Combining Learner's Preference and Similar Peers' Experience in Adaptive Learning

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Keywords: Adaptive Educational Hypermedia, Domain Model, Cognitively-Oriented Method, Open Learner Model, Learner Preference Pattern.

Abstract: Adaptive educational hypermedia (AEH) offers learning adaptation and personalization. In terms of adaptation, AEH plays the role of a tutor and controls learning. To the contrary, personalization gives learners the freedom to explore the materials they consider necessary. Challenges emerge in respect of improving adaptation and preventing learners from getting lost when exploring concepts and materials in the large. This paper discusses approaches to improve adaptation and personalization. A knowledge map that organizes and visualizes the domain model has been developed using a cognitively-oriented method. It combines the individual learner's progress and preference with similar peer experiences to improve adaptation. Furthermore, it implements an open learner model to nurture self-progress awareness.

1 INTRODUCTION

Current advancements of technology have made indirect learning viable. This changes how the learning process goes, such as removing the requirement for learners and teachers to be in the same place. Web-based courses are one of the many media that can be used for indirect learning. However, while many research papers and media publications report substantial success with Web-based education, a careful analysis of the situation and informal discussions with "on-line teachers" show that Web-based education is quite far from achieving its main goal. In many current Web-based courses, the course material is still implicitly oriented to a traditional on-campus audience, which means reasonably homogeneous, reasonably well-prepared and well-motivated students who have access to teachers and assistants to fill possible gaps and resolve misunderstandings (Oneto et al., 2009). A web-based education should be aimed at a larger audience with different knowledge, goals and learning capabilities.

That is where Adaptive Educational Hypermedia (AEH) comes in. AEH is a system that can adapt to the learner, helping tutors to create a learning process that is relevant to the learner's needs, recommending learning objects and enabling learners to choose what they like. Such a system is also capable of helping learners in their self-assessment and the personalisation of the learning process.

A challenge occurs regarding how to improve adaptation so that the recommended artefacts suit learners' needs. Sometimes a learner model is not enough, for instance when learning has just started and the learner model does not contain much information about the learner. Many adaptive systems provide a default learning scenario to anticipate this situation and it works. However, a default scenario contradicts the principle of adaptive learning.

A potential solution comes from a recommender system. Since the adaptation model of AEH is like a recommender system, the process of recommending something by referring to a similar case can be adopted in AEH. This idea meets the principle of social learning that a learner learns better when he/she is learning with experienced learners (McLeod, 2007; Vygotsky, 1978). A question then emerges regarding which experienced learners will help a learner to get the most suitable learning materials.

Another challenge occurs regarding the accessibility of the learner model. In web-based education, it is common that only teachers, not learners, can see the learner model. It is also common that learning objects are presented

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pedagogically, disregarding whether they are relevant to the learner's needs or not. To build a system able to support self-assessment and learning process personalisation efficiently, we need both a user interface that will represent learner models intuitively and a recommender that is able to direct the right learning object to the right learner.

This paper addresses two questions:

- First, from the perspectives of adaptive learning and collaborative learning, how to combine an individual user model with peers' experience;
- Second, what features are necessary to support adaptation and personalisation, thus making learners aware of their progress and able to understand the path to achieve their learning goals.

To solve the problems, we propose the integration of the Open Learner Model (Bull and Kay, 2010) and the Learner Preference Pattern(Wang et al., 2007). Open Learner Model functions as a visual interface guideline, while Learner Preference Pattern produces recommendations of suitable materials for learners. The domain model is implemented with a cognitively-oriented method (Liang et al., 2012), in the form of a knowledge graph.

2 RELATED WORK

2.1 Adaptive Educational Hypermedia

Adaptive Educational Hypermedia (AEH), known as a kind of adaptive learning system, builds a learning model based on the knowledge, preferences and goals of the learner. Unlike conventional e-learning where learners have the same learning object on the same course, this system can adapt and recommend a relevant learning object. As a learner's needs, preferences and goals change, the AEH should always oversee these changes to update the learner model. In general, the framework of AEH can be illustrated below:

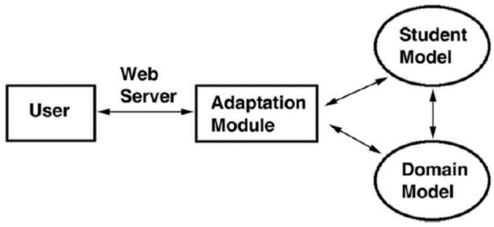

Figure 1: Diagram of AEH Framework (Triantafillou et al., 2003).

