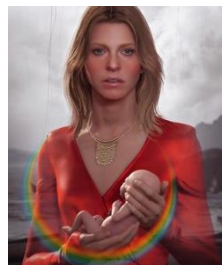


Is Going Asynchronous the Right Way of Handling Device Heterogeneity in Federated Learning?

(Handling Device Heterogeneity in Federated Learning:
The First Optimal Parallel SGD in the Presence of Data,
Compute & Communication Heterogeneity)

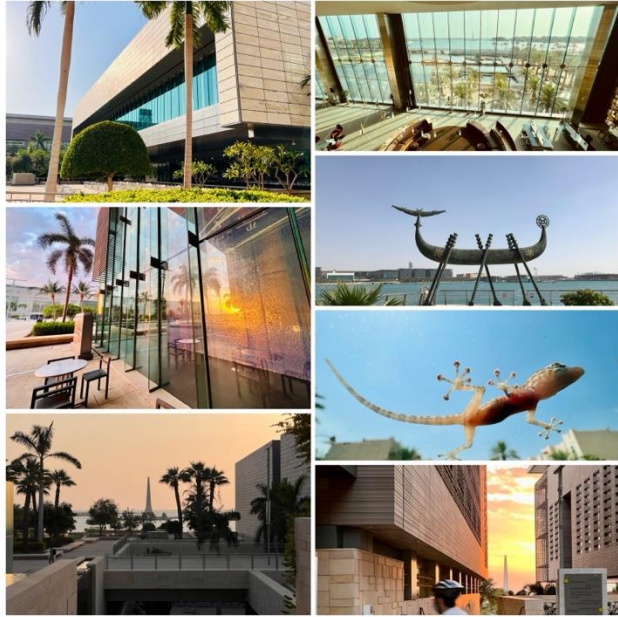
Peter Richtárik

King Abdullah University of Science and Technology
Kingdom of Saudi Arabia



April 9, 2025 @ Federated Learning One World Seminar (FLOW)

Optimization & Machine Learning Lab @ KAUST



Artavazd Maranjyan

Ivan Ilin

Kaja Gruntkowska

Alexander Tyurin

Omar Shaikh Omar





Part 1

Federated Learning



Jakub Konečný



H Brendan McMahan



THE UNIVERSITY
of EDINBURGH

**Federated Learning
was developed in 2015/2016 in a
collaboration between the University
of Edinburgh & Google**

H. Brendan McMahan, Eider Moore, Daniel Ramage, Seth Hampson, Blaise Agüera y Arcas
Communication-Efficient Learning of Deep Networks from Decentralized Data
20th International Conference on Artificial Intelligence and Statistics (AISTATS), 2017

Google AI Blog
The latest from Google Research

Federated Learning: Collaborative Machine Learning without Centralized Training Data

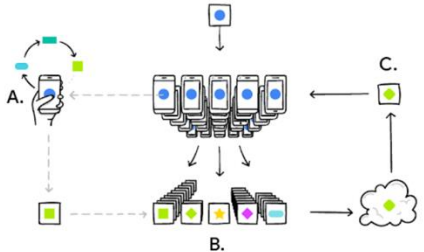
Thursday, April 6, 2017

Posted by Brendan McMahan and Daniel Ramage, Research Scientists

Standard machine learning approaches require centralizing the training data on one machine or in a datacenter. And Google has built one of the most secure and robust cloud infrastructures for processing this data to make our services better. Now for models trained from user interaction with mobile devices, we're introducing an additional approach: *Federated Learning*.

Federated Learning enables mobile phones to collaboratively learn a shared prediction model while keeping all the training data on device, decoupling the ability to do machine learning from the need to store the data in the cloud. This goes beyond the use of local models that make predictions on mobile devices (like the [Mobile Vision API](#) and [On-Device Smart Reply](#)) by bringing model *training* to the device as well.

It works like this: your device downloads the current model, improves it by learning from data on your phone, and then summarizes the changes as a small focused update. Only this update to the model is sent to the cloud, using encrypted communication, where it is immediately averaged with other user updates to improve the shared model. All the training data remains on your device, and no individual updates are stored in the cloud.

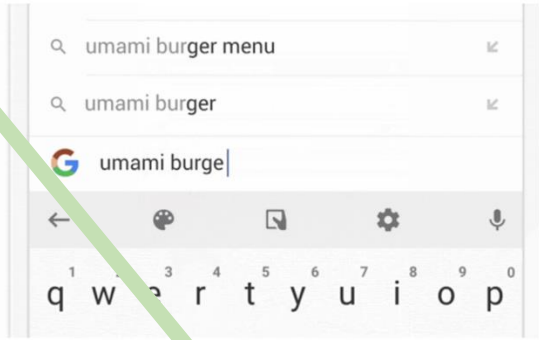


Your phone personalizes the model locally, based on your usage (A). Many users' updates are aggregated (B) to form a consensus change (C) to the shared model, after which the procedure is repeated.

Jakub Konečný, H. Brendan McMahan, Felix X. Yu, Peter Richtárik, Ananda Theertha Suresh, Dave Bacon
Federated Learning: Strategies for Improving Communication Efficiency
NIPS Private Multi-Party Machine Learning Workshop, 2016

Federated Learning allows for smarter models, lower latency, and less power consumption, all while ensuring privacy. And this approach has another immediate benefit: in addition to providing an update to the shared model, the improved model on your phone can also be used immediately, powering experiences personalized by the way you use your phone.

We're currently testing Federated Learning in [Gboard on Android](#), the Google Keyboard. When Gboard shows a suggested query, your phone locally stores information about the current context and whether you clicked the suggestion. Federated Learning processes that history on-device to suggest improvements to the next iteration of Gboard's query suggestion model.



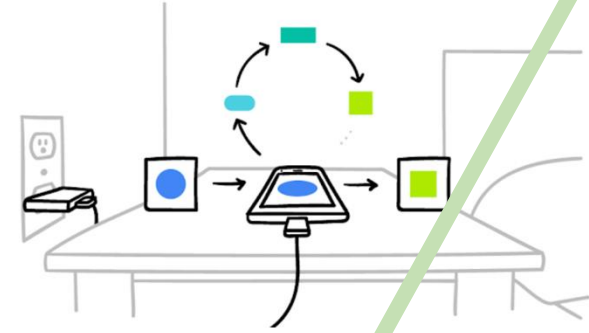
To make Federated Learning possible, we had to overcome many algorithmic and technical challenges. In a typical machine learning system, an optimization algorithm like [Stochastic Gradient Descent](#) (SGD) runs on a large dataset partitioned homogeneously across servers in the cloud. Such highly iterative algorithms require low-latency, high-throughput connections to the training data. But in the Federated Learning setting, the data is distributed across millions of devices in a highly uneven fashion. In addition, these devices have significantly higher latency, lower-throughput connections and are only intermittently available for training.

These bandwidth and latency limitations motivate our [Federated Averaging](#) algorithm, which can train deep networks using 10-100x less communication compared to a naively federated version of SGD. The key idea is to use the powerful processors in modern mobile devices to compute higher quality updates than simple gradient steps. Since it takes fewer iterations of high-quality updates to produce a good model, training can use much less communication. As upload speeds are typically [much slower](#) than download speeds, we also developed a novel way to reduce upload communication costs up to another 100x by [compressing updates](#) using random rotations and quantization. While these approaches are focused on training deep networks, we've also [designed algorithms](#) for high-dimensional sparse matrix models which excel on problems like click-through-rate prediction.

Deploying this technology to millions of heterogeneous phones running Gboard requires a sophisticated technology stack. On device training uses a miniature version of [TensorFlow](#). Careful scheduling ensures training happens only when the device is idle, plugged in, and on a free wireless connection, so there is no impact on the phone's performance.

Jakub Konečný, H. Brendan McMahan, Daniel Ramage, Peter Richtárik
Federated Optimization: Distributed Machine Learning for On-Device Intelligence
arXiv:1610.02527, 2016

Keith Bonawitz et al
Practical Secure Aggregation for Federated Learning on User-Held Data
NIPS Private Multi-Party Machine Learning Workshop, 2016



Your phone participates in Federated Learning only when it won't negatively impact your experience.

The system then needs to communicate and aggregate model updates in a secure, efficient, scalable, and fault-tolerant way. It's only the combination of research with this infrastructure that makes the benefits of Federated Learning possible.

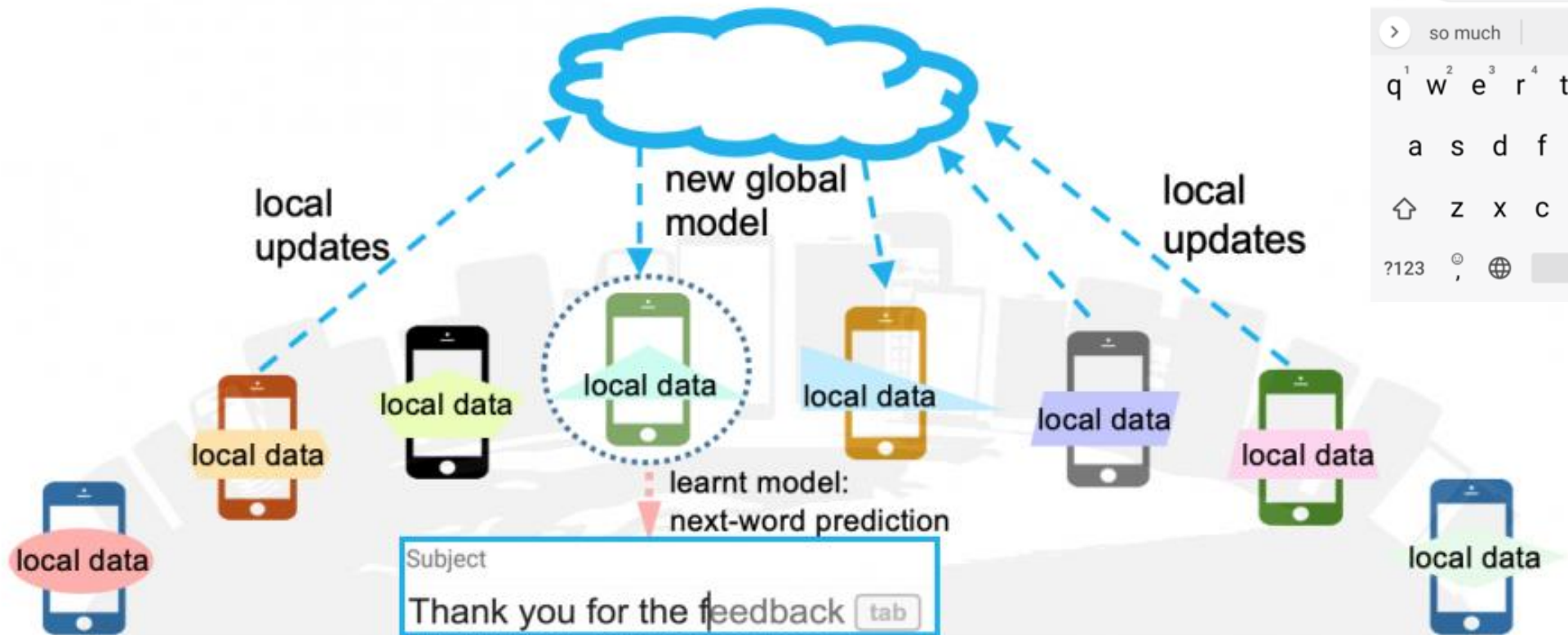
Federated learning works without the need to store user data in the cloud, but we're not stopping there. We've developed a [Secure Aggregation](#) protocol that uses cryptographic techniques so a coordinating server can only decrypt the average update if 100s or 1000s of users have participated — no individual phone's update can be inspected before averaging. It's the first protocol of its kind that is practical for deep-network-sized problems and real-world connectivity constraints. We designed Federated Averaging so the coordinating server only needs the average update, which allows Secure Aggregation to be used; however the protocol is general and can be applied to other problems as well. We're working hard on a production implementation of this protocol and expect to deploy it for Federated Learning applications in the near future.

Our work has only scratched the surface of what is possible. Federated Learning can't solve all machine learning problems (for example, learning to [recognize different dog breeds](#) by training on carefully labeled examples), and for many other models the necessary training data is already stored in the cloud (like training spam filters for Gmail). So Google will continue to advance the state-of-the-art for cloud-based ML, but we are also committed to ongoing research to expand the range of problems we can solve with Federated Learning. Beyond Gboard query suggestions, for example, we hope to improve the language models that power your keyboard based on what you actually type on your phone (which can have a style all its own) and photo rankings based on what kinds of photos people look at, share, or delete.

Applying Federated Learning requires machine learning practitioners to adopt new tools and a new way of thinking: model development, training, and evaluation with no direct access to or labeling of raw data, with communication cost as a limiting factor. We believe the user benefits of Federated Learning make tackling the technical challenges worthwhile, and are publishing our work with hopes of a widespread conversation within the machine learning community.

The First Federated Learning App: Next-Word Prediction

Federated Learning is collaborative machine learning from private data stored across a (large) number of clients/devices (e.g., hospitals, phones)



My Team: 100+ Papers on Federated Learning



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E-mail: peter.richtarik@kaust.edu.sa



News

Old News

Papers

Talks

Video Talks

Events

Code

Team

Join

Bio

Teaching

Consulting

All papers are listed below in reverse chronological order in which they appeared online.

Prepared in 2024

[271] Egor Shulgin and Peter Richtárik

On the convergence of DP-SGD with adaptive clipping

[arXiv] [method: QC-SGD, DP-QC-SGD]

[270] Igor Sokolov and Peter Richtárik

MARINA-P: Superior performance in non-smooth federated optimization with adaptive stepsizes

Federated Learning Paper

[arXiv] [method: MARINA-P]

[269] Artavazd Maranjyan, Abdurakhmon Sadiev, and Peter Richtárik

Differentially private random block coordinate descent

[arXiv] [method: DP-SkGD, DP-SkGD-BS, DP-CD]

[268] Elnur Gasanov and Peter Richtárik

Speeding up stochastic proximal optimization in the high Hessian dissimilarity setting

[arXiv] [method: L-SVRP]

[267] Yury Demidovich, Petr Ostroukhov, Grigory Malinovsky, Samuel Horváth, Martin Takáč, Peter Richtárik, and Eduard Gorbunov

Methods with local steps and random reshuffling for generally smooth non-convex federated optimization

Federated Learning Paper

[arXiv] [method: Clip-LocalGDJ, CLERR, Clipped RR-CLI]

[266] Vladimir Malinovskii, Andrei Panferov, Ivan Il'in, Han Guo, Peter Richtárik, and Dan Alistarh

Pushing the limits of large language model quantization via the linearity theorem

LLM Paper

[arXiv] [method: HIGGS]

[265] Sarit Khirirat, Abdurakhmon Sadiev, Artem Riabinin, Eduard Gorbunov, and Peter Richtárik

Error feedback under (L_0, L_1) -smoothness: normalization and momentum

Federated Learning Paper

[arXiv] [method: ||EF21||, ||EF21-SGDM||]

[264] Wojciech Anyszka, Kaja Gruntkowska, Alexander Tyurin, and Peter Richtárik

Tighter performance theory of FedExProx

Federated Learning Paper

[arXiv] [method: FedExProx]

AI

The Next Generation Of Artificial Intelligence

Rob Toews Contributor ⓘ

I write about the big picture of artificial intelligence.

