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Semantic Resolution and Mapping in E-Learning System

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Semantic Resolution and Mapping in E-Learning System

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Dedication

To any one appreciates knowledge….

To every one helped me….

To my family and friends….

Yasmin I. Bali

Declaration

I certify that this thesis submitted for the degree of Master is the result of my own research, except where otherwise acknowledged, and that this thesis (or any part of the same) has not been submitted for a higher degree to any other university or institution.

Signed

Yasmin Ibrahim Bali

Date: …………………

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Abstract

Selecting appropriate learning services for a learner from a large number of heterogeneous knowledge sources is a complex and challenging task. This research illustrates and discusses how Semantic Web technologies and ontology can be applied to e-learning systems to help the learner in selecting an appropriate learning course or retrieving relevant information. This thesis presents the main features of an e-learning scenario and the ontology on which it is based, and then illustrates the ontology scenario associated with the training domain and the application domain. It presents semantic querying and semantic mapping approaches as one process to solve the problem of the semantic resolution in an e-learning system.

A prototype implementation based on an agent system for semantic resolution in a simple RFQ (Request for Quote) of an e-learning application had been implemented. Three ontologies built by PHP and the Apache Server each for a specific domain was defined. The system ontology was enhanced by making the system learn by giving it feedback on the found results. It is found that there is a limit on how much enhancement on such enhancement after which it would become counter productive.

Several experiments were conducted to understand exactly the behavior of our proposed model through taking several cases of learner request on different databases to enhance system ontology. Results obtained from

these experiments were compared with Google in terms of the relevancy of found results with respect to the learners' queries.

الملخص

اختيار مادة تعليمة على الانترنيت لمتعلم من مزود مواد تعليمية هي عملية صعبة وتحتاج الى جهد كبير. في هذا البحث سنناقش كيف سيتم تطبيق واستعمال تقنية الويب تيكنولوجي على نظام تعليمي اليكتروني لمساعدة المتعلم في اختيار المادة التعليمية التي يحتاجها بناءا على اهتماماته. ايضا سيتم عرض أهم الخصائص اللازم توفرها في هذا النظام التعليمي الالكتروني من ناحية الجانب التعليمي والجانب التطبيقي. وكما سيتم عرض عملية Semantic Querying وعملية Semantic Mapping كخطوة واحدة لحل مشكلة Semantic Resolution في هذا النظام التعليمي الاليكتروني.

تم عمل تطبيق عملي للنظام المذكور اعلاه باستخدام لغة PHP، حيث تم تعريف ثلاث Ontologies كل واحدة ضمن نطاق معين، في النهاية تم اختبار النظام على اكثر من حالة من حيث تغيير عدد الطلبات التي يطلبها المتعلم على قواعد بيانات مختلفة وفي النهاية تم مقارنة النتائج مع نتائج خاصة بنظام مستعمل سابقا مثل Google.

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Chapter One
Introduction

1.1 Introduction

E-learning aims at enhancing traditional time/place/content predetermined learning with a just-in-time/artwork-place/customized/on-demand process of learning. It builds on several pillars, viz. management, culture and IT. E-learning needs management support in order to define a vision and plan for learning and to integrate learning into daily work. It requires changes in organizational behavior establishing a culture of "learn in the morning, do in the afternoon" (Stojanovic, 2002). Thus, an IT platform, which enables efficient implementation of such a learning infrastructure, is also needed. Our focus here lies on Web technology that enables efficient, just-in-time and relevant learning.

The new generation of the Web, the so-called Semantic Web (Stojanovic, 2002), appears as a promising technology for implementing e-learning. The Semantic Web constitutes an environment in which human and machine agents will communicate on a semantic basis. One of its primary characteristics, viz. shared understanding, is based on ontologies as its key backbone (Stojanovic, 2002). Ontology enables the organization of learning materials around small pieces of semantically annotated learning objects. It is anticipated that Ontologies and Semantic Web technologies will influence the next generation of e-learning systems and applications (Abel, 2004).

E-learning is an area that can benefit from Semantic Web technologies. Recent advances in technologies for Web-based education provide learners with a broad variety of learning content available. Learners may choose between different lecture providers and learning management systems to access the learning content. On the other hand, the increasing variety of the learning material influences effort needed to select a course or training package. Adaptive support based on learner needs, background, and other characteristics can help in selecting appropriate learning and during the learning process.

From a pedagogical perspective, our implementation e-learning scenario system can be like an “enabling technology” allowing learners to determine the learning agenda and to be in control of their own learning. In particular, it allows learners to perform semantic querying for learning materials (linked to shared ontologies) and construct their own courses, based on their own preferences, needs and prior knowledge. By allowing direct access to knowledge in whatever sequence students require them, just-in-time learning occurs (Nejd 2001). At the other end of the spectrum, tutors are freed from the task of organizing the delivery of learning materials but must produce materials that stand on their own. This includes properly describing content and contexts in which each learning material can be successfully deployed. One possibility is metadata, i.e. tags about data that allow describing, indexing and searching for data.

A key challenge in building the Semantic Web, one that has received relatively little attention, is finding semantic mappings among the ontologies. Given the decentralized nature of the development of the Semantic Web, there will be an explosion in the number of ontologies. Many of these ontologies will describe similar domains, but using different terminologies and others will have overlapping domains (Doan, 2003). To integrate data from disparate ontologies, we must know the semantic correspondences between their elements.

For example, in an e-learning environment there is a high risk that two authors express the same topic in different ways. This means semantically identical concepts may be expressed by different terms from the domain vocabulary. In the context of the Web, ontology provides a shared understanding of a domain. Such a shared understanding is necessary to overcome differences in terminology. One application’s zip code may be the same as another application’s area code (Guo, 2007). Another problem is that two applications may use the same term with different meanings. In university A, a course may refer to a degree (like computer science), while in university B it may mean a single subject (CS 101). Such differences can be overcome by mapping the particular terminology to a shared ontology or by defining direct mappings between the ontologies.

In this research, we present our effort toward the problem of semantic resolution in an e-learning system, and the current preliminary implementations of the semantic resolution algorithms and ideas in a simple e-learning scenario. In our implementation, concepts in ontologies are represented as frame-like structures, and the semantic differences between agents are resolved at runtime through inter-agent communication, and semantic mapping algorithm is using ideas from heuristic methods for approximating partial matches.

Design of a prototype implementation of an agent system for semantic resolution in a simple RFQ (Request for Quote) of an e-learning application using PHP language is done, and three ontologies were defined: the first one (application ontology) specifies the learner who wants to choose the course to study. The second one describes the providers of the training domain, including the following information: course title, general description for the course, the most important topics in course, course level and the course credit hours. And the third one is for the learner aims to provide him with a feedback concerning his search results.

In our implementation, e-learning system allows the learner to make his request by entering some keywords he search for, then the system will search for the needed information in its ontology, after the system will return -according to the learner request- all the matching courses with the percentage of matching, in addition to the total execution time for each request. We conducted many experiments then we compared the achieved results with an existing implementing system like Google.

The structure of thesis is as follows. First this chapter includes the objectives and the scope of the study, chapter 2 presents the literature review in detail. An overview for the semantic web and e-learning is given in chapter 3. Current system model and the proposed system model including the contribution of this research are presented in chapter 4. Chapter 5 presents the experimental design tool. After, chapter 6 identifies and evaluates several experiments and presents the results of this research. Finally, the conclusion and the future work are presented in chapter 7.

1.2 Problems and Objectives

Research works on Semantic Web are aimed at making the semantic of web pages understood by programs, and may serve as a basis for resolving semantic differences between heterogeneous agents. Although the technologies developed in this effort are aimed at making web pages understood by programs, and can be considered, as a basis for resolving semantic differences between heterogeneous agents. However, additional methodology and mechanisms need to be developed if semantic resolution is to be done at runtime through agent interaction. *This is the primary objective of this research project.* So this research work is coming to present semantic querying and semantic mapping approaches to solve the problem of the semantic resolution in an e-learning system, so search engine can interpret and process information to better support users' queries.

1.3 Related Works

Many researchers have tried to cover a wide range of research problems in the Semantic e-learning, First, the scenario presented by (Guo and Chen, 2007) discuss how Semantic Web technologies and ontology can be applied to e-learning systems, then (S. Hatem, A. Ramadan and C. Neagu, 2005) present the work in progress to develop a framework for the Semantic Web mining and exploration, after the research done by (Abel, Barry, Benayache, Chaput, Lenne, and Moulin, 2004) present an ontology-based document-driven memory which is particularly adapted to an e-learning situation, at the same time (Moreale and Vargas-Vera, 2004) outline an e-learning services architecture offering semantic-based services to students and tutors, also (Tane, Schmitz, and Stumme ,2004) propose what is called "The Courseware Watchdog"; which it is a comprehensive approach for supporting the learning needs of individuals in fast changing working environments, other researchers (Doan, Madhavan, Dhamankar, Domingos, and Halevy, 2003) describe GLUE; a system that employs machine learning techniques to find such mappings, and finally, (Stojanovic, Staab, and Studer, 2002) present an approach for implementing the e-learning scenario using Semantic Web technologies.

1.4 Motivation

Today’s technology enhanced learning landscape is characterized by a high and growing number of heterogeneous educational service providers. For a user with a particular educational need, a typical scenario involves the user visiting one or several online educational centers, browsing their offers, collecting information about the courses (study programs, requirements, needed tools, prices, etc.), selecting the most appropriate course for his/her needs and preferences and, finally, registering it. This manual browsing is too time consuming and, typically, a user will visit just a very few online centers before making a decision.

Therefore, learning processes need to be fast and just-in-time. Speed requires not only a suitable content of the learning material (highly specified, not too general), but also a powerful mechanism for organizing such material. Also, learning must be a customized on-line service, initiated by user profiles and business demands. In addition, it must be integrated into day-to-day work patterns and needs to represent a clear competitive edge for the business. Learning needs to be relevant to the (semantic) context of the business.

The Semantic Web constitutes an environment in which human and machine agents will communicate on a semantic basis. One of its primary characteristics, viz. shared understanding based on the ontology backbone.

The ontology structure is used to define the logical structure of the learning materials. E-learning is often self-paced environment, so training needs to be broken down into small bits of information, which can be tailored to meet individual needs and skill gaps. But these chunks of knowledge should be well connected to create the whole course. So, greater attention should be given to design the structure of e-learning materials. It is natural to develop e-learning systems on the Web; thus a Web ontology language should be used.

1.5 Contribution

Our research extends semantic resolution process to become a cycle of *hypothesize-and-test*, as with most abductive, evidential reasoning systems. So we consider the semantic mapping not as a one step operation but rather a process that may take iterations to reach a conclusion in a way very similar to the ***Hypothesize-and-Test*** **process** commonly seen in evidential reasoning.

In our proposed model, the target term identified during semantic mapping is not a logical consequence but a hypothesis; there may be more than one target terms that match the source term (either with the same or different degree of similarity); and a hypothesis is more plausible if it is more similar to the source term. **In the "hypothesize" phase,** the agent generates and ranks hypothetical target terms (as described in "Semantic Mapping" step). **In the "test" phase,** the agent generates queries (as described in the "Semantic querying" step) to test the plausibility of current hypotheses. The answers to these queries expand the semantic querying of the source term, and help to differentiate existing hypotheses and possibly lead to the formation of new hypotheses in the next cycle.

1.5.1 Research Questions

In this research, we try to answer the following questions:

- How can we provide semantics for information exchanged over the Internet?
- How can we solve the problem of the semantic resolution in an e-learning system?
- What is the relation between complexity of the search and the Time?
- What factors are affected the time of exchanged information over the Internet?
- How to choose a threshold point to stop the learning process?
- How to hide heterogeneity?

1.5.2 Research Methodology

To answer the above questions, we designed a prototype implementation of an agent system for semantic resolution in a simple RFQ of an e-learning application using PHP language, and we defined three ontologies: the first one (application ontology) specifies the learner who wants to choose the course to study. The second one describes the providers of the training domain, including the following information: course title, general description for the course, the most important topics in course, course level and the course credit hours. And the third one is for the learner aims to provide him with a feedback concerning his search results.

In our e-learning system, the learner makes his request by entering some keywords he search for, then the system will search for the needed information in its ontology, after the system will return -according to the learner request- all the matching courses with the percentage of matching, in addition to the total execution time for each request. And in the mean time the user ontology returns a feedback to user concerning his search results. We conducted many experiments then we compared the achieved results with an existing implementing system like Google.

1.5.3 Research Players

There are two players in our systems:

1. The learner who plays the role of *the initiator* which starts a conversation by issuing the RFQ which contains source concepts that may not be understood by the learner provider.

2.The learner provider who plays the role of the *participant* whose actions is in response to that of the learner.

1.5.4 Research Instrument

Design of a prototype implementation of an agent system for semantic resolution in a simple RFQ of an e-learning application using PHP language is done.

1.5.5 Research Boundaries

This thesis deals with an implementation of an agent system for semantic resolution in a simple RFQ of an e-learning application in all times.

1.5.6 Research Obstacles

Through the initial research and reviewing the related literature, there are many limitations faced the researcher, and those limitations are:

1. Rarity of locally-related studies and researches.
2. Too much time is spent in collecting data to build the needed Database.
3. Too much time is spent in testing and analyzing the system.

Chapter Two

Literature Review

A wide range of research problems in the semantic e-learning had been published. Below, we have tried to have a balanced approach in which readers will not only gain a state-of-the-art literature review, but also will be able to understand the design and development of real world applications, prototypes and tools of e-learning in the Semantic Web.

First, Stojanovic, Staab, and Studer (2002) presented an approach for implementing the e-learning scenario using Semantic Web technologies. It is primarily based on ontology-based descriptions of content, context and structure of the learning materials and benefits the providing of and accessing to the learning materials.

“Making content machine-understandable” is a popular paraphrase of the fundamental prerequisite for the Semantic Web. In spite of its potential philosophical ramifications this phrase must be taken very pragmatically: content (of whatever type of media) is 'machine-understandable' if it is bound (attached, pointing, etc.) to some formal description of itself. This vision requires development of new technologies for web-friendly data description. The Resource Description Framework (RDF) metadata standard is a core technology used along with other web technologies like XML. Ontologies are meta- data schemas, providing a controlled vocabulary of concepts, each with an explicitly defined and machine processable semantics. By defining shared and common domain theories, ontologies help both people and machines to communicate concisely, supporting the exchange of semantics and not only syntax.

In the same time, promising areas for applying the Semantic Web are unlimited. In fact, each area, in which a lot of information should be provided and accessed in a distributed manner, searches for some semantic-based solution.

Stojanovic, Staab, and Studer on their paper presented an e-learning scenario that exploits ontologies in three ways:

- for describing the semantics (content) of the learning materials. This is the domain dependent ontology,
- for defining learning context of the learning material and
- for structuring learning materials in the learning courses.

This three-dimensional space enables easier and more comfortable search and navigation through learning material.

The purpose of their paper was to clarify possibilities of using ontologies as a semantic backbone for e-learning. Primarily, the objectives are to facilitate the contribution of and efficient access to information. But, in a broader or in Semantic Web's view, an ontology-based learning process could be a relevant (problem-dependent), a personalized (user-customized) and an active (context-sensitive) process. These are prerequisites for efficient learning in the dynamically changed business. This new view enables us to go a step further and consider or interpret the learning process as a process of managing knowledge in the right place, at the right time, in the right manner in order to satisfy business objectives - knowledge management. It means the merging of e-learning and knowledge management using the Semantic Web should be the promising integration.

