

Recommender System Role in e-Learning Environment

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Abstract

A recommender system in e-learning context is a software agent that tries to "intelligently" recommend actions to a learner based on the actions of previous learners. These recommendation systems have been tried in e-commerce to entice purchasing of goods, but haven't been tried in e-learning. The majority of current web-based learning systems are closed learning environments where courses and learning materials are fixed and the only dynamic aspect is the organization of the material that can be adapted to allow a relatively individualized learning environment. The proposed framework for building automatic recommendations in e-learning platforms is composed of two modules: an off-line module which preprocesses data to build learner and content models, and an online module which uses these models on-the-fly to recognize the students' needs and goals, and predict a recommendation list. Recommended learning objects are obtained by using a range of recommendation strategies based mainly on content based filtering and collaborative filtering approaches, each applied separately or in combination.

Keywords: e-Learning, Recommender System, Recommendation Engine, Learning Management System, Adaptive Learning System.

I. INTRODUCTION

The research in e-learning field has gained more and more attention thanks to the recent explosive use of the Internet. However, Web-based learning environments are becoming very popular. In a virtual classroom, educators provide resources such as text, multimedia and simulations, and moderate and animate discussions. Remote learners are encouraged to peruse the resources and participate in activities.

In this paper, we will propose an evolving web-based learning system which can adapt itself not only to its users, but also to the open Web in response to the usage of its learning materials. Our system is open in the sense that learning items related to the course could be added, adapted, or deleted. Our proposed e-learning system adapts both to learners and the open Web.

Our system is designed to support an advanced course on data mining and web mining and their applications on e-systems.

When instructors put together an on-line course, they may compile interactive course notes, simulations, demos, exercises, quizzes, asynchronous forums, chat tools, web resources, etc. This amalgam of on-line hyperlinked material could form a complex structure that is difficult to navigate. Designers and instructors, when devising the on-line structure of the course and course material, have a navigation pattern in mind and assume all on-line learners would follow a consistent path; the path put forth in the design and materialized by some hyperlinks.

In e-commerce, recommender systems allow entities providing goods or services to guide the choices made by potential customers. The recommendation can be issued by the merchant who sells the goods or services themselves or by intermediary brokers, but we shall henceforth use the generic term merchant to refer to the entity operating the recommender system. Similarly, we use the generic term product to refer to any item offered by the merchant, whether it's a digital or physical good, or a service to be provided.

Figure 1 compares the traditional we-based adaptive learning system and our proposed open evolving learning system.

In a traditional adaptive e-learning system, the delivery of learning material is personalized according to the learner model. However, the materials inside the system are determined by the system designer/tutor. In open evolving e-learning system, learning materials are automatically found on the web and integrated into the system based on users' interactions with the system.

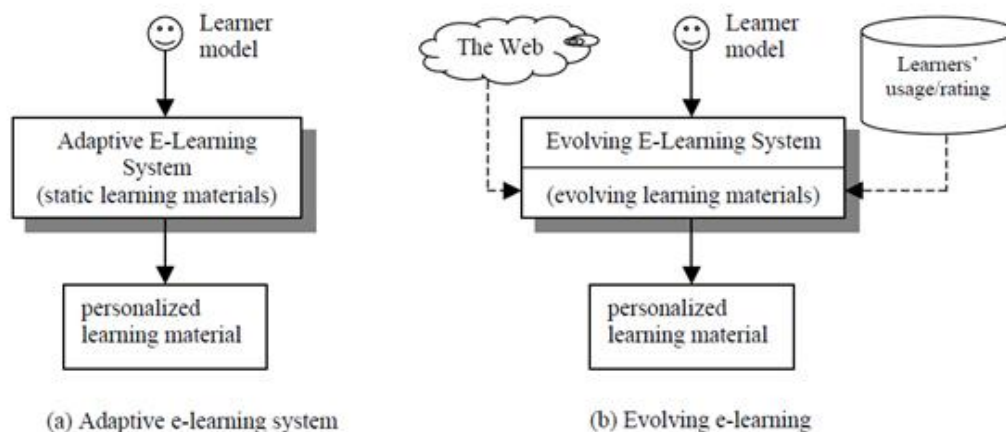


Figure 1: A comparison of evolving e-learning system vs adaptive e-learning system [3]

There are two kinds of collaboration in the system. One is the collaboration between the system and the user; another is the collaboration between the system and the open Web. Users do not have direct interactions with the open Web; though the system can retrieve relevant information related to a learner and his/her learning characteristics. Two of the major techniques that would be adopted include collaborative filtering and data clustering which have seldom been reported in the artificial intelligence in education literature.

