Lexical Network Analysis on an Online Explanation Task: Effects of Affect and Embodiment of a Pedagogical Agent

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SUMMARY The present study investigated the performance of text-based explanation for a large number of learners in an online tutoring task guided by a Pedagogical Conversational Agent (PCA). In the study, a lexical network analysis that focused on the co-occurrence of keywords in learner’s explanation text, which were used as dependent variables, was performed. This method was used to investigate how the variables, which consisted of expressions of emotion, embodied characteristics of the PCA, and personal characteristics of the learner, influenced the performance of the explanation text. The learners (participants) were students enrolled in a psychology class. The learners provided explanations to a PCA one-on-one as an after-school activity. In this activity, the PCA, portraying the role of a questioner, asked the learners to explain a key concept taught in their class. The students were randomly assigned one key term out of 30 and were asked to formulate explanations by answering different types of questions. The task consisted of 17 trials. More than 300 text-based explanation dialogues were collected from learners using a web-based explanation system, and the factors influencing learner performance were investigated. The present study will demonstrate the use of lexical network analysis that has currently been used in educational data mining. Using this method, the study will investigate design factors such as gender of PCA and learner’s and type of emotional expressions that are known as effective designs for PCAs. The study focused on the manner in which the design of such feedback can facilitate the learner’s text-based explanation performance during such activities.

1. Introduction

Online tutoring systems have become an effective method to help and support the learning of students working in classrooms. The massive use and spread of the Internet, as well as the prevailing technologies available in high tech information tools, such as mobile and tablet devices, have provided more opportunities to use these systems. In addition, because of the development of infrastructures and technologies capable of handling large-scale databases, learners have more opportunities to share and disseminate their thoughts among others at any time or place, either online or offline. Thus, studies that determine better methods for improving student engagement with online materials are important. System developers are considering many means of taking advantage of such technologies for learning. Studies on the design of intelligent tutoring systems, such as Pedagogical Conversational Agents (PCAs), which autonomously facilitate learning activities, have suggested that their use for learning is effective [1], [2]. These studies show that these systems may have the potential to perform much like a human tutor. However, only a few studies have empirically investigated the use of this technology for large numbers of students in a class or focused in particular on the learner’s cognitive processes. Also, due to the methodological difficulties, there are only a few studies that investigate the learner’s knowledge development process which can systematically analyze massive text-based dialogue with PCAs.

The study focused in particular on the use of PCAs in a concept-explanation activity task conducted through the Web, where the PCA asked the learners several questions requiring an explanation as an answer and provided feedback to help them formulate their text answers. The present study will demonstrate the use of lexical network analysis that has currently been used in educational data mining. Using this method, the study will investigate design factors such as gender of PCA and learner’s and type of emotional expressions that are known as effective designs for PCAs. The study focused on the manner in which the design of such feedback can facilitate the learner’s text-based explanation performance during such activities.

1.1 Using PCAs for Facilitating Learning Through Explanation Activities

Studies on collaborative problem solving in the fields of learning and cognitive science have revealed how concepts are understood and learned [3]. Other studies investigated whether asking conversational partners reflective questions to obtain clarification is an effective interactional strategy for gaining a deeper understanding of a concept [4]. It has been shown in many studies that the use of strategic utterances, such as asking for an explanation or providing suggestions, can stimulate the reflective thinking and metacognition processes involved in understanding. There have also been many attempts in the learning science field to capture the learning process in the classroom [5]. In the activities described in these studies, the learners worked in groups and attempted to give explanations and ask questions about key concepts in order to gain a deeper understanding of them. One interesting finding was that, regardless of whether the learner’s utterances were correct, the activity itself caused reorganization of his/her understanding of the concept. Therefore, the important factor here is the learner’s
attempt to “think aloud” by giving as many different explanations as possible. The present study will set up a learning environment where learners are required to make different explanations of one key concept from various perspectives.

Generally, it is difficult for learners to retrieve and associate the relevant knowledge required for explanation activities. This has been reported to be the case among novice problem solvers in particular [6]. It is of significance that learners frequently lose self-confidence and become passive. A challenging issue is to support the learners to consistently continue such explanation activities for a prolonged period and to examine their cognitive processes. One means of assisting novice learners is to provide a third person or a mentor who can facilitate their performance of the task by giving prompts, such as suggestions and feedback.

