

# Snake Game Using Deep Reinforcement Learning

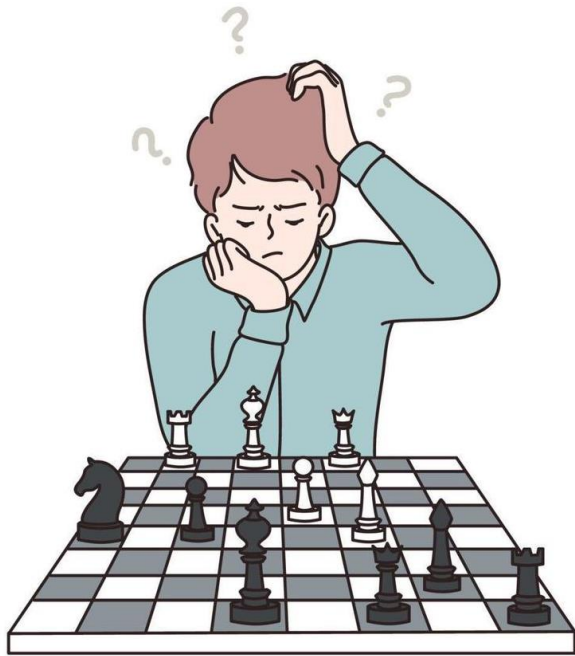
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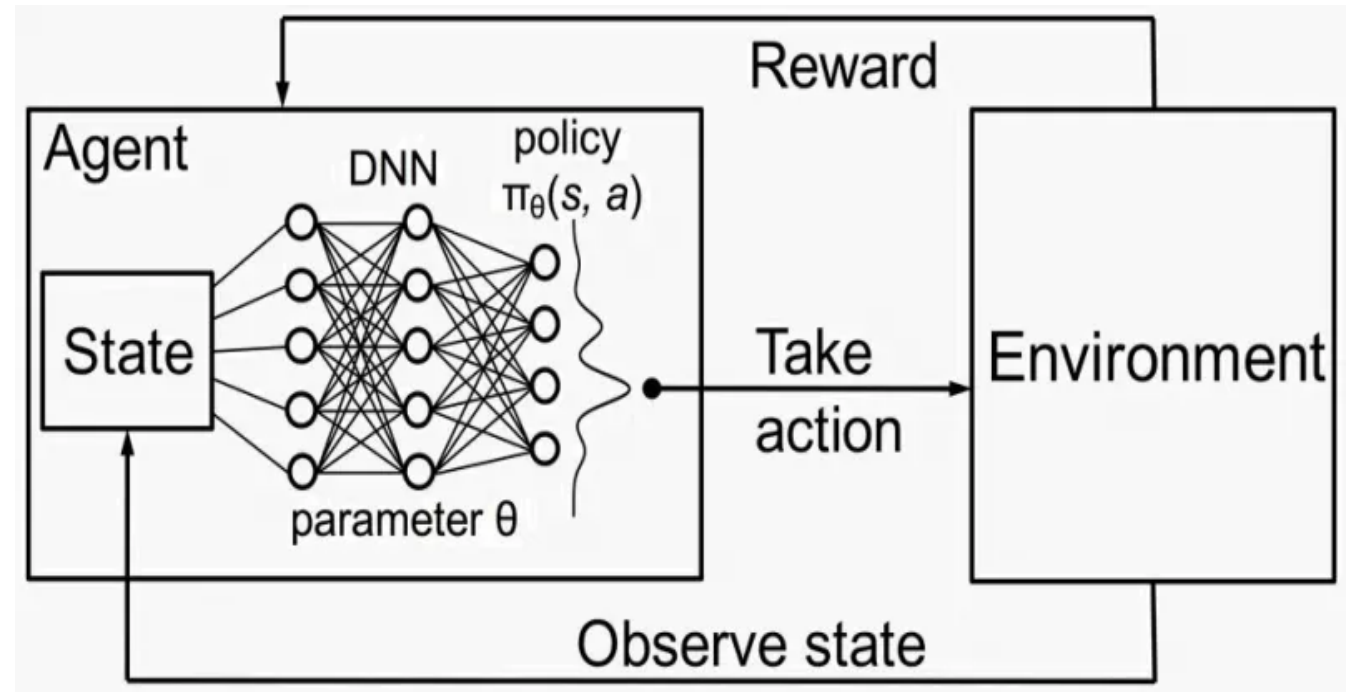
I am going to present deep learning project of automatic snake game playing based on my research paper. I will give you a comprehensive understanding of deep learning applications in game development. The main purpose is to explore and analyse the practical insights of game construction, modelling human like behaviour, results and provide recommendations. With this motivation I will discuss the following methodologies:

