OPT-AMSGrad: An Optimistic Acceleration of AMSGrad for Nonconvex Optimization

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Abstract

In this paper, we propose a new variant of AMSGrad [31], a popular adaptive gradient based optimization algorithm widely used in training deep neural networks. Our algorithm adds prior knowledge about the sequence of consecutive mini-batch gradients and leverages its underlying structure making the gradients sequentially predictable. By exploiting the predictability and ideas from Optimistic Online Learning, the proposed algorithm can accelerate the convergence and increase sample efficiency. After establishing a tighter upper bound under some convexity conditions on the regret, we offer a complimentary view of our algorithm which generalizes the offline and stochastic versions of nonconvex optimization. In the nonconvex case, we establish a $\mathcal{O}\left(\sqrt{d/T} + d/T\right)$ non-asymptotic bound independent of the initialization of the method. We illustrate the practical speedup on several deep learning models through numerical experiments.

1 Introduction

Deep learning models have been successful in several applications, from robotics (e.g. [21]), computer vision (e.g [18, 15]), reinforcement learning (e.g. [25]), to natural language processing (e.g. [16]). With the sheer size of modern data sets and the dimension of neural networks, speeding up training is of utmost importance. To do so, several algorithms have been proposed in recent years, such as AMSGRAD [31], ADAM [19], RMSPROP [35], ADADELTA [41], and NADAM [10].

All the prevalent algorithms for training deep networks mentioned above combine two ideas: the idea of adaptivity from ADAGRAD [11, 23] and the idea of momentum from NESTEROV'S METHOD [27] or HEAVY BALL method [28]. ADAGRAD is an online learning algorithm that works well compared to the standard online gradient descent when the gradient is sparse. Its update has a notable feature: it leverages an anisotropic learning rate depending on the magnitude of gradient in each dimension which helps in exploiting the geometry of data. On the other hand, NESTEROV'S METHOD or HEAVY BALL Method [28] is an accelerated optimization algorithm which update not only depends on the current iterate and current gradient but also depends on the past gradients (i.e. momentum). State-of-the-art algorithms like AMSGRAD [31] and ADAM [19] leverage these ideas to accelerate the training of nonconvex objective functions such as deep neural networks losses.

In this paper, we propose an algorithm that goes further than the hybrid of the adaptivity and momentum approach. Our algorithm is inspired by OPTIMISTIC ONLINE LEARNING [7, 29, 34, 1, 24], which assumes that, in each round of online learning, a *predictable process* of the gradient of the loss function is available. Then an action is played exploiting these predictors. By capitalizing on this (possibly) arbitrary process, algorithms in OPTIMISTIC ONLINE LEARNING enjoy smaller regret than the ones without. We combine the OPTIMISTIC ONLINE LEARNING idea with the adaptivity and the momentum ideas to design a new algorithm — OPT-AMSGRAD.

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A single work along that direction stands out. [8] develops Optimistic-Adam leveraging optimistic online mirror descent [30]. Yet, Optimistic-Adam is specifically designed to optimize two-player games, e.g. GANs [15] which is in particular a two-player zero-sum game. There have been some related works in Optimistic Online learning like [7, 30, 34] showing that if both players use an Optimistic type of update, then accelerating the convergence to the equilibrium of the game is possible. [8] was inspired by these related works and showed that Optimistic-Mirror-Descent can avoid the cycle behavior in a bilinear zero-sum game, which accelerates the convergence. In contrast, in this paper, the proposed algorithm is designed to accelerate nonconvex optimization (e.g. empirical risk minimization). To the best of our knowledge, this is the first work exploring towards this direction and bridging the unfilled *theoretical* gap at the crossroads of online learning and stochastic optimization. The contributions of this paper are as follows:

- We derive an optimistic variant of AMSGrad borrowing techniques from online learning procedures. Our method relies on (I) the addition of *prior knowledge* in the sequence of the model parameter estimations alleviating a predictable process able to provide guesses of gradients of the loss functions through the iterations and (II) the construction of a *double update* algorithm done sequentially. We interpret this two-projection step as the learning of both the global parameter and an underlying scheme which makes the gradients sequentially predictable.
- We focus on the *theoretical* justifications of our method by establishing novel *non-asymptotic* and *global* convergence rates in both the convex and nonconvex cases. Based on *convex regret minimization* and *nonconvex stochastic optimization* views, we prove, respectively, that our algorithm suffers regret of $\mathcal{O}\left(\sqrt{\sum_{t=1}^{T} \|g_t - m_t\|^2_{\psi_{t-1}}}\right)$ and achieves a rate of convergence $\mathcal{O}\left(\sqrt{d/T} + d/T\right)$.

The proposed algorithm not only adapts to the informative dimensions, exhibits momentum, but also exploits a good guess of the next gradient to facilitate acceleration. Besides the global analysis of OPT-AMSGrad, we conduct experiments and show that the proposed algorithm not only accelerates the training procedure, but also leads to better empirical generalization performance.

Section 2 is devoted to introductory notions on online learning for regret minimization and adaptive learning methods for nonconvex stochastic optimization. We introduce in Section 3 our new algorithm, namely OPT-AMSGrad and provide a comprehensive global analysis in both *convex/online* and *nonconvex/offline* settings in Section 4. We illustrate the benefits of our method on several finite-sum nonconvex optimization problems in Section 5. The supplementary material of this paper is devoted to the proofs of our theoretical results.

Notations: We follow the notations in related adaptive optimization papers [19, 31]. For any vector $u, v \in \mathbb{R}^d$, u/v represents element-wise division, u^2 represents element-wise square, $\sqrt{u}$ represents element-wise square-root. We denote $g_{1:T}[i]$ as the sum of the i_{th} element of $g_1, g_2, \ldots, g_T \in \mathbb{R}^d$.

2 Preliminaries

Optimistic Online learning. The standard setup of Online learning is that, in each round t, an online learner selects an action $w_t \in \Theta \subseteq \mathbb{R}^d$, observes $\ell_t(\cdot)$ and suffers the associated loss $\ell_t(w_t)$ after the action is committed. The goal of the learner is to minimize the regret,

$$\mathcal{R}_T(\{w_t\}) := \sum_{t=1}^{T} \ell_t(w_t) - \sum_{t=1}^{T} \ell_t(w^*) \ ,$$

which is the cumulative loss of the learner minus the cumulative loss of some benchmark $w^* \in \Theta$. The idea of Optimistic Online learning (e.g. [7, 29, 34, 1]) is as follows. In each round t, the learner exploits a guess $m_t(\cdot)$ of the gradient $\nabla \ell_t(\cdot)$ of the loss function to choose an action w_t[1]. Consider the Follow-the-Regularized-Leader (FTRL, [17]) online learning algorithm which update reads

$$w_t = \arg\min_{w \in \Theta} \langle w, L_{t-1} \rangle + \tfrac{1}{\eta} \mathsf{R}(w) \ , \tag{1}$$

[1] Imagine that if the learner would have known $\nabla \ell_t(\cdot)$ (*i.e.,* exact guess) before committing its action, then it would exploit the knowledge to determine its action and consequently minimize the regret.

where η is a parameter, $\mathsf{R}(\cdot)$ is a 1-strongly convex function with respect to a given norm on the constraint set Θ, and $L_{t-1} := \sum_{s=1}^{t-1} g_s$ is the cumulative sum of gradient vectors of the loss functions up to round $t-1$. It has been shown that FTRL has regret at most $O(\sqrt{\sum_{t=1}^{T} \|g_t\|_*^2})$. The update of its optimistic variant, noted OPTIMISTIC-FTRL and developed in [34] reads

$$w_t = \arg\min_{w \in \Theta} \langle w, L_{t-1} + m_t \rangle + \frac{1}{\eta} \mathsf{R}(w) \ , \tag{2}$$

where $\{m_t\}_{t>0}$ is a predictable process incorporating (possibly arbitrarily) knowledge about the sequence of gradients $\{g_t := \nabla \ell_t(w_t)\}_{t>0}$. Under the assumption that loss functions are convex, the regret of OPTIMISTIC-FTRL is at most $O(\sqrt{\sum_{t=1}^{T} \|g_t - m_t\|_*^2})$.

Remark: Note that the usual worst-case bound is preserved even when the predictors $\{m_t\}_{t>0}$ do not predict well the gradients. Indeed, if we take the example of OPTIMISTIC-FTRL, the bound reads $\sqrt{\sum_{t=1}^{T} \|g_t - m_t\|_*^2} \leq 2 \max\limits_{w \in \Theta} \|\nabla \ell_t(w)\| \sqrt{T}$ which is equal to the usual bound up to a factor 2. Yet, when the predictions are well designed, the regret will be lower. We will have a similar argument when we compare OPT-AMSGRAD and AMSGRAD.

We emphasize in Section 3 the importance of leveraging a good guess m_t for updating w_t in order to get a fast convergence rate (or equivalently, small regret) and present Section 5 a simple, yet effective, predictable process $\{m_t\}_{t>0}$ leading to empirical acceleration.

Adaptive optimization methods. Adaptive optimization has been popular in various deep learning applications due to their superior empirical performance. ADAM [19], a popular adaptive algorithm, combines momentum [28] and anisotropic learning rate of ADAGRAD [11]. More specifically, the learning rate of ADAGRAD at time t for dimension j is proportional to the inverse of $\sqrt{\Sigma_{s=1}^{t} g_s[j]^2}$, where $g_s[j]$ is the j-th element of the gradient vector g_s at time s. This adaptive learning rate helps accelerating the convergence when the gradient vector is sparse [11] but, when applying ADAGRAD to train deep networks, it is observed that the learning rate might decay too fast [19]. Therefore, [19] proposes ADAM that uses a moving average of gradients divided by the square root of the second moment of the moving average (element-wise multiplication), for updating the model parameter w. A variant, called AMSGRAD and detailed in Algorithm 1, has been developed in [31] to fix ADAM failures. The difference between ADAM and AMSGRAD lies in line 7 of Algorithm 1. AMSGRAD [31] adds the `max` operation to guarantee a non-increasing learning rate $\frac{\eta_t}{\sqrt{\hat{v}_t}}$, which helps for the convergence (i.e. average regret $\mathcal{R}_T/T \to 0$).

Algorithm 1 AMSGRAD [31]

1: Required: parameter β_1, β_2, and η_t.
2: Init: $w_1 \in \Theta \subseteq \mathbb{R}^d$ and $v_0 = \epsilon 1 \in \mathbb{R}^d$.
3: **for** $t = 1$ to T **do**
4: Get mini-batch stochastic gradient g_t at w_t.
5: $\theta_t = \beta_1 \theta_{t-1} + (1 - \beta_1) g_t$.
6: $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$.
7: $\hat{v}_t = \max(\hat{v}_{t-1}, v_t)$.
8: $w_{t+1} = w_t - \eta_t \frac{\theta_t}{\sqrt{\hat{v}_t}}$. (element-wise division)
9: **end for**

3 OPT-AMSGRAD Algorithm

We formulate in this section the proposed optimistic acceleration of AMSGrad, noted OPT-AMSGRAD, and detailed in Algorithm 2. It combines the idea of adaptive optimization with optimistic learning. At each iteration, the learner computes a gradient vector $g_t := \nabla \ell_t(w_t)$ at w_t (line 4), then it maintains an exponential moving average of $\theta_t \in \mathbb{R}^d$ (line 5) and $v_t \in \mathbb{R}^d$ (line 6), which is followed by the `max` operation to get $\hat{v}_t \in \mathbb{R}^d$ (line 7). The learner first updates an auxiliary variable $\tilde{w}_{t+1} \in \Theta$ (line 8) and then computes the next model parameter w_{t+1} (line 9). Observe that the proposed algorithm does not reduce to AMSGRAD when $m_t = 0$, contrary to the optimistic variant of FTRL. Furthermore, combining line 8 and line 9 yields the following single update $w_{t+1} = \tilde{w}_t - \eta_t(\theta_t + h_{t+1})/\sqrt{\hat{v}_t}$.

