GAME THEORY FINAL

AdX GAME

Daniel Cho, Junjie Zheng

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01

SIMPLIFIED GAME

Assumptions made to
create a simplified game.

SIMPLIFIED GAME

SINGLE DAY

Assume that bidding occurs on a single day for all campaigns. This not only simplifies the game, but also positively affects the quality score.

CRITICAL BIDDING

Assume that all competitive agents calculate and use their critical bid for all campaigns. This simulates truthful bidding.

CAMPAIGN BIDDING

Assume that all competitive agents bid a linear function of the campaign reach. This simplifies the many possible campaign bidding strategies.

02

MODEL STRATEGY

Base model strategy and improvements.

WATERFALL HEURISTIC

COLLECT ALL KNOWN CAMPAIGNS

Use current campaigns and store a history of campaigns in auction.

CONSTRUCT ALLOCATIONS

Use the algorithm to calculate allocations for all market segments.

FIND MINIMUM BIDS

From the allocations, find the minimum bid needed to obtain users.

WALRASIAN EQUILIBRIUM

GREEDY ALLOCATION

If enough supply remains to satisfy campaign, allocate the rest of supply if needed.
If campaign cannot afford the bundle, unallocate it.

LINEAR PROGRAMMING

Maximize total payment subtracted by sum of latent variables against some constraints.

Q-LEARNING

Using a very simplified version of Q-learning, we keep track of a Q-table that holds **market segments** to q-values. After making an initial guess, the agent keeps tracks of auction wins and losses for each segment and updates accordingly.

PROBLEM SOLUTION

VARIATION

Any amount of variation in competition agents greatly affects the results of our agent.

COMBINATION

To combat this, rather than bidding slightly higher, we raise our bid by combining our bid with the critical bid.

PROBLEM SOLUTION

COMPLEXITY

In the campaign auctions, there is a fair amount of unaddressed complexity that our agent does not make use of.

PARAMETERS

By assigning parameters that factor in the length of a campaign, similarity of campaigns, and the learning rate of the Q-Learning algorithm, our agent can leverage this complexity to obtain a higher score.

03

MACHINE LEARNING

Incorporating machine learning into agents.

LSTM Model

COARSE-GRAINED INFORMATION

Probing the underlying market doesn't seem approachable.

SENSITIVE INITIAL CONDITIONS

The way the buffer is prepared changes the quality score.

QUESTIONABLE CONVERGENCE

Relying too much on the reinforcement learning performance.

REINFORCEMENT LEARNING

PARAMETERS

Rather than empirically choosing parameters, maybe RL can do better.

ENVIRONMENT

Convert the AdX game code into a OpenAI Gym environment.

