Recommendation of Pedagogical Resources within a Learning Ecosystem

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ABSTRACT

With the current development of Information and Communication Technologies (ICT), organizations deal with great amount of information coming from many systems. Identifying a resource of relevant information to a specific context becomes a real challenge. In the course of our work we are interested in recommendation of pedagogical recources within a learning ecosystem. We have chosen to model a learning ecosystem as a system of information systems (SoIS). In this SoIS we introduce a resource recommender system. This system is based on users' votes (learners, teachers), and the similarity between the description of pedagogical resources and the learners' profile. In our approach, we take into account the willingness to collaborate. Therefore, we exploit a collaboration model that supports learning ecosystem to answer the demand for questions such as, who collaborates with whom, how, when, why, on what and where, etc. The work presented in this paper is focused on at recommendation of pedagogical recources within a learning ecosystem.

Keywords

System of Information Systems, Learning Ecosystems, Voting System, Learner Model, Resource Model, Recommender System.

1. INTRODUCTION

Today, with Information and Communication Technologies (ICT), learners operate in a learning ecosystem that can be defined as an ecological model of learning and teaching [1] including e-learning infrastructure [2]. It can be seen as a virtual learning space in which the technologies that contribute to learning (hardware,software and network) are used, in order to foster interactions between communities of users and content. In this introduction, we present both the social, scientific context of our research and the problem we wish to solve.

1.1 Social Context

In the context of "learning together", many information systems are used by learners. These systems provide heterogeneous resources (video, text, e-book, online forum, etc.) to different users (learners, teachers). According to [3], the multitude of resources, relationships and interactions can lead users to undergo an information overload that makes them unable to assimilate the available information. In order to reduce this overload, it would be useful to offer assistance to users so that they can choose the resources that may be most relevant in a given situation. One of the possible ways in this direction concerns the sharing of information, the voting systems and the similarity between the description of pedagogical resources and the learners' profile. It is therefore interesting to consider the association of these different means within the framework of a learning ecosystem in order to produce targeted recommendations. The purpose is to allow a learner to act by becoming aware of what he shares, why he shares it, with whom, when and how.

1.2 Scientific Context

Information retrieval in the context of e-learning remains a challenge. In the literature, this challenge is generally addressed by considering the profile of the learners. In particular, it is addressed in the work on information filtering in order to propose to learners relevant documents. In the context of information filtering, several approaches are possible: (i) content-based approach [4] which makes recommendations by comparing the semantic content of resources with the user's tastes; (ii) knowledgebased approach [5] which makes recommendations using user knowledge and pre-established heuristics; And (iii) collaborative filtering approach [6] that makes recommendations by analyzing both the user's opinions about the resources he has visited and those of other users on the same resources. Under the latter approach, collaborative filtering may be associated to the profile of each learner (who consults what?). Nevertheless, these systems do not consider the context of collaboration and the possibility of sharing resources from different systems.

In the context of recommendations within a learning ecosystem, we believe it is necessary to consider:

- The willingness to share resources with a community in order to achieve a common goal;

- The fact that shared resources can come from different information systems.

In order to meet these necessities, we propose to consider a learning ecosystem as a system of information systems developed from a collaborative model and including a recommender system based on the users' votes (learner, teacher) and the similarity between the description of resources and the learners' profile.

1.3 Plan

This paper is organized as follows: section 2 presents our point of view to consider a learning ecosystem as a SoIS. In section 3, the model and platform of the SoIS are presented. In section 4, we present our approach to resource recommendation based on a voting system within the SoIS. Finally, we conclude with prospects and future work in Section 5.

2. Learning ecosystem versus SoIS

Considering a learning ecosystem as a SoIS aims to simplify the management of pedagogical resources from different information systems, and control the process of sharing information among users. The goal is to minimize the time needed to capitalize resources from different information systems.

2.1 Learning ecosystem

In the age of technology 2.0, the concept of individual-plus [7] is taking off. The learner does not develop alone, and in a learning ecosystem that includes the learner himself, but also his physical and social environment: his tools (notepad, tablet, etc.), his resources (Procedures, methods, instructions, course materials, notes, documentation ...) and his partners who also have some knowledge (pairs, teachers, network of experts, co-workers ...). In this learning ecosystem, knowledge is distributed. It is also accessible through the memory of the person himself or through his tools, resources or partners. Knowledge is not limited to repeating, explaining or doing, but also being able to operate the distributed knowledge of its ecosystem at any time. According to [8] a learning ecosystem is a coherent set of training biocenes that promote "learning together" based on exchange and sharing of knowledge and / or skills to better achieve a common project.

