Proximal Policy Optimization

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Proximal Policy Optimization (PPO)

- The main motivation behind PPO is the same as for TRPO:
  - Make the biggest possible improvement step
  - Do not step too far such that the performance accidentally collapses

- PPO addresses the shortcomings of TRPO:
  - PPO uses 1st order methods with a few tricks
  - Significantly simpler to implement
  - Shows similar performance to TRPO empirically

- There are two variants:
  - PPO-penalty: TRPO with KL-penalization instead of constraint (penalty coefficient is adjusted and scaled automatically over the course of training: *Adaptive KL Penalty Coefficent*)
  - PPO-clip: no constraints! Adds a clipping to the objective function to remove incentives to move too far

Spoiler: PPO is (1) much simpler to understand and to implement, and (2) much better (empirically)

Proximal Policy Optimization (PPO)

Where are we so far?

- TRPO maximizes a "surrogate" objective subject to a constraint on the size of the policy update:

$$\max_{\theta} \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_{old}}(a_t|s_t)} \hat{A}_t \right], \qquad \text{subject to} \quad \hat{\mathbb{E}}_t \left[KL\left[\pi_{\theta_{old}}(\cdot\,|s_t), \pi_\theta(\cdot\,|s_t) \right] \right] \leq \delta$$

  with θ_{old} being the policy parameters before the update

- We did not explicitly formulate it like this, but the intuition behind it is:
  - We want to measure how π_θ performs relative to $\pi_{\theta_{old}}$ (using data from the old policy)
  - The original objective (see TRPO slides) can be exactly reformulated to this one

- We can solve this with CG after making a linear approximation to the objective and a quadratic approximation to the KL-constraint

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- Let us define the probability ratio $r_t(\theta)$:

$$r_t(\theta) = \frac{\pi_\theta(a_t|s_t)}{\pi_{\theta\,old}(a_t|s_t)} \qquad \text{, i.e., } r_t(\theta_{old}) = 1.$$

- In other words, TRPO maximizes the following objective:

$$L^{CPI}(\theta) = \hat{\mathbb{E}}_t\left[r_t(\theta)\hat{A}_t\right]$$

  penalizing changes to the policy that move $r_t(\theta)$ (too far) away from 1.

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- The PPO objective we want to maximize is given by

$$L(\theta) = \hat{\mathbb{E}}_t\left[\min\left(r_t(\theta)\hat{A}_t, \operatorname{clip}(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t\right)\right],$$

where ϵ is a hyperparameter (i.e., 0.1 or 0.2) that defines how far π_{new} may go away from π_{old}

- First term inside the $\min$ is $L^{CPI}(\theta)$
- Second term inside the $\min$ clip the probability ratio
  → removes the incentive for moving r_t outside of the interval $[1-\epsilon, 1+\epsilon]$

- We take the minimum of the clipped and unclipped objective
  → the final objective is a lower bound (i.e., a pessimistic bound) on the unclipped objective

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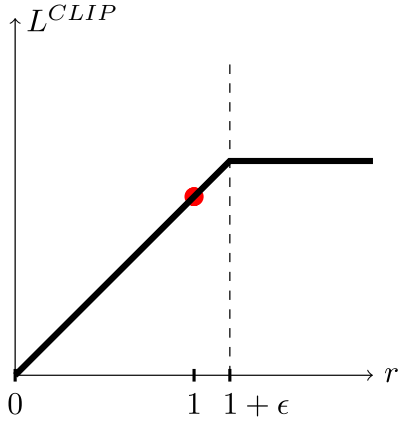
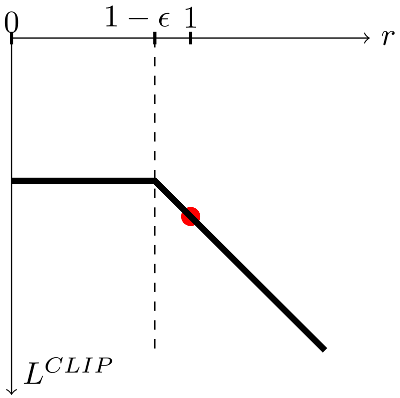
- The clipping operator is a *pessimistic bound* of the unclipped objective

$A > 0$





$A < 0$

- Plot show a single timestep of the surrogate function L^{CLIP} as a function of r
- The red circle shows the starting point for the optimization, i.e., $r = 1$

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- Automated Tuning of the gradient step *without calculating the Hessian*

Algorithm 1 PPO-Clip

Input: initial policy parameters θ_0, initial value function parameters ϕ_0

for $k = 0, 1, 2, \ldots$ **do**

Collect set of trajectories $\mathcal{D}_k = \{\tau_i\}$ by running policy $\pi_k = \pi(\theta_k)$ in the environment.