Then, the researchers Doan, Madhavan, Dhamankar, Domingos, and Halevy (2003) described GLUE, which is a system that employs machine learning techniques to find such mappings. Given two ontologies, for each concept in one ontology GLUE finds the most similar concept in the other ontology. The researchers in this work give a well founded probabilistic definition to several practical similarity measures, and show that GLUE can work with all of them. Another key feature of GLUE is that it uses multiple learning strategies, each of which exploits well a different type of information either in the data instances or in the taxonomic structure of the ontologies. This research also describes a set of experiments on several real-world domains, and show that GLUE proposes highly accurate semantic mappings. Finally, the researchers extend GLUE to find complex mappings between ontologies, and describe experiments that show the promise of the approach.

With the proliferation of data sharing applications that involve multiple ontologies, the development of automated techniques for ontology matching will be crucial to their success. The researchers described an approach that applies machine learning techniques to match ontologies. Their approach, as embodied by the GLUE system, is based on *well-founded notions of semantic similarity*, expressed in terms of the joint probability distribution of the concepts involved. They also described the use of machine learning, and in particular, of *multi-strategy learning*, for computing concept similarities.

Moreover, the researchers introduced relaxation labeling to the ontology-matching context, and showed that it can be adapted to efficiently *exploit a variety of heuristic knowledge and domain-specific constraints* to further improve matching accuracy. Their experiments showed that GLUE can accurately match 66 - 97% of the nodes on several real-world domains. Finally, they have extended GLUE to build CGLUE, a system that *finds complex mappings between ontologies*. They described experiments with CGLUE that show the promise of the approach. A side from striving to improve the accuracy of our methods, their main line of future research involves extending their techniques to handle more sophisticated mappings between ontologies, such as those involving attributes and relations.

After the research done by Tane, Schmitz, and Stumme (2004) proposed what is called "The Courseware Watchdog"; which is a comprehensive approach for supporting the learning needs of individuals in fast changing working environments, and for lecturers who frequently have to prepare new courses about upcoming topics. As shown in their research, the Courseware Watchdog addresses the different needs of teachers and students to organize their learning material. It integrates, on the one hand, the Semantic Web vision by using ontologies and a peer-to-peer network of semantically annotated learning material. On the other hand, it addresses the important problems of finding and organizing material using semantical information. Finally, it offers a first approach to the problem of evolving ontologies.

The components of the Courseware Watchdog need further improvement. For instance, focused crawling has to be improved by offering further measures for computing the relevance of documents based on ontologies and available metadata, and ontology evolution needs further techniques for better reflecting changes in the underlying learning material, such as concept drift detection. Overall, the Courseware Watchdog indicates how a Semantic Web based approach increases the support of retrieval and management of remote (learning) resources, by providing tools for discovering and organizing them.

At the same time, Moreale and Vargas-Vera (2004) outlined an e-learning services architecture offering semantic-based services to students and tutors, in particular, ways to browse and obtain information through web services. They present a proposal for a student semantic portal providing semantic services, including a student essay annotation service. They also claim that visualization of the arguments presented in student essays could benefit both tutors and students.

The main contribution of their paper was outline architecture for e-learning services in the context of a semantic portal, the description of various scenarios within this architecture, including enrolment in a course and annotation of a student essay. Also they used ontologies to describe learning materials, annotation schemas and ontology of services.

Their architecture moves away from the traditional teacher-student model in which the teacher determines the learning material to be absorbed by students and towards a new, more flexible learning structure in which students take responsibility for their own learning, determine their learning agenda, including what is to be included and in what order. As well as having more choice, students also have wider access to semantic technologies such as annotation tools. At the other end of the spectrum, tutors are freed from the task of controlling the delivery of learning materials (which is now controlled by the student) and their role focuses more on the production of materials that stand on their own by being properly annotated so that they can be located in the correct contexts by semantic services.

In their research they implemented a service that performs question answering and one that carries out argumentation annotation in student essays. A feedback service could then use the essay question (possibly in the form of tutor determined settings) to determine what categories are expected to be prominent in an essay and alert the user if a relevant category is missing or under-represented. This will give students valuable clues as to whether they are answering the question correctly. There is clearly a lot more work needed to make this technology work well enough for large-scale deployment. Further work may include implementing and evaluating a functional version of the portal with the components described here. More functionality could then be implemented or even simply be provided by invoking services made available elsewhere on the Web.

This would be a further step towards a really open system that realizes the goal of a Semantic Web. In short, in their paper they presented a proposal for a distributed e-learning architecture comprising several e-learning services. Possible services include question-answering, online courses, tutoring systems and automated marking systems. Currently, two components have been developed. One is AQUA, a question-answering system that looks for answers in different resources. The second component is a student essay service, which uses a Meta discourse annotation schema for student essays. A visualization service then also provides a visualization of annotation categories relevant to the current question types. All the functionality described here is only part of what a full-fledged student semantic portal may eventually offer in the future but it is an important first step towards a really student-centered educational environment.

Also in the mean time, the research done by Abel, Barry, Benayache, Chaput, Lenne, and Moulin (2004) presented an ontology-based document-driven memory which is particularly adapted to an e-learning situation. They provide a thoroughly discussion of a learning organizational memory and they focus on the ontologies on which it is based. Their research work is situated at the crossroad of three domains: knowledge engineering, pedagogical design and semantic web and they provide interesting insights.

A course can be seen as an organization in which different actors are involved. These actors produce documents, information and knowledge that they often share. They present in their research an ontology-based document-driven memory which is particularly adapted to an e-learning situation. The utility of a shared memory is reinforced in this kind of situation, because the interactions do not usually occur in the same place and in the same time. First they precise their conception of e-learning and they analyze actors needs. Then they present the main features of their learning organizational memory and they focus on the ontologies on which it is based. They consider two kinds of ontologies: the first one is generic and concerns the domain of training; the second one is related to the application domain and is specific to a particular training program. They present their approach for building these ontologies and they show how they can be merged. Finally they describe the learning memory and the prototype we realized for two course units proposed in our universities.

Other researchers, S. Hatem, A. Ramadan and C. Neagu (2005) presented the work in progress to develop a framework for the Semantic Web mining and exploration, their research also discuss a practical method towards a Semantic Web application to e-learning along with its design framework and it is suggested to be applied in Sultan Qaboos University in Oman.

Nowadays, knowledge is distributed throughout the Web on millions of pages, PDF files, multimedia and other resources. The learner is not necessarily someone who is registered in a course or needs e-learning to support a particular course. Students and researchers need vast amount of material and spend considerable amount of time trying to learn about a particular subject or find relevant information. This research reports on the work in progress to develop a framework for Semantic Web mining and exploration, a practical method towards Semantic Web application to e-learning along with its design framework is suggested.

Their proposed approach will ensure that SQU develops an RDF repository reflecting the actual data and the Semantics of all of its resources including courses on WebCT and materials of the Visual Library. It will enable SQU Web developer to also annotate Arabic materials. Courses that require special privileges to be accessed can be handled according to the user profiles and privileges users have. The proposal will not actually cancel the role of the current WebCT system or Visual Video system; in fact it will empower the functionality of these two systems by presenting them to many users that do not even know of their existence. In addition to that, any material available at SQU Website or any of the computing services will be easily accessed by learners according to their privileges. One important advantage to using the Semantic Web concept with e-learning is that the university can advertise the courses they have, especially those offered by the Center for Community Service and Continuing Education, to learners interested in such services. E-learning and E-Business activities via the Semantic Web are expected to be an efficient activity.

And finally, the scenario presented by Guo and Chen (2007) discuss how Semantic Web technologies and ontology can be applied to e-learning systems to help the learner in selecting an appropriate learning course or retrieving relevant information. They also, present semantic querying and semantic mapping approaches.

It is clear that new styles of e-learning are some of the next challenges for every industry. Learning is a critical support mechanism for organizations and individuals to enhance their skills in the new economy. The incredible velocity and volatility of today’s markets require just-in-time methods for supporting the need-to-know of employees, partners, and distribution paths. It is also clear that this new style of e-learning will be driven by the requirements of the new economy: efficiency, just-in-time delivery, and task relevance.

Current approaches to e-learning implement the teacher-student model: Students are presented with material and then tested to assess their learning. However, e-learning frameworks should take advantage of semantic services interoperability.

The Semantic Web could offer more flexibility in e-learning systems through use of new emergent semantic Web technologies. Numerous document resources may be used during e-learning. Some are internal and made by several actors implied in the e-learning, others are available on the Web: online courses, course supports, slides, bibliographies, frequently asked questions, lecture notes, and so forth. Ontologies are a way of representing such formal and shared information. They can be used to index data indicating their meaning, thereby making their semantics explicit and machine-accessible. They also can be used in e-learning as a formal means to describe the organization of universities and courses and to define services. An e-learning ontology should include descriptions of educational organizations (course providers), courses, and people involved in the learning process.

So, we can summarize all the previous research works in the Semantic e-learning as in the following table:

Authors	Year	Paper Title	Contribution
Ljiljana Stojanovic, Steffen Staab, and Rudi Studer	2002	E-Learning based on the Semantic Web	Using ontologies as a semantic backbone for e-learning
AnHai Doan, Jayant Madhavan, Robin Dhamankar, Pedro Domingos, and Alon Halevy	2003	Learning to Match Ontologies on the Semantic Web	Describe GLUE, a system that employs machine learning techniques to find such mappings
Julien Tane, Christoph Schmitz, and Gerd Stumme	2004	Semantic Resource Management for the Web: An E-Learning Application	How an ontology- based tool suite allows to make the most of the resources available on the web
Emanuela Moreale and Maria Vargas-	2004	Semantic Services in E-Learning: an Argumentation Case Study	An architecture for e-learning services

Vera			
Abel, Barry, Benayache, Chaput, Lenne and Moulin	2004	Ontology-based Organizational Memory for E-Learning	An ontology building process and an ontology-based organizational memory for e-learning
Muna, S. Hatem, Haider, A. Ramadan and Daniel, C. Neagu	2005	E-Learning Based on Context Oriented Semantic Web	A context oriented Semantic Web Architecture for SQU Web Services
Wen-Ying Guo, and De-Ren Chen	2007	An Ontology Infrastructure for an E-Learning Scenario	An approach for implementing the e-learning scenario using Semantic Web technologies

Table (2.1) Research Works in the Semantic E-Learning

We can see clearly from table (2.1), that many researchers have tried to cover a wide range of research problems in the Semantic e-learning, but still more research work should be done on providing semantics for information exchanged over the Internet, also we need to extend the vision of the semantic web in order to enable search engine to interpret and process information to better support users queries, so this research work is coming to present semantic querying and semantic mapping approaches to solve the problem of the semantic resolution in an e-learning system, more specifically it will extend semantic resolution process to become a cycle of *hypothesize-and-test*, as with most abductive, evidential reasoning systems. Instead of separating semantic querying and mapping as two steps, they will be interwoven together so that additional evidence will be collected only when it is needed, and the hypothesized mappings are refined and discriminated against each other with each new evidence until the solution is gradually emerged.

Chapter Three
Semantic Web and E-Learning

3.1 Introduction

Increasingly, the World Wide Web (WWW) is used to support and facilitate the delivery of teaching and learning materials (Barker, 2000). This use has progressed from the augmentation of conventional courses through web-based training and distance learning to a newer form of WWW-based education, e-learning (Drucker, 2000). E-learning is not just concerned with providing easy access to learning resources, anytime, anywhere, via a repository of learning resources, but is also concerned with supporting such features as the personal definition of learning goals, and the synchronous and asynchronous communication, and collaboration, between learners and between learners and instructors (Maurer, 2000).

Researchers have proposed that, in an e-learning environment, the educational content should be oriented around small modules coupled with associated semantics (or metadata) to be able to find what one wants, and that these modules are related by a "dependency network" or "conceptual web" to allow individualised instruction. Such a dependency network allows, for example, the learning objects to be presented to the student in an orderly manner, with prerequisite material being presented first. Additionally, in an e-learning environment, students must be able to add extra material and links (i.e. *annotate*) to the learning objects for their own benefit or for that of later students (Downes, 2001).

3.2 Semantic Web

When Tim Berners-Lee invented the World Wide Web it was a mere collection of HTML documents. Soon and rapidly it grew to the stage we have at the moment. The Internet has become more than just a source of information. It has become a source of entertainment, communication and last but not least – business opportunities. However, even with the search engines as robust as Google many people just cannot efficiently search for information (Woroniecki, 2006).

The second-generation Internet is currently the hot topic both in industry and academia. It is perceived as a remedy for all problems we know from the current Internet. However, academia and industry defines the future Web in two different ways. Research centers mainly focus on the work on the Semantic Web. In this vision, the future Internet will be more than just human-understandable text (Czaj, 2006). The idea is to add machine processable meaning to the current and future information. The search engines on the Semantic Web will be able to understand both the information they index and the users' queries they process.

Semantic Web is the Holly Grail of the contemporary Internet companies. Instead of making the information machine-understandable, Semantic Web brings the whole communities of users to interact with the information and each other. Wikis allow groups of people to edit the information in truly collaborative fashion. Endeavors like wikipedia1 proved the immense potential of community impact. Semantic Web is also about the tagging. In services like deli.cio.us or Flickr, community users annotate bookmarks or photos they share with simple set of keywords (Westerski, 2006). As opposed to the old Web everyone can annotate each resource and in contrast to the Semantic Web there is no meaning applied to each keyword.

> Now, the current WWW is a powerful tool for research and education, but its utility is hampered by the inability of the user to navigate easily the nefarious sources for the information he requires. The Semantic Web is a vision to solve this problem. It is proposed that a new WWW architecture will support not only Web content, but also associated formal semantics (Barker, 2000). The idea is that the Web content and accompanying semantics (or metadata) will be accessed by Web agents, allowing these agents to reason about the content and produce intelligent answers to users' queries.

Finally, in the future the Semantic Web may not even be noticeable. The tools of the Semantic Web will be integrated into Virtual Learning Environments and Virtual Research Environments on our desktops, as well as in browsers and search engines. What we will have is a richer experience of IT that is better able to deliver the right information at the right time in the right way, so we can get on with the serious business of research and teaching (Matthews, 2005).

3.3 Semantic Web Architecture

The term "Semantic Web" encompasses efforts to build a new WWW architecture that supports content with formal semantics. That means content suitable for automated systems to consume, as opposed to content intended for human consumption. This will enable automated agents to reason about Web content, and produce an intelligent response to unforeseen situations (Stojanovic, 2002).

3.3.1 Layers of the Semantic Web

"Expressing meaning" is the main task of the Semantic Web. In order to achieve that several layers are needed. They are presented in the figure 3.1 (Berners-Lee, 2000), among which the following layers are the basic ones:

- The XML (eXtensible Markup Language) layer, which represents data;
- The RDF (Resource Description Framework) layer, which represents the meaning of data;
- The Ontology layer, which represents the formal common agreement about meaning of data;
- The Logic layer, which enables intelligent reasoning with meaningful data.

It is worth to note that the real power of the Semantic Web will be realized when people create many systems that collect web content from diverse sources, process the information and exchange the results with other human or machine agents. Thereby, the effectiveness of the Semantic Web will increase drastically as more machine-readable Web content and automated services (including other agents) become available (Staab, 2002). This level of inter-agent communication will require the exchange of "proofs". Two important technologies for developing the Semantic Web are already in place: eXtensible Markup Language (XML) and the Resource Description Framework (RDF).

