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A REVIEW OF SEMI-AUTOMATIC APPROACHES TO BUILD CONCEPT MAPS

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Abstract. Concept Maps are graphical tools for knowledge organization and representation. In this decade, we have seen an increasing interest in building concept maps from data sources by applying computational resources, setting out to overcome the issues related to building them from scratch. Nevertheless, we have observed an absence of consistent references, which could allow for a unified vision of this research field. Therefore, considering this gap, we put forward, in this article, a set of classes, organized according to some perspectives, to analyze semi-automatic approaches for building of concept maps. This paper is a part in a research concerned with the use of concept maps in e-learning.

1 Introduction

Concept Maps are graphical tools for knowledge organization and representation (Novak & Cañas, 2006b). Concept Maps elements are defined as concepts – usually labeled by a couple of words inside a circle or a rectangle – and relationships which link two concepts to create a meaningful statement or proposition (Novak & Cañas, 2006a). A concept map can be built manually. However, the construction without computer aided tools are, generally, time consuming and complex. Consequently, there is a great enthusiasm in the use of software applications in order to promote better experiences to those working with concept maps. In addition, with the popularization of the Internet, some tools have developed and have supported really collaborative experiences, making possible the arising of new practices with concept maps (Novak & Cañas 2006a). Daley et al. (2008) noticed that concept maps have been used as knowledge representation tools in many fields, beyond the formal education boundaries, such as in software engineering processes, process and system modeling, human resources processes, and scientific research.

Over the last decade, academic community has developed an increasing interest in applying computational resources to building concept maps from different data sources. Research in this field focuses on two major challenges: (i) to overcome the difficulties in concept maps building from scratch, and (ii) to reduce the time and effort in knowledge acquisition activities in large domains highly dependent on experts (Chang et al., 2008; Lee et al, 2000). Even though the most research in building of concept maps had been introduced as "automatic approach", in our humble opinion, at least for now, the expression "semi- automatic approach" is more appropriate, given their considerable dependency on human interventions throughout the building process.

The majority of approaches to build concept maps from data sources was encouraged by educational issues among which we mention: the use of concept maps in teaching-learning process (Alves et al., 2001; Clariana & Koul, 2004; Lau et al., 2008), in selection of teaching strategies (Chang et al., 2008;Chen et al., 2008; Bai & Chen, 2008; Lee et al., 2009; Tseng et al., 2007), and in evaluation of students (Graudina & Grundspenkis, 2008;Villalon & Calvo, 2008). Other research projects had different motivations to use concept maps, of which we might highlight the following uses: to represent knowledge in a friendly way, especially for domain experts (Kumazawa et al., 2009); to support domain knowledge acquisition (Zouaq & Nkambou, 2008; Zouaq & Nkambou, 2009; Pérez & Vieira; 2004; Pérez & Vieira, 2005); to summarize digital libraries contents (Richardson & Fox, 2007) and to search an share digital documents (Gaines & Shaw, 1994; Valerio & Leake, 2006). In particular, we have interest in the practices with concept maps in educational contexts, especially in e-learning environments. Throughout our research, we have identified that there were not consistent references to allow us to compare the most significant semi- automatic concept maps building approaches. As a consequence, aiming to fulfill this gap, we try to propose, in this paper, a set of classes[1] , acting as a minimal reference, to outline concept maps building approaches by means of different perspectives. This minimal reference is supported by a review of academic publications occurred between 1994 and 2009 that, explicitly, stated the purpose of building concept maps from data sources in an automatic or semi-automatic mode.

We organized this paper as follows: in Section 2 we underline the particularities of concept maps as knowledge representation language; in Section 3, we propose a classification to semi-automatic concept maps building approaches; in Section 4 we point out our preliminary observations about this research; at last, in Section 5, we conclude with some findings and try to scratch the surface of this area of research outlining some of our future intentions.

2 Concept Maps: Structure and Theoretical Foundations

Compared to others knowledge representation languages based on maps, Concept Maps differ from them with respect to their theoretical basis, their semi-hierarchical organization and the presence of meaningful linking words to connect two concepts (Cañas et al., 2003). Novak & Gowin (1984) founded the concept maps language on the Meaningful Learning Theory (Ausubel, 1963), emphasizing the idea of "subsumption" in learning process. In few words, "subsumption" is a phenomenon that occurs during the learning process, when a learner, supported by an appropriate environment, could be able to attach new concepts to those existent inside his/her cognitive structure (Cañas et al., 2003a). Hence, from the theoretical assumptions, the main features of concept maps were derived: a) concepts should be organized in a semi-hierarchical way in which the general one subsumes a more specific one; b) concepts should be labeled by a couple of words that should define "a perceived regularity in events or objects, or records of events or objects" (Cañas et al., 2003a); c) the relationship between two concepts must be labeled in a form so that propositions could be identified.

