Intelligent Tutoring System for Negotiation Skills Training

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Abstract. Intelligent tutoring systems have proven very effective at teaching hard skills such as math and science, but less research has examined how to teach "soft" skills such as negotiation. In this paper, we introduce an effective approach to teaching negotiation tactics. Prior work showed that students can improve through practice with intelligent negotiation agents. We extend this work by proposing general methods of assessment and feedback that could be applied to a variety of such agents. We evaluate these techniques through a human subject study. Our study demonstrates that personalized feedback improves students' use of several foundational tactics.

Keywords: Negotiation Training, individualized feedback, soft skills training

1 Introduction

Research in the intelligent tutoring systems community has shown that these systems are effective at teaching hard skills including math [1] [2] [3] , reading [4] [5] , even computer literacy [6] [7]. Research has tried to extend these techniques to softer skills such as public speaking [8], collaborative problem solving [9] and more specifically negotiation [10] [11] [12]. Compared to the application of intelligent tutoring systems to hard skills training, the systems designed to teach softer skills are limited.

In this article, we tackle the domain of negotiation. Like most social skills, negotiation falls within what Aleven and colleagues [13] define as an ill-defined domain, and presents a challenge for intelligent tutors. Social skills lack clear assessment metrics and prescribed formulas to guarantee success. Though hard to teach, social skills are becoming increasingly crucial for students entering the modern workforce. The US Academy of Sciences and the World Economic Forum identify negotiation as a foundational social skill essential for the future of work through its impact on organizational creativity and productivity [14] [15]. Deficits in negotiation ability contribute to the underrepresentation and lack of advancement of women and minorities in STEM fields [16] [17]. Unfortunately, negotiation training is inaccessible to most workers who need it (e.g., even a short 5-day seminar can cost more than $10,000 per student).

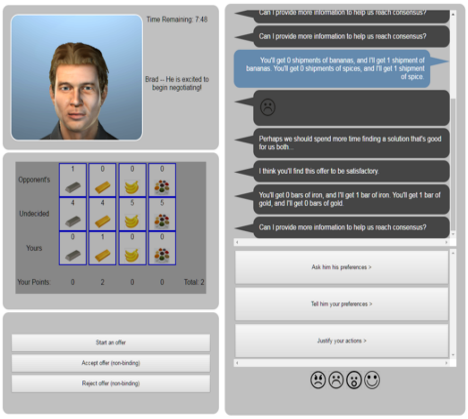
Yet there is reason for optimism. Most recently, researchers have shown that students who practice negotiating with intelligent agents can improve their skills [11] [18]. Although these systems have been shown to improve negotiation skills, with some exceptions [12], they mainly allow users to practice and do not provide feedback. Feedback is one of the most crucial aspects of the learning process [19]. In this paper, we illustrate how to build upon general intelligent agent technology to provide both experiential practice and personalized feedback. We introduce a general (domain- and algorithm-independent) approach to incorporate automatic assessment and personalized feedback into intelligent negotiation agent technology and describe a study to assess the effectiveness of our approach. In section 2, we discuss our method for automatically assessing students' ability to create and claim value. In Section 3, we incorporate these metrics into a publicly-available online negotiation platform called IAGO [20], and present experiments that assess the benefits of "mere practice" with this system compared with practice coupled with either generic or personalized feedback. In Section 4, we discuss our results and several lessons on how to improve these techniques in future research.

2 Automated Negotiation Assessment and Feedback

The ultimate goal of negotiation is to obtain good outcomes (i.e., maximize the value of the negotiated agreement, establish a fair and positive reputation, etc.). However, most negotiation training addresses tactics to achieve these ends. Thus, an intelligent negotiation tutor must not only assess outcomes, but the means by which students achieve them. Here, we review the assessments used by negotiation instructors and show how to automatically make these assessments and provide personalized feedback.

We adopt a set of general assessment metrics that address specific tactics for creating and claiming value. In our previous work we highlight these metrics and show how they are automatically calculated [21]. We assess a student's ability to create value by measuring the joint points achieved in the negotiated agreement (i.e., the points obtained by both the student and the agent). We evaluate several process measures to gain insight into why a student may have failed to create value. For example, we assess if a student employed the tactic of logrolling by the extent to which they made tradeoffs in their initial offer to the agent (specifically, the number of highest-value items they claimed minus the number of lowest-value items they offered). We also evaluate a student's ability to claim value by measuring the individual points they obtained in the final deal. We assess one process measure to gain insight into why they may have failed to claim value. Specifically, we look at the point value of the student's initial offer.