- 1. DEEP REINFORCEMENT LEARNING
- 2. Q-LEARNING AND DQ-LEARNING
- 3. DEEP Q-LEARNING PROCESS
- 4. IMPLEMENTING THE SNAKE GAME
- 5. IMPLEMENTING THE AGENT
- 6. IMPLEMENTING THE MODEL
- 7. TRAINING AND TESTING

Combines artificial neural networks with a framework of reinforcement learning that helps software agents learn how to reach their goals. That is, it unites function approximation and target optimization, mapping states and actions to the rewards they lead to.

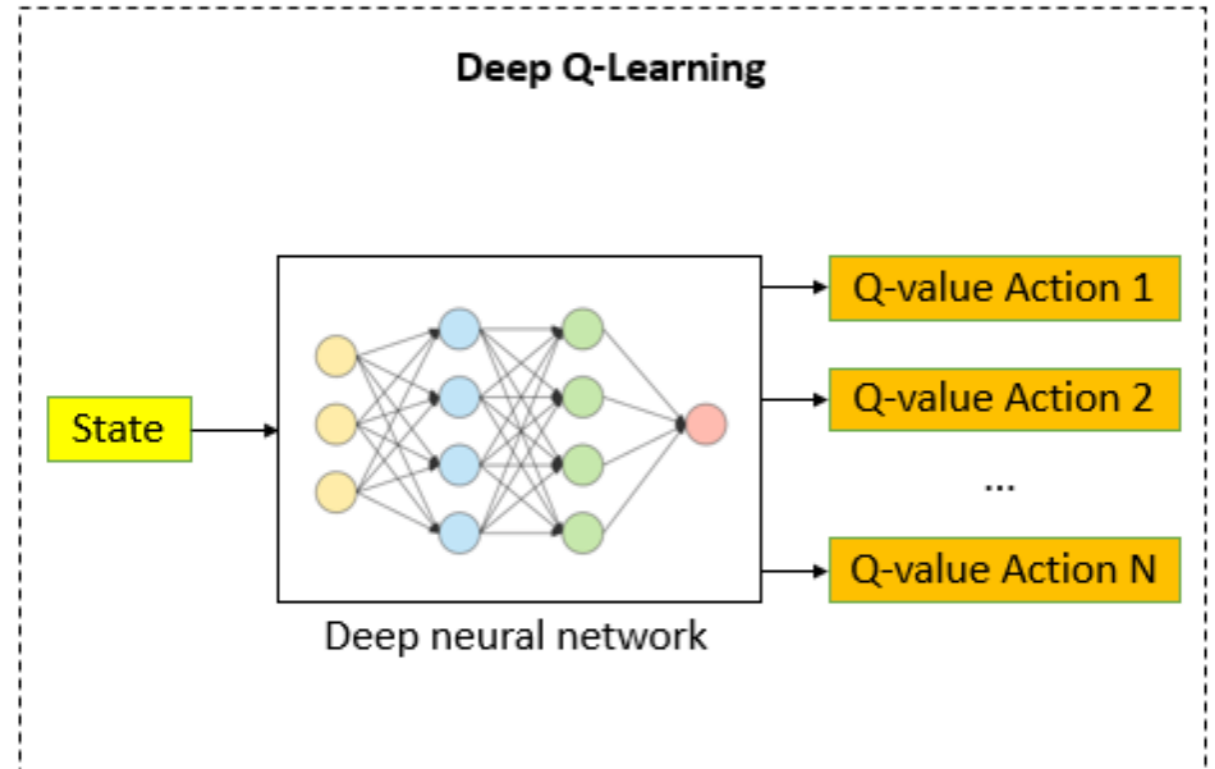
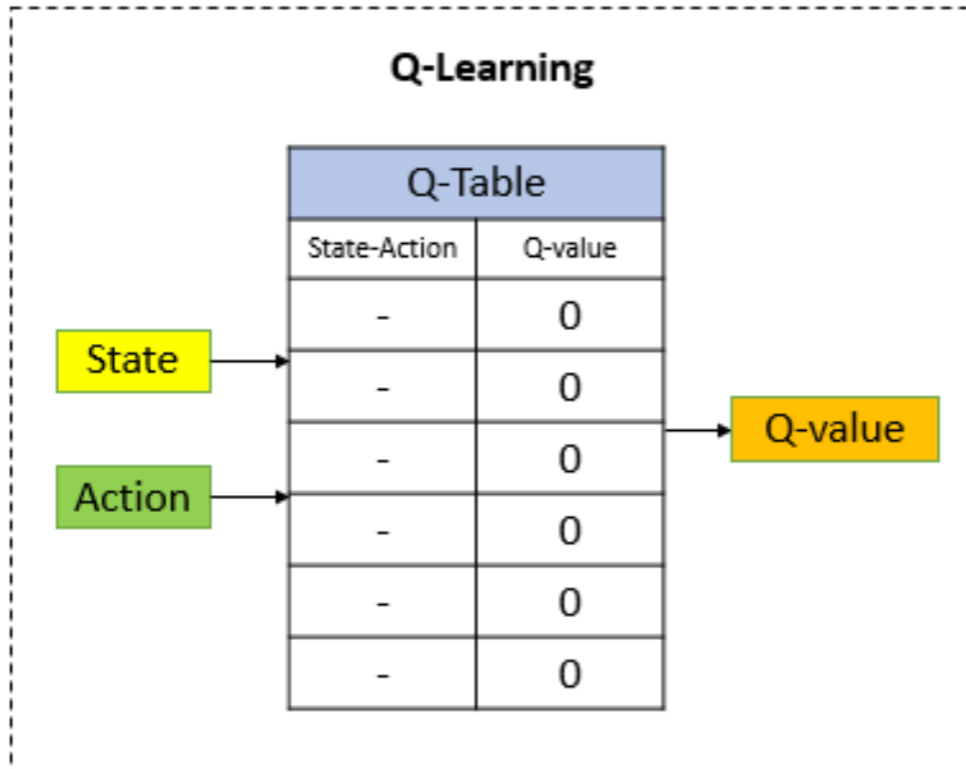


