PROJECT REPORT

CSE 546: Reinforcement Learning Spring 2024

Instructor: Dr. Alina Vereshchaka *Deadline*:

Team Number: **18**

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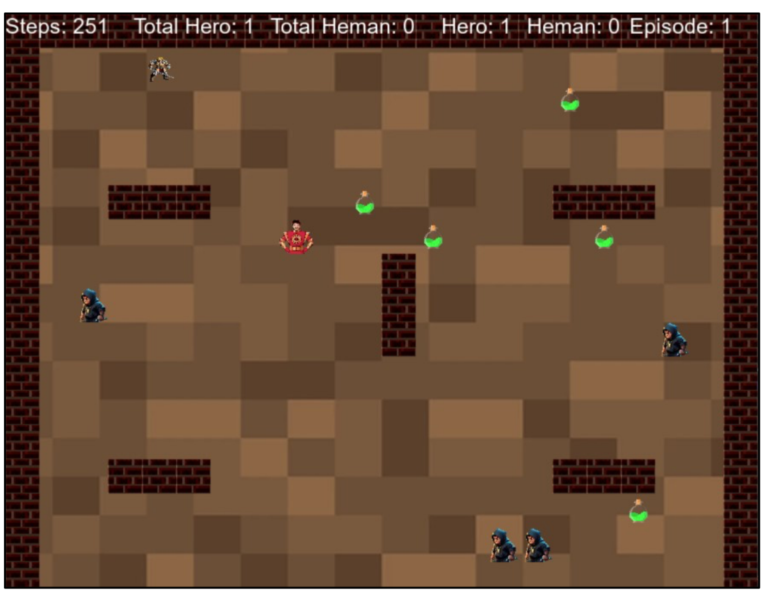
TITLE:

SHAKTIMAN: A MULTI AGENT GAME IMPLEMENTATION

INTRODUCTION:

The environment is based on the Hunter Assassin game environment. The environment consists of Heroes, Enemies, Walls, and Health. In this environment the core concept of the environment is Agents killing the enemies. There will be two AI Agents (Heman and Shakthiman) and 5 enemies, the AI agents will be trained to kill as many enemies as possible. The agent that kills maximum number of enemies is the winner.



AGENTS *and their* ALGORITHMS:

1. Shakthiman:

Shakthiman is a DQN agent. We are using a Deep Q Network to train Shakthiman. DQN is a reinforcement learning algorithm introduced by DeepMind in 2015. It combines deep learning with Q-learning to enable agents to learn control policies directly from high-dimensional sensory inputs. In DQN, we use a Q network to approximate the expected Q values of a given state. By using a target network and experience replay, we adjust the parameters and make the Q network better. At certain intervals, we copy those values to the target network. Using a target network reduces instabilities in the deep Q networks. This approach has been successfully applied to various tasks, including playing Atari games and robotic control, demonstrating its effectiveness in learning complex behaviors from raw sensory data.

NOTE: Shaktiman is also referred as Hero in some parts of our project.

2. Heman:

Heman is an Actor Critic agent. We are using the A2C method for training Heman. A2C is an abbreviation for Advantage Actor Critic, which is an RL algorithm where we improve the policy network for every episode along with the Q network. There are two networks here: one is the actor network, and the other is the critic network. The critic network generates the Q values, and these values are sent to the actor network. Based on these Q values, the actor network provides action probabilities, and the action is chosen using these probabilities. We are using a multinomial distribution to sample the action. The parameters of the critic network are updated using mean squared error. The target values are calculated using the equation (reward + gamma * future_return). The parameters of the actor network are updated using log(probabilities) * advantage values. Using these formulas, backpropagation is performed, and the weights are updated to obtain the desired output. The action is chosen by the actor network, so we use the actor network for testing. The critic network is used to train the actor network with values.

REWARDS:

The rewards will be the same for both Shakthiman and Heman.

- There will be a positive reward of +1000 if the agent catches the enemy. The reward of 1000 will be penalized by the number of steps taken to catch the enemy (1000 - 2 * number_of_steps).
- Every time the agent moves closer to the enemy, there will be a positive reward of +100. Every time the agent moves away from the enemy, there will be a negative reward of -100. If there is no change in the distance, it will get -10 (We are using Manhattan Distance).
- At the end of every episode, if Shakthiman is catching more enemies than Heman, then Shakthiman will get +500 and Heman will get -500, and vice versa.