The diversity of pedagogical resources and their means of access is interesting but can be an obstacle to learning if awareness is not there. How to access a resource, assess its relevance, measure its quality, ensure that the information produced is fair, etc.? How can we capitalize on this resource, share it with who and why? How to customize a resource consultation path taking into account indications from a learning ecosystem?

Digital ecosystems aim to ensure knowledge sharing within organizations as quickly and efficiently as possible [9]. They can be considered as platforms for cooperation, sharing and access to knowledge in order to facilitate learning [10]. From this point of view, they can therefore serve as a support for a learning ecosystem, in this case we will call them digital learning ecosystems (DLE).

2.2 SoIS

A system of systems (SoS) is a collection of dedicated systems that combine their resources and capabilities to create a new, more complex system that offers more functionality and performance than simply the sum of constituent systems [11]. Different approaches have been proposed in the literature concerning the coordination of the different SoS systems. There are mainly three approaches [12]: *Leader / Follower*, *Virtual Structure* and *Behavioral Control*. In the *Leader / Follower* approach, a leading system allows component systems to cooperate, to carry out a collaborative task [13].

In our context, we are particularly interested in a category of SoS: the SoIS. [14] Define them as systems networks interacting in a specific technological field in order to create, disseminate and use knowledge, information and skills flow technologies. Thus, a SoIS can be considered as a macro-information system giving access to the information distributed in the component systems and offering functionalities using the accessed information.

DLEs and SoIS ultimately share a number of characteristics such as:

- Distribution of resources within different systems.

- Taking into account the heterogeneous nature of resources.

- Supporting collaboration and sharing of resources.

3. MEMORAe SoIS

MEMORAe SoIS was developed as a digital support for a learning ecosystem. It follows the *Leader / Follower* approach. The function of the *leader* system is to orchestrate the SoIS. It can be seen as a knowledge base related to SoIS systems allowing the organization, sharing and access to the resources of the various component systems. It is intended to provide support to users of the DLE to facilitate collaboration and decision-making regarding the purpose of the collaboration. In the following, we justify the choice of the collaboration model MEMORAe-core2 to develop the system leader and then we specify the architecture of SoIS that we have put in place.

3.1 The Choice of MEMORAe Model

The MEMORAe-core2 collaboration model was developed as part of the MEMORAe project [15]. This project aims to manage heterogeneous information resources within organizations and to facilitate organizational learning. Collaboration is considered from the point of view of sharing and exchanging heterogeneous knowledge resources between user collaborators around the shared repository. The MEMORAe-core2 model employs the Semantic Web standards (SIOC, FOAF and BIBO).

The model of MEMORAe-core2 considers an organization as a group of members interacting with each others. Those members are modeled as users with the MEMORAe-core2 model. Every user and group of users is associated with one sharing space that will allow the sharing of heterogeneous resources. The model also provides the user with access to several knowledge bases in the form of a semantic map of concepts. The concepts of the map represent an indexing schema for users to index their resources.

Note that in MEMORAe-core2, a vote is modeled as a resource. This allows a user to specify the relevance of a resource for a topic defined in the shared repository within a shared space.

3.2 Architecture of MEMORAe SoIS

The generic architecture of the SoIS is presented in this section. As seen in (Fig. 1), the architecture of MEMORAe SoIS [16] is based on the grouping of information and heterogeneous resources of different information systems. These systems are autonomous and operate separately from one another. Each of them has its own services / functions and databases.

The SoIS is represented as a group of system and database connectors comprising the information (identifier / password) related to the connections to the component systems.

4. Recommendations within the MEMORAe SoIS

Within the MEMORAe SoIS, it is possible to share pedagogical resources from different information systems. These resources may present a degree of relevance for the same subject depending on the level of the learners. This degree of relevance is established on the basis of users' votes (learners, teachers) of the ecosystem and is exploited within a recommender System. It is the *leader* system that implements collaboration and recommendation capabilities based on the MEMORAe-core2 model.

