Deep Reinforcement Learning

EE807: Recent Advances in Deep Learning

Lecture 7

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KAIST EE

Table of Contents

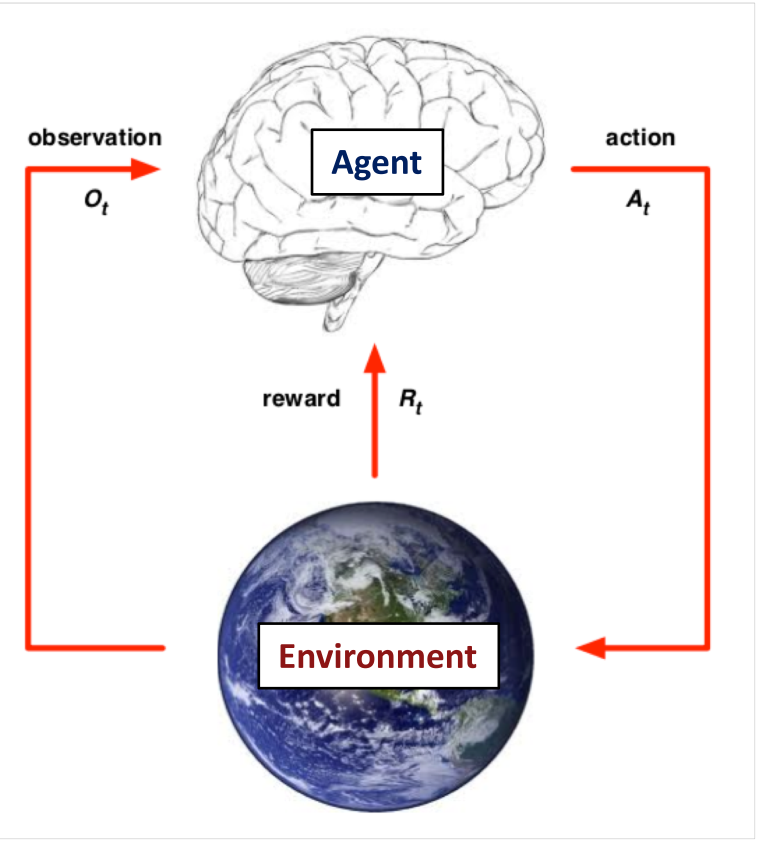
Table of Contents

What is Reinforcement Learning (RL)?

- Reinforcement learning is a **sequential decision making** problem

- **Agent**
  - Receives an observation of the current state
  - Selects an action
  - Receives a reward from the environment

- **Environment**
  - Receives an action from the agent
  - Give a reward to the agent
  - Change the environment state



Goal: Find an optimal strategy maximizing total future reward

* source : UCL Course on RL (http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html)

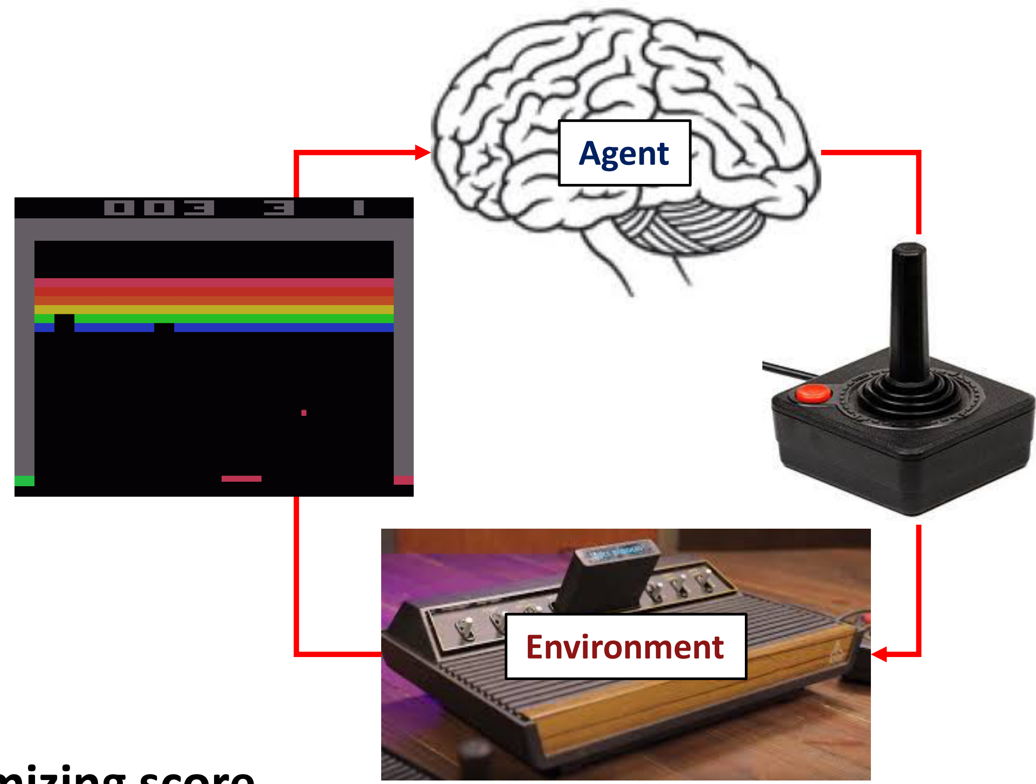
Example: Atari Game

- Reinforcement learning is a **sequential decision making** problem

- **Agent (Player)**
  - Receives RGB screen
  - Control joystick
  - Receives scores

- **Environment (Machine)**
  - Receives the joystick input
  - Give scores to the player
  - Change the environment state (e.g., memory, screen, ...)

Goal: Find an optimal strategy maximizing score

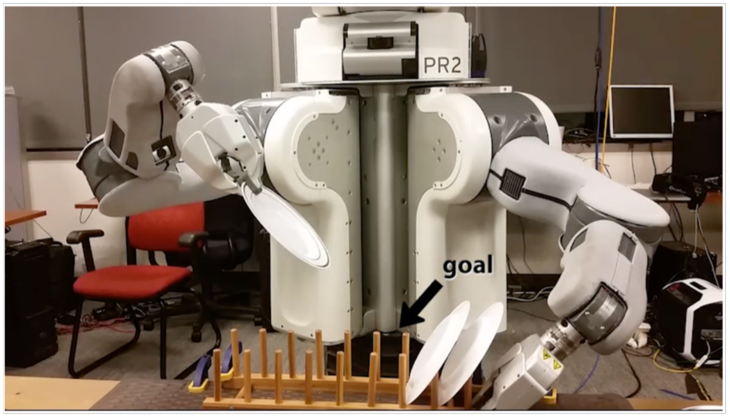


What is Reinforcement Learning (RL)?

- Reinforcement learning *vs.* Other machine learning tasks
  - No supervisor to follow, only a scalar reward signal
  - Feedback can be delayed
  - Agent's behavior affects the subsequent data

makes difficult to learn

- If defining a reward function is difficult, one can learn from demonstrations



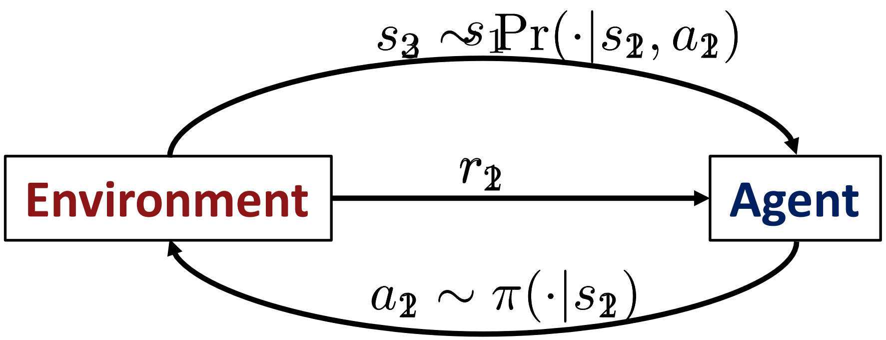
How to define reward?

