

ProxSkip: Yes! Local Gradient Steps Provably Lead to Communication Acceleration! Finally!

arXiv:2202.09357v1 [cs.LG] 18 Feb 2022

ProxSkip: Yes! Local Gradient Steps Provably Lead to Communication Acceleration! Finally!

Konstantin Mishchenko¹ Grigory Malinovsky² Sebastian Stich³ Peter Richtárik²

Abstract

We introduce ProxSkip, a surprisingly simple and provably efficient method for minimizing the sum of a smooth (f) and an expensive non-smooth proximable (ψ) function. The canonical approach to solving such problems is to use a proximal gradient descent (ProxGD) algorithm, which is based on the evaluation of the gradient of f and the prox operator of ψ . However, ProxGD is often not specifically interested in the regime in which the evaluation of f is costly relative to the evaluation of ψ , which is the case in many machine learning applications. ProxSkip allows for the expensive prox operator to be skipped in every iteration: while it is still a proximal gradient descent, the number of prox evaluations is $O(\sqrt{\log(1/\epsilon)})$ only. Our main motivation is to reduce communication costs. In particular, evaluation of the gradient operator corresponds to taking a local GD independently on all devices, and the prox operator corresponds to performing communication in the form of gradient averaging. In this context, ProxSkip offers an effective way to accelerate ProxGD without communication. Unlike other local gradient-type methods, such as FedAvg, SCAFFOLD, S-local-GD and FedUp, which either require more iterations or converge significantly worse than, or at best matching, that of vanilla GD in the heterogeneous data regime, we obtain a provable and large improvement without any heterogeneity assumptions.

1. Introduction

We study optimization problems of the form

$$\min_x (f(x) + \psi(x)). \quad (1)$$

where $f : \mathbb{R}^d \rightarrow \mathbb{R}$ is a smooth function, and $\psi : \mathbb{R}^d \rightarrow \mathbb{R}$ is a non-smooth closed and convex function.

Such problems are ubiquitous and appear in numerous applications associated with various areas of science and engineering, including signal processing (Combettes & Pesquet, 2011), image processing (Luke, 2020), data science (Fuchs & Stach, 2014) and machine learning (Dhillon, Stewart & Ben-David, 2014).

1.1. Proximal gradient descent

One of the most canonical methods for solving (1), often used as the basis for further extensions and improvements, is proximal gradient descent (ProxGD), also known as the forward-backward splitting (Bauschke & Combettes, 2009; Nesterov, 2013). This method solves (1) via the iterative process defined by

$$x_{t+1} = \text{prox}_{\psi}(x_t - \eta_t \nabla f(x_t)), \quad (2)$$

where $\eta_t > 0$ is a suitable stepsize at time t , and $\text{prox}_{\psi}(\cdot) : \mathbb{R}^d \rightarrow \mathbb{R}^d$ is the proximity operator of ψ , defined via

$$\text{prox}_{\psi}(x) = \arg \min_y \left[\frac{1}{2} \|y - x\|^2 + \eta \psi(y) \right]. \quad (3)$$

It is typically assumed that the proximity operator (3) can be evaluated in closed form, which means that the iteration (2) defining ProxGD can be performed exactly. ProxGD is most suited to evaluate the prox operator when the prox operator is relatively cheap to evaluate, so the bottleneck of (2) is in the forward step (i.e., computation of the gradient ∇f) rather than in the backward step (i.e., evaluation of prox_{ψ}). This is true for a wide range of functions, including the L_1 norm ($\psi(x) = \|x\|_1$), the L_2 norm ($\psi(x) = \|x\|_2$), and classical quadratic regularizers. For further examples, we refer the reader to the books (Punith & Boyd, 2014; Beck, 2017).

1.2. Expensive proximity operators

However, in this work we are interested in the situation when the evaluation of the proximity operator is expensive. That is, we assume that the computation of $\text{prox}_{\psi}(\cdot)$ (the backward step) is much more expensive than the evaluation of the gradient of f (the forward step).

A conceptually simple yet rich class of expensive proximity operators arises from regularizers ψ encoding a barrier or local gradient methods.

1.3. Related work

Please accept our apologies, our excitement apparently spilled over into the title. If we were to write a more scholarly title for this work, it would be something like *Breaking the Communication Barrier of Local Gradient Methods*.

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Peter Richtárik
Workshop on Federated Learning
Lagrange Mathematics and Computation Research Center
April 25, 2022



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ProxSkip: Yes! Local Gradient Steps Provably Lead to Communication Acceleration! Finally![†]

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Abstract

We introduce **ProxSkip**—a surprisingly simple and provably efficient method for minimizing the sum of a smooth (f) and an expensive nonsmooth proximable (ψ) function. The canonical approach to solving such problems is via the proximal gradient descent (**ProxGD**) algorithm, which is based on the evaluation of the gradient of f and the prox operator of ψ in each iteration. In this work we are specifically interested in the regime in which the evaluation of prox is costly relative to the evaluation of the gradient, which is the case in many applications. **ProxSkip** allows for the expensive prox operator to be skipped in most iterations, so its iteration complexity is $\mathcal{O}(\kappa \log^{1/\epsilon})$, where κ is the condition number of f , the number of evaluations is $\mathcal{O}(\sqrt{\kappa} \log^{1/\epsilon})$ only. Our motivation comes from federated learning, where the evaluation of the gradient operator corresponds to a local **GD** step independently on all workers, and evaluation of prox corresponds to (expensive) communication in the form of gradient exchange. In this context, **ProxSkip** offers a provable acceleration of communication costs. Unlike other local gradient-type methods such as **FedAvg**, **SCAFFOLD**, **S-Local-GD** and others, whose theoretical communication complexity is worse than, or at best matching, that of **GD** in the heterogeneous data regime, we offer a provable and large improvement with heterogeneity-bounding assumptions.

where $f: \mathbb{R}^d \rightarrow \mathbb{R}$ is a smooth function, and $\psi: \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$ is a proper, closed and convex regularizer.

Such problems are ubiquitous, and appear in numerous applications associated with virtually all areas of science and engineering, including signal processing (Combettes & Pesquet, 2009), image processing (Luke, 2020), data science (Parikh & Boyd, 2014) and machine learning (Shalev-Shwartz & Ben-David, 2014).

1.1 Proximal gradient descent

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

$\text{prox}_{\gamma\psi}$. This is the case for many regularizers, including the L_1 norm ($\psi(x) = \|x\|_1$), the L_2 norm ($\psi(x) = \|x\|_2^2$), and elastic net (Zhou & Hastie, 2005). For many further examples, we refer the reader to the books (Parikh & Boyd, 2014; Beck, 2017).

1.2 Expensive proximity operators

However, in this work we are interested in the situation when the evaluation of the *proximity operator is expensive*. That is, we assume that the computation of $\text{prox}_{\gamma\psi}$ (the backward step) is costly relative to the evaluation of the gradient of f (the forward step).

A conceptually simple yet rich class of expensive proximity operators arises from regularizers ψ encoding a

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Alternative Title

Coauthors



Konstantin Mishchenko



Grigory Malinovsky

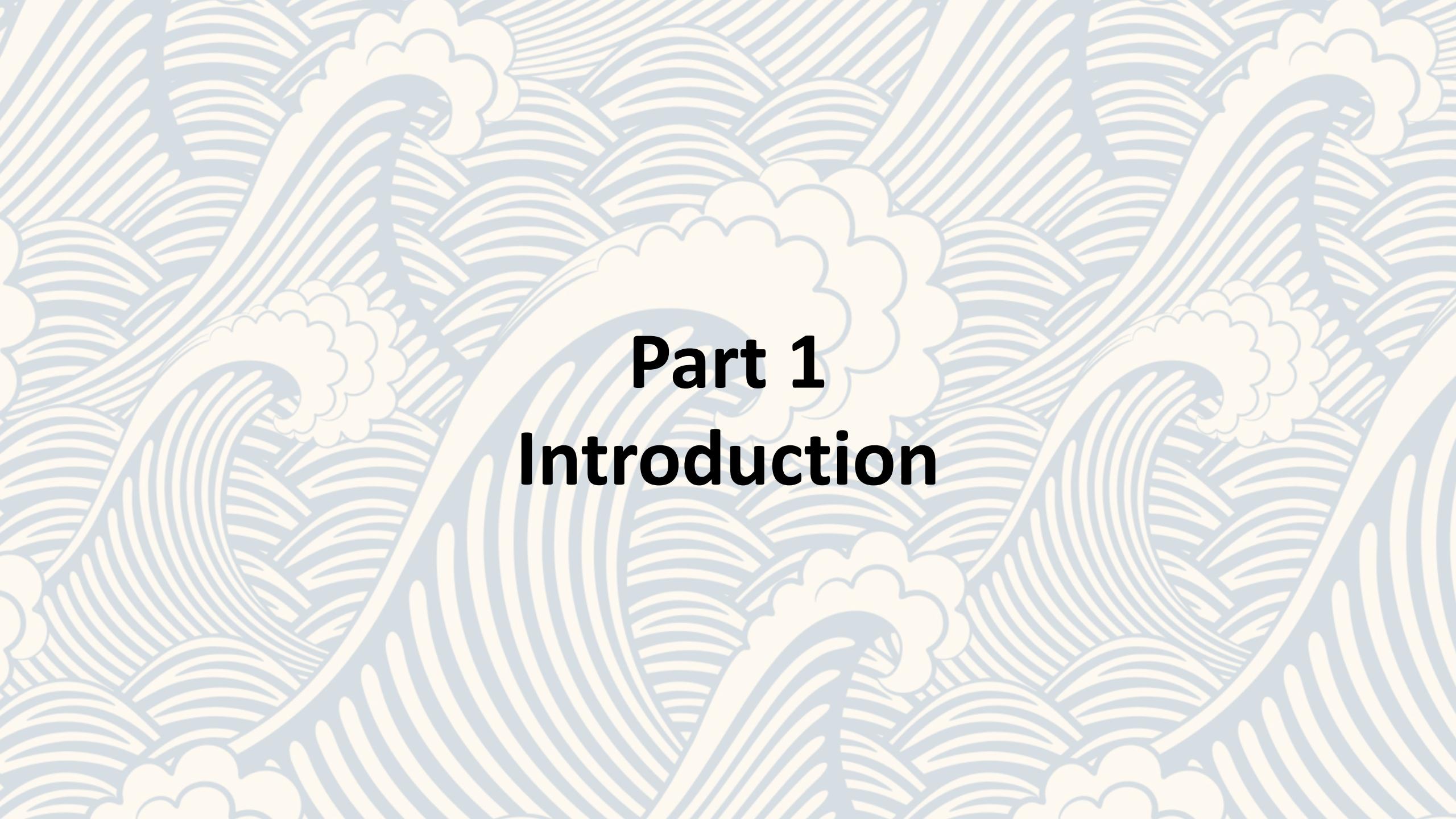


Sebastian Stich



Outline of the Talk

1. Introduction
2. Consensus Reformulation
3. Proximal Gradient Descent
- 4. ProxSkip: Algorithm**
- 5. ProxSkip: Theory**
6. Experiments
7. Extensions



