Deep Reinforcement Learning

Alexander Amini

MIT Introduction to Deep Learning

January 11, 2023

Learning in Dynamic Environments

Reinforcement Learning: Robots, Games, the World

Robotics

Game Play and Strategy


Oriol Vinyals
Co-Lead, AlphaStar Project, DeepMind

Classes of Learning Problems

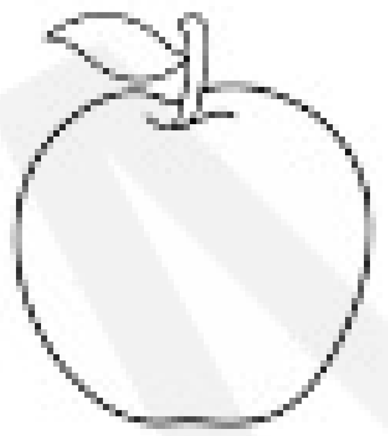
Supervised Learning

Data: (x, y)
x is data, y is label

Goal: Learn function to map

$$x \rightarrow y$$

Apple example:



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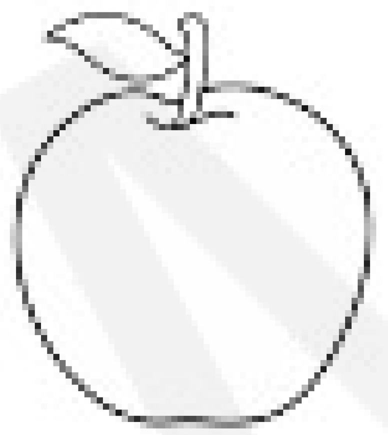

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Unsupervised Learning

Data: x
x is data, no labels!

Goal: Learn underlying structure

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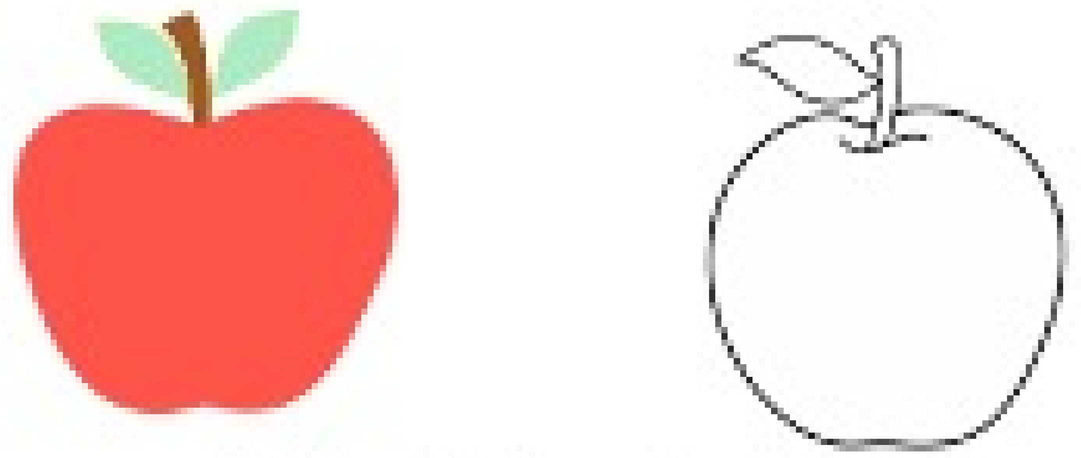

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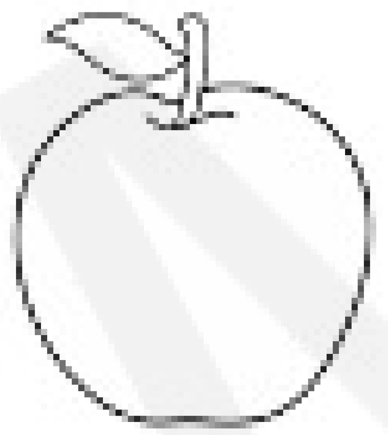

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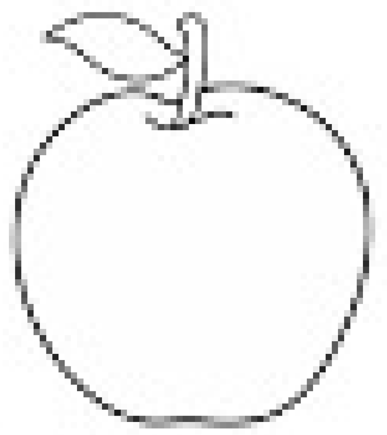

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Reinforcement Learning

Data: state-action pairs

Goal: Maximize future rewards over many time steps

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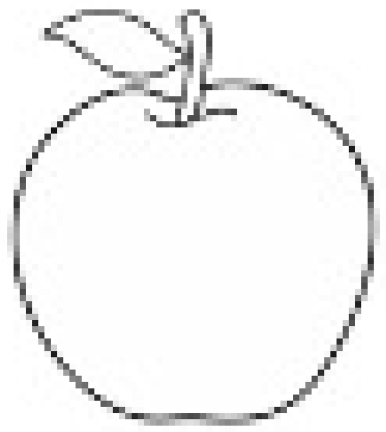

Eat this thing because it will keep you alive.

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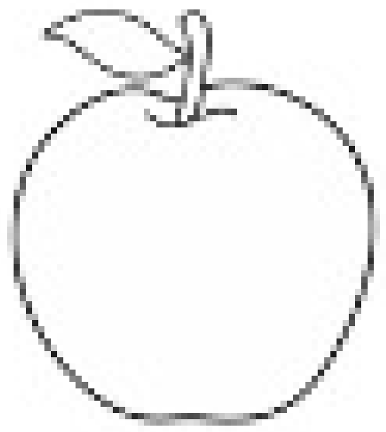

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RL: our focus today.

Reinforcement Learning (RL): Key Concepts

AGENT

Agent: takes actions.

Reinforcement Learning (RL): Key Concepts

AGENT

ENVIRONMENT

Environment: the world in which the agent exists and operates.

Reinforcement Learning (RL): Key Concepts

Action: a move the agent can make in the environment.

Action space A: the set of possible actions an agent can make in the environment

Reinforcement Learning (RL): Key Concepts

Observations: of the environment after taking actions.

Reinforcement Learning (RL): Key Concepts

State: a situation which the agent perceives.

Reinforcement Learning (RL): Key Concepts

Reward: feedback that measures the success or failure of the agent's action.

Reinforcement Learning (RL): Key Concepts

Total Reward (Return)

$$R_t = \sum_{i=t}^{\infty} r_i$$

Reinforcement Learning (RL): Key Concepts

Total Reward (Return)

$$R_t = \sum_{i=t}^{\infty} r_i = r_t + r_{t+1} \ldots + r_{t+n} + \cdots$$

Reinforcement Learning (RL): Key Concepts

Discounted Total Reward (Return)

$$R_t = \sum_{i=t}^{\infty} \gamma^i r_i$$

Reinforcement Learning (RL): Key Concepts

Discounted Total Reward (Return)

$$R_t = \sum_{i=t}^{\infty} \gamma^i r_i = \gamma^t r_t + \gamma^{t+1} r_{t+1} \ldots + \gamma^{t+n} r_{t+n} + \cdots$$

γ: discount factor; $0 < \gamma < 1$

Defining the Q-function

$$R_t = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \cdots$$

Total reward, R_t, is the discounted sum of all rewards obtained from time t

$$Q(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t]$$

The Q-function captures the **expected total future reward** an agent in state, s, can receive by executing a certain action, a

How to take actions given a Q-function?

$$Q(s_t, a_t) = \mathbb{E}[R_t | s_t, a_t]$$

(state, action)

Ultimately, the agent needs a **policy $\pi(s)$**, to infer the **best action to take** at its state, s

Strategy: the policy should choose an action that maximizes future reward

$$\pi^*(s) = \underset{a}{\operatorname{argmax}}\, Q(s, a)$$

Deep Reinforcement Learning Algorithms

Value Learning

Find $Q(s, a)$

$$a = \underset{a}{\operatorname{argmax}}\, Q(s, a)$$

Policy Learning

Find $\pi(s)$

Sample $a \sim \pi(s)$

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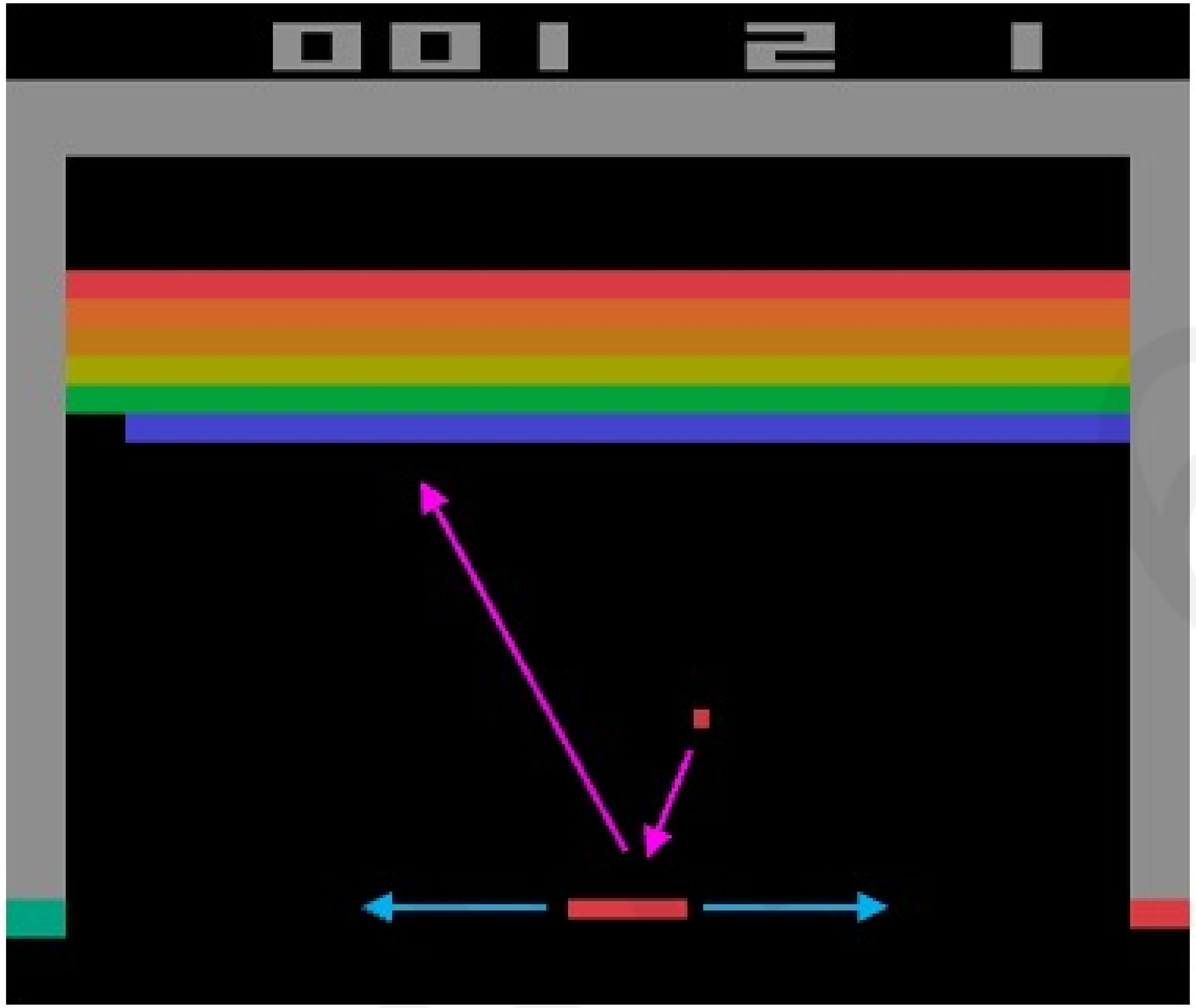
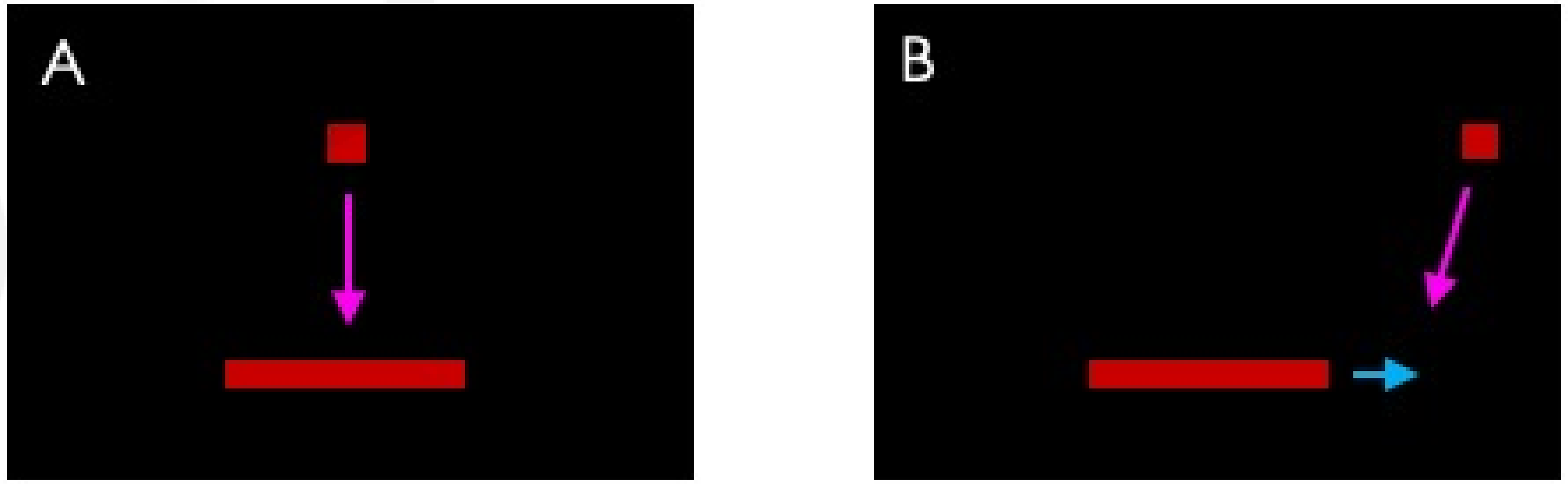
Digging deeper into the Q-function

