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Deep Reinforcement Learning

Natural gradients (TRPO, PPO)

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https://tu-chemnitz.de/informatik/KI/edu/deeprl

On-policy and off-policy methods

- DQN and DDPG are **off-policy** methods, so we can use a replay memory.
  - They need less samples to converge as they re-use past experiences (**sample efficient**).
  - The critic is biased (overestimation), so learning is **unstable** and **suboptimal**.
- A3C is **on-policy**, we have to use distributed learning.
  - The critic is less biased, so it learns better policies (**optimality**).
  - It however need a lot of samples (**sample complexity**) as it must collect transitions with the current learned policy.
- All suffer from **parameter brittleness**: choosing the right hyperparameters for a task is extremely difficult.
- For example a learning rate of 10^{-5} might work, but not $1.1 * 10^{-5}$.
- Other hyperparameters: size of the ERM, update frequency of the target networks, training frequency.
- Can’t we do better?

Where is the problem with on-policy methods?

- The policy gradient is **unbiased** only when the critic $Q_\varphi(s, a)$ accurately approximates the true Q-values of the **current policy**.

$$\begin{aligned}\nabla_\theta J(\theta) &= \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}[\nabla_\theta \log \pi_\theta(s, a)\, Q^{\pi_\theta}(s, a)] \\ &\approx \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}[\nabla_\theta \log \pi_\theta(s, a)\, Q_\varphi(s, a)]\end{aligned}$$

- If transitions are generated by a different (older) policy b, the policy gradient will be wrong.
- We could correct the policy gradient with **importance sampling**:

$$\nabla_\theta J(\theta) \approx \mathbb{E}_{s\sim\rho_b, a\sim b}[\frac{\pi_\theta(s, a)}{b(s, a)} \nabla_\theta \log \pi_\theta(s, a)\, Q_\varphi(s, a))]$$

- This is the **off-policy actor-critic** (Off-PAC) algorithm of Degris et al. (2012).
- It is however limited to linear approximation, as:
  - the critic $Q_\varphi(s, a)$ needs to very quickly adapt to changes in the policy (deep NN are very slow learners).
  - the importance weight $\frac{\pi_\theta(s,a)}{b(s,a)}$ can have a huge variance.

Degris, T., White, M., and Sutton, R. S. (2012). Linear Off-Policy Actor-Critic. in Proceedings of the 2012 International Conference on Machine Learning. arXiv:1205.4839.

Is gradient ascent the best optimization method?

- Once we have an estimate of the policy gradient:

$$\nabla_\theta J(\theta) = \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}\left[\nabla_\theta \log \pi_\theta(s,a)\, Q_\varphi(s,a)\right]$$

we can update the weights θ in the direction of that gradient:

$$\theta \leftarrow \theta + \eta \nabla_\theta J(\theta)$$

(or some variant of it, such as RMSprop or Adam).

- We search for the **smallest parameter change** (controlled by the learning rate η) that produces the **biggest positive change** in the returns.
- Choosing the learning rate η is extremely difficult in deep RL:
  - If the learning rate is too small, the network converges very slowly, requiring a lot of samples to converge (**sample complexity**).
  - If the learning rate is too high, parameter updates can totally destroy the policy (**instability**).
- The learning rate should adapt to the current parameter values in order to stay in a **trust region**.

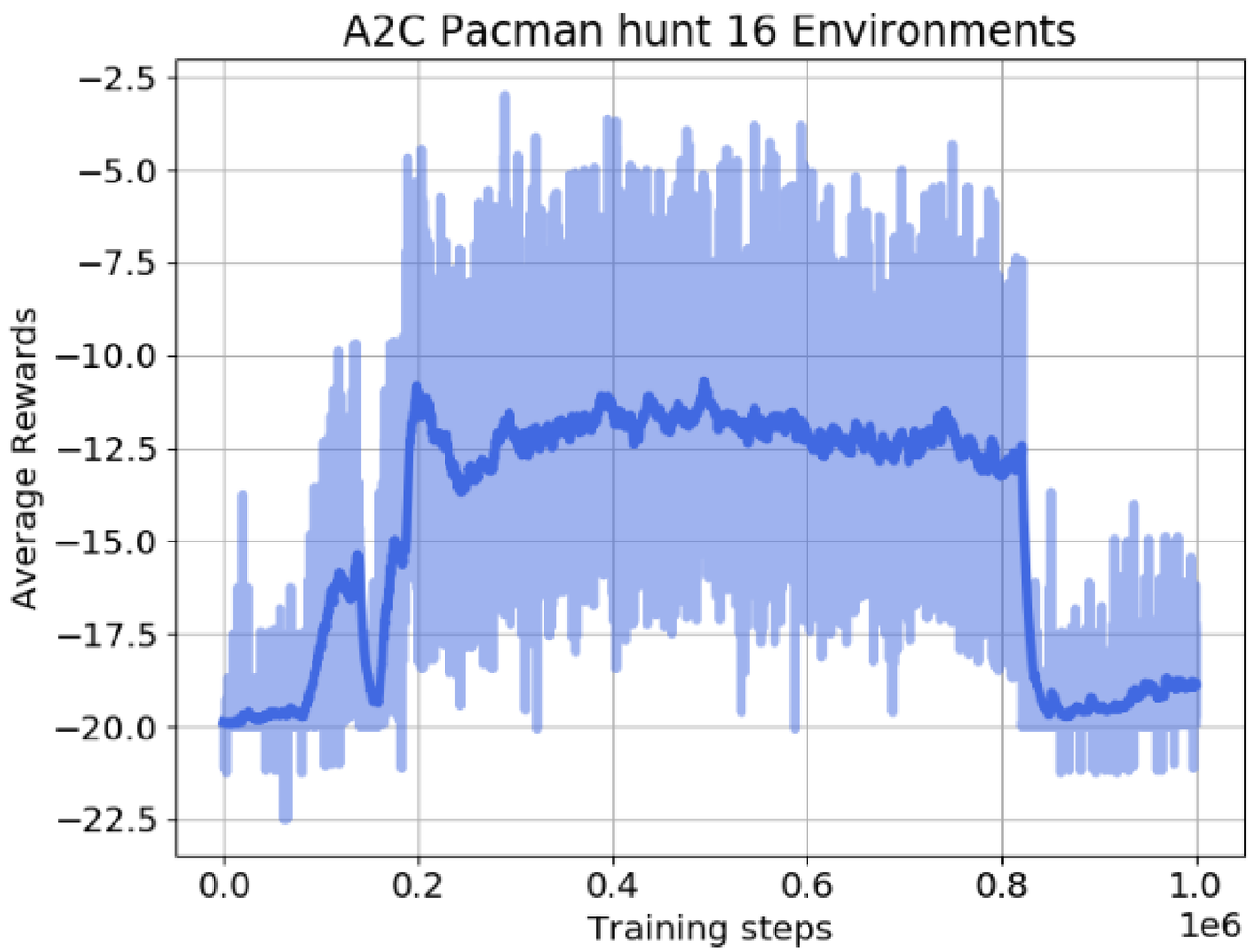
Trust regions and gradients

Source: https://medium.com/@jonathan_hui/rl-trust-region-policy-optimization-trpo-explained-a6ee04eeeee9

- The policy gradient tells you in **which direction** of the parameter space θ the return is increasing the most.
- If you take too big a step in that direction, the new policy might become completely bad (**policy collapse**).
- Once the policy has collapsed, the new samples will all have a small return: the previous progress is lost.
- This is especially true when the parameter space has a **high curvature**, which is the case with deep NN.

Policy collapse

- Policy collapse is a huge problem in deep RL: the network starts learning correctly but suddenly collapses to a random agent.
- For on-policy methods, all progress is lost: the network has to relearn from scratch, as the new samples will be generated by a bad policy.



Trust regions and gradients

Line search
(like gradient ascent)

Trust region

Source: https://medium.com/@jonathan_hui/rl-trust-region-policy-optimization-trpo-explained-a6ee04eeeee9

- **Trust region** optimization searches in the **neighborhood** of the current parameters θ which new value would maximize the return the most.
- This is a **constrained optimization** problem: we still want to maximize the return of the policy, but by keeping the policy as close as possible from its previous value.

Trust regions and gradients

Source: https://medium.com/@jonathan_hui/rl-trust-region-policy-optimization-trpo-explained-a6ee04eeeee9

- The size of the neighborhood determines the safety of the parameter change.
- In safe regions, we can take big steps. In dangerous regions, we have to take small steps.
- **Problem:** how can we estimate the safety of a parameter change?

1 - TRPO: Trust Region Policy Optimization

Trust Region Policy Optimization

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TRPO: Trust Region Policy Optimization

- We want to maximize the expected return of a policy π_θ, which is equivalent to the Q-value of every state-action pair visited by the policy:

$$\mathcal{J}(\theta) = \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}\left[Q^{\pi_\theta}(s,a)\right]$$

- Let's note θ_{old} the current value of the parameters of the policy $\pi_{\theta_{\text{old}}}$.
- (Kakade and Langford, 2002) have shown that the expected return of a policy π_θ is linked to the expected return of the current policy $\pi_{\theta_{\text{old}}}$ with:

$$\mathcal{J}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

where

$$A^{\pi_{\theta_{\text{old}}}}(s,a) = Q_\theta(s,a) - Q_{\theta_{\text{old}}}(s,a)$$

is the **advantage** of taking the action (s,a) and thereafter following π_θ, compared to following the current policy $\pi_{\theta_{\text{old}}}$.

- The return under any policy θ is equal to the return under θ_{old}, plus how the newly chosen actions in the rest of the trajectory improves (or worsens) the returns.