3 A Review of Concept Maps Building Approaches

In this section, we intend to put forward a set of classes we propose as a common basis for the analysis of semi-automatic concept maps building approaches. We organized these classes according to different perspectives:

a) Research Goals: What are the research goals? Who are the audience of the resultant concept maps?

b) Data Sources: What kind of data source was used? What methods and techniques were used to handle it? Does the data source belong a specific domain of knowledge?

c) Outputs: How the resultant output looks like? What tools were used to build the output? How the approaches assess the resultant output?

A view of perspectives and respective classes are depicted by Figure 1. Along this section, we define each one of them and also carry on a review of academic publications related to semi-automatic concept maps building.

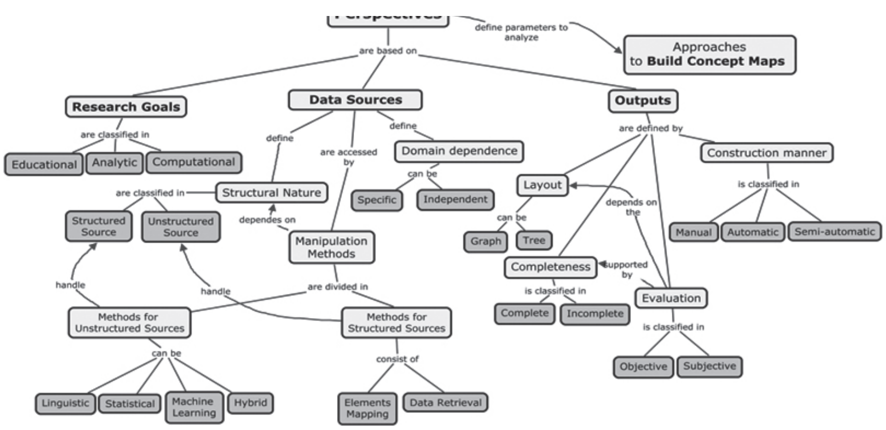

Figure 1. Classes for Analyzing the Approaches to Build Concept Maps

[1] In this paper, we used the term "class" with a sense of "division". Thus, in this paper "class" represents a label used "to outline approaches according to a particular perspective", and it must not be confused with the definition of "class" used in Software Engineering.

3.1 Research Goals Perspective

The goals established by research to build concept maps guide the choice of data sources and define a wide range of requirements, such as: the target audience, the degree of readability, the richness of propositions, etc. We propose the following classes according to the research goals perspective: educational, analytical and computational.

In the educational class the main research goal is the use of concept maps as complement resource in learning process. Among the approaches that fit in this class, we can mention those that:

a) promote interactive construction of concept maps (Alves et al., 2001; Clariana & Koul, 2004);

b) allow teachers to keep track of student comprehension about a specific topic presented in traditional learning environments (Graudina & Grundspenkis, 2008) or in e-learning environments (Lau et al., 2008);

c) sum up and share digital content (Richardson & Fox, 2007; Richardson et al.; 2008).

Analytical class is characterized by the use of concept maps as tools for domain experts that conduct activities of exploration, analysis, and pattern recognition in large data sources. This is the context of approaches that:

a) explore students' historical data, searching for learning patterns (Bai & Chen, 2008; Chang et al., 2008; Chen et al., 2008; Lee at al., 2009; Tseng et al., 2007);

b) display the information to domain experts (Gaines & Shaw, 1994; Kumazawa et al., 2009; Pérez & Vieira 2005; Pérez & Vieira; 2005);

c) propose concept maps as tools for accessing, searching and analyzing data in digital libraries (Valerio & Leake, 2006).

In computational class the core thread consists of handling concept maps as a source for knowledge acquisition by way of software applications. In this class fits the research of (Zouaq & Nkambou, 2008; Zouaq & Nkambou, 2009) that consider concept maps as intermediate representation between text and domain ontologies.

3.2 Data Source Perspective

The data source[2] used by an approach impacts the whole concept map building process. As an input, its structural nature acts both as parameter to select the manipulation method to handle it, and as constraint to determine the degree of domain dependence. Thus, under the top level perspective, we defined classes according to specific points of view, listed as follows: (i) structural nature; (ii) manipulation method, and (iii) domain dependence.

