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Multimodal Negotiation Corpus with Various Subjective Assessments for Social-Psychological Outcome Prediction from Non-Verbal Cues

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Abstract

This study investigates social-psychological negotiation-outcome prediction (SPNOP), a novel task for estimating various subjective evaluation scores of negotiation, such as satisfaction and trust, from negotiation dialogue data. To investigate SPNOP, a corpus with various psychological measurements is beneficial because the interaction process of negotiation relates to many aspects of psychology. However, current negotiation corpora only include information related to objective outcomes or a single aspect of psychology. In addition, most use the "laboratory setting" that uses non-skilled negotiators and over simplified negotiation scenarios. There is a concern that such a gap with actual negotiation will intrinsically affect the behavior and psychology of negotiators in the corpus, which can degrade the performance of models trained from the corpus in real situations. Therefore, we created a negotiation corpus with three features; 1) was assessed with various psychological measurements, 2) used skilled negotiators, and 3) used scenarios of context-rich negotiation. We recorded video and audio of negotiations in Japanese to investigate SPNOP in the context of social signal processing. Experimental results indicate that social-psychological outcomes can be effectively estimated from multimodal information.

Keywords: business negotiation, social-psychological outcomes, multimodal interaction analysis

1. Introduction

Due to the impact of COVID-19, business negotiations are shifting from face-to-face to online. Since it is relatively easy to store data of online conversations and for machines to intervene in such interactions, negotiation-related systems, such as negotiation-training systems (Greco and Murgia, 2007; Ding et al., 2017; Melzer, 2019) and negotiation-support systems (Kersten, 1989; Carbonneau et al., 2016; Jonker et al., 2016; Zhou et al., 2019), will be more accessible. As a fundamental technology for these systems, automatic negotiation-outcome prediction (Curhan and Pentland, 2007; Li et al., 2015) is important. This study investigated negotiation-outcome prediction from online negotiation data.

Previous studies have shown that negotiation outcomes can be predicted using verbal (Zhao et al., 2018; Zhou et al., 2019) and non-verbal (Curhan and Pentland, 2007; Li et al., 2015) features extracted from negotiation dialogues. In most cases, the term "negotiation outcome" refers to an economic outcome, i.e., the number of points earned by the participants' joint decision making. Previous negotiation research argues that social-psychological outcomes (Thompson, 1990) are also important, especially for long-term benefits (Barley, 1991; Oliver et al., 1994). Experimental evidence has also been provided that trust, justice, and satisfaction lead to economic outcomes in the next round (Curhan et al., 2010). Therefore, we consider it important to predict social-psychological outcome from negotiation data. We call this task social-psychological negotiation-outcome prediction (SPNOP).

The interaction process of negotiation is related to various aspects of psychology, including satisfaction, willingness to negotiate again with the same partner, (Oliver et al., 1994), trust (Naquin and Paulson, 2003), and relationships (Ingerson et al., 2015). Therefore, a corpus with such various assessments is beneficial to investigate SPNOP. Current negotiation corpora are annotated with intent labels (Konovalov et al., 2016), respondent's reactions to offers (Park et al., 2015), economic outcomes (Curhan and Pentland, 2007; Li et al., 2015) and trustworthiness scores (Lucas et al., 2016). However, there has been no negotiation corpora assessed with various psychological measurements related to negotiation. Therefore, we first created a negotiation corpus assessed with such psychological measurements.

There are two unique features in our corpus design for collecting realistic negotiations. The first feature is that we hired experienced sales people for recording, while most conventional studies used non-skilled negotiators such as college students or crowd sourcing workers. We argue that non-skilled negotiators cannot conduct realistic business negotiation because it requires expertise about products and negotiation tactics. The second feature is that we used scenarios rich in context of a negotiation, while most conventional studies used simple scenarios describing a utility function and few contexts of a negotiation. Such simple scenarios have been criticized as not being realistic for business negotiation (Balakrishnan and Eliashberg, 1995). Therefore, we describe rich contexts of a negotiation, such as relationships between negotiators and their companies, in our scenarios. These features are based on our expectation that they can fill the gap of behaviors and psychologies between simulated and actual negotia-

Table 1: Example of conventional buyer's scenario describing simple utility function

issues	points
Budget (million yen)	
0∼150	200
150∼200	100
over 200	0
# of employee users	
0∼49	0
50∼99	50
100∼	100
# of user client companies	
0∼9	0
10∼19	30
20∼	60
Delivery date	
under 1 month	30
1∼6 months	30
over 6 months	0

tion, which can improve performance of models trained from our corpus in real situations.

