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Research article

Adaptive learning objects in the context of eco-connectivist communities using learning analytics

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ABSTRACT

Eco-connectivist communities are groups of individuals with similar characteristics, which emerge in a connectivist learning process within a knowledge ecology. ARMAGAeco-c is a reflexive and autonomic middleware for the management and optimization of eco-connectivist knowledge ecologies using description, prediction and prescription models. Adaptive Learning Objects are autonomic components that seek to personalize Learning Objects according to certain contextual information, such as learning styles of the learner's, technological restrictions, among other aspects. MALO is a system that allows the management of Adaptive Learning Objects. One of the main challenges of the connectivist learning process is the adaptation of the educational context to the student needs. One of them is the learning objects. For this reason, this work has two objectives, specifying a data analytics task to determine the learning style of a student in an eco-connectivist community and, adapting instances of Adaptive Learning Objects using the learning styles of the students in the communities. We use graph theory to identify the referential member of each eco-connectivist community, and a learning paradigm detection algorithm to identify the set of activities, strategies, and tools that Adaptive Learning Objects instances should have, according to the learning style of the referential member. To test our approach, a case study is presented, which demonstrates the validity of our approach.

1. Introduction

Numerous efforts have been made in recent years to reconcile the concept of informal learning with formal educational models. In this sense, Information and Communication Technologies (ICTs) provide the ideal environment to articulate these modes of learning. In particular, ICTs provide a suitable platform for deploying emerging learning process management models, while providing the resources and tools needed to exploit such emergent learning within the formal education framework.

The development of emerging technologies in the area of education, such as new models of education, advancements in social learning theory, e-learning, the development of learning networks, among others, requires the redefinition of the processes of teaching-learning, in a highly interconnected and constantly changing world, where contextual analysis is considered as a primary task within this process [1].

Emerging learning can be defined as a type of learning that spontaneously appears from interactions between learners, and between learners and learning resources [34]. In this case, learning is seen as a process that evolves all time, allowing learners to achieve learning objectives. For this end, an emerging learning management system systematically analyzes the behavior of the learner, in search of patterns of behavior, participation, collaboration, integration, among other things, to improve this process.

Emerging learning has been approached from different perspectives. This article adopts the notion described by [2], which proposes a learning paradigm called Connectivism. This paradigm considers that learning occurs in dynamic and non-linear environments (Internet), and is addressed using the principles of chaos theory. In Connectivism, the learners' behavior is related to the development of metacognitive capacities (“know where” and “know how” to transform), and the knowledge to be explored and exploited is called “connective knowledge” [3].

An essential aspect in the management of emerging learning is the definition of the environment where it is developed. This virtual space, in addition to be open and flexible, should promote the spontaneous

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interaction between learners. Each learner is free to incorporate into the learning process the resources and individuals that contribute to their particular interests.

A tool for the analysis or evaluation of the emerging learning must define at least two elements of management [2]: a model of interaction per learner, that is, the resources and individuals that the learner spontaneously incorporates into their learning process; a workspace of interaction and collaboration, defined by common interests or activities. In order to respond to these requirements, there are different proposals; in this article, we use in the first case, the notion of Personal Learning Environment (PLE) [6]; and in the second case, the notion of learning ecosystem [7].

A PLE refers to the set of tools, sources of information, connections and activities that each individual assiduously uses to learn [6, 9]. It is shaped by the processes, experiences and strategies that the learner can put in place to learn. A PLE uses the Internet and other technologies to develop the learning process [6]. On the other hand, the learning ecosystems consist in the incorporation of actors throughout the learning process chain, learning programs and learning environments, within specific limits dominated as environmental learning boundaries [8]. In particular, a learning ecosystem is a learning community formed by learning resources and groups of individuals, which can interact synchronously and asynchronously [7].

An eco-connectivist community refers to a set of learning ecosystems that evolve within a higher degree component, called knowledge ecology [9]. In eco-connectivism, each apprentice is represented by his/her PLE, whose properties evolve naturally according to his/her interests and environmental conditions. To achieve this, the eco-connectivism specifies a set of Data Analysis (DA) tasks grouped into three major processes [27, 38]: a configuration process, with DA tasks to describe the current state of the learning process; a stabilization process, with DA tasks to predict events in the learning process; and a unification process, with DA tasks to autonomously prescribe the actions that must be followed to optimize the knowledge ecology.

In a previous work [9, 27], we have defined a computational system to support the eco-connectivism, called ARMAGAeco-c (ARMAGAeco-c (an acronym in Spanish of multi-level autonomous reflective architecture for the management of eco-connective processes). In ARMAGAeco-c, PLEs are represented by a set of links corresponding to collaborative learning resources for reading, writing, etc. The interaction between individuals is represented by a set of nodes and links, called the Personal Knowledge Network (PKN). For the eco-connectivist configuration process, ARMAGAeco-c uses Web mining techniques; for the stabilization process uses graph mining techniques, and finally, for the unification process, recommendation techniques are used [47].

The main problem with platforms as ARMAGAeco-c, are the adaptive capabilities to adequate the context to the emerging learning process. An ecology of knowledge can have a great diversity of technological requirements. Each requirement seeks to satisfy the particular needs of the individuals that compose it. In the simplest cases, these particularities are related to the personalized selection of the elements of the PLE according to the learning style, but in more complex cases, there are parameters related to physical limitations of the individuals (e.g., visual or auditory problems), or contextual (e.g., the bandwidth available for the Internet), which have a fundamental role in the personalization of the learning processes.

To address this problem, we introduce the notion of Learning Object (LO), a configurable and reusable unit that defines different educational resources (usually, multimedia elements), whose metadata information allows determining both its pedagogical intentionality and the characteristics of the elements that it includes. This meta-information, combined with information about the contextual parameters of a learning community, together with a mechanism of reasoning based on rules, could not only allow the reconfiguration of the LOs, but also, improve the precision of the personalization. In this paper, we propose the process of adaption of LOs to learning communities based on these ideas.

In this way, this work uses a novel concept, called Adaptive Learning Object (ALO), which is an autonomic Learning Object (LO) capable of getting contextual information of a learning process, and adapts it to the particular needs of that context [10]. Technically, an ALO is a multimedia digital resource that contains metadata with its description, and is able to adapt to the context.

ALOs are important for the learning ecosystems, because they can be customized according to the particular characteristics of learners and learning communities. In a previous work has been defined MALO [36, 37], a system that allows the management of ALOs.

In this paper, we specify the DA task in the eco-connectivist stabilization process implemented by ARMAGAeco-c. In addition, we specify the integration of MALO with ARMAGAeco-c, in order to enrich the adaptive capability of the unification process. For that, we extend ARMAGAeco-c with a new technique of graph mining based on the notion of centrality [10], and the notion of personalization based on learning paradigms [11] (hereinafter, referred as the Apprentice Model, AM). Then, the previous information is used by MALO, to adapt the ALOs to a particular learning ecosystem.

This article is organized as follows, the next section presents related works about autonomic systems of learning process management and adaptive learning resources. Next, we present some theoretical aspects; afterward, it is characterized our approach, using the concept of eco-connectivist communities and ALO. Then, a case study is presented. Finally, our conclusions and comments about the development perspectives of this work are presented.

2. Related works

The Virtual Learning Environments (VLEs) are digital and immaterial computing environments that provide the conditions for the realization of learning activities. They are the components used by the learners and tutors in "online" interactions of various kinds, including online learning [4, 5]. VLEs integrate heterogeneous technologies and multiple pedagogical approaches [1, 4, 5]. The development of learning processes in a VLE has been approached from several perspectives. In this paper, we propose an approach that mixes several domains linked to connectivist communities (emerging learning process), ALOs, and learning analysis tasks [35, 39]. Below, a series of papers about Connectivist Communities, Adaptive Learning Object, and Learning Analysis in VLE, related to our research.

2.1. Connectivist communities

In the context of the evolution of the paradigms that underpin the educational action, different pedagogical approaches emerge that can be used in the deployment of VLEs; among the most influential are: the sharism [13], Connectivism [2, 3] and the distributed learning, among others.

Of these approaches, it has been Connectivism that has received the most attention from the scientific community [6, 7]. This is due, fundamentally, to the level of precision with which it defines the epistemic concepts of truth, objectivity and interpretation, in a new type of knowledge called connective knowledge [3]. In this sense, proposals have been developed, both at the level of connectivist instructional designs [40, 42, 45] and VLE based on Connectivism [14, 15, 16, 41, 46].

In [14], an instructional design is proposed, focused on reusable LOs, whose selection and presentation to the learner guarantee the development of various metacognitive capacities to generate connective knowledge. In this work, the author combines constructivist and Connectivism methodologies to provide instructional designs in VLEs, whose principle of learning is the autonomy of the learner in open, social and hyperconnected environments.

On the other hand, in [15] is proposed the use of a task-based blended instructional design, framed in a connectivist vision, containing two organizational nuclei: the VLE and a Learning Management System

(LMS). For the instructional design, the author uses what in cognitive psychology is called "affordances", and proposes the use of adaptive dynamics that are configured according to the internal and external needs of the teaching-learning process.

