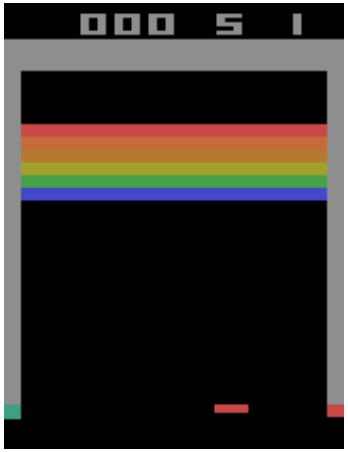


Deep Reinforcement Learning

Jay Urbain, PhD

Credits:

Mnih, V., Kavukcuoglu, K., Silver, D., Graves, A., Antonoglou, I., Wierstra, D., & Riedmiller, M. (2013). Playing atari with deep reinforcement learning. *arXiv preprint arXiv:1312.5602*.

https://arxiv.org/abs/1312.5602

Mnih, V., Kavukcuoglu, K., Silver, D., Rusu, A. A., Veness, J., Bellemare, M. G., ... & Petersen, S. (2015). Human-level control through deep reinforcement learning. *Nature*, *518*(7540), 529.

https://daiwk.github.io/assets/dqn.pdf

Andrew Ng, Kian Katanforoosh, Stanford

Topics

- Motivation
- RL Review
- Deep Q-Learning
- Application of Deep Q-Learning: Breakout (Atari)
- Training Deep Q-Networks
- Advanced topics

Demis Hassabis - Deep Mind's CEO

- "In the pursuit of the AGI (Artificial General Intelligence), we need to widen the domains in which our agents excel. Creating a program that solves a single game is no longer a challenge and it stands true even for the relatively complex games with enormous search spaces like Chess (Deep Blue) or Go (Alpha Go). The real challenge would be to create an agent that can solve multiple tasks."
- *"We have a prototype of this - the human brain. We can tie our shoelaces, we can ride cycles and we can do physics with the same architecture. So we know this is possible. "*

Motivation – Amazing Results

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.

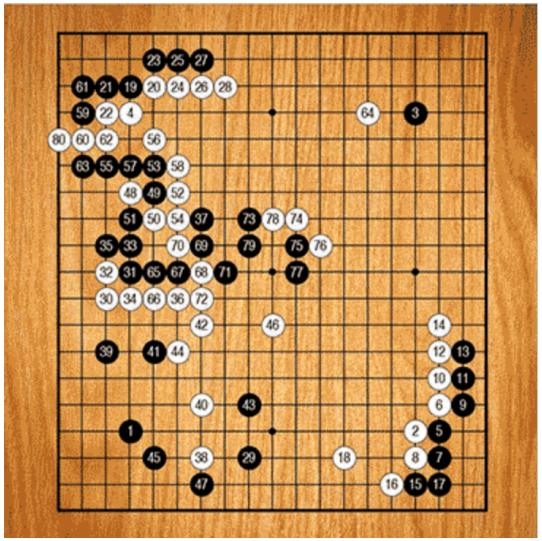
A long-standing goal of artificial intelligence is an algorithm that learns, *tabula rasa*, superhuman proficiency in challenging domains. Recently, *AlphaGo* became the first program to defeat a world champion in the game of Go. The tree search in *AlphaGo* evaluated positions and selected moves using 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

[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]

Motivation

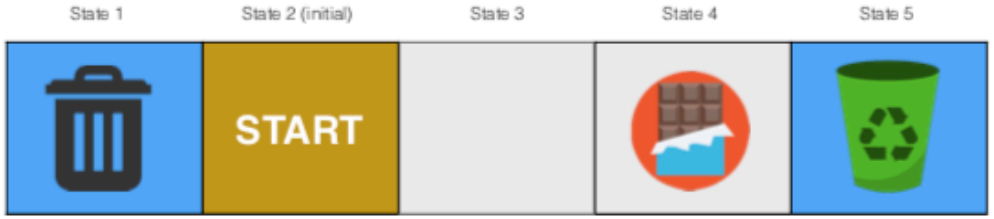
- *How would you solve Go with supervised learning?*
- **Issues:**
  - Ground truth for supervised learning is probably incorrectly defined.
  - Two many states in the game.
  - Unlikely to generalize.
- **Why RL?**
  - Delayed labels
    Making sequences of decisions
- **What is RL?**
  - Automatically learn to make good sequences of decision



RL Q-Learning Review

Andrew Ng, Kian Katanforoosh, Stanford

Problem statement



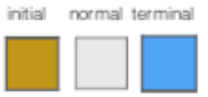
*Define reward "**r**" in every state*

Best strategy to follow if $\gamma = 1$

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

***Number of states**: 5*

***Types of states**:*



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

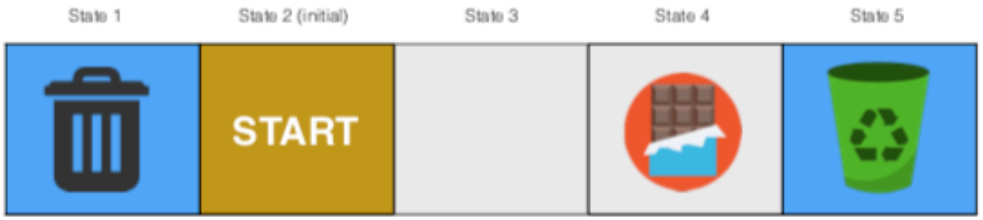
***Additional rule:** garbage collector coming in 3min, it takes 1min to move between states*

How to define the long-term return?

