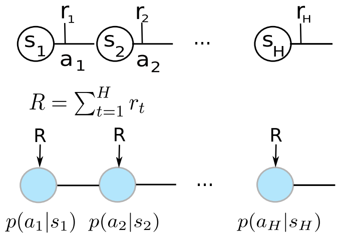
From Policy Gradient to Actor-Critic methods

Policy Gradient and Reward Weighted Regression

Olivier Sigaud

Sorbonne Université
http://people.isir.upmc.fr/sigaud

Reminder: the most basic PG algorithm



- Sample a set of trajectories from $\pi_{\boldsymbol{\theta}}$
- Compute:

$$Loss(\boldsymbol{\theta}) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{H} \log \pi_{\boldsymbol{\theta}}(\mathbf{a}_t^{(i)}|\mathbf{s}_t^{(i)}) R(\tau^{(i)}) \tag{1}$$

- Minimize the loss
- Iterate: sample again

Behavioral cloning

- Assume we have a set of expert trajectories,
- Data is a list of pairs $(\mathbf{s}_t^{(i)}, \mathbf{a}_t^{(i)})$, t is time, H is horizon, i is the trajectory index
- If the trajectories are optimal, a good option is behavioral cloning
- Use regression to find a policy $\pi_{\boldsymbol{\theta}}$ behaving as close as possible to data
- Use a validation set to avoid overfitting.
- If the policy $\pi_{\boldsymbol{\theta}}$ is deterministic, this amounts to minimizing the loss function:

$$Loss(\boldsymbol{\theta}) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{H}(\mathbf{a}_t^{(i)} - \pi_{\boldsymbol{\theta}}(\mathbf{s}_t^{(i)}))^2$$

- If the policy $\pi_{\boldsymbol{\theta}}$ is stochastic, a standard approach (among many others) consists in minimizing the log likelihood loss function:

$$Loss(\boldsymbol{\theta}) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{H}\log\pi_{\boldsymbol{\theta}}(\mathbf{a}_t^{(i)}|\mathbf{s}_t^{(i)})$$

Reward Weighted Regression

- Now, if the expert trajectories are not optimal
- Let $R(\tau)$ be the return of trajectory τ
- Still use regression, but weight each sample depending on the return of the corresponding trajectory.
- That is, imitate "more strongly" what is good in the batch than what is bad.
- Still use a validation set to avoid overfitting.
- If the policy $\pi_{\boldsymbol{\theta}}$ is deterministic, this amounts to minimizing the loss function:

$$Loss(\boldsymbol{\theta}) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{H}(\mathbf{a}_t^{(i)} - \pi_{\boldsymbol{\theta}}(\mathbf{s}_t^{(i)}))^2 R(\tau^{(i)})$$

- If the policy $\pi_{\boldsymbol{\theta}}$ is stochastic, we minimize the function:

$$Loss(\boldsymbol{\theta}) = -\frac{1}{m}\sum_{i=1}^{m}\sum_{t=1}^{H}\log\pi_{\boldsymbol{\theta}}(\mathbf{a}_t^{(i)}|\mathbf{s}_t^{(i)})R(\tau^{(i)}) \quad (2)$$

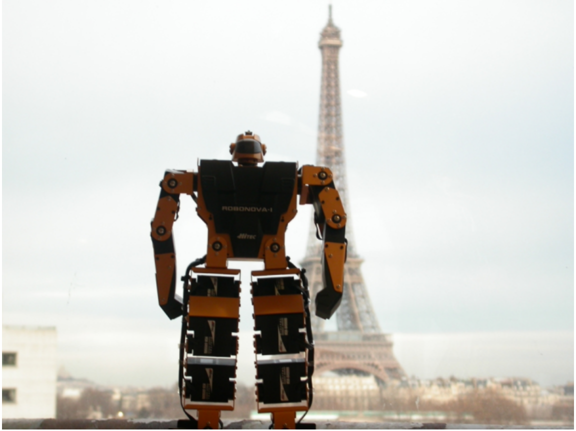
- Then we can iterate: generate new data from the new policy, and so on

PG = RWR !

- Equation (2) is the same as (1)!
- But wait, the basic PG algorithm is on-policy, and RWR uses expert data in the first step! What's happening?
- My guess: An on-policy algorithm will work under an off-policy regime if the behavioral samples are not worse than the current policy
- There also exists AWR, close to REINFORCE with $V(s)$ baseline, thus weight $= \hat{A}^{\pi}_{\boldsymbol{\phi}_j}(\mathbf{s}_t^{(i)}, \mathbf{a}_t^{(i)})$
- See my youtube video https://www.youtube.com/watch?v=ivONO2X-MHk
- And this blogpost for a wider perspective: Data-driven Deep Reinforcement Learning https://bair.berkeley.edu/blog/2019/12/05/bear/

Peng, X. B., Kumar, A., Zhang, G., and Levine, S. Advantage-weighted regression: Simple and scalable off-policy reinforcement learning. *arXiv preprint arXiv:1910.00177*, 2019

Any question?



Send mail to: `Olivier.Sigaud@upmc.fr`

Xue Bin Peng, Aviral Kumar, Grace Zhang, and Sergey Levine.
Advantage-weighted regression: Simple and scalable off-policy reinforcement learning.
arXiv preprint arXiv:1910.00177, 2019.