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Toward Egocentric Network-based Learner Profiling in Adaptive E-learning Systems: A concept paper

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ABSTRACT

Adaptive E-learning systems, which provide personalized learning experiences based on learner's specific characteristics (e.g. knowledge, skills, and competencies), are essential for developing effective learning and teaching. This paper presents a conceptual proposition consisting in developing adaptive E-learning system by incorporating egocentric network-based user profiling, an existing contribution of our research team. Actually, this contribution has been proved in the online social network context with empirical results on different social networks data (Facebook, Delicious, Twitter and DBLP). We aim to apply the existing algorithms underlying this contribution in E-learning context and present in this work a conceptual model and the construction process of learner's user profile, called "learner profile". The learner profile can be exploited in adaptive E-learning systems to provide different personalized/adapted services (books recommendation, personalized courses search, ...) to the learner.

Keywords

Adaptive E-learning, User profiling, Social profiling, Egocentric network

1. INTRODUCTION

We are living in the Industry 4.0 era where technologies play a very important role in our daily life and increase the capacity of knowledge creation and diffusion process. Rapid revolution in technology has produced a new model of education for the future — Education 4.0. Education 4.0 that focuses on educational innovation and agility has made future learning more intuitive, interactive, mobile, global, virtual, social (Community of Practice) and adaptive/personalized. Adaptive E-learning systems are considered one of the most interesting research issues that can respond to the challenges in education 4.0 context. As learners

have different needs, abilities and learning preferences, we should adapt the curriculum and teaching strategies to these different learning styles.

Adaptive systems have been broadly known and met with success in different domains where personalized responses of the system are expected (recommendation system, personalized search, ...). Different works have been proposed to improve the performance of adaptive systems. One of the important element of adaptive system is "user profile" that is used to collect user information and preferences. Adaptive systems use user profile to propose relevant content according to user's specific needs. Our research team focuses also in this research domain and has proposed in our previous works a contribution to a user profile construction process (called also "user profiling"). We have proposed a generic profile model and a social network based user profiling process that we called "social profiling". The performance of our proposition has been proven by empirical methods in the context of online social network (Facebook, Twitter, Delicious, DBLP).

In this work, we are interested in applying our existing contribution in the context of adaptive E-learning. We suggest that our existing egocentric network based user profiling algorithms can be effectively applied in the educational domain. However, it is important to take into account different factors that are specific to the educational domain. We present in this paper an overview of adaptive systems in education and describe a preliminary concept of our research that consists in adapting our existing profiling process in the domain of education (called learner profile). Then, we propose a learner profile conceptual model and the construction process of this profile, which can be then exploited in adaptive E-learning systems to provide different personalized services (book recommendation, personalized courses search, ...). The proposed learner profile consists of two different dimensions: the learner individual dimension, built by using the learner information and the learner social dimension, built by using the information from the learner egocentric network (by applying the existing egocentric network based algorithm). This preliminary work can lead to an empirical study in order to validate our proposition in our further works.

The paper is divided as follows: in the second section we present related works on user profile and adaptive systems and how user profile is used in adaptive E-learning systems. In the third section we present the proposed conceptual model of the learner profiling. In the last section, we conclude and present some perspectives of our work.

2. RELATED WORK

2.1 User profile and adaptive systems

User profile is widely addressed in user modeling, a research domain that focuses on a representation of user or a group of users

based on their personal information (affiliation, geographical information, age, ...) and characteristics (preferences, interests, ...). [1] describes the use of user models as follows: "Users are different: they have different background, different knowledge about a subject, different preferences, goals and interests. To individualize, personalize or customize actions, a user model is needed that allows for selection of individualized responses to the user." Therefore, user modeling is discussed in cross-disciplinary research topics, where a personalized response of the system is expected, such as human-computer interaction, artificial intelligence and information systems. We call such systems personalized systems or adaptive systems, which can adapt themselves to various contexts or environments, based on user's specific preferences or characteristics, stored in the user profile.

