IDC Learning: Artificial Neural Networks … and our LMS gets "intelligent"!

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The Asian Conference on Society, Education and Technology 2014
Official Conference Proceedings

Abstract

The wide spread of online courses, both in academic and business field, helps reducing the costs of training, but has negative effects. The indiscriminate and redundant delivery of digital contents and questionnaires, together with standardized rigid tutoring actions often implies a deterioration of the quality of the courses and a growing disaffection of students towards e-learning.

IDC Learning shows that the integration of Artificial Intelligence can mitigate the sense of "artificiality" and automatism characterizing the standard procedures of an LMS. *IDC Learning* is an innovative software module capable of directly "talking" to Moodle, the Open Source LMS. Its main objective consists in taking control of Moodle core functions in order to make its e-learning courses management methods more "intelligent". *IDC Learning* is entirely based on Artificial Neural Networks - Multi-Layer Perceptron and Kohonen Maps – that were trained through supervised and unsupervised learning algorithms in order to: (a) identify the different students' profiles and real-time adapt evaluation tests; (b) set up customized learning paths; and (c) guide the teaching staff to specific and sustainable tutoring actions. The module consists of three logic function blocks: (1) *I-Assessment* allows classifying the participants through assessment and measurement tools of observable indicators; (2) *D-Pathmaker* customizes content delivery depending on *I-Assessment* outputs; and (3) *C-Coaching* supports the tutoring activities and suggests possible corrective actions according to the students' performances.

The first results of the experiments with *IDC Learning* in the field of adult education highlight an increase of the effectiveness level and perceived quality by students.

Keywords: Artificial Neural Networks, LMS, evaluation, customized path, tutoring, quality, e-learning

1. Introduction: some clichés on e-learning

In recent years, many education experts, business leaders, union organizers and academics have held forth and predicted e-learning imminent end. They say that this method of content delivery and training does not guarantee an effective learning, does not promote the acquisition of complex skills and alters the actual meaning of "training" in any context.

Some e-learning detractors also claim that studying on digital contents in a digital context, like an LMS, causes a sort of technological alienation and coercive solipsism. Online the student loses contact with the social dimension of education, usually attributed to the experience that he/she can live during a “classic” face-to-face lesson. Here, in a real classroom, each student comes into physical contact with other students, teachers and tutors. This physical interaction is presumed to foster learning and make the experience more meaningful, differently from the experience of an e-learning course that is considered something more similar to a boring and obvious video game.

Moreover, many e-learning critics believe that companies and public organizations mainly and only use this form of learning for economic reasons. They say that e-learning is the cheapest solution to organize training programmes and refresher courses, especially when the target is composed of large number of students. Therefore, e-learning is not an adequate methodological solution to train people, but only an easy way out to convey and share much information with many people at the same time, with little money.

Finally, many e-learning opponents say that the structure of an online course is too much rigid, because it comes from a simple and structured design activity that is not suited to the different students’ profiles. An LMS learning environment is “cold”, standardized, characterized by banal and linear automatic activities. According to them, e-learning causes a redundant, muddled and “noisy” learning process. In other words, an e-learning course is not “intelligent” and cannot create a learning experience that answers the learners’ specific and individual needs, that is able to value their differences and effectively support them in case of difficulty. This lack of "intelligence" makes e-learning an artificial, almost inhuman and dehumanizing tool.

2. LMS Platforms: these cold, artificial and inhuman deserts

Are these criticisms only clichés? Or are they really based on rigorous issues and solid foundations?

Maybe they are banal clichés, caused by a lack of awareness of the potential of e-learning, a certain amount of digital illiteracy and a strong aversion to change. But like all clichés, these statements contain something true.

First. It is undeniable that many e-learning courses do not care about any individual difference, but deliver the same contents and learning resources to all students, indiscriminately. This often depends (a) on the lack of initial assessment tools that are capable to profile students in an analytical way, (b) on the absence of criteria and rules to create customized training programmes, and (c) on instructional design methods that follow linear, sequential and standardized patterns. Moreover, it also depends on an underdeveloped use of assessment tools.

Second. We must admit that in an LMS the automatic tools and procedures of online tutoring to support educational activities become less and less effective as the number of users increases. Tutoring actions often turn into alert or communication systems that are too simple, schematic (e.g. automatic reminders for a learning object launch, students' delay in accessing the platform or completing activities), and irrelevant from a methodological point of view. This linear automatism is even more evident in blended learning courses with activities that require online interactions with other human beings (e.g. virtual classroom, chat, social environments, etc.). In these cases, the difference between the phases managed by human teachers and those entirely managed by computer systems is huge: after attending a virtual classroom with a "human" teacher, the student feels a cold inhumanity and a sad loneliness among the LMS buttons and screens.