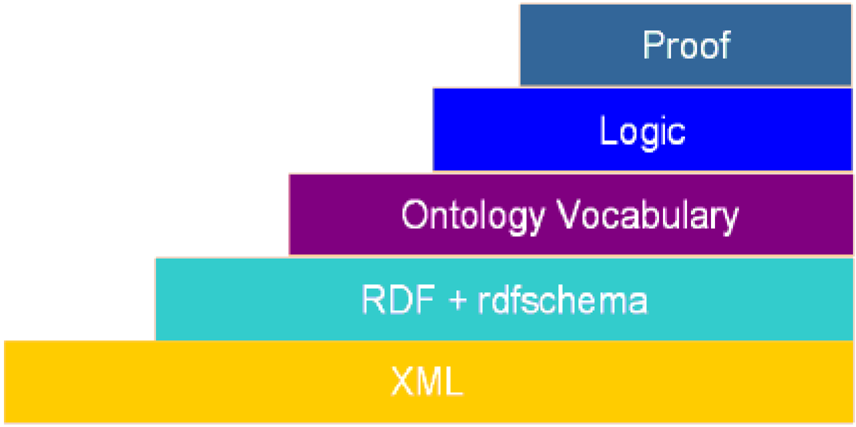


Fig (3.1) Layers of the Semantic Web Architecture

Based of the Ref (E-Learning based on the Semantic Web)

XML (Stojanovic, 2002) lets everyone create their own tags that annotate Web pages or sections of text on a page. Programs can make use of these tags in sophisticated ways, but the programmer has to know what the page writer uses each tag for. In short, XML allows users to add arbitrary structure to their documents but says nothing about what the structures mean (Erdmann & Studer, 2000). Meaning of XML-documents is intuitively clear, due to “semantic” mark-up and tags, which are domain-terms. However, computers do not have intuition. Tag-names per don't provide semantics.

DTDs (Document Type Definition) are a possibility to structure content of the documents. However, structure and semantics are not always aligned, they can be orthogonal. A DTD is not appropriate as a semantic language. The same holds for XML-Schema (Stojanovic, 2002), it only defines structure, though with a richer language. XML lacks a semantic model; it has only a “surface model", a tree. So, XML is not the solution for propagating semantics through the Semantic Web. It only has the role as a "transport mechanism", viz. as an easily machine-processable data format.

The RDF (Stojanovic, 2002), provides a means for adding semantics to a document. RDF is an infrastructure that enables encoding, exchange and reuse of structured metadata. Principally, information is stored in the form of RDF statements, which are machine understandable. Search engines, intelligent agents, information broker, browsers and human users can understand and use that semantic information. RDF is implementation independent and may be serialized in XML (i.e., its syntax is defined in XML). A process in which semantic information is added to the web documents is called semantic annotation (Handschuh, 2001). RDF, in combination with RDF Schema (Stojanovic, 2002), offers modeling primitives that can be extended according to need. Basic class hierarchies and relations between classes and objects are expressible in RDFS. However, the model suffers from a lack of distinction between object and meta level, which makes it unintuitive. In general, RDF(S) seems to suffer from a lack of formal semantics for its modeling primitives, making interpretation of how to use them properly an error-prone process.

A solution to this problem is provided by the third basic component of the Semantic Web, viz. ontologies. In philosophy, ontology is a theory about the nature of existence, about what types of things exist; ontology as a discipline studies such theories (Handschuh, 2001). Artificial Intelligence and Web researchers have co-opted the term for their own jargon, and for them an ontology describes a formal, shared conceptualization of a particular domain of interest.

Ontologies are specifications of the conceptualization and corresponding vocabulary used to describe a domain (Gruber, 1993). They are well-suited for describing heterogeneous, distributed and semi structured information sources that can be found on the Web. By defining shared and common domain theories, ontologies help both people and machines to communicate concisely, supporting the exchange of semantics and not only syntax. It is therefore important that any semantic for the Web is based on an explicitly specified ontology. By this way consumer and producer agents (which are assumed for the Semantic Web) can reach a shared understanding by exchanging ontologies that provide the vocabulary needed for discussion.

Ontologies typically consist of definitions of concepts relevant for the domain, their relations, and axioms about these concepts and relationships. Several representation languages and systems are defined. A recent proposal extending RDF and RDF Schema is OIL (Ontology Interchange Language) (Fensel, 2001). OIL unifies the epistemologically rich modeling primitives of frames, the formal semantics and efficient reasoning support of description logics and mapping to the standard Web metadata language proposals. The DAML+OIL language (Stojanovic, 2002) has also been developed as an extension to XML and RDF. It is a representation language for describing web resources and supporting inference over those resources. It provides a rich set of constructs for creating ontologies and to markup ontologies so it is machine readable and understandable.

3.4 Semantic Web and E-Learning

Key property of the Semantic Web architecture (common-shared-meaning, machine-processable metadata), enabled by a set of suitable agents, seems to be powerful enough to satisfy the e-learning requirements: fast, just-in time and relevant learning. Learning material is semantically annotated and for a new learning demand it may be easily combined in a new learning course (Staab, 2002). According to his/her preferences, user can find useful learning material very easily. The process is based on semantic querying and navigation through learning materials, enabled by the ontological background.

In fact, the Semantic Web could be treated as a very suitable platform for implementing an e-learning system, because it provides all means for (e-learning) ontology development, ontology-based annotation of learning materials, their composition in learning courses and proactive delivery of the learning materials through e-learning portals. In the following (Table 3.1) a summary view of the possibility to use the Semantic Web for realizing the e-learning requirements is presented.

Requirements	**e-Learning**	**Semantic Web**
Delivery	Pull – Student determines agenda	Knowledge items (learning materials) are distributed on the web, but they are linked to commonly agreed ontologies. This enables construction of a user-specific course, by semantic querying for topics of interest.
Responsiveness	Reactionary – Responds to problem at hand	Software agents on the Semantic Web may use commonly agreed service language, which enables co-ordination between agents and proactive delivery of learning materials in the context of actual problems. The vision is that each user has his own personalized agent that communicates with other agents.

Access	Non-linear – Allows direct access to knowledge in whatever sequence makes sense to the situation at hand	User can describe situation at hand (goal of learning, previous knowledge,...) and perform semantic querying for the suitable learning material. The user profile is also accounted for. Access to knowledge can be expanded by semantically defined navigation.
Symmetry	Symmetric – Learning occurs as an integrated activity	The Semantic Web (semantic intranet) offers the potential to become an integration platform for all business processes in an organization, including learning activities.
Modality	Continuous – Learning runs in parallel and never stops	Active delivery of information (based on personalized agents) creates a dynamic learning environment.
Authority	Distributed – Content comes from the interaction of the participants and the educators	The Semantic Web will be as decentralized as possible. This enables an effective co-operative content management.
Personalization	Personalized – Content is determined by the individual user's needs and aims to satisfy the needs of every user	A user (using personalized agent) searches for learning material customized for her/his needs. The ontology is the link between user needs and characteristics of the learning material.
Adaptively	Dynamic – Content changes constantly through user input, experiences, new practices, business rules and heuristics	The Semantic Web enables the use of knowledge provided in various forms, by semantically annotation of content. Distributed nature of the Semantic Web enables continuous improvement of learning materials.

Table (3.1) Benefits of using Semantic Web as a technology for E-Learning Based on the Ref (E-Learning based on the Semantic Web)

3.5 Short, Medium and Long Term Expectation of the Semantic Web

The development of the Semantic Web is at an extremely early stage and few applications are currently up and running. This makes reliable predictions extremely difficult to make. In this section we analyze potential Semantic Web applications. By making the potential benefits and fundamental problems of the Semantic Web explicit, we point out what the important issues are, and their implications for successful uptake in the short, medium and long terms (Ossenbruggen, 2002).

3.5.1 Short Term

Uses of the Semantic Web in the short term will emerge in situations where local benefit is gained immediately, without having to rely on a more global uptake. The usage of Semantic Web technology may not even be obvious to end users, but hidden behind the scenes (similar to the majority of current XML deployment, that is not visible to end-users but applied server-side). While these applications use Semantic Web technology, they will add little to the perception of the Semantic Web as a whole (Ossenbruggen, 2002). An example of such an application is the use of RDF in Mozilla's configuration and preference files. Here, RDF is used as a local storage format, since the application's data is more readily described in RDF's graph of triples model than in XML's ordered hierarchy model.

Similarly, applications which require the exchange of simple EER/UML (Extended Entity-Relationship/Universal Modeling Language)-like class/subclass data models over the Web, such as CASE and database modeling tools can use RDF Schema as the exchange format. This provides a common syntax for easily agreed-upon data modeling semantics.

User groups who are currently creating their own ontologies in their own languages, for example in biology, medical and arts fields, are able to provide Web-compatible serializations of their ontologies using the current version of DAML+OIL. The question is whether the currently available language (DAML+OIL) and the language to be developed for the Web OWL (Web Ontology Language) are sufficiently powerful for their purposes e.g. the full complexity of thesauri like the AAT (Art and Architecture Thesaurus) goes beyond the expressive capabilities of DAML+OIL (Ossenbruggen, 2002).

3.5.2 Medium Term

While applications that will emerge in the short term use currently available technology in a local context, medium term applications will use current technology in a more global, distributed context (Ossenbruggen, 2002). For example, the use of Dublin Core for annotating documents on the Web is only useful for finding, e.g., all articles written by a certain author, when all articles are annotated with the corresponding Dublin Core attribute. Similarly, providing CC/PP descriptions for devices is only effective when sufficient descriptions are available and are made use of in the complete information chain.

Another class of medium term applications is those that use newly-developed technology in a local context, for instance educational content adaptation services using local documents or databases. Such applications might, for example, use the future Web Ontology Language in a local context to provide advanced knowledge-intensive inference and reasoning (Ossenbruggen, 2002). These applications will be similar to today's knowledge-intensive applications, with the added benefit of using ontologies and data in a format that is easily exchangeable over the Web, and the availability of off-the-shelf tool support. Other examples include support for agent-based Semantic Web services among specific user groups, such as supplier/merchant extranet services. For example, services that allows product profiles to be compared among a number of manufacturers that have committed to a specific ontology.

3.5.3 Long Term

Long term use of the Semantic Web will be in applications that use yet-to-be developed technology requiring uptake on a global scale. For instance, in the field of e-learning it may become possible to automatically generate courses based on learning objects from all over the world. Another example of this type of application is the scenario sketched at the beginning of the Scientific American article "The Semantic Web"' by Berners-Lee et al. (Berners, 2001). The scenario sketches the ultimate goal of the Semantic Web, a Web where software agents are able to access a wide range of web services to autonomously perform a wide range of complex tasks on behalf of their user or user groups.

While this scenario has led to high expectations of the Semantic Web (and contributed significantly to the hype that surrounds it), one can doubt its feasibility, even in the longer term (Ossenbruggen, 2002). These types of applications will only work if all of the many parties involved participate and obey the right protocols, on various levels. It requires parties to:

- Employ sufficiently rich metadata annotations on all their Web content;

- Commit to common vocabularies of which the expressivity goes far beyond that of, for example, RDF Schema and DAML+OIL;

- Commit to yet-to-be-developed standards for Web service description, discovery, deployment, etc.;

- Commit to yet-to-be-developed standards for Semantic Web query languages;

- Perform all processing in a way that can be controlled, verified and trusted by the end-user.

In addition to these socio-economical problems, a fundamental conceptual problem is the "automatic lookup" of terms across ontologies to make applications work that did not *a priori* commit to a common ontology. This can only be on a "best effort" basis, which may suffice for many applications, but not for the type of applications as described in this scenario -- where trust is of key importance. An important open architectural issue is the level of distribution that is required to realize the amount of storage and processing required. Part of the initial success of the Web can be explained by its relatively simple *client/server* model; a model that still dominates the Web today: document storage is centralized at the server-side, as is large scale processing such as performed by search engines (Seti, 2001). An alternative, potentially more powerful approach is a peer-to-peer model for storing and processing data. Its success has already been demonstrated in projects such as *SetiHome* (Jacco, 2002) (distributed, client-side computing) and *Napster* (distributed, client-side storage).

The peer-to-peer approach is also being exploited by the Grid Forum (Ossenbruggen, 2002). Grid computing originated in the particle physics community (as did the current Web), this time driven by the need to process the huge amount of data that will be generated by next generation particle accelerators. Instead of relying on a few supercomputers (whose power would be insufficient and costs would be too high) the grid would distribute the work over a large number of ordinary desktop computers connected over the Internet. The concept was soon adopted by other research communities that required large amounts of storage and processing resources (ranging from climate simulations to DNA analysis). The metaphor of the electricity grid has inspired this model of computing, where the global Internet offers a wide range of computing resources that are available everywhere.

Most of the current grid-related projects focus on the lower-level aspects of the common middleware layer needed to do distributed computing in an efficient, safe and manageable way, that is, building the infrastructure for the “data grid” and the “compute grid”. Other projects, however, have already started investigating the building of a “knowledge grid” on top of these layers. The goals of such a knowledge grid are in essence identical to those of the Semantic Web. There is no reason why the architecture of Semantic Web should be restricted to the client/server model, and the computing power and distributed management of the grid model might eventually facilitate the more complex distributed reasoning required for scenarios such as that sketched by Berners-Lee et al. (Berners, 2002).

Chapter Four

System Model

4.1 Introduction

When two people engage in a conversation and one does not understand a term mentioned by the other, the listener would *ask* the other to clarify or explain the meaning of the term. The other person would try to answer it by define the term in terms she thinks the listener would understand. If the answer is not understood, more questions may follow. This process may continue until the term in question is completely understood (either the term is mapped to one the listener is familiar with or a new term with clear semantics is learned) or the listener gives it up. The listener can understand a foreign term because the two people share the meanings of some common terms, which we attempt to model by the base ontology in our approach. The process of achieving semantic resolution here involves two basic operations, ***Semantic Querying,*** which gradually reveals the definition of the foreign term in the terms of the base ontology, and ***Semantic Mapping,*** in which the definition of the foreign term is mapped to a term in the listener's ontology. (Peng, 2007). We briefly describe each in the following subsections, and address technical issues involved in the subsequent sections.

4.2 Current System Model

In this system, a learner agent broadcasts its requirements to all agents, those agents who are able to meet the demand reply with their services with product information. For example, let A1 the individual who wants to choose the course to study (learner), and A2 the learner provider. They share a common ontology ONT-0, which gives details for learning materials parameter such as course title, general description for the course, the most important topics in course, course level and the course credit hours. Each has its own specialized ontology ONT-1 defines semantics of learning materials to order for A1, while ONT-2 defines items in learning provider for A2 based on its own system (see Figure 4.1).

During negotiation:

- A1 sends a RFQ to A2 a message "English_course" for example, a term defined in ONT-1.
- Before A2 determines a quote, it needs to understand what A1 means and if there exits a semantically similar term in its catalog as defined in ONT-2.
- This process is called **"Semantic Resolution"** which consists of two steps: Semantic Querying and Semantic Mapping, which we will explain more in the following subsections.

