

An affective agent-based virtual character for learning environments

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Abstract. This paper presents a virtual character placed in an educational environment with the main purpose of stimulating cooperative learning among students. The character can communicate with users in natural language; it can suggest them appropriate contents and activities, as well as recommend student tutors that may be helpful at given learning tasks. For such, a data mining mechanism is used to find patterns in students' behavior and interactions, taking into account different social-affective aspects. The paper discusses such social-affective issues, and proposes a multi-agent architecture. Preliminary results of initial experiments are discussed, conclusions and directions for future work are presented.

Introduction

Personifying a website means adding a human component to it, for example, by using a virtual character to communicate with and present recommendations to the user. The main advantage of this approach is that the use of the human figure can help us draw the user's attention, emphasizing recommendations or highlighting any other message we may want to deliver. Many projects have used virtual characters in presentation tasks in a wide range of applications, such as e-commerce, e-learning and helpdesks. Pandzic classifies them in six categories [1]: entertainment, communication, navigation, broadcasting, commerce and education. Rist et al [2] propose a different classification based on several levels of interactivity between characters and users. The characters may present information to the user as if they were television presenters [3], without promoting a lot of interactivity. Another way they may interact with users is through dialogues in natural language, answering questions, bringing relevant information and guiding the user in the system. The third type of interaction may happen in environments where the character "lives" with other characters in a virtual world. These characters bring information to the user, playing specific roles and interacting with one another. Finally, the users may enter such virtual worlds, interact and question the characters living in it.

The idea of developing a computational character that talks to the user is old. In 1967 Weizenbaum had already developed ELIZA [4], a program that was capable to engage in conversation with the user, simulating the role of a psychiatrist. Although the use of the human figure in interfaces is still a somehow controversial topic [5], scientific results are coming to surface indicating that, at given circumstances, personification may augment user involvement and reduce workload [6]. Rickenberg and Reeves [7] found that the presence of a character in a website may increase the user's confidence, even though it may also augment the user's anxiety (which may have positive as well as negative aspects). De Angeli et al. [8] present arguments supporting the use of personified characters, explaining that by introducing social stimuli, virtual characters may improve the communication between user and computer. Virtual characters can also be found in educational environments. In [9] virtual teachers guide the students in online interactive environments. Scotty et al. [10] show how the interaction with animated and static virtual characters can affect students learning. Elliot et al. [11] also investigated the importance of the affective dimension in virtual characters, developing studies about pedagogical agents that are sensible to the states of emotion of the students and are capable of reasoning about affective aspects in problem resolution.

This paper presents an agent-based virtual character whose purpose is to stimulate cooperative learning among students by motivating their interaction and mutual assistance. The virtual character was integrated to a learning environment, communicating with the students in natural language, suggesting readings according to the activities being performed. When a student needs assistance to learn a given topic, the character is capable of finding other students that may play the role of a tutor. This is done by monitoring the students' actions and using a data mining tool to find patterns that can guide the search for the best instructor in a given situation. Such tutor recommendation service explores the social-affective dimension through the analysis of emotional states and social behavior of the users.

The next section presents social-affective issues that have to be considered in students' interaction and behavior to enable the identification of suitable tutors. Section two details the multi-agent architecture of which our virtual character is a component. Then preliminary results are discussed, conclusions and directions for future work are presented.

1. Social and Affective Issues

Current research has shown the potentiality of cooperative learning, demonstrating that group work is fundamental for the cognitive development of the student [12]. In this perspective, motivating the students to interact can lead to an effective learning practice. By identifying students with good teaching abilities and recommending them to other students with difficulties, we promote group formation and cooperative learning.

According to Andrade [13], a group can be formed due to similarity and empathy of its members or to the necessity of support for the accomplishment of some task. The latter can be motivated by prestige or status, economic benefits or the necessity and desire of contribution. Andrade also says that the affective states of the individuals have significant importance in the interaction process, and affirms that some dimensions of personality seem to have certain connections with the social performance in the interaction.

For Scherer [14], the affective states are divided in five categories: Emotion, Mood, Interpersonal Stances, Attitudes, and Personality Traits.

Emotion is the episode of evaluation of an external or internal event as being of major significance, relatively brief of synchronized responses for most organic systems. Emotion's examples are anger, sadness, joy, fear, shame, pride, elation and desperation.

