Enabling Self-Organization of the Educational Content in Ad Hoc Learning Networks

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Abstract: This paper describes a simple solution to create self-organization of the educational content in learning networks by enabling stigmergic interactions between learners. For this purpose, the learning objects have been associated with a special type of metadata, based on the concept of "virtual pheromones". By accessing the learning objects, users create trails of virtual pheromones, which are interpreted as an implicit recommendation for other learners to use those objects. The resulting system operates as a simple recommender system based on collaborative filtering in ad-hoc learning networks. We also suggest the possibility to implement such system in a P2P file sharing environment, as a solution to improve the sustainability of open education systems.

Keywords: learning networks, open education, recommender systems, stigmergy, self-organization

1. Introduction

The school-as-a-factory paradigm in education, theorized in 1911 [1], proved to be extremely enduring, as it is still in effect in many of the western education systems.

It took almost a century until the European Commission launched the Lisbon Strategy - a massive action plan for the reform of the European education according to the concept of "lifelong learning" [2], seen as a major pillar of the knowledge based society, and a key element for sustainable economic growth.

According to Drachsler [3] the concept of lifelong learning breaks several axioms of the school-as-a-factory paradigm, in what concerns:

- time: the learners access the educational materials asynchronously, and learning is no longer associated with a particular age group,
- space: learning activities are not necessarily linked to a certain place - a school or university,
- group uniformity: learners can be extremely heterogeneous in what concerns age, culture, educational background, motivation etc.,
- curriculum: learners are no longer bound to follow a particular educational content in a predefined sequence,
- role of participants: learners become the central players in the educational process. In a lifelong education system learners are free to choose what, when, where, and how to learn, and sometimes it is also possible to switch roles: learners may become tutors and vice-versa.

While more and more users get involved in various forms of lifelong learning, the open education movement produces a vast amount of open education resources (OER), defined as "openly produced educational resources, enabled by information and communication technologies, for consultation, use and adaptation by a community of users for non-commercial purposes" [4].

OER include: open educational content (courses, curricula, tutorials, access to journals, etc.), software tools (learning management systems, content development and editing tools, e-learning platforms, tools for searching and organizing educational content, etc.), and open repositories to store and deliver the educational content.

The result of this collective effort is a huge, dynamic, totally unstructured, uneven in quality, and difficult to search pool of educational material.

Finding solutions to structure this material is a major challenge for the research in this field.

Another issue is sustainability. Though OERs are free for the consumer, significant funding is required to produce and distribute these resources. Downes provides in [5] several examples of open education projects that cost hundreds of million dollars. Even Wikipedia – the classic example of collective OE achievement – still needs a few million dollars per year to operate.

Considering the fact that these materials depreciate with time – pretty fast in some knowledge areas – it results that important financial resources are needed to sustain any serious OE initiative.

Under these circumstances, the idea of creating self-organizing and self-sustainable OE systems seems to be an ideal solution.

This paper attempts to outline solutions for the above formulated problems. After a brief review of the main concepts and technologies related to open and lifelong education, we propose a simple solution to enable stigmergic interactions between users in order to create self organization of the educational content in ad hoc learning networks. We also explore the possibility to obtain sustainability of such system, by distributing the task of creating, storing and delivering the educational content to the users themselves.

Beyond this introduction, the paper is structured as follows:

– Section 2 presents the basic concepts used to describe the OE environment,
– Section 3 reviews the main approaches on organizing the educational content,
– Section 4 describes a simple method to enable stigmergic interactions between users in ad-hoc learning networks, in order to create self-organization of the shared educational content,
– Section 5 is reserved for conclusions.

2. Basic Concepts Used to Describe the Open Education Environment

2.1 Learning objects

There are, literally, dozens of different definitions for learning objects (LO) – sometimes also called "units of learning (UOL)" - in the literature (see, for example, [6], [7], [8]. For the purpose of this presentation, we propose an amendment to the definition formulated by McGreal in [6]: "a learning object is any reusable digital resource that is [can be] encapsulated in a lesson or assemblage of lessons grouped in units, modules, courses, and even programmes."

A lesson is defined as: "a piece of instruction that includes a learning purpose".