However, in an actual pedagogical situation, such as in a large classroom, it is difficult for one teacher to oversee and monitor all the learners simultaneously and supervise their explanation activity. Recent studies [6]–[9] demonstrated that the use of conversational agents that act as educational companions or tutors can facilitate the learning process. For example, in [10] it was shown that using PCAs that provide suggestions about how to formulate effective explanations can increase learners’ motivation and improve their task performance. In addition, in a number of studies conducted by the author, the use of PCAs that provide affective feedback, which may facilitate better outcomes, was investigated [11]–[13]. In these studies pairs of learners are required to make explanations to each other using a text based chat system while the PCA monitors their utterances and provides suggestions. This system was developed as individual experiment and used for students in a small class that can be only used by pair of learners.

It is not, however, fully understood whether the support given by such agents is helpful for collaborative problem solvers in a large scale classroom, and if so, what kind of support is optimal. To investigate such situation, the present study will setup a situation where learners can access to the system anytime anywhere, and directly make explanations with the PCA in an daily basis. On doing this, there is an issue to be solved such as how to analyze and capture the learning performance collected from the large scale data.

1.2 Lexical Network Analysis for Detecting Explanation Activity Performance

One of the difficulties on understanding the explanation performance collected from the a large classroom is how to analyze the textual input data in a systematic way. There are many issues and difficulties in natural language processing such as detecting the semantics and pragmatic expressions that appear in the text. To reduce such difficulties, the current study will set up a conversational situation with the PCA where learners only answer to questions using short sentences. The Question and Answering style provides a situation to keep learners dialogue simple and with a particular topic. These questions were manipulated so that the answers can be evaluated based on detection of several particular keywords.

On the basis of this, the present study will use a systematic analysis method to automatically evaluate the dialogue data. A lexical network analysis will be used to collect dependent variables in this study. This method will be adopted to evaluate the learner’s explanation performance that will be collected from a large scale class. Recently, this social network analysis method was adopted to investigate the usage of important words in collaborative learning [14]–[16]. As explained in the following section, an adequate explanation in this task is expected to include several important key terms in their explanations. The PCA will ask specific questions about what to explain to the learners. Learners are encouraged to make explanations from several perspectives, and it is expected to observe different several types of key terms in their text. Therefore, calculating the co-occurrence of the use of different important key terms is a good index for evaluating the learners’ learning performance in this study. In addition, previous preliminary results showed that, in the case of a simple sentence explaining a well-defined concept, the bag of words analysis method can be used [15], [16].

Using this automatic analysis method, analysis on learning performance can be easier and enables to conduct experiments focusing on investigating several factors that may influence interaction. The present study will use this analysis method and conduct experiment to investigate what kind of design factors influence interaction with a PCA.

1.3 Factors That Influence Learner PCA Interaction

Using the method described up in the previous section, learners’ learning performance can be detected automatically and can be studied in large scale classes. This systematic analysis method enables us to investigate various factors that are known as effective to learning. Past studies have conducted analysis using lexical network analysis [14], however there are not so many studies that investigate the educational factors of PCAs that influence learning performance using this method. In this section, we take a look what kind of educational factors can be investigated on learning with a PCA.

An effective strategy for improving a learner’s motivation during tutoring is to design effective PCAs. The influence of the types of the detailed characteristics of a PCA on the impressions of learners and their learning performance were investigated in several studies [17]. In addition, studies were conducted in which the influence that the gender of the PCA may have on the outcomes of the learners was addressed [8]. These studies indicated the manner in which the embodied characteristics of the PCAs may influence the learner’s performance.

In addition, the results of some studies indicated that the types of expressions used by the PCAs play an important role during tutoring sessions. For example, in [11], the influence of positive versus negative PCA expressions in a
human-human explanation task was investigated. In this experiment, a PCA monitored the learners’ explanations and provided adequate feedback based on their utterances. During this task, the PCA provided facilitating prompts about formulating explanations while using positive or negative textual and facial expressions. The study demonstrated the extent to which emotional states expressed by the PCA influence learning performance.

