Prediction of Strategy and Outcome as Negotiation Unfolds by Using Basic Verbal and Behavioral Features

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Abstract

Negotiations can be characterized by the strategy participants adopt to achieve their ends (e.g., individualistic strategies are based on self-interest, cooperative strategies are used when participants try to maximize the joint gain, while competitive strategies focus on maximizing each participant's score against the other) and the outcomes that each participant achieves in the negotiation. This paper investigates the process and the result of predicting the outcome and strategy of participants throughout the progress of the negotiation by using basic, easy to extract, linguistic and acoustic features. We evaluate our approach on a face-to-face negotiation dataset consisting of 41 dyadic interactions and show that it's possible to significantly improve over a majority-class baseline in tasks of predicting the strategy and outcome of the interaction by analyzing only basic low level features of the negotiation.

Index Terms: Negotiation, Machine Learning, Human Communication, Social Behavior, Sentiment Analysis, Outcome Prediction, Strategy Prediction

1. Introduction

Negotiation is a complex interaction in which two or more participants confer with another so as to arrive at the settlement of some matter. Negotiations happen all the time in our daily lives. Often, we end up negotiating to resolve a conflict or when we need to share common resources. In many cases we simply try to change a situation to our favor by negotiation for example by haggling over a price. The parties involved in the negotiation often having non-identical preferences and goals that they try to reach. Negotiation has been a subject of much study, in many disciplines, due to implications for business and politics, as well as understanding social interaction. Not all people are naturally good negotiators, so this line of research can potentially be used to ain people to improve. Also, computer agents will benefit from the ability to understand human negotiators. There is reason to believe that low-level features of the interaction are correlated with high-level notions such as strategy, and outcome. In this paper, we explore this correlation, examining a set of dyadic negotiations where there is some variation in outcome and strategy.

This paper makes two contributions: Our first goal in this research is to computationally predict the outcome of the negotiation in terms of the scores each participant receives, using different behavioral features of the participants. Our second goal is prediction of the strategy taken by the participants for achieving their goals in the negotiation. We want to be able to tell whether they are negotiating with one another competitively or cooperatively or individualistically. In both of these tasks the features used are basic verbal and behavioral features; no deep semantic analysis is done on the content of the negotiation. We investigate how far in the negotiation is the best point for making these predictions by analyzing each negotiation in cumulative quarters of the negotiation.

The remainder of the paper is organized as follows: Section 2 summarizes related work. In Section 3 we introduce the dataset and features used to examine negotiation strategies and outcomes. In Section 4, we describe machine learning experiments to predict the strategy and outcomes of the negotiation. Section 5 concludes the paper.

2. Previous Work

During a negotiation parties interdependently make decisions and deploy strategies in order to distribute resources and/or resolve conflicts. This happens during a process of social interaction [1]. It is common to categorize the negotiation into types based on the goals and intentions (or more generally, *strategies*) of the participants [2][3]. Models of conflict management typically distinguish five strategic approaches including accommodating, avoiding, competing, compromising, and integrating [4][5]. In an in individualistic negotiation participants show high self-concern and low other-concern and they try to maximize their own gain. In a cooperative style of negotiation, parties promote the other side's gain as well. In competitive negotiation, participants try to outperform the other participant. In some cases, these strategies might converge, e.g. if what is good for one is good for all, then cooperative and individualistic strategies might appear the same. Likewise, in a zero-sum game, individualistic and competitive strategies will lead to the same results. In other situations there may be a clear distinction between these three strategies.

Researchers have tried to identify and compare the characteristics of cooperative and competitive styles in negotiation [6][7]. In most competitive negotiations, dominance and assertiveness are observed in the negotiators behavior. Verbal strategies and behaviors such as demands, threats, and aggression in competitive style negotiation are typically measured and have been studied [8][6]. Since nonverbal cues such as posture and facial expression can predict behavioral outcomes [9], negotiation researchers have started to examine the effect of displaying dominant behavior or a competitive stance in negotiation across two cultures [10]. Expression of emotion also affects negotiating behavior, particularly negative emotion such as anger. Individuals with power and status have a tendency to disregard display rules and so, they may be more visibly expressive than those of lower status [11] they may exhibit dominance by yelling, frowning, staring angrily, not joining in laughter, and engaging in other emotional expressiveness [11].

