

# An Argumentation-based Conversational Recommender System for Recommending Learning Objects

Extended Abstract

Javier Palanca  
Universitat Politècnica de València  
Valencia, Spain  
jpalanca@dsic.upv.es

Stella Heras  
Universitat Politècnica de València  
Valencia, Spain  
sheras@dsic.upv.es

Paula Rodríguez Marín  
Instituto Tecnológico Metropolitano  
Medellin, Colombia  
Paularodriguez@itm.edu.co

Néstor Duque  
Universidad Nacional de Colombia  
Manizales, Caldas, Colombia  
ndduqueme@unal.edu.co

Vicente Julián  
Universitat Politècnica de València  
Valencia, Spain  
vinglada@dsic.upv.es

## ABSTRACT

In this paper, we present an argumentation-based Conversational Educational Recommender System (C-ERS), which helps students to find the more suitable learning resources considering their learning objectives and profile. The recommendation process is based on an argumentation-based technique, which selects those learning objects (LOs) for which it is able to generate a greater number of arguments justifying their suitability.

## CCS CONCEPTS

• **Information systems** → **Recommender systems**; • **Computing methodologies** → **Intelligent agents**;

## KEYWORDS

Educational Recommender Systems;Argumentation;Explanations

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## 1 INTRODUCTION

With the actual massive availability of online learning resources, Technology Enhanced Learning (TEL) systems that aim to develop socio-technical innovations for learning and education are gaining great popularity [3]. Many academic institutions offer Massive Online Open Courses (MOOCs), and most new methodologies for teaching-learning (e.g. flip teaching) rely on digital learning objects (LOs) shared on the Internet. This opens new challenges for the research community on recommender systems, where TEL (or Educational Recommender Systems, ERS) is now a hot topic. ERS can help people to find the best learning resources for their learning objectives, educational level, and learning style. The student's learning style determines which LOs are more adequate for them.

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In [7], an ERS that recommends LOs to undergraduate students by taking into account their learning profile (personal information, language, topic and format preferences, educational level, and learning style), learning history (LOs that they already used), and their similarity with other users of the system was proposed. The system consists of an argumentation-based hybrid recommendation engine that combines several recommendation techniques (content-based, collaborative, and knowledge-based). An advantage of our technique is that it offers a straightforward way of generating textual explanations from arguments.

However, online education is a tricky domain where learners can dynamically change their learning preferences or exhibit ad-hoc ones for specific topics or LOs. Hence, students can quickly leave the ERS if they do not find it useful and effective for their learning objectives. Conversational recommender systems are particularly effective for preference elicitation through question-asking and recommendation critiquing [1, 2]. In this paper we present a new conversational version of our system (C-ERS), able to interact with its users and allow them to express their opinions on the recommendations, to specify their current preferences, and to correct the system's wrong assumptions. To evaluate our system, we have performed a live-user trial with undergraduate students of the Universidad Nacional de Colombia, obtaining promising results.

## 2 CONVERSATIONAL EDUCATIONAL RECOMMENDER SYSTEM (C-ERS)

C-ERS follows a hybrid recommendation technique that uses LOs *metadata* and information about the *student's profile* to compute the recommendations. Also, student profiles include their personal information, interactivity level, language and format preferences, learning style (auditory, kinaesthetic, reader, or visual), and usage history. This technique combines content-based, collaborative and knowledge-based recommendation styles [6] by modeling this expert knowledge in a logic program. We use a defeasible argumentation formalism based on logic programming [4] to implement the logic of the recommendation system and generate arguments to support the recommendation of specific LOs. Thus, our C-ERS provides the students with those LOs that are better supported by a greater number of arguments.

A defeasible logic program  $P = (\Pi, \Delta)$ , models strict ( $\Pi$ ) and defeasible ( $\Delta$ ) knowledge about the application domain. In our C-ERS, the set  $\Pi$  represents *facts* (i.e. strict inference rules with empty body). The set  $\Delta$  represents defeasible rules that encode the defeasible inference that provide reasons to believe  $P$ . There are different types of defeasible rules that represent the underlying logic each of the system's recommendation approaches. *Content-based rules* use information about the student profile to recommend suitable LOs. *Collaborative rules* use information about the students' profile to compute a similarity degree among them and recommends a LO that was suitable for similar students. *Knowledge-based rules* use information about other LO that the user has already assessed in the past to recommend a similar LO.

