

Team: Split Second

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# MULTI-AGENT SYSTEMS SEMINAR

# Paper Being Reviewed

- Ros, R. and C. Sierra (2006). A Negotiation Meta Strategy Combining Trade-Off and Concession Moves, *Journal of Autonomous Agents and Multiagent Systems*, **12**:163-181

# Overview

- ⦿ Introduction
- ⦿ Negotiation strategies
  - NegoEngine
  - Trade-off
- ⦿ Contributions
  - Modification of the trade-off algorithm
  - Meta strategy
- ⦿ Experiments
- ⦿ Praises and Critiques
- ⦿ Q & A

# Introduction

- ⦿ Why negotiate?
  - Agent communication
  - Resolve interests conflicts
- ⦿ How to negotiate?
  - Negotiation Protocols
  - Negotiation Objects
  - Agents' Decision Making Models

# Basic Ideas of Negotiations

- ① Distributed search through a space of potential agreements.
- ② Interchange proposals to find intersections between preferences.
- ③ Terminate when encounter mutually acceptable point or when the protocol dictates that no agreement can be reached.

# Motivation

- Much work has been done in expanding the negotiation process along different dimensions: time constraints, outside options, multilateral negotiations, etc.
- Little work has been done regarding the integration of already designed tactics.
- This paper addresses the integration of two negotiation tactics to improve the outcome.
- Also a modification of one of the existing models to compute more satisfactory offers.

# Related Work

- Faratin, P., Sierra, C., & Jennings, N. R. (1998). Negotiation decision functions for autonomous agents. *Robotics and Autonomous Systems*, 24, 159–182.
- Faratin, P. Sierra, C., & Jennings, N. R. (2002). Using similarity criteria to make issue trade-offs in automated negotiations. *Artificial Intelligence* 142, 205–237.

# Negotiation Strategies

- ⊙  $i$  ( $i \in \{a, b\}$ ) – Negotiating agents
- ⊙  $j$  ( $j \in 1, \dots, n$ ) - Decision variables
- ⊙  $x_j^i \in D_j^i = [\min_j^i, \max_j^i]$  – Quantitative decision variables
- ⊙  $x_j^i \in D_j^i = \{q_1, q_2, \dots, q_p\}$  – Qualitative decision variables
- ⊙  $V_j^i: D_j^i \rightarrow [0,1]$  – Scoring function for decision variables
- ⊙  $w_j^i$  - Weight of significance
- ⊙  $\sum_{1 \leq j \leq n} w_j^i = 1$  - Assume the weights are normalized
- ⊙  $V^i(x) = \sum_{1 \leq j \leq n} w_j^i * V_j^i(x_j)$  – Scoring function for a contract
- ⊙  $x_{a \leftrightarrow b}^{t_n} = (x_{a \rightarrow b}^{t_0}, x_{b \rightarrow a}^{t_1}, x_{a \rightarrow b}^{t_2}, \dots)$  – Negotiation thread
- ⊙ { accept, reject} – Last element of the sequence



# NegoEngine

- ⦿ Defines a set of tactics
  - One at a time
  - Combination of more
- ⦿ Tactics
  - Set of functions to compute the value of a decision variable
  - Time dependent
  - Behavior dependent or Imitative

# Time Dependent

- Concede rapidly as time passes
- Value uttered by agent  $a$  at time  $t$ , with  $0 \leq t \leq t_{max}^a$ :

$$x_j^a[t] = \begin{cases} \min_j^a + \alpha^a(t)(\max_j^a - \min_j^a) & (1) \\ \min_j^a + (1 - \alpha^a(t))(\max_j^a - \min_j^a) & (2) \end{cases}$$

(1) If  $V_j^a$  is a decreasing function

(2) If  $V_j^a$  is an increasing function

$\alpha^a$  depends on time and parameter  $\beta$

$$\alpha^a(t) = \left( \frac{t}{t_{max}^a} \right)^{\frac{1}{\beta}}, \quad \beta \in \mathbb{R}^+$$

$\beta < 1$  : Boulware tactics

$\beta > 1$  : Conceder tactics

# Behavior Dependent or Imitative

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

P determines the type of imitation to be performed.