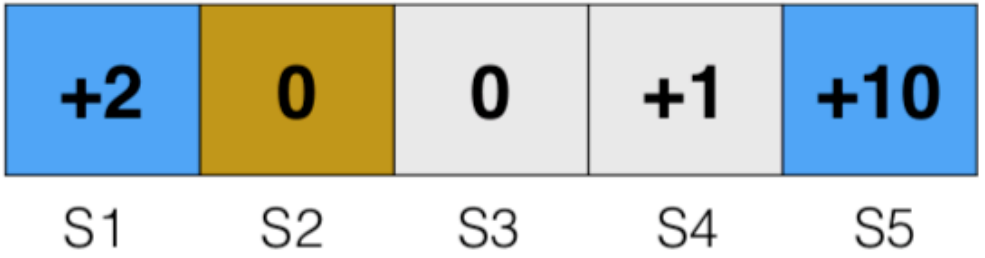
Discounted return $R = \sum_{t=0}^{\infty} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \dots$

RL

Problem statement



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



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

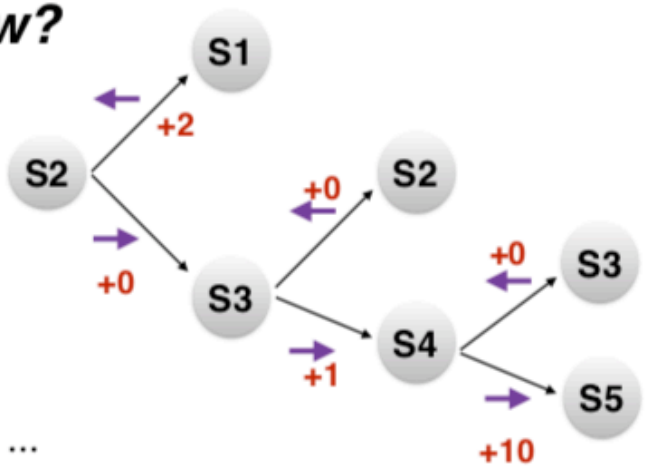
Q-table

$$Q = \begin{pmatrix} Q_{11} & Q_{12} \\ Q_{21} & Q_{22} \\ Q_{31} & Q_{32} \\ Q_{41} & Q_{42} \\ Q_{51} & Q_{52} \end{pmatrix}$$

#actions

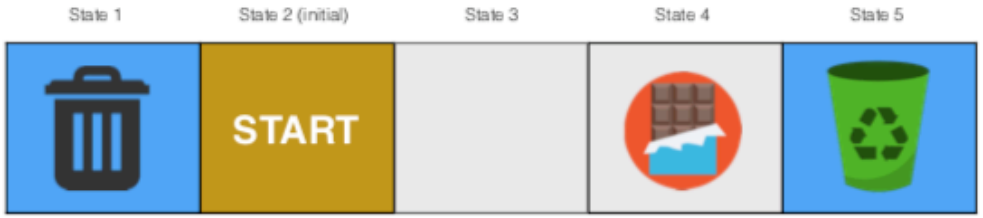
#states

How?



RL

Problem statement



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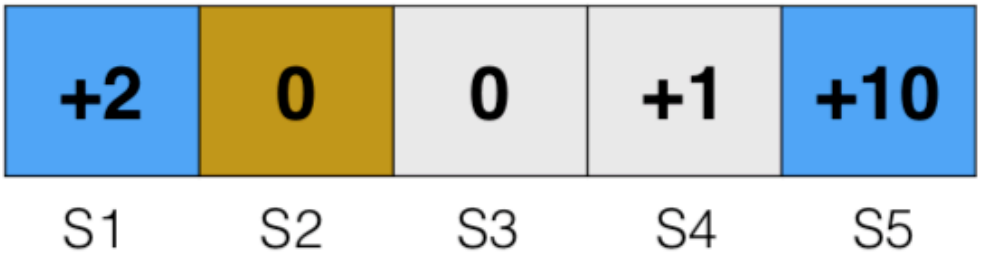

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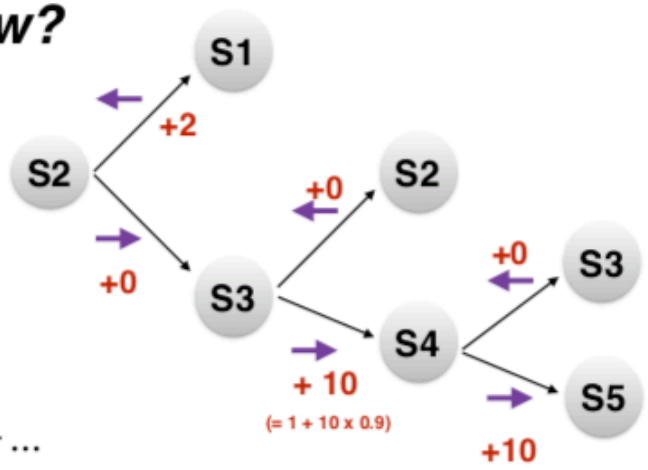

RL

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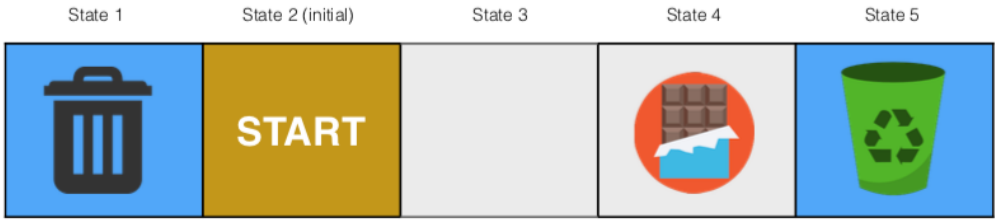

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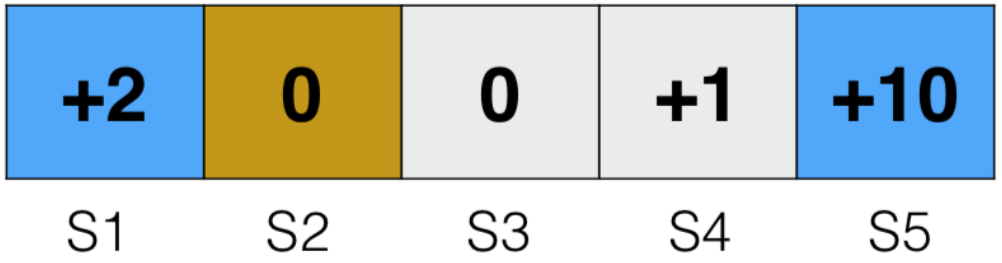

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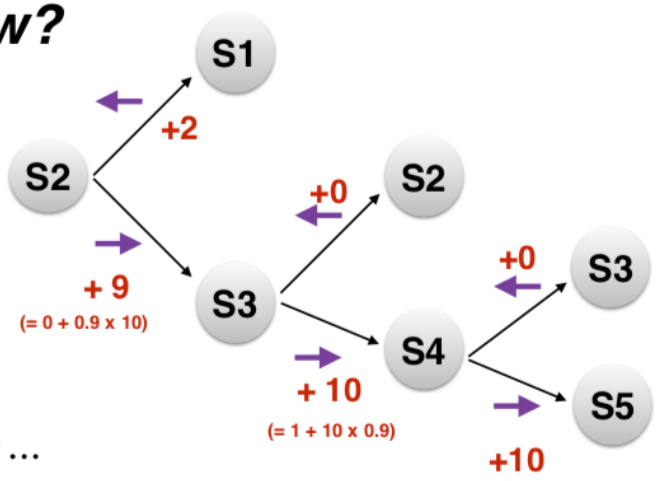

