Sparsified Distributed Adaptive Learning with Error Feedback

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Abstract

To be completed...

1 Introduction

Most modern machine learning tasks can be casted as a large finite-sum optimization problem written as:

$$\min_{\theta \in \Theta} \frac{1}{n} \sum_{i=1}^{n} f_i(\theta) \tag{1}$$

where n denotes the number of workers, f_i represents the average loss for worker i and θ the global model parameter taking value in Θ, a subset of $\mathbb{R}^d$.

Some related work:

[18] develops variant of signSGD (as a biased compression schemes) for distributed optimization. Contributions are mainly on this error feedback variant. In [26], the authors provide theoretical results on the convergence of sparse Gradient SGD for distributed optimization (we want that for AMS here). [27] develops a variant of distributed SGD with sparse gradients too. Contributions include a memory term used while compressing the gradient (using top k for instance). Speeding up the convergence in $\frac{1}{T^3}$.

2 Preliminaries

Sparse Optimization Methods.

Distributed Learning. When a large number of compute engines is available, being able to train global machine learning models while mutualizing the available and *decentralized* source of computation has been a growing focus for the community.

Decentralized optimization methods include methods such as ADMM [6], Distributed Subgradient Descent [24], Dual Averaging [11], Prox-PDA [14], GNSD [21], and Choco-SGD [20].

A recent work [7], which focuses on adaptive gradient methods, namely the Adam [19] annd the AMSGrad [25] optimization methods, develops a decentralized variant of gradient based and adaptive methods in the context of gossip protocols. To date, very few contributions provided attempt to efficiently run adaptive gradient method is such a distributed setting. Apart from [7], **(author?)** [23] proposes a decentralized version of AMSGrad [25] which provably satisfies some non-standard regret. Though, no sparsified variants of them have been proposed for practical purposes nor been studied in the literature.

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Compression-Based Distributed Optimization. While the capabilities of the compute powers is exploding, the communication complexity between either the central server and the decentralized workers or among workers is becoming ineffectively large [9, 22]. Gradient sparsification constitutes one popular method to induce sparsity through the optimization procedure and reduce the number of bits transmitted at each iteration. Extensive works have studied this technique to improve the communication efficiency of SGD-based methods such as distributed SGD. This large class of sparsification techniques include gradient quantization leveraging quantized vector of gradients in the communication phase [2, 29, 16, 28, 13, 8, 15], gradient sparsificaiton generally selection top k components of the vector to be communicated, see [27, 1], or variants of the particular SGD algorithm such as low-precision SGD [4, 18] proposing a trade-off between communication cost and precision, and signSGD [10, 30] where only the signs of the gradient vectors are communicated. Most of these works apply to the SGD method [5] as a prototype where a novel method and some convergence results are presented with a rate of $\mathcal{O}(\frac{1}{\sqrt{T}})$ where T denotes the total number of iterations, see [3], thus achieving the same rate as plain SGD, see [12, 17].

Yet these communication reduction techniques, still presents a negative dependence on the number of workers, typically a linear dependence. Hence the need for even more efficient techniques which constitutes the object of our paper.

3 Method

Consider standard synchronous distributed optimization setting. AMSGrad is used as the prototype, and the local workers is only in charge of gradient computation.

3.1 TopK AMSGrad with Error Feedback

The key difference (and interesting part) of our TopK AMSGrad compared with the following arxiv paper "Quantized Adam" https://arxiv.org/pdf/2004.14180.pdf is that, in our model only gradients are transmitted. In "QAdam", each local worker keeps a local copy of moment estimator m and v, and compresses and transmits m/v as a whole. Thus, that method is very much like the sparsified distributed SGD, except that g is changed into m/v. In our model, the moment estimates m and v are computed only at the central server, with the compressed gradients instead of the full gradient. This would be the key (and difficulty) in convergence analysis.

Algorithm 1 SPARS-AMS for Distributed Learning

1: **Input**: parameter β_1, β_2, learning rate η_t.
2: Initialize: central server parameter $\theta_0 \in \Theta \subseteq \mathbb{R}^d$; $e_{t,i} = 0$ 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-1} from central server
6:     Compute stochastic gradient $g_{t,i}$ at θ_t
7:     Compute $\tilde{g}_{t,i} = TopK(g_{t,i} + e_{t,i}, k)$
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 global model $\theta_t = \theta_{t-1} - \eta_t \frac{m_t}{\sqrt{\hat{v}_t}}$
17: **end for**

3.2 Convergence Analysis

Several mild assumptions to make: Nonconvex and smooth loss function, unbiased stochastic gradient, bounded variance of the gradient, bounded norm of the gradient, control of the distance between the true gradient and its sparse variant.

