

Sparsified Distributed Adaptive Learning with Error Feedback

Abstract

To be completed...

1 Introduction

2 Preliminaries

Distributed Learning.

Sparse Optimization.

Sketch and Quantization based FL.

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 Federated Learning

```
1: Input: parameter  $\beta_1, \beta_2$ , learning rate  $\eta_t$ .
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  $\theta_{t-1}$  from central server
6:     Compute stochastic gradient  $g_{t,i}$  at  $\theta_t$ 
7:     Compute  $\tilde{g}_{t,i} = \text{TopK}(g_{t,i} + e_{t,i}, k)$ 
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

Nonconvex smooth loss function. Bounded gradient variance.

3.2.1 Single machine

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

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

TBD...

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

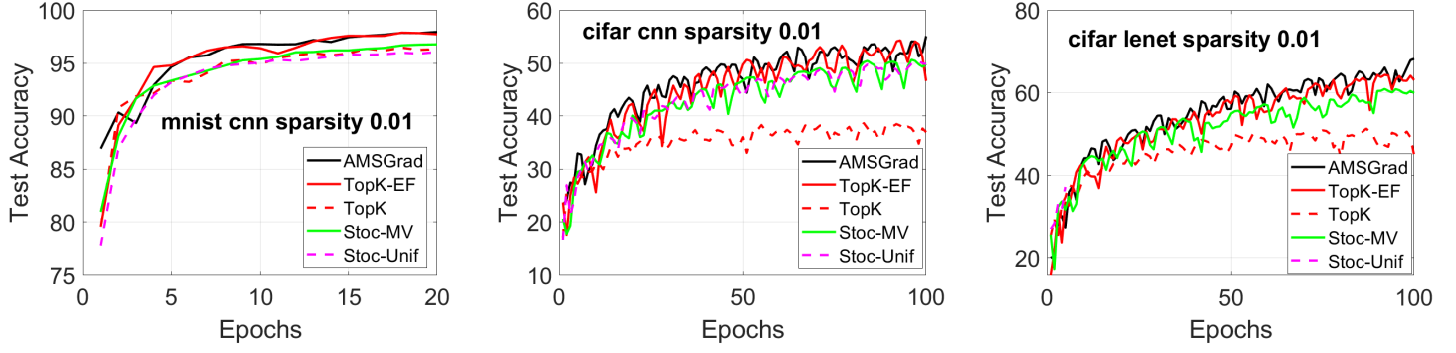


Figure 1: Test accuracy.

References:

[1] [2] [3] <https://arxiv.org/pdf/1901.09847.pdf> <https://proceedings.neurips.cc/paper/2018/file/b440509a0106086a67bc2ea9df0a1dab-Paper.pdf> https://pdfs.semanticscholar.org/8728/dee89906022c1d4f5c.pdf?_ga=2.152244026.2027005181.1606271153-15127215.1603945483

References

- [1] 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.
- [2] 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.
- [3] Sebastian U Stich, Jean-Baptiste Cordonnier, and Martin Jaggi. Sparsified sgd with memory. In *Advances in Neural Information Processing Systems*, pages 4447–4458, 2018.

A Appendix