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PERSONALIZED EDUCATION WITH THE PERCEPOLIS PLATFORM

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ABSTRACT
This paper describes Pervasive Cyberinfrastructure for Personalized Learning and Instructional Support (PERCEPOLIS), which leverages technological advances, especially in terms of pervasive computing, to facilitate personalized learning in higher education. Fundamental to PERCEPOLIS are: (a) modular course development and offering, which increases the resolution of the curriculum and allows for finer-grained personalization of learning objects and associated data collection; (b) blended learning, which allows class time to be used for active learning, interactive problem solving and reflective instructional tasks; and (c) networked curricula, in which the components form a cohesive and strongly interconnected whole where learning in one area reinforces and supports learning in other areas. Intelligent software agents are utilized in PERCEPOLIS to customize the content of a course for each learner, based on his or her academic profile and interests, with the help of context-based recommendation algorithms. This paper provides an introduction to the PERCEPOLIS platform and the educational research that underpins its design.

1. INTRODUCTION
Advances in databases, distributed computing, computational intelligence, and especially pervasive computing can be used to fundamentally transform higher education and instructional design [1]. The pervasive learning facilitated by these technologies overcomes the limitations of traditional passive lecture-based classroom learning by providing learning materials to learners according to their profile, which includes information such as learning style, interests, level of knowledge, and goals. These abilities result from the anytime, anywhere access to educational materials facilitated by pervasive computing, and the adaptive learning that results from their dynamic and intelligent recommendation to each learner [2, 3, 4]. Critical to the efficacy of this personalized learning is context-awareness of the recommendation procedure, which implies that context information can be extracted, interpreted, and leveraged by the underlying cyberinfrastructure. It also implies that the functionality of the pervasive learning system can be adapted based on its context at the time of use [5]. More specifically, pervasive learning environments provide context-aware resource recommendation services that discover and acquire the most appropriate educational resources from a potentially massive base [6].

This paper describes *Pervasive Cyberinfrastructure for Personalized Learning and Instructional Support (PERCEPOLIS)*, which leverages context-aware pervasive computing to create an adaptive learning environment that facilitates resource sharing, collaboration, and personalized learning in higher education [1]. PERCEPOLIS promotes and enables three key changes to the currently dominant pedagogy: modular course development and offering, blended learning, and networked curricula. The modular approach increases the resolution of the curriculum and allows for finer-grained personalization of learning objects and associated data collection. Blended learning allows class time to be used for active learning, interactive problem-solving and reflective instructional tasks, rather than traditional lectures. In networked curricula, which PERCEPOLIS promotes and supports, different courses form a cohesive and strongly interconnected whole, and learning in one area reinforces and supports learning in other areas.

Transparently and gracefully leveraging a wide variety of computing devices for enrichment of our living and working spaces is the key idea behind pervasive computing [7]. A simple example of a pervasive system is one in which a person's cellular phone automatically contacts his or her refrigerator, which responds with its contents, to inform the person of whether he or she has a sufficient supply of a particular item. The binary decision required in this example, i.e., whether or not a purchase is necessary, requires only trivial computational intelligence. The decision support required for personalized learning is significantly more sophisticated. In order to determine a personalized course trajectory for each learner, the system must select from a potentially large set the most appropriate learning materials for each learner, based on his or her background, interests, and needs. PERCEPOLIS requires a complex recommender system, as do most other pervasive learning environments, which leverage computational intelligence to recommend materials/resources, e.g., papers, books, hyperlinks, course enrollment, to each learner based on his or her profile, as well as recommendations made to learners with similar profiles [6, 8].

As a result of inadequate filtering techniques, the recommender systems of existing pervasive learning platforms effectively ignore the dynamic interests and preferences, access patterns, and other attributes of learners [6]. One goal of PERCEPOLIS is to remedy this shortcoming, using a context-aware resource recommendation model.

A noteworthy aspect of usage neglected by existing pervasive learning systems is the relevance of specific attributes, in particular environmental attributes, under given conditions. As an example, the networking capabilities of the user's end system should play a significant role in determining which educational artifacts to recommend, but ends up being neglected, due to the focus of the recommender system on the match between the contents of the artifacts and direct attributes of the learner [6]. In contrast, the recommender system of PERCEPOLIS takes into account the attributes of both the learner and his or her environment.

In brief, the novelty of PERCEPOLIS lies in its ability to leverage pervasive and ubiquitous computing and communication through the use of intelligent software agents that use a learner's academic profile and interests, as well as supplemental information such as his or her learning style and environment, to customize the content of a course for the learner [1].

