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Visual knowledge representation of conceptual semantic networks

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Visual Knowledge Representation of Conceptual Semantic Networks

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Abstract This article presents methods of using visual analysis to visually represent large amounts of massive, dynamic, ambiguous data allocated in a repository of learning objects. These methods are based on the semantic representation of these resources. We use a graphical model represented as a semantic graph. The formalization of the semantic graph has been intuitively built to solve a real problem which is browsing and searching for lectures in a vast repository of colleges/courses located at Western Kentucky University[1]. This study combines *Formal Concept Analysis (FCA)* with *Semantic Factoring* to decompose complex, vast concepts into their primitives in order to develop knowledge representation for the *HyperManyMedia*[2] platform. Also, we argue that the most important factor in building the semantic representation is defining the hierarchical structure and the relationships among concepts and subconcepts. In addition, we investigate the association between concepts using *Concept Analysis* to generate a lattice graph. Our domain is considered as a graph, which represents the integrated ontology of the *HyperManyMedia* platform. This approach has been implemented and used by online students at WKU[3].

1.1 Introduction

This study combines *Formal Concept Analysis (FCA)* with *Semantic Factoring* to construct and develop a multilingual ontology. In a nutshell, it answers the following question: "How is it possible to visualize an ontology graph which represents knowledge and reasoning of a massive, ambiguous, and vast set of documents using minimum vocabulary?" The model is built upon a variety of principles that we adopt. First, we use Zipf's law: "The Principle of Least Effort [36]", Zipf found a clearcut correlation between the number of words and the frequency of their usage, it is presented as $r \cdot f = c$, where r is the word's rank in a document and f its frequency of occurrence. We rely on this significant finding by minimizing the amount of effort we put to create the user ontology. The most frequent vocabulary that represent the corpus in our domain (E-learning) is used. In this sense, we observe the most frequent keywords searched by users, this information is obtained from the users' logs. Our assumption is the following: "if we capture the most frequent words used by an online user, then adding these words to the user ontology, the information retrieval model would provide the user with the most relevant documents in both languages. Second, we use the concept of " Collocation", which proved to be important in areas, such as machine translation and information retrieval [18]. Manning and Scutze [18] divided the "Collocation Concept" into three categories: (1) compounds, such as "semantic web", (2) phrasal verbs, such as "turn on", and (3) stock phrases, such as " Introduction to Literature". The third type is what we used in constructing our ontology. Since our users (students) spent 80% of their time searching for topics related to the following categories: (1) course name, (2) lecture name, and (3) professor name. Therefore, constructing an ontology that consists of collocations (e.g., "Game Theory for Managers") would increase the precision. Third, we used personalization to decrease the ambiguity of semantic search. Each user activity on to the system defines his/her area of interest (college/courses), therefore, a unique ontology is generated for each user. As a consequence, the search terms used by a user are governed by his domain of interest (e.g., if a user is searching for the keyword "History", if he is enrolled in Mathematics, the system should retrieve course "History of Mathematics", but if he is enrolled in the college of History, the same keyword search will retrieve the course "History of Civilization"). The effectiveness of our model comes from the synergy between all the previous principles.

Before diving into the theory and the methodology of implementing the system, let us begin with some descriptive definition of the system: *HyperManyMedia* is an information retrieval system that utilizes an ontology based model and provides semantic information. This approach uses two different types of ontologies, a global ontology model that represents the whole E-learning domain (content-based ontology), and a learner-based ontology model that represents the learner's profile. The implementation of the ontology model is separate from

[1] http//HyperManyMedia.wku.edu

[2] *HyperManyMedia: We proposed this term to refer to any educational material on the web (hyper) in a format that could be a multimedia format (image, audio, video, podcast, vodcast) or a text format (HTML webpages, PHP webpages, PDF, PowerPoint)*

[3] http://www.wku.edu

the design of the information retrieval system. The architecture of the *HyperManyMedia* system can provide, manage, and collect data that permits high levels of adaptability and relevance to the learner's profile. To achieve this objective, an approach for personalized search is implemented that takes advantage of the Semantic Web standards (RDF and OWL) to represent the content and the user profiles.

The main focus of this paper is the visual representation of the ontology that allows learners to navigate the system visually. The main objective of this research was to provide the user (learner) with a visual search engine to summarize the entire domain (E-learning). This can be considered as a tool to help visualize concepts and subconcepts. This visual exploration of documents enables users to have an overall view of the entire repository, without even clicking on the resources and reading each document. When a user types a query on the visual search engine, the visual search engine dynamically matches the query with the whole visual ontology (concepts, subconcepts, etc). The visual search engine presents all the sectors (concepts/subconcepts) that share the typed letters using different colors than the unmatched concepts. Therefore, the user can find what he/she is looking for immediately. As the user adds more letters to his/her query, the number of matched sectors narrows down to the most similar concepts in the ontology.

The primary contribution to the State of the Art made in this research is in the reuse of the domain ontology to build *visual search facet*s, where the hierarchic ontology structure was converted into a lattice (graph) and presented as nodes and edges, where the final representation of the graph is provided to users as sectors and subsectors.

The rest of this paper is divided into the following sections:

Section 2 (Background and Related Work): We give an overview of visual analytics, applications, and related work.

Section 3 (Methodology): This section presents the semantic domain structure and the representation of the semantic domain.

