On Distributed Adaptive Optimization with Gradient Compression

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Abstract

We study COMP-AMS, a distributed optimization framework based on gradient averaging and adaptive AMSGrad algorithm. Gradient compression is applied to reduce the communication in the gradient transmission process, whose bias is corrected by the tool of error feedback. Our convergence analysis of COMP-AMS shows two novel results in adaptive optimization: (i) like SGD, error feedback can also fix the convergence issue of compressed gradients for adaptive method, achieving same convergence rate as the full-gradient counterpart; (ii) distributed COMP-AMS has a linear speedup w.r.t. the number of local workers. Numerical experiments are conducted to justify the theoretical findings, and demonstrate significant communication reduction of the proposed method. Since COMP-AMS is simple and efficient in both communication and memory, it can serve as a convenient distributed training protocol for adaptive methods.

1 Introduction

Deep neural network has achieved the state-of-the-art learning performance on numerous AI applications, e.g., computer vision [25, 28, 55], Natural Language Processing [27, 62, 67], Reinforcement Learning [44, 52] and recommendation systems [17, 57]. With the sheet size of data observations and the increasing complexity of deep neural networks, standard single-machine training procedures encounter at least two major challenges:

- Due to the limited computing power of a single-machine, processing the massive number of data samples takes a long time — training is too slow. Many real-world applications can not even afford spending that much time on training.
- In many practical scenarios, data are typically stored in multiple servers, possibly at different locations, due to the storage constraints (massive user behavior data, Internet images, etc.) or privacy reasons [11]. Hence, transmitting data among servers might be costly.

Distributed learning framework [19] has been a common training strategy to tackle the above two issues. For example, in centralized distributed stochastic gradient descent (SGD) protocol, data are located at n local nodes, at which the gradients of the model are computed in parallel. In each iteration, a central server aggregates the local gradients, updates the global model, and transmits back the updated model to the local nodes for subsequent gradient computation. As we can see, this setting naturally solves aforementioned issues: 1) We use n computing nodes to train the model, so the time per training epoch can be largely reduced; 2) There is no need to transmit the local data to central server. Besides, distributed training also provides stronger error tolerance since the training process could continue even one local machine breaks down. As a result of these advantages, there has been a surge of study and applications on distributed systems [10, 46, 22, 26, 29, 40, 35].

Among many optimization strategies, SGD is still the most popular prototype in distributed training for its simplicity and effectiveness [15, 1, 43]. Yet, when the deep learning model is very large,

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the communication between local nodes and central server could be expensive. Burdensome gradient transmission would slow down the whole training system, or even be impossible because of the limited bandwidth in some applications. Thus, reducing the communication cost in distributed SGD has become an active topic, and an important ingredient of large-scale distributed systems (e.g. [49]). Solutions based on quantization, sparsification and other compression techniques of the local gradients are proposed, e.g., [4, 58, 56, 53, 3, 7, 18, 60, 30]. As one would expect, in most approaches, there exists a trade-off between compression and learning performance. In general, larger bias and variance of the compressed gradients usually bring more significant performance downgrade in terms of convergence [53, 2]. Interestingly, studies (e.g., [33]) show that the technique of *error feedback* can to a large extent remedy the issue of such biased compressors, achieving same convergence rate as full-gradient SGD.

On the other hand, in recent years, adaptive optimization algorithms (e.g. AdaGrad [23], Adam [34] and AMSGrad [48]) have become popular because of their superior empirical performance. These methods use different implicit learning rates for different coordinates that keep changing adaptively throughout the training process, based on the learning trajectory. In many learning problems, adaptive methods have been shown to converge faster than SGD, sometimes with better generalization as well. Despite of the great popularity of adaptive methods, the body of literature that extends them to distributed training is still very limited. In particular, even the simple gradient averaging approach, though appearing standard, has not been considered for adaptive optimization algorithms. Furthermore, adopting gradient compression in adaptive methods has also been rarely studied in literature. We try to fill this gap in this paper, by studying COMP-AMS, a distributed adaptive optimization framework using the gradient averaging protocol. Gradient compression is incorporated to reduce the communication cost. Theoretical and empirical results are presented to demonstrate the effectiveness of the proposed method.

1.1 Our Contributions

Specifically, in this paper, we focus on a *simple optimization framework* leveraging the *adaptivity* of AMSGrad and the computational virtue of *local gradient compression*. Our contributions summarize as follows:

- We consider COMP-AMS, a synchronous distributed adaptive optimization framework based on global averaging with gradient compression, which is efficient in both communication and memory as no local moment estimation is needed. Our scheme is coupled with an error-feedback technique to reduce the bias implied by the compression step.

- We provide the general convergence rate of distributed COMP-AMS (with n workers) in smooth non-convex optimization, where data heterogeneity is allowed. In the special case of $n = 1$, we derive the first result in literature that similar to SGD, gradient compression with error feedback in adaptive method achieves same convergence rate $\mathcal{O}(\frac{1}{\sqrt{T}} + \frac{1}{T})$ (omitting all constants) as the standard full-gradient counterpart. Moreover, we show that with a properly chosen learning rate, COMP-AMS achieves $\mathcal{O}(\frac{1}{\sqrt{nT}})$ convergence, implying a linear speedup in terms of the number of local workers to attain $\mathcal{O}(\delta)$-stationary point. This is also the first result in literature regarding the linear speedup property of distributed adaptive learning under gradient compression.

- We present numerical experiments on three tasks that validate our theoretical findings on the merit of error feedback and the linear speedup effect, and show that COMP-AMS with **Top-k** or **Block-Sign** compressors can reduce $\sim$30-100x communication overhead, without losing much accuracy compared with using full gradient. Finally, we provide more discussions on the comparison to other related methods and potential future directions.

In Section 2 we provide a comprehensive summary of the contributions to date, related to gradient compression, adaptive methods and the error feedback technique. We develop in Section 3 our communication-efficient COMP-AMS method, using AMSGrad as a prototype optimization algorithm. In Section 4, we establish the convergence analysis and demonstrate several implications of our result. Numerical results are illustrated in Section 5 to justify the theory and show the effectiveness of the proposed approach.

2 Related Work

2.1 Distributed SGD with Compressed Gradients

Quantization. As we mentioned before, SGD is the most commonly adopted optimization method in distributed training of deep neural nets. To reduce the expensive communication in large-scale distributed systems, extensive works have considered various compression techniques applied to the gradient transaction procedure. The first strategy is quantization. [20] condenses 32-bit floating numbers into 8-bits when representing the gradients. [49, 7, 33, 8] use the extreme 1-bit information (sign) of the gradients, combined with tricks like momentum, majority vote and memory. Other quantization-based methods include QSGD [4, 59, 66] and LPC-SVRG [64], leveraging unbiased stochastic quantization. The saving in communication of quantization methods is moderate: for example, 8-bit quantization reduces the cost to 25% (compared with 32-bit full-precision). Even in the extreme 1-bit case, the largest compression ratio is around $1/32 \approx 3.1\%$.