3.2.1 Structural Nature Perspective

The structural nature of data source is defined by the data organization. From this standpoint, data sources used by the approaches could be classified as structured and unstructured. In unstructured data sources, texts in natural language are the primary sources for extracting concept maps elements. Among the approaches that use unstructured data, we could mention those that work with:

a) texts written by domain experts (Alves et al., 2001; Gaines & Shaw, 1994; Valerio & Leake, 2006; Zouaq & Nkambou, 2008; Zouaq & Nkambou, 2009),

b) texts produced by students in response to questionnaires (Chang et al., 2008) or written freely as a discourse related to a given issue (Clariana & Koul, 2004);

c) scientific texts as, for instance, academic articles (Chang et al., 2008), abstract of theses and dissertations (Richardson et al., 2008);

d) messages from forums (Lau et al., 2008);

e) news and textbooks (Pérez & Vieira, 2004; Pérez & Vieira, 2005).

In structured data sources there is some level of formalism in the organization of data. Concept models and implementations of ontologies are examples of structured data sources and they may be seen in the approaches that use tabulation of student productions (Bai & Chen, 2008; Lee et al., 2009; Tseng et al., 2007) and in those that use domain ontology (Graudina & Grundspenkis, 2008; Kumazawa et al., 2009).

[2] If there are more than one data source referred, we should consider only the primary source, i.e., the data source used by the approach to extract concept and relations. Thus we should ignore the features of auxiliary sources, generally applied for lexical purposes, and consulted in complementary activities, such as, for example, words disambiguation, synonym identification and part-of-speech tagging.

3.2.2 Methods Perspective

The link between methods, computational techniques, and structural nature of data source, applied in the automatic construction of concept maps, distinguishes direct classes: methods for unstructured data sources and methods for structured data sources.

Methods for handling unstructured data sources have closer association with issues from Natural Language Processing and all of them could be, by this single criterion, equally identified as linguistic methods. However, the mere presence of linguistic techniques is not enough to describe the whole approach (Manzano-Macho & Gómez-Pérez, 2005). That is the reason our research considers the main technique used by the approach to discover knowledge from texts. The classes of methods are qualified as Linguistic methods, Statistical methods, Machine learning methods and Hybrid methods.

Linguistic methods class is characterized by the presence of techniques from computational linguistics (Manzano-Macho & Gómez-Pérez, 2005). They use morphology, syntactic, semantics, pragmatics, and discourse resources to handle the data source. Linguistic methods are very directly related with text structure and are based on linguistic patterns recognition. They make use of grammars, thematic roles, and named entity recognition. In general, linguistic methods are more accurate than Statistical methods, but generally they need be helped from external knowledge databases, such as dictionaries, thesaurus or lexical data sources (Zouaq & Nkambou, 2009). In this class we could find the approaches of Pérez & Vieira (2004; 2005), Richardson & Fox (2007), and Richardson & Fox (2008).

In Statistical methods class, we may observe the use of techniques based on quantitative indicators (Manzano-Macho & Gómez-Pérez, 2005). Generally, such techniques produce information for analyzing the frequency of a term and co-occurrences between terms in documents or corpus. The most popular techniques are the analysis of frequency of repetition of words or word patterns, the calculation of weights that indicates the relevance of terms in a set of documents (TF-IDF), and clustering techniques for documents. The advantages of statistical methods are their simplicity to handle documents independently from linguistic knowledge. Among their disadvantages, unpredictable results and semantic loss during the document handling (Zouaq & Nkambou, 2009) can be pointed out. The approaches of Gaines & Shaw (1994) and Clariana & Koul (2004) belong to this class.

In Machine learning methods class, techniques use machine learning to extract text elements (Manzano-Macho & Gómez-Pérez, 2005). They are generally used together with statistical methods. Examples of methods of machine learning can be found in the algorithms used in discovering co-occurring elements that may characterize association rules, and in the identification of keywords and taxonomies of elements (Zouaq & Nkambou, 2009).

In Hybrid methods class, a combination between linguistic, machine learning and statistical techniques are there so that the dominant technique could not be identified. In this class, we could insert Alves et al. (2001), Lau et al. (2008), Valerio & Leake (2006), Zouaq & Nkambou (2008; 2009).

