A Survey of Ontology Learning Procedures

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Abstract. Ontologies constitute an approach for knowledge representation that can be shared establishing a shared vocabulary for different applications and are also the backbone of the Semantic Web. Thus a fast and efficient ontology development is a requirement for the success of many knowledge based systems and for the Semantic Web itself. However, ontology development is a difficult and time consuming task. Ontology learning is an approach for the problem of knowledge acquisition bottleneck that aims at reducing the cost of ontology construction through the development of automatic methods for the extraction of knowledge about a specific domain and its representation in an ontology like structure. This paper provides a discussion on existing ontology learning techniques and the state of the art of the field.

Key words: Ontologies; Ontology Learning; Machine Learning; Knowledge Acquisition

1 Introduction

Ontologies constitute an approach for knowledge representation that is capable of expressing a set of entities and their relationships, constraints, axioms and the vocabulary of a given domain. An ontology should be machine readable in such a way that information systems are able to use them to represent and share the knowledge about the application domain.

Ontologies hold a great importance to modern knowledge based systems. For instance, they constitute a powerful tool for supporting natural language processing [1][2][3], information filtering [4][5], information retrieval [6] and data access [7]. Besides, they also provide a formalism for specifying similarity measures which have presented good effectiveness [8][5][9].

One of the greatest application of ontologies is the Semantic Web [10][11], a new generation of the Web in which the semantic of documents, in most cases currently expressed only in natural language, would be expressed using ontologies. This way, the Semantic Web is an approach for enhancing the effectiveness of Web information access.

However, the manual construction of ontologies is an expensive and time-consuming task because the professionals required for this task (i.e. a domain specialist and a knowledge engineer) usually are highly specialized. This difficulty in capturing the knowledge required by knowledge based systems is called "knowledge acquisition bottleneck".

The fast and cheap ontology development is crucial for the success of knowledge based applications and the Semantic Web. An approach for this problem is to provide an automatic or semi-automatic support for ontology construction. This field of research is usually referred to as ontology learning [12][13][14].

This paper presents a survey of ontology learning techniques. Section 2 introduces the ontology concept as it is considered in this work. Section 3 discusses the overall process of ontology learning and some commonly cited approaches. The work on the evaluation of ontology learning procedures is discussed in Section 4. Section 5 concludes this paper with a final discussion on the approached topic.

2 Ontologies

Before discussing the problem of ontology learning, we must first clarify what we mean by the term "ontology". There are a number of definitions and uses for this term and some of them can be found in [15]. For the sake of simplicity this paper uses the term "ontology" according to a formal definition proposed in [16] and defined in this section.

According to Russel and Norvig [17], the term "ontology" is concerned with a theory about the existence. The Artificial Intelligence discipline considers ontologies as a formal specification of the concepts of an interest domain, where their relationships, constraints and axioms are expressed, thus defining a common vocabulary for sharing knowledge [18]. Indeed, what must be represented in a knowledge based system is what exists. This way, the definitions are complementary.

An ontology is composed, on one hand, by concepts, taxonomic relationships (that define a concept hierarchy) and non taxonomic relationships between them and, on the other hand, by concept instances and assertions about them.

An ontology must be formal and, therefore, machine readable. This way ontologies can provide a common vocabulary between various applications. This knowledge representation structure usually consists of a set of frame-based classes organized hierarchically describing a domain. It provides the skeleton of the knowledge base. The knowledge base uses the represented concepts to describe a dynamic reality and it changes according to the changes in the reality. However, the ontology only changes if there are changes in the described domain.

More formally, an ontology can be defined, according to [16], as a tuple:

$$\vartheta := (C, R, H^C, rel, A^\vartheta). \tag{1}$$

where:

- C is the set of ontology concepts. The concepts represent the entities of the domain being modeled. They are designated by one or more natural language terms and are normally referenced inside the ontology by a unique identifier.

- $H^C \subseteq C \times C$ is a set of taxonomic relationships between the concepts. Such relationships define the concept hierarchy.
- R is the set of non-taxonomic relationships. The function $rel : R \rightarrow C \times C$ maps the relation identifiers to the actual relationships.
- A^ϑ is a set of axioms, usually formalized into some logic language. These axioms specify additional constraints on the ontology and can be used in ontology consistency checking and for inferring new knowledge from the ontology through some inference mechanism.

Besides these elements, there are also the instances of the concepts and relationships, e.g. the instances of the elements of C, H^C and R. A knowledge base is composed by an ontology ϑ and its instances.

