USING A VISUAL TOOL TO GUIDE STUDENTS IN THE COMPLEX PROCESS OF LEARNING FUZZY WEIGHTED INFORMATION RETRIEVAL SYSTEMS

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Abstract

In the information retrieval field, Fuzzy Information Retrieval Systems (FIRSs) use the potential of fuzzy techniques to improve the retrieval activities. Some models of FIRSs employ weighted queries to enhance the representation of user information needs and fuzzy connectives to evaluate such queries.

In our teaching experience we have observed that students have many problems to understand the different semantics that could be associated to the weights of queries together with their respective strategies of query evaluation, so they must process many examples and compare the results continuously. In this sense, FIRSs are suitable for applying a computer-supported learning tool, so we decided to improve the understanding of these complex FIRSs by the development of a student-oriented software tool. This tool provides an environment for demonstrating the performance of weighted queries with different semantics and their evaluations using fuzzy connectives. The use of our tool by student has allowed them to overcome the main understanding problems related to the different FIRSs models, the students' motivation has increased, and their marks in final exams have risen.

Keywords - Fuzzy Information Retrieval, Learning Tools, Education.

1 INTRODUCTION

In this globalised world, the extraordinary importance of the World Wide Web as e-business platform emphasizes the educational needs related to information retrieval field. Information retrieval may be defined as the problem of selecting documentary information from storage in response to searches provided by a user in form of queries [1, 2].

Fuzzy Information Retrieval Systems (FIRSs) use the artificial intelligence fuzzy logic tools [3] to improve the retrieval activities [4, 5]. The study of these systems is one of the matters belongs to the degree subject Information Management Intelligence Systems at the Faculty of Library and Information Sciences (University of Granada). It is becoming clear that students have to be competent in these systems. The complex skills that those FIRSs provide, mainly by the use of weighted queries and fuzzy connectives, make very hard to show the different semantics that could be associated to the

ISBN:978-84-613-5538-9

weights of queries together with their respective strategies of query evaluation in a blackboard. Furthermore, students have many problems to full understand the semantics of weights and the evaluation strategies, so they need to make many exercises and compare the results continuously.

The use of computer-supported learning tools may provide students with opportunities to promote their understanding of phenomena in science and to facilitate the visualization of abstract and unobservable concepts [6, 7, 8]. In this sense, the information retrieval is a suitable field to put into practice the computer-supported learning systems. The advantage of using these learning systems is that the students get a realistic feeling of the particular information retrieval systems used and they can develop self-learning processes on typical operations of them [9].

The specific aim of our work was to improve the understanding of FIRSs by students of the Information Retrieval Systems based on Artificial Intelligence degree subject, facilitating their self-learning processes through the use of a computer-supported tool.

We have searched the Web and peer-reviewed journals for training information retrieval tools, but we have found very few of them [9, 10, 11], which present several shortcomings, and particularly, it does not exist a FIRSs training tool. Therefore, we decided to develop a visual student-oriented tool to overcome the understanding problems related to the different FIRSs models.

Our visual learning tool provides an environment for demonstrating the use and performance of weighted queries with different semantics and their evaluations using different fuzzy connectives. Furthermore, the application provides a feedback on the evaluation of weighted queries by means of visual and intuitive tool, showing internal aspects through evaluations trees and allowing the visual comparison of the evaluation of different weighted queries.

The paper is structured as follows. In Section 2 we introduce the basic notions of FIRSs. In Section 3 we describe the main modules of the presented visual tools. In Section 4 the proposed visual tool is evaluated in order to measure its leaning skills. Finally, some conclusions are pointed out.

2 FUZZY INFORMATION RETRIEVAL SYSTEMS

The main activity of an Information Retrieval System (IRS) is the gathering of pertinent archived documents that best satisfy the user queries. These systems present three classical components to carry out their activity [12]:

- Documentary Database: for storing documents and the representation of their information contents (index terms).
- Query Subsystem: for allowing users to formulate their queries by means of a query language.
- Evaluation Subsystem: to assess the documents for a user query obtaining a Retrieval Status Value (RSV) for each document.