Example: Atari Breakout



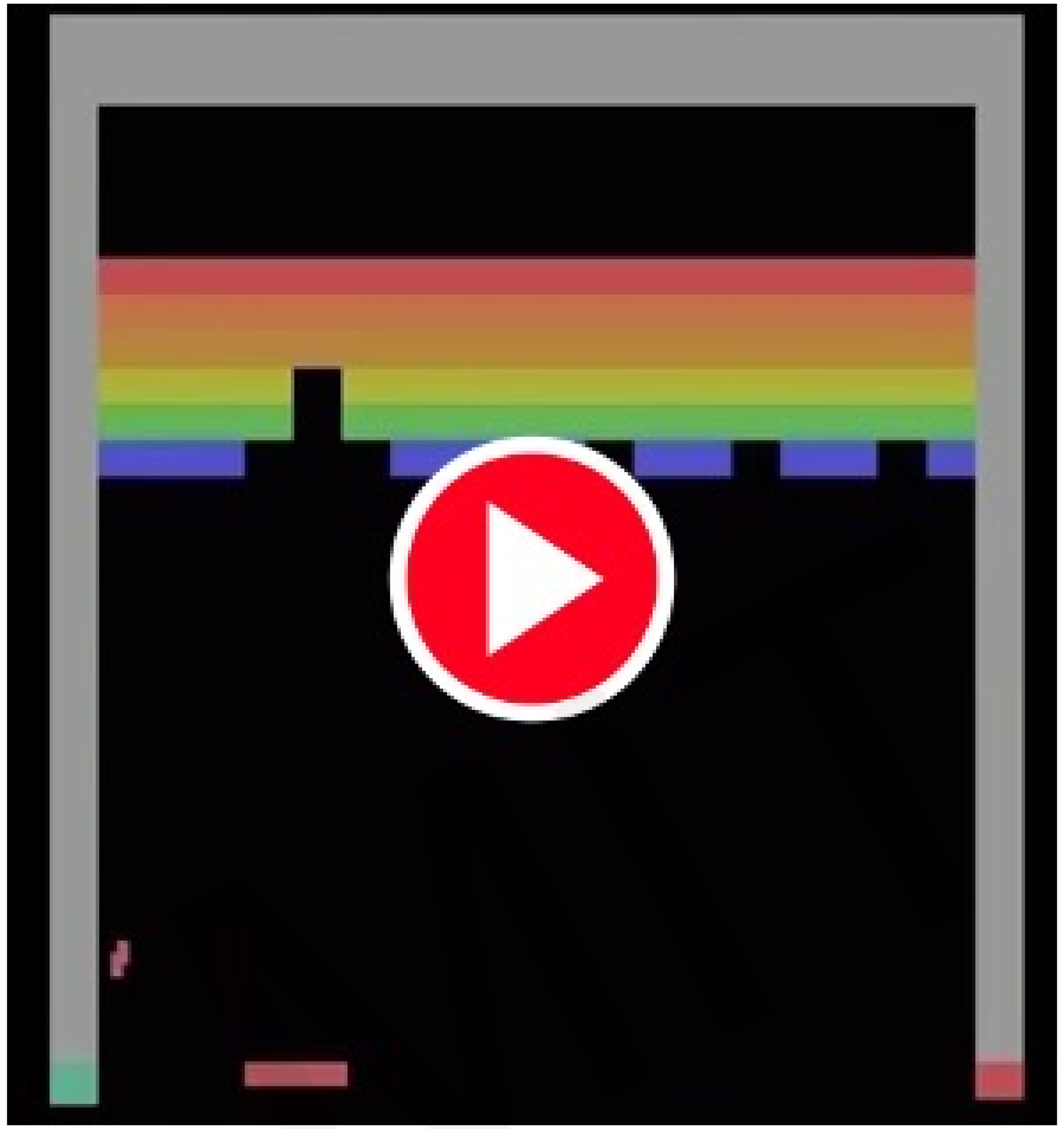
It can be very difficult for humans to accurately estimate Q-values



Which (s, a) pair has a higher Q-value?

Digging deeper into the Q-function

Example: Atari Breakout - Middle



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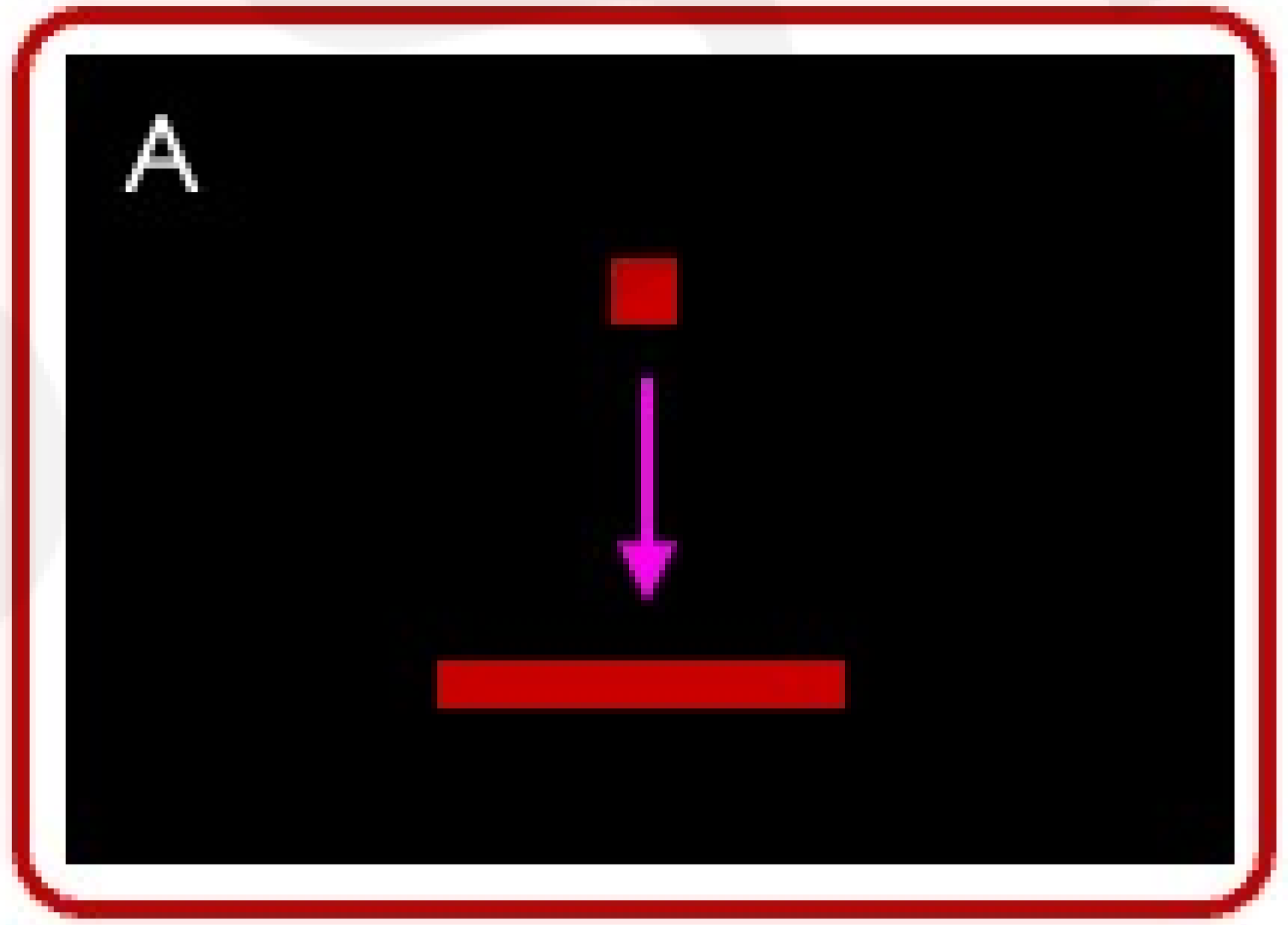

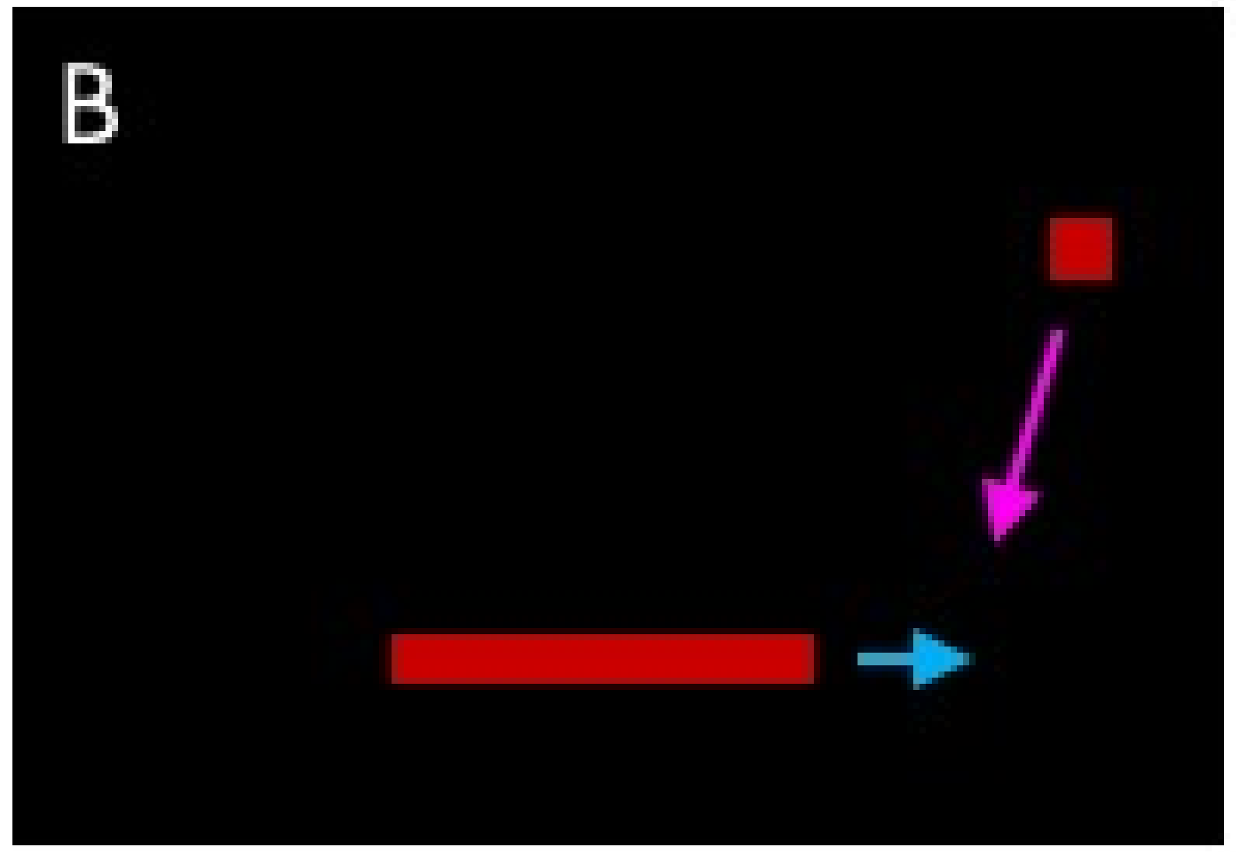

Which $(\mathbf{s}, \mathbf{a})$ pair has a higher Q-value?

Digging deeper into the Q-function

Example: Atari Breakout - Side

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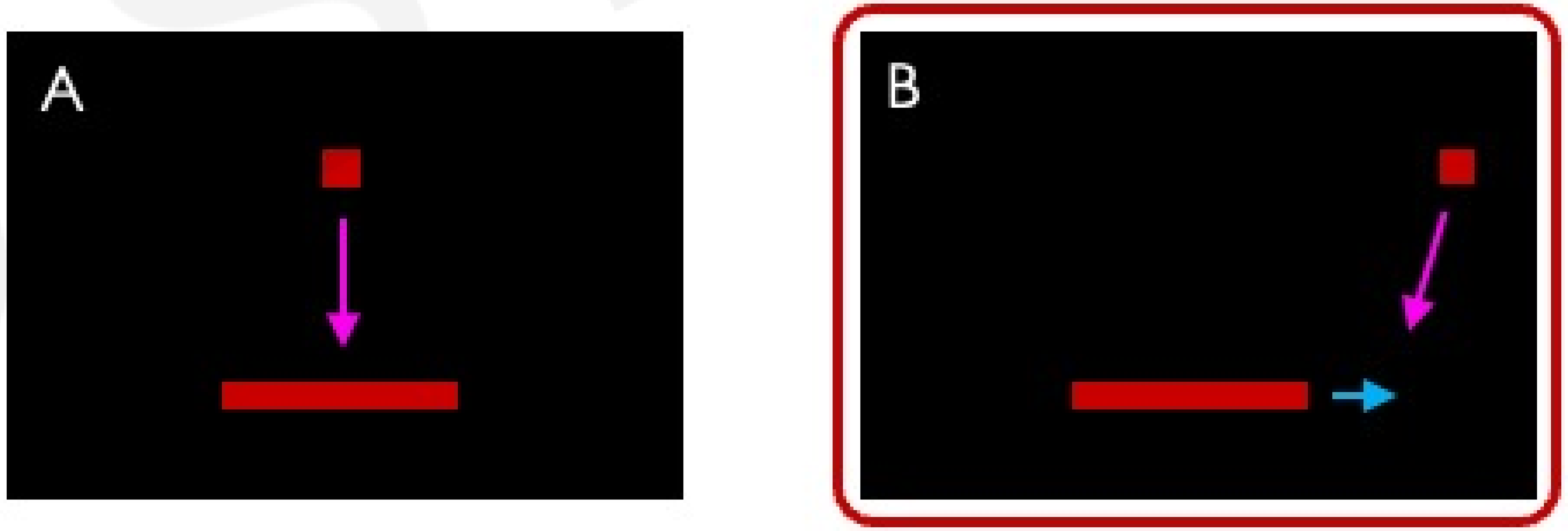
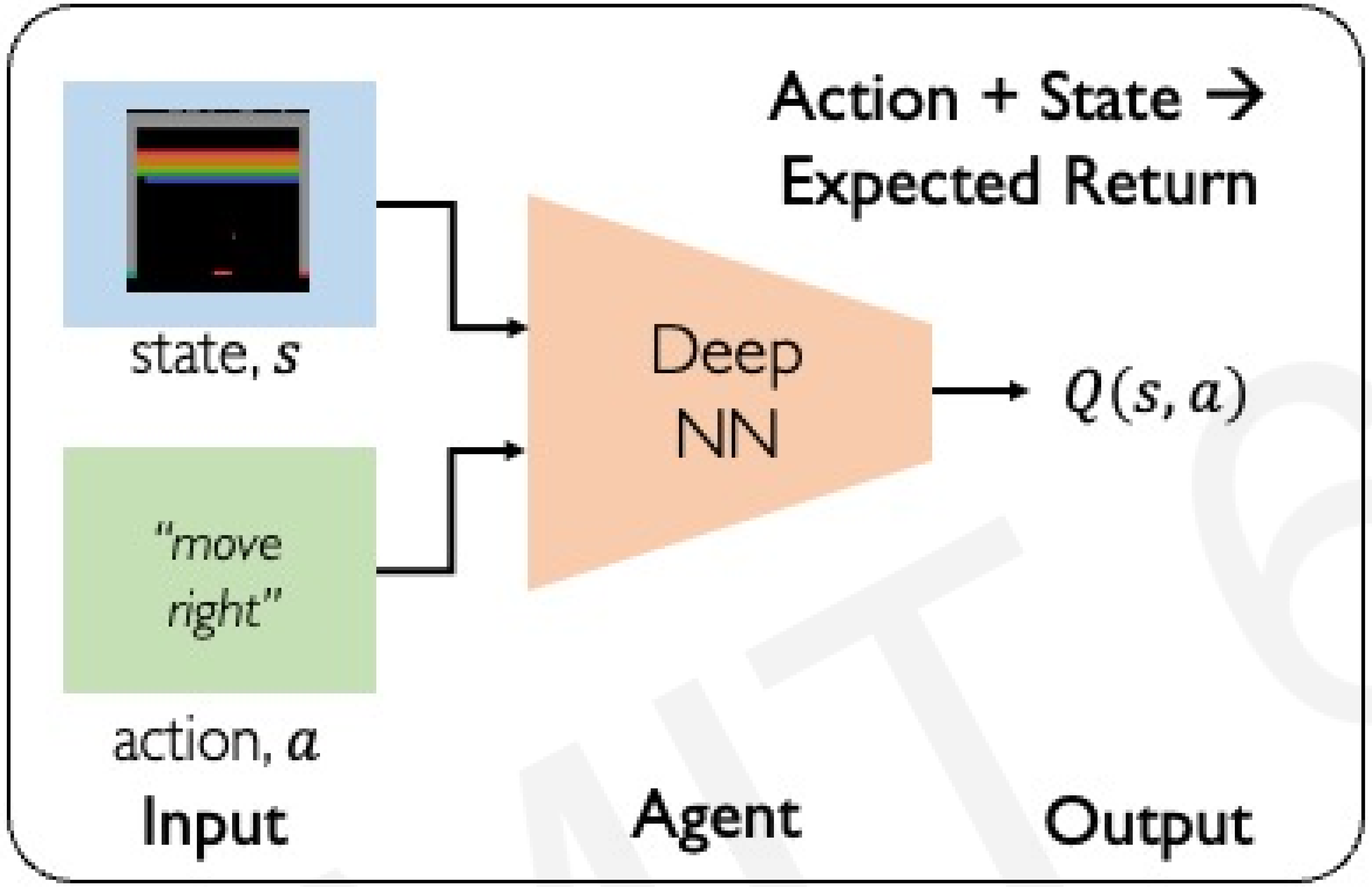


Which $(\mathbf{s}, \mathbf{a})$ pair has a higher Q-value?