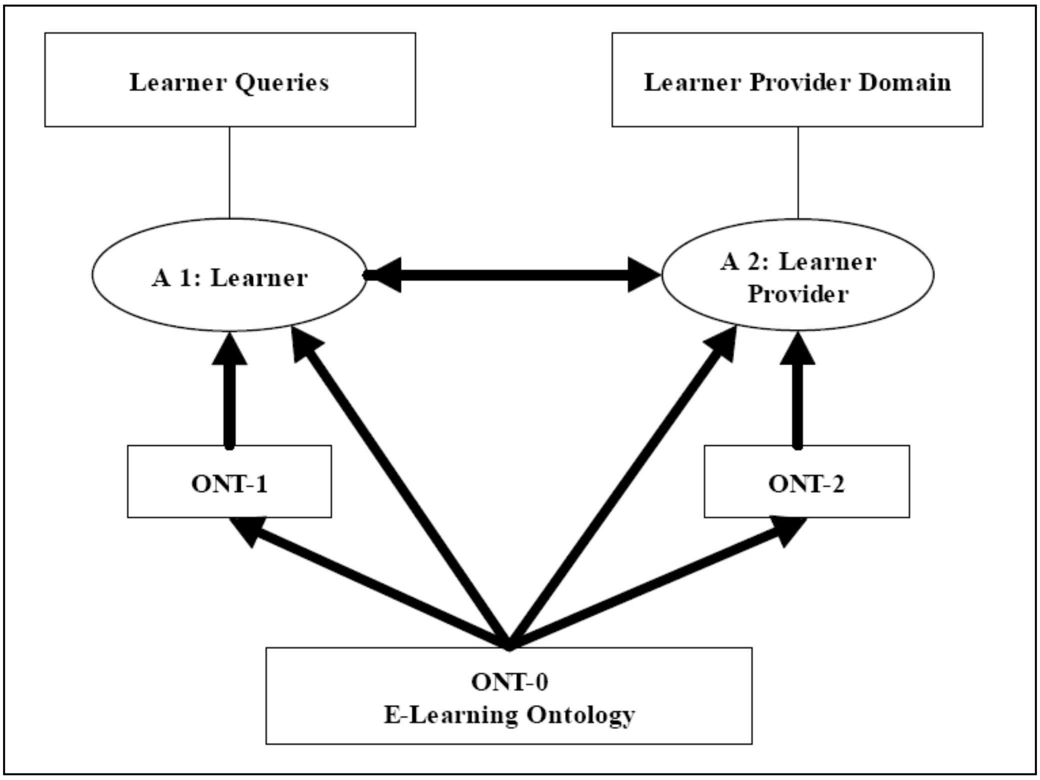


Figure (4.1) A simple RFQ E-Learning Scenario involving two agents Based on Ref ("Request for Quote" in E-Commerce)

4.2.1 Operations for Semantic Resolution

4.2.1.1 Semantic Querying

Since A2 only understand ONT-0 and ONT-2, it might not understand some terms in the RFQ from A1. Similar to a conversation of two strangers, A2 would ask what A1 means by this term via some agent communication language. We call this process of obtaining the description of a term/concept from a different ontology Semantic Querying, and call the two agent-specific ontologies ONT- 1 and ONT-2 in our example the source and target ontologies, respectively. When the querying finishes, A2 will get an extended normal form of the given ONT-1 concept with respect to ONT-0 (Ding, 2005).

4.2.1.2 Semantic Mapping

The extended normal form from the semantic querying step provides much information about an ONT-1 concept to A2. However, for A2 to truly understand this concept, it needs to map or re-classify this description into one or more concepts defined in its own (target) ontology ONT-2. This is accomplished by the Semantic Mapping step. In this step, the extended normal form of the source concept attempts to match the extended normal forms of concepts in the target ontology. Due to the structural differences, concepts from different ontologies are likely to match each other only partially. All partially matched target concepts are considered candidate maps of the source concept (Ding, 2005).

Semantic resolution is thus similar to abdicative reasoning process, semantic querying corresponding to evidence collection, and semantic mapping to hypothesis generation. All partially matched target concepts are considered candidate or hypothesized maps of the source concept, each of which can explain the source concept to different degrees based on the base ontology. If the best candidate is satisfactory, then a quote is generated by A2 and sent to A1. Otherwise, additional steps of inter-agent interactions may be taken. For example, if the best candidate, although unsatisfactory, is sufficiently better than all others, then its description is sent back to A1 for confirmation. If the first few leading candidates have similar level of satisfaction, then questions that discriminate some candidates over others will be sent to A1.

4.2.2 Communication Protocol for Semantic Resolution

Agents in the previous scenario communicate with each other by exchanging messages encoded FIPA ACL messages, following the Semantic Resolution Protocol (SRP), this SRP is used to support agent communication for both semantic querying and semantic mapping, for that we need to have (A) an agent communication language (ACL) to encode messages, (B) a content language to encode the content of a message, and (C) a communication protocol that specifies how these messages can be used for meaningful conversations (Peng, 2002). For reasons including clearly defined semantics and standardization support, we have selected FIPA ACL as the ACL for our project, we choose PHP as the content language because it is also the language for ontology specification.

The design of this system follows FIPA Interaction Protocol convention, which requires the definitions of (1) the acts involved in interaction processes, (2) the roles played by the actors in interaction processes, and (3) the phase transitions of the interaction process. There are two players in our protocol (it may be easily extended to involving multiple players in other models), the learner (A1) and the learner provider (A2). The learner plays the role of *the initiator* which starts a conversation by issuing the RFQ which contains source concepts that may not be understood by the learner provider. The learner provider plays the role of the *participant* whose actions are in response to that of the learner.

Performatives used in the protocol represent the communicative acts intended by the players (Peng, 2002). The following FIPA performatives are selected for the protocol:

A. Call-for-proposal (CFP): the action of calling for proposals to perform a given action. This is used by learner to ask the learner provider to propose a quote for a RFQ.

B. Propose: the action of submitting a proposal to perform a certain action, given certain preconditions. This is used to turn a proposed quote.

C. Accept-proposal: the action of accepting a previously submitted proposal to perform an action.

D. Reject-proposal: the action of rejecting a submitted proposal to perform an action.

E. Terminate: the action to finish the interaction process.

F. Inform: the action of informing that certain propositions are believed true.

G. Not-understood: the action of informing the other party that its message was not understood. This is used by the learner to request the learner provider or vice versa to send the description of a term it does not understand in the previous message.

H. Query-if: The action of asking another agent whether or not a given proposition is true. This is used by the learner provider in semantic mapping to ask the learner to confirm if a candidate concept is an acceptable match for the given source concept.

I. Confirm: the action of confirming that given propositions are believed to be true. This is used by the learner to confirm a target concept received in the incoming "query-if" message from the learner provider.

J. Disconfirm: the action of informing that given propositions are believed false.

The first 5 performatives are for RFQ; the rest are for semantic querying and mapping. The phase transitions in the protocol are given in the message-flow diagram in Figure 4.2.

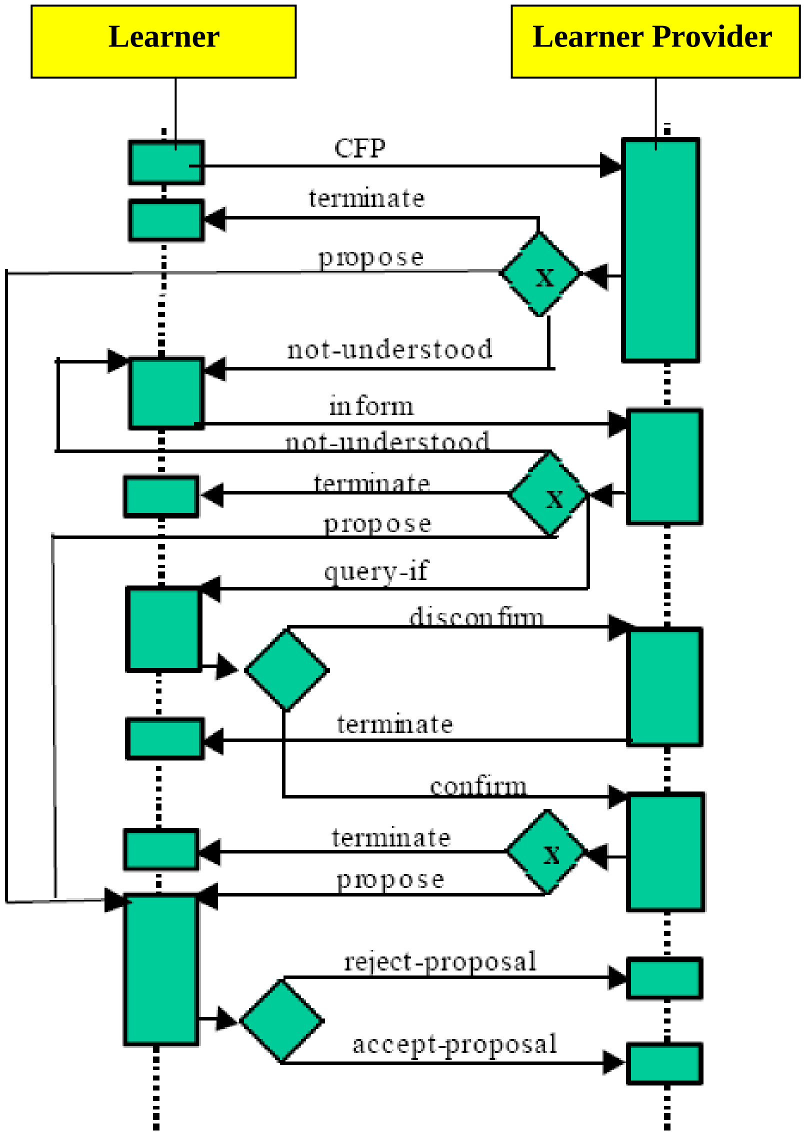


Figure (4.2) State transition diagram of the Semantic Resolution Protocol Based on Ref ("Request for Quote" in E-Commerce)

4.2.3 Algorithms for Semantic Resolution

The objective of semantic resolution is to find a concept in the target ontology whose description best matches the description of a given concept defined in the source ontology. Because agent-specific ontologies often have different structures and use different concept names, concept matching is seldom exact. Partial matches, which can occur even if a single ontology is involved, become more prevalent when different are no longer adequate. Approximate reasoning that at least gives a ranking for all partially matched target concepts is required (Ding, 2005). In many applications, these more formal approaches may not work, either because the assumptions made for them cannot be met or the information needed is not available. Heuristic approximation becomes necessary.

Since A2 only understands ONT-0, but not the "English_course" from A1's RFQ, it asks A1 by using agent communication language. After obtaining the description of the term from different ontology, A2 starts its matchmaking process. The process of matchmaking results in a learner who has a list of potential trade partners, each with an associated partially specified service description. This description defines the set of possible services interested to the learner provider.

The following is the demonstration about how to implement the RFQ case.

- The extended "English_course" in a semantic querying provides rich information to A2.
- However, in order to let A2 truly understand this concept, it is necessary to map or re-classify this description into one or more concepts defined in its own ontology ONT-2.
- This can be accomplished by introducing different ontology likely to match. All partially matched target concepts are considered as candidate maps of the source concept. If the best candidate is found, a quote is generated by A2 and then sent to A1. Otherwise, additional steps of inter-agent interactions may be taken. For example, if the best candidate, although unsatisfactory, is sufficiently better than all others, then its description is sent back to A1 for confirmation. If the first few leading candidates have similar level of

satisfaction, then questions that discriminate some candidates over others will be sent to A1.

For our scenario, Let α be the set of all training provider in a given repository (Guo, 2007). For a given query Q, the matchmaking algorithm of the repository host returns the set of all training providers that are compatible matches(Q):

matches(Q) = {A ∈ / α compatible(A, Q)}

Two descriptions are compatible if their intersection is satisfiable.

The query from the requester

Query = (training profile (items
Π Course Title
Π Course General Description
Π Course Topics
Π Course Level
Π Course HRs

4.3 Proposed System Model

Our proposed system model will be extending semantic resolution process to become a cycle of hypothesize-and-test, as with most abductive, evidential reasoning systems. So we consider the semantic mapping not as a one step operation but rather a process that may take iterations to reach a conclusion in a way very similar to the Hypothesize-and-Test process commonly seen in evidential reasoning. When we have several candidate mappings exist for the source concept, if the best candidate is satisfactory, then a quote is generated by A2 and sent to A1. Otherwise additional steps of inter-agent interactions may be taken to select one most suitable candidate. (See figure 4.3)

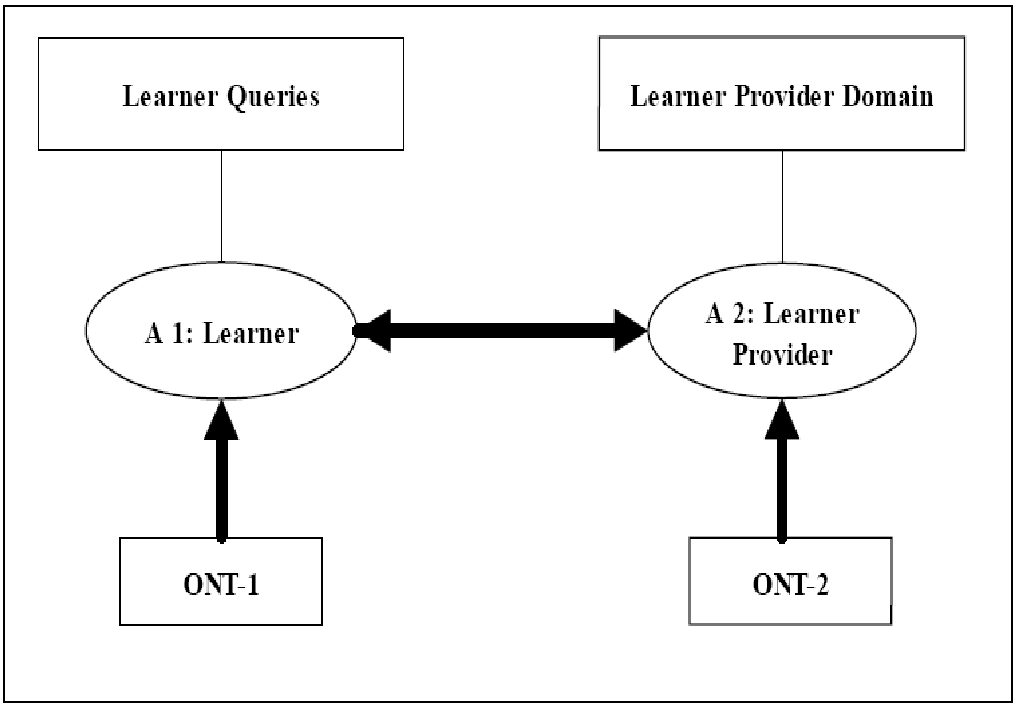


Figure (4.3) Proposed RFQ E- Learning Scenario involving two agents

Like other types of abductive reasoning, a target term identified during semantic mapping is not a logical consequence but **a hypothesis;** there may be more than one target terms that match the source term (either with the same or different degree of similarity); and a hypothesis is more plausible if it is more similar to the source term. As an abductive reasoning, the semantic resolution shall be conducted as a cycle of hypothesize-and-test. <u>**In the "hypothesize" phase,**</u> the agent generates and ranks hypothetical target terms (as described in "Semantic Mapping" step). <u>**In the "test" phase,**</u> the agent generates queries (as described in the "Semantic querying" step) to test the plausibility of current hypotheses. The answers to these queries expand the semantic querying of the source term, and help to differentiate existing hypotheses and possibly lead to the formation of new hypotheses in the next cycle.

The Contribution of this Research is extending semantic resolution process to become a cycle of *hypothesize-and-test,* as with most abductive, evidential reasoning systems. So we consider the semantic mapping not as a one step operation but rather a process that may take iterations to reach a conclusion in a way very similar to the *Hypothesize-and-Test* process commonly seen in evidential reasoning. When we have several candidate mappings exist for the source concept, if the best candidate is satisfactory, then a quote is generated by A2 and sent to A1. Otherwise, additional steps of inter-agent interactions may be taken to select one most suitable candidate.

Chapter Five

Experimental Design

5.1 Introduction and Experiments Overview

In this chapter, we will review the experiments and the test-bed implementation used to verify our model. These experiments produced the results that are discussed and evaluated in the next chapter.

In this section, we give an overview to both the objectives and the experiments setup that we conducted in order to test our model outlined in the previous chapter.

We have conducted two main experiments in order to verify our model:

1. Testing relevancy of learner request before determining Threshold Point.
2. Testing relevancy of learner request after determining Threshold Point.

In these experiments, the needed data from the Internet was collected in order to build a database, seventy five different descriptions for a chosen course was done, in one case of our testing we selected "Introduction to computer science", the data that was collected includes the following information: course title, course description, course topics, course level, and course credit hours (see Appendix A).

The procedures of conducting the experiments can be summarized as the followings:

- The learner can make his request by entering some keywords that he is searching for in the fields of the course information according to his interest.
- The system then will search for the needed information in its ontology.
- After that the system will return all the matching courses with the percentage of matching, in addition to the total execution time for each request.

