Journal of Universal Computer Science, vol. 15, no. 14 (2009), 2786-2807
submitted: 6/8/09, accepted: 15/7/09, appeared: 1/8/09 © J.UCS

A Web-Decision Support System based on Collaborative Filtering for Academic Orientation. Case Study of the Spanish Secondary School[1]

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Abstract: Collaborative Filtering has been widely used in Recommender Systems helping customers of e-shops to find out items matching their requirements in huge or complex search spaces. There exist many commercial applications that show the utility of these systems, especially in e-commerce whose features and good performance obtained has driven us to consider their application in a specific domain as *Academic Orientation,* in order to support students' decisions through their academic journey. We propose the use of the ideas behind the Collaborative Recommender Systems to develop a Web-based Decision Support System (Web-DSS) for Academic Orientation that analyze the students' skills, attitudes, preferences, etc., and then compute relevant information to support their decisions concerning their academic future. Furthermore, we shall study the performance of such techniques in Academic Orientation by using a dataset gathered from various Secondary and High Schools in Spain. *OrieB,* a web-DSS for academic orientation is then presented.

Keywords: Decision Support Systems, Recommender Systems, Collaborative Filtering, Academic Orientation.

Categories: J.4, K.3.1, L.6.2

1 Introduction

With the advent of Internet, new users' requirements arise in many areas. One of the most demanded is based on the necessity of finding out suitable items over huge and/or complex search spaces, as it happens in e-shops. More and more, users need help to explore and filter all the possibilities about the items offered in order to improve the quality of their choices, minimize the time consumed and the wrong decisions.

Different tools have been developed to accomplish the previous goals, being remarkable the use of Recommender Systems [Resnick et al. 97; Adomavicius et al. 05]. These systems offer recommendations to users according to their preference profiles, guiding them through search spaces in order to find out the most suitable items for their needs in many real-life situations. The growth of this area is basically due to the vast amount of available information in Internet and the facilities provided

[1] This contribution is partially financed by research projects TIN-2009-08286, P08-TIC-3548 and FEDER fonds.

by the Web to create users' communities in order to share experiences, tastes, interests, etc. In this sense, Recommender Systems (RS) provide users customized advices and information about products or services of interest in order to support their decision-making processes.

Usually a RS estimates the degree of like or dislike either how suitable is an item for a user. To do so, a user profile is generated from his/her preferences which is built by gathering explicit data, implicit data or both [Pazzani 99; Adomavicius et al. 05].

Recommendations suggested by a RS can be obtained in different ways [Resnick et al. 97; Schafer et al. 01] and hence there exist different types of RS, depending on the information and the technique utilized to compute its recommendations: content based [Pazzani 99; Lenar et al. 07; Martínez et al. 07], collaborative [Pazzani 99; Lee et al. 03; Herlocker et al. 04], demographic [Pazzani 99; Lenar et al. 07], knowledge based [Burke 00; Martínez et al. 08], utility based, [Burke 02; Martínez et al. 07], and several kinds of hybridations among these methods [Tran et al. 00; Burke 02].

Here, we focus on Collaborative RS (CRS henceforth), based on the Collaborative Filtering methods (CF) [Resnick et al. 94; Herlocker et al. 99; Lee et al. 03], that have been applied to different areas in the literature as decision making [Schafer et al. 01; Herlocker et al. 04; Adomavicius et al. 05], information retrieval [Belkin et al. 92; Perez-Alcazar et al. 03; Jung 05], even classification [Weiss et al. 91; Basu et al. 98; Billsus et al. 99], with successful results.

CRS compute their recommendations building groups of interest with users and then recommend items that are well considered for the majority of members belonging to the target group. This type of RS has been wide-used mainly in domains such as e-commerce and leisure applications [Aimeur et al. 08; Garfinkel et al. 08; Velusamy et al. 08] obtaining good results. Due to this success, we wonder about its performance and impact in such a topic as Academic Orientation to support students' decisions regarding their academic career.

Students must face up to several decisions that need to be made along their academic journey in order to keep on the chase of some professional competences valuables to obtain a job. However, the suitability of people in jobs or studies is not only restricted to their taste or preference, but also other factors involved in the process of acquiring maturity as an adult who develops any function. These factors such as capacities, skills, attitudes concerning the task, social attitudes, taste, preferences, etc. [Robertson et al. 93; Salgado 96; Shevin et al. 04; Briñol et al. 07], must be taken into account in such processes.

To support students, many countries have created one figure, so-called advisor, with the role of guiding them when they have to confront this decision making situation regarding their academic future. To perform such task advisors must consider many variables, including students' expedient and marks. At this point, we think that these students' marks mean much more than a simple crisp value, because they indicate not only knowledge, but also skills, preferences regarding topic areas, attitudes, etc.

Even though CRS rank the items to recommend just the best ones and in academic orientation the aim is to show the suitability of all the options rather than the best subjects that the student can choose to facilitate advisor's guidance task. The features and techniques used in CRS are easy to adapt to academic orientation goals.

The aim of this paper is to prove the suitability of the ideas behind CRS for academic orientation and then develop a Web-DSS that supports advisors in their real-world duties related to students' academic orientation.

