Stochastic Optimization with Variance Reduction for Infinite Datasets with Finite-Sum Structure

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Abstract

Stochastic optimization algorithms with variance reduction have proven successful for minimizing large finite sums of functions. Unfortunately, these techniques are unable to deal with stochastic perturbations of input data, induced for example by data augmentation. In such cases, the objective is no longer a finite sum, and the main candidate for optimization is the stochastic gradient descent method (SGD). In this paper, we introduce a variance reduction approach for these settings when the objective is strongly convex. After an initial linearly convergent phase, the algorithm achieves a $O(1/t)$ convergence rate in expectation like SGD, but with a constant factor that is typically much smaller, depending on the variance of gradient estimates due to perturbations on a *single* example. We also introduce extensions of the algorithm to composite objectives and non-uniform sampling.

1 Introduction

Many supervised machine learning problems can be cast into the minimization of an expected loss over a data distribution $\mathcal{D}$ with respect to a vector x in $\mathbb{R}^p$ of model parameters: $\mathbb{E}_{\zeta\sim\mathcal{D}}[f(x,\zeta)]$. When an infinite amount of data is available, stochastic optimization methods such as the stochastic gradient descent (SGD) or stochastic mirror descent algorithms, or their variants, are typically used (see, *e.g.*, Bottou et al., 2016; Nemirovski et al., 2009). Nevertheless, when the dataset is finite, incremental methods based on variance reduction techniques (*e.g.*, Allen-Zhu, 2016; Defazio et al., 2014a; Johnson and Zhang, 2013; Lan and Zhou, 2015; Lin et al., 2015; Schmidt et al., 2016; Shalev-Shwartz and Zhang, 2013) have proven to be significantly faster than SGD at solving the finite-sum problem

$$\min_{x\in\mathbb{R}^p}\left\{F(x) := f(x) + h(x) = \frac{1}{n}\sum_{i=1}^{n} f_i(x) + h(x)\right\},$$

where the functions f_i are smooth and convex, and h is a simple convex penalty that need not be differentiable such as the ℓ_1 norm. A classical setting is $f_i(x) = \ell(y_i, x^\top\xi_i) + (\mu/2)\|x\|^2$, where (ξ_i, y_i) is an example-label pair, ℓ is a convex loss function, and μ is a regularization parameter.

Introducing random perturbations of data is a fundamental concept in machine learning; for instance, this is a key to achieve stable feature selection (Meinshausen and Bühlmann, 2010), or for privacy-aware learning (Duchi et al., 2012). In this paper, we consider the augmentation of finite training sets with well-chosen random perturbations of each example, which can lead to smaller test error in theory (Wager et al., 2014) and in practice (Loosli et al., 2007; van der Maaten et al., 2013). Examples of such procedures include

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random transformations of images in classification problems (*e.g.*, Loosli et al., 2007) and Dropout (Srivastava et al., 2014). The objective describing these scenarios, which is the focus of this paper, is the following:

$$\min_{x \in \mathbb{R}^p} \left\{ F(x) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{E}_{\rho \sim \Gamma}[\tilde{f}_i(x, \rho)] + h(x) \right\}, \tag{1}$$

that is, we consider the finite-sum problem with $f_i(x) = \mathbb{E}_{\rho \sim \Gamma}[\tilde{f}_i(x, \rho)]$, where ρ parametrizes the random perturbation and $\tilde{f}_i(\cdot, \rho)$ is a convex smooth function with L-Lipschitz continuous gradients for all i and ρ. We also assume that F is μ-strongly convex. Because each function f_i is an expectation, computing a single gradient ∇f_i is intractable in general and standard variance reduction methods cannot be used. A natural way to optimize this objective when $h = 0$ is to use SGD by randomly choosing an index i_t at iteration t along with a perturbation $\rho_t \sim \Gamma$, and performing the update $x_t = x_{t-1} - \eta_t \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)$ with a step-size η_t. Unfortunately, this approach ignores the finite-sum structure and leads to gradient estimates with high variance and slow convergence. The goal of this paper is to introduce an algorithm, called *stochastic MISO*, that can exploit the problem structure using variance reduction. Our method achieves a $O(1/t)$ convergence rate like SGD, but with a much smaller constant term in typical settings, only depending on the variance of the gradient estimates due to the random perturbations on a single example.

To the best of our knowledge, our method is the first hybrid algorithm that naturally interpolates between incremental algorithms for finite sums (when there are no perturbations) and the stochastic approximation setting (when $n = 1$); as a first step, we tackle the problem from a convex optimization point of view. We also remark that in the stochastic composite case with $n = 1$, we obtain a novel algorithm with the same convergence properties as SGD.

Related work. Our work is inspired by the recent surge of interest for stochastic optimization methods that are dedicated to the minimization of finite sums, which arise naturally in machine learning. Surprisingly, it has been shown that by exploiting the finite-sum structure in the objective, one can develop much faster optimization methods than previous ones that did not exploit this structure, such as SGD or full gradient descent (see, among others, Schmidt et al., 2016; Shalev-Shwartz and Zhang, 2013).

Many of these methods have been motivated by the fact that their updates can be interpreted as SGD steps with unbiased estimates of the full gradient, but with a variance that decreases as the algorithm approaches the optimum (Johnson and Zhang, 2013); on the other hand, vanilla SGD requires decreasing step-sizes to achieve this reduction of variance, thereby slowing down convergence. Our work aims at extending these techniques, in particular the MISO/Finito algorithms (Defazio et al., 2014b; Lin et al., 2015; Mairal, 2015) to the case where each function in the finite sum can only be accessed via a first-order stochastic oracle.

Despite its relevance to machine learning (van der Maaten et al., 2013; Wager et al., 2014), problem (1) is not well studied in the optimization literature. Most related to our work, recent methods that use clustering information to improve the convergence of variance reduction techniques (Allen-Zhu et al., 2016; Hofmann et al., 2015) can be seen as tackling a special case of (1), where the expectations in f_i are replaced by empirical averages over points in a cluster. While the approximation assumption of N-SAGA (Hofmann et al., 2015) can be seen as a variance condition on stochastic gradients as in our case, their algorithm is asymptotically biased and does not converge to the optimum. On the other hand, ClusterSVRG (Allen-Zhu et al., 2016) is not biased, but does not support infinite datasets. The method proposed by Achab et al. (2015) uses variance reduction in a setting where gradients are computed approximately, but the algorithm computes a full gradient at every pass, which is not available in our stochastic setting.

Paper organization. In Section 2, we present our algorithm for smooth objectives, and we analyze its convergence in Section 3. We introduce an extension of the algorithm to composite objectives and non-uniform sampling in Section 4. In Section 5, we present empirical results on two significantly different problems: image classification with random transformations of the input examples, and classification of biological and text data with Dropout.

Algorithm 1 S-MISO for smooth objectives

Input: step-size sequence $(\alpha_t)_{t\geq 1}$;
Initialize $x_0 = \frac{1}{n}\sum_i z_i^0$ for some $(z_i^0)_{i=1,\dots,n}$;
for $t = 1, \dots$ **do**
Sample an index i_t uniformly at random, a perturbation $\rho_t \sim \Gamma$, and update (with $g_t = \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)$):

$$z_i^t = \begin{cases} (1-\alpha_t) z_i^{t-1} + \alpha_t (x_{t-1} - \frac{1}{\mu} g_t), & \text{if } i = i_t \\ z_i^{t-1}, & \text{otherwise.} \end{cases} \tag{2}$$

$$x_t = \frac{1}{n}\sum_{i=1}^n z_i^t = x_{t-1} + \frac{1}{n}(z_{i_t}^t - z_{i_t}^{t-1}). \tag{3}$$

end for

2 The Stochastic MISO Algorithm

In this section, we introduce the *stochastic MISO* approach for smooth objectives ($h = 0$), which relies on the following assumptions:

- (A1) **global strong convexity**: f is μ-strongly convex;
- (A2) **smoothness**: $\tilde{f}_i(\cdot, \rho)$ is L-smooth for all i and ρ (*i.e.*, differentiable with L-Lipschitz gradients);
- (A3) **small variance from perturbations**:

$$\mathbb{E}_\rho \left[\|\nabla \tilde{f}_i(x^*, \rho) - \nabla f_i(x^*)\|^2 \right] \leq \sigma^2,$$

for all i, where x^* is the (unique) minimizer of f.

Note that we will relax the smoothness assumption (A2) in Section 4 by supporting composite objectives with non-smooth regularizers, and by exploiting different smoothness parameters L_i on each example, a setting where non-uniform sampling of the training points is typically helpful to accelerate the convergence of incremental methods (*e.g.*, Xiao and Zhang, 2014). It is important to note that our variance assumption (A3) is only affected by the noise induced by the perturbations ρ and not by the randomness in the choice of the index i. In contrast, a similar assumption for the SGD algorithm on the objective (1) would take the form $\mathbb{E}_{i,\rho}[\|\nabla \tilde{f}_i(x^*, \rho)\|^2] \leq \sigma_{tot}^2$ for all x (see Appendix C). The quantity σ_{tot}^2 takes into account the noise induced by the random index i in addition to ρ, and can thus be much larger than σ^2, particularly if the perturbations on input data are small. In Section 3, we will show that after an initial linearly convergent phase, and under appropriate choice of step-sizes $(\alpha_t)_{t\geq 1}$, S-MISO satisfies $\mathbb{E}[\|x_t - x^*\|^2] \leq \epsilon$ after

$$O\left(\frac{\sigma^2}{\mu^2 \epsilon}\right)$$

iterations. This complexity is similar to that of SGD (Bottou et al., 2016; Nemirovski et al., 2009), but with σ^2 replacing the quantity σ_{tot}^2, leading to a much faster rate than SGD if $\sigma^2 \ll \sigma_{tot}^2$, something which we observed in our experiments (see Section 5).

