Methods to Incorporate Proactivity into Context-Aware Recommender Systems for E-Learning

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ABSTRACT:*Recommender systems in e-learning are powerful tools to find suitable educational material during the learning experience. By including contextual information derived from the use of ubiquitous learning environments, the possibility of incorporating proactivity to the recommendation process has arisen to enhance the traditional user request-response pattern. In this article we present methods to generate proactive recommendations to e-learning systems users when the situation is appropriate without being needed their explicit request. As a result, interesting learning objects can be recommended attending to the user's needs in every situation based on location and user context information. The impact of this proactive recommendations generated have been evaluated among teachers and scientists in a real e-learning social network called Virtual Science Hub related to the GLOBAL excursion European project. Outcomes indicate that the methods proposed are valid to generate such kind of recommendations in e-learning scenarios. The results also show that the users' perceived appropriateness of having proactive recommendations is high in general, although few situations have proved to be inappropriate by users in such educational scenario. In addition to this, details about the proactive user interfaces designed as a consequence of the previous results are provided.*

Keywords: Proactivity, Context-awareness, E-learning, Recommender Systems

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1. Introduction

Recommender systems have proved to be powerful information filtering tools that help users to find content, products or services adapted to their needs. In the last years their application in the e-learning domain has become an important research field [1]. More recently, the incorporation of contextual information about the users and their environment has attracted major interest [2] as these context-aware recommender systems allow to generate more accurate and personalized recommendations. As a consequence of knowing this contextual information, innovative recommendation techniques can be studied to improve the traditional user request-response pattern usually employed in almost every recommender system.

Following the model we proposed in [3], in this paper we present the methods needed to incorporate proactivity in a context-aware recommender system for e-learning platforms. In addition, we evaluate the appropriateness of proactivity when recommending learning content to educators in order to help them authoring better educational material for their daily classes attending to their students' necessities.

The methods proposed have been applied in a real scenario: the Virtual Science Hub (ViSH), a social e-learning network related

to the GLOBAL excursion (Extended Curriculum for Science Infrastructure Online) European project. The system developed is able to generate proactive recommendations of learning objects (LOs) to teachers and scientists in order to help them to create the lessons that their students will consume.

Regarding the impact of proactivity for ed ucators, an evaluation among 104 users (i.e. teachers and scientists) has been performed to generate a user model related to the appropriateness of proactive recommendations. This study covers not only the applicability of the methods proposed to a real deployed platform, but also the impact of proactivity in the user experience related to the educational activity of teachers and scientists collaborating in ViSH. The results obtained have led us to build user interfaces that nowadays are providing proactive recommendations to ViSH users.

The article is organized as follows: first, we present related work that positions this work within existing research that has been conducted in the area of recommender systems for elearning. Then, the ViSH scenario is described. Section IV reviews the general model for proactivity in context-aware recommender systems for e-learning we are using. After that, we detail the methods used to assess proactivity. In the following section the results from the evaluations carried out are presented. Section VIII illustrates the proactive user interfaces implemented in ViSH as a result of the outcomes achieved. Finally, some concluding remarks and future work are outlined.

2. Related Work

2.1 Recommender systems in e-learning

Attending to the survey of recommender systems in Technology Enhanced Learning (TEL) presented by Manouselis et al. [1] the main feature these systems offer consists of recommending learning resources [4]; but people [5] and activities [6] that may be important in the learning experience are also suggested in many of them. These functionalities are usually applied in TEL environments like learning networks [7] and teaching communities [8], as well as personal learning environments [9].

According to [1], in TEL a careful analysis of the targeted users and their supported tasks should be carried out. A great number of user attributes, domain characteristics, and intelligent methods can be engaged to provide personalized recommendations. Every e-learning system has its own particularities, but Manouselis et al. [1] highlight some that are quite common in these systems and that have to be considered when designing and implementing a recommender system for TEL.

However, additional context dimensions can be incorporated to improve the level of personalization and accuracy of the recommendations.

2.2 Context and Proactivity

Several definitions of context can be found, but we follow one of the most cited definitions proposed by Dey et al. [10] where: "*Context is any information that can be used to characterize the situation of an entity. An entity is a person, place, or object that is considered relevant to the interaction between a user and an application, including the user and applications themselves*". Systems that use this contextawareness information to provide enhanced recommendations are called context-aware recommender systems (CARS) [11].

In the learning domain, the application of these systems was recently surveyed by Verbert et al. in [2] wherein a context framework for TEL is also proposed containing several dimensions that are relevant for them (e.g. location, time, physical conditions or activity).