PERCEPOLIS serves as a global information sharing platform that serves as middleware connecting a) databases housing learner profile information and b) instructional platforms or databases where educational artifacts are hosted. Figure 1 depicts an overview of the cyberinfrastructure.

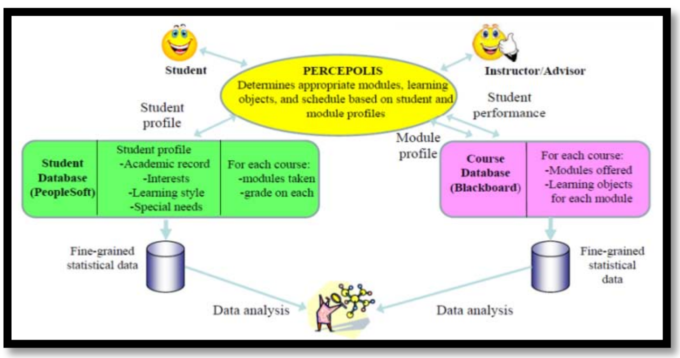

Figure 1: Overview of proposed cyberinfrastructure.

The remainder of this paper is organized as follows. In Section 2 we provide a brief survey of related literature. The major components of PERCEPOLIS are introduced in Section 3. Section 4 concludes the paper and outlines directions for future enhancements to the platform.

2. RELATED RESEARCH

The computational intelligence that facilitates personalized learning in PERCEPOLIS relies on two major technologies: intelligent software agents and a context-based recommender system [1]. A number of studies related to each technology are summarized in this section of the paper.

2.1. Intelligent Software Agent Model

An agent is a computer program that acts autonomously on behalf of a person or organization [9]. Agents can be particularly beneficial in pervasive learning environments, as they can assist in transparently managing information overload [10]. Leveraging pervasive computing and communications at various levels through the use of agent-based middleware is a defining feature of PERCEPOLIS. A number of existing personalized learning systems similarly employ multi-agent systems. We enumerate them below.

ISABEL is an agent-based e-Learning platform that enables interaction between users and e-Learning web sites and provides helpful suggestions about educational resources available to learners [11].

A generic architecture for eLearning systems is proposed in [10]. It is described as taking into account interactivity, personalization, adaptation, interoperability, collaboration, security to reinforce the quality of the learning process.

The Entre-pass system proposed in [12] is introduced as an intelligent agent-based pervasive learning environment developed to deliver preliminary entrepreneurial training to individuals working within small and micro-industries.

A distributed eLearning environment is proposed in [13]. The platform is comprised of three major parts: a front end, a Student Questioner Reasoning module, and the Student Model Agent.

The design and development of a scalable and inter-operable integration platform that enhances various assessment agents for e-learning environments is presented in [14].

An Agent Based Intelligent Tutoring System for Distance Learning (ABITS) is proposed in [15]. Three types of agents are employed in the system: evaluation, pedagogical and affective agents.

An agent-based intelligent tutoring system is introduced in [16]. Four models comprise the platform: student model, domain model, pedagogical model, and educational model. The Pedagogical Model is in turn composed of four agents representing preferences, accounting, exercises, and tests; respectively.

In Section 3, we will discuss the intelligent software agent model employed by PERCEPOLIS and will propose filtering techniques and recommendation algorithms that are used by the instructor, learner, and course agents, respectively, to determine an appropriate learning trajectory for each learner.

2.2. Context-Based Recommender Systems

Recommender systems assist users in making an informed selection of one or more items, e.g., books, articles, movies; from a pool of candidates [17]. The *context* considered by such systems in making the recommendation is broadly defined as any information that can be used to characterize an entity such as a person [18].

The educational recommender systems developed over the course of the past decade considered only two types of entities: learners and items, and did not consider context information in making recommendations. However, context-aware resource recommendation can play an important role in pervasive learning environments [6]. Two general approaches to leveraging contextual information in the recommendation processes are proposed in [19]: (1) recommendation via context-driven query and search, and (2) recommendation via contextual preference elicitation and estimation.

In the first approach, the obtained contextual information is used to submit a query or search a repository of resources, and then present the most appropriate matching resources to the learner. In contrast, the second approach tries to understand and model the needs interests of each learner by following his or her interactions (as well as those of other learners) with the educational system, or by receiving preference feedback from the learner on previously recommended learning objects.

