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Sharing notes: An academic social network based on a personalized fuzzy linguistic recommender system

C. Porcel [b,*], A. Ching-López [a], G. Lefranc [c], V. Loia [d], E. Herrera-Viedma [a,*]

[a] Department of Computer Science and Artificial Intelligence, University of Granada, Granada, Spain
[b] Department of Computer Science, University of Jaén, Jaén, Spain
[c] Escuela de Ingeniería Eléctrica, Pontificia Universidad Católica de Valparaíso, Chile
[d] Department of Management and Innovation Systems, University of Salerno, Fisciano (SA), Italy

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ABSTRACT

Social networks are Web systems that enable and encourage a collaborative work, making it possible to exchange information between users, which makes them especially useful in many areas. Specifically, they could be used in an academic environment with the aim of improving the educational processes, not replacing, but complementing the most traditional face-to-face models. But nowadays the increasingly widespread use of new technologies and social networks is causing the information we have available to grow disproportionately, making it more difficult and expensive to access information of interest. To alleviate this problem, automatic tools such as recommender systems, could be used to facilitate the accesses to relevant information, that in an academic environment would help to customize the educational processes. So, in this paper we present *SharingNotes*, an academic social network that can generate personalized recommendations to improve teaching and learning processes. To achieve this goal, it incorporates a hybrid recommender system that uses an ontology to characterize the degrees of trust among network users, and adopts the fuzzy linguistic modeling to improve the representation of information. Then, the use of this platform allows adapting the educational process to the circumstances of each student. The evaluation developed demonstrates the usefulness of this educational social network, as well as the users' satisfaction while interacting and working with it.

1. Introduction

The main reasons that govern the new education scenarios involve a reform of the educational system focused on the learning and active role of the students, as well as in building knowledge as the complete integration of information and communication technologies in education systems (Bhattacharya and Nath, 2016; Cobos et al., 2013; Moscoso, 2003; Secades and Arranz, 2016). New technologies enrich the learning process with the capabilities of spreading the information in an easy and efficient manner, besides giving the participants (professors, students, experts, and so on) tools for both personal and group communication that reinforce the tutorship action and the collaborative learning.

In this manner, social networks are one of the Web technologies that facilitate and promote this collaborative work (Capuano et al., 2018). These are defined as Web services that enable the users to set up a public or semi-public profile within a bounded environment, establish a list of users to maintain a connection with, and see and traverse its own list as well as the ones established by other users inside the system (Boyd and Ellison, 2007). To achieve this, and depending on the case, social networks give to the users some tools for building groups, private messaging, public messaging, internal e-mail or chat, among others (Herrera-Viedma et al., 2017). But more significant are the networks that provide information exchange between users, because this made them really suitable for some professional environments (Alonso et al., 2013). For example, these are successfully applied in the corporate world where they are set up as platforms that changes the corporate work strategy following the same open and dynamic way of other sites such as Facebook[1] or Twitter,[2] but specially oriented to encourage interaction, collaborative work, innovation and productivity in business

[1] https://www.facebook.com/.
[2] https://twitter.com/.

* Corresponding authors.
E-mail addresses: cporcel@ujaen.es (C. Porcel), alch@decsai.ugr.es (A. Ching-López), gaston.lefranc@gmail.com (G. Lefranc), loia@unisa.it (V. Loia), viedma@decsai.ugr.es (E. Herrera-Viedma).

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world (Vignola and Encina, 2012). One of the most popular professional social network is LinkedIn,[3] with more than 225 million users.

As aforementioned, collaborative work and social interaction among the educational system users is an important part of the learning process. These characteristics have enabled the teaching field to be another successful field of social networks application (DeHaro, 0000; Limongelli et al., 2015; Mor Mora et al., 2015), taking always into account that the collaborative social learning does not substitute the traditional model, it complements this model. In Mor Mora et al. (2015) it is demonstrated that social networks are more capable of broadcasting information than the classic educational web platforms, enhancing the performance of learning processes. In spite of many people use the general purpose social networks such as Facebook or Twitter, there are specific teaching networks as Edmodo,[4] Ning,[5] or redAlumnos,[6] which maintain in touch all the participants of the education process, and provide the material to develop their full capabilities. Edmodo is a technological, social, educational and free platform that allows communication between students and teachers in a closed and private environment as a microblogging, created for a specific use in education. It is an educational social network that allows to organize contents, make assignments and maintain an active and constant communication and interaction between teachers and students, including parents, thus favoring collaborative learning. Ning is an online platform that allows its users to create social websites and social networks. The most significant feature of Ning is that anyone can create their own personalized social network for a particular issue or need, targeting specific audiences. Many teachers are using Ning to develop educational resources. The features were customized so that participants could upload images and videos of students developing projects as well as links to blogs and Flickr. RedAlumnos is a training platform that connects teachers and students, so that the teacher can teach online courses and support their face-to-face classes. It can also be installed in a teaching center and have virtual classrooms, online exams, edublogs, chats, etc. It has free and paid services.

However, the increment of the Internet usage, specially the social networks, makes that generated content and information in this media increases everyday, in a way that the number of resources we can access is growing daily in an excessive amount. This implies that in order to develop these type of Web tool, we have to face the problem known as *Information Overload*, which can be defined as the inability to extract relevant knowledge from a large amount of information. This problem may also mean having more relevant information than one can assimilate (Meghabghab and Kandel, 2008). This large amount of available information introduces noise into our information access processes, causing us to be unable to access relevant information (Porcel and Herrera-Viedma, 2010; Porcel et al., 2010). For example, every day we receive a large number of emails that are not useful to us, but we also receive emails with information of our interest. The problem is that with so much information we do not pay the appropriate attention to an important mail and we lose information believing that it is something without value. This problem takes on special importance in Web environments such as social networks, where information grows much faster than users are able to process. Specifically, we see it in the field of educational social networks, with an exponential growth in both the number of users and the content they manage, whether messages, forums, groups or the shared teaching materials (Mor Mora et al., 2015).