One specific research line that is getting very popular is the introduction of proactivity in CARS. These systems push recommendations to the user when the current situation seems appropriate, without explicit user request [12], going beyond traditional recommender systems.

Nonetheless, in the e-learning domain proactivity has not gained much attention yet and only few researches exist. Ruiz-Iniesta et al. [13] propose a proactive recommender system in computer-supported learning that works on repositories of LOs and adapts to the student's profile. The system recommends LOs to the student who can enter a conversational process to refine the proposal. However, this approach is tailored for students and for that reason the requirements of their scenario were quite different from ours, focused on helping teachers to create their lessons in collaboration with scientists.

3. Scenario: The Virtual Science Hub

The scenario in which the previous model have been applied is the Virtual Science Hub[1](ViSH), a social e-learning network related to the GLOBAL excursion[2] (Extended Curriculum for Science Infrastructure Online) European project.

GLOBAL excursions aim is to provide educators across Europe with a range of e-Infrastructures and access to expert knowledge by connecting teachers from schools and highschools to scientists. ViSH platform allows them to share their knowledge in a social way and students to have a joyful exploration of e-Science. In addition to this, ViSH offers an authoring tool to create enhanced learning objects (LOs) and complete lessons by using resources from a selection of e-Infrastructures or LOs uploaded by users to the ViSH repository [14]. This creation process is supported by the recommender system and the social network, where scientists and teachers are able to exchange and establish collaborations.

3.1 Motivation and Project Details

The demand for a qualified workforce with science, technology, engineering and mathematics (STEM) related skills has increased and will increase even more in the next years. Greater efforts must now be made to highlight STEM as a priority area of education and increase engagement at all levels. So European Commission (EC) has defined the advancement of STEM related skills as one of the priorities for the period 2014-2020 [15].

EC shows its concern about the learning scenario in several reports. [16] points out that teachers face rapidly changing demands, technology is rapidly changing the way people teach and learn, and teachers need support to introduce Information and Communication Technologies (ICT) in their daily work.

The EC Benchmarking Reports [17] identified ICT use in almost one hundred per cent of European schools, but schools are not usually making the most of them.

Taking all this into account, and considering that e-Infrastructures are recognized by the EC as key to a knowledge-based economy and social cohesion, and so they must have a place in education and training, the GLOBAL excursion project was proposed and approved. Together with end-users, GLOBAL excursion is developing a common understanding, teaching use cases, as well as pedagogical and technical artifacts.

The e-Infrastructure providers participating in the project are initially three: the Institute for Biocomputation and Physics of Complex Systems (BIFI) from Spain, the Nanoscience Centre from the Cambridge University (UCAM) from the United Kingdom and the Computer and Automation Research Institute (SZTAKI) from Hungary. Other scientific centers are expected to participate in the near future. The materials currently provided by these partners are based on the following topics: Biotechnology and biology from BIFI, Grid computing and volunteer computing from STZAKI and Nanoscience from UCAM.

ViSH is the platform where all GLOBAL excursion activities take place. It is open source and has been completely developed by the project members following a participatory design process [18]. ViSH has been built using the latest technologies on top the social network framework Social Stream [19] which provides social network features such as following/follower relationship mechanism, private messaging or a wall to share contents with other users (e.g. educational resources).

According to the description of work of the GLOBAL excursion project, one of the features was the integration of recommendation capabilities. Even more because during the participatory design process teachers reported and insisted that they had many difficulties finding adequate resources for their everyday teaching so this feature increased its importance.

4. Model

To address the requirement of having personalized recommendations on learning objects in the ViSH scenario, we applied the general three-phase model summarized in Figure 1 to handle proactive context-aware recommendations in elearning systems [3]. It analyses different context dimensions and generates a personalized recommendation that determines not only the best item(s) in a given situation, but also whether the situation warrants a recommendation at all.

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[1] http://vishub.org

[2] http://www.globalexcursion-project.eu

Following the context framework for TEL proposed in [2], to generate proactive recommendations we are utilizing the following context dimensions:

• **Social context:** The links (e.g. common interests, related profiles, etc.) among users in the learning platform that allow us to gather them by similarity. It corresponds to the *social relations* category in [2].

• **Location context:** Geographical information (e.g. nationality or language) and temporal (e.g. current time). This dimension aggregates the *time* and *location* categories from [2].

• **User context:** The current activity and device of the user (e.g. browsing the learning platform in a tablet), as well as his/her interests, personal information, etc. This dimension merges the *user* and *activity* categories from [2].

