Using a Machine Learning Approach To Support an Intelligent Cooperative Multi-Agent System

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Abstract

In this paper, we describe a machine learning approach, ID3 Decision Tree Induction Algorithm, to analyzing and predicting learning style of learners on-line. Our goal is to adapt the interaction by choosing an appropriate presentation for the learners. One way to make a good adaptation is by extracting some knowledge about each learner such as learners' behavior during a learning session, knowledge level, and learning styles. We have developed a *Confidence Intelligent Tutoring System* (CITS), which is based on a multi-agent approach, in order to manage negotiations within a community of learners. The main goal of CITS is to adapt intelligent distance learning environments interactions among the participants to be more cooperative. This paper focuses on how CITS can extract the knowledge from learners. An experiment shows that this approach can determine learning style with 78% accuracy. Using this way, CITS can predict learning style instead of using a long questionnaire.

Résumé

Dans cet article, nous décrivons une méthode d'apprentissage machine basée sur l'algorithme d'arbre de décision ID3. Elle est utilisée pour analyser et prédire, en ligne, le style d'apprentissage de l'apprenant. Notre objectif est d'adapter les interactions en choisissant la présentation appropriée à l'apprenant. Pour faire une bonne adaptation, on peut extraire certaines connaissances concernant les apprenants, comme par exemple leur comportement durant une session d'apprentissage, leur niveau de connaissance et le style d'apprentissage qu'ils affectionnent. Nous développons un Système Tutoriel Intelligent de Confiance (STIC), s'inspirant d'une approche multi-agents, de façon à gérer des négociations dans une communauté à gérer des négociations dans une communauté d'apprenants. L'objectif principal du STIC est de permettre plus de coopération entre les participants en adaptant les interactions dans les environnements intelligents d'apprentissage à distance. Cet article se focalise sur la manière dont le STIC peut extraire de telles connaissances des apprenants. L'expérimentation a montré que cette approche peut déterminer le style d'apprentissage d'un apprenant avec une précision de 78%. En utilisant cette méthode, le STIC peut prédire le style d'apprentissage de l'apprenant sans avoir recours à un long questionnaire.

Keywords

Cooperative Multi-agent system, Intelligent Tutoring System, Intelligent Distance Learning Environments, ID3.

Introduction

Although some distance learning systems have correct information, some difficulties persist: a learner might lack the motivation to complete a learning session (Brusilovsky 1996), or dislike the learning style. We think that is primarily because every learner has distinct learning style and a different level of knowledge. The intelligent multi-agent can extend Intelligent Tutoring System (ITS) in a way that satisfies the need for a more cooperative distance learning environmen.

Our main goal here is to make the multi-agent that can serve intelligently in a cooperative distance-learning environment. To create a cooperative intelligent distance-learning environment, we need to make an adaptive support system for it. To do that, we must extract some knowledge about the learners such as learning styles, knowledge level, and behavior during the learning session. According to Dufresne (Dufresne 2001), extracting a learner model is not easy, even with an expert and a well-structured task. This research tries to find a way to extract learning style without causing any suffering.

Our approach depends on analyzing the results of an experiment to create a relation between the color sequence chosen by a learner and his learning style. We have applied the ID3 Decision Tree Induction Algorithm to identify the classification of a color sequence by testing its values for specific properties of learning styles.

The CITS system takes into consideration not only varying styles of learning but also varying levels of knowledge. This system must still be adaptive and dynamic. A major part of this paper presents answers to several questions. What type of knowledge is useful for adaptation? We think that learning style, knowledge level, and behavior during discussion are promising types. How can discern it from the learners? And how can our system acquire it to predict learning styles? We designed an agent in the multi-agent in charge of extracting this knowledge and analyzing it in order to predict learning styles. Moreover, we describe superficially the functions of other agents within CITS (Razek 2002).

This paper is organized as follows. In section 2, we related works that were developed as an adaptive support environment. In section 3, we present our definition of confidence agent and describe in detail the CITS architecture which is based on it. In section 4, using an ID3 induction algorithm, we show that the results of our experiment support this feature of CITS. Section 5 presents current implementation of CITS. Finally, in section 7, we discuss problems that are still pending and propose future projects.

