

The Complexity of Making the Gradient Small in Stochastic Convex Optimization

Dylan J. Foster¹

MIT

Ayush Sekhari²

Cornell University

Ohad Shamir³

Weizmann Institute

Nathan

Srebro⁴⁵⁶TTI

Chicago

Karthik Sridharan[¶]

Cornell University

Blake Woodworth^{||}

TTI Chicago

Abstract

We give nearly matching upper and lower bounds on the oracle complexity of finding φ -stationary points ($\|\nabla F(x)\| \leq \varphi$) in stochastic convex optimization. We jointly analyze the oracle complexity in both the local stochastic oracle model and the global oracle (or, statistical learning) model. This allows us to decompose the complexity of finding near-stationary points into *optimization complexity* and *sample complexity*, and reveals some surprising differences between the complexity of stochastic optimization versus learning. Notably, we show that in the global oracle/statistical learning model, only *logarithmic dependence on smoothness* is required to find a near-stationary point, whereas polynomial dependence on smoothness is necessary in the local stochastic oracle model. In other words, the separation in complexity between the two models can be exponential, and that the folklore understanding that smoothness is required to find stationary points is only weakly true for statistical learning.

Our upper bounds are based on extensions of a recent “recursive regularization” technique proposed by [Allen-Zhu \(2018\)](#). We show how to extend the technique to achieve near-optimal rates, and in particular show how to leverage the extra information available in the global oracle model. Our algorithm for the global model can be implemented efficiently through finite sum methods, and suggests an interesting new computational-statistical tradeoff.

1 Introduction

Success in convex optimization is typically defined as finding a point whose value is close to the minimum possible value. *Information-based complexity* of optimization attempts to understand the minimal amount of effort required to reach a desired level of suboptimality under different oracle models for access to the function ([Nemirovski and Yudin, 1983](#); [Traub et al., 1988](#)). This complexity—for both deterministic and stochastic convex optimization—is tightly understood across a wide variety of settings ([Nemirovski and Yudin, 1983](#); [Traub et al., 1988](#); [Agarwal et al., 2009](#); [Braun et al., 2017](#)), and efficient algorithms that achieve optimal complexity are well known.

Deterministic
First-Order Oracle

Sample
Complexity

Stochastic
First-Order Oracle

¹ dylanf@mit.edu

² sekhari@cs.cornell.edu

³ ohad.shamir@weizmann.ac.il

⁴ nati@ttic.edu

⁵ sridharan@cs.cornell.edu

⁶ blake@ttic.edu

Upper: Lower:	$\tilde{O}\left(\sqrt{\frac{HR}{\epsilon}}\right)$ Nesterov (2012)	$O\left(\frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{HR}{\epsilon}\right)\right)$ (Corollary 2)	$\tilde{O}\left(\sqrt{\frac{HR}{\epsilon}} + \frac{\sigma^2}{\epsilon^2}\right)$ (Corollary 1)
	$\left(\sqrt{\frac{HR}{\epsilon}}\right)$ (2017b)	$\Omega\left(\frac{\sigma^2}{\epsilon^2}\right)$ Theorem 4	$\Omega\left(\sqrt{\frac{HR}{\epsilon}} + \frac{\sigma^2}{\epsilon^2} \log\left(\frac{HR}{\epsilon}\right)\right)$ Theorem 2
		Carmon et al.	

Table 1: Upper and lower bounds on the complexity of finding x such that $\|\nabla F(x)\| \leq \varrho$ for convex problems

with H -Lipschitz gradients, where σ^2 is a bound on the variance of gradient estimates.

Recently, there has been a surge of interest in optimization for *non-convex* functions. In this case, finding a point with near-optimal function value is typically intractable under standard assumptions—both computationally and information-theoretically. For this reason, a standard task in non-convex optimization is to find an ϱ -stationary point, i.e., a point where the gradient is small ($\|\nabla F(x)\| \leq \varrho$).

In stochastic non-convex optimization, there has been a flurry of recent research on algorithms with provable guarantees for finding near-stationary points (Ghadimi and Lan, 2013, 2016; Reddi et al., 2016; Allen-Zhu, 2017; Lei et al., 2017; Jin et al., 2017; Zhou et al., 2018; Fang et al., 2018). However, the stochastic oracle complexity of finding near-stationary points is not yet well understood, so we do not know whether existing algorithms are optimal, or how we hope to improve upon them.

Recent work by [Carmon et al. \(2017a,b\)](#) establishes tight bounds on the *deterministic* first-order oracle complexity of finding near-stationary points of smooth functions, both convex and non-convex. For convex problems, they prove that accelerated gradient descent is optimal both for finding approximate minimizers and approximate stationary points, while for non-convex problems, gradient descent is optimal for finding approximate stationary points. The picture is simple and complete: the same deterministic first-order methods that are good at finding approximate minimizers are also good at finding approximate stationary points, even for non-convex functions.

However, when one turns their attention to the *stochastic* oracle complexity of finding near-stationary points, the picture is far from clear. Even for *stochastic convex optimization*, the oracle complexity is not yet well understood. This paper takes a first step toward resolving the general case by providing nearly tight upper and lower bounds on the oracle complexity of finding near-stationary points in stochastic convex optimization, both for first-order methods and for global (i.e., statistical learning) methods. At first glance, this might seem trivial, since exact minimizers are equivalent to exact stationary points for convex functions. When it comes to finding *approximate* stationary points the situation is considerably more complex, and the equivalence does not yield optimal quantitative rates. For example, while the stochastic gradient descent

(SGD) is (worst-case) optimal for stochastic convex optimization with a first-order oracle, it appears to be far from optimal for finding near-stationary points.

1.1 Contributions

We present a nearly tight analysis of the local stochastic oracle complexity and global stochastic oracle complexity (“sample complexity”) of finding approximate stationary points in stochastic convex optimization. Briefly, the highlights are as follows:

- We give upper and lower bounds on the local and global stochastic oracle complexity that match upto log factors. In particular, we show that the local stochastic complexity of finding stationary points is (up to log factors) characterized as the sum of the deterministic oracle complexity and the sample complexity.
- As a consequence of this two-pronged approach, we show that the gap between local stochastic complexity and sample complexity of finding near-stationary points is at least *exponential* in the smoothness parameter.
- We obtain the above results through new algorithmic improvements. We show that the recursive regularization technique introduced by [Allen-Zhu \(2018\)](#) for local stochastic optimization can be combined with empirical risk minimization to obtain *logarithmic* dependence on smoothness in the global model, and that the resulting algorithms can be implemented efficiently.

Complexity results are summarized in [Table 1](#). Here we discuss the conceptual contributions in more detail.

Decomposition of stochastic first-order complexity. For stochastic optimization of convex functions, there is a simple and powerful connection between three oracle complexities: Deterministic, local stochastic, and global stochastic. For many well-known problem classes, the stochastic first-order complexity is equal to the sum (equivalently, maximum) of the deterministic first-order complexity and the sample complexity. This decomposition of the local stochastic complexity into an “optimization term” plus a “statistical term” inspires optimization methods, guides analysis, and facilitates comparison of different algorithms. It indicates that “one pass” stochastic approximation algorithms like SGD are optimal for stochastic optimization in certain parameter regimes, so that we do not have to resort to sample average approximation or methods that require multiple passes over data.

We establish that the same decomposition holds for the task of finding approximate stationary points. Such a characterization should not be taken for granted, and it is not clear a priori that it should hold for finding stationary points. Establishing the result requires both developing new algorithms with near-optimal sample complexity in the global model, and improving previous local stochastic methods ([Allen-Zhu, 2018](#)) to match the optimal deterministic complexity.

Gap between sample complexity and stochastic first-order complexity. For non-smooth convex objectives, finding an approximate stationary point can require finding an *exact* minimizer of the function (consider the absolute value function). Therefore, as one would expect, the deterministic and stochastic firstorder oracle complexities for finding near-stationary points scale polynomially with the smoothness constant, even in low dimensions. Ensuring an approximate stationary point is impossible for non-smooth instances, even with an unbounded number of first-order oracle accesses. Surprisingly, we show that the sample complexity depends at most logarithmically on the smoothness. In fact, in one dimension the dependence on smoothness can be removed entirely.

Improved methods. Our improved sample complexity results for the global stochastic oracle/statistical learning model are based on a new algorithm which uses the *recursive regularization* (or, “SGD3”) approach introduced by [Allen-Zhu \(2018\)](#). The methods iteratively solves a sequence of subproblems via regularized empirical risk minimization (RERM). Solving subproblems through RERM allows the method to exploit global access to the stochastic samples. Since the method enjoys only logarithmic dependence on smoothness (as well as initial suboptimality or distance to the optimum), it provides a better alternative to *any* stochastic first-order method whenever the smoothness is large relative to the variance in the gradient estimates. Since RERM is a finite-sum optimization problem, standard finite-sum optimization methods can be used to implement the method efficiently; the result is that we can beat the sample complexity of stochastic first-order methods with only modest computational overhead.

For the local stochastic model, we improve the SGD3 method of [Allen-Zhu \(2018\)](#) so that the “optimization”

term matches the optimal deterministic oracle complexity of the initial distance to the optimum (the “radius” of the problem), $F(x_0) - F(x^*)$. This leads to a quadratic improvement in terms $\|x_0 - x^*\|$. We also extend the analysis

to the setting where initial sub-optimality $*$ is bounded but not the radius—a common setting in the analysis of non-convex optimization algorithms and a setting in which recursive regularization was not previously analyzed.

2 Setup

We consider the problem of finding an ϱ -stationary point in the stochastic convex optimization setting.

That is, for a convex function $F: \mathbb{R}^d \mapsto \mathbb{R}$, our goal is to find a point $x \in \mathbb{R}^d$ such that $\|\nabla F(x)\| \leq \varrho$, (1)

given access to F only through an *oracle*.⁷ Formally, the problem is specified by a class of functions to which F belongs, and through the type of oracle through which we access F . We outline these now.

Function classes. Recall that $F: \mathbb{R}^d \rightarrow \mathbb{R}$ is said to H -smooth if

$$F(y) \leq F(x) + \langle \nabla F(x), y - x \rangle + \frac{H}{2} \|y - x\|^2 \quad \forall x, y \in \mathbb{R}^d, \quad (2)$$

and is said to be λ -strongly-convex if

$$F(y) \geq F(x) + \langle \nabla F(x), y - x \rangle + \frac{\lambda}{2} \|y - x\|^2 \quad \forall x, y \in \mathbb{R}^d. \quad (3)$$

⁷ Here, and for the rest of the paper, $\|\cdot\|$ is taken to be the Euclidean norm.

We focus on two classes of objectives, both of which are defined relative to an arbitrary initial point x_0 provided to the optimization algorithm.

1. *Domain-bounded functions.*

$$\mathbb{F}^{\text{DB}_d}[H, \lambda; R] = \left\{ F : \mathbb{R}^d \rightarrow \mathbb{R} \mid \begin{array}{l} F \text{ is } \lambda\text{-smooth and } \\ F \text{ is } H\text{-strongly convex} \end{array} \right\}$$

$$\mathbb{F}^{\text{DB}_d}[H, \lambda; R] = \left\{ F : \mathbb{R}^d \rightarrow \mathbb{R} \mid \begin{array}{l} \text{R} \ni x_0 \in \arg\min_x F(x) \neq \emptyset \text{ s.t. } \|x_0 - x^*\| \leq R \\ F \text{ is } \lambda\text{-smooth and } F \text{ is } H\text{-strongly convex} \end{array} \right\} \quad (4)$$

2. *Range-bounded functions.*

$$\mathbb{F}^{\text{RB}}[H, \lambda; \Delta] = \left\{ F : \mathbb{R}^d \rightarrow \mathbb{R} \mid \begin{array}{l} F \text{ is } \lambda\text{-smooth and } \\ \arg\min_x F(x) \neq \emptyset \\ F(x_0) = \min_x F(x) \\ -(\lambda, H)\text{-strongly convex} \end{array} \right\} \quad (5)$$

We emphasize that while the classes are defined in terms of a strong convexity parameter, our main complexity results concern the non-strongly convex case where $\lambda = 0$. The strongly convex classes are used for intermediate results. We also note that our main results hold in arbitrary dimension, and so we drop the superscript d except when it is pertinent to discussion.

