CS230: Lecture 9
Deep Reinforcement Learning

Kian Katanforoosh

Today's outline

I. Motivation

II. Recycling is good: an introduction to RL

III. Deep Q-Learning

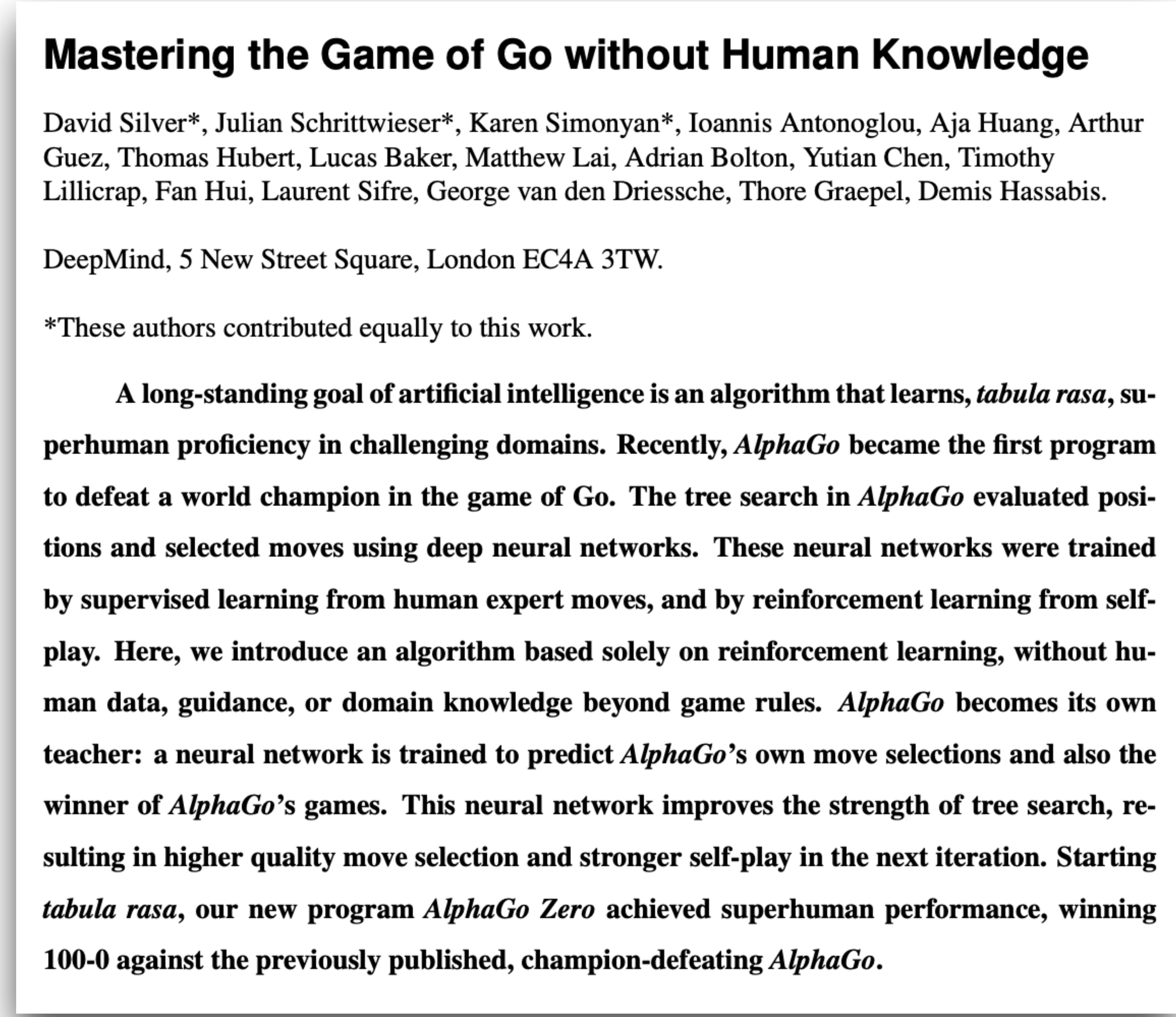
IV. Application of Deep Q-Learning: Breakout (Atari)

V. Tips to train Deep Q-Network

VI. Advanced topics

I. Motivation

Human Level Control through Deep Reinforcement Learning



Mastering the Game of Go without Human Knowledge

David Silver*, Julian Schrittwieser*, Karen Simonyan*, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy Lillicrap, Fan Hui, Laurent Sifre, George van den Driessche, Thore Graepel, Demis Hassabis.

DeepMind, 5 New Street Square, London EC4A 3TW.

*These authors contributed equally to this work.

A long-standing goal of artificial intelligence is an algorithm that learns, *tabula rasa*, superhuman proficiency in challenging domains. Recently, *AlphaGo* became the first program to defeat a world champion in the game of Go. The tree search in *AlphaGo* evaluated positions and selected moves using deep neural networks. These neural networks were trained by supervised learning from human expert moves, and by reinforcement learning from self-play. Here, we introduce an algorithm based solely on reinforcement learning, without human data, guidance, or domain knowledge beyond game rules. *AlphaGo* becomes its own teacher: a neural network is trained to predict *AlphaGo*'s own move selections and also the winner of *AlphaGo*'s games. This neural network improves the strength of tree search, resulting in higher quality move selection and stronger self-play in the next iteration. Starting *tabula rasa*, our new program *AlphaGo Zero* achieved superhuman performance, winning 100-0 against the previously published, champion-defeating *AlphaGo*.

AlphaGo

AlphaStar

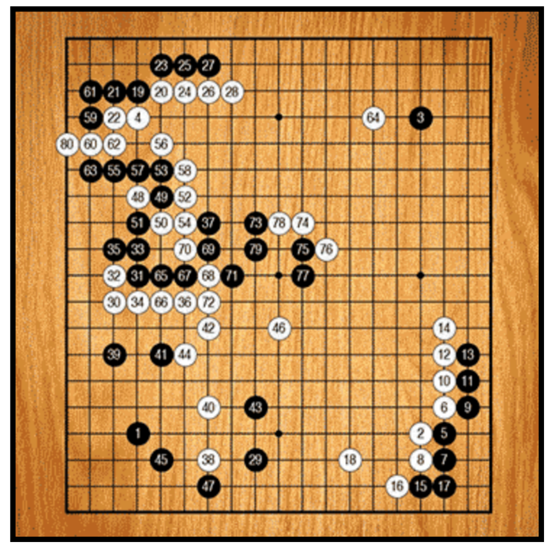
[Vinyals et al. (2019): Grandmaster level in StarCraft II using multi-agent reinforcement learning]
[Silver, Schrittwieser, Simonyan et al. (2017): Mastering the game of Go without human knowledge]
[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

I. Motivation

How would you solve Go with classic supervised learning?

Input

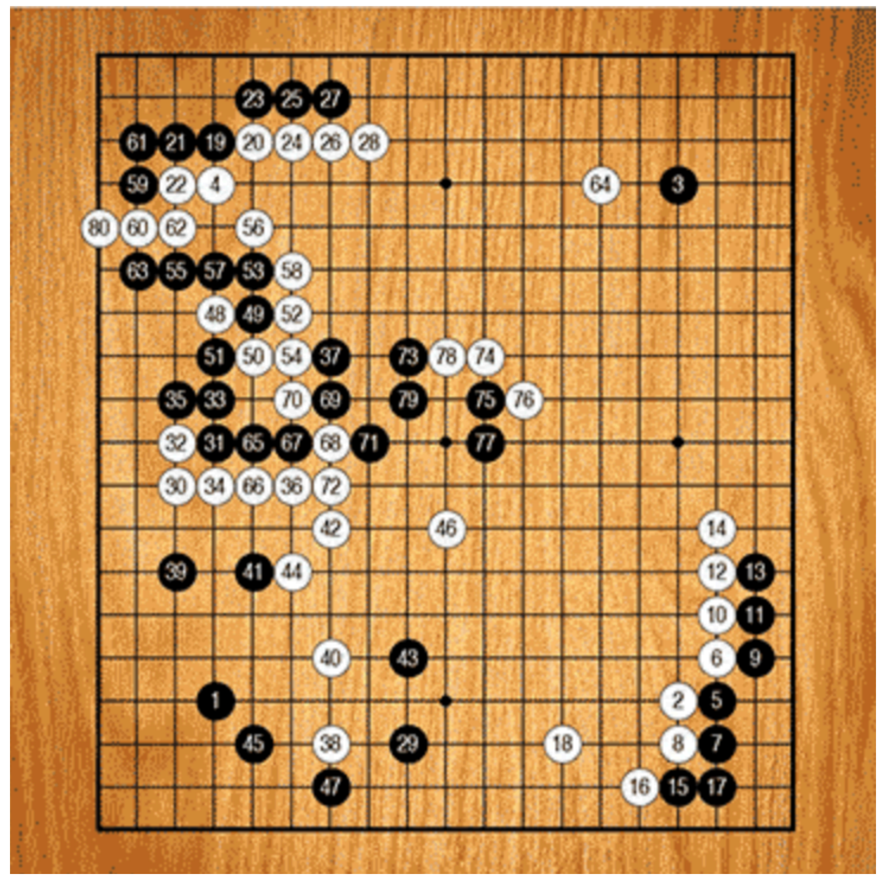


output class

The move of the professional player

<u>issues:</u>

- Ground truth probably wrongly defined.
- Too many states in this Game.
- We will likely not generalize.



Source: https://deepmind.com/blog/alphago-zero-learning-scratch/

Why RL?

- Delayed labels
- Making sequences of decisions

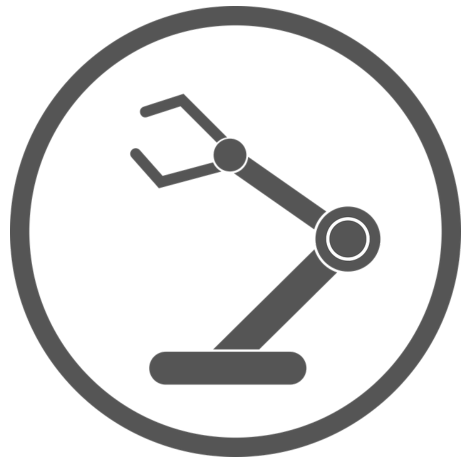
What is RL?

- Automatically learn to make good sequences of decision
- Teaching by experience vs. Teaching by example.

Examples of RL applications

Games

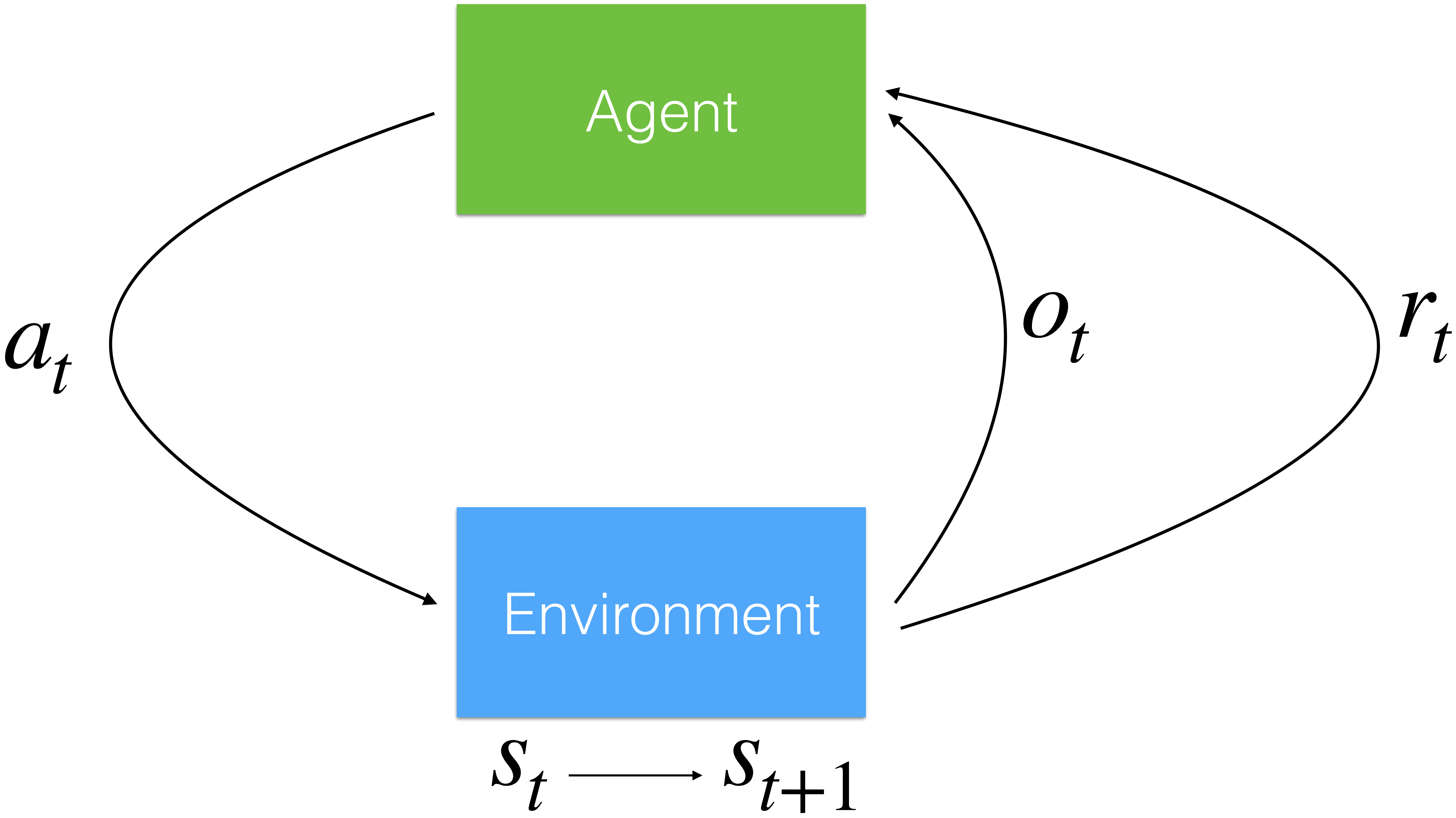
Robotics



Advertisement

I. Motivation

<u>Transition:</u> $s_t \rightarrow a_t \rightarrow (o_t, r_t) \rightarrow s_{t+1}$



Today's outline

I. Motivation

II. Recycling is good: an introduction to RL

III. Deep Q-Networks

IV. Application of Deep Q-Network: Breakout (Atari)

V. Tips to train Deep Q-Network

VI. Advanced topics

II. Recycling is good: an introduction to RL

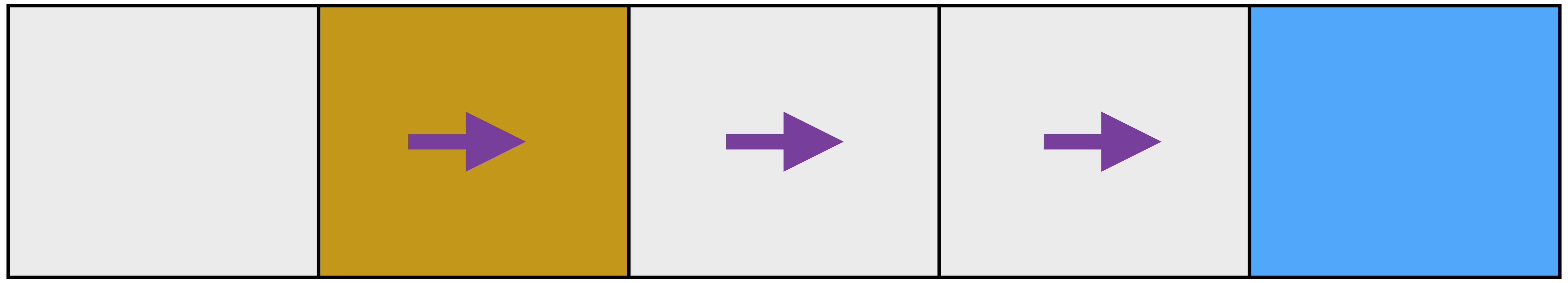
Problem statement

State 1	State 2 (initial)	State 3	State 4	State 5

*Define reward "**r**" in every state*

+2	0	0	+1	+10

Best strategy to follow if $\gamma = 1$



***Goal**: maximize the return (rewards)*

***Number of states**: 5*

***Types of states**:* initial normal terminal

***Agent's Possible actions**:*

***Additional rule:** garbage collector coming in 3min, it takes 1min to move between states*

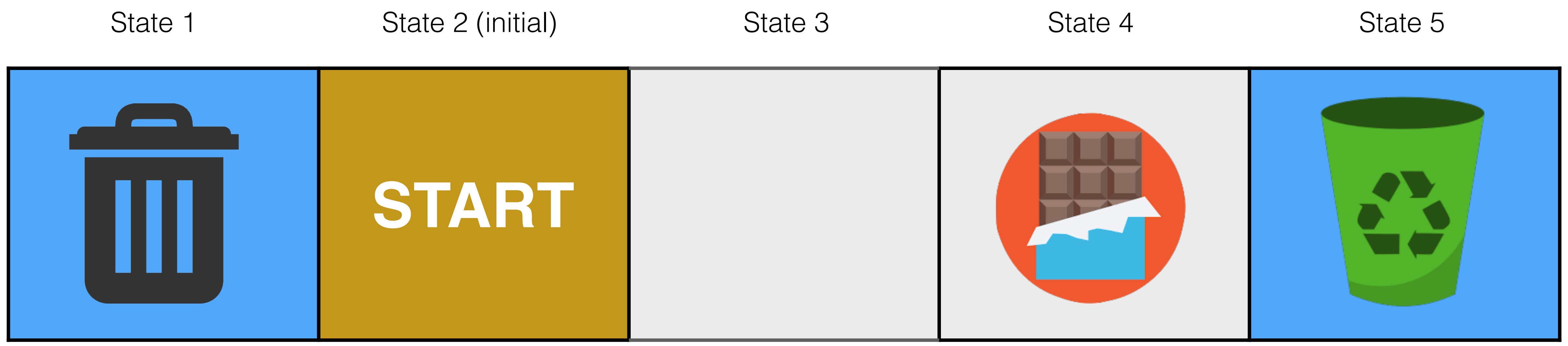
How to define the long-term return?

