Map

Alpha Zero: Actor Critic with MCTS

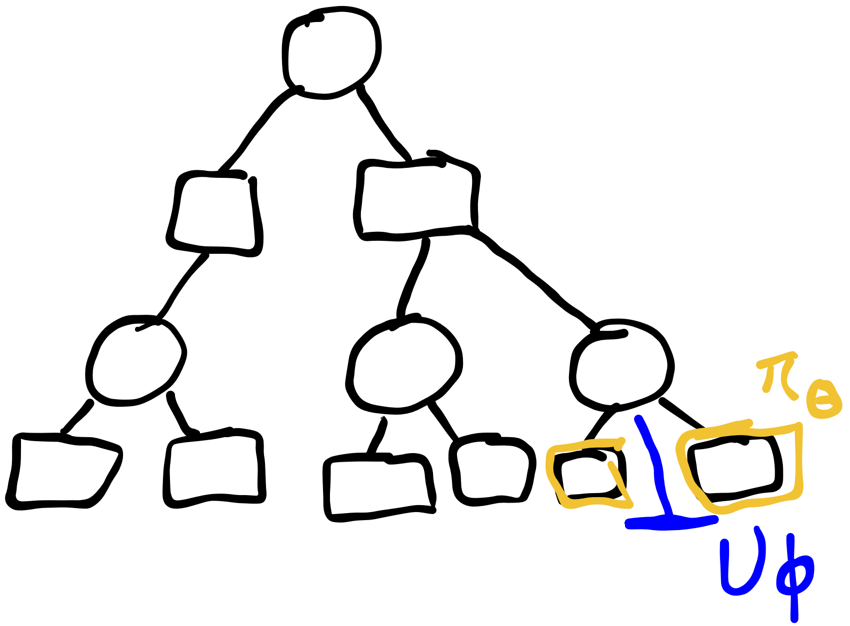
1. Use π_θ and U_ϕ in MCTS
2. Learn π_θ and U_ϕ from tree

$$\ell(\theta) = -\mathbb{E}_s\left[\sum_a \pi_{\mathrm{MCTS}}(a \mid s) \log \pi_\theta(a \mid s)\right]$$

$$\pi_{\mathrm{MCTS}}(a \mid s) \propto N(s,a)^\eta$$

$$\ell(\phi) = \frac{1}{2}\mathbb{E}_s\left[\left(U_\phi(s) - U_{\mathrm{MCTS}}(s)\right)^2\right]$$

$$U_{\mathrm{MCTS}}(s) = \max_a Q(s,a)$$



$$a = \arg\max_a Q(s,a) + c\pi_\theta(a \mid s)\frac{\sqrt{N(s)}}{1 + N(s,a)}$$

Continuous Actions: Deep Deterministic Policy Gradient

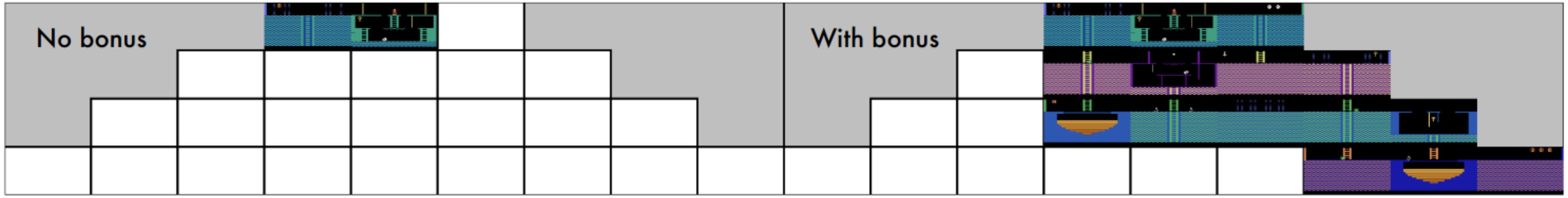
Is Exploration Important?
Montezuma's Revenge

