Autonomous Cycle of Data Analysis Tasks for Learning Processes

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Abstract. The data analysis has become a fundamental area for knowledge discovery from data extracted from different sources. In that sense, to develop mechanisms, strategies, methodologies that facilitate their use in different contexts, it has become an important need. In this paper, we propose an "Autonomic Cycle Of Data Analysis Tasks" for learning analytic (ACODAT) in the context of online learning environments, which defines a set of tasks of data analysis, whose objective is to improve the learning processes. Each data analysis task interacts with each other, and has different roles: observe the process, analyze and interpret what happens in it, or make decisions in order to improve the learning process. In this paper, we study the application of the autonomic cycle into the contexts of a smart classroom and a virtual learning platform.

Keywords: Data analysis task · Learning analytic · Smart classroom · Virtual learning environments

1 Introduction

In this paper, we propose an autonomous cycle of data analysis tasks (ACODAT), and its application in learning processes. ACODAT is composed by a set of tasks of data analysis to reach a goal for a given problem, where each task has a different role: observes the system to study, analyses it, makes decisions to improve it. In this way, there is an interaction and synergy between the tasks of data analysis, in order to generate the knowledge required, with the goal of improving the process under study. In our proposition, the autonomous cycle defines a closed loop of tasks of data analysis, which supervises constantly the process under study.

Learning Analytics (LA) is a discipline to optimize and adapt online learning environments to the needs of students; where strategies, resources and tools for teaching must be adapted to the learning styles and abilities of students. The utilization of the learning analytic in the context of learning environments is very

R. Valencia-García et al. (Eds.): CITI 2016, CCIS 658, pp. 187–202, 2016.
DOI: 10.1007/978-3-319-48024-4_15

useful, due to the large quantity of information about the learning processes generated in them, because it allows discovering knowledge to be used during the learning process, in order to improve it. In this paper, we propose an autonomous cycle of Learning Analytic, to organize the different types of tasks of Learning Analysis applied to these environments, in order to improve their learning processes. To do this, the different elements of an autonomous cycle in two different online learning environments will be analyzed, in a smart classroom and in an virtual learning environment (VLE). The obtained results are: the specification of the "autonomous cycle of data analysis tasks", which includes the analysis of the online platform to define the objective of the integration of an autonomous cycle in it, and the specification of the roles and types of tasks of data analysis.

2 State of the Art

In this section, we explain some recent works in LA. Buckingham et al. [7] have defined social learning analytics for the analysis of social aspects like tags, ratings and metadata, supplied by learners. These include content analytics, recommender systems and automated methods for examining, indexing and filtering online media assets in order to guide learners through the available resources. In general, social learning analytics allow building up a holistic picture of student progress. Baylon University is one of the university pioneers in higher educational analytics, and has created an Enrolment Predictive Model as a supportive tool for the student admissions [14]. They use a predictive model that analyzes various factors about the students. Most of these factors are about student's motivation, extracurricular activities, among others. Scores generated by the predictive model are considered by the admissions staff to identify those students most likely to be admitted. Purdue University has developed a prediction model which extracts data from the Course Management System (CMS) and predicts which students may be at a risk in academic work [6]. Using factor analysis and logistic regression mechanisms, the model predicts the student success in a given course.

Ferguson presents the challenges and opportunities of LA for both research and educational organizations, in three important respects [9]. The first is the challenge of implementing analytics that has pedagogical and ethical integrity, in a context where power and control over data is now of primary importance. The second challenge is that the educational landscape is extraordinarily turbulent at present. The last challenge is about the diversity of learning contexts, each of which has specific technical and pedagogical challenges.

In the Computers in Human Behavior Journal, Vol. 47 of 2015, it is presented a special issue about the current state of the art on LA. There is a predominance of research focused on course level analysis and visualization of student behaviors. Some of the papers in this issue explore how to gather data in educational virtual worlds. These data are later used to identify students and teachers behaviors, usage patterns, etc. Cruz-Benito et al. explore ways to define and configure student workgroups in Computer-Supported Collaborative Learning (CSCL) [8]. The authors propose a method for configuration of groups of learners based on the analysis of indicators from previous activities. Gomez-Aguilar et al. show how student interactions with their resources and peers may have an impact on their academic performance [10]. The empirical study unveils recurrent patterns in student behaviors, in terms of frequency of use and performance, which are consistent across different courses. In [11], it is defined the relation between social network analysis parameters and student outcomes, as well as between network parameters and global course performance. Their study also shows how the visualizations of social learning networks can help observing the visible and invisible interactions occurring in online distance education. [12] analyses the interactions in Virtual Learning Environments (VLE) to determine the potential relationship between learning platform interactions and two cross-curricular competences: teamwork and commitment. Munoz-Merino et al. propose a methodology for defining metrics that enable the calculation of the effectiveness of students when interacting with educational resources and activities in MOOCs [13]. They conclude that effectiveness is negatively correlated with the students behavioral patterns. In [17], they address the problem of how to define a predictive model of students performance that is both practical and understandable for users. The authors summarize different approaches used in LA, educational data mining and human-computer interaction, to explore the development of usable prediction models.

