Available online at http://www.journalcra.com

International Journal of Current Research
Vol. 11, Issue, 04, pp.3307-3313, April, 2019

DOI: https://doi.org/10.24941/ijcr.35379.04.2019

INTERNATIONAL JOURNAL OF CURRENT RESEARCH

ISSN: 0975-833X

RESEARCH ARTICLE

USER PREFERENCE TREE BASED PERSONALIZED ONLINE LEARNING MANAGMENT SYSTEM

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ARTICLE INFO

Article History:
Received 14th January, 2019
Received in revised form
17th February, 2019
Accepted 24th March, 2019
Published online 30th April, 2019

Key Words:

Personalized
FIM,
WD-FIM

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ABSTRACT

Intelligent decision is the key technology of smart systems. Data mining technology has been very important in decision-making activities. A Frequent item set mining (FIM), as an important step of association rule analysis is becoming one of the most important research fields in data mining. Weighted FIM in uncertain databases should take both existential probability and importance of items into account in order to find frequent itemsets of great importance to users. This system is intended to show the things occurred in between the searches happened in the place of client and server. The users can able to know about the process of sending ahttp request for the particular thing and getting a http response for that request. But no one can able find out the internal process of searching thousands of records from a large database. This system openlyvisible the internal process of the searching. The WD-FIM is failed to deliver the document based on their preference because the preference should be of any type like pdf, ppt, word document, text document, image and video To overcome the problem of WD-FIM it should be combined with User preference tree. This is a web based online project. The main aim of the project is a providing Learning Course to the user based on their preference. The algorithm should learn the user behavior and provide the preference type in ascending order. Many learning resource management system can offer basic course administration features, but their functionality isn't as robust. It also typically use users behavior to track learners competencies and recommend materials, but most systems lack the capability to deliver personalized materials to the user. Ex: Learning Resource Management should provide authoring, sequencing, and aggregation tools that structure content to facilitate the learning process.

Citation: Nandhini, C, Dr. Vimala Devi, M. and Suriya Gubendiran, K., 2019. "User preference tree based personalized online learning managment system", *International Journal of Current Research*, 11, (04), 3307-3313./

INTRODUCTION

Web mining refers to the use of data mining techniques to automatically retrieve, extract and evaluate (generalize/analyze) information for knowledge discovery from Web documents and services. Web data is typically unlabeled, distributed, heterogeneous, semi-structured, time varying, and high dimensional. Hence any human interface needs to handle context sensitive and imprecise queries, and provide for summarization, deduction, personalization and learning. Almost 90% of the data is useless, and often does not represent any relevant information that the user is looking for. Taking into account the huge amount of data storage and manipulation needed for a simple query, the processing essentially requires adequate tools suitable for extracting only the relevant, sometimes hidden, knowledge as the final result of the problem under consideration. The use of soft computing tools, including fuzzy logic, in data mining has been adequately reported in literature. However, the subtle differences between data mining and Web mining suggest the use of new or modified tools and algorithms for appropriate handling of the Internet. Web mining typically addresses semi-structured or unstructured data, like Web and log files with mixed knowledge involving multimedia, Cow data, etc., often represented by imprecise or incomplete information. This implies that fuzzy set theoretic approaches are useful instruments in order to mine knowledge from such data.

Web personalization: In the context of Web mining, personalization is the provision to the individual of tailored products, services, information or information relating to products or service. The goal of personalization systems is to provide users with what they need or want without explicit indication. Today, three of the major categories of existing personalization systems are manual decision rule systems, collaborative filtering system, and content-based filtering system. Personalization is based on user attributes such as department, area, or role. The amount of web-based information available has increased dramatically. How to gather useful information from the web has become a challenging issue for users. Current web information gathering systems attempt to satisfy user requirements by capturing their information needs. For this purpose, user profiles are created for user background knowledge description. User profiles represent the concept models possessed by users when gathering web information. A concept model is implicitly possessed by users and is generated from their background knowledge. While this concept model cannot be proven in laboratories, many web ontologists have observed it in user behavior. When users read through a document, they can easily determine whether or not it is of their interest or relevance to them, a judgment that arises from their implicit concept models. If a user's concept model can be simulated, then a superior representation of user profiles can be built.