2.2 Open Learner Model (OLM)

Open Learner Models are learner models that can be viewed or accessed in some way by the learner, or by other users, such as teachers, peers or parents. Their goals are to visualise knowledge, preferences and cognitive skills intuitively. This can be done using an interface designed for the learner or, in some cases, other people that will help the learning process.

OLM aims to be helpful to the learner as identified in the SMILI (Student Model that Invite the Learner In) OLM Framework as (Brusilovsky et al., 2011; Bull and Kay, 2010):

- Enabling metacognitive activities, such as planning and self-monitoring;
- Giving learners greater control and responsibility in learning processes.
- Supporting collaborative learning;
- Helping learners to interact well with peers, teachers and parents;
- Providing navigation to suitable materials, exercises, problems, activities or tasks;
- Supporting formative and summative assessments.

A former study that implements OLM is QuizMap (Brusilovsky et al., 2011). It implements a pedagogically-oriented knowledge model with OLM that enables learners to know their progress and which questions they can choose .OLM provides several concepts that can be implemented on an effective interface, such as OLMlet that integrates cognitively-oriented knowledge space with a learner model(Bull and Kay, 2010).

2.3 Learner Preference Pattern

Personalised recommendation mechanisms which take into account peers' experience have been proposed in a number of previous study (Troussas et al., 2013; Wang et al., 2007). The method proposed by Tzone I Wang et al. (Wang et al., 2007) implements two algorithms, the preference-based algorithm and the correlation-based algorithm, to rank the recommended results to advise a learner concerning the most suitable learning objects. This model uses a specific ontology of a certain course to infer which learning objects are needed for a learner. The inference is based on his/her past studying histories that are recorded as the learner's personal preference pattern.

Another consideration in selecting learning objects is by referring to the experience of similar learners (Wang et al., 2007). The similarity of learners can be inferred from similar values of certain parameters

3 OUR RESEARCH

In response to the aforementioned research questions, we have implemented an AEH with combined user model and peers' experience and applied OLM. The system is divided into 3 parts, illustrated as follow:

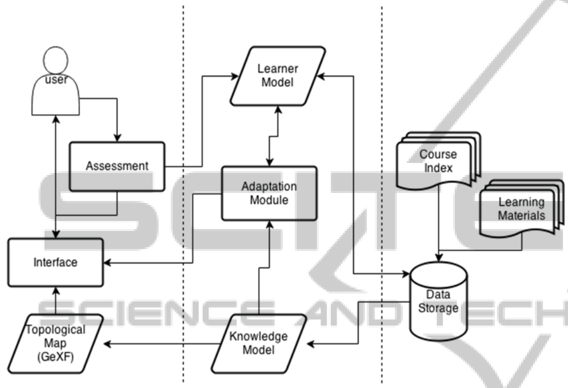

Figure 2: Overall System Structure.

The first part (illustrated by the left part) is the interface of system and learners, implemented visually based on cognitively-oriented modelling. In this part, the learner interacts with the system directly, such as by doing an assessment via pre-test, giving feedback, or reading topological maps. The second part (illustrated by the middle part) is the result of the learner and the system's interaction, contained in learner models. In our case, learner models are a sequential file stored in the hard disk. Finally, the third part (illustrated by the right part) is data storage for the course learning object, knowledge/domain model and learner model.