In the following subsections we briefly present the components of an IRS.

2.1 Documentary Database

This component stores the documents and the representation of their contents. Textual documents representation is typically based on index terms (that can be either single terms or sequences), which work as content identifiers for the documents. We assume a documentary archive built like in an usual, a finite set of index IRS [1, 2]. The database stores a finite set of documents $\mathcal{D} = \{d_1, \ldots, d_m\}$, a finite set of index terms $\mathcal{T} = \{t_1, \ldots, t_l\}$, and the representation R_{d_j} of each document d_j characterized by a numeric indexing function $\mathcal{F} : \mathcal{D} \times \mathcal{T} \rightarrow [0, 1]$ which assigns a numeric weight to each index term t_i.

In fuzzy notation, R_{d_j} is a fuzzy set represented as:

$$R_{d_j} = \sum_{i=1}^{l} \mathcal{F}(d_j, t_i)/t_i.$$

Using the numeric values in (0,1), $\mathcal{F}$ can weight index terms according to their degree of significance in describing the content of a document in order to improve the document retrieval. $\mathcal{F}(d_j, t_i) = 0$ implies that the document d_j contents do not deal at all with the concept(s) represented by the index term t_i, and $\mathcal{F}(d_j, t_i) = 1$ implies that the document d_j is perfectly represented by the concept(s) indicated by t_i. The quality of the retrieval results strongly depends on the criteria used to compute $\mathcal{F}$. In standard test collections $\mathcal{F}$ is obtained using a $tf \cdot idf$ scheme [2].

2.2 Query Subsystem

The query subsystem allows users to formulate their information needs (queries) based on a weighted Boolean query language and presents the relevant documents which are retrieved by the system. This subsystem supports the user-system interaction, and therefore, it should be able to account for the imprecision and vagueness typical of human communication. This aspect may be modelled by means of the introduction of weights in the query language. Many authors have proposed weighted IRS models using Fuzzy Set Theory [13, 14, 15, 16, 17, 18, 19].

Each user query is expressed as a combination of the weighted terms which are connected by the logical operators AND ($\wedge$), OR ($\vee$), and NOT ($\neg$). The weights associated with the query terms could be numerical values assessed in [0,1] or linguistic values taken from a linguistic term set defined in a fuzzy ordinal linguistic context [12, 20, 21, 22, 23].

A user query is any legitimate Boolean expression whose atomic components (atoms) are pairs $< t_i, w_i >$, $t_i \in \mathcal{T}$ and being $w_i \in \mathcal{I}$, $\mathcal{I} \in [0,1]$ or $\mathcal{I} \in \mathcal{S}$ the weight associated to the term t_i by the user. Then, the set $\mathcal{Q}$ of the legitimate weighted Boolean queries is defined by the following syntactic rules:

1. Atomic queries: $\forall q =< t_i, w_i > \in \mathcal{T} \times \mathcal{I} \Rightarrow q \in \mathcal{Q}$.
2. Conjunctive queries: $\forall q, p \in \mathcal{Q} \Rightarrow q \wedge p \in \mathcal{Q}$.
3. Disjunctive queries: $\forall q, p \in \mathcal{Q} \Rightarrow q \vee p \in \mathcal{Q}$.
4. Negated queries: $\forall q \in \mathcal{Q} \Rightarrow \neg(q) \in \mathcal{Q}$.
5. All legitimate queries are only those obtained by applying rules 1-4, inclusive.