Part 1

Introduction

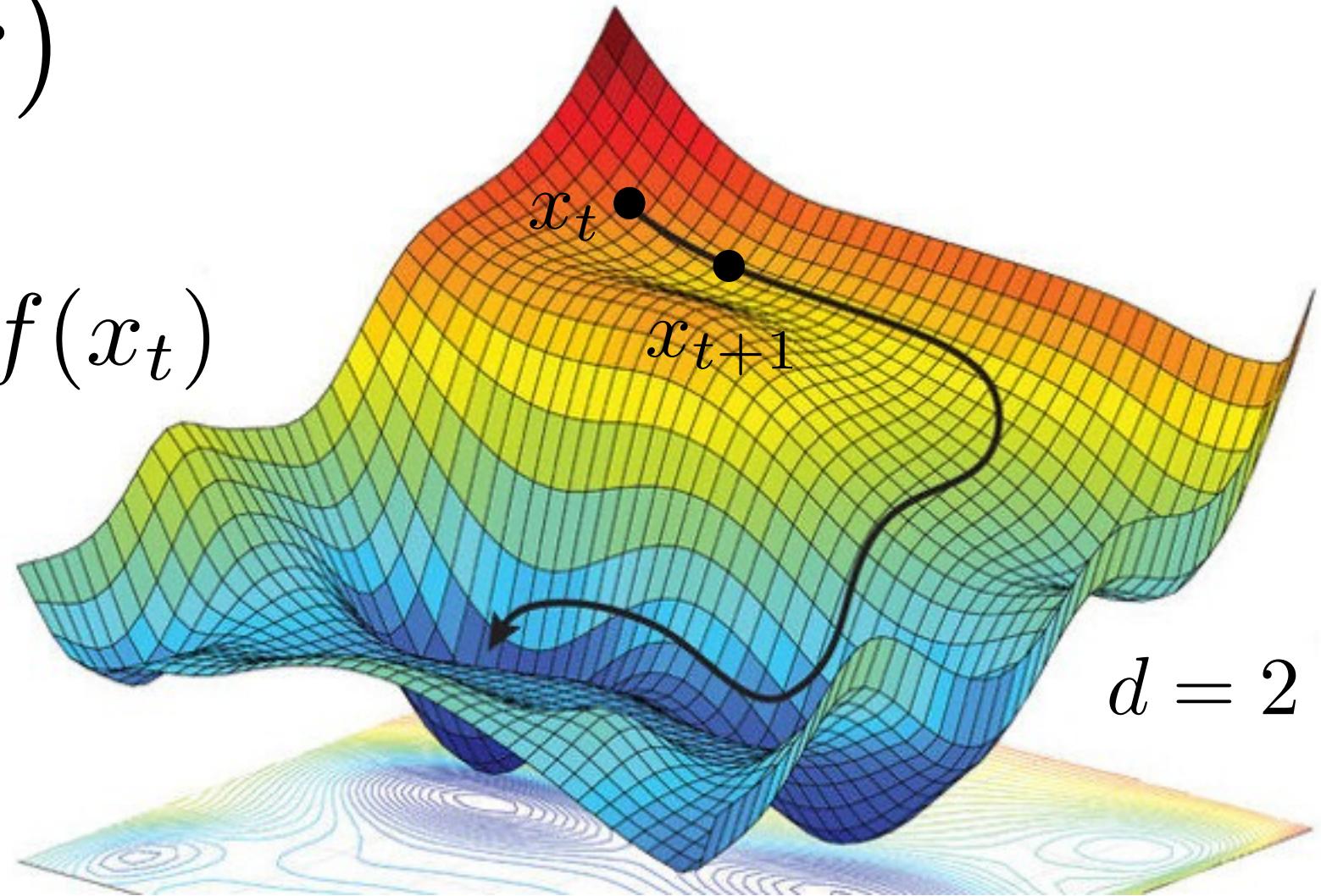
Gradient Descent

Gradient Descent

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

$$x_{t+1} = x_t - \gamma \nabla f(x_t)$$

Stepsize / Learning rate



Distributed Gradient Descent

Federated Training of a Supervised Machine Learning Model

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

model parameters / features

devices / machines

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

$$f_i(x) = \mathbb{E}_{\xi \sim \mathcal{D}_i} f_{i,\xi}(x)$$

The datasets $\mathcal{D}_1, \dots, \mathcal{D}_n$ can be arbitrarily heterogeneous

Optimization problem:

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

Distributed Gradient Descent

$$\begin{aligned} x_{t+1} &= x_t - \gamma \nabla f(x_t) \\ &= x_t - \gamma \frac{1}{n} \sum_{i=1}^n \nabla f_i(x_t) \end{aligned}$$

$f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x_t)$

d -dimensional gradient computed by machine i

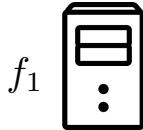
Optimization problem:

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

Distributed Gradient Descent

(Each worker performs 1 GD step using its local function, and the results are averaged)

Worker 1

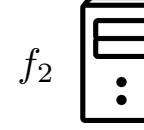


Receive x_t from the server

$$x_{1,t} = x_t$$

$$x_{1,t+1} = x_{1,t} - \gamma \nabla f_1(x_{1,t})$$

Worker 2

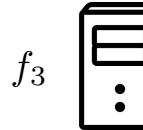


Receive x_t from the server

$$x_{2,t} = x_t$$

$$x_{2,t+1} = x_{2,t} - \gamma \nabla f_2(x_{2,t})$$

Worker 3



Receive x_t from the server

$$x_{3,t} = x_t$$

$$x_{3,t+1} = x_{3,t} - \gamma \nabla f_3(x_{3,t})$$

Server



$$x_{t+1} = \frac{1}{3} \sum_{i=1}^3 x_{i,t+1}$$

Broadcast x_{t+1} to the workers

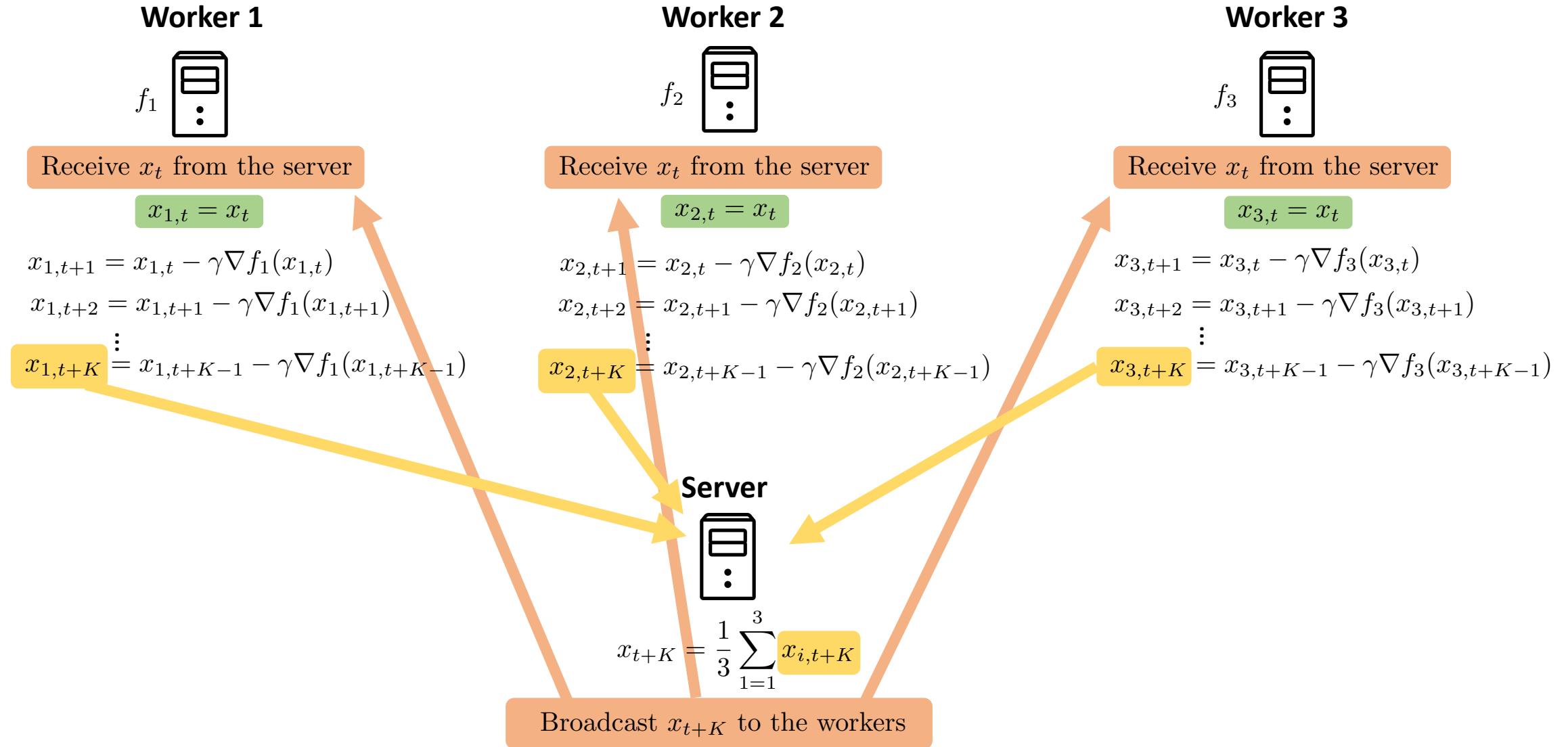
Distributed Local Gradient Descent

Distributed Local Gradient Descent

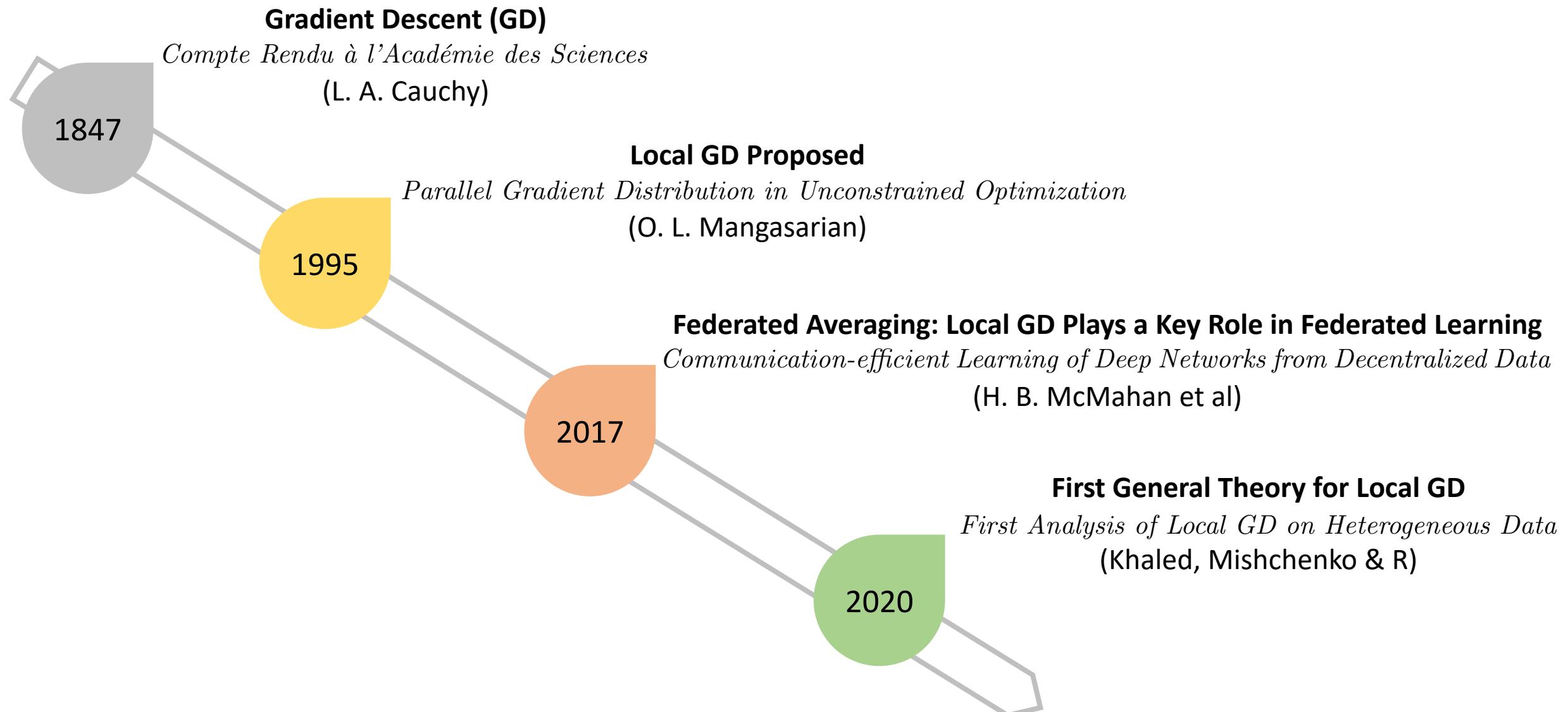
(Each worker performs K GD steps using its local function, and the results are averaged)

