

An Adaptive Personalized Course Selection System

Rashid Jayousi
Al-Quds University, Palestine
rjayousi@science.alquds.edu

Yasmin I. Bali
Al-Quds University, Palestine
y_bali81@yahoo.com

ABSTRACT

Selecting appropriate course for a learner from a large number of heterogeneous knowledge sources is a complex and challenging task. This paper presents an adaptive system based on ongoing research on semantic web technologies and ontologies. A prototype implementation based on an agent system for semantic resolution in a simple RFQ of an E-Learning application had been developed. Three ontologies each for a specific domain were defined. Several experiments were conducted to demonstrate the effectiveness of such approach through taking several cases of learner request on different databases.

Key Words: e-Learning, Ontology, Semantic Querying, Semantic Mapping.

I. 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. 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, 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 [1]. It is anticipated that Ontologies and Semantic Web technologies will influence the next generation of E-Learning systems and applications [2].

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.

From a pedagogical perspective, our proposed E-Learning Scenario system can be like an “enabling technology” allowing learners to determine the learning agenda and be in control of their own learning. In particular, it allow students to perform semantic querying for learning materials 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 [12]. At the other end of the spectrum tutors are freed from the (now student-run) 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.

Although all research works on Semantic Web are aimed at making web pages understandable by programs and may serve

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 [13].

A key challenge in building the Semantic Web, one that has received relatively little attention, is finding semantic mappings among the ontologies. 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 [3]. 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.

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. Several experiments were conducted to understand exactly the behavior of our proposed system and results obtained from these experiments will outline later which refer to the relevancy of our system in finding learners requests / queries.

In this paper, we represent our effort toward the problem of semantic resolution in an E-Learning system [13], 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.

The rest of this paper is organized as follows. First related works is given in Section 2. Section 3 describes both the current and proposed system models in addition to the semantic resolution algorithm. Test-bed design, experiments and the results are shown in section 4. And finally, a Conclusion is presented in Section 5.

2. RELATED WORKS

The system 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 [3].

S. Hatem, A. Ramadan and C. Neagu (2005) present 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 [7].

Abel, Barry, Benayache, Chaput, Lenne, and Moulin (2004) present 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 [2].

Moreale and Vargas-Vera (2004) outline 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 [8].

Tane, Schmitz, and Stumme (2004) propose 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 paper, 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 [9].

Madhavan, Dhamankar, Domingos, and Halevy (2003) describe 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 [5].

Finally, Stojanovic, Staab, and Studer (2002) present 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 [1].

3. SYSTEM MODEL

3.1. Current System Model

In this system (proposed by Zhongli Ding, 2005), 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 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 exists 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.

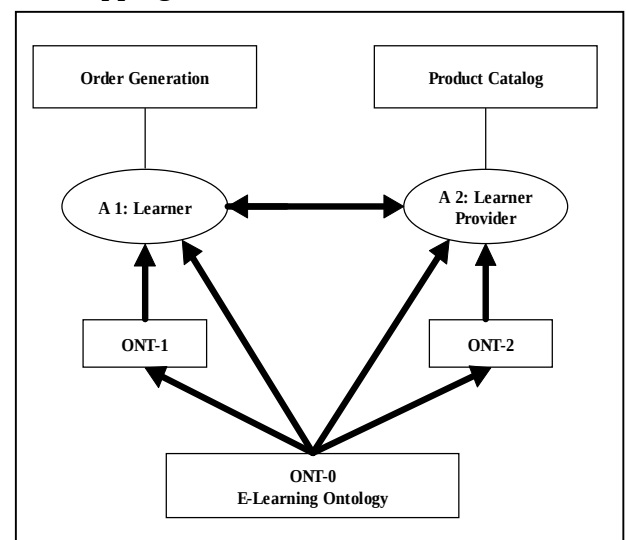


Figure 1. A simple RFQ E- Learning Scenario involving two Agents Based on Ref ("Request for Quote" in E-Commerce)

- *Operation for Semantic Resolution*

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 [4].

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 [4].

- *Communication Protocol for Semantic Resolution*

Agents in this system 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, so we need (1) an ACL to encode messages, (2) a content language to encode the content of messages, and (3) a communication protocol that specifies how these messages can be used for meaningful conversations. 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), 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 [4].

Performatives used in the protocol represent the communicative acts intended by the players. 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 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 2.

