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Research Article

ADAPTIVE E-LEARNING SYSTEM

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A R T I C L E I N F O

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A B S T R A C T

Adaptive learning is a kind of learning environment which provides individual learning. It can customize the learning style according to the individual's personality and characteristics. Adaptive E-learning, refers to a training concept in which technology is introduced step by step in all aspects of the business of training. One of the key factors in such systems is the correct and continuous identification of the user learning style, such as to provide the most appropriate content presentation to each individual user. This system is capable of recommending learning content of potential interest to a user and also the likely Web browsing action on the current item using a novel similarity measure approach. The system is able to deliver the learning objects composing a course either by following the organization defined in the course's manifesto, or by dynamically choosing the sequence in which the learning objects that compose a lesson should be delivered. The latter sequencing is done on the basis of the learner responses to tests.

INTRODUCTION

E-learning and distance education via the Internet is a means of current and promising teaching. However, it suffers from defects mainly related to the relative absence of the teacher and, therefore, the difficulty of adapting teaching to the level and behavior of the learner. Paper-based exams and traditional exams are often based on the Classical Test Theory which centers around statistical characteristics like reliability, validity and distinction and so of. But there is still shortcomings for CTT — it neglects the relationship between candidates' scores and difficulty of questions, i.e. the difficulty relative to the candidates. While, the Item Response Theory can stabilize questions' parameters freeing from the influence of tested samples. So, compared with CTT, IRT has the following advantages:

1. More accurate estimation for questions' parameters.
2. Comprehensive revolution to equivalence to tests.
3. Definitions for such integrated quality index as information and function to be a more scientific criterion for selecting questions.
4. More suitable for adaptive testing system.

If a system can correctly extract a user's intention from his/her Web-browsing behavior, when coupled with the user's personal preference, making good personalized recommendation is possible. User's evaluation feedback and browsing behavior are monitored to provide recommendation.

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LITERATURE SURVEY

There are various papers on this particular domain of Adaptive e-learning. Each having a different concept or methodology to help the user to learn better. For providing a better solution, we have referred few well-known papers and extracted concepts that could help us create the proposed solution.

F. Trif, C. Lemnaru and R. Potolea in one their paper titled "Identifying the User Typology for Adaptive E-learning Systems", have come across 4 main types of learning types namely,

Type I – Meaning Directed Style

Type II – Reproduction-Directed Style Type Iii – Application-Directed Style Type Iv – Undirected Style

In this paper we came across intermediate attributes of learning that is:

1. Study activities -these include processing strategies and regulation strategies.
2. Study motives and study moves-these include Learning orientations and mental models of knowledge.

In this paper, K-means clustering is used to understand the relativity between different learning types. The learning activities are grouped into clusters and then the clusters are mapped with the learning types. Though the paper talks about different learning types and activities, but only gives the learning style suggested by one of the expert. There are many experts who have different ways to estimate the learning style. Here, clustering is used to know the user's category. Others methods can give better results than clustering like DBSCAN or DB SCALE. [1]

Kosuke Takano and Kin Fun Li in the paper titled "An Adaptive e-Learning Recommender Based on User's Web-Browsing Behavior", have talked about feedback mechanism to understand the learners browsing behavior. [2]

In this paper, there are two types of feedback from the user, which helps in the detection of influential browsing behavior.

- Explicit Feedback: In explicit feedback, a user evaluates an item on the recommended list, by navigating to the linked page or giving it a score according to his/her preference. The recommender then associates the specific item with certain influential browsing behaviors.
- Implicit Feedback: In implicit feedback, our system suggests influential Web-browsing behaviors associated with a user's preferred item on the Web browser. This suggestion can be disabled if a user does not want to have it shown on the browser. If a user takes the suggested Web – browsing action, the system regards the content is associated with the user's frequent browsing behaviors. We call the browsing action taken as suggested, user's implicit feedback.
- Hybrid: Combination of both Implicit and Explicit. Typical web browsing behaviors include-
- web pages browsed.
- Terms on web pages selected by mouse click.
- Terms on webpages copied on clipboard.
- Keywords searched within the webpages
- Web pages saved.
- Web pages printed.
- Webpages bookmarked.

The author gives a better understanding about the different web browsing behavior and also how to capture them to help the recommender. Each browsing activity can be assigned a particular weight depending on its use by the user, this can help to understand the user better. The recommender architecture and browser action provider architecture can be understood well by referring to fig 4.2.2 of the paper.

Deng Shaoling, in the paper titled "Using learning styles to Implementing Personalized e-learning System", introduces us to different Elements of Learning Object like. [3]:

- Visual: Instance to pictures or photographs, tables, graphs and flowcharts.
- Aural: Video recordings (visual and aural).
- Verbal: Video & Audio recordings, discussions and conversations
- Physical: Learning by doing
- Social: Group work (activity) or Group studies.
- Solitary: Work Individually. Logical: Graphs and flowcharts.

This paper gives an insight about the different elements, but after researching we can say that a learning object cannot consist of all the elements. These elements can guide us to know the preference of the user's browsing behavior. Tailored courses are easy to create if we know the user's preference, behavior and intention. For creating a tailored course background knowledge about the user is very important.

Rafael Morales and Ana Silvia Agüera, in the paper titled "Dynamic Sequencing of Learning Objects", have introduced two types of dynamic sequencing of learning objects[6].

1. Traditional Sequencing
2. Socratic Sequencing

The working of traditional and Socratic sequencing can be better understood by referring tofig 4.6.1 and 4.6.2 from the paper.

