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Fuzzy Linguistic Recommender Systems for the Selective Diffusion of Information in Digital Libraries

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Abstract
The significant advances in information and communication technologies are changing the process of how information is accessed. The internet is a very important source of information and it influences the development of other media. Furthermore, the growth of digital content is a big problem for academic digital libraries, so that similar tools can be applied in this scope to provide users with access to the information. Given the importance of this, we have reviewed and analyzed several proposals that improve the processes of disseminating information in these university digital libraries and that promote access to information of interest. These proposals manage to adapt a user's access to information according to his or her needs and preferences. As seen in the literature one of the techniques with the best results, is the application of recommender systems. These are tools whose objective is to evaluate and filter the vast amount of digital information that is accessible online in order to help users in their processes of accessing information. In particular, we are focused on the analysis of the fuzzy linguistic recommender systems (i.e., recommender systems that use fuzzy linguistic modeling tools to manage the user's preferences and the uncertainty of the system in a qualitative way). Thus, in this work, we analyzed some proposals based on fuzzy linguistic recommender systems to help researchers, students, and teachers access resources of interest and thus, improve and complement the services provided by academic digital libraries.

Keywords
Digital Libraries, Dissemination of Information, Fuzzy Linguistic Modeling, Recommender Systems

1. Introduction

Digital libraries contain collections of information that via the use of several technologies have various services that are provided to users. These collections can cover different areas, such as scientific, business, academic, or personal data, and can be modeled in different digital formats. As such, the information could be digitalized or digitally born information and the services, which can be made available to individuals or user communities, can be varied. The expansion of information and communication technologies and internet access has led to the widespread use of digital libraries including various purposes, in which collaboration and sharing have become important social elements. With the increasing usage of digital libraries and the majority of contents and

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services, users expect these new services to meet their needs [1–3]. The proper functioning of digital libraries is achieved through human resources, who are responsible for enabling and managing users' access to the resources that are the most interesting to them. These human resources must do so considering users' needs and their areas of interest [4]. The library staff search, evaluate, select, catalogue, classify, preserve, and schedule access to digital documents [5]. Digital libraries have been incorporated into many environments, but we focused on the academic context. Specifically, we honed in on University Digital Libraries (UDLs), which supply several services and information resources to the users in an environment where research, teaching, and learning come together [6,7].

The exponential growth of web-based applications and digital documents causes users to have difficulties accessing the information they are looking for in a simple and time-effective way. The use of automated tools would help them to deal with and manage the large amount of information available to them in digital format online [8]. Moreover, the web influences other forms of information media, such as newspapers, journals, books, etc., and more specifically, the development and growth of academic digital libraries [7]. The major problem that these libraries have to address is the exponential growth of information because their employees have problems executing the tasks of delivering the information to users.

By default, any digital library has a traditional search tool, but these tools are no longer for users as their needs or preferences are more complex and the volume of digital resources handled by the library keeps growing. For this reason, digital libraries tools should take a more active role and offer users (individuals and communities) new services that facilitate access and personalization of information, and that make it possible for users to share their knowledge [1]. As such, it is very interesting that digital libraries could advance the users' preferences or needs and provide them resources that could be of interest to them. Given these features, a service that is especially useful and important in a UDL is the selective dissemination of information. This means that users develop and manage their interest profile, so that when new resources are added to the collection of information, the UDL can notify users that there are new resources for them [5]. Due to the problem of information overload, it is often difficult to obtain useful or relevant information when necessary. When the users of a UDL tries to access to relevant information, they often obtain non-useful information or information that does not meet their preferences. Users should be able to easily access as much of the available resources as possible but this is a difficult goal to achieve in many UDLs. [9,10].

As can be done online, we can use recommender systems to facilitate and customize access to information. A recommender system helps users to discover information items that are likely to be of interest to them. Therefore, this system is especially useful when it helps a user to discover items that he or she was previously unaware of. One of the keys to this system's success is that an effective personalization is achieved because it is able to treat each user in a customized way [11].

To achieve effective and real personalization, the system must be fed with information obtained from users, such as their assessments about items that they previously explored [12,13]. With the information or knowledge obtained from the users, the system sets and manages their profiles, which contain their preferences or needs. However, different approaches can be applied to acquire and exploit this information, depending on the recommendation approach adopted. In this sense, we can acquire implicit information (i.e., without user intervention) and analyze user behavior, or we can request the users to explicitly state their preferences.

