OPPONENT MODELING IN AUTOMATED BILATERAL NEGOTIATION

CAN MACHINE LEARNING TECHNIQUES OUTPERFORM STATE-OF-THE-ART HEURISTIC TECHNIQUES?

There is no greater danger than underestimating your opponent.

~Laozi

Author

Tudor Octavian Pocola

Supervisors

Pradeep K. Murukannaiah
Bram M. Renting

TU Delft, Delft, Netherlands

Introduction

- automated negotiation can come in the aid of humans, who appear to be ill-equipped for the task
- opponent modeling is a simple and effective technique to improve the effectiveness of these programs [1][2]
- two distinct opponent modeling methods can be identified: machine learning and heuristic algorithms
- heuristic algorithms have dominated the field in the past, but this seems to no longer be the case

Research Question

How do machine learning techniques compare with the state-of-the-heuristic techniques when used to calculate the opponent's preferences?

Related work

- a 2013 study [1] compared multiple opponent models but also the metrics used to evaluate such a model
- the study has concluded that the state-of-the-art heuristic approaches have almost perfect accuracy, with only limited room for improvement

Methodology

- the Pearson correlation of bids will be used to measure the accuracy of the models [3]
- the Smith Frequency model [4] will be used as the heuristic baseline
- the Perceptron model [5] will be used as the machine learning baseline, with two version being created:
  - The Bad Perceptron - assumes that the opponent's utility is maximal
  - The Perfect Perceptron - has access the the oppoent's actual utility

Experimental Setup

- the GENIUS framework [6] was used to create the negotiation environment
- the PPO algorithm [7] was used to create the automated negotiation agent
- the models were tested against multiple opponents: Hardliner, Conceder, Boulware, Linear

Results

- the average accuracy of the models can be seen in Figure 1
- the average accuracy against each opponent can be seen in Table 1
- the average percentage of the bid space that was explored by each opponent can also be seen in Table 1
- the correlation between each model's accuracy and the percentage of the bid space that was explored by the opponent can be seen in Figure 2
- to statistically analyze the results found in Table 1, the Pearson correlation coefficient and the p-value have been calculated for all models:
  - Smith Frequency Model: r = 0.79, p = 0.20
  - Bad Perceptron: r = 0.96, p = 0.03
  - Perfect Perceptron: r = 0.99, p = 0.005

Analysis

- Figure 1 indicates that the Perceptron Model and the Smith Frequency model have similar accuracy
- Table 1 shows that the Perfect Perceptron model is outperforming the Smith Frequency model against the Conceder agent.
- the results indicate that there is a significant positive correlation between the accuracy of the Perceptron model and the percentage of the bid space that the opponent explores

Conclusion

- our main conclusion is that machine learning techniques are at least as good as their heuristic counterparts when used to estimate the opponent's preferences
- we believe that, with further research, machine learning approaches could overtake the current state-of-the-art and become the new standard in the field
- however, we also believe that the model's accuracy is currently limited by the opponent's behavior, so these algorithms might be approaching their theoretical limit

