Recommender System for e-Learning based on Personal Learning Style

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***Abstract*—Online shopping has become an important part of lifestyle nowadays. Despite their many practical advantages, the users of online shopping systems can be overwhelmed with the abundant information about the goods they want to buy. While some users start their search with a preference for certain items or manufacturers, others may find it difficult to narrow down the range of options being offered. The recommender system can assist the users to filter the information and show the most relevant items to the users. Despite being very popular in e-commerce area, research on recommender systems for education is still underexplored. Similar to the users of e-commerce system, some students may also feel overwhelmed by the available choices of material contents offered by the e-learning system in which, it does not always suit to their learning style. This is important as some experts in educational psychology suggest that students need to learn by following their personal learning style. We propose an implementation design of e-learning recommender system based on a logic approach, APARELL (Active Pairwise Relation Learner), which has been implemented for used car sales domain. There is an opportunity to apply the same procedure for e-learning system to help the student to choose the best material according to their preferences. We also propose an ontology of material content based on the different learning styles. In this paper, we show that there is a big potential to implement a personalised recommender system in e-learning based on the students learning style.**

Keywords—recommender system, e-learning, education, pairwise user preferences, logic based approach

I. Introduction

Recommender systems are part of Information Filtering domain, where the goal is to filter the abundant information from the website to be more specific and meaningful. Nowadays, it is a quite common technology used in e-commerce system to assist users in retrieval of relevant items. Despite being very successful in e-commerce area, the implementation of recommender system for education, especially e-learning is still underexplored. The use of recommender systems for e-learning can be beneficial for both students and the instructors, as well as for the institutions. A recent study of a systematic mapping study to investigate the use of recommendation systems in education by Rivera, Tapia-Leon and Lujan-Mora [1], shows that personalisation is one of the most main issue addressed by recommender system in education. It accounts as high as 43% of 44 total papers being reviewed. This number of papers has been selected, reviewed and analysed from an initial set of 1181 papers. This number is still relatively low when it is compared to the papers about the use of recommender system in e-commerce. We observe there is still research gap in here.

In the education system, every student has their own personal learning style. According to experts in this area, when students are not performing as well as they could be, there must be another different way to teach them. It is very important when comes to choose a perfect learning style so that the students can have a good motivation to learn. Our research aims to help the students to find their preferred learning style. We propose an e-learning recommender system design based on a logic approach which can help the students to select the best e-learning material matched to their learning style.

The rest of our paper is organised as follows: in Section 2 we will discuss the related work which has been performed in the area of recommender system for e-learning. We then discuss about the e-learning case study in Section 3, where we will explain about the representation of different learning style in e-learning. This will be used as the base of our recommender algorithm. We discuss our proposed approach in Section 4. Finally, we conclude our work and provide our plan for further work in Section 5.

II. Related Work

Research area in recommender systems for e-learning is still under explored, although the first recommender system was implemented for library system [2]. Several studies on this area have started to emerge. Yu et al. [3] proposed a solution framework for recommender system in e-learning using ontology. The three ontologies were proposed, i.e. learner ontology, learning content ontology, and domain ontology. Similar work by Shishehchi, Banihashem and Zin [4] also propose the use of ontology for e-learning recommender system. Another research by Kolekar, Sanjeevi and Bormane [5] proposed a model to recognise and predict the students' learning style based on their behaviour when using an e-learning system. Personalised recommender systems in e-learning are also proposed by Tarus, Zhendong and Khadidja [6]. They propose to use ontology combined with collaborative filtering to recommend learning materials and calculate the similarity between them. Another research on this area was conducted by Benhamdi, Babouri and Chiky [7] which propose a method from a combination between collaborative and content-based filtering. They asked the users to give rating in order to get the recommendations. From the literature, none of them is using pairwise comparisons as preference elicitation method. In our paper, we offer a novel approach for recommender system in e-learning which includes the use of pairwise comparisons as preference elicitation, the use of ontology as data representation and the use of logic learning method as the learning algorithm. Educational technology is not a single entity, but a diverse array of technological devices, technology, practices, and activities [8]. Besides that, the system of modern education can be explained that the use of digital technology education, and it also includes working with most of the devices which is connected to the internet [8].

According to [9]. Learning Management System (LMS) could help lecturer and trainer to enhance and upload new materials. According to [10], MOOCs have been delivered using both centralized platforms and services. The delivery in MOCCs consists of LMS and decentralized networks which is based on aggregations of and social media learning [10].