After completing a simulated negotiation, students are assessed using the abovementioned metrics and then receive automatically-generated feedback. The generated feedback describes the extent of good outcomes achieved, and how they followed specific strategies to achieve these outcomes (e.g., did they exchange information with their opponent? Did they make ambitious offers?). They are then provided specific actionable strategies for improving in the future. When students achieve good outcomes or follow recommended tactics, this is positively reinforced (e.g., "The first offer you made would have gotten you about 76% of the points. Pretty good.") and the principle



Negotiation 1	Gold	Iron	Bananas	Spices
Agent Points	1	2	3	4
Student Points	4	3	2	1

Negotiation 2	Records	Clocks	Painting	Lamps
Agent Points	2	3	1	4
Student Points	3	2	4	1

Fig 1. The left image illustrates the IAGO agent interface. The tables on the right illustrate the issues and payoffs for the two negotiations

emphasized ("By claiming most of what you want early in the negotiation, you can manage your negotiation partner's expectations of what they will receive."). When students fail, it is highlighted (e.g., You failed to fully understand your opponent's preferences. This prevented you from making good tradeoffs") and specific suggestion is provided (e.g., "For example, if you realized your opponent wanted bananas the most, a win-win solution would be giving them all bananas and taking all the gold for yourself.").

3 Evaluating the effectiveness of personalized feedback

Negotiation Task: Participants were asked to engage in two negotiations using the IAGO online negotiation platform [22]. IAGO is designed to support tactics that expert negotiators used to create and claim value. Negotiators can exchange offers but also information (do you like A more than B?) and send other messages such as threats. The platform also provides tools to customize agent behavior including the ability to incorporate common biases shown by negotiators (such as the fixed-pie bias). It has been used by a number of researchers to build human like negotiating agents [23]. Each negotiation has the same mathematical structure (a 4-issue, 6-level multi-issue bargaining task) but used a different cover story and a different ordering of the issues to obscure this similarity. The tasks were framed as a negotiation between antique dealers on dividing the contents of an abandoned storage locker. Both the agents and participant had distinct preferences across the items, and neither knew the other's preference. Figure 1 shows the number of points each party could get for each item.

Measures: We gathered basic demographic information and self-reported negotiation skill level prior to the negotiation. During the negotiation, we automatically derived the metrics discussed in Section 2.

Participants: 120 English speaking America participants who were recruited via Mechanical Turk. To motivate their performance, participants were paid \$3/hour for their participation in the study and entered into a lottery to win a prize of \$10. Of these participants, 19 were excluded from analysis (9 failed the attention check and 10 failed to reach an agreement or experience software failure).

Experimental Manipulation: Participants were randomly assigned to one of three experimental conditions**,** Personalized Feedback, Generic Feedback or No Feedback. Participants in the personalized feedback condition were provided personalized feedback on their initial claim, understanding of their opponent's preferences and the overall value of their final claim using the methods described in section 2.1.Those in the generic feedback condition received feedback on the same metrics as the personalized feedback condition except that it was based on a hypothetical negotiation. For example, they are provided suggestions on how good that person did and how their results could have been improved. Those in the no feedback condition were told the points they received but provided no other information.

4 Results and Discussion

We evaluated the effects of practice and feedback with a 3 (feedback: none v. generic v. personalized) x 2 (time: negotiation 1 v. negotiation 2) mixed ANOVA. For value claiming, students benefited from practice alone and this benefit was enhanced by feedback (both in tactics and final outcome). Students made stronger initial claims on the second negotiation ($F(1, 98) = 33.47$, $p < .001$) than the first, and the interaction with the type of feedback nearly reached significance ($F(2, 98) = 3.01$, $p = .054$). Participants who received feedback (either personalized or generic) claimed more value. In terms of final outcome, we see a significant main effect of time ($F(1, 98) = 30.40$, $p < .001$) and a significant interaction with the type of feedback ($F(2, 98) = 3.808$, $p = .026$). Participants obtained more points in the second negotiation and those who received personalized feedback gained the most points. For creating value, we found a clear benefit of practice and a strong effect of feedback for logrolling and joint points but not for questions asked. Concerning the final outcome, we find a significant benefit of practice on joint points as they created more value in the second negotiation than the first ($F(1, 98) = 7.322$, $p = .008$). Personalized feedback yielded the highest joint points, the interaction was significant ($F(2, 98) = 8.187$, $p = .001$). Students engaged in logrolling more with practice ($F(1, 98) = 37.495$, $p < .001$) and there was a significant interaction with condition such that this improvement in logrolling from the first negotiation to the second was strengthened by personalized feedback ($F(2, 98) = 4.930$, $p = .009$). Students asked more questions with practice ($F(1, 98) = 24.461$, $p < .001$) and asked the most with personalized feedback, though the interaction with condition was not significant ($F(2, 98) = 1.711$, $p = .186$).

We show students improve in their use of both value-claiming tactics through a combination of practice and personalized feedback. Personalized feedback further increased learning by helping students to make more ambitious offers and use logrolling. Although this work is promising, our ultimate goal is to show that the benefits accrued through such automated practice, assessment and feedback will generalize outside these simulations. Future planned studies will examine if students improve in both computer-mediated and face-to-face negotiations with other students.

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