An Even More Optimal Stochastic Optimization Algorithm: Minibatching and Interpolation Learning

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Abstract

We present and analyze an algorithm for optimizing smooth and convex or strongly convex objectives using minibatch stochastic gradient estimates. The algorithm is optimal with respect to its dependence on both the minibatch size and minimum expected loss simultaneously. This improves over the optimal method of Lan (2012), which is insensitive to the minimum expected loss; over the optimistic acceleration of Cotter et al. (2011), which has suboptimal dependence on the minibatch size; and over the algorithm of Liu and Belkin (2018), which is limited to least squares problems and is also similarly suboptimal with respect to the minibatch size. Applied to interpolation learning, the improvement over Cotter et al. and Liu and Belkin translates to a linear, rather than square-root, parallelization speedup.

1 Introduction

The massive scale of many modern machine learning models and datasets give rise to complex, high-dimensional training objectives that can be very computationally expensive to optimize. To reduce the computational cost, it is therefore important to devise optimization algorithms that can leverage parallelism to reduce the amount of time needed to train. Stochastic first-order methods, which use stochastic estimates of the gradient of the training objective, are by far the most common approach and these methods can be directly improved by using minibatch stochastic gradient estimates, which are easy to parallelize across multiple computing cores or devices. Accordingly, we propose and analyze an optimal accelerated minibatch stochastic gradient descent algorithm.

Our analysis exploits that while training machine learning models, it is typically possible to drive the loss either all the way to zero, or at least very close to zero, and the performance of our algorithm improves as the minimum value of the loss approaches zero. This property has multiple names in different contexts. In learning theory, it is common to show fast rates under the assumption of “realizability”—meaning the data can be fit perfectly by the model, i.e. the loss can be driven to zero. Even when the problem is not exactly realizable, it is sometimes possible to derive “optimistic rates” that interpolate between fast rates for realizable learning and the slower agnostic rates (Srebro et al., 2010). In the context of “interpolation learning,” there has recently been great interest in understanding training “overparametrized” models—which have many more parameters than there are training examples, generally meaning that many settings of the parameters would attain zero training loss—both in terms of optimization (Jacot et al., 2018; Allen-Zhu et al., 2018; Arora et al., 2019; Chizat et al., 2019; Allen-Zhu et al., 2019) and generalization (Zhang et al., 2016; Tschöger and Bartlett, 2020; Belkin et al., 2019). Finally, in the optimization literature, there have been efforts to prove optimistic rates depending on the minimum value of the objective or on the variance of the stochastic gradients at the minimizer (Schmidt and Roux, 2013; Needell et al., 2014; Moulines and Bach, 2011; Cotter et al., 2011; Liu and Belkin, 2018; Ma et al., 2018). Regardless of the name, these ideas are all based on the same fundamental concept of exploiting the fact that the minimum value of the objective is nearly zero.
Our contributions

In Section 3, we present and analyze an accelerated minibatch SGD algorithm for optimizing smooth and convex objectives using minibatch stochastic gradient estimates. Our method closely resembles the methods of Lan (2012) and Cotter et al. (2011), but with different stepsizes and momentum parameters, and a tighter analysis. Importantly, our algorithm enjoys a linear speedup in the minibatch size all the way up to a critical threshold beyond which larger minibatches do not help. In contrast, Lan and Cotter et al.’s bounds have a worse, sublinear speedup and a correspondingly higher critical threshold.

In Section 4, we show that a modified version of our algorithm can attain substantially faster convergence when the objective satisfies a certain quadratic growth condition, which is a relaxation of strong convexity. As part of our analysis, we simplify and generalize a restarting technique (Nemirovskii and Nesterov, 1985; Ghadimi and Lan, 2013; Nesterov, 2013; Lin and Xiao, 2014; Roulet and d’Aspremont, 2020; Renegar and Grimmer, 2021), which we show amounts to a reduction from strongly convex optimization to convex optimization. The reduction in the other direction is a well-known tool in optimization analysis, but our result shows that it goes both ways and it may be of more general interest.

In Sections 5 and 6, we prove that our methods are optimal with respect to both the minibatch size and also the minimum value of the loss in the settings we consider. We then explain how our guarantees demonstrate a linear speedup in the minibatch size, which improves over a sublinear speedup in previous work (Cotter et al., 2011; Liu and Belkin, 2018).

Finally, in Section 7, we extend our results to a related setting where the bound on the minimum value of the loss is replaced by a bound on the variance of the stochastic gradients at the optimum (as in, e.g. Moulines and Bach, 2011; Schmidt and Roux, 2013; Needell et al., 2014; Bottou et al., 2018; Gower et al., 2019). Under this condition, we establish the optimal error achievable by any learning rule, including non-first-order methods, and we show that the optimal convergence rate is nevertheless achieved by SGD—a first-order method without acceleration. Further, we show that the accelerated optimization rate, $T^{-2}$, is unattainable using minibatches of size 1, but with larger minibatches, our accelerated minibatch SGD method can match the optimal error of SGD using a substantially smaller parallel runtime but the same number of samples.

2 Setting and Background

We consider a generic stochastic optimization problem

$$\min_{w \in \mathbb{R}^d} \{L(w) := \mathbb{E}_{z \sim \mathcal{D}}[\ell(w; z)]\}$$

(1)

This problem captures, for instance, supervised machine learning where $z = (x, y)$ is feature vector and label pair; $\ell(w; (x, y))$ is the loss of a model parametrized by $w$ on that example; and $L(w)$ is the expected loss. We note that there are two possible interpretations of $L$ depending on what $\mathcal{D}$ corresponds to. We can take $\mathcal{D}$ to be the uniform distribution over a set of training examples, in which case $L$ is the training loss. Alternatively, we can take $\mathcal{D}$ to be the population distribution, in which case $L$ is the population risk. An advantage of the latter view is that optimization guarantees directly imply good performance on the population, however, computing an independent, unbiased stochastic gradient estimate requires a fresh sample from the distribution, so only “one-pass” methods are possible. Nevertheless, our algorithm and analysis apply equally well in either viewpoint.

We consider optimizing objectives on $\mathbb{R}^d$, but we are most interested in dimension-free analysis, i.e. one that does not explicitly depend on the dimension, and our algorithm’s guarantees hold even in infinite dimension. Indeed, in many applications including machine learning, the dimension can be very large, so an explicit reliance on the dimension would often lead to impractical bounds.

We study the family of optimization algorithms that attempt to minimize (1) using $T$ sequential stochastic
gradient estimates with minibatches of size $b$ of the form

$$g(w_t) = \frac{1}{b} \sum_{i=1}^{b} \nabla \ell(w_t; z^i) \quad \text{for i.i.d. } z^1, \ldots, z^b \sim \mathcal{D}$$

(2)

at points $w_1, \ldots, w_T$ of the algorithm’s choice. Later, we will argue that our proposed method is optimal with respect to all of the algorithms in this family. Because it is easy to parallelize the computation of the $b$ stochastic gradients in the minibatch, $T$ roughly captures the runtime of the algorithm, while $n = bT$, the total number of samples used, captures its sample complexity.

In our analysis, we will rely on several assumptions about the losses $\ell$ and the expected loss $L$.

**Assumption 1.** For almost every $z \sim \mathcal{D}$, $\ell(w; z)$ is non-negative, convex, and $H$-smooth w.r.t. $w$, i.e.

$$\forall_{w,u,z} \quad \ell(u; z) + \langle \nabla \ell(u; z), w - u \rangle \leq \ell(u; z) + \langle \nabla \ell(u; z), w - u \rangle + \frac{H}{2} ||w - u||^2$$

This assumption holds, for instance, for training linear models with a smooth, convex, and non-negative loss function, as in least squares problems or logistic regression.

**Assumption 2.** The expected loss $L$ is convex and has minimum value $L^* = \min_w L(w)$, which is attained at a point $w^*$ with $\|w^*\| \leq B$.

The minimum value of the loss, $L^*$, is the key quantity in our analysis, and we will prove an “optimistic rate” for our algorithm, meaning it performs increasingly well as $L^* \to 0$. The key idea is to use $L^*$ to bound the variance of the stochastic gradient estimates at the point $w^*$. Following prior work (Shalev-Shwartz and Singer, 2007; Srebro et al., 2010; Cotter et al., 2011), we observe that under Assumptions 1 and 2, we can upper bound (see Lemma 3)

$$\mathbb{E}||\nabla \ell(w^*; z) - \nabla L(w^*)||^2 \leq 2HL^*$$

(3)

The $H$-Lipschitzness of $\nabla \ell$ allows us to upper bound the variance of the stochastic gradients at other, non-minimizing points $w$ too. In contrast, a common practice in the optimization literature is to simply assert that the variance of the stochastic gradient estimates is uniformly upper bounded, i.e.

$$\sup_{w} \mathbb{E}||\ell(w; z) - \nabla L(w)||^2 \leq \sigma^2$$

(4)

This bound is very convenient, but it can fail to hold even in very simple cases like least squares regression, where the variance grows with $||w||^2$. Therefore, while faster rates may be achieved under the condition (4), this is quite strong and may not correspond well with problems of interest.

For many optimization problems, particularly those arising from training machine learning models, the minimum of the loss, $L^*$, can be expected to be small. For example, machine learning models are often trained in the interpolation regime (Jacot et al., 2018; Allen-Zhu et al., 2018; Arora et al., 2019; Chizat et al., 2019; Allen-Zhu et al., 2019; Zhang et al., 2016; Tsigler and Bartlett, 2020; Belkin et al., 2019), where the training loss is under-determined, so there are many settings of the parameters which achieve exactly zero training loss. When $\mathcal{D}$ is the empirical distribution (see above), the interpolation regime therefore corresponds to $L^* = 0$. However, even if $\mathcal{D}$ is the population distribution, machine learning problems are often realizable, or nearly realizable, meaning the population risk can also be driven to zero or close to it.

In the optimization literature, it is often possible to show enhanced guarantees under the favorable condition of $\lambda$-strong convexity. However, the assumption of strong convexity is somewhat at odds with our goal of studying the interpolation or near-interpolation setting. For example, the simplest example of interpolation learning is underdetermined least squares, where the number of observations is less than the dimension; in this case, the empirical covariance is degenerate so the problem is not strongly convex. Furthermore, assuming strong convexity and $L^* \approx 0$ and $\ell$ is non-negative is very strong, and puts very strong constraints on the objective function which may often fail to hold.
We consider instead a relaxation of strong convexity, which only requires the objective to grow faster than the squared distance to the set of minimizers, which need not be a singleton (Bolte et al., 2017; Drusvyatskiy and Lewis, 2018; Necoara et al., 2019). This condition does hold for underdetermined least squares—with λ equal to the smallest non-zero eigenvalue of the covariance—and for many other problems with non-unique minimizers, and it turns out to be sufficient to achieve the faster rates that typically arise from strong convexity.

**Assumption 3.** The expected loss \( L \) is convex; it has minimum value \( L^* = \min_w L(w); L(0) - L^* \leq \Delta \); and \( L \) satisfies the following growth condition for all \( w \):

\[
L(w) - L^* \geq \frac{\lambda}{2} \min_{w^* \in \arg \min_w L(w)} \|w - w^*\|^2
\]

**Related Work**

The foundation of much of the work on optimal stochastic optimization algorithms is the accelerated SGD variant, AC-SA, of Lan (2012). This algorithm is analyzed in a different setting, where \( L \) is \( H \)-smooth, \( B \)-bounded, and convex and where the stochastic gradients have uniformly bounded variance (4), and under these conditions, it is optimal, with guarantee

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \frac{\sigma B}{\sqrt{bT}} \right)
\]

In our setting, however, there is no such explicit bound on the gradient variance, and at the same time, Lan’s analysis does not exploit the bound on \( L^* \) to achieve a better rate. Under our Assumptions 1 and 2, it is possible to derive a variance upper bound \( \sigma^2 = 2H^2B^2 + 4HL^* \), which yields

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \frac{HB^2}{\sqrt{bT}} + \sqrt{\frac{HB^2L^*}{bT}} \right)
\]

The first and third terms of this bound are tight, but we will later show that this guarantee is suboptimal because the denominator of the second term can be improved to \( bT \). When \( L^* \approx HB^2 \)—the largest possible value of \( L^* \) under mild conditions—we will later show that this bound is tight, so we can interpret this modification of Lan’s guarantee as being optimal only when \( L^* \) is large.

