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Academic Orientation Supported by Hybrid Intelligent Decision Support System

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1. Introduction

It is common that in all academic systems the students must make decisions about the future by choosing among different alternatives that include professional profiles or *modalities*, elective subjects or *optional*, etc. These decisions can have a very important influence in the academic journey of the students because sometimes a wrong decision can lead to academic failure or its correction implies a time cost for the students.

It is remarkable that in many academic systems these important decisions have to be made in early stages in which the students do not have enough maturity or knowledge to be conscious about the consequences in their future if a wrong decision is made. Ideally these multiple choices, offered to the students, want to facilitate the acquirement of some professional and valuable competences to obtain a job. Taking into account that the suitability of people in jobs or studies is not only restricted to their taste or preferences, 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. (Briñol 2007, Robertson 1993, Salgado 1996, Shevin 2004), must be taken into account in such processes.

Initially these decision making processes were made by the students themselves or with their parents support according to different criteria such as, preferences, future job market, even randomly, etc. Therefore, in order to improve this situation different countries introduced one figure, so-called *advisor*, whose role is to guide the students in their decision making situations regarding their academic future.

The academic orientation process carried out by these advisors imply the review of different information regarding the students in order to report which academic alternatives suits better their skills, competences and needs. In most of academic institutions the advisor deals yearly with several hundreds of students with different skills, personalities, etc. To make an idea, in Spain, and depending on the high school, advisors can manage from 200 to 800 students. This number of students implies a big search space to find the relevant information that can facilitate the orientation for each one in a right way, making very hard to perform successfully the academic orientation process. Hence it seems suitable the development of automated tools that support the accomplishment of the different processes of academic orientation to improve the success of advisors' tasks.

An overview of different problems in the real world that deal with search spaces drove us to pay attention to the situation raised some years ago with the advent of Internet and the increase of requirements in many areas. One of the most demanded solutions is based on the necessity of finding out suitable items over huge and/or complex search spaces in *e-shops*. The 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 (Adomavicius 2005, Resnick 1997, Rodríguez 2010). 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 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 are built by gathering explicit data, implicit data or both (Adomavicius 2005, Pazzani 1999) (see Figure 1).

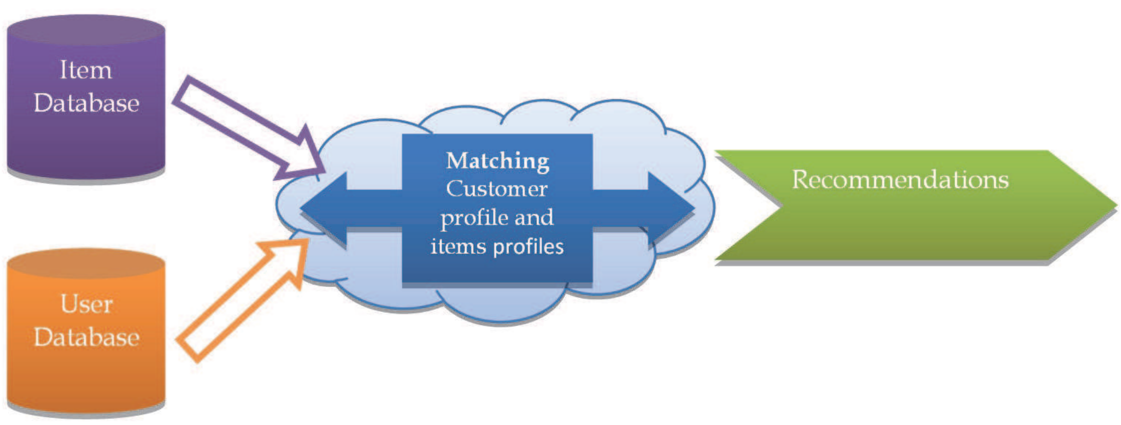

Fig. 1. Recommendation scheme

Recommendations suggested by RS can be obtained in different ways (Resnick 1997, Schafer 2001) and hence there exist different types of RS, depending on the information and the technique utilized to compute its recommendations:

- *Content-based Recommender System* (Horvath 2009, Martínez 2007b): These RS are based on features of items experienced by the customer in order to create users' profiles and use these to find out similar items.
- *Collaborative Filtering Recommender Systems* (Goldberg 1992, Takacs 2009): Instead of building users' profiles based on item features, they use customers' ratings to compute a recommendation of items for a specific user considering the similarity of the target customer and the rest of users.
- *Knowledge Based Recommender Systems* (Burke 2000, Zhen 2010): These systems base their recommendations on inferences about user's needs and preferences. They use the knowledge about customers' necessities and how an item matches these necessities to infer useful recommendations.
- *Demographic Recommender Systems* (Krulwich 1997): They categorize customers into groups using stereotype reasoning based on the information stored in the user profile that contains different demographic features.

- *Utility Based Recommender Systems* (Guttman 1998) compute their recommendations on the match between the user's need and the available options that could maximize the accomplishment of the expected utility.
- *Hybrid Recommender Systems* (Albadvi 2009, Burke 2002b): To overcome the disadvantages of previously mentioned recommender systems sometimes is used hybrid techniques which try to make useful the best of methods used in hybridization.

