can further customize and control both the semantic and
logical analysis, e.g., choose the input text or the background knowledge source, inspect the
results of shallow-deep analysis, or select and customize inference machines.

4. Improving the Inference Quality

The inference process of RTE needs high-quality background knowledge to support its
proofs. In particular, this will improve the precision and the success rate of the inference
process making the result much more conforming with real-world expectations. However,
with increasing number of background knowledge axioms the search for finite first-order
models may become more time-consuming. Thus, only knowledge relevant for the problem
should be considered in the inference process.

The integration of many ontological sources is, in general, a difficult but as argued
before a very important task. First of all, the semantics of all concepts, individuals, and
relations must be preserved across the various sources. In this section we present and
analyze formally a new graph-based technique for integration of concepts and individuals
from ontologies based on the hierarchy of WordNet (Fellbaum, 1998). Our results show
that a fine-grained and consistent knowledge coming from diverse sources (and domains)
is a necessary condition determining the correctness and traceability of results. Moreover,
our RTE application performs significantly better when a substantial amount of problem-
relevant knowledge has been integrated into the underlying inference process.
4.1 Sources of Background Knowledge

Our RTE system supports the extraction of background knowledge from different kinds of sources. It searches for and supplies problem-relevant knowledge automatically as first-order axioms and integrates them into the RTE problem.

We use WordNet 3.0 as a lexical database for synonymy, hyperonymy, and hyponymy relations. It helps the RTE system to detect an entailment between lexical units from the text and the hypothesis. It serves also as a database for individuals but rather a very small one when compared to the second source. For efficiency purposes, it was preprocessed and integrated directly into the module for logical inference (see Figure 4). Conceptually, the hyperonymy/hyponymy relation in WordNet spans a directed acyclic graph (DAG) with the root node `entity` (Fellbaum, 1998; Suchanek et al., 2008). This means that there are nodes (i.e., concepts or individuals) in the WordNet graph that are direct hyponyms of more than one concept. For that reason the knowledge axioms which are generated later from the WordNet graph may induce inconsistencies between the input problem formulas and the extracted knowledge. This can be very harmful for the further inference process. In Section 4.2 we discuss this problem more formally and present several strategies that can deal with this restriction.

YAGO (Suchanek et al., 2008) is a large and arbitrarily extensible ontology with high precision and quality which we use in our system as the second source of ontological knowledge. Its core was assembled automatically from the category system and the infoboxes of Wikipedia, and combined with taxonomic relations from WordNet (Suchanek et al., 2008). Similar to WordNet, the concepts and individuals hierarchy of YAGO spans a DAG. Thus, we must also proceed carefully when integrating data from that source into the RTE problem, (see Section 4.2). For accessing YAGO, we use a dedicated query processor (see Figure 4) with its own query language, similar to that of Suchanek et al. (2008). The query processor first normalizes the shorthand notation of the query, and after translating it into SQL, sends it to the MySQL-Server with YAGO database. The incoming results are first preprocessed by the query processor, so that only those concepts are sent back for integration which are consistent with WordNet concept hierarchy, i.e., which include the prefix `wordnet`.

Furthermore, OpenCyc 2.0 (Matuszek, Cabral, Witbrock, & DeOliveira., 2006) can also be used as a background knowledge source. The computation of axioms for a given problem is solved using a variant of Lesk’s WSD algorithm (Banerjee & Pedersen, 2002). Axioms of generic knowledge from our experimental knowledge source cover the semantics of possessives, active-passive alternation, and spatial knowledge (e.g., that Tower Bridge is located in London). Finally, our experimental presuppositional knowledge base includes axioms covering English words and phrases triggering presuppositions (see Section 4.3).

4.2 Combining Knowledge from Various Sources

In the following we describe the three-phase integration procedure that we use to find and to combine individuals and concepts from YAGO with those from WordNet in order to support RTE. In particular, we show how we can combine problem-relevant individuals and concepts from YAGO with those from WordNet so that the consistency of background knowledge axioms is preserved whereas the original logical properties of the input RTE problem do not
change. More specifically, since the input problem itself may be consistent and we want to prove it, the knowledge we integrate into it must not make it inconsistent.

To make our presentation as comprehensible and self-explanatory as possible, we make use of a small RTE problem which we augment with relevant background knowledge axioms in the course of this section. We want to prove that the text $T$:

Leibniz was a famous German philosopher and mathematician born in Leipzig. Thomas reads his philosophical works while waiting for a train at the station of Bautzen.

entails the hypothesis $H$:

Some works of Leibniz are read in a town.