In keeping with everything mentioned above, we have reviewed and analyzed different proposals that favor the dissemination of information in UDLs. Based on the success shown by the application of a recommender system, we focused on proposals that were based on these recommendation techniques [10]. Furthermore, these proposals also face the problem of there being a wide variety of ways to represent and evaluate information, which is more marked when users are part of the process, as is the case of UDLs. Therefore, we also exposed the fuzzy linguistic modeling that allowed us to represent and efficiently manage the qualitative information present in the communication processes, as in previous proposals in which fuzzy approaches were applied [7,]. Specifically, we analyzed the multi-granular approach that provides greater flexibility in the system-user interaction [14,15].

We analyzed four proposals, each of them improving the performance of the previous one:

1. The first, proposes a fuzzy linguistic recommender system that recommends both specialized resources for the user interest area and complementary resources that could be interesting to form multidisciplinary groups [16].
2. The second, proposes a new method for obtaining information about a user's preferences reducing the great effort of previous proposals. Users provide their preferences on some research resources (by means of incomplete fuzzy linguistic preference relations) and from this information the system obtains their respective preference vectors on topics of interest [17].
3. The third, improves the previous proposals with a recommender system that uses memory to avoid the information overload problem that is persistent within UDLs. The main idea is to use previously selected items to make a new selection in a new recommendation round [18].
4. The last proposal deals with the recommendation generation process related to research resources as a task with two distinct elements: Finding research resources that are relevant to the users, and finding valid research resources from the standpoint of the quality of items [13].

The paper is structured as follows: Section 2 revises the preliminaries needed to understand the analyzed proposals. In Section 3, we analyze several proposals to improve the dissemination of information in digital libraries. Section 4 shows lessons learnt and highlights some challenges to be focused on. In Section 5, we present our conclusions and ideas for possible future work.

2. Preliminaries

2.1 Basis of Recommender Systems

The main objective of these systems is to orient users in a personalized way in situations in which they must choose between a wide range of possible options [12,13]. To do so, these systems need some knowledge about the users, such as their tastes, preferences, or their ratings of previously explored resources. There are two ways to get this information: One option is to obtain it explicitly, (i.e., users directly provide their preferences), and the other, to do so implicitly (i.e., analyze user behavior, without the need for direct intervention).

Another issue to consider is the approach chosen for generating recommendations. By having analyzed the literature, we were able to verify that there are diverse classifications with a variety of approaches [12,19]. These are the most important approaches:

- By using the *content-based approaches*, the recommendations are generated by using the features used to represent the resources or items and the ratings provided by the users.
- In the *collaborative approaches*, the recommendations are generated by using only user profiles, (i.e., implicit or explicit information about users' preferences) and ignoring the resource representation.
- Other approaches extend these basic concepts and lead to new ways of generating recommendations, such as *Demographic systems*, *Knowledge-based systems*, and *Utility- based systems* [12].

Each of these approaches has its strengths and weaknesses, but the success or failure of applying a particular approach depends on the scope of application in which it is used. Therefore, a solution that is widely accepted and used in many systems is to adopt a *hybrid approach* [12]. This approach consists of a combination of other approaches and is based on the idea of taking advantage of each different approach and reducing its drawbacks.

2.2 Fuzzy Linguistic Modeling

This modeling is based on a basic concept, proposed by Zadeh [20-22] and is known as a linguistic variable. This theory has been applied and continues to be successfully applied in many areas, because it allows for the satisfactory modeling of qualitative information that is present in many real-life settings. In the following subsections, we will briefly describe the fuzzy approaches used in the proposals that we reviewed.

2.2.1 The 2-tuple fuzzy linguistic modeling

The first two models proposed were the classical and the ordinal, but using them resulted in a loss of information. To reduce these losses, the authors in [23] proposed a continuous model of information representation based on the concept of 2-tuple. To represent and aggregate the linguistic information, a 2-tuple representation model must first be established and then a 2-tuple computational model.