Oracle classes. An oracle accepts an argument $x \in \mathbb{R}^d$ and provides (possibly noisy/stochastic) information about the objective F around the point x . The oracle's output belongs to an *information space* \mathcal{I} . We consider three distinct types of oracles:

1. Deterministic first-order oracle. Denoted $\text{FO} = \nabla F$, with $\nabla F : \mathbb{R}^d \rightarrow \mathbb{R}^d$. When queried at a point

$$x \in \mathbb{R}^d, \text{ with } \mathcal{I} \subseteq \mathbb{R}^d \quad \text{over } \nabla f, \text{ with } \mathcal{I} \subseteq \mathbb{R}^d \quad \text{and returns } \mathbb{E}_{z \sim \mathcal{D}}[\nabla f(x; z)] \quad \in \mathbb{R}^d, \text{ the oracle draws an } x \in \mathbb{R}^d, \text{ the oracle draws an } z \sim \mathcal{D}$$

oracle returns

$$\text{FO}(x) = (F(x), \nabla F(x)). \quad (6)$$

2. Stochastic first-order oracle. Denoted $\text{OD}_2(\mathcal{Z})$. The oracle is specified by a function $x: \mathcal{Z} \rightarrow \mathcal{X}$ and a distribution \leq with the property that $\text{and}(\sigma)$. When queried at a point $z \sim D$

$$\mathbf{O}_{\nabla f}(x) = (f(x; z), \nabla f(x; z))_{z \sim \mathbf{D}}. \quad (7)$$

3. Stochastic global oracle. Denoted OD2^{σ} , with $\text{ZI} \subseteq (\mathbb{R}^d \mapsto \mathbb{R})$. The oracle is specified by a function $f : \mathbb{R}^d \times \mathcal{Z} \rightarrow \mathbb{R}$ and a distribution $\sup_x [\mathbb{E}_{z \sim \mathcal{D}} [\|\nabla f(x; z) - F(x)\|^2]]$

$$f^\sigma(x) = (f^\sigma(\cdot, z))_{z \sim \mathcal{D}}$$

\mathcal{R} over with the property that and $\leq \sigma$. When queried, the oracle draws an independent and returns the complete specification of the function $f \cdot z$, specifically,

0. (8)

For consistency with the other oracles, we say that f accepts an argument x , even though this the loss of a model evaluated on an instance $z \sim D$, and this component function is fully known to the() argument is ignored. The global oracle captures the *statistical learning* problem, in which $f \cdot; z$ is optimizer. Consequently, we use the terms “global stochastic complexity” and “sample complexity” interchangeably.

For the stochastic oracles, while F itself may need to have properties such as convexity or smoothness, $f(\cdot; z)$ as defined need not have these properties unless stated otherwise. F O I

Minimax oracle complexity. Given a function class and an oracle with information space \mathcal{I} , we define the minimax oracle complexity of finding an ϱ -stationary point as

where $x_t \in \mathbb{R}^d$ is defined recursively as

and the expectation is over the

stochasticity of the oracle O .⁸

$$(\mathcal{O}_\nabla^{\mathcal{F}}(H, \lambda = 0; R, \Omega \nabla F))$$

Recap: Deterministic first-order oracle complexity. To position our new results on stochastic optimization we must first recall what is known about the *deterministic* first-order oracle complexity of finding near-stationary points. This complexity is tightly understood, with

$$(\mathcal{O}_\nabla^{\mathcal{F}}(H, \lambda = 0; R, \Omega \nabla F)) \leq (\mathcal{O}_\nabla^{\mathcal{F}}(H, \lambda = 0; \Delta, \Omega \nabla F))$$

up to logarithmic factors (Nesterov, 2012; Carmon et al., 2017b). The algorithm that achieves these rates is

$$m_\varphi \mathcal{F}_{\text{DB}}(H, \lambda = 0; R, \Omega \nabla F) = \Theta(\sqrt{H}R\sqrt{\varphi}), \quad \text{and } m_\varphi \mathcal{F}_{\text{RB}}(H, \lambda = 0; \Delta, \Omega \nabla F) = \Theta(\sqrt{H}\Delta\sqrt{\varphi}),$$

accelerated gradient descent (AGD).

3 Stochastic First-Order Complexity of Finding Stationary Points

Interestingly, the usual variants of stochastic gradient descent do not appear to be optimal in the stochastic model. A first concern is that they do not yield the correct dependence on desired stationarity φ .

As an illustrative example, let $F \in \mathcal{F}_{\text{DB}}[H, \lambda = 0; R]$ and let any stochastic first-order oracle be given.

$$\mathcal{O}_\nabla^{\mathcal{F}}$$

We adopt the naive approach of bounding stationarity by function value suboptimality. In this case the standard analysis of stochastic gradient descent (e.g., Dekel et al. (2012)) implies that after m iterations,

$$\mathbb{E} \|\nabla F(x_m)\| \leq O(\sqrt{H(\mathbb{E} F(x_m) - F(x^*))}) \leq O\left(\sqrt{H(HR^2/m + \sigma R/\sqrt{m})}\right)$$

$$= O\left(\frac{H^2 R^2}{m} + \frac{H^2 R^2 \sigma^2}{m}\right), \text{ and thus}$$

$$-4 \mathbb{E} \mathcal{F}_{\text{DB}}(H, \lambda = 0; R, \Omega \nabla F) \leq O\left(\frac{\epsilon^2}{\varphi^2} + \frac{\epsilon^4}{\varphi^4}\right) (\mathcal{O}_\nabla^{\mathcal{F}}(H, \lambda = 0; R, \Omega \nabla F))^{-2}.$$

The dependence on φ is considerably worse than the φ dependence enjoyed for function suboptimality.

In recent work, Allen-Zhu (2018) proposed a new *recursive regularization* approach

and used this in an algorithm called SGD3 that obtains the correct φ^{-2} dependence.⁹

For any $F \in \mathcal{F}_{\text{DB}}[H, \lambda = 0; R]$

$$F^{(0)}(x) = F(x) \quad \mathcal{F}_{\text{DB}} \text{ and}$$

$$F^{(1)}(x) = F^{(0)}(x) + \lambda \|x - \hat{x}_1\|^2 \quad \text{approximate minimizer of } F^{(0)}$$

SGD3 iteratively augments the objective with increasingly strong regularizers, “zooming in” on an approximate stationary point. Specifically, in the first iteration, SGD is used to find \hat{x}_1 , an approximate minimizer of $F^{(0)}$. The objective is then augmented with a strongly-convex regularizer so that \hat{x}_1 is used to find \hat{x}_2 , an

. In the second round, SGD is initialized

⁸ See Section 3 for discussion of randomized algorithms.

⁹ Allen-Zhu (2018) also show that some simple variants of SGD are able to reduce the poor φ^{-4} dependence to, e.g., $\varphi^{-5/2}$, but they fall short of the φ^{-2} dependence one should hope for. Similar remarks apply for $F \in \mathcal{F}_{\text{RB}}[H, \lambda = 0; \Delta]$.

. This process is repeated, with $F^{(t)}x := F^{(t-1)}x + 2^{t-1}\lambda x - \hat{x}_t^2$ for each $t \in T$. Allen-Zhu (2018) shows that SGD3 find an ϱ -stationary points using at most $\| \cdot \|$

(10)

local stochastic oracle queries. This oracle complexity has a familiar structure: it resembles the sum of an “optimization term” (HR/ϱ) and a “statistical term” (σ^2/ϱ^2). While we show that the statistical term is tight up to logarithmic factors (Theorem 2), the optimization term does not match the lower bound for the deterministic setting (Carmon et al., 2017b).

Algorithm 1 Recursive Regularization Meta-Algorithm

Input: A function F , an oracle \mathcal{O} and an allotted number of oracle accesses $\log_2 \frac{H\lambda}{\varrho}$, m , an initial point x_0 , and an optimization sub-routine A .

$t = 1$ to T do

point $F^{(0)} := F$, $\hat{x} := x$, $T \leftarrow \lfloor \log_2 \frac{H\lambda}{\varrho} \rfloor$.

A , with A , m .

for =

$\boxed{x_t = F(x_{t-1})}$ is output of A used to optimize F initialized at x_{t-1}

$$F = F + \lambda \sum_{k=1}^{t-1} 2^{k-1} \|x - \hat{x}_k\|_2$$

end for return

Our first result is to close this gap. The key idea is to view SGD3 as a template algorithm, where the inner loop of SGD used in [Allen-Zhu \(2018\)](#) can be swapped out for an arbitrary optimization method A. This template, [Algorithm 1](#), forms the basis for all the new methods in this paper.¹⁰

Algorithm 2 AC-SA

A function \mathcal{E} accesses $x_0 = x_0$	Input: $F \in \text{FDB}[H, \lambda; R]$, a ∇f , and an allotted number of oracle stochastic first-order oracle \mathcal{O}	σ
m		
ag_0		
m		
ag		
0		
m		
$for t = 1, 2, \dots, m do$		
$\gamma_t \leftarrow \frac{4H}{t(t+1)}$		
$md \leftarrow 1 - \frac{1}{\gamma_t + (1 - \alpha_t)}$		
$x_t \leftarrow \frac{(\alpha_t)(\lambda + \gamma_t)}{2 - \lambda} x_t^{ag} + \frac{\alpha_t((1 - \alpha_t)\lambda + \gamma_t)}{\gamma_t + (1 - \alpha_t)^2\lambda} x_{t-1}^{md}$		
$\nabla f(x_{t-1}; z_t) \leftarrow \mathcal{O}_{\nabla f}(x_{t-1})$		
$\leftarrow \frac{\alpha_t \lambda}{\lambda + \gamma_t} x_t^{md} + \frac{(1 - \alpha_t)\lambda + \gamma_t}{\lambda + \gamma_t} x_{t-1} - \frac{\alpha_t}{\lambda + \gamma_t} \nabla f(x_t^{md}; z_t)$		
$\leftarrow \alpha_t x_t + (1 - \alpha_t) x_{t-1}^{ag}$		
\leftarrow		
x_t		
x_{t+1}^{ag}		
$end for return$		
x_{t+1}^{ag}		

To obtain optimal complexity for the local stochastic oracle model we use a variant of the accelerated stochastic approximation method (“AC-SA”) due to [Ghadimi and Lan \(2012\)](#) as the subroutine. Pseudocode for AC-SA is provided in [Algorithm 2](#). We use a variant called AC-SA², see [Algorithm 3](#). The AC-SA² algorithm is equivalent to AC-SA, except the stepsize parameter is reset halfway through. This leads to slightly different dependence on the smoothness and domain size parameters, which is important to control the final rate when invoked within [Algorithm 1](#).

Toward proving the tight upper bound in [Table 1](#), we first show that [Algorithm 1](#) with AC-SA² as its subroutine guarantees fast convergence for strongly-convex domain-bounded objectives.

¹⁰ The idea of replacing the sub-algorithm in SGD3 was also used by [Davis and Drusvyatskiy \(2018\)](#), who showed that recursive regularization with a projected subgradient method can be used to find near-stationary points for the Moreau envelope of any Lipschitz function.

Theorem 1. For any $\|F\| \in \mathcal{F}_{DB}[H, \lambda; R]$ and any \mathcal{O}_{∇} , [Algorithm 1](#) using AC-SA² as its subroutine finds a

$$\text{point } \hat{x} \in \left\{ \frac{\sqrt{\frac{H}{\lambda}} \log \left(\frac{H}{\lambda} \right)}{\lambda} + \frac{\sqrt{\frac{HR}{\varrho}} \log \left(\frac{H}{\lambda} \right)}{\varrho} + \left(\frac{\sqrt{H\sigma}}{\lambda\varrho} \right)^{\frac{1}{3}} \log \left(\frac{H}{\lambda} \right) + \frac{\sigma^2}{\varrho^2} \log^3 \left(\frac{H}{\lambda} \right) \text{ with } \nabla F(\hat{x}) \leq \varrho \right\}$$

using

total stochastic first-order oracle accesses. $\left(\frac{\sqrt{\frac{H}{\lambda}} \log \left(\frac{H}{\lambda} \right)}{\lambda} + \frac{\sqrt{\frac{HR}{\varrho}} \log \left(\frac{H}{\lambda} \right)}{\varrho} + \left(\frac{\sqrt{H\sigma}}{\lambda\varrho} \right)^{\frac{1}{3}} \log \left(\frac{H}{\lambda} \right) + \frac{\sigma^2}{\varrho^2} \log^3 \left(\frac{H}{\lambda} \right) \right)$

The analysis of this algorithm is detailed in [Appendix A](#) and carefully matches the original analysis of SGD3 ([Allen-Zhu, 2018](#)). The essential component of the analysis is [Lemma 2](#), which provides a bound on $\|\nabla F(\hat{x})\|$ in terms of the optimization error of each invocation of AC-SA² on the increasingly strongly convex subproblems.

Our final result for non-strongly convex objectives uses [Algorithm 1](#) with AC-SA² on the regularized objective. The performance guarantee is as follows, and concerns both bounded functions.

Corollary 1. =, [Algorithm 1](#) with AC-SA² as its subroutine applied to \hat{x} such that $\mathbb{E}\|\nabla F(\hat{x})\| \leq \varrho$

using

total stochastic first-order oracle accesses.