Deep Q Networks (DQN)

How can we use deep neural networks to model Q-functions?



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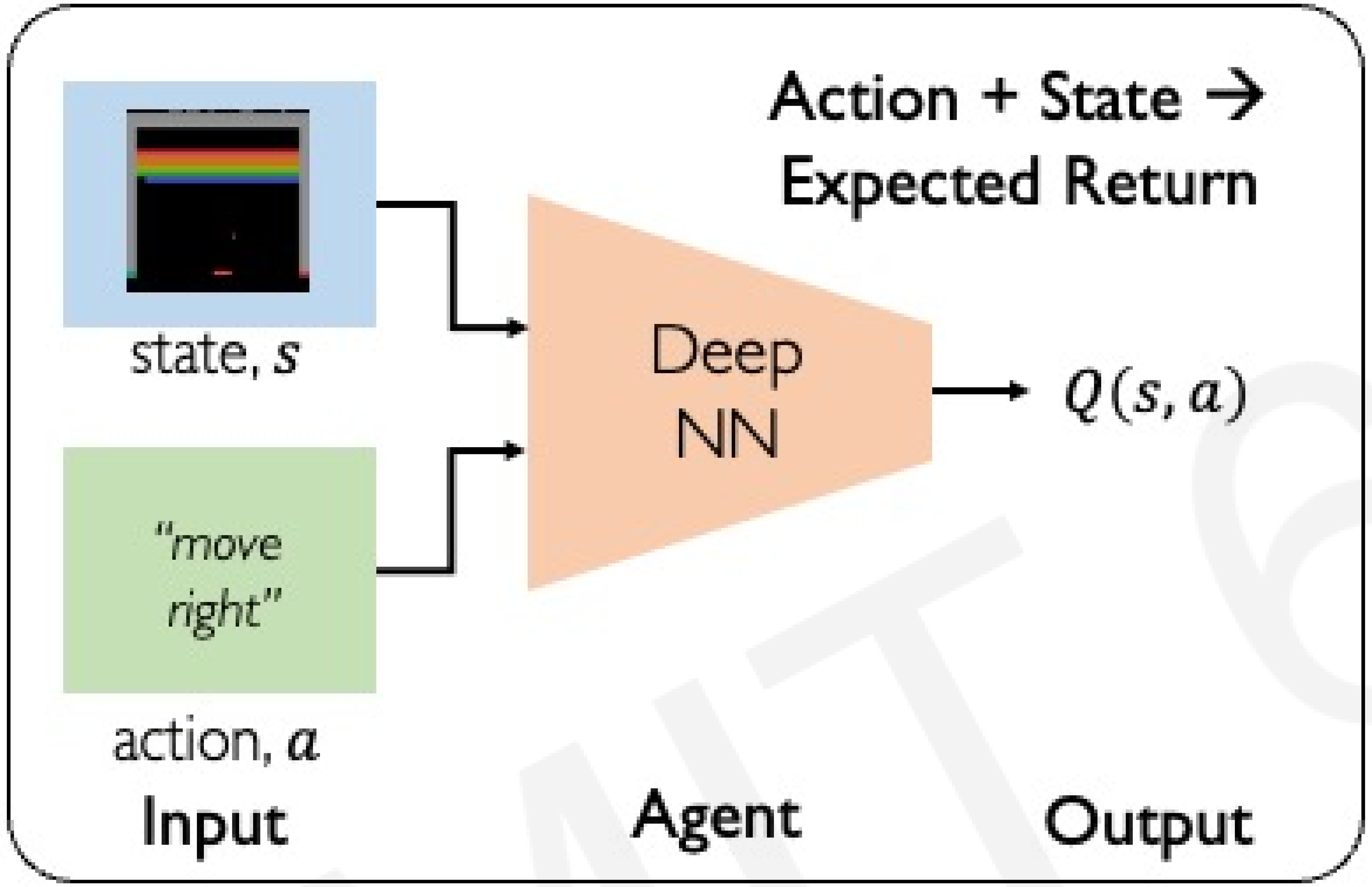

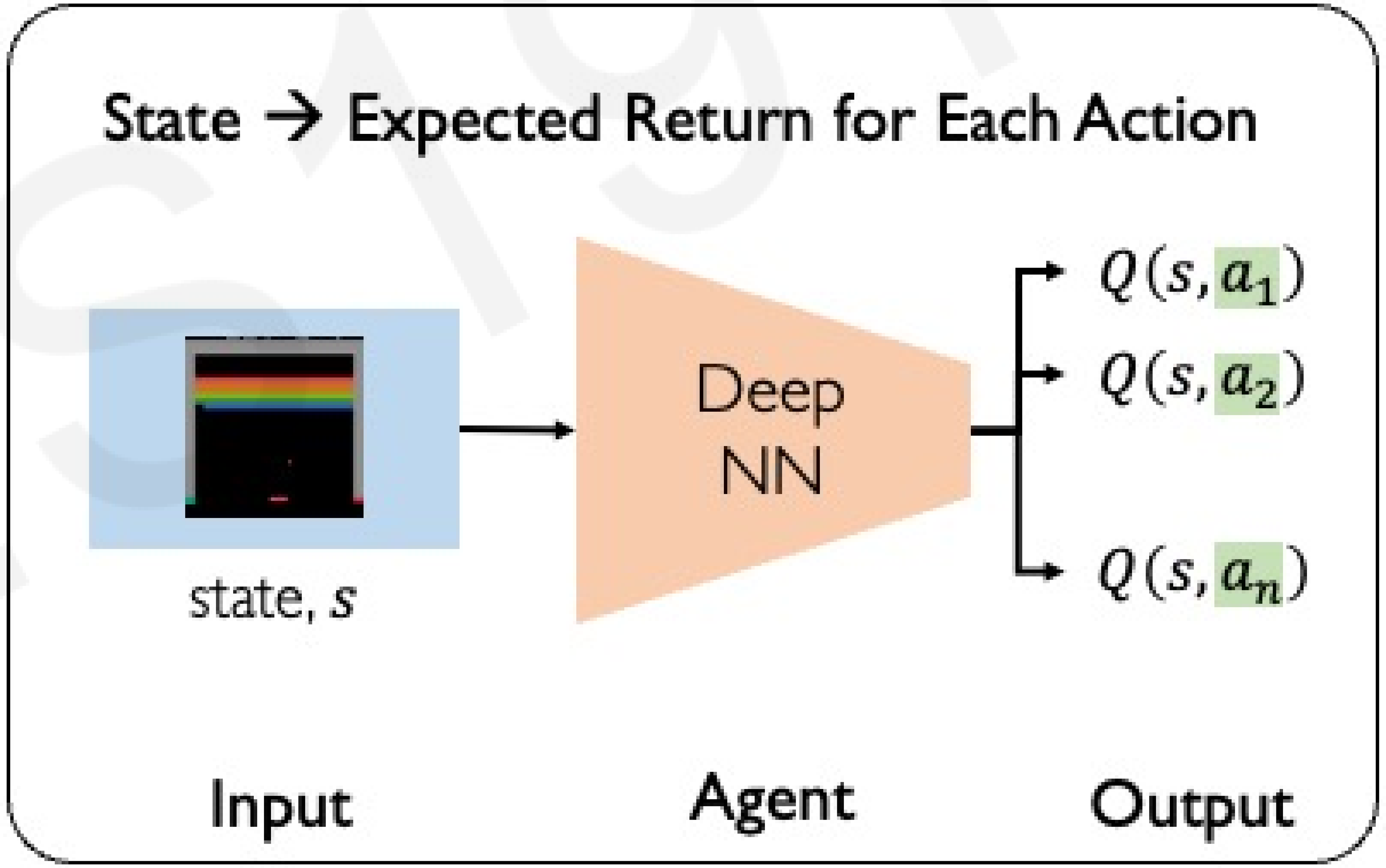

Deep Q Networks (DQN): Training

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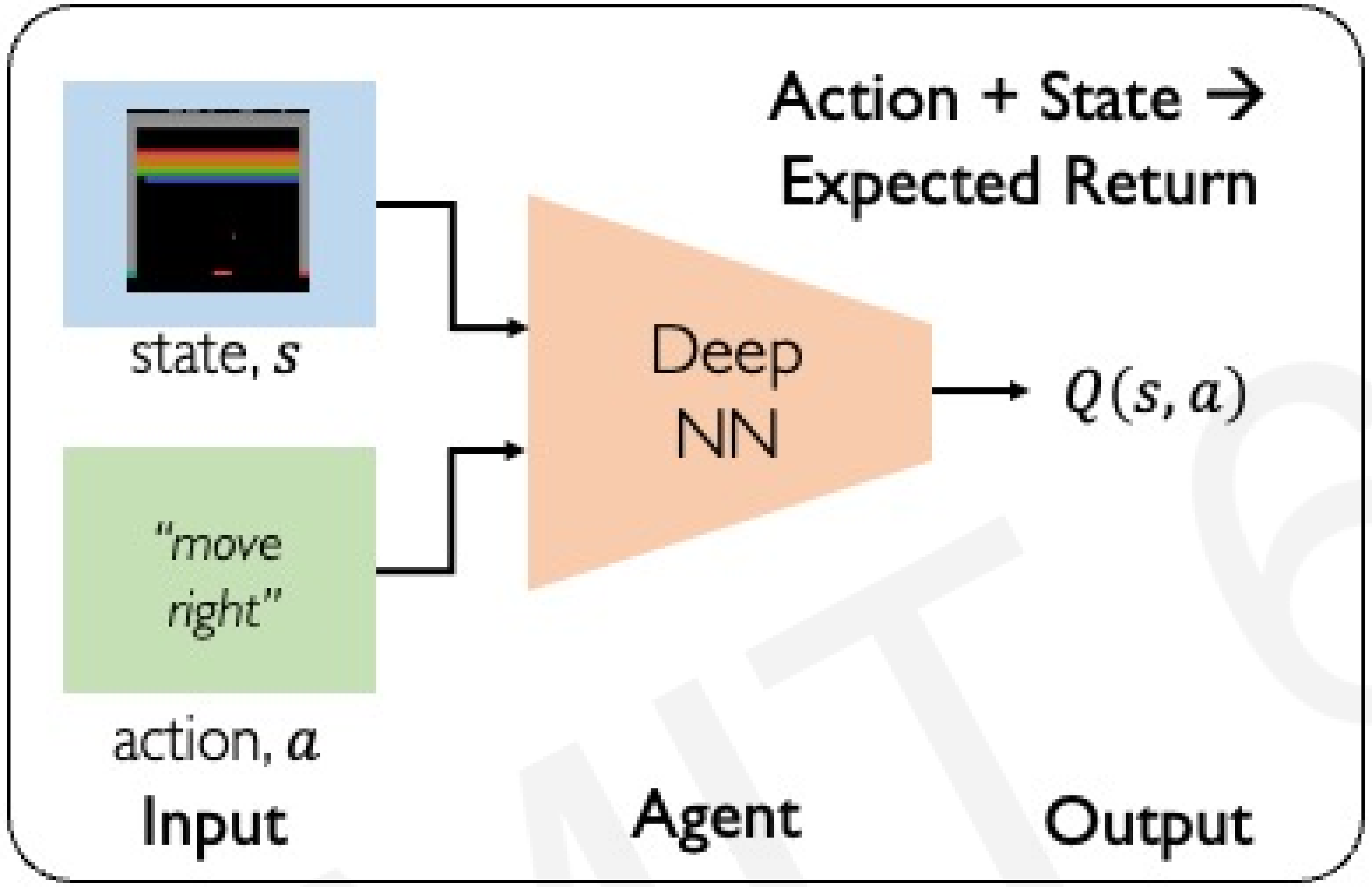

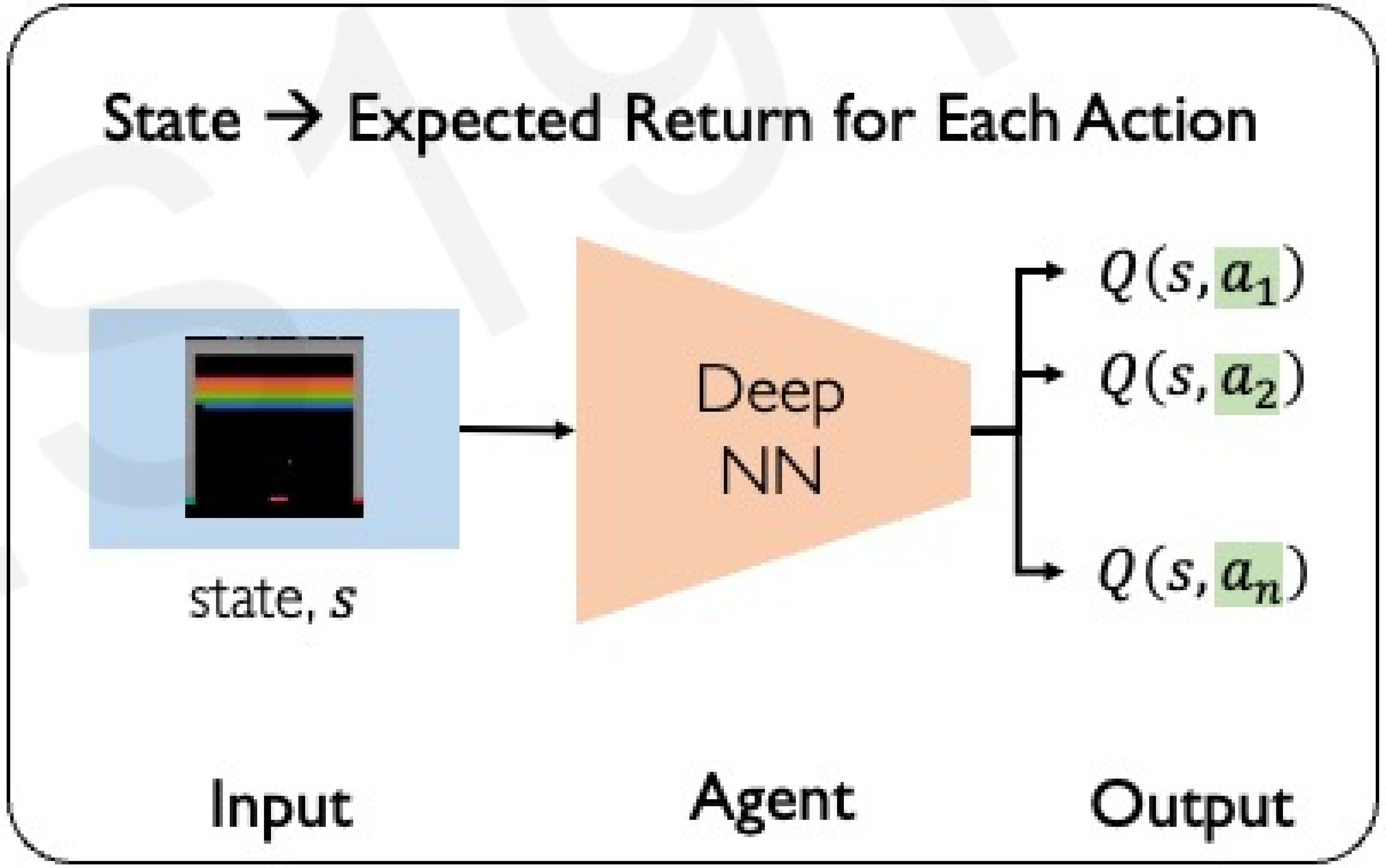

What happens if we take all the best actions?
Maximize target return → train the agent