3.1 Domain Model

Adaptive learning must be supported by a large networked knowledge space and a huge volume of learning materials in various formats. There are two main approaches to the model domain model of AEH; namely, the pedagogically-oriented topic based modelling, which is a taxonomy of coarse-grain topics that uses a tree as a structure (Brusilovsky et al., 2011; Sosnovsky and Brusilovsky, 2005), and the cognitively-oriented concept based modelling, which is a link of fine-grain concepts that uses a graph as the visualisation (Brusilovsky et al., 2011). The pedagogically-oriented method is commonly applied as it provides a firm hierarchical structure among topics that can support a sequential flow of learning. This method however, has a disadvantage in that, if the hierarchy is too deep, it may result in boredom for students as they must complete all the materials at the deepest level before they can progress to another topic.

On the other hand, the cognitively-oriented method organises a curriculum in the form of a concept graph. This method is suitable for allowing students to explore learning material concepts without restraint. The idea is that students learn, gain understanding and create connections or associations between the concepts. The disadvantage of this method is that students may get lost as they learn many topics at random and it may, therefore, result in students failing to attain the learning objectives.

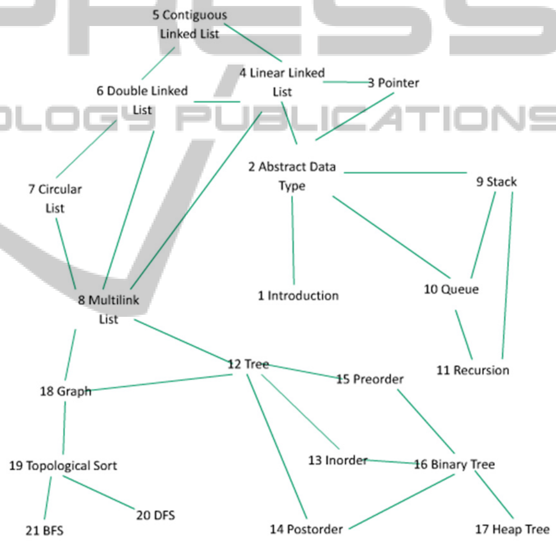

Figure 3: Cognitively-oriented domain model of Data Structure.

We have implemented cognitively-oriented domain model for Data Structures, one subject taught in the Computer Science undergraduate programme. In general, domain knowledge attributes consist of:

- Concept's ID and label
- Connection between concepts
- Learning objects related to the concept, containing ID, external link towards said learning object, and tags/keywords related to said learning object.

3.2 Learner Model

In this research, we combine individual and social learning to perform adaptive navigation. Social learning is implemented in the form of collaborative tagging. The learner model records a learner's progress, tags and ratings on learning materials. To navigate, firstly, learners have to take a competence test. As a result, learners' competence on each concept can be assessed. Finally, a list of learning materials to suit the learners' competence is delivered.

The competence test consists of several questions with each question related to each concept in the course. Students' answers are categorised as correct, incorrect or cannot be justified. Correct/incorrect answers will categorise the learner as a student having expert/intermediate cognitive skills on corresponding topics. On the other hand, when the learner answers "I do not know" for a question, he/she will be categorised as beginner on the corresponding topic. The cognitive skills will affect which learning objects to be recommended to the learner. To have more accurate learner profiles, learners can override their profiles by conducting a self-assessment.

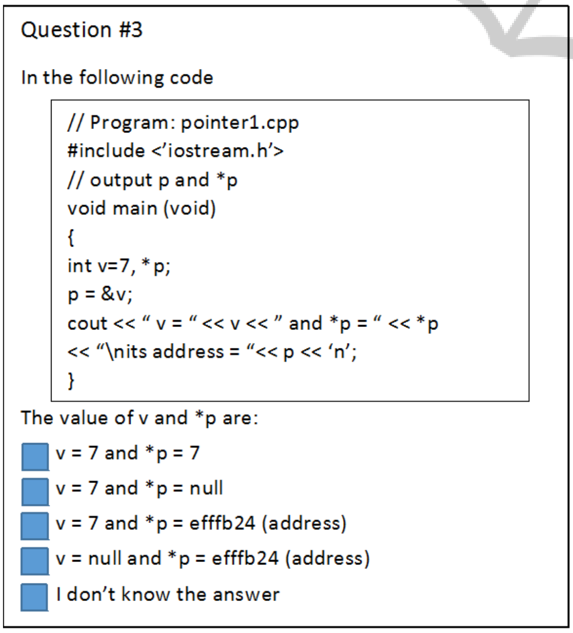

Figure 4: Competence test.