• **Resource context:** The relevant characteristics of the LOs assessed during the recommendation process (e.g. topic or educational characteristics). It corresponds to the *resource* category in [2].

In the first phase, the system generates the social context related to a user by analyzing all the user profiles and LOs that exist in the platform. Apart from gathering the users into clusters by similarity, the clusters also store information about the LOs that the users belonging to the cluster have used or created. As a result, information about the trends of LOs usage in every social cluster is achieved. This phase is executed with low frequency (e.g. once a day during the night), because the social context does not change continuously.

The second phase determines whether or not the current situation warrants a proactive recommendation considering its appropriateness. This phase is executed periodically in the background (e.g. several times per hour).

The third phase deals with evaluating the candidate items to be recommended. If one or more items are considered good enough in the current context, the recommender system would communicate it to the user. This phase is only executed when the second phase indicates a promising situation and the corresponding score exceeds a threshold.

Finally, the user has the possibility of giving feedback about the recommendation provided in order to allow the system to take that information into account for future recommendations.

5. Situation Assessment for Proactive Recommendations: Methods

Keeping in mind the general model described in the previous section, in this article we focus our attention in the second phase of that model. Hence, in this section the general methods to assess a situation for a proactive recommendation are presented.

5.1 Determination of appropriateness

One central question related to proactivity is to determine if a recommendation would be appropriate for a given user context. In this respect, we consider *location context* (devided into *geographical* and *temporal context*) and *user context* (divided into *device* and *activity context*) the most influential contextual dimensions involved in determining proactivity. Therefore, attending to the model presented in Figure 1, the system has to calculate a decision score $S1$ that will be tested against a threshold $T1$ using those contextual parameters. Only if $S1 > T1$ the proactive recommendation will be triggered.

$T1$ has to be predetermined or learned empirically after putting into operation the recommender system because it is domain-dependent. However, for the score $S1$ we have designed a general method to calculate it so as to be usable as a basis for describing the appropriateness of a situation.

As we mentioned above, the location and user context have several features that have to be treated differently among them. This leads to the introduction of two important properties for those components: Each feature value has an appropriateness factor and each *feature* has a weight. The first one indicates how appropriate a recommendation would be for this *feature value*, under the assumption that for all other features, a recommendation would be appropriate. The weight of a feature represents the importance it should have on the decision of appropriateness. In the following, formal definitions will be given based on these ideas.

Definition 1 (Feature set): Let F_M be the set of all features f of the model M. Therefore, we have two feature sets considering the context dimensions mentioned above:

• $F_{location} = \{f_{geographical}, f_{temporal}\}$
• $F_{user} = \{f_{deviceactivity}, f_{activity}\}$

Definition 2 (Value set): Let V_f be the set of possible values for a feature *f*. The concrete value of a feature $f \in F_M$ at a given point in time is given by $f.value \in V_f$.

Definition 3 (Appropriateness factor): Let $appr(f.value) \in [1,...,5]$ Q be a value for each feature value $f.value \in V_f$ indicating the appropriateness of a proactive recommendation, where $appr(f.value) = 1$ means that the recommendation would be not at all appropriate, whereas 5 means that the recommendation would be very appropriate.

Definition 4 (Feature weight): Let $f.weight \in [1,...,5] \subset Q$ be the constant property meaning the importance in the decision process of every feature $f \in F_M$, where $f.weight = 1$ means that the feature is definitely not imporant and $f.weight = 5$ means that the feature is very important.

Definition 5 (Situation model recommendation score): Let SRS_M be a value obtained by the combination of the appropriateness factors of feature values and the features weights of the respective model *M* for a specific situation.

Based on the previous definitions, the recommendation score for a specific situation associated to a context model can be defined as follows:

$$SRS_M = \frac{\sum_{f \in F_M} appr(f.value) * f.weight)}{\text{with } w_M = \sum^{w_M}_{f \in F_M} f.weight} \quad (1)$$

where w_M acts as a constant, as the weights will be known a priori and will not change during the execution of the recommendation process.

5.2 Proactivity Decision

First of all, taking into account that *S*1 was defined as a value between 0 and 1, the situation model recommendation score (1) has to be normalized:

$$\text{Norm } SRS_M = NSRS_M = \frac{SRS_M - SRS_{Mmin}}{SRS_{Mmax} - SRS_{Mmin}} \quad (2)$$

Finally, the proactive recommendation decision score (*S*1) can be calculated by a linear combination of the respective scores. But to do it, we define a new parameter called *influence* needed for the decision process.

Definition 6 (Context influence factor): Let $i_c \in [0,...,1] \subset Q$ be the influence of every context dimension belonging to a context model *M*, where their values have to comply with $\Sigma_M i_c = 1$.

