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Abstract— **We present a solution for social adaptive e-learning. In particular we want to individuate candidates acting as peer help in an e-learning academic course. Starting from a previous work in which adaptive learning functionalities were added to a traditional Learning Management System (LMS) [1], we found an interesting application of filtering techniques working together with fuzzy ontologies to individuate peer help, a fundamental step in constructing a true social environment in e-learning communities [2]. This way it is possible to use all the activities and functionalities offered by LMS improving their effectiveness with technologies based on socio-constructivism learning theory, such as: adaptive presentation, collaborative filtering, supporting peer help and peer tutoring.**

Collaborative and content based filtering; Automated techniques for user profiling style; Adaptive user interfaces and personalization techniques

I. INTRODUCTION

In present e-learning activities LMSs are the main elements of web based education. Such systems are e-learning software platforms that enable online course management, offering tools to create "virtual classrooms", manage students' enrollment, enable various types of learning activities as well as the management of learning materials needed by courses. This popularity is mainly due to the "user-friendliness" of the management of the different learning activities, the possibility to re-use didactic material. The price to be paid is in the didactic approach, the so called "one size fits all", in the sense that all students are considered in the same way: every personalization depends on the teachers action [3]. So the challenge is open to different goals, based on the application of well known learning theories that have not been fully adopted untill now, mainly because of the lack of appropriate web technologies (broadband connections, web applications) [4].

Besides the methodological problems in the learning process, practice with information technologies has lead to observe how e-learning cannot completely resolve the isolation problem in which a student finds himself in his learning activities [5]. LMS does not stimulate the practice of what we call the "social educational process"; so the lack of interaction between teacher and students or between students themselves, leads to more individual learning. Adaptive Intelligent Web Based Educational Systems try to overcome the problem of "one size fits all", but usually their approach in knowledge transfer is one-way, pushing to the development of various kinds of technologies and methods, all with the purpose to provide, as much as possible, a personalized support to the student [6].

We want to model a system that, together with the tools included in the most complete LMS, is able to give assistance to students, autonomously providing the information that are most useful to them in the learning process, using other students' experience and enabling a strong, capillary and distributed interaction. The system target could be pure online learning as well as blended learning, where the traditional face-to-face lectures are combined with online work [7].

A study of various existing forms of communities has been made (interest, learning and practice communities), trying to understand why people join structured groups, and above all, take part actively in community life, in order to understand what could be useful tools to aggregate and stimulate collaboration between students. This study highlights the difference between in loco communities and virtual communities, in which the communication medium brings the information to different levels, which is an important difference to analyze if we want to design an online educational system.

The concept of competence is another important point for the knowledge management which has been analyzed. We also refer to expert finding systems, or in general, to knowledge management systems often used by organizations in order to avoid loss of competences and information owned by their employees that they could share together as much as possible and enhance their effectiveness.

With the aim to design a system which uses processes by which expert finding systems are based upon, we have to rely upon the more competent students, to help their classmates with difficulties. This is the reason why we made an exhaustive study on the "expert" figure, both for his characterization and also as a knowledge and support source for the needs of community of participants.

We also analyze the study of human learning approaches, which views the educational process as a social activity, a collaborative construction of knowledge, instead of an individual one. This study has shown that these two areas, knowledge management and educational psychology, often treated like two different subjects, while they are really the basics for the creation of a knowledge management system in an educational area.

The challenge of the Ω–Network project is to bring the social educational process typical of *traditional classrooms* into the *virtual classrooms* context. We want to transform virtual classrooms into true learning communities, trying to avoid student's isolation and promoting collaboration.

Analyzing university courses we can observe that the community is formed by all students enrolled in degree courses. There are not separate communities for each course, but there is only one community which is split into various subgroups of the participants in single courses. We follow this approach in order to make all information potentially accessible by every single student, regardless of the course he/she is following, which is a typical schema of university reality, with students studying different arguments related to their curricula in different courses, with potentially different classmates.

Besides the learning community, we want to create a social network between students in order to promote peer transfer of knowledge, avoiding the usual exclusive dependency on the teacher and tutors. Because of this change of vision in the knowledge flow, we decided to logically separate the "course" into two parts, one official and traditionally managed by teachers and tutors, and another left to the free activities of knowledge sharing among students.