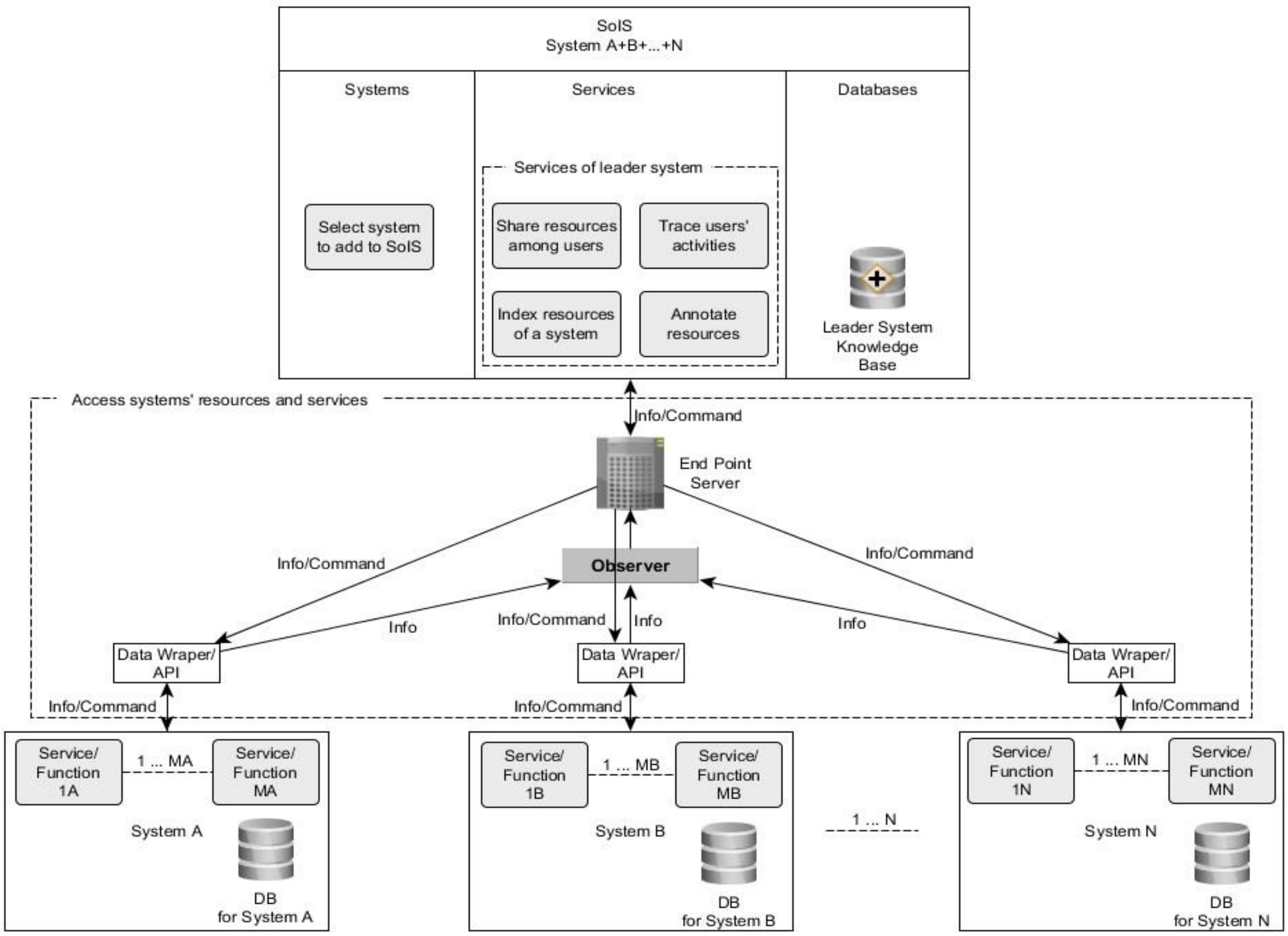

Figure 1. Architectural model of the SoIS.

The leading system of MEMORAe SoIS developed from memorae-core2 offers learners the following features:

- Create resources using a dedicated Information System. These resources can be accessed either from the MEMORAe SoIS or the dedicated system where they are created.

- Organize resources around a shared repository presented in the form of a semantic map (application ontology).

- Share resources within different sharing spaces.

- Annotate resources in order to highlight certain ideas related to the resources.

4.1 Training content modeling

With MEMORA SoIS, our aim is to offer help to learners to understand the concepts of training and to facilitate exchanges and knowledge transfer around them. We have therefore chosen to consider these concepts as components of the shared repository. Thus, course content is defined and presented in the form of a knowledge mapping (application ontology or $\mathbf{O}_{\mathbf{application}}$). This ontology is a specification of the set of concepts useful for a particular formation.

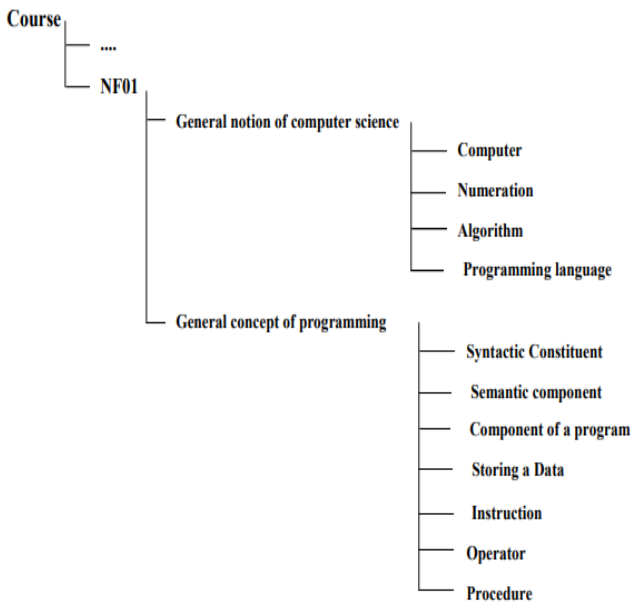

Figure 2. Extract of the application ontology of the course "Algorithmic and Programming"