Brain Stimulation: Reward/ Penalty



DRL Process

Q-Learning is a value-based algorithm that is used to find the optimal policy for an agent in a given environment. It determines the best series of actions through the Bellman Equation. Deep Q-Learning is introduced when Q-Learning fails to calculate many states and actions.



## 1. Basic Components Construction:

- Display
- Player/Snake

```
self.head = Point(self.w/2, self.h/2)
self.snake = [self.head,
               Point(self.head.x-BLOCK_SIZE, self.head.y),
               Point(self.head.x-(2*BLOCK_SIZE), self.head.y)]
```

- Food

```
def _place_food(self):
    x = random.randint(0, (self.w-BLOCK_SIZE )//BLOCK_SIZE )*BLOCK_SIZE
    y = random.randint(0, (self.h-BLOCK_SIZE )//BLOCK_SIZE )*BLOCK_SIZE
    self.food = Point(x, y)
    if self.food in self.snake:
        self._place_food()
```



## 2. Play Steps

- Direction
  - Straight – `[1, 0, 0]`
  - Right turn – `[0, 1, 0]`
  - Left turn – `[0, 0, 1]`
- Movement
  - `if direction == Direction.RIGHT: x += BLOCK_SIZE`
  - `elif direction == Direction.DOWN: y += BLOCK_SIZE`
- Reward and Score: `Reward = +10` and `penalty = -10`
- Game Over: Collisions

## 1. Initials

- Max memory, Batch size, Learning rates, Epsilon, Discount rate

## 2. Direction setup

- Point right = Point (head.x + 20, head.y)
  - Point Left = Point (head.x - 20, head.y)
- Similarly, for Up (y + 20) and Down (y - 20)

