A recommendation method for e-learning environments: the rule-based technique

Pierpaolo Di Bitonto, Maria Laterza, Teresa Roselli, Veronica Rossano

Università degli Studi di Bari "Aldo Moro", Dipartimento di Informatica - {dibitonto, marialaterza, roselli, rossano}@ di.uniba.it

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Abstract

The ever growing importance of e-learning over the last decade has triggered an explosion of resources available on the Web. Although this multiplicity of available resources can foster the development of a critical spirit, discernment and the student's ability to weigh up the merits of different points of view, it can also induce disorientation in the search for the resources best suited to her/his needs and learning style. This issue has driven research into recommendation systems, already well known in fields such as e-commerce, applied to e-learning environments. However, in such environments the recommendations can only be efficacious if the system is able to deal with the many different factors involved in the learning process, such as the learning goal and the student's cognitive features. This work proposes a recommendation strategy that combines, by adopting a hybrid cascade approach, two knowledge-based techniques that can take these factors into account in the recommendation process.

1 Introduction

The Web 2.0 revolution has transformed Internet users from simple consumers to producers, in the sense that they are no longer satisfied with just adopting the available resources but are now increasingly capable of creating new ones. Inevitably, this has led to a true explosion of the number of resources available on the Web and hence also to a growing difficulty in selecting those best suited to the individual needs. This can also have negative effects in environments where the choice of resource is critical to the success of the whole process, as in e-learning. In fact, it is now common practice for teachers at all levels to rely on the Web as a means of producing and sharing teaching materials, while students are ever ready to refer to the Web for help with their homework rather than using traditional encyclopedias (even multimedial). If all resources were equally suited to the learning process this multiplicity would foster students' development of important abilities such as analytical powers and the capacity to summarize and compare different points of view. Unfortunately, in the jungle of available resources not all of them are suited to particular needs and learning styles, and students run the risk of becoming disoriented and frustrated by their inability to find just what they were looking for. To solve this problem, recommendation systems have been developed to offer students a more evolved search system than the simple automatic searches offered by traditional search engines. These new recommendation systems are able to select not only the resources conforming to the student's specific request but also others of possible interest owing to their implicit links with the request. However, defining such recommender systems is a challenging task because it requires an in-depth analysis of all the factors involved in the learning process, ranging from the learning goal to the student's distinctive cognitive style.

An initial study of recommender systems in e-learning is reported in (Di Bitonto *et al.*, 2010). The present work illustrates a hybrid knowledge-based recommendation strategy that can suggest teaching resources taking into account not only the learning goal but also the student's cognitive profile, adopting a rule-based technique to establish the order of the recommended list.

The work is organized as follows: after a brief summary of the current state of the art of recommendation systems in e-learning, the pedagogical background to the work is examined, and then the recommendation strategy is illustrated paying particular attention to the rule-based technique. Finally, future areas of development are outlined.

2 State of the art

The first examples of recommender systems for e-learning, aimed at both students and teachers, implemented pure methods, generally of a collaborative (Schafer *et al.*, 2007) or content-based type (Pazzani & Billsus, 2007). One of the first examples was Altered Vista (Walker *et al.*, 2004), that employs a purely collaborative technique of user-based type to suggest educational resources to teachers and students, and to allow them to share these with colleagues. Another significant example is RACOFI (Anderson *et al.*, 2003), a collaborative system that suggests Learning Objects (LOs) of audio type. To calculate the best predicted resources the system can assess how similar the user is to the target user (collaborative technique), and refine the suggestions using rules that trace relations among resources. For example, if a user expresses a positive opinion of a LO by a given author, all the predictions about other LOs by the same author will be updated. This system is adopted first of all to overcome the problem of the cold-start (Schein *et al.*, 2002), in other words the need, with the collaborative method, to collect a large number of estimates before the system can make efficacious recommendations. Secondly, it can introduce into the recommendation process relations that purely collaborative methods cannot take into account. On the strength of this first experience, in later years the collaborative approach was increasingly used together with other methods, achieving hybrid solutions that can improve the recommendation process (Burke, 2002). In this scenario, Khribi, Jemni and Nasraoui (Khribi *et al.*, 2007) proposed combining collaborative and content-based methods by adopting a cascade, feature augmentation or weighted approach. This proposal was applied in a system that suggests a set of links to web pages using a cascade of collaborative and content-based methods. In this way, the set of links selected with the collaborative method is refined with the content-based method. Another example of a hybrid solution is the Personal Recommender System (PRS) (Drachsler *et al.*, 2007), that uses collaborative and knowledge-based methods (Burke, 2000) combined with a switching approach to suggest teaching resources. In this system, if the quantity of estimations of the student is sufficient to allow accurate predictions, the system will use the collaborative method, otherwise it will rely on the knowledge-based method. This approach is implemented on the basis of a domain ontology from which to infer relations among the activities the student is carrying out and hence to suggest further activities. Experimental results of the use of the PRS have shown that the system is able to overcome the cold-start problem. Instead, the Recommender System for Educational Institution proposed in (Satyanarayana & Rajagopalan, 2007) is based largely on a knowledge-based technique, that works on the domain knowledge context and then refines the recommendation using a cascade of two or more filtering techniques of other natures.