3 Ontology Learning

The term ontology learning refers to the automatic or semi-automatic support for the construction of an ontology ϑ, while the automatic or semi-automatic support for the instantiation of a given ontology is referred to as ontology population [19]. Ontology learning is concerned with knowledge discovery in different data sources and with its representation through an ontologic structure and, together with ontology population, constitutes an approach for automating the knowledge acquisition process.

According to [20] there are two fundamental aspects on ontology learning. The first one is the availability of prior knowledge. In other words, wether the learning process is performed from scratch or some prior knowledge is available. Such prior knowledge is used in the construction of a first version of the ontology. Thus, a source of prior knowledge must demand little effort to be transformed into the first version of the ontology. This version is then extended automatically through learning procedures and manually by a knowledge engineer [21].

The other aspect is the type of input used by the learning process. Benz [20] defines three different kinds of input:

- structured data: database schemes.
- semi-structured data: dictionaries like WordNet [22];
- unstructured data: natural language text documents, like the majority of the HTML based webpages;

Some approaches for ontology learning from structured data sources [23] and semi-structured ones [20] data have been proposed and presented good results. However, although they do provide some support to manual ontology development, the proposed methods for learning from unstructured data have not shown good results on the creation of semantic resources in a completely automated fashion [15]. Such methods are crucial to some areas. For instance, for the establishment of the Semantic Web, once most of the knowledge available on the Web is represented in natural language texts [24].

Before establishing the tasks in the ontology learning process, one has to define the steps for ontology development, be it manual or automatic. Although there is no standard regarding this development process, Buitelaar et. al in [19] organizes the aspects and tasks involved in ontology development into a set of layers. Such layers are shown in Fig. 1.

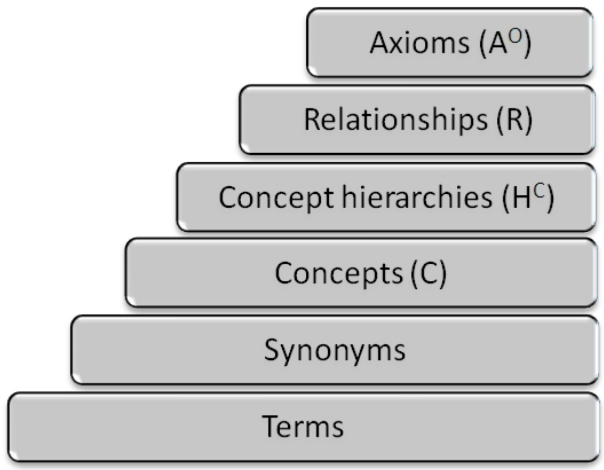

Fig. 1. Layers of the Ontology Development Process (adapted from [19])

According to the definition 1, an ontology consists of concepts, relationships between them and axioms. In order to identify the concepts of a domain, in first place, it is necessary to identify the natural language terms that refer to them. This task is specially important for ontology learning from free text. Synonym identification helps to avoid redundant concepts, since two or more natural language terms can represent the same concept. Another reason for identifying the terms is that, in the future, some of them can be used to uniquely identify their respective concepts. The terms are the source for identifying the concepts that will be part of the ontology, i.e. the set C of definition 1.

The next step is to identify the taxonomic relationships (generalization and specialization) between the concepts. The product of this task is a set H^C. It is also necessary to extract the non taxonomic relations, thus defining the set R and the function rel. Finally the extraction of the instances of the learned concepts and relationships takes place. Some authors [19] also consider rule acquisition for deriving facts that are not explicitly expressed in the ontology, that would constitute the set A^ϑ.

Although, all of the ontology learning tasks are the same no matter what kind of input is used, there are specific issues associated with learning ontologies from each type of input data. Such issues regarding the ontology learning from structured, semi-structured and unstructured data are discussed, respectively, in subsections 3.1, 3.2 and 3.3. Some examples of ontology learning applications are shown in subsection 3.4.

3.1 Ontology Learning from Structured Data

These ontology learning procedures extract parts of the ontology using the available structural information. Examples of structured information sources are database schemas, existing ontologies and knowledge bases.

The central problem in learning from structured data is to determine which pieces of structural information can provide relevant knowledge. For instance, a database schema may be used to identify ontology concepts and their relationships [25].