Discounted return $R = \sum_{t=0}^{\infty} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \dots$

Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement



*Define reward "**r**" in every state*

S1	S2	S3	S4	S5
+2	**0**	**0**	**+1**	**+10**

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

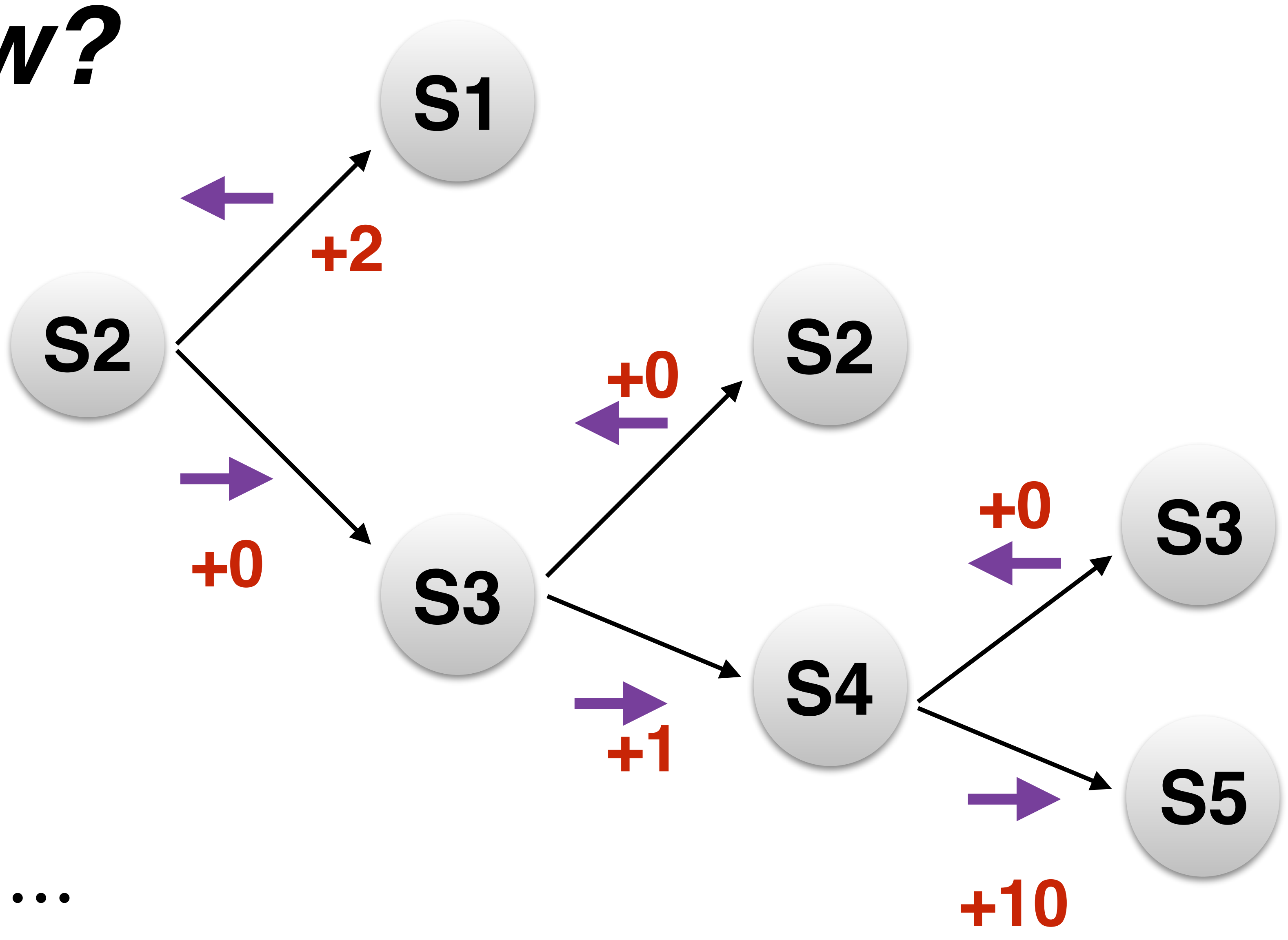
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$\begin{array}{cc} & \text{\#actions} \\ Q = & \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} & \text{\#states} \end{array}$$

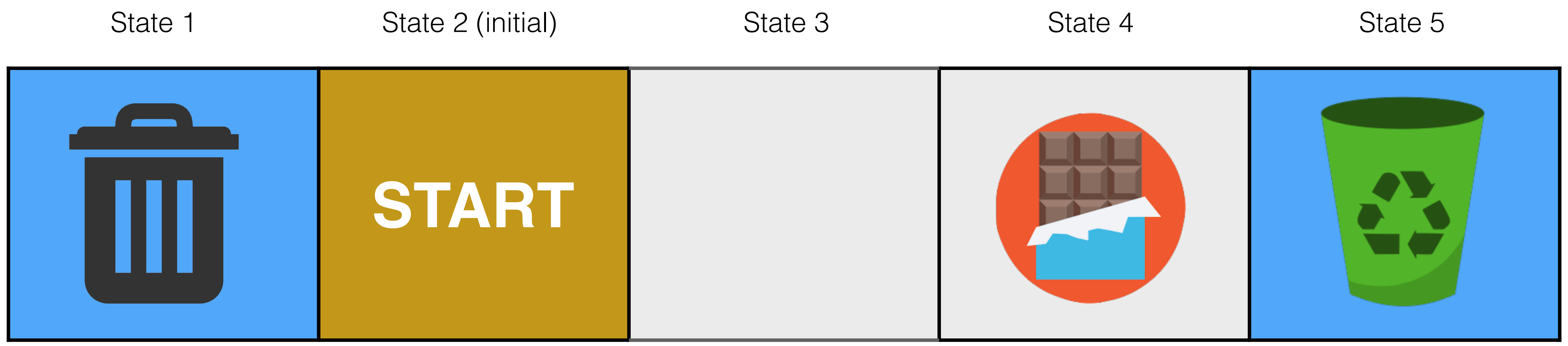
How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement



*Define reward "**r**" in every state*

S1	S2	S3	S4	S5
+2	**0**	**0**	**+1**	**+10**

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

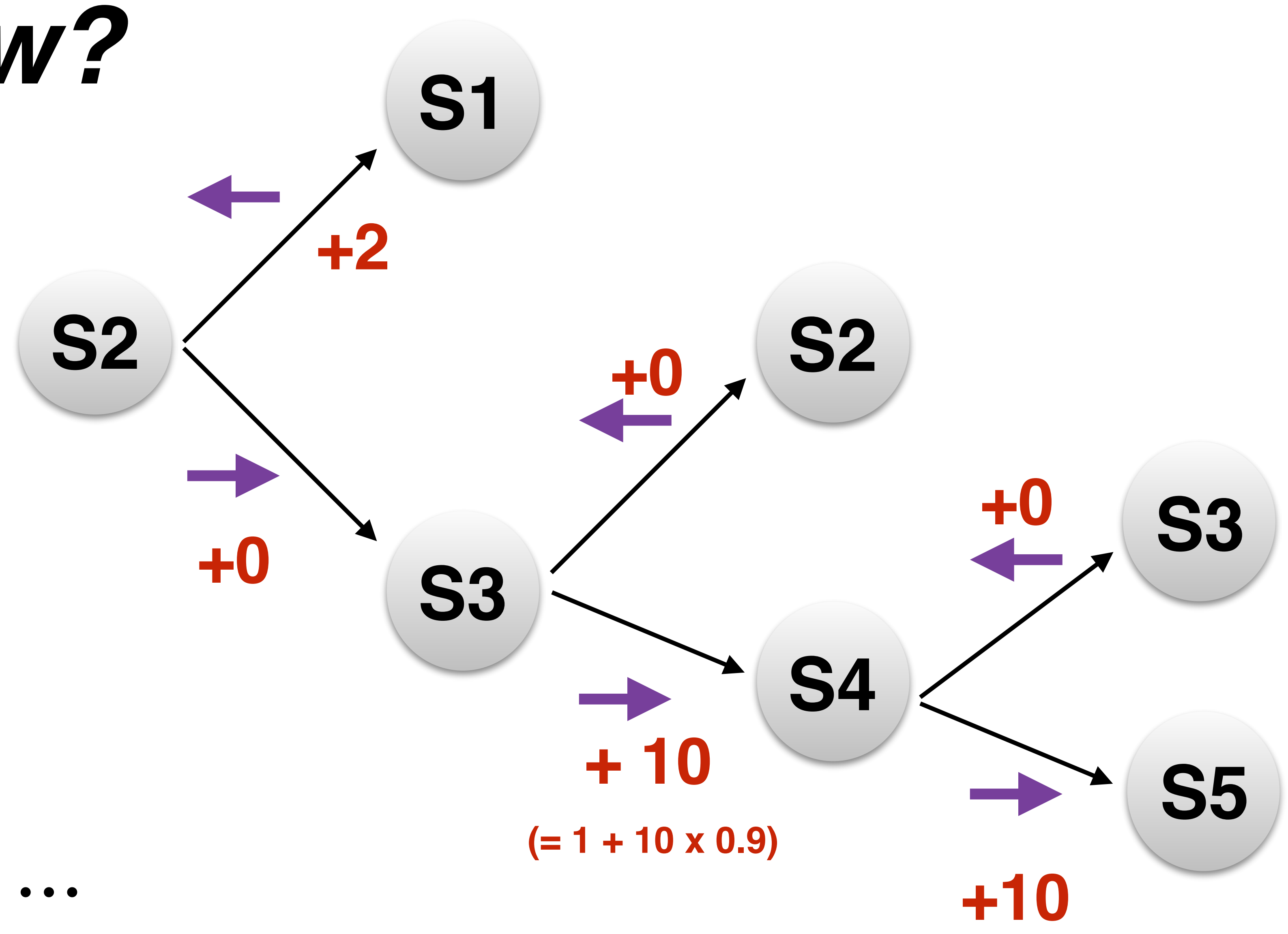
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$Q = \begin{array}{c} \text{\#actions} \\ \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} \end{array} \text{\#states}$$

How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement

*Define reward "**r**" in every state*

S1	S2	S3	S4	S5
+2	**0**	**0**	**+1**	**+10**

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

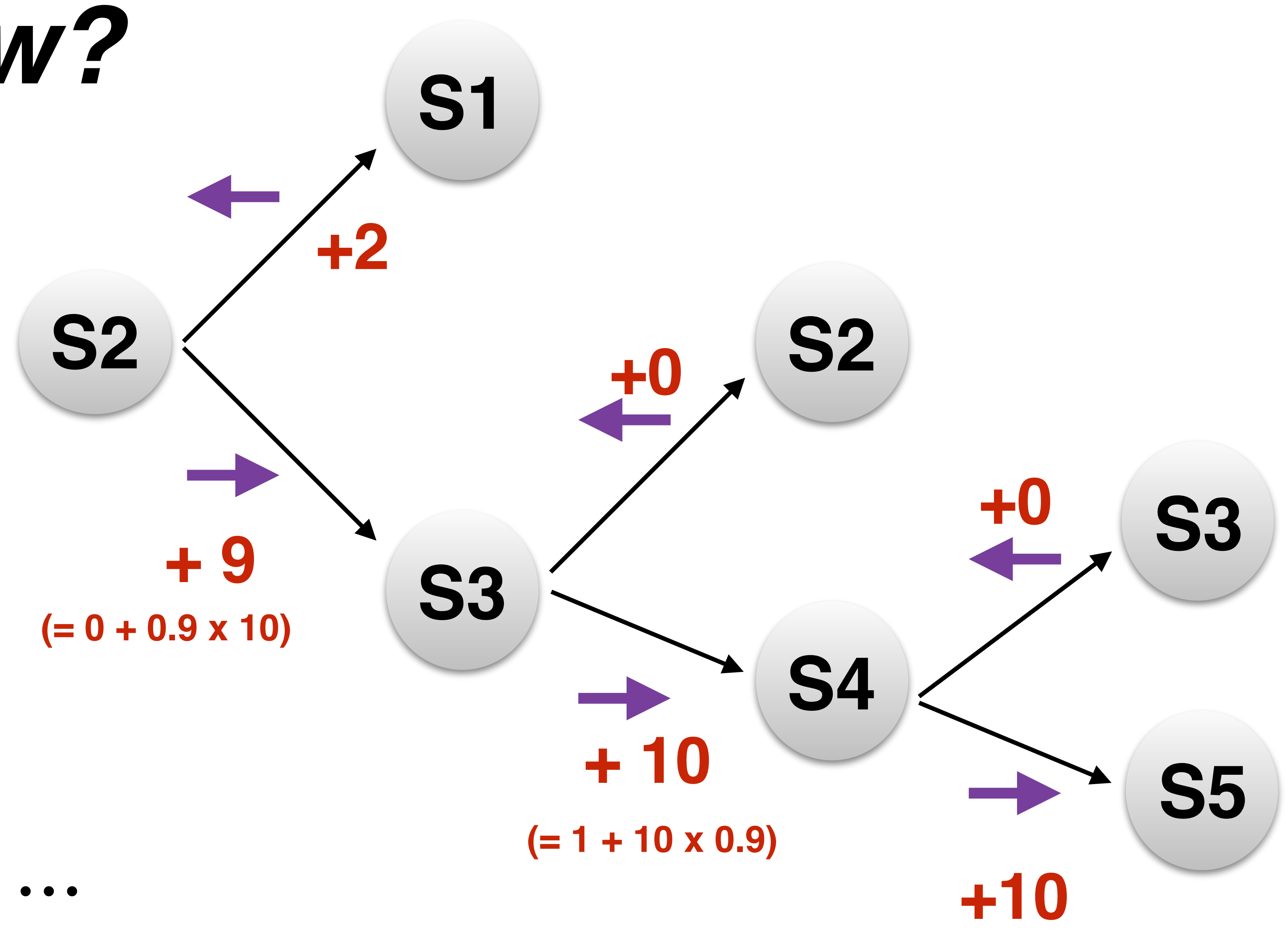
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$
\begin{array}{cc}
 & \#\text{actions} \\
Q = & \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} \#\text{states}
\end{array}
$$

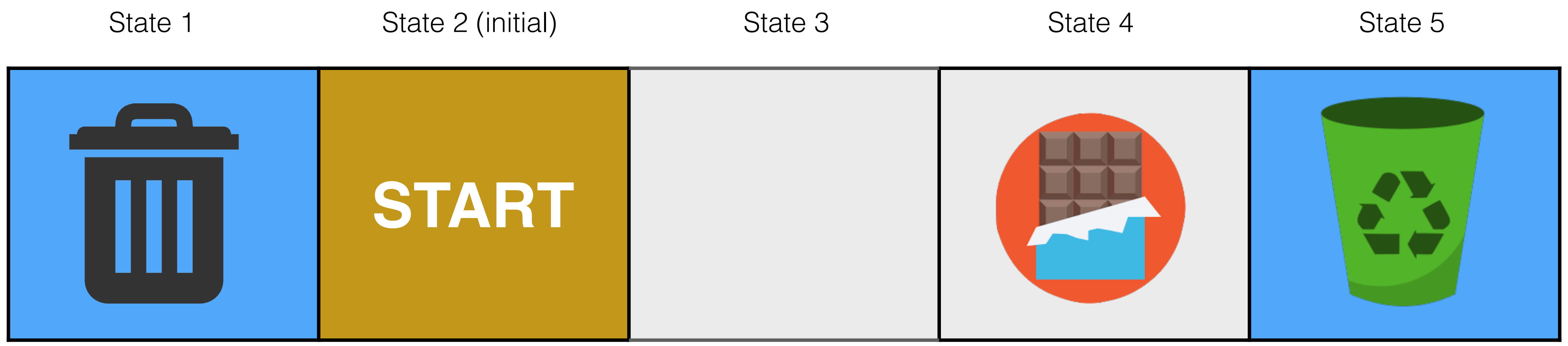
How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement



*Define reward "**r**" in every state*

+2	0	0	+1	+10
S1	S2	S3	S4	S5

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

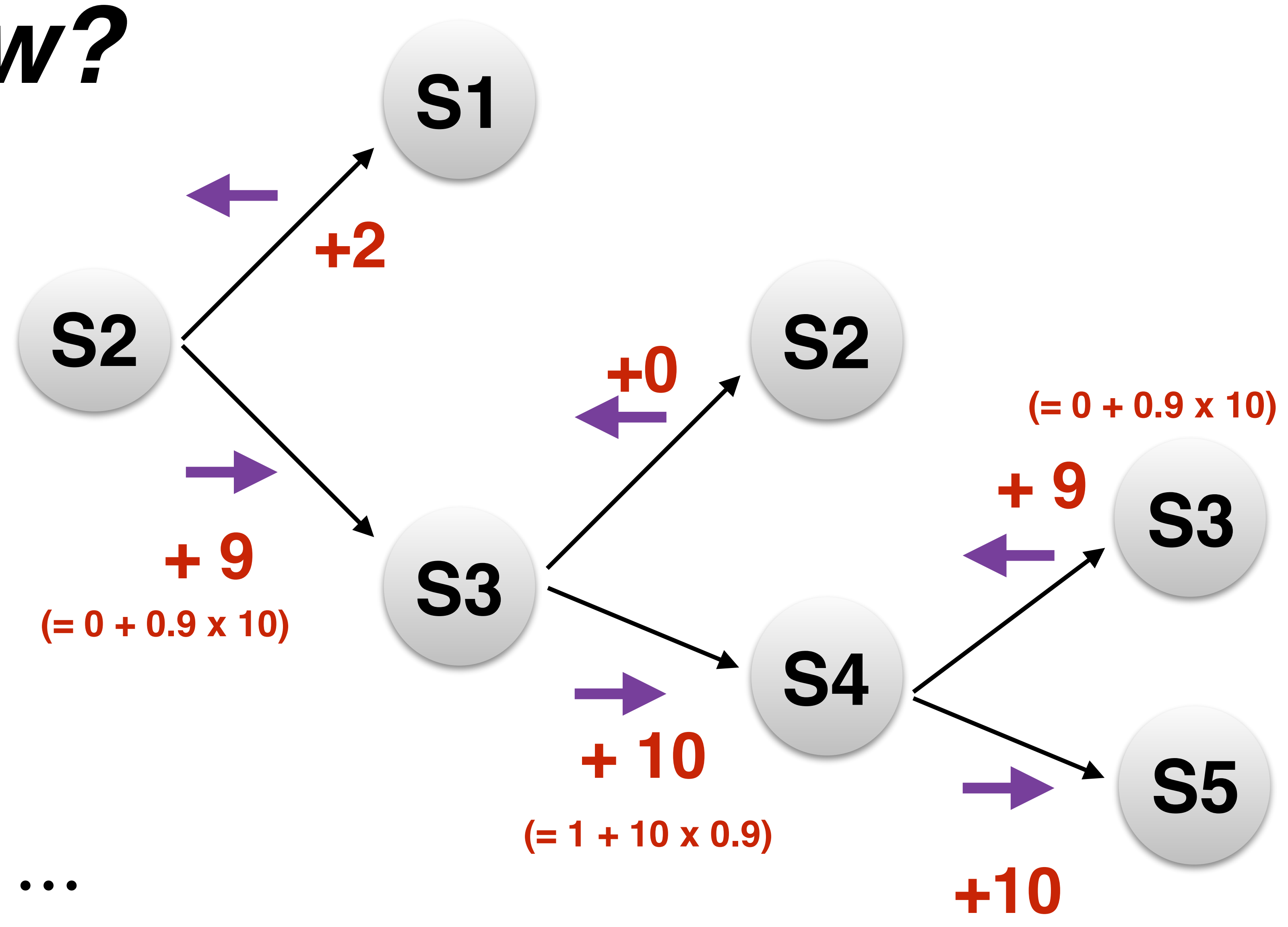
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$
\begin{array}{cc}
 & \text{\#actions} \\
Q = & \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} \text{\#states}
\end{array}
$$

How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement

*Define reward "**r**" in every state*

S1	S2	S3	S4	S5
+2	**0**	**0**	**+1**	**+10**

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

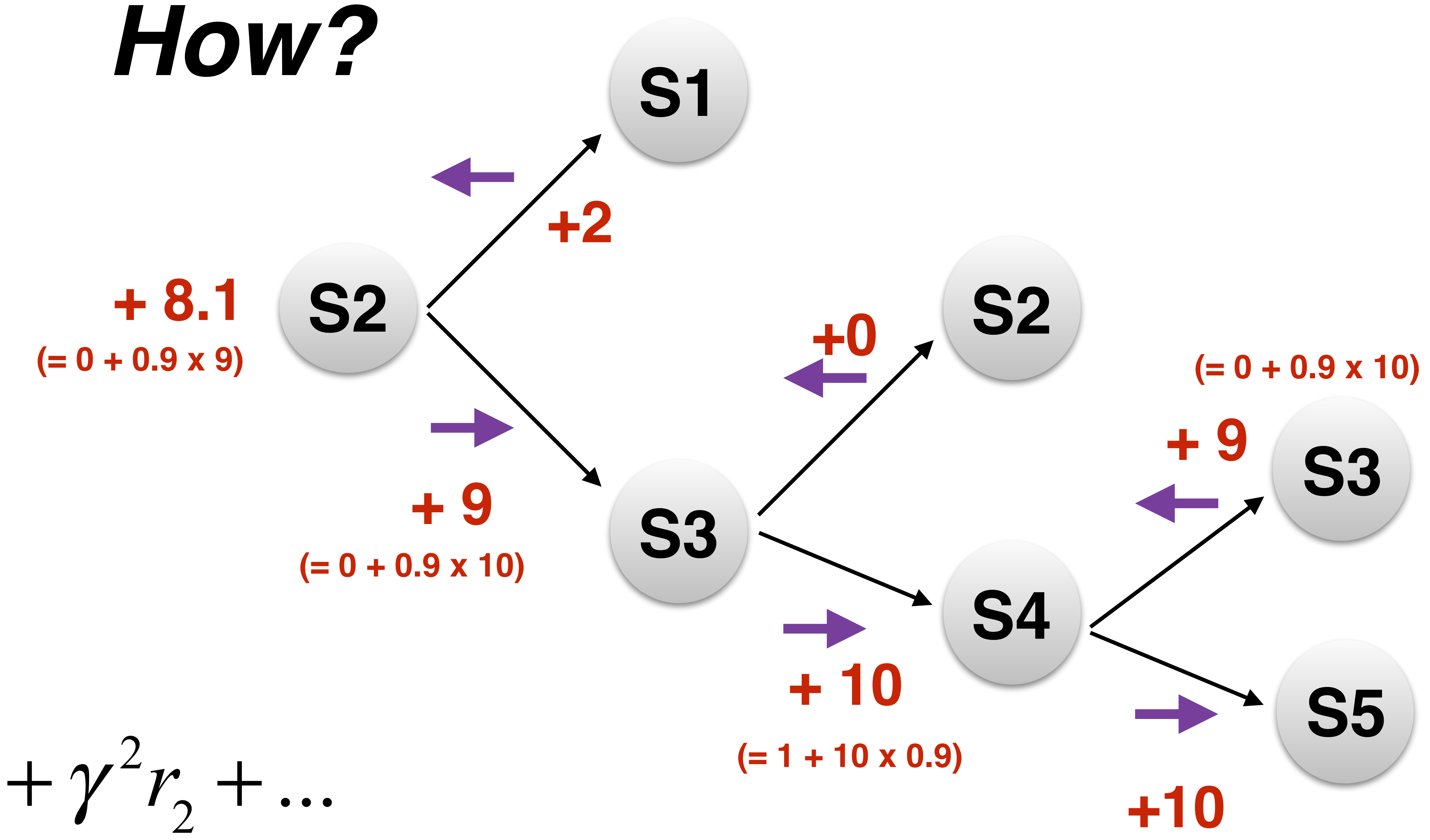
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$
\begin{array}{c}
\text{\#actions} \\
Q = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} \ \text{\#states}
\end{array}
$$

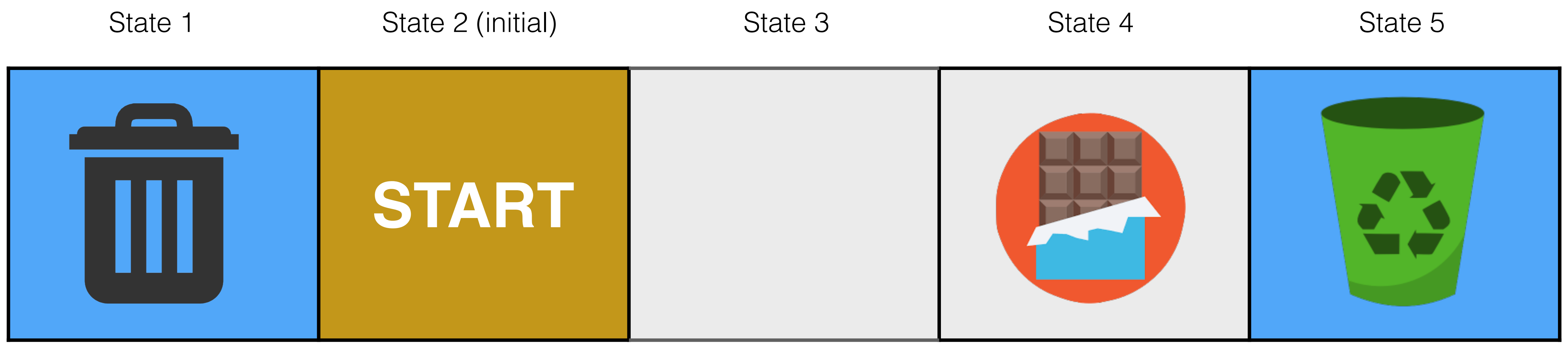
How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement



*Define reward "**r**" in every state*

S1	S2	S3	S4	S5
+2	**0**	**0**	**+1**	**+10**

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

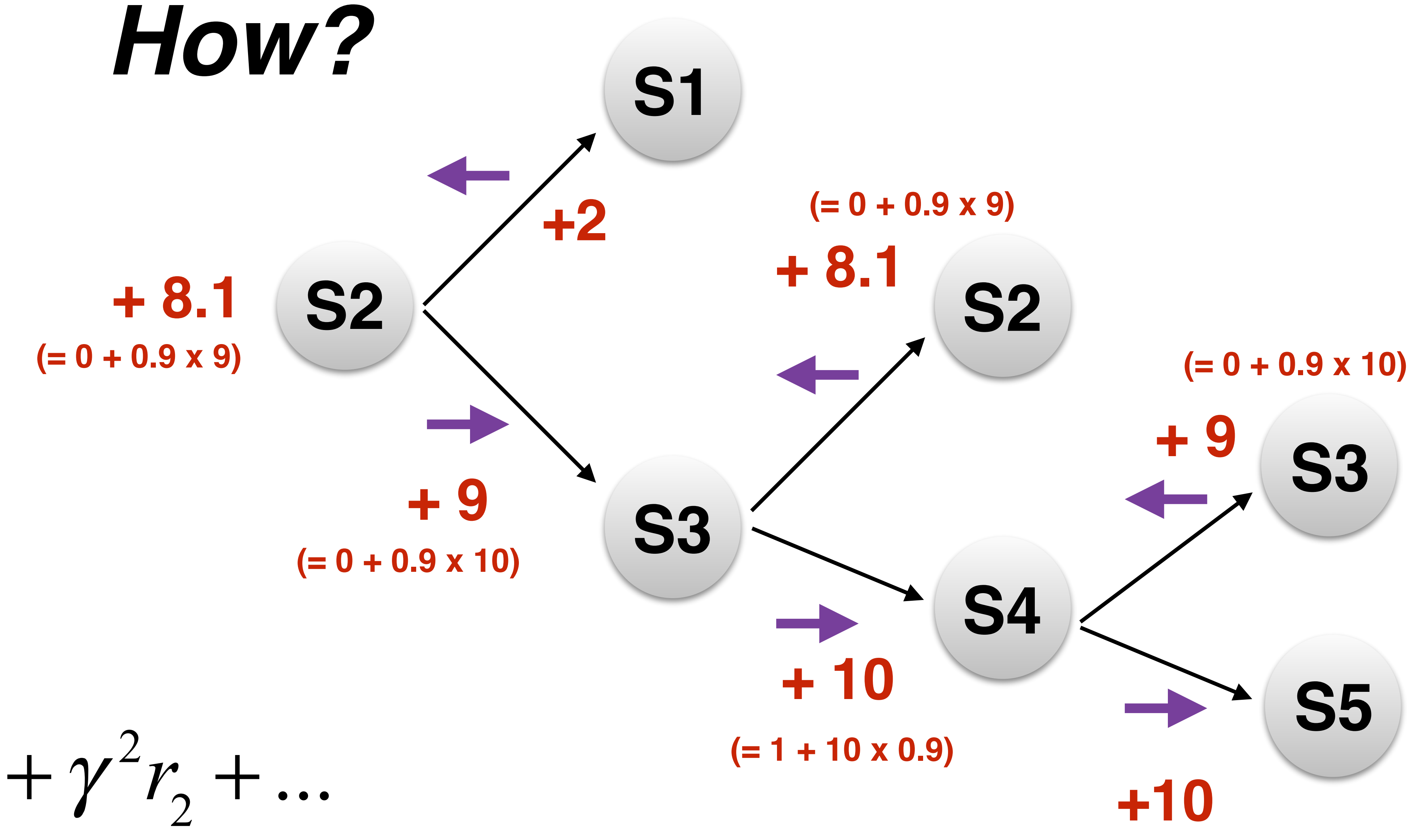
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$\begin{array}{cc} & \text{\#actions} \\ Q = & \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix} \text{\#states} \end{array}$$

How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement

*Define reward "**r**" in every state*

+2	0	0	+1	+10
S1	S2	S3	S4	S5

Assuming $\gamma = 0.9$

Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

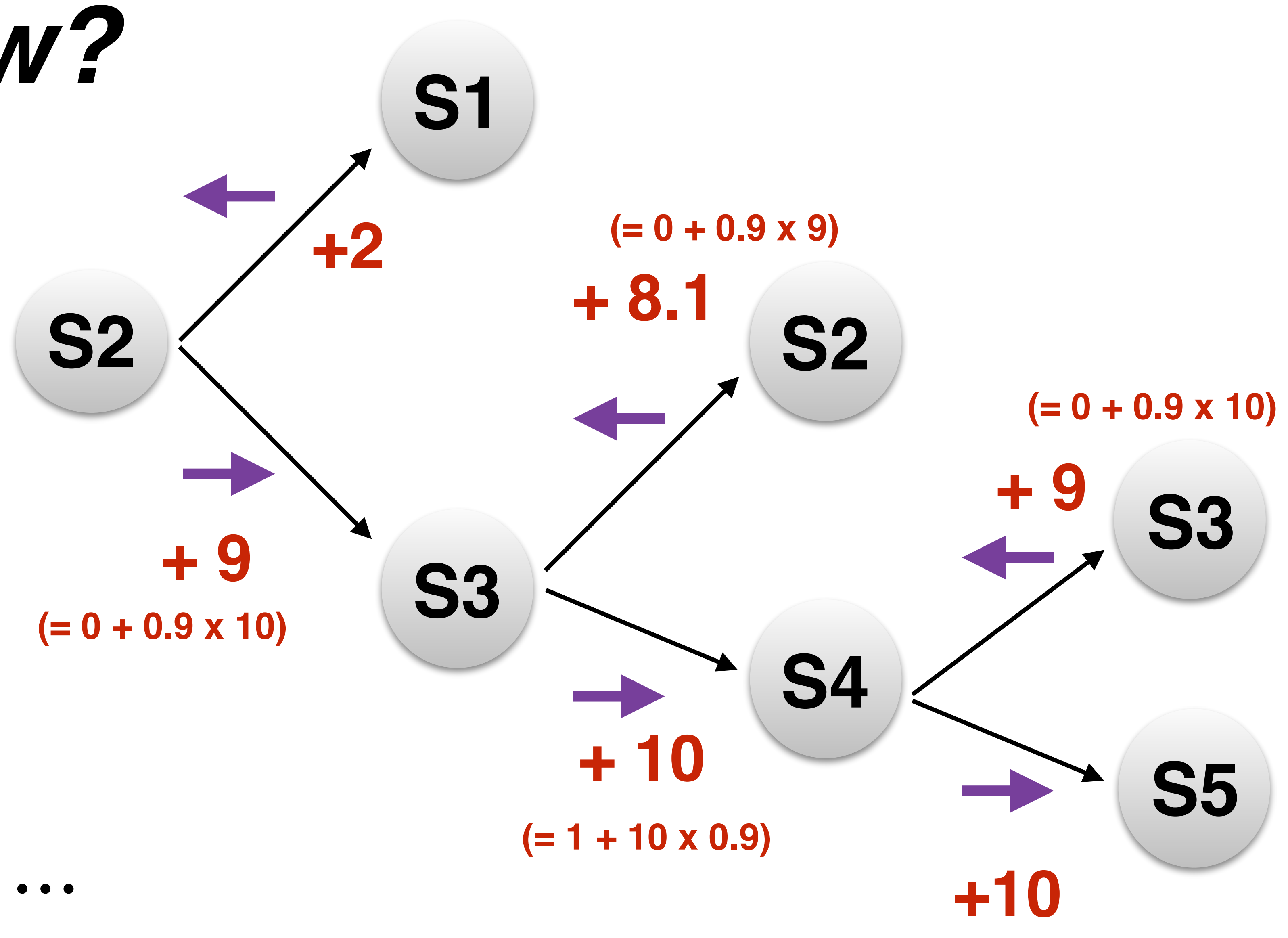
What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$\begin{array}{cc} & \#\text{actions} \\ Q = & \begin{pmatrix} 0 & 0 \\ 2 & 9 \\ 8.1 & 10 \\ 9 & 10 \\ 0 & 0 \end{pmatrix} \end{array} \quad \#\text{states}$$

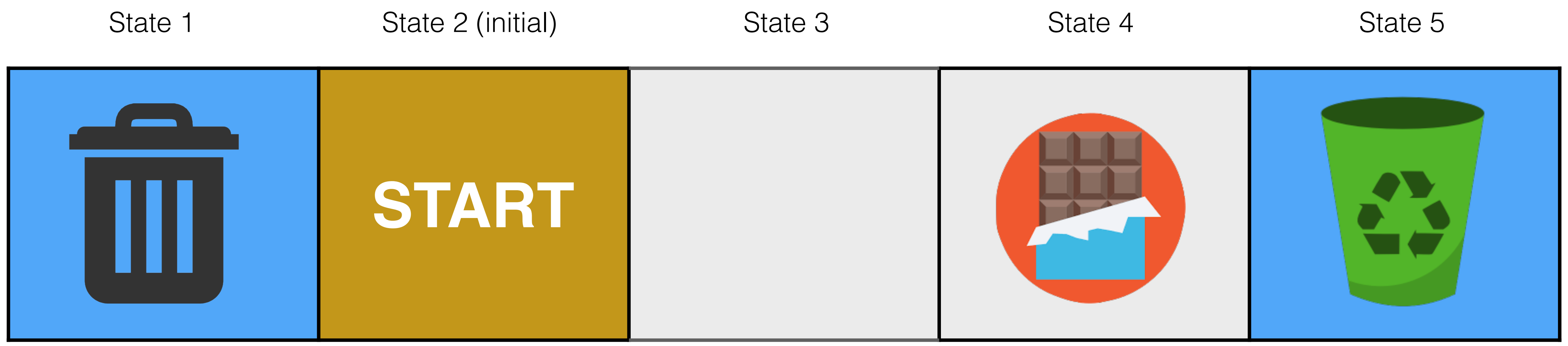
How?