For any $F \in \mathsf{F}_{RB}[H, \lambda = 0; \Delta]$ and any $O_{\nabla f}$, the same algorithm with $\lambda = \Theta(\min\{\frac{\Delta}{\sigma^2}, \frac{\sigma^2 \log^3(\sigma/\epsilon)}{\Delta}\})$ yields Algorithm 3 AC-SA²

Input: A function $F \in \mathsf{F}_{DB}[H, \lambda; R]$, a stochastic first-order oracle O , and $\frac{m}{\epsilon}$ allotted number of oracle accesses

m

$$\begin{aligned} x_1 &\leftarrow \text{AC-SA}_{F, X, 0, \frac{m}{2}} \\ x_2 &\leftarrow \text{AC-SA}_{F, X, 1, \frac{m}{2}} \end{aligned}$$

x with $\mathbb{E} \|\nabla F(x)\| \leq \epsilon$ using

$$m \leq O\left(\frac{\sqrt{H\Delta}}{\epsilon} \log\left(\frac{\sqrt{H\Delta}}{\epsilon} + \frac{\sigma^2}{\epsilon} \log^3\left(\frac{\sigma}{\epsilon}\right)\right)\right)$$

return x_2

a point (ϱ_1, ϱ_2) such that $\varrho_1 + \varrho_2 = \frac{m}{\epsilon}$

$$\varrho_1 = \varrho_2 = \frac{m}{2\epsilon}$$

total stochastic first-order oracle accesses.

This follows easily from [Theorem 1](#) and is proven in [Appendix A](#). Intuitively, when λ is chosen appropriately, the gradient of the regularized objective \tilde{F} does not significantly deviate from the gradient of F , but the number of iterations required to find an $O(\varrho)$ -stationary point of \tilde{F} is still controlled.

We now provide nearly-tight lower bounds for the stochastic first-order oracle complexity. A notable feature of the lower bound is to show that some of the logarithmic terms in the upper bound—which are not present in the optimal oracle complexity for function value suboptimality—are necessary.

[Theorem 2](#). For any $H, \Delta, R, \sigma > 0$, any $\epsilon \leq \frac{HR}{\sigma}$, the stochastic first-order oracle complexity for

range-bounded functions is lower bounded as $m \geq \Omega\left(\sqrt{\frac{HR}{\epsilon}} + \frac{\sigma^2}{\epsilon^2} \log\left(\frac{HR}{\epsilon}\right)\right)$.

For any $\varrho \leq \sqrt{\frac{HR}{\sigma}}$, the stochastic first-order complexity for domain-bounded functions is lower bounded as

$$\varrho \left(\mathsf{F}_{RB}[H, \lambda = 0; \Delta], O_{\nabla f} \right) \geq \Omega\left(\frac{\sqrt{H\Delta}}{\varrho} + \frac{\sigma^2}{\varrho^2} \log\left(\frac{H\Delta}{\varrho^2}\right)\right)$$

m

The proof, detailed in [Appendix C](#), combines the existing lower bound on the deterministic first-order oracle complexity ([Carmon et al., 2017b](#)) with a new lower bound for the statistical term. The approach is to show that any algorithm for finding near-stationary points can be used to solve noisy binary search (NBS), and then apply a known lower bound for NBS ([Feige et al., 1994; Karp and Kleinberg, 2007](#)). It is possible to extend the lower bound to randomized algorithms; see discussion in [Carmon et al. \(2017b\)](#).

4 Sample Complexity of Finding Stationary Points

Having tightly bound the stochastic first-order oracle complexity of finding approximate stationary points, we now turn to sample complexity. If the heuristic reasoning that stochastic first-order complexity should decompose into sample complexity and deterministic first-order complexity $(\varrho(F)O^\varrho) + m_\varrho(F, O^\varrho)$ is correct, then one would expect that the sample complexity should be $\tilde{O}(\sigma\varrho)$ for both domain-bounded and range-bounded function.

A curious feature of this putative sample complexity is that it does not depend on the smoothness of the function. This is somewhat surprising since if the function is non-smooth in the vicinity of its minimizer, there may only be a single ϱ -stationary point, and an algorithm would need to return *exactly* that point using only a finite sample. We show that the sample complexity is in fact almost independent of the smoothness constant, with a mild logarithmic dependence. We also provide nearly tight lower bounds.

For the global setting, a natural algorithm to try is regularized empirical risk minimization (RERM), which $\arg\min_x \frac{1}{m} \sum_{i=1}^m f(x; z_i) + \frac{\lambda}{2} \|x - x_0\|^2$. [RERM](#) based on stability returns $\hat{x} \in F$ for any domain-bounded function $F \in E(F/\|DB\|, \lambda)$.

ϱ^{-2} shows that $\nabla F \hat{x} \leq 0$; [Shalev-Shwartz et al., 2009](#) shows that $\nabla F \hat{x} \leq \nabla F x^* \leq 2H$. Choosing $m \Omega(HR\varrho + \lambda\varrho)$ yields an ϱ -stationary point. This upper bound, however, has two shortcomings. First, it scales with ϱ rather than that we hoped for and, second, it does not approach 1 as $\sigma \rightarrow 0$, which one should expect in the noise-free case. The stochastic first-order algorithm from the previous section has better sample complexity, but the number of samples still does not approach one when $\sigma \rightarrow 0$.

We fix both issues by combining regularized ERM with the recursive regularization approach, giving an upper bound that nearly matches the sample complexity lower bound $\Omega(\sigma^2/\varrho^2)$. The key tool here is a sharp analysis of regularized ERM—stated in the appendix as [Theorem 7](#)—that obtains the correct dependence on the variance σ_2 .

As in the previous section, we first prove an intermediate result for the strongly convex case. Unlike

Section 3, where F was required to be convex but the components $f(\cdot; z)$ were not required to be, we

must assume here either that $f(\cdot; z)$ is convex for all z .⁶ $O_{f^*}(\cdot)$ ()

Theorem 3. For any $F \in \mathcal{F}[H, \lambda]$ and any global stochastic oracle with the restriction that $f(\cdot; z)$ is convex for all

x with $\mathbb{E} \|\nabla F(x)\| \leq$
 $m \leq O\left(\frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{H}{\lambda}\right)\right)$ using at most
 z , Algorithm 1 with ERM as its subroutine finds

total samples.

The proof is given in Appendix B. As before, we handle the non-strongly convex case by applying the algorithm to. For any $F \in \mathcal{F}_{DB}[H, \lambda = 0; R]$ that $f(\cdot; z) = F(z) + \frac{\lambda}{2} \|x - x_0\|^2$ Corollary 2. and any $\Theta(\epsilon)$, finds a point \hat{x} global stochastic oracle O^* with the

$m \leq O\left(\frac{1}{\epsilon^2} \log\left(\frac{HR}{\epsilon}\right)\right)$ $\mathbb{E} \|\nabla F(x)\| \leq \sigma^2 \log^3\left(\frac{HR}{\epsilon}\right) \leq \rho$ using at most () ()
 $restriction = 5 + 6$ with $\lambda = R$ with

is convex for all z , with ERM as its subroutine, when applied to $F(x) = F(x) +$

total samples.

For any $F \in \mathcal{F}_{RB}[H, \lambda = 0; \Delta]$ and any global stochastic oracle O^* with the restriction that $f(\cdot; z)$ is convex

$m \leq O\left(\frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{\sqrt{H\Delta}}{\epsilon}\right)\right)$

for all z , the same approach with $\lambda = \Theta(\Delta)$ finds an ρ -stationary point using at most

total samples.

⁵While it is also tempting to try constrained ERM, this does not succeed even for function value suboptimality (Shalev-Shwartz et al., 2009).

⁶We are not aware of any analysis of ERM for strongly convex losses that does not make such an assumption. It is interesting to see whether this can be removed.

This follows immediately from [Theorem 3](#) by choosing λ small enough such that $\|\nabla F(x)\| \approx \|\nabla F^*(x)\|$.

Details are deferred to [Appendix B](#).

With this new sample provide an almost- $\Delta, R, \sigma > 0, \epsilon \leq \min\{\frac{HR}{8}, \sqrt{\frac{H\Delta}{8}}, \frac{\sigma}{4}\}$ complexity upper bound, we proceed to tight lower bound.

[Theorem 4](#). *For any H , the sample complexity to find a η -stationary point¹¹ is lower bounded as*

$$\mathbb{m}(\mathcal{F}_{DB}[H, \lambda = 0; R] \cap \mathcal{F}_{RB}[H, \lambda = 0; \Delta], \mathcal{O}_f^\sigma) \geq \Omega\left(\frac{\sigma^2}{\epsilon^2}\right)$$

This lower bound is similar to constructions used to prove lower bounds in the case of finding an approximate minimizer (Nemirovski and Yudin, 1983; Nesterov, 2004; Woodworth and Srebro, 2016). However, our lower bound applies for functions with simultaneously bounded domain and range, so extra care must be taken to ensure that these properties hold. The lower bound also ensures that $f(\cdot; z)$ is convex for all z . The proof is located in [Appendix C](#).

Discussion: Efficient implementation. [Corollary 2](#) provides a bound on the number of *samples* needed to find a near-stationary point. However, a convenient property of the method is that the ERM objective $F(t)$ with m/T

components. These subproblems can therefore be solved using at most(t) $\mathcal{O}\left(\frac{m}{T} + \sqrt{\frac{m(H+\lambda^2t)}{T\lambda^2t}} \log \frac{Ht}{\epsilon}\right)$

$\left(\left(\frac{1}{\sigma^2} + \frac{1}{\sigma^{3/2}\sqrt{H}} + 4 + HR\right)\right)$
Allen-Zhu, 2017). This im-

solved in each iteration is convex, $H + 2\lambda$ -smooth, 2λ -strongly convex, and has *finite sum* structure

gradient computations via a first-order optimization algorithm such as Katyusha (plies that the method can be implemented with a total gradient complexity of O

$$\left(\frac{1}{\epsilon^2} + \frac{1}{\epsilon^{3/2}}\right) \log\left(\frac{1}{\epsilon}\right)$$

[Section 3](#)

over all T iterations, and similarly for the bounded-range case. Thus, the algorithm is not just sampleefficient, but also computationally efficient, albeit slightly less so than the algorithm from

¹¹ This lower bound applies both to deterministic and randomized optimization algorithms.

⁸This lower bound does not enter the sample complexity quantitatively.

Removing smoothness entirely in one dimension. The gap between the upper and lower bounds for the statistical complexity is quite interesting. We conclude from [Corollary 2](#) that the sample complexity depends at most logarithmically upon the smoothness constant, which raises the question of whether it must depend on the smoothness at all. We now show that for the special case of functions in one dimension, smoothness is not necessary. In other words, all that is required to find an ϱ -stationary point is Lipschitzness.

Theorem 5. *Consider any convex, L -Lipschitz function $F: \mathbb{R} \rightarrow \mathbb{R}$ that is bounded from below,⁸ $m = O\left(\frac{\sigma^2 \log(\epsilon)}{\epsilon^2}\right)$ and any global stochastic oracle with the restriction that is convex for all z . There exists an algorithm which uses samples and outputs a point such that $E[\inf_{g \in \partial F(x)} \|g\|] \leq \varrho$.*

The algorithm calculates the empirical risk minimizer on several independent samples, and then returns the point that has the smallest empirical gradient norm on a validation sample. The proof uses the fact that any function F as in the theorem statement has a single left-most and a single right-most ϱ -stationary point. As long as the empirical function's derivative is close to F 's at those two points, we argue that the ERM lies between them with constant probability, and is thus an ϱ -stationary point of F . We are able to boost the confidence by repeating this a logarithmic number of times. A rigorous argument is included in [Appendix B](#). Unfortunately, arguments of this type does not appear to extend to more than one dimension, as the boundary of the set of ϱ -stationary points will generally be uncountable, and thus it is not apparent that the empirical gradient will be uniformly close to the population gradient. It remains open whether smoothness is needed in two dimensions or more.

The algorithm succeeds even for non-differentiable functions, and requires neither strong convexity nor knowledge of a point x_0 for which $\|x_0 - x^*\|$ or $F(x_0) - F^*$ is bounded. In fact, the assumption of Lipschitzness (more generally, L -subgaussianity of the gradients) is only required to get an in-expectation statement. Without this assumption, it can still be shown that ERM finds an ϱ -stationary point with constant probability

using $m \leq O\left(\frac{\sigma^2}{\varrho^2}\right)$ samples.

5 Discussion

We have proven nearly tight bounds on the oracle complexity of finding near-stationary points in stochastic convex optimization, both for local stochastic oracles and global stochastic oracles. We hope that the approach of jointly studying stochastic first-order complexity and sample complexity will find use more broadly in non-convex optimization. To this end, we close with a few remarks and open questions.

1. *Is smoothness necessary for finding ϱ -stationary points?* While the logarithmic factor separating the upper and lower bound we provide for stochastic first-order oracle complexity is fairly inconsequential, the gap between the upper and lower bound on the *sample complexity* is quite interesting. In particular, we show through [Theorem 4](#) and [Corollary 2](#) that

$$\Omega,$$

$$\left(\frac{\sigma^2}{\varrho^2}\right) \leq \mathbb{E}_{\text{RB}}[H, \lambda = 0; \Delta] \cdot O_f \leq O\left(\frac{\sigma^2}{\varrho^2} \log^3\left(\frac{\sqrt{H\Delta}}{\varrho}\right)\right)$$

and similarly for the domain-bounded case. Can the factor $\log^3(\frac{\sqrt{H\Delta}}{\varrho})$ on the right-hand side be removed entirely? Or in other words, is it possible to find near-stationary points in the statistical learning model without smoothness?¹², we know that this is possible in one dimension.

