Text-based Legal Ontology Enrichment

Wim Peters

Department of Computer Science, University of Sheffield, U.K.
w.peters@dcs.shef.ac.uk

Abstract. The acquisition of knowledge from text is an incomplete and incremental process. When anchored to a particular knowledge model it provides potentially useful information to the legal expert in the form of new concepts and relations, in order to improve the domain coverage. This paper explores the feasibility of various legal text-based ontology enrichment techniques, and discusses the transformation of lexical knowledge to an ontological structure.

Keywords: knowledge acquisition; lexical semantics; ontology engineering

1 Introduction

Ontology generation and population is a crucial part of knowledge base construction and maintenance that enables us to relate text to ontologies, providing on the one hand a customised ontology related to the data and domain with which we are concerned, and on the other hand a richer ontology, which can be used for a variety of semantic web-related tasks such as knowledge management, information retrieval and question answering.

Ontologies cover a particular knowledge domain in various levels of adequacy. Lacunae in domain coverage, different tasks or changes in the conceptualization require modifications of the ontology [1]. Ontology enrichment is a necessary ingredient of this ontology life cycle.

One source for enrichment of legal ontologies is the analysis of legal texts. It can generally be stated that law depends on language: regulatory knowledge must be communicated, and the written and oral transmission of social or legal rules passes through verbal expression. Therefore legal conceptual knowledge is closely related to language use within the legal domain. Legal discourse can never escape its own textuality [2], which implies that linguistic information plays an important role in its definition. In our work, we base ourselves on the postulation that there is, as in other terminological domains, a relatively high level of dependence between legal concepts and their linguistic realization in the various forms of legal language [3].

The acquisition of knowledge from resources such as texts is an incomplete and incremental process. Knowledge is quite often left implicit in text, or depends on previous analysis steps. This causes a sparseness problem for automatic acquisition.

In our work we attempt to alleviate this problem firstly by bootstrapping and constraining the acquisition process on the basis of an existing legal ontology, which provides a solid conceptual framework. Secondly, perfect automatic knowledge acquisition does not exist. The acquisition results are considered informal suggestions that need expert evaluation and formalization into an enriched ontological structure as concepts and properties. These suggestions are necessarily partial and incremental. Their fragmented nature shows them as building blocks which, under expert supervision and according to an existing knowledge structure, enables the building and addition of knowledge in a bottom-up fashion.

This paper investigates the (semi-)automatic enrichment of a legal ontology by means of a selection of NLP techniques based on pattern matching and statistical analysis. It is exploratory in character and therefore its methodologies are only indicative of the potential of the applied techniques.

The main task we set ourselves is the investigation into the feasibility of ontology enrichment techniques. This ontology enrichment can take two forms. On the one hand, new relations between existing ontology elements may emerge from textual data. On the other, new candidate concepts with new relations with existing ontology elements may be suggested by an integrated linguistic and statistical text analysis.

Recently, many relation extraction approaches have been proposed focusing on the particular task of ontology development (learning, extension, population). These approaches aim to learn taxonomic or non-taxonomic relations between concepts, instead of lexical items. Therefore, the list of techniques applied in this paper is not exhaustive. It forms a subset of the full set of methodologies available.

Most techniques described in this paper rely on robust and adaptable tools from the GATE architecture [4]. GATE is a framework for language engineering applications, which supports efficient and robust text processing. GATE uses NLP based techniques to assist the knowledge acquisition process for ontological domain modelling, applying automated linguistic analysis to create ontological knowledge from textual resources, or to assist ontology engineers and domain experts by means of semi-automatic techniques.

Our hypothesis is that the integration of corpus material, knowledge-based techniques and the use of rich linguistic processing strategies, can achieve effective results by accurately acquiring relevant relational knowledge [5]. A variety of techniques is helpful to the expert ontology engineer to extend the domain coverage of an existing ontology.