III. E-Learning Case Study

Recommender system is a feature which can enhance the use of the e-learning as the main system. Thus, implementing recommender system has to be adjusted based on the need. In this section, we describe the e-learning case study which we can propose a recommender system model.

According to the perceptual learning style theory [11], students learn from their five senses: sight, hearing, touch, smell and taste. This theory also lists the seven learning styles based on our five senses. They are print (by using written words), aural (listening), interactive (verbalization), visual (picture and graph), haptic (touch sense), kinaesthetic (body movement) and olfactory (smell and taste). From those five senses, there are only two important sensory channels which will be considered in e-learning educational environment, i.e. sight and hearing, and we can omit the other three channels [12]. Similar to this, Howard Gardner also proposed the seven different learning styles as explained in [13] includes learning by visual, aural, verbal, physical, logical, social and solitary. Each different learning style means that the learners will need different media to see how the subject can be delivered. The visual learner will prefer to use image instead of text to understand something, while on the other hand, an aural learner will prefer to use music and sound. The other examples are for social learner where the learners prefer to learn in groups instead of just learn individually like solitary learner. We use these seven learning styles for our e-learning case study. The material content for e-learning can be categorized based on these. According to [14], e-learning content can include simple learning resources, interactive e-lessons, electronic simulations and job aids. E-learning material can also have several levels of cognitive performance, i.e. remember, understand, apply, analyse, evaluate.

Another theory of learning and teaching style is proposed by Felder and Silverman [12] which divide the learning style into five categories as follows:

1. Perception
2. Input
3. Organisation
4. Understanding
5. Processing

Perception is related to how the human perceives from their external sensory, while the input concerns about how the content of the material is shown (through visual or audio). Organisation deals with how the material is organised, whether it uses inductive or deductive approach. Understanding is about the way the information is being processed in memory and the processing is the one which deal with engagement of the students during the study time.

The users of e-learning can easily use filtering feature on the system to choose the content based on its type or its level. Despite of that, not all the users feel certain about which type of learning style suitable for them. Kolekar, Sanjeevi and Bormane [5] proposed an automated model to recognise and predict the students' learning style based on their behaviour on using an e-learning system. In this paper, we propose different method to help the learners to select the best materials based on their personal style.

Based on the above mentioned theories of learning style we can propose to label each e-learning material according to the type of learning style. We only consider the style which can be implemented in e-learning system. The materials can have one or more learning styles as their attributes as illustrate in Figure 1. Although, one will argue that we can always combine all the values in the learning style (hybrid style), here we treat them as individual values to make it easier to implement. We also propose an ontology of learning material based on the learning style as shown in Figure 2.

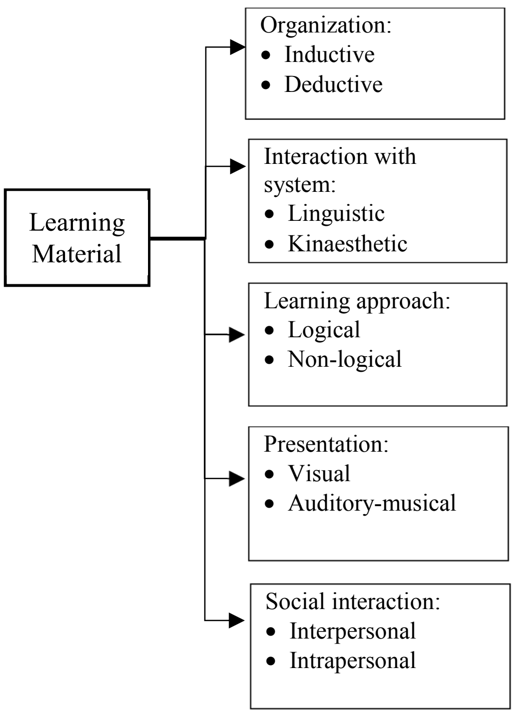

Fig. 1. Learning Material Category

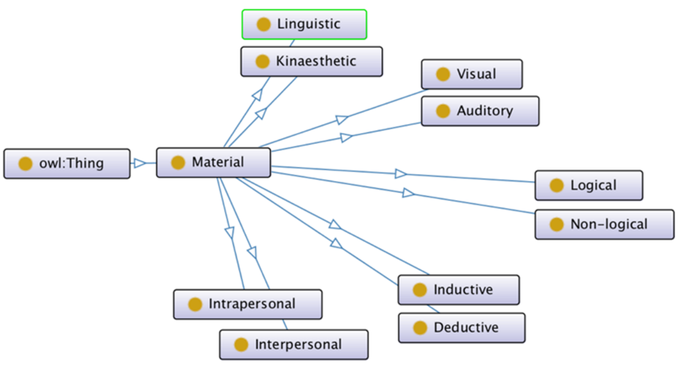

Fig. 2. E-learning Material Ontology Based on Learning Style

IV. Proposed Approach

Our proposed recommender system aims to help the users of e-learning system to find interesting learning resources based on their preferences, which is their learning style. The recommender system will consist of two main modules as follows:

A. Learning Module

We propose to use APARELL (Active Pairwise RELation Learner) [15] as the learning framework. It is a framework based on Inductive Logic Programming to learn binary preferences. The term Inductive Logic Programming (ILP) was introduced by Muggleton [16] as an intersection of machine learning, especially inductive learning, and logic programming [17]. As stated in the name, ILP is a learning algorithm based on inductive reasoning which learn from a set of facts then induce the general principles by using logic representation.

APARELL has been implemented in a real-world recommender system for used car sales domain. By using this framework, the users can express their preferences by choosing one from two options shown. It has been proved that APARELL outperforms several popular classification algorithms (Decision trees, SVM, Aleph) on the task of learning models of pairwise preferences [14]. The preferences expressed in relation *betterthan* is considered a relation with a strict order specific, which means it is anti-symmetric and also reflexive. In the relation *betterthan* we can say that if item A is better than item B, then item B cannot be better than item A. The special case of A as good as B is excluded by the assumption of *betterthan* being anti-reflexive (i.e. X cannot be seen as better than itself). The *betterthan* relation is also transitive, which means whenever item A is better than item B, and item B is better than item C, then item A is better than item C.

In APARELL, all training examples, additional domain knowledge and hypothesis are represented in the description logics. In this section, we use a simplified representation to make it easy to follow. For learning user preferences, we ask the users to give their order of preference on a set of item pairs which are then used as the set of positive examples for the learner. A sample set of positive examples is shown below:

```
material 1 betterthan material 3,
material 1 betterthan material 4,
material 1 betterthan material 5.
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The order of preference in these examples is then reversed and the result is used as negative training examples as shown below:

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material 3 betterthan material 1,
material 4 betterthan material 1,
material 5 betterthan material 1.
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Each material is a member of one or more classes. Each class represents the set of materials sharing the same value for a given attribute. For instance, material 1 belongs to the classes Visual, Interpersonal and Inductive and the attributes of material 3 are represented by its membership in the classes: Auditory, Intrapersonal and Deductive. This additional information is known as background knowledge in ILP.

From the given examples and background knowledge, APARELL searches for a hypothesis expressed as a set of consistent rules where each rule defines the domain D and range R of the relation *betterthan*. The domain and range of each rule are expressed as a conjunction of classes, e.g. $D \equiv$ (Visual $\sqcap$ Interpersonal).

The hypothesis search follows a breadth first search technique where each node corresponds to a certain combination of constraints on the class membership of the first and second materials in the pair. An example of the hypothesis search for a pair of items (material 1 better than material 3) is shown in Figure 3. The search is performed in the same way for all examples in the data set.

The output of this learning algorithm is a set of rules consistent with all the positive examples given by the users, such as:

```
(Visual) betterthan (Auditory)
(Auditory) betterthan   (Intrapersonal and
                        Deductive)
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B. Recommender Module

Our proposed system will search for e-learning material contents matched to the rules produced by the learning algorithm. This can be performed by using a graph-based recommender algorithm as explained in [18] which we will examine the user preferences by obtain the definition (as a combination of features) describing the style of learning not dominated by any other style in the preference given. All the material that match the mentioned description will then be selected to be recommended to the users.

For example, from the above rules mentioned in learning module, we have two rules consistent to the data, i.e. visual better than auditory; auditory better than intrapersonal and deductive. So that means the users will prefer the visual material than auditory or intrapersonal and deductive. We do not have the data about the other learning style so we are allowed to assume that the users still have the opportunity to explore it. We can see that a material that only belongs to one class: {Visual} will not be considered less better from any other. At the same time, it would be natural to consider any material belonging to Visual class as one of the best possible recommendations for this particular user. The attributes that the classes represent are also shown to the users as an explanation. We keep refining the models until the users confirm that the recommendation is sufficient enough meeting their need.

Here we use a specific recommendation strategy which we called it as domination strategy which means that we can only produce a set of recommendation list based on a set of characteristics which are not dominated by others. With this strategy we can provide valid recommendation list for the users. Although, in the future there is a possibility to also include the characteristics of the preferences which are not just the best one but also the second best or lower. It is possible to build a ranking from by the result of the APARELL algorithm.

