

Advanced Policy Gradient Methods: Natural Gradient, TRPO, and More

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Two Limitations of “Vanilla” Policy Gradient Methods

- ▶ Hard to choose stepsizes
 - ▶ Input data is nonstationary due to changing policy: observation and reward distributions change
 - ▶ Bad step is more damaging than in supervised learning, since it affects visitation distribution
 - ▶ Step too far \rightarrow bad policy
 - ▶ Next batch: collected under bad policy
 - ▶ Can't recover—collapse in performance
- ▶ Sample efficiency
 - ▶ Only one gradient step per environment sample
 - ▶ Dependent on scaling of coordinates

Reducing reinforcement learning to optimization

- ▶ Much of modern ML: reduce learning to numerical optimization problem
 - ▶ Supervised learning: minimize training error
- ▶ RL: how to *use all data so far and compute the best policy?*
 - ▶ Q-learning: can (in principle) include all transitions seen so far, however, we're optimizing the wrong objective
 - ▶ Policy gradient methods: yes stochastic gradients, but no optimization problem*
 - ▶ This lecture: write down an optimization problem that allows you to do a small update to policy π based on data sampled from π (*on-policy* data)

What Loss to Optimize?

- Policy gradients

$$\hat{g} = \hat{\mathbb{E}}_t \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \hat{A}_t \right]$$

- Can differentiate the following loss

$$L^{PG}(\theta) = \hat{\mathbb{E}}_t \left[\log \pi_{\theta}(a_t | s_t) \hat{A}_t \right].$$

but don't want to optimize it too far

- Equivalently differentiate

$$L_{\theta_{\text{old}}}^{IS}(\theta) = \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right].$$

at $\theta = \theta_{\text{old}}$, state-actions are sampled using θ_{old} . (IS = importance sampling)

Just the chain rule: $\nabla_{\theta} \log f(\theta) \big|_{\theta_{\text{old}}} = \frac{\nabla_{\theta} f(\theta) \big|_{\theta_{\text{old}}}}{f(\theta_{\text{old}})} = \nabla_{\theta} \left(\frac{f(\theta)}{f(\theta_{\text{old}})} \right) \big|_{\theta_{\text{old}}}$


Surrogate Loss: Importance Sampling Interpretation

- Importance sampling interpretation

$$\begin{aligned} & \mathbb{E}_{s_t \sim \pi_{\theta_{\text{old}}}, a_t \sim \pi_{\theta}} [A^{\pi}(s_t, a_t)] \\ &= \mathbb{E}_{s_t \sim \pi_{\theta_{\text{old}}}, a_t \sim \pi_{\theta_{\text{old}}}} \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} A^{\pi_{\theta_{\text{old}}}}(s_t, a_t) \right] \quad (\text{importance sampling}) \\ &= \mathbb{E}_{s_t \sim \pi_{\theta_{\text{old}}}, a_t \sim \pi_{\theta_{\text{old}}}} \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] \quad (\text{replace } A^{\pi} \text{ with estimator}) \\ &= L_{\theta_{\text{old}}}^{\text{IS}}(\theta) \end{aligned}$$

- Kakade et al.¹ and S. et al.² analyze how L^{IS} approximates the actual performance difference between θ and θ_{old} .
- In practice, L^{IS} is not much different than the logprob version $L^{\text{PG}}(\theta) = \hat{\mathbb{E}}_t \left[\log \pi_{\theta}(a_t | s_t) \hat{A}_t \right]$, for reasonably small policy changes.

¹S. Kakade and J. Langford. "Approximately optimal approximate reinforcement learning". *ICML*. 2002.

²J. Schulman, S. Levine, P. Moritz, M. I. Jordan, and P. Abbeel. "Trust Region Policy Optimization". *ICML (2015)*. 