Kian Katanforoosh

II. Recycling is good: an introduction to RL

Problem statement



*Define reward "**r**" in every state*

+2	**0**	**0**	**+1**	**+10**

Best strategy to follow if $\gamma = 0.9$

When state and action spaces are too large, this method has huge memory cost

Function telling us our best strategy

What do we want to learn?

how good is it to take action 1 in state 2

Q-table

$$
\begin{array}{cc}
 & \text{\#actions} \\
Q = \begin{pmatrix} 0 & 0 \\ 2 & 9 \\ 8.1 & 10 \\ 9 & 10 \\ 0 & 0 \end{pmatrix} & \text{\#states}
\end{array}
$$

Bellman equation (optimality equation)

$$Q^*(s,a) = r + \gamma \max_{a'}(Q^*(s',a'))$$

Policy $\pi(s) = \arg\max_{a}(Q^*(s,a))$

Kian Katanforoosh

What we've learned so far:

- *Vocabulary: environment, agent, state, action, reward, total return, discount factor.*

- *Q-table: matrix of entries representing "how good is it to take action a in state s"*

- *Policy: function telling us what's the best strategy to adopt*

- *Bellman equation satisfied by the optimal Q-table*

Kian Katanforoosh

Today's outline

I. Motivation

II. Recycling is good: an introduction to RL

III. Deep Q-Learning

IV. Application of Deep Q-Learning: Breakout (Atari)

V. Tips to train Deep Q-Network

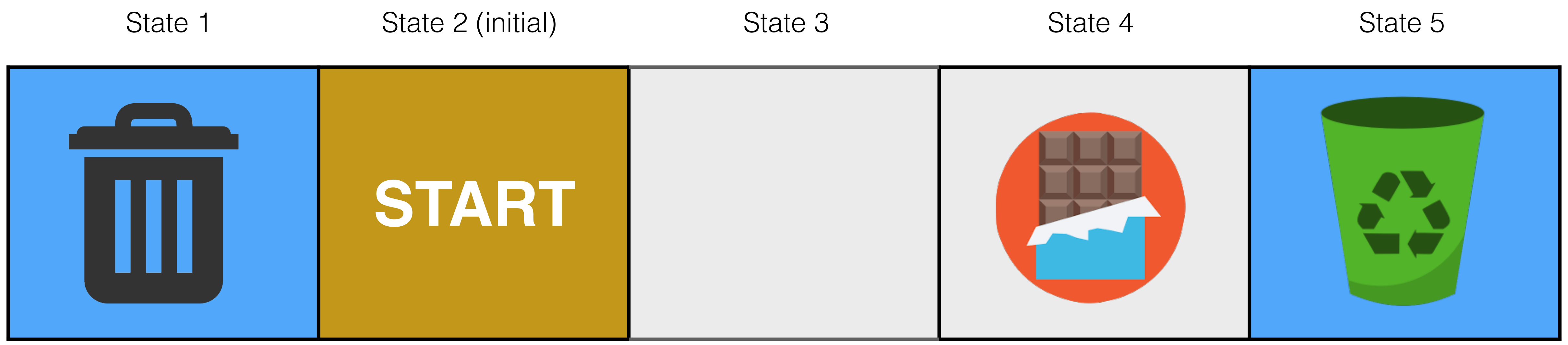
VI. Advanced topics

III. Deep Q-Learning

Main idea: *find a Q-function to replace the Q-table*

Neural Network

Problem statement



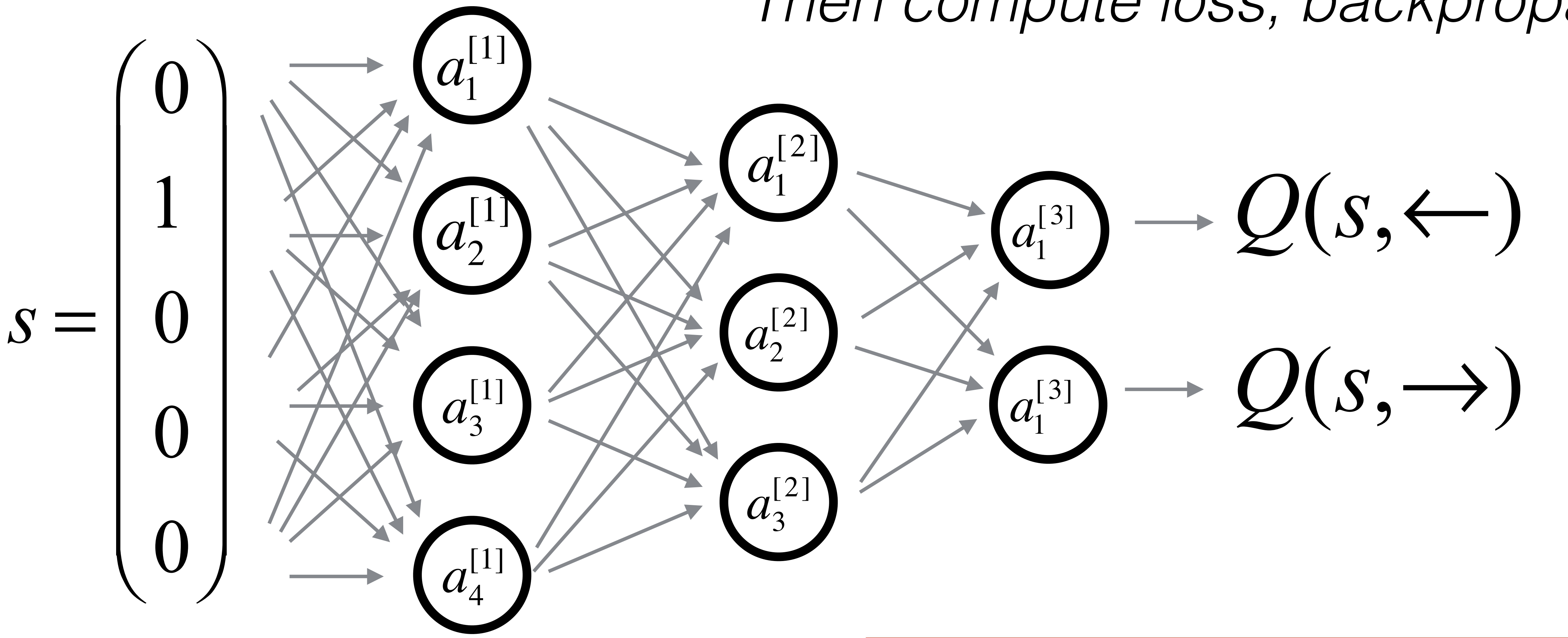
Q-table

#actions

$$Q = \begin{pmatrix} 0 & 0 \\ 2 & 9 \\ 8.1 & 10 \\ 9 & 10 \\ 0 & 0 \end{pmatrix}$$

#states

Then compute loss, backpropagate.

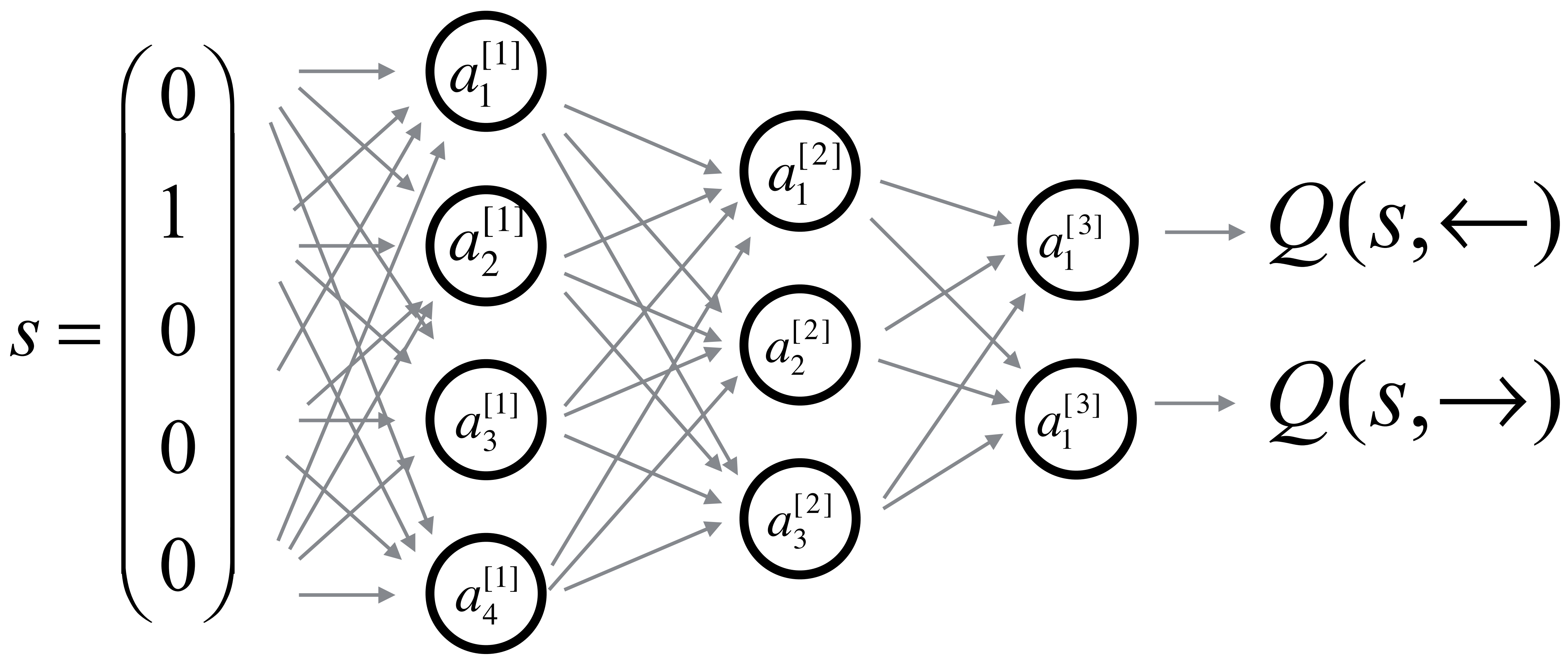


How to compute the loss?

Kian Katanforoosh

III. Deep Q-Learning

$$Q^*(s,a) = r + \gamma \max_{a'}(Q^*(s',a'))$$



Loss function

$$L = (y - Q(s,\leftarrow))^2$$

Target value

Case: $\boxed{Q(s,\leftarrow) > Q(s,\rightarrow)}$

$$y = r_{\leftarrow} + \gamma \max_{a'}(Q(s^{next}_{\leftarrow}, a'))$$

Hold fixed for backprop

Immediate reward for taking action ← in state s

Discounted maximum future reward when you are in state $s^{next}_{\leftarrow}$

Case: $\boxed{Q(s,\leftarrow) < Q(s,\rightarrow)}$

$$y = r_{\rightarrow} + \gamma \max_{a'}(Q(s^{next}_{\rightarrow}, a'))$$

Hold fixed for backprop

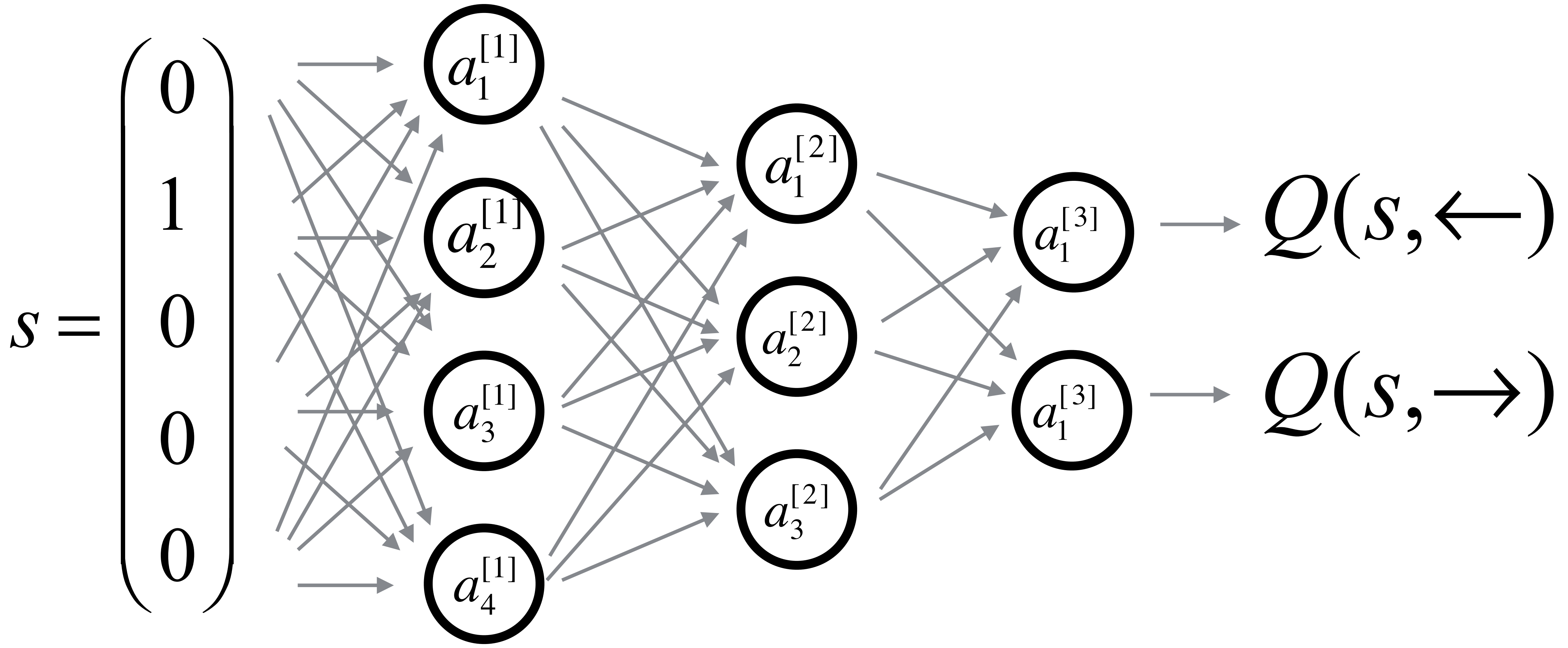
Immediate Reward for taking action → in state s

Discounted maximum future reward when you are in state $s^{next}_{\rightarrow}$

[Francisco S. Melo: Convergence of Q-learning: a simple proof]

Kian Katanforoosh

III. Deep Q-Learning



Loss function (regression)

$$L = (y - Q(s,\rightarrow))^2$$

Target value

Case: $\boxed{Q(s,\leftarrow) > Q(s,\rightarrow)}$

$$y = r_{\leftarrow} + \gamma \max_{a'}(Q(s_{\leftarrow}^{next}, a'))$$

Case: $\boxed{Q(s,\leftarrow) < Q(s,\rightarrow)}$

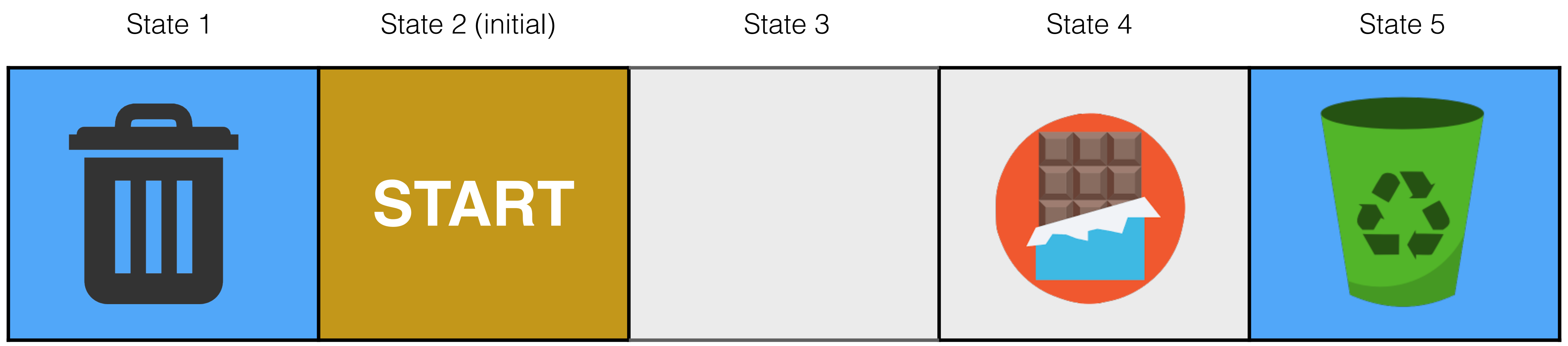
$$y = r_{\rightarrow} + \gamma \max_{a'}(Q(s_{\rightarrow}^{next}, a'))$$

