Towards an Ontology-based Recommender System for Assessment in a Collaborative Elearning Environment

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Keywords: Recommender System, Personalization, ePortfolio, Collaborative Learning, Elearning Standard, Assessment, Ontology.

Abstract: Personalized recommendations can help learners to overcome the information overload problem, by recommending learning resources according to learners' preferences and level of knowledge. In this context, we propose a Recommender System for a personalized formative assessment in an online collaborative learning environment based on an assessment ePortfolio. Our proposed Recommender System allows recommending the next assessment activity and the most suitable peer to receive feedback from, and give feedback to, by connecting that learner's ePortfolio with the ePortfolios of other learners in the same assessment platform. The recommendation process has to meet the learners' progressions, levels, and preferences stored and managed on the assessment ePortfolio models: the learner model, the pre-test model, the assessment activity model, and the peer-feedback model. For the construction of each one, we proposed a semantic web approach using ontologies and eLearning standards to allow reusability and interoperability of data. Indeed, we used CMI5 specifications for the assessment activity model. IEEE PAPI Learner is used to describe learners and their relationships. To formalize the peer-feedback model and the pre-test model we referred to the IMS/QTI specifications. Our ontology for the assessment ePortfolio is the fundamental layer for our personalized Recommender System.

1 INTRODUCTION

Learning assessment has always been a very important phase of any learning process. In particular designing assessment methods that provide insight into the success of learning activities and what can be done to improve their effectiveness is very challenging. This research attempts to address peer assessment in an Online Collaborative Learning Environment (OCLE). Students learn in groups in such an environment by asking questions, supporting their viewpoints, explaining their reasoning, and presenting their knowledge to one another. Collaboration among students has become increasingly important over time. It is concerned with instructional strategies that aim to increase learning through collaborative efforts among students working on a particular learning activity. Through various online Information and Communication Technology (ICT) tools, the students can share their experiences and knowledge with other students. In previous research work, we have already focused on the improvement of both individual learners' and group performance at a given assessment activity or a set of activities by adapting the assessment process to the learner level (Asma Hadyaoui, Lilia Cheniti-Belcadhi, 2022). Collaborative learning is more and more valued in higher education because it allows students to practice a variety of team-based tasks they will encounter in the workplace; therefore, it applies to real-world assessment providing a direct opportunity for formative peer assessment (Tillema, 2010). Peer assessment is a practice in which students provide feedback to each other (Lilia Cheniti Belcadhi and Serge Garlatti, 2015). The goal of providing feedback is to assist students in improving their learning. Receiving and offering feedback from peers is a form of learning, and learners gain from it.

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Hadyaoui, A. and Cheniti-Belcadhi, L.
Towards an Ontology-based Recommender System for Assessment in a Collaborative Elearning Environment.
DOI: 10.5220/0011543500003318
In *Proceedings of the 18th International Conference on Web Information Systems and Technologies (WEBIST 2022)*, pages 294-301
ISBN: 978-989-758-613-2; ISSN: 2184-3252

They increase their grasp of the learning objectives and success criteria by providing comments to peers. Because they are forced to integrate the learning objectives and success criteria in the context of someone else's work, which is less emotionally charged than one's own, the person giving feedback benefits just as much as the person getting input (Wiliam, 2006). Peer assessment in a collaborative learning environment is grounded in some questions that frame the assessment process of a learner: Who would be my peer now? Where to go next? What is my peer's next target? The recommendation is the answer to these questions, as it allows monitoring learners' behavior while performing assessment activities. Recommender Systems make use of different sources of information to provide users with predictions and recommendations of items. The recommendation process has to meet the learners' progressions, levels, and preferences. Therefore, how can we recommend learning and assessment resources adapted to the profile and context of each learner? How to find the most appropriate peer for a learner to receive feedback from, and to give feedback to? How to collect and manage traces of assessment activities to use them as a first layer of the recommendation process? How can we ensure the exchange and interoperability of assessment resources between different tools and learning environments? Learner characteristics such as knowledge, affective activity statement, pre-test achievement, and previous assessment result are considered as a basis for providing recommendations. Our system should be able to gather and thus save learners' traces recorded during assessment activities so that they can be reused. Furthermore, the proposed system should be capable of managing such pieces of data in the best possible way in the interest of learners. Indeed, the learner's performance in assessment activities can be collected as useful data for assessment and as evidence or proof of the learner's mastery of a certain skill. All this data will be stored in what we call an "ePortfolio". In this paper, we propose an assessment ePortfolio that should allow us to structure the content of the assessment traces to use them as evidence for the learner's competencies (Amira Ghedir, Lilia Cheniti-Belcadhi, Bilal Said, Ghada El Khayat, 2018). To model our proposed ePortfolio, we used semantic web technologies and ontologies. The suggested model's primary problems include interoperability, information sharing, scalability, and dynamic integration of different pieces of data. To overcome this issue, we are based on e-learning standards: in particular, we proposed the CMI5, the IMS/QTI, and the IEEE PAPI Learner specifications. Our assessment ePortfolio is the fundamental layer for our Recommender System. This latter is split into two recommendations: On the one hand, the next assessment activity to perform, and on the other hand, the most suitable peer to receive feedback from, and give feedback to.