We worked with a set $S=\{s0,\dots,sg\}$ of linguistic terms that has odd cardinality. We assumed that triangular membership functions were used to assign the semantics of each label and that all of the terms were distributed on a scale on which a total order has been defined. As such, when we carried out any aggregation operation with linguistic information, we obtained a value $\in [0, g]$. V does not belong to the selected label set (i.e., $V \notin \{0,\dots,g\}$) and V can be represented as a 2-tuple (si,di), where si is the linguistic label and di *is* a numerical value expressing the value of the translation between numerical values and the 2-tuple. The Δ and Δ-*1* functions are used to transform values to 2- tuples and vice versa (i.e., $\Delta(V)= (si, di)$ and $\Delta\text{-}1(si, di) = V\in[0, g]$) [23].

Negation, comparison, and aggregation operators are necessary for defining the computational model. Any of the aggregation operators can be modified, using functions Δ and Δ-*1*, for dealing without a loss of information with linguistic 2-tuples [23]. Taking this into account, we could use the arithmetic mean, the weighted average operator, or the linguistic weighted average operator.

2.2.2 Multi-granular linguistic information modeling

When dealing with linguistic information, problems arise when different experts have distinct levels of uncertainty about the same aspect or when an expert must evaluate different concepts. One way to solve these problems is to use several linguistic label sets with different granularities of uncertainty, which is known as multi-granular linguistic information [24]. Then, this new modeling is based on the concept of linguistic hierarchy. In [24], the authors proposed a multi-granular 2-tuple fuzzy linguistic model, which has been successfully used in many areas. A linguistic hierarchy (LH), is defined from a set of levels, where each level is a linguistic term set with different granularity. Moreover, in [24], the authors addressed the best way to transform labels into levels. These functions allow for the computational model to be defined by selecting a level as a reference to unify the information. As such, we could use the established operator in the 2-tuple model and were able to obtain the transformations between different levels of a linguistic hierarchy without losing information.

2.3 Incomplete Fuzzy Preference Relations

By considering a set of choice options $O=\{o1,..,on\}$, we defined the fuzzy preference relation *Pref* as a fuzzy set on the product set $O\times O$. Thus, a fuzzy preference relation is defined by the membership function of $\mu Pref\colon O\times O \rightarrow [0,1]$. When the cardinality of O is small, the preference relation may be represented by the $n\times n$ matrix *prefij*, where each element $prefij=\mu Pref\ (oi,oj)\ (i,j\ \in\{1,\ldots,n\})$ is interpreted as the preference degree of the option of *oi* over *oj* while still taking into account that $prefij=1/2$ indicates an indifference between the two options. $prefij=1$ indicates that *oi* is completely preferred over *oj*, and $prefij>1/2$ indicates that *oi* is preferred over *oj*.

As these proposals work on a linguistic context, a linguistic preference relation must be defined. Assuming that the set of alternatives is O and the linguistic term set is S, a linguistic preference relation $LPref=lprefij\ (i,j\ \in\{1,\ldots,n\})$ on O is defined as:

$$\mu LPref\colon O\times O \rightarrow S\times[0.5,0.5) \tag{1}$$

where, $lprefij=\mu LPref\,(oi,oj)$ is a 2-tuple which denotes the preference degree of option *oi* regarding to *oj*.

The problem with this representation scheme is that sometimes experts are unable to assign all the preference values. In these cases, a possible solution is to use incomplete fuzzy preference relations [25-27]. To understand this concept, let us first remember the definitions of total and partial functions. Suppose function g defined as $g\colon A \rightarrow B$. We would then say that g is a *total* function when each element of set A corresponds to an element of set B. On the contrary, we would say that g is a *partial* function if every element in set A does not correspond to an element in set B. Then, an *incomplete 2-tuple fuzzy linguistic preference relation* is a 2-tuple fuzzy linguistic preference relation in a set of options with a partial membership function.

3. Proposals to Improve the Dissemination of Information in Digital Libraries

In this section we review different proposals for facilitating or improving the dissemination of information in digital libraries.