2 The Dalos Ontology

The DALOS domain ontology[1] [10] aims to describe the domain of the consumer protection, which has been chosen as the pilot case in the recently finished DALOS project[2], which resulted in the provision of support for the legal drafting process. It has been implemented as an extension of the Core Legal Ontology (CLO)[3] developed on top of DOLCE foundational ontology [11] and on the "Descriptions and Situa-

[1] http://turing.ittig.cnr.it/jwn/ontologies/consumer-law.owl
[2] http://www.dalosproject.eu/
[3] http://www.loa-cnr.it/ontologies/CLO/CoreLegal.owl

tions" (DnS) ontology [12] within the DOLCE+ library[4]. The extension covers the entities of the chosen domain and their legal specificities. In this network of ontologies the role of a core legal ontology is to describe concepts, which belong to the general theory of law, bridging the gap between domain-specific concepts and the abstract categories of formal upper level or foundational ontologies from DOLCE.

The domain ontology is populated by the conceptual entities which characterize the consumer protection domain. Such domain-specific concepts are classified according to more general notions, imported from CLO, as Legal role and Legal situation. Examples of consumer law concepts are CommercialTransaction, Consumer, Supplier, Good and Price. The first version of the DALOS Ontological layer contains 121 named classes.

3 Ontology Enrichment

The DALOS ontology is the result of a manual effort within the DALOS project. Ontological modelling of legal domains is a constant effort. Domain descriptions need to be refined. Legislation evolves in the sense that new directives are issued, and old ones are deprecated. Therefore its coverage of the domain of consumer protection in terms of ontological vocabulary is never complete, and should be constantly adapted on the basis of expert advice and data-driven suggestions. Its incorporation of top level ontologies such as DOLCE make it descriptively adequate and robust for the higher levels of ontological legal description, but in terms of fine-grained domain-specific vocabulary it continuously remains in need of refinement and extension.

Our aim is to provide data-driven suggestions for ontology extension in the form of lexical material from the English legal texts in the DALOS corpus, which consists of directives and judgements (270,000 words in 55 directives and judgements). The results carry no more authority than suggestions for expert evaluation. For our analyses described below, the evaluator is a computational linguist, not a legal expert.

The main task these analyses perform is the general knowledge based identification of text-derived information that is of possible interest for legal ontology enrichment. Legal relevance will be an additional evaluation phase in which the data, deemed relevant from a general perspective, are assessed by an expert, and, if deemed relevant for the legal knowledge expressed by the DALOS ontology, integrated into an extended knowledge structure.

4 Acquisition from Text

The idea of acquiring semantic information from texts dates back to the early 1960s with Harris' distributional hypothesis [7] and Hirschman and Sager's work in the 1970s [8], which focused on determining sets of sublanguage-specific word classes using syntactic patterns from domain-specific corpora. Many techniques have since been proposed for the task of extracting knowledge from texts. Overall, the majority

[4] http://dolce.semanticweb.org

of approaches can be divided into pattern-based (pattern matching in a corpus) and statistically-based extraction [21]. Quite often, the two techniques are mixed (e.g. [24], [25], [26]). A description of several other approaches for conceptual relation extraction aiming at ontology learning can be found in [9].

4.1 GATE

The GATE platform[5] forms the methodological basis for our work [4]. A number of tools have been developed and used for the task of legal ontology enrichment. They all rely on the initial stage of linguistic pre-processing the corpus under examination, in order to obtain valuable linguistic information that will be used in later processing.

4.2 Pre-processing

First, tokenization and sentence splitting divide up the text into manageable units. Then part of speech tagging and lemmatization allow the inclusion of morpho-syntax into the analysis.

4.3 Term extraction

The extraction tool TermRaider produces term candidates from a corpus by first filtering out possible terms by means of a multi word unit grammar that defines the sequences of part of speech tags constituting noun phrases. The computation of term frequency/inverted document frequency (TF/IDF) [13] [20], a technique widely used in information retrieval and text mining taking into account term frequency and the number of documents in the collection, yields a score that indicates the salience of term candidates for each document in the corpus. All term candidates with a TF/IDF score higher than an empirically determined threshold are then selected.