Finally, in many e-learning courses, the student immediately understands that behind LMS glittering graphic interfaces, Flash or HTML5 animations, links and three-dimensional buttons, solitary forums, colorful online questionnaires, standardized final reports with his/her name, there is only and exclusively a machine. A stupid machine, without any kind of intelligence, unable to understand the importance of a learning experience. Therefore, the student understands to be inside an artificial container that is so far from his/her sensitivity and human emotions.

All these things produce a decline in the quality of the learning experience. In some cases, they undermine the effectiveness of online courses, do not guarantee a meaningful learning, and cause the students' widespread disaffection towards training. In sum, all these things involuntarily feed all the clichés against e-learning.

3. Our idea of LMS

IDC Learning (Intelligent Dynamic Customized Learning) shows that the integration of Artificial Intelligence (AI) can mitigate this sense of "artificiality" and automatism characterizing LMS standard procedures. *IDC Learning* is an innovative software module capable of directly "talking" to Moodle, the Open Source LMS. Its main objective consists in taking control of Moodle core functions in order to make its e-learning courses management methods more "intelligent".

Its innovative features guarantee positive results in terms of effectiveness, efficiency and perceived quality.

IDC Learning can completely customize the initial test according to the student's specific features and his/her level of knowledge. In fact, as far as the student answers the questions, *IDC Learning* collects information on his/her knowledge system and, based on the picture that it starts to configure, decides how to go on. It can stop the test without administering any more questions than necessary, if the information is enough to depict a complete picture of the student's knowledge or it can choose to gather some more information on other important areas of content, always identifying the right question at the right time. In both cases, *IDC Learning* aims at collecting the best information to effectively and real time photograph the student's knowledge system, by a limited and reduced number of questions.

This representation is nonlinear, reticular and complex, like in real life. By such a sophisticated picture, *IDC Learning* is capable to identify the student's actual gaps and then choose the best learning resources in order to create the most suitable and effective training path for him/her, like a human teacher or tutor would do. The creation of this training path happens in real time, thanks to the integration of computational tools borrowed from Artificial Intelligence.

Through these "intelligent" algorithms, *IDC Learning* can immediately grasp all the interconnections among the different knowledge systems and then can easily represent their complexity. Its capacity of effectively representing and managing complex systems guarantees an interesting increase in the level of transparency, methodological coherence and empirical adequacy of the results in all the different measurement phases. Something very distant from a cold and mechanical linear logic.

Hence, these main features guarantee the effectiveness of the entire training process, but also its efficiency. In effect, *IDC Learning* succeeds in photographing the student's knowledge/competence system by using a limited and reduced number of questions. This capacity positively affects the test duration, in particular with tests with large number of questions on widespread areas of knowledge and competence. Thanks to the use of AI, this information is gathered and used in order to let the network system learn endlessly. In fact, after the initial effort needed to design the networks, the system continues to live on his own, and to "grow" thanks to the collected data. Moreover, by simulating a human evaluator (in the phase of initial measurement) and a human tutor (in the phase of training programmes delivery), it succeeds in reducing human interventions, but at the same time always guarantees a high level of quality, even with large number of students.

Last, but not least, the students perceive *IDC Learning* as an "intelligent" presence that can help them identify what gaps in knowledge or competence they have, and which is the best, most rapid and effective way to fill them. Once in this system, the student can really "feel" the presence of *IDC Learning* and understand that it does not limit its investigation to a mere serial collection of single observations, but considers the relational structure of his/her answers, like a teacher or tutor would do in real life. This capacity makes the system different from the other ones on the market (based on linear structures that underestimate the complexity of the student knowledge and competence system) and increase the student's confidence in it. Its capacity to create customized learning programmes and guarantee customized support during the delivery complete the positive framework.

4. Artificial Neural Networks … and our LMS gets "intelligent"!

What is the secret that allows our LMS to get "intelligent"?

IDC Learning is entirely based on Artificial Neural Networks (ANN) - Multi-Layer Perceptron (MLP) and Kohonen Maps – trained through supervised and unsupervised learning algorithms.

An ANN is a hardware and/or software system for information processing that reproduces some functions of the biological neural networks. It consists of "nodes" or "artificial neurons" of input and output, i.e. the calculation units for signal transmission, interconnected through weights.

A Multilayer Perceptron (MLP) is the composition of two or more basic artificial networks. In addition to a layer of input neurons and a layer of output neurons, an MLP has one or more layers of hidden neurons, too. In this network, each neuron of each layer is connected to all the neurons of the following layer. In general, the value of the output neurons depends on the values of input, the values of the synaptic weights, and the kind of activation function used. These mathematical models can be used to solve complex problems because they enjoy the fundamental property of "learning". An ANN "learns" the underlying mechanisms of a phenomenon from the empirical data relating to its history. In fact, the training of an ANN is based on specific algorithms that imitate the research activity by trial and error through the introduction of a large number of examples and desired outputs describing the behavior of the phenomenon under consideration. Thanks to this "supervised learning" characterized by the gradual adjustment of the weights of the synaptic connections, we can reach the so-called "convergence", that allows the ANN to produce output values close to the desired ones. This kind of network can be considered like a "black box" that can generate complexity.