In this situation appears the need to have automatic tools to help users to access the information, in the correct personalization of their educational processes and to identify collaboration possibilities with other users in similar circumstances, in order to dynamize and improve educational processes. To face this problem recommender systems emerged and have evolved more and more (Burke, 2007; Hanani et al., 2001).

These are tools that facilitate the users the personalized access to information of interest, distinguishing between what can be relevant or not for them. To achieve this goal, recommender systems exploit previous behaviors and similarities between users to predict new needs. They have been applied successfully in many fields, but mostly in e-commerce (Schafer et al., 2007), film tastes, or even to the selective broadcast of researching resources (Tejeda-Lorente et al., 2014) or in educational environments as it is our case (Cobos et al., 2013; Ratneswary and Rasiah, 2014). These systems base their operation on different schemes, according to the specific scope in which they will be applied, emphasizing content-based, collaborative, knowledge-based, demographic or utility-based (Burke, 2007; Lops et al., 2011; Schafer et al., 2007). More recently, trust-based schemes have emerged, extracting knowledge from the social environment of the users (Golbeck, 2005; Lee and Ma, 2016; Park et al., 2016; Wu and Chiclana, 2014; Wu et al., 2015). Also, it has been explored how a social environment can improve the quality of the generated recommendations by the system, but only in certain cases and according to which techniques are analyzed (Bellogín et al., 2013; Deng et al., 2014; Sankar et al., 2015; Sun et al., 2015). Indeed, the collaborative approaches present a good behavior in other cases, so it seems that the ideal thought would be a hybridization between the social and collaborative approaches. And it is precisely the approach we draw in our proposal and we integrate it into our system.

In this paper, we present *SharingNotes*, an educational social network capable of generate personalized recommendations to improve teaching and learning processes. The Web platform has been developed in the University of Jaén (Spain) and it is accessible by the link: http://sharingnotes.ujaen.es/. To customize access to educational resources, it makes use of a recommender system that makes a hybridization between the content-based, collaborative and trust-based approaches. Precisely to characterize the degrees of trust among social network users, an ontology is used, and the method presented in Martínez-Cruz et al. (2015) is adopted to estimate the trust between two users when they have not explicitly valued trust between them. Therefore, the main advantage of using SharingNotes instead of other social networks is that it incorporates a recommender system to personalize the teaching and learning processes and that it has been designed specifically for a university environment. On the other hand, the drawback of this proposal is that until its use is more widespread, we will not obtain a performance of the most appropriate recommendations and really adjusted to the profile of each user.

Finally, we also face the problem of the wide variety of representations and evaluations of information, which is more pronounced when users are part of the process, as is the case at hand. Therefore, we adopt the fuzzy linguistic modeling that will help us to represent and efficiently manage the qualitative information present in the communication processes. Specifically, we integrate in the system the multi-granular approach that gives us greater flexibility in the system-user interaction, because it allows us to manage the information by representing the different concepts of the system with different linguistic label sets (Mata et al., 2009; Morente-Molinera et al., 2017, 2015). In this case, the use of simple granularity would make it difficult for users to interact with the system, by not adapting the number of labels to the degree of user experience or different concepts that must to be assessed.

The rest of the article is organized as follows. In Section 2 we include the necessary preliminaries for the understanding of the rest of the sections. In Section 3 the developed system is presented. In Section 4 we describe the experiments developed to evaluate the system. Finally, in Section 5 the conclusions are presented, and the future work is pointed out.

[3] https://www.linkedin.com/.
[4] https://www.edmodo.com/.
[5] http://www.ning.com/.
[6] http://www.redalumnos.com/.

2. Background

2.1. Recommender systems

In many areas of our lives, it is often necessary to select one among several alternatives without having an exact knowledge of each one. In these situations, the final decision usually depends on the recommendations of other people (Burke, 2007; Tejeda-Lorente et al., 2014), as it happens when we are going to buy a product, to choose between a model or another we rely on the recommendation of someone who previously acquired it, or who has more precise knowledge about it. In the processes of access to information, recommender systems are tools whose objective is to assist users in their information searching processes, filtering the retrieved information items, using past suggestions or recommendations given by other users about those items.

The main elements of a recommender systems are the following (Burke, 2007):

- User profiles that represent information needs or user preferences. The information about the users can be obtained implicitly, through some kind of observation, or explicitly, in which the user indicates their preferences or needs through some feedback to the system.
- Representation of the items that contains all the important items' characteristics. Usually experts of the specific field of application insert this information.
- Method used to generate recommendations. There are various techniques that can be used. Traditionally, we talk about content-based, collaborative (item-based or user-based), knowledge-based, demographic, or hybrid approaches that consist of a combination of different schemes to take advantage of each other and reduce their drawbacks.
- Rating history. Values that users supply to the system when they analyze an item or update a previously assigned value.

In any case, the success or failure of a technique to generate recommendations depends mostly on the scope of specific information where they are being applied, so this is an important point to consider, because a priori there are no techniques better or worse than others.

2.2. Fuzzy linguistic approach

It is a tool based on the concept of linguistic variable (Zadeh, 1975), which has given very good results for the modeling of qualitative information in a multitude of problems and scopes (Cabrerizo et al., 2013, 2015; Chang et al., 2007; Kraft et al., 1994) .

2.2.1. 2-tuple fuzzy linguistic approach

The 2-tuple fuzzy linguistic approach is a continuous model of information representation which allows to reduce the information loss of other linguistic approaches (classic and ordinal Herrera and Martínez, 2000).

Consider $S = \{s_0, \dots, s_g\}$ as a linguistic terms set with odd cardinality, where the associated semantic to each terms is calculated by triangular membership functions, and we consider that all the terms are distributed over a total ordered scale. If using a method of linguistic information aggregation, we obtain a value $\beta \in [0, g]$, and $\beta \notin \{0, \dots, g\}$, we can represent β as a 2-tuple (s_i, α_i), where s_i represent the closest index label to β, i, in the linguistic terms set ($s_i \in S$) and α is the value of the symbolic translation. This model defines a set of transformation functions between values and 2-tuple: $\Delta(\beta) = (s_i, \alpha)$ and $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ (Herrera and Martínez, 2000).