Figure 2 presents an extract of the application ontology defining formally the notions addressed in the course "Algorithmic and Programming" given to students postbac of the University of Technology of Compiègne [17]. This ontology defines and models the semantic content of this formation. The concepts defined will be used to index the pedagogical resources allowing their apprehension.

4.2 Learner Modeling

Above all, it is necessary to define the objects that are at the center of our research: learner profiles. The learner profile can be considered as the instantiation of the learner model in the system [18].

One of the essential factors in assessing the quality and usability of a referral system is its ability to respond to the needs of the learner [19]. The learner model (LM) is the component that allows to characterize each learner in the system through a profile. It keeps information about the learner, for example his / her level of knowledge on a given subject, his / her preferences, etc. [20].

In the literature, we identified a set of essential functionalities of LMs, two of which are very common: (i) learning personalization by adapting teaching to the needs of the learner [21] [22], by planning their own learning activities [23]. (ii) assessment of the learner's knowledge, for example, learner responses can be analyzed to infer beliefs, correct, erroneous or incomplete knowledge [24].

In our approach, we want to exploit the learner's profile in order to offer him mechanisms to better manage his resources for a training he wishes to validate. The characteristics of the chosen model concern identity (name, surname, etc.), preferences (type, language, style, etc.), the learner's state of knowledge on the concepts related to training.

In the end, our model of the learner for an ongoing training can be expressed by:

$$\mathbf{M_{Learner} = \{M_{ID}, M_{Pref}, M_{Kn}\}}$$

- $\mathbf{M_{ID}}$: contains general information about the learner, such as his / her name, first name, age, education (1 (engineering cycle), 2 (Master1), 3 (Master2), etc.) [23] [25], its sharing spaces within the ecosystem [15]. The email or a user name with the password can be used to identify the learner [21].

- **$\mathbf{M_{Pref}}$:** contains learner learning preferences for example the preferred type of pedagogical resources **T** (1 (text), 2 (video), 3 (audio)), the preferred format of these resources **F** (1 (PDF), 2 (Word), 3 (MP3), etc.), or the preferred language they use **L** (1 (French), 2 (English), etc.) [25]. The learner learns easily when he has the opportunity to use his preferred learning style. Each preference has certain predictable effects on learning styles. We have adopted the principles of the experiential model of [26] which includes four learning styles (**A**: concrete experience (active), **R**: reflective observation (reflexive), **Th**: abstract conceptualization (theoretician) and **P**: abstract conceptualization active experimentation (pragmatic), such as:

Table 1. Description of the four learning styles [26]

Learning style	**Description**
Active Style (A)	- Significant interest in the acquisition of knowledge through experimentation. - Knowledge development through active interaction with others. ➔ Taste for the confrontation of ideas or the solving of problems in team.
Reflected Style (R)	- Style marked by reflection. ➔ Observation, listening, accumulation of data before issuing an opinion.
Theoretical Style (Th)	- Taste for analysis and synthesis, valuation of rationality and objectivity. ➔ Acquiring new knowledge systematically.
Pragmatic style (P)	- Interest in the practical application of ideas, theories and techniques, in order to clarify and validate their functioning. - Preference for realistic and practical solutions. ➔ Need to find concrete benefits, practical advantages to new knowledge.

The component $\mathbf{M_{Pref}}$, can be formalized as a conceptual preference vector $\mathbf{V_{Pref} = (T, F, L, A, R, Th, P)}$. Using this vector, we can specify the anticipated needs of the learner [27] in order to recommend pedagogical resources adapted to his / her learning style.

Example: Table 2 represents the model of the learner **John Doe** following the course NF01 (see Fig. 2) given at the Compiègne University of Technology. We thus find the three components $\mathbf{M_{ID}, M_{Pref}, M_{Kn}}$.

