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A Recommender System for Non-traditional Educational Resources: A Semantic Approach

Agustín Cañas Rodríguez
(Universidade de Vigo, Spain
agustincanas@det.uvigo.es)

Juan M. Santos Gago
(Universidade de Vigo, Spain
jsgago@det.uvigo.es)

Luís E. Anido Rifón
(Universidade de Vigo, Spain
lanido@det.uvigo.es)

Roberto Pérez Rodríguez
(Universidade de Vigo, Spain
rperez@gist.det.uvigo.es)

Abstract This paper describes a software system that allows for discovering non-traditional educational resources, that is to say, those that go beyond educational content and incorporate elements such as: software applications that may support the teaching-learning process; events that take place outside school boundaries, such as new expositions in museums and theatre performances; and people who may participate as experts in some Learning Activity. The huge quantity of information available - potentially all that can be extracted from the Internet- enforces us to adopt a strategy that enables filtering resources in accordance with their appropriateness and relevance, that is, an strategy based on recommendations. Besides, due to their particular nature (e.g. the most relevant events are those that will take place in the same city where the school is located) the apropriateness of those resources is highly dependent on the context where teaching and learning is produced. Therefore, the recommender system takes into account contextual factors when calculating the relevance of every resource. This system was evaluated with several focus groups in the scope of the iTEC project, which belongs to the European Commision's Framework Programme 7.
Key Words: Technology Enhanced Learning, Recommender System, Multicriteria recommendation, Context-Aware Recommender, Semantic technologies
Category: L.1, L.2, L.3

1 Introduction

In the current panorama of educational practice in primary and secondary education across Europe we find that technology is increasingly present in the classroom. On the one hand, we have government programs that provide classrooms with a technological infrastructure. For instance, the Abalar[1] project, financed

[1] http://www.edu.xunta.es/espazoAbalar/

by the Galician Ministry of Education provides classrooms with an interactive digital whiteboard, Wi-Fi Internet connection, and a laptop per student, in which a Linux distribution comes already installed and ready to be used. On the other hand, students themselves, usually have mobile devices such as smartphones and tablets and carry them everywhere, including the classroom.

In addition to hardware resources, nowadays we find an enormous amount of free software resources, ready to be used in the educational practice. Besides standalone applications, we can use many applications in the cloud, both from personal computers and mobile devices. Complete suites as that of Google[2] are freely available with zero cost, ready to be used in the educational practice [Herrick, 2009, Patterson, 2007].

But the resources that may be used in the educational practice are not limited to hardware and software ones. Many everyday events, specially cultural events, may have an educational value. As [Redding et al., 1997] states:

> *"Stimulating the child's desire to discover, to think through new situations and to vigorously exchange opinions, is fostered also by family visits to libraries, museums, zoos, historical sites and cultural events."*

We might think, for instance, about events such as theatre performance and lectures that may be very relevant to illustrate some points of the curriculum and that can certainly be used during the educational practice. If there is a free performace of Hamlet in our city, why do not use it as a resource for the subject of literature, especially if Shakespeare is in the curriculum? In a similar way, experts on some matters are the best people to explain certain concepts. A doctorate student that is making its Ph.D in the area of genetic research might result very inspiring for secondary education students during their biology class.

In this context is born the iTEC project, which is the flagship FP7 project in the education area, financed by the European Comission with 12 million euros. iTEC tries to contribute to the conception of the classroom of the future, in which technology is complemented with the most innovative pedagogical approaches, which entail a major level of dynamism in the educational practice. Thus, iTEC promotes an educational practice in which students interact in small projects which include participation in events, speeches with experts, and all that seasoned with the use of technology.

In order to achieve a step along the path toward iTEC's objective we found an initial dificulty: how do we select the technologies, events, and experts that will take part in an educational experience? Firstly, there is no central directory of technologies, events, and people at an European level, in such a way that a teacher may make searches in it. And, secondly, in case it may exist, the dificulty

[2] http://www.google.com/enterprise/apps/education/

of selecting technologies, events, and experts among an enormous offer would be very difficult.

