A LINGUISTIC RECOMMENDER SYSTEM FOR UNIVERSITY DIGITAL LIBRARIES TO HELP STUDENTS IN THEIR LEARNING PROCESSES

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Abstract

The Web is one of the most important information media and it is influencing in the development of other media, as for example, newspapers, journals, books, libraries, etc. These advances in Web technologies are promoting the development of new pedagogic models. These new models aid to improve the teaching-learning process. Consequently, in last years has led to a proliferation of personalized services that have been developed to provide the users with relevant information, according with their preferences or needs. Recommender systems are tools whose objective is to evaluate and filter the great amount of information available on the Web to assist the users in their information access processes. In this paper we propose a fuzzy linguistic recommender system to facilitate learners the access to e-learning resources interesting for them. Suggesting didactic resources according to the learner's specific needs, a meaning learning is encouraged, influencing directly in the teaching-learning process. The system is able to recommend both specialized and complementary resources, and additionally it is able to discover collaboration possibilities among University membership order to form multi-disciplinar working groups. So, this system increases the internal social collaboration possibilities in an academic environment and it contributes to improve the collaborative learning.

Keywords - Recommender systems, fuzzy linguistic modeling, university digital libraries.

1 INTRODUCTION

The main ideas of the new framework of the European Space of Superior Education (ESSE) request an upgrade of the educative system centered in the teaching-learning process, an active role of the stundents and a full integration of the information and communication techonlogies in the future educative systems. In the last years, to facilitate the establishment of this education european framework, the spanish academic system is developing its main aplications scopes, that is, the teaching, research and services proccesses [29].

These advances in Web technologies are promoting too the development of new pedagogic models [37]. These models, that complement the present education, are known as e-learning [25]. The new technologies improve the teaching-learning processes, aiding the information broadcasting in an efficient and easy manner, and providing tools for the personal and global communications that allow encourage the collaborative learning.

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In this sense, digital libraries could help to carry out this aim, because it allows teachers and learners the access to a great number of electronic resources. Digital libraries are information collections that have associated services delivered to user communities using a variety of technologies. This information can be digitalized paper or born digital material and the services offered on such information can be varied and can be offered to individuals or user communities [4, 10, 33]. Digital libraries are the logical extensions of physical libraries in the electronic information society. These extensions amplify existing resources and services. As such, digital libraries offer new levels of access to broader audiences of users and new opportunities for the library. In practice, a digital library makes its contents and services accessible remotely through networks such as the Web or limited-access intranets [28]. Concretely, University Digital Libraries (UDL) provide information resources and services to learners, faculty and staff in an environment that supports learning, teaching and research. A service that is particularly important is the selective dissemination of information or filtering. Users develop interest profiles and as new materials are added to the collection, they are compared to the profiles and relevant items are sent to the users [7, 28]. Moreover we can use the connectivity inherent in digital libraries to support collaborative filtering, where users rate or add value to information objects and these ratings are shared with a large community, so that popular items can be easily located or people can search for objects found useful by others with similar profiles [12, 28, 34].

In this paper we propose the use of UDL as an educational innovation tool, incorporating techniques to help in the personalized dissemination of pedagogic resources. We propose a fuzzy linguistic recommender system to facilitate learners the access to e-learning resources interesting for them. Suggesting didactic resources according to the learner's specific needs, a meaning learning is encouraged, influencing directly in the teaching-learning process. The system allows a personalized automatic dissemination of learning resources relevant to the students (bibliography, exercises, book, book chapter, Web links, slides, and so on). Moreover the system helps to discover collaboration possibilities with other learners and to form multi-disciplinar groups to encourage the tutorial action and collaborative learning.

We combine a recommender system [3, 12, 24, 34], to filter out the information, with a multi-granular Fuzzy Linguistic Modeling (FLM) [6, 14, 15, 40], to represent and handle flexible information by means of linguistic labels. The system is oriented to students and it is able to recommend three types of resources: Resources of the course to achieve the student specialization; other resources as complementary formation; and partners or collaborators, in order to include other learners that could be interesting to discover collaboration possibilities and to form multi-disciplinar work groups. The system filters the incoming information stream and delivers it to the suitable students according to their skill levels. The proposed system has been validated with the pupils of the course "Introduction to the Computer Sciences" developed in the Economic Faculty in University of Jaén. We show results that indicate the satisfactory performance of our system.

