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A dynamic recommender system as reinforcement for personalized education by a fuzzy linguistic web system

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Abstract

The seek of a personalized and quality education is the objective of Bologna process, but to carry out this task has a major economic impact. To soften this impact, one possible solution is to make use of recommender systems, which have already been introduced in several academic fields. In this paper, we present AyudasCBI, a novel fuzzy linguistic Web system that uses a recommender system to provide personalized activities to students to reinforce their individualized education. This system can be used in order to aid professors to provide students with a personalized monitoring of their studies with less effort. To prove the system, we conduct a study involving some students, aiming at measuring their performance. The results obtained proved to be satisfactory compared with the rest of the students who did not take part of the study.

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1. Introduction

E-learning and personalized education have gained more attention with the massive use of internet. However, the continuously growing amount of information carried the information overload problem [1], making difficult the correct use of such systems. Personalized education can be very helpful aiding students to reinforce the areas where it is necessary some help as well as maximize those where they have potential or special interest. Education must also have the ability of adapt itself to the necessities of the student dynamically, that is, if an activity is not producing the expected results it should change.

The improvement of the education requires greater individualization, although the new directives followed in Europe, like the Bologna Process[1], tends to increase the numbers of teachers per student, the economic situation of the different countries in the actual crisis makes it an impossible objective to achieve. A solution for this problem is found in the use of the new technologies. Recommender Systems (RSs) have proved potential addressing the

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[1]http://www.coe.int/t/dg4/highereducation/EHEA2010/BolognaPedestrians_en.asp#P132_13851

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information overload problem providing personalized recommendations to users. They have been used in different fields like health [2] or e-commerce [3] and the use in the education and academic world is an active field of study [4, 5, 6]. RSs assist users providing them a personalized approach treating each user in a different way.

The aim of this article is to present a fuzzy linguistic Web system called AyudasCBI[2] (acronym of Spanish words for "*Ayudas en Cirugía Bocal e Implantología*", in English, *assistance in oral surgery and implantology*), to assist students. In our case the system is adapted to students of Dentistry from the Dentistry School of the University of Granada, providing them with the appropriate information to reinforce the weaker areas or to boost the stronger ones. The major innovations and contributions of the system include:

1. The provision of reliable personalized information by using a dynamic recommender system.
2. The ability to use it in any place and at any time, providing to students the necessary freedom to organize their schedules.
3. Its user-friendly nature, using fuzzy linguistic modeling to improve the representation of user preferences and facilitate user-system interactions [7, 8].
4. The reliability of the information offered and the selection of exercises, endorsed by a team of experts in oral surgery from the Dentistry School of the University of Granada.

The ratio student-professor in the Spanish public university is around 15[3], with an increasing trend during the last years. The motivation of this work is to help to adjust the university to the Bologna process, where a more individualize education must be received by the students. The resources offered by an university must been universally accessible, thus, the system proposed in this paper satisfies the requirements of the World Wide Web Consortium (W3C) Web Accessibility Initiative[4].

The paper is organized as follows: In Section 2 the background is presented, that is the basis of recommender systems and the fuzzy linguistic modeling; Section 3 presents the new system, AyudasCBI; Section 4 addresses the validation of the system, and section 5 offers conclusions based on the study findings.

2. Preliminaries

2.1. Recommender systems

RSs could be defined as systems that produce individualized recommendations as output or have the effect of guiding the user in a personalized manner towards appropriate tasks among a wide range of possible options [9]. The delivery of personalized recommendations carries knowledge about users. The knowledge from the users can be extracted from ratings provided of already explored items, as well as information provided by the users [9, 10]. For all that, how the 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 to the user some specific information [11].

Many techniques have been proposed for the generation of recommendations [12], being the content-based and the collaborative approaches the more relevant. The former is based on the similarity of an user profile with an item profile, meanwhile the later, the recommendations for a user are based on the ratings provided by other users similar to this user.

