Open Learner Model and Learner Preference Pattern within Adaptive Educational Hypermedia

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***Abstract*—Adaptive Educational Hypermedia is an education media able to adapt itself with it's learner. Thus, it requires the system to track and represents it's learner's cognitive profile, as well as making a recommendation on learning objects to it's learner. Open Learner Model Framework and recommendation through learner preference pattern can be a solution of that case.**

Keywords-component; formatting; Adaptive Educational Hypermedia; Learner Model; Personalized Recommendation

I. Introduction

Current advancements of technology made indirect learning viable. This changes how learning process goes - For one, it removes the requirement for learners and teachers to be in the same place. Web-based courses are one of many media that can be used for an inderect 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 for a traditional on-campus audience - reasonably homogeneous, reasonably well-prepared and well-motivated students who have access to teachers and assistants to fill possible gaps and resolve misunderstandings [2]. A web-based education should be aimed for a larger audience - each with different knowledge, goal, and learning capabilities.

That is where Adaptive Educational Hypermedia comes in. A system that can adapt to learner will help creating a learning process that is relevant to learner's needs. Said system also capable to help learners on their self-assessment and personalization of learning process.

On web-based education, it is learners cant usually see their own learner model. It is also common that learning objects are presented pedagogically, disregarding whether said learning object is relevant to learner's needs or not. To build a system able to support self-assessment and learning process personalization efficiently, we need both user interface that will represent learner models intuitively, and a recommender that's able to direct right learning object to right learner. Here we propose integration of Open Learner Model (Susan Bull and Judy Kay) as visual interface guideline and Learner Preference Pattern as recommender to Adaptive Educational Hypermedia as solution to said problems.

II. Summary of Related Works

A. Adaptive Educational Hypermedia

Also known as Adaptive Learning, this system build learning model based on knowledge, preference, and goal of the learner. Unlike conventional e-learning where are learner have the same learning object on the same course, this system can adapt and recommends a relevant learning object. As learner's need , preference and goal change, the AEH should always oversee this changes to update the learner model.

In general the framework of AEH can be illustrated below:

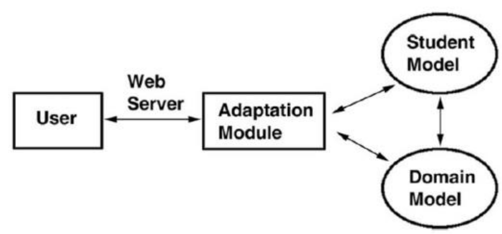


Figure 1. Diagram of AEH Framerowk [5]

B. 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 uses (e.g. teachers, peers, parents) [3]. Their goals are to visualize a knowledge, preference, and cognitive skills intutively. This can be done using 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, identifed in the SMILI (Student Model that Invite the Learner In) OLM Framework as [3]:

- Promoting metacognitive activities such as reflection, planning, and self-monitorning;

- Allowing the learner to take greater control and responsibility over their learning, encouraging learner independence;
- Prompting or supporting collaborative and/or competitive interactions amongst groups of students;
- Facilitating interaction between learners and peers, teachers, and parents;
- Facilitating navigation to materials, exercies, problems or tasks, etc., where links are available from the learner model;
- Supporting assessment - in particular providing formative assessment opportunities for students, but also enabling the learner model to be used as a summative assessment;

OLM provides several concepts that can be implemented on effective interface, such as OLMlet that integrates cognitively-oriented knowledge space with learner model:

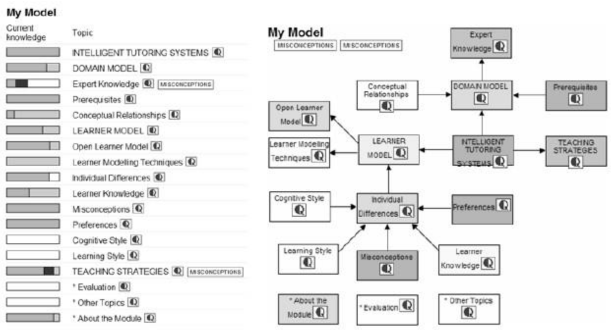


Figure 2. Skill Meter and Structured view on OLMlet [3]

