

Fast Rate Learning in Stochastic First Price Bidding

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Objectives

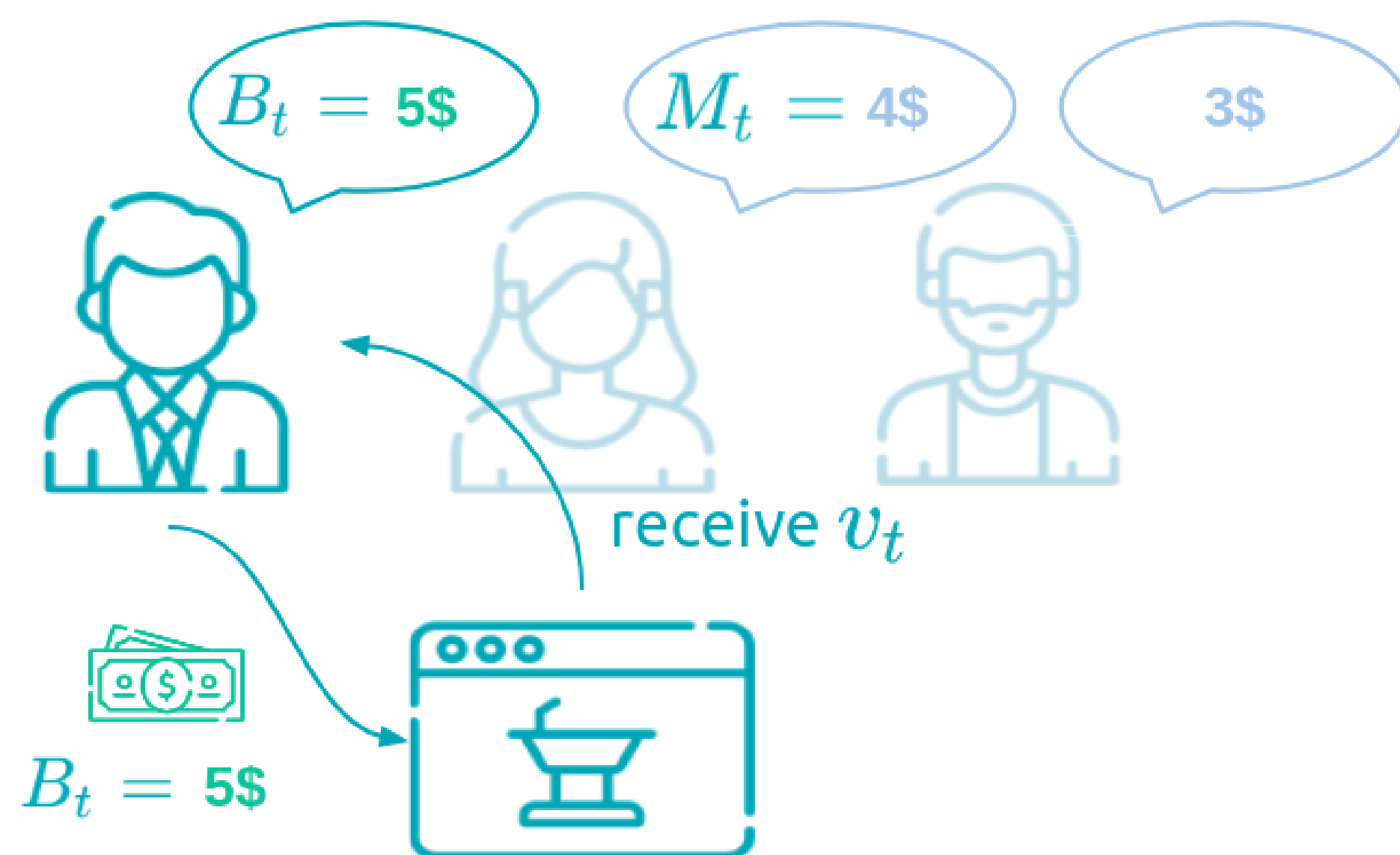
Context: First price auctions have been largely adopted in the field of **programmatic advertising**, where they have progressively replaced second-price auctions.

