Design of a Recommender System for Web Based Learning

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***Abstract*—The design of recommender systems is an ongoing research area where several researchers have devised means of incorporating intelligence in web content systems to be able to provide recommendations to learners on the basis of their learning preferences i.e. based on their learning profiles. The paper discusses the design of such a system based mapped to a content ontology and learner profiles created in the system.**

***Index Terms*—recommender systems, web-based learning systems, ontology, semantic web, RDF schema.**

I. INTRODUCTION

A system that responds to a user's request but adapts the responses so that it suits a particular user's need or interest is generally termed as personalized recommender system. Rather than simply responding to queries, a recommender system (RS) operates as a personalized information agent.

In the 1990s, recommender systems became an important research area [1] when researchers started focusing on recommendation problems faced by users when their queries were generated result sets that were not reliable. The focus grew on designing systems that could provide content for user evaluation; these could be user rated and shared among users with similar needs.

However the systems that provide guided recommendation to users have to overcome the problem of assessing ratings for the items that have not yet been accessed or viewed or rated by the user.

Different forms of recommender systems are available in a large variety of practical application. These systems target the problem of information overload that users have to face and provide the user with facilities such as individual (personalized) recommendations, exclusive content and services.

Examples of such applications include recommending books, CDs and reading lists.

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Recommender systems often combine the characteristics of using the collective traits of different category of learners, suggest preferences based on these traits and give feeling of being in control, to the learner. The Learning process is almost learner – driven in this instance. However suitable guidance is also given at various points. These attributes help the RS to have features that have the potential to leverage the learning processes [2]. There is an understandable difference in the way different learners accept instruction and how they assimilate the acquired knowledge to benefit from similar types of instruction [3]. It is understandable that instructional material should be prepared and be adaptable to match the abilities of learners, their learning styles and knowledge.

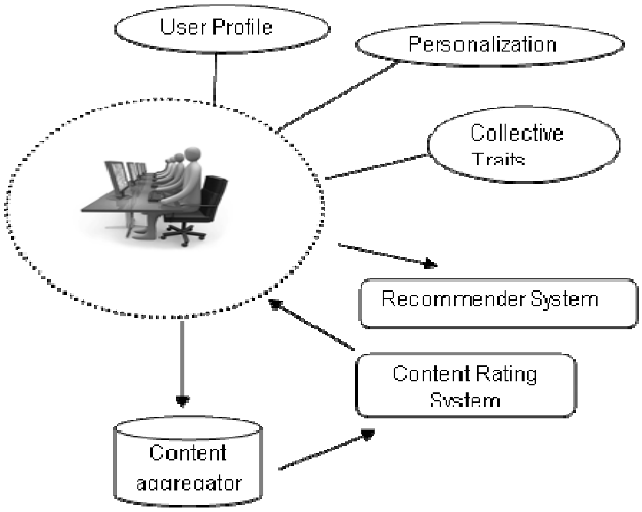

Figure 1 – Recommender System in an Online learning Environment

Learning technologies such as intelligent tutoring systems [4] or adaptive hypermedia environments [3], tailor learning content to meet the needs and abilities of learners.

A recommender system involves the following key stages

- choosing an appropriate learning approach depending on the style of the learner,
- choosing content depending on the learning style and approach choosing the appropriate content,
- choosing learning modules that can create a learning activity path.
- The knowledge that the learner has acquired and needs to acquire are then mapped appropriately to the learning activity mechanism that controls the generation of learning content in the recommender based learning management system.

The recommender system was grounded on the mechanism of Exploration Space Control (ESC). This system was discussed in [14]. It was designed to address the problem of the excess load that the learners' cognition had to face while searching for knowledge in a sea of information. It attempted to provide a mechanism to exhaust all irrelevant sources in the students learning materials database.

In ESC, the extent of the learning space, as termed by Kashihara [14] is drawn up by the domain complexity.

