AppleGameEnv:

Mastering Massive Action Space in a Non-Tabular RL Environment

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25S CS377: Introduction to RL

- Introduction
- AppleGame
- Applying RL to AppleGameEnv
- Employing Natural Language
- Limitations & Future Works

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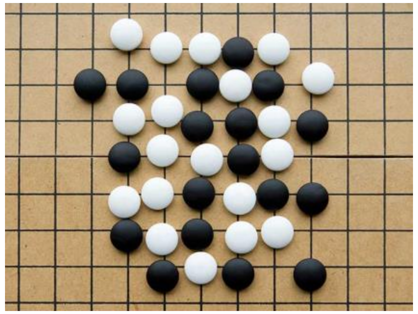
Motivation

RL has been successful in solving **<u>large state-space environments,</u>**

But in reality…

Motivation

Previous RL methods have conquered grid games.



Go

Atari

But, in common, they have **<u>low action dimensionality.</u>**

We wondered:

> **"Would these algorithms work for grid games with a non-tabular action space?"**

Motivation

And we didn't have to go far to find the perfect environment..!

A game which is

1. consistently loved by students (1M+ downloads)
2. has a high (4D) action space and state space
3. initialized randomly
4. not solved (no optimal solution)
5. yet has simple, straightforward dynamics

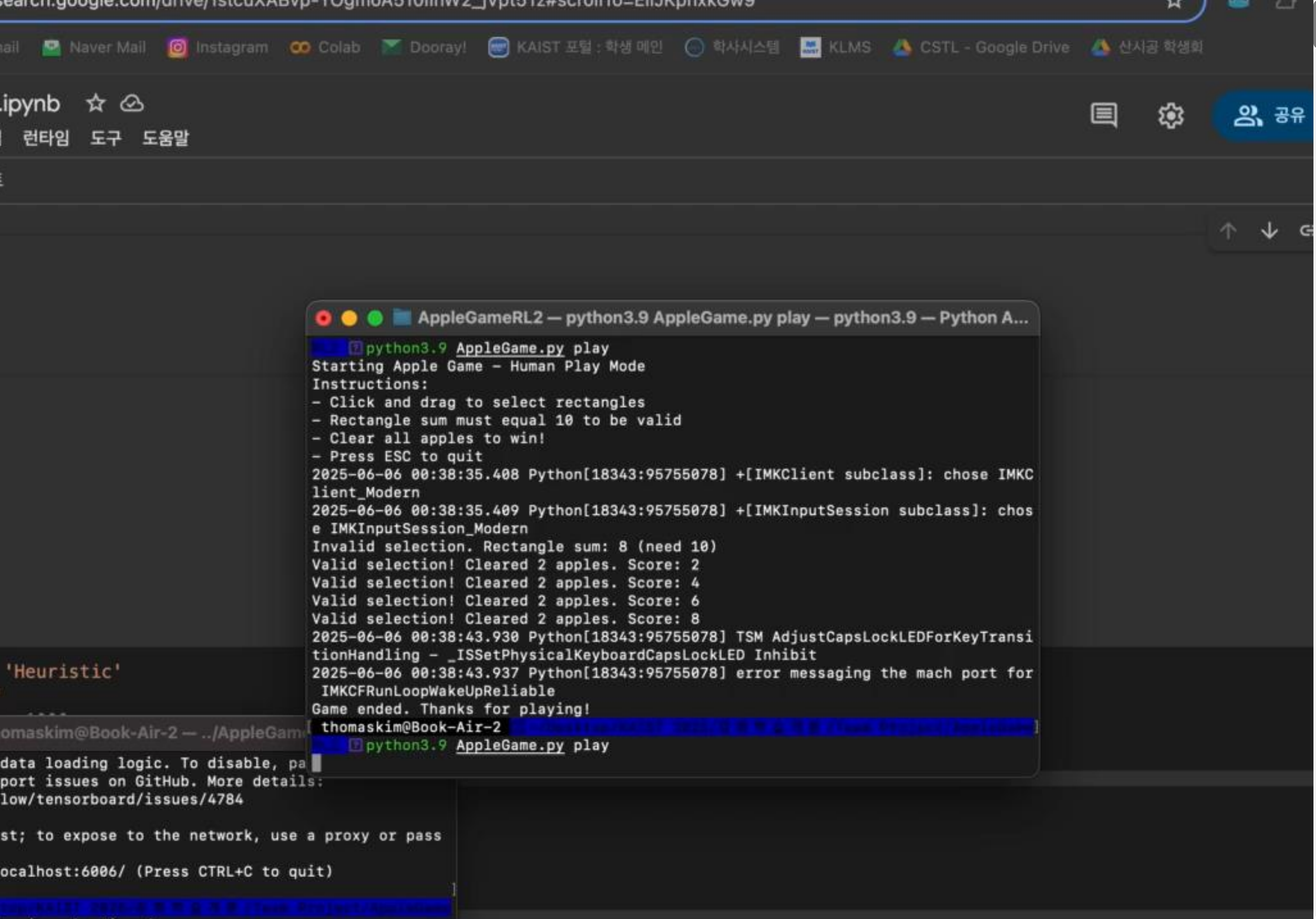
→ **AppleGame**

AppleGame

Fruit Box

- Top Puzzle Game on App Store & Google Play
- Non-tabular State/action spaces : **10^170** // **170*170**
- Randomly initialized
- Unknown optimal solution

A novel benchmark is born: AppleGameEnv



Rules

1. Select a rectangular area on the grid.

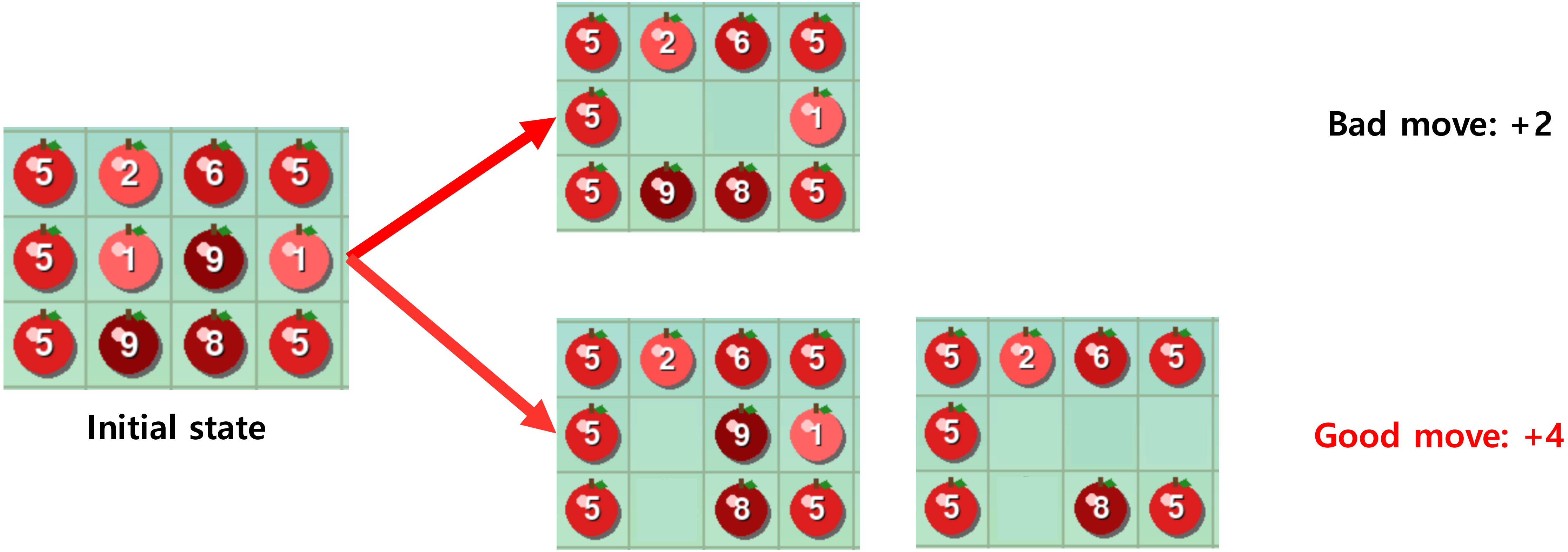
2. If the sum of all apples within the selected area equals 10, all the apples in the rectangle disappear.

   Your score is then increased by the number of apples cleared.

3. Repeat steps 1 and 2 for 120 seconds.

AppleGame: Difficulty

“The sequence of actions impacts the future”



Notations for AppleGame

State Space

$$S = \{(x, y, n) : 0 \leq x \leq 9, 0 \leq y \leq 16, 0 \leq n \leq 9\}$$

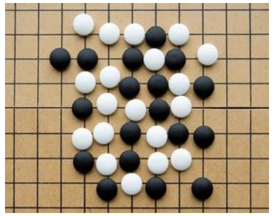
Action Space

$$A = \{(x, y, w, h) : x \geq 0, y \geq 0, 0 < x + w \leq 9, 0 < y + h \leq 16\}$$

