Predicting Partners’ Behaviors in Negotiation by Using Regression Analysis

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Abstract. Prediction partners’ behaviors in negotiation has been an active research direction in recent years. By employing the estimation results, agents can modify their own ways in order to achieve an agreement much quicker or to look after much higher benefits for themselves. Some of estimation strategies have been proposed by researchers to predict agents’ behaviors, and most of them are based on machine learning mechanisms. However, when the application domains become open and dynamic, and agent relationships are complicated, it is difficult to train data which can be used to predict all potential behaviors of all agents in a multi-agent system. Furthermore because the estimation results may have errors, a single result maybe not accurate and practical enough in most situations. In order to address these issues mentioned above, we propose a power regression analysis mechanism to predict partners’ behaviors in this paper. The proposed approach is based only on the history of the offers during the current negotiation and does not require any training process in advance. This approach can not only estimate a particular behavior, but also an interval of behaviors according to an accuracy requirement. The experimental results illustrate that by employing the proposed approach, agents can gain more accurate estimation results on partners’ behaviors by comparing with other two estimation functions.

1 Introduction

Negotiation is a means for agents to communicate and compromise to reach mutually beneficial agreements [1] [2]. However, in most situations, agents do not have complete information about their partners’ negotiation strategies, and may have difficulties to make a decision on future negotiation, such as how to select suitable partners for further negotiation [3] [4] or how to generate a suitable offer in next negotiation cycle [5]. Therefore estimation approaches which can predict uncertain situations and possible changes in future are required for helping agents to generate good and efficient negotiation strategies. Research on partners’ behaviors estimation has been a very active direction in recent years. Several estimation strategies are proposed [6] [7] by researchers. However, as these estimation strategies are used in real applications, some of limitations are emerged.
Machine learning is one of the popular mechanisms adopted by researchers in agents’ behaviors estimation. In general, this kind of approaches have two steps in order to estimate the agents’ behaviors properly. In the first step, the proposed estimation function is required to be well trained by training data. Therefore, in a way, the performance of the estimation function is almost decided by the training result. In this step, data are employed as many as possible by designers to train a system. The training data could be both synthetic or collected from the real world. Usually, the synthetic data are helpful in training a function to enhance its problem solving skill for some particular issues, while the real world collected data can help the function to improve its ability in complex problem solving. After the system being trained, the second step is to employ the estimation function to predict partners’ behaviors in future. However, no matter what and how many data are employed by designers to train the proposed function, it is unsuspicious to say that the training data will be never comprehensive enough to cover all situations in reality. Therefore, even though an estimation function is well trained, it is also very possible that some estimation results do not make sense at all for some kind of agents whose behaviors’ records are not included in the training data. At present stage, as the negotiation environment becomes more open and dynamic, agents with different kinds of purposes, preferences and negotiation strategies can enter and leave the negotiation dynamically. So the machine learning based agents’ behaviors estimation functions 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 resources in each training process.

In order to address those issues mentioned above, in this paper we propose a power regression approach to analyze and estimate partners’ behaviors in negotiation. According to our knowledge, this is the first time that the regression analysis approach is employed to estimate partners’ behaviors in negotiation. By comparing with machine learning mechanisms, the proposed approach only uses the historical offers in the current negotiation to estimate partners’ behaviors in future negotiation and does not require any additional training process. So the proposed approach is very suitable to work under an open and dynamic negotiation environment, and to make a credible judgements on partners’ behaviors timely. Also, because the proposed approach does not make any strict assumption on agents’ purposes, preferences and negotiation strategies, it can be employed widely in negotiation by different types of agents. Furthermore, the proposed approach not only represents the estimation results in the form of interval, but also gives the probability that each individual situation may happen in future. By employing the proposed representation format, agents can have an overview on partners’ possible behaviors and their favoritism easily, and then modify their own strategies based on these distributions. Therefore, the proposed approach provides more flexible choices to agents when they make decision in negotiation.

