

## MoCaNA, an automated negotiation agent based on Monte Carlo Tree Search

Cédric Buron, Sylvain Ductor, Zahia Guessoum

## ▶ To cite this version:

Cédric Buron, Sylvain Ductor, Zahia Guessoum. MoCaNA, an automated negotiation agent based on Monte Carlo Tree Search. AAMAS 2019 - 18th International Conference on Autonomous Agents and MultiAgent Systems, May 2019, Montreal, Canada. hal-02568303

HAL Id: hal-02568303

https://hal.science/hal-02568303

Submitted on 8 May 2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

## Mocana, an automated negotiation agent based on Monte Carlo Tree Search

Cédric L. R. Buron

THALES

Zahia Guessoum



Sylvain Ductor



## INTRODUCTION

## Context

- Automated negotiation;
- Complex negotiation domains;

## Example application: factoring

- Buy/Sell invoices;
- Proposal: debtor (categorical, discount rate (continuous), total amount (numerical);
- Varying time pressure, cannot rely on deadline;
- Nonlinear preferences;

Contribution: an agent able to negotiate:

- with nonlinear preferences,
- without relying on a deadline,
- on both categorical, numerical and continuous issues;

Representation of negotiation as a game; using Al for games techniques.

## ESS 22.29 Matérn 43.23 RQF 17.77 RBF 43.29 Average distance between prediction & actual values

depending on kernel

Genius interface

BIDDING STRATEGY MODELLING

- Based on a kernel:
  - Radial Basis Function,

Gaussian Process regression;

- Rational Quadratic Function,
- Matérn,
- Exponential Sine Square;

tested on 50 random negotiation sessions

- Initially used on numerical issues, can be extended to categorical;
- Generates bid distribution using history;

## UTILITY MODELLING

- Bayesian learning;
- Presupposition: concession rate from the opponent;
- Hypotheses:
  - Triangular functions
  - Order/Weight on the issues
- Computation: Hypotheses probabilities (based on opponent previous proposals);
- Resulting function: sum of the hypothesis,  $\sum\limits_{k\leq n}p_k\cdot h_k$  weighted by probabilities;
- For numerical, extended to categorical.

## $egin{array}{c} \mathbf{b_t} \\ \mathbf{p_1^{t+1}} & \mathbf{p_1^t} \\ \mathbf{p_1^{t+1}} & \mathbf{p_1^t} \\ \mathbf{p_n^{t+1}} & \mathbf{p_n^t} \\ \end{array}$

Bidding stra-

tegy modelling

Utility modelling — Bidding strategy (MCTS) — Agent

Data

# History pCP Simulation Using opponent models $(1,3) \quad 3 \quad 4 \quad (2,1)$ $1 \quad 1 \quad 2 \quad (3,3)$ $(1,2)(2,3)(3,2) \quad 1$ simulation

## BIDDING STRATEGY

- Based on Monte Carlo Tree Search;
- Uses Progressive widening for selection & expansion;
- Uses modelling for the simulation;
- Backpropagates the utility of both agents through utility modeliing;
- Prunes the proposals with utility lower than the best proposal from the opponent;
- Parallelizes simulations to make more.

## EXPERIMENTAL PROTOCOL

- Use of a genius interface (reference framework);
- Negotiation domain: ANAC:
  - Large domain (10 issues, 10 values/issue)
  - Numerical issues
- 3 min/round (suitable for the application context);
- Only 3 opponents in this context: Random Walker, Titfor-Tat and Nice Tit-for-Tat;
- Neverending sessions for MoCaNA vs. Nice Tit-for-Tat: indirect comparison (through RandomWalker);
- 20 negotiation sessions per setting with each profile;
- Representation of both average score and standard deviation.

## **OPPONENTS**

## RandomWalker

- Makes random proposals,
- Accepts a proposal if better than the generated one.

