

Pedagogical agents that support learning by explaining: Effects of affective feedback

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Abstract

The present study investigates how a conversational agent can facilitate explanation activity. An experiment was conducted where pairs of participants, who were enrolled in a psychology course, engaged in a task of explaining to their partners the meanings of concepts of technical terms taught in the course. During the task, they interacted with a conversational agent, which was programmed to provide back-channel feedbacks and metacognitive suggestions to encourage and facilitate conversational interaction between the participants. Results of an experiment suggested that affective positive feedbacks from conversational agent facilitate explanation and learning performance. It is discussed that a conversational agent can play a role for pedagogical tutoring and triggers a deeper understanding of a concept during an explanation.

Keywords: pedagogical agents; explanation activities; affective learning.

Introduction

The ever-evolving information and communication technology has made it possible to support human cognition by using systems which aids human interaction. Many researchers in computer science are tackling on the theme of developing embodied conversational agents to support education. Recent studies on cognitive science and learning science show that collaborative learning facilitates understanding or acquisition of new concepts depends greatly on how explanations are provided. In this study a collaborative activity of making explanation is experimentally investigated by using a conversational agent that serves as a teaching assistant. The goal of the experiment is to find out what kind of feedback from the agents is most conducive to successful learning performance.

Related work

Explanations during collaborative activities

Number of studies on collaborative problem solving in cognitive science revealed how concepts are understood or learned. Researchers have shown that asking reflective questions for clarification to conversational partners is an effective interactional strategy to gain a deeper understanding of a problem or a concept (e.g. Chi, Bassok, Lewis, Reimann, & Glaser, 1989; Miyake, 1986; Salomon,

2001; Okada & Simon, 1997). It has also been demonstrated that the use of strategic utterances such as asking for explanation or providing suggestions can stimulate reflective thinking and meta cognition involved in understanding a concept. Playing different roles during explanation is also said to help problem solvers reconstruct external representation and concepts (Shirouzu, Miyake, & Masukawa; 2002).

Studies that are discussed above suggest that how well one can explain is the key to understanding and learning of a concept. However, explanation becomes successful if people have difficulties in retrieving and associating relevant knowledge required for explanation activity. Researches on collaborative learning have reported that these difficulties rise among novice problem solvers (Coleman, 1998; King, 1994). Also, it may not help learn a concept if people cannot communicate with each other as in when, for example, they use technical terms or phrases unknown to others (Hayashi & Miwa, 2009).

It is assumed that one of the ways to help collaborative problem solvers is to introduce a third-person or a mentor who can facilitate the task by using prompts such as suggestions and back-channels. However, it is often difficult for one teacher to monitor several groups of collaborators and to supervise their interaction during explanation in actual pedagogical situations. Recently there are studies which demonstrate that the use of conversational agents that act as educational companions or tutors can facilitate learning process (Holmes, 2007; Baylor & Kim, 2005). Unfortunately, it has not been fully understood if and what kinds of support by such agents would be more helpful for collaborative learners. In this paper, the author will further investigate this question through the use affective expressions.

Pedagogical conversational agents as learning advisers

Researchers in the field of human computer interaction have conducted a number of experimental studies which involve the use of pedagogical agents (e.g. Kim, Baylor & Shen, 2007; Reeves & Nass, 1996; Graesser & McNamara, 2010). One point to be taken into consideration in studies of human performance is the affective factor. This factor influences people's performance in either negative or positive ways and

several studies reported that such factors are especially important in learning activities (Baylor & Kim, 2005). For example, Bower & Forgas (2001) revealed that positive moods can increase memory performance. Mayer & Turner (2002) also demonstrated that positive state of mind can improve text comprehension.

Moods may affect the performance of human activities both verbally and non-verbally. In a study by Kim, Baylor, & Shen (2007), which examined how positive and negative comments from conversational agents affect learning performance, a pictorial image of an agent was programmed to project a textual message to the participant; in the positive condition, a visual avatar produced a short comment like "this task looks fun", while in the negative condition, it produced a short comment like "I don't feel like doing this, but we have to do it anyway". The results showed that the conversational agents that provided the participants with comments in a positive mood furnished them with a higher motivation of learning.

The studies discussed above suggest that the performance of explanation would also be enhanced if suggestions are given in positive mood either verbally or through visual feedbacks.