TRPO: Trust Region Policy Optimization

- If we can estimate the advantages and maximize them, we can find a new policy π_θ with a higher return than the current one.

$$\mathcal{L}(\theta) = \mathbb{E}_{s \sim \rho_\theta, a \sim \pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s, a)\right]$$

- By definition, $\mathcal{L}(\theta_{\text{old}}) = 0$, so the policy maximizing $\mathcal{L}(\theta)$ has positive advantages and is better than $\pi_{\theta_{\text{old}}}$.

$$\theta_{\text{new}} = \text{argmax}_\theta \ \mathcal{L}(\theta) \ \Rightarrow \ \mathcal{J}(\theta_{\text{new}}) \geq \mathcal{J}(\theta_{\text{old}})$$

- Maximizing the advantages ensures **monotonic improvement**: the new policy is always better than the previous one. Policy collapse is not possible!
- The problem is that we have to take samples (s, a) from π_θ: we do not know it yet, as it is what we search. The only policy at our disposal to estimate the advantages is the current policy $\pi_{\theta_{\text{old}}}$.
- We could use **importance sampling** to sample from $\pi_{\theta_{\text{old}}}$, but it would introduce a lot of variance (but see PPO later):

$$\mathcal{L}(\theta) = \mathbb{E}_{s \sim \rho_{\theta_{\text{old}}}, a \sim \pi_{\theta_{\text{old}}}}\left[\frac{\pi_\theta(s, a)}{\pi_{\theta_{\text{old}}}(s, a)} A^{\pi_{\theta_{\text{old}}}}(s, a)\right]$$

TRPO: Trust Region Policy Optimization

- In TRPO, we are adding a **constraint** instead:
  - the new policy $\pi_{\theta_{\text{new}}}$ should not be (very) different from $\pi_{\theta_{\text{old}}}$.
  - the importance sampling weight $\frac{\pi_{\theta_{\text{new}}}(s,a)}{\pi_{\theta_{\text{old}}}(s,a)}$ will not be very different from 1, so we can omit it.
- Let's define a new objective function $\mathcal{J}_{\theta_{\text{old}}}(\theta)$:

$$\mathcal{J}_{\theta_{\text{old}}}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}},a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

- The only difference with $\mathcal{J}(\theta)$ is that the visited states s are now sampled by the current policy $\pi_{\theta_{\text{old}}}$.
- This makes the expectation tractable: we know how to visit the states, but we compute the advantage of actions taken by the new policy in those states.

TRPO: Trust Region Policy Optimization

- Previous objective function:

$$\mathcal{J}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_\theta, a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

- New objective function:

$$\mathcal{J}_{\theta_{\text{old}}}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}}, a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

- It is “easy” to observe that the new objective function has the same value in θ_{old}:

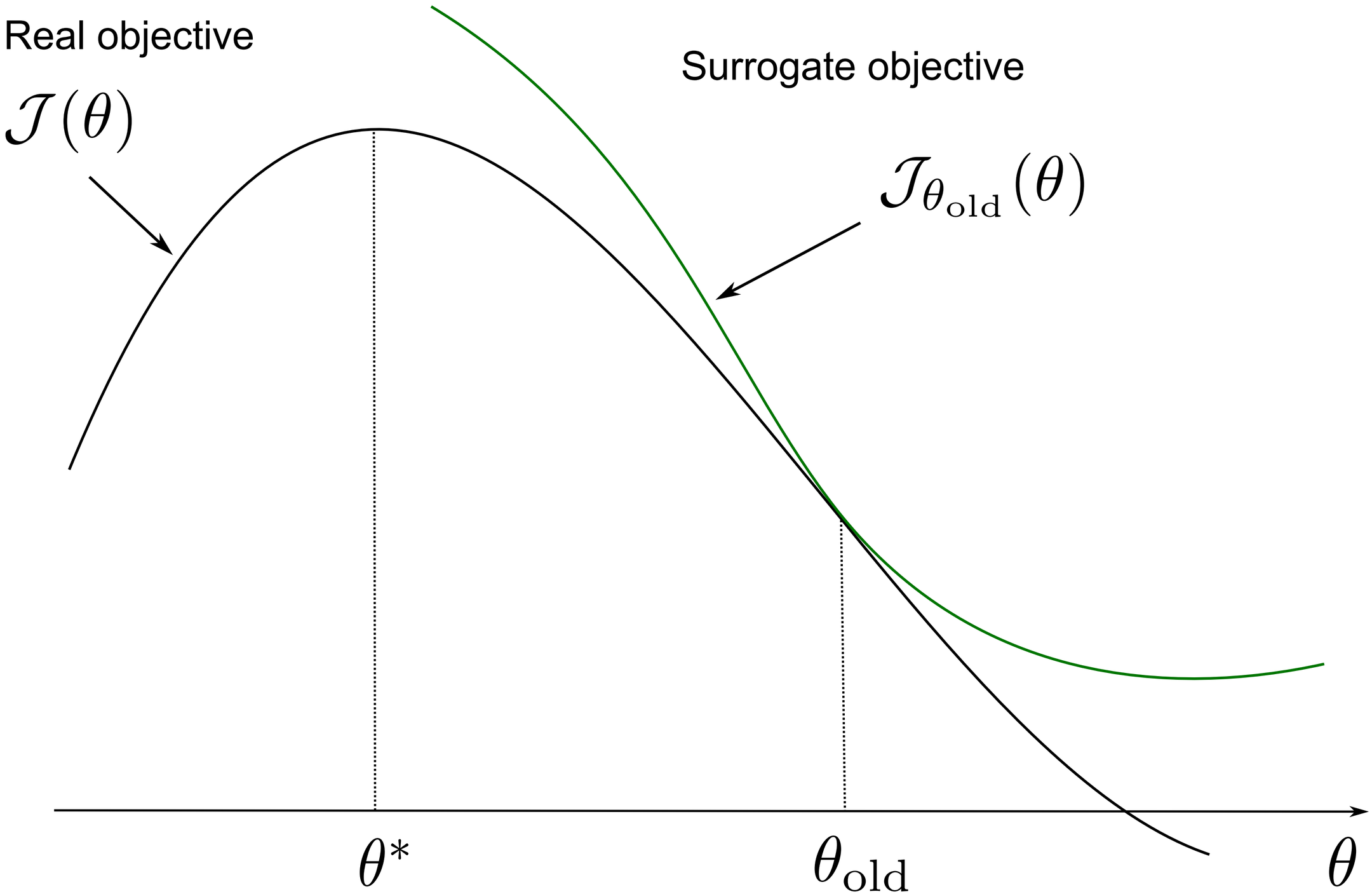
$$\mathcal{J}_{\theta_{\text{old}}}(\theta_{\text{old}}) = \mathcal{J}(\theta_{\text{old}})$$

and that its gradient w.r.t. θ is the same in θ_{old}:

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

- At least locally, maximizing $\mathcal{J}_{\theta_{\text{old}}}(\theta)$ is exactly the same as maximizing $\mathcal{J}(\theta)$.
- $\mathcal{J}_{\theta_{\text{old}}}(\theta)$ is called a **surrogate objective function**: it is not what we want to maximize, but it leads to the same result locally.

TRPO: Trust Region Policy Optimization



TRPO: Trust Region Policy Optimization

- How big a step can we take when maximizing $\mathcal{J}_{\theta_{\text{old}}}(\theta)$? π_θ and $\pi_{\theta_{\text{old}}}$ must be close from each other for the approximation to stand.
- The first variant explored in the TRPO paper is a **constrained optimization** approach (Lagrange optimization):

$$\max_\theta \mathcal{J}_{\theta_{\text{old}}}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}}, a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

$$\text{such that: } D_{\text{KL}}(\pi_{\theta_{\text{old}}} || \pi_\theta) \leq \delta$$

- The KL divergence between the distributions $\pi_{\theta_{\text{old}}}$ and π_θ must be below a threshold δ.
- This version of TRPO uses a **hard constraint**:
  - We search for a policy π_θ that maximizes the expected return while staying within the **trust region** around $\pi_{\theta_{\text{old}}}$.

TRPO: Trust Region Policy Optimization

- The second approach **regularizes** the objective function with the KL divergence:

$$\max_{\theta} \mathcal{L}(\theta) = \mathcal{J}_{\theta_{\text{old}}}(\theta) - C\, D_{\text{KL}}(\pi_{\theta_{\text{old}}} || \pi_{\theta})$$

where C is a regularization parameter controlling the importance of the **soft constraint**.