The goal of [15] is to evaluate the use of LA in Higher Education. In particular, that paper tries to reach the following objectives: to identify factors that influence the decision of an distance learning student to abandon their studies, and get the profile of susceptible students to abandon their university studies. Anupamar et al. predict the student overall performance based on decision tree approaches. They used internal assessments in the VLE and concluded that classification techniques can be applied on educational data for predicting the student outcome [5]. Finally, they argue that data mining brings a lot of advantages in learning institutions, so that these techniques can be applied to optimize the resource allocations according to the student learning capacity.

The previous works give an idea of the variety of research in LA. They show how the knowledge generated can be used to solve educational problems, support educational decision making, but at the same time, they pose new research questions. One of them is the goal of this work, How can be organized the LA tasks in order to reach strategic goals in educational institutions?

3 Eco-Connectivism as the Base of the Learning Process in the Online Learning Platform

The eco-connectivism is a framework to address and optimize Connectivist Learning Environments (CLE) assisted for computer technologies. For the eco connectivism, the system to manage/optimize is seen as an ecology of knowledge, whose constituent elements are Personal Learning Environments (PLE).

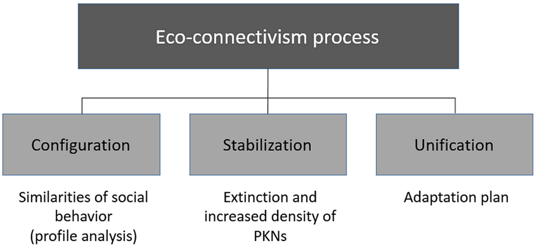


Fig. 1. Eco-connectivism phase in learning environment

The pedagogical model to manage/optimize is based on a process of ecological transformation that occurs in three phases. Figure 1 shows these phases. In the configuration phase it is established what is known as ecological survival threshold, a parameter set by an external entity (e.g. supervisor/teacher of the learning process), to specify the degree of diversity required in ecology. In previous work [1] we have defined this threshold of survival and its role within the optimization model. Also, in the configuration phase, a set of tasks is executed to establish the preliminary ecological distribution. In particular, a method of Web usage mining is executed, using records of the user navigation. Web usage mining allows for each learner, capture the fundamental elements of its PLE (consultation resources, resources reflection/production and Personal Knowledge Network (PKN)). Similarly, the Web usage mining provides the grouping necessary through interpretation of social learning patterns. Finally, the subsequent phases (stabilization and unification), are carried out according to the PKN information provided.

In the stabilization phase is established the stabilize parameters of the ecology. The ecological stability is achieved through a mechanism of migration of entities (PLEs) from non-apt ecosystem to apt ecosystems. An ecosystem is apt if it can survive. In [1], it is explained this phase.

In the unification phase, the parameterized information in the stabilization phase is used to propose an adaptive plan of the entities that have migrated, based on the information about the elements of the ecosystem where it has migrated. As explained in [1], the adaptive plan uses a model of collaborative filtering. Finally, the ecological unification is achieved when there are no entities in non-apt ecosystems.

This configuration, stabilization and unification processes, are performed cyclically and continuously throughout the learning process. An ecology of knowledge reaches the “climax” (interactivity, autonomy, interactivity and openness), once the fitness function (configuration phase) provides an ecology, in which the ability of all knowledge ecosystems equalize or exceed the threshold of ecological survival.

4 SaCI

SaCI (Salon de Clase Inteligente, for its acronym in Spanish) is a smart student-centered classroom, which supports the learning process, through of devices and applications, working together to form an intelligent environment in the context of educational learning (for more details of SaCI, see [16,18]). SaCI proposes two types of separate agent frameworks, one to represent the software components of SaCI and other to represent its hardware components [16]. SaCI generates a lot of information, this information has to be exploited to improve the performances of SaCI. ACODAT is used in this context, to exploit this large quantity of information generated in SaCI.