To establish the computational model, operators of negation, comparison and aggregation are defined. Using the functions Δ and Δ^{-1}, we can extend any of the defined aggregation operators to work with 2-tuples (Herrera and Martínez, 2000). In the system, we have used the following operators:

Definition 1 (*Arithmetic Mean*). Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples, the 2-tuple arithmetic mean $\bar{x}^e$ is computed as:

$$\bar{x}^e[(r_1, \alpha_1), \dots, (r_n, \alpha_n)] = \Delta(\sum_{i=1}^{n} \frac{1}{n} \Delta^{-1}(r_i, \alpha_i)) = \Delta(\frac{1}{n} \sum_{i=1}^{n} \beta_i). \tag{1}$$

Definition 2 (*Weighted Average Operator*). Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{w_1, \dots, w_n\}$ be their associated weights. The 2-tuple weighted average $\bar{x}^w$ is:

$$\bar{x}^w[(r_1, \alpha_1), \dots, (r_n, \alpha_n)] = \Delta(\frac{\sum_{i=1}^{n} \Delta^{-1}(r_i, \alpha_i) \cdot w_i}{\sum_{i=1}^{n} w_i}) = \Delta(\frac{\sum_{i=1}^{n} \beta_i \cdot w_i}{\sum_{i=1}^{n} w_i}). \tag{2}$$

Definition 3 (*Linguistic Weighted Average Operator*). Let $x = \{(r_1, \alpha_1), \dots, (r_n, \alpha_n)\}$ be a set of linguistic 2-tuples and $W = \{(w_1, \alpha_1^w), \dots, (w_n, \alpha_n^w)\}$ be their linguistic 2-tuple associated weights. The 2-tuple linguistic weighted average $\bar{x}_l^w$ is:

$$\bar{x}_l^w[((r_1, \alpha_1), (w_1, \alpha_1^w)) \dots ((r_n, \alpha_n), (w_n, \alpha_n^w))] = \Delta(\frac{\sum_{i=1}^{n} \beta_i \cdot \beta_{W_i}}{\sum_{i=1}^{n} \beta_{W_i}}), \tag{3}$$

with $\beta_i = \Delta^{-1}(r_i, \alpha_i)$ and $\beta_{W_i} = \Delta^{-1}(w_i, \alpha_i^w)$.

2.2.2. Multi-granular fuzzy linguistic approach

In any approach, an important parameter which has to be determined is the "granularity of the uncertainty", this means the cardinality of the linguistic terms set S. Depending on the uncertainty grade an expert indicates related to the case itself, the linguistic terms set chosen to give that knowledge will have more or less terms. When some experts have not the same uncertainty grades in a common phenomenon or when an expert has to value different concepts, it is needed various linguistic terms sets with different granularity (Herrera and Martínez, 2001). In those situations we need a tool that allow us manage the multi-granular linguistic information. In Herrera and Martínez (2001) the 2-tuple multi-granular fuzzy linguistic modeling based in the concept of linguistic hierarchy was proposed. A linguistic hierarchy, LH, is a set of levels $l(t, n(t))$, where each level t is a linguistic terms set with a different granularity $n(t)$ (Herrera and Martínez, 2001). The levels are sorted by their granularity, in that way we can define each level based on its previous one: $l(t, n(t)) \rightarrow l(t + 1, 2 \cdot n(t) - 1)$.

In Fig. 1 we can see a graphical example of a linguistic hierarchy. In this LH, the linguistic terms in each level are the following:

- $S^3 = \{a_0 = Null = N,\ a_1 = Medium = M,\ a_2 = Full = F\}$.
- $S^5 = \{b_0 = Null = N,\ b_1 = Low = L,\ b_2 = Medium = M,\ b_3 = High = H,\ b_4 = Full = F\}$
- $S^9 = \{c_0 = Null = N,\ c_1 = Very\_Low = VL,\ c_2 = Low = L,\ c_3 = More\_Less\_Low = MLL,\ c_4 = Medium = M,\ c_5 = More\_Less\_High = MLH,\ c_6 = High = H,\ c_7 = Very\_High = VH,\ c_8 = Full = F\}$

In Herrera and Martínez (2001) a family of transformation functions between labels of different levels is defined to combine multi-granular linguistic information with no loss of information:

Definition 4. Let $LH = \bigcup_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, \dots, s_{n(t)-1}^{n(t)}\}$. The *transformation function* between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ is defined as:

$$TF_{t'}^{t} : l(t, n(t)) \longrightarrow l(t', n(t')) \tag{4}$$

$$TF_{t'}^{t}(s_i^{n(t)}, \alpha^{n(t)}) = \Delta(\frac{\Delta^{-1}(s_i^{n(t)}, \alpha^{n(t)}) \cdot (n(t') - 1)}{n(t) - 1}) \tag{5}$$

To establish the computational model, we choose a level to uniform the information (e.g., the highest granularity level), and then we can use the operators defined in the 2-tuple model (previous subsection).

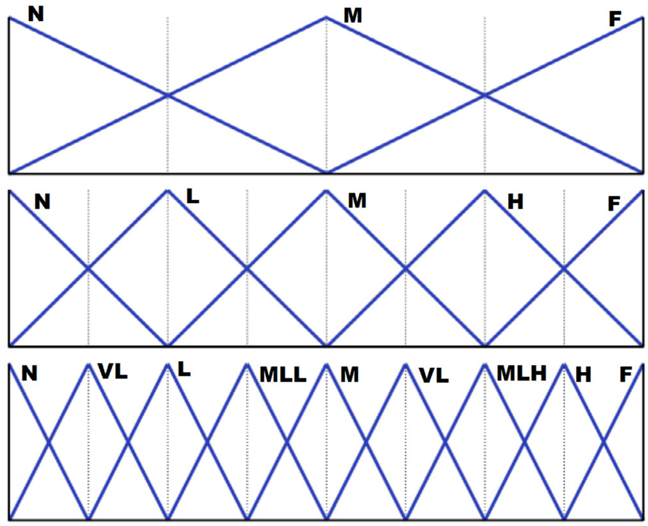

Fig. 1. Linguistic Hierarchy of 3, 5 and 9 labels.