Compared to AMSGRAD, the algorithm is characterized by a *two-level* update that interlinks some *auxiliary state* $\tilde{w}_t$ and the model parameter state, w_t, similarly to the OPTIMISTIC MIRROR DESCENT algorithm developed in [29]. It leverages the auxiliary variable (hidden model) to update and commit w_{t+1}, which exploits the guess m_{t+1}, see Figure 1. In the following analysis, we show that the interleaving actually leads to some cancellation in the regret bound. Such two-levels method where the guess m_t is equal to the last known gradient g_{t-1} has been exhibited recently in [7]. The gradient prediction process plays an important role as discussed Section 5.

Algorithm 2 OPT-AMSGRAD

1: Required: parameter β_1, β_2, ϵ, and η_t.
2: Init: $w_1 = w_{-1/2} \in \Theta \subseteq \mathbb{R}^d$ and $v_0 = \epsilon 1 \in \mathbb{R}^d$.
3: **for** $t = 1$ to T **do**
4: Get mini-batch stochastic gradient g_t at w_t.
5: $\theta_t = \beta_1 \theta_{t-1} + (1 - \beta_1) g_t$.
6: $v_t = \beta_2 v_{t-1} + (1 - \beta_2) g_t^2$.
7: $\hat{v}_t = \max(\hat{v}_{t-1}, v_t)$.
8: $\tilde{w}_{t+1} = \tilde{w}_t - \eta_t \frac{\theta_t}{\sqrt{\hat{v}_t}}$.
9: $w_{t+1} = \tilde{w}_{t+1} - \eta_t \frac{h_{t+1}}{\sqrt{\hat{v}_t}}$,
where $h_{t+1} := \beta_1 \theta_{t-1} + (1 - \beta_1) m_{t+1}$ and m_{t+1} is the guess of g_{t+1}.
10: **end for**

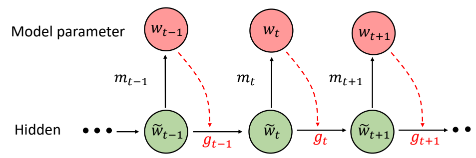

Figure 1: OPT-AMSGRAD UNDERLYING STRUCTURE.

The proposed OPT-AMSGRAD inherits three properties:

- Adaptive learning rate of each dimension as ADAGRAD [11]. (line 6, line 8 and line 9)
- Exponential moving average of the past gradients as NESTEROV'S METHOD [27] and the HEAVY-BALL method [28]. (line 5)
- Optimistic update that exploits *prior knowledge* of the next gradient vector as in optimistic online learning algorithms [7, 29, 34]. (line 9)

The first property helps for acceleration when the gradient has a sparse structure. The second one is from the long-established idea of momentum which can also help for acceleration. The last one can lead to an acceleration when the prediction of the next gradient is good as mentioned above when introducing the regret bound for the OPTIMISTIC-FTRL algorithm. This property will be elaborated whilst establishing the theoretical analysis of OPT-AMSGRAD.

4 Global Convergence of OPT-AMSGRAD

For conciseness, we place all the proofs of the following results in the supplementary material.

Notations. We denote the Mahalanobis norm $\|\cdot\|_H := \sqrt{\langle \cdot, H \cdot \rangle}$ for some positive semidefinite (PSD) matrix H. We let $\psi_t(x) := \langle x, \mathrm{diag}\{\hat{v}_t\}^{1/2} x \rangle$ for a PSD matrix $H_t^{1/2} := \mathrm{diag}\{\hat{v}_t\}^{1/2}$, where $\mathrm{diag}\{\hat{v}_t\}$ represents the diagonal matrix which i_{th} diagonal element is $\hat{v}_t[i]$ defined in Algorithm 2. We define its corresponding Mahalanobis norm $\|\cdot\|_{\psi_t} := \sqrt{\langle \cdot, \mathrm{diag}\{\hat{v}_t\}^{1/2} \cdot \rangle}$, where we abuse the notation ψ_t to represent the PSD matrix $H_t^{1/2} := \mathrm{diag}\{\hat{v}_t\}^{1/2}$. Note that $\psi_t(\cdot)$ is 1-strongly convex with respect to the norm $\|\cdot\|_{\psi_t}$. Namely, $\psi_t(\cdot)$ satisfies $\psi_t(u) \geq \psi_t(v) + \langle \psi_t(v), u - v \rangle + \frac{1}{2}\|u - v\|_{\psi_t}^2$ for any point $(u, v) \in \Theta^2$. A consequence of 1-strongly convexity of $\psi_t(\cdot)$ is that $B_{\psi_t}(u, v) \geq \frac{1}{2}\|u - v\|_{\psi_t}^2$, where the Bregman divergence $B_{\psi_t}(u, v)$ is defined as $B_{\psi_t}(u, v) := \psi_t(u) - \psi_t(v) - \langle \psi_t(v), u - v \rangle$ with $\psi_t(\cdot)$ as the distance generating function. We also define the corresponding dual norm $\|\cdot\|_{\psi_t^*} := \sqrt{\langle \cdot, \mathrm{diag}\{\hat{v}_t\}^{-1/2} \cdot \rangle}$.

4.1 Convex Regret Analysis

In this section, we assume that the loss functions $\{\ell_t\}_{t>0}$ are convex. We also assume that Θ has bounded diameter D_∞, which is a standard assumption in previous works [31, 19] on adaptive methods. It is necessary in regret analysis since if the boundedness assumption is lifted, one might construct a scenario such that the benchmark is $w^* = \infty$ and the learner's regret is infinite.

Theorem 1. *Suppose the learner incurs a sequence of convex loss functions $\{\ell_t(\cdot)\}$. Then,* OPT-AMSGRAD *(Algorithm 2) has regret*

$$\mathcal{R}_T \leq \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - \tilde{m}_t\|_{\psi_{t-1}^*}^2 + \frac{D_\infty^2}{\eta_{\min}} \sum_{i=1}^{d} \hat{v}_T^{1/2}[i] + D_\infty^2 \beta_1^2 \sum_{t=1}^{T} \|g_t - \theta_{t-1}\|_{\psi_{t-1}^*}, \tag{3}$$

where $\tilde{m}_{t+1} = \beta_1 \theta_{t-1} + (1 - \beta_1) m_{t+1}$, $g_t := \nabla \ell_t(w_t)$, $\eta_{\min} := \min_t \eta_t$ and D_∞^2 is the diameter of the bounded set Θ. The result holds for any benchmark $w^* \in \Theta$ and any step size sequence $\{\eta_t\}_{t>0}$.

Corollary 1. *Suppose $\beta_1 = 0$ and $\{v_t\}_{t>0}$ is an increasing monotone sequence, then we obtain the following regret bound for any $w^* \in \Theta$ and sequence of stepsizes $\{\eta_t = \eta/\sqrt{t}\}_{t>0}$:*

$$\mathcal{R}_T \leq \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \frac{\eta\sqrt{1+\log T}}{\sqrt{1-\beta_2}} \sum_{i=1}^{d} \|(g-m)_{1:T}[i]\|_2 + \frac{D_\infty^2}{\eta_{\min}} \sum_{i=1}^{d} \left[(1-\beta_2)\sum_{s=1}^{T} \beta_2^{T-s} g_s[i]^2\right]^{1/2},$$

where $g_t := \nabla \ell_t(w_t)$ and $\eta_{\min} := \min_t \eta_t$.

We can compare the bound of Corollary 1 with that of AMSGRAD [31] with $\eta_t = \eta/\sqrt{t}$:

$$\mathcal{R}_T \leq \frac{\eta\sqrt{1+\log T}}{\sqrt{1-\beta_2}} \sum_{i=1}^{d} \|g_{1:T}[i]\|_2 + \frac{\sqrt{T}}{2\eta} D_\infty^2 \sum_{i=1}^{d} \hat{v}_T[i]^2 \,. \tag{4}$$

For convex regret minimization, the results above yields that the learner suffers regret of $\mathcal{O}(\sqrt{\sum_{t=1}^{T} \|g_t - m_t\|^2_{\psi_{t-1}^*}})$ with an access to an arbitrary predictable process $\{m_t\}_{t>0}$ of the mini-batch gradients. The better the predictors, the lower the regret, see the second term in Corollary 1 compared to the first term in (4). The construction of the predictable process $\{m_t\}_{t>0}$ is thus of utmost importance for achieving optimal acceleration and can be learned through the iterations. We will not deal with the latter in this paper for the sake of page limit. Though, for implementation purposes, we derive a simple, yet effective, gradient prediction algorithm, see Algorithm 3 in Section 5, embedded in our OPT-AMSGRAD algorithm.

4.2 Nonconvex Analysis (Finite-Time Upper Bound)

We discuss the offline and stochastic nonconvex optimization properties of our online framework. As stated in the Introduction, this paper is about solving optimization problems instead of solving zero-sum games. Classically, the problem we are tackling reads:

$$\min_{w \in \Theta} f(w) := \mathbb{E}[f(w,\xi)] = n^{-1} \sum_{i=1}^{n} \mathbb{E}[f(w,\xi_i)] \,, \tag{5}$$

for a fixed batch of n samples $\{\xi_i\}_{i=1}^n$. The objective function $f(w)$ is (potentially) nonconvex and has Lipschitz gradients. Set the terminating number, $T \in \{0, \ldots, T_{\mathsf{max}} - 1\}$, as a discrete r.v. with:

$$P(T = \ell) = \frac{\eta_\ell}{\sum_{j=0}^{T_{\mathsf{max}}-1} \eta_j} \,, \tag{6}$$

where T_{max} is the maximum number of iteration. The random termination number (6) is inspired by [14] and is widely used for nonconvex optimization. Assume:

H1. *For any $t > 0$, the estimated weight w_t stays within a $\ell_\infty-$ball. There exists a constant $W > 0$ such that $\|w_t\| \leq W$ almost surely.*

H2. *The function f is L-smooth (has L-Lipschitz gradients) w.r.t. the parameter w. There exists some constant $L > 0$ such that for $(w, \vartheta) \in \Theta^2$:*

$$f(w) - f(\vartheta) - \nabla f(\vartheta)^\top (w - \vartheta) \leq \frac{L}{2} \|w - \vartheta\|^2 \,.$$

We assume that the optimistic guess m_t at iteration t and the true gradient g_t are correlated:

H3. *There exists a constant $a \in \mathbb{R}$ such that for any $t > 0$, $\langle m_t \,|\, g_t \rangle \leq a\|g_t\|^2$.*

Classically in nonconvex optimization [14] we make an assumption on the magnitude of the gradient:

H4. *There exists a constant $\mathsf{M} > 0$ such that for any w and ξ, it holds $\|\nabla f(w,\xi)\| < \mathsf{M}$.*

We now derive needed auxiliary Lemmas for our global analysis. The first one ensures bounded norms of quantities of interests (resulting from the bounded stochastic gradient assumption):

Lemma 1. *Assume assumption H4, then the quantities defined in Algorithm 2 satisfy for any $w \in \Theta$ and $t > 0$, $\|\nabla f(w_t)\| < \mathsf{M}$, $\|\theta_t\| < \mathsf{M}$ and $\|\hat{v}_t\| < \mathsf{M}^2$.*

Then, following [39] and their study of the SGD with Momentum we denote for any $t > 0$:

$$\overline{w}_t = w_t + \frac{\beta_1}{1-\beta_1}(w_t - \tilde{w}_{t-1}) = \frac{1}{1-\beta_1} w_t - \frac{\beta_1}{1-\beta_1}\tilde{w}_{t-1} \ , \tag{7}$$

Lemma 2. *Assume a strictly positive and non increasing sequence of stepsizes $\{\eta_t\}_{t>0}$, $\beta_1 < \beta_2 \in [0, 1)$, then the following holds:*

$$\overline{w}_{t+1} - \overline{w}_t \leq \frac{\beta_1}{1-\beta_1}\tilde{\theta}_{t-1}\left[\eta_{t-1}\hat{v}_{t-1}^{-1/2} - \eta_t \hat{v}_t^{-1/2}\right] - \eta_t \hat{v}_t^{-1/2}\tilde{g}_t \ ,$$

where $\tilde{\theta}_t = \theta_t + \beta_1\theta_{t-1}$ and $\tilde{g}_t = g_t - \beta_1 m_t + \beta_1 g_{t-1} + m_{t+1}$.