Trust Region Policy Optimization

- ▶ Define the following trust region update:

$$\begin{aligned} & \underset{\theta}{\text{maximize}} && \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] \\ & \text{subject to} && \hat{\mathbb{E}}_t [\text{KL}[\pi_{\theta_{\text{old}}}(\cdot | s_t), \pi_{\theta}(\cdot | s_t)]] \leq \delta. \end{aligned}$$

- ▶ Also worth considering using a penalty instead of a constraint

$$\underset{\theta}{\text{maximize}} \quad \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] - \beta \hat{\mathbb{E}}_t [\text{KL}[\pi_{\theta_{\text{old}}}(\cdot | s_t), \pi_{\theta}(\cdot | s_t)]]$$

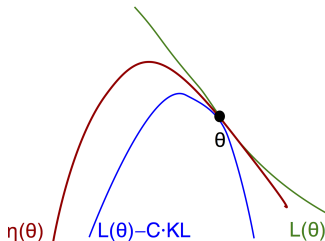
- ▶ Method of Lagrange multipliers: optimality point of δ -constrained problem is also an optimality point of β -penalized problem for some β .
- ▶ In practice, δ is easier to tune, and fixed δ is better than fixed β

Monotonic Improvement Result

- ▶ Consider KL penalized objective

$$\underset{\theta}{\text{maximize}} \quad \hat{\mathbb{E}}_t \left[\frac{\pi_{\theta}(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] - \beta \hat{\mathbb{E}}_t [\text{KL}[\pi_{\theta_{\text{old}}}(\cdot | s_t), \pi_{\theta}(\cdot | s_t)]]$$

- ▶ Theory result: if we use max KL instead of mean KL in penalty, then we get a lower (=pessimistic) bound on policy performance



Trust Region Policy Optimization: Pseudocode

- ▶ Pseudocode:

for iteration=1, 2, ... **do**

Run policy for T timesteps or N trajectories

Estimate advantage function at all timesteps

$$\begin{aligned} & \underset{\theta}{\text{maximize}} \quad \sum_{n=1}^N \frac{\pi_{\theta}(a_n | s_n)}{\pi_{\theta_{\text{old}}}(a_n | s_n)} \hat{A}_n \\ & \text{subject to} \quad \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) \leq \delta \end{aligned}$$

end for

- ▶ Can solve constrained optimization problem efficiently by using conjugate gradient
- ▶ Closely related to natural policy gradients (Kakade, 2002), natural actor critic (Peters and Schaal, 2005), REPS (Peters et al., 2010)

Solving KL Penalized Problem

- ▶ maximize $_{\theta} L_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) - \beta \cdot \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta})$
- ▶ Make linear approximation to $L_{\pi_{\theta_{\text{old}}}}$ and quadratic approximation to KL term:

$$\text{maximize}_{\theta} \quad g \cdot (\theta - \theta_{\text{old}}) - \frac{\beta}{2} (\theta - \theta_{\text{old}})^T F (\theta - \theta_{\text{old}})$$

$$\text{where} \quad g = \frac{\partial}{\partial \theta} L_{\pi_{\theta_{\text{old}}}}(\pi_{\theta})|_{\theta=\theta_{\text{old}}}, \quad F = \frac{\partial^2}{\partial^2 \theta} \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta})|_{\theta=\theta_{\text{old}}}$$

- ▶ Quadratic part of L is negligible compared to KL term
- ▶ F is positive semidefinite, but not if we include Hessian of L
- ▶ Solution: $\theta - \theta_{\text{old}} = \frac{1}{\beta} F^{-1} g$, where F is Fisher Information matrix, g is policy gradient. This is called the **natural policy gradient**³.

³S. Kakade. "A Natural Policy Gradient." *NIPS*. 2001.

Solving KL Constrained Problem

- ▶ Method of Lagrange multipliers: solve penalized problem to get $\theta^*(\beta)$. Then substitute $\theta^*(\beta)$ into original problem and solve for β .
- ▶ β only affects scaling of solution, not direction. Compute scaling as follows:
 - ▶ Compute $s = F^{-1}g$ (soln with $\beta = 1$)
 - ▶ Rescale $\theta - \theta_{\text{old}} = \alpha s$ so that constraint is satisfied. Quadratic approx $\overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) \approx \frac{1}{2}(\theta - \theta_{\text{old}})^T F(\theta - \theta_{\text{old}})$, so we want

$$\frac{1}{2}(\alpha s)^T F(\alpha s) = \delta$$
$$\alpha = \sqrt{2\delta / (s^T F s)}$$

- ▶ Even better, we can do a line search to solve the original *nonlinear* problem.

$$\text{maximize } L_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) - \mathbf{1}[\overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) \leq \delta]$$