Sparsification. Gradient sparsification is another popular solution which may provide higher compression rate. Instead of commuting the full gradient, each local worker only passes a few coordinates to the central server and zeros out the others. Thus, we can more freely choose higher compression ratio (e.g., 1%, 0.1%), still achieving impressive performance in many applications [38]. Stochastic sparsification methods, including uniform sampling and magnitude based sampling [56], select coordinates based on some sampling probability yielding unbiased gradient compressors. Deterministic methods are simpler, e.g., Random-k, Top-k [53, 51] (selecting k elements with largest magnitude), Deep Gradient Compression [38], but usually lead to biased gradient estimation. In [30], the central server identifies heavy-hitters from the count-sketch [12] of the local gradients, which can be regarded as a noisy variant of Top-k strategy. More applications and analysis of compressed distributed SGD can be found in [32, 50, 5, 6, 31], among others.

Error Feedback (EF). Biased gradient estimation, which is a consequence of many aforementioned methods (e.g., signSGD, Top-k), undermines the model training, both theoretically and empirically, with slower convergence and worse generalization [2, 9]. The technique of *error feedback* is able to "correct for the bias" and fix the convergence issues. In this procedure, the difference between the true stochastic gradient and the compressed one is accumulated locally, which is then added back to the local gradients in later iterations. [53, 33] prove the $\mathcal{O}(\frac{1}{T})$ and $\mathcal{O}(\frac{1}{\sqrt{T}})$ convergence rate of EF-SGD in strongly convex and non-convex setting respectively, matching the rates of vanilla SGD [47, 24]. More works on the convergence rate of SGD with error feedback include [70, 54], among other related papers.

2.2 Adaptive Optimization

In each SGD update, all the gradient coordinates share the same learning rate. This latter is either constant or decreasing through the iterations. Adaptive optimization methods cast different learning rate on each dimension. For instance, AdaGrad, developed in [23], divides the gradient element-wisely by $\sqrt{\sum_{t=1}^{T} g_t^2} \in \mathbb{R}^d$, where $g_t \in \mathbb{R}^d$ is the gradient vector at time t and d is the model dimensionality. Thus, it intrinsically assigns different learning rates to different coordinates throughout the training – elements with smaller previous gradient magnitude tend to move a larger step via larger learning rate. AdaGrad has been shown to perform well especially under some sparsity structure in the model and data. Other adaptive methods include AdaDelta [65] and Adam [34], which introduce momentum and moving average of second moment estimation into AdaGrad hence leading to better performances. AMSGrad [48] fixes the potential convergence issue of Adam, which will serve as the prototype in this paper. We present the pseudocode in Algorithm 1.

Algorithm 1 AMSGRAD optimization method

1: **Input**: parameters β_1, β_2, and η_t.
2: Initialize: $\theta_1 \in \Theta$ and $v_0 = \epsilon 1 \in \mathbb{R}^d$.
3: **for** $t = 1$ to T **do**
4: Compute stochastic gradient g_t at θ_t.
5: $m_t = \beta_1 m_{t-1} + (1-\beta_1) g_t$.
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: $\theta_{t+1} = \theta_t - \eta_t \frac{\theta_t}{\sqrt{\hat{v}_t}}$.
9: **end for**

In general, adaptive optimization methods in many cases exhibit faster convergence than SGD. Thus, they have been widely used in training deep learning models in language and computer vision applications, e.g., [16, 61, 68]. In distributed setting, the work [45] proposes a decentralized system in

online optimization. However, communication efficiency is not considered. The recent work [13] is the most relevant to our paper. Yet, their method is based on Adam, and requires every local node to store a local estimation of the moments of the gradient. Thus, one has to keep extra two more tensors of the model size on each local worker, which may be less feasible in terms of memory particularly with large models. We will present more detailed comparison in Section 3.

3 Communication-Efficient Adaptive Optimization

Consider the distributed optimization task where n workers jointly solve a large finite-sum optimization problem written as:

$$\min_{\theta\in\Theta} \frac{1}{n}\sum_{i=1}^{n} f_i(\theta) := \frac{1}{n}\sum_{i=1}^{n} \mathbb{E}_{x\sim\mathcal{X}_i}[F_i(\theta; x)], \tag{1}$$

where the non-convex function f_i represents the average loss (over the local data samples) for worker $i \in [n]$ and θ the global model parameter taking value in Θ, a subset of $\mathbb{R}^d$. $\mathcal{X}_i$ is the data distribution on each local node.

3.1 Gradient Compressors

In this paper, we mainly consider deterministic q-deviate compressors defined as below.

Assumption 1. *The gradient compressor $\mathcal{C} : \mathbb{R}^d \mapsto \mathbb{R}^d$ is q-deviate: for $\forall x \in \mathbb{R}^d$, $\exists\, 0 \le q < 1$ such that $\|\mathcal{C}(x) - x\| \le q\,\|x\|$.*

Note that, larger q indicates important an compression while smaller q implies better approximation of the true gradient. Hence, $q = 0$ implies no compression, i.e., $\mathcal{C}(x) = x$. We give two popular and highly efficient q-deviate compressors that will be adopted in this paper.

Definition 1 (Top-k)**.** *For $x \in \mathbb{R}^d$, denote $\mathcal{S}$ as the size-k set of $i \in [d]$ with largest k magnitude $|x_i|$. The **Top-k** compressor is defined as $\mathcal{C}(x)_i = x_i$, if $i \in \mathcal{S}$; $\mathcal{C}(x)_i = 0$ otherwise.*

Definition 2 (Block-Sign)**.** *For $x \in \mathbb{R}^d$, define M blocks indexed by $\mathcal{B}_i$, $i = 1, ..., M$, with $d_i := |\mathcal{B}_i|$. The **Block-Sign** compressor is defined as $\mathcal{C}(x) = [sign(x_{\mathcal{B}_1})\frac{\|x_{\mathcal{B}_1}\|_1}{d_1}, ..., sign(x_{\mathcal{B}_M})\frac{\|x_{\mathcal{B}_M}\|_1}{d_M}]$.*

Remark 1. *It is well-known [53, 70] that for **Top-k**, $q^2 = 1 - \frac{k}{d}$; for **Block-Sign**, by Cauchy-Schwartz inequality we have $q^2 = 1 - \min_{i\in[M]} \frac{1}{d_i}$ where M and d_i are defined in Definition 2.*

The intuition behind **Top-k** is that, it has been observed during many deep neural networks training procedure, most gradients are typically very small and can be regarded as redundant—gradients with large magnitude contain most information. The **Block-Sign** compressor is a simple extension of the 1-bit **SIGN** compressor [49, 7], adapted to different gradient magnitude in different blocks, which, for neural nets, are usually set as the distinct network layers. The scaling factor in Definition 2 is to preserve the (possibly very different) gradient magnitude in each layer. In principle, **Top-k** would perform the best when the gradient is sparse, or only has a few very large absolute values, while **Block-Sign** compressor is beneficial when most gradients have similar magnitude within each layer.

