I Already Know Your Answer: Using Nonverbal Behaviors to Predict Immediate Outcomes in a Dyadic Negotiation

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ABSTRACT

Be it in our workplace or with our family or friends, negotiation comprises a fundamental fabric of our everyday life, and it is apparent that a system that can automatically predict negotiation outcomes will have substantial implications. In this paper, we focus on finding nonverbal behaviors that are predictive of immediate outcomes (acceptances or rejections of proposals) in a dyadic negotiation. Looking at the nonverbal behaviors of the respondent alone would be inadequate since ample predictive information could also reside in the behaviors of the proposer, as well as the past history between the two parties. With this intuition in mind, we show that a more accurate prediction can be achieved by considering all the three sources (multimodal) of information together. We evaluate our approach on a face-to-face negotiation dataset consisting of 42 dyadic interactions and show that integrating all three sources of information outperforms each individual predictor.

Categories and Subject Descriptors

H.1.2 [**Models and Principles**]: User/Machine Systems – *human information processing*.
H.4.0 [**Information Systems Applications**]: General.
I.2.1 [**Artificial Intelligence**]: Applications and Expert Systems.
I.5.4 [**Pattern Recognition**]: Applications – *signal processing*.

General Terms

Algorithms, Experimentation, Human Factors, Theory.

Keywords

Negotiation, Machine Learning, Multimodal, Behavior Prediction, Human Communication, Social Behavior.

1. INTRODUCTION

Negotiation is a complex and dynamic process in which two or more parties, often having non-identical preferences or agenda, work together to reach a mutual agreement. Be it in our workplace or with our family or friends, negotiation comprises such a fundamental fabric of our everyday life that we sometimes engage in the act without even being consciously aware of it. It is then apparent that a system that can automatically predict negotiation outcomes will have substantial implications. For instance, such a system could function as a real-time decision support tool to directly help a person during a negotiation process or it could be useful in training a person to be a better negotiator.

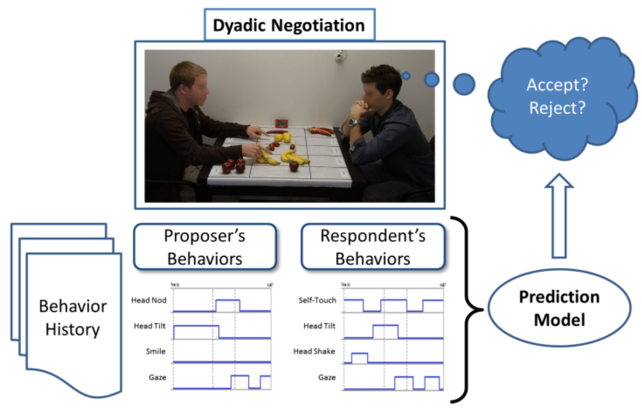

Figure 1. Multimodal factors for immediate negotiation outcome predictions including the nonverbal behaviors of the proposer and of the respondent, as well as the history information between the two parties.

Negotiation has long been and still is an active topic for research, and the reader can find a brief history of the psychological study of negotiation in [6]. For researchers endorsing a traditional cognitive view, negotiation is essentially a decision-making process, the people involved dispassionate negotiators, and the outcome a result of dynamics governed by rational strategies. There are also researchers who put more emphasis on affective aspects [11]. Some have tried to understand the general role of affect in different stages of negotiation [5] while others have investigated the influence of mood [3, 8], emotion [1, 20], and personality [4]. In addition, researchers focusing on social contexts further deepen our understanding of negotiation dynamics [14, 18].

The affective and social perspectives of negotiation give intuitions that nonverbal behaviors can give clues to the ongoing state of a negotiation process. Ambady and Rosenthal [2] showed that much inference is possible just by observing "thin slices" of nonverbal behaviors, and Curhan and Pentland [10] applied the idea in a simulated employment negotiation scenario where they found that certain speech features within the first five minutes of negotiation were predictive of the overall negotiation outcome in the end.

Although negotiation research abounds in literature, there is still limited work that investigated nonverbal behaviors in the context of negotiation, let alone computational models. In this paper, our main focus is on finding nonverbal behaviors that are related to negotiation outcomes and exploring the possibility of building an automatic system for the outcome predictions. Moreover, whereas Curhan and Pentland's work was on predicting the overall negotiation outcomes in the end, we focus on making shallow predictions of immediate outcomes (acceptances or rejections) for individual proposals made during negotiation.