Lemma 3. *Assume H4, a strictly positive and a sequence of constant stepsizes $\{\eta_t\}_{t>0}$, $\beta_1 < \beta_2 \in [0, 1)$, denote $\gamma = \beta_1/\beta_2$, then the following holds:*

$$\sum_{k=1}^{T_{\mathsf{max}}} \eta_t^2 \mathbb{E}\left[\left\|\hat{v}_t^{-1/2}\theta_t\right\|_2^2\right] \leq \frac{\eta^2 d T_{\mathsf{max}}(1-\beta_1)}{(1-\beta_2)(1-\gamma)} \ .$$

We now formulate the main result of our paper giving a finite-time upper bound of the suboptimality condition $\mathbb{E}\left[\|\nabla f(w_T)\|^2\right]$ as the convergence criterion of interest, see [14].

Theorem 2. *Assume H1-H4, $\beta_1 < \beta_2 \in [0, 1)$ and a sequence of decreasing stepsizes $\{\eta_t\}_{t>0}$, then the following result holds:*

$$\mathbb{E}\left[\|\nabla f(w_T)\|^2\right] \leq \tilde{C}_1\sqrt{\frac{d}{T_{\mathsf{max}}}} + \tilde{C}_2\frac{1}{T_{\mathsf{max}}} \ , \tag{8}$$

where T is a random termination number distributed according (6). The constants are defined as:

$$\tilde{C}_1 = C_1 + \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\left[\frac{a(1-\beta_1)^2}{1-\beta_2} + 2L\frac{1}{1-\beta_2} + \Delta f + \frac{4L\beta_1^2(1+\beta_1^2)}{(1-\beta_1)(1-\beta_2)(1-\gamma)}\right]$$
$$\tilde{C}_2 = \frac{(a\beta_1^2 - 2a\beta_1 + \beta 1)\mathsf{M}^2}{(1-\beta_1)\left((1-a\beta_1)+(\beta_1+a)\right)}\mathbb{E}\left[\left\|\hat{v}_0^{-1/2}\right\|\right]$$

We remark that the bound for our OPT-AMSGrad method matches the complexity bound of $\mathcal{O}\left(\sqrt{d/T_{\mathsf{max}}} + 1/T_{\mathsf{max}}\right)$ of [14] for SGD and [43] for AMSGrad method.

Checking H1 for a Deep Neural Network: Boundedness assumption is generally hard to verify. We show here that the weights satisfy assumption H1 and indeed stay in a bounded set when the model being trained, using our method, is a fully connected feed forward neural network. The activation function for this section will be sigmoid function and we use a ℓ_2 regularization. We consider a fully connected feed forward neural network with L layers modeled by the function $\mathsf{MLN}(w, \xi) : \Theta^d \times \mathbb{R}^p \to \mathbb{R}$:

$$\mathsf{MLN}(w, \xi) = \sigma\left(w^{(L)}\sigma\left(w^{(L-1)}\ldots\sigma\left(w^{(1)}\xi\right)\right)\right) \tag{9}$$

where $w = [w^{(1)}, w^{(2)}, \cdots, w^{(L)}]$ is the vector of parameters, $\xi \in \mathbb{R}^p$ is the input data and σ is the sigmoid activation function. We assume a p dimension input data and a scalar output for simplicity. The stochastic objective function (5) reads:

$$f(w, \xi) = \mathcal{L}(\mathsf{MLN}(w, \xi), y) + \frac{\lambda}{2}\|w\|^2 \tag{10}$$

where $\mathcal{L}(\cdot, y)$ is the loss function (can be Huber loss or cross entropy), y are the true labels and $\lambda > 0$ is the regularization parameter. For any index $\ell \in [1, L]$ we denote the output of layer ℓ by

$$h^{(\ell)}(w, \xi) = \sigma\left(w^{(\ell)}\sigma\left(w^{(\ell-1)}\ldots\sigma\left(w^{(1)}\xi\right)\right)\right) \ .$$

The following Lemma proves that assumption H1 is satisfied with a feed forward neural net (9):

Lemma 4. *Given the multilayer model (9), assume the boundedness of the input data and of the loss function,* i.e., *for any $\xi \in \mathbb{R}^p$ and $y \in \mathbb{R}$ there is a constant $T > 0$ such that $\|\xi\| \leq 1$ a.s. and $|\mathcal{L}'(\cdot, y)| \leq T$ where $\mathcal{L}'(\cdot, y)$ denotes its derivative* w.r.t. *the parameter. Then for each layer $\ell \in [1, L]$, there exist a constant $A_{(\ell)}$ such that $\left\|w^{(\ell)}\right\| \leq A_{(\ell)}$*

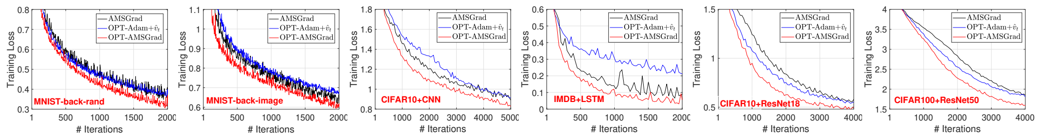

Figure 2: Training loss vs. Number of iterations. The first row are results with fully connected NN.

5 Numerical Experiments

5.1 Gradient Estimation

Some classical works in gradient prediction methods include ANDERSON acceleration [37], MINIMAL POLYNOMIAL EXTRAPOLATION [4], REDUCED RANK EXTRAPOLATION [12]. These methods aims at finding a fixed point g^* and assumes that the sequence $\{g_t\} \in \mathbb{R}^d$ has a linear relation as follows:

$$g_t - g^* = A(g_{t-1} - g^*) + e_t, \tag{11}$$

where e_t is a second order term satisfying $\|e_t\|_2 = O(\|g_{t-1} - g^*\|_2^2)$ and $A \in \mathbb{R}^{d \times d}$ is an unknown matrix, see [32] for details and results. For our numerical experiments, we run OPT-AMSGRAD using Algorithm 3 to construct the sequence $\{m_t\}_{t>0}$ and based on estimating the limit of a sequence using the last iterates [3]. Specifically, at iteration t, m_t is obtained by (a) calling Al-

Algorithm 3 REGULARIZED APPROXIMATE MINIMAL POLYNOMIAL EXTRAPOLATION [32]

1: **Input:** sequence $\{g_s \in \mathbb{R}^d\}_{s=0}^{s=r-1}$, parameter $\lambda > 0$.
2: Compute matrix $U = [g_1 - g_0, \dots, g_r - g_{r-1}] \in \mathbb{R}^{d \times r}$.
3: Obtain z by solving $(U^\top U + \lambda I)z = \mathbf{1}$.
4: Get $c = z/(z^\top \mathbf{1})$.
5: **Output:** $\Sigma_{i=0}^{r-1} c_i g_i$, the approximation of the fixed point g^*.

gorithm 3 with input being a sequence of past r gradients, $\{g_{t-1}, g_{t-2}, \dots, g_{t-r}\}$ and (b) setting $m_t := \Sigma_{i=0}^{r-1} c_i g_{t-r+i}$ where $c = [c_0, \dots, c_{r-1}]$ is obtained by Algorithm 3. To see why the output from the extrapolation method may be a reasonable estimation, assume that the update converges to a stationary point (i.e. $g^* := \nabla f(w^*) = 0$ for the underlying function f). Then, we might rewrite (11) as $g_t = Ag_{t-1} + O(\|g_{t-1}\|_2^2)u_{t-1}$, for some unit vector u_{t-1}. The equation suggests that the next gradient vector g_t is a linear transform of g_{t-1} plus an error vector that may not be in the span of A.If the algorithm is guaranteed to converge to a stationary point, the magnitude of the error component will eventually go to zero.

Computational cost. This extrapolation step consists in: (a) Constructing the linear system $(U^\top U)$ which cost can be optimized to $\mathcal{O}(d)$, since the matrix U only changes one column at a time. (b) Solving the linear system which cost is $O(r^3)$, and is negligible for a small r used in practice. (c) Outputting a weighted average of previous gradients which cost is $\mathcal{O}(r \times d)$ yielding a computational overhead of $\mathcal{O}\left((r+1)d + r^3\right)$. Yet, steps (a) and (c) are parallelizable in the final implementation.

5.2 Classification Experiments

In this section, we provide experiments on classification tasks with various neural network architectures and datasets to demonstrate the effectiveness of OPT-AMSGRAD.

Methods. We consider two baselines. The first one is the original AMSGRAD. The hyper-parameters are set to be $\beta_1 = 0.9$ and $\beta_2 = 0.999$, see [31]. The other benchmark method is the OPTIMISTIC-ADAM+$\hat{v}_t$ [8], which details are reported to the Supplementary Material. We use cross-entropy loss, a mini-batch size of 128 and tune the learning rates over a fine grid and report the best result for all methods. For OPT-AMSGRAD, we use $\beta_1 = 0.9$ and $\beta_2 = 0.999$ and the best step size η of AMSGRAD for a fair evaluation of the optimistic step. OPT-AMSGRAD has an additional parameter r that controls the number of previous gradients used for gradient prediction. In the sequel, we use $r = 5$ past gradient for empirical reasons, see Section 5.3. In all experiments, the algorithms are initialized at the same point and the results are averaged over 5 repetitions.

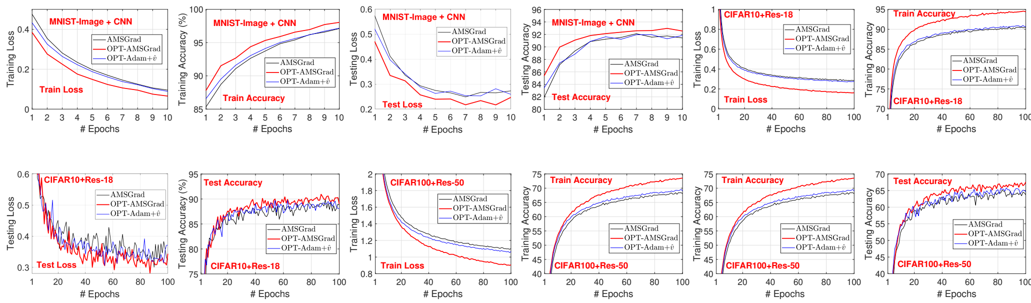

Figure 3: *MNIST-back-image* + CNN, *CIFAR10* + Res-18 and *CIFAR100* + Res-50 . We compare three methods in terms of training (cross-entropy) loss and accuracy, testing loss and accuracy.

Datasets. We compare different algorithms on *MNIST*, *CIFAR10*, *CIFAR100*, and *IMDB* datasets. For *MNIST*, we use two noisy variants named as *MNIST-back-rand* and *MNIST-back-image* from [20] ($n = 12\,000$), *CIFAR10* and *CIFAR100* ($n = 50\,000$) and *IMDB* ($n = 25\,000$).

Network architecture. We adopt a multi-layer fully connected neural network with hidden layers of 200 then 100 neurons (using ReLU activations and Softmax output) on *MNIST* variants. For CIFAR datasets, we adopt ALL-CNN network proposed by [33], built with convolutional blocks and dropout layers. In addition, we train Resnet-18 and Resnet-50 [18] achieving SOTA. For the texture *IMDB* dataset, we consider a Long-Short Term Memory (LSTM) network [13] including a word embedding layer with 5 000 input entries representing most frequent words embedded into a 32 dimensional space. The output of the embedding layer is passed to 100 LSTM units then connected to 100 fully connected ReLU layers.