Given that, the global decision score *S*1 for proactivity can be defined as follows:

$$S1 = i_{location} * NSRS_{location} + i_{user} * NSRS_{user} \quad (3)$$
$$\text{with } i_{location} + i_{user} = 1$$

6. Evaluation and Results

6.1 Description and objectives

The aim of this evaluation was to obtain the numerical values of the appropriateness factors for every feature value (Definition 3) and features weights (Definition 4) corresponding to the proactivity context modeling associated to the elearning domain. Thus the methods proposed above can be applied in the ViSH scenario so as to be able of calculating S1, and as a result, incorporate proactivity to the recommendation process. To achieve it, we asked teachers and scientists (i.e. target ViSH users) to evaluate their perception about the appropriateness of the different feature values and the weight of the features itself involved in the scenario using an online questionnaire.

6.2 Application to ViSH: features and values

Before carrying out the evaluation among users, we defined the specific context models used in ViSH focused on determining the location and user context features and their values. The feature set $F_{location}$ is composed by the features shown in the first two rows of Table 1, where the possible values for them are presented too.

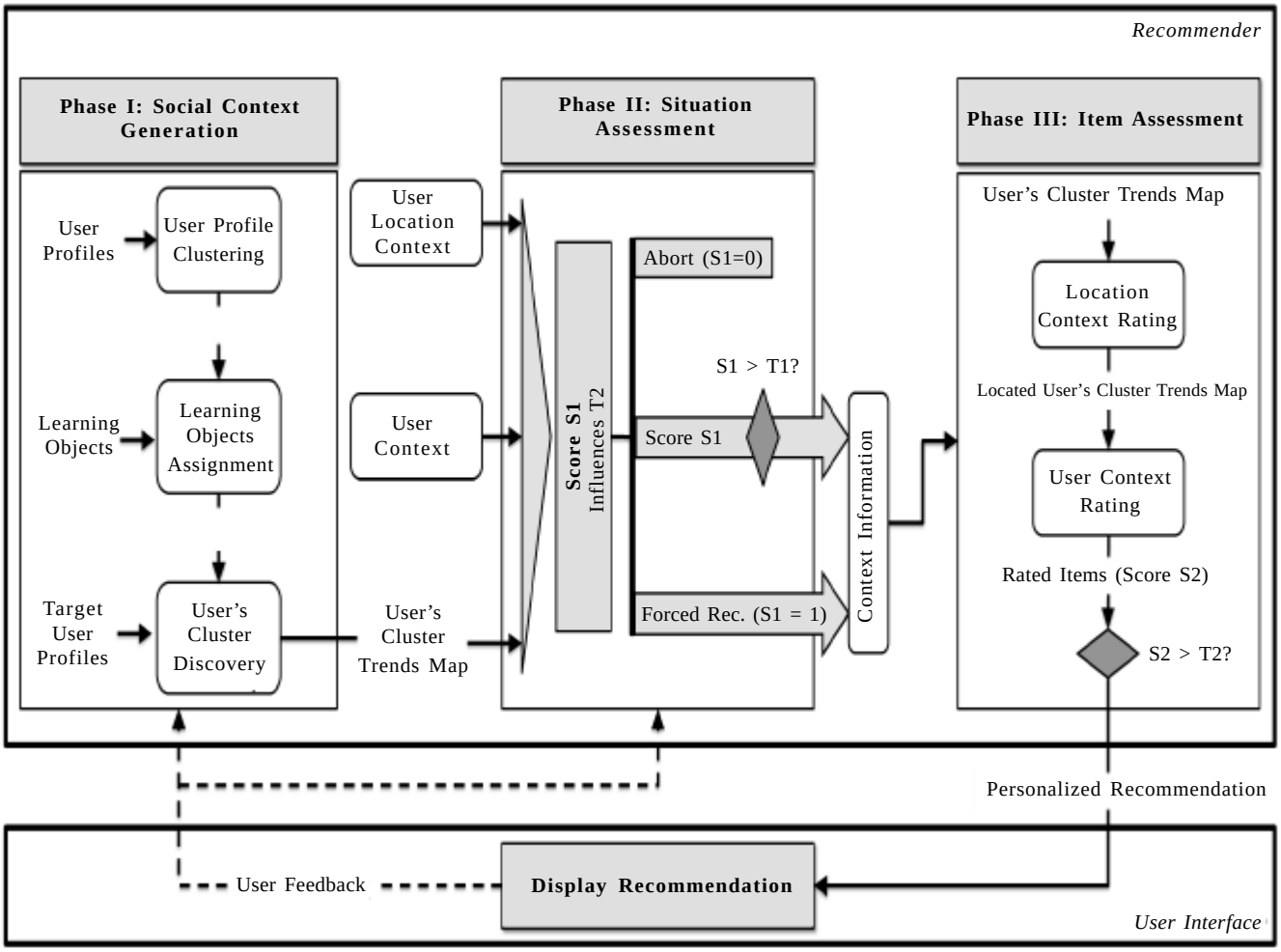


Figure 1. Model for generating proactive context-aware recommendations in e-learning systems [3]