II.RECOMMENDATIONS IN E-LEARNING DOMAINS

Making recommendations in e-learning is different from that in other domains (the most studied domain of recommender system is movie recommendations [1]-[4]). Particular issues for an e-learning recommender system include:

- a) **Liked Items:** by learners might not be pedagogically appropriate for them. For example, a learner without prior background on the techniques of web mining may only be interested in knowing the state-of-the-art of web mining techniques in e-Learning. Then, it should be recommended that he/she read some review papers, for example, an editorial article by two of the leading researchers in this area [5], although there are many high quality technical papers related to his/her interest. On the other hand, for the learner coming from industry with some prior knowledge who wants to know how web mining can be utilized to solve e-learning problems [6]. By contrast in other domains, recommendations are made based purely on users' interests .
- b) **Customization:** should not only be made about the choice of learning items, but also about their delivery [7]. For example, some instructors will recommend learners to read an interesting magazine article before reading a technical paper, because they believe it will help learners understand the technical paper and make them less intimidated.

In our proposed system, we will organize courses not only based on their main research categories, but also their technical levels. For example, review courses, workshop courses, highly technical courses etc.

Generally, the aim of Recommender System in web applications, is presenting interest information that fits the users tastes and preferences with little effort. The aim of Recommender System in e-learning applications is listing "the closest available learning objects to what the instructor describes as the module's content"[8].

III. LEARNING MANAGEMENT SYSTEM

The LMS/CMS is an e-learning platform which is considered as an important part of e-learning solutions from the university's viewpoint [9].

Anyway, LMS is software that automates the administration of training events. All LMS(s) manage the login of registered users, manage courses catalogs, track learner activities and results, and provide reports to management [10].

The market of LMS is increasing very fast; some of LMS(s) are commercial software like WEBCT, while others are free open sources like MOODLE.

IV. RECOMMENDER SYSTEMS/RECOMMENDATION ENGINES

Recommender Systems or recommendation engines form or work from a specific type of information filtering system technique that attempts to recommend information items (films, television, video on demand, music, books, news, images, web pages) that are likely to be of interest to the user. Typically, a recommender system compares a user profile to some reference characteristics, and seeks to predict the 'rating' that a user would give to an item they had not yet considered.

These characteristics may be from the information item (the content-based approach) or the user's social environment (the collaborative filtering approach)[11].

V. LIMITATIONS WITH RECOMMENDER SYSTEMS

The first limitation comes from the limited availability of real data. This leads us down to the question whether learners really behave as is modeled in the conceptual simulation model. The conceptual simulation model is derived from various theories, but at a more detailed level, we were sometimes forced to make arbitrary choices. For example: obedience towards recommendations is personalized, but is still supposed to be stable for each learner[12].

The second limitation stems from the fact that a conceptual model always represents part of the world, with as drawback that features could still be missing, notwithstanding the expert consultation that was carried out to verify the current model. Four examples are included to clarify this. First, it was not explicitly taken into account that learners' choice in performing a recommended Learning Actions (LA) depends on the enrolment-costs of that Learning Actions. Second, we did not take into account some 'constraints' that could act as 'negative feedback' in the conceptual simulation model. For example: Learning Actions might have some enrolment constraints (maximum number of learners, limited start-time, a.s.o.). Third, learners do not interact with each other in the Learning Networks (LN), only indirect social interaction is modeled. However, in reality there is always a combination of indirect and direct social interaction influencing the choices made. The lack of direct social interaction by no means should have to be problematic, as has been demonstrated by educational institutes who have adopted a blended learning or online learning approach. For instance, most open universities

successfully provide distance education by combining a blended approach to correspondence study with little or none direct social interaction. Fourth, learners can have preference for one sub domain only, whereas specific learners could like several sub domains equally or would like to indicate their preferences more gradually.