With respect to connectivist VLEs proposals, in [16] is put into practice the connectivist learning paradigm as a broad, democratic, collaborative, participatory, open and distributed form of education, based on informal learning. In that paper, the authors define the massively open online connectivist courses (MOOCC). The goal of the MOOCCs is to facilitate emerging and self-organizing patterns of collaborative learning. For this, MOOCCs must be flexibly designed, allowing learners to participate in them using their own spaces and social networks. The key component of a MOOCC is a shared hashtag that is adding activities into a shared, open, and decentralized flow.

In [17] is proposed an environment for personalized e-learning based on self-organized learning. The authors make a distinction between the deployment of courses based exclusively on repositories of LOs, and a system to store and connect both the resources and the concepts that are used to link them. The linking is based on two ontologies, to reason and act autonomously on the learning process, and to facilitate the navigation through the system.

[40] analyses connectivist MOOCs (cMOOCs) by examining participant interactions, community formation and learner behavior. Particularly, it focuses on the observation of Twitter interactions, using Social Network Analysis and content analysis tools. They demonstrate that communities in connectivist networks have chaotic relationships with other communities. Also, they find was that as the course progressed and the number of active participants decreased, interaction increased in the network. Additionally, the study reveals that, though completely online, the open online ecosystems are very convenient to facilitate the formation of communities. Finally, the content analysis of tweets demonstrated that cognitive presence was the most frequently observed, while teaching presence was the lowest. In [41] proposes a Connectivist Learning Environment Assessment Tool to examine the change in underlying values of the MOOCs, from their primary characteristics of connectivist pedagogy that are autonomy, diversity, openness, and community participation, to more market oriented characteristics linked to cognitive and behaviourist pedagogies. The tool is used for formulating a conceptual framework to reify the connectivist pedagogy and assess connectivist underpinnings of a learning environment including MOOCs. The purpose of [42] is to better understand community formation in MOOCs based on the connectivism, rhizomatic learning, actor-network theory, community of practice, and community of inquiry. Some of the findings are: respect and transparency in mutual communication, being socially visible with a digital identity, being emotionally present, opportunities to connect to personally meaningful sources or nodes, being able to wander among open ecologies, and creating well-designed learning spaces that meet diverse needs of the learners.

The authors of [43] critically examine the theoretical postulates of connectivism, and identify three important psychological and epistemological problems, namely the lack of a solution to the learning paradox, the underconceptualization of interaction and the inability to explain a concept development. These deficiencies may explain certain learning problems experienced by participants in MOOCs. The paper concludes that the connectivism as a learning theory has significant theoretical problems and should be profoundly revised to foster learning in such environments [44]. addresses an understanding of knowledge defined as a network and the lack of resources talking about this topic. In addition, it tries to clarify in what way it can affect teaching and learning processes. They analysis the connectivism bases, its way of conceiving knowledge like a network, and its learning process like an exploration of this network [45]. discusses how MOOC users learn and participate in cooperative environments that promote learning communities within external hypermedia environments, such as the social networks. Specifically, this paper deals the conversations that take place in external learning communities, like in the social networks (Google+, Twitter, etc.), in parallel with the iMOOC platform itself. They analyse how these conversations allow them to expand or strengthen their learning process developed in the MOOC. The paper [46] examines how social media are being used for formal and informal learning, by examining data from cMOOCs. They develop methods to detect and study collaborative learning processes, and focus on how to link multiple online identities of learners and their contributions in several social media, to study their learning behaviours in open online environments.

In the literature, there are more works about the conectivism and its implications in the learning process. Also, there are works about their technology implementations and the creation of learning spaces that meet diverse needs of the learners. But like can be seen in the previous works, there is no studies about how to personalize the educational resources to the learning process, according to the learning styles, and the context, for eco-connectivist communities. This is the problem addressed in this paper, with the introduction of the notion of ALO.

2.2. Adaptive learning objects

The topic of ALOs has been addressed by different authors, which have made several proposals to incorporate adaptive capacity to LOs. In [18] is proposed an ALO model comprised of four components: knowledge domain; user domain; context and session. The last one is in charge of establishing the relationships between the other three components by using rules of navigation, content presentation, and customization of the information that is presented to the user. In this work, the rules of adaptation are specified for each ALO, which makes it hard for their implementation. In addition, these are limited to the navigation patterns within it, and to the incorporation or elimination of links in the LO according to user interactions.

In [19], the authors present an ALO model for t-learning (learning through the interactive digital television), which starts from the idea of offering a LO with different behaviors, depending on the characteristics of the users. In their proposal, they use a XML file, which contains a template with rules or adaptation parameters, which indicate to the educational object what behavior or appearance to adopt, according to the preferences of the student. In this work, the manual presetting of the adaptive parameters difficulties the autonomous incorporation of changes in the learning process.

In [20] is defined an ALO model by taking advantage of the LO's granularity properties. Their proposal is based on the incorporation of four levels of functionality to the LO: courses, documents, fragments of a document and multimedia pieces. The fragments are formed by multimedia pieces related to some instructional objective and a semantic description, which allows them to assemble a new LO from the existing ones. The architecture is composed of 3 main components, a Domain Model formed by the concepts that the learner can learn (the resources available for learning) and the LOs (contents and metadata); an Apprentice Model, which represents the learner's known information (personal, preferences and knowledge); and an Adaptation Model (navigation, presentation and related contents), which addresses the adaptation of the contents that are presented to the learner, and the way the fragments are assembled. In this model, they do not consider the technological limitations that may arise from a VLE, nor do they describe the rules to be used to adapt the LO.

In [21] is proposed a reusable ALO based on the ACT-R cognitive architecture. The adaptive content aggregation supports the adaptive presentation, the adaptive navigation and the adaptive collaborative, in order to incorporate adaptation into a LO. In addition, they incorporate a learner profile model to handle information that helps to personalize the learning process. In this paper, the authors try to adapt the LO in a linear way, limiting itself to the aggregation of contents to it, and to the use of methodological strategies of learning according to the profile of the user.

Del Moral et al. present the relationship between LOs and connectivist communities [22]. They review certain factors that lead to the evolution of the e-learning paradigm towards what they call e-learning 2.0. Among the factors presented by the authors are the tools of the Web 2.0, the collaborative tools in a teaching-learning process, the collaborative construction paradigm of LOs, and the rise of connectivist communities. This work is limited to identify Web 2.0 tools that facilitate collaborative learning, but do not present how these tools can be integrated in a connectivist environment.

2.3. Learning analysis in VLEs

The interactions of users in social networks and VLE generate traces whose analysis has a great relevance in learning processes. The Learning Analysis (LA) is one of the tools used to understand this data. In a first approximation, LA represents the application of "big data" and DA in the education processes. It considers the data about learners and their contexts, for the purposes of understanding and optimizing the learning and the environments in which it occurs [23, 34, 39].

In this domain, there are several works. Some of the works in this area are: [24], which examines how LA may serve as a methodology for understanding the process of learning in Online Social Networks for medical practitioners. The author uses a set of analytical methods, such as social network analysis and context analysis, to investigate different components of the learning process in an online discussion forum for medical practitioners, and to propose intervention strategies for improving learning.

In [25], the authors address tools and instruments for social LAs. This paper highlights the most relevant educational potentials and challenges offered by the use of big data in massive online learning environments. It also mentions techniques, such as data mining, to extract valuable information about the user interactions with the social and learning platforms, which can be used to personalize the learning process.

In [26] some artificial intelligence techniques associated with adaptive educational systems are presented, such as fuzzy logic, decision trees, neural networks, Bayesian networks, generic algorithms, among others, and how these can be used to analyze the VLE to achieve more intelligent and adaptive e-learning systems. In their work, the authors consider Learning Analytics and Educational Data Mining as the main tools to achieve these objectives.

The authors of [39] propose the concept of "Autonomic Cycle Of Learning Analysis Tasks" (ACOLAT), which defines a set of tasks of learning analysis, whose objective is to improve the learning process. In the autonomic cycle, each learning analysis task interacts with each other and has different roles: Some of them must observe the learning process, others must analyze and interpret what happens in it, and finally, others make decisions in order to improve the learning process. In this article, they study the application of the autonomic cycle in a smart classroom [29, 31], which is composed of a set of intelligent components of hardware (e.g., smart board) and software (e.g., VLE), which must exploit the knowledge generated by the ACOLAT to improve the learning process in the smart classroom. In [35], the authors present the implementation of ACOLAT in a smart classroom as a service.

In general, according to the previous papers presented in this section, it is interesting to incorporate autonomy in LOs, in order to allow emerging learning processes, which take advantage of the facilities offered by the VLE and DA. With this, one of the main objectives that can be reached, is to provide a learning environment adapted to the limitations and styles of the students. Particularly, it is important to establish relationships between learning communities and learning processes in the digital age, using paradigms like the Connectivism.

3. Theory

3.1. ARMAGAeco-c

In a previous work [9, 27], we have defined a computational system to support eco-connectivism called ARMAGAeco-c, acronym in Spanish of Reflexive Architecture with Multilevel Autonomy for Management of eco-connectivist Learning, a middleware that optimize learning processes using the paradigm of eco-connectivism.

