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Exploring the Effectiveness of Social Capabilities and Goal Alignment in Computer Supported Collaborative Learning

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Abstract. In this study, we describe a conversational agent designed to support collaborative learning interactions between pairs of students. We describe a study in which we independently manipulate the social capability and goal alignment of the agent in order to investigate the impact on student learning outcomes and student perceptions. Our results show a significant interaction effect between the two independent variables on student learning outcomes. While there are only a few perceived differences related to student satisfaction and tutor performance as evidenced in the questionnaire data, we observe significant differences in student conversational behavior, which offer tentative explanations for the learning outcomes we will investigate in subsequent work.

Keywords: social interaction, conversational agents, collaborative learning

1 Introduction

Much prior work demonstrates the advantages of group learning over individual learning, both in terms of cognitive benefits as well as social benefits [1][2]. From a cognitive standpoint, a major advantage to learning in a group is that when one is exposed to an alternative perspective, it provides the opportunity to question one's own perspective, which in turn offers an opportunity for cognitive restructuring. In order to achieve this benefit, a major emphasis of work on scaffolding collaborative learning [3] has focused on drawing out aspects of an issue where there is a disagreement between students so that they will address the disagreements explicitly and benefit from that negotiation process. In line with this, work on formalizing the process of collaboration in order to identify events that are valuable for learning has in many cases focused on formalization of argumentation [4].

In this paper, we again investigate how conflict and negotiation relate to learning by characterizing spans of text as exhibiting a bias towards one stance or another. As a methodological contribution, we discuss how we use as a tool for quantifying bias a state-of-the-art topic modeling technique from the field of language technologies referred to as ccLDA [5]. On another dimension, we examine the impact of the tutor's social behaviors on student learning. As we have seen from recent work, tutors capable of engaging in social interactions with groups can be significantly more effective than tutors that have no social capability [6]. However, there is a trade-off between spending time on social behaviors and spending more time talking about task-related content. In this study, we manipulate the extent to which the agent exhibits social behaviors designed to build solidarity between the student and the agent in order to investigate whether these solidarity building behaviors either magnify or dampen the effect of the bias manipulation.

We begin with a classroom study of collaborative engineering design where students work in pairs on the design of a power plant. This learning task involves negotiating between two competing objectives. Specifically, one student in the pair is assigned to the goal of maximizing the power output of the power plant. The other student, in contrast, is assigned the goal of minimizing the negative environmental impact of the design. Similar to our prior studies of collaborative learning [6][7], a conversational agent participates with the students in the design task in order to provide support. The unique contribution of this study is that we explore the introduction of bias in the way the agent presents information towards one student's stance or the other. In addition to investigating the effect of the manipulation on learning, we investigate the extent to which students are sensitive to displays of bias in the language of their human partner and that of the agent, to what extent the agent's displayed bias affects the bias displayed by the individual students, the interaction between the individual students and the agent, and finally the interaction between the pair of students themselves.

In the remainder of the paper we first review the literature on the connection between conflict and learning. We then describe our experimental study. Next we explain our methodology for measuring bias. We then detail our results. We conclude with discussion and directions for future work.

2 Previous Work

Previous work on building socially capable conversational agents focuses on designing social interaction strategies that fall into the category that Isbister and colleagues [8] have referred to as social interface within their taxonomy. The goal of these strategies is to enable users to interact in an intuitive and natural way with the agent to perform some intended task. For example, Morkes et al [9] implemented a task-oriented conversational agent that uses preprogrammed jokes. They show that this humor-equipped agent is rated as better and easier to socialize with by human participants. In another line of work, Wang and Johnson [10] found that learners who received polite tutorial feedback reported higher increase in self-efficacy at the learning task. Social strategies are also found to be effective in multi-party conversations, such as in computer supported collaborative learning. Higashinaka et. al. [11] found that an agent's use of emphatic expressions improved both overall user satisfaction and user rating of the agent. In general, computer agents which are friendly and helpful to users are favored.