4.4 Lexico-syntactic pattern matching

Lexico-syntactic patterns are textual patterns that, with morphosyntactic normalization such as lemmatization, are highly indicative of semantic relations between textual elements. Ontology population based on this pattern approach has proven to be reasonably successful for a variety of tasks [6].

The following pattern matching strategies have been applied:

a) Headword matching

This technique looks for a match between a pair of elements, of which one is embedded into the other as the head of a syntactic construction. The ontological interpretation of this relation is the insertion of a hyponymic relation between these elements. Examples from the Dalos ontology are:

[5] www.gate.ac.uk

Contract SuperClassOff DistanceContract
Activity SuperClassOff CommercialActivity

Ten head matching relations were found in the ontology. All ten are covered in the ontology by means of superclass relations, except for one: Agent isSuperClassOff PhysicalAgent. PhysicalAgent is an object, and Agent is a top concept. PhysicalAgent is a hypernym of NaturalPerson, and the definition of Agent is: "A natural or legal person which plays the role of legal subject". We can therefore conclude on the basis of this definition that this additional a subsumption relation holds.

Matching the term candidates identified by TermRaider with existing classes resulted in 378 matching pairs. Manual evaluation of this set showed that 115 (around 30%) of them should be considered by experts for possible inclusion into the DALOS ontology. As an illustration, the following candidate subclasses of Contract were extracted, which show the detail of terminological specification in this domain: time-share contract; purchase contract; credit contract; package travel contract; consumer contract; building contract.

b) Hearst patterns

The second acquisition technique is based on Hearst patterns [14], which are a set of lexico-syntactic patterns that indicate hyponymic relations, and have been widely used by other researchers. Typically, they achieve a very high level of precision, but quite low recall [21]: in other words, they are very accurate but only cover a small subset of the possible patterns for finding hyponyms and hypernyms. The patterns can be described by the following rules, where NP stands for a Noun Phrase and the regular expression symbols have their usual meanings[6]:

{ NP such as (NP,)* (or|and) NP
Example:
"advertising and marketing practises, such as product placement, brand differentiation or the offering of incentives…"

{ NP (,NP)* (,)? (or|and) (other|another) NP
Example:
"…whereby a creditor grants or promises to grant to a consumer a credit in the form of a deferred payment, a loan or other similar financial accommodation."

No matching patterns between Dalos ontology elements were found. Table 1 below lists the results for obtained patterns between term candidates selected by TermRaider and Dalos ontology elements. The success rate is lower than expected (27% on average), given the reported high precision of Hearst patterns.

[6] () for grouping; | for disjunction; *, +, and ? for iteration

Table 1. Results from Hearst pattern matching

Hearst Pattern	Number found	Valid	Success Rate
Such as	31	11	32%
Including	0	0	-
And other	0	0	-
Or other	2	1	50%
Especially	1	0	0%

c) Mutual Information

Whereas bot a) and b) produce paradigmatic (isa) relations between terms, pointwise mutual information[7] (MI) is a well-known technique that measures the mutual dependence of the two variables as an expression of a syntagmatic relation. It is commonly used as a significance function for the computation of collocations in corpus linguistics [15]. In our case, it measures the statistically-based strength of relatedness through collocation within the same document.

Overall, forty MI relations were found between existing concepts from the Dalos ontology after matching DALOS ontology labels onto textual elements. Nine (22.5%) of the forty are not connected by any relation or concatenation of relations in the ontology. For example, the following pairs with their MI value:

ConsumerGoods	ConsumerProtection	4.10099
ConsumerProtection	Consumer	3.37321
FinancialService	Supplier	2.56943
Producer	RawMaterial	2.55241
Seller	ConsumerGoods	2.44503
ConsumerGoods	Producer	2.40581
ImmovableProperty	Contract	1.53971
ImmovableProperty	FinancialService	1.20745
FinancialService	Product	1.19957

Thirty one (77.5%) are related within the ontology, expressed by property concatenations in varying degrees of complexity.

