Introduction of Reinforcement Learning

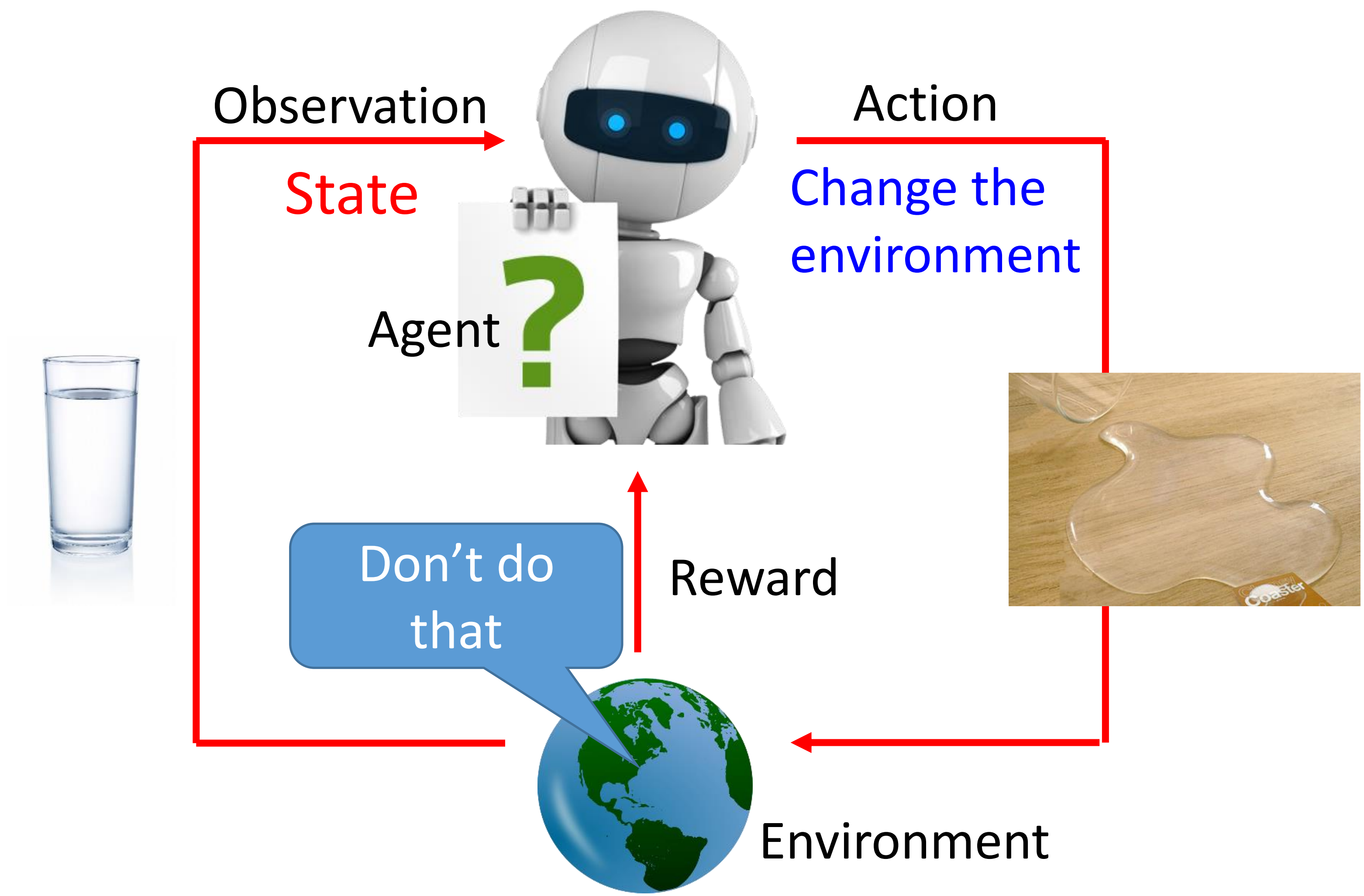
Deep Reinforcement Learning

Deep Reinforcement Learning: AI = RL + DL

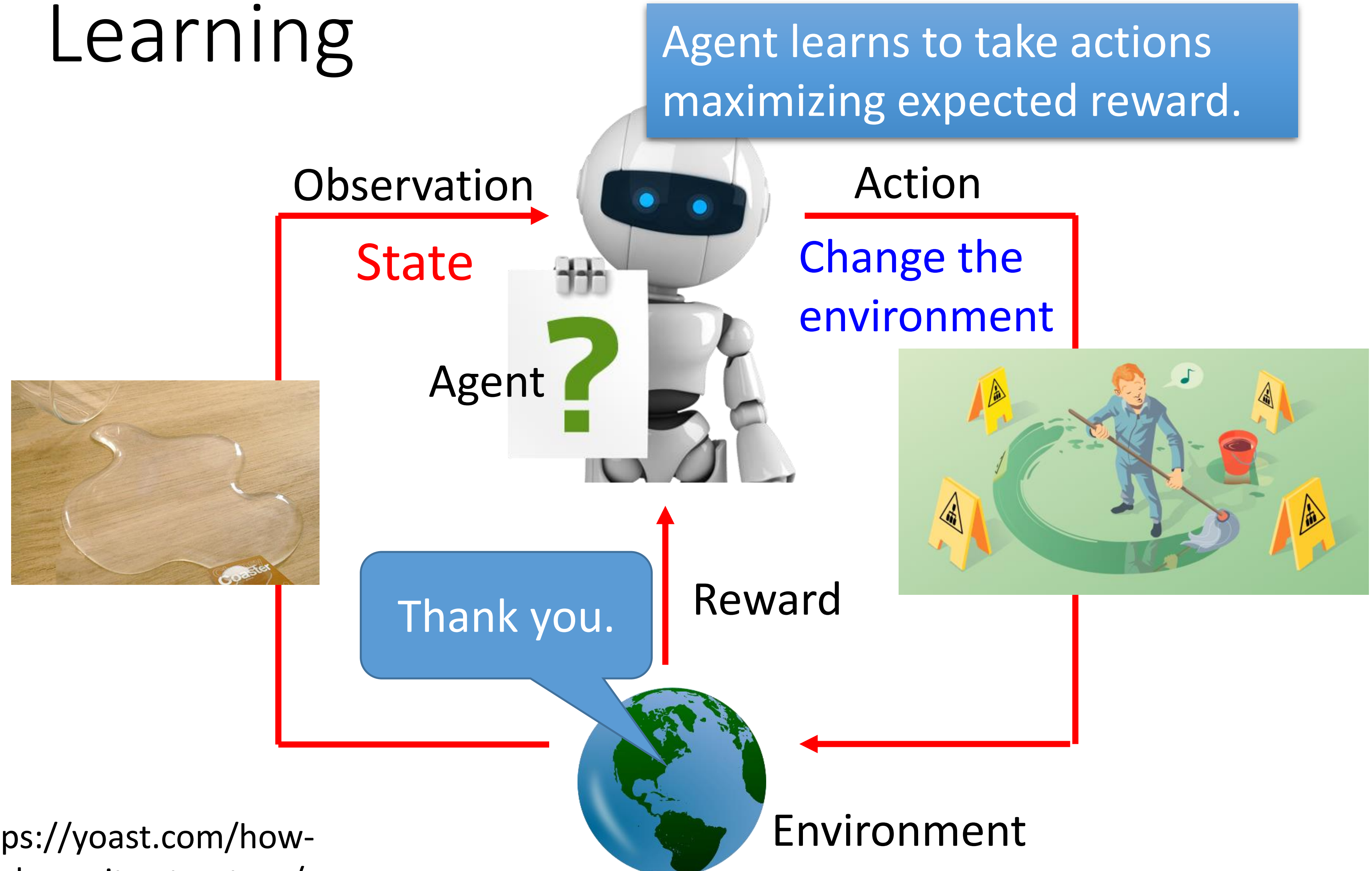
Reference

- Textbook: Reinforcement Learning: An Introduction
  - http://incompleteideas.net/sutton/book/the-book.html
- Lectures of David Silver
  - http://www0.cs.ucl.ac.uk/staff/D.Silver/web/Teaching.html (10 lectures, around 1:30 each)
  - http://videolectures.net/rldm2015_silver_reinforcement_learning/ (Deep Reinforcement Learning)
- Lectures of John Schulman
  - https://youtu.be/aUrX-rP_ss4