Optimization problem:

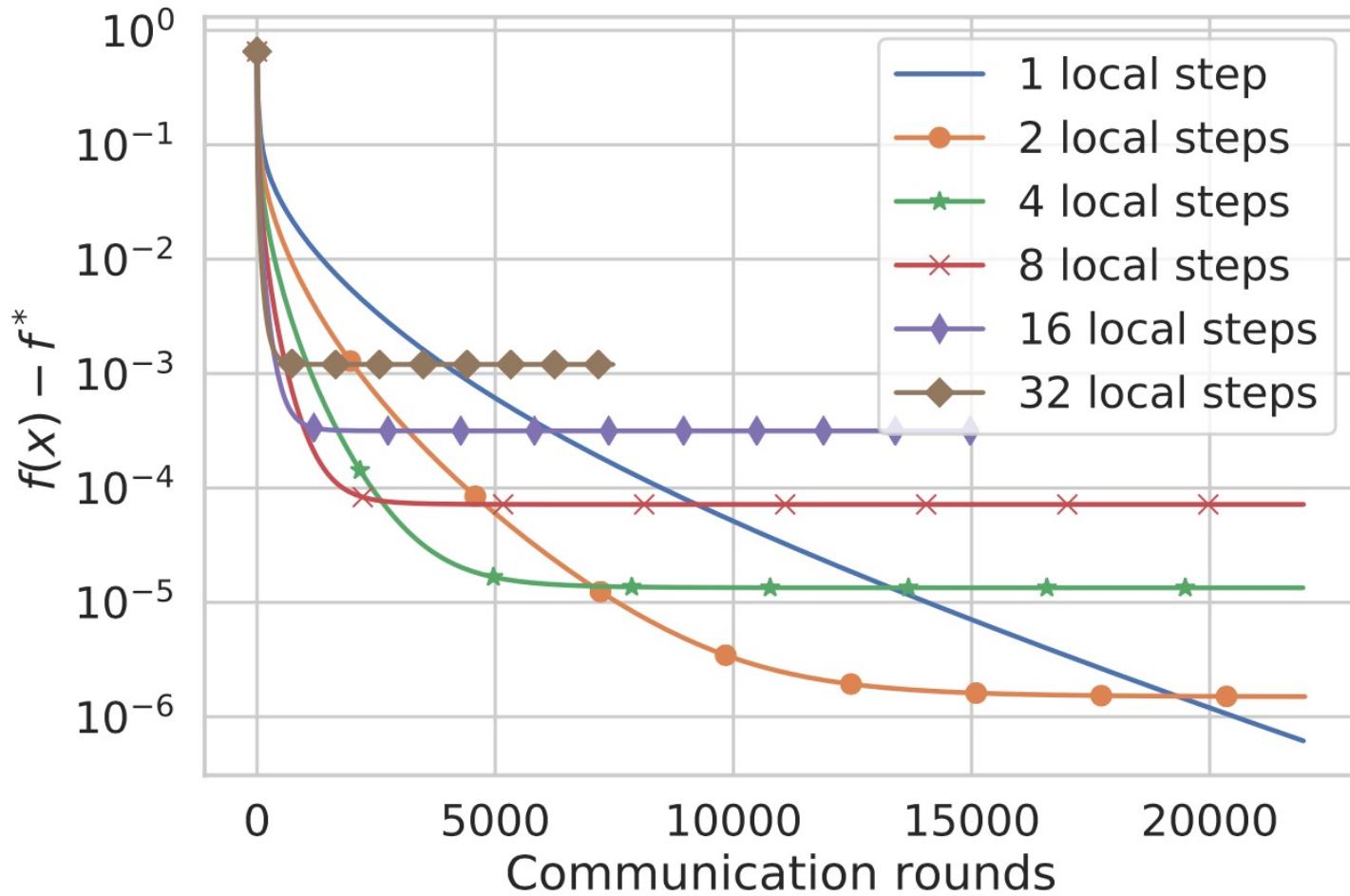
$$\min_{x \in \mathbb{R}^d} f(x) \stackrel{\text{def}}{=} \frac{1}{n} \sum_{i=1}^n f_i(x)$$



From GD to Local GD



What do the Local Steps do?



Plot taken from:



Ahmed Khaled, Konstantin Mishchenko, Peter Richtárik

First Analysis of Local GD on Heterogeneous Data

NeurIPS 2019 Workshop on Federated Learning for Data Privacy and Confidentiality, 2019

L2-regularized logistic regression
LibSVM mushrooms dataset

Linearly Converging Local GD Methods

Local GD with GD-like (=Linear) Convergence

2020

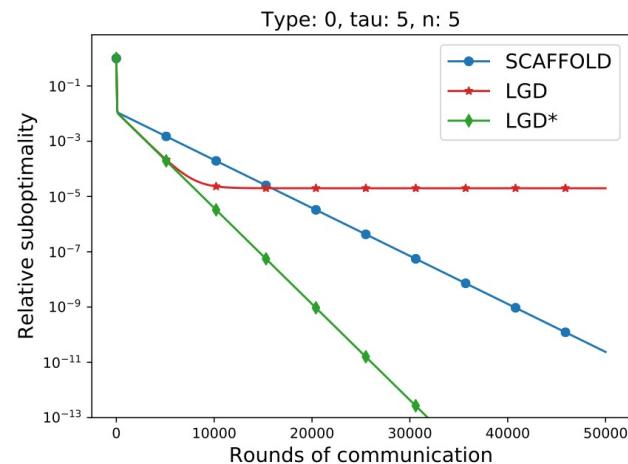
SCAFFOLD

Scaffold: Stochastic Controlled Averaging for Federated Learning
(Karimireddy, Kale, Mohri, Reddi, Stich, Suresh)

2021

S-Local-GD

Local SGD: Unified Theory and New Efficient Methods
(Gorbunov, Hanzely & R)



2021

FedLin

Linear Convergence in Federated Learning...
(Mitra, Jaafar, Pappas, Hassani)

Key Theoretical Problem in Federated Learning

Local GD and its variants are of key importance in federated learning. They work better than GD in practice in terms of communication efficiency.

Why?

Do Multiple Local GD Steps Provably Help?
No Current Theoretical Result Supports This.

Federated Learning: ProxSkip vs Baselines

Table 1. The performance of federated learning methods employing multiple local gradient steps in the strongly convex regime.

method	# local steps per round	# floats sent per round	stepsize on client i	linear rate?	# rounds	rate better than GD?
GD (Nesterov, 2004)	1	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
LocalGD (Khaled et al., 2019; 2020)	τ	d	$\frac{1}{\tau L}$	✗	$\mathcal{O}\left(\frac{G^2}{\mu n \tau \varepsilon}\right)$ ^(d)	✗
Scaffold (Karimireddy et al., 2020)	τ	$2d$	$\frac{1}{\tau L}$ ^(e)	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
S-Local-GD ^(a) (Gorbunov et al., 2021)	τ	$d < \# < 2d$ ^(f)	$\frac{1}{\tau L}$	✓	$\tilde{\mathcal{O}}(\kappa)$	✗
FedLin ^(b) (Mitra et al., 2021)	τ_i	$2d$	$\frac{1}{\tau_i L}$	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
Scaffnew ^(g) (this work) for any $p \in (0, 1]$	$\frac{1}{p}$ ^(h)	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}\left(p\kappa + \frac{1}{p}\right)$ ^(c)	✓ (for $p > \frac{1}{\kappa}$)
Scaffnew ^(g) (this work) for optimal $p = \frac{1}{\sqrt{\kappa}}$	$\sqrt{\kappa}$ ^(h)	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}(\sqrt{\kappa})$ ^(c)	✓

^(a) This is a special case of S-Local-SVRG, which is a more general method presented in (Gorbunov et al., 2021). S-Local-GD arises as a special case when full gradient is computed on each client.

^(b) FedLin is a variant with a fixed but different number of local steps for each client. Earlier method S-Local-GD has the same update but random loop length.

^(c) The $\tilde{\mathcal{O}}$ notation hides logarithmic factors.

^(d) G is the level of dissimilarity from the assumption $\frac{1}{n} \sum_{i=1}^n \|\nabla f_i(x)\|^2 \leq G^2 + 2LB^2 (f(x) - f_*)$, $\forall x$.

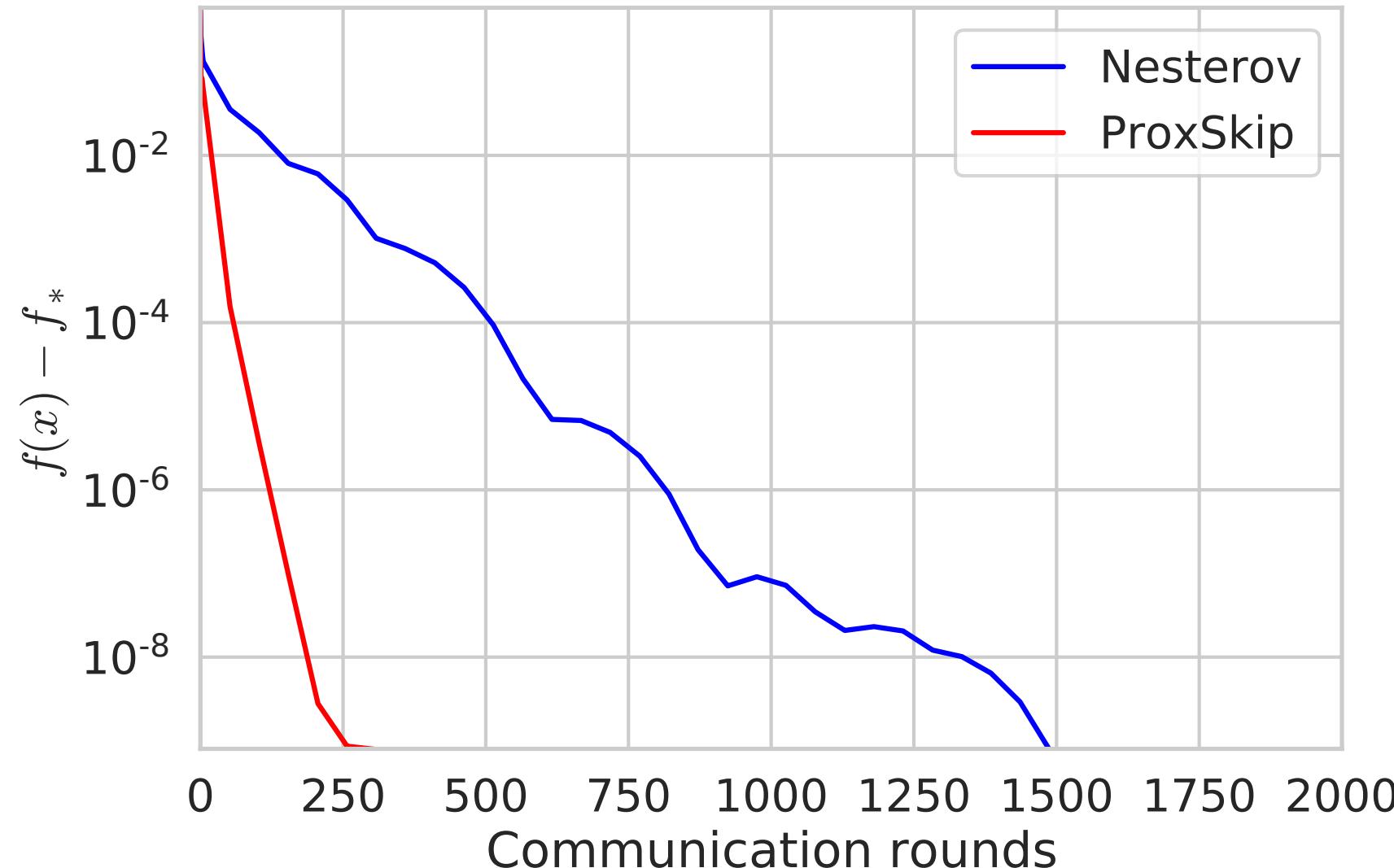
^(e) We use Scaffold's cumulative local-global stepsize $\eta_l \eta_g$ for a fair comparison.