3.2 COMP-AMS for Distributed Optimization

We present in Algorithm 2 our proposed communication-efficient distributed adaptive method in this paper, COMP-AMS. This framework can be regarded as an analogue to the standard synchronous distributed SGD protocol: in each iteration, each local worker transmits to the central server the compressed stochastic gradient computed using local data. Then the central server takes the average of local gradients, and performs an AMSGrad update. Despite that this method seems a straightforward extension of distributed SGD, no formal analysis of COMP-AMS has been conducted in literature, and training AMSGrad by compressed gradients has not been considered either.

In Algorithm 2, line 7-8 depict the error feedback operation at local nodes. $e_{t,i}$ is the accumulated error from gradient compression on the i-th worker up to time $t-1$. This residual is added back to $g_{t,i}$ to get the "correct" gradient. In Section 4 and Section 5, we will show that error feedback,

Algorithm 2 Distributed COMP-AMS with error-feedback

1: **Input**: parameters β_1, β_2, learning rate η_t.
2: Initialize: central server parameter $\theta_1 \in \Theta \subseteq \mathbb{R}^d$; $e_{1,i} = 0$ the error accumulator for each worker; sparsity parameter k; n local workers; $m_0 = 0$, $v_0 = 0$, $\hat{v}_0 = 0$
3: **for** $t = 1$ to T **do**
4: **parallel for worker** $i \in [n]$ **do**:
5: Receive model parameter θ_t from central server
6: Compute stochastic gradient $g_{t,i}$ at θ_t
7: Compute $\tilde{g}_{t,i} = \mathcal{C}(g_{t,i} + e_{t,i}, k)$
8: Update the error $e_{t+1,i} = e_{t,i} + g_{t,i} - \tilde{g}_{t,i}$
9: Send $\tilde{g}_{t,i}$ back to central server
10: **end parallel**
11: **Central server do:**
12: $\bar{g}_t = \frac{1}{n}\sum_{i=1}^n \tilde{g}_{t,i}$
13: $m_t = \beta_1 m_{t-1} + (1-\beta_1)\bar{g}_t$
14: $v_t = \beta_2 v_{t-1} + (1-\beta_2)\bar{g}_t^2$
15: $\hat{v}_t = \max(v_t, \hat{v}_{t-1})$
16: Update the global model $\theta_{t+1} = \theta_t - \eta_t \frac{m_t}{\sqrt{\hat{v}_t + \epsilon}}$
17: **end for**

similar to the case of SGD, also brings good convergence behavior under gradient compression in adaptive optimization methods.

Comparison with Quantized Adam [13]. The first crucial difference of COMP-AMS compared with [13] which develops a quantized variant of Adam [34] is that, in COMP-AMS, only compressed gradients are transmitted from the workers to the central server. In [13], each worker keeps a local copy of the moment estimates commonly noted m and v, and compresses and transmits the ratio $\frac{m}{v}$ as a whole to the server. Thus, that method is very much like the compressed distributed SGD, with the exception that the ratio $\frac{m}{v}$ plays the role of the gradient vector g communication-wise. Thus, two local moment estimators are additionally required, which have same size as the deep learning model. In our optimization method in Algorithm 2, the moment estimates m and v are kept and updated only at the central server, thus not introducing any extra variables (tensors) on local nodes during training (except for the error accumulator). In other words, COMP-AMS is not only effective in communication reduction, but also efficient in terms of memory (space), which is favorable for the distributed adaptive training of large-scale learners like BERT and CTR prediction models, e.g. [21, 69], to lower the hardware consumption happening in practice.

The second key difference is that, Adam is used as the underlying algorithm in [13]. It does not use the variable $\hat{v}$ (line 15 of Algorithm 2) ensuring a non-decreasing second moment estimation, which has been shown to be an important factor for the convergence guarantee, see [48, 14]. Indeed, the convergence rate given by [13] does not match the rate of vanilla AMSGrad and even does not converge to 0, when a decreasing learning rate, e.g., $\mathcal{O}(\frac{1}{\sqrt{T}})$, is employed, see [13, Th. 1]. This would be intuitively problematic and given the fact that decreasing learning rate is standard in theoretical analysis and practical implementation. In next section, we prove the fast convergence of COMP-AMS using compressed gradients that matches the rate of full-gradient AMSGrad.

4 Convergence Analysis

For the convergence analysis of COMP-AMS we will make following additional assumptions.

Assumption 2. *(Smoothness) For $\forall i \in [n]$, f_i is L-smooth: $\|\nabla f_i(\theta) - \nabla f_i(\vartheta)\| \leq L\|\theta - \vartheta\|$.*

Assumption 3. *(Unbiased and bounded stochastic gradient) For $\forall t > 0$, $\forall i \in [n]$, the stochastic gradient is unbiased and uniformly bounded: $\mathbb{E}[g_{t,i}] = \nabla f_i(\theta_t)$ and $\|g_{t,i}\| \leq G$.*

Assumption 4. *(Bounded variance) For $\forall t > 0$, $\forall i \in [n]$: (i) the **local variance** of the stochastic gradient is bounded: $\mathbb{E}[\|g_{t,i} - \nabla f_i(\theta_t)\|^2] < \sigma^2$; (ii) the **global variance** is bounded by $\frac{1}{n}\sum_{i=1}^n \|\nabla f_i(\theta_t) - \nabla f(\theta_t)\|^2 \leq \sigma_g^2$.*

In Assumption 3, the uniform bound on the stochastic gradient is common in the convergence analysis of adaptive methods, e.g., [48, 71, 14]. The global variance bound σ_g^2 characterizes the difference among local objective functions, which, is mainly caused by different local data distribution $\mathcal{X}_i$ in (1). In classical distributed setting where all the workers can access the same dataset and local data are assigned randomly, $\sigma_g^2 \equiv 0$. The scenario where $\mathcal{X}_i$'s are different gives rise to the recently proposed Federated Learning (FL) [42] framework where local data can be non-i.i.d. While typical FL method with periodical model averaging is beyond the scope of this present paper, we consider the global variance in our analysis to shed some light on the impact of non-i.i.d. data distribution in the federated setting for broader interest and future investigation.

Under the mild assumptions stated above, we derive the following general convergence rate of COMP-AMS in the distributed setting.

Theorem 1. *Denote* $C_0 = \sqrt{\frac{4(1+q^2)^3}{(1-q^2)^2}G^2 + \epsilon}$, $C_1 = \frac{\beta_1}{1-\beta_1} + \frac{2q}{1-q^2}$, $\theta^* = \arg\min f(\theta)$. *Under Assumption 1 to Assumption 4, with* $\eta_t = \eta \le \frac{\epsilon}{3C_0\sqrt{2L\max\{2L, C_2\}}}$, COMP-AMS *satisfies*

$$\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[\|\nabla f(\theta_t)\|^2] \le 2C_0\Big(\frac{\mathbb{E}[f(\theta_1) - f(\theta^*)]}{T\eta} + \frac{\eta L\sigma^2}{n\epsilon} + \frac{3\eta^2 LC_0C_1\sigma^2}{\epsilon^2} + \frac{12\eta^2q^2LC_0\sigma_g^2}{(1-q^2)^2\epsilon^2} + \frac{(1+C_1)G^2d}{T\sqrt{\epsilon}} + \frac{\eta(1+2C_1)C_1LG^2d}{T\epsilon}\Big).$$

The LHS of Theorem 1 is the expected squared norm of the gradient from a uniformly chosen iterate $t \in [T]$, which is a common convergence measure. From Theorem 1, we see that the more compression we apply to the gradient vectors (i.e., larger q), the larger the the gradient magnitude is, i.e., the slower the algorithm converges. This is intuitive as heavier compression loses more gradient information which would slower down the learner to find a good solution.

