Modeling Approach to Learner Based Ontologies for the Recommendation of Resources in an Interactive Learning Environments

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***Abstract*—Today, the web contains multitude sources of information and knowledge that can be used as learning materials, that's why users are faced with a large number of irrelevant answers returned by the classical information search tools. During the last decade, recommendation systems have emerged as an effective means to reduce the complexity of information search, these recommendation systems are based on a learner's profile. The construction of user profiles is at the center of the issues raised in the study of mechanisms for personalization or recommendation of resources to users that takes into account their specific needs. These profiles are constructed and enriched with the user interaction with the system. The objective of this paper is to present our approach for modeling a learner within our recommendation system. This is to develop a system to collect the learner's interaction Traces and process them, in order to propose in an automatic way educational resources adapted to their needs, through a set of agents which interact with each other.**

***Index Terms*—ILE, Trace, trace model, learner profile, modeling, ontology, multi-agent systems, semantic web.**

I. INTRODUCTION

ILE (Interactive Learning Environments) is a computing environment that uses the web as a medium for disseminating knowledge and helping the various actors interact with each other, it aims to promote, accompany and validate learning. There are several categories of an ILE, in particular the microworlds, intelligent tutoring and adaptive hypermedia. According to [1], four types of models are specified when designing an ILE, the domain model, the learner model, the pedagogical model (tutor), the expert model and the interaction model.

The learner modeling is a field of research that has been the subject of several publications, it consists of all treatments allowing developing and updating relevant information about the learner from analyzing his behavior, this analysis most often consist of observing and Tracing the information of the learner activities in the system during a learning session, followed by analyzing and interpreting it.

This article is organized as follows: section 2 presents the context and issues of our work, section 3 describes the theory of the Trace on which our module is based, section 4 presents the multi-agent technology, section 5 presents the general architecture of our Traces' collection module and the final section presents the conclusion and offers ideas for future developments.

II. WORK CONTEXT AND PROBLEMATIC

With the increasing number of websites as shown by the statistics Netcraft4 (over 644 million websites in 2013), the mass of data exchanged on the Internet is an advantage for universal access to information. In parallel, it is also a challenge because it requires significant processing to filter the data returned and find the relevant information for the user. In fact, the recommendation is a scientific field that seeks to personalize access to information for a given user, and thus facilitate his choice of content in a too extensive catalog so he can get an overall idea. In practice, recommender systems, based on knowledge about a user, filter a set of content and produce a list, often ordered, considered relevant for him.

Our research is part of the customization of ILE. The goal of our research is to study and develop a recommendation system based on Traces that will enrich the services of an ILE, it is to consider the interaction Traces left by the learners as a source of knowledge which the system can exploit to propose pedagogical resources adapted to targeted learners in order to increase their satisfaction during a learning session.

In fact, we have identified four steps for our system [2]: The collection of data based on the learner's behavior, Data processing, the construction of behavioral patterns of the learners, and the recommendation of resources.

In order to achieve the above-mentioned steps, we will create a system comprising of several modules, each of which has its own task (figure 1). The Traces left by the learners on the system allow to evolve this profile over time.

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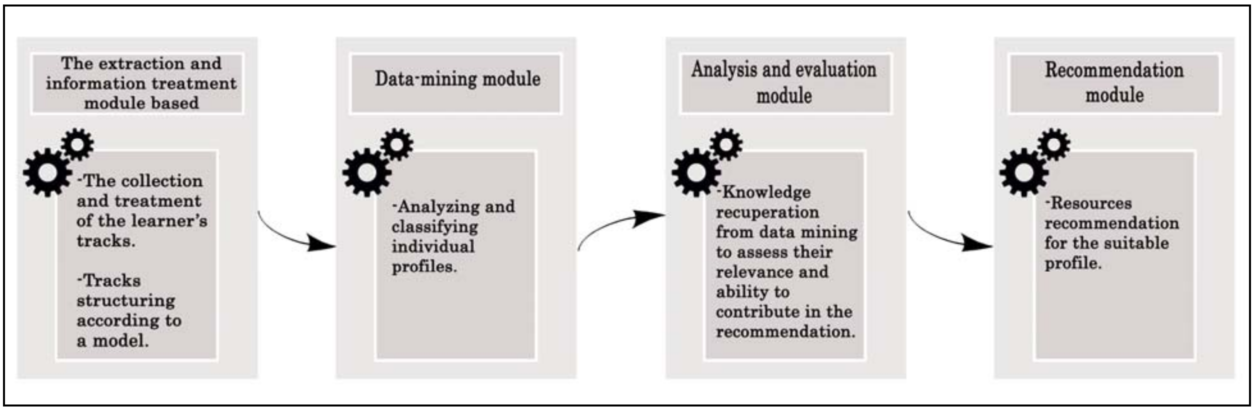

Figure 1. General architecture of the system.