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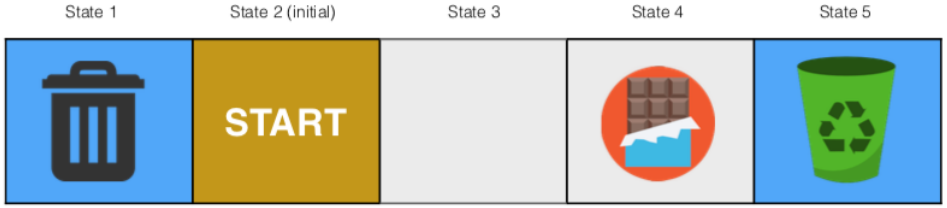

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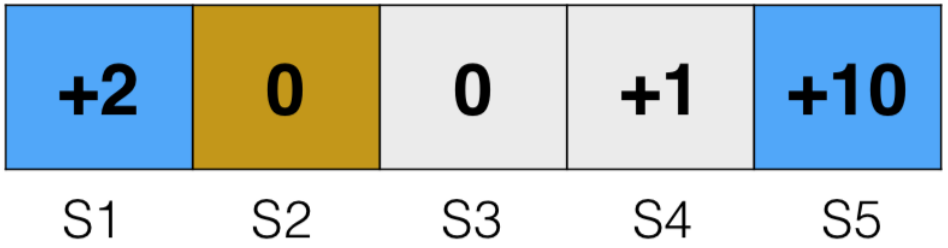

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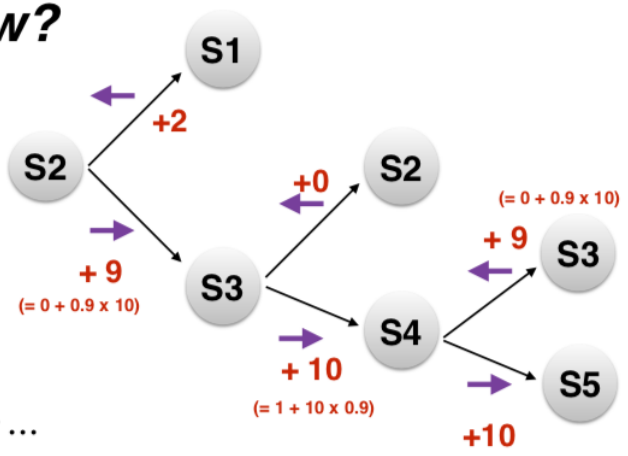

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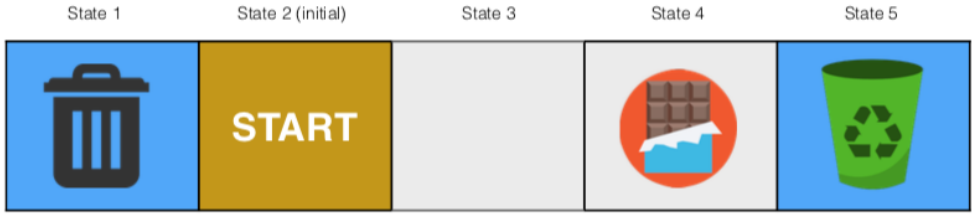
Discounted return $R = \sum_{t=0} \gamma^t r_t = r_0 + \gamma r_1 + \gamma^2 r_2 + \ldots$

Problem statement



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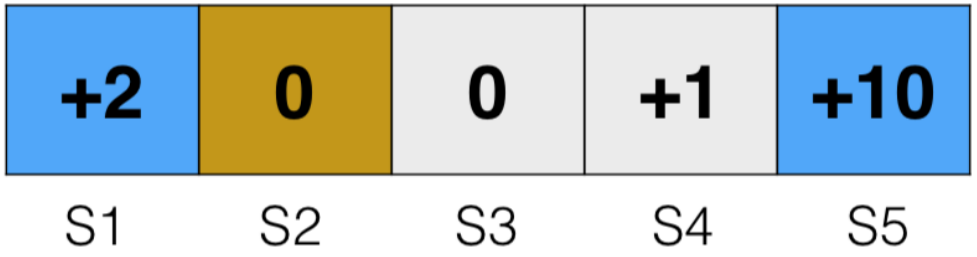

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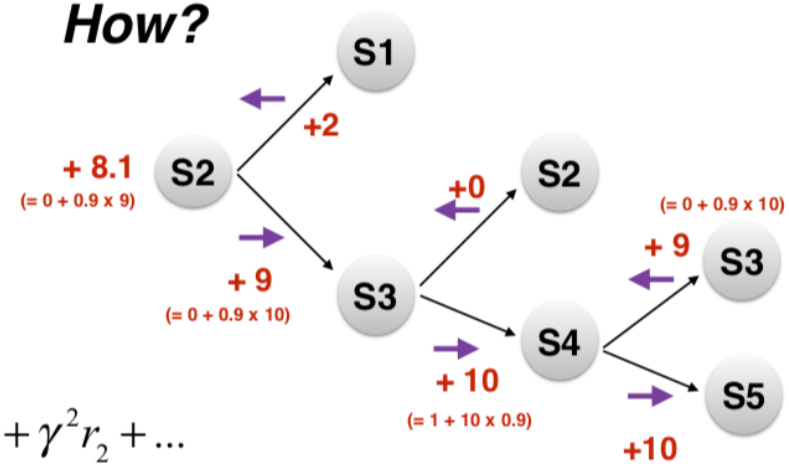

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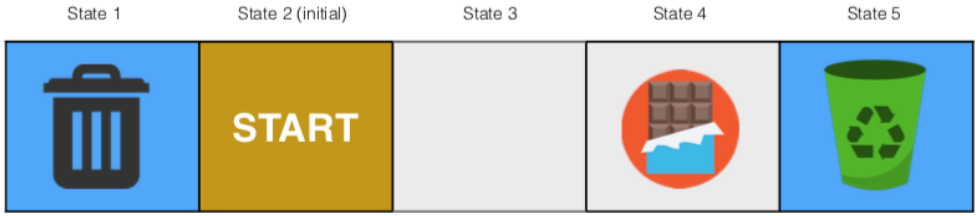

*Define reward "**r**" in every state*

+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?