Note that this definition does not make any reference to the *metadata* associated with the actual digital object. For example, a collection of digital images depicting technical diagrams, mathematical formulas etc. does not have much educational value if it is not associated with appropriate descriptive metadata (keywords, text captions, indexing and sequencing information, etc.). Though this metadata is not necessarily stored in the same "place" with the associated digital object, and sometimes it is context or domain sensitive, its presence is essential for turning a digital object into a learning object.

So, the "right" definition of a learning object is: LO=reusable digital object (a static component) + metadata (dynamic component). The resulting LO is in the same time static (reusable) and dynamic (usable in multiple lessons/contexts).

2.2 Learning networks

Based on the principles of connectivism [9], which states that "learning is a process of connecting entities", Koper in [10] defines a learning network (LN) as "a network of persons who create, share, support and study units of learning (courses, workshops, lessons, etc.) in a specific knowledge domain" , and proposes a graph model as shown in Figure 1.

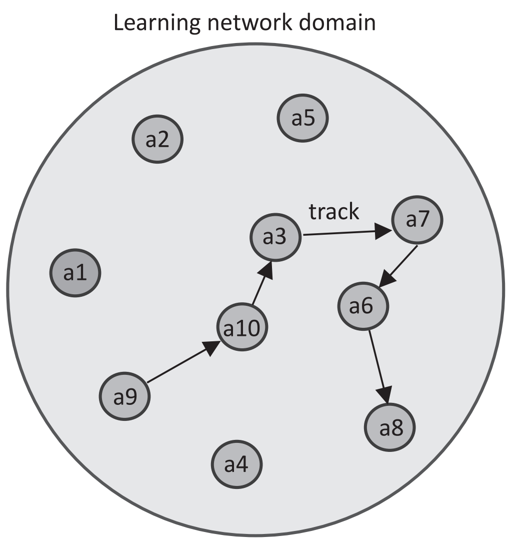

Figure 1. Model of a learning network according to Koper

The nodes of such network are called "activity nodes" (AN), and may be "participants" (learners, providers, teachers, assessors, etc.), or digital objects called "units of learning" (UOLs – a term equivalent to the concept of learning objects).

The ANs are activated in a certain sequence, while learners "travel" from one UOL to another, defining a "track", which –ideally- can be recorded and presented to other participants in the network.

There is an inherent dose of fuzzyness in this model. The "position" of a learner in the network is defined as a subset of nodes, corresponding to his current knowledge within the selected learning domain. The objective of the learning process (the target) is another subset of nodes (see Figure 2).

Obviously, determining and tracking the position of a learner within the network requires some form of assessment. This, in principle, can be achieved by means of "personal eportfolios" [11], but defining the target as a "to-do list" seems to be a complicated task, considering the fact that the learning domain itself can be dynamically modified by the participants, as they use the network.

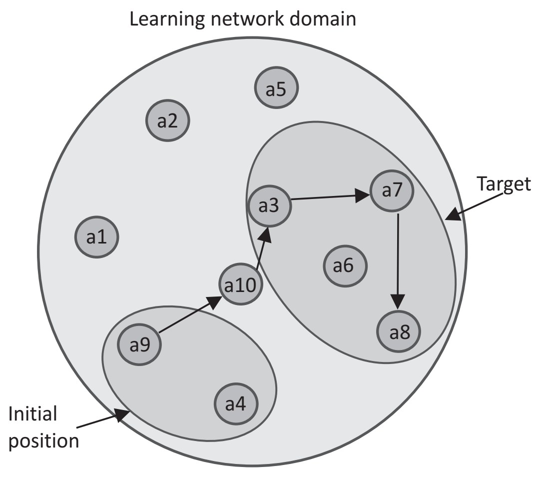

Figure 2. Position and target in a learning network according to Koper

Despite these limitations, the model proposed by Koper for the learning networks demonstrated that, in certain conditions, the lifelong learning environment may exhibit self-organization. For example, the tracks frequently used by many participants may be considered "preferable", and serve as implicit recommendation for other users (see Figure 3).

