Multi-Agent RL for the Wolf Sheep Game

Xiao'ao Song
Shahab Nikkhoo

Jun. 8, 2023

UC RIVERSIDE

Outline

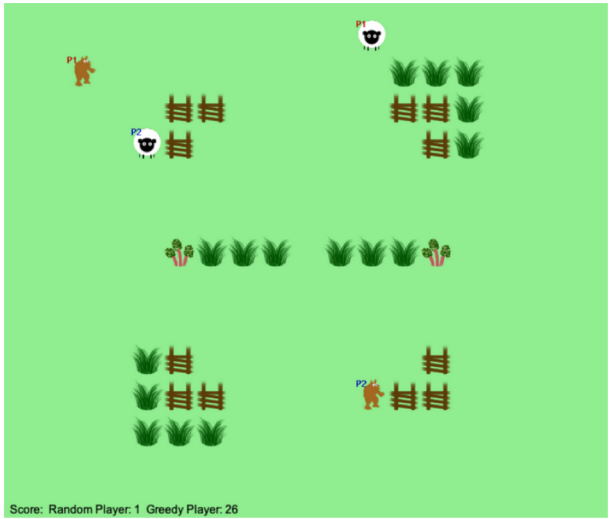
- Game introduction
  - Environment
  - Rules and Objectives
  - Agents
- Methodologies
  - Search algorithm
  - Supervised learning algorithm
    - Training data
    - Feature transformation
  - Reinforcement learning (RL) algorithm
    - Teacher-student framework
    - PPO
- Final demonstration
- Summary
- Contribution and future work

Game introduction - Environment

- Environment: fully observable, dynamic, multi-agent
- Action space: {up, down, left, right, none}
- Map size: 15 x 19
- Maps elements:
  - Empty "**.**" Grass "**g**" Rhubarb "**r**" Fence "**#**”
- 4 Agents:
  - Player 1: Sheep (S), Wolf(W)
  - Player 2: sheep (s), wolf(w)

```
.........#.........
.........#.........
.....g...#....W....
.....##..#..##.....
.....#...#...#.....
.........#..s......
.........#.........
...................
.........#.........
.........#.w.......
....g#...#...#.....
....g##..#..##.....
....ggg..#.S.......
.........#.........
.........#.........
```

- Map in matrix form



- Map in RGB image form

UC RIVERSIDE

Game introduction - Rules and Objectives

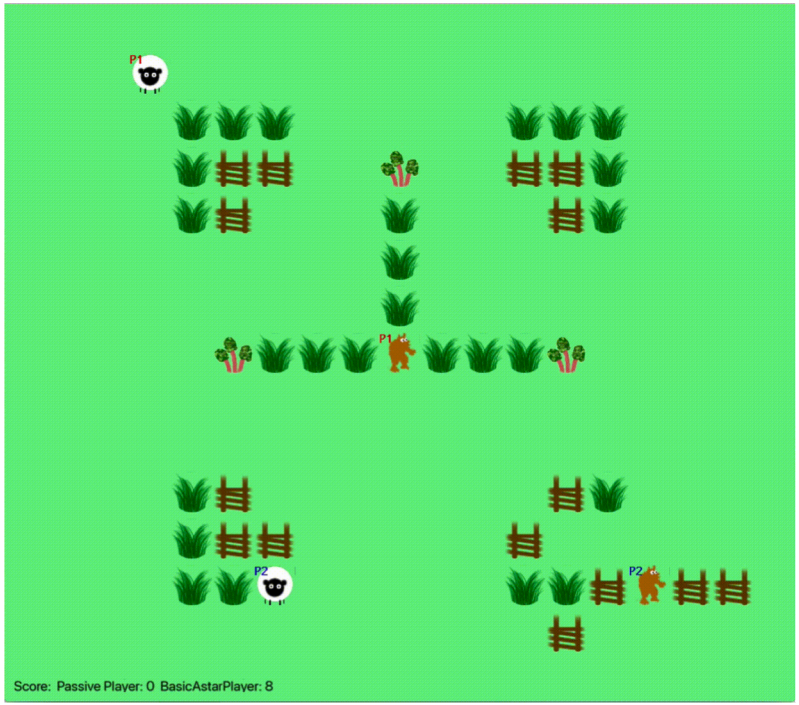
- **The Wolf moves for every second step of the sheep**

Invalid move:
- Move outside of the map or on the fence
- Move on the grid where it is occupied

Valid move:
- Consume or sabotage the food
- Move to the empty grid
- Wolf can eat enemy sheep by moving to its grid

