CS 332 Fall 2025

Project #3

Koshi Harashima, Ben Cole

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1 Outcomes from No-regret Learning in Games

Methods

Repeated first-price auction (2 bidders, fixed values, full information + full feedback). Utility if win $u = v - b$, else 0; ties split 0.5.

Algorithms: Myopic (one-step expected utility using empirical $P(\text{win} \mid b)$) vs Flexible (Exponential Weights/Hedge over k bids with full-feedback updates, $\epsilon = \sqrt{\log k/n}$).

Setup: $(v_1, v_2) \in \{(10, 10), (12, 8)\}$, $k \in \{10, 100\}$, rounds $n \in \{100, 1000\}$, Monte Carlo $n_{mc} = 10$. NE proxies computed at $(12, 8)$ with k=100, n=1000 and a longer run n=5000.

Results

Myopic vs Flexible (10,10; k=10; n=1000; n_{mc}=10): Myopic mean utility ≈ 1022.8, win rate ≈ 0.426; Flexible ≈ 1027.7, ≈ 0.574. Regret vs best fixed bid is not uniformly lower for Flexible with coarse k=10; Flexible bids are more stable (lower variance). Robustness across n, k, values preserves the ranking (Flexible > Myopic); scaling ϵ in $\{0.5, 1, 2\}\times$ default changes variance, not ranking.

NE proxies (no pure NE for complete-info FPA with $v_1 > v_2$; mixed equilibrium predicts efficient allocation and price near v_L): $(12, 8)$, k=100: efficiency 0.946 (all rounds, n=1000) → 0.959 (last 500 of n=5000); average winning price 7.80 → 7.89 vs v_L=8.0.

Takeaways

Flexible (Hedge) consistently achieves higher average utility and win rate than Myopic; Myopic overreacts to recent bids. Outcomes move toward mixed-equilibrium predictions (high-value wins; price near v_L) as n (and k) increase, but do not converge to an exact equilibrium strategy profile.

2 Manipulability of No-regret Learners in Games

Model

Same repeated FPA setting. Opponent: Flexible learner with v_1=9, k=100. Our player (exploiter) has v_2=3 and: observes for a few rounds (bid ≈ $0.2v$); predicts the opponent's next bid via exponential smoothing ($\alpha \in \{0.2, 0.4, 0.6\}$); when predicted bid falls below a threshold ratio ($\in \{0.5, 0.6, 0.7\}$), bids to win with positive margin on the grid. Main run n=100, n_{mc}=1; robustness with n_{mc}=5. Full feedback enables computing $P(\text{win} \mid b)$ for all grid bids and timing the exploit when the flexible learner's sampling puts mass on low bids.

Results

Baseline (obs = 5): Flexible win rate ≈ 0.91, mean utility ≈ 618; exploiter win rate ≈ 0.09, mean utility ≈ 11. Robustness (obs $\in \{5, 10, 15\}$, $\alpha \in \{0.2, 0.4, 0.6\}$, threshold $\in \{0.5, 0.6, 0.7\}$; n_{mc}=5): exploiter win rate ≈ 0.08–0.10, mean utility ≈ 9–12; Flexible remains ≈ 0.90–0.92 wins with high utility.