2.3. Social networks and trust networks

The concept of reliability plays a main role in social networks (Hajli et al., 2017; Nevzat et al., 2016). For instance, Epinions[7] suggests recommendations about products reviewed by trusted users. Trust networks are social networks in which the users can value explicitly their degree of trust in other users. But due to its extended use, these nets are growing in size, therefore many users do not know the vast majority of other users. Because of that, we need a technique to estimate the trust degree between two users if it is not provided explicitly. The idea is to search a path connecting both users and spread the trust degrees found along the path. Usually, we can find more than one path connecting both users, in that case we have to choose the more relevant and aggregate the trust degrees spread along the path. Another aspect to take into account is the length of the paths, known as *horizon*, H. To avoid an excessive computational complexity and to remove the less relevant paths, an upper limit usually is fixed to H, discarding the paths longer than this limit; typical values for H are 2 or 3.

To aggregate the spread trust degrees calculated from the found paths we can use several techniques, some of them based in OWA (Ordered Weighted Average) operators (Yager, 1988). In our case, we propose to adopt the MILOWA (majority guided linguistic IOWA) operator defined in Herrera-Viedma et al. (2006), because we are in an environment where we work with linguistic information and it solves the problem of how to represent the majority of the previous operators. In our previous work (Martínez-Cruz et al., 2015), the specific details to achieve the aggregation can be consulted. Point out that as variable to induce the sorting of the set of values to be aggregated, we use the average global reliability of all users of each path found. To calculate this global trust, we use the PageRank algorithm (Page et al., 1998), in view of the fact that its good results and it is one of the one the most used global trust metric in many contexts.

3. SharingNotes: the software platform

In this section we describe the developed software. More specifically we have designed, developed and settled a Web platform that allows the creation of an educational social network, incorporating mechanisms that really help to disseminate the pedagogical resources available in a personalized way among the members of the network, in order to improve the teaching–learning processes, adapting them according to the educational needs of each student. This social network aims to serve as a meeting point for students, teachers and members of an educational process who want to share academic resources, whether notes, articles, videos, photos, and so on. The platform is operational and accessible through the following link: http://sharingnotes.ujaen.es/.

To achieve an effective personalization in the access to the resources, the platform includes a fuzzy linguistic recommendation system (see Section 2.2), in addition to an ontology defined to model the trust network, as well as a domain ontology to establish the relations between users and their preferences (Martínez-Cruz et al., 2015). The multi-granular fuzzy linguistic approach is adopted because it allows us to use different sets of labels to represent the different concepts that have to be valued. These sets of labels are selected from a linguistic hierarchy (see Section 2.2) and in our case, they are the following:

- S_1: Degree of trust of one user over another.
- S_2: Membership degree of the scope of a resource concerning each of the categories used in the domain ontology.
- S_3: Estimated degree of relevance of a resource for a user.
- S_4: Degree of satisfaction expressed by a user about the resources that have been recommended to him.

Specifically, we adopted 5 labels for sets S_1, S_2 and S_4, because these values are assigned by users and 5 labels are sufficient, but neither is a very high level of detail. On the other hand, for the set S_3, as it is a value estimated by the system automatically, we used 9 labels to represent the results with an appropriate granularity. The linguistic terms used at each of these levels are as follows:

- $S^5 = \{b_0 = Null = N,\ b_1 = Low = L,\ b_2 = Medium = M,\ b_3 = High = H,\ b_4 = Full = F\}$
- $S^9 = \{c_0 = Null = N,\ c_1 = Very\_Low = VL,\ c_2 = Low = L,\ c_3 = More\_Less\_Low = MLL,\ c_4 = Medium = M,\ c_5 = More\_Less\_High = MLH,\ c_6 = High = H,\ c_7 = Very\_High = VH,\ c_8 = Full = F\}$

3.1. System architecture

Faced with this challenge of developing an educational social network, we considered the incorporation and use of content management systems (CMS) for social networks. Several options were analyzed to discard them or to select them considering the following characteristics: frequency of updates of the core of the CMS and its main components, active community of developers, available plugins, facility of development of new plugins and its interconnection with the rest of the CMS. Of those who met the requirements, we pointed out *elgg*,[8] which is becoming increasingly widespread, has a good community of quite active developers, all its core code is very well documented (facilitating custom adaptation and future improvements) and presents a nice, simple and easy-to-use interface for end users. For all these reasons, elgg was the CMS selected for the development of our social network.

Then the Web server where the social network was installed and implemented started running. In addition, a plugin for elgg was implemented that allows the exchange of links to academic resources and the creation of a section to manage the settings of the plugin, with the aim of obtaining adequate customization. Then the plugin was interconnected with the rest of the social network, adapting it to our specific needs and casuistic.

3.2. Users roles

As in any social network, to make use of it, users have to be registered. That will provide the first information that will be incorporated

[7] http://www.epinions.com.

[8] https://elgg.org.

