REVISITING CONVERGENCE: A STUDY ON SHUFFLING-TYPE GRADIENT METHODS

Anonymous authors
Paper under double-blind review

ABSTRACT

Shuffling-type gradient methods are favored in practice for their simplicity and rapid empirical performance. Despite extensive development of convergence guarantees under various assumptions in recent years, most require the Lipschitz smoothness condition, which is often not met in common machine learning models. We highlight this issue with specific counterexamples. To address this gap, we revisit the convergence rates of shuffling-type gradient methods without assuming Lipschitz smoothness. Using our stepsize strategy, the shuffling-type gradient algorithm not only converges under weaker assumptions but also match the current best-known convergence rates, thereby broadening its applicability. We prove the convergence rates for nonconvex, strongly convex, and non-strongly convex cases, each under both random reshuffling and arbitrary shuffling schemes, under a general bounded variance condition. Numerical experiments further validate the performance of our shuffling-type gradient algorithm, underscoring its practical efficacy.

1 INTRODUCTION

Gradient-based optimization has always been a critical area due to its extensive practical applications in machine learning, including reinforcement learning (Sutton and Barto, 2018), hyperparameter optimization (Feurer and Hutter, 2019), and large language models (Radford et al., 2018). While numerous gradient-based algorithms have been developed for convex functions (Nemirovskij and Yudin, 1983; Nesterov, 2013; d'Aspremont et al., 2021), research on nonconvex functions has become particularly active in recent years, driven by advances in deep learning. Notably, with unbiased stochastic gradients and bounded variance, SGD achieves an optimal complexity of $\mathcal{O}(\epsilon^{-4})$ (Ghadimi and Lan, 2013), which matches the lower bound established by Arjevani et al. (2023).

In practice, however, random shuffling-type methods have demonstrated superiority over SGD. These methods are not only easier and faster to implement but also show faster convergence rates, as evidenced by experiments cited in Bottou (2009; 2012). Theoretical studies on shuffling-type methods have been conducted in various settings in recent years, presenting unique challenges due to the lack of independence between most neighboring steps. While much of this research assumes strong convexity (Gürbüzbalaban et al., 2021; HaoChen and Sra, 2019; Safran and Shamir, 2020), studies such as Nguyen et al. (2021); Koloskova et al. (2023); Mishchenko et al. (2020) have also explored applications in nonconvex scenarios.

Although theoretical analysis has been conducted in many settings of shuffling-type gradient algorithms, **most of these works require Lipschitz smoothness assumption, which requires restrictive quadratic lower and upper bounds and thus cannot cover many popular machine learning models** such as language model (Zhang et al., 2019), phase retrieval (Chen et al., 2023), distributionally robust optimization (Chen et al., 2023), etc. We will demonstrate counterexamples in more detail in Section 2. To fill this gap, in this paper, we aim at analyzing the convergence rate of shuffling-type gradient algorithm under relaxed mild smoothness assumptions for both convex and nonconvex cases.

We consider the following finite sum minimization problem:

$$\min_{w\in\mathbb{R}^d}\left\{F(w) := \frac{1}{n}\sum_{i=1}^{n} f(w;i)\right\}, \tag{P}$$

where $f(\cdot; i) : \mathbb{R}^d \to \mathbb{R}$ is smooth and possibly nonconvex for $i \in [n] := \{1, \ldots, n\}$. Problem (P) covers empirical loss minimization as a special case, therefore can be viewed as formulation for many machine learning models, such as logistic regression, reinforcement learning, and neural networks.

We summarize our main contributions as follows:

- We proved the convergence of the shuffling-type gradient algorithm under non-uniform smoothness assumptions, where the Hessian norm is bounded by a sub-quadratic function ℓ of the gradient norm. With specific stepsizes and a general bounded variance condition, we achieved a total complexity of $\mathcal{O}(n^{\frac{p+1}{2}}\epsilon^{-3})$ gradient evaluations for the nonconvex case with random reshuffling, and $\mathcal{O}(n^{\frac{p}{2}+1}\epsilon^{-3})$ for arbitrary scheme, where $0 \leq p < 2$ is the degree of ℓ. These results match those with Lipschitz smoothness assumptions in Nguyen et al. (2021) when $p = 0$ and ℓ-smoothness degenerates to Lipschitz smoothness.
- For the strongly convex case, we established a complexity of $\widetilde{\mathcal{O}}(n^{\frac{p+1}{2}}\epsilon^{-\frac{1}{2}})$ for random reshuffling and $\widetilde{\mathcal{O}}(n^{\frac{p}{2}+1}\epsilon^{-\frac{1}{2}})$ for arbitrary scheme. In the non-strongly convex case, the complexity is $\mathcal{O}(n^{\frac{p+1}{2}}\epsilon^{-\frac{3}{2}})$ for random reshuffling and $\mathcal{O}(n^{\frac{p}{2}+1}\epsilon^{-\frac{3}{2}})$ for arbitrary scheme.
- We conducted numerical experiments to demonstrate that the shuffling-type gradient algorithm converges faster than SGD on two important non-Lipschitz applications.

2 Preliminaries

2.1 Shuffling-Type Gradient Algorithm

In practice, the random shuffling method has demonstrated its superiority over SGD, as shown in Bottou (2009) and Bottou (2012). Specifically, Bottou (2009) shows that shuffling-type methods achieve a convergence rate of approximately $\mathcal{O}(1/T^2)$, where T is the iteration count. Beyond shuffling-type stochastic gradient methods, variants such as SVRG have been applied in various scenarios, including decentralized optimization, as discussed in Shamir (2016) and De and Goldstein (2016).

The analysis of shuffling-type methods has a long history. For convex cases, Gürbüzbalaban et al. (2021) demonstrated that when the objective function is a sum of quadratics or smooth functions with a Lipschitz Hessian, and with a diminishing stepsize, the average of the last update in each epoch of RGA converges strictly faster than SGD with probability one. Additionally, they showed that when the number of epochs T is sufficiently large, the Reshuffling Gradient Algorithm (RGA) asymptotically converges at a rate of $\mathcal{O}(1/T^2)$. Similarly, Nguyen et al. (2021) established a convergence rate of $\mathcal{O}(1/T^2)$ for strongly convex and globally L-smooth functions. Furthermore, with uniform sampling and a bounded variance assumption or convexity on each component function, they showed that the convergence rate can be improved to $\mathcal{O}(1/nT^2)$.

In contrast, there is not much research on nonconvex cases. For example, Nguyen et al. (2021) demonstrated a convergence rate of $\mathcal{O}(T^{-2/3})$; Koloskova et al. (2023) proved a convergence rate of $\mathcal{O}\left(\frac{1}{T} + \min\left\{\left(\frac{n\sigma}{T}\right)^{\frac{2}{3}}, \left(\frac{n\sigma^2}{T}\right)^{\frac{1}{2}}\right\}\right)$ for single shuffling gradient method.

2.2 Counterexamples

In this section, we give some counterexamples to demonstrate the popularity of non-Lipschitz functions. First we give two machine learning examples, then we mention some common non-Lipschitz functions.

Example 1. The first example is distributionally robust optimization (DRO), which is a popular optimization framework for training robust models. DRO is introduced to deal with the distribution shift between training and test datasets. In (Levy et al., 2020), it is formulated equivalently as follows.

$$\min_{w \in \mathcal{W}, \theta \in \mathbb{R}} L(w, \theta) := \mathbb{E}_{\xi \sim P} \psi^* \left(\frac{\ell(w; \xi) - \theta}{\lambda} \right) + \theta, \tag{1}$$

where w and θ are the parameters to be optimized, ξ is a sample randomly drawn from data distribution P, $\ell(w;\xi)$ is the loss function, ψ^* is the conjugate function of the divergence function ψ we choose to measure the difference between distributions, and $\lambda > 0$ is the regularization coefficient. It is proved in (Jin et al., 2021) that $L(w,\theta)$ is not always Lipschitz-smooth even if $\ell(w;\xi)$ is Lipschitz-smooth and the variance is bounded.

Example 2. The second example is the phase retrieval problem. Phase retrieval is a nonconvex problem in X-ray crystallography and diffraction imaging (Drenth, 2007; Miao et al., 1999). The goal is to recover the structure of a molecular object from intensity measurements. Let $x \in \mathbb{R}^d$ be the true object and $y_r = |a_r^\top x|^2$ for $r = 1, \ldots, m$, where $a_r \in \mathbb{R}^d$. The problem is to solve:

$$\min_{z\in\mathbb{R}^d} f(z) := \frac{1}{2m}\sum_{r=1}^{m}(y_r - |a_r^\top z|^2)^2. \tag{2}$$

This objective function is a high-order polynomial in high-dimensional space, thus it does not belong to the L-smooth function class.

Example 3. There are many common functions that are not Lipschitz smooth, including polynomial functions with order > 2, exponential functions, logarithmic functions and rational functions.

2.3 Relaxation of Lipschitz Smoothness

Because of the existence of these counterexamples, people have recently been investigating about smoothness assumptions that are more general than the traditional Lipschitz smoothness. In Zhang et al. (2019), (L_0, L_1)-smoothness was proposed as the first relaxed smoothness notion motivated by language modeling. It is defined as below:

Definition 2.1. ((L_0, L_1)-smoothness) A real-valued differentiable function f is (L_0, L_1)-smooth if there exist constants $L_0, L_1 > 0$ such that

$$\|\nabla^2 f(w)\| \le L_0 + L_1\|\nabla f(w)\|.$$

Lipschitz smoothness can be viewed as a special case of (L_0, L_1) smoothness when $L_1 = 0$. Under (L_0, L_1)-smoothness assumption, various convergence algorithms have been developed including clipped or normalized GD/SGD (Zhang et al., 2019), momentum accelerated clipped GD/SGD (Zhang et al., 2020), ADAM (Wang et al., 2022) and variance-reduced clipping (Reisizadeh et al., 2023) with optimal sample complexity on stochastic non-convex optimization.