Learners' are guided by a defined learning space determined by the domain complexity, and also by the learners' competence, knowledge levels, learning experiences and attributes etc. The control is implemented by restricting exploration tools provided in the knowledge system' user interfaces, assembling the information to be presented for the user, recommending a few among a number of choices.

II. TYPES OF RECOMMENDER SYSTEMS

In a collaborative environment, the collaborative filtering algorithm based recommender systems use the ratings given by a set of similar users to recommend articles. However in this case the meaning of similar is ambiguous. PHOAKS [13], Group Lens [14] for recommending web links mentioned in newspaper articles, Video Recommender. These systems suffer from cold start problem that is they need users to rate the articles posted. Once a sufficient number of users (at least 18 in some systems) have rated these articles, then the system can start recommending the highly-rated articles.

In the discussion on (CB) content-based recommender systems, the system recommends those items which are similar in content so that a list of similar things the user has selected before will be generated.

An example of a content-based recommender is Fab [12], which recommends web pages. Systems like Fab rely on the ratings made by each user in order to create a training set. The ELFI [25] content-based recommender is, used for recommending project funding information from a database of entries. The system deduces both affirmative and adverse examples of interest in user interactions with a system while they are interacting and using a database.

However the cold-start problem, which affects a large variety of such items, is also inherent in this system. So the actual performance of this system can only be studied if a large number of users access the system and its contents, rate /recommend items that meet their needs. Below we discuss some hybrid systems-

- Tang and McCalla [15] have developed a ground-breaking innovative system. The PRS system was targeted for use by the learners of a data mining course who could receive a paper reading recommendation which was based entirely on their reading preferences. The system was based on a hybrid system integrating both Ontology-based Learner Model and CF techniques. In this system, learners were asked to provide their research paper selection preferences. These learning preferences ultimately were used to cluster the learners under various classifications. In a dynamic set of papers only the fittest papers were included. Although Tang and McCalla's approach is very useful, it was only applied in a limited domain. Further the system was hampered by drawbacks such as the inability to update learner models and also verify the veracity of these models

- The QSIA system proposed by [6, 7] is based on collaborative filtering and is used to primarily support collaboration among learner groups. The expert automated CF algorithm or buddy system is the integral component of this system. QSIA users are given the freedom to use the buddy system, i.e. the collaboration mechanism binding the various groups of learners or to be an autonomous user who does not rely on the buddy system.

- The CYCLADES system [10], is based on three set of algorithms- record recommendation, collection recommendation and user recommendation. The system allows users to make recommendations, collect these recommendations into folders and share their recommendations with other users. The CYCLADES repository uses open and shared digital resources, which are in the repositories of the Open Archives Initiative (OAI).

- Andronico's [11] hybrid PRS (InLinx) was another system designed to provide paper recommendation to learners based on content analysis. The system is a based on a content analysis, it clusters learners and recommends those resources that can also instruct learner by matching their learning requirements and interests also taking their learning capabilities and faults into account.
  This system was intended to perform as a recommendation based learning system. However they suffered from the same drawback as the PRS hybrid recommender system.

- Farzan and Brusilovsky [10] proposed the adaptive community-based hypermedia system CourseAgent for recommending courses that depends highly on the learners' feedback.. This interactive system relied heavily on the users's feedback and ratings of the items recommended by these users. The two tier system was based implicitly on intrinsic user comments and explicitly on the user's ratings. It was hampered by a conditional behavior in which only any explicit feedback given by the user would be rewarded by being granted an insight, to how far the learner had reached in achieving the learning goals.

- Data mining techniques were used by Hsu [19] to cluster users with similar content preferences and then administered with a combined system using both content analysis and feedback on content to support learners during reading lessons in English language [19] Learners were supported in their learning acquisition process by the (Personal Recommendation System).These e-learning systems are meant to support the learning process; the recommender system should consist of significant pedagogical rules describing the relations between learner attributes and activity attributes.