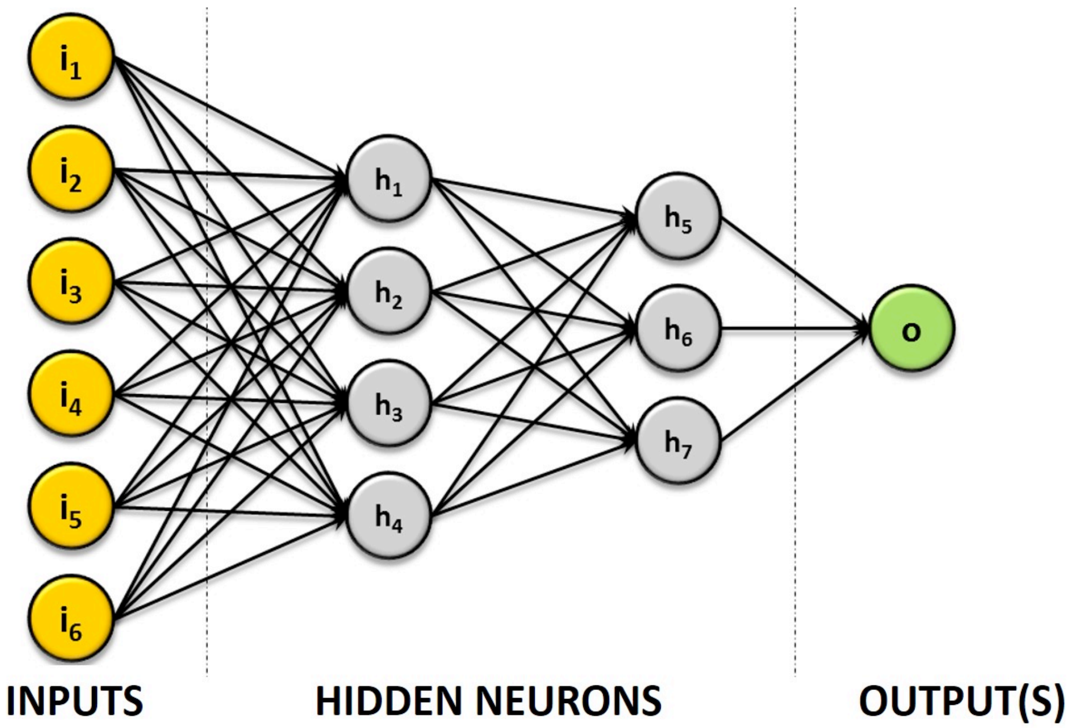

Figure 1. A Multi-Layer Perceptron

Kohonen maps (also called SOM, Self-Organizing Maps) are artificial neural networks trained by unsupervised learning that simulate some of the functions of the cerebral cortex in processing and clustering visual information. They are mathematical models than can be implemented in software applications and are able to classify large amounts of data through an adaptive transformation and compression of multidimensional input signals. Through Kohonen maps we can capture the structural logic and any inherent property of the entry patterns, without using any predefined criteria (expected output), and project the results of this processing onto an ideal screen represented by a topological map with 1, 2, 3, or *n* dimensions. We can train these neural networks through competitive algorithms: output neurons are "winners" (active) in function of the smallest Euclidean distance from each input pattern. This progressively produces a restructuring (auto-reorganization) of the synaptic weights through an optimal segmentation of the data structure into a specific amount of activation "bubbles" or clusters.

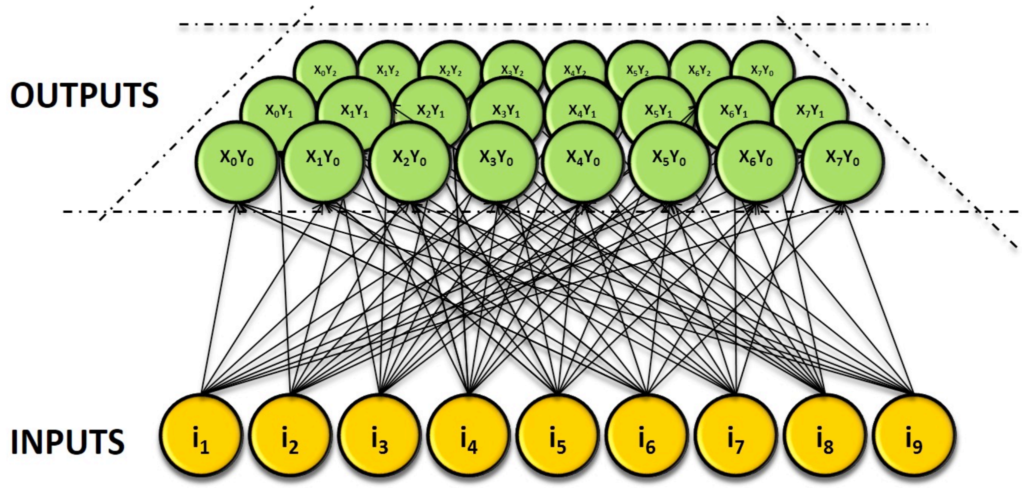

Figure 2. A Kohonen Map

5. *IDC Learning* logical and functional architecture

IDC Learning module consists of three functional blocks: (1) *I-Assessment*, (2) *D-Pathmaker*, and (3) *C-Coaching*.

