



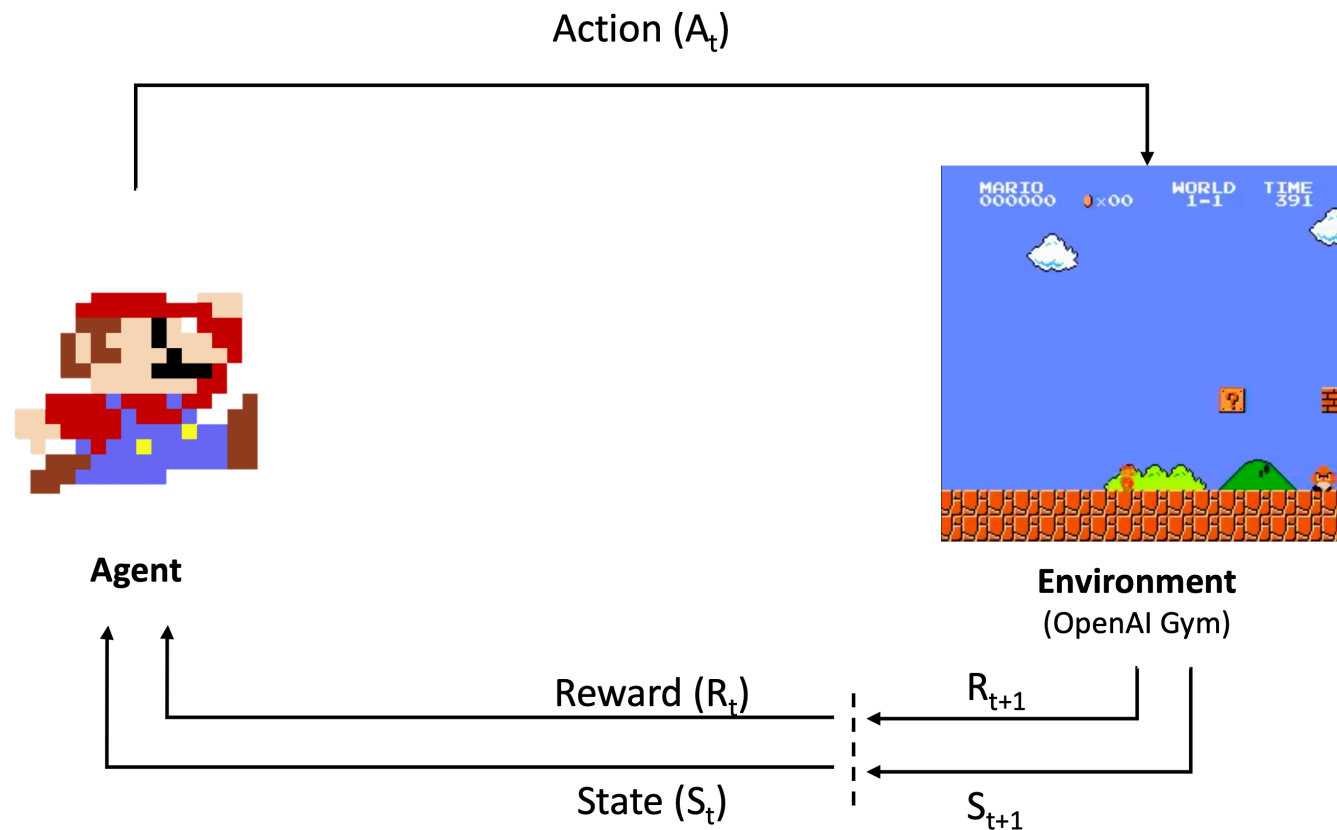
Group 20!

# CM50270 – Reinforcement Learning

Final Project Presentation

# Problem Description

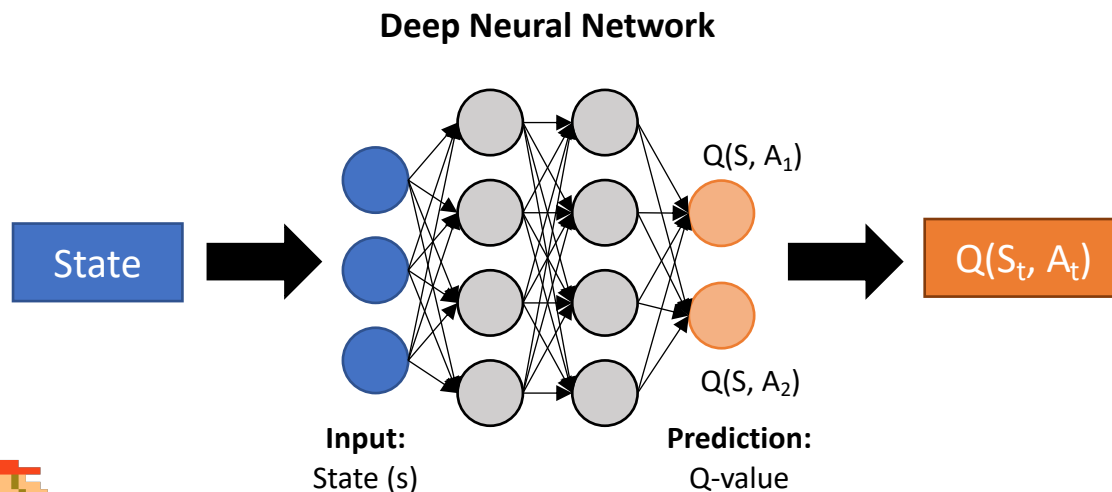
- Train RL agents to play **Super Mario Bros** World 1 Stage 1