In iTEC, a series of directories in which you can register technologies, and also events and experts, were developed. They are part of the so called iTEC Cloud. Thus, the Composer [iTEC Project, 2012] includes a directory for hardware and software technologies; the P&E Directory [Van Assche, 2012], as it name hints, enables to register educational events as well as experts in some knowledge area; and the Widget Store [Griffiths et al., 2012] is a repository of widgets ready to be used in the educational practice.

In order to solve the problem of the selection of technologies, events, and experts among a very high offer, the iTEC project proposes the SDE, which is conceived as an artificial intelligence agent that uses Semantic Web data, and that has among its objectives to act as a recommender ([Section 2] provides some hints about recommender systems). Thus, during the planification of the educational practice, a teacher may use the recommendations that come from the SDE in choosing the most appropriate technologies, events, and experts. [Section 3] discusses the SDE.

In order to conceptualise the elements that take part in the educational practice an ontology was conceived, and its final version is the result after several iterations of revisions by Control Boards[3]. We present a brief overview of its most relevant concepts. The identification of the most relevant factors in the recommendation algorithm, as well as their initial weights, result from several iterations of revisions by Control Boards. The AI agent provides an API that enables client applications to integrate its recommendations. These client applications are editors that allow teachers for designing their educational practice. So far, one client application has successfully integrated recommendations from the SDE: the Composer, that is part of the iTEC Cloud.

To date, we conducted two experiences to evaluate the SDE with teachers as end-users of this application. The first one on 18th June 2013 took place in Bolton (England), with end users. The second one took place on 29th and 30th October 2013 in Oulu (Finland). [Section 4] explains some points about those experiences as well as a design for futher evaluations. The paper finishes with some conclusions and future work.

2 Background

As [Ricci et al., 2011] state:

> *"Recommender Systems are software tools and techniques providing suggestions for items to be of use. The suggestions provided are aimed at*

[3] Control Boards members are experts in the domain and knowledge engineers

> *supporting their users in various decision-making processes, such as what items to buy, what music to listen to, or what news to read."*

Traditionally, users of recommendation systems provide ratings for some of the items, and the system uses these ratings for the items not yet assessed [Resnick and Varian, 1997]. This approach is fairly flexible insofar as the output parameters are concerned, but is limited if we consider the input information available, as it does not consider, among other things, systems basing their recommendations on objective information about the items to be recommended. Presently, we may apply the term recommender to any system offering personalized recommendations or being able to guide the user in a personalized way, selecting the most useful services from a variable-sized collection [Burke, 2002]. Indeed, the main differences between a recommender and a search engine (or an information retrieval system) are related to the level of interest or utility of the retrieved items (recommendations). Recommendations has a clear social attractiveness even before the deployment of the information society, and they became basic building blocks of new online applications, mainly for electronic commerce and digital leisure services.

Recommendation algorithms use techniques from Artificial Intelligence, Data Mining, Statistics or Marketing, among many others. Traditionally, according to the methods and algorithms used, recommendation systems are classified as: Content-based recommenders [Pazzani and Billsus, 2007], Collaborative filtering recommenders [Schafer et al., 2007] and, combining both approaches, Hybrid recommender systems [Burke, 2002]. This classification is a very generic one and it is strongly tied to the interaction of a user with a recommender system, i.e. their preferences on the items to be recommended and their relationships to other users. In spite of being the most frequent classification in the literature, for us it is preferrable to focus on a classification which has specially into account the sources of data which the system relies on, as well as the use that the information receives. Following this approach, [Burke, 2002] distinguishes between five types of recommenders:

Collaborative recommendation The most familiar, most widely implemented and most mature. These systems aggregate ratings or recommendations of objects, recognize commonalities between users on the basis of their ratings, and generate new recommendations based on inter-user comparisons.

Demographic Recommenders in this category aim to categorize the user based on personal attributes and make recommendations based on demographic classes.

Content-based The objects of interest are defined by their associated features. These systems learn a profile of the user's interest based on the features present in objects the user has rated.

Utility-based They make suggestions based on a computation of the utility of each object for the user. In these systems the central problem is how to create a utility function for each user.