The paper is structured as follows. Section 2 revises the concept and main aspects about recommender systems. The section 3 analyzes the approaches of FLM that we use to the system design, the 2-tuple FLM and the multi-granular FLM. In Section 4 we present a multi-disciplinar fuzzy linguistic recommender system to advice pedagogic resources in UDL. Section 5 reports the system evaluation and some experimental results. Finally, some concluding remarks are pointed out.

2 RECOMMENDER SYSTEMS

Recommender systems could be defined as systems that produce individualized recommendations as output or has the effect of guiding the user in a personalized way to interesting or useful objects in a large space of possible options [2]. They are becoming popular tools for reducing information overload (for example in movie recommendations [30]) and for improving the sales in e-commerce web sites [3, 5, 34].

It is a research area that offers tools for discriminating between relevant and irrelevant information by providing personalized assistance for continuous information accesses, filtering the information and delivering it to people who need it [34]. Automatic filtering services differ from retrieval services in that in filtering the corpus changes continuously, the users have long time information needs (described by mean of user profiles instead of to introduce a query into the system), and their objective is to remove irrelevant data from incoming streams of data items [12, 28, 34].

There are several approaches that have been proposed to the implementation of recommendation applications [3, 12, 34]. In this paper we propose the use of a hybrid approach to smooth out the disadvantages of each one of them and to exploit their benefits; using a hybrid strategy users are provided with recommendations more accurate than those offered by each strategy individually [11]. We follow a hybrid recommender system, in which the users' information preferences can be used to define user profiles that are applied as filters to streams of documents. The construction of accurate profiles is a key task and the system's success will depend on a large extent on the ability of the learned profiles to represent the user's preferences [32].

The recommendation activity is followed by a relevance feedback phase. *Relevance feedback* is a cyclic process whereby the users feed back into the system decisions on the relevance of retrieved documents and the system uses these evaluations to automatically update the user profiles [12, 34].

3 FUZZY LINGUISTIC MODELING

The use of fuzzy sets theory has given very good results for modeling qualitative information [40] and it has proven to be useful in many problems, e.g., in decision making [8, 14, 38], quality evaluation [22, 23], models of information retrieval [17, 18, 19, 20, 21], etc. It is a tool based on the concept of *linguistic variable* proposed by Zadeh [40]. Next we analyze the two approaches of FLM that we use in our system.

3.1 The 2-Tuple Fuzzy Linguistic Approach

The 2-tuple FLM [13, 15] is a continuous model of representation of information. To define it we have to establish the 2-tuple representation model and the 2-tuple computational model to represent and aggregate the linguistic information, respectively.

Let $S=\{s_0,...,s_g\}$ be a linguistic term set with odd cardinality, where the semantics of the labels is given by means of triangular membership functions and we consider that all terms are distributed on a scale on which a total order is defined. If a symbolic method aggregating linguistic information obtains a value $\beta \in [0,g]$, and $\beta \notin \{0,...,g\}$, then β is represented by means of 2-tuples (s_i,α_i), where s_i represents the linguistic label, and α_i is a numerical value expressing the value of the translation from the original result β to the closest index label, i, in the linguistic term set ($s_i \in S$). This model defines a set of transformation functions between numeric values and 2-tuples: $\Delta(\beta)= (s_i,\alpha_i)$ and $\Delta^{-1}(s_i,\alpha_i)= \beta \in [0,g]$ [15].

The computational model is defined by presenting the Negation operator, Comparison of 2-tuples and Aggregation operators. Using functions Δ and Δ^{-1} any of the existing aggregation operators can be easily extended for dealing with linguistic 2-tuples [15].

3.2 The Multi-Granular Fuzzy Linguistic Modeling

In any fuzzy linguistic approach, an important parameter to determine is the granularity of uncertainty, i.e., the cardinality of the linguistic term set S. According to the uncertainty degree that an expert qualifying a phenomenon has on it, the linguistic term set chosen to provide his knowledge will have more or less terms. When different experts have different uncertainty degrees on the phenomenon or when an expert has to assess different concepts, then several linguistic term sets with a different granularity of uncertainty are necessary [16]. In such situations, we need tools to manage multi-granular linguistic information. In [16] a multi-granular 2-tuple FLM based on the concept of linguistic hierarchy is proposed. A *Linguistic Hierarchy*, *LH*, is a set of levels $l(t,n(t))$, where each level t is a linguistic term set with different granularity $n(t)$ [16]. The levels are ordered according to their granularity. We can define a level from its predecessor level as:

$$l(t,n(t)) \rightarrow l(t+1,2\cdot n(t)-1)$$

In [16] was defined a family of transformation functions between labels from different levels. To define the computational model, we select a level to make uniform the information and then we can use the operators defined in the 2-tuple FLM.