Results. Firstly, to illustrate the acceleration effect of OPT-AMSGRAD at early stage, we provide the training loss against number of iterations in Figure 2. We clearly observe that on all datasets, the proposed OPT-AMSGRAD converges faster than the other competing methods since fewer iterations are required to achieve the same precision validating one of the main edges of OPT-AMSGRAD. We are also curious about the long-term performance and generalization of the proposed method in test phase. In Figure 3, we plot the results when the model is trained until the test accuracy stabilize. We observe: (1) In the long term, OPT-AMSGRAD algorithm may converge to a better point with smaller objective function value, and (2) In this three applications, the proposed OPT-AMSGRAD also outperforms the competing methods in terms of test accuracy.

5.3 Choice of parameter r

Since the number of past gradients r is important in our algorithm we compare Figure 4 the performance under different values $r = 3, 5, 10$ on two datasets. From the result we see that the choice of r does not have significant impact on the training loss. Taking into consideration both quality of gradient prediction and computational cost, $r = 5$ is a good choice for most applications here. We remark that empirically, the performance comparison among $r = 3, 5, 10$ is not absolutely consistent (i.e. more means better) in all cases. One possible reason is that for deep neural networks, the high diversity of gradients computed through the iterations, due to the nonconvexity of the loss, makes most of them inefficient for the predictable process $\{m_t\}_{t>0}$. Only recent ones ($r \leq 5$) are useful.

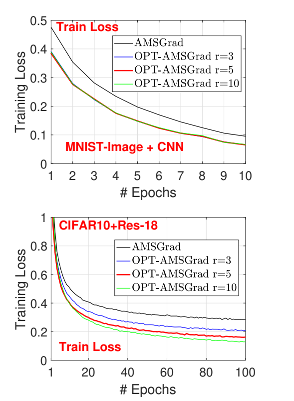

Figure 4: Training loss w.r.t. r.

6 Conclusion

In this paper, we propose OPT-AMSGRAD, which combines optimistic learning and AMSGRAD to improve sampling efficiency and accelerate the process of training, in particular for deep neural networks. With a good gradient prediction, the regret can be smaller than that of standard AMSGRAD. Experiments on various deep learning problems demonstrate the effectiveness of the proposed method in improving the training efficiency.

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A Proof of Theorem 1

Theorem. *Suppose the learner incurs a sequence of convex loss functions $\{\ell_t(\cdot)\}$. Then,* OPT-AMSGRAD *(Algorithm 2) has regret*

$$\mathcal{R}_T \leq \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - \tilde{m}_t\|^2_{\psi^*_{t-1}} + \frac{D^2_\infty}{\eta_{\min}} \sum_{i=1}^{d} \hat{v}_T^{1/2}[i] + D^2_\infty \beta_1^2 \sum_{t=1}^{T} \|g_t - \theta_{t-1}\|_{\psi^*_{t-1}} , \tag{12}$$

where $\tilde{m}_{t+1} = \beta_1 \theta_{t-1} + (1-\beta_1) m_{t+1}$, $g_t := \nabla \ell_t(w_t)$, $\eta_{\min} := \min_t \eta_t$ and D^2_∞ is the diameter of the bounded set Θ. The result holds for any benchmark $w^* \in \Theta$ and any step size sequence $\{\eta_t\}_{t>0}$.

Proof Beforehand, note:

$$\begin{aligned} \tilde{g}_t &= \beta_1 \theta_{t-1} + (1-\beta_1) g_t \\ \tilde{m}_{t+1} &= \beta_1 \theta_{t-1} + (1-\beta_1) m_{t+1} \end{aligned} \tag{13}$$

where we recall that g_t and m_{t+1} are respectively the gradient $\nabla \ell_t(w_t)$ and the predictable guess. By regret decomposition, we have that

$$\begin{aligned} &\mathit{Regret}_T := \sum_{t=1}^{T} \ell_t(w_t) - \min_{w \in \Theta} \sum_{t=1}^{T} \ell_t(w) \\ &\leq \sum_{t=1}^{T} \langle w_t - w^*, \nabla \ell_t(w_t) \rangle \\ &= \sum_{t=1}^{T} \langle w_t - \tilde{w}_{t+1}, g_t - \tilde{m}_t \rangle + \langle w_t - \tilde{w}_{t+1}, \tilde{m}_t \rangle + \langle \tilde{w}_{t+1} - w^*, \tilde{g}_t \rangle + \langle \tilde{w}_{t+1} - w^*, g_t - \tilde{g}_t \rangle . \end{aligned} \tag{14}$$

Recall the notation $\psi_t(x)$ and the Bregman divergence $B_{\psi_t}(u, v)$ we defined in the beginning of this section. Now we are going to exploit a useful inequality (which appears in e.g., [36]); for any update of the form $\hat{w} = \arg\min_{w \in \Theta} \langle w, \theta \rangle + B_\psi(w, v)$, it holds that

$$\langle \hat{w} - u, \theta \rangle \leq B_\psi(u, v) - B_\psi(u, \hat{w}) - B_\psi(\hat{w}, v) \quad \text{for any } u \in \Theta . \tag{15}$$

For $\beta_1 = 0$, we can rewrite the update on line 8 of (Algorithm 2) as

$$\tilde{w}_{t+1} = \arg\min_{w \in \Theta} \eta_t \langle w, \tilde{g}_t \rangle + B_{\psi_t}(w, \tilde{w}_t) , \tag{16}$$

By using (15) for (16) with $\hat{w} = \tilde{w}_{t+1}$ (the output of the minimization problem), $u = w^*$ and $v = \tilde{w}_t$, we have

$$\langle \tilde{w}_{t+1} - w^*, \tilde{g}_t \rangle \leq \frac{1}{\eta_t} \left[B_{\psi_t}(w^*, \tilde{w}_t) - B_{\psi_t}(w^*, \tilde{w}_{t+1}) - B_{\psi_t}(\tilde{w}_{t+1}, \tilde{w}_t) \right] . \tag{17}$$

We can also rewrite the update on line 9 of (Algorithm 2) at time t as

$$w_{t+1} = \arg\min\nolimits_{w \in \Theta} \eta_{t+1} \langle w, \tilde{m}_{t+1} \rangle + B_{\psi_t}(w, \tilde{w}_{t+1}). \tag{18}$$

and, by using (15) for (18) (written at iteration t), with $\hat{w} = w_t$ (the output of the minimization problem), $u = \tilde{w}_{t+1}$ and $v = \tilde{w}_t$, we have

$$\langle w_t - \tilde{w}_{t+1}, \tilde{m}_t \rangle \leq \frac{1}{\eta_t} \left[B_{\psi_{t-1}}(\tilde{w}_{t+1}, \tilde{w}_t) - B_{\psi_{t-1}}(\tilde{w}_{t+1}, w_t) - B_{\psi_{t-1}}(w_t, \tilde{w}_t) \right] , \tag{19}$$

By (14), (17), and (19), we obtain

$$\begin{aligned} \mathcal{R}_T &\overset{(14)}{\leq} \sum_{t=1}^{T} \langle w_t - \tilde{w}_{t+1}, g_t - \tilde{m}_t \rangle + \langle w_t - \tilde{w}_{t+1}, \tilde{m}_t \rangle + \langle \tilde{w}_{t+1} - w^*, \tilde{g}_t \rangle + \langle \tilde{w}_{t+1} - w^*, g_t - \tilde{g}_t \rangle \\ &\overset{(17),(19)}{\leq} \sum_{t=1}^{T} \|w_t - \tilde{w}_{t+1}\|_{\psi_{t-1}} \|g_t - \tilde{m}_t\|_{\psi^*_{t-1}} + \|\tilde{w}_{t+1} - w^*\|_{\psi_{t-1}} \|g_t - \tilde{g}_t\|_{\psi^*_{t-1}} \\ &+ \frac{1}{\eta_t} \left[B_{\psi_{t-1}}(\tilde{w}_{t+1}, \tilde{w}_t) - B_{\psi_{t-1}}(\tilde{w}_{t+1}, w_t) - B_{\psi_{t-1}}(w_t, \tilde{w}_t) + B_{\psi_t}(w^*, \tilde{w}_t) - B_{\psi_t}(w^*, \tilde{w}_{t+1}) - B_{\psi_t}(\tilde{w}_{t+1}, \tilde{w}_t) \right], \end{aligned} \tag{20}$$

which is further bounded by

$$\mathcal{R}_T \leq \sum_{t=1}^{T} \Big\{ \frac{1}{2\eta_t} \|w_t - \tilde{w}_{t+1}\|_{\psi_{t-1}}^2 + \frac{\eta_t}{2} \|g_t - m_t\|_{\psi_{t-1}^*}^2 + \|\tilde{w}_{t+1} - w^*\|_{\psi_{t-1}} \|g_t - \tilde{g}_t\|_{\psi_{t-1}^*} + \frac{1}{\eta_t} \big(\underbrace{B_{\psi_{t-1}}(\tilde{w}_{t+1}, \tilde{w}_t) - B_{\psi_t}(\tilde{w}_{t+1}, \tilde{w}_t)}_{A_1} - \frac{1}{2} \|\tilde{w}_{t+1} - w_t\|_{\psi_{t-1}}^2 + \underbrace{B_{\psi_t}(w^*, \tilde{w}_t) - B_{\psi_t}(w^*, \tilde{w}_{t+1})}_{A_2} \big) \Big\} , \tag{21}$$

where the inequality is due to $\|w_t - \tilde{w}_{t+1}\|_{\psi_{t-1}} \|g_t - m_t\|_{\psi_{t-1}^*} = \inf_{\beta > 0} \frac{1}{2\beta} \|w_t - \tilde{w}_{t+1}\|_{\psi_{t-1}}^2 + \frac{\beta}{2} \|g_t - m_t\|_{\psi_{t-1}^*}^2$ by Young's inequality and the 1-strongly convex of $\psi_{t-1}(\cdot)$ with respect to $\|\cdot\|_{\psi_{t-1}}$ which yields that $B_{\psi_{t-1}}(\tilde{w}_{t+1}, w_t) \geq \frac{1}{2} \|\tilde{w}_{t+1} - w_t\|_{\psi_t}^2 \geq 0$.

To proceed, notice that

$$A_1 = B_{\psi_{t-1}}(\tilde{w}_{t+1}, \tilde{w}_t) - B_{\psi_t}(\tilde{w}_{t+1}, \tilde{w}_t) = \langle \tilde{w}_{t+1} - \tilde{w}_t, \mathrm{diag}(\hat{v}_{t-1}^{1/2} - \hat{v}_t^{1/2})(\tilde{w}_{t+1} - \tilde{w}_t) \rangle \leq 0 , \tag{22}$$

as the sequence $\{\hat{v}_t\}$ is non-decreasing. And that

$$\begin{aligned} A_2 = B_{\psi_t}(w^*, \tilde{w}_t) - B_{\psi_t}(w^*, \tilde{w}_{t+1}) &= \langle w^* - \tilde{w}_{t+1}, \mathrm{diag}(\hat{v}_{t+1}^{1/2} - \hat{v}_t^{1/2})(w^* - \tilde{w}_{t+1}) \rangle \\ &\leq (\max_i (w^*[i] - \tilde{w}_{t+1}[i])^2) \cdot (\sum_{i=1}^{d} \hat{v}_{t+1}^{1/2}[i] - \hat{v}_t^{1/2}[i]) \end{aligned} \tag{23}$$

Therefore, by (21),(23),(22), we have

$$\begin{aligned} \mathcal{R}_T \leq & \frac{D_\infty^2}{\eta_{\min}} \sum_{i=1}^{d} \hat{v}_T^{1/2}[i] + \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - \tilde{m}_t\|_{\psi_{t-1}^*}^2 \\ & + D_\infty^2 \beta_1^2 \sum_{t=1}^{T} \|g_t - \theta_{t-1}\|_{\psi_{t-1}^*} . \end{aligned}$$

since $\|g_t - \tilde{g}_t\|_{\psi_{t-1}^*} = \|g_t - \beta_1 \theta_{t-1} - (1 - \beta_1) g_t\|_{\psi_{t-1}^*} = \beta^2 \|g_t - \theta_{t-1}\|_{\psi_{t-1}^*}$. This completes the proof.