Knowledge-based These recommenders attempt to suggest objects based on inferences about a user's needs and preferences. Their approaches are distinguished in that they have functional knowledge: they have knowledge about how a particular item meets a particular user need, and can therefore reason about the relationship between a need and a possible recommendation.

Once we have established a definition and classification of recommender systems that is adequate for our proposal, we want to highlight three conceptual approaches that we have taken into account when developing our proposal: multicriteria recommender systems, context-aware recommender systems and semantic recommenders. Those approaches are transversal to the types of recommenders previously presented and they try, respectively, to establish mechanisms for defining a utility function that takes into consideration several factors, to consider the context where a recommendation is produced, and to improve knowledge representation using semantic technologies. Below, we go deeper on each one of them.

2.1 Multicriteria recommender systems

In traditional recommender systems, the utility function considers only one criteria, typically a global evaluation of resources or a valoration from the user. Depending on the systems under consideration, the utility function may be a valid approach though it is rather limited, since the utility of a given element for a particular user may depend on multiple factors. Having that into consideration, in the past few years the study of multicriteria recommender systems has risen [Lakiotaki et al., 2011, Lakiotaki et al., 2008, Plantié et al., 2005].

Multiple Criteria Decision Analysis (MCDA) is a very mature and active research area [Figueira et al., 2005]. It focuses on studying methods and management processes in systems with multiple conflicting criteria in order to identifying the best possible solution from a set of available alternatives. Starting from research and theories from that area, [Adomavicius and Tuzhilin, 2011, Lakiotaki et al., 2011, Liu et al., 2011] propose to approach the problem of recommendations as one of MCDA, following the methodology that was developed by [Roy, 1996] for modelling these kind of problems. In accordance with it, there are four stages/levels of analysis when implementing the decisor: object of decision, family of criteria, global preferences model, and support for the decision-making process.

Level 1. Object of decision

Definition of the purpose of the decision system to be developed among those below:

- *Choice*: to select the most appropriate elements for a given user.
- *Sorting*: to classify all the elements available into categories, according to their appropriateness for a given user.
- *Ranking*: to sort the elements according to their appropriateness for a given user, to provide a sorted list, from best to worst alternative.
- *Description*: to describe the appropriateness of an element according to the rating criteria.

Level 2. Family of criteria

The suitability of alternatives is analysed in accordance with a family of criteria for each user, in order to modelling their characteristics and attributes. In recommender systems, these criteria may be the characteristics of an element or the multiple dimensions in which it can be evaluated. [Jacquet-Lagrèze and Siskos, 2001] identified the types of criteria most frequently used, i.e. measurable, ordinal, probabilistic and fuzzy. Anyway, in order to taking informed decisions based on multiple criteria, it is necessary to identify a consistent family of criteria (according to Roy's definition).

Level 3. Global preference model

In this stage it is necessary to develop a model of preferences that, having into account decision-making issues, allows for aggregating the different criteria for expressing preferences among the different alternatives in a set of elements. According to [Jacquet-Lagrèze and Siskos, 2001, Vincke, 1986] we can differentiate between four categories of modelling approaches:

- *Multi-Objective Optimization models*: criteria are expressed as multiple constraints of a multiobjective optimization problem. We may cite [Malekmohammadi et al., 2011] among the solutions using this model.
- *Multi-attribute utility/value theory (Value-focused)*: a value system is built to aggregate preferences for each criterion. After that, these marginal preferences are aggregated into a single utility function. These solutions are typically named MAUT (Multi-Attribute Utility Theory) or MAVT (Multi-Attribute Value Theory). Contributions based on this technique: [Abbas, 2010, Lakiotaki et al., 2011].
- *Outranking approaches*: the main idea behind this approach is that a complete classification of solutions is not always needed to assist decision. It is based on a set of decisions for pairs of elements to obtain

binary relations in a decision set. In this way, relations such as "a" is incompatible with "b", "a" is preferred to "b" or "a" and "b" are equivalents insofar as preferences are concerned are possible. Contributions based on this technique: [Doumpos et al., 2009].

– *Preference disaggregation models*: the preference model is inferred from global preferences by analysing past decisions. In many cases, these models are considered as sub-models from one of the models discussed above, as they try to infer the model in a concrete way, typically value function or outranking relations. Contributions based on this technique: [Fernandez et al., 2009].