The rest paper is organized as follows: Section 2 introduces both the background and assumption of our proposed approach; Section 3 introduces the way
that how the proposed regression analysis works; Section introduces the ways to predict partners’ behaviors under different accuracy requirements based on the regression analysis results; Section illustrates the performance of the proposed power regression function through experiments and advantages of the proposed function by comparing with other two estimation approaches; and Section concludes this paper and outlines future works.

2 Background

In this section, we introduce the background about the proposed power regression function for partners’ behaviors estimation in negotiation. The regression analysis is a combination of mathematics and probability theory which can estimate the strength of a modeled relationship between one or more dependent variables and independent variables. In order to simplify the complexity for the proposed regression analysis approach, we make a simple assumption about the negotiation as follows:

Assumption: The benefits which an agent gains from its partner in each negotiation cycle should be a serial in monotone ascending order.

The reason behind this assumption is that partners will not break their promises and the new offer will be no less than the existing one. According to the assumption above, we propose a power regression function to predict the partners’ behaviors. The proposed power regression function is given as follows:

\[ u = a \times t^b \]  

(1)

where \( u \) is the expected utility gained from a partner, \( t \) (\( 0 \leq t \leq \tau \)) is the negotiation cycle and both \( a \) and \( b \) (\( a \geq 0, b \geq 0 \)) are parameters which are independent on \( t \). Based on our assumption and the proposed power regression function, it is noticed that four types of partners’ behaviors are distinguished based on the range of parameter \( b \).

- **Boulware:** when \( b > 1 \), the rate of change in the slope is decreasing, corresponding to smaller concession in the early cycles but large concession in later cycles.
- **Linear:** when \( b = 1 \), the rate of change in the slope is zero, corresponding to making constant concession throughout the negotiation.
- **Conceder:** when \( 0 < b < 1 \), the rate of change in the slope is increasing, corresponding to large concession in early cycle but smaller concession in later cycles.
- **When** \( b = 0 \), the rate of change of the slope and the slope itself are always zero, corresponding to not making any concession throughout the entire negotiation.

In the following Section, we will introduce the proposed power regression function to analysis and estimate partners’ possible behaviors in a more efficient and accurate way.
3 Regression Analysis on Partners’ Behaviors

In this section, we introduce the proposed power regression analysis approach on the negotiation between two players. We do the equivalence transformation on Equation 1 as follows:

\[ \ln(u) = \ln(a \times t^*) = \ln(a) + b \times \ln(t) \]  

Then let \( u^* = \ln(u) \), \( a^* = \ln(a) \) and \( t^* = \ln(t) \), Equation 2 can be rewritten as \( u^* = a^* + b \times t^* \). The new function indicates a linear relationship between the variables \( t^* \) and \( u^* \). Both parameters \( a^* \) and \( b \) are independent on \( t^* \). Since the above equation only estimates partners’ possible behaviors, the difference (\( \varepsilon \)) between partners’ real behaviors (\( u^* \)) and the expected behaviors (\( u^* \)) should obey the Gaussian distribution which is \( \varepsilon \sim N(0, \sigma^2) \), where \( \varepsilon = u^* - a^* + b \times t^* \).

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 \( \hat{u}_i(\hat{u}_i \leq u_{i+1}) \) indicates the real utility value the agent gained from its partners. We transform all pairs \( (t_i, \hat{u}_i)(i \in [0, n]) \) to \( (t_i^*, \hat{u}_i^*) \) by using \( t_i^* = \ln(t_i) \) and \( \hat{u}_i^* = \ln(\hat{u}_i) \).

