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Knowledge systematization for ontology learning methods

Agnieszka Konys*

West-Pomeranian University of Technology in Szczecin, Faculty of Computer Science and Information Technology, Żołnierska 49, 71-210 Szczecin, Poland

Abstract

The need for interoperable semantics in modern information systems forces to develop more and more intelligent solutions. The increasing demand for these solutions, the explosion of various types of information and the technological development pose new challenges and requirements. Ontologies are often viewed as the answer to this need. The connections between ontologies and Semantic Web become a very promising area. The Semantic Web's success is dependent on the quality of its underline ontologies, whereas ontologies provide a shared and a common understanding of a domain enabling communication between people and heterogeneous and distributed systems. However, key issue helps ontologies to power the Semantic Web have made ontology learning from various data sources a very auspicious field of research. It aims at semi-automatically or automatically building ontologies from given data sources with a limited human exert. A huge number of available approaches for ontology learning and the prominent differences between them cause the necessity of knowledge systematization for this domain. The paper yields the author's proposal of ontological elaboration for methods for ontology learning and their features, providing formal, practical and technological guidance to knowledge management based approach to methods supporting ontology learning.

Keywords: ontology learning, knowledge systematization, ontology learning approaches, ontology

1. Introduction

Ontologies are treated as formal representations of knowledge nonetheless they are often restricted to a particular domain. One of the major roles of ontologies is to support the information exchange and share by extending syntactic interoperability of the Web to semantic interoperability. From a formal point of view, ontologies are effectively formal and explicit specifications in the form of concepts and relations of shared conceptualizations [1].

* Corresponding author. Tel.: +48-91-449-56-62; fax: +48-91-449-56-62.
E-mail address: akonys@zut.edu.pl

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Moreover, ontologies provide a shared and a common understanding of a domain that can be communicated between people and heterogeneous and distributed systems [2]. Consequently, they allow to model and share the knowledge among various applications in a specific domain. They enable enhancing existing technologies from machine learning and information retrieval (extraction) [3].

Semantic Web and its applications rely heavily on formal ontologies to structure data for comprehensive and transportable machine understanding [4]. The cheap and fast construction of domain specific ontologies is essential for the success and the proliferation of the Semantic Web. The knowledge captured in ontologies can be used to annotate web pages, specialize or generalize concepts, drive intelligent search engine by using the relation between concepts existing in ontology [5]. Ontology is one of the key elements of the Semantic Web. The application of ontology in information sharing and knowledge management requires using effective and efficient approaches to ontology development and maintenance [2, 6]. Further, ontologies play a central role in data and knowledge integration. By providing a shared schema, they facilitate query answering and reasoning over disparate data sources [4].

Ontologies play an important role in various aspects, especially including such fields as management, economy, medicine, finances and similar. They can be adapted and used in almost domains. Ontologies represent the intentional aspect of a domain for governing the way the corresponding knowledge bases are populated [2]. Among the popular ontology applications, financial ontologies [7, 8, 9] and ontology-based systems for Business Intelligence [10, 11] can be indicated. These knowledge bases can be created by extracting the relevant instances from information to populate the corresponding ontologies, a process known as ontology population or knowledge markup [2]. However, a serious obstacle for this process is to grasp the opportunity of well-defined data, stored in ontologies, and consequently, the validity and of stored knowledge and data [4, 6]. The problem of current knowledge stored in ontologies is addressed partially by the ontology learning (OL) approaches. Ontology learning has benefited from the adoption of established techniques from the related areas. The field of ontology learning builds upon well founded methods from knowledge acquisition, machine learning and natural language processing 2, 3, 6]. It refers to the process of deriving high-level concepts and relations as well as the occasional axioms from information to form ontology [4]. Notwithstanding, ontology learning is not without shortcomings. 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. For example, some approaches try to builds the ontology only [12, 13], or concepts with their hierarchy [3, 12], whereas others construct different types of ontology elements [3]. Further, some approaches start building ontology from scratch [6, 12]. Then, these approaches distinguish between such elements as linguistic, heuristic and pattern matching, machine learning and statistical techniques. Another problem refers to various types of input data they are learned: structured, semi-structured and unstructured [14, 15]. While structured data such as databases and dictionaries require less effort due to this form, semi-structured and unstructured types of data are much more difficult type to learn from. That is why the high importance is assigned to the proper selection and exploitation of OL method for a given use case [16, 17]. This problem has not been fully solved yet.

This article yields the author's proposal of solution of these problems, providing a comprehensive analysis of selected methods for ontology learning and their features. Based on this, an attempt to a taxonomy construction contains a set of selected methods with their specifications. Author's technical contribution is also provided in the form of ontological domain knowledge conceptualization. Provided ontology contains the set of various types of methods with main techniques used, and the necessary knowledge of their usage in the miscellaneous approaches. The author's ontology is in the form of the pilot study of the OL methods domain.

The article is organized as follows: Section 2 offers the state-of-the-art in ontology learning and discusses the selected OL approaches. In Section 3, the knowledge systematization in the form of analysis available OL methods is provided. It is a basement to elaborating author's taxonomy, and in the aftermath of ontology. The concluding section provides the main outcomes of the paper, and proposes some points for further discussion.

2. The State-Of-The-Art In Ontology Learning

2.1. Ontology acquisition

A process of ontology construction especially for frequently changing domains is a time-consuming and very often requires an expert participation during this process [3]. It does not mean that this process has no unfavorable. This process can be profitable in case of the domain is relatively small, and an ontology constructor has a complete and low data set. Then, it is better and faster to create ontology manually, although the process of manual ontology construction may take some effort [14]. Generally speaking, the manual acquisition of ontologies requires an extended knowledge of a particular domain. Furthermore, the manual ontology construction is expensive, tedious, error-prone process, biased towards its developer, inflexible and specific to the purpose that motivated its construction [4]. These disadvantages of manual building ontology are replaced by using semi-automatic or automatic methods for building the ontology.

During the last decade, many efforts supporting ontology learning processes have been carried out. It is forced by an increasing number of produced and gathered data, existing in different forms: structured, semi-structured and unstructured [15, 18]. Besides, the process of retrieving information from unstructured or semi-structured sources may cause some problems. Dynamic development of new technologies plays the greater role of enhancing the processes of data collection, analysis and processing [2, 19]. Ontology learning and the activities supporting automatic ontology construction may reduce some research problems [20]. Automated generation provides a fundamentally different approach to ontology creation than manual construction by a designer. The general aim of ontology automatic construction is to provide a possibility to create ontologies from different types of input sources and limit a human intervention in this process [2, 5, 19]. What is more, ontology learning, which seeks to discover ontological knowledge from various forms of data automatically or semi-automatically, can overcome the bottleneck of ontology acquisition in ontology development [20].