Level 4. Decision support process

Once finished the steps above, it is necessary to design and implement processes, methods or systems, so that the decisor may select the adequate set of alternatives. According to [Adomavicius et al., 2011], we can identify three MCDM recommender types:

– *Multi-attribute content preference modelling*: they interpret and model multi-attribute descriptions provided by users on an element to use them to recommend elements most adapted to their preferences.

– *Multi-attribute content search and filtering*: users are allowed to specify their preferences for certain attributes through search processes. From the data obtained, they recommend elements satisfying the search and/or filtering criteria most adapted to users' preferences.

– *Multi-criteria rating-based preference elicitation*: user preferences are collected from the element ratings according to several criteria. Recommendations to specific users are based on their own ratings and other users' ratings.

According to this classification, and after analysing the behaviour of classical recommenders, we could say that most of them may be studied as multicriteria recommendation systems; mainly in the case of knowledge-based and content-based systems due to the way they model users and elements.

2.2 Semantic recommender systems

The term semantic recommender system is normally used when, in a traditional recommender, we use semantic web technologies in order to represent and process information of users and/or elements with high level descriptions. According to this definition, we might think of content or knowledge based systems; nevertheless, semantic technologies are also used for collaborative recommender systems (e.g. [Martín-Vicente et al., 2012, Shambour and Lu, 2011]).

2.3 Context-aware recommender systems

Context is a very broad concept that has been studied across different research disciplines, including computer science, cognitive science or organizational sciences, among others. Looking for a formal definition, it can be stated that context is a set of circumstances that form the setting for an event, statement or idea, and in terms of which it can be fully understood [Oxford University Press, 2012].

3 A recommender system for non-traditional resources based on a teacher-centered learning context

> "Technology enhanced learning (TEL) aims to design, develop and test socio-technical innovations that will support and enhance learning practices of both individuals and organizations. It is therefore an application domain that generally covers technologies that support all forms of teaching and learning activities"[Manouselis and Costopoulou, 2007]

Due to the proliferation of online educational resources, and the ease of access to them through platforms such as MERLOT [California State University, nd], LRE [European Schoolnet, nd] or OER Commons [ISKME, nd], in the past few years a lot of researching effort has focused on recommender systems in TEL settings. As a result of that research, different solutions have been proposed to various issues. Thus, as said in [Manouselis and Costopoulou, 2007], we can find recommender systems in TEL that serve purposes similar to those of classical recommenders [Herlocker et al., 2004]: *annotation in context, find good items, find all good items, recommend sequence, browsing and find credible recommender*. Even though all those are valid for being applied to TEL, in that area gain relevance others that are more specific of scholar fields, such as: *finding peers, finding good pathways, finding novel resources, or finding non-traditional resources in a teacher-centered learning context*, which is the proposal of our work.

In the scope of the iTEC project, this work proposes a knowledge-based recommender system that, using semantic technologies and techniques that belong to multicriteria recommender systems, allows for locating the most suitable resources for a teacher to carry out a given learning activity in a certain learning context. Besides, it does not aim at retrieving the typical educational resources centered in content (e.g. open educational resources, courses, etc.) but tools (e.g. presentation tools, videoconference tools, collaborative editing tools), events (e.g. webinars, seminars, conferences) and/or people (e.g. experts, lecturers) who may contribute to the intellectual and cognitive development of learners in their learning experiences.

– *Knowledge-based*: in order to offer a recommender capable of considering the specific requirements of a learning activity in a given context, our recommender was designed as a knowledge-based system, i.e. a system based on knowledge technologies that uses techniques related to artificial intelligence in problem resolution processes in order to support decision making, learning, and human actions [Akerkar and Sajja, 2009].

– *Built on semantic technologies*: in the construction of a KBS is of crucial importance the correct design and characterisation of an underlying semantic model that grabs the implicit knowledge about the domain. Our semantic model is built on an ontology that gathers the conceptual elements and relationships between them.

– *Teacher-centered learning context*: as we said before, we want to retrieve useful recommendations of educational resources when planning learning activities in a given learning context. Our recommender takes as input, apart from the requirements of the activities that is going to take place, the current set of circumstances of the teacher, i.e. the learning context where the activity is going to be carried out.