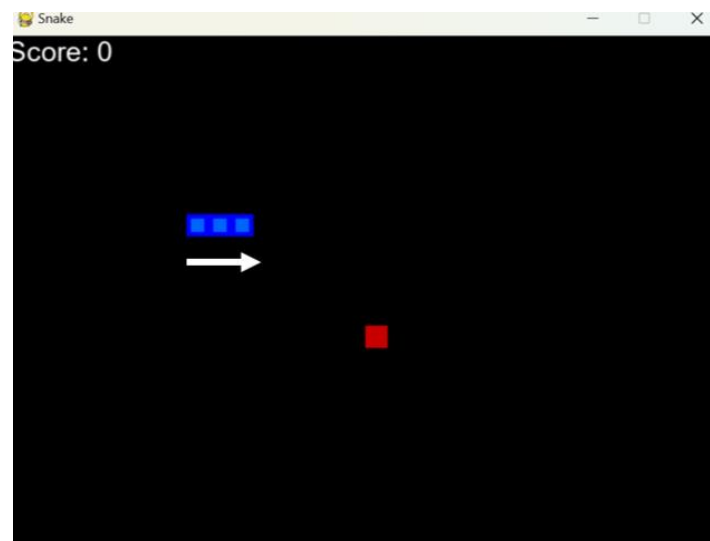
## 3. Get States: 11 States

- Move direction states = [ left, right, up, down ]
- Danger zones = [ danger straight, danger right, danger left ]
- Food direction = [ left, right, up down ]

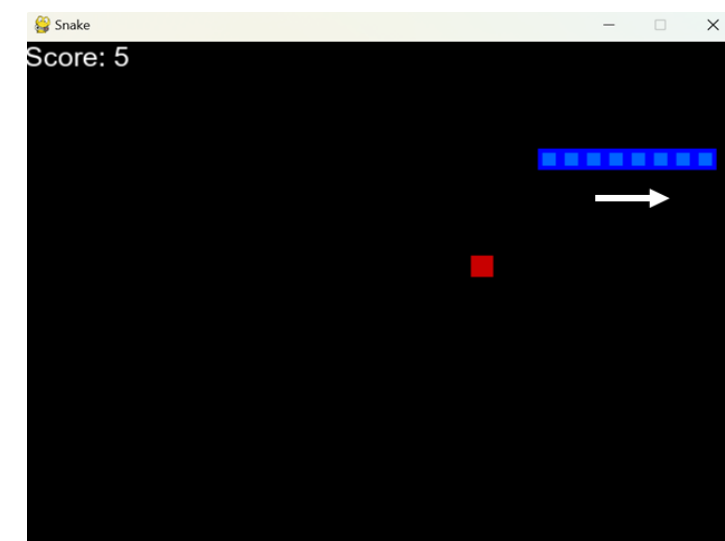
## 4. Scenarios

Danger zones	dan_straight, dan_right, dan_left	[0, 0, 0]
Direction states	left, right, up, down	[ 0, 0, 0, 0]
Food direction	left, right, up, down	[ 0, 0, 0, 0]

[0, 0, 0]  
[ 0, 1, 0, 0]  
[ 0, 1, 0, 0]



[1, 0, 0]  
[ 0, 1, 0, 1]  
[ 0, 1, 0, 1]





Saving functions: Remember, Train short & long memory

Get action: Random exploration & Exploitation:

```
def get_action(self, state):
    # random moves: tradeoff exploration / exploitation
    self.epsilon = 110 - self.n_games
    final_move = [0,0,0]
    if random.randint(0, 200) < self.epsilon:
        move = random.randint(0, 2)
        final_move[move] = 1
    else:
        state0 = torch.tensor(state, dtype=torch.float)
        prediction = self.model(state0)
        move = torch.argmax(prediction).item()
        final_move[move] = 1

    return final_move
```

## 1. Linear Qnet:

```
class Linear_QNet(nn.Module):  
    def __init__(self, input_size, hidden_size, output_size):  
        super().__init__()  
        self.linear1 = nn.Linear(input_size, hidden_size)  
        self.linear2 = nn.Linear(hidden_size, output_size)  
        self.model = Linear_QNet(11, 256, 3)
```