- Results of the experiments were compared with an existing implementing system like Google.
- In the mean time, the system will give a feedback for the learner concerning his search request.

A snapshot of the system results for one request is shown in figure 5.1.

Title ▲	General description	Topic	Credit hours	Level	Ratio
An Introduction to Computers Ration = 1.00	This course covers all parts of the computer, i	The Parts of the Computer Computer Terminology Disk Drivers Disk Utilities	3 R = 0	2 R = 0	0.33
Introduction to Computer Ration = 0.00	To understand the digital world, the best plac	History of the computers Four Components of the Computers Description of	2 R = 1	1 R = 1	0.67
Introduction to Computer Ration = 0.00	Designed to give beginning students a basic	Personal Computers PC Components Computer Terminology Windows 200	3 R = 0	1 R = 1	0.33
Introduction to Computer Ration = 0.00	Prepares students for the use of the computer	Creation and maintenance of folders and files Networks Information access	2 R = 1	1 R = 1	0.67
Introduction to Computers Ration = 1.00	This course is a general introduction to comp	Computer Anatomy Computer Software Computer Applications Computer S	3 R = 0	1 R = 1	0.67
Introduction to Computers Ration = 1.00	This course will introduce computer hardware	Hardware Software Basic Operations Keyboard Symbols Health and Safety	3 R = 0	3 R = 0	0.33
Introduction to Computers Ration = 1.00	This course is designed for students in IT, CIS	Introducing Computer Systems Presenting the Internet Interacting With You	3 R = 0	4 R = 0	0.33

Total Execution Time =0.928257

Fig (5.1) A Snapshot of the System Results Screen

5.2 Experimental Setup

The experimental environment design implements the experimental method using PHP language. PHP is a programming language, although to be more precise, it's a scripting language - that's to say that it uses an interpreter whenever a script is run rather than having a fully compiled program on the system. PHP can be run from the command line, but the most usual place for PHP is within a web page where it can add dynamic content.

One important thing to remember about PHP is that it is a server script not a client script - any code runs on the server and returns an HTML output to the client (in this case the web browser) - this is unlike Java script or VBScript where the code is downloaded on to the user's PC and then run. This means, of course, that a PHP script can only be run on a web server that already has PHP installed on it (O'Reilly, 2008).

PHP is a widely-used general-purpose scripting language that is especially suited for web development and can be embedded into HTML. It generally runs on a web server, taking PHP code as its input and creating web pages as output. It can be deployed on most web servers and on almost every operating system and platform free of charge. PHP is installed on more than 20 million websites and 1 million web servers (O'Reilly, 2008).

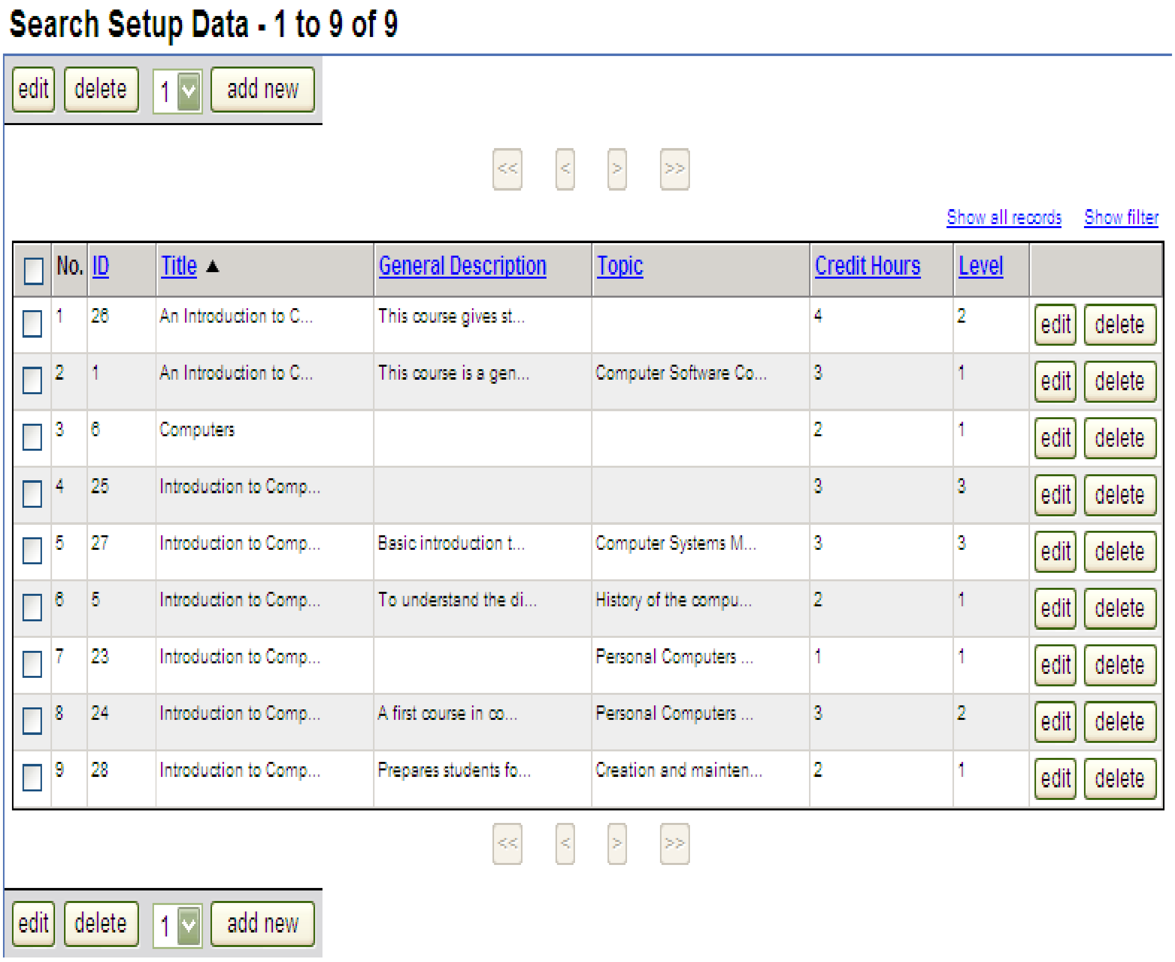
PHP has the following features:

- PHP transparently supports HTTP cookies.
- PHP supports HTTP sessions.
- PHP dealing with XForm.
- PHP handling file uploads.
- PHP using remote file.
- PHP provides Persistent database connections.

5.3 Test-bed Design

We have designed a test-bed system for testing purpose of our research problems, i.e. How to find semantic resolution between heterogeneous agents during their interaction?

For that, a learner should pass a number of stages in order to get the needed results. A snapshot of the designed learner request is shown in figure 5.2.



Search Setup Data - 1 to 9 of 9

edit | delete | 1 | add new

<< < > >>

Show all records Show filter

	No.	ID	Title ▲	General Description	Topic	Credit Hours	Level	
☐	1	26	An Introduction to C...	This course gives st...		4	2	edit delete
☐	2	1	An Introduction to C...	This course is a gen...	Computer Software Co...	3	1	edit delete
☐	3	6	Computers			2	1	edit delete
☐	4	25	Introduction to Comp...			3	3	edit delete
☐	5	27	Introduction to Comp...	Basic introduction t...	Computer Systems M...	3	3	edit delete
☐	6	5	Introduction to Comp...	To understand the di...	History of the compu...	2	1	edit delete
☐	7	23	Introduction to Comp...		Personal Computers ...	1	1	edit delete
☐	8	24	Introduction to Comp...	A first course in co...	Personal Computers ...	3	2	edit delete
☐	9	28	Introduction to Comp...	Prepares students fo...	Creation and mainten...	2	1	edit delete

<< < > >>

edit | delete | 1 | add new

Figure (5.2) A Snapshot of the Learner Request Screen

The learner can make his request according to his interest, and as we can see more than one request can be done at a time taking into consideration that the order of the requested keywords doesn't matter since the learner is searching on the keywords that he is interested in. In the mean time, we should notice that whenever the learner specifies more keywords, the result of the search will be more accurate, i.e. % of matching of the search will be low, and whenever the learner makes his request in general the % of matching of the search will be high.

After making the learner request, the system will search for the needed information in its ontology, and then it will return all the matching courses with the percentage of matching, in addition to the total execution time for each request. In the mean time the system can also give a feedback for the learner concerning his search requests, this feedback will give the learner exactly how much the search request that he did is matching with his feedback ontology.

5.4 Experiments

5.4.1 Testing Relevancy of the Learner Request before Determining Threshold Point

This experiment is the first that we have carried out. In this experiment we tested relevancy of learner request and determine Threshold Point.

The environment setup for this experiment is as follows: we fixed the number of courses in the database as well as the system ontology but varying learner requests, many experiments had been done till we reach / determine Threshold Point. The % of matching for the system is studied through these experiments as well as the relevancy of the system taking into consideration that whenever the query is complex the relevancy of the system will enhance. In this experiment the system doesn't learn from varying learner request.

Learner ontology is defined also, it aims to give the learner a feedback concerning his search request, so for each learner request, the system will give him a feedback about each request process that he is implemented.

For the comparison process with Google, the information for each request is put to a Google system, the result of this search refers to the relevancy of the learner queries with our proposed model.

Graphs were plotted for each request process; these graphs show the relation between % of matching for the courses with the time.

5.4.2 Testing Relevancy of the Learner Request after Determining Threshold Point

In this experiment, we tested the relevancy of the learner request after determining Threshold point.

For this experiment the environment setting is as follows: we fixed number of learner requests as well as number of courses in the database but varying system ontology by increasing data on the database, many experiments had been done to test relevancy of learner request during these ontology variations. The % of matching for the system is studied through these experiments as well as the relevancy of the system taking into consideration that relevancy of the learner request in this experiment will be better than in experiment one (it will take less time) since system in this case is learning from enhancing its ontology i.e. the system is building an intelligent history for each learner request.

Learner ontology is defined also, it aims to give the learner a feedback concerning his search request, so for each learner request, the system will give him a feedback about each request process that he is implemented.

For the comparison process with Google, the information for each request is put to a Google system, the result of this search refers to the relevancy of the learner queries with our proposed model.

Graphs were plotted for each request process; these graphs show the relation between % of matching for the courses with the time.

Chapter Six

Study Results

6.1 Introduction

In the previous chapter we outlined the various experiments conducted to verify our model. In this chapter we will present the results and analysis of the results obtained.

6.2 Results Overview

We have classified our research results into groups and our analysis based on varying the number of learner request, increasing the number of courses in the database and enhancing system ontology, all the results studied the behavior of our model in order to test relevancy of finding learner requests (queries) and compare it with another system like Google.

Our experiments are categorizes as follows:

1. Experiment One: testing relevancy of learner request before determining Threshold Point

This experiment has studied the relevancy of learner request and determines Threshold Point. The results obtained from this experiment show in the first two parts that the time begins high then it decreases, which mean that when the query is complex the relevancy of the system will enhance. While in the third part of the experiment, we can notice that the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system at that point reaches a saturated point which we called THRESHOLD POINT and it is in our research noticed to be equal ten (No. 10), at this point we advise the system to stop the learning process, and for Google the results came relevance with the learner queries taking into consideration that we did our experiments on benchmark of Google to ensure the fairness of the comparison between our proposed model and Google. In all parts of this experiment the system doesn't learn from varying learner request.

2. Experiment Two: testing relevancy of learner request after determining Threshold Point.

This experiment has studied the relevancy of the learner request after determining Threshold point. Results obtained from this experiment show that the relevancy of the learner request is better than in experiment one (it takes less time) since the system in this case is learning from enhancing its ontology i.e. the system is building an intelligent history for each learner request.

Also, we have noticed that the time begins high then it decreases, again it goes high then it decreases and so on since the system starts to learn from the learner ontology and so it builds an intelligent history for the search request till it reaches at Threshold Point, which it is fixed in our research (No. 10) as we saw from experiment one, and this is rights since database size is fixed, keywords that the learner is searching about is also fixed, just ontology is varying to enhance the results, so it will be fixed always, and as a result for that we advise the system to stop the learning process at that point. For Google the results came relevance with the learner queries taking into consideration that we did our experiments on benchmark of Google to ensure the fairness of the comparison between our proposed model and Google.

6.2.1 Experiments [1]: Testing Relevancy of Learner Request before Determining Threshold Point

This experiment is the first that we are carried out. In this experiment we fixed the number of courses in the database as well as the system ontology but varying learner requests, many experiments had been done till we reach / determine Threshold Point as we will see in the coming sections. This experiment consists mainly of three parts: in the first one the learner makes five requests, in the second part we increased the number of the learner request to become seven, and in the third part the learner makes ten requests. As we said earlier in this section the number of courses in the database and the system ontology was fixed and in all the experiment parts it was ten courses.

6.2.1.1 Part One of Experiment [1]

In this part, we specify the number of learner request by five requests over ten courses in the database. The learner makes his request by entering some keywords that he is interested in, and then the system returns the % of matching for the search with the total execution time. In the mean time the learner ontology returns a feedback for each request done. After that, for each request process done we search about it through Google taking into consideration that we take the order as a measure of relevancy for Google, i.e. first place is the highest while the 10^{th} the is lowest. This experiment is repeated three times, some cases are presented as in the figures below.

We start our test by figure (6.1), for request one: % of matching for the search = 98%, % of matching for the learner feedback = 86% and relevancy with Google = 3. As we can see from the graph the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

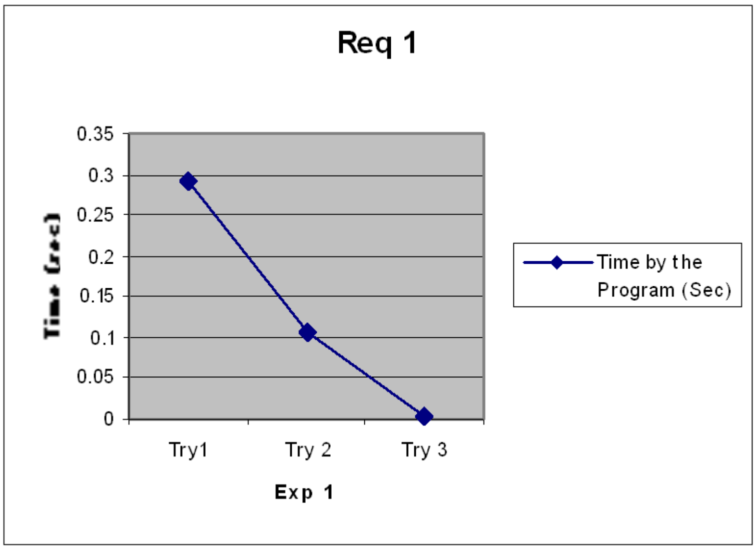


Fig (6.1) Request 1 of Part 1 of Exp.1

For request two: % of matching for the search = 76%, % of matching for the learner feedback = 99% and relevancy with Google = 6. As we can see from figure (6.2) the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

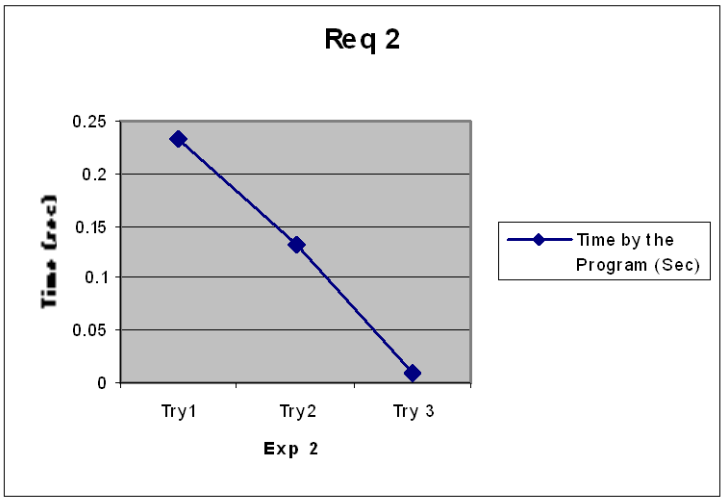


Fig (6.2) Request 2 of Part 1 of Exp.1

For request three: % of matching for the search = 26%, % of matching for the learner feedback = 67% and relevancy with Google = 11. As we can see from figure (6.3) again the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