Users specify restrictions on the relevant documents to be retrieved through weights queries. There are four kinds of semantics to interpret the weights in queries [12]:

- *Importance semantics* [13, 18]. This semantics defines query weights as measures of the relative importance of each term with respect to the others in the query. By associating relative importance weights to terms in a query, the user is asking to see all documents whose content represents the concept that is more associated with the most important term than with the less important ones. In practice, this means that the user requires that the computation of the relevance degree of a document should be dominated by the more heavily weighted terms.
- *Threshold semantics* [15, 17]. This semantics defines query weights as satisfaction requirements for each term of the query to be considered when matching document representations to the query. By associating threshold weights with terms in a query, the user is asking to see all the documents sufficiently related to the topics represented by such terms. In practice, this means that the user will reward a document whose index term weights exceed the established thresholds with a high relevance degree, but allowing some small partial credit for a document whose values are lower than the thresholds.
- *Perfection semantics* [16, 24]. This perfection semantics defines query weights as descriptions of ideal or perfect documents desired by the user. By associating weights with terms in a

query, the user is asking to see all the documents whose content satisfies or is more or less close to his ideal information needs as represented in the weighted query. In practice, this means that the user will reward a document whose index term weights are equal to or at least near to term weights for a query with the highest relevance degrees. With such a semantic, the user must be able to specify precisely the characteristics of the user's perfect document in a consistent way with the document representations.

- *Quantitative semantics*. A user may want to incorporate in the query not only qualitative criteria but also quantitative ones. To model this requirement, some existing systems allow t perform a control on the cardinality of retrieved documents by a whole query [2]. This quantitative semantics defines query weights as measures of quantity of documents for each term of query that users consider in the computation of the final set of documents retrieved [12].

2.3 Evaluation Subsystem

The goal of evaluation subsystem consists of evaluating documents in terms of their relevance to a weighted query according to four possible semantics. The evaluation subsystem for weighted Boolean queries with more than one term works by means of a constructive bottom-up process based on the criterion of separability [16, 18]. It acts in two steps:

- First, the documents are evaluated according to their relevance only to atoms of the query. In this step, a partial relevance degree is assigned to each document with respect to each atom in the query.
- Second, the documents are evaluated according to their relevance to Boolean combinations of atomic components (their partial relevance degree), and so on, working in a bottom-up fashion until the whole query is processed. In this step, a total relevance degree is assigned to each document with respect to the whole query.

To overcome the problems of equivalence in the weighted Boolean queries [16, 18] the user queries are pre-processed and put into either a conjunctive normal form (CNF) or a disjunctive normal form (DNF) using the transformation rules given in [25]. The result is that all the Boolean sub-expressions must have more than two atoms. Weighted single-term queries are kept in their original forms.

3 A VISUAL STUDENT-ORIENTED TOOL TO OVERCOME THE FIRS LEARNING PROBLEMS

The visual student-oriented learning tool that we introduce in this section has been designed to assist students with their main difficulties in learning FIRSs that we have detected during our teaching experience. This tool provides a test environment of weighted queries to be used by the students, enabling them to develop self-learning processes. Next, we summary the main learning problems that we propose to solve with our visual training system:

- To support students in the visualization of the bottom-up evaluation tree for weighted Boolean queries, showing the results step by step.
- To aid students for resolving their problems with the formulation and the evaluation process of queries that use different semantics simultaneously [12, 21, 26, 27].
- To assist students in their difficulties to understand the different meaning of the semantics associated with the query weights, by processing many examples and facilitating the comparison of their results. For example, for threshold semantics we can use three different threshold proposals: classical threshold semantics [15, 18] symmetrical threshold semantics [12] and improved threshold semantics [23].
- To help students in their full understand of the contradictions existing between different semantics, making the execution of multiple exercises easier. This is applicable, for example, to the threshold semantics and the perfection semantics, which are contradictory for values of index weight function over the considered threshold value [12].

Furthermore, we have tried to overcome the shortcomings presented by the existing IR training systems [9]:

- These systems don’t offer feedback about the performance or success of user queries.
- They don’t show how a user query is evaluated.
- They don’t compare the performance of different types of user queries and different evaluation procedures of user queries.