In order to prove the entailment above, we must know, among other things, that Bautzen is a town. We assume that no information about Bautzen, except that it is a named entity (i.e., an individual), were yielded by the deep-shallow semantic analysis. However, we expect that this missing information can be found in the external knowledge sources. The search for relevant background knowledge begins after the first-order representation of the problem is computed and translated into FOLE (see Section 3). At this stage, the RTE problem has already undergone syntactic processing, semantic construction, and anaphora resolution which together have generated a set of semantic representations of the problem in form of MRS. The translation of the specified MRS into FOLE for the hypothesis $H$ from our example above produces the following formula with a neo-Davidsonian event representation by Dowty (1989):

\[
\text{some}(X3, \text{and}(\\n\text{work}_n_2(X3), \\
\text{some}(X7, \text{and}(\\n\text{named}_r_1(X7), \text{and}(\\n\text{leibniz}_\text{per}_1(X7), \\
\text{of}_r_1(X3,X7)))), \\
\text{some}(X8, \text{and}(\\n\text{town}_n_1(X8), \\
\text{some}(E2, \text{and}(\\n\text{event}_n_1(E2), \text{and}(\\n\text{read}_v_1(E2), \\
\text{patient}_r_1(E2,X3), \\
\text{in}_r_1(E2,X8))))))).
\]

As mentioned before, the integration procedure is composed of three phases. In the first phase we search for problem-relevant knowledge in WordNet, whereas in the second phase we look for additional knowledge in YAGO which we combine afterwards with that found in the first phase. Finally, in the third phase we generate from the knowledge, we have already found and successfully combined, background knowledge axioms and integrate them into the set of FOLE formulas representing the input RTE problem.
4.2.1 Phase I: Integration of WordNet

At the beginning, we list all predicates, i.e., concepts and individuals from the input FOLE formulas. They will be used for the search in WordNet. In the current implementation we consider as *search predicates* all nouns, verbs, and named entities, together with their sense information which is specified for each predicate by the last number in the predicate name, e.g., sense 2 in `work_n.2`. In WordNet, the senses are generally ordered from most to least frequently used, with the most common sense numbered 1. Frequency of use is determined by the number of times a sense was tagged in the various semantic concordance texts used for WordNet (Fellbaum, 1998). Senses that were not semantically tagged follow the ordered senses. For our small RTE problem we can select as search predicates, e.g., `work_n.2`, `read_v.1`, or `leibniz_per.1`. It is important for the integration that the sense information computed during the semantic analysis matches exactly the senses used by external knowledge sources. This ensures that the semantic consistency of background knowledge is preserved across the semantic and logical analysis. However, this seems to be an extremely difficult task, which does not seem to be solved fully automatically yet by any current word sense disambiguation technique. Since in WordNet but also in ERG (Flickinger, 2000) the senses are ordered by their frequencies, we take for semantic representations generated during the semantic analysis the most frequent concepts from ERG.

Having identified the search predicates, we try to find them in WordNet and, by employing both the hyperonymy/hyponymy and synonymy relations, we obtain a *knowledge graph* $G_W$. A small fragment of such a knowledge graph for text $T$ of our example is given in Figure 6. In general, $G_W$ is a DAG with leaves represented by the search predicates, whereas its inner nodes and the root are given by concepts coming from WordNet. The directed edges in $G_W$ correspond to the hyponym relations, e.g., in Figure 6 named entity `leipzig` is a hyponym of concept `city`. Note that in the opposite direction they describe the hyperonym relations, e.g., concept `city` is a hyperonym of named entity `leipzig`. Each synonymy relation is represented by a *complex node* composed of synonymous concepts $C_1,...,C_n$ induced by the relation (i.e., all concepts represented by a complex node belong to the same synset in WordNet), e.g., the complex node with concepts `district` and `territory` in Figure 6.

Furthermore, it can be seen in Figure 6 that the leaf representing individual `leipzig` has more than one direct hyperonym, i.e., there are three hyponym relations for leaf `leipzig` with concepts `administrative_district`, `city`, and `planet`. As already indicated in Section 3, this property of graph $G_W$ may cause inconsistencies when the background knowledge axioms are later generated from it and integrated into the input FOLE formulas. We address this problem more carefully now. We begin with the explanation how the background knowledge axioms are generated. The method we use for it is an extension of the heuristic presented in Curran et al. (2007) and can be defined formally as follows:

**Definition 2.** There are three basic types of background knowledge axioms: **IS-A**, **IS-NOT-A**, and **IS-EQ**. They can be generated from a given knowledge graph $G$ by traversing its nodes and edges and applying the following rules:

1. Let $U$ and $V$ be two different (complex) nodes from $G$, and $C_i$ and $C_j$ two arbitrary concepts or individuals represented by $U$ and $V$, respectively. If $C_i$ is a direct hyponym of $C_j$ (i.e., there is an edge from $U$ to $V$ in $G$), then generate an **IS-A** axiom $\forall x(C_i(x) \rightarrow C_j(x))$. 