Other relaxed smoothness assumptions include asymmetric generalized smoothness motivated by distributionally robust optimization (Jin et al., 2021) and its extension to α-symmetric generalized smoothness (Chen et al., 2023) and ℓ-smoothness (Li et al., 2023a). In this paper, we use the definition of ℓ-smoothness as below:

Definition 2.2. (ℓ-smoothness) A real-valued differentiable function f is ℓ-smooth if there exists some non-decreasing continuous function $\ell : [0, +\infty) \to (0, +\infty)$ such that for any $w \in \mathrm{dom}(f)$ and constant $C > 0$, $\mathcal{B}(w, \frac{C}{\ell(\|\nabla f(w)\|+C)}) \subseteq \mathrm{dom}(f)$; and for any $w_1, w_2 \in \mathcal{B}(w, \frac{C}{\ell(\|\nabla f(w)\|+C)})$,

$$\|\nabla f(w_1) - \nabla f(w_2)\| \le \ell(\|\nabla f(w)\| + C) \cdot \|w_1 - w_2\|.$$

For nonconvex optimization problems, ℓ function is required to be sub-quadratic. (L_0, L_1)-smoothness can be regarded as a special case of ℓ-smoothness. It is straightforward to verify that both phase retrieval and DRO have ℓ-smooth loss functions. Notice that ℓ-smoothness degenerates to traditional Lipschitz smoothness if ℓ is a constant function.

3 Algorithm

As demonstrated in our counterexamples, the Lipschitz smoothness assumption does not always hold in problem (P). In such non-Lipschitz scenarios, gradients can change drastically, posing a significant

challenge for these algorithms. To address this issue, we propose a new stepsize strategy, detailed in Algorithm 1 and section 4, to improve performance under these challenging conditions. This strategy aims to choose the stepsize to accommodate the variance and instability in gradients, thereby enhancing the robustness of the optimization process.

In this algorithm, we start with an initial point $\tilde{w}_0$. During each iteration $t \in [T]$, either all the samples are shuffled, or we keep the order of the samples as in the last epoch. This reshuffling introduces variance in the order of samples, which can help mitigate issues related to gradient instability. For each step $j \in [n]$, we use the gradient from a single sample with number $\pi_j^{(t)}$ to update the weights w. The notation $\pi_j^{(t)}$ is used to denote the j-th element of the permutation $\pi^{(t)}$ for $j \in [n]$. Each outer loop through the data is counted as an epoch, and our convergence analysis focuses on the performance after the completion of each full epoch.

There are multiple strategies to determine $\pi^{(t)}$:

- If $\pi^{(t)}$ is a fixed permutation of $[n]$, Algorithm 1 functions as an incremental gradient method. This method maintains a consistent order of samples, which can simplify the analysis and implementation.
- If $\pi^{(t)}$ is shuffled only once in the first iteration and then used in every subsequent iteration, Algorithm 1 operates as a shuffle-once algorithm. This strategy introduces randomness at the beginning but maintains a fixed order thereafter, providing a balance between randomness and stability.
- If $\pi^{(t)}$ is regenerated in every single iteration, Algorithm 1 becomes a random reshuffling algorithm. This approach maximizes the randomness in the sample order, potentially offering the most robustness against the erratic behavior of non-Lipschitz gradients by constantly changing the sample order.

Algorithm 1 Shuffling-type Gradient Algorithm

Initialization: Choose an initial point $\tilde{w}_0 \in \text{dom}\,(F)$.
for $t = 1, 2, \cdots, T$ **do**
  Set $w_0^{(t)} := \tilde{w}_{t-1}$;
  Generate permutation $\pi^{(t)}$ of $[n]$.
  Compute non-increasing stepsize η_t.
  for $j = 1, \cdots, n$ **do**
    Update $w_j^{(t)} := w_{j-1}^{(t)} - \frac{\eta_t}{n} \nabla f(w_{j-1}^{(t)}; \pi_j^{(t)})$.
  end for
  Set $\tilde{w}_t := w_n^{(t)}$.
end for

Although the random reshuffling scheme is most used in practice, each of these strategies offers distinct advantages and can be selected based on the specific requirements and characteristics of the optimization problem at hand. For this reason, we will give convergence rates for random and arbitrary shuffling scheme.

4 Convergence Analysis

4.1 Main Results

In this section, we present the main results of our convergence analysis. Our findings indicate that, with proper stepsizes, it is possible to achieve the same convergence rate, up to a logarithm difference, as under the Lipschitz smoothness assumption. First, we introduce the following assumptions regarding problem (P). Assumption 4.1 is a standard assumption, and Assumption 4.2 requires all F and $f(\cdot; i)$ to be ℓ-smooth.

Assumption 4.1. dom $(F) := \{w \in \mathbb{R}^d : F(w) < +\infty\} \neq \emptyset$ and $F^* := \inf_{w \in \mathbb{R}^d} F(w) > -\infty$.

Assumption 4.2. F and $f(\cdot; i)$ are ℓ-smooth for some sub-quadratic function ℓ, $\forall i \in [n]$.

Here, we assume all functions share the same ℓ function without loss of generality, as we can always choose the pointwise maximum of all their ℓ functions. We define p to be the degree of the ℓ function such that $p = \sup_{p\geq 0}\{p| \lim_{w\to\infty} \frac{\ell(w)}{w^p} > 0\}$. Since ℓ is sub-quadratic, we have $0 \leq p < 2$.

Next, we introduce our assumption about the gradient variances.

Assumption 4.3. There exist two constants $\sigma, A \in (0, +\infty)$ such that $\forall i \in [n]$,

$$\frac{1}{n}\sum_{i=1}^{n} \|\nabla f(w; i) - \nabla F(w)\|^2 \leq A\|\nabla F(w)\|^2 + \sigma^2,\ a.s.,\ \forall w \in \mathrm{dom}(F). \tag{3}$$

If $A = 0$, Assumption 4.3 reduces to the standard bounded variance assumption.

4.1.1 Nonconvex Case

Let us denote $\Delta_1 := F(w_0^{(1)}) - F^*$. Under assumptions 4.1 to 4.3, we have the following result for random shuffling scheme. Proofs can be found in Appendix A.1.1 and A.1.2.

Theorem 4.4. *Suppose Assumptions 4.1, 4.2 and 4.3 hold, Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 with random reshuffling scheme. For any $0 < \delta < 1$, we denote $H := \frac{4\Delta_1}{\delta}$, $G := \sup\{u \geq 0 | u^2 \leq 2\ell(2u) \cdot H\}$, $G' := \sqrt{2(1 + n\sqrt{A})}G + \sqrt{n}\sigma$, $L := \ell(2G')$. For any $0 < \epsilon = \mathcal{O}(\frac{1}{\sqrt{n}})$, choose η_t and T such that*

$$\eta_t \leq \frac{1}{2L\sqrt{\frac{A}{n} + 1}},\ \sum_{t=1}^{T} \eta_t^3 \leq \frac{n\Delta_1}{L^2\sigma^2},\ T \geq \frac{32\Delta_1}{\eta_T \delta \epsilon^2},$$

then with probability at least $1 - \delta$, we have $\|\nabla F(w_0^{(t)})\| \leq G$ for every $1 \leq t \leq T$

$$\frac{1}{T}\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 \leq \epsilon^2.$$

Remark 4.5. By choosing $\eta_t = \eta = \mathcal{O}(\sqrt[3]{\frac{n^{1-p}}{T}}) = \mathcal{O}(n^{\frac{1-p}{2}}\epsilon)$, we can achieve a complexity of $T = \mathcal{O}(\frac{n^{\frac{p-1}{2}}}{\epsilon^3})$ outer iterations and $\mathcal{O}(\frac{n^{\frac{p+1}{2}}}{\epsilon^3})$ total number of gradient evaluations, ignoring constants, where p is the order of the ℓ function in Definition 2.2. As p goes to 0, ℓ-smoothness degenerates to the traditional Lipschitz smoothness, and our total number of gradient evaluations goes to $\mathcal{O}(\frac{\sqrt{n}}{\epsilon^3})$ once again, which matches the complexity in Corollary 1 of Nguyen et al. (2021). If $\epsilon \leq 1/\sqrt{n}$, one possible stepsize is $\eta = \frac{\sqrt{n}\epsilon}{2L\sqrt{\frac{A}{n}+1}}$.

Our result here has polynomial dependency on $\frac{1}{\delta}$, $T = \mathcal{O}(\delta^{-\frac{3}{2}-\frac{p}{2-p}})$. It is important to note that, in our setting, δ accounts for the probability that Lipschitz smoothness does not hold—a consideration absent in standard Lipschitz smoothness settings. In fact, a polynomial dependency on δ is typical in papers with similar smoothness assumptions, e.g. theorem 5.3 in Li et al. (2023a) and theorem 6.2 in Li et al. (2023b). By requiring $\epsilon = \mathcal{O}(\frac{1}{\sqrt{n}})$ we make sure that $\eta_t \leq \frac{1}{2L\sqrt{\frac{A}{n}+1}}$ is achievable.

Next we consider arbitrary $\pi^{(t)}$ scheme in Algorithm 1.