Deep Q Networks (DQN): Training

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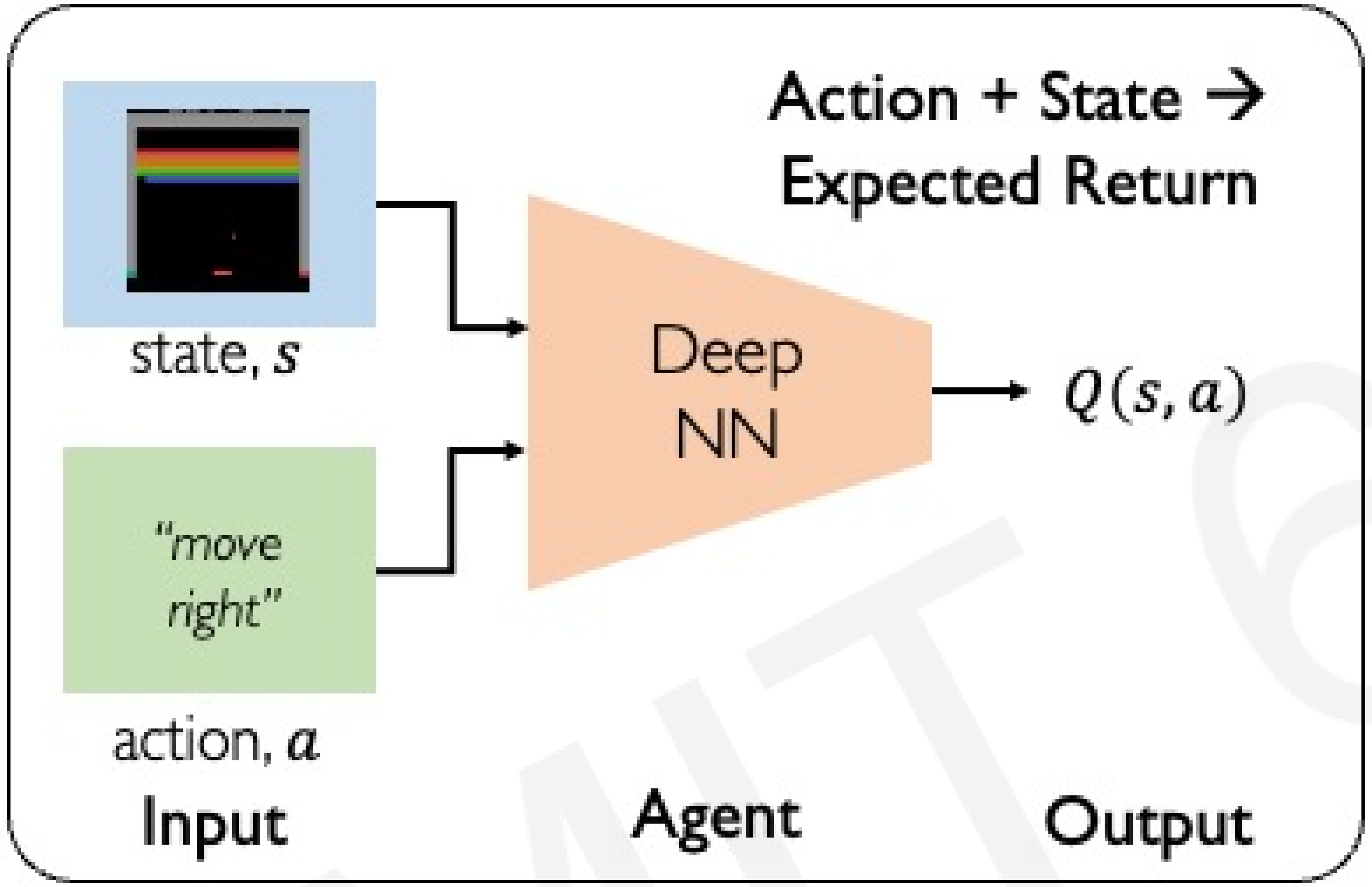

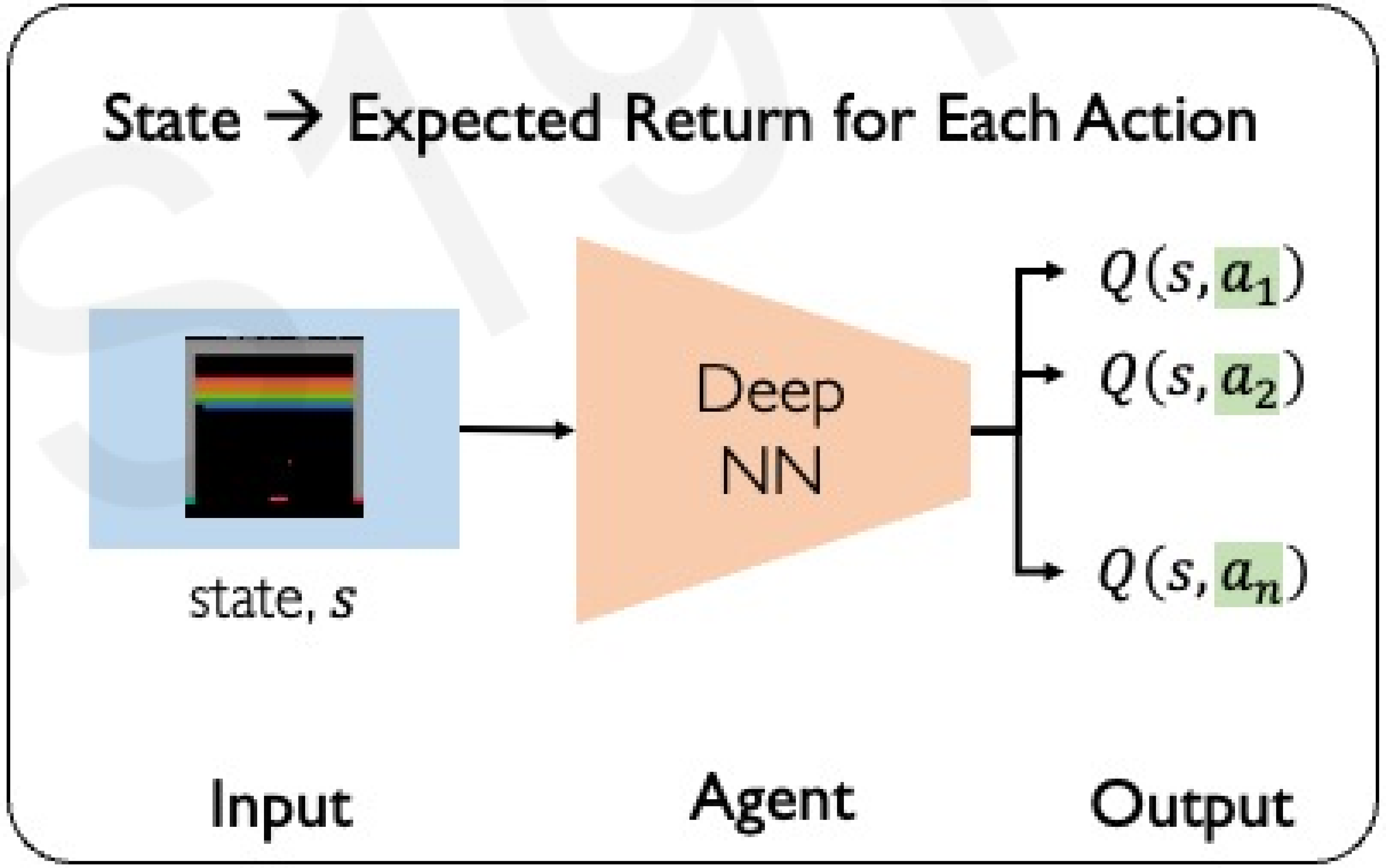

$$\overbrace{\left(r + \gamma \max_{a'} Q(s', a')\right)}^{\text{target}}$$

Take all the best actions → target return

Deep Q Networks (DQN): Training

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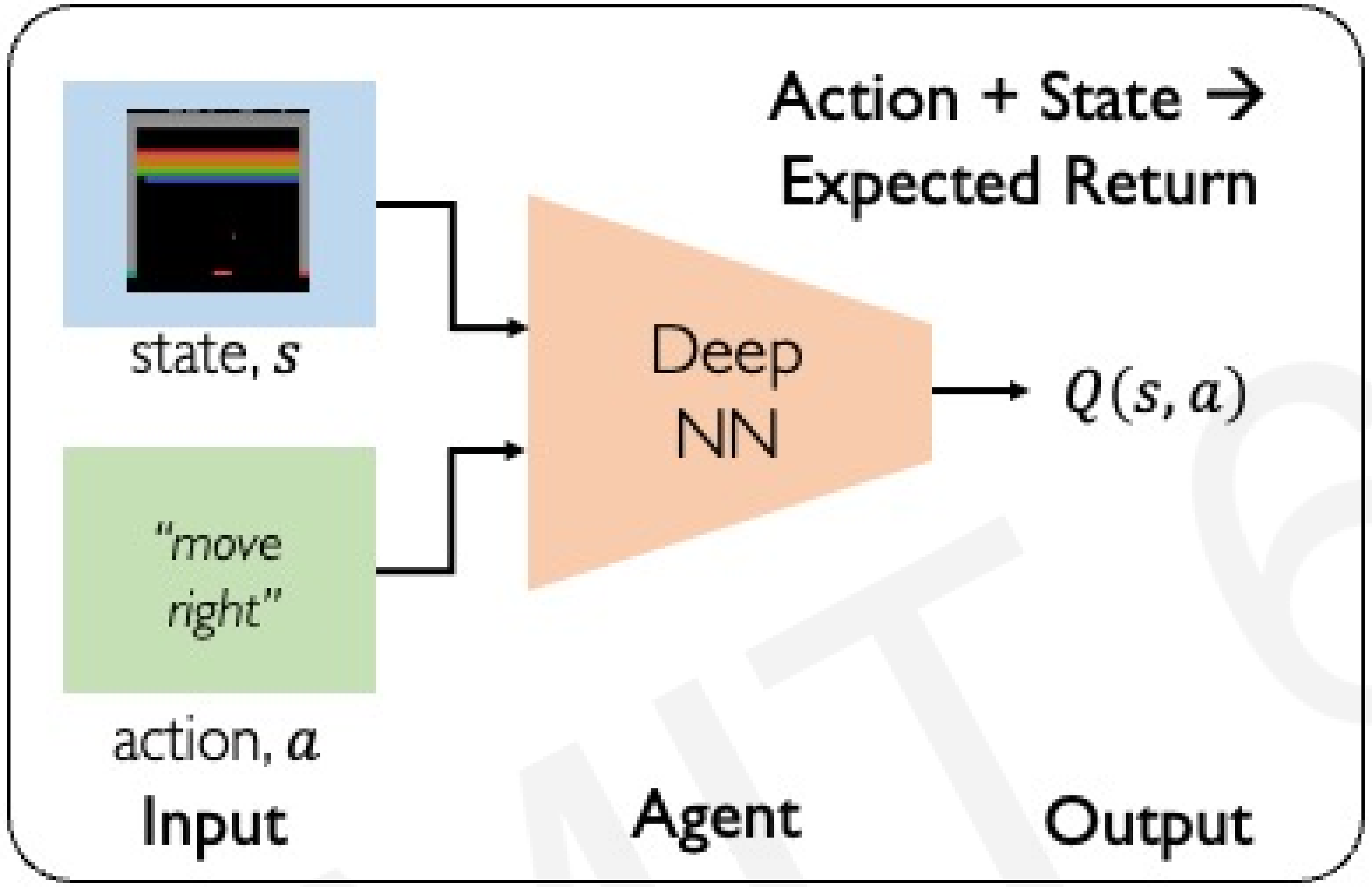

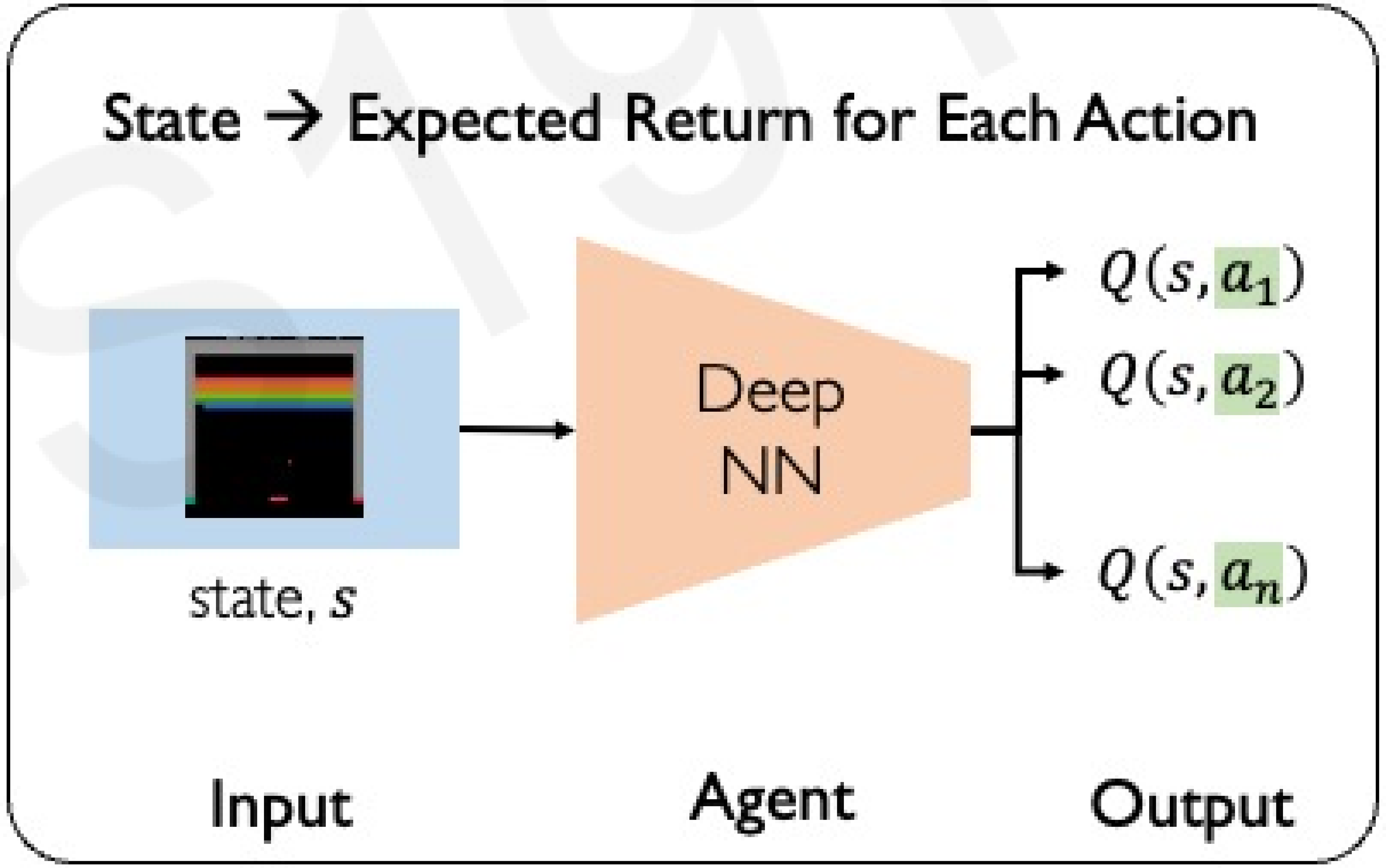

$$\underbrace{\left(r + \gamma \max_{a'} Q(s', a')\right)}_{\text{target}} \quad \underbrace{Q(s,a)}_{\text{predicted}}$$

