Deep Policy Search

3. TRPO, ACKTR and PPO

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Outline

- This class builds on my previous Policy Gradient class
- Three algorithms are presented: TRPO, ACKTR, PPO
- Two aspects distinguish TRPO:
  - Surrogate return objective
  - Natural policy gradient
- A small difference with ACKTR:
  - Using Kronecker Factored Approximated Curvature to estimate the natural gradient
- About PPO:
  - There are two PPO algorithms
  - They are well covered on youtube videos
  - So only a quick overview here
  - Easy implementation, a lot used

Surrogate return objective

- The standard policy gradient algorithm for stochastic policies is:

$$\nabla_\theta J(\theta) = \mathbb{E}_t[\nabla_\theta \log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)\hat{A}_\phi]$$

- This gradient is obtained from differentiating $Loss^{PG}(\theta) = \mathbb{E}_t[\log \pi_\theta(\mathbf{a}_t|\mathbf{s}_t)\hat{A}_\phi]$
- But we obtain the same gradient from differentiating

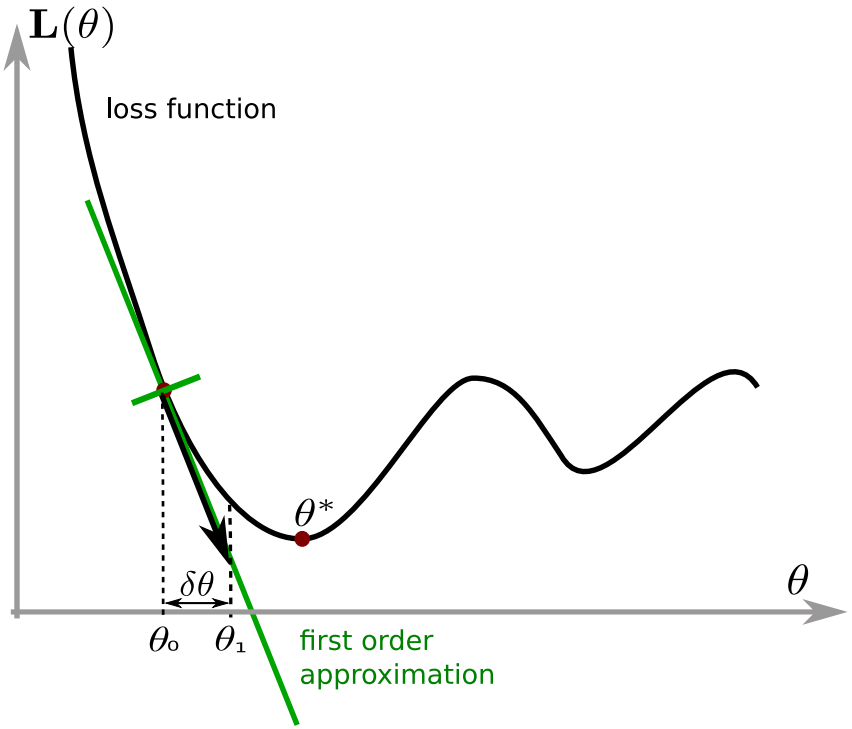
$$Loss^{IS}(\theta) = \mathbb{E}_t[\frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)}\hat{A}_\phi]$$

  where $\pi_{\theta_{old}}$ is the policy at the previous iteration

- Because $\nabla_\theta \log f(\theta)|_{\theta_{old}} = \frac{\nabla_\theta f(\theta)|_{\theta_{old}}}{f(\theta_{old})} = \nabla_\theta(\frac{f(\theta)}{f(\theta_{old})})|_{\theta_{old}}$

- Another view based on importance sampling
- See John Schulmann's Deep RL bootcamp lecture #5
  https://www.youtube.com/watch?v=SQtOI9jsrJ0 (8')

Trust region



- The gradient of a function is only accurate close to that function
- The gradient of the surrogate objective is only accurate close to the current policy π_θ
- Thus, when updated, the new policy must not move too far away from a "trust region" around the current policy

Kakade, S. & Langford, J. (2002) Approximately optimal approximate reinforcement learning. In *ICML*, volume 2, pages 267–274