Compute rewards-to-go $\hat{R}_t$.

Compute advantage estimates, $\hat{A}_t$ (using any method of advantage estimation) based on the current value function V_{ϕ_k}.

Update the policy by maximizing the PPO-Clip objective:

$$\boxed{\theta_{k+1} = \arg\max_{\theta} \frac{1}{|\mathcal{D}_k| T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^{T} \min\left(\frac{\pi_\theta(a_t|s_t)}{\pi_{\theta_k}(a_t|s_t)} A^{\pi_{\theta_k}}(s_t, a_t), \;\; g(\epsilon, A^{\pi_{\theta_k}}(s_t, a_t)) \right),}$$

typically via stochastic gradient ascent with Adam.

Fit value function by regression on mean-squared error:

$$\phi_{k+1} = \arg\min_{\phi} \frac{1}{|\mathcal{D}_k| T} \sum_{\tau \in \mathcal{D}_k} \sum_{t=0}^{T} \left(V_\phi(s_t) - \hat{R}_t \right)^2,$$

typically via some gradient descent algorithm.

end for

Advantage Clipping for conservative policy updates

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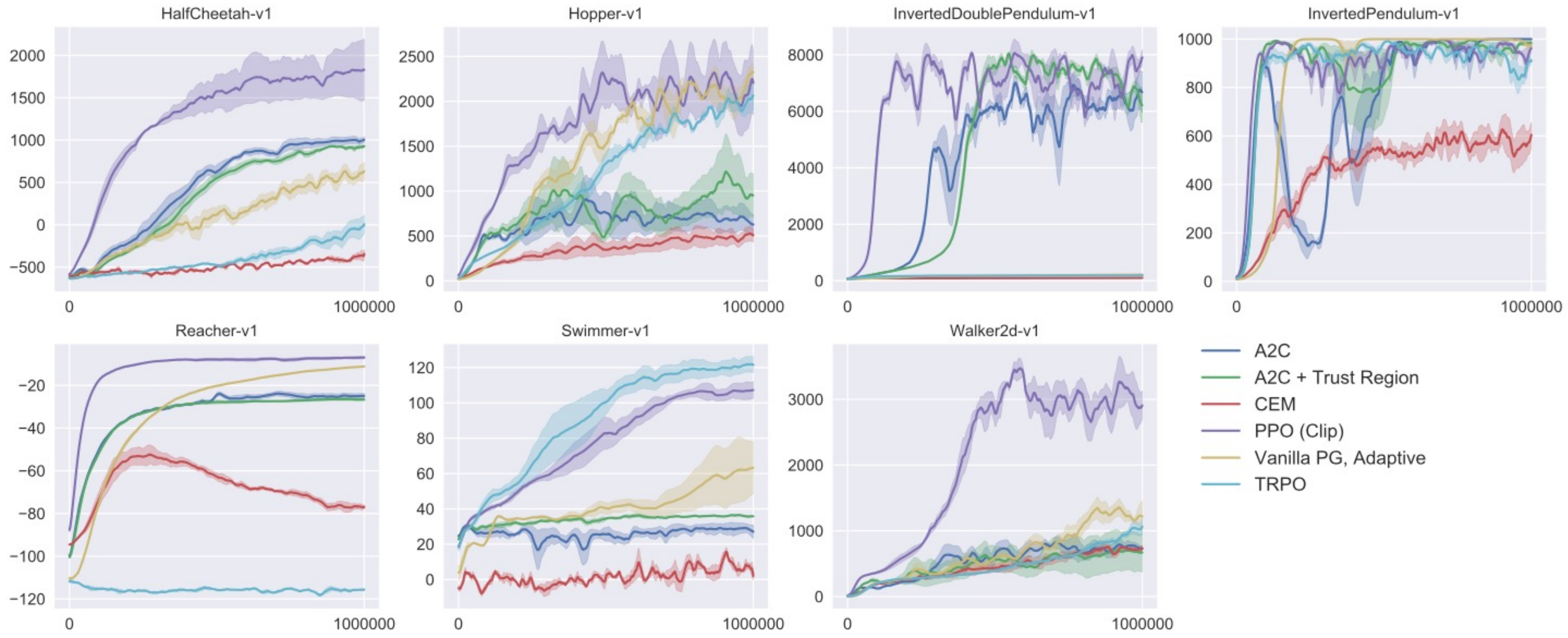
- Results of PPO-clip:
  - Against well-known competitors
  - On well-known environments
- Those results are impressive!



