Verifying Truthfulness in Auctions Using Reinforcement Learning

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CSSE490: Algorithmic Game Theory

Ideal Auctions

- Truthful
  - Agents have a dominant strategy to bid their true valuation for an object
- In auction design, we **typically assumed truthfulness to begin**, and design around it

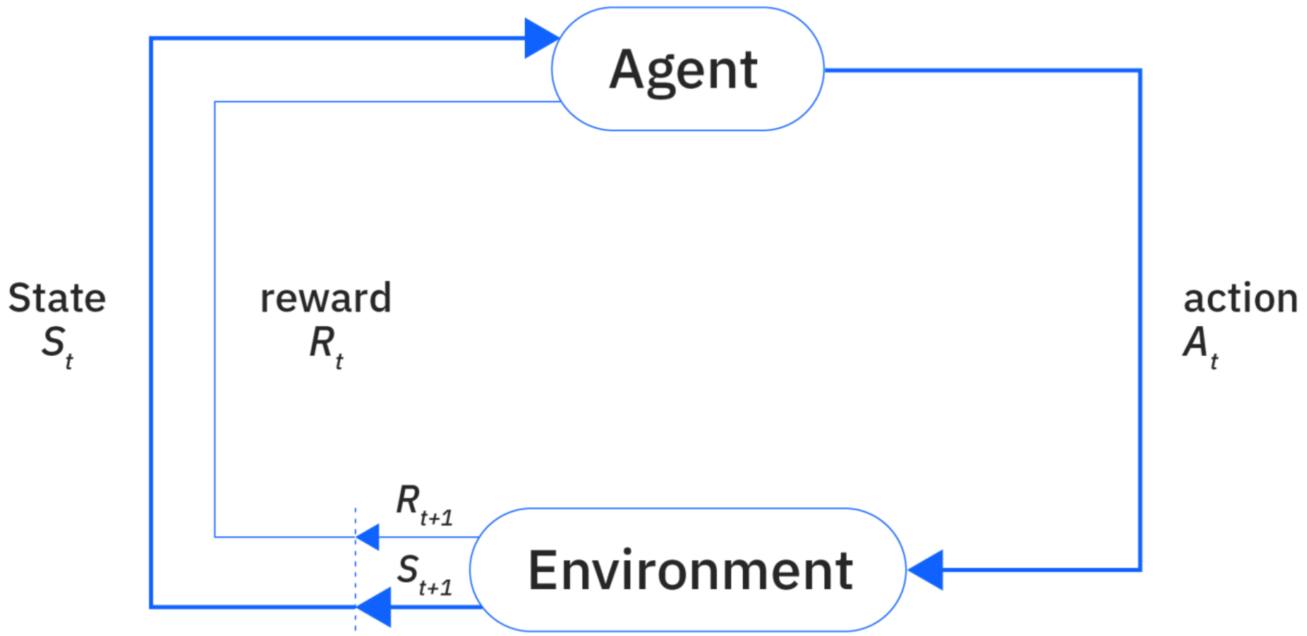
Project Goal

Verify truthfulness in these auctions using reinforcement learning

1. Start with agents bidding random initial values
2. Agent learns how to bid to maximize rewards
3. Show that the learned strategy is truthfulness

Reinforcement Learning

- Agents explore an environment by taking actions and **receiving rewards**
- Goal is to **maximize long term accumulation of rewards**