□

B Proof of Corollary 1

Corollary. *Suppose $\beta_1 = 0$ and $\{v_t\}_{t>0}$ is an increasing monotone sequence, then we obtain the following regret bound for any $w^* \in \Theta$ and sequence $\{\eta_t = \eta/\sqrt{t}\}_{t>0}$:*

$$\mathcal{R}_T \leq \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \frac{\eta\sqrt{1 + \log T}}{\sqrt{1 - \beta_2}} \sum_{i=1}^{d} \|(g - m)_{1:T}[i]\|_2 + \frac{D_\infty^2}{\eta_{\min}} \sum_{i=1}^{d} \left[(1 - \beta_2) \sum_{s=1}^{T} \beta_2^{T-s} g_s[i]^2 \right]^{1/2} ,$$

where $g_t := \nabla \ell_t(w_t)$ and $\eta_{\min} := \min_t \eta_t$.

Proof Recall the bound in Theorem 1:

$$\mathcal{R}_T \leq \frac{B_{\psi_1}(w^*, \tilde{w}_1)}{\eta_1} + \sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - \tilde{m}_t\|_{\psi_{t-1}^*}^2 + \frac{D_\infty^2}{\eta_{\min}} \sum_{i=1}^{d} \hat{v}_T^{1/2}[i] + D_\infty^2 \beta_1^2 \sum_{t=1}^{T} \|g_t - \theta_{t-1}\|_{\psi_{t-1}^*} ,$$

The second term reads:

$$\begin{aligned}
\sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - m_t\|^2_{\psi^*_{t-1}} &= \sum_{t=1}^{T-1} \frac{\eta_t}{2} \|g_t - m_t\|^2_{\psi^*_{t-1}} + \eta_T \sum_{i=1}^{d} \frac{(g_T[i] - m_T[i])^2}{\sqrt{v_{T-1}[i]}} \\
&= \sum_{t=1}^{T-1} \frac{\eta_t}{2} \|g_t - m_t\|^2_{\psi^*_{t-1}} + \eta \sum_{i=1}^{d} \frac{(g_T[i] - m_T[i])^2}{\sqrt{T\big((1-\beta_2)\sum_{s=1}^{T-1} \beta_2^{T-1-s}(g_s[i] - m_s[i])^2\big)}} \\
&\le \eta \sum_{i=1}^{d} \sum_{t=1}^{T} \frac{(g_t[i] - m_t[i])^2}{\sqrt{t\big((1-\beta_2)\sum_{s=1}^{t-1} \beta_2^{t-1-s}(g_s[i] - m_s[i])^2\big)}}.
\end{aligned}$$

To interpret the bound, let us make a rough approximation such that $\sum_{s=1}^{t-1} \beta_2^{t-1-s}(g_s[i]-m_s[i])^2 \simeq (g_t[i] - m_t[i])^2$. Then, we can further get an upper-bound as

$$\sum_{t=1}^{T} \frac{\eta_t}{2} \|g_t - m_t\|^2_{\psi^*_{t-1}} \le \frac{\eta}{\sqrt{1-\beta_2}} \sum_{i=1}^{d} \sum_{t=1}^{T} \frac{|g_t[i] - m_t[i]|}{\sqrt{t}} \le \frac{\eta\sqrt{1+\log T}}{\sqrt{1-\beta_2}} \sum_{i=1}^{d} \|(g-m)_{1:T}[i]\|_2,$$

where the last inequality is due to Cauchy-Schwarz.

$\square$

C Proofs of Auxiliary Lemmas

C.1 Proof of Lemma 1

Lemma. *Assume assumption H4, then the quantities defined in Algorithm 2 satisfy for any $w \in \Theta$ and $t > 0$:*

$$\|\nabla f(w_t)\| < \mathsf{M}, \quad \|\theta_t\| < \mathsf{M}, \quad \|\hat{v}_t\| < \mathsf{M}^2 \ .$$

Proof Assume assumption H4 we have:

$$\|\nabla f(w)\| = \|\mathbb{E}[\nabla f(w, \xi)]\| \leq \mathbb{E}[\|\nabla f(w, \xi)\|] \leq \mathsf{M}$$

By induction reasoning, since $\|\theta_0\| = 0 \leq \mathsf{M}$ and suppose that for $\|\theta_t\| \leq \mathsf{M}$ then we have

$$\|\theta_{t+1}\| = \|\beta_1 \theta_t + (1-\beta_1)\, g_{t+1}\| \leq \beta_1 \|\theta_t\| + (1-\beta_1) \|g_{t+1}\| \leq \mathsf{M} \tag{24}$$

Using the same induction reasoning we prove that

$$\|\hat{v}_{t+1}\| = \left\|\beta_2 \hat{v}_t + (1-\beta_2)\, g_{t+1}^2\right\| \leq \beta_2 \|\hat{v}_t\| + (1-\beta_1) \left\|g_{t+1}^2\right\| \leq \mathsf{M}^2 \tag{25}$$

□

C.2 Proof of Lemma 2

Lemma. *Assume a strictly positive and non increasing sequence of stepsizes $\{\eta_t\}_{t>0}$, $\beta_\in[0,1]$, then the following holds:*

$$\overline{w}_{t+1} - \overline{w}_t \leq \frac{\beta_1}{1-\beta_1} \tilde{\theta}_{t-1} \left[\eta_{t-1} \hat{v}_{t-1}^{-1/2} - \eta_t \hat{v}_t^{-1/2}\right] - \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \ , \tag{26}$$

where $\tilde{\theta}_t = \theta_t + \beta_1 \theta_{t-1}$ and $\tilde{g}_t = g_t - \beta_1 m_t + \beta_1 g_{t-1} + m_{t+1}$.

Proof By definition (7) and using the Algorithm updates, we have:

$$\begin{aligned}
\overline{w}_{t+1} - \overline{w}_t &= \frac{1}{1-\beta_1}(w_{t+1} - \tilde{w}_t) - \frac{\beta_1}{1-\beta_1}(w_t - \tilde{w}_{t-1}) \\
&= -\frac{1}{1-\beta_1} \eta_t \hat{v}_t^{-1/2}(\theta_t + h_{t+1}) + \frac{\beta_1}{1-\beta_1} \eta_{t-1} \hat{v}_{t-1}^{-1/2}(\theta_{t-1} + h_t) \\
&= -\frac{1}{1-\beta_1} \eta_t \hat{v}_t^{-1/2}(\theta_t + \beta_1 \theta_{t-1}) - \frac{1}{1-\beta_1} \eta_t \hat{v}_t^{-1/2}(1-\beta_1) m_{t+1} \\
&+ \frac{\beta_1}{1-\beta_1} \eta_{t-1} \hat{v}_{t-1}^{-1/2}(\theta_{t-1} + \beta_1 \theta_{t-2}) + \frac{\beta_1}{1-\beta_1} \eta_{t-1} \hat{v}_{t-1}^{-1/2}(1-\beta_1) m_t
\end{aligned} \tag{27}$$

Denote $\tilde{\theta}_t = \theta_t + \beta_1 \theta_{t-1}$ and $\tilde{g}_t = g_t - \beta_1 m_t + \beta_1 g_{t-1} + m_{t+1}$. Notice that $\tilde{\theta}_t = \beta_1 \tilde{\theta}_{t-1} + (1-\beta_1)(g_t + \beta_1 g_{t-1})$.

$$\overline{w}_{t+1} - \overline{w}_t \leq \frac{\beta_1}{1-\beta_1} \tilde{\theta}_{t-1} \left[\eta_{t-1} \hat{v}_{t-1}^{-1/2} - \eta_t \hat{v}_t^{-1/2}\right] - \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \tag{28}$$

□

C.3 Proof of Lemma 3

Lemma. *Assume H4, a strictly positive and a sequence of constant stepsizes $\{\eta_t\}_{t>0}$, $\beta_\in[0,1]$, then the following holds:*

$$\sum_{t=1}^{T_{\mathsf{max}}} \eta_t^2 \mathbb{E}\left[\left\|\hat{v}_t^{-1/2} \theta_t\right\|_2^2\right] \leq \frac{\eta^2 d T_{\mathsf{max}} (1-\beta_1)}{(1-\beta_2)(1-\gamma)} \tag{29}$$

Proof We denote by index $p \in [1, d]$ the dimension of each component of vectors of interest. Noting that for any $t > 0$ and dimension p we have $\hat{v}_{t,p} \geq v_{t,p}$, then:

$$\begin{aligned}
\eta_t^2 \mathbb{E}\left[\left\|\hat{v}_t^{-1/2}\theta_t\right\|_2^2\right] &= \eta_t^2 \mathbb{E}\left[\sum_{p=1}^{d} \frac{\theta_{t,p}^2}{\hat{v}_{t,p}}\right] \\
&\leq \eta_t^2 \mathbb{E}\left[\sum_{i=1}^{d} \frac{\theta_{t,p}^2}{v_{t,p}}\right] \\
&\leq \eta_t^2 \mathbb{E}\left[\sum_{i=1}^{d} \frac{(\sum_{r=1}^{t}(1-\beta_1)\beta_1^{t-r} g_{r,p})^2}{\sum_{r=1}^{t}(1-\beta_2)\beta_2^{t-r} g_{r,p}^2}\right]
\end{aligned} \tag{30}$$

where the last inequality is due to initializations. Denote $\gamma = \frac{\beta_1}{\beta_2}$. Then,

$$\begin{aligned}
\eta_t^2 \mathbb{E}\left[\left\|\hat{v}_t^{-1/2}\theta_t\right\|_2^2\right] &\leq \frac{\eta_t^2(1-\beta_1)^2}{1-\beta_2} \mathbb{E}\left[\sum_{i=1}^{d} \frac{(\sum_{r=1}^{t}\beta_1^{t-r} g_{r,p})^2}{\sum_{r=1}^{t}\beta_2^{t-r} g_{r,p}^2}\right] \\
&\overset{(a)}{\leq} \frac{\eta_t^2(1-\beta_1)}{1-\beta_2} \mathbb{E}\left[\sum_{i=1}^{d} \frac{\sum_{r=1}^{t}\beta_1^{t-r} g_{r,p}^2}{\sum_{r=1}^{t}\beta_2^{t-r} g_{r,p}^2}\right] \\
&\leq \frac{\eta_t^2(1-\beta_1)}{1-\beta_2} \mathbb{E}\left[\sum_{i=1}^{d}\sum_{r=1}^{t} \gamma^{t-r}\right] = \frac{\eta_t^2 d(1-\beta_1)}{1-\beta_2} \mathbb{E}\left[\sum_{r=1}^{t} \gamma^{t-r}\right]
\end{aligned} \tag{31}$$

where (a) is due to $\sum_{r=1}^{t}\beta_1^{t-r} \leq \frac{1}{1-\beta_1}$. Summing from $t = 1$ to $t = T_{\mathsf{max}}$ on both sides yields:

$$\begin{aligned}
\sum_{t=1}^{T_{\mathsf{max}}} \eta_t^2 \mathbb{E}\left[\left\|\hat{v}_t^{-1/2}\theta_t\right\|_2^2\right] &\leq \frac{\eta_t^2 d(1-\beta_1)}{1-\beta_2} \mathbb{E}\left[\sum_{t=1}^{T_{\mathsf{max}}}\sum_{r=1}^{t} \gamma^{t-r}\right] \\
&\leq \frac{\eta^2 dT(1-\beta_1)}{1-\beta_2} \mathbb{E}\left[\sum_{t=t}^{t} \gamma^{t-r}\right] \\
&\leq \frac{\eta^2 dT(1-\beta_1)}{(1-\beta_2)(1-\gamma)}
\end{aligned} \tag{32}$$

where the last inequality is due to $\sum_{r=1}^{t}\gamma^{t-r} \leq \frac{1}{1-\gamma}$ by definition of γ. □