Eco-connectivism is a computational specification for the optimization of the connectivist learning processes, through the detection and self-organization of learning communities [9]. These communities are called learning ecosystems, and the environment where they are developed is called knowledge ecology. Each individual in the ecology is represented by its PLE, and each PLE maintains a dynamic structure, called PKN. Eco-connectivism is based on three processes: configuration, stabilization and unification [9, 38], each one specified with DA tasks for description, prediction and prescription purposes, respectively. In ARMAGAeco-c, the configuration process employs web mining of use to detect learning ecosystems. In the stabilization process, the parameters of evaluation of the connective knowledge are used to determine the fit and unfit ecosystems of the knowledge ecology. In the unification process, the PLEs are migrated from unsuitable ecosystems to suitable ecosystems, and collaborative filtering techniques are used to facilitate the process of PLE insertion into the suitable ecosystems.

To support eco-connectivism, ARMAGAeco-c uses several concepts of computer science. In particular, the concepts of computational reflection and autonomic computing [28]. Computational reflection is a paradigm oriented to self-awareness and self-reference of the computer systems to allow them to change their behavior, according to the needs of the environment where they are executed [30]. The properties of self-awareness and self-reference are based on two processes: 1) introspection, the ability of the system to observe its own state of execution; and 2) intersection, the ability of the system to modify the state of its execution or alter its interpretation. The structure of a reflective system describes a level-based architecture, in which a level is reflective of the lower level, forming what is called a reflexive tower [31, 32]. The lower level of the reflexive tower is called base level, and each level above the base level is called a meta level.

On the other hand, autonomic computing is a self-management model that incorporates sensors and actuators to observe the environment, reason, and accordingly act. This model of computing is based on an architecture that describes several elements [32]: the autonomic manager is in charge of implementing the self-management capabilities of the architecture. To achieve this, an autonomic handler implements what is called an intelligent control loop, which is based on the processing of inputs to the system, through a series of stages that eventually lead to the execution of a suitable smart behavior. These stages of the intelligent control loop are called MAPE-K (acronym for Monitor, Analyzer, Planner and Executor), which use a knowledge source (K) [32].

In this way, ARMAGAeco-c is able to manage and optimize eco-connectivist learning environments, using a reflexive-autonomic architecture. Each reflection level of ARMAGAeco-c is seen as an autonomic handler, which implements an intelligent control loop. The first loop makes introspection on the PLE. The second loop makes introspection on the distribution of the ecology of knowledge that emerges from the learning process. The intersection of the first level of reflection is carried out through an adaptive eco-connectivist plan. The intersection of the second level of reflection is performed using LA techniques and social LA techniques, based on the data provided by the learning environment.

In addition, an Independent Reflection Model (IRM), based on a dynamic Multiagent System (MAS) [27], has been defined to implement the reflection and autonomy of ARMAGAeco-c. The IRM can generate instances of agents adapted to the level of reflection of ARMAGAeco-c. Fig. 1 shows the architecture of the IRM, which is an extension of the Foundation for Intelligent Physical Agents (FIPA) architecture specification [33], with an Intelligent Loop Layer (ILL) that provides the services to implement the autonomic capacities of each level of ARMAGAeco-c. The prefix "Ag" represents the components of the architecture. "A" is the learning agent; "C" is the collector agent; "P" is the preprocesor agent; "E" the ecologic agent; "G" the cluster agent; "M" the miner agent; "R" is the recommendator agent; and "S" the survival agent. SGA is the agent management agent, CCA is the communication control

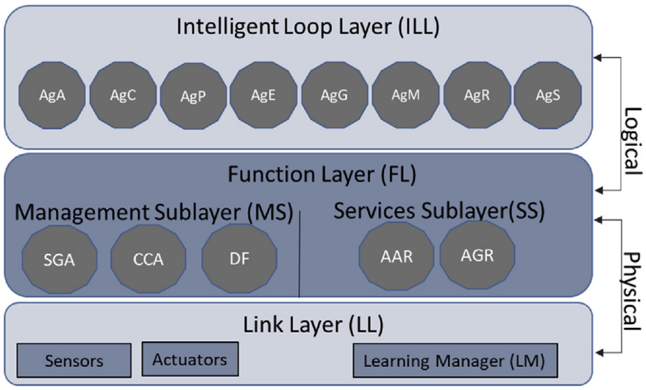

Fig. 1. IRM architecture.

agent, DF is the directory of the functions of the agents, AAR is the Application Management Agent and AGR is the Resource Management Agent [32]. Finally, each PLEs instance is in the LM container, whose behaviors are captured by the sensors and modified by the actuators provided by the IRM in the LL layer.

Fig. 2 shows the relationship between the MAPE-K stages of the autonomic process and its implementation in the ILL of the architecture. The LL and FL layers in the IRM architecture (Fig. 1) are an implementation of the FIPA standard [33], and ILL layer is an implementation of the MAPE abstraction for autonomic computing models [32].

Each agent of IRM has a role in the management and optimization of the learning process. The agents of the Functional Layer (FL) refer to the classical agents defined by FIPA for the deployment of the agent community, and their general characteristics are defined in [33]. ILL agents provide the services of monitoring, analysis, planning and execution of the autonomic management process, and their services are defined as DA tasks in [27]. AgM, AgP, AgE and AgC monitor the learning environments, AgS, AgA and AgE analyse the current situation, and the modification of the learning environments are defined by the AgG and AgR agents. Finally, these modifications are carried out by the AGR and AAR agents.

The IRM Link Layer implements the sensors and actuators of the autonomic system, and the managed elements of the system. This layer includes both, the PLE of a learning process and the learning resources incorporated into the process. At this level, ILL agents provide PLE adaptation services and knowledge description, prediction, and prescription services to other related platforms.

3.2. Adaptive learning objects (ALOs)

A LO is "any digital resource that can be used to support learning"

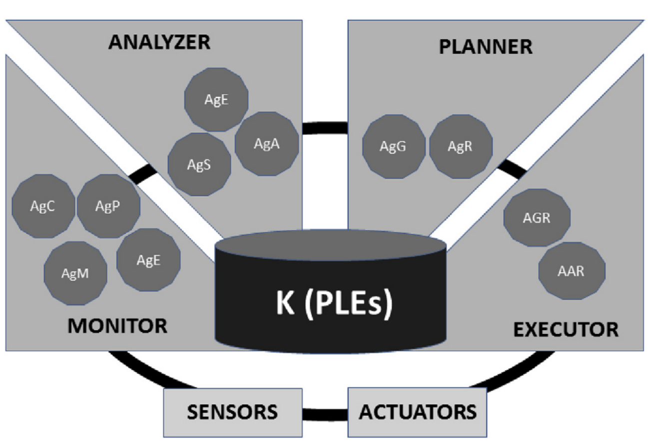

Fig. 2. Relationship between ARMAGAeco-c and IRM.

[36], "a digital or non-digital entity that can be used for learning, education or training" [21]. An ALO is "a reusable multimedia digital resource, which can be used in instruction and learning, which contains metadata for its description, and is able to adapt to the context" [10, 36, 37]. The Model of Adaptive Learning Objects (MALO) proposed in [10, 36, 37] is shown in Fig. 3. MALO is composed of 4 elements:

- LO: it is the learning object to adapt,
- Units: understood as small blocks or fragments, defined as concepts, media or pieces, in which the LO is decomposed. The concepts are the ideas that are handled in the LO; the media are the different formats used in the LO to present the ideas; while the pieces are the parts in which the LO is structurally organized.
- Rules: in an ALO, two categories of rules are defined: adaptation and conversion. The firsts specify the structural adjustments; the seconds determine contextual adjustments, which are made to the LO.
- Adaptation Metadata: it describes the data and processes that allow carrying out the LO adaptation

The adaptation and conversion rules of an ALO continuously interact in order to adapt the semantic, presentation, or organization of the LO, according to the requirements of the context; these adaptations can simultaneously occur.

The *Conversion Rules* indicate that structural adaptations that must be made to the LOs. In MALO, two (02) basic conversion rules are defined: Composition, based on the principle of reusability, allows building a new LO from other LO's of lower granularity; and Decomposition, allows decomposing a LO in several LOs of smaller granularity, or extracting units included in a digital content.

The *Adaptation Rules* define the types of adjustments to apply to the LO to contextualize it. In MALO, four types of rules are initially defined: *Semantics,* they allow defining a new semantics in a LO, incorporating other ideas, conceptualizations or lexicon, which are consistent with its content; *Presentation*, they fit the presentation of the LOs, adapting their formats to the preferences, limitations and use, both of the users and of the technology; *Organization,* they rearrange the content of the LOs according to the pieces that make them up; *Transformation*: they modify the units of measurements, quantification, etc. of a LO.

Both sets of rules (the conversion and adaptation) allow the incorporation of other rules, which give them flexibility to extend their functionalities in the future.