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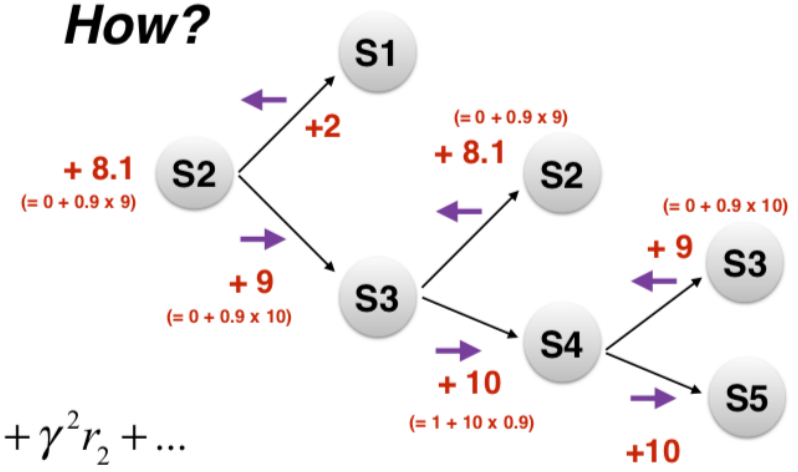
#actions

#states

How?



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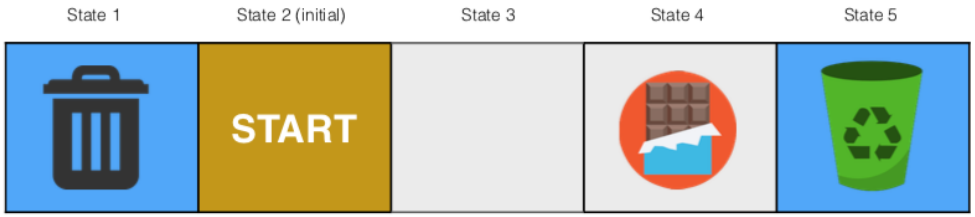

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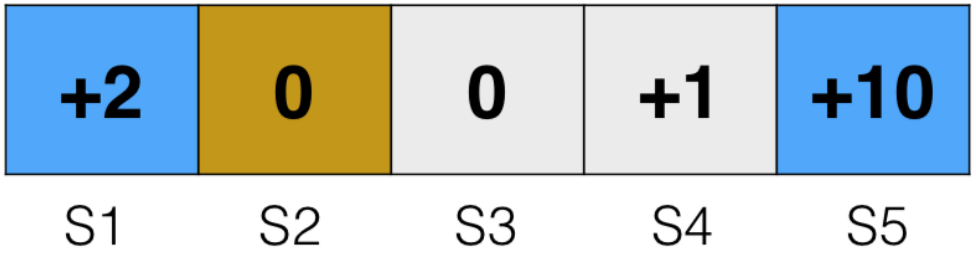


Assuming $\gamma = 0.9$

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

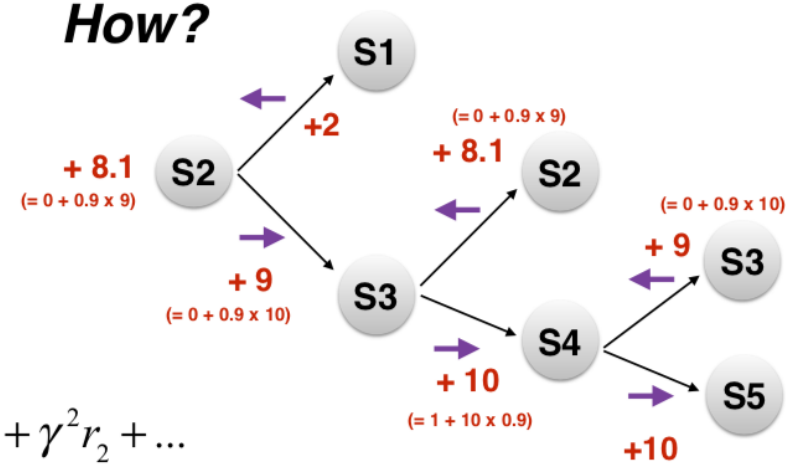
Q-table

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

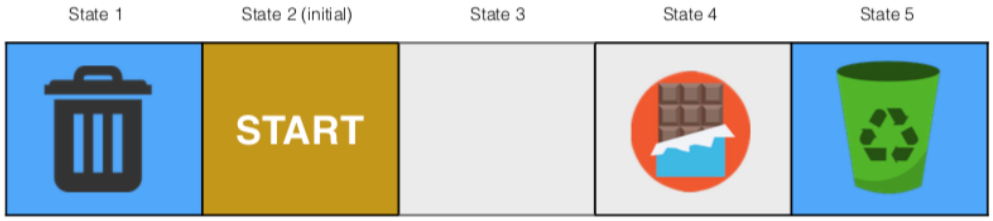
#actions

#states

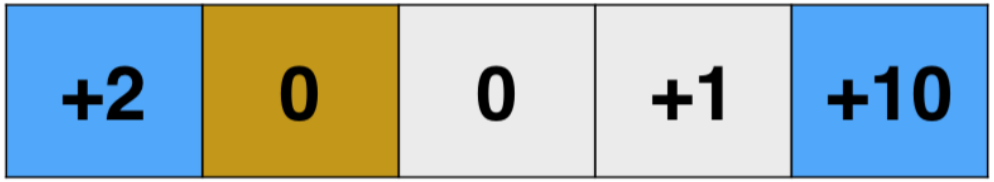
How?