Because for each \( \hat{u}_i^* = a^* + b \times t_i^* + \varepsilon_i \), \( \varepsilon_i \sim N(0, \sigma^2) \), \( \hat{u}_i^* \) is distinctive, then the joint probability density function for \( \hat{u}_i^* \) is:

\[
L = \prod_{i=1}^{n} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{1}{2\sigma^2}(\hat{u}_i^* - a^* - bt_i^*)^2\right] \\
= \left(\frac{1}{\sigma\sqrt{2\pi}}\right)^n \exp\left[-\frac{1}{2\sigma^2} \sum_{i=1}^{n} (\hat{u}_i^* - a^* - bt_i^*)^2\right] 
\]  

(3)

In order to make \( L \) to achieve its maximum, obviously \( \sum_{i=1}^{n} (\hat{u}_i^* - a^* - bt_i^*)^2 \) should achieve its minimum value. Let \( Q(a^*, b) = \sum_{i=1}^{n} (\hat{u}_i^* - a^* - bt_i^*)^2 \), we calculate the first-order partial derivative for \( Q(a^*, b) \) on both \( a^* \) and \( b \), and let the results equal to zero, which are shown as follows:

\[
\begin{align*}
\frac{\partial Q}{\partial a^*} &= -2 \sum_{i=1}^{n} (\hat{u}_i^* - a^* - bt_i^*) = 0, \\
\frac{\partial Q}{\partial b} &= -2 \sum_{i=1}^{n} (\hat{u}_i^* - a^* - bt_i^*)t_i^* = 0.
\end{align*}
\]  

(4)

Then it equals:

\[
\begin{align*}
na^* + (\sum_{i=1}^{n} t_i^*)b &= \sum_{i=1}^{n} \hat{u}_i^*, \\
(\sum_{i=1}^{n} t_i^*)a^* + (\sum_{i=1}^{n} t_i^{*2})b &= \sum_{i=1}^{n} t_i^* \hat{u}_i^*.
\end{align*}
\]  

(5)

Because Equation 5 is coefficient matrix is:

\[
\begin{vmatrix}
\sum_{i=1}^{n} t_i^* \\
\sum_{i=1}^{n} t_i^{*2}
\end{vmatrix}
= n \sum_{i=1}^{n} t_i^{*2} - (\sum_{i=1}^{n} t_i^*)^2 = n \sum_{i=1}^{n} (t_i^* - \bar{t})^2 \neq 0
\]  

(6)
So parameters $a^*$ and $b$ have their unique solutions, which is

$$
\begin{align*}
    b &= \frac{n \sum_{i=1}^{n} t_i^* \hat{u}_i^* - (\sum_{i=1}^{n} t_i^*) (\sum_{i=1}^{n} u_i^*)}{n \sum_{i=1}^{n} t_i^* (t_i^* - (\sum_{i=1}^{n} t_i^*)^2)}, \\
    a^* &= \frac{1}{n} \sum_{i=1}^{n} \hat{u}_i^* - \frac{b}{n} \sum_{i=1}^{n} t_i^*.
\end{align*}
$$

(7)

In order to simplify the solution, let

$$
\begin{align*}
    S_{xx} &= \sum_{i=1}^{n} t_i^* (t_i^* - (\sum_{i=1}^{n} t_i^*)^2), \\
    S_{yy} &= \sum_{i=1}^{n} \hat{u}_i^* (\hat{u}_i^* - (\sum_{i=1}^{n} \hat{u}_i^*)^2), \\
    S_{xy} &= \sum_{i=1}^{n} t_i^* \hat{u}_i^* - \frac{1}{n} (\sum_{i=1}^{n} t_i^*) (\sum_{i=1}^{n} \hat{u}_i^*).
\end{align*}
$$

(8)

Then $a^*, b$ are represented as:

$$
\begin{align*}
    b &= \frac{S_{xy}}{S_{xx}}, \\
    a^* &= \frac{1}{n} \sum_{i=1}^{n} \hat{u}_i^* - \left( \frac{1}{n} \sum_{i=1}^{n} t_i^* \right) b.
\end{align*}
$$

(9)

and finally $a = e^{a^*}$.