SaCI has several conversations, for example, the Online Tutoring Process (OTP), the Setting of the Environmental Variables, the Feedback Process, etc. In this work, we will focus on the Online Tutoring Process (OTP) conversation. The OTP uses hardware and software, necessary during a learning session. In the OTP conversation there are a lot of tasks, in the next Figure we can appreciate the process model of the OTP conversation in SaCI.

4.1 Model of Activities of Online Tutoring Process (OTP)

Figure 2 represents the process model of the OTP conversation, where we can see how the first activity is the initialization of the session by the students.

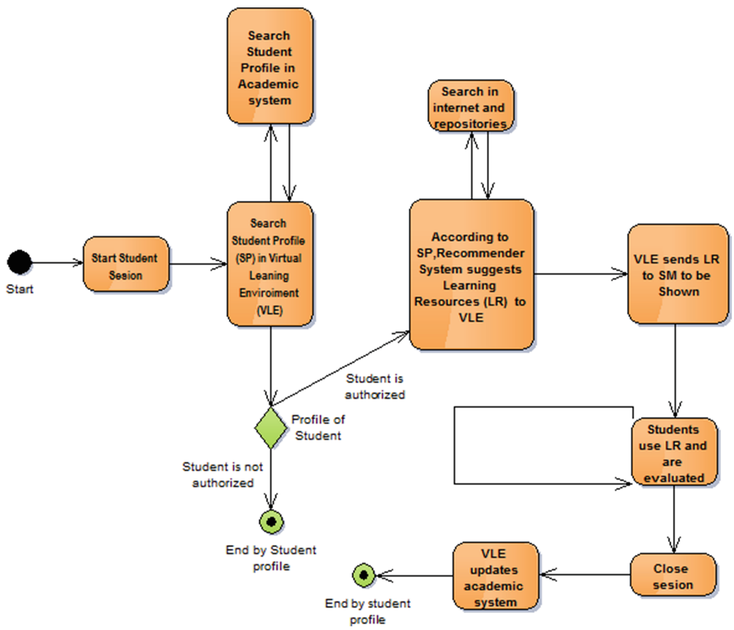


Fig. 2. OTP process model in SaCI

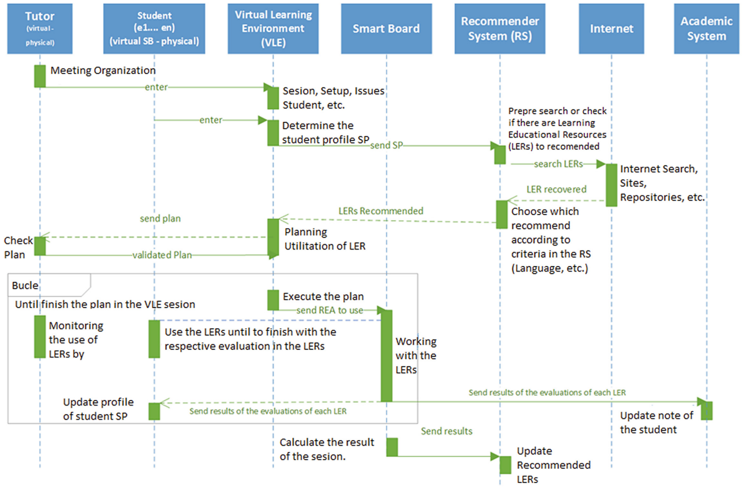


Fig. 3. OTP Conversation in SaCI (source [18])

That session is verified by the VLE, the VLE maintains communication with academic system, to obtain the Student Profile (SP). This SP is passed through a filter to decide if the SP is valid or not; if it is not valid then the process ends, otherwise it sends the profile to the recommender system (RS). The RS based on the SP makes a search in Internet of learning objects adequate to the SP of the student. This information is sent to the VLE (the information about the Learning Educational Resources (LERs) recommended sent is: title, website, etc.). The Smart Board (SM) executes the plan sent by the VLE, to work with the LERs that where sent by the recommender system to the VLE (The VLE sends the website of the LERs to the SM), where the learning objects are deployed for the students until the session finishes. In that point, the VLE sends the evaluations of the students to the academic system, the academic system updates its information, and the VLE closes the session. In Fig. 3, we can see the conversation OTP, in which we can appreciate the iteration with every agent of SaCI (the tutor, the student, the VLE, the SM, etc.). This conversation requires a continuous supervision to improve the teaching and learning process. In this work, we propose creating an autonomic cycle of learning analytical tasks, using data mining, to improve SaCI.

