

Optimal second-order method complexity without function evaluations

Serge Gratton ^{1,2} Sadok Jerad ^{1,2} Philippe L.Toint ³

¹IRIT-APO

²Toulouse INP-ENSEEIH

³University of Namur

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Problem and motivations

Approximately solving the non convex problem

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

without evaluating f .

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Why devise an algorithm that do not evaluate the function ?

- ▶ Stochastic algorithms depend heavily on accurate function values [BGMT21].
- ▶ Empirical success in modern Machine Learning (Adagrad [DHS11], Adam[KB14]).

Adaptive Regularization Methods

For a given $\epsilon \in (0, 1]$, we try to find an approximate first-order point x_ϵ

$$\|\nabla_x f(x_\epsilon)\| \leq \epsilon,$$

Adaptive regularization methods exhibits the best complexity rate at $\mathcal{O}\left(\epsilon^{-\frac{3}{2}}\right)$ for second order methods [CGT11].

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Can we devise a second order adaptive algorithm objective free function with a $\mathcal{O}\left(\epsilon^{-\frac{3}{2}}\right)$ complexity?

Affirmative

We devise an OFFO¹-AR2 that uses **only** deterministic derivatives with an optimal complexity at $\mathcal{O}\left(\epsilon^{-\frac{3}{2}}\right)$ rate.

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Numerical Results

- ▶ No improvement when very limited noise is present.
- ▶ Clear benefit when the computed derivatives are heavily-noised.

Thank you for your attention and see you at the poster corner. 😊

References I

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