4 Partners’ Behaviors Prediction

In last section, we proposed a power regression function to predict partners’ behaviors, and also specified how to decide parameters $a$ and $b$. However, it has to be mentioned that the proposed power regression function can only provide an estimation on partners’ possible behaviors, which might not exactly accord with the partners’ real behaviors. In reality, the real behaviors should similar to the estimation behaviors, and the more similar to the estimated behaviors, the higher probability it may happen. So we can deem that the differences ($\varepsilon$) between the estimation behaviors and the real behaviors obey the Gaussian distribution $N(\varepsilon, \sigma^2)$. Thus, if the deviation $\sigma^2$ can be calculated, we can make a precise decision on the range of partners’ behaviors. It is known that there is more than 99% probability that partners’ expected behaviors locate in the interval $[u - 3\sigma, u + 3\sigma]$. In this section, we introduce the proposed way to calculate the deviation $\sigma$ and to estimate the interval for partners’ behaviors.

In order to calculate the deviation $\sigma$, we firstly calculate the distance between the estimation results ($u_i$) and the real results on partners’ behaviors ($\hat{u}_i$) as $d_i = \hat{u}_i - u_i$. It is known that all $d_i$ ($i \in [1, n]$) obey the Gaussian distribution $N(0, \sigma^2)$, where $\sigma = \sqrt{\frac{\sum_{i=1}^{n} (d_i - \bar{d})^2}{n}}$ and $\bar{d} = \frac{1}{n} \sum_{i=1}^{n} d_i$. By employing the Chebyshev’s inequality, we can calculate (1) the interval of partners’ behaviors according to any accuracy requirements; and (2) the probability that any particular behavior may happen on potential partners in future.

5 Experiments

In this section, we demonstrate several experiments to test our proposed regression analysis approach. We display an overview table and figure about all
estimated results in each negotiation cycle, and a particular curve to show the situation in the last negotiation cycle. Also, we compare the proposed power regression approach with the Tit-For-Tat approach and random approach. The experimental results illustrate the outstanding performance of our proposed approach. In order to simplify the implementation process, all agents in our experiment employ the NDF negotiation strategy. The partners’ behaviors cover all possible situations in reality, which are conceder, linear and boulware.

5.1 Scenario 1

In the first experiment, a buyer wants to purchase a mouse pad from a seller. The acceptable price for the buyer is in [$0, $1.4]. The deadline for the buyer to finish the purchasing process is 11 cycles. In this experiment, the buyer adopts conceder behavior in the negotiation, and the seller employs the proposed approach to estimate the buyer’s possible price in the next negotiation cycle. The estimated results in each negotiation cycle are displayed in Table 1. Each row in Table 1 illustrates the estimation result in each negotiation cycle in the form of estimated power regression function, estimation results ($\mu$), and deviation ($\sigma$). For example, it can be seen in the 7th negotiation cycle, according to instances, the proposed approach estimates a price of $1.26 from the buyer in the next cycle. Then according to the historical record in the 8th cycle, the real price given by the buyer in this cycle is $1.27 which is very close to the estimation price. In Figure 1, we illustrate the situation on the tenth negotiation cycle. It can be seen that the accuracy of the estimation is very high because all estimated prices are in the interval of [$\mu - 2\sigma, \mu + 2\sigma$] except the 4th and 5th negotiation cycle, and all estimated results are almost exactly same as the real prices. For example, the estimation prices for 2th, 3th and 8th are $1.06$, $1.12$ and $1.26$, respectively. While the real prices given by the buyer in these cycles are $1.07$, $1.13$, and $1.26$, which almost have no difference with the real ones. Lastly, we also did a comparison between the proposed approach and other two estimation approaches (Tit-For-Tat and random approach). In Figure 2, the comparison results are illustrated. It can be seen that even though the Tit-For-Tat approach can follow the trend of buyer’s price changing, the errors (10% of acceptable price span in average) are also very big. The random approach even cannot catch the main trend. The experimental results convince us that the proposed approach outperforms both Tit-For-Tat and random approaches very much when a buyer adopts conceder negotiation behavior.

