CRIPAC 智能感知与计算研究中心 Center for Research on Intelligent Perception and Computing

中国科学院自动化研究所 Institute of Automation Chinese Academy of Sciences

2018

"Deep Learning Lecture"

Lecture 10: Reinforcement Learning

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Outline

1. Course Review
2. Background
3. Model-free learning
4. Model-based learning
5. Applications

GAN's Formulation

$$\min_G \max_D V(D,G)$$

- It is formulated as a **minimax game**, where:
  - The Discriminator is trying to maximize its reward $\boldsymbol{V(D,G)}$
  - The Generator is trying to minimize Discriminator's reward (or maximize its loss)

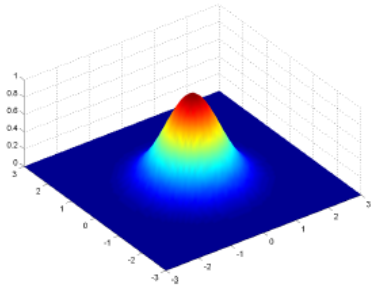
$$V(D,G) = \mathbb{E}_{x\sim p(x)}[\log D(x)] + \mathbb{E}_{z\sim q(z)}[\log(1 - D(G(z)))]$$

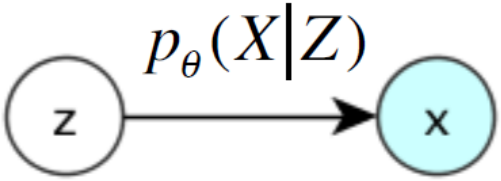
- The Nash equilibrium of this particular game is achieved at:
  - $P_{data}(x) = P_{gen}(x) \;\; \forall x$
  - $\mathrm{D}(x) = \frac{1}{2} \;\; \forall x$

Principle Idea decoder network

- We have a set of N-observations (e.g. images) $\{x^{(1)},x^{(2)},\ldots,x^{(N)}\}$
- Complex model parameterized with θ
- There is a latent space z with

$$z \sim p(z) \quad \text{multivariate Gaussian}$$
$$x|z \sim p_\theta(x|z)$$





One Example

Wish to learn θ from the N training observations $x^{(i)}$ i=1,…,N

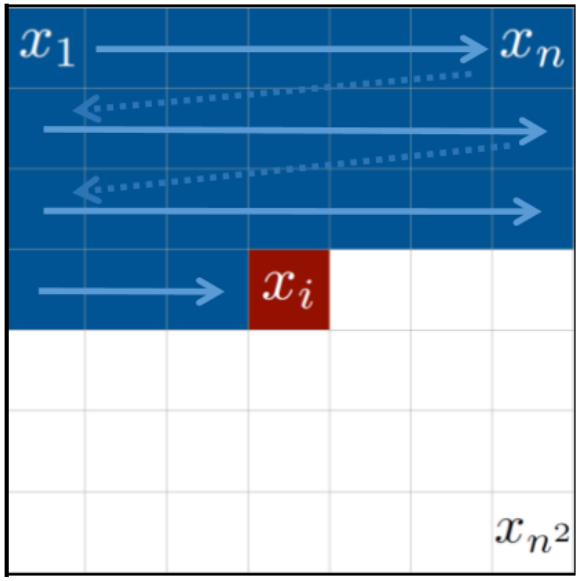
Pixel RNN

$$p(\mathbf{x}) = p(x_1, x_2, ..., x_{n^2})$$

Bayes Theorem:

$$p(\mathbf{x}) = \prod_{i=1}^{n^2} p(x_i | x_1, ..., x_{i-1})$$

A sequential model!



Pixel recurrent neural networks, ICML 2016

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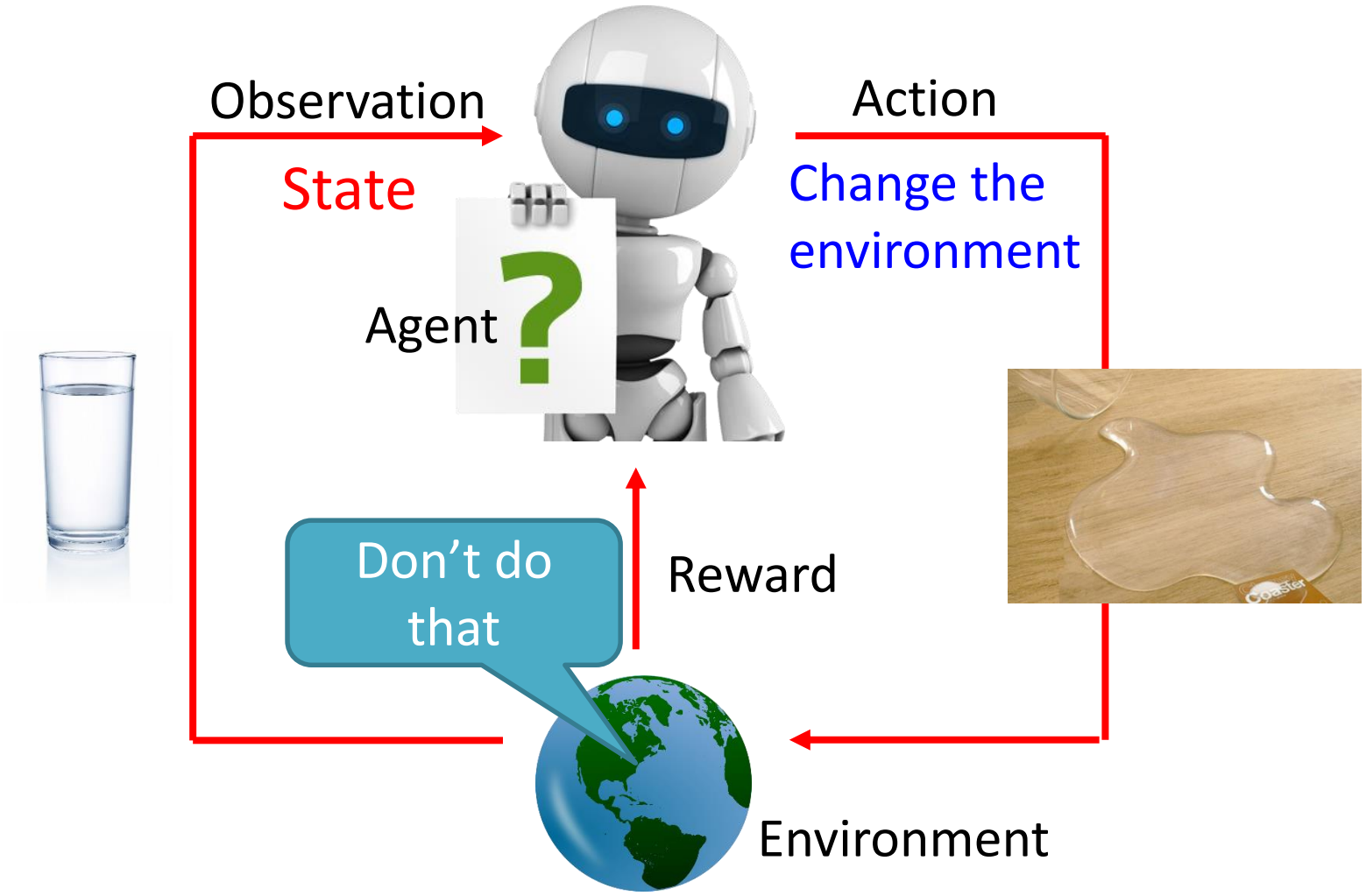
Background

Deep Reinforcement Learning: AI = RL + DL

Scenario of Reinforcement Learning

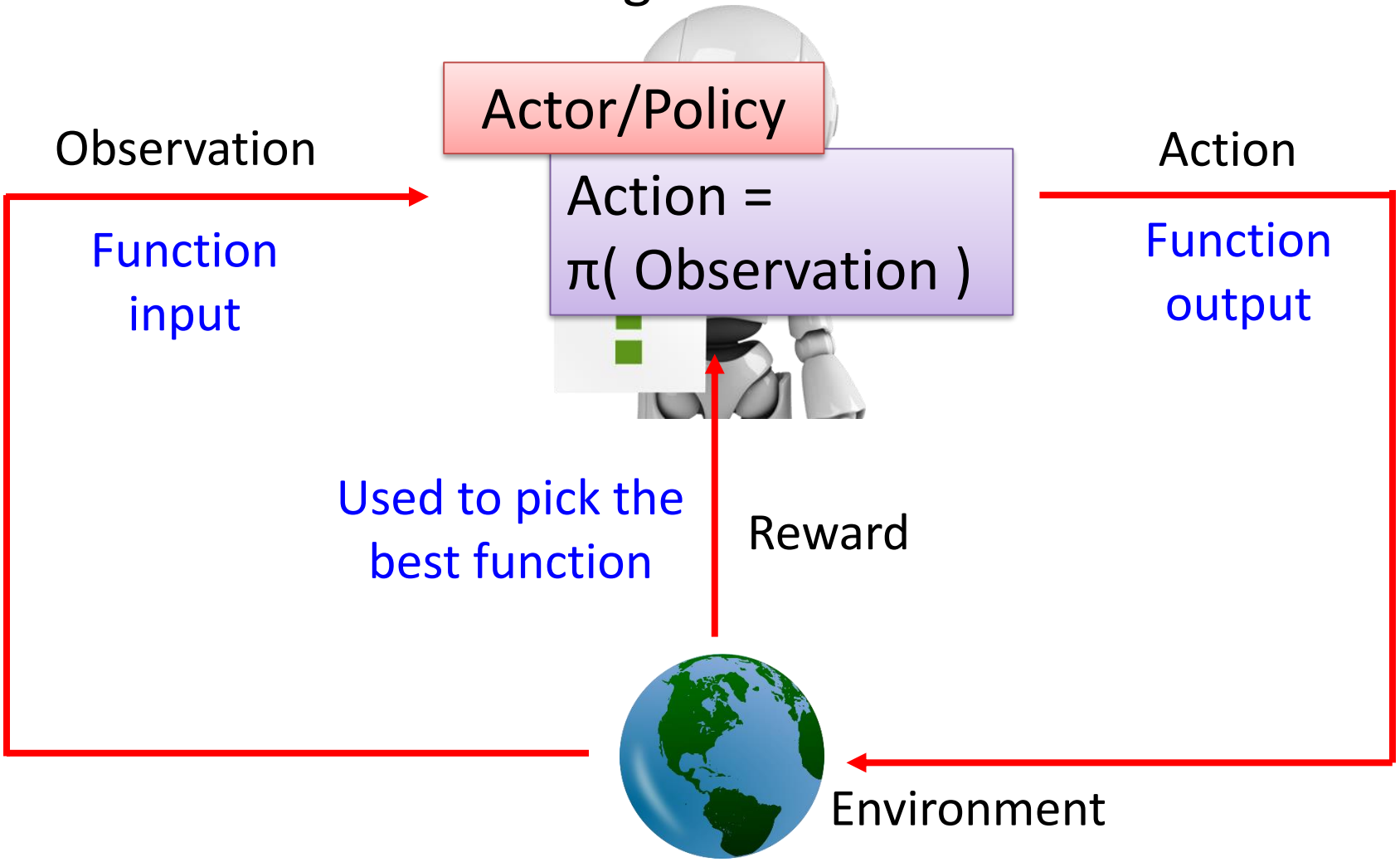


Scenario of Reinforcement Learning

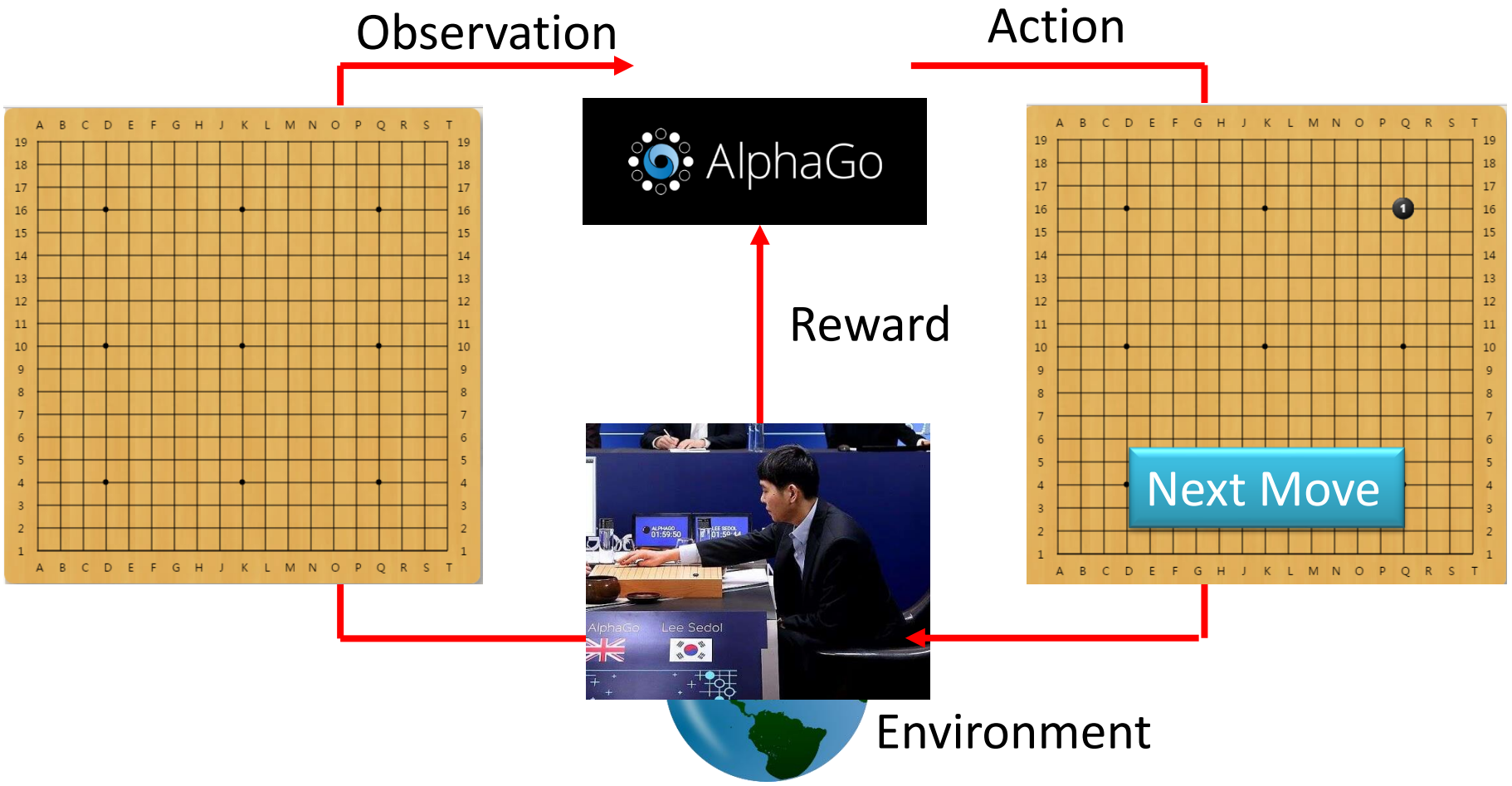
https://yoast.com/how-to-clean-site-structure/

Scenario of Reinforcement Learning

Machine Learning
≈ Looking for a Function

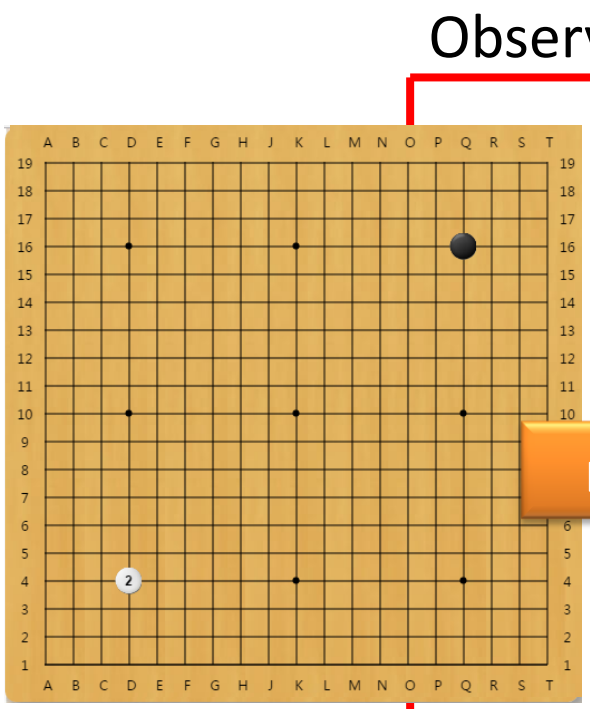


Learning to play Go



Learning to play Go

Agent learns to take actions maximizing expected reward.



Observation

Action

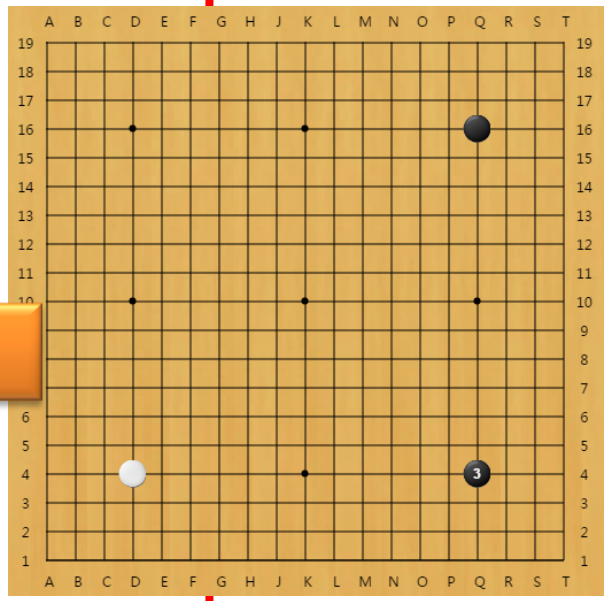
AlphaGo

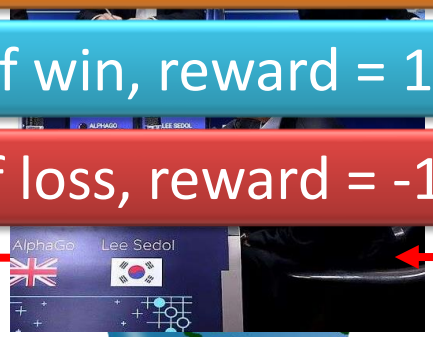
Reward

reward = 0 in most cases

If win, reward = 1

If loss, reward = -1



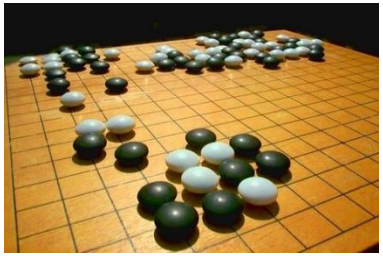


Environment

Learning to play Go

- Supervised: Learning from teacher

Next move: "5-5"



Next move: "3-3"

Learning from experience

- Reinforcement Learning

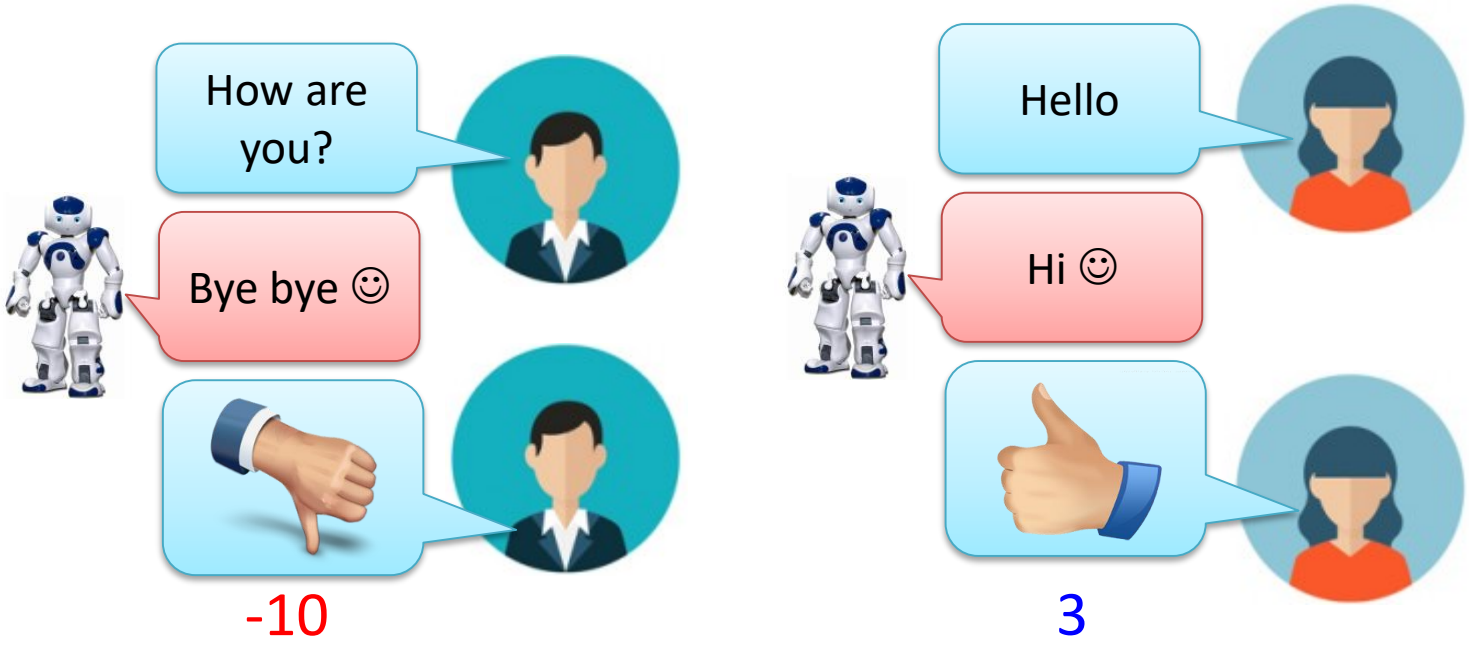
First move → …… many moves …… → Win!

(Two agents play with each other.)

Alpha Go is supervised learning + reinforcement learning.

Learning a chat-bot

- 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?