5 Computational Platform for an Educational Model Based on the Cloud Paradigm

This platform is based on an educational model, which exploits the new tools offered in the Internet. The proposed educational model focuses on the paradigm of learning by doing [3]. This model is based on a metaphor of clouds, which has been explained in detail in [3]. In general, this metaphor introduces the idea of "clouds effect", which makes their internal dynamics move with the wind (with the global and national events, industry, etc.), in order to allow the emergence of activities, generating a powerful educational synergy. This educational model is composed by three clouds.

5.1 Learning Cloud Paradigm

This cloud is related to the paradigms, strategies, forms of assessment and learning tools. Its aim is to provide the learning mechanisms necessary for the process of self-formation. It will guide the dynamics of self-training, establish ways of accrediting courses, collaborative work, among other things. The learning process provided to the students is adapted permanently, based on the characteristics of each student (learning profile of the student). Some characteristics are:

1. It is inspired on the paradigm of "learning by doing", which seeking the active participation of the students in a work, which can be artistic, technological, scientific, etc.
2. All forms of learning that promote learning by doing (active learning, agile learning, blended learning, etc.) are possible to use.
3. The collaborative work, sharing knowledge, multidisciplinary work, are issues that enrich the teaching process. The different strategies, tools, etc. must promote those aspects.
4. It requires many tools and applications from the Internet, to manage shared spaces and groups, to assign responsibilities, to monitor works/projects.

5.2 Knowledge Sources Cloud

This cloud is composed of connections to repositories in the Internet, which contain LERs and other educational digital materials. Its purpose is to enable greater access to knowledge available worldwide. Learning objects, online courses, e-books, etc., become fundamental sources of knowledge. The methodologies, tools and techniques of this cloud, must allow an access critical to the knowledge [3]. So, we are not talking about a passive, neutral, access to knowledge, but critical, seen from the process of self-formation according to the curriculum established, and the learning process dictated by the Learning Paradigm Cloud.

5.3 Self-formation Cloud

This cloud is composed of everything related to the student's education. The student self-formation consists of the building of the curriculum, which is composed of modules which are self-contained. In the curriculum, there is the option to various degrees, these depend on the number of credits reached and profile chosen by the student. The possible profiles of the students are inspired in the curriculum defined by the IEEE/ACM. Paths for these profiles initially are proposed, but as the student is autonomous, he/she guides his/her own process of self-education.

5.4 Architecture

The design of the web platform is based on SOA [4]. The system functionality is described in Fig. 4, which is composed of three layers; each one manages one of the cloud concepts (the details of this architecture are given in [4]). The first layer manages everything regarding the student, teacher and curriculum. This layer has the different services they need, both the student and the teacher, to manage the process of self-education, such as student registration services, queries to the curriculum, etc. The second layer manages the search of virtual objects, both learning objects and digital contents, and offering the student the proper learning resources to their needs, according to their educational profile and position in the curriculum. The last layer manages the learning paradigms, in order to specify the tools, types of evaluations and educational activities appropriate for the student's learning style. The implementation of each layer is made as web services, and clients to these services. Each layer is composed with an ontology that works with the web services to manage information in order to discover knowledge and use this information to interact with the other layers. Each layer has its own ontologies, whose instances represent the stored and inferred information. That is called in Fig. 4 Extended Data Base, which also has the ability to support processes of reasoning.

This platform involves three important aspects: digital resources, the learning style, and the curriculum graph. The main objective is to give customized resources to the user for a better experience. Figure 5 shows the learning process. The first step is the student login, where the user can select the module to attend, which belongs to an initial study profile related to the curriculum graph; once the user choose the module, each topic for each module has resources customized for