Our method is given in Algorithm 1. Without the perturbations and with a constant step-size, the algorithm resembles the MISO/Finito algorithms (Defazio et al., 2014b; Lin et al., 2015; Mairal, 2015), which may be seen as primal variants of SDCA (Shalev-Shwartz, 2016; Shalev-Shwartz and Zhang, 2013). MISO/Finito are part of a larger body of optimization methods that iteratively build a *model* of the objective function, typically in the form of a lower or upper bound on the objective that is easier to optimize; for instance, this strategy is commonly adopted in bundle methods (Hiriart-Urruty and Lemaréchal, 1993) or in the EM algorithm and its incremental variants (Neal and Hinton, 1998). Specifically, MISO/Finito

assumes that each f_i is strongly convex, and builds a model of the objective using lower bounds of the form $D_t(x) = \frac{1}{n}\sum_{i=1}^n d_i^t(x)$, where each d_i^t is a lower bound on f_i and takes the form

$$d_i^t(x) = c_{i,1}^t + \frac{\mu}{2}\|x - z_i^t\|^2 = c_{i,2}^t - \mu\langle x, z_i^t\rangle + \frac{\mu}{2}\|x\|^2. \tag{4}$$

These lower bounds are updated during the algorithm using strong convexity lower bounds at x_{t-1} of the form $l_i^t(x) = f_i(x_{t-1}) + \langle \nabla f_i(x_{t-1}), x - x_{t-1}\rangle + \frac{\mu}{2}\|x - x_{t-1}\|^2$:

$$d_i^t(x) = \begin{cases} (1-\alpha_t)d_i^{t-1}(x) + \alpha_t l_i^t(x), & \text{if } i = i_t \\ d_i^{t-1}(x), & \text{otherwise,} \end{cases} \tag{5}$$

which corresponds to a z_i^t update (with $g_t = \nabla f_{i_t}(x_{t-1})$)

$$z_i^t = \begin{cases} (1-\alpha_t)z_i^{t-1} + \alpha_t(x_{t-1} - \frac{1}{\mu}g_t), & \text{if } i = i_t \\ z_i^{t-1}, & \text{otherwise.} \end{cases}$$

The next iterate is then computed as $x_t = \arg\min_x D_t(x)$, which is equivalent to (3). The original MISO/Finito algorithms use $\alpha_t = 1$ under a "big data" condition on the sample size n (Defazio et al., 2014b; Mairal, 2015), while the theory was later extended in Lin et al. (2015) to relax this condition by supporting smaller constant steps $\alpha_t = \alpha$, leading to an algorithm that may be interpreted as a primal variant of SDCA (see also Shalev-Shwartz, 2016).

Note that when f_i is an expectation, it is hard to obtain such lower bounds since the gradient $\nabla f_i(x_{t-1})$ is not available in general. Nevertheless, S-MISO can exploit *approximate* lower bounds to each f_i using gradient estimates g_t, by letting the step-sizes α_t decrease appropriately as commonly done in stochastic approximation. This leads to update (2).

Separately, SDCA (Shalev-Shwartz and Zhang, 2013) considers the Fenchel conjugates of f_i, defined by $f_i^*(y) = \sup_x x^\top y - f_i(x)$. When f_i is an expectation, f_i^* is not available in closed form in general, nor are its gradients, and in fact exploiting stochastic gradient estimates is difficult in the duality framework. In contrast, Shalev-Shwartz (2016) gives an analysis of SDCA in the primal, aka. "without duality", for smooth finite sums, and our work extends this line of reasoning to the stochastic approximation and composite settings.

Relationship with SGD in the smooth case. The link between S-MISO in the non-composite setting and SGD can be seen by rewriting the update (3) as

$$x_t = x_{t-1} + \frac{1}{n}(z_{i_t}^t - z_{i_t}^{t-1}) = x_{t-1} + \frac{\alpha_t}{n}v_t,$$

where

$$v_t := x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - z_{i_t}^{t-1}. \tag{6}$$

Note that $\mathbb{E}[v_t|\mathcal{F}_{t-1}] = -\frac{1}{\mu}\nabla f(x_{t-1})$, where $\mathcal{F}_{t-1}$ contains all information up to iteration t; hence, the algorithm can be seen as an instance of the stochastic gradient method with unbiased gradients, which was a key motivation in SVRG (Johnson and Zhang, 2013) and later in other variance reduction algorithms (Defazio et al., 2014a; Shalev-Shwartz, 2016). It is also worth noting that in the absence of a finite-sum structure ($n=1$), we have $z_{i_t}^{t-1} = x_{t-1}$, hence our method becomes identical to "vanilla" SGD, up to a redefinition of step-sizes.

Memory requirements and handling of sparse datasets. The algorithm requires storing the vectors $(z_i^t)_{i=1,\dots,n}$, which takes the same amount of memory as the original dataset, and is therefore a reasonable requirement in practice. In the case of sparse datasets, it is fair to assume that the random perturbations applied to the input data preserve the sparsity patterns of the original vectors, as is the case, *e.g.*, when applying Dropout to text documents described with bag-of-words representations (Wager et al., 2014). If

we further assume the typical setting where the μ-strong convexity comes from an ℓ_2 regularizer: $\tilde{f}_i(x,\rho) = \phi_i(x^\top \xi_i^\rho) + (\mu/2)\|x\|^2$, where ξ_i^ρ is the (sparse) perturbed example and ϕ_i encodes the loss, then the update (2) can be written as

$$z_i^t = \begin{cases} (1-\alpha_t) z_i^{t-1} - \frac{\alpha_t}{\mu} \phi_i'(x_{t-1}^\top \xi_i^{\rho_t}) \xi_i^{\rho_t}, & \text{if } i = i_t \\ z_i^{t-1}, & \text{otherwise,} \end{cases}$$

which shows that for every index i, the vector z_i^t preserves the same sparsity pattern as the examples ξ_i^ρ throughout the algorithm (assuming the initialization $z_i^0 = 0$), making the update (2) efficient. The update (3) has the same cost since $v_t = z_{i_t}^t - z_{i_t}^{t-1}$ is also sparse.

3 Convergence Analysis of S-MISO

We now study the convergence properties of the S-MISO algorithm. We defer all proofs to the appendix. We start by defining the problem-dependent quantities $z_i^* := x^* - \frac{1}{\mu}\nabla f_i(x^*)$, and then introduce the Lyapunov function

$$C_t = \frac{1}{2}\|x_t - x^*\|^2 + \frac{\alpha_t}{n^2} \sum_{i=1}^n \|z_i^t - z_i^*\|^2. \tag{7}$$

Proposition 1 gives a recursion on C_t, obtained by upper-bounding separately its two terms, and finding coefficients to cancel out other appearing quantities when relating C_t to C_{t-1}. To this end, we borrow elements of the convergence proof of SDCA without duality (Shalev-Shwartz, 2016); our technical contribution is to extend their result to the stochastic approximation and composite (see Section 4) cases, and to study the convergence behavior of the algorithm in these settings.

Proposition 1 (Recursion on C_t)**.** *If $(\alpha_t)_{t\geq 1}$ is a positive and non-increasing sequence of step-sizes satisfying*

$$\alpha_1 \leq \min\left\{\frac{1}{2}, \frac{n}{2(2\kappa - 1)}\right\}, \tag{8}$$

with $\kappa = L/\mu$, then C_t obeys the recursion

$$\mathbb{E}[C_t] \leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}[C_{t-1}] + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma^2}{\mu^2}. \tag{9}$$

Comparison with SGD. A simple analysis of SGD with step-sizes $(\eta_t)_{t\geq 0}$ gives the following recursion on $B_t := \frac{1}{2}\mathbb{E}[\|x_t - x^*\|^2]$ (we provide a proof in Appendix C):

$$B_t \leq (1 - \mu\eta_t) B_{t-1} + (\mu\eta_t)^2 \frac{\sigma_{tot}^2}{\mu^2},$$

where we assume $\mathbb{E}_{i,\rho}[\|\nabla \tilde{f}_i(x^*,\rho)\|^2] \leq \sigma_{tot}^2$. Thus, after forgetting the initial condition C_0, S-MISO minimizes $B_t \leq C_t$ at a faster rate if $2\sigma^2 \leq \sigma_{tot}^2$. In particular, if the gradient variance *across examples* (bounded by σ_{tot}^2 at the optimum) is much larger than the gradient variance due to the data perturbation only $\rho \sim \Gamma$ (bounded by σ^2 at the optimum), then our algorithm has a much faster convergence rate. As shown in the experimental section, σ_{tot}^2 may be indeed orders of magnitude larger than σ^2 in real scenarios, leading to both theoretical and practical benefits.

We now state the main convergence result, which provides the expected rate $O(1/t)$ on C_t based on decreasing step-sizes, similar to (Bottou et al., 2016) for SGD. Note that convergence of objective function values is directly related to that of the Lyapunov function C_t via smoothness:[1]

$$\mathbb{E}[f(x_t) - f(x^*)] \leq \frac{L}{2}\mathbb{E}\left[\|x_t - x^*\|^2\right] \leq L\,\mathbb{E}[C_t]. \tag{10}$$

[1]Note that the constant L is an upper bound of the smoothness constant of each function $\tilde{f}_i(\cdot,\rho)$; it can be replaced here by the global smoothness constant of f, which may be smaller than L.

Theorem 2 (Convergence of Lyapunov function)**.** *Let the sequence of step-sizes* $(\alpha_t)_{t\geq 1}$ *be defined by* $\alpha_t = \frac{\beta n}{\gamma + t}$ *with* $\beta > 1$ *and* $\gamma \geq 0$ *such that* α_1 *satisfies* (8)*. For all* $t \geq 0$*, it holds that*

$$\mathbb{E}[C_t] \leq \frac{\nu}{\gamma + t + 1},$$

where

$$\nu := \max\left\{\frac{2\beta^2\sigma^2}{\mu^2(\beta - 1)}, (\gamma + 1)C_0\right\}. \tag{11}$$

Choice of step-sizes in practice. Naturally, we would like ν to be small, in particular independent of the initial condition C_0 and equal to the first term in the definition (11). We would like the dependence on C_0 to vanish at a faster rate than $O(1/t)$, as it is the case in variance reduction algorithms on finite sums. As advised in Bottou et al. (2016) in the context of SGD, we can initially run the algorithm with a constant step-size $\bar{\alpha}$ and exploit this linear convergence regime until we reach the level of noise given by σ, and then start decaying the step-size.

It is easy to see that by using a constant step-size $\bar{\alpha}$, C_t converges near a value $\bar{C} := \frac{2\bar{\alpha}\sigma^2}{n\mu^2}$. Indeed, Eq. (9) with $\alpha_t = \bar{\alpha}$ yields

$$\mathbb{E}[C_t - \bar{C}] \leq \left(1 - \frac{\bar{\alpha}}{n}\right)\mathbb{E}[C_{t-1} - \bar{C}].$$

Thus, we can reach a value C_0' with $\mathbb{E}[C_0'] \leq \bar{\epsilon} := 2\bar{C}$ in $O(\frac{n}{\bar{\alpha}}\log C_0/\bar{\epsilon})$ iterations. Then, if we start decaying step-sizes as in Theorem 2 with $\beta = 2$ and γ large enough so that $\alpha_1 = \frac{\beta n}{\gamma+1} = \bar{\alpha}$, we have

$$(\gamma + 1)\,\mathbb{E}[C_0'] \leq (\gamma + 1)\bar{\epsilon} = 8\sigma^2/\mu^2,$$

making both terms in (11) smaller than or equal to $\nu = 8\sigma^2/\mu^2$. Considering these two phases, with an initial step-size $\bar{\alpha}$ given by the upper bound in (8), the final work complexity of the algorithm for reaching $\mathbb{E}[\|x_t - x^*\|^2] \leq \epsilon$ is

$$O\left((n + \kappa)\log\frac{C_0}{\bar{\epsilon}}\right) + O\left(\frac{\sigma^2}{\mu^2\epsilon}\right). \tag{12}$$

We can use (10) in order to obtain the complexity for reaching $\mathbb{E}[f(x_t) - f(x^*)] \leq \epsilon$, and the second term becomes $O(L\sigma^2/\mu^2\epsilon)$. Note that following this step-size strategy was found to be very effective in practice (see Section 5).