Try $\alpha, \alpha/2, \alpha/4, \dots$ until line search objective improves

“Proximal” Policy Optimization: KL Penalty Version

- ▶ Use penalty instead of constraint

$$\underset{\theta}{\text{maximize}} \sum_{n=1}^N \frac{\pi_{\theta}(a_n | s_n)}{\pi_{\theta_{\text{old}}}(a_n | s_n)} \hat{A}_n - C \cdot \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta})$$

- ▶ Pseudocode:

for iteration=1, 2, ... **do**

Run policy for T timesteps or N trajectories

Estimate advantage function at all timesteps

Do SGD on above objective for some number of epochs

If KL too high, increase β . If KL too low, decrease β .

end for

- ▶ \approx same performance as TRPO, but only first-order optimization

Review

- ▶ Suggested optimizing surrogate loss L^{PG} or L^{IS}
- ▶ Suggested using KL to constrain size of update
- ▶ Corresponds to natural gradient step $F^{-1}g$ under linear quadratic approximation
- ▶ Can solve for this step approximately using conjugate gradient method

Connection Between Trust Region Problem and Other Things

$$\begin{aligned} & \underset{\theta}{\text{maximize}} \quad \sum_{n=1}^N \frac{\pi_{\theta}(a_n | s_n)}{\pi_{\theta_{\text{old}}}(a_n | s_n)} \hat{A}_n \\ & \text{subject to} \quad \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta}) \leq \delta \end{aligned}$$

- ▶ Linear-quadratic approximation + penalty \Rightarrow natural gradient
- ▶ No constraint \Rightarrow policy iteration
- ▶ Euclidean penalty instead of KL \Rightarrow vanilla policy gradient

Limitations of TRPO

- ▶ Hard to use with architectures with multiple outputs, e.g. policy and value function (need to weight different terms in distance metric)
- ▶ Empirically performs poorly on tasks requiring deep CNNs and RNNs, e.g. Atari benchmark
- ▶ CG makes implementation more complicated

Calculating Natural Gradient Step with KFAC

- ▶ Summary: do blockwise approximation to FIM, and approximate each block using a certain factorization
- ▶ Alternate expression for FIM as outer product (instead of second deriv. of KL):

$$\hat{\mathbb{E}}_t \left[\nabla_{\theta} \log \pi_{\theta}(a_t | s_t)^T \nabla_{\theta} \log \pi_{\theta}(a_t | s_t) \right]$$

Calculating Natural Gradient Step with KFAC

- ▶ Consider network with weight matrix W appearing once in network, with $y = Wx$. Then

$$\nabla_{W_{ij}} L = x_i \nabla_{y_j} L = x_i \bar{y}_j$$

$$F = \hat{\mathbb{E}}_t \left[\nabla_{W_{ij}} \log \pi_\theta(a_t | s_t)^T \nabla_{W_{ij}} \log \pi_\theta(a_t | s_t) \right]$$

$$F_{ij,i'j'} = \hat{\mathbb{E}}_t [x_i \bar{y}_j x_{i'} \bar{y}_{j'}]$$

- ▶ KFAC approximation:

$$F_{ij,i'j'} = \hat{\mathbb{E}}_t [x_i \bar{y}_j x_{i'} \bar{y}_{j'}] \approx \hat{\mathbb{E}}_t [x_i x_{i'}] \hat{\mathbb{E}}_t [\bar{y}_j \bar{y}_{j'}]$$

- ▶ Approximating Fisher block as tensor product $A \otimes B$, where A is $n_{in} \times n_{in}$ and B is $n_{out} \times n_{out}$. $(A \otimes B)^{-1} = A^{-1} \otimes B^{-1}$ and we can compute matrix-vector product without forming full matrix.
- ▶ Maintain running estimate of covariance matrices $\hat{\mathbb{E}}_t[x_i x_j]$, $\hat{\mathbb{E}}_t[\bar{y}_{i'} \bar{y}_{j'}]$ and periodically compute matrix inverses (small overhead)

ACKTR: Combine A2C with KFAC Natural Gradient

- ▶ Combined with A2C, gives excellent on Atari benchmark and continuous control from images⁴.
- ▶ Note: we're already computing $\nabla_{\theta} \log \pi_{\theta}(a_t | s_t)$ for policy gradient: no extra gradient computation needed
- ▶ Matrix inverses can be computed asynchronously
- ▶ Limitation: works straightforwardly for feedforward nets (including convolutions), less straightforward for RNNs or architectures with shared weights

⁴Y. Wu, E. Mansimov, S. Liao, R. Grosse, and J. Ba. "Scalable trust-region method for deep reinforcement learning using Kronecker-factored approximation". (2017).