In the above, the manner in which the embodied representations and the emotional states of the PCA play an important role in learning activities was described. However, studies have also shown that the learner’s personal traits may also influence his/her performance. For example, in a study reported in [18] it was shown that female learners tend to prefer agents with stylish details. However, few studies have investigated all these factors together to determine the kind of design that improves learning performance. Some studies, such as [19], investigated the effects of the gender of the learner and of the PCA together in one experiment, and found how gender may influence the learner’s feelings toward the PCA. However, the study was lacking in terms of analyzing the learning performance. Moreover, the investigation of the learning process of the learner in a massive online learning environment presents a significant challenge.

In the present study, using lexical network analysis, we conducted a large scale experiment to determine the types of factors, such as the PCA’s embodied characteristics (1) and expressions (2) and the learner’s personal characteristics that may influence performance. To investigate (1), the study focuses on the PCA’s emotional type (positive, negative, neutral) examined in [11]. To investigate (2), we focused on both the learner’s gender and the PCA’s gender. These multiple factors will be will be tested on learning performance examined by lexical network analysis. The present study will use machine learning techniques to determine which of the factors mentioned previously influence the network of terms co-occurring in the learner’s explanation. In the next section, the web-based system using the PCA and details of the lexical network analysis is explained.

2. Method

In the present study, a Web-based learning system that allows learners to give text-based explanations about key concepts was used. The students were asked to access the Web page and conduct the task within a week following the class. They were able to use the system at any time during this period. However, access to the system was restricted such that the learners could use only the networks provided by several computers inside the campus. Thirty different key terms (e.g., Gestalt, long-term memory, and cognitive dissonance) were selected from the class material and one of these was randomly assigned to each of the learners according to their ID numbers. Three or four learners were working on the same key concept, but they did not know how many or which of the other learners had previously worked on the concept. When using the system, they were guided by a pedagogical agent that (1) specified the concept that they were required to explain, (2) provided meta-cognitive suggestions, and (3) gave information about the explanations of other members inside and outside the classroom. In the next section, we explain this more precisely.

2.1 Experimental System

In this study, a Web-based tutoring system comprising a Web server, a database, and rule-based scripts was developed specifically for the experiment. The system was managed as a members-only system. The learners were required to log in to the system in order to use it. As mentioned in the previous section, each student was assigned to work on one selected key term. When the learners logged into the system, a PCA appeared on the screen. Then, they started to explain the selected key concept. The task consisted of 17 trials, each comprising two major steps, as follows. (1) Text input and (2) feedback from the PCA. In each trial, the learners received questions from the PCA about the key terms. For example, the PCA asked a series of questions, such as “Explain the key in terms of how it functions to humans.” “How do you use such a situation in your daily life?” “Think about a concept similar to this one,” etc. The PCA also encouraged the learner to input their original thoughts and use the words that were taught in the class.

Two types of embodied PCAs were used, one male and one female. In each trial, the learners were asked to do the following. (1) Input explanations and click on the next button, and (2) read the meta-suggestions on formulating effective explanations provided by the PCA. The PCA used expressions according to the experimental condition (explained in the next section).

Figure 1 shows an example of a screen shot and the order of inputting messages and receiving feedback. All data, including the input text, PCA type used, and the learner’s gender and age, were collected in the database. The average time for this activity was approximately 30 min.

2.2 Experiment Design and Learners

To express the emotion of the PCA, its facial reactions were manipulated, based on [11]. Three different conditions were provided. In the condition called the “positive condition,” the PCA expressed positive facial expressions representing a mixture of pleasantness and arousal feelings. In the condition called the “negative condition,” the PCA expressed negative feelings with a mixture of unpleasantness and arousal feelings. In the condition called the “neutral condition,” the PCA’s expression was manipulated to show no emotion. Figure 2 shows the example of the facial expressions. These faces were developed using a 3D-image/animation-design tool Poser 8 (www.e-frontier.com).

More than 300 students (learners) were selected from three large classes, each of whom was assigned to one of the three experimental conditions, according to his/her login ID number. The learners assigned to the positive condi-
tion consisted of 99 undergraduates (36 males, 63 females), to the negative condition of 111 Japanese undergraduates (31 males, 80 females), and finally, to the neutral condition of 104 Japanese undergraduates (33 males, 71 females). The gender type of the PCA was 50 male PCAs and 49 female PCAs for positive condition, 54 male PCAs, 57 female PCAs for negative condition, and 53 male PCAs, 51 female PCAs for neutral condition.

2.3 Measurements

In this study, the analysis of the collected texts comprised two steps: (1) development of a dictionary database, and (2) lexical network analysis to understand the usage of important words.