The third limitation comes from the simplification towards competences. Our conceptual simulation model does not deal with competence-hierarchies. These are complex to describe and the Personalized Recommendation System (PRS) should be able to trace how completion of a certain learning action can contribute to the -partial- attainment of more than one competence. The learning path specification which is currently under development could tackle this problem [13].

The fourth and final limitation of this study is that it shows that somewhat ontology-based recommendation, namely a limited set of Learning Action-characteristics and learner-characteristics, should preferably be part of the hybrid approach. However, this can induce considerable workload that could be minimized when using a limited vocabulary of meta data. But, how to identify such limited vocabulary that can be expected to be partly domain dependent?

There are many questions arise when dealing with recommender systems such as:

- Is it possible to apply recommender system in E-learning field?
- What are the benefits of applying recommender system on E-learning environment?
- What are the resources that could be recommend for the users of the system?
- How could we build the recommender system?

VI. METHODOLOGY

Our proposed framework is composed of two modules: an off-line module which pre-processes data to build learner and content models, and an on-line module which uses these models on-the-fly to recognize student goals and predict a recommendation list. Recommended learning objects are obtained by using a range of recommendation strategies based mainly on content based filtering and collaborative filtering, each applied separately or in combination. The recommendation procedure is performed using the following tasks:

- a) *Preliminary offline mining of learners' models* based on Web usage mining techniques. First, we will gather web learners' sessions and we will apply a clustering approach to directly cluster these sessions. Each cluster contains similar sessions, showing similar interests of different learners. Each cluster can also be viewed as one learner's model;
- b) *Preliminary offline mining of association rules* (e.g. "Resource A → Resource B") from clustered sessions;
- c) *Preliminary offline crawling and indexing of learning resources*: this step consists of crawling the entire learning resources available in a course repository and forming an inverted index mapping each keyword to a set of pages in which it is contained;
- d) *Extracting user preferences from the learner's active session* (set of URLs or list of terms extracted from these URLs);
- e) *Computing relevant links to recommend for the active learner* by applying a number of recommendation strategies.

The proposed approach, with main features depicted in Figure 2, is essentially based on two components: the Modeling phase and the Recommendation phase[16].

1. Modeling phase

Learner Modeling: Despite the availability of abundant educational resources and services, it is still difficult to decide which learning objects better match the student’s needs in a given situation, unless we accurately know the profile of that particular learner and his/her online behavior.