Section 4 (Implementation): This section presents the process of building the *HyperManyMedia* ontology, then adding the ontology to the search engine. It ends with designing a visual ontology search engine.

Section 5 (Evaluation): In this section, we test the usability of the visual search engine.

Section 6 (Conclusion): In this section, we present the novelty of our research and our contribution.

1.2 Background and Related Work

In the section, we introduce the definition of *visual analytics*, then we define several visual applications, and finally discuss related work and the significance of our visual analytic methods and techniques.

1.2.1 Visual Analytics

Everyday, data is produced with unprecedented rates in variety of fields, examples include scientific data, internet information, data management systems, business and marketing data, etc. *Visual analytics* is the bridge between the human eyes and the machine, it facilitates the process of: a) discovering hidden knowledge, b) summarizing data, c) representing data in a manner that the human cognitive system can perceive, d) helping users find needed information as fast as possible, or e) allowing users to interact with huge amounts of data easily and efficiently.

Thomas and Cook define visual analytics as "the science of analytical reasoning facilitated by interactive visual interfaces [27]". Visual analytics differs from other analytics applications by its capability to simplify complex data to provide users with quick, focused representations where users can interact with data, find the important features they are looking for, and translate the data into a visual aspect that their cognitive reasoning process can decipher in a fast manner [27]. However, visualization tools rely on methods driven from data mining, statistics, or mathematics, etc. As a consequence, designing an effective visualization tool is not an easy process, since summarizing data involves filtering out part of the data, choosing some features at the expense of others, and zooming into specific aspects in the data. Choosing the right parameters for filtering data is a deceiving process that involves varieties of methods. Therefore, an efficient visualization tool should have a flexible, interactive, dynamic interface in which users have the capability of changing those parameters and deciding which features to filter-out and which ones to keep.

1.2.2 Visual Analytic Applications

There are several visual analytic applications, each dedicated to a specific purpose. The following list is not an exhaustive list of applications, but it provides an overview about the most recent areas of research where visualization became essential:

a) *Topic summarization*: e.g., understanding newspaper articles, stories, reporting events, investigating crime reports, finding patterns in blogs, following the development of political campaigns, or observing topic trends in the bibliography of research approaches [7, 3, 25];

b) *Visual Analysis of Social Networks*: e.g., analyzing dynamic groups memberships in temporal social networks by using graphical representations [10, 12, 17, 6, 29];

c) *Visual Clustering Analysis*: e.g., using data mining techniques to find patterns in data to generate group of data based on (dis)similarity. Several visualization tools have been developed in this domain and gained great popularity, to mention some [21, 2, 28, 5, 30];

d) *Semantic Visual Analysis*: e.g., visual analysis of webpage/documents based on the semantic representation of text in a *"semantic graph*" [23, 8, 9, 22, 31], or exploring data in folksonomy systems based on a hierarchical semantic representation, *"semantic cloud or tags"* [11, 14, 24, 23, 4, 15, 16, 22, 26].

1.2.3 Related Work

Our research focuses on (c) and (d) categories, where each category assists in representing, visually, a huge, massive, dynamic, ambiguous data allocated in a repository of learning objects. We noticed that there was a high overlap between our work and several other related efforts, due to the fact that our research is built upon several areas of research, spanning knowledge extraction based on the hierarchical semantic representation, cluster analysis, and finally visual analysis.

Recently, there has been significant of interest in using visual analytics in variety of research fields, for example [23, 22] used visual analysis to present documents as a semantic directed graph, in this approach, Delia, et al took advantage of natural language processing to define named entities/co-referenced entities where triplets (subject, predicate, object) were extracted using the Penn Treebank parser for each sentence in the document and then associated to WordNet, finally a summarization of the documents was provided using machine learning techniques. Another work was introduced in [29] in which a visual analytics tool was used to present data as an interactive graph, it provides the visualization of social networks to explore communities across time, a major interesting feature in this tool is the capability to provide relations among communities, events, or evolution of neighborhoods. The similarity with our work lies in the usage of a graph to represent documents, however, the major difference is that our approach is based on the semantic representation of a graph in real time and we use the visual analytics tool not only to summarize the data, but also allow the user to browse the data and retrieve documents. [9] extented their previous work in [23, 22] to a question/answering based semantic graphs, where the sentences that have been extracted from the documents using natural language processing techniques were saved and used to implement a question answering system and it was used as an interface for search. Aras, Siegel, et al presents a new approach of extracting semantics from popular folksonomy systems to visually explore the data using hierarchical semantic representation [1].

Our approach starts with a similar concept to the work presented in [23, 22] by converting documents into a semantic directed graph, however, our approach is a web-based application, that evolves dynamically in real time. In addition, we rely on the semantic relationship between entities more than the representation of sentences in the documents. The idea is to present the hierarchical structure of concepts and subconcepts as a semantic graph. Also we use information retrieval techniques in order to retrieve documents related to the users' interest, moreover, we use clustering analysis to add additional subconcepts to the directed graph.

1.3 Methodology

1.3.1 Semantic Representation of HyperManyMedia

1.3.1.1 Formal Context Representation

The section is concerned with the representation of the semantic model (semantic set). Kavouras and Kokla[13] defines a *formal context,* SG (Simple Conceptual Graph) as a triple (D, δ, α) where D is a set of objects and δ is a set of attributes and α defines the relationship between D and δ.