Network prediction

Deep Q Networks (DQN): Training

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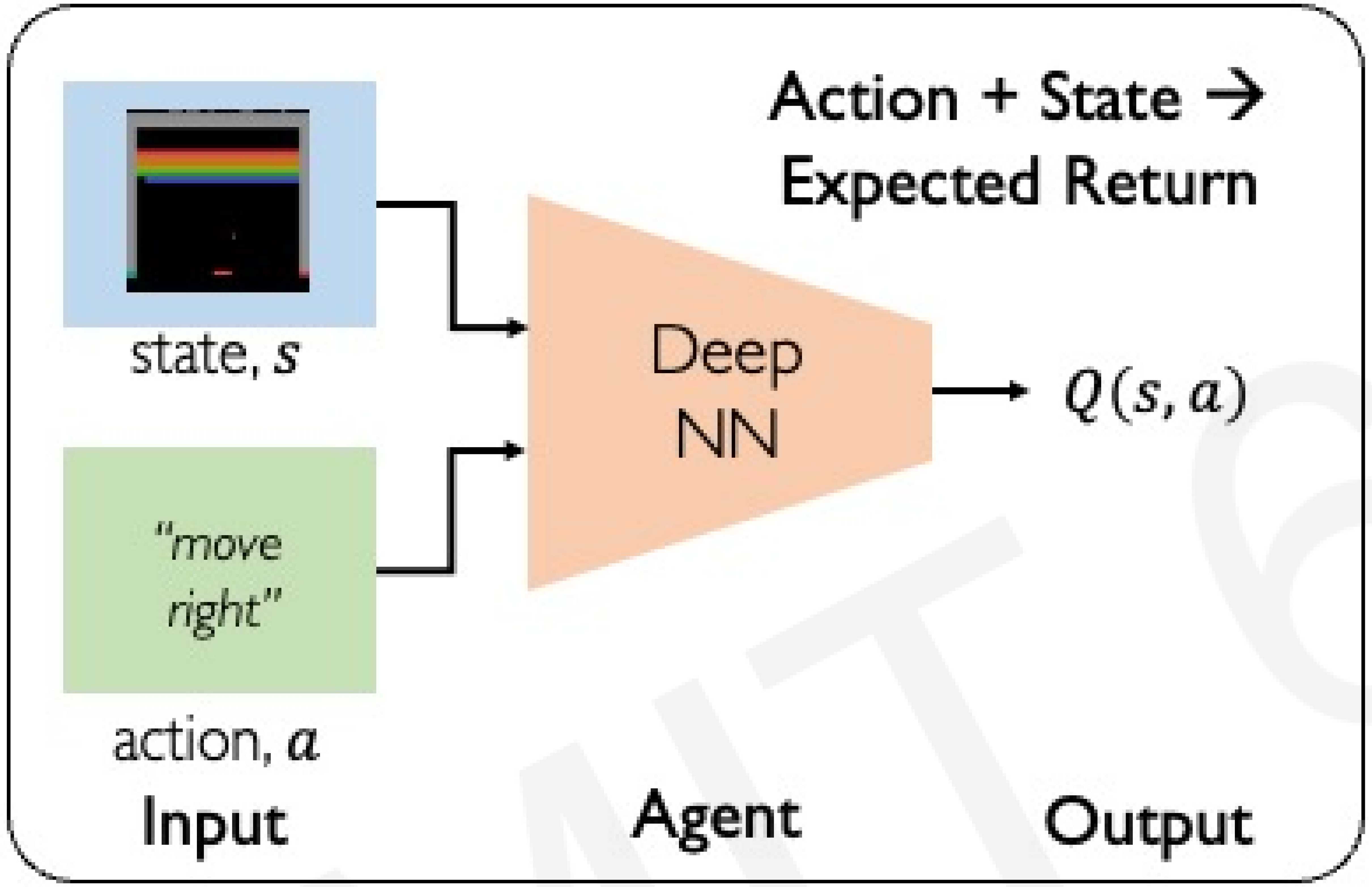
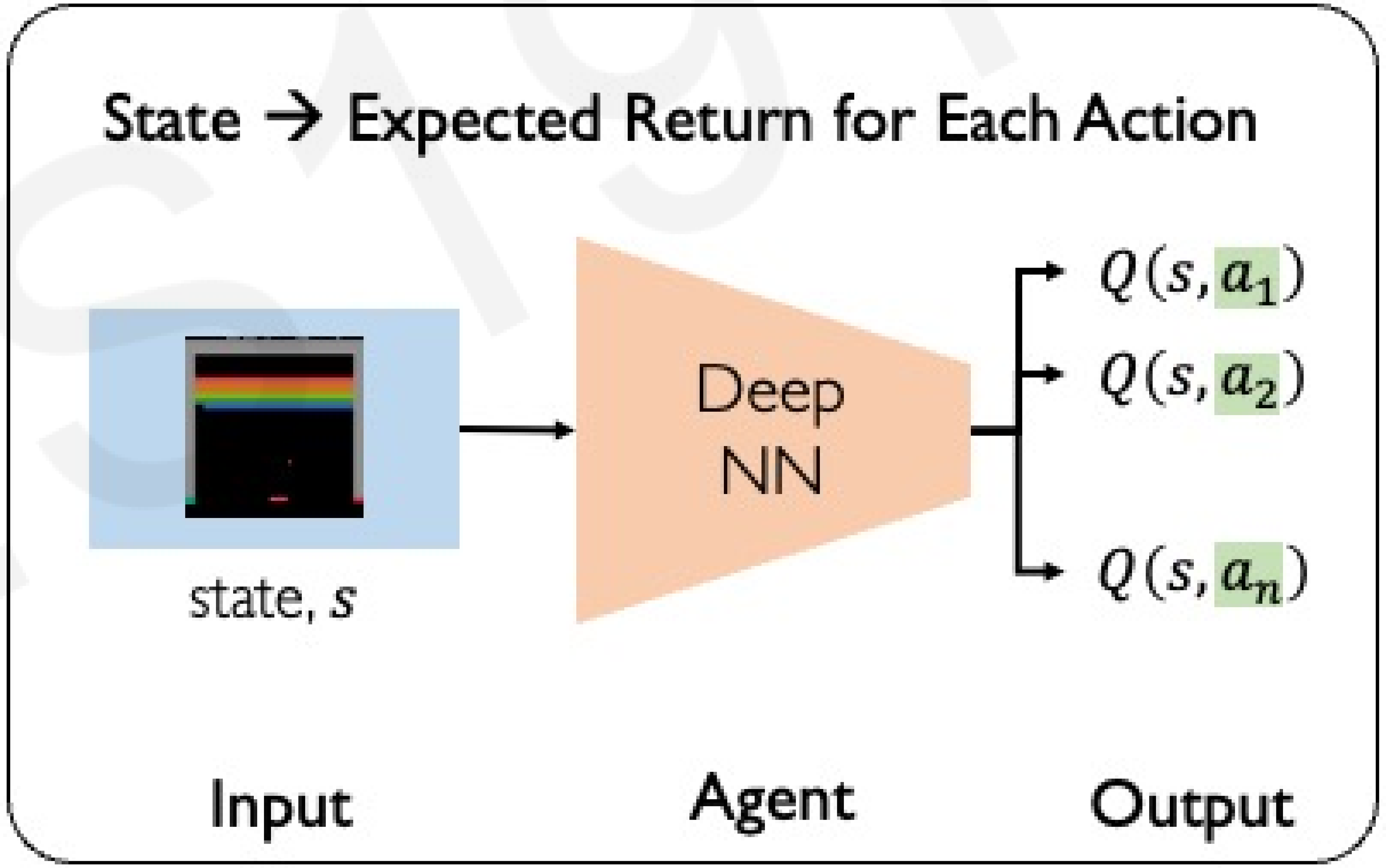


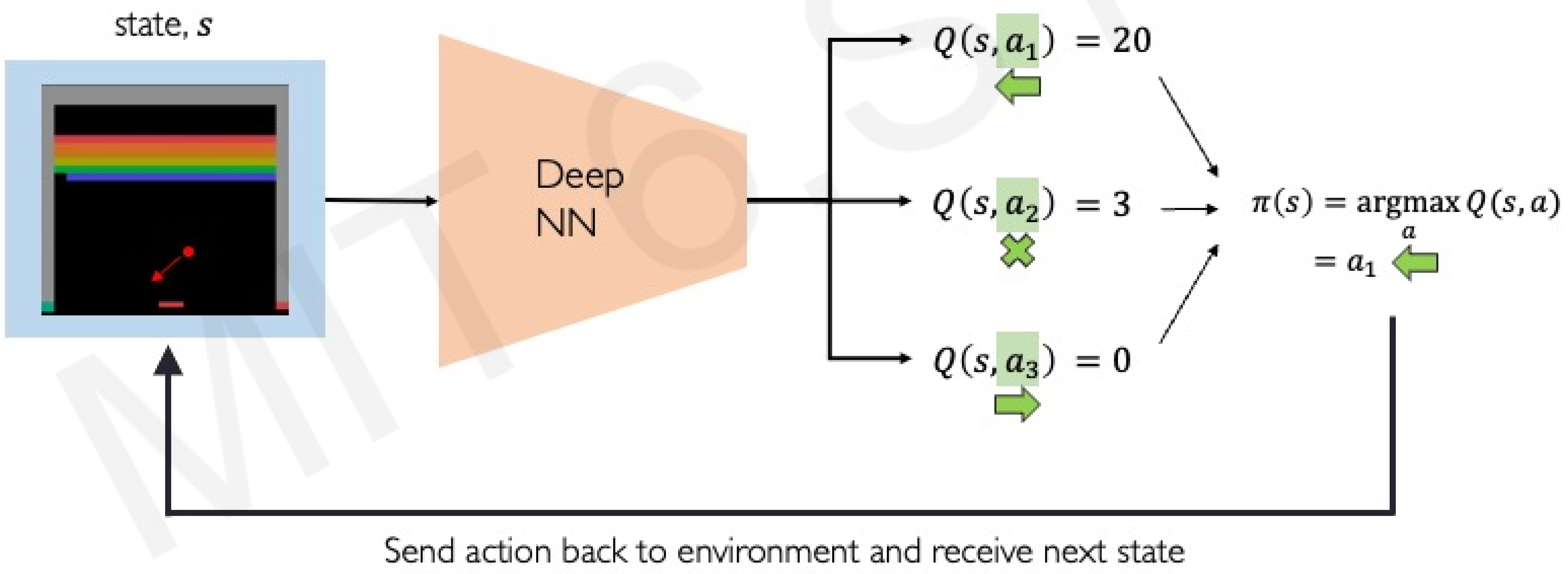


$$\mathcal{L} = \mathbb{E}\left[\left\| \overbrace{\left(r + \gamma \max_{a'} Q(s', a')\right)}^{\text{target}} - \overbrace{Q(s, a)}^{\text{predicted}} \right\|^2\right]$$