III. Literature Review

Our work is at the border of two research: modeling the user profile and recommendation systems. Our goals are trying to answer the question: how to effectively analyze the interaction's Traces with an ILE to derive the learner profiles, so as to recommend resources adapted to their tastes and needs? To do this, we study existing works that are based on the notion of Trace to enrich the profiles and improve the mechanisms of adaptation, recommendation or personalization.

There are many researches that have used the notion of Trace to analyze users behaviors and the difficulties in using computer systems. For example [3] aims to develop an adaptive aid system based on the Trace's interaction, it is to consider the Traces left by users as sources of knowledge that the system can use to generate support adapted to the targeted user. In [4] the Trace is used to analyze the behavior of an automobile driver, in order to infer or validate the hypothesis of cognitive modeling of the latter. Rossi et al exploit [5] the interaction Traces to evaluate the adequacy of the logical architecture of a Web site and its perception by the users. As part of a learning activity mediated by ILE Mazza and Dimitrova [6] propose an approach exploiting Traces from the course management systems to help teachers analyze behavioral, cognitive and social aspects of learners.

As part of our research, we thought to be inspired by these work to create a recommendation system whose role is to research and provide complementary educational resources adapted to profiles built based on the Traces collected.

IV. Traces Treatment In The Context Of Web Based Training (ILE)

We have previously presented the problematic of our work and a diagram showing the modules of our system. The work on the Traces of the learning activities aim on one hand to define the elements of the learner's activity which can be observed and useful for recommendation, and on the other hand to create higher-level information from these initial Traces.

A. Trace

In a real teaching situation, the teacher can change the progress of his course following his remarks to fit the different profiles of his learners. In distance learning, these observations are derived from collected Traces.

In the field of ILE, a Trace recounts the history and chronology of the learner's interactions with the ILE. According to [7], we can consider the Traces as pedagogical objects.

Our research on the Trace will be based on the work of the SILEX team from the LIRIS laboratory, that's why we will consider the definition given by [8], "the trace is defined as a temporal sequence of observed".

We can use all the traces left by the learner in an ILE for modeling the learners' profiles. Models obtained following this model are the operational knowledge for the recommendation of resources.

B. Traces Treatment Models

In order for the Traces to be exploited, they must be accompanied by a model that can understand and use them.

According to the study done by BEN SASSI [9], there are several treatement models which he summarized the specificity of each in this comparison table:

TABLE I.
TABLE SHOWING THE DIFFERENT SYMBOLS FOR THE TWO TYPES OF INTERACTION

Trace model	Main characteristics	Properties of the generated Trace
Jermann Model [10]	The raw Trace is retrieved, analyzed and interpreted in the system.	The nature of the generated Trace depends on the final phase of treatment. The format is often proprietary to the system.
MUSETTE model [11]	Retrieve Traces from the navigation of a user in a VLE.	The Trace is a sequence of states (entities) and transitions (events)
CSE model [12]	Raw Trace is merged from multiple Traceing sources and it is transformed, finally, in advice and guidance.	The generated Trace is owned and it is strongly attached to the situation of the learning analyzed.
TREFLE model [13]	Capitalize usage Traces and operate to assist the user in his navigation.	The modeled Trace is owned
MTSA model [14]	Structure the Traces from "log" files relating to the actions and productions of learners and calculate activity indicators, social and cognitive.	This model transforms the raw Trace in educational indicators allowing the supervision of learning.

C. Trace Based System (TBS)

After introducing the notion of Traces and Trace models. In this section, we present the notion of Trace Based system as a solution to the Trace transformation problem.

1) General principle of TBS

Trace Based System is a system that implements both the notion of notion of Traces and Trace models defined in the previous section, it offers various Traces manipulation services. According to [15], a TBS is any computer system whose operation involves in varying degrees the management, transformation and visualization of explicitly modeled Traces as such. Figure 2 shows the general architecture of a Trace Based System.

