ETH zürich

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Project #8

Extending SHAC with Variance Reduction Techniques

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1 Introduction and Motivation

Actor-Critic algorithms have achieved notable success in RL, but challenges like sample inefficiency and gradient instability remain. In 2022, the SHAC (Short-Horizon Actor-Critic) algorithm[1] mitigates some issues through efficient parallel differentiable simulation and short optimization windows. We hypothesize further improvements are possible employing **variance reduction** such as td-λ, α-gradient and checkpoint gradients.

2 SHAC (Short Horizon Critic)

Main Idea:

- Split the task horizon H into sub-windows of smaller horizons h.
- Sample N multiple-different trajectories concurrently from a differentiable environment of length h at each step.

Result:

Less problems with local minimal and exploding/vanishing numerical gradient.

More efficient and faster training.

Actor Loss

$$L_\theta := -\frac{1}{Nh}\sum_{i=1}^{N}\left[\left(\sum_{t=t_0}^{t_0+h-1}\gamma^{t-t_0}r_t^i\right)+\gamma^h V_\phi(s_{t_0+h}^i)\right]$$

Critic Loss

$$\mathcal{L}_\phi = \mathop{\mathbb{E}}_{s\in\{\tau_i\}}\left[\|V_\phi(\mathbf{s})-\tilde{V}(\mathbf{s})\|^2\right]$$

td-λ

$$\tilde{V}(\mathbf{s}_t)=(1-\lambda)\left(\sum_{k=1}^{h-t-1}\lambda^{k-1}G_t^k\right)+\lambda^{h-t-1}G_t^{h-t}$$

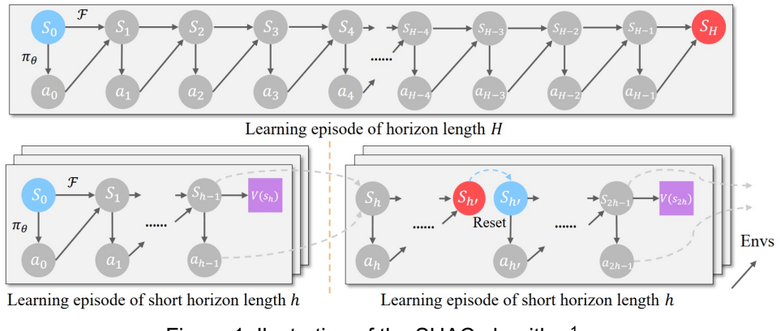


Figure 1: Illustration of the SHAC algorithm[1]

3a Method overview td-λ

Augments the Actor Loss L_θ with a td-λ formulation:

$$-\frac{1}{Nh}\sum_{i=1}^{N}\left[(1-\lambda)\left(\sum_{k=1}^{h-1}\lambda^{k-1}G_k^i\right)+\lambda^{h-1}G_h^i\right]$$

3b Method overview α-order gradient[2]

Policy with added Gaussian noise w_h:

$$V_h(\mathbf{s}_h,\mathbf{w}_{h:H},\boldsymbol{\theta})=\textstyle\sum_{h'=h}^{H}c_h(\mathbf{s}_{h'},\mathbf{u}_{h'}),$$
$$\text{s.t. } \mathbf{x}_{h'+1}=\phi(\mathbf{s}_{h'},\mathbf{u}_{h'}),\ \mathbf{u}_{h'}=\pi(\mathbf{s}_{h'},\boldsymbol{\theta})+\mathbf{w}_{h'},\ h'\geq h$$

Let the α-order gradient be a comb. of 0th and 1th grad:

$$\bar{\nabla}^{[\alpha]}F(\boldsymbol{\theta})=\alpha\bar{\nabla}^{[1]}F(\boldsymbol{\theta})+(1-\alpha)\bar{\nabla}^{[0]}F(\boldsymbol{\theta})$$

$$\hat{\nabla}^{[0]}F_i(\boldsymbol{\theta}):=\frac{1}{\sigma^2}\left[V_1(\mathbf{s}_1,\mathbf{w}_{1:H}^i,\boldsymbol{\theta})-b\right]\left[\sum_{h=1}^{H}\mathrm{D}_{\boldsymbol{\theta}}\pi(\mathbf{s}_h^i,\boldsymbol{\theta})^\intercal\mathbf{w}_h^i\right]$$