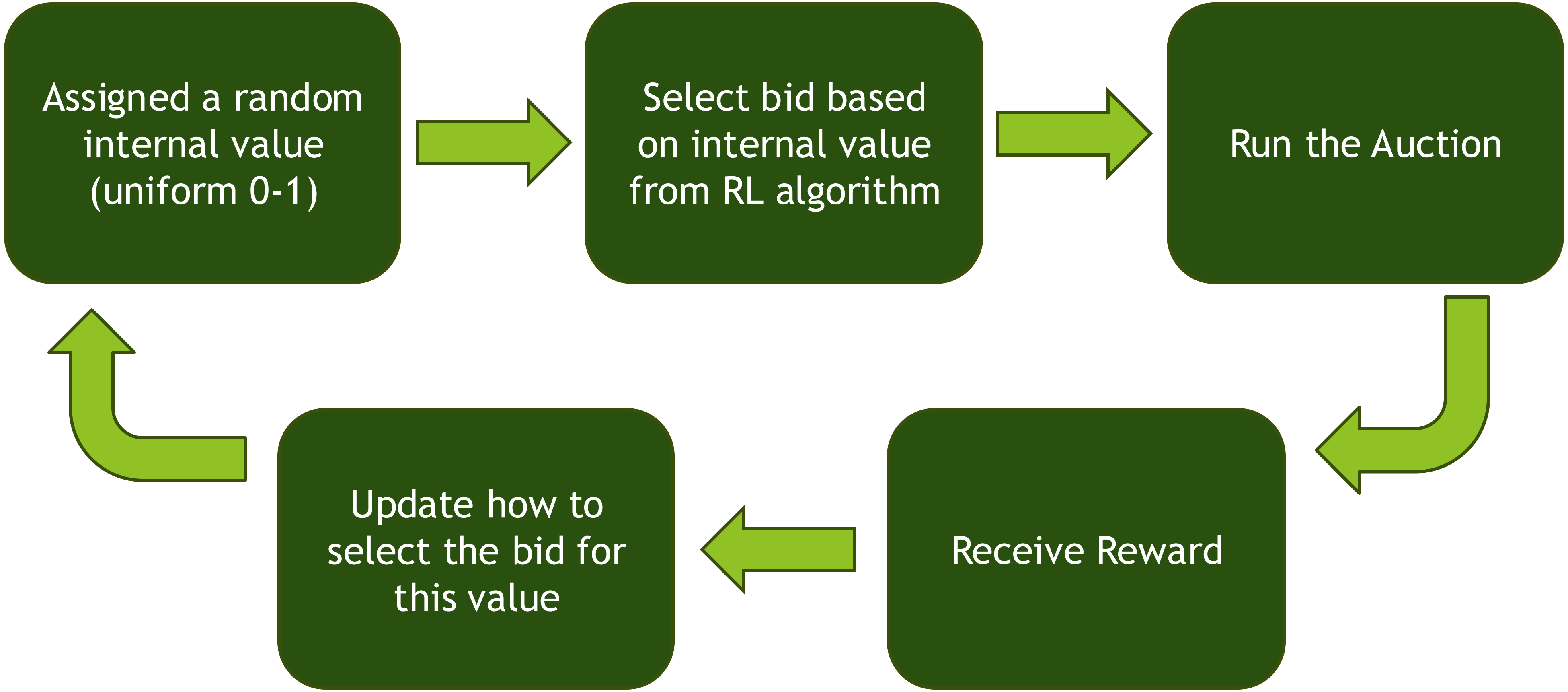
RL vs Best Response Dynamics

Aspect	Best Response Dynamics	Reinforcement Learning
Assumptions	Knows payoff structure and others' strategies	Doesn’t know environment or other agents
Adaptation	Computes best response analytically	Adjusts from reward feedback
Learning	**No learning**; purely reactive	Yes; **learns over time** through reward signals
Exploration	None (calculated)	Required to discover optimal actions

Design

Diagram | Methods | Auctions

Diagram


Assigned a random internal value (uniform 0-1)
Select bid based on internal value from RL algorithm
Run the Auction
Receive Reward
Update how to select the bid for this value