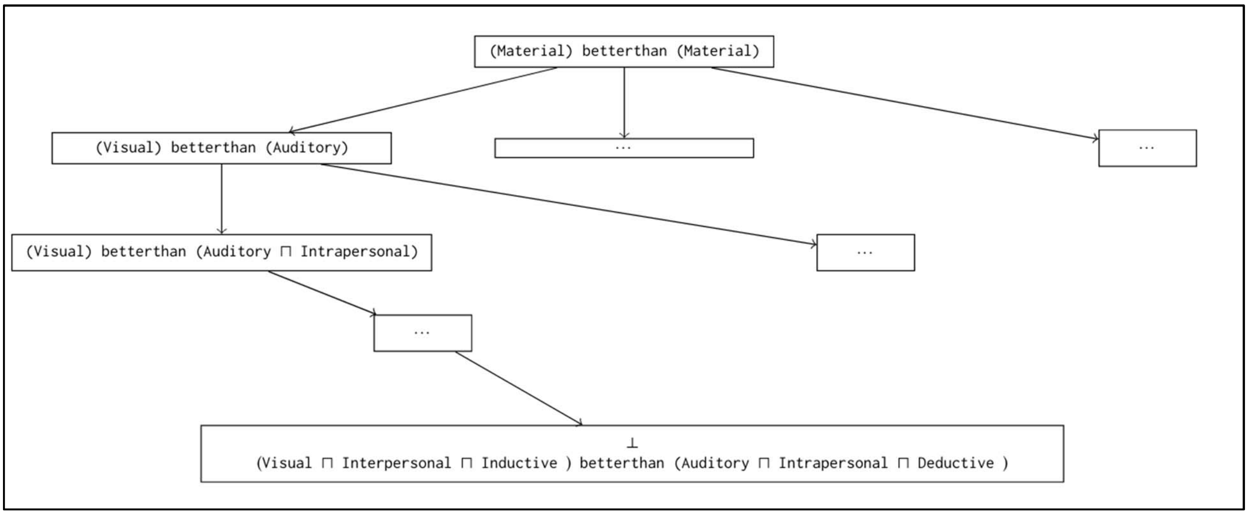

Fig. 3. Sample Hypothesis Search Tree

C. Services Design Architecture

In order to Implement the recommender system, we proposed the Services Design Architecture in Figure 4. According to the figure, we integrate university, corporate, government, payment gateway, and Bank. The entities are constructed to create the new ecosystem in e-learning processes. There are some functional services, such as Sponsorship, User Tracking, Payment Processors, Cron Job, Reporting, and Applying. The services design architecture used REST API to integrate among entities application.

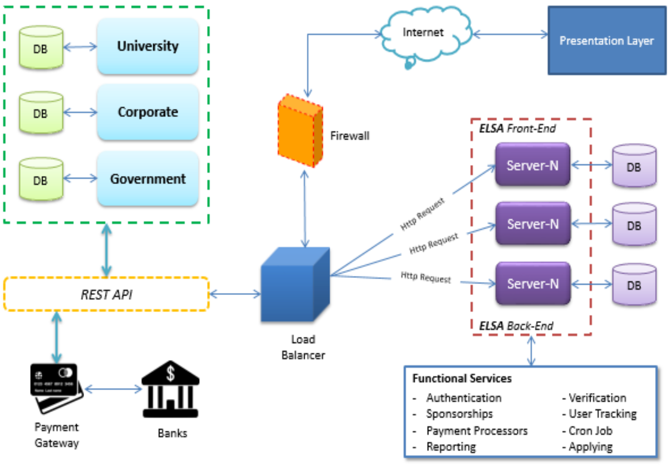

Fig. 4. Service Design Architecture

V. Conclusions and Future Work

In this paper, we have shown a propose solution of a recommender system in e-learning by using a logic based approach, APARELL. The system will learn from user's different learning style to provide a set of recommendation. We plan to continue our work by implementing this design and evaluate it online by inviting real students. We will ask the lecturer to create material based on the different learning style. The implementation of the proposed model of recommendation system can help the students to find the best material and keep them motivated during their study. Not only the students will find it useful, but also the instructors when they want to know their students learning style in order to develop a more suitable material content. We also propose services design architecture that used REST API to integrate among entities application. We plan to improve the recommendation strategy by incorporating the ranking method in specifying the best characteristics of a preference.

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