Table 2. Learner model: John Doe

Components	Attributes	Values
M_{ID}	Last name	John
	First name	Doe
	Age	19 years old
	Training	1: Engineering cycle
	Login	john.doe@utc.fr
	Password	xxxx
	Sharing space	S1, S2
M_{pref}	T (type)	1 (Text)
	F (format)	1 (PDF)
	L (language)	2 (English)
	A (active)	55%
	R (reflected)	4%
	Th (theoretician)	8%
	P (pragmatic)	65%
M_{Kn}	General notion of computer science	0.6 (medium)
	Computer	0.8 (high)
	Numeration	0.4 (low)
	Algorithm	0.6 (medium)
	Programming language	0.4 (low)
	General concept of programming	0.4 (low)
	Syntactic constituent	0.4 (low)
	Semantic component	0.4 (low)
	Component of a program	0.6 (medium)
	Storing a data	0.2 (very low)
	Instruction	0.6 (medium)
	Operator	0.4 (low)
	Procedure	0.6 (medium)

For a given concept of the $\mathbf{M_{Kn}}$ component, each cell in the table represents the level of knowledge attributed to John. Pedagogical preferences indicate that John has the profile of a learner who favors the practical aspects, motivated by the realization (P: 65%), (A: 55%) he is active, he does not like analysis and the synthesis of the course data (Th: 8%).

This information can be implicit (based on the analysis of the learner's activities during the training) [28] [29], or explicit (form completed by the learners themselves) [30]. In this article, we are interested in an explicit LM which provides the information needed to produce recommendations for pedagogical resources adapted to the learner's profile [31].

4.3 Resource Modeling

From our point of view, a pedagogical resource is first and foremost a resource, so we have chosen to model it as a specialization of the “resource” concept of the MEMORAe-core2 model. In the end, the model of a pedagogical resource has three components: $\mathbf{M_{PedagogicalResource} = \{M_{IDr}, M_{KnowledgeRelevanceDifficulty}, M_{ObjectivesPreferences}\}}$. The component $\mathbf{M_{IDr}}$ describes the following: title, author, training (adapted to which level of study), date of creation, date of sharing within a space, author of sharing, Sharing space. The component $\mathbf{M_{KnowledgeRelevanceDifficulty}}$ specifies the resource's indexes (concepts of the application ontology) within a shared space. A resource has a degree of relevance and a difficulty associated with each of its indexes within a shared space. The degree of relevance (1: highly recommended, 0.75: recommended, 0.5: undecided, 0.25: poorly recommended, 0: not recommended) is calculated from the vote of ecosystem users who have access to the sharing space where the resource is visible. The difficulty specifies a level of accessibility for a given audience (0: low, 0.5: medium, 1: high) and is defined by the authors of the resource. The third component $\mathbf{M_{ObjectivesPreferences}}$ is used to classify resources into different categories based on their **Tr** (1 (text), 2 (video), 3 (audio)), **Fr** (1 (PDF), 2 (Word), 3 (MP3), etc.), their language **Lr** (1 (French), 2 (English), etc.) and the percentage of adaptation to the different learning styles presented in the learner's preference model $\mathbf{M_{Pref}}$ (A: active, R: reflective, Th: theoretician, P: pragmatic). Each category is described in the form of a conceptual vector $\mathbf{V_{ObjectivesPreferences} = (Tr, Fr, Lr, Ar, Rr, Thr, Pr)}$. The conceptual vector of a resource makes it possible to specify that its content is rather adapted for a given learning style. For example, a "Programming Language" concept resource having the vector $V_{ObjectivesPreferences}$ = (Tr: 1, Fr: 1, Lr: 2, Ar: 25%, Rr: 30%, Thr: 5%, Pr: 75%) , Indicates that this text-based resource, in PDF format published in English, is more suited to a profile of a learner who prefers observation, listening and accumulation of data before issuing an opinion (Rr: 55%), and instead focuses on practical aspects (Pr: 75%). Filling in the information of a resource is done by the author (or annotator) who knows the content, the possible use and the purpose of this resource. Thereafter, the value of a vector $V_{ObjectivesPreferences}$ of a resource can be modified (or adjusted) manually by the author of the resource.

Example: Table 2 represents the resource models "Book1" and "Book2" which are indexed by the same concept " General notion of computer science ". They are visible in the same sharing space S1. Thus, these two resources have two IndexKeys Ind1 and Ind2 linking each pedagogical resource, the concept that indexes it and the sharing space where this resource is visible / shared.

Table 3. Pedagogical resources Models: Document (Book1 and Book2)

Document			
Components	**Attributes**	**Values (Book1)**	**Values (Book2)**
M_{IDr}	Title	Advanced info	Informatique
	Author	A1	A2
	Training	1 (Engineering cycle)	2 (Master1)
	Creation date	02/05/2010	05/03/2005
	Sharing date	10/05/2017	15/05/2017
	Share author	Majd	Marie-Hélène
	Sharing space	S1	S1

M **Knowledge-RelevanceDifficulty**	Concept	General notion of computer science	General notion of computer science
	Degree of Difficulty	0.5: medium	1: high
	Relevance	0.75: recommended	0.25: poorly recommended
M **Objectives-Preferences**	Tr	1 (Text)	1 (Text)
	Fr	1 (PDF)	1 (PDF)
	Lr	2 (english)	1 (french)
	Ar	%65	%5
	Rr	%10	%57
	Thr	%5	%75
	Pr	%52	%2