For example let us build a model (D, δ, α) satisfying G, which in our case represents a semantic representation of the *HyperManyMedia* domain.

Fig. 1.1 Illustrating the scenario of representing a simple conceptual graph

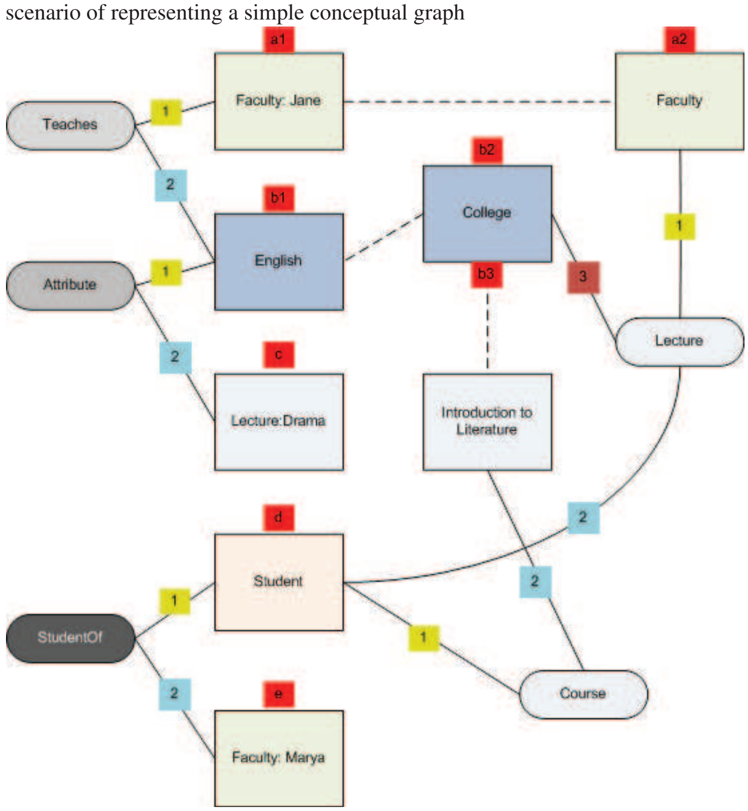

Fig 1.2 illustrates the scenario of representing a simple conceptual graph. The main objective of this section is to describe how we can present a semantic model as sets. The domain is constructed from concepts, subconcepts

Algorithm 1 Scenario of representing a simple conceptual graph to build a semantic model

D contains $colleges$, $faculties\ courses$, $lectures$, $students$, etc.

$\delta(college)$ is the subset of D containing all the $courses$.

$\delta(faculty)$ is the subset of D containing all the $faculty$ and so on, the different concept types.

$\delta(teaches)$ is the subset of $D \times D$ containing all the $couples\,(d,d')$ such that d is a $faculty$ that $teach$ to the object $(course)$ d'.

$\delta(lecture)$ is the subset of $D \times D \times D$ containing all the $triples\,(d,d',d")$ such that d and d' are $faculty$ who teaches in $(college)$ $d"$.

$\delta(Jane)$ is the element of D representing faculty $Jane$, $\delta(Drama)$ is the element of D representing a lecture named $Drama$, and so on for all other individuals.

$\alpha(a1) = \alpha(a2) = \delta(Jane), \alpha(b1) = \alpha(b2) = \alpha(b3) = u1 \in D, \alpha(c) = \delta(Drama), \alpha(d) = u2 \in D, \alpha(e) = \delta(Marya)$

$(\delta(Jane), u1) \in \delta(teaches), (\delta(Jane), u2, u1) \in \delta(lecture), (u2, \delta(Marya)) \in \delta(StudentOf), (u1, \delta(Drama)) \in \delta(attribute), etc.$

and the relationships between them. First, a model of vocabulary is defined. This model consists of a set of entities in a hierarchical structure representation. The highest level of this model is the college set, which usually in graph theory represents the *Universe se*t, under a Universe set (college), the concept types and the relation types are defined. The Universe set (college) consists of all the colleges in *HyperManyMedia* domain. As subset of the Universe, courses are defined as elements and the relationship between the *Universe set (college)* and the subset course are presented as tuples of elements of the college and an individual is interpreted as an element of the *Universe set (college)*, for example College=English, etc.

The domain provides some resources in multilingual (English and Spanish). These resources, basically, are courses designed by WKU faculty augmented with courses from MIT OpenCourseWare[4]. *HyperManyMedia* consists of the following colleges: English (Ingles), Social Work (Trabajo Social), History (Historia), Chemistry, Accounting, Math, Consumer and Family Sciences, Architect and Manufacturing Sciences, Engineering (Ingenieria) and Communication Disorders). A subset of the *Universe set (college)* is defined as *course set*, which consists of all the courses, under the concept *course set*, the *lecture set* is defined which consists of all the lectures in the domain (a total of 7,264). Our entire domain $D = Hypermanymedia$ can be defined as $Lecture\,set \;\in\; Course\ set \in College\ set \in D$. The second section concerns the presentation of the semantic set as an ontology.