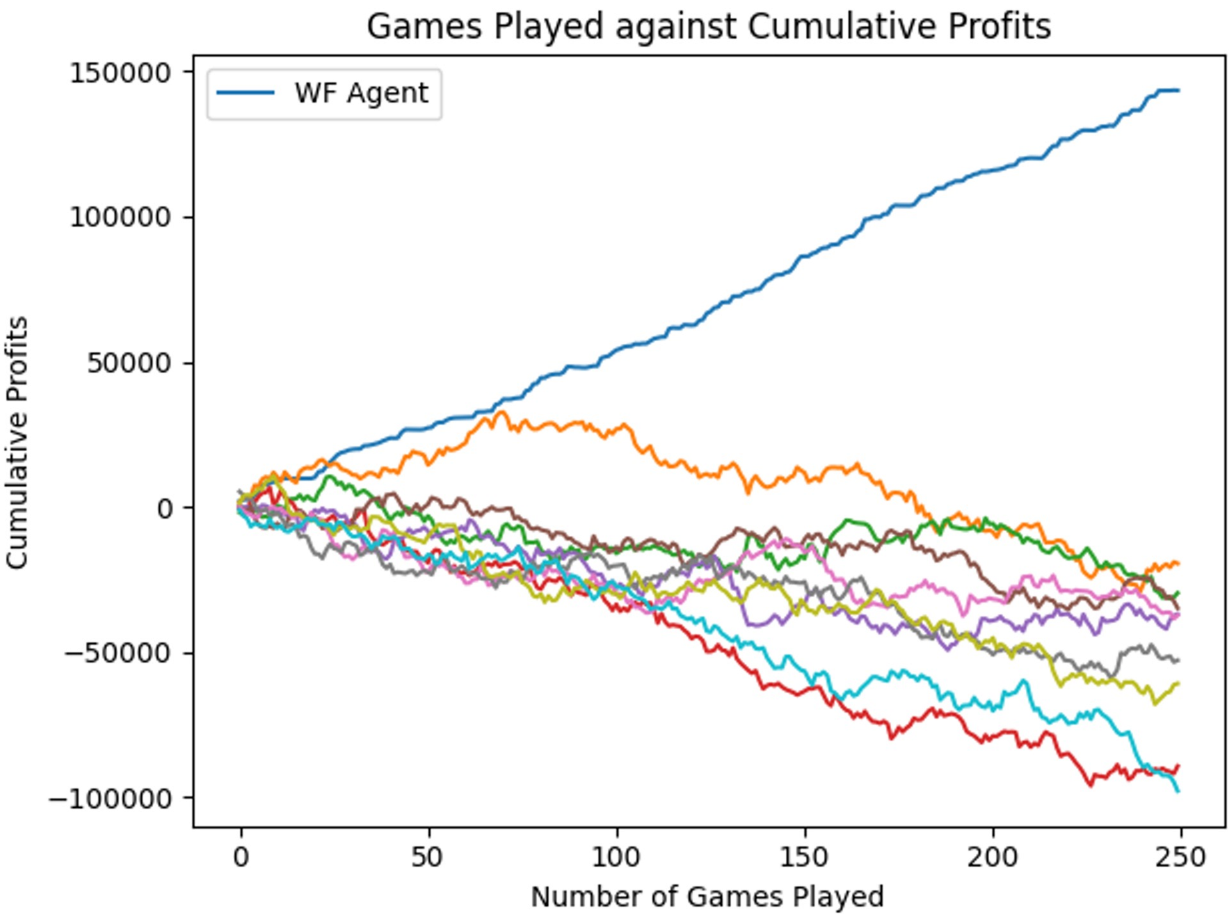
TRAINING

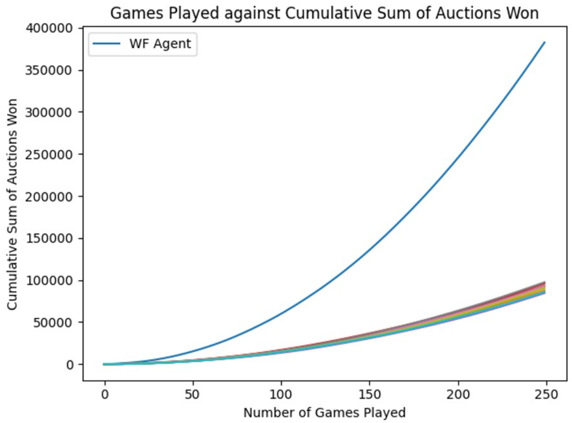
Train the RL agent against our current best agents and other randomized agents.