Related Works

Before discussing the proposed architecture, it is necessary to discuss some available systems in connection with adaptation.

ATS (Specht 1998) is a web-based ITS designed to teach an introductory statistics course. Although the ATS framework relies on the psychology of learning to adapt presentation and navigation, it does not deal with learners individually. ExploraGraph© (Dufresne 2001) was developed as an adaptive support environment. ExploraGraph navigator makes it possible to navigate through conceptual graphs of activities and knowledge elements. It can be used to develop front ends to existing web-based courses. The ExploraGraph© does not provide a way to manage learning styles.

ELM-ART (Brusilovsky 1996) is a web-based ITS designed to teach an introductory LISP course. It provides learners with visual cues (icons, fonts, colors) that show the type and the educational state of each link. ELM-ART is adaptive when it comes to navigation but not when it comes to presentation. Its adaptation is related only to knowledge level and does not support learning styles.

Not all of these systems rely on any multi-agent technique. Their adaptation is related only to knowledge level; they do not use any learning method to acquire knowledge from learners. Our multi-agent system provides a dynamic adaptation based on a machine learning technique to predict not only learning style but also the behavior of individual learners. The following section explores CITS architecture.

The CITS Architecture

The CITS architecture is based on the following definition of a *confidence agent* (Razek 2002):

> **Definition**: An agent, which can guarantee confidence conditions between learners during a learning discussion through a learning distance, is called a *confidence agent.*

The architecture is based on five types of agent (see Figure1). The mains roles and implications of these agents are the following: the *cognitive agent* discerns various types of knowledge from learners and is intended for the other agents; the *behavior agent* uses this knowledge for adaptation; the *guide agent* finds learners with similar interests and introduces them to each other; the *information agent* selects and prepares domain knowledge that should be useful for a learner, and the *confidence agent* establishes the conditions of a successful conversation between learners. The knowledge base built by this system, consists of two types of knowledge: (*i*) knowledge about the learner and (*ii*) domain knowledge. The characteristics of each agent with its learning approach are as follows:

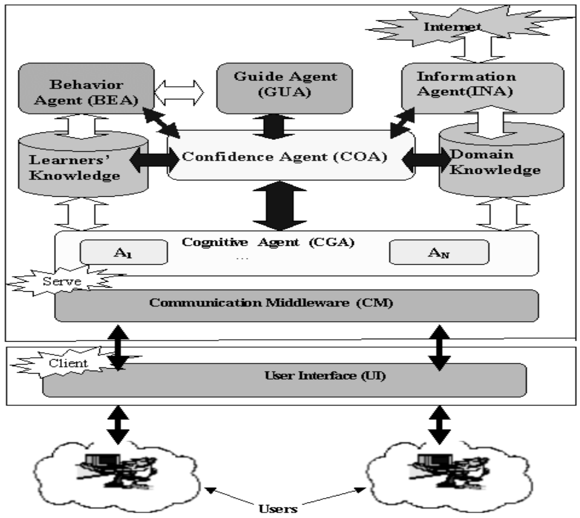

Figure 1. The CITS Architecture

The Cognitive Agent

The Cognitive Agent (CGA), close to learners, is in charge of acquiring knowledge about them - such as their learning profiles, learning style, and behaviors during learning sessions. The first time learners use the system; the CGA encourages them to fill out short questionnaires asking for name, password, sex, age, and interests (expertise, projects). This basic information is stored in the database. Afterwards, the CGA follows two methods of evaluating the learning style of each student: a short-term one, and a long-term one. In the short-term method, the CGA based on the experiment results of the ID3 Decision Tree Induction Algorithm (more details in section 4) identifies the learning style. The CGA lets learners to choose the colors they like best, second best, third, and so on, until eight have been chosen. This color sequence is then applied by an ID3 algorithm to identify each learning style.

Following Anderson (Anderson 2001), the CGA distinguishes several types of learning style: *visual;* auditory; *kinesthetic visual & auditory; visual & kinesthetic, and visual & auditory & kinesthetic.* Visual learners must see the material to learn most effectively. Auditory ones learn best by hearing it. And kinesthetic ones learn best by doing something. The choice of a learning style takes success into consideration. In other words, the style that works best is rated as the relevant one. Questions, if any, are sent a long with their profiles to the confidence agent. The CGA will send a learner's models which consists of his state of knowledge, and a list of all learners with whom he has already interacted and thus collaborated.

