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# Integrating Quality Criteria in a Fuzzy Linguistic Recommender System for Digital Libraries

A. Tejeda-Lorente[a], J. Bernabé-Moreno[a], C. Porcel[b], E. Herrera-Viedma[a,*]

[a]*Department of Computer Science and A.I., University of Granada, Granada E-18071, Spain*
[b]*Department of Computer Science, University of Jaén, Jaén E-23071, Spain*

**Abstract**

Recommender systems can be used in an academic environment to assist users in their decision making processes to find relevant information. In the literature we can find proposals based in user' profile or in item' profile, however they do not take into account the quality of items. In this work we propose the combination of item' relevance for a user with its quality in order to generate more profitable and accurate recommendations. The system measures item quality and takes it into account as new factor in the recommendation process. We have developed the system adopting a fuzzy linguistic approach.

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*Keywords:* Recommender system; item quality; university digital library; fuzzy linguistic modeling

## 1. Introduction

Nowadays, we deal with a huge amount of information that overwhelms us. The information overload makes it difficult to access to relevant information[1]. This necessitates the development of systems to provide fast and effective access to relevant information. An example of this systems are the digital libraries, where the information is generated much faster than users can process it[2,3]. Digital libraries are collections of information that have associated some services for their user communities[3]. These services have been applied in several fields but we are going to focus on the academic environment. An important service is the selective information diffusion.

A Recommender System (RS) aids users supplying items they can be interested on[4]. They are personalized services that deal with each user in a different manner. RSs are becoming a very widespread solution to deal with information overload and to improve sales in e-commerce[5,6]. With regard to University Digital Libraries (UDL), RSs can be used to help professors, student and library staff to find and select information and research resources[7,8]. In previous works, we have been applied successfully RSs in UDL[9,10,11]. But, in the same way as in the Web, the number of electronic

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* Corresponding author. Tel.: +34-958-24-4258 ; fax: +34-958-24-3317.
*E-mail address:* viedma@decsai.ugr.es

resources generated daily keep growing and the system performance is affected. Therefore, we find a persistent problem of information overload and previous proposal can be improved.

In UDL scope, collaborative approach (see section 2.1) allows users to share experiences and ratings, in a way users can receive information that other users may consider useful with similar profiles. However, this approach tend to fail when the system has few ratings, this problem is also known as the *cold start problem*. Due to this reason, our proposal is to combine collaborative approach with a content-based one to obtain a hybrid recommendation scheme (see section 2.1). Moreover, we consider that generated recommendations would be more interesting if we take into account the quality of items. In everyday life we usually buy well known products or popular brands products. These products are popular because it is considered that they are high quality and this satisfies consumers. The main idea is to combine the estimated relevance through the hybrid approach with the quality of items.

In this work we present a fuzzy linguistic recommender system based on the quality of items and applied in a UDL to aid users in their decision making processes to find relevant electronic resources. The system measures items' quality and takes it into account as new factor in the process of generating recommendations. We have been done online tests and the obtained recommendations are more accurate and useful.

The paper is organized as follow. In section 2 the background is presented. Section 3 presents the proposed system. Finally, some concluding remarks are pointed.

## 2. Preliminaries

This section purpose is to provide the background information needed to describe our work. It is divided in two parts: a description of recommender system approach (Section 2.1) and an introduction to the fuzzy linguistic approach (Section 2.2).

### 2.1. Recommender System

In order to provide personalized recommendations, systems require knowledge about users, such as ratings provided on already explored items[4,12,13]. To maintain available this knowledge it implies system should keep also user profiles that contain also users preferences and necessities. Nevertheless, the way system acquires this information depends on the recommendation scheme used. The system could obtain the information about users either in an *implicit* way, that is analyzing their behavior, or *explicitly* requiring user to specify their preferences.