In the following paragraphs, we provide two interesting extension of our main result Theorem 1. We begin with the single-machine case, when $n = 1$ and then provide a linear speedup of our methods in the general distributed optimization case.

Single machine rate ($n = 1$)**.** Note that, COMP-AMS with $n = 1$ naturally reduces to the single machine (sequential) AMSGrad (Algorithm 1) with compressed gradients instead of full-precision ones. The paper [33] shows that for SGD, error feedback fixes the convergence issue of biased compressors in the sense that SGD-EF (with compressed gradients) has the same convergence rate as vanilla SGD using full gradients. For AMSGrad, we have a similar result.

Corollary 1. *Assume* $n = 1$. *Under Assumption 1 to Assumption 4, setting the stepsize as* $\eta = \min\{\frac{\epsilon}{3C_0\sqrt{2L\max\{2L, C_2\}}}, \frac{1}{\sqrt{T}}\}$, *the sequence of iterates* $\{\theta_t\}_{t>0}$ *output from Algorithm 2 satisfies:*

$$\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[\|\nabla f(\theta_t)\|^2] \le \mathcal{O}(\frac{1}{\sqrt{T}} + \frac{\sigma^2}{\sqrt{T}} + \frac{d}{T}).$$

Corollary 1 states that with error feedback, single machine AMSGrad with biased compressed gradients can also match the convergence rate $\mathcal{O}(\frac{1}{\sqrt{T}} + \frac{d}{T})$ of standard AMSGrad [71] in non-convex optimization. It also achieves the same rate $\mathcal{O}(\frac{1}{\sqrt{T}})$ of vanilla SGD [33] when T is sufficiently large. In other words, EF also fixes the convergence issue of using compressed gradients in AMSGrad. To the best of our knowledge, this is the first result in literature showing that compressed adaptive methods with EF converges as fast as the standard counterpart. We will validate this benefit of EF in our numerical experiments.

Linear Speedup ($n > 1$)**.** In Theorem 1, the convergence rate is derived assuming constant learning rate. By carefully choosing a decreasing learning rate dependent on the number of workers, we have the following simplified statement.

Corollary 2. *Under the same setting as Theorem 1, set* $\eta = \min\{\frac{\epsilon}{3C_0\sqrt{2L\max\{2L, C_2\}}}, \frac{\sqrt{n}}{\sqrt{T}}\}$. *Ignoring irrelevant quantities, we have*

$$\frac{1}{T}\sum_{t=1}^{T}\mathbb{E}[\|\nabla f(\theta_t)\|^2] \le \mathcal{O}(\frac{1}{\sqrt{nT}} + \frac{\sigma^2}{\sqrt{nT}} + \frac{n(\sigma^2 + \sigma_g^2)}{T}). \tag{2}$$

In Corollary 2, we see that the global variance σ_g^2 appears in the $\mathcal{O}(\frac{1}{T})$ term, which says that it asymptotically has no impact on the convergence. This matches the result of momentum SGD [63]. When $T \geq \mathcal{O}(n^3)$ is sufficiently large, the third term in (2) vanishes, and the convergence rate becomes $\mathcal{O}(\frac{1}{\sqrt{nT}})$. Therefore, to reach a $\mathcal{O}(\delta)$ stationary point, one worker ($n = 1$) needs $T = \mathcal{O}(\frac{1}{\delta^2})$ iterations, while distributed training with n workers requires only $T = \mathcal{O}(\frac{1}{N\delta^2})$ iterations, which is n times faster than single machine training. That is, COMP-AMS has a linear speedup in terms of the number of the local workers. Such acceleration effect has also been reported for compressed SGD with error feedback [70, 32] and momentum SGD [63]. To our knowledge, this is also the first result showing the linear speedup for distributed adaptive methods under compression.

5 Experiments

In this section, we provide numerical results on several real-world datasets. Our main objective is to validate the theoretical results, and demonstrate that the proposed COMP-AMS can give satisfactory learning performance with significantly reduced communication costs.

5.1 Error Feedback Fixes the Convergence of Compressed AMSGrad

In Corollary 1, we established that for standard single machine AMSGrad under compression, EF helps achieve same convergence rate as the full-gradient AMSGrad. We implement COMP-AMS with a single worker and different gradient compressors, with or without EF, to justify this claim. We train MNIST [37] clssification using a simple Convolutional Neural Network (CNN). The model has two convolutional layers followed by two fully connected layers with ReLu activation. Dropout is applied after the max-pooled convolutional layer with rate 0.5. The training batch size is 200. The parameters in COMP-AMS are set as default $\beta_1 = 0.9$ and $\beta_2 = 0.999$, which is true for all the experiments in this paper. The learning rate is searched over a fine grid and the best result is reported averaged over three runs. In Figure 1, the methods are (all performed on single worker):

- TopK-EF-0.01: COMP-AMS (Algorithm 2) and **Top-k** compressor, with sparsity 0.01 (i.e., keeping 1% gradient coordinates with largest magnitude).
- TopK-EF-0.001: COMP-AMS with **Top-k** compressor, with sparsity 0.001.
- BkSign-EF: COMP-AMS with **Block-Sign** compression.
- Methods without "-EF": AMSGrad using corresponding compressors without error feedback (directly trained with compressed gradients).
- MVSS-0.01: AMSGrad with Minimal Variance Stochastic Sparsification (MVSS) [56] at 0.01 sparsity. This method probabilistically chooses gradient coordinates according to their magnitude, and divides each selected coordinate by its sampling probability to generate unbiased output (of the full gradient). Therefore, error feedback is not used for MVSS[1].

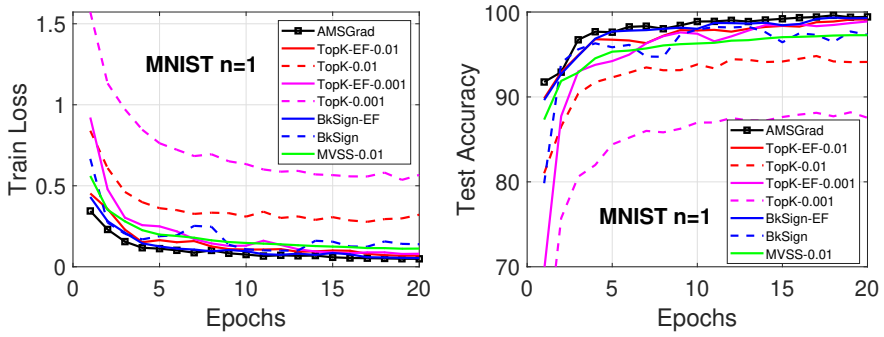

Figure 1: Training loss and test accuracy of COMP-AMS using a single machine.

