An Efficient Technique for Detecting Time-dependent Tactics in Agent Negotiations

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Abstract: The paper proposes an efficient technique for detecting a negotiation strategy used by an opponent during the encounter. It is based on simple transforms that transform the series of offers into a series of values determining the shape of the observed concession curve. It allows for detecting whether the partner is using a time-dependent tactic and what is the specific tactic through determination of the beta parameter used on the side of the negotiation partner. Such information can be further used in choosing a negotiation strategy that can cope with a particular type of the opponent behaviour, and thus improving the negotiation outcomes.

1 INTRODUCTION

Negotiation is process of exchanging offers and counter-offers between parties with conflicting interests that aims at finding a solution satisfying the interests of parties taking part in this interaction (Jennings et al., 2001). There are variety of approaches of learning and reasoning during the negotiation process.

Zeng and Sycara (Zeng and Sycara, 1996) propose a learning approach based on Bayesian updating of beliefs about the environment and negotiation partner. Li and Tesauro (Li and Tesauro, 2003) proposed an approach based on approximate optimization of expected utility using depth-limited combinatorial search and Bayesian updating. The work of Hindriks and Tykhonov (Hindriks and Tykhonov, 2008) proposes to employ Bayesian learning to learn the preference of the negotiation partner assuming a very specific form of the preferences. However, such approaches focus on learning the preferences' structure but not the negotiation strategy. Oliveira and Rocha (Oliveira and Rocha, 2000) propose a framework for multi-issue negotiation between agents where the bid formation is supported by reinforcement learning. This approach is used for both learning from previous interaction and learning from the current encounter.

Work by Nastase (Nastase, 2006) presents a concession curve analysis which is used to predict the negotiation outcomes based on the features of the concession curve. Our approach is suitable for automated negotiation and aims at extracting just one parameter describing the shape of concession curve and its nature is different from the nature of parameters exctracted in the work of Nastase that are suitable in the analysis of negotiations conducted by humans.

Works such as (Oliver, 1997)(Matos et al., 1998)(Gerding and Somefun, 2006) employ evolutionary computing to determine the optimal profile of negotiation strategies. The works by Hou (Hou, 2004) Ren and Zhang (Ren and Zhang, 2007) and the work (Brzostowski, 2007) propose to predict the concession curve using regression analysis. In this work we propose simpler method of prediction based on concession curve transforms which is computationally very cheap. The proposed approach overcomes the problem of wrong estimation of parameters encountered sometimes by regression analysis, and it gives high level of certainty that the time-dependent tactic is used when it is actually used.

The paper is structured as follows. In the second section we recall the concept of decision functions. The third section presents the transforms used to transform the series of partner's offers that is further used to determine the parameter corresponding to the shape of concession curve. The fourth section presents an evaluating experiment allowing for validation of the proposed technique. The fifth section presents conclusions.

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2 DECISION FUNCTIONS

In this work we will consider the acceptance region in a form of interval containing real numbers. Multiple attributes will be consider in further work. The negotiation agent can use a decision function for generating offers that it is going to propose. The decision function is a function mapping a time point into the value of offer. The time point corresponds to the current negotiation moment. The decision function may be dependent on different types of parameters and values. Among them there can be negotiation deadline, the borders of acceptance range and other formal descriptions of agent preferences. There are variety of ways of implementing negotiation strategy in a form of decision function. Faratin (Faratin et al., 1998) proposed different types of tactics which can be used to generate negotiation behaviour. Three types of tactics were proposed in his approach, namely: the time-dependent tactics, the behaviour-dependent tactics and resource-dependent tactics. This three types of tactics are called pure tactics. In this work we are only interested in the prediction of time-dependent tactic.

The objective of an agent is to reach an agreement with the negotiation partner in the time range $[0, t_{max}]$ (t_{max} - deadline). The tactic allows for generation of offer in each time point of this range. If before proposing the offer x an agent receives from the counterpart an offer y exceeding the value of x (in terms of utility value) then the agent accepts y. The time-dependent tactic is constructed in such a way that during the whole encounter an agent will concede up to the reservation value when it meets deadline. If an agent a using that type of tactic wants to propose an offer $x^t_{a\to b}$ for the issue j at time t ($0 \leq t \leq t_{max}$) then that offer can be generated in the following way (Faratin et al., 1998):

$$x^t_{b\to a}[j] = \begin{cases} \min^a_j + \alpha^a_j(t)(\max^a_j - \min^a_j) & \text{if } U^a_j \text{ is decreasing} \\ \min^a_j + (1-\alpha^a_j(t))(\max^a_j - \min^a_j) & \text{if } U^a_j \text{ is increasing} \end{cases}$$

where min^a_j and max^a_j are the boundaries of the acceptance range of the issue j of the agent a. The function $\alpha^a_j(t)$ is a function defined over time giving values in the interval $[0,1]$ ($0 \leq \alpha^a_j(t) \leq 1$) that can be further rescaled to fit the space in which the agent is conceding. Faratin (Faratin et al., 1998) proposed two families of functions used to implement the time-dependent tactic, namely, polynomial and exponential as follows:

- **Polynomial:** $\alpha^a_j(t) = k^a_j + (1-k^a_j)(\frac{min(t, t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}$
- **Exponential:** $\alpha^a_j(t) = e^{(1-\frac{min(t, t^a_{max})}{t^a_{max}})^{\beta} ln k^a_j}$

where k^a_j is the initial concession of agent a and β specifies the way of conceding (shape of concession curve).