This paper helps us understand the sequencing of learning objects and the similar concept can be implemented on Elements of Learning object. This sequencing can be done with the help of the Bayesian predictor which totally depends on the history of use. Changing the sequence after every test is not worth and hence the system should wait and understand the behavior of the user for some iteration. The browsing behavior can be of a large help in such a case.

Manju Bhaskar, Minu M Das, Dr. T. Chithralekha, and Dr. S. Siva satya, in the paper titled "Genetic Algorithm Based Adaptive Learning Scheme Generation for Context Aware E-Learning", introduces the following [4]:

- The Psychology of the Learner
- The Intention of the Learner
- Relation between Psychology of the Learner and
- Different abstractions of Learning Object

The paper gives us a clear understanding about the various abstractions of learning object and how they are related to the psychology and intention of the user. This knowledge helps us to bring about the adaptive nature. This abstraction may or may not hold true for each type of person. This can be used as a reference.

The relation between psychology of the learner and different abstractions of learning objects and the relation between the intention of the learner and different abstractions of the learning objects can be understood by referring to fig 4.4.1 and 4.4.2 in this paper

Xiaoping Li, Zhenghong Wang, Xiaobing Wu, Yingxiang Li and Hong Jian Dong, in the paper titled "The Design of Adaptive Test Paper Composition Algorithm Based on the Item Response Theory", talked about Classical Test Theory and Item Response Theory. The biggest advantage of Item Response Theory is that the estimations of item parameters have nothing to do with the sample being tested. It speculates the candidate's' ability through characteristic function of the question, combining the answer of the candidates. The characteristic function can be divided into one-parameter, two-parameter and three-parameter by the number of parameters in the Item Response Logistic model [5]

In this paper the main four problems are discussed:

- Entry Level
- Item Selection
- Ability Estimate
- Termination

This paper related to the difficulty of the question and distinction of the question are also important factors. The guessing coefficient is also taken into consideration which helps the system to understand the seriousness of the test given by the user.

Existing System

DOOR: DOOR Digital Open Object Repository is an Open Source piece of software for creating learning objects repositories. [7]. With DOOR you can store digital content in the form of learning objects (LO), i.e., content + metadata, in a tree-shape catalog. You can then search for LOs, retrieve them and include them in your courses or instructional units.

DOOR is compliant with international metadata standards, and implements the IMS Metadata 1.2.1 and Content Package 1.1.3 specifications. DOOR is also fully integrated with Moodle, and Open Source LMS. The DOOR-Moodle plug-in allows Moodle teachers to browse more repositories seamlessly from a single Moodle course, and then select and import LOs with their metadata.The system can be well understood by referring fig 5.1,5.2 and 5.3. [7]

Proposed System

In our proposed system, the flow of the system as shown in Fig.1 is explained as follows:

1. Learner registers himself into the system.
2. The next step the learner is presented with is a questionnaire, so that the system can understand the learner.
3. The abstraction of learning object (LO) is known with the help of step 2.
4. Learner then browses for what he needs and selects the LO.
5. Learner is provided with the abstraction with the help of data collected in step 2.
6. Learning Style Analysis takes place for the learner as he starts with the selected LO.
7. All the data for the particular learner is recorded for his profile.
8. Now when the learner finishes with the LO, he has to go through a test and a feedback session. The test is based on the LO that he studied and the feedback is about the system.

The test results obtained are used for two important criteria:

a. To understand where the LO and the learner lacked in attaining the objectives.
b. To understand the Learner's Ability.

9. The next LO is selected by the system by taking both the criteria into consideration.
10. The selected LO is recommended to the learner.
11. Now the data of the browsing behavior of the learner is given to the ACO recommender to generate a sequence of the elements of LO that suits the learner’s behavior.
12. The predicted sequence is stored for the user in his profile and produced at the time when the learner selects the next LO recommended by the system.

The learner here is being evaluated with the help of both the algorithms. We test the sequencing of the learning object and also the prediction of the next learning object. So we can say that the learner experiences both IRT and ACO. As IRT is based only on the last iteration or feedback, we tend to use ACO instead of IRT as the algorithm will help to decide the sequence not on the basis of only last iteration or feedback but on the basis of the history throughout and as the algorithm also helps in staying in sync with the latest changes in the behavior of the user, we have a change to incorporate all the aspects of behavioral styles of the user. So as IRT that is replaced to ACO is used in the sequencing of elements inside the learning object and the prediction of the next learning object is done, taking into consideration both Pre – Requisite and Post – Requisite of the upcoming LO (Learning Object).

Fig 1 Proposed System Flow

CONCLUSION

The above proposed system is adaptive in nature and will help improve the learning experience of the user. The adaptive nature is introduced because of the two main algorithm that are differentiated below.

Item Response Theory	Ant colony optimization
Input to the system is the result of the test or feedback given by the learner in the last iteration.	A history of actual fact is given as the input to the system.
It is not time consuming as it only depends on test result of last iteration and so the computation is less	It is time consuming as it depends on the history of facts and so it needs heavy computation.
Learner’s ability is taken into consideration.	Learners ability is not taken into consideration but it can be calculated but after many iterations
Precision less than ACO	More precision as the data is collected over time.
Termination of IRT if the results or the feedback are positive.	Termination of ACO takes place when the input to the system becomes stagnant.

Future Scope

Future holds a lot for this particular domain. Learning techniques and methodologies have been evolving throughout ages. Many new upcoming technologies can help make the learning process better. IoT and Augmented Reality can play a very crucial part in enhancing the experience of learning. So this will make the process of learning more interactive. The learning objects can be enhanced and made more rich further making the system better.

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