– *Multicriteria*: in that recommendation it is necessary to have into account the descriptions available about these resources. More specifically, as there are many factors characterizing a resource (e.g. a tool is characterized by its functionalities, the languages supported, usage cost, etc.; an event is characterized by its knowledge area, its location, etc.; and a person is characterized by its knowledge, its spoken languages, etc.), we will follow an approach combining the estimated partial utility of a resource according to each one of these factors.

3.1 Related work

Even though our proposal is novel in its formulation of the objectives of the recommender (teacher-centered in a learning context), in the literature we can find several recent works in the TEL field that follow the same conceptual approaches of our system (i.e. knowledge-based recommenders and semantic technologies, context-aware recommenders, multicriteria recommenders), either in an isolated way or combining different concepts. Thus, tackling the use of semantic technologies, [Sancho et al., 2005] proposes a system to adapt instruction based on ontological representations.

Also using semantic tenchnologies, and closest to the concept of recommender, [Santos and Boticario, 2011] and [Lemire et al., 2005] proposes systems to provide learners with personalised and inclusive scenarios. The first one analyse the use of recommenders in e-learning systems for guiding students in learning scenarios. The second work uses inference rules for offering recommendations of educational objects in accordance with the context.

Besides, in the line of context-aware recommendation, [Sielis et al., 2011] and [Leony et al., 2013] propose works closely related our systems. Therefore, [Sielis et al., 2011] develops a system to recommend creativity support tools and [Leony et al., 2013] proposes a generic cloud-based architecture for a system that recommends learning elements according to the affective state of the learner.

Finally, about the use of multicriteria approaches in recommenders from the TEL field, we can highlight the works from [Kurilovas et al., 2011] and [Le Roux et al., 2007]. The former does not propose a recommender as such, but they use those techniques for identifying quality criteria that allow for minimising the subjectivity of an expert when evaluating the quality and reusability of educational objects. The latter proposes a recommender that is based on collaborative filtering and that uses MCDM methods for helping students to find postgraduate courses.

3.2 Semantic modelling

As we stated before, the modelling of the knowledge about the domain is one of the fundamental points on the design of our recommender. This knowledge is represented in an ontology that gathers all the terms and relationships, as well as a set of inference rules for capturing the heuristic knowledge that cannot be expressed using the formalism of Descriptive Logic. Its specification was driven by a strict methodology, and different researching groups that participate in iTEC contributed to the final specification. [Anido et al., 2012] go further in the description of this methodology. In this paper, we present the most interesting concepts from the point of view of the recommender, i.e. learning activity, its context, and the models for the different types of resources: people, events, and tools.

Learning Activity This model includes information on the educational objectives of the activity, as well as about possible educational resources that can be used during their realisation either in an explicit way, indicating a particular resource, or implicitly as a generic description of the kind of resource needed.

Context This model includes the elements that serve to characterise the learning context in which a learning activity is going to take place, such as: start and end dates, localisation, language used for teaching, area of knowledge, age range of learners, and technology that is available in the classroom.

Person This model represents an individual that may contribute to a learning activity in the role of expert in some area of knowledge. The model includes the following properties (among others): areas of expertise, languages, address, and communication channels (e-mail, telephone, etc.).

Event This model represents something that takes place in a given location at a given date. It includes properties such as: target audience, cost, language, place (e.g. museum, zoo), and location.

Tool It serves to represent hardware and software artifacts that may be used with an educational purpose (e.g. videoconferencing tools, simulation software, serious games, etc.). This model includes properties such as: functionality that the artifact provides, language, cost, recommended age, etc.

3.3 Recommendation process

The recommendation process has three stages: pre-processing, filtering, and ordering of results by their relevance. All the stages are important though the ordering algorithm (relevance calculation) is the one that has most impact on the results.

In the pre-processing stage, the requirements of a given activity -the generic description of the kind of resources needed- are composed with those from the context, thus forming an integrated set of factors that have to be taken into account when calculating the relevance of resources.