In context-aware recommender systems location is currently one of the most important context parameters, especially in ubiquitous system in which users can access the system from different places and at different moments in time. For that reason, we have divided the location context in two features: *temporal* and *geographical*.

For the first one, we considered several periods in a day instead of exactly time values to follow a human being temporal perception.

With regard to the second one, we take into account the difference for teachers between being recommended when they are in or out their common city/working area.

Finally, regarding *Fuser*, Table 1 presents the feature set that is considered in the ViSH scenario to describe the user context together with their possible values.

When analyzing proactivity, user context has proved to be also an important context dimension in terms of "*interruptibility*" or "*time pressure*" [12]. These parameters can be derived by combining the activity the user is doing in the current situation analyzed and the device used during that activity.

Feature	Values	Average	Median	Std. Dev.
Geographical	User is in his city/working area	4.15	4	0.87
	User is out of his city/working area	3.36	3	1.16
Temporal				
	Morning	3.64	4	1.12
	Afternoon	3.45	4	1.02
	Evening	3.56	4	0.95
	Night	2.65	3	1.31
Device				
	Desktop	4.20	4	0.90
	Tablet	3.69	4	1.05
	Smartphone	3.21	3	1.30
Activity				
	Away (user is not in front of the computer/device)	2.53	2	1.11
	Idle (user is in front of the computer/device but doing nothing)	3.06	3	0.98
	Browsing the platform	3.98	4	0.96
	After filling in the profile	4.05	4	0.87
	While creating new educational content	3.52	4	1.07
	While editing educational content	3.36	4	1.12
	While looking for educational content	4.22	4	0.85
	After finishing the creation of a new educational content	3.47	4	1.07
	While viewing educational content created by others	3.76	4	1.06
	After finishing the view of educational content created by others	3.88	4	0.99

Table 1. Appropriateness Factors Of Context Model Features Values

6.3 Demographics and data collection

Of the 156 people who began the online survey through a publicly available website during the month of February 2013, 104 completed it. 64% of them were teachers, while 36% were scientists, being both groups the kind of users for which ViSH is oriented.

The teachers were recruited in schools and high-schools from different countries such as Spain, United Kingdom or Germany, being contacted either directly by e-mail or by disseminating the survey in online teacher groups like the Moodle community. The scientists were recruited from universities like the Universidad Polit´ecnica de Madrid, the University of Cambridge and research centers like the European Schoolnet, the Computer and Automation Research Institute of the Hungarian Academy of Sciences or the Institute for Biocomputation and Physics of Complex Systems.

The gender distribution was 50-50% as 52 men and 52 women completed the questionnaire, being the age distribution from 24 to 67 years old, with an average of 39.85, a median of 39 and a standard deviation of 10.25.

Concerning the usage frequency of recommender systems in general (e.g. looking up a well rated book or movie) 31.73% answered "*never*", 29.81% answered that they "*hardly*" use them (i.e. one time per month), 26.92% answered they use them "*regularly*" (i.e. at least one time per week) and 11.54% answered that they use them "*frequently*" (i.e. almost every day).

Feature weight	Average	Median	Std. Dev.
Geographical	3.45	4	1.04
Temporal	3.68	4	0.92
Device	3.61	4	1.02
Activity	4.12	4	0.83