2. *Tradeoff between computational complexity and sample complexity.* Suppose our end goal is to find a near-stationary point in the statistical learning setting, but we wish to do so efficiently. For rangebounded functions, if we use [Algorithm 1](#) with AC-SA² as a

$\tilde{\mathcal{O}}\left(\frac{\sqrt{H\Delta}}{\epsilon} + \frac{\sigma^2}{\epsilon^2}\right)$ subroutine we require \tilde{O} samples, and the total computational effort (measured by number of gradient operations) is also

. On the other hand, if we use $\tilde{\mathcal{O}}\left(\frac{\sigma^2}{\epsilon^2} + \frac{\sqrt{H}\sigma^{3/2}}{\epsilon^{3/2}}\right)$ [Algorithm 1](#) with RERM as a subroutine and implement RERM with Katyusha, then we obtain an improved sample complexity of, but at the cost of a larger number of gradient operations. Tightly characterizing such computationalstatistical tradeoffs in this and related settings is an interesting direction for future work.

3. *Active stochastic oracle.* For certain stochastic first-order optimization algorithms based on variance reduction (SCSG ([Lei et al., 2017](#)), SPIDER ([Fang et al., 2018](#))), a gradient must be computed at multiple points for the same sample $f(\cdot; z)$. We refer to such algorithms as using an “active query” first-order stochastic oracle, which is a stronger oracle than the classical first-order stochastic oracle (see [Woodworth et al. \(2018\)](#) for more discussion). It would be useful to characterize the exact oracle complexity in this model, and in particular to understand how many active queries are required to obtain logarithmic dependence on smoothness as in the global case.

4. *Complexity of finding stationary points for smooth non-convex functions.* An important open problem is to characterize the minimax oracle complexity of finding near-stationary points for smooth nonconvex functions, both for local and global stochastic oracles. For a deterministic first-order oracle,

the optimal rate is $\Theta\left(\frac{H}{\varrho}\right)$. In the stochastic setting, a simple sample complexity lower bound

follows from the convex case, but this is not known to be tight.

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¹² For a general non-smooth function F , a point x is said to be an ϱ -stationary point if there exists $v \in \partial F(x)$ such that $\|v\|_2 \leq \varrho$.

References

- Alekh Agarwal, Martin J Wainwright, Peter L Bartlett, and Pradeep K Ravikumar. Information-theoretic lower bounds on the oracle complexity of convex optimization. In *Advances in Neural Information Processing Systems*, pages 1–9, 2009.
- Zeyuan Allen-Zhu. Katyusha: The first direct acceleration of stochastic gradient methods. In *Proceedings of the 49th Annual ACM SIGACT Symposium on Theory of Computing*, pages 1200–1205. ACM, 2017.
- Zeyuan Allen-Zhu. How to make the gradients small stochastically: Even faster convex and nonconvex sgd. In *Advances in Neural Information Processing Systems*, pages 1165–1175. 2018.
- Gábor Braun, Cristóbal Guzmán, and Sebastian Pokutta. Lower bounds on the oracle complexity of nonsmooth convex optimization via information theory. *IEEE Transactions on Information Theory*, 63(7): 4709–4724, 2017.
- Yair Carmon, John C Duchi, Oliver Hinder, and Aaron Sidford. Lower bounds for finding stationary points i. *arXiv preprint arXiv:1710.11606*, 2017a.
- Yair Carmon, John C Duchi, Oliver Hinder, and Aaron Sidford. Lower bounds for finding stationary points ii: First-order methods. *arXiv preprint arXiv:1711.00841*, 2017b.
- Damek Davis and Dmitriy Drusvyatskiy. Complexity of finding near-stationary points of convex functions stochastically. *arXiv preprint arXiv:1802.08556*, 2018.
- Ofer Dekel, Ran Gilad-Bachrach, Ohad Shamir, and Lin Xiao. Optimal distributed online prediction using mini-batches. *Journal of Machine Learning Research*, 13(Jan):165–202, 2012.
- Cong Fang, Chris Junchi Li, Zhouchen Lin, and Tong Zhang. Spider: Near-optimal non-convex optimization via stochastic path-integrated differential estimator. In *Advances in Neural Information Processing Systems*, pages 687–697, 2018.
- Uriel Feige, Prabhakar Raghavan, David Peleg, and Eli Upfal. Computing with noisy information. *SIAM Journal on Computing*, 23(5):1001–1018, 1994.
- Saeed Ghadimi and Guanghui Lan. Optimal stochastic approximation algorithms for strongly convex stochastic composite optimization i: A generic algorithmic framework. *SIAM Journal on Optimization*, 22(4):1469–1492, 2012.
- Saeed Ghadimi and Guanghui Lan. Stochastic first-and zeroth-order methods for nonconvex stochastic programming. *SIAM Journal on Optimization*, 23(4):2341–2368, 2013.
- Saeed Ghadimi and Guanghui Lan. Accelerated gradient methods for nonconvex nonlinear and stochastic programming. *Math. Program.*, 156(1-2):59–99, 2016. doi: 10.1007/s10107-015-0871-8.
- Chi Jin, Rong Ge, Praneeth Netrapalli, Sham M. Kakade, and Michael I. Jordan. How to escape saddle points efficiently. In *Proceedings of the 34th International Conference on Machine Learning*, pages 1724–1732, 2017.
- Richard M Karp and Robert Kleinberg. Noisy binary search and its applications. In *Proceedings of the eighteenth annual ACM-SIAM symposium on Discrete algorithms*, pages 881–890. Society for Industrial and Applied Mathematics, 2007.

Lihua Lei, Cheng Ju, Jianbo Chen, and Michael I Jordan. Non-convex finite-sum optimization via scsg methods. In *Advances in Neural Information Processing Systems*, pages 2348–2358, 2017.

Arkadii Semenovich Nemirovski and David Borisovich Yudin. Problem complexity and method efficiency in optimization. 1983.

Yurii Nesterov. Introductory lectures on convex optimization: a basic course. 2004.

Yurii Nesterov. How to make the gradients small. *Optima*, 88:10–11, 2012.

Sashank J. Reddi, Ahmed Hefny, Suvrit Sra, Barnaba’s Po’cz’os, and Alex Smola. Stochastic variance reduction for nonconvex optimization. In *Proceedings of the 33rd International Conference on International Conference on Machine Learning*, pages 314–323, 2016.

Shai Shalev-Shwartz, Ohad Shamir, Nathan Srebro, and Karthik Sridharan. Stochastic convex optimization. In *Conference on Learning Theory*, 2009.

Joseph F Traub, Grzegorz W Wasilkowski, and Henryk Woz’niakowski. Information-based complexity. 1988.

Blake Woodworth and Nati Srebro. Tight complexity bounds for optimizing composite objectives. In *Advances in Neural Information Processing Systems 29*, pages 3639–3647. 2016.

Blake Woodworth, Jialei Wang, Brendan McMahan, and Nathan Srebro. Graph oracle models, lower bounds, and gaps for parallel stochastic optimization. In *Advances in Neural Information Processing Systems 31*, pages 8505–8515, 2018.

Dongruo Zhou, Pan Xu, and Quanquan Gu. Stochastic nested variance reduced gradient descent for nonconvex optimization. In *Advances in Neural Information Processing Systems 31*, pages 3925–3936. 2018.

A Proofs from Section 3: Upper Bounds

Theorem 6 (Proposition 9 of [Ghadimi and Lan \(2012\)](#)). For any $F \in \mathbb{F}_{DB}[H, \lambda; R]$ and any $O \in \mathbb{O}_{DB}$, the AC-SA

algorithm returns a point \hat{x}_T after making T oracle accesses such that

$$\mathbb{E}_{\in DB} [F(\hat{x}_T) - F(x^*)] \leq \frac{2HR^2}{T^2} + \frac{8\sigma^2}{\lambda T} \quad (\sigma) \quad 2 \quad .$$

Lemma 1. For any $F \in \mathbb{F}_{OvF}[H, \lambda; R]$ and any OvF , the AC-SA algorithm returns a point \hat{x}_T after making

T oracle accesses such that

$$\mathbb{E}[F(x)] - F(x^*) \leq \frac{128H^2R^2}{\lambda T^4} + \frac{256H\sigma^2}{\lambda^2T^3} + \frac{16\sigma}{\lambda T}.$$

Proof. By [Theorem 6](#), the first instance of AC-SA outputs \hat{x}_1 such that

$$\mathbb{E}[F(\hat{x}_1)] - F(x^*) \leq \frac{8HR^2}{T^2} + \frac{16\sigma^2}{\lambda T}, \quad (11)$$

and since F is λ -strongly convex,

$$\frac{\lambda}{2} \mathbb{E}\|\hat{x}_1 - x^*\|^2 \leq \mathbb{E}[F(\hat{x}_1)] - F(x^*) \leq \frac{8HR^2}{T^2} + \frac{16\sigma^2}{\lambda T} \quad (12)$$

Also by [Theorem 6](#), the second instance

of AC-SA outputs such that

$$\mathbb{E}[F(\hat{x}_2) - F(x^*)] = \mathbb{E}[\mathbb{E}[F(\hat{x}_2) - F(x^*) | x_1]] \quad (13)$$

$$\leq \mathbb{E}\left[\frac{8H\|\hat{x}_1 - x^*\|^2}{T^2} + \frac{16\sigma^2}{\lambda T}\right] \quad (14)$$

$$\leq \frac{128H^2R^2}{\lambda T^4} + \frac{256H\sigma^2}{\lambda^2 T^3} + \frac{16\sigma^2}{\lambda T} \quad (15)$$

□

Lemma [\(Claim 6.2 of Allen-Zhu \(2018\)\)](#). Suppose that for every $t = 1, \dots, T$ $\arg \min_{x \in \mathcal{X}} F^{(t-1)}(x)$, then 2 the iterates of [Algorithm 1](#)

satisfy

$$t \geq 1, \mathbb{E}[\|\hat{x}_t - x_t^*\|^2] \leq \mathbb{E}[\|\hat{x}_t - x_{t-1}^*\|^2] \leq \frac{\delta_t}{2^t},$$

1. For all $t \geq 1, \mathbb{E}[F^{(t-1)}(\hat{x}_t)] - F^{(t-1)}(x_{t-1}^*) \leq \delta_t$ where $x_{t-1}^* = \arg \min_{x \in \mathcal{X}} F^{(t-1)}(x)$

$$t \geq 1, \mathbb{E}[\|\hat{x}_t - x_t^*\|^2] \leq \mathbb{E}[\|\hat{x}_t - x_{t-1}^*\|^2] \leq \frac{\delta_t}{2^t \lambda}.$$

2. For every

$$3. For all t \geq 1, \mathbb{E}[\sum_{t=1}^T 2^t \lambda \|\hat{x}_t - x_T^*\|] \leq 4 \sum_{t=1}^T \sqrt{2^t \lambda \delta_t}$$

Theorem 1. For any fixed $\lambda, H, \sigma, \delta, \eta$, [Algorithm 1](#) using [AC-SA²](#) as its subroutine finds a point \hat{x} with $\|\nabla F(\hat{x})\| \leq \eta$ using

$$m \leq O\left(\sqrt{\frac{H}{\lambda} \log \frac{H}{\lambda}} + \sqrt{\frac{HR}{\eta}} \log \frac{H}{\lambda} + \sqrt{\frac{H\sigma}{\lambda\eta}} \log^3 \frac{H}{\lambda} + \frac{\sigma^2}{\eta^2} \log^3 \frac{H}{\lambda}\right)$$

total stochastic first-order oracle accesses.

