Using incomplete fuzzy linguistic preference relations to characterize user profiles in recommender systems

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***Abstract*—In [12] we presented a fuzzy linguistic recommender system to advise research resources in university digital libraries. The problem of this system is that the user profiles are provided directly by the own users and the process for acquiring user preferences is quite difficult because it requires too much user effort. In this paper we present a new fuzzy linguistic recommender system that facilitates the acquisition of the user preferences to characterize the user profiles. We allow users to provide their preferences by means of an incomplete fuzzy linguistic preference relation. We include tools to manage incomplete information when the users express their preferences, and, in such a way, we show that the acquisition of the user profiles is improved.**

***Keywords*-recommender systems; fuzzy linguistic modeling; incomplete preference relations.**

I. Introduction

As digital libraries become commonplace and as their contents become more varied, the users expect more sophisticated services from them [4], [14]. A service that is particularly important is the selective dissemination of information or filtering, to help the users to access interesting information for them. Users develop interest profiles and as new materials (books, papers, reports, and so on) are added to the collection, they are compared to the profiles and relevant items are sent to the users.

Recommender systems are becoming popular tools for reducing information overload and to improve the sales in e-commerce web sites [3], [13]. The use of this kind of systems allows to recommend resources interesting for the users, at the same time that these resources are inserted into the system. In the University Digital Library (UDL) framework, recommender systems [3], [13] can be used to help users (teachers, students and library staff) to find out and select their information and knowledge sources [10].

Generally, in a recommender system the users' information preferences can be used to define user profiles that are applied as filters to streams of documents [3], [13]. In [11], [12] we developed some recommender systems in an academic context. For instance, in [11] we proposed a fuzzy linguistic recommender system for a technology transfer office which helps researchers and environment companies allowing them to obtain information automatically about research resources (calls or projects) in their interest areas; in [12] we proposed a fuzzy linguistic recommender system to achieve major advances in the activities of libraries, which recommends researchers specialized resources and complementary resources related with their respective research areas. The problem of both recommender systems is that users must directly specify their user profiles by providing their preferences on all topics of interest and it requires too much user effort. In some cases there are few categories, but there could exist cases in which this number could be greater (like in [11] in which we work with 248 positions). In such a way, users have to perform a great effort to provide their preferences about topics of interest.

In this paper, we focus on the idea that a recommender system could be seen as a decision support system where the solution alternatives are the digital resources inserted into the library, and the criteria to satisfy are the user profiles. So we can adopt the typical representation formats used in decision making, as for example, fuzzy preference relations [6]. This representation format presents a high expressivity and some interesting properties that allow us to work easily. However, in real world problems it is common to find situations in which users are not able to provide all the preference values that are required, and then, we have to deal with *incomplete fuzzy preference relations* [1], [2], [9].

The aim of this paper is to present a new fuzzy linguistic recommender defined in an academic library framework which overcomes the problem of user profile characterization observed in the recommender systems defined in [11], [12]. In order to improve the system performance, we propose an alternative way to obtain accurate and useful knowledge about the user preferences. This new recommender system allows users to provide their preferences by means of incomplete fuzzy linguistic preference relations [1], and in such a way, we facilitate users the expression of their preferences and, consequently, the determination of user profiles process. The recommender system is able to complete the incomplete preference relations using the tools proposed in [1], [2], [9]. Each user profile is composed

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of both user preferences on topics of interest and user preferences on collaboration possibilities with other users. Then, the recommender system is able to recommend both research resources and collaboration possibilities to the users of a UDL.

As in [11], [12] we define this recommender system in a multi-granular fuzzy linguistic context [8]. In such a way, we incorporate in the recommender system flexible tools to handle the information by allowing to represent the different concepts of the system with different linguistic label sets.

The rest of the paper is set out as follows. Section 2 presents the 2-tuple fuzzy linguistic approach. Section 3 presents the new recommender system to dissemination information in a UDL. Finally, our conclusions are pointed out in section 4.

II. The 2-tuple fuzzy linguistic approach

The Fuzzy Linguistic Modeling (FLM) is a tool based on the concept of *linguistic variable* [16] which has given very good results for modeling qualitative information in many problems.

The 2-tuple FLM [7] is a continuous model of representation of information that allows to reduce the loss of information typical of other fuzzy linguistic approaches (classical and ordinal [5], [16]).