Research on affective and social perspectives of negotiation indicate that nonverbal behaviors can give clues to the ongoing state of a negotiation process. [9] showed that much inference about the interpersonal dynamics is possible just by observing "thin slices" of nonverbal behaviors, and [12] 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. However their negotiation scenario was fixed (with a single strategy per participant role) whereas in our work there are three different sets of instructions given to the participants, motivating the three types of strategies.

3. Dataset

The "Farmers Market" negotiation data was collected in USC's Marshall School of business, by Peter Carnevale, based on a negotiation task also used in [13]. This data set was also used in [14].

3.1. Task Details

Before each negotiation session, the experimenter told participants that they were representing a restaurant and they were asked by the restaurant owner to go the Westside Market and get some Apples, Bananas, Lemons, Peppers and Strawberries. There were 5 apples, 5 bananas, 3 lemons, 5 peppers and 5 strawberries to be split between the two sides of the negotiation. The participants were randomly assigned to represent one of two different restaurants. The participants were told that they had 12 minutes to negotiate on how to distribute the items on the table and reach an agreement.

Each item had a specific value associated with it, for example each apple was worth 1 point to one side and 3 to the other side. Each participant was only given the pay-off matrix of his assigned restaurant and the total score of the negotiation for each participant was calculated by adding up the points for each item they received in the negotiation. As an incentive, each participant could receive up to $50 depending on the final points earned by each participant for his/her restaurant.

There were three types of instructions given to the participants. All the details were the same except for their goal in the negotiation. In "individualistic" instructions participants were told that there goal was to get at as many points as they could for themselves, whereas in the "cooperative" instructions they were told that they should try to maximize the joint gain with the other side of the negotiation. In the "competitive" instructions they were told to try to get more points than the other party.

3.2. Participants

In total, 84 undergraduate business students in USC's Marshall (40 males and 44 females) participated in 42 dyadic negotiation sessions. One dyad was discarded because the participants deviated from the experimental procedure. Each session involved same-sex participants to eliminate the influence of gender.

3.3. Data Recording

Each dyadic negotiation was recorded with 4 cameras unobtrusively. One directed towards each negotiation participant and one capturing the table from above. One camera in each session was capturing both parties from the side view. The experimenter had participants sit face-to-face across each other at opposite ends of a table, on which the plastic version of the types of fruits or vegetables that were introduced to them in the instructions were placed (Figure 1).

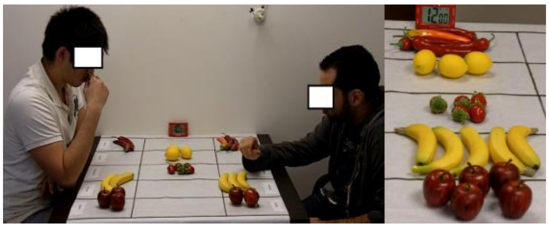

Figure 1: (left) *a scene from a sample negotiation session* (right) *Negotiation items*

3.4. Data Set Preparation

The dataset consists of audio and visual recordings, as described in Section 3.3. These were transcribed and segmented into turns for each speaker. Out of the 41 interactions, 15 were competitive, 13 were individualistic and 13 were cooperative sessions.

We also created subsets of data for each participant. This was critical because we were interested in the analysis of the exchange of the negotiation items and the points between the two parties and the instructions gave different values for the items to each role. Given that we had 41 dyadic negotiation sessions we ended up with 82 different participant subsets for our negotiation dataset.

3.5. Outcome Labels

Based on the distribution of each of the sets of fruits, and the value assigned the type of fruit for each participant role, there was a unique score for each participant for the negotiation. In order to make the prediction of outcome more tractable for our small dataset, we assigned a relative score label for each participant:

- H (higher) meaning that the speaker has more points than the other side of the negotiation.
- L (lower) meaning that the speaker has fewer points than the other side of the negotiation.
- E (equal) meaning both sides have equal points.

