Impact of deception information on negotiation dialog management: A case study on doctor-patient conversations

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Abstract Almost all of existing negotiation systems assume that their interlocutors (the user) are telling the truth. However, in negotiations, participants can tell lies to earn a profit. In this research, we proposed a negotiation dialog management system that detects user's lies and designed a dialog behavior on how should the system react with. As a typical case, we built a dialog model of doctor-patient conversation on living habits domain. We showed that we can use partially observable Markov decision process (POMDP) to model this conversation and use reinforcement learning to train the system's policy.

1 Introduction

Recently, the focus of studies about dialog system have switched from passive role systems (eg. restaurant, tourist information provider) to become more actively systems that can influence the user's decision (persuasive technology) [5, 10]. Most of current researches mainly deal with cooperative dialog, in which the system and the user work together to reach a balanced point . However, there are situations that the mutual goal cannot be reached (non-cooperative dialog) [11, 3]. There are a number of works on non-cooperative negotiation using trading game scenario [3, 12]. A drawback of these studies is that they do not cover the situation in which participants use "false promises" tactics. For example, someone pretends to give up unhealthy custom (eg. smoking/drinking) after receiving advices from friends or family but he actually does not have intention to follow the advice.

In this paper, we focus on a typical and interesting type of negotiation, the doctor-patient conversation where they discuss to find the best treatment for the patient. In this dialog, the patient has their own perspective and opinions about their health

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condition. The doctor needs to consider these opinions when making a treatment plan (recommend a new habit) and negotiates with users to reach a plan that satisfy both user's demand and requirements of the treatment. Patients sometimes tell lies because they do not want to change their habit, thus considering deceptive information will improve the negotiation strategy of the doctor.

2 Scenario and Modeling

2.1 Dialog scenario

This work considers a dialog scenario between a system (doctor) and a user (patient). They discuss about user's living habit, which can be about: sleeping, food, working/studying, exercise, social media usage and leisure activities. The system tries to convince the user that they need to change to a more healthy living habit. The system persuades the user by giving them information about the new habit (system's recommendation), health benefits of the new habit and negative effects of user's current habit. This action is denoted as Framing in this research. On the other hand, the user wants to continue the current habit and gives reasons to show that it is too difficult for him to change. The system behaves cooperatively; if user's reason is honest, system will give an easier recommendation.

To make the conversation simpler, only the system can propose recommendations, the user cannot suggest what habit they should change to. However, the users are allowed to use dishonest reasons to make the system offer an easier recommendation. The user can also pretend to accept the system's offer while they actually do not intend to change their current habit.

Figure 1 describes the proposed dialog behavior, which considers deceptions of the user. In this flowchart, rectangles indicate system actions. The set of dialog acts for the system includes:

Offer: the system suggests the user should change to a new habit.
Framing: the system provides arguments to persuade the user.
End: the system ends the conversation.

Similar to the work in ([5]), we also use framing as one of system's dialog acts. The user can react with different actions as described below:

Accept: the user agrees to change habit.
Reject: the user gives reason why they cannot change their habit.
Hesitate: the user says he/she is unsure about whether to accept the offer or not.
Question: the user asks the system about the new habit.

According to a study by [7], when the patient is lying, the doctor should tell the patient about the necessity and benefits of the treatment plan and consequences if patient refuses to follow it. Applying to the "living habit" scenario, the most logical reaction when the user is telling lie (uses fake reasons or pretend to agree)

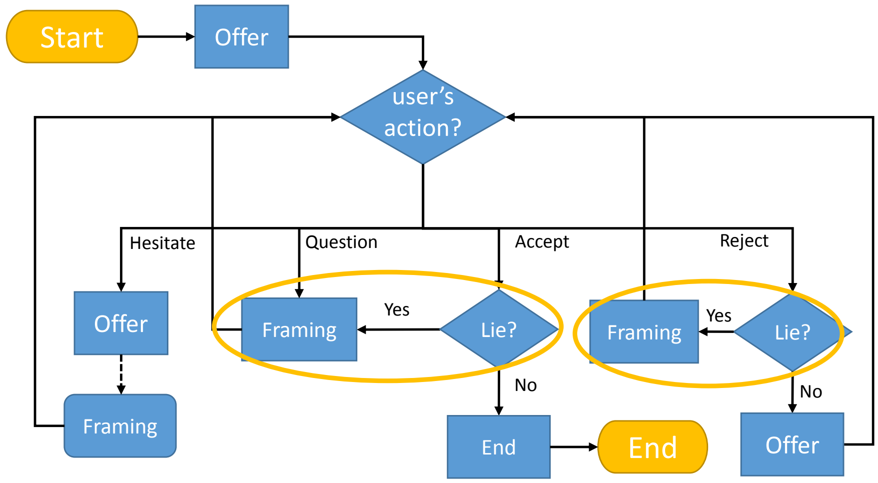

Fig. 1 *Flow chart of the conversation.*

is Framing. In contrast, a conventional negotiation system that does not consider user's deception always offer a new recommendation when the user rejects and end the conversation when the user agrees regardless whether they are telling the truth or not.