The most spread recommender systems are collaborative and content based systems both have provided good results in different areas as tourism (Sebastia 2009), e-learning (Romero 2009), academic orientation (Castellano 2009b), etc.

In (Castellano 2009b) was introduced the use of collaborative filtering for academic orientation, in the case of study of Spanish Academic System, by using *marks* as ratings of user's profile that are filtered in order to support advisors in their orientation for the students. In (Castellano 2009a) these processes were merged with fuzzy techniques (Martínez 2008, Martínez 2007a, Zadeh 1965) to improve the comprehension of the results by the advisors.

Even though the DSS, *OrieB*, presented in (Castellano 2009a, Castellano 2009b) provides good results in general, it suffers the same weaknesses and limitations that any collaborative RS (Herlocker 2004, Lee 2003, Pazzani 1999), such as, *grey sheep, historical data, cold-start, scarcity*, etc. Therefore, we detected a problem in *OrieB*, because academic systems are not static but they suffer changes quite often and new subjects can appear due to modification or adaptation of academic profiles. Hence these changes imply the appearance of *cold start* and *historical data* problems decreasing the performance of the system for academic orientation.

In this chapter we aim to improve the performance of academic orientation support by using a hybrid technique that supplies support even in those situations in which there is scarcity information or new items. First, we should find what type of information would be available when marks do not exist yet for new subjects and choose the techniques that should be hybridizing with collaborative filtering to obtain good results in the academic orientation situations in which such a filtering technique is not enough. In this case the *Competency based Education* (CBE), that is an emerging curriculum model that tries to satisfy the demands of learning contexts, by the developing competencies, enabling students to act in a complex world in constant transformation (Zalba 2006), might play an important role. A competence is the ability to perform effectively in a given situation, it is based on knowledge but it is not limited to it (Perrenoud 1999). Competences are complex knowledge and represent the know-how to integrate conceptual, procedural and attitudinal knowledge. The current importance and relevance of the CBE is showed in Tuning Educational Structures in Europe (Europe TUNING 2000). As well in different countries this educational paradigm is being developed in secondary education and high schools and students are now being evaluated focusing on competences. So the use of *competences* will be very useful in our aims because they keep relevant information for academic orientation.

Therefore, once we know the information available when the collaborative filtering is not working our second step is to define a hybrid model that that hybridizes *collaborative* and *content-based* techniques (CB), where the content-based model will be based on the textual description of subject competences. This model will be implemented in a DSS for Academic Orientation. In such a way the DSS can provide more and better support to the academic advisors in their task.

This chapter is organized as follows: Section 2 reviews recommender systems; Section 3 introduces academic orientation and competency based education; Section 4 shows the use of collaborative filtering in academic orientation and points out its weaknesses; Section 5 proposes a hybrid model for academic orientation based on collaborative and content-based techniques; Section 6 presents a Decision Support System that incorporates such a model and Section 7 concludes this chapter.

2. Recommender systems

As we have pointed out previously the techniques that we will use to support academic orientation will be based on those ones used in recommender systems that support customers in their buying processes in the e-commerce arena where customers face to huge amounts of information about items that are hard to check in an affordable time in order to buy the most suitable item/s.

Notwithstanding, there exist several techniques in the recommender systems, in this section we will only focus on the revision of collaborative, content-based and hybrid ones because they will be the used in our proposal.

2.1 Collaborative recommender systems

Collaborative recommender systems (CRS) collect human opinions of items, represented as ratings, in a given domain and group customers with similar needs, preferences, tastes, etc., in order to recommend active user items which liked in the past to users of the active user group (Herlocker 1999).

Most of CRS use explicit data directly provided by users and related to customers' perceptions and preferences that implies uncertainty, though it has been fairly usual the use of precise scales to gather such information, the use of linguistic information to model such an information seems more suitable and several proposals have been developed (Martínez 2007b, Porcel 2009).

There exist different collaborative approaches (Adomavicius 2005): (i) *Memory-based* which use heuristics that predict ratings basing on the whole dataset of previously rated items and (ii) *Model-based* which use the collection of ratings to learn a model capable of predicting ratings. According to Figure 2, both models fulfill three general tasks to elaborate the recommendations demanded by users:

- *Analyzing and selecting data sets*: data from ratings must be collected and optimized for the system (Herlocker 2004).
- *Grouping users* with similar tastes and preferences in order to compute recommendations basing on a similarity measure as Pearson Correlation Coefficient (Adomavicius 2005, Breese 1998).
- *Generating predictions*: Once users have been grouped by interest (similarity), the system uses them to compute predictions for the target customer by using different aggregation methods (Breese 1998, Herlocker 1999).

Collaborative filtering methods provide several advantages regarding other techniques used in recommender systems (Herlocker 1999, Sarwar 2001):

- Capability to manage information whose content is not easily analyzed automatically, because they do not need knowledge domain, i.e., no information or knowledge about the products is needed.

- Ability to filter items based on quality and taste, not only on its features.
- Ability to provide serendipitous recommendations. Other systems never recommend products which are *outside the box*, i.e., recommended products are not very different to the ones positively rated by the customer.
- Adaptability, its quality is improved along the time. When the number of customers and rates increases these systems work better.