  - **Imitation Learning**: copying expert's behavior
  - **Inverse RL**: inferring rewards from expert's behavior
  - But, this lecture only covers the case when the reward oracle/function is available

* source : UC Berkeley Course on DeepRL (http://rail.eecs.berkeley.edu/deeprlcourse/)

- RL can be formulated by **Markov Decision Process** $(\mathcal{S}, \mathcal{A}, \mathcal{P}, \mathcal{R}, \gamma)$
  - $\mathcal{S}$: a set of states
  - $\mathcal{A}$: a set of actions
  - $\mathcal{P}$: a conditional state transition probability, i.e.,
    $\mathcal{P}(s_t, a_t, s_{t+1}) = \Pr(s_{t+1}|s_t, a_t) = \Pr(s_{t+1}|s_t, a_t, s_{t-1}, a_{t-1}, \ldots, s_1, a_1)$
  - $\mathcal{R}$: a reward function, i.e., $r_t = \mathcal{R}(s_t, a_t)$
  - $\gamma \in [0, 1]$: a discount factor

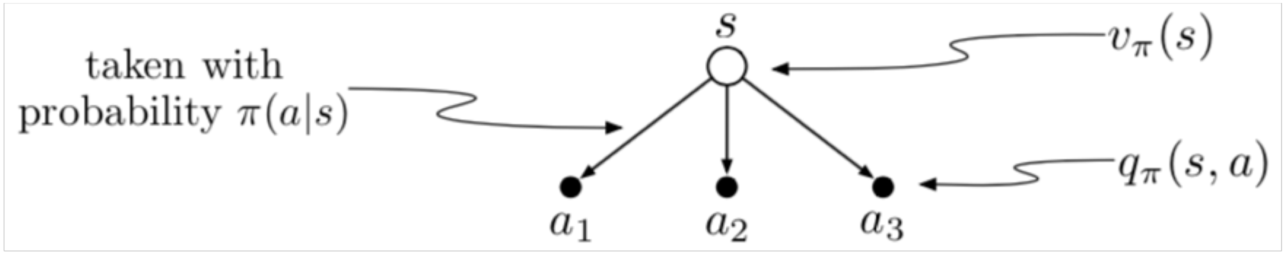
- The agent chooses an action according to $\pi(a|s)$



- **Goal:** find optimal policy $\pi(a|s)$ maximizing **total future reward** $\mathbb{E}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t\right]$

Value Functions

- Value functions of a state s under a policy π:
  - State-value function: $v_\pi(s) = \mathbb{E}_{a_1,\ldots\sim\pi}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t | s_1 = s\right]$
  - Action-value function: $q_\pi(s,a) = \mathbb{E}_{a_2,\ldots\sim\pi}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t | s_1 = s, a_1 = a\right]$



  - Advantage function: $A_\pi(s,a) = q_\pi(s,a) - v_\pi(s)$

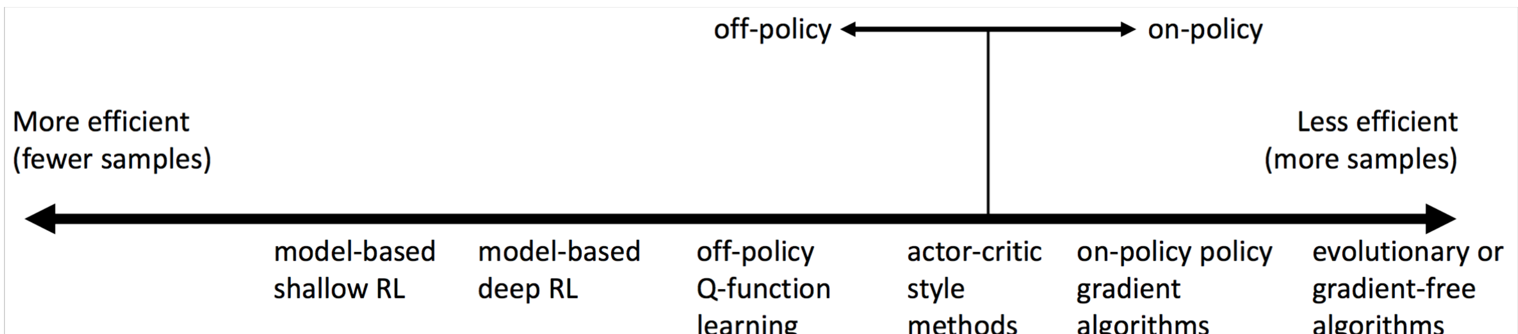
- v_π indicates which state is good / q_π, A_π indicate which action is good under π

- Optimal value functions: $v_*(s) = \max_\pi v_\pi(s),\ q_*(s,a) = \max_\pi q_\pi(s,a)$
- The optimal policy can be derived from them: $\pi_*(s) = \arg\max_a q_*(s,a)$

* source : Richard Sutton and Andrew Barto, Reinforcement Learning: An Introduction, 2nd edition, 2018

Types of RL Algorithms for Learning a Good Policy

- Model-based *vs.* model-free algorithms
  - Model-based/free: the transition probability $\mathcal{P}$ is known/unknown
- On-policy *vs.* off-policy algorithms
  - On-policy needs to generate new samples when policy is changed
  - Off-policy is able to (re)use samples which is generated from other policies
- Value-based *vs.* policy-based algorithms
  - Value-based learns value functions, and then derive policy
  - Policy-based optimizes policy directly from the objective, i.e., $\mathbb{E}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t\right]$
  - Some methods, e.g., Actor Critic, use both value and policy functions



Note: sample efficiency ≠ training time

* source : UC Berkeley Course on DeepRL (http://rail.eecs.berkeley.edu/deeprlcourse/)

Table of Contents

1. **What is Reinforcement Learning?**

2. **Value-based Methods**
   - Q-learning
   - Deep Q-network
   - Double Q-learning, Prioritized Replay, Dueling Architecture

3. **Policy Gradient Methods**
   - REINFORCE
   - Trust region policy optimization
   - Proximal policy optimization algorithms

Q-Learning with Function Approximation

Q-learning algorithm [Watkins, 1989] repeats 1-3 until convergence

1. Choose an action a from the current state s using the ε-greedy policy
   - ε-greedy choose a random action with probability ε, otherwise $a = \arg\max_a q(s,a)$
2. Observe a reward r, a new state s'
3. Update $q(s,a) \leftarrow q(s,a) + \alpha \left[r + \gamma \max_{a'} q(s',a') - q(s,a) \right]$

Incremental update

- **Intuition:** Q-learning updates the q-value incrementally to satisfy the Bellman equation for the optimal action-value function:

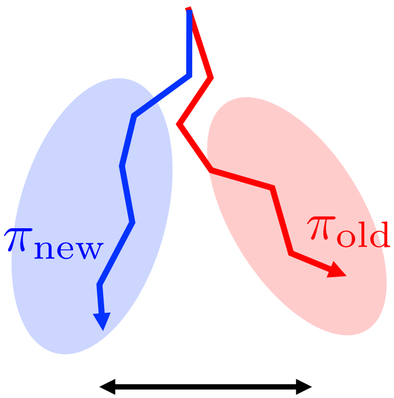
$$q_*(s,a) = \mathbb{E}_{s' \sim \Pr(\cdot|s,a)} \left[r + \gamma \max_{a'} q_*(s',a') \right]$$

- For high-dimensional state and/or action spaces, parameterize $q(s,a) \approx q(s,a;\theta)$
- The update rule for θ :

$$\theta \leftarrow \theta + \alpha \underbrace{\left[r + \gamma \max_{a'} q(s',a';\theta) - q(s,a;\theta) \right]}_{\text{called by Temporal Difference (TD) errors}} \nabla_\theta q(s,a;\theta)$$

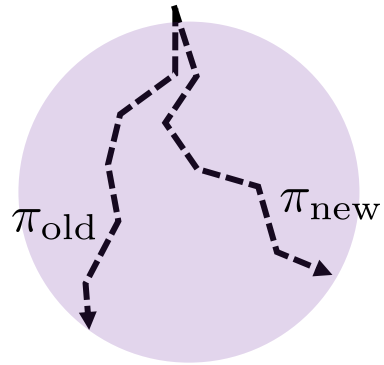
- Q-learning is known to be unstable or even to diverge when using nonlinear function approximators such as neural networks

- Because even small updates to q may significantly change …



1. Data distribution
+ high-correlated sequential data

Solution: DQN (Mnih et al., 2015)



1. Experience replay buffer:
- use previous samples
- smoothing data distribution
- remove sequential correlation

2. Correlations between $q(s, a; \theta)$ and $r + \gamma \max_{a'} q(s', a'; \theta)$

2. Slowly updated target network θ^-
- use $r + \gamma \max_{a'} q(s', a'; \theta^-)$
- reducing correlations from target

- Q-learning is known to be unstable or even to diverge when using nonlinear function approximators such as neural networks

- Because even small updates to q may significantly change …

Solution: DQN [Mnih et al., 2015]

Training Deep Q-Network [Minh et al., 2015]

$$\mathcal{L} = \mathbb{E}_{\underbrace{\boxed{(s,a,r,s')\sim U(D)}}_{\text{replay buffer}}}\left[\left(r + \gamma \max_{a'} q(s', a'; \underbrace{\boxed{\theta^-}}_{\text{target network}}) - q(s,a;\theta)\right)^2\right]$$

- Add every observation (s,a,r,s') to replay buffer D
- Update deep Q-network $\theta \leftarrow \theta - \alpha \nabla_\theta \mathcal{L}$
- Update target network $\theta^- \leftarrow \theta$ at every C steps

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1.