Theorem 4.6. *Suppose Assumptions 4.1, 4.2 and 4.3 hold. Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 with arbitrary scheme. Define $H = 2\Delta_1$, $G := \sup\{u \geq 0 | u^2 \leq 2\ell(2u) \cdot H\}$, $G' := \sqrt{2(1 + n\sqrt{A})}G + \sqrt{n}\sigma$, $L := \ell(2G')$. For any $\epsilon > 0$, choose η_t and T such that*

$$\eta_t \leq \frac{1}{L\sqrt{2(3A + 2)}},\ \sum_{t=1}^{T} \eta_t^3 \leq \frac{2\Delta_1}{3\sigma^2 L^2},\ T \geq \frac{8\Delta_1}{\eta_T \epsilon^2},$$

then we have $\|\nabla F(w_0^{(t)})\| \leq G$ for every $1 \leq t \leq T$ and

$$\frac{1}{T}\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 \leq \epsilon^2.$$

This theorem gives the convergence rate for arbitrary scheme in Algorithm 1. By choosing $\eta_t = \eta = \mathcal{O}\left(\sqrt[3]{\frac{1}{n^p T}}\right) = \mathcal{O}\left(\frac{\epsilon}{n^{\frac{p}{2}}}\right)$, we achieve a complexity of $\mathcal{O}\left(\frac{n^{\frac{p}{2}}}{\epsilon^3}\right)$ outer iterations and $\mathcal{O}\left(\frac{n^{\frac{p}{2}+1}}{\epsilon^3}\right)$ total gradient evaluations, ignoring constants. Without the randomness in π in every iteration, the complexity's dependency on n is increased by $\mathcal{O}(\sqrt{n})$. One possible stepsize is $\eta = \frac{\epsilon}{L\sqrt{2(3A+2)}}$.

4.1.2 Strongly Convex Case

For strongly convex case, we give results for both random reshuffling scheme and arbitrary scheme, with constant learning rate. Proof can be found in Appendix A.2.

Assumption 4.7. Function F in (P) is μ-strongly convex on $\mathrm{dom}(F)$.

Theorem 4.8. *Suppose Assumptions 4.1, 4.2, 4.3 and 4.7 hold. Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 with random reshuffling scheme. For any $0 < \delta < 1$, we denote $H := \max\{\frac{3\sigma^2}{4\mu}\log\frac{4}{\epsilon} + \Delta_1, \frac{4\Delta_1}{\delta}\}$, $G := \sup\{u \geq 0 | u^2 \leq 2\ell(2u)\cdot H\}$, $G' := \sqrt{2(1+n\sqrt{A})}G + \sqrt{n}\sigma$, $L := \ell(2G')$. For any $0 < \epsilon = \mathcal{O}(\frac{1}{n})$, if we choose η_t and T such that*

$$\eta_t = \eta = \frac{4\log(\sqrt{n}T)}{\mu T}, T \geq 4\sqrt{\frac{\Delta_1}{n\delta\epsilon}},$$

$$\frac{T}{\log(\sqrt{n}T)} \geq \frac{4}{\mu}\max\left\{2, L\sqrt{2(3A+2)}, L\sigma\sqrt{\frac{8}{n\mu\delta\epsilon}}, \sqrt[3]{\frac{T\sigma^2L^2}{n\Delta_1}}\right\},$$

then for any $0 < \delta < 1$, with probability at least $1-\delta$ we have

$$F(w_0^{(T+1)}) - F^* \leq \epsilon.$$

In Theorem 4.8, we can achieve a complexity of $\widetilde{\mathcal{O}}\left(n^{\frac{p-1}{2}}\epsilon^{-\frac{1}{2}}\right)$ outer iterations and $\widetilde{\mathcal{O}}\left(n^{\frac{p+1}{2}}\epsilon^{-\frac{1}{2}}\right)$ total gradient evaluations with $\eta = \widetilde{\mathcal{O}}\left(n^{\frac{1-p}{2}}\epsilon^{\frac{1}{2}}\right)$, ignoring constants. This matches the result in Nguyen et al. (2021) with the same assumptions in the degenerate case of $p = 0$. The dependence on δ is $T = \mathcal{O}(\delta^{-\frac{1}{2}-\frac{p}{2-p}})$.

Theorem 4.9. *Suppose Assumptions 4.1, 4.2, 4.3 and 4.7 hold. Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 with arbitrary scheme. We denote $H := \max\{\frac{3\sigma^2}{4\mu}\log\frac{4}{\epsilon} + \Delta_1, 2\Delta_1\}$, $G := \sup\{u \geq 0 | u^2 \leq 2\ell(2u)\cdot H\}$, $G' := \sqrt{2(1+n\sqrt{A})}G + \sqrt{n}\sigma$, $L := \ell(2G')$. For any $\epsilon > 0$, choose η_t and T such that*

$$\eta_t = \eta = \frac{4\log(\sqrt{n}T)}{\mu T}, T \geq \sqrt{\frac{\Delta_1}{n\epsilon}},$$

$$\frac{T}{\log(\sqrt{n}T)} \geq \frac{4}{\mu}\max\left\{2, L\sqrt{2(3A+2)}, \frac{L\sigma}{\mu}\sqrt{\frac{3}{\mu\epsilon}}, \sqrt[3]{\frac{T\sigma^2L^2}{n\Delta_1}}\right\},$$

then it holds that

$$F(w_0^{(T+1)}) - F^* \leq \epsilon.$$

In Theorem 4.9, we achieve a complexity of $\widetilde{\mathcal{O}}\left(n^{\frac{p}{2}}\epsilon^{-1/2}\right)$ outer iterations and $\widetilde{\mathcal{O}}\left(n^{\frac{p}{2}+1}\epsilon^{-1/2}\right)$ total gradient evaluations with $\eta = \widetilde{\mathcal{O}}\left(n^{\frac{-p}{2}}\epsilon^{\frac{1}{2}}\right)$, ignoring constants. Therefore, the randomness in $\pi^{(t)}$ of the random reshuffling scheme reduces the total complexity by an $\widetilde{\mathcal{O}}(\sqrt{n})$ term.

4.1.3 Non-strongly Convex Case

Next we consider the case where only non-strongly convexity are assumed. In the following theorem, we denote the optimal solution as w^*, the standard deviation at w^* as $\sigma_* := \sqrt{\frac{1}{n}\sum_{i=1}^n \|\nabla f(w^*; i)\|^2}$ and the average value of $\{w_0^{(t)}\}_{t=1}^T$ as $\bar{w}_T = \frac{1}{T}\sum_{t=1}^T w_0^{(t)}$. Proof can be found in Appendix A.3.

Assumption 4.10. Functions $f(\cdot; i)$ in (P) are convex on $\mathrm{dom}(F)$, for all $i \in [n]$.

Theorem 4.11. *Suppose Assumptions 4.1, 4.2, 4.3 and 4.10 hold. Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 with random reshuffling scheme. For any $0 < \delta < 1$, define H, G, G', L as in Theorem 4.4. For any $0 < \epsilon = \mathcal{O}(\frac{1}{n})$, choose η_t and T such that*

$$\eta_t = \eta \leq \min\left\{\frac{1}{2L\sqrt{\frac{A}{n}+1}}, \sqrt[3]{\frac{n\Delta_1}{T\sigma^2L^2}}, \sqrt[3]{\frac{3n\|w_0^{(1)} - w^*\|^2}{2LT\sigma_*^2}}\right\},$$

$$T \geq \frac{4\|w_0^{(1)} - w^*\|^2}{\eta\delta\epsilon},$$

then with probability at least $1-\delta$, we have $\|\nabla F(w_0^{(t)})\| \leq G$ for every $1 \leq t \leq T$ and

$$F(\bar{w}_T) - F^* \leq \epsilon.$$

By choosing $\eta = \mathcal{O}\left(\sqrt[3]{\frac{n^{1-p}}{T}}\right) = \mathcal{O}\left(n^{\frac{1-p}{2}}\epsilon^{0.5}\right)$, we achieve a complexity of $\mathcal{O}\left(\frac{n^{\frac{p-1}{2}}}{\epsilon^{1.5}}\right)$ outer iterations and $\mathcal{O}\left(\frac{n^{\frac{p+1}{2}}}{\epsilon^{1.5}}\right)$ total number of gradient evaluations, ignoring constants. The dependency on δ is $T = \mathcal{O}(\delta^{-\frac{3}{2}-\frac{p}{2-p}})$. If $\epsilon \leq 1/n$, one possible stepsize is $\eta = \frac{\sqrt{n\epsilon}}{2L\sqrt{\frac{A}{n}+1}}$.

Theorem 4.12. *Suppose Assumptions 4.1, 4.2, 4.3 and 4.10 hold. Let $\{\tilde{w}_t\}_{t=1}^T$ be generated by Algorithm 1 arbitrary scheme. Define H, G, G', L as in Theorem 4.6. For any $\epsilon > 0$, choose η_t and T such that*

$$\eta_t = \eta \leq \min\left\{\frac{1}{L\sqrt{2(3A+2)}}, \sqrt[3]{\frac{2\Delta_1}{TL^2(2G^2+3\sigma^2)}}, \sqrt[3]{\frac{\|w_0^{(1)} - w^*\|^2}{LT\sigma^2}}\right\},$$

$$T \geq \frac{\|w_0^{(1)} - w^*\|^2}{\eta\epsilon},$$

then we have $\|\nabla F(w_0^{(t)})\| \leq G$ for every $1 \leq t \leq T$ and

$$F(\bar{w}_T) - F^* \leq \epsilon.$$

By choosing $\eta = \mathcal{O}(\sqrt[3]{\frac{1}{n^pT}}) = \mathcal{O}\left(n^{-\frac{p}{2}}\epsilon^{0.5}\right)$, we have the complexity of $\mathcal{O}(\frac{n^{\frac{p}{2}}}{\epsilon^{1.5}})$ outer iterations and $\mathcal{O}(\frac{n^{\frac{p}{2}+1}}{\epsilon^{1.5}})$ total number of gradient evaluations, ignoring constants. One possible stepsize is $\eta = \frac{\sqrt{\epsilon}}{L\sqrt{2(3A+2)}}$.

4.2 Proof Sketch and Technical Novelty

Broadly speaking, our approach involves two main goals: first, demonstrating that Lipschitz smoothness is maintained with high probability along the training trajectory $\{\tilde{w}_t\}$, and second, showing that, conditioned on Lipschitz smoothness, the summation of gradient norms is bounded with high probability.