To promote active participation in community life, the system must provide the right features to the students, making it possible to manage their contents and relationships. It must provide the possibility to integrate the learning materials supplied by teachers with their own, with what in literature is called crowdsourcing, that is the contribution of all participants and not only those who have the role of teachers and tutors [8].

In order to improve the self-management features, every student has the possibility to rate other students and learning materials that were shared autonomously in this informal environment, making it possible for them to promote what is useful to the community. Evaluations of learning materials, introduced by peers (the students), has been designed according to two possible models, one with a single rating for material, evaluating then the objective coherence and utility for the community, and another with one evaluation for every single argument treated in the material, rating then how much every single argument is discussed in a useful way for the community.

Since the logical "separation" of the course is into two parts, official and free, there is only one part at a time at the frontend level with the user, even if for the system every piece of information is shared, mainly in order to make it possible for the instructors to be notified about relevant events, like materials considered very useful by the students, and that the teacher could eventually decide to integrate in the official course materials.

This paper summarizes the findings of a first study on the extension of a standard LMS with a framework that introduce adaptive methodologies for e-learning, with particular attention to social aspects. The rest of the paper is organized as follows: Section II describes the knowledge representation. Section III introduces modeling. Section IV presents the filtering algorithms. Section V describes the architecture. Section VI concludes the paper.

II. KNOWLEDGE REPRESENTATION

Adaptive support features for education are entrusted to technologies like adaptive presentation and collaborative content filtering, supported by technologies like peer help and peer tutoring. The system stores all the information in a knowledge base, and students are put in relation with each other, using similarity and neighborhood concepts, comparing students on their learning style.

Tools enabling transparency and awareness of what happens within the community will also be provided, considering what Thomas, Kellogg and Erickson have pointed out in their studies about the Babble project [9]. These tools show other students' activities and information (like Facebook social network), mainly about the ones that the system thinks could be most useful.

In order to provide its support, the system needs information about the competence and learning style of each student. For the former the system provides tools for evaluation of student's knowledge, making it possible to know at any time the level of each student and what his difficulties are in order to completely understand the arguments. Such evaluation will be performed at different times, one at course enrollment time and then during its execution. We decided to adopt a test model called cognitive efficiency test [10], which combined test performance with the mental effort required by the student to complete the test (Cognitive Efficiency = Performance / Mental Effort). We also use this idea to evaluate the learning style of every single student in using learning materials. Besides the coherence rating, the student is also asked to rate his mental effort in using the single learning material; the students have to select one of the five options (Very easy, Moderately Easy, Neither easy nor difficult, Moderately difficult, Very difficult), similarly as suggested by [10]. It is not the aim of the system to discover and define what kind of learning style every student has, but collecting different evaluations for various learning materials, it aims to have enough data to compare students' evaluations among each other and then to discover who has similar mental effort on various learning materials. This way we can create relationships between

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students in a network and use this information to provide adaptive suggestions about learning materials and discussions already held that may be most useful for the student (adaptive presentation and adaptive and collaborative content filtering), and also related to his competence level in each argument and learning style; other suggestions will be provided about "experts" (students) in areas in which the students lack of competences (peer help and peer tutoring).

Other features needed by the system are common among present e-learning systems and because of that, instead of constructing a completely new system we decided to develop an independent framework, which will rely on an existing LMS for the front end features. We do not want to repeat the same error committed in the past by other AIWBES, which led to their short lived popularity.

III. MODELING

The modeling of the core level system has been structured as expert finding systems; first we made a first domain modeling, followed by a student modeling and then by an expert modeling. We defined adaptive algorithms for the student support for these models [11].

Domain modeling has been made relying on the fuzzy ontological e-learning model Ocean, studied by Colleoni, Calegari, Ciucci and Dominoni [1]; using a method of knowledge representation and semantic web areas. Domain modeling represents a course structure, describing concepts like: *course*, *argument*, *learning material* and *test*. Every *course* is related to *arguments* that are discussed within it (ontological relation *IS_DISCUSSED_IN*) and every *argument* is related to the *learning materials* that explain it (ontological relation *DISCUSS_OF*) and *tests* that evaluate it (ontological relation *EVALUATE*).

Student modeling has been made using an outline to represent the various individual characteristics, both for their relations with the didactical knowledge base of the system and for their relations with other students of the learning community. We divided the outline into static and dynamic, in order to separate information and characteristics of the students that do not change or change rarely over time, related to the system's dynamics and activities and information that changes very often.