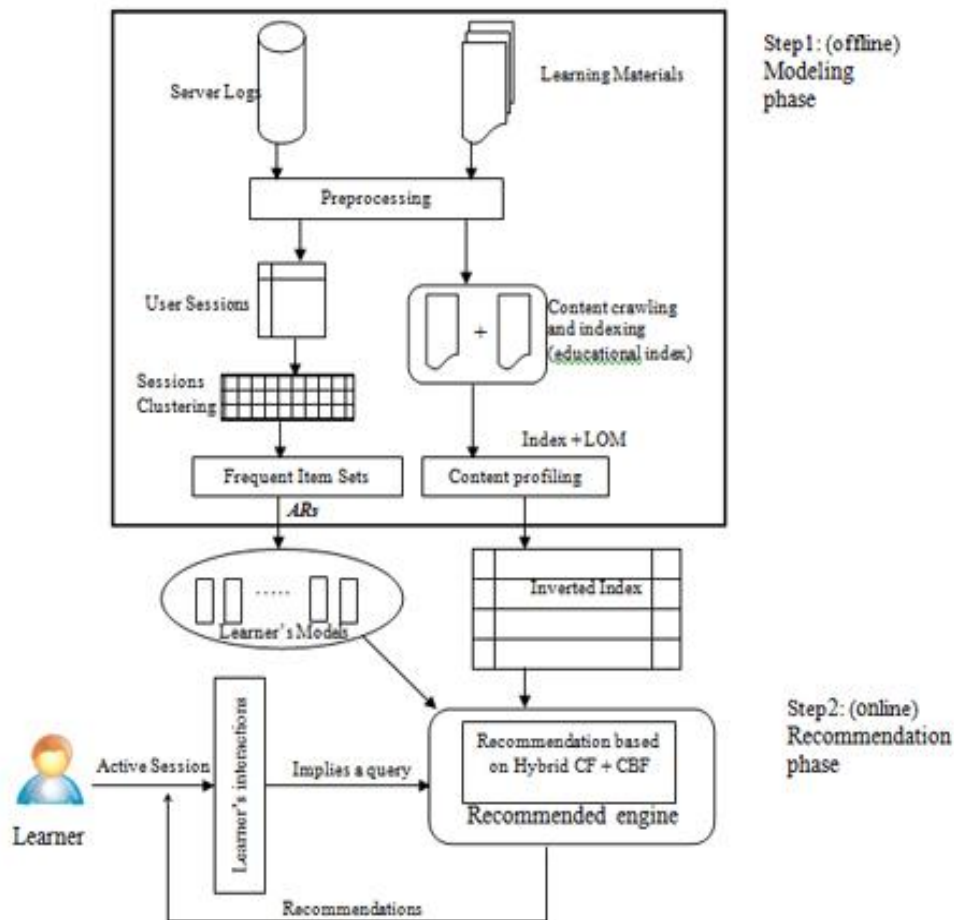


Figure 2: Proposed personalization approach [16]

A learner's model is composed by a range of relevant information about the student using the e-learning environment. Frequently common types of information used in learners' models can include the learner knowledge, demographic information, preferences, learning styles, etc. These components are strongly connected to the application of the learner model. The learner's model (reduced here to his/her learner's knowledge component) can be represented by a sequence of weighted visited learning objects.

Basically, two main learner modeling approaches can be outlined: collaborative learner modeling and automatic learner modeling. The collaborative learner modeling approach requires students to provide explicit information about their preferences and needs. In the automatic learner modeling approach, gathering information is done rather automatically based on the online behavior and activities of students.

Group Modeling: Once learners' models are delimited properly, we apply a two-level model based collaborative filtering approach in order to organize the obtained models into groups of learners based on similarities and dissimilarities among their preferences. In the first level, we apply clustering techniques based on similarities and dissimilarities among preferred visited learning objects. A variety of clustering techniques can be used for clustering sessions. Shahabi et al., [17] described a prototype system that uses viewing time as the primary feature to describe a user session and then clusters the sessions using K-Means clustering. Mobasher et al., [18] used a multivariate K-Means algorithm to obtain transaction clusters and the Association Rule Hypergraph Partitioning (ARHP) technique to obtain usage clusters. Yao et al., [19] applied the Leader algorithm for clustering.

The second level applied on each obtained cluster consists of using, first, a frequent item-set mining algorithm that extracts frequently co-occurring referred

learning objects in sessions belonging to each cluster. Then, association rules (AR) are extracted from these clusters. Association rules capture the relationships among learning objects references based on their co-occurrence across sessions.

Thereby, further in recommendation phase, the new active learner is directly classified in one of the discovered groups of students (clusters), then personalized recommended links are provided by matching the learner current navigation with the AR of the corresponding group.

Content Modeling: Generally, content modeling involves applying indexing and text mining techniques (which are part of Web content mining). The originalities of our approach are twofold:

(1) The use of the open source search engine Nutch (<http://lucene.apache.org/nutch>) in the content modeling phase, followed by content based filtering as a recommendation strategy.

(2) The automated indexing of standard defined educational content thanks to the search engine's powerful capabilities in the automated and scaled crawling and indexing phases.

2. Recommendation phase

Formulating a learner's implicit query: The learner's implicit query is a set of referred learning objects recently visited by an active learner. Such query should be extracted implicitly from the recent navigation history of the learner and could be represented by a number of referred learning objects describing these learning objects. This task is accomplished in two phases:

(1) Delimiting the current active learner session.

(2) Extracting URLs (Learning Objects references) of interest from this active session.