2.2. Ontology learning

The term of ontology learning was introduced by [16, 17] more than 25 years ago. It refers to the automatic generation of ontologies. Some of the previous works concerns ripple down rules, word sense clustering, and information extraction, logic programming and similar. The former researches concentrate on the use of inductive logic programming for learning logical theories since the mid-80s, but only few contributions from the field of concept learning were at that time. Based on the data from 2004, much of work in this area encompassed NLP, AI and machine learning techniques [5]. There is a remarkable increase of the importance of the term of ontology learning. Previous works start from 1990 and, over the years, the development of new technologies and innovation demands influences on this trend of the automatic generation of ontologies. A number of research papers has significantly grown since 2010 and this trend is still maintained (Figure 1).

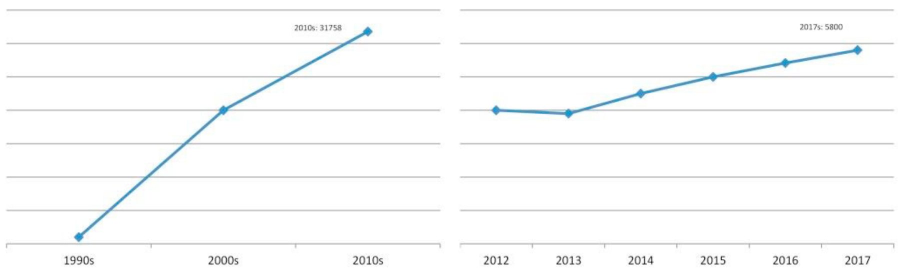

Fig. 1. The ontology learning development.

According to the literature, ontology learning refers to the automatic discovery and creation of ontological knowledge using machine learning techniques [2, 6]. Ontology learning can be defined as the set of methods and techniques used for building ontology from scratch [5], enriching, or adapting an existing ontology in a semi-automatic fashion using several sources [16]. Defining and installing a knowledge base refers to ontology population or a knowledge markup, whereas both semi and automatic support in ontology development is commonly categorized as ontology learning [13]. Moreover, ontology learning can support refining and expanding existing ontologies by incorporating new knowledge [17]. This term is concerned with knowledge acquisition from text. Compared with manually crafting ontologies, ontology learning is able to not only discover ontological knowledge at a larger scale and a faster pace, but also mitigate human-introduced biases and inconsistencies [21]. The main problem that ontology learning deals with is the knowledge acquisition bottleneck, that is to say the difficulty to actually model the knowledge relevant to the domain of interest [2].

Based on the literature, ontology can be organized in a layer cake of the following subtasks: terms, synonyms, concepts, concept hierarchies, relations and rules [6] (Figure 2). For this intent, the ontology learning procedure was defined not as a single task, but as set of subtasks organized in the layers. According to the definition, the ontology is characterized by the concepts and relations between them, hence the process of ontology development is based on these activities [1]. Ontology development implies on the knowledge acquisition about the terms and possible synonyms of these terms [20]. Terminology mining also defined as term extraction implicates on the linguistic processing based on the identifying and extracting set of phases and terms [5]. The next layer, synonym identification, attempts to determine synonym terms. The concept identification and hierarchy relationship creation layers consist of the identification of semantic classes and organizing them into taxonomy. Moreover, the concepts in the ontology are characterized by non-taxonomic relations. An ontology further consists of a taxonomy backbone (is-a relation) and other, non-hierarchical relations. The process of deriving knowledge from the ontology requires defining a set of rules that allows for such derivations [17].

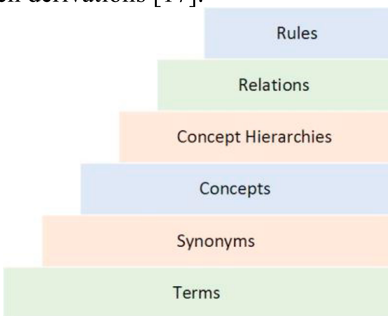

Fig. 2. The ontology learning layer cake.

2.3. Ontology learning approaches

During the last years, several ontology learning approaches have been proposed [2]. In literature, two main directions of ontology learning approaches are underlined. One of them is to develop tools that are used by knowledge engineers, whereas another one concentrates on semi-automatic or automatic ontology construction by learning it from different data sources [19, 20]. Generally, ontology learning approaches encompass methods, techniques and tools used for building ontologies from scratch, enriching or adapting an existing ontology in a semi-automatic way, using several sources [19].

On base of the literature review, the ontology learning approaches mostly use methods exploiting natural language processing (NLP), machine learning, knowledge acquisition techniques, information retrieval and extraction, artificial intelligence (AI), rule-based approaches and similar [6, 7]. Wong proposes the classification of ontology learning techniques into Statistics-Based Techniques, Linguistics-Based Techniques and Logic-Based Techniques and Resources [2, 22]. Statistic-Based Techniques predominantly rely on clustering, latent semantic analysis, co-occurrence analysis, term subsumption, contrastive analysis and association rule mining. Linguistics-based techniques are applicable to almost all tasks in ontology learning and are mainly dependent on natural language processing tools [2, 22]. They use especially the following techniques: part-of-speech (POS) tagging, sentence parsing, syntactic structure analysis, dependency analysis, semantic lexicon, lexico-syntactic patterns, semantic templates, and subcategorization frames and seed words. The last group called Logic-Based Techniques and Resources are mainly dedicated to more complex tasks involving relations and axioms [2]. These techniques have connections with advances in knowledge representation and reasoning and in machine learning, including inductive logic programming logical inference actions. Table 1 includes the selected techniques grouped by the type.

Table 1. Selected techniques for ontology learning.

Main group	Used techniques	Selected authors
Statistics-Based Techniques	Clustering	[22, 23, 24]
	Latent semantic analysis	[25]
	co-occurrence analysis (dependency measures, similarity measures)	[16, 26, 27, 28, 29, 30]
	Term subsumption	[32]
	contrastive analysis	[33]
	association rule mining	[34]
Linguistics-Based Techniques	part-of-speech tagging sentence parsing	[35, 36, 37, 38, 39]
	syntactic structure analysis	[40]
	dependency analysis	[41, 42]
	semantic lexicon	[43, 44]
	lexico-syntactic patterns	[45, 46]
	semantic templates	[47, 48]
	subcategorization frames	[49, 50]
	seed words	[51, 52, 53]
Logic-Based Techniques and Resources	inductive logic programming	[54, 55]
	logical inference	[56].

Further, ontology learning approaches can be categorized according to the types of the date from which they are learned [6, 5]. These types of data are unstructured, semi-structured, and structured. The unstructured type of data is the most demanding group to learn from it. The solutions generally exploits shallow text processing with statistical analysis [10], rule based parsers to identify dependency relations between words in natural language [7], POS taggers, pattern matching, and a machine learning approach with the basic linguistic processing [12, 14, 13, 11]. The process of building ontology from semi-structure data uses both traditional data mining and web content mining techniques [1, 17]. Another classification of ontology learning approach is based on the types of input in ontology learning and tasks. The following types of input are mentioned: terms, concepts, taxonomic relations and non-taxonomic relations, axioms. The tasks may contain the subsequent activities: pre-process texts extract terms, form concepts, label concepts, construct hierarchies, discover non-taxonomic relations, label non-taxonomic relations, and extract axioms.

