Analytic Recommendation of Learning Graphs Based on User's Learning History

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Abstract
Learning online (e-learning) has gained popularity in a world where emerging technologies are transforming the world in particular self-training due to what it provides of low-cost learning and relieving the learner of all logistical concerns that traditional learning methods impose. Although e-learning systems have managed to establish many advantages, in terms of time management, and economic level, and also provide much more learning freedom when it comes to when and where a person wants to learn. Some improvements in the learning sessions themselves are needed. Mentioning adaptability between user profiles, the variable personal user preferences during his/her learning sessions, and the learning path. In this work, and to address that issue we propose a system that recommends learning graphs to users based on their profiles, preferences, and progress, based on an analytic review of experiences from multiple users' learning sessions. Having three ontologies: User Profile Ontology to model the learner, Training Ontology, and MultiMedia Resources Ontology modeling respectively the domain and resources. We analyze the users' session history stored in those ontologies to produce recommendations based on matching profiles, taking advantage of the web semantic multiple uses.

Keywords: E-learning, Ontology, Learning Analytics

Introduction

Recommending appropriate learning content in an e-learning system is one of the biggest issues systems are facing nowadays, then it is not easy to deduce what content is suitable to a specific user or group of users.

To enhance the user experience in e-learning systems many have focused on recommending to learners items based on other users' ratings, or recommendations and/or by corresponding users' general profiles and the training objective.

All these approaches are effective to a specific limit, and the recommendation is still in mitigation; when relying upon user’s rating some cautions should be taken into consideration, seeing that the users are generally not experts in the training domain, and are rating based on very vast criteria, then the integrity of their ratings is not verified.

As far as it concerns the approach of corresponding user’s profile with content to establish recommendations; seeing that the learners are likely to be beginners seeking to learn some skills then the systems making recommendations lack valuable information to start the process of an effective recommendation. The user profile is built by extracting his/her interactions with the system and/or by implicit information the user provided, but these are not yet complete because the learner is still new to the system and has not yet started learning. So having a general profile that contains basic information about the user is not enough. This problem is widely known as the cold start, where it is hard to find criteria when the learner is a neophyte.

Looking back to the definition of a recommender system provided by Ricci, Rokach, and Shapira (2015), recommender systems are software tools and approaches that make recommendations for items that are likely to be relevant to a particular user.

Therefore the level of interest of a user alongside the basic characteristics of the user, seeing that the recommender system is particularly aimed at users that lack the necessary personal experience to assess the appropriate items for their needs.

The recommender system can effectively modify its recommendations to match each user's individual requirements and preferences by considering the user's level of interest and knowing their core attributes Benhamdi, Babouri, and Chiky (2017), Zaiane, O. R. (2002), Zhang, Lu, and Zhang (2021), Tan, Guo, and Li (2008), Sikka, Dhankhar, and Rana (2012).

This paper is organized as follows: an introductory section that provides a summary of the research topic establishes the context and emphasizes the significance of the study.

Following the introduction, the paper contains a methodology section. We detail the approaches used in our study in this area, outlining the precise techniques, tools, and procedures used to collect data, run experiments, or analyze information.

Following that, the article includes a results section that displays and explains the results of our experiments or studies. We present the conclusions, data, and statistical analyses obtained during the research process in this part.

Finally, the paper concludes with a section dedicated to the conclusion and future research work. We review the main findings, draw inferences based on the findings, and explain their consequences in this section. In addition, we discuss prospective future study directions, indicating areas that need further investigation.

Methods

Knowledge sources for recommender systems come from three points of origin Burke, R., Felfernig, A., & Göker, M. H. (2011). Firstly, from an individual provenance represented by users' personal judgment regarding a resource, user preferences, and elementary information and interaction with the system.

Secondly, it can source from social provenances such as ratings, reviews, and analysis and last from the content itself, the structuration and concept representation, and thirdly from the relation between the main actions and the expected results.

In our approach, we proceeded as follows:

(i) We structured concepts using three ontologies:

- The User Profile Ontology (UPO) contains the personal information and preferences of every user. It primarily describes learners, trainers, experts, etc. (see Figure 1). It also includes their initial or acquired skills and personalized learning path already completed or in progress (i.e., the pedagogical resources already used, assessments conducted, skills acquired or being acquired through a path).