Acceleration by iterate averaging. When one is interested in the convergence in function values, the complexity term $O(L\sigma^2/\mu^2\epsilon)$ mentioned above can be problematic for ill-conditioned problems (large $\kappa = L/\mu$). The following theorem presents an iterate averaging scheme which brings the complexity term down to $O(\sigma^2/\mu\epsilon)$.

Theorem 3 (Convergence under iterate averaging)**.** *Let the step-size sequence* $(\alpha_t)_{t\geq 1}$ *be defined by*

$$\alpha_t = \frac{2n}{\gamma + t} \quad \text{for } \gamma \geq 1 \text{ s.t. } \alpha_1 \leq \min\left\{\frac{1}{2}, \frac{n}{4(2\kappa - 1)}\right\}.$$

We have

$$\mathbb{E}[f(\bar{x}_T) - f(x^*)] \leq \frac{2\mu\gamma(\gamma - 1)C_0}{T(2\gamma + T - 1)} + \frac{16\sigma^2}{\mu(2\gamma + T - 1)},$$

where

$$\bar{x}_T := \frac{2}{T(2\gamma + T - 1)}\sum_{t=0}^{T-1}(\gamma + t)x_t.$$

The proof uses a similar telescoping sum technique to Lacoste-Julien et al. (2012). Note that if $T \gg \gamma$, the first term, which depends on the initial condition C_0, decays as $1/T^2$ and is thus dominated by the second term. Moreover, if we start averaging after an initial phase with constant step-size $\bar{\alpha}$, we can consider $C_0 \approx \frac{4\bar{\alpha}\sigma^2}{n\mu^2}$. In the ill-conditioned regime, taking $\bar{\alpha} = \alpha_1 = 2n/(\gamma+1)$ as large as allowed we have γ of the order of $\kappa \gg 1$. The full convergence rate then becomes

$$\mathbb{E}[f(\bar{x}_T) - f(x^*)] \leq O\left(\frac{\sigma^2}{\mu(\gamma+T)}\left(1 + \frac{\gamma}{T}\right)\right).$$

When T is large enough compared to γ, this becomes $O(\sigma^2/\mu T)$, leading to a complexity term $O(\sigma^2/\mu\epsilon)$.

4 Extension to Composite Objectives and Non-Uniform Sampling

In this section, we study extensions of S-MISO to different situations where our previous smoothness assumption (A2) is not suitable, either because of a non-smooth term h in the objective or because it ignores additional useful knowledge about each f_i such as the norm of each example.

In the presence of non-smooth regularizers such as the ℓ_1-norm, the objective is no longer smooth, but we can leverage its composite structure by using proximal operators. To this end, we assume that one can easily compute the proximal operator of h, defined by

$$\text{prox}_h(z) := \arg\min_{x \in \mathbb{R}^p} \left\{ \frac{1}{2}\|x - z\|^2 + h(x) \right\}.$$

When the smoothness constants L_i vary significantly across different examples (typically through the norm of the feature vectors), the uniform upper bound $L = L_{\max} = \max_i L_i$ can be restrictive. It has been noticed (see, *e.g.*, Schmidt et al., 2016; Xiao and Zhang, 2014) that when the L_i are known, one can achieve better convergence rates—typically depending on the average smoothness constant $\bar{L} = \frac{1}{n}\sum_i L_i$ rather than $L_{\max}$—by sampling examples in a non-uniform way. For that purpose, we now make the following assumptions:

- (A4) **strong convexity**: $\tilde{f}_i(\cdot, \rho)$ is μ-strongly convex for all i, ρ;
- (A5) **smoothness**: $\tilde{f}_i(\cdot, \rho)$ is L_i-smooth for all i, ρ;
- (A6) **small variance from perturbations at** x^*: $\mathbb{E}_\rho\left[\|\nabla \tilde{f}_i(x^*, \rho) - \nabla f_i(x^*)\|^2\right] \leq \sigma_i^2$ for all i.

Note that our proof relies on a slightly stronger assumption (A4) than the global strong convexity assumption (A1) made above, which holds in the common situation where strong convexity comes from an ℓ_2 regularization term. In order to exploit the different smoothness constants, we allow the algorithm to sample indices i non-uniformly, from any distribution q such that $q_i \geq 0$ for all i and $\sum_i q_i = 1$.

The extension of S-MISO to this setting is given in Algorithm 2. Note that the step-sizes vary depending on the example, with larger steps for examples that are sampled less frequently (typically "easier" examples with smaller L_i). Note that when $h = 0$, the update directions are unbiased estimates of the gradient: we have $\mathbb{E}[x_t - x_{t-1}|\mathcal{F}_{t-1}] = -\frac{\alpha_t}{n\mu}\nabla f(x_{t-1})$ as in the uniform case. However, in the composite case, the algorithm cannot be written in a proximal stochastic gradient form like Prox-SVRG (Xiao and Zhang, 2014) or SAGA (Defazio et al., 2014a).

Relationship with RDA. When $n = 1$, our algorithm performs similar updates to Regularized Dual Averaging (RDA) (Xiao, 2010) with strongly convex regularizers. In particular, if $\tilde{f}_1(x, \rho) = \phi(x^\top \xi(\rho)) + (\mu/2)\|x\|^2$, the updates are the same when taking $\alpha_t = 1/t$, since

$$\text{prox}_{h/\mu}(\bar{z}_t) = \arg\min_x \left\{ \langle -\mu \bar{z}_t, x\rangle + \frac{\mu}{2}\|x\|^2 + h(x) \right\},$$

Algorithm 2 S-MISO for composite objectives, with non-uniform sampling.

Input: step-sizes $(\alpha_t)_{t\geq 1}$, sampling distribution q;
Initialize $x_0 = \mathrm{prox}_{h/\mu}(\bar{z}_0)$ with $\bar{z}_0 = \frac{1}{n}\sum_i z_i^0$ for some $(z_i^0)_{i=1,\dots,n}$ that safisfies (15);
for $t = 1, \dots$ **do**
Sample an index $i_t \sim q$, a perturbation $\rho_t \sim \Gamma$, and update (with $\alpha_t^i = \alpha_t/q_i n$, $g_t = \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)$):

$$z_i^t = \begin{cases} (1-\alpha_t^i) z_i^{t-1} + \alpha_t^i (x_{t-1} - \frac{1}{\mu} g_t), & \text{if } i = i_t \\ z_i^{t-1}, & \text{otherwise} \end{cases} \tag{13}$$

$$\bar{z}_t = \frac{1}{n}\sum_{i=1}^n z_i^t = \bar{z}_{t-1} + \frac{1}{n}(z_{i_t}^t - z_{i_t}^{t-1})$$

$$x_t = \mathrm{prox}_{h/\mu}(\bar{z}_t). \tag{14}$$

end for

and $-\mu\bar{z}_t$ is equal to the average of the gradients of the loss term up to t, which appears in the same way in the RDA updates (Xiao, 2010, Section 2.2). However, unlike RDA, our method supports arbitrary decreasing step-sizes, in particular keeping the step-size constant, which can lead to faster convergence in the initial iterations (see Section 3).

Lower-bound model and convergence analysis. Again, we can view the algorithm as iteratively updating approximate lower bounds on the objective F of the form $D_t(x) = \frac{1}{n}\sum_i d_i^t(x) + h(x)$ analogously to (5), and minimizing the new D_t in (14). Similar to MISO-Prox, we require that d_i^0 is initialized with a μ-strongly convex quadratic such that $\tilde{f}_i(x, \tilde{\rho}_i) \geq d_i^0(x)$ with $\tilde{\rho}_i \sim \Gamma$. Given the form of d_i^t in (4), it suffices to choose z_i^0 that satisfies

$$\tilde{f}_i(x, \tilde{\rho}_i) \geq \frac{\mu}{2}\|x - z_i^0\| + c, \tag{15}$$

for some constant c. In the common case of an ℓ_2 regularizer with a non-negative loss, one can simply choose $z_i^0 = 0$ for all i, otherwise, z_i^0 can be obtained by considering a strong convexity lower bound on $\tilde{f}_i(\cdot, \tilde{\rho}_i)$. Our new analysis relies on the minimum $D_t(x_t)$ of the lower bounds D_t through the following Lyapunov function:

$$C_t^q = F(x^*) - D_t(x_t) + \frac{\mu\alpha_t}{n^2}\sum_{i=1}^n \frac{1}{q_i n}\|z_i^t - z_i^*\|^2. \tag{16}$$

The convergence of the iterates x_t is controlled by the convergence in C_t^q thanks to the following lemma:

Lemma 4 (Bound on the iterates)**.** *For all t, we have*

$$\frac{\mu}{2}\,\mathbb{E}[\|x_t - x^*\|^2] \leq \mathbb{E}[F(x^*) - D_t(x_t)]. \tag{17}$$

The following proposition gives a recursion on C_t^q similar to Proposition 1.

Proposition 5 (Recursion on C_t^q)**.** *If $(\alpha_t)_{t\geq 1}$ is a positive and non-increasing sequence of step-sizes satisfying*

$$\alpha_1 \leq \min\left\{\frac{n q_{\min}}{2}, \frac{n\mu}{4L_q}\right\}, \tag{18}$$

with $q_{\min} = \min_i q_i$ and $L_q = \max_i \frac{L_i - \mu}{q_i n}$, then C_t^q obeys the recursion

$$\mathbb{E}[C_t^q] \leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}[C_{t-1}^q] + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma_q^2}{\mu}, \tag{19}$$

with $\sigma_q^2 = \frac{1}{n}\sum_i \frac{\sigma_i^2}{q_i n}$.

