Fuzzy Components for Negotiating Agents Architectures

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1 The Negotiation Model

In this paper we explore an existing model of negotiation [9, 6] based on a set of mutually influencing two-parties, many-issues negotiation. This negotiation model can operate in a wide range of environments and has a large number of parameters that need to be fixed for each step of the negotiation.

This paper sketches two types of agent architectures: *Fuzzy* and *Case-Based.* At each step of the negotiation process the agents fix a weighted combination of tactics to employ and the parameter values related to these tactics by different means: using a set of fuzzy rules or a base of cases. The aim of the research is to study the evolution of agent populations built with these two architectures: fuzzy and case-based applying Genetic Algorithms [2]. The ultimate goal is to determine which negotiation strategy is more successful.

Negotiation can range over a number of quantitative and qualitative issues, $x_1, \cdots, x_n$. Quantitative issues could describe aspects like price, longitude, and are defined over a real domain, $x_j \in \mathcal{D}_j = [min_j, max_j]$. Qualitative issues describe aspect like color, brightness, and are defined over a totally ordered domain, $x_k \in \mathcal{D}_k = \langle e_1, \cdots, e_m \rangle$ where $e_1, \cdots, e_m$ are linguistic labels.

Each agent has a scoring function $V_j^a : \mathcal{D}_j^a \rightarrow [0,1]$ that gives the score agent a assigns to the value x of issue j in the range of its acceptable values $\mathcal{D}_j^a$. The scoring functions are either monotonically increasing or decreasing. When an agent receives an offer, it rates it using a function that combines the scores of the different issues in the following way:

$$V^a(x) = \sum_{1 \leq j \leq n} w_j^a V_j^a(x_j)$$

where w_j^a is the importance of issue j for agent a. We assume the weights are normalised. If the score of the received offer is greater than that of the counter offer the agent would send at this point, then the offer is accepted. If the pre-established deadline (t_{max}^a) by when the negotiation must have completed is reached, the offer is rejected. Otherwise, a counter offer is submitted.

We denote by $x_{a \rightarrow b}^t$ the offer proposed by agent a to agent b at time t, and $x_{a \rightarrow b}^t[j]$ be the value for issue j. A *Negotiation Thread* between agents $a, b \in Agents$, at time t_n, noted $X_{a \leftrightarrow b}^{t_n}$, is any finite sequence of offers and counter-offers between both agents.

Lineal combinations of functions called *tactics* generate offers and counter-offers. In this case, the tactics are assigned a weight to indicate their relative importance. As the negotiation proceeds, new criteria may become relevant and the relative importance of existing criteria may vary. To reflect this fact, an agent has a *strategy* which varies the weights of the different tactics over time in response to various environmental and negotiation cues (section 1.2).

1.1 Tactic Families

A tactic generates a value for a single negotiation issue based upon a single criterion: time remaining and/or the behaviour of the opponent. If multiple criteria are important in determining the value of a negotiation issue, then multiple tactics can be combined.

Tactics may use the value of an isssue in a proposal to calculate a new value for that issue in a counter proposal. If the issue is qualitative its values are linguistic labels. To simplify the definition of tactics we deffuzify the labels using the centroid method and have tactics over a real domains.

1.1.1 Time-dependent tactics

These tactics consider the remaining negotiation time.

$$x_{a \rightarrow b}^t[j] = \begin{cases} min_j^a + \alpha^a(t)(max_j^a - min_j^a) & \text{If } V_j^a \text{ is dec} \\ min_j^a + (1 - \alpha^a(t))(max_j^a - min_j^a) & \text{If } V_j^a \text{ is inc} \end{cases}$$

Where $\alpha^a(t)$ is a polynomial function parameterised by a value $\beta \in \mathbb{R}^+$ that determines the convexity of the curve:

$$\alpha^a(t) = \left(\frac{t}{t_{max}^a} \right)^{\frac{1}{\beta}}$$

We have classified them into two sets which show clearly different behaviours: **Boulware** (don't start conceding until the deadline is nearly up) with $\beta \ll 1$, and **Conceder** (start giving ground fairly quickly) with $\beta \gg 1$.