Research Goal

This study investigates how conversational agents can facilitate understanding and learning of concepts. This paper will focus on an agent which has a role that assists paired participants to explain concepts to their partners during the collaborative peer-explanation activity. A natural language processing agent monitored the interaction between the participants and provided prompts to them which were generated by pre-defined rules. The research goal of this study is to understand if the use of positive expressions provided by a conversational agent facilitates collaborative learners' understanding of concepts.

Method

Experimental task and procedure

The experiment was conducted in a room where the computers were all connected by a local area network. Participants were given four technical terms presented on the screen. They were: 'schema', 'short-term / long-term memory', 'figure-ground reversal', and 'principle of linguistic relativity', which had been introduced in a psychology class. Along with the keyterms, a brief explanation of the concept was described by a few sentences. They were asked to describe the concepts of these words. After this pre-test, they logged in the computer and used the program installed in a USB flash drive (see the next section for detail). The pairs of participants were communicated through the chat program and one of the paired participants was instructed to explain to their partner the meanings of the words presented on their computer screen one by one. When two of the four concepts were explained to their partner, they switched the roles and the other partner explained the

rest of the two words to his/her partner. This was repeated but the words they explained the second time were different from those in the first time. All participants received the same prompts of suggestions from the agent on how explanations should be given and how questions should be asked about the concepts. After this pre-test, they took the same test in the post-test. The descriptions of the concepts they provided in the post-test were compared with those of the pre-test to analyze if the participants gained a deeper understanding of the concepts after the collaborative activity. The whole process of the experiment took approximately 80 minutes (see Figure 1).

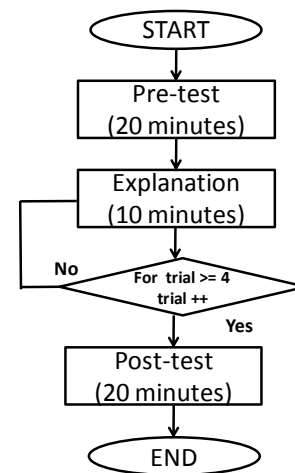


Figure 1: Experiment flow.

Experimental system

In the experiments, a computer-mediated chat system was set up through computer terminals connected via a local network and the interactions of the participants during the activity were monitored. The system used in the experiments was programmed in Java (see Figure2).

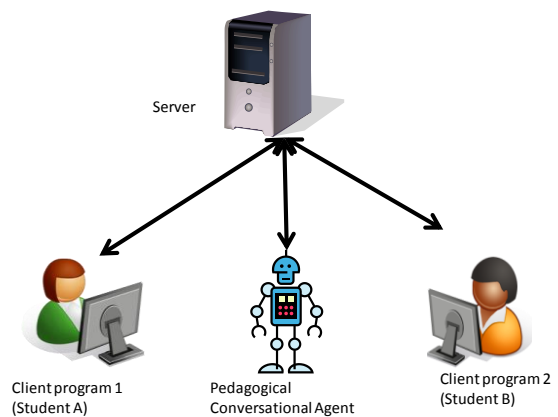


Figure 2: Experimental Setting.

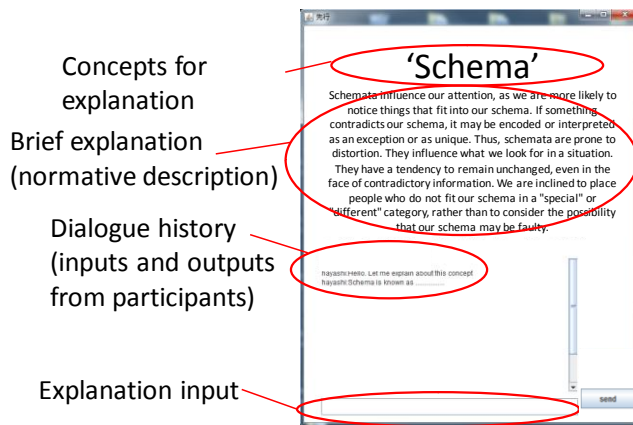


Figure 3: Screenshot of the chat system.

The system consists of three program modules of Server, Chat Clients, and Agent, all of which are simultaneously activated. Multi-threads are used so that the server program can send all messages to the clients' chat system and the agent simultaneously.

The pedagogical agent used in this study is a simple rule-based production system typical of artificial intelligence. It is capable of meaningfully responding to input sentences from users and consists of three main modules: Semantic Analyzer, Generator, and Motion Handler (see Figure 4).