Scenario of Reinforcement Learning

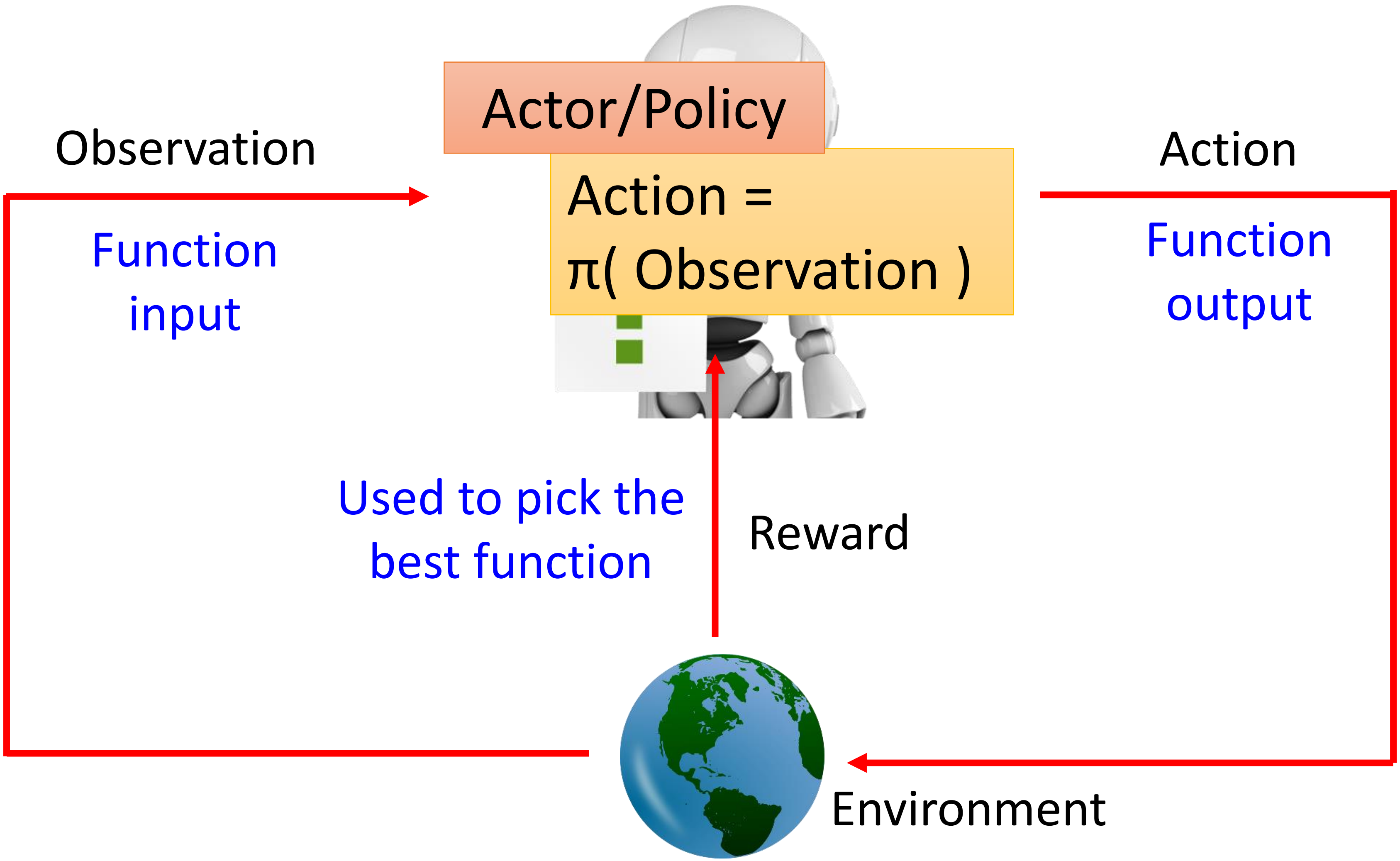


Scenario of Reinforcement Learning

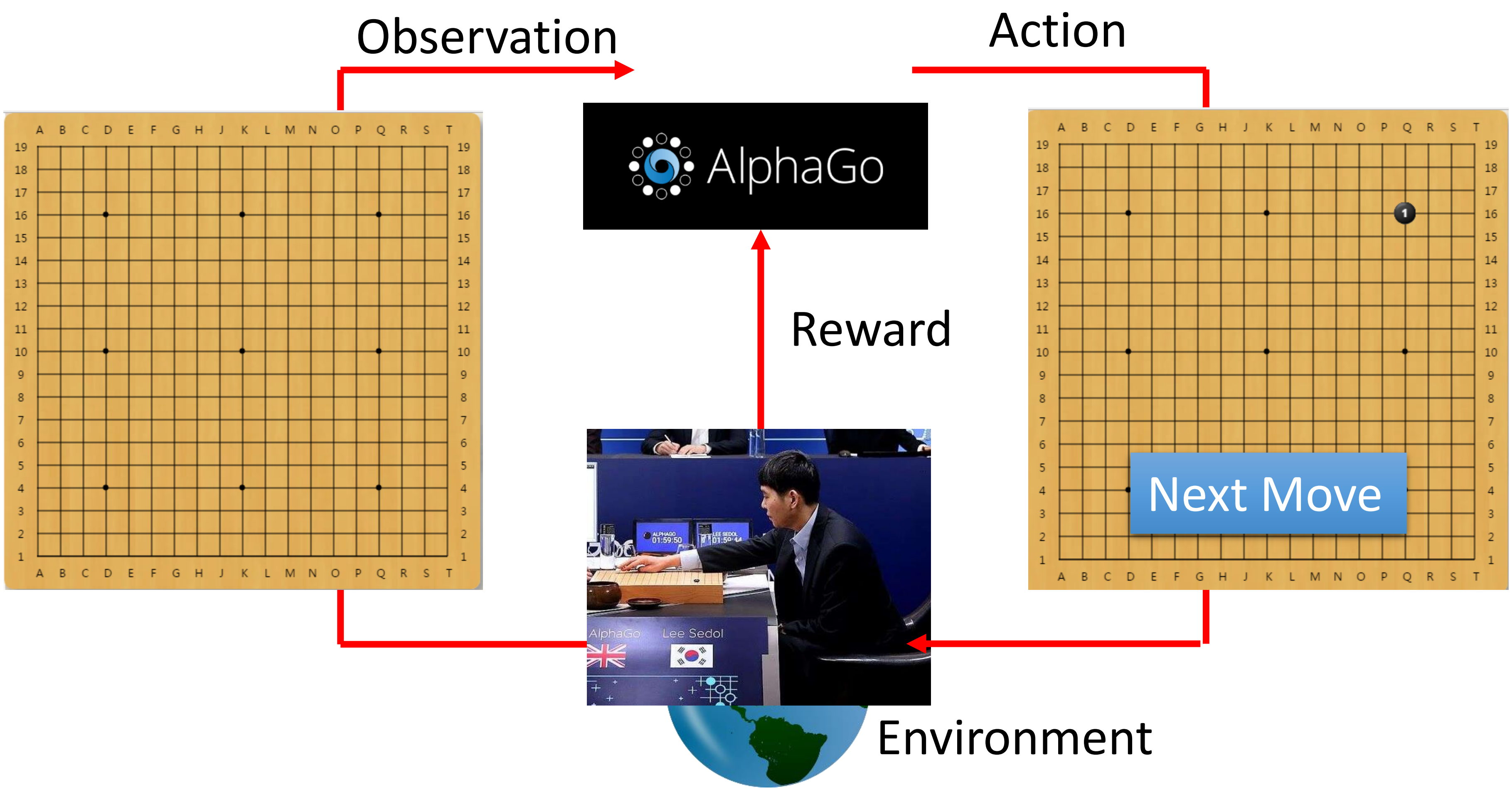


https://yoast.com/how-to-clean-site-structure/

Machine Learning
≈ Looking for a Function

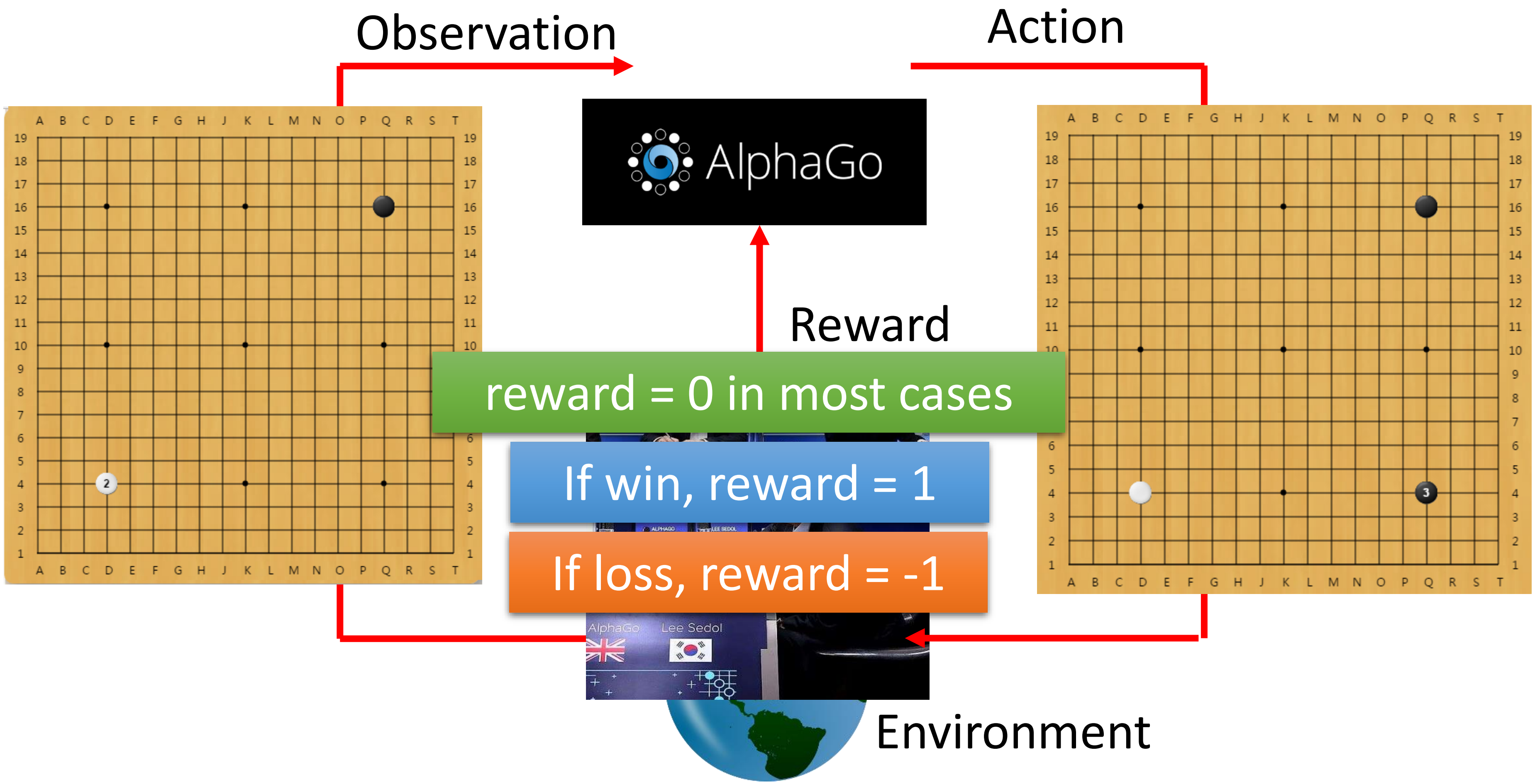


Learning to play Go



Learning to play Go

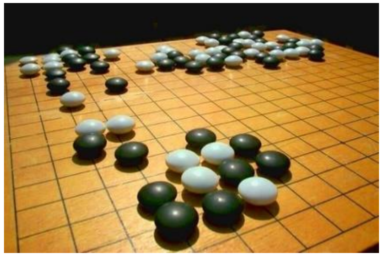
Agent learns to take actions maximizing expected reward.



Learning to play Go

- Supervised: Learning from teacher

Next move: "5-5"



Next move: "3-3"

- Reinforcement Learning Learning from experience

First move → …… many moves …… → Win!

(Two agents play with each other.)

Alpha Go is supervised learning + reinforcement learning.

Learning a chat-bot

https://image.freepik.com/free-vector/variety-of-human-avatars_23-2147506285.jpg

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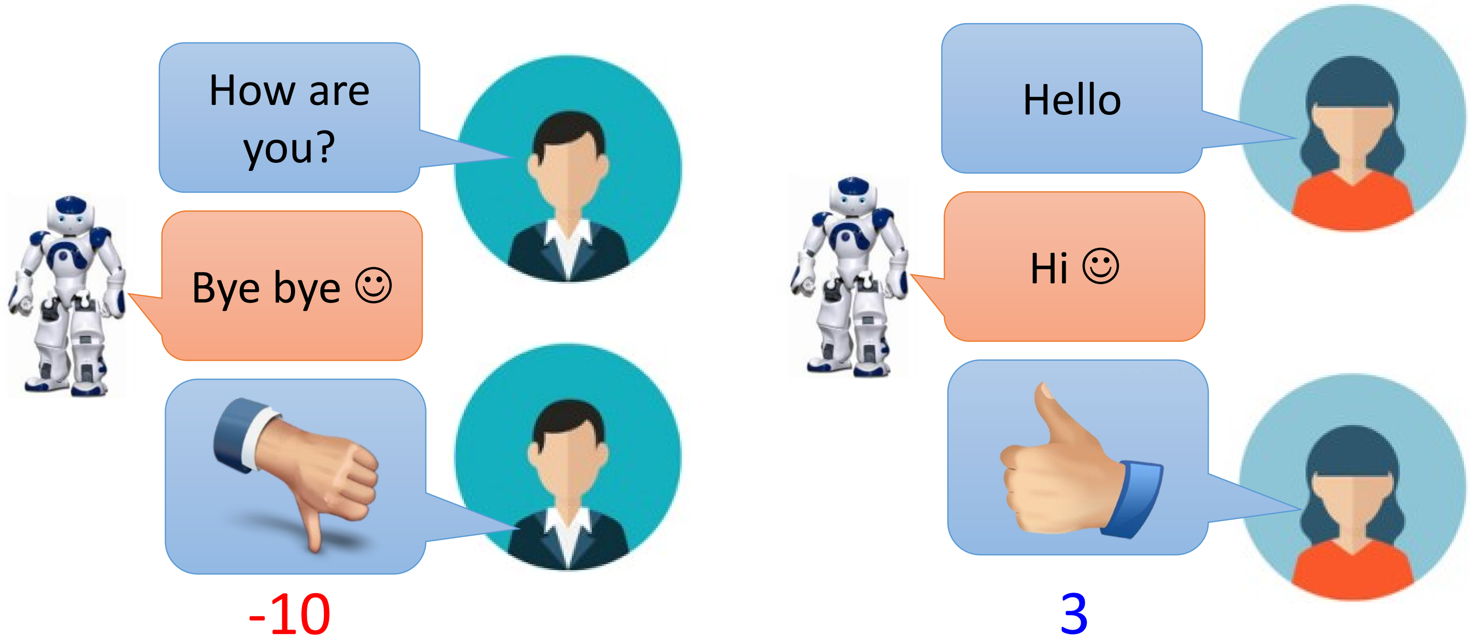
- Machine obtains feedback from user



- Chat-bot learns to maximize the ***expected reward***

Learning a chat-bot

- Let two agents talk to each other (sometimes generate good dialogue, sometimes bad)

How old are you?

See you.

See you.

See you.

How old are you?

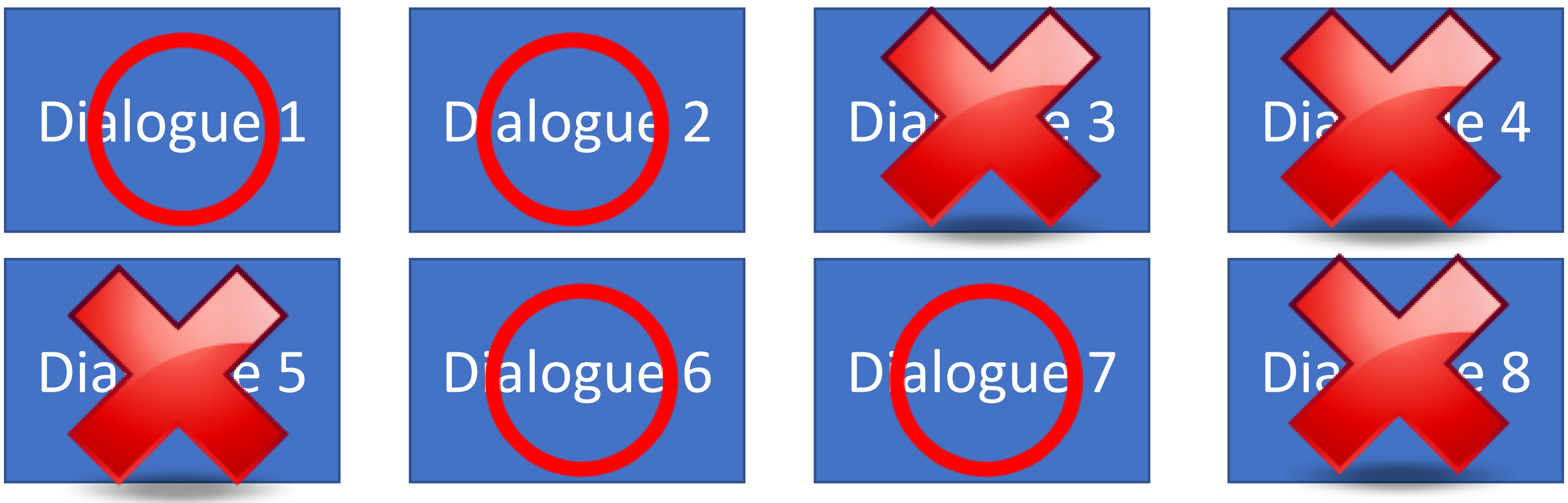
I am 16.

I though you were 12.

What make you think so?