# RL Algorithms Suitable for the Problem

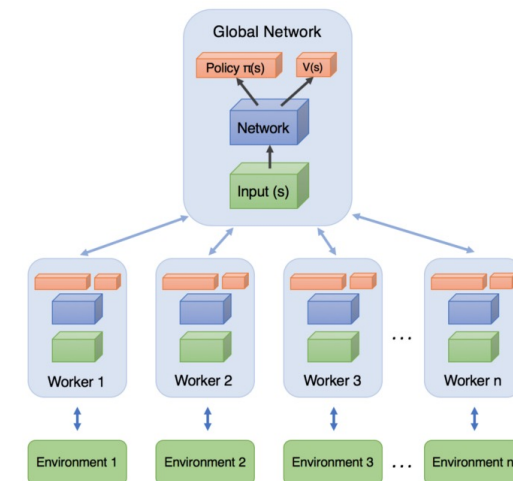
## Deep Q-Network

- Value-based learning
- Instead of storing Q-values in tabular form, uses a DNN for prediction of Q-values
- Uses Experience Replay to learn from past experiences
- Method used in official [PyTorch tutorial](#) (clears the first stage, suggested running at least 40,000 episodes)

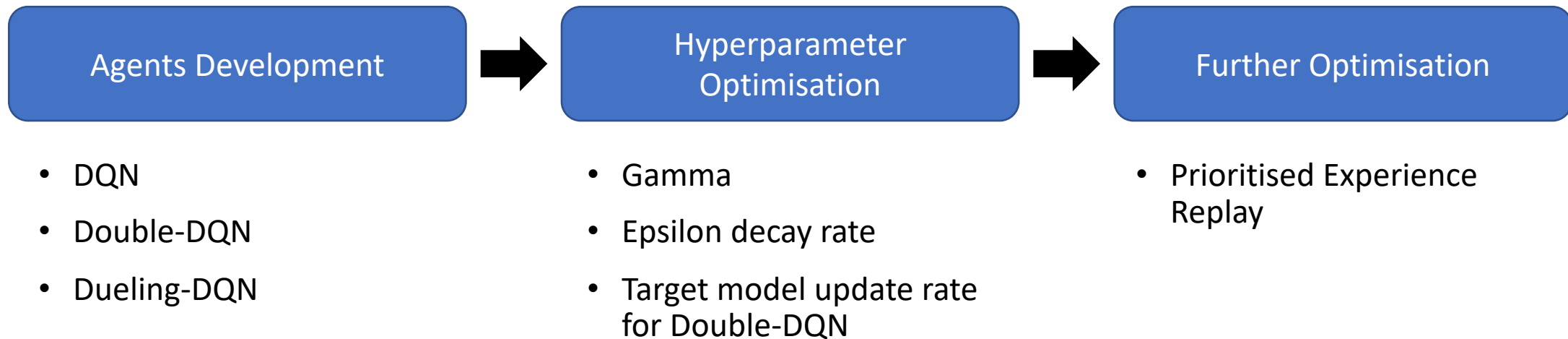


## Actor Critic

- Combines both value-based and policy gradient learning
- Composes of 2 parts:
  - **Actor**: Estimates actions based on policy, updates policy according to critic's feedback
  - **Critic**: Estimates values of actions taken and evaluate the action
- In a [GitHub repository](#), 19 stages solved using A3C method