The remaining sections of the paper are structured as follows. First, we present the use and application of a Recommender System. After that, we present our contribution, in the form of a general architecture design for the proposed Recommender System and an ontological model for the assessment ePortfolio. Finally, concluding notes and future research actions related to thematics are explored.

2 LITERATURE REVIEW

Users of eLearning are frequently met with an innumerable number of products and eLearning materials. Therefore, customization is required to provide an exceptional user experience. This type of recommender tool is essential in numerous Web domains, including eLearning sites (Dhavale, 2020).

2.1 Recommender System (RS)

RSs are systems that are designed to provide recommendations and suggestions for users based on many different factors. They are useful for recommending things that users have already selected (Lilia Cheniti Belcadhi and Serge Garlatti, 2015). There are some initiatives in the field of RS to offer new and better recommendations to improve performance. The recommendations are aimed to aid users in making various decisions, such as what to buy, what music to listen to, or what news to read. RSs have proven to be an effective way for online users to manage information overload, and they have become one of the most efficient and widely used tools in e-commerce. They produce meaningful recommendations to a user for items or products based on their preferences. Recommendations of books on Amazon, movies on Netflix, or songs on Spotify is the real-world example of RSs (Sushma Malik, Mamta Bansal, 2019). The RS has traditionally been used in a business context, but this has shifted over time to include other sectors such as health, education, and government. In (Herlocker, Jonathan L. and Konstan, Joseph A. and Riedl, John, 2000), RS was presented as predicting a person's affinity for articles or information by connecting that person's interests with the registered interests of people and by sharing skills among peers. In education, finding educational resources that meet specific learning needs has become increasingly difficult. According to (Maria-Iuliana Dascalu, Constanta-Nicoleta Bodea, Monica Nastasia Mihailescu, Elena Alice Tanase, Patricia Ordoñez de Pablos, 2016), RS is gaining utility and popularity in various fields. EduRecomSys, for instance, was proposed in (Maritza Bustos López, Giner Alor-Hernández, José Luis Sánchez-Cervantes, Mario Andrés Paredes-Valverde, María del Pilar Salas-Zárate, 2020) as an educational RS that suggests users' educational resources based on the preferences/interests of other users and the user's previously detected emotion.

3 RECOMMENDER SYSTEM DESCRIPTION

The RS is a system of users, user interfaces, datasets, and recommendation algorithms. The data utilized to create the recommendations are drawn from the learners' ePortfolios. A recommendation algorithm can be applied based on the user requirements deduced from his ePortfolio.

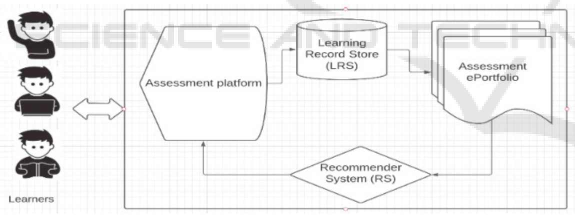

Figure 1: System design schema for the RS.