Proximal Policy Optimization: KL Penalized Version

- ▶ Back to penalty instead of constraint

$$\underset{\theta}{\text{maximize}} \sum_{n=1}^N \frac{\pi_{\theta}(a_n | s_n)}{\pi_{\theta_{\text{old}}}(a_n | s_n)} \hat{A}_n - C \cdot \overline{\text{KL}}_{\pi_{\theta_{\text{old}}}}(\pi_{\theta})$$

- ▶ Pseudocode:

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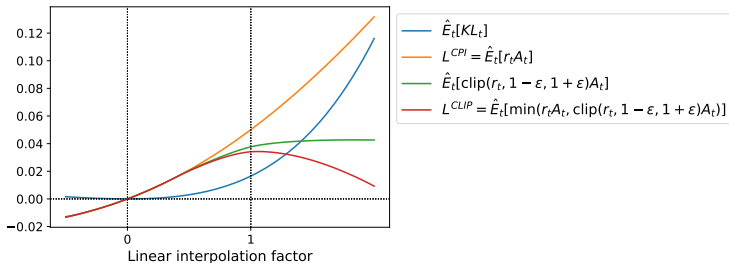
Proximal Policy Optimization: Clipping Objective

- Recall the surrogate objective

$$L^{IS}(\theta) = \hat{\mathbb{E}}_t \left[\frac{\pi_\theta(a_t | s_t)}{\pi_{\theta_{\text{old}}}(a_t | s_t)} \hat{A}_t \right] = \hat{\mathbb{E}}_t \left[r_t(\theta) \hat{A}_t \right]. \quad (1)$$

- Form a lower bound via clipped importance ratios

$$L^{CLIP}(\theta) = \hat{\mathbb{E}}_t \left[\min(r_t(\theta) \hat{A}_t, \text{clip}(r_t(\theta), 1 - \epsilon, 1 + \epsilon) \hat{A}_t) \right] \quad (2)$$



- Forms pessimistic bound on objective, can be optimized using SGD

Proximal Policy Optimization

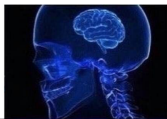
- ▶ Pseudocode:
 - for** iteration=1, 2, ... **do**
 - Run policy for T timesteps or N trajectories
 - Estimate advantage function at all timesteps
 - Do SGD on $L^{CLIP}(\theta)$ objective for some number of epochs
 - end for**
- ▶ A bit better than TRPO on continuous control, much better on Atari
- ▶ Compatible with multi-output networks and RNNs

Further Reading

- ▶ S. Kakade. "A Natural Policy Gradient." *NIPS*. 2001
- ▶ S. Kakade and J. Langford. "Approximately optimal approximate reinforcement learning". *ICML*. 2002
- ▶ J. Peters and S. Schaal. "Natural actor-critic". *Neurocomputing* (2008)
- ▶ J. Schulman, S. Levine, P. Moritz, M. I. Jordan, and P. Abbeel. "Trust Region Policy Optimization". *ICML* (2015)
- ▶ Y. Duan, X. Chen, R. Houthoofd, J. Schulman, and P. Abbeel. "Benchmarking Deep Reinforcement Learning for Continuous Control". *ICML* (2016)
- ▶ J. Martens and I. Sutskever. "Training deep and recurrent networks with Hessian-free optimization". *Springer*, 2012
- ▶ Z. Wang, V. Bapst, N. Heess, V. Mnih, R. Munos, et al. "Sample Efficient Actor-Critic with Experience Replay". (2016)
- ▶ Y. Wu, E. Mansimov, S. Liao, R. Grosse, and J. Ba. "Scalable trust-region method for deep reinforcement learning using Kronecker-factored approximation". (2017)
- ▶ J. Schulman, F. Wolski, P. Dhariwal, A. Radford, and O. Klimov. "Proximal Policy Optimization Algorithms". (2017)
- ▶ blog.openai.com: recent posts on baselines releases

That's all. Questions?

Vanilla Policy
Gradient



Natural Policy
Gradient



TRPO



ACKTR & PPO