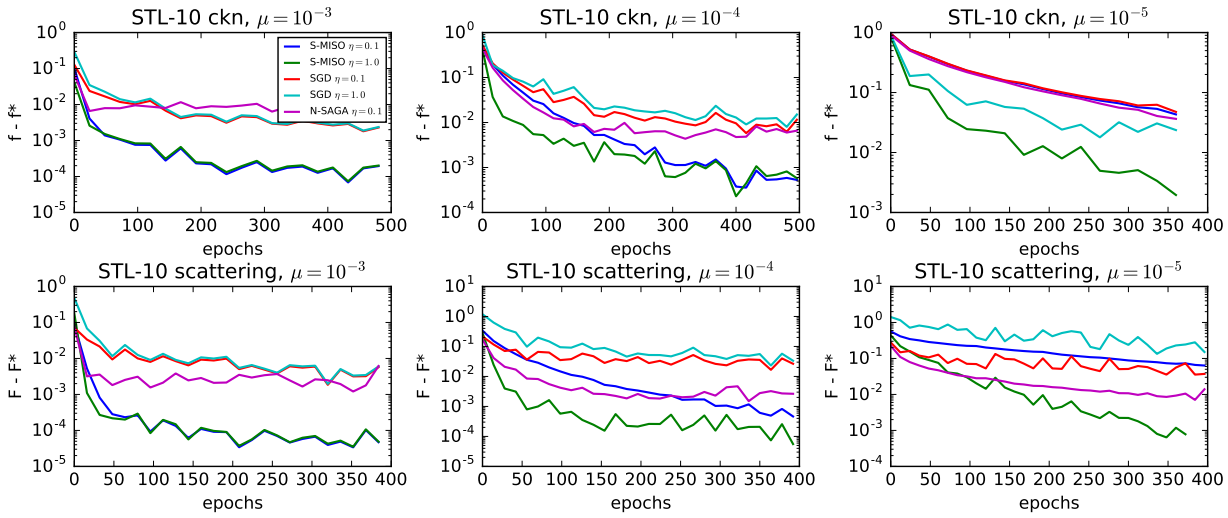

Figure 1: Impact of conditioning on the different methods for data augmentation on STL-10 (controlled by μ, where $\mu = 10^{-4}$ gives the best test accuracy). Values of the training loss are shown in **logarithmic scale** (1 unit = factor 10). $\eta = 0.1$ satisfies the theory for all methods, and we include curves for larger step-sizes $\eta = 1$. We omit N-SAGA for $\eta = 1$ because it plateaus very quickly and far from the optimum. For the scattering representation, the problem we study is ℓ_1-regularized, thus we use the composite variants of the algorithms (for SGD, we use a variant of FOBOS (Duchi and Singer, 2009), see Appendix C).

Note that if we consider the quantity $\mathbb{E}[C_t^q/\mu]$, which is an upper bound on $\frac{1}{2}\mathbb{E}[\|x_t - x^*\|^2]$ by Lemma 4, we have the same recursion as (9), and thus can apply Theorem 2 with the new condition (18). If we choose

$$q_i = \frac{1}{2n} + \frac{L_i - \mu}{2\sum_i (L_i - \mu)}, \tag{20}$$

we have $q_{\min} \geq 1/2n$ and $L_q \leq 2(\bar{L} - \mu)$, where $\bar{L} = \frac{1}{n}\sum_i L_i$. Then, taking $\alpha_1 = \min(1/4, n\mu/8(\bar{L} - \mu))$ satisfies (18), and using similar arguments to Section 3, the complexity for reaching $\mathbb{E}[\|x_t - x^*\|^2] \leq \epsilon$ is

$$O\left(\left(n + \frac{\bar{L}}{\mu}\right)\log\frac{C_0^q}{\bar{\epsilon}}\right) + O\left(\frac{\sigma_q^2}{\mu^2\epsilon}\right),$$

where $\bar{\epsilon} = 4\bar{\alpha}\sigma_q^2/n\mu$, and $\bar{\alpha}$ is the initial constant step-size. For the complexity in function suboptimality, the second term becomes $O(\sigma_q^2/\mu\epsilon)$ by using the same averaging scheme presented in Theorem 3 and adapting the proof. Note that with our choice of q, we have $\sigma_q^2 \leq \frac{2}{n}\sum_i \sigma_i^2 = 2\bar{\sigma}^2$, for general perturbations, where $\bar{\sigma}^2 = \frac{1}{n}\sum_i \sigma_i^2$ is the variance in the uniform case. Additionally, it is often reasonable to assume that the variance from perturbations increases with the norm of examples, for instance Dropout perturbations get larger when coordinates have larger magnitudes. Based on this observation, if we make the assumption that $\sigma_i^2 \propto L_i - \mu$, that is $\sigma_i^2 = \bar{\sigma}^2\frac{L_i - \mu}{\bar{L} - \mu}$, then for both $q_i = 1/n$ (uniform case) and $q_i = (L_i - \mu)/n(\bar{L} - \mu)$, we have $\sigma_q^2 = \bar{\sigma}^2$, and thus we have $\sigma_q^2 \leq \bar{\sigma}^2$ for the choice of q given in (20), since σ_q^2 is convex in q. Thus, we can expect that the $O(1/t)$ convergence phase behaves similarly or better than for uniform sampling, which is confirmed by our experiments (see Section 5).

5 Experiments

We present experiments comparing S-MISO with SGD and N-SAGA (Hofmann et al., 2015) on four different scenarios, in order to demonstrate the wide applicability of our method: we consider an image classification

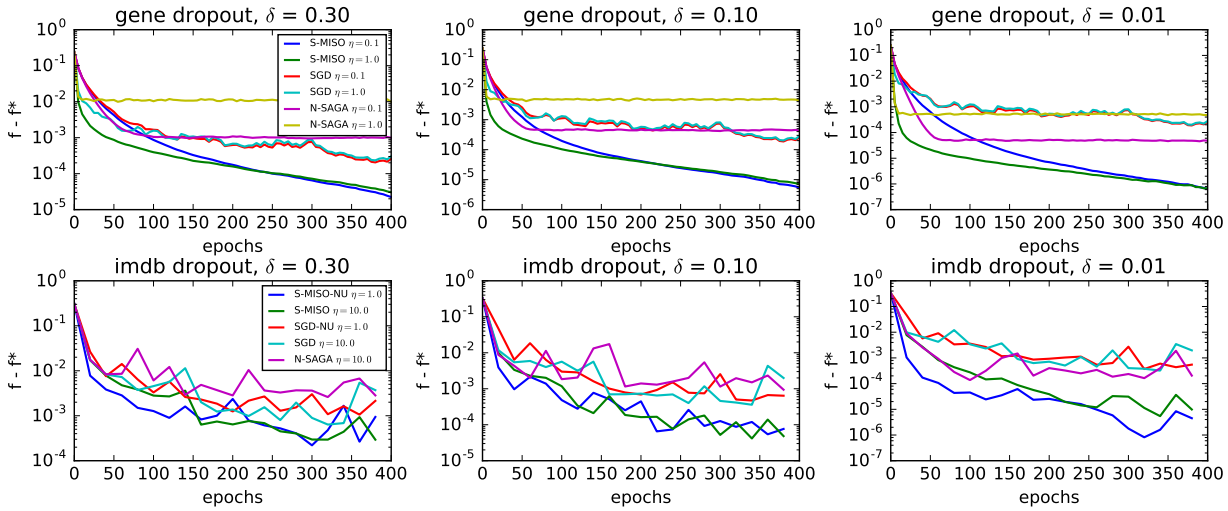

Figure 2: Impact of perturbations on the methods (controlled by the Dropout rate δ). The gene data is ℓ_2-normalized hence we consider similar step-sizes as Figure 1. The IMDB dataset is highly heterogeneous, thus we also include non-uniform (NU) sampling variants. For uniform sampling, theoretical step-sizes perform very poorly for all methods, thus we show a larger tuned step-size $\eta = 10$.

dataset with two different image representations and random transformations, and two classification tasks with Dropout regularization, one on genetic data, and one on (sparse) text data. Figures 1 and 2 show the curves we obtain for an estimate of the training objective using 5 sampled perturbations per example. The plots are shown on a logarithmic scale, and the values are compared to the best value obtained among the different methods in 500 epochs. The strong convexity constant μ is the regularization parameter. For all methods, we consider step-sizes supported by the theory as well as larger step-sizes that may work better in practice.

Choices of step-sizes. For both S-MISO and SGD, we use the step-size strategy mentioned in Section 3 and advised by Bottou et al. (2016), which we have found to be most effective among many heuristics we have tried: we initially keep the step-size constant (controlled by a factor $\eta \leq 1$ in the figures) for 2 epochs, and then start decaying as $\alpha_t = C/(\gamma + t)$, where $C = 2n$ for S-MISO, $C = 2/\mu$ for SGD, and γ is chosen large enough to match the previous constant step-size. For N-SAGA, we maintain a constant step-size throughout the optimization, as suggested in the original paper (Hofmann et al., 2015). The factor η shown in the figures is such that $\eta = 1$ corresponds to an initial step-size $n\mu/(L - \mu)$ for S-MISO (from (18) in the uniform case) and $1/L$ for SGD and N-SAGA (with $\bar{L}$ instead of L in the non-uniform case).

Image classification with "data augmentation". The success of deep neural networks is often limited by the availability of large amounts of labeled images. When there are many unlabeled images but few labeled ones, a common approach is to train a linear classifier on top of a deep network learned in an unsupervised manner, or pre-trained on a different task (*e.g.*, on the ImageNet dataset). We follow this approach on the STL-10 dataset (Coates et al., 2011), which contains 5K training images from 10 classes and 100K unlabeled images, using a 2-layer unsupervised convolutional kernel network (Mairal, 2016), giving representations of dimension 9 216. The perturbation consists of randomly cropping and scaling the input images. We use the squared hinge loss in a one-versus-all setting. The vector representations are ℓ_2-normalized such that we may use the upper bound $L = 1 + \mu$ for the smoothness constant. We also present results on the same dataset using a scattering representation (Bruna and Mallat, 2013) of dimension 21 696, with random gamma corrections (raising all pixels to the power γ, where γ is chosen randomly around 1). For this representation,

we add an ℓ_1 regularization term and use the composite variant of S-MISO.

Figure 1 shows convergence results on one training fold (500 images), for different values of μ, allowing us to study the behavior of the algorithms for different condition numbers. The low variance induced by the data transformations allows S-MISO to reach suboptimality that is orders of magnitude smaller than SGD after the same number of epochs. Note that one unit on these plots corresponds to one order of magnitude in the logarithmic scale. N-SAGA initially reaches a smaller suboptimality than SGD, but quickly gets stuck due to the bias in the algorithm, as predicted by the theory (Hofmann et al., 2015), while S-MISO and SGD continue to converge to the optimum thanks to the decreasing step-sizes. The best validation accuracy for both representations is obtained for $\mu \approx 10^{-4}$ (middle column in Figure 1), and we observed relative gains of up to 1% from using data augmentation. We computed empirical variances of the image representations for these two strategies, which are closely related to the variance in gradient estimates, and observed these transformations to account for about 10% of the total variance across multiple images.

Dropout on gene expression data. We trained a binary logistic regression model on the breast cancer dataset of van de Vijver et al. (2002), with different Dropout rates δ, *i.e.*, where at every iteration, each coordinate ξ_j of a feature vector ξ is set to zero independently with probability δ and to $\xi_j/(1-\delta)$ otherwise. The dataset consists of 295 vectors of dimension 8 141 of gene expression data, which we normalize in ℓ_2 norm. Figure 2 (top) compares S-MISO with SGD and N-SAGA for three values of δ, as a way to control the variance of the perturbations. We include a Dropout rate of 0.01 to illustrate the impact of δ on the algorithms and study the influence of the perturbation variance σ^2, even though this value of δ is less relevant for the task. The plots show very clearly how the variance induced by the perturbations affects the convergence of S-MISO, giving suboptimality values that may be orders of magnitude smaller than SGD. This behavior is consistent with the theoretical convergence rate established in Section 3 and shows that the practice matches the theory.