Learning a chat-bot

- By this approach, we can generate a lot of dialogues.
- Use some pre-defined rules to evaluate the goodness of a dialogue

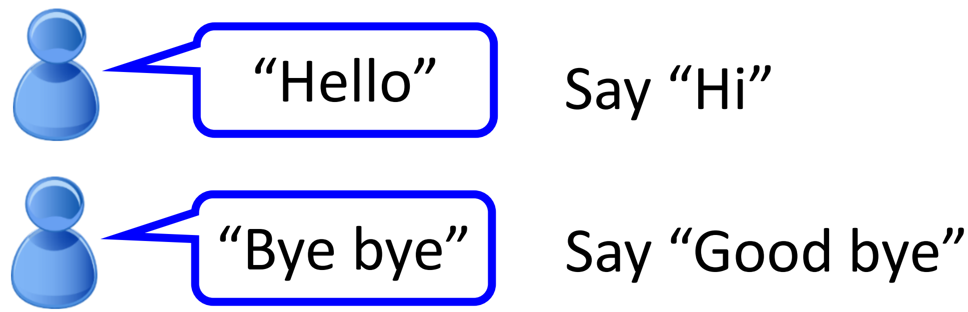


Machine learns from the evaluation

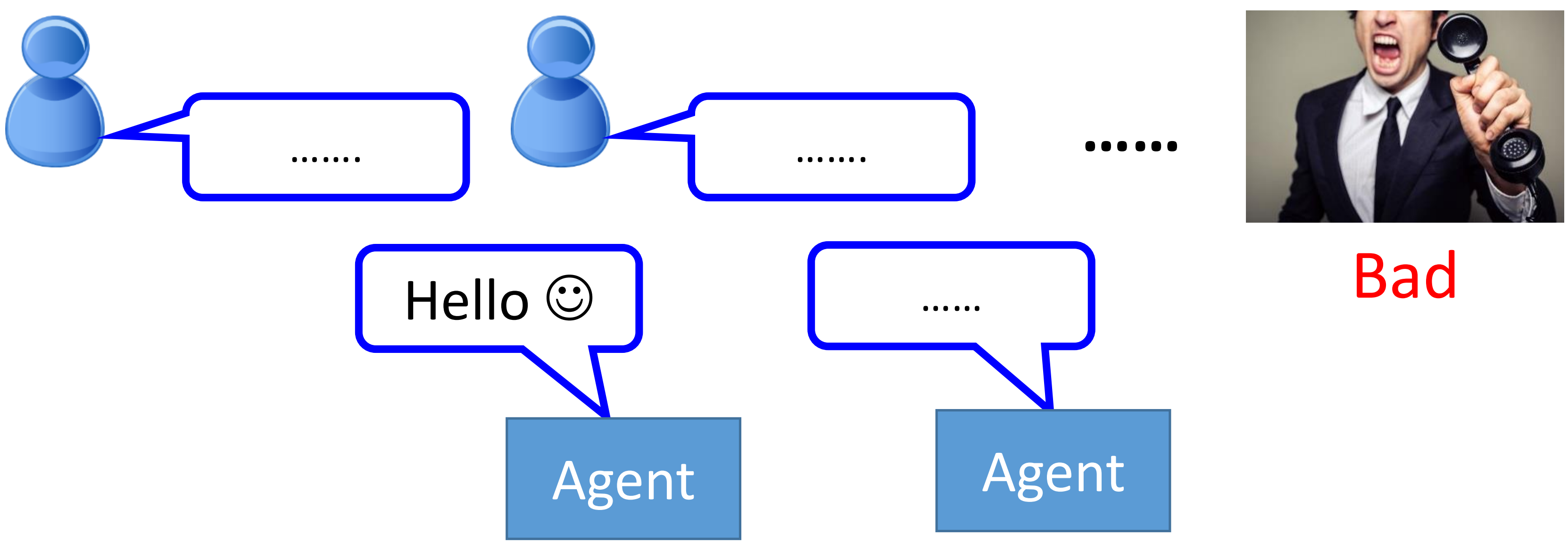
Deep Reinforcement Learning for Dialogue Generation
https://arxiv.org/pdf/1606.01541v3.pdf

Learning a chat-bot

- Supervised



- Reinforcement



More applications

- Flying Helicopter
  - https://www.youtube.com/watch?v=0JL04JJjocc
- Driving
  - https://www.youtube.com/watch?v=0xo1Ldx3L5Q
- Robot
  - https://www.youtube.com/watch?v=370cT-OAzzM
- Google Cuts Its Giant Electricity Bill With DeepMind-Powered AI
  - http://www.bloomberg.com/news/articles/2016-07-19/google-cuts-its-giant-electricity-bill-with-deepmind-powered-ai
- Text generation
  - https://www.youtube.com/watch?v=pbQ4qe8EwLo

Example: Playing Video Game

- Widely studies:
  - Gym: https://gym.openai.com/
  - Universe: https://openai.com/blog/universe/

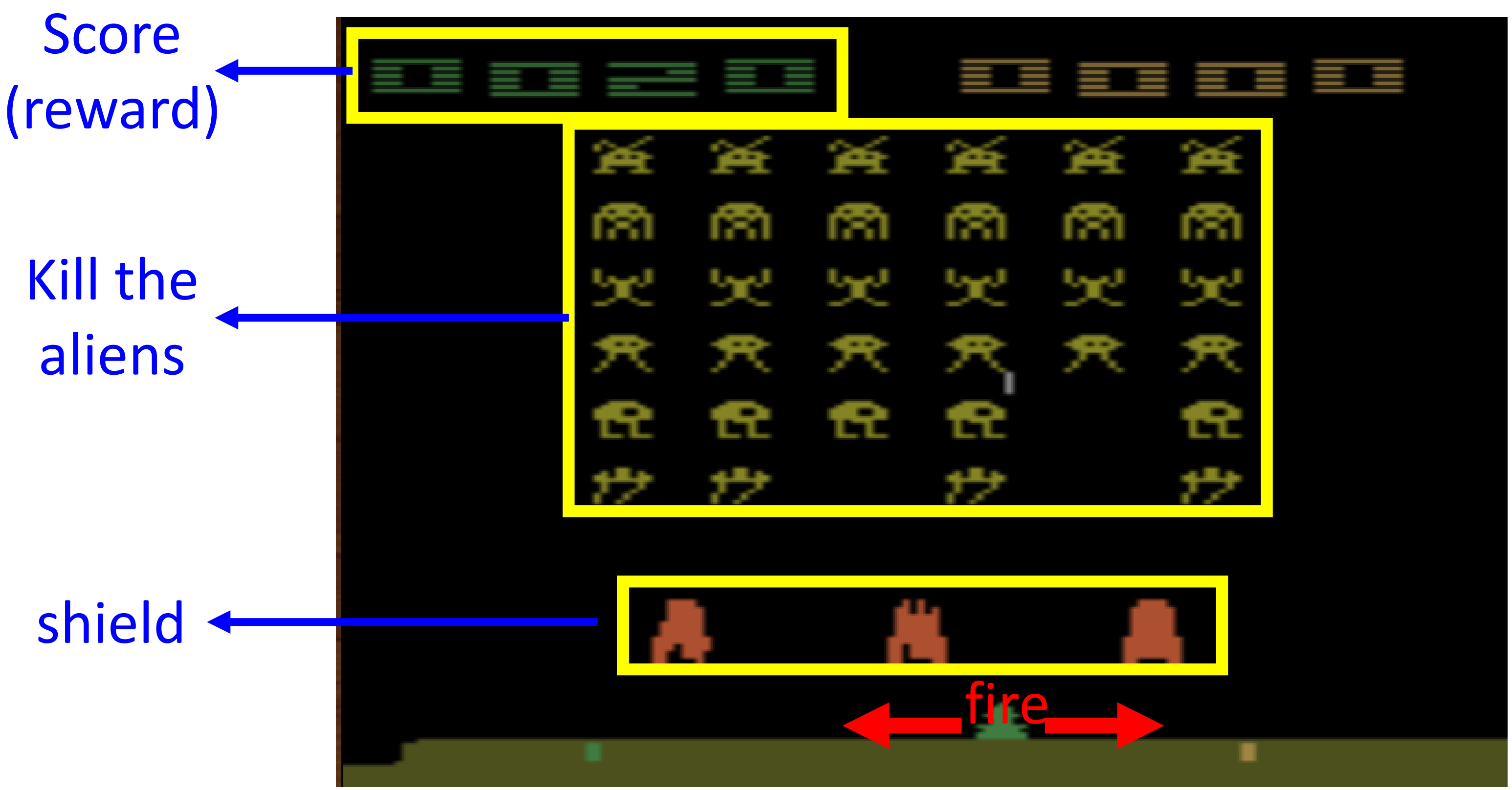
Machine learns to play video games as human players

- ➢ What machine observes is pixels
- ➢ Machine learns to take proper action itself

Example: Playing Video Game

- Space invader

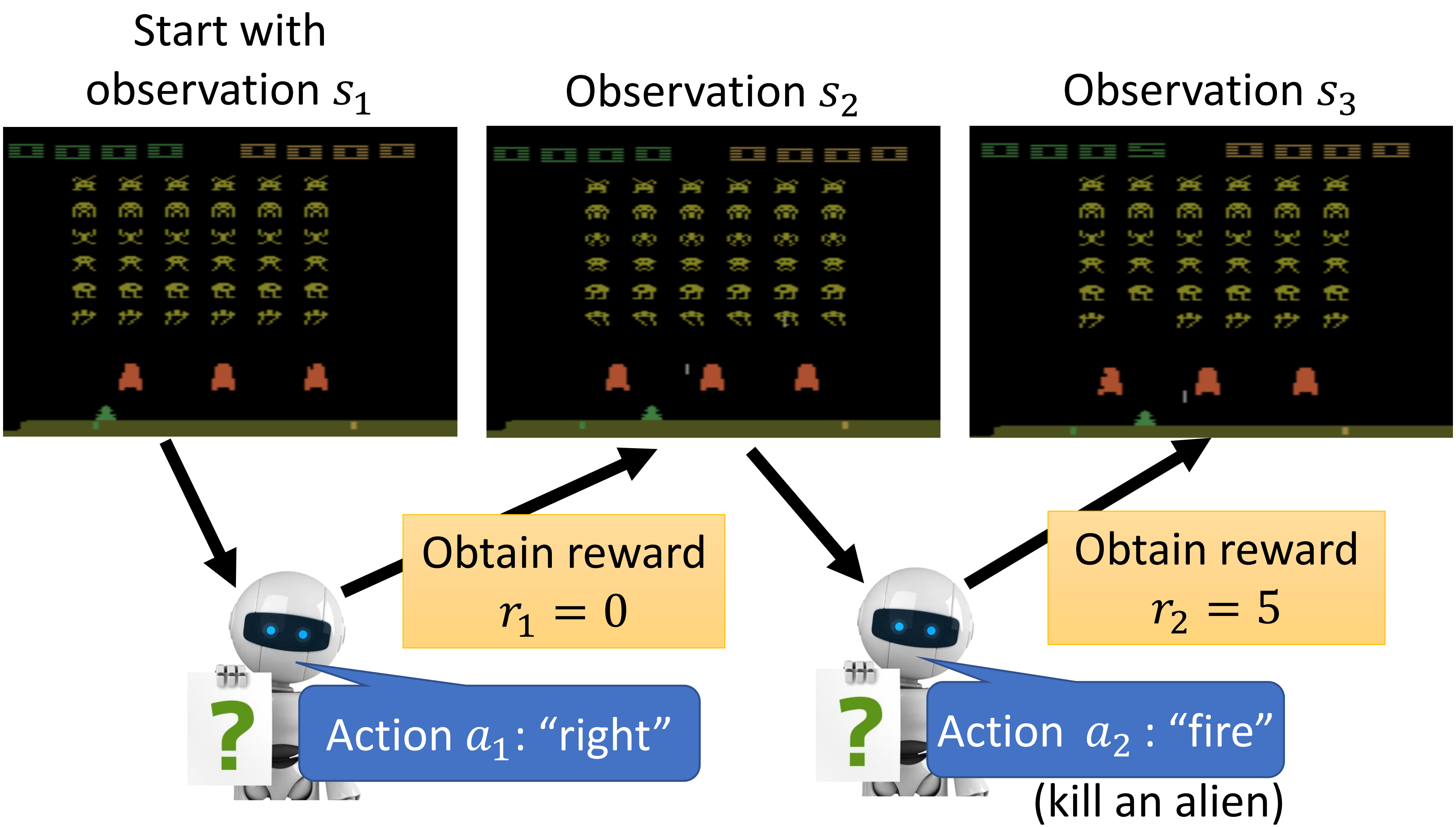
Termination: all the aliens are killed, or your spaceship is destroyed.



Example: Playing Video Game

- Space invader
  - Play yourself: http://www.2600online.com/spaceinvaders.html
  - How about machine: https://gym.openai.com/evaluations/eval_Eduozx4HRyqgTCVk9ltw

Example: Playing Video Game

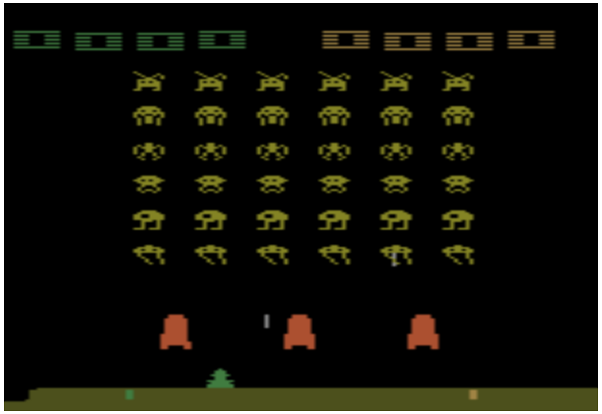


Usually there is some randomness in the environment

Example: Playing Video Game

Start with observation s_1

Observation s_2



Observation s_3

After many turns

Game Over (spaceship destroyed)

Obtain reward r_T

Action a_T

This is an ***episode***.