This visual student-oriented learning tool is composed of three main components: module of instructional test collections, module for formulating weighted queries, and module for evaluating weighted queries. We describe them in the following subsections.

3.1 Module of Instructional Test Collections

A test collection consists of a collection of documents, a set of queries and evaluation results for showing which documents are relevant with respect to a given query. Our aim is to encourage the analysis of individual queries and, as in [9, 28] we only need instructional test collections.

There are several ways to measure the quality of an IRS, such as the system efficiency and effectiveness, and several subjective aspects related to user satisfaction [1]. Traditionally, the retrieval effectiveness is based on the document relevance with respect to the user’s needs. There are different criteria to measure this aspect, but precision and recall [29] are the most used. Precision is the ratio between the relevant documents retrieved by the IRS in response to a query and the total number of documents retrieved, whilst recall is the ratio between the number of relevant documents retrieved and the total number of relevant documents for the query that exist in the database [29].

Students have the possibility of building their own test collections to analyze the performance of different weighted queries in FIRS by means of the precision and recall achieved across the whole set of queries. The definition of the test collection may be done adding documents represented as a set of index terms. Documents are indexed by means of a random numeric indexing function, between 0 and 1, which describe the subject content of the documents (Fig. 1). The tool also allows the removal of documents and terms, as well as the automatic generation of new terms – documents association tables.

DB Management

Doc. \ Term	T1	T2	T3	T4	T5	T6	T7	T8	T9
D1	0,62	0,98	0,46	0,36	0,35	0,65	0,1	0,77	0,9
D2	0,28	0,18	0,32	0,08	0,76	0,79	0,69	0	0,28
D3	0,66	0,54	0,59	0,06	0,57	0,54	0,26	0,94	0,75
D4	0,9	0,28	0,59	0,14	0,02	0,07	0,72	0,16	0,45
D5	0,19	0,58	0,05	0,66	0,49	0,11	0,15	0,92	0,73
D6	0,14	0,32	0,25	0,13	0,94	0,16	0,2	0,36	0,95
D7	0,77	0,98	0,13	0,55	0,86	0,47	0,54	0,91	0,09
D8	0,74	0,67	0,98	0,07	0,34	0,1	0,37	0,83	0,36
D9	0,45	0,94	0,4	0,16	0,03	0,43	0,78	0,66	0,87
D10	0,16	0,79	0,22	0,12	0,41	0,39	0,75	0,05	0,28
D11	0,12	0,69	0,11	0,51	0,3	0,9	0,87	0,61	0,62
D12	0,37	0,27	0,22	0,09	0,78	0,51	0,15	0,86	0,67
D13	0,4	0,02	0,72	0,03	0,45	0,92	0,32	0,37	0,95
D14	0,49	0,4	0,48	0,69	0,38	0,07	0,09	0,52	0,7
D15	0,85	0,4	0,62	0,47	0,88	0,56	0	0,71	0,1
D16	0,58	0,12	0,65	0,86	0,02	0,21	0,41	0,38	0,22
D17	0,45	0,86	0,46	0,36	0,6	0,12	0,71	0,85	0,1
D18	0,41	0,43	0	0,62	0,52	0,17	0,85	0,89	0,03
D19	0,01	0,4	0,61	0,05	0,15	0,1	0,72	0,79	0,5
D20	0,71	0,39	0,71	0,9	0,05	0,87	0,49	0,04	0,21
D21	0,96	0,92	0,2	0,17	0,71	0,8	0,08	0,24	0,91
D22	0,89	0,98	0,44	0,31	0,2	0,09	0,86	0,49	0,59
D23	0,29	0,57	0,24	0,51	0,25	0,63	0,4	0,51	0,84

Fig. 1. Defining a test collection.