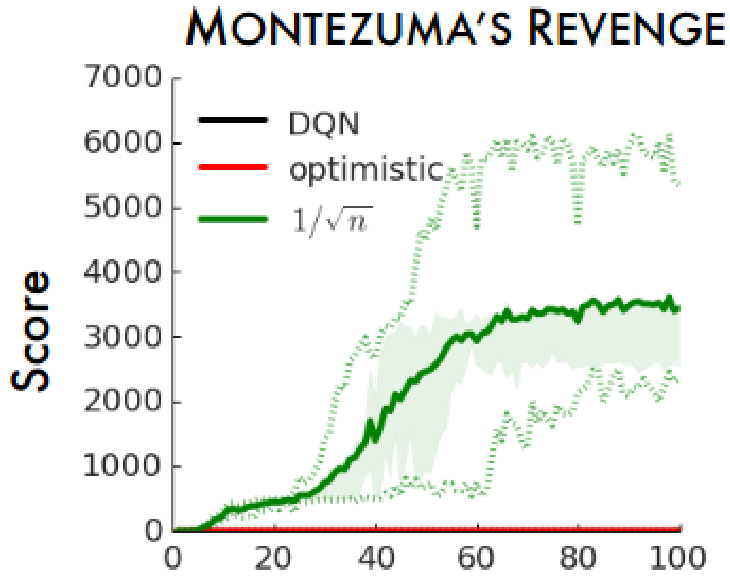
Is Exploration Important?
Theory

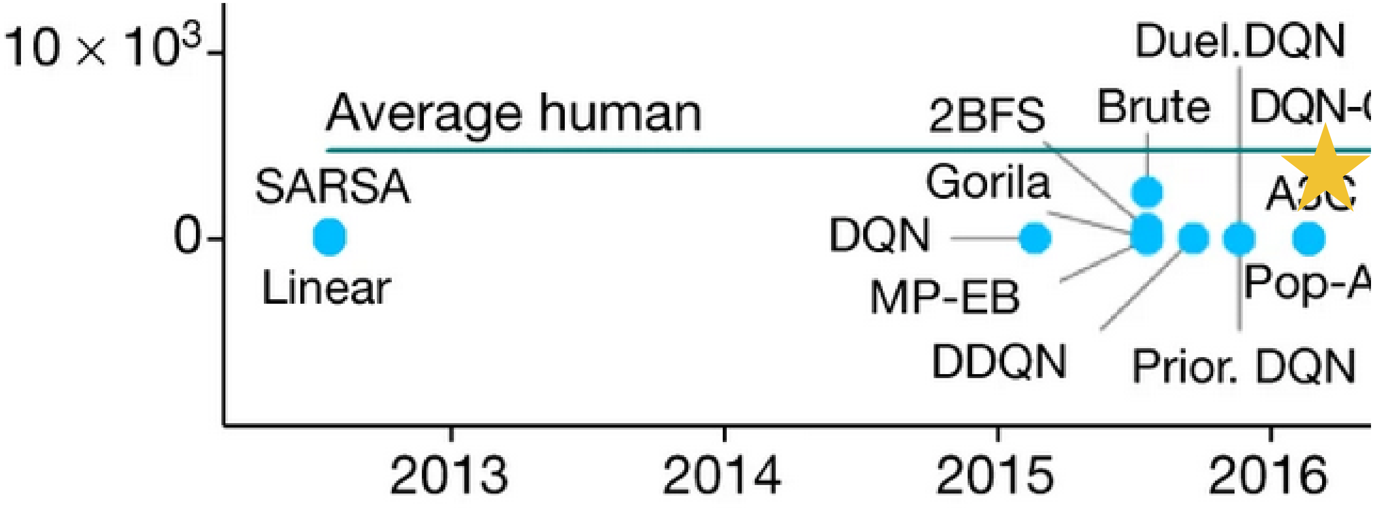
Exploration Bonus

Example 1: Learn Pseudocount

$B(s,a) \approx \frac{1}{\sqrt{\hat{N}(s)}}$ where $\hat{N}(s)$ is a learned function approximation







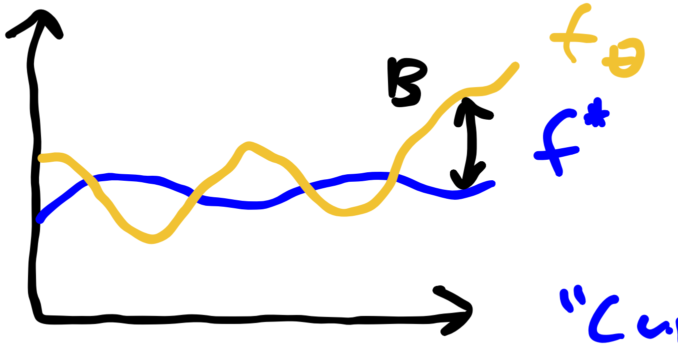
Bellemare, et al. 2016 "Unifying Count-Based Exploration..."

Exploration Bonus

Example 2: Learn a function of the state and action

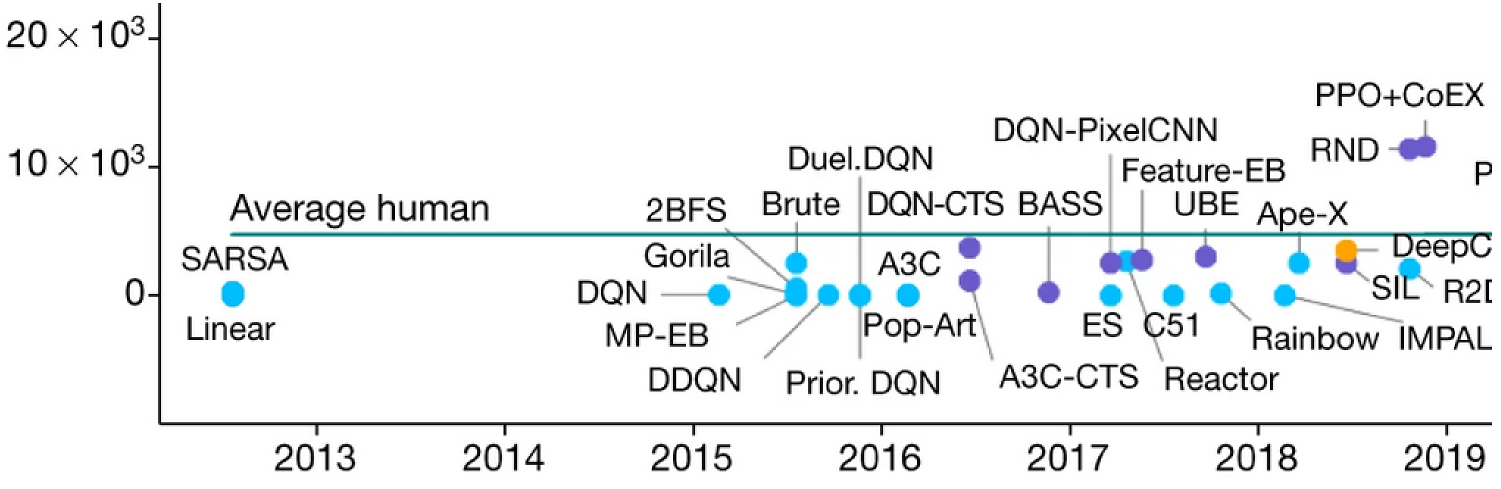
$$B(s,a) = \|\hat{f}_\theta(s,a) - f^*(s,a)\|^2$$

What should f^* be?



- $f^*(s,a) = s'$ (Next state prediction) "Curiosity"
- $f^*(s,a) = f_\phi(s,a)$ where f_ϕ is a random neural network.