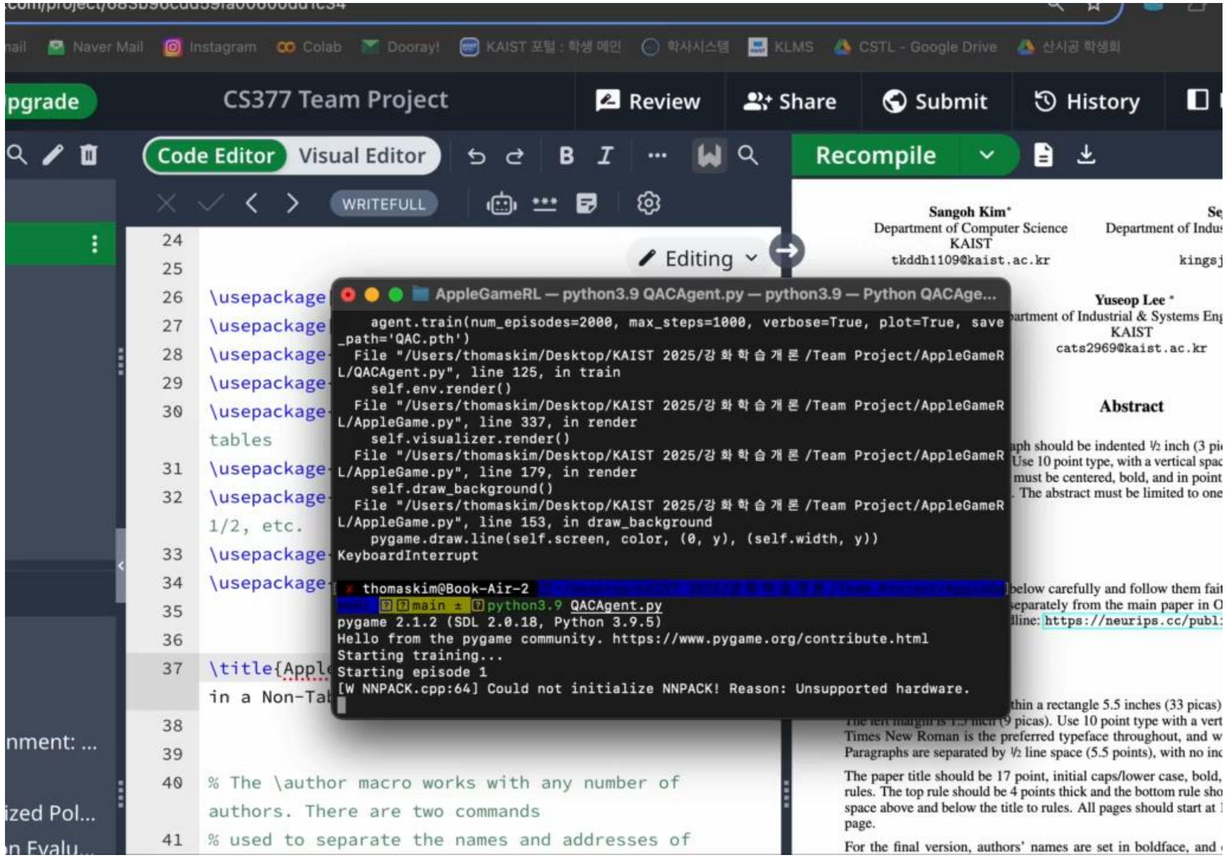
Grid Size

$$(height) * (width) = 10 * 17$$

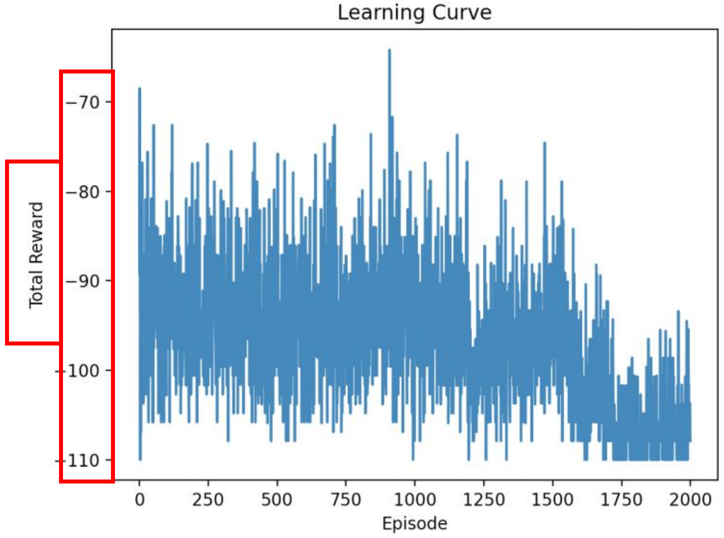
AppleGame: Comparison

Games	State Space	Action Space
	10^170	**170*170**
	2.8*10^4	18
	4.7 *10^108	128

Problem 1: Invalid Actions

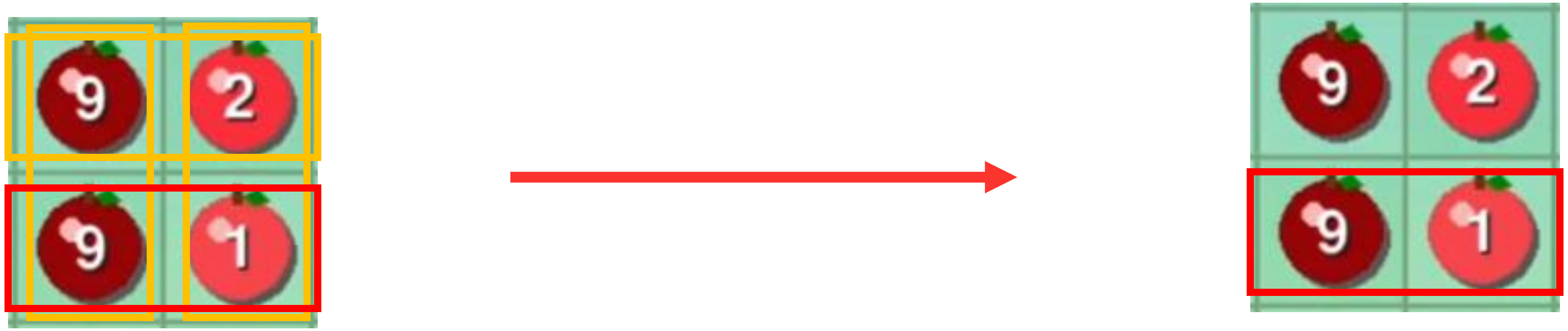


Most actions taken are invalid (not sum to 10)



Leads to bad results (on average, 20/170) and longer runs

Solution 1: Action Masking



(0,0,1,0)

Invalid (0,0,0,1)

(0,1,1,0)

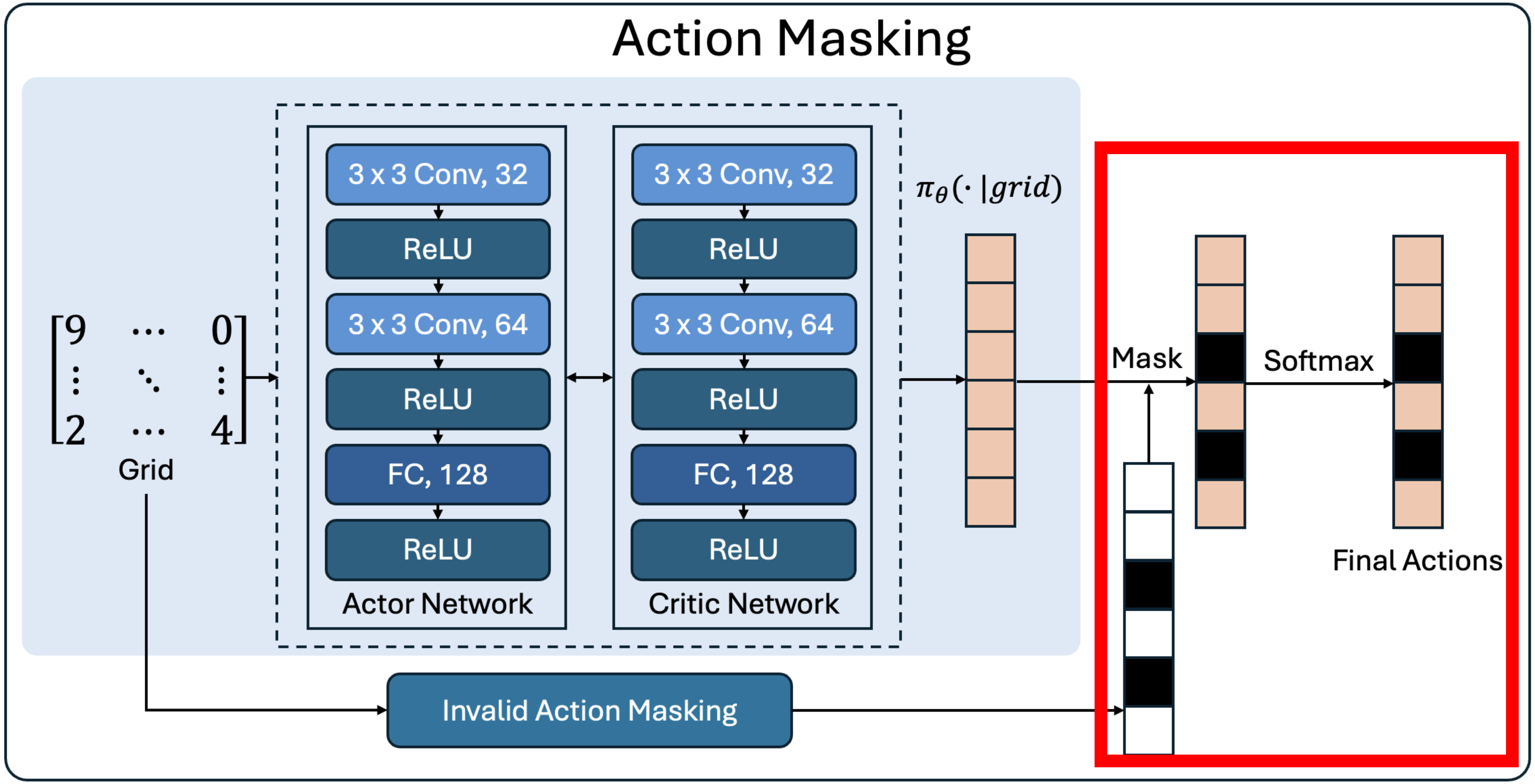
Valid (1,0,1,1)

