MASECO – a Multi-Agent System for Evaluation and Classification of OERs and OCW Based on Quality Criteria

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Abstract. Finding effectively open educational resources and open courseware that are the most relevant and that have the best quality for a specific user's need, in a particular context, becomes more and more demanding. Hence, even though teachers and learners (enrolled students or self-learners as well) get to a greater extent support in finding the right educational resources, they still cannot rely on support for evaluating their quality and relevance, and, therefore, there is a stringent need for effective search and discovery tools that are able to locate high quality educational resources. We propose here a multi-agent system for evaluation and classification of open educational resources and open courseware (called MASECO) based on our socio-constructivist quality model. MASECO supports learners and instructors in their quest for the most appropriate educational resource that fulfills properly their educational needs in a given context. Faculty, educational institutions, developers, and quality assurance experts may also benefit from using it.

1 Introduction

The Open Educational Resources (OERs) movement started in 2002 with the *Education Program of the Hewlett Foundation* introducing a key element into its strategic plan *Using Information Technology to Increase Access to High-Quality Educational Content*, which aimed at helping equalizing *the distribution of high quality knowledge and educational opportunities for individuals, faculty, and institutions* worldwide using the ICT support. The initial focus was twofold: funding *production* of exemplars of high-quality content and building community, collaboration, and a shared knowledge base about the *creation, dissemination, access, use and evaluation* of open educational resources [1].

The OER original model included, beside funding and promoting, living specifications of high-quality open content, establishing quality benchmarks for various forms of content, which have faded out in the more recent OER logic models. The desideratum of high-quality has been reached mainly by financing branded content from prestigious institutions. However, despite the strong arguments for this approach, it is crucial to *find additional mechanisms for vetting and enhancing educational objects in social settings, ways to close loops and converge to higher quality and more useful*

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materials [1]. While providing high-quality educational materials from top institutions will remain essential to the success of the OER Initiative (the spin-off open courseware movement rooted in the MIT OCW project is a prominent such successful example), the increasing role of the open repositories in this process is essential for creation of appropriate learning loops that continuously improve these materials through reflected use, re-use, re-mix etc. [1]. In this chapter, for the sake of easiness in phrasing, we use the acronym OCW for both OpenCourseWare and open courseware, where the former refers to projects based on the MIT OCW paradigm, while the latter regard any free offering of online courseware based on other paradigms.

One major challenge that the OER movement has had to face, due mainly to its significant success, has to do with the fast growing number of both open educational repositories and instructional resources available freely. Thus, finding effectively the resources that are the most relevant and that have the best quality becomes more and more demanding [2]. Hence, even though teachers and learners (enrolled students or self-learners as well) get more and more support in finding the right educational resources, they still cannot rely on support for evaluating their quality and relevance [3], and therefore there is a stringent need for effective search and discovery tools [2]. OPAL, one of the last Hewlett Foundation funded projects, has evaluated a wide range of international OER projects focusing on quality issues, and the conclusion was that *systematic quality assurance mechanisms for OER are lacking in higher education and adult education* .. and that it is necessary to overcome the insecurity concerning how to validate the value of open educational resources and practices *when quality management approaches are largely absent for OERs* [4]. It is argued that OER providers themselves should be the first to ask for accreditation, certification, and quality assurance, so that their offerings comply with the standards in the field, and, therefore there will be more confidence in and acceptance of OERs [5].

The recent 2012 Paris OER Declaration, issued at the 2012 OER Congress in Paris, recommends that future support is needed for *facilitating finding, retrieving and sharing of OERs, for fostering awareness and use, for facilitating enabling environments for use of ICT, for reinforcing the development of strategies and policies, for promoting the understanding and use of open licensing frameworks, for supporting capacity building for the sustainable development of quality learning materials, for fostering strategic alliances, for encouraging the development and adaptation in a variety of languages and cultural contexts, for encouraging research, and for encouraging the open licensing of educational materials produced with public funds* [6].

In spite of the scale, pervasiveness, and influence of the growing movement of free sharing of educational resources and courseware on users around the world, there is yet no quality assessment framework that could provide support for (1) *learners* in their quest for finding the most appropriate educational resources for their educational needs in a given context, for (2) *instructors* who are interested in educational resources that support their teaching and learning activities, and provide for both achievement of learning goals, objectives, and outcomes, and for reflective learning, for (3) *faculty or institutions* that are or want to become involved in this movement, and they may be interested in the challenges and benefits of this process, for

(4) *developers* who need guidelines for designing and building such educational resources, or for (5) *experts in quality assurance* of educational resources [7, 8, 9].

We propose here a multi-agent system for evaluation and classification of open courseware and open educational resources (called MASECO) based on our socio-constructivist quality model introduced in [7]. The main goal of MASECO is supporting OER/OCW users, being them learners, instructors, developers, evaluators, faculty, institutions, consortiums etc. to fulfill better their needs, and accomplish appropriately their educational aims, in any specific context. The criteria that constitute the backbone of the model have been grouped in four categories related with content, instructional design, technology, and courseware evaluation. Therefore, our work mainly supports two of the 2012 Paris OER Declaration recommendations that refer to support for both locating and retrieving OER that are relevant to specific needs (*facilitate finding, retrieving and sharing of OER*) and for promoting quality assurance of OERs (*sustainable development of quality learning materials*).

MASECO has three main components as follows: (1) an OER/OCW Management System, which is built on top of a database management system, and which manages both OERs and OCW (storing and updating information related to the OER and the OCW included in the system), (2) a *Classification Agent* that classify OERs and OCW using various classifiers, and (3) a *Communication Agent*, which manages the communication between agents and between the system and the environment.

Several use scenarios may take place according to the user's type. For example, for a regular user, the working scenario is as follows: the user interacts with the system through the Communication Agent, and she makes a request of the "best" OER or OCW according to her needs, within a given context. The Communication Agent corroborates information from the OER/OCW Management System and sends it together with the user's needs to the OER/OCW Classification Agent, which returns a result to the Communication Agent. Finally, the Communication Agent transmits the system's answer back to the user. A developer may update and improve MASECO, so he interacts with it for updating both the OER/OCW database, and for initiation of training sessions for the neural network of the Classification Agent.

Our work is focused in the first place on helping learners, as they often do not have the background knowledge, information seeking or metacognitive skills necessary to evaluate effectively the educational value of digital resources, which is understandable taking into account that this capacity to evaluate and discriminate lays on the highest level of critical thinking skill in Bloom's taxonomy for thinking about educational goals [10, 11]. Nevertheless, all the other actors involved in educational processes mentioned before can benefit highly from using MASECO.

The structure of the chapter is as follows: the next section addresses issues of quality assurance for OERs and OCW as they are reflected in the literature, while the third one is concerned with the related work on concrete solutions for evaluation and classification of OER and OCW. Section 4 includes the research methodology. In Section 5, we give a detailed description of using MASECO for evaluation and classification of OERs and OCW with respect to the architecture, the conceptual models, the use scenarios, the used classifiers, the experimental results, and some discussion around the whole experience, the lessons learned, and the challenges that remain. The last section includes some conclusions, along with future work ideas.

2 Quality Assurance for OERs and OCW

Quality of open educational content is seen as a strong base for future sustainability of the OER/OCW movement, no matter what approach of ensuring quality is followed [1], given that movement's sustainability is essential to the successful, large scale OER/OCW acceptance, and embedding in education [12], being it at resource's production level or at resource's sharing level [13]. Quality Assurance (QA) is a frequently raised topic, as learning resources are expected to be trusted and authoritative [1, 3, 12, 13, 14, 15]. Moreover, common lack of reviewing and quality assurance is seen as a critical issue that is holding back the increased uptake and usage of OCW and OERs [3, 12, 16]. Furthermore, ensuring quality of open content is seen as one of the major challenges to the growing OER/OCW movement, along with both lack of awareness regarding copyright issues and sustainability of the OER/OCW initiatives in the long run [3]. Other works see quality assurance as a key factor for sustainability, besides funding and support [12].

OER quality can be approached twofold: first, design processes that guarantee content quality and suitable formats, and secondly, development (or maintenance) processes to ensure currency [12]. Two quality assurance directions are followed: the first one is concerned with discovering the way in which experts and users assess quality of digital resources in general, striving to identify both major factors influencing human judgments and lower level features of resources that people attend to when assessing quality. The second direction consists of applying machine learning algorithms when seeking solutions for this kind of problem. Of course, there are several issues to consider, such as including consistency (or not) of humans when making potentially subjective assessments and various features chosen to focus on when training machine learning algorithms. However, when asked to evaluate the quality of digital resources, people usually rely on a set of criteria (that often are implicit) to guide their reasoning [17]. In addition to scalability, another challenge of assessing educational resource quality is the matter of perspective: the quality is rather contextual than intrinsic to the resource. It depends on the configuration that corroborates the users' constituency, the educational setting, and the intended educational purpose of the resource [17].

Moreover, traditional quality assurance mechanisms are not appropriate for assessing quality of OCW and OERs because of their high developing and changing rate. Easy to use, dynamic, and user-centered quality mechanisms are considered more suitable for ensuring quality of OCW and OERs through various community approaches: *peer reviews, user commenting, and rating* (not to exclude branding, of course). Self-sustainable, competent, and aware communities that work coordinately on resource creation and improvement, quality assurance, and experience sharing should be invigorated [3, 18, 19]. Open peer review according to a set of agreed criteria is seen as well suited for this task [20]. Other low-level elements that describe the use of a particular educational resource may be useful, such as the number of downloads, the argument for such an approach being that *quality is not an inherent part of a learning resource, but rather a contextual phenomenon*, and a learning resource maybe be or not useful in a specific learning situation, and therefore, the learner should be the judge of that [3, 5, 21]. It is argued that in spite of offering high quality materials and best pedagogical design and methods, OERs and OCW will prove their true value for learners only if they match the learners' own context, and therefore they are genuinely reusable (or at least fully adaptable) [22].

Over time, several solutions have been envisaged for coping with ensuring quality of OERs and OCW. For instance, some institution-based providers rely on the reputation (*brand*) of the institution to convince the learners that the offered open educational materials are of high quality. Of course, most probably, the materials are subjected to some *internal quality assurance procedures* before being released as open content, but these are not open to the public so that they could be followed [3]. Likewise, a Global Index system has been proposed, which aimed at helping potential users to locate and access easily the needed courseware [16, 23]. It was supposed to be based on a *vetting mechanism* supported by a volunteer group acting as a de facto editorial board. More recent works sustain a similar idea of creation of *learning exchanges* that are focused directories linking to only high-quality repositories, and using only commonly established standards for classification and sharing [24].

Other approach suggests establishing formal co-operations between educational organizations that are involved in sharing and reusing of OERs from a common pool of content, tools and services, which it is thought as having a positive impact also on the quality leveraging of OERs, for example by being assessed critically by partner institutions, which may result in improved internal quality criteria and control [14, 15]. *Word-of-mouth* method is also seen as a viable quality management process [3].

Peer reviewing has been primarily used for quality assurance by some well-known open educational resources repositories, such as MERLOT (Multimedia Educational Resource for Learning and Online Teaching) or NLN Materials (National Learning Network Materials). All the MERLOT resources are assessed by discipline-specific editorial boards with regard to their quality of content, potential effectiveness as a teaching-learning tool, and their ease of use, while the NLN materials are peer reviewed by a range of colleges [4, 21, 25, 26]. In MERLOT, all the peer reviewers in a specific editorial board share and compare their evaluations to create test cases, which are used further on to develop evaluation guidelines that are to be applied to all the resources of each particular discipline [2].