3.1 The Learning Record Store (LRS)

It is essential to add an LRS to our system to truly support the CMI5 specifications (Rustici-Software, 2022). In addition, our assessment ePortfolio is primarily based on stored and collected. Learners' profiles and assessment pieces of information are calculated and stored based on the learner's traces tracked while performing assessment activities. An indicator is a significant element, identified using a set of data, that makes it possible to evaluate a situation, a process, a product, etc. To calibrate the value, other variables are used. Many works on indicators have been published, with most of them adhering to these criteria. For example, (Olga C. Santos, Antonio R. Anaya, Elena Gaudioso, Jesus G. Boticario, 2003) provides a tool that calculates the degree of involvement of each learner during the learning unit based on the interactions.

3.2 The Assessment Platform

The collaborative online assessment platform includes a range of situations in which interactions take place among students. Multiple sections of the application permit collaborative learning. It is a platform that can be used to perform remote collaborative tasks by allowing students to interact in real-time and discuss collaborative topics in teams. A pre-test is required to access the different activities. The concept of Assessment activity is the basic abstract concept of the platform executed by an actor, which can be a single person or a group of learners. Activities also have resources, representing elements created or manipulated by the activity. These resources are used to perform an assessment activity that has learning outcomes or learning objectives when it is performed.

3.3 The Recommender Engine

We used RS to enhance the learner's experience in the assessment process. We used recommendations for two purposes: to recommend the most appropriate peer learner to receive and provide feedback, and then to recommend the next assessment activity. To this end, various data sources generate personalized recommendations. All these data are managed on learners' ePortfolios, which will be described later as a learner model of our proposed intelligent system for assessment in a collaborative e-learning environment. A determining factor in the design of an RS is the filtering model that is used according to the type of system. In general, recommendations are primarily based on three approaches, namely content-based, collaborative filtering, and hybrid approaches (Keyvan Vahidy Rodpysh, Seyed Javad Mirabedini, Touraj Banirostam, 2021). There are traditionally three content filtering approaches, which can be categorized as Content-Based: Try to recommend a similar article based on the user's past preferences; Collaborative filtering: Identifies users whose tastes match those of a particular user and recommends to this user content that other users like, and hybrid is a combination of the last two approaches. The three categories all have their characteristics and suitable application scenarios (Daniel Valcarcea,Alfonso

Landina,Javier Parapar,Alvaro Barreiro, 2019). In our case, a collaborative filtering approach is applied.

Collaborative filtering (CF) filters the data stream that an RS can recommend to a target user based on their tastes and preferences (Fkih, 2021). The CF technique is extremely sensitive to the similarity measure used to quantify the strength of dependency between two users. Indeed, our proposed RS computes the similarity between learners using the learner's previous data collected and managed on his assessment ePortfolio, which is based on the Memory-based Collaborative filtering approach. Our primary goal is to describe the degree of similarity among learners and to discover homogeneous learners' ePortfolios: assessment activities achievements, scores, results, and pre-test performance. Our proposed recommendation engine is considered a pipelined invocation of two RSs, with two recommendation techniques executed sequentially. In this pipeline, the recommendations of the successor, which is the assessment activity RS, are limited by the predecessor, which is the peer learner RS, implying that one RS pre-processes input for the subsequent.

- **The Peer Learner RS.** In this phase, we propose to select the set of nearest learners, for each assessment activity performed using the (top-k) technique, which selects the k-most similar users, k here denotes the number of users. In our case, the k value is one because it will recommend the most appropriate peer for the active learner to receive and provide feedback for the current assessment activity in a peer-assessment context.
- **The Assessment Activity RS.** This method involves giving recommendations based on correlations between assessment activity statements among system learners. The assessment activity RS will look for the pre-selected learner who is the most similar to the target learner, and only assessment activities that this later performed well will be recommended to the target learner. The entire recommendation process is depicted in Figure 2.

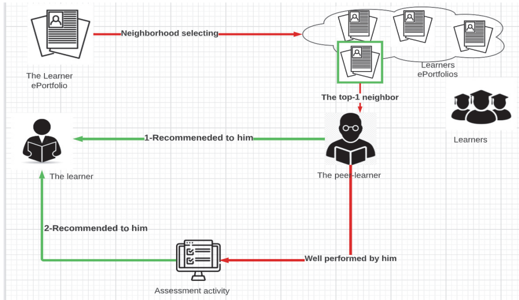

Figure 2: Description of the recommendation process.