One of the most popular method used to obtain recommendations is the *collaborative approach*[12]. In this approach the recommendations for a user are based on the ratings provided by other user similar to this user. Another method more simple but not less important is the *content-based approach*[13]. This approach generates the recommendations taking into account items characteristics and the ratings that a user has given to items similar to them. Each approach has certain advantages and disadvantages, so that a frequent solution is to combine different approaches to reduce the disadvantages of each one of them and to exploit their benefits adopting a hybrid approach. Using a hybrid strategy, users are provided with more accurate recommendations than those offered by each strategy individually[14]. For this reason, in this paper we propose the use of a hybrid approach[15,16].

### 2.2. Fuzzy linguistic approach

The fuzzy linguistic approach is a tool based on the concept of linguistic variable proposed by Zadeh[17]. This theory has given very good results to model qualitative information and it has been proven to be useful in many problems.

#### 2.2.1. The 2-Tuple Fuzzy Linguistic Approach
The 2-Tuple Fuzzy Linguistic Approach[18] is a continuous model of information representation that allows reduction in the loss of information that typically arises when using other fuzzy linguistic approaches, both classical and ordinal[19,17,20]. To define it both the 2-tuple representation model and the 2-tuple computational model to represent and aggregate the linguistic information have to be established.

Let $\mathcal{S} = \{s_0, ..., s_g\}$ be a linguistic term set with odd cardinality. 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. In this fuzzy linguistic context, if a symbolic method aggregating linguistic information obtains a value $\beta \in [0, g]$, and $\beta \notin \{0, ..., g\}$, we can represent $\beta$ as a 2-tuple $(s_i, \alpha_i)$, where $s_i$ represents the linguistic label, and $\alpha_i$ is a numerical value expressing the value of the translation between numerical values and 2-tuple: $\Delta(\beta) = (s_i, \alpha)$ y $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ [18].

In order to establish the computational model negation, comparison and aggregation operators are defined. Using functions $\Delta$ and $\Delta^{-1}$, any of the existing aggregation operators can be easily be extended for dealing with linguistic 2-tuples without loss of information [18]. 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:*

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

**Definition 2.** *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 associated weights. The 2-tuple weighted average $\overline{x}_l^w$ is:*

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

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

### 2.2.2. Multi-Granular Linguistic Information Approach

In either 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 responsible of rate a phenomenon provides, the term sets chosen to provide this knowledge will have more or less terms. When different experts have different uncertainty degrees on the phenomenon or when a single expert has to evaluate different concepts, then several linguistic term sets with a different granularity of uncertainty are necessary [21]. In such situations we need tools to manage the multi-granular linguistic information. In [22] a multi-granular 2-tuple fuzzy linguistic modeling 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 $n(t)$. The levels are ordered according to their granularity, so that we can distinguish a level from the previous one, 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: $l(t, n(t)) \rightarrow l(t + 1, 2 \cdot n(t) - 1)$. In [22] a family of transformation functions between labels from different levels was introduced. To establish the computational model we select a level that we use to make the information uniform and thereby we can use the defined operator in the 2-tuple model.This result guarantees that the transformations between levels of a linguistic hierarchy are carried out without loss of information.

### 2.2.3. Fuzzy preference relations

**Definition 3.** *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 matrix $P = (p_{ij})$, with $p_{ij} = \mu_P(x_i, x_j)$ $(\forall i, j \in \{1, \ldots, n\})$ 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, our system integrates the multi-granular fuzzy linguistic modeling based on 2-tuples, so we must define a linguistic preference relation as follows.

**Definition 4.** *Let $X = \{x_1, .., x_n\}$ be 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:$\mu_P : X \times X \longrightarrow S \times [0.5, 0.5]$*
*where $p_{ij} = \mu_P(x_i, x_j)$ is a 2-tuple which denotes the preference degree of alternative $x_i$ regarding to $x_j$.*

However, in real group decision making problem 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[23,24].

**Definition 5.** *A function f : X ⟶ Y is partial when not every element in the set X necessarily maps onto an element in the set Y.*

**Definition 6.** *An incomplete fuzzy linguistic preference relation P on a set of alternatives X, is a fuzzy set on the set X × X characterized by a partial membership function.*

## 3. System Description

In this work we face the recommendation process of UDL resources as a task with two distinguish elements: Relevant resources for users and quality items. We propose a method to combine the estimated relevance for a resource along with its quality.