Backpropagation Compute $\frac{\partial L}{\partial W}$ and update W using stochastic gradient descent

Kian Katanforoosh

Recap'

$$y = r_{\leftarrow} + \gamma \max_{a'}(Q(s^{next}_{\leftarrow}, a'))$$



DQN Implementation:

- *Initialize your Q-network parameters*
- *Loop over episodes:*
    - *Start from initial state s*
    - *Loop over time-steps:*
        - *Forward propagate s in the Q-network*
        - *Execute action a (that has the maximum Q(s,a) output of Q-network)*
        - *Observe reward r and next state s'*
        - *Compute targets y by forward propagating state s' in the Q-network, then compute loss.*
        - *Update parameters with gradient descent*

Kian Katanforoosh

Today's outline

I. Motivation

II. Recycling is good: an introduction to RL

III. Deep Q-Networks

IV. Application of Deep Q-Network: Breakout (Atari)

V. Tips to train Deep Q-Network

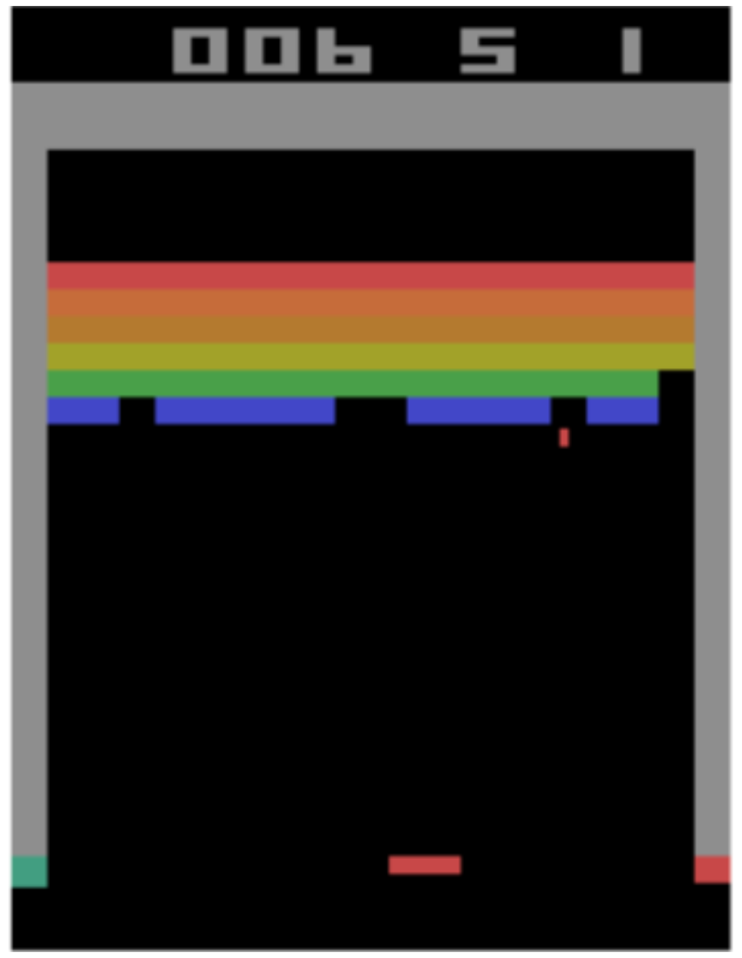
VI. Advanced topics

Goal: play breakout, i.e. destroy all the bricks.

Demo

input of Q-network

s =



Output of Q-network

Q-values

$$\begin{pmatrix} Q(s,\leftarrow) \\ Q(s,\rightarrow) \\ Q(s,-) \end{pmatrix}$$

Would that work?

[Video credits to Two minute papers: Google DeepMind's Deep Q-learning playing Atari Breakout https://www.youtube.com/watch?v=V1eYniJ0Rnk]

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

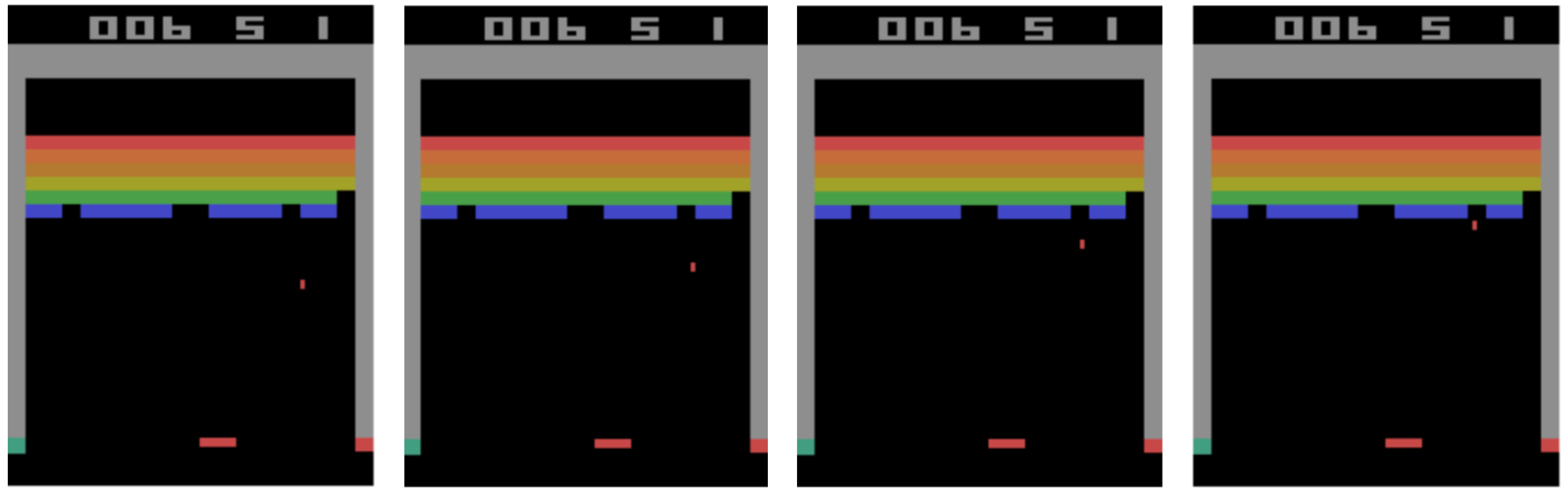
Kian Katanforoosh

IV. Deep Q-Learning application: Breakout (Atari)

Goal: play breakout, i.e. destroy all the bricks.

Demo

input of Q-network

$s =$ 

$\downarrow$

Preprocessing

$\downarrow$

$\phi(s)$

- Convert to grayscale
- Reduce dimensions (h,w)
- History (4 frames)

Output of Q-network

Q-values

$$\begin{pmatrix} Q(s,\leftarrow) \\ Q(s,\rightarrow) \\ Q(s,-) \end{pmatrix}$$

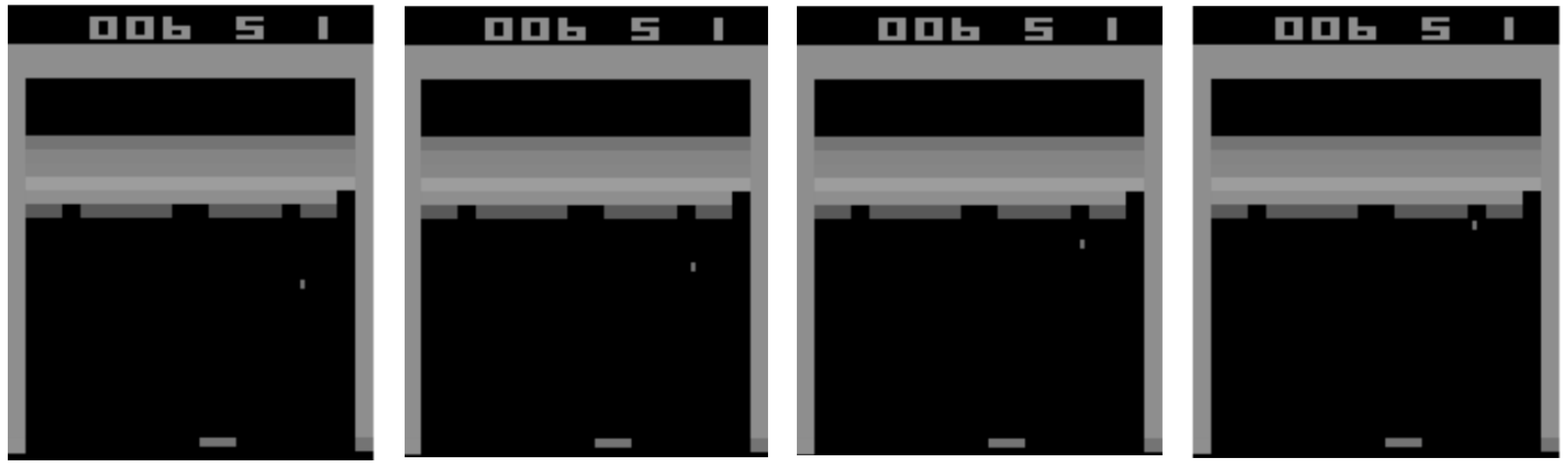
What is done in preprocessing?

[Video credits to Two minute papers: Google DeepMind's Deep Q-learning playing Atari Breakout https://www.youtube.com/watch?v=V1eYniJ0Rnk]
[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

IV. Deep Q-Learning application: Breakout (Atari)

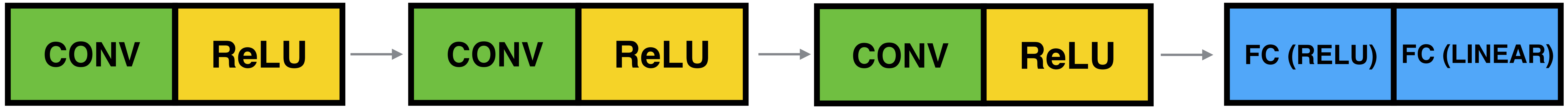
input of Q-network

$$\phi(s) =$$



Deep Q-network architecture?

$$\phi(s) \rightarrow$$



$$\rightarrow \begin{pmatrix} Q(s,\leftarrow) \\ Q(s,\rightarrow) \\ Q(s,-) \end{pmatrix}$$

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Recap' (+ preprocessing + terminal state)

Some training challenges:
- Keep track of terminal step
- Experience replay
- Epsilon greedy action choice (Exploration / Exploitation tradeoff)

DQN Implementation:

- *Initialize your Q-network parameters*
- *Loop over episodes:*
  - *Start from initial state* $\cancel{s}$ $\phi(s)$
  - *Loop over time-steps:*
    - *Forward propagate* $\cancel{s}$ $\phi(s)$ *in the Q-network*
    - *Execute action a (that has the maximum Q(*$\cancel{s}$ $\phi(s)$*,a) output of Q-network)*
    - *Observe reward r and next state s'*
    - ***Use s' to create*** $\phi(s')$
    - *Compute targets y by forward propagating state* $\cancel{s'}$ $\phi(s')$ *in the Q-network, then compute loss.*
    - *Update parameters with gradient descent*

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Recap' (+ preprocessing + terminal state)

Some training challenges:

- Keep track of terminal step
- Experience replay
- Epsilon greedy action choice (Exploration / Exploitation tradeoff)

DQN Implementation:

- *Initialize your Q-network parameters*
- *Loop over episodes:*
  - *Start from initial state* ~~*s*~~ $\phi(s)$
  - *Loop over time-steps:*
    - *Forward propagate* ~~*s*~~ $\phi(s)$ *in the Q-network*
    - *Execute action a (that has the maximum Q(*~~*s*~~ $\phi(s)$*,a) output of Q-network)*
    - *Observe reward r and next state s'*
    - ***Use s' to create*** $\phi(s')$
    - *Compute targets y by forward propagating state* ~~*s'*~~ $\phi(s')$ *in the Q-network, then compute loss.*
    - *Update parameters with gradient descent*

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Recap' (+ preprocessing + terminal state)

DQN Implementation:

- *Initialize your Q-network parameters*
- *Loop over episodes:*
  - *Start from initial state ~~s~~* $\phi(s)$
  - ***Create a boolean to detect terminal states: terminal = False***
  - *Loop over time-steps:*
    - *Forward propagate ~~s~~* $\phi(s)$ *in the Q-network*
    - *Execute action a (that has the maximum Q(~~s~~* $\phi(s)$*,a) output of Q-network)*
    - *Observe reward r and next state s'*
    - *Use s' to create* $\phi(s')$
    - ***Check if s' is a terminal state.*** *Compute targets y by forward propagating state ~~s~~* $\phi(s')$ *in the Q-network, then compute loss.*
    - *Update parameters with gradient descent*

$$\begin{cases} if \quad terminal = False \quad : \quad y = r + \gamma \max_{a'}(Q(s',a')) \\ if \quad terminal = True \quad : \quad y = r \qquad (break) \end{cases}$$

Some training challenges:

- Keep track of terminal step
- Experience replay
- Epsilon greedy action choice (Exploration / Exploitation tradeoff)

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

IV - DQN training challenges

Experience replay

1 experience (leads to one iteration of gradient descent)

Current method is to start from initial state s and follow:

E1 $\phi(s) \rightarrow a \rightarrow r \rightarrow \phi(s')$

E2 $\phi(s') \rightarrow a' \rightarrow r' \rightarrow \phi(s'')$

E3 $\phi(s'') \rightarrow a'' \rightarrow r'' \rightarrow \phi(s''')$

...

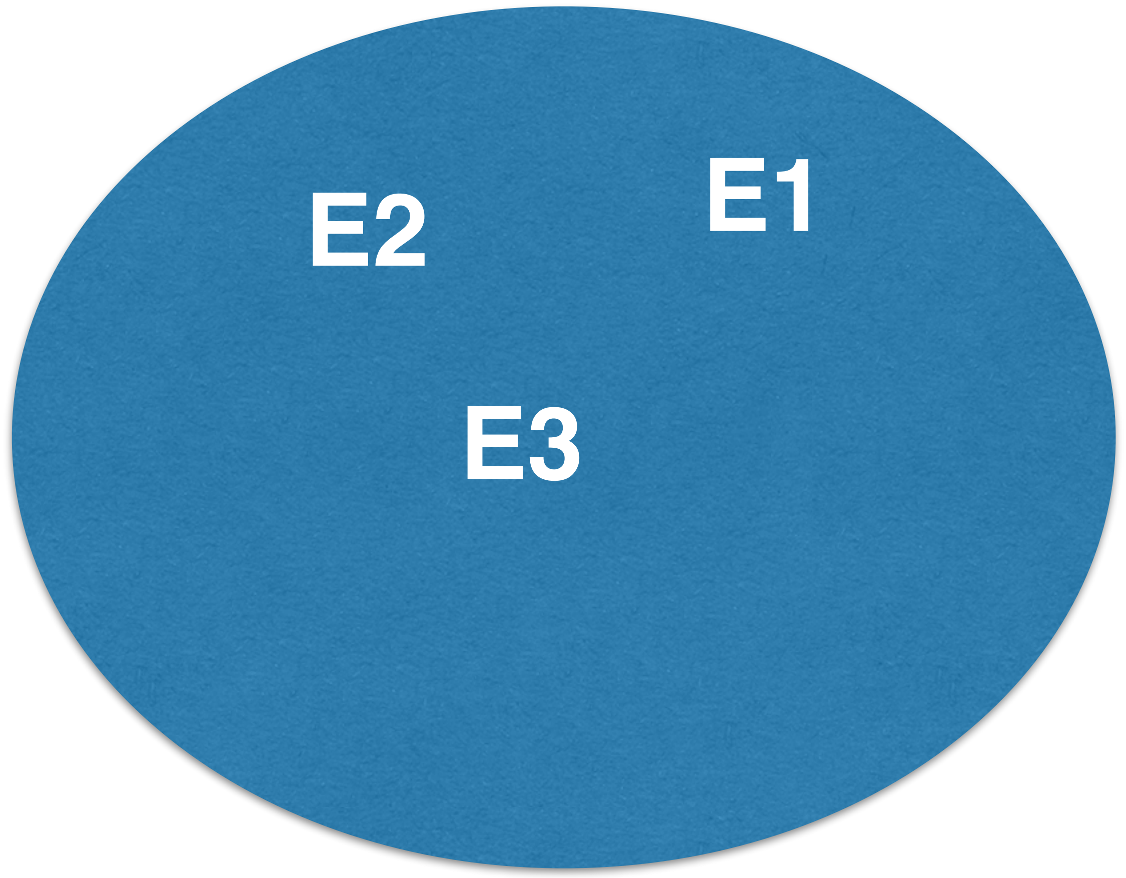
Experience Replay

E1

E2

E3

...