In other, more directly comparable existing work, Cotter et al. (2011) propose and analyze a minibatch SGD algorithm and an accelerated variant similar to AC-SA under our Assumptions 1 and 2. Their accelerated method is guaranteed to achieve suboptimality

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \frac{HB^2}{\sqrt{bT}} + \frac{HB^2\sqrt{\log T}}{bT} + \sqrt{\frac{HB^2L^*}{bT}} \right)
\]

In the special case of \( b = 1 \), we will show that this is optimal (up to a minor \( \sqrt{\log T} \) factor). However, the \( \sqrt{bT} \) dependence in the second term can be improved to \( bT \), so Cotter et al.’s analysis is suboptimal when \( b > 1 \). We also extend our analysis to the Assumptions 1 and 3.

In other related work, Liu and Belkin (2018) propose a different minibatch accelerated SGD method. In the special case of least squares objectives—where \( \ell(w; (x, y)) = \frac{1}{2}((w \cdot x) - y)^2 \)—that also satisfy Assumptions 1 and 3 with \( L^* = 0 \), they show that their algorithm attains suboptimality

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \Delta \exp \left( -\frac{c'\sqrt{\lambda T}}{\sqrt{H}} \right) + \Delta \exp \left( -\frac{c'\lambda T}{H} \right) \right)
\]

As with Cotter et al., we show that the \( \sqrt{bT} \) dependence of this guarantee is suboptimal and can be improved to \( bT \). In addition, our analysis goes beyond the special case of least squares with \( L^* = 0 \).

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1The minimum \( L^* \leq O(HB^2) \), for example, when \( \ell(w; z) = 0 \) is realized within a ball of radius \( O(B) \).
Algorithm 1: Accelerated Minibatch SGD

\[ w^{ag}_0 = w_0 = 0 \]

\[ \text{for } t = 0, 1, \ldots, T - 1 \text{ do} \]

\[ \beta_t = 1 + \frac{b}{8} \text{ and } \gamma_t = \gamma(t + 1) \text{ for } \gamma = \min \left\{ \frac{1}{12H}, \frac{b}{24H(T+1)}, \sqrt{\frac{bB^2}{H(T+1)^3}} \right\} \]

\[ w^{md}_t = \beta_t^{-1} w_t + (1 - \beta_t^{-1}) w^{ag}_t \]

\[ \tilde{w}_{t+1} = w_t - \gamma_t g_t(w^{md}_t) \text{ where } g_t(w^{md}_t) = \frac{1}{b} \sum_{i=1}^b \nabla \ell(w^{md}_t, z^i_t) \text{ for i.i.d. } z^1_t, \ldots, z^b_t \sim D \]

\[ w_{t+1} = \min \left\{ 1, \frac{B}{\|w_{t+1}\|} \right\} \tilde{w}_{t+1} \]

\[ w^{ag}_{t+1} = \beta_t^{-1} w^{ag}_{t+1} + (1 - \beta_t^{-1}) w_t^{ag} \]

\[ \text{Return: } w_T^{ag} \]

In other related work, Bassily et al. (2018) study non-accelerated algorithms in a similar setting. Zhang et al. (2017) consider a related setting where the losses \( \ell \) are Lipschitz rather than smooth, and where the dimension of the problem is sufficiently small relative to the other problem parameters. Zhang and Zhou (2019) study our smooth setting but with an additional restriction that \( \ell \) is Lipschitz and \( L \) is strongly convex, but show only polynomial convergence versus our linear convergence. Srebro et al. (2010) study the performance of the empirical risk minimizer under Assumptions 1 and 2 as well as stochastic first-order methods with \( b = 1 \); their methods are optimal for \( b = 1 \), but they do not analyze the effect of the minibatch size. Vaswani et al. (2019) consider a different noise assumption, which is similar to requiring \( L^* = 0 \).

3 A Better Accelerated Minibatch SGD Method

Our Algorithm 1 is very similar to the AC-SA algorithm of Lan (2012) and to the AG algorithm of Cotter et al. (2011); the difference is that we use different stepsize and momentum parameters and provide a tighter analysis for our setting. Our method provides the following guarantee:

**Theorem 1.** Let \( \ell \) and \( L \) satisfy Assumptions 1 and 2, then Algorithm 1 guarantees for a universal constant \( c \)

\[ \mathbb{E} \ell(w_T^{ag}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \frac{HB^2}{bT} + \sqrt{\frac{H^3B^2L^*}{bT}} \right) \]

We prove this in Appendix A using a similar approach as the analysis for AC-SA of Lan (2012). As discussed previously, Lan’s analysis relies on a uniform upper bound on the stochastic gradient variance on the set \( \{ w : \| w \| \leq B \} \). While an upper bound can be derived in our setting, it resembles \( H^2B^2 \) which is too large to achieve good performance. Our analysis, in contrast, exploits the fact that the points \( w^{md}_0, \ldots, w^{md}_{T-1} \), at which the stochastic gradients are actually computed approach \( w^* \) as the algorithm proceeds, which implies that the stochastic gradient variance decreases over time. It is difficult to identify precisely why our analysis improves in its dependence on the minibatch size, \( b \), compared with Cotter et al.’s bound. However, the primary difference between our analyses is that Cotter et al. use stepsizes \( \gamma_t \propto t^p \) for \( p < 1 \), while our stepsizes scales linearly with \( t \). Our choice leads to somewhat simpler computations, which may explain our tighter bound.

4 The Reduction and Faster Rates

Our algorithm can also be extended to the setting of Assumptions 1 and 3 using a restarting argument (Nemirovskii and Nesterov, 1985; Ghadimi and Lan, 2013; Nesterov, 2013; Lin and Xiao, 2014; Roulet and d’Aspremont, 2020; Renegar and Grimmer, 2021). The proof is based on a simple idea, which we will show amounts to a reduction from strongly convex optimization to convex optimization. However, previous applications of restarting schemes tend to involve relatively complex and specialized proofs. Here, we simplify and generalize the approach, and we present it in a way that will hopefully be convenient for future use. We then apply it to provide an enhanced guarantee for Algorithm 1 under Assumptions 1 and 3.
Convex optimization algorithms guarantee reducing the value of the objective by an amount that depends on some measure of the distance between the initialization and a minimizer of the objective. The key idea in the analysis is that when the objective is $\lambda$-strongly convex, reducing the value of the objective implies reducing the distance to the minimizer:

$$\|w - w^*\|^2 \leq \frac{2(L(w) - L^*)}{\lambda} \tag{9}$$

Therefore, if we apply an algorithm for convex objectives to a strongly convex objective several times in succession, each time reducing the suboptimality by a constant factor, then (1) roughly log $1/\epsilon$ applications will suffice to reach $\epsilon$-suboptimality and (2) reducing the suboptimality by a constant factor will get no harder with each application since the distance to the optimum is decreasing. Using this idea allows us to take an algorithm with a guarantee for convex objectives and derive an algorithm with a corresponding, better guarantee for strongly convex objectives. We also show that strong convexity can be replaced by a weaker condition that generalizes Assumption 3.

In order to present the reduction, we first define

**Definition 1.** Given $\psi : \mathbb{R}^d \to \mathbb{R}_+$, we say that $L$ satisfies the $(\lambda, \psi)$-growth condition (hereafter $(\lambda, \psi)$-GC) if for all $w$

$$L(w) - L^* \geq \lambda \psi(w)$$

For example, the $(\lambda, \psi)$-GC for $\psi(w) = \frac{1}{2}\|w - w^*\|^2$ is equivalent to $\lambda$-strong convexity, and the condition in Assumption 3 is equivalent to the $(\lambda, \psi)$-GC for $\psi(w) = \arg\min\{w^*(w + L(w))\}\|w - w^*\|^2$. The second ingredient of the reduction is the “time” needed by an algorithm to optimize convex or strongly convex objectives:

**Definition 2.** Let $L$ be any set of convex functions. We define $\text{Time}(\epsilon, B, \psi, L, A)$ to be the time needed by the algorithm $A$ to find a point $\hat{w}$ with $L(\hat{w}) - L^* \leq \epsilon$ given a point $w_0$ with $\mathbb{E}(w_0) \leq B$, for any $L \in L$. Similarly, we define $\text{Time}_{\lambda}(\epsilon, \Delta, \psi, L, A)$ to be the time needed by $A$ to find $\hat{w}$ with $L(\hat{w}) - L^* \leq \epsilon$ given a point $w_0$ with $\mathbb{E}(w_0) - L^* \leq \Delta$, for any $L \in L$ that also satisfies the $(\lambda, \psi)$-GC.

We are deliberately vague about the precise meaning of “time” here. Typically, it would correspond to the number of iterations of the algorithm, but it could also count the number of times the algorithm accesses a certain oracle, or even the wall-clock time of an implementation of the algorithm, but it can correspond to essentially any (subadditive) property of the algorithm. With these definitions in hand, we present the reduction, Algorithm 2, which guarantees:

**Theorem 2.** For any algorithm $A$ and $\theta > 1$, $\text{GC2Cvx}(A, \theta)$ defined in Algorithm 2 guarantees

$$\text{Time}_{\lambda}(\epsilon, \Delta, \psi, L, A) \leq \sum_{t=1}^{[\log_\theta \frac{\Delta}{\epsilon}]} \text{Time}(\theta^{-t} \Delta, \theta^{1-t}, \frac{\Delta}{\lambda}, \psi, L, A)$$

We prove this very concisely in Appendix B and also discuss several example applications of the Theorem in order to give a better sense of how it can be applied. This reduction complements a standard tool in the optimization toolbox, which goes in the opposite direction. Specifically, it is very common to take an algorithm for optimizing $\lambda$-strongly convex objectives and to apply it to convex objectives by optimizing the $\lambda$-strongly convex surrogate $L_\lambda(w) = L(w) + \frac{\lambda}{2}\|w\|^2$. Sometimes, this approach is slightly suboptimal, and the similar, multistep procedure of Allen-Zhu and Hazan (2016) is required, nevertheless, it was already
known that strongly convex optimization is, for this reason, “easier” than convex optimization. Our result shows that the reverse is also true, so strongly convex and convex optimization are, in a certain sense, equally hard.

In combination, these two reductions going in each direction appear to be optimal in a certain way. In all of the examples we have tried, composing both reductions—converting a convex algorithm to a strongly convex one, and then converting that strongly convex algorithm back to a convex one—results in only a constant-factor degradation in the guarantee. We have also consistently observed that applying the reduction, Algorithm 2, to an optimal algorithm for convex optimization yields an optimal algorithm for strongly-convex optimization, and we conjecture that this holds universally.

Before moving on, we note that the reduction Algorithm 2 can result in an unusual method. For example, the algorithm GC2Cvx(Alg 1, c) analyzed below involves repeated invocations of Algorithm 1, resulting in the stepsize and momentum parameters being reset periodically. As a whole, it resembles Algorithm 1, however it has a strange, non-monotonic stepsize and momentum schedule. Therefore, while this technique can be useful for deriving new optimization algorithms with better theoretical guarantees, these methods may not always be aesthetically pleasing or practical, and it may still be useful to study more “natural” methods that can be directly analyzed under the \((\lambda, \psi)\)-GC.

