

# Adaptive Proximal Gradient Method for Convex Optimization

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Yura Malitsky

Konstantin Mishchenko



universität  
wien

**SAMSUNG**  
**Research**

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

▷  $f$  is convex and differentiable

M.-M. *Adaptive gradient descent without descent*, ICML-2020

### AdGD

$$x_{k+1} = x_k - \alpha_k \nabla f(x_k)$$

$$L_k = \frac{\|\nabla f(x_k) - \nabla f(x_{k-1})\|}{\|x_k - x_{k-1}\|}$$

$$\alpha_k = \min \left\{ \sqrt{1 + \frac{\alpha_{k-1}}{\alpha_{k-2}}} \alpha_{k-1}, \frac{1}{2L_k} \right\}$$

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## Questions:

- Is the **first term** in the update of  $\alpha_k$  necessary?

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- Is the **first term** in the update of  $\alpha_k$  necessary?
- Is **2** in the update of  $\alpha_k$  necessary?
- Can we extend this algorithm to  $\min f(x) + g(x)$  with prox-friendly  $g$ ?

## Question 1

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**Theorem.** There is a convex, 1-smooth function  $f$ , such that for any  $c \geq 1$ , there is a point  $x_0$  where this algorithm diverges.

## Question 1

$$\begin{aligned}x_{k+1} &= x_k - \alpha_k \nabla f(x_k) \\L_k &= \frac{\|\nabla f(x_k) - \nabla f(x_{k-1})\|}{\|x_k - x_{k-1}\|} \\ \alpha_k &= \min \left\{ \sqrt{1 + \frac{\alpha_{k-1}}{\alpha_{k-2}}}, \frac{1}{2L_k} \right\} \\ \alpha_k &= \frac{1}{cL_k}\end{aligned}$$

**Theorem.** There is a convex, 1-smooth function  $f$ , such that for any  $c \geq 1$ , there is a point  $x_0$  where this algorithm diverges.

**Answer:** The first term is needed (maybe in another form).

## Question 2

$$x_{k+1} = x_k - \alpha_k \nabla f(x_k)$$

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- The second term  $\frac{1}{2L_k}$  can be replaced by  $\frac{1}{\sqrt{2}L_k}$  with exactly the same guarantees as before.

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- The second term  $\frac{1}{2L_k}$  can be replaced by  $\frac{1}{\sqrt{2}L_k}$  with exactly the same guarantees as before.
- The full update can be replaced by ..., which allows to use a fixed step  $\alpha_k = \frac{1}{L}$ .

## Question 3

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

- ▷  $f$  is convex and differentiable
- ▷  $g$  is convex lsc and prox-friendly

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### Prox-AdGD

$$\begin{aligned}x_{k+1} &= \text{prox}_{\alpha_k}(x_k - \alpha_k \nabla f(x_k)) \\L_k &= \frac{\|\nabla f(x_k) - \nabla f(x_{k-1})\|}{\|x_k - x_{k-1}\|} \\ \alpha_k &= \min \left\{ \sqrt{1 + \frac{\alpha_{k-1}}{\alpha_{k-2}}} \alpha_{k-1}, \frac{1}{\sqrt{2}L_k} \right\}\end{aligned}$$