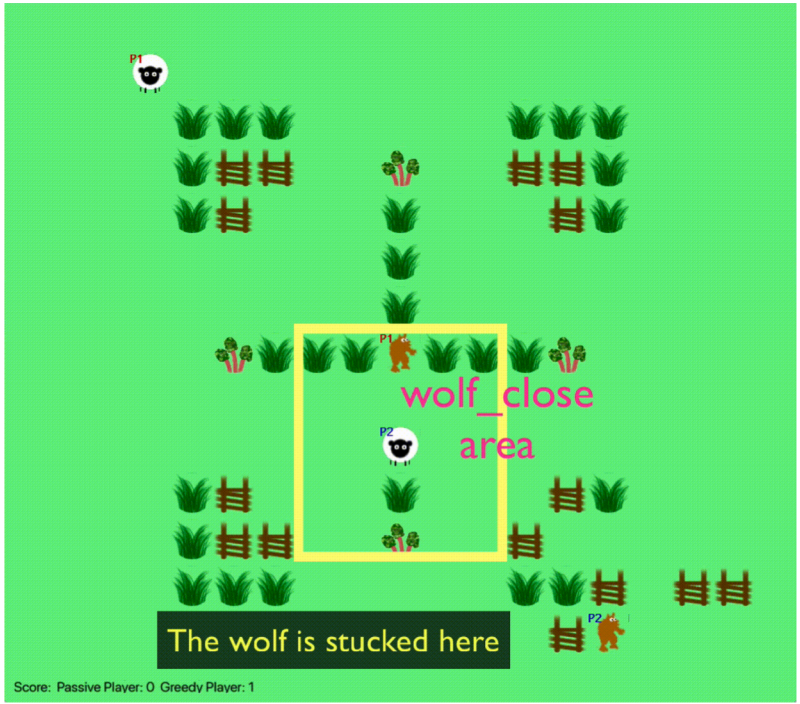
Sheep Objectives:
- Avoid the enemy wolf
- Collect as many food as possible

Wolf Objectives:
- Catch the enemy sheep
- Block the enemy wolf
- Sabotage the food



Game introduction – Default agents

- Random player: moves randomly every turn
- Keyboard player: moves by receiving your keyboard command
- Passive player: stays in place every turn
- Greedy player: uses a simply greedy approach. It includes the following helper functions:
  - get_player_position()
  - food_present()
  - valid_move()
  - closest_goal()
  - wolf_close()
  - run_from_wolf()
  - gather_closest_goal()
  - move_wolf()
  - move_sheep()