We recorded video and audio of negotiations to construct our corpus. This is because studies in the social-signal-processing field have shown that non-verbal features are effective in predicting psychological information such as emotion (Vijayalakshmi and Mohanaiah, 2020), personality (Pianesi et al., 2008; Batrinca et al., 2011), communication skills (Nguyen et al., 2014; Okada et al., 2016; Ishii et al., 2018), leadership (Sanchez-Cortes et al., 2011), persuasion (Park et al., 2014) and engagement (Ishii et al., 2013). Lucas et al. (Lucas et al., 2016) investigated the estimation of trustworthiness from a negotiation dialogue. Motivated by these studies, we investigated whether non-verbal features are effective in predicting various types of psychological information related to negotiation. We provide feature analysis results to show how the features of each modality (visual or prosodic) and each negotiator (buyer or seller) correlate with social-psychological outcomes.

We define social-psychological outcomes as subjective evaluation scores by the buyer, with the aim of building a support system for sellers. We collect a seller's self-evaluations as well as a buyer's evaluations. This is to investigate the effectiveness of using a seller's self-evaluation scores in predicting a buyer's evaluations. While a previous study pointed out that self-evaluations in social judgements have a bias (Brown, 1986), they are expected to have a certain correlation with a buyer's evaluations. Our experimental results indicate the effectiveness of using self-evaluation scores as well as non-verbal features for SPNOP.

Table 2: One of our buyer scenarios (product: chat tool) with rich description of negotiation context

Background

- You (Suzuki) are in charge of general affairs at a publishing company (R Publishing).
- R Publishing is a company with 100 employees and 20 client companies.
- The employees have been complaining about e-mail systems. Due to the large number of e-mails received, messages have been frequently overlooked.
- You would like to solve this problem. You are considering introducing a chat tool to all your employees that will enable them to contact all their client companies.
- The president told you that your budget is up to 2 million yen.
- Today, you are negotiating with a sales person from an IT company (Mr. Yamada from N Technologies) about a text chat tool called "N Chat". The negotiation is online and you have 15 minutes available for conversation.
- Last week, the seller contacted you for the first time by phone. You made an appointment for today's online negotiation.
- You have been wary of sales people because you once received a persistent sales call from another IT company.
- If negotiations break down, the employees will have to keep using e-mail.

Goals and Priority

1. You want to keep your budget under 2 million yen.
2. You want to introduce a chat tool to all 100 employees.
3. You want the chat tool to enable your employees to communicate with all 20 of your business partners.
4. You want to introduce this chat tool within the next 6 months.

2. Corpus design and collection process

Our multimodal negotiation corpus has three features; 1) was assessed with various psychological measurements, 2) used skilled negotiators, and 3) used scenarios context-rich negotiation. This section details the corpus design and collection process. We describe the details of the negotiation scenarios in Sec. 2.1, psychological measurements in Sec. 2.2, and other collection processes including the use of skilled negotiators in Sec. 2.3.

2.1. Negotiation scenario

To collect realistic business negotiations, we use scenarios rich in negotiation context, while most conventional studies used simple scenarios (Park et al., 2015; Li et al., 2015; Konovalov et al., 2016). A simple conventional scenario is shown in Table 1. Such scenarios often use a simple utility function that consists of a limited number of issues (e.g. budget, number of employee users, number of client companies, and delivery date)

Table 3: Social-psychological assessments used for our corpus. We used 5-point Likert scale for each question (1: disagree to 5: agree). Text was translated from Japanese by authors.