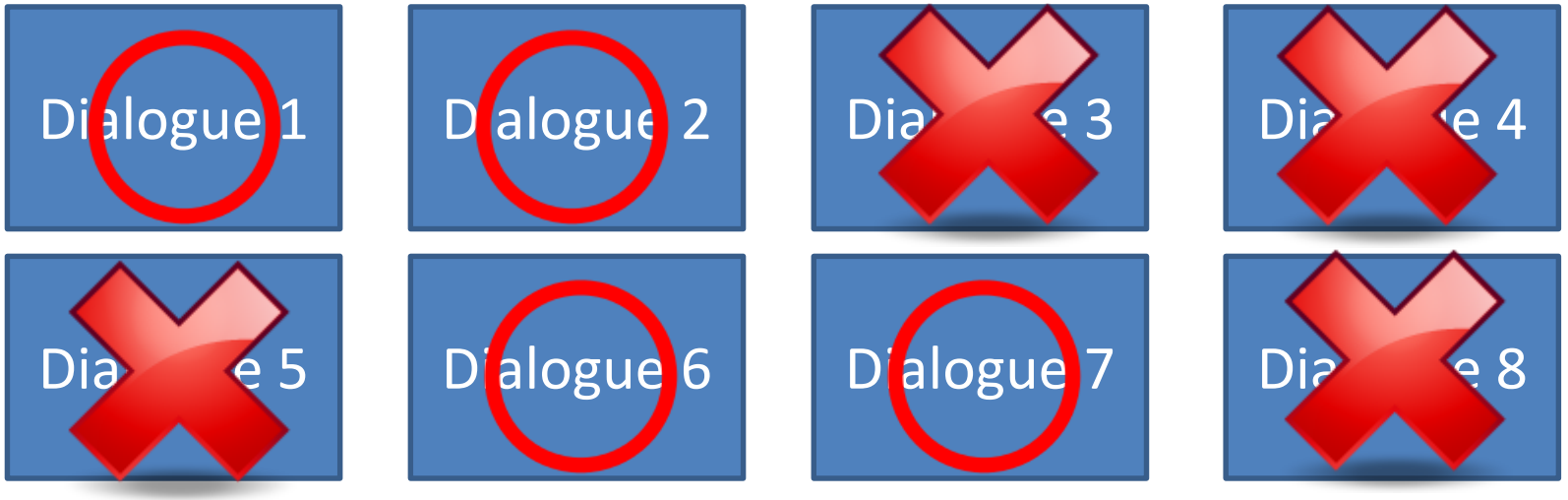
I am 16.

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

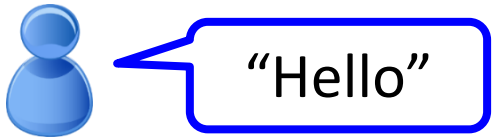


Machine learns from the evaluation

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

Learning a chat-bot

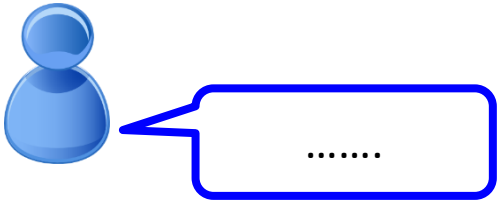
- Supervised

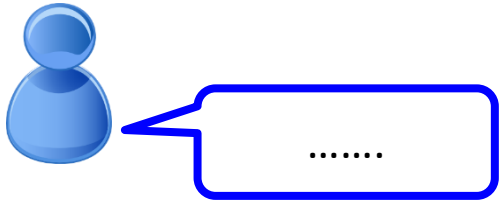


Say “Hi”

Say “Good bye”

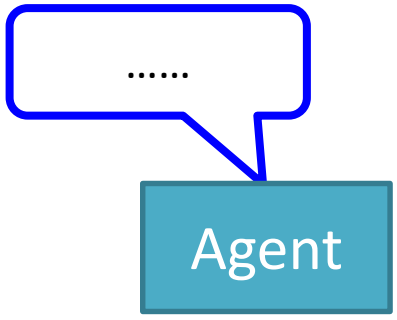
- Reinforcement





.....

Bad



More applications

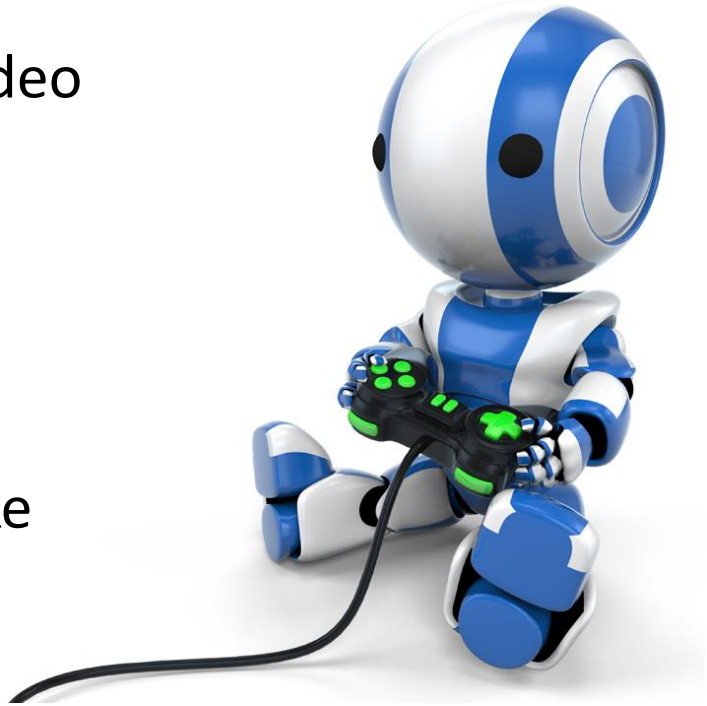
- Flying Helicopter
  - https://www.youtube.com/watch?v=0JL04JJjocc
- Driving
  - https://www.youtube.com/watch?v=0xo1Ldx3L5Q
- Robot
  - https://www.youtube.com/watch?v=370cT-OAzzM
- Google Cuts Its Giant Electricity Bill With DeepMind-Powered AI
  - http://www.bloomberg.com/news/articles/2016-07-19/google-cuts-its-giant-electricity-bill-with-deepmind-powered-a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

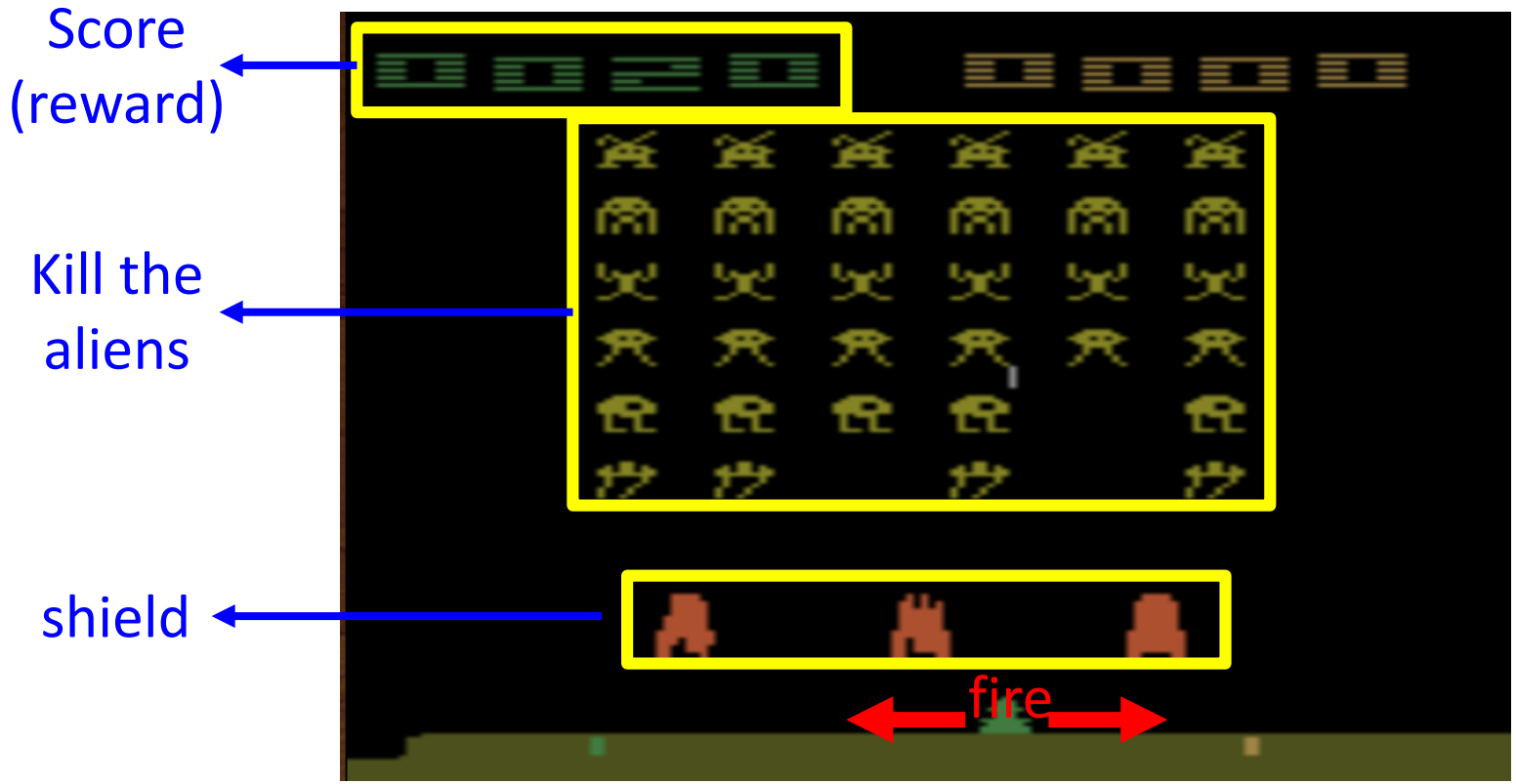
- What machine observes is pixel
- Machine learns to take proper action itself



Example: Playing Video Game

- Space invader

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

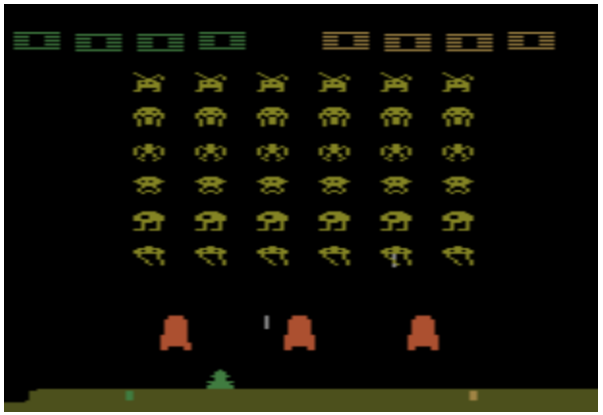


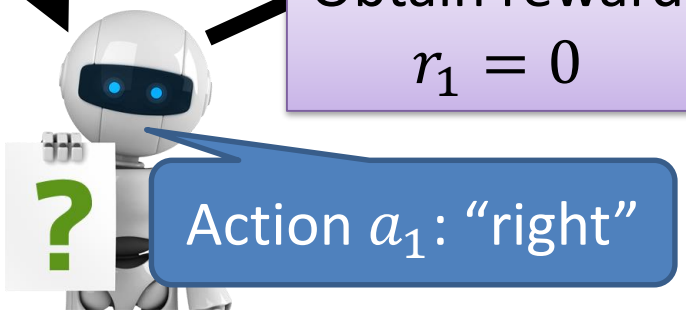
Example: Playing Video Game

Start with observation s_1

Observation s_2

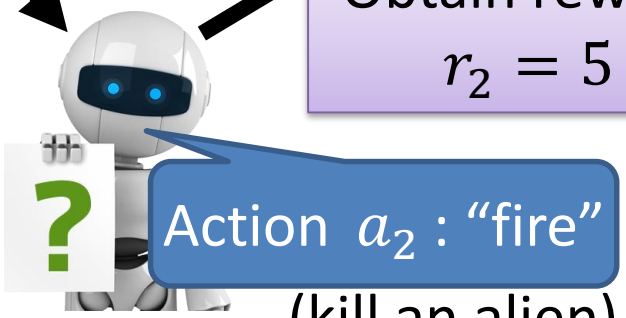
Observation s_3





Obtain reward $r_1 = 0$

Action a_1: "right"



Obtain reward $r_2 = 5$

Action a_2: "fire"

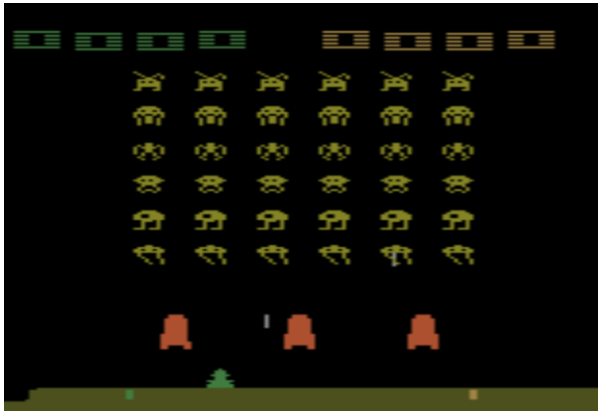
(kill an alien)

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***.

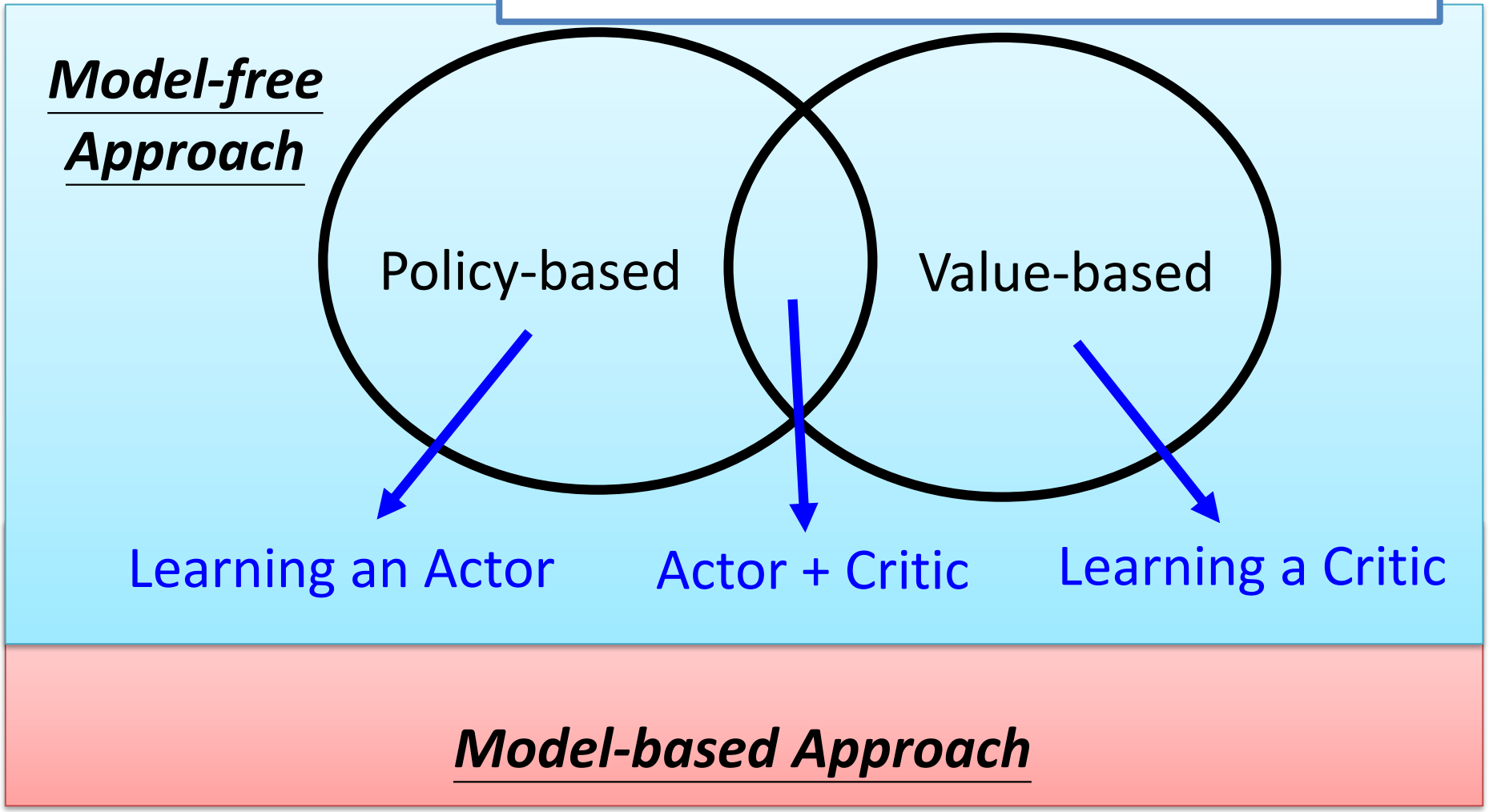
Learn to maximize the expected cumulative reward per episode