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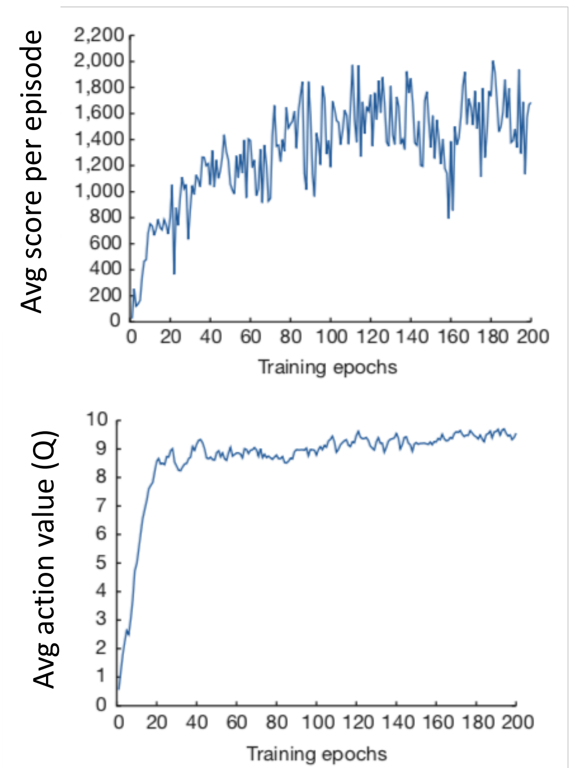
2. Correlations between $q(s,a;\theta)$ and $r + \gamma \max_{a'} q(s',a';\theta)$

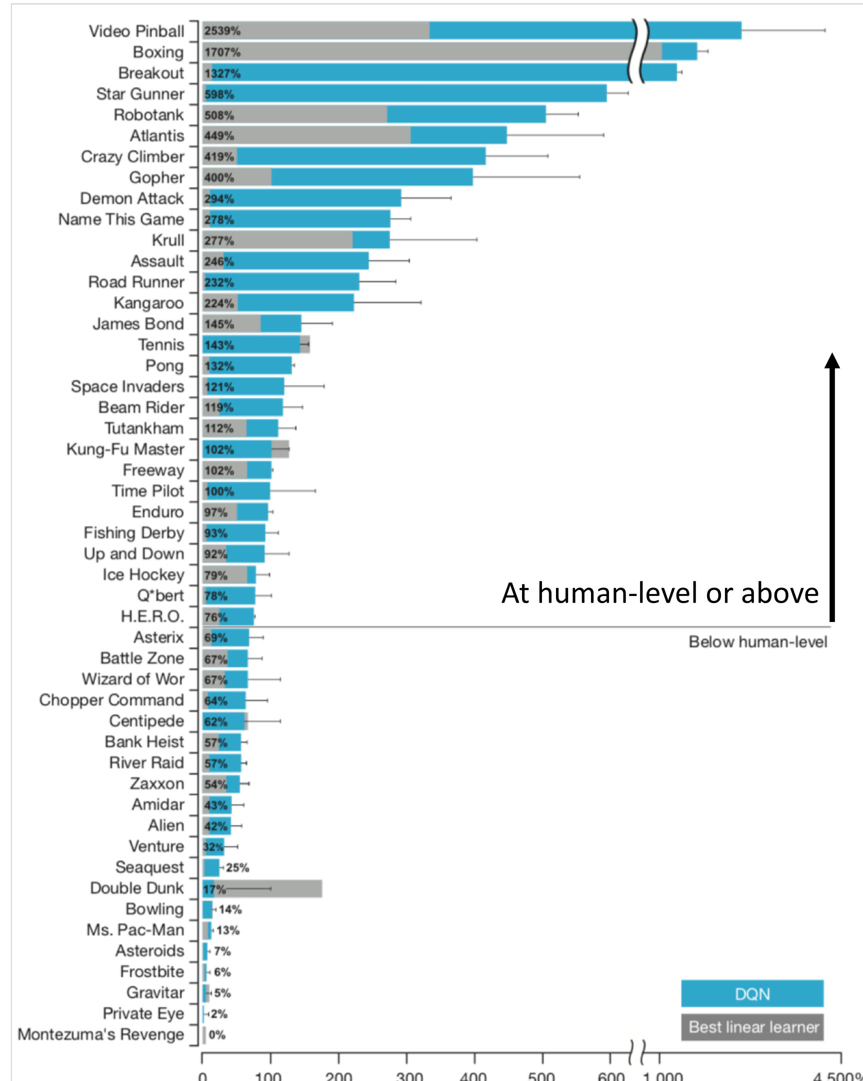
- use $r + \gamma \max_{a'} q(s',a';\theta^-)$
- reducing correlations from target

Deep Q-Network for Atari Games

- [Minh et al., 2015] uses same architecture/hyper-parameters for all Atari games
  ⇒ Robustness of DQN

- Training curve





- [DQN Breakout video]

* source : Minh et al., Human-level Control through Deep Reinforcement Learning, Nature 2015

- Q-learning is known to **overestimate** action values

$$\theta \leftarrow \theta + \alpha \left[r + \gamma \max_{a'} q(s', a'; \theta) - q(s, a; \theta) \right] \nabla_\theta q(s, a; \theta)$$

because the max step $\max q(\cdot, \cdot)$ is used to update the same function $q(\cdot, \cdot)$

- In practice, overestimation errors will differ for actions $\Longrightarrow$ poor policy

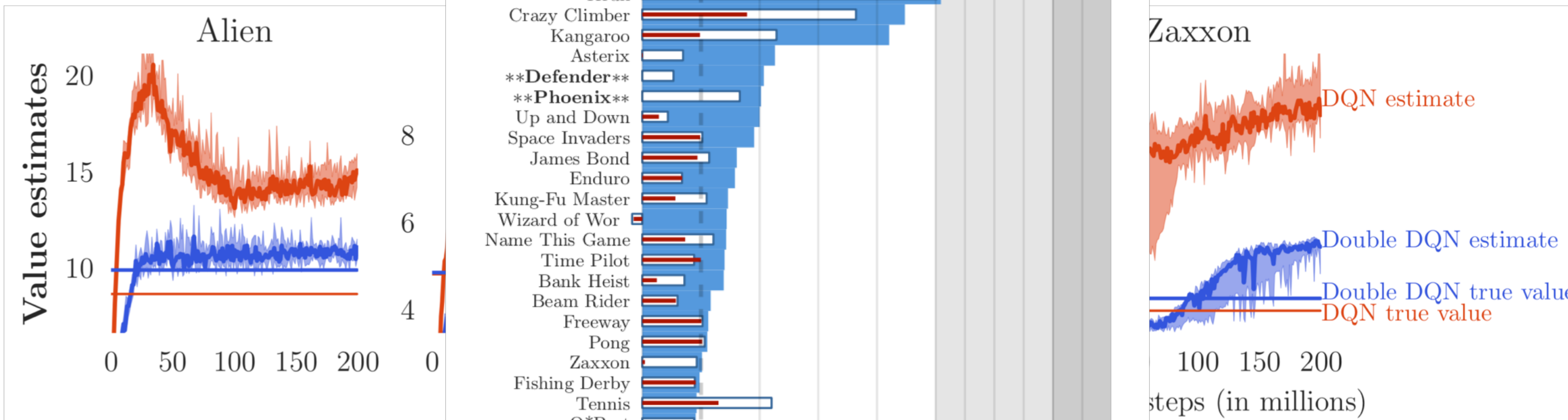
Double Q-learning [van Hasselt, 2010] separates selection and evaluation:

$$\theta_1 \leftarrow \theta_1 + \alpha \left[r + \gamma \boxed{q(s', \boxed{\arg\max_{a'} q(s', a'; \theta_1)}; \theta_2)} - q(s, a; \theta_1) \right] \nabla_{\theta_1} q(s, a; \theta_1)$$

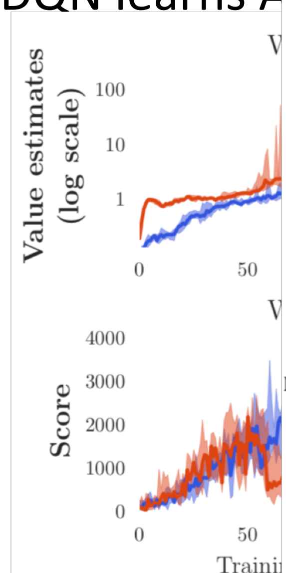
- **Double DQN** [van Hasselt et al., 2015] uses $\theta_1 = \theta$ and $\theta_2 = \theta^-$ (target network)