	Questions for buyers	Questions for sellers
Q1	You are satisfied with the negotiation outcomes.	The buyer is satisfied with the negotiation outcomes.
Q2	You trust the seller as a result of the negotiation.	The buyer trusts you as a result of the negotiation.
Q3	You would like to have another business negotiation with the seller.	The buyer would like to have another negotiation meeting with you.
Q4	The seller is a skilled sales person.	You think that you are a skilled sales person.
Q5	The seller's explanation was easy to understand.	Your explanation was easy to understand.
Q6	The seller has sufficient knowledge of the product.	You have sufficient knowledge of the product.
Q7	The seller was confident in his conversation.	You were confident in your conversation.
Q8	The seller listened carefully to your needs and opinions.	You listened carefully to the buyer's needs and opinions.
Q9	The seller sympathized or agreed with your needs and opinions.	You sympathized or agreed with the buyer's needs and opinions.
Q10	The seller was responsive to your needs and opinions.	You were responsive to the buyer's needs and opinions.
Q11	The seller made a creative proposal.	You made a creative proposal.
Q12	The seller nurtured his/her relationship with you.	You nurtured your relationship with the buyer.

and a pre-defined point for each option. They hardly describe negotiation context. Such simple scenarios are considered useful in quantifying the economic outcome, the target variable in conventional studies. However, they have been criticized as not being realistic for business negotiation (Balakrishnan and Eliashberg, 1995). Since negotiation outcomes are affected by various contexts, such as time constraints (Stuhlmacher and Champagne, 2000) and relationships (Gelfand et al., 2006), it is important to specify such contexts by the scenario. Therefore, we used scenarios with rich description of such negotiation contexts.

Our buyer's scenario is shown in Table 2. Scenarios for both a buyer and seller specify various factors including the following:

- position of the buyer/seller in each company
- background of negotiation goals
- relationships between the two companies
- relationships between the two individuals
- time constraints
- communication before each negotiation session
- alternative options for each company.

They also specify goals of the negotiation. Our buyer's scenario specifies the priority of each issue, rather than setting their points. For a seller's goals, we set a point for each option. All the scenarios involved an online conversation using a web conferencing system. The negotiations were between a buyer ("Suzuki") and seller ("Yamada"). The scenarios were about three different products (chat tools, insurance, and TVs). We prepared 4 different scenarios for each of the 3 products, 12 scenarios in total. The scenarios were sent to the participants one week before the recording so that they could read them and prepare for the sessions.

2.2. Social-psychological assessments of negotiation

As described in the previous section, our corpus was assessed with various psychological measurements related to negotiation. Since there is no general consensus on universally applicable methodologies for evaluating a negotiator's performance (Smolinski and Xiong, 2020), we designed an original social-psychological assessment applicable to business negotiations. Our design is based on two previous studies and an informal and preliminary test referring to them. One of the references was a negotiation-competency model proposed in the field of negotiation pedagogy (Smolinski and Xiong, 2020). It consists of 15 questions in 4 categories (language & emotionality, negotiation intelligence, relationship building, and moral wisdom). The other was a subjective value inventory of a negotiation proposed in the field of psychology (Curhan et al., 2006). It consists of 16 questions in 4 categories (feelings about instrumental outcome, self, negotiation process, and relationship).

For our assessment, we selected questions from the questionnaires in the two studies. We did not use all the questions because participants in the preliminary test commented that certain questions were difficult to answer for the following two reasons. First, some questions did not match the context of the business-negotiation scenarios used in this study. For example, concepts such as fairness, self-image, and usage of objective criteria were hardly considered especially in business-to-consumer scenarios, and they could not comment on them. Second, some questions about concepts used in the negotiation studies, such as best alternative to negotiated agreement and Parato efficiency, were difficult to comment on for non-experts of negotiation studies. Some questions were simplified and rewritten for ease of understanding. On the basis of the above procedure, we derived the 12-question questionnaire shown in the "Questions for buyers" row in

Figure 1: Photo of participants engaged in negotiation task

Table 3.
As described in the previous section, we also had the sellers conduct a self-evaluation. The questionnaire for self-evaluation was designed so that each question corresponds to the questions of the buyer's questionnaires, as shown in the "Questions for sellers" row in Table 3. We used a 5-point Likert scale (1: disagree to 5: agree) for both buyer and seller questionnaires.