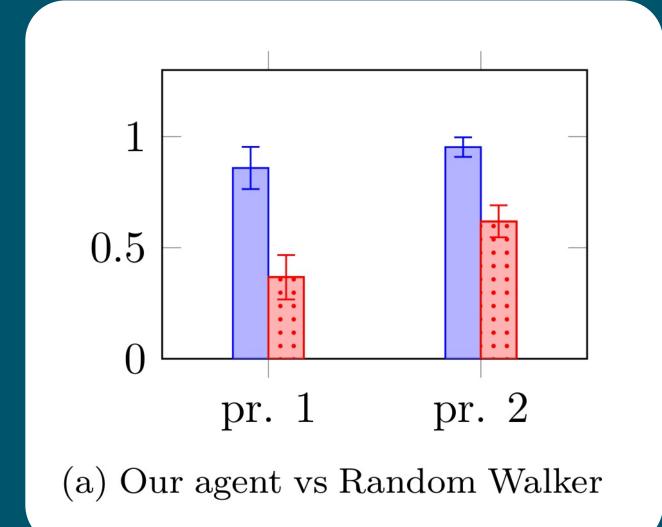
## Tit-For-Tat

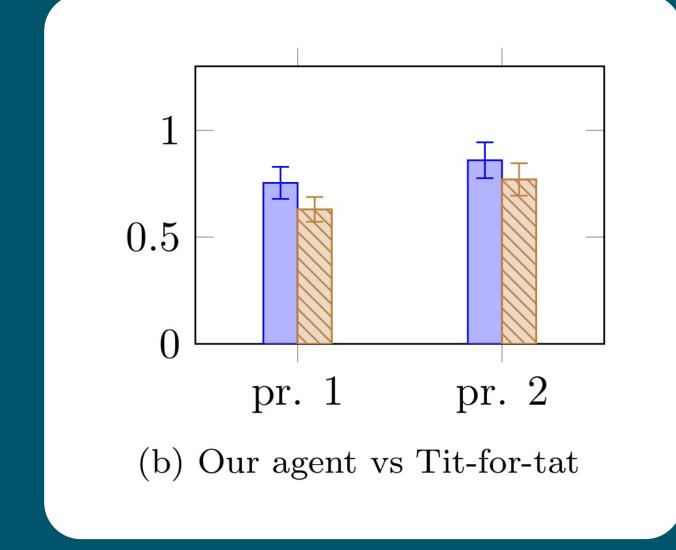
- Returns moves (concession = concession of the opponent),
- Accepts a proposal if better than the generated one.

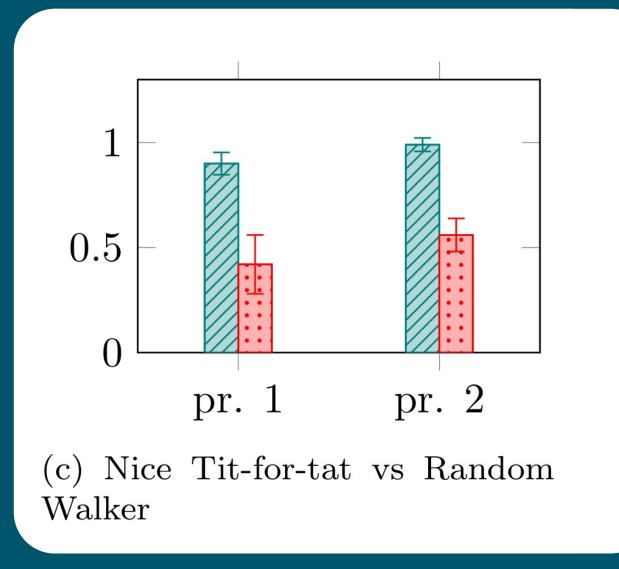
## NIce Tit-for-Tat

- Identical to Tit-for-Tat but:
- Computation made on a Nash Point, computed through utility modelling (bayesian learning).

## RESULTS







## Conclusion

- At least as good as any agent in this context;
- Possibility to improve (RAVE/AMAF);
- Many things to test (other opponent modeling, other AI for games as CFR minimization...)
- Possibility to expand to multilateral negotiation.

Our agent Random Walker Tit-for-tat Nice Tit-for-tat