Efficient Distributed Stochastic Dual Coordinate Ascent

Mingrui Liu, Jeff Hajewski
Department of Computer Science
University of Iowa
Iowa City, IA 52242
mingrui-liu@uiowa.edu, jeffery-hajewski@uiowa.edu

Abstract

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1 Introduction

In recent years, we come into the big data era. Many large-scale machine learning problems, most of which are essentially optimization problems with huge magnitude of data size, need to be tackled. Two common countermeasures to deal with this are employing stochastic optimization algorithms, and utilizing computational resources in a parallel or distributed manner[3].

In this paper, we consider a class of convex optimization problems with special structure, whose objective can be expressed as the sum of a finite sum of loss functions and a regularization function:

$$\min_{w\in\mathbb{R}^d} F(w), \text{where } P(w) = \frac{1}{n}\sum_{i=1}^{n}\phi(w^\top x_i, y_i) + \lambda g(w), \tag{1}$$

where $w \in \mathbb{R}^d$ denotes the weight vector, $(x_i, y_i), x_i \in \mathbb{R}^d, y_i \in \mathbb{R}, i = 1, \ldots, n$ are training data, $\lambda > 0$ is a regularization parameter, $\phi(z, y)$ is a convex function of z, and $g(w)$ is a convex function of w. We refer to the problem in (1) as Regularized Finite Sum Minimization (RFSM) problem. When $g(w) = 0$, the problem reduces to the Finite Sum Minimization (FSM) problem.

Both RFSM and FSM problems have been extensively studied in machine learning and optimization literature. When n is large, numerous sequential stochastic optimization algorithms were proposed[2, 13, 10, 15, 14, 7, 11, 17, 16, 18, 5, 21, 9, 4, 1, 8], and there also exist several parallel or distributed stochastic algorithms[3, 12, 22, 19, 20]. Specifically, S. Shalv-Shwartz and T. Zhang [15] proposed an Stochastic Dual Coordinate Ascent (SDCA) which provided strongly theoretical guarantee regarding the duality gap. T. Yang [19] developed a Distributed Stochastic Dual Coordinate Ascent (DisDCA) algorithm and its practical variant, and analyzed the tradeoff between communication and computation. However, to get a more efficient distributed SDCA is a open problem. In this paper, we first provide a GPU implementation of the vanilla distributed SDCA[19], and then give an asynchronous distributed SDCA to make full use of computational resources.

2 Related Work

First we review the related work of sequential stochastic convex optimization for solving FSM and RFSM problems. The first numerical scheme of stochastic optimization stems from stochastic gradient

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descent (SGD)[2, 10], which was designed to avoid the calculation of full gradient and gets faster convergence than gradient descent (GD). To improve the converge rate of SGD, many new algorithms were proposed by exploiting the finite sum structure, including the Stochastic Average Gradient (SAG)[13], Stochastic Dual Coordinate Ascent (SDCA)[15], Stochastic Variance Reduced Gradient (SVRG)[7], Accelerated Proximal Coordinate method (APCG)[9], SAGA[6], Prox-SDCA[16], Prox-SVRG[18], and Stochastic Primal-dual Coordinate method (SPDC)[21]. Recently, the optimal first-order stochastic optimization method were developed[1, 8]. Although there exist rich literature studying sequential stochastic optimization with strong theoretical guarantee, less efforts have been devoted to considering them in a parallel or distributed manner. It constitutes a huge gap between theory and practice, since nowadays the size of data increases at a rapid speed, which makes one-core processor very difficult to handle it properly.

We will build off of work from [CITE YANG 1 & 2], incorporating work from [CITE LI PS]. In [CITE YANG], SDCA is implemented in a distributed, syncrhonized fashion. While the achieved results were quite promising, they did not take advantage of hardware acceleration or asynchronous communication. [CITE LI PS] builds an asynchronous communication framework using the concept of parameter servers, which are central data stores for model parameters, and distributed workers working in an asynchronous fashion (i.e., communication and parameter updates are non-blocking operations).

3 The Proposed Work

We will approach this problem from both theoreticl and implementation perspectives. On the theoretical side we hope to make guarantees on convergence of our proposed approach, while on the implementation side we hope to build a scalable system that can take advantage of its hardware.

3.1 Theory

3.2 Implementation

There are two key aspects to the implementation: taking advantage of the GPU and working in a distributed setting.

3.2.1 GPU

When available, GPU acceleration will be used via CUDA. We will start by using CUDA libraries such as `cuBLAS` for efficient math operations. We will also add CUDA kernals for portions of our algorithms that are easily parallelized in a SIMD fashion.

3.2.2 Asynchronous Communication

In addition to using GPUs for math operations, we will distribute the workload over a cluster of computers. Each comptuer will work on a small subproblem used in the parameter update and send this result to a parameter server, which will handle parameter updates and synchronoization across workers. The architecture used will be similar to that of [CITE PS], using a central parameter server that communicates asynchronously with distributed workers. This asyncrhonous communication framework will be built using MPI and C++ threading facilities.

4 Plan

We will work in parallel, making progress on both the theory and implementation aspects of the project.

4.1 Theory

4.2 Implementation

The first part of the implementation approach will be adding CUDA support for the core math operations. The focus is on correctness, rather than optimizing runtime. This is also the simpler portion of the project and will require less time that the asynchronous communciation frmaework.

The second part of the implementation is building the asynchronous communication framework. This will be the most complex part of the implementation and require the most time and effort.

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Use unnumbered third level headings for the acknowledgments. All acknowledgments go at the end of the paper. Do not include acknowledgments in the anonymized submission, only in the final paper.

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