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

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1 Bidding strategy

1.1 General strategy

For the auction agent we implemented a bidding strategy on top of our stochastic local search solution from the last assignment. We tweaked the search's parameters in order to have faster convergence but otherwise the algorithm remains unchanged. The bidding strategy we opted for follows a simple, aggressive but powerful concept:

> Take the first tasks at loss and subsequently enjoy lower marginal costs!

All our design choices rely on this idea. If the vehicle already travels to cities on the map then – assuming maps dense enough, like the ones we were given – it is likely that part of a new parcel's journey is already on the vehicles path. If this is the case then this part of the parcel's delivery is already paid for and we can offer it at a lower price than the cost.

At each bidding round we compute two values that we will discuss in the following subsection. Combined with some bookkeeping about won tasks and gains, we calculate the final bid. This calculation is different on depending three phases the agent can be in and that are explained below.

1.2 Marginal cost and expected gains

Upon receiving a task to bid for, we let the planner schedule a plan based on the solution of the last iteration but with the additional task that is offered. The cost of this new schedule minus the cost of the previous one yields the marginal cost. This is the cost that our schedule incurs from delivering the additional task. However, this does not take into account the possibility of future tasks. If for example the next auctioned task has the same route as the current one, then – provided enough capacity – we could deliver the next task for free.

To account for future tasks we introduce the **expected maximum gain** $\mathbb{E}[maxGain]$ of a schedule. It measures how much more gains could be made if all our vehicles $v \in \mathcal{V}$ were full at each move $m \in \mathcal{M}$.

$$
\begin{aligned}
\mathbb{E}[maxGain] &= \sum_{v \in \mathcal{V}} \sum_{m \in \mathcal{M}} length(m) \cdot cost(v) \cdot loadFactor \cdot \mathbb{E}[remainingTasks] \\
loadFactor &= \max\left(0, \min\left(\frac{\mathbb{E}[load(v,m)] - load(v,m)}{capacity(v)}, 1\right)\right) \\
\mathbb{E}[load(v,m)] &= \sum_{c_p \in \mathcal{C}} \sum_{c_d \in \mathcal{C}} \mathbb{P}(task(c_p \to c_d)) \cdot \mathbb{E}[weight(c_p, c_d)] \cdot \mathbb{1}\{task(c_p \to c_d) \text{ contains } m\}
\end{aligned}
$$

Where $load(v, m)$ is the current load of vehicle v when performing move m. For better understanding, let us look at a toy example. Consider one vehicle with $capacity(v) = 2$ and cities $A \leftrightarrow B \leftrightarrow C$. If the vehicle is initially at A and already delivers a task of weight 1 from $B \to C$ then it could still take tasks with weight 2 from $A \to B$ and weight 1 from $B \to C$. But this is only true if there are future auctions where such tasks might appear. This is captured by $\mathbb{E}[load(v, m)]$ which takes into account the probability distribution of tasks and their expected weights from `TaskDistribution` as well as the guessed $\mathbb{E}[remainingTasks]$. The guess is a simple decreasing log function based on the assumption that there will usually be between 10 and 60 tasks in total.

As with the marginal cost it is now possible to calculate the marginal expected gain at each round by subtracting the previous expected gain. If this quantity is large it indicates that taking the offered task will augment our possibilities of making profit in the future. If on the other hand it is small or even negative it shows us that auctioned task does not bring us any benefit in future auctions and it is therefore less valuable to us. In that sense the marginal expected gain can be seen as a *utility function* that estimates how a task will change our chances of profit in the future.

1.3 Bidding phases

With those computations in place we calculate our bids based on three states. In all of them we put a lower bound l on the bids that is some fraction of the path's cost. This is a price that nobody can beat but it prevents the agent from bidding 0 when the marginal cost is 0.

- **Phase 1**: At the beginning we want to take all the tasks. Therefore we bid at deficital prices. The amount of deficit we make depends on how much utility the task will bring us in the future. We lower the bid for high utilities (α was determined experimentally and set to 0.1):

$$bid = \max(l, marginalCost - marginalExpectedGain \cdot \alpha)$$

- **Phase 2**: Once the number of won tasks plus the number of auctioned tasks is larger than 6, we go into the second phase. This phase aims to catch up the deficits that were made in phase 1. The idea is to always be profitable after 10 rounds. Therefore the bids in this phase take into account the current deficit d of the agent:

$$bid = \max(l, marginalCost + d / \max(1, 10 - round))$$

- **Phase 3**: When the agent is profitable again it transitions to the last phase. Similarly as in phase 1, the bids are determined by the utility of the offered task but unlike before they are never deficital. (β was determined experimentally and set to 0.2):