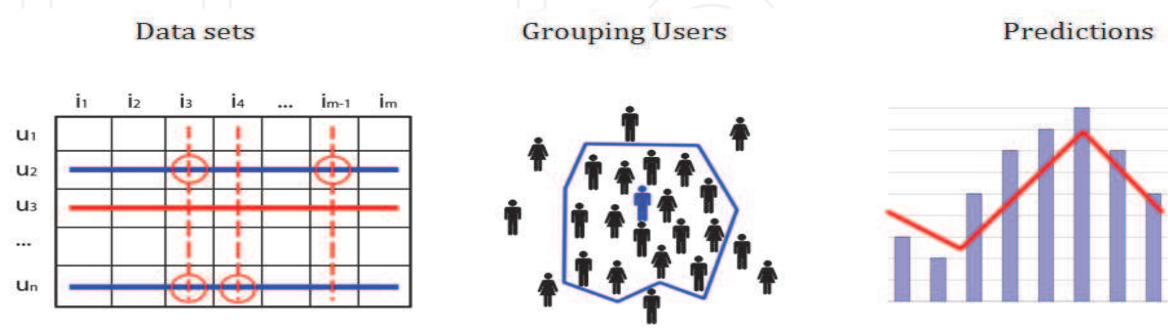

Fig. 2. Processes performed in the collaborative recommendation scheme

Despite the general good performance of these systems, they present several weaknesses and limitations:

- *The cold-start problem*: This problem is presented with both users and products. When a new user access to the system, it has not any information about him/her. Therefore, the system cannot compare him/her with the users of the database and cannot provide recommendations. When a new item is added and it has not been assessed by any user yet, it cannot be recommended. This is the problem we focus on this paper, so it will be further detailed below.
- *The "grey sheep" problem:* This system does not work properly with "grey sheep" users, which are in the frontier of two groups of users.
- *Historical data set:* Being an adaptive system can be an advantage but can be also a disadvantage when the system is starting and the historical data set is small.

Obviously, no recommender system can work without some initial information but the quality and efficiency of the system depends on the ability to predict successful recommendations with the minimum amount of information about users and items. Some solutions to this problem require knowledge about the items, or content based information, for example, a movie recommender system needs to know attributes like actors, the genre, etc. This kind of knowledge is not always available or is scarce. Other proposed solutions are only partial solutions because improve the recommendations when the data about the user is small but do not work when this set is empty (new user).

2.2 Content-based recommender systems

Content-Based Recommender Systems (CBRS) recommend similar items to those ones that the user liked in the past by comparing various candidate items with items previously rated by the user and the bestmatching item(s) are recommended (Adomavicius 2005, Jung 2004, Symeonidis 2007). The content-based approach to recommendation has its roots in information retrieval and information filtering research (Adomavicius 2005, Martínez 2007a, Pazzani 1999). CBRS need user profiles that contain information about users' tastes, preferences, and needs. Profiles can be built using information collected from users explicitly, e.g., through questionnaires, or implicitly inferred from user behavior over time. On the contrary to collaborative recommender systems, the content based ones assume that the user does not interact with other users. These systems exploit the information related to the description content of the previously evaluated items such that the system learns the relationship between a single user and the description of the new items. Let S be a set of items to be recommended, the description of each item s_i is provided by m features c_j, such as is showed in Table 1.

	c_1	…	c_j	…	c_m
s_1	v_{11}	…	v_{1j}	…	v_{1m}
…	…	…	…	…	…
s_n	v_{n1}	…	v_{nj}	…	v_{nm}

Table 1. Item description

In content-based recommendation methods each user's profile is built with information related to previous items selected by the user in the past. Therefore the user's profile P of user u is computed based on the description of previously experienced items and optionally some explicit rating r_i about them *(Adomavicius 2005)*.

	c_1	…	c_m	R_u
s_1^u	v_{11}^u	…	v_{1m}^u	r_1^u
…	…	…	…	…
$s_{n_u}^u$	$v_{n_u 1}^u$	…	$v_{n_u m}^u$	$r_{n_u}^u$
P_u	p_1^u	…	p_m^u	
W_u	w_1^u	…	w_m^u	

Table 2. User Profile

The user's profile (see Table 2) is used to determine the appropriateness of the item for recommendation purposes by matching it with the items descriptions (see Table 1). Since, as mentioned earlier, CBRS are designed mostly to recommend text-based items, the content in these systems is usually described with keywords which can represent, for example, features of an item.

More formally, let *ContentBasedProfile(c)* be the profile of user, *c,* containing tastes and preferences of this user, for example a vector of weights ($w_{c1}, \ldots, w_{ck}$) where each weight w_{ci} denotes the importance of keyword k_i to user c.