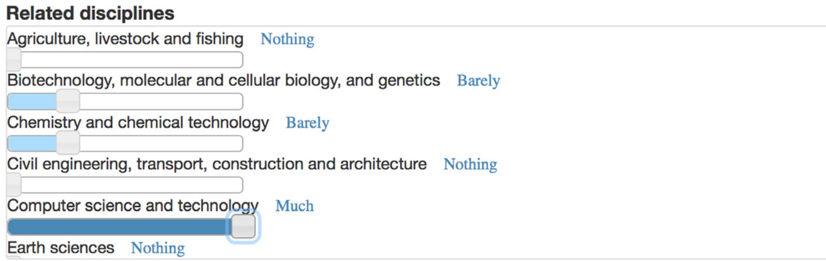

Fig. 2. Assignment of disciplines to a resource using linguistic labels.

into the profile of each one. In the system the following roles are distinguished:

- Users, whether teachers or students. The profile of a user is composed of information of the user itself, as well as several widgets, which can be selected and customized by users. A priori, five widgets are set: message board, recent activity, last published resources, list of followed users and list of groups of which is member. As we have commented everything is customizable, but we wanted to highlight the basic aspects of profile configuration, which are:
  - Image. Users can select an image as a profile icon.
  - Basic data. It allows to edit the basic information of the user, where the users can select which data to show and to whom.
  - Modify preferences. From this option the users can modify the user name (not the nickname), password, contact email and language.
  - Account statistics. Displays information about user activity on the social network.
  - Notifications. It allows users to activate or deactivate email notifications for actions taken on their contents, comments, new followers, group invitations, followed user actions, as well as group notifications.
- Groups. The system gives the option to establish groups of users, either by their preferences or needs, because they are classmates or members of the same university, or for other reasons. It is possible to control the type of content that can be created by members of the groups, being able to manage the activities and resources, that although published by a user, belong to the group, and if it is private only its members can see it. There is also the option to create and participate in discussions, which is a way of communicating like a forum.
- Administrators. They are in charge of the installation, configuration and maintenance of the elgg CMS. They will make the configuration of the data directories, contents and users, permissions, database and available plugins.

Talking about the interaction between users, you can follow other users, so that we have available users who we follow, as well as followers, that is, users who follow us. Users will be able to assign levels of confidence they have in other users, using a selected label of the set S_1. In this way the links between some users are established, what allows us to apply the proposed method for the estimation of the degree of trust for users not directly connected. To do this, the approach introduced in Section 2.3 is used. Users can also send messages, which would be similar to sending an email, but only for registered users on the Web.

3.3. Resources

In our system, an academic resource is a Web link to notes, documents, video tutorials, articles, and so on. They are divided into universities and grades, also they are classified according to the disciplines which they are related to.

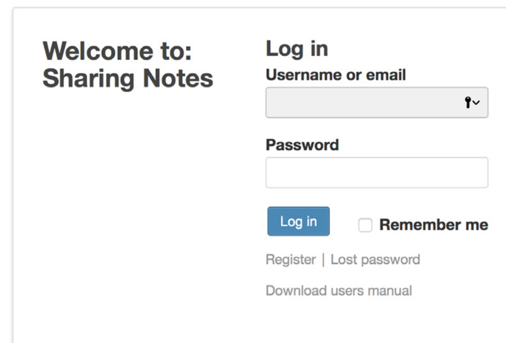

Fig. 3. Access screen to SharingNotes.

The information that is incorporated for each resource is the following one:

- Title and link to the resource.
- User and creation date.
- University and the belonging grade. This information is used to apply different filters.
- Resource rating. The user who is viewing it at any given time can value it (using a slider that will assign a label from the set S_4) or can also see the average ratings of other users.
- Tags: are words that describe the resource and are used to perform searches faster and more efficiently.
- Users who can access the resource. The following types of access are distinguished:
  - Private: only accessible by the user who has published it.
  - Draft: not yet published, so it is only accessible to the user who created it.
  - Limited: only accessible by certain users, for example, those belonging to a certain group.
  - Registered users: this is a resource accessible by any user, as long as it is registered. The more similar to a public state.
- Resource description. If so desired, a description about the resource could be inserted.
- Disciplines to which the resource belongs. When inserting a resource is essential to complete correctly this field as it will help to get better recommendations. To classify the publication as belonging to a discipline, simply slide the selector of that discipline to the appropriate label, chosen from the set S_2, as shown in Fig. 2.

3.4. System's operation

SharingNotes presents a similar operation to other social networks, although in this case, particularized to an academic environment. When

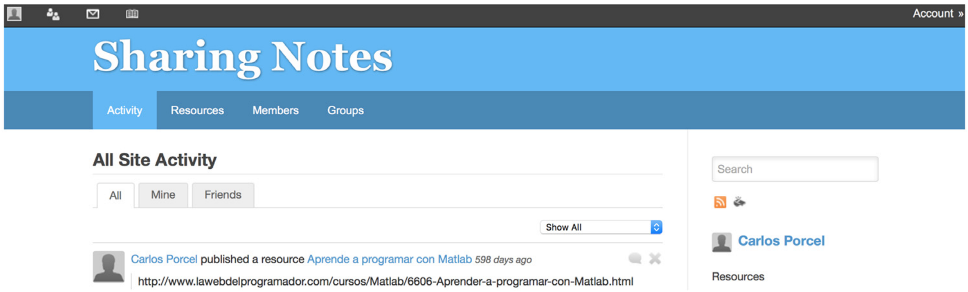

Fig. 4. Main screen for users of the system.

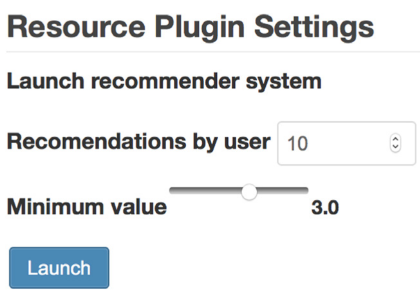

Fig. 5. Screen used by admins to manually generate recommendations.

accessing, the screen shown in Fig. 3 appears, where users enter their system access data (user or mail and password), or in the case of new users, they can register in the system; in this screen it is also possible to remember the password if we have forgotten and access the user manual for less experienced or beginner users.

Once we have signed into the system, the screen shown in Fig. 4 appears, where we can identify the four fundamental elements on which our social network is based: recent activity, academic resources, members and groups. In all these elements we can filter what is shown according to the entire network, only what is property of the user or the resources of the followed users. As we have commented, the operation is similar to other social networks so we can visualize the activity in the network, publish new resources or access and value existing resources, view information of other users and follow them, as well as forming new groups or visualize or join the existing ones.