In human-computer interaction, user profile is exploited to adapt user interface features according to the user needs and to provide an adaptive presentation that consists in modifying presented content according to the preferences maintained in the user profile : for example modifying presentation order or level, hiding content, suggesting shortcuts based on user specific preferences. In information systems, user profile is an essential element for adaptive information mechanisms (e.g. personalized information retrieval, recommendation). These mechanisms rely on user profiles to propose relevant content according to the user specific needs. In personalized information retrieval, user profile is used by the mechanism in order to refine the retrieval and present relevant search results, when users with different backgrounds may express different information needs with the same query. User profile is also widely used in recommendation systems that propose individualized information/object recommendations to users or guide the users in a personalized way to interesting or useful objects in a large space of possible options, (as we can observe now in some e-commerce sites such as Amazon.com). Such systems have a great usefulness in environments where the amount of information vastly exceeds any individual's capability to survey it. Note that in this work, we mainly focus on the use of user profile in information system field.

In the literature, different user profiling techniques and various models of user profile are discussed. User profiles are generally represented as sets of weighted keywords, semantic networks, weighted concepts, or association rules. For more details on these representation model, we refer the reader to the excellent text written by experts in this field [2]. According to [2], user interests can be extracted from information explicitly given by the users (explicit information) or implicitly gathered when they interact with the system (implicit information). Several works also propose to extract the user interests from their social networks (social profiles). Our research focuses on the latter approach and we have proposed in our team different works that aim at developing a user profile building process based on information from user social network(s). This approach consists in applying the social network analysis (SNA) techniques to identify the user interests or preferences based on the interests or preferences of the neighbors in the social network of the concerned user. This technique is based on the homophily and the influence social theory that describe the fact that users tends to connect and collaborate with those who share common interests and tend to influence each other via the links they have in their social network.

In [3], [4], one of our team propositions, the authors presents a user's profile as a vector of weighted user's interests. Each user's profile is composed of two dimensions. Firstly, the user dimension which contains user's interests computed by using only

the user behavior. Secondly, the social dimension which contains user's interests computed by using the behavior of people in the user's egocentric network (G). They have proposed using the user's egocentric network, a specific social network containing only direct neighbors of the focal user. Obviously, this work considers that the user is better described by communities of people around him, especially the people that are directly connected to him as demonstrated in [5], [6]. The authors describe the egocentric network of a user as follows: for each user (u) we consider the undirected graph $G(u) = (V, E)$ where V is the set of nodes directly connected to u, and E is the set of relationships between each node pair of V. The egocentric network can help reducing the number of potential people that can be relevant for the user and hence reduce the computation time and favor scalability. They have introduced a generic algorithm to enrich user's interests. This algorithm can be reused in any application context and in any mechanism.

The performance of the proposed process has been proved with empirical results. Different works have been proposed by our team to extend this work. [7] proposed to use the snowball-sampling technique to identify and add user's distance-2 neighbors (friends of a friends) into the user's egocentric network to improve the performance of the CoBSP algorithm for users having a small or spars egocentric network. In [8] we proposed to improve the performance of the CoBSP by taking into account dynamic characteristics of social networks. We applied a time-aware method into the CoBSP algorithm. The aim of this strategy is to weight user's interests according to their relevance and freshness. The time awareness weight of an interest is computed by combining the relevance of individuals in the user's egocentric network (computed by taking into account the freshness of their ties) with the information relevance (computed by taking into account its freshness). The experiments on scientific publications networks (DBLP/Mendeley) allow us to demonstrate in these works the effectiveness of our proposition compared to the existing time-agnostic egocentric network-based user profiling process. In [9], which is the extended version of [8] we have proposed a parametric study to analyze the results of intensive experiments and to study also the impact of the individual temporal score compared to the information temporal score. In [10] we have applied our existing time-aware social profiling method on Twitter, which has different characteristics from those of other social networking sites. Although, compared to the time-agnostic baseline method, the improvement is still low, the experiments using a parametric study showed us the benefit of applying a time-aware social profiling process on Twitter. We also found that our method performs well on sparse networks and that the information dynamic influences more the quality of our proposed time-aware method than the relationships dynamic while building the social profile on Twitter.