The static profilation will be performed at system enrollment time, with the compiling of a questionnaire and eventually with the use of additional data derivable from an entrance test. Dynamic outline data are those that best describe the interaction of the student with the didactics and with the rest of the community. The characteristics modeled are the competence level of the student related to a single argument (relation *HAS_COMPETENCE_IN*), fundamental for the recognition of the expert students, followed by other relations, such as the similarity between students and their specific didactical aspects, like the learning style in using learning material (relation *ARGUMENT_COGNITIVE_EFFORT_FOR*), or like the socio-didactical similarity (relation *SOCIODIDACTICAL_SIMILAR_TO*), that is the social compatibility between two students, related to didactical activities. Both these characteristics and relations are derived
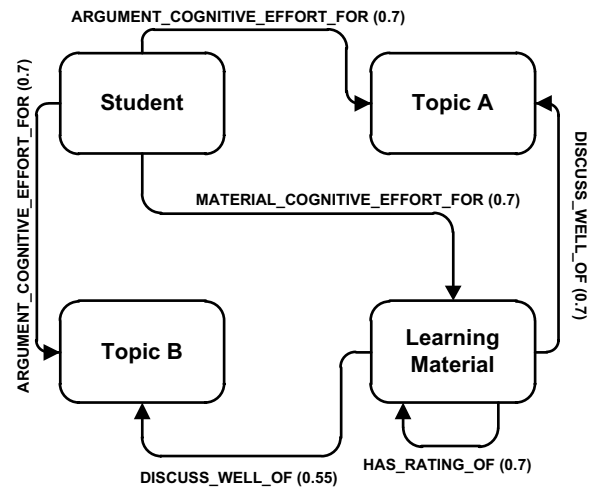

Figure 1. Relations between a student, learning material and topics.

combining static outline data with student's activities, respectively from the self evaluation about each student's cognitive effort in using the learning material, respect to every single argument, and the rating about the activities of other students.

Competence is represented using a *decreasing model*, based on the *discount rate law* used in mathematical finance [12]. Every test is equivalent to an independent evaluation of the state of competence in a well-defined time, a value that decreases over time due to a function and a *competence decrease rate*, tending toward the 0 value. For every argument student's competence level is updated at every test execution, or in case of inactivity, every regular interval set as system parameter. Updating consists in the actualization of every single competence state evaluated in a test and then merged with previous results.

Expert student modeling came off from another interpretation of competence relation. Three classes are defined to divide students and every class is associated to a fuzzy set, so that they could be used from the system adaptive logic. These classes are taken from the Dreyfus and Dreyfus model and are novice, competent and expert, where *expert* substitute *proficient*, only for nomenclature purposes and for having uniformity in using the expert term [13].

In Fig. 1 an example of student's cognitive effort using fuzzy ontologies.

IV. FILTERING ALGORITHMS

The adaptive logic of the system is fulfilled by the features of event management and of request management for the adaptive support. The system uses Information Retrieval algorithms called *User-based nearest neighbor algorithms* [14]. For the "information need", and for the list of useful learning materials, the filtering is subordinated to the relation of didactical similarity in using learning materials. Materials presented to the student are the ones that students most similar to him have rated as *easy* (relation *MATERIAL_COGNITIVE_EFFORT_FOR*) and that the community has evaluated as useful. For the "competence
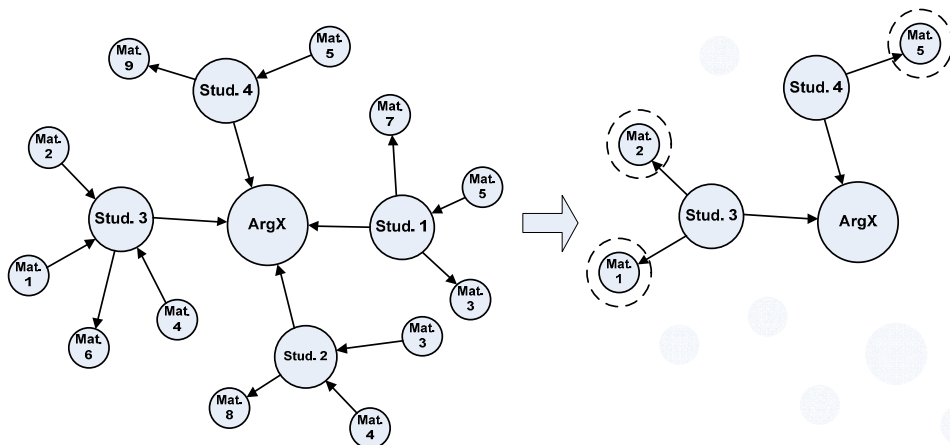
Figure 2. Initial and final stage of filtering algorithm