2.3.1 Preprocessing

The objective of the first stage of the analysis was to develop a dictionary database to capture the important words used during the explanation activities. To build a supervised learning data set, an expert (teacher) was asked to create explanations for all the questions posed in all trials. Based on the text of these explanations, 10 significant words were chosen for each of the 30 key terms that were presented to the learners. These key terms were registered in a “semantic database” to be used for the network analysis.

2.3.2 Network Analysis

Using the semantic dictionary database as the training data set, the learners’ textual inputs were further analyzed. For each trial input, the number of appearances of the semantic keywords in the dictionary was counted. The data related to these semantic key words were then analyzed using the social network analysis method. For each learner, a network was developed based on a bipartite graph of keywords (10 keywords x explanations (17 trials). Figure 3 shows an example of one learner’s lexical network data on the topic of “cognitive apprenticeship.”

Each node represents the semantic category of the keyword that was frequently used in the learner’s explanation. In the figure, the nodes are “learn,” “acquire,” “teach,” “expertise,” “process,” “knowledge,” “instruct,” “novice,” “procedural,” and “guidance.” The following equation represents the network density, where $n$ denotes the number of nodes and $l$ the number of links.

$$d = \frac{l}{n(n-1)}$$

(1)
2.3.3 Checking Performance with Human Coded Data

Now we check the validity of the lexical analysis performance with human coded learning performance. Since there were a large amount of data for coding all the textual data, we used only the description of the 17th trial for analysis. For human coding, the descriptions were scored in the following way which was used in the previous study [11]: one point was awarded for a wrong description or no description, two points for a nearly correct description, three points for a fairly correct description, four points for an excellent description, and five points for an excellent description with concrete examples. Using the evaluation data of human and the automated analysis used by the lexical network analysis, we conducted a Pearson’s correlation analysis. The results show that there was significant correlation with the lexical analysis data and the human coded data \( r = 0.476, p < .01 \). This shows that learning performance detected based the lexical network analysis show relative performance with human coding scheme that was used in a similar explanation task conducted in a previous study [11].

2.3.4 Classifying Learning Performance

The present study will investigate several design factors that could be effective on learning performance. On analysis, the study will conduct machine learning techniques to classify which factors were most effective to high learning performance. To see this, we distinguish the levels of learning performance in several levels. The values of \( d \) acquired for each of the learners were classified into the following five categories.

\[
f(d) = \begin{cases} 
  \text{vhigh} & (1 \geq d > 0.22) \\
  \text{high} & (0.22 \geq d > 0.089) \\
  \text{neutral} & (0.089 \geq d > 0.044) \\
  \text{low} & (0.044 \geq d > 0) \\
  \text{vlow} & (d = 0) 
\end{cases}
\]  

The parameters were set such that the distribution would be even. The distribution for each five category is shown in Fig. 4, where it can be seen that that the five categories are evenly distributed.

3. Results

3.1 Overall Analysis: Decision Tree Analysis

To investigate which factor (types of emotion, embodied gender, and learner’s gender) influences the dependent variables, we performed a decision tree analysis. Using the results of the network analysis as the dependent variable, we performed a decision tree analysis to determine the optimization of the influence of each factor. The analysis was conducted using R. Figure 5 shows the results of the analysis. The most frequent dependent variable is shown in each node and the number at each node represents the numbers for each (“very low,” “low,” “middle,” “high,” and “very high,” respectively). The figure shows that the most influential factor in the tree is whether or not the condition is neutral. If the condition was positive or negative, then the gender of the PCA had a strong influence.

3.2 Lexical Network Analysis

To investigate these two factors in more depth, a statistical analysis was performed using a 2 (emotion: positive vs. negative) x 2 (PCA’s gender: male vs. female) between-subject factor analysis (ANOVA). Figure 6 shows the results of the lexical network analysis by conditions. The vertical axis shows the average degree of \( d \) and the horizontal axis the two conditions.

There was significant interaction between the two factors \( F(1, 206) = 16.5228, p = .037, \eta^2_p = .037 \). Simple effects for the interactions show that learners using a female PCA achieve a higher performance when the PCA expresses a positive mood than when it expresses a negative mood \( F(1, 206) = 21.0095, p = .002, \eta^2_p = .047 \). This shows that learners using a positive female PCA perform better than negative female PCA.