Let $S = \{s_0, ..., s_g\}$ be a linguistic term set with odd cardinality, where the mid term represents an indifference value and the rest of the terms are symmetrically related to it. We assume that the semantics of labels is given by means of triangular membership functions and consider all terms distributed on a scale on which a total order is defined, $s_i \leq s_j \iff i \leq j$. In this fuzzy linguistic context, if a symbolic method [5] aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$, then an approximation function is used to express the result in S. β is represented by means of 2-tuples (s_i, α_i), $s_i \in S$ and $\alpha_i \in [-.5, .5)$ where s_i represents the linguistic label of the information, 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 2-tuple representation model defines a set of transformation functions between numeric values and 2-tuples $\Delta(\beta) = (s_i, \alpha)$ and $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ [7].

The computational model is defined by presenting a negation operator, comparison of 2-tuples and aggregation operators [7]. Using functions Δ and Δ^{-1} that transform without loss of information numerical values into linguistic 2-tuples and viceversa, any of the existing aggregation operators can be easily extended for dealing with linguistic 2-tuples. Some examples are:

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

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

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

$$\overline{x}_l^w[((r_1, \alpha_1), (w_1, \alpha_1^w))...((r_n, \alpha_n), (w_n, \alpha_n^w))] = \Delta(\frac{\sum_{i=1}^{n} \beta_i \cdot \beta_{W_i}}{\sum_{i=1}^{n} \beta_{W_i}}), \quad (2)$$

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

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. 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. In [8] a multi-granular 2-tuple FLM based on the concept of linguistic hierarchy is proposed.

A. Linguistic Hierarchy

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 $n(t)$ from the remaining of levels of the hierarchy. The levels are ordered according to their granularity, i.e., a level $t+1$ provides a linguistic refinement of the previous level t. We can define a level from its predecessor level as: $l(t, n(t)) \rightarrow l(t+1, 2 \cdot n(t) - 1)$. Table I shows the granularity needed in each linguistic term set of the level t depending on the value *n(t)* defined in the first level (3 and 7 respectively).

Table I
Linguistic hierarchies.

	Level 1	Level 2	Level 3
l(t,n(t))	l(1,3)	l(2,5)	l(3,9)
l(t,n(t))	l(1,7)	l(2,13)	

In [8] a family of transformation functions between labels from different levels was introduced:

Definition 3: Let $LH = \bigcup_t l(t, n(t))$ be a linguistic hierarchy whose linguistic term sets are denoted as $S^{n(t)} = \{s_0^{n(t)}, ..., s_{n(t)-1}^{n(t)}\}$. The transformation function between a 2-tuple that belongs to level t and another 2-tuple in level $t' \neq t$ is defined as:

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

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

As it was pointed out in [8] this family of transformation functions is bijective. This result guarantees that the transformations between levels of a linguistic hierarchy are carried out without loss of information.

B. Incomplete fuzzy linguistic preference relations

Definition 4: A fuzzy preference relation P on a set of alternatives $X = \{x_1, .., x_n\}$ is a fuzzy set on the product set $X \times X$, i.e., it is characterized by a membership function $\mu_P : X \times X \longrightarrow [0, 1]$.

When cardinality of X is small, the preference relation may be conveniently represented by the $n \times n$ matrix $P = (p_{ij})$, being $p_{ij} = \mu_P(x_i, x_j)$ $(\forall i, j \in \{1, \ldots, n\})$ interpreted as the preference degree or intensity of the alternative x_i over x_j, where:

- $p_{ij} = 1/2$ indicates indifference between x_i and x_j,
- $p_{ij} = 1$ indicates that x_i is absolutely preferred to x_j,
- and $p_{ij} > 1/2$ indicates that x_i is preferred to x_j.

However, as we have mentioned, our system integrates the multi-granular FLM based on 2-tuples, so we must define a linguistic preference relation as follows.

Definition 5: Let $X = \{x_1, .., x_n\}$ a set of alternatives and S a linguistic term set. A linguistic preference relation $P = p_{ij}(\forall i, j \in \{1, \ldots, n\})$ on X is:

$$\mu_P : X \times X \longrightarrow S \times [0.5, 0.5) \quad (3)$$

where $p_{ij} = \mu_P(x_i, x_j)$ is a 2-tuple which denotes the preference degree of alternative x_i regarding to x_j.

As aforementioned, in many real world GDM problems the experts are often not able to provide all the preference values that are required. In order to model these situations, we use incomplete fuzzy preference relations [1], [2], [9].

Definition 6: A function $f : X \longrightarrow Y$ is *partial* when not every element in the set X necessarily maps onto an element in the set Y. When every element from the set X maps onto one element of the set Y, then we have a *total* function.