4 ASSESSMENT EPORTFOLIO

The suggested assessment ePortfolio is split into four models: The pre-test model, the assessment activities model, the peer-feedback model, and the learner model. Our proposed assessment ePortfolio manages pre-tests, assessment activities, peer feedback, and learner profiles. To do that, we take IMS/QTI, CMI5, and IEEE PAPI standards into consideration and incorporate their characteristics into our proposed ontological model so that it conforms to international standards. Moreover, assessment ePortfolio takes advantage of the semantic web technologies that offer better data organization, indexing, and management and ensures this model's reusability, interoperability, and extensibility. The objective of the semantic web is to equip the current Web with metadata, transforming it into a Web of Data that is easily consumable by machines. Semantic-web ontologies are the artifacts of this Web of Data, each of which consists of a data model and data that must comply with it; they are based on the semantic-web technologies, i.e., RDF, RDF Schema, and OWL for modeling structure and data, and SPARQL for querying them (Rivero et al., 2013).

4.1 Assessment ePortfolio Model

Our proposed assessment ePortfolio brings together the four models described before. Therefore, it describes assessment activities in which the learner has participated, is participating, or plans to participate; competencies and skills of the student; learner's preferences; learner's goals and plans; the results of the pre-test, assessment activities achievements; and peer-feedback.

Figure 3: The ontological model of ePortfolio for peer assessment in an online collaborative platform.

4.2 The Learner Model

Learners play a critical role in evaluating learning activities, given that they are the individuals who use the activities to learn. Knowledge about how they engage with activity and, importantly, their attitudes towards a particular activity, both provide knowledge about the effectiveness of the activity and how it can be improved. The learner model is a representation of the learner profile deduced from his knowledge, goals, experiences, interests, backgrounds, learning styles, learning activities, and assessment results. The user model or learner model is constructed from these features. It is responsible for discovering the individual learning behavior of the learner (Abdalla Alameen, Bhawna Dhupia, 2019). The learner profile can be conceived at the epistemic and behavioral levels (Kirsti Lonka, Elina Ketonen & Jan D. Vermunt, 2020). It aims to identify the individual characteristics of each learner's strengths, preferences, and motivations (Hongchao Peng, Shanshan Ma & Jonathan Michael Spector , 2019). At the epistemic level, the data collected in the learning environment is used to infer the learner's knowledge status. This includes theoretical and declarative knowledge and procedural knowledge (Katrin Saks, Helen Ilves and Airi Noppel, 2021). The updating of the learner profile means updating values associated with the learner activities progression, pre-test achievements, scores, and peer feedback received. It is based on the learner's assessment ePortfolio. The process of updating the learner's profile is necessary to keep track of the learner's evolving competencies. This update affects the accuracy of the formative assessment activities proposed to the learner, which in turn will help increase the learner's performance.

Standardization addresses not only the learning objects but also the learner information; therefore, learner characteristics should be well-defined to facilitate their use in various e-learning platforms and to allow for more accurate personalization. Within this context, attempted to model the learner data in a formal way that promotes reuse and interoperability, that is the IEEE PAPI Learner (Public and Private Information for Learners) because it considers the performance information as the most important information about a learner (Othmane Zine ,DerouichAziz,Talbi Abdennebi , 2019).

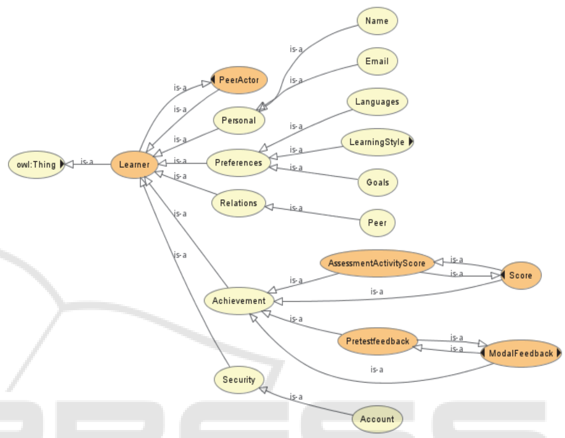

Figure 4: The ontological model of the learner model.