Six MI pairs have a direct connection between its members, as illustrated below:

Advertising subClassOf CommercialCommunication	4.59607
Consumer isConsumerRoleOf NaturalPerson	3.89793
NaturalPerson hasRole Supplier	2.72426
NaturalPerson hasSellerRole Traider	2.69349
Advertising isAbout Product	2.34477
CreditAgreement hasParticipant Consumer	2.25352

A number of concepts (Consumer, Supplier, Trader, Producer, Organizer and Seller) are all subconcepts of LegalRole in the DALOS ontology. As co-hyponyms they are

[7] See http://www.collocations.de/ and http://en.wikipedia.org/wiki/Mutual_information

not directly related, but indirectly through their hypernym. The 11 MI pairs in which they are collocations seem to express ontological relations that are applicable to this whole set of co-hyponyms, in varying property configurations, such as Contract and CreditAgreement, of which Contract is the strongest indicator.

Supplier	Seller	5.91
Contract	Organizer	4.53
Consumer	Supplier	3.80
Consumer	Seller	3.48
CreditAgreement	Supplier	3.34
Supplier	Contract	3.21
Seller	Contract	2.70
DistanceContract	Consumer	2.61
Trader	Consumer	2.56
Contract	Consumer	2.46
Contract	FinancialService	2.03
Supplier	Producer	2.00

The remaining fourteen of the MI concept pairs have complex indirect links between them, which consist of a concatenation of object properties. For example:

Producer Product 4.21
Product isObjectOf Advertising Isactedin CommercialTransaction hasParticipant Agent hasRole Producer

Consumer CommercialCommunication 3.37
CommercialCommunication isActedIn CommercialTransaction hasParticipant Consumer

Consumer GeographicalAddress 2.45
GeographicalAddress isQualityOf NaturalPerson hasConsumerRole Consumer

Product Consumer 0.21
Product isObjectOf Advertising Isactedin CommercialTransaction hasParticipant Agent hasRole Consumer

These results indicate the potential for statistical techniques - in this case the computation of mutual information values for pairs of ontology members- for the identification of fine-grained relations between concepts. 77.5% of the extracted MI relations are already attested in the ontology. The 22.5% of the MI pairs without ontological confirmation make ontological sense to the inexpert eye in that they express fine-grained relations that should be expertly evaluated for inclusion into the ontology, and linked to existing ontology elements by means of existing or new object properties.

The value of the MI score does not seem to matter much in terms of validity of a relation between the ontology elements, nor does it seem indicative of the length of the path between the ontology elements. The actual detection of a relation by means of MI computation seems to be crucial in this case, and it is up to experts to determine the granularity of the property vocabulary in the ontology, and decide whether this relation needs to be made explicit by means of one object property, or a concatenation of object properties.

d) Verbal complementation patterns

Verbal patterns typically reflect lexicalized semantic relations between its arguments. Patterns defined in GATE can consist of any type of annotation that has been added in GATE, e.g. part of speech, string value, lemma etc. The corpus indexing and querying tool in GATE, called ANNIC[8] (ANNotations In Context) [16], allows the evaluator to enter search patterns over text annotations, and detect semantic relations between ontology elements at the fine-grained text level.

As proof of concept, the following simple pattern was defined, which identifies pairs of elements from the Dalos ontology that are mentioned in the texts as verb arguments. The surface representation restricts the verb context to a two-token window on either side.

{DalosConcept}({Token})*2{Token.category=="VERB"}({Token})*2 {DalosConcept}

A graphical user interface allows the user to query a corpus and inspect the results from the query. The screenshot in Figure 1 below illustrates how the results are displayed in the GATE interface. Annotations over spans of text are displayed as rows with coloured blocks indicating part of speech, string and DalosConcept. Contexts to the left and right of the text matching the search pattern are displayed at the bottom.