Objective: designing an **online learning algorithm for bidding in first price auctions**, in the case where the buyer plays against a *stationary stochastic environment*.

Model

For $t = 1 \dots T$, the bidder of interest

- 1 Submits her bid B_t for the item of **unknown value** V_t . $\{V_t\}_{t \geq 1}$ i.i.d in $[0, 1]$;
- 2 Observes the maximum of the other bids : M_t . $\{M_t\}_{t \geq 1}$ is i.i.d in $[0, 1]$ (with cdf F).
- 3 If $M_t \leq B_t$, she **observes and receives** V_t , and **pays** B_t . Otherwise, she loses the auction and does not observe V_t .



The (pseudo-) regret is defined by

$$R_T^{v,F} := T \max_{b \in [0,1]} U_{v,F}(b) - \sum_{t=1}^T \mathbb{E}[U_{v,F}(B_t)].$$

where the utility is

$$U_{v,F}(b) := \mathbb{E}[(V_t - b)_+ \mathbf{1}\{M_t \leq b\}] = (v - b)F(b).$$

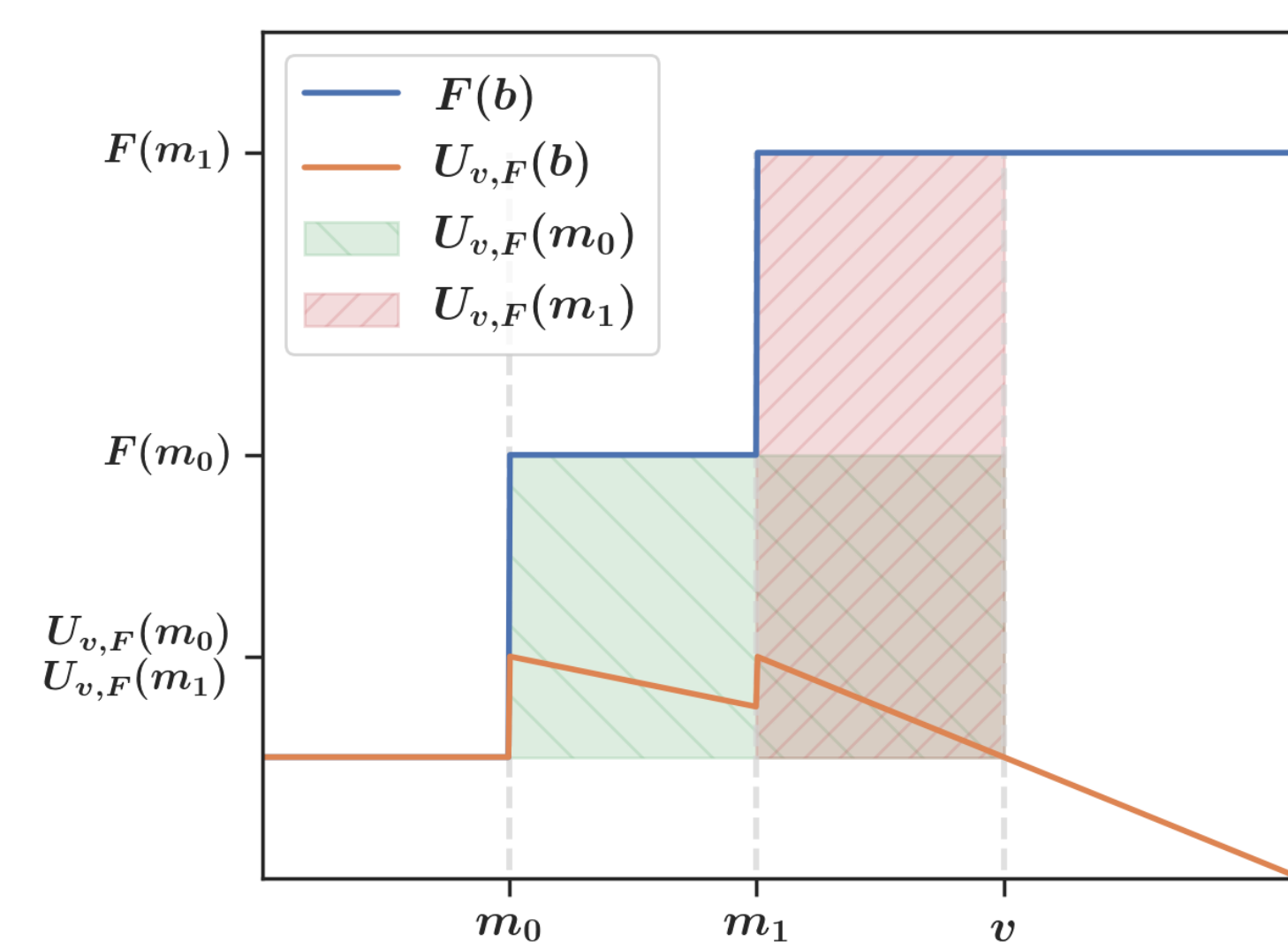
Some Intuition

Exploration/Exploitation Trade-Off where Exploitation consists in bidding close to a certain optimum and Exploration consists in bidding high enough (bidding 1 means observing everything).

Properties of First Price Auctions

Difficulties: Unlike in second price auctions, the maximizer of the utility is **not available in close form**. More generally, there could be **multiple maximizers**, or arbitrarily close maxima. Thus, we define