3 TIME-DEPENDENT TACTICS TRANSFORMS

Let us consider a function transform of the following form:

$$F^1_\beta(f)(x) = \frac{Log(\frac{f(x)-f(0)}{f(t_e)-f(0)})}{Log(x) - Log(t_e)} \quad (1)$$

where $t_e \in (0, x)$. We will prove that this transform can transform the polynomial decision function into very simple function which is constant and equals to β value.

Theorem 1. *Let the function f be defined in the form of polynomial decision function:*

$$f(t) = min^a_j + (k^a_j + (1-k^a_j)(\frac{min(t, t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}})(max^a_j - min^a_j)$$

The transform F^1_β transforms the function f into constant function which equals $\frac{1}{\beta}$ for all values of the domain ($x \in [0, t^a_{max}]$).

Proof. $f(0) = \min^a_j + k^a_j(\max^a_j - \min^a_j)$

$$F^1_\beta(f)(x) = \frac{Log(\frac{(1-k^a_j)(\frac{min(x,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}(\max^a_j - \min^a_j)}{(1-k^a_j)(\frac{min(t_e,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}(\max^a_j - \min^a_j)})}{Log(x) - Log(t_e)} = $$

$$= \frac{Log(\frac{(\frac{min(x,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}}{(\frac{min(t_e,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}})}{Log(x) - Log(t_e)}$$

We make a simplifying assumption that x does not exceed t^a_{max}, then:

$$F^1_\beta(f)(x) = \frac{\frac{1}{\beta}Log(\frac{x}{t_e})}{Log(x) - Log(t_e)} = \frac{1}{\beta}$$

□

Let us now consider a transform of the following form:

$$F^2_\beta(f)(x) = \frac{\frac{x\partial f(x) - f(0)}{\partial x}}{f(x) - f(0)} \quad (2)$$

we will prove that this transform acts similarly to the transform F^1_β.

Theorem 2. *Let the function f be defined in the form of polynomial decision function:*

$$f(t) = min^a_j + (k^a_j + (1-k^a_j)(\frac{min(t,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}})(max^a_j - min^a_j)$$

The transform F^2_β transforms the function f into constant function which equals $\frac{1}{\beta}$ for all values of the domain ($x \in [0, t^a_{max}]$).

Proof.

$$F^2_\beta(f)(x) = \frac{x\frac{\partial(1-k^a_j)(\frac{min(x,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}}{\partial x}}{(1-k^a_j)(\frac{min(x,t^a_{max})}{t^a_{max}})^{\frac{1}{\beta}}}$$

Let us further assume that $x \in [0, t^a_{max}]$ then

$$F^2_\beta(f)(x) = \frac{\frac{1}{\beta}\frac{x}{t^a_{max}}(\frac{x}{t^a_{max}})^{\frac{1}{\beta}-1}}{(\frac{x}{t^a_{max}})^{\frac{1}{\beta}}} = \frac{1}{\beta}$$

□

As we have shown in the case of time-dependent tactic there exist transforms that allow to determine the value of β parameter when the agent is using time-dependent tactic generated with the use of polynomial decision function. However, the transforms work for continuous functions. Therefore, we form linearly interpolated function $g(x)$ from the concession curve and then we transform the obtained function into functions h^1 and h^2 using two transformation methods. In the next step we sample the transforms in hypothetical points densly selected from the domain of transforms. The obtained series h^1_i and h^2_i are averaged to approxiamate the value of β and the standard deviations for series are computed. The deviations are used to determine the level of certainty that the polynomial decision function was used by the predicted partner.

4 EVALUATING EXPERIMENT

We run 25 negotiations for different values of β parameters for both parties using the polynomial decision function. For a fixed value of deadline (common for both parties), aspiration levels and reservation values we run negotiations for differing values of β parameter (five possible values for both parties). We set up the experiment in the following way: For the first party (party a with one issue):

$$min^a = 15 \quad max^a = 25 \quad t^a_{max} = 20$$

For the second party (party b with one issue):

$$min^b = 10 \quad max^a = 20 \quad t^b_{max} = 20$$

As shown in the Table 1 the estimations of the value

Table 1: The values of β estimated from the view point of the first party for the second party using the mean value of series h^1_i.