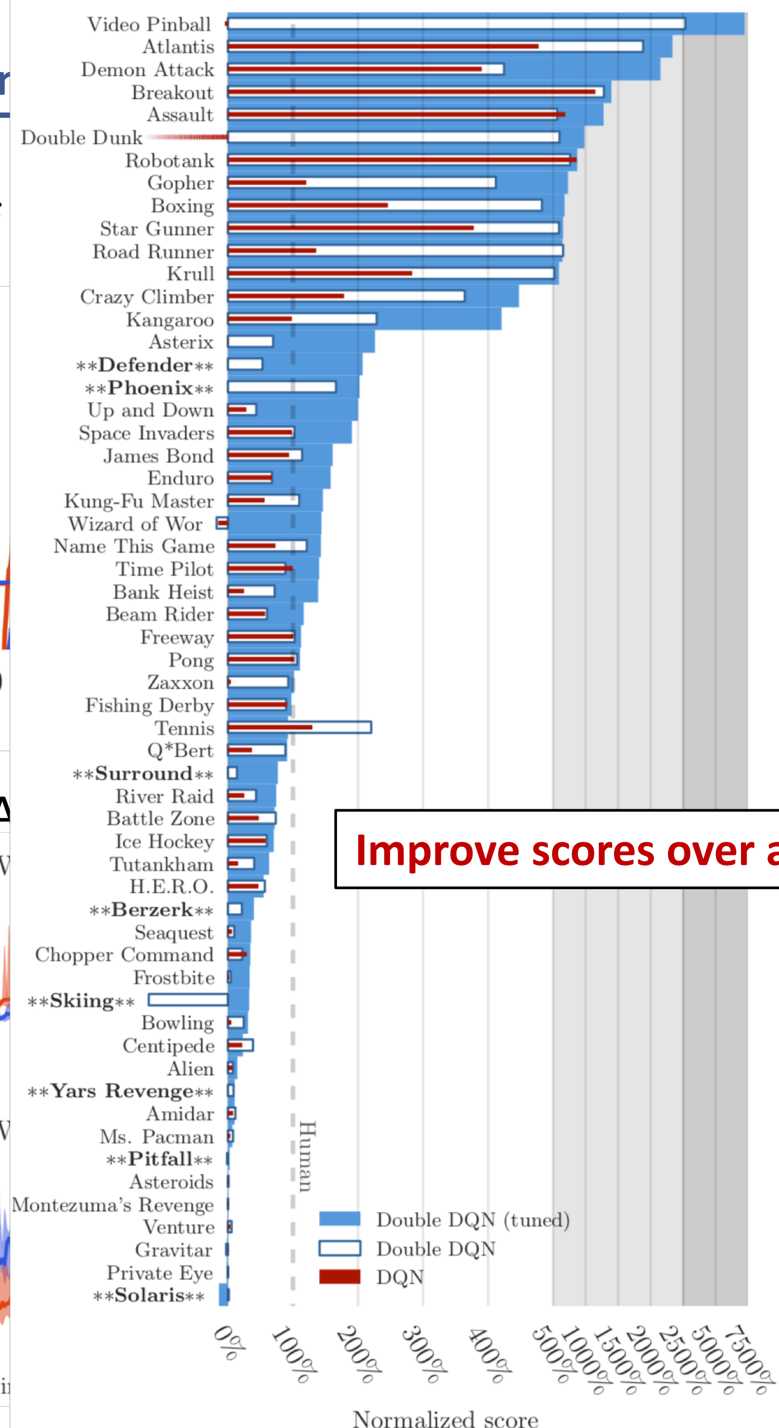
Advanced Deep Q-learnin

- Value estimations of ... es



- Double DQN learns A





Improve scores over almost games

...earning with Double Q-learning, AAAI 2016

- DQN samples transitions (s, a, r, s') **uniformly** from **experience replay buffer**

- **Problem:** Unimportant data (e.g., small TD error) might be used with same probability as important ones $\Longrightarrow$ sample inefficiency
- **Solution** [Schaul et al., 2016]: **Prioritize** data and **sample them based on the priority**

Q1) How to prioritize? $\theta \leftarrow \theta + \alpha \boxed{r + \gamma \max_{a'} q(s', a'; \theta) - q(s, a; \theta)} \nabla_\theta q(s, a; \theta)$

$\Rightarrow$ Use TD error δ

measure how much update is required

Q2) How to sample?

- ~~Greedy: sample transitions of maximum TD errors~~ some transitions are never selected
- Stochastically sample with probability $P(i) = p_i^\alpha / \sum_k p_k^\alpha$
  - Proportional: $p_i = |\delta_i| + \epsilon$
  - Rank-based: $p_i = 1/\text{rank}(i)$

sampling probability of i-th data

- Prioritized replay $P(D)$ introduces **bias**
  - Because original Q-learning with/without replay buffer uses uniform distribution:

$$\mathbb{E}_{(s,a,r,s')\sim U(D)}[\delta^2] \neq \mathbb{E}_{(s,a,r,s')\sim P(D)}[\delta^2]$$

where $\delta = r + \gamma \max_{a'} q(s', a'; \theta^-) - q(s, a; \theta)$

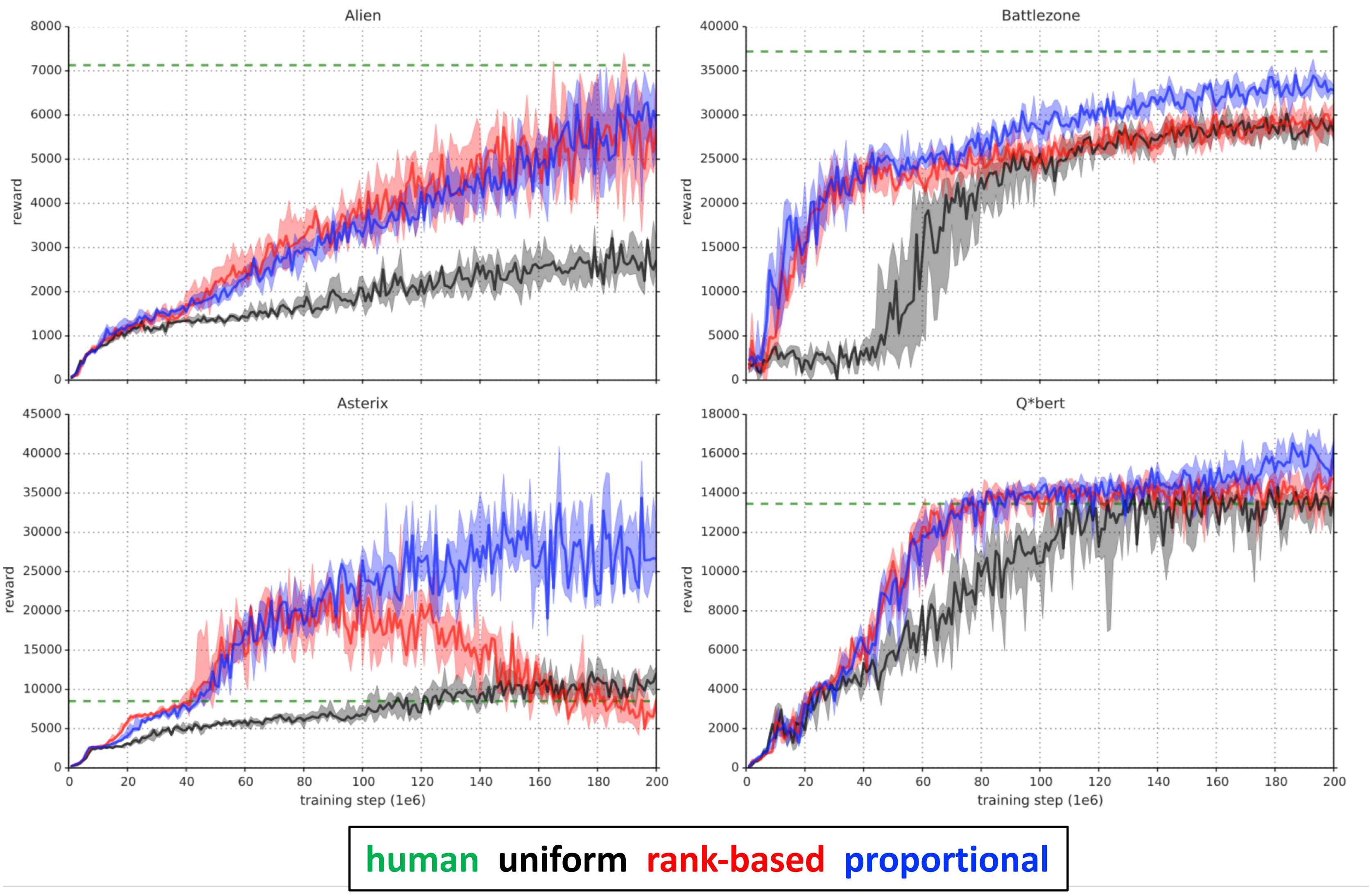
- To correct this bias, use **importance-sampling** weights $w_i = \left(\frac{1}{N}\frac{1}{P(i)}\right)^\beta$
  - In practice, increase β linearly from β_0 to 1

DQN with prioritization [Schaul et al., 2016]

1. Update parameters using $\nabla_\theta \mathcal{L}$ where $\mathcal{L} = \mathbb{E}_{(s,a,r,s')\sim P(D)}[w\delta^2]$
2. Update priorities for sampled transitions $p_i \leftarrow |\delta_i|$