5.2 Scenario 2

In the second experiment, a buyer wants to buy a keyboard from a seller. The desired price for the buyer is in the interval of [$0, $14]. We let the buyer employ the linear negotiation strategy, and still set the deadline to 11 cycles. The estimated results are displayed in Table 2. For example, in the 6th cycle, the estimated price is $7.57 and the real price is $7.4. In Figure 3, the situation
Table 1. Prediction results for scenario 1

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Instance</th>
<th>Power regression function</th>
<th>Estimated function $(\mu, \sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>(0.98, 1.07)</td>
<td>$\text{price}=0.98 t^{0.14}$</td>
<td>(1.14, 0.00)</td>
</tr>
<tr>
<td>3</td>
<td>(0.98, 1.07, 1.12)</td>
<td>$\text{price}=0.98 t^{0.13}$</td>
<td>(1.17, 0.00)</td>
</tr>
<tr>
<td>4</td>
<td>(0.98, 1.07, 1.12, 1.13)</td>
<td>$\text{price}=0.98 t^{0.11}$</td>
<td>(1.18, 0.01)</td>
</tr>
<tr>
<td>5</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14)</td>
<td>$\text{price}=0.99 t^{0.10}$</td>
<td>(1.18, 0.02)</td>
</tr>
<tr>
<td>6</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14, 1.23)</td>
<td>$\text{price}=0.98 t^{0.11}$</td>
<td>(1.22, 0.02)</td>
</tr>
<tr>
<td>7</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26)</td>
<td>$\text{price}=0.98 t^{0.12}$</td>
<td>(1.26, 0.02)</td>
</tr>
<tr>
<td>8</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27)</td>
<td>$\text{price}=0.97 t^{0.12}$</td>
<td>(1.28, 0.02)</td>
</tr>
<tr>
<td>9</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27, 1.30)</td>
<td>$\text{price}=0.97 t^{0.13}$</td>
<td>(1.30, 0.02)</td>
</tr>
<tr>
<td>10</td>
<td>(0.98, 1.07, 1.12, 1.13, 1.14, 1.23, 1.26, 1.27, 1.30, 1.32)</td>
<td>$\text{price}=0.97 t^{0.13}$</td>
<td>(1.32, 0.02)</td>
</tr>
</tbody>
</table>

on the 10th cycle is displayed. It can be seen that the estimated power regression function fits the real prices very well. In Figure 2 the comparison results among Tit-For-Tat approach, random approach and our proposed approach is illustrated. It can be seen that errors between the estimated prices and the real prices is the smallest value by employing the proposed approach, while it is the biggest value by employing the random approach. Even the Tit-For-Tat approach can fellow partner’s trend, but distances between the estimated prices and the real prices are also very big. The second experimental results demonstrate that when partners perform as the linear behaviors, the proposed approach also outperforms other two approaches used for agents’ behavior estimation.
Table 2. Prediction results for scenario 2

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Instance</th>
<th>Power regression function</th>
<th>Estimated function $(\mu, \sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>(0.79, 1.50)</td>
<td>price=$0.79t^{1.94}$</td>
<td>(2.20, 0.00)</td>
</tr>
<tr>
<td>3</td>
<td>(0.79, 1.50, 3.15)</td>
<td>price=$0.74t^{1.23}$</td>
<td>(4.09, 0.21)</td>
</tr>
<tr>
<td>4</td>
<td>(0.79, 1.50, 3.15, 4.35,)</td>
<td>price=$0.74t^{1.26}$</td>
<td>(5.62, 0.18)</td>
</tr>
<tr>
<td>5</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09)</td>
<td>price=$0.75t^{1.22}$</td>
<td>(6.71, 0.24)</td>
</tr>
<tr>
<td>6</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09, 5.74)</td>
<td>price=$0.77t^{1.17}$</td>
<td>(7.57, 0.34)</td>
</tr>
<tr>
<td>7</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40,)</td>
<td>price=$0.77t^{1.11}$</td>
<td>(8.77, 0.31)</td>
</tr>
<tr>
<td>8</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94)</td>
<td>price=$0.79t^{1.15}$</td>
<td>(9.76, 0.35)</td>
</tr>
<tr>
<td>9</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94, 8.55)</td>
<td>price=$0.80t^{1.12}$</td>
<td>(10.62, 0.42)</td>
</tr>
<tr>
<td>10</td>
<td>(0.79, 1.50, 3.15, 4.35, 5.09, 5.74, 7.40, 7.94, 8.55, 10.15)</td>
<td>price=$0.81t^{1.11}$</td>
<td>(11.68, 0.40)</td>
</tr>
</tbody>
</table>