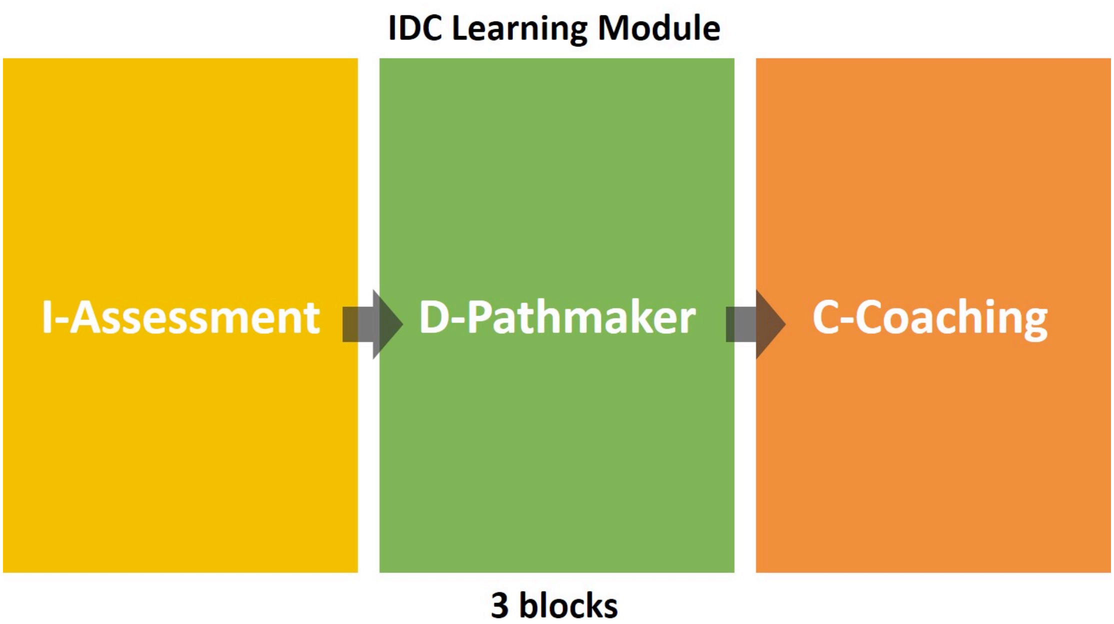

Figure 3. *IDC Learning* Module

5.1. *I-Assessment*

(1) *I-Assessment* allows to classify the participants through assessment and measurement tools of observable indicators.
In order to simulate a human evaluator, it needs to "know" (and then have a representation of) the topic to be tested and to adapt the questionnaire to the student's performance. According to this representation, and to the student's answer, it can reach a complete description of his/her knowledge, without administering all the questions, but choosing how and if to go on with the test. Then, it needs a copy, a complete and detailed picture of the knowledge system, represented by an orbital map that clearly identifies the different topics and subtopics to be tested. In this orbital map, each topic and subtopic is related to learning objectives that are identified and described in terms of observable indicators and complexity levels. According to these two features, the best and most effective assessment tools to check student's knowledge, together with the different learning resources needed to reach the learning objectives, are selected, designed and organized in structured clusters.