Finally, we apply Theorem 2 to Algorithm 1 and derive the following stronger guarantee under Assumptions 1 and 3, which we prove in Appendix C:

**Theorem 3.** Let \(\ell\) and \(L\) satisfy Assumptions 1 and 3, then the output of GC2Cvx(Alg 1, c) guarantees for universal constants \(c, c'\)

\[
\mathbb{E} L(\hat{w}) - L^* \leq c \cdot \left( \Delta \exp \left( -c' \sqrt{T} \frac{\Delta}{H} \right) + \Delta \exp \left( -c' \sqrt{\lambda n T} \frac{\Delta}{H} \right) + \frac{H L^*}{\lambda T} \right)
\]

### 5 The Optimality of Our Algorithms

Here, we argue that the guarantees in Theorems 1 and 3 are optimal. First, it is well-known that even without any noise, i.e. \(\ell(w; z) = L(w)\), any first-order method will have error at least (Nemirovsky and Yudin, 1983)

\[
L(\hat{w}) - L^* \geq c \cdot \frac{HB^2}{T^2} \quad \text{or} \quad L(\hat{w}) - L^* \geq c \cdot \Delta \exp \left( -c' \sqrt{\frac{\Delta T}{H}} \right)
\]

(10)

under Assumptions 1 and 2 or Assumptions 1 and 3, respectively (in fact, the latter holds even under the stronger condition of \(\lambda\)-strong convexity). Therefore, the first terms in our method’s guarantees in Theorems 1 and 3 are tight, and correspond to the rate achieved by accelerated gradient descent (Nesterov, 1983).

For the remaining second and third terms in each guarantee, we prove a lower bound that applies for any learning rule that uses \(n\) i.i.d. samples from the distribution, even non-first-order methods. This lower bound also applies to minibatch first-order algorithms with \(n = bT\) being the total number of stochastic gradient estimates, since each \(\nabla \ell(w, z)\) is computed using a single sample.

**Theorem 4.** For \(\ell(w; (x, y)) = \frac{1}{2}(\langle w, x \rangle - y)^2\) the square loss, for any learning algorithm that takes \(n\) samples as input, there exists a distribution over \((x, y)\) pairs such that \(\ell\) and \(L\) satisfy Assumptions 1 and 2, and for a universal constant \(c\), the algorithm’s output will have error at least

\[
\mathbb{E} L(\hat{w}) - L^* \geq c \cdot \left( \frac{HB^2}{n} + \sqrt{\frac{H B^2 L^*}{n}} \right)
\]

Similarly, there exists a distribution over \((x, y)\) pairs such that \(\ell\) and \(L\) satisfy Assumptions 1 and 3 (and, in fact, \(L\) is \(\lambda\)-strongly convex), and for a universal constant \(c\), the algorithm’s output will have error at least

\[
\mathbb{E} L(\hat{w}) - L^* \geq c \cdot \left( \Delta \cdot \mathbb{I}_{n \leq \frac{4}{\lambda}} + \min \left\{ \frac{H L^*}{\lambda n}, \Delta \right\} \right)
\]
We prove this in Appendix D using an argument similar to that of Srebro et al. (2010). The lower bound for deterministic first-order optimization, (10), plus the sample complexity lower bound, Theorem 4, together imply a lower bound for the minibatch first-order algorithms that we consider, which matches our guarantees:

**Corollary 1.** There exists \( \ell(w; z) \) such that for any algorithm that uses \( T \) minibatch stochastic gradients of size \( b \), there exists a distribution over \( z \) such that \( \ell \) and \( L \) satisfy Assumptions 1 and 2, and for a universal constant \( c \), the algorithm’s output will have error at least

\[
\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \frac{HB^2}{T^2} + \frac{HB^2}{bT} + \sqrt{\frac{HB^2L^*}{bT}} \right)
\]

Similarly, there exists \( \ell(w; z) \) such that for any algorithm that uses \( T \) minibatch stochastic gradients of size \( b \), there exists a distribution over \( z \) such that \( \ell \) and \( L \) satisfy Assumptions 1 and 3 (and, in fact, \( L \) is \( \lambda \)-strongly convex), and for universal constants \( c, c' \), the algorithm’s output will have error at least

\[
\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \Delta \exp \left( -c' \cdot \frac{\sqrt{bT}}{\sqrt{H}} \right) + \Delta \cdot 1_{bT \leq \frac{H}{2\lambda}} + \min \left\{ \frac{HL^*}{\lambda bT}, 1 \right\} \right)
\]

It is easy to see that this precisely matches our algorithm’s guarantee, Theorem 1, under Assumptions 1 and 2, and therefore our algorithm is optimal in that setting. Under Assumptions 1 and 3, this lower bound and the upper bound, Theorem 3, nearly match, with the only difference being the terms \( \exp(-c\frac{\sqrt{bT}}{\sqrt{H}}) \) in the upper bound versus \( 1_{bT \leq \frac{H}{2\lambda}} \) in the lower bound. However, this gap is small—for \( bT \leq \frac{H}{2\lambda} \), \( \exp(-c\frac{\sqrt{bT}}{\sqrt{H}}) \) is at most 1, so the upper bound is within a constant factor of the lower bound. For \( bT > \frac{H}{2\lambda} \), \( \exp(-c\frac{\sqrt{bT}}{\sqrt{H}}) \) is obviously more than a constant factor larger than \( 1_{bT \leq \frac{H}{2\lambda}} = 0 \), but it is nevertheless exponentially small, so the gap between the upper and lower bound is still nearly negligible.

We note that because Theorem 4 applies to any learning rule that uses \( n = bT \) i.i.d. samples, not just first-order methods, if the second and third terms of our algorithms’ guarantees are larger than the first terms, then our methods are actually optimal amongst all learning rules. Therefore, for small enough \( b \), our first-order algorithm is just as good, in the worst case, as any other method including, for example, exact (regularized) empirical risk minimization.

Finally, in the special case that \( b = 1 \), while it is true that our minibatch accelerated SGD algorithm is optimal—even amongst all learning rules that use \( n = bT = T \) samples, it is also the case that plain old SGD is also optimal, which guarantees under Assumptions 1 and 2 (Cotter et al., 2011)

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \sqrt{\frac{HB^2L^*}{bT}} \right)
\]

matching the lower bound, Theorem 4, with \( n = bT = T \). In other words, the novelty and advantage of our method appears primarily through in how it leverages minibatches to achieve better performance and a smaller parallel runtime, as we will now discuss.

### 6 The Minibatch Parallelization Speedup

Previously, we showed that our algorithms are optimal in terms of their upper bounds on the error as a function of \( b \) and \( L^* \). Here, we consider the related question of the algorithm’s runtime. Since it is easy to parallelize the computation of minibatch stochastic gradients of size \( b \), the total runtime of a minibatch first-order method scales in direct proportion to \( T \), but may grow much more slowly with \( b \)—and it may not grow at all if \( b \) parallel computers are available. Specifically, if \( M \) computing cores or devices are available to parallelize the minibatch computations, then any minibatch first-order algorithm’s runtime would scale with

\[
\text{Runtime} \propto T \times \left[ \frac{b}{M} \right] \times \text{Time to compute } \nabla \ell(w; z)
\]
For this reason, it is natural to ask to what extent we can reduce the runtime without hurting performance, i.e. how much we can reduce the number of iterations, $T$, by increasing the minibatch size, $b$. To answer this question, it will be convenient to rewrite our guarantees in Theorems 1 and 3 by fixing the error, $\epsilon$, and asking how large $T$ must be in order to guarantee error $\epsilon$. Under Assumptions 1 and 2, and Assumptions 1 and 3, respectively, this is (ignoring constants)

$$T(\epsilon) = \sqrt{\frac{HB^2}{\epsilon} + \frac{1}{b} \left( \frac{HB^2}{\epsilon} + \frac{HB^2L^*}{\epsilon^2} \right)}$$

(13)

Written this way, it is easy to see that the number of iterations needed by our algorithm to reach accuracy $\epsilon$ decreases linearly with the minibatch size $b$ up until the first term becomes larger than the second and third terms. Although it may not be practical to fully parallelize the computation of the minibatches across $b$ workers for large $b$, this nevertheless represents a substantial potential speedup with absolutely no cost to the algorithm’s theoretical guarantees (Dekel et al., 2012; Cotter et al., 2011), which continues until

$$b \geq \frac{HB^2}{\epsilon} + \frac{\sqrt{HB^2L^*}}{e^{3/2}} \quad \text{and} \quad b \geq \frac{H}{\lambda} + \frac{\sqrt{HL^*}}{\epsilon \log \frac{\epsilon}{\lambda}}$$

(15)

Once $b$ passes these thresholds, no more improvement is possible by increasing the minibatch size, and the iteration complexity is dominated by the first term, which corresponds to the time needed to reach $\epsilon$ error using exact accelerated gradient descent (Nesterov, 1983). In other words, once the minibatch size is this large, the algorithm performs essentially the same as if there were no noise in the gradients.

Our algorithms’ speedup from minibatching improves significantly over previous results. As mentioned in the previous section, while SGD can attain the same error as our method using the same total number of samples, $n = bT$, it can only do so with $b = 1$, and the number of iterations it requires to attain error $\epsilon$ under Assumptions 1 and 2 is (ignoring constants) (Cotter et al., 2011)

$$T(\epsilon) = \frac{HB^2}{\epsilon} + \frac{1}{b} \frac{HB^2L^*}{\epsilon^2}$$

(16)

Comparing this with our method (13), we see that SGD always requires at least as many iterations, and quadratically more for large $b$. In fact, in the case $L^* = 0$, SGD sees no speedup at all from minibatching, whereas our method can be sped up substantially.

Improving over SGD, the minibatch accelerated SGD algorithm of Cotter et al. (2011) requires under Assumptions 1 and 2 (ignoring constants and log factors)

$$T(\epsilon) = \sqrt{\frac{HB^2}{\epsilon}} + \frac{1}{\sqrt{b}} \frac{HB^2}{\epsilon^2} + \frac{1}{b} \frac{HB^2L^*}{\epsilon^2}$$

(17)

Therefore, their analysis exhibits three regimes rather than our two: first a linear $1/b$ speedup for $b \leq L^2/\epsilon^2$, then a $1/\sqrt{b}$ speedup for

$$\frac{L^2}{\epsilon^2} \leq b \leq \frac{HB^2}{\epsilon} + \frac{\sqrt{HB^2L^*}}{e^{3/2}}$$

(18)

and finally no speedup for larger $b$. Therefore, even under the favorable condition that $L^* = 0$, Cotter et al.’s method has a sublinear parallelization speedup from minibatching, and consequently, their method can result in a substantially smaller speedup than ours for any particular minibatch size. The minibatch size they need to reach error $\epsilon$ in $\sqrt{HB^2/\epsilon}$ iterations—the optimal number for first-order methods, which corresponds to exact accelerated gradient descent—is the righthand side of (18), which can be larger by a factor of as much as $\sqrt{HB^2}/\epsilon$.

Similarly, under Assumptions 1 and 3, and in the special case of least squares problems, the algorithm and analysis of Liu and Belkin (2018) exhibits a similar sublinear speedup from minibatching:

$$T(\epsilon) = \sqrt{\frac{H}{\lambda} \log \frac{\epsilon}{\lambda}} + \frac{1}{\sqrt{b}} \frac{H}{\lambda} \log \frac{\epsilon}{\lambda} + \frac{1}{b} \frac{HL^*}{\lambda \epsilon}$$

(19)
Like with Cotter et al.’s analysis, compared with our method, which enjoys a linear speedup all the way up to the critical minibatch size, we see that Liu and Belkin’s algorithm has only a $1/\sqrt{b}$ speedup in some regimes, so it can require much larger minibatches to match accelerated gradient descent.

