

Optimization with Markovian Noise

First Order Methods

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Introduction

Problem statement

We study the minimization problem

$$\min_{x \in \mathbb{R}^d} f(x) := \mathbb{E}_{Z \sim \pi}[F(x, Z)] \quad (1)$$

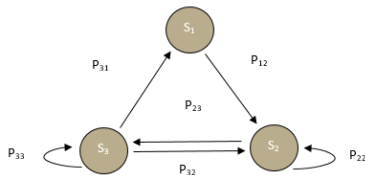
Where Z is a Markov Chain.

Introduction

Quick intro to Markov Chains

Initial State	Succeeding State		
	S_1	S_2	S_3
S_1	0	P_{12}	0
S_2	0	P_{22}	P_{23}
S_3	P_{31}	P_{32}	P_{33}

Transition Matrix

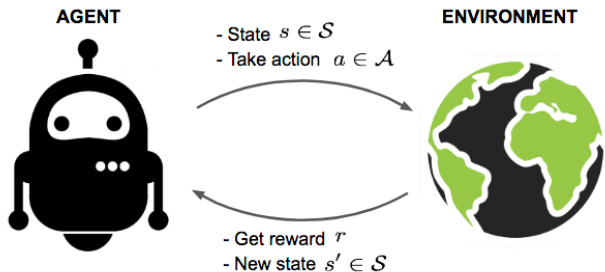


Transition Diagram

Introduction

Motivation

...Reinforcement Learning...



Our research aims to expand the results of [1].

Following the article, we consider additional assumptions:

- (A1,A2) f is (μ, L) -smooth.
- (A3) Z is uniformly geometrically ergodic with mixing time τ .
- (A4) F is (σ, δ) -bounded:

$$\|\nabla F(x, Z) - \nabla f(x)\|^2 < \sigma^2 + \delta^2 \|\nabla f(x)\|^2$$

The main result of [1] is the following

Theorem. Under A1-A4 the problem (1) can be solved (in terms of $\mathbb{E} [\|x^{(k)} - x^*\|^2] \leq \varepsilon$) in

$$\tilde{\mathcal{O}} \left(\tau \left[(1 + \delta^2) \sqrt{\frac{L}{\mu}} \log \frac{1}{\varepsilon} + \frac{\sigma^2}{\mu^2 \varepsilon} \right] \right) \text{ oracle calls.} \quad (2)$$

And the bound is tight for $\delta = 1$.

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Our Contribution

Main Results

Our main focus is on the optimality of the bound (2).

Summary of the interim results:

① For $\delta = 1$ the bound is tight. (**Theorem**, [1])

② For $\delta > 1$ the bound is tight. (**New**)

The proof generalizes the previous result but keeps the main idea.

③ For $\delta < \frac{\mu}{4L}$ and $\sigma = 0$ the bound is **not** tight. (**New**)

For now, we have an upper bound of $\tilde{\mathcal{O}}\left(\frac{L}{\mu} \log \frac{1}{\varepsilon}\right)$ oracle calls which is better than (2) if τ is large.

Our Contribution

Future work

Our main goal is to determine the algorithmic complexity of the problem. To do so, we need to eliminate the gaps between the lower and upper bounds:

- 1 For $\delta < \frac{\mu}{4L}$ we believe that the upper bound can be improved using Nesterov acceleration [2].
- 2 For $\frac{\mu}{4L} < \delta < 1$ current methods are not working and more research is needed.

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Bibliography I

- [1] Aleksandr Beznosikov et al. *First Order Methods with Markovian Noise: from Acceleration to Variational Inequalities*. 2023. arXiv: 2305.15938 [math.OC].
- [2] Yurii Nesterov. “A method for solving the convex programming problem with convergence rate $O(1/k^2)$ ”. In: *Proceedings of the USSR Academy of Sciences* 269 (1983), pp. 543–547.