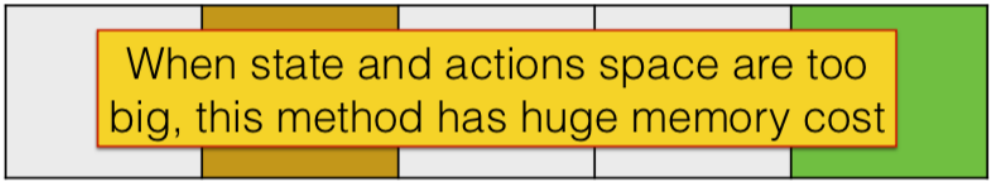
Problem statement



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



Best strategy to follow if $\gamma = 0.9$



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

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

#actions

#states

Bellman equation (optimality equation)

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

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

Summary so far

- *Vocabulary: environment, agent, state, action, reward, total return,*
- *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 P*

Problems:

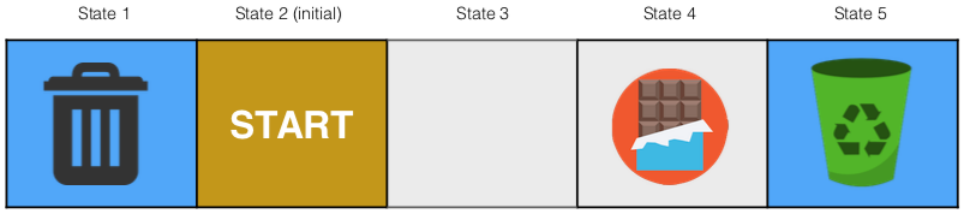
- Complex problems have intractable number of states
- Tabular data does not generalize to unseen examples

Deep Q-Learning

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

Neural Network

Problem statement



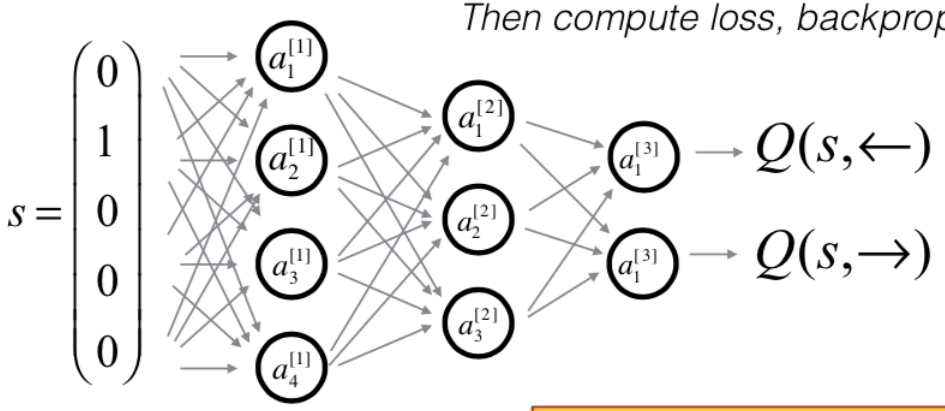
Q-table

#actions

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

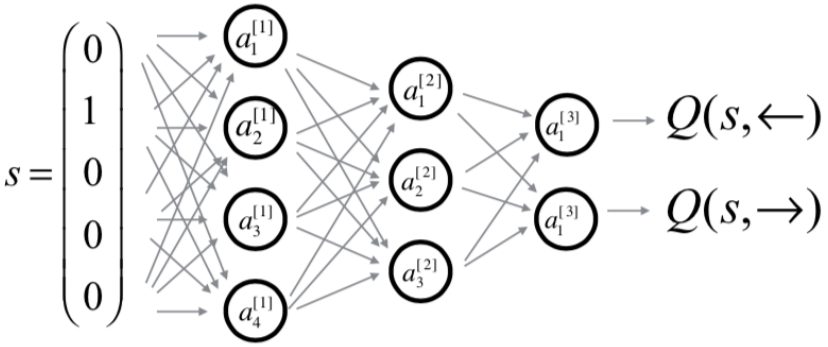
#states

Then compute loss, backpropagate.



How to compute the loss?

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



Loss function

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

Target value

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

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

Hold fixed for backprop

Immediate reward for taking action ← in state s

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

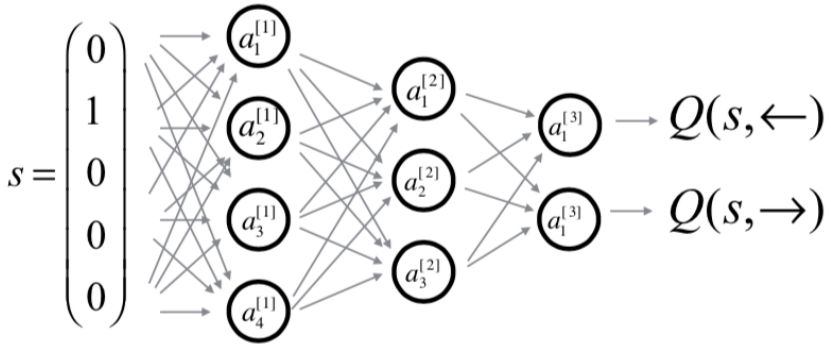
Case: $\boxed{Q(s,\leftarrow) < Q(s,\rightarrow)}$

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

Hold fixed for backprop

Immediate Reward for taking action → in state s

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



Loss function (regression)

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

Target value

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

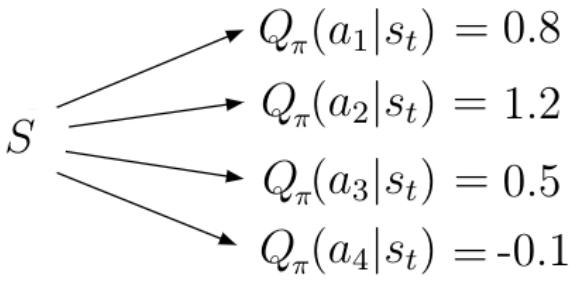
$$y = r_{\leftarrow} + \gamma \max_{a'}(Q(s_{\leftarrow}^{next}, a'))$$

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

Q-Learning Algorithm



Action-Value function - recursive

$$Q_\pi(s,a) = \mathbb{E}_\pi[G_t|S_t = s, A_t = a]$$
$$= \mathbb{E}_\pi[r + \gamma Q_\pi(s_{t+1}, a_{t+1})|S_t = s, A_t = a]$$

Action-Value function with probabilities - recursive

$$Q_\pi(s,a) = R_s^a + \gamma \sum_{s' \in S} \mathcal{P}_{ss'} \sum_{a' \in A} \pi(a'|s') Q_\pi(s', a')$$

Q-Learning Algorithm – Temporal Difference

Action-Value Temporal Difference for iterative execution

$$Q(s_t, a_t) \longleftarrow Q(s_t, a_t) + \alpha\Big(\underbrace{R_{t+1} + \gamma Q(s_{t+1}, a_{t+1})}_{\text{TD-Target}} - Q(s_t, a_t)\Big)$$

Calculate in second pass

Calculate in first pass

DQN Implementation:

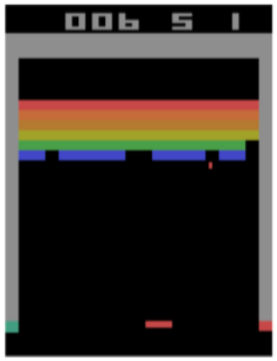
- *Initialize your Q-network parameters*
- *Loop over episodes:*
    - *Start from initial state s*
    - *Loop over time-steps:*
        - *Forward propagate s in the Q-network*
        - *Execute action a (that has the maximum Q(s,a) output of Q-network)*
        - *Observe reward r and next state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

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

Demo

input of Q-network

s =



Output of Q-network

Q-values

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

Will this work?