Reinforcement Learning Methods

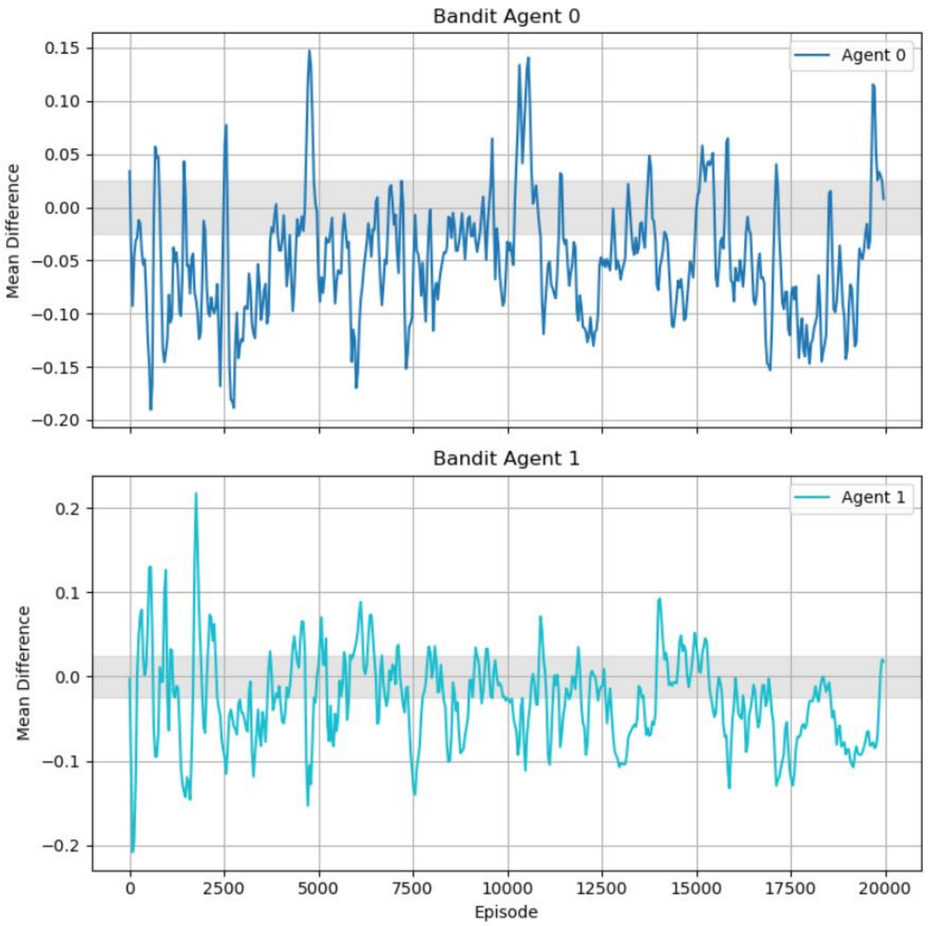
Method	Q-Learning	Thomson Bandit (Supervised)	SAC
Type	Dynamic Programming	Contextual Bandit	Deep RL (actor-critic)
Exploration	ε-greedy	Bayesian (dropout)	Entropy-based (stochastic policy)
Action Space	Discrete Bids	Continuous Bids	Continuous Bids

Auction Modes

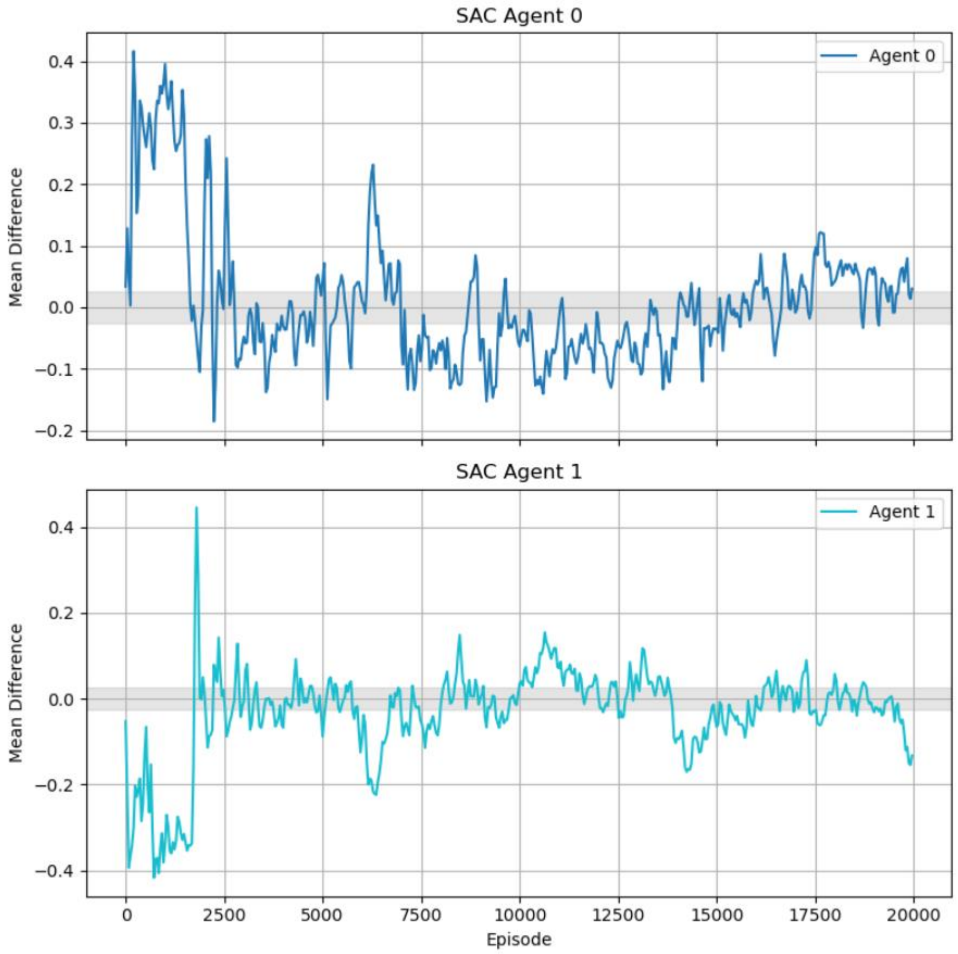
Auction Type	Payment Style	Number of Agents	Number of Items
Simple Second Price	Second highest bid	2	1
Multi Agent	Second highest bid	4	1
Multi-k-Item	K winners pays the **(k+1)th highest bid**	5	3
Adversarial	K winners pays the **(k+1)th highest bid**	5	2