Definition 7: A two-tuple fuzzy linguistic preference relation P on a set of alternatives X with a partial membership function is an *incomplete two-tuple fuzzy linguistic preference relation.*

III. A RECOMMENDER SYSTEM USING INCOMPLETE LINGUISTIC PREFERENCE RELATIONS TO CHARACTERIZE USER PROFILES.

In this section we present a new fuzzy linguistic recommender system in which the user profiles are obtained from user preferences represented by incomplete fuzzy linguistic preference relations [1]. This proposal contributes with some advantages with regard to previous systems [12], [11] because it facilitates the expression of their preferences to the users and reduces the user effort to characterize their user profiles. It is applied to advise UDL users on the best research resources that could satisfy their information needs in UDL. Moreover, the system recommends collaboration possibilities to meet other researchers of related areas which could collaborate with them in projects or interest works. In such a way, this new recommender system improves the services that a UDL provides to the users, because it is easier to obtain the knowledge about the users and it allows to decrease the time cost to establish the user profiles.

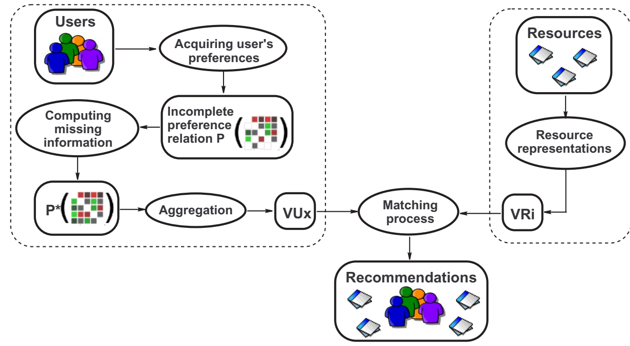

Figure 1. Operating scheme.

In figure 1 we can see the basic operating scheme, which is explained in the following subsections.

A. Information representation

In this system the user-system communication is carried out by using a multi-granular fuzzy linguistic approach [8], in order to allow a higher flexibility in the communication processes of the system. 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, i.e., $S_i \in LH$. 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. We take into account the following concepts that can be assessed in the system:

- **Importance degree** of a discipline with respect to a resource scope or user preferences (S_1).
- **Relevance degree** of a resource for a user (S_2).
- **Compatibility degree** between two users (S_3).
- **Preference degree** of a resource regarding another one (S_4).

Following a linguistic hierarchy of three levels of 3, 5 and 9 labels, in our system we use two levels, the level 2 (5 labels) to assign importance and preference degrees ($S_1 = S^5$ and $S_4 = S^5$), and the level 3 (9 labels) to assign relevance and compatibility degrees ($S_2 = S^9$ and $S_3 = S^9$). Using this LH, the linguistic terms in each level are:

☐ Agriculture, animal breeding and fishing	☐ Vegetal and animal biology and ecology
☐ Biotechnology, molecular and cellular biology and genetics	☐ Food science and techonology
☐ Materials science and techonology	☐ Earth science
☐ Social science	☑ Computers science and techonology
☐ Law	☐ Economy
☐ Energy and combustibles	☐ Pharmacology and pharmacy
☐ Philology and philosophy	☐ Physics and space sciences
☐ History and art	☐ Civil engineering, transportations, construction and architecture
☐ Industrial, mechanics, naval and aeronautic engineering	☐ Mathematics
☐ Medicine and veterinary	☐ Environment and environmental technology
☐ Multi-disciplinar	☐ Scientific policy
☐ Psychology and education sciences	☐ Chemistry and chemistry technology
☐ Telecommunications, electric engineering, electronics and automatics	

Figure 2. Disciplines of the resource scope.

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

1) Resources representation: The considered resources are journal articles, conference contributions, book chapters, books or edited books. Once the library staff insert all the available information about a new resource, the system obtains an internal representation mainly based in the resource scope. We use the *vector model* to represent the resource scope. Thus, to represent a resource i, we use a classification composed by 25 disciplines (see figure 2). In each position we store a linguistic 2-tuple value representing the importance degree of the resource scope with respect to the discipline represented by that position:

$$VR_i = (VR_{i1}, VR_{i2}, ..., VR_{i25}) \tag{4}$$

Then, each component $VR_{ij} \in S_1$, with $j = \{1, ..., 25\}$, indicates the linguistic importance degree of the discipline j with regard to the resource i. These importance degrees are assigned by the library staff when they add a new resource.

2) User profiles: The user profiles are composed of two kinds of user preferences:

1) User preferences on topics of interest, and
2) user preferences on collaboration possibility with other users.