Proof. As in the final

$$F(x) = F(x) + \lambda \sum_{t=1}^{T-1} 2^{t-1} \|x - \hat{x}_t\|^2, \text{ so}$$

iteration, $F^{(T-1)}$

$$\|\nabla F^{(T-1)}(\hat{x}_T)\| = \left\| \nabla F^{(T-1)}(x_T) + \lambda \sum_{t=1}^{T-1} 2^t (\hat{x}_t - \hat{x}_T) \right\| \quad (16)$$

$$\leq \|\nabla F^{(T-1)}(\hat{x}_T)\| + \lambda \sum_{t=1}^{T-1} 2^t \|\hat{x}_t - \hat{x}_T\| \quad (17)$$

$$\leq \|\nabla F^{(T-1)}(\hat{x}_T)\| + \lambda \sum_{t=1}^{T-1} 2^t (\|\hat{x}_t - x_{T-1}^*\| + \|\hat{x}_T - x_{T-1}^*\|) \quad (18)$$

$$\leq 2 \|\nabla F^{(T-1)}(\hat{x}_T)\| + \lambda \sum_{t=1}^{T-1} 2^t \|\hat{x}_t - x_{T-1}^*\| \quad (19)$$

14

T 1

$$\leq 2 \|\nabla F^{(T-1)}(\hat{x}_{T-1})\| + 4 \sum_{t=1}^{T-1} \lambda 2^t \delta_t \quad (20)$$

t=1

— T 1 —

$$\leq 4 \sqrt{H} \delta_T + 4 \sum_{t=1}^{T-1} \lambda 2^t \delta_t \quad (21)$$

t=1

T —

$$\leq 4 \sum_{t=1}^{T-1} \lambda 2^{t+1} \delta_t \quad (22)$$

$$(17) \text{ and } (18) \quad \text{of } \hat{x}_{T-1} = H + \lambda 2^{\log_{\lambda} T} < 2H$$

Above, rely on the triangle inequality; (19) follows from the λ -strong convexity of $H + \lambda \sum_{t=1}^{T-1} 2^t \delta_t$

$F^{(T-1)}$; (20) applies the third conclusion of Lemma 2; (21) uses the fact that $H + \lambda 2^T \lfloor \frac{H}{\lambda} \rfloor$ is λ -smooth; and finally (22) uses that

We chose $F^{(T-1)}, \hat{x}_{T-1}$ to be AC-SA² applied to $F^{(T-1)}$ initialized at x_{T-1}^* using m T stochastic gradients. Therefore, (22) follows from

$$\delta_t \leq \frac{128H^2 \mathbb{E} \|x_{T-1}^* - x_{T-1}^*\|^2}{2^t} = \frac{256H\sigma^2}{2^{t-1} \lambda (m/T)^4} + \frac{2^{2t-2} \lambda^2 (m/T)^3}{2^{t-1} \lambda (m/T)} + \frac{16\sigma^2}{2^{t-1} \lambda (m/T)} \quad (23)$$

If $t > 1$ we can bound $\mathbb{E} \|\hat{x}_{T-1} - x_{T-1}^*\|^2 \leq \frac{\delta_{T-1}}{2^{t-1} \lambda}$, thus

Using part two of Lemma 2, for

$$(24) \quad \delta_t \leq \frac{128H^2\delta_{t-1}}{2^{2t-2}\lambda^2(m/T)^4} + \frac{256H\sigma^2}{2^{2t-2}\lambda^2(m/T)^3} + \frac{16\sigma^2}{2^{t-1}\lambda(m/T)}$$

We can

$$\begin{aligned} 8 \sum_{t=1}^{\sqrt{\lambda 2^{t-1} \delta_t}} & \leq 8 \overbrace{\frac{128H^2 \|\mathbf{x}_0 - \mathbf{x}^*\|_2^2}{m T^4} + \frac{256H\sigma^2}{\lambda m T^3} + \frac{16\sigma^2}{m T}}^{\text{Term 1}} \\ & + 8 \sum_{t=2}^T \overbrace{\frac{128H^2 \delta_{t-1}}{2^{t-1}\lambda m T^4} + \frac{256H\sigma^2}{2^{t-1}\lambda m T^3} + \frac{16\sigma^2}{m T}}^{\text{Term 2}} \\ & < 8 \overbrace{\frac{128H^2 \|\mathbf{x}_0 - \mathbf{x}^*\|_2^2}{m T^4} + 8 \overbrace{\frac{256H\sigma^2}{\lambda m T^3} + 8 \overbrace{\frac{16\sigma^2}{m T}}^{\text{Term 3}}}}^{\text{Term 4}} \\ & + \sum_{t=2}^T \overbrace{\frac{128H^2 \delta_{t-1}}{2^{t-1}\lambda m T^4} + \frac{256H\sigma^2}{2^{t-1}\lambda m T^3} + \frac{16\sigma^2}{m T}}^{\text{Term 5}} \end{aligned}$$

therefore bound T

$$\dot{\epsilon} \quad (25)$$

$$16\sigma^2 \quad (26)$$

$$\begin{aligned} & \sum_{t=2}^8 \frac{2_{t-1}\lambda(m/T)^4}{2_{t-1}\lambda(m/T)^3} \frac{2_{t-1}\lambda(m/T)^3}{\{m/T\}} \\ & = 2^{2+} \frac{64\sqrt{2}H\|\mathbf{x}_0 - \mathbf{x}^*\|T^2}{2\sqrt{2}\sum_{t=2}^8 (27) m \lambda m / 2} \frac{128\sqrt{H\sigma T_3} 2^{3/2} t_{T1} \sqrt{1_{t-1}}}{= 2^{2+} t} \\ & + \frac{\sqrt{m}}{m} + \sum \frac{128H T_2 T}{m^2 \lambda} \delta_{t-1} \end{aligned}$$

$$\begin{aligned}
&\leq \frac{64\sqrt{2}H\|x_0 - x^*\|T^2}{m^2} + \frac{512\sqrt{H}\sigma T^{3/2}}{\sqrt{\lambda}m^{3/2}} \\
&\quad + \frac{32\sigma T^{3/2}}{\sqrt{m}} + \frac{128HT^2}{m^2} \sum_{t=1}^T \sqrt{\frac{\delta_t}{2^{t-1}\lambda}} \\
&= \boxed{15} \tag{28}
\end{aligned}$$

$$64\sqrt{2}H\|x_0 - x^*\|T^2 + 2512T\sqrt{H}\sigma T^{3/2}$$

$$\begin{aligned}
&\leq \frac{\boxed{29}}{m\lambda m} \\
&\quad \checkmark \quad \frac{32\sigma T}{\lambda 2} \quad \frac{128HT}{\delta \cdot m} \\
&\quad ++ \quad \sum_{t=1}^T \frac{\delta_t}{2^{t-1}\lambda}
\end{aligned}$$

Above, we arrive at (25) by upper bounding each δ_t via (24); (26) follows from the fact that for $a, b \geq 0$,

$\sqrt{a+b} \leq \sqrt{a} + \sqrt{b}$; (28) uses the fact that $\sum_{t=1}^T \frac{1}{2^{t-1}\lambda} \leq 4$ and $\sqrt{\frac{\delta_T}{2^{T-1}\lambda}} \geq \epsilon$; and finally, (29) follows by multiplying each non-negative term in the sum by 2^{t-1} . Rearranging inequality (29) and combining with (22) yields

$$\mathbb{E} \|\nabla F(\hat{x}_T)\| \leq \left(\frac{1}{1 - \frac{16HT^2}{\lambda m^2}} \right) \left(\frac{64\sqrt{2}H\|x_0 - x^*\|T^2}{m^2} + \frac{512\sqrt{H}\sigma T^{3/2}}{\sqrt{\lambda}m^{3/2}} + \frac{32\sigma T^{3/2}}{\sqrt{m}} \right). \tag{30}$$

Choosing $m > 8T\sqrt{H}$ ensures that the first term is at most 2, and then solving for m such that the second term is $O(\epsilon)$ completes the proof. \square

term

is

$$[H, \lambda = 0; R] \implies \tilde{F} \in \mathcal{F}_{DB}[H + \lambda, \lambda; R] \text{ and } \forall x \|\nabla F(x)\| \leq 2\|\nabla \tilde{F}(x)\| + \lambda R.$$

$$[H, \lambda = 0; \Delta] \implies$$

$$\|\nabla F(x)\| + \sqrt{2\lambda\Delta}$$

$\nabla \tilde{F}(x)$. Since $\nabla \tilde{F}(x) = \nabla F(x) + \lambda(x - x_0)$

$$\|\nabla F(x)\| \leq \|\nabla \tilde{F}(x)\| + \lambda \|x - x_0\| \tag{31}$$

$$\leq \|\nabla \tilde{F}(x)\| + \lambda \|x_0 - \tilde{x}^*\| + \lambda \|x - \tilde{x}^*\| \tag{32}$$

$$\leq 2\|\nabla \tilde{F}(x)\| + \lambda \|x_0 - \tilde{x}^*\|, \tag{33}$$

for the last inequality. Similarly, $0 = \nabla \tilde{F}(\tilde{x}^*) = \nabla F(\tilde{x}^*) + \lambda(x_0 - \tilde{x}^*)$

$$\langle \tilde{x}^*, x_0 - \tilde{x}^* \rangle \tag{34}$$

$$= \langle \nabla F(\tilde{x}^*), x_0 - \tilde{x}^* \rangle + \langle \nabla F(\tilde{x}^*), \tilde{x}^* - x^* \rangle \tag{35}$$

$$\leq \langle \nabla F(\tilde{x}^*), x_0 - x^* \rangle \tag{36}$$

$$= \langle \lambda(x_0 - \tilde{x}^*), x_0 - x^* \rangle \tag{37}$$

$$= \lambda \|x_0 - \tilde{x}^*\| \tag{38}$$

Lemma 3.

1. $F \in \mathbb{F}_{DB}$

2. $F \in \mathbb{F}_{RBDB}[\quad = \vee \quad / \quad \| \quad (\) \| \leq \| (\) \|$

$F^* H + \lambda, \lambda; R 2\Delta \lambda$ and $\forall x \nabla F x \geq \nabla F^* x$. Proof. Let $\tilde{x}^* \in \operatorname{argmin}_{x \in \mathbb{R}^n} F(x)$,

where we used the λ -strong convexity of $F^*(\lambda x^* -$

x_0 . Therefore,

$$\lambda \|x_0 - \tilde{x}^*\|^2 = \langle \nabla F^*(\lambda x^* - x_0), x_0 - \tilde{x}^* \rangle$$

$$= \nabla F$$

$$\leq \lambda \|x_0 - \tilde{x}^*\| \|x_0 - \tilde{x}^*\|.$$

The first inequality follows from the convexity of F and the second from the Cauchy-Schwarz inequality. When $F \in \mathbb{F}_{DB}[H, \lambda = 0; R]$, then $\|x_0 - \tilde{x}^*\| \leq R$, which, combined with (33) proves the first claim.

Alternatively, when $F \in \mathbb{F}_{RB}[H, \lambda = 0; \Delta = 0]$,

$$\|x_0 - \tilde{x}^*\| < \frac{\sqrt{\frac{(\tilde{x}^* - F(x_0))^2}{\lambda}}}{\sqrt{\frac{(\tilde{x}^* - F(x^*))^2}{\lambda}}} = \frac{\|x_0 - \tilde{x}^*\|}{\|x^* - \tilde{x}^*\|} \quad (33)$$

(33), completes the proof.

$$\|F(x_0) - F(\tilde{x}^*)\| \leq \|F(x_0) - F(x^*)\| + \|F(x^*) - F(\tilde{x}^*)\| \leq \Delta \|x_0 - x^*\| + \lambda \|x^* - \tilde{x}^*\| \quad (39)$$

Rearranging,

$$\|x - x^*\| \leq \sqrt{2\Delta} \quad (40)$$

This, combined with \square

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Corollary

$0; R]$ and

AC-SA² as

its

$\mathcal{F}_{RB}[H, \lambda = 0; \Delta]$

subroutine $\mathbb{E}[\cdot]$ ($\lambda = \Theta\left(\min\left\{\frac{\epsilon}{\Delta}, \frac{\sigma^4 \log^4(\sigma/\epsilon)}{\epsilon^2 \log^4(\sigma/\epsilon)}\right\}\right)$)

$\|x - x^*\| \leq O\left(\frac{\sqrt{H\Delta}}{\epsilon} \log\left(\frac{\sqrt{H\Delta}}{\epsilon}\right) + \frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{\sigma}{\epsilon}\right)\right)$

$F(x) + \frac{\lambda}{2} \|x - x_0\|^2$ for $\lambda = \Theta\left(\min\left\{\frac{\epsilon}{R}, \frac{H\epsilon^4}{\sigma^4 \log^4(\sigma/\epsilon)}\right\}\right)$ \hat{x} such that $\nabla F(\hat{x}) \leq \epsilon$ using

$$m \leq O\left(\frac{\sqrt{H\Delta}}{\epsilon} \log\left(\frac{\sqrt{H\Delta}}{\epsilon}\right) + \frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{\sigma}{\epsilon}\right)\right)$$

total stochastic first-order oracle accesses.

For any $F \in \mathcal{F}_{RB}[H, \lambda = 0; \Delta]$ and any $\mathbb{E}[\cdot]$, the same algorithm with $\mathbb{E}[\cdot]$ yields a point using

total stochastic first-order oracle accesses.

Proof.