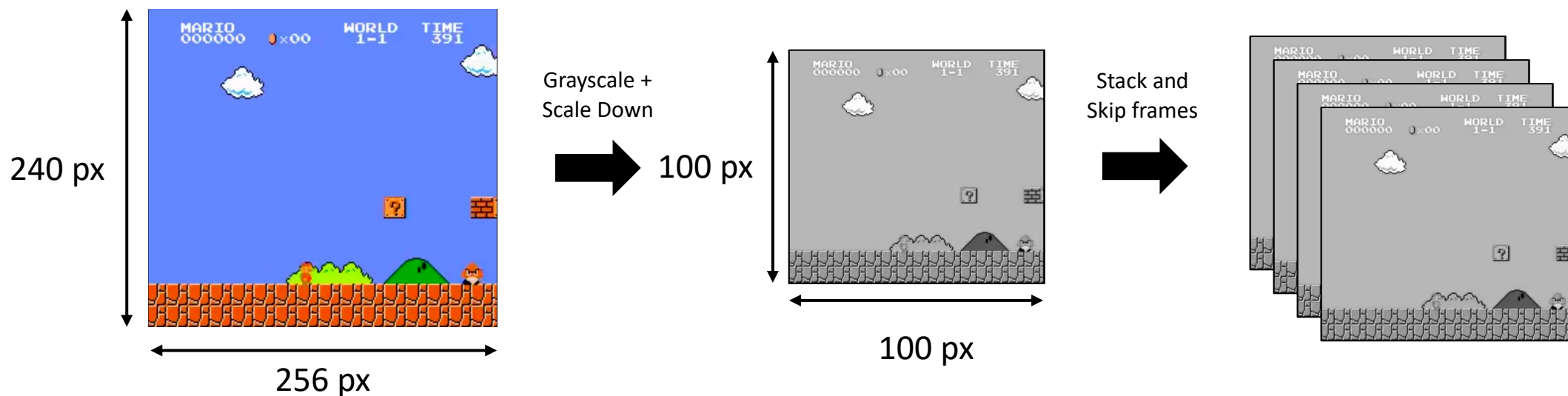


# Implementation Process



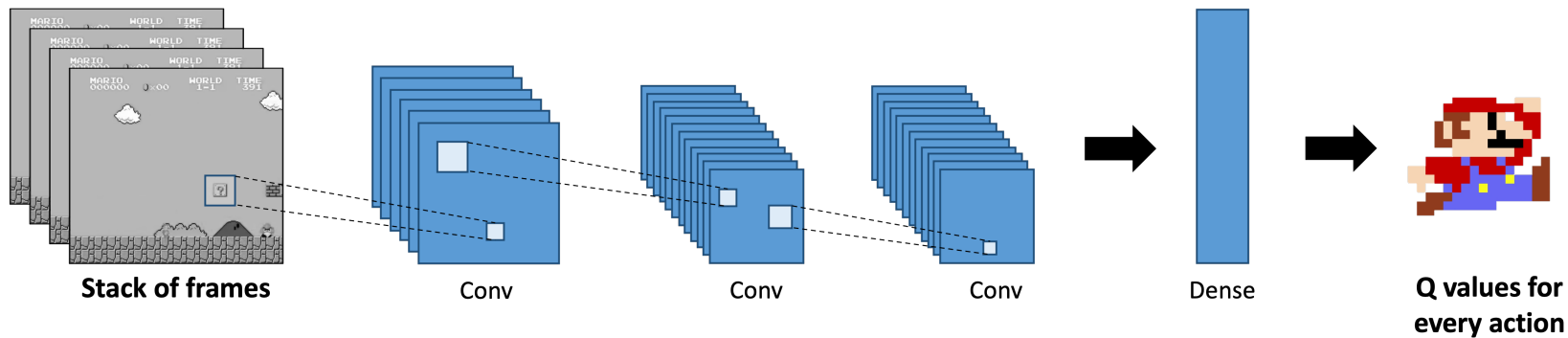
# Frames Preprocessing

- States represented as pixel frames
- Referenced DeepMind Atari agents' environment preprocessing steps to downsize the number of feature vectors in the DNN → enhances computational efficiency



# Agents Implemented - DQN

- Use CNN as the DQN for computing the Q-values
- Architecture of the CNN:



- At each timestep, perform **Experience Replay** to update the model weights:

$$y_i = \begin{cases} r_i & \text{if terminal } s_{i+1} \\ r_i + \gamma \max_{a'} \hat{Q}(s_{i+1}, a', \theta) & \text{otherwise} \end{cases}$$

Rewards: clipped at  $[-15, 15]$

$$\text{Gradient descent step: } \nabla_{\theta} L_{\delta}(y_i - \hat{Q}(s_i, a_i, \theta))$$

Huber Loss

# Agents Implemented – Double-DQN

- Problem of DQN: **Shifting target**
- Solution: Introduction of a **target network**
- At every time step:
  - **Choose best action** according to **online network ( $Q_1$ )** prediction
  - Perform Experience Replay to update weights of online model based on Q-value predictions of target model ( $Q_2$ )

$$y_i = \begin{cases} r_i & \text{if terminal } s_{i+1} \\ r_i + \gamma \max_{a'} \widehat{Q}_2(s_{i+1}, a', \theta_2) & \text{otherwise} \end{cases}$$