2. Let \( V \) be a (complex) node from \( G \) and \( U = \{U_1, ..., U_n\} \) the set of all children of \( V \) in \( G \). All concepts and individuals represented by (complex) nodes from \( U \) are direct hyponyms of the concepts or individuals represented by \( V \). The sets of concepts and individuals represented by nodes from \( U \) are pairwise disjoint. For every pair \((i, j)\) such that \( i = 1, ..., n - 1 \) and \( j = i, ..., n \) generate an IS-NOT-A axiom \( \forall x (C_i(x) \rightarrow \neg C_j(x)) \) where \( C_i \) and \( C_j \) are two arbitrarily chosen concepts or individuals represented by \( U_i \) and \( U_j \), respectively.

3. Let \( U \) be some complex node from \( G \) and \( C = \{C_1, ..., C_n\} \) a set of synonymous concepts represented by \( U \). For every pair \((i, j)\) such that \( i = 1, ..., n - 1 \) and \( j = i, ..., n \) generate an IS-EQ axiom \( \forall x (C_i(x) \leftrightarrow C_j(x)) \).

Notice that since all concepts or individuals represented by a given complex node are synonymous, Rule 1 and Rule 2 from Definition 2 need to be applied only to one arbitrarily chosen concept or individual represented by that node. By applying the rules from Definition 2 to graph \( G_W \) from Figure 6 the following axioms can be generated (not a complete list here):

\[
\text{IS-A: } \forall x (\text{object}_n.1(x) \rightarrow \text{entity}_n.1(x))
\]
\[
\text{IS-NOT-A: } \forall x (\text{region}_n.3(x) \rightarrow \neg \text{unit}_n.6(x))
\]
\[
\text{IS-EQ: } \forall x (\text{district}_n.1(x) \leftrightarrow \text{territory}_n.1(x))
\]

Furthermore, observe that the set of all background knowledge axioms \( A_K \) generated for knowledge graph \( G_W \) according to Definition 2 is a finite set of first-order sentences (i.e.,
formulas of first-order logic without free variables) restricted to unary predicate symbols and no function symbols. This monadic fragment of the first-order logic is known to be decidable for logical validity (Boolos et al., 2002). However, in order to show the consistency (i.e., the absence of contradictions) of $A_K$ generated for an arbitrary knowledge graph $G_W$, we need to show that $A_K$ is satisfiable. We conjecture here that every $A_K$ is satisfiable in some finite model. To prove this, one need to give, for instance, some method which describes formally the construction of a finite model for every set of axioms $A_K$ generated for an arbitrary knowledge graph $G_W$ according to Definition 2. Since the predicate calculus of first order is complete (Gödel, 1930), one can also proceed in a purely syntactical way by showing that there is no formula $f$ such that both $f$ and its negation are provable from axioms $A_K$ under its associated deductive system. In the further research we examine our conjecture more carefully, i.e., we will try either to prove it or to deliver some counterexample.

**Proposition 1.** Let $F$ be a set of FOLE formulas representing semantically an RTE problem $P$, and $A_K$ a set of background knowledge axioms computed for $P$ according to Definition 2. Furthermore, let $f$ be a formula like $\exists x (C_k(x) \land \ldots)$ from $F$ and $A = \{A_1, A_2, A_3\} = \{\forall x (C_i(x) \rightarrow \neg C_j(x)), \forall x (C_k(x) \rightarrow C_i(x)), \forall x (C_k(x) \rightarrow C_j(x))\}$ a set of one IS-NOT-A and two IS-A axioms, respectively. If $A \subseteq A_K$, then $F \cup A_K$ is inconsistent.

**Proof.** To show the inconsistency of $F \cup A_K$, we need to prove its unsatisfiability. Note that the three axioms from $A$ reflect the situation depicted in Figure 7. To give a proof, we show first that $\{f\} \cup A$ is unsatisfiable. To this end we transform $\{f\} \cup A$ into an equivalent conjunctive normal form. The resulting set of clauses $\{\{f\}, \{A_1\}, \{A_2\}, \{A_3\}\}$ is unsatisfiable if and only if there exists a derivation of the empty clause using alone the resolution rule. It is clear that the empty clause can be derived, showing that $\{f\} \cup A$ is unsatisfiable and since $\{f\} \cup A \subseteq F \cup F_K$, the claim follows. 