- Prioritized replay buffer can be combined with Double Q-learning

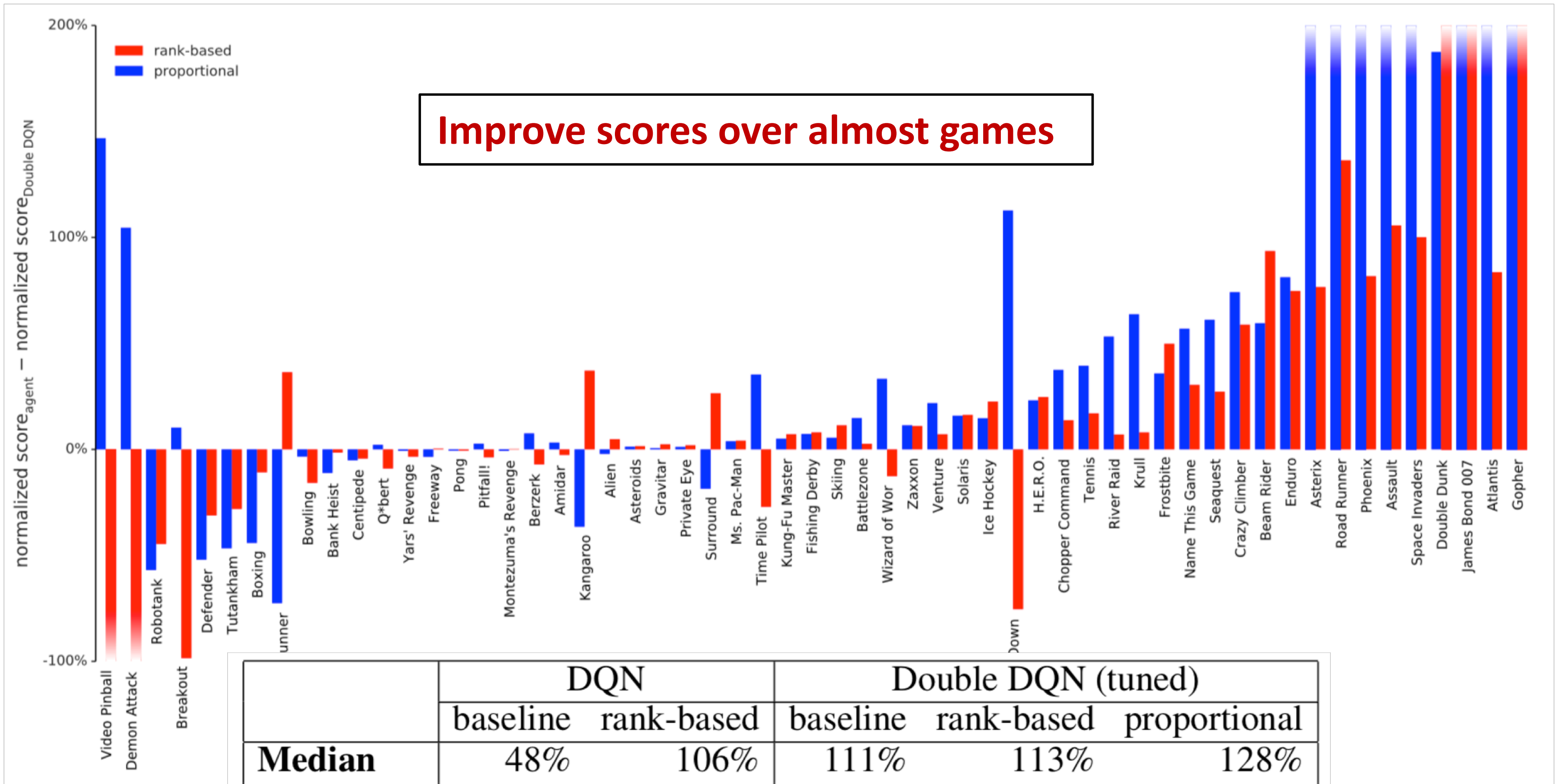
- Learning speed compared to uniform sampling



* source : Schaul et al., Prioritized Experience Replay, ICLR 2016

Advanced Deep Q-learning (2) Prioritized Replay

- Comparison scores with Double DQN on Atari games



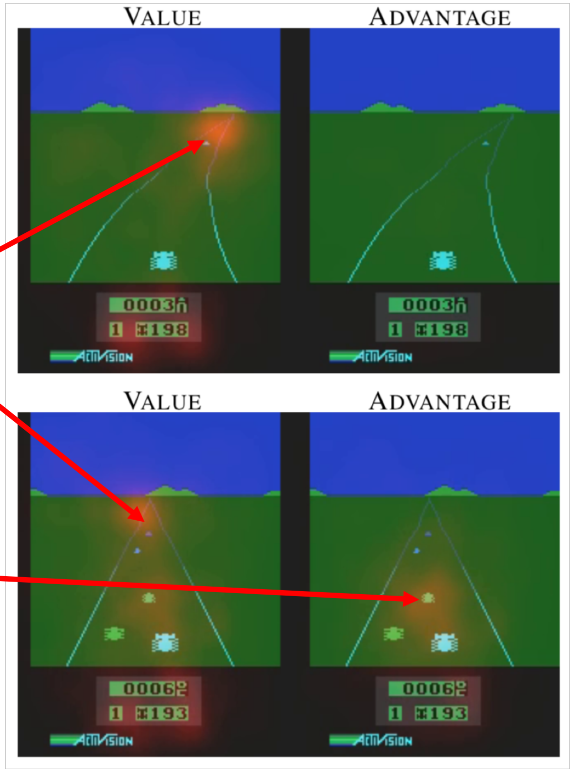
Improve scores over almost games

	DQN		Double DQN (tuned)		
	baseline	rank-based	baseline	rank-based	proportional
Median	48%	106%	111%	113%	128%
Mean	122%	355%	418%	454%	551%
> baseline	–	41	–	38	42
> human	15	25	30	33	33
# games	49	49	57	57	57

* source : Schaul et al., Prioritized Experience Replay, ICLR 2016

Intuition from an example: driving car

- In many states, it is unnecessary to estimate the value of each action choice
    - State-value function pays attention to the road
- In some states, left/right actions should be taken to avoid collision
    - Advantage function pays attention to the front of car when action selection is crucial



- Recall advantage function: $A_\pi(s,a) = q_\pi(s,a) - v_\pi(s)$

Idea [Wang et al., 2016] Decouple action-value q to state-value v and advantage A

$$q(s,a;\theta,\phi_v,\phi_A) = v(s;\theta,\phi_v) + A(s,a;\theta,\phi_A)$$

learn which state is valuable without effect of action

* source: Wang et al., Dueling Network Architectures for Deep Reinforcement Learning, ICML 2016

- In $q = v + A$, v can be arbitrary given an action-value q

Q) How to force v to be the (unique, correct) state-value?

A) Make the maximum of the advantage be zero

$$q(s,a;\theta,\phi_v,\phi_A) = v(s;\theta,\phi_v) + (A(s,a;\theta,\phi_A) - \max_{a'} A(s,a';\theta,\phi_A))$$

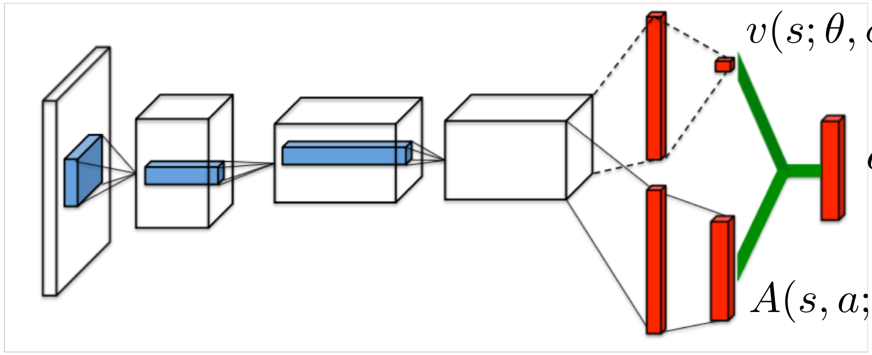
- Then, $q(s,a^*;\theta,\phi_v,\phi_A) = v(s;\theta,\phi_v)$

this can be derived from $\pi(s) = \arg\max_a q(s,a)$

- In practice, use average instead of maximum for learning stability:

$$q(s,a;\theta,\phi_v,\phi_A) = v(s;\theta,\phi_v) + \left(A(s,a;\theta,\phi_A) - \frac{1}{m}\sum_{a'} A(s,a';\theta,\phi_A)\right)$$

- **Dueling architecture** [Wang et al., 2016]