Learn to maximize the expected cumulative reward per episode

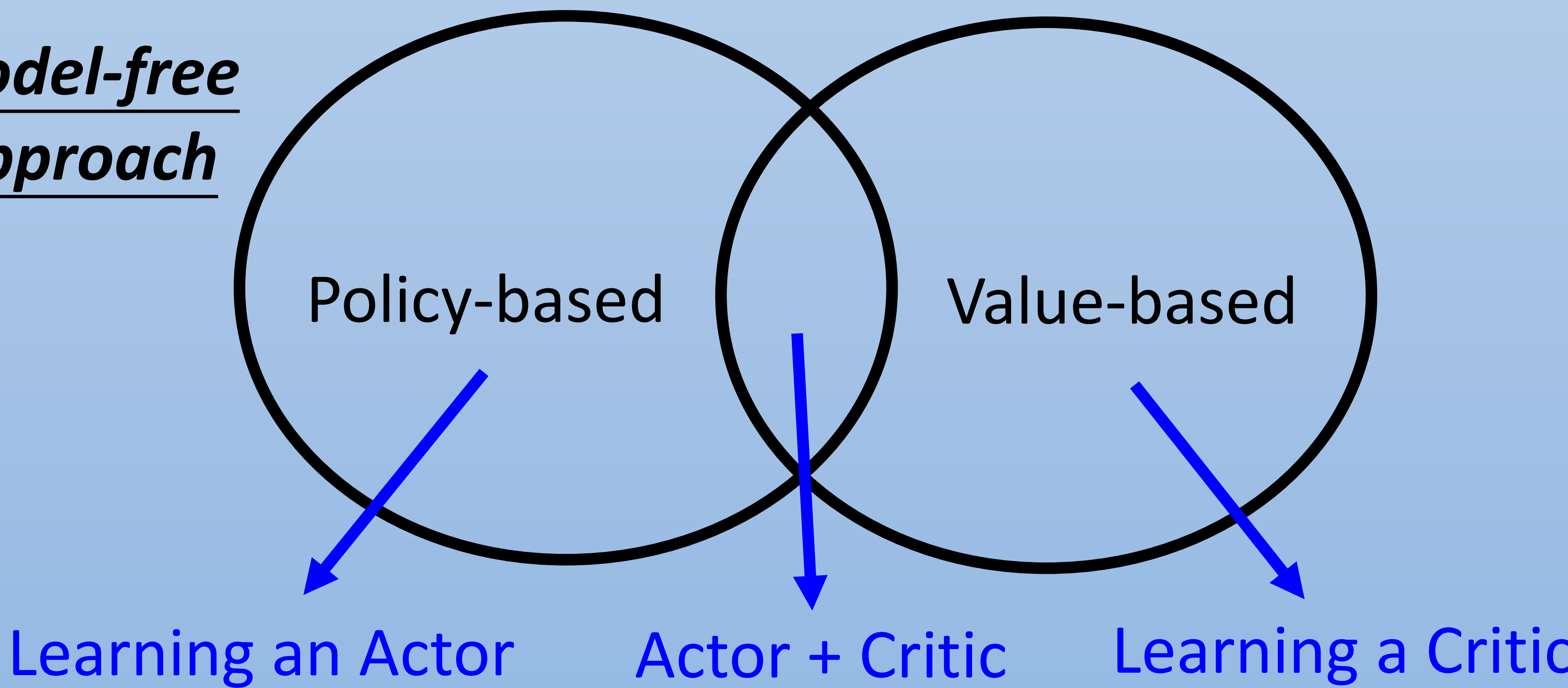
Properties of Reinforcement Learning

- **Reward delay**
  - In space invader, only “fire” obtains reward
    - Although the moving before “fire” is important
  - In Go playing, it may be better to sacrifice immediate reward to gain more long-term reward
- Agent’s actions **affect the subsequent data it receives**
  - E.g. Exploration

Outline

Alpha Go: policy-based + value-based + model-based

Model-free Approach



Model-based Approach

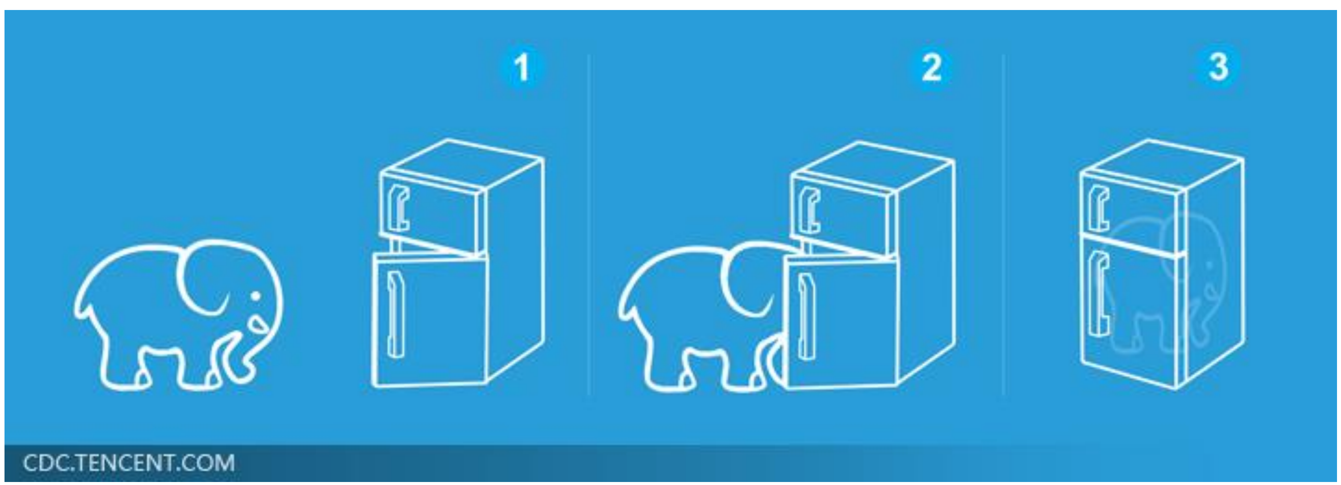
Policy-based Approach

Learning an Actor

Three Steps for Deep Learning

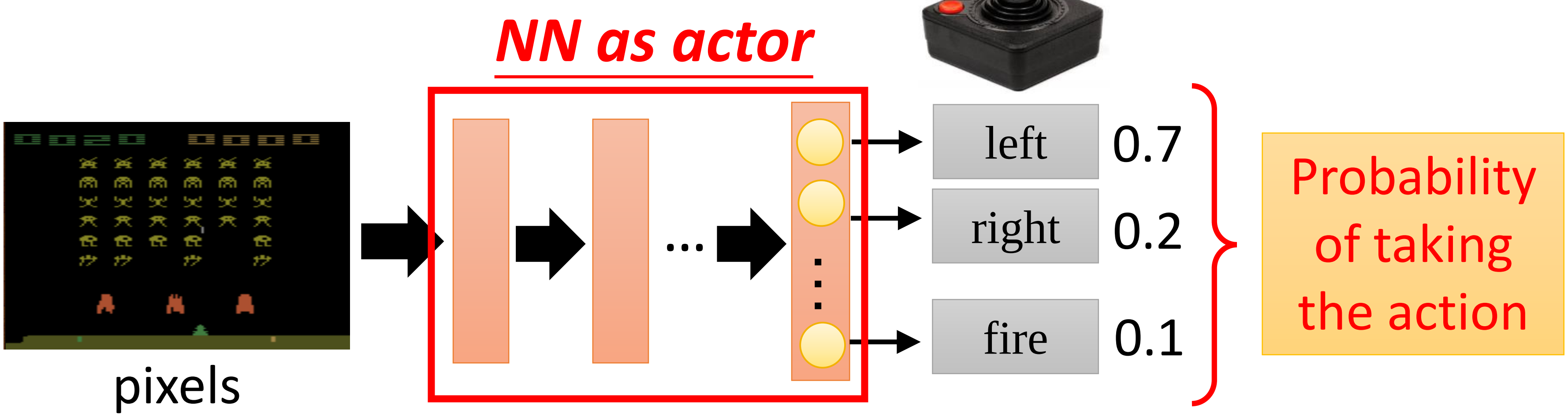
Step 1: Neural Network as Actor → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Neural network as Actor

- Input of neural network: the observation of machine represented as a vector or a matrix
- Output neural network : each action corresponds to a neuron in output layer



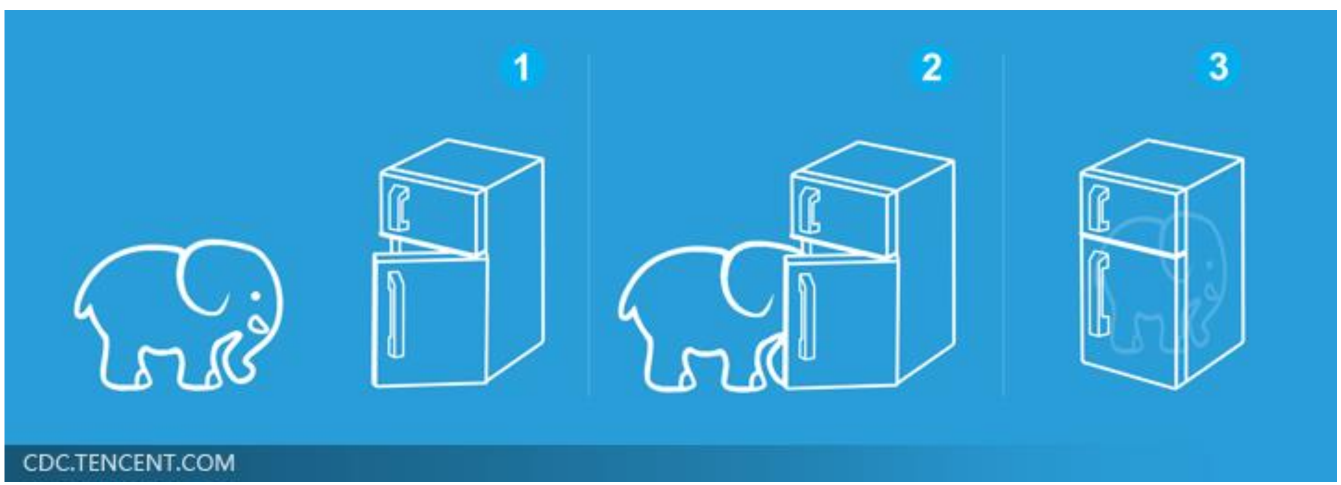
What is the benefit of using network instead of lookup table?

generalization

Three Steps for Deep Learning

Step 1: Neural Network as Actor → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……

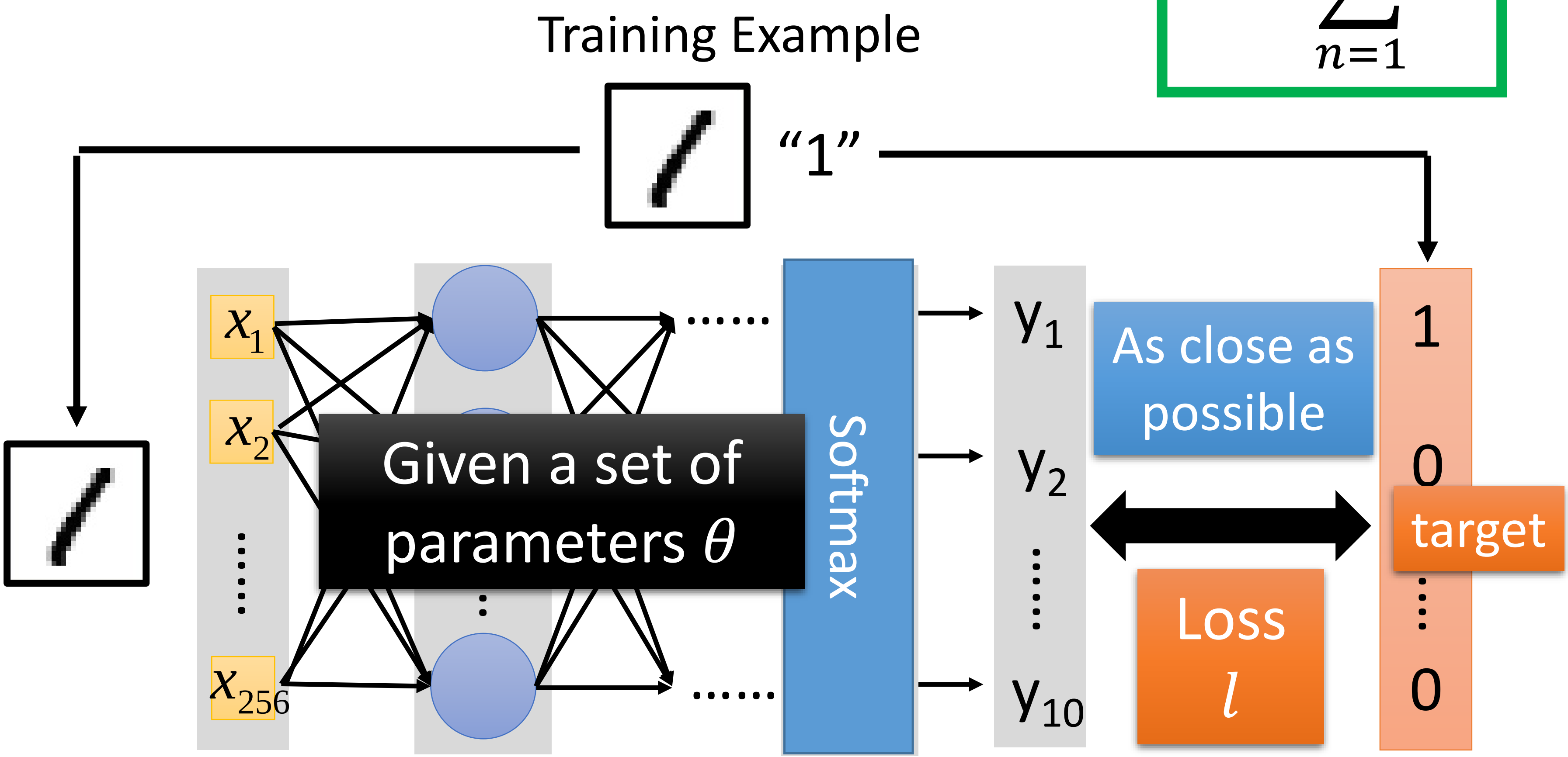


Goodness of Actor

Total Loss:

$$L = \sum_{n=1}^{N} l_n$$

- Review: Supervised learning



Goodness of Actor

- Given an actor $\pi_\theta(s)$ with network parameter θ
- Use the actor $\pi_\theta(s)$ to play the video game
  - Start with observation s_1
  - Machine decides to take a_1
  - Machine obtains reward r_1
  - Machine sees observation s_2
  - Machine decides to take a_2
  - Machine obtains reward r_2
  - Machine sees observation s_3
  - ……
  - Machine decides to take a_T
  - Machine obtains reward r_T END