2. NONVERBAL FACTORS IN FACE-TO-FACE NEGOTIATION

To predict whether the respondent will accept or reject a proposal during negotiation, looking at the nonverbal behaviors of the respondent alone would be inadequate since ample predictive information could also reside in the behaviors of the proposer, as well as the past history between the two parties (see Figure 1).

2.1 Proposer's and Respondent's Behaviors

In a business negotiation setting, Niemeier et al. [19] investigated various nonverbal communication channels including proxemics, body postures, gestures, facial expressions and paralanguage, arguing that they could hint at the emotional attitudes of the negotiators. In a study of cooperativeness and competitiveness during negotiation, Johnson [16, 17] similarly found that cooperativeness is expressed through "warm" behaviors including a soft tone of voice, smiles, interested facial expressions, direct eye contact, open gestures, close spatial distance, and an occasional soft touch, while competitiveness is expressed through "cold" behaviors including tense postures, avoidance of eye contact, closed gestures, distant spatial distance, and avoidance of touching.

Head movements can also provide rich information. For instance, the proposer could show eagerness by nodding his head while staring at the respondent, giving more emotional burden to the respondent if not accepting the offer. Similarly, the respondent could shake his head while listening to the proposal or tilt his head in confusion. Another interesting nonverbal behavior in the context of negotiation is self-touching, which Ekman et al. [13] call a type of adaptors. According to Harrigan et al. [15], the overall consensus is that negative affect, such as anxiety or discomfort, triggers self-touching behaviors.

2.2 History

The history information can be thought of as capturing the ongoing relationship between the negotiators. For instance, in the absence of other contexts, if the respondent has mostly rejected the proposer's offers in the past, it would mean something quite different from the opposite case. Moreover, reciprocity can be a good predictor of the outcomes in mixed-motive settings [12].

3. DATASET

In total, 84 undergraduate business students (40 males and 44 females) participated in 42 dyadic negotiation sessions, of which one dyad was discarded because the participants deviated from the experimental procedure. Each session involved same-sex participants to eliminate the influence of gender, and 3 video cameras were placed unobtrusively to record a near-frontal view of each negotiator, as well as an overall side view of the interaction.

In each session, two participants sat face-to-face across each other at opposite ends of a table, on which several types of plastic fruits

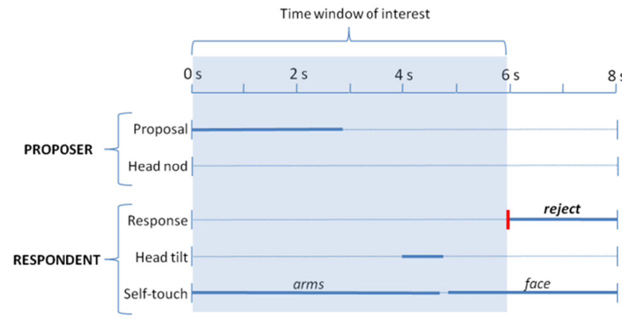

Figure 2. An example of a rejected proposal-response event.

or vegetables were placed. The participants were randomly assigned to represent one of two different restaurants, which had different pay-off matrices associated with the items on the table. Each participant was told only the pay-off matrix of his/her assigned restaurant, and the participants had 12 minutes to negotiate on how to distribute the items on the table. As an incentive, each participant could receive up to $50 depending on the final points earned by each participant for his/her restaurant.

The annotations of nonverbal behaviors were done with ELAN software [7]. Below is a summary of the annotations made.

- *Proposal-response event:* For each negotiation session, all the events of proposal-response pairs were identified. A proposal is defined as an utterance made with a clear offer related to negotiating the items, and if it is followed by a clear utterance of acceptance or rejection, we group the start of the proposal until the end of the matching response as a proposal-response event. A total of 253 proposal-response events were identified, out of which 190 were accepted proposals and 63 were rejected proposals.

Within the time window of each proposal-response event identified, the following nonverbal behaviors were annotated for both of the negotiators in a dyad.