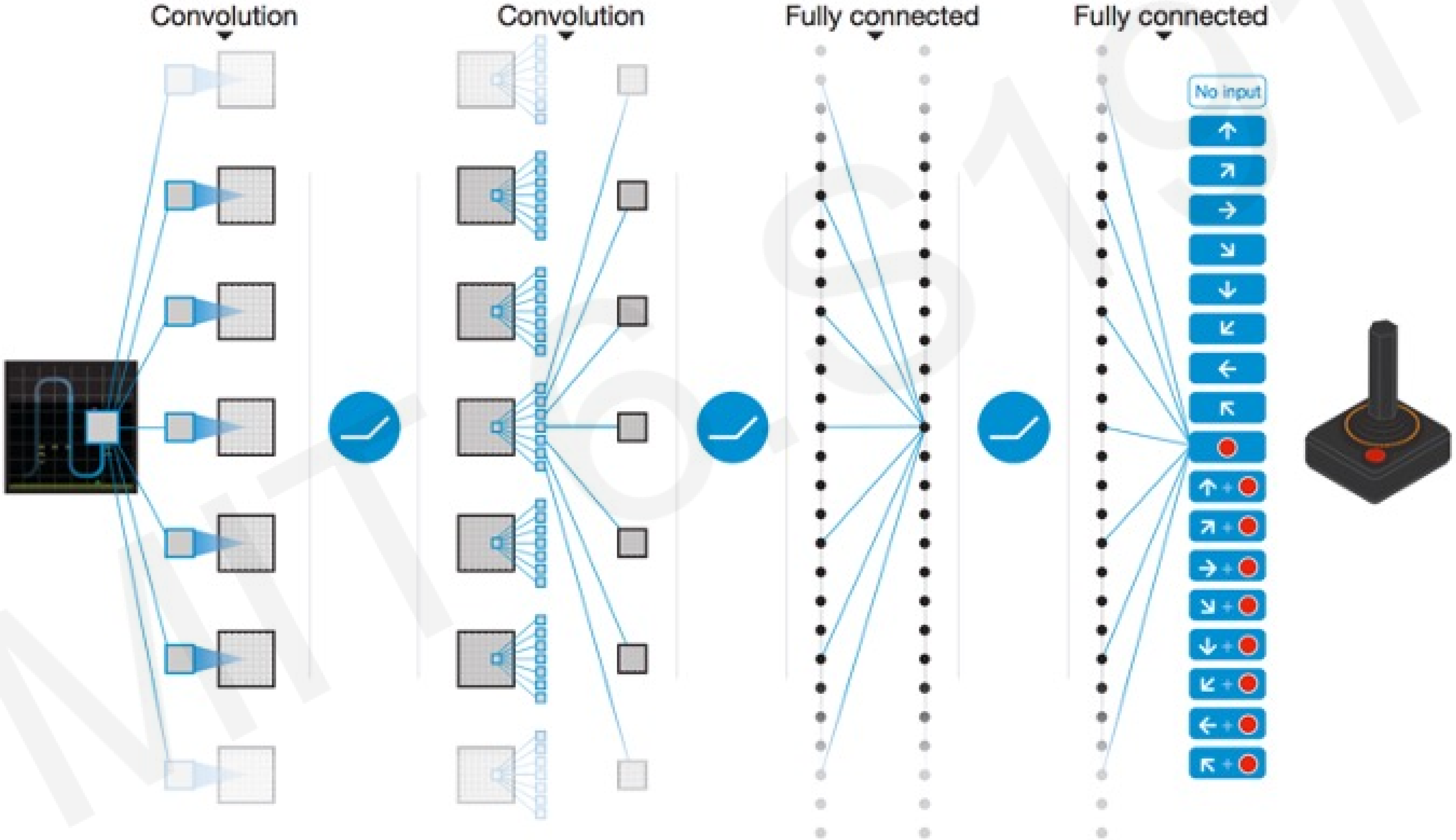
Q-Loss

Deep Q Network Summary

Use NN to learn Q-function and then use to infer the optimal policy, $\pi(s)$



DQN Atari Results



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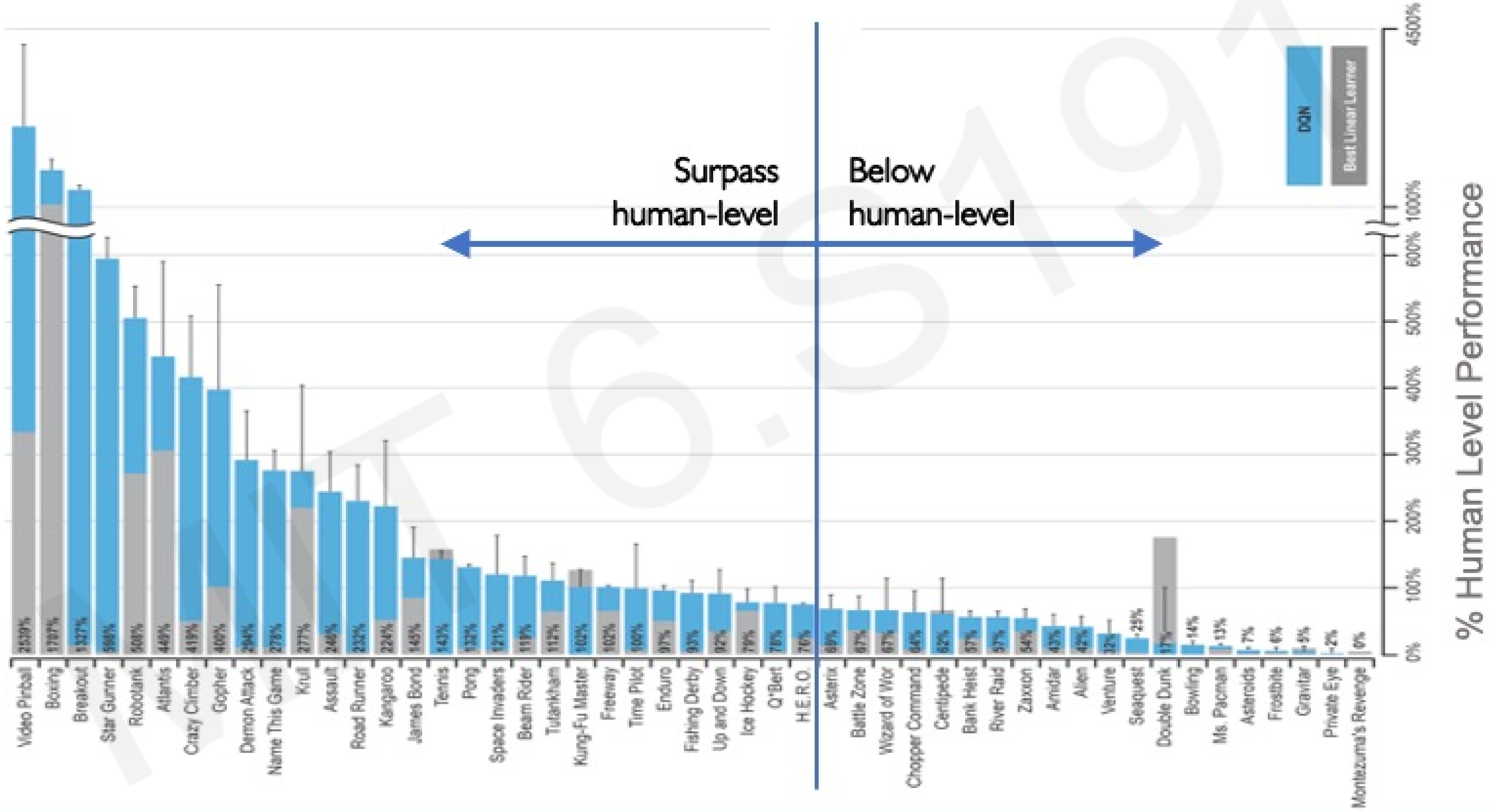

Downsides of Q-learning

Complexity:
- Can model scenarios where the action space is discrete and small
- Cannot handle continuous action spaces

Flexibility:
- Policy is deterministically computed from the Q function by maximizing the reward → cannot learn stochastic policies

To address these, consider a new class of RL training algorithms: Policy gradient methods

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Find $Q(s,a)$

$$a = \underset{a}{\operatorname{argmax}}\, Q(s,a)$$

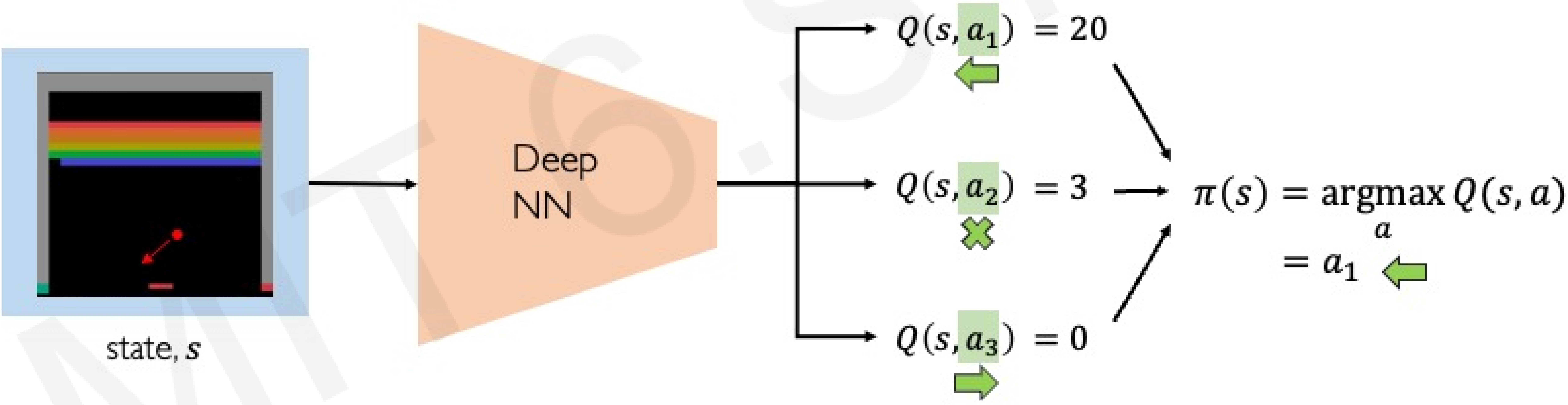
Policy Learning

Find $\pi(s)$

Sample $a \sim \pi(s)$

Deep Q Networks (DQN)

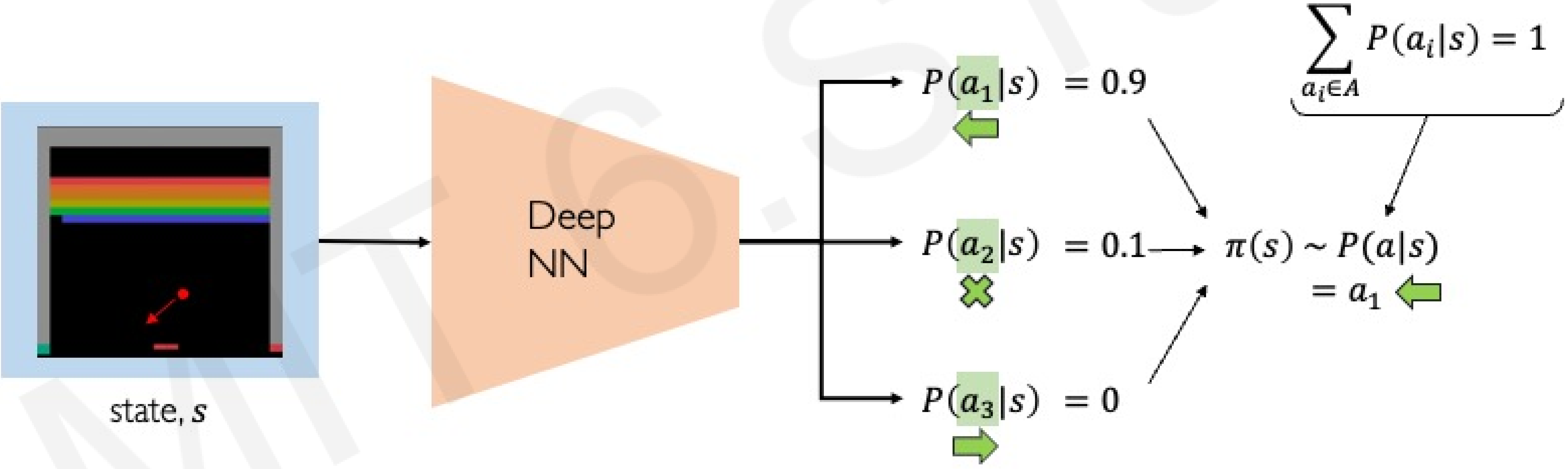
DQN: Approximate Q-function and use to infer the optimal policy, $\pi(s)$



Policy Gradient (PG): Key Idea

DQN: Approximate Q-function and use to infer the optimal policy, $\pi(s)$

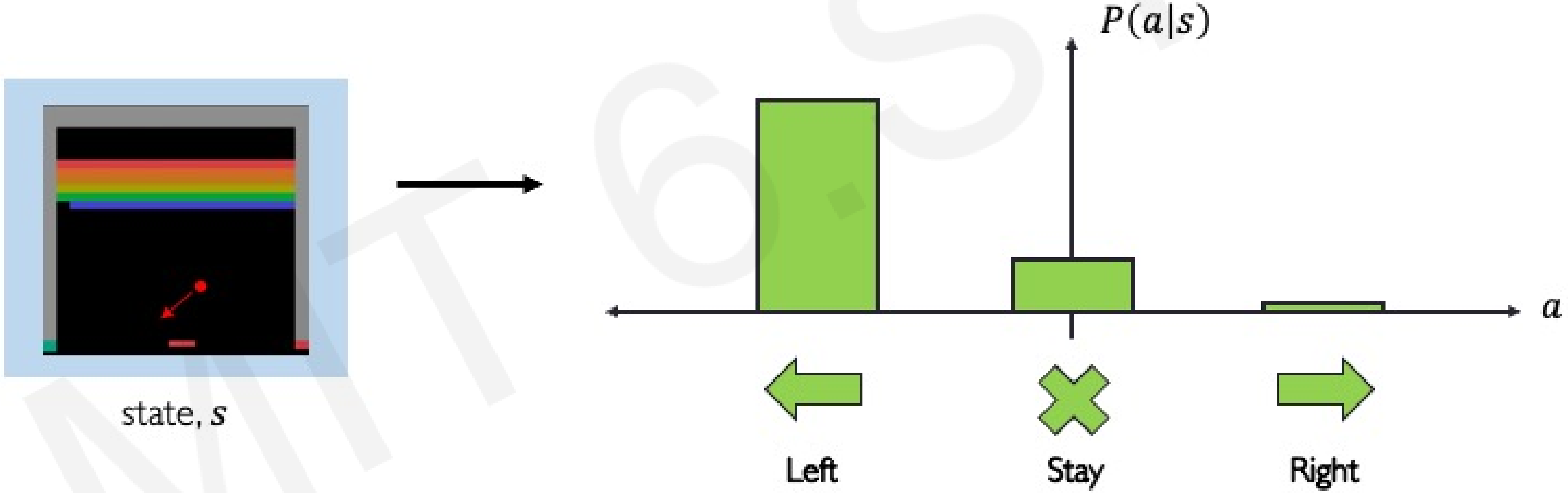
Policy Gradient: Directly optimize the policy $\pi(s)$



What are some advantages of this formulation?

Discrete vs Continuous Action Spaces

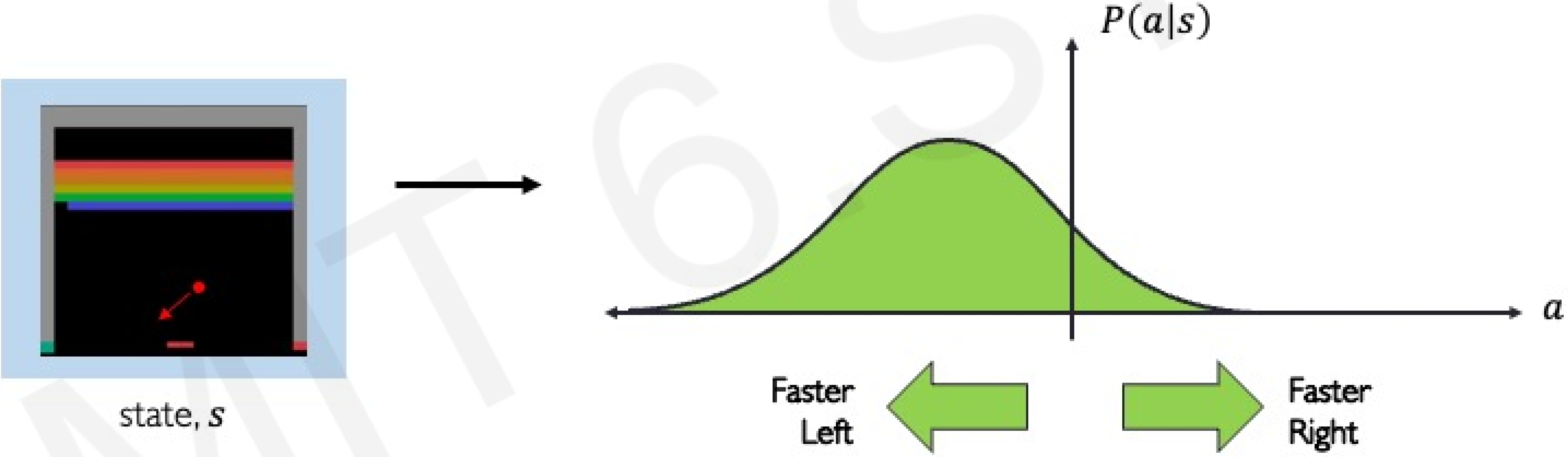
Discrete action space: which direction should I move?



Discrete vs Continuous Action Spaces

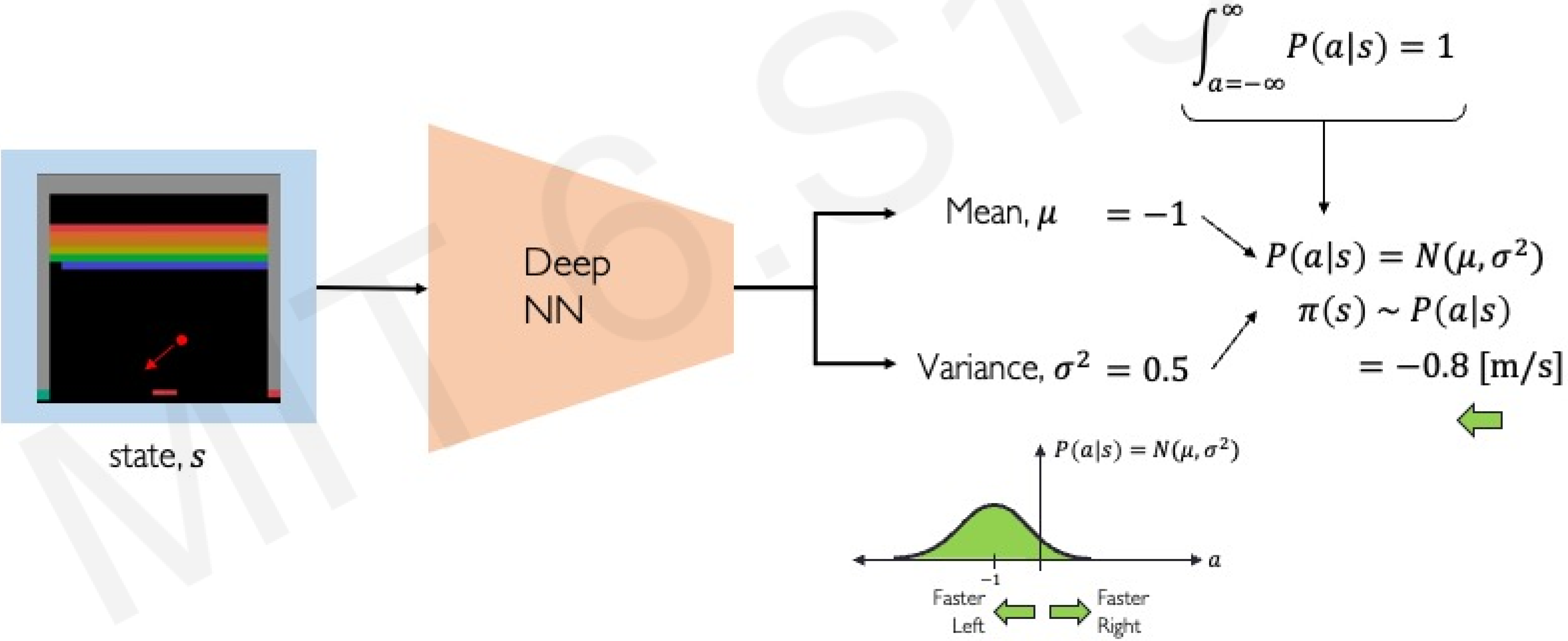
Discrete action space: which direction should I move?