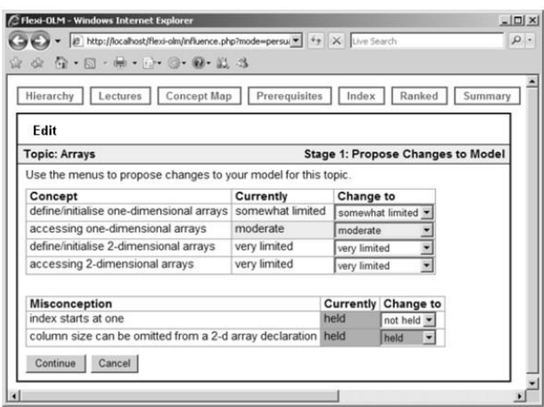


Figure 3. Editing Learner Model in Flexi-OLM [3]

C. Learner Preference Pattern

A personalized recommendation mechanizsm proposed by Tzone I Wang et al. It used two alghoritms, the Preference-based algorithm and the Correlation-based algorithm, to rank the recommended results to advise a learner with the most suitable learning objects. A system realizing this model can [6]:

- Use the specific ontology to infer what learning objects are needed for a course established for a specific learner requiring a specific subject.
- Build each learner's personal preference pattern according to past studying histories.
- Recommend suitable learning objects according to a learner's preference and intention.
- Refer to the experiences of similar learners when looking for learning objects that should be helpful for each learner.
- Provide adaptive, personalized learning objects and materials for each learner.

III. Implementations

A. System Overview

By it's outline, the system is divided into 3 parts, illustrated as follows:

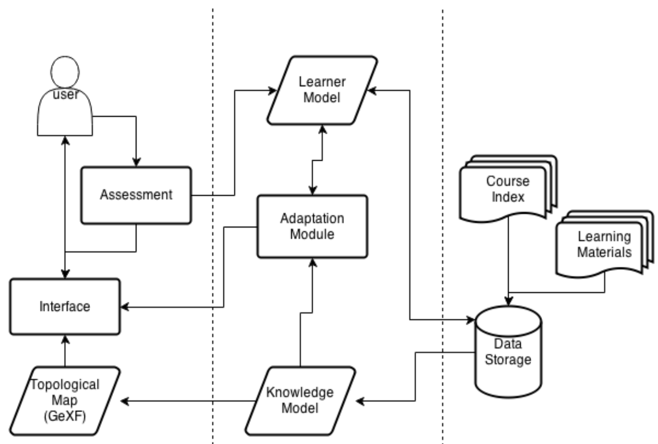


Figure 4. Overall System Structure

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, learner interacts with system directly; such as doing assessment via pretest, giving feedbacks, or reading topological maps.

Second part (illustrated by the middle part) is the result of learner and system's interaction, contained in learner models. In our case, learner models is a sequential file stored in the hard disk.

Third part (illustrated by the right part) is data storages for course learning object, knowledge/domain model, and learner model. This storage can be a database or a sequential file.

B. Knowledge Model

Also known as Domain Model, knowledge model is a model storing all the details and attributes of a course in AEH. In this case, system uses a cognitively-oriented model using Open Learner Model (Susan Bull, Judy Kay) as the interface guideline that will map the course into a graph and concepts to nodes. Attributes included in each node in the knowledge model includes:

- 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.

CSG2A3 Algorithms and Data Structure is used as the sample course the knowledge model based in. Connection between concepts are illustrated as follows:

Figure 5. Connection between concepts in Algorithms and Data Structure

C. Learner Model

Also known as Student Model, Learner Model is cognitive, preference, and progress data of a learner that is recorded and will be updated by system everytime the learner give a feedback. Parameters contained in learner models are described as follows:

TABLE I. PARAMAEERS IN LEARNER MODEL

Attrbutes	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 probably interested in
TagValues	Array<Float>	Values of preference score for each tags
CognitiveObjects	Array<String>	Array of concepts this learner have learned
CognitiveValues	Array<Int>	Values of cognitive skills this learner currently have ("beginner", "intermediate", or "expert")

New learners will be assessed through a test of several questions related to each concept in the course, with each question being multiple choice with 1 right answer, 3 answer and 1 "i dont know" answer. If the learner answer a question correctly, then their skill level will be categorized as "expert". A wrong answer will give the learner an "intermediate" cognitive skill, and "i dont know" will make them a "beginner" in that concept. These 3 cognitive skill categories will affect what learning objects are recommended to said learner.