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Oct 12, 2020, 09:22pm EDT

1. Unsupervised Learning
2. Federated Learning
3. Transformers
4. Neural Network Compression
5. Generative AI
6. "System 2" Reasoning

<https://www.forbes.com/sites/robtoews/2020/10/12/the-next-generation-of-artificial-intelligence/?sh=4d14f60159eb>

<https://www.forbes.com/sites/robtoews/2020/10/29/the-next-generation-of-artificial-intelligence-part-2/?sh=e02f2567a304>



Meta



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FedML



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SAMSUNG





**NATIONAL ARTIFICIAL INTELLIGENCE
RESEARCH AND DEVELOPMENT
STRATEGIC PLAN
2023 UPDATE**

A Report by the
SELECT COMMITTEE ON ARTIFICIAL INTELLIGENCE
of the
NATIONAL SCIENCE AND TECHNOLOGY COUNCIL

May 2023



The National Artificial Intelligence R&D Strategic Plan

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 AI as a National Priority..... 1

Strategy 1: Make Long-Term Investments in Fundamental and Responsible AI Research 3

 Advancing Data-Focused Methodologies for Knowledge Discovery..... 3

 Fostering Federated ML Approaches 4

 Understanding Theoretical Capabilities and Limitations of AI 4

 Pursuing Research on Scalable General-Purpose AI Systems 5

 Developing AI Systems and Simulations Across Real and Virtual Environments 5

 Enhancing the Perceptual Capabilities of AI Systems 5

 Developing More Capable and Reliable Robots 6

 Advancing Hardware for Improved AI 6

 Creating AI for Improved Hardware 7

 Embracing Sustainable AI and Computing Systems 8

Federated Learning Issues & Tools

Communication Complexity

local training compression
stochastic approximation variance reduction
momentum

Data Heterogeneity

drift reduction personalization
variable local training

Device Heterogeneity

partial participation

asynchronicity

Privacy

differential privacy
homomorphic encryption
secure multiparty computation



Part 2

Introduction

Optimization Problem

$$\min_{x \in \mathbb{R}^d} f(x) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n f_i(x)$$

parallel machines

model parameters / features

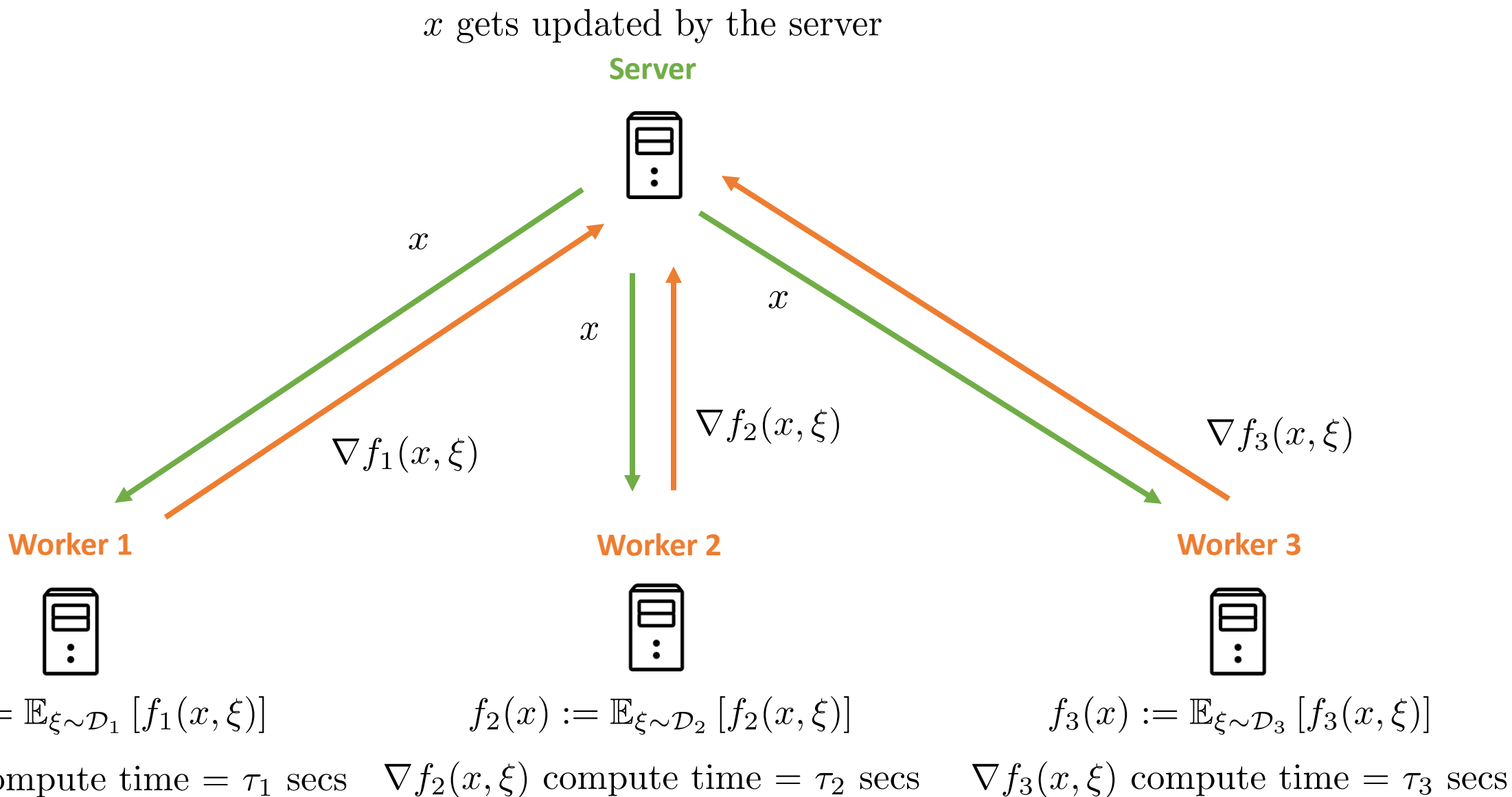
Loss on local data \mathcal{D}_i stored on machine i

$$f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$$

- ! It takes τ_i seconds for worker i to compute $\nabla f_i(x, \xi)$, where $\xi \sim \mathcal{D}_i$ $0 < \tau_1 \leq \tau_2 \leq \dots \leq \tau_n$
- ! It takes θ_i seconds for worker i to communicate $g \in \mathbb{R}^d$ to the server

Find a (possibly random) vector $\hat{x} \in \mathbb{R}^d$ such that $\mathbb{E} [\|\nabla f(\hat{x})\|^2] \leq \varepsilon$

Parallel Computing Architecture



Three Types of Heterogeneity

Data	data distributions $\mathcal{D}_1, \dots, \mathcal{D}_n$ can be different
Compute	compute times τ_1, \dots, τ_n are nonzero and can be different
Communication	communication times $\theta_1, \dots, \theta_n$ are nonzero and can be different

Typical Assumptions

- 1 $\inf f \in \mathbb{R}$
- 2 $f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$

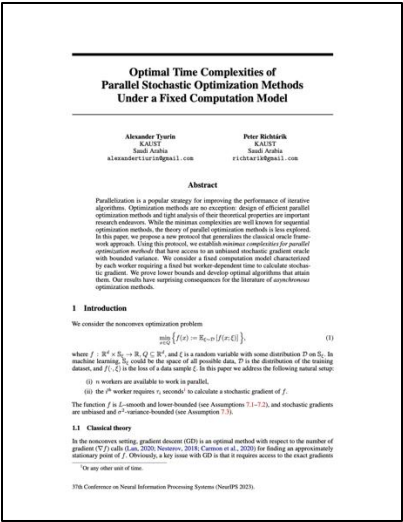
Gradient of local functions is Lipschitz:

$$\max_{i \in \{1, \dots, n\}} \sup_{x \neq y} \frac{\|\nabla f_i(x) - \nabla f_i(y)\|}{\|x - y\|} \leq L$$

Stochastic gradients have bounded variance:

$$\max_{i \in \{1, \dots, n\}} \sup_{x \in \mathbb{R}^d} \mathbb{E}_{\xi \sim \mathcal{D}_i} [\|\nabla f_i(x, \xi) - \mathbb{E}_{\xi \sim \mathcal{D}_i} [\nabla f_i(x, \xi)]\|^2] \leq \sigma^2$$

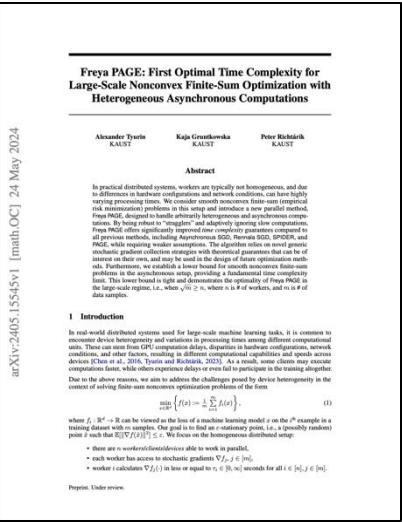
Our Papers on Optimal Parallel SGD



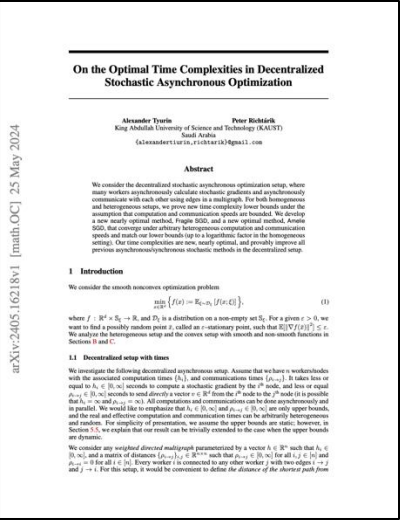
5/2023



2/2024



5/2024



5/2024



10/2024

Our Papers

5/2023

Rennala SGD
Malenia SGD
Acc. Rennala SGD



Alexander Tyurin and P.R.
Optimal time complexities of parallel stochastic optimization methods under a fixed computation model
NeurIPS 2023

***First optimal
parallel SGD under...***

***... computation
(and/or data) heterogeneity***

2/2024

Shadowheart SGD



Alexander Tyurin, Marta Pozzi, Ivan Ilin and P.R.
Shadowheart SGD: Distributed asynchronous SGD with optimal time complexity under arbitrary computation and communication heterogeneity
arXiv:2402.04785, 2024

***... communication
(and computation) heterogeneity***

[Rennala SGD as a special case]

5/2024

Freya PAGE
Freya SGD



Alexander Tyurin, Kaja Grunkowska, and P.R.
Freya PAGE: First optimal time complexity for large-scale nonconvex finite-sum optimization with heterogeneous asynchronous computations
arXiv:2405.1554, 2024

***... computation heterogeneity for
finite-sum problems***

in the large-scale regime: $m \geq n^2$

5/2024

Fragile SGD, Amelie SGD
+ accelerated variants



Alexander Tyurin and P.R.
On the optimal time complexities in decentralized stochastic asynchronous optimization
arXiv:2405.16218, 2024

***... computation and
communication heterogeneity in
the decentralized setup***

Our Papers

10/2024

MindFlayer SGD
Vecna SGD



Artavazd Maranjyan, Omar Shaikh Omar and P.R.

MindFlayer: Efficient asynchronous parallel SGD in the presence of heterogeneous and random worker compute times

Conference on the Mathematical Theory of Deep Neural Networks (DeepMath 2024)

... random compute times

1/2025

Ringmaster SGD



Artavazd Maranjyan, Alexander Tyurin and P.R.

Ringmaster ASGD: The first asynchronous SGD with optimal time complexity

arXiv:2501.16168, 2025

1st fully asynchronous optimal parallel SGD

2/2025

ATA



Artavazd Maranjyan, El Mehdi Saad, P.R. and Francesco Orabona

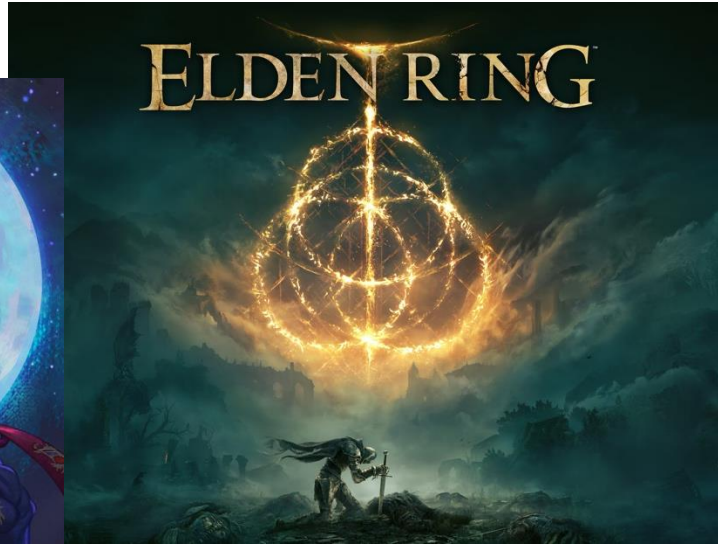
ATA: Adaptive task allocation for efficient resource management in distributed machine learning

arXiv:2502.00775, 2025

Peter, What About the Weird Algorithm Names?

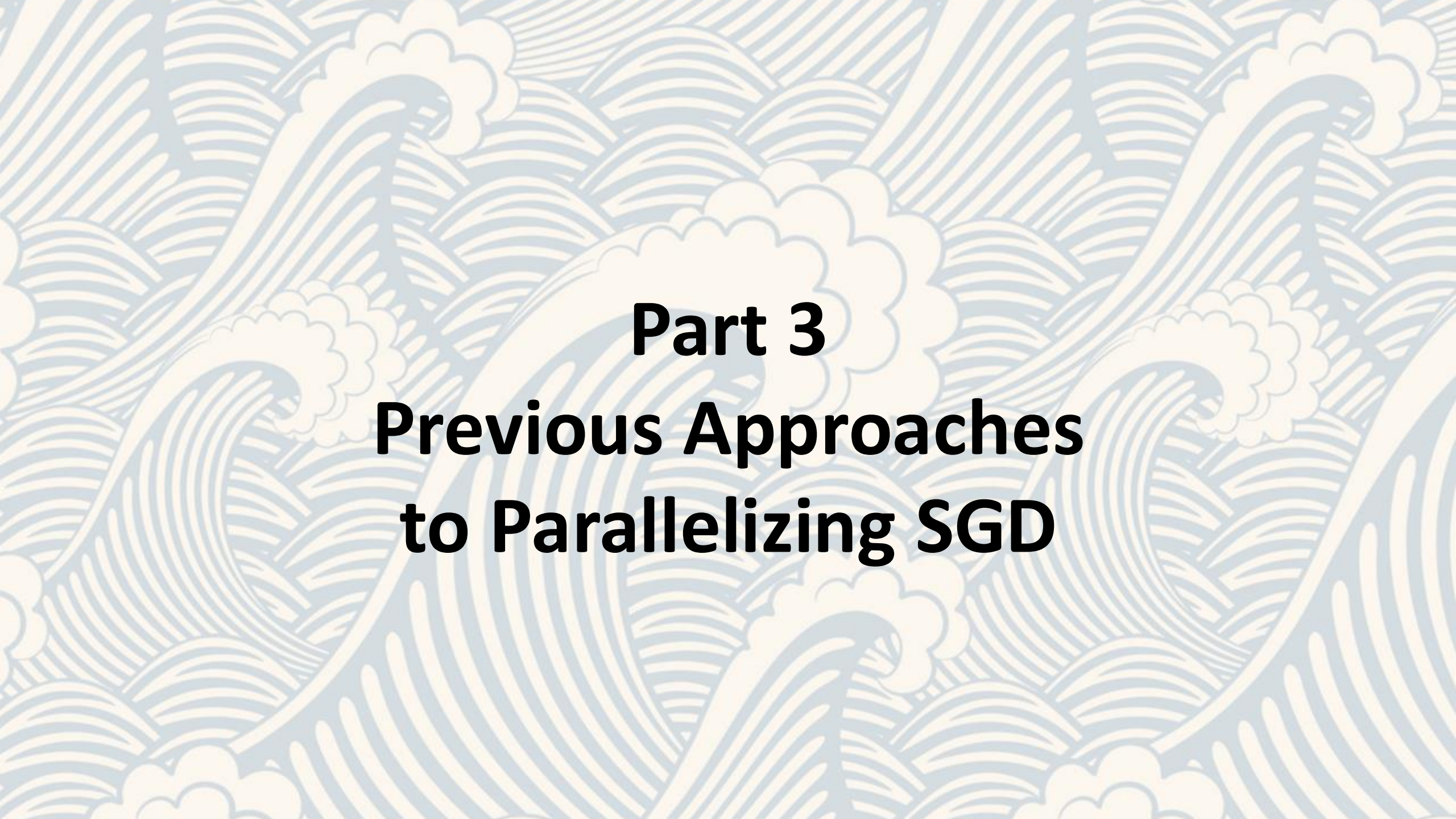


Rennala, Queen of the Full Moon is a Legend Boss in Elden Ring. Though not a demigod, Rennala is one of the shardbearers who resides in the Academy of Raya Lucaria. Rennala is a powerful sorceress, head of the Carian Royal family, and erstwhile leader of the Academy.