Due to the limitations of the current version of the IEEE-LOM standard to provide information about the methods and services required to adapt an ALO, it was proposed to incorporate an extension, defined as Category 10, into the standard, in order to facilitate the search, evaluation, recovery and application of the methods of adaptation of an ALO [37]. In the category 10, a detailed description of the data necessary that allow the process of autonomous adaptation of the LO, is made. Its ontological model (OLOMCat10) is presented in Fig. 4.

OLOMCat10 relates Category 10 with 3 major components: a base rule, a rule catalog, and a service catalog. The base rule is the initial rule that triggers the ALO adaptation process. The catalogs contain information about the rules and services, as well as possible virtual addresses where they could be found. Their purpose is the ubiquity, making the ALOs independent of the rules of adaptation and the services used to transform them.

Below are presented two (02) examples, in order to visualize the behavior of an ALO. The first is shown in Fig. 5, which consider the application of conversion rules.

Suppose a LO, whose content is about object-oriented programming, which is formed by three (03) parts, called units: object-oriented programming languages (U1), data types (U2) and data structures (U3). The ALO receives a request that the LO should only contain the units U2 and U3. To attend this requirement, it applies the conversion rules, such that the LO is decomposed into units (Decomposed LO), then composition rules are applied to generate a LO formed with only the required parts

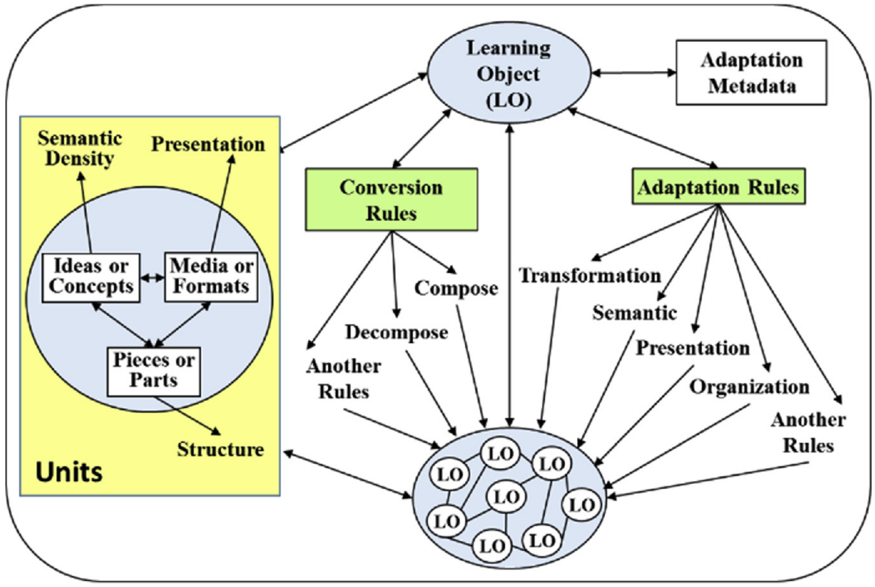

Fig. 3. Model of adaptive learning objects (MALO).

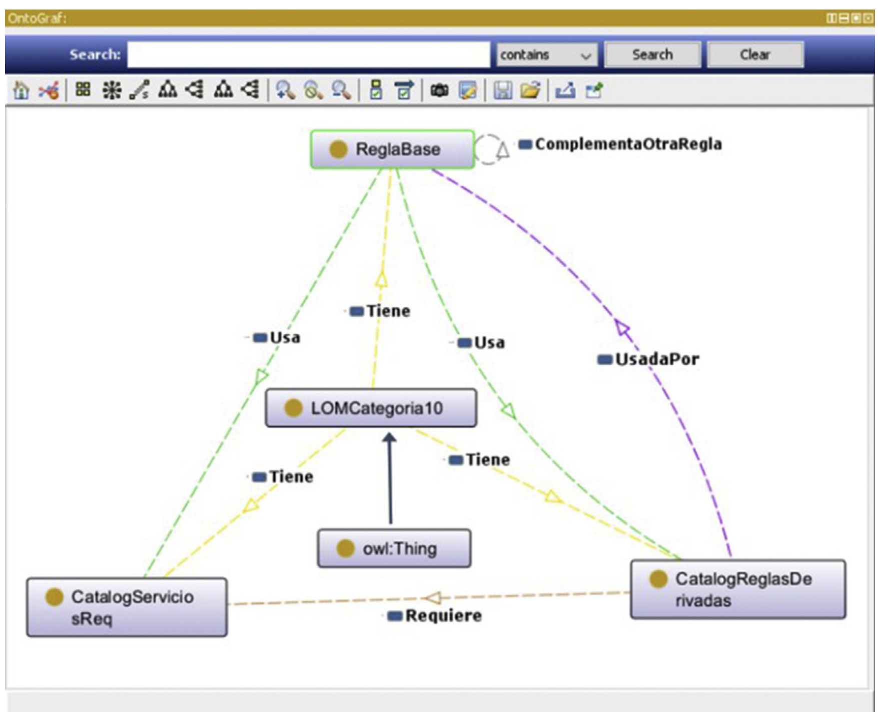

Fig. 4. LOM standard extension ontological model (OLOMCat10).

(Adapted LO). In this process, the ALO uses the OLOMCat10 ontology, which facilitates the discovery of services and complementary rules, necessary to carry out the adaptations.

In the second example (see Fig. 6), adaptation rules are applied.

Taking the result of the previous example, it is determined that the LO content is in the English language; however, the students only know the Spanish language. The ALO receives a request to autonomously convert the LO language. To do this, the presentation rules are activated, and the ALO uses the OLOMCat10 ontology to discover the base rules, the complementary rules and the services that facilitate its adaptation, in order to translate its content from English to Spanish, resulting in a LO adapted to the student language.

The procedures in examples 1 and 2 can be dynamically combined with other requirements, making possible a chain of adaptations of the ALO to the context.

MALO originally establishes six (06) sets of generic rules, grouped into two (02) conversion rules and four (04) adaptation rules. In order to carry out the adaptation process, the generic rules, in turn, have associated a set of specific rules in charge of executing one task at a time. The specific rules are based on autonomous computing, ontology management, and the use of services, to respond to changes in the VLE. Table 1 presents a set of rules and tasks considered in the adaptation process.

The previous tasks are not exhaustive and each task constitutes a specific rule. An important feature of MALO is the flexibility to

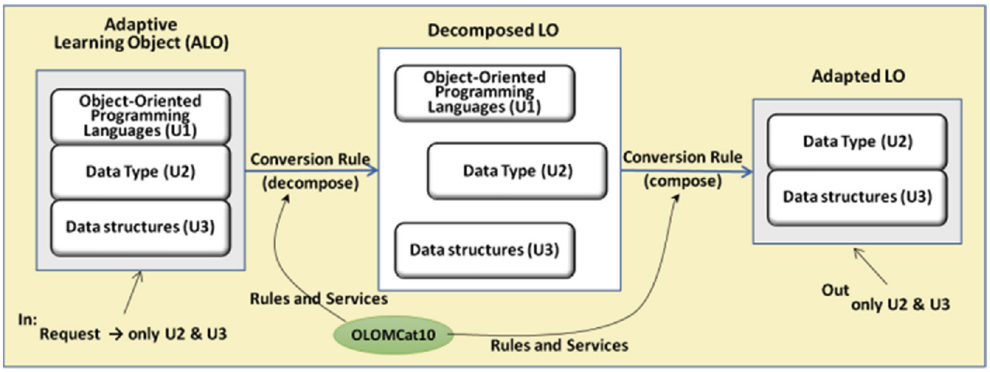

Fig. 5. Application of conversion rule.

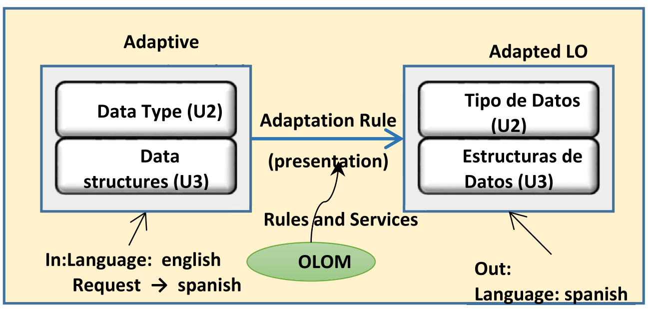

Fig. 6. Application of adaptation rule.

Table 1
MALO specific rules.

RULE	TYPE	TASK
Adaptation	Presentation	Translate, Convert audio to text, Convert text to audio, Modify image resolution, Modify video resolution
	Semantic	Get semantic level, Get lexical level, Get idea, Add concept, Get Summary
	Organization	Reorder, Group
	Transformation	change units of measurement, customize audio
Conversion	Compose	Add unit
	Decompose	Extract unit

incorporate to the basic rules, any number of specific rules that are required. In this aspect, the adaptation metadata (ontology OLOMCat10) has an important role since they register in their catalogs the new rules and/or discovered services. For more details about the rules, their conditions, types and requirements, see [10, 36, 37].