Total reward: $R_\theta = \sum_{t=1}^{T} r_t$

Even with the same actor, R_θ is different each time

Randomness in the actor and the game

We define $\bar{R}_\theta$ as the <u>*expected value*</u> of R_θ

$\bar{R}_\theta$ evaluates the goodness of an actor $\pi_\theta(s)$

Goodness of Actor

We define $\bar{R}_\theta$ as the *expected value* of R_θ

- $\tau = \{s_1, a_1, r_1, s_2, a_2, r_2, \cdots, s_T, a_T, r_T\}$

$$P(\tau|\theta) =$$

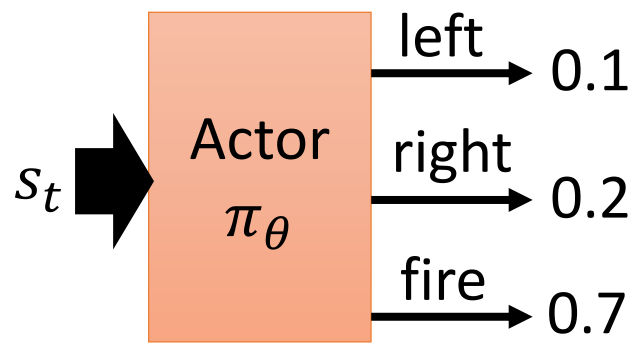
$$p(s_1)p(a_1|s_1,\theta)p(r_1,s_2|s_1,a_1)p(a_2|s_2,\theta)p(r_2,s_3|s_2,a_2)\cdots$$

$$= p(s_1)\prod_{t=1}^{T} p(a_t|s_t,\theta)p(r_t,s_{t+1}|s_t,a_t)$$

not related to your actor

Control by your actor π_θ

$$p(a_t = \text{"}fire\text{"}|s_t,\theta) = 0.7$$



Goodness of Actor

- An episode is considered as a trajectory τ
  - $\tau = \{s_1, a_1, r_1, s_2, a_2, r_2, \cdots, s_T, a_T, r_T\}$
  - $R(\tau) = \sum_{t=1}^{T} r_t$
  - If you use an actor to play the game, each τ has a probability to be sampled
    - The probability depends on actor parameter θ: $P(\tau|\theta)$

$$\bar{R}_\theta = \boxed{\sum_{\tau}} R(\tau) \boxed{P(\tau|\theta)} \approx \boxed{\frac{1}{N}\sum_{n=1}^{N}} R(\tau^n)$$

Use π_θ to play the game N times, obtain $\{\tau^1, \tau^2, \cdots, \tau^N\}$

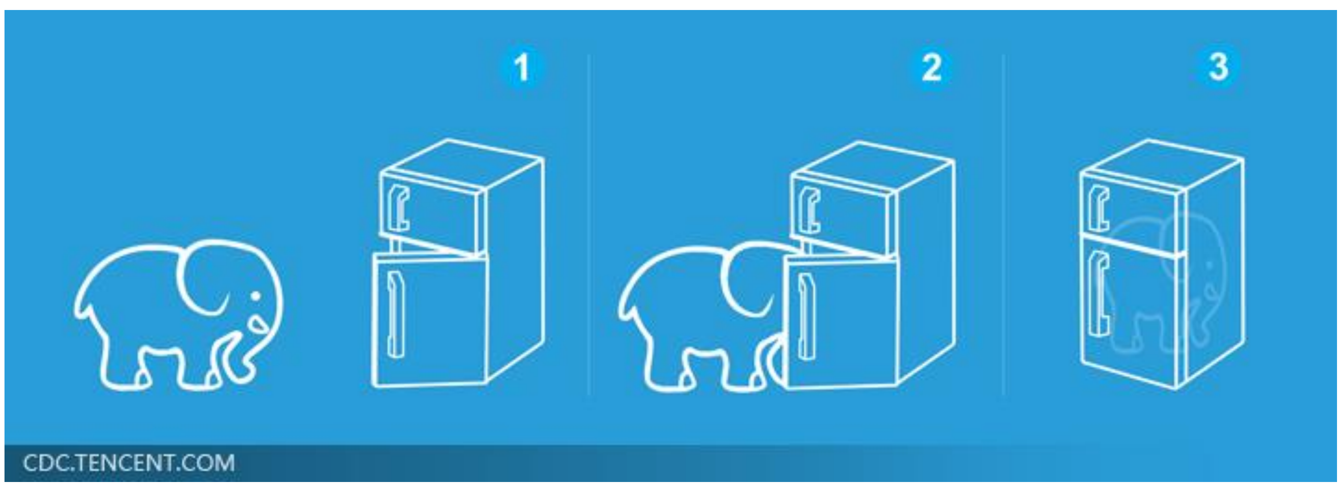
Sampling τ from $P(\tau|\theta)$ N times

Sum over all possible trajectory

Three Steps for Deep Learning

Step 1: Neural Network as Actor → Step 2: goodness of function → Step 3: pick the best function

Deep Learning is so simple ……



Gradient Ascent

- Problem statement

$$\theta^* = arg \max_{\theta} \bar{R}_\theta$$

- Gradient ascent
  - Start with θ^0
  - $\theta^1 \leftarrow \theta^0 + \eta \nabla \bar{R}_{\theta^0}$
  - $\theta^2 \leftarrow \theta^1 + \eta \nabla \bar{R}_{\theta^1}$
  - ……

$$\theta = \{w_1, w_2, \cdots, b_1, \cdots\}$$

$$\nabla \bar{R}_\theta = \begin{bmatrix} \partial \bar{R}_\theta / \partial w_1 \\ \partial \bar{R}_\theta / \partial w_2 \\ \vdots \\ \partial \bar{R}_\theta / \partial b_1 \\ \vdots \end{bmatrix}$$

Policy Gradient

$$\bar{R}_\theta = \sum_\tau R(\tau)P(\tau|\theta) \qquad \nabla\bar{R}_\theta = ?$$

$$\nabla\bar{R}_\theta = \sum_\tau R(\tau)\nabla P(\tau|\theta) = \sum_\tau R(\tau)P(\tau|\theta)\frac{\nabla P(\tau|\theta)}{P(\tau|\theta)}$$

$R(\tau)$ do not have to be differentiable

It can even be a black box.

$$= \boxed{\sum_\tau} R(\tau)\boxed{P(\tau|\theta)}\nabla logP(\tau|\theta)$$

$$\boxed{\frac{dlog\left(f(x)\right)}{dx} = \frac{1}{f(x)}\frac{df(x)}{dx}}$$

$$\approx \frac{1}{N}\sum_{n=1}^{N} R(\tau^n)\underline{\nabla logP(\tau^n|\theta)}$$

Use π_θ to play the game N times,
Obtain $\{\tau^1, \tau^2, \cdots, \tau^N\}$

Policy Gradient

$\nabla log P(\tau|\theta) = ?$

- $\tau = \{s_1, a_1, r_1, s_2, a_2, r_2, \cdots, s_T, a_T, r_T\}$

$$P(\tau|\theta) = p(s_1)\prod_{t=1}^{T} p(a_t|s_t,\theta)p(r_t, s_{t+1}|s_t, a_t)$$

$$log P(\tau|\theta)$$

$$= log p(s_1) + \sum_{t=1}^{T} log p(a_t|s_t,\theta) + log p(r_t, s_{t+1}|s_t, a_t)$$

$$\nabla log P(\tau|\theta) = \sum_{t=1}^{T} \nabla log p(a_t|s_t,\theta)$$

Ignore the terms not related to θ

Policy Gradient

$$\nabla logP(\tau|\theta) = \sum_{t=1}^{T} \nabla logp(a_t|s_t,\theta)$$

$$\theta^{new} \leftarrow \theta^{old} + \eta \nabla \bar{R}_{\theta^{old}}$$

$$\nabla \bar{R}_\theta \approx \frac{1}{N}\sum_{n=1}^{N} R(\tau^n) \nabla logP(\tau^n|\theta) = \frac{1}{N}\sum_{n=1}^{N} R(\tau^n) \sum_{t=1}^{T_n} \nabla logp(a_t^n|s_t^n,\theta)$$

$$= \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n} R(\tau^n) \nabla logp(a_t^n|s_t^n,\theta)$$

What if we replace $R(\tau^n)$ with r_t^n ......

If in τ^n machine takes a_t^n when seeing s_t^n in

$R(\tau^n)$ is positive → Tuning θ to increase $p(a_t^n|s_t^n)$

$R(\tau^n)$ is negative → Tuning θ to decrease $p(a_t^n|s_t^n)$

It is very important to consider the cumulative reward $R(\tau^n)$ of the whole trajectory τ^n instead of immediate reward r_t^n

Policy Gradient

Given actor parameter θ

τ^1: (s_1^1, a_1^1) $R(\tau^1)$

(s_2^1, a_2^1) $R(\tau^1)$

$\vdots$ $\vdots$

τ^2: (s_1^2, a_1^2) $R(\tau^2)$

(s_2^2, a_2^2) $R(\tau^2)$

$\vdots$ $\vdots$

Update Model

$$\theta \leftarrow \theta + \eta \nabla \bar{R}_\theta$$

$$\nabla \bar{R}_\theta =$$

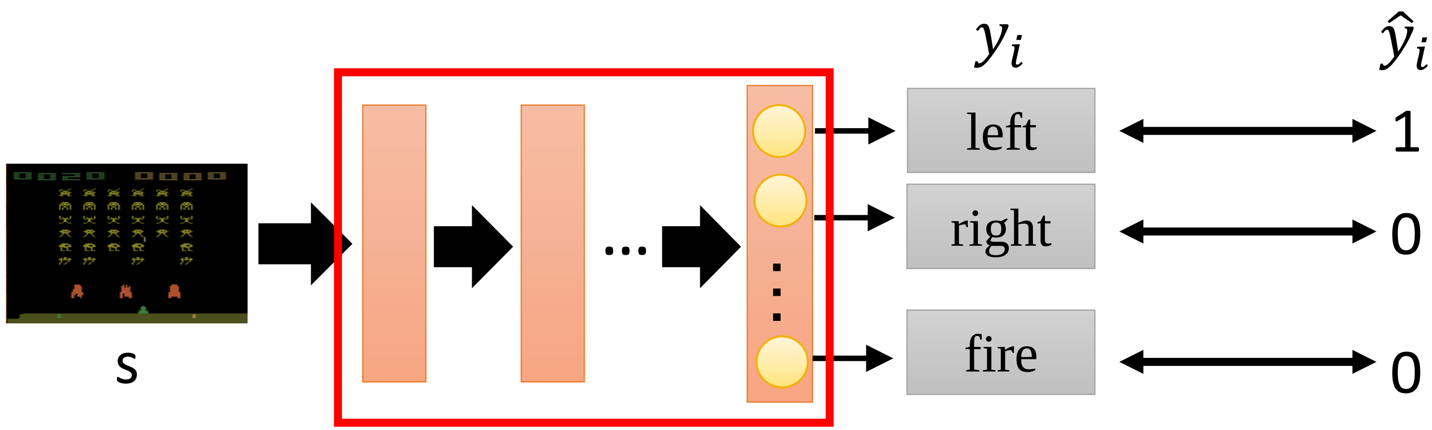
$$\frac{1}{N} \sum_{n=1}^{N} \sum_{t=1}^{T_n} R(\tau^n) \nabla log p(a_t^n | s_t^n, \theta)$$

