MCTS-based Automated Negotiation Agent

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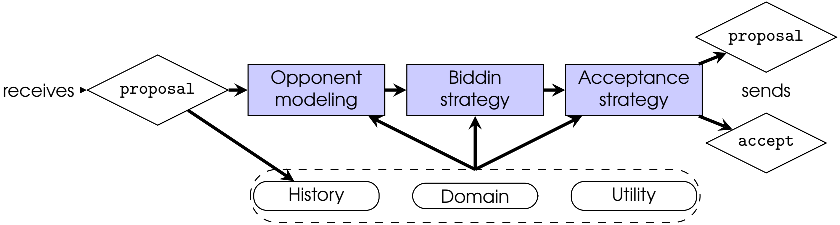
Goal: an agent able to negotiate when:

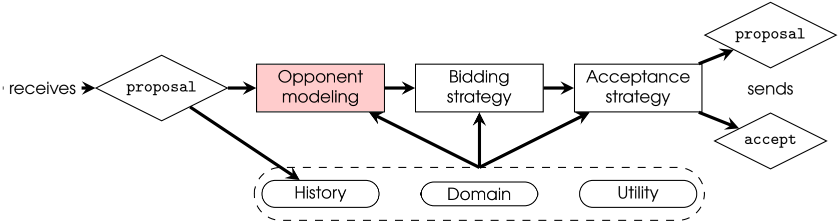
- the protocol is bargaining with or *without* deadline
- goods are multi-issues, categorical and/or continuous

Example: invoice trading for supply chain

BOA [1]: Bidding Strategy, Opponent modeling & Acceptance strategy



Opponent modeling



Gaussian Process regression (extension of multivariate Gaussian) [8]

Let (x_i, y_i). Suppose:

$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \end{pmatrix} \sim \mathcal{N}(\mathbf{0}, K(x_i))$$

with K, covariance matrix representing the proximity of the negotiation turns with each others, according to a covariance function k:

$$K(x_i) = (k_{jk}) = (k(x_j, x_k))$$

Then, we predict for turn x_*:

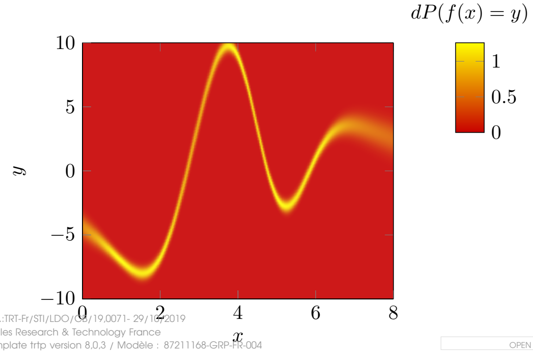
$$\begin{pmatrix} y_1 \\ \vdots \\ y_n \\ y_* \end{pmatrix} \sim \mathcal{N}(\mathbf{0}, K(x_i, x_*))$$

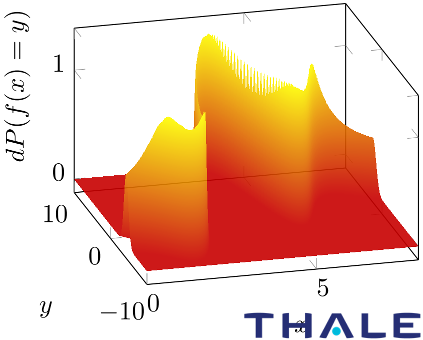
Opponent modeling: opponent bidding strategy

Following multivariate Gaussian theorem:

$$\begin{cases} \bar{y_*} = K_* K^{-1} \mathbf{y} \\ \sigma_* = \mathrm{var}(y_*) = K_{**} - K_* K^{-1} K_*^\top \end{cases}$$

where $K_* = (k(x_*, x_1), \ldots, k(x_*, x_n))$ et $K_{**} = k(x_*, x_*)$.