- Learning Resource Recommending Systems such as the RACOFI (Rule-Applying Collaborative Filtering) Composer use the hybrid approach where a content feedback engine works with users' ratings for learning resources. This system is based on an inference rule engine that is capable of extracting association rules between the learning resources. These systems are then used by them for generating recommendation to match user queries or interests. [5]. However the impact of these on leveraging pedagogical values has not been measured so far.

- Shen and Chen [25] investigated the use of sequencing in recommender systems. The required mapping between an ontology based course-map and learner aptitude makes this approach time consuming. There needs to be a clearer perspective of the domain to which this methodology is applicable. Moreover, the system focused more on the gaps in learning abilities and did not determine learner preferences. The veracity of this approach was not confirmed.

- Jeong et al [24] have suggested a method to solve the data scarcity problem by filling unrated items based on their similarity with rated items by using extrapolation method. This method is an extension of the memory-based method and involves a lot of time consuming computations, which the authors fear will slow the system.

ATI research [22] examines how individual learning differences or aptitudes can affect learner responses to different instruction styles. ATI focusses primarily on the student capabilities termed as Aptitudes or learner characteristics, such as learning abilities, attitudes, personality variables, demographic factors, etc. The instruction styles are termed as treatments. These are forms of instruction, or sets of conditions, associated with instruction. ATI studies the reasons for the variation in learner achievement and learner with the interaction (combination) of instructional conditions with student competencies.

RS systems for pedagogical purposes are important in the following scenarios. This is because, e-learning systems need to satisfy the learner’s typical demands and that include [19]:

- Training events in the system that can match the learning objectives, educational background, learning style and educational needs.
- The system must provide a platform to support the continuous education requirement of learners.
- Workplace training must be integrated in the e-learning system using a variety of learner knowledge models.
- The system must provide a cost-effective solution to the global requirements of learners.

Recommender Systems throw up a variety of interesting challenges for researchers to delve into. One foremost challenge is related to learner preferences when a search query returns a result with a multitude of comparable learning objects. This brings up the issue of arranging these learning objects in some order based on learner’s knowledge requirement.

A course mapping and concept description engine is used to map the Learner Profile containing their aptitudes, interests and learning styles and concept map approach to enrich the learning experience. This is envisioned by creating a platform to provide unremitting interaction between the learners and the resources in the learning objects repository

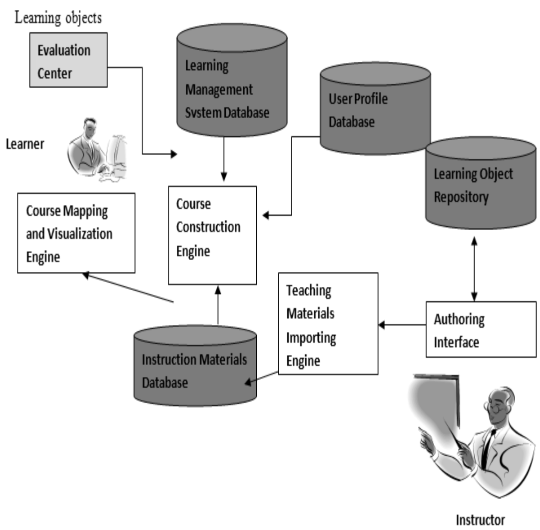

Fig.2. Scenarios in Web Based Learning.

There needs to be a correlation between the objects in the learning space or collection, which can be constructed using concept maps. The system has been designed by using a modified concept map approach to model aspects of the inferred knowledge acquired by the learner during the learning process into various other modes of application.

This inferred knowledge is gathered after each learning experience. This knowledge might be applicable in one domain or several domains, but the learner needs to visualize the inferred knowledge and its relation with the knowledge required to complete the learning path successfully.

Recommendation systems need to apply certain levels of personalization to make the system provide specialized experience to learners

To this purpose, a course provider or teacher has to choose and apply the [15] personalization strategy which matches the aptitude of the learners and the attributes of the course. In order to achieve this objective, the two complementary personalization levels in the personalized recommendation

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system will be consisting of 16 personalization parameters [23].