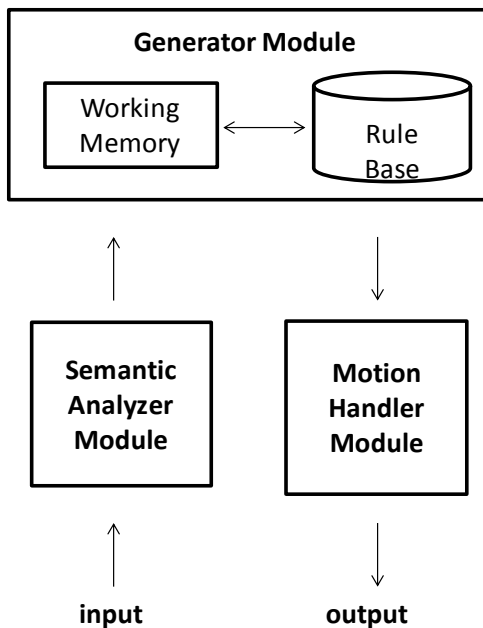


Figure 4: Architecture of message production.

Textual input of all conversational exchanges produced by paired participants is sent to the semantic analyzer of the conversation agent. The semantic analyzer then scans the text and detects keywords relevant to the concepts if they

are being used in the explanation task (e.g. "I think that a *schema* is some kind of *knowledge* that is used based on one's own *experience*." (detected key words are shown in bold italic). Next, the extracted keywords are sent to the working memory in the generator and processed by the rule base, where various types of rule-based statements such as 'if X then Y' are stored to generate prompt messages (if there are several candidates of matching statements for the input keywords, a simple conflict-resolution strategy is utilized). When the matching process is completed, prompt messages are selected and sent back to the working memory in the generator. The messages generated by the rule base are also sent to the motion handler module to activate an embodied conversation agent, a computer-generated virtual character which can produce human-like behaviors such as blinking and head-shaking. Each output message is textually presented in a text filed on the computer display (See next sections for details).

Several types of output messages are presented by the agent depending on the content of input text from the participants (see Table 1 below for examples). Only short back-channels are sent when there are several related key words in a text (Type 1 output); Messages of encouragement are given when the agent detects some keywords related to the target concept (Type 2 output, Type 3 output, Type 4 output).

Table 1: Types of output messages from the agent.

Type of messages	Examples
<u>Input messages</u> (Detected key words are in Bold)	"I think that a schema is some kind of knowledge that is used based on one's own experience ."
<u>Output: type 0</u> Back-channels	"That's the way", "Keep going!", "Um-hum"
<u>Output: type 1</u> Positive Suggestion (Used in Positive condition)	"Wow! You used a few very good keywords. That's great! It is better if you explain it from a different perspective!"
<u>Output: type 2</u> Negative Suggestion(Used in Negative condition)	"Well, you used few keywords. That is not enough. It is not satisfactory unless you explain it from a different perspective."
<u>Output: type 3</u> Normal Suggestion (Used in Neutral condition)	"You used few important keywords. Try to explain from a different perspective."

Participants and conditions

In this study, 90 participants participated in the experiment. The participants were all undergraduate students who were taking a psychology course and participated in them as part of the course work. They were randomly assigned to three conditions, which varied with respect to how prompts of

suggestions were presented and how conversational agents were used (see the sections below for details).

To find out how affective factors influence the task of explanation, three types of avatars were created: one is the positive agent with friendly facial expression which was used for the "positive condition", and the negative agent with unfriendly facial expression which was used for the "negative condition", and finally the neutral agent with no facial expression which was used for "neutral condition". In the positive condition ($n = 31$), the participants were given positive suggestions, which were synchronized with the facial expressions of the positive agent. In the negative condition ($n = 28$), the participants were given negative suggestions, which were synchronized with the facial expressions of the negative agent. In the neutral condition ($n = 31$), the participants were given suggestions without emotional expressions.

The messages were given through chat dialogue and the virtual character moved its head gestures while the participants chat on the computer (For examples of suggestion for the conversational agent see Table 1). Since there was odd number of participants in positive and neutral condition, one group was composed by three.

Dependant variables

To evaluate the outcome of (1) quality of the performance of learning, and (2) interaction process, two types of measures were used.