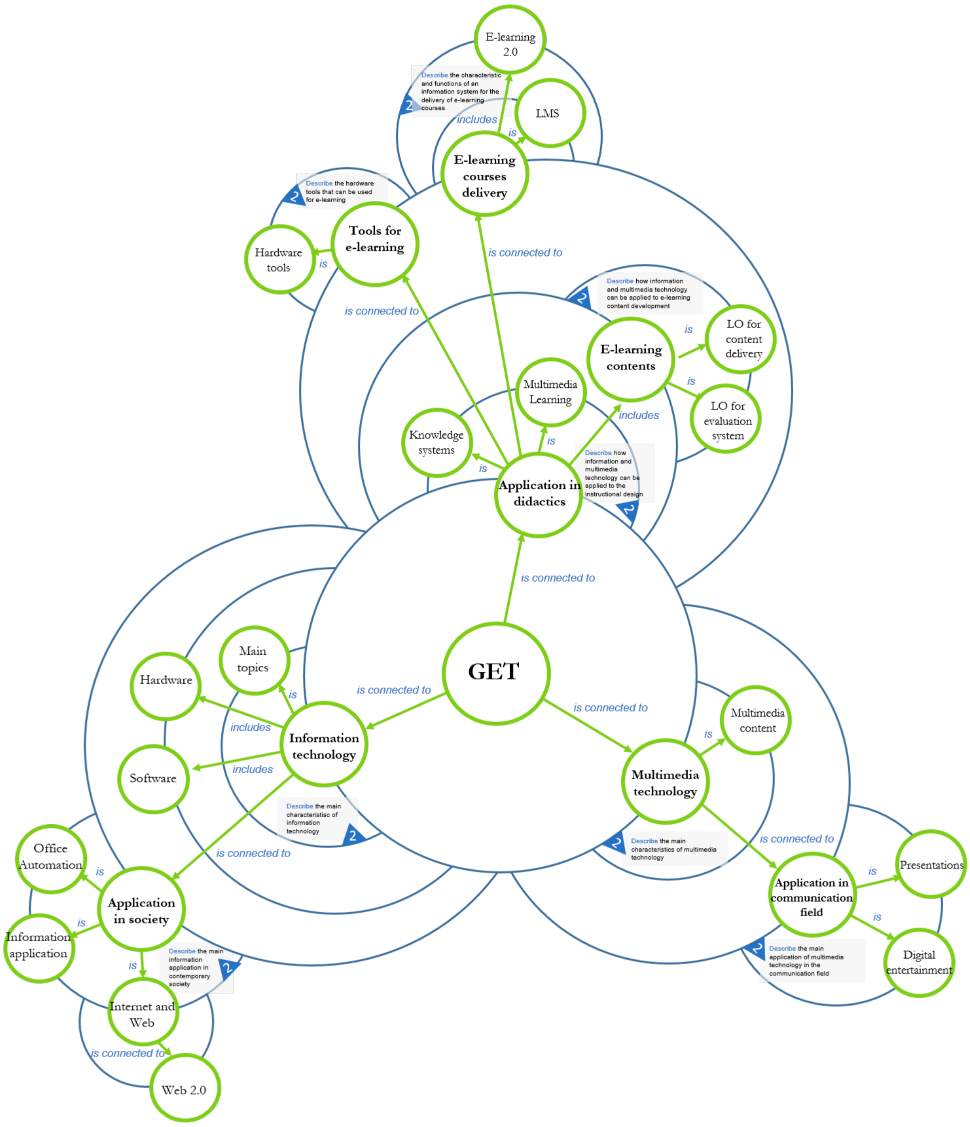

Figure 4. An example of "Orbital Map"

Now, this system needs a brain. This brain consists in an MLP that makes the test engine intelligent and effectively simulates a human evaluator. It starts with a random question, and then, according to the student's answer, decides how to go on. As far as the items are administered, the MLP collects information on the student's level of knowledge.

From the collected data, *I-Assessment* can gather two important kinds of information: 1) a clear picture of the entire orbital map of the student's knowledge and competences (processed by the MLP), and 2) the identification of the student's profile.

The analysis of the user's features and the assignment of a specific profile is based on the functions of cluster analysis of a Kohonen neural map. The topology of the profiles results from a process of unsupervised learning of the Kohonen map through the input of patterns included in an archive of previously profiled users. In the database made by the system for the neural network learning, each user is associated with a record whose fields correspond to the descriptive variables of each single user: age, gender, level of education, professional qualifications, role, digital skills, and detailed picture of the skills related to the topic of the course. Thanks to this phase of learning from real data, the Kohonen map processes the different records of the database, self-organizes through sophisticated learning algorithms (that is why this kind of map is also known as a SOM, i.e. Self-organizing Map) and, finally, defines a set of clusters corresponding to specific users' profiles. The cluster analysis activity allows to compress the amount of attributes of the vector that describes each user, by identifying sub-symbolic and geometric reticular correlations among the different variables.

Certainly, the module manager can restart the map learning process whenever he/she considers it appropriate. Alternatively, he/she can decide to let the network continue learning from empirical data, and guarantee the highest level of system flexibility and adaptability.

Thanks to learning, the group of functions managed by the Kohonen map in *I-Assessment* allows the system to "recognize" new users and to classify them according to the (static) descriptive variables and the results of the intelligent assessment. This profiling is crucial for the activities managed by the other two *IDC Learning* sub-modules and effectively simulates the complex activities managed by any teacher in order to check the students' initial knowledge and individual peculiarities. In this way, it succeeds in guiding the following learning activities in an "intelligent" way.