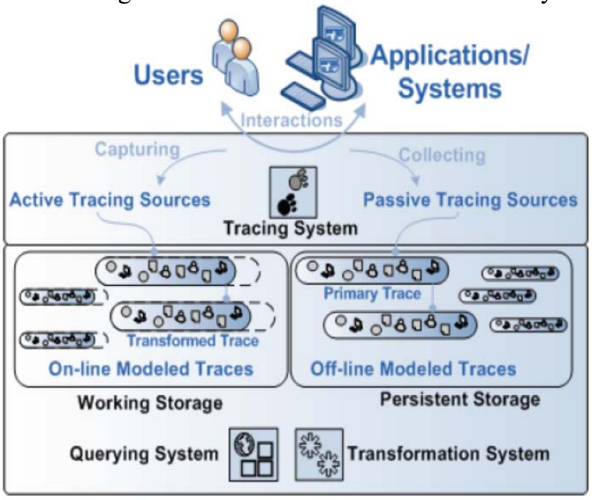

Figure 2. Trace-based system architecture [16].

2) Data Collecting in TBS

The collection process is to capture the learner‘s interactions from Tracing sources to create the so-called first Trace. The latter, as its name suggests can be considered as a modeled Trace and may then be manipulated through transformations and queries.

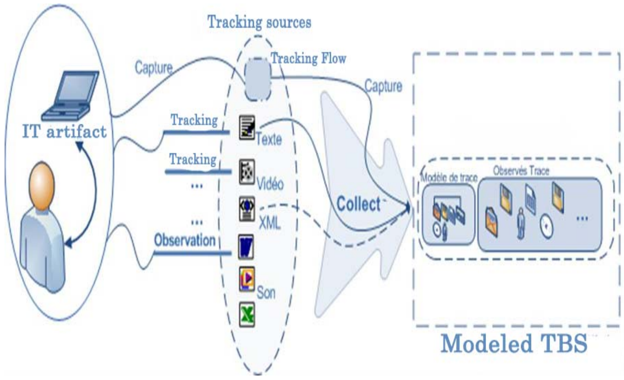

Figure 3. Data collection process in an TBS

According to [17], there are three approaches to collection Trace in open and distance learning environments:

- Server-centric approaches: which focuses on the research of the user navigation patterns on a given website based on the analysis of the Web server logs. These logs contain all the actions performed on the server. Traces generated from these logs require many operations (filtering, recomposition sessions, etc.).
- User-centered approaches: who is interested to instrument the client to observe all of the learner’s specific interactions outside the learning platform.
- Approaches based on specific software which is focused on the identification of the interaction at the collection time through a specific tool to the Traceed environment.

3) Data Modeling in TBS

Automatic transformations are applied in the SBT according to a transformation engine; it allows the reformulation of already collected m-Traces by applying transformation requests to produce a new Trace.

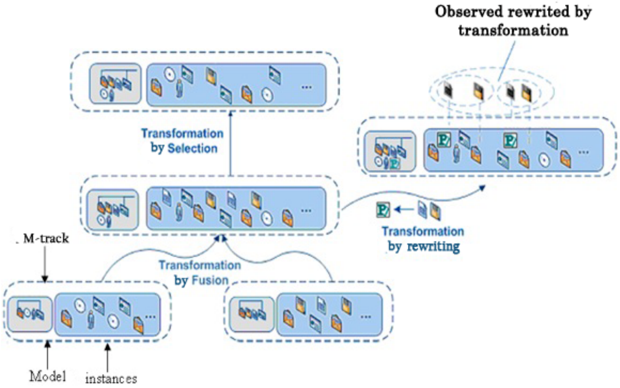

Figure 4. Traces transformation process in a TBS

The collection phase provides Traces labeled "raw Traces" or "primitive Traces" which are difficult to use. To make it possible to exploit these Traces, it is necessary to perform pretreatments in order to structure and facilitate their exploitation. This phase can be divided into three steps: fusion, filter and structure [18].

We can distinguish three types of transformations:

- Transformations selection type allows the creation of a new Trace containing all observed respecting a given selection filter.
- Transformations rewrite type patterns allow replacing one or more observed by another observed.
- Transformations by fusion meant to gather observed originating from several m-Trace sources in order to obtain a new Trace.