4 SYSTEM DESIGN

The teachers, students and UDL staff manages and spreads a lot of pedagogical resources, such as papers, bibliography, exercises, Web links, slides, and so on. Nowadays, this amount of information is growing up and they are in need of automated tools to filter and spread that information to the users in a simple and timely manner. So, the digital libraries should anticipate the users' needs and recommend about resources that could be interesting for them. Digital libraries must move from being passive, with little adaptation to their users, to being more proactive in offering and tailoring information for individuals and communities, and in supporting community efforts to capture, structure and share knowledge [4, 10. 33].

In this section we present a fuzzy linguistic recommender system designed using a hybrid approach and assuming a multi-granular FLM. It is used to advice students on the best pedagogical resources that could satisfy their information needs. To achieve this goal, we incorporate the system in a UDL, because we consider them as effective tools for educational innovation. The system suggests didactic resources proposed by the teachers, according to the learner's specific needs. So, a meaning learning is encouraged, influencing directly in the teaching-learning process. Moreover, the system recommends complementary resources that could be used by the users to meet other researchers of related areas with the aim to discover collaboration. So, this system increases the internal social collaboration possibilities in an academic environment and it contributes to encourage the tutorial action and to improve the collaborative learning.

In the proposed system we develop a hybrid recommendation approach [3, 12, 27]. The system filters the incoming information stream and delivers it to the suitable students according to their skill levels. It recommends students resources of the own course to achieve the student specialization, but the system also recommends resources as complementary formation and the partners or collaborators, in order to include other learners that could be interesting to discover collaboration possibilities. We use typical similarity functions based on a threshold values to identify specialization resources [31]. On the other hand, we use Gaussian similarity functions to identify complementary resources [1, 39].

Fig.1 shows the system architecture. In the recommendation process, a key factor is to choose a suitable representation for the resources and student needs. The aim is to recommend the most suitable resources to cover the student pedagogic needs, so we need a representation to link the resources with the students needs. For this reason, we use as representation scheme, the skills that must be covered in a course. So, on the one hand, a pedagogical resource satisfies or aids to cover with a certain degree some of the course skills, and by other hand a student needs to cover some skills to a accurate course learning.

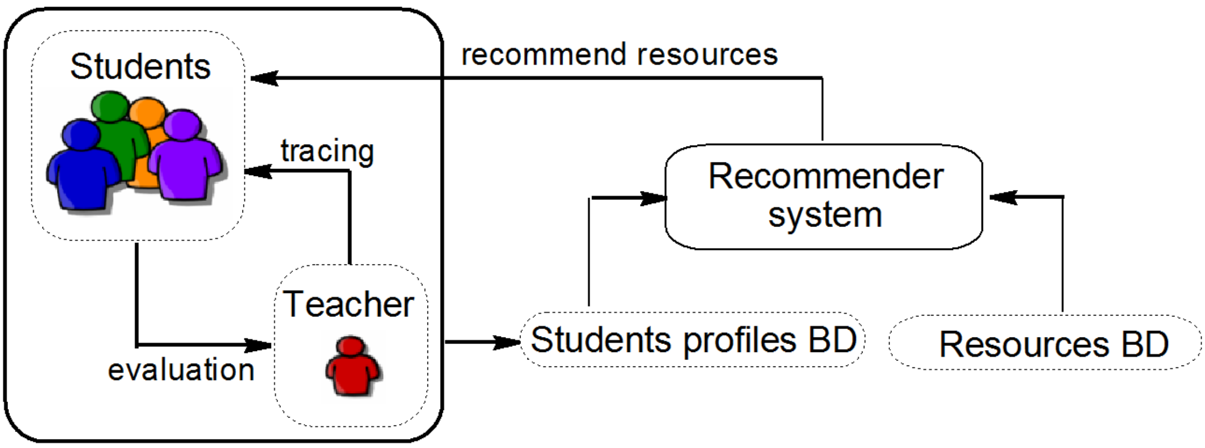

Fig.1. System architecture.