All **possible actions**

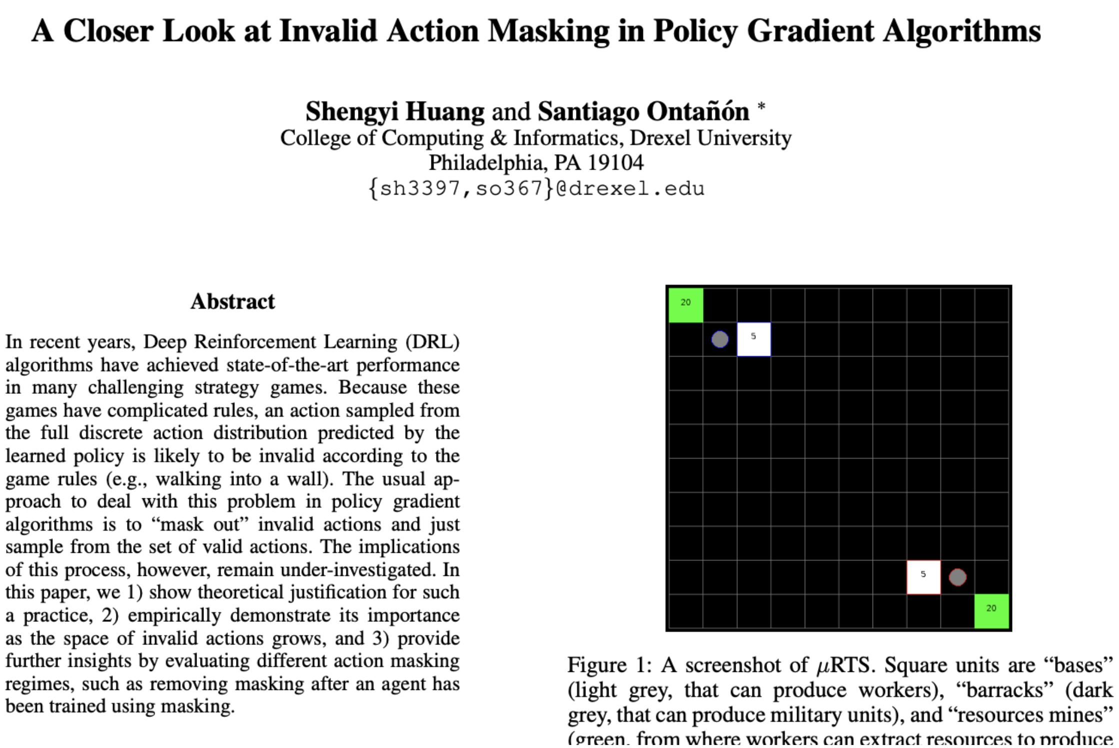
(1,0,1,1)

only **valid actions**

Solution 1: Action Masking



Solution 1: Action Masking



A Closer Look at Invalid Action Masking in Policy Gradient Algorithms

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Abstract

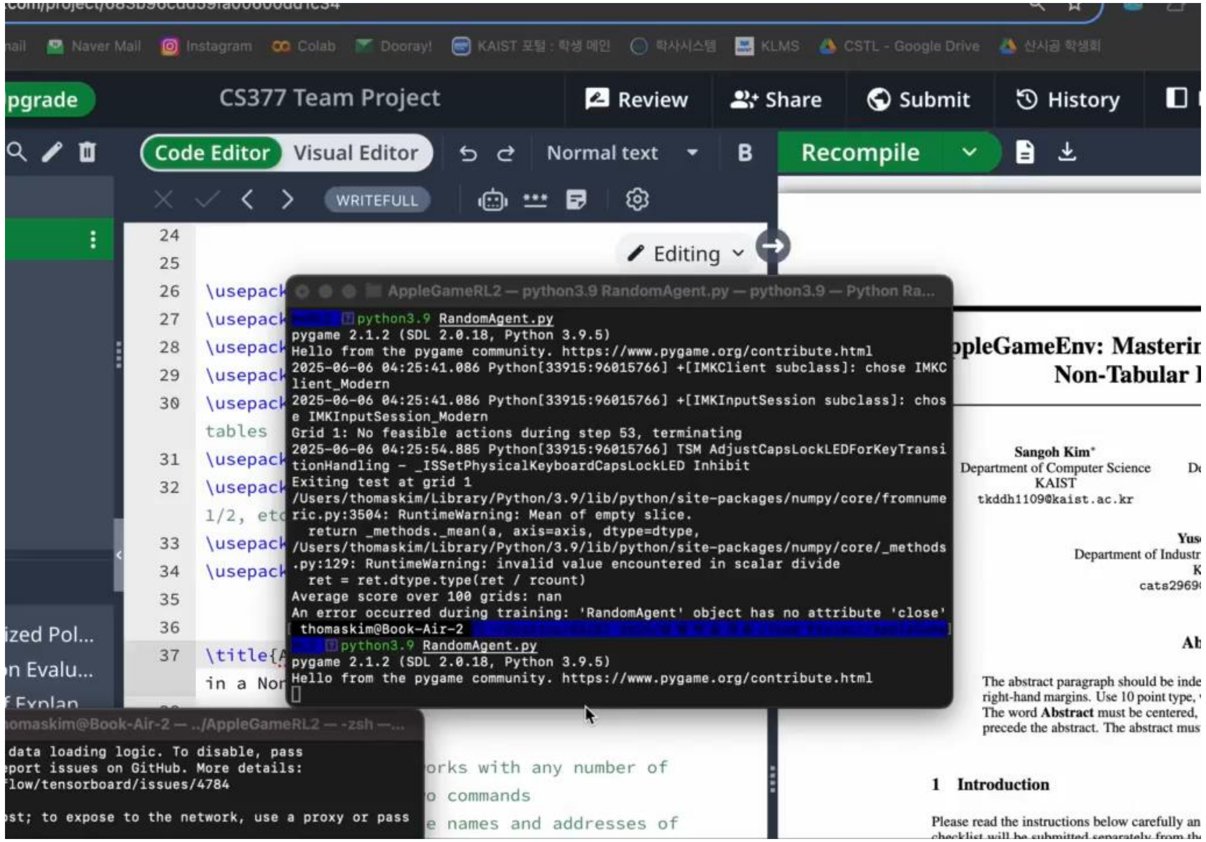
In recent years, Deep Reinforcement Learning (DRL) algorithms have achieved state-of-the-art performance in many challenging strategy games. Because these games have complicated rules, an action sampled from the full discrete action distribution predicted by the learned policy is likely to be invalid according to the game rules (e.g., walking into a wall). The usual approach to deal with this problem in policy gradient algorithms is to "mask out" invalid actions and just sample from the set of valid actions. The implications of this process, however, remain under-investigated. In this paper, we 1) show theoretical justification for such a practice, 2) empirically demonstrate its importance as the space of invalid actions grows, and 3) provide further insights by evaluating different action masking regimes, such as removing masking after an agent has been trained using masking.

Figure 1: A screenshot of μRTS. Square units are "bases" (light grey, that can produce workers), "barracks" (dark grey, that can produce military units), and "resources mines" (green, from where workers can extract resources to produce

The gradient produced by invalid action masking is a valid policy gradient, and it works by applying a state-dependent differentiable function

Solution 1: Action Masking

Thanks to Action Masking, learning becomes more efficient!



Greedy(Random) Algorithm + Action Masking

Experiments

We randomly generate 100 'golden grids' for evaluation

Novice
Sangoh Kim

(<1 Month)

Casual
Yuseop Lee

(~1 year)

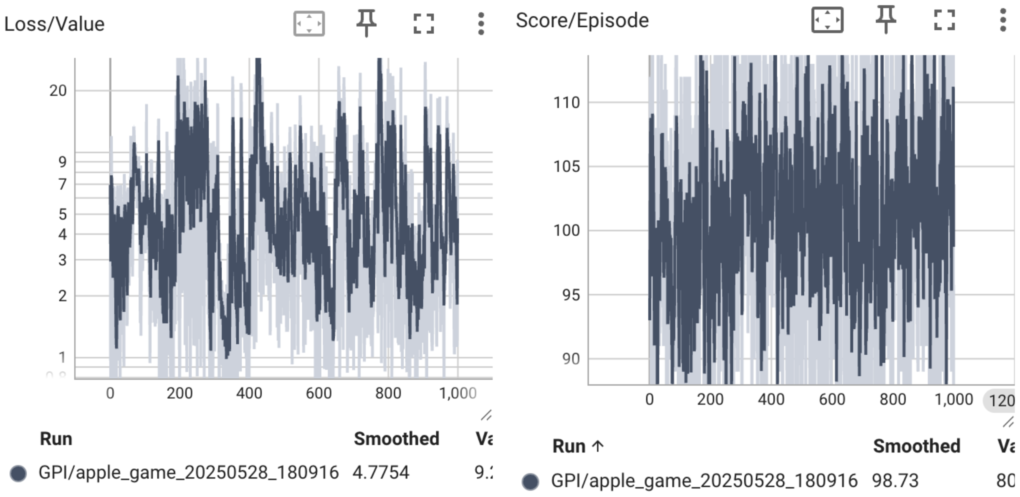
Expert
Sejong Kim

Over 3 years
Plays ~50 times a week

Experiments (1): Value-Based Algorithm

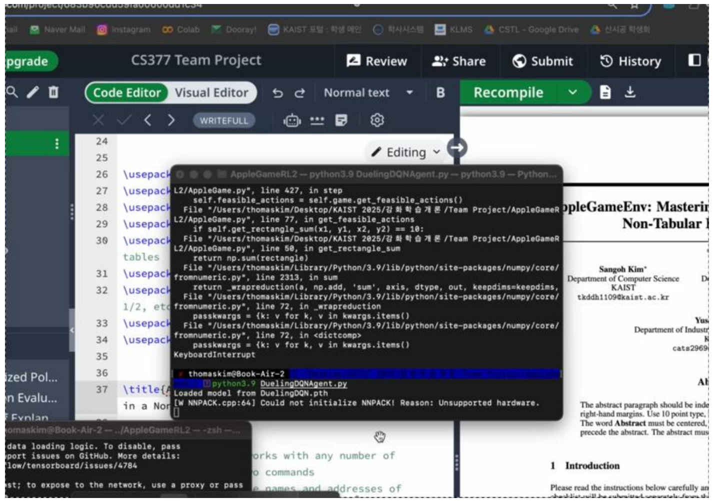
Algorithm	Average Total Score
GPI	102.8
DQN	**108.6**
DuelingDQN	**109.8**

Learning Curves (Loss | Total Score)