5.3 Scenario 3

In the third experiment, a buyer wants to purchase a monitor from a seller. The suitable price for the buyer is in [0, $250]. In this experiment, the buyer employs a boulware strategy in the negotiation. The deadline is still 11 cycles. According to Table 3, the estimated power regression function at the $10th$ cycle is $price = 0.64 \times t^{2.45}$. Also, the result estimated that it is more than 68.2% that the real price at the $11th$ cycle is in [222.17, 236.07]. According to Figure 5, it can be seen that the estimated power function almost exactly fits all the real prices given by the buyer. Therefore, the seller could have enough reasons to trust and adopt the estimation result for the next cycle. Finally, the Figure 6...
illustrates the comparison results with other two estimation functions. It can be seen that when the agent performs a boulware behavior, the proposed approach outperforms other two approaches.

From the experimental results in the above three experiments on three general kinds of agents, we can say that the estimated power function regression approach can estimate partners’ potential behaviors successfully, and also the estimation results are accurate and reasonable enough to be adopted by agents to modify their strategies in negotiation. The comparison results among three types of agents’ behaviors estimation approaches demonstrate the outstanding performance of our proposed approach.

Fig. 5. Prediction results for scenario 3  
Fig. 6. Results comparison for scenario 3

<table>
<thead>
<tr>
<th>Cycle</th>
<th>Instance</th>
<th>Power regression function</th>
<th>Estimated $(\mu, \sigma)$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>(0.59, 4.71)</td>
<td>price=0.59$t^{3.91}$</td>
<td>(15.95, 0.00)</td>
</tr>
<tr>
<td>3</td>
<td>(0.59, 4.71, 8.06)</td>
<td>price=0.65$t^{2.45}$</td>
<td>(19.50, 1.11)</td>
</tr>
<tr>
<td>4</td>
<td>(0.59, 4.71, 8.06, 21.94)</td>
<td>price=0.64$t^{2.32}$</td>
<td>(36.60, 1.27)</td>
</tr>
<tr>
<td>5</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51)</td>
<td>price=0.67$t^{2.30}$</td>
<td>(49.70, 2.59)</td>
</tr>
<tr>
<td>6</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51, 46.12)</td>
<td>price=0.68$t^{2.38}$</td>
<td>(69.68, 2.36)</td>
</tr>
<tr>
<td>7</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45)</td>
<td>price=0.67$t^{2.41}$</td>
<td>(99.99, 3.50)</td>
</tr>
<tr>
<td>8</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38)</td>
<td>price=0.67$t^{2.41}$</td>
<td>(132.56, 3.29)</td>
</tr>
<tr>
<td>9</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38, 148.86)</td>
<td>price=0.65$t^{2.43}$</td>
<td>(176.42, 5.15)</td>
</tr>
<tr>
<td>10</td>
<td>(0.59, 4.71, 8.06, 21.94, 27.51, 46.12, 78.45, 99.38, 148.86, 199.08)</td>
<td>price=0.64$t^{2.43}$</td>
<td>(229.12, 6.95)</td>
</tr>
</tbody>
</table>
6 Related Work

In this section, we introduce some related works and give discussions on the proposed approach. In [10], Schapire et al. proposed a machine learning approach based on a boosting algorithm. In the first place, the estimation problem is reduced to a classification problem. All training data are arranged in ascending order and then partitioned into groups equally. For each of the breakpoints, a learning algorithm is employed to estimate the probability that a new bid at least should be greater than the breakpoint. The final result of this learning approach is a function which gives minimal error rate between the estimated bid and the real one. Based on this function, agents’ behaviors can be estimated. However, the accuracy of this approach is limited by the training data and classification approach. So applications based on this approach can hardly achieve a satisfactory level when negotiations happen in an open and dynamic environment.