E-Learning: The World Wide Web (www) is considered as an information hub now a day because itcontains huge amount of information and we can access it through different website. But the storage and display of information and material on website is not quite enough and specially for e-learner it becomes hectic, hazardous, boring and time consuming because one cannot find or understand the relevant information from the web after spending much of his time in searching its desired information although the most of the time the website contain the desired information of the user but because of the poor structure of the website or some times by putting so much material on single page of website without providing any guidance, the user can not be able to find or catch that information properly and sometimes the information may be overlook by the user. That's why the user or visitor loses its interest and leaves the website without getting its desired information.

The general benefits of Web-based training when compared to traditional instructor-ledtraining include all those shared by other types of technology-based training. These benefits are that the training is usually self-paced, highly interactive, results in increased retention rates, and has reduced costs associated with student travel to an instructor-led workshop. Today, E-learning has emerged as a new alternative to conventional learning to achieve the goal of education for all. The concept E-learning has numerous definitions and sometimes confusing interpretations. In our purpose we adopt a definition of E-learning as the use of Internet technologies to provide and enhance students' learning anytime and anywhere. One of its advantages is the learning method which can be more adaptive than conventional learning. Indeed, traditional learning based on "one size fits all" approach, tends to support only one educational model, because in a typical classroom situation, a teacher often has to deal with several students at the same time. Such situation forces each student to receive the same course materials, disregarding their personal needs, characteristics or preferences. Once the teachers learned to provide the detailed, structured instruction the students needed, the class productivity increased. Therefore, implementing learning concept in the context of conventional learning is quite difficult due to diverse preferences, prior knowledge, and intelligence of the learners. This problem can be resolved in E-learning system context in which each student can be arranged to receive a teaching strategy which is more fine-tuned to his/her learning style. In our purpose, we define a teaching strategy, called also learning scenario, as the ways a teacher can present instructional materials or conduct instructional activities which called also learning scenarios. On the other hand, Internet offers the perfect technology and environment for individualized learning because learners can be uniquely identified, content can be specifically personalized, and learner progress can be monitored, supported and assessed. Existing successful examples from e-commerce system may inspire and help us to build a good personalized e-learning system which can provides learners a new way to break free with the more traditional educational models. In response to individual needs, personalization in education not only facilitates students to learn better by using different ways to create various learning experiences, but also teachers' needs in preparing and designing varied teaching or instructional packages. However, an important consideration is often being ignored or overlooked in accomplishing a personalized E-learning framework. This consideration concerns a whole-person understanding about key psychological sources that influence how individuals want and intend to learn online. Up to now, developments have focused on technology rather than more important learner-centric issues. Indeed, each learner has a learning style that allows him to learn better and to ignore that can lead to unstable or ineffective online learning solutions. In fact, it is commonly believed that most people prefer some kind of interacting with, taking in, and processing stimuli or information or simply using a visual medium. So to learn effectively and better, learner has to be aware of his preferences that make easy to manage his own way of learning.

Literature survey: In recent years, most innovations in the area of educational systems have introduced new web-based technologies to train learners any time and any place. The creation of the technology for personalized lifelong learning has been recognized as a grand challenge by peak research bodies [Kay, 2000]. The goal of technology-enhanced learning (TEL) is designing, developing, and testing socio technical innovations that will support and enhance the learning practices of both individuals and organizations. Similar to other fields where there is a massive increase in product variety, in TEL, there is also a need for better find ability of (mainly digital) learning resources. Considering this proliferation of online learning resources and the various opportunities for interacting with such resources in both formal and non formal settings, it is necessary to create a technology to help user groups identify suitable learning resources from a potentially overwhelming variety of choices. As a consequence, the concept of recommender systems has already appeared in TEL. Recommender systems address information overload and make a PLE for users. PLE's Solutions should provide facilities for empowering learners in using this kind of technology. Using this approach, we can improve a personal learning path according to pedagogical issues and available resources. In the TEL domain, a number of recommender systems have been introduced to propose learning resources to users. Such systems could potentially play an important educational role, considering the variety of learning resources that are published online and the benefits of collaboration between tutors and learners [Kumar, 2005]. The recommender systems support a number of relevant user tasks within some particular application content. Most of recommendation goals and user tasks in other areas, such as e-commerce, are valid in the case of TEL recommender systems as well. However, recommendation in a TEL context has many particularities that are based on the richness of the pedagogical theories and models [Manouselis, 2011]. Most recommendation systems are designed either based on content-based filtering or collaborative filtering (CF).Content-based filtering techniques suggest items similar to the ones that each user liked in the past, taking into account the object content analysis that the user has evaluated in the past [Lops, 2011].