1.3.1.2 Semantic Factoring

This section defines *Semantic Factoring* which is described by Kavouras and Kokla [13] as follows: "*Semantic Factoring* is a conceptual analysis process that decomposes a complex concept into its definition, primitive concepts, called *Semantic Factoring*". Kavouras and Kokla [13] emphasize the usefulness of using *Semantic Factoring* in constructing and developing knowledge representation of systems, especially, in the system that uses multilingual corpora. As we mentioned in the above section, our corpora is bilingual (English and Spanish). Kavouras and Kokla [13] argue that the most important factor in building the semantics is by defining the hierarchical structures in concepts, in addition to finding the association between concepts using *Concept Analysis* to generate a lattice graph, which represents the integrated ontology in *HyperManyMedia*.

[4] MIT OpenCourseWare: http://ocw.mit.edu/OcwWeb/web/home/home/index.htm

1.4 Implementation

The *HyperManyMedia* search engine is an extended version of Nutch[5] search engine, which is an open source information retrieval system. We modified Nutch by adding plugins to support a multi-model search interface, such as metadata search [33, 34] and semantic search [32, 35] mechanisms. This paper is concerned with our visual search interface that recently has been added to *HyperManyMedia*: *A Visual Ontology-based Interface*. The following sections describe the implementation of this interface.

1.4.1 Building Multilingual HyperManyMedia Ontology

1.4.1.1 Introduction

The general research field of Multi-language Information Retrieval (MLIR) can be categorized into four major areas introduced by Peters, Braschler, et al [20] as follows: (a) Multilingual Retrieval, (b) Bilingual Retrieval, (c) Monolingual Retrieval, and (d) Domain Specific Retrieval. According to Oard and Dorr [19], there are three different approaches to build a Multi-Language Information Retrieval system: (1) Text Translation Approach, (2) Thesaurus-based Approach, and (3) Corpus-based Approach. The approach that we followed is a synergistic approach between (1) *The Thesaurus-based Approach* and (2) *The Corpus-based Approach:*

1. *The Thesaurus-based Approach*
   Thesaurus based text retrieval allows the learners to explore more information during the searching process. The information retrieval system is capable of bringing more insight about the system in a way similar to a multilingual dictionary, but with visualized hints which can be considered as a powerful tool. We consider our *thesaurus-based approach* to be what is called a "controlled vocabulary" approach, since the semantic search is provided to the user/learner as a hierarchical structure. From the beginning, the search engine presents the concept of "college" as an upper-level concept and the right-side interface shows the user the subclasses and the multilingual synonyms, assuming that the user is not aware of the semantic concept, and with time, will understand the relationship between entities and he/she will be ready to formulate her own query terms. We consider this approach to be a kind of query expansion.
2. Corpus-based Approach
   Our approach can also be considered as *Term Vector Translation*, which is defined by Oard and Dorr as follows: "statistical multilingual text retrieval techniques in which the goal is to map statistical information about term use between languages... techniques which map sets of $tfidf$ term weights from one language to another [19]". We used a query translation method to retrieve multilingual documents with expansion techniques for phrasal translation. Our search engine uses the Vector Space Model to match the query term with the indexed documents.

This study uses Protégé[6], an open source ontology editor and knowledge-based framework that supports two ways of modeling ontologies: (1) Protégé-Frames, and (2) Protégé-OWL editors to design and build the structure of the *HyperManyMedia* ontology. Our current ontology consists of ~32,000 lines of code[7].

1.4.1.2 Multilingual Ontology Design

The platform consists of vast resources of Colleges/Courses/Lectures. Table 1.1 shows a summary of *HyperManyMedia* resources. The main question is how to design an ontology that can summarize the whole domain?

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[5] http://lucene.apache.org/nutch/

[6] http://protege.stanford.edu/

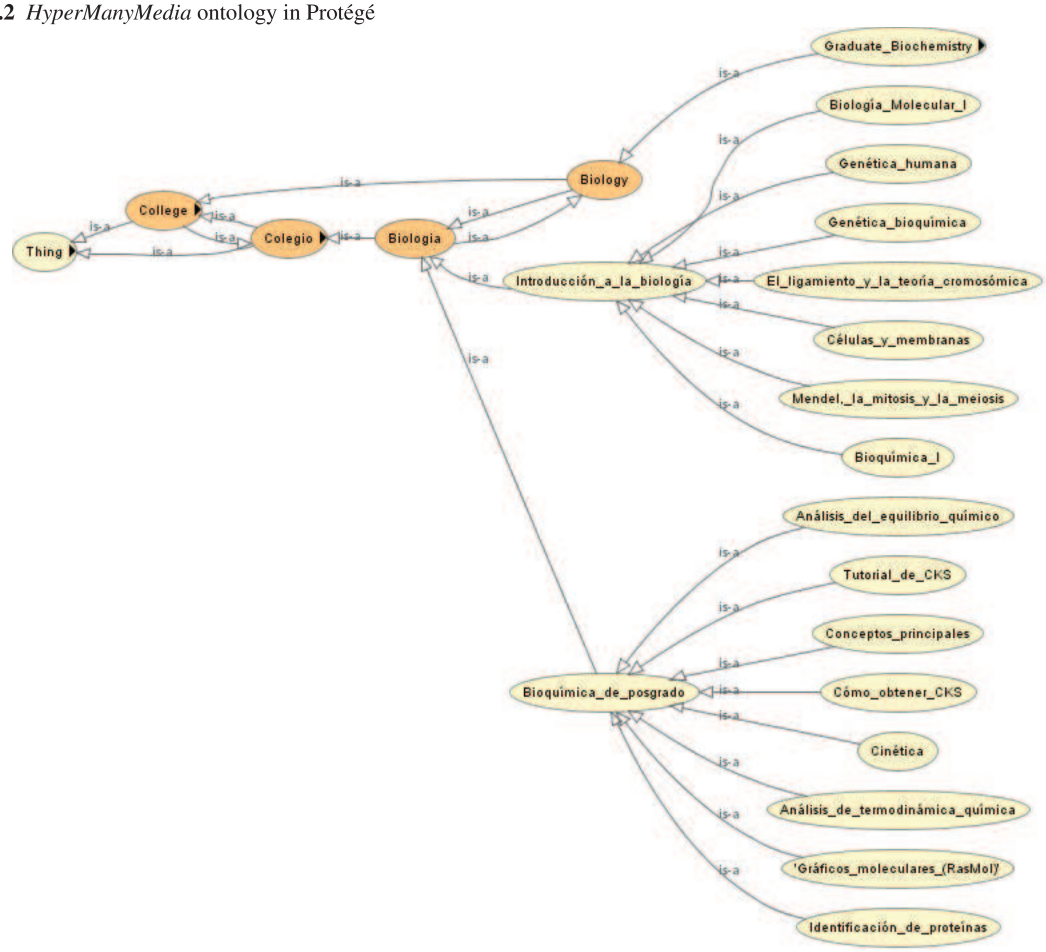
[7] http://www.wku.edu/~leyla.zhuhadar/semanticowl.owl