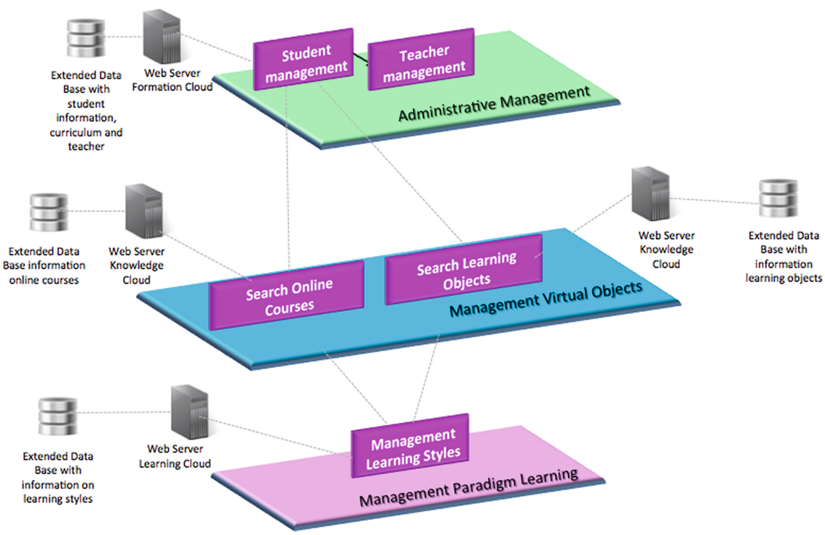


Fig. 4. General architecture (source [4])

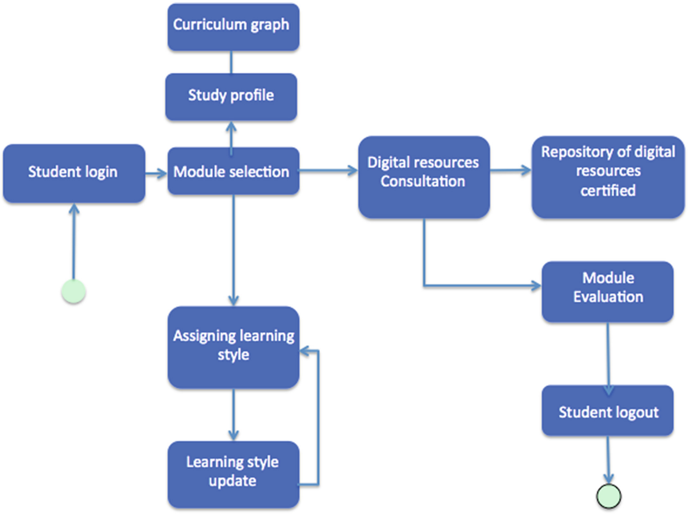


Fig. 5. Learning process

the student, as a result of a learning paradigm that is in continuous assessment. The digital resources are ready to be consulted, for this, the connections are established with them (with the repositories where they are stored). The evaluation process is the way to validate the learning process, and if necessary, to update the learning style. This method of allocating a specific paradigm related to student characteristics, ensures optimization of the learning process on the web platform.

6 Autonomic Cycles in Each Context

We can build an autonomic cycle to improve some specific aspects of the learning process, with the main objectives of customizing the learning process to the student. This will result in adaptations of the platforms.

In order to make an autonomic cycle to optimize the learning process, we will divide the tasks of analysis of data in three types, which are observation, analysis and decision-making.

6.1 Autonomic Cycles for SaCI

Figure 6 shows a general autonomic cycle of tasks of learning analytical, with the objective to update the learning process for the students in SaCI.

This autonomic cycle of tasks of learning analytical can be instanced to reach the specific objective of: Avoid school dropouts. The specific tasks of this autonomous cycle are defined as follows (see Tables 1, 2 and 3):

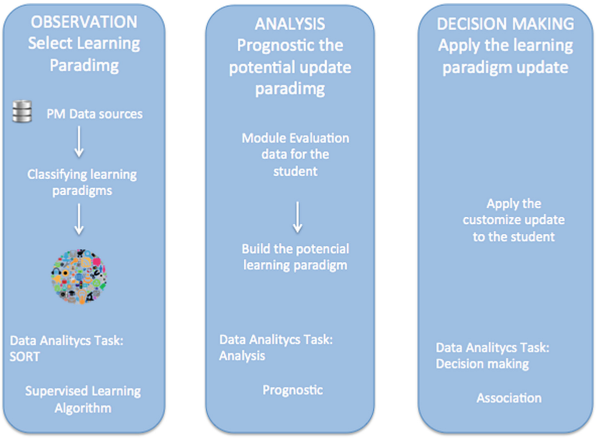


Fig. 6. Objective of the autonomic cycle and corresponding tasks for SaCI

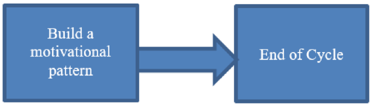
Table 1. Classify the students as deserters or not