2.3. Collection process

We hired experienced sales people as sellers to make negotiation interactions more realistic. There were two sales people for each of three products, six in total. To ensure that our corpus includes negotiations of various skills that may occur in real situations, we hired one experienced sales person (more than 10 years) and another less experienced sales person (less than 3 years) for each product. We also hired 12 people as buyers who had sufficient knowledge of the products. There were three males and three females for sellers and six males and six females for buyers. Their ages were between 19 and 60.
Two sellers, one experienced and the other less experienced, and four buyers were assigned to each of three products. For each product, each of the 2 sellers was paired with 2 buyers; there were 4 pairs for each product, 12 pairs in total. We did not consider all dyads to be same-gender (Lucas et al., 2016) to prioritize the conditions related to sales background and product knowledge. Each of the 12 pairs participated in 4 different negotiations using 4 different buyer scenarios and a common seller scenario; there were 48 sessions in total. While there were multiple sessions for each pair, we instructed them to act in accordance with the scenario that they were meeting for the first time and not to consider past sessions.
For all scenarios, we set a common time constraint of 15 minutes. Fourteen minutes after the start of negotiations, we instructed the participants to conclude the negotiation naturally through the chat function of the web conferencing system. Once the negotiation was over, participants were asked to answer the questionnaire described in Sec. 2.2. All participants were Japanese, and the recorded conversations were in Japanese. They gave their written informed consent before starting the experiment.
The corpus is composed of 764 minutes of recordings (average duration: 15.9 minutes). Video and audio were recorded during the business negotiation using a camera and a microphone installed on the client PC. Video was recorded at 25 fps with 1280 × 720 resolution. Camera views were frontal and recorded the upper part of the body (see Fig. 1). Audio was recorded at 32 kHz. Recorded video and audio were synchronized. Participants were instructed to use a headphone.

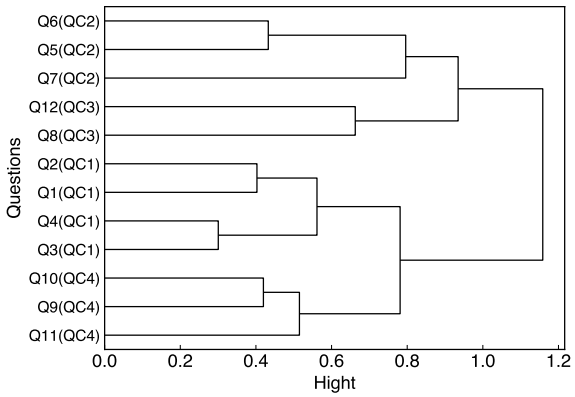

Figure 2: Clustering results of social-psychological outcomes on basis of correlation. QC1, QC2, QC3, and QC4 denote question classes derived from this tree clustering.

3. Analysis and experiments

3.1. Clustering of social-psychological outcomes

The goal of this study was to predict social-psychological outcomes from multimodal negotiation data. To assess various aspects of negotiation outcomes, we used the 12-question questionnaire. Such a large number of objective variables makes it difficult to interpret experimental results. Therefore, we first conducted hierarchical clustering of the questions for the buyers on the basis of the similarity of their scores.
We built dendrograms to represent the hierarchy in the 12 questions. Dendrograms are tree diagrams illustrating the hierarchical relationship between data. The clustering was based on correlation. Figure 2 shows the results of clustering. We derived four question classes (QCs) from these results so that each QC would consist of multiple questions. Question class 1 (QC1) consisted of questions 1, 2, 3, and 4, and was about overall impression, e.g., satisfaction and trust. Question class 2 (QC2) consisted of questions 5, 6, and 7, and was about presentation, e.g., explanation clarity and knowledge. Question class 3 (QC3) consisted of questions 8 and 12, and was about attitude, e.g., listening and consideration of relationships. Question class 4 (QC4) consisted of questions 9, 10, and 11, and was about proposal, e.g., responsivity and creativity. We used these four QCs in the following analysis and experiments.