In a multi-party conversation between students and a computer tutor, it is important to build rapport between students and the computer tutor so that students respect the role of the tutor as a participant in the conversation and thus are more likely to engage with them in a productive way. At the same time, it is also important to ensure that rapport building activities do not detract from the students' task-related objectives. Her we draw wisdom from previous work [12] describing conversational processes through which the participants align to one another as an attempt to promote efficiency and effectiveness in their communication. Although this work pertains to human-human conversation, there is reason to apply it to human-computer interaction as well. Reeves and Nass [13] have shown that although people do not generally believe that computers have either human perceptions or human feelings, they still behave towards computers in a way that seems to assume that they do. This is displayed in the way that humans respond to what would be social cues in human-human interactions even when those cues are coming from computers. The pattern of results from the Reeves and Nass studies might suggest that in conversational interactions between humans and computer agents, we may see the same alignment strategies surfacing. And this has been confirmed by a series of studies conducted by Nass and his colleagues [14][15]. They report that human users align to conversational agents at both lexical and syntactical levels. The extent of the alignment depends on the users' beliefs about their conversational partners' competence.

Due to the restricted syntactic complexity exhibited in the conversational behavior of our tutor agents, in this study we only focus on examining lexical alignment. We explain in Section 4 how a ccLDA model is used to measure the bias of a student's stance in terms of the topics represented in the user's utterances, which are modeled as distributions of lexical items. These topics are later used to measure the alignment of student utterances at the lexical level.

3 Method

We are conducting our research on dynamic support for collaborative design learning in the domain of thermodynamics, using as a foundation the CyclePad articulate simulator [6], which allows students to implement design ideas using graphical interface widgets. In the collaborative design exercise described below, students work in pairs to struggle with trade-offs between power output and environmental friendliness in the design of a Rankine cycle, which is a type of heat engine.

106 undergraduate students from a mechanical engineering class at Carnegie Mellon University participated in the study by attending one of six lab sessions, in which we strictly controlled for time. At the beginning of each lab session, students were lead through formal training on the simulation software Cyclepad. They then practiced to optimizing some Rankine cycles in Cyclepad using information from a booklet given to them, which was developed by a professor from the Mechanical Engineering Department. Subsequent to this, they took the pre-test, immediately before the experimental manipulation. The exploratory design exercise, which followed, was where the students worked in pairs using CyclePad and the ConcertChat collaboration environment [16]. Students are randomly assigned into pairs and paired students do not sit next to each other so that their only

communication is through the ConcertChat online learning environment. We assigned each student within each pair to a different competing goal, with one student instructed to increase power output as much as possible and the other student instructed to make the design as environmentally friendly as possible. Students were instructed that they should negotiate with their partner in order to meet their own assigned design objective, namely either to maximize Power output (in the Power condition) or to minimize environmental impact (in the Green condition). This collaborative design exercise was followed by the post-test and the questionnaire and finally a closing activity in which the student was able to work independently with CyclePad to improve the design they developed with their partner.

As mentioned, during the collaborative design interaction, students use a collaboration software package called ConcertChat [16] to chat with each other in pairs as well as using the digital whiteboard associated with that environment to pass graphical information back and forth to one another. In all cases, a tutor agent participated with the students in the chat. The experimental manipulation only affected how the tutor agent behaved. In all other respects, the experience of students in all conditions was the same.

The experimental manipulation was a 3X3 between subjects design. Each student pair is assigned to one of the nine conditions randomly. For the first independent variable, we contrast 3 social conditions (High, Low, and None) where dialogue agents present different amounts of social behavior within the chat environment. Our dialog agent exhibits three different types of positive social-emotional behavior: showing solidarity, precipitating tension release, and agreeing. In most cases, these strategies are realized by prompts that appear in the chat. The frequency of social behavior in our socially capable tutors is regulated using a parameter that specifies the percentage of tutor turns that can be social prompts. Specifically, the threshold parameter is 15% in the case of the Low social tutor and 30% in the High social tutor. In the Nonsocial condition, no social behavior is realized.