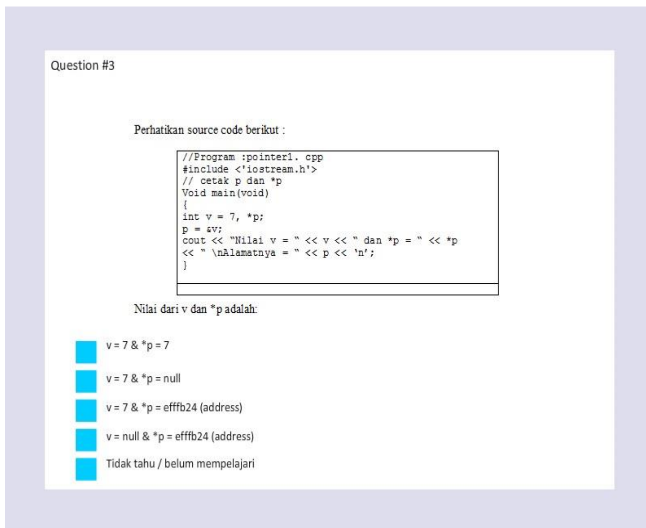


Figure 6. Cognitive skill assessment test

On visualizing the learner model on the topological map, the system uses colorcode to intuitively label nodes with corresponding learner's cognitive skill, grey for "beginner", red for "intermediate", and green for "expert/mastered".

Figure 7. Colorcode in learner's cognitive skill

Using OLMlet's skill meter and structured view as the guideline, we can visualize colorcoded learner models on topological map, pictured as follows:

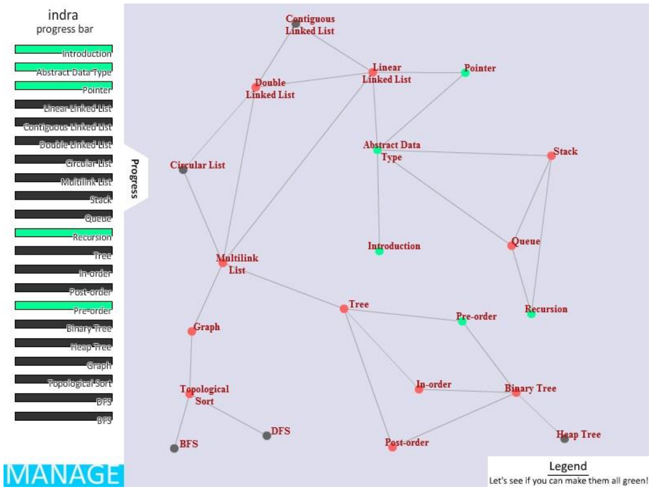
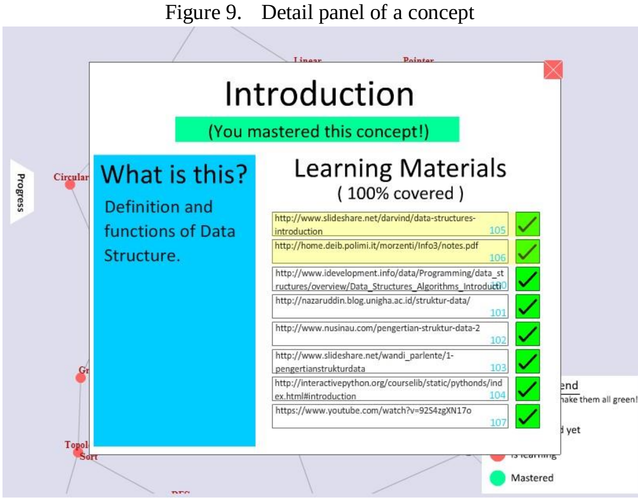


Figure 8. Learner Model visualized in topological map

The progress bar indicates learner's learning progress on each concepts; it's empty when learner havent learned anything and fills up each time the learner reads a learning material related to each corresponding concept. Each nodes in the graph can be clicked to open the detail panel of corresponding concept. It contains definition, learner's cognitive skill, as well as learning materials.

