

Optimal Gradient Sliding and its Application to Distributed Optimization Under Similarity



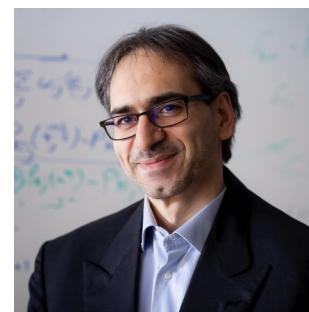
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Distributed Optimization Problem

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

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f_i on local devices

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f_i on local devices → **Communication bottleneck!**

Distributed Optimization Problem

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f_i on local devices

Communication bottleneck!

Use similarity of local functions!

Similarity

$$\|\nabla^2 f_i(x) - \nabla^2 f(x)\| \leq \delta$$



local



global

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local



global

For uniform data similarity parameter is **small**

$$\delta = \tilde{O}(1/\sqrt{n})$$

n – number of local samples

Similarity

$$\|\nabla^2 f_i(x) - \nabla^2 f(x)\| \leq \delta$$

↑ ↑
local global

For uniform data similarity parameter is **small**

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Long similarity story

Reference	Communication complexity	Local gradient complexity	Order	Limitations
DANE [42]	$\mathcal{O}\left(\frac{\delta^2}{\mu^2} \log \frac{1}{\varepsilon}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \sqrt{\frac{\delta^3}{\mu^3}} \log^2 \frac{1}{\varepsilon}\right)$ (2)	1st	quadratic
DiSCO [51]	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} (\log \frac{1}{\varepsilon} + C^2 \Delta F_0) \log \frac{L}{\mu}\right)$	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} (\log \frac{1}{\varepsilon} + C^2 \Delta F_0) \log \frac{L}{\mu}\right)$	2nd	C - self-concordant (3)
AIDE [40]	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon} \log \frac{L}{\delta}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon} \log \frac{L}{\delta}\right)$ (4)	1st	quadratic
DANE-LS [50]	$\mathcal{O}\left(\frac{\delta}{\mu} \log \frac{1}{\varepsilon}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \frac{\delta^{3/2}}{\mu^{3/2}} \log \frac{1}{\varepsilon}\right)$ (5)	1st/2nd	quadratic (6)
DANE-HB [50]	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \frac{\delta}{\mu} \log \frac{1}{\varepsilon}\right)$ (5)	1st/2nd	quadratic (6)
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SPAG [21]	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \log \frac{1}{\varepsilon}\right)$ (1)	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \sqrt{\frac{L}{\delta}} \log^2 \frac{1}{\varepsilon}\right)$ (1,2)	1st	M - Lipschitz hessian
DiRegINA [12]	$\mathcal{O}\left(\frac{\delta}{\mu} \log \frac{1}{\varepsilon} + \sqrt{\frac{M\delta R_0}{\mu}}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \sqrt{\frac{\delta}{\mu}} \log^2 \frac{1}{\varepsilon} + \sqrt{\frac{ML\delta R_0}{\mu}} \log \frac{1}{\varepsilon}\right)$ (2)	2nd	M - Lipschitz hessian
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This paper	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon}\right)$	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \log \frac{1}{\varepsilon}\right)$	1st	
Lower	[4]	$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon}\right)$	—	
	[37]	—	$\mathcal{O}\left(\sqrt{\frac{L}{\mu}} \log \frac{1}{\varepsilon}\right)$	non-distributed

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2014 — 1st method

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2014 — 1st method

2015 — lower bounds

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2014 — 1st method

2015 - 2022 — no optimal methods in general

2015 — lower bounds

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2014 — 1st method

We present optimal method in communications and local computations!

2015 — lower bounds

Idea

$$\min_{x \in \mathbb{R}^d} r(x) = \underbrace{f_1(x)}_{:=q(x)} + \underbrace{\frac{1}{n} \sum_{i=1}^n [f_i(x) - f_1(x)]}_{:=p(x)}$$

Idea

$$\min_{x \in \mathbb{R}^d} r(x) = \underbrace{f_1(x)}_{:=q(x)} + \frac{1}{n} \underbrace{\sum_{i=1}^n [f_i(x) - f_1(x)]}_{:=p(x)}$$

μ -strongly-convex

L -smooth and convex

δ -smooth and non-convex

The diagram illustrates the decomposition of a function $r(x)$ into two components: $q(x)$ and $p(x)$. The function $r(x)$ is defined as the sum of $f_1(x)$ and a term involving the average of other functions $f_i(x)$ for $i=1, 2, \dots, n$. The term $f_1(x)$ is labeled $q(x)$ and is associated with the properties "mu-strongly-convex" and " L -smooth and convex". The term involving the average is labeled $p(x)$ and is associated with the property " δ -smooth and non-convex". Orange arrows point from the text labels to their corresponding parts in the equation.