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

Methods of Reinforcement Learning

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



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Policy-based Approach

Learning an Actor

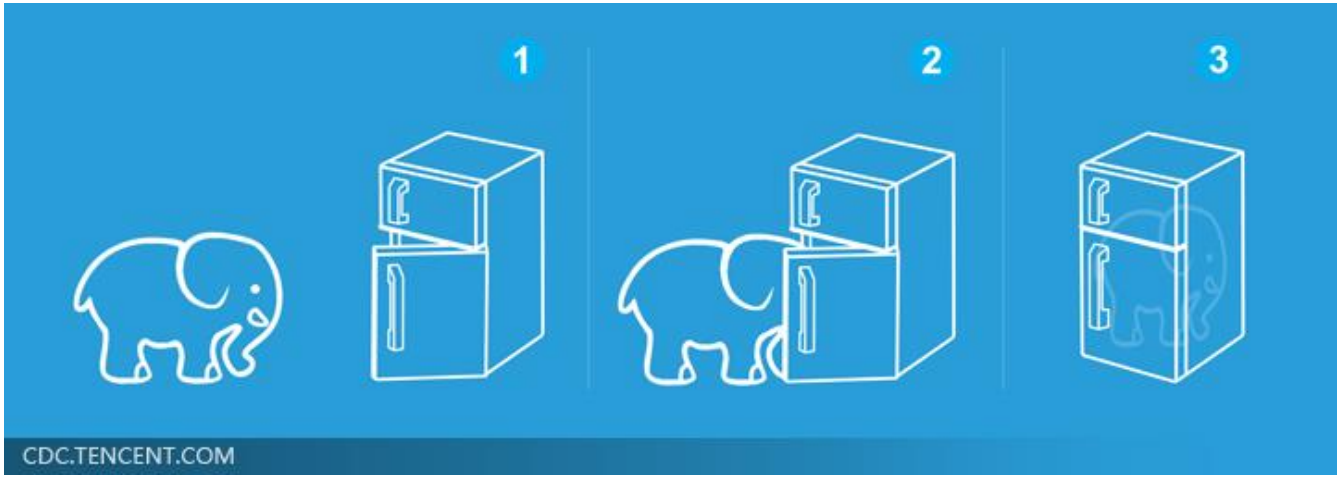
Three Steps for Deep Learning

Step 1: Neural Network as Actor

Step 2: goodness of function

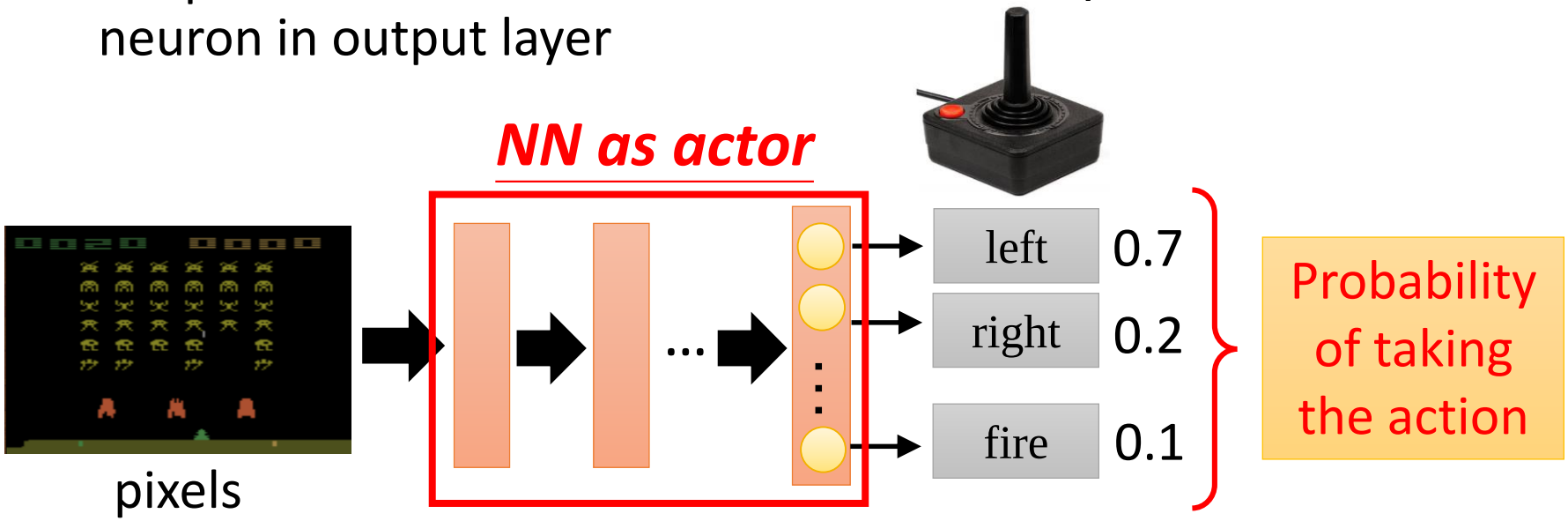
Step 3: pick the best function

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

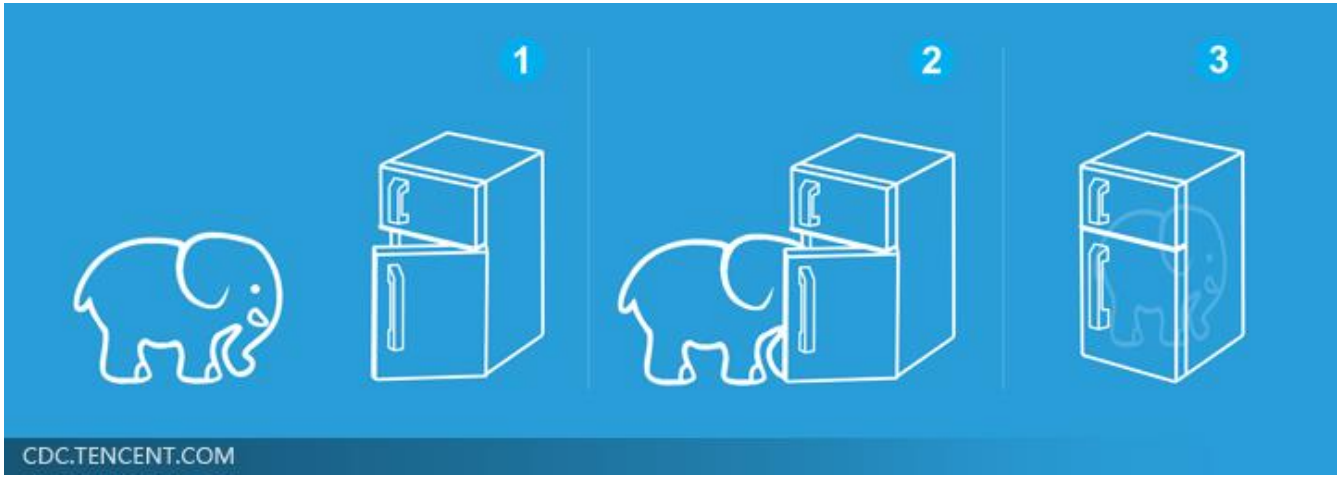
Three Steps for Deep Learning

Step 1: Neural Network as Actor

Step 2: goodness of function

Step 3: pick the best function

Deep Learning is so simple ……

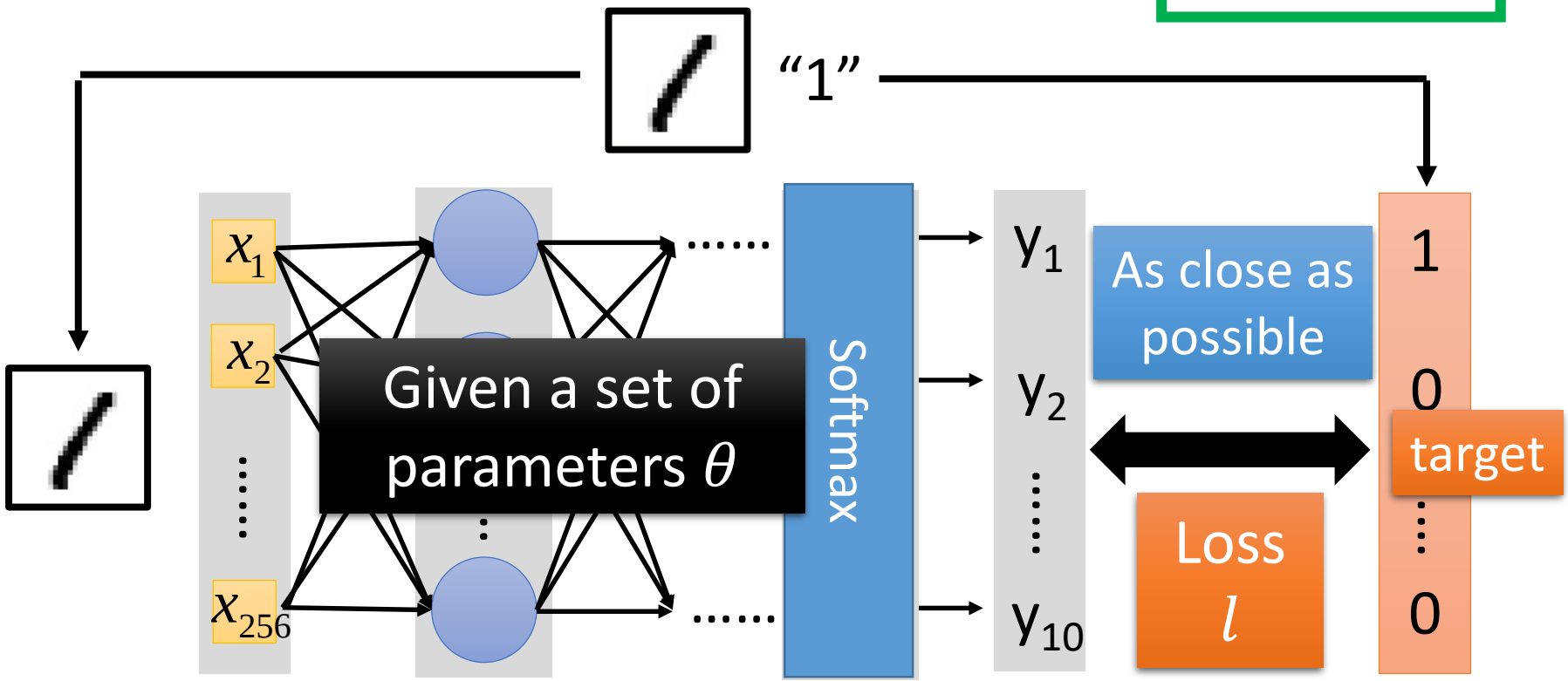


Goodness of Actor

- Review: Supervised learning

Total Loss:

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



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 *expected value* 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

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

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

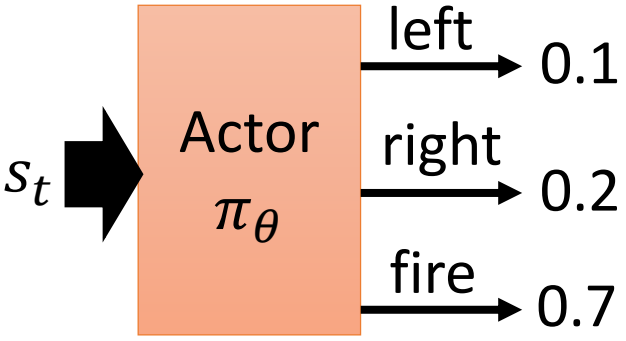
$$p(s_1)p(a_1|s_1,\theta)p(r_1,s_2|s_1,a_1)p(a_2|s_2,\theta)p(r_2,s_3|s_2,a_2)\cdots$$

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

not related to your actor

Control by your actor π_θ

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



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: $P(\tau|\theta)$

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

Sum over all possible trajectory

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

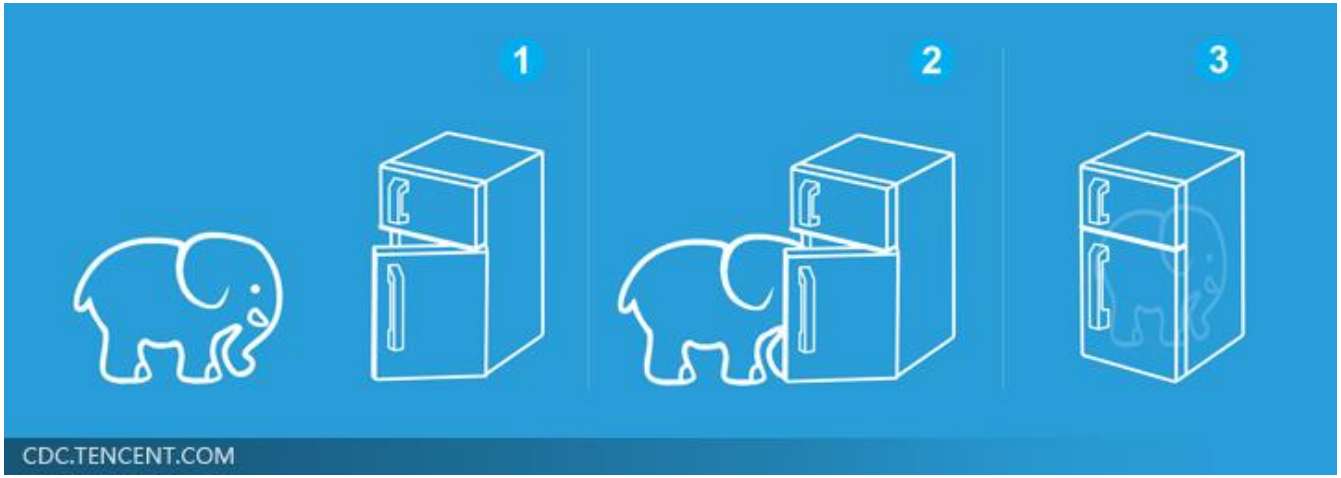
Three Steps for Deep Learning

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

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

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

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

It can even be a black box.

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

$$\frac{dlog\big(f(x)\big)}{dx} = \frac{1}{f(x)}\frac{df(x)}{dx}$$

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

Use π_θ to play the game N times,

Obtain $\{\tau^1, \tau^2, \cdots, \tau^N\}$

Policy Gradient

$\nabla logP(\tau|\theta) = ?$

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

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

$$logP(\tau|\theta)$$

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

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

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 .....

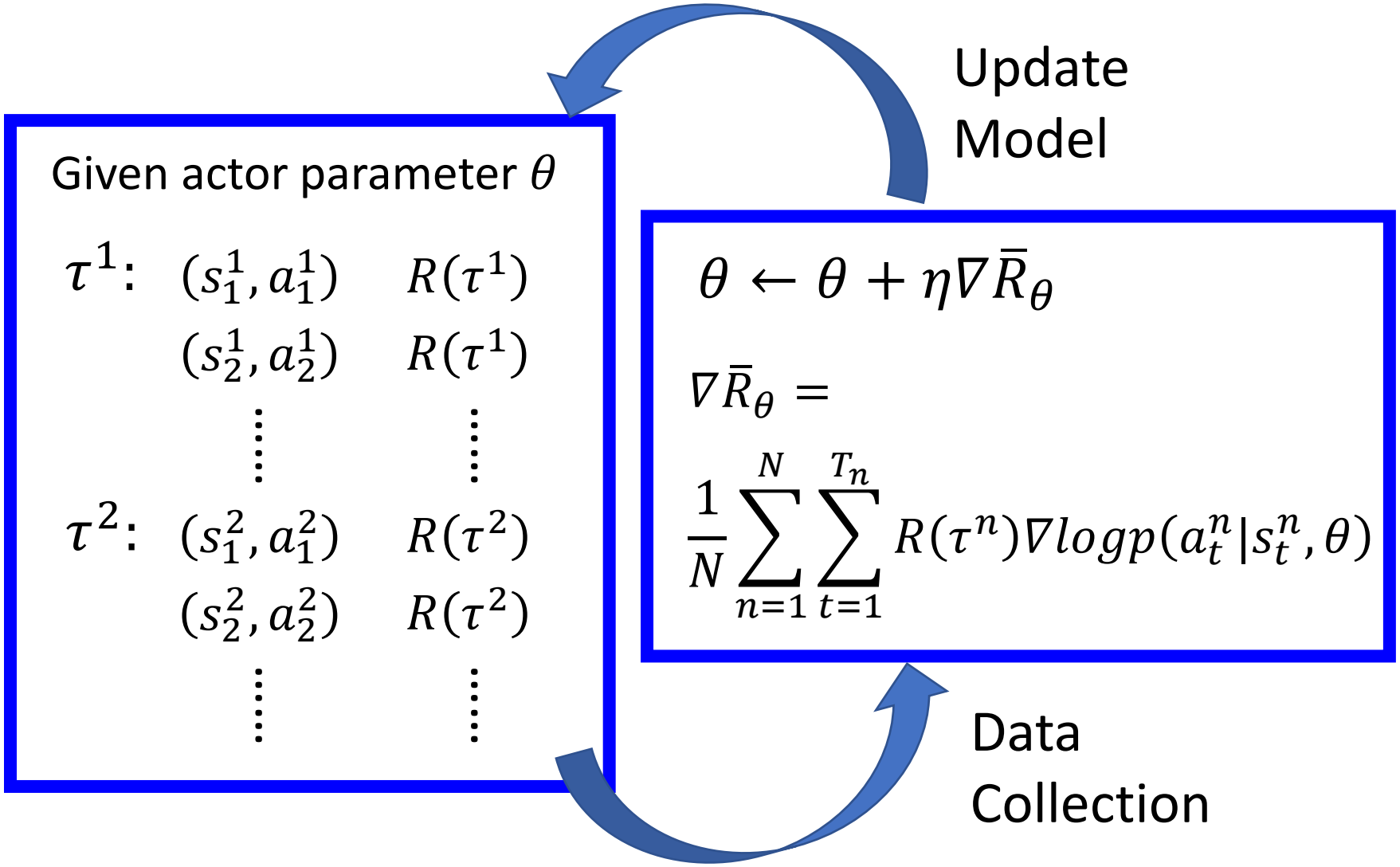
If in τ^n machine takes a_t^n when seeing s_t^n in

$R(\tau^n)$ 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

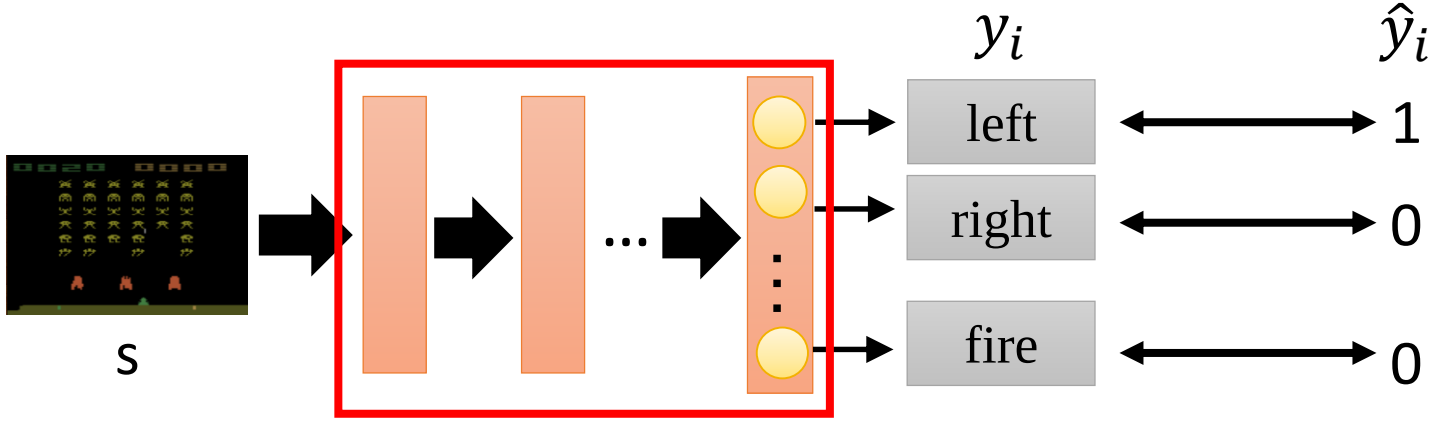
Policy Gradient



Policy Gradient

Considered as Classification Problem

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



Maximize: $logy_i = logP("left"|s)$

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

Policy Gradient

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

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

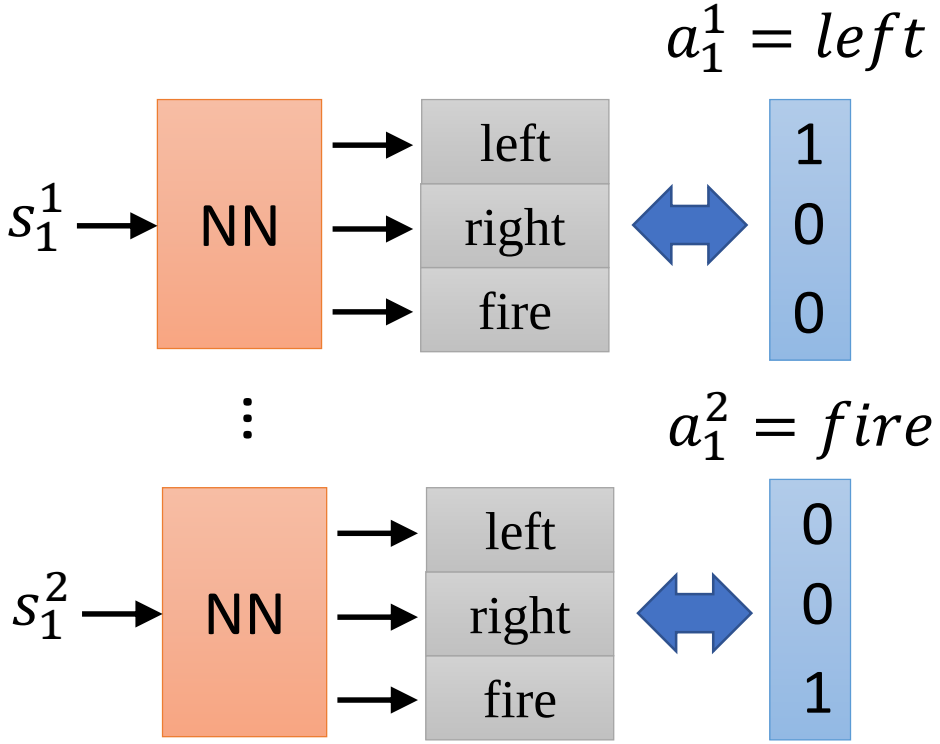
Given actor parameter θ

τ^1: (s_1^1, a_1^1) $R(\tau^1)$

(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

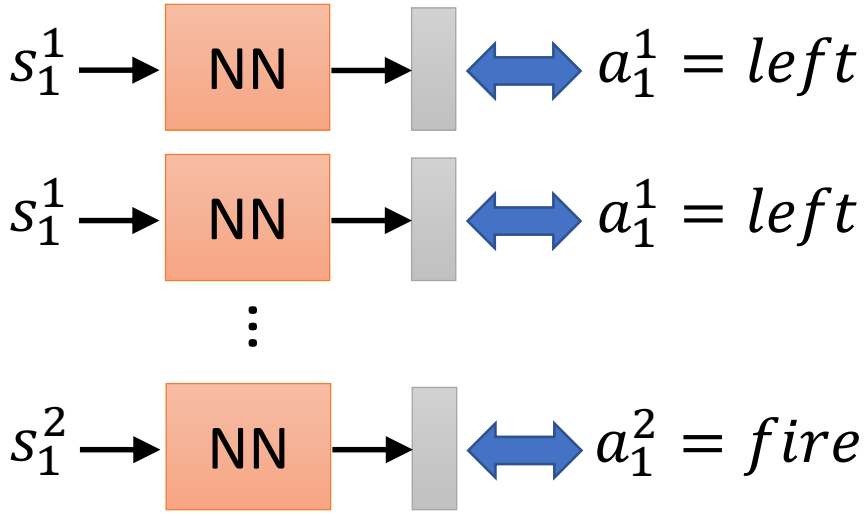
$$\theta \leftarrow \theta + \eta \nabla \bar{R}_\theta$$

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

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 $R(\tau^n)$



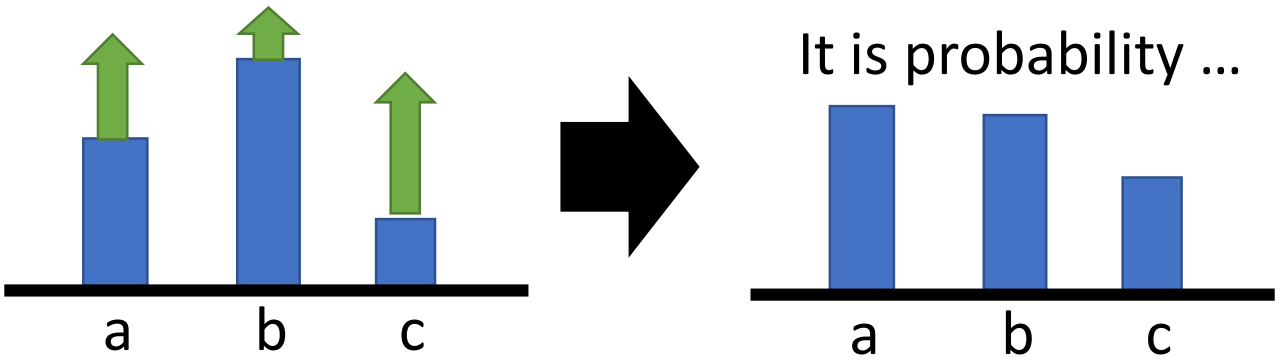
Add a Baseline

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

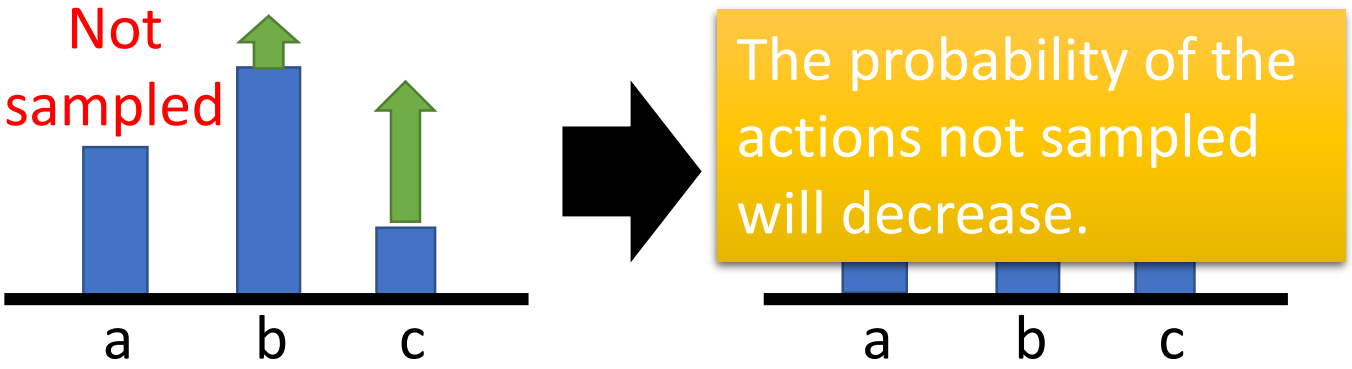
$$\theta^{new} \leftarrow \theta^{old} + \eta \nabla \bar{R}_{\theta^{old}}$$

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

Ideal case



Sampling ……



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

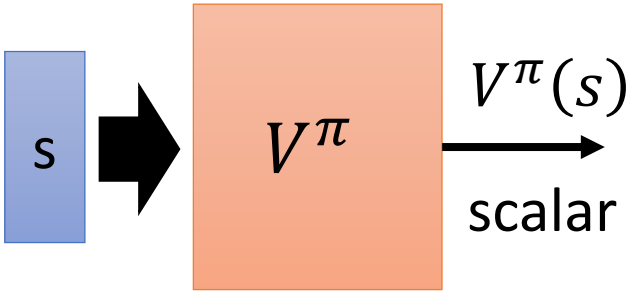
An actor can be found from a critic.