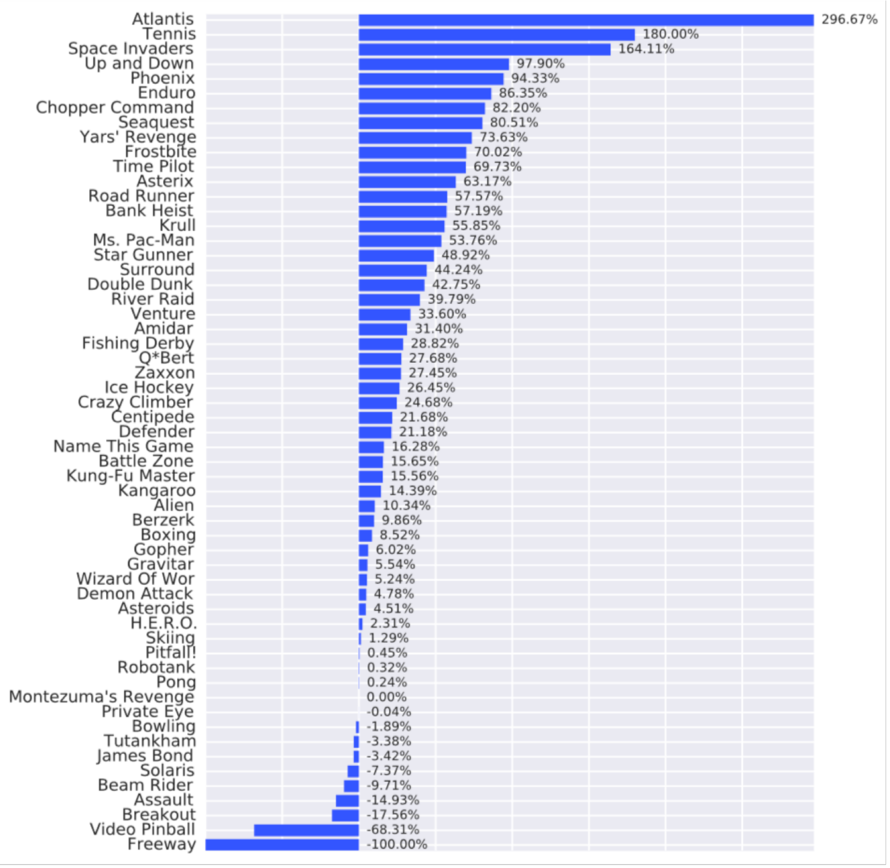


* source: Wang et al., Dueling Network Architectures for Deep Reinforcement Learning, ICML 2016

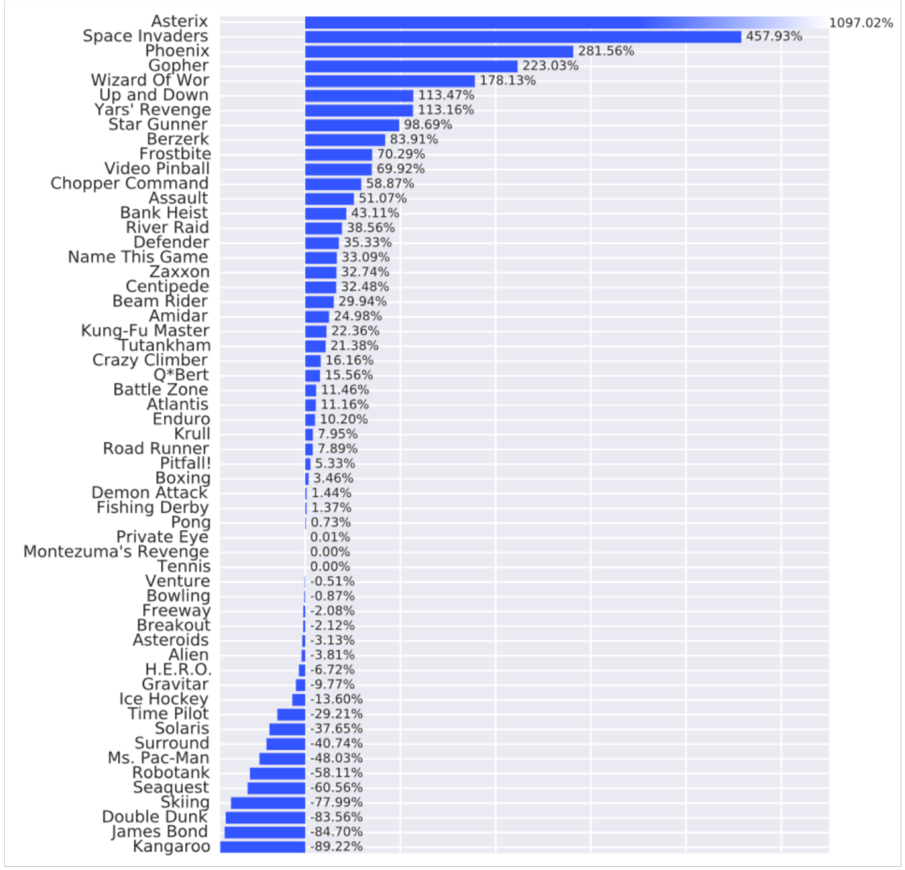
Advanced Deep Q-learning (3) Dueling Architecture

- This dueling architecture also improves DQN performance

vs Double DQN



vs Double DQN + Prioritized replay



* source: Wang et al., Dueling Network Architectures for Deep Reinforcement Learning, ICML 2016

Table of Contents

- Value-based methods (e.g., Q-learning) optimize policies indirectly:

Find $q(s,a;\theta) \approx q_*(s,a) \quad \Rightarrow \quad \pi(s;\theta) = \arg\max_a q(s,a;\theta)$

- **Policy gradient methods** (e.g., REINFORCE, Actor-Critic) **optimize policies directly** via maximizing total reward $\mathbb{E}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t\right]$:

$$\arg\max_\theta \boxed{\mathbb{E}_{a_t \sim \pi(\cdot|s_t;\theta)}\left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t\right]}$$

where θ is the policy parameters

  - **Approximated value functions might be used** with these methods to resolve optimization issues such as high variance

- **Policy gradient theorem:** If $J(\theta)$ is **the above objective**, then

$$\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}\left[\nabla_\theta \log \pi(a|s;\theta) q_{\pi_\theta}(s,a)\right]$$

  - Simply, higher action-value $q_{\pi_\theta}(s,a)$ increases action probability $\pi(a|s;\theta)$
  - Action evaluation & selection should be performed by same policy, i.e., **on-policy**

REINFORCE [Willams, 1992] uses Monte-Carlo estimates of the policy gradient

1. Sample an episode $\{s_1, a_1, r_1, \ldots, s_T, a_T, r_T\} \sim \pi_\theta$
2. Compute $\Delta\theta \leftarrow \sum_{t=1}^{T} \nabla_\theta \log \pi(a_t|s_t;\theta) \boxed{\left(\sum_{s=t}^{T} \gamma^{s-t} r_s\right)}$
3. Update $\theta \leftarrow \theta + \alpha\Delta\theta$

Unbiased estimator of $q_{\pi_\theta}(s_t, a_t)$

- **Issue:** REINFORCE has high variance when estimating gradients
- **Solution:** Use any baseline function $b(s)$ not depending on actions

$$
\begin{aligned}
\mathbb{E}_{\pi_\theta}\left[\nabla \log \pi(a|s;\theta) b(s)\right] &= \sum_s \mu(s) \sum_a \pi(a|s;\theta) \frac{\nabla \pi(a|s;\theta)}{\pi(a|s;\theta)} b(s) \\
&= \sum_s \mu(s) b(s) \nabla \sum_a \pi(a|s;\theta) \\
&= \sum_s \mu(s) b(s) \nabla 1 = 0
\end{aligned}
$$

REINFORCE [Willams, 1992] uses Monte-Carlo estimates of the policy gradient

1. Sample an episode $\{s_1, a_1, r_1, \dots, s_T, a_T, r_T\} \sim \pi_\theta$
2. Compute $\Delta\theta \leftarrow \sum_{t=1}^{T} \nabla_\theta \log \pi(a_t|s_t;\theta) \boxed{\left(\sum_{s=t}^{T} \gamma^{s-t} r_s\right)}$
3. Update $\theta \leftarrow \theta + \alpha\Delta\theta$

Unbiased estimator of $q_{\pi_\theta}(s_t, a_t)$

- **Issue:** REINFORCE has high variance when estimating gradients
- **Solution:** Use any baseline function $b(s)$ not depending on actions
  - $\mathbb{E}_{\pi_\theta}\left[\nabla \log \pi(a|s;\theta) b(s)\right] = 0$
  - $\nabla_\theta J(\theta) = \mathbb{E}_{\pi_\theta}\left[\nabla \log \pi(a|s;\theta) \boxed{(q_{\pi_\theta}(s,a) - b(s))}\right]$

This can reduce the variance

- Which $b(s)$ should be used?
  - One natural choice is $b(s) = v_{\pi_\theta}(s)$ since $\mathbb{E}_{a\sim\pi(\cdot|s;\theta)}\left[q_{\pi_\theta}(s,a) - v_{\pi_\theta}(s)\right] = 0$
  - In practice, use $b(s) = v(s;w) \approx v_{\pi_\theta}(s)$ with parameters w and learn the function using TD errors such as Q-learning [Sutton et al., 2000]

Issues in ”vanilla” policy gradient methods such as REINFORCE

- Hard to choose step-size α
  - small changes in parameter space can cause poor policy
- Only one gradient step per each sample
  - Sample inefficiency

Solution: formulate an optimization problem on generated data from old policy

- That allows small changes in policy space
- That guarantees improvement of policy performance

Trust Region Policy Optimization [Schulman et al., 2015]: for each iteration, solve

$$\begin{aligned} \underset{\theta}{\text{maximize}} \quad & \mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} A_{\pi_{\theta_{\text{old}}}}(s,a)\right] \\ \text{subject to} \quad & \mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[D_{\text{KL}}(\pi_{\theta_{\text{old}}}(\cdot|s)||\pi_\theta(\cdot|s))\right] \leq \delta \end{aligned}$$