The following four drawbacks have been enumerated for the learning recommender systems currently used in pervasive learning systems [6]:

(1) Existing recommendation algorithms are based on either content-filtering or collaborative recommendation algorithms. The authors assert that neither category is sufficient on its own.
(2) The recommendation techniques surveyed could not take into account the access time of historical records, so if the learners' interests change with the lapse of time, this change will not be observed.
(3) According to the repeatability and periodicity of learning process, it is possible to have some dependence relationships among learners' historical access records. However, the recommender systems do not model learners' preferences and ignore the mentioned relationships.
(4) These systems focus on logical attributes, e.g., similarity among learners' preferences, and neglect situational attributes. For instance, pervasive learning environments should support a broad range of devices, from desktop computers to smart phones. Consequently, they should be able to account for device (and network) capabilities when recommending learning artifacts.

The influence of pervasive games on English learning achievement and motivation is investigated in [20] through a context-aware pervasive learning environment denoted as Handheld English Language Learning Organization (HELLO). The system utilizes sensors, augmented reality, the Internet, pervasive computing, and related information technologies.

JAPELAS is a context-aware support system for the learning of formal expressions in the Japanese language [21]. The systems can recommend appropriate expressions to learners according to learner's situation and personal information.

ePH, a system that enables the sharing of public interest information and knowledge and can be accessed via always-on, context-aware services, has been described in [22]. A multi-agent architecture and multi-dimensional context model are employed by the system.

Addressing the gap between the learning accomplished during indoor computer-based learning activities in comparison to outdoor field trips is the objective of the system described in [23]. The solution proposed is the use of pervasive learning systems where mobile devices can be used to collect and report contextual information, which can be commented on by other users who may be in different physical or virtual environments.

PERKAM is a pervasive computing environment that allows learners to share knowledge, interact, collaborate, and exchange individual experiences. Radio-frequency identification is used to identify and profile the learner, objects, location, and environment and to subsequently recommend the most appropriate learning materials.

3. FEATURES AND COMPONENTS OF PERCEPOLIS

One of the key features of PERCEPOLIS is its modular approach to course development and offering, which enables finer-grained personalization of learning and data collection processes by increasing the resolution of the curriculum. Each course is decomposed into several content modules - some mandatory and others that are elective. Mandatory modules are dictated by course and curriculum objectives, and elective modules can be chosen to supplement the learner's knowledge of prerequisites or to engage an interested learner in more advanced topics. Each module as a standalone object has its own learning artifacts, such as prerequisite modules, lecture notes, problems, sample solutions, and programming or laboratory exercises. Modules in different courses can be linked to each other, facilitating implementation of a networked curricular model. The most appropriate mandatory and elective modules for each learner are determined by a recommendation algorithm, as outlined in Section 3.2.

PERCEPOLIS is composed of three major components: i) a multi-database system that stores, integrates, and retrieves learning artifacts; ii) the intelligent multi-agent system introduced in Section 2; and iii) a context-aware recommender system responsible for identification of the most appropriate and beneficial learning artifacts to each learner, based on information such as the learner's needs and interests. We articulate details of ii) and iii) in the remainder of this section.

3.1. Intelligent Software Agents

PERCEPOLIS recognizes three sets of entities as comprising the educational environment: i) the set of instructors/advisors, I; ii) the set of learners, L; and iii) the set of courses, C. Each course $c \in C$ is a collection of interrelated mandatory and elective modules. Each of I, L, and C is represented by a community of software agents that communicate and negotiate with each other to determine the best trajectory for each learner through a course or curriculum. The filtering techniques and recommendation algorithms used to this end are described in the following section.

3.2. Recommendation Algorithms

The focus of content-based filtering techniques is solely on identifying resources that are similar to what learners have accessed in the past. This complicates the recommendation of new learning artifacts. Collaborative filtering technique due to only considering similarity between learners' rating information neglects content-based relativity between resources [6, 17]. Therefore, we use a combination of content- and collaborative-based filtering techniques in designing recommendation algorithms for PERCEPOLIS.

Two types of contextual information are utilized:

(1) *Explicit contextual information,* which is provided directly by the learner or institution by completing surveys. This information can be classified into four categories:

   a. The *learner profile* includes academic records (list of the courses and modules has been passed, grades, GPA, target degree, major, etc.), personal profile (location, disabilities, interests, needs and skills.

   b. The *module profile* includes information such as prerequisites, contents (by topic and learning artifact), and author.

   c. *The instructor/mentor profile* includes a list of courses taught, skills, research interests, etc.

   d. *The environment profile* includes information about the institution and facilities, e.g., list of laboratories, disability accommodations, and computing facilities.