"Random Network Distillation"



Exploration Bonus

Example 3: Thompson Sampling

1. Maintain a distribution over Q ← Hard
2. Sample Q
3. Act according to Q

- Bootstrapping with multiple Q networks
- Dropout

Exploration Bonus

Example 4: Go-Explore

"First return, then explore"

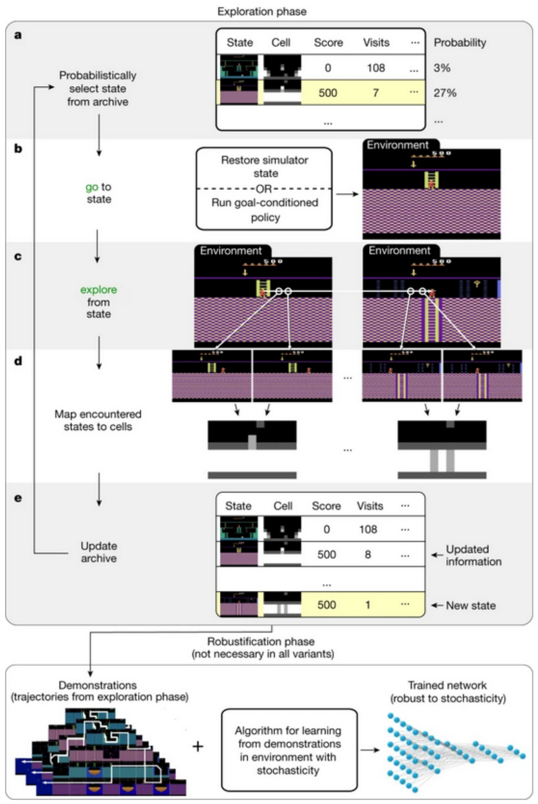
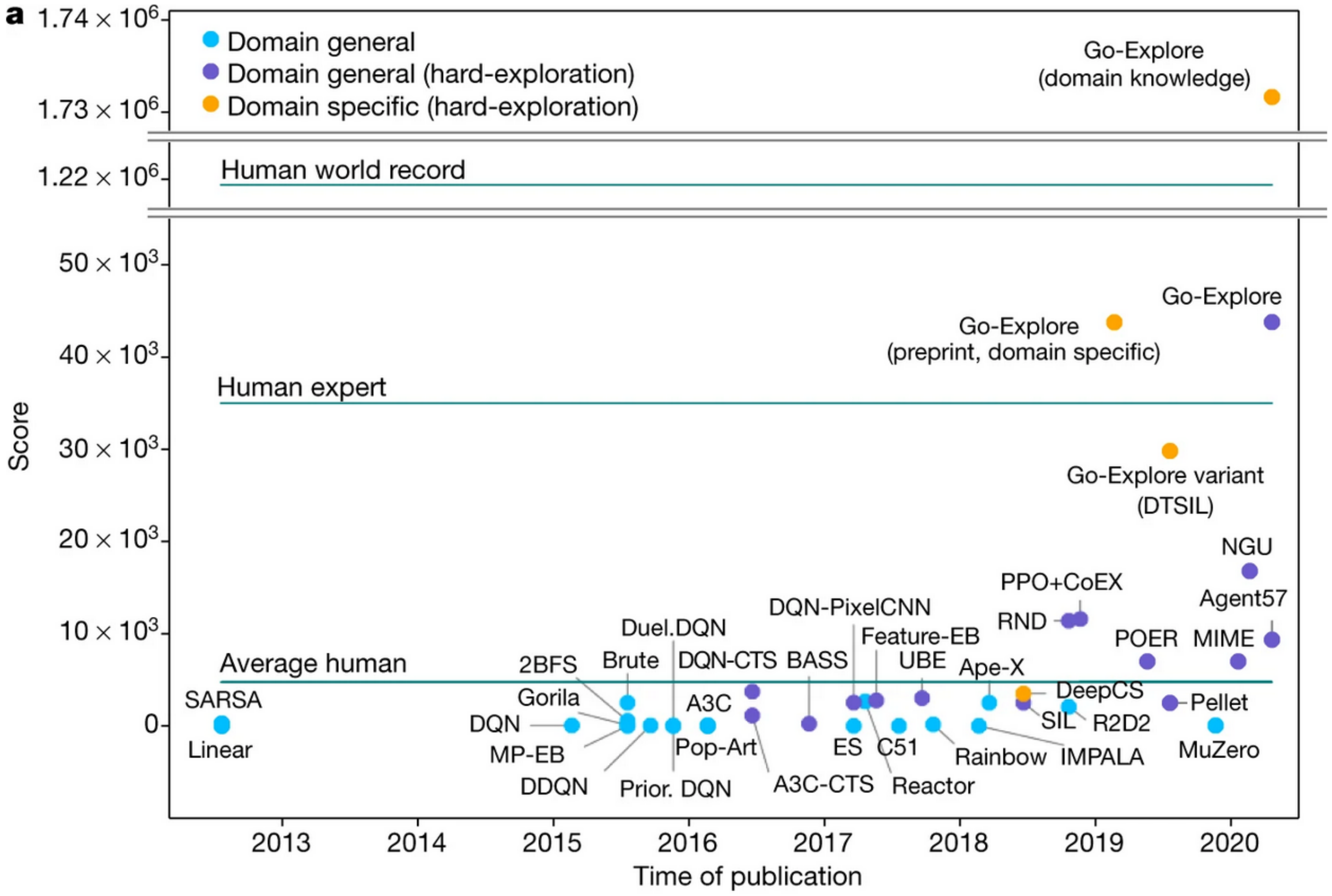


Fig. 1: Overview of Go-Explore.