3.2 Ontology Learning from Semi-structured Data

Usually the quality of the results of ontology learning procedures using structural information is better than the ones using completely unstructured input data [21]. Unfortunately, most of the available knowledge is in the form of unstructured text. For this reason techniques for learning ontologies from semi-structured data [26] (e.g. data composed by some structural information plus free text) have been developed.

Examples of semi structured data are dictionaries, like WordNet [22] or the Wiktionary [27], HTML and XML documents, document type definitions (DTD), Wikis and User Tags. With the advent of the Web 2.0 and the Semantic Web, grows the interest for the development of procedures for extracting ontologies from semi-structured web documents [28] and from user tags [20].

3.3 Ontology Learning from Unstructured Data

Methods for extracting ontology parts from unstructured data are those that do not rely on any structural information for improving the quality of its results. They are important because unstructured data is the most available format for ontology learning input [21]. Unstructured documents consists of natural language texts such as Word, PDF documents or Web pages.

For extracting knowledge from these sources, statistical and linguistic approaches are often used. One commonly accepted assumption in statistical approaches is the Harris distributional hypothesis [29]. This hypothesis states that similar words tend to occur in similar contexts.

While statistical approaches often rely on word frequencies and word co-occurrence, linguistic approaches make use of natural language processing techniques, like syntactic, morpho-syntactic, lexico-syntactic and syntactic-semantic analysis, for extracting information from text [2].

There are also the pattern based approaches, which search the texts for certain patterns that indicate some kind of relation. One commonly cited approach is the Hearst patterns [30]. Hearst defined some lexico-syntactic patterns that indicate hyponymy/hypernymy relationships in the text.

Some ontology learning from text approaches uses clustering algorithms. In hierarchical clustering, term sets can be organized into a hierarchy that can be transformed directly into an ontology prototype. For this intent, the distance measure between terms has to be defined in such a way that it can be used as a criteria for merging terms [2].

An evaluation of the clustering methods for ontology learning from unstructured data can be found in [31]. In the first place, every clustering methods can be applied to various representation models, such as the vector space approach, associative networks or set theory based, as shown in [32].

Methods using distributional similarity can be divided into syntactic and window based approaches.

Syntactic approaches use similarity considering the relationships between predicate and argument. Hindle [33] aims at finding similar nouns by comparing their behavior regarding the predicate argument structure. For each verb-subject and verb-object pair in their set of six million analyzed words, he computes the co-occurrence weights as being the mutual information existing on the pairs.

An entire class of syntactic approaches is included in the Mo'k workbench [34], that provides a framework for defining term hierarchical clustering based on similarity and on limited contexts.

There is another set of methods which produce paradigmatic relations (relations between the meaning of terms) as a mechanism for identifying the candidate terms without the need for syntactic pre-processing. A source for paradigmatic relationships is the second order co-occurrence, which does not rely on grammatical analysis. While the first order co-occurrence scores high pairs of words that appear together frequently in a certain text window, the second order co-occurrence scores high the ones that have similar first order co-occurrence [15].

3.4 Ontology Learning Applications

This subsection presents some examples of ontology learning applications.

Text2Onto A tool for ontology learning from textual sources is the Text2Onto framework [35]. The Text2Onto is a framework which represents the learned knowledge into a meta level through modeling primitives from a model called probabilistic ontology model (POM). POM is a collection of modeling primitives independent from any ontology representation language. Such primitives are defined in the Modeling Primitives Library (MPL). The main modeling primitives are:

- concepts (Concepts C)
- concept inheritance (Taxonomic relationships H^C)
- concept instantiation (Instances)
- properties/relations (Non taxonomic relationships R)
- domain and range restrictions (Axioms A^ϑ)
- mereological relations (Part-of relations R)

– equivalence

Text2Onto uses data driven change discovery for algorithms for supporting automatic and semi-automatic adaptation of a given ontology according to changes in a data set and provides several algorithms for instantiating each modeling primitive from POM (which can be associated with the tasks of ontology learning shown in Fig. 1).

WebKB The WebKB [28] is a research project that aims at creating a knowledge base with the knowledge contained in the World Wide Web. This represents an approach for ontology population from semi-structured and unstructured input data. This is achieved through a trainable information extraction system that instantiates a given knowledge base consisting of an ontology defining the classes and relations of interest, and optionally, instances of some of these classes and relations. WebKB uses logical and statistical learning algorithms for these tasks.