What is really distinctive of the operation of other educational social networks is the fact of generating recommendations of academic resources that allow to personalize the access to information of interest. These recommendations are generated automatically as resources are added to the system, although it is also possible to generate them manually by the system administrators, who can also customize the process as shown in Fig. 5. There are more customization options that are not shown in the figure due to space issues. As we can see, we can configure the maximum number of resources to be recommended per user, as well as a threshold value for the estimated relevance (label of the set S_3, i.e., below that value the resource is will not be considered relevant for the user). The system estimates the relevance automatically, obtaining a value that is translated to a label of the set S_3 and if it is above the established threshold, the resource will be considered relevant for the user and therefore it will be recommended to the user.

With respect to the **recommendation scheme** adopted in our system, comment that we have analyzed, implemented, and evaluated some of the most common algorithms in recommendation systems, such as: content-based, user-based collaborative and items-based collaborative (see Section 2.1). In order to facilitate the versatility and usefulness of the algorithms, and since they are independent of the Web tool itself, these implementations were performed in a different environment, using the Java programming language, without incorporating them into the CMS discussed above. By working with a social network, new techniques for generating recommendations could be studied and established. In this sense, we actively developed our starting hypothesis, which was that by exploiting the trust derived from the network of collaborators or the reputation of a specific user, we could improve the recommendations generated. In particular, some of the most used techniques found in the literature were adopted, such as MoleTrust and TrustAll (Massa and Avesani, 2009). But then we proposed our own scheme based on trust, in which to generate the recommendations user ratings are not taken into account, but trust among them (Martínez-Cruz et al., 2015). A flow chart about how the system works is shown in Fig. 6. In this scheme, ontologies were used to facilitate the representation of the information, so we had to study and apply the related APIs that allowed its incorporation into the adopted CMS.

As you would expect nowadays, the social network can grow a lot, therefore, it is quite common the case in which two users do not know each other, so there would be no degree of trust between them. To solve this, we designed a procedure to estimate this trust in cases where there is no direct connection between two members. Moreover, as usual there are more than one way to connect two members, we have proposed and implemented several operators that allow the aggregation of the information about trust in each of the paths found, as discussed in Section 2.3.

With all these premises, numerous experiments were carried out with the various schemes, which were analyzed to obtain the best configuration to incorporate it into the new system. Many of these results were included in our previous work (Martínez-Cruz et al., 2015) and therefore, seeing the results obtained, the scheme of recommendation finally adopted and incorporated into the social network is precisely the scheme proposed and developed in that paper. It is a hybrid scheme between social, collaborative and content-based approaches, although giving more relevance to the social scheme because once the users began to interact more with the system, it showed a better behavior. Logically, the trust estimation technique was also incorporated, which also helped to alleviate the problem of the lack of data at the beginning of the system with social information.

In particular, to avoid the cold-start problem, the content-based schema was adopted, using the disciplines assigned when creating a resource (see Fig. 2). When a user has valued at least 20 resources, the user-based collaborative scheme is adopted. And finally, when there are at least 6 followed users (explicit degrees of trust are available), the trust-based scheme as presented in Martínez-Cruz et al. (2015) is used.

4. System evaluation

To evaluate a recommender system, we can make use of offline and online experiments, both with their advantages and disadvantages. Traditionally, the offline evaluation has been more used, centered on specific metrics, in many cases adopted from the area of information retrieval, such as precision, coverage, recall, F1, and so on. To obtain them, various standard data sets available online are used. However, due to the philosophy of this kind of systems, it is becoming increasingly common

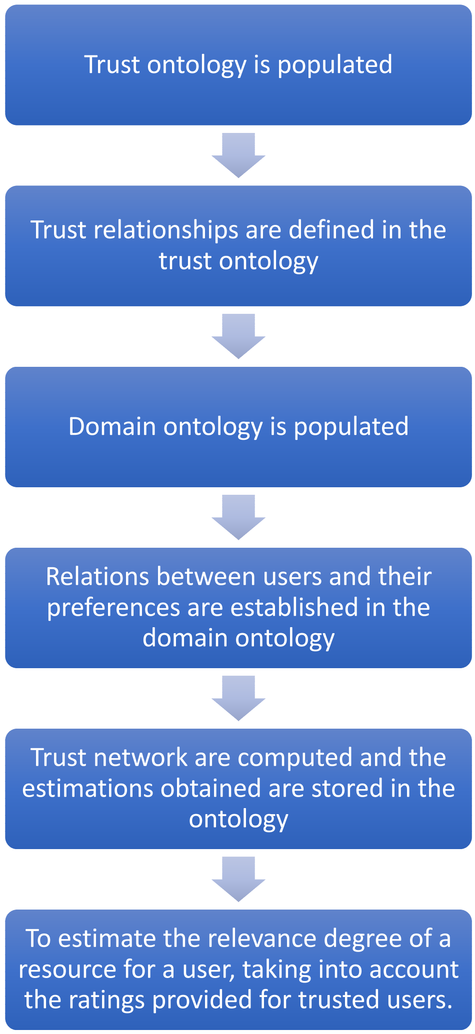

Fig. 6. Overview of system operation.

to adopt user-oriented evaluation methods (Knijnenburg et al., 2012; McNee et al., 2006), in which aspects such as satisfaction, usability, degree of fulfillment of diverse objectives, and so on. In our case, we add the fact that when evaluating recommendation systems applied in the educational field, we have neither data sets nor standardized evaluation procedures. In addition, in an environment such as the educational one, it does not seem very propitious to focus the system evaluation process on technical aspects and to leave aside other aspects such as the needs and characteristics of the students (Manouselis et al., 2011).