Optimal Parallel Stochastic Gradient Methods

	Data Heterogeneity (\mathcal{D}_i different)	Compute Heterogeneity (τ_i different)	Communication Heterogeneity (θ_i different)	Smooth Nonconvex	Smooth Convex	Infinite / Finite Sum?	Supports Decentralized Setup?	Optimal Time Complexity?
Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0	✓		Inf	✗	✓
Malenia SGD Tyurin & R (NeurIPS '23)	✓	✓	0	✓		Inf	✗	✓
Accelerated Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0		✓	Inf	✗	✓
Shadowheart SGD Tyurin, Pozzi, Ilin & R '24	✗	✓	✓	✓		Inf	✗	✓
Freya PAGE Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✓ big data regime
Freya SGD Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✗
Fragile SGD Tyurin & R '24	✗	✓	✓	✓		Inf	✓	nearly
Amelie SGD Tyurin & R '24	✓	✓	✓	✓		Inf	✓	✓



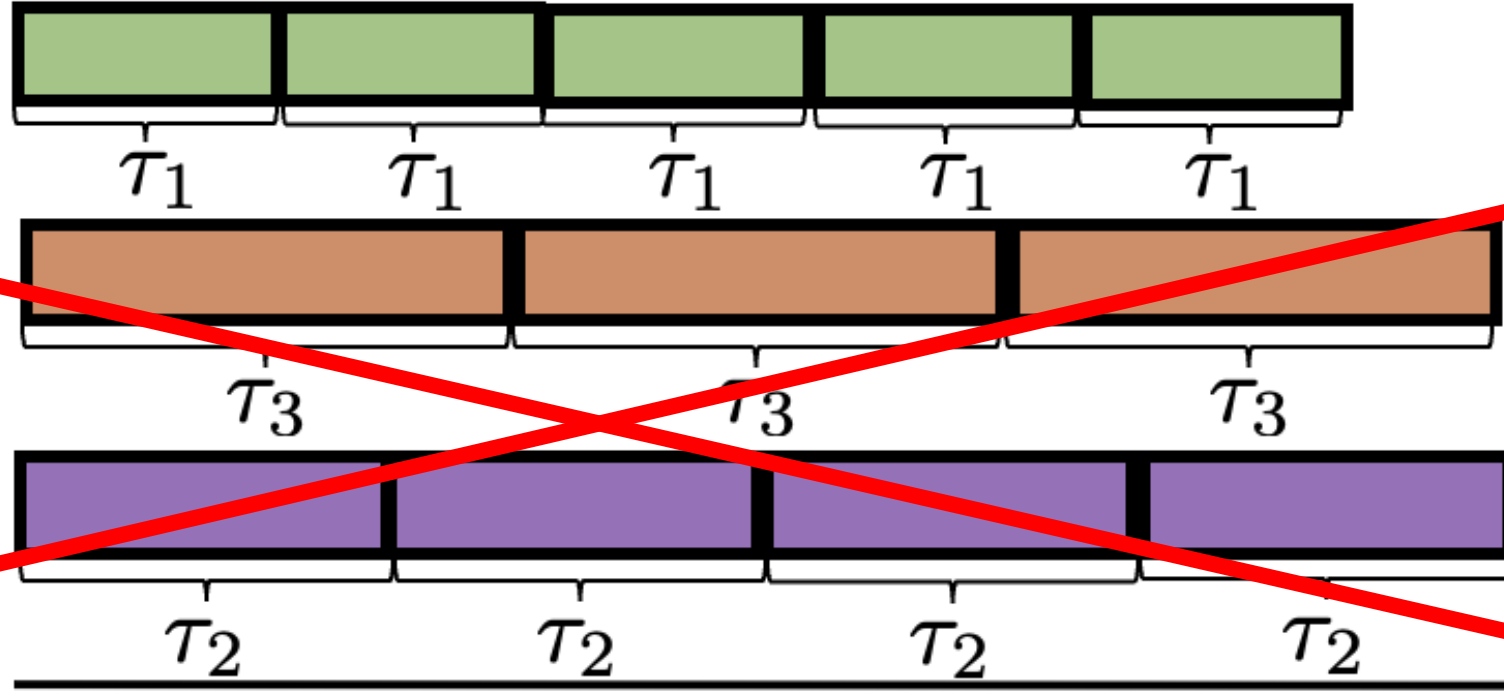
Part 3

Previous Approaches to Parallelizing SGD

Hero SGD

Algorithmic idea: The fastest worker does it all!

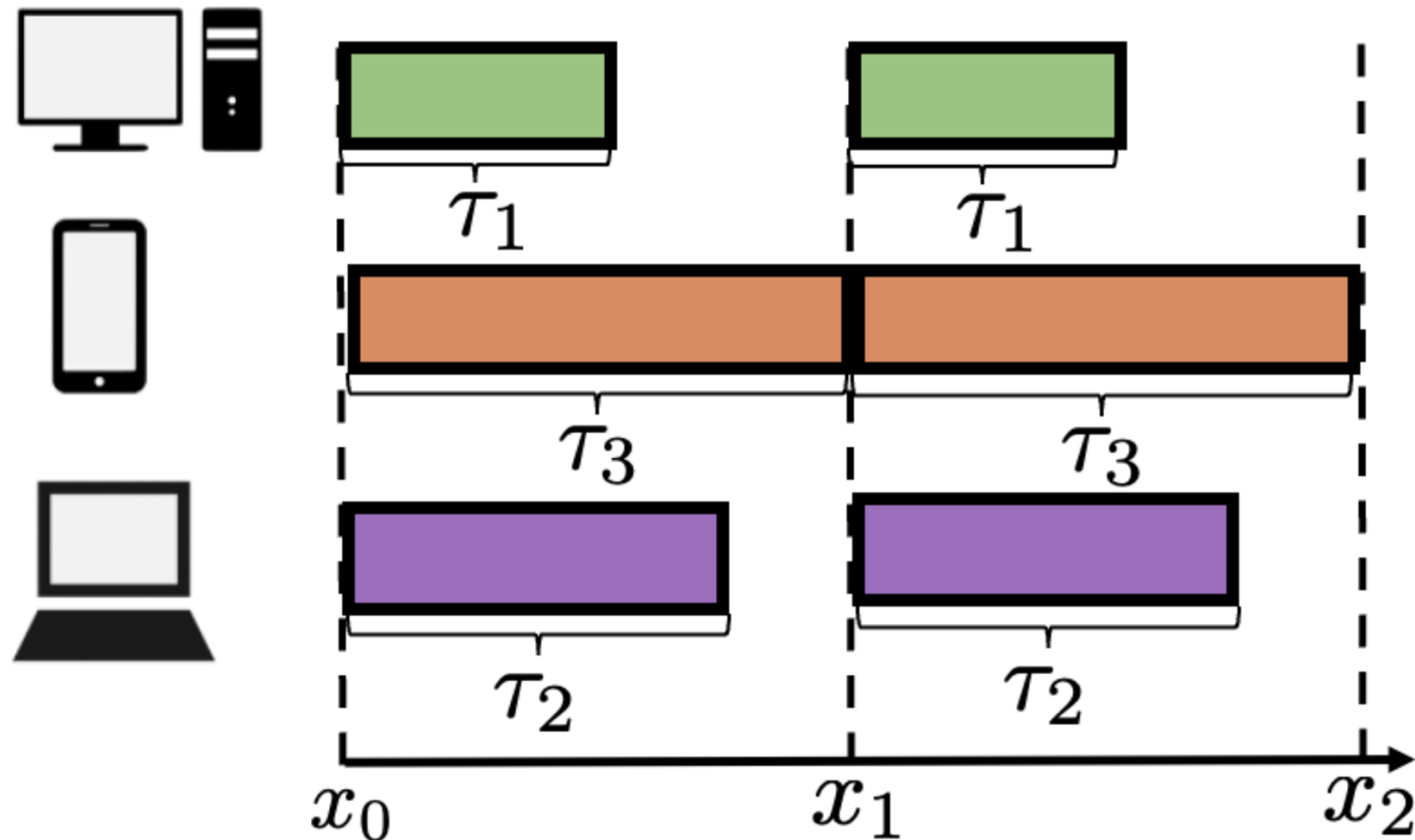
The hero!



time

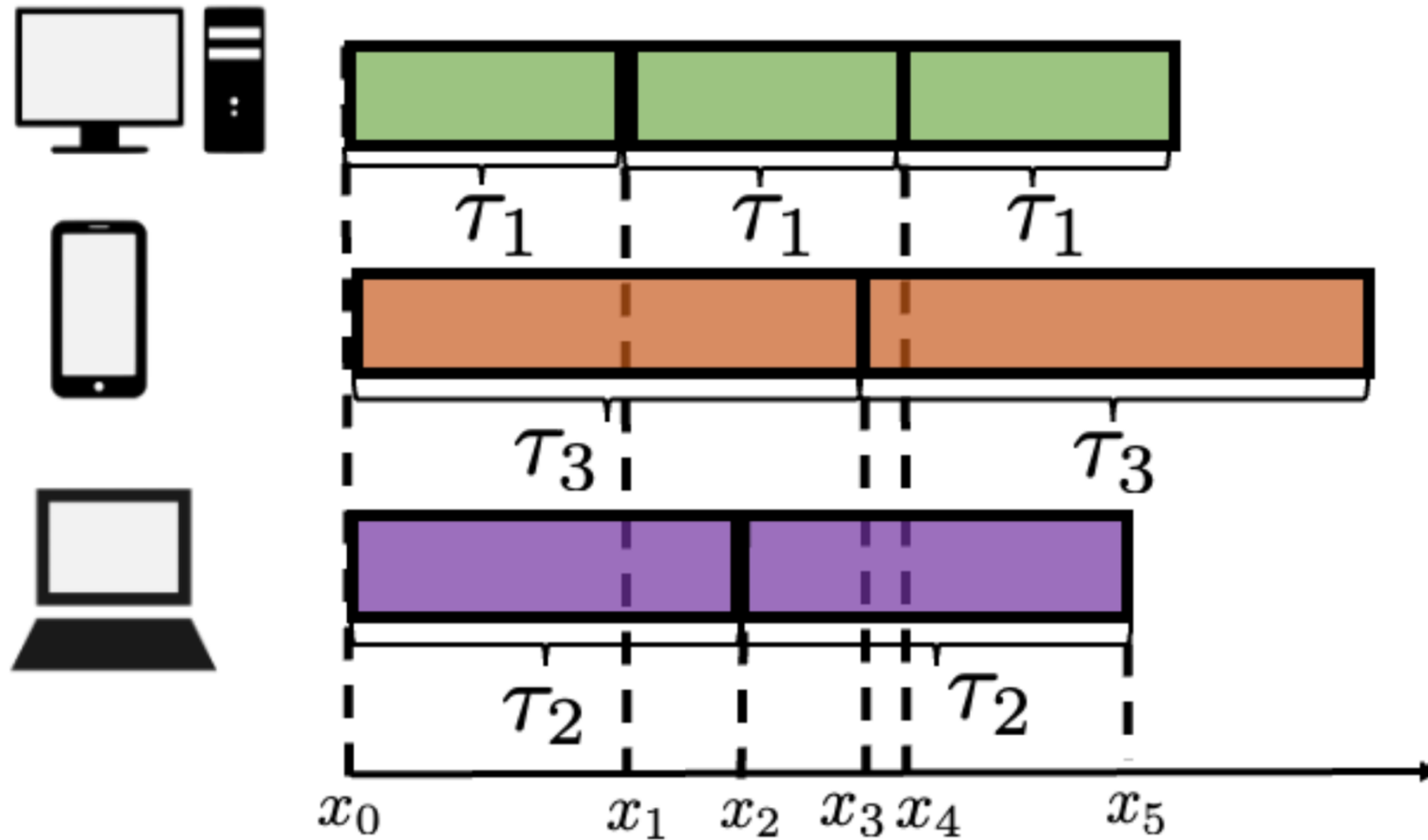
(Fair) Minibatch SGD

Algorithmic idea: Each worker does one job only!



Asynchronous SGD

Algorithmic idea: All workers are slaves and useful



published in NIPS 2011

HOGWILD!: A Lock-Free Approach to Parallelizing Stochastic Gradient Descent

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Abstract

Stochastic Gradient Descent (SGD) is a popular algorithm that can achieve state-of-the-art performance on a variety of machine learning tasks. Several researchers have recently proposed schemes to parallelize SGD, but all require performance-destroying memory locking and synchronization. This work aims to show using novel theoretical analysis, algorithms, and implementation that SGD can be implemented *without any locking*. We present an update scheme called HOGWILD! which allows processors access to shared memory with the possibility of overwriting each other's work. We show that when the associated optimization problem is *sparse*, meaning most gradient updates only modify small parts of the decision variable, then HOGWILD! achieves a nearly optimal rate of convergence. We demonstrate experimentally that HOGWILD! outperforms alternative schemes that use locking by an order of magnitude.

1 Introduction

With its small memory footprint, robustness against noise, and rapid learning rates, Stochastic Gradient Descent (SGD) has proved to be well suited to data-intensive machine learning tasks [3, 5, 24]. However, SGD's scalability is limited by its inherently sequential nature; it is difficult to parallelize. Nevertheless, the recent emergence of inexpensive multicore processors and mammoth, web-scale data sets has motivated researchers to develop several clever parallelization schemes for SGD [4, 10, 12, 16, 27]. As many large data sets are currently pre-processed in a MapReduce-like parallel-processing framework, much of the recent work on parallel SGD has focused naturally on MapReduce implementations. MapReduce is a powerful tool developed at Google for extracting information from huge logs (e.g., "find all the urls from a 100TB of Web data") that was designed to ensure fault tolerance and to simplify the maintenance and programming of large clusters of machines [9]. But MapReduce is not ideally suited for online, numerically intensive data analysis. Iterative computation is difficult to express in MapReduce, and the overhead to ensure fault tolerance can result in dismal throughput. Indeed, even Google researchers themselves suggest that other systems, for example Dremel, are more appropriate than MapReduce for data analysis tasks [20].

For some data sets, the sheer size of the data dictates that one use a cluster of machines. However, there are a host of problems in which, after appropriate preprocessing, the data necessary for statistical analysis may consist of a few terabytes or less. For such problems, one can use a single inexpensive work station as opposed to a hundred thousand dollar cluster. Multicore systems have significant performance advantages, including (1) low latency and high throughput shared main memory (a processor in such a system can write and read the shared physical memory at over 12GB/s with latency in the tens of nanoseconds); and (2) high bandwidth off multiple disks (a thousand-dollar RAID

NeurIPS 2020 Test of Time Award



Hogwild: A lock-free approach to parallelizing stochastic gradient descent

Authors Benjamin Recht, Christopher Re, Stephen Wright, Feng Niu

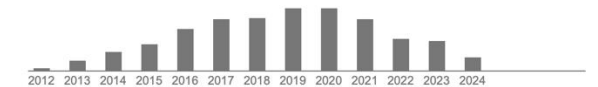
Publication date 2011

Conference Advances in Neural Information Processing Systems

Pages 693-701

Description Stochastic Gradient Descent (SGD) is a popular algorithm that can achieve state-of-the-art performance on a variety of machine learning tasks. Several researchers have recently proposed schemes to parallelize SGD, but all require performance-destroying memory locking and synchronization. This work aims to show using novel theoretical analysis, algorithms, and implementation that SGD can be implemented without any locking. We present an update scheme called Hogwild which allows processors access to shared memory with the possibility of overwriting each other's work. We show that when the associated optimization problem is sparse, meaning most gradient updates only modify small parts of the decision variable, then Hogwild achieves a nearly optimal rate of convergence. We demonstrate experimentally that Hogwild outperforms alternative schemes that use locking by an order of magnitude.