Continuous action space: how fast should I move?



Policy Gradient (PG): Key Idea

Policy Gradient: Enables modeling of continuous action space



Training Policy Gradients: Case Study

Reinforcement Learning Loop:

Case Study – Self-Driving Cars

Agent: vehicle

State: camera, lidar, etc

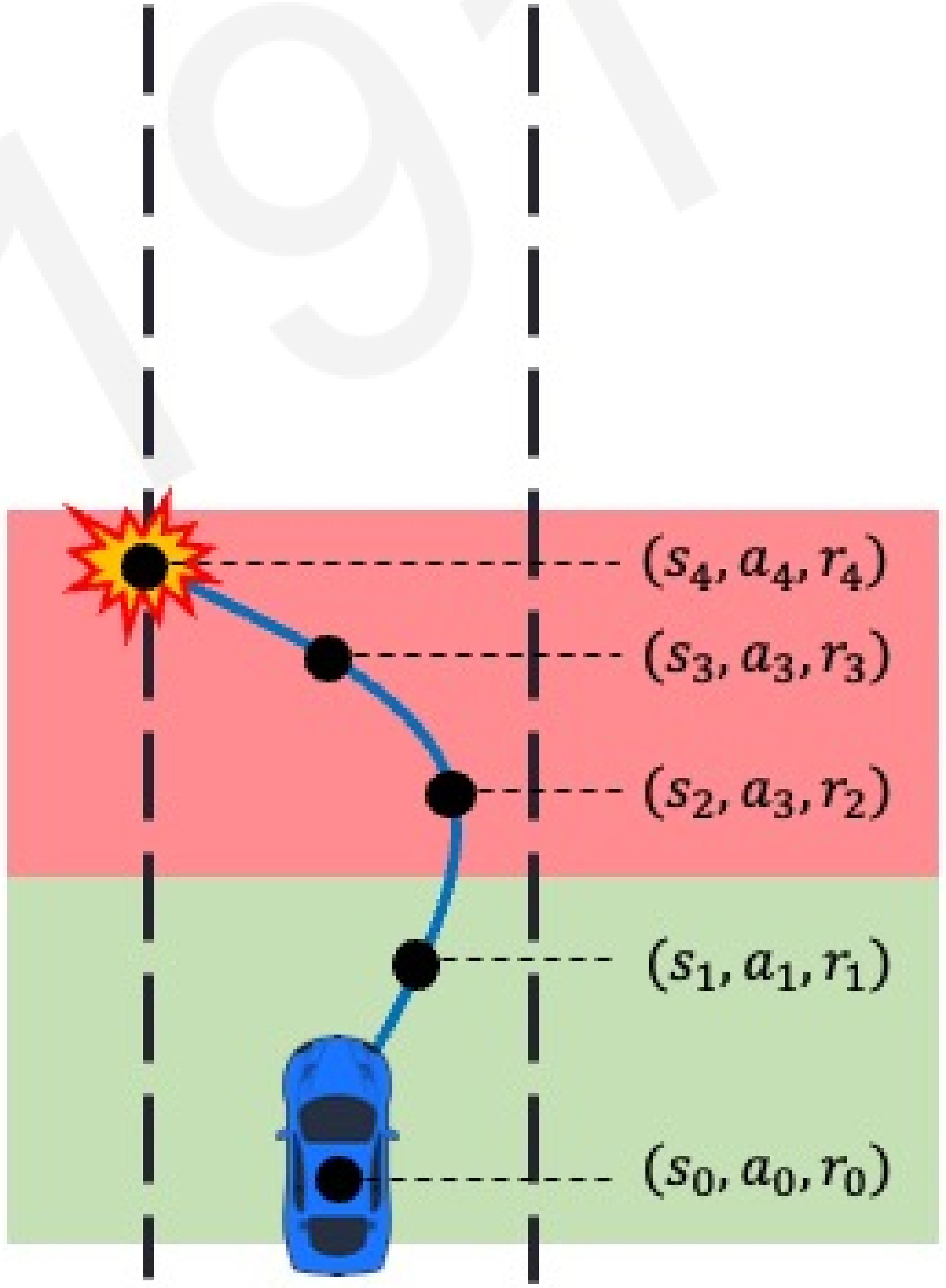
Action: steering wheel angle

Reward: distance traveled

Training Policy Gradients

Training Algorithm

1. Initialize the agent
2. Run a policy until termination
3. Record all states, actions, rewards
4. Decrease probability of actions that resulted in low reward
5. Increase probability of actions that resulted in high reward



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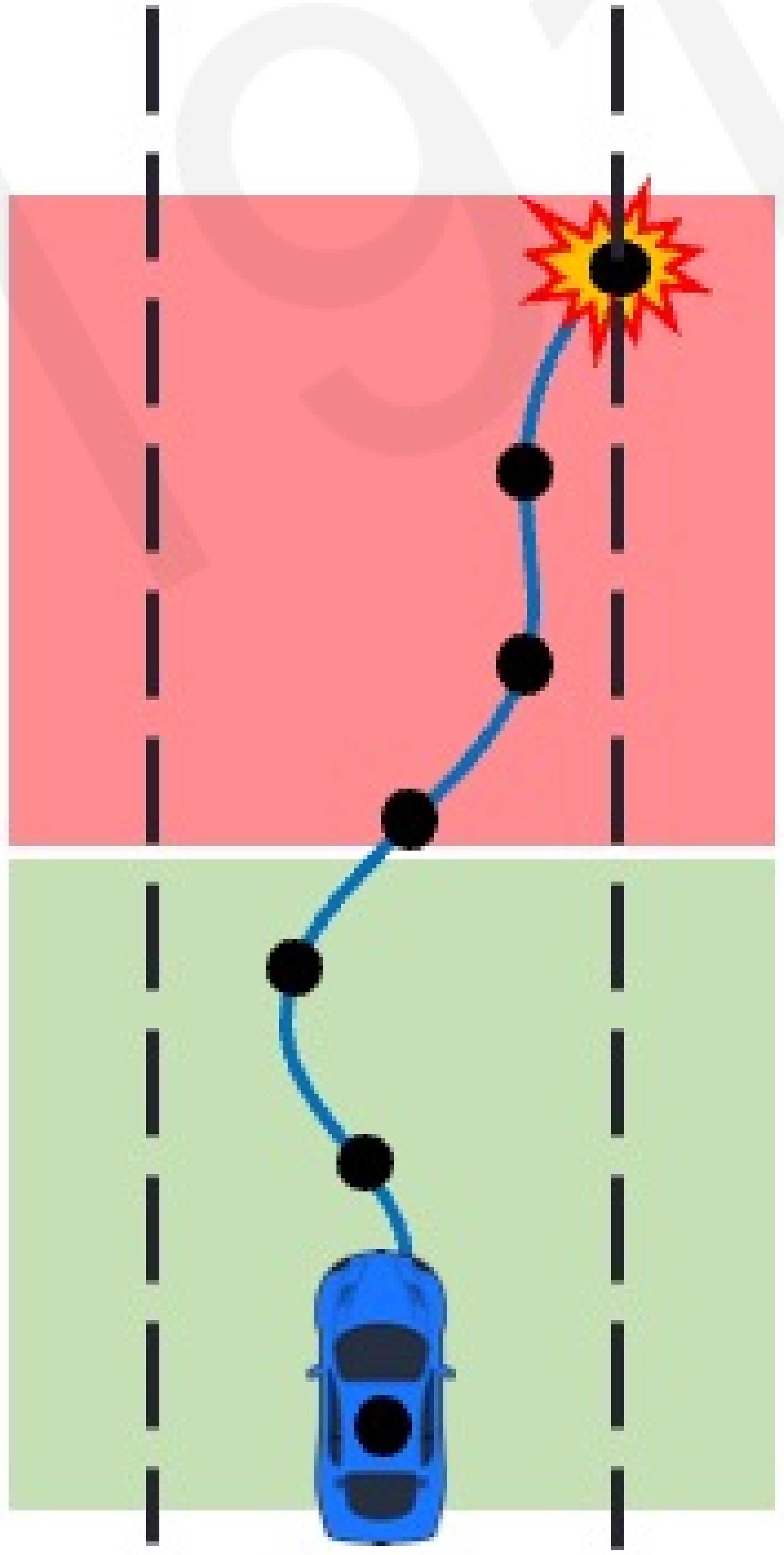

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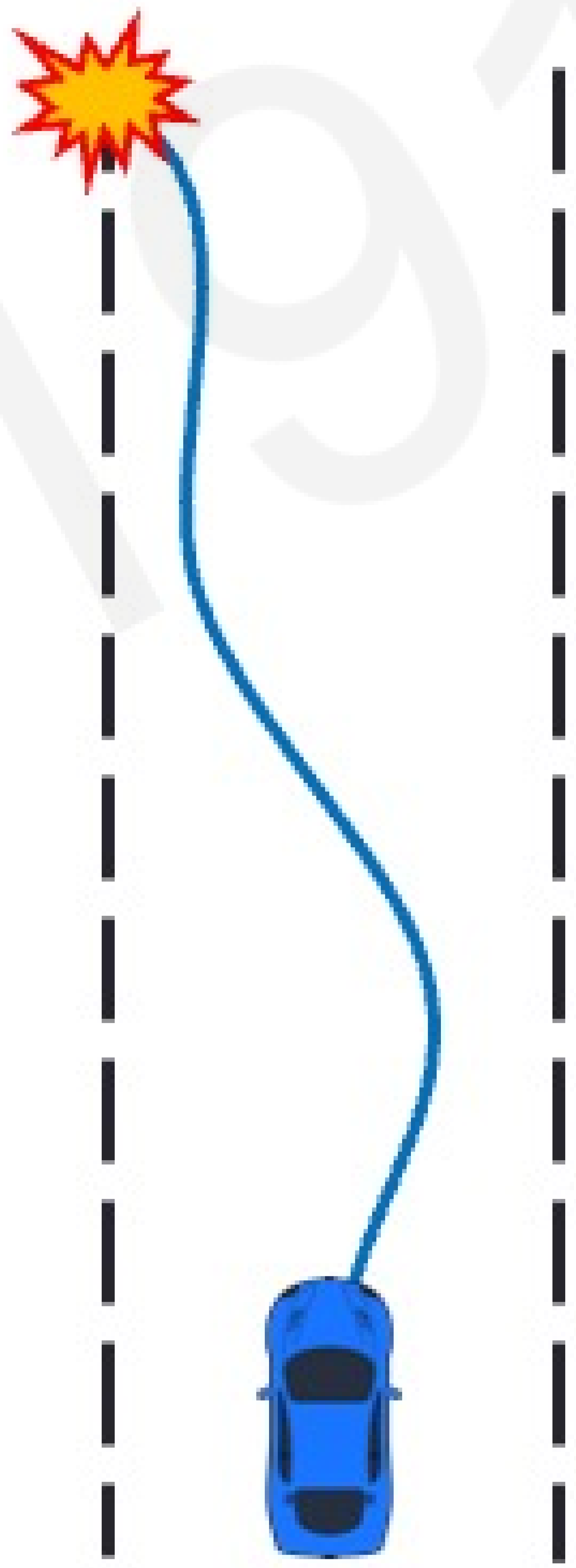

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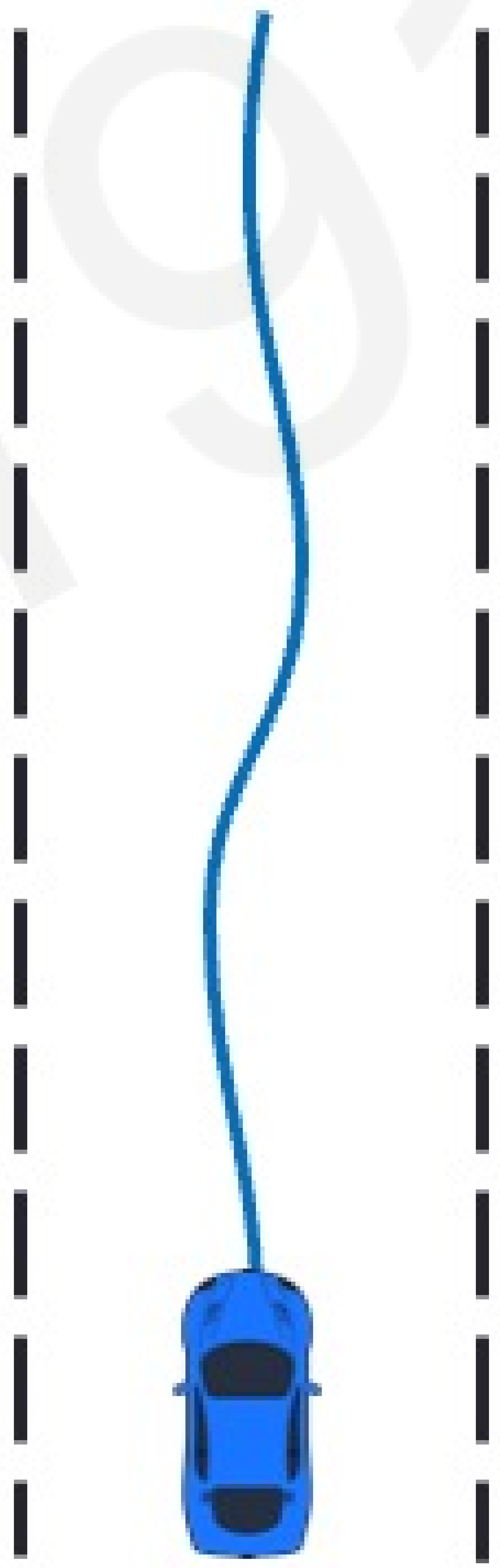

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log-likelihood of action

$$\textbf{loss} = -\underbrace{\log \mathrm{P}(a_t|s_t)}_{\text{log-likelihood of action}}\ \underbrace{R_t}_{\text{reward}}$$

reward

Gradient descent update:

$$w' = w - \nabla\, \textbf{loss}$$
$$w' = w + \boxed{\nabla \log \mathrm{P}(a_t|s_t)\, R_t}$$

Policy gradient!

