Asynchronous Optimization Algorithms with GPUs

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CSST Peer Seminar Sept. 4, 2019

Optimization with coordinate descent

Problem:

$$\underset{x \in \mathbb{R}^d}{\mathsf{minimize}} \ f(x).$$

Solve with stochastic coordinate descent (SCD):

Write
$$\nabla_i f(x) = \frac{\partial f}{\partial x_i}(x)$$
.

```
while not converged, every agent do
```

```
\label{eq:continuity} \begin{split} // & \text{Synchronize} \\ & \text{select } i(k) \in \{1,...,d\} \text{ randomly} \\ & w \leftarrow \alpha \nabla_{i(k)} f(x) \\ // & \text{Synchronize} \\ & x_{i(k)} \leftarrow x_{i(k)} - w \end{split}
```

end

Optimization with Finito

Problem:

$$\underset{x \in \mathbb{R}^d}{\text{minimize}} \ f(x), \ \text{where} \ f = \frac{1}{n} \sum_{i=1}^n f_i$$

Solve with Finito:

Let
$$z_1,...,z_n \in \mathbb{R}^d, x = \frac{1}{n} \sum_{i=1}^n z_i$$
.

```
while not converged, every agent do
```

```
 \begin{array}{l} \text{// Synchronize} \\ \text{ select } i(k) \in \{1,...,n\} \text{ randomly} \\ w \leftarrow x - z_i - \alpha \nabla f_{i(k)}(x) \\ \text{// Synchronize} \\ z_i \leftarrow z_i + w \\ x \leftarrow x + \frac{1}{n}w \end{array}
```

end

Asynchronous optimization algorithms

- ► Introduced in 2011 as *Hogwild!* (Async SGD¹)
- ► Explored in e.g. AsySCD², AsySPCD³, ARock⁴, ASAGA⁵, etc.
- ► Those paper experiment only with CPUs
 - ~10 cores in multi-core CPUs
 - Communication through shared memory simpler memory model

¹Niu, Recht, Ré, and Wright; NIPS 2011

²Liu, Wright, Ré, Bittorf, and Sridhar; JMLR 2013

³Liu, and Wright; SIOPT 2015

⁴Peng, Xu, Yan, and Yin; SISC 2016

⁵Leblond, Pedregosa, and Lacoste-Julien; AISTATS 2017

Graphic Processing Units (GPU)

- ► ~1000 slower processors (compared to CPUs)
- Usage
 - Originally designed for generating output images to a display device
 e.g. graphics and gaming
 - Has been used recently for medium & large-scale computation
 e.g. deep learning



- ▶ Difficulties of GPU computing in optimization:
 - Limited capability to communicate and coordinate (e.g. synchronize)
 Not all parallel things are GPU parallelizable
 - Small local memory

Parallelism in scientific computing

- ► Past:
 - Thought at a high level in an abstract way (i.e. simpler model)
 - Implementation: multi-core CPU / supercomputer
- ▶ Present: GPU computing becomes popular with deep learning boom e.g. GPUs are common platform for training neural network
- But GPUs are not widely used in optimization
- My research question: Can asynchronous optimization algorithms implemented with GPUs provide substantial speed-up?

Experiments

- Experiment Details:
 - Cost function: Binary regularized logistic regression
 - Datasets: Synthetic datasets and CIFAR-10 (cat & dog classes)
- ▶ Primary results:
 - GPUs give 10–30x speed-up over CPU counterparts
 - Asynchronous GPU algorithms give 1.7x speed-up over synchronous GPU algorithms

CPU models: Intel(R) Core(TM) i9-9940X CPU @ 3.30GHz (28 virtual cores)

GPU models: GeForce RTX 2080 Ti (4352 CUDA Cores)

Convergence plot

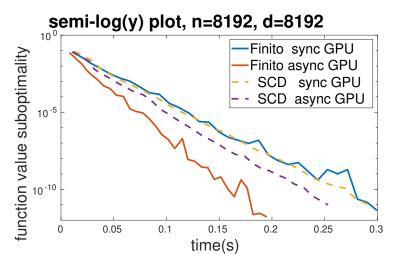


Figure: Convergence plot for SCD/ Finito implemented with GPU

Insights

- Couple a warp (32 threads) into a single agent
- ▶ Device memory access in GPU is expensive try to reduce it e.g. Recall in Finito, $x, z_i \in \mathbb{R}^d$,

end

Novel observations and future work

- Much speed-up of asynchronous GPU algorithms comes from reducing memory access
 - → Can **multi-GPU** bring further speed-ups?
- Sometimes synchronous algorithms catch up with asynchronous counterparts
 - \rightarrow Find out when this happens and explore the theory if possible
- ▶ Robustness of asynchronous algorithms —
 Sometimes they converge but their synchronous counterparts diverge
 → How this holds generally is useful for laborious parameter tuning.
- ► Trade-off for increasing number of agents Faster iteration & worse convergence behavior
 - \rightarrow Explore

Q & A