For the first goal, in Lemma A.4, we prove by induction that when starting an iteration with a bounded gradient, the entire training trajectory during this iteration will have bounded gradients. Consequently, we only need to verify the Lipschitz smoothness condition at the start of each iteration. However, at this point, the two goals become intertwined. We need Lipschitz smoothness to bound the gradient differences, but we also need the gradient norm bounds to establish Lipschitz smoothness. Our solution is to address both issues simultaneously.

Assuming that, before a stopping time τ, Lipschitz smoothness holds, we bound the gradient norm up to that time in Lemma A.5. However, this process is nontrivial. Since we are examining behavior before a stopping time, every expectation is now conditioned on $t < \tau$, rendering all previous estimations for shuffling gradient algorithms inapplicable. This presents a contradiction: we want to condition on $t < \tau$ when applying Lipschitz smoothness, but we do not want this condition when estimating other quantities. In Lemma A.5, we find a method to separately handle these two requirements, allowing us to achieve both goals simultaneously.

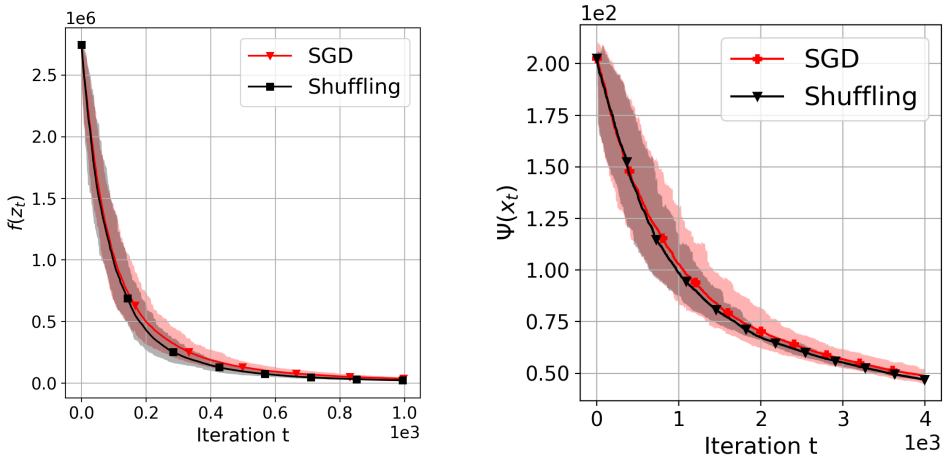

Figure 1: Experimental Results on Phase Retrieval (left) and DRO (right).

4.3 Limitations and Future works

Although we have proved upper bounds for the complexity of shuffling gradient algorithms, there are certain limitations in our work that we leave for future research:

- First, as is common with many optimization algorithms, it is challenging to verify that the bounds presented are indeed the lower bounds. Future work could explore improving these results, for instance, by reducing the dependency on δ to a logarithmic factor, or by proving that the current bounds are, in fact, tight lower bounds.
- Second, although we showed results for arbitrary shuffling schemes, there are better results for single shuffling under Lipschitz smoothness, for example Ahn et al. (2020) proved $\mathcal{O}(\frac{1}{nT^2})$ convergence rate for strongly convex objectives. It is interesting to see whether we can achieve the same convergence rate with ℓ smoothness as well.
- Lastly, shuffling gradient methods have been integrated with variance reduction techniques (Malinovsky et al., 2023). Exploring the performance of these algorithms under relaxed smoothness assumptions is another promising direction for future work.

5 Numerical Experiments

We compare reshuffling gradient algorithm (Algorithm 1) with SGD on phase retrieval and distributionally robust optimization (DRO), which are ℓ-smooth but not Lipschitz smooth. The whole experiment is run on Python 3.9 in a MacBook Pro laptop with 500 GB Storage and 8-core CPU (16 GB Memory). We use similar setup as in (Chen et al., 2023).

In the phase retrieval problem (2), we select $m = 3000$ and $d = 100$, and generate independent Gaussian variables $x, a_r \sim \mathcal{N}(0, 0.5I_d)$, initialization $z_0 \sim \mathcal{N}(5, 0.5I_d)$, as well as $y_i = |a_r^\top z|^2 + n_i$ with noise $n_i \sim \mathcal{N}(0, 4^2)$ for $i = 1, ..., m$. We select constant stepsizes 2×10^{-6} and $\eta_j^{(t)} \equiv \frac{0.007}{m}$ for SGD and Algorithm 1 respectively by fine-tuning and run each algorithm 100 times which takes around 17 minutes in total. We plot the learning curves of the objective function values averaged among the 100 times, as well as the 95% and 5% percentiles in the left of Figure 1, which shows that Algorithm 1 converges faster than SGD on this generalized smooth optimization.

In the DRO problem (1), we select $\lambda = 0.01$ and $\psi^*(t) = \frac{1}{4}(t+2)_+^2 - 1$ (corresponding to ψ being χ^2 divergence). For the stochastic samples ξ, we use the life expectancy data[1] designed for

[1] https://www.kaggle.com/datasets/kumarajarshi/life-expectancy-who?resource=download

regression task between the life expectancy (target) and its factors (features) of 2413 people, and preprocess the data by filling the missing values with the median of the corresponding features, censorizing and normalizing all the features[2], removing two categorical features ("country" and "status"), and adding standard Gaussian noise to the target to get robust model. We use the first 2000 samples $\{x_i, y_i\}_{i=1}^{2000}$ with features $x_i \in \mathbb{R}^{34}$ and targets $y_i \in \mathbb{R}$ for training. We use the loss function $\ell_\xi(w) = \frac{1}{2}(y_\xi - x_\xi^\top w)^2 + 0.1 \sum_{j=1}^{34} \ln\left(1 + |w^{(j)}|\right)$ of $w = [w^{(1)}; \ldots; w^{(34)}] \in \mathbb{R}^{34}$ for any sample x_ξ, y_ξ. We use initialization $\eta_0 = 0.1$ and $w_0 \in \mathbb{R}^{34}$ from standard Gaussian distribution.

Then similar to phase retrieval, we implement both SGD and Algorithm 1 100 times with stepsizes $\eta_j^{(t)} = 10^{-7}$, which takes 11-12 hours. The average, 5% and 95% percentiles of the function values $\Psi(x_t) := \min_{\eta \in \mathbb{R}} L(x_t, \eta)$ among the 100 implementations are plotted in the right of Figure 1, which again shows faster convergence of Algorithm 1 than SGD on this generalized smooth optimization.

6 Conclusion

In this paper, we have advanced the understanding of shuffling-type gradient algorithms under non-uniform smoothness assumptions and improved these algorithms with specific learning rates. We provided counterexamples to illustrate the existence and divergence of non-Lipschitz functions for (P). Our results show that these algorithms converge efficiently under a general bounded variance assumption. Additionally, we established robust convergence rates for both strongly convex and non-strongly convex cases, demonstrating the versatility and effectiveness of our approach. These convergence results outperform SGD also when Lipschitz smoothness is violated, which is demonstrated by numerical experiments. Future research can build on these findings to explore further generalizations and applications in various optimization contexts.

References

K. Ahn, C. Yun, and S. Sra. Sgd with shuffling: optimal rates without component convexity and large epoch requirements. *Advances in Neural Information Processing Systems*, 33:17526–17535, 2020.

Y. Arjevani, Y. Carmon, J. C. Duchi, D. J. Foster, N. Srebro, and B. Woodworth. Lower bounds for non-convex stochastic optimization. *Mathematical Programming*, 199(1):165–214, 2023.

L. Bottou. Curiously fast convergence of some stochastic gradient descent algorithms. 2009. URL `https://api.semanticscholar.org/CorpusID:16822133`.

L. Bottou. *Stochastic Gradient Descent Tricks*, pages 421–436. Springer Berlin Heidelberg, Berlin, Heidelberg, 2012. ISBN 978-3-642-35289-8. doi: 10.1007/978-3-642-35289-8_25. URL `https://doi.org/10.1007/978-3-642-35289-8_25`.

Z. Chen, Y. Zhou, Y. Liang, and Z. Lu. Generalized-smooth nonconvex optimization is as efficient as smooth nonconvex optimization. *arXiv preprint arXiv:2303.02854*, 2023.

S. De and T. Goldstein. Efficient distributed SGD with variance reduction. In F. Bonchi, J. Domingo-Ferrer, R. Baeza-Yates, Z. Zhou, and X. Wu, editors, *IEEE 16th International Conference on Data Mining, ICDM 2016, December 12-15, 2016, Barcelona, Spain*, pages 111–120. IEEE Computer Society, 2016. doi: 10.1109/ICDM.2016.0022. URL `https://doi.org/10.1109/ICDM.2016.0022`.

J. Drenth. *Principles of protein X-ray crystallography*. Springer Science & Business Media, 2007.

A. d'Aspremont, D. Scieur, A. Taylor, et al. Acceleration methods. *Foundations and Trends® in Optimization*, 5(1-2):1–245, 2021.

M. Feurer and F. Hutter. Hyperparameter optimization. *Automated machine learning: Methods, systems, challenges*, pages 3–33, 2019.

[2]The detailed process of filling missing values and censorization can be seen in `https://thecleverprogrammer.com/2021/01/06/life-expectancy-analysis-with-python/`

S. Ghadimi and G. Lan. Stochastic first-and zeroth-order methods for nonconvex stochastic programming. *SIAM journal on optimization*, 23(4):2341–2368, 2013.

M. Gürbüzbalaban, A. E. Ozdaglar, and P. A. Parrilo. Why random reshuffling beats stochastic gradient descent. *Math. Program.*, 186(1):49–84, 2021. doi: 10.1007/S10107-019-01440-W. URL https://doi.org/10.1007/s10107-019-01440-w.

J. Z. HaoChen and S. Sra. Random shuffling beats SGD after finite epochs. In K. Chaudhuri and R. Salakhutdinov, editors, *Proceedings of the 36th International Conference on Machine Learning, ICML 2019, 9-15 June 2019, Long Beach, California, USA*, volume 97 of *Proceedings of Machine Learning Research*, pages 2624–2633. PMLR, 2019. URL http://proceedings.mlr.press/v97/haochen19a.html.