We identify only the records representing the last visited pages called the sliding window. This is done by taking into account the timestamp when a learner connected to the system and the timestamp of a recommendation demand. In order to express with more details learner preferences and interests, we can associate to each URL, composing learner sessions, a given value this value stored in a data store to make it easy to gather the visited resources.

Recommendation process: The recommendation process task is accomplished using basically: content-based filtering (CBF) and collaborative filtering (CF) approaches. Then the results of both techniques are combined together to produce a single recommendation set [20].

(1) *Content Base System:* in this case the objects are selected by detecting the similarities between the current course attributes (name, keywords, abstract,... etc) and the other courses.

(2) *Collaborative Filtering Systems:* it recommends items or objects to a target user, based on similar users' preferences, and on the opinions of other users with similar tastes. The suitable one for our LMS named as Memory-Based Algorithm (also known as k-nearest neighbor method) which is suitable to environments where the user preferences have to update rapidly.

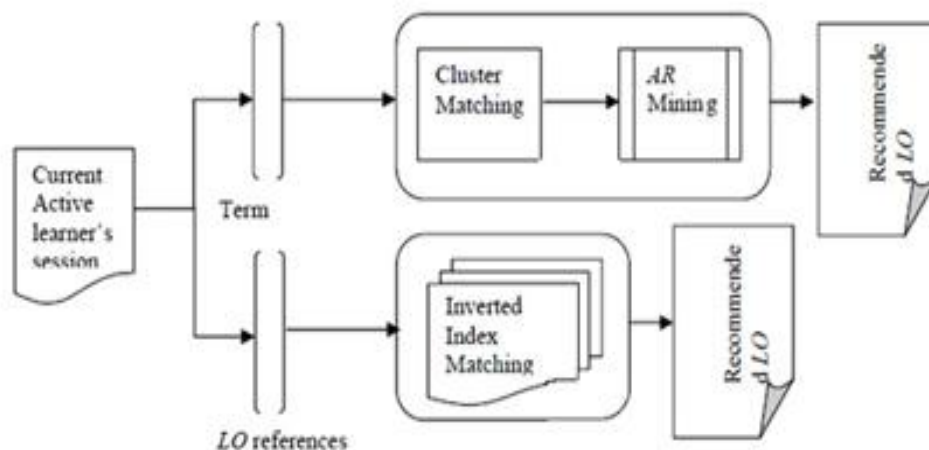


Figure 3: Recommendation process [20]

VII. RECOMMENDER SYSTEM (RS) IN LEARNING MANAGEMENT SYSTEM (LMS)

Many approaches to recommender systems have been proposed in the literature. According to Burke [21], the best known of these are as follows:

a) *Collaborative filtering*: Accumulates visitor ratings, identifies visitors with common ratings and offers recommendations based on inter-visitor comparison. In other words, recommendations for a given visitor are based on the behavior and the evaluations of the other visitors.

b) *Content-based filtering*: Uses the features of the resources and the visitor's interest in these features to resource recommendations.

c) *Demographic filtering*: Groups visitors according to their demographic information. Resources are recommended to a given visitor based on the group to which he belongs.

d) *Utility-based filtering*: Uses the features of a resource to compute its utility. The visitor must input the utility function to apply over the products that describe his preferences. Applying the utility function enables resource ranking from which recommended products emerge.

e) *Rule-based filtering*: it is filtering information according to set of rules expressing the information filtering policy [22].

f) *Knowledge-based filtering*: Bases the recommendation of resources on inferences about the visitor's needs and interests. Here, the knowledge is about the association of a particular resource to the need of a particular visitor.

VIII. THE PROPOSED RECOMMENDER SYSTEM

The proposed recommender system will play a vital role in e-Learning environment. Where it offers recommended courses on the new users, help new users to learn fast and find the useful resources. The proposed framework for individualized learning objects selection will select a short list of suitable learning objects appropriate for the learner and the learning context [14].

The suitable approach to recommended learning objects in LMS will not be based one approach [23] but it will be mixed some of the features of the previous approaches.