A study of the literature demonstrates that the tendency to formulate recommendations according to hybrid approaches is predominating, based more and more frequently on the knowledge-based method both to offset the disadvantages of the other methods and because, unlike these, it is able to consider aspects unrelated to either the resource or the user in formulating the recommendation. In line with this tendency, the present work proposes a recommendation strategy that combines, using a hybrid cascade approach, two knowledge-based techniques: one ontology-based and the other rule-based. The former selects the resources on the basis of domain relations and the latter refines the recommendation by taking into account the student's cognitive characteristics.

3 Pedagogical background

Before illustrating the proposed recommendation strategy, the reference pedagogical context is described, in terms of both the educational standpoint and the identification of the student's cognitive characteristics. A teaching strategy must take into account the goals (the results the student needs to attain in terms of skills or knowledge), the content form (layout, internal structure, conceptual organization), the teaching strategy adopted to facilitate learning (role play, tutorials, problem solving, …). The choice of the most appropriate combination of these three factors for the individual student depends on her/his cognitive and meta-cognitive characteristics. For this reason, in recent decades research in the psycho-pedagogical field has been focused on learning styles. One of the most authoritative theories is the ILS (Index of Learning Style) drawn up by Felder and Silvermann (Felder & Silverman, 1988), that describes the student's cognitive style according to four dimensions: perceptive – intuitive modality, visual – verbal modality, applicative – reflective modality, sequential – global modality. The theory outlines the typical behavior of each learner type. For example, the perceptive student prefers to acquire knowledge from external sources, is practical, tolerant of details, good at memorizing and oriented towards observable facts and phenomena. For this reason, it is best to present her/him with specific examples of concepts and procedures to be applied in practice. The ILS provides tools for individuating the cognitive style, and guidelines for associating the best teaching resources to each student profile. The proposed recommendation strategy is based on this theory.

4 The recommendation strategy

The technique proposed in this paper combines two knowledge-based methods in a cascade approach: the ontology-based technique (high priority) has the task of searching for the LOs explicitly requested by the user and related ones according to the prior defined domain relations; instead, the rule-based technique (low priority), operates on the student's cognitive and meta-cognitive characteristics to search for those LOs best suited to the learning style. The high priority technique (Di Bitonto *et al.*, 2009) presents the traced LOs in two macro categories: TopicRequested and TopicRelated. The LOs the student explicitly requests belong to the first category and the LOs retrieved by the high priority technique, grouped by topic, to the second. For example, if the student asks for LOs on second degree equations, the LOs on this topic will be classified as TopicRequested, LOs about first degree equations or the geometric interpretation of second degree equations as TopicRelated. In section 4.3, the rule-based technique is described in greater detail.

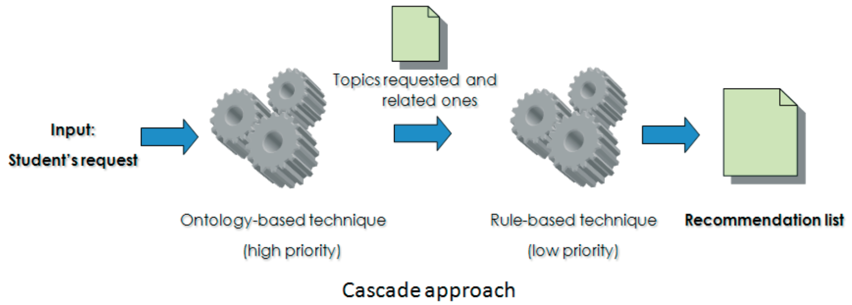

Fig. 1 - Hybridization strategies

4.1 Knowledge of LOs

Each LO is described according to three dimensions: Learning goal, Content form, Teaching strategy. The respective values for each of these are manually inserted at the time the LOs are uploaded in the platform.