The two concepts that have been discussed in the previous sections: *Formal Context Representation* and *Semantic Factoring* were considered in the design. Fig 1.2 represents the *HyperManyMedia* ontology in Protégé.

Table 1.1 Summary of HyperManyMedia Resources

Total #of colleges= 11	Total #of courses= 64
Total #of WKU courses= 27	Total #of MIT courses= 37
Total #of English courses= 45	Total #of Spanish courses= 19
	Total # of Lectures=7264

Fig. 1.2 *HyperManyMedia* ontology in Protégé



First, a vocabulary V is defined. This vocabulary consists of all concepts that are considered as part of the domain. This vocabulary is defined as a hierarchical tree, where the upper level (first-level) represents the *College set* and the instances represents all the colleges: English (Ingles), Social Work (Trabajo Social), History (Historia), Chemistry, Accounting, Math, Consumer and Family Sciences, Architect and Manufacturing Sciences, Engineering (Ingenieria) and Communication Disorders). The lower level (second-level) is considered as a SubConcept, which is the *Course set,* that consists of all the courses. Finally, the lowest level (third-level) is considered as SubSubConcept, which is the *Lecture set*, that consists of all the lectures.

1.4.1.3 Defining Objects Properties

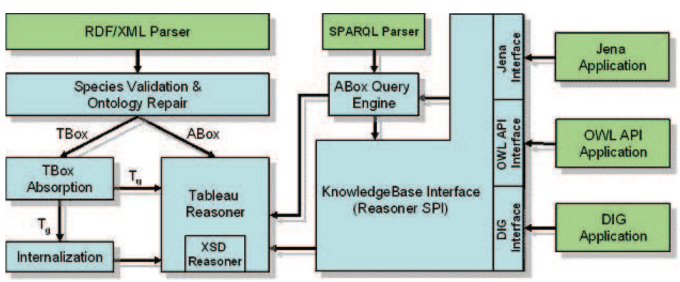
Six types of objects properties were defined in Protégé to fit the design of the multilingual ontology, as shown in Table 1.2

Table 1.2 Defining Objects Properties

Object Property	*Definition*
Sub_class_of	*this property is defined to generate the hierarchical structure of the domain (*Concept, SubConcept, SubSubConcept*)*
has_Language	*this property is defined to distinguish between English and Spanish resources*
has_College	*this property is defined to distinguish a College*
has_Course	*this property is defined to distinguish a Course*
has_Lecture	*this property is defined to distinguish a Lecture*
has_Professor	*this property is defined to distinguish a Professor*

- Protégé Reasoner (Pellet)
  Pellet is an additional component added to Protégé which provides a web service composition to detect unsatisfiable concepts and to diagnose bugs, such as (1) root clash, or (2) propagating errors due to dependencies between classes, etc. Refer to this site [8] for detailed information regarding the development of this reasoner. The architecture of *Pellet* is shown in Fig *1.3* (source [9]). We used *Pellet* to validate and repair our ontology, most of the generated errors in our design were related to having multilingual classes and multi-level subclasses.

Fig. 1.3 Pellet Reasoner



- Multilingual Ontology Specification
  In section 1.4.1 we reviewed different techniques to build a Multilingual Information Retrieval system that instead of using a thesaurus, explore the statistical information about the corpora. Oard and Dorr survey's [19] distinguishes three techniques: (1) *Automatic Thesaurus Construction, (2) Term Vector Translation and (3) Latent Semantic Indexing (LSI)*. Our approach is considered as a *Term Vector Translation*. Oard and Dorr [19] define this approach as follows: "We consider statistical multilingual text retrieval techniques in which the goal is to map statistical information about term use between languages... techniques which map sets of $tfidf$ term weights from one language to another [19]." We used a query translation method to retrieve multilingual documents with an expansion techniques for phrasal translation. In the following section we discuss how our information retrieval system works.