In content-based systems, the utility function $u(c,s)$ is usually defined as:

$$u(c,s) = score(ContentBasedProfile(c),Content(s)) \tag{1}$$

Both *ContentBasedProfile(c)* of user c and *Content(s)* of document s can be represented as vectors $\overrightarrow{v_c}$ and $\overrightarrow{v_s}$ of keyword weights. Moreover, utility function $u(c,s)$ is usually represented in the information retrieval literature by some scoring heuristic defined in terms of vectors $\overrightarrow{v_c}$ and $\overrightarrow{v_s}$, such as the cosine similarity measure

$$u(c,s) = \cos\left(\overrightarrow{v_c}, \overrightarrow{v_s}\right) = \frac{\overrightarrow{v_c} \bullet \overrightarrow{v_s}}{\overrightarrow{v_c}_2 \times \overrightarrow{v_s}_2} = \frac{\sum_{i=1}^{K} v_{i,c} v_{i,s}}{\sqrt{\sum_{i=1}^{K} v_{i,c}^2}\sqrt{\sum_{i=1}^{K} v_{i,s}^2}} \tag{2}$$

where K is the total number of keywords in the system. Depending on the information and the content based technique used, such keywords or features could be either equally important or weighted according to their relevance, for example, using TF-IDF (frequency/inverse document frequency) which is one of the best-known measures for specifying keyword weights in Information Retrieval (Adomavicius 2005, Symeonidis 2007).
Although CB approach enables personalized and effective recommendations for particular users, it has also some disadvantages (Adomavicius 2005, Lenar 2007, Symeonidis 2007):

- Limited Content Analysis: Content-based techniques are limited by the features that are explicitly associated with the objects that these systems recommend. Therefore, in order to have a sufficient set of features, the content must either be in a form that can be parsed automatically by a computer (e.g., text) or the features should be assigned to items manually. Another problem with limited content analysis is that, if two different items are represented by the same set of features, they are indistinguishable.
- Overspecialization: When the system can only recommend items that score highly against a user's profile, the user is limited to being recommended items that are similar to those already rated. In certain cases, items should not be recommended if they are too similar to something the user has already seen.
- CB is based only on the particular user relevance evaluations, but users usually are very reluctant to give them explicit, so usually other implicit, possibly less adequate, methods must be used.

To overcome these problems, CB and CF techniques have been combined to improve the recommendation procedure.

2.3 Hybrid recommender systems

Due to limitations observed in both previous recommendation techniques, nowadays it has been used to overcome these limitations the hybridization technique. This technique combines two or more recommendations methods in order to obtain a better performance and/or accuracy that in each of the methods separately. It is common to combine collaborative filtering technique (CF) with another method to avoid cold start problem.
Following it is presented the classification of hybridizing techniques for recommender systems presented by Burke (Burke 2002a):

1. *Weighted* systems: recommendations of each system are combined giving each one a specific weight of the final recommendation, depending on the system which computed them. Importance of each item is computed based on results obtained from recommendation techniques present in the system. All capacities of the system are used in recommendation process in an easy and direct way, and also it is easy to adjust weights manually or by simple algorithms. However, this technique start from the hypothesis of giving a uniform importance value to each of the distinct techniques composing the system, and this is not always true.
2. *Switching* hybrid systems use several criteria to alternate recommendation technique whenever is needed each moment. This method brings an additional complexity in the recommendation process as it is needed to determine choosing method criteria, as it is another parameterization level. On the other hand, if the criterion is selected properly it can take advantage of qualities of composing recommendation systems and avoid weakness of systems in those situations.

3. *Mixed* hybrids result from various recommendation methods showing them at the same time. It can be used in situations where a big number of recommendations are required. So can be avoid the *new item* problem if always content-based recommendations are shown, because this component compute its recommendations using features of new items, regardless they have been rated or not. However, *new user* problem is not solved.
4. *Feature combination*: another way of hybridization is to manage collaborative information as a data feature associated with each example, and to use content-based techniques over this extended dataset. This kind of hybridization allows using collaborative data without an exclusive dependence, decreasing system sensibility to the number of users that have rated an item. Moreover, allow system to obtain information about inherent similarity not possible to find in content-based systems.
5. *Cascade* method combines techniques by means of process composed of several phases: preliminary selection of items to recommend by means of one of the methods. In following phases other techniques are used to filter the set of candidates. This technique avoids second method to manage items discarded by first method, or with enough negative ratings to never be recommended. Thanks to this, phases next to the initial one are more efficient. Moreover, an item rated negatively cannot be recommended because recommendations are refined in each phase.
6. *Feature augmentation*: this technique produces a valuation or a classification of an item as a new keyword or feature, and this information is incorporated in the process using next recommendation method. This method is interesting because it allows improving performance of main recommendation technique without altering original operation and conception.
7. *Meta-level*: another way of combining several recommendation techniques is using model generated by a method as input for another. This differs from *increase of features* as this use model learned to generate features as inputs, not the whole model. The profit of this kind of hybridization is that model apprehended is a compressed representation of user's interests and collaborative filtering operates easier with these datasets.

As we have seen, hybridization can support the overcoming of some problems associated with certain recommendation techniques. Although hybrid recommender systems which use collaborative and content-based methods always will present the *cold start* problem as both need a dataset to operate, once the system has a minimum dataset it can overcome certain limitations inherent to collaboration filtering.