### 3.1. Information representation

In order to represent the different concepts to be assesses by the system, we will use different label sets $(S_1, S_2, ...)$ selected from a $LH$[22]. In the proposed system the concepts represented are the following:

- **Importance degree** of a discipline regarding to a resource scope, which is assessed in $S_1$.
- **Similarity degree** among resources or users, which is assessed in $S_2$.
- **Relevance degree** estimated of a resource for a user, which is assessed in $S_3$.
- **Satisfaction degree** of a user regarding to a recommended resource, which is assessed in $S_4$.
- **Preference degree** of a resource regarding to other, which is assessed in $S_5$.

In our system we use label sets selected of two level from a $LH$ of three levels of 3, 5 and 7 labels each one. Specifically, level 2 level (5 labels) is used to represent importance and preference degree $(S_1 = S^5$ y $S_5 = S^5)$, and the level 3 (9 labels) is used to represent similarity, relevance and satisfaction $(S_2 = S^9, S_3 = S^9$ y $S_4 = S^9)$.

#### 3.1.1. Resources representation

In our system, the considered resources are journal articles, conference contributions, book chapters, books or edited books. The system obtains an internal representation mainly based in the resource scope. To do that, we use a classification composed by 25 disciplines (see figure 1). Then, to represent a resource $i$ we use a vector model, that is, we obtain a vector $VR_i = (VR_{i1}, VR_{i2}, ..., VR_{i25})$, where $VR_{ij} \in S_1$ shows the importance degree of discipline $j$ regarding to resource scope $i$. This value is initially assigned by the UDL staff when the new resource is inserted in the system.

#### 3.1.2. User profiles

To acquire users' preferences, we use the proposed method in[9]. It consists of requesting users to provide their preferences over 5 resources, using a incomplete fuzzy linguistic preference relation. Furthermore, in accordance with results presented in[24], it is enough for users to provide a row of the relation. Then, we use the method presented in[24] to complete the relation and then we can obtain a vector that represent users' preferences over their topics of interest. Moreover, in this way we manage to reduce the cold start problem, since thanks to the supplied information by users when they register in the system, they can already start receiving recommendations. The process is described bellow:

1. Acquiring users preferences over a limited number of resources. System shows to users the 5 more representative resources $R = \{r_1, .., r_5\}$ and users as asked to express their preferences by means of an incomplete fuzzy linguistic preference relation. In the preference relation, each value $p_{ij} \in S_5$ represent the preference degree of $i$ over $j$. To provide only one row is enough:

☐ 1. Agriculture, animal breeding and fishing
☐ 2. Vegetal and animal biology and ecology
☐ 3. Biotechnology, molecular and cellular biology and genetics
☐ 4. Food science and technology
☐ 5. Materials science and technology
☐ 6. Earth science
☐ 7. Social science
☐ 8. Computers science and techonology
☐ 9. Law
☐ 10. Economy
☐ 11. Energy and combustibles
☐ 12. Pharmacology and pharmacy
☐ 13. Philology and philosophy
☐ 14 Physics and space sciences

☐ 15. History and art
☐ 16. Civil engineering, transportations, construction and architecture

☐ 17. Industrial, mechanics, naval and aeronautic engineering
☐ 18. Mathematics
☐ 19. Medicine and veterinary
☐ 20. Environment and environmental technology
☐ 21. Multi-disciplinar
☐ 22. Scientific policy
☐ 23. Psychology and education sciences
☐ 24. Chemistry and chemistry technology
☐ 25. Telecommunications, electric, engineering, electronics and automatics

Fig. 1. Discipline of the resources scope

$$
P = \begin{pmatrix}
- & p_{12} & p_{13} & p_{14} & p_{15} \\
x & - & x & x & x \\
x & x & - & x & x \\
x & x & x & - & x \\
x & x & x & x & -
\end{pmatrix}
\tag{3}
$$