[8] http://www.mindswap.org/2003/pellet/
[9] http://www.mindswap.org/2003/pellet/architecture.png

1.4.1.4 Adding the Ontology to the Search Engine

The *HyperManyMedia* search engine uses a combination of the Vector Space Model (VSM) and the Boolean Model to find the most relevant documents for a query submitted by a user. The score of query q for document d is related to the cosine similarity between the document and query vectors in a Vector Space Model (VSM).

$$cos(x.x') = \frac{x^T \cdot x'}{|x| \cdot |x'|} = \frac{x^T . x'}{\sqrt{x^T x} \cdot \sqrt{x'^T x'}} \tag{1.1}$$

where $x \in \mathbb{R}^{|\mathbb{V}|}$, $x and x'$ are vector-space representations of two documents, T the 'transpose' operator and $x^T \cdot x'$ indicates the dot product between two vectors. It uses several refinements on VSM by extending the Boolean vector model and adding weights associated with terms and fields. *HyperManyMedia*'s scoring is influenced by the sum of the score for each term of a query. For each field, the score is the product of the following factors: Its "tf", "idf", and index-time boosting (refer to Table 1.3). The score is computed as follows,

$$\begin{aligned} score(q,d) &= coord(q,d) \times queryNorm(q) \times \sum(tf(tind) \\ &\times idf(t)^2 \times t.getBoost() \times norm(t,d)) \end{aligned} \tag{1.2}$$

Table 1.3 Terms used for computing the relevance of a query to a document

Term	Description
coord(q,d)	Score factor based on the number of query
norm(q)	Normalization factor for query q
tf (t in d)	Term frequency of term t in the document d
idf(t)	Inverse document frequency of term t overall documents
boost(t field in d)	Boosting factor for specific field
norm(t,d)	Normalization factor for term t in document d
Score(q)	Relevance of query q to document d

The semantic search engine in *HyperManyMedia* is governed by the RDF/OWL file that contains the complete ontology structure of the domain.

1.4.2 Designing a Visual Ontology-based Search Engine

This phase represents the mechanism of adding a visual ontology search interface to *HyperManyMedia* platform. The user navigates through the domain ontology by clicking on nodes. The complete graph represents the E-learning ontology, and each node represents a concept or subconcept. We used a specific DocuBurst as part of Prefuse[10] libraries, which works on documents level.

1.4.2.1 Prefuse Visualization Toolkit

This section represents the mechanism of adding a visual ontology search interface to the *HyperManyMedia* platform. The user navigates through the domain ontology by clicking on nodes. The complete graph represents the E-learning ontology, and each node represents a concept or subconcept.

Definition: The Prefuse Visualization Toolkit is a Java-based toolkit for building interactive information visualization applications. It supports a rich set of features for data modeling, visualization, and interaction. It

[10] http://prefuse.org/

provides optimized data structures for tables, graphs, and trees, a host of layout and visual encoding techniques, and support for animation, dynamic queries, integrated search, and database connectivity.

1.5 Evaluation

1.5.1 Evaluation Methodology

Section 1.3, provides a description of our methodology of designing and implementing a visual knowledge representation of a graphical model to solve a real problem of browsing and searching for lectures in a vast repository of colleges/course. It combines *Formal Concept Analysis (FCA)* with *Semantic Factoring* to decompose complex, vast concepts into their primitives in order to develop a knowledge representation for the *HyperManyMedia* platform. The main objective of this section is to test the usability of the Visual search engine.

1.5.2 Evaluation Results

Table 1.4 Usability Test for the Visual Search Engine

Test Type	Hierarchical Level	English Resources (Concepts/ SubConcepts)	Spanish Resources (Concepts/ SubConcepts)
Left button click	College (Concept)	√	√
	Course (SubConcept)	√	√
	Lecture (SubSubConcept)	√	√
	descriptive features from (SubSubSubConcept)	√	√
Right button click			
	Course (SubConcept)	√	√
	Lecture (SubSubConcept)	√	√
	descriptive features from (SubSubSubConcept)	√	√
Double-click			
	Course (SubConcept)	√	√
	Lecture (SubSubConcept)	√	√
	descriptive features from (SubSubSubConcept)	√	√

1.5.2.1 Usability Test

The usability test consists of evaluating each concept and subconcept presented in the visual interface. The test covered three levels of testing: 1) based on the hierarchical level of the ontology domain, 2) based on the English resources in each level, and 3) based on the Spanish resources in each level (refer to Table 1.4 for more details).

- **Functionality Test:**
  Testing the usability of the visual interface is related to the functions provided by the visual interface using the mouse. The following functionality is provided and each one serves a different purpose. In Table 1.4, we distinguish each one of these functionalisties and we run the test on each level separately.

