Exercise 5: An Auctioning Agent for the Pickup and Delivery Problem

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1 Bidding strategy

The bid to be placed depends mainly on two values: the added cost of our agent for taking the task, and the predicted bid of the opponent. If the agent cost is bigger than the predicted opponent bid, we bid the agent cost, since we are likely to lose anyway. If it is smaller, the following formula is used in order to maximise profit, with a risk factor α:

$$\text{bid} = \text{agent cost} + \alpha \times (\text{predicted opponent bid} - \text{agent cost})$$

If α is closer to 0, we are likely to win the auction but with a low profit. If α is closer to 1 (or higher), we maximise profit if our prediction of the opponent bid is accurate, but we may lose a lot of potential profit if not.

1.1 Agent cost estimate

The immediate cost of taking an action is given by the marginal cost of the task t :

$$c_{add}(A_i, T, t) = cost(A_i, T \cup t) - cost(A_i, T)$$

The costs are computed using stochastic local search, in the same way as for the centralized agent.

We also consider the average future cost savings of taking task t, after taking n additional tasks $\{t_1, ..., t_n\}$, which are random tasks sampled from the known task distribution:

$$savings(t, n) = \overline{c_{add}(A_i, T \cup t, \{t_1, ..., t_n\})) - c_{add}(A_i, T, \{t_1, ..., t_n\})} - c_{add}(A_i, T, t)$$

This is a negative value, due to the fact that the having more tasks makes it more likely that a part of the path of taking a new task is already being done for another task.

Theses potential savings are approximately taken into account in the estimated cost, with a discount factor γ, since we cannot know if there will be any task left afterward:

$$\text{cost estimate} = c_{add}(A_i, T, t) + \gamma * savings(t, 2) + \gamma^2 * savings(t, 4) \tag{1}$$

The discount factor starts at 0.5, making it likely to get a first task even-tough its marginal cost is high, and is then decreased by 50 % of itself after every task acquired.

1.2 Opponent bid estimate

To compute the estimated cost of taking the task for the opponent, the same formula (1) is used for the opponent. The main difference is that we do not know the vehicles of the opponent. Their cost per km and their capacity is assumed to be the same as our best vehicle. We also need to estimate their departing city. For that, we know that the marginal cost cannot be lower than the bid. Thus, we can iteratively estimate what cities are potential starting points, by examining the previous bid :

- We compute the marginal cost departing from each city.
- If the bid is smaller than the marginal cost, we eliminate the city.

Then, we define the predicted cost as the average of the costs of each potential departing city. The opponent bid is then assumed to be proportional to its estimate, with an uncertainty factor C:

$$\text{estimated opponent bid} = C * \text{estimated opponent cost}$$

1.3 Learning from previous rounds

The value of the factor C is updated after every bid through learning: ($\alpha_r = 0.2$)

$$r = \frac{\text{opponent bid}}{\text{estimated opponent cost}}, \quad C_{t+1} = \alpha_r r + (1 - \alpha_r) C_t$$

2 Results

2.1 Experiment 1: Comparisons with dummy agents

2.1.1 Setting

We will now compare the performance against dummy agents, as a function of the number of auctioned tasks. We chose $\alpha = 0.9$, and tested against a two dummy agent who bid the marginal cost times a random coefficient equal to 1 + (a random number between 0 and 0.05 * time the number of the auctioned tasks). The difference between the two is that the "good" dummy agent uses the same algorithm as our agent to compute the marginal cost, while the "bad" one uses marginal cost = distance to pickup city + task distance, which is often much higher.

2.1.2 Observations

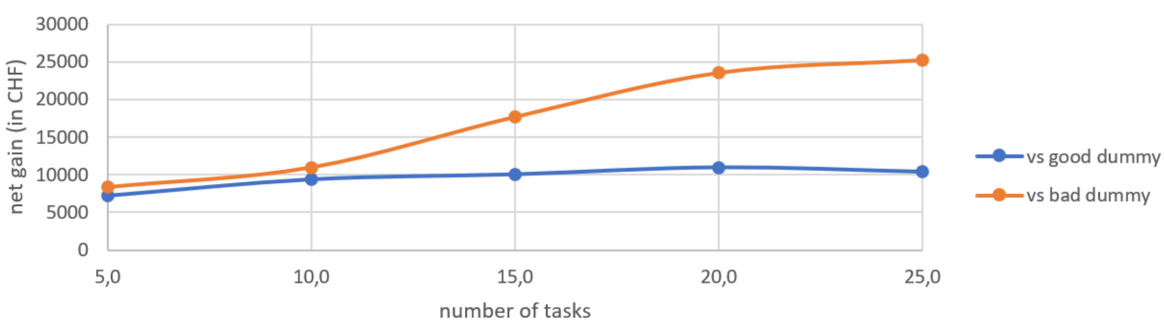

Figure 1: Final gain (reward minus cost) as a function of the number of auctioned tasks