(Uber AI Labs)

Soft Actor Critic: Entropy Regularization

$$U(\pi) = E\left[\sum_{t=0}^{\infty} \gamma^t \left(r_t + \alpha \mathcal{H}(\pi(\cdot \mid s_t))\right)\right]$$

$$V(\mathbf{s}_t) = \mathbb{E}_{\mathbf{a}_t \sim \pi}\left[Q(\mathbf{s}_t, \mathbf{a}_t) - \log \pi(\mathbf{a}_t | \mathbf{s}_t)\right]$$

$$\mathcal{T}^\pi Q(\mathbf{s}_t, \mathbf{a}_t) \triangleq r(\mathbf{s}_t, \mathbf{a}_t) + \gamma\, \mathbb{E}_{\mathbf{s}_{t+1} \sim p}\left[V(\mathbf{s}_{t+1})\right]$$

$$\pi_{\text{new}} = \arg\min_{\pi' \in \Pi} \mathrm{D_{KL}}\left(\pi'(\,\cdot\,|\mathbf{s}_t) \,\middle\|\, \frac{\exp\left(Q^{\pi_{\text{old}}}(\mathbf{s}_t, \,\cdot\,)\right)}{Z^{\pi_{\text{old}}}(\mathbf{s}_t)}\right)$$

Soft Actor Critic

Algorithm 1 Soft Actor-Critic

Initialize parameter vectors ψ, $\bar{\psi}$, θ, ϕ.
for each iteration **do**
  for each environment step **do**
    $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$
    $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$
    $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$
  end for
  for each gradient step **do**
    $\psi \leftarrow \psi - \lambda_V \hat{\nabla}_\psi J_V(\psi)$
    $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$
    $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$
    $\bar{\psi} \leftarrow \tau\psi + (1 - \tau)\bar{\psi}$
  end for
end for

$$J_V(\psi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}}\left[\tfrac{1}{2}\left(V_\psi(\mathbf{s}_t) - \mathbb{E}_{\mathbf{a}_t \sim \pi_\phi}\left[Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \log \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)\right]\right)^2\right]$$

$$J_Q(\theta) = \mathbb{E}_{(\mathbf{s}_t, \mathbf{a}_t) \sim \mathcal{D}}\left[\frac{1}{2}\left(Q_\theta(\mathbf{s}_t, \mathbf{a}_t) - \hat{Q}(\mathbf{s}_t, \mathbf{a}_t)\right)^2\right]$$

$$\hat{Q}(\mathbf{s}_t, \mathbf{a}_t) = r(\mathbf{s}_t, \mathbf{a}_t) + \gamma\, \mathbb{E}_{\mathbf{s}_{t+1} \sim p}\left[V_{\bar{\psi}}(\mathbf{s}_{t+1})\right]$$

$$J_\pi(\phi) = \mathbb{E}_{\mathbf{s}_t \sim \mathcal{D}}\left[\mathrm{D}_{\mathrm{KL}}\left(\pi_\phi(\,\cdot\,|\mathbf{s}_t) \,\middle\|\, \frac{\exp\left(Q_\theta(\mathbf{s}_t, \cdot\,)\right)}{Z_\theta(\mathbf{s}_t)}\right)\right]$$

Soft Actor Critic

Advantages:

Disadvantages

- Sta
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Algorithm 1 Soft Actor-Critic

Input: θ_1, θ_2, ϕ ▷ Initial parameters
  $\bar{\theta}_1 \leftarrow \theta_1, \bar{\theta}_2 \leftarrow \theta_2$ ▷ Initialize target network weights
  $\mathcal{D} \leftarrow \emptyset$ ▷ Initialize an empty replay pool
  for each iteration **do**
    for each environment step **do**
      $\mathbf{a}_t \sim \pi_\phi(\mathbf{a}_t|\mathbf{s}_t)$ ▷ Sample action from the policy
      $\mathbf{s}_{t+1} \sim p(\mathbf{s}_{t+1}|\mathbf{s}_t, \mathbf{a}_t)$ ▷ Sample transition from the environment
      $\mathcal{D} \leftarrow \mathcal{D} \cup \{(\mathbf{s}_t, \mathbf{a}_t, r(\mathbf{s}_t, \mathbf{a}_t), \mathbf{s}_{t+1})\}$ ▷ Store the transition in the replay pool
    end for
    for each gradient step **do**
      $\theta_i \leftarrow \theta_i - \lambda_Q \hat{\nabla}_{\theta_i} J_Q(\theta_i)$ for $i \in \{1, 2\}$ ▷ Update the Q-function parameters
      $\phi \leftarrow \phi - \lambda_\pi \hat{\nabla}_\phi J_\pi(\phi)$ ▷ Update policy weights
      $\alpha \leftarrow \alpha - \lambda \hat{\nabla}_\alpha J(\alpha)$ ▷ Adjust temperature
      $\bar{\theta}_i \leftarrow \tau\theta_i + (1-\tau)\bar{\theta}_i$ for $i \in \{1, 2\}$ ▷ Update target network weights
    end for
  end for
Output: θ_1, θ_2, ϕ ▷ Optimized parameters

Wisdom

Deep RL: The Dream

openai / **gym**

Watch 995

Code | Issues 112 | Pull requests 13 | Actions | Projects | **Wiki** | Security | Insights

Leaderboard

Aman Arora edited this page 3 days ago · 352 revisions

This page tracks the performance of user algorithms for various tasks in gym. Previously, users could submit their scores directly to gym.openai.com/envs, but it has been decided that a simpler wiki might do this task more efficiently.

This wiki page is a community driven page. Anyone can edit this page and add to it. We encourage you to contribute and modify this page and add your scores and links to your write-ups and code to reproduce your results. We also encourage you to add new tasks with the gym interface, but not in the core gym library (such as roboschool) to this page as well.

Links to videos are optional, but encouraged. Videos can be youtube, instagram, a tweet, or other public links. Write-ups should explain how to reproduce the result, and can be in the form of a simple gist link, blog post, or github repo.

We have begun to copy over the previous performance scores and write-up links over from the previous page. This is an ongoing effort, and we can use some help.