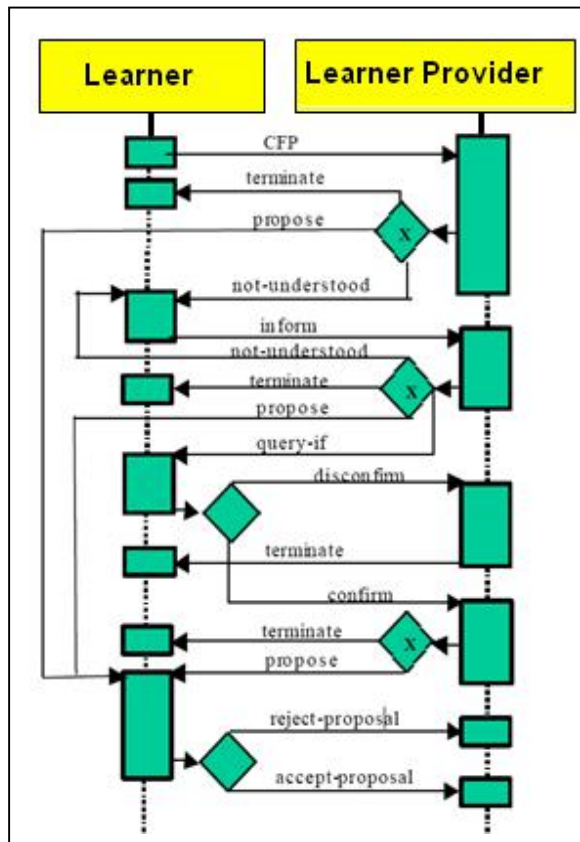


Figure 2. State transition diagram of the Semantic Resolution Protocol Based on Ref ("Semantic Resolution for E-Commerce")

3.2 Our Proposed System Model

In this research (proposed by Jayousi and Bali, 2008) we currently design an implementation of an agent system for semantic resolution in a simple RFQ of E-Learning application using PHP language.

Our proposed system model will extend 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 3)

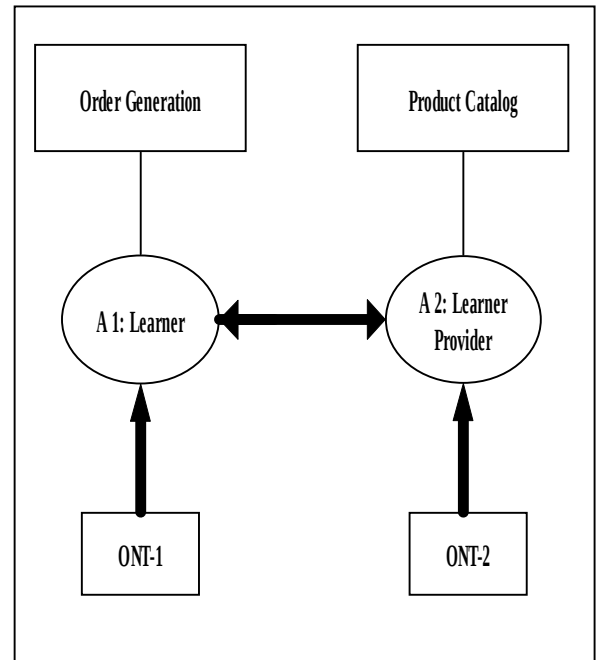


Figure 3. Proposed RFQ E-Learning Scenario involving two agents

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. 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.

For the ontology design in the previous propose E-Learning scenario, we defined three classes: 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 requests.

In our implementation [13], the proposed E- Learning system will let the learner to make his request by entering some keywords that he is searching for, then the system will search for the needed information in its ontology, after that 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 did many experiments and compared the achieved results with an existing implementing system like Google.

3.3 Semantic Resolution Algorithm

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.

For our scenario, Let α be the set of all training provider in a given repository [3]. For a given query Q the matchmaking algorithm of the repository host returns the set of all training providers that are compatible matches (Q):

$Matches(Q) = \{A \in \alpha \text{ compatible}(A, Q)\}$

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. TEST-BED DESIGN, EXPERIMENTS AND THE RESULTS

4.1 Test-bed Design

In order to test our proposed model, 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. The learner can make his request according to his interest; more than one request can be done at a time. 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. the complexity (% of matching courses) of the search will be low, and whenever the learner makes his request in general the complexity 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.

4.2 Experiments

I- This experiment is the first one that we are 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 complexity of the system is studied through these experiments as well as the relevancy of the system taking into consideration that when the complexity is increased the relevancy of the system will enhance. In this experiment the system doesn't learn from varying learner request.

II- In the second part of the experiment, we tested also the relevancy of the learner request but 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, many experiments had been done to test relevancy of learner request during these ontology variations. The complexity of 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 for both the above two mentioned experiments; this ontology aims to give the learner a feedback concerning his search request.

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 request/queries with our proposed model. Graphs were plotted for each request process; these graphs show the relation between the complexity of the search (% of matching courses) with the time.

4.3 Results

a) Results of Experiment One:

Experiment one described in the previous sub-section consist 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. And as we said before the number of courses in the database and the system

ontology was fixed and in all the experiment parts it was ten courses.

The learner in the three parts of this experiment makes his request by entering some keywords that he is interested in, and then the system returns the % of matching (complexity) of 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 seven times, two cases will be presented below.