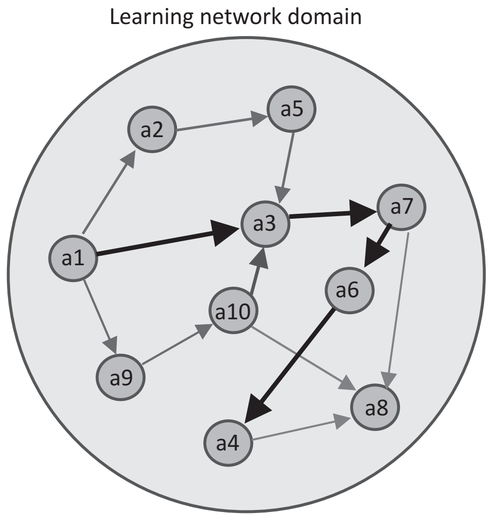

Figure 3. Indirect coordination between agents in learning networks

We will have a closer look at the mechanisms that create self-organization in sections 3 and 4.

2.3 A MAS model for learning environments

Parunak [12] proposes a general model of Multi Agent Systems (MAS) as shown in Figure 4.

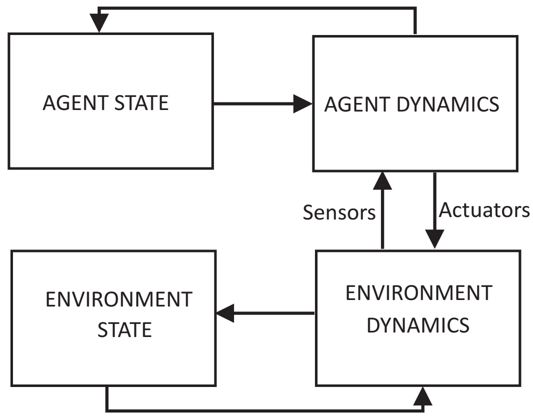

Figure 4. The general model of a MAS according to Parunak

According to this model, a MAS is a population of "agents", each having an internal state (normally not visible to other agents), a "dynamics" (a program that governs the way the agent evolves and interacts with the environment), and a set of sensors and actuators that enable it to sense and modify the state of the environment.

The environment has its own state, which is – at least in some aspects – visible for the agents, and a dynamics (a program that governs its evolution resulting from the interaction with the agents).

Typically, the environment is a “space” structured according to a specific topology (e.g. a cartesian space, a graph, etc.). As a consequence, the agents are *localized* in a certain region of the environment.

By applying this model to the learning environment, we get a structure as presented in Figure 5.

In this approach, the population of agents (learners) interact with a (large) set of learning objects, by means of a communication medium and a set of software tools (sensors and actuators) for accessing, indexing, searching, editing the digital content.

Normally, the learning objects available for the learners at a certain moment cover multiple knowledge domains, so that the boundaries of the domain of interest for a specific learner must be defined by applying a set of filters to the whole set of digital objects. In the simplest implementation, the topology of the learning environment is a category list of the learning objects, so that the “place” of an agent in the environment is defined by the LO accessed by that agent at a given moment.

For an agent involved in lifelong learning, the learning management system should be able to provide answers to the following fundamental questions:

[Q1] Given my (self-assessed) level of knowledge and my (self-selected) educational target, what learning objects are available allowing for me to achieve my goal?

[Q2] Having a record of my past actions, what is the next suitable step towards my goal?

[Q3] Is there an optimal route for me to attain a certain learning objective?

3. Organization and Self Organization in Learning Networks

3.1 Ad-Hoc transient communities

Before attempting to describe the mechanisms of organization of the educational content in a learning network, we need to understand the principles of organization of the network itself. Berlanga et al. in [13] introduce the concept of “ad-hoc transient community”, defined as “communities that serve a particular goal, exist for a limited period of time, and operate according to specific social exchange policies”.

In order to enable knowledge sharing, such a community should fulfil the following conditions:

The boundary condition: members of the community should have a common goal, and accept a set of rules regarding their activity.

The heterogeneity condition. It is obvious that, if all the participants in a learning network would be beginners, they wouldn't have much to learn from each other.

The accountability condition requires that users are recognizable (multiple aliases are forbidden), and their activity should be logged.