Environments

Classic control

CartPole-v0

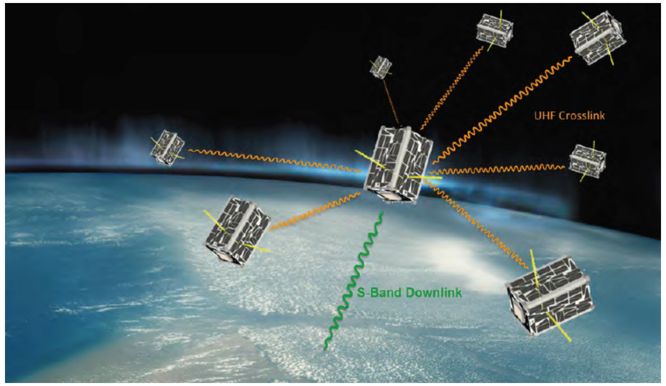
A pole is attached by an un-actuated joint to a cart, which moves along a frictionless track. The system is controlled by applying a force of +1 or -1 to the cart. The pendulum starts upright, and the goal is to prevent it from falling over. A reward of +1 is provided for every timestep that the pole remains upright. The episode ends when the pole is more than 15 degrees from vertical, or the cart moves more than 2.4 units from the center.

- Environment Details
- *CartPole-v0 defines "solving" as getting average reward of 195.0 over 100 consecutive trials.*
- *This environment corresponds to the version of the cart-pole problem described by Barto, Sutton, and Anderson [Barto83].*

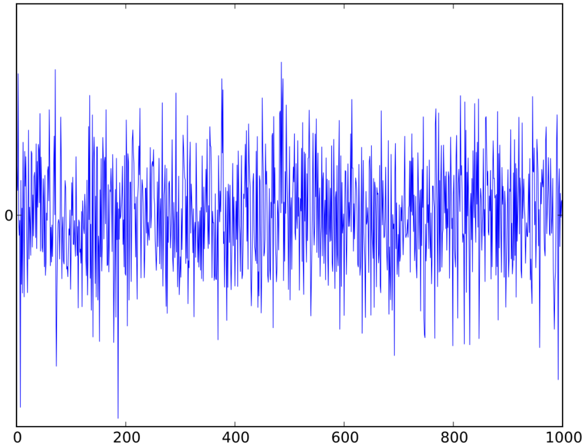
User	Episodes before solve	Write-up	Video
Zhiqing Xiao	0 (use close-form preset policy)	writeup	
Hengjian Jia	0 (use close-form PID policy)	code/writeup	
Keavnn	0	writeup	
Shakti Kumar	0	writeup	Video
Nextgrid.ai 🔥	0	writeup	Video
iRyanBell	2	writeup	

Using Deep RL for your problem

1. Some interesting problem (smallsat swarm)
2. Spend weeks theorizing about the exact-right cost function and dynamics
3. Decide RL can solve all of your problems
4. Fire up open-ai baselines
5. Does it work??



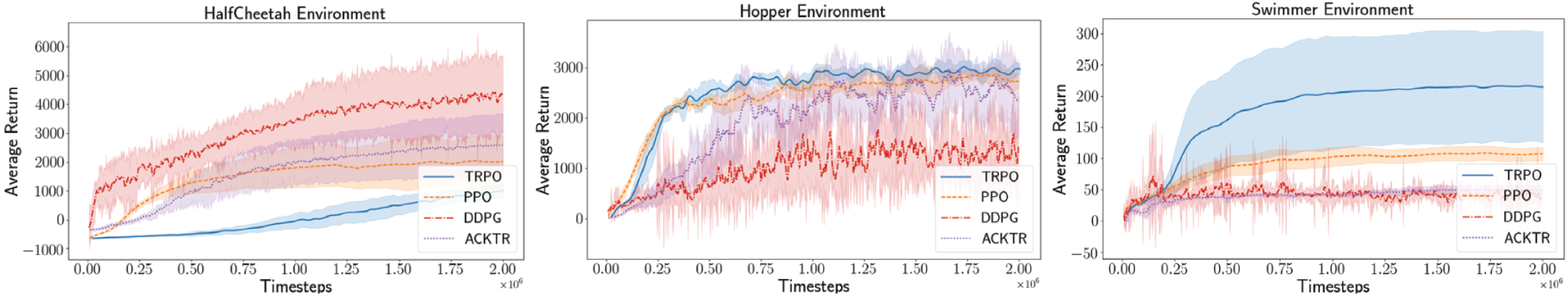
openai / **baselines**



Why not?

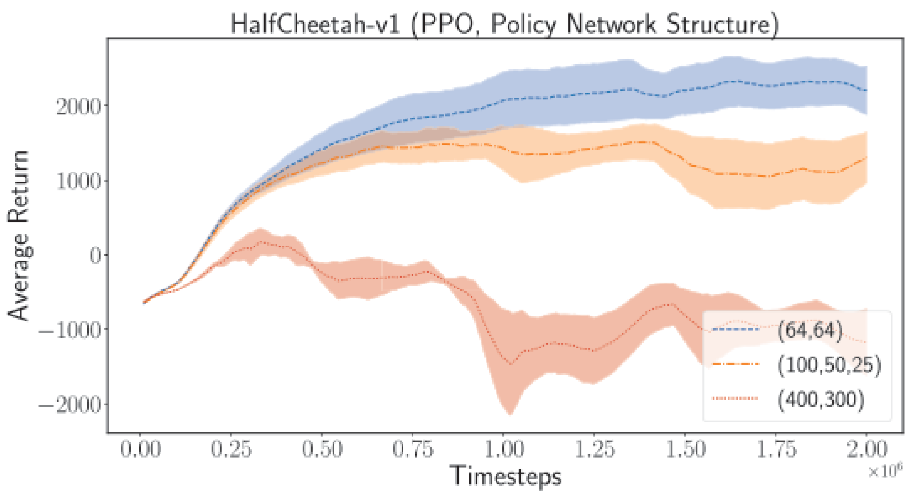
- Hyperparameters?
- Reward scaling?
- Not enough training time????