Thus, according to Proposition 1, we cannot in general integrate all background knowledge axioms $A_K$ generated from knowledge graph $G_W$ by the rules given in Definition 2 into the RTE problem when its original logical property (i.e., consistency or inconsistency) has to be preserved. To deal with that problem, we propose two strategies:

1. Only Rule 1 and Rule 3 from Definition 2 are used for the generation of knowledge axioms from knowledge graph $G_W$.

2. Some edges from knowledge graph $G_W$ are removed, so that afterwards each concept or individual from $G_W$ is hyponym of concept(s) of at most one (complex) node, i.e.,
every child node in $G_W$ can have only one father node. Thus, after the deletion of edges is done, $G_W$ becomes a directed tree and all rules from Definition 2 are applied to it.

Both strategies can cause some loss in effectiveness of the entire RTE inference process. By using the first strategy, no IS-NOT-A axioms are generated and the situation described in Proposition 1 does not hold. However, the generated background knowledge is not as precise as before (there are no uniqueness constraints for concepts). The elimination of conflicting edges from $G_W$ by the second strategy results in loss of knowledge, too. For instance, in Figure 7 either the edge representing axiom $A_2$ or the edge representing axiom $A_3$ will be removed. To overcome this restriction and make use of all knowledge from $G_W$, we could integrate all available hyponym relations into the RTE problem separately, one after the other. Unfortunately, this would result in many parallel entailment problems (one for each reading), which we must solve and evaluate separately. Furthermore, we observed that for now it is difficult to automate the task for selecting edges for removal from $G_W$.

In our implementation we follow the second strategy by which we transform knowledge graph $G_W$ into knowledge tree $T_K$ with root node entity, the most general concept in WordNet (Fellbaum, 1998). Currently, the edges for removal can be selected either manually by the analyst from the list of proposals made by the application, or automatically by leaving only concepts with the most frequent senses. Here, we use a variant of Lesk’s WSD algorithm (Banerjee & Pedersen, 2002). Figure 8 shows a fragment of tree $T_K$ for our example. The construction of the tree was optimized so that only those concepts from $G_W$ appear in $T_K$ which are directly relevant for the inference problem, e.g., only search predicates can serve as leaves in $T_K$, or every non-branching node between two other nodes is removed. Hence, all knowledge which will not add any inferential power to the process is removed from $T_K$.  

![Figure 8: Fragment of knowledge tree $T_K$ after optimization](image-url)
One can see in Figure 8 that not all search predicates were recognized precisely enough during the first phase. More specifically, the named entity bautzen was not classified as a town as we would expect it. Since a suitable individual was not found in WordNet, the named entity bautzen was assigned directly to the root of tree \( T_K \). It is clear that without having more information about bautzen, we cannot prove the entailment.

4.2.2 Phase II: Integration of YAGO

In this phase we consult YAGO about search predicates that were not recognized in the first phase. We formulate for each such predicate an appropriate query and send it to the query processor (see Figure 4). To this end, we use relation type, one of the build-in ontological relations of YAGO. For our small RTE problem, we ask YAGO with a query bautzen type ? of what type (or in YAGO nomenclature: of what class) the named entity bautzen is. If it succeeds, it returns knowledge graph \( G_Y \) with WordNet concepts which classify the named entity from the query. Figure 9 depicts graph \( G_Y \) for our example. We can see that bautzen was now classified more precisely, among other things, as a town.

In general, each graph \( G_Y \) is a DAG composed of partially overlapping paths leading (with respect to the hyperonymy relation) from some root node (i.e., the most general concept in \( G_Y \), e.g., node object in Figure 9) to the leaf representing the search predicate (e.g., the complex node bautzen in Figure 9). Observe that there is one and only one leaf node in every graph \( G_Y \). Since the result of every YAGO-query is in general represented by a DAG, we cannot integrate it completely into the knowledge tree \( T_K \) without violating the original logical properties of the input problem (see discussion above). According to the leaf of \( G_Y \) in Figure 9, the named entity bautzen can also be classified as an asteroid or an administrative district.

In order to preserve the correctness of results, we select for the integration into knowledge tree \( T_K \) only those concepts, individuals, and relations from \( G_Y \) which lay on the longest path from the most general concept in \( G_Y \) to one of the direct hyperonyms of the leaf, and which has the most common nodes with tree \( T_K \) from the first phase. In Figure 9 the concepts and individuals on the gray shaded path were chosen by our heuristic for the integration into \( T_K \). After the path has been selected, it is optimized and integrated into \( T_K \). Figure 10 depicts the knowledge tree \( T_K \) after the gray shaded path from Figure 9 was integrated into it.
The selection of a relevant path could also be done manually by some analyst with sufficient knowledge about the problem. A fully automatic selection turns out to be a much more difficult task. Another strategy is to integrate all available paths separately, one after the other. Here, however, this would result in three parallel entailment problems, which we must solve and evaluate separately.