4. Model

4.1. Adequacy of ARMAGAeco-c to MALO

Based on the benefits of ALO, and taking advantage of ARMAGAeco-c, this paper integrates a dynamic self-configuration model of ALO into the eco-connectivist communities, according to the common characteristics (pattern) of a community of learning (ecosystem). For this, we calculate the most prominent individual of a community using the concept of the eigenvector centrality on graphs. Then, based on this prominent individual, we characterize an Apprentice Model (AM) using the algorithm proposed in [12], which determines the learning paradigm of an individual, relating learning styles to learning resources. Our goal is the adaption of the ALOs, not to an individual, but to a community.

Algorithm 1 shows the steps to calculate the AM of the centrality node associated with an eco-connectivist community.

Algorithm 1. Apprentice model (AM) calculation.

	INPUT: k learning ecosystems
1	For each learning ecosystem
2	Calculate the centrality node of the learning community.
3	Calculate the AM associated with the centrality node of the community.
	OUTPUT: list with the k AMs associated with the k centrality nodes.

The input parameter of the Algorithm 1 corresponds to the result of the eco-connectivist configuration phase processed by ARMAGAeco-c. In this phase, the ecology of knowledge is partitioned into a set of subgraphs, called learning ecosystems. For our algorithm, each learning ecosystem corresponds to a learning community that must be processed and enriched with an AM. A learning community is an unprocessed directed subgraph of the input partition.

Step 2 of the Algorithm 1 computes the most prominent node of the subgraph. For this, we use the notion of centrality of a graph, through the eigenvector centrality method, which represents the best estimate of prominence in social networks [11]. Here, the centrality of an individual is proportional to the sum of the centralities of its neighbors in the graph. Eq. (1) expresses mathematically this notion of centrality, where λ is the proportionality constant and a_{ij} is the element of row i and column j of the adjacency matrix of the analyzed subgraph. In particular, the eigenvector associated with the most prominent centrality node of the analyzed graph will be the one with the highest eigenvalue; which is obtained using Eq. (2), which starts with $\vec{c_0} = \vec{1}$ (where c is the centrality, k is the current ecosystem, and M is the adjacency matrix), whose succession converges to the eigenvector corresponding to the greatest eigenvalue. So, for our algorithm, this centrality represents the learner, who's LO generate the greatest social impact on the related learning ecosystem. For this calculation, the connectivity information is obtained from the activity that is recorded in the individuals' PLEs, which is modeled as a non-directed graph.

$$c_i = \lambda \sum_{j=1}^{n} a_{ij}\, c_j \tag{1}$$

$$\overrightarrow{c_{k+1}} = \frac{M\vec{c_k}}{\|M\vec{c_k}\|} \tag{2}$$

Step 3 of the Algorithm 1 calculates the AM related to the individual centrality of the analyzed community. As we said before, to characterize the AM, we use the algorithm in [12], which determines the learning paradigms, relating learning resources to learning styles. Learning resources are established in three dimensions (strategies, tools and evaluation instruments), according to the individual's learning style. In this algorithm, the learning style is obtained through the model of Felder and Silverman; the strategies refer to the set of activities (techniques and means) that are planned according to the needs of the students; the tools are those means that allow carrying out the process of learning; and the evaluation instruments are the techniques to obtain evidence of learner performance. Table 2 shows some resources associated with the dimensions of the learning paradigms [12].

4.2. ALO services

For the management of ALOs, a basic service system is used that group them in link, analysis and presentation services, as shown in Fig. 7.

The *link services* facilitate the connection of the ALO to the VLE, allowing obtaining information about the context, the resources available for the learning, as well as the rules and services for the adaptation of the ALO. Among the link services are:

- Addressing: allows the connection to ALO Rules and Services catalogs, data repositories, Learning Management Systems (LMS), virtual libraries, physical libraries, among others.
- Search engine: provides mechanisms for locating units (parts, concepts or media) within the content of a LO, as well as for discovering learning resources in the VLE.
- Environment readers: allow obtaining information about the context, such as limitations and preferences of the users, technology, etc.

The *analysis services* allow analyzing the data obtained from the link services, facilitating the evaluation of the content of a LO, as well as determining the learning style of an apprentice, analyzing limitations and preferences, both of users and technological, among other things. In the process of adaptation, the ALO has the possibility of commissioning the analysis to other components or agents with whom it interacts.

The *presentation services* allow adapting the content and structure of an ALO, according to the information obtained from the link and analysis services. The presentation services are required by the Rules, and applied to the Units. For this, the ALO uses a series of information stored in the adaptation metadata (Category 10) defined in the MALO, which allows them through the link services, instantiating to Rule Catalogs and other services. The intersection between MALO and the management services is shown in Fig. 8.

4.3. Architectural integration

In this section, we extend the ARMAGAeco-c architecture shown in Fig. 1, in order to add to the eco-connectivist unification phase a new task of social DA, which allows the incorporation of an auto-configuration service of ALOs, according to the learning patterns of a learning ecosystem. That is, in the Directory Facilitator (DF) of the Management Sublayer (MS), the service of prediction of AMs is registered, based on the centrality nodes of the learning ecosystems (see Algorithm 1). This service will be provided by MAS ILL agents (see Fig. 1). In addition, we integrate the LL of the IRM with an instance of the MALO presented in Section 3.2, and define a new ALO management service in the SS of the FL, to provide the necessary communication routes to the MALO instance. The integration of ARMAGAeco-c with MALO is presented in Fig. 8.

As is shown in Fig. 9, the integration between ARMAGAeco-c and MALO is through the IRM link layer, using routing services. Once the connection is established, ARMAGAeco-c will be able to request a series

Table 2
Examples of some resources to characterize the AM.

Dimension	Associated learning resources
Strategies	Group discussion, simulations, expositions, workshops, talks, case method, problem-based learning, reading, role-playing, brainwriting, etc.
Tools	Diagrams, concept maps, graphics, narrative text, videos, labs, blogs, forums, games, chats, simulations
Instruments	Self-evaluation, examination, project, dissertation, questionnaires, workshops

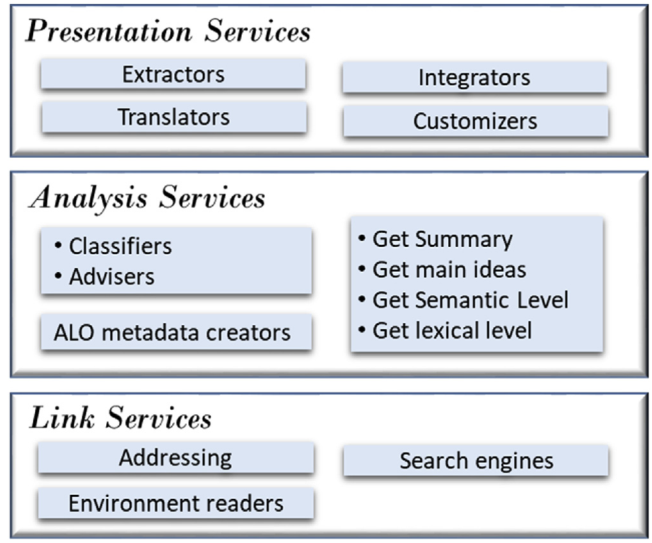

Fig. 7. Management services architecture of an ALO.

of services in order to satisfy the needs of the communities. Through the connectivity services on the environment (link services), an ALO will receive information from the context of the PLEs, which will be the input to process its adaptation. Algorithm 2 indicates the steps to be taken to process the ALO adaptation services from the ARMAGAeco-c IRM.

Algorithm 2. Integrating the ALO as a service for ARMAGAeco-C.

INPUT: Learning Ecology
1 Determine purpose of learning
2 Determine the k ecosystems (communities) of learning present in the ecology of learning
3 For each learning community.
3.1 Get AM
3.2 Get Context Information
3.3 Establish connection to ALO using MALO link services
3.4 If successful connection
3.4.1 Send AM and context information to the ALO.
3.4.2 The ALO
3.4.2.1 Receives AM and context through environment-readers services
3.4.2.3 Determines required adaptation types using the MALO Adaptation Rules
3.4.2.4 If type = semantic then
Adapt LO semantics
3.4.2.5 If type = organization then
Adapts the organization of the LO
3.4.2.6 If type = presentation then
Adapt the presentation of the LO
3.4.2.7 If type = transformation then
Transforms LO content
3.4.2.8 If type = other then
Generates the rules of another type of adaptation of the OA
3.4.2.9 Combines the types of LO adaptation to complete the process
3.4.3 Receive the ALO adapted to the learning ecosystem.
3.5 Update the PLEs
OUTPUT: Learning Ecosystems adapted to the AMs

Step 1 of the Algorithm 2 sets the learning purpose. That is, it defines the domain and area of knowledge of the ecology of knowledge to be managed by ARMAGAeco-c. Step 2 corresponds to the processing of learning ecosystems. This step is performed by the IRM of the ARMAGAeco-c platform, to describe the learning process in terms of learning communities.