Total citations Cited by 2719



Scholar articles Hogwild: A lock-free approach to parallelizing stochastic gradient descent
B Recht, C Re, S Wright, F Niu - Advances in neural information processing systems, 2011
Cited by 2718 Related articles All 35 versions

Hogwild: A lock-free approach to parallelizing stochastic gradient descent *
RB NiuF - ... Systems, Granada, Spain, 2011
Cited by 2 Related articles

Our Inspiration: Two Beautiful Papers

Asynchronous SGD Beats Minibatch SGD Under Arbitrary Delays

Konstantin Mishchenko Francis Bach Mathieu Even Blake Woodworth

DI ENS, Ecole normale supérieure,
Université PSL, CNRS, INRIA
75005 Paris, France

Abstract

The existing analysis of asynchronous stochastic gradient descent (SGD) degrades dramatically when any delay is large, giving the impression that performance depends primarily on the delay. On the contrary, we prove much better guarantees for the same asynchronous SGD algorithm regardless of the delays in the gradients, depending instead just on the number of parallel devices used to implement the algorithm. Our guarantees are strictly better than the existing analyses, and we also argue that asynchronous SGD outperforms synchronous minibatch SGD in the settings we consider. For our analysis, we introduce a novel recursion based on “virtual iterates” and delay-adaptive stepsizes, which allow us to derive state-of-the-art guarantees for both convex and non-convex objectives.

1 Introduction

We consider solving stochastic optimization problems of the form

$$\min_{\mathbf{x} \in \mathbb{R}^d} \{F(\mathbf{x}) := \mathbb{E}_{\xi \sim \mathcal{D}} f(\mathbf{x}; \xi)\}, \quad (1)$$

which includes machine learning (ML) training objectives, where $f(\mathbf{x}; \xi)$ represents the loss of a model parameterized by \mathbf{x} on the datum ξ . Depending on the application, \mathcal{D} could represent a finite dataset of size n or a population distribution. In recent years, such stochastic optimization problems have continued to grow rapidly in size, both in terms of the dimension d of the optimization variable—i.e., the number of model parameters in ML—and in terms of the quantity of data—i.e., the number of samples $\xi_1, \dots, \xi_n \sim \mathcal{D}$ being used. With d and n regularly reaching the tens or hundreds of billions, it is increasingly necessary to use parallel optimization algorithms to handle the large scale and to benefit from data stored on different machines.

There are many ways of employing parallelism to solve (1), but the most popular approaches in practice are first-order methods based on stochastic gradient descent (SGD). At each iteration, SGD employs stochastic estimates of ∇F to update the parameters as $\mathbf{x}_k = \mathbf{x}_{k-1} - \gamma_k \nabla f(\mathbf{x}_{k-1}; \xi_{k-1})$ for an i.i.d. sample $\xi_{k-1} \sim \mathcal{D}$. Given M machines capable of computing these stochastic gradient estimates $\nabla f(\mathbf{x}; \xi)$ in parallel, one approach to parallelizing SGD is what we call “Minibatch SGD.” This refers to a synchronous, parallel algorithm that dispatches the current parameters \mathbf{x}_{k-1} to each of the M machines, waits while they compute and communicate back their gradient estimates $\mathbf{g}_{k-1}^1, \dots, \mathbf{g}_{k-1}^M$, and then takes a minibatch SGD step $\mathbf{x}_k = \mathbf{x}_{k-1} - \gamma_k \cdot \frac{1}{M} \sum_{m=1}^M \mathbf{g}_{k-1}^m$. This is a natural idea with long history [16, 18, 55] and it is a commonly used in practice [e.g., 22]. However, since Minibatch SGD waits for all M of the machines to finish computing their gradient estimates before updating, it proceeds only at the speed of the *slowest* machine.

There are several possible sources of delays: nodes may have heterogeneous hardware with different computational throughputs [23, 25], network latency can slow the communication of gradients, and

36th Conference on Neural Information Processing Systems (NeurIPS 2022).

Sharper Convergence Guarantees for Asynchronous SGD for Distributed and Federated Learning

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Abstract

We study the asynchronous stochastic gradient descent algorithm for distributed training over n workers which have varying computation and communication frequency over time. In this algorithm, workers compute stochastic gradients in parallel at their own pace and return those to the server without any synchronization. Existing convergence rates for this algorithm for non-convex smooth objectives depend on the maximum gradient delay τ_{\max} and show that an ε -stationary point is reached after $\mathcal{O}(\sigma^2 \varepsilon^{-2} + \tau_{\max} \varepsilon^{-1})$ iterations, where σ denotes the variance of stochastic gradients.

In this work we obtain (i) a tighter convergence rate of $\mathcal{O}(\sigma^2 \varepsilon^{-2} + \sqrt{\tau_{\max} \tau_{\text{avg}}} \varepsilon^{-1})$ *without any change in the algorithm*, where τ_{avg} is the average delay, which can be significantly smaller than τ_{\max} . We also provide (ii) a simple delay-adaptive learning rate scheme, under which asynchronous SGD achieves a convergence rate of $\mathcal{O}(\sigma^2 \varepsilon^{-2} + \tau_{\text{avg}} \varepsilon^{-1})$, and does not require any extra hyperparameter tuning nor extra communications. Our result allows to show *for the first time* that asynchronous SGD is *always faster* than mini-batch SGD. In addition, (iii) we consider the case of heterogeneous functions motivated by federated learning applications and improve the convergence rate by proving a weaker dependence on the maximum delay compared to prior works. In particular, we show that the heterogeneity term in convergence rate is only affected by the average delay within each worker.

1 Introduction

The stochastic gradient descent (SGD) algorithm [43, 13] and its variants (momentum SGD, Adam, etc.) form the foundation of modern machine learning and frequently achieve state of the art results. With recent growth in the size of models and available training data, parallel and distributed versions of SGD are becoming increasingly important [57, 17, 16]. Without those, modern state-of-the-art language models [44], generative models [40, 41], and many others [50] would not be possible. In the distributed setting, also known as data-parallel training, optimization is distributed over many compute devices working in parallel (e.g. cores, or GPUs on a cluster) in order to speed up training. Every worker computes gradients on a subset of the training data, and the resulting gradients are aggregated (averaged) on a server.

The same type of SGD variants also form the core algorithms for federated learning applications [34, 24] where the training process is naturally distributed over many user devices, or clients, that keep their local data private, and only transfer (e.g. encrypted or differentially private) gradients to the server.

A rich literature exists on the convergence theory of above mentioned parallel SGD methods, see e.g. [17, 13] and references therein. Plain parallel SGD still faces many challenges in practice, motivat-

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Optimal Time Complexities of
Parallel Stochastic Optimization Methods
Under a Fixed Computation Model

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Abstract

Parallelization is a popular strategy for improving the performance of iterative algorithms. Optimization methods are no exception: design of efficient parallel optimization methods and tight analysis of their theoretical properties are important research endeavors. While the minimax complexities are well known for sequential optimization methods, the theory of parallel optimization methods is less explored. In this paper, we propose a new protocol that generalizes the classical oracle framework approach. Using this protocol, we establish *minimax complexities for parallel optimization methods* that have access to an unbiased stochastic gradient oracle with bounded variance. We consider a fixed computation model characterized by each worker requiring a fixed but worker-dependent time to calculate stochastic gradient. We prove lower bounds and develop optimal algorithms that attain them. Our results have surprising consequences for the literature of *asynchronous* optimization methods.

1 Introduction

We consider the nonconvex optimization problem

$$\min_{x \in Q} \left\{ f(x) := \mathbb{E}_{\xi \sim \mathcal{D}} [f(x; \xi)] \right\}, \quad (1)$$

where $f : \mathbb{R}^d \times \mathcal{S}_\xi \rightarrow \mathbb{R}$, $Q \subseteq \mathbb{R}^d$, and ξ is a random variable with some distribution \mathcal{D} on \mathcal{S}_ξ . In machine learning, \mathcal{S}_ξ could be the space of all possible data, \mathcal{D} is the distribution of the training dataset, and $f(\cdot; \xi)$ is the loss of a data sample ξ . In this paper we address the following natural setup:

- (i) n workers are available to work in parallel,
- (ii) the i^{th} worker requires τ_i seconds¹ to calculate a stochastic gradient of f .

The function f is L -smooth and lower-bounded (see Assumptions 7.1–7.2), and stochastic gradients are unbiased and σ^2 -variance-bounded (see Assumption 7.3).

1.1 Classical theory

In the nonconvex setting, gradient descent (GD) is an optimal method with respect to the number of gradient (∇f) calls (Lin, 2020; Nevelev, 2019; Carmon et al., 2020) for finding an approximately stationary point of f . Obviously, a key issue with GD is that it requires access to the exact gradients

¹Or any other unit of time.

Part 4

Rennala SGD



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Optimal time complexities of parallel stochastic optimization
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Setup

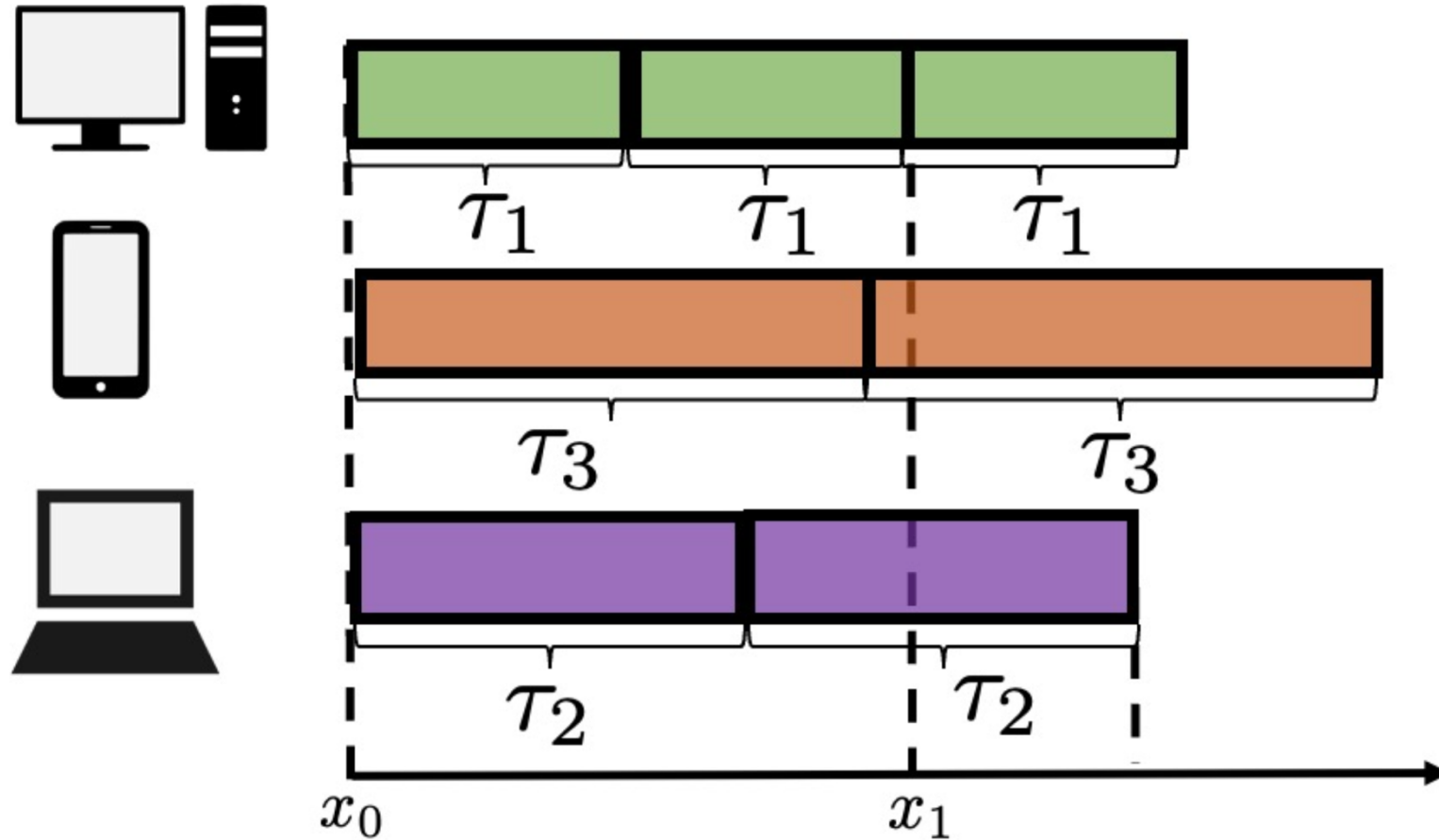
Optimal Parallel Stochastic Gradient Methods



	Data Heterogeneity (\mathcal{D}_i different)	Compute Heterogeneity (τ_i different)	Communication Heterogeneity (θ_i different)	Smooth Nonconvex	Smooth Convex	Infinite / Finite Sum?	Supports Decentralized Setup?	Optimal Time Complexity?
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Malenia SGD Tyurin & R (NeurIPS '23)	✓	✓	0	✓		Inf	✗	✓
Accelerated Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0		✓	Inf	✗	✓
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Amelie SGD Tyurin & R '24	✓	✓	✓	✓		Inf	✓	✓

Rennala SGD

Algorithmic idea: Minibatch SGD with asynchronous minibatch collection



Upper Bound

Theorem (informal)

Assume data homogeneity and zero communication times.
Then Rennala SGD solves the problem in

Number of parallel machines

$$96 \times \min_{m \in \{1, \dots, n\}} \left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\frac{L\Delta}{\varepsilon} + \frac{L\Delta\sigma^2}{\varepsilon^2 m} \right)$$

seconds.

Compute times

$$0 < \tau_1 \leq \tau_2 \leq \dots \leq \tau_n$$

Algorithm outputs \hat{x} such that $\mathbb{E} [\|\nabla f(\hat{x})\|^2] \leq \varepsilon$

Gradient of f is L -Lipschitz

$$\Delta := f(x^0) - \inf f$$

$$\sup_{x \in \mathbb{R}^d} \mathbb{E}_{\xi \sim \mathcal{D}} [\|\nabla f(x, \xi) - \nabla f(x)\|^2] \leq \sigma^2$$

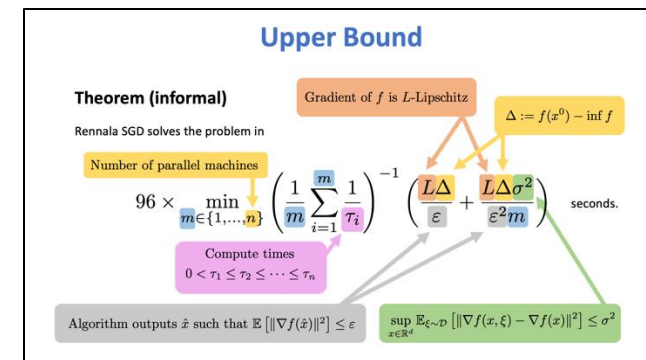
Matching Lower Bound

Theorem (informal)

It is not possible to design a method that will find a solution faster than in

$$\Omega \left(\min_{m \in \{1, \dots, n\}} \left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\frac{L\Delta}{\varepsilon} + \frac{L\Delta\sigma^2}{\varepsilon^2 m} \right) \right)$$

seconds.