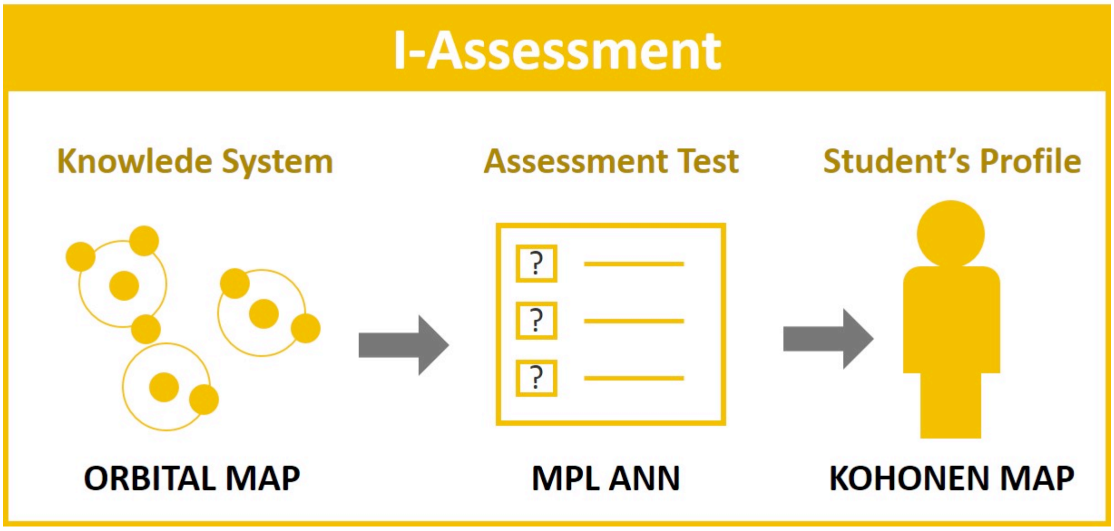

Figure 5. I-Assessment

5.2. *D-Pathmaker*

(2) *D-Pathmaker* customizes content delivery depending on *I-Assessment* outputs.
The reticular description made through the orbital map allows to manage contents, objectives, items and learning resources in such an effective way that also the content delivery is highly customized according to the student's performance in the initial evaluation phase. After finishing the test, *D-Pathmaker* receives a detailed picture of the student from *I-Assessment* and check his/her gaps. According to this picture, thanks to the specular correspondence of the items with the learning objectives, it succeeds in setting up customized learning paths that help the student to reach the learning objectives where he/she demonstrated gaps.

The information related to the user's profile - generated by the Kohonen map in *I-Assessment* – allows to calibrate and configure the learning path for each participant in a very detailed way. *D-Pathmaker* integrates the results of the initial assessment on contents with the additional data about the student's features expressed through the initial cluster analysis.

Moreover, the profiling process of each learner can also go on and be constantly updated according to the evolution of his/her performance during the course, in training or online evaluation activities. In this way, the system can simulate the tasks of a "human" teacher in an "intelligent" way and can continually monitor the student's activities (e.g. participation in training activities, level of interaction during the lessons, results on exercises, etc.) in order to better calibrate his/her teaching strategies in a flexible and adaptive way.

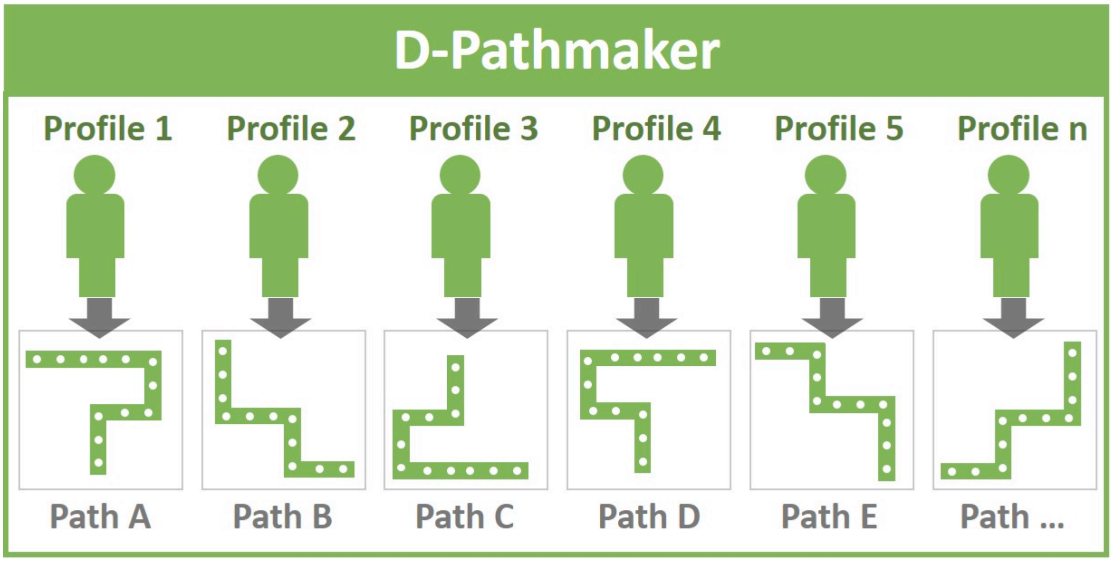

Figure 6. *D-Pathmaker*

5.3. *C-Coaching*

(3) *C-Coaching* supports the tutoring activities and suggests possible corrective actions according to the students' performances. In other words, it guides the teaching staff to specific and sustainable tutoring actions. How does it work?