$$b_{v,F}^* = \max_{b \in [0,1]} \left\{ \arg \max U_{v,F}(b) \right\}.$$



General Lower Bound

Any strategy, whether it assumes knowledge of F or not, must satisfy

$$\liminf_{T \rightarrow \infty} \frac{\max_{v \in [0,1], F \in \text{cdf}} R_T^{v,F}}{\sqrt{T}} \geq \frac{1}{64},$$

Regular Case. Under general regularity assumptions on F (see paper):

- there exists one unique maximizer $b_{v,F}^*$ of the utility
- $\psi_F : v \mapsto b_{v,F}^*$ is Lipschitz continuous with a Lipschitz constant 1.
- there exist two constants c and C such that $\forall b \in [b_{v,F}^* - \Delta, b_{v,F}^* + \Delta]$, $c(b_{v,F}^* - b)^2 \leq U_{v,F}(b_{v,F}^*) - U_{v,F}(b) \leq C(b_{v,F}^* - b)^2$

Estimation method: We estimate $U_{v,F}$ thanks to the average of V_t and to the empirical c.d.f.

$$\hat{V}_t := \frac{1}{N_t} \sum_{s=1}^{t-1} V_s \mathbf{1}\{M_s \leq B_s\},$$

$$\hat{F}_t(b) := \frac{1}{t-1} \sum_{s=1}^{t-1} \mathbf{1}\{M_s < b\}.$$

The Algorithm and its Analysis

UCBid1+ Algorithm

Initially set $B_1 = 1$;

for $t \geq 2$, do

$$B_t = \max_{b \in [0,1]} \left\{ \arg \max (\hat{V}_t + \epsilon_t - b) \hat{F}_t(b) \right\},$$

where $\epsilon_t := \sqrt{\gamma \log(t-1)/2N_t}$.