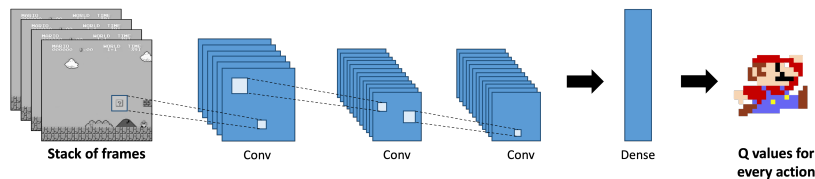
Rewards: clipped at  $[-15, 15]$

Gradient descent step:  $\nabla_{\theta} L_{\delta}(y_i - \widehat{Q}_1(s_i, a_i, \theta))$

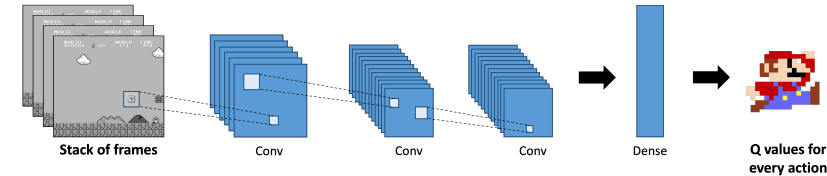
Huber Loss

- Target network copies the weights of online network at every N steps

Online network



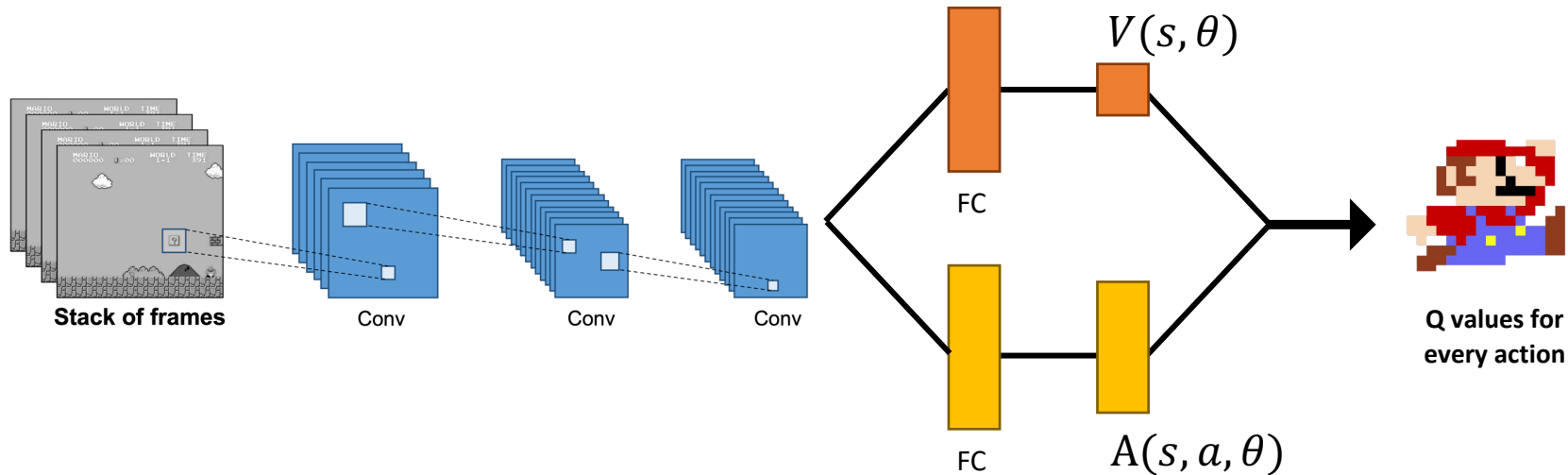
Target network (Frozen weights)



copy weights from **online** every N steps

# Agents Implemented – Dueling-DQN

- Introduces a **value** branch and an **advantage** branch in the CNN



Final aggregation of streams:

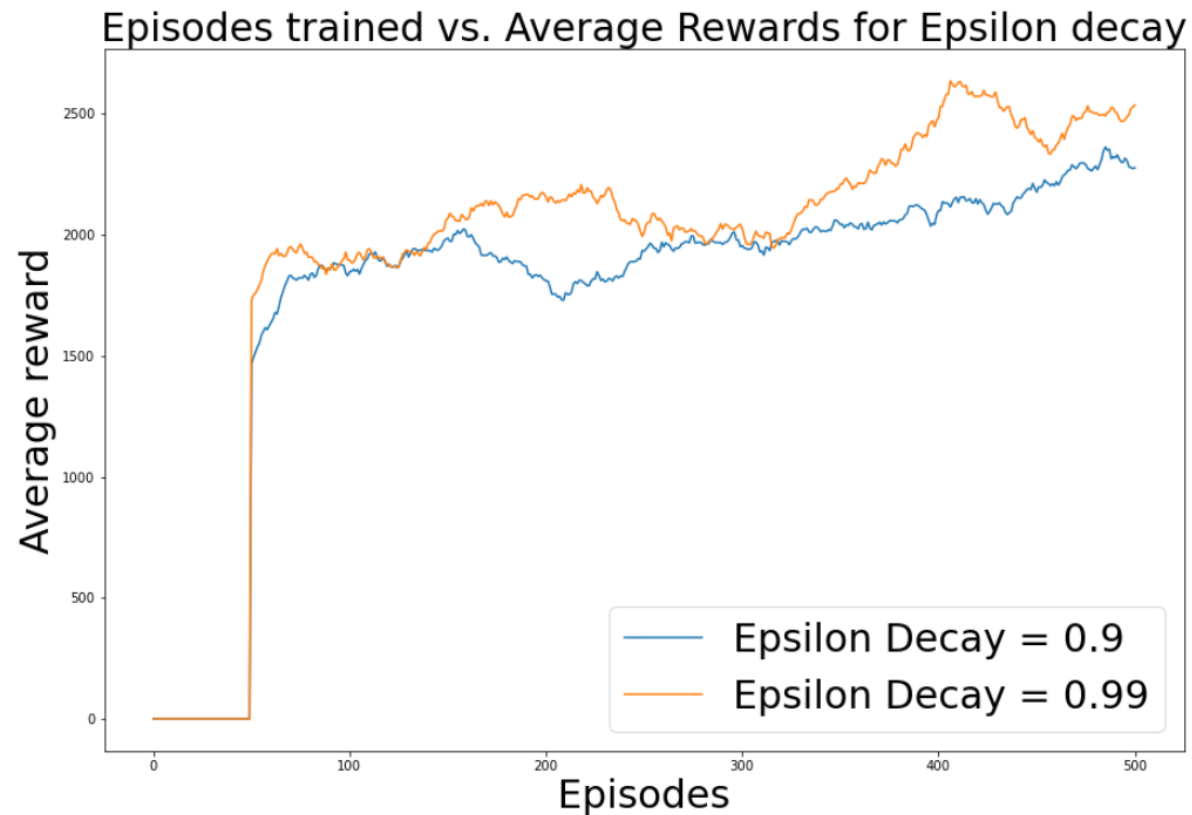
$$Q(s, a, \theta) = V(s, \theta) + A(s, a, \theta) - \frac{1}{|A|} A(s, a, \theta)$$