(2) *Implicit contextual information* is gathered inference, and falls into one of two categories:

   a. *Learner tacit profile* such as learning style, type of devices used (hardware, operating system, networking); access records; tacit skills, e.g. passing a certain module may enable a new skill; skill level, e.g., amateur or professional; tacit interests, e.g. passing a certain module with high grade may reflect the learner's interest in that topic.

   b. *Module tacit profile,* such as level of difficulty (inferred from the grades), audience (based on frequency of use in specific courses, or learners who have taken the module).

PERCEPOLIS includes algorithms for the following tasks:

(1) Recommending the *N* most appropriate courses for the learner. The algorithms for recommending courses offered in and outside of the learner's department, respectively, are depicted in Fig. 2 and 3.

(2) Recommending the *N* most appropriate modules (mandatory and elective modules) for each course selected. The algorithms for selecting mandatory and elective modules are depicted in Fig. 4 and 5.

The interests and needs of a learner may change in the course of his or her perusal of learning artifacts. PERCEPOLIS recognizes this dynamism by providing updated recommendations in the course of the learning process, based on the progress of learner in the target course.

The search routine depicted in Fig. 6 is used by the recommendation algorithms in Fig. 4 and 5. It is based on the Summary Schemas Model, which facilitates the retrieval of information from multi-database environments where inconsistent terminology is used in the underlying local databases [25, 26].

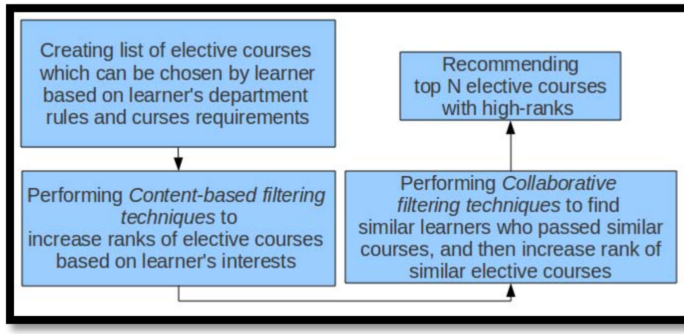

Figure 2: Recommendation algorithm for in-department courses

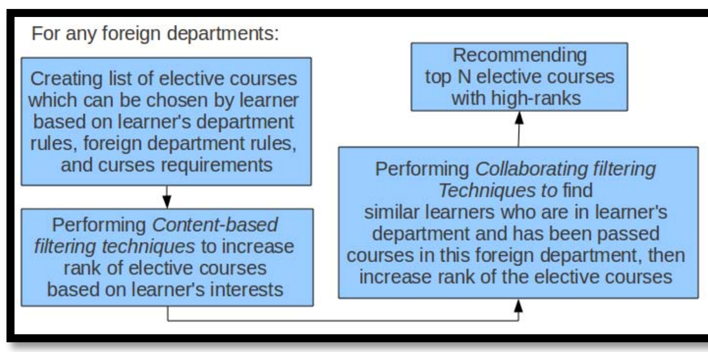

Figure 3: Recommendation algorithm for out-department courses

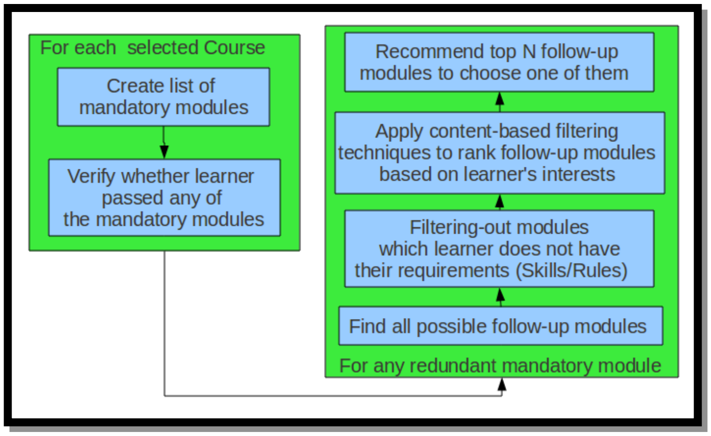

Figure 4: Recommendation algorithm for finding mandatory modules and the most proper top N follow-up modules