## 7 Stochastic Optimization with Bounded Variance at the Optimum

So far, we have considered optimizing objectives where the instantaneous losses are non-negative and the value of the minimum of the expected loss is bounded and small, but in other contexts we may want to understand the complexity of optimization in terms of bounds on the variance of the stochastic gradients. In the optimization literature, it is common to assume that the variance of the stochastic gradients is bounded uniformly on the entire space, i.e. $\sup_w \mathbb{E}\|\nabla \ell(w; z)\|^2 \leq \sigma^2$. When, in addition to this variance bound, the objective $L$ is $H$-smooth and convex, and has a minimizer with norm at most $B$, then it has long been known that $T$ steps of SGD achieves error (Nemirovsky and Yudin, 1983)

$$\mathbb{E}L(w_T) - L^* \leq \frac{HB^2}{T} + \frac{\sigma B}{\sqrt{T}} \tag{20}$$

However, the assumption of uniformly upper bounded variance can be strong, and it turns out that when $\ell$ is also $H$-smooth, the $\sigma$ in SGD’s guarantee can easily be replaced with $\sigma_*$, an upper bound on the standard deviation of the variance just at the minimizer specifically, i.e. $\mathbb{E}\|\nabla \ell(w^*; z)\|^2 \leq \sigma_*^2$ (Moulines and Bach, 2011; Schmidt and Roux, 2013; Needell et al., 2014; Bottou et al., 2018; Gower et al., 2019; Stich, 2019), i.e. SGD guarantees

$$\mathbb{E}L(w_T) - L^* \leq \frac{HB^2}{T} + \frac{\sigma_* B}{\sqrt{T}} \tag{21}$$

Indeed, for other non-accelerated algorithms, the weaker bound $\sigma_*$ often suffices and a global variance bound is unnecessary (e.g. Woodworth et al., 2020; Koloskova et al., 2020). However, it was not clear whether it is possible to make this substitution of $\sigma_*$ for $\sigma$ for accelerated methods. For example, Lan (2012)’s optimal stochastic first-order algorithm guarantees

$$\mathbb{E}L(w_T) - L^* \leq \frac{HB^2}{T^2} + \frac{\sigma B}{\sqrt{T}} \tag{22}$$

Can we replace this $\sigma$ with $\sigma_*$ too? This would represent a significant improvement. As discussed previously, we can expect $\sigma_*$ to be small—potentially even zero, and anyways often much smaller than $\sigma$—for problems of interest, including training machine learning models in the (near-) interpolation regime. More generally, it is often desirable, and generally much easier, to control the stochastic gradient variance at a single point versus globally. As an example, for “heterogeneous” distributed optimization—where different parallel workers have access to samples from different data distributions—it is common to bound a measure of the “disagreement” between these different data distributions specifically at the minimizer, which amounts to bounding the variance of the stochastic gradients at $w^*$ (see, e.g., the discussion in Woodworth et al., 2020).

Unfortunately, a consequence of our lower bound, Theorem 4, is that the $\sigma$ in the accelerated rate (22) cannot generally be replaced by $\sigma_*$ in the same way as it can be for the unaccelerated rate (21). In fact, since Theorem 4 applies to any learning rule that uses $n$ samples, this holds also for non-first-order methods too.

**Corollary 2.** For $\ell(w; (x, y)) = \frac{1}{2}(\langle w, x \rangle - y)^2$ the square loss, for any learning algorithm that uses $n$ i.i.d. samples, there exists a distribution over $(x, y)$ such that $\mathbb{E}\|\ell(w^*; z)\|^2 \leq \sigma_*^2$, and for a universal constant $c$, the algorithm’s output has error at least

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \frac{HB^2}{n} + \frac{\sigma_* B}{\sqrt{n}} \right)$$

There is also a distribution over $(x, y)$ such that $\mathbb{E}\|\ell(w^*; z)\|^2 \leq \sigma_*^2$, and for a universal constant $c$, the algorithm’s output has error at least

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \frac{HB^2}{n} + \frac{\sigma_* B}{\sqrt{n}} \right)$$

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \frac{\Delta}{n} + \min\left\{ \frac{\sigma_*^2}{\lambda n}, \Delta \right\} \right)$$
As in Section 5, since a single stochastic gradient estimate \( \nabla \ell(w; z) \) can be computed with one sample, this lower bound also applies to minibatch first-order algorithms with \( n = bT \), and the lower bound (10) for deterministic first-order optimization still holds so we also have

**Corollary 3.** For any algorithm that uses \( T \) minibatch stochastic gradients of size \( b \), there exists an objective \( L(w) = \mathbb{E}_z \ell(w; z) \) where \( L \) has a minimizer with norm less than \( B \), \( \ell \) is \( H \)-smooth and convex, and \( \mathbb{E} \| \ell(w^*; z) \|^2 \leq \sigma_*^2 \), so that for a universal constant \( c \), the algorithm’s output has error at least

\[
\mathbb{E} L(\hat{w}) - L^* \geq c \cdot \left( \frac{H B^2}{T^2} + \frac{H B^2}{bT} + \frac{\sigma_* B}{\sqrt{bT}} \right)
\]

There is also an objective that satisfies \( L(0) - L^* \leq \Delta \), \( L \) is \( \lambda \)-strongly convex, and \( \ell \) is \( H \)-smooth and convex, so that for universal constants \( c, c' \), the algorithm’s output has error at least

\[
\mathbb{E} L(\hat{w}) - L^* \geq c \cdot \left( \Delta \exp \left( -\frac{c' \sqrt{\lambda T}}{\sqrt{\lambda T}} \right) + \Delta \cdot \mathbb{1}_{bT \leq \frac{H}{\lambda}} + \min \left\{ \frac{\sigma_*^2}{\lambda bT}, \Delta \right\} \right)
\]

Ignoring again the small gap between \( \exp(-\frac{c' \sqrt{\lambda T}}{\sqrt{\lambda T}}) \) and \( \mathbb{1}_{bT \leq \frac{H}{\lambda}} \) (see the discussion below Corollary 1), this shows, in essence, that when \( b = 1 \), it is impossible to achieve the accelerated optimization rates of \( T^{-2} \) and \( \exp(-\sqrt{\lambda T}/\sqrt{\lambda T}) \) under the conditions of Corollary 3. Furthermore, when \( b = 1 \), the guarantee of regular, unaccelerated SGD actually matches the lower bound, so there is no room for acceleration. Lan’s accelerated SGD algorithm relied crucially on the uniformly bounded variance, and the \( \sigma \) in (22) cannot generally be replaced with \( \sigma_* \). In fact, Corollary 2 shows that no learning rule, even non-first-order methods, can ensure error \( n^{-2} \) using just \( n \) samples.

However, the good news is that our guarantees for minibatch accelerated SGD also apply in this setting:

**Theorem 5.** Let \( L(w) = \mathbb{E}_z \ell(w; z) \) have a minimizer with norm at most \( B \), \( \ell \) be \( H \)-smooth and convex, and let \( \mathbb{E} \| \nabla \ell(w^*; z) \|^2 \leq \sigma_*^2 \). Then Algorithm 1 guarantees

\[
\mathbb{E} L(w_{ag}^{\text{alg}}) - L^* \leq c \cdot \left( \frac{H B^2}{T^2} + \frac{H B^2}{bT} + \frac{\sigma_* B}{\sqrt{bT}} \right)
\]

Let \( \ell(w) = \mathbb{E}_z \ell(w; z) \) satisfy \( L(w) - L^* \geq \frac{1}{\lambda} \min_{w^* \in \arg \min_w L(w)} \| w - w^* \|^2 \) for all \( w \), let \( L(0) - L^* \leq \Delta \), let \( \ell \) be \( H \)-smooth and convex, and let \( \mathbb{E} \| \nabla \ell(w^*; z) \|^2 \leq \sigma_*^2 \). Then GC2Cvx(Alg 1, e) guarantees

\[
\mathbb{E} L(\hat{w}) - L^* \leq c \cdot \left( \Delta \exp \left( -\frac{c' \sqrt{\lambda T}}{\sqrt{\lambda T}} \right) + \Delta \exp \left( -\frac{c' \sqrt{\lambda bT}}{H} \right) + \frac{\sigma_*^2}{\lambda bT} \right)
\]

The first part of the Theorem is demonstrated in the proof of Theorem 1 in Appendix A, and the second part follows an essentially identical argument as in the proof of Theorem 3.

Corollary 3 showed that it is impossible to achieve error like \( T^{-2} \) using first-order methods with \( b = 1 \). However, Theorem 5 shows it is possible to achieve error like \( T^{-2} \) with parallel runtime \( T \) using our minibatch accelerated SGD method with \( b > 1 \). In other words, while SGD with minibatches of size \( b = 1 \) matches the lower bound in Corollary 2 with \( n = bT = T \), and therefore attains the smallest possible error using \( n \) samples, our method is able to more quickly attain this same optimal error using \( n = bT \) samples with \( b \gg 1 \). As discussed in Section 6, this means our algorithm’s parallel runtime, \( T \), can be much smaller than SGD’s, with up to a quadratic improvement. Since the lower bound, Corollary 3, and upper bound, Theorem 5, match, this also tightly bounds the complexity of stochastic first-order optimization with a bound on \( \sigma_* \).

8 Conclusion

We proposed and analyzed a minibatch accelerated SGD algorithm for optimizing objectives whose minimum value is near zero. We show that our method is simultaneously optimal with respect to the minibatch size,
and the minimum of the loss, $L^*$, which improves over previous results including Cotter et al. (2011) and Liu and Belkin (2018) which were optimal with respect to $L^*$ but not $b$, and Lan (2012) which was optimal with respect to $b$ but not $L^*$. In Section 6, we describe how our method’s improvements over prior work, which takes the form of a better dependence on the minibatch size, $b$, translates into the potential for a substantial reduction in the runtime via parallelizing the computation of the minibatch stochastic gradients. Finally, we extend our results to the closely related setting where the $L^*$ bound is replaced by a bound on the variance of the stochastic gradients at the point $w^*$, specifically, and we tightly characterize the minimax optimal rates in this setting. Our algorithm and analysis is of particular interest in the context of training machine learning models in the “interpolation”/“realizable”/“overparametrized” setting, where there exist parameters that exactly or nearly minimize the training and/or population loss, i.e. $L^*$ and $\sigma^*$ are small.

A shortcoming of our method is that its implementation, specifically setting the stepsizes, depends on potentially unknown quantities such as $L^*$ and $B$, and on the time horizon $T$. The dependence on $T$ is not a particularly serious problem because it is straightforward to convert our method to an anytime algorithm using the classic “doubling trick”, although this is not very practical and it would be interesting to develop an anytime variant of Algorithm 1.

On the other hand, the requirement of knowing $L^*$ and $B$ to implement the algorithm is a trickier issue. This problem is not unique to our method, and most of the accelerated stochastic first-order methods that we are aware of, including the work of Lan (2012) and Cotter et al. (2011), use these parameters to choose stepsizes and momentum parameters. While these quantities are generally unknown, our algorithm only needs an upper bound on them, so for any known upper bound $\hat{L}^* \geq L^*$ and $\hat{B} \geq B$, our algorithm can be implemented using the estimates $\hat{L}^*$ and $\hat{B}$, with a corresponding degradation in the guarantee depending on how tight the upper bounds are. Furthermore, when applying stochastic first-order algorithms in practice, one typically sets stepsize parameters via cross-validation rather than according to the theoretical prescriptions, so this may not be a big issue in practice.

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References

Zeyuan Allen-Zhu and Elad Hazan. Optimal black-box reductions between optimization objectives. In D. Lee, M. Sugiyama, U. Luxburg, I. Guyon, and R. Garnett, editors, Advances in Neural Information Processing Systems, volume 29. Curran Associates, Inc., 2016. URL https://proceedings.neurips.cc/paper/2016/file/1f50893f80d6830d62765ffad7721742-Paper.pdf.