1 with $\lambda = \frac{256H \log^2(m)}{m^2} \leq O(H)$
 $\frac{2(H+\lambda)}{\lambda} \leq \frac{1}{\delta}$; and finally that

as its subroutine to optimize $\bar{F}(x) = F(x)$

\bar{F} is $H + \lambda \leq O(H)$ \rightarrow smooth and $\lambda \leq \frac{1}{\delta}$

We use Algorithm

AC-SA²

$+ \frac{\lambda}{2} \|x - x_0\|^2$. Our choice of ensures that (H) -strongly convex; that

$$\frac{16(H+\lambda) \log^2(m)}{\lambda m} \leq \frac{H}{\lambda m} \leq m^2$$

satisfies

Therefore, by Theorem 1, in particular, (30), the output

(41)

$$\mathbb{E} \|\nabla \bar{F}(\hat{x})\| \leq O\left(\frac{H \|x_0 - \bar{x}^*\| \log^2(H/\lambda)}{m^2} + \frac{\sqrt{H\sigma} \log^{3/2}(H/\lambda)}{\sqrt{\lambda} m^{3/2}} + \frac{\sigma \log^{3/2}(H/\lambda)}{\sqrt{m}}\right) \quad (41)$$

$$\leq O\left(\frac{H \|x_0 - \bar{x}^*\| \log^2(m)}{m^2} + \frac{\sigma \log^{3/2}(m)}{\sqrt{m}}\right), \quad (42)$$

where $\tilde{x}^* = \operatorname{argmin}_x F(x)$. For $F \in \mathsf{FDB}[H, \lambda = 0; R]$, by part one of [Lemma 3](#), $\|x_0 - \tilde{x}^*\| \leq R$ and

$$\frac{\log^2(m)}{\sqrt{m}} + \frac{\sigma \log^{3/2}(m)}{\sqrt{m}} \|\hat{x}\| \leq O\left(\frac{1}{m^2} + \frac{1}{O(\epsilon)}\right)$$

$$\|H\hat{x}\| \leq O(\epsilon)$$

$$(43) \quad \lambda = \Theta\left(\min\left\{\frac{1}{R}, \frac{1}{\sigma^4 \log^4(\sigma/\epsilon)}\right\}\right).$$

Solving for m such that this

expression is

$$\text{Lemma 3: } \|x - \tilde{x}^*\| \leq \frac{\sqrt{2\Delta/\lambda}}{m}, \quad \|\hat{x}\| \leq \sqrt{\frac{1}{m}}.$$

completes the first part of the proof. For this m , $\sqrt{H\Delta} \log(m) = \sigma \log^{3/2}(m)$

$$\varrho = \frac{H\varrho^4}{\varrho^2} \quad (44)$$

For $F \in \mathsf{FRB}[H, \lambda = 0; \Delta]$, by part two of [and](#)

$$). \quad (45)$$

$$\lambda = \Theta\left(\min\left\{\frac{1}{\Delta}, \frac{1}{\sigma^4 \log^4(\sigma/\epsilon)}\right\}\right)$$

Solving for m such that this expression is

completes the proof. For this m , ϱ completes the proof. \square

$$\varrho_2 = \frac{H\varrho^4}{\varrho^2} \quad (46)$$

B Proofs from [Section 4](#): Upper Bounds

[Theorem 7](#). For any $F \in \mathsf{F}[H, \lambda]$ and any \mathcal{O}^{σ} with the restriction that $f(x; z)$ is λ -strongly convex with respect

to x for all z , define the empirical risk minimizer via

$$\hat{x} = \arg \min_{x \in \mathbb{R}^d} \frac{1}{m} \sum_{t=1}^m f(x; z_t)$$

Then the empirical risk minimizer enjoys the guarantee

$$\mathbb{E}\|\hat{x} - x^*\|_2^2 \leq \frac{4\sigma^2}{\lambda^2 m} \quad (47)$$

$\widehat{F}_m(\cdot) = \frac{1}{m} \sum_{t=1}^m f(x_t; z_t)$ be the empirical objective. Since \widehat{F}_m is itself λ -strongly convex, and so we have

$$\text{each } \widehat{F}_m(\hat{x}) \geq \widehat{F}_m(x^*) + \frac{\lambda}{2} \|\hat{x} - x^*\|^2 \quad (48)$$

Proof. Let $Fx = \frac{1}{m} \sum_{t=1}^m f(x; z_t)$
 \widehat{F}_m is λ -strongly convex for

$$\langle \nabla \widehat{F}_m(\hat{x}), \hat{x} - x^* \rangle + \frac{\lambda}{2} \|\hat{x} - x^*\|^2 \leq \widehat{F}_m(\hat{x}) - \widehat{F}_m(x^*) \quad (49)$$

Since, x^* is the empirical risk minimizer, we have= rearranging,) |||| $\widehat{F}_m(x^*) - \widehat{F}_m(\hat{x}) \leq \|\hat{x} - x^*\|^2$, and so,

$$\frac{\lambda}{2} \|\hat{x} - x^*\|^2 \leq \langle \nabla \widehat{F}_m(\hat{x}), \hat{x} - x^* \rangle \leq \|\nabla \widehat{F}_m(\hat{x})\| \|\hat{x} - x^*\|.$$

If $\hat{x} - x^* = 0$, then we are done. Otherwise,

$$\|\hat{x} - x^*\| \leq \frac{2}{\lambda} \|\nabla \widehat{F}_m(\hat{x})\| \leq \frac{2}{\lambda} \|\nabla F_m(x^*)\|.$$

Now square both sides and take the expectation, which gives

$$\begin{aligned} & \mathbb{E} \|\hat{x} - x^*\|^2 \leq \frac{4}{\lambda^2} \mathbb{E} \|\nabla F_m(x^*)\|^2 \\ & \text{and any global stochastic oracle } \mathcal{O} \\ & \mathbb{E} \|\hat{x} - x^*\|_2^2 \leq \frac{4}{\lambda^2} \mathbb{E} \|\nabla F_m(x^*)\|^2 \end{aligned}$$

The final result follows by observing that $\|\nabla F_m(x^*)\| \leq \frac{\sigma}{m}$. \square

Theorem 3. For any $F \in \mathcal{F}[H, \lambda]$ with the restriction that $\|\nabla F(\cdot; z)\| \leq f(\cdot; z)$ is convex for all z , [Algorithm 1](#) with ERM

as its subroutine finds \hat{x} with $\nabla F(\hat{x}) \leq \varrho$ using at most

$$m \leq O\left(\frac{\sigma^2}{\varrho^2} \log^3\left(\frac{H}{\lambda}\right)\right)$$

total samples.

Proof. Consider

$$\begin{aligned} \|\nabla F(\hat{x}_T)\| &= \left\| \nabla F^{(0)}(\hat{x}_T) + \lambda \sum_{t=1}^T 2^t (\hat{x}_t - \hat{x}_T) \right\| \\ &\leq \|\nabla F^{(T)}(\hat{x}_T)\| + \lambda \sum_{t=1}^{T-1} 2^t \|\hat{x}_t - \hat{x}_T\| \\ &\leq \|\nabla F^{(T)}(\hat{x}_T)\| + \lambda \sum_{t=1}^{T-1} 2^t (\|\hat{x}_t - x_t^*\| + \|\hat{x}_T - x_T^*\|) \end{aligned}$$

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$$F^{(T)}(x) = F(x) + \lambda \sum_{t=1}^T 2^{t-1} \|x - \hat{x}_t\|^2$$

$T = \sum_{t=1}^T t$

. Then

(48)

(49)

(50)

$$\leq 2 \|\nabla F(\hat{x})\| + \lambda \sum_{t=1}^T 2^t \|x_t^* - x\|$$

$$\leq 2 \|\nabla F(\hat{x})\| + \lambda \sum_{t=1}^T 2^t \|x_t^* - x\|$$

(51)

$$\leq 6H\|\hat{x} - x\| + \lambda \sum_{t=1}^T 2^t \|x_t^* - x\|$$

$$\leq 6H\|\hat{x} - x\| + \lambda \sum_{t=1}^T 2^t \|x_t^* - x\|$$

$$\leq 12\lambda \sum_{t=1}^T 2^t \|x_t^* - x\|.$$

$$\leq 12\lambda \sum_{t=1}^T 2^t \|x_t^* - x\|$$

(51) follows from the $(\lambda \sum_{t=1}^T 2^t)$

Above, (49) and (50) rely on the triangle inequality; -strong convexity of $F^{(T)}$; (52) uses the fact that $F^{(T)}$ is $H + \lambda \sum_{t=1}^T 2^t \leq H + \lambda 2^{T+1} = H + 2\lambda 2^{\lceil \log H/\lambda \rceil} \leq 3H$ -smooth.

Define $P_k = \sum_{t=1}^k 2^t \|\hat{x}_t - x_k^*\|$ for $1 \leq k \leq T$ with $P_0 = 0$. Note that our upper bound (53) is equal to $12\lambda P_T = 12\lambda \sum_{k=1}^T P_k - P_{k-1}$, so we will estimate the terms of this sum.

$$P - P \quad 2x^{\hat{\wedge}} - \quad \parallel \quad \parallel \quad x + \sum 2 \quad x^{\hat{\wedge}} - x \quad - x^{\hat{\wedge}} - x \quad k- \\ k \quad k-1 = kk \quad *kt=-111\,tt\left(\parallel *t**k\parallel \quad \parallel t \quad *k-1\parallel\right) \quad (54)$$

$$\leq 2k\chi^* - x^* + \sum 2 \quad x - x \quad (55)$$

$$k \parallel_{kk} k*k \parallel_{t=1} k \parallel_{k*k-1} k-1 \parallel$$

$$(56) \quad (55) \quad \leq 2^k (\|x^* - x\| + \|x - x^*\|)$$

$$\leq 2. \quad (57)$$

Above, we used the reverse triangle inequality to derive . By optimality of x^*_{k-1} and x^*_k ,

$$\|\hat{x}_k - x_{k-1}^*\|^2 - \|\hat{x}_k - x_k^*\|^2 = \frac{F^{(k)}(x_{k-1}^*) - F^{(k)}(x_k^*) + F^{(k-1)}(x_k^*) - F^{(k-1)}(x_{k-1}^*)}{2^{k-1}\lambda} \geq 0. \quad (58)$$

Thus $\|\hat{x}_k - x_k^*\| \leq \|\hat{x}_k - x_{k-1}^*\|$ and, combining (53) and (57) yields

$$(59) \quad \mathbb{E}^{t-1} \lambda \left[\nabla F(\bar{x}_T) \leq 36\lambda \sum_{t=1}^T 2^t \|\bar{x}_t - x_{t-1}^*\| \right]$$

Since \hat{x}^* is the output of ERM on the $-$ strongly convex function F using m/T samples, by [Theorem 7](#),

$$\mathbb{E} \|\hat{x}_t - x_{t-1}^*\| \leq \frac{2\sigma\sqrt{T}}{2^{t-1}\lambda\sqrt{m}} \text{ and}$$

|| (

$$361 \leq 2 \hat{y} = y (60) \leq 361$$

$$\mathbb{E} \nabla F \geq 36\lambda \sum_{t=1}^{T-1} 2\|x_t - x^*\| \leq 36\lambda \sum_{t=1}^{T-1} 2\|x_t - x^*\| \quad (61)$$

$$T) \leq \max_{t=TT1}^t \mathbb{E} \|\mathbf{v}_t - \mathbf{v}_{t-1}\|$$

$$\sigma \quad T$$

$$144\sigma T_3 / \sqrt{m} \quad (62)$$

Solving for m such that the expression is less than ϱ completes the proof. \square

Corollary 2. For $F \in \mathcal{F}_{DB}[H, \lambda = 0; R]$ any and any global stochastic oracle O^σ with the

restriction $\varrho \|\nabla F(x_0)\|^2$ with $\lambda = \frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{HR}{\epsilon}\right)$ finds a point \hat{x} with $\mathbb{E}\|\nabla F(\hat{x})\| \leq \varrho$ using at most $O(\varrho/\epsilon)$ that $f \cdot z$ is convex

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for all z , with ERM as its subroutine,

when applied to $F \sim x F x +$

total samples.

For any $F \in \mathsf{FRB}[H, \lambda = 0; \Delta]$ and any global stochastic oracle \mathcal{O}^{σ} with the restriction that $f(\cdot; z)$ is convex for

$$m \leq O\left(\frac{\lambda}{\epsilon^2} \log\left(\frac{\lambda}{\epsilon}\right)\right) \quad \lambda = \Theta(\epsilon^2/\Delta) \text{ finds an } \epsilon$$

all z , the same approach with $\sigma^2 = \frac{3}{\lambda} \sqrt{H\Delta}$

stationary point using at most

total samples.

Proof. The objective $F(x) = F(x_0) + \frac{\lambda}{2} \|x - x_0\|^2$ is $(H + \lambda)$ function-smooth and λ -strongly convex. Thus by [Theorem 3](#), in particular [\(62\)](#)

$$\|F(x) - F(x^*) - \mathbb{E}\nabla F(x^*)\| \leq \sqrt{3} \frac{144\sigma \log(2/\lambda)}{H+\lambda} \quad (63)$$

m

For $F \in \mathsf{FDB}[H, \lambda = 0; R]$, with $\lambda = \Theta(\varrho/R)$ and $m = \Omega(\varrho \log^3(\frac{HR}{\varrho}))$ and using part one of [Lemma 3](#)

we conclude

$$\mathbb{E}\|\nabla F(x^*)\| \leq O(\varrho + \lambda R) \leq O(\varrho), \quad (64)$$

which completes the first part of the proof.