In this paper, we are interested in applying our existing contribution in the context of adaptive E-learning. We suggest that our existing egocentric network based user profiling algorithm can be applied in the educational domain. We present in the next section the related work on adaptive E-learning systems.

2.2 Adaptivity in E-learning Systems

The term E-Learning, originated from Electronic Learning, is learning utilizing electronic technologies to access educational curriculum outside of a traditional classroom. In most cases, it refers to a web-based course, program or degree. Therefore, E-learning mostly involves the usage of computer and interactive networks simultaneously. The platform used to support a number

of E-learning activities is known as Learning Management Systems (LMS). In this paper, the term “LMS users” refer to learners who can navigate the content on the LMS. In most cases, there are different groups of LMS users with different characteristics and needs. The adaptation of E-learning system to a specific individual or to a specific group based on their characteristics, knowledge preferences or needs, becomes a major challenge in E-learning development. Adaptivity is important in the field of E-learning for many reasons and goals:

- it can help learners to effectively navigate the content based on the learners profile (preferences, specific needs, interests),
- it can provide relevant contents (courses, book, activity, ...) according to learner specific needs,
- it can personalize the learning activity based on the user preferences and learning characteristics,
- it can provide an effective method to improve the learner skills or overcome learning problems.

An adaptive system for E-learning is known as an adaptive E-learning system. An adaptive e-learning system is an interactive system that personalizes and adapts E-learning content, pedagogical models, and interactions between participants in the environment to meet the individual needs and preferences of users if and when they arise [11], [12]. Techniques and mechanisms exploited in adaptive system can be also used in adaptive E-learning system. To fit the needs in the field of E-learning, adaptive mechanisms are more specialized and focus on the adaptation of learning activities, learning contents and the presentation of these contents [13].

2.3 User profiling in adaptive E-learning

In general, adaptive E-learning systems use a user profile to personalize the content according to the learner specific needs. In this context, we use the term “learner profile” to assign the user profile of a learner. Therefore, the information stored in the learner profile are mainly restricted in the domain of education. According to [14]–[16], we consider the following information as important information in the learner profile:

- **Demographic** describes the descriptive personal information of the learner related to age, gender, academic level, occupation, etc. In general, demographic information is used to identify a person
- **Background and experience** including skills, knowledge that learner gained in the past.
- **Learning styles** describe the student preferences for the presentation of courses material, how to work with material and how to deal with provided content [17]
- **Competences** describe individual’s abilities to respond to certain demands placed on them by their environment or a set of personal characteristics (e.g. skills, knowledge, attitudes) that an individual possesses or needs to acquire. This is in order to perform an activity within a specific context, whereas performance may range from the basic level of proficiency to the highest levels of excellence [18]. We can also consider learner aptitudes as a kind of competence. According to [16], there are eight forms of aptitudes: linguistic, logical/mathematical, spatial, kinesthetic, musical, interpersonal, intrapersonal, naturalist.
- **Interests** are particularly essential in commercial recommendation system. It is also important in adaptive educational system.

- **Goals** describe learner’s purposes or objectives in learning course. According to [16], there are two kinds of goals: i) long-term, which are relatively permanent and relate to the long-term plan of the learner. ii) short-term goal, which are related to the problem that the learner intends to solve in a specific period or context passing an examination, doing an exercise. Short-term goal is also called as problem-solving goal.
- **Emotional state** describes the sentiment state of the learner. Normally the sentiment state of the learner is not given explicitly. A sentiment analysis is needed in this case.
- **Reading difficulties** specific the difficulties in reading of a student, information about his/her school life, history of his learning difficulties, his associated difficulties, and his reading and writing habits.
- **Cognitive traits** describe cognitive processes involved in reading such as phonological processing, orthographic processing, lexical access, processing speed, working memory, and semantic processing.