3.1 A Multi-disciplinary Recommender System for Advice Research Resources in UDLs

The first proposal is presented in [16], where the authors present a fuzzy linguistic recommender system that recommends two kind of resources: specific resources related to the user research area and complementary resources. This second class of resources makes it possible to include resources from associated areas that could lead to motivating collaboration possibilities with different researchers and to form working groups. The vector model [28] is used to model both the topics of interest that characterize the user profiles and the resource scope. A classification composed by 25 disciplines is used, and in each position of the resource or user vector, a linguistic 2-tuple value represents the importance degree of the discipline regarding the resource or the user's topics of interest. The recommendation approach is based on matching amongst the terms used in the representation obtained for the resources and the users [28]. The vector model is used to represent both the resource scope and the topics of interest of the user. Since the system works with linguistic values, a linguistic similarity measure $\sigma l(V1,V2)$ is defined based on a cosine measure. Fig. 1 shows the operation structure of this proposal.

The recommendation strategy has two phases.

1. To generate recommendations for resource *i*, the systems computes $\sigma l(UVi,RVj)$ between the resource scope vector (*UVi*) and vectors of all available resources (*RVj, j=1 … m,* being the quantity of resources). The resource *j* is selected if $\sigma l(UVi,RVj)$ *is* greater than or equal to a linguistic threshold value and is used filter the information.
   The next step is to recover the users who assigned positive ratings to the resources selected in the previous step. To get the significance of resource *r* for user *u*, the system computes the arithmetic mean from the value $\sigma l(UVi,RVj)$ using the previous ratings provided by *u* about similar resources and with the ratings given by other users. At that point, the system sends the resource information and its calculated linguistic relevance degree to the selected users if the obtained relevance degree is greater than a threshold. If not, the system proceeds to evaluate whether the resource could be used as a complementary recommendation or not.
   To estimate the complementary recommendations, the system computes $\sigma l\ (RVr, UVu)$ amongst the representations of resource *r* and user *u (*for all users of the system). Next, a multidisciplinary function is applied to the value $\sigma l(RVr,RVu)$. The idea of applying this function is to assign greater weights to matching middle values, because values of total similarity contribute with effective recommendations but are probably known by the users. As it is the case for null values, the similarities between areas show the worthless relationship. To do this in the proposed approach, a triangular function is used. Finally, if the value obtained with the multidisciplinary function is greater than a previously defined linguistic threshold, the system defines the resource as being complementary
2. The process of generating recommendations for user *u*, is similar, but computes $\sigma l(UVu,UVw)$ between the topics of interest vectors of the new user (*UVu*) against all users in the system (*UVw, w=1…n*, where *n* is the number of users). If, $\sigma l(UVu,UVw)$ is greater than or equal to a linguistic threshold value, user *w* is selected as a close neighbor of *u*. Next, the system searches for the resources that satisfy these users. To obtain the relevance of resource *r* for user *u*, the system aggregates $\sigma l(UVu,UVw)$ with the previous assessments provided about *r* by the nearest

neighbors of u. If the computed relevance degree is greater than the linguistic threshold, the system recommends the resource information and its estimated linguistic relevance degree to the user. If not, the system estimates whether the resource could be interesting as a complementary recommendation for the user or not. The system computes $\sigma l(UVu,RVr)$ between user u and resource r (for all resources). Then, it applies the triangular function to the value $\sigma l(UVu,UVr)$. Depending on the multidisciplinary value obtained, the system recommends the resource as complementary. It does so if the value is greater than the threshold.

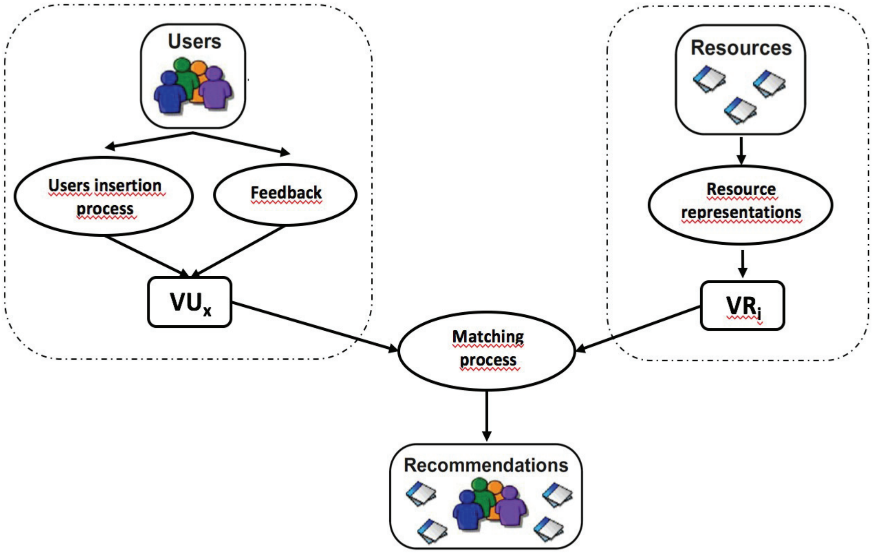

Fig. 1. Operating structure of first proposal.