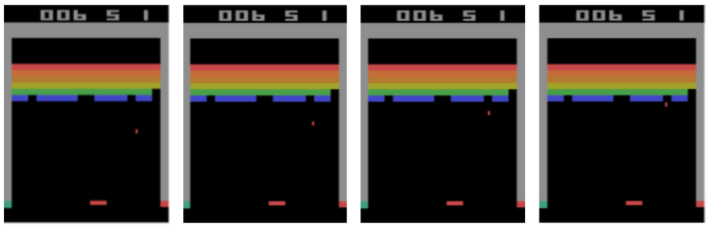
[Two minute papers: Google DeepMind's Deep Q-learning playing Atari Breakout https://www.youtube.com/watch?v=V1eYniJ0Rnk]
[Mnih, Kavukcuoglu, Silver et al. (2015): Human Level Control through Deep Reinforcement Learning]

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

Demo

input of Q-network

s =



Output of Q-network

Q-values

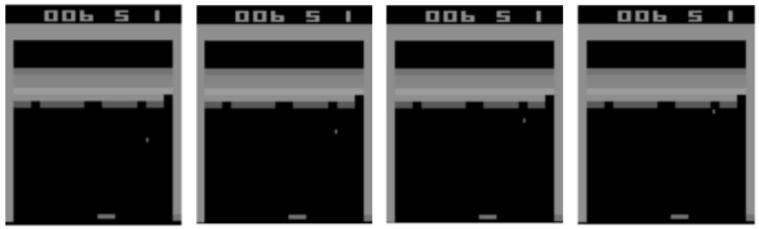
$$\begin{pmatrix} Q(s,\leftarrow) \\ Q(s,\rightarrow) \\ Q(s,-) \end{pmatrix}$$

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

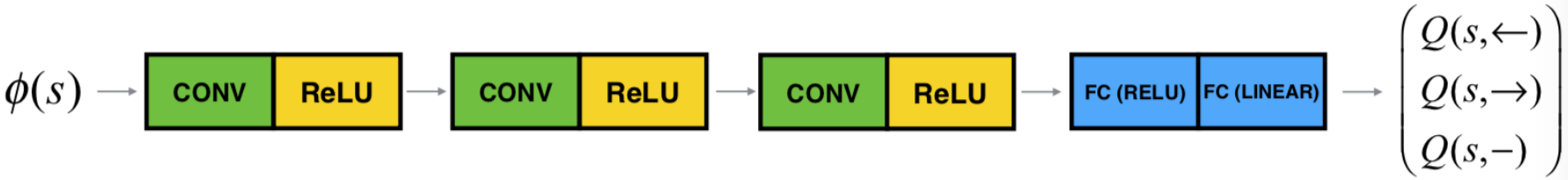
$\phi(s)$

Need to deal with perceptual aliasing

input of Q-network

$\phi(s) =$ 

Deep Q-network architecture?



DQN Implementation:

- *Initialize your Q-network parameters*
- *Loop over episodes:*
  - *Start from initial state s* $\phi(s)$
  - *Loop over time-steps:* $\phi(s)$
    - *Forward propagate s in the Q-network*
    - *Execute action a (that has the maximum Q(s,a) output of Q-network)* $\phi(s)$
    - *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*

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* $\phi(s)$
  - ***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,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*

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

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

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

$\cdots$

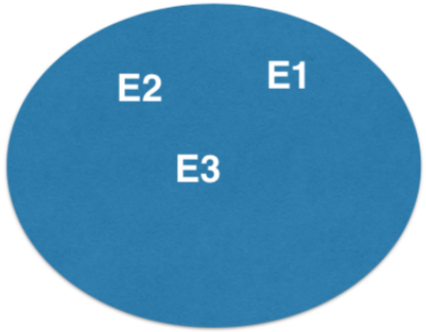
Experience Replay

E1

E2

E3

$\cdots$



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

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
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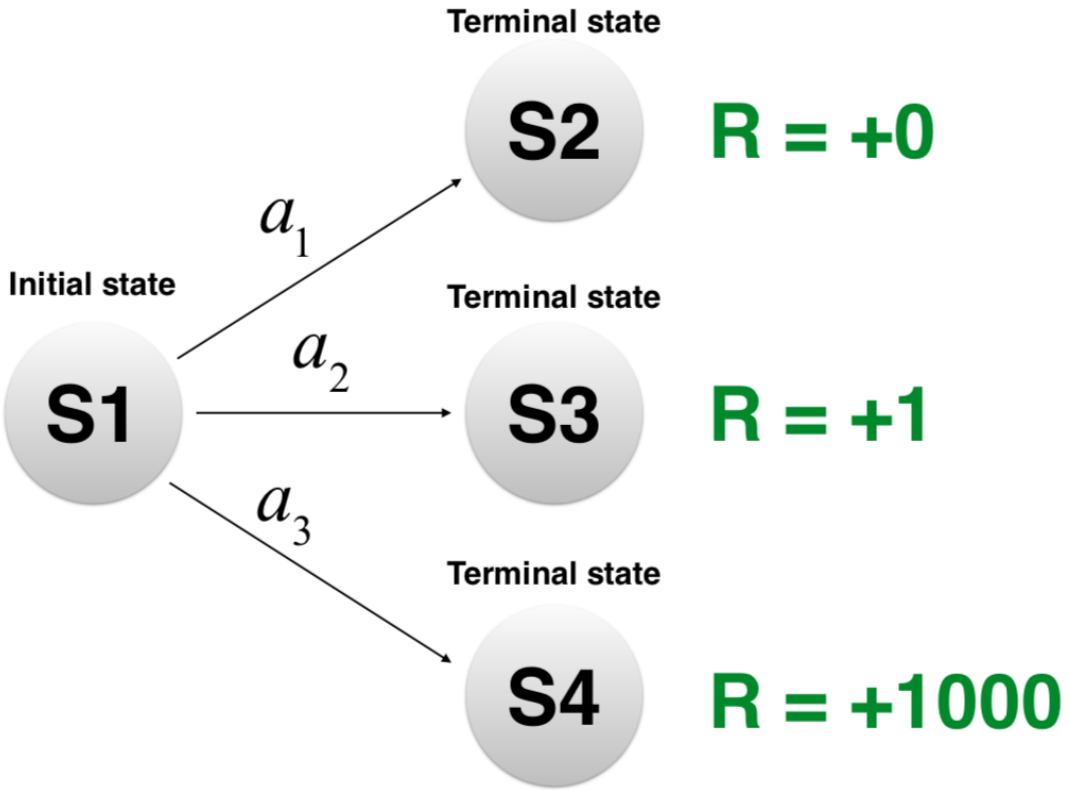
- Epsilon greedy action choice (Exploration / Exploitation tradeoff)