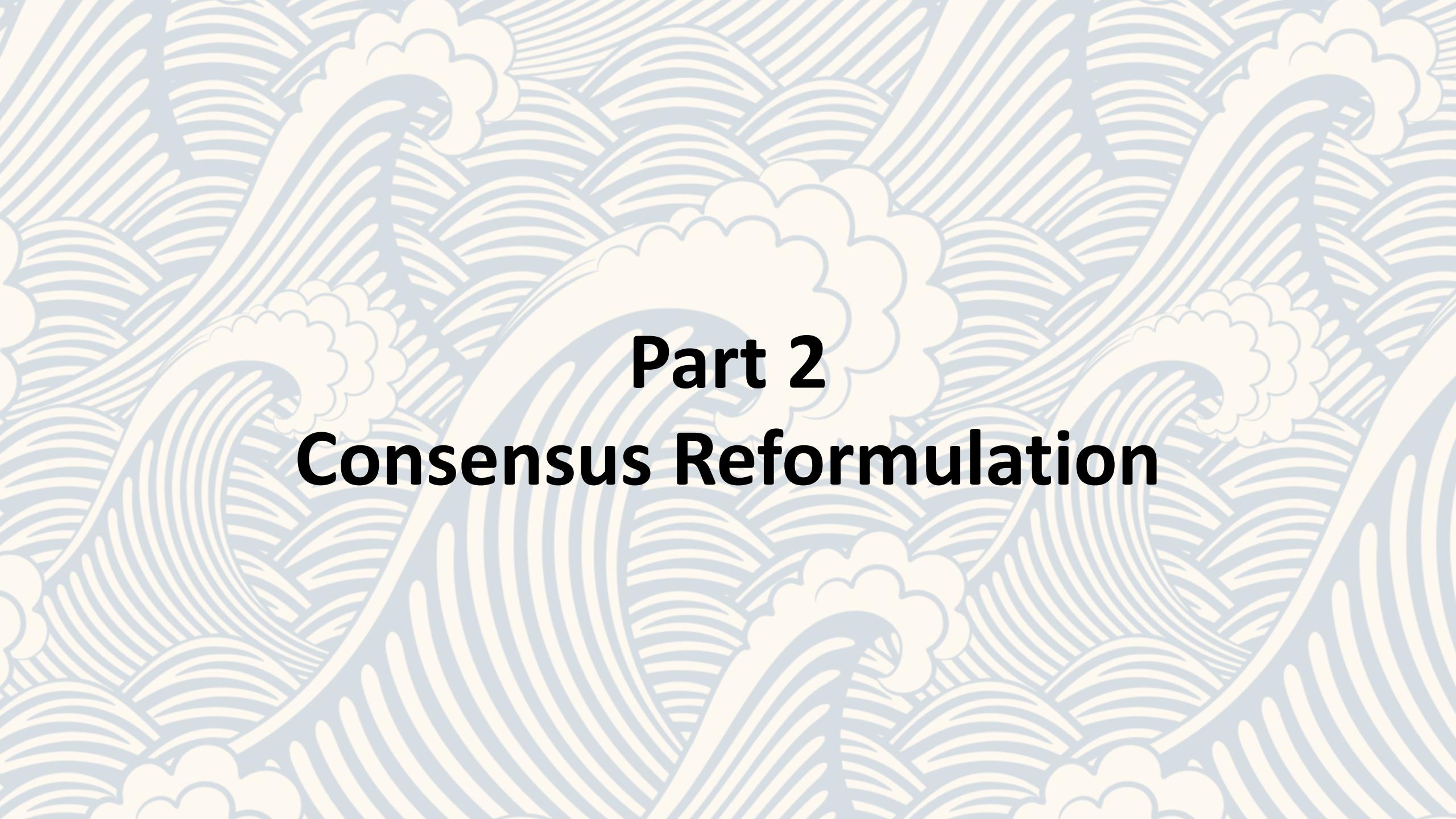
^(f) The number of sent vectors depends on hyper-parameters, and it is randomized.

^(g) Scaffnew (Algorithm 2) = ProxSkip (Algorithm 1) applied to the consensus formulation (6) + (7) of the finite-sum problem (5).

^(h) ProxSkip (resp. Scaffnew) takes a *random* number of gradient (resp. local) steps before prox (resp. communication) is computed (resp. performed). What is shown in the table is the *expected* number of gradient (resp. local) steps.

Federated Learning: ProxSkip vs Nesterov





Part 2

Consensus Reformulation

Consensus Reformulation

Original problem:
optimization in \mathbb{R}^d

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

Bad: Non-differentiable function

Consensus reformulation:
optimization in \mathbb{R}^{nd}

$$\min_{x_1, \dots, x_n \in \mathbb{R}^d} \left\{ \frac{1}{n} \sum_{i=1}^n f_i(x_i) + \psi(x_1, \dots, x_n) \right\}$$

Good: Indicator function of a nonempty closed convex set

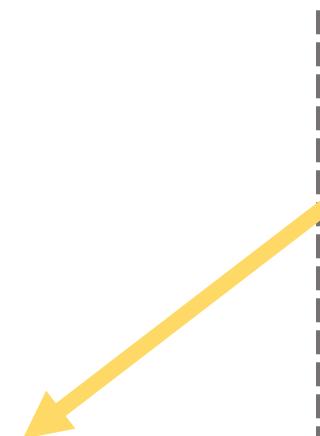
$$\psi(x_1, \dots, x_n) \stackrel{\text{def}}{=} \begin{cases} 0, & \text{if } x_1 = \dots = x_n, \\ +\infty, & \text{otherwise.} \end{cases}$$

Generalization 1: Constrained Optimization

Consensus reformulation:

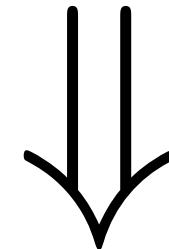
optimization in \mathbb{R}^{nd}

$$\min_{x_1, \dots, x_n \in \mathbb{R}^d} \left\{ \frac{1}{n} \sum_{i=1}^n f_i(x_i) + \psi(x_1, \dots, x_n) \right\}$$



$$\psi(x_1, \dots, x_n) \stackrel{\text{def}}{=} \begin{cases} 0, & \text{if } x_1 = \dots = x_n, \\ +\infty, & \text{otherwise.} \end{cases}$$

Generalization 1



$$\psi(x_1, \dots, x_n) \stackrel{\text{def}}{=} \begin{cases} 0, & \text{if } (x_1, \dots, x_n) \in C, \\ +\infty, & \text{otherwise.} \end{cases}$$

Arbitrary closed convex set
(constraint)

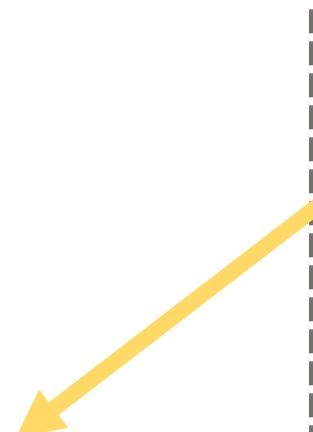


Generalization 2: Composite Optimization

Consensus reformulation:

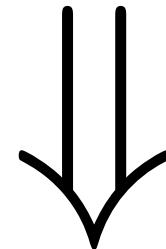
optimization in \mathbb{R}^{nd}

$$\min_{x_1, \dots, x_n \in \mathbb{R}^d} \left\{ \frac{1}{n} \sum_{i=1}^n f_i(x_i) + \psi(x_1, \dots, x_n) \right\}$$



$$\psi(x_1, \dots, x_n) \stackrel{\text{def}}{=} \begin{cases} 0, & \text{if } x_1 = \dots = x_n, \\ +\infty, & \text{otherwise.} \end{cases}$$

Generalization 2



$\psi(x_1, \dots, x_n) : \mathbb{R}^{nd} \rightarrow \mathbb{R} \cup \{+\infty\}$
is a proper closed convex function

The epigraph of ψ is a closed and convex set

$$\text{epi}(\psi) \stackrel{\text{def}}{=} \{(x, t) \mid \psi(x) \leq t\}$$



Conceptual Simplification: from nd to d'

Composite optimization:

optimization in \mathbb{R}^{nd}

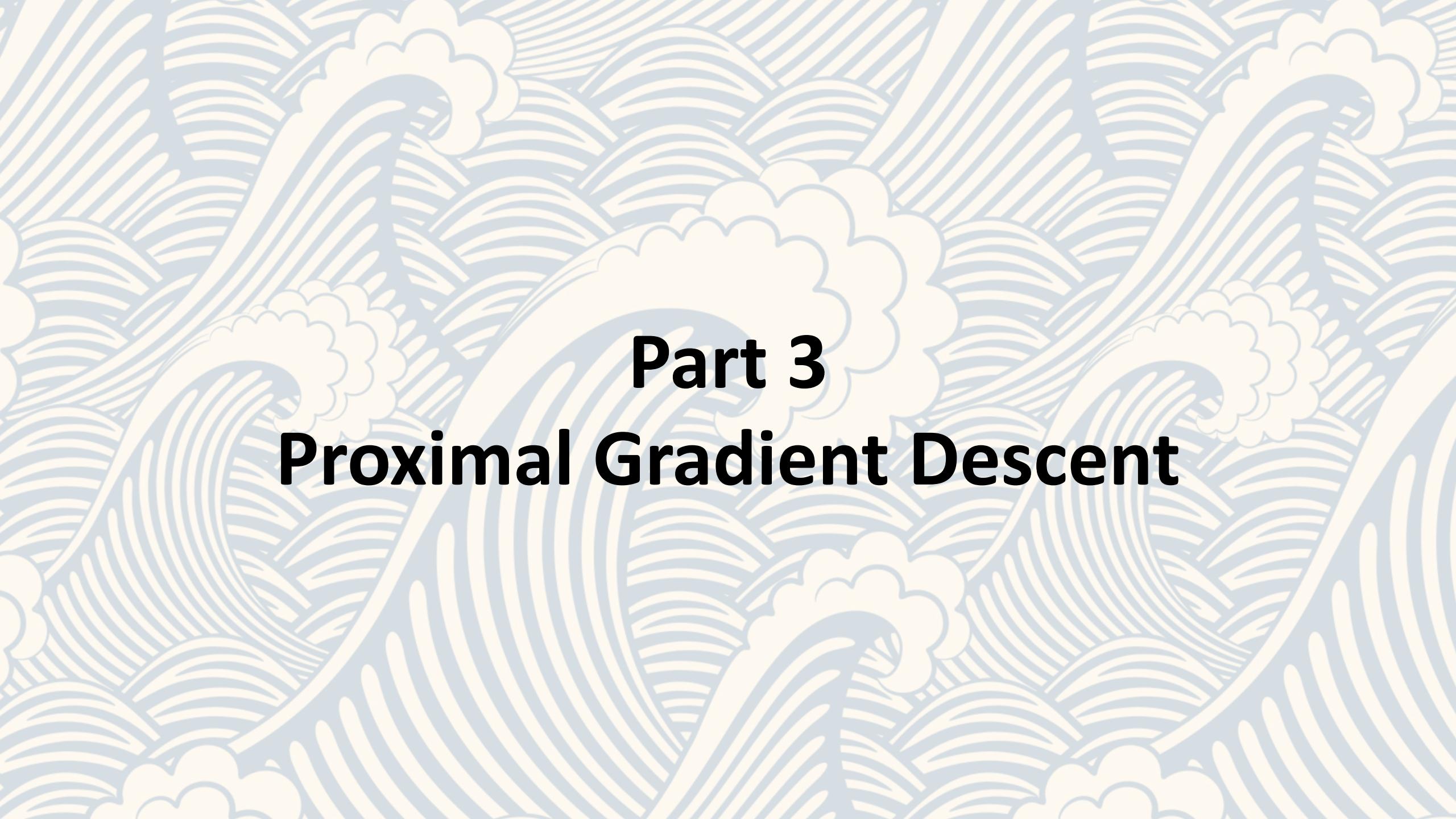
$$\min_{x_1, \dots, x_n \in \mathbb{R}^d} \left\{ \frac{1}{n} \sum_{i=1}^n f_i(x_i) + \psi(x_1, \dots, x_n) \right\}$$