Methods used to manipulate structured data sources usually apply element mapping and data retrieval techniques. Based on these techniques, we identified two major classes for manipulation of structure data sources: Element mapping methods and Data retrieval methods. Graudina & Grundspenkis (2008) and Kumazawa, Saito, Kozaki, Matsui, & Mizoguchi (2009) approaches can be fit in Element Mapping method class because they perform the mapping of concepts, properties, and associations from domain ontologies to elements of concept maps. The approaches of Bai & Chen (2008), Chen et al. (2008), Lee et al. (2009) and Tseng et al. (2007) do not require a great effort to identify concepts because all the concepts to build a map are defined from the handling of focal questions; thus, they belong to Data retrieval methods class.

3.2.3 Domain Dependence Perspective

According to the domain dependence, we observed that approaches could be classified as domain-independent or domain-specific class. In domain-independent class the selection of data sources are not restricted to a specific domain neither the approach requires an earlier knowledge to deal with it. In this class we might outline the research of (Alves et al., 2001; Pérez and Vieira, 2005; Pérez and Vieira, 2005; Valerio & Leake, 2006). Approaches in Domain-specific class handle data sources that belong to a specific domain, such as the approaches that deal with: E-learning (Chen et al., 2008), Informatics in Education (Zouaq & Nkambou, 2008; Zouaq & Nkambou, 2009), Anatomy and Physiology of human heart (Clariana & Koul, 2004), Manufacturing Software (Gaines & Shaw, 1994), Computer Science (Graudina & Grundspenkis, 2008; Richardson & Fox, 2007; Richardson et al., 2008), Sustainability Science (Kumazawa et al., 2009). The research of Bai & Chen (2008), Chang et al. (2008), Lau et al. (2008), Lee et al (2009) and Tseng et al. (2007) does not refer to a specific domain, but it is not independent of domain because all the concepts should be defined during the focal question planning.

3.3 The Outcomes Perspective

From the perspective of approaches outcomes, a concept map constructed can be analyzed considering (i) the form of its graphical presentation, (ii) the completeness of its definition, (iii) how it was built, and (iv) the mechanisms used to assess its quality. The graphical layout of a concept map may be directly observed from the concept map. If there is an explicit topology, the concept map belongs to a tree class, otherwise, a graph class. These mathematical structure definitions can be found in Graph Theory (Diestel, 2005).

Completeness of a concept map is evaluated using formal definition of Concept Map, in a sense that a concept map should have understandable concepts and well-formed relations. Here, we could identify two classes: complete or incomplete maps. Maps of incomplete class do not show propositions, generally because labels are not clear enough to build propositions. In maps of complete class propositions are obviously defined.

We may classify approaches according to different manners to build a concept map – we defined this perspective as construct manner. Some of these approaches provide automatic and native resources, while others have interoperability with third-party tools, and also there are those in which the concept map construction procedure is not mentioned. We proposed the following classes of classification: automatic, semi-automatic, and manual representation class. Automatic representation is the class for tools with native resources to automatically build and show concept maps, as in Bai & Chen (2008), Chang et al. (2008), Chen et al. (2008), Kumazawa et al. (2009), Lau et al. (2008), Lee et al. (2009), Tseng et al. (2007) Zouaq & Nkambou (2008; 2009). In the semi-automatic representation class, a set of propositions are produced so that they could be imported by a third-party tool, as observed in Alves et al. (2001), Clariana & Koul (2004), Gaines & Shaw (1994), Graudina & Grundspenkis (2008), Richardson & Fox (2007) and Richardson et al. (2008). In manual representation class, only concepts and relations are extracted from the data source but propositions are not defined. In this last class, we only can build maps manually, using a third-party tool, as in Valerio & Leake (2006).

Concerning the quality of concept maps, we propose classes for evaluation methods used by the concept map building approaches. Evaluating a map consists of validating propositions and elements in a concept map, trying to identify the ill-formed propositions. The classes of evaluation are separated in: Objective or Subjective class. In subjective class, an evaluation is conducted by human experts that use their own criteria to validate concept maps. Sometimes the evaluation given is not repeatable and uniform because it depends on personal feelings. Almost all of the approaches analyzed in our research are skeptical of subjective evaluation. In objective evaluation class, an evaluation could be conducted both by human experts and computational resources because it is founded on rating scores, by defining different rates to propositions, hierarchy levels, quantity of ramifications, cross-links and specific examples, as originally proposed by (Novak & Gowin, 1984). Table 1 summarizes the approaches in classes, according to each of the perspectives.