3. PROPOSITION: EGOCENTRIC NETWORK BASED LEARNER PROFILING

Our proposition consists in defining a conceptual model of a learner profile and the construction method of this profile. This construction method is known as “user profiling”, so-called in this context “learner profiling”. The data used to extract the information and construct the learner profile will be collected from the E-learning platform (registered courses, surfing behaviors, discussions in the forum). Based on the profile of each learner, we can improve his/her personality skill by recommending courses or strategies to improve or promote his/her capacity. The built profile from the E-learning platform can be also used to recommend extracurricular activities to students. This will help learners to complete their specific needs or to promote their talent in a proper way (cf. Figure 1).

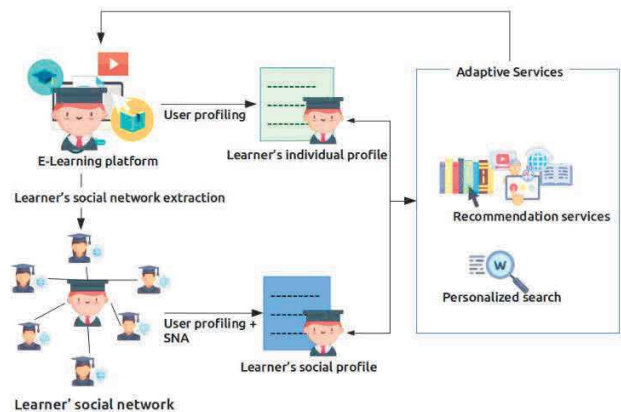


Figure 1: Adaptive E-learning platform based on social network based learner profiling

3.1 Existing egocentric network based user profiling

The proposed learner profile is based on the generic model proposed in our team [3], [4]. This model is composed of 2 different types of profile: user profile and social profile, which are both represented by a vector of weighted keywords. As this model of user profile is generic, it can be used

independently by different mechanisms (e.g. personalization, recommendation, ...).

User profile represents the user's information. This profile can contain different attributes such as user demographic information (name, age, and gender), user geographical information, interests explicitly indicated by the user or interests extracted implicitly by the system from the user's activities.

Social profile contains a list of interests extracted from the information shared in the user social network. More precisely, this work considers the egocentric network that represents the set of users directed neighbors (ref. section 2.1). We can adopt the user profiling techniques to build and represent the social profile. The main difference between the social profiling and the user profiling is the source of information used to construct these profiles. In the case of user profile, user interests are extracted from the user's own activities (shared information, search logs, ...). In the case of social profile, user interests are extracted from the information gathered by the members of the user's social network.

3.2 Learner profiling

The technique used to construct the learner profile will rely on our existing technique presented in the section 3.1. To fit the context of E-learning, the information used to extract the learner profile and the information stored in the profiles will be more restricted to the educational domain. Therefore, we have to adapt our proposition in two aspects: the representation of the learner profile and the data collection method.

3.2.1 Learner profile representation

Based on the generic profile presented in the section 3.1, we define the learner individual profile and the learner social profile as follows:

a. Learner Individual profile represents the learner's information. This profile can contain different attributes related to the learner. Note that, in this preliminary work, we suggest taking into account only information that can be explicitly given by the learner or can be gathering implicitly on the platform. In fact, the learning style, emotional state, reading difficulties and cognitive traits are information that are not obviously present in the E-learning platform and need more complex/manual methods to identify these kinds of information. Therefore, we eliminate them from the proposed learner individual profile. Thus, the learner individual profile is composed of the following information: demographic information that contain the personal information of the learner (affiliation, academic level, age, and gender), background and experiences, competences, interests, goals and user environment.

b. Learner Social profile represents the information extracted from the learner neighbors in his/her egocentric network. The learner social profile can be used as a complement profile for the learner individual profile in order to recommend new information, items or documents to the learner or to complete missed information of the learner. This type of profile contains the information that we consider determinable. In other word, we consider only the information that can be inferred from the learner neighbors: interests, preferences, goals. As do in the case of the learner individual profile, we ignore the information that is not obviously presented in the E-learning platform.

3.2.2 Data collection method

We distinguish information according to the technique used to collect the information: explicit method and implicit method. The information that can be collect explicitly by asking the learner to fill a formula on the platform are demographic information that contain the personal information of the learner (affiliation, academic level, age, gender), background and experiences, competences, interests, goals. The information that can be collect implicitly from the activity of the learner on the platform are background and experiences, competences, interests and user environment.