J. Jin, B. Zhang, H. Wang, and L. Wang. Non-convex distributionally robust optimization: Non-asymptotic analysis. *Advances in Neural Information Processing Systems*, 34:2771–2782, 2021.

A. Koloskova, N. Doikov, S. U. Stich, and M. Jaggi. Shuffle sgd is always better than sgd: improved analysis of sgd with arbitrary data orders. *arXiv preprint arXiv:2305.19259*, 2023.

D. Levy, Y. Carmon, J. C. Duchi, and A. Sidford. Large-scale methods for distributionally robust optimization. *Advances in Neural Information Processing Systems*, 33:8847–8860, 2020.

H. Li, J. Qian, Y. Tian, A. Rakhlin, and A. Jadbabaie. Convex and non-convex optimization under generalized smoothness. In *Thirty-seventh Conference on Neural Information Processing Systems*, 2023a.

H. Li, A. Rakhlin, and A. Jadbabaie. Convergence of adam under relaxed assumptions, 2023b.

G. Malinovsky, A. Sailanbayev, and P. Richtárik. Random reshuffling with variance reduction: New analysis and better rates. In *Uncertainty in Artificial Intelligence*, pages 1347–1357. PMLR, 2023.

J. Miao, P. Charalambous, J. Kirz, and D. Sayre. Extending the methodology of x-ray crystallography to allow imaging of micrometre-sized non-crystalline specimens. *Nature*, 400(6742):342–344, 1999.

K. Mishchenko, A. Khaled, and P. Richtárik. Random reshuffling: Simple analysis with vast improvements. *Advances in Neural Information Processing Systems*, 33:17309–17320, 2020.

A. S. Nemirovskij and D. B. Yudin. Problem complexity and method efficiency in optimization. 1983.

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

L. M. Nguyen, Q. Tran-Dinh, D. T. Phan, P. H. Nguyen, and M. Van Dijk. A unified convergence analysis for shuffling-type gradient methods. *The Journal of Machine Learning Research*, 22(1): 9397–9440, 2021.

A. Radford, K. Narasimhan, T. Salimans, I. Sutskever, et al. Improving language understanding by generative pre-training. 2018.

A. Reisizadeh, H. Li, S. Das, and A. Jadbabaie. Variance-reduced clipping for non-convex optimization. *arXiv preprint arXiv:2303.00883*, 2023.

I. Safran and O. Shamir. How good is SGD with random shuffling? In J. D. Abernethy and S. Agarwal, editors, *Conference on Learning Theory, COLT 2020, 9-12 July 2020, Virtual Event [Graz, Austria]*, volume 125 of *Proceedings of Machine Learning Research*, pages 3250–3284. PMLR, 2020. URL http://proceedings.mlr.press/v125/safran20a.html.

O. Shamir. Without-replacement sampling for stochastic gradient methods: Convergence results and application to distributed optimization. *CoRR*, abs/1603.00570, 2016. URL http://arxiv.org/abs/1603.00570.

R. S. Sutton and A. G. Barto. *Reinforcement learning: An introduction*. MIT press, 2018.

B. Wang, Y. Zhang, H. Zhang, Q. Meng, Z.-M. Ma, T.-Y. Liu, and W. Chen. Provable adaptivity in adam. *arXiv preprint arXiv:2208.09900*, 2022.

B. Zhang, J. Jin, C. Fang, and L. Wang. Improved analysis of clipping algorithms for non-convex optimization. *Advances in Neural Information Processing Systems*, 33:15511–15521, 2020.

J. Zhang, T. He, S. Sra, and A. Jadbabaie. Why gradient clipping accelerates training: A theoretical justification for adaptivity. *arXiv preprint arXiv:1905.11881*, 2019.

A APPENDIX / SUPPLEMENTAL MATERIAL

A.1 NONCONVEX CASE ANALYSIS

In this section we prove the theorems in section 4.1.1.

A.1.1 LEMMAS

In this part we use notations as defined in Theorem 4.4, for completeness we repeat them here:

$$H := \frac{4\Delta_1}{\delta}, G := \sup\{u \geq 0 | u^2 \leq 2\ell(2u) \cdot H\} < \infty,$$
$$G' := \sqrt{2(1+n\sqrt{A})}G + \sqrt{n}\sigma, L := \ell(2G').$$

We first state some lemmas that are useful in our proof. The following lemma is a natural corollary of Definition 2.2, by the fact that ℓ is non-decreasing.

Lemma A.1. *If F is ℓ-smooth, for any $w \in dom(F)$ satisfying $\|\nabla F(w)\| \leq G$, we have $\mathcal{B}(w, G/\ell(2G)) \subseteq dom(F)$. For any $w_1, w_2 \in \mathcal{B}(w, G/\ell(2G))$),*

$$\|\nabla F(w_1) - \nabla F(w_2)\| \leq \ell(2G)\|w_1 - w_2\|,$$
$$F(w_1) \leq F(w_2) + \langle \nabla F(w_2), w_1 - w_2 \rangle + \frac{\ell(2G)}{2}\|w_1 - w_2\|^2.$$

The following lemma gives relationship between $\|\nabla f(w;i)\|$ and $\|\nabla F(w)\|$.

Lemma A.2. *If Assumption 4.3 is true, we have*

$$\|\nabla f(w;i)\| \leq \sqrt{2(1+n\sqrt{A})}\|\nabla F(w)\| + \sqrt{2n}\sigma.$$

Proof. From Assumption 4.3 we have that

$$\begin{aligned}
\|\nabla f(w;i)\|^2 &\leq 2\|\nabla f(w;i) - \nabla F(w)\|^2 + 2\|\nabla F(w)\|^2 \\
&\leq 2\sum_{i=1}^{n}\|\nabla f(w;i) - \nabla F(w)\|^2 + 2\|\nabla F(w)\|^2 \\
&\leq 2nA\|\nabla F(w)\|^2 + 2n\sigma^2 + 2\|\nabla F(w)\|^2 \\
&= 2(1+nA)\|\nabla F(w)\|^2 + 2n\sigma^2.
\end{aligned}$$

Taking square root on both sides and notice that $\|\nabla F(w)\| \geq 0$, $\sigma > 0$ we have the conclusion. □

According to Lemma A.2, for w such that $\|\nabla F(w)\| \leq G$ is true, we have

$$\|\nabla f(w;i)\| \leq \sqrt{2(1+n\sqrt{A})}G + \sqrt{n}\sigma = G'$$

holds for all $i \in [n]$.

In our proof, we want that with high probability, Lipschitz smoothness in Lemma A.1, for both $F(w)$ and $f(w;i)$, between $w_0^{(t)}$ and $w_j^{(t)}$ is true, for $t \in [T]$, $i = 0, 1, \cdots, n$ and $j \in [n]$. For that purpose, we can prove the following inequalities with high probability, for $t \in [T]$:

$$\begin{aligned}
\|\nabla F(w_0^{(t)})\| &\leq G; \\
\|w_0^{(t)} - w_0^{(t+1)}\| &\leq G'/\ell(G+G'); \\
\|\nabla f(w_0^{(t)};i)\| &\leq G', \forall i \in [n]; \\
\|w_0^{(t)} - w_j^{(t)}\| &\leq G'/\ell(2G'), \forall j \in [n].
\end{aligned} \tag{4}$$

By Lemma A.2 we know that the third inequality in (4) holds if the first inequality is true. Noticing that $\ell(G+G') \leq \ell(2G')$, it suffices to prove that, for $t \in [T]$,

$$\|\nabla F(w_0^{(t)})\| \leq G, \|w_0^{(t)} - w_j^{(t)}\| \leq G'/\ell(2G'), \forall j \in [n]. \tag{5}$$

For the first inequality, it can be hard to bound the gradient norm directly. The following lemma states the connection between gradient norm and function value of an ℓ-smooth function.

Lemma A.3. *(Lemma 3.5 in Li et al. (2023a)) If F is ℓ-smooth, then*

$$\|\nabla F(w)\|^2 \leq 2\ell(2\|\nabla F(w)\|) \cdot (F(w) - F^*)$$

for any $w \in dom(F)$.

Since ℓ is sub-quadratic, with Lemma A.3 we can bound the gradient norm by bounding the difference between the function value and the optimal value. To ease the proof, let us define the following stopping time:

$$\tau := \min\{t | F(w_0^{(t)}) - F^* > H\} \wedge (T+1).$$

For $t < \tau$, we have $\|\nabla F(w_0^{(t)})\| \leq G$ based on the definition of τ and Lemma A.3, so the first inequality in (5) is satisfied. The following lemma proves that the other inequality in (5) is true for $t < \tau$ as well, therefore guarantees the Lipschitz smoothness before τ.

Lemma A.4. *For $t < \tau$, $\eta_t \leq \frac{1}{2L}$, we have for all $k \in [n]$ and $t \in [T]$, $\|w_0^{(t)} - w_k^{(t)}\|^2 \leq G'/\ell(2G')$.*

Proof. We use induction to prove that

$$w_j^{(t)} \in \mathcal{B}(w_0^{(t)}, \frac{G'}{\ell(2G')}), j = 0, 1, \ldots, n.$$

First of all, this claim is true for $j = 0$. Now suppose the claim is true for $j \leq k-1$, i.e.,

$$\|w_0^{(t)} - w_j^{(t)}\| \leq \frac{G'}{\ell(2G')}, j = 0, 1, \ldots, k-1,$$

we try to prove it for $w_k^{(t)}$. From Lemma A.1, we have Lipschitz smoothness, for all $f(w; i)$, between $w_0^{(t)}$ and $w_j^{(t)}$, if $j \leq k-1$.