1.1.2 Imitative tactics

These tactics generate the new offer depending on the opponent's behaviour.

$$x_{a \rightarrow b}^{t_{n+1}}[j] = \begin{cases} min_j^a & \text{if } \; P \leq min_j^a \\ max_j^a & \text{if } \; P > max_j^a \\ P & \text{otherwise} \end{cases}$$

The tactics differ depending on which aspect of the opponent's behaviour they imitate and to what degree, determine by P.

- **Relative Tit-For-Tat** (Relative-TFT)
The agent reproduces, in percentage terms, the behaviour that its opponent has performed.
$$P = \frac{x_{b\to a}^{t_{n-2\delta}}[j]}{x_{b\to a}^{t_{n-2\delta+2}}[j]} x_{a\to b}^{t_{n-1}}[j]$$
- **Absolute Tit-For-Tat** (Absolute-TFT)
The opponent behaviour is imitated in absolute terms. $P = x_{a\to b}^{t_{n-1}}[j] + x_{b\to a}^{t_{n-2\delta}}[j] - x_{b\to a}^{t_{n-2\delta}}[j]$
- **Averaged Tit-For-Tat** (Average-TFT)
The agent uses the average of the percentage change of its opponents to determine its offer.
$$P = \frac{x_{b\to a}^{t_{n-2\delta}}[j]}{x_{b\to a}^{t_n}[j]} x_{a\to b}^{t_{n-1}}[j]$$

1.2 Strategies

The negotiation strategy determines the best course of action to reach an agreement. The main point, in every step of the negotiation process, is to determine: which weighted combination of tactics to employ and the value of the parameters associated with these tactics. A *weighted counter proposal* is a linear combination of the tactics given by a matrix of weights Γ. Given a set of tactics, different types of negotiation behaviour can be obtained by weighting the tactics in a different way. That is, by changing the matrix Γ — particular to each negotiation thread.

The agents have a representation of its mental state (MS_a^t) at time t, which contains information about its beliefs, its knowledge of the environment (time, resources, etc.), and any other attitudes (desires, goals, obligations, intentions, etc.). A *Negotiation Strategy* for agent a is any function f such that, given a's mental state at time t_n, $MS_a^{t_n}$, and a matrix of weights at time t_n, $\Gamma_{a\to b}^{t_n}$, generates a new matrix of weights for time t_{n+1}, i.e. $\Gamma_{a\to b}^{t_{n+1}} = f(\Gamma_{a\to b}^{t_n}, MS_a^{t_n})$

In this paper we propose as negotiation strategy a *Set of Fuzzy Rules* and a *Case Base Reasoner* to determine at each step of the negotiation the Γ matrix and the parameters related to the used tactics.

2 Fuzzy Rules Agents

Systems based on fuzzy rules [4, 3] have proved to be an important tool to model complex systems. We had defined a type of agents that use a family of fuzzy rules to model the negotiation strategy. These rules analyse the environment to adjust the parameters and the weighted combination of tactics. The rules follow the following pattern:

Rule$_i$: **IF** x_1 is A_{i1} and ... and x_n is A_{in} **THEN** y is B_i

where $x_1, \cdots, x_n$ and y are the mental state variables and $A_{i1}, \cdots, A_{in}, B_i$ are linguistic labels of the variables $x_1, \cdots, x_n, y$ in the universe of discourse $U_1, \cdots, U_n, V$ of the variables. These linguistic labels are characterised by their membership functions $A_{ij} : U_j \to [0,1]$, $j = 1, \cdots, n$; $B_i : V \to [0,1]$ and have a trapezoidal shape.