end

Regret Upper Bound

In all generality, when $\gamma > 2$

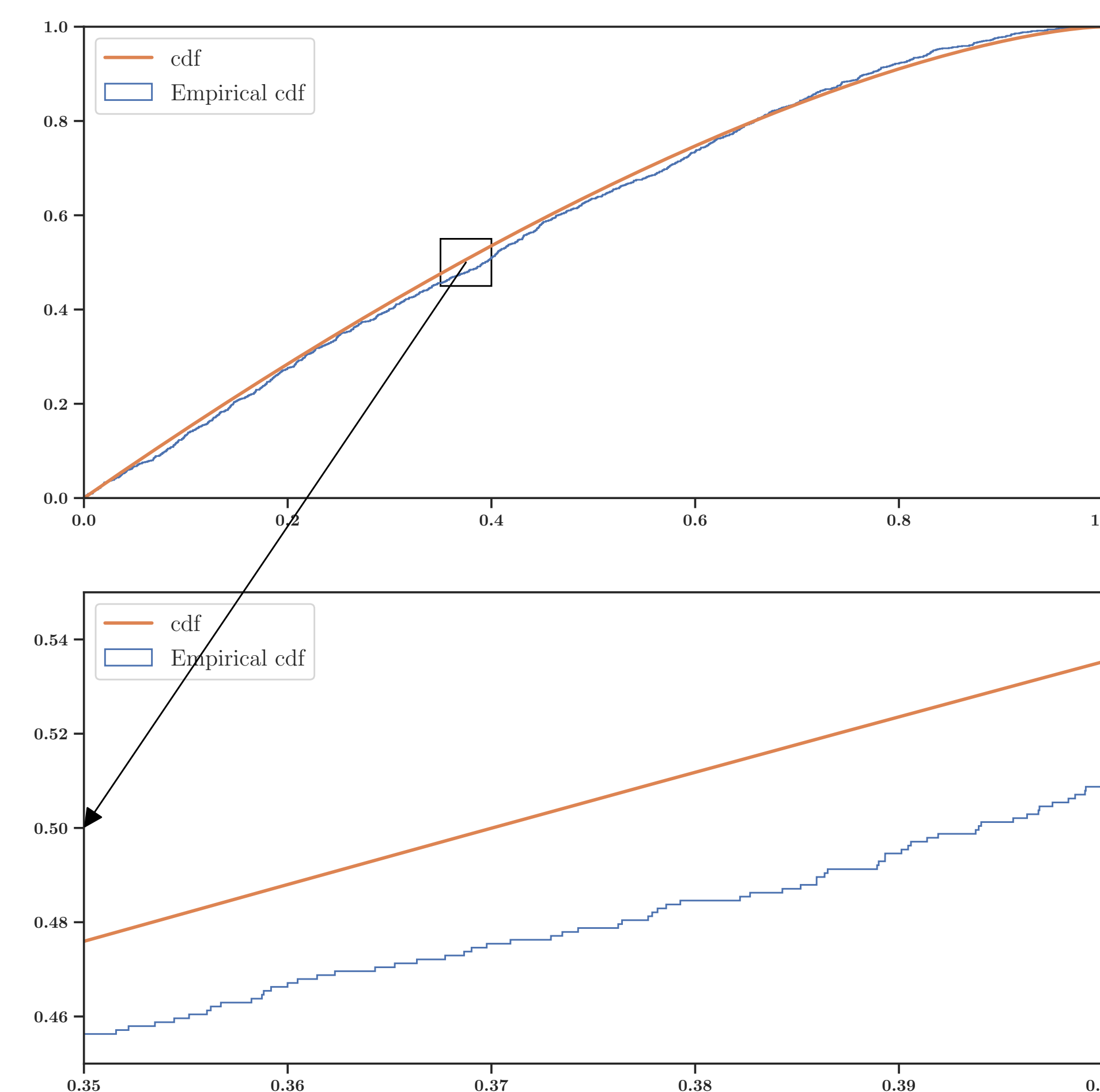
$$R_T^{v,F} \leq C_{v,F} \sqrt{\frac{\gamma v}{U_{v,F}(b_{v,F}^*)}} \sqrt{T \log T} + O(\log T),$$