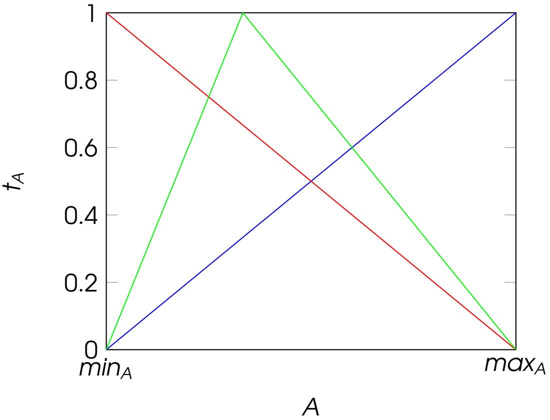




Opponent modeling: opponent utility

- **Based on Bayesian learning [6]**
- **Bayesian learning hypothesis:**
  - triangular functions t_i for each issue
  - a rank τ_i for the issue $i \rightarrow$ weight $w_i = 2\frac{\tau_i}{n \cdot (n+1)}$
- **For an offer $(x_1, \ldots, x_n)$, prediction:**

$$h(b) = \sum_{1 \leqslant i \leqslant n} w_i \cdot t_i(x_i)$$



Opponent modeling: opponent utility

- **Probability of each hypothesis supposed Gaussian**
- **Concessions supposed monotonous and approx. regular**
  - ($\approx u^0 : b \mapsto 1 - \alpha_u \cdot round(b)$, whith α_u a parameter)

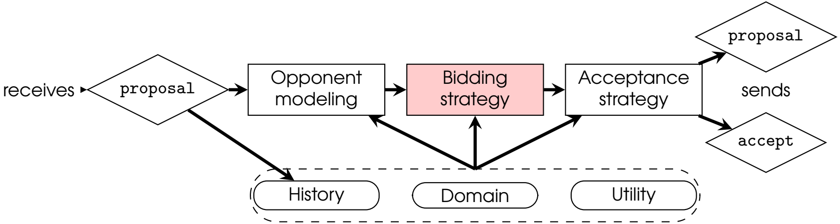
$$P(b|h_j) = \frac{1}{\sigma \cdot \sqrt{2\pi}} \cdot e^{-\frac{\left(u_j(b) - u^0(b)\right)^2}{2\sigma^2}} \text{ et } P(hj|b) = \frac{P(h_j)P(b|h_j)}{\sum_{k \leqslant m} P(h_k)P(b|h_k)}$$

  - $P(h_j)$ updated when an offer b received. Model: weighted sum

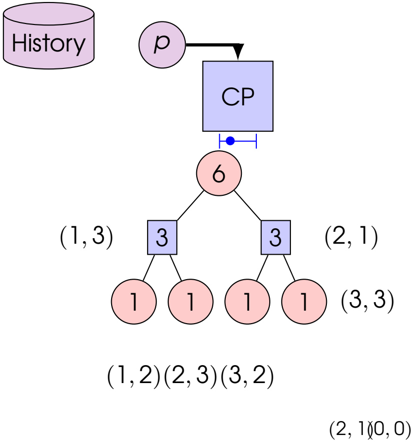
$$u = \sum_j P(hj|b) \cdot h_j$$

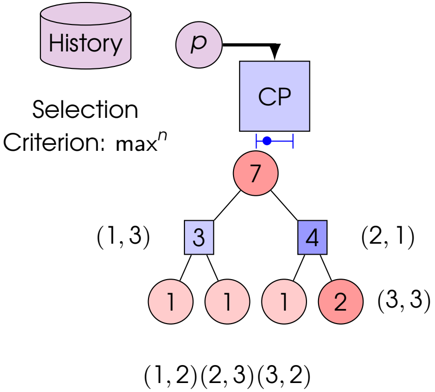
- **effective for numerical a issues, can be easily generalized to categorical**