However, the traditional peer reviewing process, which is focused on assessing the factual accuracy, intellectual content, and educational context of a resource, is not the most suitable for educational resources, as their educational quality is hard to evaluate outside the instructional context. Therefore, it is the educator's responsibility, when reusing a particular resource, to create suitable pedagogical scenarios within proper educational contexts [21]. MERLOT, for example, complements the formal peer review with recording user comments and ratings.

In [27] the authors analyze deeply the traditional peer review process, and after identifying the pressures this process has to face, and pointing out the fallacies of reviewing in the online world, they propose a general set of principles for understanding how peer review should be applied today to different kinds of content and in new platforms for managing quality. These principles consider not only the materials' content, but also their context of use, and while the focus here is on OERs, though they may be applied *across multiple levels of knowledge production, including scholarship and reference materials in addition to educational publishing* [27].

Context of use may indicate where a resource is being used by learners, such as in a classroom, in a laboratory, or as part of an encyclopedia, or it can describe the stage of a scientific work from the perspective of authors, such as draft, revised version, or updated version. It can also refer to contexts of reuse such as a translation, a derivative work for a different goal, or a constantly updated resource like a Wikipedia article. *The stress is on understanding the variety of contexts in which a resource exists and not only the end-user consumption of a resource* [27]. What resources are good in what contexts it is an outcome of the reviewing process.

The principles for review that authors propose are as follows: *(1) principle of maximum bootstrapping: designers of new systems should build on and adapt existing communities of expertise, existing norms for quality, and existing mechanisms of review; (2) principle of objectified evaluations: treat reviews as their own kind of object, disassociated from a single resource, specifying context of use, and potentially applicable to multiple versions; (3) principle of multiple magnifications: more reviews are better, more data about reviewers is better, because multiple, combined views on an object are now possible, with a corollary for the third principle: review is not blind, but pseudonymous and persistent*.

Another approach considers *a voluntary (or mix of voluntary and paid) wiki-like model, in which OERs are the object of micro-contributions from many. This approach raises complex issues of quality, but much work on collective "converging to better" is under way* [1]. Such an approach is taken in Connexions, where the traditional pre-publication review is replaced with a post-publication review based on a more open community of third party reviewers. Acknowledging that there are multiple perspectives on quality, Connexions permits third parties to use a mechanism, which provide different views onto collections [5, 17]. The mechanism that allows this process is based on the *lenses*. For example, a user, be it an individual, an institution or an organization may set up their own reviewing, then it is able to select the modules and collections that meet their quality standards, and, when the repository is accessed through that user's lens, only the materials they estimate as having the appropriate quality may be viewed. While Connexions users have access to all modules and courses in the Content Commons (whatever their stage of development and quality level), they also have the opportunity to preferentially locate and view modules and courses rated high quality by choosing from a range of different lenses provided by third parties, each lens having a different focus [1, 4, 28]. So, in this model, *pre-publication credentialed materials are not merely distributed through the network; post-publication materials are credentialed through use in the networks* [1].

Other approaches investigate the viability of generating dynamic use histories for educational resources, which will record each instance of using or reusing a particular resource. This will provide for searching the most used resources for a given topic [21], while other sees the quality assurance process as corroborating checking, peer reviewing, feedback, rating or voting or recommendation, and branding or provenance or reputation [29]. It remains to be seen which approach will gain acceptance within educational communities, but most probably that will combine some of the approaches presented briefly here and, in our opinion, it will have to do with user communities.

3 Related Work: QA and Classification of OER/OCW

After pursuing a very thorough search in various prestigious digital libraries and indexing databases, we have become aware that the related work is very scarce, with just a few works hardly similar with ours in some particular respects.

In [30] the author envisages various teaching and learning activities happening in a semantic web-based education environment, in which intelligent *pedagogical agents* provide the infrastructure needed for information and knowledge flows between user clients (authors, teachers, learners etc.) and educational servers. These agents are autonomous software entities that provide for human learning and cooperate with various actors involved in pedagogical processes and with each other, in the context of interactive learning environments. They assist searchers in locating, browsing, selecting, re-mixing, integrating, adapting, personalizing, re-using etc. educational materials located on different servers [30, 31].

Automatic identification of educational materials by classifying documents found on the web with respect to their educational value is explored in [32, 33]. The authors formulate the task as a text categorization problem, and prove that the generally accepted concept of a learning object's "educational value" can be reliably assigned through automatic classification by carrying out several experiments on a dataset of manually annotated documents, which show that the generally accepted notion of a learning object's "educational value" is a property that can be, in authors' view, reliably assigned through automatic classification. Furthermore, an examination of cross-topic and cross-domain portability illustrates that the *automatic classifier can be ported to other topics and domains, with minimal performance loss*. The authors have identified also several features of educational resources: the educational value, the relevance, the content categories (definition, example/use, questions and answers, illustration, other), and the resource type (class web page, encyclopedia, blog, mailing lists/forums, online book, presentation, publication, how-to article, reference manual, other). The expertise of the annotators is also retained as it is important when evaluating the educative value of a resource. The resources have been scored on a four point scale mapped to four labels: non-educational, marginally educational, educational, and strongly educational. Both papers present an experiment on a dataset of materials in Computer Science, while the second presents also another experiment on a dataset in Biology, to prove cross-domain portability.

Automatic classification of didactic functions of information objects, based on machine learning, aiming at increasing the re-use rate of digital learning resources, at various levels of granularity, is addressed in [34]. Each information object was manually labeled with its didactic function, according to Meder's didactic ontologies [35]. The function types have been hierarchically ordered on three levels as follows: the first one differentiates between receptive knowledge types and interactive assessments; the former is further divided into source, orientation (facts or overview), explanation (what-explanation or example), and action knowledge (checklist or principle), while the latter consists of either multiple choice tests or assignment tests. Nine features have been used to evaluate whether multimedia features can be used for classification of didactic functions. Four different classifiers were used and evaluated: a

Bayes network classifier, a Support Vector Machine (SVM), a rule based learner and a decision tree learner. The classifiers worked on the three levels of details presented above, on a set of medical educational resources (training corpus of 166 information objects, further 207). Their results have been compared with the human evaluation (six evaluators). The main performance measure was classification accuracy, which has reached a level of over 70% when hierarchical classification has been performed and a level of 85% when multi-label classification has been used. The authors have identified also two extra features that could improve these results: position of an information object within the learning object or course it belongs to (that may show author's intended learning strategy), and the style of speech (as it may vary and depends closely on particular didactic goals).

In [29] authors consider four quality dimensions for OERs: content, pedagogical effectiveness, ease of use, and reusability, each one of them being detailed further on. The *content dimension* includes accuracy, currency, and relevance; the *pedagogical effectiveness* relies on learning objectives, prerequisites, learning design, learning styles, and assessment; the *ease of use* is related to clarity, visual attractiveness, engagement, clear navigation, and functionality, while *reusability* depends on format, localization, and metadata-based discoverability.

In [17] the authors worked on the idea that identifying concrete factors of quality for web-based educational resources, both used by experts in quality assessment and easily recognized by non-experts, can make manageable machine learning approaches to automatically determine quality characterization and educational value. The aim of their work was dual: empowering learners with tools for evaluation of quality of online educational resources and helping digital librarians to manage large educational collections. They were driven by the need to develop both methodologies able to identify dimensions of quality that are associated with specific educational goals and algorithms able to characterize resources with respect to these dimensions. Twelve dimensions of quality have been identified as the most important: good general set-up, appropriate pedagogical guidance, appropriate inclusion of graphics, readability of text, inclusion of hands-on activities, robust pedagogical support, age appropriateness, suitability of activities, connections to real-world applications, reflecting the source's authority, focus on key content, and access to relevant data. They constructed a training corpus of 1000 digital resources annotated with these quality indicators, and trained machine learning models which were able to identify important indicators, with accuracies of over 80%. The indicator extraction process has resulted in one numeric vector per educational resource in the digital library. The machine learning system (based on SVM) has analyzed the corresponding vectors for the training corpus, and it has learned a statistical model for some selected indicators. Further on, it has evaluated whether the quality indicators are present or not in a resource, based on applying those models to the vector corresponding to that particular resource.

In [11] the authors subscribe their work to the high goal of developing a computational model of quality that come close to human expert evaluations, based on machine learning and natural language processing, and, moreover, to provide automatic tools that implements that model. They started with performing an extensive literature review and meta-analysis, and, consequently identified 16 features of resources or metadata that could be useful for detecting quality variations across resources, lying in five categories: *provenance* (cognitive authority, site domain), *description* (element count, description length, metadata currency), *content* (resource currency, advertising, alignment to educational standards, word/link/image count on the first page of the resource, multimedia), *social authority* (Google's PageRank, annotations), and *availability* (cost, functionality). The experiment consisted in manual annotations for collections of DLESE digital library (600 resources), according to evaluators' *gestalt sense of quality* and personal preferences regarding quality. The collection rankings have been used as rankings for individual resources contained in the collections (to avoid the huge amount of effort necessary for manual annotations of each individual resource). Three classification categories have been used, namely A+, A, and A-, and each one was containing 200 resources. Within each classification category, the resources were further divided randomly into training and testing sets where 80% of the resources were used to train the model and the remaining 20% were used to test the accuracy of the trained model. The authors have computed metrics for evaluation of the quality indicators (only for the first page of each resource), and have experimented in a series of add-one-in analyses to see which indicators have positive, respective negative contributions to the classification. When all the indicators were used, their models were able to identify whether a resource was from a high (A+), medium (A), or low (A-) quality collection with 76.67% accuracy, while when using only the quality indicators that positively contributed to the classification increased the models' accuracy to 81.67%.

In [36] the authors propose a measure of relevance, which integrates a variety of existing quality indicators, and which can be automatically computed, building on work in [37] and [27]. In [37], the author shows that the current systems for recommending educational materials lack a *weighting mechanism* that would allow assessment data from various sources to be considered. Consequently, he proposes an integrated quality indicator that combines explicit expert and user evaluations, anonymous evaluations and implicit indicators (such as favorites and retrievals). In [36] the authors reflect on Connexions, where each lens focuses the user's view on a subset of available modules and collections deemed high quality by the controlling authority, and propose combining lenses for filtering content. Therefore, they propose a relevance indicator that can be calculated automatically, as a sum of three weighted sums of quality indicators, which can be classified into three categories: *evaluative* that includes all explicit expert and user evaluations (overall rating, content quality, effectiveness, ease of use, comments), *empirical* that refers to information on materials usage, such as retrievals, the number of users who bookmark them, and so on (personal collections, exercises, used in classroom), and *characteristic* that refers to descriptive information about the materials, as obtained from their metadata (reusability). Thus, the explicit evaluations made by users or experts, the descriptive information obtained from metadata and the usage data are used in order to increase the reliability of recommendations by integrating various quality aspects.

In [38] the authors show that quality of learning objects may be improved by better educating their designers, by incorporative formative assessments and learning testing in design and development models, and by providing summative reviews that should be maintained as metadata, which users can use when searching, sorting, and selecting learning resources. They also point out the variety of settings in which OERs are produced and consumed, which results in needing more than one evaluation model. The authors present here also their instrument for reviewing learning objects (called LORI) that incorporates several aspects related to quality of such objects: content quality, learning goal alignment, feedback and adaptation, learners' motivation, presentation design, interaction usability, accessibility, reusability, and standards compliance. Furthermore, they use this instrument within a suite of tools for collaborative evaluation that small evaluation teams (including subject matter experts, learners, instructional designers) use to produce *an aggregated view of ratings and comments*. Adapted from LORI, in [39] seven rubrics are provided, five of them being adapted from LORI (*content quality, motivation, presentation design, usability, accessibility*), while the other two are new: educational value and overall rating. *Educational value* refers to its potential to provide learning on the addressed subject, to the accuracy, clarity, and unbiasedness of the information presentation, while the *overall evaluation* captures the perceived usefulness of resources in educational contexts.