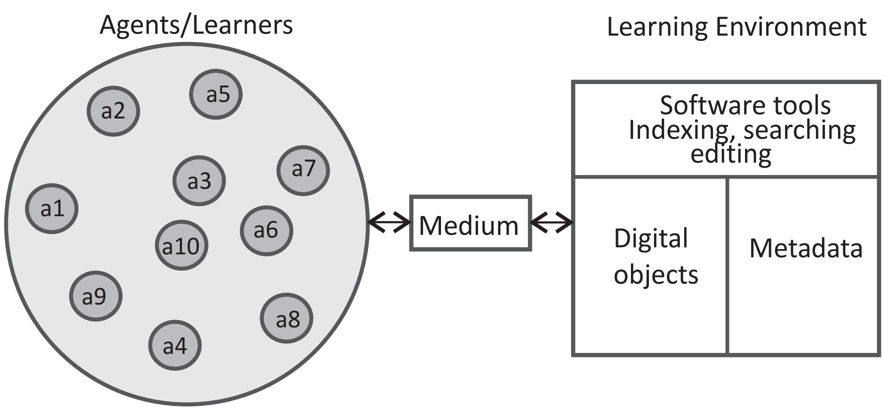

Figure 5. MAS model of the learning environment

Though there are multiple reasons to keep detailed user profiles on file (see [14]), the accountability condition is often difficult to fulfil in networks based on crowdsourced content, like those based on P2P file sharing.

Since crowdsourcing is essential for creating self-sustainable OE systems, for the purposes of this presentation, we will only consider learning networks with low user accountability, and we define *ad hoc learning networks* as "web based transient communities, wherein a number of *anonymous users* share a large amount of learning objects".

3.2 Database tools

Organizing learning objects according to the principles of database applications development (Figure 6) has several important advantages:

– allows the use of well established software technologies at the server side, reducing the cost of development;
– there is no need for special software on the client terminals, making the system available for almost every Internet, or mobile Internet user;
– powerful and flexible search tools are available (e.g. fuzzy querying [15].

This approach provides satisfactory answers to the question Q1 formulated in Section 2C, but attempting to answer Q2 and Q3 within this conceptual framework tends to turn the system into a formal e-learning system, not very suitable for unsupervised lifelong learning (see [16]).

3.3 Recommender systems

Initially developed in the context of e-commerce applications (e.g. [17]), Recommender Systems (RSs) have been lately successfully used in e-learning and other knowledge management systems.

RSs seem to be the best available solution to the question Q2, formulated in Section 2C.

A comprehensive survey on the existing solutions for RSs is available in [18] and [3]. In a very general taxonomy [18], RSs use either content-based recommendations (user receives recommendations for items similar to what he recently used), collaborative recommendations (based on what similar users preferred in the past), or hybrid solutions, which combine user focused with content focused approaches.

An interesting variation on the idea of collaborative recommendations is proposed by Benz et al. in [19], and relies on bookmark sharing. This concept, also called "social bookmarking" has been successfully implemented on a web site (delicious.com, formerly del.icio.us), and benefits from a plugin extension for Mozilla Firefox.

3.4 Stigmergy

Initially introduced to describe the apparently intelligent behavior of the colonies of ants, the concept of stigmergy is defined as the coordination mechanism between simple agents that indirectly communicate by means of traces they leave in the environment.

Discovered in the context of a research on insects [20], the stigmergy derives from the