- This **surrogate objective function** is a **lower bound** of the initial objective $\mathcal{J}(\theta)$:

1. The two objectives have the same value in θ_{old}:

$$\mathcal{L}(\theta_{\text{old}}) = \mathcal{J}_{\theta_{\text{old}}}(\theta_{\text{old}}) - C\, D_{KL}(\pi_{\theta_{\text{old}}} || \pi_{\theta_{\text{old}}}) = \mathcal{J}(\theta_{\text{old}})$$

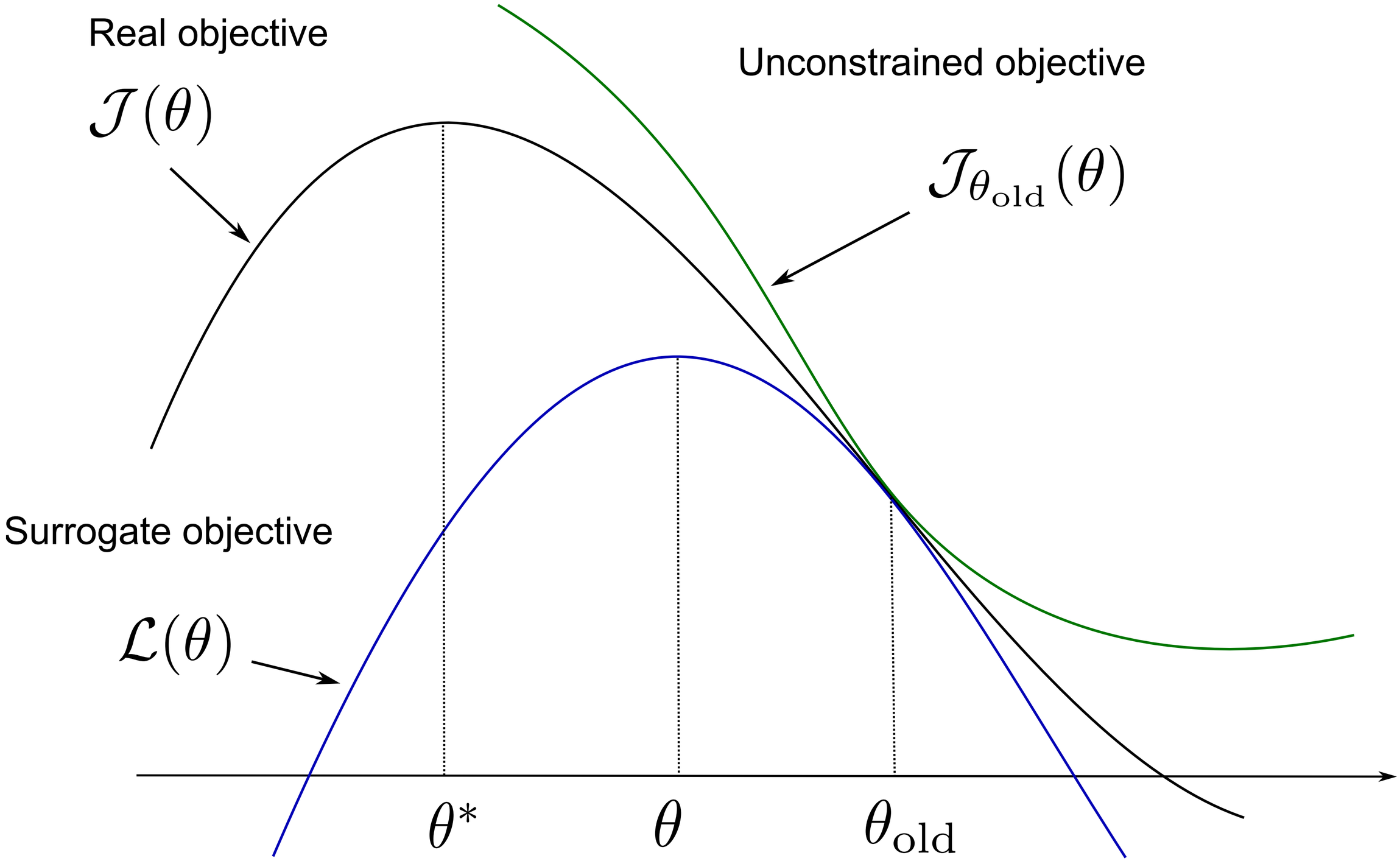
2. Their gradient w.r.t θ are the same in θ_{old}:

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

3. The surrogate objective is always smaller than the real objective, as the KL divergence is positive:

$$\mathcal{J}(\theta) \geq \mathcal{J}_{\theta_{\text{old}}}(\theta) - C\, D_{KL}(\pi_{\theta_{\text{old}}} || \pi_{\theta})$$

TRPO: Trust Region Policy Optimization



TRPO: Trust Region Policy Optimization

The policy π_θ maximizing the surrogate objective $\mathcal{L}(\theta) = \mathcal{J}_{\theta_{\text{old}}}(\theta) - C\, D_{\text{KL}}(\pi_{\theta_{\text{old}}} || \pi_\theta)$:

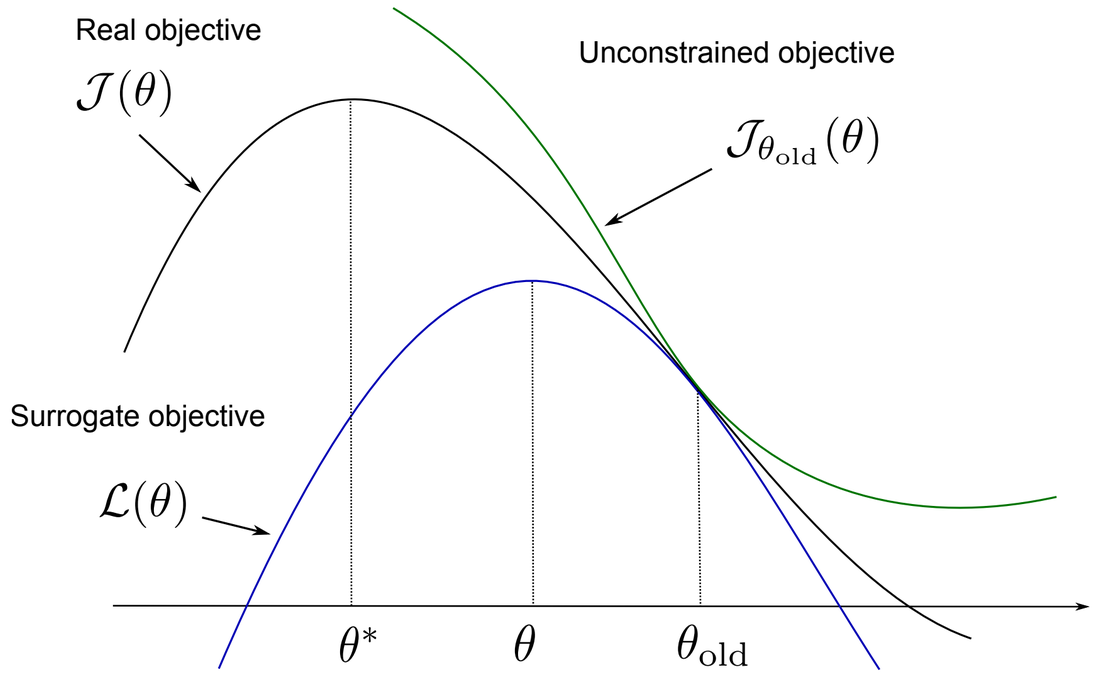
- has a higher expected return than $\pi_{\theta_{\text{old}}}$:

$$\mathcal{J}(\theta) > \mathcal{J}(\theta_{\text{old}})$$

- is very close to $\pi_{\theta_{\text{old}}}$:

$$D_{\text{KL}}(\pi_{\theta_{\text{old}}} || \pi_\theta) \approx 0$$

- but the parameters θ are much closer to the optimal parameters θ^*.



- The version with a soft constraint necessitates a prohibitively small learning rate in practice.
- The implementation of TRPO uses the hard constraint with Lagrange optimization, what necessitates using conjugate gradients optimization, the Fisher Information matrix and natural gradients: very complex to implement…
- However, there is a **monotonic improvement guarantee**: the successive policies can only get better over time, no policy collapse! This is the major advantage of TRPO compared to the other methods: it always works, although very slowly.

2 - PPO: Proximal Policy Optimization

Proximal Policy Optimization Algorithms

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PPO: Proximal Policy Optimization

- Let's take the unconstrained objective function of TRPO:

$$\mathcal{J}_{\theta_{\text{old}}}(\theta) = \mathcal{J}(\theta_{\text{old}}) + \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}},a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

- $\mathcal{J}(\theta_{\text{old}})$ does not depend on θ, so we only need to maximize the advantages:

$$\mathcal{L}(\theta) = \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}},a\sim\pi_\theta}\left[A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

- In order to avoid sampling action from the **unknown** policy π_θ, we can use importance sampling with the current policy:

$$\mathcal{L}(\theta) = \mathbb{E}_{s\sim\rho_{\theta_{\text{old}}},a\sim\pi_{\theta_{\text{old}}}}\left[\rho(s,a)\, A^{\pi_{\theta_{\text{old}}}}(s,a)\right]$$

with $\rho(s,a) = \frac{\pi_\theta(s,a)}{\pi_{\theta_{\text{old}}}(s,a)}$ being the **importance sampling weight**.

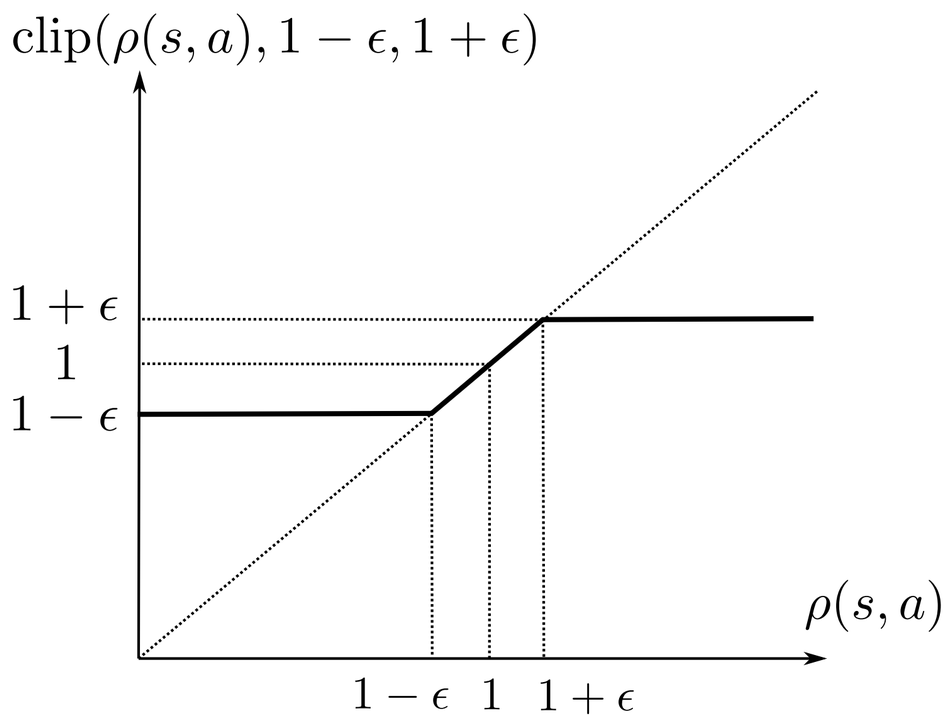
- But the importance sampling weight $\rho(s,a)$ introduces a lot of variance, worsening the sample complexity.
- Is there another way to make sure that π_θ is not very different from $\pi_{\theta_{\text{old}}}$, therefore reducing the variance of the importance sampling weight?