0th order grad, , τ_i

$$\hat{\nabla}^{[1]}F_i(\boldsymbol{\theta}):=\nabla_{\boldsymbol{\theta}}V_1(\mathbf{s}_1,\mathbf{w}_{1:H}^i,\boldsymbol{\theta})$$

1th order grad, τ_i

α minimizing variance

$$\min_{\alpha\in[0,1]}\ \alpha^2\hat{\sigma}_1^2+(1-\alpha)^2\hat{\sigma}_0^2$$
$$\text{s.t. }\ \epsilon+\alpha\underbrace{\|\bar{\nabla}^{[1]}F-\bar{\nabla}^{[0]}F\|}_{B}\leq\gamma$$

Express the Actor Loss L_θ as objective F_θ, use α-gradient:

$$-\frac{1}{Nh}\sum_{i=1}^{N}\left[\left(\sum_{t=t_0}^{t_0+h-1}\gamma^{t-t_0}R(s_t^i,a_t^i)\right)+\gamma^h V_\phi(s_{t_0+h}^i)\right]\cong\mathbb{E}_{\mathbf{s}_{t_0}\sim\rho}\mathbb{E}_{\mathbf{w}_h\overset{\text{iid}}{\sim}p}V_{t_0}(\mathbf{s}_{t_0},\mathbf{w}_{t_0:t_0+h},\boldsymbol{\theta})$$

$(Def)\ F_\theta$

3c Method overview checkpoint gradients

Checkpoint gradients reduce variance in gradient estimation by periodically storing full-batch gradient computations and using them to update gradients efficiently.

General Framework:

$$x_{t+1}=x_t-\alpha h_t,\qquad t=1,\ldots,T,$$

where

$$h_t=\begin{cases}\frac{1}{D}\sum_{i=1}^{D}\nabla f(x_t;\xi_t^i), & \text{if } t\equiv 0 \pmod{Q};\\ (1-\eta)\left(h_{t-1}-\frac{1}{S}\sum_{i=1}^{S}\nabla f(x_{t-1};\xi_t^i)\right)+\frac{1}{S}\sum_{i=1}^{S}\nabla f(x_t;\xi_t^i), & \text{otherwise.}\end{cases}$$

4 Experiments

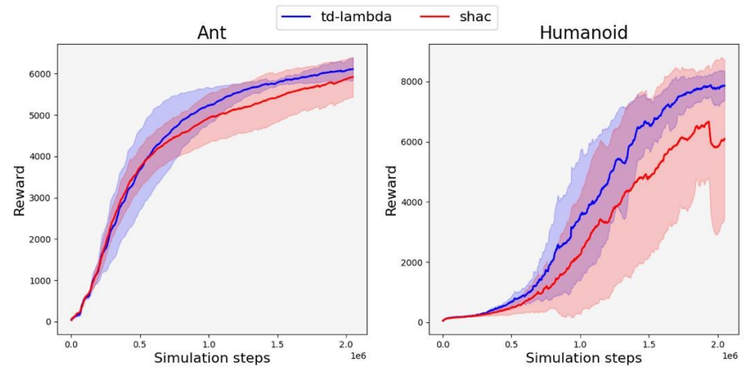
Experimental Environment

- Differentiable simulator: Dflex simulator[4]
- Environments: Ant, Humanoid, SNUHumanoid (RL Games)[3]

Parameters

- Fixed Stochastic Model, #Actors = 64, #Simulations Steps = 1000, Window Length = 32, γ = 0.99.

5 Results



6 Further Extensions

- Same number of Actors between all methods
- Verify scaling on number of environments
- Combine the methods
- 0th order method only

References

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4. GitHub - NVlabs/DiffRL: [ICLR 2022] Accelerated Policy Learning with Parallel DifferentiableSimulation — github.com. https://github.com/NVlabs/DiffRL, . [Accessed 28-03-2024]
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