Composite optimization:

optimization in $\mathbb{R}^{d'}$

$$\min_{x \in \mathbb{R}^{d'}} \{f(x) + \psi(x)\}$$

$$\left\{ \begin{array}{l} d' = nd \\ x = (x_1, \dots, x_n) \\ f(x) = \frac{1}{n} \sum_{i=1}^n f_i(x_i) \\ \psi(x) = \psi(x_1, \dots, x_n) \end{array} \right\}$$



Part 3

Proximal Gradient Descent

Three Assumptions

The epigraph of ψ is a closed and convex set

$$\text{epi}(\psi) \stackrel{\text{def}}{=} \{(x, t) \in \mathbb{R}^d \times \mathbb{R} \mid \psi(x) \leq t\}$$

$$\min_{x \in \mathbb{R}^d} f(x) + \psi(x)$$

A1 f is μ -convex and L -smooth:

$$\frac{\mu}{2}\|x - y\|^2 \leq D_f(x, y) \leq \frac{L}{2}\|x - y\|^2$$

Bregman divergence of f :

$$D_f(x, y) \stackrel{\text{def}}{=} f(x) - f(y) - \langle \nabla f(y), x - y \rangle$$

A2 $\psi : \mathbb{R}^d \rightarrow \mathbb{R} \cup \{+\infty\}$ is proper, closed, and convex

A3 ψ is proximable

The proximal operator $\text{prox}_\psi : \mathbb{R}^d \rightarrow \mathbb{R}^d$ defined by

$$\text{prox}_\psi(x) \stackrel{\text{def}}{=} \arg \min_{u \in \mathbb{R}^d} \left(\psi(u) + \frac{1}{2}\|u - x\|^2 \right)$$

can be evaluated exactly (e.g., in closed form)

Key Method: Proximal Gradient Descent

proximal operator:

$$\text{prox}_\psi(x) \stackrel{\text{def}}{=} \arg \min_{u \in \mathbb{R}^d} \left(\psi(u) + \frac{1}{2} \|u - x\|^2 \right)$$

$$x_t - \gamma \nabla f(x_t)$$

stepsize

gradient operator

$$x \mapsto x - \gamma \nabla f(x)$$

Proximal Gradient Descent: Theory

Theorem:

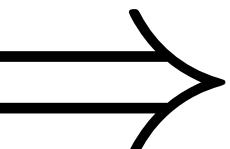
f is μ -convex and L -smooth:
 $\frac{\mu}{2}\|x - y\|^2 \leq D_f(x, y) \leq \frac{L}{2}\|x - y\|^2$
 $\frac{L}{\mu}$ is the condition number of f

$$t \geq \frac{L}{\mu} \log \frac{1}{\varepsilon} \quad \Rightarrow \quad \|x_t - x_\star\|^2 \leq \varepsilon \|x_0 - x_\star\|^2$$

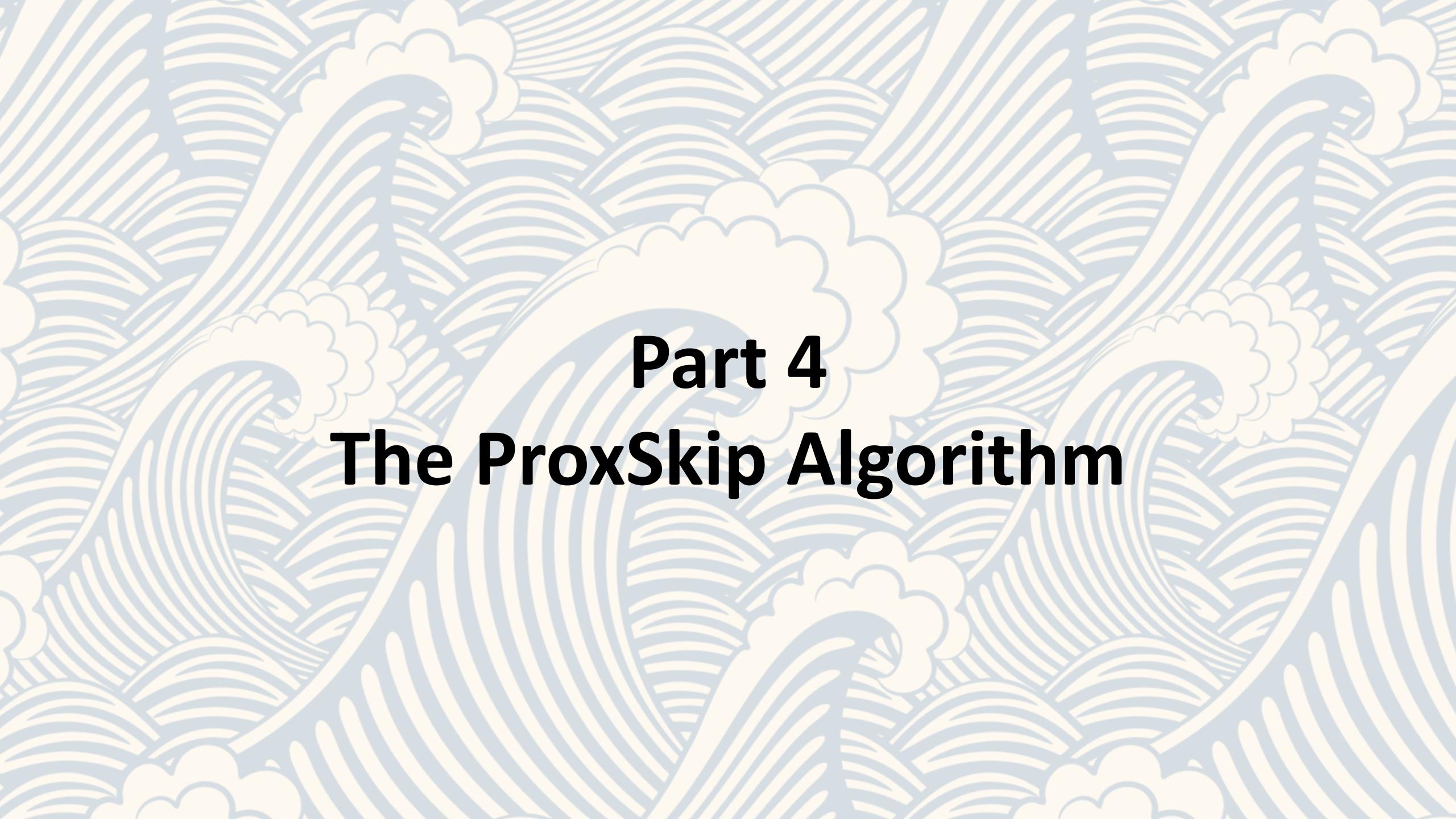
iterations

Error tolerance

$$x_\star \stackrel{\text{def}}{=} \arg \min_{x \in \mathbb{R}^d} f(x) + \psi(x)$$



(for stepsize $\gamma = \frac{1}{L}$)



Part 4

The ProxSkip Algorithm

What to do When the Prox is Expensive?

Can we somehow get away with
fewer evaluations of the proximity operator
in the Proximal GD method?

Approach 1



We'll skip ALL prox evaluations!



The method is NOT implementable!



Serves as an inspiration for Approach 2

Approach 2 (ProxSkip)



We'll skip MANY prox evaluations!



The method is implementable!

**Approach 1:
Simple, Extreme but
Practically Useless Variant**

Removing ψ via a Reformulation

$$\min_{x \in \mathbb{R}^d} f(x) - \langle h_\star, x \rangle$$

$$h_\star \stackrel{\text{def}}{=} \nabla f(x_\star)$$

$$x_\star \stackrel{\text{def}}{=} \arg \min_{x \in \mathbb{R}^d} f(x) + \psi(x)$$



x_\star is a solution of the above problem!

By the 1st order optimality conditions, the solution satisfies $\nabla f(x) - \nabla f(x_\star) = 0$



We do not know $h_\star = \nabla f(x_\star)$!

Apply Gradient Descent to the Reformulation

$$h_\star \stackrel{\text{def}}{=} \nabla f(x_\star)$$
$$x_\star \stackrel{\text{def}}{=} \arg \min_{x \in \mathbb{R}^d} f(x) + \psi(x)$$

$$x_{t+1} = x_t - \gamma (\nabla f(x_t) - h_\star)$$



We do not need to evaluate the prox of ψ at all!



We do not know h_\star and hence can't implement the method!

Idea: Try to “Learn” the Optimal Gradient Shift

$$x_{t+1} = x_t - \gamma (\nabla f(x_t) - h_t)$$

Desire: $h_t \rightarrow h_*$



Perhaps we can learn h_* with only occasional access to ψ ?

Approach 2: The ProxSkip Method

ProxSkip: The Algorithm (Bird's Eye View)

1

$$\hat{x}_{t+1} = x_t - \gamma (\nabla f(x_t) - h_t)$$

2a

with probability $1 - p$ do

$$1 - p \approx 1$$

$$x_{t+1} = \hat{x}_{t+1}$$

$$h_{t+1} = h_t$$

2b

with probability p do

$$p \approx 0$$

evaluate $\text{prox}_{\frac{\gamma}{p}\psi}(?)$

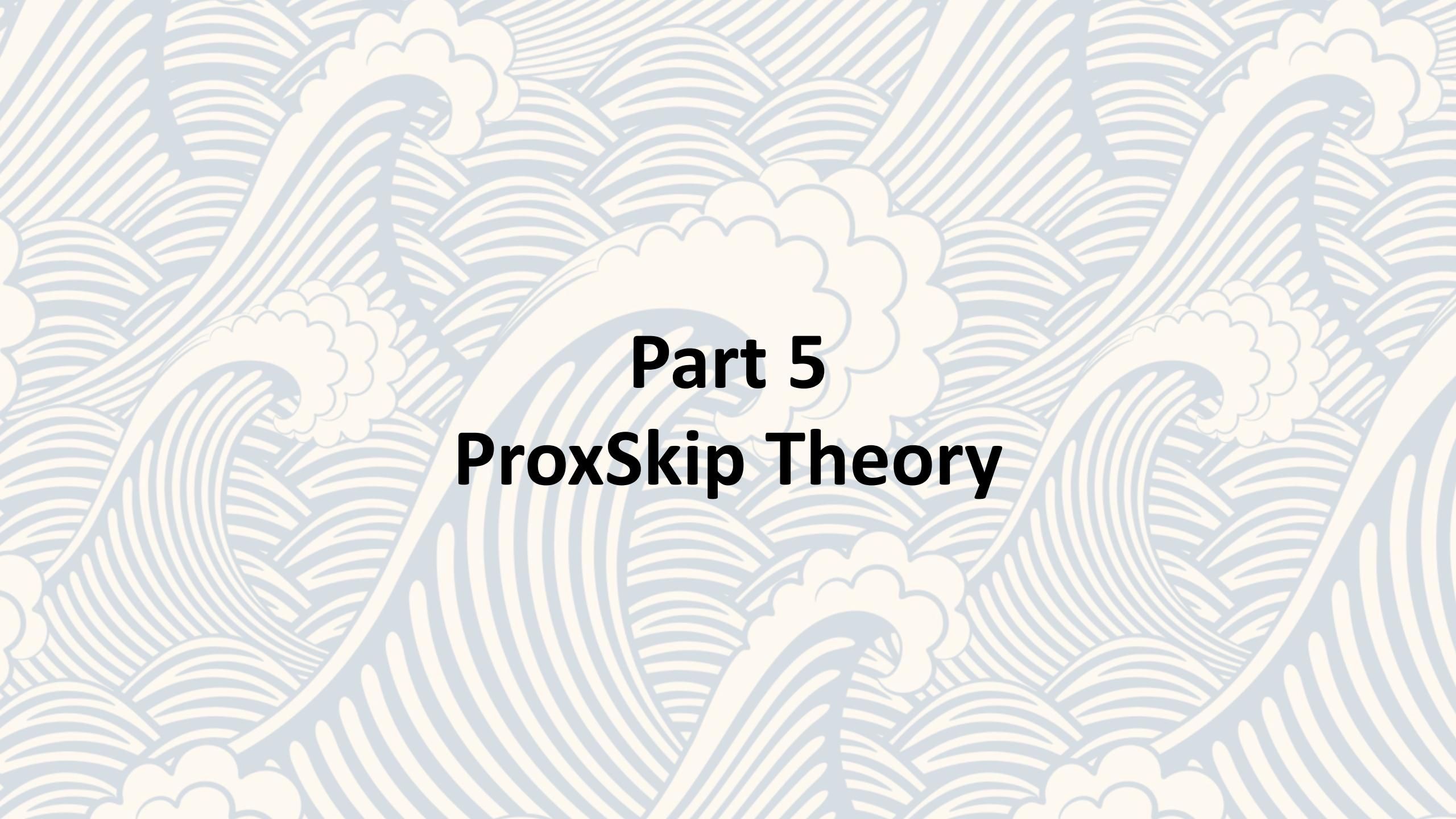
$$x_{t+1} = ?$$

$$h_{t+1} = ?$$

ProxSkip: The Algorithm (Detailed View)