To do so, we set our paper out as follows: Sections 2 and 3 review in short general concepts about CRS and Academic Orientation. Section 4 presents a real case study about the performance of CF in academic orientation. In Section 5 is then presented OrieB, a Web-based DSS that supports advisors. Finally the paper is concluded in section 6.

2 Collaborative Recommender Systems

We pointed out in the introduction that the aim of this paper is to apply the techniques used by CRS in order to build a Web-DSS for Academic Orientation. Therefore, first we review the main concepts and techniques related to them.

Collaborative recommender systems gather human judgments (known as ratings) for items in a given domain and group customers with similar needs, preferences, tastes, etc. [Herlocker et al. 99]. In a CRS, customers share each other their judgments and opinions about items they have already experienced, such that, the system can support them in order to make right and better decisions about the items involved in the system. The CRS provide useful customized recommendations for interesting items by using collaborative filtering algorithms which try to predict user's satisfaction regarding an unrated item based on users with similar profiles to the target user.

Collaborative filtering methods provide several advantages regarding other techniques used in recommender systems [Herlocker et al. 99; Sarwar et al. 01]:

i. Support for filtering items whose content is not easily analyzed automatically.
ii. Ability to filter items based on quality and taste, not only on its features.
iii. Ability to provide serendipitous recommendations.

Judgments and opinions used by the CRS are classified into two main categories:

1. *Explicit data:* they are directly provided by the users according to their own experience and knowledge (i.e.: "Please rate this on a scale of 1-5").
2. *Implicit data:* which are inferred by the RS through knowledge discovery processes like data-mining, navigation monitoring, etc. [Herlocker et al. 04]. For example, by using implicit data such as play lists or music heard.

In the following, we shall show the general working of CF in CRS with a scheme based on the k-NN algorithm [Herlocker et al. 99; Sarwar et al. 00; Kiang 03] that will be used in our proposal.

2.1 General tasks for providing CF recommendations

There are different CF approaches. [Adomavicius et al. 05] classify CF algorithms into two general classes: (i) *Memory-based* algorithms, heuristics that make rating predictions based on the entire collection of rated items and (ii) *Model-based* algorithms which use ratings to learn a *model* capable of make rating predictions. We shall explain memory-based and afterwards we shall point out main differences with model-based ones focusing on the item-based collaborative filtering.

All approaches fulfill three general tasks to elaborate the recommendations demanded by users:

- Analyzing and selecting data sets
- Grouping users
- Generating predictions

These tasks are further detailed in the following subsections based on a k-NN scheme that will be used in our proposal.

2.1.1 Analyzing and selecting data sets

What properties should the dataset have in order to best model the tasks for which the recommender has been developed? Is it any dataset suitable to obtain good results in a CRS? It is necessary to analyze certain issues that can define further processes: the nature of the content being recommended, the nature of the specific recommender system and the distribution properties of the data [Resnick et al. 94; Herlocker et al. 99]. A dataset must be then collected an optimized for the system [Herlocker et al. 04].

2.1.2 Grouping users

In order to elaborate recommendations, CF selects a group of users with similar tastes, preferences, and behaviors. There exist many methods to group users based on neighbor selection methods such as *k*-nearest neighbor selection [Breese et al. 98; Kiang 03], threshold-based neighbor selection [O'Mahony et al. 04], and clustering-based grouping [Ungar et al. 98; Kohrs et al. 99].

The most used scheme is based on Neighborhood Formation due to its robustness and accuracy [Kiang 03]. This method calculates the degrees of similarity between the target user's profile and all the other users' profiles by using the correlation of preferences for co-rated items. CF then filters suitable items based on users similarities, and recommends the items to the target user [Kim et al. 06]. Neighborhood formation concerns the identification of similar users that are used as predictors. Previous work indicates that neighbors with a high degree of similarity to the target user are more valuable as predictors than those with lower similarity. Therefore, a greater accuracy and performance can be achieved by adjusting and limiting neighborhood size [Herlocker et al. 99; O'Mahony et al. 04], in order to avoid the noise produced by users and/or items, whose values as predictors becomes less valuable because their similarity moves away. In section 4.2.2 we can view how our experimental results confirm this assertion.

The use of the k-NN scheme has been successfully applied to many domains [Martínez et al. 07]. This method builds k-sized neighborhoods by simply selecting the k most similar users to the target user.

2.1.3 Generating predictions

Once users have been grouped by interest (similarity), CF algorithms use them to compute predictions for the target user. This can be done by aggregating ratings from groups of users in several manners such as simple average, weighted average, adjustments, etc. [Breese et al. 98; Herlocker et al. 99; Adomavicius et al. 05].

2.2 CF based on the K-NN scheme

Due to the success of the k-NN scheme in CF [Breese et al. 98; Sarwar et al. 00; Schafer et al. 01], and due to the nature of our dataset that suits perfectly with the configuration of dataset needed by the k-NN scheme, we shall use it in our proposal. So, here we make a brief review of its use in CRS. To predict user's satisfaction CF needs a dataset built with a set of votes where each $v_{u,j}$ corresponds to the vote assigned by user u regarding item j.

In Figure 1 we can view the three main tasks carried out by a CRS based on the Neighborhood-used-based methods. We shall review the different possibilities to accomplish the grouping and the prediction processes.