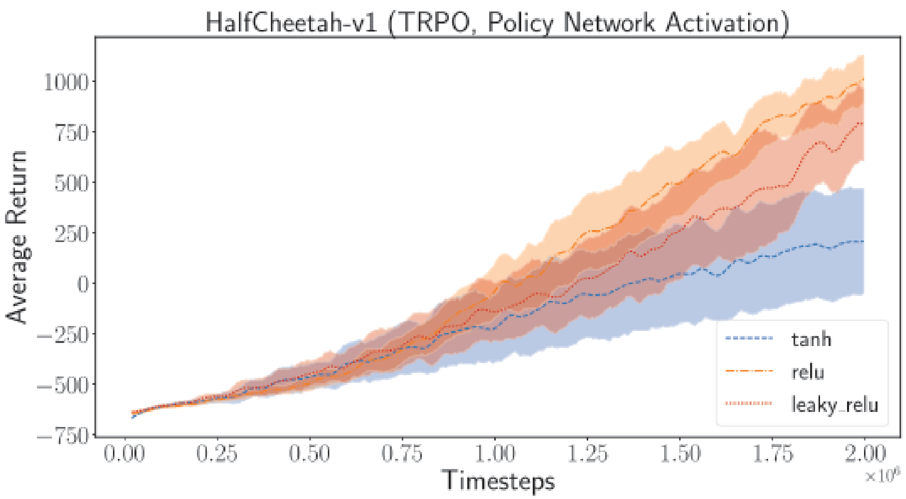
Algorithms

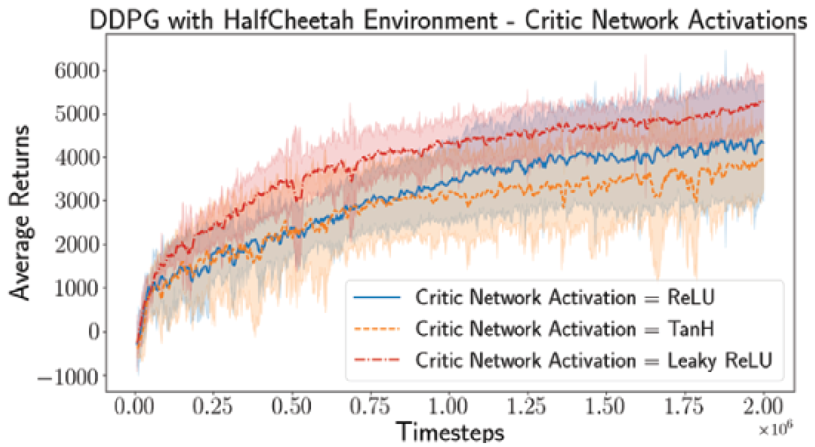


HalfCheetah Environment
Average Return
6000
5000
4000
3000
2000
1000
0
−1000
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Timesteps
×10^6
TRPO
PPO
DDPG
ACKTR
Hopper Environment
Average Return
3000
2000
1000
0
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Timesteps
×10^6
TRPO
PPO
DDPG
ACKTR
Swimmer Environment
Average Return
300
250
200
150
100
50
0
−50
0.00
0.25
0.50
0.75
1.00
1.25
1.50
1.75
2.00
Timesteps
×10^6
TRPO
PPO
DDPG
ACKTR