Using this query, 56 patterns were extracted, of which 37 (66%) were evaluated as deserving expert attention. For example:

NaturalPerson	conclude	Contract	with Seller or Supplier
NaturalPerson	buy	Product	
Seller/Supplier	dissolve	Contract	
Consumer	enter into	CreditAgreement	
Consumer	purchase	Product	
Consumer	rely on	Guarantee	
Consumer	acquire	Services	
CompetentAuthority	assess	Product	

8 http://videolectures.net/gate06_aswany_ac/

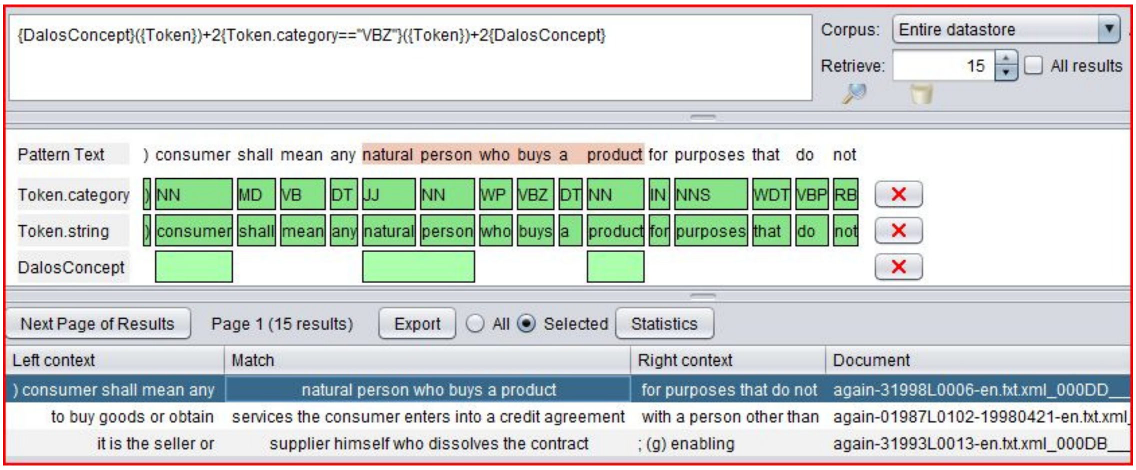

Fig. 1. Snapshot of ANNIC functionality

5 Formalization of acquired lexical knowledge

Surface patterns and text spans are potential lexical realizations of underlying ontological relations and concepts. Ontologies themselves are conceptual constructs without linguistics. From a formal ontological point of view, concepts are abstract notions whose labels (often constituted by textual elements) are arbitrary. The lexical senses of the lexicalizations that function as labels for these concepts, are only considered to be evocative or indicative of the ontological meaning of the concepts. There is an implicit mapping assumption between lexical and conceptual knowledge, which underlies "ontology lexicalization", namely that (intensional) senses from a lexical model are mapped to (extensional) interpretations on ontology elements (individuals, classes, restrictions, properties) [17].

The reification of lexical material into ontological elements can happen in various ways. Some authors state that there is a direct relation between lexical form and surface syntactic pattern and ontological content [18]. Others advocate a formalization process that transforms surface patterns into ontology concepts and object properties in a number of stages, maintaining the philosophical distinction between lexical meaning and conceptualization, and allowing predication over these various levels of semantic representation [19].

The first stage is a transformation of linguistic elements (abstracted away from surface forms by means of lemmatization and other linguistic normalization processes such as morphological decomposition) into a semantic metamodel, which expresses the semantics of the domain. The next step, the transformation of this semantic domain knowledge into an ontological representation language construct such as OWL[9],

[9] http://www.w3.org/2004/OWL

decides on the ontological status of the semantic knowledge, e.g. whether it should be encoded as class, an attribute of an object property.

6 Discussion

When applying a variety of NLP techniques for ontology extension, each technique provides its specific spectrum of potential ontological enrichment based on the nature of the linguistic and statistical algorithms involved. Overall, the four acquisition techniques described in this paper (head matching, Hearst patterns, mutual information and simple verb complementation patterns) form a representative combination of acquisition techniques for both paradigmatic and syntagmatic lexical semantic relations. They perform reasonably well for establishing relations between ontology elements (81.2% average success rate excluding Hearst patterns, for which no hits were found). Since Hearst patterns are very sparse at best, future work on text-based ontological relation acquisition will look at the extension of the Hearst pattern set with more textual patterns reflecting the paradigmatic isa-relation (taken from e.g. [27]).

