Proximal Policy Optimization (PPO)

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T3 Drive

Schwächen von Policy Gradient Methoden (PGM)

- Schwer gute Resultate mit PGM zu erreichen
- PGM reagieren empfindlich bei der Wahl der Stepsize
- Ist die Stepsize zu
  - klein gewählt, ist der Fortschritt hoffnungslos langsam
  - groß gewählt und der Input verrauscht, dann führt das starken Einbrüchen in der Performance
- Ineffizientes Sampling, da hier Millionen oder auch Milliarden Timesteps benötigt werden um einfache Aufgaben zu erlernen

Vanilla Policy Gradient (VPG) | Trust Region Policy Optimization (TRPO) | Proximal Policy Optimization (PPO)

$$\nabla_\theta J(\pi_\theta) = \mathop{\mathrm{E}}_{\tau\sim\pi_\theta}\left[\sum_{t=0}^{T} \nabla_\theta \log \pi_\theta(a_t|s_t) A^{\pi_\theta}(s_t, a_t)\right]$$

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$$\mathcal{L}(\theta_k, \theta) = \underset{s,a\sim\pi_{\theta_k}}{\mathrm{E}} \left[\frac{\pi_\theta(a|s)}{\pi_{\theta_k}(a|s)} A^{\pi_{\theta_k}}(s,a) \right]$$

Nebenbedingung:

$$\bar{D}_{KL}(\theta||\theta_k) = \underset{s\sim\pi_{\theta_k}}{\mathrm{E}} \left[D_{KL}\left(\pi_\theta(\cdot|s)||\pi_{\theta_k}(\cdot|s)\right)\right] \leq \delta$$

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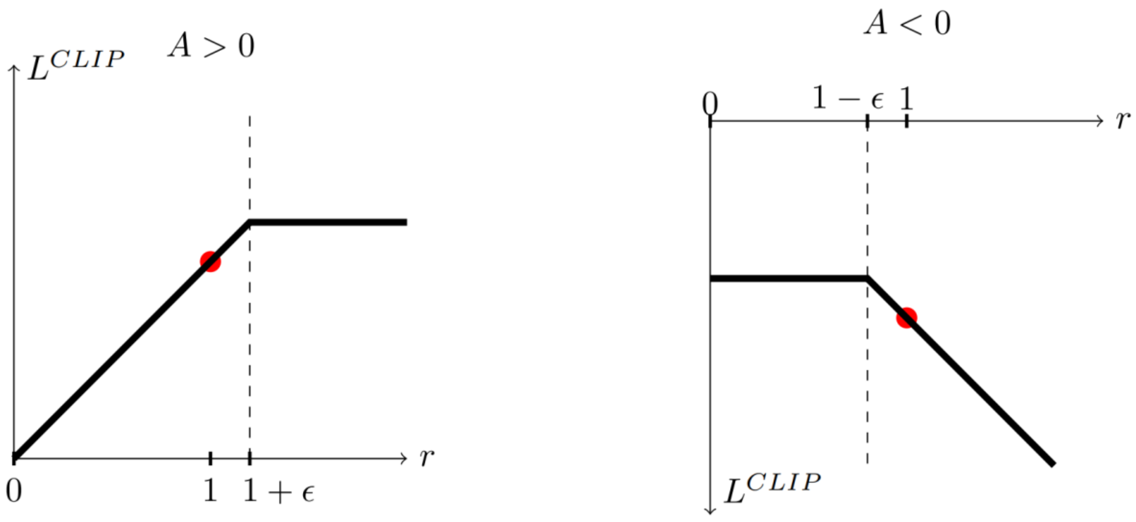
Vanilla Policy Gradient (VPG) → Trust Region Policy Optimization (TRPO) → **Proximal Policy Optimization (PPO)**

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



Probability Ratio:

$$r_t(\theta) = \frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}$$

Estimated Advantage Funktion:

$$\hat{A}_t = -V(s_t) + r_t + \gamma r_{t+1} + \cdots + \gamma^{T-t+1} r_{T-1} + \gamma^{T-t} V(s_T)$$

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

Entropy Bonus für hinreichende Exploration:

S

Squared-error loss:

$L_t^{VF} = (V_\theta(s_t) - V_t^{\text{targ}})^2$

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$$L^{KLPEN}(\theta) = \hat{\mathbb{E}}_t\left[\frac{\pi_\theta(a_t \mid s_t)}{\pi_{\theta_{\text{old}}}(a_t \mid s_t)}\hat{A}_t - \beta\,\mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]\right]$$

$$d = \hat{\mathbb{E}}_t[\mathrm{KL}[\pi_{\theta_{\text{old}}}(\cdot \mid s_t), \pi_\theta(\cdot \mid s_t)]]$$

$$d < d_{\text{targ}}/1.5,\ \beta \leftarrow \beta/2$$

$$d > d_{\text{targ}} \times 1.5,\ \beta \leftarrow \beta \times 2$$

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No clipping or penalty: $L_t(\theta) = r_t(\theta)\hat{A}_t$

Clipping: $L_t(\theta) = \min(r_t(\theta)\hat{A}_t, \mathrm{clip}(r_t(\theta)), 1-\epsilon, 1+\epsilon)\hat{A}_t$