[1] We also tested MVSS with error feedback, but the performance is uncompetitive with other methods.

From the train loss and test accuracy in Figure 1, we observe:

- AMSGrad without EF (dash curves) performs very poorly in terms of both convergence speed (more fluctuations in later epochs) and generalization (much worse test accuracy). With error feedback, the training loss and test accuracy both approach those of full-gradient AMSGrad with faster convergence. The issue of biased compression is fixed.
- **Top-k**-EF-0.01 performs better than **Top-k**-EF-0.001, which justifies the influence of q in Theorem 1 that higher compression ratio would undermine the learning performance.
- MVSS-0.01 is outperformed by the proposed EF-corrected **Block-Sign** and **Top-k** even with 0.001 sparsity. This suggests that using biased compressors with EF in COMP-AMS is more effective than using unbiased stochastic compressors.

5.2 Linear Speedup of COMP-AMS

Corollary 2 reveals the linear speedup of COMP-AMS in distributed training. We validate this claim in Figure 2, where the training loss on MNIST against the number of iterations is provided. Here we use COMP-AMS with **Top-k** and 0.01 sparsity. We test $n = 1, 2, 4, 8$, where the local mini-batch size is 100. As suggested by the theory, we use $10^{-4}\sqrt{n}$ as the learning rate. From Figure 2, we observe that the number of iterations for multiple workers to achieve a certain loss decreases as n increases. For example, to achieve 0.5 loss, we need around $700, 400, 240, 120$ iterations for $n = 1, 2, 4, 8$ respectively, which decreases approximately linearly. This numerically justifies the linear speedup effect ($\mathcal{O}(\frac{1}{\sqrt{nT}})$ convergence rate) of COMP-AMS.

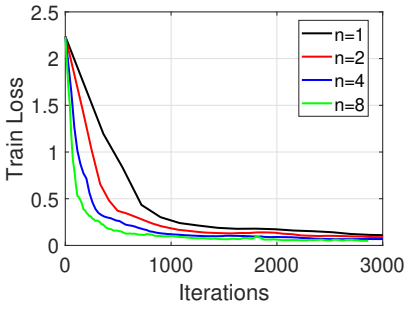

Figure 2: Training loss of COMP-AMS with **Top-k**-0.01 on MNIST.

5.3 General Evaluation and Communication Efficiency

In this section, we present general evaluation of distributed training on more datasets and compare the communication efficiency. For CIFAR-10 dataset [36], we train a larger CNN model with 3 convolutional layers. For IMDB movie review [41] sentiment analysis, we train a LSTM network with 64 cells, equipped with an embedding layer which embeds top 1000 words in the movie reviews into 32-dimensional vectors. The local batch size is 100. The detailed architecture can be found in the supplement. We compare COMP-AMS with full gradient, **Top-k** and **Block-Sign** compression, with Quantized Adam (QADAM) [13] (see supplement for the details). To match the compression ratio of COMP-AMS, we present 1-bit QAdam for highest communication reduction.

In Figure 3, we provide the test accuracy on three tasks against the number of epochs and the number of bits transmitted per local worker, respectively. On all three datasets, COMP-AMS with **Top-k**-0.01 and **Block-Sign** compression achieves same accuracy as using full gradients, with substantial 100x and 30x communication saving, respectively. While performing well on MNIST, more extreme compression (i.e., **Top-k**-0.001) leads to unnegligible loss in convergence speed and accuracy on the other two datasets. These results demonstrate the trade-off between compression and accuracy, and that under COMP-AMS framework, we can achieve significant (around 30-100x) communication reduction with similar model accuracy.

5.4 Discussion on COMP-AMS and QADAM

Noticeably, compared with QADAM, we see that on CIFAR-10 and IMDB, COMP-AMS converges to a worse stationary point/local optimum (worse generalization). Firstly, we should note that according to our theory and numerical results (e.g., Figure 2), distributed COMP-AMS in principle would at least have same learning performance as standard AMSGrad (trained on single machine) by properly choosing the learning rate. While the generalization of deep networks is still mysterious from rigorous theoretical perspective, we suspect that the performance gap of COMP-AMS might be a consequence of larger variance of the effective update, which is the price of abandoning local moment estimation. For the ease of illustration, we consider Adam (Algorithm 1 without line 7). In

distributed adaptive training, we are essentially using the effective update ratio $\frac{m_t}{\sqrt{v_t}}$ by aggregating local information. For COMP-AMS, we first take the average (for the 1st and 2nd moments separately) and then take the ratio, while in QADAM we first take the ratio and then compute the average. Hence, in QADAM, there is only one additive error coming from linear averaging, which may better approximate the true ratio itself. On the other hand, since COMP-AMS is simpler and does not keep local moment estimates, we have two "sources" of error coming from both 1st and 2nd moment estimation, and the later introduces multiplicative error (from the denominator) which may lead to higher variance and more unstable estimation, from the statistical point of view. As a result, we can use larger learning rate for QADAM (indeed, the found optimal learning rate of QADAM is usually larger than that of COMP-AMS), which may speedup the algorithm and help escape local optima.

Nevertheless, as mentioned before, COMP-AMS is a very simple strategy that does not require extra local moment estimators (tensors), which is memory and hardware-friendly when training very large models in practice. Together with its high communication efficiency and linear speedup property, COMP-AMS would be a useful protocol in many applications. While in this paper we mainly consider the generic algorithm, we would like to place more investigation on the generalization ability (of both COMP-AMS and QADAM) and possible heuristics to further improve the performance of COMP-AMS (e.g., by warm-up or variance reduction techniques [39]) as future work.

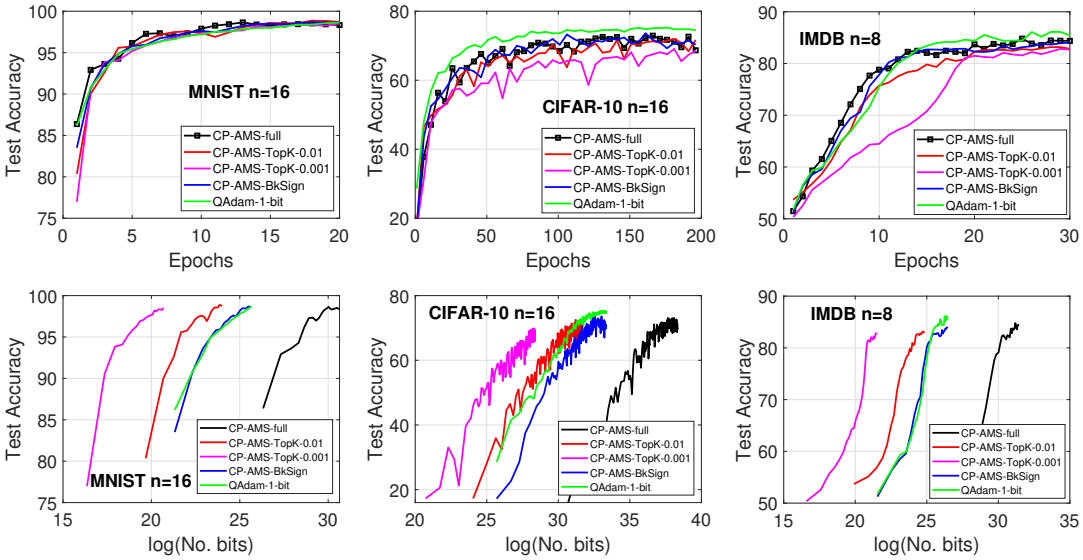

Figure 3: Test accuracy of distributed COMP-AMS. Top row: accuracy vs. epochs. Bottom row: accuracy vs. number of bits transmitted per worker.