3.2 Dealing with Incomplete Information in a Fuzzy Linguistic Recommender System to Disseminate Information in a UDL

The second proposal is presented in [17]. The problem of the previous proposal is that users must explicitly specify the information used to define their profiles stablishing directly their preferences on all topics of interest, with the consequent effort on the part of the users that this implies.

The system presented in [17] and introduced in this subsection, proposes the use of incomplete fuzzy linguistic preference relations so that users can provide their preferences more easily [25], and this facilitates the determination of user profiles. To decrease that effort and make the process of acquiring user preferences easier, a different method to obtain user preferences on topics of interest is proposed. The system shows the users the five most representative resources, so they can then use an incomplete fuzzy relation of preference to establish their preferences about the shown resources. The main benefit of this technique is that it is sufficient for users to supply only a row of the matrix, because this matrix is completed using the method proposed in [26]. Once the system completes the matrix, it is possible to get a final vector that models user preferences about subjects of interest.

Fig. 2 shows the operation structure of this proposal. The novelties with respect to the previous proposal are represented in blue.

The recommendation strategy is built on a matching process developed among user profiles and resource representations, using a linguistic similarity measure based on cosine measure, *σl(V1,V2)*. To generate the recommendations for a resource *r*, *σl* is computed, between the representation vector of the resource (*RVr*) and all the user preference vectors, *{UV1,…,UVm}*, with *m* being the quantity of registered users. All users for which the obtained similarity value exceed the linguistic threshold previously defined, are chosen to obtain recommendations about resource *r*. Moreover, for users who want it, the system also recommends collaboration possibilities. The linguistic compatibility degree is obtained computing *σl(UVu1,UVu2)* between each two users *u1* and *u2* who want to collaborate.

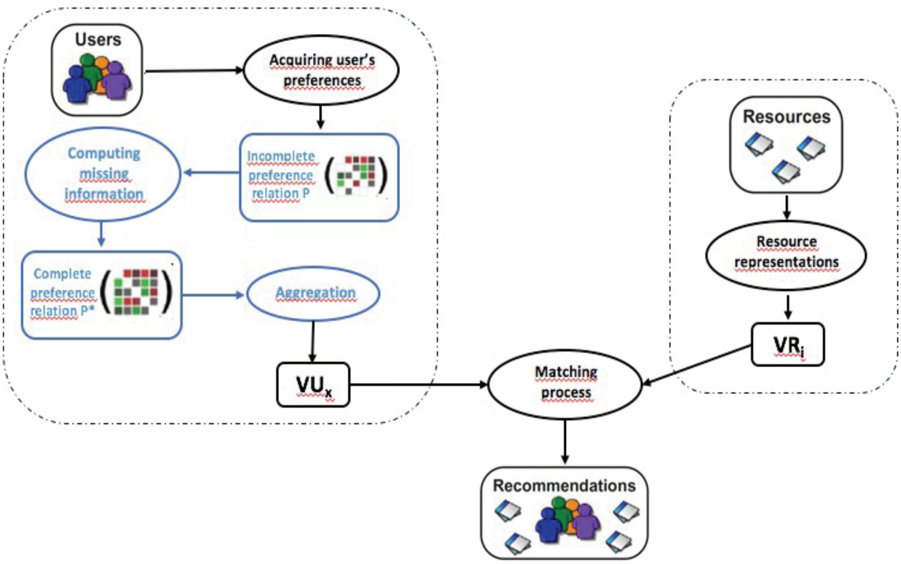

Fig. 2. Operating structure of second proposal.