Algorithm 1 ProxSkip

```
1: stepsize  $\gamma > 0$ , probability  $p > 0$ , initial iterate  $x_0 \in \mathbb{R}^d$ , initial control variate  $\mathbf{h}_0 \in \mathbb{R}^d$ , number of iterations  $T \geq 1$ 
2: for  $t = 0, 1, \dots, T - 1$  do
3:    $\hat{x}_{t+1} = x_t - \gamma(\nabla f(x_t) - \mathbf{h}_t)$            ◊ Take a gradient-type step adjusted via the control variate  $\mathbf{h}_t$ 
4:   Flip a coin  $\theta_t \in \{0, 1\}$  where  $\text{Prob}(\theta_t = 1) = p$       ◊ Flip a coin that decides whether to skip the prox or not
5:   if  $\theta_t = 1$  then
6:      $x_{t+1} = \text{prox}_{\frac{\gamma}{p}\psi}(\hat{x}_{t+1} - \frac{\gamma}{p}\mathbf{h}_t)$           ◊ Apply prox, but only very rarely! (with small probability  $p$ )
7:   else
8:      $x_{t+1} = \hat{x}_{t+1}$                                               ◊ Skip the prox!
9:   end if
10:   $\mathbf{h}_{t+1} = \mathbf{h}_t + \frac{p}{\gamma}(x_{t+1} - \hat{x}_{t+1})$           ◊ Update the control variate  $\mathbf{h}_t$ 
11: end for
```



Part 5

ProxSkip Theory

ProxSkip: Bounding the # of Iterations

Theorem:

f is μ -convex and L -smooth:
 $\frac{\mu}{2}\|x - y\|^2 \leq D_f(x, y) \leq \frac{L}{2}\|x - y\|^2$
 $\frac{L}{\mu}$ is the condition number of f

$$t \geq \max \left\{ \frac{L}{\mu}, \frac{1}{p^2} \right\} \log \frac{1}{\varepsilon} \quad \Rightarrow \quad \mathbb{E} [\Psi_t] \leq \varepsilon \Psi_0$$

iterations

p = probability of evaluating the prox

Lyapunov function:

$$\Psi_t \stackrel{\text{def}}{=} \|x_t - x_\star\|^2 + \frac{1}{L^2 p^2} \|h_t - h_\star\|^2$$

ProxSkip: Optimal Prox-Evaluation Probability

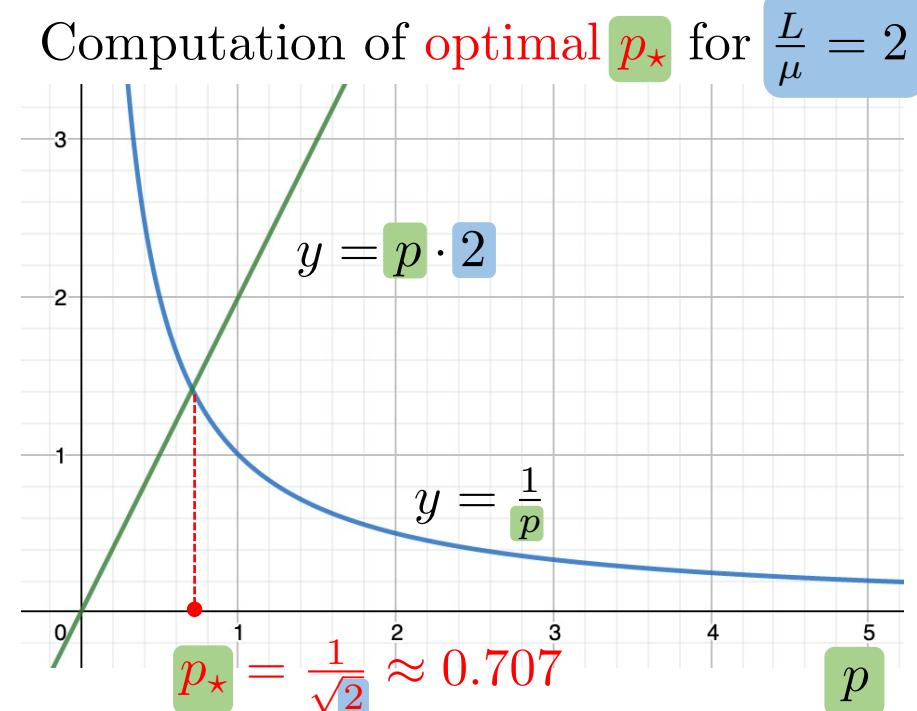
Since in each iteration we evaluate the prox with probability p ,
the expected number of prox evaluations after t iterations is:

$$p \cdot t = p \cdot \max \left\{ \frac{L}{\mu}, \frac{1}{p^2} \right\} \cdot \log \frac{1}{\varepsilon} = \max \left\{ p \cdot \frac{L}{\mu}, \frac{1}{p} \right\} \cdot \log \frac{1}{\varepsilon}$$

$\frac{L}{\mu}$ is the condition number of f

Minimized for p satisfying $p \cdot \frac{L}{\mu} = \frac{1}{p}$

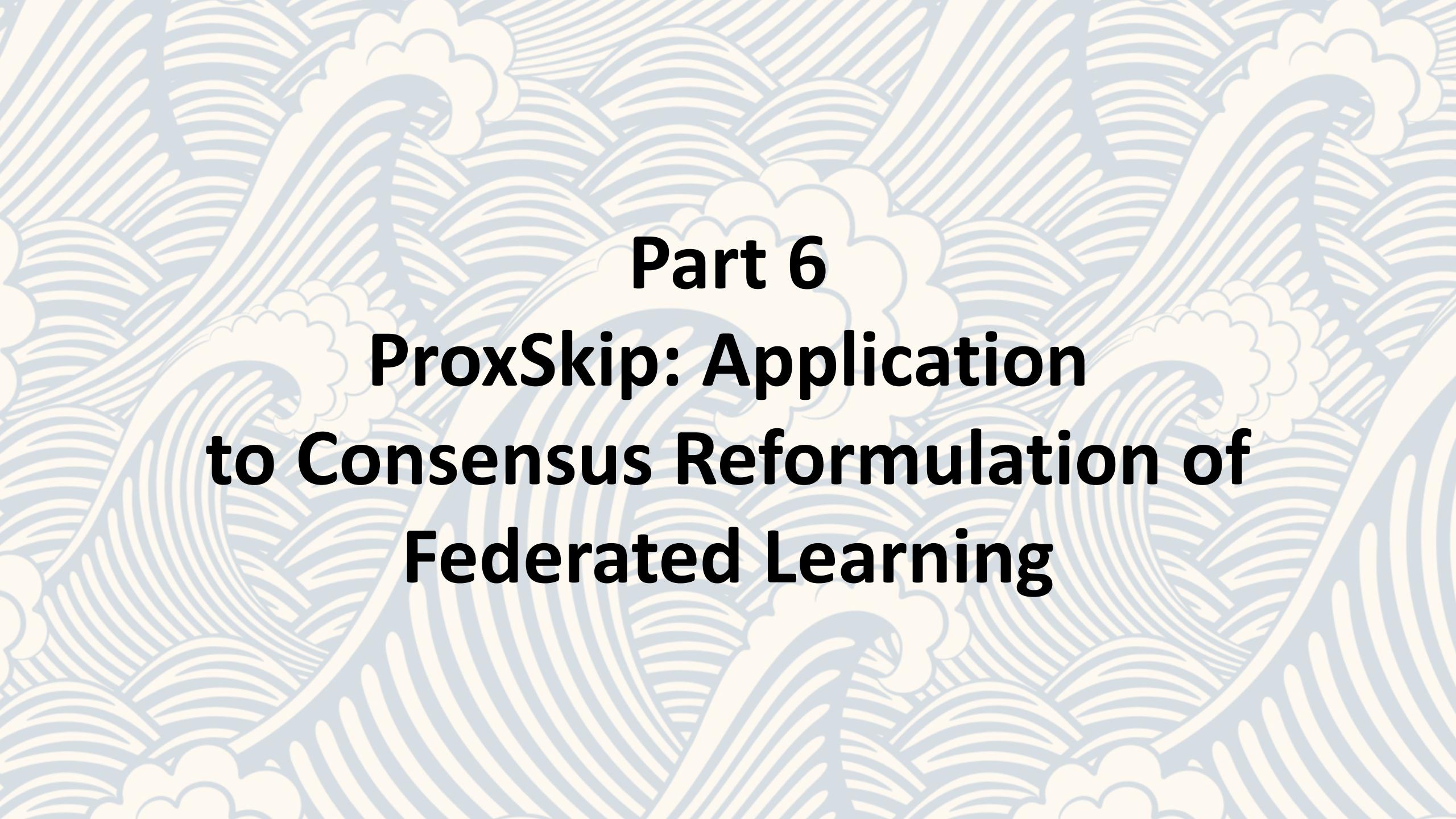
$$\Rightarrow p_{\star} = \frac{1}{\sqrt{L/\mu}}$$



ProxSkip: # of Gradient and Prox Evaluations

$$p_\star = \frac{1}{\sqrt{L/\mu}} \Rightarrow$$

# of iterations	$\max \left\{ \frac{L}{\mu}, \frac{1}{p^2} \right\} \cdot \log \frac{1}{\varepsilon}$	$\frac{L}{\mu} \cdot \log \frac{1}{\varepsilon}$
# of gradient evaluations	$\max \left\{ \frac{L}{\mu}, \frac{1}{p^2} \right\} \cdot \log \frac{1}{\varepsilon}$	$\frac{L}{\mu} \cdot \log \frac{1}{\varepsilon}$
Expected # of prox evaluations	$\max \left\{ p \cdot \frac{L}{\mu}, \frac{1}{p} \right\} \cdot \log \frac{1}{\varepsilon}$	$\sqrt{\frac{L}{\mu}} \cdot \log \frac{1}{\varepsilon}$
Expected # of gradient evaluations between 2 prox evaluations	$\frac{1}{p}$	$\sqrt{\frac{L}{\mu}}$



Part 6

ProxSkip: Application to Consensus Reformulation of Federated Learning

Federated Learning: ProxSkip vs Baselines

Table 1. The performance of federated learning methods employing multiple local gradient steps in the strongly convex regime.

method	# local steps per round	# floats sent per round	stepsize on client i	linear rate?	# rounds	rate better than GD?
GD (Nesterov, 2004)	1	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
LocalGD (Khaled et al., 2019; 2020)	τ	d	$\frac{1}{\tau L}$	✗	$\mathcal{O}\left(\frac{G^2}{\mu n \tau \varepsilon}\right)$ ^(d)	✗
Scaffold (Karimireddy et al., 2020)	τ	$2d$	$\frac{1}{\tau L}$ ^(e)	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
S-Local-GD ^(a) (Gorbunov et al., 2021)	τ	$d < \# < 2d$ ^(f)	$\frac{1}{\tau L}$	✓	$\tilde{\mathcal{O}}(\kappa)$	✗
FedLin ^(b) (Mitra et al., 2021)	τ_i	$2d$	$\frac{1}{\tau_i L}$	✓	$\tilde{\mathcal{O}}(\kappa)$ ^(c)	✗
Scaffnew ^(g) (this work) for any $p \in (0, 1]$	$\frac{1}{p}$ ^(h)	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}\left(p\kappa + \frac{1}{p}\right)$ ^(c)	✓ (for $p > \frac{1}{\kappa}$)
Scaffnew ^(g) (this work) for optimal $p = \frac{1}{\sqrt{\kappa}}$	$\sqrt{\kappa}$ ^(h)	d	$\frac{1}{L}$	✓	$\tilde{\mathcal{O}}(\sqrt{\kappa})$ ^(c)	✓

^(a) This is a special case of S-Local-SVRG, which is a more general method presented in (Gorbunov et al., 2021). S-Local-GD arises as a special case when full gradient is computed on each client.