# Imitation Families

- Relative Tit-For-Tat : the agent reproduces the opponent's behavior  $\delta \geq 1$  steps ago.

$$P = \frac{x_j^a[t_{n-2\delta}]}{x_j^a[t_{n-2\delta+2}]} x_j^a[t_{n-1}]$$

- Absolute Tit-For-Tat : same as before, but in absolute terms.

$$P = x_j^a[t_{n-1}] + x_j^a[t_{n-2\delta}] - x_j^a[t_{n-2\delta+2}]$$

- Averaged Tit-For-Tat : applies the average of percentages of changes

$$P = \frac{x_j^a[t_{n-2\lambda}]}{x_j^a[t_n]} x_j^a[t_{n-1}]$$

# Combination Strategy

- ⦿ Compute the values for the decision variables
- ⦿ A linear combination of these values is the final value of each decision variable
- ⦿ Use a matrix of weights  $\Gamma$ 
  - Column – a tactic
  - Row – a decision variable

$\Gamma$  may change the behavior of agents during the negotiation

# Trade-Off

- ◎ To find a proposal with the same utility as the previous one offered but be more acceptable for its opponent.
- ◎ Proposal exchanges:
  - Same utility as the previous offer,  $x$ (aspiration level)
  - Similar to the offer from the opponent
- ◎ Maintain aspiration level
- ◎ Maximize acceptance probability

# Trade-Off

- iso-curves – formed by all the proposals with the same utility value for an agent :

$$iso_a(\theta) = \{x | V^a(x) = \theta\}$$

- Criteria evaluation function :

$$h: D \rightarrow [0,1]$$

- Similarity function :

$$Sim_h(x, y) = 1 - |h(x) - h(y)|$$

- Aggregation of individual similarities :

$$Sim_j(x_j, y_j) = \sum_{1 \leq i \leq m} w_i * (1 - |h_i(x_j) - h_i(y_j)|)$$

$\sum_{1 \leq i \leq m} w_i = 1$  is the set of weights representing the importance of the criteria functions

- Similarity between two contracts :

$$Sim(x, y) = \sum_{j \in J} w_j^a * Sim_j(x_j, y_j)$$

# Trade-Off

- Given the proposal  $x$  offered by agent  $a$ , and a subsequent offer  $y$  received from agent  $b$ , where  $\theta = V^a(x)$ , agent  $a$  makes trade-off the following way:

$$\text{trade-off}_a(x, y) = \arg \max_{z \in \text{iso}_a(\theta)} \{Sim(z, y)\}$$



# Modification of the Trade-off Algorithm

## Algorithm Smart Trade-off

1. Store received proposal  $y$  in the contract history
2. **For** each decision variable  $i$  **do**  
    Compute\_variability( $i$ )
3. Order the decision variables based on their variability
4. Compute a new offer using the trade-off algorithm

# Meta Strategy

## ⦿ NegoEngine

- Pros:

- Compute offers using the remaining time
- Compute offers using opponent's behavior

- Cons:

- Every offer proposed is a concession

## ⦿ Trade-off

- Pros:

- Maintain aspiration level

- Cons:

- Time not taken into account

# Meta Strategy

- ⦿ Combination of negoEngine and trade-off.
- ⦿ Exploit as much offers as possible at the current aspiration level.
- ⦿ Reduce aspiration level if no agreement reached.
- ⦿ Deadlock detected : last offer does not improve the utility of the offer proposed 2 steps before.
- ⦿ Maintain aspiration level with time and opponent's behavior taking into consideration.

# Algorithm Meta Strategy

- 1. While** deadline is not reached,  $t_{max}$ , **or** no agreement is found,  $V^a(y) < V^a(x)$ , **do**
  - a)** Given the last offer  $x$  proposed by agent  $a$ , compute  $\theta$ ,  $\theta = V^a(x)$
  - b)** **If** no deadlock **then** propose a new offer  $x'$  using the smart trade-off tactic. **Else** propose a new offer  $x'$  using the negoEngine tactic.
- 2. If** the deadline  $t_{max}$  is reached **then** withdraw and terminate.  
**else** accept the proposal  $y$  and terminate.

