# Superfast second-order methods for Unconstrained Convex Optimization

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#### **Recent developments: Tensor Methods**

**Problem:** 



 $\min_{x \in \mathbb{E}} f(x) \quad | \text{ where } f(\cdot) \text{ is a differentiable function on } \mathbb{E}.$ 

**Taylor approximation:** 

$$\Omega_{x,\rho}(y)=f(x)+\sum_{k=1}^{p}rac{1}{k!}D^{k}f(x)[y-x]^{k},\quad y\in\mathbb{E},$$

where  $D^k f(x)[h]^k$  is the *k*th-order derivative of  $f(\cdot)$  at  $x \in \mathbb{E}$ along direction  $h \in \mathbb{E}$ .

**Lipschitz continuity**  $\| \| D^p f(x) - D^p f(y) \| \le L_p \| x - y \|$   $x, y \in \mathbb{E}$ , where the norm  $\|\cdot\|$  is Euclidean and  $p \ge 1$ .

Augmented Taylor approximation:

$$\hat{\Omega}_{x,p,H}(y) = \Omega_{x,p}(y) + \frac{H}{(p+1)!} \|y-x\|^{p+1}, y \in \mathbb{E}.$$

Main property:

$$f(y) \leq \hat{\Omega}_{x,p,L_p}(y)$$
 for all  $y \in \mathbb{E}$ .

# Implementability ( $p \ge 1$ )

**Th.** (N.2019) If  $f(\cdot)$  is convex and  $H \ge pL_p$ , then  $\hat{\Omega}_{x,p,H}(\cdot)$  is <u>convex</u>. **NB:** For p = 3, function  $\tau^3 + H\tau^4$ ,  $\tau \in \mathbb{R}$ , is *never* convex.

**Corollary.** The point 
$$T_{p,H}(x) = \arg\min_{y \in \mathbb{E}} \hat{\Omega}_{x,p,H}(y)$$
 is computable.

**Basic Tensor Method:**  $x_{k+1} = T_{p,H}(x_k)$  Convergence:  $O(k^{-p})$ .

Accelerated Tensor Methods. Convergence:  $O(k^{-(p+1)})$ . (Baes 2009, N.2019. Tool: Estimating sequences.)

**Extensions** (Monteiro, Svaiter (2014) for p = 2)  $O(k^{-(3p+1)/2})$ .

**NB:** Very expensive line search (Bubeck, Jiang, Lee, Li, Sidford (2019), Gasnikov, Gorbunov, Kovalev, Mohhamed, Chernousova (2019)).

Maximal rate (Agarwal, Hazan (2017), Arjevani, Shamir, Shiff (2017))

$$O(k^{-(3p+1)/2}): \quad p=2 \Rightarrow O(k^{-7/2}), \quad p=3 \Rightarrow O(k^{-5}).$$

Main difficulty: Implementation of Tensor Step.

#### Accelerated 3rd-order method (N.2019)

**Assumption:**  $||D^3f(x) - D^3f(y)|| \le L_3||x - y||, x, y \in \mathbb{E}.$ 

Augmented Taylor Polynomial:

$$\begin{split} \hat{\Omega}_{x,p,H}(h) &= f(x) + \langle f'(x), h \rangle + \frac{1}{2} \langle f''(x)h, h \rangle \\ &+ \frac{1}{6} D^3 f(x) [h]^3 + \frac{H}{24} \|h\|^4. \end{split}$$

Main Theorem:  $D^3f(x)[h] \leq f''(x) + \frac{L_3}{2} ||h||^2 I$  for all  $x, h \in \mathbb{E}$ ,

where I is the identity matrix.