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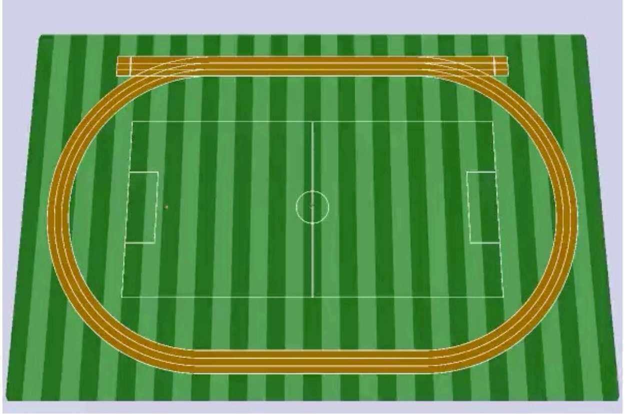

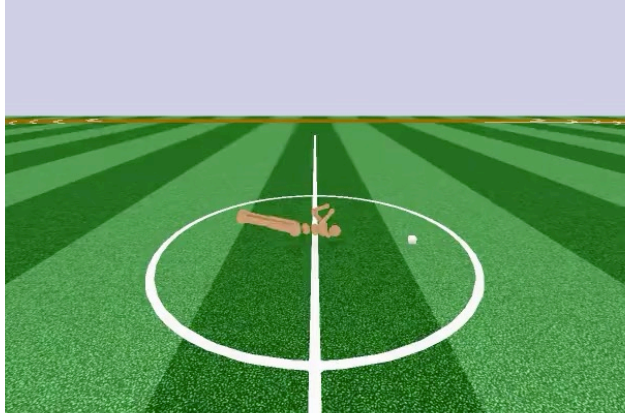

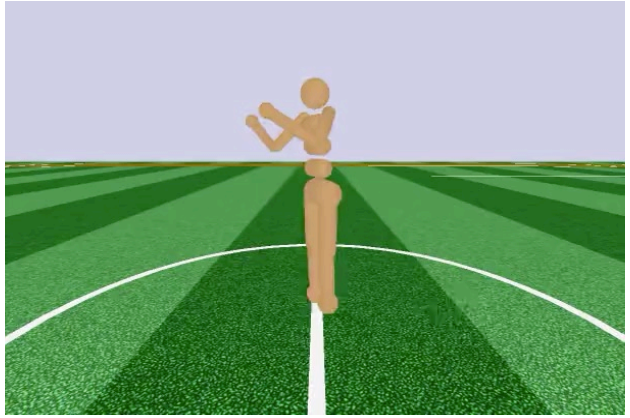

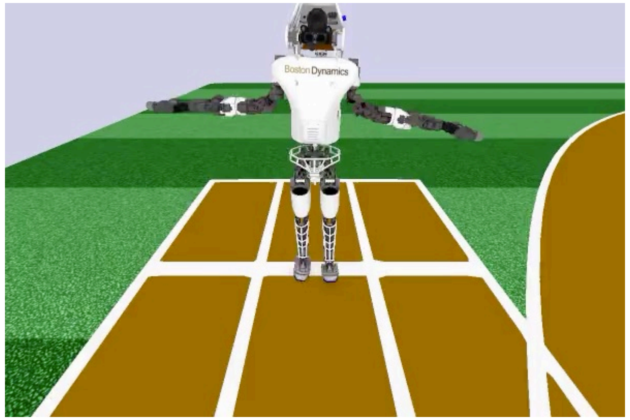

Videos from https://openai.com/blog/openai-baselines-ppo/

Proximal Policy Optimization (PPO)