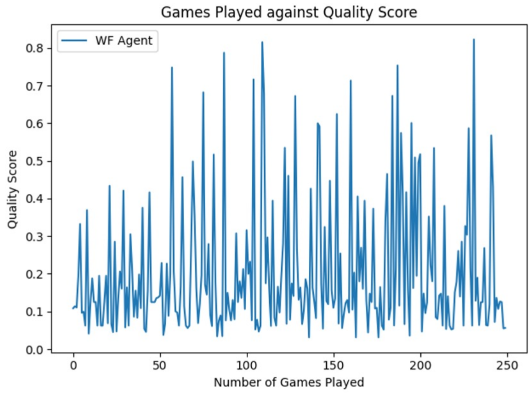
04

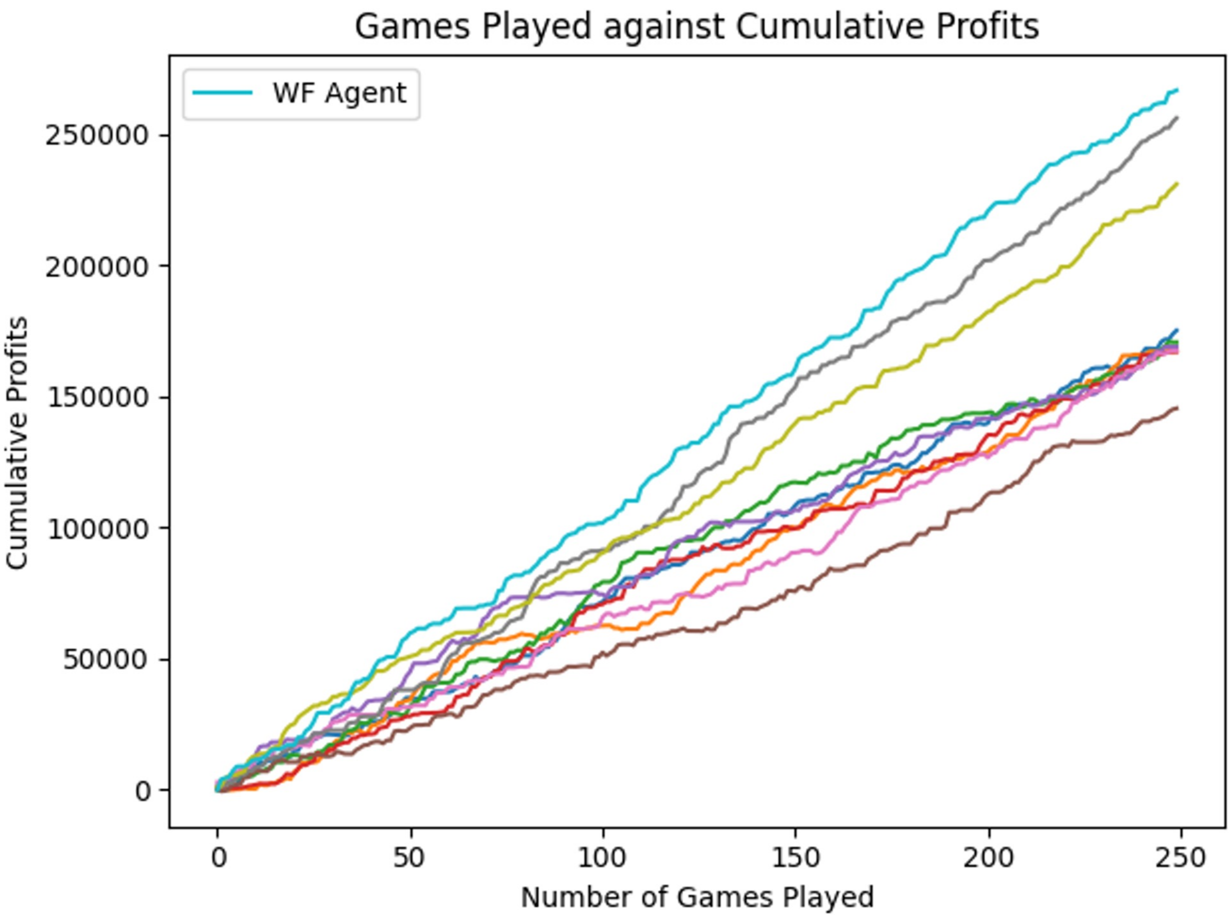
MODEL RESULTS

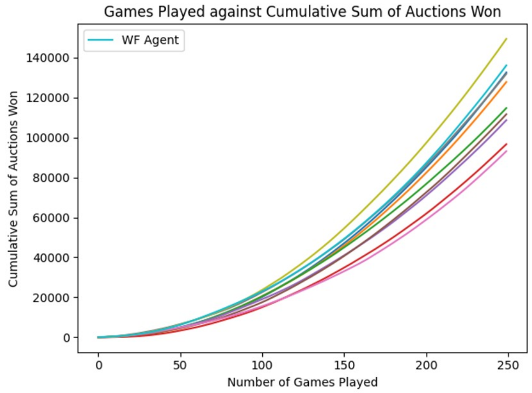
Results of LSTM and RL incorporation.

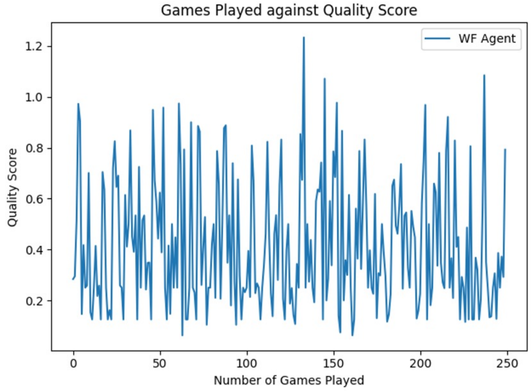

Games Played against Cumulative Profits
WF Agent
Cumulative Profits
150000
100000
50000
0
−50000
−100000
0
50
100
150
200
250
Number of Games Played


Games Played against Cumulative Sum of Auctions Won
WF Agent
Cumulative Sum of Auctions Won
400000
350000
300000
250000
200000
150000
100000
50000
0
0
50
100
150
200
250
Number of Games Played