Table 2. Weighting Of Context Model Features

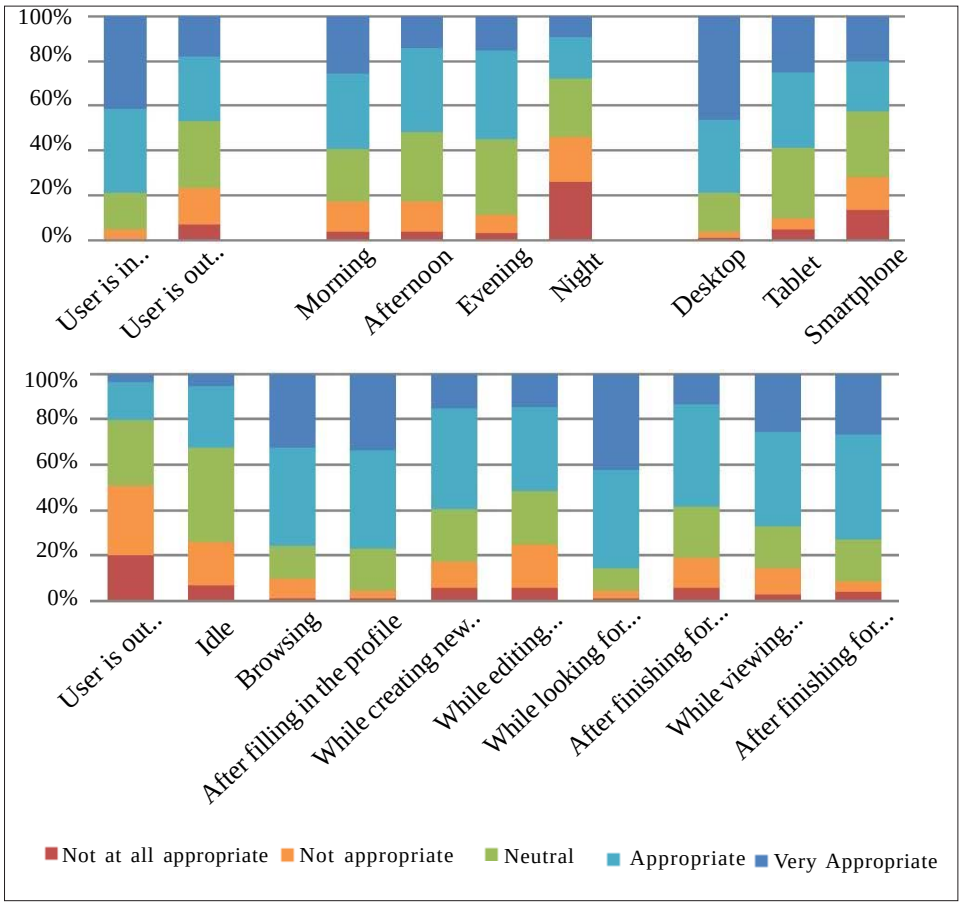


Figure 2. Evaluation results of appropriateness corresponding to the geographical, temporal, device and activity context feature values

Finally, the users were asked about if they had ever heard about proactive recommender systems: 43.27% answered "*yes*", whereas 56.73% said "*no*".

7.4 Results

Figure 2 presents graphically the participants' answers to a 5- point Likert scale questionnaire when asked about evaluating the appropriateness of being recommended in different contextual situations related to the values corresponding to the geographical, temporal, device and activity features. Table 1 summarizes the statistical results in terms of appropriateness for every feature value evaluated by the participants.

In the last part of the evaluation, the users were asked to rate the importance of every feature in order to allow us determine their weight in the situation model recommendation score calculation (1). Figure 7 presents graphically the results provided by the 5-point Likert scale questionnaire used. Finally, Table 4 shows the statistical results for the features weights.

7. Discussion

Attending to Nielsen [20], when collecting usability metrics, testing 20 users typically offers a reasonable tight confidence interval. Our sample consisted of 104 participants, so it is appropriate for our quantitative study.

The first and primary outcome is that considering the average values obtained in Tables 1 and 2, it is possible to apply now the methods proposed here in the ViSH scenario to achieve proactivity. In other words, the weight value (Definition 4) for the geographical, temporal, device and activity features and appropriateness factor of every feature value (Definition 3) are known to be able of calculating $S1$ (3) in the situation assessment process (the second phase of the model illustrated in Figure 1).