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

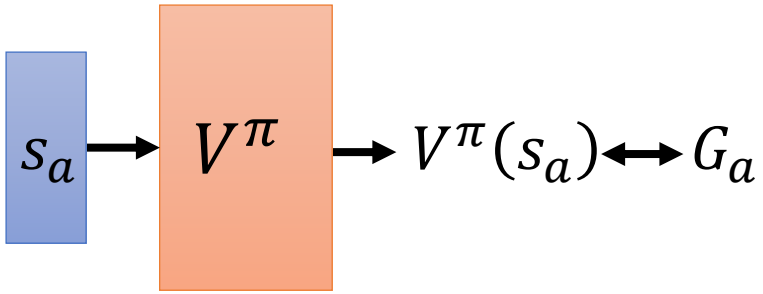
$V^{\pi}(s)$ is smaller

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

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

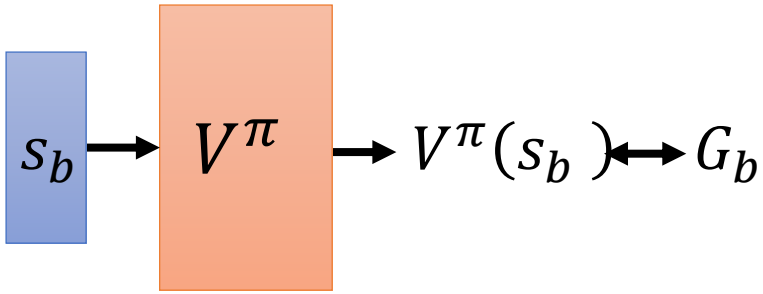
After seeing s_a,

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



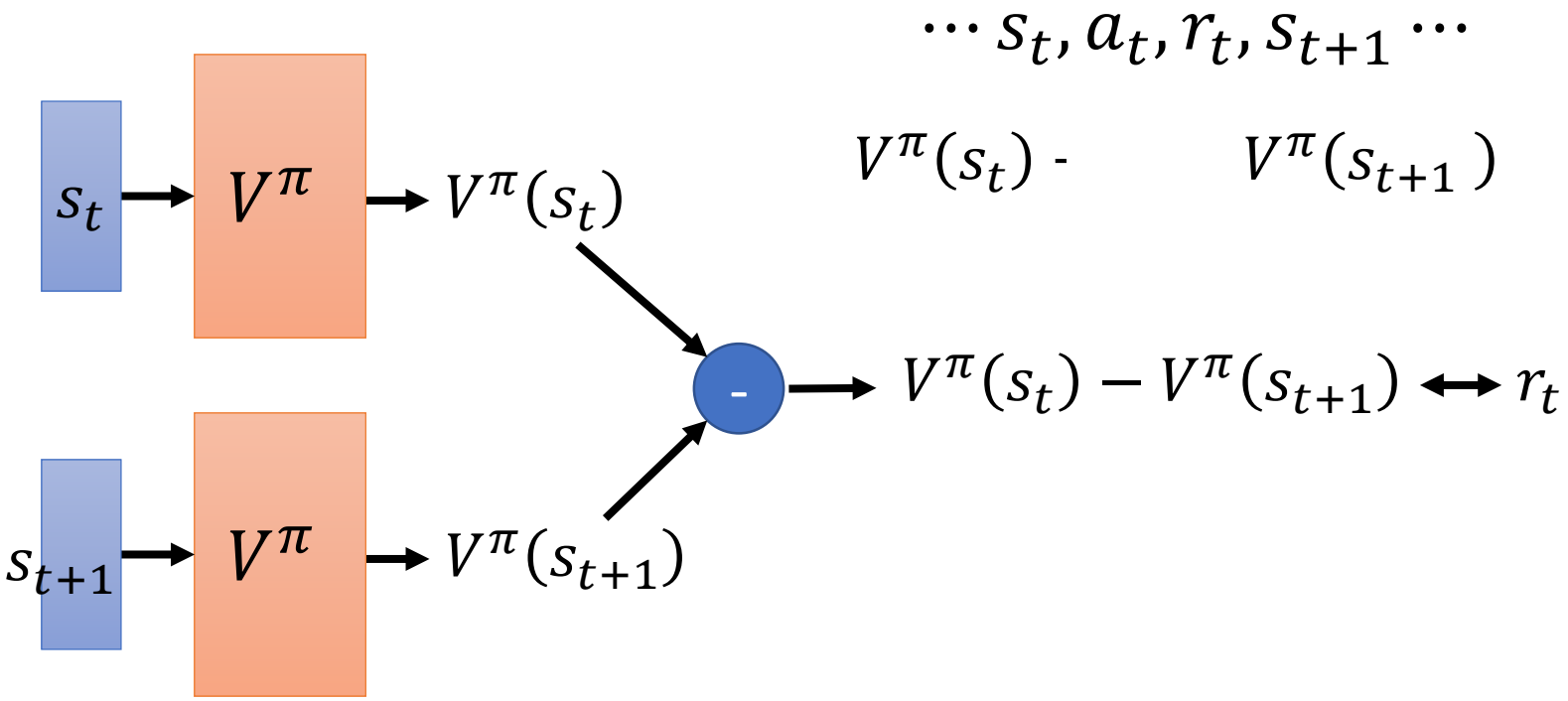
After seeing s_b,

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



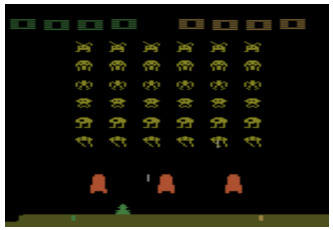
How to estimate $V^{\pi}(s)$

- Temporal-difference approach



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

MC v.s. TD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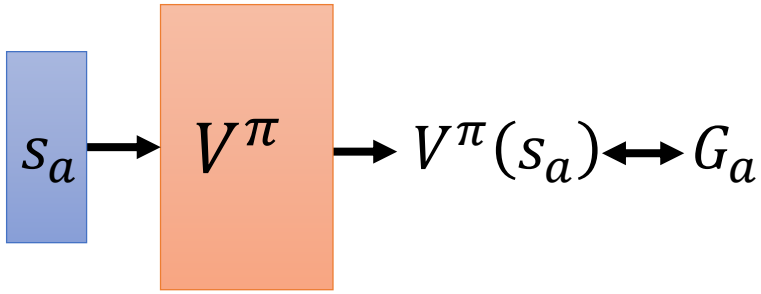
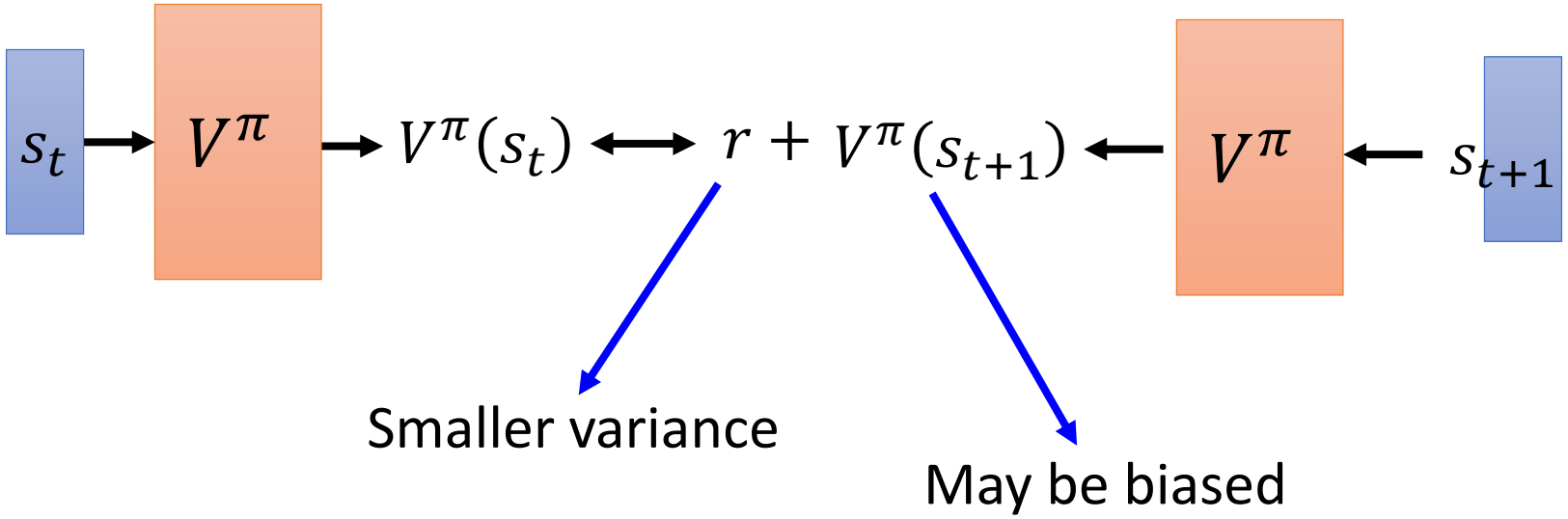


Larger variance

unbiased



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

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

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

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

Temporal-difference:

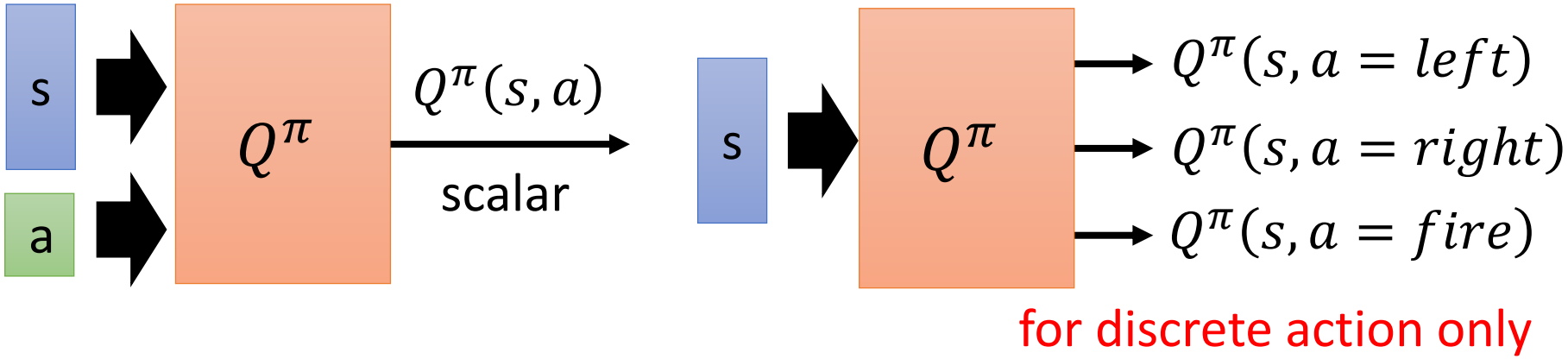
$$V^{\pi}(s_b) + r = V^{\pi}(s_a)$$

3/4 0 3/4

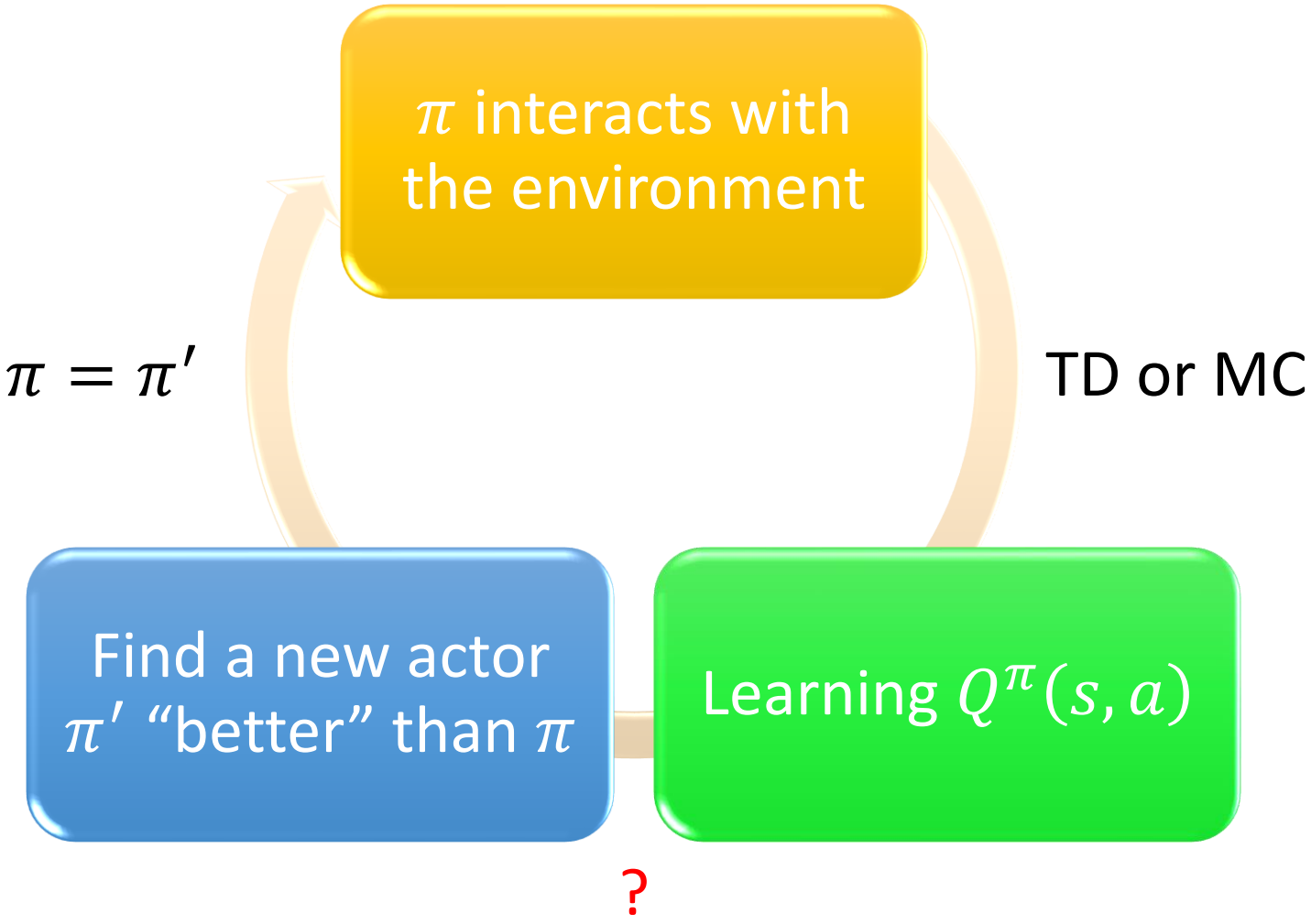
(The actions are ignored here.)

Another Critic

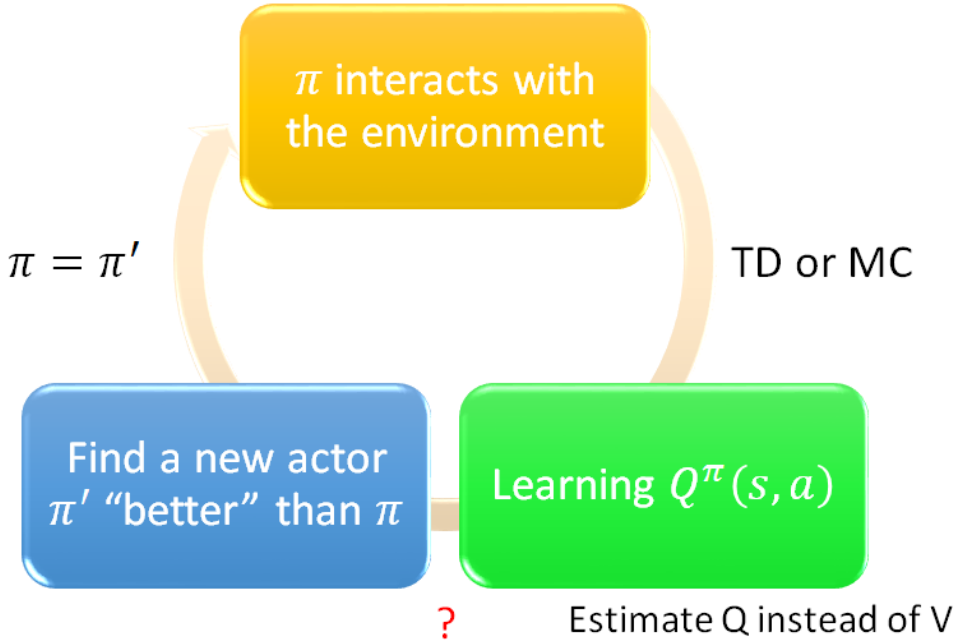
- State-action value function $Q^{\pi}(s, a)$
  - When using actor π, the *cumulated* reward expects to be obtained after seeing observation s and taking a



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": $V^{\pi'}(s) \geq V^{\pi}(s)$, for all state s

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

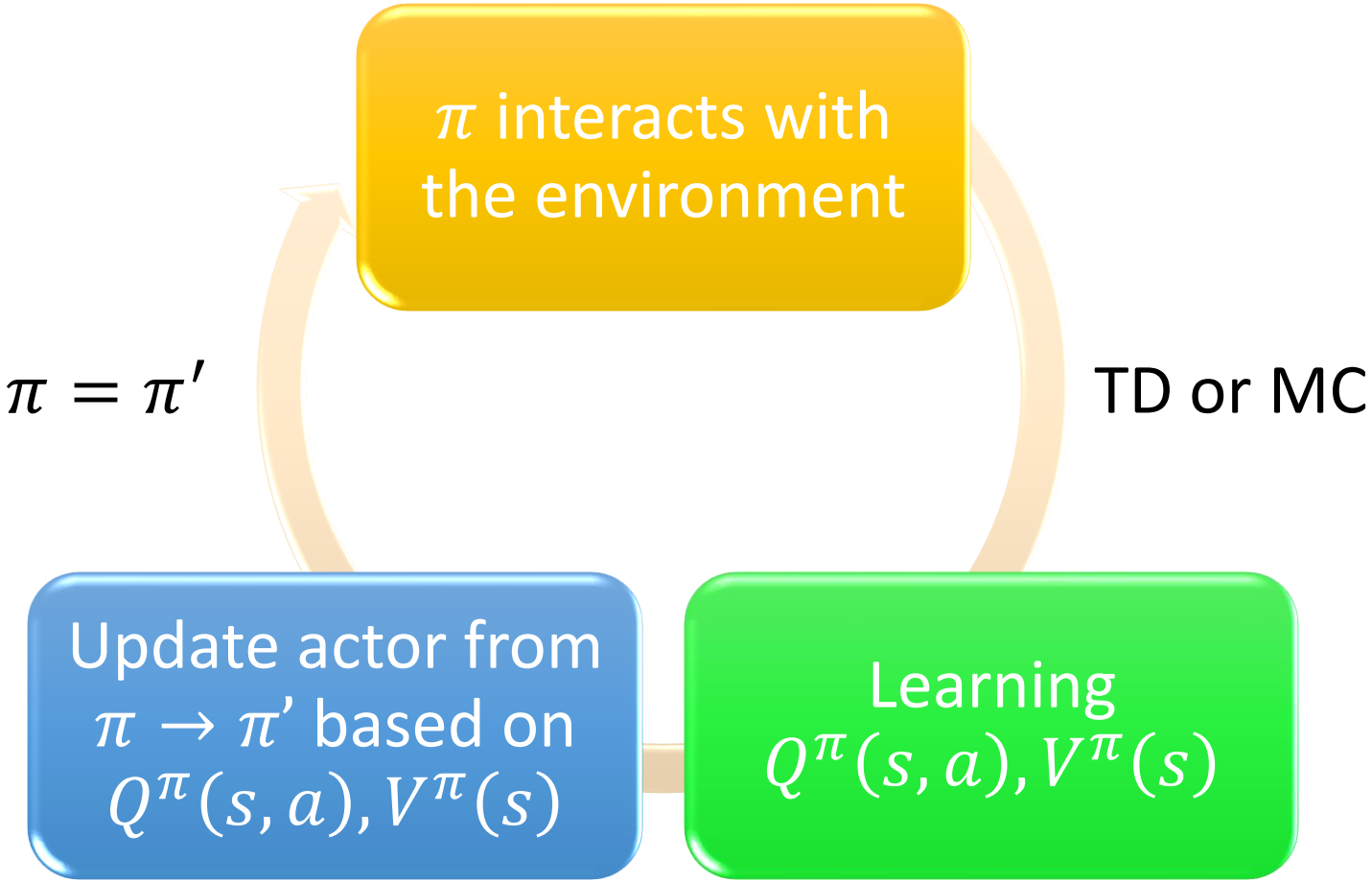
➢ π' does not have extra parameters. It depends on Q

➢ Not suitable for continuous action a

Deep Reinforcement Learning

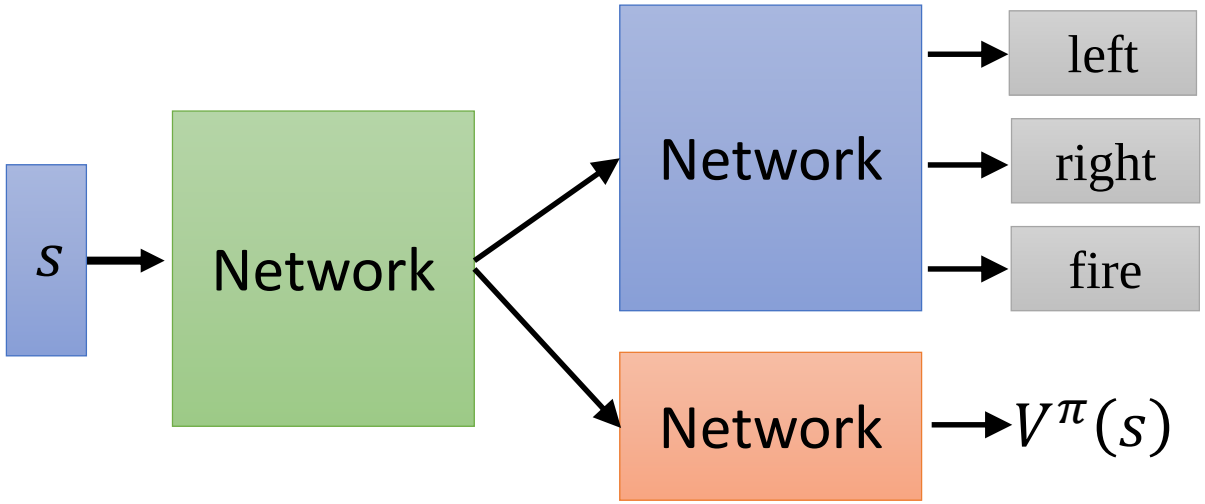
Actor-Critic

Actor-Critic



Actor-Critic

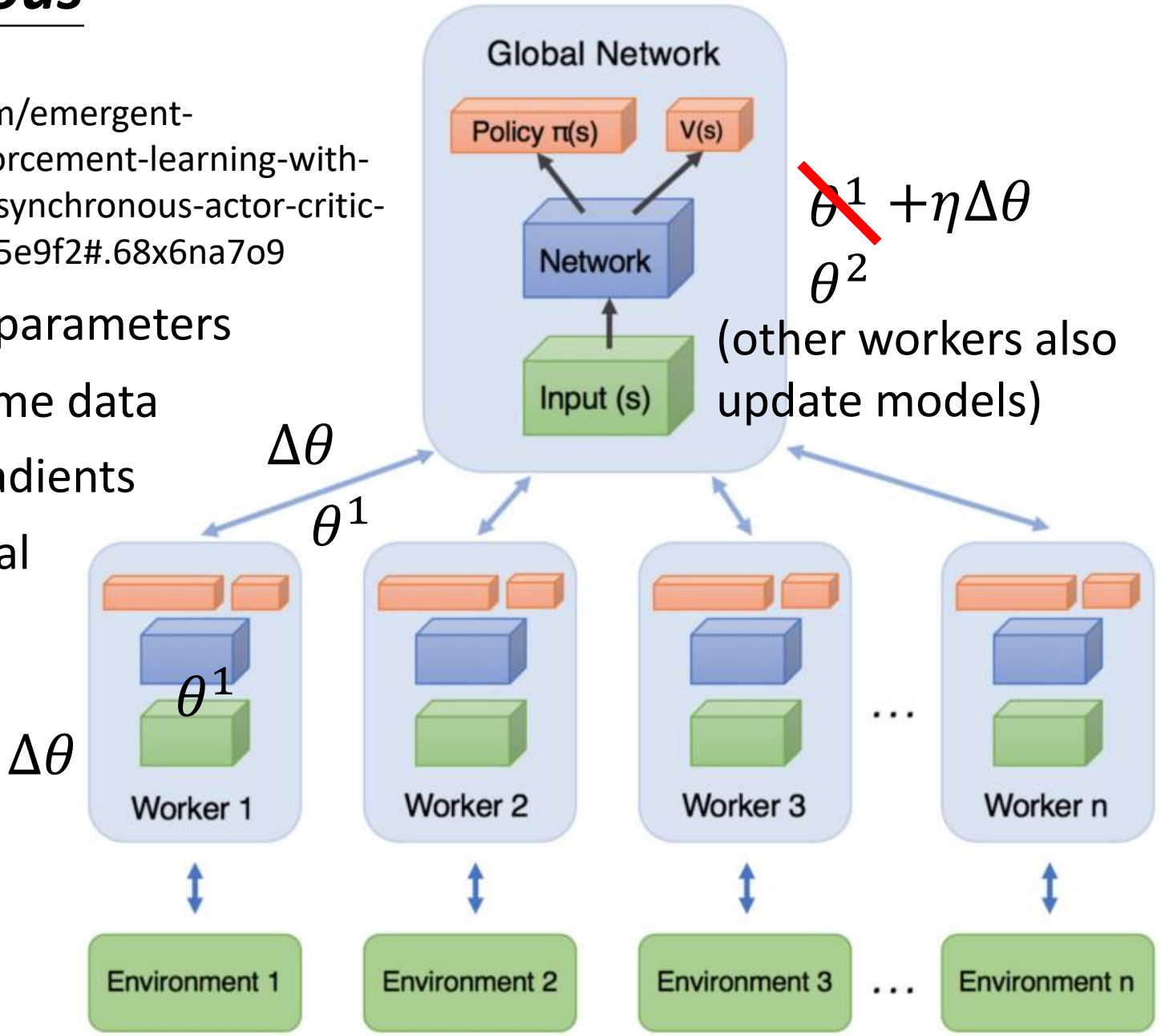
- Tips
  - The parameters of actor $\pi(s)$ and critic $V^{\pi}(s)$ can be shared