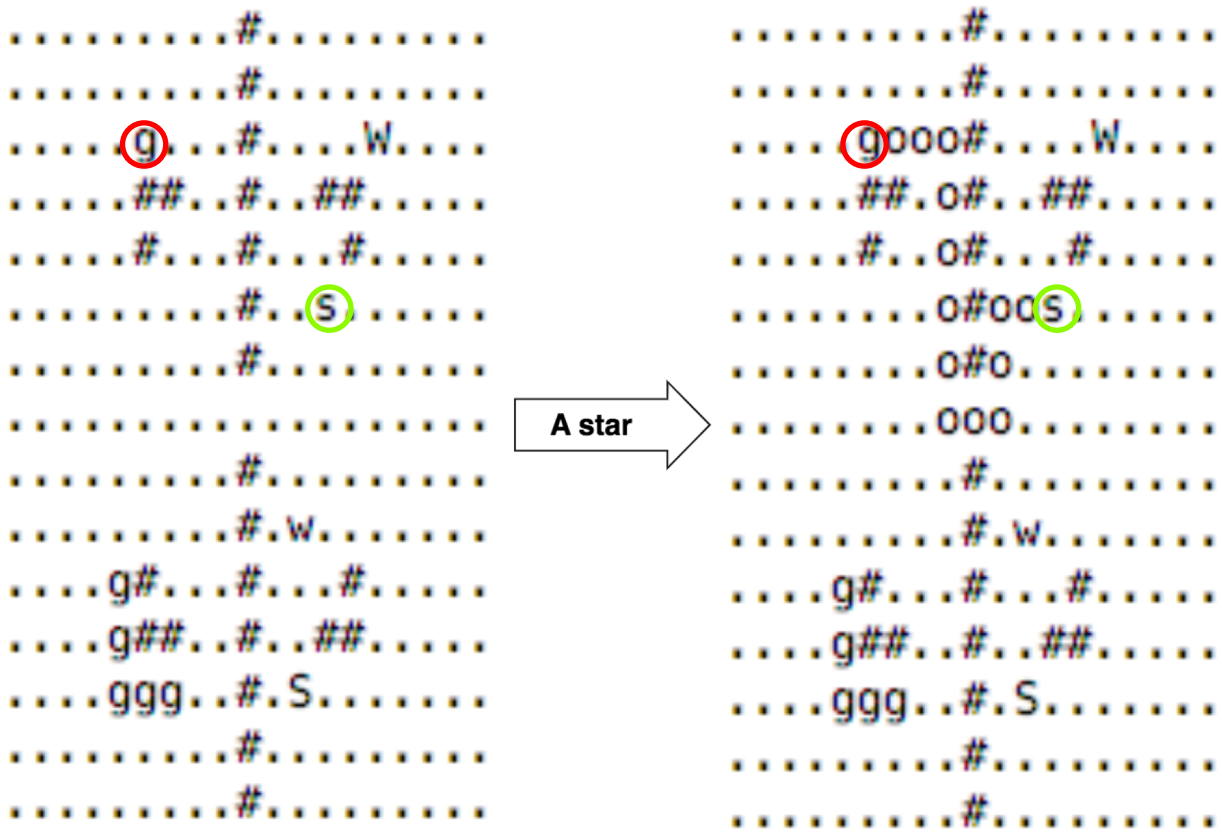


- Drawback of Greedy player

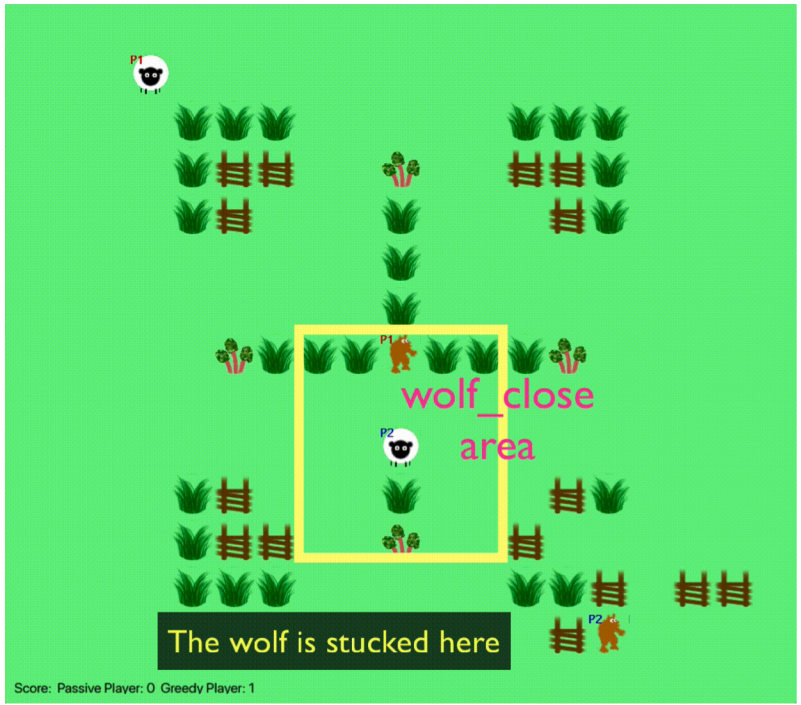
Credits to
Prof. Abraham Bernstein

This project used the GUI from the DDIS group of the University of Zurich.

Methodologies – Search-based algorithm: A*



Methodologies – Search-based algorithm: A*



- Greedy player

- A* player

Methodologies – Supervised learning algorithm: MLP

- Sample training data

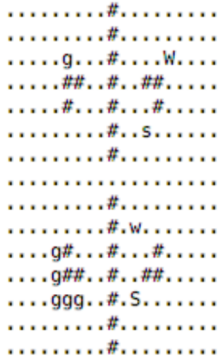
	field_before	field_after	turn_made_by	move_made	score1	score2	reason
0	[['g', 'g', 'g', 'g', 'g', 'g', 'g', 'g', 'g',...	[['g', 'g', 'g', 'S', 'g', 'g', 'g', 'g', 'g',...	player1 sheep	-1	1	0	max_iterations
1	[['g', 'g', 'g', 'S', 'g', 'g', 'g', 'g', 'g',...	[['g', 'g', 'g', 'S', 'g', 'g', 'g', 'g', 'g',...	player2 sheep	-1	1	1	max_iterations
2	[['g', 'g', 'g', 'S', 'g', 'g', 'g', 'g', 'g',...	[['g', 'g', 'S', '.', 'g', 'g', 'g', 'g', 'g',...	player1 sheep	-2	2	1	max_iterations
3	[['g', 'g', 'S', '.', 'g', 'g', 'g', 'g', 'g',...	[['g', 'g', 'S', '.', 'g', 'g', 'g', 'g', 'g',...	player2 sheep	-1	2	2	max_iterations
4	[['g', 'g', 'S', '.', 'g', 'g', 'g', 'g', 'g',...	[['g', 'g', 'S', '.', 'g', 'g', 'g', 'g', 'g',...	player1 wolf	2	2	2	max_iterations