Replay memory (D)

Training: E1 → E2 → E3

Training: E1 → sample(E1, E2) → sample(E1, E2, E3) → sample(E1, E2, E3, E4) → ...

Can be used with mini batch gradient descent

Advantages of experience replay?

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Recap' (+ experience replay)

DQN Implementation:

- *Initialize your Q-network parameters*
- ***Initialize replay memory D***
- *Loop over episodes:*
  - *Start from initial state* $\phi(s)$
  - *Create a boolean to detect terminal states: terminal = False*
  - *Loop over time-steps:*
    - *Forward propagate* $\phi(s)$ *in the Q-network*
    - *Execute action a (that has the maximum Q(*$\phi(s)$*,a) output of Q-network)*
    - *Observe reward r and next state s'*
    - *Use s' to create* $\phi(s')$
    - ***Add experience*** $(\phi(s),a,r,\phi(s'))$ ***to replay memory (D)***
    - ***Sample random mini-batch of transitions from D***
    - *Check if s' is a terminal state. Compute targets y by forward propagating state* $\phi(s')$ *in the Q-network, then compute loss.*
    - *Update parameters with gradient descent*

Some training challenges:
- Keep track of terminal step
- Experience replay
- Epsilon greedy action choice (Exploration / Exploitation tradeoff)

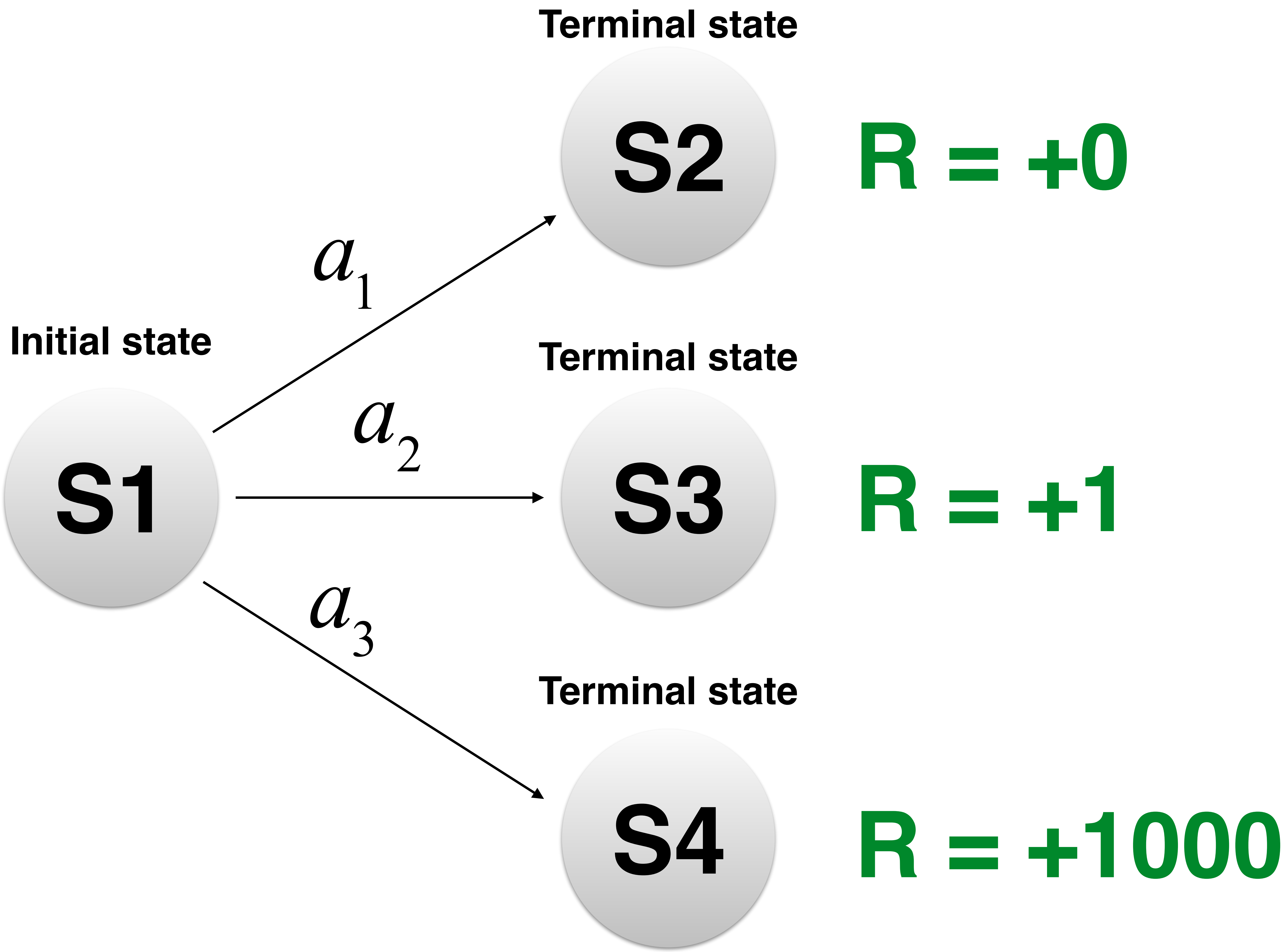
The transition resulting from this is added to D, and will not necessarily be used in this iteration's update!

Update using sampled transitions

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Exploration vs. Exploitation



Just after initializing the Q-network, we get:

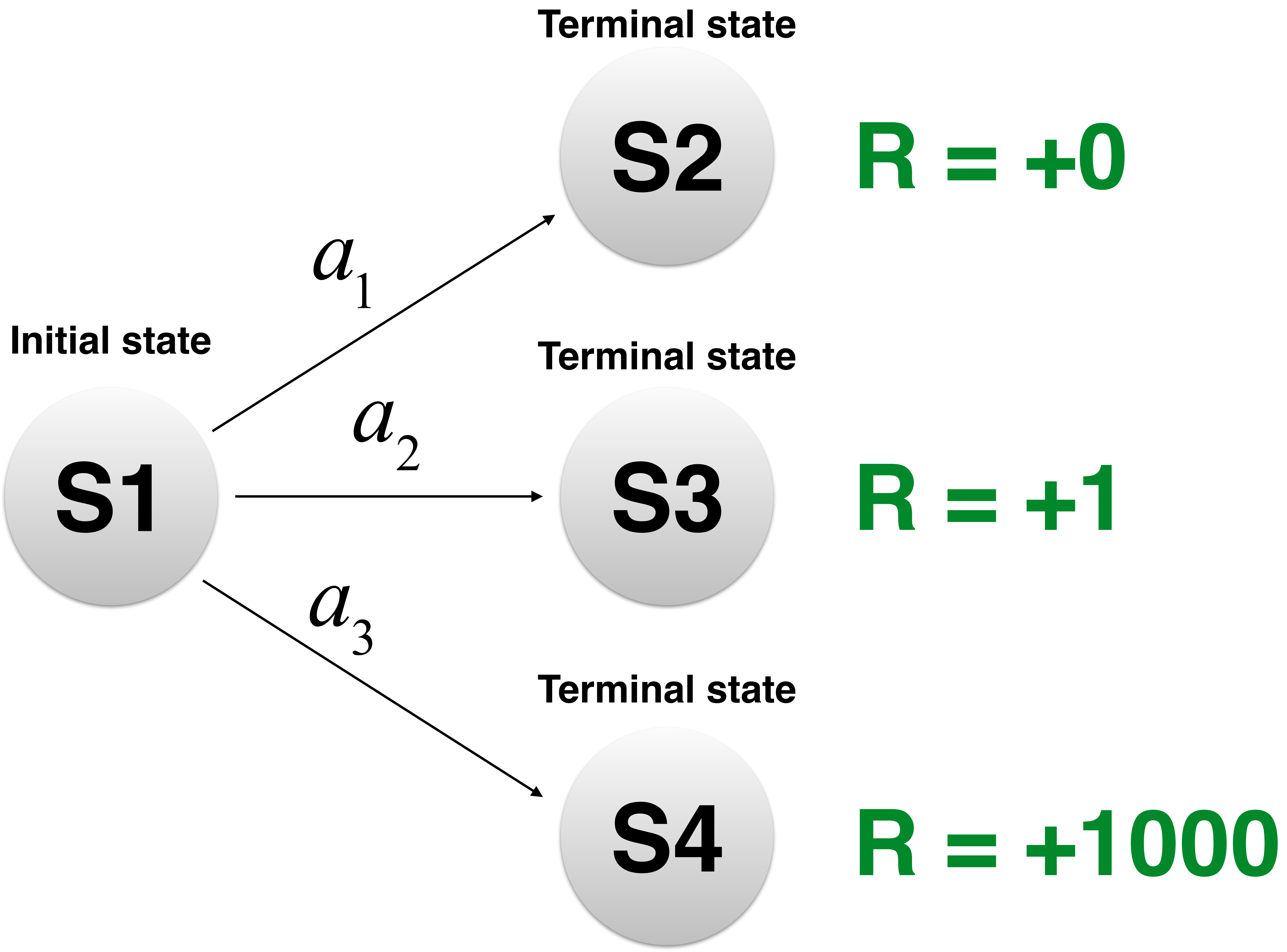
$$Q(S1, a_1) = 0.5$$

$$Q(S1, a_2) = 0.4$$

$$Q(S1, a_3) = 0.3$$

Kian Katanforoosh

Exploration vs. Exploitation



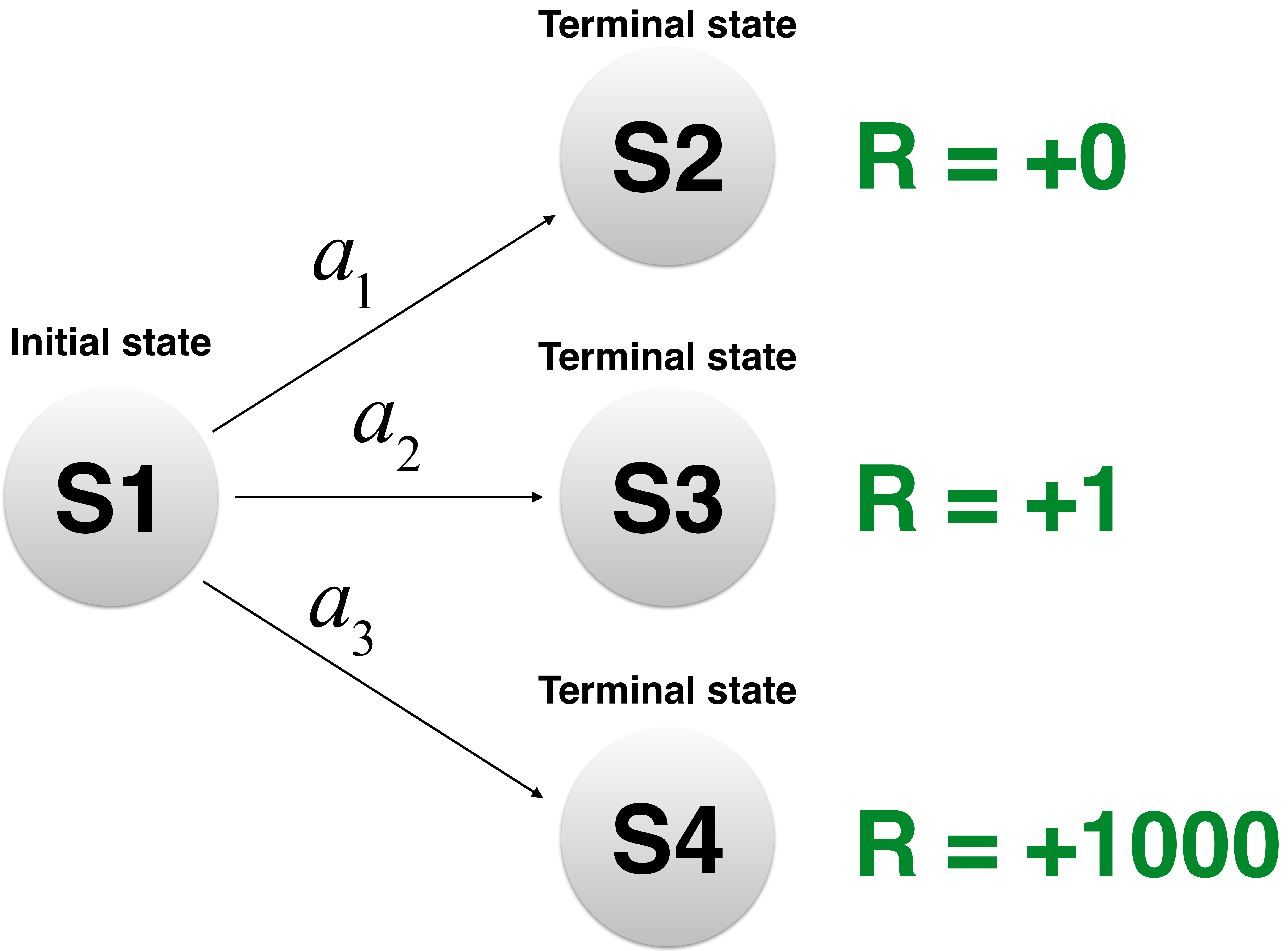
Just after initializing the Q-network, we get:

$$Q(S1, a_1) = \cancel{0.5} \quad 0$$

$$Q(S1, a_2) = 0.4$$

$$Q(S1, a_3) = 0.3$$

Exploration vs. Exploitation



Just after initializing the Q-network, we get:

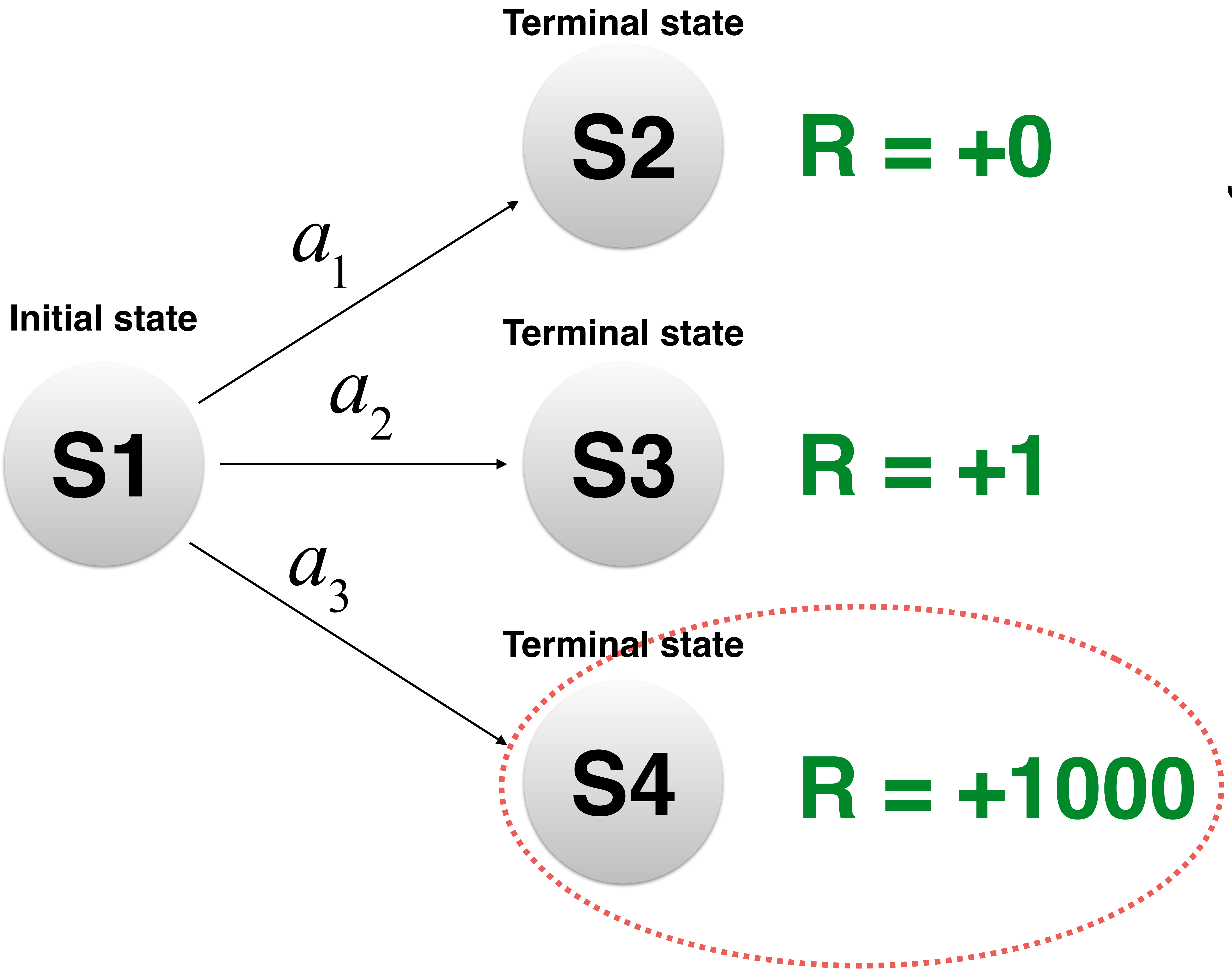
$$Q(S1, a_1) = \cancel{0.5} \quad 0$$

$$Q(S1, a_2) = \cancel{0.4} \quad 1$$

$$Q(S1, a_3) = 0.3$$

Kian Katanforoosh

Exploration vs. Exploitation



Just after initializing the Q-network, we get:

$$Q(S1, a_1) = \cancel{0.5} \quad 0$$

$$Q(S1, a_2) = \cancel{0.4} \quad 1$$

$$Q(S1, a_3) = 0.3$$

Will never be visited, because Q(S1,a3) < Q(S1,a2)