We observe that the net gain doesn't increase as much as it should with the number of tasks against the "good" agent. This is due to the fact that after a certain amount of tasks, the cost of acquiring a new one becomes low for both players, therefore they both bid values close to their marginal cost, thus making low gain.

Against the "bad" agent, our agent is able to raise his prices and exploit his opponent's high bids to generate more profit.

We plot here the evolution of bids and our predictions for 14 tasks and against the "good" agent.

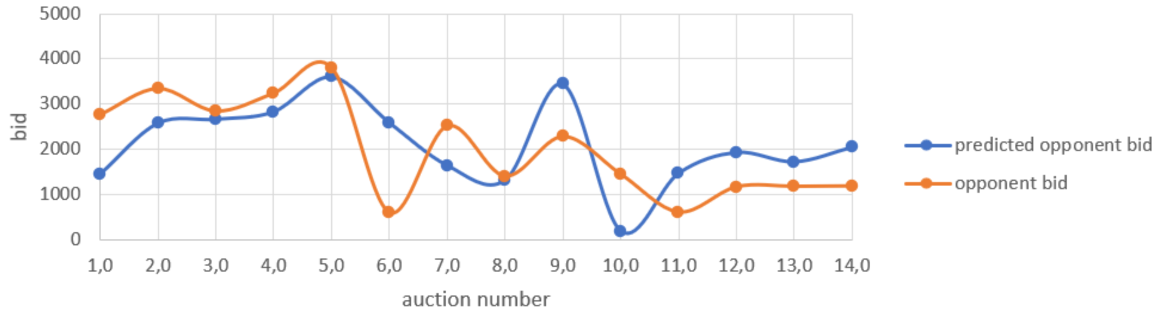

Figure 2: Evolution of opponent bids and our prediction during the auction against the "good" agent

We see that our agent is able to predict the opponents bid within a somewhat large margin. We notice that despite the fact that we do not predict the exact bid, we manage to predict its global trend (i.e if it will decrease, or increase). Also, we notice that our predicted value can be lower or bigger than the real value, this should be taken into account to choose our α value, considering this error margin accordingly.

We also see the decrease in bids with each new auction, as explained before.

2.2 Experiment 2: impact of the risk factor α

2.2.1 Setting

We kept all the default settings, and measured our agent performance for α equals to 0.1, 0.3, 0.5, 0.7, 0.9, 1.2 and 1.4 against the "good" dummy agent.

2.2.2 Observations

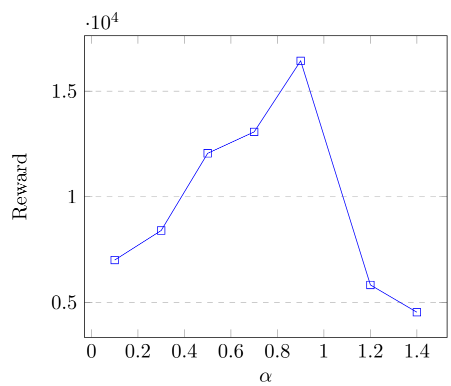

Figure 3: Reward as a function of α

We observe that for higher values of α, we obtain higher rewards. This is expected since alpha controls how much profit we make. We reach a maximum reward around $\alpha = 0.9$ That is because this value is where we make maximum profit, while remaining more affordable than our opponent, thus winning the auction round. Above the value of $\alpha = 0.9$, the rewards start fluctuating, and in many cases, decreasing.

Our choice for the optimal α depends on how confident we are of our estimation. Indeed, our estimation is not perfect, so we must take into account an error margin around the estimated value. If we choose a small α, we don't take risk, however our rewards will remain small. If we choose a higher α, we take more risks (i.e, to be in the error margin, and consequently lose the auction round) but have great rewards from time to time.