Since we have

$$\|\nabla f(w_0^{(t)}; i)\| \leq G', \forall i \in [n],$$

for any $i \in [n]$ and $j \in [k-1]$ we have

$$\|\nabla f(w_j^{(t)}; i)\| \leq \|\nabla f(w_0^{(t)}; i)\| + \|\nabla f(w_j^{(t)}; i) - \nabla f(w_0^{(t)}; i)\| \leq G' + L\|w_j^{(t)} - w_0^{(t)}\| \leq 2G'.$$

Hence, by the algorithm design we have

$$\|w_k^{(t)} - w_0^{(t)}\| = \left\| \sum_{j=0}^{k-1} \frac{\eta_t}{n} \nabla f(w_j^{(t)}; \pi_j^{(t)}) \right\| \leq \sum_{j=0}^{k-1} \frac{\eta_t}{n} \|\nabla f(w_j^{(t)}; \pi_j^{(t)})\| \leq \sum_{j=0}^{k-1} \frac{2G'\eta_t}{n} \leq \frac{G'}{L} = \frac{G'}{\ell(2G')},$$

where the third inequality uses $k \leq n$ and $\eta_t \leq \frac{1}{2L}$. By induction, the claim is true. □

Therefore, we have the desired Lipschitz smoothness property in Lemma A.1 for $t < \tau$. The only thing left to prove is $\mathbb{P}(\tau \leq T) \leq \delta/2$.

To simplify the notations, let us define

$$\epsilon_k^{(t)} := \frac{1}{n} \sum_{j=0}^{k-1} (\nabla f(w_j^{(t)}; \pi_{j+1}^{(t)}) - \nabla f(w_0^{(t)}; \pi_{j+1}^{(t)}))$$

as the average of differences between the gradients at the start of iteration t and the actual gradients we used until step j in the t-th outer iteration. It is worth mentioning that the actual step in t-th outer iteration is $-\eta_t[\nabla F(w_0^{(t)}) + \epsilon_n^{(t)}]$.

Now we bound the probability of event $\{\tau \leq T\}$ by bounding the expectation of function value at the stopping time.

Lemma A.5. *With parameters chosen in Theorem 4.4, we have*

$$\mathbb{E}[F(w_0^{(\tau)}) - F^*] \leq 2\Delta_1.$$

Proof. For any $t < \tau$,

$$\begin{aligned}
&F(w_0^{(t+1)}) - F(w_0^{(t)}) \\
\leq &\langle \nabla F(w_0^{(t)}), w_0^{(t+1)} - w_0^{(t)} \rangle + \frac{L}{2}\|w_0^{(t+1)} - w_0^{(t)}\|^2 \\
= &-\eta_t \langle \nabla F(w_0^{(t)}), \nabla F(w_0^{(t)}) + \epsilon_n^{(t)} \rangle + \frac{L\eta_t^2}{2}\|\nabla F(w_0^{(t)}) + \epsilon_n^{(t)}\|^2 \\
= &-\frac{\eta_t}{2}(\|\nabla F(w_0^{(t)})\|^2 + \|\nabla F(w_0^{(t)}) + \epsilon_n^{(t)}\|^2 - \|\epsilon_n^{(t)}\|^2) + \frac{L\eta_t^2}{2}\|\nabla F(w_0^{(t)}) + \epsilon_n^{(t)}\|^2 \\
\leq &-\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta_t}{2}\|\epsilon_n^{(t)}\|^2 \\
\leq &-\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\|w_k^{(t)} - w_0^{(t)}\|^2. \qquad (6)
\end{aligned}$$

Here the first and last inequality is from Lemma A.1 and the second is because $\eta_t \leq \frac{1}{2L}$. Taking summation from $t = 1$ to $t = \tau - 1$ and taking expectation we have

$$\mathbb{E}[F(w_0^{(\tau)}) - F^*] \leq \Delta_1 - \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2] + \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\|w_k^{(t)} - w_0^{(t)}\|^2]. \qquad (7)$$

Now let us get a bound for the last term on the right hand side. For any $t \in [T]$, $k \in [n]$, from Algorithm 1 and Cauchy-Schwarz inequality we have

$$\begin{aligned}
\|w_k^{(t)} - w_0^{(t)}\|^2 = &\frac{k^2\eta_t^2}{n^2}\Big\|\frac{1}{k}\sum_{j=0}^{k-1}\nabla f(w_j^{(t)}; \pi_{j+1}^{(t)})\Big\|^2 \\
\leq &\frac{3k^2\eta_t^2}{n^2}\|\frac{1}{k}\sum_{j=0}^{k-1}(\nabla f(w_0^{(t)}; \pi_{j+1}^{(t)}) - \nabla F(w_0^{(t)}))\|^2 + \frac{3k^2\eta_t^2}{n^2}\|\nabla F(w_0^{(t)})\|^2 \\
&+ \frac{3k\eta_t^2}{n^2}\sum_{j=0}^{k-1}\|\nabla f(w_j^{(t)}; \pi_{j+1}^{(t)}) - \nabla f(w_0^{(t)}; \pi_{j+1}^{(t)})\|^2.
\end{aligned}$$

Let us denote the 3 terms on the RHS as $A_1(t,k), A_2(t,k)$ and $A_3(t,k)$, i.e. $\|w_k^{(t)} - w_0^{(t)}\|^2 \leq A_1(t,k) + A_2(t,k) + A_3(t,k)$. Since we are interested in $\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\|w_k^{(t)} - w_0^{(t)}\|^2]$, we need to bound $\mathbb{E}[\sum_{t=0}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=1}^{n-1}A_i(t,k)]$ for $i = 1, 2, 3$.

For $A_1(t,k)$, since $\pi^{(t)}$ is randomly chosen, let $\mathcal{F}_t := \sigma(\pi^{(1)}, \cdots, \pi^{(t)})$ be the σ-algebra generated in Algorithm 1, for $t \in [T]$ we have

$$\begin{aligned}
\mathbb{E}[\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}A_1(t,k)|\mathcal{F}_{t-1}] = &\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\frac{3k^2\eta_t^2}{n^2}\mathbb{E}[\|\frac{1}{k}\sum_{j=0}^{k-1}\nabla f(w_0^{(t)}; \pi_{j+1}^{(t)}) - \nabla F(w_0^{(t)})\|^2|\mathcal{F}_t] \\
= &\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\frac{3k^2\eta_t^2}{n^2}\frac{n-k}{k(n-1)}\frac{1}{n}\sum_{i=0}^{n-1}\|\nabla f(w_0^{(t)}; i+1) - \nabla F(w_0^{(t)})\|^2 \\
\leq &\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\frac{3\eta_t^2 k(n-k)}{n^2(n-1)}(A\|\nabla F(w_0^{(t)})\|^2 + \sigma^2) \\
\leq &\frac{\eta_t^3 L^2}{2n}(A\|\nabla F(w_0^{(t)})\|^2 + \sigma^2).
\end{aligned}$$

Here the second equation comes from variance of randomized reshuffling variables, (Lemma 1 in Mishchenko et al. (2020)); the first inequality is from assumption 4.3; the last inequality is because $\sum_{k=0}^{n-1} k(n-k) = \frac{(n-1)n(n+1)}{6} \leq \frac{n^2(n-1)}{3}$.

Let $\{Z_t\}_{t\leq T}$ be a sequence such that $Z_1 = 0$ and for any $t \in [2, T]$,

$$Z_t - Z_{t-1} = -\frac{\eta_t^3 L^2}{2n}(A\|\nabla F(w_0^{(t)})\|^2 + \sigma^2) + \frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1} A_1(t-1,k).$$

We know $\{Z_t\}$ is a supermartingale. Since τ is a bounded stopping time, by optional stopping theorem, we have $\mathbb{E}[Z_\tau] \leq \mathbb{E}[Z_1]$, which leads to

$$\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1} A_1(t,k)] \leq \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t^3 L^2}{2n}(A\|\nabla F(w_0^{(t)})\|^2 + \sigma^2)].$$

For $A_2(t,k)$, for any $t \in [T]$, taking summation over k we have $\sum_{k=0}^{n-1} A_2(t,k) \leq n\eta_t^2\|\nabla F(w_0^{(t)})\|^2$, therefore

$$\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1} A_2(t,k)] \leq \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t^3 L^2}{2}\|\nabla F(w_0^{(t)})\|^2].$$

For $A_3(t,k)$, for any $t < \tau$, by Lemma A.1 we have

$$A_3(t,k) \leq \frac{3kL^2\eta_t^2}{n^2}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2.$$

Taking summation over k, taking expectation we have

$$\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1} A_3(t,k)] \leq \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{3\eta_t^3 L^4}{4n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2].$$

Now putting these together, we have

$$\begin{aligned}\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t L^2}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2] \leq& \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t^3 L^2}{2n}(A\|\nabla F(w_0^{(t)})\|^2 + \sigma^2)] + \mathbb{E}[\sum_{t=1}^{\tau-1}\frac{\eta_t^3 L^2}{2}\|\nabla F(w_0^{(t)})\|^2] \\ &+ [\sum_{t=1}^{\tau-1}\frac{3\eta_t^3 L^4}{4n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2].\end{aligned}$$

Since $\eta_t \leq \frac{1}{2L} < \frac{1}{\sqrt{3}L}$ we have $\frac{3\eta_t^3 L^4}{4n} \leq \frac{\eta_t L^2}{4n}$, rearranging the terms we have

$$\mathbb{E}[\sum_{t=1}^{\tau-1}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2] \leq \mathbb{E}[\sum_{t=1}^{\tau-1} 2\eta_t^2\sigma^2] + 2n\mathbb{E}[\sum_{t=1}^{\tau-1}\eta_t^2(\frac{A}{n}+1)\|\nabla F(w_0^{(t)})\|^2]. \tag{8}$$

Put this into (7) we have,

$$\begin{aligned}&\mathbb{E}[F(w_0^{(\tau)}) - F^*] \\ \leq& \Delta_1 + \mathbb{E}\Big[\sum_{t=1}^{\tau-1}\Big(-\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta_t L^2}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2\Big)\Big] \\ \overset{(8)}{\leq}& \Delta_1 + \mathbb{E}\Big[\sum_{t=1}^{\tau-1}\frac{L^2\sigma^2\eta_t^3}{n} - \sum_{t=1}^{\tau-1}\Big((\frac{\eta_t}{2} - (\frac{A}{n}+1)\eta_t^3 L^2)\|\nabla F(w_0^{(t)})\|^2\Big)\Big] \\ \leq& \Delta_1 + \mathbb{E}\Big[\sum_{t=1}^{\tau-1}\frac{L^2\sigma^2\eta_t^3}{n} - \sum_{t=1}^{\tau-1}\Big(\frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2\Big)\Big] \qquad (9) \\ \leq& \Delta_1 + \frac{L^2\sigma^2}{n}\sum_{t=1}^{T}\eta_t^3.\end{aligned}$$

Here the third inequality is from $\eta_t \leq \frac{1}{2L\sqrt{\frac{A}{n}+1}}$ and the last inequality is because $\eta_t > 0$ and $\tau \leq T+1$.