Despite, we have put forward an evaluation with a double aspect: offline and online. This section describes the different experiments and results obtained for the evaluation of the following aspects: accuracy in the prediction of valuations, coverage, satisfaction of actual users with the recommendations received and system usability tests. The first two aspects are evaluated by offline experiments, using a standard data set, while the last two are evaluated with online experiments, keeping the system fully operational and interacting with real users within the system.

4.1. Offline tests

As discussed in previous sections, in this paper we present an educational social network that includes a recommender system to customize access to relevant teaching resources. However, it should be clarified that a new approach to the generation of recommendations is not really proposed, but, given the good results obtained with it, we adopt our approach previously presented in Martínez-Cruz et al. (2015). We emphasize this because the offline experiments performed to evaluate the precision and coverage affect exclusively the recommendation approach and not its integration in the Web platform. Therefore, these experiments, as well as the data set used (variation of the Epinions dataset (Massa and Avesani, 2009)) and results obtained were already analyzed in Martínez-Cruz et al. (2015), so they can be consulted in detail in that work.

Analyzing the conclusions obtained in the cited study, we can see that, except for very specific configurations, the approach based on trust, and therefore adopted in the social network presented in this work, surpasses in global performance other approaches analyzed; particularly, the Mean Average Error (MAE) achieves an improvement of 2.42%. Although, the best results of our proposal become clear if we analyze the coverage, clearly exceeding the other approaches analyzed.

4.2. Online tests

This subsection describes the online experiments that have been carried out, using the first fully operational version of the Web system. Being online tests, these experiments were developed directly with the users, through various polls that were filled out after having interacted with the system. The answers and opinions provided to each question are used for the validation of both user satisfaction and the usability of the system, which are explained below. But first we will detail the characteristics of the users who have participated in these experiments.

These online experiments have been carried out on a large group of users, considering both students and teachers, from Spanish universities in Jaén,[9] Granada[10] and Universidad Internacional de La Rioja (UNIR).[11] To consider a wide range and diversity of users, we have considered three levels with the idea of incorporating users with different computer skills: education directly related to computing, education not directly related but very in touch with information technologies, and thirdly, education whose relationship with computing is very scarce or practically null. Specifically, the subjects and education plans considered, together with the number of participants involved with each, are specified in Table 1, adding a total of 425 participants.

4.2.1. Evaluation of users satisfaction

This section describes the online experiments developed to evaluate user satisfaction with the system. The users were working and interacting with the system and then provided their thoughts on their degree of satisfaction achieved in different aspects. To measure this degree of satisfaction it was used a label from the set S_4 showed in Section 3. On the other hand, the different aspects that compose the questionnaire and, therefore, had to evaluate the users, are based on the model proposed in Manouselis et al. (2011) to evaluate the success of a recommender system applied in the educational field. We have adopted this model because of the numerous similarities with the case in hand, and therefore, because of its ease of application with a low need for adaptation. In addition, from the user's point of view it is easier for them to provide information if there are few questions, considering that users are usually reluctant to answer surveys. In particular, the following four issues were assessed:

- **Q1**. *Do you like the recommendations received and made by the system?* The idea is to measure the reaction of users, analyzing what they think and feel when using the system.
- **Q2**. *With the help of the system, do you consider that you have learned the necessary, as well as new ideas?* In this case we focus on learning, assessing if it is considered that there has been an increase in the acquisition of new knowledge or skills.

[9] http://www.ujaen.es/serv/vicint/home/index.
[10] http://www.ugr.es/en/.
[11] https://en.unir.net/.

Table 1
Users description and considered academic degrees.

Signature	Degree	University	Number of participants
Teachers	Various	Jaen and Granada	14
Information capture and storing methods	Data science practitioner expert	UNIR	84
Computer basics	Degree in civil engineering	Granada	42
Data structure	Degree in computer engineering	Granada	63
Design and development of computer systems	Degree in computer engineering	Granada	50
Distributed large-scale data computing	Master in computer engineering	Jaen	6
Distributed databases	Degree in computer engineering	Jaen	5
Computing	Degree in industrial engineering	Jaen	93
Computer systems applied to finance analysis	Degree in finance and accounting	Jaen	50
Computer tools in business finance	Degree in finance and accounting	Jaen	18

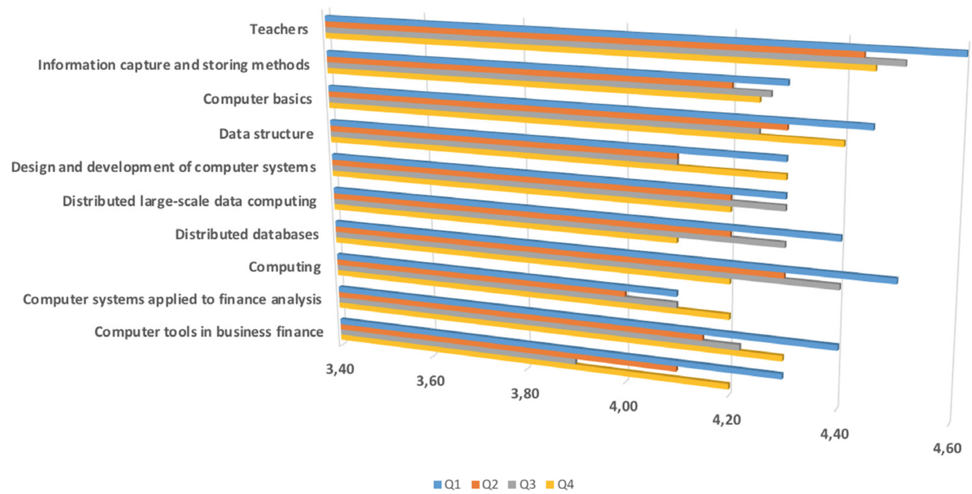

Fig. 7. Average of the satisfaction degree given by the user to each question.

- **Q3**. *Do you think the new information and ideas that the system has recommended you are useful?* In this case we intend to assess the behavior considering how the knowledge and skills acquired could be applied or used in real life.
- **Q4**. *Do you think the ideas and information recommended improve the effectiveness and results of the learning process?* With this last question we look at the results, valuing the effects on the behavior of the users in their learning environment.