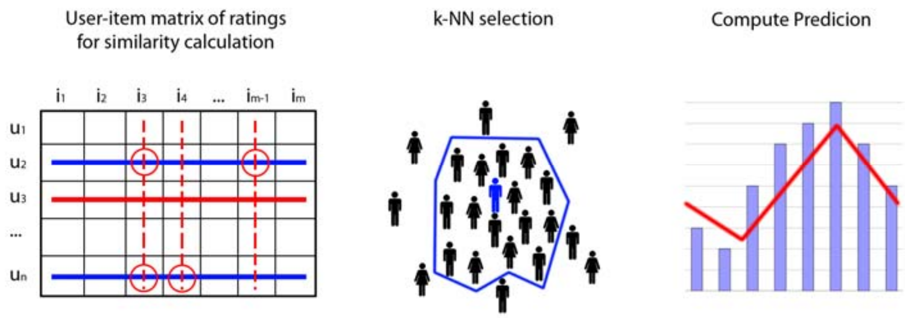

Figure 1: Tasks concerning Neighbourhood-user-based methods

2.2.1 Grouping users

In this phase users are grouped by a k-NN algorithm according to their similarity. Therefore, a measure of similarity must be chosen. In [Breese et al. 98] are introduced two similarity measures as the most used in the CF field:

1. Pearson Correlation Coefficient (PCC), a measure that appears as a general formulation of statistical CF. If j represents the items for which two users have provided their votes, the correlation between user u and user i can be seen in Eq. 1.

$$w(u,i) = \frac{\sum_j (v_{u,j} - \overline{v_u})(v_{i,j} - \overline{v_i})}{\sqrt{\sum_j (v_{u,j} - \overline{v_u})^2 \sum_j (v_{i,j} - \overline{v_i})^2}} \quad \text{(Eq. 1)}$$

2. Vector Similarity or Cosine Similarity measure has been successfully used in information retrieval [Belkin et al. 92; Pazzani et al. 97]. Its computation is carried out by Eq. 2.

$$w(u,i) = \cos(\vec{v}_u, \vec{v}_i) = \frac{\vec{v}_u \vec{v}_i}{\|\vec{v}_u\|^2 \times \|\vec{v}_i\|^2} = \frac{\sum_j v_{u,j} v_{i,j}}{\sqrt{\sum_j (v_{u,j}^2)}\sqrt{\sum_j (v_{i,j}^2)}} \quad \text{(Eq. 2)}$$

Here, $\vec{v}_u$ is the target user's profile and $\vec{v}_i$ is the other user's profile.

2.2.2 Prediction methods

Once the grouping task has been carried out, the CRS computes predictions of those items not rated yet by the target user, in order to choose which one/s will be recommended.

In memory-based CF algorithms, the prediction for the target user is based on the aggregation of their profile and the set of weights calculated from the users' database. The simplest aggregation case could be a weighted average (Eq. 3) by using similarity as weights [Adomavicius et al. 05]. However, the most common aggregation approach is to use the weighted sum (Eq. 4) [Breese et al. 98; Herlocker et al. 99].

$$v_{u,i} = \frac{\sum_j w_{u,j} v_{j,i}}{\sum_j w_{u,j}} \quad \text{(Eq. 3)}$$

$$v_{u,i} = \overline{v_u} + \frac{\sum_j w_{u,j}(v_{j,i} - \overline{v_j})}{\sum_j w_{u,j}} \quad \text{(Eq. 4)}$$

2.2.3 The k-NN Item-based collaborative filtering

We have revised the use of CF in CRS based on a memory-based approach. But this model presents a drawback so-called *scalability problem.* It means the more data in the database the less computing performance of the system. To avoid this problem, model-based algorithms generate a model from the dataset for computing the predictions. There exist different approaches to model-based algorithms as association rules, Bayesian networks, etc. [Breese et al. 98; Condliff et al. 99; Kohrs et al. 99]. But due to the fact that, in academic orientation the items are not static like in e-commerce, i.e., the same subject might have slightly different contents meanwhile the same DVD or CD has always the same content and features we consider that the k-NN approach is more flexible to adapt those slight differences inherent to academic orientation.

Therefore, from this point of view the k-NN model based approach known as item-based avoids the scalability bottleneck with a meaningless loss of accuracy by exploring the relationships between items, rather than between users [Sarwar et al. 01; Deshpande et al. 04]. This similarity between items can be computed completely offline.

3 Academic orientation and collaborative filtering

The goal of this paper is to develop a DSS for Academic Orientation, so we will make a brief introduction about Educational Systems, Academic Orientation, the tasks and figures involved in it and why CF and CRS might be useful for such a goal.

3.1 Educational systems

The concept of academic orientation is related to the student curriculum guidance, it means that students have to make decisions about their curriculum in order to obtain a degree in the topic they prefers the most or their skills are the most appropriate. So the academic orientation consists of supporting students in such decisions helping them by means of advices and additional information to facilitate their decisions, such that, students will be successful in their academic choice.

In order to make clear the concept of academic orientation we have studied different educational systems to extract common features in order to show the generality of our proposal. We have observed two common features: Evaluation and Specialization.

3.1.1 Evaluation

The main point that all academic institutions and educational systems have in common, is that they evaluate their students by means of different evaluation tools (tests, essays, tasks, exercises, etc.). The final result of this process is a *mark* that reflects not only the students' knowledge but also their skills, preferences, tastes about the subject, etc.