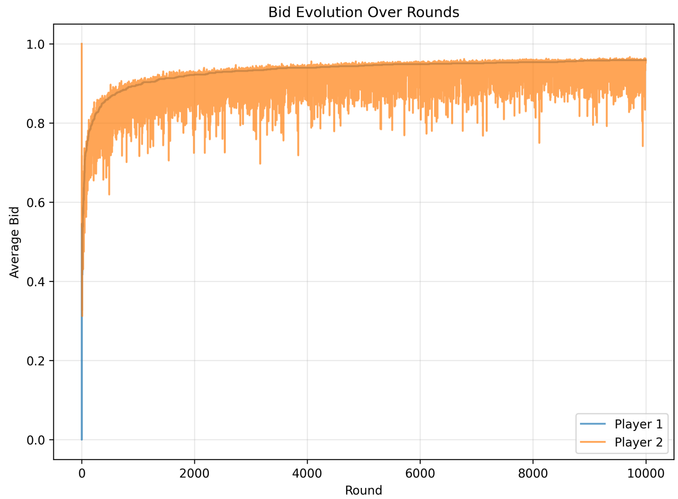
Takeaways

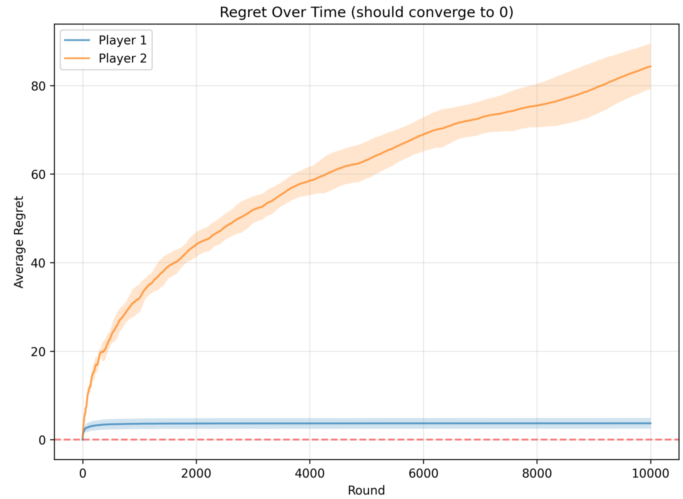
Under full feedback, prediction-based exploitation yields occasional low-price wins for a low-value bidder, but gains are small; the flexible learner remains dominant. The effect is robust to reasonable observation/smoothing/threshold choices.

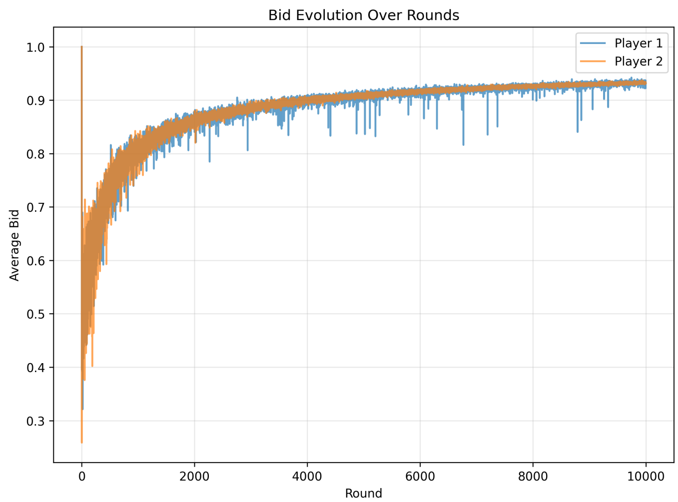
AI and Collaboration

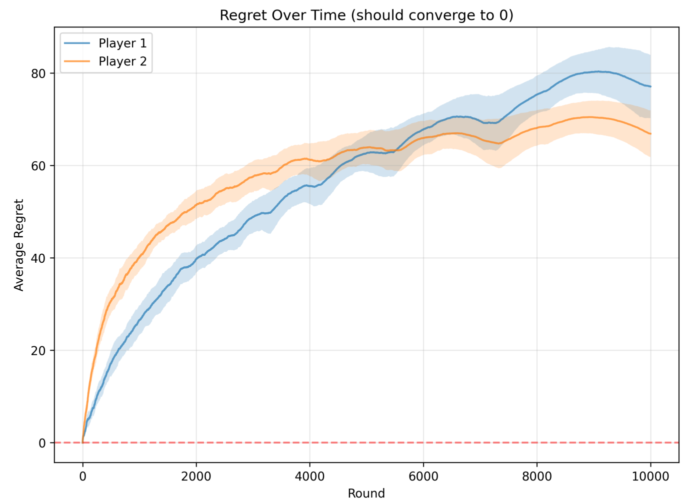
Both authors jointly designed experiments and interpreted results;
AI was used to assist with code organization, plotting, slide layout, and editing text; all code and results were reviewed and validated by the authors.