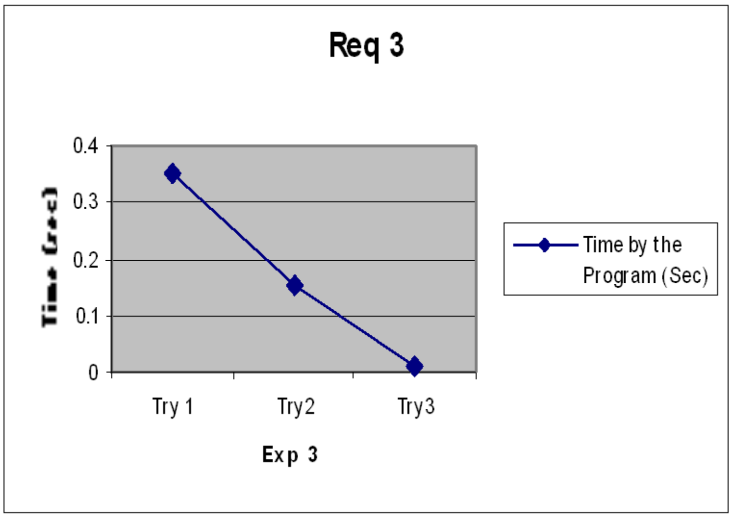


Fig (6.3) Request 3 of Part 1 of Exp.1

For request four: % of matching for the search = 88%, % of matching for the learner feedback = 88% and relevancy with Google = 2. As we can see from figure (6.4) again the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

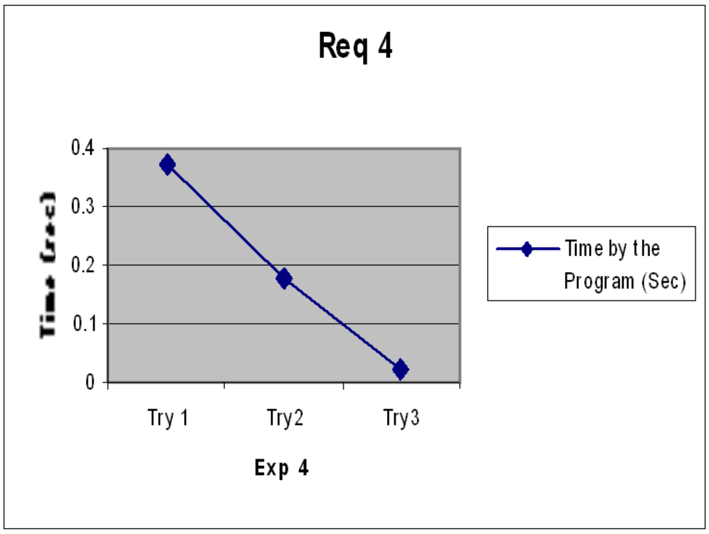


Fig (6.4) Request 4 of Part 1 of Exp.1

6.2.1.2 Part Two of Experiment [1]

In this part, we specify the number of learner request by seven requests over ten courses also in the database, and no change for the system ontology as well. The same as in part one the learner makes his request by entering some keywords that he is interested in, and then the system returns the % of matching for the search with the total execution time. In the mean time the learner ontology returns a feedback for each request done. After that, for each request process done we search about it through Google taking into consideration that we take the order as a measure of relevancy for Google, i.e. first place is the highest while the 10th is the lowest. This experiment is repeated six times, some cases are presented as in the figures below.

We start our test in the second part of this experiment by figure (6.5), for request one: % of matching for the search = 77%, % of matching for the learner feedback = 77% and relevancy with Google = 5. As we can see from the graph the time also starts high i.e. % of matching for the search is high since the learner makes his request in general then it decreases slowly.

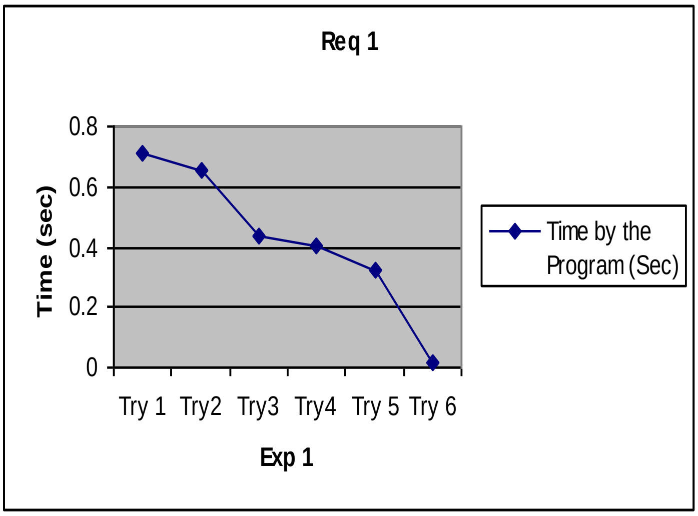


Fig (6.5) Request 1 of Part 2 of Exp.1

For request two: % of matching for the search = 50%, % of matching for the learner feedback = 83% and relevancy with Google = 5. As we can see from figure (6.6) the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

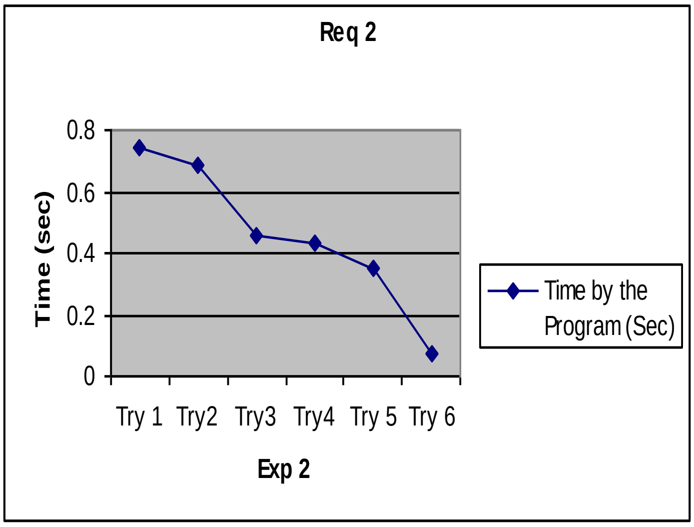


Fig (6.6) Request 2 of Part 2 of Exp.1

For request three: % of matching for the search = 88%, % of matching for the learner feedback = 100% and relevancy with Google = 2. As we can see from figure (6.7) again the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

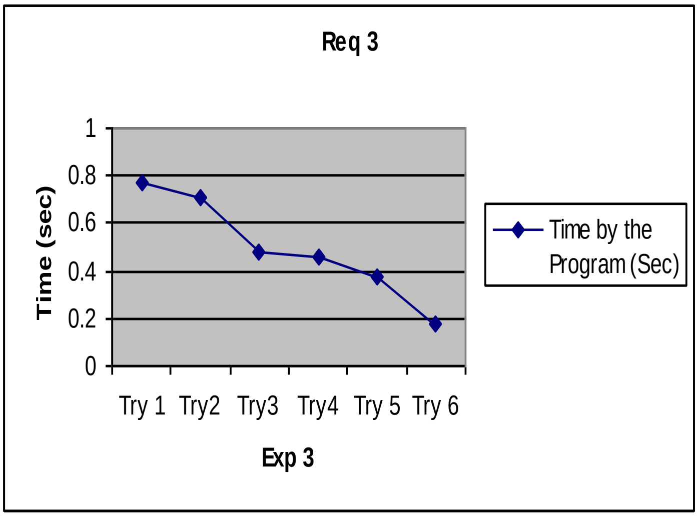


Fig (6.7) Request 3 of Part 2 of Exp.1

For request four: % of matching for the search = 100%, % of matching for the learner feedback = 100% and relevancy with Google = 1. As we can see from figure (6.8) again the time starts high i.e. % of matching for the search is high since the learner makes his request in general, then it decreases slowly.

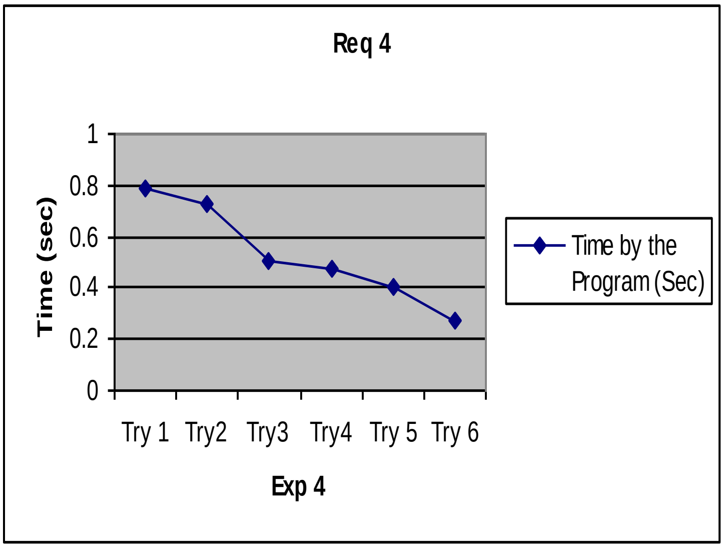


Fig (6.8) Request 4 of Part 2 of Exp.1

6.2.1.3 Part Three of Experiment [1]

In this part, we specify the number of learner request by ten requests over ten courses also in the database, and no change for the system ontology as well. The same as in part two the learner makes his request by entering some keywords that he is interested in, and then the system returns the % of matching for the search with the total execution time. In the mean time the learner ontology returns a feedback for each request done. After that, for each request process done we search about it through Google taking into consideration that we take the order as a measure of relevancy for Google, i.e. first place is the highest while the 10^{th} is the lowest. This experiment is repeated seven times, some cases are presented as in the figures below.

We start our test for the third part of this experiment by figure (6.9), for request one: % of matching for search = 95%, % of matching for learner feedback = 95% and relevancy with Google = 4. As we can see from the graph the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches a saturated point which we called later THRESHOLD POINT.

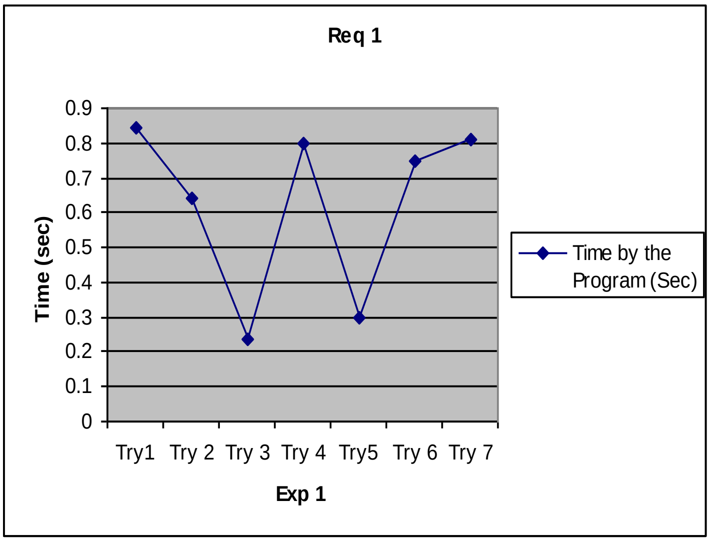


Fig (6.9) Request 1 of Part 3 of Exp.1

For request two: % of matching for search = 84%, % of matching for learner feedback = 80% and relevancy with Google = 3. As we can see from figure (6.10) the time starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches a saturated point which we called Threshold Point.

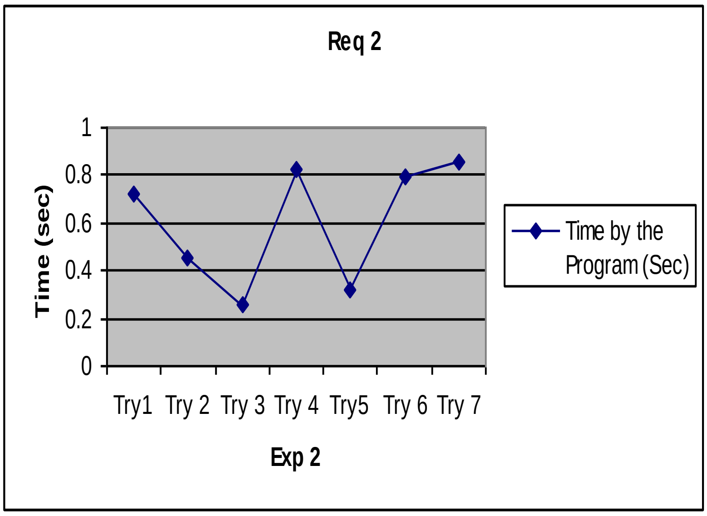


Fig (6.10) Request 2 of Part 3 of Exp.1

For request four: % of matching for search = 89%, % of matching for learner feedback = 82% and relevancy with Google = 5. As we can see from figure (6.11) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches a saturated point which we called Threshold Point.

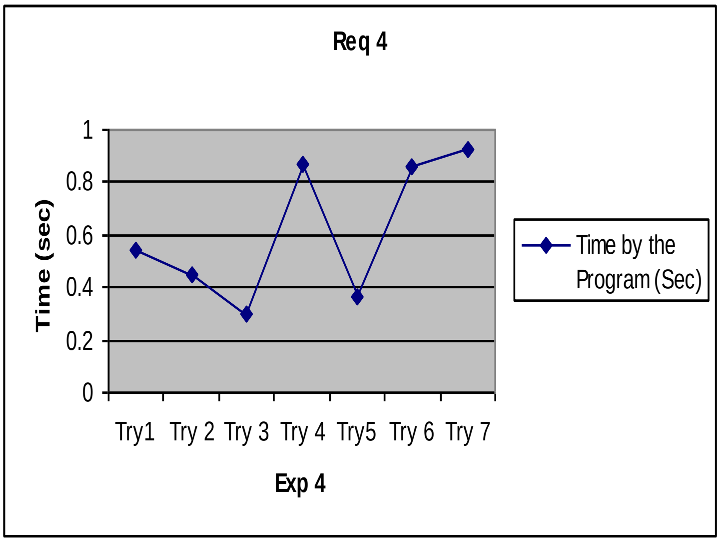


Fig (6.11) Request 4 of Part 3 of Exp.1

For request seven: % of matching for search = 97%, % of matching for learner feedback = 77% and relevancy with Google = 4. As we can see from figure (6.12) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches a saturated point which we called Threshold Point.

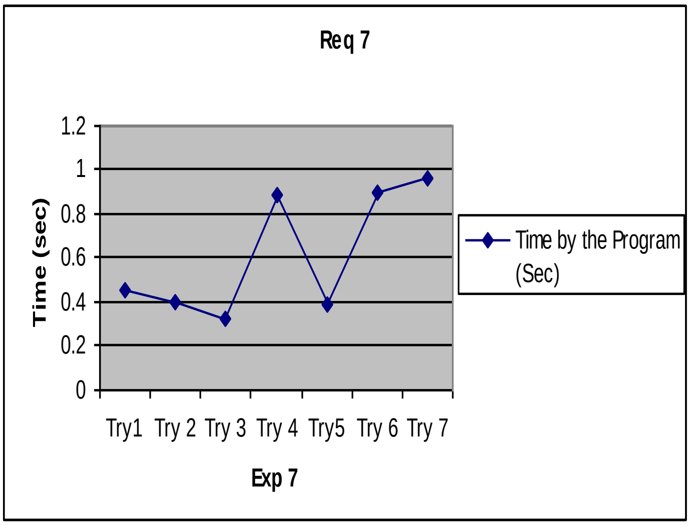


Fig (6.12) Request 7 of Part 3 of Exp.1

6.2.1.4 Discussion

Based on all the above figures, we can notice from part one and two of this experiment that the time begins high then it decreases, which mean that when the query is complex the relevancy of the system will enhance. While in the third part of the experiment, we can notice that the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system at that point reaches a saturated point which we called THRESHOLD POINT and it is in our research noticed to be equal ten (No. 10), at this point we advise the system to stop the learning process, and for Google the results came relevance with the learner queries. In all parts of this experiment the system doesn't learn from varying learner request.