First, for the learning performance, the results of the pre- and post- tests were compared to find out how the explanation task with different conditions facilitated their understanding or learning of the concepts. For the comparison, their descriptions were scored in the following way: 1 point for a wrong description or no description, 2 points for a nearly-correct description, 3 points for a fairly-correct description, 4 points for an excellent description, and 5 points for an excellent description with concrete examples. It was judged that the greater the difference in scores between the two tests the higher the degree of the effect of explanation.

Second, for the analysis of explanation process, all the dialogs during the task were analyzed. The main focus of the analysis was to investigate what kind of explanations were used during their interaction. Each dialog sentences that included explanations were coded by the following two categories: (1) explanations that were made by using terms and phrases presented by the system (see Figure 3 for an example of the description), and (2) explanations that were generated based on subjective inference. The former is called "normative explanations". On the other hand, the utterance in the latter is called "subjective explanations".

Results

Quality of performance

The results showed that the participants' understanding of the concepts improved after the explanation task in all

conditions (see Figure 5). The vertical axis in Figure 5 represents the average scores of the tests for the three groups at the times of pre- and post- tests. A statistical analysis was performed using a 2 x 3 mix factor ANOVA with the two evaluation period (the pre-test vs. the post-test) and the three conditions with different feedback (Positive vs. Negative vs. Neutral) as independent factors.

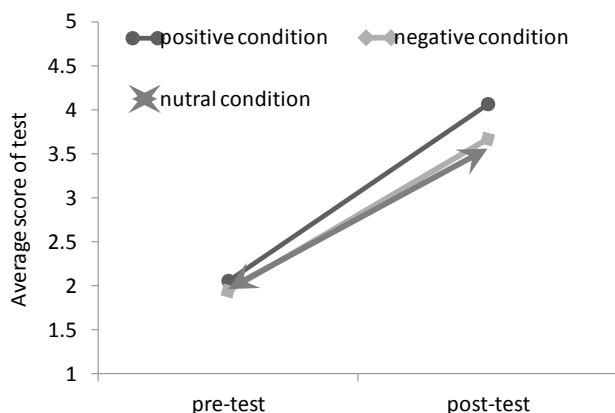


Figure 5: Results of the quality of the performance of learning.

There was significant interaction between the two factors ($F(2, 87) = 3.388, p < .05$). First, an analysis of the simple main effect was done on each level of the feedback factor. In the Positive, Negative, and Neutral condition, the average scores in post-test was higher than pre-test respectively ($F(1,87) = 254.397, p < .01$; $F(1,87) = 172.796, p < .01$; $F(1,87) = 155.812, p < .01$). Next, an analysis of the simple main effect was done on each level of the period factor. In the pre-test, there was no differences between conditions ($F(2,174) = 0.202, p = .82$). Although in the post-test there were differences between conditions ($F(2,174) = 9.094, p < .01$). Further analysis on the post-test was conducted using the Ryan's method. Results indicate that the average score of Positive condition was higher than Negative condition and the average score of Positive condition was higher than Neutral condition respectively ($p < .01$; $p < .01$). There were no differences between Negative condition and Neutral condition ($p = .51$).

The overall result suggests that the collaborative activities facilitated the participants' understanding or learning of the concepts more when the positive suggestions were presented to the participants.

Interaction process

Figure 6 indicates the relationships between the usage of normative explanations and subjective explanations. The vertical axis represents the average ratio of each participant's explanation type. The horizontal axis shows each of the three conditions.

The analysis of ANOVA with the factor of explanation type (normative explanations vs. subjective explanations)

was conducted on each condition. The results show that participants in the Neutral condition and Negative conditions used more subjective explanations than normative explanations, respectively ($F(1, 27) = 7.326, p < .05$; $F(1, 30) = 25.116, p < .01$). On the other hand, there were no statistical differences between the two conditions in the Positive condition ($F(1, 30) = 0.46, p = .50$). These results indicate that participants in the Negative and Neutral conditions made explanations mostly based on subjective explanations.

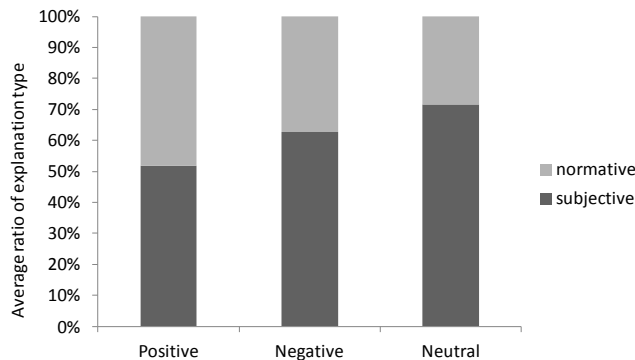


Figure 6: Results of the type of explanation activities.