3.3 An Improved Recommender System for Avoiding Persistent Information Overload in a UDL

The third proposal we analyzed is presented in [18]. Although the application of the two previous approaches makes it possible to deal with the information overload problem, the amount of accessible digital content grows at a significant rate and the problem rises again. Therefore, it can be said that the persistent problem of information overload remains.

The idea of this proposal is to use a battery to store items that were selected but not recommended. It is in this way that the system is able to include these interesting resources in forthcoming rounds of recommendations. For example, this could be useful in cases where there are not enough items to recommend or if the user requests outputs obtained by combining items selected in different recommendation cycles. Users are asked to express their preferences about the quantity of items to obtain in each recommendation round and about the freshness for them of those resources.

As shown in Fig. 3, this system works in two phases. The main novelties with respect to the preceding proposal are shown in orange. The two phases are as listed below.

1. To generate the recommendations using the recommendation approach of the previous proposal [17].

2. To apply a second filter or selection process according to the user's restrictions, and to take into account the number of recommendations that the user would like to receive, which are described below.
   a. If the number of resources selected in phase 1 is less than the desirable number of recommendations the user would like, the system recovers the resources that were previously selected but not recommended. Then, the system reapplies the process of generating recommendations, but now with the incorporation of recovered items.
   b. If the quantity of selected items is sufficient, the system checks the restrictions talking about the novelty of the resources (i.e., if the user is also interested in the resources selected in previous recommendation rounds that could still be relevant). If the user wants both kinds of resources, the system loops within the process of generating recommendations of the first phase and incorporates the recovered resources.

Lastly, the system shows users the resource information and the calculated linguistic relevance degree. For users who want to collaborate, the system also sends them potential collaborations that are categorized by their linguistic compatibility degrees.

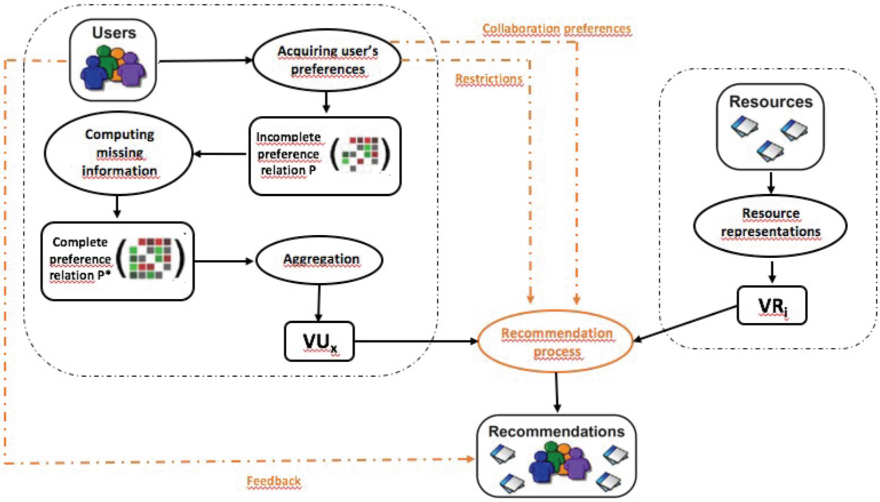

Fig. 3. Operating structure of third proposal.

3.4 A Quality-based Recommender System to Disseminate Information in a UDL

Finally, we analyzed the proposal presented in [13]. By having analyzed the previous proposals, different aspects that may limit their performance were found. They do not really work as a recommendation system because they base their operations on matching calculations, which limits their performance. Furthermore, the amount of digital resources produced daily grows unimpeded, so the problem appears again and the system's performance decreases.

In this proposal, the system incorporates a hybrid recommendation approach [29] that changes between a collaborative recommendation approach and a content-based one with the idea of sharing individual experiences for the entire community's knowledge. This double perspective makes it possible to minimize the cold-start problem because the system switches from one approach to another depending on the circumstances.

Furthermore, now the recommendations generation process is a task with two distinct elements: One is finding resources that are relevant to the users and the second is finding valid resources from the standpoint of the *quality of the items* [30]. The operation structure of this proposal is illustrated in Fig. 4, where the innovations with respect to the previous proposal are shown in green.