4.3 The Pre-test Model

Pre-tests are non-graded assessment tools used to determine pre-existing subject knowledge. Typically, pre-tests are administered before a course to determine knowledge baseline, but here they are used to test learners before assessment activities performance and may let learners escape some of them. The pre-test is an important stage to conceive our RS as it allows us to handle the cold start problem issue with RSs. To provide the basis for interoperability specifications for the pre-test creation process: from construction to evaluation, Question & Test Interoperability (QTI) provides a good starting point for modeling and designing the pre-test model. The QTI standard (Consortium, 2022) specifies how to represent pre-tests and the corresponding result reports. Figure 5 illustrates the ontological model for the pre-test.

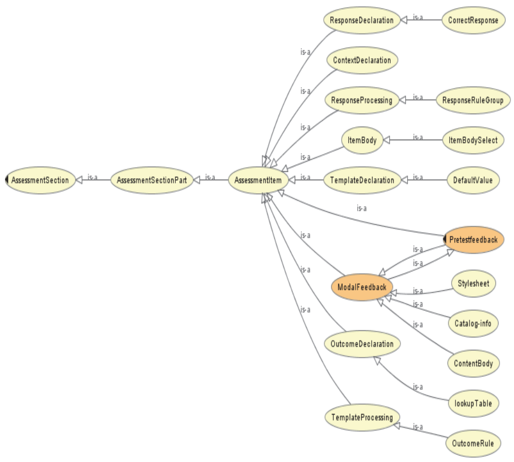

Figure 5: The ontological model of the Pre-test model.

An assessment item involves the question and the instructions of how this question should be introduced and the answer treatment to be applied to the candidate's response. Each answer to the question can also have different structures. The response processing determines the assessment method. Results of a test can be recorded and saved for future reference by other systems (Consortium, 2022).

4.4 The Assessment Activities Model

The RS protocol enables the packaging and delivery of distributed learning resources such as traditional courseware and content that cannot be accessed via a web browser (e.g., mobile apps, and offline content). To replace SCORM as the meta-data standard for computer-based training, the CMI5 specification duplicates SCORM features (xAPI). This allows it to collect data with reliability (Brian Miller, Tammy Rutherford, Alicia Pack, George Vilches, Jim Ingram, 2021). As a result, we used CMI5 specifications to handle assessment activities in which the learner has taken part, is taking part, or plans to take part in, using the statement class. CMI5 is the most recent eLearning standard. It specifies how learning products packaged as learning objects and imported into the framework interact with the latter to track learner progress. Therefore, it can be considered an excellent way to model a formative assessment. The ontological model is represented as follows.

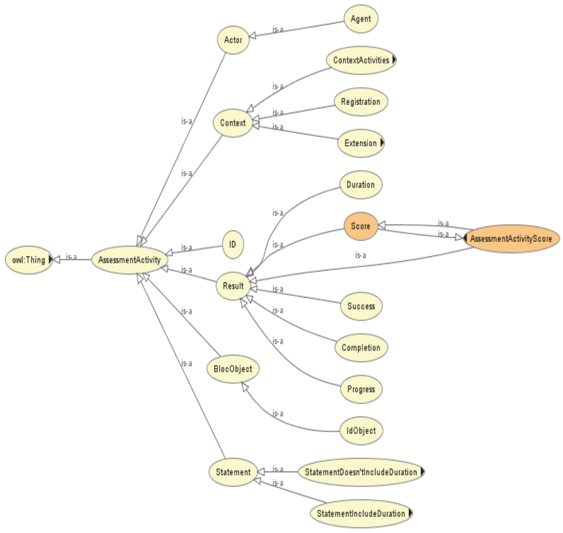

Figure 6: The ontological model of the assessment activities model.

4.5 The Peer-feedback Model

Our assessment ePortfolio focuses on peer feedback about the assessment process as it emphasizes the value of assessment and, as a result, improves student learning. Indeed, the peer assessment process can improve student learning. To formalize the learners' peer feedback, we require a response template that follows the RISE model (Wray, 2022). When writing their feedback, learners consider the following prompts: a) Reflection: Recall, ponder, and share what you've learned; b)Inquiries: questions are used to gather information and/or generate ideas; c)Suggestion: offer suggestions about how to improve the present iteration; d)Elevated: in subsequent iterations, raise the degree of intent. The peer learner will be guided while providing his feedback with questions related to each prompt. As with the pre-test, the feedback questions are consistent with IMS/QTI specifications. The ontological model is represented as follows.