PPO: Proximal Policy Optimization

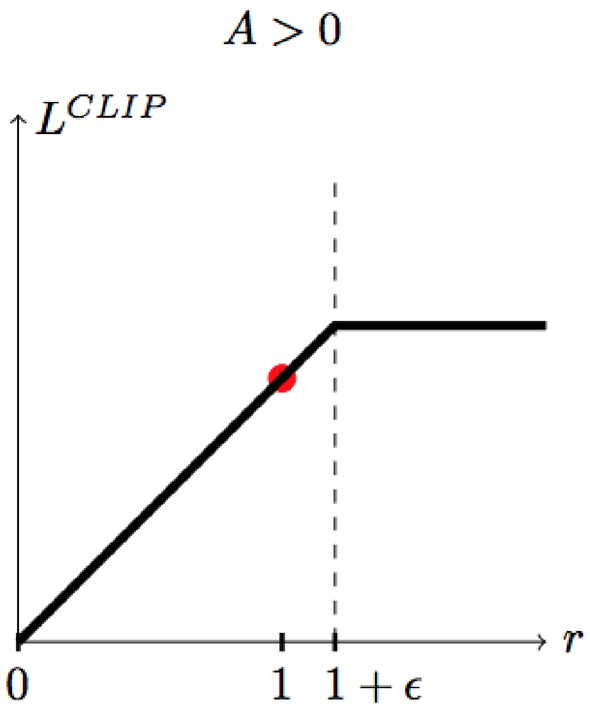
- The solution introduced by PPO is simply to **clip** the importance sampling weight when it is too different from 1:

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

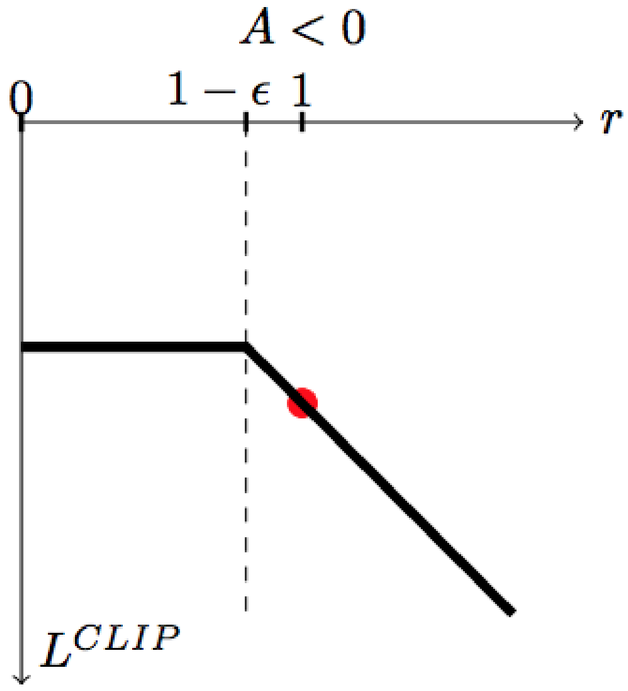
- For each sampled action (s, a), we use the minimum between:
  - the TRPO unconstrained objective with IS $\rho(s,a)\,A^{\pi_{\theta_{\text{old}}}}(s,a)$.
  - the same, but with the IS weight clipped between $1-\epsilon$ and $1+\epsilon$.



PPO: Proximal Policy Optimization

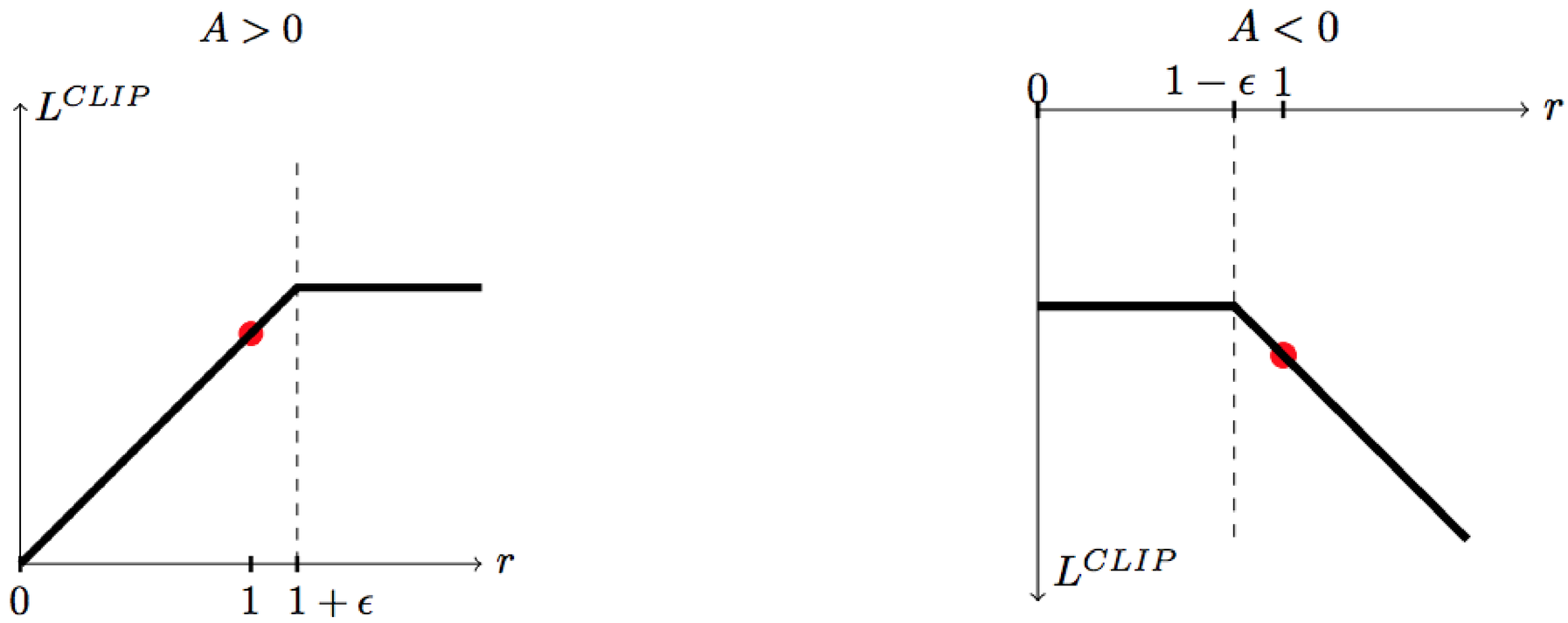


- If the advantage $A^{\pi_{\theta_{\text{old}}}}(s,a)$ is positive (better action than usual) and:
  - the IS is higher than $1+\epsilon$, we use $(1+\epsilon)\,A^{\pi_{\theta_{\text{old}}}}(s,a)$.
  - otherwise, we use $\rho(s,a)\,A^{\pi_{\theta_{\text{old}}}}(s,a)$.



- If the advantage $A^{\pi_{\theta_{\text{old}}}}(s,a)$ is negative (worse action than usual) and:
  - the IS is lower than $1-\epsilon$, we use $(1-\epsilon)\,A^{\pi_{\theta_{\text{old}}}}(s,a)$.
  - otherwise, we use $\rho(s,a)\,A^{\pi_{\theta_{\text{old}}}}(s,a)$.

PPO: Proximal Policy Optimization



- This avoids changing too much the policy between two updates:
  - Good actions ($A^{\pi_{\theta_{\text{old}}}}(s,a) > 0$) do not become much more likely than before.
  - Bad actions ($A^{\pi_{\theta_{\text{old}}}}(s,a) < 0$) do not become much less likely than before.

PPO: Proximal Policy Optimization

- The PPO **clipped objective** ensures than the importance sampling weight stays around one, so the new policy is not very different from the old one. It can learn from single transitions.

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

- The advantage of an action can be learned using any advantage estimator, for example the **n-step advantage**:

$$A^{\pi_{\theta_{\text{old}}}}(s_t, a_t) = \sum_{k=0}^{n-1} \gamma^k\, r_{t+k+1} + \gamma^n\, V_\varphi(s_{t+n}) - V_\varphi(s_t)$$

- Most implementations use **Generalized Advantage Estimation** (GAE, Schulman et al., 2015).
- PPO is therefore an **actor-critic** method (as TRPO).
- PPO is **on-policy**: it collects samples using **distributed learning** (as A3C) and then applies several updates to the actor and critic.

Schulman, J., Moritz, P., Levine, S., Jordan, M., and Abbeel, P. (2015). High-Dimensional Continuous Control Using Generalized Advantage Estimation. arXiv:1506.02438.