Practical Considerations

Algorithm 1 PPO, Actor-Critic Style

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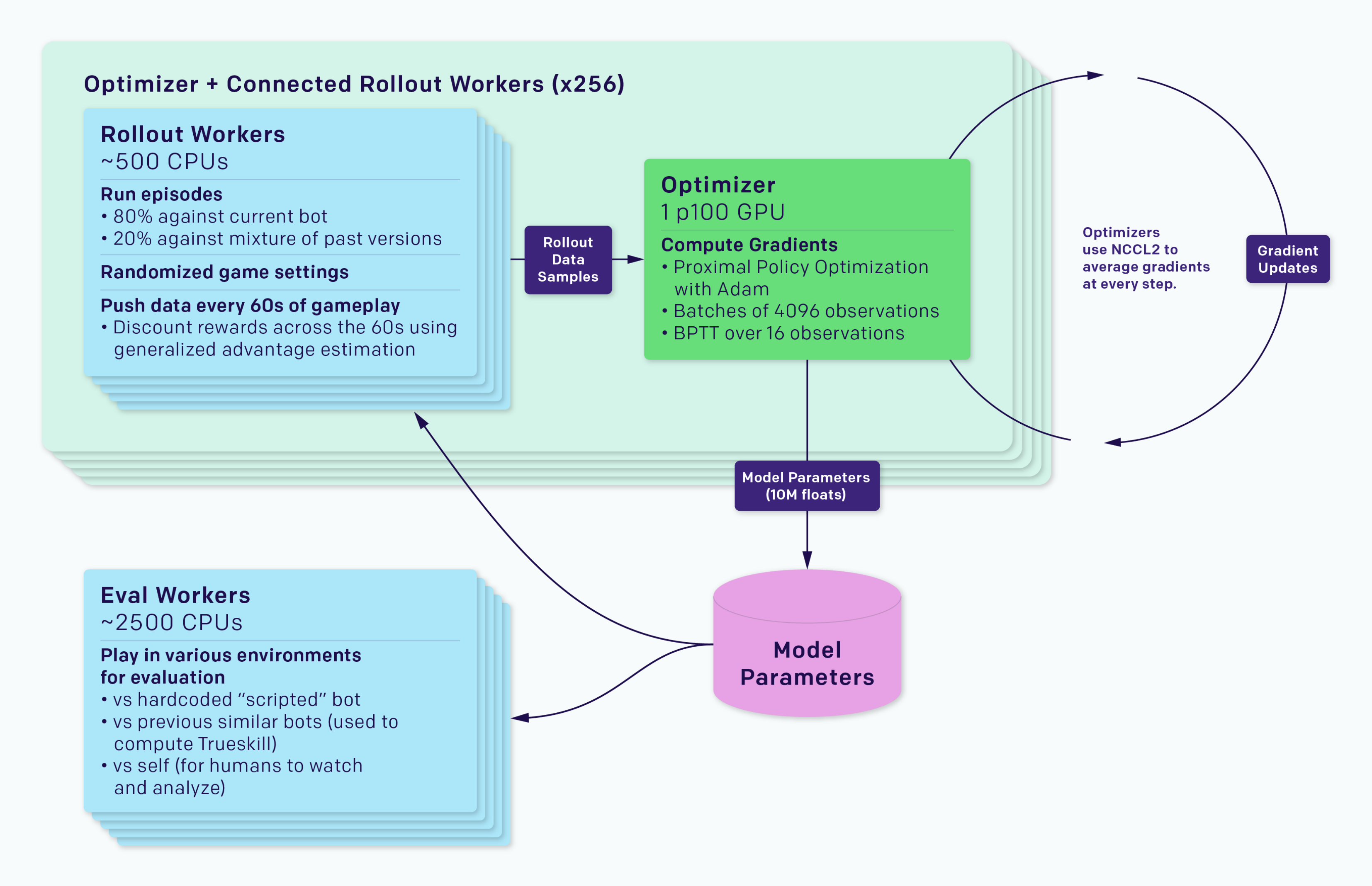
for iteration$=1, 2, \ldots$ **do**
  for actor$=1, 2, \ldots, N$ **do**
    Run policy $\pi_{\theta_{\text{old}}}$ in environment for T timesteps
    Compute advantage estimates $\hat{A}_1, \ldots, \hat{A}_T$
  end for
  Optimize surrogate L wrt θ, with K epochs and minibatch size $M \leq NT$
  $\theta_{\text{old}} \leftarrow \theta$
end for

- There is two alternating threads in PPO:
  1. Policy interacts with the environment, collects data and computes advantage estimates (using fitted baselines estimates)
  2. 2^{nd} thread collects all the experiences and runs SGD to optimize the policy using the clipped objective

PPO in Action: OpenAI Five on DOTA II



https://openai.com/blog/openai-five/

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Practical Considerations

- One more thing….
- PPO combines a few more things in the final objective:

$$L_t^{CLIP+VF+S}(\theta) = \hat{\mathbb{E}}_t[L_t^{CLIP}(\theta) - c_1 L_t^{VF}(\theta) + c_2 S[\pi_\theta](s_t)]$$

