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Prediction of partners' behaviors in agent negotiation under open and dynamic environments

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Prediction of Partners' Behaviors in Agent Negotiation under Open and Dynamic Environments

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Abstract

Prediction of partners' behaviors in negotiation has been an active research direction in recent years in the area of multi-agent and agent system. So by employing the prediction results, agents can modify their own negotiation strategies in order to achieve an agreement much quicker or to look after much higher benefits. Even though some of prediction strategies have been proposed by researchers, most of them are based on machine learning mechanisms which require a training process in advance. However, in most circumstances, the machine learning approaches might not work well for some kinds of agents whose behaviors are excluded in the training data. In order to address this issue, we propose three regression functions to predict agents' behaviors in this paper, which are linear, power and quadratic regression functions. The experimental results illustrate that the proposed functions can estimate partners' potential behaviors successfully and efficiently in different circumstances.

I. Introduction

Negotiation is a means for agents to communicate and compromise to reach mutually beneficial agreements [5]. One of the crucial issues in negotiation is how to predict partners' behaviors and use the prediction results to maximum agents' own benefits. Up to now, several prediction strategies [6] [2] have been proposed by researchers, and machine learning is one of the most popular mechanisms. However, the existing machine learning approaches may not work well in some more flexible application domains for the reasons of (1) lacking of sufficient data to train the system, and (2) requesting plenty of time and space resources during the training process.

In order to address the issues mentioned above, we propose three regression functions to estimate partners' behaviors in multi-agent negotiation in this paper, which are linear, power and quadratic regression function. According to our literature review, this is the first time that the regression analysis approach is employed into the partners' behaviors prediction. The proposed approach only uses the historical offers in the current negotiation and does not require any additional training process. Also, because the proposed approach does not make any assumption on agents' purposes, preferences and negotiation strategies, it can be employed widely in negotiation by different types of agents.

The rest paper is organized as follows: Section II introduces the three proposed regression functions, respectively; Section III illustrates the performance of the proposed regression functions through experiments; Section IV lists some related work; and Section V concludes this paper and outlines future works.

II. Regression Analysis in Agent Negotiation

In this section, we introduce three different regression functions in detail for the prediction of partners' behaviors during negotiation. The proposed approach is covers most of general agents' negotiation behaviors, which are conceder, linear and boulware [3].

A. Linear Regression Function

We propose the linear regression function as follows:

$$u = b \times t + a \tag{1}$$

where u denotes the estimated value for an agent's utility, t $(0 \leq t \leq \tau)$ denotes the negotiation time and a, b are the parameters which need to be calculated. Both parameters a and b are independent on t.

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Let pairs $(t_0, \hat{u_0}), \ldots, (t_n, \hat{u_n})$ are the instances in the current negotiation, where t_i $(t_i < t_{i+1})$ indicates the negotiation cycle and $\hat{u}_i$ $(\hat{u}_i \leq \hat{u_{i+1}})$ indicates the real utility value the agent gained from its partners. Let ε is the difference between u_i and $\hat{u}_i$, because for each $\hat{u}_i = b \times t_i + a + \varepsilon_i$, $\varepsilon_i \sim N(0, \sigma^2)$, $\hat{u}_i$ is distinctive, then the joint probability density function for $\hat{u}_i$ is:

$$\begin{aligned} L &= \prod_{i=1}^{n} \frac{1}{\sigma\sqrt{2\pi}} \exp[-\frac{1}{2\sigma^2}(\hat{u}_i - bt_i - a)^2] \\ &= (\frac{1}{\sigma\sqrt{2\pi}})^n \exp[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\hat{u}_i - bt_i - a)^2] \end{aligned} \tag{2}$$

In order to make L to achieve its maximum, obviously $\sum_{i=1}^{n}(\hat{u}_i - bt_i - a)^2$ should achieve its minimum value. Let

$$Q(a, b) = \sum_{i=1}^{n}(\hat{u}_i - bt_i - a)^2 \tag{3}$$

We calculate the first-order partial derivative for $Q(a, b)$ on a and b, and let the results equal to zero as follows:

$$\begin{cases} \frac{\partial Q}{\partial a} = -2\sum_{i=1}^{n}(\hat{u}_i - bt_i - a) = 0 \\ \frac{\partial Q}{\partial b} = -2\sum_{i=1}^{n}(\hat{u}_i - bt_i - a)t_i = 0 \end{cases} \tag{4}$$