The starting point for our proposal is composed by three information items: students, subjects and marks (see Table 1).

	Mathematics	Literature	Biology	Economy
John	9	6	4	8
Miranda	5	9	Not available	6
Claire	4	3	7	Not available
William	7	2	Not available	6

Table 1: A fragment of a rating/mark matrix for students and subjects

3.1.2 Specialization

Most educational systems all over the world from early educational stages to University degrees allow students to choose among different specialization branches according to their skills, preferences, attitudes and marks, building a personalized so-called Academic Profile.

These specialization academic branches are based on certain patterns. Each branch consists of a set of subjects: several ones are compulsory, so-called core subjects, and others, the elective subjects, are optional.

On the other hand, an academic branch can group subjects in different modules where each module tries to specialize students in a topic or area. These modules are called profiles or modalities and may be different depending on each country and sometimes on the institution. The modalities consist of modality and elective subjects. The former are specific of the modality although can be shared by several modalities. The latter can be selected independently of the modality.

Most of academic institutions (Secondary school, High school, Universities) follow this scheme by offering at least core and elective subjects, adding others the possibility of choosing modalities and their modality subjects, in order to build an academic profile. For example, in a computer engineering degree the student can specialize in software, and within this area, he or she can choose to be an expert in Recommender Systems, by choosing artificial intelligence, programming and object oriented databases subjects. So, an academic profile concerns several subjects of each group.

The point is that, to reach this level of specialization in a specific area in which a student is supposed to be more capable, the student needs to make decisions in order to obtain the appropriate knowledge and abilities. The more accurate those decisions are the better the development of the student's potential.

3.2 Academic orientation tasks. Advisors

Students must make hard decisions about the future since early ages despite their personality and maturity could not be enough to make properly those important decisions. So that, some educational systems have created a figure to guide the students in their academic orientation decision making, so-called *Advisor*.

Without lost of generality we focus on the Spanish Educational System, advisors for secondary and high schools (other stages are similar).

In Spain the advisor's duties are mainly three:

a) Diversity management
b) Personal attention
c) Academic-professional orientation.

We will focus our paper on the academic orientation task. Usually, each advisor deals yearly with several hundreds of students (between 200 and 500 each year), depending on the institution. Therefore, with such a number of students where each one has his/her own personality and skills, the advisor's tasks are really hard to perform successfully for all students. The development of supporting tools for advisors can then improve the success of their tasks.

Regarding academic orientation, the advisors usually face two main types of students.

- Students with no idea about what profile to choose. Advisor should help them to build their academic profile by choosing modality and subjects.
- Students that want to study a profile independently of their skills to acquire such a specialization. Here, advisors can help students if they are able to identify topics or subjects in which those students can find difficulties to achieve successful results.

3.3 CF in academic orientation

Keep in mind that CRS deal with *customers, items and ratings*. However Academic Orientation deals with *students, subjects and marks*. It is then easy to see how to adapt the dataset about Academic Orientation to apply CF techniques. Another point is that we consider generically that students with similar marks share similar skills. So if we analyze the performance of students in a given group, G_i, in different curriculum modalities. This analysis might be then utilized to support future students classified in G_i for their academic decisions.

Therefore, the application of the ideas of CRS and CF to academic orientation will consist of:

a) **Dataset**: a dataset with students' marks must be gathered.
b) **Grouping students**: according to our previous consideration, the students will be grouped based on the marks because the group will indicate a kind of shared skills, preferences and attitudes.
c) **Predictions**: the computed values predicting future performance in the subjects by the students could be used by the advisors in order to support student decisions.

In order to check the validity of our hypothesis about the Academic Orientation and CRS, we have carried out a performance survey revised in the following section.

4 A real case study: the Spanish educational system

Here, we present a survey accomplished on a case study with a real dataset from several Spanish schools by applying a CRS model in Academic Orientation. The main aim of the survey is to evaluate if the predictions obtained by the CF techniques are valuable for the advisors in order to support students' decisions. Given that CF is dependent on each particular domain we have studied different algorithms approaches to know which one obtains the best performance.

First, we introduce the framework of the case study and then we present the experimentation and results.

4.1 Spanish baccalaureate

Currently, the Baccalaureate is a non-compulsory phase of the Spanish educational system comes after the secondary school and lasts two years. It offers 4 different modalities that specialize the students for further academic stages:

a) Arts
b) Nature and Sanity Sciences
c) Human studies
d) Technologies

The structure of Baccalaureate is:

- **Core subjects**, common to all students of the same grade independently of the modality chosen.
- **Modality subjects** depend on the modality elected.
- **Elective subjects** facilitate the access to other knowledge areas not necessarily related to the modality chosen.

Every student must choose a modality and six modality subjects, three per year. As well as they choose two elective subjects from a list of subjects offered by the High School.

Once it has been introduced the framework, we present a survey that tries to study the performance of CF in order to support students about the best choices over modalities, modality and elective subjects.

In the following section we show a detailed study of the results of our survey for this specific domain.

4.2 Survey

First we present our dataset and fix the metrics to measure quality of the results of CF in academic orientation. We shall then describe the experimentation we have carried out and finally we shall show the experimental results and findings.