Asynchronous

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

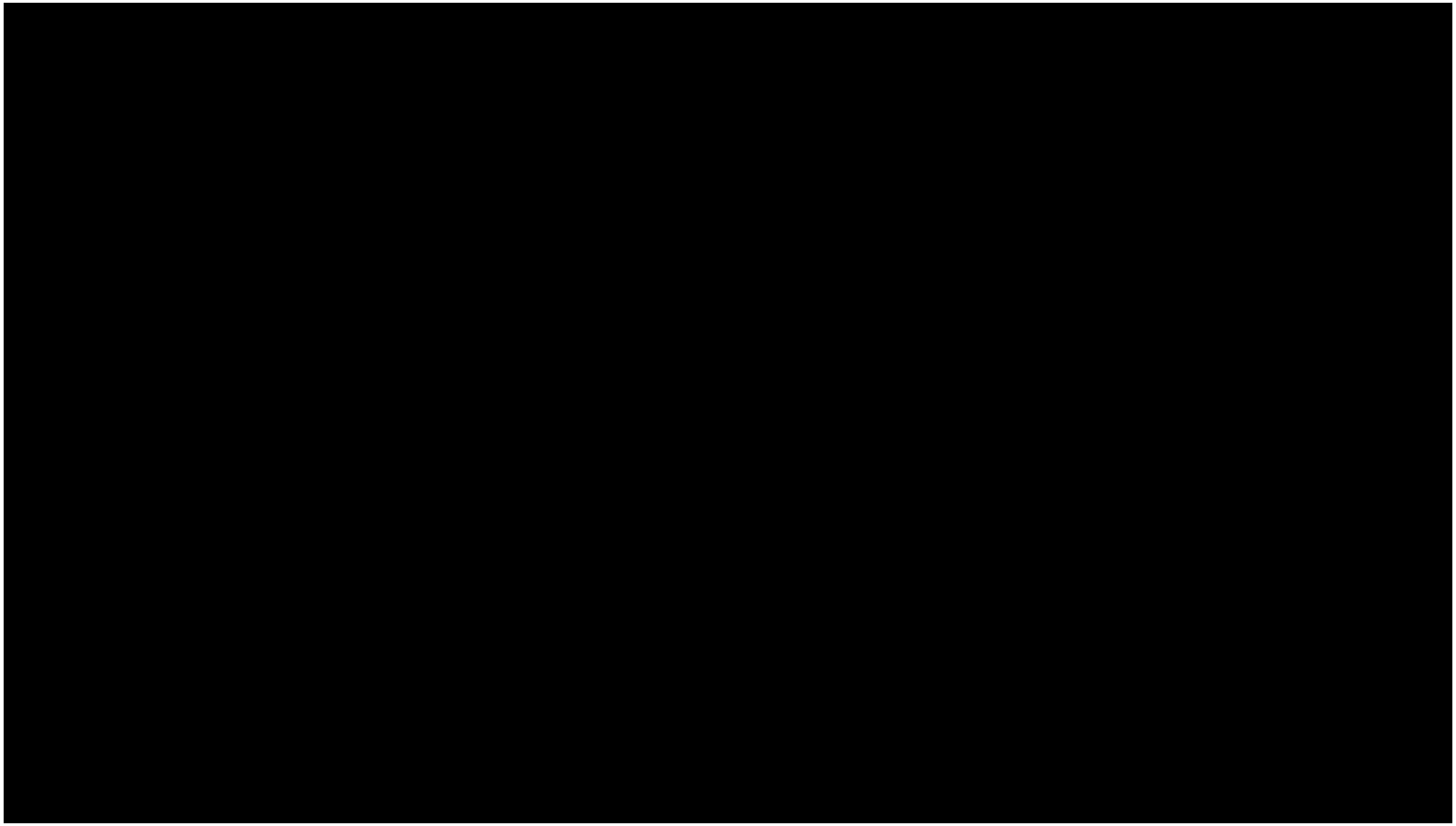
1. Copy global parameters
2. Sampling some data
3. Compute gradients
4. Update global models



Demo of A3C

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

- Racing Car (DeepMind)



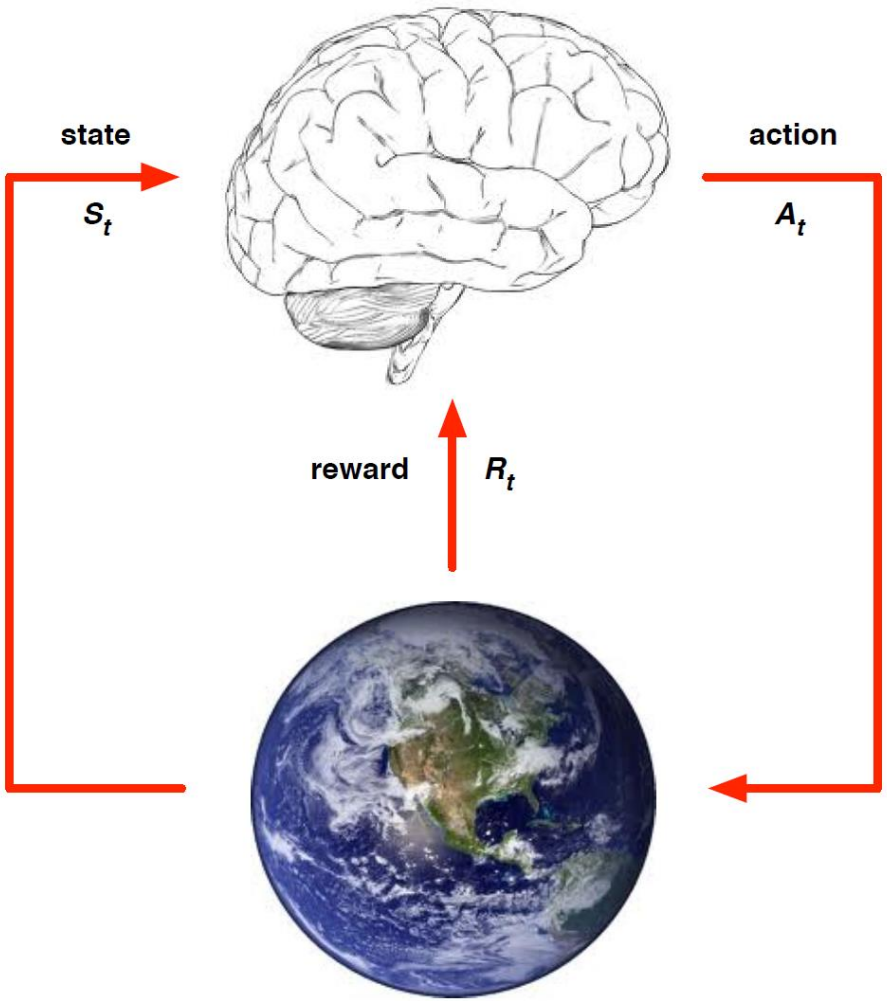
Outline

1. Course Review
2. Background
3. Model-free learning
4. Model-based learning
5. Applications

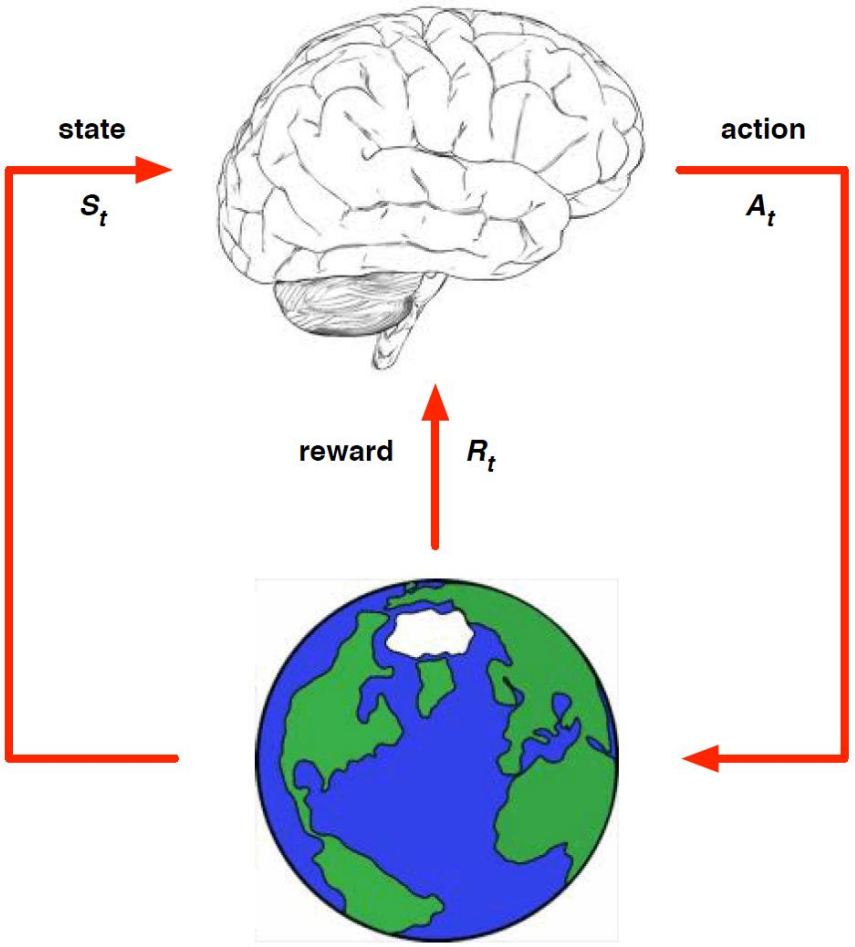
Model-Based and Model-Free RL

- Model-Free RL
  - No model
  - Learn value function (and/or policy) from experience
- Model-Based RL
  - Learn a model from experience
  - Plan value function (and/or policy) from model

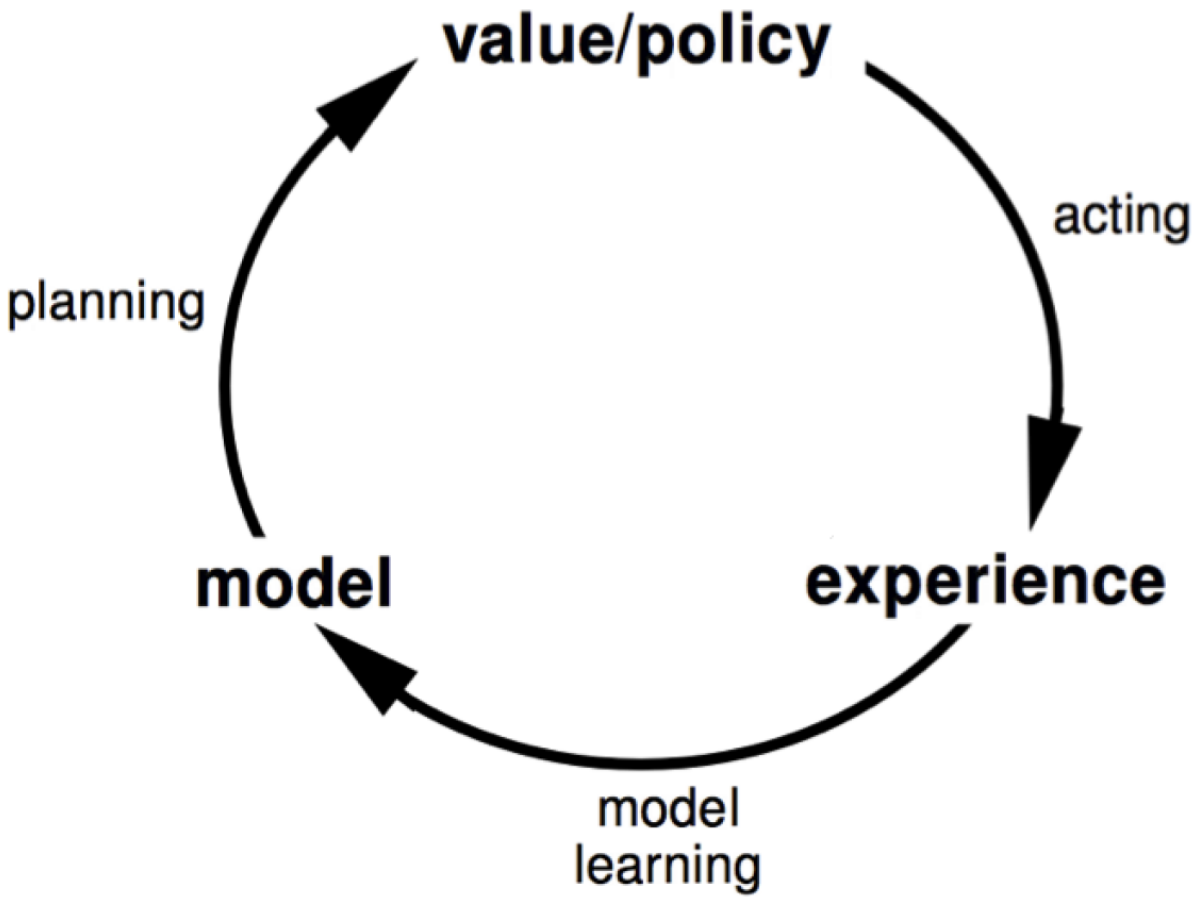
Model-Free RL



Model-Based RL



Model-Based RL



Advantages of Model-Based RL

Advantages:

- Can efficiently learn model by supervised learning methods
- Can reason about model uncertainty

Disadvantages:

- First learn a model, then construct a value function
  $\Rightarrow$ two sources of approximation error

What is a Model?

- A *model* $\mathcal{M}$ is a representation of an MDP $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R} \rangle$, parametrized by η
- We will assume state space $\mathcal{S}$ and action space $\mathcal{A}$ are known
- So a model $\mathcal{M} = \langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$ represents state transitions $\mathcal{P}_\eta \approx \mathcal{P}$ and rewards $\mathcal{R}_\eta \approx \mathcal{R}$

$$S_{t+1} \sim \mathcal{P}_\eta(S_{t+1} \mid S_t, A_t)$$
$$R_{t+1} = \mathcal{R}_\eta(R_{t+1} \mid S_t, A_t)$$

- Typically assume conditional independence between state transitions and rewards

$$\mathbb{P}\left[S_{t+1}, R_{t+1} \mid S_t, A_t\right] = \mathbb{P}\left[S_{t+1} \mid S_t, A_t\right] \mathbb{P}\left[R_{t+1} \mid S_t, A_t\right]$$

Model Learning

- Goal: estimate model $\mathcal{M}_\eta$ from experience $\{S_1, A_1, R_2, ..., S_T\}$
- This is a supervised learning problem

$$S_1, A_1 \rightarrow R_2, S_2$$
$$S_2, A_2 \rightarrow R_3, S_3$$
$$\vdots$$
$$S_{T-1}, A_{T-1} \rightarrow R_T, S_T$$

- Learning $s, a \rightarrow r$ is a *regression* problem
- Learning $s, a \rightarrow s'$ is a *density estimation* problem
- Pick loss function, e.g. mean-squared error, KL divergence, ...
- Find parameters η that minimise empirical loss

Examples of Models

- Table Lookup Model
- Linear Expectation Model
- Linear Gaussian Model
- Gaussian Process Model
- Deep Belief Network Model
- ...

Table Lookup Model

- Model is an explicit MDP, $\hat{\mathcal{P}}, \hat{\mathcal{R}}$
- Count visits $N(s, a)$ to each state action pair

$$\hat{\mathcal{P}}^a_{s,s'} = \frac{1}{N(s,a)} \sum_{t=1}^{T} \mathbf{1}(S_t, A_t, S_{t+1} = s, a, s')$$

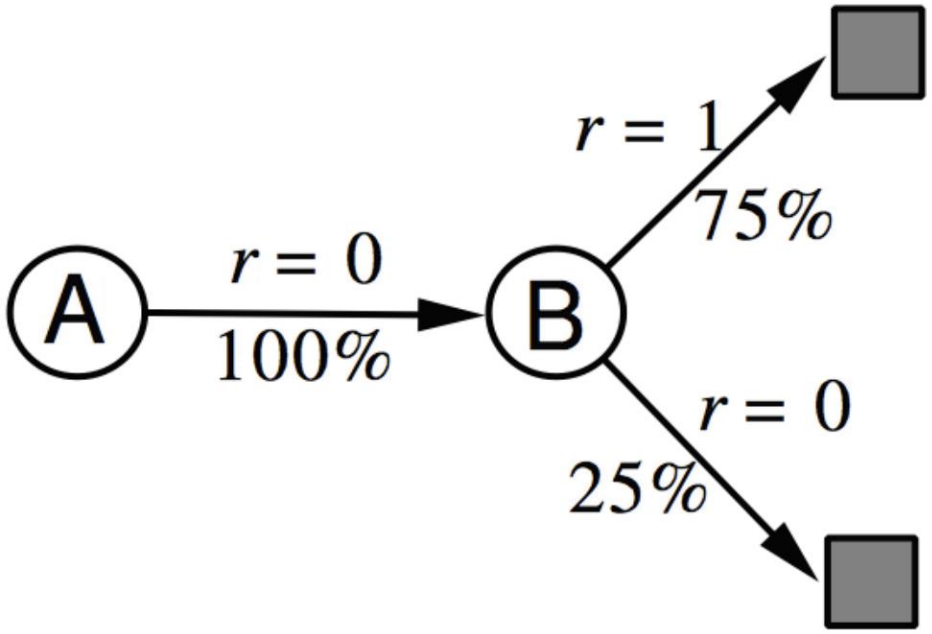
$$\hat{\mathcal{R}}^a_s = \frac{1}{N(s,a)} \sum_{t=1}^{T} \mathbf{1}(S_t, A_t = s, a) R_t$$

- Alternatively
  - At each time-step t, record experience tuple $\langle S_t, A_t, R_{t+1}, S_{t+1} \rangle$
  - To sample model, randomly pick tuple matching $\langle s, a, \cdot, \cdot \rangle$

AB Example

Two states A, B; no discounting; 8 episodes of experience

$$\begin{array}{l} \mathrm{A}, 0, \mathrm{B}, 0 \\ \mathrm{B}, 1 \\ \mathrm{B}, 1 \\ \mathrm{B}, 1 \\ \mathrm{B}, 1 \\ \mathrm{B}, 1 \\ \mathrm{B}, 1 \\ \mathrm{B}, 0 \end{array}$$



We have constructed a table lookup model from the experience

Planning with a Model

- Given a model $\mathcal{M}_\eta = \langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$
- Solve the MDP $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$
- Using favourite planning algorithm
  - Value iteration
  - Policy iteration
  - Tree search
  - ...