Rennala SGD = first optimal parallel SGD

Classical Oracle: Keeps Track of # Iterations

Function class

Distribution governing noise

Oracle class

Algorithm class

Protocol 1 Classical Oracle Protocol

- 1: **Input:** function $f \in \mathcal{F}$ oracle and
- 2: **for** $k = 0, \dots, \infty$ **do**
- 3: $x^k = A^k(a^1, \dots, a^k)$
- 4: $g^{k+1} = O(x^k, \xi^{k+1})$
- 5: **end for**

$\triangleright x^0 = A^0$ for $k = 0$.

Stochastic gradient:
 $g^{k+1} = \nabla f(x^k, \xi^{k+1})$

Iteration complexity (measure):

$$m_{\text{oracle}}(\mathcal{A}, \mathcal{F}) = \sup_{A \in \mathcal{A}} \sup_{f \in \mathcal{F}} \inf \left\{ k \in \mathbb{N} \mid \mathbb{E} [\|\nabla f(x^k)\|^2] \leq \varepsilon \right\}$$

[Nemirovsky and Yudin, 1983] [Nesterov, 2018]

[Carmon et al, 2020] [Arjevani et al, 2022]

Natural for sequential methods, where a single worker does all the work!

New Oracle: Keeps Track of Time

Protocol 2 Time Oracle Protocol

- 1: **Input:** functions $f \in \mathcal{F}$, oracle and distribution $(O, \mathcal{D}) \in \mathcal{O}(\mathcal{F})$, $\epsilon \in \mathcal{A}$
 - 2: $s^0 = 0$
 - 3: **for** $k = 0, \dots, \infty$ **do**
 - 4: $(t^{k+1}, x^k) = A^k(g^1, \dots, g^k),$ $\triangleright t^{k+1} \geq t^k$
 - 5: $(s^{k+1}, g^{k+1}) = O(t^{k+1}, x^k, s^k, \epsilon)$
 - 6: **end for**
-

Iteration complexity

$$m_{\text{oracle}}(\mathcal{A}, \mathcal{F}) := \inf_{(O, \mathcal{D}) \in \mathcal{O}(\mathcal{F})} \sup_{f \in \mathcal{F}} \min \{k \in \mathbb{N} \mid \mathbb{E} [\|\nabla f(x^k)\|^2] \leq \epsilon\}$$

Time complexity (complexity measure):

$$m_{\text{time}}(\mathcal{A}, \mathcal{F}) := \inf_{A \in \mathcal{A}} \sup_{f \in \mathcal{F}} \sup_{(O, \mathcal{D}) \in \mathcal{O}(f)} \inf \left\{ t \geq 0 \mid \mathbb{E} \left[\inf_{k \in S_t} \|\nabla f(x^k)\|^2 \right] \leq \epsilon \right\}$$

$$S_t := \{k \in \mathbb{N} \cup \{0\} \mid t^k \leq t\}$$

Natural for parallel methods!

Data Homogeneous Regime

Method	Time Complexity
Minibatch SGD	$\tau_n \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{n\varepsilon^2} \right)$
Asynchronous SGD (Cohen et al., 2021) (Koloskova et al., 2022) (Mishchenko et al., 2022)	$\left(\frac{1}{n} \sum_{i=1}^n \frac{1}{\tau_i} \right)^{-1} \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{n\varepsilon^2} \right)$
Rennala SGD (Theorem 7.5)	$\min_{m \in [n]} \left[\left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{m\varepsilon^2} \right) \right]$
Lower Bound (Theorem 6.4)	$\min_{m \in [n]} \left[\left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{m\varepsilon^2} \right) \right]$

Experimental Results (Sample)

$$\tau_i = \sqrt{i} \text{ seconds}$$

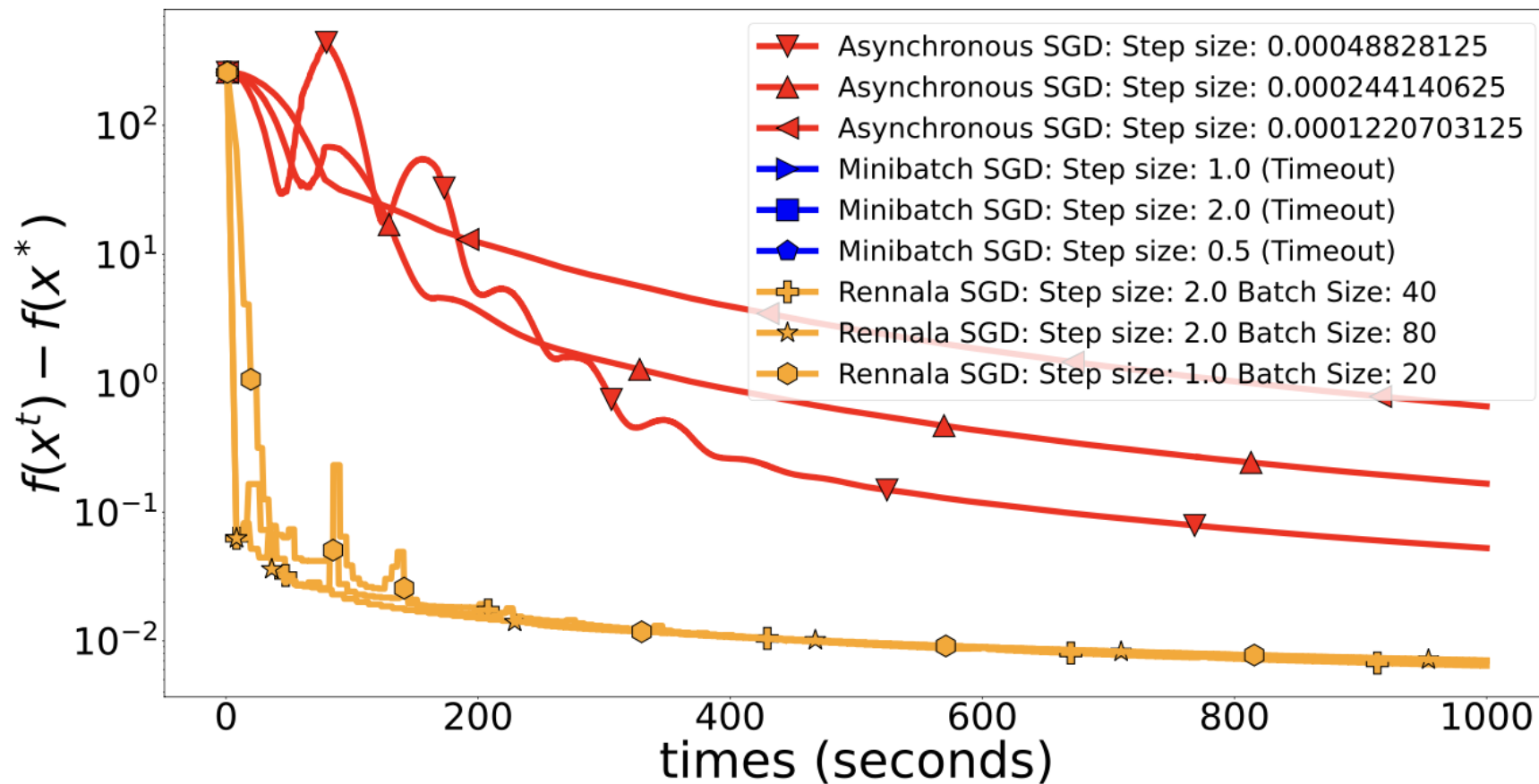


Figure 3: # of workers $n = 10000$.



**The End
(kind of)**

Optimal Time Complexities of Parallel Stochastic Optimization Methods Under a Fixed Computation Model

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Part 5

Two Extensions



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Extension 1

Handling Data Heterogeneity

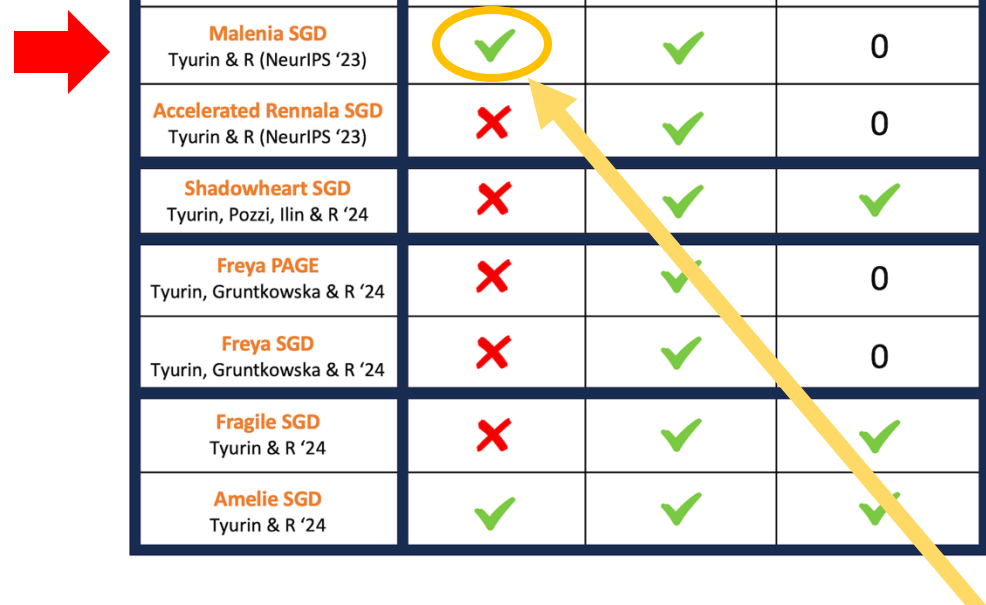
(Malenia SGD)

Malenia SGD: Setup

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x) \right\}$$

$$f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$$

Optimal Parallel Stochastic Gradient Methods



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Accelerated Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0		✓	Inf	✗	✓
Shadowheart SGD Tyurin, Pozzi, Ilin & R '24	✗	✓	✓	✓		Inf	✗	✓
Freya PAGE Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✓ big data regime
Freya SGD Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✗
Fragile SGD Tyurin & R '24	✗	✓	✓	✓		Inf	✓	nearly
Amelie SGD Tyurin & R '24	✓	✓	✓	✓		Inf	✓	✓

The distributions $\mathcal{D}_1, \dots, \mathcal{D}_n$ are allowed to be different

Malenia SGD

Method 6 Malenia SGD

```
1: Input: starting point  $x^0$ , stepsize  $\gamma$ , parameter  $S$ 
2: Run Method 7 in all workers
3: for  $k = 0, 1, \dots, K - 1$  do
4:   Init  $g_i^k = 0$  and  $B_i = 0$ 
5:   while  $\left(\frac{1}{n} \sum_{i=1}^n \frac{1}{B_i}\right)^{-1} < \frac{S}{n}$  do
6:     Wait for the next worker
7:     Receive gradient, iteration index, worker's index  $(g, k', i)$ 
8:     if  $k' = k$  then
9:        $g_i^k = g_i^k + g$ 
10:       $B_i = B_i + 1$ 
11:    end if
12:    Send  $(x^k, k)$  to the worker
13:  end while
14:   $g^k = \frac{1}{n} \sum_{i=1}^n \frac{1}{B_i} g_i^k$ 
15:   $x^{k+1} = x^k - \gamma g^k$ 
16: end for
```

Minibatch size

$$S = \max \left\{ \left\lceil \frac{\sigma^2}{\varepsilon} \right\rceil, n \right\}$$

Method 7 Worker's Infinite Loop

```
1: Init  $g = 0$ ,  $k' = -1$ , and worker's index  $i$ 
2: while True do
3:   Send  $(g, k', i)$  to the server
4:   Receive  $(x^k, k)$  from the server
5:    $k' = k$ 
6:    $g = \widehat{\nabla} f_i(x^k; \xi)$ ,  $\xi \sim \mathcal{D}$ 
7: end while
```

(Nonconvex) Data Heterogeneous Regime

Method	Time Complexity
Minibatch SGD	$\tau_n \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{n\varepsilon^2} \right)$
Malenia SGD (Theorem A.4)	$\tau_n \frac{L\Delta}{\varepsilon} + \left(\frac{1}{n} \sum_{i=1}^n \tau_i \right) \frac{\sigma^2 L\Delta}{n\varepsilon^2}$
Lower Bound (Theorem A.2)	$\tau_n \frac{L\Delta}{\varepsilon} + \left(\frac{1}{n} \sum_{i=1}^n \tau_i \right) \frac{\sigma^2 L\Delta}{n\varepsilon^2}$

Extension 2

Handling the Convex Regime

(Accelerated Rennala SGD)

Accelerated Rennala SGD: Setup

Optimal Parallel Stochastic Gradient Methods



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Convex (Data Homogeneous) Regime

Method	Time Complexity
Minibatch SGD	$\tau_n \left(\min \left\{ \frac{\sqrt{L}R}{\sqrt{\epsilon}}, \frac{M^2 R^2}{\epsilon^2} \right\} + \frac{\sigma^2 R^2}{n\epsilon^2} \right)$
Asynchronous SGD (Mishchenko et al., 2022)	$\left(\frac{1}{n} \sum_{i=1}^n \frac{1}{\tau_i} \right)^{-1} \left(\frac{LR^2}{\epsilon} + \frac{\sigma^2 R^2}{n\epsilon^2} \right)$
(Accelerated) Rennala SGD (Theorems B.9 and B.11)	$\min_{m \in [n]} \left[\left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\min \left\{ \frac{\sqrt{L}R}{\sqrt{\epsilon}}, \frac{M^2 R^2}{\epsilon^2} \right\} + \frac{\sigma^2 R^2}{m\epsilon^2} \right) \right]$
Lower Bound (Theorem B.4)	$\min_{m \in [n]} \left[\left(\frac{1}{m} \sum_{i=1}^m \frac{1}{\tau_i} \right)^{-1} \left(\min \left\{ \frac{\sqrt{L}R}{\sqrt{\epsilon}}, \frac{M^2 R^2}{\epsilon^2} \right\} + \frac{\sigma^2 R^2}{m\epsilon^2} \right) \right]$
Lower Bound (Section M) (Woodworth et al., 2018)	$\tau_1 \min \left\{ \frac{\sqrt{L}R}{\sqrt{\epsilon}}, \frac{M^2 R^2}{\epsilon^2} \right\} + \left(\frac{1}{n} \sum_{i=1}^n \frac{1}{\tau_i} \right)^{-1} \frac{\sigma^2 R^2}{n\epsilon^2}$

∇f is L -Lipschitz, f is M -Lipschitz, and $\|x^0 - x^*\| \leq R$



Further Extensions



Shadowheart SGD

Optimal Parallel SGD under Compute Heterogeneity & Communication Heterogeneity

Alexander Tyurin, Marta Pozzi, Ivan Ilin and P.R.
Shadowheart SGD: Distributed asynchronous SGD with optimal time complexity under arbitrary computation and communication heterogeneity
arXiv:2402.04785, 2024



Shadowheart SGD: Setup

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x) \right\}$$

$$f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$$

Optimal Parallel Stochastic Gradient Methods

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Fragile SGD Tyurin & R '24	✗	✓	✓	✓		Inf	✓	nearly
Amelie SGD Tyurin & R '24	✓	✓	✓	✓		Inf	✓	✓

$\mathcal{D}_1 = \dots = \mathcal{D}_n$

Communication costs $\theta_1, \dots, \theta_n$ are nonzero (and possibly different)

Optimization Problem

$$\min_{x \in \mathbb{R}^d} f(x) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n f_i(x)$$

\uparrow # model parameters / features

\uparrow # parallel machines

! It takes τ_i seconds for worker i to compute $\nabla f(x, \xi_i)$, where $\xi_i \sim \mathcal{D}_i$.
It takes θ_i seconds for worker i to communicate $g \in \mathbb{R}^d$ to the server.