4.2.1 Preliminaries

Dataset

Here, we introduce the main features of the dataset used in this case study.

Our dataset consists of data from anonymous students coming from several schools and different years, gathered from 1998 to 2007 that reflects their marks in the secondary and in the high school. The marks are assessed in a 0-10 scale.

It is important to choose a suitable and optimized dataset in order to obtain good results (see section 2.1.1). We have pre-processed the dataset to improve its quality, and deleted those students' marks which only have recorded data for one year because this kind of students cannot be used as predictors due to the fact that we have detected the reasons to leave the baccalaureate are diverse and the use of these students can bias the results.

The detailed description of the dataset can be seen in Table 2.

Number of students	**794**
Number of promotions observed:	9
Total amount of marks:	13421
Total number of subjects:	74
Core subjects	11
Modality subjects	32
Elective subjects	31

Table 2: Dataset (Students Marks)

Metrics

Metrics are used in general in order to check the performance of any system. There exist several types of metrics but a majority of the published empirical evaluations of recommender systems so far has focused on the evaluation of a recommender system's *accuracy*. Accuracy metric empirically measure how close a recommender system's predicted ranking of items for a user differs from the user's true ranking of preference. Accuracy measures may also measure how well a system can predict an exact rating value for a specific item [Herlocker et al. 04].

Although accuracy metrics probably are not suitable for all domains or systems, our aim is to prove the validity of CF in order to support academic orientation tasks and to do this, we need to prove that CF performs well as predictor of marks. The use of accuracy metrics is the best option. We have utilized the Mean Absolute Error (MAE) because the satisfaction in academic orientation is different from e-commerce and other metrics are not suitable either possible to compute. To complement this metric usually Coverage is used at once:

- **Mean absolute error** (MAE, Eq. 5) is an accuracy metric that measures the average absolute deviation between a predicted rating and the user's true rating [Herlocker et al. 04]:

  $$MAE = \left|\overline{E}\right| = \frac{\sum_{i=1}^{n} \left| p_i - r_i \right|}{P} \quad \text{(Eq. 5)}$$

  Being p_i the prediction provided by the system for the subject *i*, r_i the user's real rating (mark), and *P* the total number of predictions for which we have the real rating.
- **Coverage** [Herlocker et al. 04] is a measure of the percentage of items for which a recommendation system can provide predictions. We compute coverage as the percentage of items over all users for which a prediction was requested and the system was able to produce a prediction [Herlocker et al. 99].

Experimentation

Due to the fact that, our proposal will use a K-NN scheme we shall study both User-based collaborative filtering (UCF) and Item-based collaborative filtering (ICF) performances in our case study.

The main aim of our case study is to optimize different parameters of the k-NN scheme to obtain the most accurate predictions in order to support students' decisions. Such parameters will be:

- k: neighborhood size
- *N*: the *significance weighting*, in order to better determine the number *N* of common ratings to take into account while computing similarity between neighbors [Herlocker et al. 99]. The more common-rated items, the more reliable will be similarity obtained.
- Prediction method.

This survey has been run 50 times for each configuration. In Table 3, we review in short these configurations. All configurations were tested by using the weighted sum and the weighted average prediction methods and with and without application of the Case Amplification extension [Breese et al. 98].

User-CF (UCF)						Item-CF (ICF)					
PCC		PCC-F		COS		PCC		PCC-F		COS	
SW	INV	SW	INV	SW	INV	SW	INV	SW	INV	SW	INV

PCC: Pearson Correlation Coefficient with user relative average [2]
PCC-F: Pearson Correlation Coefficient with fixed average
COS: Vector Similarity or Cosine Similarity
SW: Significance Weighting [Herlocker et al. 99] with variations of factor *N* for co-rated items
INV: Inverse Frequency
For all variations, parameter *k* of the *k*-NN method was varied widely from 5 to 50.

Table 3: Different configurations used in survey for similarity computation

4.2.2 Experimental results

We have obtained many and different results from our survey, but in Table 4 we highlight the most important ones related to our aim. All the highlighted results have been obtained with the weighted sum prediction method.

MAE for ICF with PCC and SW configuration				**MAE for UCF with PCC-F and SW configuration**			
	K=10	**K=15**	K=20		K=25	**K=30**	K=35
N=20	0,9069	0,9053	0,9067	N=35	0,9319	0,9300	0,9308
N=25	0,9075	0,9036	0,9060	N=40	0,9278	0,9261	0,9271
N=30	0,9097	**0,9020**	0,9072	N=45	0,9278	0,9261	0,9272
N=35	0,9094	0,9026	0,9095	**N=50**	0,9249	**0,9234**	0,9243
N=40	0,9114	0,9045	0,9111	N=55	0,9304	0,9297	0,9292

Table 4: Experimental results

[2] As seen in Eq. 1 PCC uses two users' averages for its computation. This can be modified as we have done in PCC-F by fixing those averages to the average of the scale used, 5 in our case. This can provide us absolute similarities more than relative similarities. As example, student A has marks 3 and 5 in subjects S and T, while student B has 8 and 10. For PCC they have maximun similarity, because it computes correlation basing on the average, but for PCC-F they will not be so similar.