Once all the answers on degrees of satisfaction were collected (labels of the set S_4), we proceeded to compute aggregate data using the 2-tuple arithmetic mean (Herrera and Martínez, 2000; Martínez-Cruz et al., 2015) to work with 2-tuples. Then, the final average values were obtained using the function Δ^{-1} (see Section 2.2) defined to transform 2-tuple into values.

The Fig. 7 shows at a glance the answers provided to the different questions by the users of each of the academic disciplines, as well as teachers. Taking this data into account, Table 2 shows the final mean values for each user group. With these results, we obtained an average satisfaction score of all users together of 4.26 (85.9%) and with a mode value of 4.25 (85%). These results are quite positive and show not only that the system satisfies users without additional training (the only requirement is the availability of the Internet and a Web browser), it also generates recommendations that satisfy the needs of the users. In addition, informal comments received from teachers were very positive about how our social network facilitates the task and considers it very useful for students.

4.2.2. System's usability evaluation

In this section we describe the experiments performed to evaluate the usability of the system, as well as the results obtained with these experiments. To raise them we rely on the guidelines and heuristics presented by Nielsen in his work (Nielsen, 2005), for their great impact among the community of user interface developers and numerous previous studies in which they have been applied. These guidelines allow the user to evaluate the usability of the system by assessing the following elements:

1. Visibility of the system status: the system keeps the user informed about what he is doing at any moment.
2. Relationship between the system and the real world: the system communicates with the user using a familiar language.
3. User control and freedom: The system includes methods for users to regain control after accessing unwanted functions or options.
4. Consistency and standards: The system adopts standardized conventions that allow users not to have to ask if different words, situations or actions mean the same thing.
5. Error prevention: The system includes confirmation options to prevent errors.
6. Recognition rather than remember: the system keeps the various options visible to minimize the need for users to memorize them.
7. Flexibility and efficiency of use: the system allows to accelerate the interaction of expert users, for actions that they carry out frequently.
8. Aesthetic and minimalist design: the dialogs displayed by the system contain relevant and widely used information, thus facilitating its visibility.
9. It helps users to recognize, diagnose and recover from errors: error messages are expressed in plain language, indicating the problem and suggesting a solution.
10. Help and Documentation: The system provides user-friendly documentation and easy access.

To answer each of these questions, each user indicated their opinion about the degree of compliance of the system for each one. To do this they had to select one of the labels from the set S_4 of the linguistic

Table 2
Summary of the satisfaction rate given by the users.

Signature	Degree	Rating obtained
Teachers	Various	4.5
Information capture and storing methods	Data science practitioner expert	4.26
Computer basics	Degree in civil engineering	4.35
Data structure	Degree in computer engineering	4.20
Design and development of computer systems	Degree in computer engineering	4.25
Distributed large-scale data computing	Master in computer engineering	4.25
Distributed databases	Degree in computer engineering	4.35
Computing	Degree in industrial engineering	4.10
Computer systems applied to finance analysis	Degree in finance and accounting	4.28
Computer tools in business finance	Degree in finance and accounting	4.13

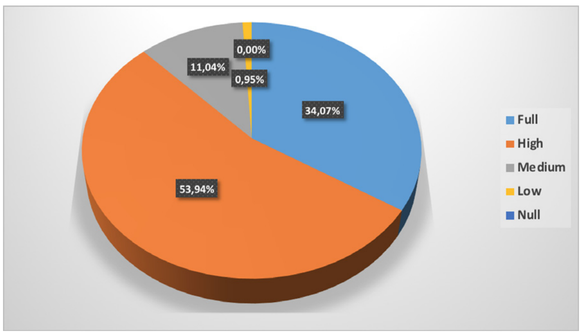

Fig. 8. Usability tests results.

hierarchy LH defined in Section 3. Of the 425 users who participated in the tests and used the system as described at the beginning of the section, only 317 completed the usability questionnaire. As shown in Fig. 8, of those 317, a large majority (88.01%) indicated a degree of *Full* (34.07%) and *High* (53.94%), while only 11.99% of the total responses belonged to the *Medium* (11.04%), *Low* (0.95%) y *Null* (0%). These results reflect a great satisfaction on the user part regarding the usability of the system. Despite this, we also open a suggestion box in which users can leave their feedback with the idea of incorporating them into the system in future versions.

5. Concluding remarks

In this paper we have designed, developed and implemented SharingNotes, a Web platform that allows the creation of an educational social network, incorporating mechanisms that really help to disseminate pedagogical resources in a personalized way. The idea is that using this platform we can improve the teaching–learning processes, adapting the materials to the educational needs of each student. This social network aims to serve as a meeting point for students and teachers who want to share educational resources in a personalized way. The platform is operational and accessible through the following link: http://sharingnotes.ujaen.es/.

To achieve that goal, SharingNotes integrates a hybrid recommender system based on trust, collaborative and content-based approaches, and incorporates ontologies to improve the representation of user profiles and the trust between the users of the social network. To facilitate the management and representation of information, we adopt the multi-granular fuzzy linguistic modeling that gives us greater flexibility in the system-user interaction, because it allows us to manage the information by representing the different concepts of the system with different linguistic label sets. Regarding the process of generating recommendations, note that in order to take advantage of the specific casuistry of a social network, when the trust-based approach is activated, users with a similar history of valuations are not taken into account, but trusted users are, information that can be extracted from the social environment of users. In addition, it is applied a method for estimating trust between user pairs (which have not explicitly provided it) consists of finding all possible paths that connect those users, exploring the ontology used to represent the trust network. And finally, we aggregate the trust information obtained from the most relevant paths.

We also have evaluated the proposed system, developing offline and online experiments. The obtained results reveal a high system performance in terms of precision, as well as great satisfaction and usability for users.

As possible future work, we propose to explore the application of our own specific metrics to the analysis of social networks, and incorporate them in new recommendation approaches.

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