Further, the results show that learners using a PCA ex-
expressing a negative mood performed better when the PCA was male than when it was female \(F(1, 206) = 22.0543, p = .001, \eta^2_p = .048\). The results reveal that learners using a negative male PCA perform better compared to negative female PCA.

4. Discussion

Previous studies in tutoring systems has attempted to use PCAs to motivate learner’s learning activities [7], [8] and facilitate learning performance [6], [9]. In such studies the use of lexical analysis method has been known and used as an effective way to capture learning performance [14]–[16]. However, there were only a few studies that investigated the explanation activities in a large scale class. Also, there are no studies that further investigate the learning performance detected by the automated analysis as a dependant variable and investigate several factors that influence learning with the PCA.

Having acquired a large scale data set from our online explanation activity experiment, we conducted an analysis to determine the factors that influence the learner’s performance. To capture the performance of the learner’s explanation activities, we used a lexical network analysis method and calculated the index of the learner’s usage of co-occurring words during his/her explanation activities. The method used in this study provided potential implications that lexical network analysis can be applied to explanation activities performed in a large scale learning task. Some studies point out the negative side of the bag-of-words method on detecting the descriptions. However, the present study shows how it can be effective on detecting the performance of explanation performance if it is situated in a simple question and answering context and requires to use particular keywords.

Results from previous study show that positive emotional states are effective compared to negative expressions [11]. The point that learners are influenced by emotional states are consistent with previous study. Although the present study show more detailed implications. The results of the analysis show that two factors, the expressions and the gender of the PCA, significantly influence the learner’s explanation performance. A detailed factorial analysis showed that when a PCA with female characteristics is used, positive emotional expressions are effective. In addition, when a PCA that appears to have negative embodied characteristic, it is more effective if it has male characteristics. Also, the present study focused on human-agent interaction, the previous study focused on the use of a PCA that interrupt in human-human interaction.

In the study of [20], the type of gender of learner and gender of the PCA was also investigated in a single experiment. In this experiment, learners engaged in a online task while reading descriptions presented by a PCA. During this activity, learners inputted their emotional states using an emoticon and analyzed how gender of the PCA and learner’s gender influenced their emotion. Results of experiments revealed that male students felt more pleasantness bipolar and female students were sensitive to the activation bipolar of the Russell’s two-dimensional circumflex model [21]. Further investigations also show that female learners with arousal states evaluated the agent positively. Male learners with pleasure feelings evaluated the agent positively in some degree. This study has not detected any of the effects of the PCA’s gender. Moreover, only the type of emotional expression was investigated as a dependant variable. Thus the results do not show how such design can affect learning performance.

The present study investigated which factors influence the learning process through several independent variables, including (1) the PCA’s embodied character, (2) the PCA’s expressions, and (3) the learner’s type of gender. However, other variables, such as age, detailed characteristics, and other personal characteristics, may also influence learning performance. In addition, concerning the types of expressions, the manner in which the PCA provides information to the learner could be analyzed. Such an analysis may provide new knowledge not only about which factors influence communication in learning activities, but also about more general communication behaviors involved in human-human and human-agent interactions. To understand the human factors in online activities, it is necessary to collect more data and search for patterns. This study provided implications for the effective design of online tutoring systems that incorporate PCAs with emotional expressions and embodied characteristics.

5. Conclusion

Using lexical network analysis, this study investigated how the PCA’s gender and the learner’s gender, and the types of the PCA’s emotional expressions influence the learner’s explanation performance. Learner’s gave explanations to a PCA on a one-on-one basis, as an after school work activity in a introductory psychology class. The PCA played the role of questioner and asked the learners to explain a key concept taught in their class and students were asked to for-
mulate explanations of the term by answering different types of questions. The study collected over 300 learner’s text-based explanation dialogues using a web-based explanation system and investigated which factors influenced learning performance. Machine learning results show that during the explanation activity, the expression and the gender of the PCA influence the learners’ performance. Results of factorial analysis reveal that (1) learners using a negative male PCA perform better compared to a negative female PCA, and (2) learners using a positive female PCA perform better than negative female PCA. These results imply that the design factors such as the type of gender and expressions of their emotional states affect explanation performance. This paper also provides insight into capturing behavior of humans performing online tasks and suggestions related to the design of efficient online tutoring system using PCA.

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References


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