3. Knowledge systematization for ontology learning methods

The field of ontology learning builds upon well founded methods from knowledge acquisition, machine learning and natural language processing. The ontology learning tasks are comparable, even though there are specific issues associated with ontology learning from each type of input data. On base of the deep literature review, some various types of methods for ontology learning were discussed in this paper. These approaches address specified subtasks, and were classified according to the format of input data they use. Moreover, according to their output their approached are vary between linguistic, heuristic and pattern matching machine learning and statistical techniques. The table 2 provides a set of selected ontology methods taking into consideration most frequent used techniques.

Table 2. Selected ontology learning methods.

Selected ontology learning methods	Most frequent used techniques	Authors or/and name of methods
Methods for ontology learning from dictionary	Linguistic patterns, statistical approach, PageRank Algorithm, analysis of dictionary definitions and word-sense disambiguation of a genus word	[57, 58, 59]

Methods for ontology learning from texts	Statistical approach, topic signatures, clustering methods (techniques), different metrics of semantic distance, term extraction based on distributional analysis, relation extraction based on linguistic patterns, knowledge extraction with syntactic patterns with a concordance, NLP techniques, semantic relativeness, extraction techniques, concept hypothesis based on linguistic and conceptual quality labels, mappings, several linguistic heuristic, graph theory, linguistic analysis, verb-patterns, text-mining approaches, pattern ranking and Formal Concept Analysis	[3, 53, 57, 45, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84]
Ontology learning from knowledge base	Statistical measure estimating the existence of a relationship between a pair of classes, KR frameworks suitable for representing onto-relational rules, ILP frameworks suitable for learning onto-relational rules	[2, 85]
Methods for ontology learning from semi-structured schemata	Techniques based on the Graph Theory, machine learning: pattern recognition, cluster mining approach, mapping techniques	[86, 87, 88, 89]
Methods for ontology learning from relational schemata	Mapping techniques, reverse engineering	[90, 91, 92, 93]
Term Extraction and Concept Formation	A sentence parser, a linguistic property of terms, the use of richness estimators, the BootCat technique for bootstrapping text corpora and terms using Web data and search engines, exploring Wikipedia for classifying terms into predefined ontological classes	[2, 22, 94, 95, 96, 97, 98]
Methods for relation discovery	Taxonomic and non-taxonomic relation discovery, the dependency paths extracted from parse trees, syntactic dependencies, the tokenizer, part-of-speech tagger, and verb phrase chunker, mapping and logic-based mapping, lexical simplification, word disambiguation, and association inference for acquiring coarse-grained relations	[2, 22, 42, 46, 99, 100, 101, 102, 103, 104, 105, 106]
Ontology Learning from Social Data and Across Different Languages	A probabilistic topic model to represent the tags and their annotated documents, learning ontologies of social concepts and relations from query logs and Web 2.0 question/answer applications, corpus-based ontology learning with tags derived from Web 2.0 services, exploitation of cross-language information from parallel corpora, mining of parallel sentences and parallel technical terms	[107, 108, 109, 110, 111, 112]
Linked Data Mining	Clustering approaches	
Concept Learning in Description Logics and OWL	Learning schema axioms from existing ontologies and instance data, Inductive Logic Programming methods, onto-relational learning, which combines methods for learning OWL axioms with rule learning approaches	

3.1. Knowledge engineering for ontology learning methods

The main role of an exploitation of knowledge base is to support the finding and reusing of relevant knowledge [14, 18]. Further, the generally accepted approach for structuring the domain knowledge is constructing domain ontologies to model concepts and relationships. Ontology-based modeling is a well-known approach to support both knowledge integration and interoperability between information technology systems during collaborative business process [14, 21]. Moreover, to cope with the complexity of engineering knowledge [14, 15] in OL methods domain, ontology design is proposed as a promising approach.

3.2. Taxonomy

Based on the analysis of selected ontology learning approaches, the lack of knowledge systematization in this field is remarkable. Despite a lot of work which is done in the field of ontology learning, many activities are needed to order, exploiting the main categories and used techniques and tasks. Due to a number of existing methods for ontology learning and the set of various aspects they refer to, an attempt of knowledge systematization in this domain is proposed. For this reason, a plethora of ontology learning methods have been analyzed. The current state of the work includes 8 categories according to the format of input data they use and applied techniques. These methods have different features according to achieve their deferent goals.

The basis for the taxonomy construction was the Table 2. Performing the deep domain analysis is the first step of the ontology construction process. The first step of knowledge engineering is taxonomy construction stage. The taxonomy contains the set of methods for ontology learning: methods for ontology learning from dictionary, methods for ontology learning from texts, ontology learning from knowledge base, methods for ontology learning from semi-structured schemata, methods for ontology learning from relational schemata, term extraction and concept formation, methods for relation discovery, ontology learning from social data and across different languages, linked data mining, concept learning in description logics and OWL. Then, the set of 2 properties and 118 sub-properties was constructed. The main criteria encompass the set of used techniques and the names of authors referring to the selected methods for ontology learning. They were organized in hierarchical form including main criteria and sub-criteria, distinctive for a given group. The number of properties is constructed as follows:

- used techniques (NPL techniques, Analysis of dictionary definitions and word-sense disambiguation of a genus word, Knowledge extraction with syntactic patterns with a concordance, Semantic relativeness, Verb-patterns, Extraction techniques, Syntactic dependencies, Inductive logic programming methods, Topic signatures, Dependency paths extracted from parse trees, Sentence parser, Logic-based mapping, Linguistic analysis, Exploitation of cross-language information from parallel corpora, Term extraction based on distributional analysis, Different metrics of semantic distance, Reverse engineering, Relation extraction based on linguistic patterns, Non-taxonomic relation discovery, Taxonomic relation discovery, Graph theory, Text-mining approaches, ILP frameworks, Linguistic property of terms, Verb phrase chunker, POS tagger, Techniques based on the graph theory, Cluster mining approach, Mining of parallel sentences and parallel technical terms, Lexical simplification, Knowledge rules frameworks, Corpus-based ontology learning, Tokenizer, Formal concept analysis, Pattern recognition, Exploring, Association inference for acquiring coarse-grained relations, Learning schema axioms, Probabilistic topic model, Statistical approach, Onto-relational rules, Word disambiguation, Linguistic patterns, PageRank algorithm, Several linguistic heuristic, Pattern ranking, Bootstrapping text corpora and terms using web data and search engines, Onto-relational learning, Machine learning, Usage of richness estimators,, Mapping techniques, Concept hypothesis based on linguistic and conceptual quality labels, Clustering methods and techniques);
- authors (Guo, Sanchez and Moreno, Nobécourt, Hearst, Khan and Luo, Pei et al., Kashyap, Rigau et al., Massey and Wong, Weichselbraun et al., Doan et al., Bachimont, Wagner, Mintz et al., Lonsdale et al., Zhang and Ciravegna, Mika, Sclano and Velardi, Coppola et al., Hahn et al., Hjelm and Volk, Aguirre et al., Kietz et al., Tang et al., Porzel and Malaka, Missikoff et al., Papatheodorou et al., Specia and Motta, AL LOG, Snow et al., Wang et al., Faatz and Steinmetz, Deitel et al., Suryanto and Compton, Cimano, Johannesson, Blomqvist, Aussenac Gilles et al., Stojanovic et al., CARIN, Alfonseca and Manandhar, Nanda et al., Hwang, Agbago and Barriere, Lu et al., Stumme et al., Baroni and Bernardini, Learning SHIQ plus LOG rules, Weber and Buitelaar, Roux et al., Gupta et al., Jannink and Wiederhold, Sombatsrisomboon et al., Xu et al., Wong et al., Learning CARIN ALN rules, Ciaramita et al., Ruiz-Casado et al., Learning AL LOG rules, Moldovan and Girju, Liu et al., Volz et al., Etzioni et al., Wermter and Hahn, Kotis and Papasalouros, DL plus LOG) [2, 3, 22, 42, 46, 57, 58, 59, 53, 57, 45, 60, 61, 62, 63, 64, 65, 66, 67, 68, 69, 70, 71, 72, 73, 74, 75, 76, 77, 78, 79, 80, 81, 82, 83, 84, 85, 86, 87, 88, 89, 90, 91, 92, 93, 94, 95, 96, 97, 98, 99, 100, 101, 102, 103, 104, 105, 106, 107, 108, 109, 110, 111, 112].