To represent the linguistic information we use different label sets, i.e. the communication among the users and the system is carried out by using multi-granular linguistic information, in order to allow a higher flexibility in the communication processes of the system. Therefore, the system uses different label sets (S_1, S_2, …) to represent the different concepts to be assessed in its filtering activity. These label sets S_i are chosen from those label sets that compose a *LH*. We should point out that the number of different label sets that we can use is limited by the number of levels of *LH*, and therefore, in many cases the label sets S_i and S_j can be associated to a same label set of *LH* but with different interpretations depending on the concept to be modeled. In our system, we distinguish between three concepts that can be assessed:

- **Importance degree** used to define the importance of a resource to acquire a course skill or a pedagogical need identified in a student by a teacher. It is a label of S_1.

- **Relevance degree** of a resource for a student. It is a label of S_2.
- **Complementary degree** between the resource and the user pedagogical needs. It is a label of S_3.

Specifically we follow a *LH* of 3 levels (3, 5 and 9 labels), but we only use two levels. That is, we use the level 2 (5 labels) to assign importance degree ($S_1 = S^5$) and the level 3 (9 labels) to assign relevance degrees ($S_2 = S^9$) and complementary degrees ($S_3 = S^9$). Using this *LH* the linguistic terms in each level are:

- $S_5 = \{b_0 = Null = N; b_1 = Low = L; b_2 = Medium = M; b_3 = High = H; b_4 = Total = T\}$
- $S_9 = \{c_0 = Null = N; c_1 = Very\ Low = VL; c_2 = Low = L; c_3 = More\ Less\ Low = MLL; c_4 = Medium = M; c_5 = More\ Less\ High = MLH; c_6 = High = H; c_7 = Very\ High = VH; c_8 = Total = T\}$

4.1 Resources representation

As we have said, the items recommended by our system are pedagogical resources. To characterize a resource, we use a representation based in the skills that must be covered with the resource. The teachers and the library staff must insert all the available information, as the title, author(s), kind of resource (if it is a book, or book chapter, or a paper, bibliography, exercises, Web links, slides, and so on), date, source, text, access link to the resource and the skills that could be covered with the resource. These skills must be established by the educative authorities or in a specific manner by the teacher. We have validated the system with the pupils of the course "Introduction to the Computer Sciences" developed in the Economic Faculty in University of Jaén. In the curriculum of this course, the following descritors are specified:

- Enterprise management tools.
- Spreadsheets.
- Database management systems.
- Word processor.
- Commerce diagrams.
- Communications.

Then, we represent each resource taking into account the degree in which each skill is covered by the resource. We use the vector model to represent the resource scope [26]. Thus, to represent a resource *i*, we use a skill vector composed by 6 elements. In each position we store a linguistic 2-tuple value representing the importance degree in which the corresponding skill in that position could be covered by the resource: $VR_i = (VR_{i1},\ldots, VR_{i6})$. Each component $VR_{ij} \in S_1$, with $j = 1\ldots6$. These importance degrees are assigned by the teachers and library staff when they add a new resource.

4.2 Student profiles representation

In this case, we want to obtain the data base to identify the pedagogic needs of each student, used to personalize the resources dissemination. The teachers propose activities to evaluate the students, and the results are analyzed to establish the needs of each student and so to form his/her profile. The teachers establish these needs and they value the degree in which each student must cover the skills to complete the course learning.

To characterize an user, the system stores the following basic information: nickname, password (necessary to access the system), passport number, name and surname, department and center, address, phone number, mobile phone and fax, web, email (elemental information to send the resources and recommendations), and skill needs.

We use also the vector model [26] to represent the skill needs. Then, for a student *x*, we have a vector of 6 elements: $VU_x = (VU_{x1},\ldots, VU_{x6})$, where each component $VU_{xy} \in S_1$, with $y = 1\ldots6$, stores a linguistic 2-tuple indicating the importance degree of the skill *y* with regard to the needs of the student *x*. These 2-tuples values are also assigned by the teachers.

The student profiles are actualized during the feedback phase, in which the students evaluate the resources provided by the system. Teachers also analyze the students evolution and they evaluate the recommended resources. Both evaluations are relevance degrees, so they are labels of S_2, and the system aggregates them using the arithmetic mean operator defined in [15].

4.3 Recommendation strategy

In this phase the system generates the recommendations to deliver the research resources to the fitting users. We use a hybrid approach [2, 27] between the content-based and collaborative schemes.