The main contribution of this proposal is how users provide their preferences on topics of interest used to represent the source resources. In previous proposals [11], [12] we represented such user preferences using the vector model. The problem is that the users must insert or edit all the features corresponding to the disciplines, i.e., in our case 25 categories. Thus, in previous proposals we worked with vectors composed of 25 positions (each one corresponding to a discipline), but there could exist cases in which this number could be greater. In such a way, users have to perform a great effort to provide their preferences about topics of interest. To reduce this effort and make the process for acquiring the user preferences easier, in this model we propose an alternative method to obtain the user preferences on topics of interest.

We ask users to provide their preferences on some research resources, usually a limited number of resources, four or five. The choice of research resources is made by the personal staff taking into account the resources most relevant for the users previously inserted in the system. We propose users to represent their preferences by means of incomplete fuzzy linguistic preference relations. Then, the system presents users only a selection of the most representative resources, and the users provide their preferences about these resources by means of an incomplete fuzzy preference relation. Furthermore, according to results presented in [2], it is enough that the users provide only a row of the preference relation. Then, we use the method proposed in [2] to complete the relations. Once the system completes the fuzzy linguistic preference relation provided by the user, it is possible to obtain a vector representing the user preferences on the topics of interest. Next, we explain this process in detail:

1) **Acquiring the user preferences on a limited number of research resources**: At the beginning, the main goal is to help the users to provide their preferences assuring that these preferences are as consistent as possible. The system shows users the five most representative resources, $R = \{r_1, .., r_5\}$, and asks them to express their preferences by means of an incomplete fuzzy linguistic preference relation. The users only fill those preferences that they wish, assigning labels of S_4. In the preference relation, each preference value p_{ij} represents the linguistic preference degree of resource i over the resource j according to the user feeling. As aforementioned, the simplest case would be to provide a relation with only one row of preference values:

$$P = \begin{pmatrix} - & p_{12} & p_{13} & p_{14} & p_{15} \\ x & - & x & x & x \\ x & x & - & x & x \\ x & x & x & - & x \\ x & x & x & x & - \end{pmatrix} \tag{5}$$

Then, the system completes the preference relation P using the method proposed in [2], and obtains the relation P^*:

$$P^* = \begin{pmatrix} - & p_{12} & p_{13} & p_{14} & p_{15} \\ p^*_{21} & - & p^*_{23} & p^*_{24} & p^*_{25} \\ p^*_{31} & p^*_{32} & - & p^*_{34} & p^*_{35} \\ p^*_{41} & p^*_{42} & p^*_{43} & - & p^*_{45} \\ p^*_{51} & p^*_{52} & p^*_{53} & p^*_{54} & - \end{pmatrix} \tag{6}$$

where $p_{1j} \in S_4$ are the degrees inserted by the user about the preferences of the resource x_1 with respect to x_j, p_{ii} represents indifference, and each p^*_{ij} is the estimated degree for the user about his/her preference of the resource x_i with respect to x_j.

2) In order to obtain **user preferences on topic of interest, i.e., user preference vector**, firstly we calculate the user preference degrees on each considered resource according to the preference relation P^*, and secondly, we use these preference degrees together with the vectors that represent each research resource to obtain the user preference vector. The preference degrees coincide with the dominance degrees of a linguistic preference relation [6]. To obtain them we propose the application of the arithmetic mean $\overline{x}^e$ (definition 1). Then, the preference degree of the resource i for the expert called DG_i, is computed as follows:

$$DG_i = \overline{x}^e[p^*_{i1}, \ldots, p^*_{i5}] \quad (7)$$

Then, to obtain the user preference vector x, i.e. $VU_x = (VU_{x1}, VU_{x2}, ..., VU_{x25})$, from the aggregation of the vectors that represents the characteristics of the chosen research resources, i.e,, $\{VR_1, ..., VR_5\}$, weighted by means of the user preference degrees $\{DG_1, \ldots, DG_5\}$. To do that, we use the linguistic weighted average operator defined in definition 2, and then each position $k = \{1, \ldots, 25\}$ of the vector VU_x, is computed as follows:

$$VU_{xk} = \overline{x}^w_l[(VR_{1k}, DG_1), \ldots, (VR_{5k}, DG_5)] \quad (8)$$

On the other hand, to complete the user profile, the system asks every user to express his/her collaboration preferences, i.e., if he/she wants to receive recommendations on collaboration possibilities with others users. This could help users to develop multi-disciplinar works or participate in collaborative research projects [12]. They should respond to this question with “Yes” or “No”.