DLLearner An approach for learning ontologies from structured data is proposed in [23]. This approach is based on inductive logic programming (ILP) [36]. An ILP algorithm aims at learning a logic program from examples and prior knowledge. Traditional ILP methods work usually with predicate logics for representing prior knowledge and the learned hypothesis.

Description logics is the formalism in which the OWL (the W3C ontology recommendation for the Semantic Web) is based. A refinement operator for description logics is proposed in [23]. This refinement operator is used in a description logics based ILP procedure. The proposed algorithm learns a definition of a concept in description logics and takes as input a knowledge base and a training set with positive and negative examples of instances of the target concept.

HASTI HASTI [37] is an automatic ontology building system, which uses as input unstructured data in the form of natural language texts in Persian. HASTI uses no prior knowledge, i.e. it builds ontologies from scratch. Its lexicon is nearly empty initially and will grow gradually by learning new words. The ontology in HASTI is a small kernel at the beginning. HASTI learns concepts, taxonomic and non-taxonomic conceptual relations, and axioms, to build ontologies upon the existing kernel. The learning approach in HASTI is a hybrid symbolic approach, a combination of linguistic, logical, template driven and semantic analysis methods. It performs online and offline clustering to organize its ontology.

4 Methods for the Evaluation of Ontology Learning Procedures

Comparing techniques for learning ontologies is not a trivial task. For a given domain, there is not a unique possibility of conceptualization [38] and these possibilities may differ in their usefullness but not in their soundness and justification [15]. Besides that, there is "no clear set of knowledge to be acquired" [39].

Although the evaluation of ontology learning procedures is still an open problem, there is already some work in this direction. In [40] two basic approaches for evaluating these systems are presented: the evaluation of the underlying learning methods and the evaluation of the learned ontology. However, because of the difficulty concerning the measurement of the correctness of the learning procedure, the former approach is less addressed.

According to [41], the resulted ontologies can be compared by evaluating them in a running application, a posteriori evaluation by experts, or evaluation by comparison of learned results against a pre-defined gold standard.

The automatically learned ontologies are useful to the extent they improve the effectiveness of the systems in which they are employed. Thus, the comparison of ontologies in a running application aims at evaluating the effectiveness of a system using the evaluated ontologies. For instance, a comparison between concept hierarchies in the context of a word sense disambiguation task is shown in [42] and in the context of text clustering is shown in [43].

Manual evaluation has advantages, since experts are supposed to know the concepts and their relationships in their domain of expertise and, therefore, they are supposedly able to tell wether a given ontology represents the domain or not.

Although a posteriori evaluation by experts and their evaluation in a running application have their advantages, they also have their drawbacks. For instance manual ontology evaluation is subjective and time consuming. Besides that, these two methods are not feasible for large-scale evaluations [41]. Thus the comparison against a gold standard [44] is a plausible alternative. For a primary work on the comparison between two ontologies please refer to [45]. In [41], a framework for gold-standard based evaluation of ontology learning is introduced. However how can one say that an ontology is good enough for being a gold standard? The gold standard is a hand crafted ontology, developed by an error prone process. If the gold standard ontology presents modeling problems, the evaluation method rewards ontologies with similar problems and penalizes ontologies with concepts or relationships not appearing in the gold standard.

5 Conclusions

This work presented a survey and a definition of the set of tasks known as ontology learning. For this intent, the ontology learning procedure was defined not as a single task, but as set of subtasks organized in the layers of Fig. 1. A definition of an ontology was provided, the tasks involved in the ontology learning process were identified and the most commonly cited approaches for this problem were introduced. Such approaches were classified according to the format of input data they use. Such data can be structured, semi-structured or unstructured.

Another fundamental difference between the cited approaches is the extent to which they automate the ontology development process. This can be observed when we compare which tasks are automated by each approach. This comparison is found in table 1.

Table 1. Comparative table between some of the cited approaches

	Terms	Synonyms	C	H^C	R	A^ϑ
DLLearner			X	X		
OL from Folksonomies			X	X	X	
Text2Onto	X			X	X	X
HASTI			X	X	X	X
Cluster Based	X	X	X	X		

The field of ontology learning builds upon well founded methods from knowledge acquisition, machine learning and natural language processing. Although progress has been made over the last years, this field of research has not yet reached the goal of fully automating the ontology development process. It is possible to see that the most of the already cited approaches focus on concept identification and hierarchy extraction. Work on automatic learning of non taxonomic relationships have already been conducted but have not reached yet an advanced development stage. But, of the ontology learning subtasks, the one that is currently in the earlier stage of development is the axiom learning.