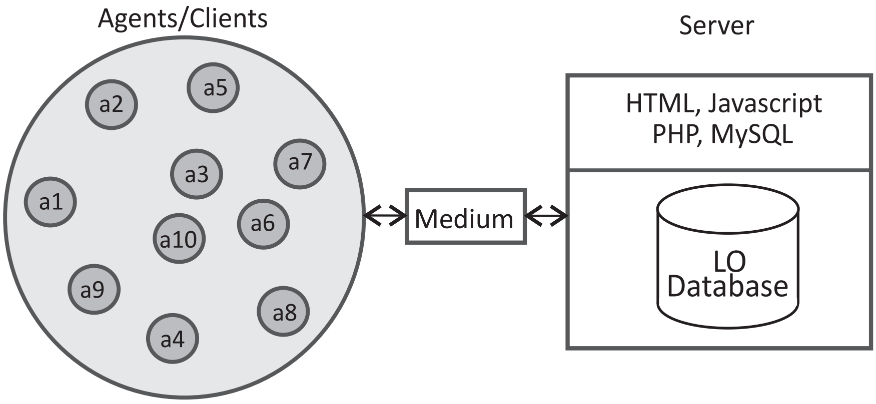

Figure 6. A Database approach on organizing learning networks

capacity of the agents to modify the environment by deploying small amounts of chemicals, called pheromones [21], and to sense such modifications of the environment created by other agents. Upon sensing these traces, other agents are stimulated to perform similar actions, thus reinforcing the traces, in a self-catalytic process. Unreinforced traces evaporate, and eventually disappear. As a result, simple, local and unplanned actions of the agents emerge in a complex, global, and apparently intelligent behavior of the system as a whole.

This self-organization mechanism has been called swarm intelligence [22].

Stigmergy was extensively studied in the context of robotics, for military applications, routing data packets in computer networks, web mining, mobile sensor networks, etc. Various solutions have been proposed for the implementation of artificial pheromones, e.g. by recording special data structures in RFID tags deployed in the environment [23], but any model of synthetic pheromones should address the following aspects:

– Diffusion: pheromones diffuse in space so that the agents can sense pheromone traces at a certain distance from the actual source. Distant sources are sensed with a lower intensity, depending on the distance between the source and the point where it is sensed;
– Evaporation: pheromone intensity decreases in time;
– Aggregation: pheromones from multiple sources superpose their effects.

This very simple scheme of interaction may describe well the behavior of simple agents, but is it appropriate to describe the complex decision making process of BDI agents, like humans? (BDI stands for Beliefs, Desires, Intentions.)

Parunak in [12] provides many examples of stigmergic behavior in human agents, and Omicini et al. [24] explain this by introducing the concept of “behavior implicit communication” (BIC).

When someone chooses to buy a product, watch a movie, visit a web page etc., he actually sends an involuntary message containing information about a personal decision that “indicates” a certain object. If many others do the same, this can be an implicit recommendation for the respective object.

Koper in [10] calls this process “indirect social interaction”, and suggests that it can be used as starting point for a solution to the problem of selecting an “optimal” route towards a certain learning objective.

The next section explains *how* to do that.

4. Enabling Stigmergic Interactions in Learning Networks

4.1 Model of virtual pheromones

We defined the concept of “virtual pheromones” in [25] as “traces left by the agents not in the environment, but in an abstract representation thereof – a map”.

Assuming a cartesian map of the environment, and a set of n pheromone sources S1,…,Sn, as shown in Figure 7, due to diffusion, the pheromone from the source S_k can be sensed at the distance x with an intensity:

$$p(x) = \begin{cases} p_k\left(1-\dfrac{x}{\sigma}\right) & 0 < x < \sigma \\ 0 & x \geq \sigma \end{cases} \quad (1)$$

where σ is the sensitivity range of the agents, and p_k is the intensity of the source S_k.

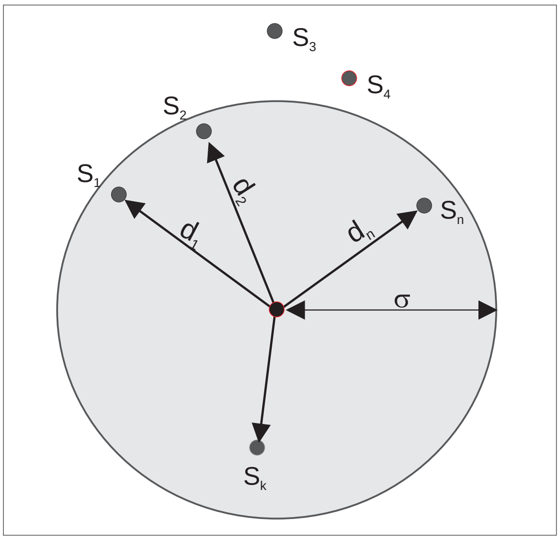

Figure 7. Notations used to describe the model of virtual pheromones

For all N pheromones sources, the resultant intensity is:

$$P_R = \sum_{k=1}^{N} p_k \left(1 - \frac{d_k}{\sigma}\right) \quad (2)$$

and, assuming a linear evaporation curve with the slope defined by the constant τ :

$$P_R(t) = \left(1 - \frac{t}{\tau}\right) \sum_{k=1}^{N} p_k \left(1 - \frac{d_k}{\sigma}\right) \quad (3)$$

Note that the expression (3) is valid in any environment (space), provided that there is a means to determine the distance between any two points of that space. So, in order to use this model of pheromones in learning environments, it is mandatory to define a distance between “places” of the respective environment (LOs, or learners).