Kian Katanforoosh

Recap’ (+ epsilon greedy action)

DQN Implementation:

- *Initialize your Q-network parameters*
- *Initialize replay memory D*

- *Loop over episodes:*

    - *Start from initial state* $\phi(s)$

    - *Create a boolean to detect terminal states: terminal = False*

    - *Loop over time-steps:*

        - ***With probability epsilon, take random action a.***
        - ***Otherwise:***
            - *Forward propagate* $\phi(s)$ *in the Q-network*
            - *Execute action a (that has the maximum Q(*$\phi(s)$*,a) output of Q-network).*

        - *Observe reward r and next state s’*

        - *Use s’ to create* $\phi(s')$

        - *Add experience* $(\phi(s), a, r, \phi(s'))$ *to replay memory (D)*

        - *Sample random mini-batch of transitions from D*

        - *Check if s’ is a terminal state. Compute targets y by forward propagating state* $\phi(s')$ *in the Q-network, then compute loss.*

        - *Update parameters with gradient descent*

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Overall recap'

DQN Implementation:

- *Initialize your Q-network parameters*
- ***Initialize replay memory D***
- *Loop over episodes:*
  - *Start from initial state* $\phi(s)$
  - ***Create a boolean to detect terminal states: terminal = False***
  - *Loop over time-steps:*
    - ***With probability epsilon, take random action a.***
    - ***Otherwise:***
      - *Forward propagate* $\phi(s)$ *in the Q-network*
      - *Execute action a (that has the maximum Q(*$\phi(s)$*,a) output of Q-network).*
    - *Observe rewards r and next state s'*
    - ***Use s' to create*** $\phi(s')$
    - ***Add experience*** $(\phi(s), a, r, \phi(s'))$ ***to replay memory (D)***
    - ***Sample random mini-batch of transitions from D***
    - ***Check if s' is a terminal state****. Compute targets y by forward propagating state* $\phi(s')$ *in the Q-network, then compute loss.*
    - *Update parameters with gradient descent*

- **Preprocessing**
- **Detect terminal state**
- **Experience replay**
- **Epsilon greedy action**

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

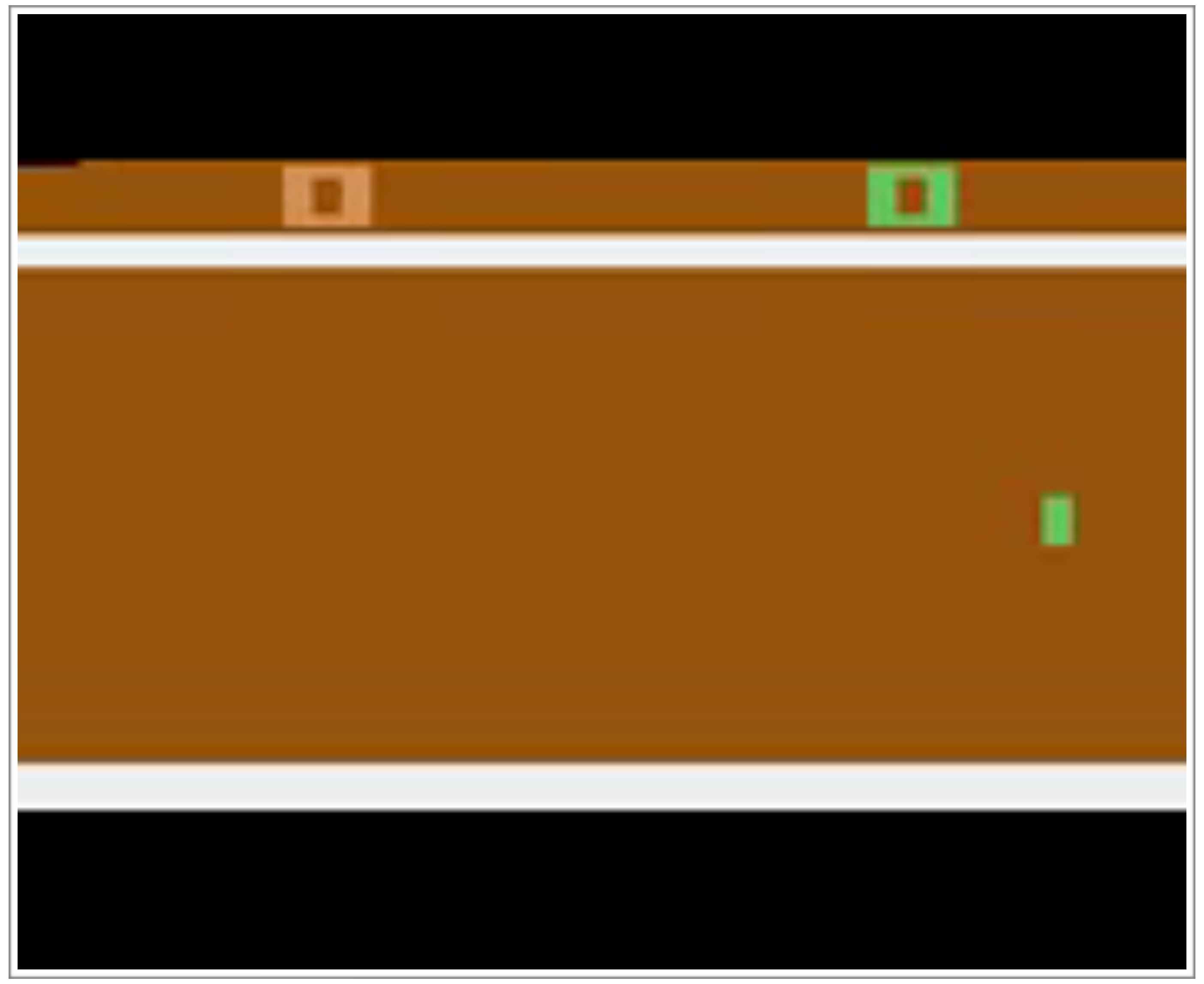
Results

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]
[Credits: DeepMind, DQN Breakout - https://www.youtube.com/watch?v=TmPfTpjtdgg]

Kian Katanforoosh

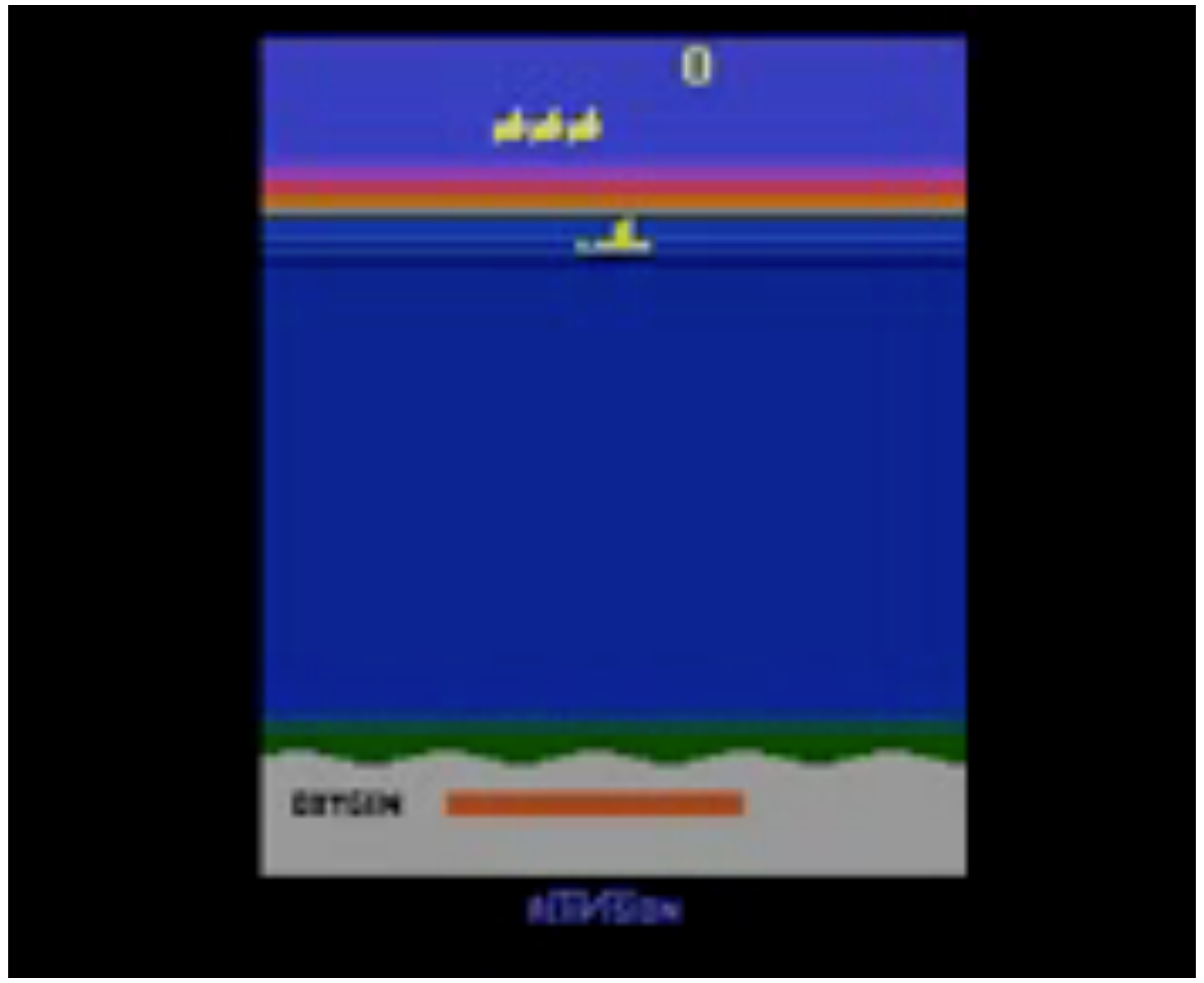
Other Atari games

Pong



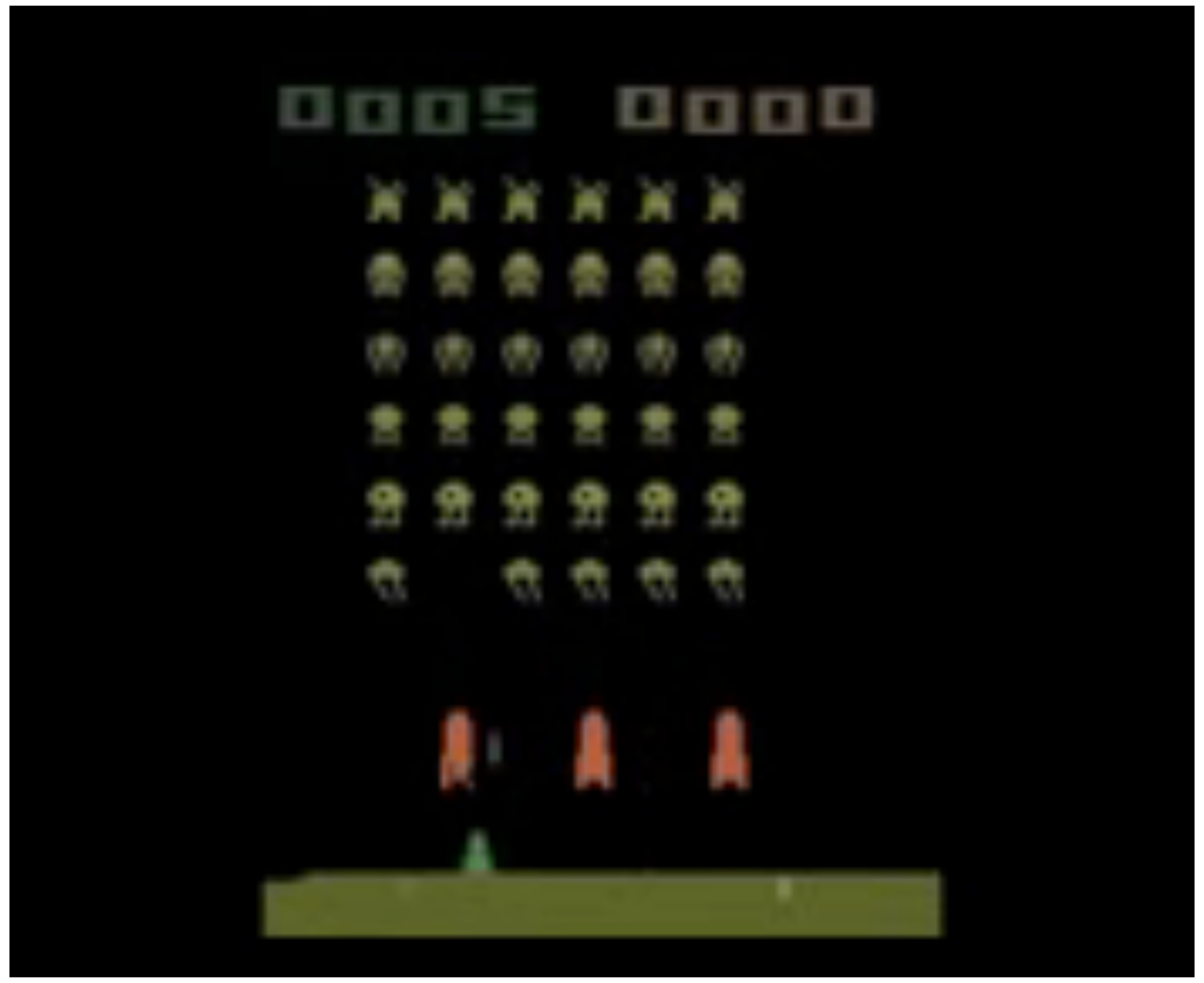
[Chia-Hsuan Lee, Atari Seaquest Double DQN Agent - https://www.youtube.com/watch?v=NirMkC5uvWU]

SeaQuest



[moooopan, Deep Q-Network Plays Atari 2600 Pong - https://www.youtube.com/watch?v=p88R2_3yWPA]

Space Invaders



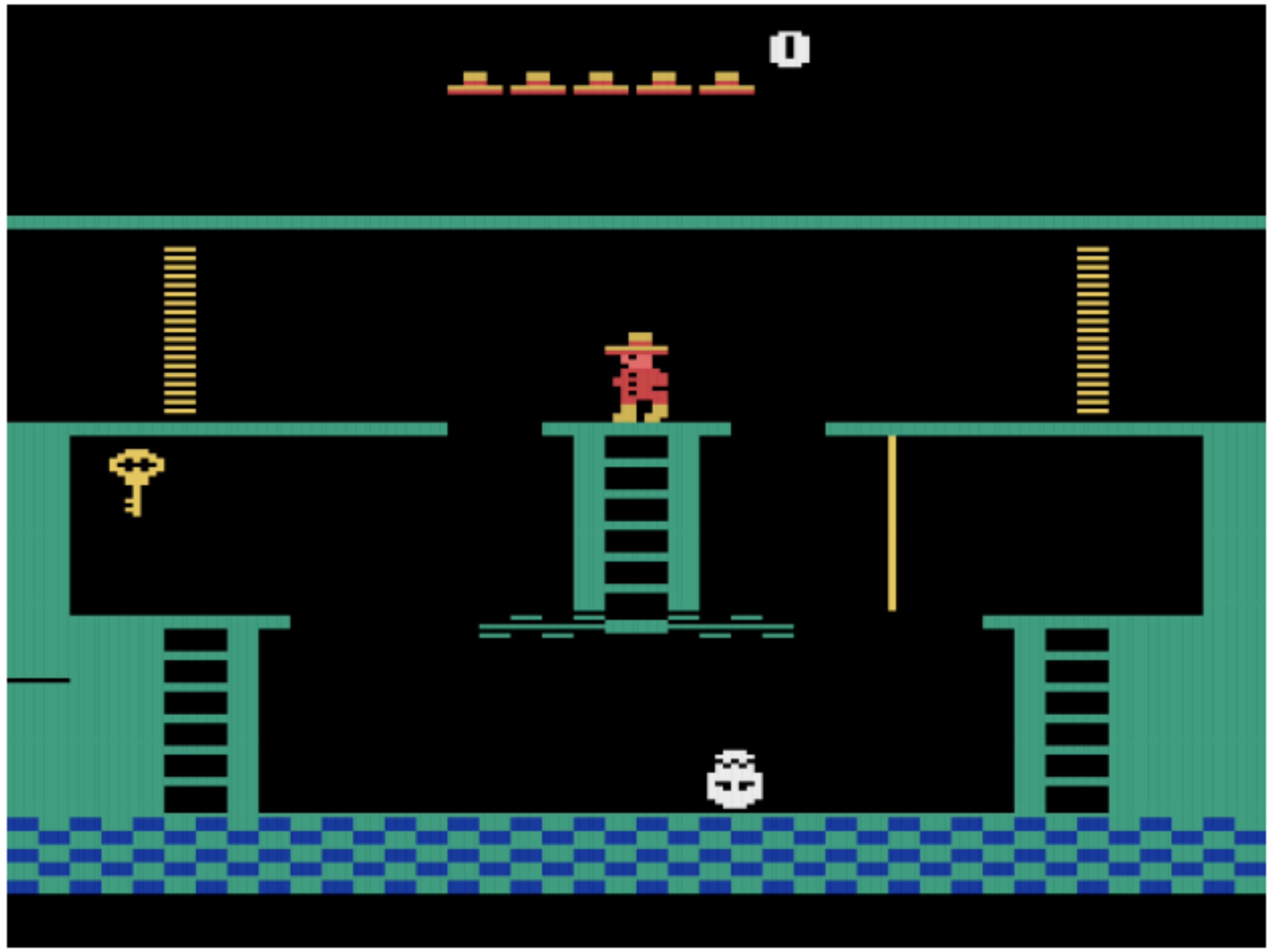
[DeepMind: DQN SPACE INVADERS - https://www.youtube.com/watch?v=W2CAghUiofY&t=2s]