^(b) FedLin is a variant with a fixed but different number of local steps for each client. Earlier method S-Local-GD has the same update but random loop length.

^(c) The $\tilde{\mathcal{O}}$ notation hides logarithmic factors.

^(d) G is the level of dissimilarity from the assumption $\frac{1}{n} \sum_{i=1}^n \|\nabla f_i(x)\|^2 \leq G^2 + 2LB^2 (f(x) - f_*)$, $\forall x$.

^(e) We use Scaffold's cumulative local-global stepsize $\eta_l \eta_g$ for a fair comparison.

^(f) The number of sent vectors depends on hyper-parameters, and it is randomized.

^(g) Scaffnew (Algorithm 2) = ProxSkip (Algorithm 1) applied to the consensus formulation (6) + (7) of the finite-sum problem (5).

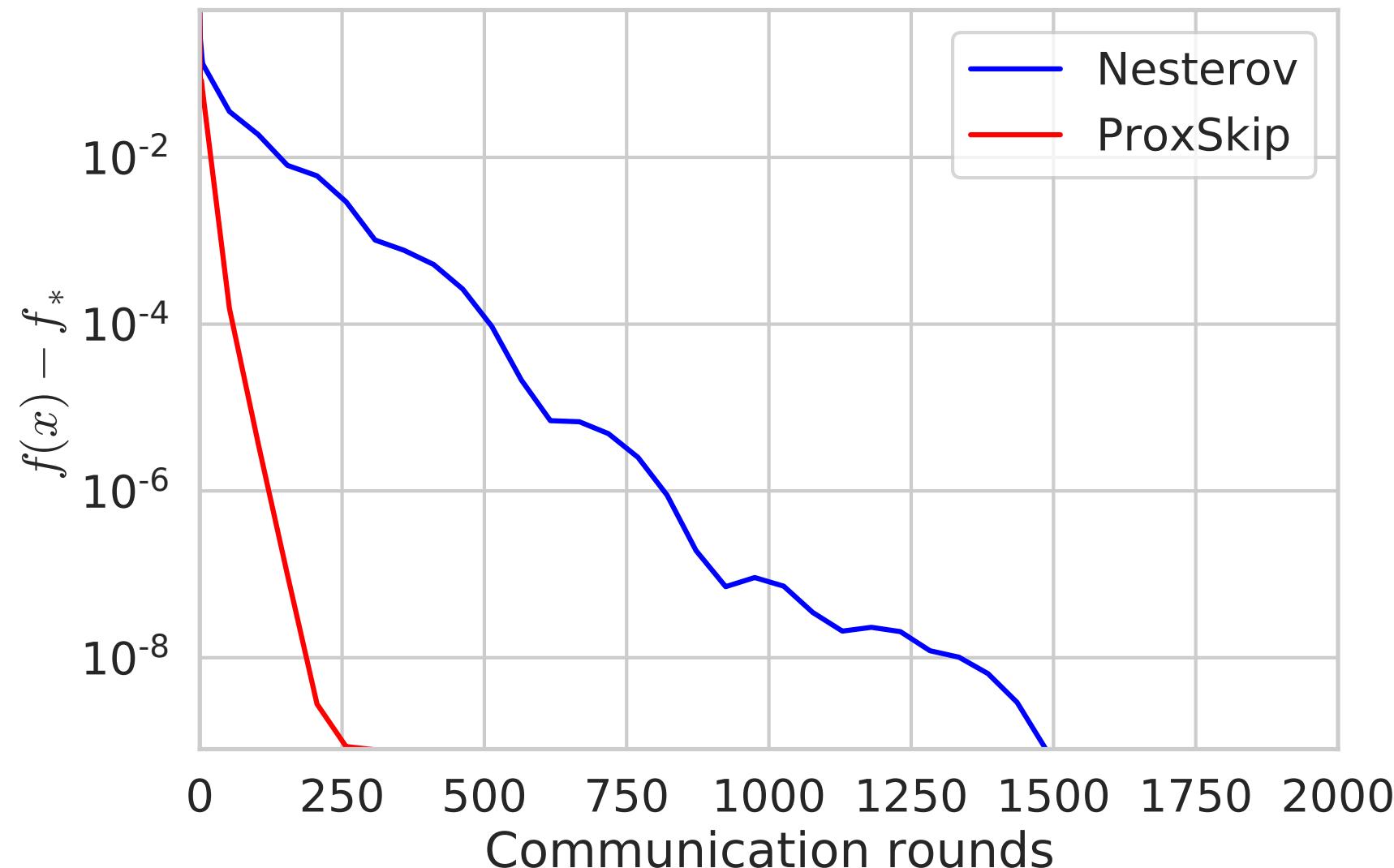
^(h) ProxSkip (resp. Scaffnew) takes a *random* number of gradient (resp. local) steps before prox (resp. communication) is computed (resp. performed). What is shown in the table is the *expected* number of gradient (resp. local) steps.



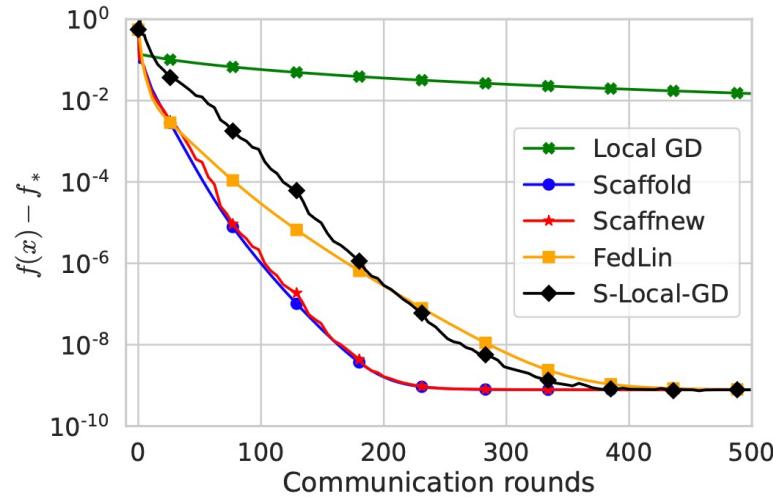
Part 7

Experiments

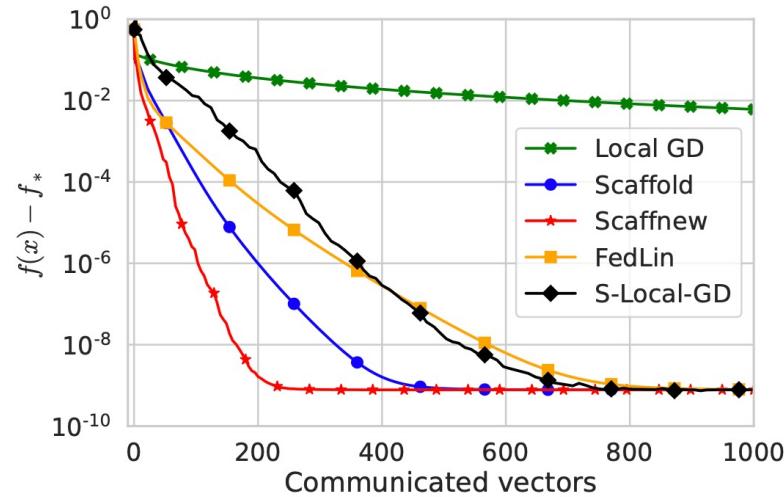
Scaffnew (=ProxSkip applied to FL) vs Nesterov



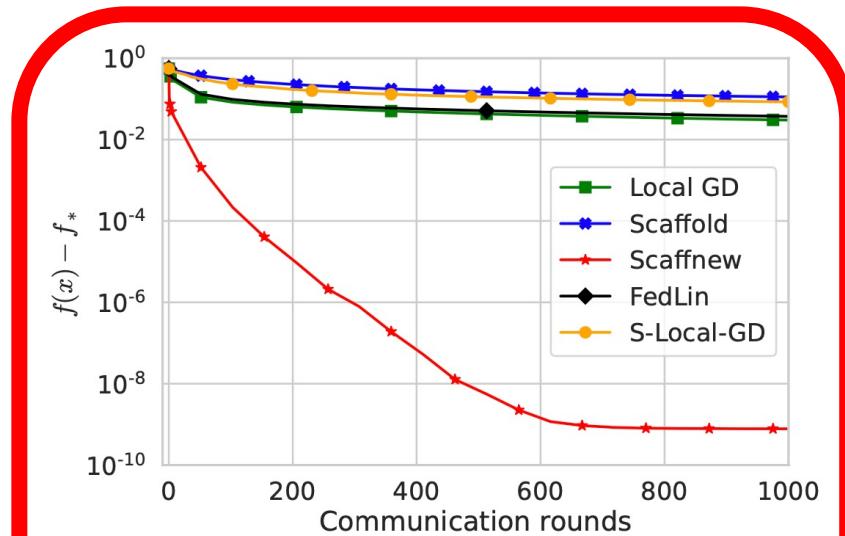
Scaffnew (=ProxSkip applied to FL) vs Baselines



(a) tuned hyper-parameters



(b) tuned hyper-parameters



(c) theoretical hyper-parameters

Figure 1. Deterministic Problem. Comparison of **Scaffnew** to other local update methods that tackle data-heterogeneity and to **LocalGD**. In (a) we compare communication rounds with optimally tuned hyper-parameters. In (b) we compare communicated vectors (**Scaffold**, **FedLin** and **S-Local-GD** require transmission of additional variables). In (c), we compare communication rounds with the algorithm parameters set to the best theoretical stepsizes used in the convergence proofs.