D Proof of Theorem 2

Theorem. *Assume H2-H4, $(\beta_1, \beta_2) \in [0, 1]$ and a sequence of decreasing stepsizes $\{\eta_t\}_{t>0}$, then the following result holds:*

$$\mathbb{E}\left[\|\nabla f(w_T)\|^2\right] \leq \tilde{C}_1 \sqrt{\frac{d}{T_{\mathsf{max}}}} + \tilde{C}_2 \frac{1}{T_{\mathsf{max}}} \tag{33}$$

where T is a random termination number distributed according (6) and the constants are defined as follows:

$$\begin{aligned}
\tilde{C}_1 &= C_1 + \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\left[\frac{a(1-\beta_1)^2}{1-\beta_2} + 2L\frac{1}{1-\beta_2}\right] \\
C_1 &= \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\Delta f + \frac{4L\left(\frac{\beta_1}{1-\beta_1}\right)^2 \mathsf{M}}{(1-a\beta_1)+(\beta_1+a)} \frac{(1+\beta_1^2)(1-\beta_1)}{(1-\beta_2)(1-\gamma)} \\
\tilde{C}_2 &= \frac{\mathsf{M}}{(1-\beta_1)\left((1-a\beta_1)+(\beta_1+a)\right)} \tilde{\mathsf{M}}^2 \mathbb{E}\left[\left\|\hat{v}_0^{-1/2}\right\|\right]
\end{aligned} \tag{34}$$

Proof Using H2 and the iterate $\overline{w}_t$ we have:

$$
\begin{aligned}
f(\overline{w}_{t+1}) &\leq f(\overline{w}_t) + \nabla f(\overline{w}_t)^\top(\overline{w}_{t+1} - \overline{w}_t) + \frac{L}{2}\left\|\overline{w}_{t+1} - \overline{w}_t\right\|^2 \\
&\leq f(\overline{w}_t) + \underbrace{\nabla f(w_t)^\top(\overline{w}_{t+1} - \overline{w}_t)}_{A} + \underbrace{\left(\nabla f(\overline{w}_t) - \nabla f(w_t)\right)^\top(\overline{w}_{t+1} - \overline{w}_t)}_{B} + \frac{L}{2}\left\|\overline{w}_{t+1} - \overline{w}_t\right\|
\end{aligned} \tag{35}
$$

Term A. Using Lemma 2, we have that:

$$
\begin{aligned}
\nabla f(w_t)^\top(\overline{w}_{t+1} - \overline{w}_t) &\leq \nabla f(w_t)^\top\left[\frac{\beta_1}{1-\beta_1}\tilde{\theta}_{t-1}\left[\eta_{t-1}\hat{v}_{t-1}^{-1/2} - \eta_t\hat{v}_t^{-1/2}\right] - \eta_t\hat{v}_t^{-1/2}\tilde{g}_t\right] \\
&\leq \frac{\beta_1}{1-\beta_1}\left\|\nabla f(w_t)\right\|\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2} - \eta_t\hat{v}_t^{-1/2}\right\|\left\|\tilde{\theta}_{t-1}\right\| - \nabla f(w_t)^\top\eta_t\hat{v}_t^{-1/2}\tilde{g}_t
\end{aligned} \tag{36}
$$

where the inequality is due to trivial inequality for positive diagonal matrix. Using Lemma 1 and assumption H3 we obtain:

$$
\nabla f(w_t)^\top(\overline{w}_{t+1} - \overline{w}_t) \leq \frac{\beta_1(1+\beta_1)}{1-\beta_1}\mathsf{M}^2\left[\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}\right\| - \left\|\eta_t\hat{v}_t^{-1/2}\right\|\right] - \nabla f(w_t)^\top\eta_t\hat{v}_t^{-1/2}\tilde{g}_t \tag{37}
$$

where we have used the fact that $\eta_t\hat{v}_t^{-1/2}$ is a diagonal matrix such that $\eta_{t-1}\hat{v}_{t-1}^{-1/2} \succcurlyeq \eta_t\hat{v}_t^{-1/2} \succcurlyeq 0$ (decreasing stepsize and $\max$ operator). Also note that:

$$
\begin{aligned}
-\nabla f(w_t)^\top\eta_t\hat{v}_t^{-1/2}\tilde{g}_t &= -\nabla f(w_t)^\top\eta_{t-1}\hat{v}_{t-1}^{-1/2}\bar{g}_t - \nabla f(w_t)^\top\left[\eta_t\hat{v}_t^{-1/2} - \eta_t\hat{v}_t^{-1/2}\right]\bar{g}_t \\
&\quad - \nabla f(w_t)^\top\eta_{t-1}\hat{v}_{t-1}^{-1/2}(\beta_1 g_{t-1} + m_{t+1}) \\
&\leq -\nabla f(w_t)^\top\eta_{t-1}\hat{v}_{t-1}^{-1/2}\bar{g}_t + (1 - a\beta_1)\mathsf{M}^2\left[\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}\right\| - \left\|\eta_t\hat{v}_t^{-1/2}\right\|\right] \\
&\quad - \nabla f(w_t)^\top\eta_t\hat{v}_t^{-1/2}(\beta_1 g_{t-1} + m_{t+1})
\end{aligned} \tag{38}
$$

using Lemma 1 on $\|g_t\|$ and where that $\tilde{g}_t = \bar{g}_t + \beta_1 g_{t-1} + m_{t+1} = g_t - \beta_1 m_t + \beta_1 g_{t-1} + m_{t+1}$. Plugging (38) into (37) yields:

$$
\begin{aligned}
&\nabla f(w_t)^\top(\overline{w}_{t+1} - \overline{w}_t) \\
&\leq -\nabla f(w_t)^\top\eta_{t-1}\hat{v}_{t-1}^{-1/2}\bar{g}_t + \frac{1}{1-\beta_1}(a\beta_1^2 - 2a\beta_1 + \beta 1)\mathsf{M}^2\left[\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}\right\| - \left\|\eta_t\hat{v}_t^{-1/2}\right\|\right] \\
&- \nabla f(w_t)^\top\eta_t\hat{v}_t^{-1/2}(\beta_1 g_{t-1} + m_{t+1})
\end{aligned} \tag{39}
$$

Term B. By Cauchy-Schwarz (CS) inequality we have:

$$
\left(\nabla f(\overline{w}_t) - \nabla f(w_t)\right)^\top(\overline{w}_{t+1} - \overline{w}_t) \leq \left\|\nabla f(\overline{w}_t) - \nabla f(w_t)\right\|\left\|\overline{w}_{t+1} - \overline{w}_t\right\| \tag{40}
$$

Using smoothness assumption H2:

$$
\begin{aligned}
\left\|\nabla f(\overline{w}_t) - \nabla f(w_t)\right\| &\leq L\left\|\overline{w}_t - w_t\right\| \\
&\leq L\frac{\beta_1}{1-\beta_1}\left\|w_t - \tilde{w}_{t-1}\right\|
\end{aligned} \tag{41}
$$

By Lemma 2 we also have:

$$
\begin{aligned}
\overline{w}_{t+1} - \overline{w}_t &= \frac{\beta_1}{1-\beta_1}\tilde{\theta}_{t-1}\left[\eta_{t-1}\hat{v}_{t-1}^{-1/2} - \eta_t\hat{v}_t^{-1/2}\right] - \eta_t\hat{v}_t^{-1/2}\tilde{g}_t \\
&= \frac{\beta_1}{1-\beta_1}\tilde{\theta}_{t-1}\eta_{t-1}\hat{v}_{t-1}^{-1/2}\left[I - (\eta_t\hat{v}_t^{-1/2})(\eta_{t-1}\hat{v}_{t-1}^{-1/2})^{-1}\right] - \eta_t\hat{v}_t^{-1/2}\tilde{g}_t \\
&= \frac{\beta_1}{1-\beta_1}\left[I - (\eta_t\hat{v}_t^{-1/2})(\eta_{t-1}\hat{v}_{t-1}^{-1/2})^{-1}\right](\tilde{w}_{t-1} - w_t) - \eta_t\hat{v}_t^{-1/2}\tilde{g}_t
\end{aligned} \tag{42}
$$

where the last equality is due to $\tilde{\theta}_{t-1}\eta_{t-1}\hat{v}_{t-1}^{-1/2} = \tilde{w}_{t-1} - w_t$ by construction of $\tilde{\theta}_t$. Taking the norms on both sides, observing $\left\| I - (\eta_t \hat{v}_t^{-1/2})(\eta_{t-1}\hat{v}_{t-1}^{-1/2})^{-1} \right\| \leq 1$ due to the decreasing stepsize and the construction of $\hat{v}_t$ and using CS inequality yield:

$$\|\overline{w}_{t+1} - \overline{w}_t\| \leq \frac{\beta_1}{1-\beta_1} \|\tilde{w}_{t-1} - w_t\| + \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\| \tag{43}$$

We recall Young's inequality with a constant $\delta \in (0, 1)$ as follows:

$$\langle X \mid Y \rangle \leq \frac{1}{\delta} \|X\|^2 + \delta \|Y\|^2$$

Plugging (41) and (43) into (40) returns:

$$\begin{aligned} \left(\nabla f(\overline{w}_t) - \nabla f(w_t)\right)^\top \left(\overline{w}_{t+1} - \overline{w}_t\right) \leq & L \frac{\beta_1}{1-\beta_1} \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\| \|w_t - \tilde{w}_{t-1}\| \\ & + L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \|\tilde{w}_{t-1} - w_t\|^2 \end{aligned} \tag{44}$$

Applying Young's inequality with $\delta \to \frac{\beta_1}{1-\beta_1}$ on the product $\left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\| \|w_t - \tilde{w}_{t-1}\|$ yields:

$$\left(\nabla f(\overline{w}_t) - \nabla f(w_t)\right)^\top \left(\overline{w}_{t+1} - \overline{w}_t\right) \leq L \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\|^2 + 2L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \|\tilde{w}_{t-1} - w_t\|^2 \tag{45}$$

The last term $\frac{L}{2} \|\overline{w}_{t+1} - \overline{w}_t\|$ can be upper bounded using (43):

$$\begin{aligned} \frac{L}{2} \|\overline{w}_{t+1} - \overline{w}_t\|^2 & \leq \frac{L}{2} \left[\frac{\beta_1}{1-\beta_1} \|\tilde{w}_{t-1} - w_t\| + \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\| \right] \\ & \leq L \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\|^2 + 2L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \|\tilde{w}_{t-1} - w_t\|^2 \end{aligned} \tag{46}$$

Plugging (39), (45) and (46) into (35) and taking the expectations on both sides give:

$$\begin{aligned} & \mathbb{E}\left[f(\overline{w}_{t+1}) + \frac{1}{1-\beta_1} \tilde{\mathsf{M}}^2 \left\| \eta_t \hat{v}_t^{-1/2} \right\| - \left(f(\overline{w}_t) + \frac{1}{1-\beta_1} \tilde{\mathsf{M}}^2 \left\| \eta_{t-1} \hat{v}_{t-1}^{-1/2} \right\| \right) \right] \\ & \leq \mathbb{E}\left[-\nabla f(w_t)^\top \eta_{t-1} \hat{v}_{t-1}^{-1/2} \overline{g}_t - \nabla f(w_t)^\top \eta_t \hat{v}_t^{-1/2} (\beta_1 g_{t-1} + m_{t+1}) \right] \\ & + \mathbb{E}\left[2L \left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\|^2 + 4L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \|\tilde{w}_{t-1} - w_t\|^2 \right] \end{aligned} \tag{47}$$

where $\tilde{\mathsf{M}}^2 = (a\beta_1^2 - 2a\beta_1 + \beta 1)\mathsf{M}^2$. Note that the expectation of $\tilde{g}_t$ conditioned on the filtration $\mathcal{F}_t$ reads as follows

$$\begin{aligned} \mathbb{E}\left[\nabla f(w_t)^\top \overline{g}_t \right] & = \mathbb{E}\left[\nabla f(w_t)^\top (g_t - \beta_1 m_t) \right] \\ & = (1 - a\beta_1) \|\nabla f(w_t)\|^2 \end{aligned} \tag{48}$$