An interesting approach is taken in [40] where the authors address very important issues when it comes to quality rating and recommendation of learning objects such as sharing evaluative data of learning objects across different repositories and combining various explicit and implicit measures of both quality and preference to make recommendations for appropriate learning objects that fulfill user's needs. In their endeavor, they had used Bayesian Belief Networks (BBNs), a powerful probabilistic knowledge representation and reasoning technique for partial beliefs under uncertainty. Moreover, BBN allow them to approach problems of insufficient and partial reviews in learning object repositories, as well as corroborating data from different quality evaluation instruments. They have been working with two learning object quality rating standards: MERLOT and LORI. First, they had produced a correlated structure between MERLOT Peer Review and LORI, and afterward they had constructed a BBN based on this structure, which has helped them to, for example, infer how a learning object would be rated on MERLOT's ease-of-use item, given actual ratings on LORI's interaction-usability and accessibility items. They present real-world BBNs that have been constructed to *probabilistically model relationships among different roles of reviewers (both expert and anonymous), among various explicit and implicit ratings, and among items of different evaluation measurements*, along with the results of a qualitative study and of simulated test cases. Their BBNs are able to derive *the implications of observed events, the rated attributes, by propagating revised probabilities throughout the network, when each attribute's value is updated*. Based on their experience they conclude that *the BBN model makes quantitatively reliable inferences about different dimensions of learning object quality* and that *the availability and accuracy of quality ratings can be largely improved in a learning object repository*.

Finally, Achieve in collaboration with leaders from the OER community have developed a rubric, aiming at helping various actors involved in education to determine the degree of alignment of OERs to the Common Core State Standards and to determine quality aspects of OERs [41]. Recently, Achieve has teamed up with OER Commons to develop an online evaluation tool based on that rubric, and currently, OER Commons hosts both the tool and its resulting assessment data [42]. Each resource of OER Commons may be evaluated, the resulting information is stored in a pool of metadata, and it may be shared through the Learning Registry with other interested repositories [43]. The Achieve rubrics includes the following components: degree of alignment to standards, quality of explanation of the subject matter, utility of materials designed to support teaching, quality of assessment, quality of technological interactivity, quality of instructional and practice exercises, opportunities for deeper learning, and assurance of accessibility.

4 The Research Methodology

During the initial stage of this work we have been searching for OCW and/or OERs that cover the necessary content for an introductory course on databases. We had performed several thorough searches in various repositories, such as MIT OpenCourseWare, OCW Consortium, Saylor Foundation, University of Washington Computer Science and Engineering courses, Coursera, OER Commons, Webcast.Berkeley, Connexions, Universia OCW, ParisTech, Open.Michigan, University of California, Irvine, University of Southern Queensland, Utah State University, Intute, Textbook search [44-57], and much more others. We have been using either the repository's specific search capabilities, or "classic" Google searches. Furthermore, we have exploited Google's custom OER/OCW search and particular OCW search engines alike [58, 59]. Our first goal has been the identification of as many possible candidates for our further research on quality assessment. The wanted candidates have consisted of "full" online open courseware and/or educational resources that provided support for a course on database fundamentals (being it OpenCourseWare or any other kind of complete courseware – even as a proper mix of OERs - available freely online).

Despite our best efforts we have ended up with just eight viable candidates for our further work, this being due to a variety of reasons, for instance some open courseware was available only in some foreign languages we could not understand, or others consisted only in video recordings of actual teaching of the course content in the classroom. The finalists are eight open courseware that offer educational materials on databases [60-67], provided by various open courseware repositories that comply with different open courseware paradigms, as follows (each one of them has been assigned an acronym, for easier further presentation and discussions):

- the MIT OpenCourseWare on *Database Systems* – 1-MIT-OCWDB;
- the Saylor Foundation's *Introduction to Modern Database Systems* open courseware – 2-Saylor-DB;
- the Stanford's Professor Jennifer Widom *Introduction to Databases* open courseware – 3-St-WidDB;
- the Introduction to Database Systems courseware provided by Nguyen Kim Anh in Connexions – 4-Cnx-NKA;
- the King Fahd University's KFUPM OpenCourseWare on *Database Systems* – 5-KF –DBSs;
- the University of Washington's Introduction to Data Management open courseware– 6-UW-DMg^{344};
- the Universidad Carlos III de Madrid's *Database Fundamentals (Fundamentos de las bases de datos)* OpenCourseWare – 7-UC3M;
- the Universidad Politecnica de Madrid's Database Administration (*Administracion de bases de datos*) OpenCourseWare – 8-UPM-BD.

To score the candidates we have used our own rubric based on our quality assurance criteria for open courseware and open educational resources that builds up on our previous work in [68, 69], which it was introduced in [7], put to work in [8] and [9], and refined further for this work. These criteria correspond to the quality characteristics of *quality in use*, *internal and external product quality* according to ISO/IEC 25000 SQuaRE standard, and they cover the next user needs: effectiveness, efficiency, satisfaction, reliability, security, context coverage, learnability, and accessibility. These quality criteria may be used for quality assessment of either small learning units or an entire courseware. They have been grouped in four categories related with *content, instructional design, technology* and *courseware evaluation,* which will be briefly explained further on.

Content related. This category includes criteria that reflect whether the resource provides the online learners with multiple ways of both engaging with their learning experiences and achieving of the content's mastery. First criterion refers to the easiness of using the resource, reflected by *readability* and *uniformity of language, terminology, and notations*. Another useful element is the *availability of the course syllabus,* so that users become aware since the very beginning of the content scope and sequence. The *comprehensiveness of the lecture notes*, i.e. whether the course content and assignments demonstrate sufficient wideness, deepness and rigor to reach the standards being addressed, is also to be retained in our quality model. *Modularity of the course content* is also important, as modular course components are units of content that may be distributed and accessed independently, giving each user both the *possibility to select the most suitable learning unit* at a particular time and the *opportunity to choose the most appropriate learning path* that matches the user's needs and abilities. The course materials may be approached easily *top-down, bottom-up*, or in a *combined* way. *Availability of assignments* (with or without solutions), being them exercises, projects, and activities, is important as well, as they are content items that enhance the primary content presentation. When looking at a particular learning resource, other than an entire courseware, which can be a small learning unit, a course module, a lesson etc., users are particularly interested in various characteristics of the resource: *accuracy, reasonableness, self-containedness, context, relevance, availability of multimedia inserts*, *correlation of the resource with the course in its entirety, links to related readings,* and *links to other resources (audio, video etc.).*

Instructional design related criteria address the instructional design and other pedagogical aspects of teaching and learning for that resource. They include the educational resource's *goal and learning objectives*, which are expected to be clearly stated and measurable, as the learner's level of knowledge mastery and practical abilities is to be measured against both the main goal and each and every learning objective. The educational materials are ought to provide for multiple opportunities for learners to be actively engaged in the learning process, having meaningful and authentic learning experiences during undertaking various *appropriate instructional activities*: problem- or project-based learning, e-simulations, learning games, webcasts, scavenger hunts, guided analysis, guided research, discovery learning, collaborative learning groups, case studies etc. *Learning outcomes* state the learner's achievements after performing a learning activity, i. e. what learners will know and/or will be able to do as a result of such an activity, in terms of knowledge, skills, and attitudes. The *availability of the evaluation and auto-evaluation means* (with or without solutions) is also important from a pedagogical point of view. The teacher users may be also interested in the *learning theory* (behaviorist, cognitivist, constructivist, humanist and motivational etc.) and in the *instructional design model* (ADDIE, ARCS, ASSURE etc.) that have been used to develop that particular educational resource. Moreover, learning experiences that provide for *reflective learning* will always add to the overall quality of educational resources. Under the reflection perspective, the desired outcome of education becomes the construction of coherent functional knowledge structures adaptable to further lifelong learning. Reflection has a dual sense here: one would be the process by which an experience, in the form of thought, feeling or action is brought into consideration (while is happening or subsequently), and the other refers to the creation of meaning and conceptualization from experience and to the potentiality to look at things from another perspective (critical reflection) [70-73].

Technology related. Both open educational resources and open courseware are expected to benefit fully from ICT technologies, to have user-friendly interfaces, to comply with standards for *interoperability*, and to provide for appropriate access for learners with special needs (*accessibility*). *Extensibility* of each educational resource, aiming at expanding learning opportunities, from a technological point of view, refers to easiness of adding content, activities, and assessments both for developers and learners. A high quality *user interface* is based on technical aspects related to the capabilities of the supporting hardware, software and networking. A clear specification of the technology *requirements* at user's end (both hardware and software), along with the *prerequisite skills* to use that technology are useful to help users understand how the resource should be used to benefit fully from its content. A high quality open educational resource is expected to work smoothly on a variety of platforms in use around the world (*multi-platform*). Having a true engaged learning relies on learner's opportunity to interact with the content and with other learners, which is not possible without a suite of rich *supporting tools*.

Courseware evaluation. Despite the initial claim of just offering high quality educational materials to learners worldwide, with no other intention to support learners during their learning journeys, all major open courseware initiatives have started to be more involved with their learners. Hence, regular assessment of effectiveness of open courseware becomes essential, along with using the results for further improvements. Each prospective user would most probably first be interested in the *courseware overview*, which includes information about the *content scope and sequence, the intended audience, the grade level, the periodicity of updating the content, the author's credentials and the source credibility, its availability in multiple-languages, instructor facilitation or some kind of semi-automated support, suitableness for self-study and/or classroom-based study and/or peer collaborative study, the time requirements, the grading policy*, along with *instructions about using* that courseware and its components, in order to establish the most suitable learning paths, the reliability, and the availability of links to other educational resources (readings, OCW, OER etc.). *Prerequisite knowledge* and *required competencies* are also useful for to be known by users at the beginning of a learning process. *Matching the course schedule*, if any, with learner's own pace, is also desirable. Another useful criterion regards the *terms of use (service), i.e.* availability of repository or institutional policies with respect to copyright and licensing issues, security for primary, secondary and indirect users, anonymity, updating and deleting personally identifiable information, age restrictions, netiquette, etc. OERs and OCW that are *free of bias and advertising* are also desirable. Suitable design and presentation of educational content is also considered, along with *user interface richness (style)* as it is defined by its navigational consistency, friendliness, multimedia inserts, interactivity, adaptability (both to user's needs and context) etc. Another quality criterion is concerned with the option to provide, or aiming to provide, a formal degree or a certificate of completion (*degree or certificate*). *Participatory culture and Web 2.0* facets are also important being them related to contribution to the content, collection of users' feedback, collaboration with fellow teachers/learners/developers and so on, or to sharing the development or using experience.

To sum up, we have evaluated each resource's quality using a number of 69 criteria that are presented briefly in Table 1 (our rubric). The fulfillment of each criterion has been assessed on a scale between 0 and 5, where the scoring meaning has been as follows: 0=absence, 1=poor, 2=satisfactory, 3=good, 4=very good and 5=excellent. The assessment has been performed independently by three evaluators having between 10-20 years of experience with teaching both fundamentals of and advanced databases for undergraduate and graduate students. For the next step of the process, which will be presented in the following section, we have used a "negotiated value" around the arithmetic mean of the scores, which has resulted from a panel reviewing process that involved the three reviewers.