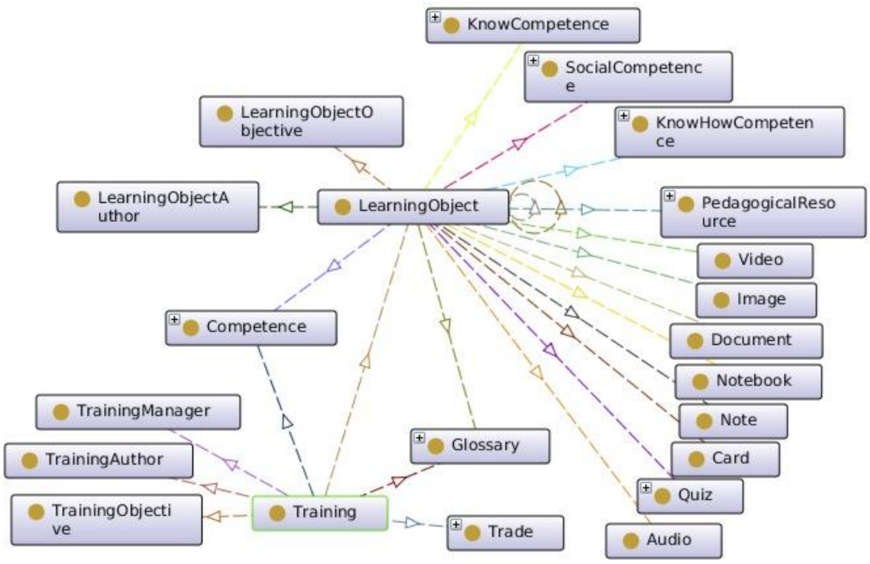

Figure 1: partial view of ontology UPO

- The second ontology is the Training Ontology (TO) which describes the skills required for a trade, as well as the objects and pedagogical resources used in various Learning Objects inside the *Training* class (see Figure 2). These learning objects are associated with available training programs, enabling the construction of a learning path so that users regardless of their level, can acquire the necessary skills.

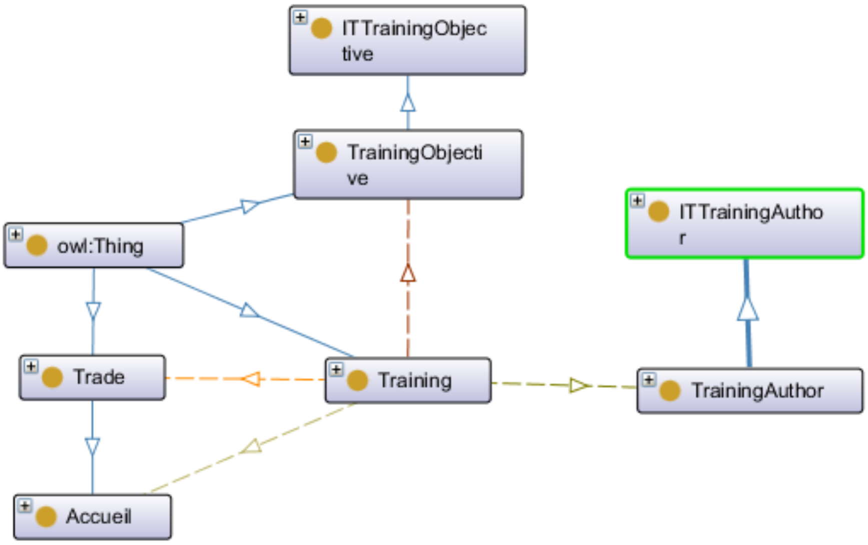

Figure 2: Partial view of Training Ontology (TO)

- The third ontology is MultiMedia Resources Ontology (MMRO) for modeling multimedia resources in different formats mainly in the class *MultimediaResource* (see Figure 3).