Cognitive skills are not the only information recorded in the learner model. The learner model contains cognitive, preferences and the learning progress of a learner, as well as the tagging and rating he/she put to learning objects. Every time a learner has learned a new material, she/he will asked to give a feedback in the form of rating:

- 1, if the material is not helpful at all.
- 2, if the material is not really helpful.
- 3, if the material is quite helpful.
- 4, if the material is really helpful.

The rating will be recorded in the learner's model and will be used in the recommendation process for her/himself or other learners who have similar models. Table 1 presents the attributes of the learner model.

Table 1: Domain knowledge attributes.

Attributes	Type	Description
Id	String	id of learner
RatingObjects	Array <String>	Array of objects current learner have given feedback
RatingValues	Array <Float>	Values of objects current learner have given feedback
Tags	Array <String>	Array of tags/keywords this learner is probably interested in
TagValues	Array <Float>	Values of preference score for each tag
CognitiveObjects	Array <String>	Array of concepts this learner has learned
CognitiveValues	Array <Int>	Values of cognitive skills this learner currently has ("beginner", "intermediate", or "expert")

On visualising the learner model on the topological map, the system implements an overlay model combined with OLM. It uses colour codes to intuitively label nodes with the corresponding learner's cognitive skill, grey for beginner when the topic is not learned yet, red for intermediate when the topic is being learned, and green for expert when the topic has been mastered. Implementing OLMlet's skill meter (Bull and Kay, 2010)and structured view as a guideline, we can visualise colour-coded learner models on a topological map as shown in Figure 5. The progress bar indicates the learner's learning progress on each concept; it is empty when the learner has not learned anything and fills up each time the learner reads some learning material related to each corresponding concept. Each node in the graph can be clicked to open the detail panel of the corresponding concept. It contains a definition, the learner's cognitive skill, as well as learning materials. Learning objects on the detail panels are sorted based on their recommendation score. Learning objects with the highest RS are then highlighted and marked as recommended to read.

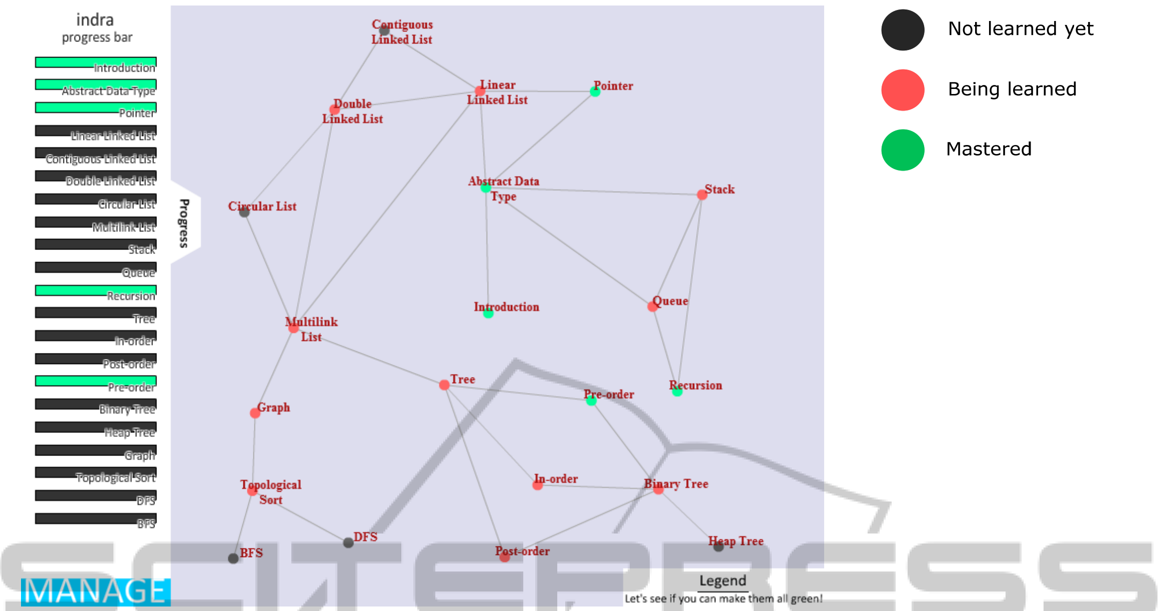

Figure 5: Competence test.