Trust Region Policy Optimization

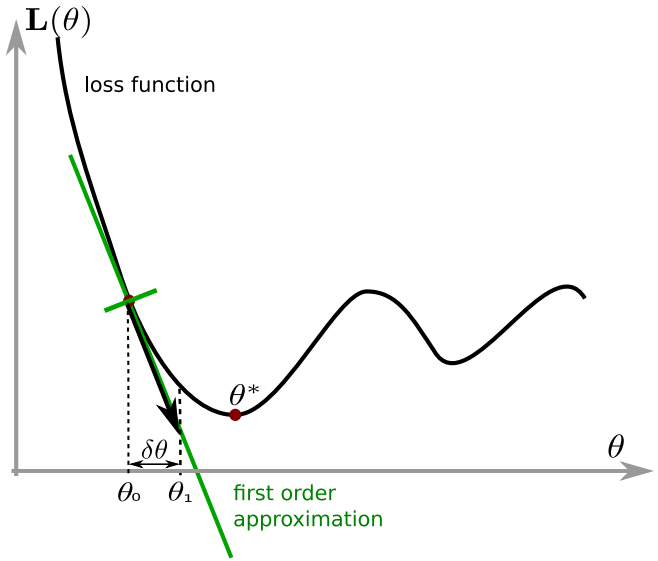
- Theory: monotonous improvement w.r.t. the cost function (Assumptions do not hold in practice)
- To ensure small steps, TRPO uses a natural gradient update instead of standard gradient
- Minimize Kullback-Leibler divergence to previous policy
-

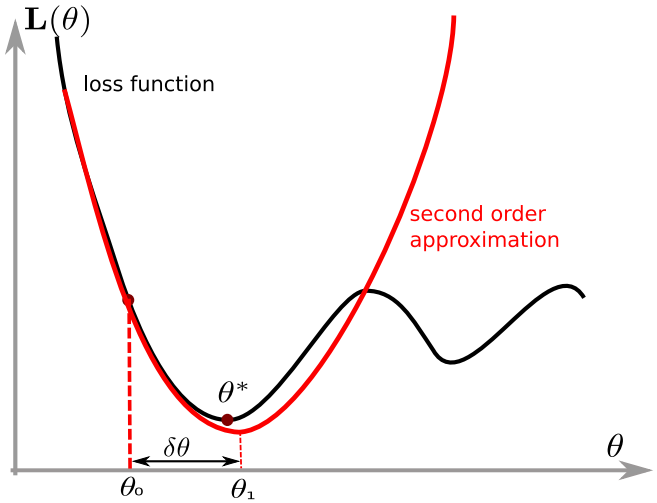
$$\max_{\theta} \mathbb{E}_t\left[\frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)} A_{\pi_{\theta_{old}}}(\mathbf{s}_t, \mathbf{a}_t)\right]$$

$$\text{subject to } \mathbb{E}_t[KL(\pi_{\theta_{old}}(.|\mathbf{s})||\pi_\theta(\mathbf{a}_t|\mathbf{s}_t))] \leq \delta$$

Schulman, J., Levine, S., Moritz, P., Jordan, M. I., & Abbeel, P. (2015) Trust Region Policy Optimization. *CoRR, abs/1502.05477*

First order versus second order derivative

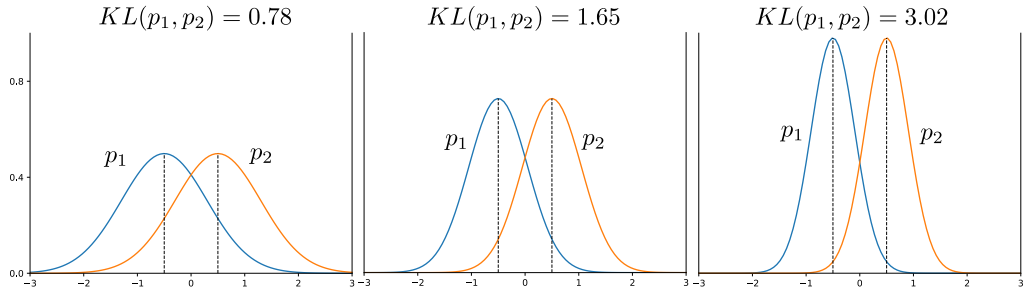




- In first order methods, need to define a step size
- Second order methods provide a more accurate approximation
- They also provide a true minimum, when the Hessian matrix is symmetric positive-definite matrix (SPD)
- In both cases, the derivative is very local
- The gradient should not be applied too far away from the current point

Pierrot, T., Perrin, N., & Sigaud, O. (2018) First-order and second-order variants of the gradient descent: a unified framework. *arXiv preprint arXiv:1810.08102*

Natural Policy Gradient



- One way to constrain to stochastic policies to stay close to each other is constraining the KL divergence
- Under KL constraint, it is easier to move further away when the variance is large
- Thus the mean policy converges first, then the variance is reduced
- Ensures a large enough amount of exploration noise
- Other properties listed in the Pierrot et al. (2018) paper
- In TRPO, optimization performed using a conjugate gradient method to avoid approximating the Fisher Information matrix

Sham M. Kakade. A natural policy gradient. In *Advances in neural information processing systems*, pp. 1531–1538, 2002