The Behavior Agent

Some learners reported aggravation with distance learning due to difficulties in adapting to the limitations of distance education methods. We can reduce those limitations by using their own learning styles and knowledge levels. The behavior agent (**BEA**) is in charge of confirming learning styles which were initially received from questionnaires submitted by the CGA. The BEA confirms of infirm and completes the information about a learning style. We suggest a long-term method to verify whether the style identified by CGA is correct or must be changed. The long-term method studies behavior during each learning session. What fragment of text has a learner read? How many images has he requested? How many videos has he watched? How many audio has he listened to? And so on. Analyzing these results, the BEA can change a learning style or adapt it.

The Guide Agent

The guide agent (**GUA**) selects and classifies information that can be useful for the learner. It uses a hierarchy to classify relations between subject matter and knowledge level. Consider one example, learner L_3 asks a question about the AVL tree in Data Structure subject. The problem is how the GUA selects another learner with an adequate knowledge on the AVL tree to communicate with learner L_3.

As shown in Figure 2, the first level identifies the subject. The second identifies its sections/aspects. The third ranks level of understanding according to the following scheme (Magoulas 1999): {EI, I, RI, RS, AS, S}. The last level consists of all learners. Each section/aspect in the second level is associated with all ranks in the third. The ranks of all students are associated with those of corresponding learners at the last level. Back now to the example. The GUA goes to the AVL tree section at the second level and then checks the associated learner with the rank S. If there is at least one Learner, say L_1, he or she will be selected. If not, it will select rank AS and so on. The GUA agent takes into account the new learner's knowledge level. It should be better than that of learner L_3.

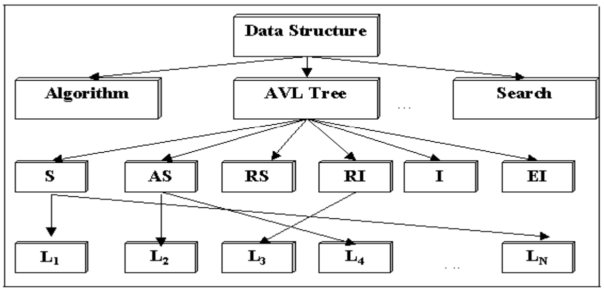

Figure 2. Hierarchy Classification for the Subject and the Learners

The Information Agent

The information agent (INA) deals with domain knowledge and information gained during the learning session. It knows which information might be useful at a specific point in the process of learning and even the level at which it could be presented efficiently. As we mentioned connection with the BEA, not all learners

The problem is to estimate a learning style, which corresponds such color sequences. To solve this problem, we utilize color sequences and their

prefer the same style. Some prefer to deal with abstract information; others prefer to watch videos. And still others prefer to hear audiotapes or access applets. Therefore, the knowledge base of the INA recommends three types of learning material: 1) material of domain knowledge, 2) material consisting of image, video, audio, and applet files 3) material consisting of HTML pages coming from Internet.

The Confidence Agent

More knowledge comes from the cooperative learning sessions. Basically, the CITS allows each learner to build more knowledge on a given subject after discussions. The goals are to acquire new materials on the subject from learners themselves and to modify the presented material's weight according to their recommendations. For example, if the COA has many answers for one request, the COA offers them to learners and asks them to recommend what they prefer.

After the COA has interacted with enough learners, it can establish good relations between requests and responses. At the next learning session, the COA can recommend the highest weight response to a learner who makes the same request. In the following section, we discuss the experimental method used to predict learning style.

Experiment Method

The short-term approach depends on analyzing the results of an experiment to create a relation between the color sequence chosen by a learner and his learning style. We apply an ID3 Decision Tree Induction Algorithm to identify the classification of a color sequence by testing its values for the specific properties of a learning style. In our experiment, 212 learners on-line were invited to take the test. Each was asked to choose a color, and then to select second best, third best, and so on until eight have been chosen. To complete the experiment, each was asked to fill a little questionnaire about his learning style.