Data Collection

Policy Gradient

Considered as Classification Problem

Minimize: $-\sum_{i=1}^{3} \hat{y}_i log y_i$



Maximize: $log y_i =$

$log P("left"|s)$

$$\theta \leftarrow \theta + \eta \nabla log P("left"|s)$$

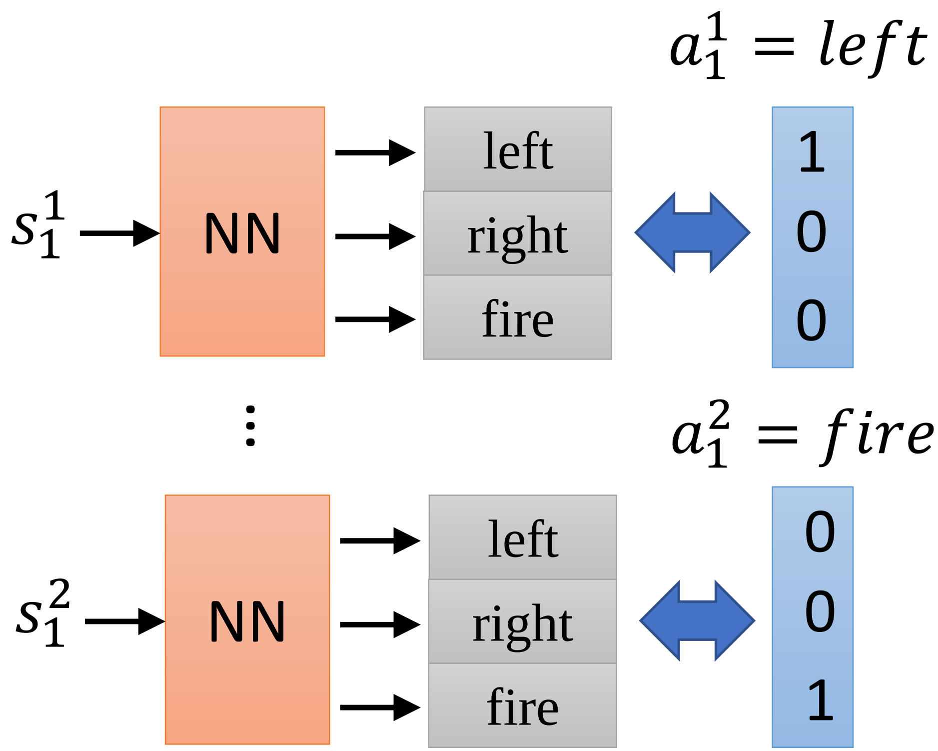
Policy Gradient

$$\theta \leftarrow \theta + \eta \nabla \bar{R}_\theta$$

$$\nabla \bar{R}_\theta = \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n} \nabla logp(a_t^n | s_t^n, \theta)$$

Given actor parameter θ

τ^1:	(s_1^1, a_1^1)	$R(\tau^1)$
	(s_2^1, a_2^1)	$R(\tau^1)$
	⋮	⋮
τ^2:	(s_1^2, a_1^2)	$R(\tau^2)$
	(s_2^2, a_2^2)	$R(\tau^2)$
	⋮	⋮



Policy Gradient

$$\theta \leftarrow \theta + \eta \nabla \bar{R}_\theta$$

$$\nabla \bar{R}_\theta = \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n} R(\tau^n) \nabla log p(a_t^n | s_t^n, \theta)$$

Given actor parameter θ

τ^1: (s_1^1, a_1^1) $R(\tau^1)$ 2

(s_2^1, a_2^1) $R(\tau^1)$ 2

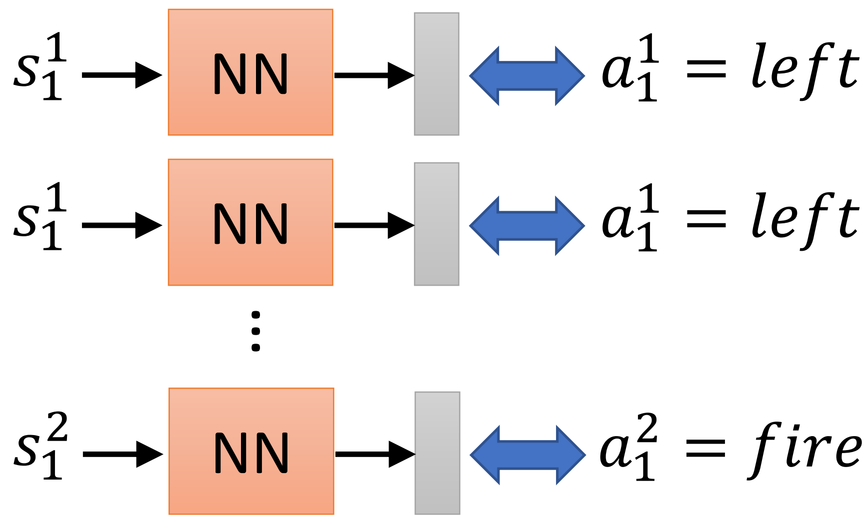
⋮ ⋮

τ^2: (s_1^2, a_1^2) $R(\tau^2)$ 1

(s_2^2, a_2^2) $R(\tau^2)$ 1

⋮ ⋮

Each training data is weighted by $R(\tau^n)$

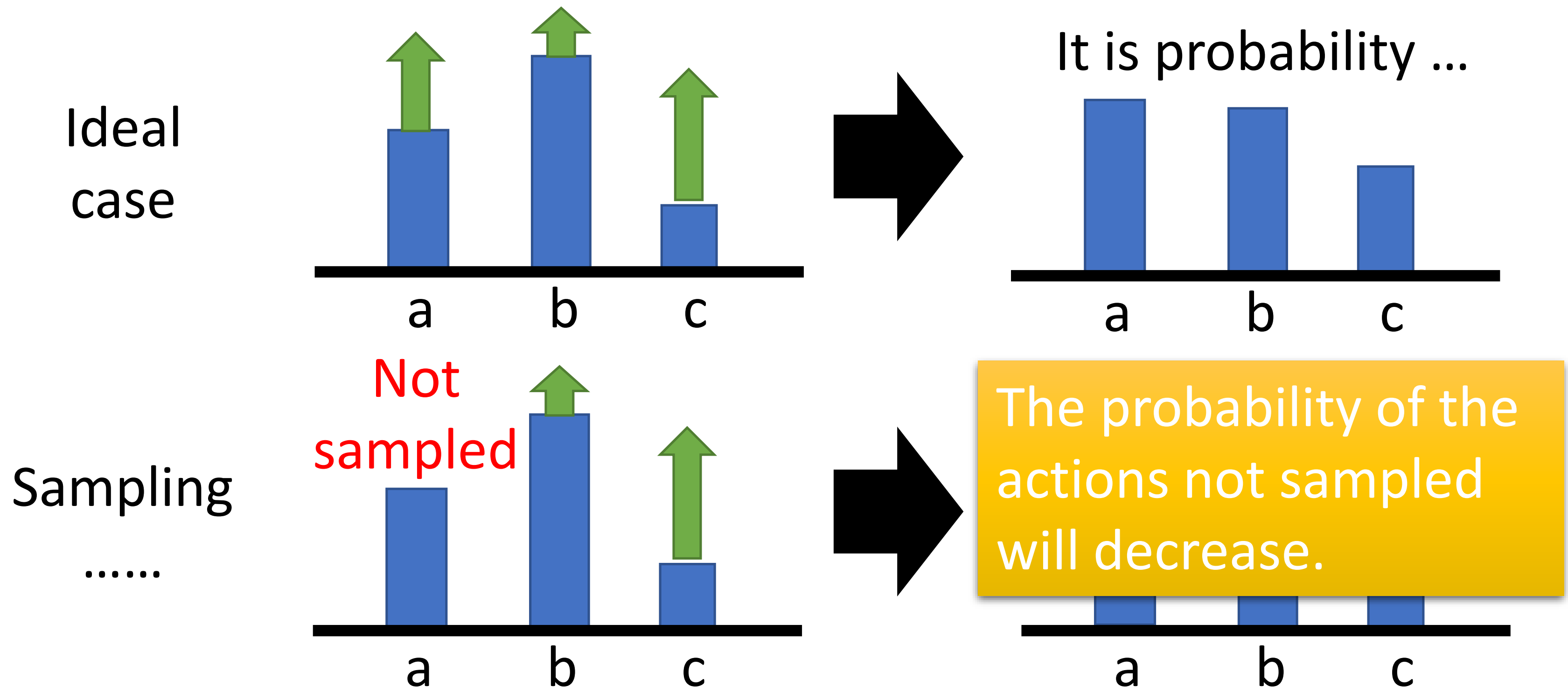


Add a Baseline

It is possible that $R(\tau^n)$ is always positive.

$$\theta^{new} \leftarrow \theta^{old} + \eta \nabla \bar{R}_{\theta^{old}}$$

$$\nabla \bar{R}_\theta \approx \frac{1}{N}\sum_{n=1}^{N}\sum_{t=1}^{T_n}(R(\tau^n) - b)\nabla \log p(a_t^n|s_t^n,\theta)$$



Value-based Approach

Learning a Critic

Critic

- A critic does not determine the action.
- Given an actor π, it evaluates the how good the actor is

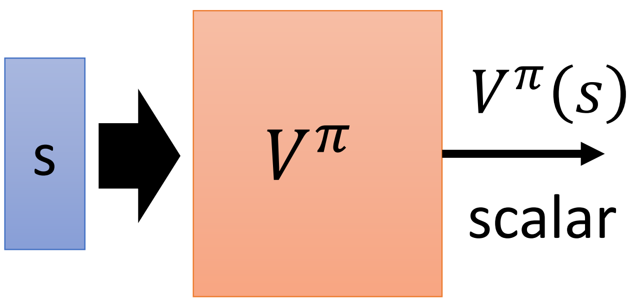
An actor can be found from a critic.

e.g. Q-learning

http://combiboilersleeds.com/picaso/critics/critics-4.html

Critic

- State value function $V^{\pi}(s)$
  - When using actor π, the *cumulated* reward expects to be obtained after seeing observation (state) s



$V^{\pi}(s)$ is large

$V^{\pi}(s)$ is smaller

Critic

$$V^{以前的阿光}(大馬步飛) = \text{bad}$$

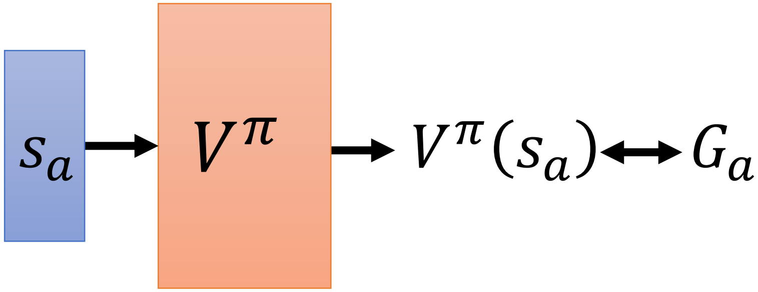
$$V^{變強的阿光}(大馬步飛) = \text{good}$$

How to estimate $V^{\pi}(s)$

- Monte-Carlo based approach
  - The critic watches π playing the game

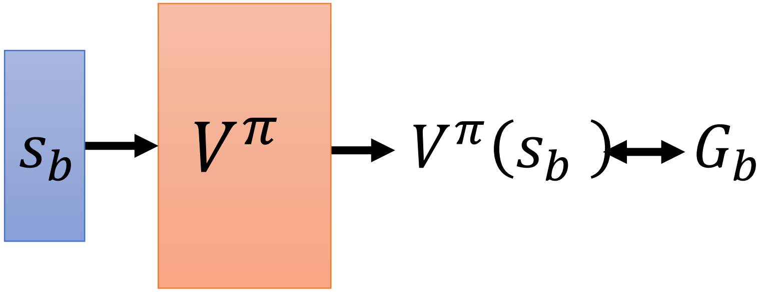
After seeing s_a,

Until the end of the episode, the cumulated reward is G_a



After seeing s_b,

Until the end of the episode, the cumulated reward is G_b

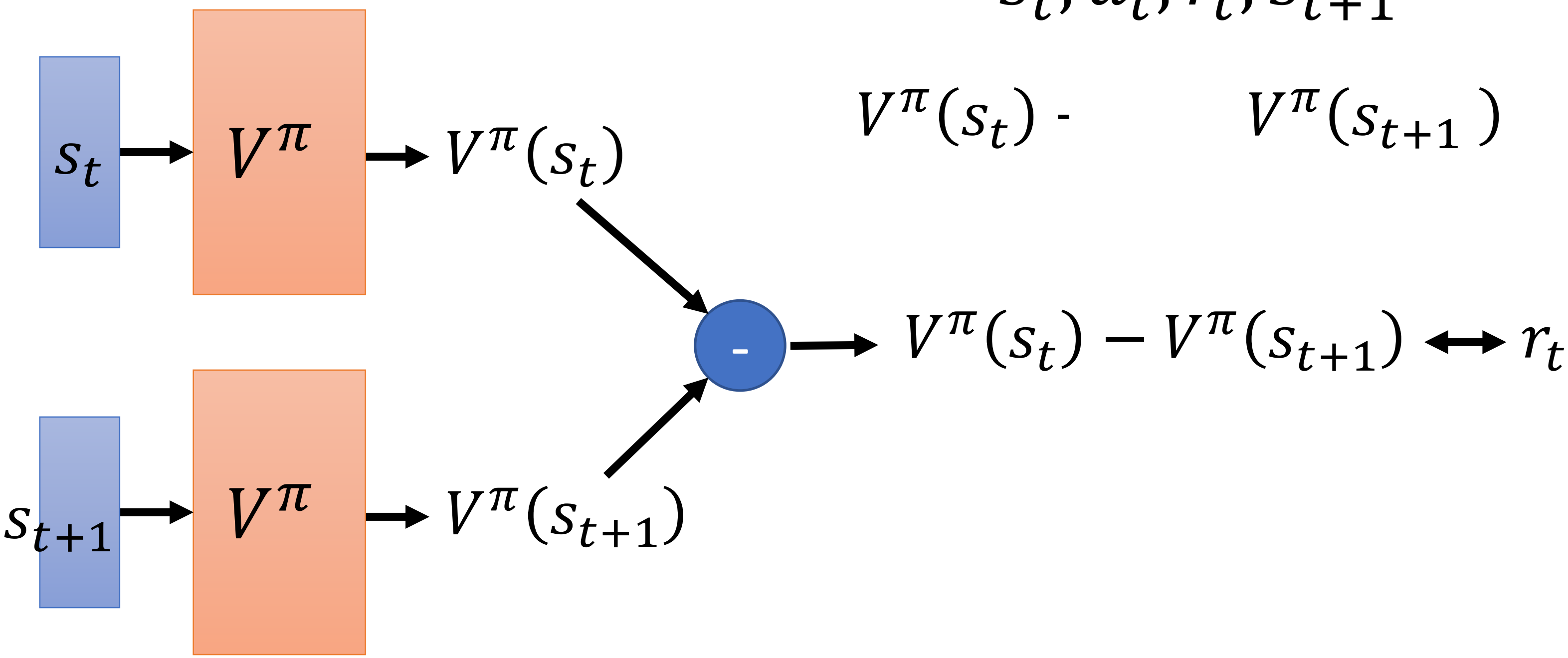


How to estimate $V^{\pi}(s)$

- Temporal-difference approach

$$\cdots s_t, a_t, r_t, s_{t+1} \cdots$$

$$V^{\pi}(s_t) = V^{\pi}(s_{t+1}) + r_t$$



Some applications have very long episodes, so that delaying all learning until an episode's end is too slow.