- If there are still enemies left after the episode, both of them will be rewarded -500.
- If any of the agents die due to 0 health, then the agent will be penalized with -1000.

HEALTH:

- If an agent hits the wall, then he loses 1.5 health points. The total health is 100. If the agent dies by depleting all his health, he will be penalized with a reward of -1000.
- There are 5 health potions available that will help the agent regain health. If the agent reaches a health potion, then it will gain +4 health points.

OBSERVATIONS:

This is a fully observable environment; the agent will be given all the elements present in the environment so that it can learn every element. There are 24 observations given to each network. The first four observations indicate the presence of walls in four directions relative to Heman. The next four observations represent the current direction of Heman: whether he is moving up, down, left, or right. Another four observations indicate the enemies' positions relative to Heman: whether an enemy is above, to the right, to the left, or below. These constitute the first 12 observations. The next 12 observations will be the same properties for Shakthiman. Both the Heman networks and Shakthiman networks will be given these 24 observations.

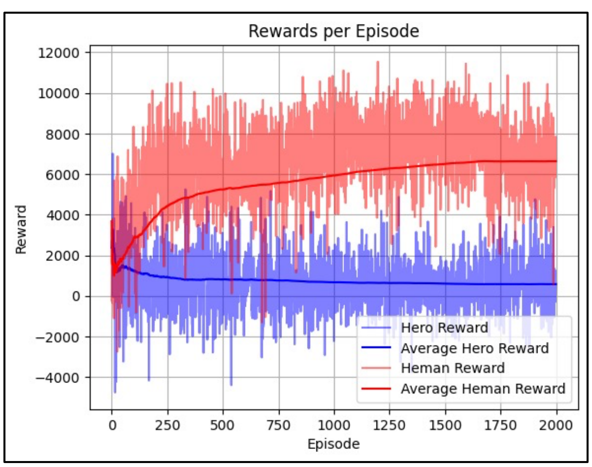
Steps:

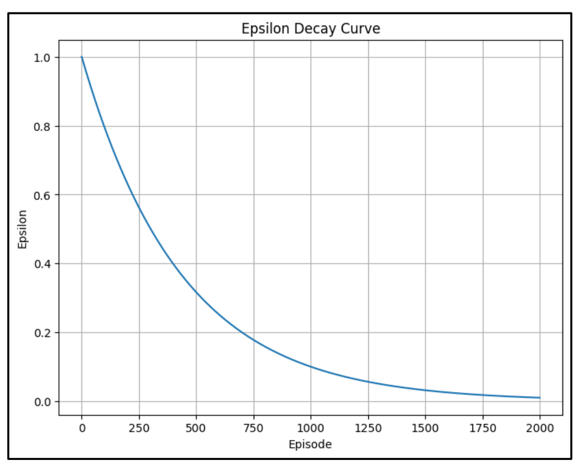
The agent can take four possible steps: up, down, right, or left.

GOAL:

The goal of both agents is to kill the maximum number of enemies in the minimum number of steps without losing health.

TRAINING PLOTS:





The blue curve represents the rewards obtained by the "Hero" agent, which is using the Deep Q-Network (DQN) algorithm. The orange curve represents the rewards obtained by the "Heman" agent, which is using the Advantage Actor-Critic (A2C) algorithm.

the performance of both agents fluctuates significantly during the initial stages of training, with periods of high rewards followed by periods of low or negative rewards. As training progresses, the agents' performances gradually improve, and the reward curves become smoother, indicating more stable and consistent behavior.

The second graph is the epsilon decay curve for the training process of 2000 episodes.