## 2. QTrainer:

$$Loss = (Q_{new} - Q)^2$$

## 3. Q Value and Bellman Equation:

$$NewQ(s, a) = Q(s, a) + \alpha [R(s, a) + \gamma \max Q'(s', a') - Q(s, a)]$$

New Q value for that state and that action

Current Q value

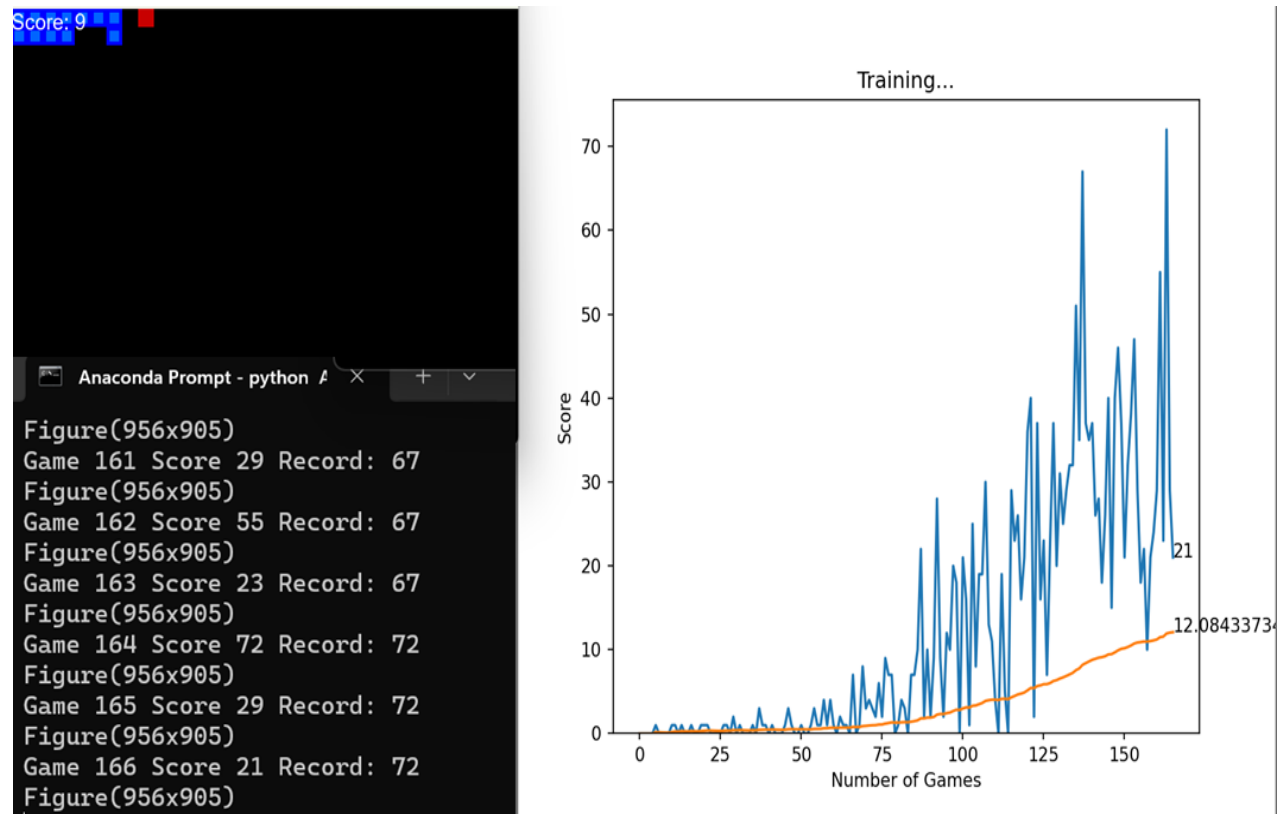
Reward for taking that action at that state

Maximum expected future reward given the new  $s'$  and all possible actions at that new state