Head matching and Hearst patterns between term candidates and ontology elements have an average success rate of 28.5%, which is lower than expected. Overall, we can conclude that the techniques work well for identifying relations between ontology elements.

The reification of these surface syntactic and collocational relations may take several forms, depending on the strategy chosen. For some of the extracted relations based on verbal and deverbal lexicalizations, the proposed corresponding ontological relations are not always disjoint. For instance, in a number of cases, it is possible to group certain relations together under synonymy. As an example, the textual fragments "supply of services" and "provision of services" contain deverbal nouns, which, when translated into verbal counterparts, yield the following object properties:

AGENT supply SERVICE
AGENT provide SERVICE

Since "supply" and "provide" are synonyms in WordNet [22], the object can be renamed into a common label, which covers both verbal lexicalizations. Further mapping with lexical resources such as VerbNet [23] will further classify the relations into more general classes, and provide semantic role arguments (e.g. agent, instrument etc.). Together with further analysis of the lexicalizations that instantiate these patterns, this will lead to an incremental creation of semantic frames, which then can be transformed into their ontological counterparts with ontologically proper constraints on the domain and range of the reified properties.

References

1. Stojanovic, L., Maedche, A., Motik, B. and Stojanovic, N.: User-driven ontology evolution management. In: European Conference of Knowledge Engineering and Management *(*EKAW 2002), pp. 285–300, Springer, Heidelberg (2002)

2. Macdonald, D., Legal bilingualism, McGill Law Journal 1997,42 McGill L.J. 119 (1997)

3. Peters, W,, Tiscornia, D, Sagri, M.T., The Structuring of Legal Knowledge in Lois. In: Artificial Intelligence and Law, Volume 15, Issue 2, Legal knowledge extraction and searching & legal ontology applications, pp. 117-135 (2007)

4. H. Cunningham, H., Maynard, D., Bontcheva, K. and Tablan, V.: Gate: A Framework and Graphical Development Environment for Robust Nlp Tools and Applications. In: Proceedings of the 40th Anniversary Meeting of the Association for Computational Linguistics (ACL'02) (2002)

5. Specia, L., Baldassarre, C., Motta, E., Relation Extraction for Semantic Intranet Annotations, Technical Report kmi-06-17, Open University, Milton keynes (2006)

6. Etzioni, O., Cafarella, M., Downey, D., Kok, S., Popescu, A., Shaked,T., Soderland, S., Weld, D.S., Yates, A.: Web-scale Information Extraction in KnowItAll. In: Proceedings of WWW-2004 (2004)

7. Z. Harris, Z., Mathematical Structures of Language, Wiley (1968)

8. Hirschman, L., Grishman, R., Sager, N.: Grammatically based automatic word class formation. Information Processing and Retrieval 11 (1975)

9. Gómez-Pérez, A., Manzano-Macho, D., A survey of ontology learning methods and techniques. In: The Knowledge Engineering Review archive, Volume 19, Issue 3,pp. 187-212 (2004)

10. Agnoloni, T., Bacci, L. and Francesconi, E., Ontology Based Legislative Drafting: Design and Implementation of a Multilingual Knowledge Resource..In: Gangemi, A. and Euzenat, J. (Eds.) Knowledge Engineering: Practice and Patterns Knowledge Engineering: Practice and Patterns, 16th International Conference, EKAW 2008, Acitrezza, Italy, September 29 - October 2, 2008, Springer Lecture Notes in Computer Science, Volume 5268/2008 (2008)

11. Gangemi, A., Sagri, M. and Tiscornia, D., A constructive framework for legal ontologies. In: Law and the Semantic Web (Benjamins, R., Casanovas, P, Gangemi, A. and Selic, B. (eds.), Springer Verlag, (2005)