Table 1. Criteria for Quality Assurance of OCW and OER

Content related	*To what degree an OER/OCW allows learners to have* ***engaging learning experiences*** *that provide for* ***mastery of the content.***	
	• CR1: readability	0-5
	• CR2: uniformity of language, terminology, and notations	0-5
	• CR3: availability of the course syllabus	0-5
	• CR4: comprehensiveness of the lecture notes	0-5
	• CR5: modularity of the course content	0-5
	• CR6: possibility to select the most suitable learning unit	0-5
	• CR7: opportunity to choose the most appropriate learning path	0-5
	• CR8: top-down, bottom-up or combined approach	0-5
	• CR9: availability of assignments (with or without solutions)	0-5
	• CR10: *resource related*: accuracy[1], reasonableness[2], self-containedness[3], context[4], relevance[5], multimedia inserts[6], interactive elements[7], correlation with the entire course[8], links to related readings[9], links to other resources (audio, video etc.)[10]	0-5 x10

Instructional design	*Criteria that address the **instructional design**, and other **pedagogical aspects** of T&L for that resource.*	
	• ID1: goal and learning objectives (<u>outline</u> the material)	0-5 (1 global + 4 per unit)
	• ID2: learning outcomes (students will know/be able to do – <u>skills, abilities, attitudes</u>)	0-5 (1 global + 4 per unit)
	• ID3: appropriate instructional activities	0-5
	• ID4: availability of the evaluation and auto-evaluation means (with sol.)	0-5 (ex./others(1+1.5) x2)
	• ID5: learning theory	0-5
	• ID6: instructional design model	0-5
	• ID7: *reflective learning opportunities* in which the desired outcome of education becomes the construction of coherent functional knowledge structures adaptable to further lifelong learning	0-5
Technology related	*Both OERs and O CW are expected to **benefit fully from ICT technologies**, and to comply with various standards*.	
	• TR1: conformity with standards for interoperability	0-5
	• TR2: compliance with standards for accessibility	0-5
	• TR3: *extensibility*: easiness of adding content, activities and assessments, from a technological point of view (both developers and learners)	0-5 (2.5+2.5)
	• TR4: user interface's basic technological aspects (hw-device, sw., networking)	0-5
	• TR5: supporting technology requirements at user's end	0-5
	• TR6: prerequisite skills to use the supporting technology	0-5
	• TR7: multi-platform capability	0-5
	• TR8: supporting tools	0-5
Courseware evaluation	*Despite of the original claim of just offering high quality educational materials, all major open courseware initiatives have recently become more **involved with their learners**. Hence, regular assessment of **effectiveness of open courseware** becomes essential, along with using the results for further improvements.*	
	• CW1: *courseware overview*: content scope[1] and sequence[2], intended audience[3], grade level[4], periodicity[5] of content updating, author's credentials[6], source credibility[7], multiple-languages[8], instructor facilitation[9] or semi-automated support[10], suitableness for self-study[11], classroom-based[12] study, and/or peer collaborative[13] study, time requirements[14], grading policy[15], instructions on using[16] the courseware, reliability[17], links to other[18] educational resources	0-5 x18

	(readings, OCW, OERs etc.)	
	• CW2: availability of prerequisite knowledge	0-5
	• CW3: availability of required competencies	0-5
	• CW4:matching the course schedule with learner's own pace	0-5
	• CW5: *terms of use (service)*: availability of repository or institutional policies wrt copyright and licensing issues, security for primary, secondary and indirect users, anonymity, updating and deleting personally identifiable information, age restrictions, netiquette, etc.	0-5
	• CW6: freeness of bias and advertising	0-5
	• CW7: suitable design and presentation of educational content	0-5
	• CW8: *user interface richness (style)*: navigational consistency[1], friendliness[2], multimedia[3], interactivity[4], adaptability[5](both to user's needs and context) etc.	0-5x5
	• CW9: providing a formal degree or a certificate of completion	0-5
	• CW10: *participatory culture and Web 2.0 facets*: contribution to the content[1], collection of users' feedback[2], collaboration with fellows[3], sharing the development[4]/using[5]*experience*	0-5x5

5 Using MASECO for QA and Classification of OERs/OCW

In this section we will present briefly our approach of evaluating and classifying open courseware (that can be used also for open educational resources) with help from a multiagent system. We started with the working definition from [74] that states that *an agent is a computational mechanism that exhibits a high degree of autonomy, performing actions in its environment based on information (sensors, feedback) received from the environment*. A multi-agent environment includes more agents, which interact with one another, and further, they have to work under constraints of the environment not knowing constantly and continuously everything about the world that other agents know. These constraints are essential to the definition of a real multi-agent system [74].

MASECO is a multi-agent system whose main goal is to register and classify OERs and OCW, based on a quality model. The architecture of the system contains three main components: two intelligent agents (the Communication Agent and the Classification Agent), and the OER/OCW management system. The classification process aims to assign objects to predefined categories. Most automatic classification endeavors are grounded in the area of machine learning, which describe algorithms that learn behavior (e.g. how to classify an object) based on training information [34, 75, 76]. Typical methods are Support Vector Machines (SVM), decision tree learners, Bayes classifiers, and artificial neural networks. Such algorithms work as follows: they start with a training corpus of objects, for which the category is known. After a training phase new objects can be classified as well. Of course, classifiers do not take complete objects as input, and rely on mapping each object to a set of features. In our case, this set consists of the 69 scores obtained for the quality criteria presented in the previous section, and our Classification Agent uses artificial neural networks to perform this task.

The two agents have been built using the BDI (Beliefs, Desires, Intentions) approach [77, 78]: the informational, motivational, and deliberative states of an agent are described by means of beliefs, goals, plans, and intentions. Each of the agents is based on the INTERRAP architecture [79], which defines an agent as having three layers: a behavior-based layer, a local planning layer, and a cooperative planning layer, which allow the agent to combine reactive and deliberative reasoning, and to interact with other agents or with the environment. The INTERRAP architecture was also used in the iLearning system [80], and the promising results obtained there have determined us to further use the same architecture in MASECO.

There are two general usages of the term "agent" [81]: weak and strong. The weak notion denotes a hardware or software system having the following properties: autonomy, social ability, reactivity, and pro-activeness. The stronger notion of an agent is used by the AI researchers to describe systems that exhibit, in addition to the above mentioned properties, concepts that are mostly applied to humans, such as knowledge, belief, intention, and obligation.

Generally, a multi-agent system is considered to be a network of multiple intelligent agents, which are interacting with each other, with and within an environment, in order to solve problems otherwise difficult (or even impossible) to be solved only by one agent. Together they can combine different intelligent techniques to attain superior performance, either from a computational point of view, or with respect to the complexity of the interaction between them. Multi-agent systems can be considered as a distributed artificial intelligence, emphasizing the joint cooperation of agents with their own behavior and autonomy.

The main characteristics of a multi-agent system are as follows [82]:

- each agent has an incomplete view, with incomplete information and limited capabilities for solving the main problem;
- there is no global control of the system;
- the data is decentralized;
- the computation is asynchronous.

There are many learning methods that can be used in multi-agent systems. The choice of the learning method depends on the given problem, and it can be sometimes a very difficult task. Standard supervised, unsupervised, and reinforcement learning techniques can be used as starting points. *Supervised learning* requires the existence of an expert to provide a set of training examples (training data set). Each example is a *pair* consisting of an input object and a desired output value (target). By analyzing the training data set, the algorithm produces either a classifier (discrete output) or a regression (continuous output). *Unsupervised learning* does not require the existence of an expert. It tries to find the hidden structure in unlabeled data, so that there is no error when evaluating a potential solution. Many methods used for unsupervised learning are from data mining. *Reinforcement learning* is a method where the system learns from the continuous interaction with the environment. The goal of the agent is to collect as much reward as possible, so it can use its past experience, and it can choose any necessary action. MASECO uses two learning techniques: supervised learning and reinforcement learning. Supervised learning is used for the training of the Classification Agent, while reinforcement learning is used by both the Communication Agent and the Classification Agent.

The agents of MASECO have the following properties:

- *reactivity* – the agents maintain a permanent connection to the environment and they adapt to its changes, like for example, the appearance of a new OER or OCW;
- *interactivity* – the agents collaborate in order to reach the system's objective;
- *autonomy* – the agents know when and how to initiate the required actions;
- *proactivity* – the agents have explicit goals and objectives;
- *instruction* –the agents use automated learning techniques.

5.1 The INTERRAP Architecture

The INTERRAP architecture was proposed by Jörg Müller [79]. The model is a layered, hybrid BDI model, with three layers that describe an agent:

- a *behavior based layer* incorporating reactivity and procedural knowledge for routine tasks;
- a *local planning layer* that provides facilities for means-ends reasoning for achievement of local tasks and for producing goal-directed behavior;
- a *cooperative planning layer* that enables agents to reason about other agents and that supports coordinated action with other agents.

Beliefs are split into *a world model* – containing object-level beliefs about the environment, *a mental model* – holding meta-level beliefs about the environment, and a *social model* – holding meta-level beliefs about other agents [78, 79]. Specific situations, namely relevant subsets of the agent's beliefs, trigger the initiation of actions. Situations are abstract representations of classes of world states, which are of interest for an agent. The three classes of beliefs correspond with three classes of situations as follows: *bevioral situations* that are a subset of the world model, *local planning situations*, which description is based on both world and mental models, and *cooperative planning situations* that contain in addition parts of the social model. Accordingly, the agent's goals can be reaction goals, local goals, and cooperative goals. *The operational primitives enable the agent to do means-end reasoning about how to achieve certain goals*. *They include patterns of behaviors and joint plans.*[79].

5.2 The Architecture of MASECO

MASECO is a multi-agent system, which includes both intelligent agents and an OER/OCW Management System (built on top of a database management system). For the time being, there are two types of agents: a Communication Agent and Classification Agent, which, despite having different goals, they collaborate with each other. The Communication Agent, besides its role as a communication facilitator internally between the components of the system, and externally between the system and the environment, acts as a supervisor and coordinates the whole working scenario. The database management system contains all the information regarding any known OER/OCW to the system. The Classification Agent knows how to classify any of the OER/OCW, and it collaborates with the Communication Agent in order to obtain all the necessary information it needs to perform this task. This agent is intelligent, reactive, and task oriented. The conceptual model of MASECO is presented in Fig. 1. The Communication Agent can communicate with the environment, with real users, or with other existing Multi-Agent Systems (MAS).

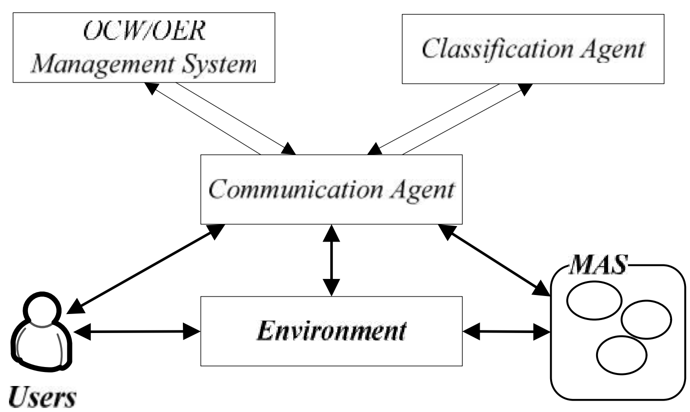

Fig. 1. MASECO – the conceptual model

MASECO use scenarios are presented in Fig. 2 (bird eye's view) and Fig 3 (more detailed).