- In the context of supervised learning, we just need the following data to form (X , Y) pairs:
  - field_before: map before the move was made.
  - move_made: the actual move the agent made (e.g. -1).

UC RIVERSIDE

Methodologies – Supervised learning algorithm: MLP

- Due to limited computing resource, we preprocess the data to reduce the dimensionality of the data from high to low.



Φ(input map) -> vector

Sheep features: dim: 15 x 19 -> 1 x 16

[sheep_fencing, sheep_stuckable, stay_preferable, food_available, path_available, move_up_closer, move_down_ closer, move_left_ closer, move_right_ closer, target_neighboring, up_walkable, down_walkable, left_walkable, right_walkable, stay_safeable, run_fromwolf]

Wolf features: dim: 15 x 19 -> 1 x 11

[sheep_stuckable, stay_preferable, path_available, move_up_closer, move_down_ closer, move_left_ closer, move_right_ closer, up_walkable, down_walkable, left_walkable, right_walkable]

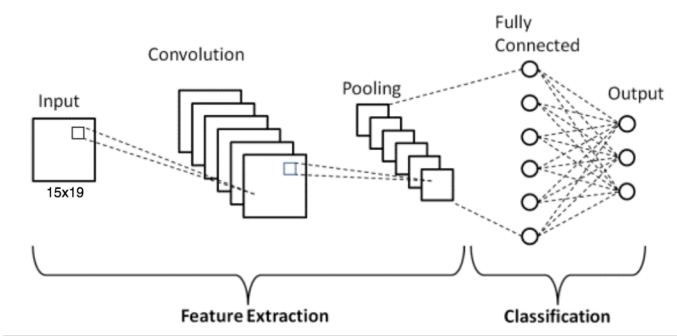
- All of the above features only have value 1 or 0, e.g.:
  - Sample **Sheep** feature vector: [0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1, 0, 0, 0, 1, 1] and it takes action: UP
  - Sample **Wolf** feature vector: [0, 0, 0, 1, 1, 1, 0, 0, 0, 0, 1] and it takes action: NONE

Methodologies – Supervised learning algorithm: MLP

- Now, we can learn a simple network based on many ($\Phi(X)$, Y) pairs:
  - We have our policy networks now!

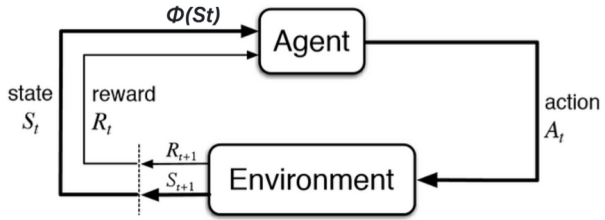
```
sheep_model = MLPClassifier( solver='lbfgs',
                             activation='relu',
                             alpha=1e-4,
                             hidden_layer_sizes=(16,16),
                             random_state=1,
                             max_iter=200,
                             tol = 0.0001    )
sheep_model.fit(X_sheep,Y_sheep)
```

- A few notes on preprocessing:
  - We hand-craft features to reduce dimensionality, then train a simple MLP
  - However, they are totally learnable (e.g. CNN)
  - If no budget limit, one can use end-to-end learning without any preprocessing (a comparison is provided at the end).



Methodologies – RL: PPO

- In contrast to supervised learning, RL has no labels but learns from the rewards.



- Proximal Policy Optimization (PPO) :
  - On-policy optimization algorithms.
  - Balance between sample efficiency and stability.
  - Robust to hyperparameter choices and often converges reliably.
  - Employs a surrogate objective function with a clipping mechanism to ensure stable updates