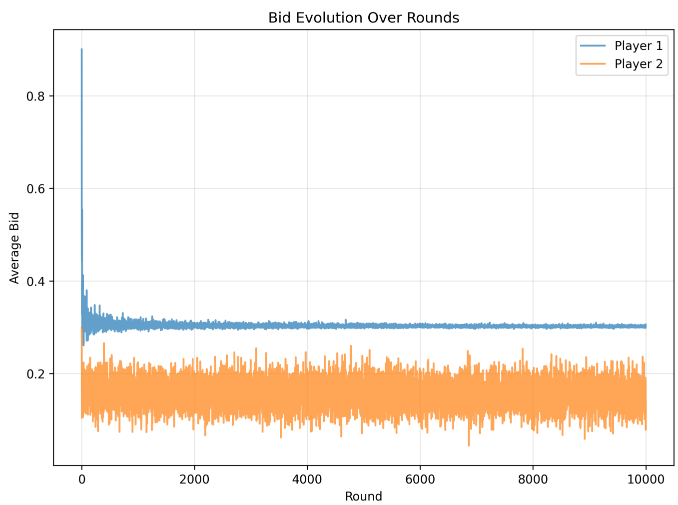
Figures

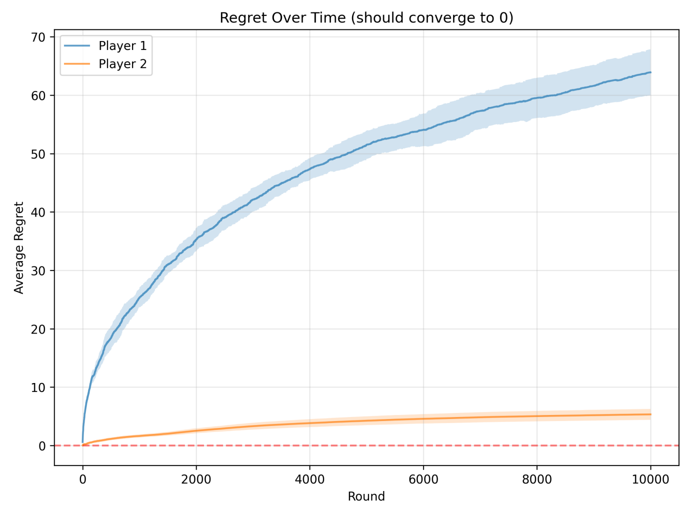

Bid Evolution Over Rounds
Average Bid
Round
Player 1
Player 2

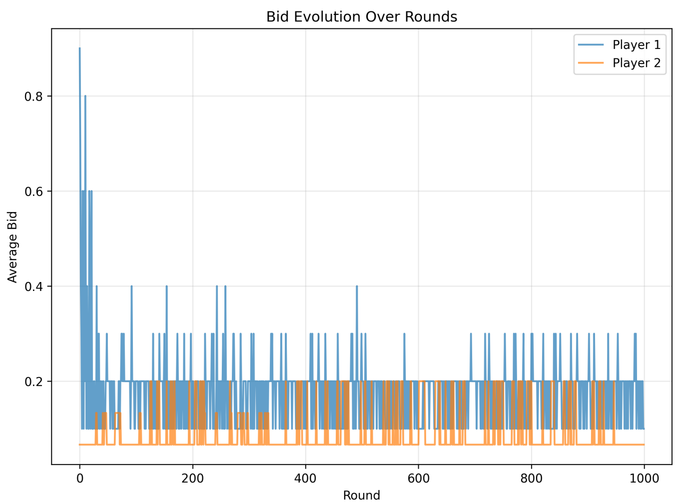

Regret Over Time (should converge to 0)
Average Regret
Round
Player 1
Player 2

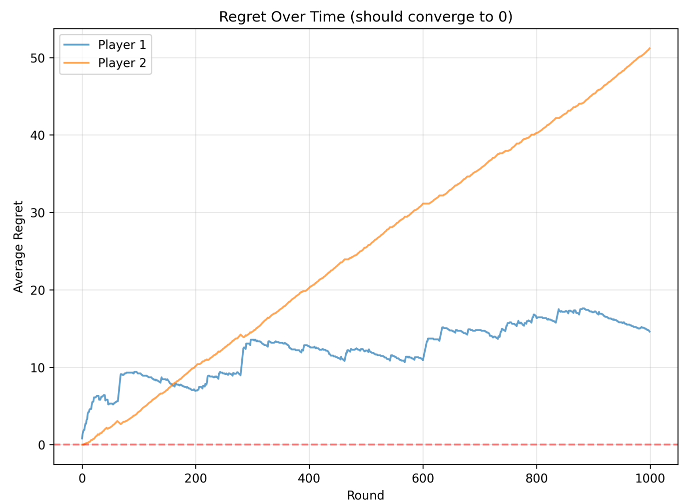

Bid Evolution Over Rounds
Average Bid
Round
Player 1
Player 2


Regret Over Time (should converge to 0)
Average Regret
Round
Player 1
Player 2


Bid Evolution Over Rounds
Average Bid
Round
Player 1
Player 2


Regret Over Time (should converge to 0)
Average Regret
Round
Player 1
Player 2


Bid Evolution Over Rounds
Player 1
Player 2
Average Bid
Round
0.2
0.4
0.6
0.8
0
200
400
600
800
1000


Regret Over Time (should converge to 0)
Player 1
Player 2
Average Regret
Round
0
10
20
30
40
50
0
200
400
600
800
1000