6.2.2 Experiments [2]: Testing Relevancy of Learner Request after Determining Threshold Point.

This experiment is the second one. In this experiment we fixed number of learner request but varying system ontology by increasing number of courses in the database as we will see in the coming sections. This experiment consists mainly of five parts: in the first one the number of courses in the database was twelve, in the second part we increased the number of the courses to become twenty five, in the third part we increase the courses to become thirty seven courses, in the fourth part it become fifty four courses and finally in the fifth part it become seventy five courses. System ontology is enhancing each time the learner makes his requests, and as we said earlier in this section the number of learner requests was fixed and it was in all the experiments parts twenty requests.

The idea behind conducting the several parts of this experiment is to understand exactly the behavior of our model during conducting several cases on different databases, and to have clearer picture on how the system can build an intelligent history for each search request done. Each part of this experiment is repeated six to seven times, some cases are presented as in the figures below.

6.2.3.1 Part One of Experiment [2]

We start our test for the second experiment part one by figure (6.13) where the number of request is twenty and the number of courses in the database is twelve, for request one: % of matching for the search = 95%, % of matching for the learner feedback = 95% and relevancy with Google = 2. As we can see from the graph the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

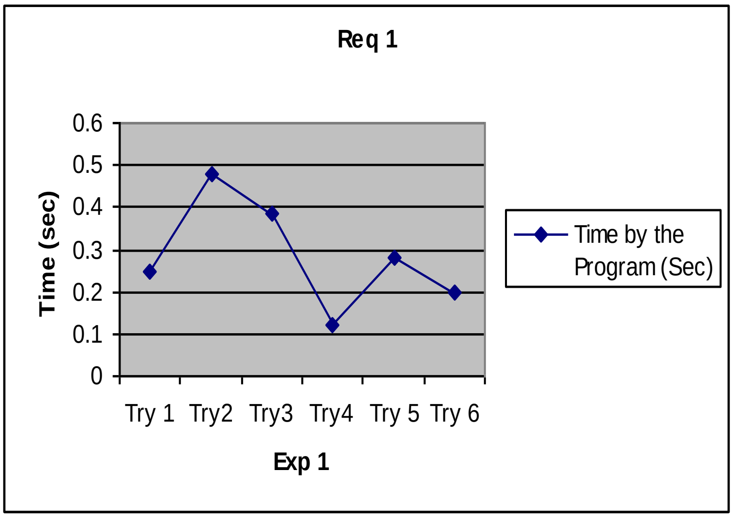


Fig (6.13) Request 1 of Part 1 of Exp.2

For request three: % of matching for the search = 97%, % of matching for the learner feedback = 90% and relevancy with Google = 3. As we can see from figure (6.14) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

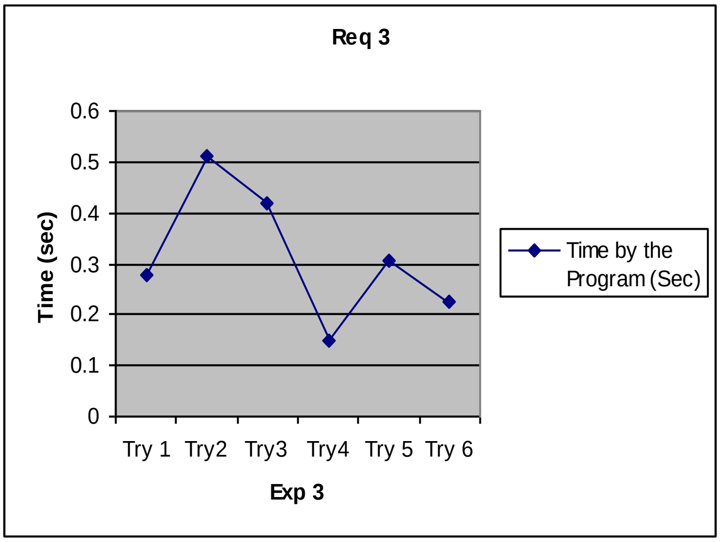


Fig (6.14) Request 3 of Part 1 of Exp.2

For request five: % of matching for the search = 100%, % of matching for the learner feedback = 80% and relevancy with Google = 2. As we can see from figure (6.15) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

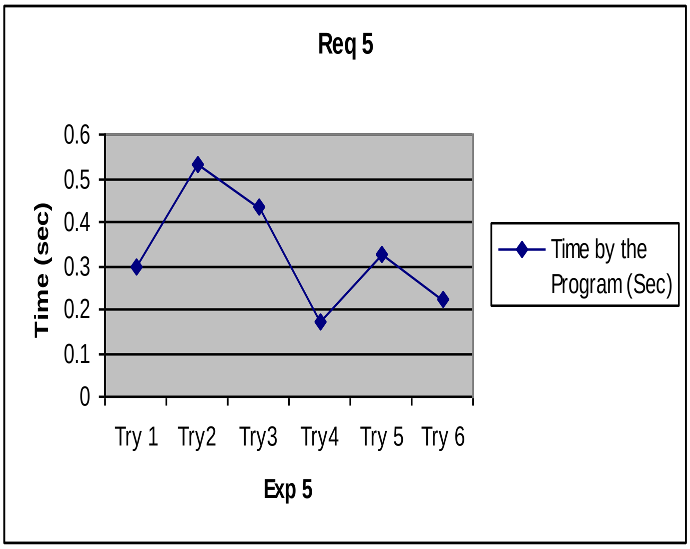


Fig (6.15) Request 5 of Part 1 of Exp.2

6.2.3.2 Part Two of Experiment [2]

We start our test for the second experiment part two by figure (6.16) where the number of request is twenty also and the number of courses in the database is twenty five, for request one: % of matching for the search = 43%, % of matching for the learner feedback = 44% and relevancy with Google = 17. As we can see from the graph the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

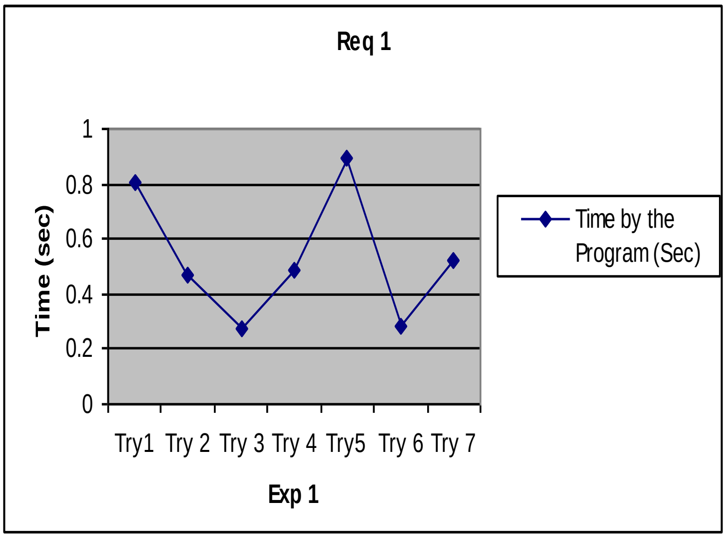


Fig (6.16) Request 1 of Part 2 of Exp.2

For request eight: % of matching for the search = 88%, % of matching for the learner feedback = 88% and relevancy with Google = 4. As we can see from figure (6.17) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

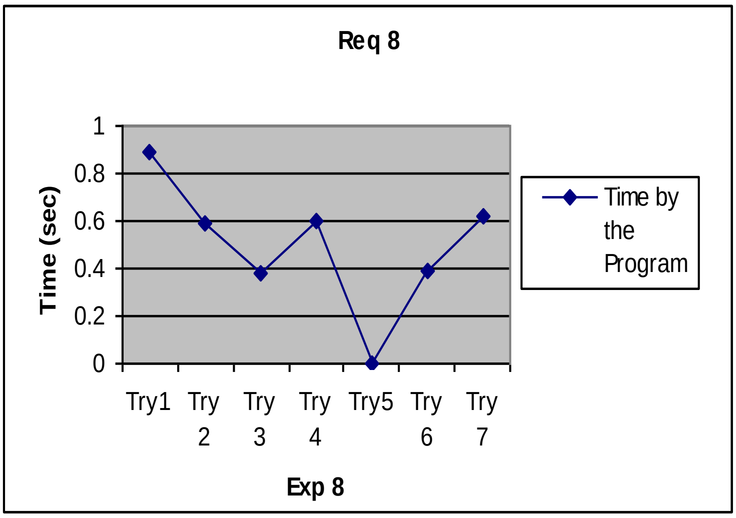


Fig (6.17) Request 8 of Part 2 of Exp.2

For request twelve: % of matching for the search = 98%, % of matching for the learner feedback = 88% and relevancy with Google = 2. As we can see from figure (6.18) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

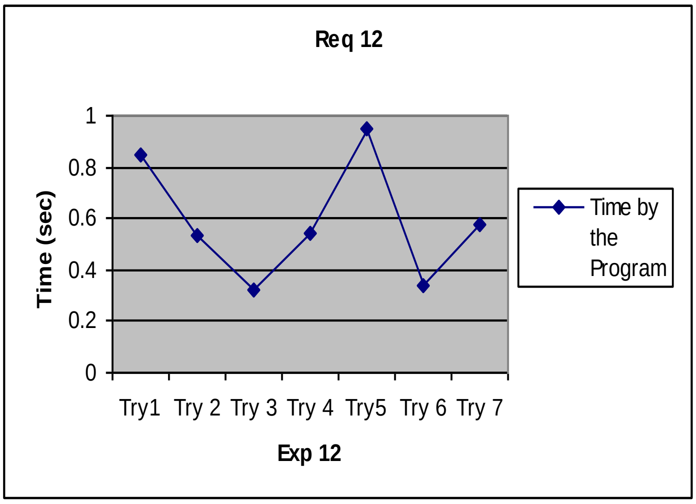


Fig (6.18) Request 12 of Part 2 of Exp.2

6.2.3.3 Part Three of Experiment [2]

We start our test for the second experiment part three by figure (6.19) where the number of request is twenty also and the number of courses in the database is thirty seven, for request one: % of matching for the search = 73%, % of matching for the learner feedback = 22% and relevancy with Google = 7. As we can see from the graph the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

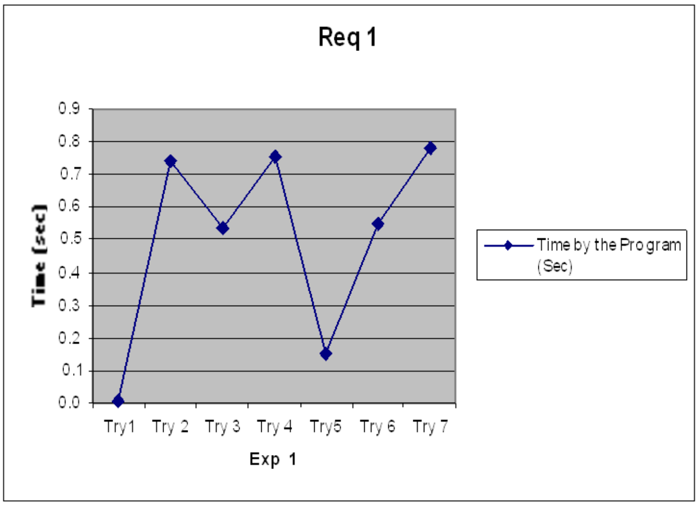


Fig (6.19) Request 1 of Part 3 of Exp.2

For request ten: % of matching for the search = 51%, % of matching for the learner feedback = 82% and relevancy with Google = 9. As we can see from figure (6.20) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

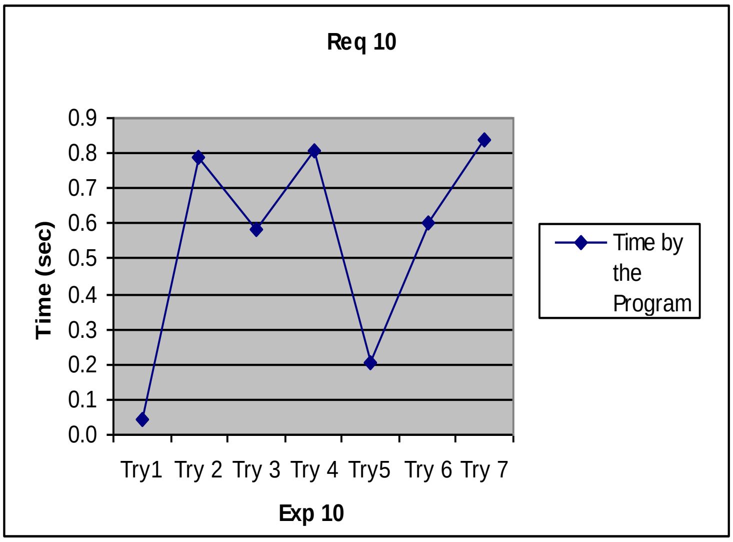


Fig (6.20) Request 10 of Part 3 of Exp.2

For request seventeen: % of matching for the search = 60%, % of matching for the learner feedback = 67% and relevancy with Google = 10. As we can see from figure (6.21) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

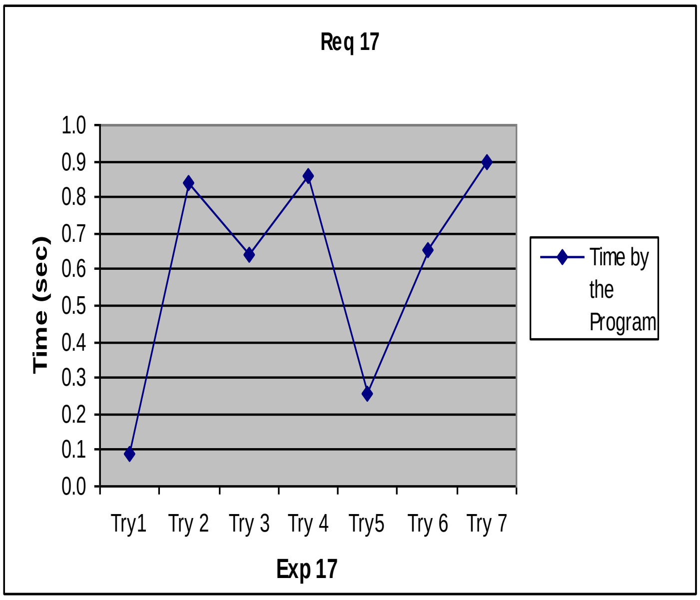


Fig (6.21) Request 17 of Part 3 of Exp.2

6.2.3.4 Part Four of Experiment [2]

We start our test for the second experiment part four by figure (6.22) where the number of request is twenty also and the number of courses in the database is fifty four, for request one: % of matching for the search = 62%, % of matching for the learner feedback = 77% and relevancy with Google = 13. As we can see from the graph the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