Advantage estimation

- To get $\hat{A}_\phi$, an empirical estimate of $V^\pi(s)$ is needed
- TRPO uses a MC estimate approach through regression, but constrains it (as for the policy):

$$\min_\phi \sum_{n=0}^{N} ||V_\phi(s_n) - V(s_n)||^2$$

$$\text{subject to } \frac{1}{N} \sum_{n=0}^{N} \frac{||V_\phi(s_n) - V_{\phi_{old}}(s_n)||^2}{2\sigma^2} \leq \epsilon$$

- Equivalent to a mean KL divergence constraint between V_ϕ and $V_{\phi_{old}}$

Properties

- Does not move far away from current policy, thus on-policy
- Key: use of line search to deal with the gradient step size
- More stable than DDPG, performs well in practice, but less sample efficient
- Conjugate gradient approach not provided in standard tensor gradient librairies, thus not much used
- Greater impact of PPO
- Related work: NAC, REPS


Jan Peters and Stefan Schaal. Natural actor-critic. *Neurocomputing*, 71 (7-9):1180–1190, 2008


Jan Peters, Katharina Mülling, and Yasemin Altun. Relative entropy policy search. In *AAAI*, pp. 1607–1612. Atlanta, 2010

ACKTR

- K-FAC: Kronecker Factored Approximated Curvature: efficient estimate of natural gradient
- Using block diagonal estimations of the Hessian matrix, to do better than first order
- ACKTR: TRPO with K-FAC natural gradient calculation
- But closer to actor-critic updates
- The per-update cost of ACKTR is only 10% to 25% higher than SGD
- Improves sample efficiency
- Not much excitement: less robust gradient approximation?

Yuhuai Wu, Elman Mansimov, Shun Liao, Roger Grosse, and Jimmy Ba (2017) Scalable trust-region method for deep reinforcement learning using Kronecker-factored approximation. *arXiv preprint arXiv:1708.05144*

Proximal Policy Optimization (Algorithm 1)

- The conjugate gradient method of TRPO is not available in deep learning libraries
- Same idea as TRPO, but uses a soft constraint on trust region rather than a hard one
- Instead of:

$$\max_{\theta} \mathbb{E}_t\left[\frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)} A_{\pi_{\theta_{old}}}(\mathbf{s}_t, \mathbf{a}_t)\right]$$

$$\text{subject to } \mathbb{E}_t[KL(\pi_{\theta_{old}}(.|s)||\pi_\theta(\mathbf{a}_t|\mathbf{s}_t))] \leq \delta$$

- Rather use:

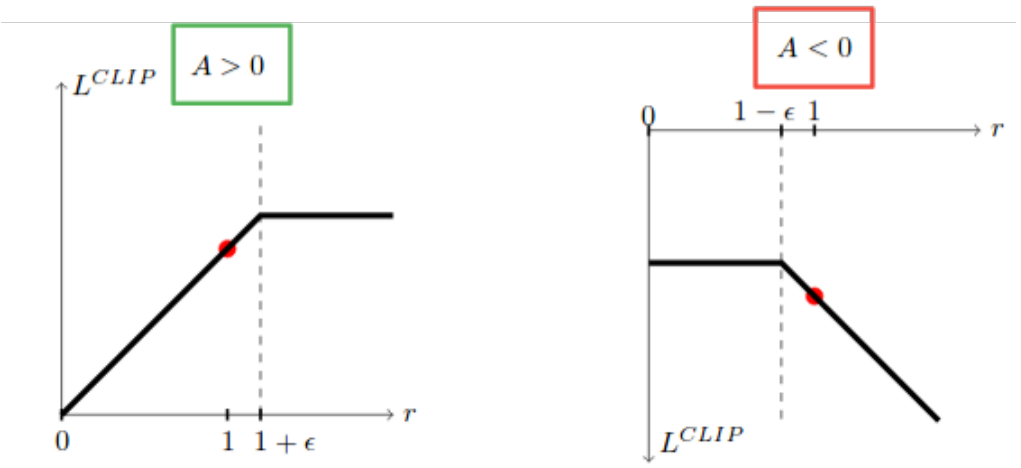
$$\max_{\theta} \mathbb{E}_{s\sim\rho, a\sim\pi}\left[\frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)} A_{\pi_{\theta_{old}}}(\mathbf{s}_t, \mathbf{a}_t)\right] - \beta \mathbb{E}_{s\sim\rho}[KL(\pi_{\theta_{old}}(.|\mathbf{s})||\pi_\theta(\mathbf{a}_t|\mathbf{s}_t))]$$

- Makes it possible to use SGD instead of conjugate gradient


Schulman, J., Wolski, F., Dhariwal, P., Radford, A., and Klimov, O. (2017). Proximal Policy Optimization Algorithms. arXiv preprint arXiv:1707.06347.


