

# Biding Algorithm - Problem Definition

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## 0.1 General problem description

Our goal is to maximize our profit margin  $M_p$  over all  $n$  elements in the set  $T$  of all  $t_i$  auctions. Where  $r(t_i)$  is the revenue from an auction ( $r(t_i) = 0$  if the auction is lost) and  $c(t_i)$  is the cost that carrying out an auctioned contract ( $r(t_i) = 0$  if the auction is lost). In an adversarial setting where the contract is awarded to the lowest bidding agent  $a$  (*closed-bid first-price reverse auction*). Where  $a \in A$  the set of all agents in the game. Our own agent is denoted as  $\alpha \in A$ .

$$M_p = \sum_{t_i \in T} r(t_i) - \sum_{t_i \in T} c(t_i) \quad (1)$$

At each step  $i$  our profit margin varies by a values  $\Delta M_p(i)$  :

$$\Delta M_p(i) = r(t_i) - c(t_i) \quad (2)$$

For a given *task* our decision algorithm has the following informations :

Cost of adding a given task to the plan :	$c(t_i)$	$\forall t_i$
Price offered by every agent for previous bids :	$p(t_i, a)$	$\forall t_i, a$
Cost of carrying out auction for previous bids :	$c(i)$	$\forall i$
Winner of a given bid :	$w(i)$	$\forall i$

The problem can essentially be thought of as a *multi-armed bandit* problem with an exploration/exploitation tradeoff, we will use a variation on *Thomson Sampling*. The general idea is to fit a probability distribution to estimate our winning probability at each bid. And then pick a bidding amount from that probability distribution in such a way that our expected winning value  $\mathbb{E}(\Delta M_p(i))$  is maximal (greedy algorithm). Or to pick a value at random out of a distribution constructed in such a way that our expected winning value is maximized over time but we don't give up on exploration, which actually tends to yield better results than the greedy solution (*Thomson Sampling*).

## 1 Defining error

We define the error made for a given auction as follows :

$$e(i) = \min_{\forall a \in A / \alpha} \{p(t_i, a)\} - p(t_i, \alpha) \quad (3)$$

For auctions that our agent won we have  $e(i_{won}) \geq 0$ , for auctions lost we have  $e(i_{won}) \leq 0$ .

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**Algorithm 1:** Thompson Sampling For Automatic Bidding

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1 repeat
2   | Compute
3 until no task remains to be auctioned;
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