Algorithm 1 PPO, Actor-Critic Style

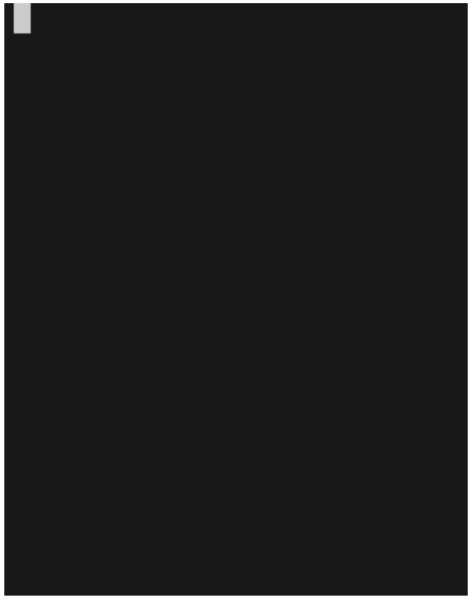
```
for iteration=1, 2, ... do
    for actor=1, 2, ..., N do
        Run policy π_θold in environment for T timesteps
        Compute advantage estimates Â_1, ..., Â_T
    end for
    Optimize surrogate L wrt θ, with K epochs and minibatch size M ≤ NT
    θ_old ← θ
end for
```

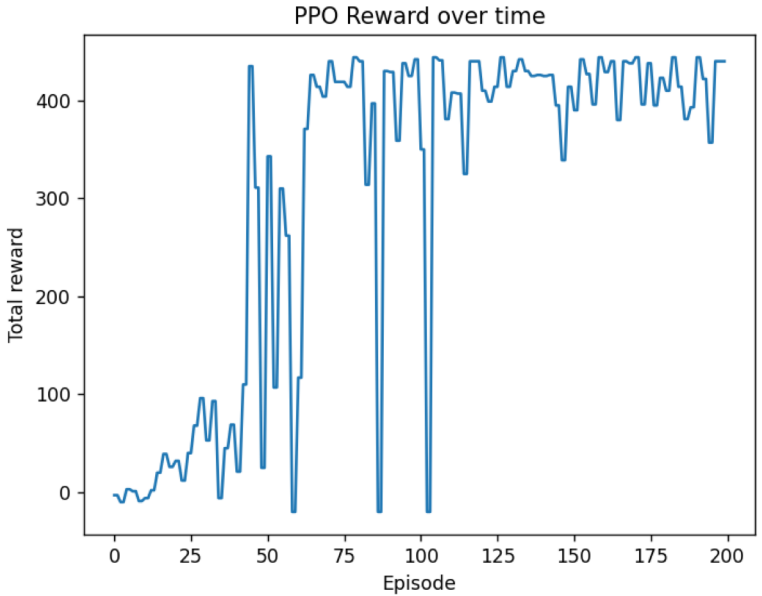
UC RIVERSIDE

Methodologies – RL: PPO feature vector learning

Design the rewards (for Sheep)

- Collect grass/rhubarb : +1 / +5; Trapping enemy sheep: +100; Each step: -0.2; Got eaten: -100





- Input is 1 x 16 vector, output is a scalar
- The learning process is fast and stable

UC RIVERSIDE

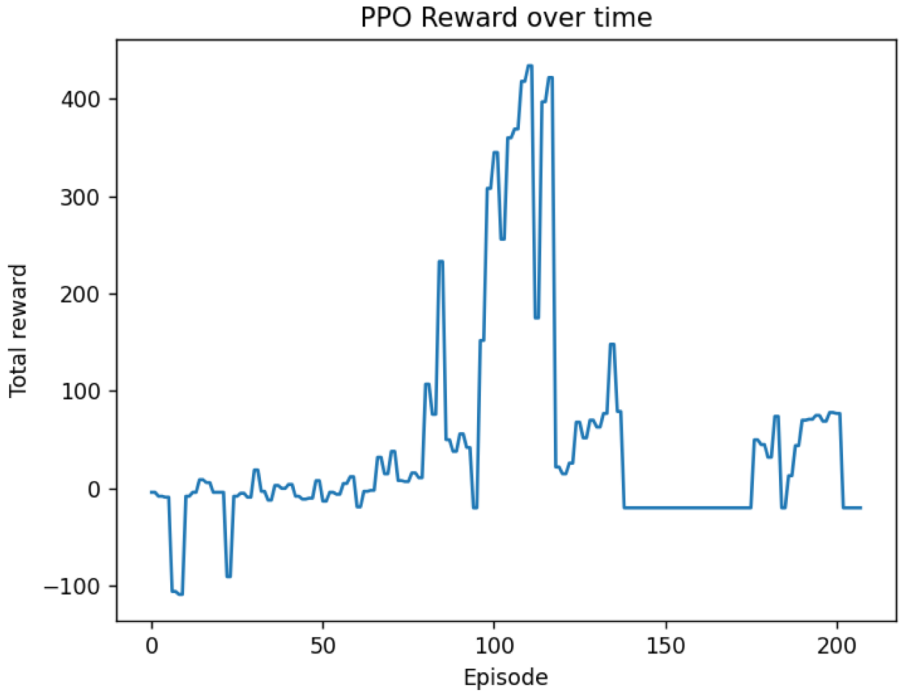
Methodologies – RL: PPO end-to-end learning