Zeyuan Allen-Zhu, Yuanzhi Li, and Yingyu Liang. Learning and generalization in overparameterized neural networks, going beyond two layers. arXiv preprint arXiv:1811.04918, 2018.

Zeyuan Allen-Zhu, Yuanzhi Li, and Zhao Song. A convergence theory for deep learning via over-parameterization. In International Conference on Machine Learning, pages 242–252. PMLR, 2019.

Sanjeev Arora, Simon Du, Wei Hu, Zhiyuan Li, and Ruosong Wang. Fine-grained analysis of optimization and generalization for overparameterized two-layer neural networks. In International Conference on Machine Learning, pages 322–332. PMLR, 2019.

Raef Bassily, Mikhail Belkin, and Siyuan Ma. On exponential convergence of sgd in non-convex overparametrized learning. arXiv preprint arXiv:1811.02564, 2018.
Mikhail Belkin, Daniel Hsu, Siyuan Ma, and Soumik Mandal. Reconciling modern machine-learning practice and the classical bias–variance trade-off. *Proceedings of the National Academy of Sciences*, 116(32):15849–15854, 2019.

Jérôme Bolte, Trong Phong Nguyen, Juan Peypouquet, and Bruce W Suter. From error bounds to the complexity of first-order descent methods for convex functions. *Mathematical Programming*, 165(2):471–507, 2017.

Léon Bottou, Frank E Curtis, and Jorge Nocedal. Optimization methods for large-scale machine learning. *Siam Review*, 60(2):223–311, 2018.

Lénaïc Chizat, Edouard Oyallon, and Francis Bach. On lazy training in differentiable programming. *Advances in Neural Information Processing Systems*, 32:2937–2947, 2019.

Andrew Cotter, Ohad Shamir, Nati Srebro, and Karthik Sridharan. Better mini-batch algorithms via accelerated gradient methods. In J. Shawe-Taylor, R. S. Zemel, P. L. Bartlett, F. Pereira, and K. Q. Weinberger, editors, *Advances in Neural Information Processing Systems 24*, pages 1647–1655. Curran Associates, Inc., 2011. URL http://papers.nips.cc/paper/4432-better-mini-batch-algorithms-via-accelerated-gradient-methods.pdf.

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.

Dmitriy Drusvyatskiy and Adrian S Lewis. Error bounds, quadratic growth, and linear convergence of proximal methods. *Mathematics of Operations Research*, 43(3):919–948, 2018.

Saeed Ghadimi and Guanghui Lan. Optimal stochastic approximation algorithms for strongly convex stochastic composite optimization, ii: shrinking procedures and optimal algorithms. *SIAM Journal on Optimization*, 23(4):2061–2089, 2013.

Robert Mansel Gower, Nicolas Loizou, Xun Qian, Alibek Sailanbayev, Egor Shulgin, and Peter Richtárik. Sgd: General analysis and improved rates. In *International Conference on Machine Learning*, pages 5200–5209. PMLR, 2019.

Arthur Jacot, Franck Gabriel, and Clément Hongler. Neural tangent kernel: convergence and generalization in neural networks. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, pages 8580–8589, 2018.

Anastasia Koloskova, Nicolas Loizou, Sadra Boreiri, Martin Jaggi, and Sebastian Stich. A unified theory of decentralized sgd with changing topology and local updates. In *International Conference on Machine Learning*, pages 5381–5393. PMLR, 2020.

Guanghui Lan. An optimal method for stochastic composite optimization. *Mathematical Programming*, 133(1-2):365–397, 2012. URL https://pdfs.semanticscholar.org/1621/f05894ad5fd6a8fcb8827a8c7aca36c81775.pdf.

Qihang Lin and Lin Xiao. An adaptive accelerated proximal gradient method and its homotopy continuation for sparse optimization. In *International Conference on Machine Learning*, pages 73–81. PMLR, 2014.

Chaoyue Liu and Mikhail Belkin. Mass: an accelerated stochastic method for over-parametrized learning. *arXiv preprint arXiv:1810.13395*, 2018.

Siyuan Ma, Raef Bassily, and Mikhail Belkin. The power of interpolation: Understanding the effectiveness of sgd in modern over-parametrized learning. In *International Conference on Machine Learning*, pages 3325–3334. PMLR, 2018.

Eric Moulines and Francis Bach. Non-asymptotic analysis of stochastic approximation algorithms for machine learning. *Advances in neural information processing systems*, 24:451–459, 2011.
Ion Necoara, Yu Nesterov, and Francois Glineur. Linear convergence of first order methods for non-strongly convex optimization. *Mathematical Programming*, 175(1):69–107, 2019.

Deanna Needell, Rachel Ward, and Nati Srebro. Stochastic gradient descent, weighted sampling, and the randomized kaczmarz algorithm. *Advances in neural information processing systems*, 27:1017–1025, 2014.

Arkadii S Nemirovskii and Yu E Nesterov. Optimal methods of smooth convex minimization. *USSR Computational Mathematics and Mathematical Physics*, 25(2):21–30, 1985.

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

Yu Nesterov. Gradient methods for minimizing composite functions. *Mathematical Programming*, 140(1):125–161, 2013.

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

Yuriii E Nesterov. A method for solving the convex programming problem with convergence rate $o(1/k^2)$. In *Dokl. akad. nauk Sssr*, volume 269, pages 543–547, 1983.

James Renegar and Benjamin Grimmer. A simple nearly optimal restart scheme for speeding up first-order methods. *Foundations of Computational Mathematics*, pages 1–46, 2021.

Vincent Roulet and Alexandre d’Aspremont. Sharpness, restart, and acceleration. *SIAM Journal on Optimization*, 30(1):262–289, 2020.

Mark Schmidt and Nicolas Le Roux. Fast convergence of stochastic gradient descent under a strong growth condition. *arXiv preprint arXiv:1308.6370*, 2013.

Shai Shalev-Shwartz and Yoram Singer. Online learning: Theory, algorithms, and applications. 2007.

Nathan Srebro, Karthik Sridharan, and Ambuj Tewari. Optimistic rates for learning with a smooth loss. *arXiv preprint arXiv:1009.3896*, 2010.

Sebastian U Stich. Unified optimal analysis of the (stochastic) gradient method. *arXiv preprint arXiv:1907.04232*, 2019.

Alexander Tsigler and Peter L Bartlett. Benign overfitting in ridge regression. *arXiv preprint arXiv:2009.14286*, 2020.

Sharan Vaswani, Francis Bach, and Mark Schmidt. Fast and faster convergence of sgd for over-parameterized models and an accelerated perceptron. In *The 22nd International Conference on Artificial Intelligence and Statistics*, pages 1195–1204. PMLR, 2019.

Blake Woodworth, Kumar Kshitij Patel, and Nathan Srebro. Minibatch vs local sgd for heterogeneous distributed learning. *arXiv preprint arXiv:2006.04735*, 2020.

Chiyuan Zhang, Samy Bengio, Moritz Hardt, Benjamin Recht, and Oriol Vinyals. Understanding deep learning requires rethinking generalization. *arXiv preprint arXiv:1611.03530*, 2016.

Lijun Zhang and Zhi-Hua Zhou. Stochastic approximation of smooth and strongly convex functions: Beyond the $o(1/t)$ convergence rate. In *Conference on Learning Theory*, pages 3160–3179. PMLR, 2019.

Lijun Zhang, Tianbao Yang, and Rong Jin. Empirical risk minimization for stochastic convex optimization: $o(1/n)$-and $o(1/n^2)$-type of risk bounds. In *Conference on Learning Theory*, pages 1954–1979. PMLR, 2017.
A Proof of Theorem 1

Lemma 1 (c.f. Lemma 1 (Lan, 2012)). Let $w_{t+1}$, $w_t$, and $w_t^{md}$ be updated as in Algorithm 1. Then for any $w \in \{w : \|w\| \leq B\}$

$$
\gamma_t \langle g_t(w_t^{md}), w_{t+1} - w_t^{md} \rangle \leq \gamma_t \langle g_t(w_t^{md}), w - w_t^{md} \rangle + \frac{1}{2} \|w - w_t\|^2 - \frac{1}{2} \|w - w_{t+1}\|^2 - \frac{1}{2} \|w_{t+1} - w_t\|^2
$$

Proof. First, we show that

$$
w_{t+1} = \arg \min_{w : \|w\| \leq B} \gamma_t \langle g_t(w_t^{md}), w - w_t^{md} \rangle + \frac{1}{2} \|w - w_t\|^2
$$

Let $\hat{w}$ be this arg min, which is unique since the objective is strongly convex. The KKT optimality conditions for $\hat{w}$ are that there exists $\lambda$ such that

$$
\|\hat{w}\| \leq B
$$

$$
\lambda \geq 0
$$

$$
\lambda(\|\hat{w}\| - B) = 0
$$

$$
\gamma_t g_t(w_t^{md}) + \hat{w} - w_t + \lambda \hat{w} = 0 \iff \hat{w} = \frac{w_t - \gamma_t g_t(w_t^{md})}{1 + \lambda}
$$

Let

$$
\lambda = \frac{1}{\min \left\{ 1, \frac{B}{\|w_t^{md}\|} \right\}} - 1
$$

We will now show that $w_{t+1}$ and this $\lambda$ satisfy these KKT conditions. Since $w_{t+1} = \min \left\{ 1, \frac{B}{\|w_t^{md}\|} \right\} \hat{w}_{t+1}$, we have primal feasibility $\|w_{t+1}\| \leq B$. Also, because $\frac{1}{\min \left\{ 1, \frac{B}{\|w_t^{md}\|} \right\}} \geq \frac{1}{B}$, we have dual feasibility $\lambda \geq 0$. Next, if $\|w_{t+1}\| < B$, then it must be the case that $\min \left\{ 1, \frac{B}{\|w_t^{md}\|} \right\} = 1$, which implies $\lambda = 0$, which establishes the complementary slackness condition. Finally, we have stationarity because

$$
w_{t+1} = \min \left\{ 1, \frac{B}{\|\hat{w}_{t+1}\|} \right\} \hat{w}_{t+1} = \frac{w_t - \gamma_t g_t(w_t^{md})}{1 + \lambda}
$$

From here, we let $p(w) = \gamma_t \langle g_t(w_t^{md}), w - w_t^{md} \rangle$, so $w_{t+1} = \arg \min_{w : \|w\| \leq B} p(w) + \frac{1}{2} \|w - w_t\|^2$. The first-order optimality condition for $w_{t+1}$ is that for all $w \in \{w : \|w\| \leq B\}$,

$$
\langle \nabla p(w_{t+1}) + w_{t+1} - w_t, w - w_{t+1} \rangle \geq 0
$$

This, combined with the convexity of $p$ implies

$$
p(w) + \frac{1}{2} \|w - w_t\|^2 = p(w) + \frac{1}{2} \|w_{t+1} - w_t\|^2 + \frac{1}{2} \|w - w_{t+1}\|^2 + \frac{1}{2} \|w_{t+1} - w_t, w - w_{t+1}\|^2
$$

$$
\geq p(w_{t+1}) + \frac{1}{2} \|w_{t+1} - w_t\|^2 + \frac{1}{2} \|w - w_{t+1}\|^2 + \langle \nabla p(w_{t+1}) + w_{t+1} - w_t, w - w_{t+1} \rangle
$$

$$
\geq p(w_{t+1}) + \frac{1}{2} \|w_{t+1} - w_t\|^2 + \frac{1}{2} \|w - w_{t+1}\|^2
$$