The proposed taxonomy is a basis for the ontology construction. It provides both knowledge systematization for ontology learning methods and offers broader view of them. Further, the generally accepted approach for structuring the domain knowledge is constructing domain ontologies to model concepts and relationships. In this case, the ontology containing the set of methods for ontology learning is proposed.

3.3. Ontology

The process of ontology construction is based on an incremental process starting by the identification of main concepts from the identified methods for ontology learning. This process is followed by the extraction of all concepts, properties and relationships from the common meta-model to form the backbone of the ontology. The ontology was built using the Protégé application. The applied technology standard is OWL (Ontology Web Language). The main structure of the proposed ontology is modeled in Protégé software. The class Criteria takes a central place in the ontology (Figure 3). This class is detailed to define different sub-classes in detail: Used techniques and Authors.

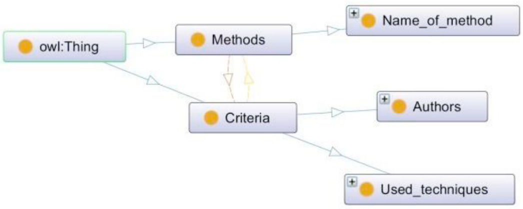

Fig. 3. Design of the class Criteria of the ontology for ontology learning methods.

The class Methods contain the sub-class: Name of method, which has the following set: methods for ontology learning from dictionary, methods for ontology learning from texts, ontology learning from knowledge base, methods for ontology learning from semi-structured schemata, methods for ontology learning from relational schemata, term extraction and concept formation, methods for relation discovery, ontology learning from social data and across different languages, linked data mining, concept learning in description logics and OWL (Figure 4).

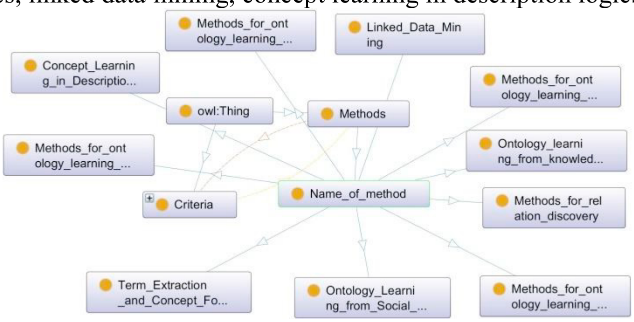

Fig. 4. Design of the class Methods and sub-class: Name of method.

Then, the class Methods for ontology learning from text has the used techniques: topic signature, statistical approach, clustering methods and techniques, concept hypothesis based on linguistic and conceptual quality labels extraction techniques, formal concept analysis, graph theory, linguistic analysis, machine learning, mapping techniques, NLP techniques, semantic relativeness, statistical approach, term extraction based on distributional analysis, topic signatures, verb-patterns; and the authors using these methods: Aguirre et al., Alfonseca and Manandhar, Aussenac Gilles et al., Bachimont, Cimano, Coppola et al., or Faatz and Steinmetz, Guo, Gupta et al., Hahn et al., Hearst, Hwang, Khan and Luo, Kietz et al., Lonsdale et al., Missikoff et al., Moldovan and Girju, Nanda et al., Nobécourt, Porzel and Malaka, Roux et al., Ruiz-Casado et al., Stumme et al., Wagner, Wang et al., Xu et al. (Figure 5).

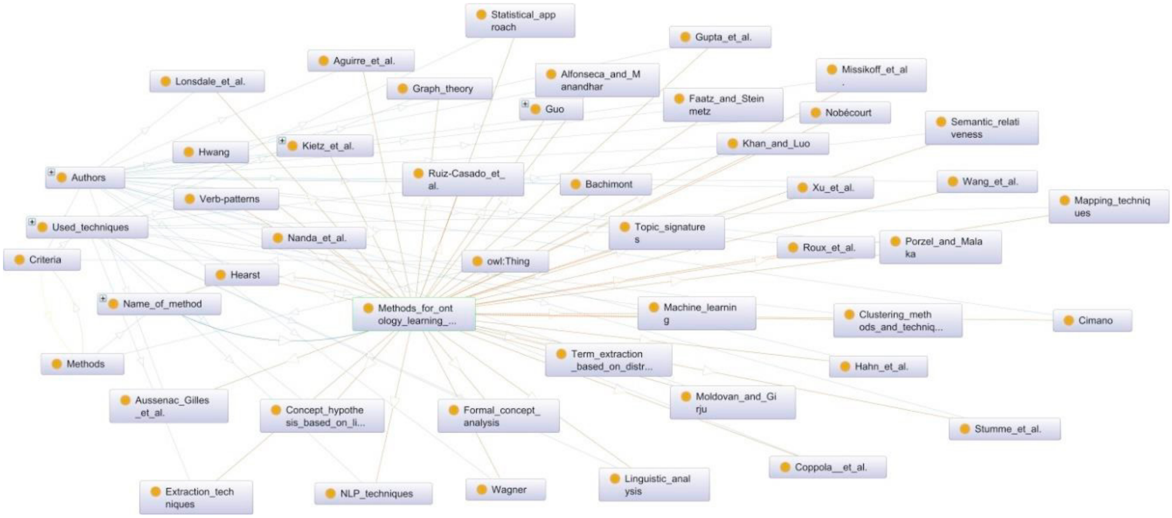

Fig. 5. Typology of the class Methods for ontology learning from text.