4.2 Embedding pheromone information in databases

Consider a system with the structure presented in figure 6. Every LO *x* in the database is associated with metadata consisting in a set of keyword tags:

$$K_x = \{k_1, k_2, .., k_{\mu x}\} \quad (4)$$

where

$$\mu_x = |K_x| \quad (5)$$

is the cardinal of the set K_x.

For any two items *i*, *j* in the database, it is possible to compute the co-presence CP_{ij}:

$$CP_{ij} = |K_i \cap K_j| \quad (6)$$

And the Jaccard similarity index:

$$S_{ij} = \frac{|K_i \cap K_j|}{|K_i \cup K_j|} \quad (7)$$

and, finally, the distance between elements i and j, d_{ij} :

$$d_{ij} = 1 - S_{ij} \quad (8)$$

Having a distance, it is possible to associate pheromone information with all the items in the database, according to the following algorithm:

Every time a user accesses an object *k* in the database, the pheromone intensity associated with that object increases with a constant ratio p_k;

Compute the distances d_{ik} between the object k and all other objects with (8);

Diffuse the effect of the new pheromone source S_k over the entire space, and increase the pheromone intensity of all items i with

$$\delta p_i = p_k \left(1 - \frac{d_{ik}}{\sigma}\right) \quad (9)$$

At regular time intervals, decrease the pheromone intensity associated with all the objects in the database with a constant ratio to reflect evaporation.

As a result, the pheromone intensity field in the database can be used along with other metadata to filter the items most “valued” by the community of learners. Filtered results can be presented to the users as a simple ordered list (see Figure 8).

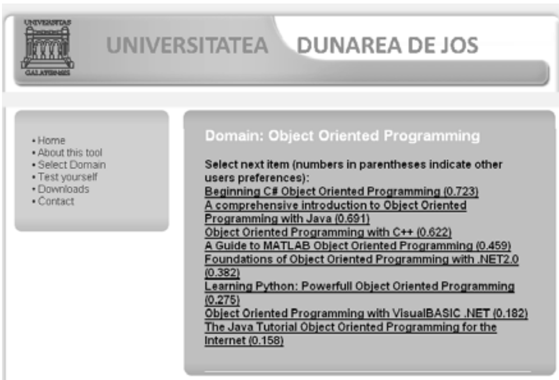

Figure 8. A screenshot of the web user interface of the experimental application

This simple scheme implements a rudimentary recommender system based on stigmergy, which actually allows basic self-organization in learning networks with very low user accountability. It provides satisfactory answers to question Q1 formulated in Section 2C, but leaves unanswered questions Q2, and Q3.

4.3 Related work

Besides the already cited work of Koper [10], there is a number of research papers proposing solutions based on swarm intelligence to the problem of automatic generation of learning pathways (see for example [26], [27], [28]. A comprehensive survey of the literature on this topic is available in [29].

However, all of the existing solutions are learner oriented, assuming that detailed profiles and activity logs are available for all users of the system. This makes them unsuitable for systems with low user accountability.

Another interesting research direction deriving from the concept of collaborative learning environment is the idea of "collaborative idea generation" [30].

4.4 A note on self-sustainability

Any solutions for learning networks relying on one or more central servers raise questions about the long term sustainability of the system. The answer could be to design a totally distributed system, based on a P2P file-sharing protocol, like Bittorrent [31]. Recent research [32], [33] suggests that it is possible to search and filter distributed databases built over Bittorent, but the research in this direction is still in an early stage.

5. Conclusions

Unlike the majority of the solutions related to the use of swarm intelligence in open and lifelong education systems, this paper proposed a method to enable stigmergic interactions between learners, in systems with very low user accountability, like those based on P2P file sharing protocols. This limitation leads to lower self-organization, but promises self-sustainability of the resulting system, which is, at least from an economic perspective, an important advantage.

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