A challenge in producing adaptive learning based on the learner model and peers' experience is to find peers who have a similarity with the learner and have mastered the topic learned. The experience of similar learners is considered more useful than that of the other learners. Similarity can be inferred from any attribute in the learner model. Our research refers to the tags and ratings they gave to the learning materials.

Adaptation is performed in the form of adaptive navigation as shown in Figure 6.

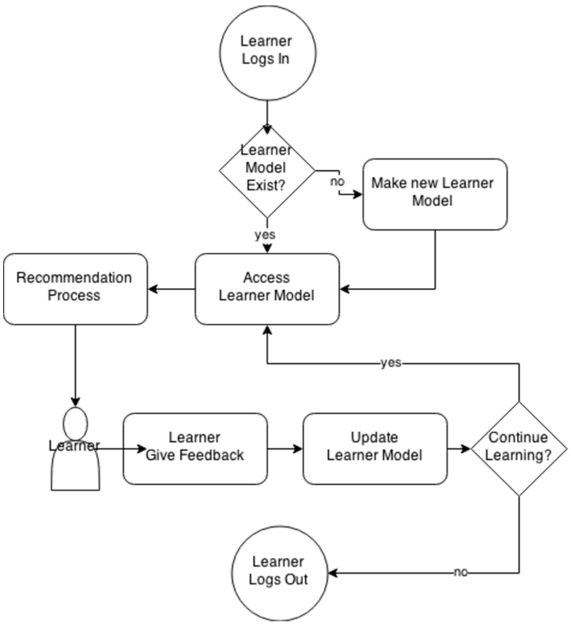

Figure 6: Learner model life cycle.

Learning objects on the detail panels are sorted based on their recommendation score. Learning objects with the highest RS are then highlighted and marked as "recommended" to read.

3.3 Learning Object Recommendation

The chart below illustrates the calculation process of calculating recommendation score:

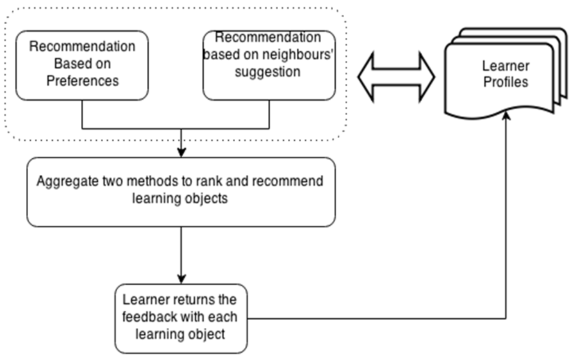

Figure 7: Learning object recommendation.

We improved the Learner Preference Pattern method (Wang et al., 2007) to calculate the recommendation score. Each learning object in a concept is sorted based on their RS from the highest to the lowest one. There are 2 factors affecting the recommendation score: the preference score that represents which materials interest a learner to learn and the helpfulness score that formulates which materials the learner considers necessary. We consider that the preference score and helpfulness score equally influence the recommendation score. Hence we define the recommendation score for a learning object as follows:

*0.5 * preference score + 0.5 * helpfulness score*

To calculate the preference score, first of all we need to calculate the Basic Preference Weight (BPW), a weight that represents the degree of a learner's preference for a feature value in a feature [6]. In our case, the features are the tags each learning object has. These tags vary. For example, "video" for learning object links using video as a learning medium or "english" if the object uses English as the language. To get BPW, the value of a tag on a learning object, the score of such a tag is divided by the maximum score of the learning object tags.

BPW of the k-th feature value of the i-th feature = (The preference score of the k-th feature value) / (the maximum preference score of tags given to the learning object)

The preference score for a learning object is calculated by summarising all the BPW scores of tags given to the learning objects, and then dividing by the number of tags given to the learning objects.