In the filtering stage, some candidates are selected from the Knowledge Base, thus restricting the final number of resources whose relevance is going to be calculated. Due to the impact of this stage in the results, there are three configurable running modes:

- *Strict*: only resources that comply strictly with the requirements of the learning activity are selected.
- *Permissive*: in addition to the resources selected in the point above, this mode includes those resources with incomplete/black properties. Thus, it does not discard those resources that are not perfectly defined.
- *No filtering*: in this mode there is no filtering stage. This mode is specially useful in testing/depuration, as well as in scenarios with a low number of available resources.

Once a subset of valid resources has been obtained, the next stage consists on calculating the degree of relevance for each resource -having into account the requirements of the activity and the context. The heterogeneus nature of the resources and its complex description enforced us to follow a rigorous strategy for obtaining an adequate utility function. Thus, we followed an approach inspired in multi criteria recommender systems, which use analysis techniques from the field of MCDA. Concretely, we followed the general methodology proposed by [Roy, 1996]. We set as the mechanism for calculating the relevance of resources the [Equation 1], where f_i represents the marginal utility function for a given factor and w_i the weight that such a factor will have in the final value of relevance.

$$\sum_{i=0}^{n} w_i \cdot f_i \tag{1}$$

Below, we detail the process that we followed for selecting the factors and their associated weights. [Cañas et al., 2013] go further on the decisions made in each of the stages of the followed methodology.

3.4 Selection and weighting of factors

Both the selection and weighting of factors that are taken into account in the recommendation process have been driven by iTEC Control Boards: a group of experts that collaborate in the project and that include people with technological and pedagogical expertise. In concrete, 53 experts from different institutions participated in this process.

- *Selection*: we generated a document including a description of the general recommendation strategy, as well as the data model of every type of resource, with a collection of all the factors that a priori might play a role in the recommendation process. For each factor, the document included a thorough description of its meaning. After a productive discussion, with more than 100 written commentaries on the idoneity of the factors, we got the set of selected factors.
- *Weighting*: the experts rated the impact that each one of the factors may have in the calculation of the relevance of resources. The following tables summarise the factors that were selected by the Control Boards with their associated weights. [Cañas et al., 2013] go further on the weighting of factors.

[Tables 1, 2, 3] shows selected factors and its weighting.

4 Evaluation of the recommender

At the time of writing this paper, two testing sessions with end users were completed. The first session consisted of a workshop with iTEC end users[4] in the UK, and the second one was a session in Finland. On 18th June 2013 took place in Bolton (UK) a demonstration and testing session of the technologies developed in iTEC (cf. [Figure 1]). As part of it, a presentation of the SDE was performed, and participants could test and assess this tool through a testing questionnaire. In a similar way, the SDE was evaluated in a session in Finland (cf. [Figure 2]).

FACTOR (f_i)	DESCRIPTION	WEIGHT (w_i)
Functionality	Functionality offered by a tool to a given degree.	0.1307
Language	Language(s) supported by the tool's user interface.	0.1031
Type	Type of the tool (i.e. application or device).	0.1011
Shell	It ranks tools according to their running environment.	0.0976
Age	It prioritizes tools having as their explicitly specified audience one of the audiences specified for the context.	0.0976
Cost	It prioritizes tools having no usage cost within a specified school (or context).	0.0970
Rating	Community popularity.	0.0916
Technology	It is targeted to discriminate whether a school already has a given tool.	0.0916
Competences	It references the technical expertise of a teacher.	0.0883
Education level	It is intended to prioritize tools being explicitly targeted to an education level among those defined for the activity.	0.0979

Table 1: Selected factors and associated weights for resources of type tool.

FACTOR (f_i)	DESCRIPTION	WEIGHT (w_i)
Language	It is intended to prioritize persons having as their mother tongue the languages in which an activity is developed.	0.1359
Expertise	It reflects the expertise of a person in a given subject.	0.1343
Experience	It considers previous experience of a person, according to the Learning Activities already performed by this person.	0.1238
Communication	It takes into account the communication tools a person participating in a Learning Activity has available.	0.1186
Reliability	It indicates the degree of trust that the community, as a whole, has in the person to be selected.	0.1119
Organization	It is intended to prioritize persons belonging to the same organization as the Learning Activity creator.	0.0998
Rating	It indicates the degree of popularity of a person.	0.0984
Geographical	It indicates the degree of geographical proximity of the person to the location of the school.	0.0915
Personal relations	It considers existing relations between the Learning Activity creator and the people who may participate in it.	0.0856

Table 2: Selected factors and their associated weights for a resource of type person.