GPI

Simulation Video



DuelingDQN

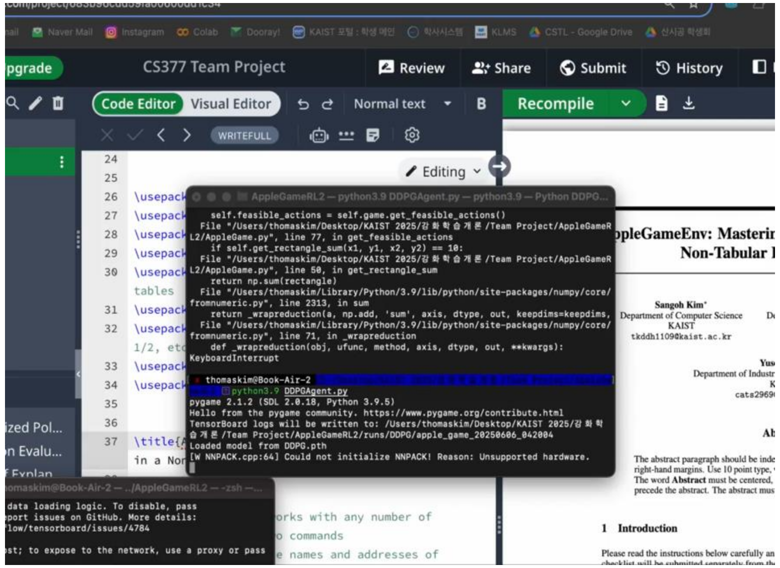
Experiments (2): Policy-Based Algorithm

Algorithm	Average Total Score
REINFORCE	106.2
DDPG	105.6

Learning Curves (Loss | Total Score)

DDPG

Simulation Video

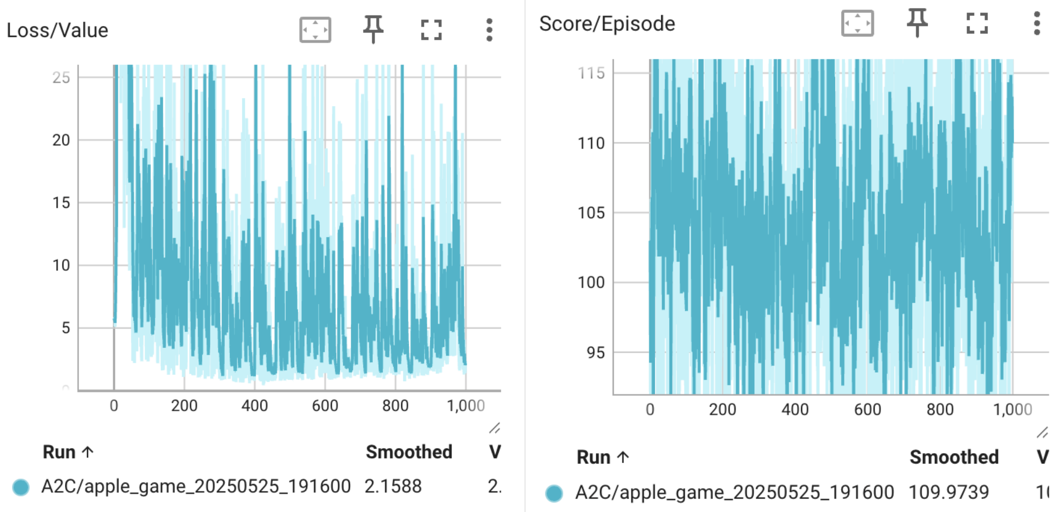


DDPG

Experiments (3): Actor-Critic Algorithm

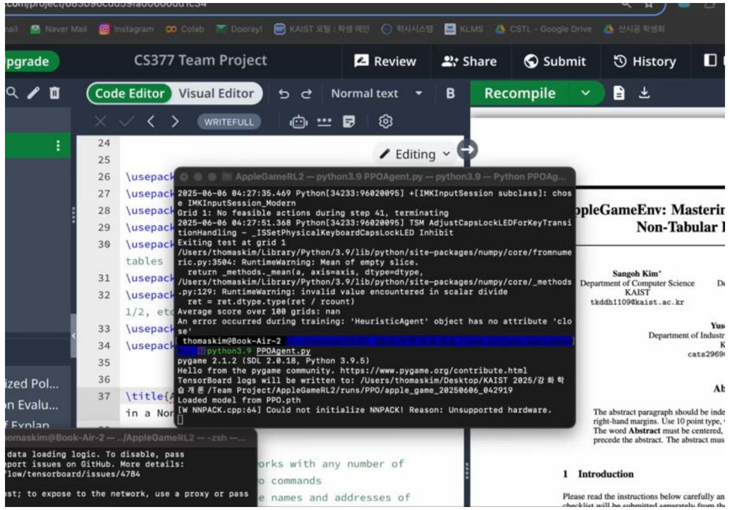
Algorithm	Average Total Score
A2C	105.3
QAC	103.2
PPO	106.2

Learning Curves (Loss | Total Score)