Mood is a diffuse affective state that consists in a subjective feeling change, with low intensity, but long duration without apparent cause. Dipert [15] considers that moods differ from emotions most strongly in not having an intentional object. Their causes are typically

conceptual or evaluative (things are or are not going well). He mentions some examples of moods: cheerful, gloomy, irritable, listless, depressed, and buoyant.

Interpersonal Stance is an affective position in relation to the other person in a specific interaction. Distant, cold, warm, supportive and contemptuous are examples of interpersonal stances.

Attitudes are relatively tolerant, affectively colored beliefs, preferences and predisposition in relation to objects or people. Examples of attitudes are liking, loving, hating, desiring and valuing

Personality Traits are emotionally laden, stable personality dispositions and behavioral tendencies, typical of a person. For example: nervous, anxious, reckless, morose, hostile, envious and jealousy.

The cognitive approach to the modeling of emotions considers that different emotional states are attained according to evaluations based on world stimuli and the behavior of the individual. In this area, Ortony et al. [16] worked in the construction of a classification model for emotions and in the description of the reasoning process that involves them. At present, there are four basic ways to recognize emotions through a computer system: voice; facial expressions; physiological signs (blood pressure, skin conductivity, etc...); and, observable behavior. The latter corresponds to the observation of the user's interaction with the system, e.g. chosen options or typing speed.

Beyond the affective aspects, the service of recommendation of students tutors must also take into account social aspects of the students. In this field, Social Networks are a very popular approach for the analysis of human interactions. The most important concept of such approach is centrality: if an individual is central in a group, he/she is popular and gets a great amount of attention from the group members.

The work of Yang & Tang [18] investigates the relationship between the performance of the students and their position in three types of social networks: friendship, advice and adversity networks. An individual that is central in a friendship network has greater chances to have access to resources that can be important for his/her academic success. Therefore, there is a great possibility that this individual gives help and is helped. The advice networks consist of relationships through which the individuals can share information related to their work [19]. A student who is central in an advice network is capable of accumulating information, knowledge and experience on tasks related to the resolution of problems. Adversity network include those relationships that involve negative exchanges [18]. If a person is central in an adversity network, this person has little possibility to get information or knowledge from others.

2. The Multi-Agent Architecture

Our virtual character has been integrated to an educational environment to assist students in learning algorithms. The multi-agent architecture proposed here was based on an initial model presented by [20]. This model has many agents to provide services to an ITS (Intelligent Tutoring System) in different tasks. There are agents to select exercises, to support users' communication, to log users, to store users and profiles, and other. The architecture includes a *Social Agent* that interacts with a *Mining* and a *Recommender Agent*, whose goal is to identify suitable tutors and to offer their help. The interaction with the system is supported by a *Virtual Character*. All agents communicate through an *Agents Environment* using a specific interaction protocol. *Student Agents* are used to represent each student and to communicate. Our multi-agent society is presented in Figure 1.

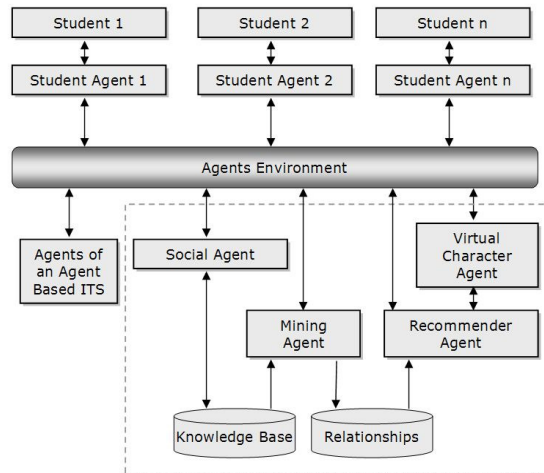


Figure 1. Multiagent Architecture

2.1. The Social Agent

The main goal of the social agent is to collect data about students' interactions and to provide such information for the mining agent. The information collected can be classified in six different categories: Social Profile; Acceptance Degree; Sociability Degree; Mood State; Tutorial Degree and Performance.

The Social Profile (SP) is built during the students' interaction through a synchronous mechanism (e.g. chat tool). During the students' interaction, some information are collected. For instance, number of times that a student had the initiative to talk with another; number of times that a student answered a communication request; individuals with whom the student interacts or has interacted, and number of interactions; individuals with whom the student interacts regularly, and number of interactions.