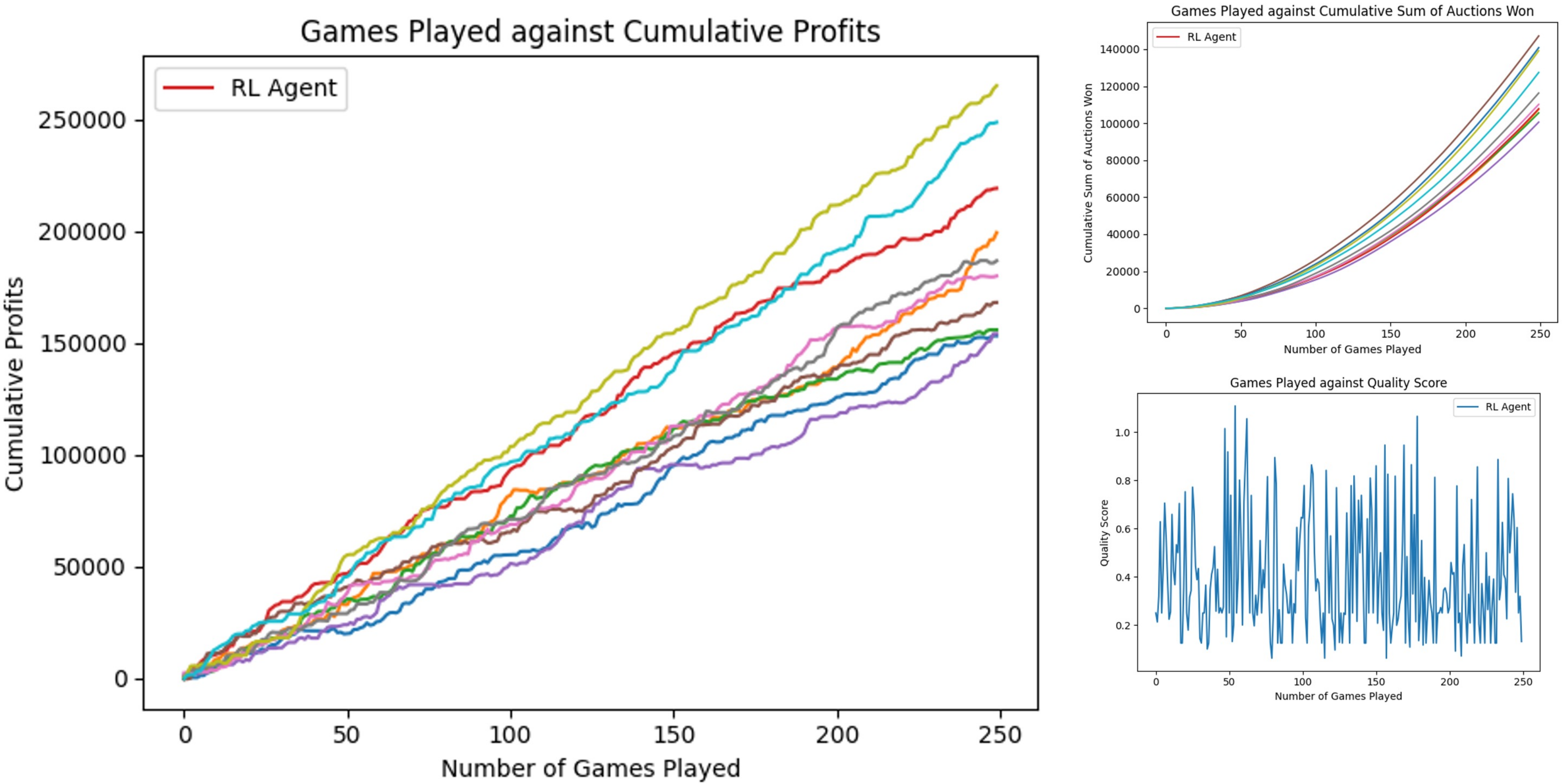

Games Played against Quality Score
WF Agent
Quality Score
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0.0
0
50
100
150
200
250
Number of Games Played


Games Played against Cumulative Profits
WF Agent
Cumulative Profits
0
50000
100000
150000
200000
250000
0
50
100
150
200
250
Number of Games Played


Games Played against Cumulative Sum of Auctions Won
WF Agent
Cumulative Sum of Auctions Won
0
20000
40000
60000
80000
100000
120000
140000
0
50
100
150
200
250
Number of Games Played


Games Played against Quality Score
WF Agent
Quality Score
0.2
0.4
0.6
0.8
1.0
1.2
0
50
100
150
200
250
Number of Games Played

Training Curves for RL Agent
Normalized Profits
Number of Games Played
1.5
1.0
0.5
0.0
−0.5
0
50000
100000
150000
200000
250000
300000
Min
Max
Mean


Games Played against Cumulative Profits
RL Agent
Cumulative Profits
250000
200000
150000
100000
50000
0
0
50
100
150
200
250
Number of Games Played
Games Played against Cumulative Sum of Auctions Won
RL Agent
Cumulative Sum of Auctions Won
140000
120000
100000
80000
60000
40000
20000
0
Number of Games Played
Games Played against Quality Score
RL Agent
Quality Score
1.0
0.8
0.6
0.4
0.2
Number of Games Played