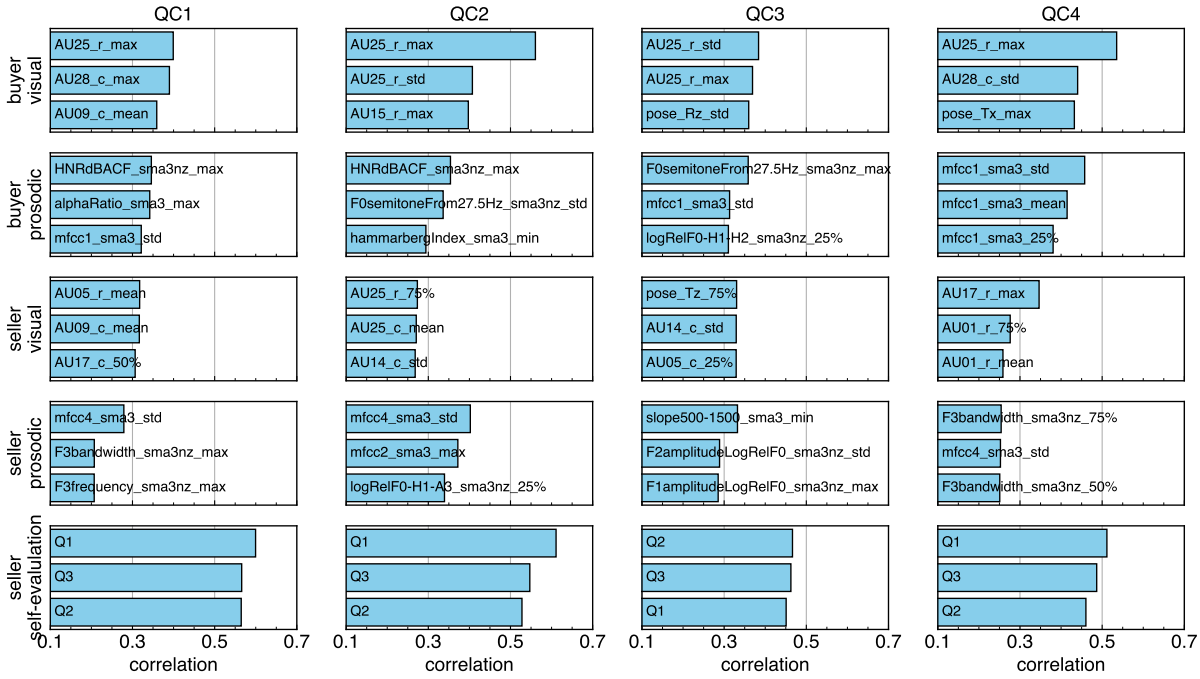

Figure 3: Correlation between social-psychological outcomes and non-verbal/self-evaluation features. For each category, we show features with top-3 correlations.

3.2. Feature analysis

To investigate how non-verbal features of each modality (visual or prosodic) and each negotiator (buyer or seller) correlate with social-psychological outcomes, we analyzed the linear relationships between the features and outcomes. We also investigated the correlation between the self-evaluation scores and outcomes.

3.2.1. Experimental setup

We extracted visual features related to the head and face behavior of the buyer and seller. Specifically, we used OpenFace (Baltrušaitis et al., 2016) to extract the location of the head (pose_Tx, pose_Ty, pose_Tz), rotation angles of head motion (pose_Rx, pose_Ry, pose_Rz), eye-gaze angles (gaze_angle_x, gaze_angle_y), as well as action units (AUs) (Eckman and Friesen, 1977). We used both intensities (e.g. AU01_r) and occurrences (e.g. AU01_c) of {AU:1, 2, 4, 5, 6, 7, 9, 10, 12, 14, 15, 17, 20, 23, 25, 26, 45}. We also used occurrences of AU28.

We also extracted prosodic features of the buyer and seller. We used openSMILE (Eyben et al., 2013) for extracting a set of low-level descriptors using the extended Geneva Minimalistic Acoustic Parameter Set (eGeMAPS) configuration (Eyben et al., 2015). The eGeMAPS consists of 25 features related to frequency, energy/amplitude, and spectrum.

These visual and prosodic features were later summarized over the whole conversation producing summary values per feature. We used the mean (_mean), standard deviation (_std), minimum (_min), maximum (_max), and quartiles (_25%, _50%, _75%) as summary values. These values were used as non-verbal features of a dialogue. We also used 5-point scores of a seller's self-evaluation as "self-evaluation features". We did not use any verbal features such as Bag-of-words for the initial investigation of SPNOP.

We first computed Pearson's pairwise correlations between social-psychological outcomes and features (non-verbal and self-evaluation). We then calculated the averages of the absolute values of the correlations for each QC.