In addition to the preference score, to increase the accuracy of recommendations, feedback from other learners with similar experience and preferences is taken into account. The similarity of two learners, called learner1 and learner2, is calculated as follows:

$$Sim(learner1, learner2) = Sum((rating1-avg1)(rating2-avg2)) / Sqrt(Sum((rating1-avg1)^2 (rating2-avg2)^2))$$

Where rating1 and rating2 are feedback scores that learners 1 and 2 have given to learning objects; avg1 and avg2 are the averages of feedback scores they have given. The formula is applied to learning objects they have both learned.

The system will first iterate all the learner profile database and calculate each one's similarity. A perfectly-similar learner compared to a currently active learner will have a similarity of 1. A learner having similarity of more than 50% (0.5) will be considered "similar enough" and will be included in a group of similar learners. Using the similar learners group, we can then calculate the helpfulness score of a learning object for a learner by the following formula:

The average of all feedback given by the learner + Difference_error_score.

The Difference error score is taken into account to counterbalance the difference between a learner and the similar learners' consideration in rating a same learning object (lo). The difference error score summarises the difference between the learner and each similar learner as follows:

Difference_Error_Score = Sum (difference_score (L_id, L_simm)

Where *(difference_score (L_id, L_simm)* is equal to:

*(ratings(L_simm, lo) – avg(ratings(L_simm)) *Sim (L_id, L_Simm)*

After accessing the recommended learning objects, learners can give a feedback rating in the scale of 1 to 4 (very helpful, quite helpful, not really helpful, not helpful at all). Learner's profile, Tags and TagValues representing the learner's preference toward a certain tag will be updated. The change in the Learner's profile follows these rules:

- a feedback rating of 1 or 2 will not change the learner's profile
- a feedback rating of 3 or 4 will increase all preference scores of tags in the learning object by Δs amount, as expressed by the following:

*(feedbackRating * totalTags) / (4 * the number of learning objects having the same tag)*

4 TESTING

We have conducted two kinds of test. The first test is a comparison test between two cases, to test whether the tool takes into account learner models in recommending suitable learning materials. The correctness is detected from different recommendations that should be produces for different learners. The second test isa usability test by eliciting learners' experience of using this AEH. There are three parameters tested including learnability, helpfulness and efficiency. This paper focuses on the first test.

In the first test, a comparison of recommendations for two learners having different preferences was carried out. The first learner considers Indonesian articles are helpful and the second learner considers that watching English videos is helpful for his learning. To find out the learners' skills, they were required to complete the pre-test. It resulted in the learner models shown in Figures 8 and 9. They presented different cognitive skills of the two learners. The first one, as shown in Figure 8, is novice in all topics, except in the first and second topics. The second learner, as shown in Figure 9, has expertise in many topics. A comparison of learning material recommendations is applied to the *Pointer* topic, which has not been learned by both learners.

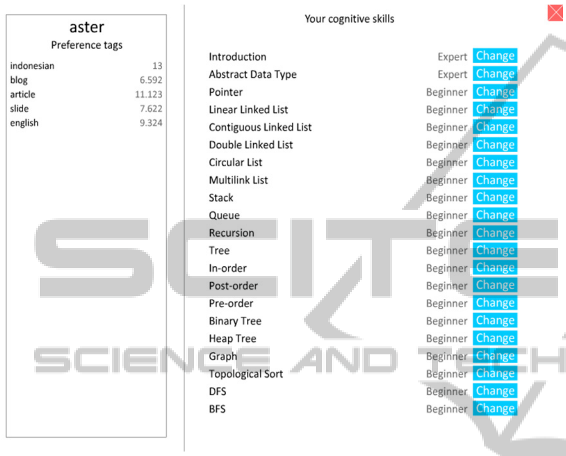

Figure 8: A model of a learner who prefers Indonesian articles.