Figure 4, presents the result of the first request, complexity of search = 76%, complexity of the learner feedback = 86% and relevancy with Google = 3. As we can see from the graph the time (% of matching) starts high i.e. complexity of the search high since the user learner makes his request in general, then it decreases slowly.

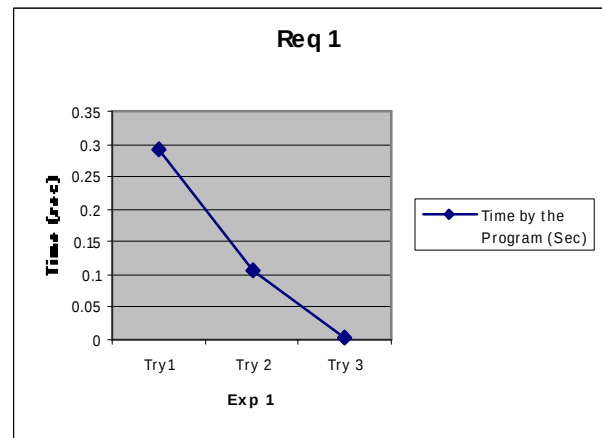


Figure 4. Request 1 of Exp. 1

Another case showed is figure 5, for request two: complexity of search = 95%, complexity of the learner feedback = 95% also and relevancy with Google = 1. 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 a saturated point which we called later **THRESHOLD POINT**.

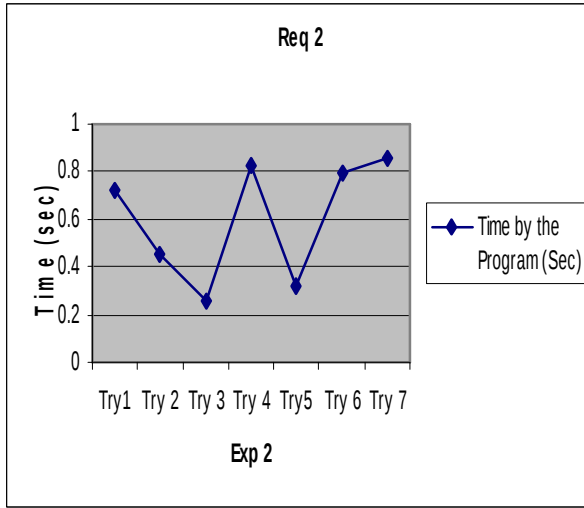


Figure 5. Request 2 of Exp. 1

In figure 4, we can notice that the time (% of matching) begins high then it decreases, which means that when the complexity is increased the relevancy of the system will enhance. In figure 5, we can notice that the time (% of matching) 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. This is noted to be number ten (No. 10), this was noticed to be the case for several tried cases. It seems to be the case that at which we advise the system to stop the learning process. This needs further investigations' from our side to show the significance of this observation.

b) Results of Experiment Two:

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 previously 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 system 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.

The learner in the five parts of this experiment makes his request by entering some keywords that he is interested in, and then the system returns the % of matching (complexity) of 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. . Each part of this experiment is repeated six to seven times, two cases are presented as in the figures below.

Figure 6, presents the result of the first request, complexity of search = 100%, complexity of the learner feedback = 80% and relevancy with Google = 2. As we can see from the graph the time (% of matching) begins to high then it decreases, again it goes high then it decreases and it continue like that since the system reaches at Threshold Point.

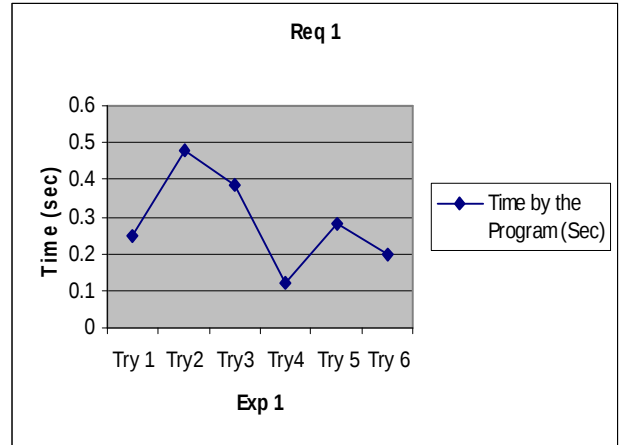


Figure 6. Request 1 of Exp. 2

Another case is presented in figure 7, for request twelve: complexity of search = 51%, complexity of the learner feedback = 82% and relevancy with Google = 7. 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.