3.2 Module for Formulating Weighted Queries

Students would define their weighted queries using the formulation module through a fuzzy weighted Boolean query language. With this language each query is expressed as a combination of the weighted index terms that are connected by the logical operators AND, OR, and NOT. The weights are numerical or ordinal linguistic values taken from a set *S* of nine labels defined as:

S = {Null, Extremely_Low, Very_Low, Low, Medium, High, Very_High, Extremely_High, Total}

Students formulate a weighted query by choosing the search terms, the unitary or binary operators, the numeric or linguistic values of weights, and the semantics associated to the weights. Following this procedure it is easy to compound complex expressions. To facilitate the query formulation it's possible to remove the last operations. The tool allows the formulation of queries that use different semantics simultaneously (Fig. 2).

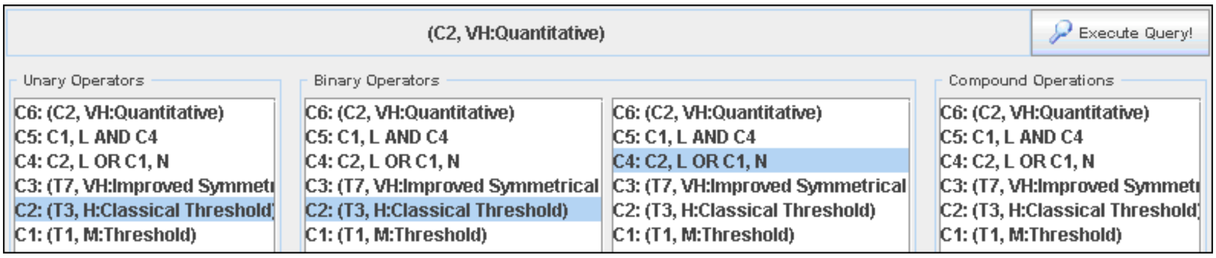

Fig. 2. Formulation of Weighted Queries.

3.3 Module for Evaluating Weighted Queries

The evaluation module performs the measurement and provides to the students a feedback on the evaluation of weighted queries by means of visual tools. This feedback is given by showing internal aspects of evaluations of weighted queries using trees. Furthermore, this module allows the visual comparison of the evaluation for different weighted queries. For example, Fig. 3 shows the evaluation result for assessing the next weighted query:

q = ((T3, EL: Threshold), M) OR ((T6, L: Threshold), H)

This linguistic weighted query is compound of two subqueries joint by a disjunctive connective "OR" that use two semantics simultaneously, threshold and quantitative ones. The results of the assessment for all relevant documents are shown in decreasing order and, we have selected for displayed the evaluation tree of the weighted query corresponding to document D2.

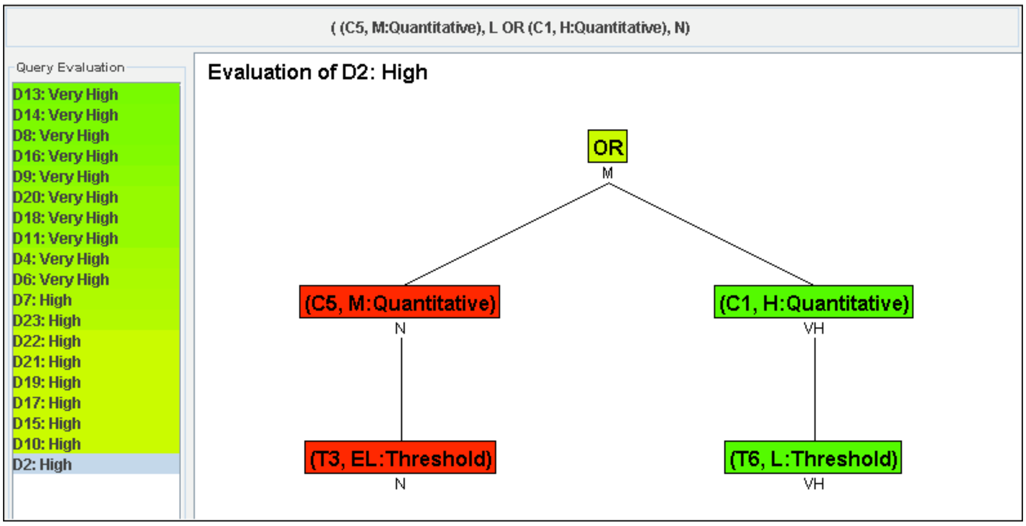

Fig. 3. Evaluation Results.