6 Conclusion

In this paper, we study the simple, convenient, yet unexplored gradient averaging strategy for distributed adaptive optimization called COMP-AMS. **Top-k** and **Block-Sign** compressor are incorporated for communication efficiency, whose biased is compensated by the error feedback strategy. We develop the convergence rate of COMP-AMS, and for the first time in literature show that for AMSGrad, gradient averaging with error feedback matches the convergence of full-gradient AMSGrad, and linear speedup can be obtained in distributed training. Numerical experiments are conducted to justify our theory, and demonstrate that similar performance can be achieved with significantly reduced communication. Though COMP-AMS generalizes slightly worse than QADAM since no local moment estimation is required, this in turn brings high memory/hardware efficiency that makes it a useful distributed learning scheme in practice. We hope that our work could originate more related research on the theory and application of distributed adaptive optimization.

References

[1] Naman Agarwal, Ananda Theertha Suresh, Felix X. Yu, Sanjiv Kumar, and Brendan McMahan. cpsgd: Communication-efficient and differentially-private distributed SGD. In *Advances in Neural Information Processing Systems 31: Annual Conference on Neural Information Processing Systems 2018, NeurIPS 2018, December 3-8, 2018, Montréal, Canada*, pages 7575–7586, 2018.

[2] Ahmad Ajalloeian and Sebastian U Stich. Analysis of sgd with biased gradient estimators. *arXiv preprint arXiv:2008.00051*, 2020.

[3] Alham Fikri Aji and Kenneth Heafield. Sparse communication for distributed gradient descent. *arXiv preprint arXiv:1704.05021*, 2017.

[4] Dan Alistarh, Demjan Grubic, Jerry Li, Ryota Tomioka, and Milan Vojnovic. Qsgd: Communication-efficient sgd via gradient quantization and encoding. In *Advances in Neural Information Processing Systems*, pages 1709–1720, 2017.

[5] Dan Alistarh, Torsten Hoefler, Mikael Johansson, Sarit Khirirat, Nikola Konstantinov, and Cédric Renggli. The convergence of sparsified gradient methods. *arXiv preprint arXiv:1809.10505*, 2018.

[6] Debraj Basu, Deepesh Data, Can Karakus, and Suhas N. Diggavi. Qsparse-local-sgd: Distributed SGD with quantization, sparsification and local computations. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 14668–14679, 2019.

[7] Jeremy Bernstein, Yu-Xiang Wang, Kamyar Azizzadenesheli, and Animashree Anandkumar. signsgd: Compressed optimisation for non-convex problems. In *International Conference on Machine Learning*, pages 560–569. PMLR, 2018.

[8] Jeremy Bernstein, Jiawei Zhao, Kamyar Azizzadenesheli, and Anima Anandkumar. signsgd with majority vote is communication efficient and fault tolerant. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019.

[9] Aleksandr Beznosikov, Samuel Horváth, Peter Richtárik, and Mher Safaryan. On biased compression for distributed learning. *CoRR*, abs/2002.12410, 2020.

[10] Stephen Boyd, Neal Parikh, Eric Chu, Borja Peleato, Jonathan Eckstein, et al. Distributed optimization and statistical learning via the alternating direction method of multipliers. *Foundations and Trends® in Machine learning*, 3(1):1–122, 2011.

[11] Ken Chang, Niranjan Balachandar, Carson K. Lam, Darvin Yi, James M. Brown, Andrew Beers, Bruce R. Rosen, Daniel L. Rubin, and Jayashree Kalpathy-Cramer. Distributed deep learning networks among institutions for medical imaging. *J. Am. Medical Informatics Assoc.*, 25(8):945–954, 2018.

[12] Moses Charikar, Kevin C. Chen, and Martin Farach-Colton. Finding frequent items in data streams. In *Automata, Languages and Programming, 29th International Colloquium, ICALP 2002, Malaga, Spain, July 8-13, 2002, Proceedings*, volume 2380 of *Lecture Notes in Computer Science*, pages 693–703. Springer, 2002.

[13] Congliang Chen, Li Shen, Haozhi Huang, Qi Wu, and Wei Liu. Quantized adam with error feedback. *arXiv preprint arXiv:2004.14180*, 2020.

[14] Xiangyi Chen, Sijia Liu, Ruoyu Sun, and Mingyi Hong. On the convergence of A class of adam-type algorithms for non-convex optimization. In *7th International Conference on Learning Representations, ICLR 2019, New Orleans, LA, USA, May 6-9, 2019*. OpenReview.net, 2019.

[15] Trishul Chilimbi, Yutaka Suzue, Johnson Apacible, and Karthik Kalyanaraman. Project adam: Building an efficient and scalable deep learning training system. In *Symposium on Operating Systems Design and Implementation*, pages 571–582, 2014.

[16] Dami Choi, Christopher J. Shallue, Zachary Nado, Jaehoon Lee, Chris J. Maddison, and George E. Dahl. On empirical comparisons of optimizers for deep learning. *CoRR*, abs/1910.05446, 2019.

[17] Paul Covington, Jay Adams, and Emre Sargin. Deep neural networks for youtube recommendations. In *Proceedings of the 10th ACM Conference on Recommender Systems, Boston, MA, USA, September 15-19, 2016*, pages 191–198. ACM, 2016.

[18] Christopher De Sa, Matthew Feldman, Christopher Ré, and Kunle Olukotun. Understanding and optimizing asynchronous low-precision stochastic gradient descent. In *Proceedings of the 44th Annual International Symposium on Computer Architecture*, pages 561–574, 2017.

[19] Jeffrey Dean, Greg Corrado, Rajat Monga, Kai Chen, Matthieu Devin, Quoc V. Le, Mark Z. Mao, Marc'Aurelio Ranzato, Andrew W. Senior, Paul A. Tucker, Ke Yang, and Andrew Y. Ng. Large scale distributed deep networks. In *Advances in Neural Information Processing Systems 25: 26th Annual Conference on Neural Information Processing Systems 2012. Proceedings of a meeting held December 3-6, 2012, Lake Tahoe, Nevada, United States*, pages 1232–1240, 2012.

[20] Tim Dettmers. 8-bit approximations for parallelism in deep learning. In Yoshua Bengio and Yann LeCun, editors, *4th International Conference on Learning Representations, ICLR 2016, San Juan, Puerto Rico, May 2-4, 2016, Conference Track Proceedings*, 2016.

[21] Jacob Devlin, Ming-Wei Chang, Kenton Lee, and Kristina Toutanova. BERT: pre-training of deep bidirectional transformers for language understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, NAACL-HLT 2019, Minneapolis, MN, USA, June 2-7, 2019, Volume 1 (Long and Short Papers)*, pages 4171–4186. Association for Computational Linguistics, 2019.