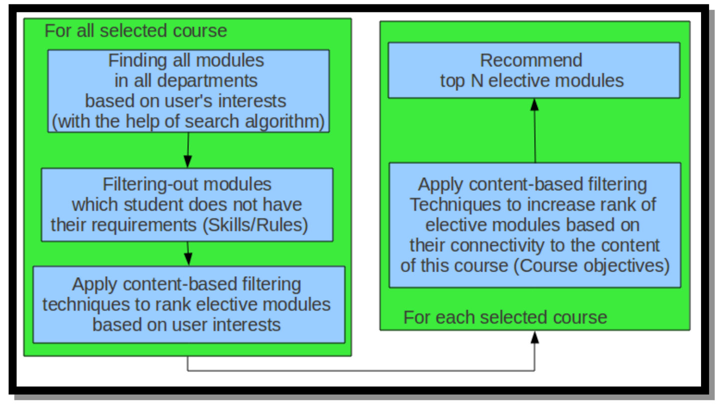

Figure 5: Recommendation algorithm for finding the most proper top N elective modules for selected courses

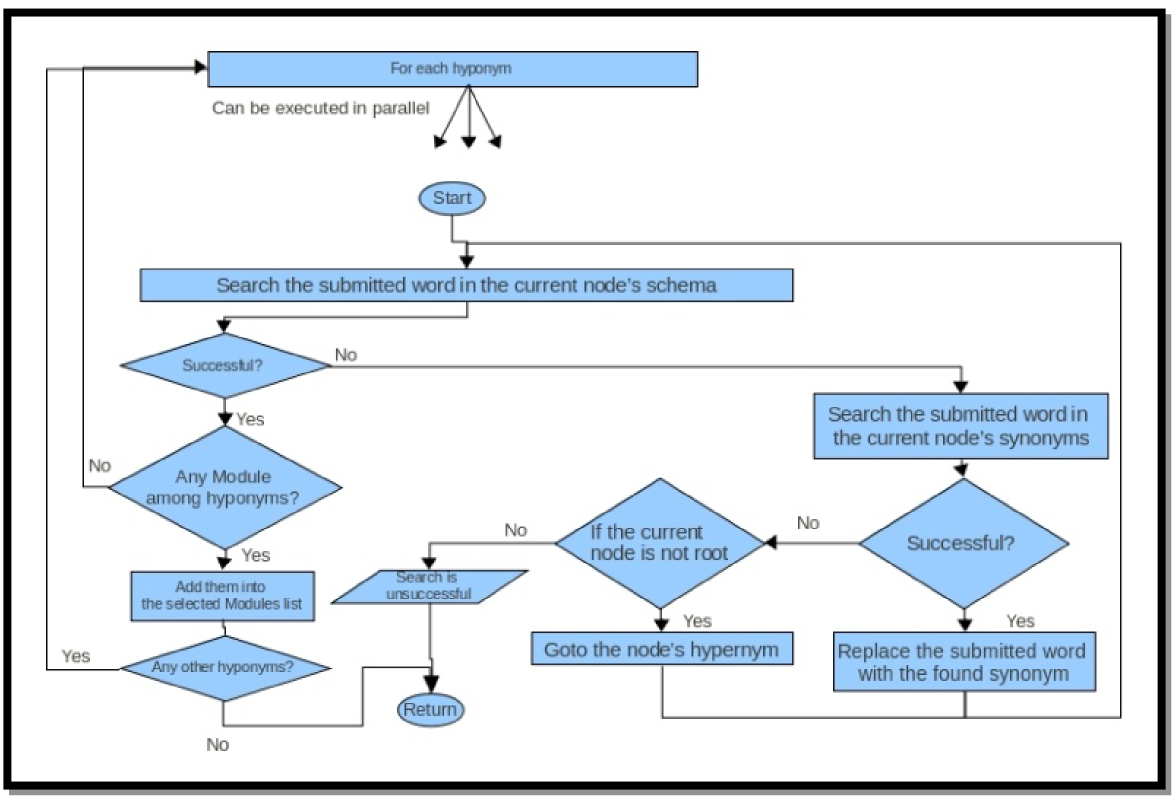

Figure 6: Proposed search algorithm based on Summary Schema Model using hyponym/hypernym/synonym concepts

4. CONCLUSIONS

In this paper, we introduced PERCEPOLIS, a pervasive learning cyberinfrastructure that facilitates self-paced personalized learning. We proposed a context-based recommender system that utilizes a combination of content-based filtering and collaborative filtering techniques to determine the most appropriate and beneficial educational artifacts for each learner, based on a wide array of learner attributes and environmental considerations.

Extensions to this research planned for the immediate future include enhancement and predictive modeling of the recommendation algorithms for performance and accuracy and implementation of a complete prototype of the cyberinfrastructure.

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