Fig. 1.4 One Level Filtering of the query "Engineering"

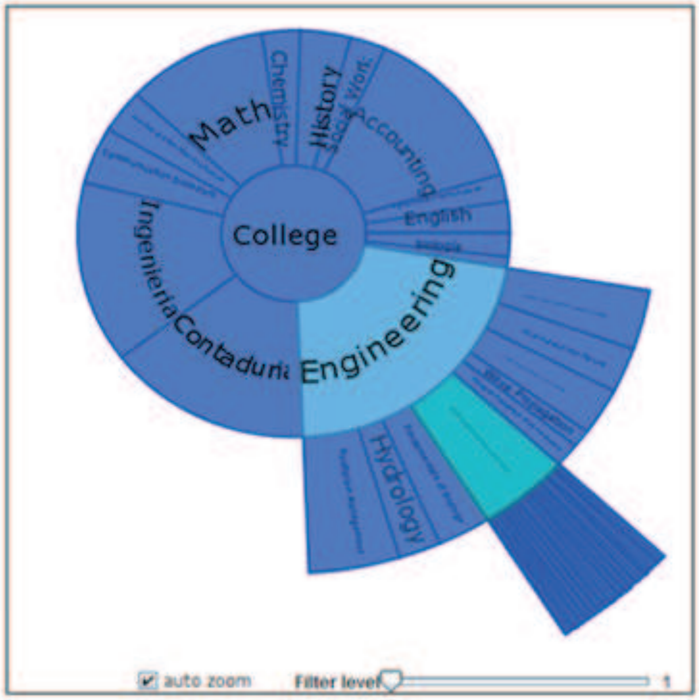
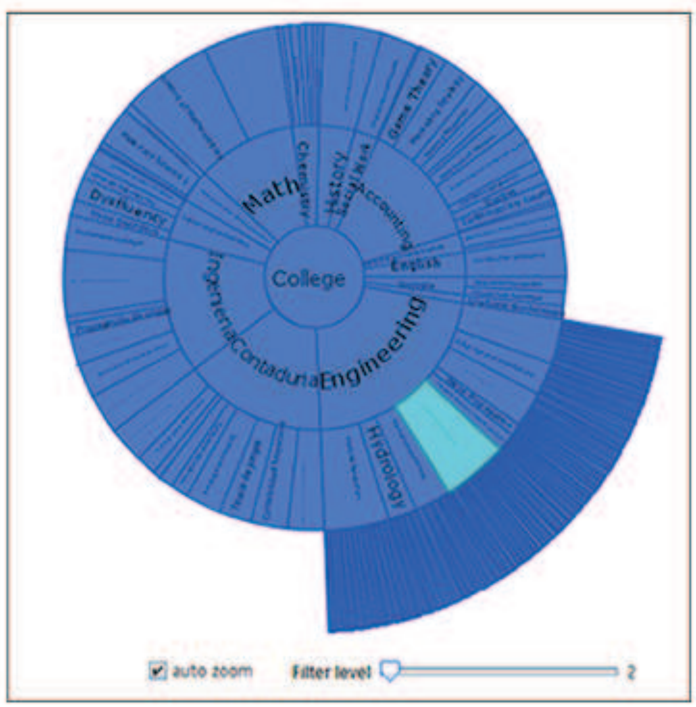


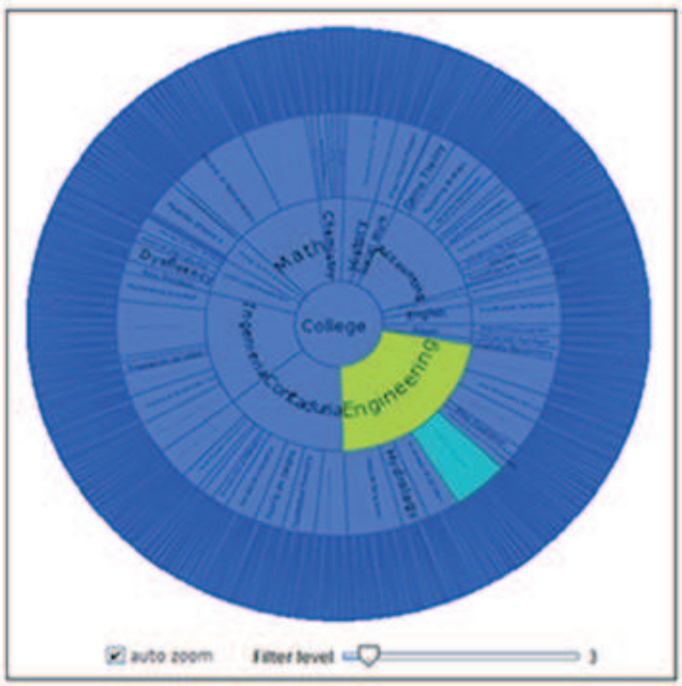
Fig. 1.5 Two Level Filtering of the query "Engineering"



1. Left Mouse Button Click on a Sector:
   If the level of filtering is equal to 1, the user is able to move from concept to subconcepts (e.g., Engineering –> Hydrology) and all the concepts underneath the specific concept “Engineering”; thus, all concepts under Engineering can be seen and retrieved visually (refer to Figure 1.4).

   a. In each sector, the user can go to a deeper level of granularity until reaching the leaves of that level in the graph.
   b. If the level of filtering is higher than 1 (refer to Figure 1.5 and 1.6), the user is able to see from the beginning an increased level of granularity equal to the level of filtering. However, by clicking on a specific concept, the level of granularity of that specific concept can be extended further. The process stops when it reaches the leaves in the graph.