Task number	1
Task name	Classify the students in deserters and not deserters
Description	Classifies the general population in groups, according to whether or not deserters
Data source	Databases of SaCI
Task type of data analytics	Classification
Tasks that is related	Classify the students in deserters and no deserters → Elaborate a desertor profile
Task type in the cycle	Monitoring

Table 2. Prognostic the potential group of deserters

Task number	2
Task name	Prognostic the potential group of deserters
Description	Prognostic the potential group of deserters according with the performance of the students
Data source	Databases of SaCI
Task type of data analytics	Prognostic
Tasks that is related	Prognostic the potential group of deserters → Build a motivacional pattern
Task type in the cycle	Analysis

Table 3. Build a motivational pattern

Task number	3
Task name	Build a motivational pattern
Description	Apply motivational techniques for every student according with the student profile
Data source	Databases of SaCI
Task type of data analytics	Association
Tasks that is related	
Task type in the cycle	Execution

6.2 Autonomic Cycles for the Educational Model Based on the Cloud Paradigm

As part of the automation process it is been determined work flows in each layer of platform of educational processes. One of the processes that are involved directly with the student lies in the selection of educational profile that the user makes initially at the moment to do the register on the platform. Selecting this profile may not be successful for the student; it is for this reason that the student tasks suggest the more tailored to their needs and according to a study of their profile information, is proposed. This objective is shown in the Fig. 7.

In order to specify the tasks related to the autonomic cycle, a division in three important aspects is made (see Tables 4, 5 and 6).

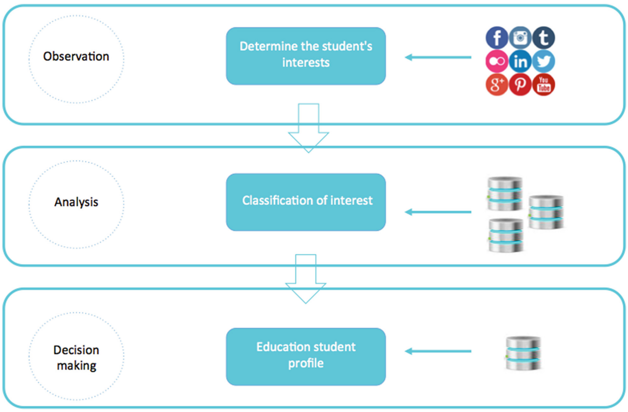


Fig. 7. Autonomic cycle for selection of educational profile

Table 4. Classify the students interest, needs and information

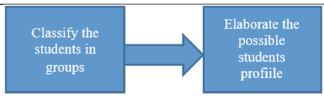
Task number	1
Task name	Classify the students interest
Description	Classifies the general population in groups, according to the needs and interest
Data source	Databases of web platform
Task type of data analytics	Classification
Tasks that is related	
Task type in the cycle	Monitoring

Table 5. Prognostic the potential educational profile

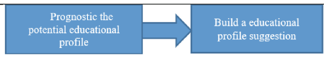
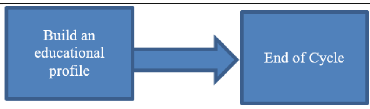
Task number	2
Task name	Prognostic the potential educational profile
Description	Prognostic the potential educational profile according with the performance of the student
Data source	Databases of web platform
Task type of data analytics	Prognostic
Tasks that is related	
Task type in the cycle	Analysis

Table 6. Build an educational profile suggestion

Task number	3
Task name	Build an educational profile suggestion
Description	Apply inferred techniques for the information of every student
Data source	Databases of web platform
Task type of data analytics	Association
Tasks that is related	
Task type in the cycle	Execution

6.3 Autonomic Cycles Based on Eco-Connectivism Paradigm for Each Platform

In a previous work we have specified ARMAGAeco-c [1], a reflective middleware that provides a model of autonomic computing to manage and optimize a learning process using the eco-connectivism paradigm. ARMAGAeco-c describes two levels of reflection, each with an autonomic loop task. The first makes introspection over the PLE of apprentices. The second makes introspection over the knowledge ecology distribution emerging from the process. The intersection of the first level of reflection is carried out through eco- connectivist plan adaptation. The intersection of the second level of reflection is performed with analytical learning procedures and analytical social learning.