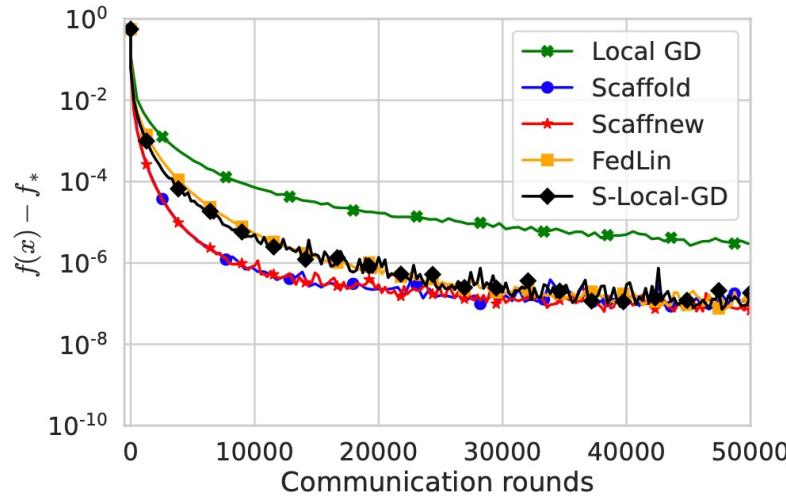
L2-regularized logistic regression:

$$f(x) = \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-b_i a_i^\top x)) + \frac{\lambda}{2} \|x\|^2$$

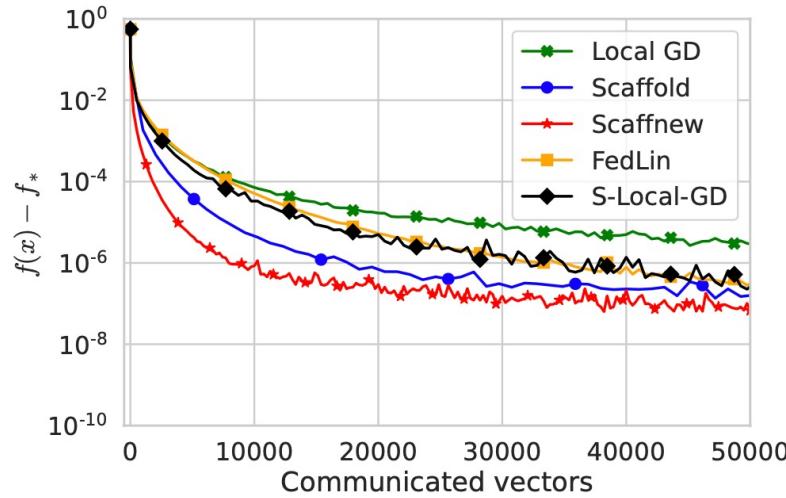
$$a_i \in \mathbb{R}^d, b_i \in \{-1, +1\}, \lambda = L/10^4$$

w8a dataset from LIBSVM library (Chang & Lin, 2011)

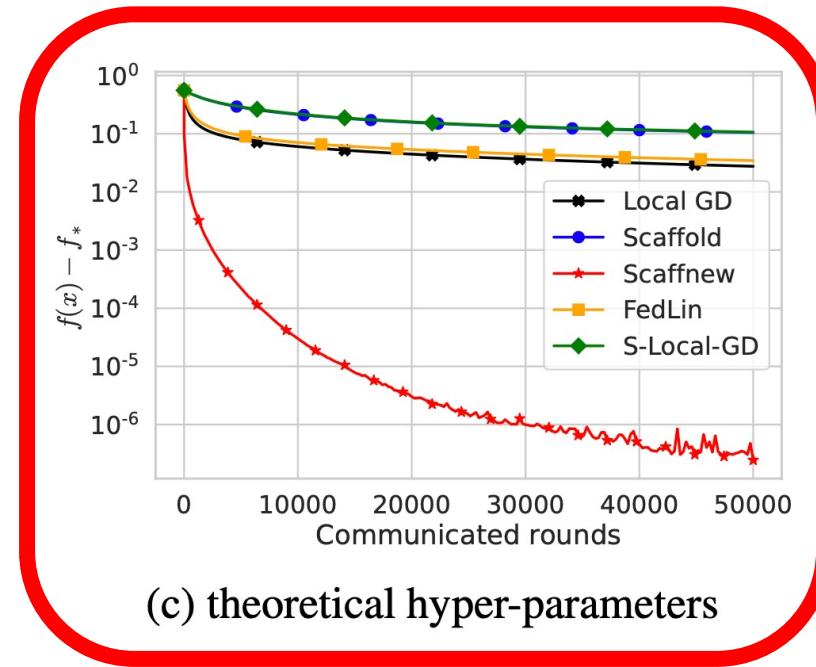
Scaffnew (=ProxSkip applied to FL) vs Baselines



(a) tuned hyper-parameters



(b) tuned hyper-parameters



(c) theoretical hyper-parameters

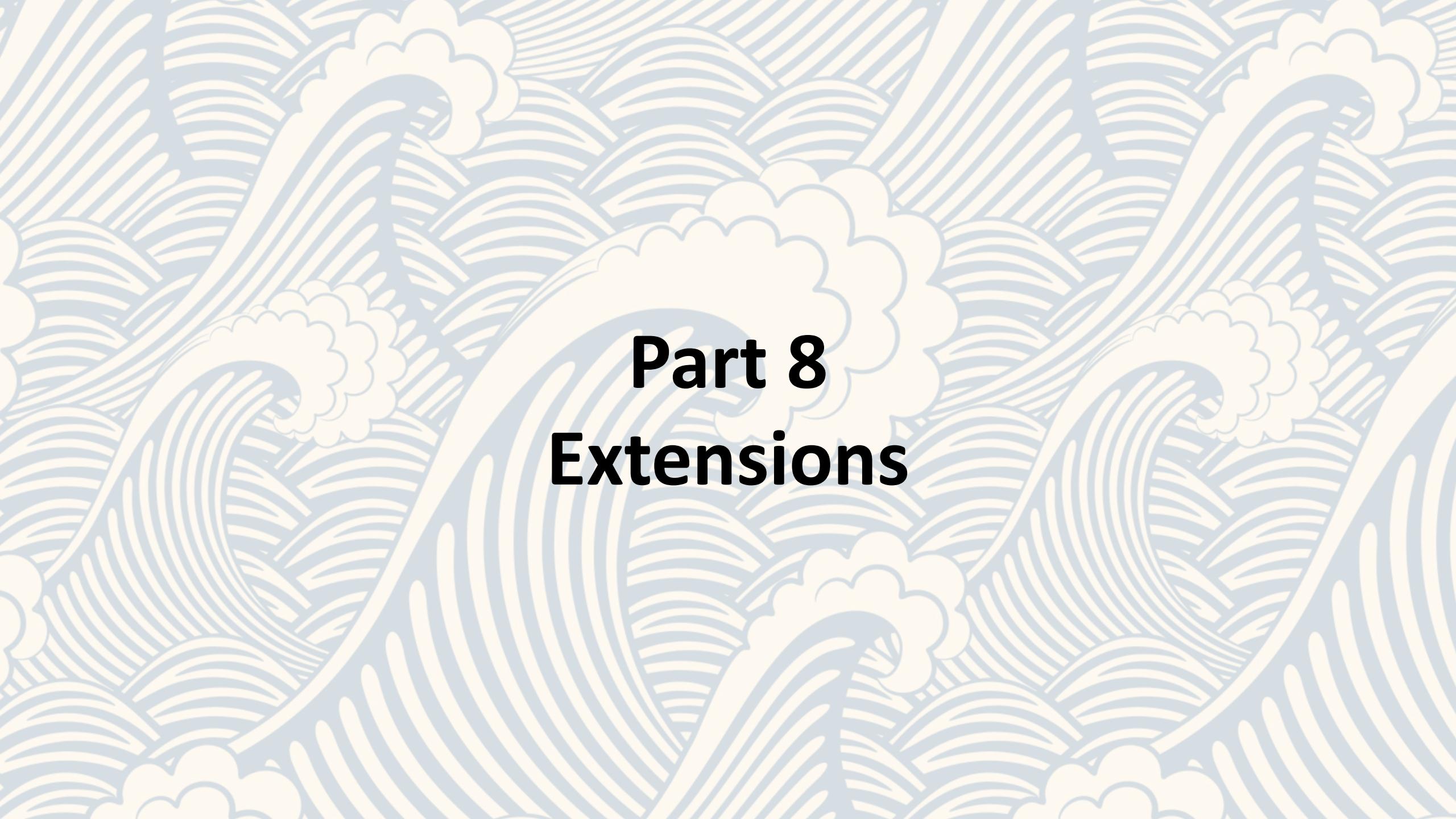
Figure 2. Stochastic Problem. Comparison of **Scaffnew** to other local update methods that tackle data-heterogeneity and to **LocalSGD**. In (a) we compare communication rounds with optimally tuned hyper-parameters. In (b) we compare communicated vectors and in (c), we compare communication rounds with the algorithm parameters set to the best theoretical stepsizes used in the convergence proofs.

L2-regularized logistic regression:

$$f(x) = \frac{1}{n} \sum_{i=1}^n \log(1 + \exp(-b_i a_i^\top x)) + \frac{\lambda}{2} \|x\|^2$$

$$a_i \in \mathbb{R}^d, b_i \in \{-1, +1\}, \lambda = L/10^4$$

w8a dataset from LIBSVM library (Chang & Lin, 2011)



Part 8

Extensions

Extension 1: From Gradients to Stochastic Gradients

- As described, in ProxSkip each worker computes the **full gradient** of its local function
- It's often better to consider a **cheap stochastic approximation of the gradient** instead
 - We consider this extension in the paper
 - We provide theoretical convergence rates

$$\nabla f_i(x_t) \Rightarrow g_i(x_t)$$

Full gradient Stochastic gradient

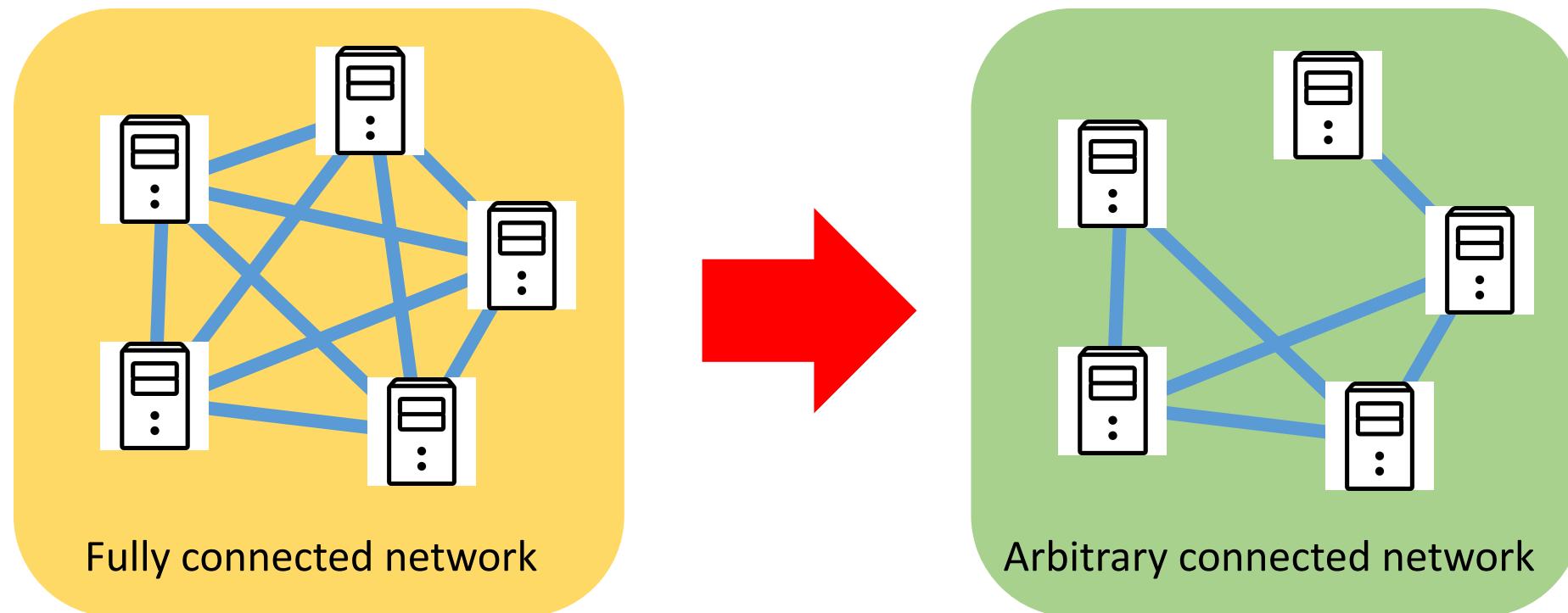
Assumptions:

(unbiasedness) $\mathbb{E} [g_{i,t}(x_t) \mid x_t] = \nabla f_i(x_t)$

(expected smoothness) $E \left[\|g_{i,t}(x_t) - \nabla f(x_\star)\|^2 \mid x_t \right] \leq 2AD_f(x_t, x_\star) + C$
(Gower et al, 2019)

Extension 2: From Fully Connected Network to Arbitrary Connected Network

- In each communication round of ProxSkip, **each worker sends messages to all other workers** (e.g., through a server).
 - We can think of ProxSkip workers as the nodes of a **fully-connected network**.
 - In each communication round, all **workers communicate with their neighbors**.
- In the paper we provide extension to **arbitrary connected networks**.





The End