need" the process is similar to the previous case, but the discriminating relation is the socio-didactical similarity (relation *SOCIODIDACTICAL_SIMILAR_TO*).

Next we present in detail how collaborative filtering algorithms works on the knowledge base in order to retrieve useful learning materials. The filtering process use four ontological relations to filter information gathered from the knowledge base:

- *HAS_COMPETENCE_IN*;
- *ARGUMENT_COGNITIVE_EFFORT_FOR*;
- *MATERIAL_COGNITIVE_EFFORT_FOR*;
- *RATING_OF*.

Input:

- *Student*: who needs information (either he asked for it or it is given autonomously by the system).
- *Topics*: obtained from the context (activity) in which the student is working.

Output:

- *Ordered list of learning materials*: in decreasing order according to the utility rating, eventually divided into official and unofficial materials.

The first steps are focused on gathering individual student information and then algorithm execute the filtering using this information.

1. Once we have *student* and *topics* we analyze the *HAS_COMPETENCE_IN* relation, then obtaining student's competence level, which is very useful in order to choose a proper neighborhood.
2. We think that, regardless the competence level reached (novice, competent and expert), it is useful to give support information anyway. A constant K_v is chosen, defined on the range [0,1], used for quantifying the dimension of the correct neighborhood.
We thought about three different ways to choose this constant K_v:

- Using a constant value, regardless of the student competence level;
- Defining K_v on the competence level, ignoring fuzzy sets, restricting the range as the competence increases, so that a more comprehensive view of the materials will be given for novice students, who need a lot of integrative information, and giving more precise suggestions to expert students, who do not need strong support anymore;
- Defining K_v using other variables associated to fuzzy sets, defined on competence relations (α_n: novice, α_c: competent, α_e: expert), and using fuzziness values on these sets to weight the final constant value. These variables associated to fuzzy sets are chosen aiming the same goal as before, to modify the neighborhood range on the competence variation.

For example, for a novice student:

$$K_v = \alpha_n * f_n(\textit{competence level}). \qquad (1)$$

3. A neighborhood is selected on the relation *ARGUMENT_COGNITIVE_EFFORT_FOR*, due to the range calculated at the previous step.
4. As in step 2, a constant K_c is chosen, defining the maximum competence level of students of the neighborhood that will be considered. That is because we want to prevent a novice student from being immediately related to an expert student, ignoring competent students.
5. From the neighborhood are selected only the students with a competence level higher than the input student's one and lower than the calculated constant K_c.
6. In the final step the algorithm has to select the learning materials. It collect all materials from the students selected in the previous step and select only the ones with value Very Simple and Moderately Simple on the *MATERIAL_COGNITIVE_EFFORT_FOR*

relation. Materials are then presented ordered by value of *RATING_OF* relation.

In Fig. 2 are represented the initial and final stage of the algorithm: it starts with the representation of all students and learning materials related to a particular Argument (*topic*), and ends with the selection of most useful materials. The students focused in the figure are the ones selected by the algorithm, according to the learning style similarity relation, and then are presented only most useful (according to a chosen threshold) learning materials, selected from the only ones about the particular argument.

V. ARCHITECTURE

The system is designed with an architecture divided into three principal parts (Fig. 3), the Ω–Network framework, which contains the adaptive functionalities and the knowledge base, LMS integrative modules, which have to provide functionalities exposed by the framework to the users, and an intermediate wrapper between them, which allows the two other parts to communicate.

The framework takes the name Ω–Network, extending the previous Ω-framework, an extension of the system proposed by one of us [1]; it is developed using .NET technology, with a modular architecture (Fig. 4), based on the AIWBES structures (communication modules, core module, student modules, tutoring modules and knowledge base modules).