Observe finally that the integration of selected parts of the knowledge graph $G_Y$ into tree $T_K$ is performed sequentially for each search predicate which was not classified in the first phase (note that each search generates its own knowledge graph $G_Y$).

Additionally to the first query to YAGO, we can also formulate a second one like `bautzen isCalled ?`, in which we ask what are the names of the named entity in other languages. In Figure 9 we can see four different names for this entity. This complementary information can be combined afterwards into the FOLE formulas of the RTE problem as new predicates, e.g.,

$$\exists x ((\text{bautzen}(x) \lor \text{budysin}(x) \lor \text{budissa}(x) \lor \text{budziszyn}(x)) \land ...)$$

### 4.2.3 Phase III: Generation of Background Knowledge Axioms

After the second phase of the integration procedure is finished and the final knowledge tree $T_K$ has been computed, the background knowledge axioms are generated from $T_K$ according to Definition 2. The resulting axioms are added into the FOLE formulas of the input RTE problem. Such an extended input problem is passed over to the inference process (see Figure 4) and solved correspondingly. For the knowledge tree given in Figure 10, the following axioms (here not a complete list) can be generated.

\[
\text{all}(X, \text{imp(city\_n\_1}(X), \text{location\_n\_1}(X))).
\]
\[
\text{all}(X, \text{imp(event\_n\_1}(X), \text{not(object\_n\_1}(X))).
\]
The axioms are in FOLE format and are rather self-explanatory and can be interpreted as follows:

\[ \forall x (\text{city}_n(x) \rightarrow \text{location}_n(x)) \]
\[ \forall x (\text{event}_n(x) \rightarrow \neg \text{object}_n(x)) \]

### 4.3 Presupposition Resolution

Many words and phrases trigger presuppositions which have clearly semantic content important for the inference process. We try to represent some of them explicitly. Our trigger-based mechanism uses noun phrases as triggers, but it can be extended to verb phrases, particles, etc. After a presupposition is triggered, the mechanism resolves it, and integrates it as a new FOLE axiom into the RTE problem. The automatic axiom generation is based on \(\lambda\)-conversion and employs abstract axioms and a set with possible axiom arguments. The axioms and their arguments are still part of an experimental knowledge source (see Presuppositional Knowledge in Figure 4). Here is an example for an abstract axiom which allows for a translation from a noun phrase into an intransitive verb phrase:

\[
\lambda P[\lambda R[\lambda S[
\forall x_1 (\forall x_2 (P@x_1 \land R@x_2 \land \text{nn}_r(x_1, x_2)) \rightarrow \exists x_3 (R@x_3 \land \exists x_4 (S@x_4 \land \text{event}_n(x_4) \land \text{agent}_r(x_4, x_3))))]]].
\] (1)

If text \(T\) (expressed with FOLE formulas) contains a noun phrase being a key for some entry in the set of possible axiom arguments, then the arguments pointed by that key are applied to their abstract axiom, and a new background axiom is generated. For a complex noun phrase price explosion with its semantic representation \(\text{price\_explosion}_n\) the following arguments can be considered:

\[
\lambda x[\text{explosion}_n(x)]
\lambda x[\text{price}_n(x)]
\lambda x[\text{explode\_v}_n(x)]
\]

which after being applied to the abstract axiom (1) produce the following background knowledge axiom:

\[
\forall x_1 (\forall x_2 (\text{explosion}_n(x_1) \land \text{price}_n(x_2) \land \text{nn}_r(x_1, x_2)) \rightarrow \exists x_3 (\text{price}_n(x_3) \land \exists x_4 (\text{explode\_v}_n(x_4) \land \text{event}_n(x_4) \land \text{agent}_r(x_4, x_3))))).
\] (2)

The presupposition axioms having complexity similar to (2) are first combined with the existing background knowledge axioms and finally integrated as background knowledge into the input RTE problem.

### 5. Conclusion and Future Work

In this paper a new adaptable, linguistically motivated system for RTE was presented. Its deep-shallow semantic analysis, employing a broad-coverage HPSG grammar ERG, was
combined with a logical inference process supported by an extended usage of external background knowledge. The architecture of our system and the correctness of our three-phase integration procedure were discussed in detail and the functionality of the system was explained with several examples.

The system was successfully implemented and evaluated in terms of success rate and efficiency. For now, it is still impossible to measure its semantic accuracy as there is no corpus with gold standard representations which would make comparison possible. Measuring semantic adequacy could be done systematically by running the system on controlled inference tasks for selected semantic phenomena.