RESULTS:

Testing Actor Critic (Heman) by taking another agent as random:

We can clearly see that Heman which is having Actor Critic algorithm is performing extremely good when compared with the random agent. By looking at this plot we can confirm that the A2C agent (Heman) is trained properly.

```
Episode 1: Hero Reward = 858, Heman Reward = 6088
Heman Won !!

Episode 2: Hero Reward = 778, Heman Reward = 5706
Heman Won !!

Episode 3: Hero Reward = 1116, Heman Reward = 6996
Heman Won !!

Episode 4: Hero Reward = 2268, Heman Reward = 5528
Heman Won !!

Episode 5: Hero Reward = -560, Heman Reward = 6920
Heman Won !!

Episode 6: Hero Reward = 1296, Heman Reward = 5930
Heman Won !!

Episode 7: Hero Reward = 684, Heman Reward = 5836
Heman Won !!

Episode 8: Hero Reward = -578, Heman Reward = 8264
Heman Won !!

Episode 9: Hero Reward = 44, Heman Reward = 6656
Heman Won !!

Episode 10: Hero Reward = 948, Heman Reward = 6646
Heman Won !!
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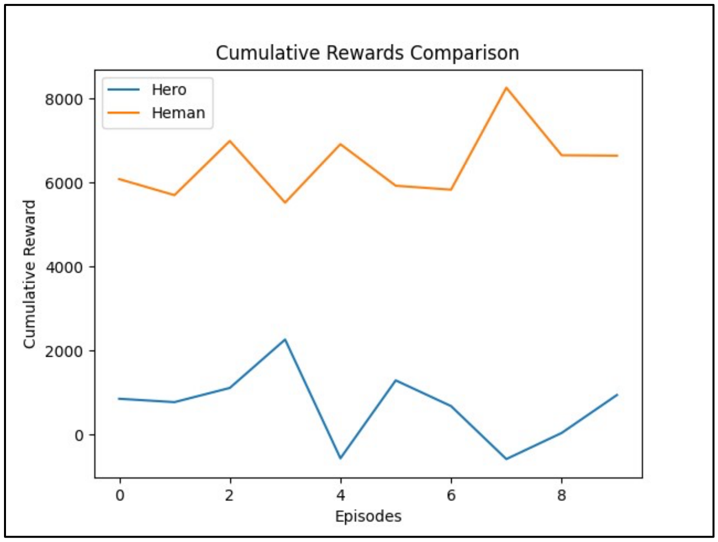


Testing DQN (Hero) by taking another agent as random:

We can clearly see that Hero which is having DQN algorithm is performing extremely good when compared with the random agent. By looking at this plot we can confirm that the DQN agent (Hero) is trained properly.

```
Episode 1: Hero Reward = 8566, Heman Reward = -40
Hero Won !!

Episode 2: Hero Reward = 6580, Heman Reward = 3720
Hero Won !!

Episode 3: Hero Reward = 7518, Heman Reward = 838
Hero Won !!

Episode 4: Hero Reward = 5638, Heman Reward = -68
Hero Won !!

Episode 5: Hero Reward = 7254, Heman Reward = 166
Hero Won !!

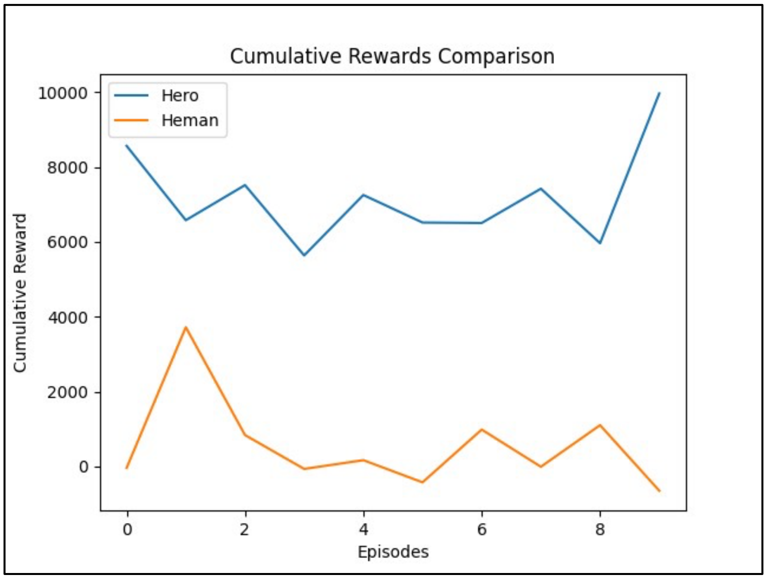
Episode 6: Hero Reward = 6518, Heman Reward = -426
Hero Won !!