V. Used Technologies

A. Semantic Web and Ontologies

W3C has defined “The Semantic Web is an extension of the current Web in which information is provided in a well-defined significance, enabling computers and people to work better in cooperation” [19].

In the vision of Tim Berners Lee, the Semantic Web is structured into different layers:

- Syntactic layer (XML)
- Metadata layer (RDF / RDFS)
- Semantic layer (the ontology languages)
- Logic layer (automated reasoning)
- Validation and evidence layer (proof)

Among the basic concepts of semantic web, we found ontologies. These last appeared in the early 90s in the Engineering community knowledge, they play an important role in the new generation of Knowledge Based information systems; they are also a keystone of multi-agent systems using high-level communication.

Initially, Ontology was an area of philosophy concerning "the study of being qua being, that is to say the study of general properties of what exists". In the field of artificial intelligence, there are several definitions of the concept of ontology, according to Gruber [20]: ontology is a specification of conceptualization. The ontology enables the representation of knowledge based on conceptualization. Ontology can be defined as a consensual conceptual vocabulary. Sowa [21] defines ontology as an area whose object is to study the categories that exist or may exist in a certain area.

B. The Multi-agent Technology

Multi-Agent Systems (MAS) are systems composed of a set of agents located in a certain environment and interacting according to certain relationships, they appeared in the 90s. According to Ferber [22]: “Multi-agent systems are applications in the field of artificial intelligence where they reduce the complexity of solving problems by dividing the necessary knowledge into subsets, by associating an independent intelligent agent to each of these agents, thus we speaks of distributed artificial intelligence”.

MAS have the following main features:

- Each agent has information or capabilities to solve incomplete problems, so each agent has a limited viewpoint.
- There is no global system control.
- Data is decentralized.
- Calculations are asynchronous.

VI. Proposed Approach

A. To a Recommendation System Incorporating a TBS

Our ultimate goal is to develop a recommender system based on Trace interaction. This is to consider the Traces left by the learners as sources of knowledge that the system can exploit to propose complementary learning resources according to their profiles. These resources will be proposed to enhance the acquisition of knowledge, they aim to complete and exceed the initial objectives.

Our recommendation system is based on four modules as shown in Figure 6, each module including one or more agents to circulate fulfill its own tasks:

- *The extraction module and information treatment on the learner’s behavior* is called the "collection agents" which are responsible for capturing information from the observed system, translating them into observed and relationships according to a Trace model, and finally, transmit this information to a TBS in the form of a Tracing flow.
- *Data-mining module*: calls two agents, each of which encapsulates a method of search, namely "clustering agent", "association rule agent"
- *Analysis and evaluation module*: calls for "the inspector agent" whose role is to research relevant resources for the constructed profiles.
- *Recommendation module*: the results of the analysis and evaluation module will be exploitable by the recommendation module through "the recommendation agent" whose role is to provide the found resources for learners.

The implementation of the modeled Trace Based System developed by the SILEX team (Lab Liris - http://liris.cnrs.fr) in “The extraction module and information treatment about the learner's behavior" of our system has led to the creation of a system that allows the transformation of Traces to exploit at the end by "the data-mining module" for the development of groups of learners with similar interests.