There not exist a great difference between accuracy obtained from both ICF and UCF, but it is remarkable that ICF performs better because it has several advantages with regards to UCF related to online computation and scalability.

In Table 4 is shown that the MAE is around 0,9 in a scale of marks from 0 to 10, which represents a predicting error obtained is less than 10%. For ICF, coverage was always greater than 99%, while for UCF was around 97%.

It is interesting to remark the difference between the value for k in ICF and UCF approaches. In ICF this value is lower than in UCF because the number of subjects is significant lower comparing to the number of students therefore it is difficult that exist groups with a lot of similar subjects; hence the use of more than 15 subjects as predictors makes accuracy decrease by the introduction of noise. There is always a value for k from which systems start to decrease their accuracy. However the number of students is much greater so that in UCF the number of students that can be used as predictors is 30 before accuracy start to decrease.

Due to the fact that, depending on the type of subject we chase different objectives in Academic Orientation, we have analyzed the results for each type of subject: core, modality and/or elective subject. Such results are shown in Figure 2.

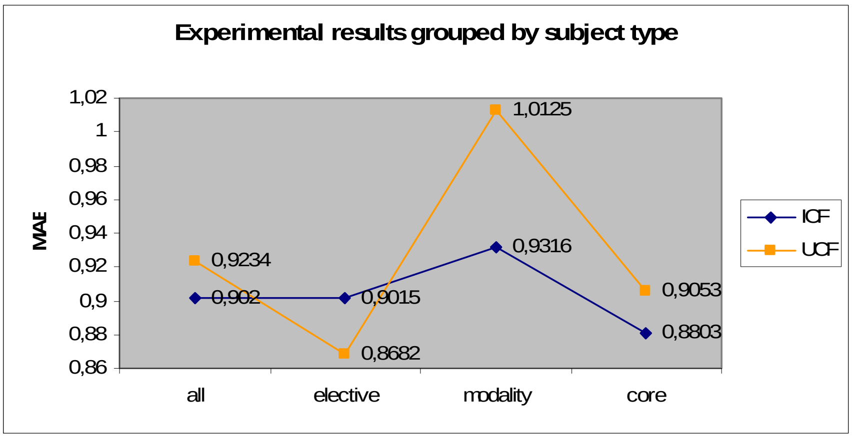

Figure 2: Experimental results grouped by subject type

It is remarkable the different performance of UCF, it reaches a great accuracy with elective subjects but not with modality subjects. This fact makes us think about future hybridization between UCF and ICF techniques in order to obtain better predictions.

4.3 Findings

From our survey we have obtained that the mean absolute error (MAE) obtained is lower than 10%. This confirm our intuition that marks means more than a crisp value, and they contain much valuable information concerning students such as capabilities, skills, tastes, preferences, etc. Hence, the survey confirms that CF might be considered as a good performance predictor with this kind of information.

At this point, we can provide an answer to the question: Is it possible to make good recommendations based on CF algorithms? It seems that the accuracy obtained in our survey in order to foresee the future performance of the students (<10%), it is good enough to achieve our objective of helping advisors to support students' decisions.

The initial aims of the survey were to answer the question: Is CF good enough to provide support about modality programs, modality and elective subjects? The findings of our survey shows that CF is suitable for these objectives and additionally we found an unexpected functionality that initially we did not take into account:

- **Modality recommendations**: Concerning only to the modality or modalities which suits a student better. The better the predictions for the subjects belonging to a modality, the better the expectations of success for the student in that area. The performance foresight for a student in a modality might be computed by aggregating the predictions for the subjects of such a modality.
- **Modality and Elective subject recommendations**: They both are similarly computed. The main issue is to decide when the predicted mark is good enough to recommend that subject. A conservative approach is to recommend those subjects whose predictions are over the average. Another one is to give an ordered list of subjects whose predictions are good enough to pass the subject.
- **Reinforcement recommendations for core subjects**: When we analyzed the survey results, we realized that CF can be used to obtain information that helps advisors in their orientation task, such that, they can warn the students which core subjects might be hard for them according to their background. The students will then pay more attention these subjects from the very beginning in order to improve their performance.

5 OrieB: a Web-DSS for academic orientation

Once we have seen that the use of the CF is appropriate for Academic Orientation, the next step was to implement a Web-DSS, OrieB, for academic orientation to support Spanish advisors in their task of helping students which modality to choose in Baccalaureate, after finishing Secondary School.

Specifically, the system will aid advisors to obtain useful information about which subjects in each modality and which elective subjects suit better a student or which core subject might be extra hard for her. Therefore, the advisors can develop their duties quicker and with reliable information.

A Spanish Beta version of OrieB is located in the URL, http://www.iescastillodelayedra.com/orieb/. This version has been tested by the orientation team of the Castillo de la Yedra Secondary Educational Institution.

Due to the importance that the information provided by this system can perform in the future decisions of students in early ages that they are not mature. We decided that it can be used just for advisors in order to support students but not directly by the students due to their lack of maturity.