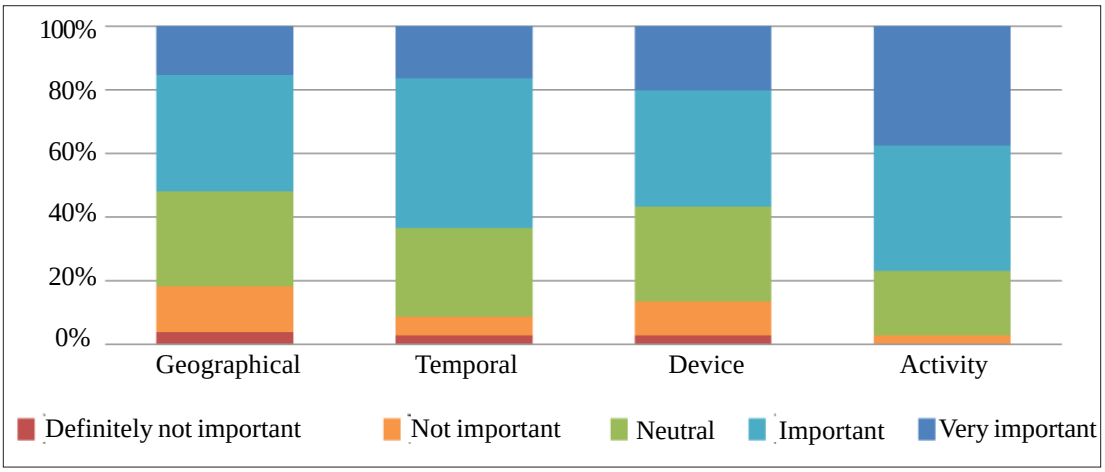


Figure 3. Evaluation results of weights corresponding to every context feature

As a result of this, we have also built a proactivity user modeling valuable for other researchers that want to include proactive recommendations in their learning scenarios. In this respect, we have shown that in most situations the acceptance (i.e. appropriateness) of having this kind of recommendations in Technology Enhanced Learning is high, as the teachers and scientists evaluated have considered them suitable for their learning processes due to the average values given in Table 1.

If we go into detail of every part of the survey, regarding the appropriateness results illustrated in Figure 2, it shows some clear outcomes related to recommend in e-learning systems. Specifically, several situations have proved to be inappropriate to be recommended based on the users' responses for each contextual feature evaluated:

• For the geographical feature, proactively recommending at night (average appropriateness factor of 2.65).

• For the temporal feature, proactively recommending when the user is away of the computer/device (average appropriateness factor of 2.53).

• For the device feature, proactively recommending when using a smartphone (average appropriateness factor of 3.21)

• For the activity feature, proactively recommending when the user is away or idle (average appropriateness factor of 2.53 and 3.06 respectively).

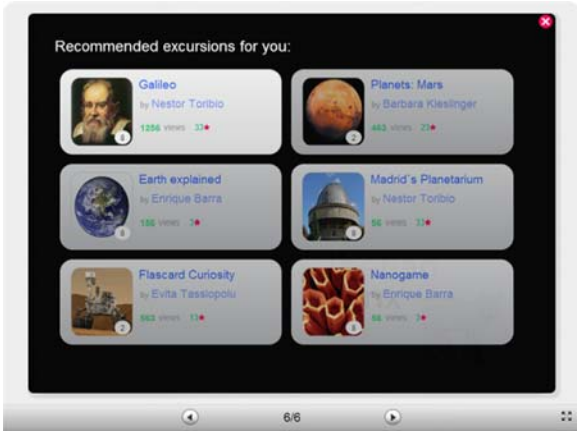
From these results, another important outcome can be extracted: Despite in other proactive systems (e.g. tourism) the temporal and activity context to recommend are not totally set (i.e. the situation for recommending is less strict), in an educational scenario with teachers and scientist it seems clear that they do not want to be interrupted during their free time for working purposes.

With regard to Figure 3 it is remarkable that activity is clearly the most important feature (i.e. it has the highest weight with an average of 4.12) to take into account when proactively recommending. This outcome is backed by previous results [12] which also shown that understanding the current activity of the user to determine his/her current task and the level of interruptibility allowed are the most influential parameters in proactive recommendations.

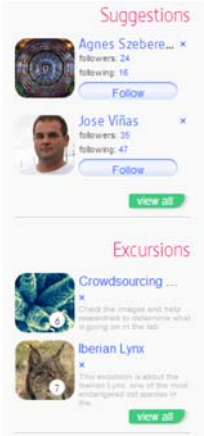
Apart from this, among the 104 subjects who completed the survey, one participant articulated total disapproval with the idea of proactive recommender systems. This attitude was also expressed by always giving low values for the appropriateness factor and weight. As we already discussed in section II, the idea of proactivity can be seen controversial as it is very recent, so the people is still not used to it in general. Despite of that, 43.27% of participants had heard about proactive recommender systems, a higher number than expected if we considered the penetration of proactivity in this kind of systems, even more when only 11.54% of participants use recommenders systems frequently in their daily life.

8. User Interface for Proactive Recommendations

Our model [3] suggests proactive context-aware recommendations of LOs and similar peers. But when the recommendation



(a)



(b)

(c)

Figure 4. Screenshots of ViSH user interfaces for proactive recommendations

is generated, it is sent to the e-learning system to visualize it in the most adequate way to the user. As we have applied this model in the ViSH scenario, in order to design proactive user interfaces for it we have taken into account that ViSH can be accessed from different kind of devices (i.e. mobile, tablet and desktop/laptop computer). Therefore the look and feel of the recommendations displayed depends on the device.