Design the rewards (for Sheep)

- Collect grass/rhubarb : +1 / +5; Trapping enemy sheep: +100; Each step: -0.2; Got eaten: -100

- Input map is 15 x 19 matrix
  output action is a scalar

- The learning process is unstable and needs significant time



Methodologies – RL: teacher - student framework

- In stead of doing everything from scratch, we can utilize the MLP model we get previously to guide our agent to learn. This is called teacher-student framework.

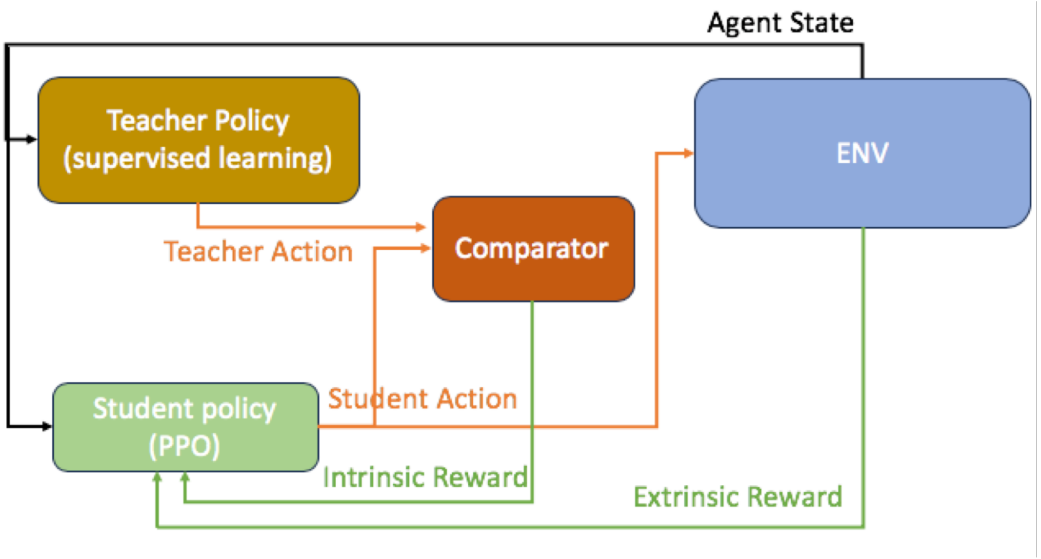
- Re-design the rewards (for Sheep)

Intrinsic:

  - Student a == Teacher a : 0
  - Student a != Teacher a : -3

Extrinsic:

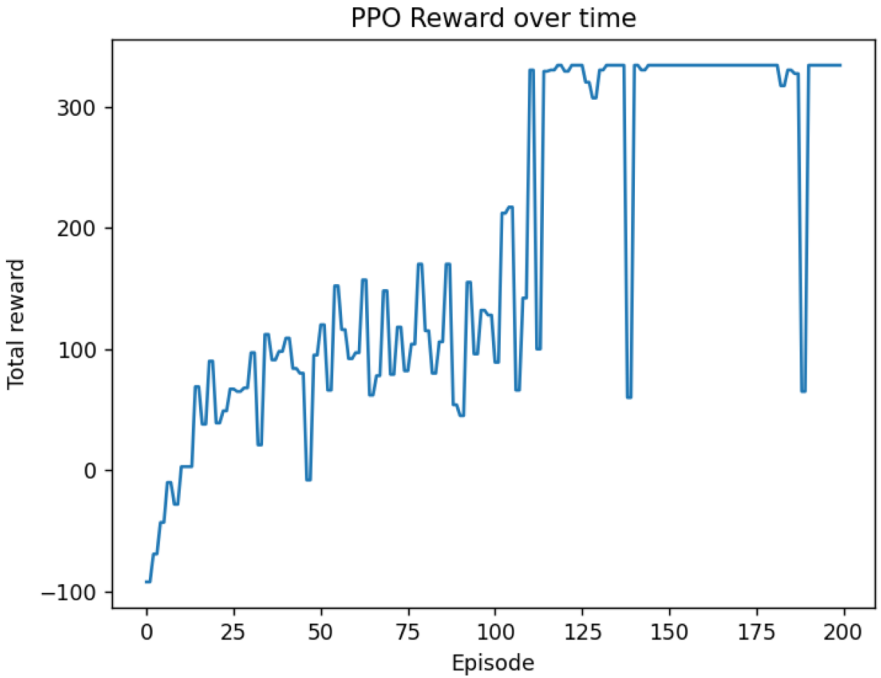
  - Collect grass/rhubarb : +1 / +5;
  - Trapping enemy sheep: +100;
  - Each step: -0.2;
  - Got eaten: -100