Step 3 corresponds to an iterative process. Steps 3.1 through 3.5 are processed in this iteration, once per learning community. Step 3.1 allows obtaining the AM, according to the Algorithm 1. Step 3.2 obtains contextual information (optional) that enriches the information on the AM. Step 3.3 connects it to the MALO instance. Specifically, a connection

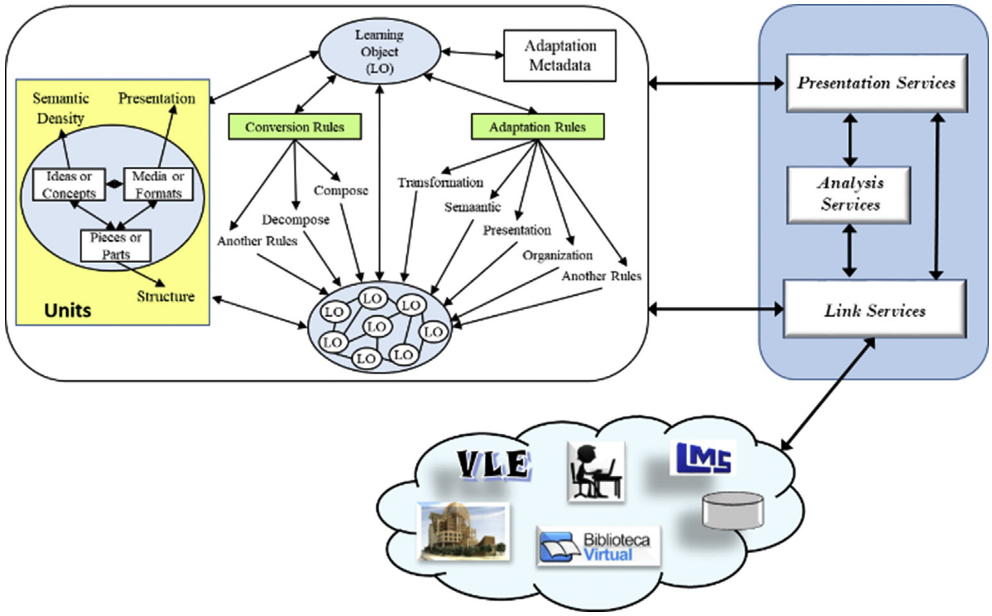

Fig. 8. Integration of MALO and the management services.

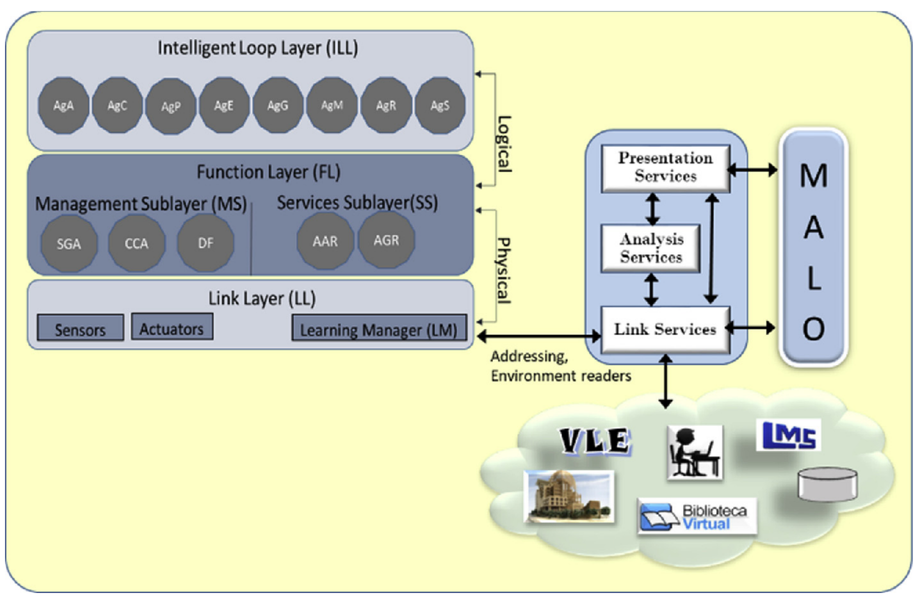

Fig. 9. ARMAGAeco-c and MALO integration.

is established between the IRM SS and the routes provided by the MALO instance. These routes correspond to services "without session" published by the MALO and discovered by the IRM. If the connection is successful (see step 3.4), then the AM information required by MALO is transferred (step 3.4.1). In particular, the SS requests to the MALO an ALO adapted to the AM of the centrality node of a particular learning ecosystem. Step 3.4.2 (and steps 3.4.2.1 to 3.4.2.8) corresponds to the implementation of the adaptation service provided by the MALO. In step 3.4.3 is received the ALO adapted to the AM. Finally, in the step 3.5, the IRM performs the process of updating the PLEs. It updates the PLE of each ecosystem member and, with it, the learning resources (activities, strategies and evaluation instruments). This last task allows the completion of the unification phase of the eco-connectivism.

5. Study area

For the development of the case study, a simulation was executed based on the following steps, with the support of pandas, scikit-learn, matplotlib and seaborn python libraries:

1. Determination of the context and the information sources
2. Determination of the learning communities
   2.1 Definition of the learning communities using a clustering model.
   2.2. Execution of the DA tasks using ARMAGAeco-c, in order to calculate the AM of each community.
3. Determination of the adapted ALO for each community using MALO.

The explanation of the previous steps and their results, are presented below.

5.1. Determination of the context and the information sources

The case study is a course, whose domain of knowledge is the Knowledge Management (KM). Students of both sexes, aged between 17 and 25, have been enrolled in the course. There are 57 students in the KM course. 31 students are Spanish speakers, with little competencies in the use of Web 2.0 tools, without previous knowledge in KM. The other 26 students are English speakers, with high competencies in the use of Web 2.0 tools, and previous knowledge in KM, but they have visual problems and Low-Bandwidth network connections. Each participant of the course has a PLE that characterizes him as a unique individual within a knowledge ecology. Details of the case study are given in Table 3.

In general, the adaptation of the teaching-learning process to the needs of the students or the learning ecosystem happens in the first instance, by the acquisition and modeling of the context, in order to apply data analytical techniques that allow to obtain patterns or deduce knowledge from the data compiled. Due to this situation, it is necessary to store the data of the interactions that occur in the VLE. To facilitate this task, a data model was designed, which is presented in Fig. 10. In this data model, eight (08) entities are defined: learning style (according to the learning paradigm being used, in our case, the Felder and Silverman model [14]), Students (student data), language (language used by students), activities (carried out by learning), Communities (characteristics of the learning community), previous knowledge (knowledge of the members of a learning community), Adaptive Learning Object (ALOs used), Virtual Course (contains information of virtual courses).

5.2. Determination of the learning communities

In this phase is used ARMAGAeco-c, in order to determine the learning communities. Specifically, it instances the data model of the Fig. 10, to determine the learning communities. For that, it executes a clustering algorithm. Next, it determines the most prominent individual of each learning community, based on the concept of "eigenvector centrality" of a graph, which will be the AM of each community (see [38] for more details). Specifically, ARMAGAeco-c follows the next procedure:

1. Instance the ARMAGAeco-c data model (see Fig. 10)
2. Define the ecology of knowledge
3. Identify the PLE of the students in the "Students" table

Table 3
Case: KM course.

Course activities	- Define the elements involved in Knowledge Management (Concepts) - Develop Knowledge Management Systems (Modeling)
Learning Objects involved	LO 1: Knowledge Management (KM) Virtual Course LO 2: Develop interactive and reflexive activities to design KM systems. LO 3: Description of Web 2.0 tools
Virtual Course Content	Virtual course content is composed of three (03) parts: *Concepts:* in this part, the learner must identify the elements and stages involved in the KM. All content is presented in English. *KM Models:* different models of KM are explained through videos. *Tools:* A series of Web 2.0 tools are presented that can be used at each stage of the KM.
Scenarios	Learning Community 1: - Spanish-speaking learning community, without previous knowledge about KM, and little knowledge of Web 2.0 tools - Limitations: Only Spanish language domain - AM: blended learning. Learning Community 2: - English-speaking learning community with basic knowledge on KM, and experience with Web 2.0 tools - Limitations: community with visual problems and Low-Bandwidth network connection. - AM: active learning

4. Define the Learning communities' instances (LC)
   4.1. Get AM type (see Table 2) using Algorithm 1
   4.2. Determine the limitations
   4.3. Determine the preferences

The first step is to determine the ecology of knowledge. For that is, it is required to define the "Communities" table, using the data in the "Students" and "Virtual Course" tables. In our case study, the information of these tables comes from databases that stores academic and contextual information of the students of the course of KM. Additionally, an eco-connectivist community detection algorithm, explained in [38], is applied to determine the communities. ARMAGAeco-c automatically calculates the number of ecosystems using the "elbow point" in the curve. For this case study, the elbow point is approximately equal to two (02), as is shown in Fig. 11.

In the second step, a clustering algorithm is applied to separate individuals according to their learning styles, physical limitations and contextual variables (this information is in the "Students" and "Virtual Course" tables). They are the learning communities. Fig. 12 shows the result of the algorithm, and each cluster is defined by a language, previous knowledge and domain Web 2.0 tools.