MC v.s. TD

$$s_a \rightarrow V^\pi \rightarrow V^\pi(s_a) \longleftrightarrow G_a$$

Larger variance

unbiased

$$s_t \rightarrow V^\pi \rightarrow V^\pi(s_t) \longleftrightarrow r + V^\pi(s_{t+1}) \longleftarrow V^\pi \longleftarrow s_{t+1}$$

Smaller variance

May be biased

MC v.s. TD

[Sutton, v2, Example 6.4]

- The critic has the following 8 episodes
  - $s_a, r = 0, s_b, r = 0$, END
  - $s_b, r = 1$, END
  - $s_b, r = 1$, END
  - $s_b, r = 1$, END
  - $s_b, r = 1$, END
  - $s_b, r = 1$, END
  - $s_b, r = 1$, END
  - $s_b, r = 0$, END

$$V^\pi(s_b) = 3/4$$

$V^\pi(s_a) =?$ 0?   3/4?

Monte-Carlo: $V^\pi(s_a) = 0$

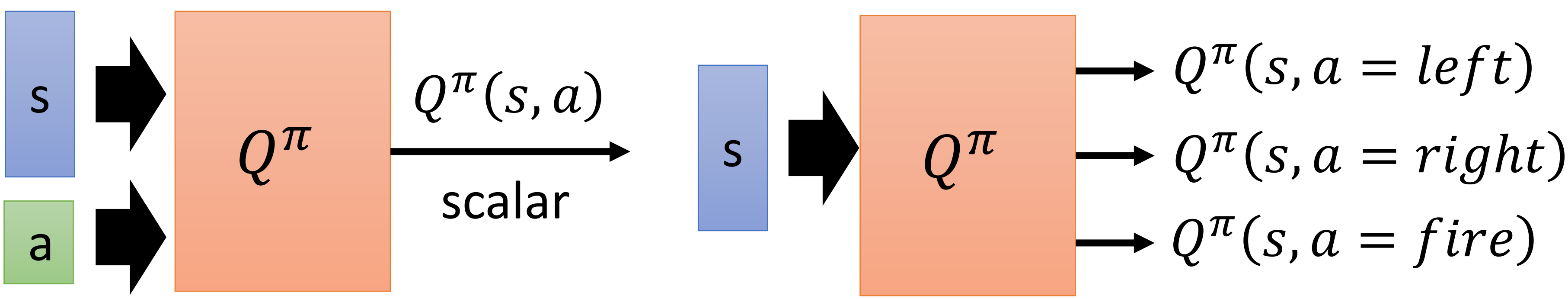
Temporal-difference:

$$\underset{3/4}{V^\pi(s_b)} + \underset{0}{r} = \underset{3/4}{V^\pi(s_a)}$$

(The actions are ignored here.)

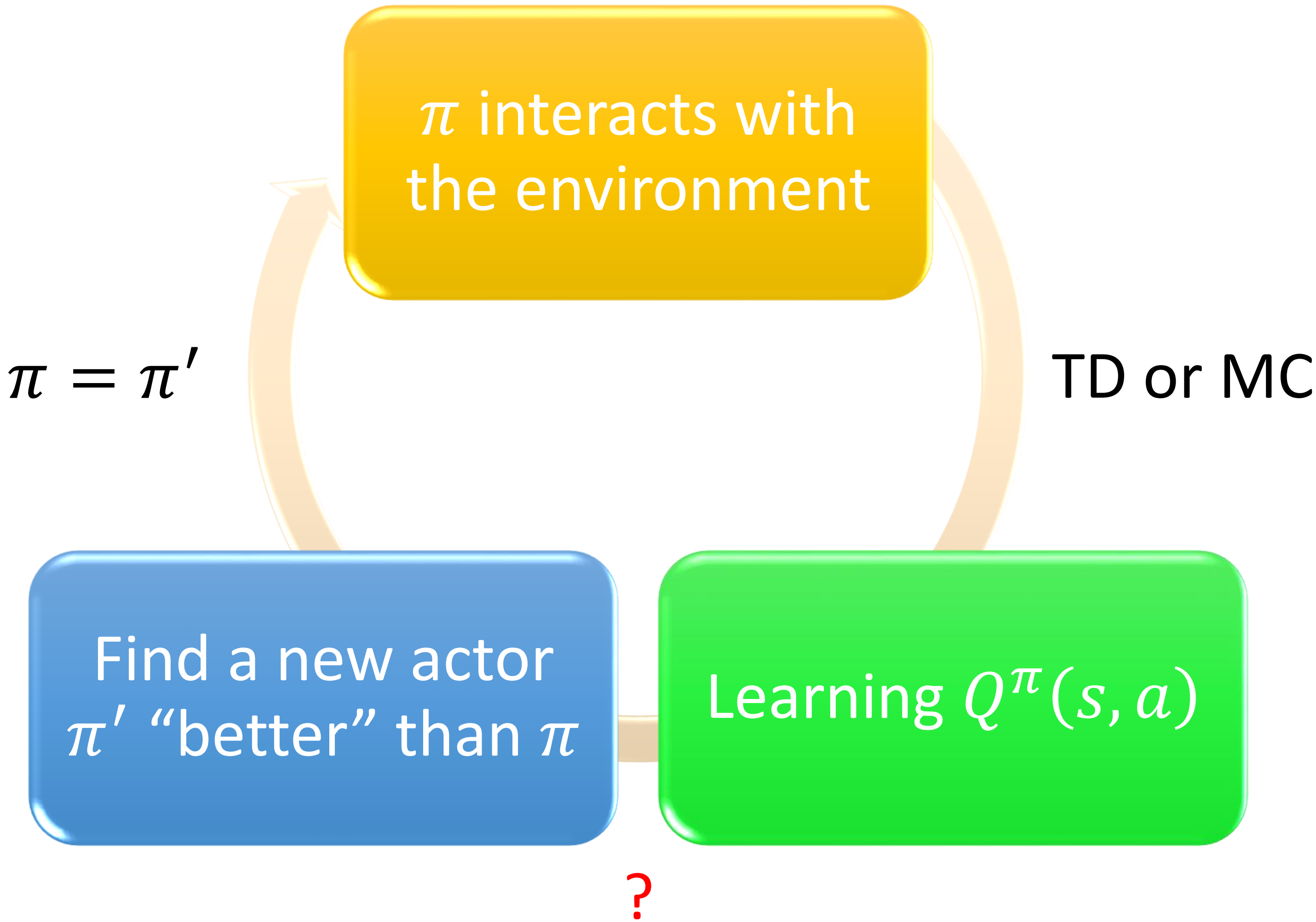
Another Critic

- State-action value function $Q^{\pi}(s,a)$
  - When using actor π, the *cumulated* reward expects to be obtained after seeing observation s and taking a

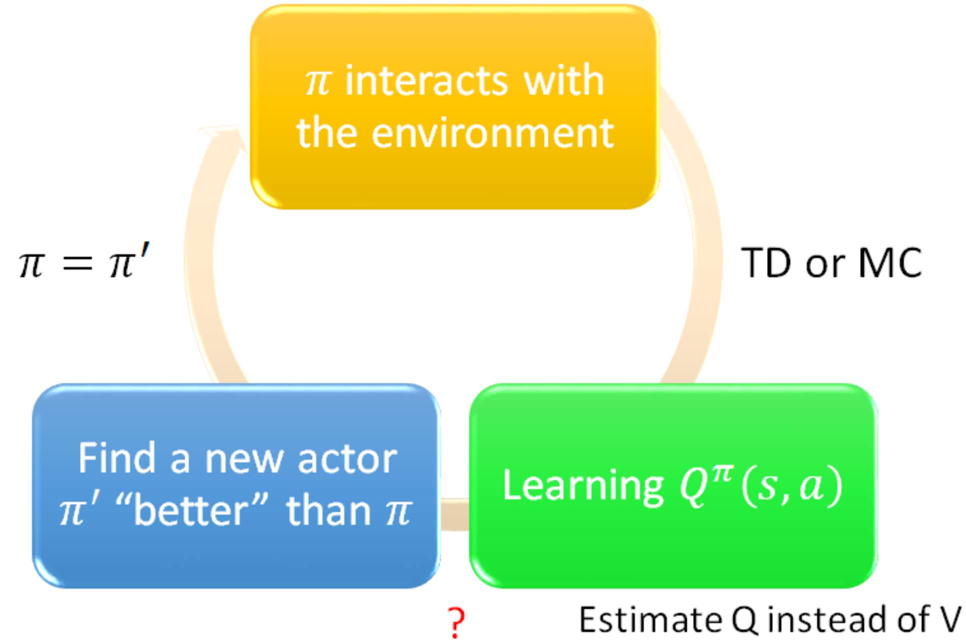


for discrete action only

Q-Learning


π interacts with the environment
TD or MC
Learning $Q^{\pi}(s,a)$
?
Find a new actor π' “better” than π
$\pi = \pi'$

Q-Learning



- Given $Q^\pi(s,a)$, find a new actor π' "better" than π
  - "Better": $V^{\pi'}(s) \ge V^\pi(s)$, for all state s

$$\pi'(s) = arg\max_a Q^\pi(s,a)$$

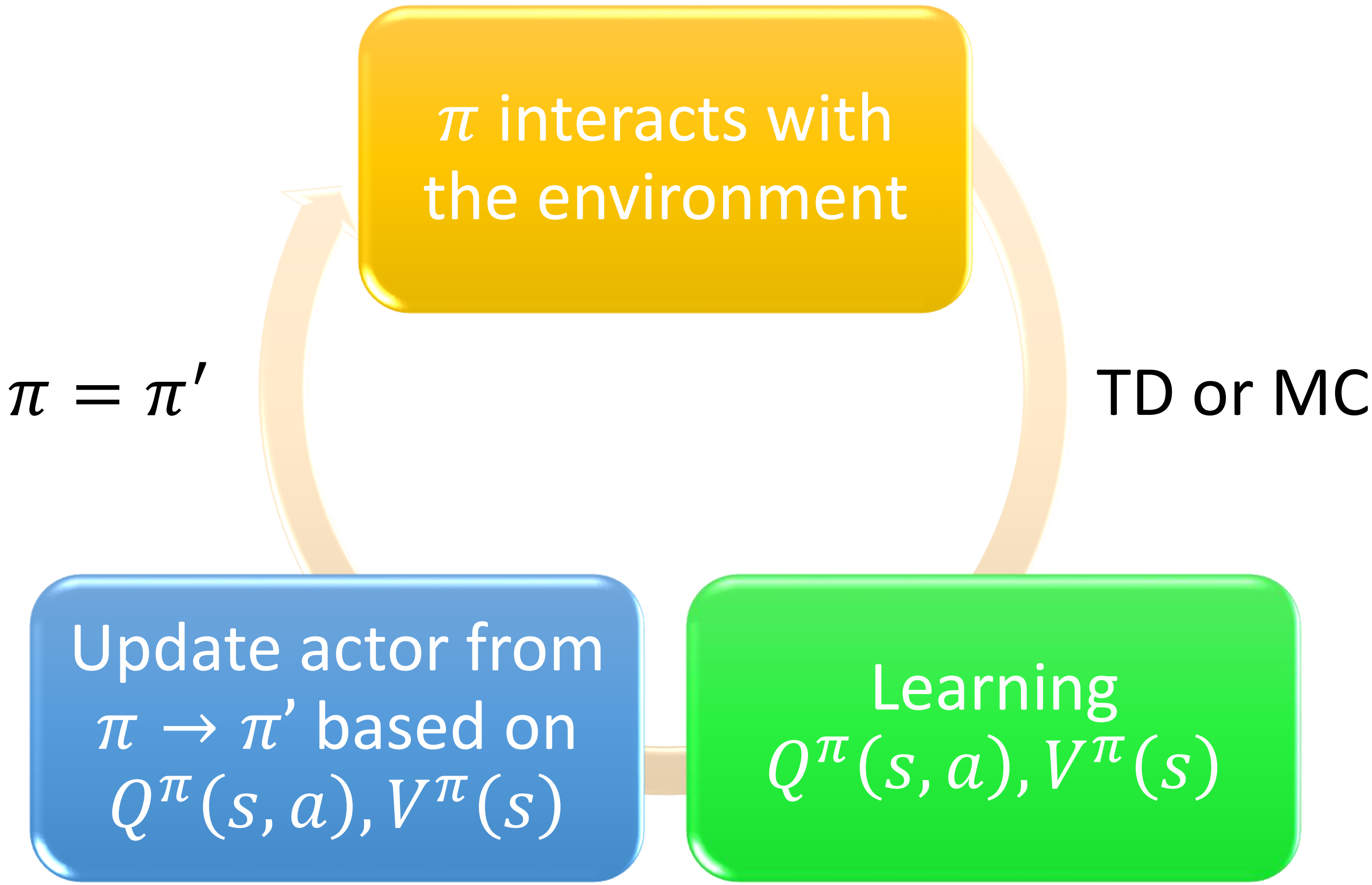
➢ π' does not have extra parameters. It depends on Q