Similarly, for $F \in [H, \lambda = 0; \Delta]$, with $\lambda = \Theta(\epsilon^2/\Delta)$ and $m = \Omega\left(\frac{\sigma^2}{\epsilon^2} \log^3\left(\frac{\sqrt{H\Delta}}{\epsilon}\right)\right)$, FRB , by part two of

$$\mathbb{E}\|\nabla F(\hat{x})\| \leq O\left(\epsilon + \sqrt{\lambda\Delta}\right) \leq O(\epsilon),$$

[Lemma 3](#) we conclude [\(65\)](#)

which completes the proof. \square

Theorem 5. Consider any convex, L -Lipschitz function $F : \mathbb{R} \rightarrow \mathbb{R}$ that is bounded from below,¹³ and any global stochastic oracle O_{f_0} with the restriction that \cdot is convex for all $\mathbb{E}_{g \in \partial F}$.

There exists an algorithm m_{\leq} which uses $n = O\left(\frac{\sigma^2 \log(\frac{L}{\epsilon})}{\epsilon^2}\right)$ samples and outputs a point such that $[\inf_{x \in \mathbb{R}} F(x)] \leq |g| \leq \epsilon$.

$|g| \leq \epsilon$.

Proof. Our algorithm involves calculating the ERM on several independent samples, evaluating the gradient norm at these ERMs on a held-out sample, and returning the point with the smallest gradient norm.

Let $\nabla_- F(x)$ denote the left-derivative of F at x , and let $\nabla_+ F(x)$ denote the right-derivative. Since F is bounded from below,¹³ $\lim_{x \rightarrow -\infty} \nabla_- F(x) \leq 0$ and $\lim_{x \rightarrow \infty} \nabla_+ F(x) \geq 0$, thus there exists at least one $\forall x < a \nabla_+ F(x) < -\epsilon$. The point a is the left-most ϵ -stationary point. It is possible that $\nabla_+ F(a) \geq -\epsilon$.

that $\in \mathbb{R} \{ \} = - \leq \epsilon$, in ϵ -stationary point for F . Consequently, there is a unique $a \in \mathbb{R}$ for which and

which case there are no $x < a$. Similarly, there is a unique $b > a$ for which $\nabla_+ F(b) \geq \epsilon$ and $\forall x > b \nabla_- F(x) < -\epsilon$. The point b is the right-most ϵ -stationary point. It is possible that $b = \infty$, in which case there are no $x > b$.

By convexity, $\forall x \in \mathbb{R} \quad y \nabla F(x) \leq \nabla F(y) \leq \nabla F(x)$. Therefore, $\inf_{g \in \partial F(x)} |g| \leq \inf_{g \in \partial F(y)} |g| \leq \epsilon$.

Therefore, $\inf_{g \in \partial F(x)} |g| \leq \epsilon$.

$|\nabla_+ F(x)| > \epsilon$ and $x > b$ \Rightarrow $\inf_{g \in \partial F(x)} |g| \leq \epsilon$. Therefore, $|\nabla_+ F(x)| \geq \epsilon$.

Consequently, all that we need to show is that our algorithm returns a point within the interval $[a, b]$.

Let $\hat{F}(x) = \frac{1}{m} \sum_{i=1}^m f(x; z_i)$ be the empirical objective function and let \hat{x} be the minimizer of \hat{F} . Consider first the case that $\hat{x} > b$, we will argue that $\hat{x} \geq a$. Observe that if $\nabla_- \hat{F}(a) < 0$, then since

¹³ This lower bound does not enter the sample complexity quantitatively.

is convex, it is decreasing on $[-\infty, a]$. Since $a = -\infty, \nabla F(a) = -\rho$, so the value ∇F is the sum of i.i.d. random variables that have mean $\mathbb{E}[\nabla F] \leq -\rho$ and variance $\text{Var}[\nabla F] = \frac{\sigma^2}{m}$.

By Chebyshev's inequality, the random variable $\nabla F(a)$ will not deviate too far from its mean:

$$\mathbb{P}[\nabla F(a) \geq 0] \geq 1 - \frac{\sigma^2}{m\rho^2}. \quad (66)$$

Similarly,

$$\mathbb{P}[\nabla_{+\hat{F}}(b) < 0] < \frac{\sigma^2}{m\rho^2}. \quad (67)$$

Therefore, with probability at least $1 - \frac{2\rho^2}{m\rho^2} = \frac{1}{2}$, the minimum of \hat{F} lies in the range $[a, b]$ and thus the

ERM \hat{x} is an ρ -stationary point of F .

Consider calculating k ERMs $\hat{x}_1, \dots, \hat{x}_k$ on k independent samples of size m . Then with probability at least $1 - \left(\frac{2\rho^2}{m\rho^2}\right)^k = 1 - \left(\frac{1}{2}\right)^k$, at least one of these points is an ρ -stationary point of F .

Now, suppose we have km additional heldout samples which constitute an empirical objective \hat{F} . Since the ERMs \hat{x}_i are independent of these samples,

$$\mathbb{E} \left[\max_{i \in [k]} \left\| \nabla \hat{F}(\hat{x}_i) - \nabla F(\hat{x}_i) \right\|^2 \right] \leq \sum_{i=1}^k \mathbb{E} \left[\left\| \nabla \hat{F}(\hat{x}_i) - \nabla F(\hat{x}_i) \right\|^2 \right] \leq \frac{k\sigma^2}{km} \quad (68)$$

Condition on the event that at least one of the ERMs is an ϵ -stationary point of F and denote one of those ERMs as \hat{x} . Denote this event E . Let $\hat{x} = \arg \min_{x \in \mathcal{X}} \nabla \hat{F}(x)$ where we abuse notation and say

$\|\nabla F(\hat{x}_i)\| := \inf_{g \in \partial F(\hat{x}_i)} \|g\|$ for cases where F is not differentiable at \hat{x}_i . Then

$$\mathbb{E}[\|\nabla F(\hat{x}_i)\| | E] \leq \mathbb{E}[\|\nabla \hat{F}(\hat{x}_i)\| | E] + \mathbb{E}\left[\max_{i \in [k]} \|\nabla \hat{F}(\hat{x}_i) - \nabla F(\hat{x}_i)\| | E\right] \quad (69)$$

$$\leq \mathbb{E}[\|\nabla \hat{F}(\hat{x}_i)\| | E] + \sqrt{\frac{\sigma^2}{m}} \quad (70)$$

$$\leq \mathbb{E}[\|\nabla \hat{F}(\hat{x}_{i^*})\| | E] + \sqrt{\frac{\sigma^2}{m}} \quad (71)$$

$$\leq \mathbb{E}[\|\nabla F(\hat{x}_{i^*})\| | E] + \mathbb{E}\left[\max_{i \in [k]} \|\nabla \hat{F}(\hat{x}_i) - \nabla F(\hat{x}_i)\| | E\right] + \sqrt{\frac{\sigma^2}{m}} \quad (72)$$

$$\leq \epsilon + 2\sqrt{\frac{\sigma^2}{m}}. \quad (73)$$

$m = \Omega\left(\frac{\sigma^2}{\epsilon^2}\right)$ and $k = \Omega\left(\log\frac{L}{\epsilon}\right)$. The event $1 - \left(\frac{2\sigma^2}{m\epsilon^2}\right)^k \geq 1 - \frac{\epsilon}{L}$ that one of the ERMs is an ϱ -stationary point happens with probability at least. Choosing $\varrho = \epsilon + 2\sqrt{\frac{\sigma^2}{m}}$ ensures. Therefore,

$$\mathbb{E}[\|\nabla F(\hat{x}_i)\|] = \mathbb{P}[E]\mathbb{E}[\|\nabla F(\hat{x}_i)\| | E] + \mathbb{P}[E^c]\mathbb{E}[\|\nabla F(\hat{x}_i)\| | E^c]$$

$$\leq 1 - \frac{\epsilon}{L} \left(\epsilon + 2\sqrt{\frac{\sigma^2}{m}} \right) + \left(\frac{\epsilon}{L}\right)(L)$$

$$\leq \mathcal{O}(\epsilon). \quad (74)$$

$$\mathcal{O}(km) = \mathcal{O}\left(\frac{\sigma^2 \log\left(\frac{L}{\epsilon}\right)}{\epsilon^2}\right) \quad (75)$$

$$\leq \mathcal{O}(\epsilon). \quad (76)$$

This entire algorithm required

samples in total, completing the proof. \square

C Proofs of the Lower Bounds

Theorem 4. For any $\Delta, R, \sigma > 0$, $\epsilon \leq \min\left(\frac{HR}{8}, \sqrt{\frac{H\Delta}{8}}, \frac{\sigma}{4}\right)$, H , the sample complexity to find a ϱ -stationary point¹⁴ is lower bounded as

$$\mathbb{m}(\mathcal{F}_{DB}[H, \lambda = 0; R] \cap \mathcal{F}_{RB}[H, \lambda = 0; \Delta], \mathcal{O}_f^\sigma) \geq \Omega\left(\frac{\sigma^2}{\epsilon^2}\right)$$

Proof. For a constant $b \in \mathbb{R}$ to be chosen later, let

$$\dots \quad (77)$$

¹⁴ This lower bound applies both to deterministic and randomized optimization algorithms.

The distribution $\in \mathcal{D}$ of the random variable z is the uniform distribution over $\{z_1, \dots, z_m\}$ where the vectors $z_i \in \mathbb{R}^d$ are orthonormal ($d \leq m$). Therefore,

$$(78) \quad \begin{aligned} f(x; z) &= \mathbb{E}[f(x; z)] \\ F(x) &= \sigma \left(x, \frac{1}{m} \sum_{i=1}^m z_i \right) + \frac{b}{2} \|x\|^2. \end{aligned}$$

This function is clearly convex, - $\|x^*\|^2 \leq R^2$. Furthermore, $F(0) - F(x^*) = \frac{\sigma^2}{2m}$. Choosing $b = \max \left\{ \frac{\sigma}{R\sqrt{m}}, \frac{\sigma^2}{2\Delta m} \right\}$ ensures both simultaneously. $\frac{1}{m} \sum_{i=1}^m \|\sigma z_i - \frac{\sigma}{m} \sum_{j=1}^m z_j\|^2 = \sigma^2 \left(1 - \frac{1}{m}\right)(x; z) = \nabla F(x)$ and f is \mathcal{D}_{RB} smooth, and attains its unique minimum at $x^* = -b \frac{\sigma}{m} \sum_{i=1}^m z_i$ which $b \geq \frac{\sigma}{\sqrt{m}}$ ensures, so has norm, so choosing

choosing $b \geq \frac{\sigma^2}{2\Delta m}$ ensures $x^* \leq \Delta$ ensures both simultaneously.

Finally, $\mathbb{E}\|\nabla f\| \in \mathcal{D} \leq \sigma^2 \mathcal{O}$

Therefore, $F(0)$ properly define a \mathcal{D} .

Suppose, for now, that $\langle \cdot, v_i \rangle \geq -\frac{\sigma}{\sqrt{m}}$ for all $i \geq m/2$. Then

$$(79) \quad \begin{aligned} \|\nabla F(x)\|^2 &= \frac{\sigma^2}{m} + b^2 \|x\|^2 + \frac{2}{m} \sum_{i=1}^m \langle x, v_i \rangle \\ &\geq \frac{\sigma^2}{m} + b^2 \|x\|^2 + \frac{\sigma b}{m} \sum_{i=1}^m \langle x, v_i \rangle - \frac{\sigma b}{m} \sum_{i=1}^m \langle x, v_i \rangle = \frac{\sigma^2}{4m} \end{aligned}$$

$$(80) \quad \begin{aligned} \|\nabla F(x)\|^2 &\geq \frac{\sigma^2}{4m} \end{aligned}$$

$$m \leq \frac{m}{2} \min_{i < m/2} \langle \cdot, v_i \rangle^2$$

$$(81) \quad \begin{aligned} &\geq \frac{m}{4m} \min_{y \in \mathbb{R}} \frac{3\sigma^2 + b^2 m}{2} y \\ &= \frac{\sigma^2}{4m}. \end{aligned}$$

$$(82)$$

Therefore, for all such x , $\|\nabla F(x)\| \geq \frac{\sigma}{2\sqrt{d}}$ vectors. This holds for any $b \geq \begin{bmatrix} z_1, \dots, z_m \\ \vdots \\ z_{m/2-1} \end{bmatrix} 0$ and

$\{z_{m/2}, \dots, z_m\}$ set. From here, we will argue that any randomized algorithm with access to less than $m/2$ samples from

is likely to output such an x . We consider a random function instance determined by drawing the orthonormal set $\{z_1, \dots, z_m\}$ uniformly at random from the set of orthonormal vectors in \mathbb{R}^d . We will argue that with moderate probability over the randomness in the algorithm and in the draw of $\{z_1, \dots, z_m\}$, the output of the algorithm has small inner product with $\{z_{m/2}, \dots, z_m\}$. This approach closely resembles previous work (Woodworth and Srebro, 2016, Lemma 7).