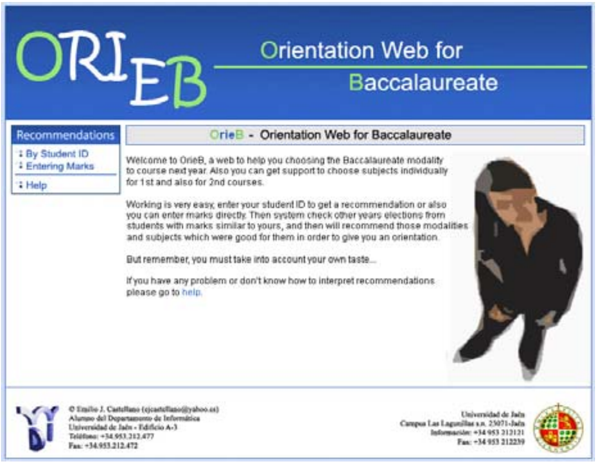

Figure 3: Home Page of OrieB

5.1 OrieB interface

Figure 3 shows the home page of our site. When an advisor wants to use OrieB to support a student, she just needs to type the student ID (a unique number for each student which identifies him or her from others) or introduce the student's marks in the last year. The latter choice (Figure 4) offers the possibility of entering several marks instead of using all of them in order to obtain a more general orientation. However, the more marks filled, the more accurate and customized will be the advices obtained by the system.

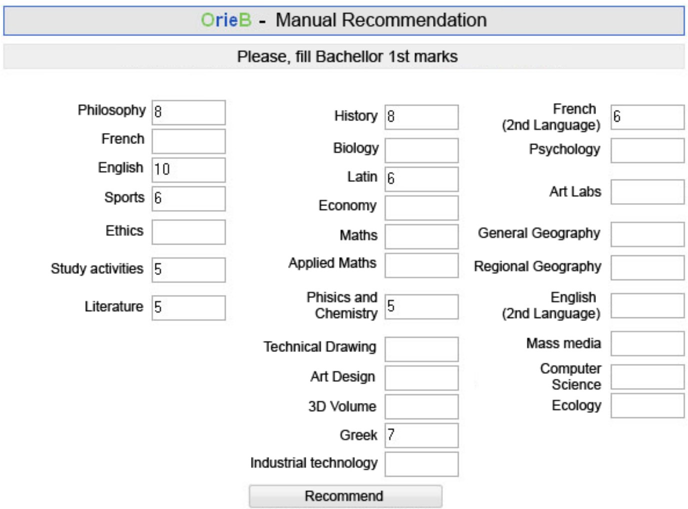

Figure 4: Manual filling of marks

5.2 Supporting decisions

In order to support advisors in their Academic Orientation tasks introduced in subsection 3.2, the proposed Web-DSS, OrieB, offers three different types of support:

- Modality recommendation
- Subject recommendation
- Warning difficulties in core subjects

They all are based on predictions computed by an item-based collaborative filtering approach which uses a model for the predictions (we must remark that this was the method which better results offered in our survey).

We are going to show in further detail how the DSS provides its support for each case.

5.2.1 Support for choosing a modality

In order to aid advisors guiding students regarding their professional future OrieB provides orientation about the modality that better suits with the academic results obtained by each student. To do so, the system computes a modality recommendation which will show a list with the modalities available ordered by interest (Figure 5).

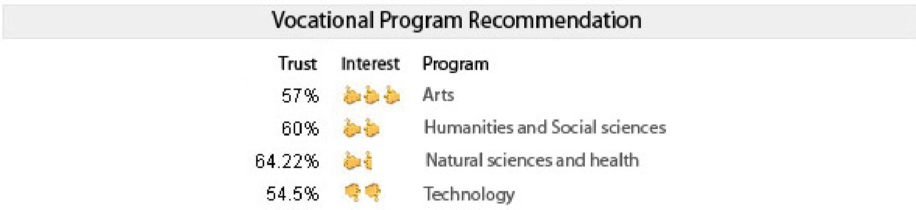

Figure 5: Modality recommendation

Each recommendation of modality incorporates an interest value and a trust value. Both interest and trust values are computed basing on CF predictions and taking into account how they were obtained.

Interest value expresses the appropriateness of a modality for the target student, the degree in which a modality will be a good choice for the student. It is obtained from a simple aggregation of those prediction values obtained for all subjects that belong to each modality. This is based on the idea that one modality will be better for a student if marks predicted for its subjects are higher than those computed for other modalities.

To express interest we use graphical metaphors [Shneiderman et al. 09]:

- <u>Maximum interest:</u> corresponding to three hands with thumb up, that can decrease as number of thumbs shown decrease.
- <u>Minimum interest</u>: represented as three hands with thumb down, that can raise as number of thumbs shown decrease.

Trust value comes from the consideration of two different values. The first value tries to take into account one of the most important CF drawbacks, sparsity, which can cause the impossibility of obtaining predictions for some subjects. In fact, it is very probable that we will not obtain predictions for all subjects for a specific modality so that a high value for predictions can be deceitful. Also it is necessary to use *variance* because we will trust only in those modalities from which homogeneous predictions were obtained for their subjects. This way, trust is computed taking into account the number of subjects for which predictions were obtained and the total number of subjects for the modality, and also the variance of those predictions.

Trust is represented with a number between 0 (minimum value of trust) and 100 (maximum value of trust).

Take as example predictions obtained in Table 5, corresponding to three different students who doubt to choose between modalities A and B, with subjects Ai and Bi.