Reference	Research Goals Perspective	Data Sources Perspective			Outputs Perspective		
		Domain Dependence	Structure	Method	Construction Manner	Layout/ Completeness	Evaluation
Alves et al. (2001)	Educational	Domain Independent	Unstructured	Hybrid Method	Semi-automatic	Graph Complete	Subjective
Bai et al (2008)	Analytic	Domain Specific	Structured	Data Retrieval	Automatic	Graph Incomplete	Not found
Chang et al. (2008)	Analytic	Domain Specific	Unstructured	Statistical Method	Automatic	Tree Incomplete	Not found
Chen et al. (2008)	Analytic	Domain Specific	Unstructured	Statistical Method	Automatic	Graph Incomplete	Subjective
Clariana and Koul (2004)	Educational	Domain Specific	Unstructured	Statistical Method	Semi-automatic	Graph Incomplete	Objective
Gaines and Shaw (1994)	Analytic	Domain Specific	Unstructured	Statistical Method	Semi-automatic	Graph Incomplete	Subjective
Graudina and Grundspenkis (2008)	Educational	Domain Specific	Structure	Elements Mapping	Semi-automatic	Graph Incomplete	Subjective
Kumazawa et al. (2009)	Analytic	Domain Specific	Structure	Elements Mapping	Automatic	Graph Incomplete	Subjective
Lau et al. (2008)	Educational	Domain Specific	Unstructured	Hybrid Method	Automatic	Graph Incomplete	Subjective
Lee et al. (2009)	Analytic	Domain Specific	Structure	Data Retrieval	Automatic	Graph Incomplete	Subjective
Pérez and Vieira (2004)(2005)	Educational	Domain Independent	Unstructured	Linguisti c Method	Not found	Graph Complete	Subjective
Richardson and Fox (2007); Richardson et al. (2008)	Educational	Domain Specific	Unstructured	Linguisti c Method	Semi-automatic	Graph Complete	Subjective
Tseng et al. (2007)	Educational	Domain Specific	Structure	Data Retrieval	Automatic	Graph Incomplete	Subjective
Valerio and Leake (2006)	Analytic	Domain Independent	Unstructured	Hybrid Method	Manual	Graph Complete	Subjective
Zouaq and Nkambou (2008)(2009)	Computatio nal	Domain Independent	Unstructured	Hybrid Method	Automatic	Graph Complete	Subjective

Table 1. Classification of semi-automatic approaches to build Concept Maps

4 Data Analysis Results

In this section, we present, by means of charts in Figure 2, some observations derived from data analysis of Table 1. The chart of Figure 2(a) shows that most of the approaches analyzed are recent: 10 of 15 approaches (66.67%) were published in the last three years. Figure 2(b) illustrates that 14 of 15 approaches (93.34%) were concerned with human readers. This number was calculated by the sum of numbers from Educational (46.67%) and Analytic approaches (46.67%). In Figure 2(c), we present numbers that revealed a connection between structure and domain dependence of used data sources. Approaches that have used structured sources were totally domain dependent, but approaches based on handling unstructured sources could be domain independent. Figure 2(d) indicates the tradeoff of the most applied manipulation methods and data sources' structural nature. For unstructured sources, there are three suitable methods: Linguistic, Hybrid and Statistical. In Figure 2(e) we can observe that only Hybrid and Linguistic Methods have produced complete Concept Maps and complete outputs represented just 5 of 15 approaches (33.33%). Finally, in Figure 2(f), other important information can be observed: all of the five approaches that built concept maps that are represented as complete graphs were based in unstructured data sources.