Results

Simple

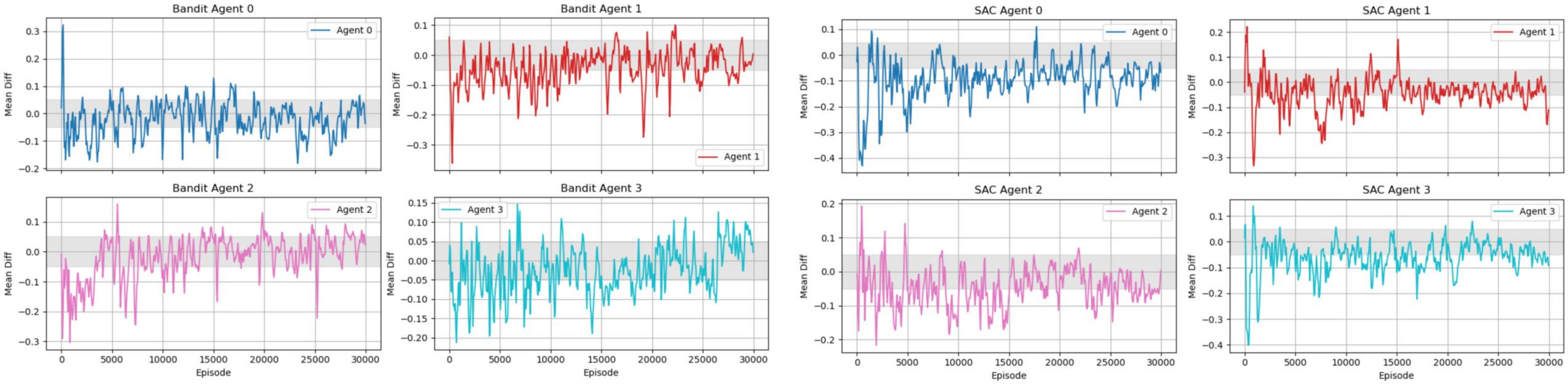


Bandit Agent 0
Agent 0
Mean Difference
Bandit Agent 1
Agent 1
Mean Difference
Episode