Based on Maturana [17] we defined the Acceptance Degree (AD), which measures the acceptance between students. Maturana affirms that the acceptance of other individuals is a necessary condition for social development. Such data is collected through a graphical interface that enables each student to indicate his/her acceptance degree for other students. This measurement may also be considered from a point of view of Social Networks. As the AD is indicated by the students themselves based on their affective structures, the measurement can indicate different emotions, such as love, envy, hatred, etc. The average of all ADs received by a student influences his/her Sociability Degree (SD).

The Mood State (MS) represents our belief in the capability of a student to play the role of a tutor if he/she is not in a positive mood (although the student may have all the technical and social requirements to be a tutor). We consider three values for the MS: "bad mood", "regular mood" and "good mood". These states are indicated by the students in a graphical interface through corresponding clip-arts.

After a helping session, a small questionnaire is submitted to the student who got assistance, with the purpose of collecting information about the performance of the tutor. The questions made are based on concepts from Social Networks and Sociometry, and may be answered by four qualitative values: "excellent", "good", "regular", and "bad". The questions are presented below:

- How do you classify the sociability of your class fellow?
- How do you classify the help given by your class fellow?

The answer to the first question together with the average of the ADs of a student, form his/her Sociability Degree (SD). This grade indicates how other individuals see the social capability of this student.

The Tutorial Degree (TD) measures a student's pedagogical capacity to help, to explain and teach. This value is obtained from the answers given for the second question of the questionnaire above and from the marks the tutor got when he/she studied the contents for which he/she was asked for help. These grades were called Performance (P) and were used in the computation of the TD because, when a tutor is not able to help another student, it does not necessarily mean that the student is a bad tutor. He/she may simply not know very well the content for which his/her help was requested.

The data collected is stored in a knowledge base, which is accessed by a mining agent in order to identify behavioral patterns. Next subsection explains this mining process.

2.2. The Mining Agent

The main task of the mining agent is to extract profiles from the data collected and to store them in a knowledge representation mechanism called item descriptors. These descriptors store information about how the social-affective characteristics described in item 2.1. may affect a student tutoring ability. Users' features may be classified in the descriptors as:

- demographic: data describing an individual, such as age, gender, occupation, address;
- behavioral: data describing tutoring and social capacity, navigation and study patterns.

It has been shown that both types of data are important when building a user profile [21] and inferring user's needs [34]. Demographic material is represented here in attribute-value pairs. Behavioral information is represented by actions carried out by the user, such as the selection of a topic for reading. Emotional states and social behavior can either be inferred or collected explicitly in the questionnaires.

While attributes used to define demographic features are typically single-valued, behavioral data is usually multi-valued. For instance, a person can only belong to one age group (demographic), but he/she may be friendly and patient at the same time (behavioral). Nevertheless, both types of information are represented in our model in a similar way.

The descriptor lists every term that is correlated to it. We use confidence as a correlation factor in order to determine how relevant a piece of information is. This is the same as computing the conditional probability $P(d_j|e)$, i.e. the probability that the item represented by descriptor d_j holds a possible answer given evidence e . Therefore, the descriptors can be learned through the analysis of actual records. For each item for which we want to define a recommendation strategy, a descriptor is created with the item defined as its target. Then, the confidence between the target and other existing demographic features and behavioural data is computed. This process continues until all descriptors have been created. For the recommendation of tutors, descriptors are built indicating the features of good and bad instructors.

2.3. The Recommender Agent

Given a list of possible user tutors $U=\{u_1, u_2, \dots, u_m\}$, the recommendation process starts with the gathering of demographic and behavioural information about each of them. Next, the data collected for each user is matched against a descriptor d_j which lists the most important features of good instructors, according to the terms $T=\{t_1, t_2, \dots, t_k\}$ stored in the descriptor. The system computes a score for each student that ranges from not similar (0) to very similar (1), according to the formula:

$$Score(d_j) = 1 - \prod_{kji} (Noise(t_p))$$

where $Score(d_j)$ is the final score of the descriptor d_j ; $Noise(t_p)$ is the value of the noise parameter of term t_p , a concept used in noisy-OR probability models [23] and computed as $1 - P(d_j | t_p)$. The individual with the highest score is selected to assist the student needing

assistance. That expression contains an assumption of independence of the various t_p - which the designer of a practical system should be trying to achieve in the choice of terms.