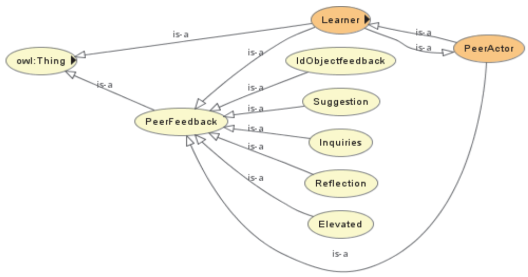

Figure 7: The ontological model of the peer-feedback model.

5 DISCUSSION

The following questions were posed at the beginning of this paper: Who would be my peer now? And where do we go from here? To address these concerns, we proposed guiding learners through the assessment process using personalized recommendations in a peer assessment context. We proposed a pipelined invocation of two RSs, with two sequential recommendation techniques. The recommendations of the next assessment activity to be performed in this pipeline are constrained by the selection of peer learners, which implies that one RS pre-processes input for the subsequent. Several RSs have been used in the educational field to recommend course material for Computer Science students. In general, an RS in an eLearning context tries intelligently to recommend actions to a learner based on the actions of previous learners. eLearning Recommendation System plays an important role in providing accurate and right information to the user (Pradnya Vaibhav Kulkarni, Sunil Rai, Rohini Kale, 2020). Mainly, all recommendation techniques used concentrated on a single final educational subject. Authors (Soulef Benhamdi, Abdesselam Babouri & Raja Chiky, 2017) developed a new approach to personalization that provides students with the best learning materials based on their preferences, interests, background knowledge, and memory capacity to store information. Barria-Pineda et al. in (Jordan Barria-Pineda, Peter Brusilovsky, 2019) have assisted students in reducing misunderstandings about programming problems and suggesting the most appropriate content. In (Safat Siddiqui, Mary Lou Maher, Nadia Najjar, Maryam Mohseni and Kazjon Grace, 2022), proposed a solution to aid students in the selection of papers. The majority of recommendation techniques suffered from the cold-start problem in some form or another. Because we consider the learner ePortfolio as the first layer of the recommendation process, our proposed approach avoids this issue. The assessment ePortfolio is an effective method for providing learner-centered assessment as well as a vehicle for peer assessment. We collected and managed data on each learner using the assessment ePortfolio, then matched that learner's ePortfolio to the ePortfolios of a community of learners. We were able to structure the content of the assessment traces using the assessment ePortfolio to use them as evidence for the learner's competencies. Our work is based on e-learning standards to address interoperability, information sharing, scalability, and dynamic integration of heterogeneous pieces of information. As an open standard for semantic knowledge representation, Ontology Web Language (OWL) was adopted for ontology implementation. Protégé 5.2 is the tool used for modeling and building it. We utilized the Semantic Web Rule Language (SWRL) to express the ontology's inference rules. To assess ontology, we presented several use cases based on a real collaborative assessment scenario involving a group of learners. To conduct such an evaluation, we developed instances for the proposed ontology.

6 CONCLUSION AND FUTURE WORK

While several RSs exist in learning systems, this is not yet the case for the personalization of the recommendation in an online collaborative peer assessment context. The scope of this research paper is to recommend the assessment activity to be performed and a peer to receive feedback from and give feedback to. It is not only about a recommendation process, but our aim is how to make our recommendation personalized. To this end, we have proposed an assessment ePortfolio as the base layer of the RS. Our proposed ePortfolio is split into four models: A pre-test model, an assessment model, a peer-feedback model, and a learner model. We used ontology to formalize and describe them. In our scenario, the interoperability between assessment ePortfolios is hindered. For this reason, it is desirable to use a common standard to unify the information description process. We referred to the CMI5 specifications to formalize the assessment activities process, the IMS/QTI for the pre-test and the peer-feedback models, and the IEEE PAPI Learner is used to describe learners and their relationships. Future work will focus on integrating other types of assessments into our ePortfolio model such as group assessments, to better design the assessment process and adapt it further to learners' context.

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