Then, the proposed system complete the relation $P$ using the method proposed in[24], and we obtain the relation $P^*$:

$$
P^* = \begin{pmatrix}
- & p_{12} & p_{13} & p_{14} & p_{15} \\
p_{21}^* & - & p_{23}^* & p_{24}^* & p_{25}^* \\
p_{31}^* & p_{32}^* & - & p_{34}^* & p_{35}^* \\
p_{41}^* & p_{42}^* & p_{43}^* & - & p_{45}^* \\
p_{51}^* & p_{52}^* & p_{53}^* & p_{54}^* & -
\end{pmatrix}
\tag{4}
$$

where $p_{1j} \in S_5$ are the degrees inserted by the user over the resource preferences $x_1$ regarding to $x_j$, $p_{ii}$ indicates indifference, and each $p_{ij}^*$ is the estimated degree for the user over the resource preferences $x_1$ regarding to $x_j$.

2. Obtaining the *user preference vector*. To calculate resource preference degrees $i$ for an expert called $DG_i$, we can apply the arithmetic mean operator defined in definition 1[18]: $DG_i = \overline{x}^e[p_{i1}^*, \ldots, p_{i5}^*]$.

3. Now we can obtain the user preference vector $x$, i.e. $VU_x = (VU_{x1}, VU_{x2}, ..., VU_{x25})$, as the aggregation of vectors representing selected resources characteristics ($\{VR_1, ..., VR_5\}$) weighted through preference degrees $\{DG_1, \ldots, DG_5\}$, using the operator $\overline{x}_l^w$ defined in definition 2[18]: $VU_{xk} = \overline{x}_l^w[(VR_{1k}, DG_1), \ldots, (VR_{5k}, DG_5)]$, with $k = \{1, \ldots, 25\}$.

### 3.2. Recommendation Scheme

In order to generate recommendations to be delivered to suitable users, we implement a hybrid approach which switches between content-based approach and collaborative[4]. The former is applied when a new item is inserted and the later when a new user is registered. We rely on a matching process by similarity measures among vectors. Particularly, we use the standard cousin measure, but defined it in a linguistic context.

$$\sigma_l(V_1, V_2) = \Delta(g \times \frac{\sum_{k=1}^{n}(\hbar_1 \times \hbar_2)}{\sqrt{\sum_{k=1}^{n}(\hbar_1)^2} \times \sqrt{\sum_{k=1}^{n}(\hbar_2)^2}}) \tag{5}$$

where $\sigma_l(V_1, V_2) \in S_2 \times [-0.5, 0.5]$, $g$ is the granularity of the term set used to express the relevance degree ($S_3$), $n$ the number of disciplines, $\hbar_i = \Delta^{-1}(v_{ik}, \alpha_{vik})$ y $(v_{ik}, \alpha_{vik})$ is the 2-tuple linguistic value of the term $k$ in the vector $V_i$.

### 3.2.1. Content-based recommendations

When a new resource $i$ is registered in the system, the content-based approach is used to know if a user $e$ could be interested on it as follows:

1. Estimate $\sigma_l(VR_i, VU_e) \in S_2$. As $S_2 = S^9$, we consider that $i$ is related with $e$ if $\sigma_l(VR_i, VU_e) > (s_4^9, 0)$.
2. If $i$ is related with $e$, the system recommends $i$ to $e$ with a predicted relevance degree $i(e) \in S_3 \times [-0.5, 0.5]$ obtained as follows:

    (a) Look for all the resources previously assessed by $e$ in a satisfactory way.
    (b) To aggregate all the rating of $e$ over these resources, weighted by the similarity between $i$ and each of the resources. To do that we use the operator defined in the definition 2.