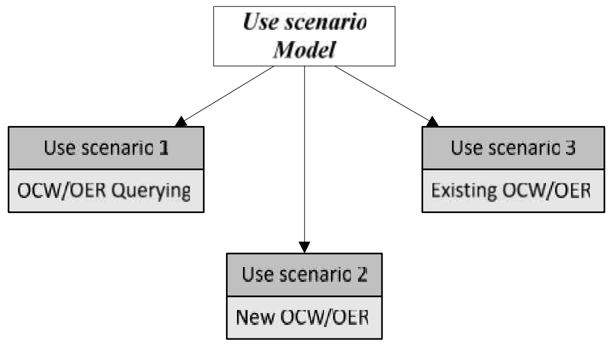

Fig. 2. MASECO - use scenarios (bird eye's view)

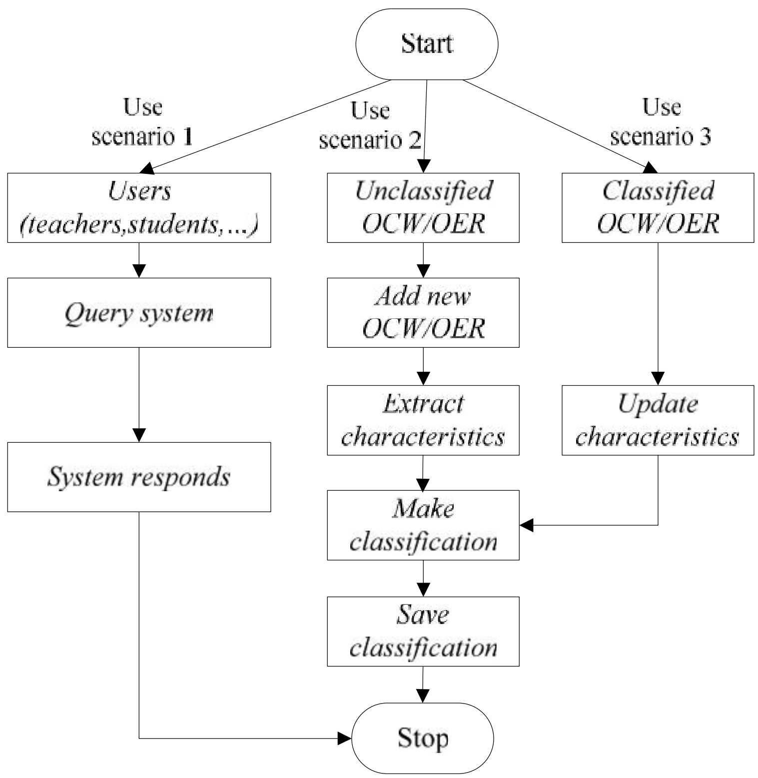

Fig. 3. MASECO - use scenarios, in detail

MASECO interacts with the environment using the Communication Agent. Through the agent's sensors, the system receives data, requests, and commands, and it sends them to the agent's control unit. The control unit of the Communication Agent decides the use type (1, 2 or 3). In the first case, a simple querying of the OER/OCW management system is performed, and the classification of the particular OER/OCW is returned to the environment. In the second two cases, the Communication Agent sends a request to the Classification Agent to classify a new OER/OCW, respectively to update and re-classify an OER/OCW already stored within the system. The control unit of the Classification Agent initiates the extractions of the characteristics (features) of the respective resource, processes the data collected from the environment, and it further on classifies the resource, supported by an artificial neural network. Both the data extracted from the environment and the data resulted from the processing are stored, respectively updated in the OER/OCW management system. The models for the two agents will be presented further on, in this section.

The ontology of MASECO is defined mainly by the OER/OCW model (Fig. 4), the use model (Fig. 2), and the classification instrument model (Fig. 5).

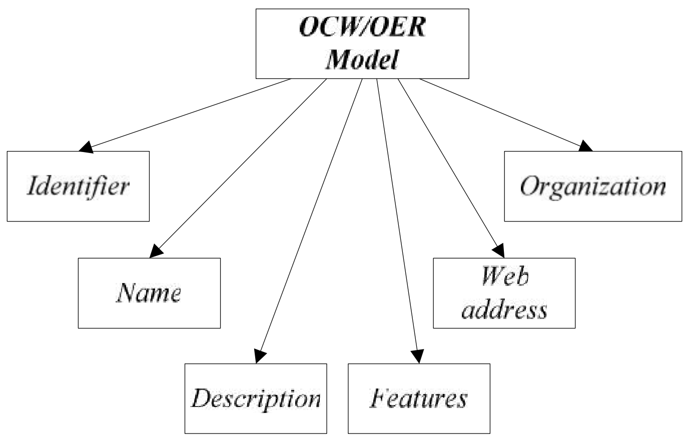

Fig. 4. The OER/OCW data model

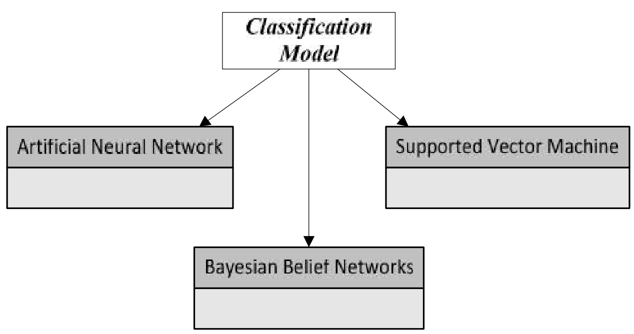

Fig. 5. The classification methods model

As we said previously here, the Communication Agent has the role of supervisor of MASECO. Its architecture is based on the agent model from the INTERRAP system, and it is shown in Fig. 6. The *world model* includes knowledge about OCW and OERs, and the agent updates information about OCW and OERs in the database. The *mental model* includes knowledge about itself, and its capacity to solve certain tasks. The *social model* includes knowledge about the Classification Agent, its capacities, action times, classification algorithms, etc. The situations that are recognized by the Communication Agent are as follows: *routine situations* (for instance to respond to a human user at a OER/OCW classification request and to justify that classification) that have a reflection goal, *local planning situations*, namely procedures for feature extraction (even by interacting with a human user) that have a local goal, and cooperative situations that include the cooperation with the Classification Agent for performing a classification, which have a cooperative goal.

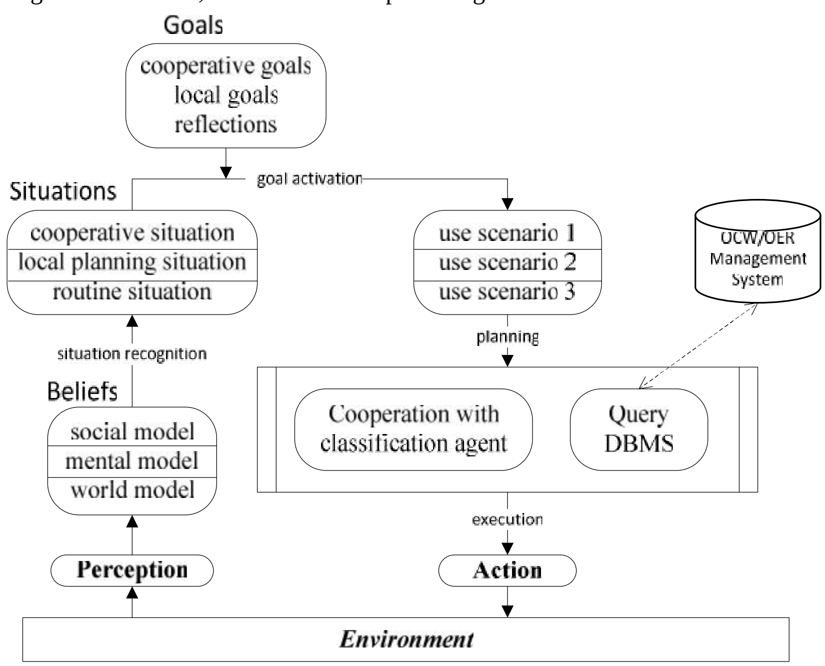

Fig. 6. The Communication Agent model

The Classification Agent is simpler, and it is described in Fig. 7. It contains only two layers: a local planning layer and a cooperative layer. The local planning layer contains a classification plan, based on a classification algorithm. The cooperation layer is necessary to obtain the required information about the OER/OCW resource for the classification step. The Classification Agent has the ability to learn how to classify an open educational resource or open courseware. At the time being, MASECO uses for classification an artificial neural network. We have also tried other classifier and those results will be presented in a further sub-section.

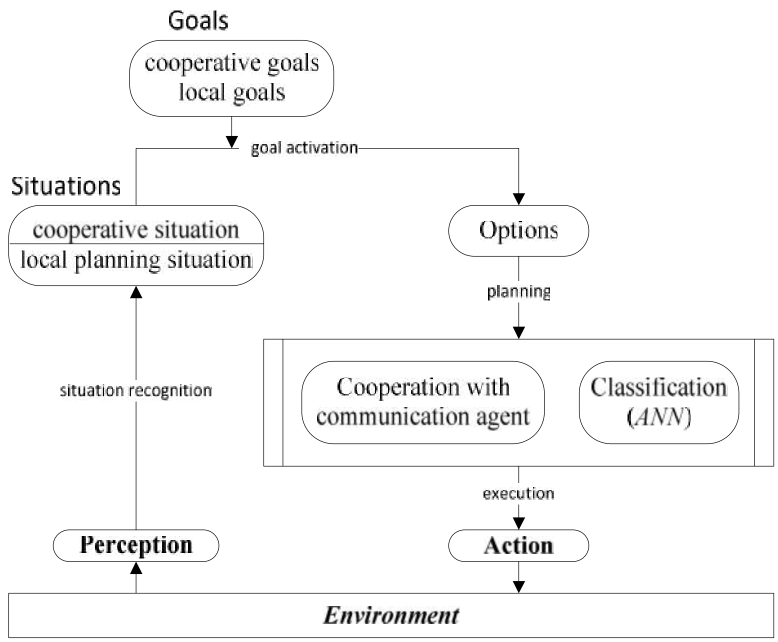

Fig. 7. The Classification Agent model

5.3 How MASECO classifies OERs/OCW using Artificial Neural Networks

Multi-class pattern classification refers to the problem of finding a correspondence between a set of inputs (that represents some characteristics) and a set of outputs (that represents two or more pattern classes). The classification relies on a variety of classifiers: feed-forward artificial neural networks, supported vector machine, decision trees, Bayesian belief networks, rule-based etc. A classification system usually has two components: a feature extractor and a class selector [83]. The architecture of MASECO's OER/OCW classification sub-system, which is a part of the Classification Agent, it is shown in Fig.8.

Any OER/OCW that is to be classified will be pre-processed and its feature set will be extracted and stored in the corresponding feature vector, which will be the input for the classifier. The label of the obtained class is randomly checked and the results are interpreted by the learning strategies of the Classification Agent. The procedures of this agent decide on the classifier, which is, in fact, the kernel of any classification system. This may be modified by the actors of the Classification Agent, resulting in the selection of another classifier, or in a change of its structure. For example, the need for a new class of OER/OCW may determine the change of the neural network structure, e.g. the increasing of the neuron number on the output layer (as this number equals the number of classes).