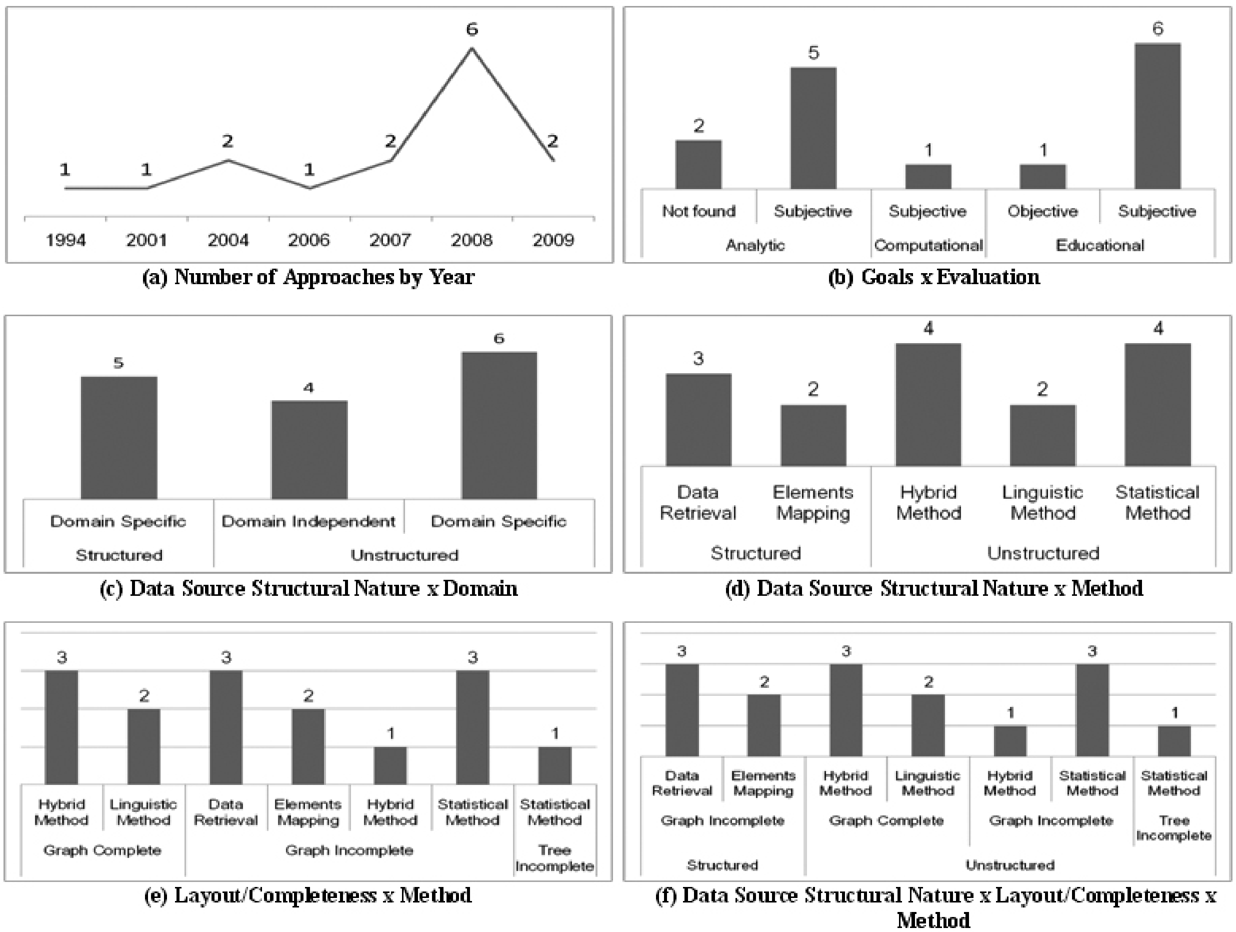

Figure 2 . Data Analysis of investigated approaches

5 Conclusions and Future Works

As we could see in the previous sections, the research in automatic building of Concept Maps has produced interesting results, especially in the works of Alves et al. (2001) and Zouaq & Nkambou (2008; 2009). However, we cannot deny that these approaches are far from being truly automatic. For these reasons we consider the term "semi-automatic" much more appropriate to refer to the approaches investigated, so far. However, we are aware that intense work is being done towards human independence in this process.

Handling unstructured data is a tangible challenge to computer applications. Large amounts of unstructured data are available in the Internet and digital libraries and their contents are increasing every day. So, it is expected that 10 of 15 approaches (66.67%) are concerned with methods for unstructured data.

A curious observation appeared in our research related to domain ontologies: two approaches used Concept Maps as output to represent ontology to human readers (Graudina and Grundspenkis, 2008; Kumazawa et al., 2009). On the other hand, there are approaches that use Concept Maps as intermediate representation between unstructured data and domain ontologies (Zouaq & Nkambou, 2008; Zouaq & Nkambou, 2009). We can assume that, despite of the fact Concept Maps are usually underestimated because of their simplicity and also because of their lack of formalism, they still are very useful to human understanding. We are aware that the set of classes presented here is incomplete and extensions may be added to improve it. This paper should not be understood as a fait accompli, but much on the contrary, we try to propose just a starting point to begin a debate. The next steps of this work will consist of the definition of a hybrid approach to manipulate texts in Brazilian Portuguese Language to produce complete Concept Maps and its application on e-learning environments. To achieve this result, we are developing techniques to recognize the core elements of concept maps based on linguistic chunks such as Noun Phrases, Verbal Phrases and Prepositional Phrases. Besides, we will try to represent their intrinsic dependency by graphs.

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