[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

Kian Katanforoosh

Difference between with and without human knowledge

Imitation learning



[Source: Bellemare et al. (2016): Unifying Count-Based Exploration and Intrinsic Motivation]

[Ho et al. (2016): Generative Adversarial Imitation Learning]

Today's outline

I. Motivation

II. Recycling is good: an introduction to RL

III. Deep Q-Networks

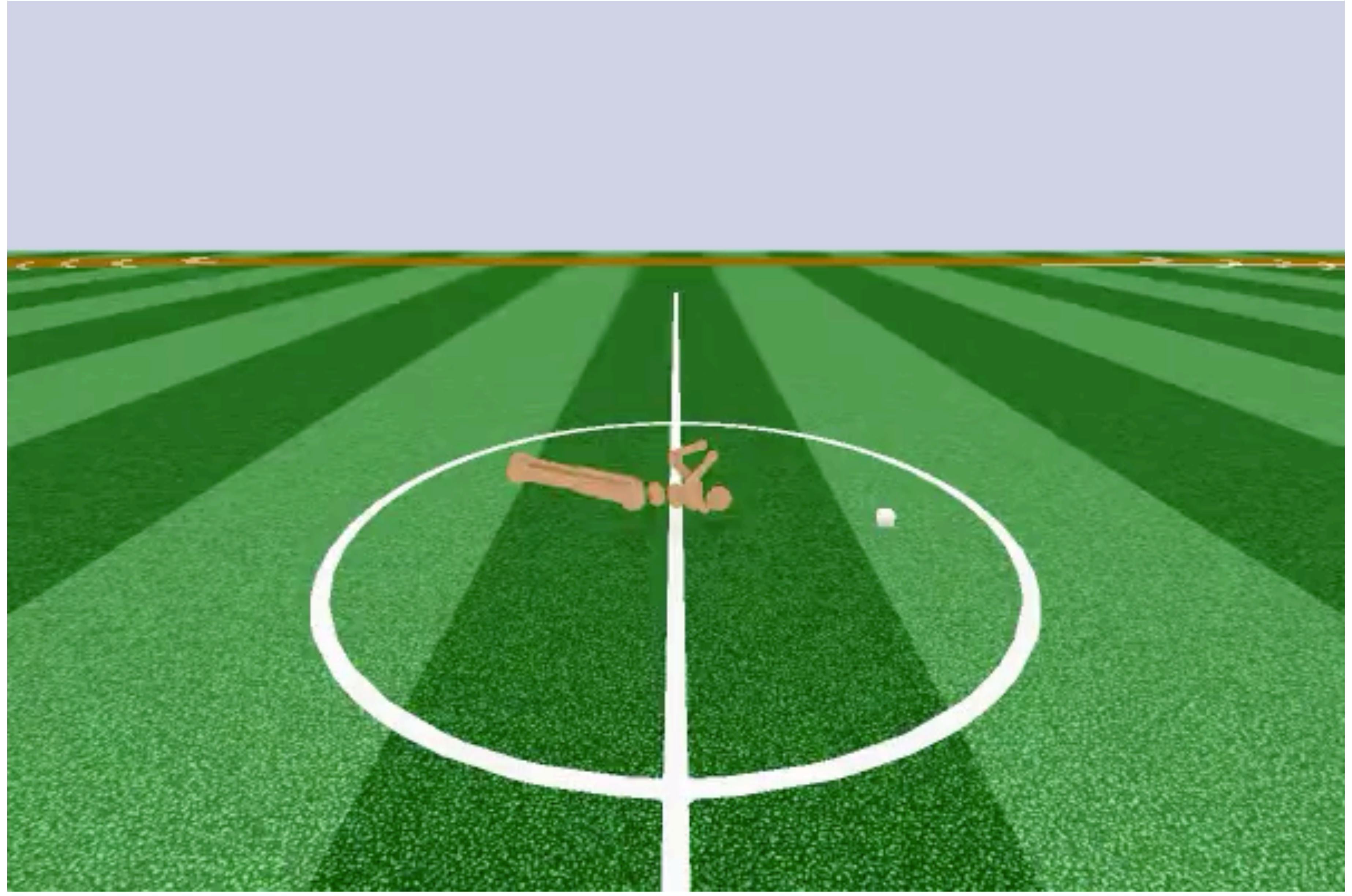
IV. Application of Deep Q-Network: Breakout (Atari)

V. Tips to train Deep Q-Network

VI. Advanced topics

Policy Gradient Methods

PPO



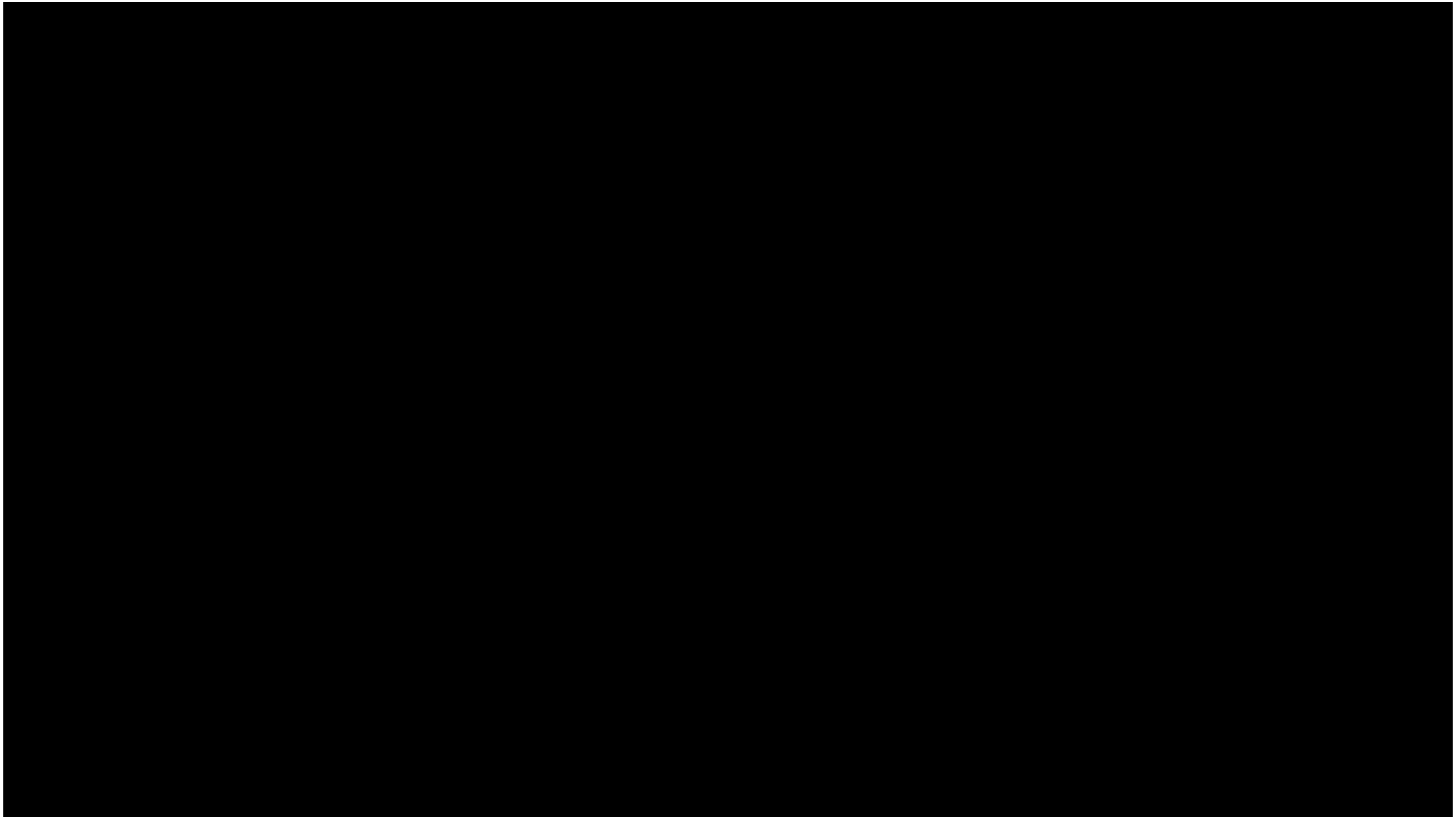
[Open AI Blog]

TRPO

[TRPO]

[Schulman et al. (2017): Trust Region Policy Optimization]
[Schulman et al. (2017): Proximal Policy Optimization]

VI - Advanced topics Competitive self-play



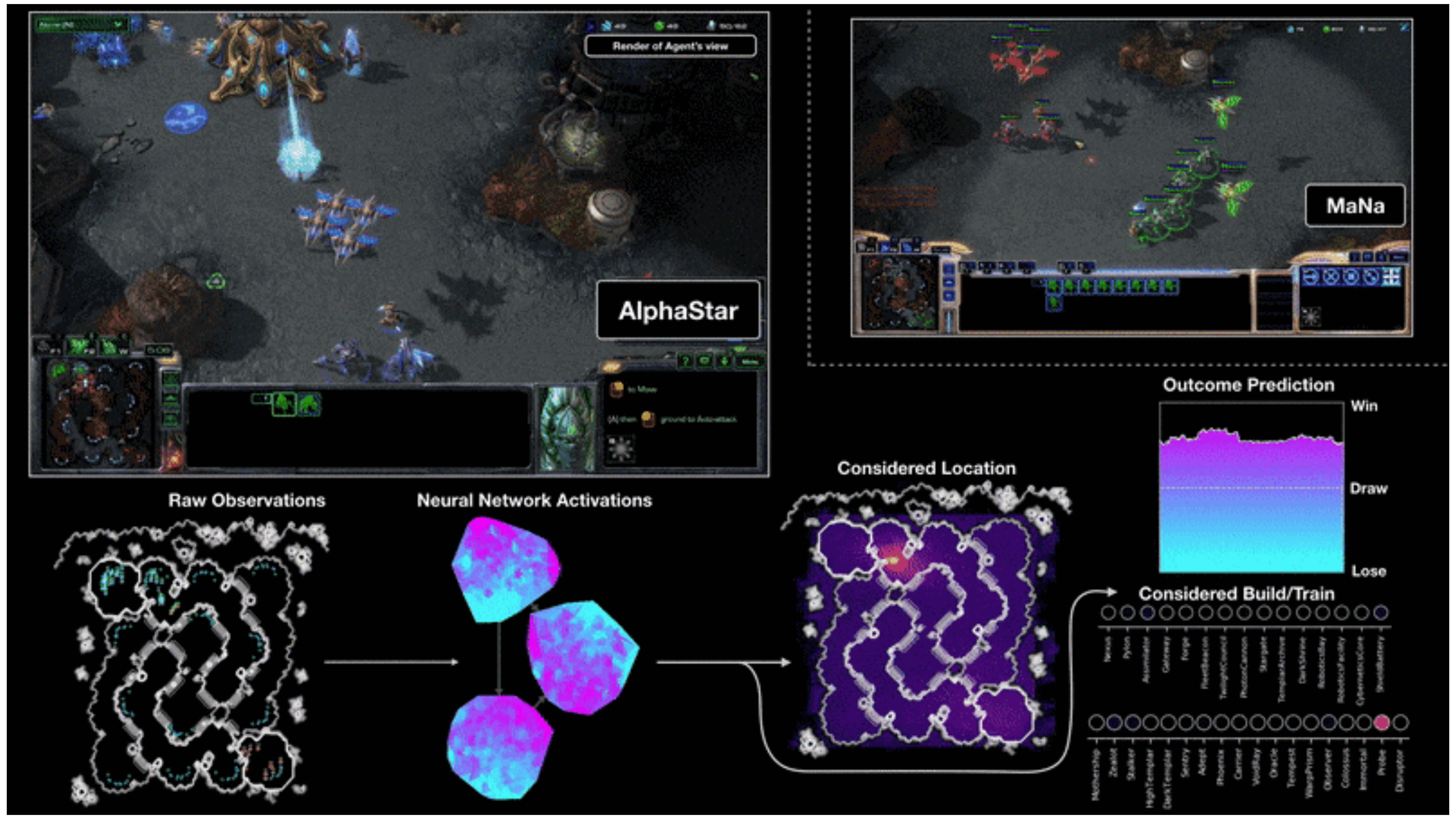
[Bansal et al. (2017): Emergent Complexity via multi-agent competition]
[OpenAI Blog: Competitive self-play]

VI - Advanced topics

Open AI Five

[OpenAI Blog Five]

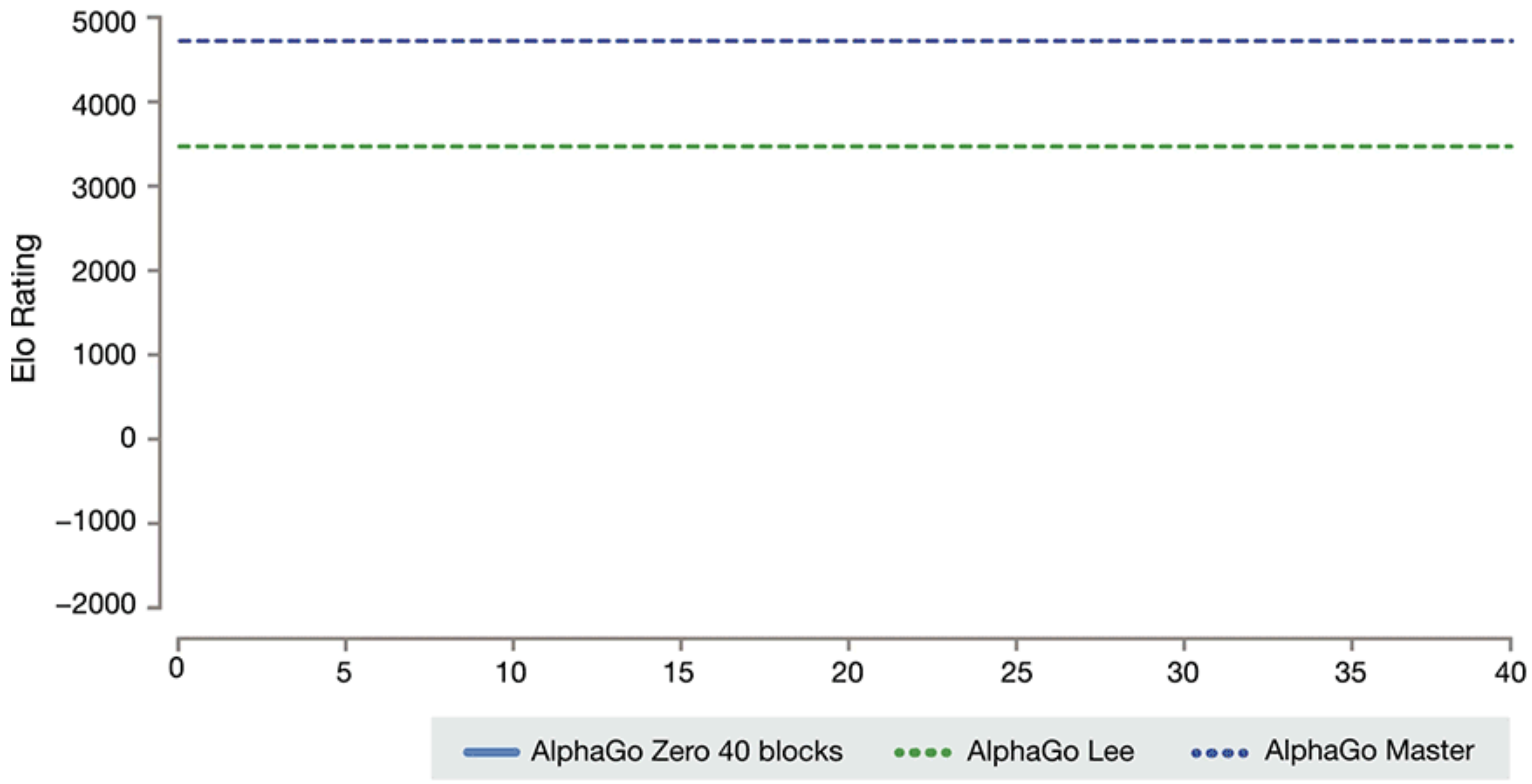
Deep Mind: Alpha Star



AlphaStar: Mastering the Real-Time Strategy Game StarCraft

Kian Katanforoosh

Alpha Go



[DeepMind Blog]

[Silver, Schrittwieser, Simonyan et al. (2017): Mastering the game of Go without human knowledge]

Announcements

This week is the project week!

Tips: If you're interested in testing your ML/DL skills or preparing for job interviews in AI, you can take the Workera assessment.

Note: Please monitor your AWS credits and idle instances to ensure you're within your budget!

Kian Katanforoosh