Find a (possibly random) vector $\hat{x} \in \mathbb{R}^d$ such that $\mathbb{E}[\|\nabla f(\hat{x})\|^2] \leq \epsilon$.

Loss on local data \mathcal{D}_i stored on machine i :
 $f_i(x) := \mathbb{E}_{\xi_i \sim \mathcal{D}_i} [f(x, \xi_i)]$

Shadowheart SGD

Unbiased compressor:

$$\mathbb{E} [\mathcal{C}_{ij}(g)] = g \quad \& \quad \mathbb{E} \left[\|\mathcal{C}_{ij}(g) - g\|^2 \right] \leq \omega \|g\|^2 \quad \forall g \in \mathbb{R}^d$$

Aggregation weight associated with worker i

$$w_i = \left(\omega b_i + \omega \frac{\sigma^2}{\varepsilon} + m_i \frac{\sigma^2}{\varepsilon} \right)^{-1}$$

of compressed batches sent by worker i to the server

$$m_i = \left\lfloor \frac{t^*}{\theta_i} \right\rfloor$$

Batch size to compress by worker i

$$b_i = \left\lfloor \frac{t^*}{\tau_i} \right\rfloor$$

$\gamma = \frac{1}{2L}$

$$x^{k+1} = x^k - \gamma \cdot \frac{\sum_{i=1}^n w_i \sum_{j=1}^{m_i} \mathcal{C}_{ij} \left(\sum_{l=1}^{b_i} \nabla f(x^k, \xi_{il}^k) \right)}{\sum_{i=1}^n w_i m_i b_i}$$

Equilibrium time: $t^* : \left(\omega, \frac{\sigma^2}{\varepsilon}, (\tau_i)_{i=1}^n, (\theta_i)_{i=1}^n \right) \mapsto \mathbb{R}_+$

Shadowheart SGD

Table 1: Time Complexities of Centralized Distributed Algorithms. Assume that it takes at most h_i seconds to worker i to calculate a stochastic gradient and τ_i seconds to send *one coordinate/float* to server. Abbreviations: L = smoothness constant, ε = error tolerance, $\Delta = f(x^0) - f^*$, n = # of workers, d = dimension of the problem. We take the RandK compressor with $K = 1$ (Def. C.1) (as an example) in QSGD and Shadowheart SGD. Due to Property 5.2, the choice $K = 1$ is optimal for Shadowheart SGD up to a constant factor.

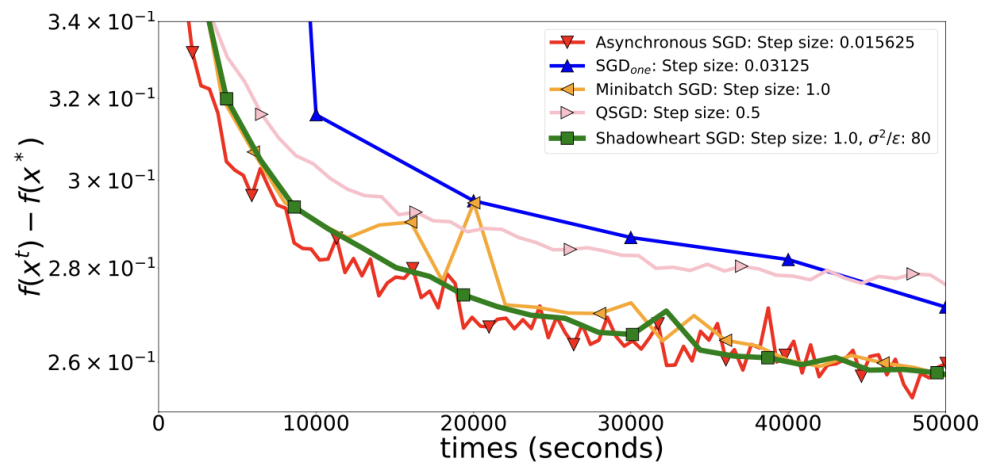
Method	Time Complexity	$\max\{h_n, \tau_n\} \rightarrow \infty$, $\max\{h_i, \tau_i\} < \infty \forall i < n$ (the last worker is slow)	Time Complexities in Some Regimes $h_i = h, \tau_i = \tau \forall i \in [n]$ (equal performance)	Numerical Comparison ^(b) $\sigma^2/\varepsilon =$ 1 10^3 10^6		
Minibatch SGD (see (3))	$\max_{i \in [n]} \max\{h_i, d\tau_i\} \left(\frac{L\Delta}{\varepsilon} + \frac{\sigma^2 L\Delta}{n\varepsilon^2} \right)$	∞ (non-robust)	$\max\{h, d\tau, \frac{d\tau\sigma^2}{n\varepsilon}, \frac{h\sigma^2}{n\varepsilon}\} \frac{L\Delta}{\varepsilon}$ (worse, e.g., when τ , d or n large)	$\times 10^3$	$\times 10^3$	$\times 10^4$
QSGD (see (7)) (Alistarh et al., 2017) (Khaled & Richtárik, 2020)	$\max_{i \in [n]} \max\{h_i, \tau_i\} \left(\left(\frac{d}{n} + 1 \right) \frac{L\Delta}{\varepsilon} + \frac{d\sigma^2 L\Delta}{n\varepsilon^2} \right)$	∞ (non-robust)	$\geq \frac{dh\sigma^2}{n\varepsilon} \frac{L\Delta}{\varepsilon}$ (worse, e.g., when ε small)	$\times 3$	$\times 10^2$	$\times 10^4$
Rennala SGD (Tyurin & Richtárik, 2023c), Asynchronous SGD (e.g., (Mishchenko et al., 2022))	$\geq \min_{j \in [n]} \max \left\{ h_{\bar{\pi}_j}, d\tau_{\bar{\pi}_j}, \frac{\sigma^2}{\varepsilon} \left(\sum_{i=1}^j \frac{1}{h_{\bar{\pi}_i}} \right)^{-1} \right\} \frac{L\Delta}{\varepsilon}$ ^(a)	$< \infty$ (robust)	$\geq \max \left\{ h, d\tau, \frac{h\sigma^2}{n\varepsilon} \right\} \frac{L\Delta}{\varepsilon}$ (worse, e.g., when τ , d or n large)	$\times 10^2$	$\times 10$	$\times 1.5$
Shadowheart SGD (see (9) and Alg. 1) (Corollary 4.4)	$t^*(d-1, \sigma^2/\varepsilon, [h_i, \tau_i]_1^n) \frac{L\Delta}{\varepsilon}$ ^(c)	$< \infty$ (robust)	$\max \left\{ h, \tau, \frac{d\tau}{n}, \sqrt{\frac{d\tau h\sigma^2}{n\varepsilon}}, \frac{h\sigma^2}{n\varepsilon} \right\} \frac{L\Delta}{\varepsilon}$	$\times 1$	$\times 1$	$\times 1$

The time complexity of Shadowheart SGD is not worse than the time complexity of the competing centralized methods (see Sec. 6), and is *strictly* better in many regimes. We show that (12) is the *optimal time complexity* in the family of centralized methods with compression (see Sec. 7).

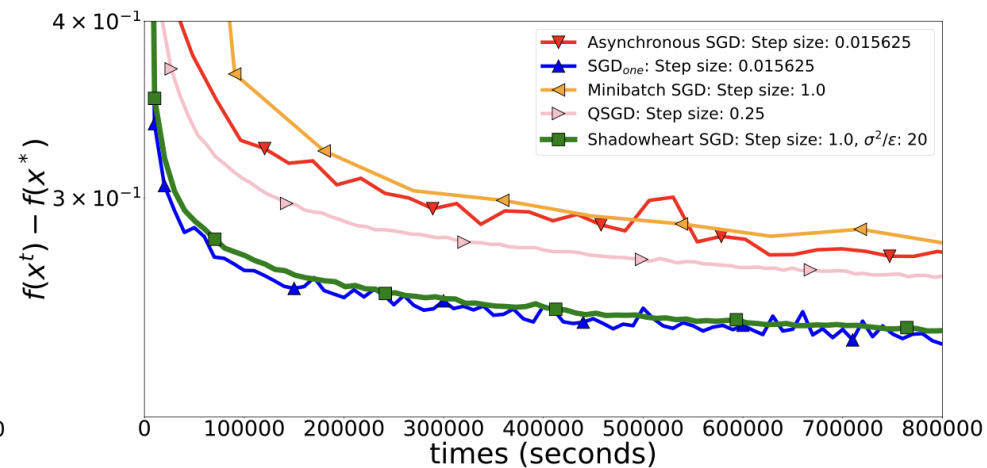
^(a) Upper bound time complexities are not derived for Rennala SGD and Asynchronous SGD. However, we can derive the lower bound using Theorem N.5 with $\omega = 0$. One should take $d\tau_i$ instead of τ_i when apply Theorem N.5 because these methods send d coordinates. $\bar{\pi}$ is a permutation that sorts $\max\{h_i, d\tau_i\} : \max\{h_{\bar{\pi}_1}, d\tau_{\bar{\pi}_1}\} \leq \dots \leq \max\{h_{\bar{\pi}_n}, d\tau_{\bar{\pi}_n}\}$

^(b) We numerically compute time complexities for $d = 10^6$, $n = 10^3$, $h_i \sim U(0.1, 1)$, $\tau_i \sim U(0.1, 1)$ (uniform i.i.d.), and three noise regimes $\sigma^2/\varepsilon \in \{1, 10^3, 10^6\}$. We report the factors by which the time complexities of the competing methods are worse compared to the time complexity of our method Shadowheart SGD. So, for example, Minibatch SGD, QSGD and Asynchronous SGD can be worse by the factors $\times 10^4$, $\times 10^4$, and $\times 10^2$, respectively.

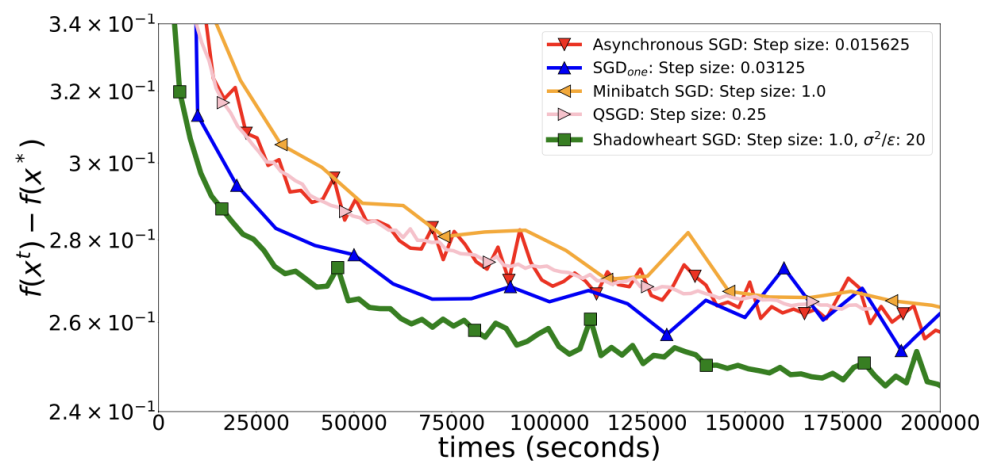
^(c) The mapping t^* is defined in Def. 4.2.



Fast communication: $\dot{\theta}_i = \frac{\sqrt{i}}{d}$



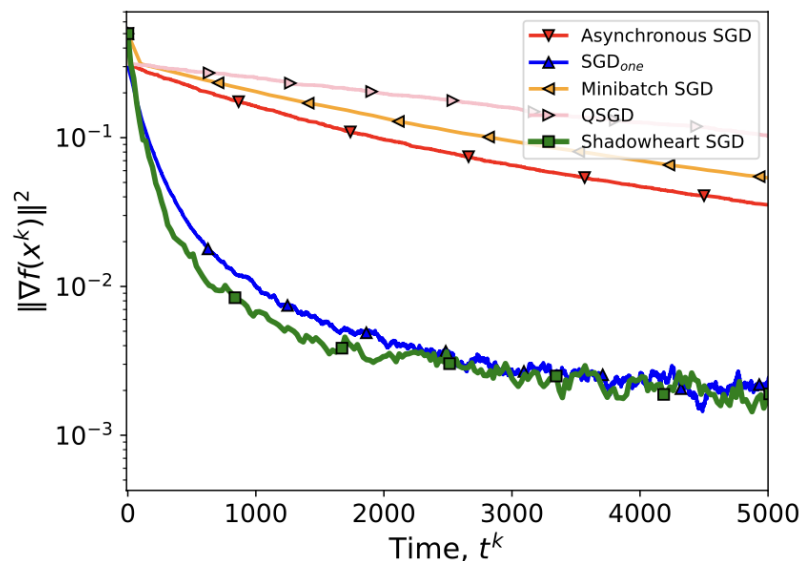
Slow communication: $\dot{\theta}_i = \frac{\sqrt{i}}{d^{1/2}}$



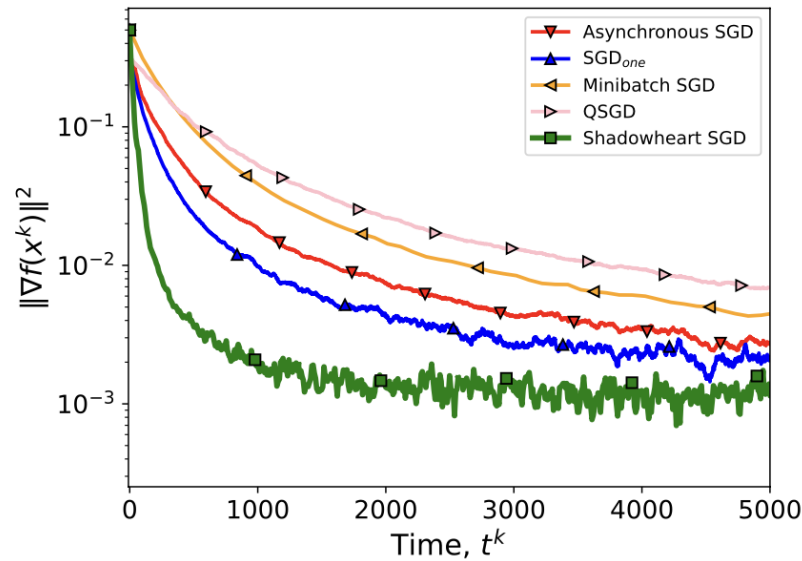
Medium-speed communication: $\dot{\theta}_i = \frac{\sqrt{i}}{d^{3/4}}$

Computation times: $\tau_i = \sqrt{i}$ for all machines $i = 1, \dots, n$

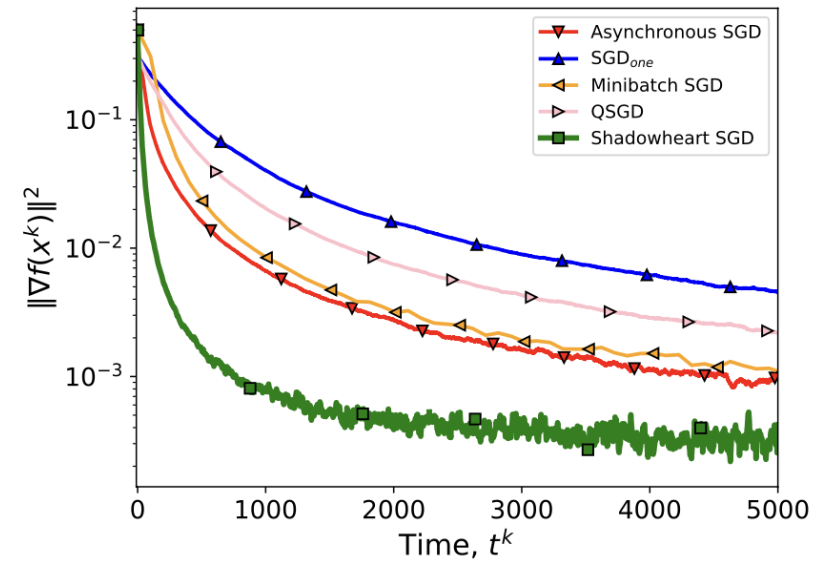
Shadowheart SGD: Adding More Workers...