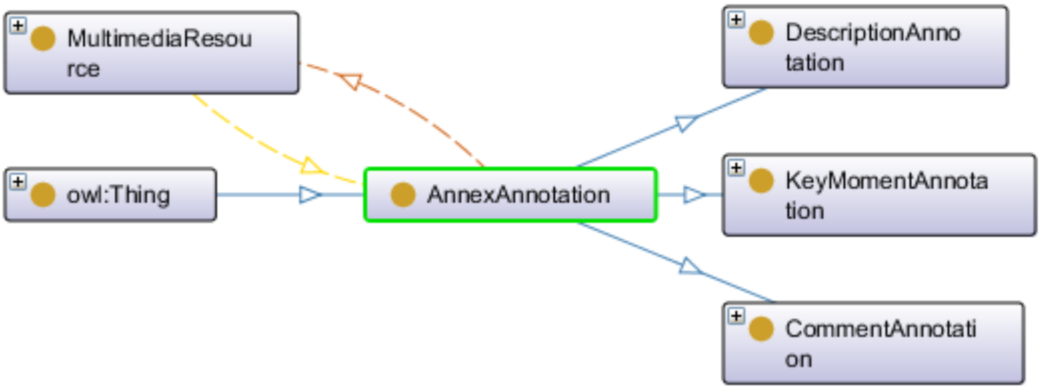

Figure 3: Partial view of MMRO ontology

(ii) Afterwards, we implemented a user interface (UI) enabling users to input their fundamental preferences regarding learning sessions, and specific training. The latter is composed of a sequence of learning objects containing various forms of resources forming the learners' learning graph. This learning graph is constituted of several levels. Each level has its own set of learning objects (LO) and pedagogical resources (PR) linked to one LO in the set of LO. The users' progression between levels of the learning graph requires successful completion of the evaluation. When the user fails the evaluation he/she is offered to go back and rewatch the same LO of the current level with the same or different PR. Users must select at least one pedagogical resource associated with one learning objective of the current level to validate the learning object and progress to the next level.

(iii) The learning paths are structured as follows: The expert defines the format, language, content, and the different attributes of the pedagogical resources and the learning objects. Each learning object has at least one pedagogical resource, and each learning object has at least a prerequisite learning object. The graph is structured based on the level and the prerequisite learning objects.

(iv) Each time a user chooses a training a new instance of a personalized learning path is created, this learning path will contain the traces of user interactions with the system. Furthermore, whenever a user selects a pedagogical resource linked to a learning object for visualization the interaction of the user with the system is captured and stored inside the UPO. This path, containing the details of their learning history, will then be extracted for subsequent analysis in order to see which path represents the highest success rate taking into account the profile pattern of the users that took this path.

Before the end of the learning session, an evaluation is conducted to measure the level of proficiency.

Results

Users Traces

In this section, we present the results of the experiment we conducted. After multiple users connected and constructed their profiles during registration and while choosing a specific training, we collected their learning session history (see Figure 4) from the UPO. This includes all learning objects referenced as ***LOs***, pedagogical resources referenced as ***PRs***, and associated attributes and properties during the learning session.

These results are analyzed by specifying the activity name parameter (i.e., determining which entity from the graphs will serve as the measurement item). In this case, we defined the learning objects as the quantifiable factor since they form the core of the original learning graph, and all other entities are linked to them.

	idUser	training	learningObject	pedagogicalResource	time
1	"625902183"	"DEV"	"LO1"	"PR52"	"01/06/2023, 11:15:5011:15:50"
2	"625902183"	"DEV"	"LO1"	"PR7"	"01/06/2023, 11:16:4611:16:46"
3	"625902183"	"DEV"	"LO2"	"PR10"	"01/06/2023, 11:18:3311:18:33"
4	"625902183"	"DEV"	"LO2"	"PR12"	"01/06/2023, 11:17:3811:17:38"
5	"625902183"	"DEV"	"LO2"	"PR50"	"01/06/2023, 11:18:1911:18:19"
6	"625902183"	"DEV"	"LO3"	"PR17"	"01/06/2023, 11:19:1511:19:15"
7	"120905340"	"DEV"	"LO1"	"PR6"	"08/06/2023, 15:41:5315:41:53"
8	"120905340"	"DEV"	"LO2"	"PR9"	"08/06/2023, 15:42:4715:42:47"
9	"120905340"	"DEV"	"LO3"	"PR14"	"08/06/2023, 15:43:3215:43:32"
10	"120905340"	"DEV"	"LO4"	"PR21"	"08/06/2023, 15:45:3915:45:39"
11	"120905340"	"DEV"	"LO5"	"PR24"	"08/06/2023, 15:45:5015:45:50"
12	"935326815"	"DEV"	"LO1"	"PR4"	"09/06/2023, 16:22:4016:22:40"
13	"935326815"	"DEV"	"LO2"	"PR10"	"09/06/2023, 16:22:4916:22:49"
14	"935326815"	"DEV"	"LO4"	"PR21"	"09/06/2023, 16:22:5416:22:54"

Figure 4: Fragmented view of detailed users interactions with the system

In this partial view of the results set, we find the training ***DEV*** in this case, the time user selected a pedagogical resource ***PRs*** the learning object connected to that resource, and the identifier of the user in question.