- *Head nod*: Whether there is a vertical downward (or repeated upward and downward) movement of the head.
- *Head shake*: Whether there is a repeated horizontal left and right movement of the head.
- *Head tilt*: Whether there is a rotation of the head to the left or to the right. With a frontal view of the face in 3D coordinates, rotation around the z-axis.
- *Gaze*: Whether the gaze of a negotiator is directed toward the other party, toward the table, or somewhere else.
- *Smile*: Whether a negotiator is smiling or not.
- *Self-touch*: Whether a negotiator is touching his/her own body with his/her hands (e.g. touching the face with the hand). Only the upper portion of the body was visible in the videos.

4. AUTOMATIC PREDICTIONS OF NEGOTIATION OUTCOMES

Our goal is to predict whether the respondent will accept or reject a given proposal. Thus, for each proposal-response event, we are only interested in the nonverbal behaviors within the time window from the start of the proposal until the start of the response (see Figure 2). This time window is called the *time window of interest* henceforth.

4.1 Feature Encoding

Each of the annotated nonverbal behaviors defined in Section 3 was converted into binary features. For example, the proposer's binary smile feature will be whether the proposer smiled or not within the *time window of interest*. We encoded the binary features for both the proposer's and the respondent's nonverbal behaviors. We also added another feature called *binary response time* to the respondent's feature set.

- *Binary response time*: For each proposal-response event, the response time was computed as *the time when the respondent started uttering acceptance or rejection* minus *the time when the proposer finished uttering his/her proposal*. After taking the means of the response times for all accepted and for all rejected cases, the midpoint of the two means was found and used as a threshold (1.4 seconds in our experiments). Using this threshold, the response time in each proposal-response event was converted into a binary feature. (*The time when the respondent started uttering acceptance or rejection* was also his/her first utterance made in the proposal-response event for about 89% of the time, which means something for implementing real-time systems).

To capture the history information, we used the following 2 features.

- *Negotiation history*: The total net response history of the respondent at the time of the proposal-response event (+1 and -1 for each previous acceptance and rejection respectively). Normalized to z-scores.

- *Response time history*: The mean of all the previous response times of the respondent at the time of the proposal-response event. This feature could help better understand the *binary response time* feature by providing the general response time characteristic / habit of each negotiator. Normalized to z-scores.

We note that the features were extracted from all the three sources of information (the proposer's nonverbal behaviors, the respondent's nonverbal behaviors, and history). No acoustic features were used because the video cameras, which were used to record the negotiation interactions, yielded poor audio quality.

4.2 Prediction Model and Experimental Methodology

For the prediction model, a support vector machine (SVM) classifier with the radial basis function kernel was trained and tested using Chang and Lin's LIBSVM library [9]. A subset of features were selected to be included in each source of information (proposer, respondent, and history) based on the prediction performance as individual features and also as a group. Also, various explorative methods have been performed including greedy forward feature subset selection.

In order to make balanced sample sets for predictor (classifier) training and testing, all of the 63 samples of the rejected proposal-response events were combined with 63 randomly selected samples of the accepted events, and 3 such randomly balanced sets were created. Each randomly balanced set was again randomly separated into 4 folds with almost an equal number of accept and reject samples. It is worth noting that no 2 folds contained the samples from the same negotiation session. In other words, the 4 folds were created such that they were all session-independent to one another. Then, 4-fold testing hold-out validation was performed with 1 hold-out fold for validation to find the optimal parameters using a grid search technique and another hold-out fold for testing. All the prediction results were averaged over 12 test results (3 sets × 4-fold cross-validation).

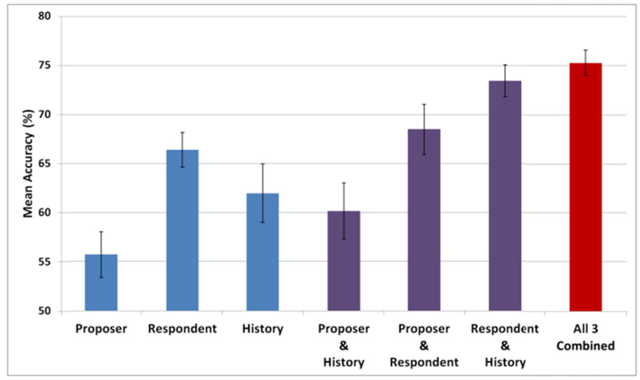

Figure 3. Mean accuracies of negotiation outcome predictions using multimodal (multi-source) features. The error bars show standard errors.