3.4. Ontology for methods for ontology learning - validation stage using competence questions

This section presents the exemplary competence questions and validates their utility in retrieving information with response to the user needs. In order to use the ontology from knowledge repository, query algorithms are used to provide useful information at the end of reasoning process. To verify the correctness of the proposed ontology, the competence questions are constructed and implemented using Description Logic query mechanism. The case study focuses on the choosing the OL methods using basic techniques: statistical approach, mapping and NLP techniques, and referring to the method proposed by Bachimont. Thus, following the proposed ontology, the definition containing the set of criteria was constructed as follows (Figure 6). The specification includes the criteria: used techniques and authors, and sub-criteria: statistical approach, NLP techniques and mapping techniques, and Bachimont. Each of the criteria and sub-criteria should be fulfilled to belong to the final ranking.

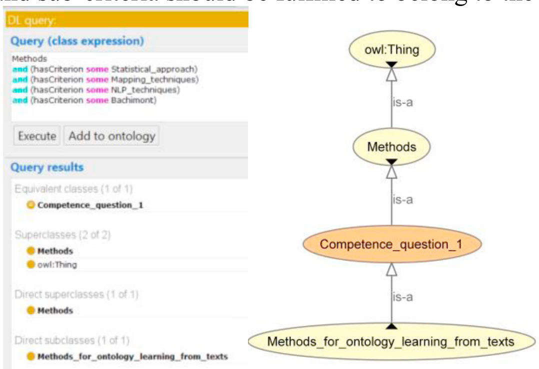

Fig. 6. (a) Results of using Description Logic query to extract methods for ontology learning; (b) Visualizing query using OWLViz.

Defining the necessary and sufficient conditions, and afterwards implementing it into the Protégé software permits on starting the reasoning process. Based on the experimentation results, the final set of the approaches is obtained. In accordance with the constructed definition, only one set of methods matches these requirements: methods for ontology learning form text (Figure 6). Full set of comparative competency questions is provided in author’s ontology and it is publicity available (https://webprotege.stanford.edu/#projects/54f204bf-9852-4c53-8d9b-2c04cc8d07b6).

4. Conclusions

The analysis of the selected approaches allows to indicate both the general trends and missing aspects concerning the approaches for ontology learning. The most cited approaches vary between linguistic, heuristic and pattern matching, machine learning and statistical techniques. It is remarkable the increase of application of lexico-syntactic patterns, association rule mining, and rules based on syntactic dependencies on very large datasets from the Web. Moreover, the measures for scoring and extracting terms from texts have more or less stabilized.

Currently, there is a lack of general usage guideline and applications for automatically learned ontologies, although this field of research has been elaborated for years. It may be caused by the involvement of consensus and high-level abstraction requiring human cognitive processing. The Web may very well be the key ingredient in constructing ontologies with minimal human intervention required for cross-language and cross-domain applications and, finally, the Semantic Web. Further promising application potential for ontology learning lies in the field of Linked Data. Besides, ontology population will also continue to play a crucial role in taming and structuring the large amount of unstructured data available. In the context of ontology learning, ontology evaluation is still remaining an important open problem.

The aim of the paper was to provide knowledge systematization in OL methods domain. The proposed author's ontology allows both the knowledge of OL methods and the detailed guide for usage. In author's opinion, the process of ontology construction has been finished successfully. The verification of ontology correctness has been made on base of the set of competence questions, and provided results by them. The proposed author's ontology is in a pilot study form and it is a basement for further development.

Deep literature study provides a full set of OL approaches. However, presented approaches do not address all of existing challenges and some shortcomings are worthwhile and still needed to solve. The current state of the art of ontology learning methods enables pointing some key issues related to them. It seems that the promising aspects may concentrate on the Web data for ontology learning and its problems of noise, authority and validity. Thus, the issues of authority and validity in Web data sources must also be investigated, providing a set of integrated techniques for addressing spelling errors, abbreviations, grammatical errors, word variants, and in texts. Another interesting aspect is to ensure or adapt the technique for exploiting the structural richness of collaboratively maintained Web data. Very demanding issue is to put much effort into ensuring the efficiency and robustness of existing techniques for Web-scale ontology learning. Some effort should be obviously made using language-independent constructs as the representation of ontological entities.

Nowadays a huge number of social data is produced every second, and consequently much work should be done for the integration of social data into the learning process to incorporate consensus into ontology building. Various types of data, especially unstructured pose new challenges to ensure the applicability of existing techniques for learning ontologies for different writing systems. Next, the majority of the ontologies at the moment are lightweight. To be able to semi-automatically learn formal ontologies, it is required to improve on current axiom learning techniques as well as to find ways of incorporating. Further, subsequent key issue encompasses the extension of existing lightweight ontologies to formal ones. In opposite to lightweight ontologies, the role of formal ontology language will become much more significant with regard to heavyweight ontologies.

The related area of ontology mapping (ontology alignment) will become more pertinent. Similarly, the focus on logic-based techniques applied in ontology learning helps in reaching towards the learning of full-fledged ontologies. Investigating transfer learning and ontology re-use may support the adaptation existing ontologies to new domains by partially re-using existing schematic structures. Last, crowdsourcing ontologies can be a promising alternative to purely automatic approaches as it combines the speed of computers with the accuracy of humans.

References

[1] Gruber TR. A translation approach to portable ontology specifications. Knowledge Acquisition 1993;5:199–220.

[2] Wong W, Liu W, Bennamoun M. Ontology learning from text: A look back and into the future. ACM Computing Surveys 2012;44:1–36.

[3] Cimiano P, Völker J. Text2Onto. In: Montoyo A, Muńoz R, Métais E, editors. Natural Language Processing and Information Systems, vol. 3513, Berlin, Heidelberg: Springer Berlin Heidelberg; 2005, p. 227–38.

[4] Hazman M, R. El-Beltagy S, Rafea A. A Survey of Ontology Learning Approaches. International Journal of Computer Applications 2011;22:36–43.

[5] Drumond L, Girardi R. Survey of Ontology Learning Procedures. CEUR Workshop Proceedings 2008;427.

[6] Karoui L, Aufaure M-A, Bennacer N. Ontology Discovery from Web Pages: Application to Tourism. Workshop on Knowledge Discovery and Ontologies 2004:115–20.

[7] FIBO, Financial Industry Business Ontology, https://www.edmcouncil.org/financialbusiness

[8] FIGI, Financial Instrument Global Identifier

[9] Financial Report Ontology, https://financialreportontology.wikispaces.com/

[10] Cheng H, Lu Y-C, Sheu C. An ontology-based business intelligence application in a financial knowledge management system. Expert Systems with Applications 2009;36:3614–22.

[11] FKMS, Financial Knowledge Management System

[12] Sánchez D, Batet M, Isern D, Valls A. Ontology-based semantic similarity: A new feature-based approach. Expert Systems with Applications 2012;39:7718–28.

[13] Sabou M, Wroe C, Goble C, Mishne G. Learning domain ontologies for Web service descriptions: an experiment in bioinformatics, ACM Press; 2005, p. 190.

[14] RESERVED

[15] RESERVED

[16] Maedche A, Staab S. Ontology learning for the Semantic Web. IEEE Intelligent Systems 2001;16:72–9.