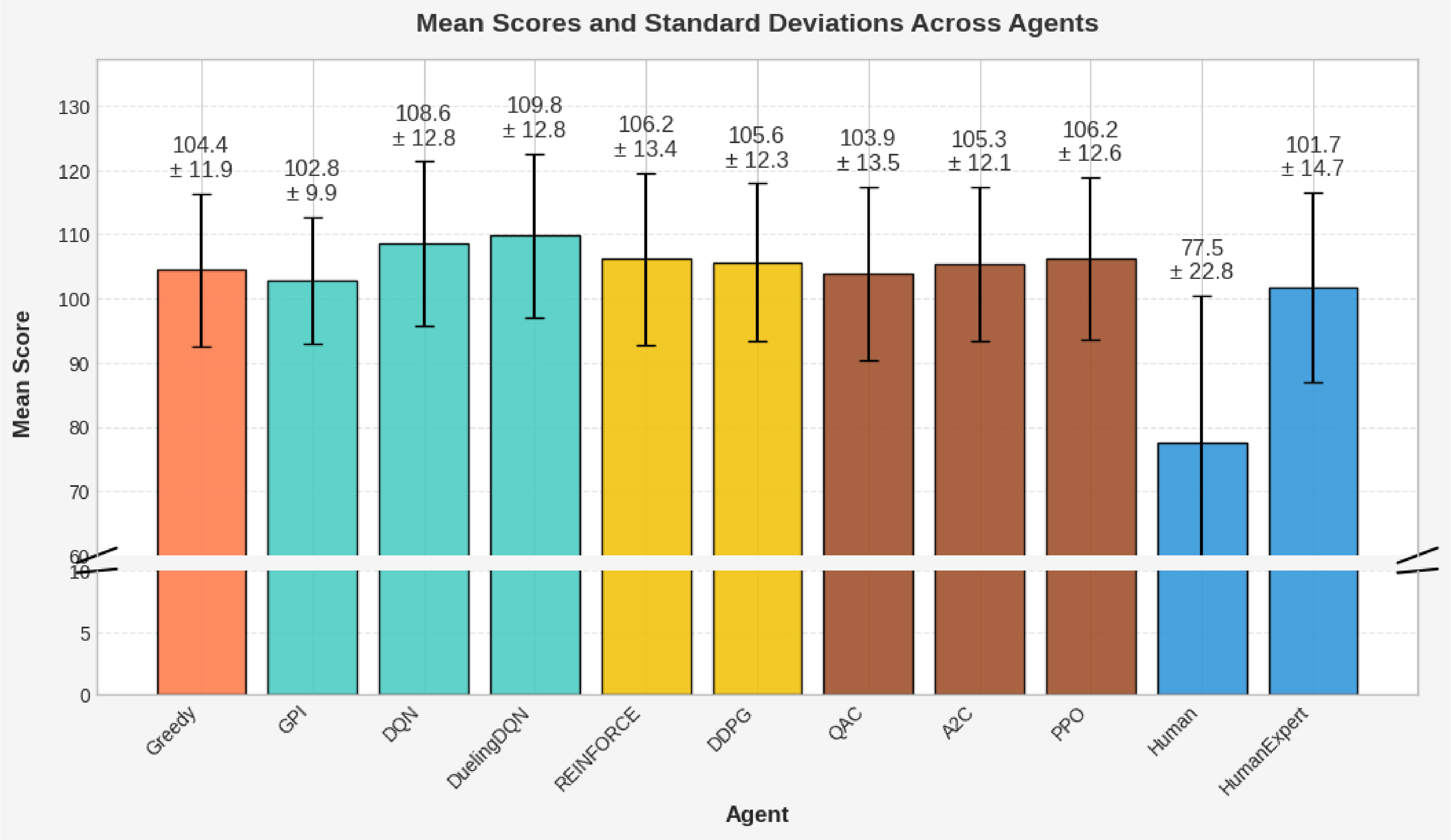
A2C

Simulation Video

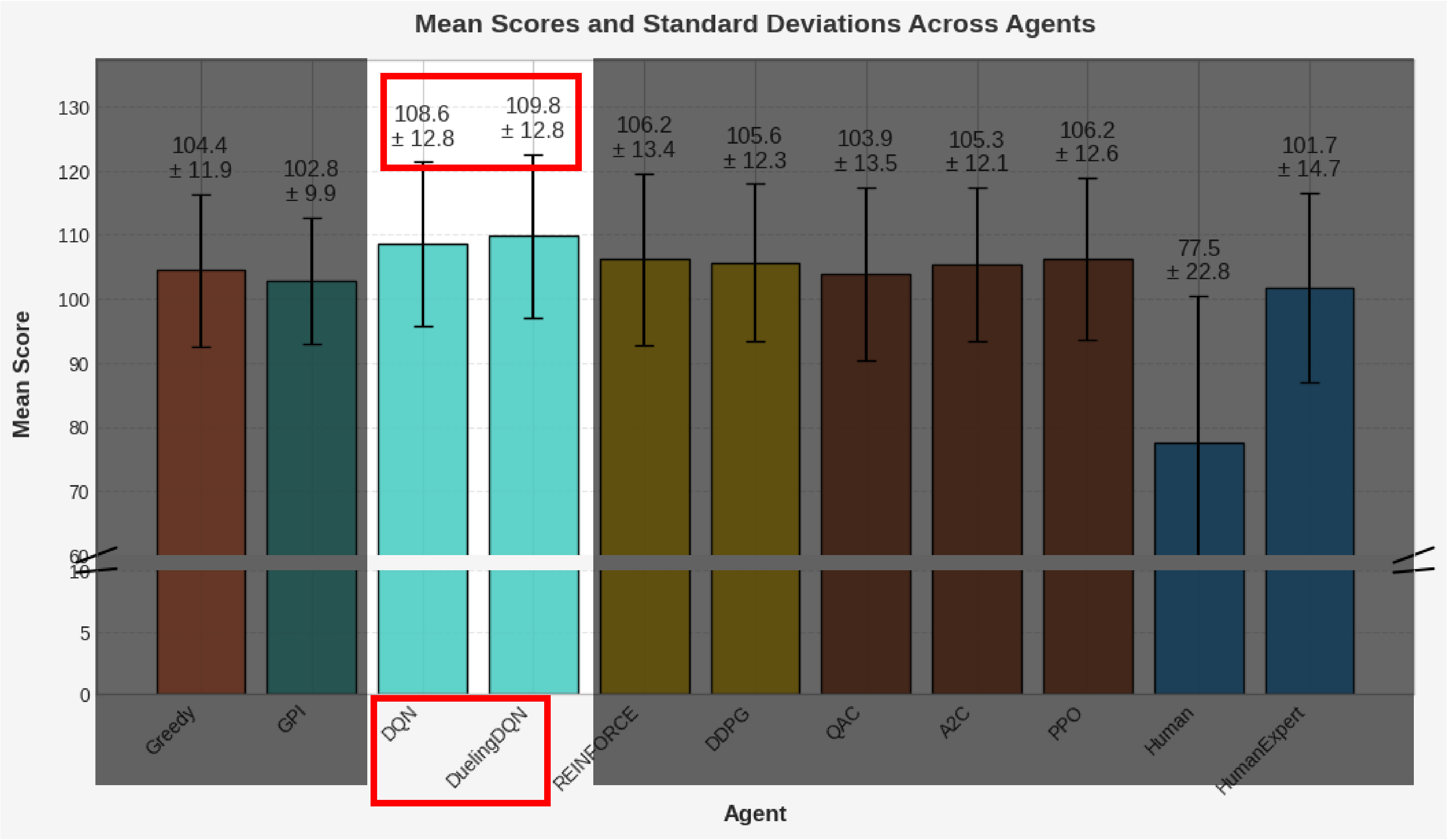


PPO

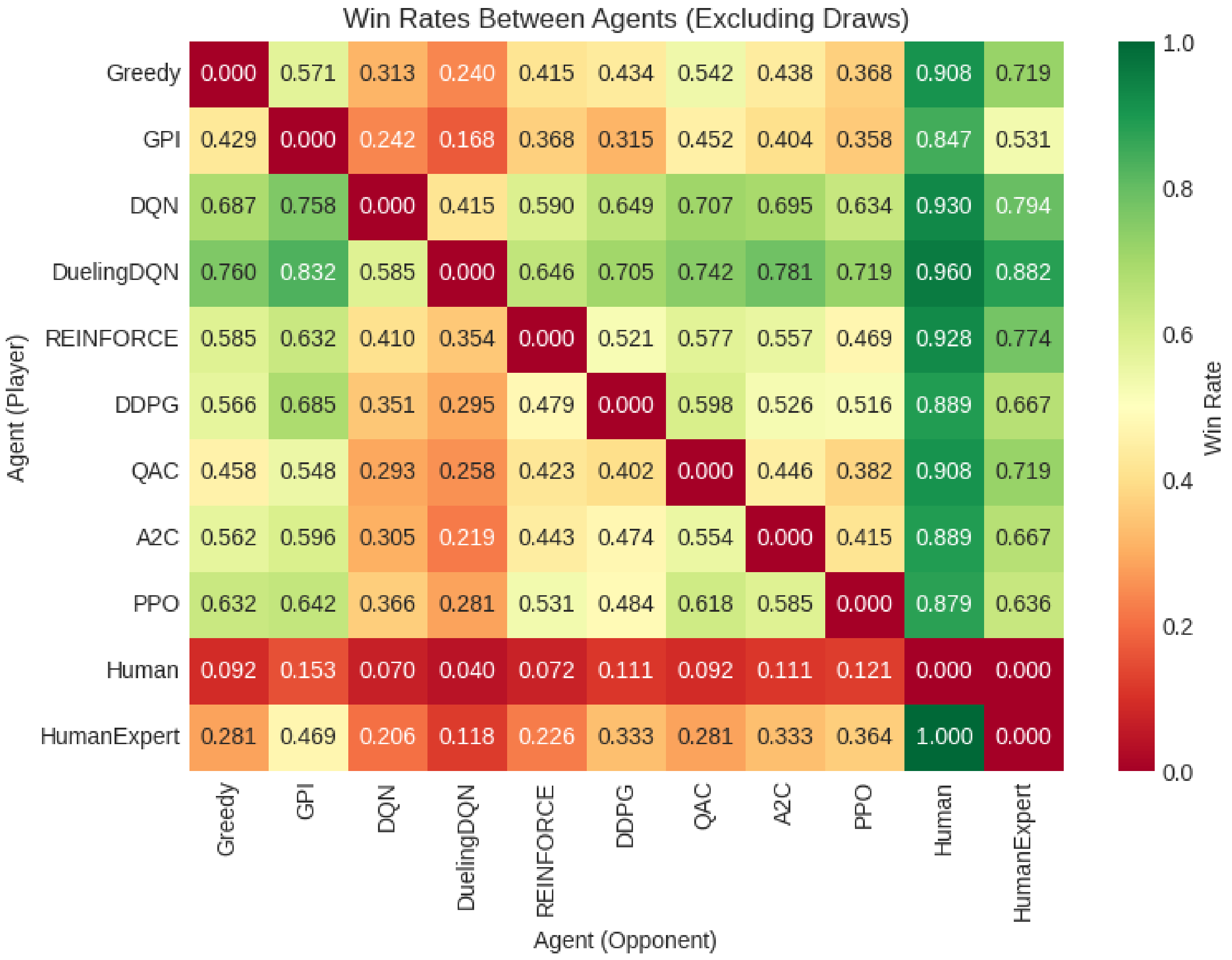
Quantitative Results: Mean Score



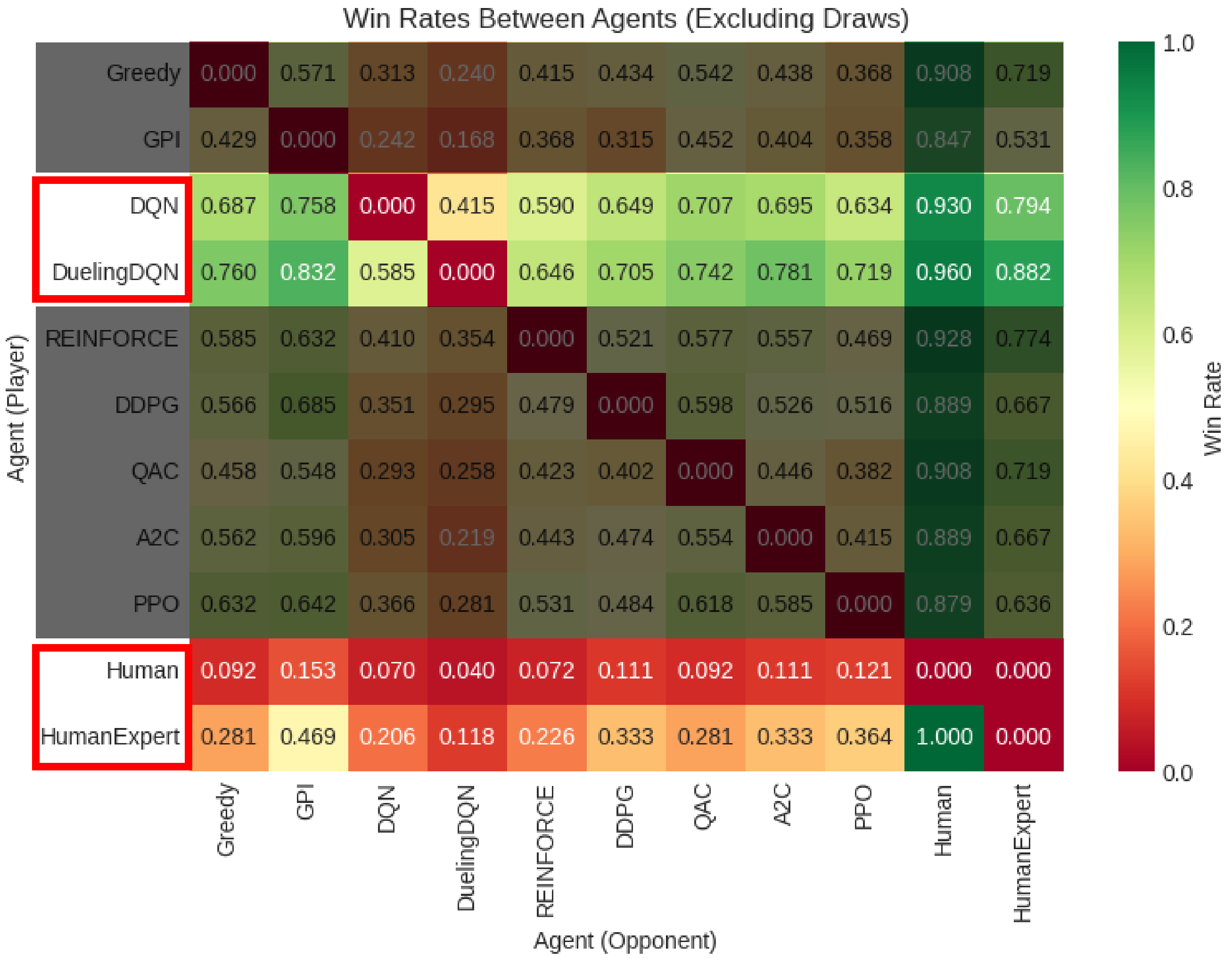
Quantitative Results: Mean Score



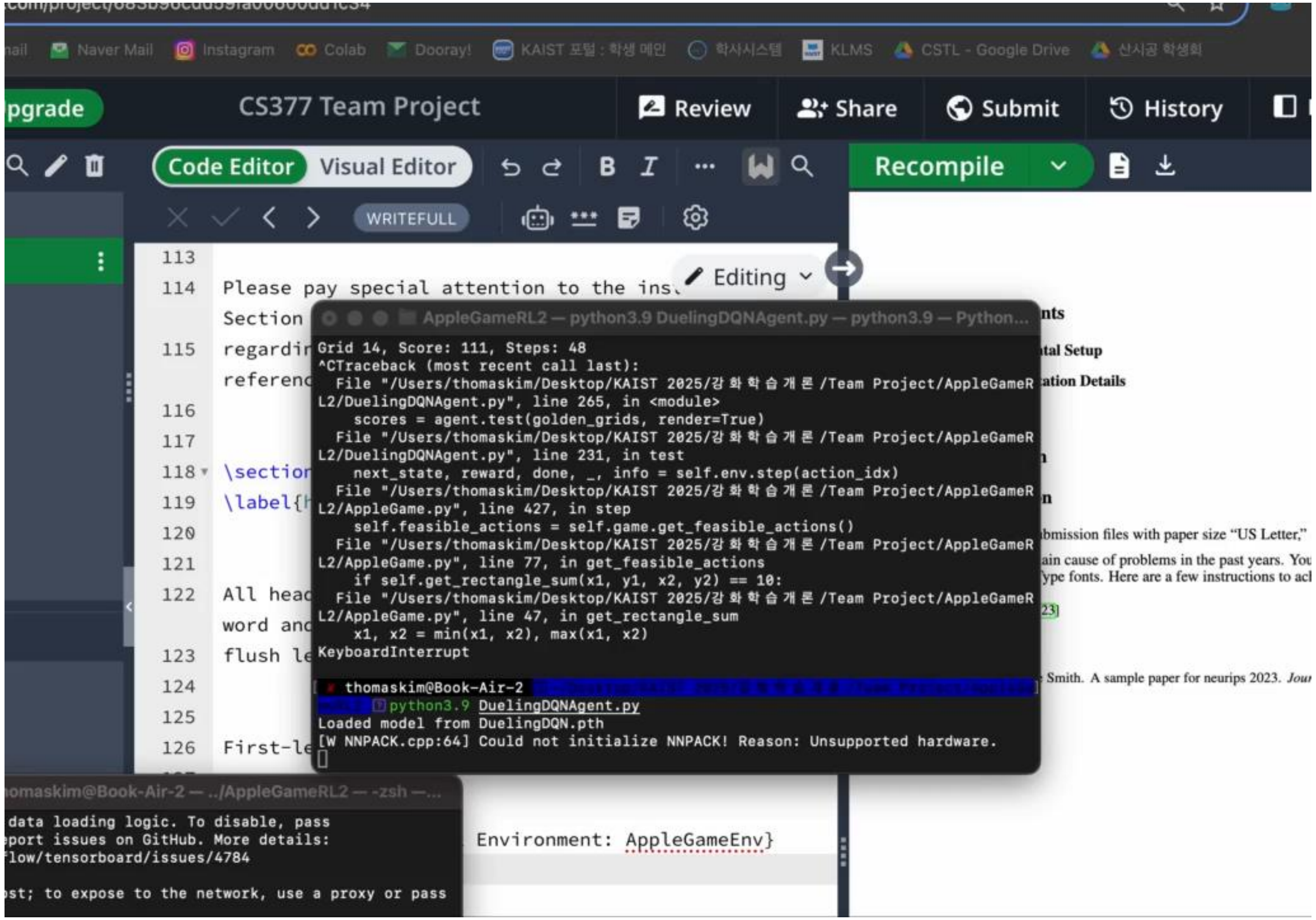
Quantitative Results: Win Rates



Quantitative Results: Win Rates



Problem 2: Interpreting Agents



We can state that:

"Tendency to remove neighboring apples from left to right."

But, do we truly understand their black box models?

- Introduction
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- Limitations & Future Works

Solution 2: Language GPI(LGPI)

Environment

```
grid = np.array([
    [4, 5, 2, 6, 6, 1, 8, 7, 7, 3, 2, 9, 4, 7, 3, 1, 8],
    [4, 1, 8, 7, 1, 5, 8, 1, 4, 3, 4, 4, 4, 8, 8, 1, 1],
    [0, 7, 5, 6, 5, 1, 8, 8, 3, 3, 7, 4, 3, 1, 3, 4, 9],
    [0, 4, 8, 3, 7, 9, 7, 3, 8, 9, 4, 4, 3, 9, 2, 9, 2],
    [3, 5, 1, 7, 2, 3, 8, 6, 5, 3, 1, 9, 1, 1, 9, 2, 2],
    [3, 6, 4, 2, 4, 4, 5, 2, 2, 6, 2, 4, 7, 1, 4, 7, 7],
    [6, 2, 8, 4, 8, 9, 7, 2, 9, 5, 8, 4, 9, 8, 9, 8, 6],
    [1, 2, 6, 5, 3, 8, 3, 4, 9, 9, 4, 5, 8, 7, 5, 6, 3],
    [1, 5, 3, 1, 4, 4, 6, 9, 8, 7, 8, 9, 8, 8, 6, 3, 8],
    [6, 5, 7, 2, 2, 1, 9, 9, 7, 6, 7, 8, 9, 5, 1, 6, 9]
])
```

Grid

LLM

Thought1: Compared to other actions
Thought2: it is less ……
Thought3: It's more impactful than….
Thought4: It offers focused vertical clearing…
…

Create thoughts
for each action

Thought: The evaluation suggests that broader horizontal actions tend..

Deciding action

Action N

Creating Thoughts for Each Action

Thought1: Compared to other actions, it offers a moderate vertical removal that could impact multiple elements but is less extensive than horizontal actions. It might be beneficial if vertical removal of this column is strategic, but **less impactful than broader horizontal options.**
Thought2: Compared to other actions, it is less extensive than the others with larger dimensions, making it more targeted but less impactful overall.
Thought3: It's more impactful than small vertical segments, **potentially clearing a full row segment**, which can significantly alter the state in that area.
Thought4: It offers focused **vertical clearing in a different column**, useful if targeting that specific column is strategic, but less extensive than larger horizontal actions.
...