Sample-Based Planning

- A simple but powerful approach to planning
- Use the model only to generate samples
- Sample experience from model

$$S_{t+1} \sim \mathcal{P}_\eta(S_{t+1} \mid S_t, A_t)$$
$$R_{t+1} = \mathcal{R}_\eta(R_{t+1} \mid S_t, A_t)$$

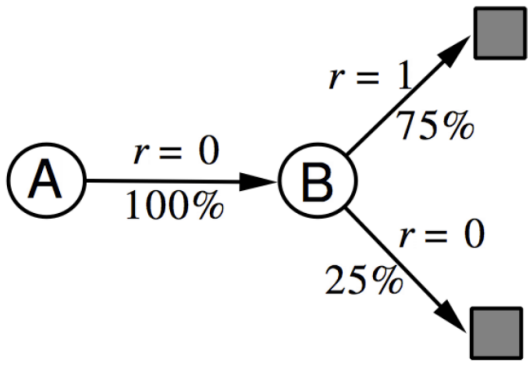
- Apply model-free RL to samples, e.g.:
  - Monte-Carlo control
  - Sarsa
  - Q-learning
- Sample-based planning methods are often more efficient

Back to the AB Example

- Construct a table-lookup model from real experience
- Apply model-free RL to sampled experience

Real experience

A, 0, B, 0
B, 1
B, 1
B, 1
B, 1
B, 1
B, 1
B, 0



Sampled experience

B, 1
B, 0
B, 1
A, 0, B, 1
B, 1
A, 0, B, 1
B, 1
B, 0

e.g. Monte-Carlo learning: $V(A) = 1, V(B) = 0.75$

Planning with an Inaccurate Model

- Given an imperfect model $\langle \mathcal{P}_\eta, \mathcal{R}_\eta \rangle \neq \langle \mathcal{P}, \mathcal{R} \rangle$
- Performance of model-based RL is limited to optimal policy for approximate MDP $\langle \mathcal{S}, \mathcal{A}, \mathcal{P}_\eta, \mathcal{R}_\eta \rangle$
- i.e. Model-based RL is only as good as the estimated model
- When the model is inaccurate, planning process will compute a suboptimal policy
- Solution 1: when model is wrong, use model-free RL
- Solution 2: reason explicitly about model uncertainty

Outline

1. Course Review
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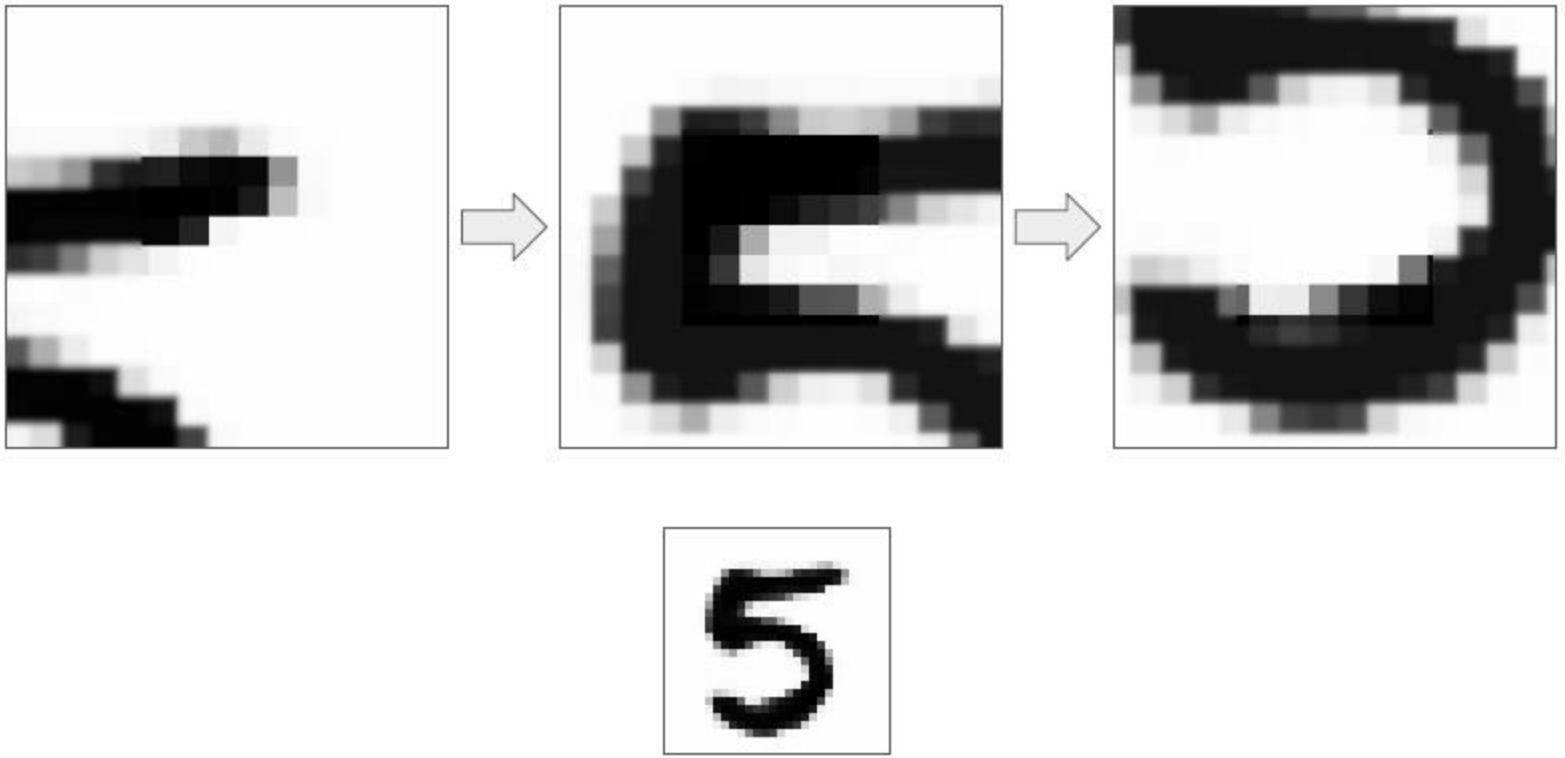
Applications

Recurrent Models of Visual Attention

Volodymyr Mnih, Nicolas Heess, Alex Graves, Koray Kavukcuoglu

Motivation

- **Task**: Classify digits in MNIST
- **Motivation**: Full image convolution is expensive!
  - Humans focus attention selectively on parts of an image
  - Combine information from different fixations over time



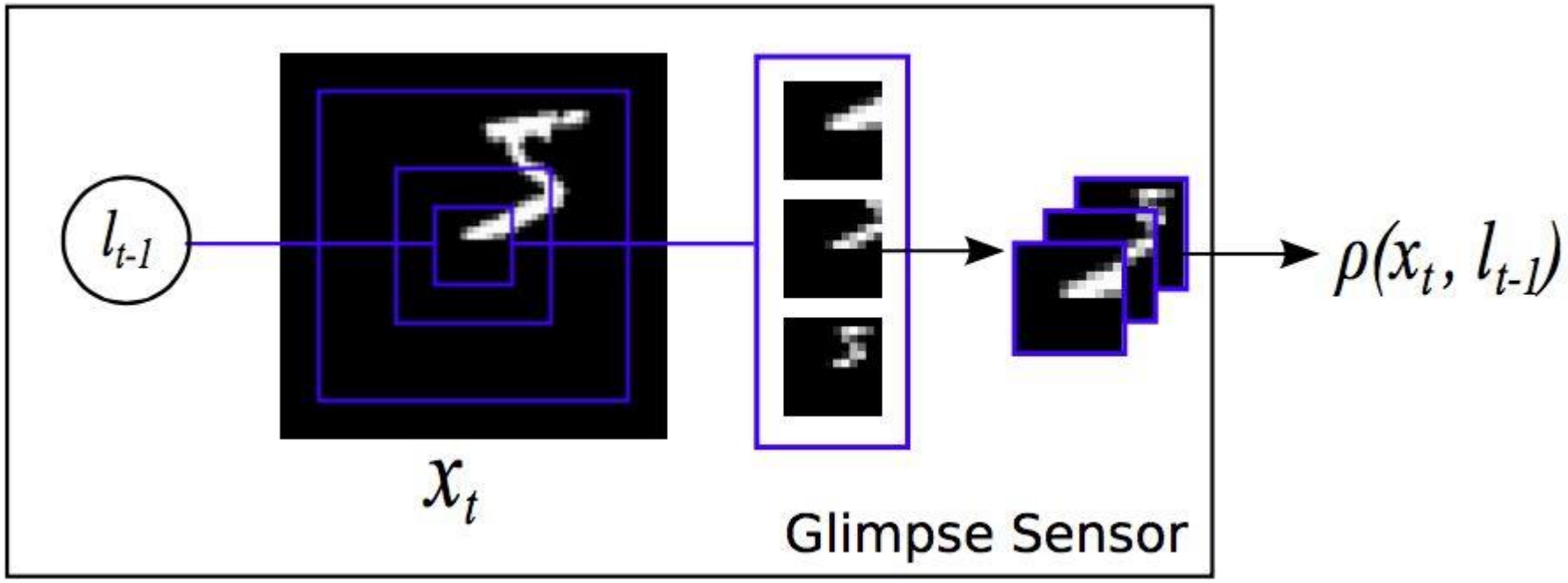
Overview

- True state of the environment is unobserved
  - **Glimpses** can be seen as a partial view of the state
- **State:** $h_t = f_h\,(h_{t-1}\,,\, g_t\,;\, \vartheta_h\,)$
- **Actions:**
  - Location: $l_t \sim p(.|f_l\,(h_t\,;\, \vartheta_l\,))$
  - An environment action: $a_t \sim p(.|f_a\,(h_t\,;\, \vartheta_a\,))$

- **Reward: Cross-Entropy Loss**
  - Agent needs to learn a stochastic policy
  - Policy π is defined by the Location Network in the RNN

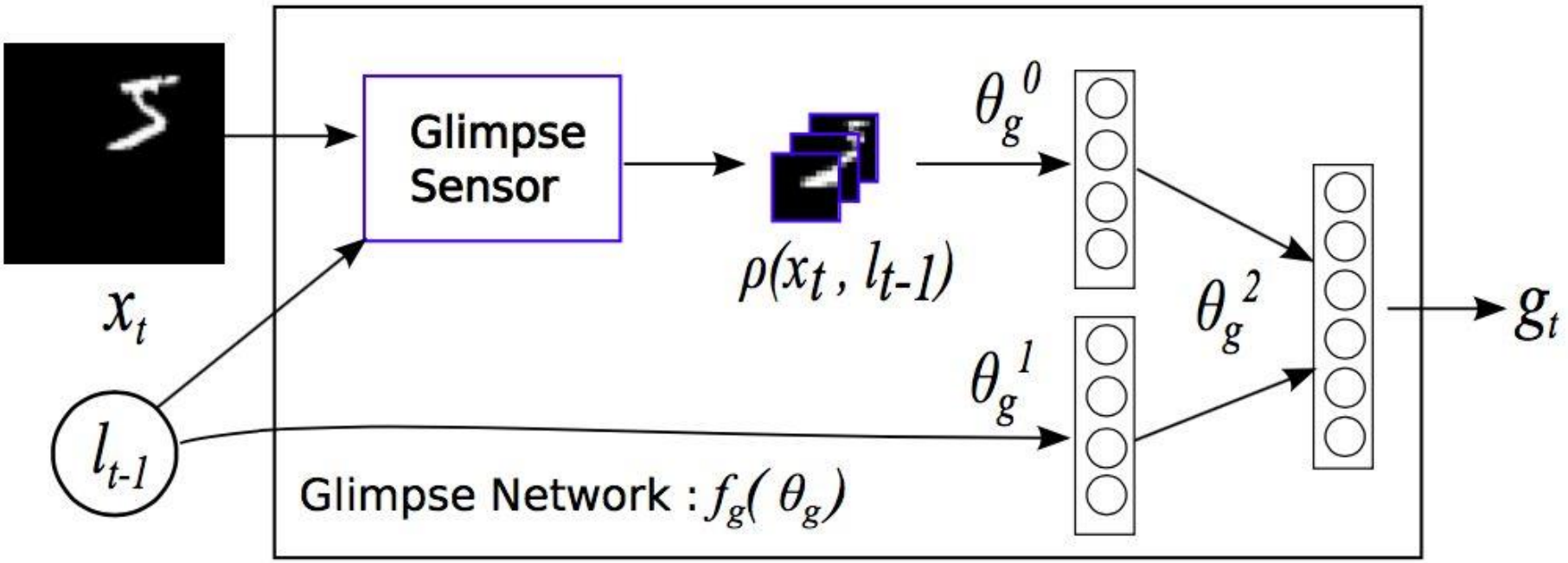
Glimpse

- Retina-like representation $\rho(x_t, l_{t-1})$
  - Contains multiple resolution patches
- Centered at location l_{t-1} of image x_t

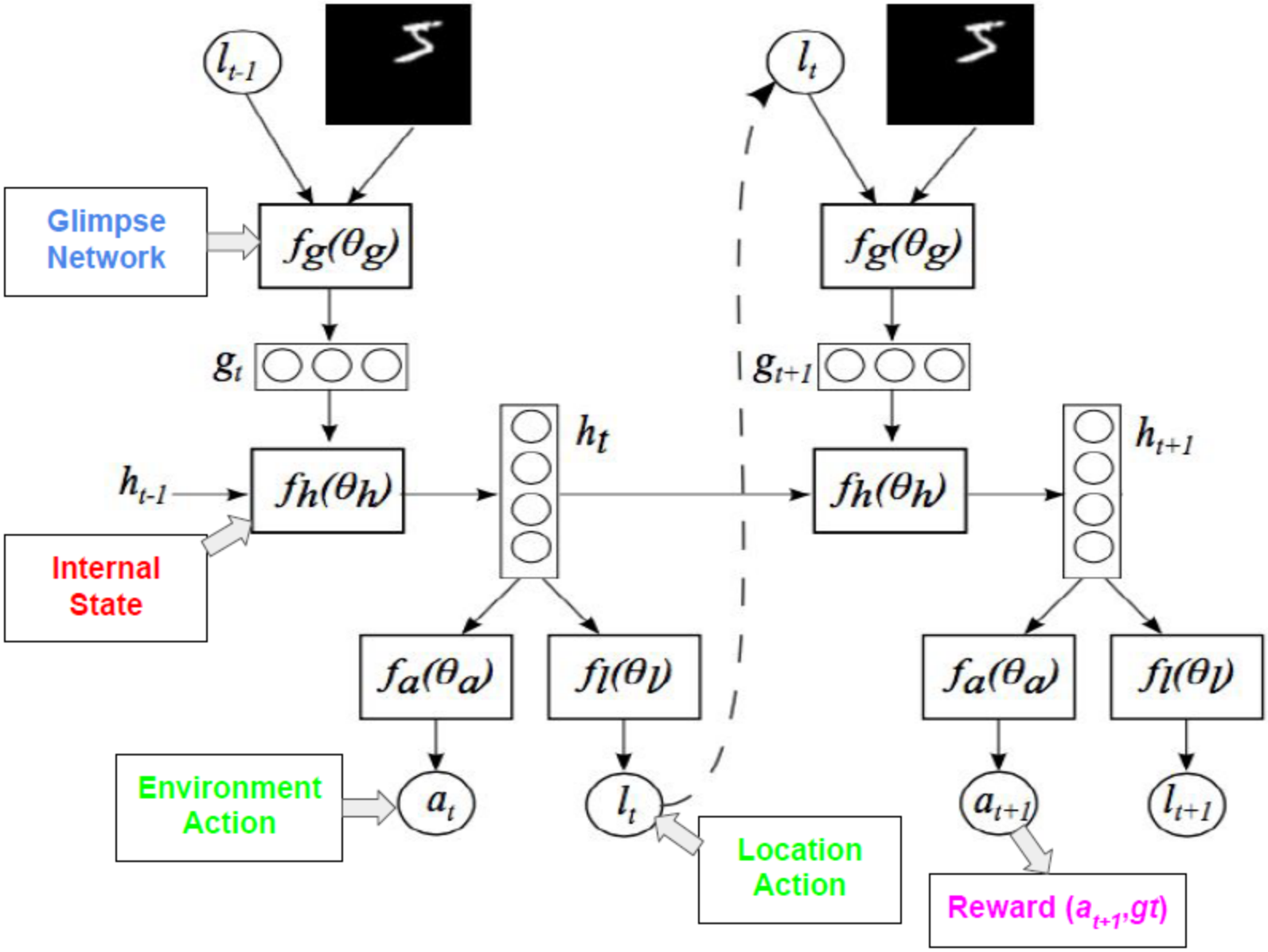


Glimpse Network

- ***ρ(x$_t$, l$_{t-1}$)*** *and* ***l$_{t-1}$*** *are mapped into a hidden space*



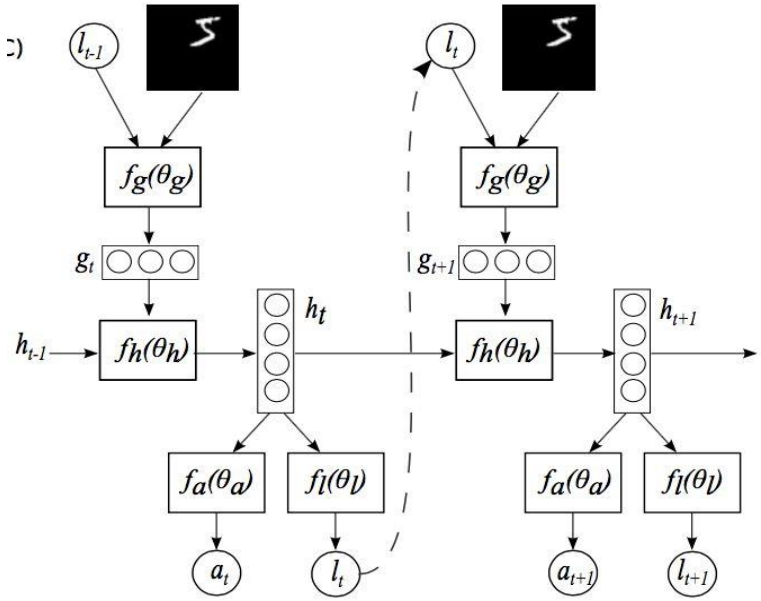
Model Architecture



Training

"OK, I've shown you the ropes, given you the low down, and gotten you up to speed. All that's left is actually training you."

Training



- Parameters of the agent are: $\vartheta = \{\vartheta_g, \vartheta_h, \vartheta_a\}$
  - Can be trained using standard backpropagation
- **RL Objective:** Maximize the reward given by: $J(\vartheta) = E[R]$
  - Can maximize $J(\vartheta)$ using REINFORCE

$$\nabla_\theta J = \sum_{t=1}^{T} \mathbb{E}_{p(s_{1:T};\theta)} \left[\nabla_\theta \log \pi(u_t | s_{1:t}; \theta) R\right] \approx \frac{1}{M} \sum_{i=1}^{M} \sum_{t=1}^{T} \nabla_\theta \log \pi(u_t^i | s_{1:t}^i; \theta) R^i$$

Results

Results

(a) 60x60 Cluttered Translated MNIST

Model	Error
FC, 2 layers (64 hiddens each)	28.58%
FC, 2 layers (256 hiddens each)	11.96%
Convolutional, 2 layers	8.09%
RAM, 4 glimpses, 12 × 12, 3 scales	4.96%
RAM, 6 glimpses, 12 × 12, 3 scales	4.08%
RAM, 8 glimpses, 12 × 12, 3 scales	4.04%
RAM, 8 random glimpses	14.4%

(b) 100x100 Cluttered Translated MNIST

Model	Error
Convolutional, 2 layers	14.35%
RAM, 4 glimpses, 12 × 12, 4 scales	9.41%
RAM, 6 glimpses, 12 × 12, 4 scales	8.31%
RAM, 8 glimpses, 12 × 12, 4 scales	8.11%
RAM, 8 random glimpses	28.4%

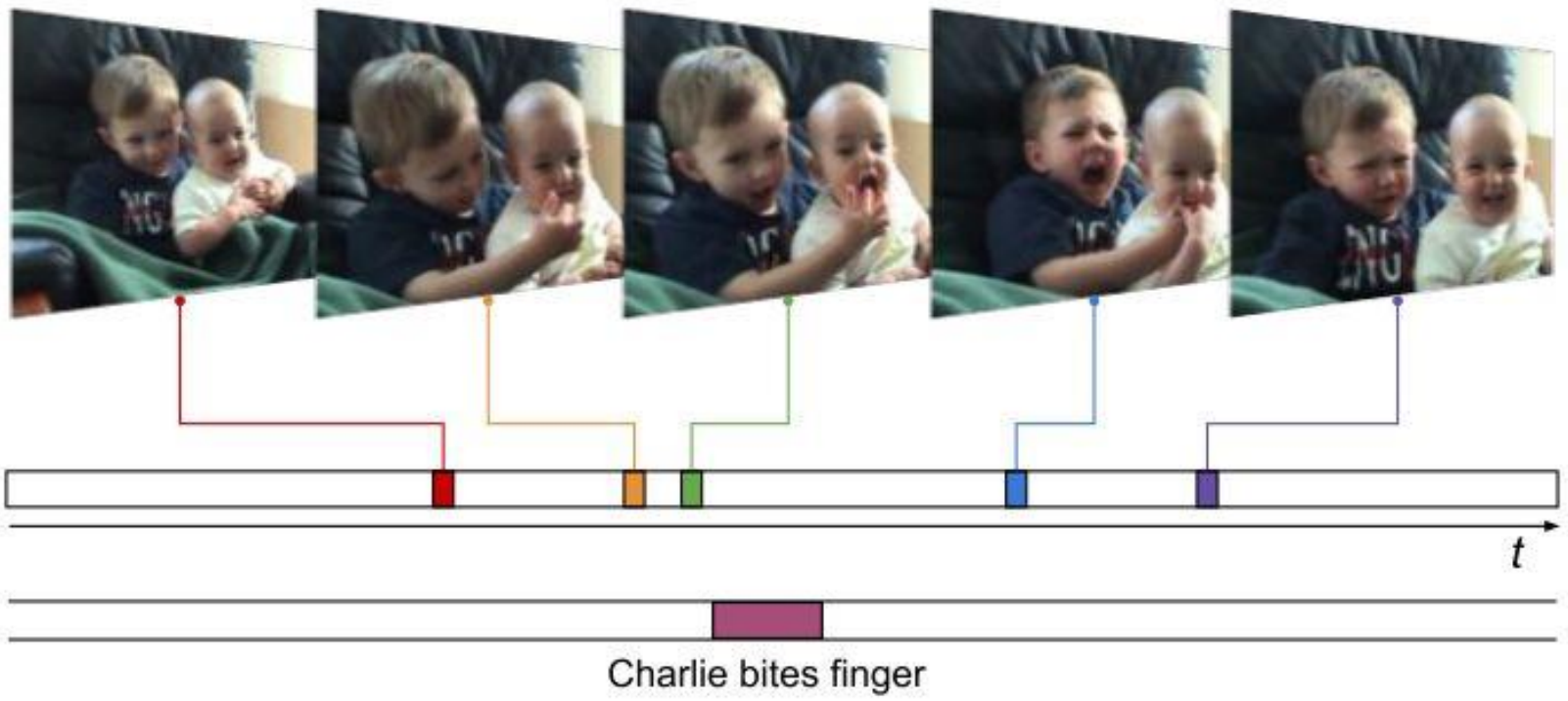
Applications

End-to-end Learning of Action Detection from Frame Glimpses in Videos

Serena Yeung, Olga Russakovsky, Greg Mori, Li Fei-Fei

Motivation

- **Task:** Detect and classify moments in an untrimmed video
- **Motivation**: Looking at all frames in a video is slow!
  - Process of detecting actions is one of observation and refinement