- Teacher student framework diagram

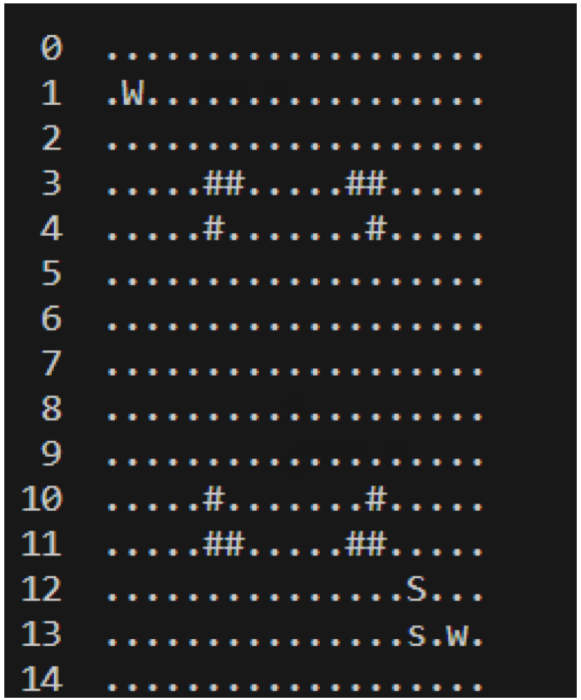
Methodologies – RL: teacher - student framework

- Teacher Policy
  - has access to privileged data
  - informed trajectory based on A*
- Student Policy
  - has access to map features
  - doesn't have the best trajectory, only the closeness measure
- Time efficient: fast learning process guided by teacher policy