Bidding satrtegy: MCTS

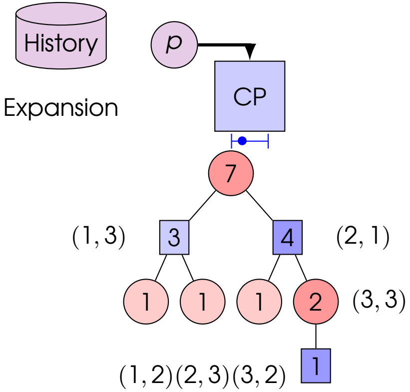


Bidding satrtegy: MCTS

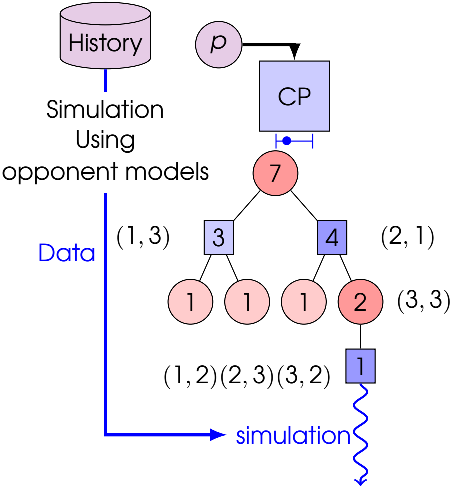



History
p
CP
Selection
Criterion: max^n
7
(1, 3)
3
4
(2, 1)
1
1
1
2
(3, 3)
(1, 2)(2, 3)(3, 2)

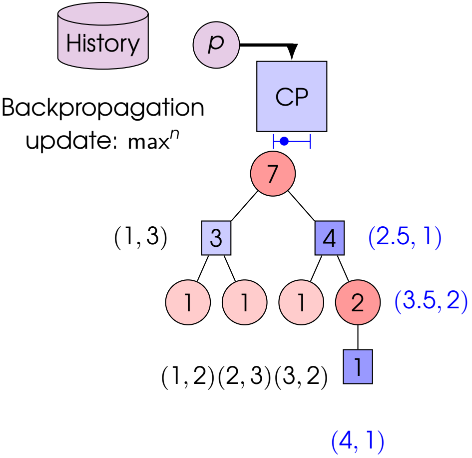
Bidding satrtegy: MCTS



Bidding satrtegy: MCTS



Bidding satrtegy: MCTS



Selection of j maximizing [4]:

$$C_j = \frac{\bar{X}_j}{n_j + 1} + C \cdot n^{\alpha_s} \sqrt{\frac{\ln(n)}{n_j + 1}}$$

with n total number of simulations, n_j number of times j has been simulated and $\bar{X}_j$ average score of j, C and α_s model parameters.

Expansion of a new node iff [4]

$$n_p^{\alpha_s} \geqslant n_c$$

with n_p number of times the parent has been simulated and n_c number of its children.

Simulation based on opponent models of bidding strategy & utility

Backpropagation of the scores; agent & opponent scores

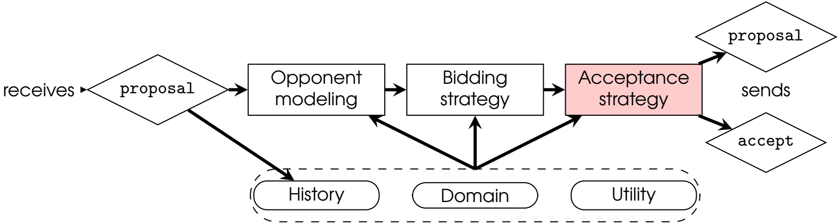
Simulation & backpropagation based on opponent models:

- strategy model (gaussian process regression) [8]
- utility model (apprentissage bayésien) [6]

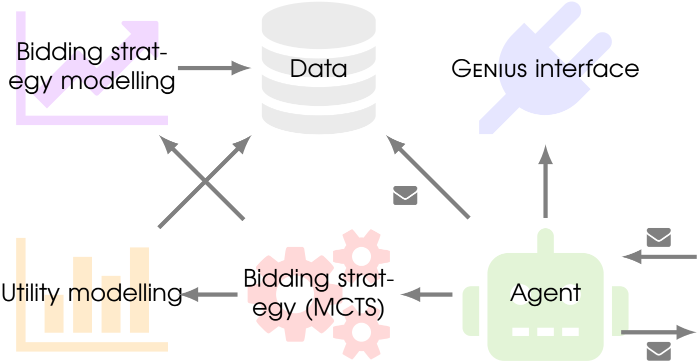
Pruning

- based on opponent's offers
- delete nodes whose utility is lower than the best opponent proposalsuppression des nœuds dont l'utilité est pire que la meilleure proposition adverse,