An expert system is currently being defined, that can calculate the values of the three dimensions on the basis of the data contained in the imsmanifest.xml file (if the LO is standard SCORM) and the LOM file associated to the learning resource.

The Learning goal reports the type of knowledge the student can acquire using the LO. It may be declarative, if it helps to learn concepts, definitions or the theoretical principles underlying a particular topic; procedural, if it is about how to apply the knowledge to a practical case in a deterministic manner. The Content form reports the way the knowledge can be used and is expressed according to three aspects: the presentation form, the type of knowledge and the internal structure. The presentation form indicates the type of teaching material: video, text, audio, etc. The type of knowledge indicates whether the concepts presented are theoretical or procedural, and hence presented in declarative form or as procedures to be followed and applied. The internal structure indicates the presence of concepts, observations, theorems and descriptions. Finally, the Teaching strategy indicates the type of teaching the LO implements in the interaction with the student to foster learning, which may be of passive or active type. For example, "role-playing" is an active strategy, and "tutorials" is passive. For each cognitive style, a value ranging from 0 to 1 indicates how far the LO contents conform to these.

4.2 Student characteristics

The student cognitive profile consists of components that express both the student's prior knowledge of the teaching domain and her/his learning style, needed to select the teaching modalities best suited to that particular student.

The domain knowledge is currently inserted manually in the platform but a system for automatically retrieving this information is now being defined, starting from the tracing data. The descriptors chosen to represent the student's knowledge are: Topic, Knowledge level and Typical mistakes (established a priori). Topic has as value the name of a topic seen by the student; Knowledge level expresses the student's actual knowledge of the topic (divided into theoretical knowledge on a scale of 0-5 and ability to apply it, again on a scale of 0-5). Finally, Typical mistakes indicates common mistakes made by student types when dealing with the topic in question.

Instead, the learning style is deduced from the answers to the ILS Felder and Silvermann questionnaire the student will complete during the first interaction with the platform. The chosen descriptors of the learning styles are: perceptive, intuitive, visual, verbal, etc. Each is again expressed on a scale 0-5 and indicates the student's propensity for each cognitive style (e.g. perceptive: 3, intuitive: 1, visual: 5, …).

4.3 The rule-based technique

The ontology-based technique (high priority) selects a set of LOs organized in two macro categories: TopicRequested and TopicRelated. Subsequently, the rule-based technique (low priority) establishes the order of presentation of the LOs to the student. The first topic presented is always the one explicitly requested by the student. A list of correlated topics follows. For each topic, a set of rules assesses each LO in terms of the previously described descriptor values Topic, Knowledge level, Typical mistakes (typical mistakes made by this student profile) and Learning goal. At the end of each assessment, each LO is assigned a weight according to how well it conforms to the student's prior knowledge of the domain. The greater the weight the better suited the LO; according to this weight, the LO is classified as advised or unadvised. The sum of the weights of the LO for the given topic determines their position in the recommendation list. The higher the value the earlier the LO will be presented. For each topic the student is presented first with the LOs labeled advised and then the unadvised ones. The order of the LOs in each category depends on the student's distinctive learning style. The position of the LO is established on the value of the following linear combination: $a_1\alpha + a_2\beta + \ldots + a_7\gamma + a_8\delta$, where the Greek letters represent the values (on the scale 0-5) of the student's learning profile (e.g. perceptive: 3, intuitive: 1, visual: 5, …), while $a_1, \ldots, a_n$, that range from [0-1], represent the cognitive component values of the teaching strategy the LO was created to implement. For example, if a student requests a LO about second degree equations, the ontology-based technique selects a set of LOs like the one in figure 2 (a), by selecting LOs on the topic "Second degree equations" and others on correlated topics like "First degree equations" or "Geometric interpretation of second degree equations".