We compared the results to a table of responses to classify their learning styles. We found six learning styles: visual, auditory, kinesthetic, visual-auditory, visual-kinesthetic, auditory-kinesthetic, and visual-auditory-kinesthetic style. Learners were asked for feedback, which might or might not have agreed with the results. The feedback was then classified into three categories: a positive category in which learners agree with the result, a negative category in which **they disagree**, and a no-comment category in which they are neither agree nor disagree.

Table 1 shows color sequence with its corresponding learning styles and learner's feedback corresponding learning styles belonged to the positive category. Figure 3 shows three paths of learner's feedback; the upper path represents that the learners agree with the learning style result, the middle one represents that they do not agree, and the lower path represents that they do not give any comment. The overall of results is 78 % agree, 12 % not agree, and 10% no comment.

Learner Name	Color Sequence	Learning Style	Feedback
	First, Second, Third, Fourth, Fifth, Sixth, Seventh, Eight		
Robert Poddar	blue,Red,Purple,Gray,Black,Green,Brown,Yellow	Visual	Agree
Sandy	Yellow,blue,Gray,Brown,Red,Purple,Green,Black	Auditory	Not-Agree
Mike Watts	Red,blue,Yellow,Brown,Gray,Purple,Black,Green	Visual& Auditory	Agree
Linda	blue,Red,Purple,Yellow,Green,Brown,Gray,Black	Visual & Auditory & Kinesthetic	No comment

Table 1An example of color sequence

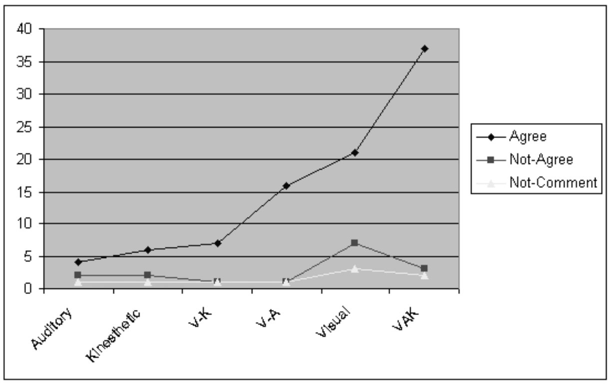

Figure 3. Learner's feedback

Experiment Result and Implementation

An ID3 algorithm (Luger 2002) induces concepts from examples. It represents concepts as decision trees. ID3 measures the information gained for each property and then selects the one that gains the greatest information. This allows our system (CITS) to establish the classification of learning styles by testing their values for specific properties. Following Shannon's method (Luger 2002), we define the amount of information in each color sequence as a function of the probability of occurrence of each possible choice. Given our set of training instances (U), if we make property (P), with 8 values, the root of our goal tree, this will partition U into subsets, {Blue, Green, Red, Yellow, Purple, Brown, Black, Gray}. The expected information needed to complete the tree, after making Purple the subset (p) the root, is:

$$E(p) = \sum_{j=1}^{8} P(U_j)\left[\sum_{i=1}^{6} -l(m_i)\log_2(l(m_i)\right]$$

Where

- $P(U_j)$ represents the probability for the occurrence of a certain color in j^{th} choice of the eight choices.
- $l(m_i)$ is the probability for the occurrence of each learning style m_i.

The information gain provided by making this experiment at the root of our goal tree is equal to the total information in the tree minus the amount of information needed to complete the classification after performing the experiment. The amount of information needed to complete the tree is defined as the weighted average by multiplying the information content of each sub-tree by the percentage of the examples present in that sub-tree and summing these products.
The gain from property p is computed as:

$$Gain(p) = \sum_{i=1}^{8} -l(U_i)\log_2(l(U_i)) - E(p)$$

In our experiment, we found that the sixth-choice property provides the greatest information gain. Therefore, ID3 will select it as the root of the tree. The algorithm continues to apply this analysis recursively to each sub-tree until it has completed the tree. Figure 4 shows the decision tree solution of our experiment by which the system can predict the learning style of a new learner based on his favorite color sequence.