Then it equals:

$$\begin{cases} na + (\sum_{i=1}^{n} t_i)b = \sum_{i=1}^{n} \hat{u}_i, \\ (\sum_{i=1}^{n} t_i)a + (\sum_{i=1}^{n} t_i^2)b = \sum_{i=1}^{n} t_i\hat{u}_i \end{cases} \tag{5}$$

Because the value of Equation 5's coefficient matrix is $(n\sum_{i=1}^{n} t_i^2 - (\sum_{i=1}^{n} t_i)^2)$ and does not equal zero. Both parameters a and b have an unique solution, which is

$$\begin{cases} b = \frac{n\sum_{i=1}^{n} t_i\hat{u}_i - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} \hat{u}_i}{n\sum_{i=1}^{n} t_i^2 - (\sum_{i=1}^{n} t_i)^2} \\ a = \frac{\sum_{i=1}^{n} \hat{u}_i \sum_{i=1}^{n} t_i^2 - \sum_{i=1}^{n} t_i \sum_{i=1}^{n} t_i u_i}{n\sum_{i=1}^{n} t_i^2 - (\sum_{i=1}^{n} t_i)^2} \end{cases} \tag{6}$$

B. Power Regression Function

For the power regression, we propose the regression function as follows:

$$u = a \times t^b \tag{7}$$

Firstly, we do the equivalence transformation on Equation 7:

$$\ln(u) = \ln(a \times t^b) = \ln(a) + b \times \ln(t) \tag{8}$$

Let $u^* = \ln(u)$, $a^* = \ln(a)$ and $t^* = \ln(t)$, the Equation 8 can be rewritten as $u^* = a^* + b \times t^*$. Then by employing the steps mentioned in the Subsection II-A (recall Equations 2 to 5), we can get solutions for parameter b and a as follows:

$$\begin{cases} b = \frac{n\sum_{i=1}^{n} t_i^* \hat{u_i^*} - \sum_{i=1}^{n} t_i^* \sum_{i=1}^{n} u_i^*}{n\sum_{i=1}^{n} t_i^{*2} - (\sum_{i=1}^{n} t_i^*)^2} \\ a = \exp(\frac{\sum_{i=1}^{n} u_i^* \sum_{i=1}^{n} t_i^{*2} - \sum_{i=1}^{n} t_i^* \sum_{i=1}^{n} t_i^* u_i^*}{n\sum_{i=1}^{n} t_i^{*2} - (\sum_{i=1}^{n} t_i^*)^2}) \end{cases} \tag{9}$$

C. Quadratic Regression Function

In this subsection, a quadratic regression function is proposed to predict agents' behaviors as follows:

$$u = a \times t^2 + b \times t + c \tag{10}$$

Let $x = t^2$ and $y = t$, then the Equation 10 is transferred to a linear function as $u = a \times x + b \times y + c$. The joint probability density function for the difference between the predicted value u_i and the real value $\hat{u}_i$ is:

$$\begin{aligned} L &= \prod_{i=1}^{n} \frac{1}{\sigma\sqrt{2\pi}} \exp[-\frac{1}{2\sigma^2}(\hat{u}_i - ax_i - by_i - c)^2] \\ &= (\frac{1}{\sigma\sqrt{2\pi}})^n \exp[-\frac{1}{2\sigma^2}\sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c)^2] \end{aligned} \tag{11}$$

In order to make L to achieve its maximum, $\sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c)^2$ should achieve its minimum value. Let

$$Q(a, b, c) = \sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c)^2 \tag{12}$$

We calculate the first-order partial derivative for $Q(a, b, c)$ on a, b and c, and let the results equal to zero.

$$\begin{cases} \frac{\partial Q}{\partial a} = -2\sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c)x_i = 0 \\ \frac{\partial Q}{\partial b} = -2\sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c)y_i = 0 \\ \frac{\partial Q}{\partial c} = -2\sum_{i=1}^{n}(\hat{u}_i - ax_i - by_i - c) = 0 \end{cases} \tag{13}$$

Equation 13 can be rewritten as follows:

$$\begin{cases} (\sum_{i=1}^{n} x_i^2)a + (\sum_{i=1}^{n} x_iy_i)b + (\sum_{i=1}^{n} x_i)c = \sum_{i=1}^{n} x_i\hat{u}_i \\ (\sum_{i=1}^{n} x_iy_i)a + (\sum_{i=1}^{n} y_i^2)b + (\sum_{i=1}^{n} y_i)c = \sum_{i=1}^{n} y_i\hat{u}_i \\ (\sum_{i=1}^{n} x_i)a + (\sum_{i=1}^{n} y_i)b + nc = \sum_{i=1}^{n} \hat{u}_i \end{cases} \tag{14}$$