**Proof:**  $\forall x, h \in \mathbb{E} \Rightarrow 0 \leq f''(x-h) \leq f''(x) - D^3 f(x)[h] + \frac{L_3}{2} ||h||^2 I.$ 

**Corollary:** for function  $\rho_x(h) = \frac{1}{2} \langle f''(x)h, h \rangle + \frac{L_3}{4} ||h||^4$ , we have  $\left(1 - \frac{1}{\sqrt{2}}\right) \rho_x''(h) \preceq \hat{\Omega}_{x,p,6L_3}''(h) \preceq \left(1 + \frac{1}{\sqrt{2}}\right) \rho_x''(h).$ 

Thus, we can use *relative non-degeneracy condition*! (Bauschke, Bolte, Teboulle (2016), Lu, Freund, N. (2018))

#### **Relative non-degeneracy**

**Convex problem:**  $f^* = \min_{x \in \mathbb{E}} f(x).$ 

**Scaling function:**  $\rho(\cdot)$  is strictly convex.

Relative non-degeneracy: $\mu\rho''(x) \preceq f''(x) \preceq L\rho''(x) \quad \forall x \in \mathbb{E}.$ Bregman distance: $\beta_{\rho}(x,y) = \rho(y) - \rho(x) - \langle \rho'(x), y - x \rangle.$ Main property: $\mu\beta_{\rho}(x,y) \leq \beta_{f}(x,y) \leq L\beta_{\rho}(x,y) \quad \forall x, y \in \mathbb{E}.$ 

Bregman-Distance Gradient Method (BDGM):

 $\begin{aligned} x_{k+1} &= \arg\min_{x\in\mathbb{E}} [f(x_k) + \langle f'(x_k), x - x_k \rangle + L\beta_{\rho}(x_k, x)], \ k \geq 0. \end{aligned}$ (Nonsmooth: Beck, Teboulle, *ORLetters*(2003). Smooth: N. *MP*(2005).)

**Convergence:** for  $\gamma = \frac{\mu}{L}$  and  $k \ge 0$  we have  $\beta_{\rho}(x_{k+1}, x^{*}) \le (1 - \gamma)\beta_{\rho}(x_{k+1}, x^{*}) - \frac{1}{2L}(f(x_{k}) - f^{*}).$ **Our case:**  $\mu = 1 - \frac{1}{\sqrt{2}}, \ L = 1 + \frac{1}{\sqrt{2}}, \ \gamma = 3 - 2\sqrt{2} > \frac{1}{6}.$ 

#### Accelerated 3rd-order method

Let  $x_0 \in \mathbb{E}$ ,  $\psi_0(x) = \frac{1}{4} \|x - x_0\|^4$ ,  $A_k = \frac{10}{7L_2} \left(\frac{2}{3}\right)^3 \left(\frac{k}{4}\right)^4$ ,  $a_{k+1} = A_{k+1} - A_k$ . **Iteration**  $k \ge 0$ : **1.** Define  $v_k = \arg \min_{x \in \mathbb{R}} \psi_k(x)$  and  $y_k = \frac{A_k}{A_{k+1}} x_k + \frac{a_k}{A_{k+1}} v_k$ . **2.** Set  $\varphi_k(h) = \langle f'(y_k), h \rangle + \frac{1}{2} \langle f''(y_k)h, h \rangle + \frac{1}{6} D^3 f(y_k)[h]^3 + \frac{6L_3}{24} ||h||^4$ .  $\rho_k(h) = \frac{1}{2} \langle f''(y_k)h, h \rangle + \frac{L_3}{4} \|h\|^4$ . Set  $h_{k,0} = 0$  and iterate BDGM:  $h_{k,i+1} = \arg\min_{k \in \mathbb{T}} \left\{ \langle \varphi'_k(h_{k,i}), h - h_{k,i} \rangle + L\beta_{\rho_k}(h_{k,i}, h) \right\},\$  $i \geq 0$ . When stop at  $i_k$ , define  $x_{k+1} = y_k + h_{k,i_k}$ .