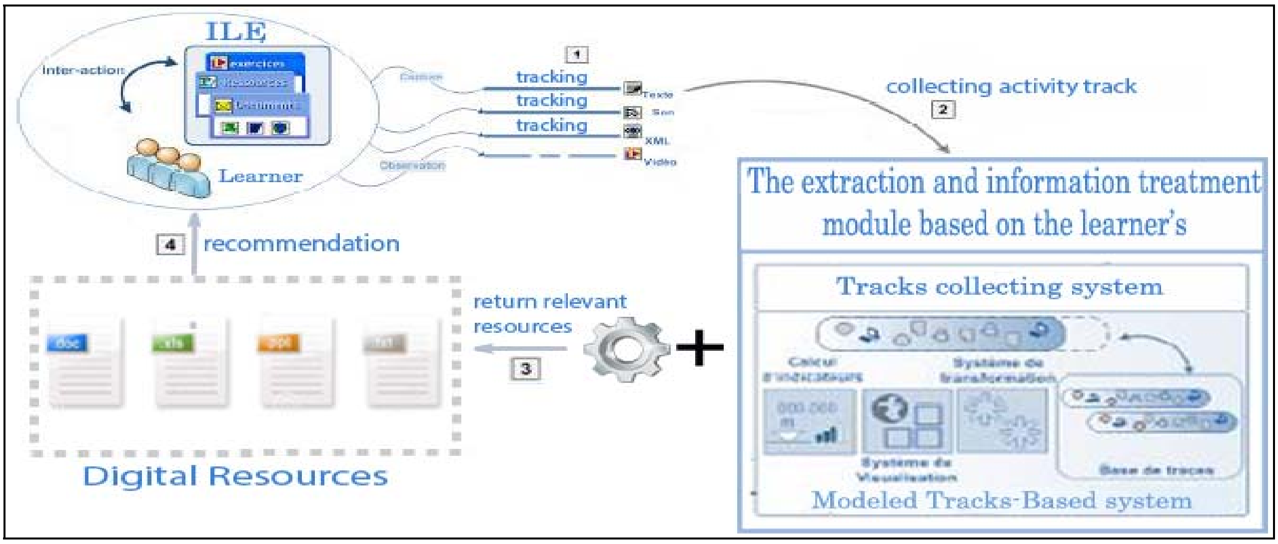

Figure 5. Our recommendation system architecture built around a TBS for transforming the learner's tracks

B. *Trace Modeling in the Recommendation System*

In order to establish our own Trace model, it was necessary to identify the objects that describe the system and the operations performed by the learner. In our case, we will consider the actions performed on the resources. For this, we can distinguish two levels of navigation:

- Course navigation: during a learning session, the learner is required to consult during the course which he is registered in. Monitoring the learner at this level is to measure, as far as possible, the degree of assimilation of the contents presented and the progress of the learner in the course according to the expectations set by the teacher.
- Plate-form navigation: This is to identify the different activities carried out by the learner on the platform: consulting his inbox, forum participation, consultation during his studies, etc.

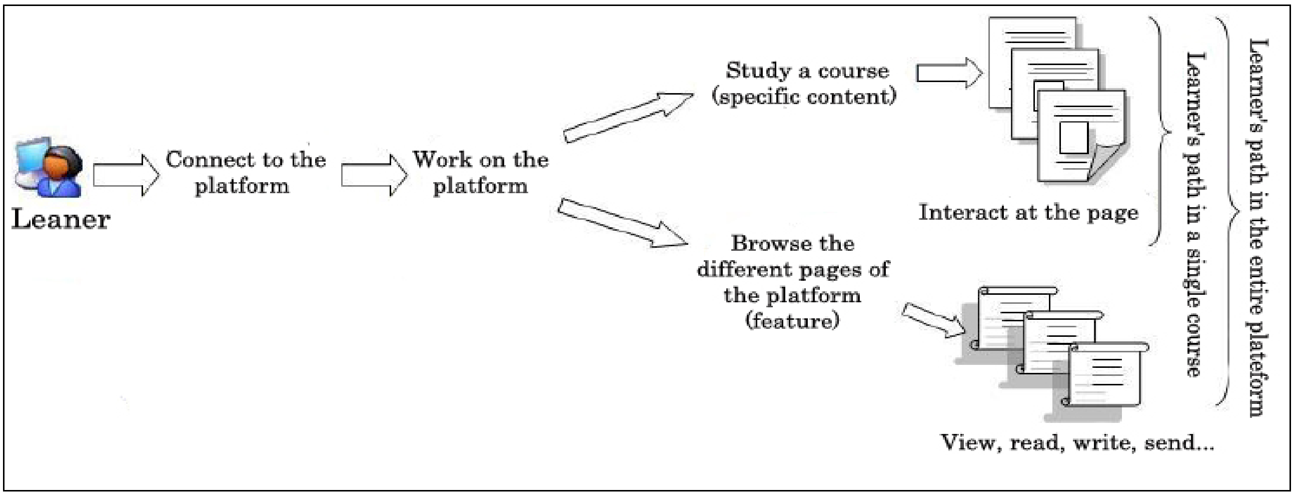

Figure 6. Learner interactions included in the recommendation system

After the research we've conducted, we found that the model proposed in [17] is the most suitable for our needs. Therefore, we will use it as a Trace model for our recommender system. The Traces are structured by temporal sequences of states (pages) and transitions (actions performed on pages). These Traces are recorded for each learner between the moments of the beginning and the end of the learning session.