Content-based Filtering: This strategy uses the features of items for recommendation. These features may be used by case-based reasoning (CBR) or data mining techniques for recommendation. CBR assumes that if a user likes a certain item, she/he will probably also like similar items. This approach recommends new but similar items. However, data mining techniques recommend items based on the matching of their attributes to the user profile. CBR mechanisms have to evaluate all the cases in the case base to retrieve those most similar case(s), which makes their efficiency strongly and negatively related to the size of the applicable case base [Chang, 2005]. The performances of CBR mechanisms are closely related to the case representation and indexing approach, so their superior performances are unstable and cannot be guaranteed. Semantic and multicriteria recommender systems also consider attributes of items. Semantic recommender systems, instead of using syntactic matching techniques, use inference techniques borrowed from the Semantic Web. This approach uses reasoning about the semantics of items and user preferences to discover complex associations between them [Blanco-Fernandez, 2008]. Rating systems can model a user's utility for a given item with the user's ratings for each individual criterion [Adomavicius, 2011]. Since more people will lurk in a virtual community than will participate, they usually do not spend time to rate based on each individual criterion in multicriteria recommenders. Khribi et al. [2009] used learners' recent navigation histories, similarities, and dissimilarities among the contents of the learning resources for online automatic recommendations.

In fact, the existing metrics in content-based filteringonly detect the similarity between items that share the same attributes. Indeed, the basic process performed by a content-based recommender consists of matching up the attributes of a user profile in which preferences and interests are stored with the attributes of a content object(item) to recommend to the user new interesting items [Lops, 2011]. This causes overspecialized recommendations that only include items very similar to those the user already knows. To avoid the overspecialization of content-based methods, researchers proposed new personalization strategies, such as collaborative filtering and hybrid approaches mixing both techniques.

Collaborative filtering: Collaborative filtering is regarded as one of the important and useful strategies in recommender systems [Bobadilla, 2010]. CF approaches used in e-learning environments focus on the correlations among users having similar interests and can be divided into three categories. Neighbor-based CF finds similar items or users based on rating data and predict ratings using the weighted average of similar users or items. Model-based techniques predict the ratings of a user by learning from complex patterns based on the training data (rating matrix). In the demographics approach, users with similar attributes are matched; then, this method recommends items that are preferred by similar users. The collaborative e-learning field is strongly growing [Garcı´a, 2009; Garcı´a, 2011], converting this area into an important receiver of applications and generating numerous research papers. One of the first attempts to develop a collaborative filtering system for learning resources was the Altered Vista system [Walker, 2004]. The proposed system collects user provided evaluations from learning resources and then propagates them into the form of word-of-mouth recommendations about the qualities of the resources. Lemire et al. [2005] proposed a rule-applying collaborative filtering (RACOFI) composer system. RACOFI combines two recommendation approaches by integrating a collaborative filtering engine, which works with ratings that users provide for learning resources, with an inference rule engine that is mining association rules between the learning resources and using them for recommendation. The questions sharing and interactive assignments (QSIA) for learning resources sharing, assessing, and recommendation were developed by Rafaeli et al. [2005]. Manouselis et al. [2007] tried to use a typical neighborhood-based set of CF algorithms to support learning object recommendation. Their research considers multidimensional ratings that users provide for learning resources. According the results of this study, it seems that the performance of the same algorithms changes depending on the context where testing takes place. Since, in an e-learning environment, learning resources are provided in a variety of multimedia formats, including text, hypertext, image, video, audio, and slides, it is difficult to calculate the content similarities of two items [Chen, 2012]. Wecan use users' preference information as a good indication for recommendation in e-learning systems [Yu, 2011]. Regardless of its success in many application domains, collaborative filtering has two serious drawbacks. First, its applicability and quality is limited by the so-called sparsity problem, which occurs when the available data are insufficient for identifying similar users. Therefore, many research works have been run to alleviate the sparsity problem using data mining techniques. For example, Romero et al. [2009] developed a specific web mining tool for discovering suitable rules in a recommender engine. Their objective was to recommend to a student the most appropriate links/WebPages to visit next. Second, it requires knowing many user profiles to elaborate accurate recommendations for a given user. Therefore, in some e-learning environments, that number of learners is low; recommendation results have no adequate accuracy.