PRLA- The course ontology needs to update learning objects also the learner profiles need to be populated and updated as soon as the learner crosses different levels of knowledge acquisition group.
PRLB – The system needs to group learners with matching domain interests, aptitude and learning styles, after mining the user profiles for extracting this information. The ontology needs to be embedded with the learner group triples.
PRLC – The system needs build a list of top-rated or recommended learning objects for various learner groups based on the information extracted in PRLA and PRLB.

The three tiers are controlled by the following personalization parameters of e-learning scenarios. They are knowledge seeking task, learner current knowledge, learning requirements, language preference, kolb learning cycle, honey-Mumford, Felder-Silverman learning style, La Garanderie learning style, learner participation level, ability to progress on task, learner enthusiasm to achieve the next level of learning, learning resource navigation preference, learner cognition attributes and preferred instruction style.

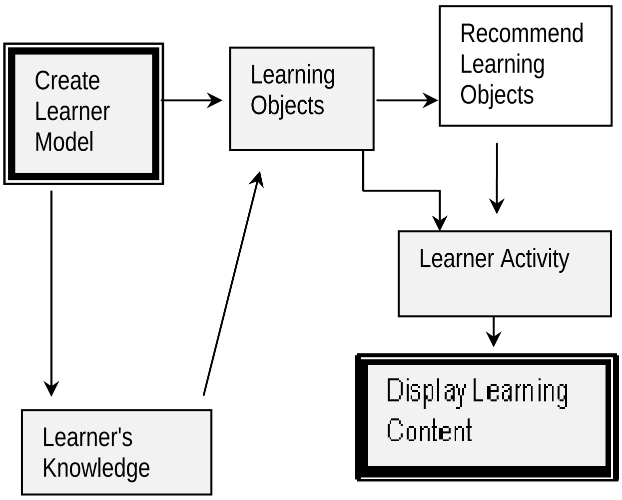

Fig. 3. Selecting Learning Objects Using Learner Models

Personalization involves the following key stages – they include choosing an appropriate learning approach depending on the style of the learner, depending on the learning style and approach for choosing the appropriate content, in turn these contents need to devise the appropriate teaching activities suitable for that learner. The learning modules need to consist of suitable learning content modules called learning objects which are then included in the learning activity structure. The knowledge that the learner has acquired and needs to acquire are then mapped appropriately to the learning activity mechanism that controls the generation of learning content.

III. SEMANTIC WEB

The Semantic Web concept tries to solve the deficiencies faced web services by providing reliable, large-scale interoperation of Web services. To embed intelligence and machine understandable services in the web, so that knowledge discovery becomes possible and the Web can achieve its full potential. The role of intelligent agents in such a system is to assist in discovery of knowledge, execution of user queries, and automatic alignment of web content [5].

Below are listed the solutions provide by SW for the integration of SW with existing domain knowledge structures:

1) RDF and OWL the two ontology languages for labeling content in knowledge databases. [12]
2) Ontologies are not static structures they are dynamic in that they develop over- time and need maintenance, SW attributes several ontology management technologies for ontology engineering task [12].
3) Techniques for supporting ontology-based systems and combining these with personalization technologies have been extensively employed in different domains such as e-learning, language learning to collect and assemble more interesting objects that can attend to individual learner's preferences [15].

The main advantage of the Semantic Web is to enhance search mechanisms with the use of Ontology's [3].

Learner profiles (helps to maintains learner aptitude, and response to experience) are mapped to recommendation lists or items evaluated by the learner. Personalization approaches then recommend those objects that are to have a greater match with the items in the learner profile. Learner profiles are usually the base for learner's score on items evaluated in the duration the learner has an interaction with the system.

IV. ONTOLOGY MODEL

An LO model has been created to incorporate necessary (rich) structure description. Learning Object can be represented using the IEEE LOM [18].