[17] Buitelaar P, Magnini B. Ontology Learning from Text: An Overview. In: Buitelaar P, Cimiano P, Magnini B, editors. Ontology Learning from Text: Methods, Applications and Evaluation, IOS Press; 2005, p. 3–12.

[18] RESERVED

[19] Gomez-Perez A, Manzano-Macho D. OntoWeb Deliverable 1.5: A Survey of Ontology Learning Methods and Techniques, Universidad Politecnica de Madrid; 2003.

[20] Shamsfard M, Abdollahzadeh Barforoush A. The state of the art in ontology learning: a framework for comparison. The Knowledge Engineering Review 2003;18:293–316.

[21] RESERVERD

[22] Wong W, Liu W, Bennamoun M. Ontology learning from text: A look back and into the future. ACM Computing Surveys 2007;44:1–36.

[23] Linden K, Piitulainen JO. Discovering Synonyms and Other Related Words. Proceedings of COLING 2004 CompuTerm 2004: 3rd International Workshop on Computational Terminology, Geneva , Switzerland: 2004, p. 63–70.

[24] Vitányi PMB, Balbach FJ, Cilibrasi RL, Li M. Normalized Information Distance. In: Emmert-Streib F, Dehmer M, editors. Information Theory and Statistical Learning, Boston, MA: Springer US; 2009, p. 45–82.

[25] Turney PD. Mining the Web for Synonyms: PMI-IR versus LSA on TOEFL. In: De Raedt L, Flach P, editors. Machine Learning: ECML 2001, vol. 2167, Berlin, Heidelberg: Springer Berlin Heidelberg; 2001, p. 491–502.

[26] Budanitsky A. Lexical semantic relatedness and its application in natural language processing. Computer Systems Research Group, University of Toronto; 1999.

[27] Church KW, Hanks P. Word association norms, mutual information, and lexicography. Computational Linguistics 1990;16:22–9.

[28] Resnik 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 1999;11:95–130.

[29] Strehl A. Relationship-based clustering and cluster ensembles for high-dimensional data mining. Doctoral Dissertation. The University of Texas, 2002.

[30] Senellart P, Blondel VD. Automatic Discovery of Similar Words. In: Berry MW, editor. Survey of Text Mining, Berlin: Springer-Verlag; 2003.

[31] Maedche A, Staab S. Measuring Similarity between Ontologies. In: Gómez-Pérez A, Benjamins VR, editors. Knowledge Engineering and Knowledge Management: Ontologies and the Semantic Web, vol. 2473, Berlin, Heidelberg: Springer Berlin Heidelberg; 2002, p. 251–63.

[32] Fotzo HN, Gallinari P. Learning «generalization/specialization» relations between concepts: application for automatically building thematic document hierarchies. RIAO '04 Coupling approaches, coupling media and coupling languages for information retrieval, Vaucluse, France: 2004, p. 143–55.

[33] Velardi P, Navigli R, Cucchiarelli A, Neri F. Evaluation of OntoLearn, a methodology for automatic learning of ontologies. In: Buitelaar P, Cimiano P, Magnini B, editors. Ontology Learning from Text: Methods, Evaluation and Applications, Hershay: IOS Press; 2005, p. 92–105.

[34] Srikant R, Agrawal R. Mining generalized association rules. Future Generation Computer Systems 1997;13:161–80.

[35] Brill E. A simple rule-based part of speech tagger, Association for Computational Linguistics; 1992, p. 152.

[36] Schmid H. Probabilistic part-of-speech tagging using decision trees. In: Jones DB, Somers HL, editors. Proceedings of the International Conference on New Methods in Language Processing, London, New York: Routledge; 1994, p. 154–64.

[37] Lin D. PRINCIPAR: an efficient, broad-coverage, principle-based parser. vol. 1, Association for Computational Linguistics; 1994, p. 482.

[38] Lin D. Dependency-Based Evaluation of Minipar. In: Abeillé A, editor. Treebanks, vol. 20, Dordrecht: Springer Netherlands; 2003, p. 317–29.

[39] Sleator D, Temperley D. Parsing English with a Link Grammar. 1995.

[40] Hippisley A, Cheng D, Ahmad K. The head-modifier principle and multilingual term extraction. Natural Language Engineering 2005;11:129–57.

[41] Gamallo P, Gonzalez M, Agustini A, Lopes G, de Lima VS. Mapping Syntactic Dependencies onto Semantic Relations. Proceedings of the ECAI Workshop on Machine Learning and Natural Language Processing for Ontology Engineering, 2002.

[42] Ciaramita M, Gangemi A, Ratsch E, Šaric J, Rojas I. Unsupervised learning of semantic relations between concepts of a molecular biology ontology. Proceedings of the 19th international joint conference on Artificial intelligence, Edinburgh, Scotland: 2005, p. 659–64.

[43] Pedersen T, Patwardhan S, Michelizzi J. WordNet::Similarity: measuring the relatedness of concepts. HLT-NAACL--Demonstrations '04 Demonstration Papers at HLT-NAACL 2004, Boston, Massachusetts: 2004, p. 38–41.

[44] Miller GA. WordNet: a lexical database for English. Communications of the ACM 1995;38:39–41.

[45] Hearst M. Automated discovery of WordNet relations. In: Fellbaum C, editor. WordNet: An Electronic Lexical Database and Some of its Applications, MIT Press; 1998.

[46] Sombatsrisomboon R, Matsuo Y, Ishizuka M. Acquisition of hypernyms and hyponyms from the WWW. Proceedings of the 2nd International Workshop on Active Mining, 2003.

[47] Spiliopoulou M, Rinaldi F, Black WJ, Zarri GP, Mueller RM, Brunzel M, et al. Coupling information extraction and data mining for ontology learning in PARMENIDES. RIAO '04 Coupling approaches, coupling media and coupling languages for information retrieval, Vaucluse, France: 2004, p. 156–69.

[48] Vargas-Vera M, Dominque J, Kalfoglou Y, Motta E, Buckingham-Schum S. Template-driven information extraction for populating ontologies. 'IJCAI'2001 Workshop on Ontology Learning - in the Proceedings of the Second Workshop on Ontology Learning OL'2001, Seattle, USA: 2001.

[49] Agustini A, Gamallo P, Lopes GP. Selection Restrictions Acquisition for Parsing Improvement. In: Bartenstein O, Geske U, Hannebauer M, Yoshie O, editors. Web Knowledge Management and Decision Support, vol. 2543, Berlin, Heidelberg: Springer Berlin Heidelberg; 2003, p. 129–43.

[50] Gamallo P, Agustini A, Lopes G. Learning subcategorisation information to model a grammar with co-restrictions. Traitement Automatic de La Langue 2003;44:93–117.

[51] Yangarber R, Grishman R, Tapanainen P, Huttunen S. Automatic acquisition of domain knowledge for Information Extraction. vol. 2, Association for Computational Linguistics; 2000, p. 940.

[52] Baroni M, Bernardini S. Bootcat: Bootstrapping corpora and terms from the Web. Proceedings of the 4th Language Resources and Evaluation Conference (LREC), 2004.