Analyzed Users Data

In this section, we find the multiple paths passed by different users and the activities they have taken (the resources they watched). These users had the full freedom to choose any resources in any language or format from the filtered list of resources based on their preferences. Users take an evaluation at the end of the learning graph to pass to the next level. The profile and the personalized learning path of those who passed it the first time and those who had the full score are stored to be referenced.

The identified learning graph or graphs will then be recommended to new users with shared interests, preferences, and characteristics for the same training. The path is suggested but not imposed on users; essentially it serves as a road map for users.

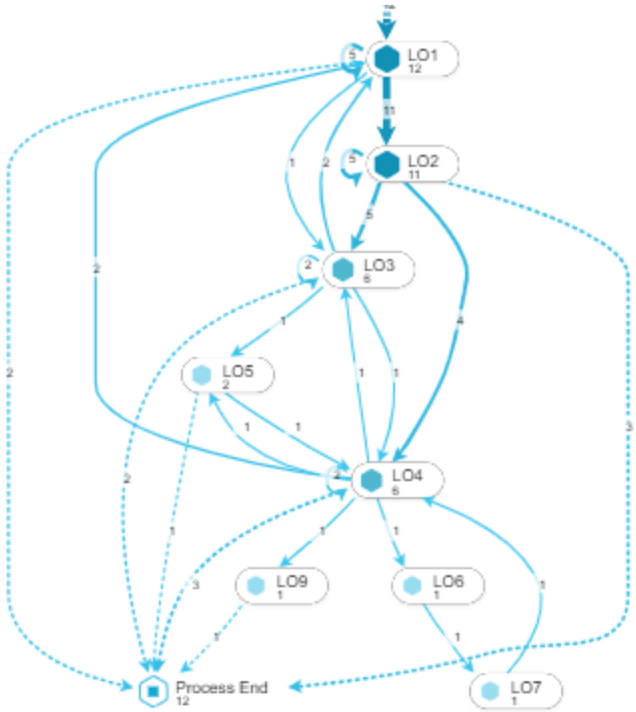

Figure 5: Fragmented view of multiple learning paths from a graph

The results of our analysis presented in this work provide a summary of the data collected and evaluated. The purpose of this analysis is to discover crucial results that will lead to determining what path a specific user took in our case, and what are the most visited learning objects and pedagogical resources. We can determine the profile of the users that passed the evaluation at the end of the learning session for further recommendation to users.

Conclusions and Future Work

We focused on the issue of personalized learning recommendations in this work by developing a system that considers users' profiles and preferences. The goal is to deliver meaningful and relevant recommendations to learners based on their individual traits and learning path.

By considering users' past learning experiences and patterns by examining their session history contained in the three presented ontologies (UPO, TO and MMRO). This analytic examination enables us to detect commonalities and patterns among various learners, allowing us to efficiently compare and match user profiles with training objectives and available resources.

In the future, we hope to improve the suggestion parameters by identifying the characteristics of the users' profiles in a way that depicts their cognitive level, as it is one of the primary criteria of a user's profile. We may further personalize the recommendation system and deliver more tailored ideas to each user by considering aspects such as cognitive ability, learning styles, and preferences. This technique will enable us to improve the system's accuracy and efficacy in matching the individual demands and preferences of users, thereby improving their overall experiences.

Second, we intend to create a complete profile method that captures the cognitive traits of users. Attention, reasoning ability, and information processing methods will all be taken into account by this mechanism. Users will be given evaluations or questionnaires aimed to collect information about their qualities and technical abilities regarding the training in question. This data will subsequently be utilized to build detailed profiles that reflect the cognitive strengths and limitations of the users.

Third, we will incorporate these cognitive profiles into the current recommendation system. The system will be able to create highly relevant and tailored recommendations by combining user preferences, interests, and cognitive qualities. For example, if a user prefers visual learning and has superior spatial reasoning skills, the system may prioritize offering interactive visual learning resources or simulations.

In addition, we want to continuously enhance and increase the system's ability to adapt to changing cognitive profiles of users. Users' cognitive status may change over time as they interact with the system. As a result, we want to use adaptive algorithms to update and alter the suggestion parameters in response to continuous user interactions and input. This adaptability ensures that the system remains sensitive to the changing cognitive needs and preferences of the users.

Fourth, we improve our networked ontologies and enrich them with external ontologies from certain standards or norms in the field of education.

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