For example: In the domain of the Real Estate Agency we could have the following rules:

- IF *agency is going_bankrupt* and $\gamma_{price,conceder}$ *is medium* THEN $\triangle\gamma_{price,boulware}$ *is positive_high*
If the Real Estate Agency is going bankrupt and we are not very tough in negotiating price, we change it by making the agent behave in a more boulware way, because it has, in such conditions, a higher opportunity of getting a lower price for a property.
- IF *time_on_sell is long* and $\gamma_{j,tft}$ *is high* THEN $\triangle\gamma_{j,boulware}$ *is positive_high*
If the Real Estate Agency has a property that wasn't sold for a long period we can obtain more profit by not conceding in the same way as the agency, because if the house has not been sold for a long time, means probably that its price is far beyond the reasonable one. In other words we should not imitate the conceding steps of the agency in the same amount, hence we increase our boulware behaviour for all issues.
- IF w_{bright} *is high* and *house is bright* and $\gamma_{surface,boulware}$ *is medium* THEN $\beta_{boulware}$=1
The agent behaves less boulware if it gives a lot of importance to brightness and it is a feature of the house being offered.

The following steps do the handling of this set of rules:

Fuzzification: The membership functions of the input variables about the current negotiation thread and the weighted tactics are applied to their actual values to determine the truth degree of each condition.
Rule Evaluation: In this process the truth value of the premise of each rule is propagated to the conclusions. The result of this process is the assignment of a fuzzy subset to some output variables.
Defuzzification: Our goal is to determine a new matrix Γ and values for the parameters associated to each tactic, for this reason we need to obtain an exact value for these variables. As we mentioned in section 1.1 we employ the centroid method to obtain the crisp values.
Normalisation: Finally, a normalisation of the values of gamma, Γ, obtained by defuzzification is done.

3 Case-Based Negotiating Agents

Case-based reasoning solve a new problem by adapting a previous similar situation [1, 5]. Using CBR terminology, a *case* in negotiation can be thought of as a negotiation process that has been stored and can be reused in solving new negotiation processes. The main tasks that a case-based negotiating agent has to deal with are the representation of the negotiation cases in its case base, the retrieval of a past case similar to the new one and the adaptation of its solution to the current negotiation process. Then the new offer is calculated using the weighted combination and the parameters gave by this case.

The Case Base, CB, is composed of a set of cases that represents those negotiation where the agent was involved. But also, CB is extended by negotiations performed by other agents. Cases in CB have a valuation that show how much this case has contributed to the solution of other cases.

Each case store information about the agents like: the set of resources and their relative importance, the t_{max}, the issues information, the negotiation thread, the Γ matrix and tactics parameters at each step of the negotiation and the scoring obtained.

3.1 Case Retrieval

The case retrieval process is executed concurrently with the other activities of a case-based agent. The objective is to find the case in CB *most similar* to the current negotiation. We denote by N the current negotiation. When an agent sends an offer, it immediately begins to retrieve those cases that are more similar to the current negotiation from its CB. When it receives a counter-offer to its offer it is incorporated into the negotiation thread and used to finally select the most similar case from those that were obtained in the meantime.

3.1.1 Filtering

Not all cases stored in CB can be compared with N for different reasons. This is why we build a subset F selecting from CB those cases that satisfy all the following criteria:

1. **Class of t_{deal}.** We divide CB into two classes that depend on the value of t_{deal} (the time that negotiation takes) with respect to a cut value θ: Short t_{deal}, with $C[t_{deal}] \leq \theta$, and Large t_{deal}, with $C[t_{deal}] > \theta$.

   The rationale here is that the negotiation strategies are radically different depending on how much time is available.
2. **Duration of negotiation.** With t being the time consumed so far in the current negotiation, we select the cases with a duration longer than the value of t, but not longer than the t_{max} defined in N. That is: $t < C[t_{deal}] \leq N[t_{max}]$.
3. **Sets of Issues**. We select the cases from CB that contain at least the set of issues of N for each step of the negotiation, to make the comparison between them possible. That is: $\forall k \leq t \quad S(N[Issues,k]) \subseteq S(C[Issues,k])$ where S is a function that transforms a vector into a set.
4. **Who began the negotiation and with which role?** Only the cases in which the agent that began the negotiation is the same as in N and had the same role are considered.