3. Academic background

In section 1 was introduced the aim of this chapter: to develop a DSS for *academic orientation* by using a hybrid model that uses a *competency based education* paradigm, in order to overcome the new subject problem. To facilitate the understanding of the proposal this section reviews some concepts and issues related to educational systems, academic orientation and competency based education, focusing on the Spanish Academic System.

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 3).

	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 3. A fragment of a rating/mark matrix for students and subjects

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 3).

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 which try 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 loss 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 Competency based education

In a changing world based in changing technology and services, it is necessary for academic systems to have solid foundations capable of allowing a flexible configuration of learning process formulated as flexible academic profiles. Zalba (Zalba 2006) considers that a design and development of a Competency Based Education (CBE) is the best choice in order to set up a curriculum based on social context and necessities.
Actually it is necessary to introduce the concept of academic competence or competence to generalize. It is difficult to define objectively what an Academic Competence is, but it can be understood as a multidimensional construct composed of the skills, attitudes, and behaviors of a learner that contribute to academic success in the classroom. In general, a competence must entail a set of skills of problem solving — enabling the individual to resolve genuine problems or difficulties that he or she encounters and, when appropriate, to create an effective product — and must also entail the potential for finding or creating problems — and thereby laying the groundwork for the acquisition of new knowledge (Gardner 1993).

The CBE is an emerging curriculum model that tries to satisfy the demands of learning contexts, by the developing competencies, enabling students to act in a complex world in constant transformation (Zalba 2006). In short, a competence is the ability to perform effectively in a given situation, it is based on knowledge but it is not limited to it (Perrenoud 1999). Competences are complex knowledge and represent the know-how to integrate conceptual, procedural and attitudinal knowledge.

The current importance and relevance of the CBE is showed in Tuning Educational Structures in Europe. The contribution of universities to the Bologna process and the Tuning Latin America project (González 2008). In this new context, competences serve as well as unification and comparability tools. They are a measure of students' capabilities development, and a start point and guidance not only for subjects but for academic and professional profiles, in which competences emerge as an important element to guide the selection of knowledge appropriate to particular ends. Learners can develop a particular competence or set of competences in order to finally acquire certain knowledge, attitudes and professional capabilities. Tuning serves as a platform for developing reference points at subject area level. These are relevant for making programs of studies (bachelor, master, etc.) comparable, compatible and transparent. Reference points are expressed in terms of learning outcomes and competences. Learning outcomes are statements of what a learner is expected to know, understand and be able to demonstrate after completion of a learning experience. According to Tuning, learning outcomes are expressed in terms of the level of competence to be obtained by the learner.

In contemporary educational systems using CBE, flexible profiles are defined basing on the possibility of choosing with flexibility different subjects from a determined set. So, if students want to create their own academic profile, they only have to choose the subjects they consider interesting for their purposes. But, in order to choose correctly, it is necessary to take into account that subjects are affected by competences in two ways:

- A subject needs that students accomplish certain level of development for specific competences before students are ready to confront this subject.
- Each subject itself contributes to the development of certain competences in a major or minor degree.

So, in order to acquire certain development of competences, learners must study subjects in a retroactive way, so that stepwise they develop the desired competences. In other words, to course certain subjects it is necessary to have studied and passed those subjects capable of develop competences prerequisite of more advanced subjects.

We will take these ideas as basis for our further explanation of the use of CB in Academic Orientation.

4. *OrieB*: Collaborative filtering in academic orientation

In (Castellano 2009b) it was presented *OrieB* a DSS based on collaborative filtering which offers recommendations to students as subjects susceptible of being good elections in order to perform an adequate academic path. As collaborative techniques deal with *customers, items and ratings*, *OrieB* deals with *students, subjects and marks*, so the dataset about Academic Orientation is adapted to apply CF techniques. Another point is that we considered 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 so that *OrieB* consists of:

a. **Dataset**: a dataset with students' marks obtained from coursed subjects.
b. **Grouping students**: students are grouped based on the similarity of its marks and those from other students. This similarity is computed used Pearson Correlation Coefficient (Castellano 2009b).
c. **Predictions**: system makes a prediction about the mark that student would obtain for candidate subjects so this prediction could be used by the advisors in order to support student decisions.

Data analysis about the performance of CF in academic orientation and hence in *OrieB* was done and presented in (Castellano 2009b). The results the survey showed that the system was capable to support successfully *advisors* in an accurate way.

A further detailed explanation about the previous survey, the decision support model and OrieB can be revised in (Castellano 2009b).

This approach has certain limitations suffered by Orieb which we are trying to solve in this chapter:

- *New item problem*: whenever institutions due to either new laws or academic needs a new subject is required, OrieB has no possibility of recommend it as it has no marks available from students, because no one has study this subject yet and no one has a mark, and CF is unable to works without this kind of data. This limitation could be overcome with a content-based recommendation which studies competences required for the subject and student's competences developement.
- *The "grey sheep" problem:* Although OrieB is not much affected for this limitation because the range of elections is much closed, CBRS would offer more personalization because it would take into account not only subject's mark prediction, but also information about that subject.
- Same as before, *historical data set* problem can be solved by using actual student's competences development and information about subjects.

As we can see, the use of a CBRS can help improving OrieB in several ways. Next section will explain how to context a CBRS in Academic Orientation area.