Reinforcement Learning in Real Life

Training Algorithm

1. Initialize the agent
2. Run a policy until termination
3. Record all states, actions, rewards
4. Decrease probability of actions that resulted in low reward
5. Increase probability of actions that resulted in high reward

Data-driven Simulation for Autonomous Vehicles

VISTA: Photorealistic and high-fidelity simulator for training and testing self-driving cars

Deploying End-to-End RL for Autonomous Vehicles

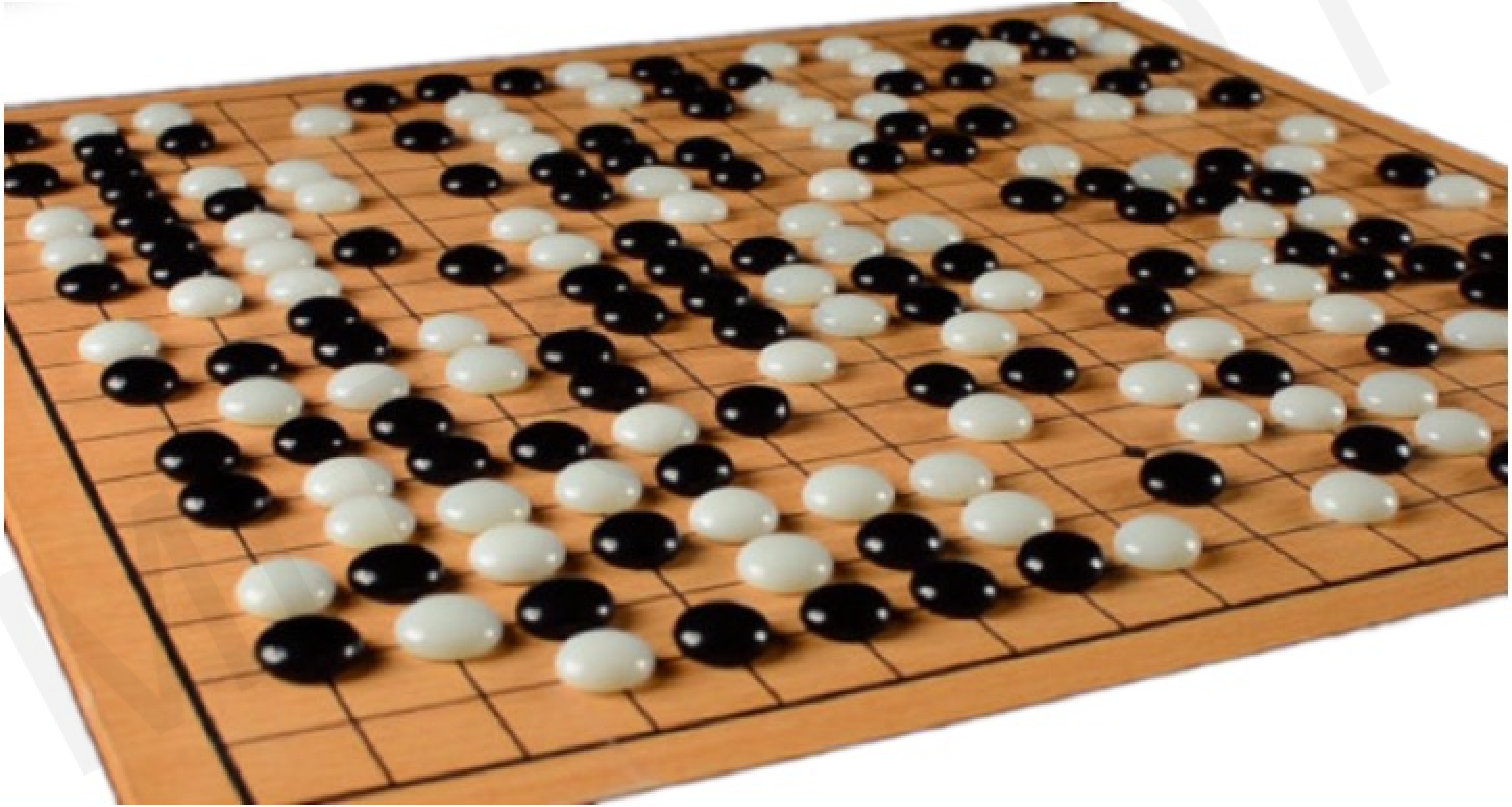
Policy Gradient RL agent trained entirely within VISTA simulator

End-to-end agent directly deployed into the real-world

First full-scale autonomous vehicle trained using RL entirely in simulation and deployed in real life!

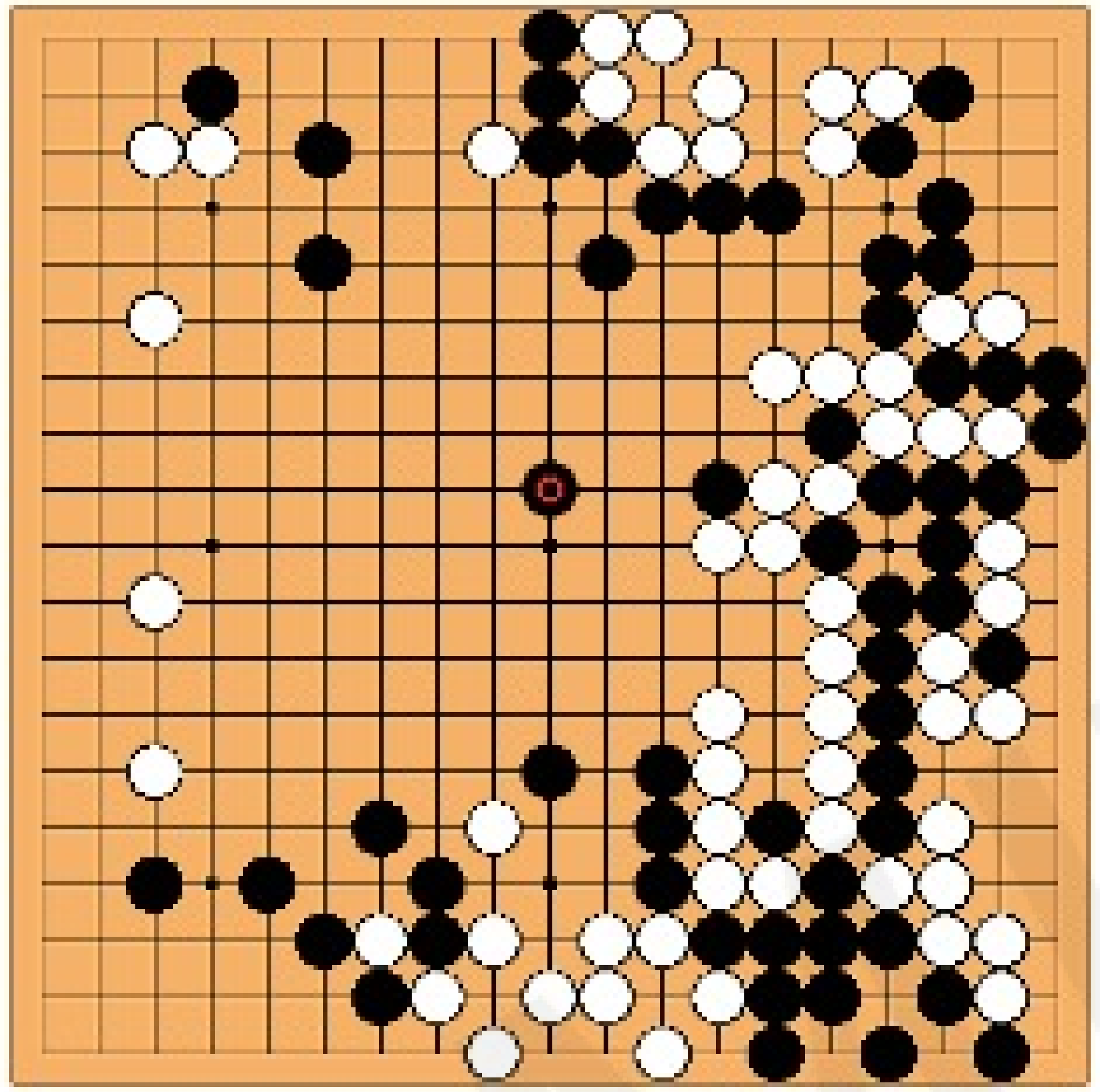
Deep Reinforcement Learning Applications

Reinforcement Learning and the Game of Go



The Game of Go

Aim: Get more board territory than your opponent.



Board Size $n \times n$	Positions 3^{n^2}	% Legal	Legal Positions
1×1	3	33.33%	1
2×2	81	70.37%	57
3×3	19,683	64.40%	12,675
4×4	43,046,721	56.49%	24,318,165
5×5	847,288,609,443	48.90%	414,295,148,741
9×9	$4.434264882 \times 10^{38}$	23.44%	$1.03919148791 \times 10^{38}$
13×13	$4.300233593 \times 10^{80}$	8.66%	$3.72497923077 \times 10^{79}$
19×19	$1.740896506 \times 10^{172}$	1.20%	$2.08168199382 \times 10^{170}$

Greater number of legal board positions than atoms in the universe.

AlphaGo Beats Top Human Player at Go (2016)

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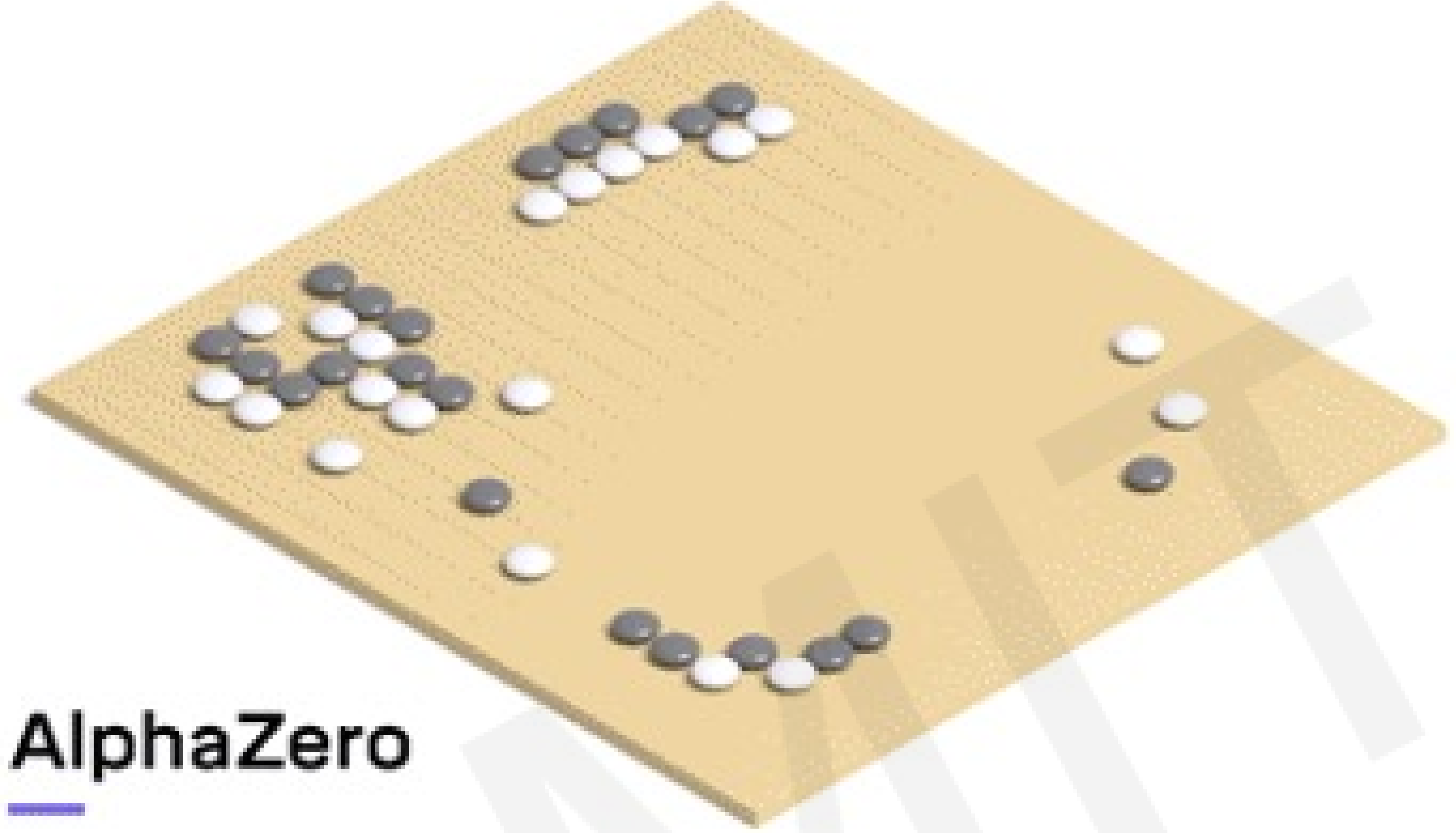
AlphaZero: RL from Self-Play (2018)

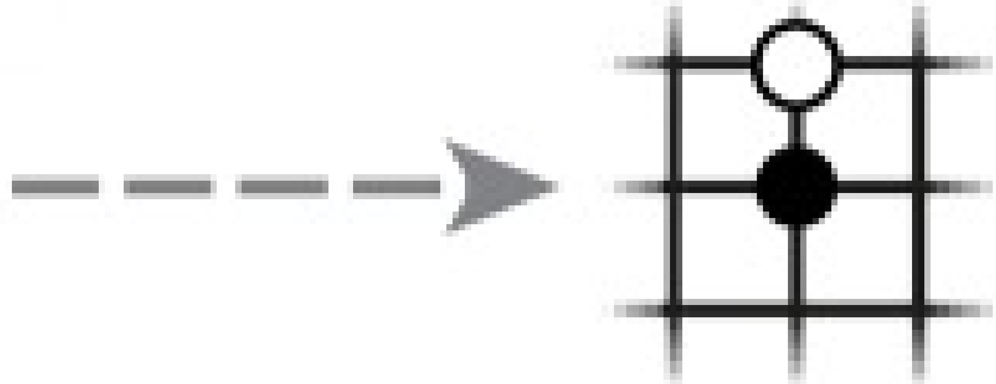


MuZero: Learning Dynamics for Planning (2020)

MuZero: Learning Dynamics for Planning (2020)

How MuZero acts in its environment:

1) Observe **2) Search** **3) Plan** **4) Act**



Deep Reinforcement Learning: Summary

Foundations

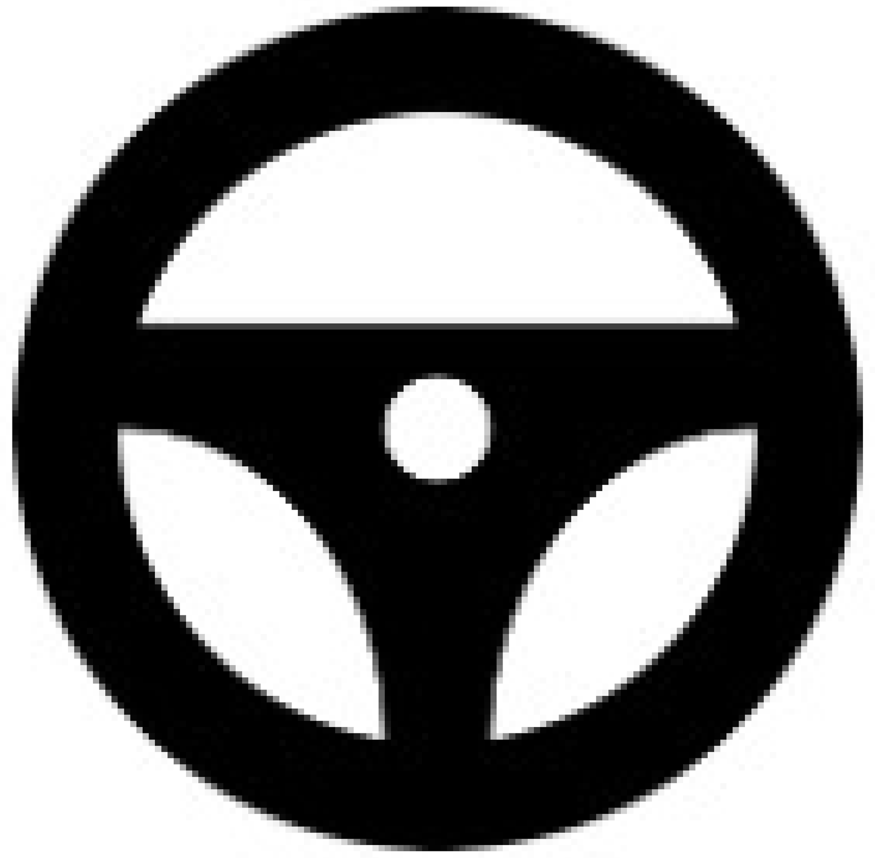
- Agents acting in environment
- State-action pairs → maximize future rewards
- Discounting

Q-Learning

- Q function: expected total reward given **s, a**
- Policy determined by selecting action that maximizes Q function

Policy Gradients

- Learn and optimize the policy directly
- Applicable to continuous action spaces



MIT
Introduction to Deep Learning

Lab 3: Debiasing, Uncertainty, and Robustness

Link to download labs:
http://introtodeeplearning.com#schedule

1. Open the lab in Google Colab
2. Start executing code blocks and filling in the #TODOs
3. Need help? Come to 32-123!