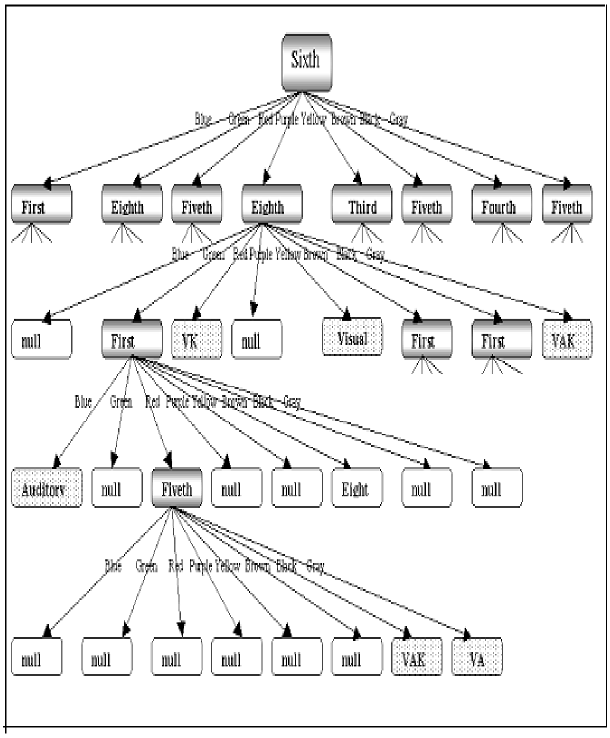

Figure 4. Decision tree of the experiment result

Implementation

The current version of CITS can be used for a cooperative knowledge, in which two or more learners share their knowledge. The system is built in Visual J++ and operates under windows 2000. Figure 5 shows an interaction between two learners using CITS. The interface of the current version provides them with two functions. One of these is a discussion window that permits communication among learners. The second is a whiteboard window, where learners can draw anything related to their discussion. Indeed, we need to design an agent communication language. There are two ways of doing so (Finin 1997): a procedural way and a declarative one. In the procedural way, communication is based on executable content and uses programming languages such as Java or Tcl. Extra details on how communication agent languages are developed in CITS is taking place at (Razek 2002).

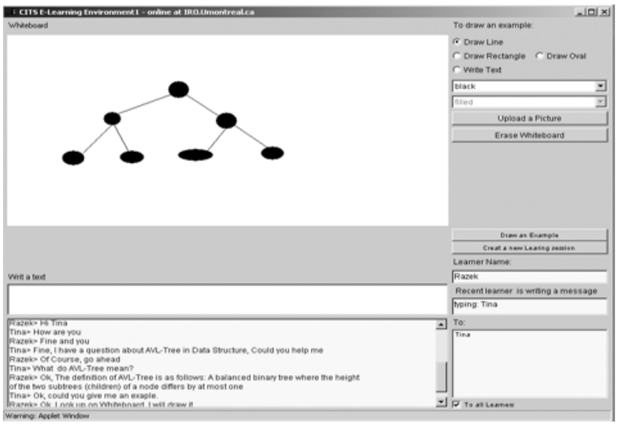

Figure5 CITS's User Interface.

Conclusion & Future work

We have proposed a new architecture, based on a multi-agent technique, to improve cooperative environments. We have defined the principles of a confidence agent, which aims to provide more efficient and acceptable learning and teaching. To promote some of these principles, we have presented a new system called Confidence Intelligent Tutoring System. Using a combination of learner's knowledge level, learning style, and behavior during learning session, the proposed system allows two or more groups with their own learning styles to communicate with each other under the guidance of a confidence agent. This way not only provides the group with a good learning environment but also keeps personal information from others.

The first version of this architecture is currently implemented. We must still evaluate how this confidence agent improves cooperative learning and detects the most important parameters. One opportunity for improvement would be in the way that knowledge is represented. We use XML language to represent knowledge, and XSL-Templates to adapt presentation according to need but it is also the role of the COA to deduce which representation is more adapted between learners involved in a discussion. Anther opportunity for improvement would be in the way that CITS will be deployed on the Internet. We use Java Web Start technology to provide a flexible and robust deployment solution for CITS based on Java Network Launching Protocol (JNLP).

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