4.4 Pedagogical Resources Recommendation Module

Our module of recommendations for pedagogical resources is based on the semantic links between the concepts of training, the indexed resources taking into account the degree of relevance calculated, the level of difficulty they present and the learner model (identity, preferences, knowledge). The objective of a learner by training is to acquire the knowledge related to the latter. Thus, for a learner *l* wishing to apprehend a knowledge *c* (concept) having access to the space *s*, we will recommend to him resources of the system which are:

- Indexed by the concept *c* and / or the *sc* concepts specializing *c*.

- Accessible in the sharing space of the community to which learner *l* belongs.

- Having a difficulty adapted to the level of knowledge of the learner *l* for the concept *c* which indexes this resource.

- Having characteristics (format, language, style ...) similar to the learning preferences of the learner *l* for the concept *c*.

- Having a high degree of relevance.

4.4.1 Voting system

In order to allow learners to vote on the interest of a Pedagogical resource on a concept to be apprehended we rely on the memorae-core2 model in which the concept of voting is defined as a resource with a target.

The target is an IndexKey represented by a concept linking a resource, a concept that indexes that resource, and a sharing space where that resource is visible / shared. In this way, it becomes possible to vote on the interest of a resource within a community for a particular concept. The degree of relevance of a resource for a community on a subject / knowledge will be calculated by the weighted average of the votes cast.

Here, for example, we show how two resources "Book1" and "Book2" are indexed by the same "General notion of computer science" concept, having two different levels of difficulty ("medium" for Book1 and "high" for Book2) and are visible in the same sharing space S1 of group 1. Thus , These two resources have two IndexKeys Ind1 and Ind2 respectfully as shown in the following table:

Table 4. Table showing two different IndexKeys

Ind1: About_instance: General notion of computer science; Visible_for: S1; Index: Book1.	Ind2: About_instance: General notion of computer science; Visible_for: S1; Index: Book2.

Example: On May 30, 2017, Elsa judged "Book1" very relevant to understand the concept "General notion of computer science" and attributed a vote of value 5/5 within the sharing space S1. At the same time, Marie-Hélène, in the same space S1, did not agree and voted 3/5 for the same resource. In addition, Elsa awarded a vote of value 1/5 to the resource "Book2" indexed by the same concept "General notion of computer science" visible in S1 because, according to her, it is less relevant. After these three activities, we get three vote resources, as shown in Table 5:

Table 5. Three different votes for: Book1 and Book2

Vote1	**Vote2**	**Vote3**
Creator: Elsa	Creator: Marie-Hélène	Creator: Elsa
Value_of_vote: 5	Value_of_vote: 3	Value_of_vote: 1
IndexKey: Ind1	IndexKey: Ind1	IndexKey: Ind2
Date: 30 mai 2017	Date: 30 mai 2017	Date: 30 mai 2017

4.4.2 Similarity measure

In the literature, many works dealing with the recommendation use the Pearson correlation coefficient for the calculation of the similarity between the users of a system. This coefficient measures the linear correlation between two independent quantitative variables. In recommendation systems, this coefficient serves to measure the dependence between two conceptual vectors. Given that our work is aimed at producing targeted resource recommendations, we propose to use the Pearson r correlation coefficient to analyze the similarity between the learner model and the pedagogical resource models. This coefficient is calculated from the quantitative information presented in the models (learner, resources) and can take a value ranging from +1 (strong positive correlation) to -1 (strong negative correlation).

Pearson Correlation Coefficient:

$$r_{XY} = \frac{\sum_{i=1}^{n}(X - m_X)(Y - m_Y)}{\sqrt{\sum_{i=1}^{n}(X - m_X)^2 \sum_{i=1}^{n}(Y - m_Y)^2}}$$

Where:

$$r \in \Re \qquad -1 \leq r \leq 1$$

$$m_X = \frac{\sum_{i=1}^{n} X_i}{n} \qquad m_Y = \frac{\sum_{i=1}^{n} Y_i}{n}$$

n**:** the number of quantitative elements of the learner or resource model.

***X*:** a vector of size n which represents the different quantitative information of the learner model.

***Y*:** a vector of size n which represents the different quantitative information of the resource model.

$\boldsymbol{m_X}$**:** the mean of the vector *X*; $\boldsymbol{m_Y}$**:** the mean of the vector *Y*.