Nevertheless, for our tests we used the RTE problems from the development sets of the past RTE Challenge (Giampiccolo et al., 2007). Our system with successfully integrated background knowledge was able to solve correctly about 67 percent of the RTE problems. This is comparable or slightly better than the vast majority of other approaches from that RTE Challenge which are based on some deep approach and combined with logical inference. Unfortunately, it is still not so good as the result of 72 percent achieved by Tatu and Moldovan (2006). This can be explained, among other things, by a more extensive and fine grained usage of specific semantic phenomena, e.g., a sophisticated analysis of named entities, in particular person names, distinguishing first names from last names.

It is interesting to look at the inconsistent cases of the inference process which were produced during the evaluation. They were caused by errors in presupposition and anaphora resolution, incorrect syntactic derivations, and inadequate semantic representations. They give good indications for further improvements. Here, particularly the word sense disambiguation problem will play a decisive role for matching the set of senses of the semantic analyzers with multiple, and likely different, sets of senses from the different knowledge resources. Once tackled more precisely, it should decisively improve the success rate of the system. Moreover, the system presented here should be extended with methods for word sense disambiguation, paraphrase detection, and a better anaphora resolution within a discourse. We are considering also the enhancing of the logical inference module with statistical inference techniques in order to improve its performance and recall. Since the strength but in some extent also the weakness of our system lies in the difficulties regarding the computation of a (nearly) full semantic representation of the input problem (see, e.g., Burchardt, Reiter, Thater, and Frank (2007) for a good discussion), it might be recommended to integrate some models of natural language inference which identifies valid inferences by their lexical and syntactic features, without full semantic interpretation, like, e.g., the one proposed by MacCartney and Manning (2009).

Furthermore, we intend to develop for the inference process some temporal calculus supported by the temporal information from YAGO. Here, the event calculus of Shanahan (1999) can be considered as a good starting point. Finally, it would be interesting to extend the semantic analysis of our system, so that RTE problem instances in languages other than English could be supported.

References

Akhmatova, E. (2005). Textual entailment resolution via atomic propositions. In Proceedings of the First PASCAL Challenges Workshop on Recognising Textual Entailment, pp.
61–64, Southampton, UK.

Androutsopoulos, I., & Malakasiotis, P. (2010). A survey of paraphrasing and textual entailment methods. *Journal of Artificial Intelligence Research, 38*, 135–187.

Auer, S., Bizer, C., Kobilarov, G., Lehmann, J., Cyganiak, R., & Ives, Z. (2007). DBpedia: A nucleus for a web of open data. In *Proceedings of the 6th International Semantic Web Conference (ISWC).*

Banerjee, S., & Pedersen, T. (2002). An adapted Lesk algorithm for word sense disambiguation using WordNet. In *Proceedings of the 3rd International Conference on Computational Linguistics and Intelligent Text Processing*, pp. 136–145, London, UK.

Bender, E. M., Flickinger, D., & Oepen, S. (2002). The grammar matrix: An open-source starter-kit for the rapid development of cross-linguistically consistent broad-coverage precision grammars. In *Proceedings of the Workshop on Grammar Engineering and Evaluation at the 19th International Conference on Computational Linguistics.*

Bentivogli, L., Dagan, I., Dang, H. T., Giampiccolo, D., & Magnini, B. (2009). The fifth PASCAL recognizing textual entailment challenge. In *TAC 2009 Workshop, Gaithersburg, Maryland.*

Bizer, C., Heath, T., & Berners-Lee, T. (2008). Linked data: Principles and state of the art. In *Proceedings of the 17th World Wide Web Conference (WWW).*

Blackburn, P., Bos, J., Kohlhase, M., & De Nivelle, H. (1998). Automated theorem proving for natural language understanding. In *Problemsolving Methodologies with Automated Deduction (Workshop at CADE-15).*

Blackburn, P., & Bos, J. (2005). *Representation and Inference for Natural Language. A First Course in Computational Semantics.* CSLI.

Boolos, G. S., Burgess, J. P., & Jeffrey, R. C. (2002). *Computability and Logic.* Cambridge University Press.

Bos, J. (2003). Exploring model building for natural language understanding. In *Proceedings of ICoS-4*, pp. 25–26.

Bos, J. (2005). Towards wide-coverage semantic interpretation. In *Proceedings of the 6th International Workshop on Computational Semantics IWCS-6*, pp. 42–53.

Bos, J. (2008). Let’s not argue about semantics. In *Proceedings of the Sixth International Language Resources and Evaluation (LREC’08)*, pp. 28–30, Marrakech, Morocco.

Bos, J., & Markert, K. (2005a). Combining shallow and deep NLP methods for recognizing textual entailment. In *Proceedings of the First PASCAL Challenges Workshop on Recognising Textual Entailment*, pp. 65–68, Southampton, UK.

Bos, J., & Markert, K. (2005b). Recognising textual entailment with logical inference. In *Proceedings of the 2005 Conference on Empirical Methods in Natural Language Processing (EMNLP)*, pp. 628–635, Vancouver, Canada.