Since each approach has certain advantages and disadvantages, the most adopted solution addressed in the different literature is the combination of the both in a hybrid recommender system [9]. Among the proposed strategies to combine the recommendation approaches we will pay special attention to the *weighted* one, where the recommendations from more than one technique are presented together aggregated [9].

[2]Accessible in: `http://sci2s.ugr.es/AyudasCBI`

[3]`http://www.mecd.gob.es/dms/mecd/educacion-mecd/areas-educacion/universidades/estadisticas-informes/datos-cifras/DATOS_CIFRAS_13_14.pdf`

[4]`http://www.w3.org/WAI/`

2.2. Fuzzy linguistic modeling

In some situations, the information cannot be precisely appraised in a quantitative manner but can be qualitatively evaluated. The fuzzy linguistic modeling is a tool based on the concept of *linguistic variable* [13] which has given very good results for modeling qualitative information in many problems in which quantitative information cannot be assessed precisely [14].

The 2-tuple fuzzy linguistic modelling (2-tuple FLM) [15] is a continuous model of representation of information that allows to reduce the typical loss of information we can find in other fuzzy linguistic approaches (classical and ordinal, see [13]).

Let $S = \{s_0, ..., s_g\}$ 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 $\beta \notin \{0, ..., g\}$,. β is represented by means of 2-tuples (s_i, α_i), where $s_i \in S$ 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 model defines a set of transformation functions between numeric values and 2-tuples $\Delta(\beta) = (s_i, \alpha)$ and $\Delta^{-1}(s_i, \alpha) = \beta \in [0, g]$ [15].

In order to establish the computational model we define a negation, comparison and aggregation operators. Using functions Δ and Δ^{-1} that transform numerical values into linguistic 2-tuples and viceversa without loss of information, any of the existing aggregation operators (i.e. arithmetic mean, weighted average operator or linguistic weighted average operator) can be easily extended for dealing with linguistic 2-tuples [15].

A problem modeling the information arises when different experts have different uncertainty degrees on the phenomenon, so an important parameter to determine is the "granularity of uncertainty", i.e., the cardinality of the linguistic term set S [16]. 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 $n(t)$ 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: $l(t, n(t)) \rightarrow l(t + 1, 2 \cdot n(t) - 1)$. A graphical example of a three level linguistic hierarchy is shown in Figure 1. Using this LH, the linguistic terms in each level are the following:

- $S^3 = \{a_0 = Null = N,\ a_1 = Medium = M,\ a_2 = Total = T\}$.
- $S^5 = \{b_0 = None = N,\ b_1 = Low = L,\ b_2 = Medium = M,\ b_3 = High = H,\ b_4 = Total = T\}$
- $S^9 = \{c_0 = None = N,\ c_1 = Very\_Low = VL,\ c_2 = Low = L,\ c_3 = More\_Less\_Low = MLL,\ c_4 = Medium = M,\ c_5 = More\_Less\_High = MLH,\ c_6 = High = H,\ c_7 = Very\_High = VH,\ c_8 = Total = T\}$

As it was pointed out in [16] the family of transformation functions between labels from different levels is bijective. This result guarantees that the transformations between levels of a linguistic hierarchy are carried out without loss of information.

3. AyudasCBI: A Web system to assist dentistry students in the field of oral surgery and implantology

In this section we present AyudasCBI, a Web system to assist students from the Dentistry School of University of Granada. The system is accessible at: *http://sci2s.ugr.es/ayudasCBI*. It is oriented to students from the subjects: *Oral Surgery I*, *Oral Surgery II* and *Implantology*. It is based on the knowledge that students shows to the system and recommends videos or different resources based on the actual needs of each one.

In the Figure 2 we can see that the system has three main components:

1. *Videos and resources* for recommendation to students according to their necessities.
2. *Student profiles* that stores the characteristics of each student. On one hand, the representation of their qualifications and the result of periodic tests. On the other hand, their personal evaluations obtained after they provide feedback about the resources recommended.
3. *A personalized method for generating recommendations* that implements the hybrid recommendation policy based on information from the resources and student profile databases.