This method is based on the assumption that any term matching the user's terms should increase the confidence that the descriptor holds the most appropriate recommendation. In a real-life example, let us suppose that we have a certain degree of confidence that a student who has shown a good ability in answering factorial exercises is our best bet to help another student who is having problem with the subject. Knowing that that same student is friendly and is in a good mood should increase the total confidence on his recommendation as a tutor.

2.4. The Virtual Character Agent

The virtual character agent has the goal of communicating with the user through a natural language mechanism, identifying when to recommend a tutor to a student needing assistance and triggering the recommendation process. The agent uses the Artificial Intelligence Markup Language (AIML) to represent its conversational knowledge [24], employing a mechanism of stimuli-response. The stimuli (sentences and fragments that may be used to question the agent) are stored and used to search for pre-defined replies.

The most important tags of AIML are:

<aiml>: indicates the beginning of a document;

<category>: marks the units in the knowledge base

<pattern>: keeps a pattern that is searched for in sentences that the user may enter to communicate with the virtual character;

<template>: contains the possible answers to the users' input.

In addition to the existing AIML tags, new ones were created to manage the agents' emotional appearance. For instance, we used the tag **<humor>** to control the image changes reflecting different moods of the virtual character (happy, receptive, annoyed, etc).

This agent also has the ability to detect that a student is having some difficulties in performing a certain task (e.g. the student is solving a given exercise more than once, the student is spending too much time at a given activity, etc.). At this moment, the agent triggers the search for a tutor by sending a message to the recommender agent. When the most suitable tutors logged in are identified, the virtual character is the one to suggest to the student needing assistance that other class fellows may help him with the given task. By taking into account different aspect of the affective and the social states of the students, we classify our virtual character as an affective subsystem.

3. Validation and Discussion

This paper presented a social-affective virtual character that interacts with the users in order to motivate group formation among students and promote collaborative learning. We used mining algorithms to identify suitable students that can play the role of a tutor, and to recommend them to other students needing assistance. Our tutor recommendation mechanism explores the social-affective dimension through the analysis of emotional states and social behaviour of the users.

An Environment for the Learning of Algorithms (3A) has been developed at the Department of Computer Science of the University of Caxias do Sul in conformity with our architecture. The main goal of the system has been to make the courses more dynamic, increase the interest and participation of the students and provide an environment where they may interact in order to improve their knowledge. The environment presents students with the regular contents of algorithms, it proposes exercises, provides a forum for discussion and a tool for the testing and running of algorithms. Having been developed as a dynamic website, the system enables teachers and administrators to modify contents easily. The system

promotes the communication among students through the use of a virtual character that has the ability to find suitable student tutors and suggest them to individuals showing difficulty in learning a given topic. Figure 2 shows the interface of the system.



Figure 2. System Interface

The menu on the left shows the main sections of the learning environment (Contents, Exercises, Algorithm tool, Forum and Links). In the central area, the section selected in the menu is displayed. In the example, the item selected is "*Comando de Leitura*", or "*The Command Read*". On the right, we may see the virtual character, which provides a textbox to let the user enter questions and remarks. Below, there are other textboxes used to let students chat with each other. On the upper part of the screen, there is a panel with different resources allowing the users to insert information about their social-affective states and to choose school mates for interaction.

An experiment was carried out in order to identify the impact of using a virtual character in the user interface. We simply built different versions of the system, one of them without any character and the other ones mediated by a virtual character developed according to a different set of features (gender, age, cartoon or photographic style, animated or non-animated style). We noticed in the experiment a clear preference of the students for the interfaces containing the virtual characters, specially one which was "inhabited" by a known professor. This evidence can reinforce the importance of embodying social-affective features in educational systems.

The 3A environment has started to be used in 2 courses at the Department of Computer Science. Descriptors were built manually in order to get the system to recommend contents and tutors. The data collected so far has not been sufficient for us to carry out conclusive experiments as to whether the system is making tutoring recommendations appropriately. However, the results obtained so far show that the use of Social Profile, Mood State, Performance Acceptance, Sociability and Tutorial Degree in tutor recommendation, is a promising alternative. Other experiments carried out and reported in [25] also show that the item descriptors approach has a good performance in terms of processing time and accuracy, when compared with collaborative filtering, one of the most popular approaches in recommender systems.

One of our biggest challenges now concerns the automatic inference of students' affective states. For the moment, we are using questionnaires and graphic interface controls to let the user indicate such states. Thus, little is done to automatically infer the social-affective information necessary for tutor recommendation. This will be one of our main research efforts in the near future.

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