Bos, J., & Markert, K. (2006). When logical inference helps determining textual entailment (and when it doesn’t). In *Proceedings of the Second PASCAL Challenges Workshop on Recognizing Textual Entailment, Venice, Italy.*
Brants, T. (2000). TnT – a statistical part-of-speech tagger. In *Proceedings of the Sixth Applied Natural Language Processing Conference ANLP-2000*, pp. 224–231, Seattle, WA.

Burchardt, A., Reiter, N., Thater, S., & Frank, A. (2007). A semantic approach to textual entailment: System evaluation and task analysis. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*.

Cafarella, M. J., Re, C., Suciu, D., & Etzioni, O. (2007). Structured querying of web text data: A technical challenge. In *Proceedings of the Third Biennial Conference on Innovative Data Systems Research (CIDR)*, pp. 225–234.

Callmeier, U. (2000). PET – a platform for experimentation with efficient HPSG processing techniques. *Natural Language Engineering, 6*(1), 99–108.

Chatterjee, N., Goyal, S., & Naithani, A. (2005). Resolving pattern ambiguity for english to hindi machine translation using WordNet. In *Workshop on Modern Approaches in Translation Technologies*.

Claessen, K., & Sörensson, N. (2003). New techniques that improve MACE-style model finding. In *Proceedings of the CADE-19 Workshop: Model Computation – Principles, Algorithms, Applications*, Miami, FL.

Coote, R., & Wotzlaw, A. (2010). Generation of first-order expressions from a broad coverage HPSG grammar. In *Proceedings of the International MultiConference on Computer Science and Information Technology (IMCSIT)*, pp. 33–36, Wisla, Poland.

Copestake, A. (2003). Report on the design of RMRS. Tech. rep. D1.1b, University of Cambridge, UK.

Copestake, A., Flickinger, D., Pollard, C., & Sag, I. A. (2005). Minimal recursion semantics: An introduction. *Research on Language and Computation, 3*, 281–332.

Cramer, B., & Zhang, Y. (2009). Construction of a German HPSG grammar from a detailed treebank. In *Proceedings of the Workshop on Grammar Engineering Across Frameworks*. Association for Computational Linguistics.

Curran, J. R., Clark, S., & Bos, J. (2007). Linguistically motivated large-scale NLP with C&C and boxer. In *Proceedings of the 45th Annual Meeting of the ACL on Interactive Poster and Demonstration Sessions*, pp. 33–36, Prague, Czech Republic.

Dagan, I., Dolan, B., Magnini, B., & Roth, D. (2009). Recognizing textual entailment: Rational, evaluation and approaches. *Natural Language Engineering. Special Issue on Textual Entailment, 15*(4), i–xvii.

de Melo, G., Suchanek, F., & Pease, A. (2008). Integrating yago into the suggested upper merged ontology. In *Proceedings of the 20th IEEE International Conference on Tools with Artificial Intelligence (ICTAI)*.

de Nivelle, H. (2003). Bliksem 1.10 user manual. URL: http://www.ii.uni.wroc.pl/~nivelle/software/bliksem/index.html.

Dowty, D. (1989). On semantic content of the notion of "thematic role". In Barbara Partee, G. C., & Turner, R. (Eds.), *Properties, Types and Meaning*, Vol. 2, pp. 69–129. Dordrecht (Kluwer).
Drozdzyński, W., Krieger, H.-U., Piskorski, J., Schäfer, U., & Xu, F. (2004). Shallow processing with unification and typed feature structures – foundations and applications. *Künstliche Intelligenz, 18*(1), 17–23.

Fellbaum, C. (Ed.). (1998). *WordNet: An Electronic Lexical Database*. The MIT Press, Cambridge, MA.

Flickinger, D. (2000). On building a more efficient grammar by exploiting types. *Natural Language Engineering, 6*(1), 15–28.

Giammarco, D., Magnini, B., Dagan, I., & Dolan, B. (2007). The third PASCAL recognizing textual entailment challenge. In *Proceedings of the ACL-PASCAL Workshop on Textual Entailment and Paraphrasing*, pp. 1–9, Prague, Czech Republic.

Gödel, K. (1930). Die Vollständigkeit der Axiome des logischen Funktionenkalküls. *Monatshefte für Mathematik und Physik, 37*, 349–360.

Hunt, W., Lita, L., & Nyberg, E. (2004). Gazetteers, wordnet, encyclopedias, and the web: analyzing question answering resources. Tech. rep. CMU-LTI-04-188, Language Technologies Institute, Carnegie Mellon.

Ifrim, G., & Weikum, G. (2006). Transductive learning for text classification using explicit knowledge models. In *Proceedings of the 10th European Conference on Principles and Practice of Knowledge Discovery in Databases (PKDD)*.