First of all, this block extracts students' data coming from the core functions of LMS tracking: it connects itself to a database containing information on the course and extracts the meaningful values for the tutoring activities (e.g. fruition percentages, connection times, results of assessment, etc). The system administrator can define the connections agenda (in relation to the various steps of the course), as well as the rhythms of data upgrading and connection to the database (e.g. daily, every 48h, once a week, etc.).

Secondly, it elaborates these data together with those coming from *I-Assessment* and *D-Pathmaker* through an ANN that elaborates an estimate of the non-effectiveness risk in relation to the whole population and to each single student profile. The module can be trained and continuously upgraded through insertion of new data or direct intervention of human experts.

At the end, *C-Coaching* compares the output of the ANN with control variables and, if there are non-coherent values (e.g. high probability of non-effectiveness risk), it produces or suggests a series of activities to the various actors involved in the training process. E.g. it manages alerts to remember students to participate to a specific activity (especially, when low percentage of presences has been recorded); it sends assessment results to didactic administrators or online tutors, with suggestions on possible actions; it defines customized supporting activities for students based on their fruition data and test results. The module has also a function to plan the threshold values for the control of the course (that correspond to the output variables of the ANN); a function to define tutoring actions and the conditions to activate their interventions (e.g. passing a critical threshold, alignment of two or more critical situations, etc.); a report on the evolution of the course and on the monitoring of activities of *C-Coaching*; a database for the historical filing of data elaborated by the ANN.

Thanks to this structure, *C-Coaching* succeeds in guaranteeing a customized support to each student and helps him/her reaching the learning objectives in a very effective way.

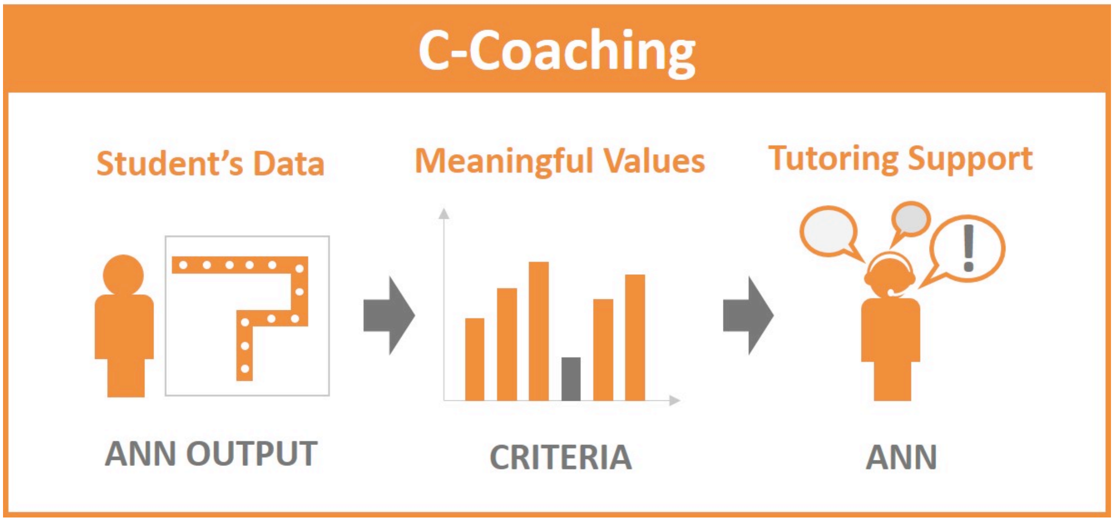

Figure 7. *C-Coaching*

6. E-learning and Artificial Intelligence: the new alliance for online meaningful learning

In the era of *Matrix*, *Avatar*, *Tron*, *2001: A Space Odyssey*, *Minority Report* and *The Hitchhiker's Guide to the Galaxy*, information technology is often seen as a big shapeless mess. A shapeless mess that many organizations have chosen for the design and delivery of artificial learning courses in order to save money and reach the largest number of students, in every place and without any time limits.

However, few people have actually understood and understand the revolutionary potentiality of this tool that can turn a machine into a powerful ally of the human being for information and content processing during the acquisition of new knowledge, skills and competences. A revolutionary potentiality that is dimmed by a rigid, artificial and inhuman use of information technology through learning environments, like LMS, that are not effective, not usable, cold and "indifferent" to the specific students' needs. For years e-learning has been the most exemplar product of this shapeless mess. Therefore, it has produced criticisms, hostilities and clichés that threatened its effectiveness and full inclusion among educators', methodologists', and academics' effective "tools".