2.2 Policy Management using POMDP

To find the best strategy of dialog system against the user deception, considering errors of dialog act classification and deception detection for user utterance is necessary, because these models do not have 100% accuracy. Partially observable Markov decision process (POMDP) is widely used to learn the best strategy of dialog systems for such error containing cases [14].

The equation for updating belief state of a POMDP can be written as:

$$b^{t+1} \propto P(o^{t+1}|s^{t+1}) \sum_{s_i} P(s^{t+1}|s^t, \hat{a}^t) b^t \tag{1}$$

Apart from user's action s^t, the proposed dialog system also uses deception information for dialog management. To solve this problem, we used method in a similar work for user focus by [14]. By extending Equation (1) with deception information of the current turn d^t and next turn d^{t+1}, we have the belief update of the proposed system:

$$b^{t+1}_{s,d} \propto \quad P(o^{t+1}_s, o^{t+1}_d | s^{t+1}, d^{t+1}) \sum_s \sum_d P(s^{t+1}, d^{t+1} | s^t, d^t, \hat{a}^t) b^t_{s,d} \tag{2}$$

With the observation result come from SLU and Deception Detection modules being denoted as o_s and o_d respectively.

In this research, we use Q-learning [13], a popular method to train the optimal policy π^*. We utilize Grid-based Value Iteration method proposed by [2]. The belief is calculated by:

$$b_{s_i} = \begin{cases} \mu & \text{if } s = o \\ \frac{1-\mu}{|S|-1} & \text{otherwise} \end{cases} \tag{3}$$

μ represent the rounded probability for every 0.1 that the observation comes from Spoken Language Understanding and Deception Detection equal to actual user's dialog act and deception information. Using this formula, any belief b will be "mapped" into a certain fixed point b' in the belief state, as shown in the example below:

$$\begin{aligned} &b{=}\{\{A{:}0.147, H{:}0.386, Q{:}0.235, R{:}0.232\}; \{L{:}0.735, T{:}0.265\}\} \\ &\quad \rightarrow b'{=}\{\{A{:}0.2, H{:}0.4, Q{:}0.2, R{:}0.2\}; \{L{:}\ 0.7, T{:}0.3\}\} \end{aligned} \tag{4}$$

The 2-tuple $\{L,T\}$ is random variable of deception information($\{Lie, Truth\}$) and $\{A,H,Q,R\}$ is the random variable of user's dialog act($\{Accept, Hesitate, Question, Reject\}$.) Those probabilities come from the results of user's dialog act classification and deception detection respectively. Table 1 show the reward received for each turn.

Dialog state		Rewards		
User DA (s)	d	Offer	Framing	End
Accept	0	-10	-10	+100
	1	-10	+10	-100
Reject	0	+10	+10	-100
	1	-10	+10	-100
Question	0	-10	+10	-100
Hesitate	0	+10	+10	-100

Table 1 Rewards in each turn.

2.3 Deception Detection using multi-modal approach

There are various clues that can help us to detect lies, which include lexical modal, acoustic modal, gestures and facial expressions. As a result, multi-modal approach that combines those modalities was proved to be very efficient in detecting deception [8]. Thus, we also utilized multi-modal approach with acoustic and facial features to build the deception detection module.

To extract facial features, we used OpenFace toolkit developed by [1]. All features provided by this are used for deception detection. From this tool, we were able to extract 14 face AU (Action Unit) regression and 6 AU classification values as well as head position, head direction parameters. All these values are then normalized and discretized into 5 different levels of intensity.

Acoustic features are extracted from audio files using OpenSMILE tool [4]. The acoustic feature template was taken from the work by [6]. From the pitch and loudness values, we calculated maximum (*max*), minimum (*min*), mean (*mean*) and standard deviation (*std*). The duration-related features include: percentage of frame with voice, percentage of frame with lower pitch than previous frame (falling pitch), percentage of frame with higher pitch than previous frame (raising pitch).

The classification model that we used for deception detection is Multi Layer Perceptron with hierarchical structure to combine acoustic and facial features. This method was proposed by [9] for emotion detection task. In particular, for our research, we put facial features directly into the first layer of the network while acoustic features are incorporated at the second hidden layer.

To test the effectiveness of the deception detection module, we used data from recorded conversations between 2 participants. One of them plays the role of a doctor and the other one's role is a patient. In this conversation, the "patient" will try to get a prescription from the "doctor" by telling lies about his health condition. Deception label for each utterance was manually annotated by themselves. The total number of utterances in this data is 146. We took 34 of them (17 honest, 17 deceptive) to use as test data. Results of the experiment are shown in Table 2.