Dropout on movie review sentiment analysis data. We trained a binary classifier with a squared hinge loss on the IMDB dataset (Maas et al., 2011) with different Dropout rates δ. We use the labeled part of the IMDB dataset, which consists of 25K training and 250K testing movie reviews, represented as 89 527-dimensional sparse bag-of-words vectors. In contrast to the previous experiments, we do not normalize the representations, which have great variability in their norms, in particular $L_{\max}$ is roughly 100 times larger than $\bar{L}$. Figure 2 (bottom) compares non-uniform sampling versions of S-MISO and SGD with their uniform sampling counterparts as well as N-SAGA. Note that we use a large step-size $\eta = 10$ for the uniform sampling algorithms, since $\eta = 1$ was significantly slower for all methods, likely due to outliers in the dataset. In contrast, the non-uniform sampling algorithms required no tuning and just use $\eta = 1$. The curves clearly show that S-MISO-NU has a much faster convergence in the initial phase, thanks to the larger step-size allowed by non-uniform sampling, and later converges similarly to S-MISO, *i.e.*, at a much faster rate than SGD when the perturbations are small. The value of μ used in the experiments was chosen by cross-validation, and the use of Dropout gave improvements in test accuracy from 88.51% with no dropout to $88.68 \pm 0.03\%$ with $\delta = 0.1$ and $88.86 \pm 0.11\%$ with $\delta = 0.3$ (based on 10 different runs of S-MISO-NU after 400 epochs).

Effect of averaging. We also study the effect of the iterate averaging scheme of Theorem 3 in Appendix D.

6 Conclusion

In this paper, we introduced the S-MISO method, a hybrid stochastic/incremental optimization algorithm, which is able to exploit underlying finite-sum structures in stochastic optimization problems. Our approach uses variance reduction in settings where random perturbations of training examples in a finite dataset are considered during learning, thereby making the dataset infinite, and thus unsuitable for standard incremental methods. The algorithm naturally interpolates between stochastic approximation (when $n = 1$) and a classical variance reduction algorithm for finite sums (when there are no perturbations). Our method supports composite objectives, non-uniform sampling, and gives convergence guarantees that are similar to SGD, but

with a significantly smaller constant term that depends on the variance of gradient estimates induced by the perturbations on a single example, rather than across all data.

We demonstrated the effectiveness of the method for data augmentation and Dropout. Another promising application is in using perturbations for stable feature selection (Meinshausen and Bühlmann, 2010), but this requires another statistical analysis that goes beyond the scope of this paper.

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Appendix

Sections A and B of this appendix present the proofs of the results in Sections 3 and 4 of the paper, respectively. In Section C, we provide proofs of a simple result for SGD and proximal SGD, giving a recursion that depends on a variance condition at the optimum (in contrast to Bottou et al. (2016); Nemirovski et al. (2009) where this condition needs to hold everywhere), for a more natural comparison with S-MISO.

A Proofs for the Smooth Case (Section 3)

A.1 Proof of Proposition 1 (Recursion on Lyapunov function C_t)

We begin by stating the following lemma, which extends a key result of variance reduction methods (see, *e.g.*, Johnson and Zhang, 2013) to the situation considered in this paper, where one only has access to noisy estimates of the gradients of each f_i.

Lemma A.1. *Let i be uniformly distributed in $\{1,\dots,n\}$ and $\rho \sim \Gamma$. Under assumptions (A2) and (A3) on the functions $\tilde{f}_1,\dots,\tilde{f}_n$ and their expectations $f_1,\dots,f_n$, we have, for all $x \in \mathbb{R}^p$,*

$$\mathbb{E}_{i,\rho}[\|\nabla \tilde{f}_i(x,\rho) - \nabla f_i(x^*)\|^2] \leq 4L(f(x) - f(x^*)) + 2\sigma^2.$$

Proof. We have

$$\begin{aligned}\|\nabla \tilde{f}_i(x,\rho) - \nabla f_i(x^*)\|^2 &\leq 2\|\nabla \tilde{f}_i(x,\rho) - \nabla \tilde{f}_i(x^*,\rho)\|^2 + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2 \\ &\leq 4L(\tilde{f}_i(x,\rho) - \tilde{f}_i(x^*,\rho) - \langle \nabla \tilde{f}_i(x^*,\rho), x - x^*\rangle) + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2.\end{aligned}$$

The first inequality comes from the simple relation $\|u+v\|^2 + \|u-v\|^2 = 2\|u\|^2 + 2\|v\|^2$. The second inequality follows from the smoothness of $\tilde{f}_i(\cdot,\rho)$, in particular we used the classical relation

$$g(y) \geq g(x) + \langle \nabla g(x), y - x\rangle + \frac{1}{2L}\|\nabla g(y) - \nabla g(x)\|^2,$$

which is known to hold for any convex and L-smooth function g (see, *e.g.*, Nesterov, 2004, Theorem 2.1.5). The result follows by taking expectations on i and ρ and noting that $\mathbb{E}_{i,\rho}[\nabla \tilde{f}_i(x^*,\rho)] = \nabla f(x^*) = 0$, as well as assumption (A3). □

We now proceed with the proof of Proposition 1.

Proof. Define the quantities

$$A_t = \frac{1}{n}\sum_{i=1}^n \|z_i^t - z_i^*\|^2$$
$$\text{and} \quad B_t = \frac{1}{2}\|x_t - x^*\|^2.$$

The proof successively describes recursions on A_t, B_t, and eventually C_t.

Recursion on A_t. We have

$$\begin{aligned}A_t - A_{t-1} &= \frac{1}{n}(\|z_{i_t}^t - z_{i_t}^*\|^2 - \|z_{i_t}^{t-1} - z_{i_t}^*\|^2) \\ &= \frac{1}{n}\left(\left\|(1-\alpha_t)(z_{i_t}^{t-1} - z_{i_t}^*) + \alpha_t\left(x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_{i_t}(x_{t-1},\rho_t) - z_{i_t}^*\right)\right\|^2 - \|z_{i_t}^{t-1} - z_{i_t}^*\|^2\right) \\ &= \frac{1}{n}\left(-\alpha_t\|z_{i_t}^{t-1} - z_{i_t}^*\|^2 + \alpha_t\left\|x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_{i_t}(x_{t-1},\rho_t) - z_{i_t}^*\right\|^2 - \alpha_t(1-\alpha_t)\|v_t\|^2\right), \qquad (21)\end{aligned}$$

where we first use the definition of z_i^t in (2), then the relation $\|(1-\lambda)u+\lambda v\|^2 = (1-\lambda)\|u\|^2+\lambda\|v\|^2-\lambda(1-\lambda)\|u-v\|^2$, and the definition of v_t given in (6). A similar relation is derived in the proof of SDCA without duality Shalev-Shwartz (2016). Using the definition of z_i^*, the second term can be expanded as follows

$$\begin{aligned}\left\|x_{t-1}-\frac{1}{\mu}\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-z_{i_t}^*\right\|^2 &= \left\|x_{t-1}-x^*-\frac{1}{\mu}(\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-\nabla f_{i_t}(x^*))\right\|^2\\ &= \|x_{t-1}-x^*\|^2-\frac{2}{\mu}\langle x_{t-1}-x^*,\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-\nabla f_{i_t}(x^*)\rangle\\ &\quad+\frac{1}{\mu^2}\left\|\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-\nabla f_{i_t}(x^*))\right\|^2. \end{aligned} \tag{22}$$

We then take conditional expectations with respect to $\mathcal{F}_{t-1}$, defined in Section 2. Unless otherwise specified, we will simply write $\mathbb{E}[\cdot]$ instead of $\mathbb{E}[\cdot|\mathcal{F}_{t-1}]$ for these conditional expectations in the rest of the proof.

$$\begin{aligned}\mathbb{E}\left[\left\|x_{t-1}-\frac{1}{\mu}\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-z_{i_t}^*\right\|^2\right] &\le \|x_{t-1}-x^*\|^2-\frac{2}{\mu}\langle x_{t-1}-x^*,\nabla f(x_{t-1})\rangle\\ &\quad+\frac{4L}{\mu^2}(f(x_{t-1})-f(x^*))+\frac{2\sigma^2}{\mu^2}\\ &\le \|x_{t-1}-x^*\|^2-\frac{2}{\mu}(f(x_{t-1})-f(x^*)+\frac{\mu}{2}\|x_{t-1}-x^*\|^2)\\ &\quad+\frac{4L}{\mu^2}(f(x_{t-1})-f(x^*))+\frac{2\sigma^2}{\mu^2}\\ &= \frac{2(2\kappa-1)}{\mu}(f(x_{t-1})-f(x^*))+\frac{2\sigma^2}{\mu^2},\end{aligned}$$

where we used $\mathbb{E}[\nabla f_{i_t}(x^*)]=\nabla f(x^*)=0$, Lemma A.1, and the μ-strong convexity of f. Taking expectations on the previous relation on A_t yields

$$\begin{aligned}\mathbb{E}[A_t-A_{t-1}] &= -\frac{\alpha_t}{n}A_{t-1}+\frac{\alpha_t}{n}\,\mathbb{E}\left[\left\|x_{t-1}-\frac{1}{\mu}\nabla\tilde{f}_{i_t}(x_{t-1},\rho_t)-z_{i_t}^*\right\|^2\right]-\frac{\alpha_t(1-\alpha_t)}{n}\,\mathbb{E}[\|v_t\|^2]\\ &\le -\frac{\alpha_t}{n}A_{t-1}+\frac{2\alpha_t(2\kappa-1)}{n\mu}(f(x_{t-1})-f(x^*))-\frac{\alpha_t(1-\alpha_t)}{n}\,\mathbb{E}[\|v_t\|^2]+\frac{2\alpha_t\sigma^2}{n\mu^2}.\end{aligned} \tag{23}$$

Recursion on B_t. Separately, we have

$$\begin{aligned}\|x_t-x^*\|^2 &= \left\|x_{t-1}-x^*+\frac{\alpha_t}{n}v_t\right\|^2\\ &= \|x_{t-1}-x^*\|^2+\frac{2\alpha_t}{n}\langle x_{t-1}-x^*,v_t\rangle+\left(\frac{\alpha_t}{n}\right)^2\|v_t\|^2\\ \mathbb{E}[\|x_t-x^*\|^2] &= \|x_{t-1}-x^*\|^2-\frac{2\alpha_t}{n\mu}\langle x_{t-1}-x^*,\nabla f(x_{t-1})\rangle+\left(\frac{\alpha_t}{n}\right)^2\mathbb{E}[\|v_t\|^2]\\ &\le \|x_{t-1}-x^*\|^2-\frac{2\alpha_t}{n\mu}(f(x_{t-1})-f(x^*)+\frac{\mu}{2}\|x_{t-1}-x^*\|^2)+\left(\frac{\alpha_t}{n}\right)^2\mathbb{E}[\|v_t\|^2],\end{aligned}$$

using that $\mathbb{E}[v_t]=-\frac{1}{\mu}\nabla f(x_{t-1})$ and the strong convexity of f. This gives

$$\mathbb{E}[B_t-B_{t-1}] \le -\frac{\alpha_t}{n}B_{t-1}-\frac{\alpha_t}{n\mu}(f(x_{t-1})-f(x^*))+\frac{1}{2}\left(\frac{\alpha_t}{n}\right)^2\mathbb{E}[\|v_t\|^2]. \tag{24}$$