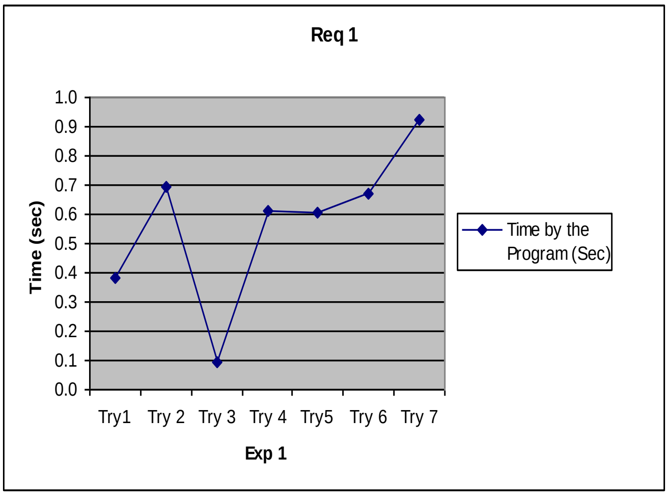


Fig (6.22) Request 1 of Part 4 of Exp.2

For request twelve: % of matching for the search = 88%, % of matching for the learner feedback = 92% and relevancy with Google = 1. As we can see from figure (6.23) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

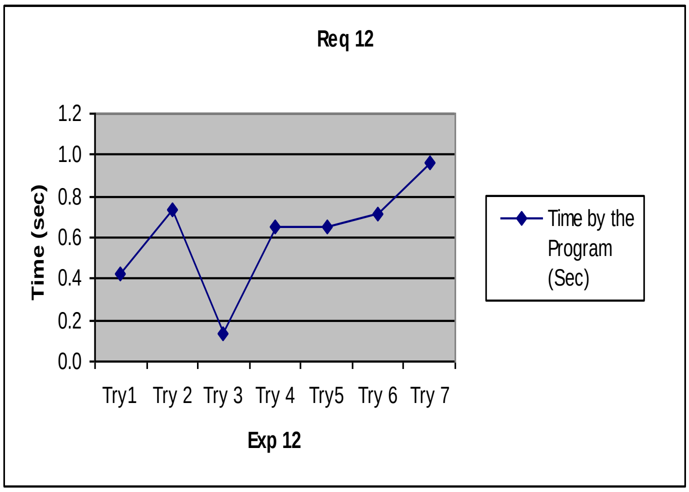


Fig (6.23) Request 12 of Part 4 of Exp.2

For request twenty: % of matching for the search = 33%, % of matching for the learner feedback = 33% and relevancy with Google = 15. As we can see from figure

(6.24) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

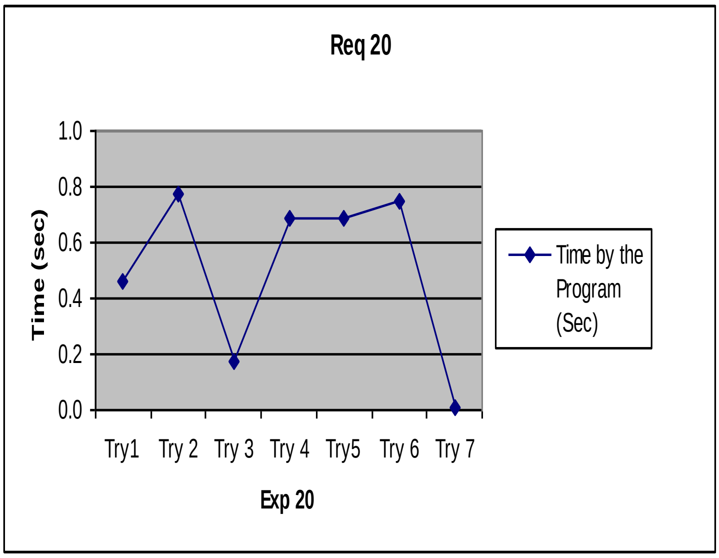


Fig (6.24) Request 20 of Part 4 of Exp.2

6.2.3.5 Part Five of Experiment [2]

We start our test for the second experiment part five by figure (6.25) where the number of request is twenty also and the number of courses in the database is seventy five, for request one: % of matching for the search = 100%, % of matching for the learner feedback = 100% and relevancy with Google = 4. As we can see from the graph the time (% of matching) begins high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

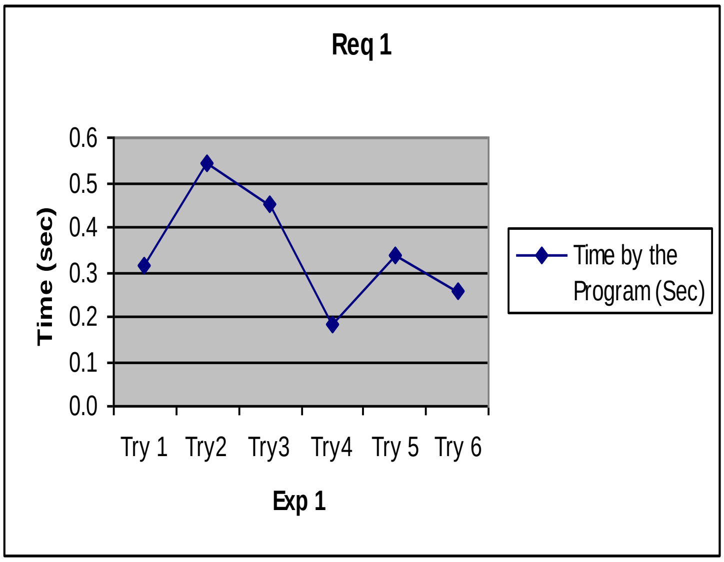


Fig (6.25) Request 1 of Part 5 of Exp.2

For request fifteen: % of matching for the search = 99%, % of matching for the learner feedback = 95% and relevancy with Google = 3. As we can see from figure (6.26) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

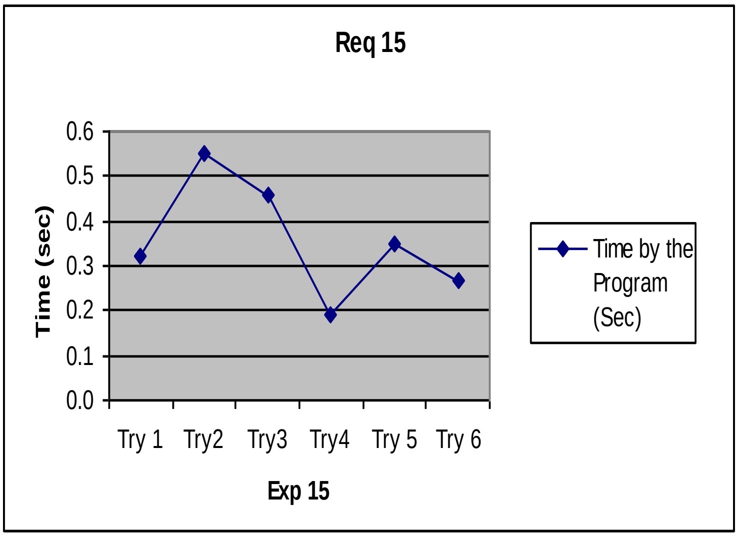


Fig (6.26) Request 15 of Part 5 of Exp.2

For request twenty five: % of matching for the search = 80%, % of matching for the learner feedback = 68% and relevancy with Google = 4. As we can see from figure (6.27) the time also starts high then it decreases, again it goes high then it decreases and it continue like it since the system reaches at Threshold Point. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

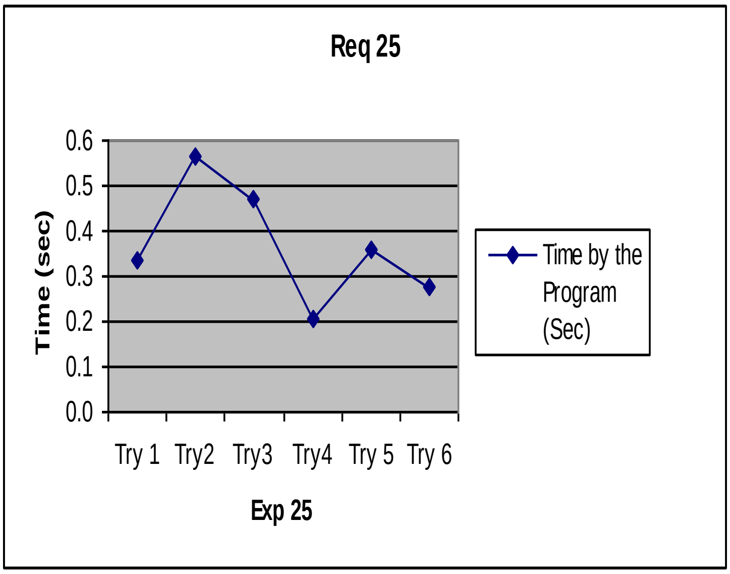


Fig (6.27) Request 25 of Part 5 of Exp.3

6.2.2.6 Discussion

Based on all the above figures, we can notice that the time begins high then it decreases, again it goes high then it decreases and so on since the system starts to learn from the learner ontology and so it builds an intelligent history for the search request till it reaches at Threshold Point, which it is fixed in our research (No. 10) as we saw from experiment one, and this is rights since database size is fixed, keywords that the learner is searching about is also fixed, just ontology is varying to enhance the results, so it will be fixed always, and as a result for that we advise the system to stop the learning process at that point. For Google the results came relevance with the learner queries. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

6.3 Overall Summary

In this chapter, we have studied the effect of changing number of learner request over different databases and enhancing the system ontology to test the relevancy of finding learner queries. The initial results indicate a significance improvement on the returned results relevancy when the search is conducted using the model presented in this research compared with other search techniques.

In experiment one; we tested the relevancy of learner request by fixing number of courses in the database as well as the system ontology but varying learner requests. The results of part one and two of this experiment show that the time begin high then it decreases, which mean that when the query is complex the relevancy of the system will enhance. While in the third part of the experiment, we can notice that the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system at that point reaches a saturated point which we called THRESHOLD POINT and it is in our research noticed to be equal ten (No. 10), at this point we advise the system to stop the learning process, and for Google the results came relevance with the learner queries. In all parts of this experiment the system doesn't learn from varying learner request.

In the second experiment, we tested also the relevancy of finding learner queries by fixing number of learner requests as well as the number of courses in the database but varying system ontology. The results show that the relevancy of the learner request in this experiment is better than in experiment one (it takes less time) since the system in this case is learning from enhancing its ontology i.e. the system is building an intelligent history for each learner request.

Also, we have noticed that that the time begins high then it decreases, again it goes high then it decreases and so on since the system starts to learn from the learner ontology and so it builds an intelligent history for the search request till it reaches at Threshold Point, which it is fixed in our research (No. 10) as we saw from experiment one, and this is rights since database size is fixed, keywords that the learner is searching about is also fixed, just ontology is varying to enhance the results, so it will be fixed always, and as a result for that we advise the system to stop the learning process at that point. For Google the results came relevance with the learner queries. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

Chapter Seven
Conclusion and Future Work

7.1 Conclusion

The work presented in this thesis presents the first step of the effort toward a comprehensive solution to the problem of semantic resolution. The proposed model of this research views the semantic resolution as evidential reasoning, in which the evidences are incrementally accumulated via semantic querying and the solution gradually emerges through semantic mapping in a one step process.

A prototype implementation based on an agent system for semantic resolution in a simple RFQ of an e-learning application had been implemented. Three ontologies each for a specific domain were defined. Several experiments were conducted to understand exactly the behavior of our proposed model through taking several cases of learner request on different databases to enhance system ontology and later these results were compared with Google.

<u>The Results of these experiments can be summarized as the following:</u>

<u>1. In experiment one;</u> we tested the relevancy of learner request by fixing number of courses in the database as well as the system ontology but varying learner requests. The results of part one and two of this experiment show that the time begins high then it decreases, which mean that when the query is complex the relevancy of the system will enhance. While in the third part of the experiment, we can notice that the time begins high then it decreases, again it goes high then it decreases and it continue like that since the system at that point reaches a saturated point which we called THRESHOLD POINT and it is in our research noticed to be equal ten (No. 10), at this point we advise the system to stop the learning process, and for Google the results came relevance with the learner queries. In all parts of this experiment the system doesn't learn from varying learner request.

<u>2. In the second experiment,</u> we tested also the relevancy of finding learner queries but we fixed the number of learner requests as well as the number of courses in the database but varying system ontology. The results show that the relevancy of the learner request in this experiment is better than in experiment one (it takes less time) since the system in this case is learning from enhancing its ontology i.e. the system is building an intelligent history for each learner request.

Also, we have noticed that the time begins high then it decreases, again it goes high then it decreases and so on since the system starts to learn from the learner ontology and so it builds an intelligent history for the search request till it reaches at Threshold Point, which it is fixed in our research (No. 10) as we saw from experiment one, and this is rights since database size is fixed, keywords that the learner is searching about is also fixed, just ontology is varying to enhance the results, so it will be fixed always, and as a result for that we advise the system to stop the learning process at that point. For Google the results came relevance with the learner queries. This model seems to be not scalable because after enhancing the model ontology it reaches at Threshold point then we advice the system to stop the learning process, but it is scalable if it is expanded to be used to deal with more subject and topics as each subject can have its own ontology. For the performance of our proposed model, it is relevant to our achieved results.

7.2 Future Work

In this research we present an approach for implementing an e-learning scenario using Semantic Web technologies. It is primarily based on ontology- based descriptions of the learning materials and thus provides flexible and personalized access to these learning materials. However, in this research we are only concerned by the fact that a service is represented by input and output properties of the service profile, and we still need do more research on other key operations necessary to support e-learning interactions in the future, such as negotiation, proposals, and agreements, so that the Semantic Web can provide an ideal framework for the standardization of the e-learning. As the learner data are sensitive, the trust and security issues have to be further investigated. The technical infrastructure for this approach to personalization has to be investigated in more detail. Mapping or mediating between different schemas should be investigated as well when we want to provide communication between different peers. Different identification schemes have to be investigated more deeply to support better exchange of learner profile fragments between distributed nodes.

Appendix A

Database Sample

No	Title	General Description	Topics
1	Introduction to Computers	This course is a general introduction to computers and their applications that assumes no previous knowledge of the subject. It introduces computers and their uses in the arts and sciences -- what they are, how they work, how they can be programmed, what they can and cannot do. It is for people who read about such topics as VLSI or WWW and want to understand them, for people who need to have data processed on the job, and for people who see the computerization of our society and ask about the meaning of it.	Computer Anatomy Computer Software Computer Applications Computer Science
2	Introduction to Computing	This course covers fundamental principles, concepts, and methods of computing, with emphasis on applications in the physical sciences and engineering. This course includes basic problem solving and programming techniques; fundamental algorithms and data structures; use of computers in solving engineering and scientific problems. This course also introduces the student to software development environments for engineering program design. In this course, the student will acquire the software "literacy" that has become indispensable for creative work in Science and Engineering. Understanding the material in this course will enhance the students understanding of both fundamental and advanced topics in engineering software design.	Introduction to Computing Matlab environment & Array Introduction/X-Windows & U C Programming – Introductio
3	Introduction to Computer	To understand the digital world, the best place to begin is the device you are using right now—the computer. In this course, you will learn a bit about the history of computers, the four essential components of a computer, and the differences between your brain and a computer.	History of the computers Four Components of the Com Description of the Computer
4	Introduction to Computers	This course will introduce computer hardware and software, basic operations of computers, keyboard, an introduction to Internet, security and networking.	Hardware Software Basic Operations Keyboard Symbols Health and Safety Internet Viruses Security Networks
5	An Introduction to Computers	This course covers all parts of the computer, introducing computer terminology, disk drivers and utilities, discussing starting and stopping of the computer, how to install and uninstall computer software, and guidelines to purchase computers.	The Parts of the Computer Computer Terminology Disk Drivers Disk Utilities Starting and Stopping the Co Installation and uninstalling S Purchase Computer

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