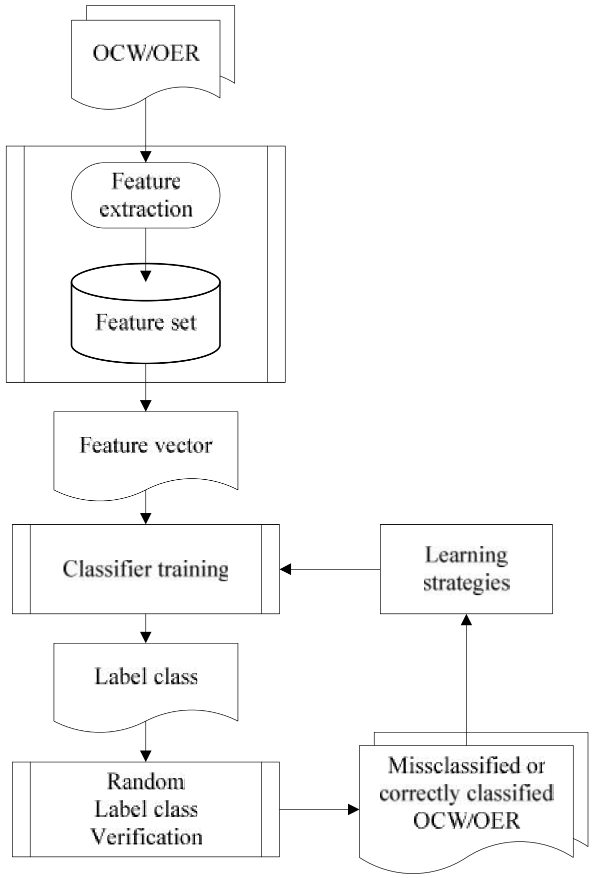

Fig. 8. The Classification sub-system, a part of the Classification Agent

The two processes, feature extraction and class selector can be formalized as follows: [83, 84]: feature extraction is defined as a transformation $X=$ cEPF, where $P=(p_1,p_2,\ldots,p_m)$ represents the pattern vector that describes an object, and $X=(x_1,x_2,\ldots,x_d)$ is the feature vector (m is the number of object characteristics and d is the dimension of the feature space. Using the vector X, the class selector chooses a class c_iČC, where $C=\{c_1,c_2,\ldots,c_k\}$ is a set of classes (k is the number of classes). In our case, the process of feature extraction has been done using human experts, while the class selector uses artificial neural networks. Considering that our goal has been to classify OER/OCW resources in more than two classes, we had used a multi-class neural network.

A multi-class neural network classification problem can be formalized as follows [85]. Having a d-dimensional feature space Ω with all the vector elements Y, and a set of training data $\Omega_{training} \subset \Omega$, for each element from the $\Omega_{training}$ set we consider as associated a class label cl from the $Class\_labels=\{cl^1,cl^2,\ldots,cl^k\}$ set, where $cl^i \neq cl^j$, for all $i \neq j$ and $k[2$. A classification system (F) based on artificial neural networks can be trained on $\Omega_{training}$ such that for each feature vector YČΩ, $F(Y)$Č$Class_labels$.

There are two major system architectures, a single artificial neural network system with *m* outputs that are determined by the codification scheme for pattern classes, and a system consisting of *m* artificial neural networks (binary artificial neural networks with a single output node or artificial neural networks with multiple output nodes). Three types of approaches for modeling pattern classes are available: one-against-one (OAO), one-against-all (OAA) and P-against-Q (PAQ). The experimental results show that an architecture with only one neural network performs well when the training data set is not too large and the pattern classes are not too many [85].

Artificial neural networks were introduced in 1943 by Warren McCulloch and Walter Pitts in [86]. These structures inspired from biology, from the neural circuit of nervous systems, are composed of interconnected computing units. In 1958, Frank Rosenblatt introduced the ability to learn and, consequently, he developed the perceptron model [87]. The model of an artificial neuron is presented in Fig. 9.

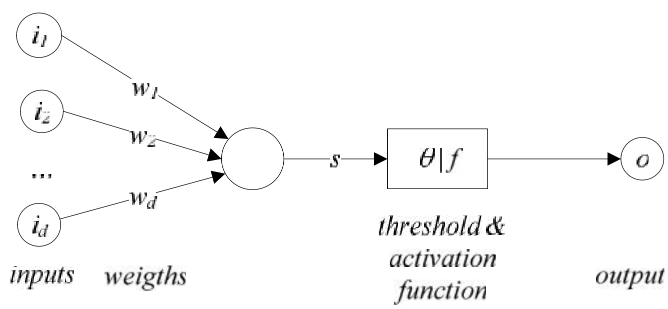

Fig. 9. Model of an artificial neuron

Each input of each artificial neuron has associated a synaptic weight w. This weight determines the effect of the corresponding input to the activation level of the neuron. The weighted sum of all the inputs $\Sigma w_j i_j$, with j=1..d, defines the activation of the artificial neuron and it is called *net input*. The f function represents the activation function or specific function, and θ represents the threshold value. The output o of the neuron is computed using the following formula:

$$o = f\left(\sum_{j=1}^{d} w_j i_j - {}^{-}\right) \tag{1}$$

The activation function f can have any of the possible forms presented in Table 1. In its simplest form, this is a binary function: either the neuron is firing or not, and it is described mathematically by the step function. In this case a large number of neurons must be used in computation beyond linear separation of categories. Other, more complex functions are also possible for the activation function. The *nonlinearity* of the activation function allows networks of neurons to compute nontrivial problems using a smaller number of nodes.

Table 2. Activation functions for artificial neural networks

Step function	$f(s)=\begin{cases}0, s\le 0\\1, s>0\end{cases}$
Signum function	$f(s)=\begin{cases}-1, s\le 0\\1, s>0\end{cases}$
Linear function	$f(s)=s$
Sigmoid function	$f(s)=\dfrac{1}{1+e^{-ks}}, k>0$
Generalized sigmoid function	$f(s)=\dfrac{1}{1+a*e^{-bs}}, b>0$
Other interval-linear functions	$f(s)=\begin{cases}-1, s\le -1\\s, -1<s<1\\1, s\ge 1\end{cases}$ $f(s)=\begin{cases}0, s\le 0\\s, 0<s<1\\1, s\ge 1\end{cases}$

More details about artificial neural networks and their applications can be found in [88]. We have also experimented with them before to adapt the teaching and learning process to the needs of learners within e-learning systems [89].

One of the first artificial neural networks was the feedforward neural network. In this case, the units (neurons) are connected in such a way not to form a directed cycle and the information flows from the input to the output, in only one direction, through any (if existing) hidden nodes. The simplest form is the single-layer perceptron network, which consists of only one layer, the output nodes. The inputs are fed directly to the output layer. A *perceptron* often refers to networks consisting of just one neuron. However, a single layer network is quite limited in its computational power. Multiple layers of such computational units (neurons), interconnected in a feedforward way, form the Multi-Layer Perceptron (MLP).

In MASECO, for the k-class classification of OERs and OCW, we have chosen a feedforward multi-layer artificial neural network (MLP), which is shown in Fig. 10.

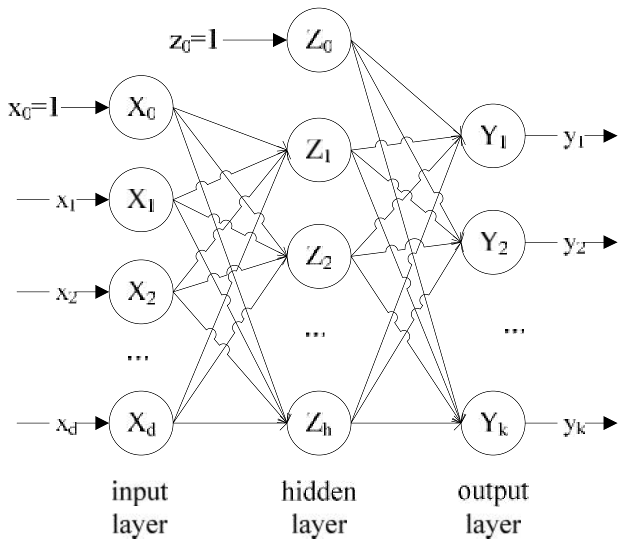

Fig. 10. MASECO - k-class classifier (MLP)

The multi-layer perceptron has the following structure:

- *One input layer* – with d units of input that transmit the signal they receive;
- *One output layer* – with k units of output, with one neuron for each classification category;
- *One hidden layer* – with h units of neurons, which receive the information from the input layer and process it;
- *Connections* – each input neuron is connected to all the neurons from the hidden layer, so that we have complete connectivity; in a similar way, all the neurons from the hidden layer are forward connected to all the neurons from the output layer; each connection has an associated weight factor, w_{ij}, with $i=1..d$, $j=1..h$ for the input-hidden layers connectivity, and v_{ij}, $i=1..h$, $j=1..k$ for the hidden-output layers connectivity; these weights can be easily represented as two matrices: $W=(w_{ij})$, $i=1..d$, $j=1..h$, and $V=(v_{ij})$, $i=1..h$, $j=1..k$, respectively;
- *Bias* – X_0 and Z_0 are used to define a threshold for the activation of the neurons.

In MASECO OERs and OCW can be classified in three categories: Satisfactory, Good, and Very Good. To define the pattern recognition problem, we had to arrange the characteristics of each resource as a column of dimension 69 (one value for each feature) in a matrix p, and similarly the target vectors in a matrix t with columns of dimension 3, representing the classification categories as shown below:

− (1, 0, 0) -- satisfactory
− (0, 1, 0) -- good
− (0, 0,1) -- very good

The tuple (p, t) defines a pattern.

The data set contains 140 input vectors of 69 elements each, one element for each characteristic and 140 target vectors of 3 elements each. It contains information extracted from the analysis of eight courseware and trivial data, with very low or very high characteristics. The numerical data is presented as such in Annex 1.

To perform our experiments we had used the Neural Network Pattern Recognition Tool of MATLAB. The generated network has been a feedforward network with one input layer, one hidden layer, and one output layer. On the input layer there are 69 neurons, while on the output layer only 3 neurons are present, which correspond to the three classes. The transfer functions for each layer are sigmoid. The number of neurons on the hidden layer is 10, which provides a neural network with good performances. The performance of the neural network might be improved by increasing the number of neurons in the hidden layer. The proposed network is shown in Fig. 11.

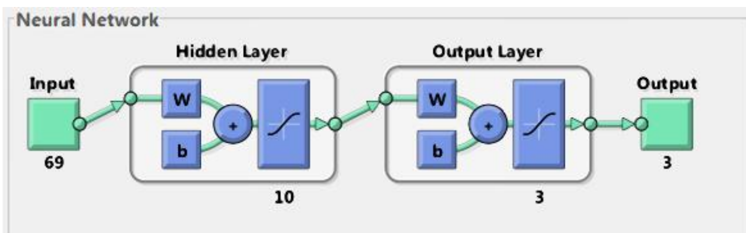

Fig. 11. MASECO – the neural network for OER/OCW classification

Multi-layer networks use different learning techniques. In our case, we have been using back-propagation. The output values are compared with the correct answer by computing a predefined error-function. In our case, the Classification Agent learns based on (p, t) tuples, namely pairs of OER/OCW and the corresponding class. Using some techniques, the error is fed back through the network and the algorithm adjusts the weights of each connection with the goal of minimizing the error function. After a large number of training cycles, the system will converge to a small error of the calculated function, so that we can consider that the network has "learned" the target function. Our network has been trained using scaled conjugate gradient backpropagation (*trainscg*).