(a) $n = 10$



(b) $n = 10^2$



(c) $n = 10^3$

$$\tau_i^k, \dot{\theta}_i^k \sim \text{Uniform}(0.1, 1) \text{ for all } i \in \{1, \dots, n\} \text{ and } k \geq 0$$

Freya PAGE: First Optimal Time Complexity for Large-Scale Nonconvex Finite-Sum Optimization with Heterogeneous Asynchronous Computations

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Kaja Gruntkowska

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Pinar Michaux

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Abstract

In practical distributed systems, workers are typically not homogeneous, and due to differences in hardware configurations and network conditions, can have highly varying processing times. We consider stochastic nonconvex finite-sum optimization with heterogeneous workers. Freya PAGE, designed to handle adversarial heterogeneity and asynchronous computations. By being robust to "stragglers" and explicitly ignoring slow computations, Freya PAGE offers significantly improved time complexity guarantees compared to all previous methods, including Alternating GD, Random GD, SPIDER, and PAGE, when requiring modest assumptions. The algorithm relies on novel general stochastic gradient reflection strategies with bounded parameters that can be of interest in their own, and may be used in the design of other optimization methods. Furthermore, we establish a lower bound for smooth nonconvex finite-sum problems in the asynchronous setting, providing a fundamental time complexity floor. This lower bound is tight and demonstrates the optimality of Freya PAGE in the large-scale regime, i.e., when $n \gg \frac{1}{\epsilon}$, where n is # of workers, and ϵ is # of data samples.

1 Introduction

In real-world distributed systems used for large-scale machine learning tasks, it is common to encounter device heterogeneity and variations in processing times among different computational units. These can arise from CPU performance differences in hardware configurations, network conditions, and other factors, resulting in different computational capabilities and delays across devices [Chen et al., 2019, Tyurin and Richtarik, 2022]. As a result, some slower may become computational bottlenecks, while others experience delays or even fail to participate in the training algorithm. Due to the above reasons, we aim to address the challenges posed by device heterogeneity in the context of solving finite-sum nonconvex optimization problems of the form

$$\min_{\theta \in \mathbb{R}^d} \left\{ f(\theta) = \frac{1}{n} \sum_{i=1}^n f_i(\theta) \right\}, \quad (1)$$

where $f_i: \mathbb{R}^d \rightarrow \mathbb{R}$ can be viewed as the loss of a machine learning model θ on the i^{th} example in a training dataset with n samples. Our goal is to find an ϵ -stationary point, i.e., a (possibly random) point θ such that $\mathbb{E} \|\nabla f(\theta)\|^2 \leq \epsilon$. We focus on the homogeneous distributed setting

- there are n worker/coordinates able to work in parallel,
- each worker has access to stochastic gradients $\nabla f_i(\theta)$, $i = 1, \dots, n$,
- worker i calculates $\nabla f_i(\theta)$ in time or equal to $\tau_i \in [0, \infty]$ seconds for all $i \in [n]$, $\tau_i \in [\tau_{\min}, \tau_{\max}]$.

Preprint. Under review.

Shadowheart

Freya



Freya PAGE

Optimal Parallel SGD for Large-Scale Finite-Sum Problems

Alexander Tyurin, Kaja Gruntkowska, and P.R.

Freya PAGE: First optimal time complexity for large-scale nonconvex finite-sum optimization with heterogeneous asynchronous computations

arXiv:2405.1554, 2024



Freya PAGE: Setup

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x) \right\}$$

$$f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$$

Optimal Parallel Stochastic Gradient Methods

	Data Heterogeneity (\mathcal{D}_i different)	Compute Heterogeneity (τ_i different)	Communication Heterogeneity (θ_i different)	Smooth Nonconvex	Smooth Convex	Infinite / Finite Sum?	Supports Decentralized Setup?	Optimal Time Complexity?
Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0	✓		Inf	✗	✓
Malenia SGD Tyurin & R (NeurIPS '23)	✓	✓	0	✓		Inf	✗	✓
Accelerated Rennala SGD Tyurin & R (NeurIPS '23)	✗	✓	0		✓	Inf	✗	✓
Shadowheart SGD Tyurin, Pozzi, Ilin & R '24	✗	✓	✓	✓		Inf	✗	✓
Freya PAGE Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✓ big data regime
Freya SGD Tyurin, Gruntkowska & R '24	✗	✓	0	✓		Finite	✗	✗
Fragile SGD Tyurin & R '24	✗	✓	✓	✓		Inf	✓	nearly
Amelie SGD Tyurin & R '24	✓	✓	✓	✓		Inf	✓	✓

$$\mathcal{D}_1 = \dots = \mathcal{D}_n$$

\mathcal{D}_i = uniform distribution over m outcomes

PAGE: Optimal Serial SGD for Finite-Sum Nonconvex Optimization

PAGE: A Simple and Optimal Probabilistic Gradient Estimator for Nonconvex Optimization

Zhize Li¹ Hongyan Bao¹ Xiangliang Zhang¹ Peter Richtárik¹

Abstract

In this paper, we propose a novel stochastic gradient estimator—Probabilistic Gradient Estimator (PAGE)—for nonconvex optimization. PAGE is easy to implement as it is designed via a small adjustment to vanilla SGD: in each iteration, PAGE uses the vanilla minibatch SGD update with probability p_t or reuses the previous gradient with a small adjustment, at a much lower computational cost, with probability $1 - p_t$. We give a simple formula for the optimal choice of p_t . Moreover, we prove the first tight lower bound $\Omega(n + \frac{\sqrt{d}}{p})$ for nonconvex finite-sum problems, which also leads to a tight lower bound $\Omega(b + \frac{\sqrt{d}}{p})$ for nonconvex online problems, where $b := \min(\frac{d}{p}, n)$. Then, we show that PAGE obtains the optimal convergence results $O(n + \frac{\sqrt{d}}{p})$ (finite-sum) and $O(b + \frac{\sqrt{d}}{p})$ (online) matching our lower bounds for both nonconvex finite-sum and online problems. Besides, we also show that for nonconvex functions satisfying the Polyak-Lejasiewicz (PL) condition, PAGE can automatically switch to a faster linear convergence rate $O(\log \frac{1}{\epsilon})$. Finally, we conduct several deep learning experiments (e.g., LeNet, VGG, ResNet) on real datasets in PyTorch showing that PAGE not only converges much faster than SGD in training but also achieves the higher test accuracy, validating the optimal theoretical results and confirming the practical superiority of PAGE.

1. Introduction

Nonconvex optimization is ubiquitous across many domains of machine learning, including robust regression, low rank matrix recovery, sparse recovery and supervised learning

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(Jain & Kar, 2017). Driven by the applied success of deep neural networks (LeCun et al., 2015), and the critical place nonconvex optimization plays in training them, research in nonconvex optimization has been undergoing a renaissance (Ghadimi & Lan, 2013; Ghadimi et al., 2016; Zhou et al., 2018; Fang et al., 2018; Li, 2019; Li & Richtárik, 2020).

1.1. The problem

Motivated by this development, we consider the general optimization problem

$$\min_{x \in \mathbb{R}^d} f(x), \quad (1)$$

where $f: \mathbb{R}^d \rightarrow \mathbb{R}$ is a differentiable and possibly nonconvex function. We are interested in functions having the finite-sum form

$$f(x) := \frac{1}{n} \sum_{i=1}^n f_i(x), \quad (2)$$

where the functions f_i are also differentiable and possibly nonconvex. Form (2) captures the standard empirical risk minimization problems in machine learning (Shalev-Shwartz & Ben-David, 2014). Moreover, if the number of data samples n is very large or even infinite, e.g., in the online/streaming case, then $f(x)$ usually is modeled via the online form

$$f(x) := \mathbb{E}_{\zeta \sim \mathcal{D}} [F(x, \zeta)], \quad (3)$$

which we also consider in this work. For notational convenience, we adopt the notation of the finite-sum form (2) in the descriptions and algorithms in the rest of this paper. However, our results apply to the online form (3) as well by letting $f_i(x) := F(x, \zeta_i)$ and treating n as a very large value or even infinite.

1.2. Gradient complexity

To measure the efficiency of algorithms for solving the nonconvex optimization problem (1), it is standard to bound the number of stochastic gradient computations needed to find a solution of suitable characteristics. In this paper we

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x) \right\}$$
$$f_i(x) := \mathbb{E}_{\xi \sim \mathcal{D}_i} [f_i(x, \xi)]$$

$$\mathcal{D}_1 = \dots = \mathcal{D}_n$$

\mathcal{D}_i = uniform distribution over m outcomes

$$\min_{x \in \mathbb{R}^d} \left\{ f(x) = \frac{1}{m} \sum_{i=1}^m f_i(x) \right\}$$

(after butchering/redefining notation)



Zhize Li, Hongyan Bao, Xiangliang Zhang, and P.R.
**PAGE: A simple and optimal probabilistic
gradient estimator for nonconvex optimization**
ICML 2021

Table 1: Comparison of the *worst-case time complexity* guarantees of methods that work with asynchronous computations in the setup from Section 1 (up to smoothness constants). We assume that $\tau_i \in [0, \infty]$ is the bound on the times required to calculate one stochastic gradient ∇f_j by worker i , $\tau_1 \leq \dots \leq \tau_n$, and $m \geq n \log n$. Abbr: $\delta^0 := f(x^0) - f^*$, $m = \#$ of data samples, $n = \#$ of workers, $\varepsilon =$ error tolerance.

Method	Worst-Case Time Complexity	Comment
Hero GD (Soviet GD)	$\tau_1 m \frac{\delta^0}{\varepsilon} \quad (\tau_n \frac{m}{n} \frac{\delta^0}{\varepsilon})$	Suboptimal
Hero PAGE (Soviet PAGE) [Li et al., 2021]	$\tau_1 m + \tau_1 \frac{\delta^0}{\varepsilon} \sqrt{m} \quad (\tau_n \frac{m}{n} + \tau_n \frac{\delta^0}{\varepsilon} \frac{\sqrt{m}}{n})$	Suboptimal
SYNTHESIS [Liu et al., 2022]	—	Limitations: bounded gradient assumption, calculates the full gradients ^(a) , suboptimal. ^(b)
Asynchronous SGD [Koloskova et al., 2022] [Mishchenko et al., 2022]	$\frac{\delta^0}{\varepsilon} \left(\left(\sum_{i=1}^n \frac{1}{\tau_i} \right)^{-1} \left(\frac{\sigma^2}{\varepsilon} + n \right) \right)$	Limitations: σ^2 -bounded variance assumption, suboptimal when ε is small.
Rennala SGD [Tyurin and Richtárik, 2023]	$\frac{\delta^0}{\varepsilon} \min_{j \in [n]} \left(\left(\sum_{i=1}^j \frac{1}{\tau_i} \right)^{-1} \left(\frac{\sigma^2}{\varepsilon} + j \right) \right)$	Limitations: σ^2 -bounded variance assumption, suboptimal when ε is small.
Freya PAGE (Theorems 7 and 8)	$\min_{j \in [n]} \left(\left(\sum_{i=1}^j \frac{1}{\tau_i} \right)^{-1} (m + j) \right) + \frac{\delta^0}{\varepsilon} \min_{j \in [n]} \left(\left(\sum_{i=1}^j \frac{1}{\tau_i} \right)^{-1} (\sqrt{m} + j) \right)^{(c)}$	Optimal in the large-scale regime, i.e., $\sqrt{m} \geq n$ (see Section 5)
Lower bound (Theorem 10)	$\min_{j \in [n]} \left(\left(\sum_{i=1}^j \frac{1}{\tau_i} \right)^{-1} (m + j) \right) + \frac{\delta^0}{\sqrt{m\varepsilon}} \min_{j \in [n]} \left(\left(\sum_{i=1}^j \frac{1}{\tau_i} \right)^{-1} (m + j) \right)$	—

Freya PAGE has *universally* better guarantees than all previous methods: the dependence on ε is $\mathcal{O}(1/\varepsilon)$ (unlike Rennala SGD and Asynchronous SGD), the dependence on $\{\tau_i\}$ is harmonic-like and robust to slow workers (robust to $\tau_n \rightarrow \infty$) (unlike Soviet PAGE and SYNTHESIS), the assumptions are weak, and the time complexity of Freya PAGE is optimal when $\sqrt{m} \geq n$.

^(a) In Line 3 of their Algorithm 3, they calculate the full gradient, assuming that it can be done for free and not explaining how.

^(b) Their convergence rates in Theorems 1 and 3 depend on a bound on the delays Δ , which in turn depends on the performance of the slowest worker. Our method does not depend on the slowest worker if it is too slow (see Section 4.3), which is required for optimality.

^(c) We prove better time complexity in Theorem 6, but this result requires the knowledge of $\{\tau_i\}$ in advance, unlike Theorems 7 and 8.

Algorithm 1 Freya PAGE

1: **Parameters:** starting point $x^0 \in \mathbb{R}^d$, learning rate $\gamma > 0$, minibatch size $S \in \mathbb{N}$, probability $p \in (0, 1]$, initialization $g^0 = \nabla f(x^0)$ using **ComputeGradient**(x^0) (Alg. 2)

2: **for** $k = 0, 1, \dots, K - 1$ **do**

3: $x^{k+1} = x^k - \gamma g^k$

4: Sample $c^k \sim \text{Bernoulli}(p)$

5: **if** $c^k = 1$ **then** (with probability p)

6: $\nabla f(x^{k+1}) = \text{ComputeGradient}(x^{k+1})$ (Alg. 2)

7: $g^{k+1} = \nabla f(x^{k+1})$

8: **else** (with probability $1 - p$)

9: $\frac{1}{S} \sum_{i \in \mathcal{S}^k} (\nabla f_i(x^{k+1}) - \nabla f_i(x^k)) = \text{ComputeBatchDifference}(S, x^{k+1}, x^k)$ (Alg. 3)

10: $g^{k+1} = g^k + \frac{1}{S} \sum_{i \in \mathcal{S}^k} (\nabla f_i(x^{k+1}) - \nabla f_i(x^k))$

11: **end if**

12: **end for**

(note): \mathcal{S}^k is a set of i.i.d. indices that are sampled from $[m]$, *uniformly with replacement*, $|\mathcal{S}^k| = S$

Algorithm 2 ComputeGradient(x)