According to the results achieved in the evaluation process, we have seen that smartphones are considered the most inappropriate devices to receive proactive suggestions. Nevertheless, we have still decided to design a mobile user interface for them due to the following factors:

• The device feature was considered by users the third in importance when recommending proactively. Thus, as it will not be the most influential factor to determine if a situation warrants a proactive recommendation, it can be still considered.

• The quick grow of smartphones penetration in our society [21] make mandatory for any information system like ViSH to have a mobile application because it allows users to be active in the platform in an ubiquitous way. Therefore, the proactivity feature has to be also offered by the smartphone visualization.

On the other hand, bearing in mind the weight of each feature analyzed (Figure 3), the user experience has to be designed to make a trade-off among them so as to allow the user not only accepting the recommendations provided if the situation is appropriate, but also giving feedback about the items recommended or the moment in time chosen to generate the proactive recommendation, completing this way the feedback loop illustrated in Figure 1.

For these reason, we implemented in ViSH several user interfaces to incorporate proactive recommendations in different situations adapted to every kind of device using HTML5 technologies in order to create a "*responsive design*" application.

Figure 4 illustrates three examples among the different ways the suggestions sent by the recommender engine are presented to the user:

• Figure 4a shows a personalized recommendation provided to the user "*after finishing the view of educational content created by others*". In ViSH, educators can create Virtual Excursions [22], which are a composition of LOs following a "*slide presentation*" paradigm. In the screenshot depicted we can see that after the user has completed the review of an excursion, the platform proactively recommends similar excursions that may be of interest for him/her. Moreover, if the user clicks (or press in a mobile device) the close button (i.e. *X* icon), this feedback will be taken into account for next situation assessment processes to increase for example the threshold T1, meaning that it will be more difficult to meet the condition of recommending proactively in that kind of situation.

• Figure 4b shows a recommendation of both, LOs (excursions) and similar peers that appears while the user is "*browsing the platform*". Recommending in such moment could be very useful for a new user that maybe is evaluating what he/she can do in the platform or what type of content can be accessed. By proactively recommending we try to save time for users, at the same time we make easier for them to understand what ViSH is about. Again, the user can dismiss the recommendations by clicking the close button, providing as a result feedback to the recommender system.

• Figure 4c shows a smartphone view in which the user is recommended with a set of suitable resources "*after filling in his/her profile*". The idea is very similar to the first one, but this time it is totally focused on new registered users. By proactively recommending just after filling the profile the recommender is helping the user to understand the benefits of using ViSH for his/her teaching activities showing an initial and personalized glimpse of the available contents.

These interfaces were designed in the participatory design process carried out at the beginning of the project. But after an alpha version period a usability and user experience evaluation was performed. This evaluation consisted on gathering feedback from the first users, clickmaps and scrollmaps [23], property checklists [24] and interviews with potential users [25] to analyze how they used the platform. As a result of this study the interfaces were improved.

9. Conclusion and Future Work

In this article we have studied the appropriateness and importance of providing proactive recommendations to support the teaching experience of teachers and scientists involved in a social learning network. To do it we have presented the general definitions and methods needed to implement the situation assessment phase corresponding to the model for generating proactive context-aware recommendations in elearning systems that we proposed in [3]. They allow to calculate the appropriateness of a situation to generate proactive recommendations based on several context dimensions (i.e. location and user context).

To support our approach we have evaluated those methods in a real social learning platform called ViSH related to the GLOBAL excursion European project scenario. Results from the evaluation among educators in the such scenario have leaded us to generate a proactivity user model valuable for other researchers. Furthermore, we have presented some examples of user interfaces for proactive recommendations implemented in ViSH attending to the outcomes achieved from the evaluation.

Whereas results of this study indicate that perceived appropriateness of receiving proactive recommendations is high, among the future lines of research opened, it would be useful to perform an A/B testing study [26] among ViSH users to evaluate the usability differences between educators using the interfaces proposed and those not using them. Aspects like the usefulness of such type of recommendations in their daily work as teachers, in addition to the influence in the quality of the lessons created thank to the suggestions received could be measured to appreciate the impact of having this kind of recommendation in social learning networks designed for knowledge sharing.

Finally, it would be beneficial for this research to extend the case study to other e-learning platforms so as to apply the methods proposed in other scenarios that want to include proactivity, comparing this way the validity of the results achieved here.

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