$\frac{1}{\beta}(a)$ / $\frac{1}{\beta}(b)$	0.1	0.5	1	2	10
0.1	0.0986	0.0996	0.0997	0.0998	0.0998
0.5	0.4990	0.4993	0.4994	0.4995	0.4995
1	1	1	1	1	1
2	2.004	2.003	2.003	2.003	2.002
10	10.1274	10.1274	10.1274	10.1159	10.1159

Table 2: The values of standard deviations for series h^1_i for different negotiation scenarios analogous to the first Table.

$\frac{1}{\beta}(a)$ / $\frac{1}{\beta}(b)$	0.1	0.5	1	2	10
0.1	0.0006	0.0005	0.0004	0.0003	0.0003
0.2	0.0014	0.0012	0.0011	0.0010	0.0009
1	0	0	0	0	0
5	0.0088	0.0086	0.0083	0.0081	0.0079
10	0.311	0.311	0.311	0.307	0.307

β parameter determined with the transform approach are quite precise. This means that it is possible to determine the strategy that agent b used using simple method of sequence of offers transformations. The next Table (2) presents the standard deviations (namely how the estimated value of β deviates from the mean value of β over the negotiation scenario). For all β values the standard deviations are close to zero. Low standard deviations means that we have high degree of confidence that the estimated values of β are close to the actual values of β. One exception is the value of β equal to 10 where the standard deviation is around 0.311. Therefore, the certainty that the β value 10 was used is lower. The reason for lower certainty in this case is the shape of concession curve which is quite flat up to the solving negotiation round. The Table 3 presents the estimations of β value for the second type of transform in analogous way as the first Table. As we can see the results are similar; the estimations are close to the actual value of β used by the counterpart. However, as we can see in

Table 3: The values of β estimated from the view point of the first party for the second party using the mean value of series h^2_i.

$\frac{1}{\beta}(a)$ / $\frac{1}{\beta}(b)$	0.1	0.5	1	2	10
0.1	0.0996	0.0995	0.0995	0.0996	0.0999
0.5	0.4987	0.4988	0.4989	0.4989	0.49986
1	1	1	1	1	1
2	2.0082	2.0080	2.0078	2.0073	1.9919
10	10.2397	10.2397	10.2397	9.97882	9.97882

Table 4: The values of standard deviations for series h_i^2 for different negotiation scenarios analogous to the third Table.

$\frac{1}{\beta}(b)$ \ $\frac{1}{\beta}(a)$	0.1	0.5	1	2	10
0.1	0.0094	0.0054	0.0045	0.0040	0.0038
0.2	0.0152	0.01266	0.01179	0.0110	0.0107
1	0	0	0	0	0
2	0.0093	0.0906	0.880	0.0858	0.09393
10	4.6394	4.6394	4.6394	4.6499	4.6499

Table 5: The values of estimated β parameters by the use of nonlinear regression analysis.

$\frac{1}{\beta}(b)$ \ $\frac{1}{\beta}(a)$	0.1	0.5	1	2	10
0.1	0.388	0.0297	0.0331	0.3524	0.03727
0.2	0.4987	0.4989	0.4990	0.4991	0.4992
1	1	1	1	1	1
2	2	2	2	2	2
10	10	10	10	10	10

Table 4 the standard deviations for the β value equal to 10 are quite high (around 4.6394). Similarly, as in the case of first transform the reason for that is the flatness of the concession curve generated using the β value equal to 10.

As we can see in the Table 5 the values of β estimated with the use of non-linear regression analysis are very precise except for small values of $\frac{1}{\beta}$. The reason for this is that the regression algorithm gets stucked in the local minimum while estimating β value. That may happen for sharp values of β parameters such as 0.1 That is were the method based on transforms outperforms the regression-based approach. Low number of data causes the regression algorithm to obtain wrong estimations. As we can see in Table 6 the values of estimated variance are very close to 0 for all estimated values of β which means the result of regression analysis may be quite misleading when the algorithm gets stucked in local minimum. Such a result is obtained in the first row (when estimating the value 0.1). The value of estimated variance indicates how certain we are that the polynomial time-dependent tactic was used. The method based on transforms manages to estimate the value of β quite precisely even if the certainty (standard deviation) that the polynomial time-dependent tactic was used is not very high.

Table 6: The values of estimated variance (approximations) obtained by the regression algorithm when estimating the values of β.

$\frac{1}{\beta}(b)$ \ $\frac{1}{\beta}(a)$	0.1	0.5	1	2	10
0.1	0	0.000158	0.000252	0.000311	0.000377
0.2	0	0	0	0	0
1	0	0	0	0	0
2	0	0	0	0	0
10	0	0	0	0	0

5 CONCLUSIONS

We proposed a novel approach for detecting the time-dependent tactic used by the negotiation partner. We use simple transforms to transform the series of offers into a series of values indicating what value of β parameter is used on the side of the negotiation partner. Using this method we are able to determine if the partner is using time-dependent tactics. Moreover, we are able to determine the β parameter used by partner. Such an approach may be further used to choose a negotiation strategy that can cope with a particular type of behaviour.

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