While in the regular case

$$R_T^{v,F} \leq O(T^{1/3+\epsilon}),$$

for any $\epsilon > 0$

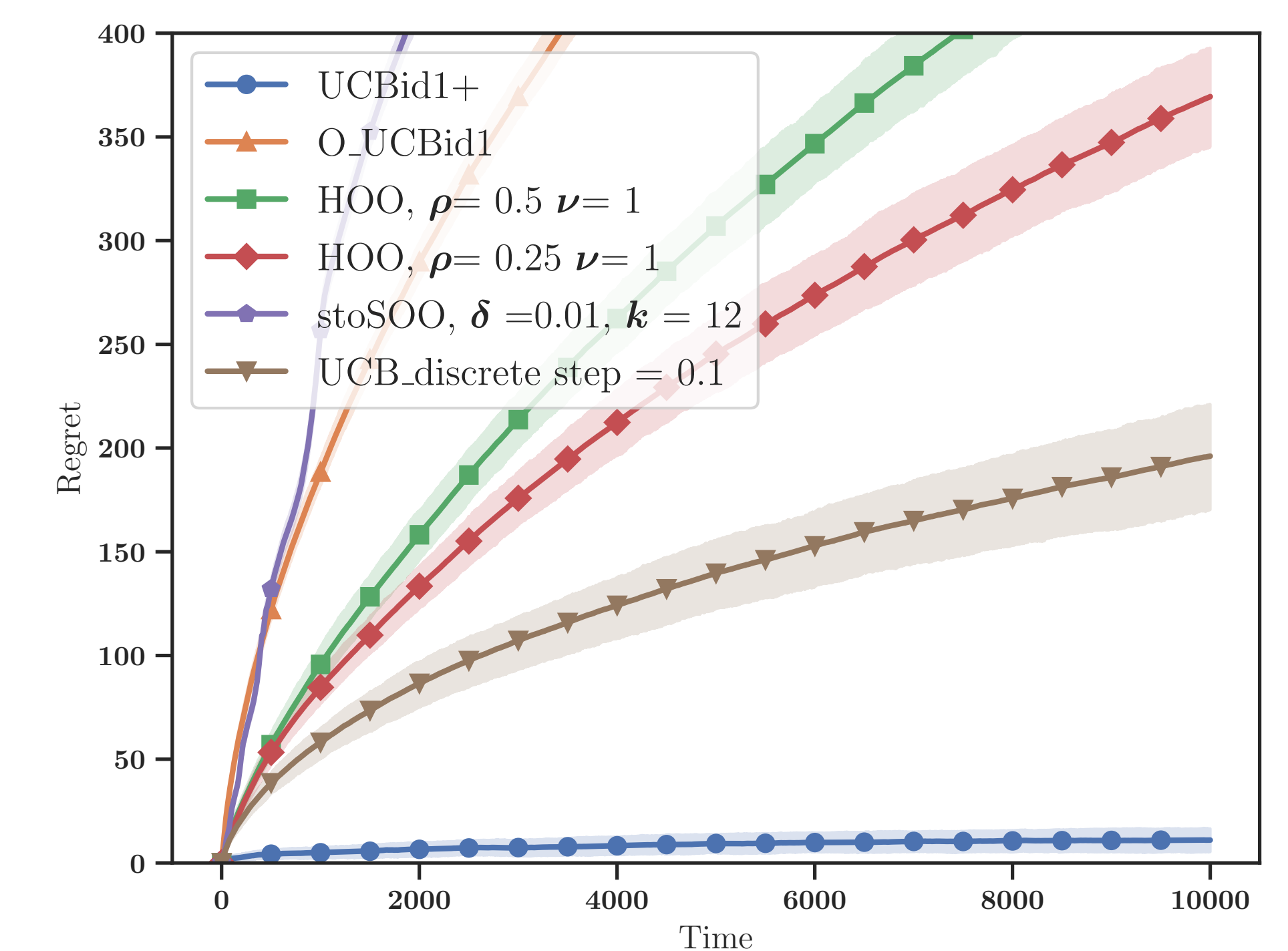
The proof relies on a new local concentration inequality on F , more efficient than DKW locally.



Remark: We also study the setting in which one knows F in advance. Then one can directly resort to F instead of \hat{F} , which leads to a significantly reduced regret ($O(\log^2 T)$) in the regular case.