Another great open question related to ontology learning is the evaluation of the proposed methods [41]. As shown in this paper there is already some work conducted in this direction but the establishment of formal, standard methods to evaluate ontology learning systems by proving their learning methods or proving the accuracy, efficiency and completeness of the built ontology is still an open problem [40].

Many of the ontology learning, methods discussed here address each one (or some) of the subtasks but not all of them in a coherent way. At last, another issue in this area is the development of methodologies which integrates methods for such a task.

Because of the complexity of ontology development and the importance of the ontologies for the Semantic Web (given that the ontologies constitute its backbone), we believe that ontology learning will remain an active and central field of research, at least, over the next years.

References

1. Girardi, R., Ibrahim, B.: Using english to retrieve software. Journal of Systems Software, Special Issue on Software Reusability **30**(3) (1995) 249–270

2. Girardi, R.: Classification and Retrieval of Software through their Descriptions in Natural Language. PhD thesis, Universit de Geneve (1995)
3. Cimiano, P., Hotho, A., Staab, S.: Learning concept hierarchies from text corpora using formal concept analysis. Technical report, Institute AIFB, Universität Karlsruhe (2004)
4. Middleton, S., Shadbolt, N., De Roure, D.: Ontological user profiling in recommender systems. ACM Transactions on Information Systems **22** (2004) 54–88
5. Drumond, L., Girardi, R., Silva, F.: A similarity analysis model for semantic web information filtering applications. In: Proceedings of the International Conference on Software Engineering and Knowledge Engineering. (2008)
6. Vailet, D. and Fernández, M. and Castells, P.: An Ontology-Based Information Retrieval Model. In: The Semantic Web: Research and Applications. Springer (2005) 455–470
7. Acciarri, A., Calvanese, D., De Giacomo, G., Lembo, D., Lenzerini, M., Palmieri, M., Rosati, R.: QuOnto: Querying Ontologies. Proceedings of the National Conference on Artificial Intelligence **20**(4) (2005) 1670
8. d'Amato, C., Fanizzi, N., Esposito, F.: A semantic similarity measure for expressive description logics. In Pettorossi, A., ed.: Proceedings of Convegno Italiano di Logica Computazionale (CILC05). (2005)
9. Resnick, P.: Semantic similarity in a taxonomy: an information-based measure and its application to problems of ambiguity in natural language. Journal of Artificial Intelligence Research **11** (1999) 95–130
10. Shadbolt, N., Hall, W., Berners-Lee, T.: The semantic web revisited. Intelligent Syst **21**(3) (2006) 96–101
11. Drumond, L., Girardi, R.: Uma análise das técnicas e ferramentas para o desenvolvimento de aplicações para a web semântica. REIC - Revista Eletrônica de Iniciação Científica **6**(1) (2006) In Portuguese.
12. Cimiano, P., Völker, J., Studer, R.: Ontologies on demand? - a description of the state-of-the-art, applications, challenges and trends for ontology learning from text. Information, Wissenschaft und Praxis **57**(6-7) (2006) 315–320
13. Omelayenko, B.: Learning of ontologies for the web: the analysis of existent approaches. In: Proceedings of the International workshop on Web Dynamics. (2001)
14. Nováček, V.: Ontology learning. Master's thesis, Faculty of Informatics, Masaryk University, Czech Republic (2006)
15. Biemann, C.: Ontology learning from text: A survey of methods. LDV Forum **20**(2) (2005) 75–93
16. Maedche, A.: Ontology Learning for the Semantic Web. Kluwer Academic Publishing (2002)
17. Russell, S., Norvig, P.: Artificial Intelligence: A Modern Approach. 2 edn. Prentice Hall (2003)
18. Gruber, T.: Toward principles for the design of ontologies used for knowledge sharing. International Journal of Human-Computer Studies (1995) 907–928
19. Buitelaar, P., Cimiano, P., Magnini, B.: Ontology learning from text: An overview. ontology learning from text: Methods, evaluation and applications. Frontiers in Artificial Intelligence and Applications Series **123** (2005)
20. Benz, D.: Collaborative ontology learning. Master's thesis, University of Freiburg (2007)
21. Dellschaft, K.: Measuring the similarity of concept hierarchies and its influence on the evaluation of learning procedures. Master's thesis, Universität Koblenz Landau, Campus Koblenz, Fachbereich 4 Informatik, Institut für Computervisualisitk (2005)