3.2.2. Results of feature analysis

Figure. 3 shows the results of the correlation analysis. For each feature category (buyer's visual, buyer's prosodic, seller's visual, seller's prosodic, and seller's self-evaluation features) and each QC, we show the features with top-3 correlations.

Regarding non-verbal features, we observed that the correlation tended to be buyer-visual $>$ buyer-prosodic $>$ seller-visual $\fallingdotseq$ seller-prosodic. It was revealed that a buyer's non-verbal features more correlated with the social-psychological outcomes of negotiation than a seller's. We also observed that correlations of self-evaluation features were higher than those of non-verbal features. Introducing self-evaluation into SPNOP should improve estimation accuracy. When we compared the results between QCs, the correlations of QC3 were lower than the other QCs. This indicates that predicting the QC3 score is more difficult than for the other QCs. When we compared the results in accordance with features, the buyer's features related to AU25 (parting of the lips) showed constantly high correlation with each QC. This suggests that buyer's

Table 4: Evaluation results (accuracy) of SPNOP task

Method	QC1	QC2	QC3	QC4	ALL
CB	0.50	0.50	0.50	0.50	0.50
MB	0.62	0.72	0.72	0.68	0.68
NVB	0.69	0.76	**0.78**	**0.76**	0.74
SE	0.72	0.72	0.59	0.68	0.69
NVB+SE	**0.74**	**0.81**	0.76	**0.76**	**0.77**

speech activity has a certain importance for classification compared with the other features.

3.3. SPNOP experiments

To investigate whether social psychological outcomes can be predicted on the basis of non-verbal and self-evaluation features, we conducted SPNOP experiments.

3.3.1. Experimental setup

We define SPNOP in this study as a classification task; we binarized the 5-point social-psychological outcome scores into bad (score $\leq$ 3) and good (score $\geq$ 4). We compared the prediction accuracy of the following models.

- CB: baseline that randomly assigns the labels.
- MB: baseline that assigns the majority label to all observations.
- NVB: model using non-verbal features (visual and prosodic features of both the buyer and seller).
- SE: model using self-evaluation features.
- NVB+SE: model using both non-verbal and self-evaluation features.

We used EXtreme Gradient Boosting (XGBoost) for the classification models. We used a leave-one-out cross-validation method for training and testing and correlation-based feature selection in the training set. For all of the models, 20 features were selected and used for the training except for SE, because it has at most 12 features. All features in the training and testing sets of each fold were standard normalized per the distribution of the training set. We measured the performance of the models in terms of prediction accuracy. We trained and tested a model for each question of social-psychological outcomes then averaged the prediction accuracy over each QC and all questions.

3.3.2. Results of SPNOP

The results are summarized in Table 4. NVB outperformed MB. This confirms that social-psychological outcomes can be effectively predicted on the basis of non-verbal features. SE was comparable with MB, suggesting that SE does not work as an estimation model. This result was in contrast to those mentioned in Sec. 3.2.2, where self-evaluation features showed high correlation with social-psychological outcomes. We consider this is because correlations between a seller's self-evaluation scores were so high that SE could only capture certain aspects of negotiation, which made prediction less robust. In the overall average, NVB+SE showed superior performance to NVB, which confirms that introducing self-evaluation features into SPNOP is effective in terms of overall prediction accuracy. For QC3, however, the accuracy of NVB+SE was slightly lower than that of NVB. This is because self-evaluation features have lower correlation with QC3 than that with the other QCs. It was revealed that the effect of introducing seller's self-evaluation scores depends on the target questions.

4. Conclusion and future work

We presented a novel multimodal negotiation corpus for SPNOP, a novel task that estimates various subjective evaluation scores from negotiation dialogue data. The main difference between our corpus and current corpora is that ours was assessed with various psychological measurements while other corpora only include information related to objective outcomes or a single aspect of psychology. Our corpus has two unique features to collect realistic negotiations; we used skilled negotiators and scenarios with context-rich negotiation and recorded video and audio of negotiations to investigate SPNOP in the context of social signal processing. Experimental results indicate that social-psychological outcomes can be effectively estimated by non-verbal features. For future work, we will evaluate the performance when applying the models trained from our corpus to negotiations in real situations. We will also investigate the effectiveness of verbal features for SPNOP.

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