Substituting the definition of $p$ and rearranging completes the proof. □
Lemma 2. Let \( \ell(\cdot; z) \) be \( H \)-smooth, convex, and non-negative for each \( z \), let the stochastic gradient variance at \( w^* \) be bounded \( \mathbb{E}||\nabla \ell(w^*; z) - \nabla L(w^*)||^2 \leq \sigma^2 \), and let \( g(w^m_t) = \frac{1}{b} \sum_{i=1}^{b} \nabla \ell(w^m_t; z_i) \) be a minibatch stochastic gradient of size \( b \). Then

\[
\mathbb{E}||g(w^m_t) - \nabla L(w^m_t)||^2 \leq \frac{8H^2B^2}{b\beta^2_t} + \frac{8H}{b} \mathbb{E}[L(w^o_t) - L^*] + \frac{4\sigma^2}{b}
\]

Proof. By the independence of the stochastic gradients \( \nabla \ell(w^m_t; z_i) \) and the inequality \( ||a + b||^2 \leq 2||a||^2 + 2||b||^2 \), we can upper bound

\[
\mathbb{E}||g(w^m_t) - \nabla L(w^m_t)||^2
\]

\[
= \frac{1}{b} \sum_{i=1}^{b} \mathbb{E}||\nabla \ell(w^m_t; z_i) - \nabla L(w^m_t)||^2
\]

\[
\leq \frac{2}{b} \mathbb{E}||\nabla \ell(w^m_t; z_i) - \nabla \ell(w^m_t; z_1)||^2 + \frac{2}{b} \mathbb{E}||\nabla \ell(w^m_t; z_1)||^2
\]

\[
\leq \frac{2H^2}{b} \mathbb{E}||w^m_t - \nabla \ell(w^m_t; z_1)||^2 + \frac{4}{b} \mathbb{E}||\nabla \ell(w^m_t; z_1)||^2 + \frac{4}{b} \mathbb{E}||\nabla \ell(w^*; z_1)||^2
\]

For the final inequality, we used that \( \ell(\cdot; z) \) is \( H \)-smooth, so \( \nabla \ell(\cdot; z) \) is \( H \)-Lipschitz.

For the first term on the right hand side, we note that due to the algorithm's projections, all of the iterates \( w^m_t, w^a_t \), and \( w_t \) lie within the set \( \{ w : ||w|| \leq B \} \). Therefore,

\[
w^m_t = \beta_t^{-1} w_t + (1 - \beta_t^{-1}) w^a_t \implies ||w^m_t - w^a_t|| = \beta_t^{-1} ||w_t - w^a_t|| \leq 2B\beta_t^{-1}
\]

For the second term, we apply (Theorem 2.1.5 Nesterov, 2004):

\[
\mathbb{E}||\nabla \ell(w^a_t; z_1) - \nabla \ell(w^*; z_1)||^2
\]

\[
\leq 2HE[(\ell(w^a_t; z_1) - \ell(w^*; z_1)) + (\nabla \ell(w^*; z_1), w^a_t - w^*)]
\]

\[
= 2HE[L(w^a_t) - L^*]
\]

For the third term, we use the variance bound at \( w^* \):

\[
\mathbb{E}||\nabla \ell(w^*; z_1)||^2 = \mathbb{E}||\nabla \ell(w^*; z_1) - \nabla L(w^*)||^2 \leq \sigma^2
\]

Combining these with (38) completes the proof.

Lemma 3. Let \( \ell(\cdot; z) \) be \( H \)-smooth and non-negative for all \( z \) and let \( L^* = \min_w L(w) \). Then

\[
\mathbb{E}||\nabla \ell(w^*; z)||^2 = \mathbb{E}||\nabla \ell(w^*; z) - \nabla L(w^*)||^2 \leq 2HL^*
\]

Proof. This follows almost immediately from (Theorem 2.1.5 Nesterov, 2004). For each \( z \), let \( w^*_z \in \arg \min_w \ell(w; z) \), then

\[
\mathbb{E}||\nabla \ell(w^*; z)||^2 = \mathbb{E}||\nabla \ell(w^*; z) - \nabla \ell(w^*_z; z)||^2
\]

\[
\leq 2HE[(\ell(w^*_z; z) - \ell(w^*_z; z) - (\nabla \ell(w^*_z; z), w^* - w^*_z))]
\]

\[
= 2HL^* - 2HE(\ell(w^*_z; z))
\]

\[
\leq 2HL^*
\]

For the final inequality, we used that \( \ell \) is non-negative.
Theorem 1. Let $t$ and $L$ satisfy Assumptions 1 and 2, then Algorithm 1 guarantees for a universal constant $c$

$$
\mathbb{E}L(w_t^{ag}) - L^* \leq c \cdot \left( \frac{HB^2}{T^2} + \frac{HB^2}{bT} + \sqrt{\frac{HB^2L^*}{bT}} \right)
$$

Proof. This proof is based on similar ideas as the proof of Lemma 5 and Theorem 2 due to Lan (2012). The key difference is that Lan considers a setting in which the variance of the stochastic gradients are uniformly bounded, while in our setting, we do not directly assume any bound on this quantity.

Let $d_t = w_{t+1} - w_t$, it can be easily seen that

$$
w_{t+1}^{ag} - w_t^{md} = \beta_t^{-1}w_{t+1} + (1 - \beta_t^{-1})w_t^{ag} - w_t^{md} = \beta_t^{-1}d_t
$$

The above observation, along with the $L$-smoothness of $L$ implies

$$
\beta_t \gamma_t L(w_{t+1}^{ag}) \leq \beta_t \gamma_t \left[ L(w_t^{md}) + \langle \nabla L(w_t^{md}), w_{t+1}^{ag} - w_t^{md} \rangle + \frac{H}{2} \|w_{t+1}^{ag} - w_t^{md}\|^2 \right]
$$

Using the convexity of $L$, we can upper bound:

$$
\beta_t \gamma_t \left[ L(w_t^{md}) + \langle \nabla L(w_t^{md}), w_{t+1}^{ag} - w_t^{md} \rangle \right]
$$

$$
= \beta_t \gamma_t \left[ L(w_t^{md}) + \langle \nabla L(w_t^{md}), \beta_t^{-1}w_{t+1} + (1 - \beta_t^{-1})w_t^{ag} - w_t^{md} \rangle \right]
$$

$$
= (\beta_t - 1) \gamma_t \left[ L(w_t^{md}) + \langle \nabla L(w_t^{md}), w_t^{ag} - w_t^{md} \rangle \right]
$$

$$
\leq (\beta_t - 1) \gamma_t L(w_t^{ag}) + \gamma_t \left[ L(w_t^{md}) + \langle g_t(w_t^{md}), w_{t+1}^{ag} - w_t^{md} \rangle \right] - \gamma_t \langle \delta_t, w_{t+1} - w_t^{md} \rangle
$$

where $\delta_t := g_t(w_t^{md}) - \nabla L(w_t^{md})$. We now apply Lemma 1 to conclude that for any $w \in \{w : \|w\| \leq B\}$

$$
\gamma_t \langle g_t(w_t^{md}), w_{t+1} - w_t^{md} \rangle
$$

$$
\leq \gamma_t \langle g_t(w_t^{md}), w - w_t^{md} \rangle + \frac{1}{2} \|w - w_t^{md}\|^2 - \frac{1}{2} \|w - w_{t+1}\|^2 - \frac{1}{2} \|w_{t+1} - w_t\|^2
$$

Because there exists a minimizer of $L$ with norm at most $B$, we can apply this with $w = w^* \in \arg\min_{w: \|w\| \leq B} L(w)$. This, plus the convexity of $L$ allows us to upper bound the second term in (52) as

$$
\gamma_t L(w_t^{md}) + \gamma_t \langle g_t(w_t^{md}), w_{t+1} - w_t^{md} \rangle
$$

$$
\leq \gamma_t L(w_t^{md}) + \gamma_t \langle g_t(w_t^{md}), w^* - w_t^{md} \rangle + \frac{1}{2} \|w^* - w_t\|^2 - \frac{1}{2} \|w^* - w_t\|^2 - \frac{1}{2} \|w_{t+1} - w_t\|^2
$$

$$
\leq \gamma_t L^* + \gamma_t \langle \delta_t, w^* - w_t^{md} \rangle + \frac{1}{2} \|w^* - w_t\|^2 - \frac{1}{2} \|w^* - w_t\|^2 - \frac{1}{2} \|w_{t+1} - w_t\|^2
$$

Therefore, returning to (52), we conclude that

$$
\beta_t \gamma_t \left[ L(w_t^{md}) + \langle \nabla L(w_t^{md}), w_{t+1}^{ag} - w_t^{md} \rangle \right] \leq (\beta_t - 1) \gamma_t L(w_t^{ag}) + \gamma_t L^*
$$

$$
+ \gamma_t \langle \delta_t, w^* - w_t^{md} \rangle + \frac{1}{2} \|w_{t+1} - w_t\|^2 + \|w_t - w^*\|^2 - \|w_{t+1} - w^*\|^2
$$

(57)
Plugging this back into (49) and subtracting $\beta_t \gamma_t L^*$ from both sides, this implies
\[
\beta_t \gamma_t [L(w_{t+1}^{ag}) - L^*] \leq (\beta_t - 1) \gamma_t [L(w_t^{ag}) - L^*] + \frac{1}{2} \|w_t - w^*\|^2 - \frac{1}{2} \|w_{t+1} - w^*\|^2
\]
\begin{align*}
&+ \frac{H \gamma_t - \beta_t}{2 \beta_t} \|w_t - w_{t+1}\|^2 + \gamma_t \langle \delta_t, w^* - w_{t+1} \rangle \\
&= (\beta_t - 1) \gamma_t [L(w_t^{ag}) - L^*] + \frac{1}{2} \|w_t - w^*\|^2 - \frac{1}{2} \|w_{t+1} - w^*\|^2 \\
&+ \frac{H \gamma_t - \beta_t}{2 \beta_t} \|w_t - w_{t+1}\|^2 + \gamma_t \langle \delta_t, w_t - w_{t+1} \rangle + \gamma_t \langle \delta_t, w^* - w_t \rangle \\
&\leq (\beta_t - 1) \gamma_t [L(w_t^{ag}) - L^*] + \frac{1}{2} \|w_t - w^*\|^2 - \frac{1}{2} \|w_{t+1} - w^*\|^2 \\
&+ \frac{H \gamma_t - \beta_t}{2 \beta_t} \|w_t - w_{t+1}\|^2 + \gamma_t \|\delta_t\| \|w_t - w_{t+1}\| + \gamma_t \langle \delta_t, w^* - w_t \rangle
\end{align*}
(58)

Because $\beta_t = 1 + \frac{t}{b} > \frac{\beta_t + t}{b} \geq 2H \gamma_t$, the first two terms on the second line of the right hand side are a quadratic polynomial of the form $-\frac{\gamma_t}{2} y^2 + by$ (here, $y$ corresponds to $\|w_t - w_{t+1}\|$), which can be upper bounded by $-\frac{\gamma_t}{2} y^2 + by \leq \max_y \left\{ -\frac{\gamma_t}{2} y^2 + by \right\} = \frac{b^2}{2}$. We conclude
\[
\beta_t \gamma_t [L(w_{t+1}^{ag}) - L^*] \leq (\beta_t - 1) \gamma_t [L(w_t^{ag}) - L^*] + \frac{1}{2} \|w_t - w^*\|^2 - \frac{1}{2} \|w_{t+1} - w^*\|^2 \\
+ \frac{\beta_t \gamma_t^2}{2(\beta_t - H \gamma_t)} \|\delta_t\|^2 + \gamma_t \|\delta_t\| (w^* - w_t)
\]
(61)