B. Recommendation strategy

In this phase the system generates the recommendations to deliver the information resources to the fitting users. This process is based on a matching process developed between user profiles and resource representations . To do that, we can use different kinds of similarity measures, such as Euclidean Distance or Cosine Measure. Particularly, we use the standard cosine measure. As the components of the vectors used to represent user profiles and research resources are 2-tuple linguistic values, then we define the cosine measure in a 2-tuple linguistic context. Given two vectors of 2-tuple linguistic values,

$$V_1 = ((v_{11}, \alpha_{v11}), (v_{12}, \alpha_{v12}), \ldots, (v_{125}, \alpha_{v125}))$$

and

$$V_2 = ((v_{21}, \alpha_{v21}), (v_{22}, \alpha_{v22}), \ldots, (v_{225}, \alpha_{v225}))$$

then the linguistic similarity between both, called $\sigma_l(V_1, V_2) \in S_1$ is defined as:

$$\sigma_l(V_1, V_2) = \Delta(g \times \frac{\sum_{k=1}^{n}(\hbar_1 \times \hbar_2)}{\sqrt{\sum_{k=1}^{n}(\hbar_1)^2} \times \sqrt{\sum_{k=1}^{n}(\hbar_2)^2}}) \quad (9)$$

where g is the granularity of S_1, n is the number of terms used to define the vectors, $\hbar_i = \Delta^{-1}(v_{ik}, \alpha_{vik})$ and (v_{ik}, α_{vik}) is the 2-tuple linguistic value of term k in the vector (V_i).

When a new resource i is inserted into the system, we calculate the linguistic similarity measures, $\sigma_l(VR_i, VU_j)$, between the representation vector of this new resource (VR_i) and all the user preference vectors, $\{VU_1, \ldots, VU_m\}$, where m is the number of users in the system. These user preference vectors are obtained as we have indicated in section III-A2.

Then, if $\sigma_l(VR_i, VU_j) \geq \psi$, the user j is selected to receive recommendations about resource i. Previously, we have defined a linguistic threshold value (ψ) to filter the output of the system. Next, the system applies to each $\sigma_l(VR_i, VU_j)$ the transformation function defined in definition 3, to obtain the relevance degree of the resource i for the user j, expressed using a label of the set S_2.

The collaboration preferences provided by the users are used to classify the selected users in two sets, collaborators $\mathcal{U_C}$ and non-collaborators $\mathcal{U_N}$. For the users of $\mathcal{U_N}$ the system has finished the recommendation process, and therefore it sends them the resource information together with its linguistic relevance degree.

For the users in $\mathcal{U_C}$ the system calculates the collaboration possibilities. To do it, between each two users $x, y \in \mathcal{U_C}$, the system performs the following steps:

1) Calculate the linguistic similarity measure between both users, $\sigma_l(VU_x, VU_y)$.
2) Obtain the linguistic compatibility degree between both users, which must be expressed in S_3. To do that, we apply the transformation function defined in 3 on $\sigma_l(VU_x, VU_y)$.

Finally the system sends to the users of $\mathcal{U_C}$ the resource information, its calculated linguistic relevance degree and the collaboration possibilities characterized by its linguistic compatibility degrees.

C. System evaluation

At present we have implemented a trial version, in which the system works only with few researchers. This beta version has been used to prove the system functionality, but we are working to obtain a definitive version. The purpose of the experiments is to test the performance of the proposed system, so we compared the recommendations made by the system with the information provided by the library staff. When the users receive a recommendation, they provide a feedback to the system assessing the relevance of the recommended resource, i.e., they provide their opinions about the recommendation supplied by the system. If they are satisfied with the recommendation, they provide a higher value.

We have designed experiments in which the system is used to recommend research resources that best satisfy the preferences of 6 users; all of them completed the registration process and they inserted their preferences about the five most relevant resources presented by the system. From this information, the system builds the user profiles. These user profiles obtained from the provided preferences and the resources previously inserted, constituted our training data set. Then, we added 20 new resources that constituted the test data set. The system filtered these 20 resources and recommended each one to the suitable users. To obtain data to compare, the 20 new resources also were recommended using the advices of the library staff. With this information, we calculate the precision (ratio of the selected relevant items to the selected items), recall (ratio of the selected relevant items to the relevant items) and F1 (combination metric that gives equal weight to both precision and recall), which are measures widely used to evaluate the quality of the recommendations [15]. The average of precision, recall and F1 metrics are 67.50%, 61.39% and 63.51% respectively, improving the measures obtained with the previous proposal [11]. These values reveal a good performance of the proposed system and therefore a great satisfaction of the users.

IV. Conclusions

We have presented a fuzzy linguistic recommender system acting in a UDL which uses incomplete fuzzy linguistic preference relations to characterize the user profiles. In such a way, we facilitate user the expression of their preferences to obtain the user profiles and overcome those problems detected in [11], [12].

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