5. RESULTS AND DISCUSSIONS

Figure 3 shows the results of prediction accuracies for using different combinations of the 3 sources of information, and a general trend of performance improvement was evident when combining more modalities (note that chance is 50%). Except for the combination of the proposer and history features, all the other possible combinations of different sources of information showed significant improvements over using an individual source alone. Especially, using all the three sources of information together yielded the best result with the accuracy of over 75%, which emphasizes the importance of taking into account all the three sources of information for making negotiation outcome predictions. Paired-sample t-tests showed that the differences between the results of the 3-source classifier and those of all other classifiers were statistically significant at $p < 0.01$, except for the respondent+history classifier which was still at $p < 0.05$. In addition, the respondent+history classifier's performance was statistically significant over the individual classifiers using just the respondent ($p < 0.01$) or the history ($p < 0.05$) information. The proposer+respondent classifier's accuracy was also statistically significant at $p < 0.01$ compared to the classifier with just the proposer's information.

The prediction results using individual features from each source of information (proposer's behaviors, respondent's behaviors, and history information) are summarized in Table 1. From the proposer's behaviors, head tilt was slightly predictive of the outcome. Although head nod performed at chance, the prediction made by combining the two features together was higher than that made with head tilt alone. From the respondent's nonverbal behaviors, the *binary response time*, self-touch and head tilt were all very useful in the outcome predictions. When the three features were combined together, the prediction rate notably improved to over 66%. Lastly, both of the two history features also proved useful in the predictions.

Although not shown here, head nod and head shake behaviors of the respondent, if experimented individually, also yielded prediction accuracies of close to 57%. However, they did not perform too well when combined with other features together. In addition, a lot of head nods and shakes occurred too close to actual responses, which defeats the purpose of making the predictions in the first place. Smiles were not useful because

Table 1. Negotiation outcome predictions using individual features.

Source	Feature	Accuracy (%)	F_1
Proposer	Head Nod	50.00	0.3532
	Head Tilt	54.17	0.4549
	Combined	**55.73**	**0.5047**
Respondent	Head Tilt	58.33	0.5275
	Self-Touch	56.51	0.4933
	Binary Resp. Time	60.16	0.5572
	Combined	**66.41**	**0.6579**
History	Neg. History	63.02	0.6229
	Resp. Time History	59.64	0.5748
	Combined	**61.98**	**0.6156**

people tend to smile in so many different situations (with happy smiles, polite smiles, embarrassed smiles, etc.), and gaze was also not useful in our scenario possibly because the participants mostly had their eyes on the negotiating items on the table.

From the proposer's nonverbal behaviors, head tilt seems to indicate the proposer's lack of confidence (thus more likely to be rejected) of the respondent's answer as the proposal is being made. From the respondent's behaviors, the reason that the *binary response time* feature is useful seems clear. The more the respondent likes a proposal, the sooner he/she accepts it. As for self-touch, it seems to hint at the respondent's discomfort either of the proposal or of the fact that he/she will soon reject it. Head tilt of the respondent might mean that he/she needs to think more deeply about the proposal, which eventually could yield more rejections than acceptances. From the history information, the result of the *negotiation history* feature is interesting because it seems to capture the relationship between the negotiators in a dyad. The more someone rejected your proposals, the more you can expect him/her to reject your offers in the future. In the context of our experimental scenario, the feature might have captured the cooperativeness or competiveness between the negotiators.

6. CONCLUSION AND FUTURE WORK

In this paper, we showed that it is important to consider multiple sources of information (especially nonverbal behaviors) to predict a proposal's immediate outcome (acceptance or rejection) during a dyadic negotiation. For future work, more nonverbal behaviors in negotiation contexts could be explored, and the influence of another source of information, namely mutual behaviors, could also be examined. Our results suggest that machine analysis of human negotiations have potential to add fundamental insight into how people negotiate and provide practical tools to benefit human negotiators.

7. ACKNOWLEDGMENT

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