Less than $\frac{m}{2}$ samples fix less than $m/2$ of the vectors z_i ; assume w.l.o.g. that the algorithm's sample $\{z_1, \dots, z_{m/2-1}\}$

The vectors z_i are a uniformly random orthonormal set, therefore for any $i \leq m/2$,

z_i | S -dimensional unit sphere in the $d-m-2+1$) is distributed uniformly on the $(z_1, \dots, z_{m/2-1})$. Let \hat{x} subspace

orthogonal to span

then it is easily confirmed that $\|\nabla F(\cdot)\| \geq \frac{\sigma^2}{2}$

orthogonal to span $\{v_1, v_2, \dots, v_r\}$ then it is easily confirmed that $\|v_{r+1}\| = r$ be the

output of any

$$\begin{aligned} \mathbb{P}\left[\langle \hat{x}, v_i \rangle < -\frac{\sigma}{8bm} \mid S, \hat{x}\right] &\leq \mathbb{P}\left[|\langle \hat{x}, v_i \rangle| \geq \frac{\sigma}{8bm} \mid S, \hat{x}\right] \\ &\leq \mathbb{P}\left[\frac{2\sigma}{b\sqrt{m}} \left\| \begin{pmatrix} \hat{x} \\ \|\hat{x}\| \end{pmatrix}, v_i \right\| \geq \frac{\sigma}{8bm} \mid S, \hat{x}\right] \end{aligned}$$

algorithm whose

input is S . If $\|\hat{x}\| \geq \frac{2\sigma}{b\sqrt{m}}$

$$\left\| \left\langle \frac{\hat{x}}{\|\hat{x}\|}, v_i \right\rangle \right\| \geq \frac{1}{16\sqrt{m}} \left\| S, \hat{x} \right\|$$

\hat{x} is orthogonal to $\text{span } z_1, \dots, z_n$

. Otherwise, we analyze

(83)

(84)

(85)

This probability only increases if we assume that $(1_m' 2_{-1})$, in which case we are considering the inner product between a fixed unit vector and a uniformly random unit vector. The probability of the inner product being large is proportional to the surface area of the “cap” of a unit sphere in $(d - m/2 + 1)$ -dimensions lying above

and below circles of radius $\sqrt{1 - \frac{1}{256m}}$. These end caps, in total,

have surface area less than the same radius.

$$\mathbb{P} \left[\left\langle \hat{X}, V_i \right\rangle < -\frac{\sigma}{8bm} \mid S, \hat{X} \right] < \frac{\bar{\mathbb{A}}}{1 - \frac{1}{256m}} \left(1 - \frac{1}{512m} \right)^{d - \frac{m}{2}}$$

$$= \frac{1}{1 - \frac{d}{512m} - \frac{1}{1024}} \left(\frac{d - m}{2} \right)^{-\frac{m}{2}}$$

than that of a sphere with
Therefore, i

$$(86) \quad \backslash \quad (87) \quad \text{d.m.}$$

$$\leq \exp \left[-\frac{1}{2} - \frac{d}{2} \right]. \quad (88)$$

$$\begin{aligned}
& \hat{x} \text{ being small, so for } d > \frac{m}{2m} \log \frac{1}{2m} \\
& \left[\langle \hat{x}, v_i \rangle < -\frac{\sigma}{8bm} \right] \subseteq \left\{ \|\hat{x}\| < \frac{2\sigma}{b/m} \right\} < \frac{1}{2m}. \\
& \|\hat{x}\| > 2\sigma \text{ or } \langle \hat{x}, v_i \rangle > -\frac{\sigma}{8bm} \text{ for all } i > m/2 \text{ with probability at least } 1/2 \\
& \text{for } z_1, \dots, z_m, \text{ and consequently, that } \mathbb{E}_{\hat{x}} \|\nabla F(\hat{x})\|^2 > \frac{\sigma^2}{8m} \\
& \text{. For this } \mathbb{E}_{\hat{x}} \left[\frac{\|\hat{x}\|^2}{m} \right] < \frac{4\sigma^2}{R} + \frac{4\sigma^2}{\Delta} \\
& \sigma < \min \left(\frac{HR}{8}, \frac{H\Delta}{8} \right). \quad \square \\
& (1024 \cdot 512 \cdot m)
\end{aligned}$$

This did not require anything but the norm of \hat{x} , this ensures that

$$P \quad (89)$$

A union bound ensures that either $\|\hat{x}\| > m$

Setting $O = \lfloor \frac{m}{2} \rfloor$ ensures this is at least $\sigma \sqrt{O} \in (m/2, m)$. $b = \max\{R, \Delta\}$ which must be less than H , consequently, this lower bound applies for

Theorem 8. For any $H, R, \sigma \geq 0$ and any $\rho \geq 0, \sigma \leq 2$, there exists a $F: H \times \mathcal{X} \rightarrow \mathbb{R}$ and a Δ , such that for any algorithm interacting with the stochastic first-order oracle, and returning an ρ -approximate stationary point with some fixed constant probability, the expected number of queries is $\Omega\left(\frac{\sigma^2}{\rho^2} \cdot \log\left(\frac{HR}{\rho}\right)\right)$ at least

Moreover, a similar lower bound holds if the radius constraint R is replaced by a suboptimality constraint Δ .

Proof. We prove the lower bound by reduction from the noisy binary search (NBS) problem: In this classical problem, we have N sorted elements, and we wish to insert a new element e using only queries of the form “is $e > a_j$?” for some j . Rather than getting the true answer, an independent coin is flipped and we get the correct answer only with probability $\frac{1}{2} + p$ for some fixed parameter p . Moreover, let j^* be the unique index such that $a_{j^*} < e < a_{j^*+1}$ ¹⁵. It is well-known (see for example Feige et al.

(1994); Karp and Kleinberg (2007)) that in order to identify j^* with any fixed constant probability, at least $\Omega(\log(N)/p^2)$ queries are required.

¹⁵ This is w.l.o.g., since if $e < a_1$ or $e > a_N$, we can just add two dummy elements smaller and larger than all other elements and e , increasing N by at most 2, hence not affecting the lower bound.

Let us first consider the case where the radius constraint R is fixed. We will construct a convex stochastic optimization problem with the given parameters, such that if there is an algorithm solving it (with constant probability) after T local stochastic $\left\lceil \frac{\sigma^2}{\epsilon^2} \cdot \log \left(\frac{HR}{\epsilon} \right) \right\rceil$ oracle queries, then it can be used to solve an NBS problem (with the same probability) using $2T$ queries, where $p = \varrho/\sigma$ and¹⁶ $N = HR/4\varrho$. Employing the lower bound above for NBS, this immediately implies the Ω lower bound in our theorem.

To describe the reduction, let us first restate the NBS problem in a slightly different manner. For a fixed query budget T , let Z be a $T \times N$ matrix, with entries in $\{-1, +1\}$ drawn independently according to the following distribution:

$$\Pr_{Z \in \mathcal{Z}}(Z_{tj} = 1) = \begin{cases} 1-p & j \leq j^* \\ 2p & j > j^* \end{cases}$$

Each Z_{tj} can be considered as the noisy answer provided in the NBS problem to the t -th query, of the form “is $e > a_j$ ” (where -1 corresponds to “true” and 1 corresponds to “false”). Thus, an algorithm for the NBS problem can be seen as an algorithm which can query T entries from the matrix Z (one query from each row), and needs to find j^* based on this information. Moreover, it is easy to see that the NBS lower bound also holds for an algorithm which can query *any* T entries from the matrix: Since the entries are independent, this does not provide additional information, and can only “waste” queries if the algorithm queries the same entry twice.

We now turn to the reduction.

Given an NBS problem on $N = HR/4\varrho$ elements with $p = \varrho/\sigma$ and a

randomly-drawn matrix Z , we first divide the interval $[0, R]$ into N equal sub-intervals of length $t = R/N$ each,

¹⁶ $/4\varrho$ is a whole number – otherwise, it can be rounded and this will only affect constant factors in the lower bound.

and w.l.o.g. identify each element a_j with the smallest point in the interval. Then, for every (statistically independent) row Z of Z , we define a function $f(x, Z)$ on by $f(0, Z) = 0$, and the rest is defined via its derivative as follows:

$$f(x, Z_t) = \begin{cases} \frac{x-a_j}{R/N} \sigma Z_{t,j+1} + \left(1 - \frac{x-a_j}{R/N}\right) \sigma Z_{t,j} & x \in [a_j, a_{j+1}) \text{ for some } j < N \\ -2\epsilon & x < 0 \\ 2\epsilon & x > R \end{cases}.$$

Note that by construction $\frac{x-a_j}{R/N} \in [0, 1]$ and $Z_{t,j} \in [-1, +1]$, so $|f'(x, Z_t)| \leq \max\{2\epsilon, \sigma\} \leq \sigma$. Moreover, since the expected value of $\sigma Z_{t,j}$ is $\sigma \cdot (-2p) = -2\varrho$ if $j \leq j^*$, and $\sigma \cdot (2p) = 2\varrho$ if $j > j^*$, it is easily verified

that

$$\mathbb{E}_Z[f'(x, Z_t)] = \begin{cases} -2\epsilon & x < a_{j^*} \\ 2\epsilon & x \geq a_{j^*} \end{cases}.$$

Noting that

$$4\epsilon \frac{\varrho}{R/N} = H(x - a_{j^*}) \in [0, 4\epsilon]$$

$$\begin{cases} -2\epsilon + 4\epsilon \frac{x-a_j}{R/N} & x \in [a_{j^*}, a_{j^*+1}) \\ 2\epsilon & x \geq a_{j^*+1} \end{cases}.$$

In the above, we get that $F(x) := \mathbb{E}_Z[f(x, Z_t)]$, and with

when for simplicity we assume that $x \in [a_{j^*}, a_{j^*+1})$.

Overall,

we get a valid convex stochastic optimization problem (with parameters $HR \|\cdot\| \leq \|\cdot\|_1 \leq \|\cdot\| \leq$ function with H -Lipschitz gradients, with a unique minimum at some $x : x \in \arg\min F$ only

H, R, σ as required), such that if we can identify x such that $F(x) = \varrho$, then we can uniquely identify

j^* . Moreover, given an algorithm to the optimization problem, we can simulate a query to a local stochastic

oracle (specifying an iterate t and a point x) by returning $f(x, Z_t)$ as defined above, which requires querying

at most 2 entries $Z_{t,j}$ and $Z_{t,j+1}$ from the matrix Z . So, given an oracle query budget T to the stochastic problem,

we can simulate it with at most $2T$ queries to the matrix Z in the NBS problem.

To complete the proof of the theorem, it remains to handle the case where there is a suboptimality constraint

Δ rather than a radius constraint R . To that end, we simply use the same construction as above, with $R = \frac{\Delta}{2\varrho}$.

Since the derivative of F has magnitude at most 2ϱ , and its global minimum satisfies $|x^*| \leq R$, it follows that

F in the lower bound, the result follows. \square

$(0) - F(x^*) \leq 2\epsilon R = \Delta$. Plugging in $R = \frac{\Delta}{2\epsilon}$ Theorem 2. , the stochastic first-order oracle complexity for rangebounded functions is lower bounded as m

$$(\mathcal{F}_{DB}[H, \lambda = 0; R], \mathcal{O}_{\nabla f}^{\sigma}) \geq \Omega\left(\sqrt{\frac{HR}{\epsilon}} + \frac{\sigma^2}{\epsilon^2} \log\left(\frac{HR}{\epsilon}\right)\right).$$

For any $\epsilon \leq \sqrt{\frac{H\Delta}{8}}$, the stochastic first-order complexity for domain-bounded functions is lower bounded as

$$m_{\varrho}(\mathcal{F}_{RB}[H, \lambda = 0; \Delta], \mathcal{O}_{\nabla f}^{\sigma}) \geq \Omega\left(\frac{\sqrt{H\Delta}}{\varrho} + \frac{\sigma^2}{\varrho^2} \log\left(\frac{H\Delta}{\varrho^2}\right)\right).$$

Proof. By Theorem 8, oracle $\mathcal{O}_{\nabla f}^{\sigma}$ calls $\Omega(\sqrt{H\Delta}/\varrho^2)$ samples and $\Omega(\sqrt{H\Delta}/\varrho^2)$ logit $\Omega(\sqrt{H\Delta}/\varrho^2)$ -stationary point. Furthermore, a deterministic first-order oracle is a special case of a stochastic first-order oracle (corresponding to the case $\sigma = 0$). Therefore, lower bounds for deterministic first-order optimization apply also to stochastic first-order optimization. Therefore, the lower bound of (Carmon et al., 2017b, Theorem 1) completes the proof.

□