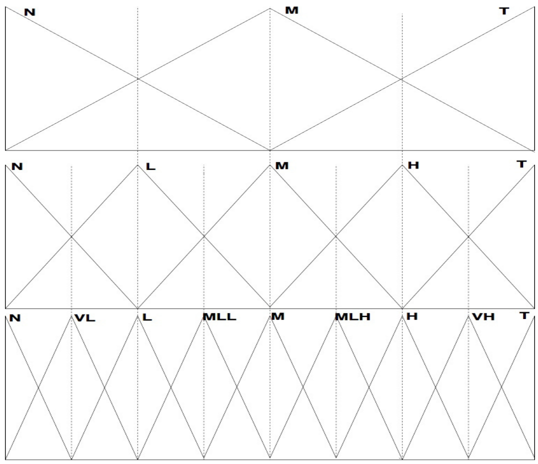

Fig. 1. Linguistic Hierarchy of 3, 5 and 9 labels

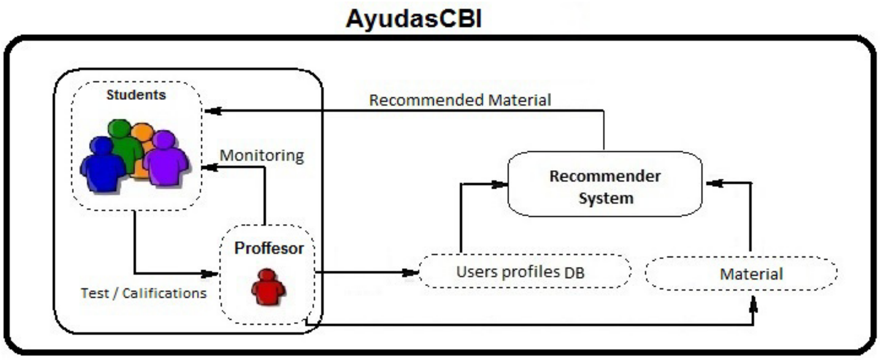

Fig. 2. Operating scheme

Moreover, and thinking on the development of aptitudes like teamwork, the system recommends collaboration possibilities between students with the same necessities in order to encourage them to work together.

3.1. Information representation

In order to represent the different concepts necessaries in the system, we use different linguistic labels sets ($S_1, S_2, ...$). We selected the *LH* presented in section 2.2. The different concepts assessed in the system are the following:

- The *necessities degree* of students with respect to each of the defined necessities subgroups, which is labeled in S_1.
- The *degree of similarity* between the necessities of two students or between resources and students, which is labeled in S_3.
- The predicted *degree of relevance* of a resource for a student, which is labeled in S_2.
- The *degree of satisfaction* with a recommended resource expressed by a student, which is labeled in S_4.

We use a set with 5 labels, that is level 2, to represent the degrees of necessities and satisfaction ($S_1 = S^5$ and $S_4 = S^5$) and 9 labels from level 3 to represent the degrees of predicted relevance ($S_2 = S^9$) and similarity ($S_3 = S^9$).

3.2. Resource representation

A multimedia database was developed and contained videos with a wide set of different oral surgeries or implants for all possible necessities inside the subjects covered. Also, different sets of scientific papers or class notes are introduced into the system. All videos, papers and notes can be combined among different subgroups called activities in the construction of a customized program for each student. Videos were recorded on real surgeries produced in dentistry's offices or in university's labs. Those activities are the items to be recommended by our system. Each combination of videos, notes or papers make the different activities suitable for a student with a specific necessity. First, we consider students that have their profiles already updated into the system based on their results obtained during their monitoring, then the professors establish the following four reinforcing subgroups: basic oral surgery, advanced oral surgery, basic implantology, advanced implantology, and postural syndrome.