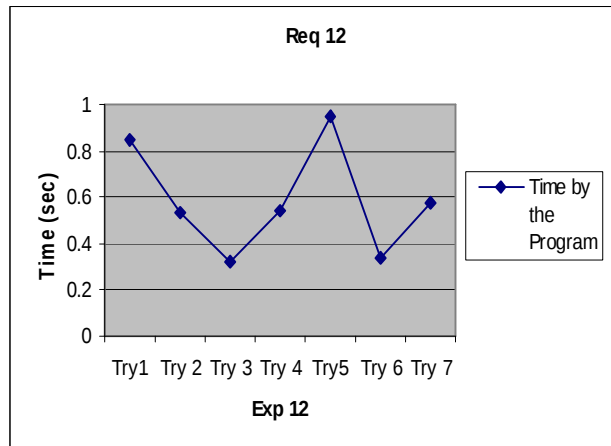


Figure 7. Request 12 of Exp.2

Based on the two presented figures, we can notice that the time (% of matching) 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 is fixed in our research (No. 10) as we saw in the experiment one, and this is right 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 come relevance with the learner queries.

5. Conclusion

The work presented in this paper outlines the first step of our ongoing effort toward a comprehensive solution to the problem of semantic resolution. Many issues, both practical and theoretical, remain to be addressed. To answer some of them, we will continue our project along the following directions. First, we plan to carry more experiments based on the prototype outlined in this paper. This system will be used as a testbed to validate the methods we develop and to test emerging tools and approaches. It can also serve as a bridge connecting the

research community and the industry by incorporating ontologies of real-world enterprises engaged in E-Learning activities. This model 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. The initial results indicate a significance improvement on the returned results relevancy when the search is conducted using the model presented in this paper compared with other search techniques.

REFERENCES

- [1] Ljiljana Stojanovic, Steffen Staab and Rudi Studer, E-Learning based on the Semantic Web, FZI Research Center for Information Technologies at the University of Karlsruhe, 76131 Karlsruhe, Germany, (2002)
- [2] Abel, M.-H., Benayache, A., Lenne, D., Moulin, C., Barry, C., & Chaput, B., Ontology-based Organizational Memory for E-Learning, *Educational Technology & Society*, 7 (4), 98-111, (2004)
- [3] Wen-Ying Guo and De-Ren Che, An Ontology Infrastructure for an E-Learning Scenario, China, *Journal of Distance Education Technologies*, 5(1), 70-78, (2007)
- [4] Yun Peng, Youyong Zou, and Xiaocheng Luan, Semantic Resolution for E-Commerce, Department of Computer Science and Electrical Engineering University of Maryland Baltimore County (UMBC) Baltimore, MD 21250, USA, (2002)
- [5] AnHai Doan, Jayant Madhavan, Robin Dhamankar, Pedro Domingos, and Alon Halevy, Learning to Match Ontologies on the Semantic Web, Department of Computer Science, University of Illinois

- at Urbana-Champaign, Urbana, IL 61801, USA, (2003)
- [6] Sampson, D. G., Lytras, M. D., Wagner, G., & Diaz, P, Ontologies and the Semantic Web for E-Learning. *Educational Technology & Society*, 7 (4), 26-28, (2004)
- [7] Muna, S. Hatem, Haider, A. Ramadan and Daniel, C. Neagu, E-Learning Based on Context Oriented Semantic Web, 1,2College of Science, Department of Computer Science, Sultan Qaboos University, P.O. Box 36, Al-Khod 123, Muscat, Oman, (2005)
- [8] Moreale, E., & Vargas-Vera, M. Semantic Services in E-Learning: an Argumentation Case Study. *Educational Technology & Society*, 7 (4), 112-128, (2004)
- [9] Julien Tane, Christoph Schmitz and Gerd Stumme, Semantic Resource Management for the Web: An E-Learning Application, Learning Lab Lower Saxony, Expo Plaza 1, D30539 Hannover, Germany, (2004)
- [10]Wen-Ying Guo, De-Ren Chen, and Xiao-Lin Zheng, A Semantic Web Approach to "Request for Quote" in E-Commerce, College of Computer Science, Zhejiang University, Hangzhou, 310027, China, (2006)
- [11]Biswanath Dutta, Semantic Web Based E-Learning, Documentation Research and Training Centre Indian Statistical Institute, Bangalore, (2006)
- [12] Nejd W. Learning Repositories – technologies and Context, To appear in Proceedings of ED-MEDIA 2001 World Conference on Educational Multimedia, Hypermedia & Telecommunications, June 25-30, Tampere, Finland, (2001)
- [13] Rashid Jayousi and Yasmin Bali, Querying and Semantic Mapping Approaches for Semantic Resolution in E-Learning System, appear in the proceedings of the Second IFIP International Conference Technologies, Mobility and Security (NTMS'2008), Morocco, (November 2008)
- [14] Zhongli Ding, Semantic Resolution in a simple E-Commerce Application, Department of Computer Science and Electrical Engineering, University of Maryland Baltimore County (UMBC) Baltimore, MD 21250, USA, (2005)