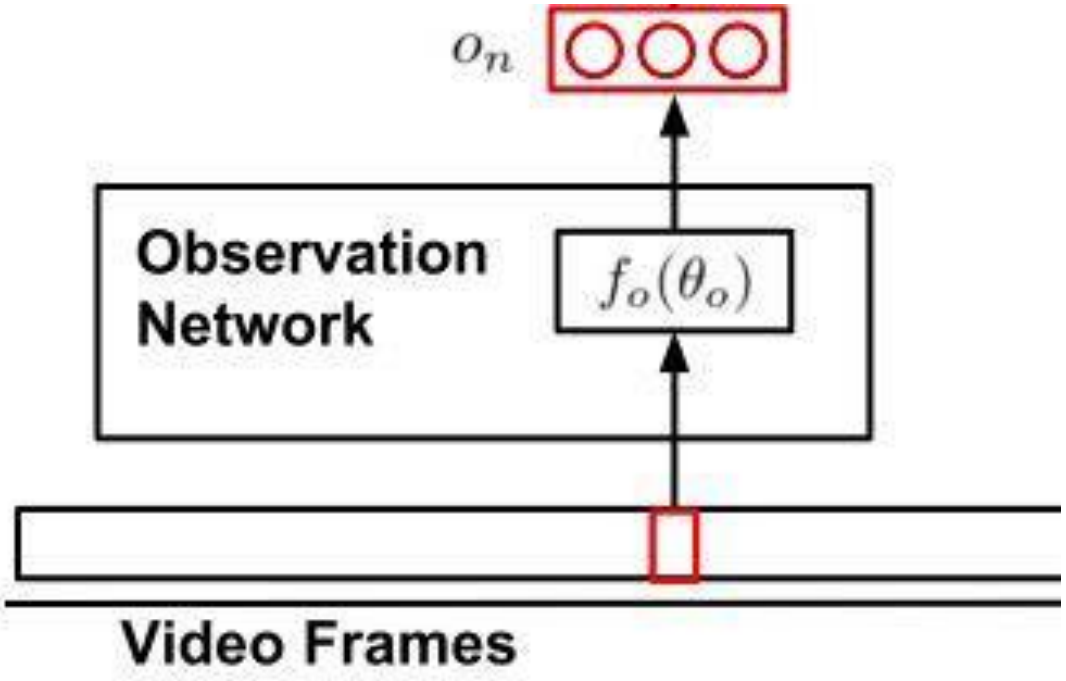


Overview

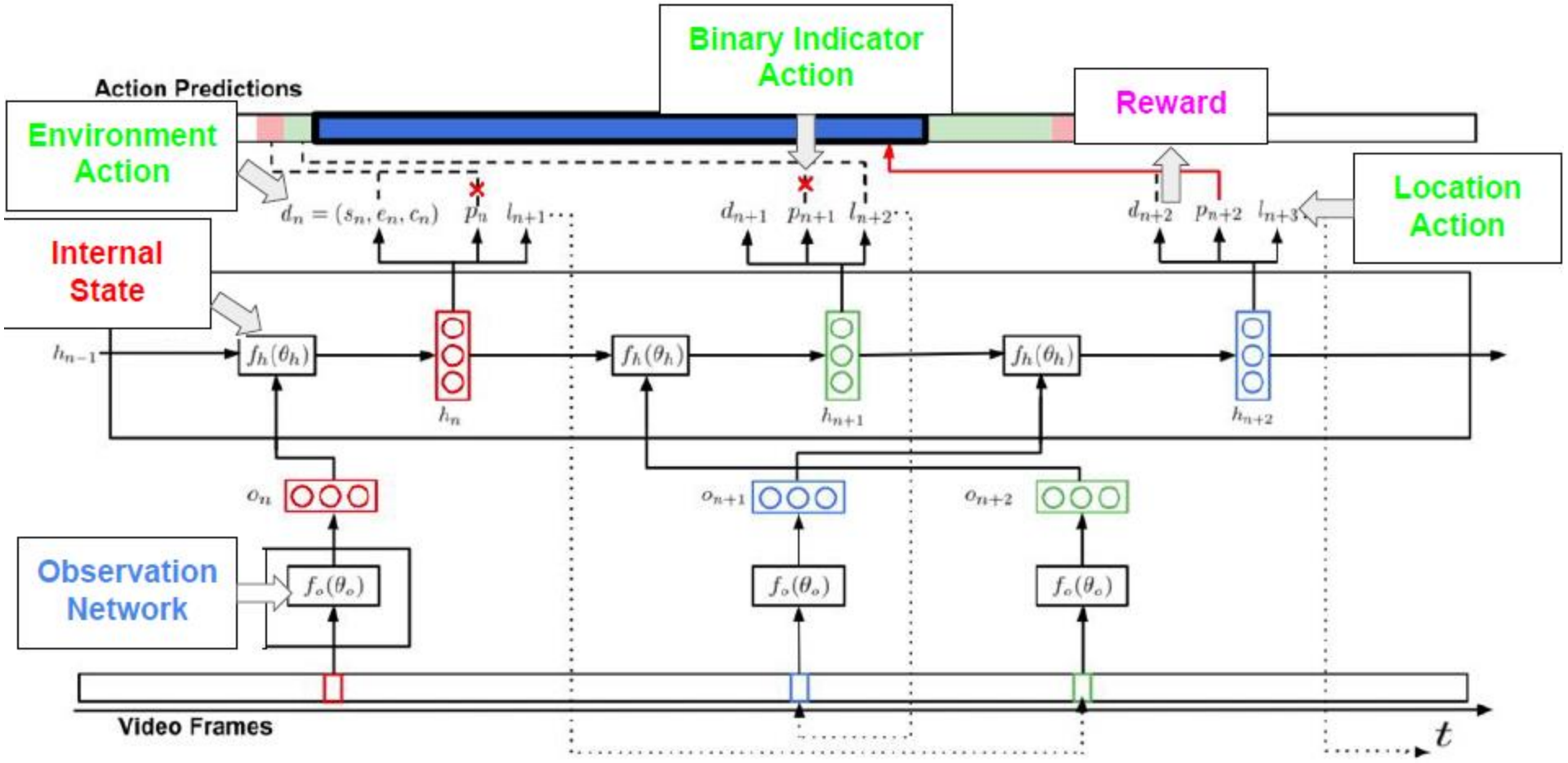
- True state of the environment is unobserved
  - **Observation Network** can be seen as a partial view of the state
- **State:** $h_n = f_h(h_{n-1}, o_n; \vartheta_h)$
- **Actions:**
  - Candidate detection: $d_n = f_d(h_n; \vartheta_d)$
  - Binary indication: $p_n = f_p(h_n; \vartheta_p)$
  - Temporal location: $l_{n+1} = f_l(h_n; \vartheta_l)$
- **Reward** $$R_N = \begin{cases} R_0 & \text{if } M > 0 \text{ and } N_p = 0 \\ N_+ R_+ + N_- R_- & \text{otherwise} \end{cases}$$
- Agent needs to learn a stochastic policy
  - Policy π is defined by the Location Network in the RNN

Observation Network

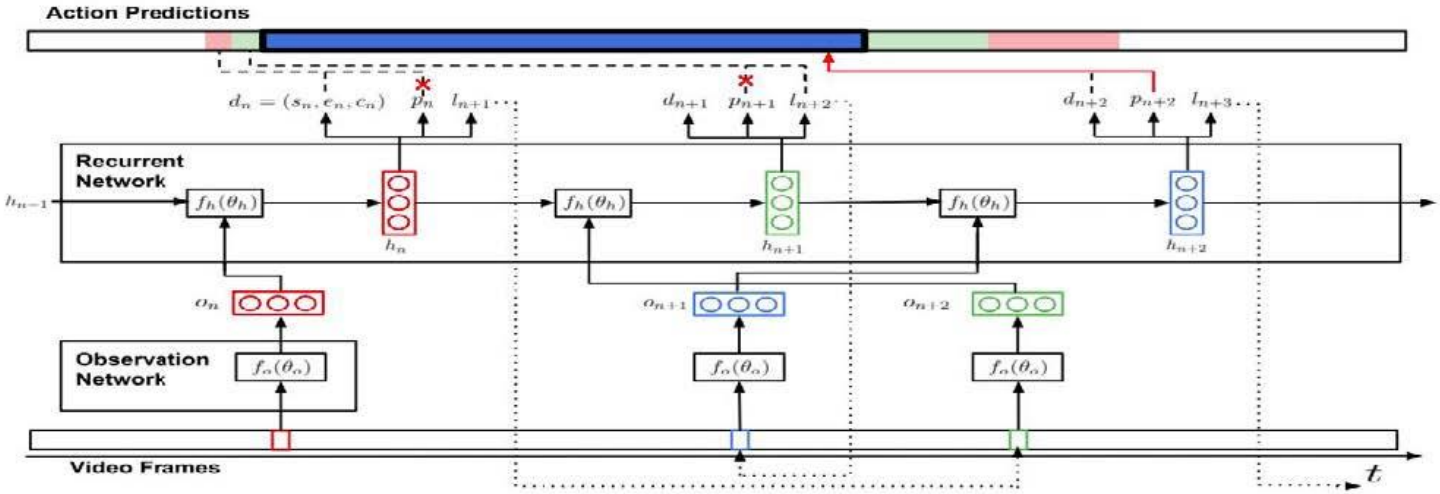
- Observes a single video frame at each timestep and encodes the frame and it's location into a feature vector $\boldsymbol{o_n}$
  - Inspired by the **Glimpse network**



Model Architecture



Training



- Parameters of the agent are: ***ϑ = { ϑo, ϑh, ϑd }***
  - Can be trained using standard backpropagation
- **RL Objective: Maximize the reward given by: *J(ϑ) = E[R]***

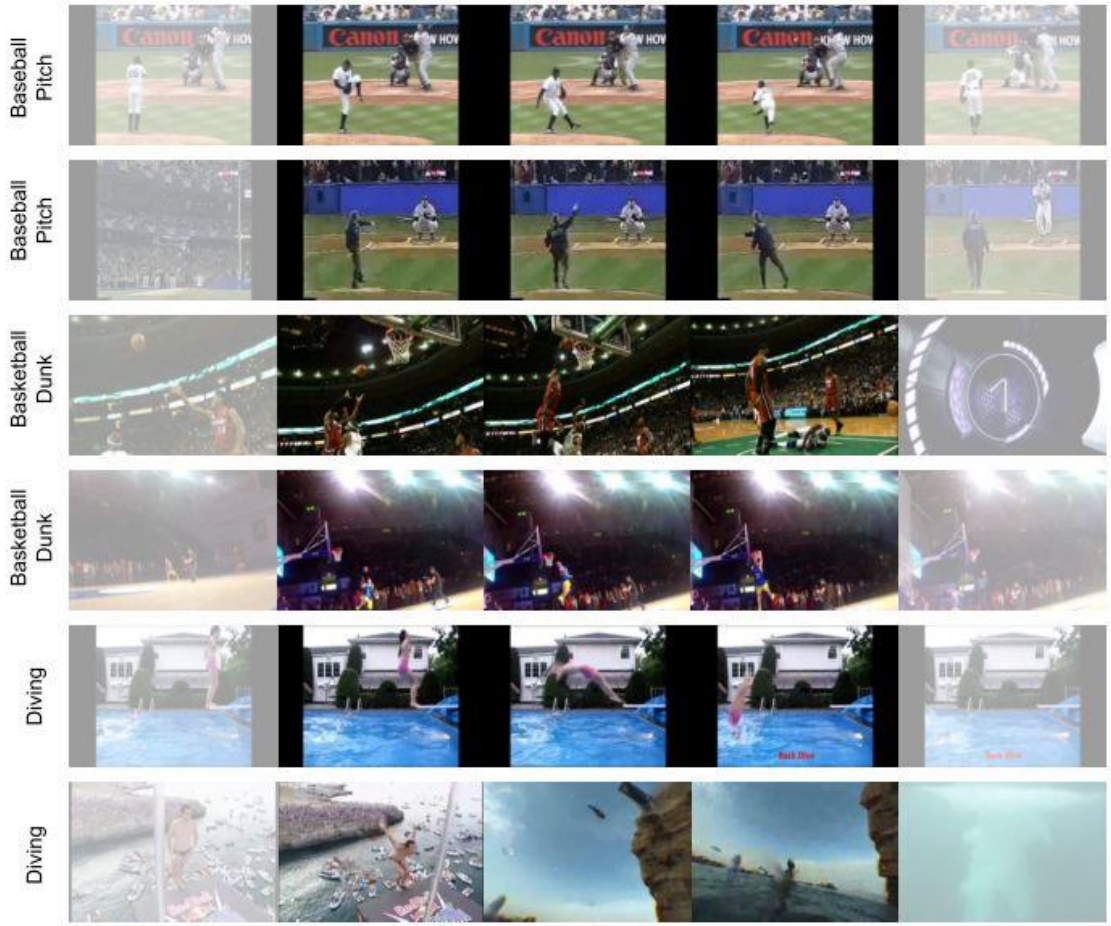
$$L(D) = \sum L_{cls}(d_n) + \gamma \sum \sum \mathbb{1}[y_{nm} = 1] L_{loc}(d_n, g_m)$$

Can maximize $J(\theta)$ using **REINFORCE**

$$\nabla_\theta J = \sum_{t=1}^{T} \mathbb{E}_{p(s_{1:T};\theta)} \left[\nabla_\theta \log \pi(u_t | s_{1:t}; \theta) R \right] \approx \frac{1}{M} \sum_{i=1}^{M} \sum_{t=1}^{T} \nabla_\theta \log \pi(u_t^i | s_{1:t}^i; \theta) R^i$$

Results - I

- THUMOS 14’ Dataset
  - Correct Predictions



Results - II

	[23]	Ours		[23]	Ours
Baseball Pitch	8.6	**14.6**	Hamm. Throw	**34.7**	28.9
Basket. Dunk	1.0	**6.3**	High Jump	17.6	**33.3**
Billiards	2.6	**9.4**	Javelin Throw	**22.0**	20.4
Clean and Jerk	13.3	**42.8**	Long Jump	**47.6**	39.0
Cliff Diving	**17.7**	15.6	Pole Vault	**19.6**	16.3
Cricket Bowl.	9.5	**10.8**	Shotput	11.9	**16.6**
Cricket Shot	2.6	**3.5**	Soccer Penalty	**8.7**	8.3
Diving	4.6	**10.8**	Tennis Swing	3.0	**5.6**
Frisbee Catch	1.2	**10.4**	Throw Discus	**36.2**	29.5
Golf Swing	**22.6**	13.8	Volley. Spike	1.4	**5.2**
mAP				14.4	**17.1**

- **Key Takeaways:**
  - Accuracy is comparable to state-of-the-art
  - Less frames observed

Disentangle latent factor

AlphaGo:

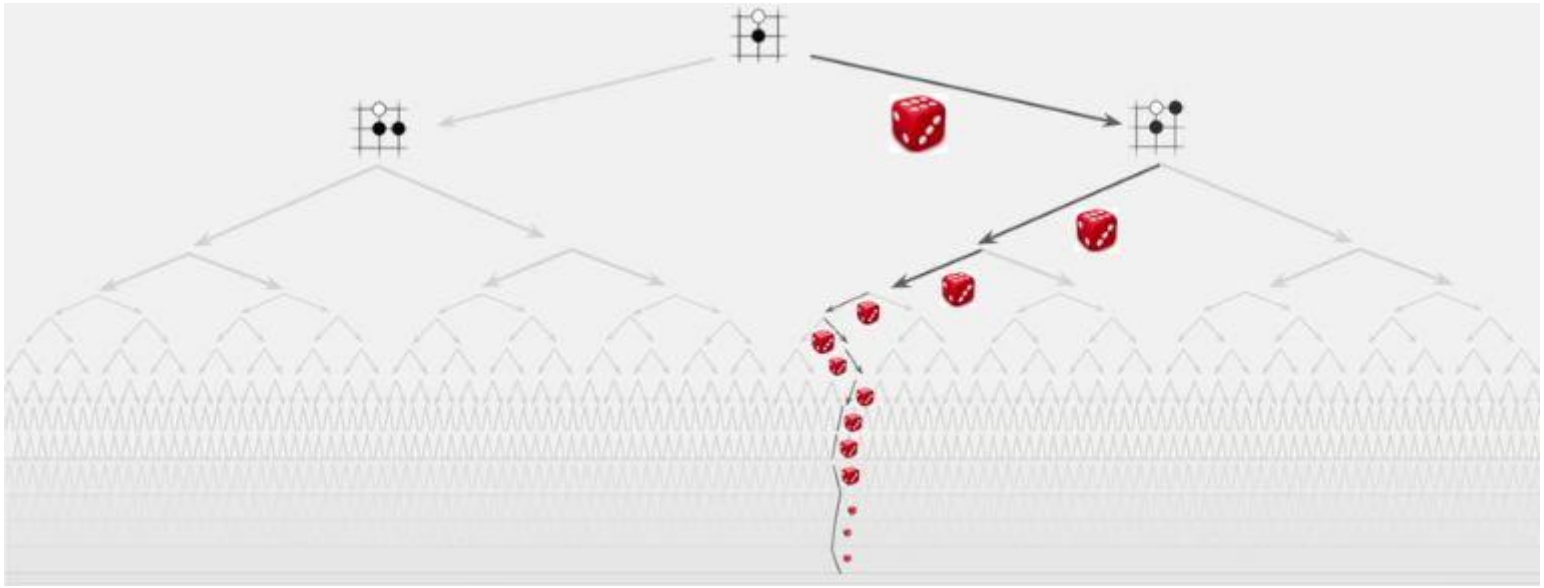
A bit of everything

(but mostly plain PG + planning)

https://www.youtube.com/watch?v=4D5yGiYe8p4

Background: Monte-Carlo Tree Search

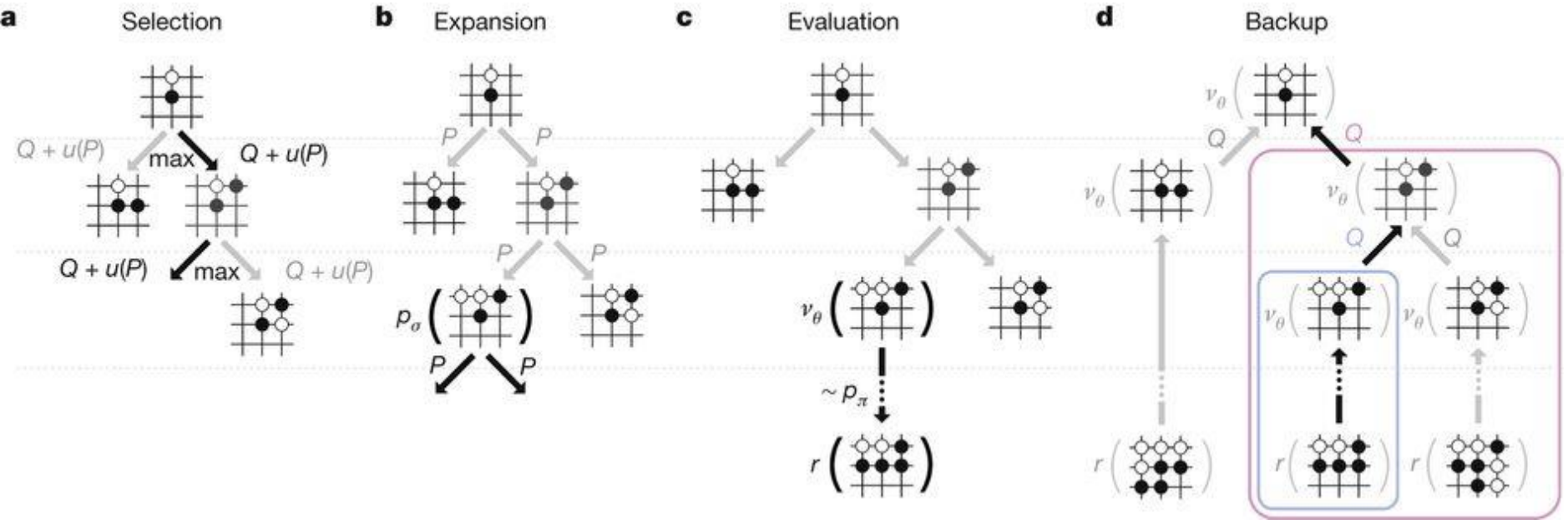
- Another planning method.
- Sample future paths using stochastic policy
  - Biased towards reasonable moves
  - The predictron paper may do this if they modeled the environment $\mathbb{P}(s'|s,a)$.



Background: Monte-Carlo Tree Search

Deterministic environment version.

- 1. Select path according to π plus exploration
- 2. Expand leaf node s (compute children and their $\mathbb{P}(\cdot)$)
- 3. Evaluate V(s) by rolling out (play till the end)
- 4. Backup: update Q(s,a) along the path (count)



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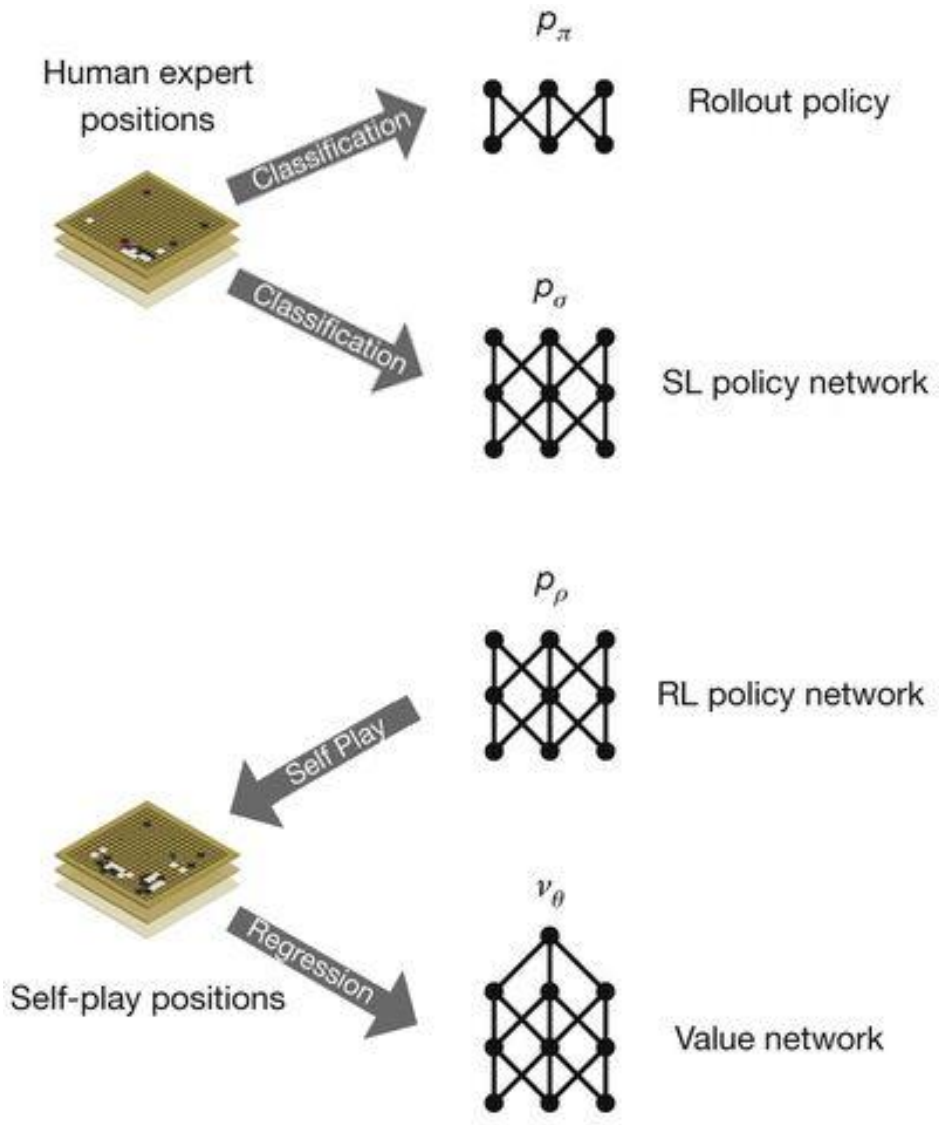
AlphaGo models overview