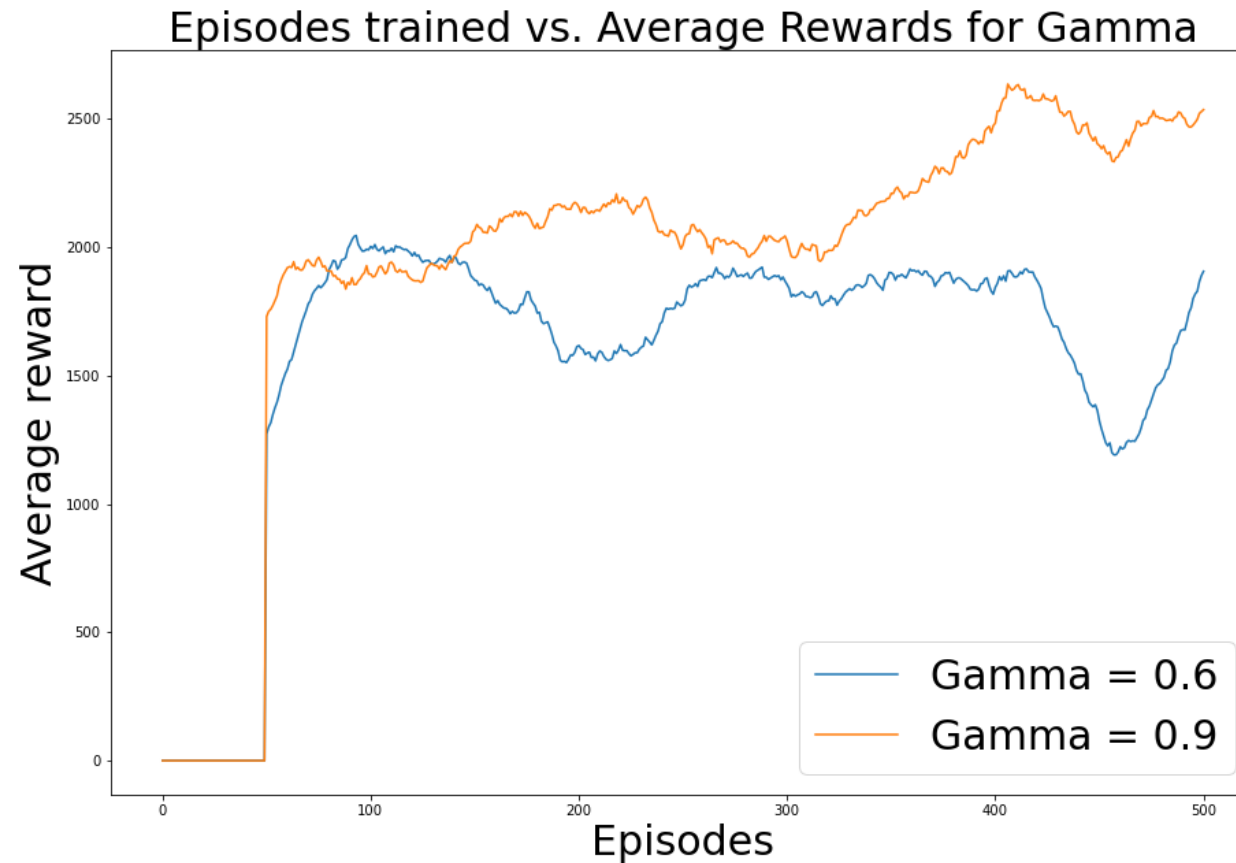
# Hyperparameter Optimisation

- **Epsilon Decay**- Controlled the ratio of time the agent spent exploring vs exploiting



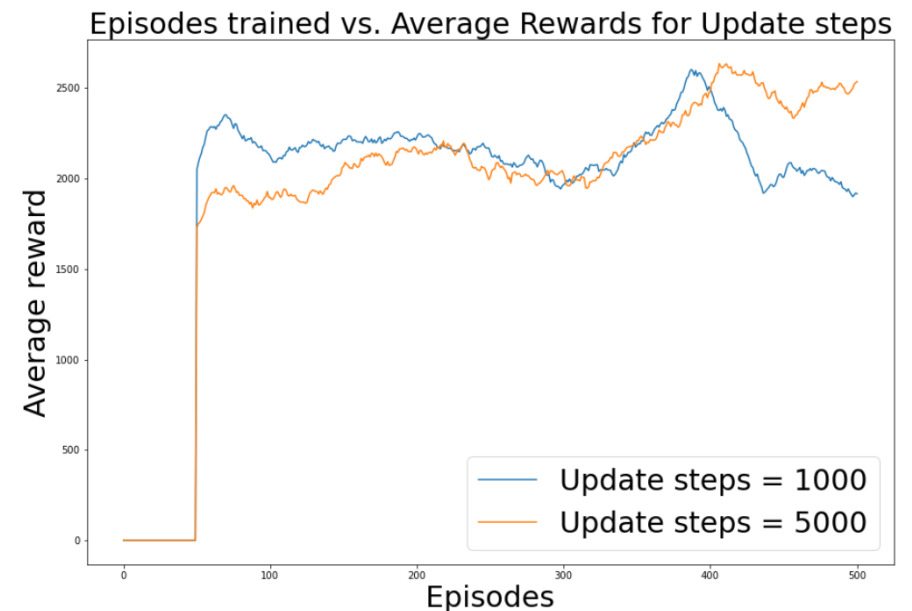
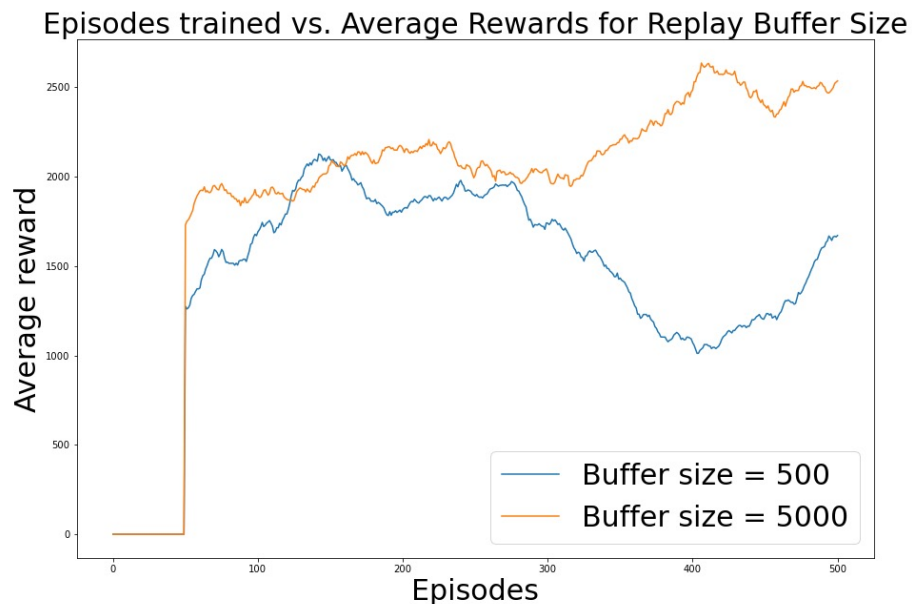
# Hyperparameter Optimisation