We have divided the data set into three categories: training, validation, and testing. This has been done randomly. From the available 140 data samples available, we had used 70% for training, 15% for validation, and 15% for testing (see Fig. 12). The results of the training are shown in Fig. 13.

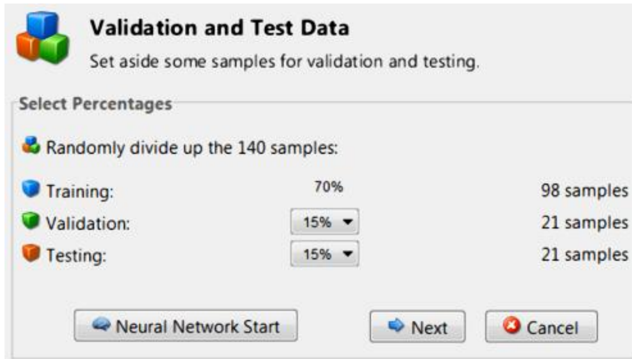

Fig. 12. Data set selection for training, validation, testing

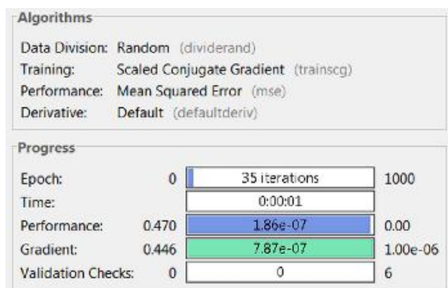

Fig. 13. Network training net_OCW

The confusion matrix shows the percentages of correct and incorrect classifications. In general, a confusion matrix is a symmetrical array of the number of classified data compared to the actual data (the truth). The diagonal values represent the percentage of correctly classified data in each class. Correct classifications are the green squares (light gray in black and white) on the matrices diagonal, while incorrect classifications form the red squares (medium gray in black and white). The blue squares represent the overall accuracies (the bottom right corner in all four matrices). If the network has learned to classify properly, the percentages for the incorrect classifications should be very small, indicating few misclassifications. The confusion matrices for training, testing, and validation data of our experiments are presented in Fig. 14, where we can see that the overall accuracies of All Confusion Matrix is high (99.3%).

Fig. 14. Confusion matrices from training the neural network for OER/OCW

The Receiver Operating Characteristic (ROC), or ROC curve, is a graphical plot illustrating the performance of a binary classifier system. It is created by plotting the true positive rate or sensitivity versus the false positive rate (1-specificity), at various threshold levels. The ROC curve shows the functionality of the network. The best possible prediction method would show points in the upper-left corner, with 100% sensitivity and 100% specificity, i. e. the point (0,1). This point is also called a *perfect classification*. A completely random guess would give a point along a diagonal line. In our case, the classification, as shown by the ROC curve, is very good as closest to the top border and to the left one the curve is, the classification is better (Fig. 15).

5.4 Classification of OERs and OCW using Bayesian Belief Networks

In this sub-section we will overview briefly our experience about trying to classify OERs and OCW using Bayesian Belief Networks (BBNs), which are a very potent model for probabilistic knowledge representation and reasoning for partial beliefs under uncertainty [40, 90]. Uncertainty may refer to, for example, insufficient knowledge. In our case, this can refer to a partial quality evaluation that does not include all the 69 criteria or to the situation in which there are not enough assessments for some resources. BBNs combine two powerful theories that concern graphs and probabilities and provide for representing and updating beliefs (probabilities) about events of interest, as the quality score of an OER or OCW in this case.

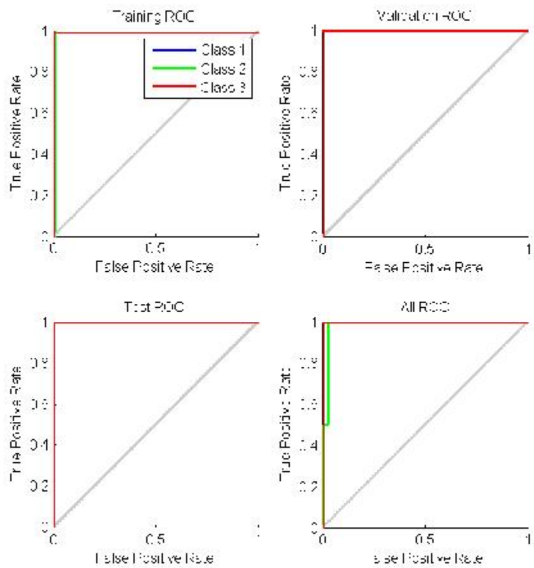

Fig. 15. The Receiver Operating Characteristic (ROC) curve

Moreover, they allow performing probabilistic inference, for example to infer a quality score. From a mathematical point of view BBNs are directed acyclic graphs *in which the nodes represent propositional variables of interest (for example a feature of an objector the occurrence of an event), and the links represent informational or causal dependencies among the variables, which are quantified by conditional probabilities for each node given its parents in the network* [90]. Therefore, the probability of any subset of variables may be calculated given evidence about any other subset, and the reasoning process can work by propagating information in any direction. However, Bayesian networks are direct representations of the world and not of the reasoning process [90]. BBNs rely on both Bayes' Theorem (that has been introduced by Thomas Bayes, and it has been further explained by Richard Price in the sense that he has expressed the philosophical basis of Bayesian statistics [91]) and Bayesian probability theory with its core propagation mechanism. *The real power comes when we apply the above theorem to propagate consistently the impact of evidence on the probabilities of uncertain outcomes in a BBN, which will derive all the implications of the beliefs that are input to it. They are usually the facts that can be checked against observations* [90].

Our purpose here has been, once again, to predict accurately the class of each OER or OCW based on its quality scores. During our classification we have been using the following probability model for the classifier based on Bayes's Theorem [92, 94] (see Eq. 2). This classifier learns the class-condition probabilities $P(F_i=f_i|C=c_l)$ of each variable F_i in the data set (the quality scores), i=1..69, given the class label c_l. A new test case ($F_1=f_1$, …, $F_{69}=f_{69}$) is next classified based on Bayes's Theorem to compute the posterior probability of each class c_l given the vector of observed (evaluated) variable values (where C is the class variable and f_i refers to each possible value of F_i).

$$P(C = c_l \mid F_1 = f_1, \dots, F_{69} = f_{69}) = \frac{P(C = c_l) P\left(F_1 = f_1, \dots, F_{69} = f_{69} \mid C = c_l\right)}{P(F_1 = f_1, \dots, F_{69} = f_{69})} \quad (2)$$

In our first attempt, we had used naïve Bayesian networks that characterize the situation in which the features that determine the membership to a class are independent, each attribute having a unique parent [93] (see Fig. 16).

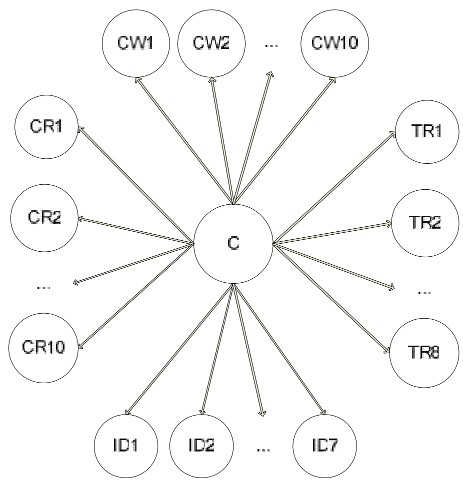

Fig. 16. The naïve BBN used for classification

Our first attempt to classify with the above naïve BBN has failed as it can be seen in the next screenshot (Fig. 17). This is due to the fact that naïve BBN treats by default all features as being a part of a normal distribution, and, therefore, it cannot work with a column that has zero variance for all the features related to a single class, which is, in fact, the case for some of the criteria and classes in our test. The reason is that there is no way for a naïve BBN to find the parameters of the probability distribution by fitting a normal distribution to the features of that specific class. To "force" a classification, we have altered insignificantly the scores that had this problem and, after training (Fig. 18), we had obtained successful classifications for several tests (one of them is shown in Fig. 19 – a classification of a resource having very high scores as very good, i. e. in the class 3).