Once a professor creates a new activity into the system, he/she provides the activity with an internal representation that is mainly based on its appropriateness for each reinforce subgroup. An activity i is represented as a vector $VT_i = (VT_{i1}, VT_{i2}, ..., VT_{i4})$, where each component $VT_{ij} \in S_1$ is a linguistic assessment that represents the how appropriate is the activity i with respect to the reinforcing subgroup j. How appropriate is an activity for each group is determined by the professors when they create new activity into the system.

For instance, if a new activity n, thought to those student who are good in implantology but they can have a better understanding, is created by the professor, then, he/she would select for it the reinforcement subgroups 2 and 3 with a membership degree "*medium*", "*total*" for the subgroup 4 and "*none*" for the subgroup 1. These membership degrees belong to the label set S_1, i.e. in our proposal the set S^5, with labels $b_0, b_1, ..., b_4$. So, n is represented as: $VT_n = ((b_0, 0), (b_2, 0), (b_2, 0), (b_4, 0))$.

In the Figure 3 we can see the example of an activity in the system.

3.3. Student profiles

The student profiles stored in the database represent their necessities. To acquire student necessities the system proceed as follows: First, students must complete their profiles with the grades obtained in previous subjects related with this oral surgery and implantology; Second, they have to periodically carry out different test inserted in the system by the professors to be able of evaluate their abilities. After obtaining the test results, the professors assess the membership of the student necessity in each one of the four reinforcing subgroups. A student i is represented as a vector $VP_i = (VP_{i1}, VP_{i2}, ..., VP_{i4})$, where each component $VP_{ij} \in S_1$ is a linguistic assessment (i.e., a 2-tuple) that represents the degree of how appropriate i is for each subgroup j.

For instance, suppose a student s whose necessity is basic oral surgery and basic implantology. Then, the professor would select for this student the reinforcing subgroups 1 and 3 with a membership degree "Total" and "Medium" respectively, because there are dependencies between groups and it is necessary to know about the first group to understand the second, the rest of the reinforcement subgroup have a membership degree with a value of "None", i.e. in our proposal the set S^5, with labels $b_0, b_1, ..., b_4$. So, s is represented as: $VT_p = ((b_4, 0), (b_0, 0), (b_2, 0), (b_0, 0))$.

Since student are performing test over the whole semester, their membership to the different subgroup will be changing together with their new results.

3.4. Recommendation Scheme

AyudasCBI is based on a weighted hybrid recommendation strategy between content-based and collaborative approach, which apply different weights to the both approaches. The content-based approach is applied to discover which are the better activities for each student, while the collaborative one is applied to soften or reinforce the recommendation based on the different feedbacks provide by similar students. We rely on a matching process by similarity measures among vectors. Particularly, we use the Pearson product-moment correlation coefficient, but defined in a linguistic context:

$$\sigma_l(V_1, V_2) = \Delta\left(g \times \frac{\sum_{k=1}^{n}(\Delta^{-1}((v_{1k}, \alpha_{v1k}) - (\overline{V}_1, \alpha_{\overline{V}_1})) \times \Delta^{-1}((v_{2k}, \alpha_{v2k}) - (\overline{V}_2, \alpha_{\overline{V}_2})))}{\sqrt{\sum_{k=1}^{n}(\Delta^{-1}((v_{1k}, \alpha_{v1k}) - (\overline{V}_1, \alpha_{\overline{V}_1})))^2} \times \sqrt{\sum_{k=1}^{n}(\Delta^{-1}((v_{2k}, \alpha_{v2k}) - (\overline{V}_2, \alpha_{\overline{V}_2})))^2}}\right) \tag{1}$$

Fig. 3. Activity example

with $\sigma_l(V_1, V_2) \in S_3 \times [-0.5, 0.5]$, and where g is the granularity of the term set used to express the similarity degree, i.e. S_3, n is the number of terms used to define the vectors (i.e. the number of reinforcing subgroups that have been considered) and (v_{ik}, α_{vik}) is the 2-tuple linguistic value of the reinforcing subgroup k in the activity or student vector V_i (label of S_1).