$A_\pi(s,a) = q_\pi(s,a) - v_\pi(s)$ is also approximated by neural networks

Derive TRPO

- Let $\eta(\pi) = \mathbb{E}_\pi[v_\pi(s_1)] = \mathbb{E}_\pi[\sum_{t=1}^{\infty} \gamma^{t-1} r_t]$ be the performance of a policy
- This performance can be written as

$$
\begin{aligned}
\eta(\pi) &= \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t \right] \\
&= \eta(\pi_{\text{old}}) + \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^{t-1} r_t - v_{\pi_{\text{old}}}(s_1) \right] \\
&= \eta(\pi_{\text{old}}) + \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^{t-1} \big(\overbrace{r_t + \gamma v_{\pi_{\text{old}}}(s_{t+1})}^{q_{\pi_{\text{old}}}(s,a)} - v_{\pi_{\text{old}}}(s_t) \big) \right] \\
&= \eta(\pi_{\text{old}}) + \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^{t-1} A_{\pi_{\text{old}}}(s_t, a_t) \right] \\
&= \eta(\pi_{\text{old}}) + \sum_s \rho_\pi(s) \sum_a \pi(a|s) A_{\pi_{\text{old}}}(s,a)
\end{aligned}
$$

where $\rho_\pi(s) = \sum_{t=1}^{\infty} \gamma^{t-1} \Pr(s_t = s|\pi)$

Derive TRPO

- Let $\eta(\pi) = \mathbb{E}_\pi[v_\pi(s_1)] = \mathbb{E}_\pi[\sum_{t=1}^{\infty} \gamma^{t-1} r_t]$ be the performance of a policy
- This performance can be written as

$$\eta(\pi) = \eta(\pi_{\text{old}}) + \mathbb{E}_\pi \left[\sum_{t=1}^{\infty} \gamma^{t-1} A_{\pi_{\text{old}}}(s_t, a_t) \right]$$
$$= \eta(\pi_{\text{old}}) + \sum_s \rho_\pi(s) \sum_a \pi(a|s) A_{\pi_{\text{old}}}(s, a)$$

- Define $\mathcal{L}_{\pi_{\text{old}}}(\pi) = \eta(\pi_{\text{old}}) + \sum_s \rho_{\pi_{\text{old}}}(s) \sum_a \pi(a|s) A_{\pi_{\text{old}}}(s, a)$

- $\mathcal{L}_{\pi_{\theta_{\text{old}}}}(\cdot)$ is a local approximation of $\eta(\cdot)$ at $\theta = \theta_{\text{old}}$:

$$\mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta_{\text{old}}}) = \eta(\pi_{\theta_{\text{old}}})$$
$$\nabla_\theta \mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_\theta)\big|_{\theta=\theta_{\text{old}}} = \nabla_\theta \eta(\pi_\theta)\big|_{\theta=\theta_{\text{old}}}$$

- For fixed θ_{old}, we can omit $\eta(\pi_{\theta_{\text{old}}})$: $\mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_\theta) = \mathbb{E}_{\pi_{\theta_{\text{old}}}} \left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} A_{\pi_{\theta_{\text{old}}}}(s, a) \right]$

Theorem [Schulman et al., 2015]

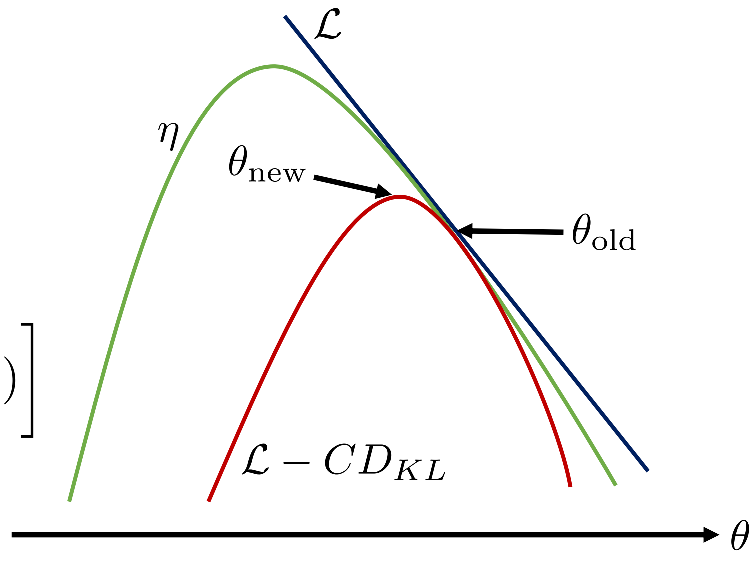
- $\eta(\pi_\theta) \geq \mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_\theta) - CD_{\text{KL}}^{\max}(\pi_{\theta_{\text{old}}}, \pi_\theta)$
- C is some constant and $D_{\text{KL}}^{\max}(\pi_{\theta_{\text{old}}}, \pi_\theta) = \max_s D_{\text{KL}}(\pi_{\theta_{\text{old}}}(\cdot|s)||\pi_\theta(\cdot|s))$

- Policy iteration **guarantees non-decreasing performance**:

$$\theta_{\text{new}} \leftarrow \arg\max_\theta \mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_\theta) - CD_{\text{KL}}^{\max}(\pi_{\theta_{\text{old}}}, \pi_\theta)$$

- In practice,
  - Theoretical guaranteed C updates very small steps in policy
  - Use a constraint instead of the penalty
  - Use average instead of maximum

$$\underset{\theta}{\text{maximize}} \quad \mathcal{L}_{\pi_{\theta_{\text{old}}}}(\pi_\theta) = \mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)} A_{\pi_{\theta_{\text{old}}}}(s,a)\right]$$
$$\text{subject to} \quad \mathbb{E}_{\pi_{\theta_{\text{old}}}}[D_{\text{KL}}(\pi_{\theta_{\text{old}}}(\cdot|s)||\pi_\theta(\cdot|s))] \leq \delta$$

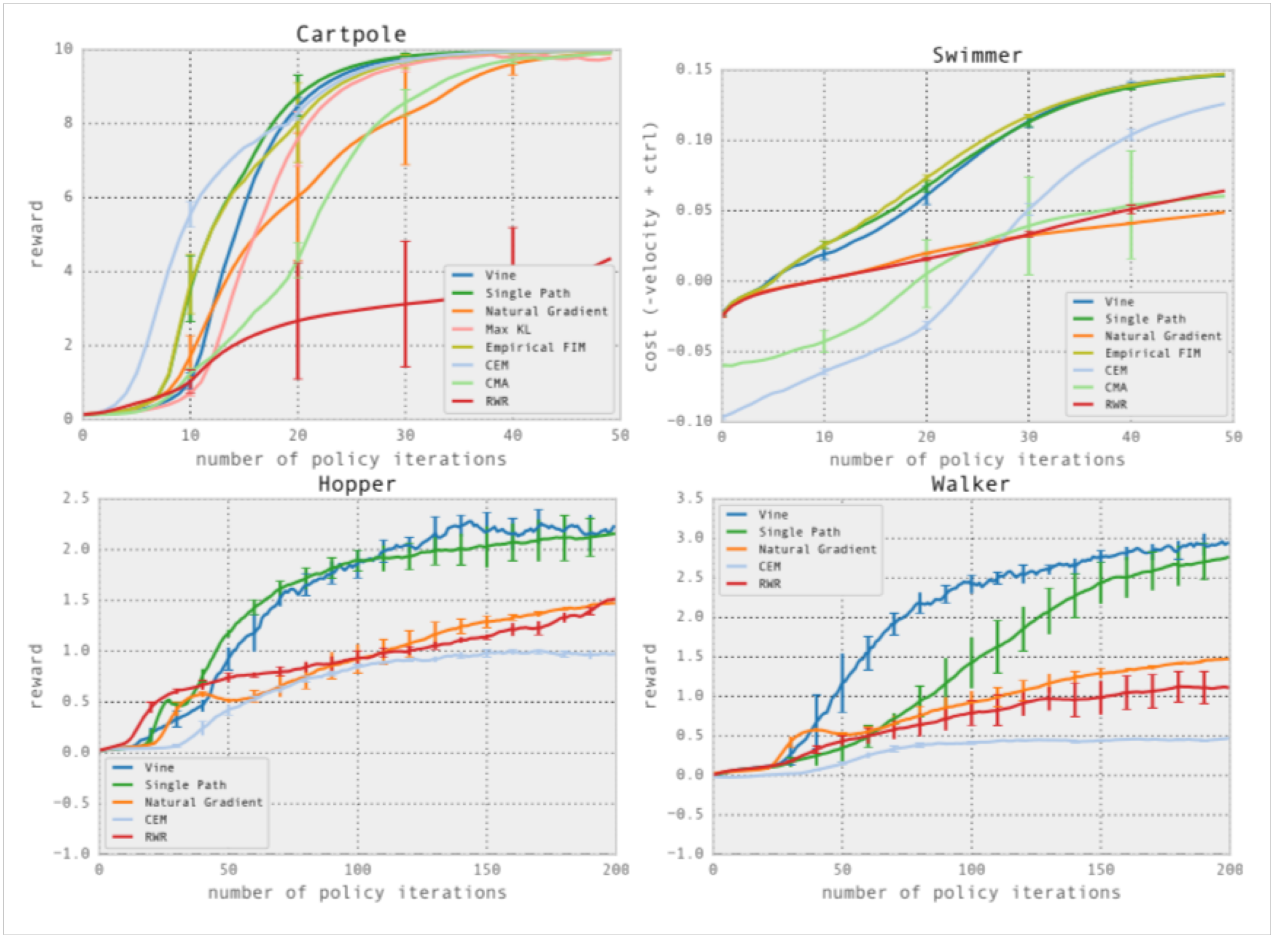


* source : Deep RL Bootcamp Lecture (https://youtu.be/xvRrgxcpaHY)