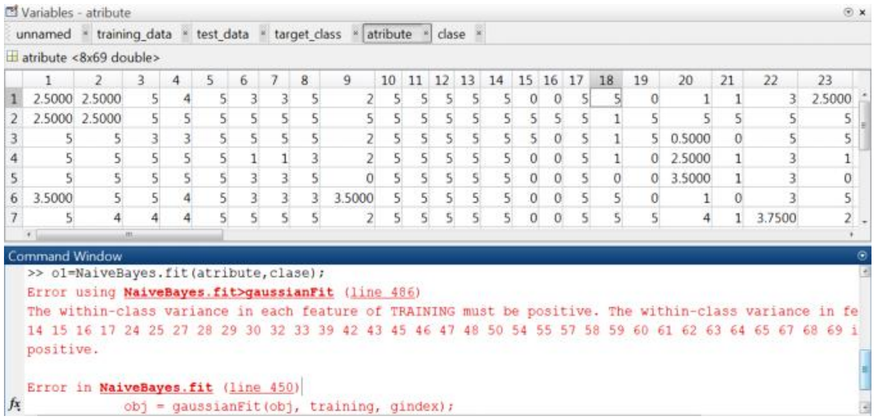

Fig. 17. Failed naïve BBN-based classification

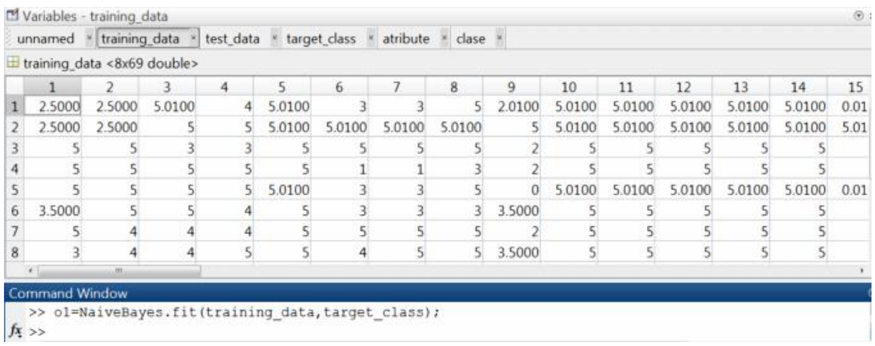

Fig. 18. The training of our naïve BBN

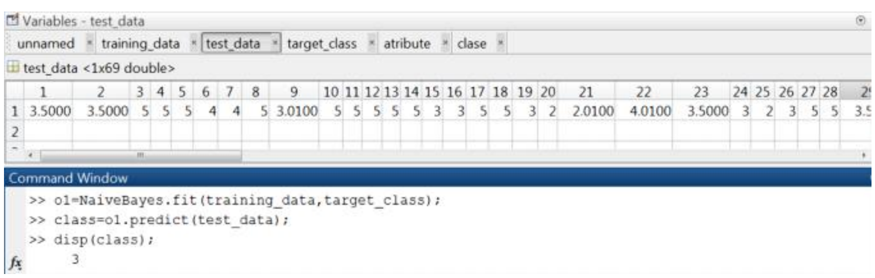

Fig. 19. Successful naïve BBN-based classification

5.5 Discussion

We have experienced here with our multi-agent system the evaluation and classification of OERs and OCW based on a quality model with 69 quality criteria. To see whether such educational resources can be classified automatically has been our main goal. From our experience we have learned that this can be done provided that the right classifiers are used. Our first attempt that had used artificial neural network has been successful for our data set, while the second one that had used naïve Bayes networks has had some problems as we show in the previous sub-section. Of course, we consider as future work taking into account the intrinsic dependences that exist between some of the quality scores (features). For instance, the quality model scores the availability of assignments (with or without solutions) as a content-related criterion and the availability of evaluation and auto-evaluation means (with solutions) as an instructional-design related one. Of course, the evaluation in the two cases is capturing different aspects: in the first case, it refers to what the resource has to offer in terms of providing for engaging learning experiences that contribute to the mastery of the content (and having assignments with solutions may be very helpful in that respect), whilst in the second case, it reveals the importance of having your level of knowledge tested and self-tested. Another example refers to the aspects related to the user interface. First, we analyze it from a technological point of view with respect to the hardware, software and networking capabilities, and, secondly, we evaluate its richness (style), but once again, one cannot have a rich interface based on poor technological means. So the next step in this direction would be to determine the actual dependencies that exist between the quality criteria and, consequently, between the obtained scores. Based on those dependencies, in our future trials of classification of OERs and OCW using Bayesian Networks, we intend to use *Tree Augmented Naive Bayes (TAN)*, which outperforms the naive Bayes classification, yet at the same time preserves the computational simplicity and robustness that characterize the naive Bayes method [92]. Of course, other classifiers are also envisaged: completely unrestricted Bayes classifiers, decision trees, rule-based, SVM etc., along with comparisons and cross-validation of the results. Furthermore, our current neural network is static, and we need to experiment whether a dynamic one that changes its structure to include new characteristics, new categories etc. would serve better our purposes.

Moreover, we are aware that we have to extend significantly both the set of evaluated resources and the pool of reviewers. Currently, we are in course of gathering together various OCW and OERs (around 10 resources per subject) that are necessary to graduate majoring in Computer Science, in a common repository of resources. Further on, we intend to have all the collected resources evaluated against the quality model by as many reviewers as possible so that we obtain a significantly larger amount of data to work on, using various classifiers. Some of these operations will be performed automatically by MASECO's agents.

Other issue to be considered concern the "contributing problem", i. e. how to convince as many reviewers as possible to perform quality assessment using our quality model. Quality reviews are not common because evaluating the quality of educational resources takes time, effort, and expertise [40]. We plan to develop a rubric-applying tool that facilitates human assessment so that the evaluators become keen to perform it. We also consider evaluating automatically some of the criteria, which can be learned by parsing intelligently each resource website. Human evaluators may keep these automatic results or they may change them to reflect their viewpoint. This could help also with incomplete evaluations that have scores only for some of the quality criteria. To obtain assessments from learners' point of view we think to involve our undergraduate and graduate students in making evaluation for their semester projects.

A weighting mechanism between the assessments of various users could be also useful to favor, for instance, a subject-matter expert's or a instructional designer's evaluation when compared with one of an anonymous on-line user. False positive (unfair) evaluations should be banned somehow. Especially when the number of quality assessments for a particular resource is low, the danger of altering the real quality resulted from evaluation is high in case of unfair assessment. BBNs seem to be helpful again in these situations as they are able to reduce the negative impact of distorted rating to a minimum degree [40].

Another direction to work on is concerned with objective measurements that could be included in the quality model: number of accesses, time spent with a resource, number of bookmarks, number of times a bookmark is followed, number of citations etc. Nevertheless, the semantics of such information has to be modeled properly within the quality model, if ought to complement seamlessly the explicit quality ratings.

6 Conclusions and Future work

The open education movement has the potential to change the education world to a status quo of increasing richness and diversity, where educational resources, teaching and learning styles, and the huge variety of educational content can be tailored to more specific user needs and contexts. The ability to approach and solve quality assurance issues is a key aspect of this movement. The capacity to maintain the openness of the growing number of open education projects worldwide, and to further innovate on ways to guide the improvement of quality of open educational resources and open courseware through cooperation and collaboration, may open up new ways for education that are able to *match the complexity of the contemporary world and the many challenges it faces* [17].

Computational models of quality and automated approaches for computing the quality of digital educational resources will most probably be a part of the next generation of cognitive tools aimed at supporting users in making quality decisions. Therefore, ascertaining useful quality indicators and developing algorithms for automatically computing quality metrics and classifying resources based on these indicators are important steps towards reaching this goal. Concerns about the quality of educational resources found in digital libraries and repositories often revolve around issues of accuracy of content, suitability to the intended audience, appropriate design and information presentation, and completeness of associated descriptions (metadata and others) [11]. Having modeled and developed the proper suite of tools for assessing quality, we may imagine future educational infrastructures that support various users of educational resources in several quality evaluation processes. The cost of developing new educational resources may be also reduced by providing reliable quality assurance mechanisms that can support users in finding, using, and reusing high-quality open courseware and open educational resources [14]. The OER/OCW movement has also benefits from an individual point of view as well, as open sharing is claimed to increase publicity, reputation, and altruism of sharing with peers.

While the traditional view of quality assurance of educational content is seen as the responsibility of subject and instructional experts, in the context of OCW, OERs, and Web 2.0, guaranteeing quality seems more and more a community endeavor based on the collaboration between experts in education, subject scholars, students, teachers, developers etc. both during and after the teaching and learning process through study groups and practice communities around the world [95]. The emergent competition among OER/OCW initiatives calls for establishing of strong brands, of vivant user communities, and of improved quality of both resources and infrastructures [3].

Open sharing of OERs and OCW provides for broader and faster dissemination of knowledge, and thus ever more people are involved in problem solving, which in turn leads to rapid quality improvement and faster decentralized technical and scientific development. Therefore, *free sharing of software, scientific results and educational resources reinforces societal development and diminishes social inequality* [3]. This way, the OER Initiative's initial goal of *building a community so that the emerging OER movement will create incentives for a diverse set of institutional stakeholders to enlarge and sustain this new culture of contribution* may be reached [1].

We introduced here a multi-agent system (called MASECO) for evaluation and classification of open courseware and open educational resources, which is based on our socio-constructivist quality model, and which aims to support OER/OCW users to fulfill better their needs, and to accomplish appropriately their educational aims, in any given context. Our future work will research various issues related to quality evaluation of open educational resources and open courseware, both automatic and within communities of users. Some of these ideas have already been mentioned in the Discussion sub-section. Moreover, to disseminate this work further, one of the first things to do consists of creating a project wiki, as a starting point to build a community of users that could help with evaluating the materials, aiming at developing an educational repository that includes links to the most valuable educational resources for specific teaching and learning needs in various contexts. In this perspective, we consider the distributed management of information among the agents, as opposed to the centralized approach taken currently. We think also about proving out our approach cross-discipline and cross-domain with help from a case-based recommender system. Another idea we would like to pursue refers to refining our quality model towards a hierarchical approach, aiming at categorizing open educational resources for specific contextual needs (for example, most suitable for classroom study or for self-study).

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66. Universidad Charlos III de Madrid’s Database Fundamentals, http://ocw.uc3m.es/ingenieria-informatica/fundamentos-de-las-bases-de-datos

67. Universidad Politecnica de Madrid's Database Administration, http://ocw.upm.es/lenguajes-y-sistemas-informaticos/administracion-de-bases-de-datos
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Appendix. The quality scores obtained by the eight open courseware on databases

	1 MIT OCWDB	2 Saylor DB	3 St WidDB	4 Cnx NKA	5 KF DBSs	6 UW DMq344	7 UC3M DADB	8 UPM BD
CR1	2.5	2.5	5	5	5	3.5	5	3
CR2	2.5	2.5	5	5	5	5	4	4
CR3	5	5	3	5	5	5	4	4
CR4	4	5	3	5	5	4	4	5
CR5	5	5	5	5	5	5	5	5
CR6	3	5	5	1	3	3	5	4
CR7	3	5	5	1	3	3	5	5
CR8	5	5	5	3	5	3	5	5
CR9	2	5	2	2	0	3.5	2	3.5
CR10.1	5	5	5	5	5	5	5	5
CR10.2	5	5	5	5	5	5	5	5
CR10.3	5	5	5	5	5	5	5	5
CR10.4	5	5	5	5	5	5	5	5
CR10.5	5	5	5	5	5	5	5	5
CR10.6	0	5	5	0	0	0	0	0
CR10.7	0	5	0	0	0	0	0	0
CR10.8	5	5	5	5	5	5	5	5
CR10.9	5	1	1	1	0	5	5	1
CR10.10	0	5	5	0	0	0	5	0
ID1	1	5	0.5	2.5	3.5	1	4	4
ID2	1	5	0	1	1	0	1	1
ID3	3	5	5	3	3	3	3.75	3
ID4	2.5	5	5	1	0	5	2	2.5
ID5	0	0	0	0	0	0	0	0
ID6	0	0	0	0	0	0	0	0
ID7	0	5	5	0	0	1	0	0
TR1	5	5	5	5	5	5	5	5
TR2	5	5	5	5	5	5	5	5
TR3	2.5	2.5	2.5	4	2.5	2.5	2.5	2.5
TR4	2	3	2	5	2	2	2	2
TR5	5	5	5	5	5	0	0	0
TR6	5	5	5	5	5	5	5	5
TR7	5	5	5	5	5	5	5	5
TR8	5	5	5	5	0	5	2	0
CWL1	4	5	4	2	5	4	5	4
CWL2	4	5	4	0	5	4	5	4
CWL3	5	4	0	0	0	0	1	3
CWL4	5	4	0	0	5	0	0	3
CWL5	0	0	0	0	0	0	0	0
CWL6	5	2.5	5	2.5	4.75	4.75	2.5	2.5
CWL7	5	5	5	3	3	5	5	5
CWL8	0	0	0	0	0	0	0	0
CWL9	0	0	2	0	0	0	0	0
CWL10	0	2	2	0	0	2	0	0
CWL11	5	5	5	5	5	5	5	5
CWL12	5	5	5	5	5	5	5	5

	1 MIT OCWDB	2 Saylor DB	3 St WidDB	4 Cnx NKA	5 KF DBSs	6 UW DMg344	7 UC3M DADB	8 UPM BD
CW1.13	0	5	5	0	0	0	0	0
CW1.14	0	5	0	0	0	0	0	0
CW1.15	2	5	5	2	2	2	0	2
CW1.16	4	5	5	0	0	0	0	0
CW1.17	5	5	5	4	3	5	5	5
CW1.18	1	5	1	1	0	5	2	2
CW2	5	5	5	0	0	0	5	0
CW3	5	5	5	0	0	0	0	0
CW4	5	5	5	5	5	5	5	5
CW5	5	5	5	5	5	5	5	0
CW6	5	5	5	5	5	5	5	5
CW7	2	5	5	2	2	2	2	2
CW8.1	5	5	5	5	5	5	5	5
CW8.2	2	5	4	3.75	2	2	2	2
CW8.3	0	5	3	0	0	0	0	0
CW8.4	0	5	1	0	0	0	0	0
CW8.5	2	5	2	5	2	2	2	2
CW9	0	5	5	0	0	0	0	0
CW10.1	0	2	0	3	0	0	0	0
CW10.2	2	5	5	5	2	0	0	0
CW10.3	0	3	3	0	0	0	0	0
CW10.4	0	3	5	4	0	0	0	0
CW10.5	0	3	5	4	0	0	0	0