There were 34 samples in our dataset that were tagged as E and 24 tagged as L and 24 tagged as H.

3.6. Qualitative Analysis

Each of the negotiations were watched in multiple passes, in order to try to identify appropriate types of features for recognizing strategies and outcomes. Initial observations indicated that in most negotiations one side of the negotiation dominates the negotiation and controls the flow of the conversation. Following previous research, we hypothesized that there is a correlation between the amount of dominance in the negotiation and the final outcome. We attempt to approximate a measure of dominance by measuring acoustic features such as pitch and energy as well as the amount of silence or speaking by the user. We also observed that the competitive negotiations are longer and people are more silent throughout the negotiation because they are thinking more about what they want to do or say. In the competitive negotiations the negotiators make more strategic moves during the negotiation, so more words are exchanged. We predicted that there would be differences in the occurrences of the number of words associated with the different negotiation items used by the two parties because each role in the negotiation had different preferences for the items and values. In terms of the final score for the negotiation we observed that in the competitive negotiations the average scores of the participants is lower than the average score of the cooperative condition. The difference in the scores of the sides of the negotiation in the competitive condition is higher than the cooperative condition.

3.7. Features and Feature Extraction

We used three categories of features: linguistic (verbal) features, acoustic features, and task features. Linguistic features were extracted by processing the transcripts for each participant. These features include:

- The number of words spoken by each speaker in each turn of the dialogue
- The number of turns taken during the negotiation
- The number of times words corresponding to the negotiation items are spoken.
- Sentiment(positive, negative) and subjectivity scores calculated (according to the SentiWordNet 3.0 lexicon[15]) for words and turns and the whole dialogue up until the end point. Stemming, lemmization and normalization of the words was performed prior to analysis.

The following acoustic features were extracted from the audio recordings of participants, using OPENEAR [16]

- The mean and standard deviation of the following acoustic features calculated at the end of each quarter of the negotiation task: peak slope, Normalized amplitude quotient (NAQ), f0, voiced/unvoiced, energy, energy slope, spectral stationary.
- The amount of silence and speaking time for each speaker during the negotiation

We also used the following task features, which were manually annotated, by examining videos and transcripts (using ELAN [17]):

- The number of offers, acceptance or rejection made by each role in the negotiation.
- The score and number of each type fruit items distributed and allocated to each side of the negotiation.

All of the above features were extracted and calculated for 4 different spans of negotiation: the first quarter, first half, first three quarters, and the whole negotiation.

4. Experiments

4.1. Method

Considering the size of our dataset which consists of 82 samples and the distribution of the samples in different classes, we decided to use 10-fold cross validation paradigm for our prediction tasks. For the prediction model, a support vector machine (SVM) classifier with the radial basis function kernel was trained and used. The result of our classification tasks are user independent since we did not have the same person from the training data in the test data. The participants from the same negotiation were split across training and test sets. We trained and tested on each of the four negotiation spans described above.

We used Information Gain Attribute Evaluation and Ranker as for determining the most discriminative features.

4.2. Prediction of the Negotiation Outcome for the Participant

In this task the goal is to predict how a participant in the negotiation is going to do in terms of the scores at the end of the negotiation. The model predicts whether the negotiator would score higher, lower or equal to the other player at the end of the different quarters of the negotiation by using the 3 (E,H,L) tags introduced in section (3.4). The following table shows the distribution of the Outcome Labels by the end of each quarter:

Score by the end of	E	L	H
First quarter	64	9	9
Second quarter	50	16	16
Third quarter	28	27	27
Fourth quarter	34	24	24

Table 1: score tags at the end of each quarter

All of the extracted features were used for this task. When the prediction model is applied at the end of each quarter as the negotiation progresses, it is able to make the correct prediction of the final outcome with average accuracy of (q_1=85.37%, q_2=60.98%, q_3=62.64%, q_4=64.87%) across the ten folds validation.