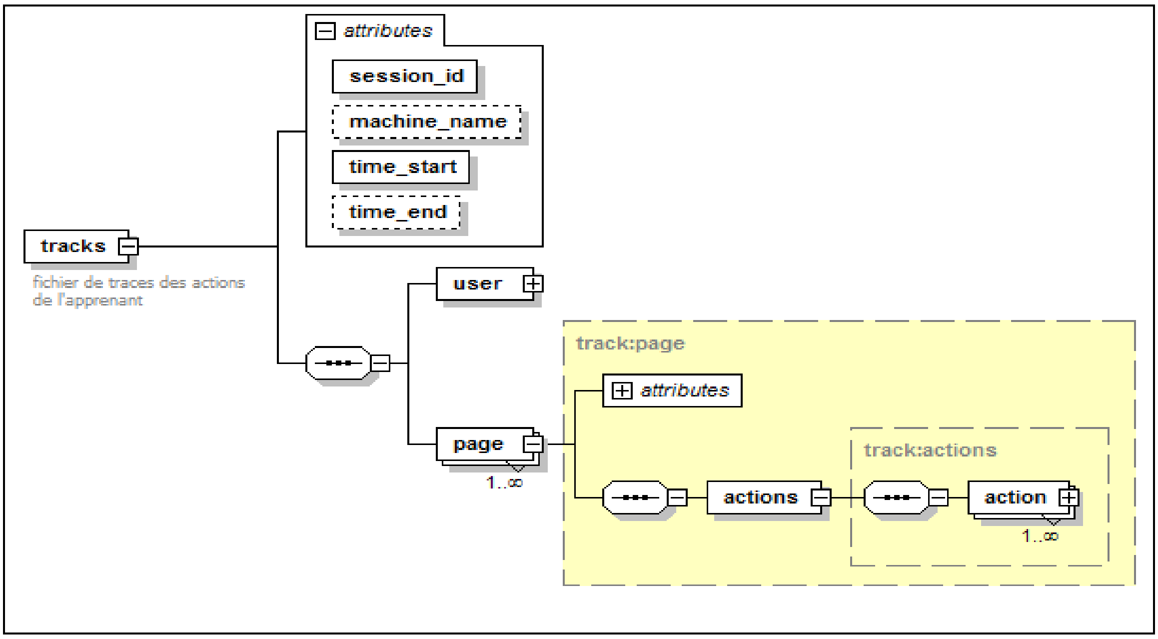

Figure 7. Trace model of our recommendation system

The page is not limited to a web page, for this, we will record the URI (Uniform Resource Identifier), its title and order of appearance.

The learner‘s interactions with the page are recorded in the "actions" element. It contains components of type "action" identified by the order of appearance, date, time of execution, and the interaction type made (open a file or url, send messages, post message in the forum, etc.).

C. Learner Modeling Approach Based on Ontology in a Recommender System

1) Construction of the learner's profile

The objective of the learner modeling is to provide a complete and accurate description as possible in all aspects related to the user's behavior description. The user models in ILE are generally compatible with the standards IMS and PAPI [2].

The proposal of complementary educational resources requires knowledge on the learners (credentials, interests, skills, historical). For this, we thought to model the learner in an approach based on ontology.

- **Domain ontology**

The domain ontology O_{domain} allows to describe the concepts of a domain of knowledge relative to an educational field: IT, chemistry, law, etc... It can have multiple ontology areas, each specific to a given teaching discipline and describes different concepts.

- **Learner ontology**

The learner ontology $O_{learner} = \{ O_{identity}, O_{historic}, O_{interest\_centers} \}$ is composed of three parts. The first part, $O_{identity}$ describes a learner‘s specific information: name, speciality, level of study, language. The $O_{historic}$ component is responsible for keeping trace of the learner's historical status. For the last component, we thought to use the learner's navigation traces to fill their center of interest in the form of weighted term. We then made the choice to study the contribution of TF-IDF approach. The TF-IDF (Term Frequency-Inverse Document Frequency) [23] is a method often used in information retrieval and in particular in text mining. Typically the TF-IDF approach studies the relationship between words, documents and corpus. We define the equation TF-IDF inspired by the equation proposed by wang [24] adapted to our need to calculate the weight in relation to the navigation in the educational resources and the learner‘s productions as follows:

$$Tf_{i,j} = \frac{n_{i,j}}{\sum_k n_{k,j}} \qquad (1)$$

$$Idf_i = \log \frac{|P|}{|\{p_i \in p\}|} \qquad (2)$$

TABLE II.
TABLE SHOWING THE DIFFERENT SYMBOLS FOR THE TWO TYPES OF INTERACTION

	Navigation in the resources	Learner's productions
$n_{i,j}$	Number of nodes visited by the learner j related to the concept i	Number of actions concerning the concept i made by the learner j
$\sum_k n_{k,j}$	Total number of nodes visited by the learner j, where nk, j is the number of nodes visited in connection with the concept k	Number of actions concerning all concepts made by the learner j, where nk, j is the number of actions concerning the concept k
$\|P\|$	Total number of learners enrolled in a group	Total number of learners enrolled in a group
$\|\{p : ti \in p\}\|$	The number of learners who have visited at least one node in relation with the concept i	the number of learners in this group who achieved at least one action concerning the concept i

The weighting of the terms for the two types of interaction is calculated by the formula:

$$C_{i,j} = tf_{i,j} * idf_{i,j} \qquad (3)$$

The total weighting of concepts constituents the learner's interests is calculated by the formula:

$$CT_{i,j} = C(n)_{i,j} + C(p)_{i,j} \qquad (4)$$

- **Competence ontology**

The ontology $O_{Competence}$ specifies the level of each learner (novice, beginner, intermediate, expert) on the concepts of the domain ontology through assessment tools integrated in each resource. This ontology is based on the work of researchers in the field of human resources management [25]. In our approach, we chose to use the ontology given by [26] to describe the level of skill acquisition by learners.

- **Quiz ontology**

The ontology Quiz is based on the work of [27], its objective is to validate the learners' level that have a concept in their area of interest, but have not yet studied the course within the platform. It also aims to discover if a learner has reached an expert level for a concept in case he has exceeded the initial objectives.

- **Social Network ontology**

The objective of the ontology Social Network is to refine the learners' profiles with information that is not available in the platform such as areas of interest to a learner that he hasn't studied yet.

2) Cold start problem

Most of recommender systems suffer from the problem of cold start, and several researchers have proposed solutions to resolve this problem. In our case, we thought of two solutions, the first if there is a shortage at the community level at the platform, and consist of recovering the learner's specialty to propose a list of recovered concepts from the ontology domain. With this, the learner has the possibility to choose what interests him.

The second solution is the use of the concept presented in [28] to build a social map from the list of learners who have the same specialty as the learner newly registered, to offer him the possibility to select the communities that interest him and thereafter to receive resources already available to these communities.

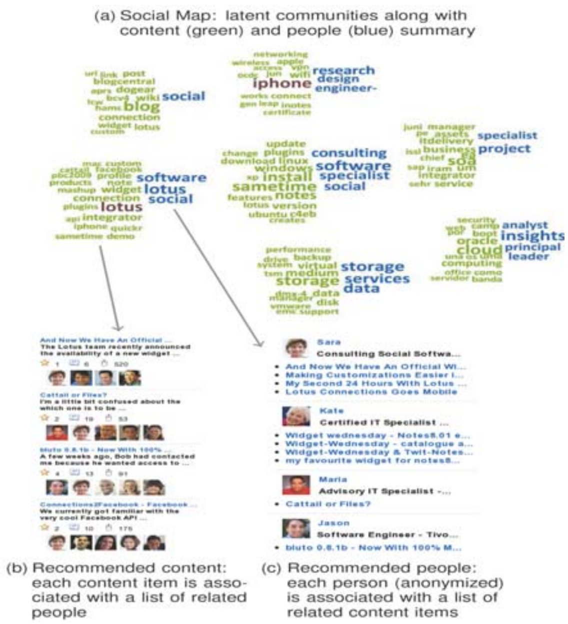

Figure 8. Who is talking about what: social map based recommendation [28]

CONCLUSION & PERSPECTIVES

We have presented in this paper the architecture of a recommender system incorporating a SBT and the approach of modeling a learner profile based on Ontology. The objective is to develop a solution that allows us to use the interaction traces as sources of knowledge that the system can use to provide complementary educational resources to learners during a education session.

We plan to focus in our future research to define the architecture of other modules to start the development of a prototype of our recommendation system.

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