Figure 4 Learning Object Representation Model

The LO RDF schema in shown in Figure 4. The LO in the repository are (author, domain, learning outcome/s learning

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objective keywords, date of creation location (URI) summary content description).

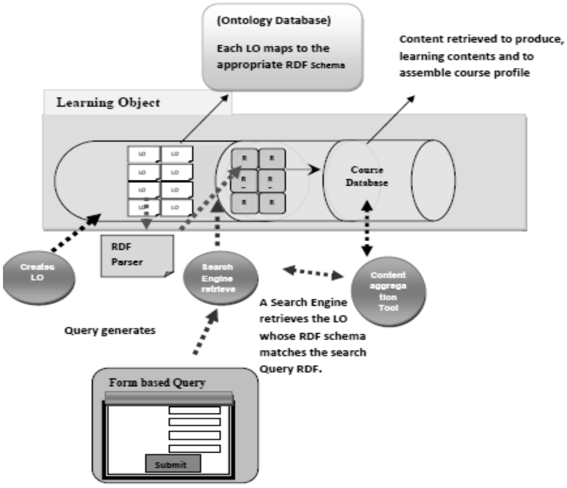

Fig.5. Course Content Recommender Model

The system shown in Figure 5 helps to recommend learning objects to learners based on well-structured queries against the metadata in the repository

The RDF parser converts the LOs in the repository to RDF triples. Each RDF triple is then mapped to the corresponding LO in the LO repository.

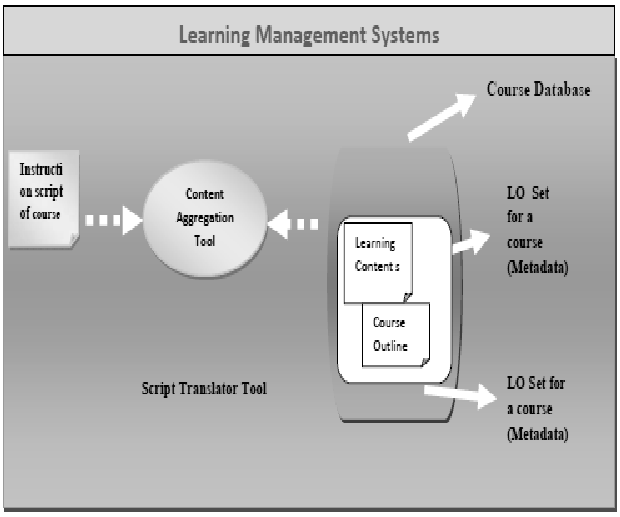

Fig.6. Design of recommender based Learning Management Systems

The system depicted in Figure 6 consists of the following modules:

- The instruction script of the course, which is embedded with user profiles, from where the learning preferences have been extracted,
- A content aggregation tool is used to collate recommended learning material into recommender lists,
- A course database which will contain an LO set for a course called the Metadata and also the course outlines for each course.
- The script translator tool that will deduce the Learning objects with the highest recommendation and these will then be collated into a recommendation list for that particular Learning Material.

The LO Database consists of a rich LO repository with rich metadata (RDF schema for each Learning Object). The ontology database maps each LO to its equivalent RDF schema using an RDF parser. Once a learner query is received, the search engine collates all related LOs to a single grouped entity or lesson using a content aggregation tool. These lessons are then used to construct a course after assembling the course contents in the particular order required for a course profile.

In this manner the system not only works as learning object recommender system but it can also assemble a complete new course. This will be investigated in our subsequent work

CONCLUSION

The paper discusses the issue of designing a recommender system for learning in online environment. The CRS is a hybrid recommender system as it based on learner profiles, and content recommendation from the user collaboration.

We have started work in the direction of using data mining techniques to use the course ontologies, learner's styles and learner aptitude to construct a complete new course from existing learning contents in a course repository. The recommender system will recommend the contents to be added to the new course.

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