Check [7] starting with single machine and extending to distributed settings (several machines).

3.2.1 Single machine

Under the centralized setting, the goal is to derive an upper bound to the second order moment of the gradient of the objective function at some iteration $T_f \in [1, T]$.

We begin by making the following assumptions.

Assumption 1. *(Smoothness) For $i \in [\![n]\!]$, f_i is L-smooth:* $\|\nabla f_i(\theta) - \nabla f_i(\vartheta)\| \leq L \|\theta - \vartheta\|$.

Assumption 2. *(Unbiased and Bounded gradient) For any iteration index $t > 0$ and worker index $i \in [\![n]\!]$, the stochastic gradient is unbiased and bounded from above: $\mathbb{E}[g_{t,i}] = \nabla f(\theta_t)$ and $\|g_{t,i}\| \leq G$.*

Assumption 3. *(Bounded variance) For any iteration index $t > 0$ and worker index $i \in [\![n]\!]$, the variance of the noisy gradient is bounded: $\mathbb{E}[|g_{t,i} - \nabla f(\theta_t)|^2] < \sigma^2$.*

Denote by $Q(\cdot)$ the quantization operator Line 7 of Algorithm 1, which takes as input a gradient vector and returns a quantized version of it, and note $\tilde{g} := Q(g)$. Assume that

Assumption 4. *(Bounded Quantization) There exists a constant $q > 0$ such that $\|g - \tilde{g}\| \leq q \|g\|$.*

We first define multiple auxiliary sequences. For the first moment, define

$$
\begin{aligned}
\bar{m}_t &= m_t + \mathcal{E}_t, \\
\mathcal{E}_t &= \beta_1 \mathcal{E}_{t-1} + (1 - \beta_1)(e_{t+1} - e_t),
\end{aligned}
$$

such that

$$
\begin{aligned}
\bar{m}_t &= \bar{m}_t + \mathcal{E}_t \\
&= \beta_1(m_t + \mathcal{E}_t) + (1 - \beta_1)(\bar{g}_t + e_{t+1} - e_1) \\
&= \beta_1 \bar{m}_{t-1} + (1 - \beta_1) g_t.
\end{aligned}
$$

Denote the following auxiliary variables at iteration $t + 1$

$$
z_{t+1} = \theta_{t+1} + \frac{\beta_1}{1 - \beta_1}(\theta_{t+1} - \theta_t) \tag{2}
$$

3.2.2 Multiple machine

4 Experiments

Our proposed TopK-EF with AMSGrad matches that of full AMSGrad, in distributed learning. Number of local workers is 20. Error feedback fixes the convergence issue of using solely the TopK gradient.

5 Conclusion

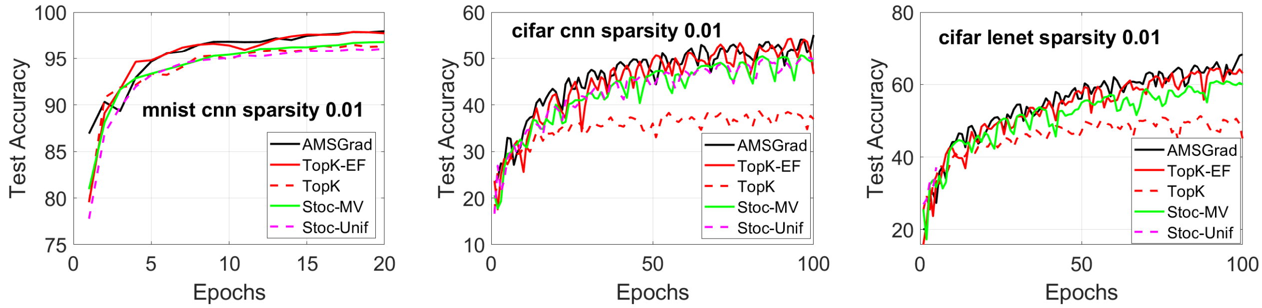

Figure 1: Test accuracy.

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A Appendix