Recursion on C_t. If we consider $C_t = p_t A_t + B_t$ and $C'_{t-1} = p_t A_{t-1} + B_{t-1}$, combining (23) and (24) yields

$$\mathbb{E}[C_t - C'_{t-1}] \leq -\frac{\alpha_t}{n} C'_{t-1} + \frac{2\alpha_t}{n\mu}(p_t(2\kappa - 1) - \frac{1}{2})(f(x_{t-1}) - f(x^*)) + \frac{\alpha_t}{n}\left(\frac{\alpha_t}{2n} - p_t(1-\alpha_t)\right)\mathbb{E}[\|v_t\|^2] + \frac{2\alpha_t p_t \sigma^2}{n\mu^2}.$$

If we take $p_t = \frac{\alpha_t}{n}$, and if $(\alpha_t)_{t\geq 1}$ is a decreasing sequence satisfying (8), then the factors in front of $f(x_{t-1}) - f(x^*)$ and $\mathbb{E}[\|v_t\|^2]$ are non-positive and we get

$$\mathbb{E}[C_t] \leq \left(1 - \frac{\alpha_t}{n}\right) C'_{t-1} + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma^2}{\mu^2}.$$

Finally, since $\alpha_t \leq \alpha_{t-1}$, we have $C'_{t-1} \leq C_{t-1}$. After taking total expectations on $\mathcal{F}_{t-1}$, we are left with the desired recursion.

□

A.2 Proof of Theorem 2 (Convergence of C_t under decreasing step-sizes)

Proof. Let us proceed by induction. We have $C_0 \leq \nu/(\gamma+1)$ by definition of ν. For $t \geq 1$,

$$\begin{aligned}
\mathbb{E}[C_t] &\leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}[C_{t-1}] + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma^2}{\mu^2} \\
&\leq \left(1 - \frac{\beta}{\hat{t}}\right)\frac{\nu}{\hat{t}} + \frac{2\beta^2\sigma^2}{\hat{t}^2\mu^2} \quad (\text{with } \hat{t} := \gamma + t) \\
&= \left(\frac{\hat{t} - \beta}{\hat{t}^2}\right)\nu + \frac{2\beta^2\sigma^2}{\hat{t}^2\mu^2} \\
&= \left(\frac{\hat{t} - 1}{\hat{t}^2}\right)\nu - \left(\frac{\beta - 1}{\hat{t}^2}\right)\nu + \frac{2\beta^2\sigma^2}{\hat{t}^2\mu^2} \\
&\leq \left(\frac{\hat{t} - 1}{\hat{t}^2}\right)\nu \leq \frac{\nu}{\hat{t}+1},
\end{aligned}$$

where the last two inequalities follow from the definition of ν and from $\hat{t}^2 \geq (\hat{t}+1)(\hat{t}-1)$. □

A.3 Proof of Theorem 3 (Convergence in function values under iterate averaging)

Proof. From the proof of Proposition 1, we have

$$\mathbb{E}[C_t] \leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}[C_{t-1}] + \frac{2\alpha_t}{n\mu}\left(\frac{\alpha_t}{n}(2\kappa - 1) - \frac{1}{2}\right)\mathbb{E}[f(x_{t-1}) - f(x^*)] + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma^2}{\mu^2}.$$

The result holds because the choice of step-sizes $(\alpha_t)_{t\geq 1}$ safisfies the assumptions of Proposition 1. With our new choice of step-sizes, we have the stronger bound

$$\frac{\alpha_t}{n}(2\kappa - 1) - \frac{1}{2} \leq -\frac{1}{4}.$$

After rearranging, we obtain

$$\frac{\alpha_t}{2n\mu}\mathbb{E}[f(x_{t-1}) - f(x^*)] \leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}[C_{t-1}] - \mathbb{E}[C_t] + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma^2}{\mu^2}. \tag{25}$$

Dividing by $\frac{\alpha_t}{2n\mu}$ gives

$$\begin{aligned}\mathbb{E}[f(x_{t-1}) - f(x^*)] &\leq 2\mu\left[\left(\frac{n}{\alpha_t} - 1\right)\mathbb{E}[C_{t-1}] - \frac{n}{\alpha_t}\mathbb{E}[C_t]\right] + 4\frac{\alpha_t}{n}\frac{\sigma^2}{\mu} \\ &= \mu\left((\gamma + t - 2)\,\mathbb{E}[C_{t-1}] - (\gamma + t)\,\mathbb{E}[C_t]\right) + \frac{8}{\gamma + t}\frac{\sigma^2}{\mu}.\end{aligned}$$

Multiplying by $(\gamma + t - 1)$ yields

$$\begin{aligned}(\gamma + t - 1)\,\mathbb{E}[f(x_{t-1}) - f(x^*)] &\leq \mu\left((\gamma + t - 1)(\gamma + t - 2)\,\mathbb{E}[C_{t-1}] - (\gamma + t)(\gamma + t - 1)\,\mathbb{E}[C_t]\right) + \frac{8(\gamma + t - 1)}{\gamma + t}\frac{\sigma^2}{\mu} \\ &\leq \mu\left((\gamma + t - 1)(\gamma + t - 2)\,\mathbb{E}[C_{t-1}] - (\gamma + t)(\gamma + t - 1)\,\mathbb{E}[C_t]\right) + \frac{8\sigma^2}{\mu}.\end{aligned}$$

By summing the above inequality from $t = 1$ to $t = T$, we have a telescoping sum that simplifies as follows:

$$\begin{aligned}\mathbb{E}\left[\sum_{t=1}^{T}(\gamma + t - 1)(f(x_{t-1}) - f(x^*))\right] &\leq \mu\left(\gamma(\gamma - 1)C_0 - (\gamma + T)(\gamma + T - 1)\,\mathbb{E}[C_T]\right) + \frac{8T\sigma^2}{\mu} \\ &\leq \mu\gamma(\gamma - 1)C_0 + \frac{8T\sigma^2}{\mu}.\end{aligned}$$

Dividing by $\sum_{t=1}^{T}(\gamma + t - 1) = (2T\gamma + T(T-1))/2$ and using Jensen's inequality on $f(\bar{x}_T)$ gives the desired result. □

B Proofs for Composite Objectives and Non-Uniform Sampling (Section 4)

We recall here the updates to the lower bounds d_i^t in the setting of this section, which are analogous to (5) but with non-uniform weights and stochastic perturbations, and will be useful in the proofs:

$$d_i^t(x) = \begin{cases}(1 - \frac{\alpha_t}{q_i n})d_i^{t-1}(x) + \frac{\alpha_t}{q_i n}(\tilde{f}_i(x_{t-1}, \rho_t) + \langle \nabla \tilde{f}_i(x_{t-1}, \rho_t), x - x_{t-1}\rangle + \frac{\mu}{2}\|x - x_{t-1}\|^2), & \text{if } i = i_t \\ d_i^{t-1}(x), & \text{otherwise.}\end{cases} \tag{26}$$

B.1 Proof of Lemma 4 (Bound on the iterates)

Proof. Let $F_t(x) := \frac{1}{n}\sum_{i=1}^{n} f_i^t(x) + h(x)$, where $f_i^0(x) = \tilde{f}_i(x, \tilde{\rho}_i)$ (where $\tilde{\rho}_i$ is used in (15)), and f_i^t is updated analogously to d_i^t as follows:

$$f_i^t(x) = \begin{cases}(1 - \frac{\alpha_t}{q_i n})f_i^{t-1}(x) + \frac{\alpha_t}{q_i n}\tilde{f}_i(x, \rho_t), & \text{if } i = i_t \\ f_i^{t-1}(x), & \text{otherwise.}\end{cases}$$

By induction, we have

$$F_t(x^*) \geq D_t(x^*) \geq D_t(x_t) + \frac{\mu}{2}\|x_t - x^*\|^2, \tag{27}$$

where the last inequality follows from the μ-strong convexity of D_t and the fact that x_t is its minimizer.

Again by induction, we now show that $\mathbb{E}[F_t(x^*)] = F(x^*)$. Indeed, we have $\mathbb{E}[F_0(x^*)] = F(x^*)$ by construction, then

$$\begin{aligned}
F_t(x^*) &= F_{t-1}(x^*) + \frac{\alpha_t}{q_i n^2}(\tilde{f}_{i_t}(x^*, \rho_t) - f_{i_t}^{t-1}(x^*)) \\
\mathbb{E}[F_t(x^*)|\mathcal{F}_{t-1}] &= F_{t-1}(x^*) + \frac{\alpha_t}{n}(f(x^*) - \frac{1}{n}\sum_{i=1}^n f_i^{t-1}(x^*)) \\
&= F_{t-1}(x^*) + \frac{\alpha_t}{n}(F(x^*) - F_{t-1}(x^*)),
\end{aligned}$$

After taking total expectations and using the induction hypothesis, we obtain $\mathbb{E}[F_t(x^*)] = F(x^*)$, and the result follows from (27). □

B.2 Proof of Proposition 5 (Recursion on Lyapunov function C_t^q)

We begin by presenting a lemma that plays a similar role to Lemma A.1 in our proof, but considers the composite objective and takes into account the new strong convexity and non-uniformity assumptions.

Lemma B.1. *Let $i \sim q$, where q is the sampling distribution, and $\rho \sim \Gamma$. Under assumptions (A4), (A5) and (A6) on the functions $\tilde{f}_1, \dots, \tilde{f}_n$ and their expectations $f_1, \dots, f_n$, we have, for all $x \in \mathbb{R}^p$,*

$$\mathbb{E}_{i,\rho}\left[\frac{1}{(q_i n)^2}\|\nabla \tilde{f}_i(x,\rho) - \mu x - (\nabla f_i(x^*) - \mu x^*)\|^2\right] \leq 4L_q(F(x) - F(x^*)) + 2\sigma_q^2,$$

with $L_q = \max_i \frac{L_i - \mu}{q_i n}$ and $\sigma_q^2 = \frac{1}{n}\sum_i \frac{\sigma_i^2}{q_i n}$.