For *John* it is clear that the modality recommended would be A due to its higher predictions. With *Paul* we confirm that it is more reliable to recommend modality B, because the number of predictions we have is greater although prediction value is lower. And finally we can notice how important is for *Mary* to take into account the variance. It would not be appropriate to recommend Modality A in this case.

	Modality A				**Modality B**			
	A1	**A2**	**A3**	**A4**	**B1**	**B2**	**B3**	**B4**
John	10	8	7	10	3	5	2	4
Paul	?	10	?	?	6	?	7	8
Mary	10	3	3	10	6	7	6	7

Table 5: Examples of modality selection

5.2.2 Support for choosing elective and modality subjects

Once students have chosen what modality they prefer, they need to complete their curriculum with modality and elective subjects. To support this decision OrieB offers separate recommendations for each group of subjects (Figures 6 and 7).

However, although they belong to distinct groups, the recommendation is obtained in the same manner.

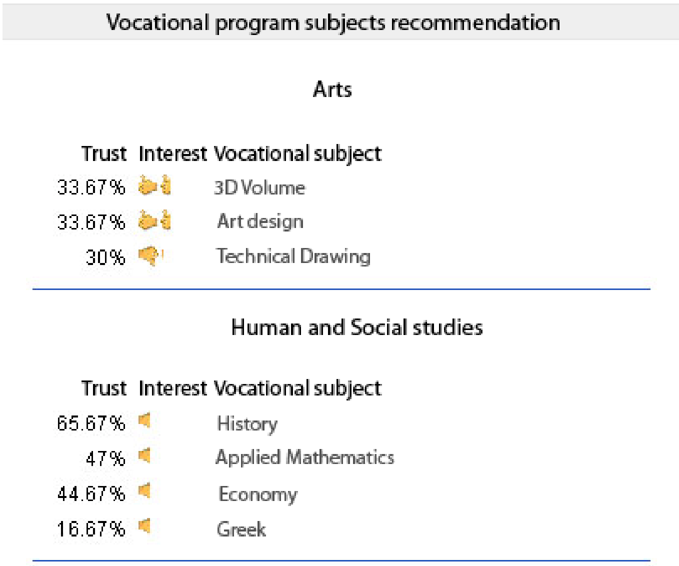

Figure 6: Modality subjects recommendation

Modality subjects are grouped into each modality and then ordered according to their prediction while elective subjects are shown all in the same group also ordered by their prediction.

All modalities are shown if they have at least one subject with prediction so that advisor can take into account all possibilities for students.

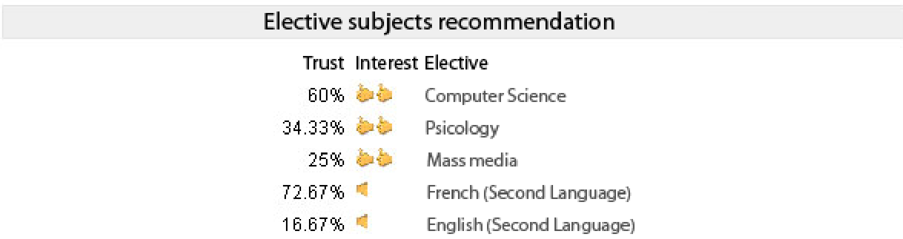

Figure 7: Elective subjects recommendation

Due to the fact that recommendations are computed based on students' similarities, and the sparsity can bias the results, the system will offer a trust measure in order to increase the trust of the system. This additional information expresses how reliable is each single recommendation taking into account the manner in which these predictions are computed, what is:

- Predictions obtained from a greater number of marks (more neighbors) will be more trusted than those formed with few marks.

- Predictions obtained from homogeneous marks will be more reliable than those obtained from unrelated marks.

5.2.3 Warning difficulties in core subjects

Finally, students also may need advises about those core subjects in which they can find problems or difficulties. In this sense, if the system computes a low prediction for a specific core subject, it will warn the advisor that probably student will find difficulties with that subject. Therefore, advisor must recommend to the student that she should work harder with that subject.

Core subject difficulty advising

Trust	Subject
74.33%	English
82%	Literature
16.67%	French

Figure 8: Core subject difficulty advising

System offers a list with those core subjects with low predictions and a value of trust, computed as in previous section.

6 Concluding Remarks

Academic orientation is an important area in education at different stages and levels, that tries to guide students through their academic careers. The orientation task may be carried out in different ways and by different actors. Without loss of generality, we have focused on the Spanish education system in which such a task is carried out by experts so-called *advisors.*

Our aim is to support such advisors in their duties related to academic orientation by developing a decision support system. In order to do so, we have paid attention to recommender systems that supports customers' decisions in e-commerce. Even though e-commerce and academic orientation are not similar topics at all, we have realized that the structure of the datasets used by recommender systems and those ones related to academic orientation are quite similar.

Therefore in first place, we have checked the validity of using collaborative filtering techniques, utilized in recommender systems, in academic orientation. We have applied collaborative filtering to a real case study of academic orientation, by using a dataset of students from different Spanish schools. The findings we have obtained were quite successful. Hence, we have used some results and models from the previous case study to implement a Web-Decision Support System for academic orientation based on collaborative filtering, so-called OrieB.

OrieB provides information that the advisors use to support students in their academic decisions, such as, the election of a profile among several ones, the election of elective subjects, and so on.

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