Once the number of communities is obtained, ARMAGEeco-c determines the representative of each community as the individual closest to the center of each group (denoted with the green crosses in Fig. 12). In our proposal, the group representative is the AM of knowledge ecology. Finally, ARMAGEeco-c defines the learning style of the AM like the learning style of the community, using the algorithm of [12]. This algorithm compares the educational characteristics of the AM, defined by their educational activities, strategies, and skills, with the types of learning style established by the Felder and Silverman model, to determine the style corresponding to each group (for more details, see [12]). With the learning style established by the Felder and Silverman model, ARMAGEeco-c knows the strategies, tools and evaluation instruments to be used in each community.

Fig. 12 shows two clusters that then become two learning communities. Although Fig. 12 shows 3 clusters, they are really two clusters for ARMAGEco. ARMAGEco-uses the concept of inertia to estimate the value of "k" in each iteration (which can be seen in the graph of the elbow point) for the k-means algorithm. In ARMAGAeco-c execution (first iterations), k-means algorithm (and thus the k calculation using inertia) is strongly influenced by the heterogeneity of the learning profiles (there is a high bias), so it is possible to observe non-globular groups. As the rules of MALO are applied, the bias decreases and the clusters become more homogeneous, giving rise to groups of greater globularity. In the specific case of the iteration shown in Fig. 12, the distant red dots (on the left) are treated by ARMAGAeco-c in the same way as the more concentrated red dots (on the right), under the premise that none of the apprentices labeled as red have mastery (or very low) on the subject of learning in question (knowledge management). ARMAGAeco-c is giving priority to adaptation by knowledge domain, rather than other characteristics, so that, in later iterations, many more globular groups can be secured.

In this way, for this case study, ARMAGAeco-c determined two (02) learning communities (ecosystems). The Learning Community 1 (LC1) is a Spanish-speaking community, without previous knowledge about KM, with very little knowledge about Web 2.0 tools.

The Learning Community 2 (LC2) has good English proficiency, basic knowledge of KM, and experience with Web 2.0 tools, but with visual limitations and low-bandwidth network connection.

In this case study, ARMAGAeco-c defines the AM of the Learning Community 1 (LC1), as a middle active, high sensory, middle visual, and high sequential Learning Style (LS), according to the algorithm of [14], which defines a learning paradigm of *blended learning* (b-learning). Similarly, the AM of the Learning Community 2 (LC2) is defined as middle reflexive, high intuitive, balanced verbal and middle global, which represents an *active learning paradigm*.

Table 4 shows the AMs of the LC1 and LC2 communities, and the

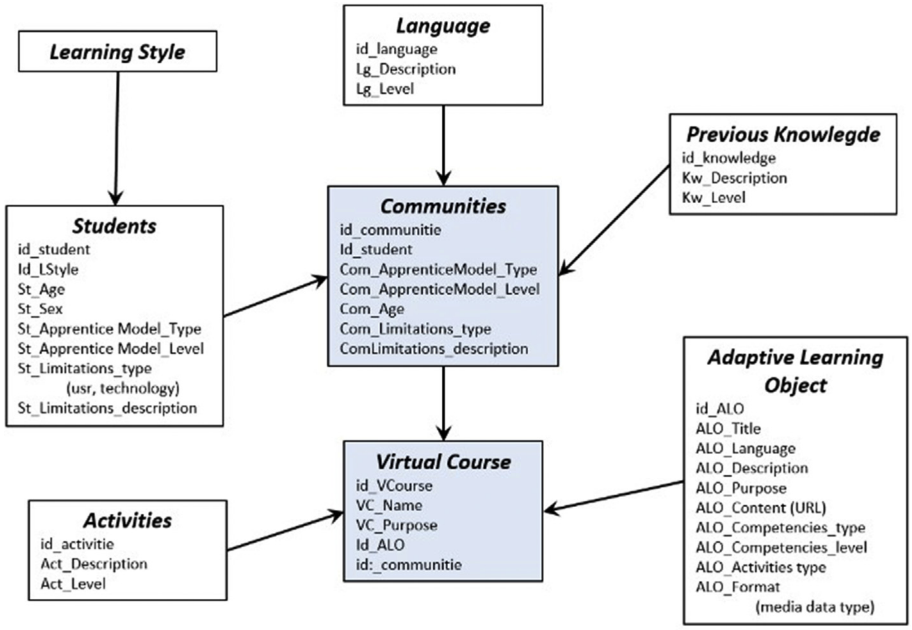

Fig. 10. Case Study: ARMAGAeco-c data model.

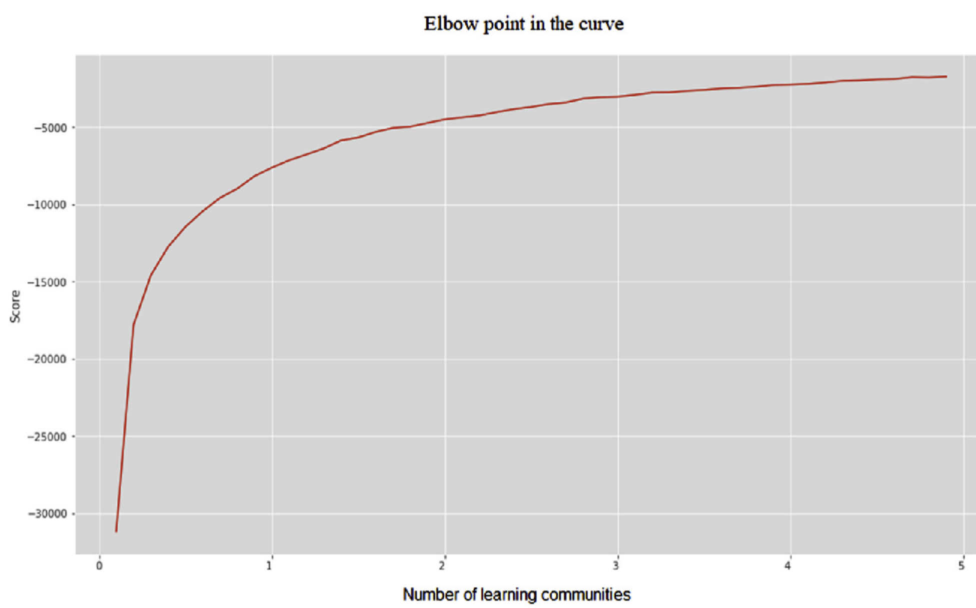

Fig. 11. Estimation of the number of LCs.

resources corresponding to strategies, tools and evaluation instruments, of the blended and active paradigms, according to [12]. The three numerical values associated with each AM are interpreted as the number of elements or resources used in the calculation in each dimension. For the blended AM, 17 types of strategies (STR), 13 types of tools (TOO) and 19 types of instruments (INS) were used. In the case of the active AM were used 19 STR, 11 TOO and 19 INS.

5.3. Determination of the adapted ALOs for each community

In the case study, ARMAGAeco-c is basically required to identify the characteristics of the learning communities, that is, the AM of each community. The information determined by ARMAGAeco-c is supplied to the ALO to make the corresponding adaptations. For that, ARMAGAeco-c uses the MALO services. As a result, we will have an ALO adapted to the AM and context of the learning community. The ARMAGAeco-c MALO integration is carried out by ARMAGAeco-c, according to the next procedure:

1. Iteratively apply the ALO rules on the LC (see Fig. 3)
2. Generate a new ALO metadata
3. Return the ALO adapted to the requirements of the LCs

In general, ARMAGAeco-c uses MALO as a service, to obtain the ALO for each LC, from the AM obtained in the previous step. That is, using the ALO rules on LCs and data of the “Communities” table, the instances of the “Adaptive Learning Object” table are generated. The Table 5 summarizes the ALO rules applied, and the Table 6 summarizes the final state of the ecology of knowledge for the KM course composed of 57 students.

Through the integration of ARMAGAeco-c and MALO, it was possible

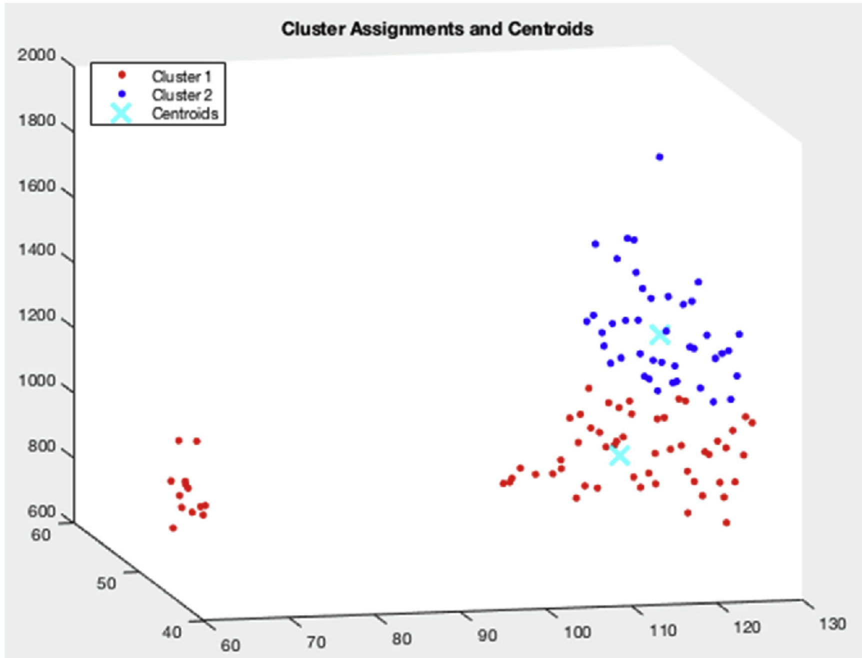

Fig. 12. Cluster assignments and centroids.