Nevertheless, technology cannot and should not be a deterrent for the human being. Information Technology is the "intelligent" product of the creative and original application of our scientific knowledge and of a specific computer system for the resolution of problems that usually affect information management made by people.
In the case of LMS and e-learning courses, computer technology can be a signal amplifier of the educational activity, but only if it is provided with that minimum of

"intelligence" that makes it a “human” tool for people. This is the meaning of our proposal. That is why we decided to introduce Artificial Neural Networks in a linear platform as Moodle. Our goal is to give an intelligent shape to a series of functions, procedures, instructions, rules, teaching patterns, and interaction tools in order to foster learning and reconfigure an artificial tool into a "human" shape.

This has been possible - and it will continue to be thanks to this research branch - thanks to the implementation of algorithms that can simulate the activities of an intelligent teaching staff: rigorous analysis and analytical review of students’ initial knowledge, configuration of customized learning paths, improvement of education through experience and error analysis, and rational support of study programmes.

In this sense, *IDC Learning* various fragments have been already tested in different contexts (academic, business, military, professional, etc.), with positive results both in terms of effectiveness and perceived quality by students. In these testing activities, we verified a higher degree of involvement and motivation of the participants, who perceived a clear change of direction. Many learners have emphasized the sense of this passage from the artificial and inhuman dimension of the online environment into an "intelligent" educational experience, characterized by adequate decisions, flexible programmes, adaptive assessment, and effective tutoring models. Moreover, they understood that an online course can be something different from a boring and banal video game.

That is why we believe that, against the clichés on e-learning, one possible solution is the integration of artificial intelligence. In order to guarantee a greater attention to the humanistic dimension of the learning experience and, finally, to foster a meaningful and unforgettable learning that is open to all the people who want to learn.

References

Heaton, J. (2012). *Introduction to the Math of Neural Networks*. Heaton Research Inc.

Floreano, D. (1996). *Manuale sulle reti neurali*. Il Mulino, Bologna.

Gurney, K. (2003). *An Introduction to Neural Networks*. CRC Press, London.

Kohonen, T. (1997). *Self-Organizing Maps, Springer Series in Information Sciences*, Second edition.

Ronsivalle, G. B., Pellegrini, D., Conte, M., Orlando, M. (2008). *The Guardian Tutor 1.0. An Artificial Neural Network As Support To Tutoring System*. ICERI 2008, Madrid

Ronsivalle, G. B. (2011). *An "intelligent" assessment of learning outcomes. Neuronal and Bayesian networks to "observe" knowledge, abilities and competences*. The 2nd International Conference on Education, Training and Informatics: ICETI, Orlando.

Ronsivalle, G. B., Mezzetti, C., Pellegrini, D., Apostoli, A. (2011). *Microphysics of E-Learning Tutor: GT Brain™*. ICODL 2011 (International Conference on Open and Distance Learning): "Alternative Forms in Education", Loutraki, Corinto

Ronsivalle, G. B., Orlando, M. (2012). *ID4C (Instructional Design for Competencies: A Model Compliant with the EQF*. In Stelios Orphanos (Ed.): "Organizing and Improving School Environment". Athens Institute for Education and Research, Atene

Ronsivalle, G.B. (2013). *Self-Organizing Map.* In Dizionario "Informatica Treccani" (AA.VV.), Istituto dell'Enciclopedia Italiana, Roma

Ronsivalle, G. B., Carta, S., Orlando, M. (2013). *.GET Guida alla Education Technology. Informatica e multimedialità per educatori e professionisti della formazione*. Collana "Manuali del sapere", Maggioli Editore

Ronsivalle, G. B., Carta, S., Orlando, M. (2013). *The OrBITal Map: a new design tool for an effective representation of knowledge systems and instructional objectives*. Asian Conference on Society, Education and Technology, ACSET 2013, Osaka

Ronsivalle, G. B., Carta, S., Metus, V., Orlando, M. (2014). *Artificial Neural Networks, Evaluation and Complexity: Information Technology and Nonlinear Algorithms to Measure Knowledge Systems*. 8th International Technology, Education and Development Conference, INTED 2014, Valencia

Ronsivalle, G. B., Carta, S., Metus, V., Orlando, M. (2014). *Beyond Competences: Kohonen Neural Maps "Photograph" the Human Capital*. ICERI2014 (The 7th International Conference of Education, Research and Innovation), Seville

Ronsivalle, G. B., Carta, S., Metus, V., Orlando, M. (2014). *NEURALEDUGAMING: A Mathematical "Brain" to Make Digital Edugames Smart*. ICERI2014 (The 7th International Conference of Education, Research and Innovation), Seville