5. CB and academic orientation

So far we have seen the use of CF in academic orientation and some limitations that it presented such the cold start. Consequently a good way to overcome the cold start might be the use of the hybridizing with content based techniques as it has been done in other applications.

In this section we propose a content based model for academic orientation that afterwards it will be hybridized with the CF technique already revised.

It has been pointed out that to perform efficiently a CBRS requires:

- Item profiles which contains information to be used in the recommendation process
- User profiles in order to match item profiles searching adequate candidates.

These profiles need to be based on a set of keywords or features. In our case, items will be subjects and users will be students. Features chosen to elaborate profiles are Academic Competences.

Following European Union guidelines, Spanish Academic System is based in eight competences which are:

- Linguistic communication
- Mathematic

- Digital and Information manipulation
- Environment knowledge
- Social and Civic
- Artistic and cultural
- Learn to learn capacity
- Initiative and autonomy

5.1 Profile construction

First of all, we need to explain how will be designed and formed the subject and student profiles.

5.1.1 Subject profile construction

A subject needs that a student had developed certain set of competences if he or she wants to pass it. So, the subject profile will consist in the competences and de level of development that the subject needs to be studied correctly. For example, the subject Spanish Literature will need a high level of development for Linguistic and Arts competences and hardly in Mathematics competence.

So, we need to know which level of development each subject needs for each competence. This information was gathered by means of a questionnaire. We ask a big number of teachers from several High Schools in which degree (in a 1-5 scale) they think that subjects they teach need from students to have been developed each competence. Once we had questionnaire's results, next step was to aggregate them with a simple mean, in order to obtain a number which represent the level of development required for each competence. So, subject's profiles will remain as we can see in Table 4.

Competences /Subject	Mathematics	Spanish Literature	Social Sciences
Linguistic	1	5	3
Mathematic	5	1	2
Digital	3	2	2
Environment	2	2	5
Social	2	4	5
Arts	2	5	4
Learn to learn	4	3	3
Initiative	3	4	3

Table 4. Subject profiles constructed from competences

5.1.2 Student profile construction

In order to be consequent with subject profiles, student profiles must be built based on competences. In a specific moment each student has a degree of development for each competence. For example, it is known that some students outstand in Mathematics and Digital competences, but lack of Initiative and Arts ones, while on other students can happen just the opposite, or any other combination.

Spanish Academic System is about to evaluate by means of competences so that in a nearby future will be possible to know the level of development of each competence in any moment. However, in the present time this is not completely real. For this reason, in our proposal we consider that student's competences should be weighted according to the mark obtained by student in the subjects has already studied. According to the discussion presented in section 3, where we said that subjects develop competences, in the same teacher's questionnaire presented before we ask them for specifying in which grade (in a 1-5 scale) each subject contribute to the development of a competence. Once we have got these results, we grouped subjects by grades in order to aggregate with a weighted average the percentage in which each subject contributes with each competence. Supposing that in a certain grade we have only three subjects, an example of the result of our quiz can be seen in Table 5.

Competences /Subject	Mathematics	Spanish Literature	Social Sciences
Linguistic	5%	70%	25%
Mathematic	80%	1%	19%
Digital	65%	15%	20%
Environment	25%	10%	65%
Social	5%	35%	60%
Artistic	10%	40%	50%
Learn to learn	30%	30%	40%
Initiative	20%	40%	40%

Table 5. Percentage of contribution of subjects in competences

From this table and students' marks in these subjects (for example, those on Table 6) we can calculate an approximation of the development level of development for each competence. The student profile can be seen on Table 7.

Subject/ Student	Mathematics	Spanish Literature	Social Sciences
John	10	1	3
Helen	2	10	8
Peter	4	5	10
Anne	9	6	9

Table 6. Example of students' marks in a 0-10 scale

Competences /Subject	John	Helen	Peter	Anne
Linguistic	0,98	4,55	3,10	3,45
Mathematic	4,29	1,61	2,58	4,49
Digital	3,63	2,20	2,68	4,28
Environment	2,28	3,35	4,00	4,35
Social	1,33	4,20	3,98	3,98
Artistic	1,45	4,10	3,70	3,90
Learn to learn	2,25	3,40	3,35	4,05
Initiative	1,80	3,80	3,40	3,90

Table 7. Student profiles

Now, with subjects and students profiles, we will see how a CBRS would work in order to make a recommendation.

5.2 Neighborhood formation

To provide recommendations, system needs to find those subjects that require a competence degree such that user had already developed. This is not exactly to find subjects with profiles equal to a student profile, but to find subjects profiles with required level of competences equal or lower that level in user profile. For example, looking at Table 4 we could think that a student with 5 in all competences will not be recommended any subject as he or she do not match well with the levels specified. However, the reality is that this student is able of studying any of them, because the requirements are fulfill enough.

To solve this question, we need a similarity measure which treat as well student which exceed requirements as students that simple fulfill them. For this reason we will not use similarity measure explained before, the cosine, and we will use a normalized variant of the Euclidean distance upgraded in order to follow this guideline, hence if student has a greater level for the desired competences, the similarity will give a positive result.