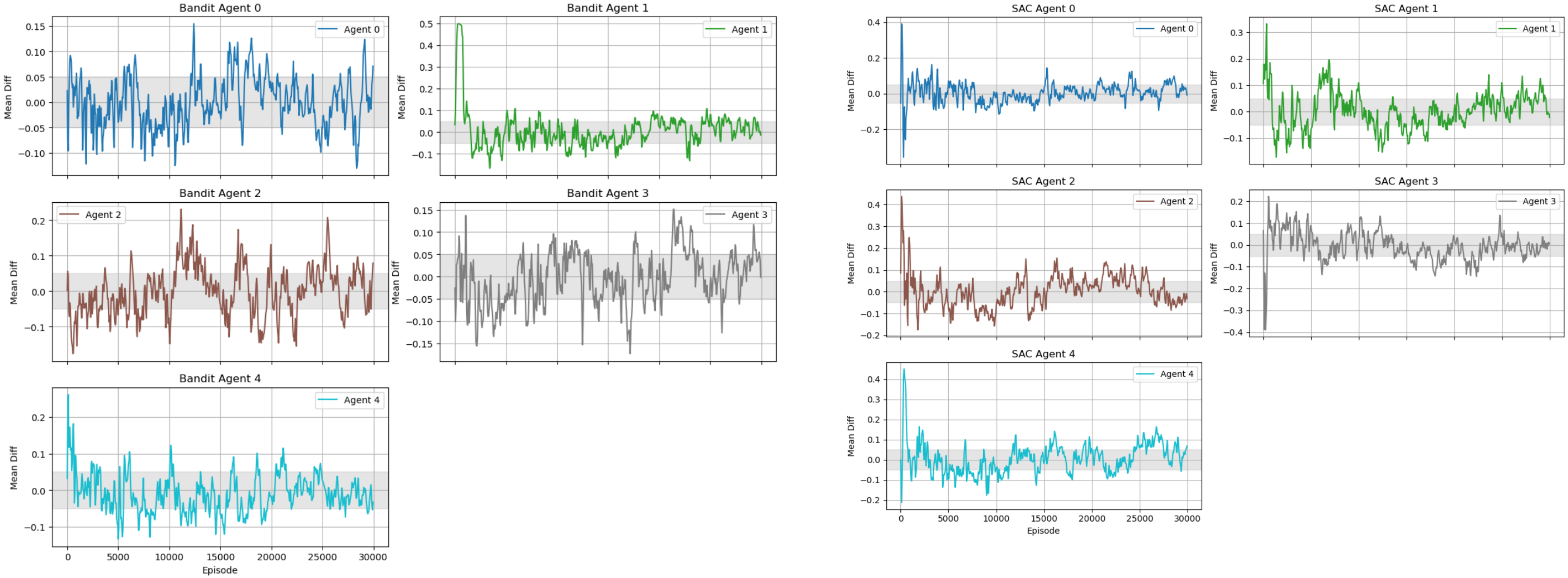


SAC Agent 0
Agent 0
Mean Difference
SAC Agent 1
Agent 1
Mean Difference
Episode

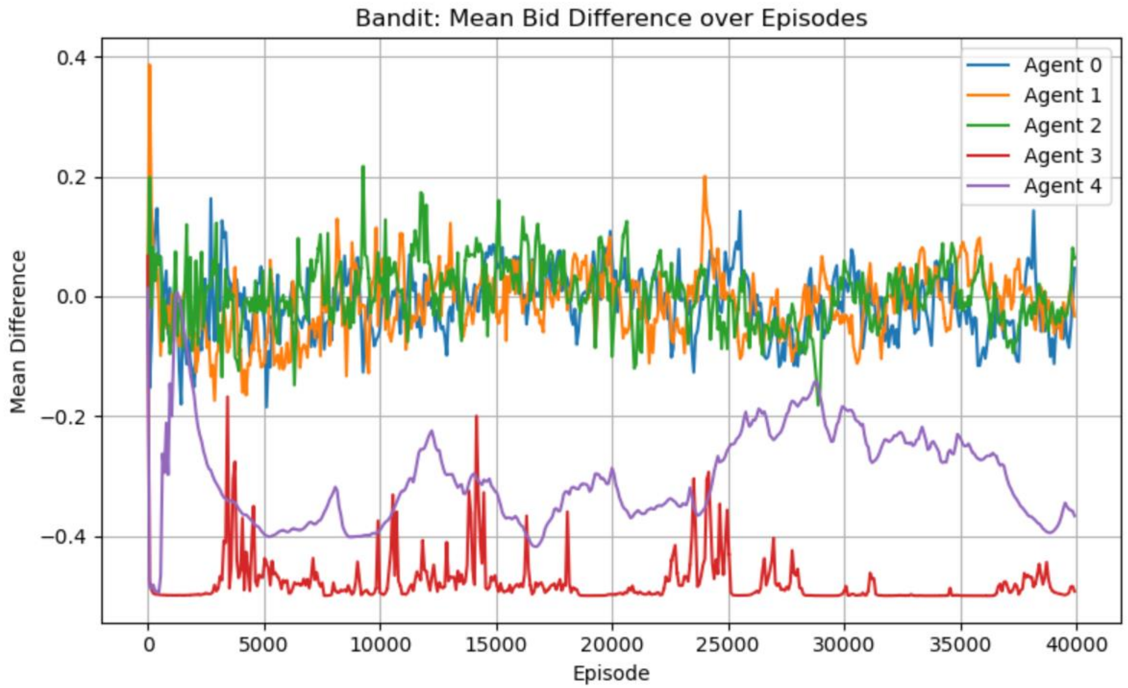
Multi-Agent

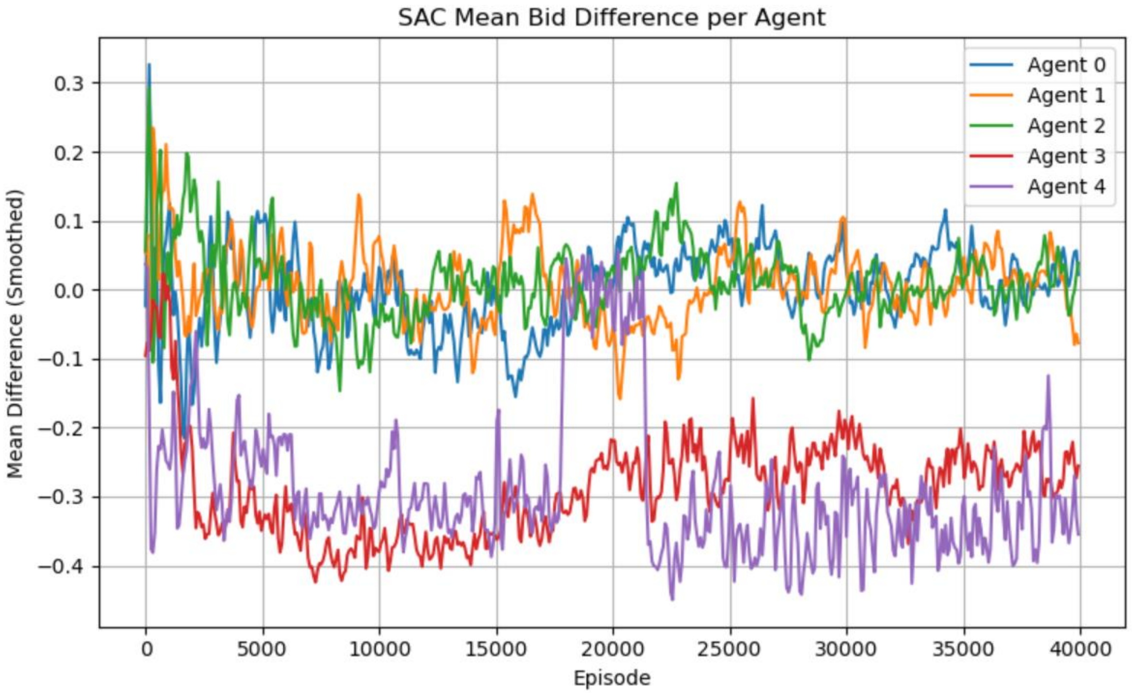

Bandit Agent 0
Bandit Agent 1
Bandit Agent 2
Bandit Agent 3
SAC Agent 0
SAC Agent 1
SAC Agent 2
SAC Agent 3
Agent 0
Agent 1
Agent 2
Agent 3
Mean Diff
Episode

Multi-k-Item


Bandit Agent 0
Bandit Agent 1
Bandit Agent 2
Bandit Agent 3
Bandit Agent 4
SAC Agent 0
SAC Agent 1
SAC Agent 2
SAC Agent 3
SAC Agent 4
Agent 0
Agent 1
Agent 2
Agent 3
Agent 4
Mean Diff
Episode

Adversarial Agents





Results

- Agent bids did converge towards internal values
- **Imperfect convergence** is a symptom of RL algorithms
  - Sensitive to initial conditions and random selection
- Shows truthful bidding is the dominant strategy
  - Regardless of how other agents bid
    - Most apparent in adversarial auction design

Future Work

- **Took a truthfulness approach:** Could explore maximizing social welfare, maximizing revenue by ‘learning’ payment structure or optimal reserve price
- **Move towards best response dynamics:** Use RL to learn how one agent responds to another
- **Look at combinatorial auctions:** implement combinatorial auctions (with and without additive valuations) in both a discrete and continuous space

Thank you