4 EVALUATION OF THE COMPUTERIZED LEARNING SYSTEM

The computer-supported learning system for FIRSs was tested in the field with students, in order to evaluate its performance and influence on their learning.

Although we have some limitations in this study, due to the small number of students (eighteen) participating, its findings provide some interesting insights into students learning and teaching about FIRSs.

Previously, we should point out that in our classes the students are allowed to interact with the system for a maximum of 60 minutes, two days by week during four months. This is done under the supervision of the teacher. In addition, students can use the system in their free time from both the computer laboratory or from their house using Internet, (obviously, in those cases they do not have direct supervision from the teacher).

To get an objective appreciation on the learning outcome, we have developed two different research studies:

1. *Does the use of the visual computer-supported learning tool improve the scores between different academic years?*

In this case, we analyze the scores achieved by different groups of pupils across two different academic years in order to study if the visual computer-supported learning tool, as a complement to traditional lectures and exercises, has any positive impact on the learning outcome:

- Academic year 2005-2006: Pupils that did not use the system, and
- Academic year 2007-2008: Pupils that used the first stable version of the learning system. In academic year 2006-2007 an incomplete and non stable version (β version) was used for the first time. In this sense, scores from this academic year cannot be considered as relevant to analyze the learning outcome.

On both groups of pupils, the same methodology with exercises and didactic procedure was carried out along course.

2. *Does a strong use of the visual computer-supported learning tool improve the scores in final exams?*

In this case, we analyze the student scores in academic year 2007-2008 depending on the intensity of the use of the visual computer-supported learning tool.

In both studies, our primary concern for accuracy and to overcome problems with statistical power, is due to the very small sample size ($n = 18$ for academic year 2007-2008 and $n = 16$ for academic year 2005-2006). For such small data sets, it is basically impossible to tell if the data comes from a variable that is normally distributed [30], as with small sample sizes ($n < 20$) tests of normality may be misleading. In this situation, nonparametric tests are an appropriate approach. In addition, the use of nonparametric methods may be necessary when data has a ranking but no clear numerical interpretation, such as when assessing preferences.

4.1 Comparing Scores between Different Academic Years 2007-2008 and 2005-2006

The main aim of this research study is the following:

Was the learning effect on the remembering, understanding and applying level in the pupils from the academic year 2007-2008 higher than in the pupils from the academic year 2005-2006?

To do so, student scores on final exams from both academic years, 2007-2008 and 2005-2006, are directly compared by using the Mann-Whitney's nonparametric statistical test (for more detail see [31, 32]).

Then, we analyze the research null hypothesis:

$$H0: Scores_{2007-2008} = Scores_{2005-2006},$$

with ScoresX being the scores on final exams in participants from group X (X = 2007 − 2008 or X = 2005 − 2006). Table 1 shows the scores for participants in groups 2007 − 2008 and 2005 − 2006 (0 is the lowest possible score whilst 10 is the maximum one).

The Mann-Whitney's U test (at 95% confidence interval) reflects there is significant difference in scores between group 2007 − 2008 and group 2005 − 2006, i.e., $U_{2007-2008} = 202$ ($z = -2.00119$), $U_{2005-2006} = 86$ ($z = 2.00119$), and consequently, the null research hypotheses H_0 is rejected ($z > 1.96$). So, given that the scores in group 2007-2008 (median rank = 18.06) are higher than scores in group 2005-2006 (median rank = 12.69) (see data in Tab. 1), the alternative hypothesis:

$$Scores_{2007-2008} > Scores_{2005-2006}$$

is supported.

