

HOCKEY GAME

王峻睿 B05502087

吳由由 B06902104

吳采耘 B06902041



X INTRODUCTION

Hockey Game is a classical game in which **two players** play against each other by trying to make the ball touch the **opponent's edges** with a disk.

X CNN

1. **Convolution:** Line up the feature and the image. Multiply each image pixel by corresponding feature pixel. Add the values and find the sum. Divide the sum by the total number of pixels in the feature.
2. Rectified Linear Unit (**ReLU**) transform function only activates a node if the input is **above a certain quantity**.
3. Pooling Layer **shrinks the image** stack into a smaller size.
4. Fully connected layer is the **classification** layer. When certain values are arranged the way they are, they can be mapped to an actual object which we require.

X EXPERIMENTAL METHODS

- We **preprocessed the images** by converting to grayscale, resizing them to 80x80, and then stacked together the last four frames to produce an 80x80x4 input array.
- The output layer, obtained with a simple matrix multiplication, has the same dimensionality as the number of valid actions which can be performed in the game. The values at this output layer represent the Q function. At each time step, the network performs whichever action corresponds to the **highest Q value** using a **ε greedy policy**.
- At startup, we initialize all weight matrices randomly using a normal distribution with a standard deviation of 0.01. Bias variables are all **initialized at 0.01**. We then initialize the replay memory with a **max size of 500,000 observations**.
- We start training by choosing actions uniformly at random for **50,000 time steps**, without updating the network weights. This allows us to **populate the replay memory** before training begins.
- After that, we **linearly anneal ε** from 1 to 0.05 over the course of the next 500,000 frames. During this time, at each time step, the network samples minibatches of size 100 from the replay memory to train on, and performs a gradient step on the loss function with a **learning rate of 0.000001**. After annealing finishes, the network continues to train indefinitely, with **ε fixed at 0.1**.

X REFERENCES

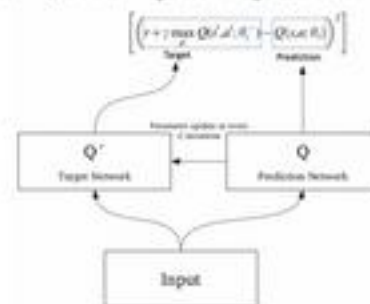
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X DEEP Q-NETWORK

Q-value:

- From being at **state s** and performing **action a** is the reward **r(s,a)** plus the **highest Q-value** from the next state **s'**. Gamma is the **discount factor** which controls the contribution of rewards. Alpha is the **learning rate** or step size.

$$Q(S_t, A_t) \leftarrow Q(S_t, A_t) + \alpha [R_{t+1} + \gamma \max_a Q(S_{t+1}, a) - Q(S_t, A_t)]$$



Deep Q-Network:

- All the **past experience** is stored by the user in memory
- The next action is determined by the **maximum output** of the Q-network
- The loss function here is mean **squared error** of the **predicted Q-value** and the **target Q-value - Q***.