# EXPERIMENTS

# Agent Models

- ⦿ Evaluate NegoTO Model versus
  - Random Agent (e.g. TO, Nego, Nego, TO...)
  - Alternate Agent (TO,Nego,TO,Nego...)
  - TO Agent
  - Nego Agent
- ⦿ negoEngine Tactic
  - Varied behaviour (Very Boulware, Boulware, neutral, conceder, very conceder)
  - Combined time dependent and tit-for-tat tactics, with ratio 1:9

# Experimental Setup

- Two Agents (a and b) Negotiating over clothes

- Four factors: Color, Material, Price, Delivery Time

$$D_c = [0, 5]$$

$$D_m = [0, 4]$$

$$D_p = [30\text{euros}, 70\text{euros}]$$

$$D_d = [5\text{days}, 15\text{days}]$$

- Weights and Valuation Functions

$$W^a = [0.35, 0.15, 0.45, 0.05]$$

$$\begin{aligned} V_c^a(x) &= \frac{x}{5} \\ V_m^a(x) &= \frac{x}{4} \\ V_p^a(x) &= \frac{70-x}{70-30} \\ V_d^a(x) &= \frac{15-x}{15-5} \end{aligned}$$

$$W^b = [0.10, 0.15, 0.40, 0.35]$$

$$\begin{aligned} V_c^b(x) &= \frac{5-x}{5} \\ V_m^b(x) &= \frac{4-x}{4} \\ V_p^b(x) &= \frac{x-30}{70-30} \\ V_d^b(x) &= \frac{x-5}{15-5} \end{aligned}$$

# Experimental Setup

- Similarity Function:
  - 4 Parameters: Price, Delivery, Color, Material
  - Each has heuristic function
- Price and Delivery have 2 criteria (High, Low; Fast, Slow)
  - Combine criteria to form single heuristic via a weight

Heuristics for Similarity Function:

High Price

$$h_{hp}(x) = \begin{cases} 1 & x > 100 \\ \frac{x-20}{80} & x \in [20, 100] \\ 0 & x < 20 \end{cases}$$

Fast Delivery

$$h_{fd}(x) = \begin{cases} 1 & x < 5 \\ \frac{30-x}{25} & x \in [5, 30] \\ 0 & x > 30 \end{cases}$$

Low Price

$$h_{lp}(x) = \begin{cases} 1 & x < 20 \\ \frac{100-x}{80} & x \in [20, 100] \\ 0 & x > 100 \end{cases}$$

Slow Delivery

$$h_{sd}(x) = \begin{cases} 1 & x > 30 \\ \frac{x-5}{25} & x \in [5, 30] \\ 0 & x < 5 \end{cases}$$