[22] John C Duchi, Alekh Agarwal, and Martin J Wainwright. Dual averaging for distributed optimization: Convergence analysis and network scaling. *IEEE Transactions on Automatic control*, 57(3):592–606, 2011.

[23] John C. Duchi, Elad Hazan, and Yoram Singer. Adaptive subgradient methods for online learning and stochastic optimization. In *COLT 2010 - The 23rd Conference on Learning Theory, Haifa, Israel, June 27-29, 2010*, pages 257–269, 2010.

[24] Saeed Ghadimi and Guanghui Lan. Stochastic first-and zeroth-order methods for nonconvex stochastic programming. *SIAM Journal on Optimization*, 23(4):2341–2368, 2013.

[25] Ian J. Goodfellow, Jean Pouget-Abadie, Mehdi Mirza, Bing Xu, David Warde-Farley, Sherjil Ozair, Aaron C. Courville, and Yoshua Bengio. Generative adversarial nets. In *Advances in Neural Information Processing Systems 27: Annual Conference on Neural Information Processing Systems 2014, December 8-13 2014, Montreal, Quebec, Canada*, pages 2672–2680, 2014.

[26] Priya Goyal, Piotr Dollár, Ross B. Girshick, Pieter Noordhuis, Lukasz Wesolowski, Aapo Kyrola, Andrew Tulloch, Yangqing Jia, and Kaiming He. Accurate, large minibatch SGD: training imagenet in 1 hour. *CoRR*, abs/1706.02677, 2017.

[27] Alex Graves, Abdel-rahman Mohamed, and Geoffrey E. Hinton. Speech recognition with deep recurrent neural networks. In *IEEE International Conference on Acoustics, Speech and Signal Processing, ICASSP 2013, Vancouver, BC, Canada, May 26-31, 2013*, pages 6645–6649. IEEE, 2013.

[28] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *2016 IEEE Conference on Computer Vision and Pattern Recognition, CVPR 2016, Las Vegas, NV, USA, June 27-30, 2016*, pages 770–778. IEEE Computer Society, 2016.

[29] Mingyi Hong, Davood Hajinezhad, and Ming-Min Zhao. Prox-pda: The proximal primal-dual algorithm for fast distributed nonconvex optimization and learning over networks. In *International Conference on Machine Learning*, pages 1529–1538, 2017.

[30] Nikita Ivkin, Daniel Rothchild, Enayat Ullah, Vladimir Braverman, Ion Stoica, and Raman Arora. Communication-efficient distributed SGD with sketching. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 13144–13154, 2019.

[31] Jiawei Jiang, Fangcheng Fu, Tong Yang, and Bin Cui. Sketchml: Accelerating distributed machine learning with data sketches. In *Proceedings of the 2018 International Conference on Management of Data, SIGMOD Conference 2018, Houston, TX, USA, June 10-15, 2018*, pages 1269–1284. ACM, 2018.

[32] Peng Jiang and Gagan Agrawal. A linear speedup analysis of distributed deep learning with sparse and quantized communication. In *Proceedings of the 32nd International Conference on Neural Information Processing Systems*, pages 2530–2541, 2018.

[33] Sai Praneeth Karimireddy, Quentin Rebjock, Sebastian U Stich, and Martin Jaggi. Error feedback fixes signsgd and other gradient compression schemes. *arXiv preprint arXiv:1901.09847*, 2019.

[34] Diederik P Kingma and Jimmy Ba. Adam: A method for stochastic optimization. *arXiv preprint arXiv:1412.6980*, 2014.

[35] Anastasia Koloskova, Sebastian U Stich, and Martin Jaggi. Decentralized stochastic optimization and gossip algorithms with compressed communication. In *International Conference on Machine Learning*, pages 3478–3487, 2019.

[36] Alex Krizhevsky, Geoffrey Hinton, et al. Learning multiple layers of features from tiny images. 2009.

[37] Yann LeCun, Léon Bottou, Yoshua Bengio, and Patrick Haffner. Gradient-based learning applied to document recognition. *Proceedings of the IEEE*, 86(11):2278–2324, 1998.

[38] Yujun Lin, Song Han, Huizi Mao, Yu Wang, and Bill Dally. Deep gradient compression: Reducing the communication bandwidth for distributed training. In *6th International Conference on Learning Representations, ICLR 2018, Vancouver, BC, Canada, April 30 - May 3, 2018, Conference Track Proceedings*. OpenReview.net, 2018.

[39] Liyuan Liu, Haoming Jiang, Pengcheng He, Weizhu Chen, Xiaodong Liu, Jianfeng Gao, and Jiawei Han. On the variance of the adaptive learning rate and beyond. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020.

[40] Songtao Lu, Xinwei Zhang, Haoran Sun, and Mingyi Hong. Gnsd: A gradient-tracking based nonconvex stochastic algorithm for decentralized optimization. In *2019 IEEE Data Science Workshop (DSW)*, pages 315–321, 2019.

[41] Andrew Maas, Raymond E Daly, Peter T Pham, Dan Huang, Andrew Y Ng, and Christopher Potts. Learning word vectors for sentiment analysis. In *Proceedings of the 49th annual meeting of the association for computational linguistics: Human language technologies*, pages 142–150, 2011.

[42] Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, and Blaise Aguera y Arcas. Communication-efficient learning of deep networks from decentralized data. In *Artificial Intelligence and Statistics*, pages 1273–1282. PMLR, 2017.

[43] Hiroaki Mikami, Hisahiro Suganuma, Yoshiki Tanaka, Yuichi Kageyama, et al. Massively distributed sgd: Imagenet/resnet-50 training in a flash. *arXiv preprint arXiv:1811.05233*, 2018.

[44] Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin A. Riedmiller. Playing atari with deep reinforcement learning. *CoRR*, abs/1312.5602, 2013.

[45] Parvin Nazari, Davoud Ataee Tarzanagh, and George Michailidis. Dadam: A consensus-based distributed adaptive gradient method for online optimization. *arXiv preprint arXiv:1901.09109*, 2019.

[46] Angelia Nedic and Asuman Ozdaglar. Distributed subgradient methods for multi-agent optimization. *IEEE Transactions on Automatic Control*, 54(1):48, 2009.

[47] Arkadi Nemirovski, Anatoli Juditsky, Guanghui Lan, and Alexander Shapiro. Robust stochastic approximation approach to stochastic programming. *SIAM Journal on optimization*, 19(4):1574–1609, 2009.

[48] Sashank J Reddi, Satyen Kale, and Sanjiv Kumar. On the convergence of adam and beyond. In *International Conference on Learning Representations*, 2018.

[49] Frank Seide, Hao Fu, Jasha Droppo, Gang Li, and Dong Yu. 1-bit stochastic gradient descent and its application to data-parallel distributed training of speech dnns. In *INTERSPEECH 2014, 15th Annual Conference of the International Speech Communication Association, Singapore, September 14-18, 2014*, pages 1058–1062. ISCA, 2014.