12. C. Masolo, C. Vieu, L. Bottazzi, E. Catenacci, C. Ferrario, R. Gangemi, A. and

Guarino, N., Social roles and their descriptions, In: Welty, C. (ed.), Proceedings of the Ninth International Conference on the Principles of Knowledge Representation and Reasoning, Whistler, (2004)

13. Buckley, C. and Salton, G., Term-weighting approaches in automatic text retrieval. In: Information Processing and Management, vol. 24, no. 5, pp. 513–523 (1988)

14. Hearst, M., Automatic acquisition of hyponyms from large text corpora. In: Proceedings of the Fourteenth International Conference on Computational Linguistics, Nantes, France (1992)

15. Smadja F. A & McKeown, K. R. , Automatically extracting and representing collocations for language generation. In: Proceedings of ACL'90, pp. 252–259, Pittsburgh, Pennsylvania (1990)

16. Aswani, N., Tablan, V., Bontcheva, K. and Cunningham,H., Indexing and Querying Linguistic Metadata and Document Content. In: Proceedings of 5th International Conference on Recent Advances in Natural Language Processing, Borovets, Bulgaria (2005)

17. Peters, W., Montiel-Ponsoda, E., Aguado de Cea, G. and Gómez-Pérez, A., Localizing Ontologies in Owl. In: Proceedings of the ISWC 2007 workshop Ontolex2007, Busan, Korea (2007)

18. Cimiano, P., Haase, P., Herold, M., Mantel, M., and Buitelaar, P., LexOnto: A Model for Ontology lexicons for Ontology-based NLP. In: Proceedings of the ISWC 2007 workshop Ontolex2007, Busan, Korea (2007)

19. Picca, D., Gangemi, A. and Gliozzo, A., LMM: an OWL Metamodel to Represent Heterogeneous Lexical Resources. In: Proceedings of the International Conference on Language Resources and Evaluation (LREC), Marrakech, Morocco (2008)

20. Maynard, D., Li, Y.and Peters, W., Nlp techniques for term extraction and ontology population. In: Buitelaar, P. and Cimiano, P. (eds.), Ontology Learning and Population: Bridging the Gap between Text and Knowledge, pp. 171-199, IOS Press, Amsterdam (2008)

21. Cimiano, P., Pivk, A., Schmidt-Thieme, L. and Staab, S. Learning taxonomic relations from heterogeneous sources. In: Proceedings of the ECAI 2004 Ontology Learning and Population Workshop (2004)

22. Fellbaum, Christiane (ed.), WordNet*:* An Electronic Lexical Database. Cambridge, Mass.: MIT Press. (1998

23. Kipper, K., Korhonen, A., Ryant, N. and Palmer, M., Extensive Classifications of English verbs. Proceedings of the 12th EURALEX International Congress, Turin, Italy (2006)

24. Pantel, P. and Pennacchiotti, M., Automatically harvesting and ontologizing semantic relations. In Paul Buitelaar and Philipp Cimiano (eds.), Ontology Learning and Population: Bridging the Gap between Text and Knowledge, pp.171-195, IOS Press, Amsterdam (2008)

25. Cimiano, P., Hartung, M., and Ratsch, E., Finding the Appropriate Generalization Level for Binary Relations Extracted from the Genia Corpus. Proceedings of the International Conference on Language Resources and Evaluation (LREC), Genoa, Italy. (2006)

26. Schutz, A. and Buitelaar, P., RelExt: A Tool for Relation Extraction from Text in Ontology Extension. International Semantic Web Conference 2005:593-606 (2005)

27. de Cea, G.A., Gómez-Pérez, A., Ponsoda, E.M., Suarez-Figueroa, M.C.: Natural language-based approach for helping in the reuse of ontology design patterns. In: Proceedings of the 16th International Conference on Knowledge Engineering and Knowledge Management Knowledge Patterns (EKAW 2008), Acitrezza, Italy (2008)