To construct the learner individual profile, we suggest to use the explicit information given by the user. And we will use the classical user profiling technique in the literature to build the learner profiling.

To construct the learner social profile, the information used to build this kind of profile will be collected explicitly and implicitly. As previously mentioned, the proposed social profile construction approach is based on a SNA technique to identify the information in the constructed profile. In the context of E-learning, the theory of homophily and social influence are also applicable. Students tend to involve in the group of students who share the same personality or interests (sport, music, studying, ...). We can define the social network of students in the E-learning platform and the learner egocentric network as follows: the egocentric network of the learner is represented by the set of the other learners who are directly connected to the concerned learner. We describe the egocentric network of a learner as follows: for each user (u) we consider the undirected graph $G(u) = (V, E)$ where V is the set of nodes directly connected to u , and E is the set of relationships between each node pair of V .

3.2.3 Learner social profile construction method

The proposed learner profile construction method is based on in our existing contribution.

a. Notation

Throughout this section, we denote I as the focal learner for whom we desire to build social profile. We use the term individuals **NEIGHBORS** to represent the social neighbors of I . For each neighbor $neighbor \in NEIGHBORS$, the set of information shared by $neighbor$ is denoted $Info_{neighbor}$. Each piece of information $Info_{neighbor}$ contains a set of terms that we call here "elements", denoted E .

b. Learner social profile construction

To build the learner social profile, we suggest applying two different social profile building approaches: individual-based approach (IBSP) and community-based approach (CoBSP) [10], in order to find out the best approach that is the most effective in the educational domain. Both social profiling processes have the same concept of computation, only the level of computation is different (individual or community level). We summarize the global view of both social profiling approaches for a given learner u , as follows:

Step1: collect the information from learner's social neighbors: for each $neighbor \in NEIGHBORS$ we collect the $Info_{neighbor}$.

Step2: elements extraction and weighting: for each $Info_{neighbor}$ we extract the set of element E and aggregate them at the individual level (for IBSP) or community level (for CoBSP) by using a weighting function. The weight of each element e is a combination of structural score and semantic score. The structural score of e from an $neighbor$ (resp. community c), is the centrality value of $neighbor$ (resp. c) in the egocentric network. The

semantic score of e depends on the time-frequency (tf) of e . The score combination is made by a linear combination function:

$$\text{score}(e) = \alpha(\text{semantic-score}) + (1-\alpha)\text{structural score}$$

$\alpha \in [0,1]$ is the proportion between the structural score and the semantic score.

Step3: elements combination and social profile derivation: we combine the weighted elements from every individual (for IBSP) or community (for CoBSP) by using a linear combination method. Finally, we derive all aggregated elements considered as learner interests to the learner social profile according to their score. The derived social learner profile is represented in the form of a vector of weighted elements.

The proposition will be validated by the relevant of the learner individual and social profile, obtained by the user's survey, expert survey and the accuracy of recommendation services incorporating the two profiles: courses recommendation, content recommendation, and external sources recommendation.

4. CONCLUSION AND PERSPECTIVES

We have presented in this work an overview of adaptive systems in education. Then, we have presented a preliminary concept of our work that consists in adapting our existing profiling process in the domain of education (called learner profiling). We have proposed a learner profile conceptual model and the construction method of this profile. The proposed learner profile which consists of two different dimensions: the learner individual dimension, built by using the learner information and the learner social dimension, built by using the information from the learner egocentric network (by applying the existing egocentric network based algorithm). The learner profile can be exploited in adaptive E-learning systems to provide different personalized/adapted services (books recommendation, personalized courses search, ...) to the learner.

In our future work, we envisage implementing the proposed model and method on a real dataset (E-learning system data) in order to validate our proposition. We can also use the SNA tools to improve the collaborative learning: to measure student interaction, identify patterns of interaction in student groups, provide instructive guidance accordingly, and evaluate the impact of instruction that aims to develop students' interpersonal skills for working collaboratively in groups.

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