TRPO Experiments

- TRPO agent video

- Training curves (TRPO: vine & single path)



* source : Schulman et al., Trust Region Policy Optimization, ICML 2015

Issues in TRPO

- To solve the optimization problem, quadratic approximation for the constraint is required
- In some cases, such approach is not possible

Adaptive KL Penalty Coefficient [Schulman et al., 2017]

$$\arg\max_\theta \mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}A(s,a)\right] - \beta\mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[\text{KL}\left(\pi_{\theta_{\text{old}}}(\cdot|s)||\pi_\theta(\cdot|s)\right)\right]$$

  - KL divergence is small/large $\Rightarrow$ decrease/increase β, respectively.
  - For each iteration, do SGD on the above objective multiple times
  - This needs only first-order derivatives

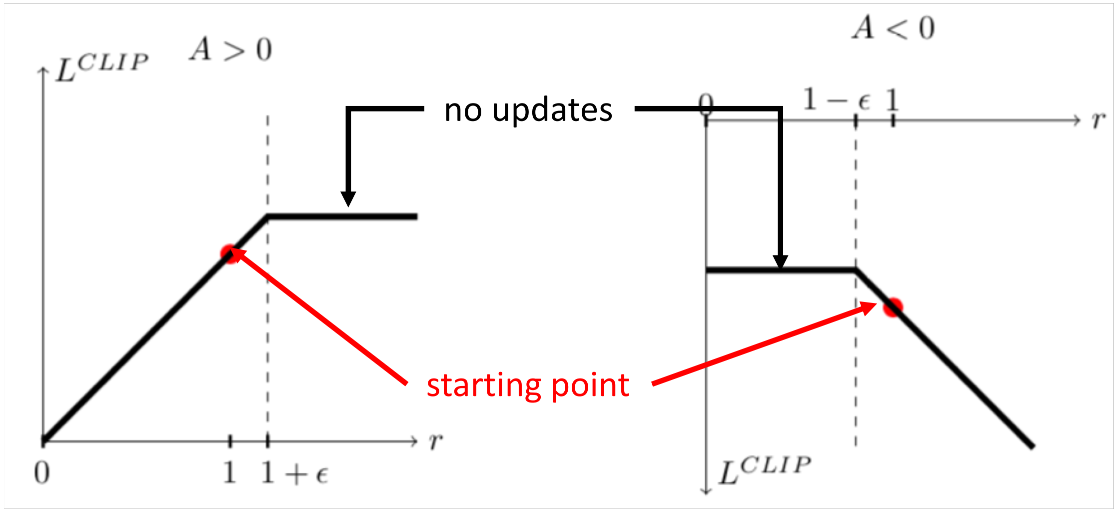
- Still, this has limitations:
  - Hard to use multi-output architectures (e.g., policy & value functions) due to the KL divergence term
  - Empirically poor performance when using deep CNNs / RNNs

Clipped Surrogate Objective [Schulman et al., 2017]

$$\mathcal{L}^{\text{CLIP}}_{\pi_{\theta_{\text{old}}}}(\pi_\theta) = \mathbb{E}_{\pi_{\theta_{\text{old}}}}\left[\min(r(\theta)A, \text{clip}(r(\theta), 1-\epsilon, 1+\epsilon)A)\right]$$

where $r(\theta) = \frac{\pi_\theta(a|s)}{\pi_{\theta_{\text{old}}}(a|s)}$

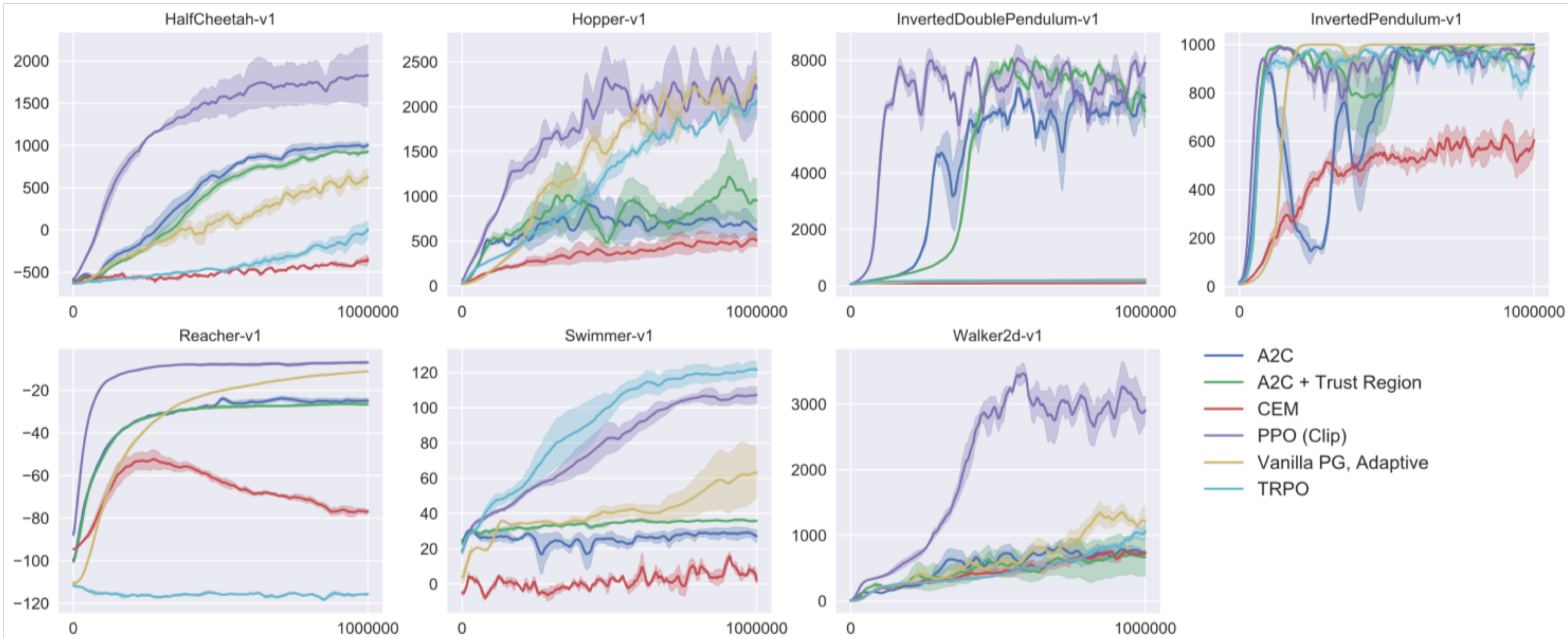
- The objective suppresses changes in policy without KL divergence
- This figure simply shows how $\mathcal{L}^{\text{CLIP}}$ works



- This objective can be used with multi-output architectures

* source : Schulman et al., Proximal Policy Optimization Algorithms, 2017

- On MuJoCo Environments, PPO (clip) outperforms other policy gradient methods



- PPO agent video

* source : Schulman et al., Proximal Policy Optimization Algorithms, 2017

Summary

- Reinforcement learning is another field of machine learning
  - RL agents learn the best strategy using only scalar rewards, no supervision
  - There are many various algorithms: Q-learning, actor-critic,
  - Sometimes the reward signal is not given

- RL with deep learning, or DeepRL
  - Has many issues about optimization, sample efficiency, stability
  - To overcome, many methods (e.g., distributed, off-policy) are proposed
  - Achieves super-human performance on many tasks

- RL can be applied to a lot of tasks:
  - Games (Chess, Go, Starcraft, …)
  - Combinatorial optimization (NP problems such as TSP)
  - Robotics
  - AutoML: finding best hyper-parameters / architectures
  - …

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[Schulman et al., 2017] Proximal Policy Optimization Algorithms, 2017
link: https://arxiv.org/abs/1707.06347

Books

Sutton and Barto, Reinforcement Learning: An Introduction, 2nd edition, 2018
link: http://incompleteideas.net/book/the-book-2nd.html

Lectures

UCL Course on Reinforcement Learning
link: http://www0.cs.ucl.ac.uk/staff/d.silver/web/Teaching.html

UC Berkeley Course on Deep Reinforcement Learning
link: http://rail.eecs.berkeley.edu/deeprlcourse/

Deep RL Bootcamp Lectures
link: https://youtu.be/xvRrgxcpaHY