Episode 7: Hero Reward = 6506, Heman Reward = 984
Hero Won !!

Episode 8: Hero Reward = 7422, Heman Reward = -10
Hero Won !!

Episode 9: Hero Reward = 5966, Heman Reward = 1102
Hero Won !!

Episode 10: Hero Reward = 9968, Heman Reward = -650
Hero Won !!
```



Testing Both DQN and Actor Critic Agent:

We can see both the agents are competitively getting the enemies and both of them are showing good results by caching the enemies with less number of steps over the time.

```
Episode 1: Hero Reward = 6710, Heman Reward = 4462
Hero Won !!

Episode 2: Hero Reward = 6346, Heman Reward = 4406
Hero Won !!

Episode 3: Hero Reward = 4060, Heman Reward = 4988
Heman Won !!

Episode 4: Hero Reward = 6958, Heman Reward = 3812
Hero Won !!

Episode 5: Hero Reward = 6790, Heman Reward = 1782
Hero Won !!

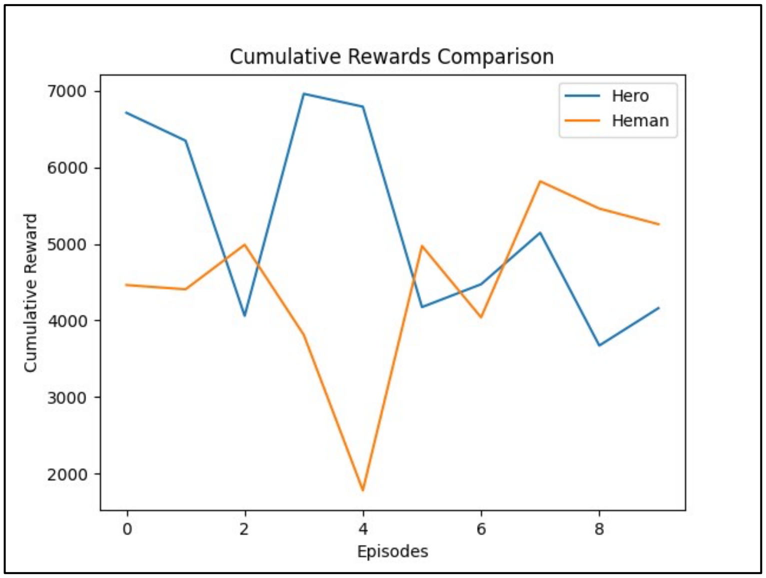
Episode 6: Hero Reward = 4174, Heman Reward = 4972
Heman Won !!

Episode 7: Hero Reward = 4472, Heman Reward = 4040
Hero Won !!

Episode 8: Hero Reward = 5144, Heman Reward = 5816
Heman Won !!

Episode 9: Hero Reward = 3672, Heman Reward = 5460
Heman Won !!

Episode 10: Hero Reward = 4160, Heman Reward = 5256
Heman Won !!
```



RUNNING GUIDE:

Training:

You can directly run the Python code for training to see the training process (video is provided).

Testing:

You can find 3 Testing files.

1. Hero Random and Heman with A2C trained weights.
2. Heman Random and Hero with DQN trained weights.
3. Both Hero and Heman are with trained weights.

TEAM CONTRIBUTION:

1. **Surya Suhas Reddy:** Worked on the Initial Development of the Game environment and built the project's structure - 30%.
2. **Leela Satya Praneeth:** Worked on the DQN Model and has made a significant contribution in building Shakthi Man - 30%
3. **Sai Venkat Reddy:** Worked on Actor-Critic Model and has made a significant contribution in building Heman - 30%

We got assistance from TAs about changes and improvements in the model during the SCRUM Meetings, which helped us to deliver successful results - 10%.

REFRENCES:

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4. Mnih, V., Badia, A. P., Mirza, M., Graves, A., Lillicrap, T. P., Harley, T., ... & Kavukcuoglu, K. (2016). Asynchronous methods for deep reinforcement learning. In International conference on machine learning (pp. 1928-1937). http://proceedings.mlr.press/v48/mniha16.pdf