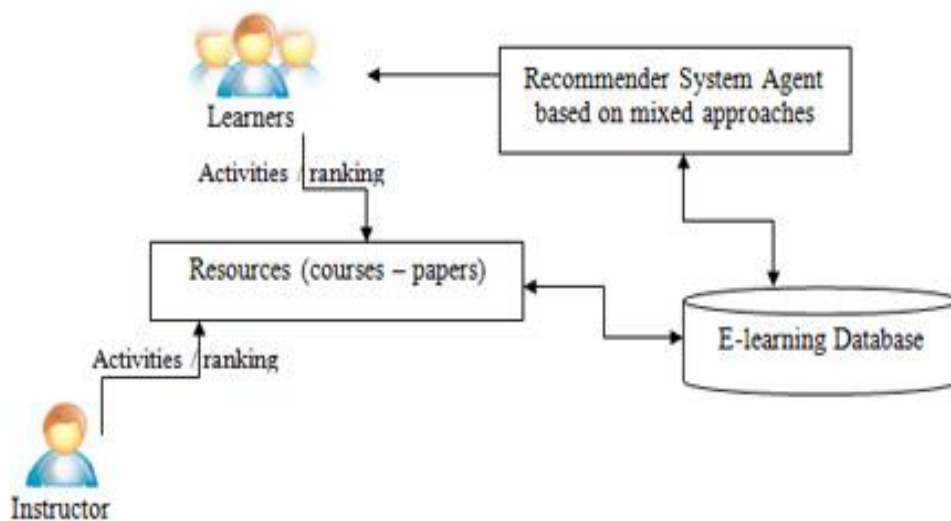


Figure 4: The Proposed Recommender System

The technology used is PHP language as a programming and MYSQL database as the storage database for the system resources. Also some of javascript will be applied in order to accomplish the web application.

IX. CONCLUSION

In this paper we have presented how recommender systems can be applied to E-Learning System. More specifically, we have investigated the task of item recommendation, where interesting and relevant items are retrieved and recommended to the user, based on a variety of information sources about and characteristics of the user and the items. The recommendation algorithms proposed based on two different characteristics: the usage data contained in the teacher recommendation, and the metadata describing the user peripherals or characteristics on E-Learning database over the website.

In deciding which tasks to tackle it is essential to profile the users: what do they want, how and what are they currently using the system for? We believe that focusing on real-world tasks in research can drive successful innovation, but only if the tasks under investigation are also desired by the users.

In the experimental evaluation of our work, we have focused on using publicly available data sets and comparing our work against other approaches, something which is lacking from much of the related work. We are aware, however, that our comparisons are by no means complete as we picked only two promising approaches to compare our work with. Model-based collaborative filtering algorithms, for instance, were lacking from our comparison. In ‘regular’ recommendation experiments in different domains, model-based algorithms have been shown to hold a slight edge over memory-based algorithms or group-based algorithm, but without proper comparison on multiple social bookmarking data sets we cannot draw any conclusions about this.

REFERENCES

- [1] Basu, C., Hirsh, H. and Cohen, W.W. "*Recommendation as classification: using social and content-based information in recommendation.*," In Proceedings of the Fifteenth National Conference on Artificial Intelligence, 714-720, AAAI/IAAI 1998.
- [2] Herlocker, J.L., Konstan, J.A., Borchers, A. and Riedl, J. "*An algorithmic framework for performing collaborative filtering.*" In Proceedings of the 22nd Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'99), 230-237, Berkley, USA. 1999.
- [3] Schein, A., Popescul, A., Ungar, L. and Pennock, D. "*Methods and metrics for cold-start recommendations.*" In Proceedings of the 25th Annual International ACM SIGIR Conference on Research and Development in Information Retrieval (SIGIR'02), Tampere, Finland, August 2002.
- [4] Melville, P., Mooney, R. and Nagarajan, R. "*Content-boosted collaborative filtering for improved recommendations.*" In Proceedings of the 18th National Conference on Artificial Intelligence (AAAI-2002), 187-192, Edmonton, Canada. 2002.
- [5] Kohavi, R. and Provost, F. "*Applications of data mining to electronic commerce. Data Mining and Knowledge Discovery, an editorial of the special issue of Data Mining on Electronic Commerce*", 5(1/2): 1-7, 2001.
- [6] Kohavi, R., Brodley, C., Frasca, B., Mason, L. and Zheng, Z. J. "*KDD-Cup 2000 organizers' report: peeling the onion. SIGKDD explorations*", 2(2): 86-98, 2000.