If student only need to fulfill the competence but system must take into account the rest of them, we will chose as competence development level the minimum between the student's value and de required for the subject so that it will be the same if student simply fulfill the requirement or overpass it anyway. This is achieved by using the minimum between the level required for the subject and the level accomplished by the student, instead of using only the level accomplished. This way the system treats equally those subjects with overpassed and simply fulfilled competence requirements, giving priority to those competence requirements not accomplished.

Consequently, let $r_{i,c}$ be the required level of development for competence *i* in subject *c*, and $v_{i,s}$ the computed value for student *s* in competence *i.* A is the amplitude of the value of development domain calculated as $A = b - a$, being *b* the top limit and *a* the bottom limit of such domain. In our case, interval of values used is between 1 and 5, both included.

$$u(c,s) = \frac{\sqrt{\sum_{i=1}^{n} \frac{(r_{i,c} - \min(r_{i,c}, v_{i,s}))}{A^2}}}{\sqrt{n}} \quad (3)$$

Equation 3 computes the similarity measure able of comparing student's capabilities and subject's requirements. The greater the value obtained the greater prepared will be the student to course that subject.

5.3 Top-N list generation

This equation will be applied to those subjects belonging to the target grade which student has to study next. The most often used technique for the generation of the top-*N* list is the one that select the *N* most valuated candidates with the similarity measure.

Once these *N* candidates are selected, they are presented as recommendation by the system.

6. Hybrid-OrieB: CB and CF in academic orientation

In section 4 was overviewed OrieB (Castellano 2009b), a web based Decision Support System built to support Spanish advisors in their task of helping students which modality to

choose in Baccalaureate, after finishing Secondary School. Specifically, the system aided advisors to obtain useful information about which subjects in each modality and which elective subjects suited better a student or which core subject might be extra hard. Thanks to this system advisors can develop their duties quicker and with reliable information.
However as it was pointed out, this system presented overall the new item problem which makes impossible to offer complete recommendations because in a continuous changing system, new subjects appears almost every year and CF is no able to support this kind of information. To solve this limitation and those seen in previous sections a new Hybrid-OrieB system has been built, using both CF and CB approaches in order to provide better recommendations and to overcome CF inherent limitations.

Fig. 3. Home Page of OrieB

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 will be used just for advisors in order to support students but not directly by the students due to their lack of maturity.
The next step consists of choosing a hybridization method and presents the new system.

6.1 Hybridizing CF and CB for academic orientation

The main purpose of this chapter is to avoid the *new item* problem in OrieB by hybridizing CF and CB. When a new subject is presented in the system, it has no marks from students as it hasn't been studied yet by anybody. CF is unable to recommend this kind of subjects. This fact points out to the use of CB, as CB will always provide a recommendation for every target subject so that new subjects will not be a problem.
At this point, the system would obtain 2 lists of recommendations, one from CB and one from CF. Provided that CF uses 15 top subjects to elaborate its recommendation, we will set N for CB also in 15. So, we will have 2 lists of 15 subjects each with which we are going to work the hybridization.
In this sense, system will use subjects in both lists as follows:

- If dataset has no marks for a selected subject, CB recommendation will be used and the subject will be used to build the recommendation, because it is a *new subject*.
- If dataset presents any marks for that subject, system will weight recommendation of CF and CB using its own computed CF trust (Castellano 2009a, Castellano 2009b). Let

scf be the similarity computed by means of CF, *scb* the similarity computed by means of CB, and *t* trust computed for CF recommendation. New utility function for this subject will be computed as follows:

$$u'(c,s) = (scf * t) + \left(scb * \frac{1}{t}\right) \tag{4}$$

- If CF selects a subject not included by CB, it also will be used to perform the final recommendation because CF can offer serendipitous recommendations.

From previous procedure system will obtain a list with at the maximum 30 subjects in the case that CB recommends subjects that CF don't and vice versa. With this list system only has to order by similarity and recommend the same as done in the old OrieB. This way we have built a hybrid system by weighting and mixing results from separated CRS and CBRS.

6.2 Hybrid-OrieB

Once presented how system works internally in this section we will show what kind of recommendations and information OrieB offers and how to obtain it.

6.2.1 Interface

When advisors want to use OrieB to support a student, they just need 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. But if not all marks are filled, the approximation of student's development level of competences can be not as accurate as desired. This way so the more marks filled the more accurate and customized will be the advices obtained by the system.