Jong-Bok, K., & Jaehyung, Y. (2005). Parsing mixed constructions in a typed feature structure grammar. *Lecture Notes in Artificial Intelligence, 3248*, 42–51.

Kamp, H., & Reyle, U. (1993). *From Discourse to Logic. Introduction to Modeltheoretic Semantics of Natural Language, Formal Logic and Discourse Representation Theory*. Dordrecht: Kluwer Academic Publishers.

Koller, A., & Thater, S. (2005). Efficient solving and exploration of scope ambiguities. In *Proceedings of the ACL 2005 on Interactive poster and demonstration sessions*, pp. 9–12, Ann Arbor, Michigan.

Lohnstein, H. (1996). *Formale Semantik und natürliche Sprache. Einführendes Lehrbuch*. Westdeutscher Verlag.

MacCartney, B., & Manning, C. D. (2009). An extended model of natural logic. In *Proceedings of the 8th International Conference on Computational Semantics (IWCS-8)*, pp. 140–156.

Marcus, M. P., Marcinkiewicz, M. A., & Santorini, B. (1993). Building a large annotated corpus of English: The Penn Treebank. *Computational Linguistics, 19*(2), 313–330.

Marimon, M. (2002). Integrating shallow linguistic processing into a unification-based spanish grammar. In *Proceedings of the 19th International Conference on Computational Linguistics (COLING)*.

Matuszek, C., Cabral, J., Witbrock, M., & DeOliveira., J. (2006). An introduction to the syntax and content of Cyc. In *Proceedings of the 2006 AAAI Spring Symposium on Formalizing and Compiling Background Knowledge and Its Applications to Knowledge Representation and Question Answering*, Stanford, CA.
McCune, W. (2001). *Mace 2.0 Reference Manual and Guide*. Argonne National Laboratory, IL.

McCune, W. (2003a). *Mace4 Reference Manual and Guide*. Argonne National Laboratory, IL.

McCune, W. (2003b). *OTTER 3.3 Reference Manual*. Argonne National Laboratory, IL.

McCune, W. (2009). Prover9 manual. URL: http://www.cs.unm.edu/~mccune/prover9/manual/2009-11A/.

Milne, D. N., Witten, I. H., & Nichols, D. M. (2007). A knowledge-based search engine powered by wikipedia. In *Proceedings of the 16th ACM Conference on Information and Knowledge Management (CIKM)*, pp. 445–454.

Noy, N. F., Doan, A., & Halevy, A. Y. (2005). Semantic integration. *AI Mag.*, 26(1), 7–9.

Riazanov, A., & Voronkov, A. (2002). The design and implementation of VAMPIRE. *AI Commun.*, 15(2,3), 91–110.

Russell, B. (1905). On denoting. *Mind, New Series*, 14(56), 479–493.

Schäfer, U. (2007). *Integrating Deep and Shallow Natural Language Processing Components – Representations and Hybrid Architectures*. Ph.D. thesis, Saarland University, Saarbrücken, Germany.

Shanahan, M. (1999). The event calculus explained. In Wooldridge, M. J., & Veloso, M. (Eds.), *Artificial Intelligence Today*, pp. 409–430. Springer-Verlag.

Siegel, M., & Bender, E. M. (2002). Efficient deep processing of japanese. In *Proceedings of the 3rd Workshop on Asian Language Resources and International Standardization. Coling 2002 Post-Conference Workshop*.

Suchanek, F., Kasneci, G., & Weikum, G. (2008). YAGO - a large ontology from Wikipedia and WordNet. *Elsevier Journal of Web Semantics*, 6(3), 203–217.

Tatu, M., & Moldovan, D. (2006). A logic-based semantic approach to recognizing textual entailment.. In *Proceedings of the COLING/ACL on Main conference poster sessions*, pp. 819–826, Morristown, NJ.

Thater, S. (2007). *Minimal Recursion Semantics as Dominance Constraints: Graph-Theoretic Foundation and Application to Grammar Engineering*. Ph.D. thesis, Saarland University, Saarbrücken, Germany.

Van der Sandt, R. A. (1992). Presupposition projection as anaphora resolution. *Journal of Semantics*, 9(4), 333–377.

Wotzlaw, A. (2010). Towards better ontological support for recognizing textual entailment. In *Proceedings of the 17th International Conference Knowledge Engineering and Management by the Masses (EKAW)*, pp. 316–330, Lisbon, Portugal.

Wotzlaw, A., & Coote, R. (2010). Recognizing textual entailment with deep-shallow semantic analysis and logical inference. In *Proceedings of the 4th International Conference on Advances in Semantic Processing*, pp. 118–125, Florence, Italy.