[53] Hwang CH. Incompletely and imprecisely speaking: Using dynamic ontologies for representing and retrieving information. Proceedings of the 6th International Workshop on Knowledge Representation meets Databases (KRDB'99), Linköping, Sweden: 1999.

[54] Lavrac N, Dzeroski S. Inductive Logic Programming: Techniques and Applications. New York, NY: Routledge; 1993.

[55] Zelle JM, Mooney RJ. Learning semantic grammars with constructive inductive logic programming. Proceedings of the eleventh national conference on Artificial intelligence, Washington, D.C.: 1993, p. 817–22.

[56] Oliveira A, Pereira F, Cardoso A. Automatic reading and learning from text. Proceedings of the International Symposium on Artificial Intelligence (ISAI), 2001.

[57] Hearst MA. Automatic acquisition of hyponyms from large text corpora. vol. 2, Association for Computational Linguistics; 1992, p. 539.

[58] Jannink J, Wiederhold G. Ontology maintenance with an algebraic methodology: A case study. Proceedings of AAAI workshop on Ontology Management, 1999.

[59] Rigau G, Rodríguez H, Agirre E. Building accurate semantic taxonomies from monolingual MRDs. vol. 2, Association for Computational Linguistics; 1998, p. 1103–9.

[60] Aguirre E, Ansa O, Hovy E, Martinez D. Enriching very large ontologies using the WWW. Proceedings of the Workshop on Ontology Construction of the European Conference of AI (ECAI-00), 2000.

[61] Alfonseca E, Manandhar S. An unsupervised method for general named entity recognition and automated concept discovery. Proceedings of the 1st International Conference on General WordNet, Mysore, India: 2002.

[62] Alfonseca E, Manandhar S. Improving an Ontology Refinement Method with Hyponymy Patterns. Language Resources and Evaluation (LREC-2002), Las Palmas, Spain: 2002.

[63] Aussenac-Gilles N, Biébow B, Szulman S. Corpus Analysis For Conceptual Modelling. Workshop on Ontologies and Text, Knowledge Engineering and Knowledge Management: Methods, Models and Tools. , 12th International Conference EKAW'2000, Juan-Les-Pins, France: Springer-Verlag; 2000.

[64] Bachimont B, Isaac A, Troncy R. Semantic Commitment for Designing Ontologies: A Proposal. In: Gómez-Pérez A, Benjamins VR, editors. Knowledge Engineering and Knowledge Management: Ontologies and the Semantic Web, vol. 2473, Berlin, Heidelberg: Springer Berlin Heidelberg; 2002, p. 114–21.

[65] Faatz A, Steinmetz R. Ontology enrichment with texts from the WWW. Semantic Web Mining 2nd Workshop at ECML/PKDD-2002, Helsinki, Finland: 2002.

[66] Gupta KM, Aha DW, Marsh E, Maney T. An architecture for engineering sublanguage WordNets. Proceedings of the First International Conference On Global WordNet, Mysore, India: 2002, p. 207–15.

[67] Hahn U, Schnattinger K. Towards text knowledge engineering. AAAI '98/IAAI '98 Proceedings of the fifteenth national/tenth conference on Artificial intelligence/Innovative applications of artificial intelligence, Madison, Wisconsin, USA: 1998, p. 524–31.

[68] Khan L, Feng Luo. Ontology construction for information selection, IEEE Comput. Soc; 2002, p. 122–7.

[69] Kietz JU, Maedche A, Volz R. A Method for Semi-Automatic Ontology Acquisition from a Corporate Intranet. In: Aussenac-Gilles N, Biébow B, Szulman S, editors. EKAW'00 Workshop on Ontologies and Texts, Juan-Les-Pins, France: 2000.

[70] Lonsdale D, Ding Y, Embley DW, Melby A. Peppering Knowledge Sources with SALT; Boosting Conceptual Content for Ontology Generation. Proceedings of the AAAI Workshop on Semantic Web Meets Language Resources, Edmonton, Canada: 2002.

[71] Missikoff M, Navigli R, Velardi P. Integrated approach to Web ontology learning and engineering. Computer 2002;35:60–3.

[72] Moldovan DI, Girju RC. An interactive tool for the rapid development of knowledge Bases. International Journal on Artificial Intelligence Tools 2001;10:65–86.

[73] Nobécourt J. A method to build formal ontologies from text. In: Aussenac-Gilles N, Biébow B, Szulman S, editors. EKAW'00 Workshop on Ontologies and Texts, Juan-Les-Pins, France: 2000.

[74] Roux C, Proux D, Rechermann F, Julliard L. An ontology enrichment method for a pragmatic information extraction system gathering data on genetic interactions. Proceedings of the ECAI2000 Workshop on Ontology Learning(OL2000), Berlin, Germany: 2000.

[75] Warner A. Enriching a lexical semantic net with selectional preferences by means of statistical corpus analysis. Proceedings of the ECAI-2000 Workshop on Ontology Learning, Berlin: 2000, p. 37–42.

[76] Xu F, Kurz D, Piskorski J, Schmeier S. A Domain Adaptive Approach to Automatic Acquisition of Domain Relevant Terms and their Relations with Bootstrapping. Proceedings of LREC 2002, the third international conference on language resources and evaluation, Las Palmas, Canary Island, Spain: 2002.

[77] Coppola B, Gangemi A, Gliozzo A, Picca D, Presutti V. Learning domain ontologies by corpus-driven framenet specialization. In: Lehmann J, Völker J, editors. Perspectives on Ontology Learning, Studies on the Semantic Web, AKA Heidelberg / IOS Press; 2014.

[78] Blomqvist E. OntoCase - A Pattern-Based Ontology Construction Approach. In: Meersman R, Tari Z, editors. On the Move to Meaningful Internet Systems 2007: CoopIS, DOA, ODBASE, GADA, and IS, vol. 4803, Berlin, Heidelberg: Springer Berlin Heidelberg; 2007, p. 971–88.

[79] Guo Q, Jia J, Shen G, Zhang L, Cai L, Yi Z. Learning robust uniform features for cross-media social data by using cross autoencoders. Knowledge-Based Systems 2016;102:64–75.

[80] Stumme G, Mädche A. FCA-Merge: A Bottom-Up Approach for Merging Ontologies. JCAI'01-Proceedings of the 17th International Joint Conference on Artificial Intelligence, Seattle, USA: Morgan Kaufmann; 2001.

[81] Nanda J, Simpson TW, Kumara SRT, Shooter SB. A Methodology for Product Family Ontology Development Using Formal Concept Analysis and Web Ontology Language. Journal of Computing and Information Science in Engineering 2006;6:103.

[82] Wang H, Yang X. Research and implementation of the civil aviation emergency management domain ontology construction method. Civil Aviation University of China 2010.