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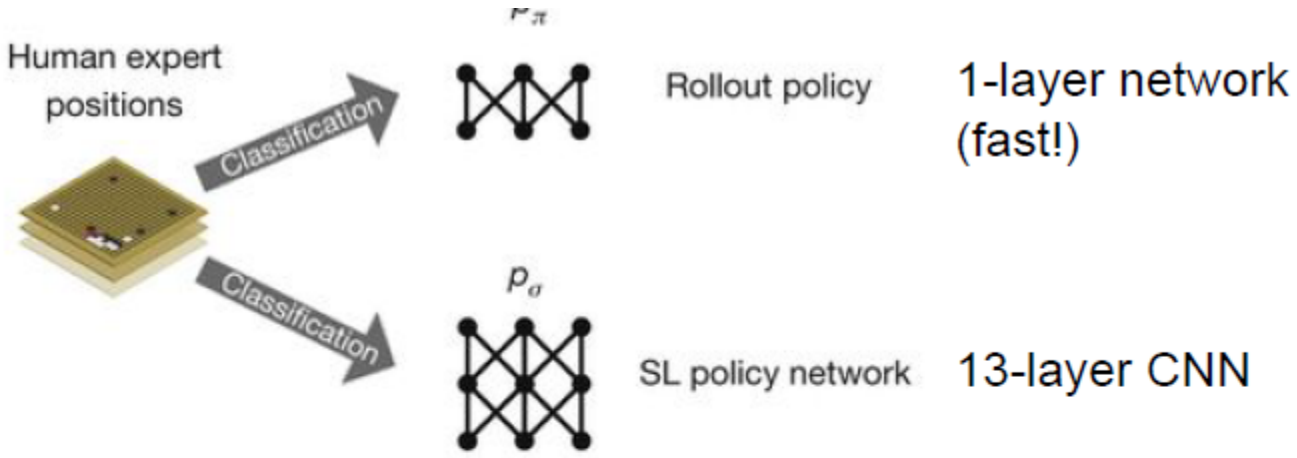
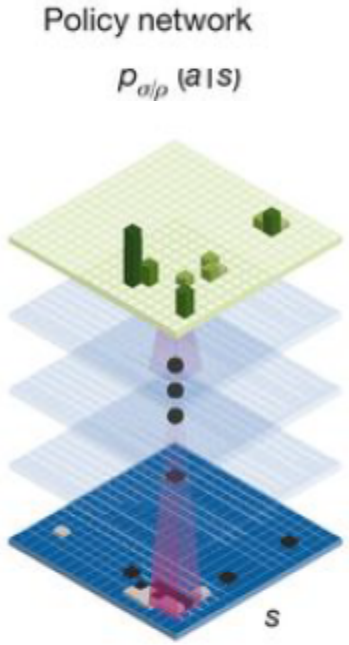
AlphaGo models





- Supervised learning
  - On human expert moves
  - One small (very fast rollout)
    - 2μs; 24.2% accuracy
  - One deeper
    - 57% accuracy w/ handcrafted features;
    - 55.7% using only raw board + past move

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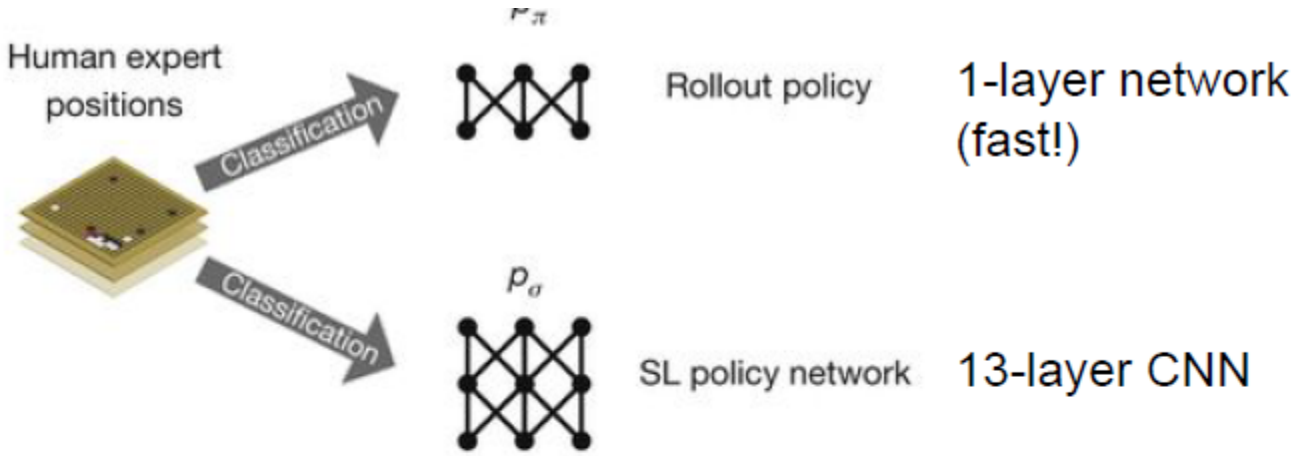
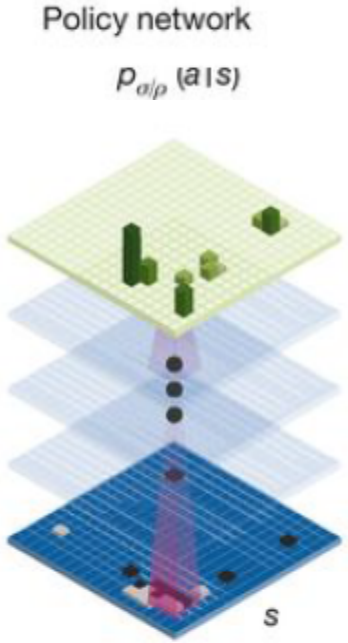
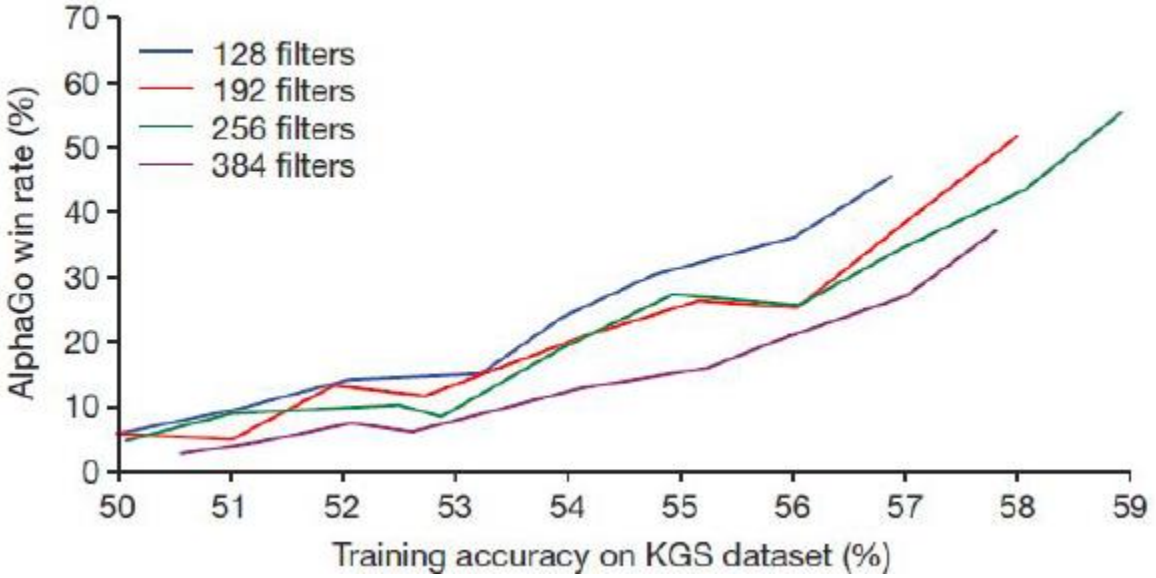
AlphaGo models





Importance of classification accuracy

(win rate against final AlphaGo)



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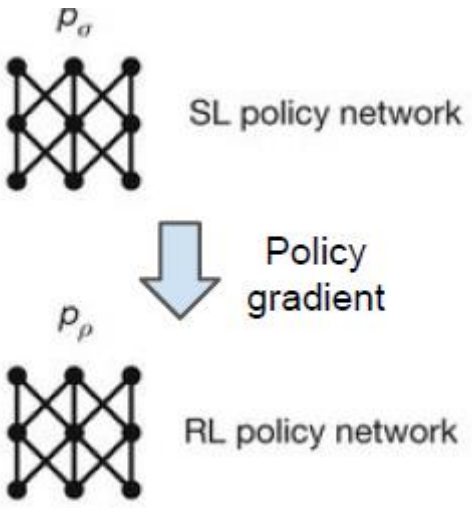
AlphaGo models

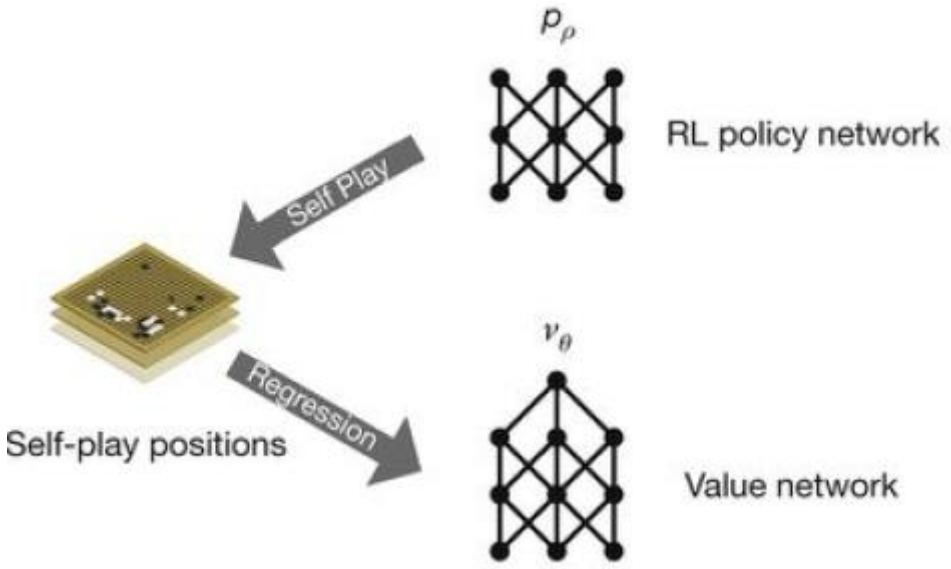
- Policy gradient
  - Improve SL policy to RL policy
    - Playing against its past iterations (less overfitting)

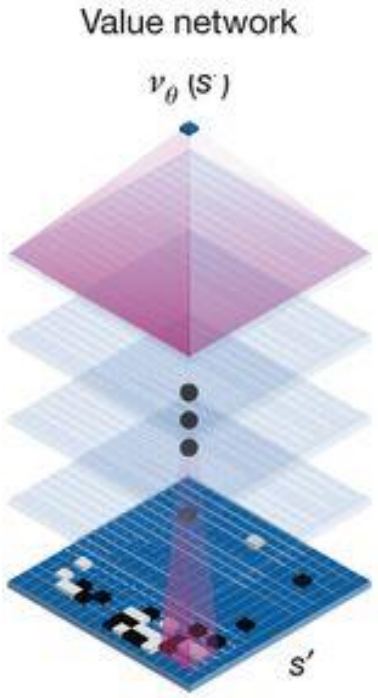


  - Training: PG w/o discount (rewards R_{win} = +1;R_{lose}= -1)
- Wins 80% against SL policy
  - 85% to Pachi (open source s-o-t-a)
  - Ranks ~ 3 amateur dan

AlphaGo models

- Value network: evaluate the win-rate of state
  - Use self-play instead of human moves (less overfit)
  - Under "optimal policy" (the RL one)
  - David: "perhaps the key of AlphaGo dev.“
    - (first strong state evaluator)





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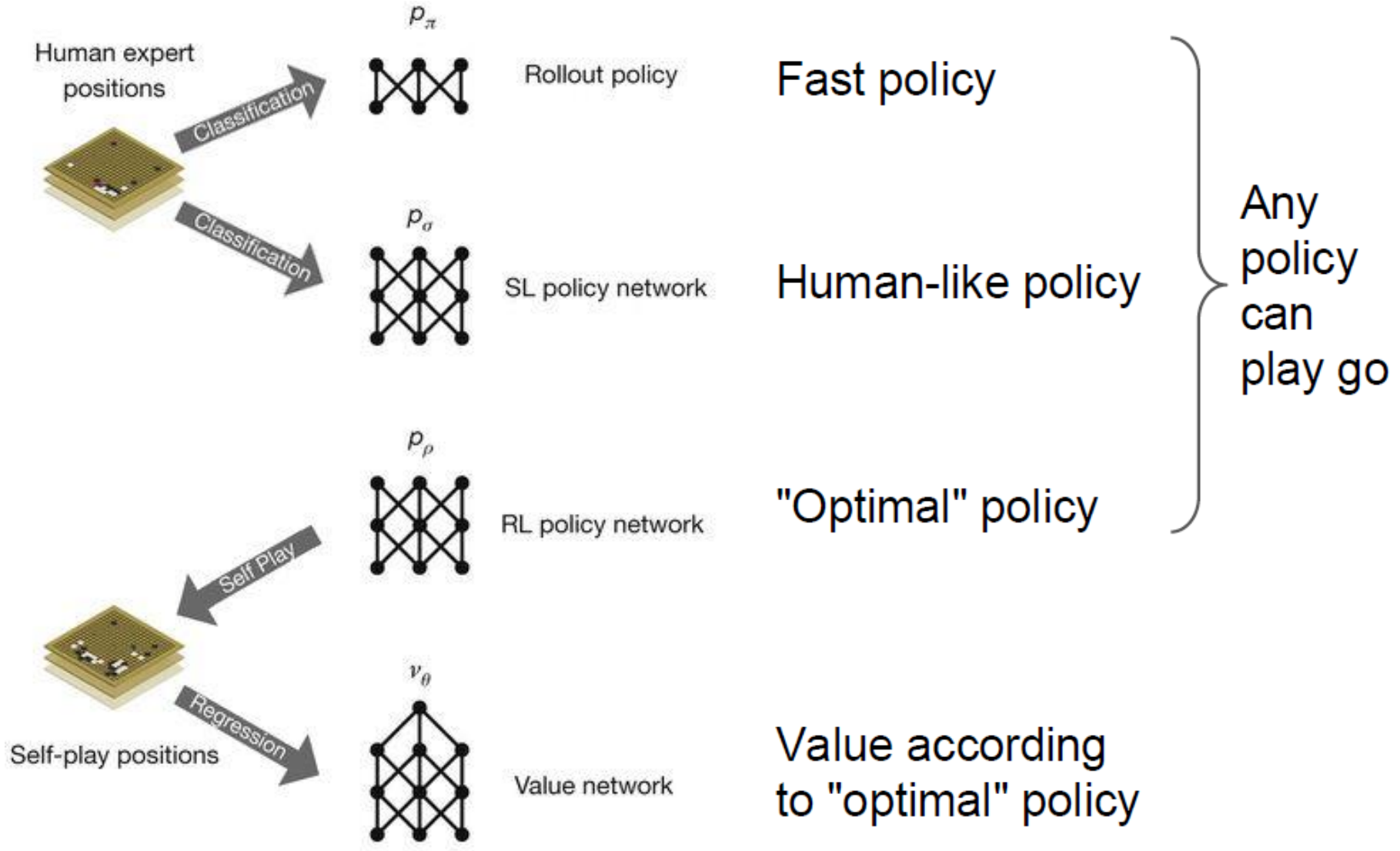
AlphaGo models recap



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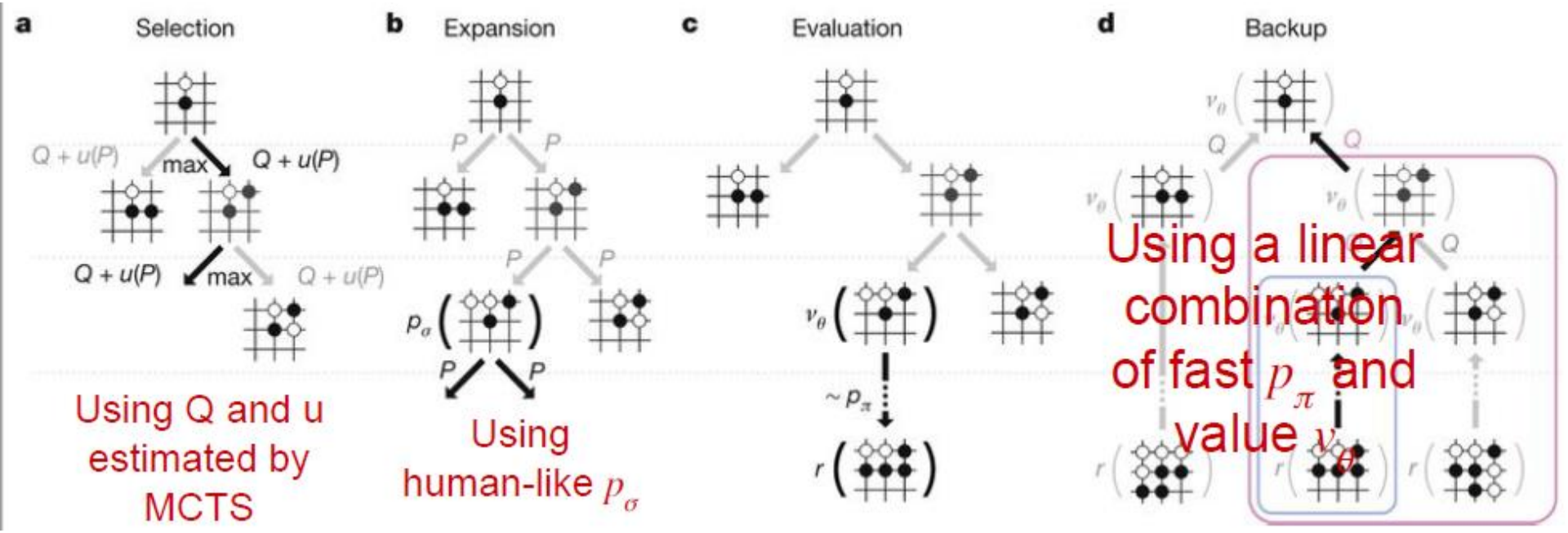
Putting everything together w/ MCTS

- - Deterministic environment version.
- 1. Select path by maximizing estimated *Q* and exploration *u*
- 2. Expand leaf node s(compute children's $\mathbb{P}(\cdot)$ using P_σ),
- 3. Evaluate V(s) by rolling out (using fast P_π and value v_θ)
- 4. Backup: update *Q*(s,*a*) along the path (using count)



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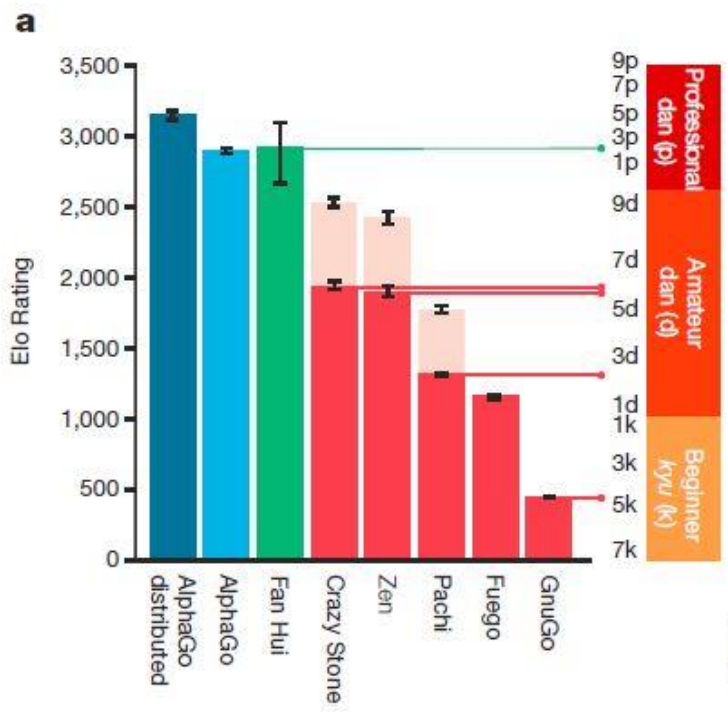
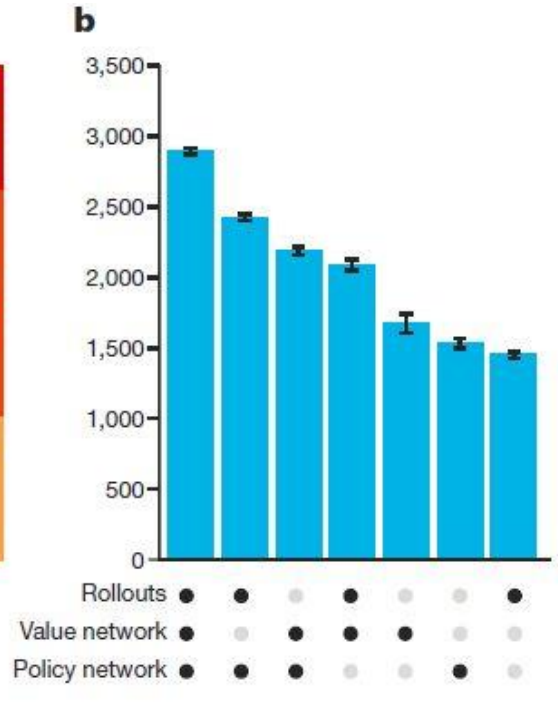
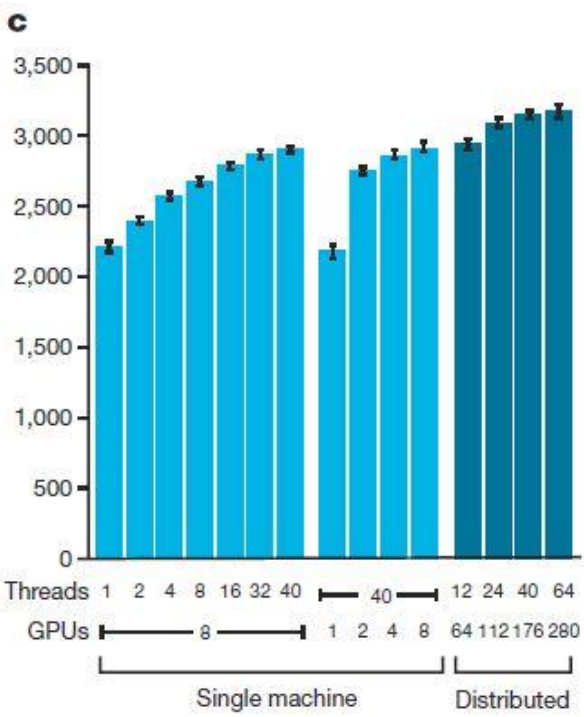
AlphaGo results



AlphaGo vs human or related work



Ablation study of the components



Ablation study of distributed MCTS

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Acknowledgement

Some of the materials in these slides are drawn inspiration from:

- Shubhendu Trivedi and Risi Kondor, University of Chicago, Deep Learning Course

- Hung-yi Lee, National Taiwan University, Machine Learning and having it Deep and Structured course

- Xiaogang Wang, The Chinese University of Hong Kong, Deep Learning Course

- Fei-Fei Li, Standord University, CS231n Convolutional Neural Networks for Visual Recognition course

Next time

- Attention and Memory

Questions?

Thank You !

WeChat Group for Deep Learning