Table 4
Some examples of the STR, TOO and INS of the AMs of the case study.

AM	Resources according to paradigm Blended (17,13,19), Active (19,11,19)		
	STR	TOO	INS
LC1	Discussion group, expositions, workshops, laboratories, search, talks, questionnaires, narrative texts, portfolios, lectures, audio, video	Blog, email, forums, google docs, webquest, wikis, LMS, videoconferences	Self-evaluation, examination, project, dissertation, questionnaires, workshops
LC2	Group discussion, problem solving, simulations, projects, case method, problem-based learning, tutorials	Blog email, forums, google docs, webquest, wikis, games, videoconferences	Self-evaluation, examination, project, dissertation, questionnaires, workshops

to adapt the ALO to the requirements of the eco-connectivist communities. ARMAGAeco-c provided the ALO with information about the context and AM of the communities. ALOs generate the corresponding adaptations, according to the requirements of each community.

For the first scenario, the LO1 was modified to produce an ALO adapted to the needs of the Community 1, inserting iterative activities according to the Learning Style, and Web 2.0 Tools related to the KM. Additionally, the language of LO1 was translated into Spanish, because the community has low domain of the English.

For the second scenario, the LO1 was modified to produce an ALO adapted to the needs of Community 2, inserting reflexive activities according to the Learning Style of the eco-connectivist community. For its visual limitations, LO1 text is presented in the form of audio. Additionally, due to the technological limitations of the environment of this community, the resolution of the videos and audios contained in the LO1 is reduced.

Now, we test the utilization of the adapted LOs with respect to the utilization of the original LO, in each community, during the course, and particularly, during the realization of the practical activities defined in each LO.

Table 5
ALO rules applied for LC1 and LC2.

Rule Type	LC1	LC2
Conversion	The contents of LO1 are decomposed into 3 units: Concepts, KM Models and KM Tools.	
Semantic	Determine iterative activities	Determine reflexive activities
Decompose	LO2 into 2 units: iterative and reflexive activities. Extract from the Iterative Activities unit of LO2	
Composition	Insert into the unit KM models of LO1 the required iterative activities, extracted from LO2	
Semantic	Determine Web 2.0 tools related to KM	
Decompose	Decompose the LO3 in 2 units: tools for the KM and other tools. Extract from the KM tools unit of the LO3, the description of the required tools	
Presentation		The entire text of the LO1 is converted to audio. Decrease the video and audio resolution contained in the LO1
Composition	Are inserted in the KM Tools unit of LO1, the description of the required tools, extracted from LO3	
Transformation	Translate LO1 language into Spanish.	

In Table 7, we see that the adapted LO are used mainly by the communities for what have been adapted. The students prefer, and are more comfortable with them, to learn. It is very important, because the results show the usability of the adapted LOs with respect to the original one.

6. Discussion

For the comparison of our approach with previous works described in Section 2, we define a set of criteria shown in the Table 8.

With respect to the utilization of DA tasks, few proposals use them. Particularly, in our case, they are used in order to use graph mining and clustering techniques to discover learning communities and their characteristics. With respect to the learning communities, several works

Table 6
Ecology of knowledge (final state).

Table	Attribute	LC1	LC2
Communities	id_community	1	2
	Students	31	26
	Com_Apprendice_Model_Type	Iterative	Reflexive
	Com_Apprendice_Model_Level	Not specified	Not specified
	Com_Limitations	Only Spanish-speaking	Visual problems, low bandwidth
	Com_Preferences	Not specified	Not specified
Adaptative Learning Object	Id_ALO	1	2
	ALO_Title	KM	KM
	ALO_Language	Spanish	English
	ALO_Description		
	ALO_Purpose		
	ALO_Activities_Type	Iterative	Reflexive
	ALO_Format	Text and images	Narrative Text and audios

Table 7
Utilization of the LO by the LCi.

LO	Activities	LC1	LC2
Original LO	Formation	0	6
	Practices	0	3
LO1	Formation	31	0
	Practices	25	0
LO2	Formation	0	26
	Practices	0	24

support that, in our approach because is based on them the adaptive process of the LOs. For that, it is required discover them. With respect to the management of ALOs, the works in this area are different to the previous one (for the management of learning communities). Our work is the only that combines them, in order to adapt the ALOs to each learning community.

Almost every works can be used in a VLE and can use its information. At the level of the extensibility and flexibility, some of them are flexible to include new functionalities, and extensible. Our approach is extensible and flexible, because it can include new technologies (for example, linked data paradigm), and functionalities (for example, analyze the learning style of the students according to the learning actions of the student with the adapted ALO).

In general, our proposal integrates the middleware of ARMAGAeco-c that is reflexive and autonomous, with the MALO platform that incorporates adaptation properties to the ALOs, which results in a model with distributed adaptation capabilities that confers a greater flexibility and autonomy to the emerging learning processes.

7. Conclusions

In recent years, there has been an expansion in the implementation of collaborative VLEs, facilitated by the development of ICTs and the Internet. However, these environments require a constant improvement of the teaching-learning processes that occur in them, being the DA a powerful tool to help in that process.

As a result of this work, a DA task was developed based on graph mining techniques to characterize an AM that represents an eco-connectivist learning community. The AM was built based on the learning style of the individual's centrality of each community. In addition, ARMAGAeco-c was integrated with MALO, in order to meet the needs of the eco-connectivist learning communities, based on their AMs. ARMAGAeco-c supplies the ALOs with information about the context and the AM of the communities, and MALO, based on this information, generates the corresponding adaptations, according to the requirements of each community.

To make possible the integration between ARMAGAeco-c and MALO, it was required to define a series of services necessary to facilitate the routing and exchanging of messages between both platforms.

The integration of ARMAGAeco-c and MALO offers benefits, such as facilitating the incorporation of autonomic adaptation capabilities to the LOs used in the teaching-learning processes in eco-connectivist environments, according to the characteristics of each community (see Section 5, particularly Table 5). Also, the modularity, flexibility and extensibility of the proposed design confers the versatility of incorporating of new services, such as the management and analysis of the context; or other resources and learning management systems.

Our proposal is based on the autonomic computing paradigm, which can be included in any platform that supports connectivist learning processes based on those principles, such as ARMAGAeco, and its utilization is transparent to the specific computer knowledge that the user might have.

There are several future works, in order to give continuity to the proposal presented here. Among these, we must carry out a detailed description of the service architecture of ALO. Another future work is the incorporation of the notion of autonomous cycles of DA tasks [39, 43], which will allow the automation of the supervision processes on the ARMAGAeco-c-MOAA platform. Another interesting work is to discover the profile (pattern) of each learning community in an automated way. For example, by using data and semantic mining techniques over the members of each learning community, to determine their profiles. Finally, other future works are the development of a complete prototype of the ARMAGAeco-c-MOAA platform, in order to be used in real contexts; and the analysis of its educational impact, based on some statistical metrics about the improvement of the performance of the students. At this moment, there is a KM course that is using the ALOs proposed by ARMAGAeco-c-MOAA. A preliminary comparison will be carried out between the final score of the students in the KM course that use the ALOs proposed by ARMAGAeco-c-MOAA, with the final score of students that do not use them. With this initial comparison, we will be able to determine if the proposed ALOs by ARMAGAeco-c help the students to improve their final scores. Finally, another future interesting work is a quantitative comparison with other approaches, using benchmark datasets, to determine the performance and capabilities of our proposal.

Table 8
Comparison of our work with previous studies.

Criterium	Previous Studies													Our app
	[17]	[18]	[19]	[20]	[21]	[22]	[23]	[24]	[26]	[27]	[44]	[45]	[46]	
DA techniques for Knowledge extraction	N	N	N	N	N	N	N	N	Y	Y	Y	N	Y	Y
Management of Learning Communities	Y	Y	Y	Y	N	N	N	N	Y	Y	N	Y	Y	Y
Management of ALO	N	N	N	N	Y	Y	Y	Y	N	N	N	Y	N	Y
Adaptability to VLE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	N	Y
Design Flexibility	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	N	N	Y
Design Extensibility	Y	N	Y	Y	N	N	Y	N	N	N	N	N	N	Y

Declarations

Author contribution statement

Diego Mosquera, Carlos Guevara, Jose Aguilar: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Additional information

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