CSCI 166 DQN Project Report

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Environment

For our project we chose the Demon Attack environment from Gymnasium. In this Atari game, the player moves a laser cannon to fire at waves of different demons (enemies) who will try to attack the player. The game ends when the player is hit and all bunkers (health points) are destroyed.

Observations

The variant we were using "ALE/DemonAttack-v5", has an rgb observation type which results in the following observation space: *`Box(0, 255, (210, 160, 3), np.uint8)`*.

Actions

Action	Meaning	Description
0	NOOP	Do nothing
1	FIRE	Shoot laser cannon
2	RIGHT	Move right
3	LEFT	Move left
4	RIGHTFIRE	Move right and shoot
5	LEFTFIRE	Move left and shoot

Rewards

Points are only given when you kill demons with your lasers. The amount of points gained is determined by what type of demon killed and the current wave. No points are lost when a player is hit or when all bunkers are destroyed resulting in game over. No points are also gained for the amount of time surviving.

Model & Training

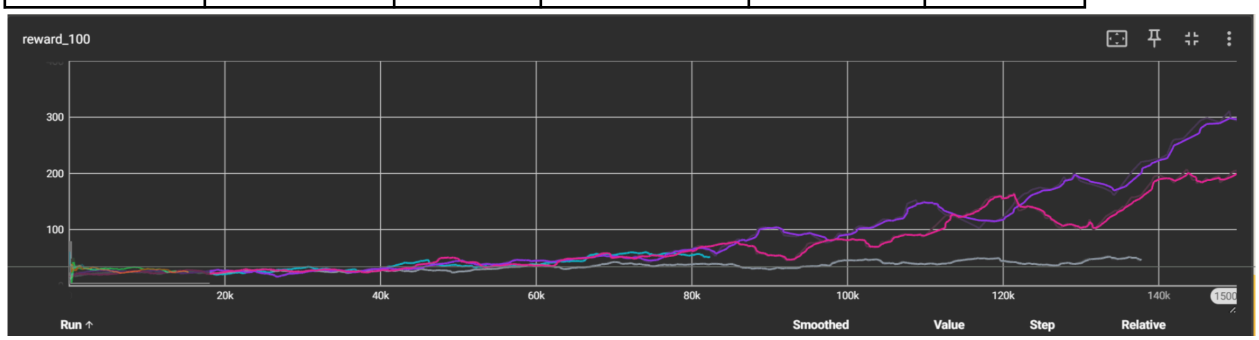
DQN Extensions

For our baseline model we first added Double DQN to improve stability. To further enhance our model and increase the speed of learning we added Dueling.

Experimentation

Core Hyperparameters

Color	Learning rate	Gamma	Epsilon decay	Replay size	Batch size
Purple	1e-4	0.99	150000	10000	32
Gray	1e-4	0.99	300000	10000	32
Blue	2e-4	0.99	150000	10000	32
Pink	1e-4	0.97	150000	10000	32
Orange	1e-4	0.99	150000	50000	32
Green	1e-4	0.99	150000	10000	64