- **Gamma**- Decides how much importance is given to future rewards



# Hyperparameter Optimisation

- **Replay Buffer Size-** How many tuples of experience we retain
- **Update steps-** How often we sync the weights from the DQN with the target network



# Performance Comparison

## Agent types:

DQN

DDQN

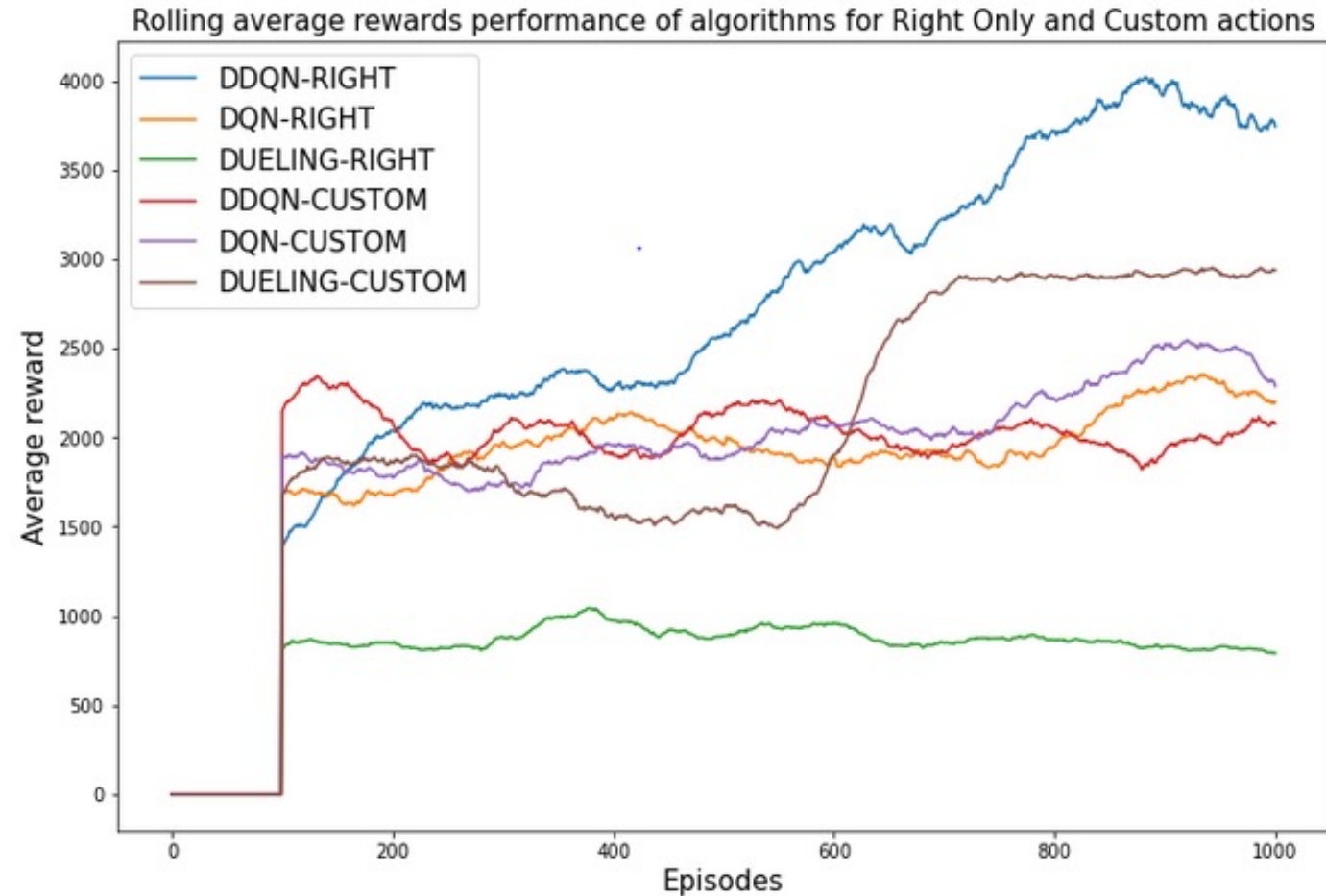
Dueling-DQN

Trained on: 1000 episodes

## Actions:

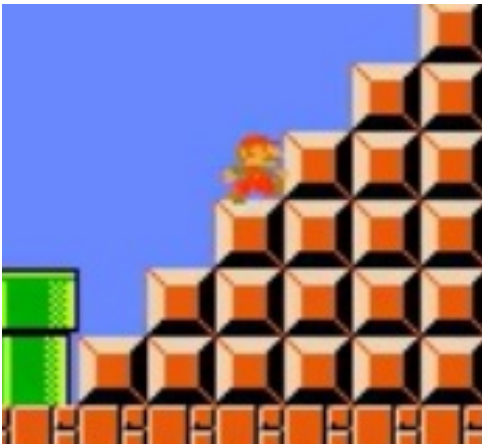
Right only

Custom: Right and Right/A

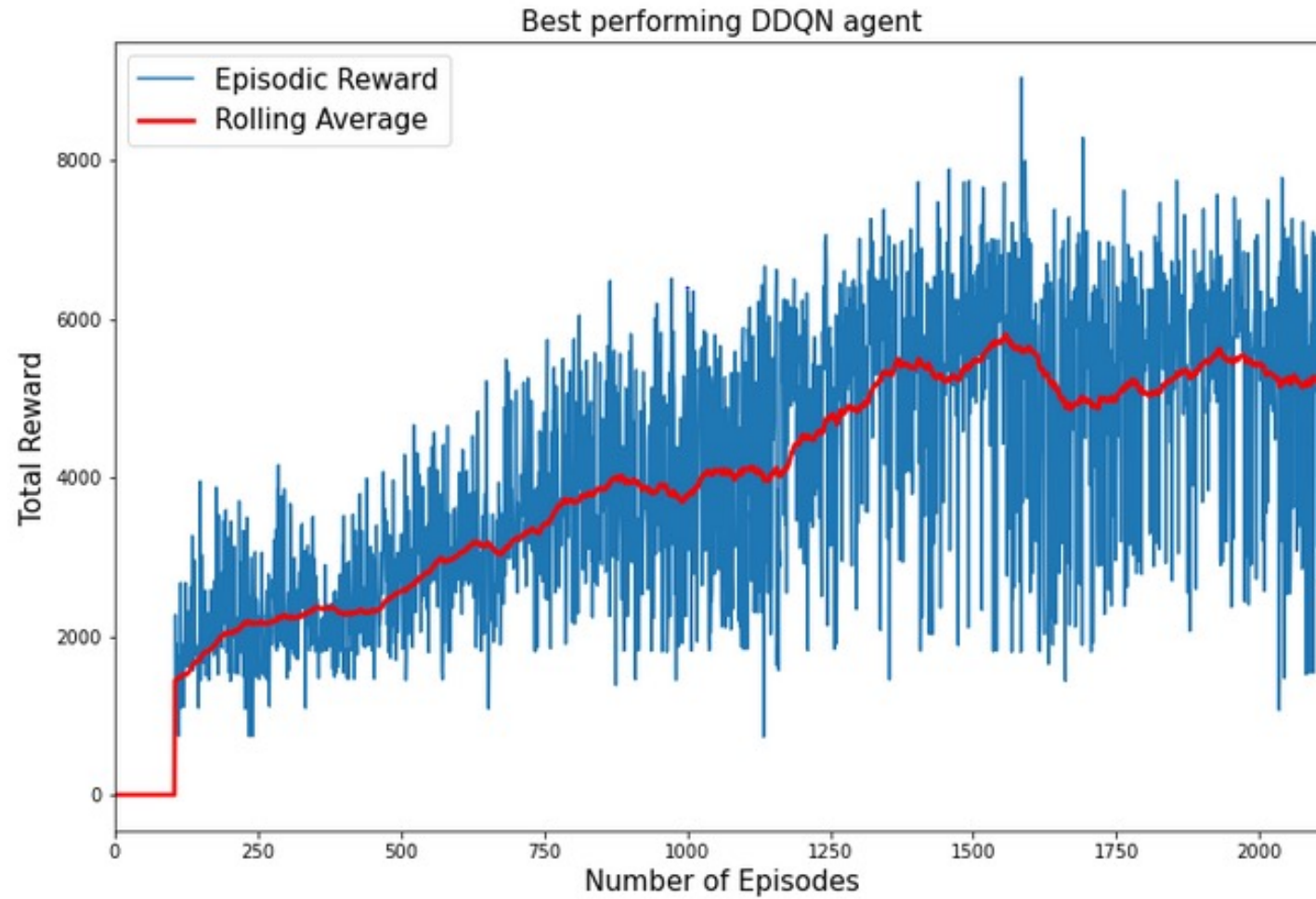


# Performance of our Best Agent

```
Model type: Double DQN (DDQN)
Experience replay: Uniform
Mario's moveset: RIGHT_ONLY (no op, right, right + A, right + B, right + A + B)
Max memory for experiences: 20000
Max epsilon: 1.0
Min epsilon: 0.1
Epsilon decay: 0.99
Steps until target network updates: 5000
Batch size for experience replay: 64
Gamma: 0.9
Learning rate: 0.00025
Episodes of training: 2500
Environment: SuperMarioBros-v0
Record rate: 20 episodes
```



# Learning Curve



THANK YOU