PPO: Proximal Policy Optimization

- Initialize an actor π_θ and a critic V_φ with random weights.
- **while** not converged :
  - for N workers in parallel:
    - Collect T transitions using π_θ.
    - Compute the advantage $A_\varphi(s, a)$ of each transition using the critic V_φ.
  - for K epochs:
    - Sample M transitions $\mathcal{D}$ from the ones previously collected.
    - Train the actor to maximize the clipped surrogate objective.

$$\mathcal{L}(\theta) = \mathbb{E}_{s,a\sim\mathcal{D}}[\min(\rho(s,a)\,A_\varphi(s,a), \text{clip}(\rho(s,a), 1-\epsilon, 1+\epsilon)\,A_\varphi(s,a))]$$

    - Train the critic to minimize the advantage.

$$\mathcal{L}(\varphi) = \mathbb{E}_{s,a\sim\mathcal{D}}[(A_\varphi(s,a))^2]$$

PPO: Proximal Policy Optimization

- PPO is an **on-policy actor-critic** PG algorithm, using distributed learning.
- **Clipping** the importance sampling weight allows to avoid **policy collapse**, by staying in the **trust region** (the policy does not change much between two updates).
- The **monotonic improvement guarantee** is very important: the network will always find a (local) maximum of the returns.
- PPO is much less sensible to hyperparameters than DDPG (**brittleness**): works often out of the box with default settings.
- It does not necessitate complex optimization procedures like TRPO: first-order methods such as **SGD** work (easy to implement).
- The actor and the critic can **share weights** (unlike TRPO), allowing to work with pixel-based inputs, convolutional or recurrent layers.
- It can use **discrete or continuous action spaces**, although it is most efficient in the continuous case. Go-to method for robotics.
- Drawback: not very **sample efficient**.

PPO: Proximal Policy Optimization

- Implementing PPO necessitates quite a lot of tricks (early stopping, MPI).
- OpenAI Baselines or SpinningUp provide efficient implementations:

https://spinningup.openai.com/en/latest/algorithms/ppo.html

https://github.com/openai/baselines/tree/master/baselines/ppo2

```
import gym
from spinup import ppo
import tensorflow as tf

env_fn = lambda : gym.make('LunarLander-v2')

ppo(env_fn=env_fn,
    ac_kwargs={'hidden_sizes': [64,64],
               'activation': tf.nn.relu},
    steps_per_epoch=5000, epochs=250)
```

PPO : Mujoco control

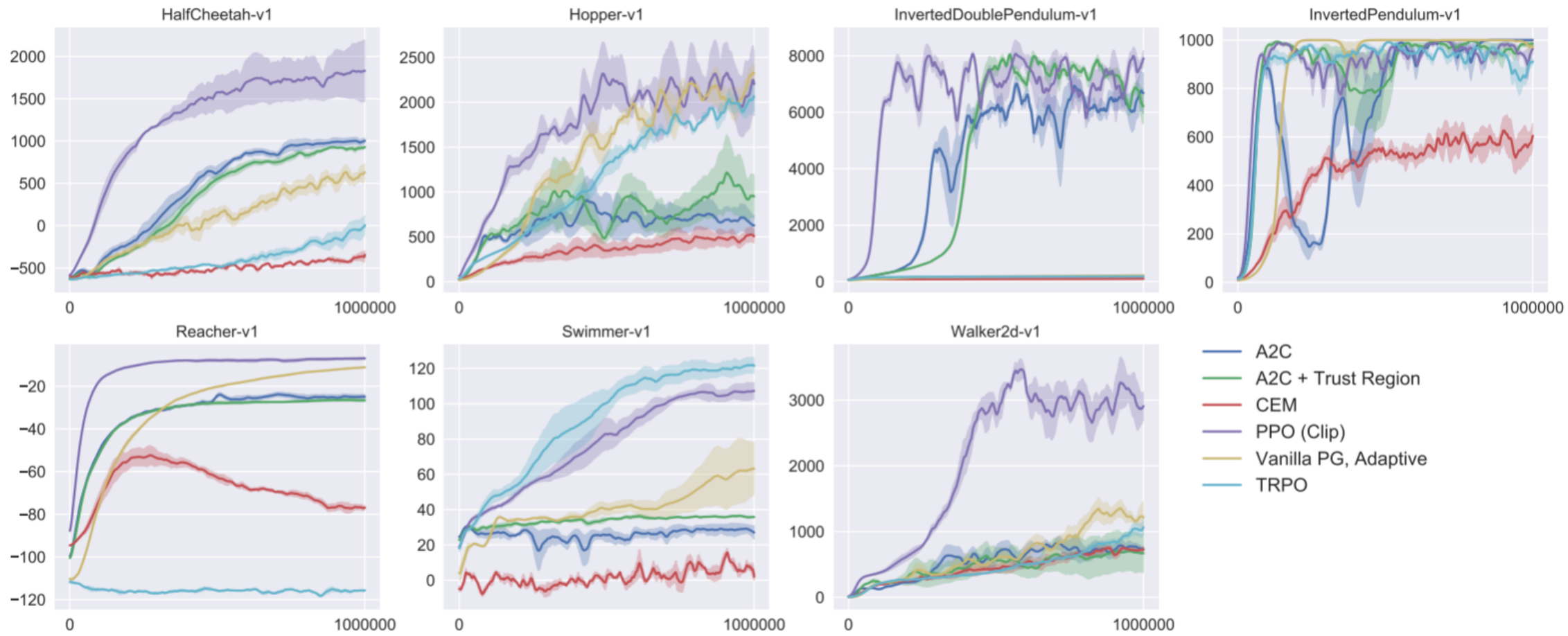
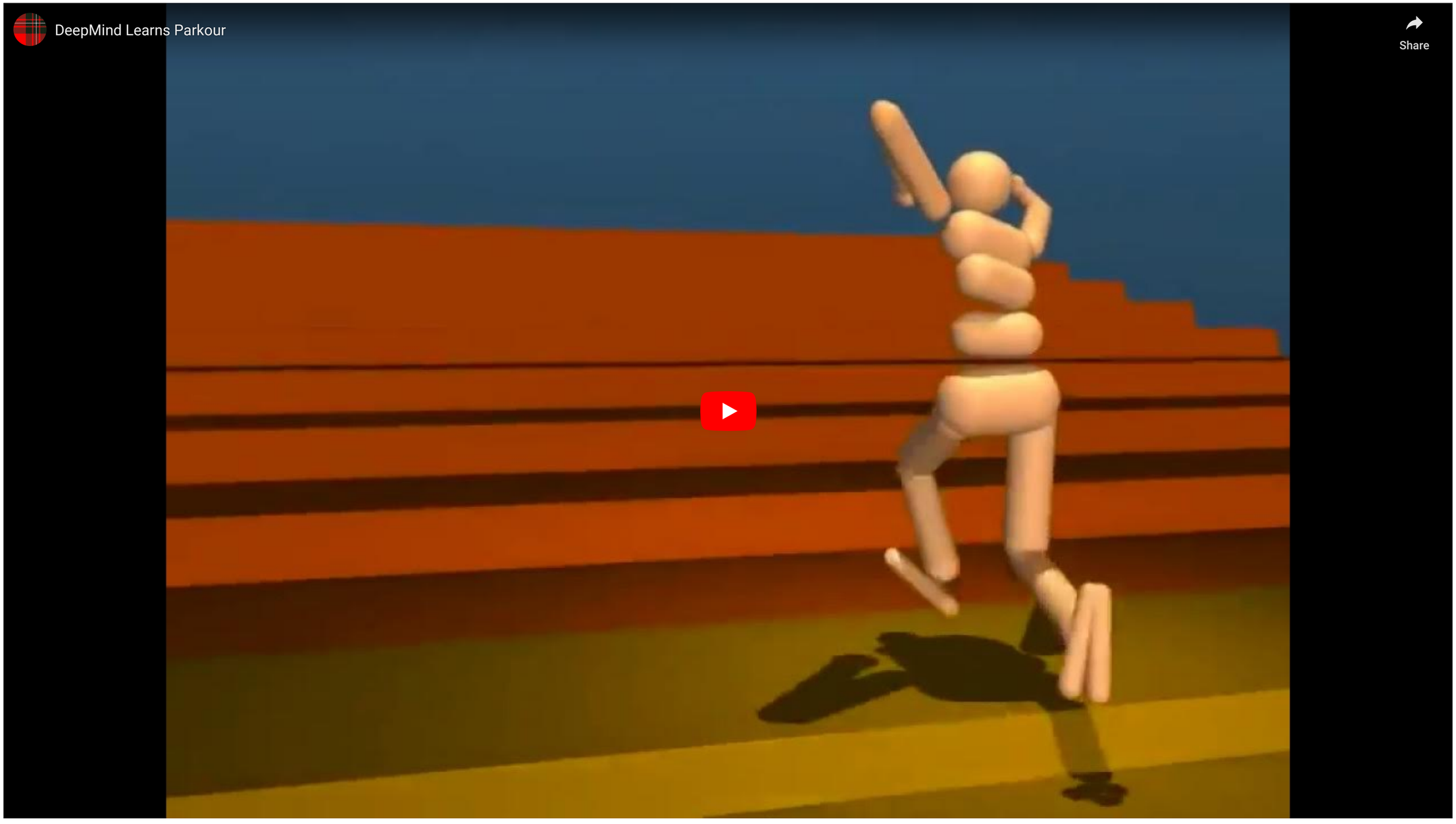


Figure 3: Comparison of several algorithms on several MuJoCo environments, training for one million timesteps.