FACTOR (f_i)	DESCRIPTION	WEIGHT (w_i)
Subject	It is used to rate an event according to the event thematic area(s).	0.1574
Required tools	It is intended to promote online events that can be accesed using some of the tools available.	0.1444
Cost	It is intended to prioritize free events.	0.1385
Geographical	Degree of geographical proximity of an event to the location of the school where the activity is performed.	0.1238
Rating	Popularity.	0.1186
Organization	Relevance of the event's organizer.	0.1186
Audience	It prioritizes events having as their explicitly audience one of the audiences specified for the context.	0.0995
Education level	It is intended to prioritize events being explicitly targeted to an educational level among those defined for the activity.	0.0995

Table 3: Selected factors for a resource of type event.

Figure 1: Testing the recommender in Bolton (UK)

On average, participants on the evaluations think that recommendations on non-traditional educational resources may foster innovation in the classroom. Teachers agree with the vision that new technologies may be very useful in teaching-learning environments, but one hindrance towards the realisation of that vision is the difficulty of knowing what technologies are most adequate for whom. Overall, participants think that recommendations from the SDE is one step forward towards filling the gap between existent, suitable, and useful technologies and being aware of their existence.

[4] Twenty-five teachers participated in Bolton

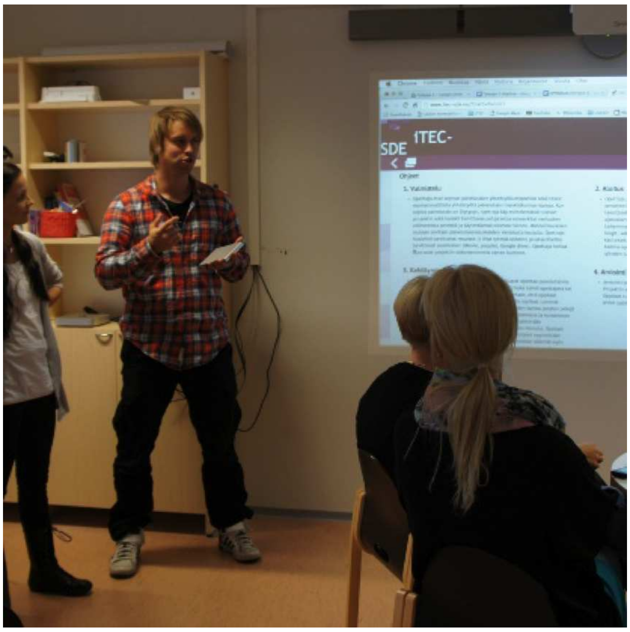

Figure 2: Testing the SDE in Oulu (Finland)

4.1 Planning upcoming user studies

In order to evaluate the recommender, we devised a basic design for an experiment of the type User Study [Shani and Gunawardana, 2011]. The experiment is composed of the following steps:

1. We ask the participants to think about a Learning Story on any subject that they usually teach.
2. Then, they must use the SDE in order to get recommendations of elements that they might find interesting. In case they find interesting any of those elements they are asked to mark them as favourites.
3. After that, they have to use the faceted search on the knowledge base of the SDE. In case they find some interesting elements they must mark them as favourites.

4.2 Measuring precision and recall

In the field of information retrieval, precision can be defined as the fraction of retrieved elements that are actually relevant for a given user. Recall can be defined as the fraction of relevant instances that are actually retrieved in a recommendation. In order to being able to calculate those measures, we need to capture the interaction of participants in the experiment with the user interface, and define when a particular element is relevant for a given user. For the SDE, an element is relevant for a certain user when he/she bookmarks it -that is, the element is saved as a favourite one.