In the past decades, various issues concerning adaptive learning have attracted the attentions of many researchers from the fields of computer science and education. In the meanwhile, various ways of measuring learning styles were proposed to assist instructors or educational researchers to more realize the characteristics of learners. In the following subsection, relevant studies addressing learning styles and the Myers-Briggs Type Indicator model are given..

Learning Styles: Many researchers have long tried to relate personality profile of learners' to teaching and learning style. Cooper and Miller [Mojtaba1`Salehi, 2013], report that the level of learning style/teaching style congruency is related to academic performance and to student evaluations of the course and instructor. Furthermore, Jungian based psychologists add that people's personality preferences influence the way they may or may not want to become more actively involved in their learning, as well as take responsibility for the self-direction and discipline [MojtabaSalehi, 2013; Yi Li, 2012]. So we may to identify a student's individual learning style and then adapt instruction toward that person's strengths and preferences. In fact, adjusting instruction to accommodate the learning styles of different types of students can increase both the students' achievement and their enjoyment of learning. In this sense, it is necessary to deploy resources to support the learning process in a way that it not only suits the preferences of a few but all learners. There are many studies on the effectiveness of using teaching strategies based on personality but it's still very difficult to draw a definitive idea on the relationship between them [Kay, 2008; Kumar, 2005].

Mostof these studies rely on Kolb's Learning styles Inventory [Manouselis, 2011] and Solomon-Felder Index of learning styles [Lops, 2011]. Keefe in [Chang, 2005] described the learning style as both a student characteristic and an instructional strategy. As a student characteristic, learning style is an indicator of how a student learns and likes to learn. As an instructional strategy, it informs the cognition, context and content of learning. It can also be defined as the way a person collects processes and organizes information. Thereby, the learning style provides educators an overview of the tendencies and preferences of the individual learner. There are many models of learning styles existing in literature. Individual learning styles differ, and these individual differences become even more important in the area of education a learning style as was 'a description of the attitudes and behavior which determine an individual's preferred way of learning'. Several studies show that students learn in different ways, depending upon many personal factors and everyone has a distinct learning style. These researches show also that matching users' learning styles with the design of instruction is an important factor with regard to learning outcome. A number of experiments indicate that the user's performance is much better if the teaching methods are matched to the preferred learning styles.

Therefore, when an instructor's style matches a learner's learning style; this affects the learner's experience and ability to do well. Until today, a lot of research works has been done about learning styles and developed a good deal of learning style models but there does not seem to be any agreement of acceptance of any one theory. There have been several models for defining and measuring learning styles, proposed. Therefore, in our study, we adopted the MBTI model as one the well-known source information for personalization.

Adaptive educational experience

To design, adaptive E-Learning systems are grouped in the following approaches:

- Personalization of the learning content, based on learners' preferences, educational background and experience
- Personalization of the representation manner and the form of the learning content
- Full personalization, which is a combination of the previous two types.