(a)

```
<output>
  <argomentoRichiesto
        nome = "Equazioni di secondo grado" >
    <LO id = "01"
         nome = "Il Delta">
    <LO id = "05"
        nome = "Risolvere le equazioni di  secondo grado">
     …
    <LO id = "33"
         nome = "Equazioni di secondo grado">
     …
    </LO>
    …
  </argomentoRichiesto >
  <argomentoCorrelato
       nome = "Equazioni di primo grado" >
    <LO id = "54"
       nome = "Equazioni di primo grado">
        …
  </argomentoCorrelato >
  <argomentoCorrelato
       nome = Int. geom. delle equazioni di secondo gr a-
do" >
    <LO id = "76" nome = "Delta e parabole">
        …
  </argomentoCorrelato >
  …
</output>
```

(b)

```
<output>
  <argomentoRichiesto
        nome = "Equazioni di secondo grado" >
    <LO id = "05"
         nome = "Risolvere le equazioni di secondo grado">
    <LO id = "33"
        nome = "Equazioni di secondo grad o">
     …
    <LO id = "01"
          nome ="Il Delta">
     …
    </LO>
    …
  </argomentoRichiesto >
  <argomentoCorrelato
       nome = "Equazioni di primo grado" >
    <LO id = "54"
       nome = "Equazioni di primo grado">
        …
  </argomentoCorrelato >
  <argomentoCorrelato
       nome = Int. geom. delle equazioni di secondo gr ado"
>
    <LO id = "76" nome = "Delta e parabole">
        …
  </argomentoCorrelato >
  …
</output>
```

Fig. 2 - Examples of establishing the order of LOs with the rule-based technique

The rule-based technique orders the topics and related LOs as follows: the first topic is the one asked for, i.e. "Second degree equations", and for each LO on this topic, the technique calculates its adequacy to the student's prior knowledge of the domain. Let's take, for instance, an LO that deals with the topic "the Delta", and suppose that the student's level of knowledge of this is scored 5 for the theory, and 2 for practical skills and that s/he doesn't make typical mistakes. Let's also suppose that an LO is of declarative type, i.e. offers theoretical knowledge of the delta, ignoring the question of how to calculate it. Since the LO conveys knowledge the student already possesses, it will be assigned a very low weight, meaning that there is a mismatch for this student and so it is labeled unadvised. The process continues for each LO on the topic and produces a list of advised and unadvised LOs. Each is assigned a weight and a category. The sum of the weights of the various LOs determines the place in the recommendation list. Let's consider 3 LOs: "the Delta", "Second degree equations", and "Solve second degree equations". If the LO "the Delta" is unadvised while the other two are advised, these latter will be presented first. The order of appearance of the advised LOs depends on the student's learning style. For example, if the student's learning style and the LO teaching strategies of the advised LO are represented by the following vectors:

Student's learning style Vector							
perceptive	intuitive	visual	verbal	applicative	reflective	sequential	global
0	2	1	5	3	0	3	1

LO teaching style Vector "Second degree equations"							
perceptive	intuitive	visual	verbal	applicative	reflective	sequential	global
0.2	0.7	1	0	0	0.4	1	0

LO teaching strategy Vector "Solve second degree equations"							
perceptive	intuitive	visual	verbal	applicative	reflective	sequential	global
0.7	0.2	0.3	1	0.4	0	1	0.2

the linear combination of the student Vector with the LO "Second degree equations" Vector yields the result 5.406, while the combination of the student Vector values with the LO Vector "Solve second degree equations" yields the result 10.1. This means that the LO Vector "Solve second degree equations" will be presented before the Vector "Second degree equations", as shown in figure 2 (b).

5 Conclusions

With the aim of supporting the student's choice of the learning resources best suited to her/his needs, the present contribution proposes a recommendation strategy that combines in a hybrid approach two knowledge-based techniques with a cascade method. The recommendation process can take into account the reference learning context in terms of both the LO learning goals and method for imparting the teaching actions and the student's cognitive profile. Although research in the ambit of recommendation systems for e-learning has proposed various solutions that exploit the potential of hybrid approaches and knowledge-based methods, the strategy presented in this work is innovative in that it can process suggestions taking into account both domain information and the student's cognitive profile.

An experimentation is currently being designed to assess the students' degree of satisfaction and also to individuate the minimum information needed to be able to supply adequate recommendations. This experimentation will help to verify the applicability of the proposed strategy to e-learning environments, where all the data serving to trace the student's activities may not always be available.

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