Stochastic Variance-Reduced Policy Gradient

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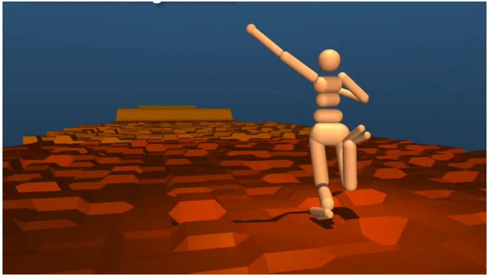
Outline

Stochastic Variance-Reduced (Policy) Gradient

- **SVRG** for Reinforcement Learning
  - Motivation
  - Challenges
- **SVRPG**
  - Convergence Properties
  - Heuristics
  - Experiments

Policy Gradient

An effective **Reinforcement Learning (RL)** solution to **continuous** control problems:

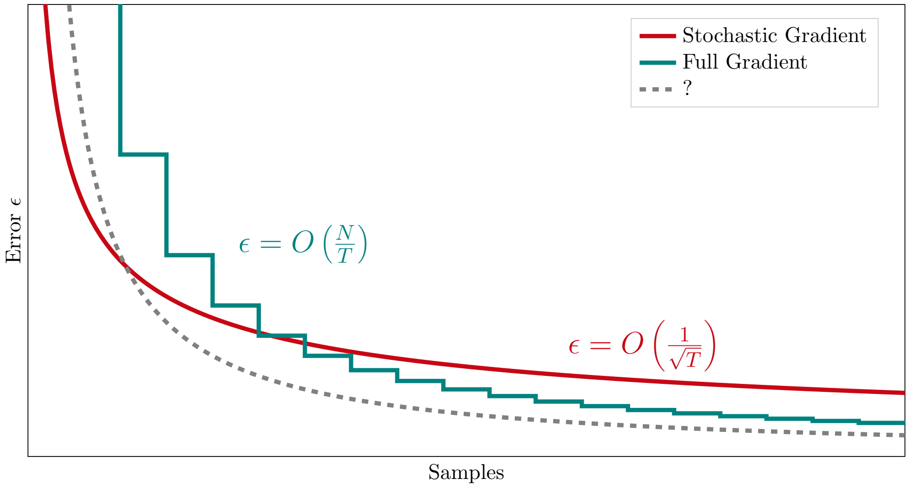


Robotics (Heess et al., 2017)

Video games (OpenAI, 2018)

Mostly based on **Stochastic Gradient Ascent** (Robbins and Monro, 1951)

Full vs Stochastic Gradient
Non-convex optimization



Can we do something better?

A solution from **finite-sum optimization**:

$$\underbrace{\blacktriangledown J(\boldsymbol{\theta})}_{\text{SVRG estimator}} = \underbrace{\nabla J(\widetilde{\boldsymbol{\theta}})}_{\text{FG in snapshot parameter}} + \underbrace{\nabla J(\boldsymbol{\theta})\big|_{\tau_i}}_{\text{SG in current parameter}} - \underbrace{\nabla J(\widetilde{\boldsymbol{\theta}})\big|_{\tau_i}}_{\text{Correction term}}$$

- Unbiased
- Linear convergence
- More data-efficient than FG
- Easily applicable to **Supervised Learning (SL)**

Not trivial! There are three **challenges**:

1. **Non-concavity** of $J(\boldsymbol{\theta})$ (Allen-Zhu and Hazan, 2016; Reddi et al., 2016)
2. **Infinite dataset**: we would need *infinite samples* to compute FG (Harikandeh et al., 2015; Bietti and Mairal, 2017)
3. **Non-stationarity**: $\tau \sim p_{\boldsymbol{\theta}}$ (new!)

RL so far: *policy evaluation* (Du et al., 2017) and *off-policy control* (Xu et al., 2017)

Our work: **on-policy control**

$$\underbrace{\blacktriangledown J(\boldsymbol{\theta})}_{\text{SVRPG estimator}} = \underbrace{\widehat{\nabla}_N J(\widetilde{\boldsymbol{\theta}})}_{\substack{\text{Large N}\\ \text{to approximate FG}}} + \underbrace{\widehat{\nabla}_B J(\boldsymbol{\theta})}_{B<<N} - \underbrace{\omega(\boldsymbol{\theta}, \widetilde{\boldsymbol{\theta}})\widehat{\nabla}_B J(\widetilde{\boldsymbol{\theta}})}_{\substack{\text{Importance weighting}\\ \text{for non-stationarity}}}$$

- Unbiased
- More data-efficient than FG

Convergence Properties

Convergence to **local** optimum:

$$\mathbb{E}\left[\left\|\nabla J(\boldsymbol{\theta})\right\|^2\right] \leq \frac{J(\boldsymbol{\theta}^*) - J(\boldsymbol{\theta}_0)}{\psi T} + \underbrace{\frac{\zeta}{N}}_{\text{Infinite dataset}} + \underbrace{\frac{\xi}{B}}_{\text{Nonstationarity}}$$

- Linear convergence + error (similar to Harikandeh et al., 2015)

Heuristics

Meta-parameter selection

- **Adaptive step size**: two ADAM annealing schedules

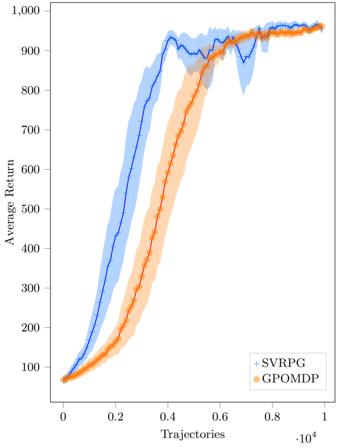
$$\underbrace{\alpha_{FG}}_{\text{used at the snapshot}} \qquad \underbrace{\alpha_{SG}}_{\text{used inside epoch}}$$

- **Adaptive epoch size**: take new snapshot when the effective step size becomes too small

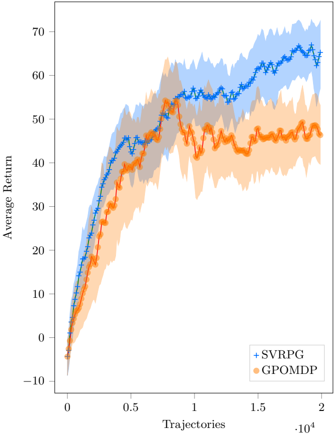
$$\frac{\alpha_{SG}}{B} < \frac{\alpha_{FG}}{N} \implies \textbf{snapshot}$$

Results

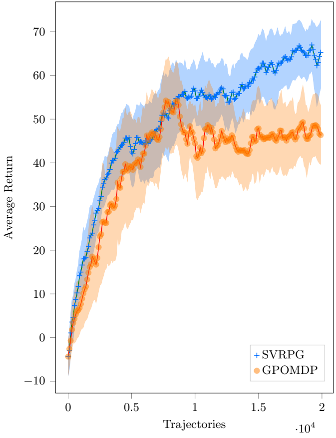
Cart-Pole



Swimmer



Half-Cheetah



Conclusions

- Efficient policy optimization is challenging
- **SVRPG**: on-policy control based on SVRG
- Meta-parameters still crucial to tame different sources of variance
- Future work: adaptive batch size, natural gradient, actor-critic

Thank you for your attention

- Poster: today 06:15 – 09:00 PM @ **Hall B #65**
- Contact: `matteo.papini@polimi.it`
- Online resources: `t3p.github.io`

References

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Adaptive Step Size

Adaptive Epoch Size

Normalized Importance Weights

Actor-Critic SVRPG

The Full Comparison