For the second 3 level independent variable, we designed 3 conditions in which the dialogue agent showed alignment either towards the Green condition, the Power condition, or neither. In this way, students could be thought of as being in one of three different conditions in relation to the tutor agent, namely Match (where the student's goal orientation condition matched the alignment of the tutor), Mismatch (where the student's condition is the opposite of the goal alignment exhibited by the tutor), or Neutral (where the tutor showed no bias). In all cases, the information presented by the tutor is the same. The only difference is the bias exhibited. For example, where the Green biased tutor might say "What is bad about increasing the heat input to the cycle is that it increases the heat rejected to the environment." The neutral tutor would simply say "Increasing heat input to the cycle increases the heat rejected to the environment."

As outcome measures, we examined learning gains between Pre and Post test. 35 multiple choice and short answer questions were used to test analytical and conceptual knowledge of Rankine cycles. We also analyzed the conversational behavior in the chat logs. Finally, we evaluated answers to affective questionnaire items that measure students' self-efficacy, perceptions of task success, and assessment of the quality of the interaction with their partner and with the agent.

4 Modeling Conversational Dynamics

In this study, we measure the bias of a system/user utterance towards one stance or another by applying a topic discovery model on our tutoring dialogs [5]. Latent Dirichlet Allocation (LDA) models have been widely used to discover topics on large collections of unannotated data [17] by modeling the word distributions represented in the data. For example, it has been used to predict responses to political webposts [18], to study the history of different research fields [19], and so on. What is unique about our application of this technology is that we apply it to conversational data for the purpose of modeling how users are interacting with each other. For each utterance, we compute a score to represent to which degree the utterance displays a bias towards one perspective or another.

In our study, we apply a cross-collection Latent Dirichlet Allocation (ccLDA) model [5], which is a variant of the LDA model that represents how the same topics might be represented differently by speakers representing different points of view. In the ccLDA approach, corpora are represented as collections of documents. ccLDA will construct a topic model for each collection, where these collection-specific topic models represent what is distinct about how those topics are expressed within that collection. A background model is also constructed to represent the commonalities across different collections. A model with this structure can be used to compare multiple text collections by capturing similarities and differences across them in terms of how the same topics are expressed. Since the two students who participate in each pair are assigned different objectives at the beginning, it is intuitive to apply the ccLDA model to model how the students in the two different conditions discuss similar topics, but express a different point of view through those topics.

Table 1. Topics Extracted from ccLDA

Topic 1			Topic 2		
Background	Green	Power	Background	Green	Power
Heat	11000	yah	power	low	generates
quality	values	blades	decreases	500	makes
right	different	sir	nuclear	12800	85
max	makes	dunno	make	sort	different
decrease	larger	kk	85	1	7000
possible	graphs	x85	cycle	tutors	12000
goes	bit	rejected	work	effeciency	qdot

To use the ccLDA model, we first separate our dialog data into three collections: those turns that were contributed by the student in the Green condition, those turns that were contributed by students in the Power condition, and those turns contributed by the tutor agent. Thus, for every dialogue, we produce two documents, one containing the concatenation of all the contributions from the student assigned to the Green condition, and the other containing the concatenation of all of the contributions from the student assigned to the Power condition. Our ccLDA model has two collections, namely, a Green collection and a Power collection. We do not include the tutor turns within either collection. When we apply ccLDA to this corpus, then, we get three different topic models, namely, one associated with the Green perspective, one associated with the Power perspective, and one background model representing what is common between the two. When applying ccLDA, one must set a parameter for the number of topics. Because our corpus is relatively small, we set this value to 2. Thus, in all three models, we have the same 2 topics, where a topic is defined as a distribution of words, where the probabilities represent the strength of association between the word and the topic within the model. Table 1 gives an example of the top 7 words selected for each data collection for the two topics.