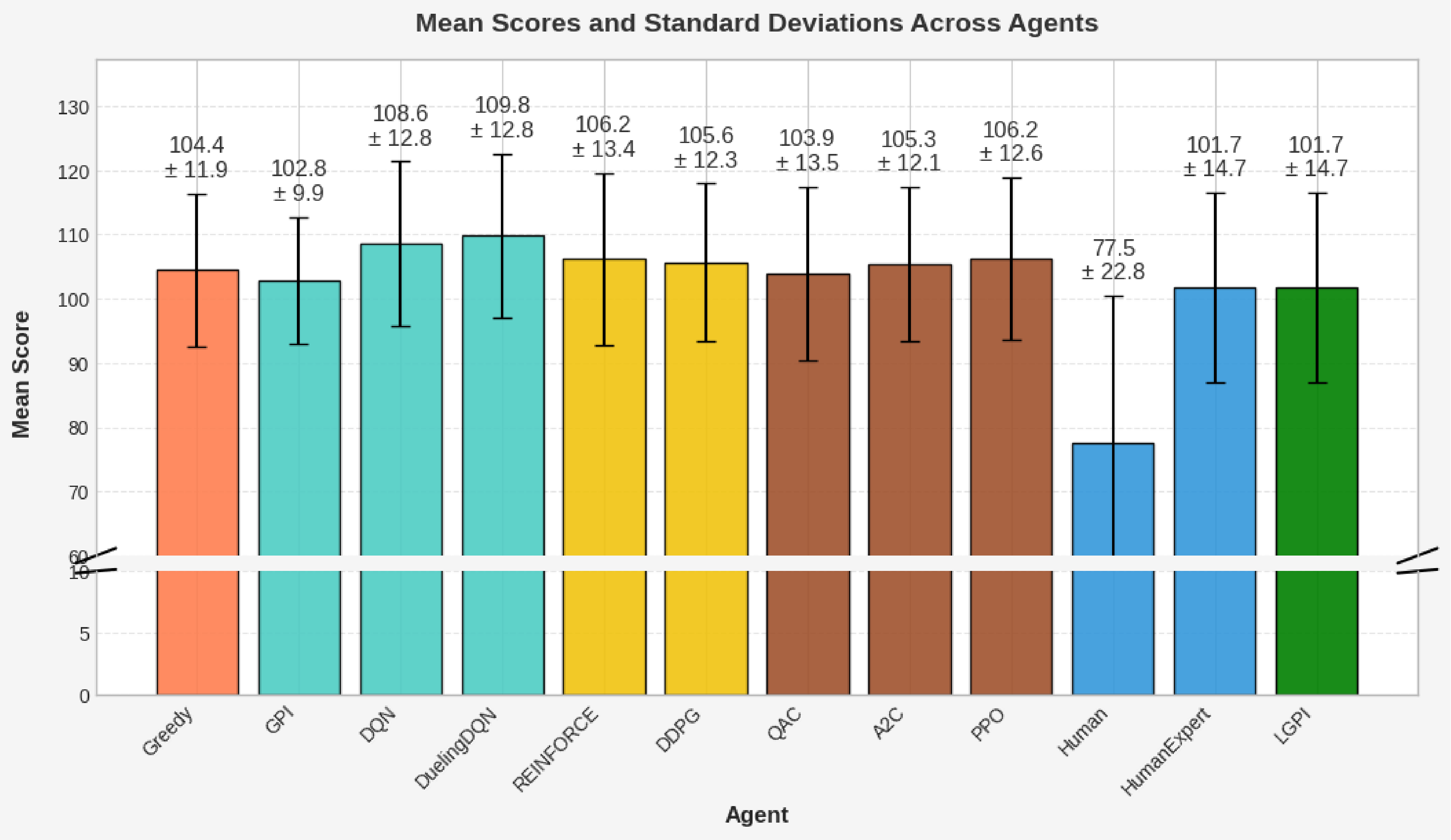
Create thoughts for each action

Deciding action

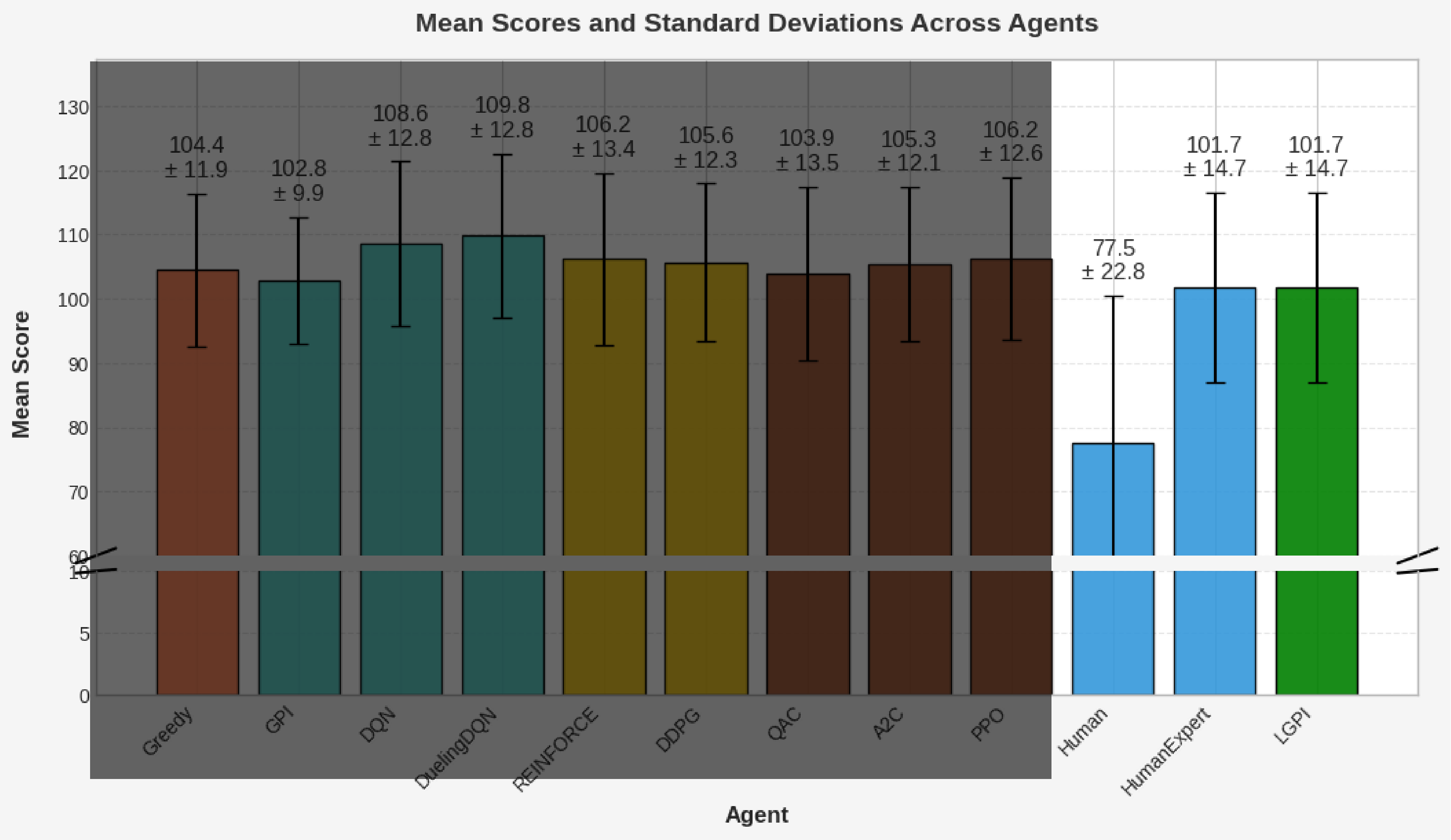
Thought: The evaluation suggests that broader horizontal actions tend to be more impactful for clearing multiple cells and potentially completing lines, which is often more advantageous in such puzzle games. **For instance, action 3 (horizontal removal across 4 cells in row 8) and action 13 (horizontal removal of 3 cells in row 5) both offer significant impact.** Comparing these, action 3 covers more cells in a crucial row, possibly leading to larger clearing effects. Similarly, actions 8 and 9 target specific segments, but their impact is more localized. Vertical actions tend to be less impactful unless they target high-value or strategic cells, but broader horizontal moves (like action 3) typically maximize the clearing potential and score. **Therefore, action 3 appears to be the most impactful candidate with a high potential to clear a significant portion of the grid, making it the best choice among the options.**