The following user story serves to illustrate how the experiment works: *"John Doe plans to create a Learning Story about astronomy. After registering in the SDE -entering his profile and his learning context- the system displays 10 recommended applications that might be interesting for him. From that set of recommendations, John selects two which he considers very relevant: Google Moon and Sky Map. Besides, John performs a faceted search on the SDE's knowledge base and he find two more applications: Virtual Planetarium and Solar System for Kids; which he bookmarks as favourites"*. For this user story, the measures of precision and recall would be, respectively:

- *Precision*: there are 2 relevant applications from the 10 that the SDE recommends. In this particular case, the recommender has a precision of 20%.
- *Recall*: the recommender has displayed 2 applications from the set of 4 applications which are relevant. Therefore, the recommender has a recall of 50% for this particular case.

In order to get the overall measures of precision and recall we just have to apply the same strategy over the complete set of recommendations for all participants in the experiment.

4.3 Adjusting the weights of factors

We also need a metric that allows us to calculate to what extent the weights of factors are appropriate, so that we may tune them in order to improve recommendations. Let's see the implementation of a strategy for adjusting the weight of factors, which we illustrate with another user story: *"John Doe is planning a Learning Story about Astronomy. He would like to incorporate the attendance to some event on Astronomy as part of the Learning Story. In order to discover events that may have an educational value he uses the SDE, which displays 10 recommended events, most of them at less than 20km of distance from John's school. Nevertheless, John bookmarks one that will take place at 50km of distance. John is not satisfied with those events, therefore he performs a faceted search on the SDE's knowledge base and chooses 2 more events, which will take place in a city that is at 100km of distance from John's school"*. This user story highlights that the importance that the recommender concedes to geographic proximity is overestimated -at least in John's case. In order to calculate in which sense the factor of geographic proximity must be adjusted we perform the following calculations:

- We calculate the mean value of the distance of events that appear in the recommended results.
- We calculate the mean value of the distance of the events that John Doe bookmarks as favourites.
- Since the mean value of the distance for the events that John has bookmarked as favourites is bigger than the mean value of the distance for the recommended ones, this enables us to infere that the weight of the factor known as geographic proximity has been overestimated.

We have to repeat the same calculations for all the participants in the experiment in order to known whether the geographic proximity factor has been overestimated or underestimated.

Following this approach, we can calculate how accurate is the weight of the factor known as rating. Let's see how this could work with another user story: *"Jane Smith is preparing a Learning Story about Biology, and she decides to check the recommendations from the SDE. The mean value for the rating of the applications that the SDE recommends is of 7. Jane bookmarks as favourite one she considers to be interesting: BioBlender, whose rating is 9.5. Besides, Jane performs a faceted search and bookmarks another application whose rating is 8.5"*. This user story allows us to illustrate the case in which the importance that the SDE concedes to the factor known as rating is understimated for a particular user. We just need to repeat this calculation for every user participating in the experiment in order to decide in which direction the weight of the factor known as rating must be adjusted.

5 Conclusions

This paper has described a recommender system for non-traditional educational resources -tools, people, events- that is based on semantic technologies and that was developed, and evaluated, in the scope of a large scale FP7 european project in the area of education. As the main contributions of our research we can highlight the following ones.

The definition of a semantic model that characterises the universe of discourse that the recommender uses, and that is also the basis for the definition of a common language shared between the different iTEC working packages. This semantic model was implemented as an ontology, which constitutes the core of the intelligence of the recommender. The scope of the ontology developed is very broad, as it models concepts such as learning activities, contexts, technologies, events, people, and many other elements that are specific to the euducation area.

The recommender system presented in this paper provides recommendations for technologies, events, and people (e.g. experts). This constitutes an innovative approach, at least in the area of recommender systems applied to education. Besides, the recommendation strategy is based on the learning context, rather than on students' and teachers' preferences. The recommender's API is publicly available, and it is ready to be consumed from client applications that want to make use of recommendations. We tested the recommender with final users, in two experiences with teachers in Oulu (Finland) and Bolton (UK), and the first results were quite promising.

As future work, we plan to extend the testing of the recommender to all the classrooms involved in the iTEC project (around 200 schools all over Europe), which will serve to refine the recommendation algorithms, taking into account ratings of recommendations by final users.

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