Acceptance strategy



Overview


Bidding strat-
egy modelling
Data
Genius interface
Utility modelling
Bidding strat-
egy (MCTS)
Agent

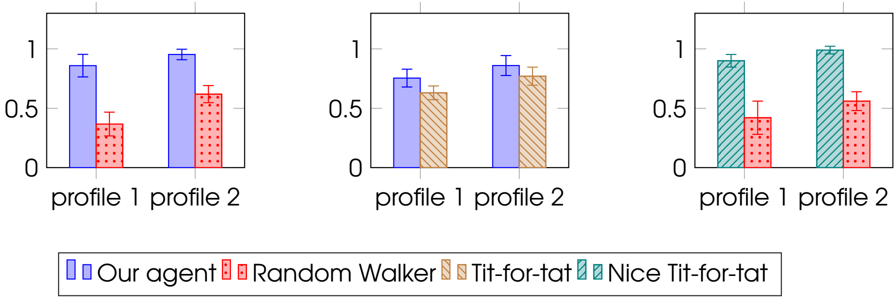
Agents that can negotiate without deadlines:

- RandomWalker [2],
- Tit-for-tat [5],
- Nice Tit-for-tat [2].

Negotiation domain: ANAC 2014 [7]

- very large (discrete though),
- numerical,
- nonlinear preferences,
- set without deadline.

Negotiating with Nice TIt-For-Tat: unable to conclude; negotiations never end



Conclusion and perspectives

Conclusion:

- an agent able to negotiate without predetermined deadline with continuous & categorical issues,
- negotiation strategy based on MCTS, with 2 opponent models and pruning,
- experimental results: outperforms Random Walker & Tit-for-Tat; no significant difference with Nice Tit-for-Tat.

Perspectives:

- customized version to adapt to the context where the deadline is known,
- adapt to the multilateral context,
- use MCTS variations & improvements (AMAF, RAVE. . .) [3].

References I

Tim Baarslag. “Exploring the Strategy Space of Negotiating Agents: A Framework for Bidding, Learning and Accepting in Automated Negotiation”. In: Cham: Springer International Publishing, 2016. Chap. A Component-Based Architecture to Explore the Space of Negotiation Strategie, pp. 53–69.

Tim Baarslag, Koen Hindriks, and Catholijn Jonker. “A Tit for Tat Negotiation Strategy for Real-Time Bilateral Negotiation”. In: *Complex Automated Negotiations: Theories, Models, and Software Competitions*. Ed. by Takayuki Ito et al. Vol. 435. Springer Berlin Heidelberg, 2013, pp. 229–233.

Cameron C Browne et al. “A Survey of Monte Carlo Tree Search Methods”. In: *IEEE Transactions on Computational Intelligence and AI in Games* 4.1 (2012), pp. 1–43.

Adrien Couëtoux. “Monte Carlo Tree Search for Continuous and Stochastic Sequential Decision Making Problems”. PhD thesis. Université Paris XI, 2013.

Peyman Faratin, Nicholas R Jennings, and Carles Sierra. “Negotiation decision functions for autonomous agents”. In: *Robotics and Autonomous Systems* 24.3-4 (1998), pp. 159–182.

Koen Hindriks and Dmytro Tykhonov. “Opponent Modelling in Automated Multi-issue Negotiation Using Bayesian Learning”. In: *Proceedings of the 7th International Joint Conference on Autonomous Agents and Multiagent Systems*. Vol. 1. International Foundation for Autonomous Agents and Multiagent Systems, 2008, pp. 331–338.

Raz Lin et al. “Genius: an integrated environment for supporting the design of generic automated negotiators”. In: *Computational Intelligence* 30.1 (2014), pp. 48–70.

References II

Colin R Williams et al. “Using Gaussian Processes to Optimise Concession in Complex Negotiations Against Unknown Opponents”. In: *Proceedings of the Twenty-Second International Joint Conference on Artificial Intelligence - Volume Volume One*. IJCAI’11. AAAI Press, 2011, pp. 432–438.