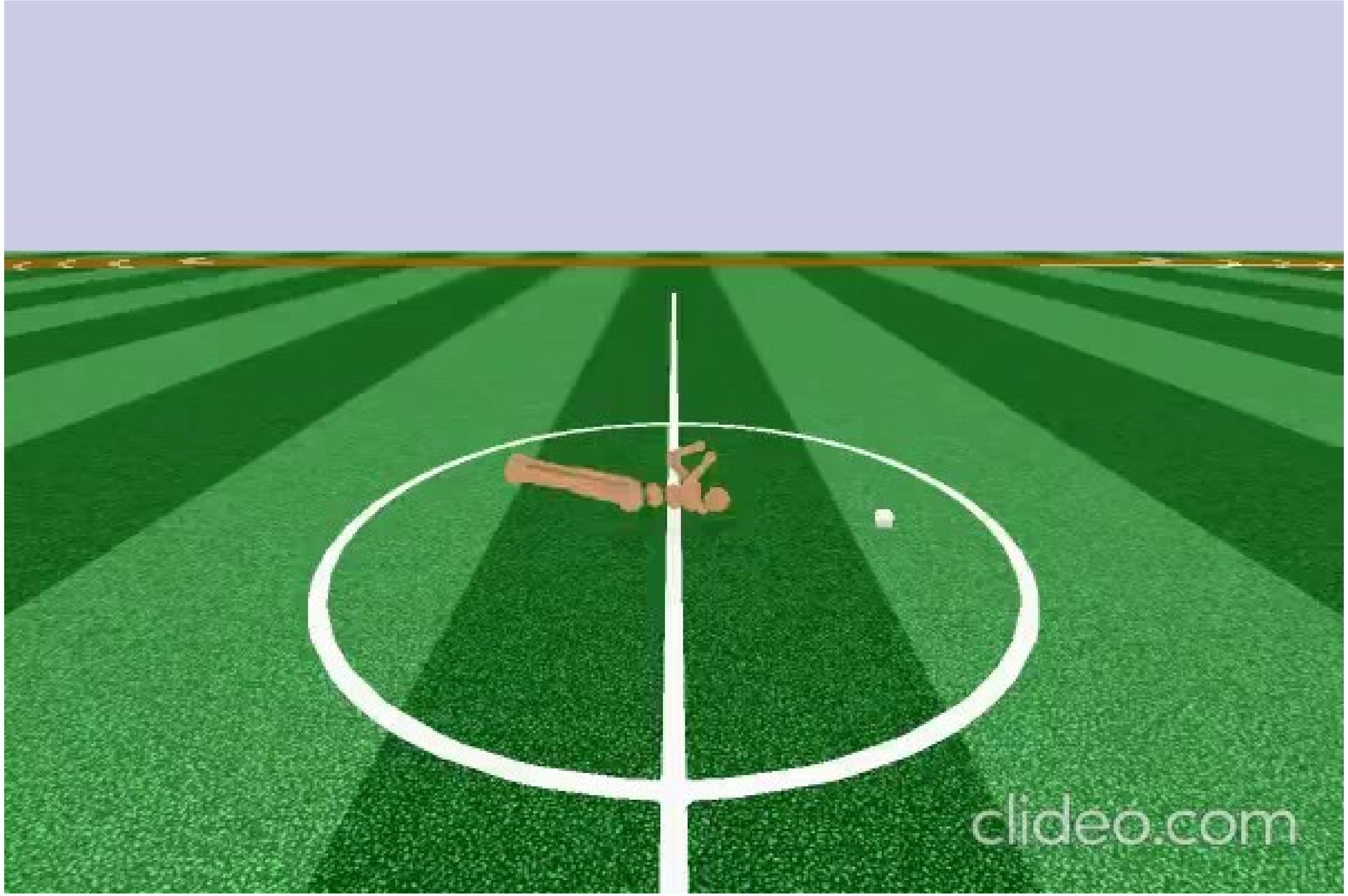
KL penalty (fixed or adaptive) $L_t(\theta) = r_t(\theta)\hat{A}_t - \beta\,\mathrm{KL}[\pi_{\theta_{\mathrm{old}}}, \pi_\theta]$

algorithm	avg. normalized score
No clipping or penalty	-0.39
Clipping, $\epsilon = 0.1$	0.76
Clipping, $\epsilon = 0.2$	**0.82**
Clipping, $\epsilon = 0.3$	0.70
Adaptive KL $d_{\mathrm{targ}} = 0.003$	0.68
Adaptive KL $d_{\mathrm{targ}} = 0.01$	0.74
Adaptive KL $d_{\mathrm{targ}} = 0.03$	0.71
Fixed KL, $\beta = 0.3$	0.62
Fixed KL, $\beta = 1.$	0.71
Fixed KL, $\beta = 3.$	0.72
Fixed KL, $\beta = 10.$	0.69

Tabelle: Basierend auf sieben simulierte Roboteraufgaben in OpenAI Gym mit MuJoCo Physics Engine

Proximal Policy Optimization (PPO) in Action

Roboschool (trained by OpenAI)



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