Table 2. Three types of topic associations

Author	Text	G_Max	P_ Max	G_Avg	P_Avg	G_Wt	P_ Wt
Stu1	whats ur goal?	0	0	0	0	0	0
Stu2	green as possible	1	0	0.5	0	0.5	0
Stu1	mine is generates the most power	0	2	0	2	0	2
…							
Tutor	If you increase the max temperature, what happens to the efficiency?	1	0	0.5	0	0.5	0
Tutor	Cycle Efficiency improves by increasing Tmax.	0	0	0	0	0	0

We designed three metrics for estimating bias towards either the Green perspective (G) or the Power perspective (P) using our ccLDA model. An example where these metrics are applied is presented in Table 2.

Max Topic-word association (G_Max and P_Max). In the Max Topic-word approach, for each collection specific model we compute a score for each topic, where we count the number of words in the list of the N most strongly associated words with that topic in the corresponding model. The largest number identified for any one topic within that collection specific model is the score for that collection. In this way, we can compute a score for each perspective, since there is one collection specific model per perspective. Hence, for a piece of text that has 2 terms matching with Topic 0 of Green and 1 term with Topic 1 of Green, we would consider 2 to be the score for Green. By averaging over all contributions for the same student within a conversation, it is possible to use this metric to get an average Max Topic-word score for each student for each perspective.

Average Topic-word association (G_Avg and P_Avg). In the Average Topic-word approach, we find the topic-word associations, as in the previous approach. But here, we average scores across topics within a collection specific model rather than choosing the maximum value.

Weighted Topic-word association (G_Wt and P_Wt). This is a heuristic approach that is similar to the previous approach but which uses the weights of topic terms provided in the ccLDA probability model distributions. Whereas in the Average Topic-word approach, each word contributes 1 to the topic specific sum we compute for each topic in each collection specific model, here we add a weight that is computed by multiplying the weight of the term within the background model with the weight of that word in the topic within the collection specific model. We observe that the background models prioritize important, domain-specific terms by giving higher weights. Hence, in this approach, we consider the product of the weight of a word in the Background model and its weight in the specific collection so that the relative weighting of domain important terms is more important for the final weight than terms that are less important for the domain.

We validated the metrics by verifying that students in the Green condition were assigned higher Green bias scores than students in the Power condition, and vice versa. This was true in all cases, although the differences were only statistically significant for the first two metrics. All three metrics were highly correlated, with R values between .68 and .99. We further validated the metrics using data from a questionnaire where students were asked to rate their partner based on how hard they perceived that their partner attempted to build an environmentally friendly power plant. The first and third metrics showed a significant correlation in the expected direction with these answers.

5 Results

We analyze student performance from three directions. The first one is the direct outcome of the tutoring sessions – the learning gains; the second is perceived user performance – user's subjective opinions from the questionnaire data; and the last one is the observed user performance – measures related to conversational behaviors.

5.1 Learning Outcomes

Recall that our experimental manipulation was composed of two independent factors, which we refer to here as Social (No Social, Low Social, and High Social) and Match (Yes-Match, No-Match, and Neutral). We first look at the most important evaluation standard in tutoring applications – the student learning gains. Using an ANCOVA with Objective Post-test as the dependent variable, Objective Pretest as a covariate, and Social and Match as independent variables, and Session as a random variable, we determined that there was a significant effect of the Social Manipulation ($F(2,94) = 5.27$, $p < .01$) where the Low Social condition was significantly better than the other two, with an effect size of .83 standard deviations in both cases. There was a marginal interaction between Social and Match $F(2,94) = 2.57$, $p = .08$, where Low Social is only significantly better than the other conditions in the case where Match is Yes-Match. All other combinations of Social and Match were statistically indistinguishable.

In general, students learn the most in the condition with the tutor that showed a bias towards their design goal (Yes-Match) and Low Social. Based on the interaction effect between Social and Match, we believe that it is beneficial for the computer tutor to not only establish the appropriate level of social connection with the students, but also been viewed as supportive of the students' objectives in order to maximize student learning outcomes.