Since $\sum_{t=1}^{T} \eta_t^3 \leq \frac{n\Delta_1}{\sigma^2 L^2}$, we have $\mathbb{E}[F(w_0^{(\tau)}) - F^*] \leq 2\Delta_1$. □

Now we can bound the probability that $\tau = T+1$.

Lemma A.6. *With the parameters in Theorem 4.4, we have*

$$\mathbb{P}(\tau \leq T) \leq \delta/2.$$

Proof. From Lemma A.5 and the value of H we have

$$\mathbb{P}(\tau \leq T) \leq \mathbb{P}(F(w_0^{(\tau)}) - F^* > H) \leq \frac{\mathbb{E}[F(w_0^{(\tau)}) - F^*]}{H} \leq \frac{2\Delta_1}{H} = \frac{\delta}{2}.$$

□

A.1.2 Proof for Theorems in Nonconvex cases

Proof for Theorem 4.4

Proof. From (9) we have

$$\mathbb{E}[F(w_0^{\tau}) - F^*] + \mathbb{E}\Big[\sum_{t=1}^{\tau-1} \frac{\eta_t}{4} \|\nabla F(w_0^{(t)})\|^2\Big] \leq \Delta_1 + \frac{L^2\sigma^2}{n} \sum_{t=1}^{T} \eta_t^3 \leq 2\Delta_1. \tag{10}$$

Therefore, since $\delta \leq 1$ we have

$$\begin{aligned}
\frac{8\Delta_1}{\eta_T} &\geq \mathbb{E}\Big[\sum_{t=1}^{\tau-1} \|\nabla F(w_0^{(t)})\|^2\Big] \\
&\geq \mathbb{P}(\tau = T+1)\mathbb{E}\Big[\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 | \tau = T+1]\\
&\geq \frac{1}{2}\mathbb{E}\Big[\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 | \tau = T+1\Big].
\end{aligned}$$

By Markov's inequality and our choice of T, we have

$$\mathbb{P}\Big(\frac{1}{T}\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 > \epsilon^2 | \tau = T+1\Big) \leq \frac{16\Delta_1}{\eta_T T \epsilon^2} \leq \frac{\delta}{2}.$$

From Lemma (A.6) we have $\mathbb{P}(\tau \leq T) \leq \frac{\delta}{2}$. Therefore,

$$\begin{aligned}
&\mathbb{P}\Big(\{\frac{1}{T}\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 > \epsilon^2\} \cup \{\tau \leq T\}\Big)\\
\leq &\mathbb{P}(\tau \leq T) + \mathbb{P}\Big(\frac{1}{T}\sum_{t=1}^{T} \|\nabla F(w_0^{(t)})\|^2 > \epsilon^2 | \tau = T+1)\\
\leq &\frac{\delta}{2} + \frac{\delta}{2} = \delta.
\end{aligned}$$

Since $L = \ell(2G') = \Omega(G'^p) = \Omega(n^{\frac{p}{2}})$, with $\eta = \mathcal{O}(\sqrt[3]{\frac{n^{1-p}}{T}})$ and $T = \mathcal{O}(\frac{n^{\frac{p-1}{2}}}{\epsilon^3})$ we have the complexity. □

The following lemma is useful in the proof of arbitrary scheme.

Lemma A.7. *(lemma 6 in (Nguyen et al., 2021)) For $t < \tau$ and $0 < \eta_t \leq \frac{1}{L\sqrt{3}}$, we have*

$$\sum_{j=0}^{n-1} \|w_j^{(t)} - w_0^{(t)}\|^2 \leq n\eta_t^2[(3A+2)\|\nabla F(w_0^{(t)})\|^2 + 3\sigma^2].$$

Proof for Theorem 4.6

Proof. From inequality (6) we have for any $t < \tau$,

$$\begin{aligned}
&F(w_0^{(t+1)}) - F(w_0^{(t)}) \\
\leq &-\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta_t L^2}{2n}\sum_{k=0}^{n-1}\|w_k^{(t)} - w_0^{(t)}\|^2 \\
\leq &-\frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta_t^3 L^2[(3A+2)\|\nabla F(w_0^{(t)})\|^2 + 3\sigma^2]}{2} \\
\leq &-\frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2 + \frac{3\eta_t^3 L^2\sigma^2}{2},
\end{aligned}$$

where the second inequality is from Lemma A.7 and the last inequality is from $\eta_t \leq \frac{1}{L\sqrt{2(3A+2)}}$. Now taking summation of t from 1 to $\tau - 1$ we have

$$F(w_0^{(\tau)}) - F^* \leq F(w_0^{(\tau)}) - F^* + \sum_{t=1}^{\tau-1}\frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2 \leq \Delta_1 + \frac{3L^2\sigma^2}{2}\sum_{t=1}^{\tau-1}\eta_t^3 \leq 2\Delta_1,$$

where the last inequality is because $\tau \leq T+1$ and the choice of η_t. Therefore we have $\tau = T+1$ since $H \geq 2\Delta_1$. On the other hand, we also have

$$\begin{aligned}
\frac{8\Delta_1}{\eta_T} &\geq \sum_{t=1}^{\tau-1}\|\nabla F(w_0^{(t)})\|^2 \\
&= \sum_{t=1}^{T}\|\nabla F(w_0^{(t)})\|^2.
\end{aligned}$$

Therefore, we have

$$\frac{1}{T}\sum_{t=1}^{T}\|\nabla F(w_0^{(t)})\|^2 \leq \frac{8\Delta_1}{T\eta_T} \leq \epsilon^2$$

from our choice of T. □

A.2 Strongly Convex Case Analysis

Lemma A.8. *If we let $H \geq \frac{3\sigma^2}{4\mu}\log(\frac{4}{\epsilon}) + \Delta_1$ for some large enough $C > 0$ and $\eta_t = \eta$, we have $\tau \geq \frac{2}{\mu\eta}\log(\frac{4}{\epsilon})$.*

Proof. From inequality (6) we have for $t < \tau$

$$\begin{aligned}
F(w_0^{(t+1)}) - F(w_0^{(t)}) &\leq -\frac{\eta}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta L^2}{2n}\sum_{k=0}^{n-1}\|w_k^{(t)} - w_0^{(t)}\|^2 \\
&\leq -\frac{\eta}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{\eta^3 L^2[(3A+2)\|\nabla F(w_0^{(t)})\|^2 + 3\sigma^2]}{2} \\
&\leq \frac{3\eta\sigma^2}{8},
\end{aligned}$$

where the last inequality is from $\eta \leq \frac{1}{L\sqrt{2(3A+2)}} \leq \frac{1}{2L}$. From the definition of τ we have

$$\tau \geq 1 + \frac{8(H - \Delta_1)}{3\eta\sigma^2} \geq \frac{2}{\mu\eta}\log(\frac{4}{\epsilon}).$$

□

Proof for Theorem 4.8

Proof. From Lemma A.6 and the parameter choices we have $\mathbb{P}(\tau \le T) \le \frac{\delta}{2}$.

Now we try to bound $F(w_0^{(\tau)}) - F^*$. In the strongly convex case, for $t < \tau$ we have

$$F(w_0^{(t+1)}) \le F(w_0^{(t)}) - \frac{\eta_t}{2}\|\nabla F(w_0^{(t)})\|^2 + \frac{L^2\eta_t}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2$$

$$\le F(w_0^{(t)}) - \frac{\mu\eta_t}{2}(F(w_0^{(t)}) - F^*) - \frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2 + \frac{L^2\eta_t}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2,$$

here the first inequality is from (6) and the second one is from strongly convexity. We can rearrange the items and write the above inequality as

$$F(w_0^{(t+1)}) - F^* \le \Big(1 - \frac{\mu\eta_t}{2}\Big)(F(w_0^{(t)}) - F^*) + \frac{L^2\sigma^2\eta_t^3}{n} + A(t), \tag{11}$$

where $A(t)$ is defined as

$$A(t) := \frac{L^2\eta_t}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2 - \frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2 - \frac{L^2\sigma^2\eta_t^3}{n}. \tag{12}$$