➢ Not suitable for continuous action a

Deep Reinforcement Learning

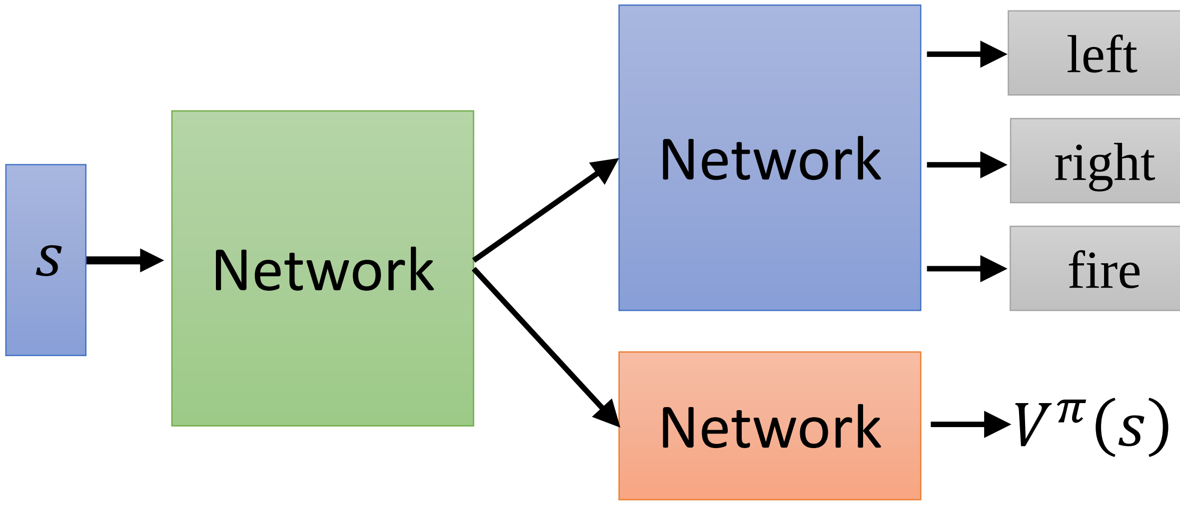
Actor-Critic

Actor-Critic



Actor-Critic

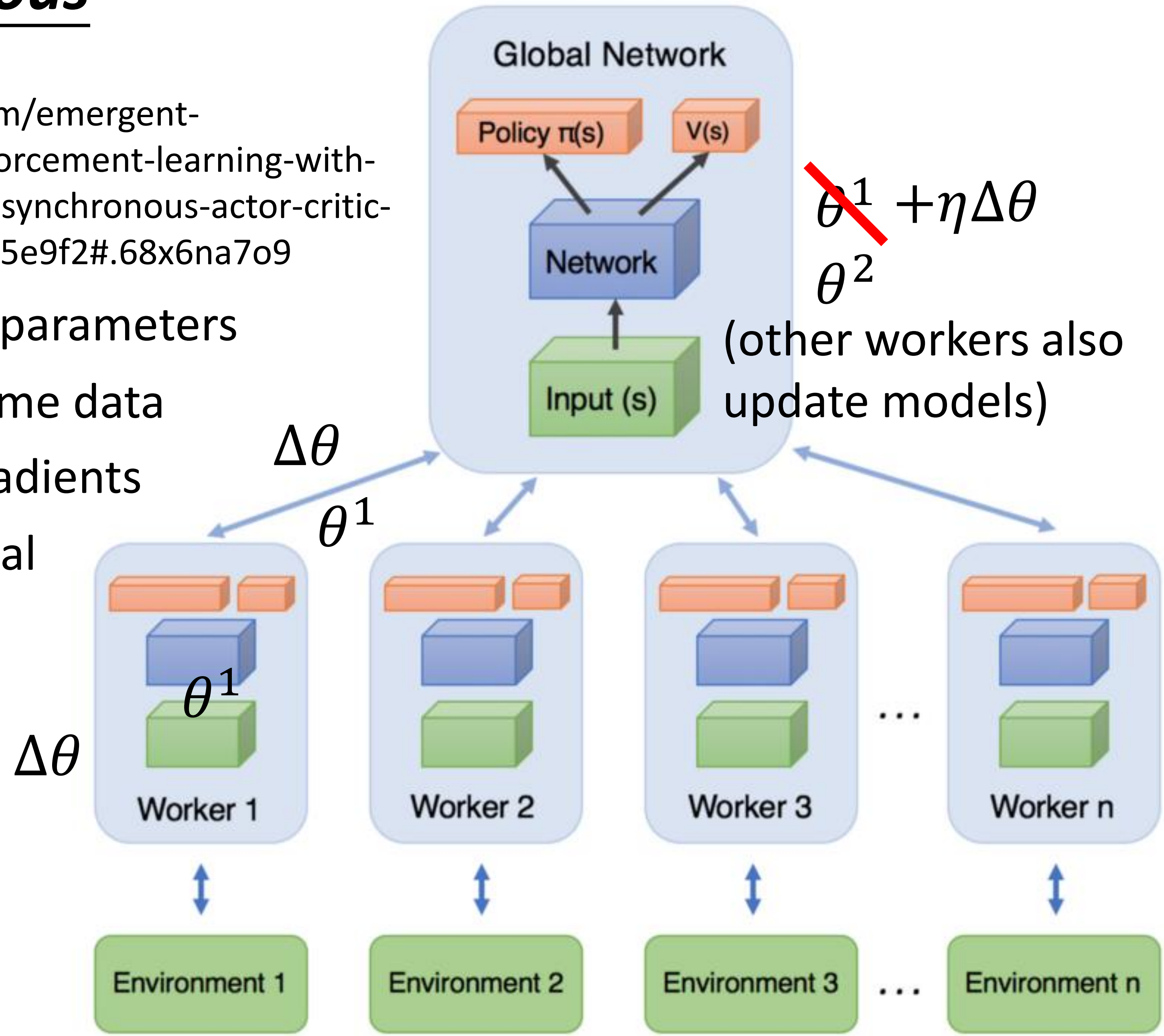
- Tips
  - The parameters of actor $\pi(s)$ and critic $V^\pi(s)$ can be shared



Asynchronous

Source of image: https://medium.com/emergent-future/simple-reinforcement-learning-with-tensorflow-part-8-asynchronous-actor-critic-agents-a3c-c88f72a5e9f2#.68x6na7o9

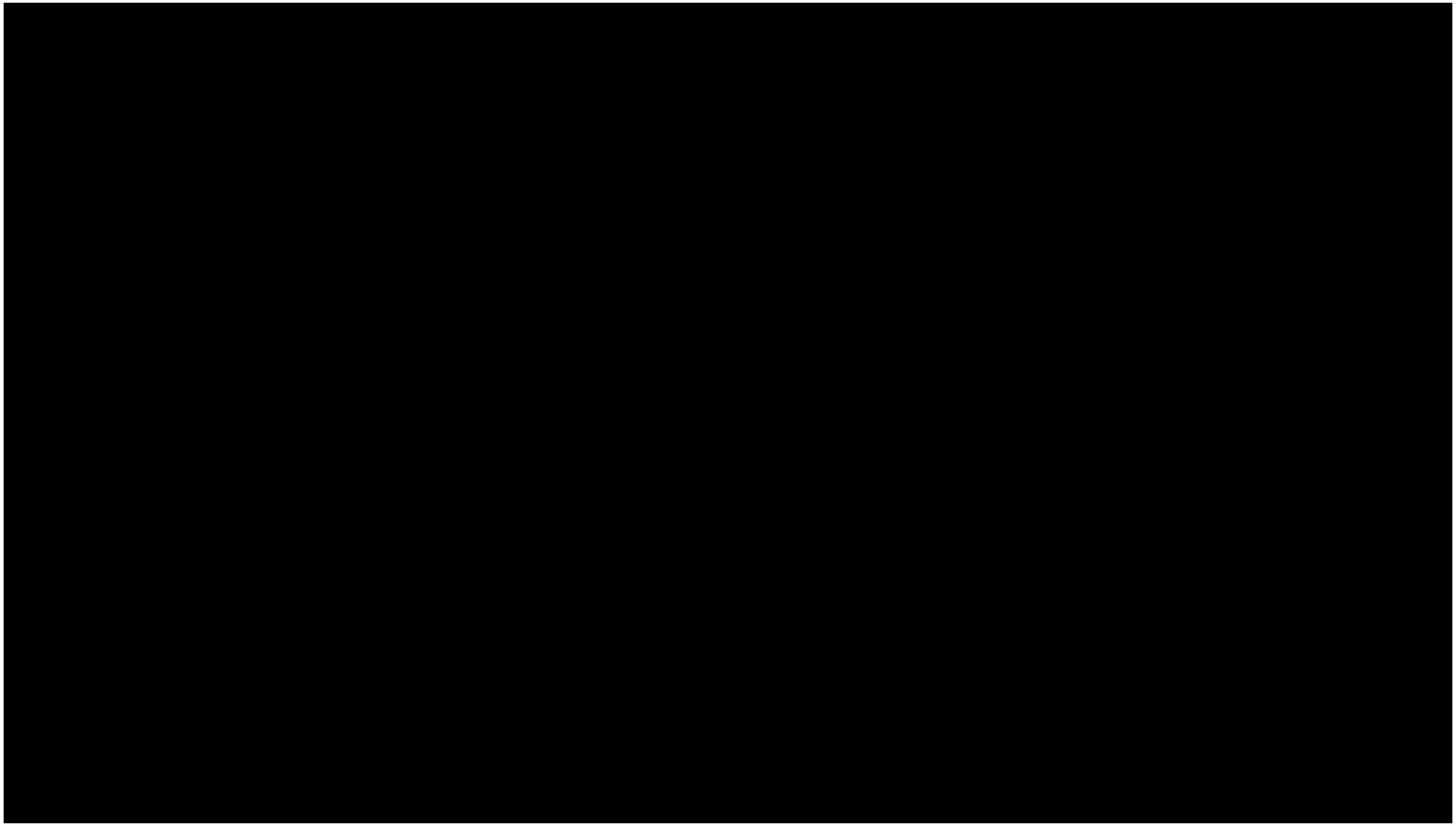
1. Copy global parameters
2. Sampling some data
3. Compute gradients
4. Update global models



Demo of A3C

https://www.youtube.com/watch?v=0xo1Ldx3L5Q

- Racing Car (DeepMind)

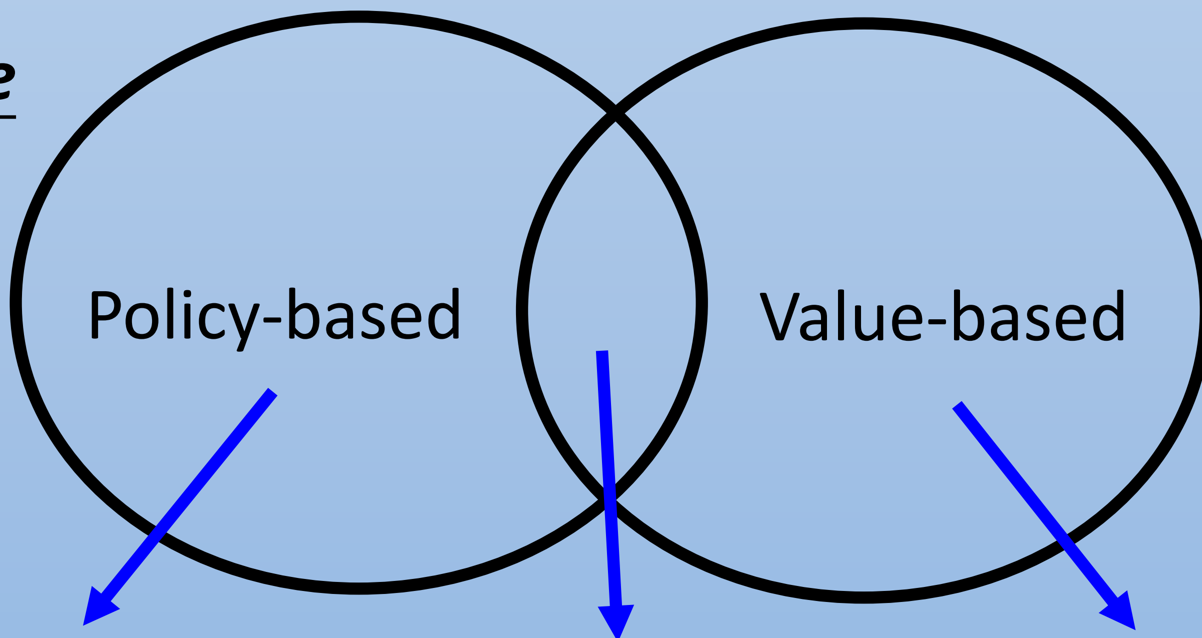


Demo of A3C

- Visual Doom AI Competition @ CIG 2016
- https://www.youtube.com/watch?v=94EPSjQH38Y

Concluding Remarks

Model-free Approach



Model-based Approach