Models	Audio	Video	Features combine	Decision combine	Hierarchical
Accuracy	55.89%	52.95%	61.75%	58.83%	64.71%
F-measure	51.61%	42.85%	55.17%	56.25%	60.00%

Table 2 Deception detection accuracy.

3 Experiments of dialog management system

3.1 Data

Due to the difficulties of recruiting actual doctors and patients to collect the data, the participants who took part in data collection are students who have good level of English fluency. All participants are working at the same academic environment at the time of data collection. There are total of 7 participants who take part in the recordings. 4 of them played the role of the system and 6 played the role of the user.

The data used for training are recorded using the "living habits" dialog scenario in Wizard-of-Oz (WoZ) setup. Each recording session is carried out by 2 participants who play the role of the system and the user respectively. Each session consists of 6 dialogs for each of the living habit topic. The participants who play the role of the user (patient) are given payment as reward for the outcome of the conversation. If they pretend to agree with the system's offer, they will receive lower payment. On the other hand, if they choose to truly agree with the system's offer they will get higher payment with a condition that they will need to change to the new habit for one week. The payment is to create the situation where the user has to choose between an easy activity (continue current habit) with low reward and an activity that is difficult but has higher reward in return (change to new habit) to observe more lies. In the end, the recorded training data are about 3 hours 20 minutes long and contains 29 dialogs with average of 5.72 turns per dialog. Labels of DA are annotated by one expert and labels of deception are provided by the participant who made the deception.

With test corpus, recordings are done as direct conversations between participants. The recording setup is similar to WoZ scenario but without the help of TTS since the participants are now talking directly with each other. The test data set is about 2 hours 35 minutes in length and contains 30 dialogs with average of 4.73 turns per dialog. Table 3 shows statistics of the collected data.

Data	System DA			User DA				% lie in user's utterances
	End	Framing	Offer	Hesitate	Question	Accept	Reject	
Train	14.43%	43.30%	42.27%	21.69%	3.61%	51.81%	22.89%	18.07%
Test	17.54%	36.26%	46.20%	17.64%	9.86%	19.72%	52.82%	19.01%

Table 3 Deception and dialog acts statistic.

3.2 Results

First, we test the negotiation efficiency of the learned policy by comparing it with a baseline negotiation policy that does not concern about user's deception. We let the system interacted with a simulated user created from test data for 100,000 dialogs. The simulator is created with the same method as described in [14]. In particular, user's dialog acts and deceptions are generated using **intention model** and **deception model** as below:

$$\begin{aligned} \textbf{intention model} &: P(s^{t+1}|d^{t+1}, s^t, d^t, \hat{a}^t) \\ \textbf{deception model} &: P(d^{t+1}|s^t, d^t, \hat{a}^t) \end{aligned} \tag{5}$$

For evaluation, these probabilities are calculated from test data using maximum likelihood.

Performance is evaluated with success rate and average offer per succeeded dialog. Success rate is the percentage of dialogs in which user truly accepts the system's offer. For the second evaluation metric, average offer; since every time the system makes an Offer action, the new habit will be easier but gives less health benefit, thus it is less favorable for the system. Therefore, using fewer offers to successfully persuade the user is better. From the results shown in Table 4, it is clear that our proposed system outperforms the baseline.

Next, we evaluate the performance of the system's dialog acts decision. The accuracy are measured with 2 metrics. DA accuracy refers to the accuracy of the system's chosen dialog acts against reference actions that were chosen by human. Deception

Dialogue policy	Success rate	Avg. offer
Conventional	21.83%	2.472
Proposed policy	**29.82%**	2.447

Table 4 Success rate and average offer per succeeded dialogs.

handling indicates the accuracy of dialog acts decision when user is lying. From the results of Table 5, we can see that our proposed system outperformed the baseline again. Especially, for deception handling, the proposed system achieved higher accuracy in both situations: using gold-label and using predicted results.

Dialog system	DA accuracy	Deception handling
Conventional	68.15%	35.00%
Proposed policy + gold-label deception	**80.45%**	**80.00%**
Proposed policy + predicted deception	**79.32%**	**55.00%**

Table 5 Dialog selection acts accuracy.

4 Conclusions

In this paper, we present a negotiation strategy that counter deception in doctor-patient conversation. We also propose a dialog system that utilize this strategy and showed the construction and performance of each module. Experiment results proved that the proposed strategy outperformed normal negotiation strategy significantly, beating it by more than 8% in chance of successful persuasion. DA accuracy experiments indicated that the learned policy achieved a good level of naturalness when compared to human behavior in the same scenario. In future, we would like to conduct experiments of the system with human.

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