The wrapper is built using the same technologies used by the considered LMS (open source) like Moodle, Dokeos and Docebo: it uses PHP language and MySQL as a database management system. This component has a double function:

- It centralizes requests originating from LMS modules and forwards them to the framework, being the only component that needs direct connection with the framework;
- It stores mapping data between identifiers of framework objects and equivalent LMS ones, so that it could execute a parsing on every message.

The LMS modules load the wrapper as a library, and then the communication between these components takes place through direct method calling. The framework exposes its services using WCF (Windows Communication Foundation) in order to maintain the maximum compatibility, being less related to single technologies, and so the wrapper will query it using Web Services.

VI. CONCLUSIONS

In this paper an overview of the Omega Framework was given and the way in which a standard LMS with its normal functionalities can be extended in order to create an intelligent system for e-learning, with particular attention given to social aspects.

Our vision is that the education process is not driven only by a block of well-formed structured information expressed respecting pure educational formalism, like the formalisms of mathematics, but it is full of implicit, informal natural parts in the form of trails and errors. These pieces of the
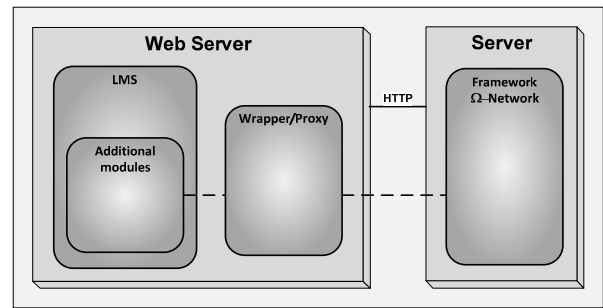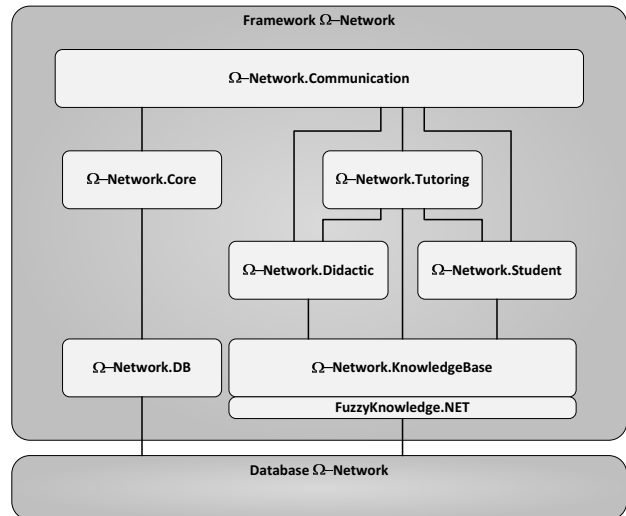

Figure 3. System architecture

Figure 4. Ω-Network architecture.

entire educational process are not an "undesired" collateral effect that we do not want or need to introduce in the LMS, but are the most relevant part of the entire process of learning with profit and competence. The informal processes of learning are causally anterior and concur to create the ability to formally control the material that is object of the education [15]. We think that the informal process of understanding formal information, given during the frontal part of the lessons, is an inherent part of education and is a social process.

That is why we want to introduce a set of objective measures of social relations and a set of cooperation instruments useful for guiding and understanding the social (collective) process of learning.

With the expression "social process of learning" we intend to describe an iterative multipart process that has a social weight. For a community of learners, to understand formal information is a question of 1) creating intermediate informal information generated by the community of learners itself through a trial and error process, and 2) every step of this creation is evaluated by the community of learners.

In this scenario learners must encounter the information they need. We think that the learner himself is the best person to judge which information is best suited for him/her, but a learner can also consider information interesting which is created by learners who are similar to him/her. We consider learners similar when they have cognitive

similarity, and we have proposed a way to measure cognitive similarity. We also consider information coming from people we already know to be more trustworthy. Thus, we consider that information of our "net of trusted" is more important.

In this process, the information is something that is dynamically emergent, and all information competes to emerge in the system. Learners are the people who must judge what is well suited for them (comprehensible), the LMS is the instrument to carry out that process, and not a poor alternative to a better way of teaching.

We also think that this process of information emersion should not be driven by the direct intervention of the teacher, but should be only encouraged, and that an electronic system is perfectly suited for this purpose.

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