In [11], Gal and Pfeffer presented another machine learning approach based on a statistical method. The proposed approach is trained by agents’ behaviors according to their types firstly. Then for an unknown agent, it will be classified into a known kind of agents according to their similarities. Finally, based on these probabilities, the unknown agent’s behavior is estimated by combining all known agents’ behaviors. The limitation of this approach is that, in reality, it is impossible to train a system with all different types of agents. Therefore if an unknown agent belongs to a type which is excluded in the system, the estimation result may not reach an acceptable accuracy level.

Chajewska et al. [7] proposed a decision-tree approach to learn and estimate agent’s utility function. The authors assumed that each agent is rational which looks for maximum expected utility in negotiation. Firstly, a decision tree is established which contains all possible endings for the negotiation. Each possible ending is assigned with a particular utility value and possibility. Based on the partner’s previous decisions on the decision tree, a linear function can be generated to analogy the partner’s utility function, and each item in the function comes from an internal node on the decision tree. The limitation of this approach is the requirement that all possible negotiation endings and the corresponding probabilities should be estimated in advance, which is impossible in some application domains when the variance of negotiation issues is discrete or the negotiation environment is open and dynamic.

Brzostowski and Kowalczyk [12] presented a way to estimate partners’ behaviors based only on the historical offers in the current negotiation. In this first place, partners’ types are estimated based on the given functions. For each type of agents, a distinct prediction function is given to estimate agents’ behaviors. Therefore, based on the classification about partners’ types and their individual estimation functions, the proposed approach can predict partners’ behaviors in next negotiation cycle. However, a partner can only perform as a time-dependent agent or a behavior-dependent agent, which limits some applications. Also the accuracy of classification on partners’ types may impact the accuracy of prediction result.
By comparing our approach with the above estimation strategies on agents’ behaviors, our proposed approach has two attractive merits. (1) The proposed approach do not need any training or preparation in advance, and it can estimate partners’ behaviors based only on the current historical records and generate reasonable and accurate estimation results quickly and timely. Therefore, agents can save both space and time resources by employing the proposed approach; and (2) the proposed approach estimates partners’ possible behaviors in the form of interval, and the probability that each particular behavior will happen in the future is also represented by the proposed power regression function. Therefore, agents can adopt the estimation results by the proposed approach much easier and more convenient to administrate their own negotiation behaviors in future.

7 Conclusion and Future Work

In this paper, we proposed power regression function to estimate partners’ behaviors in negotiation. We introduced the procedures to calculate the parameters in the regression function, and the method to predict partners possible behaviors. The experimental results demonstrate that the proposed approach is novel and valuable for the agents’ behaviors estimation because (1) it is the first time that the regression analysis approach is applied on the agents’ behaviors estimation; (2) the proposed approach does not need any training process in advance; (3) the representation format of the estimation results is easy to be further adopted by agents; and (4) the probability that each estimation behavior will happen in future on partners is also a significant criterion for agents to dominate their own behaviors in future.

The future works of this research will focus on two directions. Firstly, the multi-attribute negotiation is another promoting issue in recent years. Therefore, one of the emphases in our future works is to extend the proposed approach from the single-issue negotiation to the multi-issue negotiation. Secondly, as the negotiation environment becomes more open and dynamic, the proposed approach should be extended in order to predict not only agents’ possible behaviors, but also impacts from potential changes on the negotiation environment.

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