Summing from $t = 1$ to $t = T$ leads to

$$\begin{aligned} & \frac{1}{\mathsf{M}} \sum_{t=1}^{T_{\mathsf{max}}} \left((1 - a\beta_1)\eta_{t-1} + (\beta_1 + a)\eta_t \right) \|\nabla f(w_t)\|^2 \leq \\ & \mathbb{E}\left[f(\overline{w}_1) + \frac{1}{1-\beta_1} \tilde{\mathsf{M}}^2 \left\| \eta_0 \hat{v}_0^{-1/2} \right\| - \left(f(\overline{w}_{T_{\mathsf{max}}+1}) + \frac{1}{1-\beta_1} \tilde{\mathsf{M}}^2 \left\| \eta_{T_{\mathsf{max}}} \hat{v}_{T_{\mathsf{max}}}^{-1/2} \right\| \right) \right] \\ & + 2L \sum_{t=1}^{T_{\mathsf{max}}} \mathbb{E}\left[\left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\|^2 \right] + 4L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \sum_{t=1}^{T_{\mathsf{max}}} \mathbb{E}\left[\|\tilde{w}_{t-1} - w_t\|^2 \right] \\ & \leq \mathbb{E}\left[\Delta f + \frac{1}{1-\beta_1} \tilde{\mathsf{M}}^2 \left\| \eta_0 \hat{v}_0^{-1/2} \right\| \right] + 2L \sum_{t=1}^{T_{\mathsf{max}}} \mathbb{E}\left[\left\| \eta_t \hat{v}_t^{-1/2} \tilde{g}_t \right\|^2 \right] + 4L \left(\frac{\beta_1}{1-\beta_1} \right)^2 \sum_{t=1}^{T_{\mathsf{max}}} \mathbb{E}\left[\|\tilde{w}_{t-1} - w_t\|^2 \right] \end{aligned} \tag{49}$$

where $\Delta f = f(\overline{w}_1) - f(\overline{w}_{T_{\max}+1})$. We note that by definition of $\hat{v}_t$, and a constant learning rate η_t, we have

$$
\begin{aligned}
\|\tilde{w}_{t-1} - w_t\|^2 &= \left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}(\theta_{t-1} + h_t)\right\|^2 \\
&= \left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}(\theta_{t-1} + \beta_1\theta_{t-2} + (1-\beta_1)m_t)\right\|^2 \\
&\le \left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}\theta_{t-1}\right\|^2 + \left\|\eta_{t-2}\hat{v}_{t-2}^{-1/2}\beta_1\theta_{t-2}\right\|^2 + (1-\beta_1)^2\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}m_t\right\|^2
\end{aligned}
\tag{50}
$$

Using Lemma 3 we have

$$
\begin{aligned}
&\sum_{t=1}^{T_{\max}} \mathbb{E}\left[\|\tilde{w}_{t-1} - w_t\|^2\right] \\
&\le (1+\beta_1^2)\frac{\eta^2 d T_{\max}(1-\beta_1)}{(1-\beta_2)(1-\gamma)} + (1-\beta_1)^2 \sum_{t=1}^{T_{\max}} \mathbb{E}\left[\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}m_t\right\|^2\right]
\end{aligned}
\tag{51}
$$

And thus, setting the learning rate to a constant value η and injecting in (49) yields:

$$
\begin{aligned}
\mathbb{E}\left[\|\nabla f(w_T)\|^2\right] &= \frac{1}{\sum_{j=1}^{T_{\max}}\eta_j}\sum_{t=1}^{T_{\max}}\eta_t\|\nabla f(w_t)\|^2 \\
&\le \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\frac{1}{\sum_{j=1}^{T_{\max}}\eta_j}\mathbb{E}\left[\Delta f + \frac{1}{1-\beta_1}\tilde{\mathsf{M}}^2\left\|\eta_0\hat{v}_0^{-1/2}\right\|\right] \\
&+ \frac{4L\left(\frac{\beta_1}{1-\beta_1}\right)^2\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\frac{1}{\sum_{j=1}^{T_{\max}}\eta_j}(1+\beta_1^2)\frac{\eta^2 d T_{\max}(1-\beta_1)}{(1-\beta_2)(1-\gamma)} \\
&+ \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\frac{1}{\sum_{j=1}^{T_{\max}}\eta_j}(1-\beta_1)^2\sum_{t=1}^{T_{\max}}\mathbb{E}\left[\left\|\eta_{t-1}\hat{v}_{t-1}^{-1/2}m_t\right\|^2\right] \\
&+ \frac{2L\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\frac{1}{\sum_{j=1}^{T_{\max}}\eta_j}\sum_{t=1}^{T_{\max}}\mathbb{E}\left[\left\|\eta_t\hat{v}_t^{-1/2}\tilde{g}_t\right\|^2\right]
\end{aligned}
\tag{52}
$$

where T is a random termination number distributed according (6). Setting the stepsize to $\eta = \frac{1}{\sqrt{dT_{\max}}}$ yields :

$$
\begin{aligned}
&\mathbb{E}\left[\|\nabla f(w_T)\|^2\right] \\
&\le C_1\sqrt{\frac{d}{T_{\max}}} + C_2\frac{1}{T_{\max}} \\
&+ D_1\frac{\eta}{T_{\max}}\sum_{t=1}^{T_{\max}}\mathbb{E}\left[\left\|\hat{v}_{t-1}^{-1/2}m_t\right\|^2\right] + D_2\frac{\eta}{T_{\max}}\sum_{t=1}^{T_{\max}}\mathbb{E}\left[\left\|\hat{v}_{t-1}^{-1/2}\tilde{g}_t\right\|^2\right]
\end{aligned}
\tag{53}
$$

where

$$
\begin{aligned}
C_1 &= \frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\Delta f + \frac{4L\left(\frac{\beta_1}{1-\beta_1}\right)^2\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\frac{(1+\beta_1^2)(1-\beta_1)}{(1-\beta_2)(1-\gamma)} \\
C_2 &= \frac{\mathsf{M}}{(1-\beta_1)\left((1-a\beta_1)+(\beta_1+a)\right)}\tilde{\mathsf{M}}^2\mathbb{E}\left[\left\|\hat{v}_0^{-1/2}\right\|\right]
\end{aligned}
\tag{54}
$$

Simple case as in [43]: if $\beta_1 = 0$ then $\tilde{g}_t = g_t + m_{t+1}$ and $g_t = \theta_t$. Also using Lemma 3 we have that:

$$
\sum_{t=1}^{T_{\max}}\eta_t^2\mathbb{E}\left[\left\|\hat{v}_t^{-1/2}g_t\right\|_2^2\right] \le \frac{\eta^2 d T_{\max}}{(1-\beta_2)}
\tag{55}
$$

which leads to the final bound:

$$\begin{aligned}&\mathbb{E}\left[\|\nabla f(w_T)\|^2\right]\\&\leq \tilde{C}_1\sqrt{\frac{d}{T_{\mathsf{max}}}}+\tilde{C}_2\frac{1}{T_{\mathsf{max}}}\end{aligned} \tag{56}$$

where

$$\begin{aligned}\tilde{C}_1&=C_1+\frac{\mathsf{M}}{(1-a\beta_1)+(\beta_1+a)}\left[\frac{a(1-\beta_1)^2}{1-\beta_2}+2L\frac{1}{1-\beta_2}\right]\\\tilde{C}_2&=C_2=\frac{\mathsf{M}}{(1-\beta_1)\left((1-a\beta_1)+(\beta_1+a)\right)}\tilde{\mathsf{M}}^2\mathbb{E}\left[\left\|\hat{v}_0^{-1/2}\right\|\right]\end{aligned} \tag{57}$$

□

E Proof of Lemma 4 (Boundedness of the iterates)

Lemma. *Given the multilayer model (9), assume the boundedness of the input data and of the loss function,* i.e., *for any $\xi \in \mathbb{R}^p$ and $y \in \mathbb{R}$ there is a constant $T > 0$ such that:*

$$\|\xi\| \leq 1 \quad a.s. \quad and|\mathcal{L}'(\cdot, y)| \leq T \tag{58}$$

where $\mathcal{L}'(\cdot, y)$ denotes its derivative w.r.t. *the parameter. Then for each layer $\ell \in [1, L]$, there exist a constant $A_{(\ell)}$ such that:*

$$\left\|w^{(\ell)}\right\| \leq A_{(\ell)}$$

Proof Recall that for any layer index $\ell \in [1, L]$ we denote the output of layer ℓ by $h^{(\ell)}(w, \xi)$:

$$h^{(\ell)}(w,\xi)=\sigma\left(w^{(\ell)}\sigma\left(w^{(\ell-1)}\ldots\sigma\left(w^{(1)}\xi\right)\right)\right)$$

Given the sigmoid assumption we have $\left\|h^{(\ell)}(w, \xi)\right\| \leq 1$ for any $\ell \in [1, L]$ and any $(w, \xi) \in \mathbb{R}^d \times \mathbb{R}^p$. Observe that at the last layer L:

$$\begin{aligned}\|\nabla_{w^{(L)}}\mathcal{L}(\mathsf{MLN}(w,\xi),y)\|&=\|\mathcal{L}'(\mathsf{MLN}(w,\xi),y)\nabla_{w^{(L)}}\mathsf{MLN}(w,\xi)\|\\&=\left\|\mathcal{L}'(\mathsf{MLN}(w,\xi),y)\sigma'(w^{(L)}h^{(L-1)}(w,\xi))h^{(L-1)}(w,\xi)\right\|\\&\leq\frac{T}{4}\end{aligned} \tag{59}$$

where the last equality is due to mild assumptions (58) and to the fact that the norm of the derivative of the sigmoid function is upperbounded by $1/4$.

From Algorithm 2, and with $\beta_1 = 0$ for the sake of notation, we have for iteration index $t > 0$:

$$\begin{aligned}\|w_t-\tilde{w}_{t-1}\|&=\left\|-\eta_t\hat{v}_t^{-1/2}(\theta_t+h_{t+1})\right\|\\&=\left\|\eta_t\hat{v}_t^{-1/2}(g_t+m_{t+1})\right\|\\&\leq\hat{\eta}\left\|\hat{v}_t^{-1/2}g_t\right\|+\hat{\eta}a\left\|\hat{v}_t^{-1/2}g_{t+1}\right\|\end{aligned} \tag{60}$$

where $\hat{\eta} = \max_{t>0} \eta_t$. For any dimension $p \in [1, d]$, using assumption H3, we note that

$$\sqrt{\hat{v}_{t,p}} \geq \sqrt{1-\beta_2}g_{t,p} \quad \text{and} \quad m_{t+1} \leq a\left\|g_{t+1}\right\|$$

. Thus:

$$\begin{aligned}\|w_t-\tilde{w}_{t-1}\|&\leq\hat{\eta}\left(\left\|\hat{v}_t^{-1/2}g_t\right\|+a\left\|\hat{v}_t^{-1/2}g_{t+1}\right\|\right)\\&\leq\hat{\eta}\frac{a+1}{\sqrt{1-\beta_2}}\end{aligned} \tag{61}$$

In short there exist a constant B such that $\|w_t - \tilde{w}_{t-1}\| \leq B$.