22. Miller, G.: Wordnet: a lexical database for english. Commun. ACM **38**(11) (1995) 39–41
23. Lehmann, J., Hitzler, P.: A refinement operator based learning algorithm for the alc description logic. In: Proccedings of the 17th International Conference on Inductive Logic Programming (ILP), Springer (2007)
24. Maedche, A., Staab, S.: Ontology learning for the semantic web. IEEE Intelligent Systems **16**(2) (2001) 72–79
25. Kashyap, V.: Design and creation of ontologies for environmental information retrieval. In: Proceedings of the 12th Workshop on Knowledge Acquisition, Modeling and Management. (1999)
26. Pernelle, N., Rousset, M., Ventos, V.: Automatic construction and refinement of a class hierarchy over semistructured data. In: Proceedings of the IJCAI 2001 Workshop on Ontology Learning (OL2001). (2001)
27. Foundation, W.: Wiktionary
28. Craven, M., DiPasquo, D., Freitag, D., McCallum, A.K., Mitchell, T.M., Nigam, K., Slattery, S.: Learning to construct knowledge bases from the World Wide Web. Artificial Intelligence **118**(1/2) (2000) 69–113
29. Harris, Z.: Mathematical Structures of Language. Wiley (1968)
30. Hearst, M.: Automatic acquisition of hyponyms from large text corpora. In: Proceedings of the 14th International Conference on Computational Linguistics. (1992)
31. Maedche, A., Staab, S. In: Ontology learning. Springer (2004) 173190
32. Cimiano, P., Hotho, A., Staab, S.: Comparing conceptual, divisive and agglomerative clustering for learning taxonomies from text. In: Proceedings of the European Conference on Artificial Intelligence (ECAI). (2004) 435–443
33. Hindle, D.: Noun classification from predicate-argument structures. In: Proceedings of the 28th annual meeting on Association for Computational Linguistics, Morristown, NJ, USA, Association for Computational Linguistics (1990) 268–275
34. Bisson, G., Nédellec, C., Canamero, L.: Designing clustering methods for ontology building the mok workbench. In: Proceedings of the ECAI 2000 Workshop on Ontology Learning. (2000)
35. Cimiano, P., Völker, J.: Text2onto - a framework for ontology learning and data-driven change discovery. In: Proceedings of the 10th International Conference on Applications of Natural Language to Information Systems (NLDB'2005). (2005)
36. Lavrac, N., Dzeroski, S.: Inductive Logic Programming: Techniques and Applications. Ellis Horwood (1994)
37. Shamsfard, M., Barforoush, A.: An introduction to hasti: An ontology learning system. In: Proceedings of 6th Conference on Artificial Intelligence and Soft Computing (ASC2002). (2002)
38. Smith, B.: Ontology. In: The Blackwell Guide to Philosophy of Computing and Information. Blackwell (2003)
39. Brewster, C., Alani, H., Dasmahapatra, S., Wilks, Y.: Data driven ontology evaluation. In: Proceedings of the International Conference on Language Resources and Evaluation. (2004)
40. Shamsfard, M., Barforoush, A.: The state of the art in ontology learning: A framework for comparison. Knowledge Engineering Review **18**(4) (2003) 293–316
41. Dellschaft, K., Staab, S.: On how to perform a gold standard based evaluation of ontology learning. In: Proceedings of ISWC-2006 International Semantic Web Conference. (2006)

42. Agirre, E., Ansa, O., Hovy, E., Martinez, D.: Enriching very large ontologies using the www. In: Proceedings of the ECAI 2000 Workshop on Ontology Learning (OL'2000). (2000)
43. Bloehdorn, S., Cimiano, P., Hotho, A.: Learning ontologies to improve text clustering and classification. From Data and Information Analysis to Knowledge Engineering (2006) 334–341
44. Cimiano, P., Pivk, A., Schmidt-Thieme, L., Staab, S.: Learning taxonomic relations from heterogenous sources of evidence. In: Ontology Learning from Text: Methods, Applications, Evaluation. IOS Press (2005)
45. Maedche, A., Staab, S.: Measuring similarity between ontologies. In: EKAW '02: Proceedings of the 13th International Conference on Knowledge Engineering and Knowledge Management. Ontologies and the Semantic Web, London, UK, Springer-Verlag (2002) 251–263