$$bid = \max(l, marginalCost + \max(1, 1 - marginalExpectedGain \cdot \beta)$$

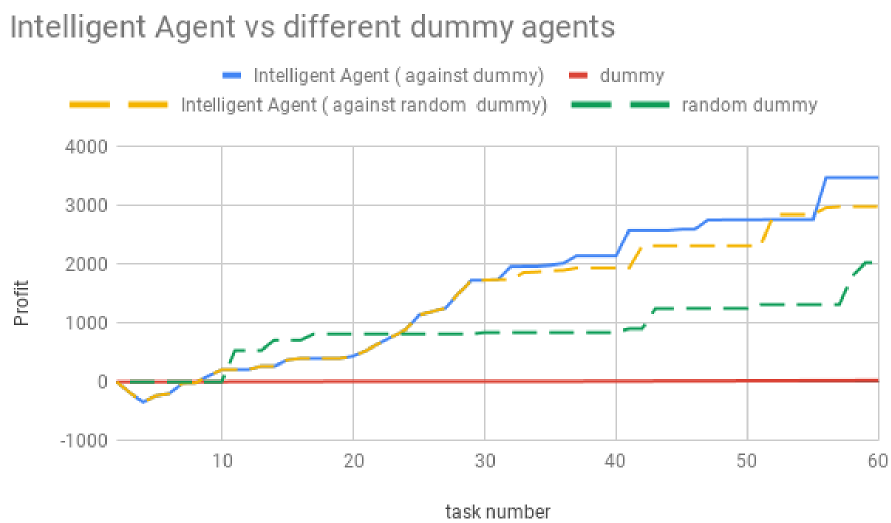
2 Results

2.1 Experiment 1: Comparisons with dummy agents

2.1.1 Setting

We use the default configuration file `auction.xml` with 60 tasks and run two auctions (5 seconds bid time, 15 seconds plan time). In the first auction, our agent competes against our "dummy" agent which always bids: $marginalCost + 1$. In the second auction, our agent competes against our "random dummy" agent which always bids: $marginalCost \cdot (\texttt{Math.random}() \cdot 0.5 + 1)$. For all three agents, the marginal cost is calculated using the same stochastic local search algorithm.

2.1.2 Observations



In the plot 2.1.2 we observe that our agent wins the auction against both dummy agents at the end of the 60 tasks. However, because the first tasks are taken at loss and because the "random dummy" agent is lucky on task 10 and gains 500 profit, our agent would have lost had there been less than 23 tasks.

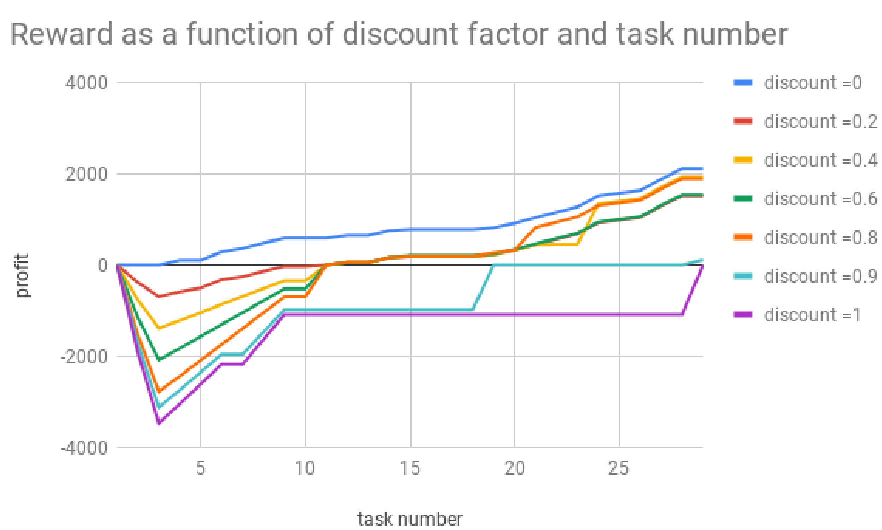
Out of the numerous runs we did against the random agent, our agent almost always won the auction after 10-13 tasks. Moreover, we know that all auctions will have at least 10 tasks and that random agents can get lucky against any algorithm so we decided that winning most of the time was sufficient.

2.2 Experiment 2: Varying the discount factor α in phase 1 of our strategy

2.2.1 Setting

We used the default configuration file `auction.xml` with 30 auctioned tasks (5 seconds bid time, 15 seconds plan time) and ran multiple auctions while varying the discount factor α in phase 1 of our bidding strategy. Our agent competed against our "dummy" agent which always bids: $marginalCost + 1$.

2.2.2 Observations



In the plot 2.2.2 we see how our agent's losses increase during phase 1 of our strategy as a function of the discount factor α. We remark that up to the discount factor of $\alpha = 0.8$ our agent is able to recover its losses by the 10th task. With a larger α however, we see that the agent looses most of its bids because they are too high, trying to regain its high losses from before.

Our conclusion from this experiment is that our strategy is functional with $\alpha \leq 0.8$. Indeed, whatever losses we incur in phase 1 of our strategy, we are later able to regain them because of lower marginal costs due to having a lot more tasks than our opponent.