Idea

$$\min_{x \in \mathbb{R}^d} r(x) = \underbrace{f_1(x)}_{:=q(x)} + \frac{1}{n} \sum_{i=1}^n [f_i(x) - f_1(x)]$$

only local computations communications

μ -strongly-convex L -smooth and convex δ -smooth and non-convex

The diagram illustrates the decomposition of a function $r(x)$ into two components: $q(x)$ and $p(x)$. The function $r(x)$ is defined as $f_1(x) + \frac{1}{n} \sum_{i=1}^n [f_i(x) - f_1(x)]$. The term $f_1(x)$ is labeled $q(x)$ and is associated with the properties "mu-strongly-convex" and " L -smooth and convex". The term $\frac{1}{n} \sum_{i=1}^n [f_i(x) - f_1(x)]$ is labeled $p(x)$ and is associated with the property " δ -smooth and non-convex". Two orange arrows point from the text descriptions to their respective terms in the equation. Additionally, two orange arrows point from the labels "only local computations" and "communications" to the terms $q(x)$ and $p(x)$ respectively.

Algorithm

Algorithm 1 Accelerated Extragradient

- 1: **Input:** $x^0 = x_f^0 \in \mathbb{R}^d$
 - 2: **Parameters:** $\tau \in (0, 1]$, $\eta, \theta, \alpha > 0$, $K \in \{1, 2, \dots\}$
 - 3: **for** $k = 0, 1, 2, \dots, K - 1$ **do**
 - 4: $x_g^k = \tau x^k + (1 - \tau)x_f^k$
 - 5: $x_f^{k+1} \approx \arg \min_{x \in \mathbb{R}^d} [A_\theta^k(x) := p(x_g^k) + \langle \nabla p(x_g^k), x - x_g^k \rangle + \frac{1}{2\theta} \|x - x_g^k\|^2 + q(x)]$
 - 6: $x^{k+1} = x^k + \eta \alpha (x_f^{k+1} - x^k) - \eta \nabla r(x_f^{k+1})$
 - 7: **end for**
 - 8: **Output:** x^K
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6:    $x^{k+1} = x^k + \eta \alpha (x_f^{k+1} - x^k) - \eta \nabla r(x_f^{k+1})$ 
7: end for
8: Output:  $x^K$ 
```

3 ideas:

- Extragradient: 2 steps per iteration

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```
1: Input:  $x^0 = x_f^0 \in \mathbb{R}^d$ 
2: Parameters:  $\tau \in (0, 1]$ ,  $\eta, \theta, \alpha > 0$ ,  $K \in \{1, 2, \dots\}$ 
3: for  $k = 0, 1, 2, \dots, K - 1$  do
4:    $x_g^k = \tau x^k + (1 - \tau)x_f^k$ 
5:    $x_f^{k+1} \approx \arg \min_{x \in \mathbb{R}^d} [A_\theta^k(x) := p(x_g^k) + \langle \nabla p(x_g^k), x - x_g^k \rangle + \frac{1}{2\theta} \|x - x_g^k\|^2 + q(x)]$ 
6:    $x^{k+1} = x^k + \eta \alpha (x_f^{k+1} - x^k) - \eta \nabla r(x_f^{k+1})$ 
7: end for
8: Output:  $x^K$ 
```

3 ideas:

- Extragradient: 2 steps per iteration
- Sliding (inexact prox)

Algorithm

Algorithm 1 Accelerated Extragradient

- 1: **Input:** $x^0 = x_f^0 \in \mathbb{R}^d$
- 2: **Parameters:** $\tau \in (0, 1]$, $\eta, \theta, \alpha > 0$, $K \in \{1, 2, \dots\}$
- 3: **for** $k = 0, 1, 2, \dots, K - 1$ **do**
- 4: $x_g^k = \tau x^k + (1 - \tau)x_f^k$
- 5: $x_f^{k+1} \approx \arg \min_{x \in \mathbb{R}^d} [A_\theta^k(x) := p(x_g^k) + \langle \nabla p(x_g^k), x - x_g^k \rangle + \frac{1}{2\theta} \|x - x_g^k\|^2 + q(x)]$
- 6: $x^{k+1} = x^k + \eta \alpha (x_f^{k+1} - x^k) - \eta \nabla r(x_f^{k+1})$
- 7: **end for**
- 8: **Output:** x^K

3 ideas:

- Extragradient: 2 steps per iteration
- Sliding (inexact prox)
- Acceleration

Convergence

Theorem. Let assumptions from previous slides be satisfied with $\mu \leq \delta \leq L$. Then, to find ε -solution of the distributed optimization problem Algorithm 1 requires

$$\mathcal{O}\left(\sqrt{\frac{\delta}{\mu}} \log \frac{1}{\varepsilon}\right) \text{ communication rounds and } \mathcal{O}\left(\sqrt{\frac{L}{\mu}} \log \frac{1}{\varepsilon}\right) \text{ local gradient computations.}$$

Convergence

Theorem. Let assumptions from previous slides be satisfied with $\mu \leq \delta \leq L$. Then, to find ε -solution of the distributed optimization problem Algorithm 1 requires

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Optimal estimates in terms of
communications and local computations

Thank you!