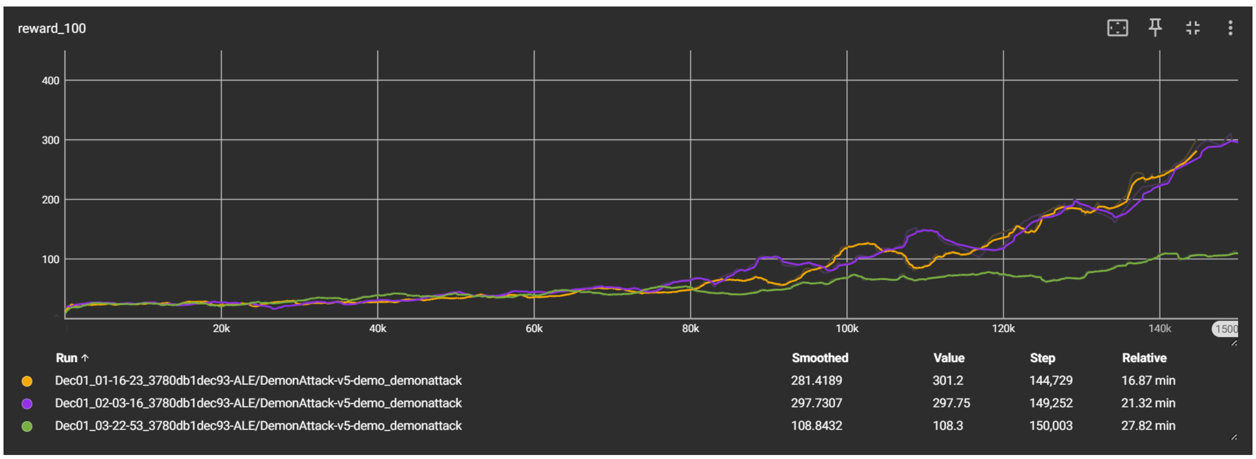


Reflection

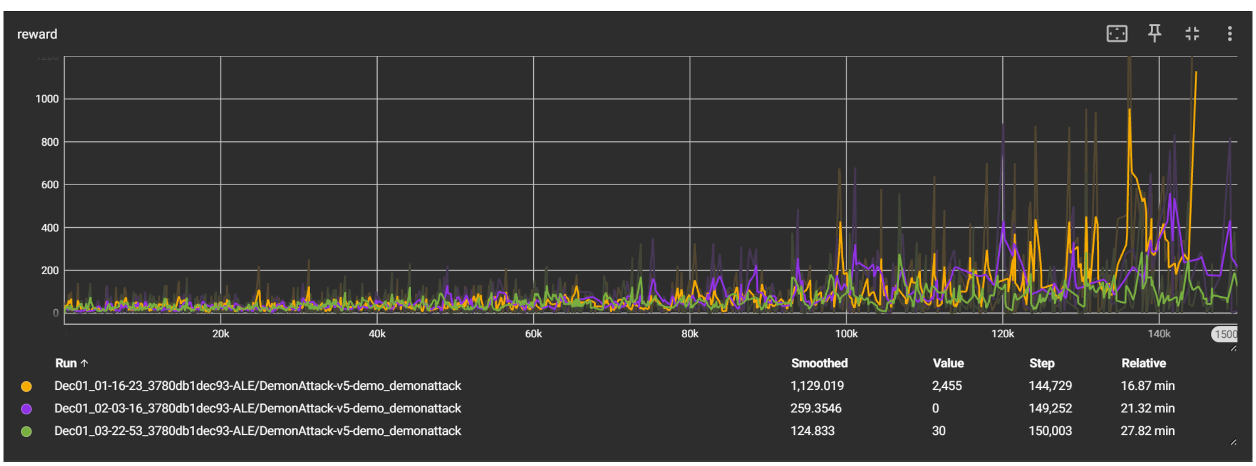
We chose the Demon Attack Atari environment because it is similar to the game *Galaga* which we liked playing as children. The best extensions to the DQN were Double DQN and Dueling. While it did not improve the reward per step, it did improve the stability of the rewards. This came with the minor drawback of slightly slower speed per step.

Demon Attack has almost immediate reward after firing but the reward can be noisy because moving towards targets or dodging bullets are not rewarded. Double DQN likely helps with the stability of the rewards. Dueling likely had a minor or negligible effect on Demon Attack because some actions immediately affect reward but it may help when it takes steps that don't give immediate rewards. Meanwhile N-step Returns results in worse rewards for Demon Attack most likely because rewards can be quickly determined per action, and using N-step returns worsens learning because it smooths out the good and bad actions.

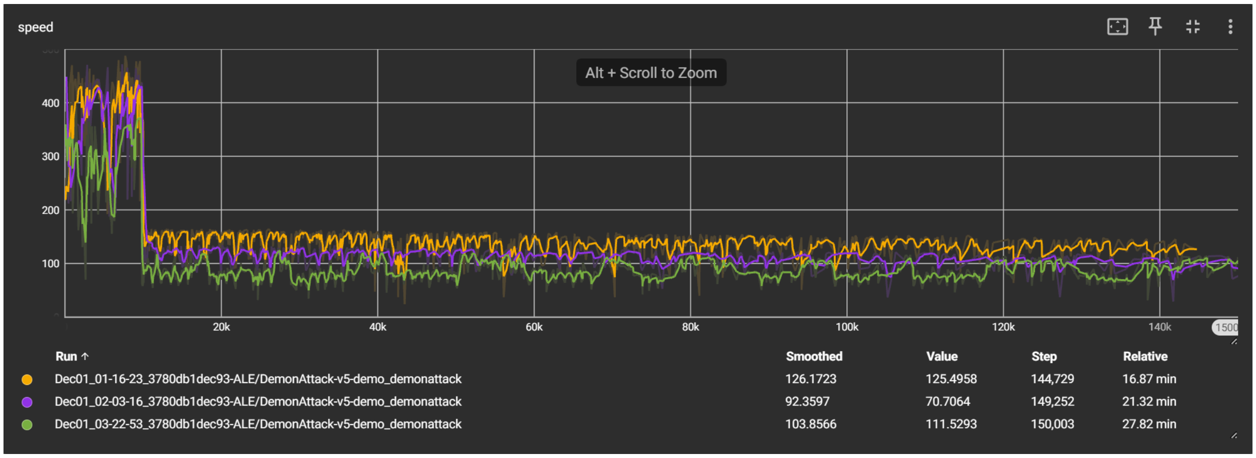
Something we'd try next to improve our model would be reward shaping to see if it would improve the speed of learning or make the final model be more directed to the Demon Attack environment. The current environment isn't penalized based on the amount of hits it takes or rewarded for clearing different waves quickly. Changing the reward structure could make the model avoid taking hits and increase the speed at which the model kills demons. This could result in more human-like playing.



Caption: Mean rewards / steps



Caption: Rewards / steps



Caption: Speed (frames per sec) / steps

Key

Orange	Baseline model
Purple	Double DQN and Dueling DQN
Green	Double DQN, Dueling DQN, and N-step return