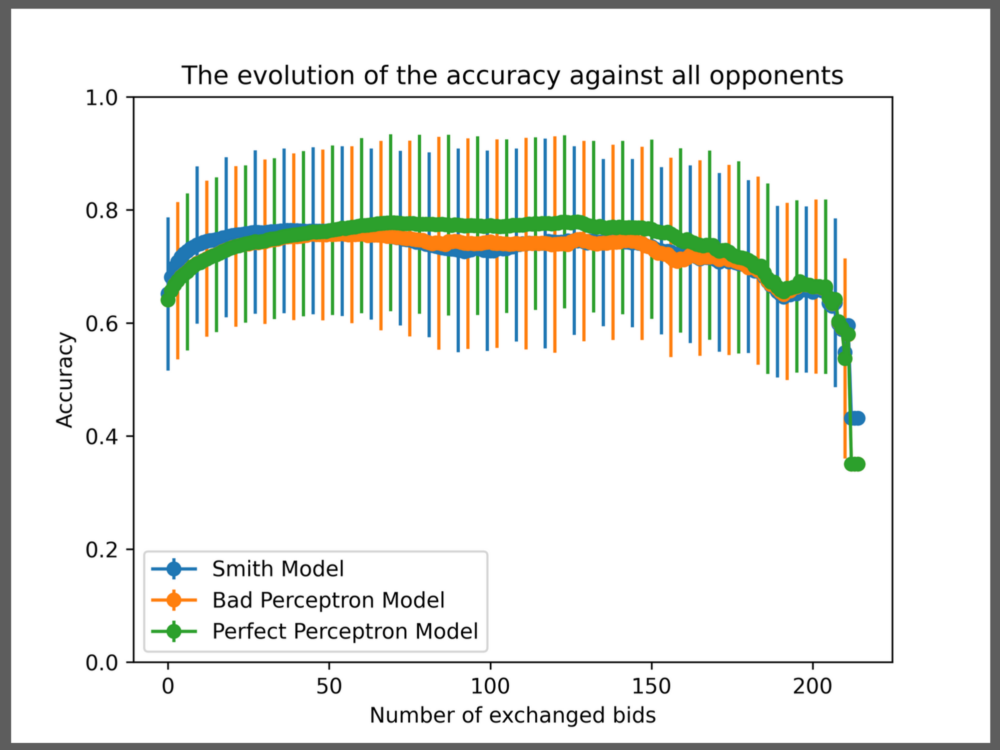

Figure 1 - The mean and standard deviation of the accuracy, against all opponents

	Hardliner	Conceder	Boulware	Linear
Smith Frequency	0.69	0.75	0.73	0.83
Bad Perceptron	0.68	0.77	0.72	0.79
Perfect Perceptron	0.68	0.84	0.73	0.82
Explored Bid Space	0.08%	1.64%	0.45%	1.55%

Table 1 - The first three rows show the average accuracy of each model against all opponents. The last row shows the average explored bid space for each opponent.

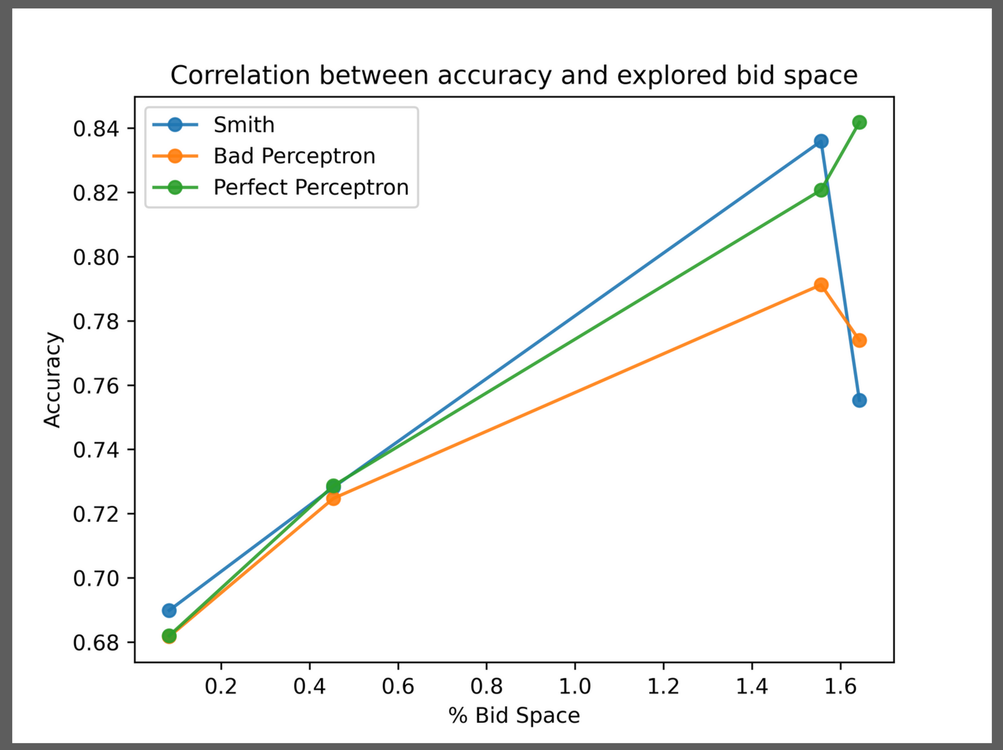

Figure 2 - The correlation between a model's accuracy and the percentage of the bid space that was explored by the opponent

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