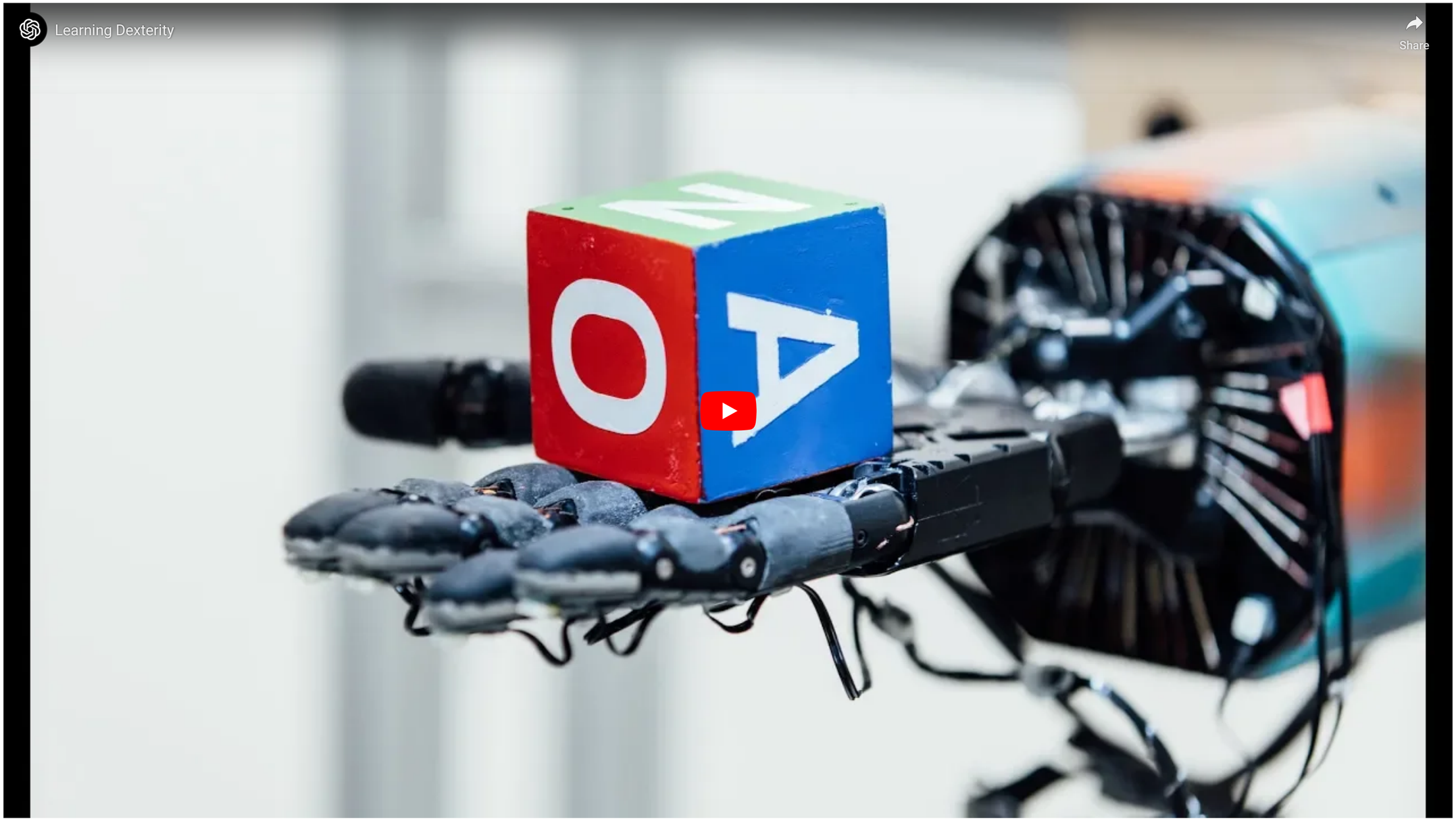
PPO : Parkour

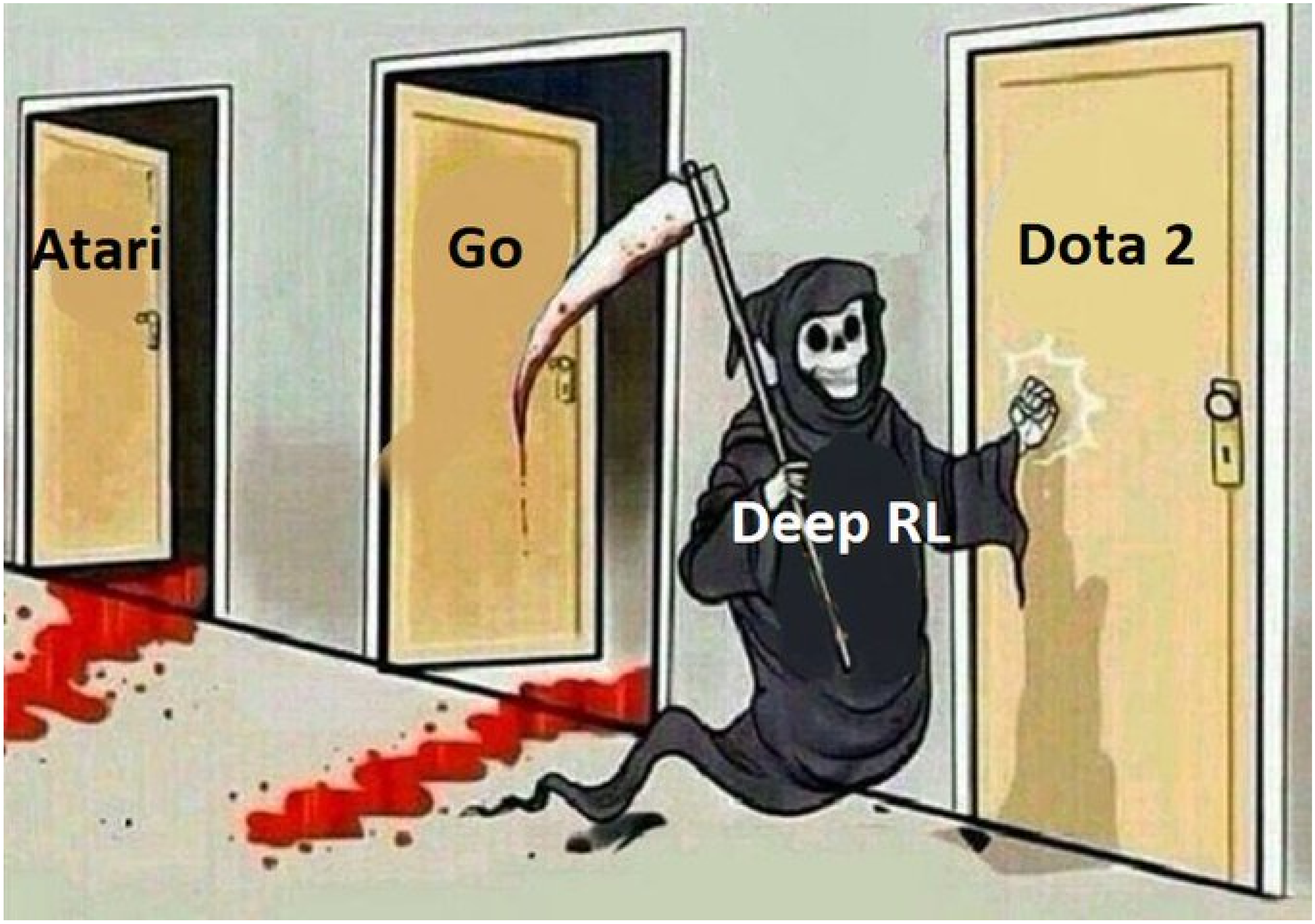


PPO : Robotics

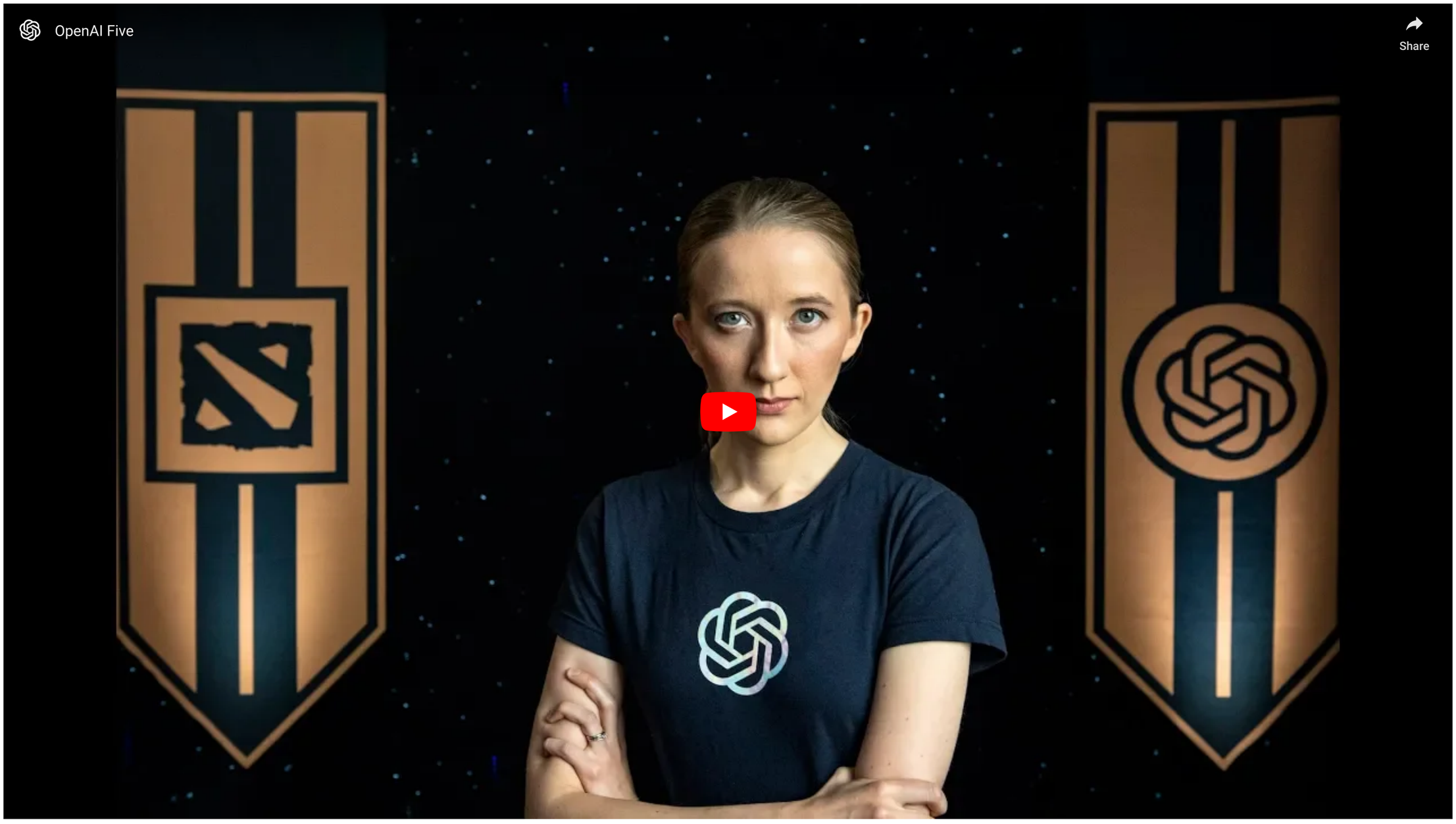
Check more robotic videos at: https://openai.com/blog/openai-baselines-ppo/