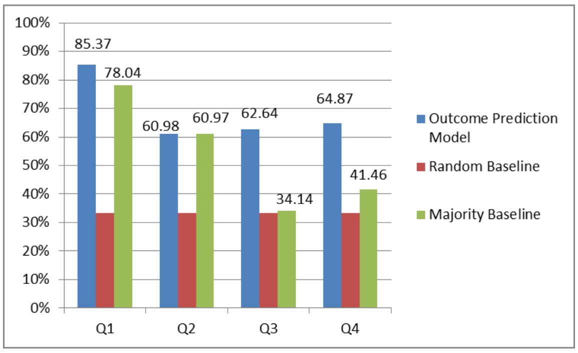

Figure 3: *Accuracy of the outcome prediction model compared to random prediction*

Although the prediction accuracy is significantly above random selection of one of the three classes (scoring higher, lower or equal) at all four points but it is very interesting to see that the highest accuracy of the prediction of the outcome is at the end of the first quarter of the negotiation. This accuracy is significantly higher than the result of the prediction at later stages in the negotiation (p-value=0.0005). Feature selection (with Information Gain Attribute Evaluation that uses Ranker as search method) showed that the most important features for the model in order of importance are the difference between the scores as well features related to the word count and turn count of the speakers and the number of rejections. For the later points the highly ranked features are the features associated with the number of times the participants have mentioned the name of the negotiation issues and the number of rejections by both parties. One possible interpretation of these results is that active engagement at the beginning of the negotiation would strongly affect the final outcome of the negotiation. It is important to note that in many negotiations, the initial phase of the negotiation involves a lot of conversation around topics that are not directly to the task such as greeting and self-introduction phase, which can be a possible explanation of the observed results. These results are consistent with the previous findings in the business literature that highlight the importance of a good active start to the negotiation, as well as previous work that tries to predict the negotiation outcome by using only the first 5 minutes of the negotiation [15].

4.3. Prediction of the Strategy

In this task the goal is to predict whether the negotiators are being cooperative, competitive or individualistic about the gain they will make over the negotiation issues. It is important to note that none of the features used require an understanding of the content or a semantic analysis of the conversation. However, using these basic features it's possible to make the classification into the mentioned three classes with accuracy that is significantly higher than chance. The average accuracy of the prediction at the four different points in the negotiation are as follows (q_1=53.89%, q_2=46.25%, q_3=53.19%, q_4=70.56%) across the ten folds validation. The main features selected by Information Gain Attribute Evaluation and Ranker as search method are the amount of silence and speaking time for the participants as well as the number of words and number of the offers exchanged.

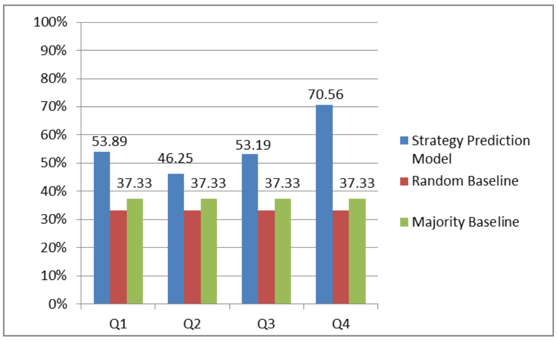

Figure 4: *Accuracy of the strategy prediction model compared to random prediction*

Contrary to the trend in the prediction of the outcome, the average accuracy of the prediction of the negotiation type increases as the negotiation progresses and the prediction accuracy at the end of the negotiation are significantly higher than all other previous points. However, the result of the prediction at the end of the first quarter of the negotiation might be a good enough a guess for many purposes.

5. Conclusion and future work

In this work we demonstrated that high level negotiation information, such as the participants' goals and final quantitative gain of the negotiation, are predictable based on simple features that can be easily extracted. Another main contribution of the paper is the comparison between the results of the prediction at different points in the negotiation. Our results are significantly above the baseline and the analysis of the different results for the different points in the negotiation validates the findings in common business literature in regards to the importance of the first impression in the negotiation. In future we expect to be able to do the classification of based on HMM and HCRF methods due to their ability to capture the temporal aspect of the negotiation.

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