Then let

$$PU = \begin{vmatrix} \sum_{i=1}^{n} x_i^2 & \sum_{i=1}^{n} x_iy_i & \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} x_iy_i & \sum_{i=1}^{n} y_i^2 & \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} y_i & n \end{vmatrix} \tag{15}$$

$$PA = \begin{vmatrix} \sum_{i=1}^{n} x_i\hat{u}_i & \sum_{i=1}^{n} x_iy_i & \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} y_i\hat{u}_i & \sum_{i=1}^{n} y_i^2 & \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} \hat{u}_i & \sum_{i=1}^{n} y_i & n \end{vmatrix} \tag{16}$$

$$PB = \begin{vmatrix} \sum_{i=1}^{n} x_i^2 & \sum_{i=1}^{n} x_i \hat{u}_i & \sum_{i=1}^{n} x_i \\ \sum_{i=1}^{n} x_i y_i & \sum_{i=1}^{n} y_i \hat{u}_i & \sum_{i=1}^{n} y_i \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} \hat{u}_i & n \end{vmatrix} \tag{17}$$

$$PC = \begin{vmatrix} \sum_{i=1}^{n} x_i^2 & \sum_{i=1}^{n} x_i y_i & \sum_{i=1}^{n} x_i \hat{u}_i \\ \sum_{i=1}^{n} x_i y_i & \sum_{i=1}^{n} y_i^2 & \sum_{i=1}^{n} y_i \hat{u}_i \\ \sum_{i=1}^{n} x_i & \sum_{i=1}^{n} y_i & \sum_{i=1}^{n} \hat{u}_i \end{vmatrix} \tag{18}$$

Because $PU \neq 0$, so parameters a, b and c have an unique solution, which is $a = \frac{PA}{PU}$, $b = \frac{PB}{PU}$ and $c = \frac{PC}{PU}$.

III. Experiments

In this section, we demonstrate three scenarios to test our proposed approaches. In order to simplify the implementation process, all agents in the experiment employ the NDF negotiation strategy [3]. Agents' negotiation behaviors cover all general possible situations, which are conceder, linear and boulware. In the experiment, we use the average error ($AE_i = \sum_{k=1}^{i} (\hat{u}_i - u_i)/i$, where i is the negotiation cycle) to evaluate the experimental results. The AE_i indicates the difference between the estimated results and the real value. The smaller the value of AE_i, the better the prediction result.

A. Scenario 1

In the first scenario, a buyer wants to purchase a mouse pad from a seller. The acceptable price for the buyer is in $[\$0, \$1.4]$. The deadline for the buyer to finish this purchasing process is 11^{th} cycles. In this experiment, the buyer adopts conceder negotiation behavior, and the seller employs the proposed approaches to estimate the buyer's price. The estimated results are displayed in Figure 1.

It can be seen that the linear approach dose not fit the instances very well, because it can only estimate the main trend of the buyer's offers but cannot provide more accurate values. The average error for the linear function is $AE_{10}^{l} = 0.0189$, which is 1.35% of the buyer's reserve price.

To contrast, the power approach provides more accurate prediction results. According to the Figure 1, the prediction results almost fit all real price except the 4^{th} and 5^{th} negotiation cycles. The average error for the power approach is $AE_{10}^{p} = 0.0165$, which is 1.17% of the buyer's highest price.

The quadratic function's curve is in the middle of other two curves. Even though the quadratic function looks no better than the power function, the average error of the quadratic approach is the lowest ($AE_{10}^{q} = 0.0147$), which is only 1.05% of the buyer's reserve price. The reason is because the quadratic approach aim to find a better regression curve to decrease the average error, but not to provide more accurate values in some particular negotiation cycles.

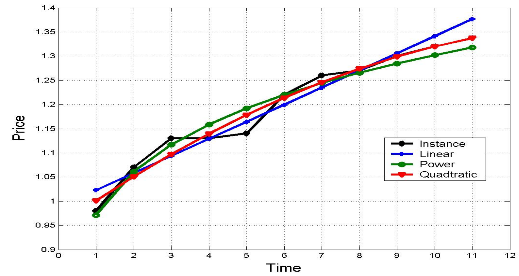

Fig. 1. Prediction results for scenario 1

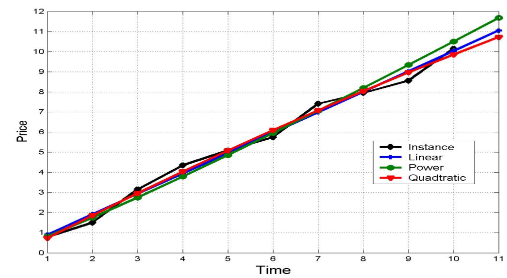

Fig. 2. Prediction results for scenario 2

B. Scenario 2

In the second scenario, a buyer wants to buy a keyboard from a seller. The desired price for the buyer is in $[\$0, \$14]$. We let the buyer to employ the linear negotiation strategy. The prediction results are shown in Figure 2.