The program that represents the logic of the C-ERS can be queried to resolve if an argument that supports a specific recommendation can be derived. Thus, when the C-ERS is requested to recommend LOs for a specific student, it tries to derive all possible defeasible rules by backward chaining facts and defeasible rules and following a similar mechanism to the *Selective Linear Definite (SLD)* derivation of standard logic programming. Therefore, since the system can generate an argument to support the literal that can be derived from each defeasible rule, arguments in this framework are defined as follows: An *argument*  $\mathcal{A}$  for  $h$  ( $\langle h, \mathcal{A} \rangle$ ) is a minimal non-contradictory set of facts and defeasible rules that can be chained to derive the literal (or conclusion)  $h$ .

In our argumentation formalism, arguments can be *attacked* by other arguments that *rebut* them (i.e. propose the opposite conclusion) or *undercut* them (i.e. attack clauses of their body). Attacks between arguments are resolved by using a probability measure that estimates the probability that an argument succeeds based on the aggregated probability of the facts and clauses in the body of the rules used to generate the argument. Thus, our C-ERS uses a simplified *probabilistic argumentation* framework [5] that assigns probability values to arguments and aggregates these probabilities to compute a *suitability* value to rank and recommend LOs.

Our argumentation-based recommendation technique can also generate explanations from arguments as justification texts. These can be offered to the user to persuade them to try certain LOs and to explain why the system has proposed a specific LO. With each explanation, the user can interact with the system by selecting 1 of the 3 possible pre-defined responses (one to accept the explanation and hence the recommendation, one to ask for more justifications, and another one to reject the recommendation). The natural order to perform the backward chaining of rules and facts to derive arguments that support recommendations allows us to establish a conversational process between the C-ERS and the user. By this process, the system is able to elicit the actual preferences of the user and allows him/her to correct the system's wrong assumptions.

### 3 EVALUATION

For the evaluation tests of our C-ERS, we implemented a prototype of the system that makes use of the LOs available at FROAC (Federation of Learning Objects Repositories of Colombia). Concretely, we used a database 75 LOs of different areas, and 50 students of a computer systems management course of the Universidad Nacional

de Colombia. With the evaluation tests, we obtained a database of 472 ratings in total.

We evaluated the *effectiveness* of C-ERS to provide recommendations that suit the students' profile and learning objectives. We compared the average ratings provided by the students, both when LOs are provided with and without explanations. Students provided higher ratings to those LOs that presented explanations (3.23 versus 2.6 on a scale of 0 to 5), which demonstrates the advantages of using explanations to offer effective recommendations. In addition, the quantity of objects that got high ratings (from 3 to 4) was greater when explanations were included.

To evaluate the *persuasive power* of C-ERS, we compared the initial rating provided by the student to LOs and the final one after a 'conversation' where the system tried to persuade the student to change the rating by providing her/him with explanations. A wide percentage of ratings were improved by the interchange of explanations (75% improved, 19% unchanged, and 6% decreased), which demonstrates the persuasive power of explanations to improve the opinion of students about the LOs recommended.

To evaluate the *scrutability* of C-ERS, we analysed the average percentage of students that rejected explanations because they changed any of their initially declared preferences. A significant percentage of students decided to change their preferences at any step of the recommendation process. In average over the total number of the recommendation processes where they participated, 38% of students decided to change any preference. Our C-ERS system is able to capture these changes and allow students to indicate that it has made a wrong inference about his/her preferences in a reasonable time (an average of 2.2 explanations to convince the students), which is crucial in this educational recommendation domain to provide them with recommendations that actually suit their learning objectives.

### 4 CONCLUDING REMARKS

Actually, the current system constitutes a proof of concept tested with a small set of 50 students of computer science. This could entail some bias in the students' profile. As future work, we plan to extend the evaluation tests to a large number of students with more heterogeneous profiles. Moreover, we want to study to what extent the new user model acquired with the new preferences elicited during the conversation should be updated and stored permanently. Finally, we plan to enhance the interaction mode of the system with a new natural language interface, able to conduct dialogs in natural language with the students.

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