Deciding action

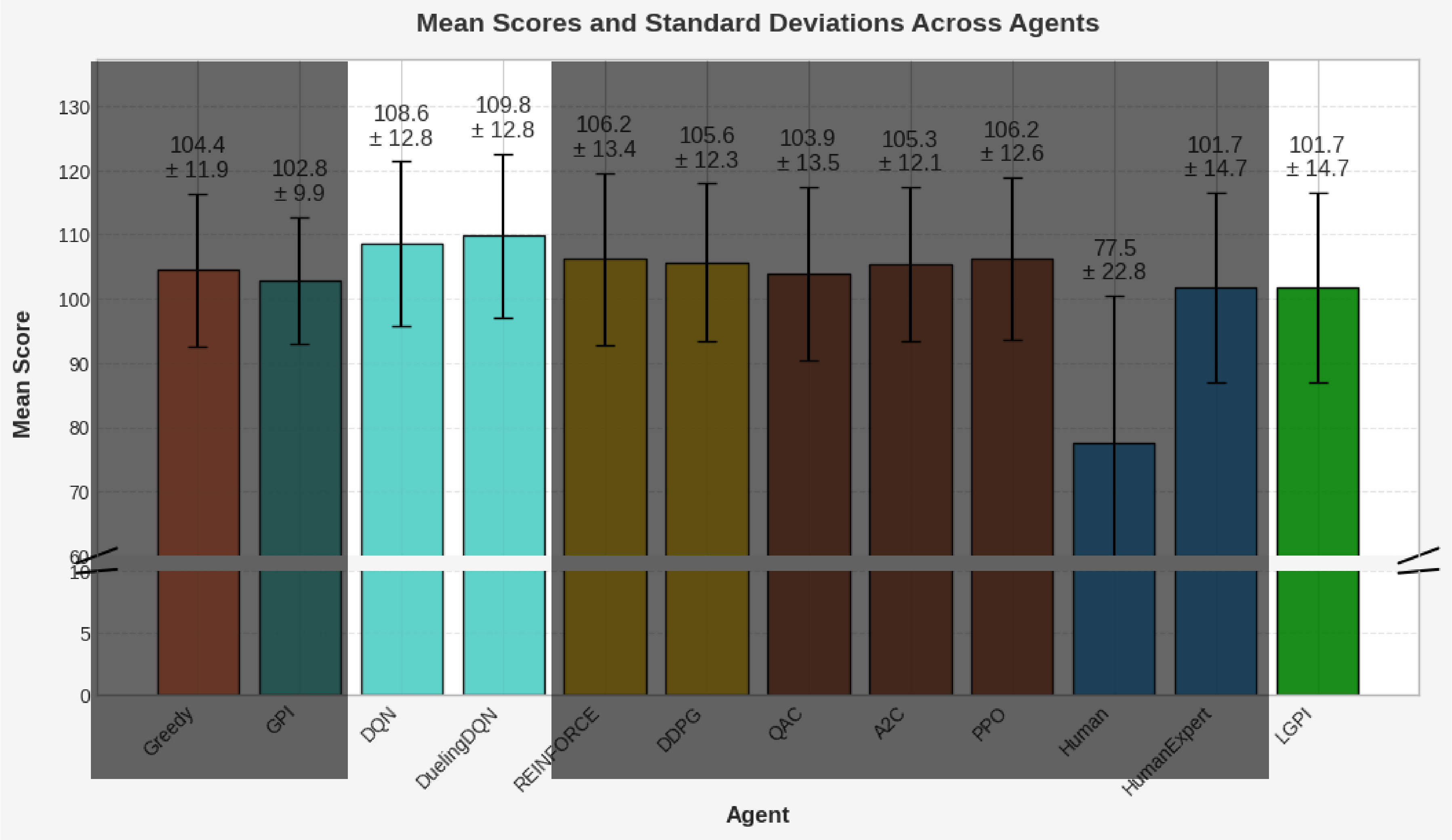
Results: LGPI



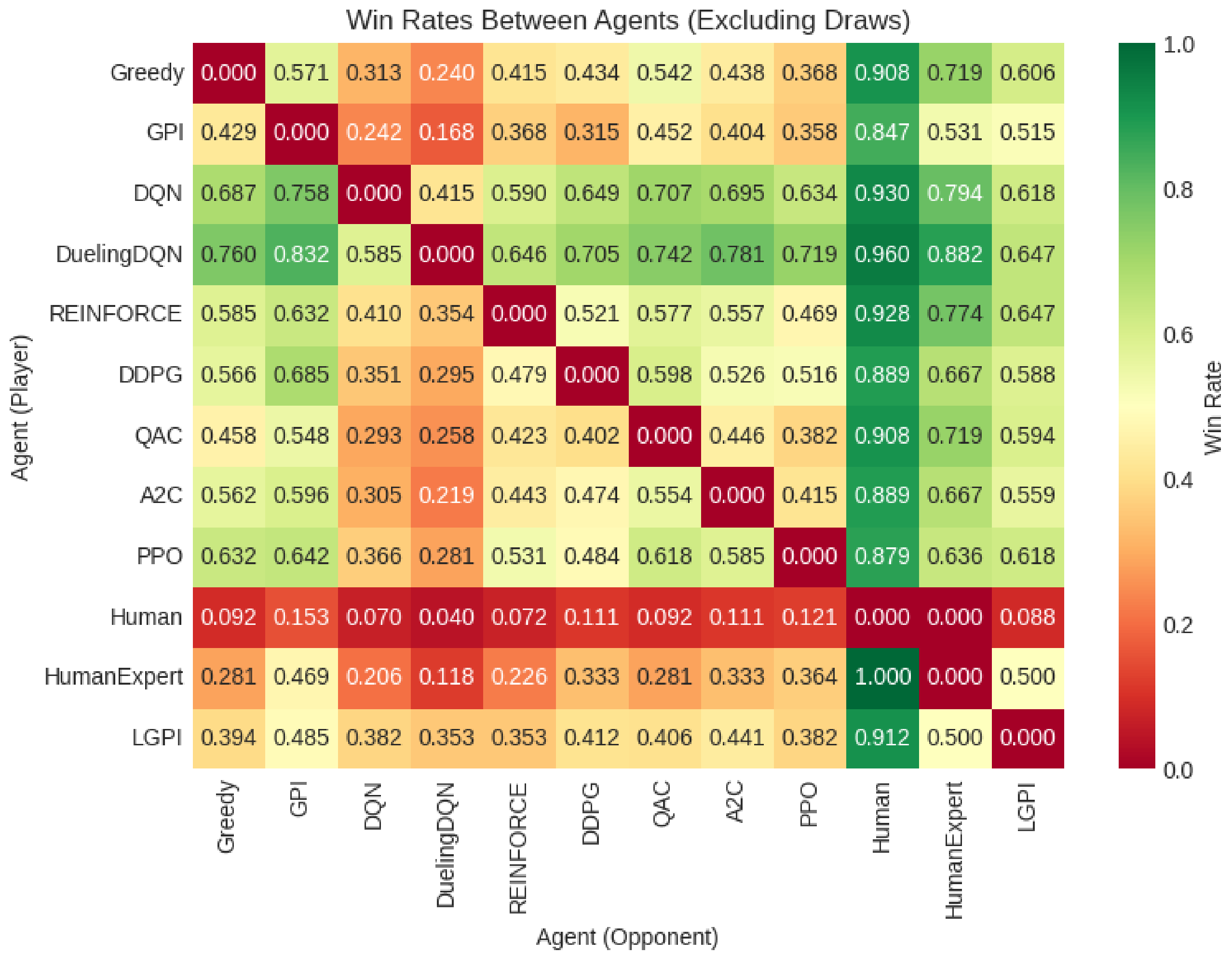
Results: LGPI



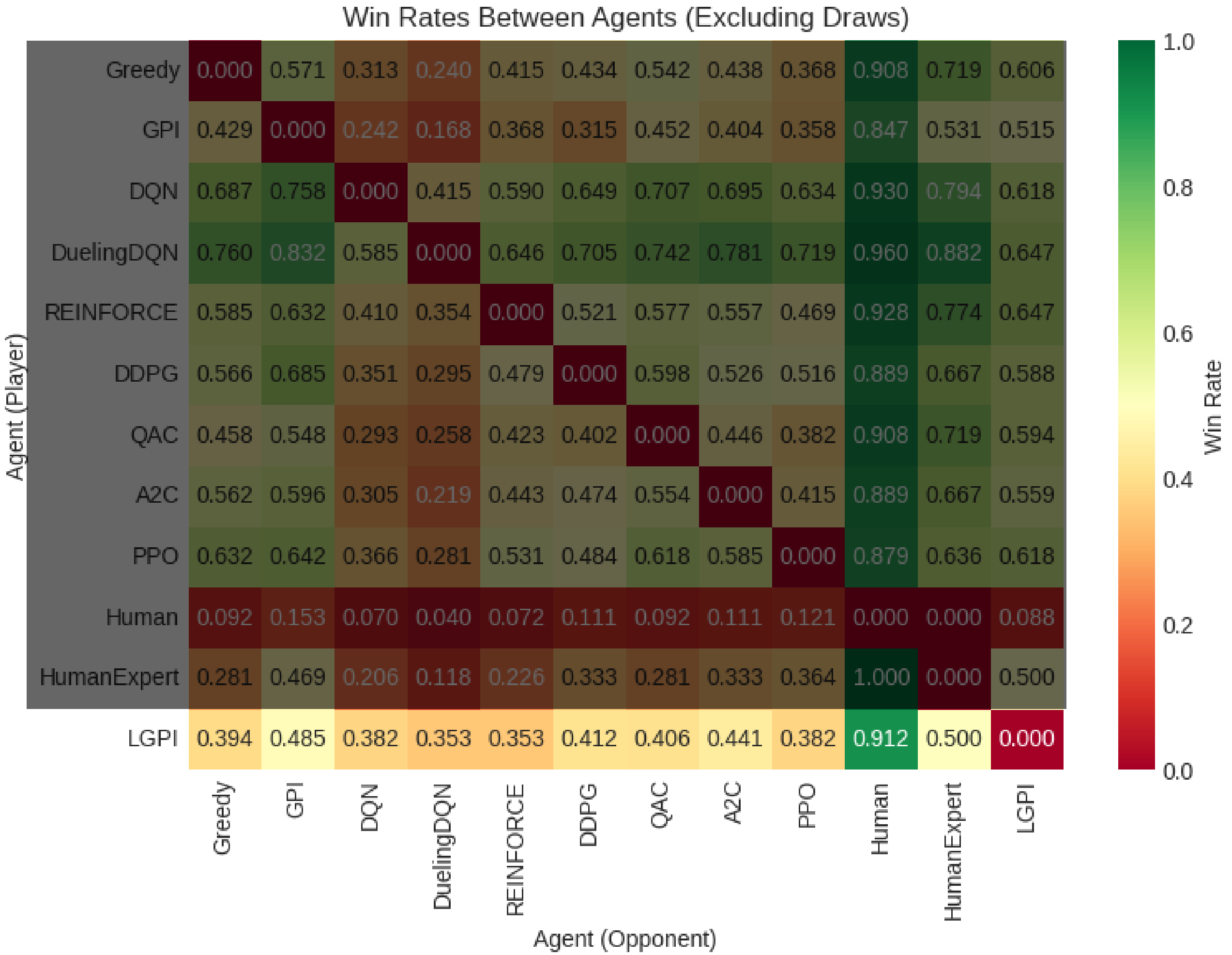
Results: LGPI



Results: LGPI



Results: LGPI



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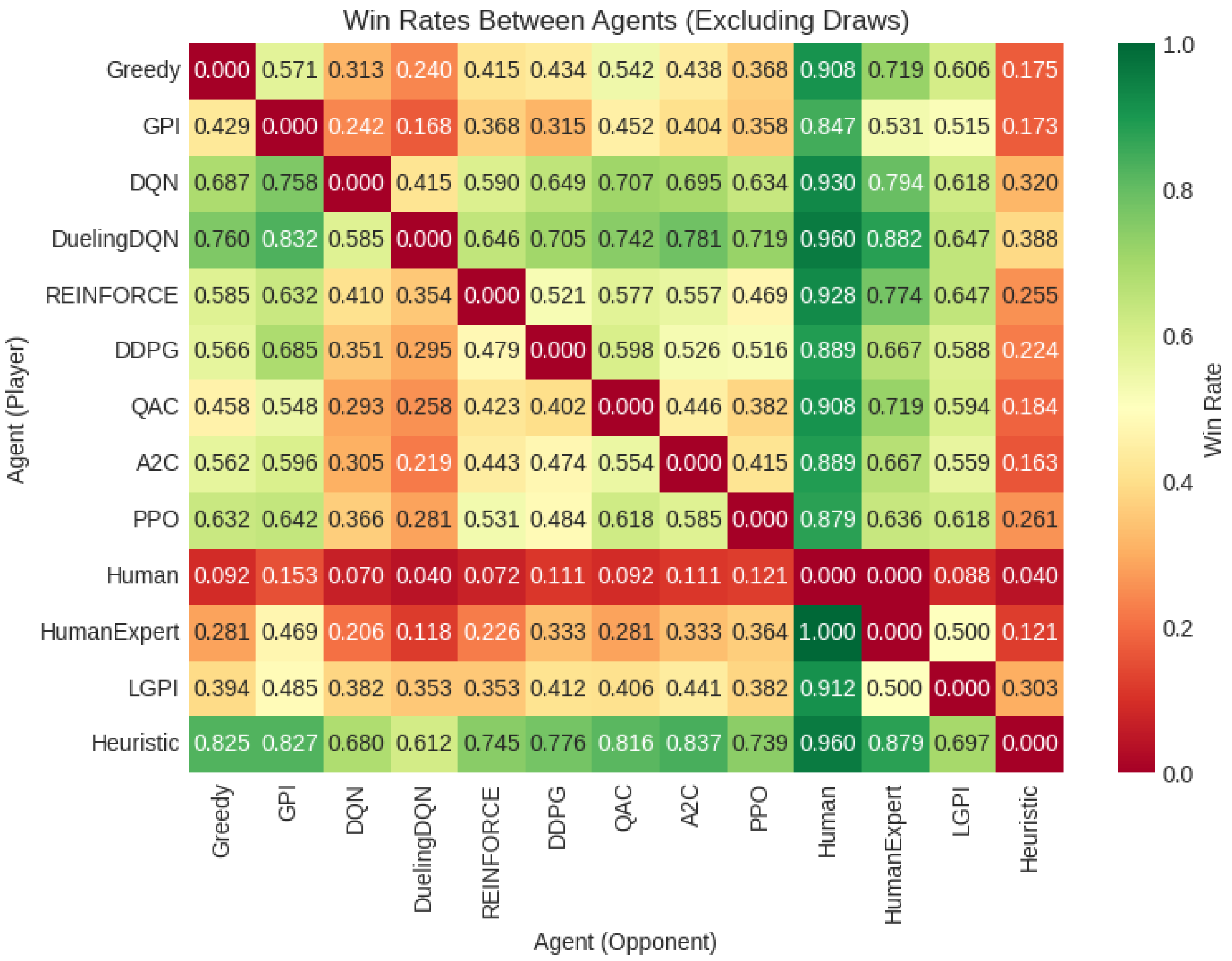
Problem 3: HeuristicAgent

```python
class HeuristicAgent:

    def test(self, golden_grids, render=False, start_idx=1, model_path=None,
        deterministic=None):
        scores = []
        clock = pygame.time.Clock()
        total_grids = len(golden_grids)
        for idx, grid in enumerate(golden_grids):
            global_idx = start_idx + idx
            state, info = self.env.reset(fixed_grid=grid)
            feasible_actions = info.get('feasible_actions', [])
            done = False
            episode_score = 0
            step = 0
            max_steps = 1000
            state_render = "playing"
            if render and not self.env.visualizer.initialized:
                self.env.visualizer.initialize()
```

1) Early game, prioritize clearing smaller groups of adjacent apples **(e.g., 9-1, 8-2)**
2) End game, maximize apples cleared per move **(e.g., 3-3-4, 1-2-3-4, 1-1-2-3-2-1)**

Results: HeuristicAgent



Results: HeuristicAgent

Limitations & Future Works

Due to financial / time constraints, we were unable to conduct numerous epochs & post-training for NLRL. (as discussed in the original paper).

However, even with off-the-shelf models, natural language proved useful in providing interpretability with spatial reasoning for value-based algorithms(TD).

Also, existent methods demonstrated a human-like strategy, showing their effectiveness in AppleGameEnv.

Despite this, all 10 agents fell short of a simple heuristic agent in performance.
This implies a **gap in algorithms for large, dynamic action-space MDPs** like AppleGame.

What We learned

- How to model a non-tabular environment for RL
- Engineering techniques (action masking, hyperparameter tuning)
- How to use Natural Language for interpretability

Thank you for listening!!
For more information, visit https://github.com/thomaskim1130/AppleGameRL