Discussion

Affective expressions of the conversational agent

The results of the experiment suggested that the greater the positive affective expressions from the conversational agent the more it can facilitate explanation activities which leads to a deeper understanding of concepts (i.e., Positive condition > Negative condition, Positive condition > Neutral condition). The results of the dialogue analysis somewhat support these result. That is, participants in the Negative and Neutral condition used more subjective inferences and interpretations about the key concept instead of using normative phrases, which might led to construction of misunderstandings on the concepts. On the other hand, participants in the Positive condition used normative expressions that were on track. It is assumed that the affective expressions generated by the agents facilitated the participants' motivation to keep their attention to the computer system which provided important information.

These results provide more reliable findings than those compared with experiments conducted by the authors' previous work (Hayashi, 2012). In those experiments, the influences of affective feedbacks were examined during collaborative activities. Unfortunately, there was no neutral condition and dialogue analyses were not further conducted. The present study makes it clear that positive emotions expressed by a pedagogical agent facilitated explanation activities at the interaction level. This suggests that the participants might have paid more attention during the interaction process and worked harder when they received positive comments than they received neutral and negative

comments. One of the interesting finding is that, the learning performance of the participants in the Negative condition and Neutral condition were the same in this experiment. It is assumed that negative affective feedbacks were not able to trigger such motivation and enhance performance as much as the Positive condition. This may be affected by the lack of attention to the agent. This point will be further investigated elsewhere.

Awareness towards the conversational agent

Studies in social psychology have suggested that work efficiency is improved when a person is being watched by someone, or, that the presence of an audience facilitates the performance of a task. This impact that an audience has on a task-performing participant is called the "audience effect". Another relevant concept on task efficiency, but from a slightly different perspective, is what is called "social facilitation theory". The theory claims that people tend to do better on a task when they are doing it in the presence of other people in a social situation; it implies that person factors can make people more aware of social evaluation. Zajonc (1965), who reviewed social facilitation studies concluded that the presence of others have positive motivational affects.

Holmes (2007) is one of the experimental studies which investigated the effects of a tutoring agent. In this experiment, an agent, which played the role of an assistant, was brought in to help a participant who explained a concept. In the experiment, three different environments were set up for the 'explaining activity'. They were: (1) two participants working with a text-based prompt, (2) two participants working with a visual image of pedagogical agent which produced a text-based prompt (3) one participant working with a visual image of pedagogical agent which produced a text-based prompt (in this setup, participants did not have a human co-learner and directly interacted with the agent). The result showed that the participants in the last two conditions did better than the first where only textual prompts were presented. It also showed that the participants in the second condition did not engage in the explanation activity as much as those in the third. The first finding of Holmes (2007) is that the participants in the last two conditions, who worked with the agent, performed better may be attributed to the fact that their task of explanation was being watched or monitored by the agent. Also, the second finding that the effect of the agent for the participants in a pair was not as high as for those directly interacting with it alone may be because the level of attention of the participants in the second condition was not as great as that in the third condition; it may be that the participants in the second were less conscious of the presence of the monitoring agent than those in the third group.

These results of the present study suggest that participants would do better in the task of explanation if they are more conscious of the presence of the agents or if they are given an explicit direction to pay attention to the agent. The

results of the present experiment provide new evidence that the positive feed backs made by the agents can facilitate such "audience effect".

Conclusion and future work

The present study investigated the effectiveness of the use of a conversational agent in a collaborative activity, where paired participants explained each other the meaning of technical terms taught in a psychology class for a better understanding. Conversational agents were used to encourage and facilitate the students' interaction through both verbal and visual input. The experimental results suggested that the presence of a conversational agent with positive expressions can trigger a deeper understanding of a concept during an explanation.

Pedagogical agent can play several different roles for collaborative learning activities and several studies have looked into the effectiveness of the use of a pedagogical agent with different roles. For example, Baylor & Kim (2007) investigated the effectiveness of the use of a pedagogical agent which plays the roles of an expert teacher, a motivator, and a mentor (both an expert and motivator). However, not much is known yet about what roles it can play effectively. Another issue to be further investigated is the effect of the personality of the agent upon these roles. These and other related topics need to be further studied in future.

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