Fig. 1.6 Three Level Filtering of the query “Engineering”



2. Double-Click on a Sector:

   a. In this case, the order of the visualization changes (e.g., double clicking on Engineering will bring the Engineering to the high level of the graph and it will be considered as the main concept the user would like to search underneath (refer to Figure 1.7).
   b. The user can navigate up and down through the graph (ontology); the upper hierarchy level represents an upper concept of the current node, and the lower level represents a subconcept of the current node.

   Table 1.4 presents the test that we ran on each individual hierarchical level in the visual search interface.
3. Right Mouse Button Click on a Sector:
   The retrieval system considers the concept/subconcept in this node as a query term and it retrieves all related concepts matching that query.

   a. The graph underneath that specific node becomes the root of the graph and all the concepts underneath this node are updated.

Fig. 1.7 Double-click on the “Engineering” Sector

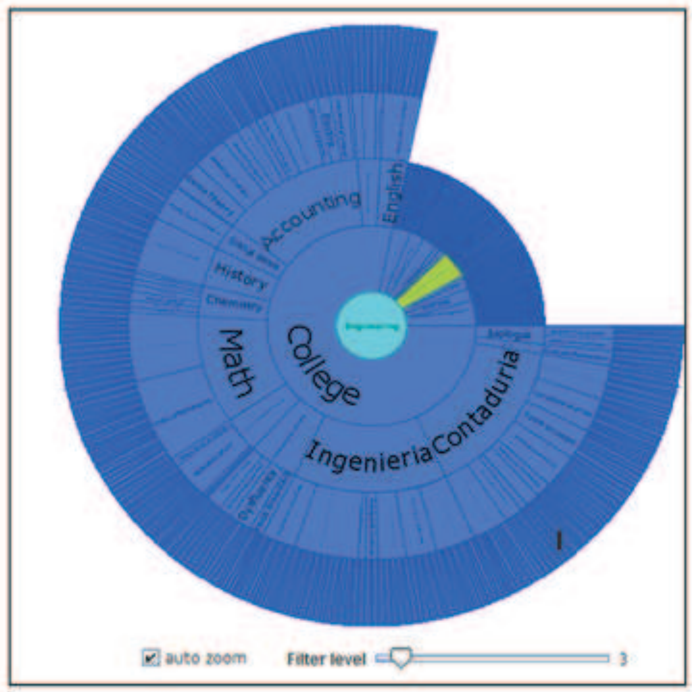
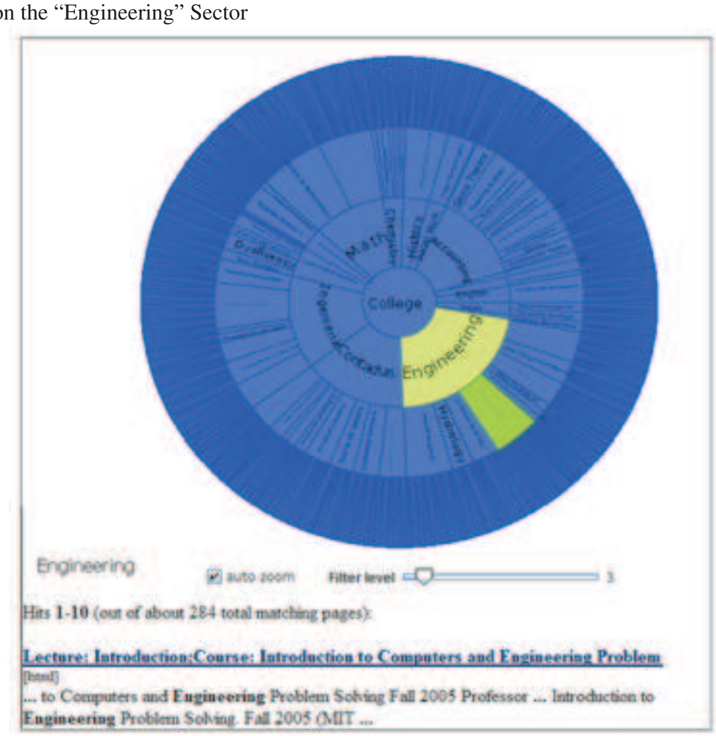


Fig. 1.8 Right clicking on the “Engineering” Sector



b. This procedure is repeated until the user reaches the leaves of the tree under that specific concept.

Figure 1.8 illustrates the retrieved documents after the user clicks with the right mouse button on the "Engineering" sector.

1.6 Conclusion

This study presents a visual information retrieval system that uses the representation of the semantic model (semantic set). It takes advantage of the *formal context concept* to define a simple conceptual graph as triples. In addition, it uses Protégé as a knowledge-based framework to build triples by adding sets of objects, sets of attributes, and defining the relationships between them. The semantic model satisfies the representation of the *HyperManyMedia* ontology. An important concept was considered in the design of the ontology which is the *Semantic Factoring* that decomposes a complex, vast concept into its primitives to develop the knowledge representation. Also, we argued that the most important factor in building the semantic model is defining the hierarchical structure in concepts. Another important factor is, discovering the association between concepts using *Concept Analysis* to generate a lattice graph, which represents the integrated ontology in the *HyperManyMedia* platform. Our approach has been implemented on the *HyperManyMedia* platform, and is already being used by online students at WKU[11]. An extension of the visual ontology search will be considered as future work, where tag clouds will be added to *HyperManyMedia* platform. The meaning of these tags will be generated by the semantic search of the users.

[11] http://www.wku.edu

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