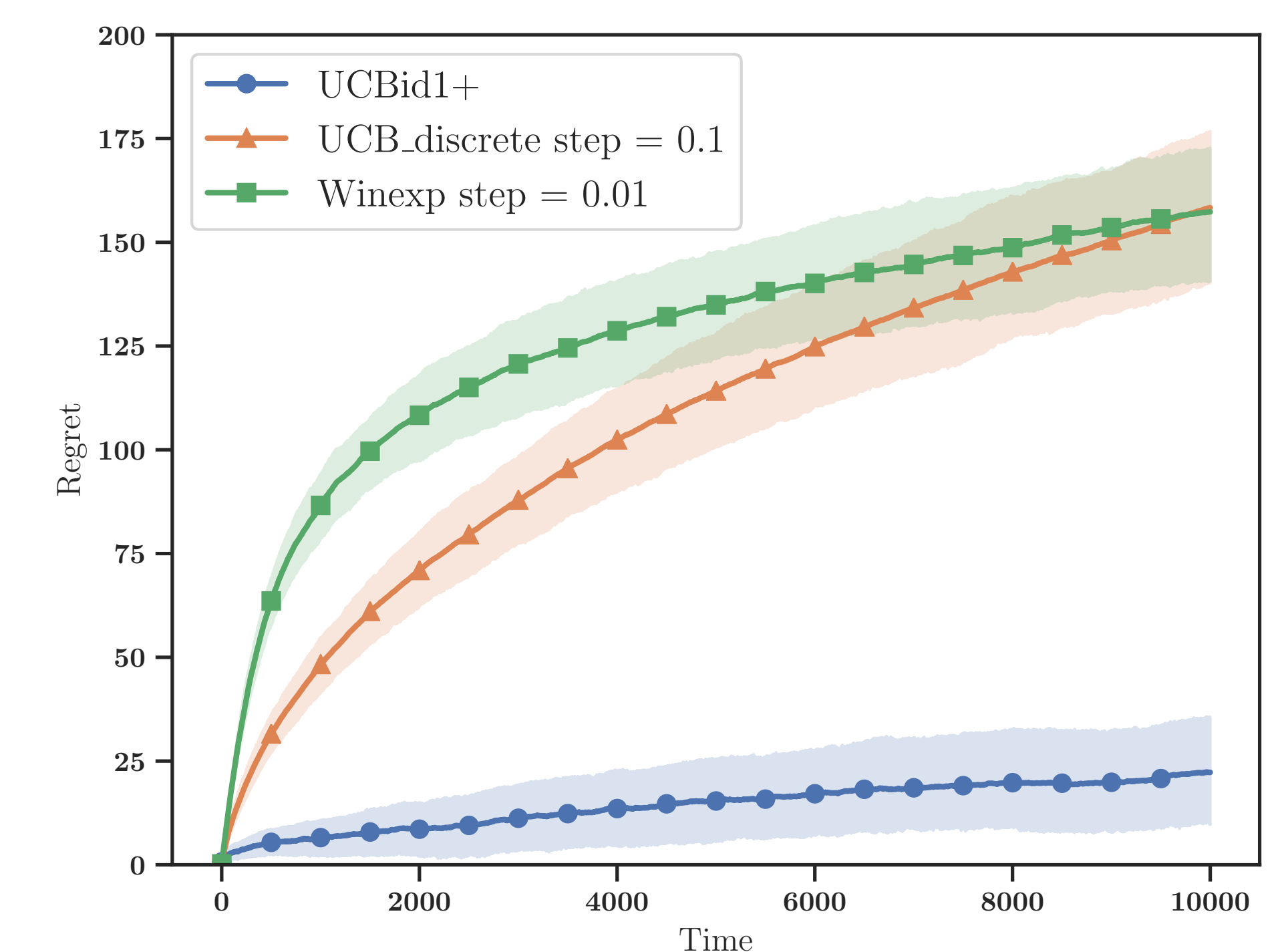
Simulations

With $M_t \sim \text{Beta}(1, 6)$ and $v = 1/2$



Real Data Experiments

Real-world bidding dataset: 56607 bids that were made on a specific placement on Adverline's inventory on auctions that Numberly participated to, for a specific campaign.



Acknowledgements

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