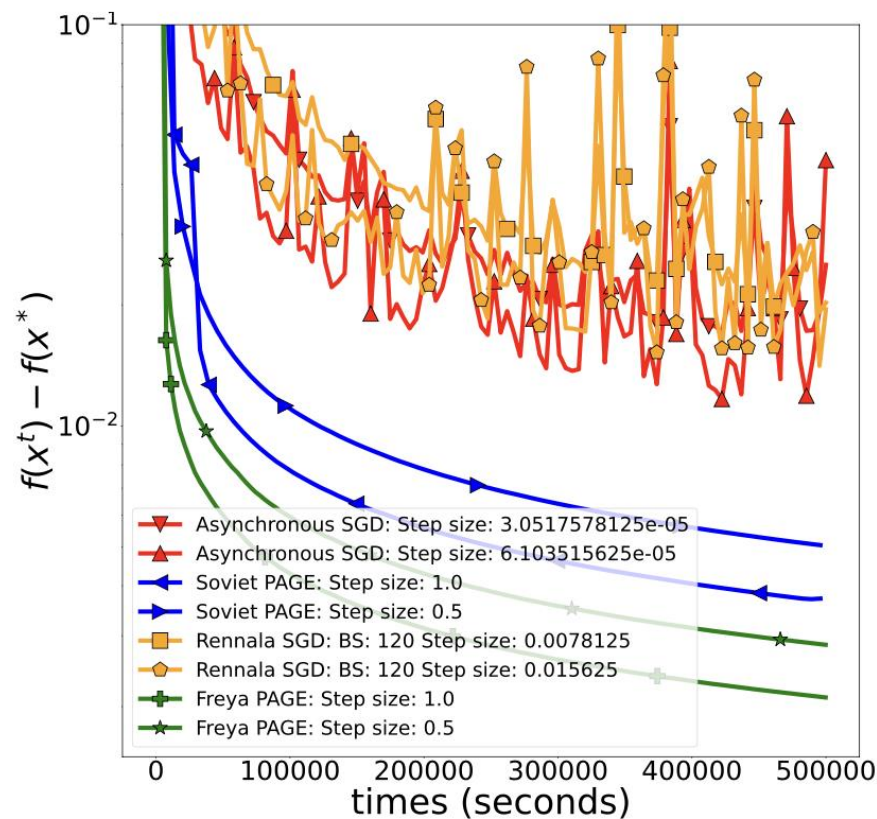
1: **Input:** point $x \in \mathbb{R}^d$
2: Init $g = 0 \in \mathbb{R}^d$, set $\mathcal{M} = \emptyset$
3: Broadcast x to all workers
4: For each worker $i \in [n]$, sample j from $[m]$ uniformly and ask it to calculate $\nabla f_j(x)$
5: **while** $\mathcal{M} \neq [m]$ **do**
6: Wait for $\nabla f_p(x)$ from a worker
7: **if** $p \in [m] \setminus \mathcal{M}$ **then**
8: $g \leftarrow g + \frac{1}{m} \nabla f_p(x)$
9: Update $\mathcal{M} \leftarrow \mathcal{M} \cup \{p\}$
10: **end if**
11: Sample j from $[m] \setminus \mathcal{M}$ uniformly and ask this worker to calculate $\nabla f_j(x)$
12: **end while**
13: **Return** $g = \frac{1}{m} \sum_{i=1}^m \nabla f_i(x)$

Algorithm 3 ComputeBatchDifference(S, x, y)

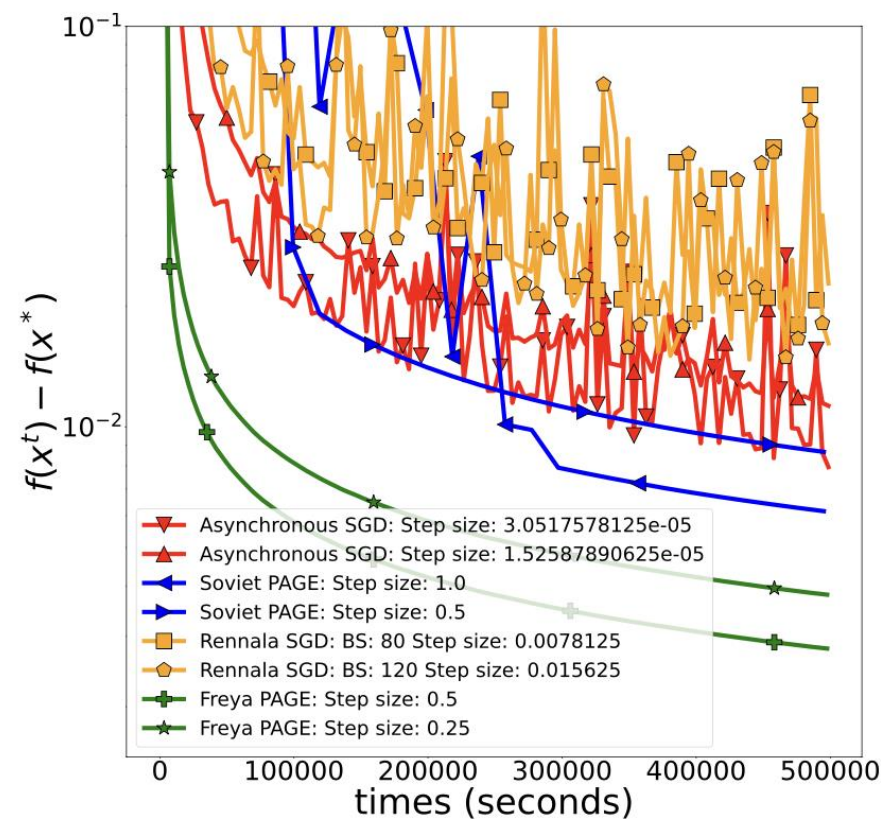
1: **Input:** batch size $S \in \mathbb{N}$, points $x, y \in \mathbb{R}^d$
2: Init $g = 0 \in \mathbb{R}^d$
3: Broadcast x, y to all workers
4: For each worker, sample j from $[m]$ uniformly and ask it to calculate $\nabla f_j(x) - \nabla f_j(y)$
5: **for** $i = 1, 2, \dots, S$ **do**
6: Wait for $\nabla f_p(x) - \nabla f_p(y)$ from a worker
7: $g \leftarrow g + \frac{1}{S} (\nabla f_p(x) - \nabla f_p(y))$
8: Sample j from $[m]$ uniformly and ask this worker to calculate $\nabla f_j(x) - \nabla f_j(y)$
9: **end for**
10: **Return** g

Notes: i) the workers can aggregate ∇f_p locally, and the algorithm can call AllReduce once to collect all calculated gradients. ii) By splitting $[m]$ into blocks, instead of one ∇f_p , we can ask the workers to calculate the sum of one block in Alg. 2 (and use a similar idea in Alg. 3).

Freya PAGE: Experiment 1



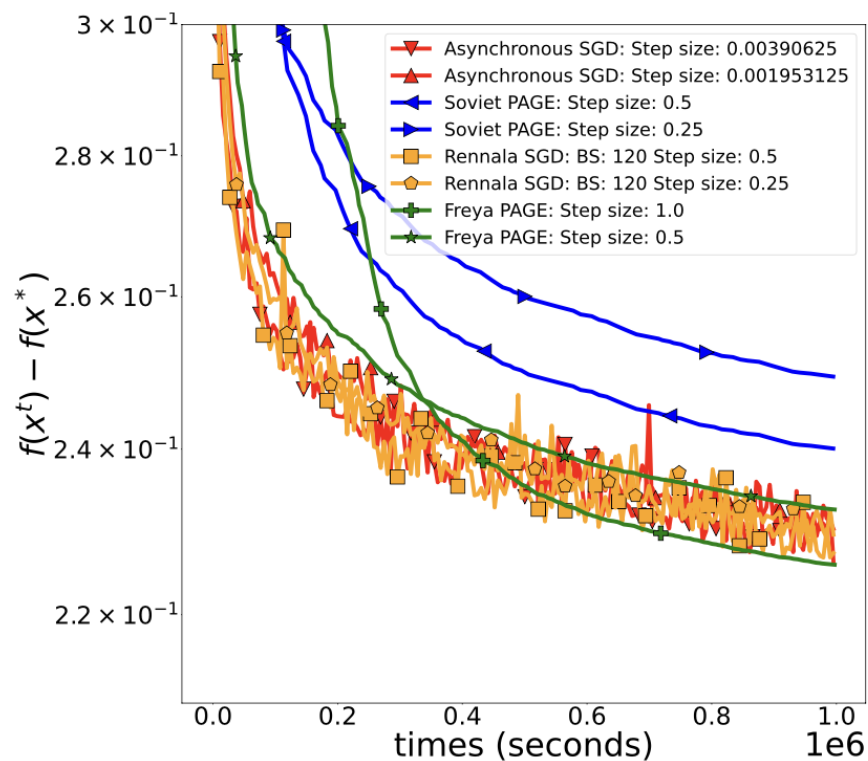
(a) $n = 1000$



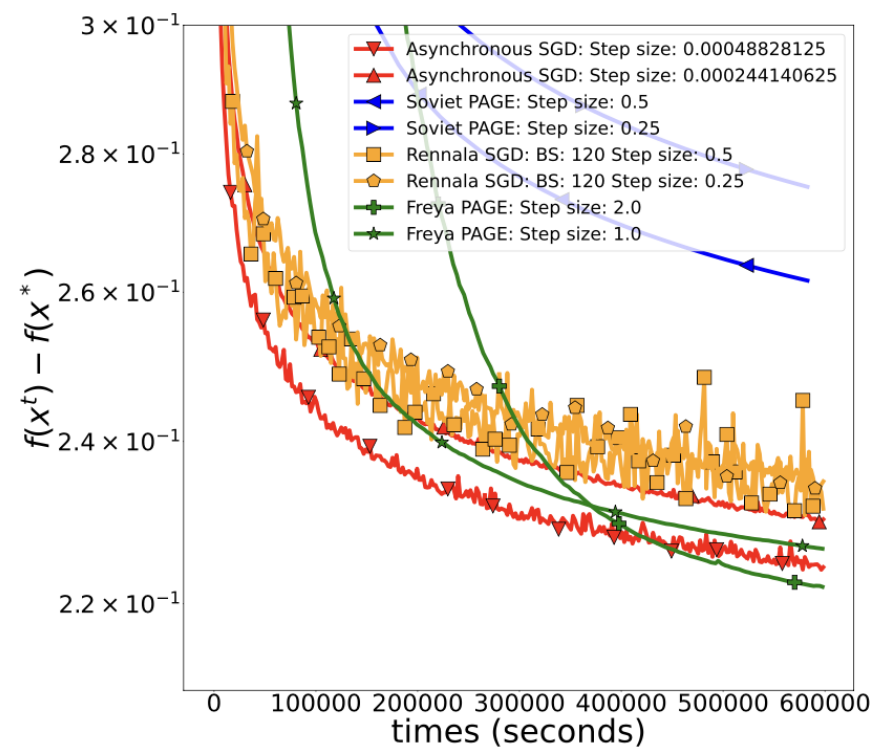
(b) $n = 10000$

Figure 1: Experiments with nonconvex quadratic optimization tasks. We plot function suboptimality against elapsed time.

Freya PAGE: Experiment 2



(a) $n = 100$



(b) $n = 10000$

Figure 2: Experiments with the logistic regression problem on the MNIST dataset.

Freya PAGE: Experiment 2

Table 2: Mean and variance of algorithm accuracies on the MNIST test set during the final 100K seconds of the experiments from Figure 2b.

Method	Accuracy	Variance of Accuracy
Asynchronous SGD [Koloskova et al., 2022] [Mishchenko et al., 2022]	92.60	5.85e-07
Soviet PAGE [Li et al., 2021]	92.31	1.62e-07
Rennala SGD [Tyurin and Richtárik, 2023]	92.37	3.12e-06
Freya PAGE	92.66	1.01e-07

On the Optimal Time Complexities in Decentralized Stochastic Asynchronous Optimization

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Abstract

We consider the decentralized stochastic asynchronous optimization setup, where many workers asynchronously calculate stochastic gradients and asynchronously communicate with each other using edges in a network. For both homogeneous and heterogeneous setups, we prove new time complexity lower bounds under the assumption that the communication and computation times are bounded. We provide a new nearly optimal method, Fragile SGD, and a new optimal method, Anneal SGD, that converge under arbitrary heterogeneous computation and communication times and that have lower bounds up to a logarithmic factor in the homogeneous setting. Our time complexities are new, nearly optimal, and globally superior to all previous decentralized stochastic methods in the decentralized setup.

1 Introduction

We consider the smooth stochastic optimization problem

$$\min_{x \in \mathbb{R}^d} \{f(x) := \mathbb{E}_{\xi \sim \mathcal{D}} \ell(x; \xi)\}, \quad (1)$$

where $f: \mathbb{R}^d \rightarrow \mathbb{R}$, and \mathcal{D} is a distribution on a compact set \mathcal{X} . For a given $\epsilon > 0$, we want to find a possibly random point \hat{x} , called an ϵ -stationary point, such that $\mathbb{E}[\|\nabla f(\hat{x})\|^2] \leq \epsilon$. We analyze the heterogeneous setup and the correct setup with respect to new optimal bounds on the number of iterations.

1.1 Decentralized setup with time

We investigate the following decentralized asynchronous setup. Assume that we have n workers with the associated computation times $\{t_i\}_{i=1}^n$ and communication times $\{c_{ij}\}_{i,j=1}^n$. t_i takes time to equal to t_i , c_{ij} takes time to compute a stochastic gradient by the i -th node, and time to equal to c_{ij} . \mathcal{D} is a random variable taking values in \mathcal{X} . For the i -th node, the i -th node is available that $t_i, c_{ij} \in [0, \infty)$. All computation and communication times are time asynchronous and in parallel. We would like to emphasize that $t_i, c_{ij} \in [0, \infty)$ and $c_{ij} \in [0, \infty)$ are only upper bounds, and the real effective computation and communication times can be arbitrarily heterogeneous and random. For simplicity of presentation, we assume the upper bounds are finite, however, in Section 2, we explain that our results can be trivially extended to the case where the upper bounds are infinite.

We consider any weighted directed multigraph parametrized by a matrix $A \in \mathbb{R}^{n \times n}$ such that $A_{ij} \in [0, \infty)$ and a matrix of distances $\{d_{ij}\}_{i,j=1}^n \in \mathbb{R}^{n \times n}$ such that $d_{ij} \in [0, \infty)$ for all $i, j \in [n]$ and $d_{ii} = 0$ for all $i \in [n]$. Every vertex is connected to any other vertex j with an edge (i, j) and $j \neq i$. For this setup, it would be convenient to define the distance of the shortest path from

Amelie SGD

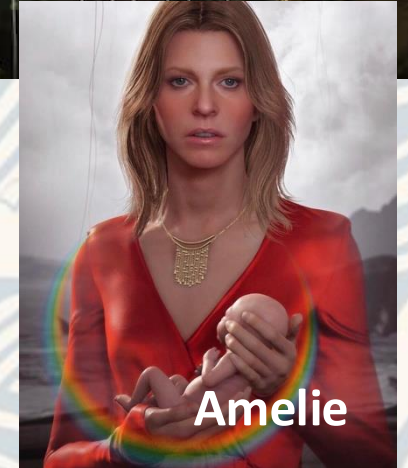
Optimal Decentralized SGD under Computation & Communication Heterogeneity



Alexander Tyurin and P.R.

On the optimal time complexities in decentralized stochastic asynchronous optimization

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Decentralized Setup: Amelie SGD

Method	The Worst-Case Time Complexity Guarantees	Comment
Minibatch SGD	$\frac{L\Delta}{\varepsilon} \max \left\{ \left(1 + \frac{\sigma^2}{n\varepsilon}\right) \max\left\{ \max_{i,j \in [n]} \tau_{i \rightarrow j}, \max_{i \in [n]} h_i \right\} \right\}$	suboptimal if σ^2/ε is large
RelaySGD, Gradient Tracking (Vogels et al., 2021) (Liu et al., 2024)	$\geq \frac{\max_{i \in [n]} L_i \Delta}{\varepsilon} \frac{\sigma^2}{n\varepsilon} \max_{i \in [n]} h_i$	requires local L_i -smooth. of f_i , suboptimal if σ^2/ε is large (even if $\max_{i \in [n]} L_i = L$)
Asynchronous SGD (Even et al., 2024)	—	requires similarity of the functions $\{f_i\}$, requires local L_i -smooth. of f_i
Amelie SGD and Lower Bound (Thm. 7 and Cor. 2)	$\frac{L\Delta}{\varepsilon} \max \left\{ \max_{i,j \in [n]} \tau_{i \rightarrow j}, \max_{i \in [n]} h_i, \frac{\sigma^2}{n\varepsilon} \left(\frac{1}{n} \sum_{i=1}^n h_i \right) \right\}$	Optimal up to a constant factor



**The End
(for real)**