When a new activity i is entered into the system, there is no possibility of applying both approaches, thus only a content-based approach is used to know if it could be appropriate for a student p, as follows:

Compute $\sigma_l(VT_i, VP_p) \in S_3$. As $S_3 = S^9$, activity i is considered suitable for student p if $\sigma_l(VT_i, VP_p) > (s_4^9, 0)$. If activity i is considered suitable for student p, then the system recommends i to p with an estimated relevance degree $i(p) \in S_2 \times [-0.5, 0.5]$

If some feedback has already been proportioned for the activity i then the weighted scheme works as follows for a student p:

1. Look for similar students into the whole group VP, that is: Compute $\sigma_l(VP_p, VP_n) \in S_3$ for each student n. As $S_3 = S^9$, student n is considered similar to student p if $\sigma_l(VP_p, VP_n) > (s_4^9, 0)$.
2. If student p is considered similar to student n, then the system stores the feedback given from this student for the activity i together with the similarity degree, that is: $(i(p), \sigma_l(VP_p, VP_n))$.
3. When the system has all the students similar to p, it will estimate the Linguistic Weighted Average (LWA) of their feedback together with their similarities as wights, (c_E, a_E) [17].
4. The final recommendation of an activity i for a student p will be the result of the LWA of:
   (a) The result of the content-based approach for the student p and the activity i.
   (b) The LWA obtained from the feedback provided to activity i by the students similar to p.

   both weighted with $w = (s_4^9, 0)$.

As mentioned above, AyudasCBI also recommends collaboration between students. Student will always see in their screen a suggestion of other students similar to them in order to suggest collaborations between each others.

3.5. Feedback phase

When students have completed the recommended activities, they are asked to assess the relevance of these recommendations in order to evaluate the satisfaction with the activity. Students communicate their linguistic evaluation judgments to the system, $rc \in S_4$, indicating how much the recommended activities helped them. If the system register more than 50% of negative feedback on an activity it will alert the professor with an email informing the activity must be changed and it will deactivate automatically the activity.

4. Evaluating AyudasCBI

In this section we present the evaluation of the proposed recommender system. We will use online experiments based on the evaluation of the recommendations.

Since we can not compare our method with others approaches using a standard data set due to the singularity of the system and the importance of the feedback phase, we will perform a practical study where a group of 50 volunteers students will test the system during one semester in different subjects: *Oral surgery I*, *Oral surgery II* and *Implantology I*.

Commonly used measures to evaluate recommender systems are precision, recall and F1. They are used to evaluate whether a recommender system properly recommends items that users will consider relevant [18]. In this work, we do not believe in the opinions of experts that say if a recommendation is good or not, that is the intention of the professor when he/she creates the activity, we will evaluate the result of the recommendations based on results obtained by the students and the feedback provided.

After one semester of usage the results of the students who used the system were in average a 15.5% better than the users that only assist to lessons. The LWA of the feedback provided by users on the improvement received by the recommendations were $(b_0^5, 7)$, that is between medium and high.

The results demonstrate that the website is not only positively perceived by its users but also it increases their results compared to the ones who did not use it.

5. Concluding remarks

This study presents a fuzzy linguistic Web tool named AyudasCBI, which incorporates a recommender system to provide personalized activities to students with necessities in the subjects oral surgery I and II and implantology II of dentistry degree in the University of Granada. A professor establishes the necessities of a student after evaluating the results of different tests and its grades. Those necessities are used to generate the recommendations regarding other students and the activities presented in the system. The system also provides students with advice for collaborations with other students with similar necessities in order to promote the teamwork. The main benefits of this system are the increase of the personalize degree of the education received by the students that also have the possibility of following the activities anywhere and at anytime. It potentially contributes to the reduction in the economic impact of a higher personalized education. We have applied AyudasCBI in a real environment, and the experimental results demonstrate the good results of the usage of the system as well as the perception by the students by enhancing the effectiveness of professors dealing with large group of students.

As future work, we consider to study the possibility of automatize the creation of activities by the system bases on individual feedback provided by the student of each component of the activities as well as let the students create their own activities.

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