Hence, we define F as the set of cases that satisfy all criteria.

3.1.2 Final Selection

The cases that satisfied all the aforementioned criteria compose the set F from where we will select the most similar case with respect to the current negotiation. The similarity at time t between the case N and all the cases $C \in F$ is measured in the following way:

$$\begin{aligned} Sim(N,C,t) &= \rho_1 * \sum_{k=1}^{t-1} \frac{2k}{t(t-1)} * Sim\_Step(N,C,k) + \\ &\quad \rho_2 * C[Valuation] + \rho_3 * C[Utility] \end{aligned}$$

In this similarity measure we take into account three factors:

- The similarity between the offers of both cases for all previous instance k of the negotiation. With the factor $\frac{2k}{t*(t+1)}$ [1] we concede an increasing importance to the similarity of the offers in the last steps of the negotiation.
- The Valuation of the case, $C[Valuation] \in [0,1]$.
- The utility, $C[Utility] \in [0,1]$, obtained by this case during the negotiation. We define the utility as follow:

$$Utility = \tanh\left(\frac{V^a(x_c^{t_{deal}})}{V^a(x_c^{Nash})}\right)$$

  where $x_c^{t_{deal}}$ is the final deal, and x_c^{Nash} represents the deal that would be made at the Nash equilibrium point.

The factors $\rho_i \in [0,1]$ determine the relative relevance of the three elements mentioned in the similarity measure and satisfy: $\rho_1 + \rho_2 + \rho_3 = 1$. The similarity of cases will change by varying the value associated with each ρ_i.

The similarity degree between two offers is defined as:

$$\begin{aligned} Sim\_Step(N,C,k) = \sum_{j=i_1}^{i_n} AE\Bigg(&\frac{V_j^a(N[Thread,k,j])}{V_j^a(N[Thread,k+1,j])} * \\ &* \frac{V_j^a(C[Thread,k+1,j])}{V_j^a(C[Thread,k,j])}\Bigg) * N[weights,k,j] * \\ &* Sim\_Weight(N,C,k,j) \end{aligned}$$

with $N[issues,k] = [i_1, \cdots, i_{n_k}]$

In this function we take into account the similarity between the vector *Thread* for both cases. We consider a quotient between the scoring value for issue j in the step k and the scoring for the same issue in the step $k+1$. This quotient is computed for both cases, N and C, and then the quotient of both is the argument of the function $AE = Almost\_Equal$ that shows how close to 1 was the result.

Also the function *Sim_Step* consider the similarity between the vectors of weights of the case C and N. We give more importance to the similarty between those issues that agent a considers more relevant in the current step of negotiation. The similarity between the vectors of weight is calculated in the following way:

$$Sim\_Weight(N,C,k,j) = \frac{\left|N[weights,k,j] - \frac{C[weights,k,j]}{\aleph(N,C,k)}\right|}{card(N[issues,k])}$$

$$\aleph(N,C,k) = \sum_{j=i_1}^{i_n} C[weights,k,j]$$

3.2 Adaptation

The case with the highest similarity contains the vector of $Parameters_{t+1}$ and the Γ_{t+1} matrix; these elements are to be used in the next step of the negotiation process. However, this solution can be improved by adapting the values of the

[1] $\sum_{k=1}^{t-1} \frac{2k}{t(t-1)} = 1$; so we employ this component as a weighting mechanism that produces a normalised output.