It can be seen that when the buyer employ the linear negotiation strategy, the prediction results by using the three proposed approaches are almost same. A little differences appear in the 3^{rd}, 4^{th}, 9^{th} and 10^{th} negotiation cycles. The average errors for the linear, power and quadratic functions are $AE_{10}^{l} = 0.256$, $AE_{10}^{p} = 0.341$ and $AE_{10}^{q} = 0.241$, respectively. Therefore, we can still conclude that all proposed regression function perform very well when the buyer employs linear negotiation strategy and the quadratic approach outperforms other two approaches a little bit.

C. Scenario 3

In the third scenario, a buyer wants to purchase a monitor from a seller. The suitable price for the buyer is in $[\$0, \$250]$ and the buyer employs the boulware negotiation strategy.

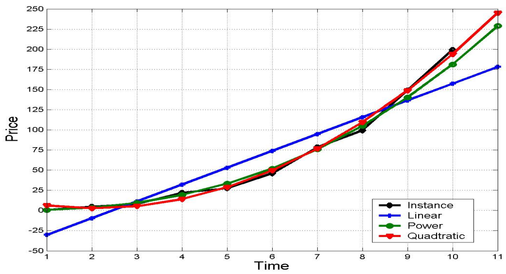

Fig. 3. Prediction results for scenario 3

The prediction results are shown in Figure 3. It can be seen that the linear approach performs much worse than other two proposed approaches. In actually, only one prediction result (the 3^{rd} negotiation cycle) in the linear function is same as the real value. The average error for the linear function is $EA^l_{10} = 19.872$, which is 7.94% of the buyer's reserve price.

In contrast, both the power and quadratic functions give more accurate prediction results. Especially, the quadratic function almost fits all real prices except the 4^{th} and 8^{th} negotiation cycles. The prediction results by using the power regression approach is also accurate enough to illustrate the buyer's negotiation strategy. According to experimental results, the average error for the power function is $EA^p_{10} = 5.196$ (i.e. 2.08% of the buyer's reserve price) and the average error for the quadratic function is $EA^q_{10} = 4.071$ (i.e. 1.63% of the buyer's reserve price). Therefore, we can conclude that the quadratic approach also outperform other two approaches when the buyer's negotiation strategy is boulware, and both the quadratic and power approaches can give very accurate prediction results.

From these experimental results in the above, we can conclude that the proposed regression functions can estimate partners' potential behaviors successfully in different circumstances, and also the estimation results are accurate and reasonable enough to be adopted by agents to modify their strategies during negotiation.

IV. Related Work

In this section, we list some related works. In [4], Gal and Pfeffer presented a machine learning approach based on a statistical method. The limitation of this approach is the difficult of training the proposed system perfectly. Therefore, for some unknown kind of agents whose behaviors are excluded in the training data, the prediction result may not reach the acceptable accuracy requirements.

Chajewska et. al. [2] proposed a decision-tree approach to learn and to estimate agents' utility functions. The authors assumed that each agent is rational and looks for maximum benefits during negotiation. Since this approach requires that all possible negotiation endings and the corresponding probabilities should be estimated in advance, its application may be limited when the variance of negotiation issues is discrete or the negotiation environment is open and dynamic.

Brzostowski and Kowalczyk [1] presented a way to estimate partners' behaviors by employing a classification method. However, their approach only works for the time-dependent agent and the behavior-dependent agent, which limits its application domains.

By comparing with the above approaches, our proposed approach will have more wide application domains because it can estimate partners' behaviors based only on the current historical records so as to save both space and time resources. Therefore, the proposed functions can be employed by agents in open and dynamic negotiation environments to predict partners' behaviors and to modify agents' own negotiation strategies.

V. Conclusion and Future Work

In this paper, we proposed three regression functions to estimate partners' behaviors in negotiation. The experimental results demonstrated that the proposed approach is novel and valuable for the agents' behaviors prediction because it is the first time that the regression analysis approach is applied on this research area. This approach is also very suitable to work in open and dynamic negotiation environments. The future work includes to extend current approach to handel multi-issue negotiation and to test it in real world applications.

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