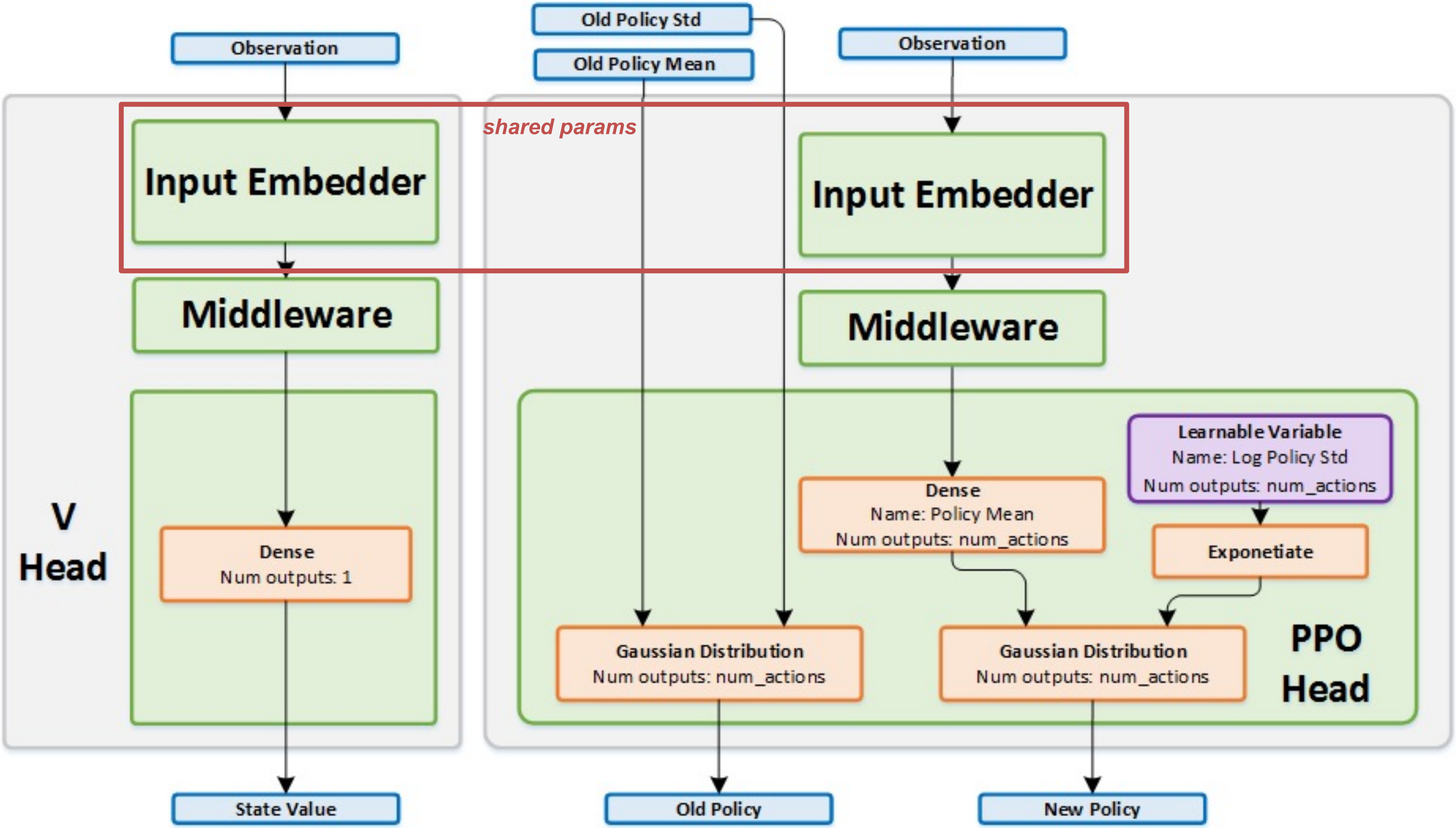
clipped surrogate objective

Sqared error loss for $\left(V_\theta(s_t) - V_t^{targ}\right)^2$

entropy bonus (exploration)