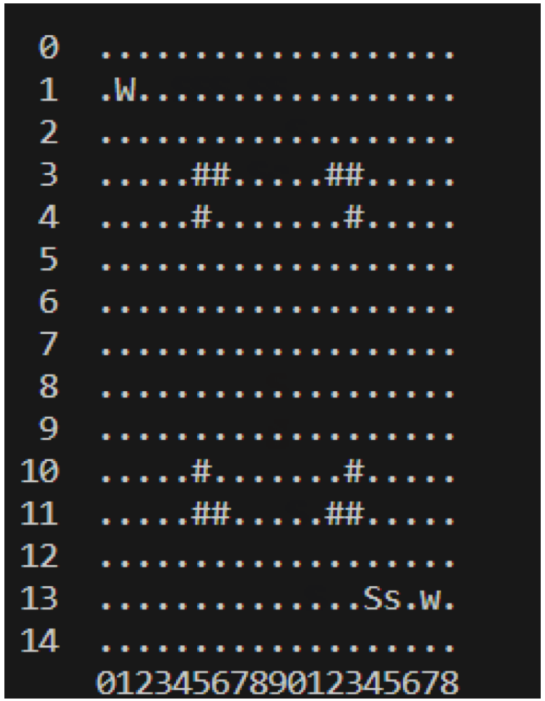


Methodologies – RL: teacher - student framework

- Ideal student policy will replicate the teacher policy



- Teacher policy



- Student policy

UC RIVERSIDE

Final demonstration

Map 1
- Full of food

Opponent agent:
- Greedy player

Our agent:
- RL player

Order:
- Second move

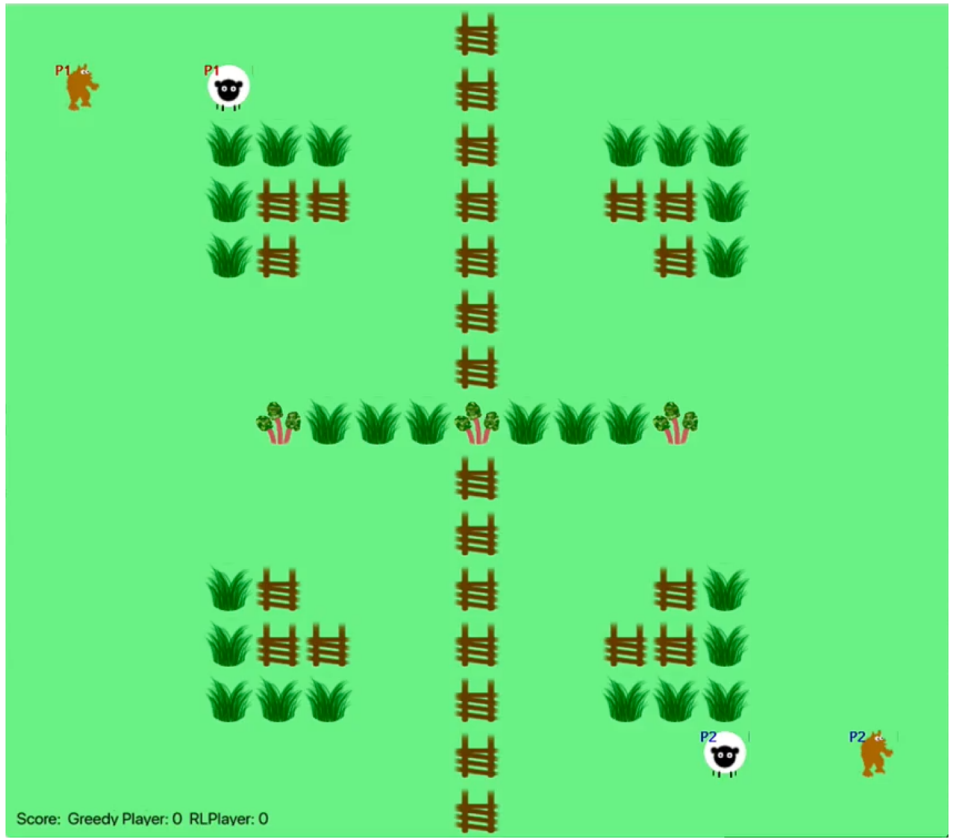
Final demonstration

Map 2
- Fence in the middle

Opponent agent:
- Greedy player

Our agent:
- RL player

Order:
- Second move



Summary

Search-based

- Pros: rule-based, flexible
- Cons: needs hand craft

```
2736        badSpot_1, badSpot_2 = alterI
2737
2738        if badSpot_1 < badSpot_2:
2739            post_move = _move1
2740        elif badSpot_1 > badSpot_2:
2741            post_move = _move2
2742        else:
2743            print("the two ways are i
2744            post_move = _move1
2745
2746        if post_move == 'up':
2747            suggestedAction = Node(P
2748        elif post_move == 'down':
2749            suggestedAction = Node(P
2750        elif post_move == 'left':
2751            suggestedAction = Node(P
2752        elif post_move == 'right':
2753            suggestedAction = Node(P
2754        else:
2755            suggestedAction = Node(P
2756
2757        return suggestedAction
```

Nearly 3000 lines of code!

Learning-based

- Pros: no hand crafting
- Cons: needs data

```
my_map_p1_v2_gready_scraping_results.csv',
map2_p1_v2_jcd_scraping_results.csv',
test_p1_v2_gready_scraping_results.csv',
map2_p1_v2_gready_scraping_results.csv',
test3_p2_v2_gready_scraping_results.csv',
test_p2_v2_jcd_scraping_results.csv',
test3_p2_v2_jcd_scraping_results.csv',
map3_p1_v2_jcd_scraping_results.csv',
map1_p1_v2_gready_scraping_results.csv',
map3_p1_v2_gready_scraping_results.csv',
my_map_2_p2_v2_gready_scraping_results.csv',
my_map_p1_v2_jcd_scraping_results.csv',
map1_p2_v2_gready_scraping_results.csv',
my_map_2_p1_v2_gready_scraping_results.csv',
map3_p2_v2_gready_scraping_results.csv',
map3_p2_v2_jcd_scraping_results.csv',
test_p2_v2_gready_scraping_results.csv',
map1_p1_v2_jcd_scraping_results.csv',
my_map_p2_v2_gready_scraping_results.csv',
test3_p1_v2_gready_scraping_results.csv',
map2_p2_v2_gready_scraping_results.csv']
```

At least 3~4k data samples!

RL-based

- Pros: no need to collect data
- Cons: needs huge time to learn

At least 3h per training

Contribution and future work

- Wrote the **gym env**ironment for the Wolf-sheep game.
- Developed **Search**-based, Supervised **learning**-based and **RL**-based agents.
- Tested our agents in multiple **unseen maps**.

In future work:

- Learn end-to-end model to process high-dimensional data directly.
- Learn one model for multi-agents (depends on the situation).
- Test on more maps that contain some corner cases.