Additionally, we have defined an Independent Reflection Model (IRM), based on a dynamic Multi-Agent System (MAS). IRM can generate instances of agents adapted to the level of reflection of ARMAGAeco-c. Figure 8 shows the architecture of IRM. Figure 9 shows the distribution of the agents in the middleware, whose agents allow the implementation of the loop MAPE+K proposed in [1].

Through the autonomic loop of ARMAGAeco-c, it is possible to enrich a process of conventional learning (e.g. constructivist model, social constructive or immersive), in which qualitative and quantitative knowledge is generated, combined with the connective knowledge paradigm. The latter allows exploring and exploiting the social dynamics of the learning environment, with the aim of establishing and evaluating knowledge networks (networks learning) that emerge during the process.

ARMAGAeco-c can be integrated into learning environments according to the methodological aspects proposed in [1]. The intent of this article is to show how ARMAGAeco-c can be used for two purposes:

1. Enrich other autonomous systems with the paradigm of connective knowledge. This includes the incorporation of the social learning analytics tasks.
2. Guide and optimize the learning processes in environments that incorporate the use of social networking and collaboration tools.

In particular, we consider the implementation of the autonomic loops for SaCI and for the Computational Platform for the Educational Model based on the

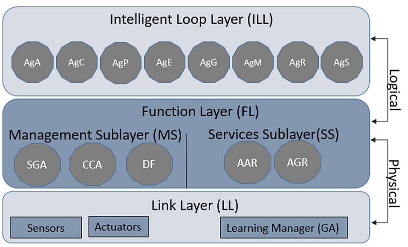


Fig. 8. IRM-architecture

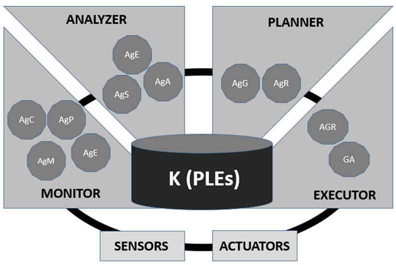


Fig. 9. IRM-ARMAGA relationship

Cloud Paradigm, in order to influence the decisions made by the agents (in the case of SaCI) and ontologies (in the other case) during the learning process. In the particular case of SaCI, a new restriction must be satisfied: to achieve an ecology of knowledge based on four fundamental criteria: interactivity, autonomy, diversity and openness.

In both platforms, MRI-ARGAMAeco-c parameterizes the connective knowledge. For SaCI, it comes from an external source which extends the conceptual minable view, with performance parameters related to collaborative learning. It also provides a strategy for organizing working groups, which optimizes student performance in the learning process. This latter is related to the appearance of diversity, and is controlled by the threshold ecological survival.

In the other case, it will extend the management learning paradigms layer. On the one hand, with the connective knowledge, MRI-ARGAMAeco-c updates the student's learning style. This indirectly influences the other layers (management of virtual objects and administrative management), for the proper selection of digital resources during the learning process. Finally, as for the SaCI, ARMAGAeco allows communities to establish a model to characterize and optimize the social relationships of learning.

7 Conclusion

In recent years has grown the idea of using large-scale educational data, to transform practice in education. LA has appeared as a domain which tries to define useful applications with these data, in order to improve the learning processes. In this paper, we propose an autonomous cycle of LA. The utilization of this knowledge in real time is an enormous challenge for learning platforms.

We have proposed a LA autonomic closed loop, which allows an effective use of the results of the LA tasks. We test our approach in two contexts: SaCI, and a Computational Platform for the Educational Model based on the Cloud Paradigm. LA tasks allow an autonomic behavior, in order to manage a diversity of situations, educational materials, students styles, etc. In this way, the educational platform can carry out a correct adaptation of its components. The introduction of ACODAT improves the learning process, utilizing a large amount of knowledge effectively, based on the understanding and covering the actual needs of the students, etc. Our architecture can use data mining and semantic mining techniques, and can be based on organizational databases (data warehouse) or big data. ACODAT focuses on providing capabilities to discover the students with difficulties of learning, to define the guidance to the students to improve their learning capacities, among other things.

The eco-connectivism paradigm introduces the social learning process. Particularly, this paradigm allows including social learning analysis tasks, to use the knowledge in Internet. Future works must implement these cycles in real situations, for real problems.

Acknowledgement. Dr. Aguilar has been partially supported by the Prometeo Project of the Ministry of Higher Education, Science, Technology and Innovation (SENESCYT) of the Republic of Ecuador.

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