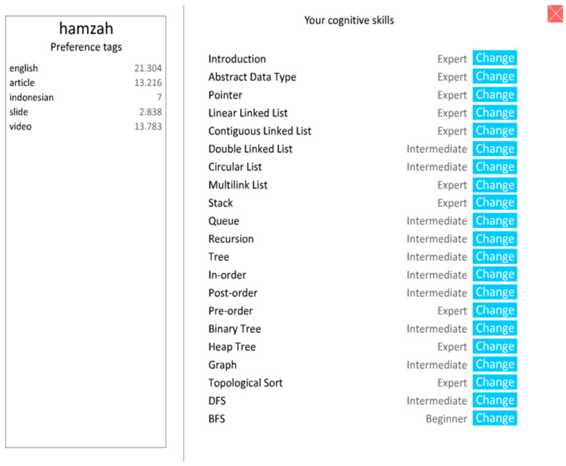

Figure 9: A model of a learner who prefers English materials.

The process to find recommended materials for the first learner will find materials which are articles written in Indonesian and for beginners and it is based on similar learners' experience. In this case, two learners were detected having similar models. The recommended materials are sorted and highlighted.

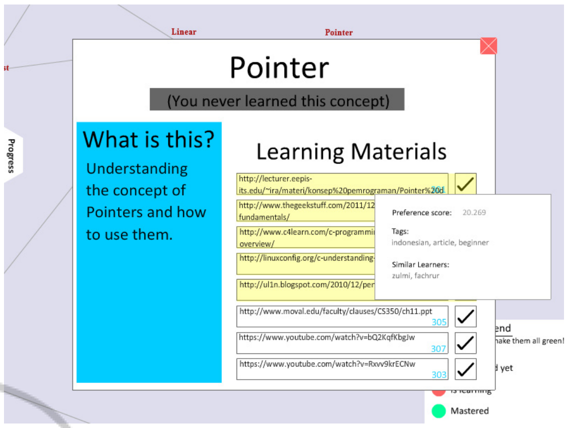

Figure 10: A learning object recommendation for the first learner.

On the other hand, the recommendation for the second learner presents different learning materials.

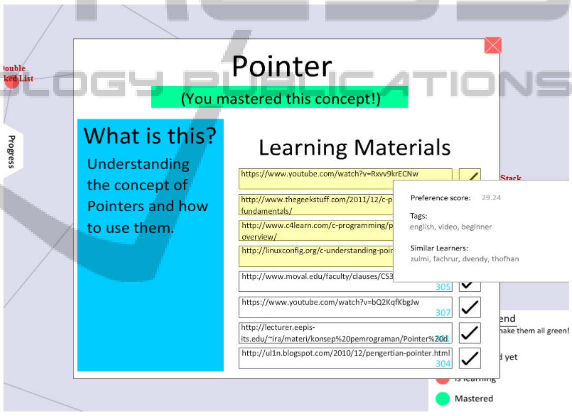

Figure 11: A learning object recommendation for the second learner.

5 CONCLUSIONS

In this paper, an implementation of the Open Learner Model and Recommendation based on Learning Preference Pattern in an Adaptive Educational Hypermedia is proposed to help self-learning for Data Structure. A cognitively-oriented Open Learner Model provides a guideline for an intuitive cognitively-oriented model suited to these needs. Colour codes for visualising learners' cognitive skills and a progress bar to track the learner's learning progress are also applied. Learning Objects Recommendation based on the Learner Preference Pattern are capable of recognising adapt on feedback and the changes learners made, then gives them learning object recommendations tailored to their current preference and cognitive skills.

In a real case of AEH, OLM and learner preference pattern are correlated. OLM is applied as a guideline for a domain model implemented with a cognitively-oriented method that represents domain knowledge and materials in a graph of concepts. Hence, it could help learners for self-assessment. On the other hand, the learner preference pattern is applied for finding and recommending learning objects. It controls learners by recording their cognitive skill progress and preference, and then adapts their learning based on the learner model.

As our research is tested with a small number of participants and limited preferences, further development of this research can include more preferences and applied to larger participants. Furthermore, the future work can be focusing on learner similarity. As learner model captures various parameters of learners, there might be many combinations of parameters to be considered in detecting learner similarity.

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