PPO: dexterity learning




Atari
Go
Dota 2
Deep RL

3 - OpenAI Five: Dota 2



Why is Dota 2 hard?

Long Time Horizons

- Most actions in Dota 2 have minor impact individually but contributed to the team's strategy.
- The game is about 20,000 moves long(compared to an average 40 moves of a chess match).

Partially Observed Stage

- At any given time, a team can only see a small area around them.
- Dota 2 strategies require making inference based on incomplete data.

Continuous Action Space

- Each hero is face with about 1000 actions each tick (compared to about 35 in chess)
- Actions can have completely different objectives such as targeting an enemy or improving the position on the ground

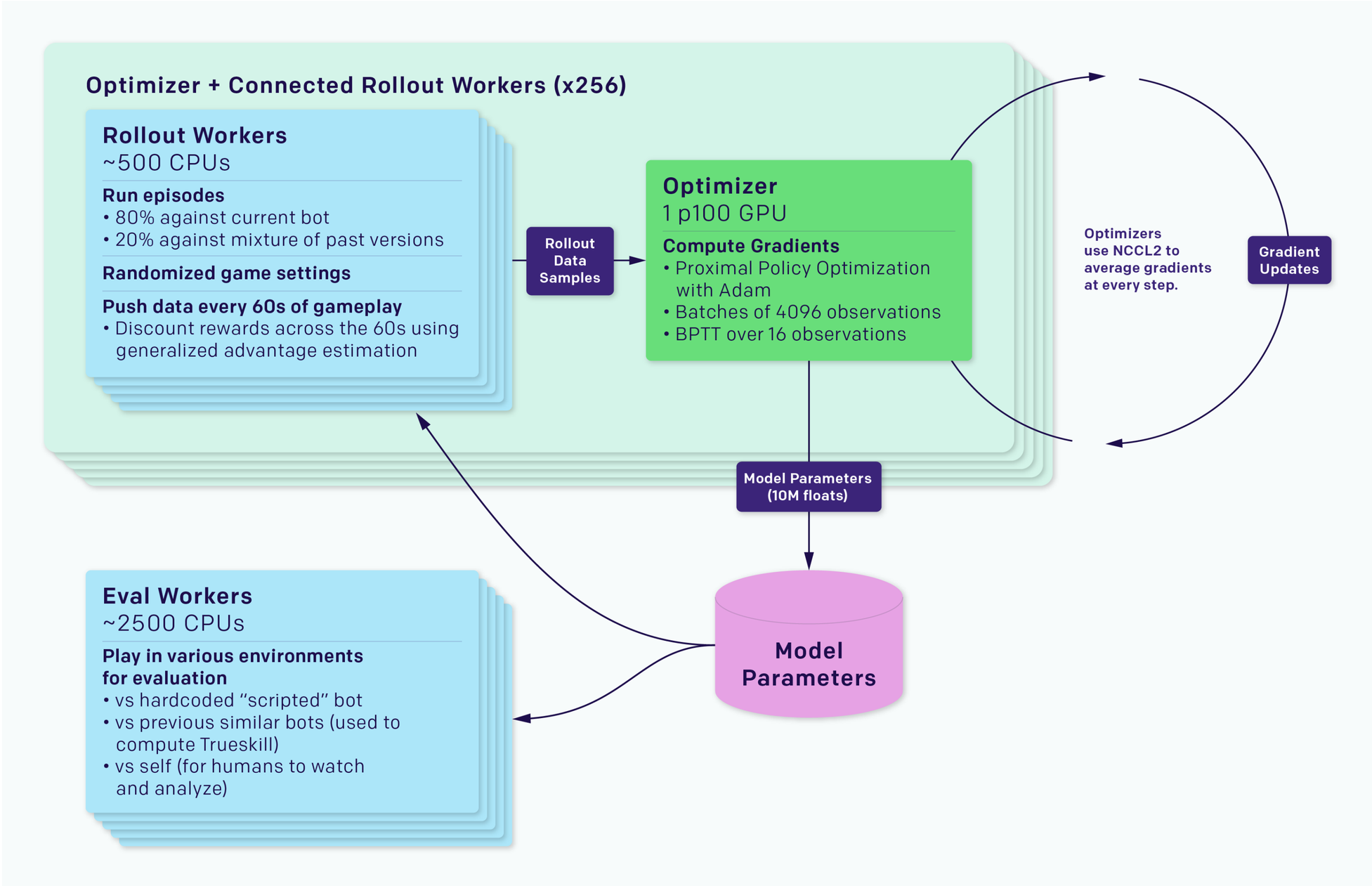
Continuous Observation Space

- The observation space in Dota 2 includes heterogenous components such as heroes, treesm buildings, trees, etc
- At any given point, the observations in a Dota 2 game can be quantified as 20,000 floating point numbers. The same quantifications for Chess and Go are about 70 and 400 numbers respectivey

Feature	Chess	Go	Dota 2
Total number of moves	40	150	20000
Number of possible actions	35	250	1000
Number of inputs	70	400	20000

OpenAI Five: Dota 2

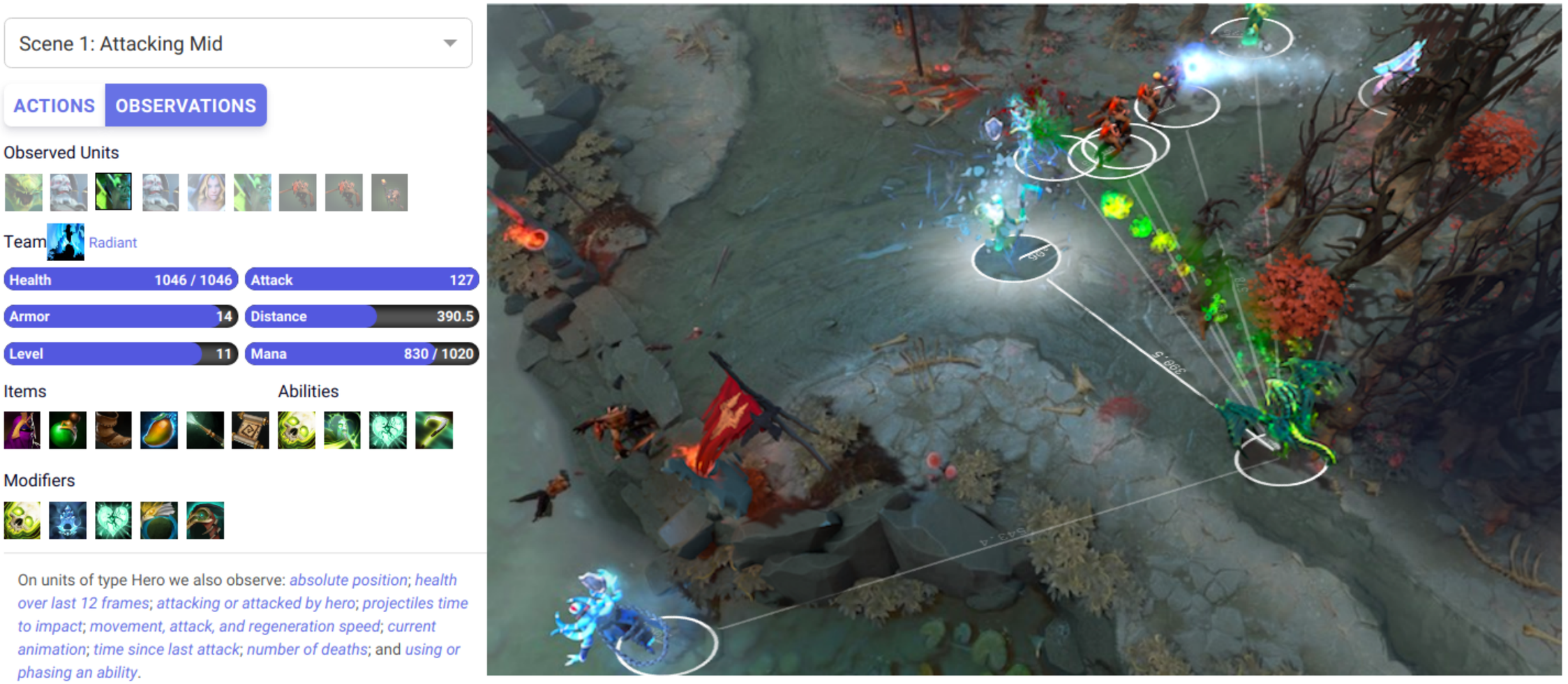
- OpenAI Five is composed of 5 PPO networks (one per player), using 128,000 CPUs and 256 V100 GPUs.