2007-2008	9	8.5	7.5	7	7	3.5	5	6	7.5	5	7	7.25	5	5	3	9	8.5	8
2005-2006	8	8	7.5	7	6.5	3.5	4	6	7	5	3	2	5	5	3	0		

Tab. 1. Students scores.

4.2 Researching If a Strong Use of Computer-Supported Learning System Improves Student Scores in the Academic Year 2007-2008

In order to study if a strong use of the visual learning tool implies higher scores on final exams, a correlation test is applied, i.e, the Spearman's rank correlation test or Spearman's rho -ρ- (see [32]).

In a correlation test, the correlation value is 1 in the case of an increasing linear relationship, −1 in the case of a decreasing linear relationship, and some value in between in all other cases, indicating the degree of linear dependence between the variables. The closer the correlation is to either −1 or 1, the stronger the correlation between the variables. If the variables are independent then the correlation is 0.

Then, pupils from the academic year 2007-2008 were asked for his/her level of use of the learning tool. It was done using a nine point checklist (0: "never used", 1: "sometimes used", ..., 8: "only the tool is used for studying/learning (no more materials are used)"). In Fig. 4, scores and declared use are plotted.

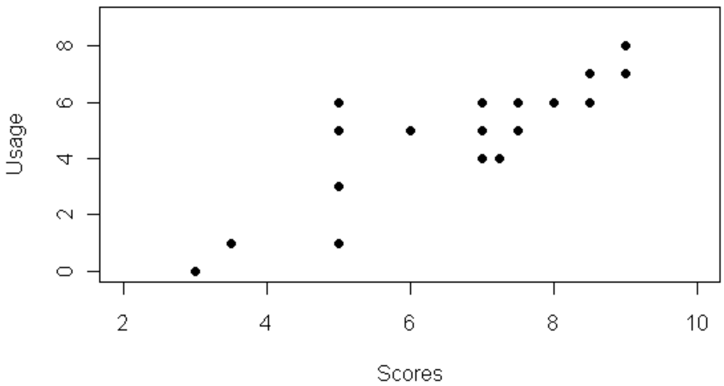

Fig. 4. Plot with scores and declared usage in group 2007-2008.

In our study, Spearman's test with $\rho = 0.81$ indicates there is a high correlation (with p-value=4.636e−05) between scores and declared usage. This represents a statistical statement indicating the presence of an effect or a difference. Such as a positive correlation (and close to 1) reveals that the increase in scores for participants in group 2007 − 2008 would be a consequence of a strong use of our visual computer-supported learning tool.

Table 2

Scores and declared use in academic year 2007-2008.

Scores	9	8.5	7.5	7	7	3.5	5	6	7.5	5	7	7.25	5	5	3	9	8.5	8
Usage	7	7	6	6	5	1	6	5	5	5	4	4	3	1	0	8	6	6

5 CONCLUSIONS

The use of the visual learning tool has offered students the opportunity to see and compare the achieved results of different weighted queries. Our tool has enabled students to develop self-learning processes on typical FIRS operations and more flexible learning opportunities at their own pace, thus they have got a realistic feeling of the particular FIRS used.

The development of self-learning processes has been an important motivational factor that has leaded to increase learning gains [33]. We have achieved enhance students' learning on FIRS, their motivation has increased, and their marks in final exams have risen.

We have evaluated its performance on students' learning and our results reveal that the use of this tool enhances students' learning on weighted query based FIRSs, their scores in the final exams, and their involvement and motivation.

On the other hand, we have observed that its performance could be improved if we incorporate more multimedia instruction elements in the system activity.

ACKNOWLEDGMENTS

This work has been supported by the project: "PROYECTO DE EXCELENCIA: Desarrollando el Modelado Lingüístico Difuso y su uso en Aplicaciones WEB". Junta de Andalucía. Ref. P09-TIC-05299.

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