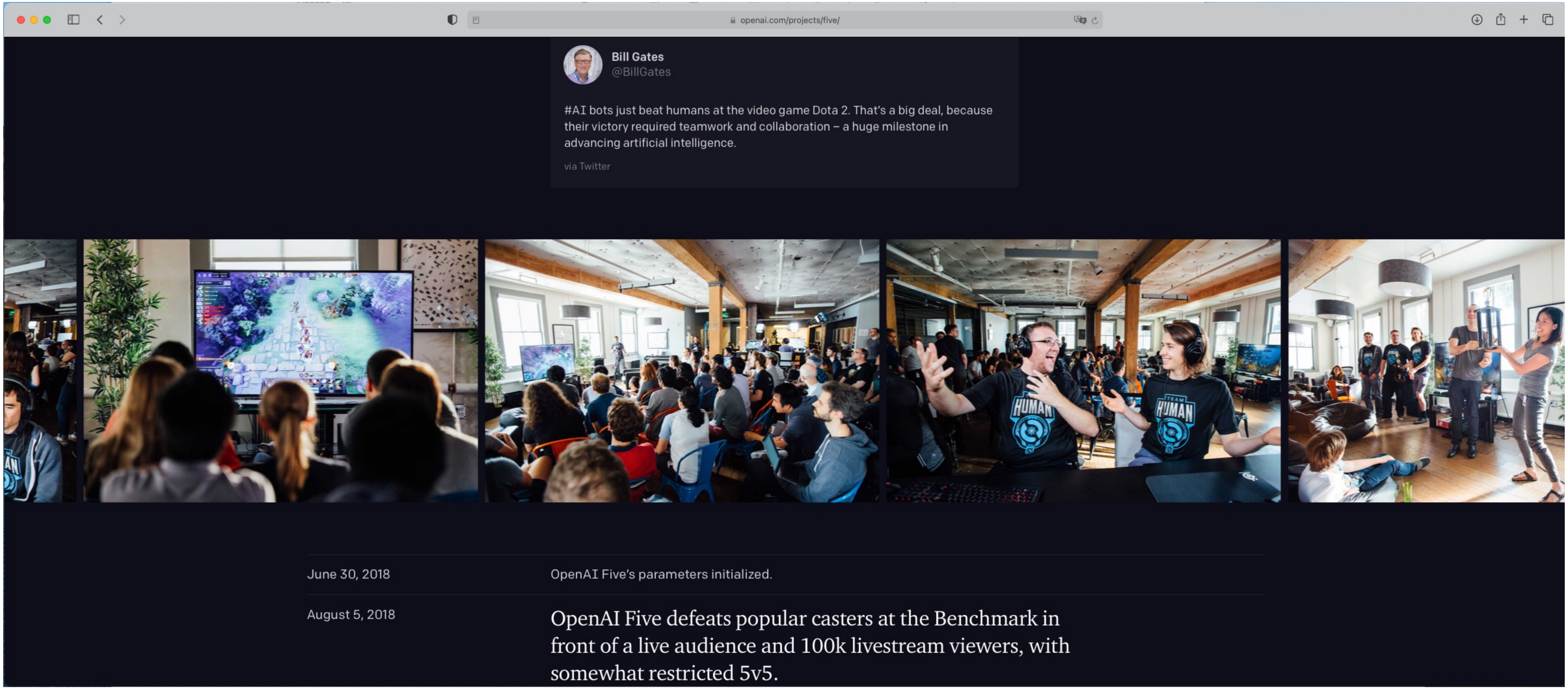
- *Note: you likely need similar features to represent the policy and the state-values*
  → OpenAI Five shares parameters between the policy network and the value network
  → Both error terms are combined in a single loss function

PPO in Action: OpenAI Five vs. DOTA II



https://intellabs.github.io/coach/components/agents/policy_optimization/ppo.html

PPO in Action: OpenAI Five vs. DOTA II



https://openai.com/projects/five/

PPO in Action: OpenAI Five vs. DOTA II

- **High-level info:**
  - 180 years of self-play per day and hero (~900 yrs/day), no human data
  - Running on 256 P100 GPUs and 128,000 CPU cores
- **Technical stats:**
  - Observation size: ~36.8kB @ ~7Hz
  - Batch size: 1,048,576 observations = 36 GB ☺
  - Separate single-layer, 1024 unit LSTM per hero
  - See https://openai.com/blog/openai-five/ for an interactive demo!
  - Reward: net worth, kills, deaths, assist, last hits, etc.
  - ”Team spirit” – trade own rewards over team reward (heroes do not communicate)
- **Challenge: exploring combinatorial-vast space of combining actions w/ long planning horizons**
  - 80% of games against itself, 20% against past selves (avoid “strategy collapse”)
  - After several hours: concepts such as laning, farming or fighting emerged
  - After several days: basic human strategies such as steal bounty runes from opponents, rotate heroes around the map to gain lane advantage etc.