[50] Zebang Shen, Aryan Mokhtari, Tengfei Zhou, Peilin Zhao, and Hui Qian. Towards more efficient stochastic decentralized learning: Faster convergence and sparse communication. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 4631–4640. PMLR, 2018.

[51] Shaohuai Shi, Kaiyong Zhao, Qiang Wang, Zhenheng Tang, and Xiaowen Chu. A convergence analysis of distributed sgd with communication-efficient gradient sparsification. In *IJCAI*, pages 3411–3417, 2019.

[52] David Silver, Julian Schrittwieser, Karen Simonyan, Ioannis Antonoglou, Aja Huang, Arthur Guez, Thomas Hubert, Lucas Baker, Matthew Lai, Adrian Bolton, Yutian Chen, Timothy P. Lillicrap, Fan Hui, Laurent Sifre, George van den Driessche, Thore Graepel, and Demis Hassabis. Mastering the game of go without human knowledge. *Nat.*, 550(7676):354–359, 2017.

[53] Sebastian U Stich, Jean-Baptiste Cordonnier, and Martin Jaggi. Sparsified sgd with memory. In *Advances in Neural Information Processing Systems*, pages 4447–4458, 2018.

[54] Sebastian U. Stich and Sai Praneeth Karimireddy. The error-feedback framework: Better rates for SGD with delayed gradients and compressed communication. *CoRR*, abs/1909.05350, 2019.

[55] Athanasios Voulodimos, Nikolaos Doulamis, Anastasios D. Doulamis, and Eftychios Protopapadakis. Deep learning for computer vision: A brief review. *Comput. Intell. Neurosci.*, 2018:7068349:1–7068349:13, 2018.

[56] Jianqiao Wangni, Jialei Wang, Ji Liu, and Tong Zhang. Gradient sparsification for communication-efficient distributed optimization. In *Advances in Neural Information Processing Systems*, pages 1299–1309, 2018.

[57] Jian Wei, Jianhua He, Kai Chen, Yi Zhou, and Zuoyin Tang. Collaborative filtering and deep learning based recommendation system for cold start items. *Expert Systems with Applications*, 69:29–39, 2017.

[58] Wei Wen, Cong Xu, Feng Yan, Chunpeng Wu, Yandan Wang, Yiran Chen, and Hai Li. Terngrad: Ternary gradients to reduce communication in distributed deep learning. *arXiv preprint arXiv:1705.07878*, 2017.

[59] Jiaxiang Wu, Weidong Huang, Junzhou Huang, and Tong Zhang. Error compensated quantized SGD and its applications to large-scale distributed optimization. In *Proceedings of the 35th International Conference on Machine Learning, ICML 2018, Stockholmsmässan, Stockholm, Sweden, July 10-15, 2018*, volume 80 of *Proceedings of Machine Learning Research*, pages 5321–5329. PMLR, 2018.

[60] Guandao Yang, Tianyi Zhang, Polina Kirichenko, Junwen Bai, Andrew Gordon Wilson, and Chris De Sa. Swalp: Stochastic weight averaging in low precision training. In *International Conference on Machine Learning*, pages 7015–7024. PMLR, 2019.

[61] Yang You, Jing Li, Sashank J. Reddi, Jonathan Hseu, Sanjiv Kumar, Srinadh Bhojanapalli, Xiaodan Song, James Demmel, Kurt Keutzer, and Cho-Jui Hsieh. Large batch optimization for deep learning: Training BERT in 76 minutes. In *8th International Conference on Learning Representations, ICLR 2020, Addis Ababa, Ethiopia, April 26-30, 2020*. OpenReview.net, 2020.

[62] Tom Young, Devamanyu Hazarika, Soujanya Poria, and Erik Cambria. Recent trends in deep learning based natural language processing [review article]. *IEEE Comput. Intell. Mag.*, 13(3):55–75, 2018.

[63] Hao Yu, Rong Jin, and Sen Yang. On the linear speedup analysis of communication efficient momentum SGD for distributed non-convex optimization. In *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 7184–7193. PMLR, 2019.

[64] Yue Yu, Jiaxiang Wu, and Junzhou Huang. Exploring fast and communication-efficient algorithms in large-scale distributed networks. In *The 22nd International Conference on Artificial Intelligence and Statistics, AISTATS 2019, 16-18 April 2019, Naha, Okinawa, Japan*, volume 89 of *Proceedings of Machine Learning Research*, pages 674–683. PMLR, 2019.

[65] Matthew D. Zeiler. ADADELTA: an adaptive learning rate method. *CoRR*, abs/1212.5701, 2012.

[66] Hantian Zhang, Jerry Li, Kaan Kara, Dan Alistarh, Ji Liu, and Ce Zhang. Zipml: Training linear models with end-to-end low precision, and a little bit of deep learning. In *Proceedings of the 34th International Conference on Machine Learning, ICML 2017, Sydney, NSW, Australia, 6-11 August 2017*, volume 70 of *Proceedings of Machine Learning Research*, pages 4035–4043. PMLR, 2017.

[67] Lei Zhang, Shuai Wang, and Bing Liu. Deep learning for sentiment analysis: A survey. *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, 8(4), 2018.

[68] Tianyi Zhang, Felix Wu, Arzoo Katiyar, Kilian Q. Weinberger, and Yoav Artzi. Revisiting few-sample BERT fine-tuning. *CoRR*, abs/2006.05987, 2020.

[69] Weijie Zhao, Deping Xie, Ronglai Jia, Yulei Qian, Ruiquan Ding, Mingming Sun, and Ping Li. Distributed hierarchical GPU parameter server for massive scale deep learning ads systems. In *Proceedings of Machine Learning and Systems 2020, MLSys 2020, Austin, TX, USA, March 2-4, 2020*. mlsys.org, 2020.

[70] Shuai Zheng, Ziyue Huang, and James T. Kwok. Communication-efficient distributed blockwise momentum SGD with error-feedback. In *Advances in Neural Information Processing Systems 32: Annual Conference on Neural Information Processing Systems 2019, NeurIPS 2019, December 8-14, 2019, Vancouver, BC, Canada*, pages 11446–11456, 2019.

[71] Dongruo Zhou, Yiqi Tang, Ziyan Yang, Yuan Cao, and Quanquan Gu. On the convergence of adaptive gradient methods for nonconvex optimization. *CoRR*, abs/1808.05671, 2018.

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes]
   (b) Did you describe the limitations of your work? [Yes] Section 5 on the limitations of using compression techniques
   (c) Did you discuss any potential negative societal impacts of your work? [N/A]
   (d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes]
2. If you are including theoretical results...
   (a) Did you state the full set of assumptions of all theoretical results? [Yes]
   (b) Did you include complete proofs of all theoretical results? [Yes]
3. If you ran experiments...
   (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [No] We included the data and model architecture, and can provide the code upon request
   (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes]
   (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [No] Our results are average over several runs, which provide clear comparison. We did not include error bar for clarity of the figures.
   (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [No]
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   (a) If your work uses existing assets, did you cite the creators? [Yes]
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5. If you used crowdsourcing or conducted research with human subjects...
   (a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A]
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