The system incorporates a new module that performs a *re-ranking* process that considers the estimated relevance of a resource along with its quality. However, the problem is how to obtain resource quality without much interaction from users. Therefore, a novel way to estimate the quality of resources is proposed. It is based on the idea of whether one resource is usually preferred than others, and indicates that the resource has a certain quality. To do so, the system incorporates the method presented in [17] in which users are asked to provide their preferences on five research resources by means of an incomplete fuzzy preference relation. At that time, the system completes this preference relation. This method is used to obtain user profiles and to estimate the quality of these resources. It is assumed that resources that are usually preferred over others have a higher quality. As such, the times that each resource has been selected to be shown and the times that each resource has been preferred over another can be counted. The shown resources will differ over time, so the system must record each time a resource is selected and each time a resource is favored over another. The superiority of a resource is estimated in connection to the probability that the resource is chosen over another one.

Once a research resource is considered appropriate for a user, and both the calculated relevance degree and the resource quality score have been computed, the last step is to aggregate both in a single score. To do this, the system uses a multiplicative aggregation in which the estimated relevance is multiplied by the translated quality score (with the corresponding linguistic transformations). Then, the system recommends these resources to the user along with the final estimated scores to justify the recommendation.

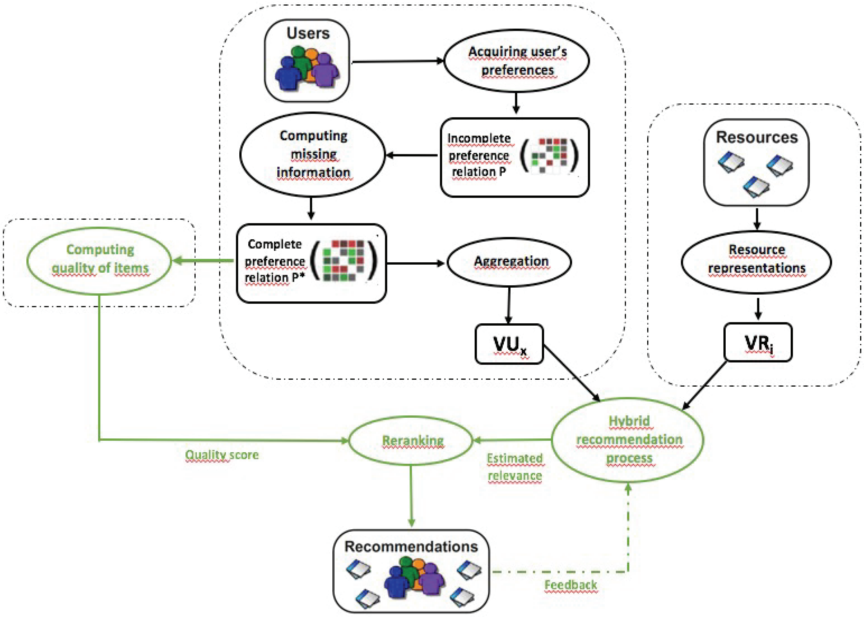

Fig. 4. Operating structure of fourth proposal.

4. Lessons Learned and Challenges

In this section, we provide a description of what we learned during the development of this work, focus on the advantages and disadvantages of what has been achieved so far, and highlight the new challenges must be addressed in order to improve the proposals.

Over time, we observed how UDLs have evolved to satisfy the needs of teaching and learning in relation to educational processes. A natural evolution of these web tools can occur if focus is placed on how traditional libraries have evolved. It is known that libraries play social and intellectual roles in the sense that they connect and bring people and ideas together [31]. Traditionally, libraries have provided a place for teachers and students to meet outside the classroom. This eases the interaction between people with different perspectives, and goes beyond a simple subject or group. This interaction between people in a library provides a global scope that allows to analyze those who participate in certain specialized studies and new possibilities for alternative ideas are opened. This favors the collaboration between and the formation of multidisciplinary groups. UDLs make these things possible by breaking the physical barriers of a library, and facilitating access to resources and information about other users beyond a physical space in one that extends all over the web.

However, the enormous increase in the use of web technologies, and, therefore, the creation of digital resources, makes the spread of information an increasingly important service for a UDL. In turn, this growth means that in order for them to continue being useful tools, they need to be adapted fit to the new scenarios that are emerging, and the information dissemination services need to be optimized. Hence, it is necessary to keep them updated with the new features, which implies the need for a continuous development of the tools so that they continue to be useful.