Proof. Since $\tilde{f}_i(\cdot, \rho)$ is μ-strongly convex and L_i-smooth, we have that $\tilde{f}_i(\cdot,\rho) - \frac{\mu}{2}\|\cdot\|^2$ is convex and $(L_i - \mu)$-smooth (this is a straightforward consequence of Nesterov, 2004, Eq. 2.1.9 and 2.1.22). Then, we have

$$\begin{aligned}
&\|\nabla \tilde{f}_i(x,\rho) - \mu x - (\nabla f_i(x^*) - \mu x^*)\|^2 \\
&\quad\leq 2\|\nabla \tilde{f}_i(x,\rho) - \mu x - (\nabla \tilde{f}_i(x^*,\rho) - \mu x^*)\|^2 + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2 \\
&\quad\leq 4(L_i - \mu)\left(\tilde{f}_i(x,\rho) - \frac{\mu}{2}\|x\|^2 - \tilde{f}_i(x^*,\rho) + \frac{\mu}{2}\|x^*\|^2 - \langle \nabla \tilde{f}_i(x^*,\rho) - \mu x^*, x - x^*\rangle\right) + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2 \\
&\quad= 4(L_i - \mu)\left(\tilde{f}_i(x,\rho) - \tilde{f}_i(x^*,\rho) - \langle \nabla \tilde{f}_i(x^*,\rho), x - x^*\rangle - \frac{\mu}{2}\|x - x^*\|^2\right) + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2 \\
&\quad\leq 4(L_i - \mu)\left(\tilde{f}_i(x,\rho) - \tilde{f}_i(x^*,\rho) - \langle \nabla \tilde{f}_i(x^*,\rho), x - x^*\rangle\right) + 2\|\nabla \tilde{f}_i(x^*,\rho) - \nabla f_i(x^*)\|^2.
\end{aligned}$$

The first inequality comes from the classical relation $\|u+v\|^2 + \|u-v\|^2 = 2\|u\|^2 + 2\|v\|^2$. The second inequality follows from the convexity and $(L_i - \mu)$-smoothness of $\tilde{f}_i(\cdot,\rho) - \frac{\mu}{2}\|\cdot\|^2$. Dividing by $(q_i n)^2$ and taking expectations yields

$$\begin{aligned}
&\mathbb{E}_{i,\rho}\left[\frac{1}{(q_i n)^2}\ \|\nabla \tilde{f}_i(x,\rho) - \mu x - (\nabla f_i(x^*) - \mu x^*)\|^2\right] \\
&\qquad\leq 4\sum_{i=1}^n \frac{q_i(L_i - \mu)}{(q_i n)^2}\left(f_i(x) - f_i(x^*) - \langle \nabla f_i(x^*), x - x^*\rangle\right) + 2\sum_{i=1}^n \frac{q_i}{(q_i n)^2}\sigma_i^2 \\
&\qquad= 4\frac{1}{n}\sum_{i=1}^n \frac{L_i - \mu}{q_i n}\left(f_i(x) - f_i(x^*) - \langle \nabla f_i(x^*), x - x^*\rangle\right) + 2\frac{1}{n}\sum_{i=1}^n \frac{\sigma_i^2}{q_i n} \\
&\qquad\leq 4L_q(f(x) - f(x^*) - \langle \nabla f(x^*), x - x^*\rangle) + 2\sigma_q^2 \\
&\qquad\leq 4L_q(f(x) - f(x^*) + h(x) - h(x^*)) + 2\sigma_q^2 = 4L_q(F(x) - F(x^*)) + 2\sigma_q^2,
\end{aligned}$$

where the last inequality follows from the optimality of x^*, which implies that $-\nabla f(x^*) \in \partial h(x^*)$, and in turn implies $\langle -\nabla f(x^*), x - x^*\rangle \leq h(x) - h(x^*)$ by convexity of h. □

We can now proceed with the proof of Proposition 5.

Proof. Define the quantities

$$A_t = \frac{1}{n}\sum_{i=1}^{n} \frac{1}{q_i n}\|z_i^t - z_i^*\|^2$$
$$\text{and} \quad B_t = F(x^*) - D_t(x_t).$$

The proof successively describes recursions on A_t, B_t, and eventually C_t (we drop the superscript in C_t^q for simplicity), using the same approach as for the proof of Proposition 1.

Recursion on A_t. Using similar techniques as in the proof of Proposition 1, we have

$$\begin{aligned}
A_t - A_{t-1} &= \frac{1}{n}\left(\frac{1}{q_{i_t} n}\|z_{i_t}^t - z_{i_t}^*\|^2 - \frac{1}{q_{i_t} n}\|z_{i_t}^{t-1} - z_{i_t}^*\|^2\right) \\
&= \frac{1}{n}\left(\frac{1}{q_{i_t} n}\left\|\left(1 - \frac{\alpha_t}{q_{i_t} n}\right)(z_{i_t}^{t-1} - z_{i_t}^*) + \frac{\alpha_t}{q_{i_t} n}\left(x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - z_{i_t}^*\right)\right\|^2 - \frac{1}{q_{i_t} n}\|z_{i_t}^{t-1} - z_{i_t}^*\|^2\right) \\
&= \frac{1}{n}\left(-\frac{\alpha_t}{(q_{i_t} n)^2}\|z_{i_t}^{t-1} - z_{i_t}^*\|^2 + \frac{\alpha_t}{(q_{i_t} n)^2}\left\|x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - z_{i_t}^*\right\|^2 - \frac{\alpha_t}{(q_{i_t} n)^2}\left(1 - \frac{\alpha_t}{q_{i_t} n}\right)\|v_{i_t}^t\|^2\right),
\end{aligned}$$

where $v_i^t := x_{t-1} - \frac{1}{\mu}\nabla \tilde{f}_i(x_{t-1}, \rho_t) - z_i^{t-1}$. Taking conditional expectations w.r.t. $\mathcal{F}_{t-1}$ and using Lemma B.1 to bound the second term yields

$$\mathbb{E}[A_t - A_{t-1}] \leq -\frac{\alpha_t}{n} A_{t-1} + \frac{4\alpha_t L_q}{n\mu^2}(F(x_{t-1}) - F(x^*)) + \frac{2\alpha_t \sigma_q^2}{n\mu^2} - \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\alpha_t}{n}\frac{1}{q_i n}\left(1 - \frac{\alpha_t}{q_i n}\right)\|v_i^t\|^2\right) \tag{28}$$

Recursion on B_t. We start by using a lemma from the proof of MISO-Prox (Lin et al., 2015, Lemma D.4), which only relies on the form of D_t and the fact that x_t minimizes it, and thus holds in our setting:

$$\begin{aligned}
D_t(x_t) &\geq D_t(x_{t-1}) - \frac{\mu}{2}\|\bar{z}_t - \bar{z}_{t-1}\|^2 \\
&= D_t(x_{t-1}) - \frac{\mu}{2(q_{i_t} n)^2}\left(\frac{\alpha_t}{n}\right)^2 \|v_{i_t}^t\|^2
\end{aligned} \tag{29}$$

We then expand $D_t(x_{t-1})$ using (26) as follows:

$$\begin{aligned}
D_t(x_{t-1}) &= D_{t-1}(x_{t-1}) + \frac{\alpha_t}{n}\frac{1}{q_{i_t} n}\left(\tilde{f}_{i_t}(x_{t-1}, \rho_t) - d_{i_t}^{t-1}(x_{t-1})\right) \\
&= D_{t-1}(x_{t-1}) + \frac{\alpha_t}{n}\frac{1}{q_{i_t} n}\left(\tilde{f}_{i_t}(x_{t-1}, \rho_t) + h(x_{t-1}) - d_{i_t}^{t-1}(x_{t-1}) - h(x_{t-1})\right).
\end{aligned}$$

After taking conditional expections w.r.t. $\mathcal{F}_{t-1}$, (29) becomes

$$\mathbb{E}[D_t(x_t)] \geq D_{t-1}(x_{t-1}) + \frac{\alpha_t}{n}(F(x_{t-1}) - D_{t-1}(x_{t-1})) - \frac{\mu}{2n}\sum_{i=1}^{n}\left(\frac{\alpha_t}{n}\right)^2 \frac{1}{q_i n}\|v_i^t\|^2.$$

Subtracting $F(x^*)$ and rearranging yields

$$\mathbb{E}[B_t - B_{t-1}] \leq -\frac{\alpha_t}{n} B_{t-1} - \frac{\alpha_t}{n}(F(x_{t-1}) - F(x^*)) + \frac{\mu}{2n}\sum_{i=1}^{n}\left(\frac{\alpha_t}{n}\right)^2 \frac{1}{q_i n}\|v_i^t\|^2. \tag{30}$$

Recursion on C_t. If we consider $C_t = \mu p_t A_t + B_t$ and $C'_{t-1} = \mu p_t A_{t-1} + B_{t-1}$, combining (28) and (30) yields

$$\mathbb{E}[C_t - C'_{t-1}] \leq -\frac{\alpha_t}{n} C'_{t-1} + \frac{2\alpha_t}{n}(2p_t L_q/\mu - \frac{1}{2})(F(x_{t-1}) - F(x^*)) + \frac{\mu\alpha_t}{n^2}\sum_{i=1}^{n}\frac{\delta_i^t}{q_i n}\|v_i^t\|^2 + \frac{2\alpha_t p_t \sigma_q^2}{n\mu}, \quad (31)$$

with

$$\delta_i^t = \frac{\alpha_t}{2n} - p_t\left(1 - \frac{\alpha_t}{q_i n}\right).$$

If we take $p_t = \frac{\alpha_t}{n}$, and if $(\alpha_t)_{t\geq 1}$ is a decreasing sequence satisfying (18), then we obtain the desired recursion after noticing that $C'_{t-1} \leq C_{t-1}$ and taking total expectations on $\mathcal{F}_{t-1}$.

□

Note that if we take

$$\alpha_1 \leq \min\left\{\frac{n q_{\min}}{2}, \frac{n\mu}{8L_q}\right\},$$

then (31) yields

$$\mathbb{E}\left[\frac{C_t^q}{\mu}\right] \leq \left(1 - \frac{\alpha_t}{n}\right)\mathbb{E}\left[\frac{C_{t-1}^q}{\mu}\right] - \frac{\alpha_t}{2n\mu}(F(x_{t-1}) - F(x^*)) + 2\left(\frac{\alpha_t}{n}\right)^2 \frac{\sigma_q^2}{\mu^2}.$$

This relation takes the same form as Eq. (25), hence it is straightforward to adapt the proof of Theorem 3 to this setting, and the same iterate averaging scheme applies.