Taking the expectation of both sides, and noting that the noise in the $t^{th}$ stochastic gradient estimate, $g_t(w_t^{md})$, is independent of $w_t$ so that $E \langle \delta_t, w^* - w_t \rangle = 0$, we have
\[
\beta_t \gamma_t E[L(w_{t+1}^{ag}) - L^*] \leq (\beta_t - 1) \gamma_t E[L(w_t^{ag}) - L^*] + \frac{1}{2} E \|w_t - w^*\|^2 - \frac{1}{2} E \|w_{t+1} - w^*\|^2 \\
+ \gamma_t^2 E \|\delta_t\| \|w_t^{md} - \nabla F(w_t^{md})\|^2
\]
(62)

We now use Lemma 2 to bound the variance of the minibatch stochastic gradient at $w_t^{md}$, which yields
\[
\beta_t \gamma_t [L(w_{t+1}^{ag}) - L^*] \leq (\beta_t - 1) \gamma_t E[L(w_t^{ag}) - L^*] + \frac{1}{2} E \|w_t - w^*\|^2 - \frac{1}{2} E \|w_{t+1} - w^*\|^2 \\
+ \frac{8H^2 B^2 \gamma_t^2}{b \beta_t^2} + \frac{8H \gamma_t^2}{b} E[L(w_t^{ag}) - L^*] + \frac{4 \sigma^2 \gamma_t^2}{b}
\]
(64)

From here, we recall that
\[
\beta_t = 1 + \frac{t}{b} \quad \gamma_t = \gamma(t+1) \quad \gamma = \min \left\{ \frac{1}{12H}, \frac{b}{24H(T+1)} \right\}
\]
(65)
This ensures that $\beta_t \geq 1$ and $2H\gamma_t \leq \beta_t$ for all $t$. Furthermore, for $0 \leq t \leq T - 1$

$$
\left( \beta_{t+1} - 1 + \frac{8H\gamma_{t+1}}{b} \right) \gamma_{t+1} - \beta_t \gamma_t
$$

$$
= \left( \beta_t - \frac{5}{6} + \frac{8H\gamma_t}{b} \right) \gamma(t + 2) - \beta_t \gamma(t + 1)
$$

$$
= \gamma \left(1 + \frac{t}{6} - \frac{5(t + 2)}{6} + \frac{8H\gamma(t + 2)^2}{b}\right)
$$

$$
= \gamma \left( \frac{2}{3} - \frac{2t}{3} + \frac{(t + 2)}{3} \cdot \frac{24H(t + 2)\gamma}{b}\right)
$$

$$
\leq \gamma \left( -\frac{t}{3} \right) \leq 0
$$

Therefore, $\left( \beta_{t+1} - 1 + \frac{8H\gamma_{t+1}}{b} \right) \gamma_{t+1} \leq \beta_t \gamma_t$ for all $0 \leq t \leq T - 1$. We can now unroll the recurrence (65) to conclude

$$
\left( \beta_T - 1 + \frac{8H\gamma_T}{b} \right) \gamma_T \mathbb{E}[L(w^*_T) - L^*] \leq \beta_{T-1} \gamma_{T-1} \mathbb{E}[L(w^*_T) - L^*]
$$

$$
\leq \left( \beta_{T-1} - 1 + \frac{8H\gamma_{T-1}}{b} \right) \gamma_{T-1} \mathbb{E}[L(w^*_T) - L^*] + \frac{1}{2} \mathbb{E}\|w_{T-1} - w^*\|^2 - \frac{1}{2} \mathbb{E}\|w_T - w^*\|^2
$$

$\vdots$

$$
\leq \frac{1}{2} \mathbb{E}\|w_0 - w^*\|^2 + \sum_{t=0}^{T-1} \left[ \frac{8H^2B^2\gamma_t^2}{b\beta_t^2} + \frac{4\sigma^2\gamma_t^2}{b} \right]
$$

$$
\leq \frac{B^2}{2} + \sum_{t=0}^{T-1} \left[ \frac{288H^2B^2\gamma^2(t + 1)^2}{b(t + 6)^2} \right]
$$

$$
\leq \frac{B^2}{2} + \frac{288H^2B^2\gamma^2T^3}{b} + \frac{4\sigma^2\gamma^2T^3}{b}
$$

In addition, we have

$$
\left( \beta_T - 1 + \frac{8H\gamma_T}{b} \right) \gamma_T = \left( \frac{T}{6} + \frac{8H\gamma(T + 1)}{b} \right) \gamma(T + 1) \geq \frac{\gamma T^2}{6}
$$

Therefore,

$$
\mathbb{E}[L(w^*_T) - L^*] \leq \frac{3B^2}{\gamma T^2} + \frac{1728H^2B^2}{bT} \gamma + \frac{24\sigma^2 T}{b} \gamma
$$

With our choice of $^2$

$$
\gamma = \min \left\{ \frac{1}{12H}, \frac{b}{24H(T + 1)}, \sqrt{\frac{B^2}{\sigma^2 T}} \right\}
$$
this means

$$\mathbb{E}[L(w_T^\theta) - L^*] \leq \frac{3B^2}{T^2 \min\left\{\frac{1}{12H}, \frac{b}{24H(T+1)} \right\} \sqrt{\frac{b^2}{24T}}} + \frac{72HB^2}{T(T+1)} + \frac{24\sigma B}{\sqrt{6T}}$$  \quad (83)$$

$$\leq \frac{36HB^2}{T^2} + \frac{72HB^2(T+1)}{bT^2} + \frac{3\sigma B}{\sqrt{6T}} + \frac{72HB^2}{T(T+1)} + \frac{24\sigma B}{\sqrt{6T}}$$  \quad (84)$$

$$\leq \frac{108HB^2}{T^2} + \frac{144HB^2}{bT} + \frac{27\sigma B}{\sqrt{6T}}$$  \quad (85)$$

We complete the proof by applying Lemma 3, which shows that $\mathbb{E}||\nabla \ell(w^*; z) - \nabla L(w^*)||^2 \leq \sigma_*^2$ for $\sigma_*^2 = 2HL^*$. 

B Additional Applications of Theorem 2

To better understand Theorem 2, it is useful to consider a few examples:

Example: Gradient Descent for Lipschitz Objectives  Let $\mathcal{L}_G$ be the set of all $G$-Lipschitz, convex objectives, and let $\psi(w) = \frac{1}{2}||w - w^*||^2$. It is well known that the gradient descent algorithm, which we denote $A_{GD}$, requires

$$\text{Time}(\epsilon, B^2, \psi, \mathcal{L}_G, A_{GD}) \leq c \cdot \frac{G^2B^2}{\epsilon^2}$$  \quad (86)$$

gradients to find an $\epsilon$-suboptimal point, where $c$ is a universal constant. Theorem 2 implies that

$$\text{Time}_{\lambda}(\epsilon, \Delta, \psi, \mathcal{L}_G, GC2Cvx(A_{GD}, \epsilon))$$

$$\leq \sum_{t=1}^{[\log \hat{\Delta}]} \text{Time}\left(e^{-t}\Delta, e^{-1-t}\frac{\Delta}{\lambda}, \psi, \mathcal{L}_G, A_{GD}\right)$$  \quad (87)$$

$$\leq cG^2 \sum_{t=1}^{[\log \hat{\Delta}]} \frac{e^{-1-t}\frac{\Delta}{\lambda}}{e^{-2t}\Delta^2}$$  \quad (88)$$

$$\leq c \frac{e^2G^2}{(e-1)\lambda\Delta} [\log \hat{\Delta}]$$  \quad (89)$$

$$\leq c' \frac{G^2}{\lambda \epsilon}$$  \quad (90)$$

Therefore, our reduction recovers (up to constant factors) the existing guarantee for Lipschitz and strongly convex optimization (Nemirovsky and Yudin, 1983). We emphasize that this guarantee (90) has nothing to do with gradient descent specifically—for any algorithm $A$ with

$$\text{Time}(\epsilon, B^2, \psi, \mathcal{L}_G, A) \leq c \cdot \frac{G^2B^2}{\epsilon^2},$$  \quad (91)$$

the modified algorithm GC2Cvx($A, \epsilon$) will have the same rate (90).

Example: Accelerated SGD for Smooth Objectives  For $\mathcal{L}_H$, the class of convex and $H$-smooth objectives, Lan (2012) proposed an algorithm, AC-SA which, for $\psi(w) = \frac{1}{2}||w - w^*||^2$, requires

$$\text{Time}(\epsilon, B^2, d_2, \mathcal{L}_H, A_{AC-SA}) = c \cdot \left(\sqrt{\frac{HB^2}{\epsilon}} + \frac{\sigma^2B^2}{\epsilon^2}\right)$$  \quad (92)$$
stochastic gradients with variance bounded by \( \sigma^2 \) to find an \( \epsilon \)-suboptimal point, which is optimal. In follow-up work Ghadimi and Lan (2013) describe a “multi-stage” variant of AC-SA which is optimal for strongly convex objectives. This algorithm closely resembles GC2Cvx(\( AC-SA, e \)) with some small differences, and their analysis is what inspired Theorem 2 in the first place. But, in contrast to their long and fairly complicated analysis, Theorem 2 can be used to prove their guarantee using the following simple computation:

\[
\text{Time}_\lambda(\epsilon, \Delta, \psi, L, \text{GC2Cvx}(AC-SA, e)) \\
\leq \sum_{t=1}^{\lceil \log \frac{\Delta}{\epsilon} \rceil} \text{Time}\left( e^{-t}, e^{1-t} \frac{\Delta}{\lambda}, \psi, L, AC-SA \right)
\]

\[
= c \cdot \left( \sqrt{H} \sum_{t=1}^{\lceil \log \frac{\Delta}{\epsilon} \rceil} e^{-t} \frac{\Delta}{\lambda} \epsilon + \sigma^2 \sum_{t=1}^{\lceil \log \frac{\Delta}{\epsilon} \rceil} e^{1-t} \frac{\Delta}{\lambda} \epsilon \right)
\]

\[
\leq ec \cdot \left( \sqrt{H} \frac{\log \frac{\Delta}{\epsilon}}{\lambda} + \frac{\sigma^2}{\lambda \Delta} \sum_{t=1}^{\lceil \log \frac{\Delta}{\epsilon} \rceil} e^t \right)
\]

\[
\leq ec \cdot \left( \sqrt{H} \frac{\log \frac{\Delta}{\epsilon}}{\lambda} + \frac{e \sigma^2}{(e-1) \lambda \Delta} \exp \left( \frac{\log \frac{\Delta}{\epsilon}}{\epsilon} \right) \right)
\]

\[
\leq c' \cdot \left( \sqrt{H} \frac{\log \frac{\Delta}{\epsilon}}{\lambda} + \frac{\sigma^2}{\lambda \epsilon} \right)
\]

This is, up to constant factors, the optimal rate for strongly convex objectives, and matches Ghadimi and Lan’s analysis.