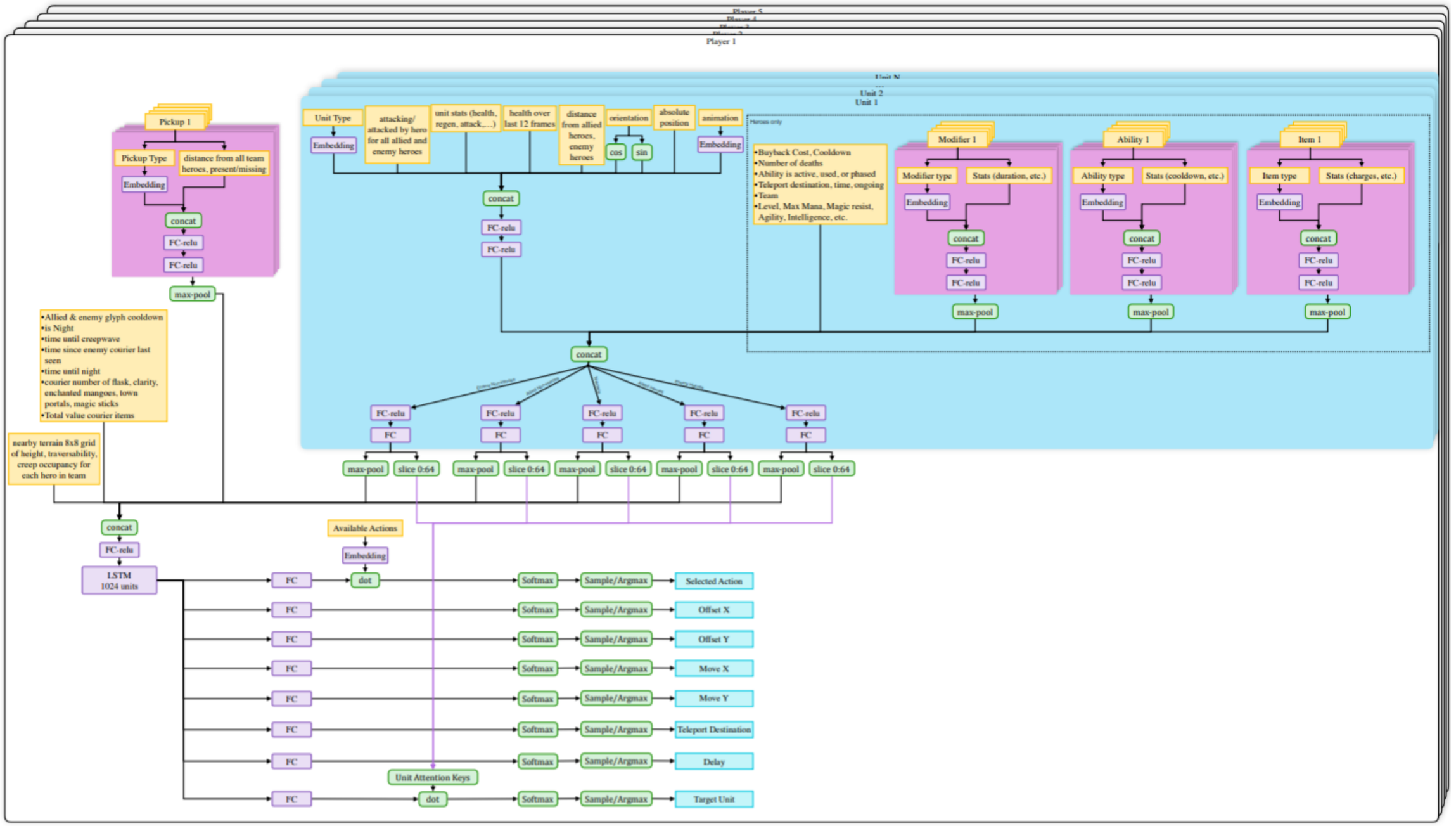
OpenAI Five: Dota 2

	OPENAI 1V1 BOT	OPENAI FIVE
CPUs	60,000 CPU cores on Azure	128,000 preemptible CPU cores on GCP
GPUs	256 K80 GPUs on Azure	256 P100 GPUs on GCP
Experience collected	~300 years per day	~180 years per day (~900 years per day counting each hero separately)
Size of observation	~3.3 kB	~36.8 kB
Observations per second of gameplay	10	7.5
Batch size	8,388,608 observations	1,048,576 observations
Batches per minute	~20	~60

OpenAI Five: Dota 2



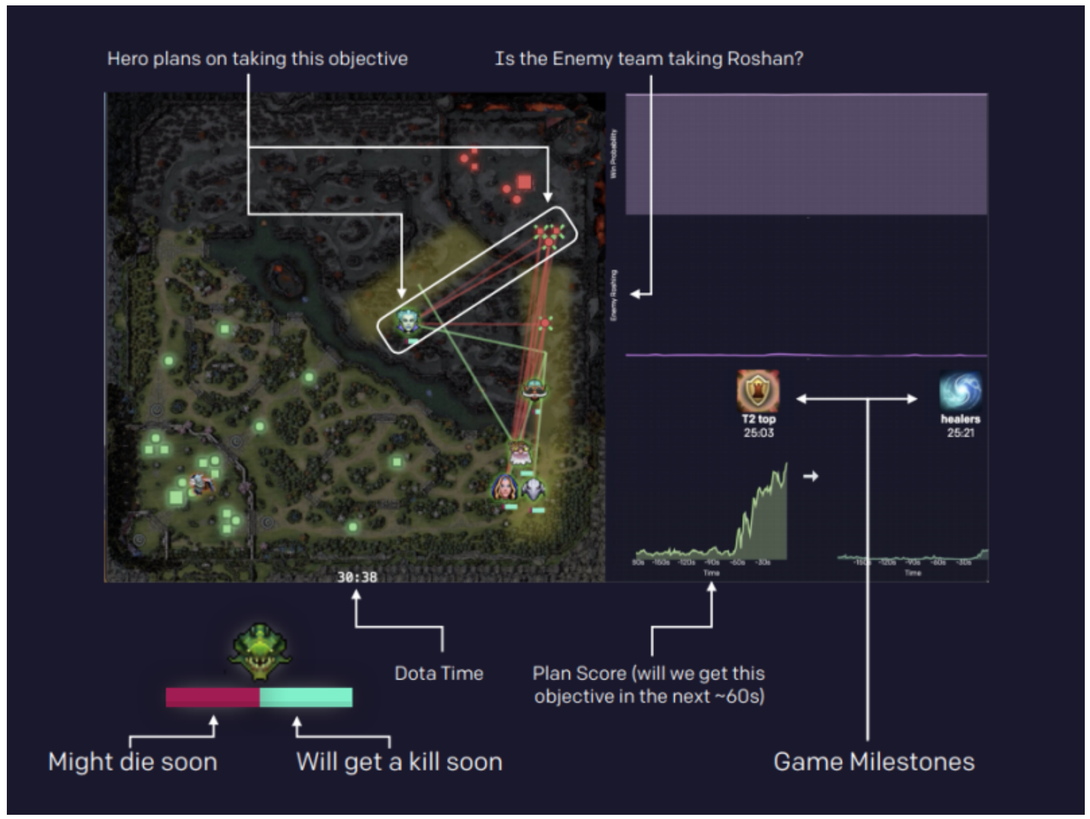
OpenAI Five: Dota 2



https://d4mucfpksywv.cloudfront.net/research-covers/openai-five/network-architecture.pdf

OpenAI Five: Dota 2

- The agents are trained by **self-play**. Each worker plays against:
  - the current version of the network 80% of the time.
  - an older version of the network 20% of the time.
- Reward is hand-designed using human heuristics:
  - net worth, kills, deaths, assists, last hits…



- The discount factor γ is annealed from 0.998 (valuing future rewards with a half-life of 46 seconds) to 0.9997 (valuing future rewards with a half-life of five minutes).
- Coordinating all the resources (CPU, GPU) is actually the main difficulty:
  - Kubernetes, Azure, and GCP backends for Rapid, TensorBoard, Sentry and Grafana for monitoring…

4 - ACER: Actor-Critic with Experience Replay

SAMPLE EFFICIENT ACTOR-CRITIC WITH EXPERIENCE REPLAY

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ACER: Actor-Critic with Experience Replay

- ACER is the off-policy version of PPO:
  - Off-policy actor-critic architecture (using experience replay),
  - Retrace estimation of values (Munos et al. 2016),
  - Importance sampling weight truncation with bias correction,
  - Efficient trust region optimization (TRPO),
  - Stochastic Dueling Network (SDN) in order to estimate both $Q_\varphi(s, a)$ and $V_\varphi(s)$.
- The performance is comparable to PPO. It works sometimes better than PPO on some environments, sometimes not.
- Just FYI…