Figure 9. Detail panel of a concept



Learning objects on the detail panels are sorted based on their Recommendation Score (RS). Learning objects with the highest RS are then highlighted and marked as "recommended" to read. In general, a cycle of creating, accessing, and updating learner values are illustrated as follows:

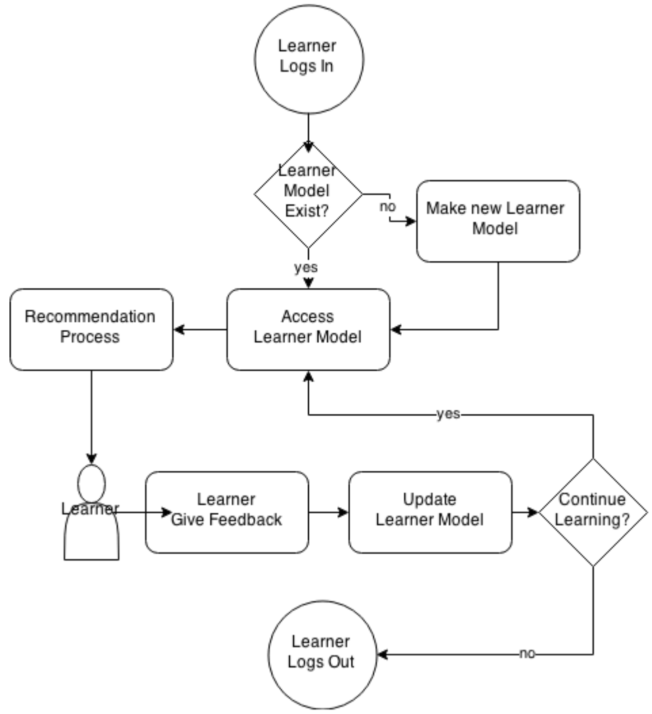


Figure 10. Learner model cycle chart

D. Learning Object Recommendation

Learner Preference Pattern is used to calculate Recommendation Score (RS). Each learning object in a concept is sorted based on their RS from highest to lowest one. There are 2 factors affecting the Recommendation Score: Preference Score (PS), which is based and Helpfulness Score (HS). The chart below illustrates the calculation process of Recommendation Score:

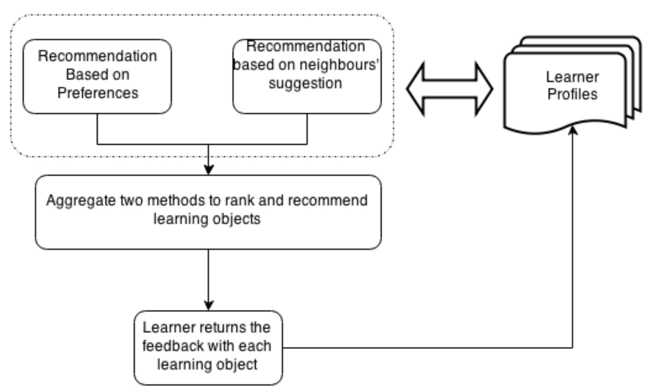


Figure 11. Recommendation Phase using LPP [6]

When aggregating PS and HS to calculate RS, we use a formula expressed below:

$$RS = wPS + (1 - w)HS$$

w represents the weight factor of preference score, ranging from 0 to 1. In this paper, we use a weight of 0.5

upon consideration of it's MAE (Mean Absolute Error) presented by Tzone I wang *et al* [3].

PS calculation are done by following expressions:

$$PS = 5x\frac{\sum BPW(fv_k^{fi})}{total\ tag\ of\ learning\ object}$$

$$BPW(fv_k^{fi}) = \frac{fs_k^{fi}}{max(fs_k^{fi})|\forall fs_j^{fi} \epsilon score\ of\ tag\ fi)}$$

Where k in fv is the k-th value of i-th tag in a learning object, and fs is the score of tag fv that is contained in current learner model. The score is then divided by the total tags current learning object has.