Color and Material

$$h(x) = \frac{x - \min}{\max - \min}$$

Weights for agent

A: lp = .8, hp = .2

Fd = .8, sd = .2

Weights for agent

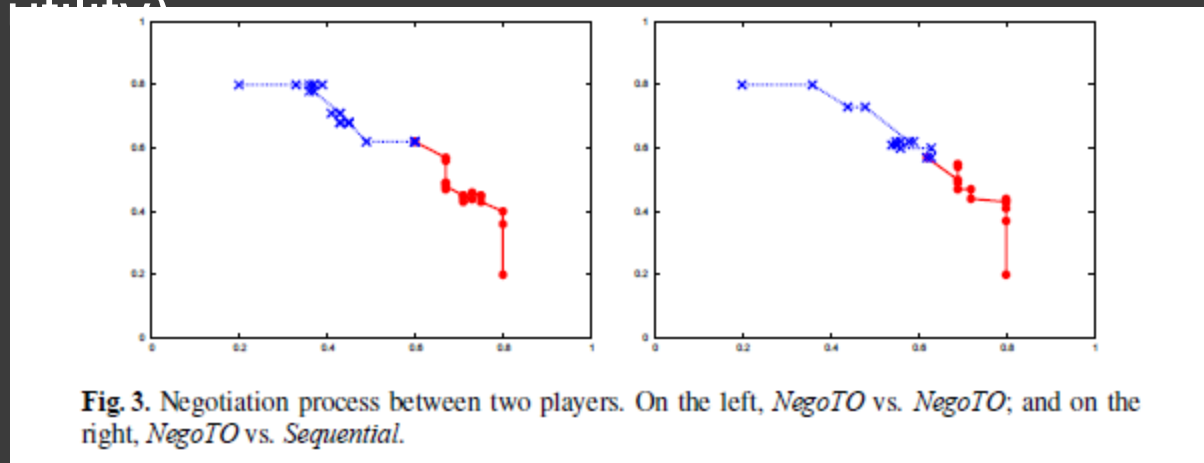
B: lp = .2, hp = .8

Fd = .2, sd = .8



# Results

- Changing tactic of negoEngine did not affect results (aggressive versus conceding)
- Buyer (red, y-axis is utility) Seller (blue, x-axis is utility)



# Results

$agent_i$	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	*	-
NegoTO	0.611	0.572	0.350	0.039
Random	0.649	0.514	0.333	0.135
Sequential	0.634	0.514	0.326	0.120
TO	0.734	0.490	0.360	0.244
Nego	0.742	0.303	0.224	0.439

negoTO

agent

$agent_i$	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	*	-
NegoTO	0.562	0.592	0.332	0.030
Random	0.592	0.553	0.327	0.039
Sequential	0.608	0.543	0.330	0.065
TO	0.658	0.512	0.337	0.146
Nego	0.630	0.399	0.252	0.231

Alternate agent

$agent_i$	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	*	-
NegoTO	0.543	0.613	0.333	0.070
Random	0.576	0.558	0.321	0.018
Sequential	0.550	0.574	0.316	0.024
TO	0.598	0.562	0.336	0.036
Nego	0.637	0.407	0.259	0.230

Random agent

$agent_i$	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	*	-
NegoTO	0.437	0.776	0.339	0.339
Random	0.562	0.606	0.340	0.044
Sequential	0.503	0.638	0.321	0.135
TO	0.636	0.565	0.360	0.071
Nego	0.579	0.453	0.262	0.127

TO agent

agent	$V^a(\mathbf{x})$	$V^i(\mathbf{x})$	*	-
NegoTO	0.341	0.728	0.248	0.387
Random	0.483	0.591	0.286	0.109
Sequential	0.423	0.605	0.256	0.183
TO	0.484	0.600	0.290	0.115
Nego	0.506	0.494	0.250	0.011

nego agent

**Measured 2 Criteria: Total Utility, and Utility Difference**

**Classified two Cases: Best Case (keep aspiration value constant)**

**Worst Case (behaves Sequentially due to recurrent deadlock)**

# Praises

- ⦿ The two models chosen complement each other well.
  - The Trade-off model maintains the agent's utility while sacrificing negotiation time.
  - The negoEngine model ensures that agent's offers converge if given enough time (sacrifices utility)
  - The Weakness of one model is the Strength of the other
- ⦿ Modification of the Trade-off model
  - Models real-life situations well (most preferred items under negotiation tend not to change, so the model avoids mutating these items)
  - Many methods, including the window method presented, could be applied to choose what preference ordering the opponent agent has presented. This opens the door for many avenues of research regarding the best method to determine the opponent's ordering.
  - The modification is a good way to illuminate an agent to the incomplete information he has about his opponent. This also, gives another way for researchers to model agents in incomplete information environments.

# Critiques

## ⦿ Qualitative Variables

- The Qualitative valuations might not have a consistent ordering between two agents.
- For example, agent A could order {Red, Green, Blue, Yellow} whereas agent B could order {Green, Yellow, Blue, Red}.

## ⦿ Correlation between variables under negotiation

- One variable's valuation could be affected by other variables states. This was not addressed in the experiment conducted; and also it was not considered how this affects the similarity function.
- In the real world a person's valuation of an item may be distorted by item parameters whose sub-valuation is dependent on others. For example, given a Nylon coat you prefer Red as the color; but if it is not Nylon you prefer Blue as the color.

# Critiques

## ⦿ Statistical Analysis

- Multi Comparison Test

- Separates Items into statistically different groups
- Apply to: 1) total utility 2) utility difference; see if any model in both top groups



## ⦿ Variability of results not addressed

- Three Items to measure: consistency, total utility, utility difference

Q & A