Heess, N., Sriram, S., Lemmon, J., Merel, J., Wayne, G., Tassa, Y., Erez, T., Wang, Z., Eslami, A., Riedmiller, M., et al. (2017) Emergence of locomotion behaviours in rich environments. *arXiv preprint arXiv:1707.02286*

Proximal Policy Optimization (Algorithm 2)



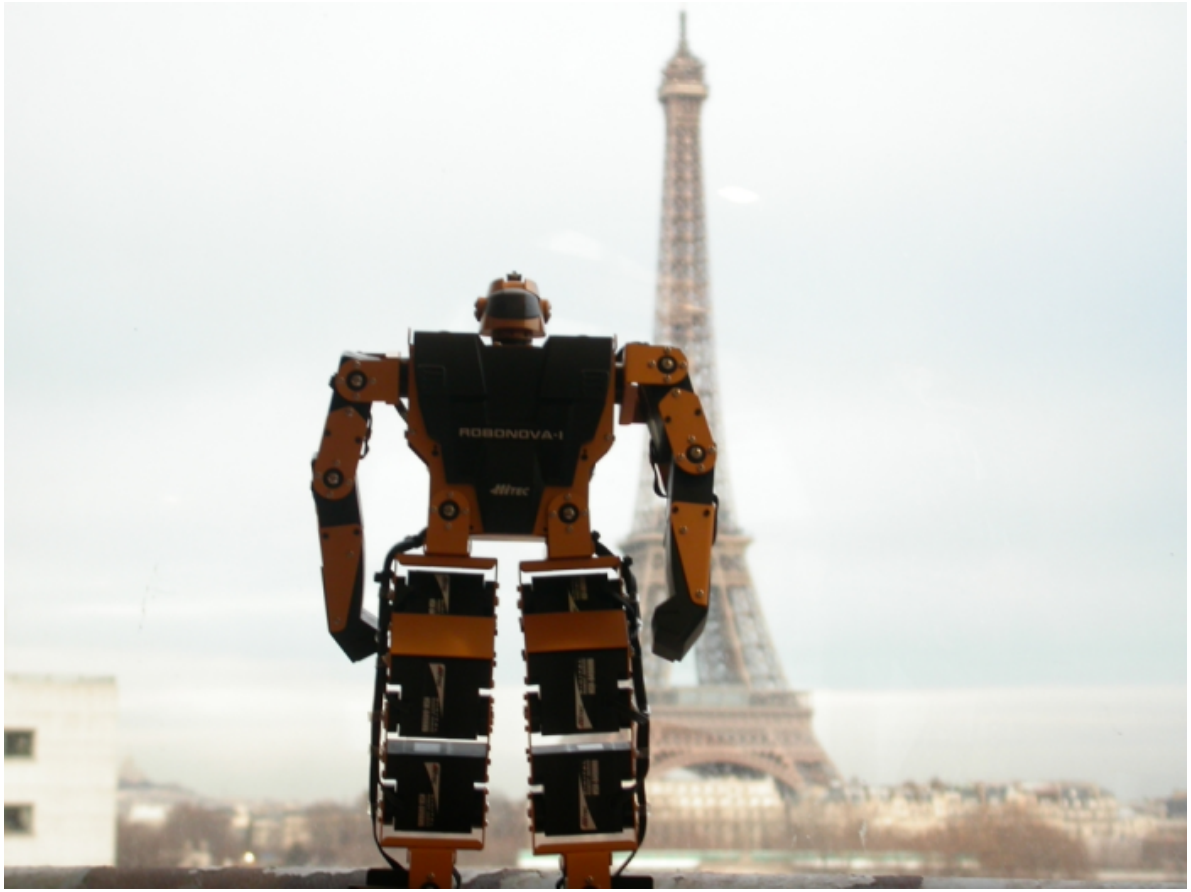
- $\frac{\pi_\theta(a|s)}{\pi_{\theta_{old}}(a|s)}$ may get huge if $\pi_{\theta_{old}}$ is very small
- Clipped importance sampling loss (clipping the surrogate objective)
- $$r_t(\theta) = \frac{\pi_\theta(\mathbf{a}_t|\mathbf{s}_t)}{\pi_{\theta_{old}}(\mathbf{a}_t|\mathbf{s}_t)}$$
- $$L^{CLIP}(\theta) = \mathbb{E}_t[min(r_t(\theta)\hat{A}_t, clip(r_t(\theta), 1-\epsilon, 1+\epsilon)\hat{A}_t)]$$
- Back-propagate $L^{CLIP}(\theta)$ through a policy network

PPO properties

- Uses N-step return instead of Monte Carlo: more step-based than TRPO
- Simpler implementation, better performance
- But still on-policy because π_θ and $\pi_{\theta_{old}}$ cannot differ much
- Massive parallel versions exist (a lot used by OpenAI)

Frans, K. & Hafner, D. (2016) Parallel trust region policy optimization with multiple actors.

Any question?



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