[83] Ruiz-Casado M, Alfonseca E, Castells P. Automatic Extraction of Semantic Relationships for WordNet by Means of Pattern Learning from Wikipedia. In: Montoyo A, Muńoz R, Métais E, editors. Natural Language Processing and Information Systems, vol. 3513, Berlin, Heidelberg: Springer Berlin Heidelberg; 2005, p. 67–79.

[84] Porzel R, Malaka R. A task-based approach for ontology evaluation. Proceedings of the 16th European Conference on Artificial Intelligence, 2004.

[85] Suryanto H, Compton P. Discovery of Ontologies from Knowledge Bases. In: Gil Y, Musen M, Shavlik J, editors. Proceedings of the First International Conference on Knowledge Capture, Victoria, British Columbia Canada: 2001, p. 171–8.

[86] Delteil A, Faron-Zucker C, Dieng R. Learning ontologies from RDF annotation. OL'01 Proceedings of the 2nd International Conference on Ontology Learning, vol. 38, Seattle, USA: 2001, p. 7–12.

[87] Doan A, Domingos P, Levy A. Learning Source Descriptions for Data Integration. Proceedings of the Third International Workshop on the Web and Databases, Dallas, TX: ACM SIGMOD; 2000, p. 81–6.

[88] Papatheodorou C, Vassiliou A, Simon B. Discovery of Ontologies for Learning Resources using Word-based Clustering. EdMedia: World Conference on Educational Media and Technology, Denver, Colorado, USA: Association for the Advancement of Computing in Education; 2002.

[89] Maedche A, Volz R. The Ontology Extraction & Maintenance Framework Text-To-Onto. Proceedings : 2001 IEEE International Conference on Data Mining, San Jose, Calif: IEEE Computer Soc.; 2001.

[90] Johannesson P. A Method for Transforming Relational Schemas into Conceptual Schemas. In: Rusinkiewicz M, editor. 10th International Conference on Data Engineering, Houston: IEEE Press; 1994, p. 115–22.

[91] Kashyap V. Design and Creation of Ontologies for Environmental Information Retrieval. Twelfth Workshop on Knowledge Acquisition, Modelling and Management, Banff, Alberta, Canada: 1999.

[92] Rubin DL, Hewett M, Oliver DE, Klein TE, Altman RB. Automatic data acquisition into ontologies from pharmacogenetics relational data sources using declarative object definitions and XML, World Scientific; 2001, p. 88–99.

[93] Stojanovic L, Stojanovic N, Volz R. Migrating data-intensive web sites into the Semantic Web, ACM Press; 2002, p. 1100.

[94] Sclano F, Velardi P. TermExtractor: a Web Application to Learn the Shared Terminology of Emergent Web Communities. In: Gonçalves RJ, Müller JP, Mertins K, Zelm M, editors. Enterprise Interoperability II, London: Springer London; 2007, p. 287–90.

[95] Wermter J, Hahn U. Finding new terminology in very large corpora, ACM Press; 2005, p. 137.

[96] Wei XL, Sun Y, Zhang SK. Ontological concept extraction method based on maximum entropy model. Computer Engineering 2009;35.

[97] Zhang Z, Ciravegna F. Named entity recognition for ontology population using background knowledge from Wikipedia. In: Wong W, Liu W, Bennamoun M, editors. Ontology Learning and Knowledge Discovery Using the Web: Challenges and Recent Advances, Hershey, PA: IGI Global; 2011.

[98] Massey L, Wong W. A cognitive-based approach to identify topics in text using the Web as a knowledge source. In: Wong W, Liu W, Bennamoun M, editors. Ontology Learning and Knowledge Discovery Using the Web: Challenges and Recent Advances, Hershey, PA: IGI Global; 2011.

[99] Specia L, Motta E. A Hybrid Approach for Relation Extraction Aimed at the Semantic Web. In: Larsen HL, Pasi G, Ortiz-Arroyo D, Andreasen T, Christiansen H, editors. Flexible Query Answering Systems, vol. 4027, Berlin, Heidelberg: Springer Berlin Heidelberg; 2006, p. 564–76.

[100] Snow R, Jurafsky D, Ng AY. Learning syntactic patterns for automatic hypernym discovery. NIPS'04 Proceedings of the 17th International Conference on Neural Information Processing Systems, Vancouver, British Columbia, Canada: 2005, p. 1297–304.

[101] Sánchez D, Moreno A. Learning non-taxonomic relationships from web documents for domain ontology construction. Data & Knowledge Engineering 2008;64:600–23.

[102] Perkowitz M, Etzioni O. Adaptive Web sites: Automatically synthesizing Web pages. Proceedings of the 1998 15th National Conference on Artificial Intelligence, AAAI, Madison, WI, USA: 1998, p. 727–32.

[103] Pei M, Nakayama K, Hara T, Nishio S. Constructing a Global Ontology by Concept Mapping Using Wikipedia Thesaurus. Proceedings of the 22nd International Conference on Advanced Information Networking and Applications - Workshops, IEEE; 2008, p. 1205–10.

[104] Liu W, Weichselbraun A, Scharl A, Chang E. Semi-Automatic Ontology Extension Using Spreading Activation. Journal of Universal Knowledge Management 2005;0:50–8.

[105] Weber N, Buitelaar P. Web-based ontology learning with isolde. Proceedings of the Workshop on Web Content Mining with Human Language, International Semantic Web Conference, vol. 11, Athens, GA, USA: 2006.

[106] Mintz M, Bills S, Snow R, Jurafsky D. Distant supervision for relation extraction without labeled data. Proceedings of the Joint Conference of the 47th Annual Meeting of the ACL and the 4th International Joint Conference. Natural Language Processing of the AFNLP, vol. 2, Suntec, Singapore: 2009, p. 1003–11.

[107] Tang J, Leung H, Luo Q, Chen D, Gong J. Towards Ontology Learning from Folksonomies. Twenty-First International Joint Conference on Artificial Intelligence. Web and Knowledge-Based Information Systems, Pasadena, California, USA: 2009, p. 2089–94.

[108] Kotis K, Papasalouros A. Automated learning of social ontologies. In: Wong W, Liu W, Bennamoun M, editors. Ontology Learning and Knowledge Discovery Using the Web: Challenges and Recent Advances, Hershey, PA: IGI Global; 2011.

[109] Mika P. Ontologies are us: A unified model of social networks and semantics. Web Semantics: Science, Services and Agents on the World Wide Web 2007;5:5–15.

[110] Weichselbraun A, Wohlgenannt G, Scharl A. Augmenting Lightweight Domain Ontologies with Social Evidence Sources, IEEE; 2010, p. 193–7.

[111] Hjelm H, Volk M. Cross-language ontology learning. In: Wong W, Liu W, Bennamoun M, editors. Ontology Learning and Knowledge Discovery Using the Web: Challenges and Recent Advances, Hershey, PA: IGI Global; 2011.

[112] Lu B, Tsou B, Jiang T, Zhu J, Kwong O. Mining parallel knowledge from comparable patents. In: Wong W, Liu W, Bennamoun M, editors. Ontology Learning and Knowledge Discovery Using the Web: Challenges and Recent Advances, Hershey, PA: IGI Global; 2011.