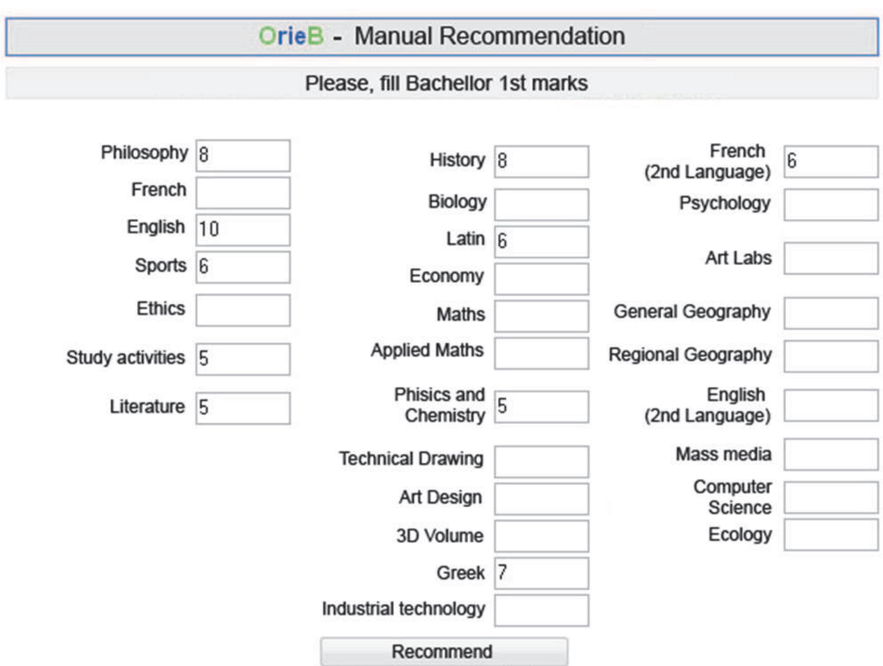

Fig. 4. Manual filling of marks

6.2.2 Supporting decisions

In order to help advisors in their tasks, OrieB offers three different types of support:

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

Module or Vocational Program Recommendations

In order to aid advisors guiding students about the Module that better suits them according to their marks OrieB computes a Module recommendation based on a ordered list by interest (see Figure 5).
Each recommendation for a module incorporates an interest value and a trust value.
Interest value expresses the appropriateness of a module for the target student based on the predicted marks. System offers a linguistic term to make and explain recommendations than precise numerical values that can mislead the students in their decisions. So, OrieB will provide linguistic recommendations (Castellano 2009a).
Trust value shows the confidence about the previous interest value based on the ratio between the number of subjects whose predictions were obtained and the total number of subjects for the module, and the standard deviation of those predictions (Castellano 2009a).

Vocational Program Recommendation

Trust	Interest	Program
57%	Very High	Arts
60%	High	Humanities and Social sciences
64.22%	Medium	Natural sciences and health
54.5%	Very Low	Technology

Fig. 5. Vocational Program Recommendation

Support for choosing Elective and Module Subjects

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

Recommendation	Elective subject
Very high	Mass Media
High	Psichology
High	Computer science
Medium	French (2nd Language)

Fig. 6. Subject recommendation in OrieB

Warning Difficulties in Core Subjects

Finally, students also may need advices about what core subjects could be difficult for them. In this sense, the system offers a list with those core subjects with predictions lower than medium, it will warn the advisor which core subjects could cause difficulties to the student, with a trust level of the recommendation.

Core subject difficulty advising

Trust	Subject
74.33%	English
82%	Literature
16.67%	French

Fig. 7. Core subject difficulty advising

7. Concluding remarks

In this chapter we have introduced the problem of Academic Orientation, presented a system which make use of Collaborative Filtering techniques in order to recommend students an academic path by using their marks, and studying its limitations, proposed a hybrid CB and CF system in order to overcome the problems of *scarcity* and *new item* problem.

This system helps advisors in their task of supporting students and opens a matter of study in the Academic Orientation with CBE in which academic profiles are going to be more flexible and systems more capable of giving better recommendations for students in matter of improve and develop capabilities.

The origin of upgrading the support model for academic orientation with content based techniques is because of the recent adaptation of the Spanish Academic System to the Competence Based Education. This change provoked the appearance of new subjects and profiles that CF models in OrieB cannot managed because of the lack of data.

Consequently to overcome the *cold start* problem with these new subjects and due to the available information the more suitable model to achieve the goal of supporting advisors was the hybridizing with a content based model which provides a higher coverage but regarding the accuracy we need to wait to obtain real data sets. Additionally this upgraded version is ready to be extended and useful amid the ongoing changes of the academic system.

Eventually, we want to highlight though OrieB is performing pretty well, there exist different challenges that should guide our research in the future:

- OrieB does not take into account subjective information provided by students such as preferences, yet. So the system should be able to include not only information relative to their academic tour but also subjective and own information .
- Information provided by the system should not directly guide students because some reasoning about the results are necessary, so only advisors can use OrieB. More visual and self-explicative recommendations would be needed in this sense not only for allowing students using the system but also for providing advisors a better way of exploring and explaining academics alternatives to students.
- So far OrieB is focused on secondary and Baccaulerate grades. It seems interesting its extension to higher education.

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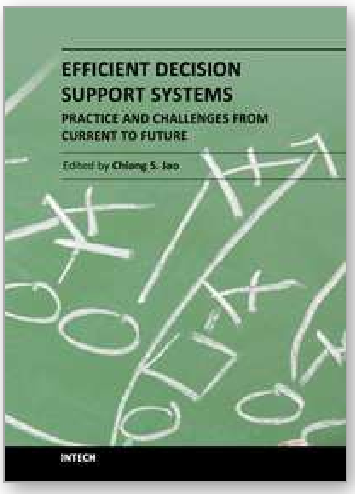

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