Both the processes are based on a Matching Process among the students and resources representations [12, 26]. We use the vector model [26] to represent both the resources and the student skill needs. This vector model uses similarity calculations to do the matching process, such as Euclidean Distance or Cosine Measure. Exactly we use the standard cosine measure [26]. However, as we have linguistic values, we need to introduce a new linguistic similarity measure (see fig. 2).

$$\sigma_l(V_1, V_2) = \Delta\left(g \times \frac{\sum_{k=1}^{n}(\Delta^{-1}(v_{1k}, \alpha_{v1k}) \times \Delta^{-1}(v_{2k}, \alpha_{v2k}))}{\sqrt{\sum_{k=1}^{n}(\Delta^{-1}(v_{1k}, \alpha_{v1k}))^2} \times \sqrt{\sum_{k=1}^{n}(\Delta^{-1}(v_{2k}, \alpha_{v2k}))^2}}\right)$$

Fig.2. Linguistic similarity measure.

In the formula, g is the granularity of the used term set, n is the number of terms used to define the vectors (i.e. the number of skills) and (v_{ik}, α_{vik}) is the 2-tuple linguistic value of term k in the resource vector or in the student skills vector (V_i). With this similarity measure we obtain a linguistic value in S_1. As we represent both the resources and students following the vector model, we can use σ_l to calculate the similarity among the two resources, two students, or a resource and a user.

When a new resource is inserted into the system, there isn't any evaluation about it, so the content-based-approach is followed. The linguistic similarity measure $\sigma_l(V_i, V_j)$ is computed among the new resource vector (V_i) against all the stored resources in the system (V_j, $j = 1..m$ where m is the number of resources). If $\sigma_l(V_i, V_j) \geq \alpha$ (linguistic threshold value to filter out the information), the resource j is chosen. Next, the system searches for the students which were satisfied with these chosen resources (previously they have rated the resource as good). To obtain the relevance of the resource i for a selected user x, the system aggregates the $\sigma_l(V_i, V_j)$ with the assessments previously provided by x about the similar resources and with the assessments provided by others users. To aggregate the information we need to transform the value $\sigma_l(V_i, V_j)$ in a linguistic label in S_2, using the transformation function defined in [16]. If the calculated relevance degree is greater than a linguistic threshold μ, then, the system sends the resource information and its calculated linguistic relevance degree (label of S_2) to the selected students. If not, the system estimates if the resource could interesting as a complementary recommendation.

To obtain the complementary recommendations, the system calculates the linguistic similarity measure $\sigma_l(V_i, V_x)$ among the resource i and the student x, for all students. Then, it applies a multi-disciplinar function to the value $\sigma_l(V_i, V_x)$. This function must give greatest weights to similarity middle values (near $0,5$), because values of total similarity contribute with efficient recommendations but are probably known for the students. Same, null values of similarity show a null relationship between skills. To establish this function we can use the centered OWA operators in which the OWA weights are generated from a Gaussian type function [39]. In the proposed system we use a triangular function (see figs. 3 and 4).

$$g(x) = \begin{cases} 2x & \text{for } 0 \leq x \leq 1/2 \\ 2 - 2x & \text{for } 1/2 < x \leq 1 \end{cases}$$

Fig.3. Triangular function definition.

Next, if the obtained multi-disciplinar value is greater than a previously defined linguistic threshold γ, the system recommends the complementary resource. To express multi-disciplinar values as a linguistic label in S_3, the transformation function is used. Finally, the system sends to the appropriate students the resource information and its estimated linguistic complementary degree (label of S_3).

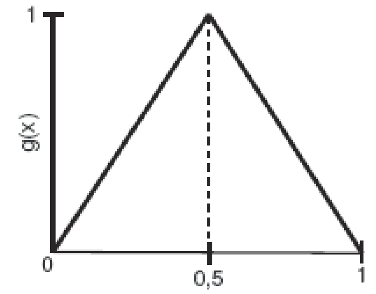

Fig. 4. Triangular function representation.

By the other hand, the system also recommends to the student selected in the previous step about collaboration possibilities with other students with similar pedagogical needs. We follow a memory-based algorithm, which generates the recommendations according to the preferences of nearest neighbors, also known as nearest neighbor algorithms. These algorithms present good performance as related research reported [36]. At this point, we only search for the nearest neighbor to generate the collaboration recommendations.