Let $\eta_t = \eta := \frac{4\log(\sqrt{n}T)}{\mu T}$, we want $1 - \frac{\mu\eta}{2} > 0$, therefore we need $\frac{T}{\log(\sqrt{n}T)} \ge 2$. Taking expectation and summation we have

$$\begin{aligned}
\mathbb{E}[F(w_0^{(\tau)}) - F^*] &\le \mathbb{E}[(1 - \frac{\mu\eta}{2})^{\tau-1}\Delta_1] + \frac{2L^2\sigma^2\eta^2}{n\mu}[1 - (1 - \frac{\mu\eta}{2})^{\tau-1}] \\
&\quad + \mathbb{E}[\sum_{t=1}^{\tau-1}(1 - \frac{\mu\eta}{2})^{\tau-1-t}A(t)] \\
&\le \Delta_1\mathbb{E}[\exp(-\mu\eta\tau/2)] + \frac{2L^2\sigma^2\eta^2}{n\mu} + \mathbb{E}[\sum_{t=1}^{\tau-1}A(t)] \\
&\le \frac{\delta\epsilon}{8} + \frac{1}{nT^2}\Big(\Delta_1 + \frac{L^2\sigma^2\log^2(\sqrt{n}T)}{\mu^3}\Big) + \mathbb{E}[\sum_{t=1}^{\tau-1}A(t)],
\end{aligned}$$

where the second inequality is from $1 - x \le \exp(-x)$ for $x \in (0, 1)$ and the last inequality is from Lemma A.8, $\mathbb{P}(\tau \le T) \le \delta/2$ and the value of η. Now if we look at the last item, we can notice from (8), by using $\eta \le \frac{1}{L\sqrt{2(3A+2)}} \le \frac{1}{2L\sqrt{\frac{A}{n}+1}}$, that we already have

$$\mathbb{E}[\sum_{t=1}^{\tau-1}A(t)] \le 0.$$

Therefore, we have

$$\begin{aligned}
\frac{\delta\epsilon}{8} + \frac{1}{nT^2}\Big(\Delta_1 + \frac{8L^2\sigma^2\log^2(\sqrt{n}T)}{\mu^3}\Big) &\ge \mathbb{E}[F(w_0^{(\tau)}) - F^*] \\
&\ge \mathbb{P}(\tau = T+1)\mathbb{E}[F(w_0^{(T+1)}) - F^*|\tau = T+1] \\
&\ge \frac{1}{2}\mathbb{E}[F(w_0^{(T+1)}) - F^*|\tau = T+1].
\end{aligned}$$

$$\begin{aligned}
\mathbb{P}(F(w_0^{(T+1)}) - F^* > \epsilon|\tau = T+1) &\le \frac{\mathbb{E}[F(w_0^{(T+1)}) - F^*|\tau = T+1]}{\epsilon} \\
&\le \frac{\delta}{4} + \frac{2}{\epsilon nT^2}\Big(\Delta_1 + \frac{8L^2\sigma^2\log^2(\sqrt{n}T)}{\mu^3}\Big) \\
&\le \frac{\delta}{4} + \frac{\delta}{8} + \frac{\delta}{8} = \frac{\delta}{2},
\end{aligned}$$

where the last line is from the constraint on T.

□

Proof for Theorem 4.9

Proof. Similar to proof of Theorem 4.6 we have $\tau = T + 1$.

Similar to proof of Theorem 4.8 we have

$$F(w_0^{(t+1)}) - F^* \leq \Big(1 - \frac{\mu\eta_t}{2}\Big)(F(w_0^{(t)}) - F^*) + \frac{3L^2\sigma^2\eta_t^3}{2} + A(t), \tag{13}$$

and this time $A(t)$ is defined as

$$A(t) := \frac{L^2\eta_t}{2n}\sum_{j=0}^{n-1}\|w_j^{(t)} - w_0^{(t)}\|^2 - \frac{\eta_t}{4}\|\nabla F(w_0^{(t)})\|^2 - \frac{3L^2\sigma^2\eta_t^3}{2}. \tag{14}$$

From Lemma A.7 and $\eta \leq \frac{1}{\sqrt{2(3A+2)}}$ we have $A(t) \leq 0$.

Let $\eta_t = \eta := \frac{4\log(\sqrt{n}T)}{\mu T}$, similarly we have

$$\begin{aligned}
F(w_0^{(T+1)}) - F^* &\leq (1 - \frac{\mu\eta}{2})^T\Delta_1 + \frac{3L^2\sigma^2\eta^2}{2\mu}[1 - (1 - \frac{\mu\eta}{2})^T] \\
&\quad + \sum_{t=1}^{T}(1 - \frac{\mu\eta}{2})^{T-t}A(t) \\
&\leq \Delta_1\exp(-\mu\eta T/2) + \frac{3L^2\sigma^2\eta^2}{2\mu} + \sum_{t=1}^{T}A(t) \\
&\leq \frac{1}{nT^2}\Big(\Delta_1 + \frac{3nL^2\sigma^2\log^2(\sqrt{n}T)}{2\mu^3}\Big).
\end{aligned}$$

Therefore, we have $F(w_0^{(T+1)}) - F^* \leq \epsilon$ by the choice of T.

□

A.3 Non-strongly Convex Case Analysis

Proof for theorem 4.11

Proof. From Lemma A.6 we know $\mathbb{P}(\tau \leq T) < \frac{\delta}{2}$.

For $t < \tau$, if $\eta_t = \eta$, from lemma 7 in (Nguyen et al., 2021) we have that

$$\|w_0^{(t+1)} - w^*\|^2 \leq \|w_0^{(t)} - w^*\|^2 - 2\eta[F(w_0^{(t)}) - F^*] + \frac{2L\eta^3}{n^3}\sum_{i=1}^{n-1}\|\sum_{j=i}^{n-1}\nabla f(w^*;\pi_{j+1}^{(t)})\|^2, \tag{15}$$

where w^* is the optimal solution. If we denote $A(t) := \sum_{i=1}^{n-1} \| \sum_{j=i}^{n-1} \nabla f(w^*; \pi_{j+1}^{(t)})\|^2$ and let $\sigma_* := \sqrt{\frac{1}{n}\sum_{i=1}^{n} \|\nabla f(w^*; i)\|^2}$, we have that for any $t \in [T]$

$$\begin{aligned}
\mathbb{E}[A(t)] &= \sum_{i=0}^{n-1}(n-i)^2 \mathbb{E}\left[\left\|\frac{1}{n-i}\sum_{j=i}^{n-1}\nabla f(w^*; \pi_{j+1}^{(t)} - \nabla F(w^*)\right\|^2\right] \\
&= \sum_{i=0}^{n-1}\frac{(n-i)^2 i}{n(n-i)(n-1)}\sum_{j=0}^{n-1}\|\nabla f(w^*; \pi_{j+1}^{(t)})\|^2 \\
&= \frac{n(n+1)\sigma_*^2}{6}.
\end{aligned}$$

By optional stopping theorem we know that

$$\mathbb{E}\Big[\sum_{t=1}^{\tau-1}\Big(A(t) - \frac{n(n+1)\sigma_*^2}{6}\Big)\Big] = 0.$$

Taking summation from $t = 0$ to $\tau - 1$ for (15) and taking expectation we have

$$\begin{aligned}
2\eta\mathbb{E}[\sum_{t=1}^{\tau-1}(F(w_0^{(t)}) - F^*)] &\le \|w_0^{(1)} - w^*\|^2 + \frac{2L\eta^3}{n^3}\mathbb{E}[\sum_{t=1}^{\tau-1}\frac{n(n+1)\sigma_*^2}{6}] \\
&\le \|w_0^{(1)} - w^*\|^2 + \frac{2LT\eta^3\sigma_*^2}{3n},
\end{aligned}$$

where the second inequality uses $\tau \le T + 1$. Therefore, we have

$$\begin{aligned}
\frac{1}{2\eta}\Big(\|w_0^{(1)} - w^*\|^2 + \frac{2LT\eta^3\sigma_*^2}{3n}\Big) &\ge \mathbb{E}[\sum_{t=1}^{\tau-1}(F(w_0^{(t)}) - F^*)] \\
&\ge \frac{1}{2}\mathbb{E}[\sum_{t=1}^{T}(F(w_0^{(t)}) - F^*)|\tau = T+1].
\end{aligned}$$

If we define $\bar{w}_T = \frac{1}{T}\sum_{t=1}^{T} w_0^{(t)}$, from convexity we have

$$F(\bar{w}_T) - F^* \le \frac{1}{T}\sum_{t=1}^{T}[F(w_0^{(t)}) - F^*].$$

Consider the event $\mathcal{F} := \{F(\bar{w}_T) - F^* > \epsilon\}$, we have

$$\begin{aligned}
\mathbb{P}(\mathcal{F}|\tau = T+1) &\le \mathbb{P}(\frac{1}{T}\sum_{t=1}^{T}(F(w_0^{(t)}) - F^*) > \epsilon|\tau = T+1) \\
&\le \frac{\mathbb{E}\left[\sum_{t=1}^{T}(F(w_0^{(t)}) - F^*)|\tau = T+1\right]}{T\epsilon} \\
&\le \frac{1}{\eta T\epsilon}\Big(\|w_0^{(1)} - w^*\|^2 + \frac{2LT\eta^3\sigma_*^2}{3n}\Big) \\
&\le \frac{2}{\eta T\epsilon}\|w_0^{(1)} - w^*\|^2 \\
&\le \frac{\delta}{2},
\end{aligned}$$

where the last two inequalities are from the choices of η and T, separately. □

Proof for Theorem 4.12

Proof. Similar to proof of Theorem 4.6 we have $\tau = T + 1$.

From (15), by Assumption 4.3 we have

$$\|w_0^{(t+1)} - w^*\|^2 \leq \|w_0^{(t)} - w^*\|^2 - 2\eta[F(w_0^{(t)}) - F^*] + \frac{2L\eta^3}{n^3}\sum_{i=1}^{n-1}(n-i)^2\sigma^2.$$

Taking summation from $t = 0$ to $T - 1$, notice that $\sum_{i=1}^{n-1} i^2 \leq \frac{n^3}{2}$ we have

$$2\eta\sum_{t=1}^{T}(F(w_0^{(t)}) - F^*) \leq \|w_0^{(1)} - w^*\|^2 + LT\eta^3\sigma^2.$$

Therefore we have

$$F(\bar{w}_T) - F^* \leq \sum_{t=1}^{T}(F(w_0^{(t)}) - F^*) \leq \frac{1}{2\eta T}\Big(\|w_0^{(1)} - w^*\|^2 + LT\eta^3\sigma^2\Big) \leq \epsilon.$$

□