Policy Network Architecture

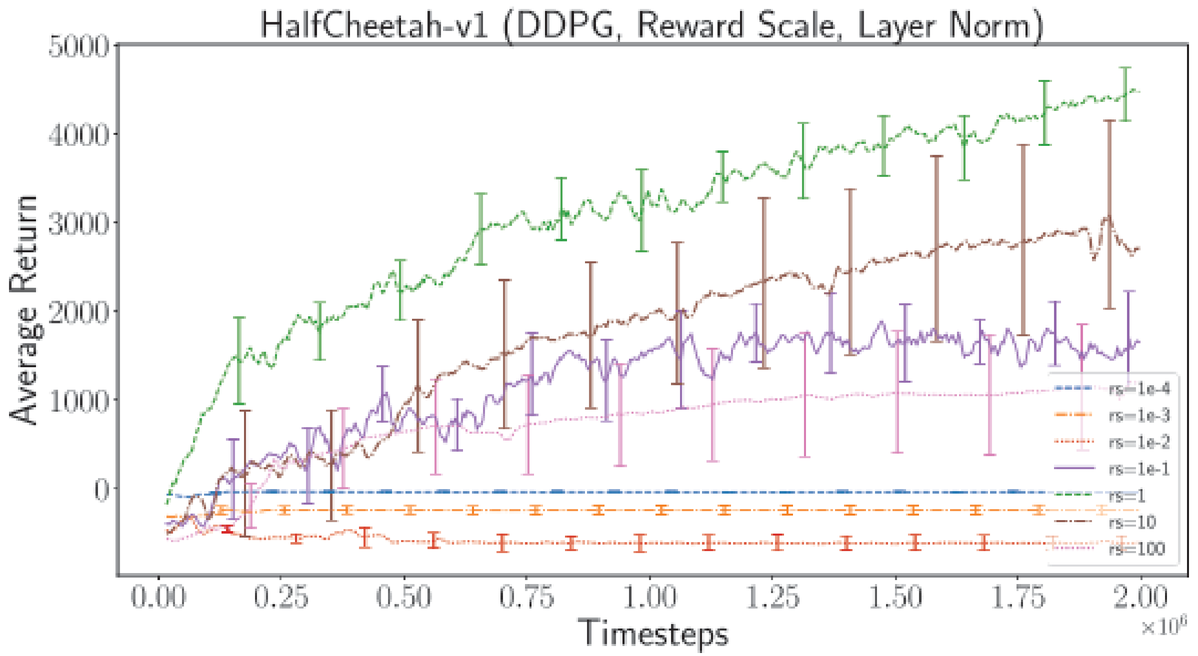


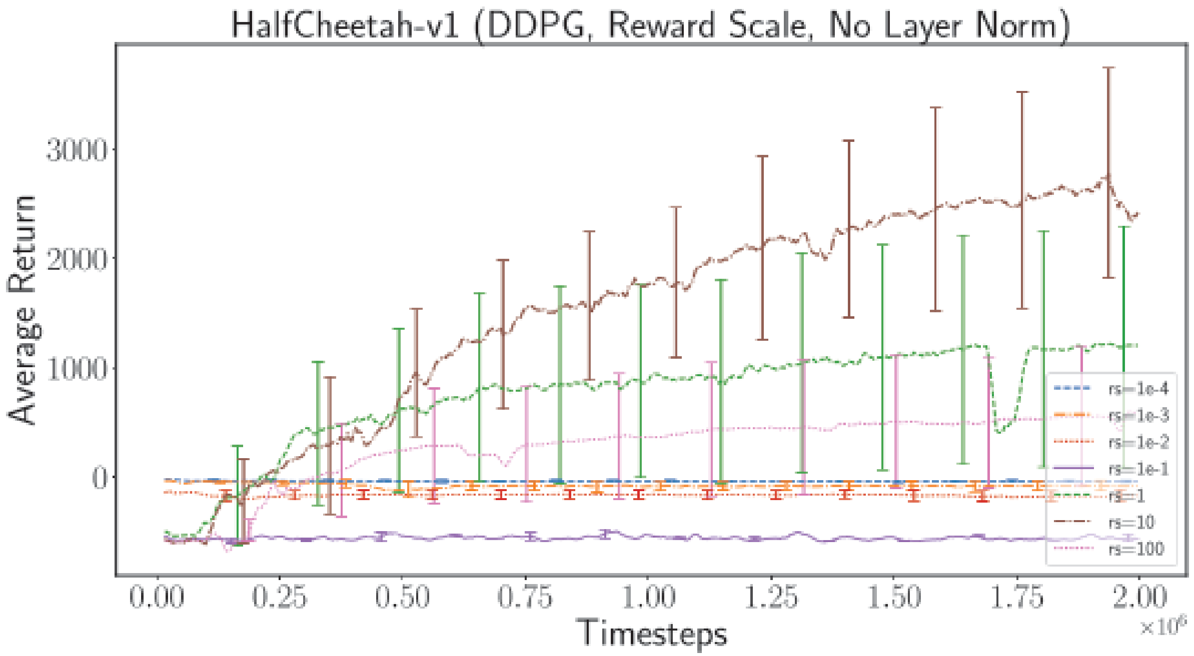




Reward Rescaling

"simply multiplying the rewards generated from an environment by some scalar"





Statistical Significance

"Unfortunately, in recent reported results, it is not uncommon for the top-N trials to be selected from among several trials (Wu et al. 2017; Mnih et al. 2016)"