BPW represents Basic Preference Weight, a weight to represent the degree of a learner's preference for a feature value in a feature [6]. The feature is, in our case, the tag each learning object has. This tag varies e.g. "video" for learning object links using video as learning media, or "english" if the object uses english as a language. To get BPW value of a tag, the score of said tag is divided by the max score of a tag a learning object has. BPW is a floating number ranging from 0 to 1.

HS represents Helpfulness Score. To increase the accuracy of recommendation, system will also use feedbacks of other learner with similar experience and preference.To get a list of similar learners, we use this formula:

$$sim(uid, sl) = \frac{\sum_{s\epsilon s_{uidl,sl}}(r_{uid,s} - \overline{r_{uid}})(r_{sl,s} - \overline{r_{sl}})}{\sqrt{\sum_{s\epsilon s_{uid,sl}}(r_{uid,s} - \overline{r_{uid}})^2(r_{sl,s} - \overline{r_{sl}})^2}}$$

The system will first iterate all learner profile database and calculate each one's similarty. a perfectly-similar learner compared to current active learner will have a similarity of 1. A learner having similarity 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 HS using following formula:

$$HS(lo) = avg(FB_{uid}^{all}) + rErrorScore(uid, sim_{uid,lo})$$

$$rErrorScore(uid, Sim_{uid,lo}) = (\sum_{sl\epsilon sim_{uid,lo}}^{|sim_{uid,lo}|}(r_{sl,lo} - \overline{r_{sl}}))(\sum_{sl\epsilon sim_{uid,lo}}^{|sim_{uid,lo}|}|sim(uid, sl)|)$$

Differnt learners may evaluate a same learning object on different basis due to inherent characteristic differences. The relative error should be corrected to counterbalance the different learner attitudes toward a same learning object. So, rErrorScore (relative error score) is calculated for this purpose [6].

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

- a feedback rating of 1 or 2 (not helpful at all, not really helpful), there's no change at all in learner's profile
- a feedback rating of 3 or 4 (qute helpful, really helpful) will increase all preference score in tags that's also included in the learning object by Δs amount, as expressed by the following:

$$\delta s = rating\ x\ FVS$$

$$FVS = log\frac{total\ tags\ in\ learning\ object}{otal\ learning\ objects\ having\ same\ tag}$$

Pictured below, we can see the differences the system will recommend between learners with different preferences. Two different samples are shown, first with someone with a tendency to consider articles in indonesian heplful:

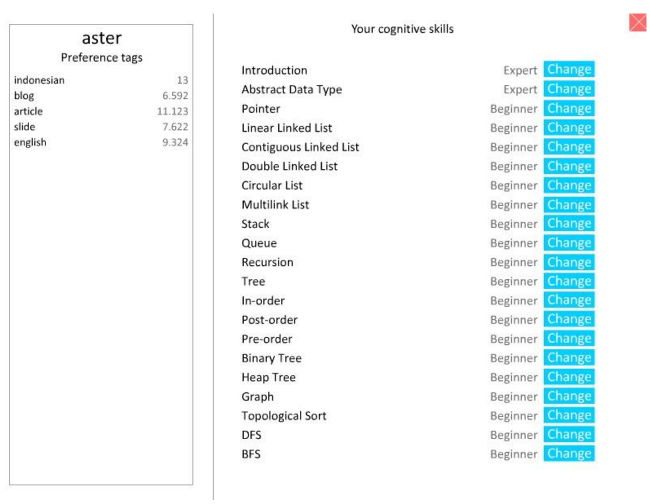


Figure 12. First sample's learner profile

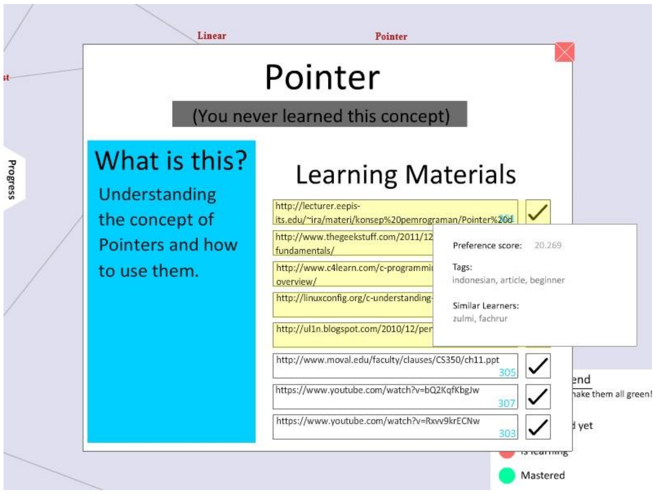


Figure 13. First sample's system recommendation

And pictured below is the second sample with tendency to consider in watching english videos are helpful for his learning:

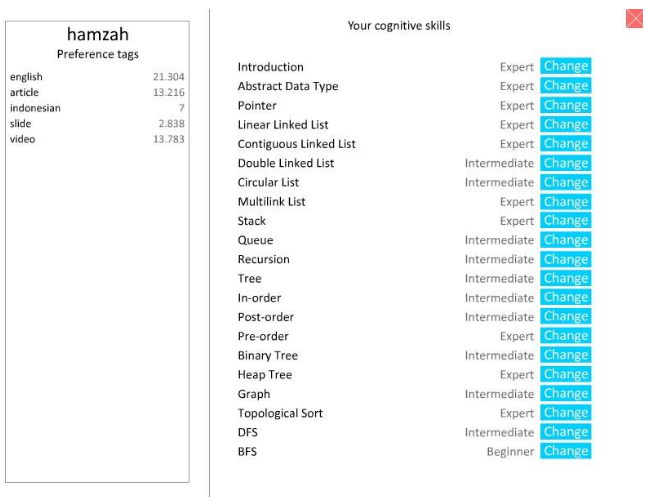


Figure 14. Second sample's learner profile

Figure 15. Second sample's system recommendation

IV. SUMMARY

In this paper, an implementation of Open Learner Model and Recommendation based on Learning Preference Pattern in an Adaptive Educational Hypermedia is proposed to help self-learning for it's users. Open Learner Model provides a guideline for an intuitive cognitively-oriented model suited for this needs. Color codes to for a learner cognitive skill visualization on each concepts, and progress bar to track learner's learning progress is also applied. Learning Objects Recommendation based on Learner Preference Pattern are capable to recognize adapt on feedbacks and changes learners made, then give them learning object recommendations tailored to their current preference and cognitive skill.

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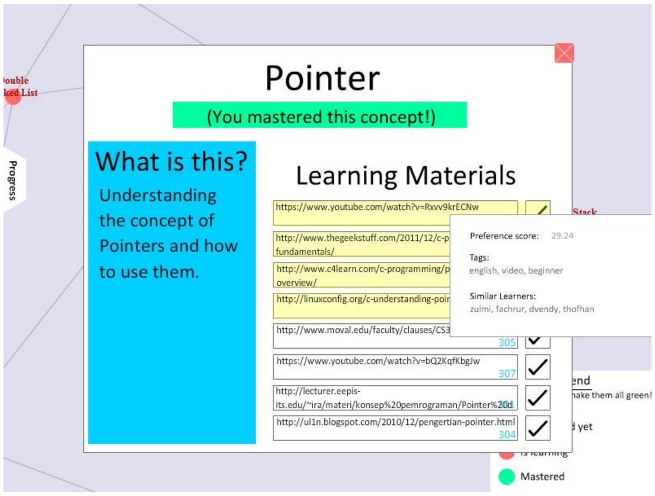
Pointer
(You mastered this concept!)
What is this?
Understanding the concept of Pointers and how to use them.
Learning Materials
https://www.youtube.com/watch?v=Rxvv9krECNw
Preference score: 29.24
Tags:
english, video, beginner
Similar Learners:
zulmi, fachrur, dvendy, thofhan
https://www.youtube.com/watch?v=bQ2KqfKbgJw
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Mastered
Progress