Table 6. Similarity measure between John and resources Book1 and Book2

	Learner: John (*X*)	**Resource: Book1 (*Y1*)**	**Resource: Book2 (*Y2*)**
Training	1	1	2
KnowledgeLevel / Difficulty Level	0.6	0.5	1
Relevance	1(By default)	0.75	0.25
Type	1	1	1
Format	1	1	1
Language	2	2	1
Active style	55%	65%	5%
Reflected style	4%	10%	57%
Theoretical Style	8%	5%	75%
Pragmatic Style	65%	70%	2%

Returning to our example, Table 6 presents the vector *X* for the learner "John" and the vectors *Y1* and *Y2* for the two pedagogical resources "Book1" and "Book2".

Applying the above formulas: (In our case n = 10)

Calculation of the mean of *X*:

$$m_X = \frac{1+0.6+1+1+1+2+0.55+0.04+0.08+0.65}{10} = 0.792$$

Calculation of the mean of *Y1*:

$$m_{Y2} = \frac{2+1+0.25+1+1+1+0.05+0.57+0.75+0.02}{10} = 0.764$$

Calculation of the mean of *Y2*:

$$m_{Y1} = \frac{1+0.5+0.75+1+1+2+0.65+0.1+0.05+0.7}{10} = 0.775$$

Computing the Pearson Correlation Coefficient (*X* and *Y1*):

$$r_{XY1} = 0{,}9845$$

Computing the Pearson Correlation Coefficient (*X* and *Y2*):

$$r_{XY2} = 0{,}3111$$

The result of computing the Pearson Correlation Coefficient r_{XY1} evokes a very strong correlation between the model of "John" and the model of the resource "Book1". On the contrary, the value of r_{XY2} evokes a rather poor correlation, the coefficient is less than 0.5.

So the resource "Book1" will be recommended to John by the recommender system because it is more adapted to his style of learning and it is better voted than the resource "Book2".

Formally a recommendation R consists of a proposal of one or more Pedagogical resources:

$$R = <l, c, s, (r_1, r_2, \ldots, r_n)>$$

Where:

l: learner, *s*: sharing space, *c*: concept concerned by the recommendation, (r1, r2, ..., rn): all the ordered resources of space *s* that are considered relevant to concept *c* and are adapted to the learner's profile.

The recommendation is to suggest to the pedagogical resources derived from the SoIS component systems deemed relevant to the concept *c* by the members of his / her community and that best fit his or her preferences and level of knowledge.

5. CONCLUSION AND FUTURE WORK

In our work, we are interested in learning ecosystems and the the recommendation of pedagogical resources. We have chosen to model a learning ecosystem as an information systems system (SoIS) in which we introduce a resource recommender system based on the users' voting (learners, teachers) of the ecosystem. In our approach, we take into account the willingness to collaborate. Therefore, we exploit the memorae-core2 model to answer the demand for questions such as, who collaborates with whom, how, when, why, on what and where, etc.

A first prototype has been developed and is being tested with postbac students from the University of Technology of Compiègne following a computer course.

In future work we are interested in integrating the execution traces that can be used to implicitly determine the level of knowledge the learning style of the learner and allow him to see his progress. This would help us to improve and enrich the information used by the recommender system.

On the other hand, there is another technique for comparing similarity and diversity between samples (learners, resources) such as the Jaccard index in order to make a comparative evaluation between the latter and our approach [32].

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7. REFERENCES

[1] Frielick, S. 2004. Beyond constructivism: An ecological approach to e-learning.

[2] Gütl, C., and Chang, V. 2008. "Ecosystem-based theoretical models for learning in environments of the 21st century." International. Journal of Emerging Technologies in Learning (iJET) 3: 50- 60.

[3] Guy, I., and Carmel, D.2011. Social recommender systems. In Proceedings of the 20th international conference companion on World Wide Web. ACM 283-284.

[4] Pazzani, M., and Billsus, D. 2007. The Adaptive Web, chapter Content-Based Recommendation Systems, pages 325–341. Springer Berlin / Heidelberg.

[5] Burke, R., Hammond, K., and Cooper, E. 1996. Knowledgebased navigation of complex information spaces. In Proc. of the 13th National Conference on Artificial Intelligence, pages 462–468, Canada.

[6] Goldberg, D., Nichols, D., Oki, B.M. and Terry, D. 1992. Using collaborative filtering to weave an information tapestry. Communications of the ACM, 35(12):61– 70.

[7] Perkins, D-N.1995. « L'individu-plus. Une vision distribuée de la pensée et de l'apprentissage » French journal of pedagogy Year 1995 Volume 111 Issue 1 pp. 57-71.

[8] Mediani, C., Abel, M-H.2016.Recommandation argumentée de ressources pédagogiques au sein d'un écosystème apprenant. IC2016.

[9] Price, C., and Turnbull, D.2007. The organizational challenges of global trends. A McKinsey global survey. McKinsey Quarterly.