Until now, most of researches emphasize only on the first aspect (personalization of the learningcontent) to build a personalized e-learning framework and a few focus on the second aspect (personalization of the teaching strategies). In fact, we believe that it is of great importance to provide a personalized system which can automatically adapt to learners' learning styles and intelligently recommend online activities with the full personalization which is a combination of the first and the second aspect. Since that the problem is not how to create electronic learning materials (what we teach), but how to locate and utilize the available information in personalized way (how we teach). In this sense, our work is new and significantly different from the previous efforts done by others in the field. Teaching strategy refers to ways of presenting instructional materials or conducting instructional activities. Teaching strategies are the elements given to the students by the teachers to facilitate a deeper understanding of the information. The emphasis relies on the design, programming, elaboration and accomplishment of the learning content. Teaching strategies must be designed in a way that students are encouraged to observe, analyze, express an opinion, create a hypothesis, look for a solution and discover knowledge by themselves. The strategies that teachers choose to use in their practice are usually determined by the learningtheory they use. Historically, there have been three main theories of learning, behaviorism, cognitive and constructivism. In the context of e-learning, a major discussion in instructional theory is the potential of learning objects to structure and deliver content. It is extremely difficult for a teacher to determine the optimal learning strategy for every student in a class. Even he is able to determine all strategies, it is even more difficult to apply multiple teaching strategies in a classroom.

Objective of the project: With the explosion of e-learning resources and the digitalization of a lot of conventional learning resources, it is difficult for learners to discover the most appropriate resources using a keyword search method. On the other hand, several research works have addressed the need for personalization in web-based learning environments. Researchers utilize recommendation techniques to resolve information overload in the new learning environment.Many systems need to react immediately to online requirements and make recommendations for all users regardless of ratings, history on visited resources, which demands a high scalability of a system.

Existing system: Feature subset selection can be viewed as the process of identifying and removing as many irrelevant and redundant features as possible. This is because irrelevant features do not contribute to the predictive accuracy and redundant features do not redound to getting a better predictor for that they provide mostly information which is already present in other feature(s). Of the many feature subset selection algorithms, some can effectively eliminate irrelevant features but fail to handle redundant features yet some of others can eliminate the irrelevant while taking care of the redundant features.

Disadvantages

- In the e-learning environment, since various learners have different knowledge and different preferences, the commonly used items (resources) between them are few, and therefore, the similarity value between users will be unreliable. This leads to sparsity and also the cold-start problem.
- Low accuracy on content because searching of required document take too much of time.
- This is challenging because the searching of all suitable attributes for a learner and resource is an almost impossible mission.
- It is time consuming
- It leads to error prone results
- It consumes lot of manpower to better results
- It lacks of data security
- Retrieval of data takes lot of time

Proposed System: The rapid development of e-learning systems provides learners with great opportunities to access learning activities online, and this greatly supports and enhances learning practices.

However, an issue reduces the success of application of e-learning systems: too many learning activities (such as various leaning materials, subjects, and learning resources) are emerging in an e-learning system, making it difficult for individual learners to select proper activities for their particular situations/requirements because there is no personalized service function. Recommender systems, which aim to provide personalized recommendations for products or services, can be used to solve this issue. However, e-learning systems need to be able to handle certain special requirements: 1) leaning activities and learners' profiles often present tree structures; 2) learning activities contain vague and uncertain data, such as the uncertain categories that the learning activities belong to; 3) there are pedagogical issues, such as the precedence relations between learning activities. To deal with the three requirements, this study first proposes a *user preference tree-structured learning activity model* and a *learner profile model* to comprehensively describe the complex learning activities and learner profiles.

A user prference tree matching-based hybrid learning activity recommendation approach is then developed. This approach takes advantage of both the knowledge-based and collaborative filtering-based recommendation approaches, and considers both the semantic and collaborative filtering similarities between learners. Finally, an e-learning recommender system prototype is well designed and developed based on the proposed models and recommendation approach. Experiments are done to evaluate the proposed recommendation approach, and the experimental results demonstrate good accuracy performance of the proposed approach. A comprehensive case study about learning activity recommendation further demonstrates the effectiveness of the fuzzy tree matching-based personalized e-learning recommender system in practice.

Advantages of proposed system

- Improving the learning experience using an e-learning platform.
- Establishment of a new recommendation approach based on the explicit and implicit attributes of learning resources.
- To generate the quick reports
- To provide necessary information briefly at first.
- To provide data security
- To provide huge maintenance of records.