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

Update using sampled transitions

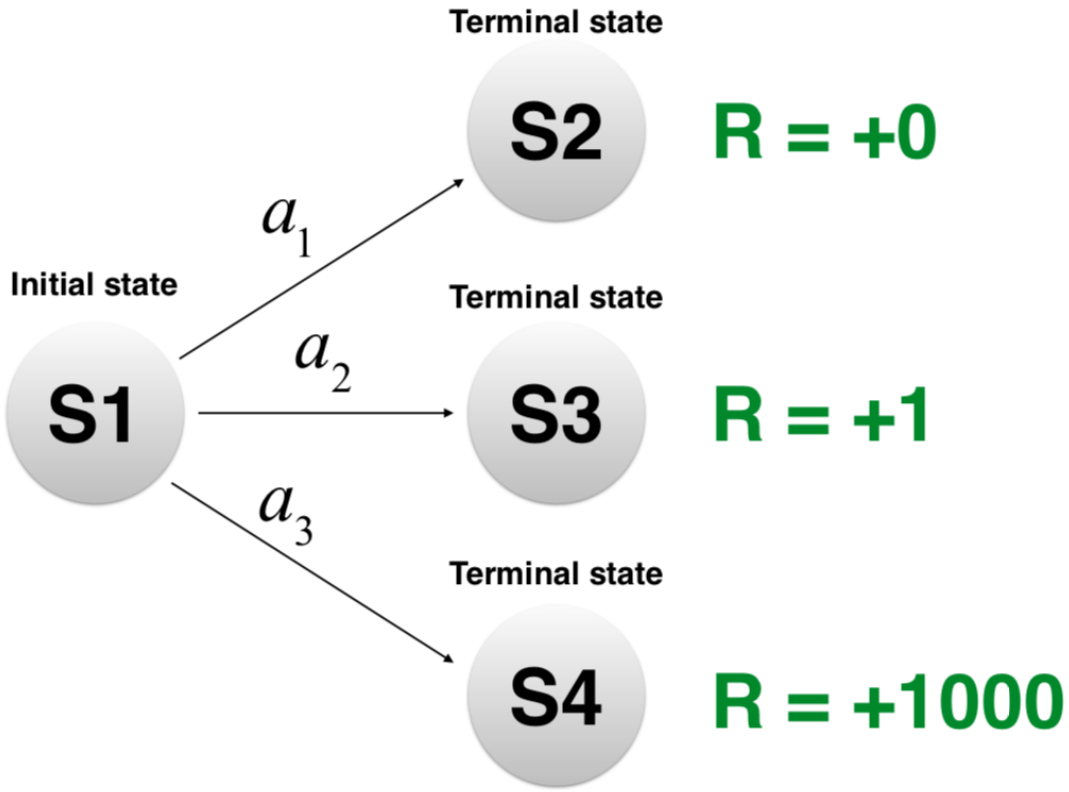


Just after initializing the Q-network, we get:

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

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

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



Just after initializing the Q-network, we get:

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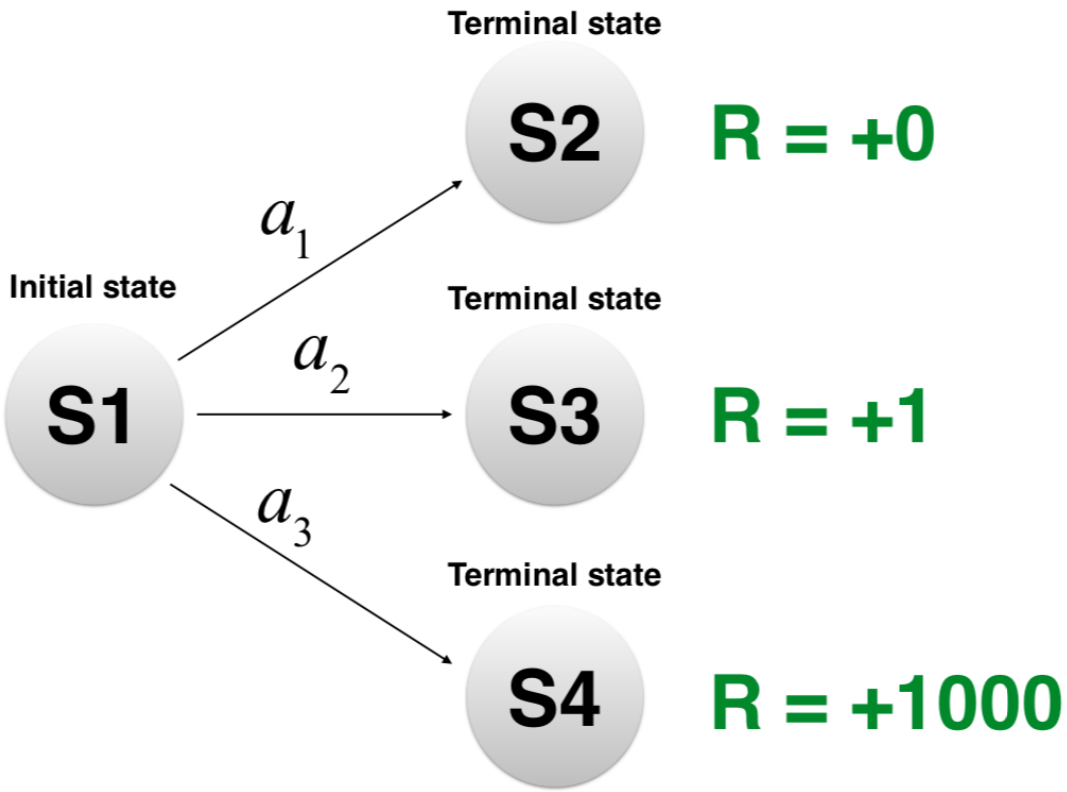
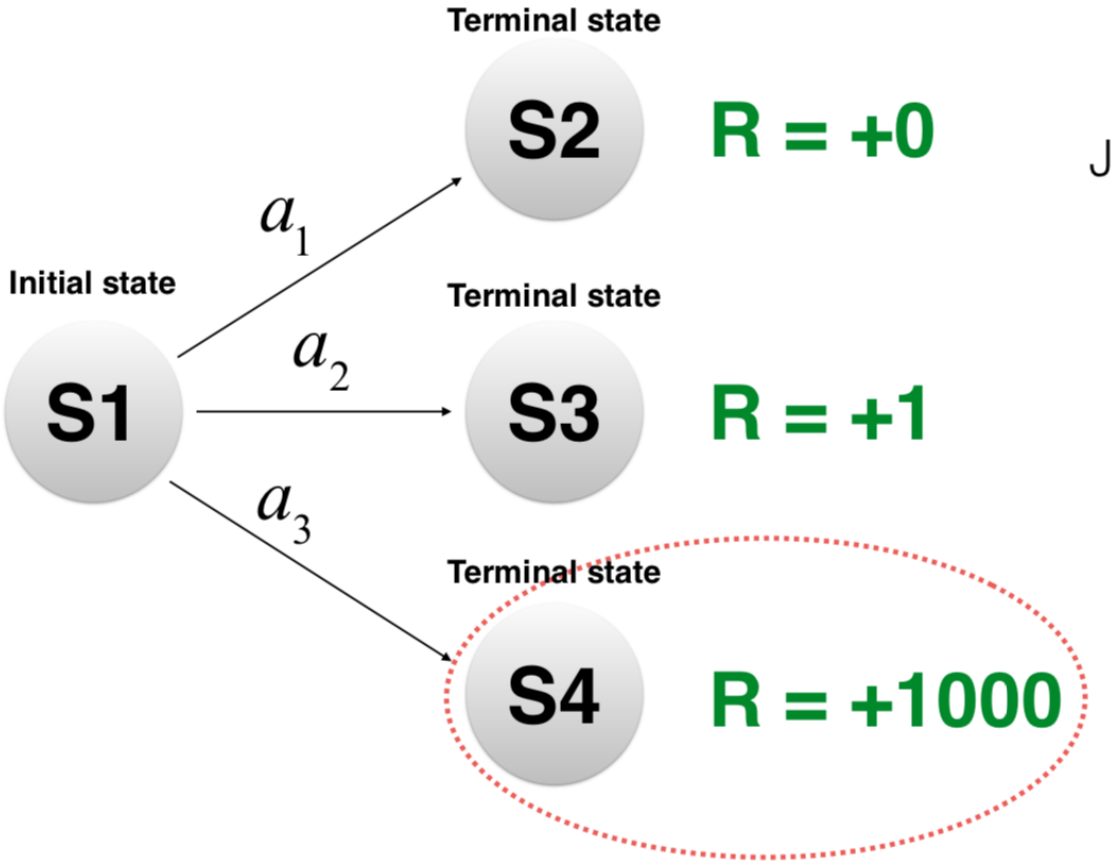


Just after initializing the Q-network, we get:

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

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

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



Just after initializing the Q-network, we get:

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

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

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

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

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*
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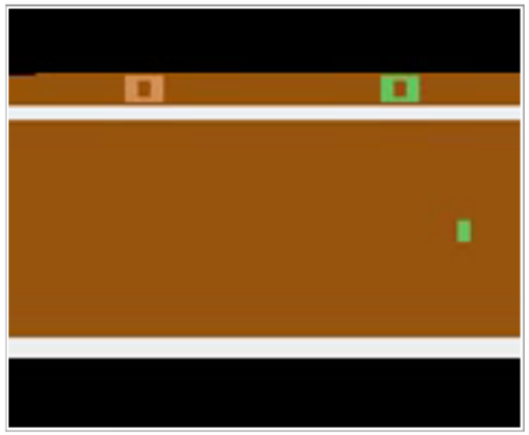
        - *Update parameters with gradient descent*

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

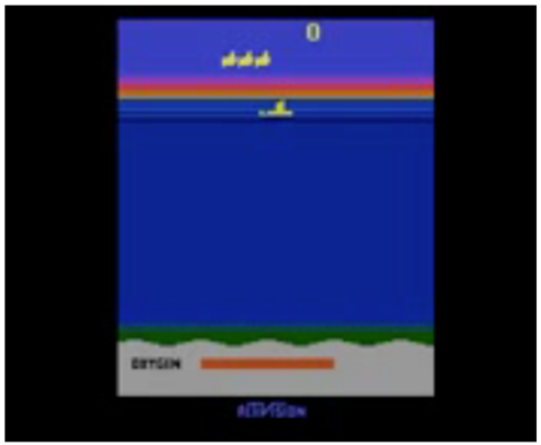
Demo

Pong



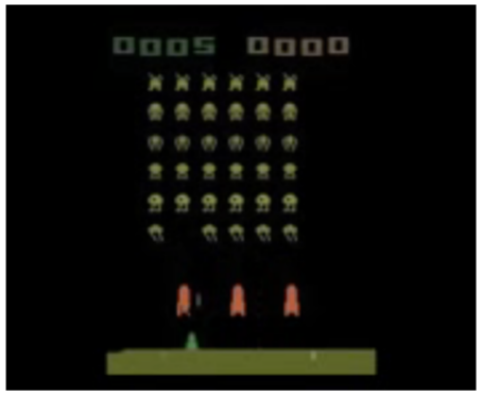
[Chia-Hsuan Lee, Atari Seaquest Double DQN Agent - https://www.youtube.com/watch?v=NirMkC5uvWU]

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]