In this scenario, quite a few milestones have been achieved over the last few years thanks to the application and rapid advance of information technologies. The possibility of working with enormous amounts of information, such as images, audio, video, and multimedia material [32], can be highlighted. However, it is crucial to not just work with these amounts of information, but to do so in a personalized way. So far, numerous techniques, such as the proposal presented in Subsection 3.1, have been applied. The problem is that on certain occasions it is the users themselves who must explicitly manage the information. In this context, it could be helpful the application of automatic learning techniques that make it possible to automate the construction of user models. Some progress has also been made in regards to this topic, such as the last three proposals presented in this paper (see Subsections 3.2, 3.3, and 3.4).

However, despite all these advances and the advantages of applying these techniques their main restriction is the need to interact with UDL staff to establish internal representations of teaching and researching resources. As a result, there is a significant challenge that must be addressed: To continue to improve the automatic establishment of user profiles and to study and apply automatic techniques that allow for the modeling of internal representations of the resources.

Moreover, following the idea that UDLs are updated with the new trends and characteristics of the environment, it is fundamental to deal with the massive expansion of social networks, both in terms of publishing users' content and those who share social resources [33]. Social networks have been attracting a huge number of active participants, especially some of them such as Twitter (https://twitter.com/), which provides the possibility of quick interactions between users due to the existing limitations on the number of characters for each message. Therefore, it has been observed that social networks effectively manage the problem of knowledge acquisition by attracting millions of active users, which is undoubtedly a fact to take into account in order to improve the services provided by a UDL. All the information that a user actively provides can be exploited to obtain the correct personalization, with little effort on the part of the users. This ultimately contributes to generating more useful and effective recommendations for them.

A third challenge that we identified is that the development and application of recommender systems in UDLs is still in its initial stages. Apart from theoretical studies, it is very difficult to find examples of real UDLs that are experiencing the extension of their services via the application of recommender systems [33].

As such, wed believe that the opportunities and challenges for future UDLs pass through a triple perspective, as described below.

- As the information that is electronically generated is continuing to grow, and is expected to keep doing so, new tools or techniques will have to be created. The idea is to favor the personalization of services and the dissemination of information in a personalized way, which will make it possible to automatically establish user profiles and the internal representation of resources.
- Consider the social environment of the users. The idea would be to exploit diverse information extracted from different social media sites that users participate in. Doing so would help in the automatic construction of user profiles.
- Propose and implement real systems that facilitate the work of disseminating information in UDLs, and with its usage, as widespread as possible, obtain sufficient knowledge to facilitate the evaluation of these and other proposals that may arise.

Finally, we reckon that depending on the number of challenges accomplished, new challenges will appear. Effectively achieving adequate personalization and properly exploiting information extracted from the social network environment, new services of interest for users can be offered, which will also require addressing and solving new challenges.

5. Conclusions and Future Work

We have focused on the dissemination of information in a UDL, since it a very important service, and it is fundamental that it works correctly to fulfill its main mission, which is to provide users with access to content of interest. To achieve this, automatic tools are needed to help address its main problem, which is the exorbitant amount of digital content present in this area.

Recommender systems have been successfully applied in academic environments to help users in accessing relevant data. For this reason, we found it really interesting and in this paper, we have reviewed and analyzed several proposals based on a recommender system that help students, researchers, and teachers find the information they need. These proposals can improve and expand the services provided by the UDL to their final users. The four different proposals reviewed follow an evolution in the time. All of them are based on the application of a recommender system and use fuzzy linguistic modeling. Furthermore, each proposal improved the performance of its predecessor(s).

Analyzing these proposals, we were able to conclude and point out that although some progress has been made, it is fundamental to continue working to solve the information overload problem, which is even more pressing with the continuous advances in technology and social networks. By focusing on future research, we believe that a promising direction is to study automatic techniques to establish the representation of resources. Moreover, given the current situation of the intensive use of social networks, another idea is to explore new enhancements in recommendation techniques and to explore new methodologies for the generation of recommendations (i.e., extracting knowledge from the information that is shared in social networks).

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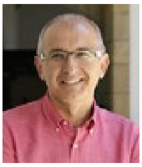

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