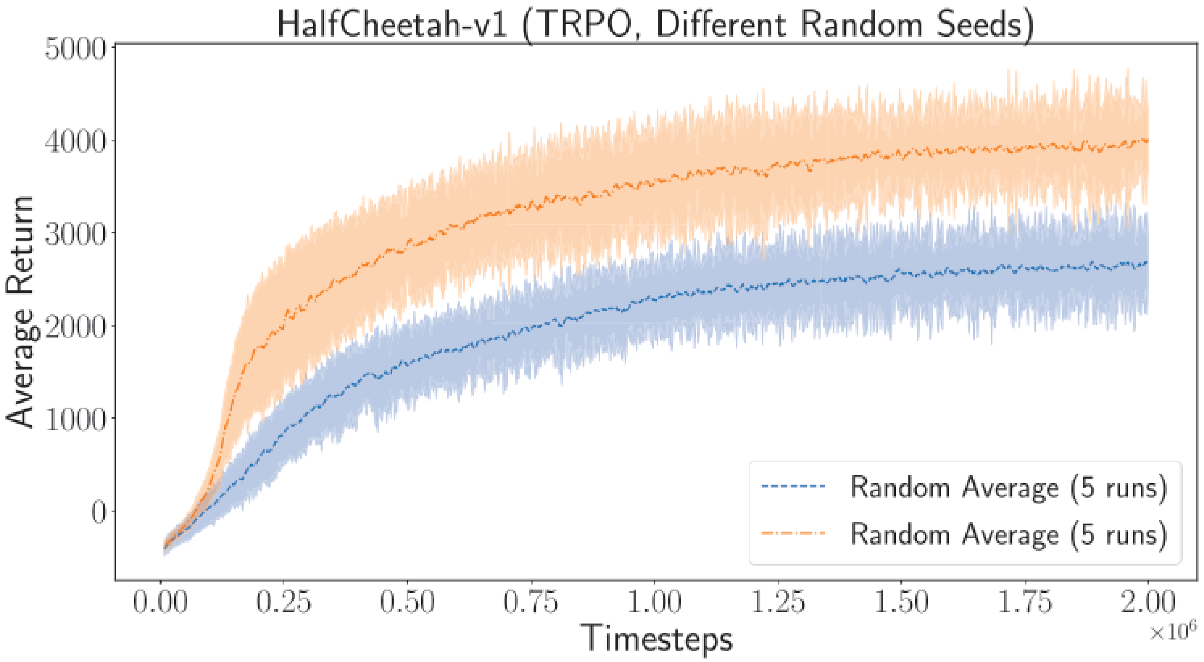
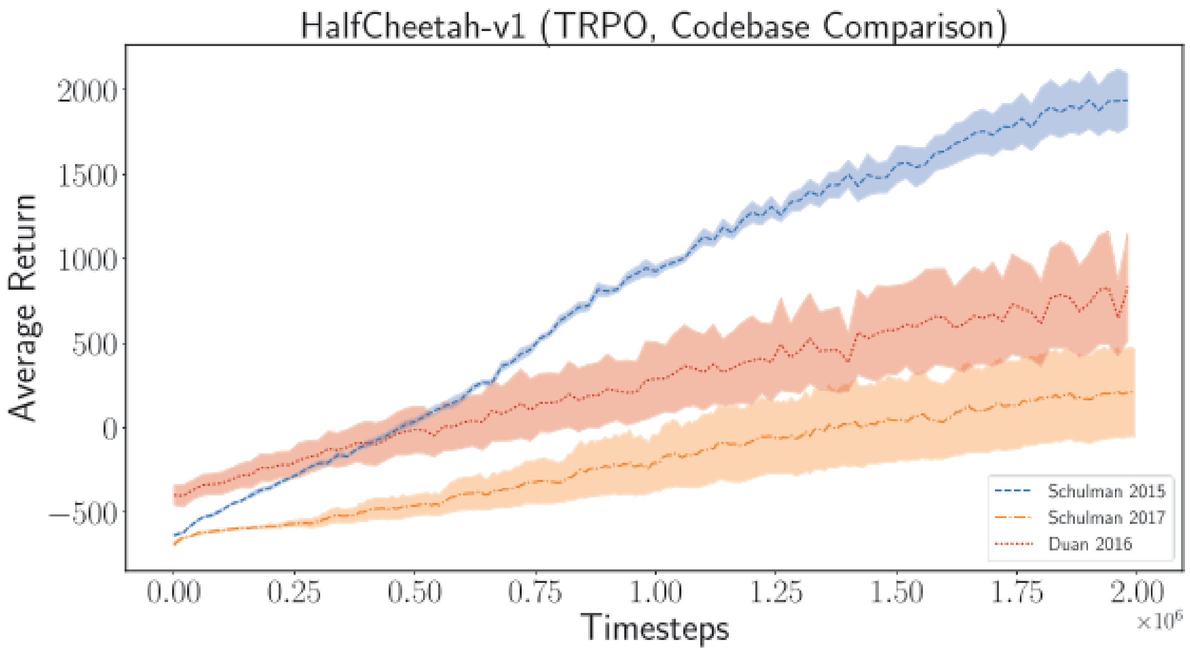
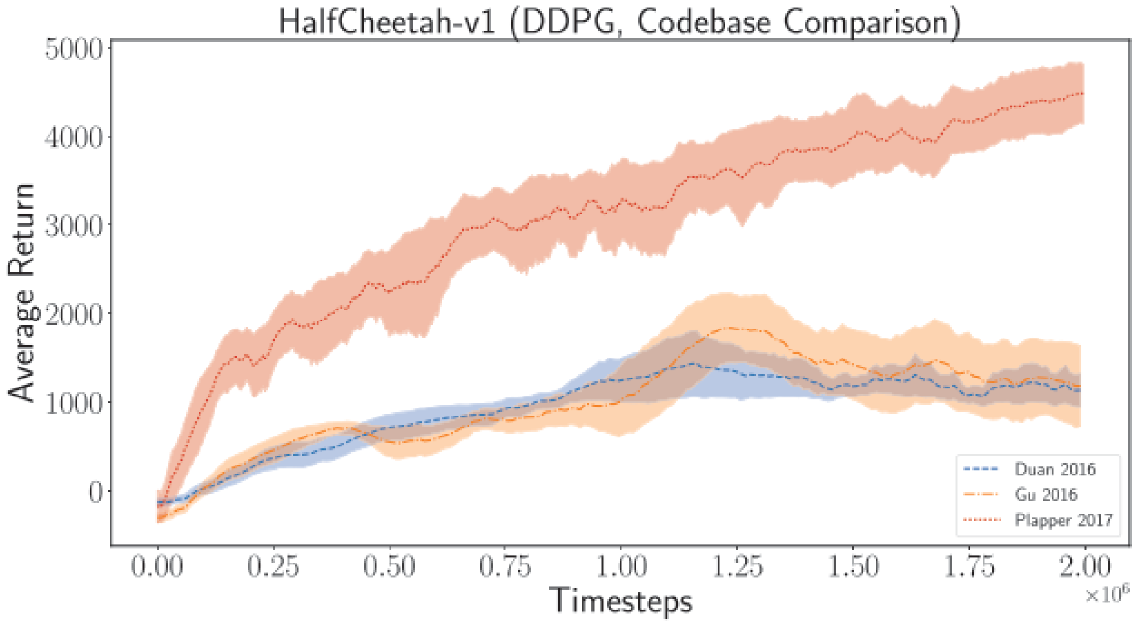


Figure 5: TRPO on HalfCheetah-v1 using the same hyperparameter configurations averaged over two sets of 5 different random seeds each. The average 2-sample t-test across entire training distribution resulted in $t = -9.0916$, $p = 0.0016$.

Codebases



HalfCheetah-v1 (TRPO, Codebase Comparison)
Average Return
Timesteps
$\times 10^6$
Schulman 2015
Schulman 2017
Duan 2016



HalfCheetah-v1 (DDPG, Codebase Comparison)
Average Return
Timesteps
$\times 10^6$
Duan 2016
Gu 2016
Plapper 2017

How to choose an RL Algorithm

(According to Sergey Levine)

Sample Efficiency

Ease of Use / Stability

← Fewer Samples

More Stable (?) →

Model-Based RL

Off-Policy Q-Learning

On Policy Policy Gradient

Evolutionary/ Gradient Free

Model-Based Deep RL

Actor Critic

(Most people use SAC or PPO)

Where Does RL Work?

- Cooling servers
- Winning at Go