## C Proof of Theorem 3

**Theorem 3.** Let \( \ell \) and \( L \) satisfy Assumptions 1 and 3, then the output of GC2Cvx(Alg 1, e) guarantees for universal constants \( c, c' \)

\[
\mathbb{E}L(\hat{w}) - L^* \leq c \cdot \left( \Delta \exp \left( -c' \sqrt{\lambda} T \right) + \Delta \exp \left( -\frac{c' \lambda b T}{H} \right) + \frac{H L^*}{\lambda b T} \right)
\]

**Proof.** Let \( \psi(w) = \frac{1}{2} \min_{w^*} \epsilon \arg \min_w L(w) \|w - w^*\|^2 \), so \( L \) satisfies the \((\lambda, \psi)\)-GC. By Theorem 1, Algorithm 1 guarantees that\(^3\)

\[
\text{Time}\left( \epsilon, \frac{B^2}{2}, \psi, \mathcal{L}, \text{Alg 1} \right) \leq c \cdot \left( \sqrt{\frac{HB^2}{\epsilon} + \frac{HB^2}{b\epsilon} + \frac{HB^2 L^*}{b^2 \epsilon^2}} \right)
\]

\(^3\)Theorem 1, as stated, requires a bound on \( \|w^*\| \). However, given \( w_0 \) with \( \psi(w_0) \leq \frac{1}{2} B^2 \), there is a minimizer with norm at most \( B \) in the shifted coordinate system \( w \mapsto w - w_0 \).
where, in this case, the “time” refers to the number of iterations, $T$. Applying Theorem 2, this implies

$$\text{Time}_\lambda(\epsilon, \Delta, \psi, \mathcal{L}, \text{GC2Cvx(Alg 1, $e$)}) \leq \sum_{t=1}^{\lceil \log \Delta \rceil} \text{Time}(e^{-t \Delta}, e^{1-t \Delta}, \lambda, \psi, \mathcal{L}, \text{Alg 1}) \leq c \cdot \sum_{t=1}^{\lceil \log \Delta \rceil} \left( \sqrt{\frac{eH}{\lambda} + \frac{H \psi}{b \lambda}} \left\lceil \log \frac{\Delta}{\epsilon} \right\rceil + \frac{eHL^*}{b \lambda \epsilon} \sum_{t=1}^{\lceil \log \Delta \rceil} e^t \right)$$

(100)

$$\leq e^3 c \cdot \left( \sqrt{\frac{H}{\lambda} + \frac{H}{b \lambda}} \left\lceil \log \frac{\Delta}{\epsilon} \right\rceil + \frac{H L^*}{b \lambda \epsilon} \right)$$

(102)

Solving for $\epsilon$ completes the proof.

D Proof of Theorem 4

**Lemma 4.** Let $\mu$ be an unknown parameter in $\{\pm a\}$. The output $\hat{\mu}$ of any algorithm which receives as input $k$ i.i.d. samples $x_1, \ldots, x_k \sim N(\mu, s^2)$ will have mean squared error at least

$$\max_{\mu \in \{\pm a\}} \mathbb{E}(\hat{\mu} - \mu)^2 \geq \left( 1 - \frac{a \sqrt{k}}{s} \right) a^2$$

**Proof.** This lemma is nearly identical to many lower bounds for Gaussian mean estimation. We include the proof to be self-contained and to account for the fact that $\mu$ has only two possible values.

The KL divergence between $k$ i.i.d. samples from $N(-a, s^2)$ and $N(a, s^2)$ is

$$D_{KL}(N(-a, s^2)^{\otimes k} || N(a, s^2)^{\otimes k}) = \frac{2ka^2}{s^2}$$

(103)

By Pinsker’s inequality, the total variation distance between the output of the algorithm if $\mu = -a$ and the output of the algorithm if $\mu = a$ is upper bounded by

$$\delta(\hat{\mu}, \hat{\mu}_a) \leq \frac{a \sqrt{k}}{s}$$

(104)

Finally, we note that

$$(\hat{\mu} - a)^2 \leq a^2 \Rightarrow (\hat{\mu} - (-a))^2 > a^2$$

(105)

and vice versa. Therefore, we conclude that

$$\max_{\mu \in \{\pm a\}} \mathbb{E}(\hat{\mu} - \mu)^2 \geq \left( 1 - \frac{a \sqrt{k}}{s} \right) a^2$$

(106)

This completes the proof.

**Theorem 4.** For $\ell(w; (x, y)) = \frac{1}{2}(\langle w, x \rangle - y)^2$ the square loss, for any learning algorithm that takes $n$ samples as input, there exists a distribution over $(x, y)$ pairs such that $\ell$ and $L$ satisfy Assumptions 1 and 2, and for a universal constant $c$, the algorithm’s output will have error at least

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \frac{HB^2}{n} + \sqrt{\frac{HB^2 L^*}{n}} \right)$$
Similarly, there exists a distribution over \((x, y)\) pairs such that \(\ell\) and \(L\) satisfy Assumptions 1 and 3 (and, in fact, \(L\) is \(\lambda\)-strongly convex), and for a universal constant \(c\), the algorithm’s output will have error at least

\[
\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \left( \Delta \cdot \mathbb{1}_{n \leq \frac{\sigma^2}{\Delta}} + \min\left\{ \frac{HL^*}{\lambda n}, \Delta \right\} \right)
\]

**Proof.** We will prove the first terms and the second terms of the lower bounds separately.

**The first terms of each bound** These lower bounds are based on a simple least squares problem in dimension \(2n\). The loss is, again,

\[
\ell(w; (x; y)) = \frac{1}{2} (\langle w, x \rangle - y)^2
\]

(107)

The data distribution is specified in terms of a sign vector \(\sigma \in \{\pm 1\}^{2n}\). The \(x\) distribution is the uniform distribution over \(\{\sqrt{H}e_1, \ldots, \sqrt{H}e_{2n}\}\), and \(y|x = \langle x, \frac{B}{\sqrt{2n}}\sigma \rangle\). Because \(\|x\|^2 = H\), it is easy to confirm that \(\ell\) is \(H\)-smooth, convex, and non-negative, so it satisfies Assumption 1. In addition, the expected loss is

\[
L(w) = \mathbb{E}_{x,y} \frac{1}{2} (\langle w, x \rangle - y)^2 = \frac{1}{4n} \sum_{i=1}^{2n} (\sqrt{H}w_i - \frac{\sqrt{H}B}{\sqrt{2n}}\sigma_i)^2
\]

(108)

It is easy to see that \(L\) is minimized at the point \(w^* = \frac{B}{\sqrt{2n}}\sigma\), which has norm \(B\) and that \(L(w^*) = L^* = 0\). Therefore, \(L\) satisfies Assumption 2.

Alternatively, \(L(0) - L^* = \frac{HB^2}{4n}\), so choosing \(B^2 = \frac{4n\Delta}{\lambda}\) ensures that \(L(0) - L^* \leq \Delta\). Also, \(L\) is \(\frac{B^2}{4n}\)-strongly convex, so it satisfies Assumption 3 as long as \(n \leq \frac{\Delta}{\lambda}\).

Finally, any algorithm which sees \(n\) samples from the distribution will have received no information whatsoever about the \(\geq n\) coordinates of the sign vector \(\sigma\) that were not involved in the sample. Therefore, for any algorithm, there is a setting of \(\sigma\) such that \(\mathbb{P}(\hat{w}; \sigma \leq 0) \geq \frac{1}{2}\); and for this setting of \(\sigma\)

\[
\mathbb{E}L(\hat{w}) - L^* \geq \frac{1}{4n} \cdot n \cdot \frac{1}{2} \frac{HB^2}{2n} = \frac{HB^2}{16n}
\]

(109)

This proves the first term of the first lower bound under Assumptions 1 and 2. For Assumptions 1 and 2, we have instead

\[
\mathbb{E}L(\hat{w}) - L^* \geq \frac{HB^2}{16n} = \Delta
\]

(110)

Of course, this latter bound holds only when \(n \leq \frac{\Delta}{\lambda}\).

We note that since \(L^* = 0\) in this example, the variance of gradients at the optimum, \(\mathbb{E}\|\nabla \ell(w^*; (x, y))\|^2 = 0\). Therefore, these lower bounds hold when the bound on \(L^*\) is replaced by the bound \(\mathbb{E}\|\nabla \ell(w^*; (x, y))\|^2 \leq \sigma^2\).

**The second terms of each bound** These lower bounds are also both based on the following simple 1-dimensional least squares problem. The loss is given by

\[
\ell(w; (x; y)) = \frac{1}{2} (wx - y)^2
\]

(111)

The distribution is defined using a sign \(\sigma \in \{\pm 1\}\) to be chosen later. With probability \(1 - p\), \((x, y) = (0, 0)\), and with probability \(p\), \(x = \sqrt{H}\) and \(y \sim \mathcal{N}(\sigma\sqrt{H}B, s^2)\).

Because \(x^2 \leq H\), it is easy to confirm that \(\ell(w; (x; y))\) is \(H\)-smooth, convex, and non-negative, so it satisfies Assumption 1. Also, the expected loss is

\[
L(w) = \mathbb{E}_{x,y} \frac{1}{2} (wx - y)^2 = \frac{p}{2} (\sqrt{H}w - \sqrt{H}B\sigma)^2 + \frac{ps^2}{2}
\]

(112)

It is easy to see that \(L\) is convex and is minimized at \(w^* = B\sigma\), which has \(L^2\) norm \(B\) and the minimizing value is \(L(w^*) = \frac{ps^2}{2}\). Therefore, choosing \(s^2 = \frac{2L^2}{p}\) ensures that \(L\) satisfies Assumption 2.
Alternatively, $L(0) - L^* = \frac{pHB^2}{2}$, so choosing $pB^2 \leq \frac{2\Delta}{H}$ ensures $L(0) - L^* \leq \Delta$. Furthermore,

$$L(w) - L^* = \frac{p}{2} \left( \sqrt{H}w - \sqrt{H}B\sigma \right)^2 = \frac{Hp}{2} ||w - w^*||^2$$

(113)

Therefore, choosing $p = \frac{\Delta}{H}$ ensures that $L$ is $\lambda$-strongly convex, so it satisfies Assumption 3.

Under either set of assumptions, minimizing $L$ using $n$ samples $(x_1, y_1), \ldots, (x_n, y_n)$ amounts to a Gaussian mean estimation problem using just the subset of $k$ samples for which $x \neq 0$. By Lemma 4, this means that for any algorithm, for some setting of $\sigma \in \{\pm 1\}$,

$$\mathbb{E}[L(\hat{w}) - L^* | k] \geq \frac{pHB^2}{2} \left( 1 - \sqrt{\frac{HB^2k}{s^2}} \right)$$

(114)

Applying Jensen’s inequality to the convex function $-\sqrt{k}$, we conclude that

$$\mathbb{E}L(\hat{w}) - L^* \geq \frac{pHB^2}{2} \left( 1 - \sqrt{\frac{HB^2np^2}{2L^*}} \right)$$

(115)

For Assumptions 1 and 2, we set the remaining parameter as $p^2 = \frac{L^*}{2HB^2n}$ and conclude

$$\mathbb{E}L(\hat{w}) - L^* \geq \sqrt{\frac{HB^2L^*}{32n}}$$

(116)

For Assumptions 1 and 3, we consider two cases: If $\Delta \leq \frac{HL^*}{4\lambda n}$, we set $B^2 = \frac{2\Delta}{H}$ to conclude

$$\mathbb{E}L(\hat{w}) - L^* \geq \left( 1 - \sqrt{\frac{\Delta\lambda n}{HL^*}} \right) \geq \frac{\Delta}{2}$$

(117)

Otherwise, we set $B^2 = \frac{L^*}{2\lambda np} \leq \frac{2\Delta}{Hp}$ and conclude

$$\mathbb{E}L(\hat{w}) - L^* \geq \frac{HL^*}{8\lambda n}$$

(118)

Therefore, under Assumptions 1 and 2, the loss is at least

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \min \left\{ \frac{HL^*}{4\lambda n}, \Delta \right\}$$

(119)

We note that by Lemma 3, the variance of gradients at the optimum, $\mathbb{E}||\nabla \ell(w^*; (x, y))||^2 \leq 2HL^*$. Therefore, when the bound on $L^*$ is replaced by the bound $\mathbb{E}||\nabla \ell(w^*; (x, y))||^2 \leq \sigma^2$, we have the lower bounds

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \frac{\sigma^2 B}{\sqrt{n}}$$

(120)

in the convex case and

$$\mathbb{E}L(\hat{w}) - L^* \geq c \cdot \min \left\{ \frac{\sigma^2}{\lambda n}, \Delta \right\}$$

(121)

in the strongly convex case. This completes the proof.\[\square\]