Modules

- Preprocessing
- Finding similarities
- Clustering
- Ranking Prediction
- Material Management
- Learning Topics Management
- Analysis User Behavior
- Learning & Content Delivery
- Reports and Performance

Preprocessing: In this module, Words in Page, File Type and File Size are extracted. The snippets/id generated by a search engine which provides useful clues related to the semantic relations that exist between Documents. Snippets are useful for search because, most of the time, a user can quickly access the material by snippet .Using snippets as contexts is also computationally efficient because it obviates the need to download the source documents from the web, which can be time consuming if a document is large. It uses counts / Threshold based co-occurrence measures.

Finding similarities: In this module, an automatic method to estimate the page count and user view count, users history of access using web search engines with threshold. Accurately measuring the similarities Threshold between words is an important in web mining, information retrieval, and natural language processing. Web mining applications such as, community extraction, relation detection, and entity is ambiguation, require the ability to accurately measure the semantic similarities Threshold between concepts or entities. Based on the similarity threshold in the document the ranking takes place.

Clustering: Based on the access of the user, the documents are clustered. They are clustered by checking those documents with their threshold. This kind of clustering makes it easy for the users further search and makes the search easy and fast.They are clustered by checking whether those documents match the same format which the user has accessed previously. By that way of grouping, only user interested document formats are been recommended to the users. This kind of clustering makes it easy for the users further search and makes the search easy and fast.

Ranking Prediction: It proposed two methods for learning resource recommendation:explicit attribute-based collaborative filtering(EAB-CF) like file type , size and implicit attribute-based collaborative filtering like page count, view count(IAB-CF). To improve the quality of recommendations, we create a hybrid of two methods by the weighted combination method. A linear combination of EAB-CF and IAB-CFis used for recommendation (EB-IB-CF).

Material Management: This module Used by the admin of the website and used Manage the materials in a centralized database. The admin has privilege to upload , update and delete the document. The each action should be updated at centralized database properly. The uploaded document forms the data set.

Learning Topics Management: In this module admin of the website can perform

- upload the document
- extract topic details from the document
- Upload those topic details into a database.

The uploaded topic details are file name, file size, file type i.e. extension of the documents like .docx , .pptx.

Analysis User Behavior: This module used by the users. Admin provide the sample dataset to the user. The user is work with those sample set and collect behavior details like which type of document he/she want. The behavior details should be stored it may be get updated while working with real data set.

Learning & content delivery: In this module the user search the document by providing simple topic. Based on the user and topic the preference details are collected from the database. The document should be delivered to the user based on the user preference order For example User a preference order should be .docx , .pptx ,.jpg.

reports and performance: The first report should provide the major topic details along with document count. After clicking the major topic the minor topic details are generated along with count. The minor topic details are arranged based on user preference. The document under the minor topic details are arranged based on user preference

Conclusion

Personalized learning occurs when e-leaning systems make deliberate efforts to design educational experiences that fit the needs, goals, talents, and interests of their learners. In this work, we conducted a research on the effects of student's psychology to improve their learning performance. We propose a personalized e-learning system Learn Fit which can which takes the dynamic learner's personality into account. In this system some modules for personality recognition and selecting appropriate teaching strategy are used to achieve the learning. The results indicate that placing the learner beside an appropriate teaching style matching with learner's preference lead to improvement and make the virtual learning environment more enjoyable. Although the innovative approach presented in this article has demonstrated is benefits, it also depicted the limitation of actual application. The major difficulty is to develop four versions of the same course to meet the personalization of learning process. Finally, the evaluation results show that students understood the process and liked being involved in it, in spite the fact that it was not a simple task. Finally, this study's results should be carefully interpreted as MBTI is only one of many popular personality assessment instruments and our approach can be altered in many different ways.

Future Enhancements

- In future, still more parameters could be taken into account in order to improve the recommendations to make the user's search easier than now.
- Before Clustering request and response time should be calculated .The document which contain less response time can attain large rank and placed top of the cluster.
- Online Video Streaming will be included in this website.

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