$Parameters_{t+1}$ and the Γ_{t+1} to the current mental state (MS_a^{t+1}). This adaptation process is modelled by a set of *Adaptation Fuzzy Rules.* These rules represent conditions of the environment in which the agent acts and determine variations in the value of the parameters of the tactics and the γ_{ij}'s. In general these rules follow the following pattern:

Rule$_i$: **IF** x_1 is A_{i1} and ... and x_n is A_{in} **THEN** y is B_i

where $x_1, \cdots, x_n$ and y are the mental state variables and $A_{i1}, \cdots, A_{in}, B_i$ are linguistic labels of the variables $x_1, \cdots, x_n, y$ in the universe of discourse $U_1, \cdots, U_n, V$ of the variables. These linguistic labels are characterised by their membership functions $A_{ij} : U_j \rightarrow [0, 1]$, $j = 1, \cdots, n$; $B_i : V \rightarrow [0, 1]$ and have a trapezoidal shape.

In general the rule conditions express a state of the environment and the negotiation tactics. The rule consequents change the weighted combinations and the tactic parameters. A variation in a γ_{ij} generates automatically a normalisation of the rest of gammas.

Example: In the domain of the Real Estate Agency, we could have the following fuzzy rules:

IF *highway is near* and $\gamma_{price,boulware}$ *is medium* THEN $\triangle\beta_{boulware}$ *is negative_small*

IF *park is near* and $\gamma_{price,boulware}$ *is high* THEN $\triangle\gamma_{price,conceder}$ *is positive_high*

The linguistic labels *positive_high* represents a big positive number and *negative_small* a small negative number. If the first rule applies, the agent will behave in a more boulware fashion in all issues by decreasing its $\beta_{boulware}$ value. On the contrary (second rule) if a park is near the house and the agent's attitude to the price is mainly boulware, it will become more conceder, i.e. the $\gamma_{price,conceder}$ related to the conceder tactic increases the value and via the normalisation process $\gamma_{price,boulware}$ will decrease.

4 Evolving the Negotiation Strategies

GAs generate a sequence of ever improving ("fitter") populations as the outcome of a search method modelled by a *selection mechanism*, *crossover* (recombining existing genetic material in new ways) and *mutation* (introducing new genetic material into the population by random modifications) [7]. In our case we employ the GA to make an evolutionary approach of the *Fuzzy Rules*, of fuzzy agents, and the *Case Base* and the *Adaptation Fuzzy Rules* associated with Cased-Based agents. We form a population, where each agent becomes an individual, and model as genetic material the different sets of rules and/or the case base. The overall aim of the search in all cases is to find a set of rules and a base of cases that are optimally adapted for particular negotiation situations.

The genetic materials of the individuals model the negotiating agents. For both type of agents, fuzzy and CBR exist common information that is kept as a genetic material, for instance: the set resources, the set of issues, Γ matrix and tactics parameters. However those individuals that represents a fuzzy agents, also must keep a representation of the set of rules and in the CBR case a representation of it Case Memory and the adaptation fuzzy rules.

We form different populations for Fuzzy and CBR agents and we make evolve both populations to determine the best strategy in both cases. The fitness function measures how well was the agent's performance from the beginning until the last negotiation. To calculate the fitness function we perform a Tournament in which the agents may negotiate. We consider as fitness function the quotient between the scoring obtained at the end of all negotiations and the scoring obtained at the beginning of the negotiation.

$$F^a = V^a_{resource^{MT}} \div V^a_{resource^1}$$

Where $resource^1$ denote the resource at the beginning of the Tournament and $resource^{MT}$ at the end.

5 Conclusions

In this paper we presented the main technical ideas of our current work on automated negotiation. We presented two agent architectures for negotiation, *Case-Based* and *Fuzzy.* Three basic techniques: *Case-Based Reasoning, Fuzzy Sets and Genetic Algorithms* are used as the basis to make an evolutionary analysis of negotiation strategies. Over both architectures we propose an evolutionary study applying GA, to determine the best strategy for the negotiation model mentioned in this paper.

Many aspects of these architectures need to be studied and adjusted during the experimental process that is currently ongoing. We think that this combination technique is a step forwards the design of flexible and accountable trading agents.

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