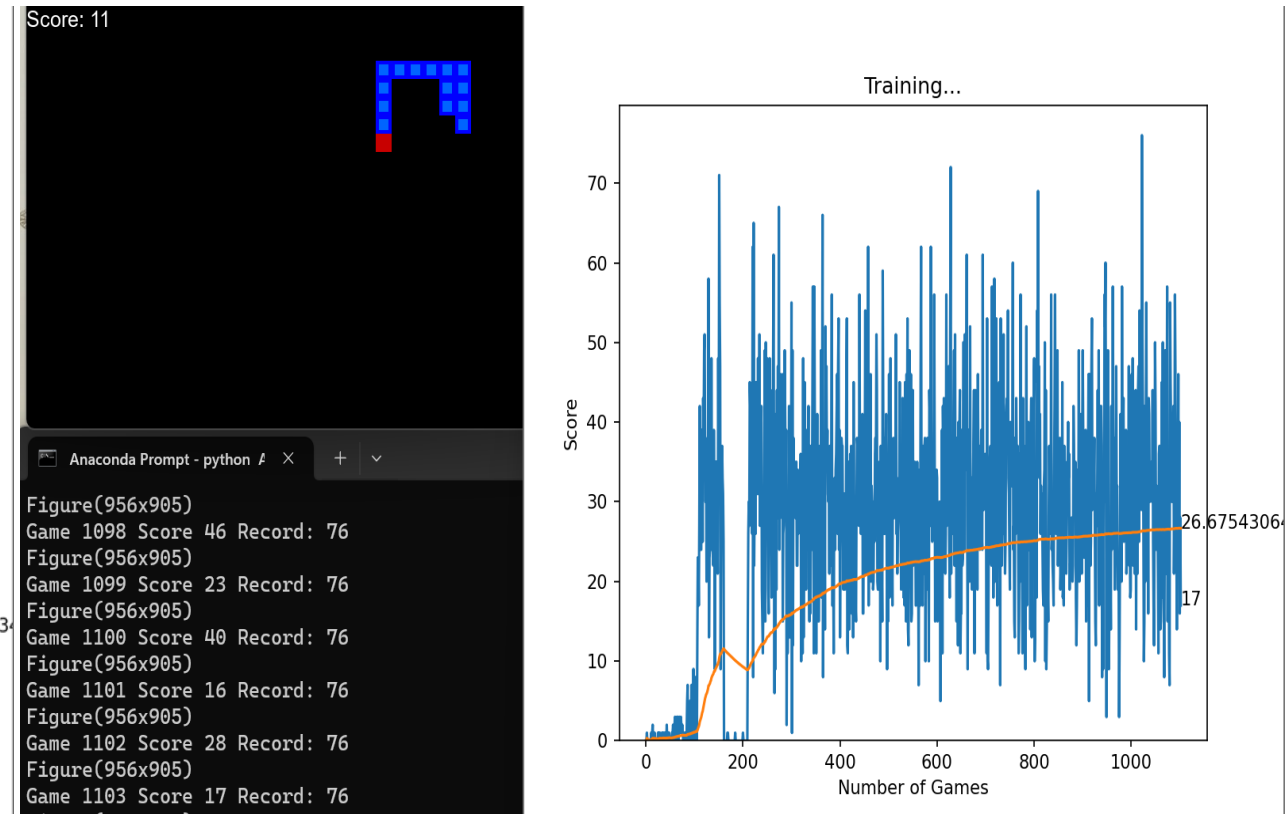
Learning Rate

Discount rate

- 1 Initialize Q-values
- 2 Choose action  $a$  for state  $s$  (Best Q-value)
- 3 Perform action  $a$ , new state  $s'$
- 4 Measure reward  $R$
- 5 Update  $Q$  with Bellman Equation
- 6 Update weights of the Neural Network



Test 1



Test 2

1. <https://medium.com/@vishnuvijayanpv/deep-reinforcement-learning-value-functions-dqn-actor-critic-method-backpropagation-through-83a277d8c38d>
2. Baeldung on Computer Science, “Q-learning vs. deep q-learning vs. deep q-network – baeldung on computer science,” 2023. [Online]. Available: <https://www.baeldung.com/cs/q-learning-vs-deep-q-learningvs-deep-q-network>
3. freeCodeCamp.org, “Diving deeper into reinforcement learning with q-learning,” freeCodeCamp.org, 10/04/2018. [Online]. Available: <https://www.freecodecamp.org/news/diving-deeperinto-reinforcement-learning-with-q-learning-c18d0db58efe/>
4. Patrick Loeber, “Python + pytorch + pygame reinforcement learning – train an ai to play snake,” 2022. [Online]. Available: <https://www.youtube.com/watch?v=L8ypSXwyBds>