Proof by induction: As in [9], we will prove the containment of the weights by induction. Suppose an iteration index T and a coordinate i of the last layer L such that $w_{T,i}^{(L)} \geq \frac{T}{4\lambda} + B$. Using (59), we have

$$\nabla_i f(w_t^{(L)} \geq -\frac{T}{4} + \lambda \frac{T}{\lambda 4} \geq 0$$

where $f(\cdot)$ is defined by (10) and is the loss of our MLN. This last equation yields $\theta_{T,i}^{(L)} \geq 0$ (given the algorithm and $\beta_1 = 0$) and using the fact that $\|w_t - \tilde{w}_{t-1}\| \leq B$ we have

$$0 \leq w_{T-1,i}^{(L)} - B \leq w_{T,i}^{(L)} \leq w_{T-1,i}^{(L)} \tag{62}$$

which means that $|w_{T,i}^{(L)}| \leq w_{T-1,i}^{(L)}$. So if the first assumption of that induction reasoning holds, *i.e.,* $w_{T-1,i}^{(L)} \geq \frac{T}{4\lambda} + B$, then the next iterates $w_{T,i}^{(L)}$ decreases, see (62) and go below $\frac{T}{4\lambda} + B$. This yields that for any iteration index $t > 0$ we have

$$w_{T,i}^{(L)} \leq \frac{T}{4\lambda} + 2B$$

since B is the biggest jump an iterate can do since $\|w_t - \tilde{w}_{t-1}\| \leq B$. Likewise we can end up showing that

$$|w_{T,i}^{(L)}| \leq \frac{T}{4\lambda} + 2B$$

meaning that the weights of the last layer at any iteration is bounded in some matrix norm.

Now that we have shown this boundedness property for the last layer L, we will do the same for the previous layers and conclude the verification of assumption H1 by induction.

For any layer $\ell \in [1, L-1]$, we have:

$$\nabla_{w^{(\ell)}} \mathcal{L}(\mathsf{MLN}(w, \xi), y) = \mathcal{L}'(\mathsf{MLN}(w, \xi), y) \left(\prod_{j=1}^{\ell+1} \sigma' \left(w^{(j)} h^{(j-1)}(w, \xi) \right) \right) h^{(\ell-1)}(w, \xi) \tag{63}$$

This last quantity is bounded as long as we can prove that for any layer ℓ the weights $w^{(\ell)}$ are bounded in some matrix norm as $\left\| w^{(\ell)} \right\|_F \leq F_\ell$ with the Frobenius norm. Suppose we have shown $\left\| w^{(r)} \right\|_F \leq F_r$ for any layer $r > \ell$. Then having this gradient (63) bounded we can use the same lines of proof for the last layer L and show that the norm of the weights at the selected layer ℓ satisfy

$$\left\| w^{(\ell)} \right\| \leq \frac{T \prod_{t > \ell} F_t}{4^{L-\ell+1}} + 2B$$

Showing that the weights of the previous layers $\ell \in [1, L-1]$ as well as for the last layer L of our fully connected feed forward neural network are bounded at each iteration, leads by induction, to the boundedness (at each iteration) assumption we want to check. $\square$

F Comparison to some related methods

Comparison to nonconvex optimization works. Recently, [40, 5, 38, 42, 44, 22] provide some theoretical analysis of ADAM-type algorithms when applying them to smooth nonconvex optimization problems. For example, [5] provides a bound, which is $\min_{t\in[T]} \mathbb{E}[\|\nabla f(w_t)\|^2] = O(\log T/\sqrt{T})$. Yet, this data independent bound does not show any advantage over standard stochastic gradient descent. Similar concerns appear in other papers.

To get some adaptive data dependent bound that are in terms of the gradient norms observed along the trajectory) when applying OPT-AMSGRAD to nonconvex optimization, one can follow the approach of [2] or [6]. They provide ways to convert algorithms with adaptive data dependent regret bound for convex loss functions (e.g. ADAGRAD) to the ones that can find an approximate stationary point of nonconvex loss functions. Their approaches are modular so that simply using OPT-AMSGRAD as the base algorithm in their methods will immediately lead to a variant of OPT-AMSGRAD that enjoys some guarantee on nonconvex optimization. The variant can outperform the ones instantiated by other ADAM-type algorithms when the gradient prediction m_t is close to g_t. The details are omitted since this is a straightforward application.

Comparison to AO-FTRL [26]. In [26], the authors propose AO-FTRL, which has the update of the form $w_{t+1} = \arg\min_{w\in\Theta}(\sum_{s=1}^{t} g_s)^\top w + m_{t+1}^\top w + r_{0:t}(w)$, where $r_{0:t}(\cdot)$ is a 1-strongly convex loss function with respect to some norm $\|\cdot\|_{(t)}$ that may be different for different iteration t. Data dependent regret bound was provided in the paper, which is $r_{0:T}(w^*) + \sum_{t=1}^{T} \|g_t - m_t\|_{(t)^*}$ for any benchmark $w^* \in \Theta$. We see that if one selects $r_{0:t}(w) := \langle w, \mathrm{diag}\{\hat{v}_t\}^{1/2} w\rangle$ and $\|\cdot\|_{(t)} := \sqrt{\langle \cdot, \mathrm{diag}\{\hat{v}_t\}^{1/2} \cdot\rangle}$, then the update might be viewed as an optimistic variant of ADAGRAD. However, no experiments was provided in [26].

Comparison to OPTIMISTIC-ADAM [8]. We are aware that [8] proposed one version of optimistic algorithm for ADAM, which is called OPTIMISTIC-ADAM in their paper. A slightly modified version is summarized in Algorithm 4. Here, OPTIMISTIC-ADAM+$\hat{v}_t$ is OPTIMISTIC-ADAM in [8] with the additional max operation $\hat{v}_t = \max(\hat{v}_{t-1}, v_t)$ to guarantee that the weighted second moment is monotone increasing.

Algorithm 4 OPTIMISTIC-ADAM [8]+$\hat{v}_t$.

Required: parameter β_1, β_2, and η_t.
Init: $w_1 \in \Theta$ and $\hat{v}_0 = v_0 = \epsilon 1 \in \mathbb{R}^d$.
for $t = 1$ to T **do**
  Get mini-batch stochastic gradient vector $g_t \in \mathbb{R}^d$ at w_t.
  $\theta_t = \beta_1 \theta_{t-1} + (1-\beta_1) g_t$.
  $v_t = \beta_2 v_{t-1} + (1-\beta_2) g_t^2$.
  $\hat{v}_t = \max(\hat{v}_{t-1}, v_t)$.
  $w_{t+1} = \Pi_k[w_t - 2\eta_t \frac{\theta_t}{\sqrt{\hat{v}_t}} + \eta_t \frac{\theta_{t-1}}{\sqrt{\hat{v}_{t-1}}}]$.
end for

We want to emphasize that the motivations are different. OPTIMISTIC-ADAM in their paper is designed to optimize two-player games (e.g. GANs [15]), while the proposed algorithm in this paper is designed to accelerate optimization (e.g. solving empirical risk minimization quickly). [8] focuses on training GANs [15]. GANs is a two-player zero-sum game. There have been some related works in OPTIMISTIC ONLINE LEARNING like [7, 30, 34]) showing that if both players use some kinds of OPTIMISTIC-update, then accelerating the convergence to the equilibrium of the game is possible. [8] was inspired by these related works and showed that OPTIMISTIC-MIRROR-DESCENT can avoid the cycle behavior in a bilinear zero-sum game, which accelerates the convergence. Furthermore, [8] did not provide theoretical analysis of OPTIMISTIC-ADAM.

G Additional Remarks and Runs on the Gradient Prediction Process

Two illustrative examples. We provide two toy examples to demonstrate how OPT-AMSGRAD works with the chosen extrapolation method. First, consider minimizing a quadratic function

$H(w) := \frac{b}{2}w^2$ with vanilla gradient descent method $w_{t+1} = w_t - \eta_t \nabla H(w_t)$. The gradient $g_t := \nabla H(w_t)$ has a recursive description as $g_{t+1} = bw_{t+1} = b(w_t - \eta_t g_t) = g_t - b\eta_t g_t$. So, the update can be written in the form of $g_t = Ag_{t-1} + O(\|g_{t-1}\|_2^2)u_{t-1}$, with $A = (1 - b\eta)$ and $u_{t-1} = 0$ by setting $\eta_t = \eta$ (constant step size). Therefore, the extrapolation method should predict well.

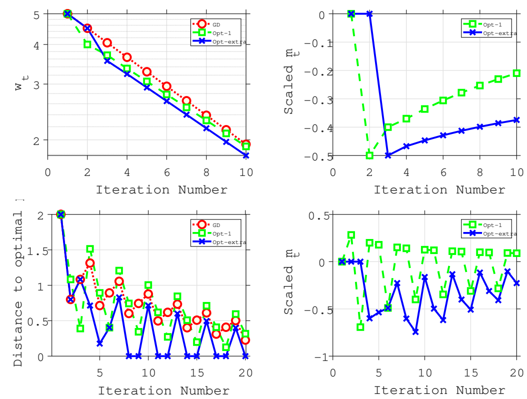

Figure 5: (a): The iterate w_t; the closer to the optimal point 0 the better. (b): A scaled and clipped version of m_t: $w_t - w_{t-1/2}$, which measures how the prediction of m_t drives the update towards the optimal point. In this scenario, the more negative the better. (c): Distance to the optimal point -1. The smaller the better. (d): A scaled and clipped version of m_t: $w_t - w_{t-1/2}$, which measures how the prediction of m_t drives the update towards the optimal point. In this scenario, the more negative the better.

Specifically, consider optimizing $H(w) := w^2/2$ by the following three algorithms with the same step size. One is Gradient Descent (GD): $w_{t+1} = w_t - \eta_t g_t$, while the other two are OPT-AMSGRAD with $\beta_1 = 0$ and the second moment term $\hat{v}_t$ being dropped: $w_{t+\frac{1}{2}} = \Pi_\Theta\big[w_{t-\frac{1}{2}} - \eta_t g_t\big]$, $w_{t+1} = \Pi_\Theta\big[w_{t+\frac{1}{2}} - \eta_{t+1} m_{t+1}\big]$. We denote the algorithm that sets $m_{t+1} = g_t$ as Opt-1, and denote the algorithm that uses the extrapolation method to get m_{t+1} as Opt-extra. We let $\eta_t = 0.1$ and the initial point $w_0 = 5$ for all the three methods. The simulation results are on Figure 5 (a) and (b). Sub-figure (a) plots update w_t over iteration, where the updates should go towards the optimal point 0. Sub-figure (b) is about a scaled and clipped version of m_t, defined as $w_t - w_{t-1/2}$, which can be viewed as $-\eta_t m_t$ if the projection (if exists) is lifted. Sub-figure (a) shows that Opt-extra converges faster than the other methods. Furthermore, sub-figure (b) shows that the prediction by the extrapolation method is better than the prediction by simply using the previous gradient. The sub-figure shows that $-m_t$ from both methods all point to 0 in all iterations and the magnitude is larger for the one produced by the extrapolation method after iteration 2. [2]

Now let us consider another problem: an online learning problem proposed in [31] [3]. Assume the learner's decision space is $\Theta = [-1, 1]$, and the loss function is $\ell_t(w) = 3w$ if $t \bmod 3 = 1$, and $\ell_t(w) = -w$ otherwise. The optimal point to minimize the cumulative loss is $w^* = -1$. We let $\eta_t = 0.1/\sqrt{t}$ and the initial point $w_0 = 1$ for all the three methods. The parameter λ of the extrapolation method is set to $\lambda = 10^{-3} > 0$. The results are on Figure 5 (c) and (d). Sub-figure (c) shows that Opt-extra converges faster than the other methods while Opt-1 is not better than GD. The reason is that the gradient changes from -1 to 3 at $t \bmod 3 = 1$ and it changes from 3 to -1 at $t \bmod 3 = 2$. Consequently, using the current gradient as the guess for the next clearly is not a good choice, since the next gradient is in the opposite direction of the current one. Sub-figure (d) shows that $-m_t$ by the extrapolation method always points to $w^* = -1$, while the one by using the previous negative direction points to the opposite direction in two thirds of rounds. It shows that the extrapolation method is much less affected by the gradient oscillation and always makes the prediction in the right direction, which suggests that the method can capture the aggregate effect.

[2] The extrapolation method needs at least two gradients for prediction. This is why in the first two iterations, m_t is 0.

[3] [31] uses this example to show that ADAM [19] fails to converge.