The first step is to identify the students most similar to a selected student x (with similar educative needs), using the linguistic similarity measure $\sigma_l(V_x, V_y)$ among the skill need vector of the user x (V_x) against the other students (V_y). If $\sigma_l(V_x, V_y) \geq \delta$ (linguistic threshold value), the student y is chosen as near neighbor of x, so the system considers that x and y could collaborate and it recommends such collaboration.

Finally, the system sends to the selected students the information of all identified resources as specialization or complementary resource, the estimated specialization or complementary linguistic degrees, and the detected collaboration possibilities.

4.4 Feeback phase

In this phase the system recalculates and updates the recommendations of the accessed resources. This feedback activity is developed in three steps:

1. The system recommends the student U a resource R, and then it asks the user his/her opinion or evaluation judgements about it.
2. The student gives his/her linguistic evaluation judgements, $rc_y \in S_2$.
3. This evaluation is registered in the system for future recommendations. The system recalculates the linguistic recommendations of R by aggregating the opinions provided by other users together with rc_y provided by U.

5 SYSTEM EVALUATION

The proposed system could be applied in a multi-disciplinar environment, including any course or degree. However, to prove the system functionality, we have implemented a trial version in which we have applied the system with the pupils of the course “Introduction to the Computer Sciences” developed in the Economic Faculty in University of Jaén. The obtained results indicate us the satisfactory performance of our system.

For the evaluation of recommender systems precision, recall and F1 are measures widely used to evaluate the quality of the recommendations [5, 9, 35]. To calculate these metrics we need a contingency table to categorize the items with respect to the information needs. The items are classified as both relevant or irrelevant and selected (recommended to the user) or not selected. The contingency table (table 1) is created using these four categories.

Precision is defined as the ratio of the selected relevant items to the selected items, that is, it measures the probability of a selected item being relevant:

$$P = N_{rs} / N_s$$

Recall is calculated as the ratio of the selected relevant items to the relevant items, that is, it represents the probability of a relevant items being selected:

$$R = N_{rs} / N_r$$

F1 is a combination metric that gives equal weight to both precision and recall:

$$F1 = (2 \cdot R \cdot P) / (R+P)$$

Table 1. Contingency table.

	Selected	Not selected	Total
Relevant	N_{rs}	N_{rn}	N_r
Irrelevant	N_{is}	N_{in}	N_i
Total	N_s	N_n	N

We considered a data set with 20 pedagogic resources of different areas, collected by the teachers from different information sources. These resources were included into the system following the indications described above. We limited these experiments to 10 students who evaluated the provided recommendations.

Then, we compared the recommendations provided by the system with the recommendations provided by the teachers, and the obtained contingency table for all users is shown in table 2. This contingency table, allow us to calculate the precision, recall and F1. The average of precision, recall and F1 metrics is 63.88%, 63.33% and 62.70% respectively. These values reveal a good performance of the proposed system and therefore a great satisfaction by the users.

Table 2. Experimental contingency table.

	User1	User2	User3	User4	User5	User6	User7	User8	User9	User10
N_{rs}	3	2	2	1	4	3	6	4	3	4
N_{rn}	2	1	3	1	2	1	3	2	1	2
N_{is}	1	2	1	2	1	1	2	2	2	3
N_r	5	3	5	2	6	4	9	6	4	6
N_s	4	4	3	3	5	4	8	6	5	7

6 CONCLUSIONS

The advances in Web technologies are promoting the development of new pedagogic models which improve the teaching-learning processes, aiding the information broadcasting in an efficient and easy manner, and providing tools for the personal and global communications that allow encourage the collaborative learning. In this sense, digital libraries could help to carry out this aim, because it allows teachers and learners the access to a great number of electronic resources. So, UDL can be used as innovation tools.

In this paper we have proposed a fuzzy linguistic recommender system to facilitate learners the access to e-learning resources interesting for them. Suggesting didactic resources according to the learner's specific needs, a meaning learning is encouraged, influencing directly in the teaching-learning process. The system allows a personalized automatic dissemination of learning resources relevant to the students (bibliography, exercises, book, book chapter, Web links, slides, and so on). Moreover the system helps to discover collaboration possibilities with other learners and to form multi-disciplinar groups. So, this system increases the internal social collaboration possibilities in an academic environment and it contributes to encourage the tutorial action and to improve the collaborative learning. The system has been designed combining a hybrid recommendation approach with a multi-granular FLM, to represent and handle flexible information.

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