C SGD Recursions

Proposition C.1 (Simple SGD recursion with variance at optimum)**.** *Under assumptions (A1) and (A2), if $\eta_t \leq 1/2L$, then the SGD recursion $x_t := x_{t-1} - \eta_t \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)$ satisfies*

$$B_t \leq (1 - \mu\eta_t)B_{t-1} + \eta_t^2 \sigma_{tot}^2,$$

where $B_t := \frac{1}{2}\mathbb{E}[\|x_t - x^*\|^2]$ and σ_{tot} is such that

$$\mathbb{E}_{i,\rho}\left[\|\nabla \tilde{f}_i(x^*, \rho)\|^2\right] \leq \sigma_{tot}^2.$$

Proof. We have

$$\begin{aligned}
\|x_t - x^*\|^2 &= \|x_{t-1} - x^*\|^2 - 2\eta_t\langle \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t), x_{t-1} - x^*\rangle + \eta_t^2 \|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)\|^2 \\
&\leq \|x_{t-1} - x^*\|^2 - 2\eta_t\langle \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t), x_{t-1} - x^*\rangle \\
&\quad + 2\eta_t^2 \|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2 + 2\eta_t^2 \|\nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2 \\
\mathbb{E}\left[\|x_t - x^*\|^2 | \mathcal{F}_{t-1}\right] &\leq \|x_{t-1} - x^*\|^2 - 2\eta_t\langle \nabla f(x_{t-1}), x_{t-1} - x^*\rangle \\
&\quad + 2\eta_t^2 \,\mathbb{E}_{i_t,\rho_t}\left[\|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2\right] + 2\eta_t^2 \,\mathbb{E}_{i_t,\rho_t}\left[\|\nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2\right] \\
(*) &\leq \|x_{t-1} - x^*\|^2 - 2\eta_t\left(f(x_{t-1}) - f(x^*) + \frac{\mu}{2}\|x_{t-1} - x^*\|^2\right) \\
&\quad + 4L\eta_t^2\left(f(x_{t-1}) - f(x^*)\right) + 2\eta_t^2 \sigma_{tot}^2 \\
&= (1 - \mu\eta_t)\|x_{t-1} - x^*\|^2 - 2\eta_t(1 - 2L\eta_t)(f(x_{t-1}) - f(x^*)) + 2\eta_t^2 \sigma_{tot}^2,
\end{aligned}$$

where inequality $(*)$ follows from the strong convexity of f and $\mathbb{E}_{i,\rho}[\|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2]$ is bounded by $2L(f(x_{t-1}) - f(x^*))$ as in the proof of Lemma A.1. When $\eta_t \leq 1/2L$, the second term is non-positive and we obtain the desired result after taking total expectations. □

Note that when $\eta_t \leq 1/4L$, we have

$$\mathbb{E}\left[\|x_t - x^*\|^2\right] \leq (1 - \mu\eta_t)\,\mathbb{E}\left[\|x_{t-1} - x^*\|^2\right] - \eta_t(f(x_{t-1}) - f(x^*)) + 2\eta_t^2\sigma_{tot}^2.$$

This takes a similar form to Eq. (25), and one can use the same iterate averaging scheme as Theorem 3 with step-sizes $\eta_t = 2/\mu(\gamma + t)$ by adapting the proof.

We now give a similar recursion for the proximal SGD algorithm (see, *e.g.*, Duchi and Singer, 2009). This allows us to apply the results of Theorem 2 and the step-size strategy mentioned in Section 3.

Proposition C.2 (Simple recursion for proximal SGD with variance at optimum)**.** *Under assumptions (A1) and (A2), if $\eta_t \leq 1/2L$, then the proximal SGD recursion $x_t := \operatorname{prox}_{\eta_t h}(x_{t-1} - \eta_t \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t))$ satisfies*

$$B_t \leq (1 - \mu\eta_t)B_{t-1} + \eta_t^2\sigma_{tot}^2,$$

where $B_t := \frac{1}{2}\,\mathbb{E}[\|x_t - x^*\|^2]$ and σ_{tot} is such that

$$\mathbb{E}_{i,\rho}\left[\|\nabla \tilde{f}_i(x^*, \rho) - \nabla f(x^*)\|^2\right] \leq \sigma_{tot}^2.$$

Proof. We have

$$\begin{aligned}
\|x_t - x^*\|^2 &= \|\operatorname{prox}_{\eta_t h}(x_{t-1} - \eta_t \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t)) - \operatorname{prox}_{\eta_t h}(x^* - \eta_t \nabla f(x^*))\|^2 \\
&\leq \|x_{t-1} - \eta_t \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - x^* + \eta_t \nabla f(x^*)\|^2 \\
&= \|x_{t-1} - x^*\|^2 - 2\eta_t \langle \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla f(x^*), x_{t-1} - x^* \rangle + \eta_t^2 \|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla f(x^*)\|^2 \\
&\leq \|x_{t-1} - x^*\|^2 - 2\eta_t \langle \nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla f(x^*), x_{t-1} - x^* \rangle \\
&\quad + 2\eta_t^2 \|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2 + 2\eta_t^2 \|\nabla \tilde{f}_{i_t}(x^*, \rho_t) - \nabla f(x^*)\|^2,
\end{aligned}$$

where the first equality follows from the optimality of x^* and the following inequality follows from the non-expansiveness of proximal operators. Taking conditional expectations on $\mathcal{F}_{t-1}$ yields

$$\begin{aligned}
\mathbb{E}\left[\|x_t - x^*\|^2 | \mathcal{F}_{t-1}\right] &\leq \|x_{t-1} - x^*\|^2 - 2\eta_t \langle \nabla f(x_{t-1}) - \nabla f(x^*), x_{t-1} - x^* \rangle \\
&\quad + 2\eta_t^2\, \mathbb{E}_{i_t,\rho_t}\left[\|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2\right] + 2\eta_t^2\, \mathbb{E}_{i_t,\rho_t}\left[\|\nabla \tilde{f}_{i_t}(x^*, \rho_t) - \nabla f(x^*)\|^2\right] \\
(*) &\leq \|x_{t-1} - x^*\|^2 - 2\eta_t \left(f(x_{t-1}) - f(x^*) + \frac{\mu}{2}\|x_{t-1} - x^*\|^2 - \langle \nabla f(x^*), x_{t-1} - x^* \rangle\right) \\
&\quad + 4L\eta_t^2 \left(f(x_{t-1}) - f(x^*) - \langle \nabla f(x^*), x_{t-1} - x^* \rangle\right) + 2\eta_t^2 \sigma_{tot}^2 \\
&= (1 - \mu\eta_t)\|x_{t-1} - x^*\|^2 - 2\eta_t(1 - 2L\eta_t)(f(x_{t-1}) - f(x^*) - \langle \nabla f(x^*), x_{t-1} - x^* \rangle) + 2\eta_t^2 \sigma_{tot}^2,
\end{aligned}$$

where inequality $(*)$ follows from the μ-strong convexity of f and $\mathbb{E}_{i,\rho}[\|\nabla \tilde{f}_{i_t}(x_{t-1}, \rho_t) - \nabla \tilde{f}_{i_t}(x^*, \rho_t)\|^2]$ is bounded by $2L(f(x_{t-1}) - f(x^*) - \langle \nabla f(x^*), x_{t-1} - x^* \rangle)$ as in the proof of Lemma B.1. By convexity of f, we have $f(x_{t-1}) - f(x^*) - \langle \nabla f(x^*), x_{t-1} - x^* \rangle \geq 0$, hence the second term is non-positive when $\eta_t \leq 1/2L$. We conclude by taking total expectations. □

We note that Propositions C.1 and C.2 can be easily adapted to non-uniform sampling with sampling distribution q and step-sizes $\eta_t / q_{i_t} n$, leading to step-size conditions $\eta_t \leq 1/2L_q$, with $L_q = \max_i \frac{L_i}{q_i n}$ and variance $\sigma_{q,tot}^2 = \mathbb{E}_{i,\rho}[\frac{1}{(q_i n)^2}\|\nabla \tilde{f}_i(x^*, \rho) - \nabla f(x^*)\|^2]$.

D Averaging Experiments

Figure 3 shows a comparison of S-MISO and SGD with the averaging scheme proposed in Theorem 3 (see Section C for comments on how it applies to SGD), on the breast cancer dataset presented in Section 5, for different values of the regularization μ (and thus of the condition number $\kappa = L/\mu$), and Dropout rates δ. We can see that the averaging scheme gives some small improvements for both methods, and that the

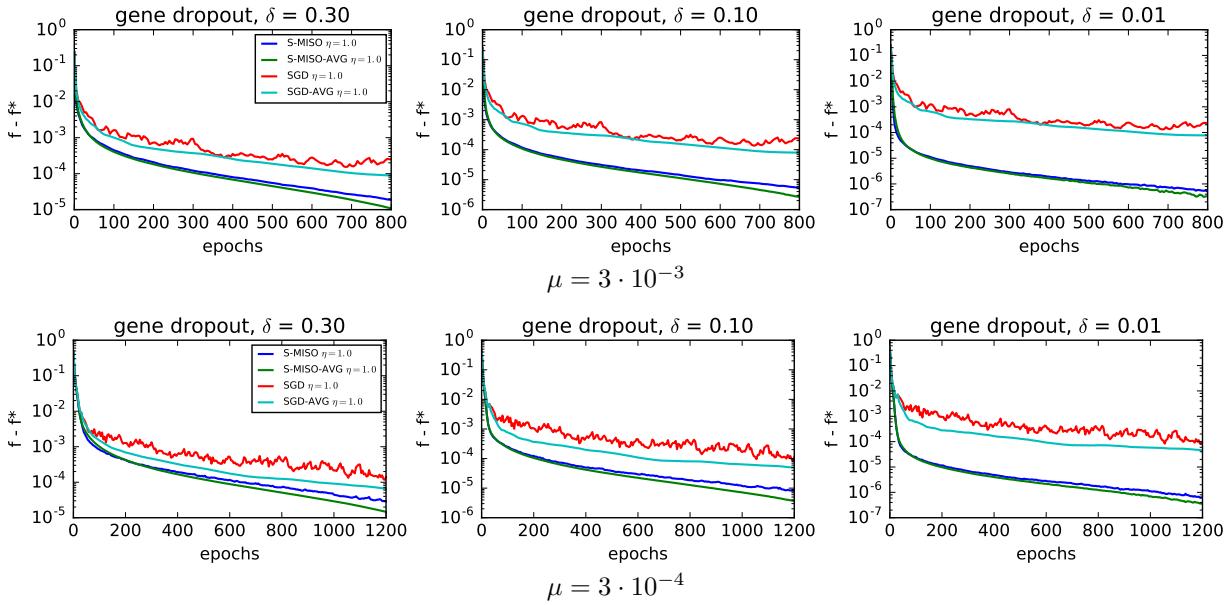

Figure 3: Comparison of S-MISO and SGD with averaging, for different conditioning (controlled by μ) and different Dropout rates δ. We begin step-size decay and averaging at epoch 3 (top) and 30 (bottom).

improvements are more significant when the problem is more ill-conditioned (Figure 3, bottom). We note that the time at which we start averaging can have significant impact on the convergence, in particular, starting too early can significantly slow down the initial convergence, as commonly noticed for stochastic gradient methods (see, *e.g.*, Nemirovski et al., 2009).