5.2 Questionnaire Data

We then look into the questionnaire data to see whether the students perceive the social and goal manipulation we designed in this study. Using an ANOVA for each questionnaire question as the dependent variable and Social and Match as independent variables, we determined that there was a marginal effect of Match on rating of tutor as supporting the student's objectives ($F(1,102) = 2.77$, $p = .09$), where the tutor was seen as supporting students marginally more in the case where the goals matched. There was no effect of either variable on the perception of whether the tutor supported the partner's goal.

The effect of the Match manipulation was demonstrated in other aspects of the experience however, according to the questionnaire. For example, on the questions designed to assess the extent to which a student's partner influenced their perspective as a result of the conversation, we observed a significant interaction effect between the Social manipulation and the Match manipulation, such that when the tutor did not exhibit any bias, there was no significant effect of the Social manipulation, but with either agent that showed a bias, either matching the student's bias or the partner's bias, the High social condition significantly reduced the perceived influence of the partner's perspective. Using our bias detection approach, we determined that students were significantly more distinct from their partner in terms of measure of bias in the case where the tutor showed a bias towards one perspective or another, thus magnifying the contrast between the students. This could explain the pattern of behavior we see here. In the case of the neutral tutor, the polarization was less, so the dampening effect of the Social manipulation would not be felt as strongly.

5.3 Conversation Data

Apart from questionnaire data, we can observe an effect of our experimental manipulation on conversational patterns. We have already discussed effects related to bias in the conversation. Here we measure the extent to which students were sensitive to the social aspects of the tutor's behavior that we manipulated through our two independent variables. We began by manually classifying student turns into three categories:

- AboutSocial – student turns on social behaviors, including greetings, farewell, smiling faces, rude words, jokes
- Offtask – student turns talking about off-task topics, like weekend plans, etc
- AboutTutor – student turns that make negative comments about the tutor

We computed the number of AboutSocial, Offtask, AboutTutor turns for each student. Using an ANOVA for each of the three categories as a dependent variable and Social and Match as independent variables, we observe that there is a significant effect on AboutSocial ($F(2,29)=9.91$, $p<0.0001$), where a student's social behavior is significantly lower in the condition with the No Social tutor than with the Low Social tutor (with an effect size of 1.8) and High Social tutor (with an effect size of 2.0). Similarly, there is a significant effect on Offtask ($F(2,97) = 3.30$, $p < .05$), where students engage in more off task behavior in the No social condition than in the Low and High social conditions (with effect size of .35 standard deviations in both cases). We also observe a significant effect on AboutTutor ($F(2,97) = 5.74$, $p < .005$), where students utter more negative comments about the tutor in the High social condition than in the Low Social condition (an effect size of 1.1) and the No Social condition (an effect size of 1.28).

Based on our results, we suggest that students will show more social behaviors as well as focus more on the task when the tutor exhibits social behaviors. However, when the tutor performs too much social behavior, the students get distracted and start to make fun of the tutor. This is in addition to the dampening effect of the influence students were perceived to have on one another in the High social condition.

6 Conclusions and Current Directions

In this paper we have described an investigation into the issue of competing biases or stances, and how their presence in a conversation, from human or computer participants, affects the learning, interactions, and perceptions of the encounter. Specifically, we describe a conversational agent that has the ability to exhibit bias towards one perspective or another as well as the ability to exhibit social-emotional behaviors that are designed to build solidarity. We describe a study in which we independently manipulate the social capability and goal alignment of the agent in order to investigate the impact on student learning outcomes, interactions, and perceptions. We observe a significant interaction effect between the social and goal alignment manipulation which suggest that the two strategies need to be considered together when designing tutoring systems. In addition, while there are less perceived differences in the student questionnaire data, we observe significant differences in student conversational behaviors in different experimental conditions. We suggest that an appropriate amount of tutor social behavior can help to engage students in the conversation. Furthermore, aligning with student's goals can improve the students' learning. In the future, we will further investigate how to design the appropriate level of tutor social behaviors and how to design tutor's dialog content to align with the learning objectives of both student partners in the conversation.

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