### 3.2.2. Collaborative recommendations

When a new user $e$ is registered in the system, recommendations over resources already inserted are generated as described below:

1. Select the set of users $\aleph_e$ more similar to $e$. In order to do that, we estimate the similarity between vector representing $e$ ($VU_e$), against the rest of users vectors ($VU_y$, $y = 1..n$ being $n$ the number of users): $\sigma_l(V_e, V_y) \in S_2$. As $S_2 = S^9$, we consider that $y$ is similar to $e$ if $\sigma_l(VU_e, VU_y) > (s_4^9, 0)$.
2. Retrieve the resources positively rated previously by users similar to $e$.
3. All the positively rated resources by user similar to $e$ will be recommended to $e$ with an estimated relevance degree $j(e) \in S_3 \times [-0.5, 0.5]$, calculated as the aggregation of all the ratings, weighted by the similarity between $e$ and their nearest neighbors. To do that we use the operator defined in the definition 2.

### 3.3. Quality estimation

The main idea is that if a resource is used to be chosen against others, we can have an idea about this resource has a certain level of quality. For this purpose we adopt the method presented in [9], where users express their preferences by incomplete fuzzy linguistic preference relations [23]. With this method we can count the number of times a resource is chosen to be shown among the outstanding resources, as well as the number of times it has been chosen over the rest. The displayed resources will vary over time, so that the system records each time a resource is chosen and the number of times it is preferred to other. This approach allows us to have this data available, such that we do not need more information about users or resources, avoiding a complexity increase in the system. Hence, we compute the quality of a resource $i$ as the probability of this resource be preferred over other having been selected, that is:

$$q(i) = p_i/s_i \tag{6}$$

where $p_i$ is the total number of times $i$ has been preferred over other and $s_i$ is the total of times the resource $i$ has been selected.

### 3.4. Reranking

Once the resource $i$ is considered relevant to $e$, we aggregate its estimated relevance $i(e) \in S_3$ together with its quality score $q(i) \in [0, 1]$:

1. We translate the quality score to the rank where relevance is defined: $tq(i) = q(i) \times g$, where $g$ is the granularity of $S_3$; as $S_3 = S^9 \Rightarrow g = 8$.
2. In order to obtain the final relevance degree we use a multiplicative aggregation operator due to its simplicity and god performance:

$$FinalRelevance(i) = \Delta(\frac{\Delta^{-1}(i(e) \times tq(i))}{g}) \tag{7}$$

where $\Delta$ and $\Delta^{-1}$ are the transformation functions between 2-tuples values and symbolic values [18].
3. We translate the final relevance value to the interval $[0, g]$.

### 3.5. Feedback phase

Finally, the generation of recommendation is completed with this phase, whereby users supply their opinions about the recommendations received from the system. These linguistic evaluation judgments will be label of $S_4$.

### 3.6. System evaluation

We have developed online experiment to test the accuracy of the system predicting the rating that user would give to a recommended resource. To do that, we used a data set with 200 resources of different areas and 30 users. Later, 100 new resources were added and recommended. The rating given by user over these recommendations of the new resources were registered in the system. This rating was compared with the estimated rating by the system, it allowed us to estimate the Mean Absolute Error (MAE), which measures the mean absolute deviation between a estimated value and the real value assigned by the user. In our case, we obtain an average MAE for all the user of *0.765*. To compare results, we repeat the experiment but using the scheme proposed in [9], where the quality of resources was not taken into account. In this case, we obtained an average MAE of *0.7823*. The result implies that through the application of the new approach, i.e. taking into account items' quality, we obtain an improvement of 4.8%. That is, the predictions generated with the new system are more close to the users' preferences.

## 4. Concluding Remarks

In this work we faced the recommendations generation process as a task with a dual perspective: not only finding relevant resources, but also the resource has to be valid from the standpoint of the quality of items. We presented a fuzzy linguistic hybrid recommender system and we applied it in a UDL to assist users in their decision making processes to find relevant information. The system measures the quality of resources and takes it into account as a new factor to consider in the recommendation process. We developed online tests and obtained satisfying experimental results.

As future work, we consider to studying automatics techniques to establish the internal representation of resources. It would be interesting to explore new ways of improving the process of generation recommendations, as for example, using bibliometric tools [25,26].

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