- [7] Kobsa, A., Koenemann, J., Pohl, W. "*Personalized hypermedia presentation techniques for improving online customer relationships. The Knowledge Engineering Review*", 16(2), 111-155, 2001.
- [8] Calvo R., "*User Scenarios for the Design and Implementation of iLMS*," in Proceedings of the AIED 2003 Workshop, Towards Intelligent Learning Management Systems, pp 14-22, 2003.
- [9] Itmazi J., Gea M., Paderewski P., and Guitierrez F., "*A Comparison and Evaluation of Open Source Learning Management Systems*," in Proceeding of the IADIS International Conference-Applied Computing 2005, Portugal, 2005.
- [10] Brandon-Hall, "e-Learning Glossary of Terms," www.brandonhall.com/public/pdfs/glossary.pdf, 2003.
- [11] Wikipedia: http://en.wikipedia.org/wiki/Recommender_system
- [12] KOPER E J. R. "*Increasing learner retention in a simulated learning network using indirect social interaction.*" Journal of Artificial Societies and Social Simulation, 8(2). Retrieved, October 30, 2007.
- [13] JANSSEN J , Berlanga A J, Vogten H and Koper E J R., "*Towards a learning path specification.*", International Journal of Continuing Engineering Education and Lifelong Learning, 18(1), 77-97, 2008.
- [14] Liu J. and Gree J., "*Individualized Selection of Learning Object*," In Proceeding of the ITS 2004: International Conference on Intelligent Tutoring Systems, Macei-Alagoes, 2005.
- [15] Lu J., "*A Personalized e-Learning Material Recommender System*" in Proceeding of the 2nd International Conference on Information Technology for Application (ICTA 2004), pp 374, China, 2004.
- [16] Khribi, M. K., Jemni, M., & Nasraoui. O. "*Automatic Recommendations for E-Learning Personalization Based on Web Usage Mining Techniques and*

- Information Retrieval*". The 8th IEEE International Conference on Advanced Learning Technologies, July 1-5, Santander, Spain, 2008.
- [17] Shahabi, C., Zarkesh, A. M., Adibi, J., & Shah, V. "*Knowledge Discovery from User's Web-page Navigation*". Paper presented at the 7th IEEE International Conference on Research Issues in Data Engineering, April 7-8, Birmingham, UK, 1997.
- [18] Mobasher, B., Cooley, R., & Srivastava, J. "*Automatic personalization based on Web usage mining*", Communications of the ACM, 43(8), 142-151, 2000.
- [19] Yao, Y. Y., Hamilton, H. J., & Wang, X. "*Page Prompter: An Intelligent Agent for Web Navigation Created Using Data Mining Techniques.*" Paper presented at the 3rd International Conference on Rough Sets and Current Trends in Computing, October 14-16, Malvern, PA, USA, 2002.
- [20] Nasraoui, O., Zhang, Z., & Saka, E. "*Web Recommender System Implementations in Multiple Flavors: Fast and (Care) Free for All.*" Proceedings of the ACM-SIGIR Open Source Information Retrieval, July, Seattle, WA, 2006.
- [21] Burke, R. "*Hybrid recommender systems: survey and experiments. Customer Model.*" Customer-Adapted Interaction 4(12), 331–370, 2002.
- [22] Terveen L. and Hill W., "*Beyond Recommender System: Helping People Help Each Other,*" in: Carroll J. (eds.), Human-Computer Interaction in the New Millennium, ACM Press, pp. 487-509., 2001.
- [23] Itmazi J. and Gea M., "*The Recommendation Systems: Types, Domains and the Ability Usage in Learning Management System,*" in Proceedings of the International Arab Conference on Information Technology (ACIT 2006) Yarmouk University, Jordan, 2006.