**3.** Update  $\psi_{k+1}(x) = \psi_k(x) + a_{k+1}[f(x_{k+1}) + \langle f'(x_{k+1}), x - x_{k+1} \rangle].$ 

**Convergence:**  $O(k^{-4})$ . **Question:** What is the order of this method? **NB:** We use  $D^3 f(y_k)[h]^2 = \lim_{\tau \to 0} \frac{1}{\tau^2} [f'(y_k + \tau h) + f'(y_k - \tau h) - 2f'(y_k)].$ WHAT ABOUT THE "LOWER BOUND"  $O(k^{-7/2})$ ?

## **Implementation details**

#### What do we need:

- 1. Justification of tensor methods with inexact tensor steps.
- 2. Justification of BDGM with inexact gradients.

#### What do we get:

Second-order method with the rate of convergence  $O(k^{-4})$ .

**Complexity of iteration:**  $O(\ln \frac{1}{\epsilon})$  calls of oracle.

Problem class: functions with bounded fourth derivative.

## Conclusion

1. Denote  $M_p(f) = \sup_{x \in \mathbb{E}} \|D^p f(x)\|$ . Then  $M_3(f) \leq \sqrt{2M_2(f)M_4(f)}$ .

Thus, there is no contradiction with the lower bound  $O(k^{-7/2})$ .

**2.** Expansion of the lower-order methods onto the field of high-order methods.

The rate of convergence is the same!

**3.** Old situation: Problem class  $\Leftrightarrow$  Order of the method. This is 1D-picture.

4. New situation: 2D-picture.

Parameters: Order of bounded derivative + Order of the method. We need to fill the table!

#### Some hints for future research

**1.** <u>Functions with bounded 2rd derivative</u>  $\geq O(k^{-2})$ 

Worst function:  $f_2(x) = |x^{(1)}|^2 + \sum_{i=1}^{k-1} |x^{(i+1)} - x^{(i)}|^2 - x^{(1)}.$ 

**NB:** Derivatives of order  $p \ge 3$  are zeros. No help from bounding them.

**2.** Functions with bounded 3rd derivative  $\geq O(k^{-7/2})$ 

Worst function: 
$$f_3(x) = |x^{(1)}|^3 + \sum_{i=1}^{k-1} |x^{(i+1)} - x^{(i)}|^3 - x^{(1)}$$
.

**NB:** 3rd derivative is discontinuous. There is no high-order derivatives.

**3.** <u>Functions with bounded 4th derivative</u>  $\geq O(k^{-5})$ 

Worst function:  $f_4(x) = |x^{(1)}|^4 + \sum_{i=1}^{k-1} |x^{(i+1)} - x^{(i)}|^4 - x^{(1)}.$ 

**NB:** Derivatives of order  $p \ge 5$  are zeros. No help from bounding them.

Hint: Bounds (1) and (3) are indeed unimprovable.

## Some references

**1.** Yurii Nesterov. Inexact basic tensor methods. *CORE Discussion Paper* 2019/23 (November 2019).

- Acceptable accuracy for auxiliary problem in tensor methods.
- Convergence rate  $O(k^{-6})$  for FGM used inside Cubic Reg. Newton.

**2.** Yurii Nesterov. Superfast second-order methods for unconstrained convex optimization. *CORE Discussion Paper* 2020/07 (January 2020). Presented at OWOS 29/06/2020.

**3.** Yurii Nesterov. Inexact accelerated high-order proximal-point methods. *CORE Discussion Paper* 2020/08 (February 2020).

Bi-Level Unconstrained Minimization (BLUM) based on high-order proximal-point operators. Will be presented at SIAM MDS  $\underline{TOMORROW}$ .

**4.** Yurii Nesterov. Inexact accelerated high-order proximal-point methods with auxiliary search procedure. *CORE Discussion Paper* 2020/10. 2nd-order implementation of 3rd-order scheme with the rate  $O(k^{-5})$ .

THANK YOU FOR YOUR ATTENTION!