[10] Serge, A.,and Nicole, K.2016. Les écosystèmes numériques Intelligence collective, développement durable, interculturalité, transfert de connaissances, 14, October, 2016.

[11] Popper, S., Bankes, S., Callaway, R., and DeLaurentis, D. July 21–22, 2004. System-of-Systems Symposium: Report on a Summer Conversation, Potomac Institute for Policy Studies, Arlington, VA.

[12] Lozano, R., Spong, M-W., Guerrero, J-A., and Chopra, N. Controllability and Observability of Leader-Based Multi-agent Systems. 20 Jan 2010.

[13] Dong, H., and Hussain, F-K., "Digital ecosystem ontology," in EmergingTechnologies and Factory Automation, 2007. ETFA. IEEE Conference on. IEEE, 2007, pp. 814–817.

[14] Carlsson, B., and Stankiewicz, R.1991. "On the nature, function and composition of technological systems," Journal of evolutionary economics, vol. 1, no. 2, pp. 93–118.

[15] Abel, M.-H.2015. "Knowledge Map-Based Web Platform to Facilitate Organizational Learning Return of Experiences" Computers in Human Behavior, 2015, pp. 960-966.

[16] Saleh, M., Abel, M. H., Misséri, V., Moulin, C., and Versailles, D.2016. Moving Integration of Brainstorming Platform in a System of Information Systems. MEDES'16, November 2016, Biarritz, France.

[17] Ahcene, B. « CONSTRUCTION D'UNE MEMOIRE ORGANISATIONNELLE DE FORMATION ET EVALUATION DANS UN CONTEXTE ELEARNING : LE PROJET MEMORAE », Thesis presented for the degree of Doctor of the UTC, Supported on: December 5, 2005.

[18] Jean-Daubias, S., Eyssautier-Bavay, C., and Lefevre, M., « Modèles et outils pour rendre possible la réutilisation informatique de profils d'apprenants hétérogènes ». STICEF, vol 16, 2009, ISSN 1764-7223.

[19] Brusilovsky, P.1996.Methods and techniques of adaptive hypermedia. User Model. User-Adapt. Intract. 6(2-3) 87-129.

[20] Zhang, Y-F.2010. MODÉLISATION DE L'APPRENANT DANS LE CADRE D'UN ENVIRONNEMENT INFORMATIQUE POUR L'APPRENTISSAGE HUMAIN OFFRANT DES CONSEILS PERSONNALISÉS. University of laval, Quebec.

[21] Hatzilygeroudis, I., and Prentzas, J., "Using a hybrid rule-based approach in developing an intelligent tutoring system with knowledge acquisition and update capabilities", Expert Systems With Applications, Vol. 26, No. 4, 2004, pp. 477-492.

[22] Kabassi, K., and Virvou, M., "Personalised adult e-training on computer use based on multiple attribute decision making", Interacting With Computers, Vol. 16, No. 1, 2004, pp.115-132.

[23] Carmona, C., and Conejo, R.2004.A Learner Model in a Distributed Environment‖, Adaptive Hypermedia and Adaptive Web-Based Systems, Third International Conference, AH 2004, Eindhoven, The Netherlands, Proceedings, pp. 353-359.

[24] Kabassi, K., and Virvou, M.2003."Using Web Services for Personalized Web-Based Learning", Educational Technology & Society, Vol. 6, No. 3, 2003, pp.61-71.

[25] Cheung, B., Hui, L., Zhang, J., and Yiu, S.M., "SmartTutor: An intelligent tutoring system in web-based adult education", The Journal of Systems and Software, Vol. 68, No. 1, 2003, pp. 11-25

[26] Honey, P. and Mumford, A.2000.The Learning Styles Helper's Guide, Peter Honey Associates.

[27] ElHassan, A., and Elbachiri, E. "Adaptation du contenu des ressources pédagogiques et des profils des apprenants dans l'e-learning," Journées scientifiques Resatice, Rabat, 2007.

[28] Sassi, M. B., and Laroussi, M.2009. "Analyse des traces dans Moodle," in Proc. Conférence on Environnements Informatiques pour l'Apprentissage Humain, 2009.

[29] Ruggiero, I. S. W. V., and Rosatelli, M., "An Approach in Personalisation and Privacy in E-Learning Systems," InTech, February 2010.

[30] Lacurezeanu, R., Bresfelean, V. P., and Buchmann, R. "Mining the students' preferences regarding e-learning environments," in Proc. the 9th WSEAS international conference on Software engineering, parallel and distributed systems, 2010.

[31] Ruggiero, I. S. W. V., and Rosatelli, M. "An Approach in Personalisation and Privacy in E-Learning Systems," InTech, February 2010.

[32] Negre, E.2015.Information and Recommender System. Volume 4.