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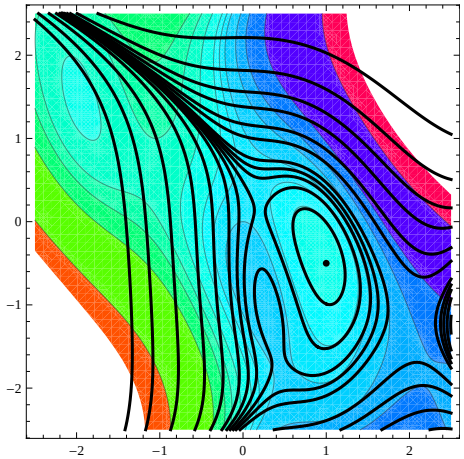

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Worst-case evaluation complexity for unconstrained nonlinear optimization using high-order regularized models*

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Abstract

The worst-case evaluation complexity for smooth (possibly nonconvex) unconstrained optimization is considered. It is shown that, if one is willing to use derivatives of the objective function up to order p (for $p \geq 1$) and to assume Lipschitz continuity of the p-th derivative, then an ϵ-approximate first-order critical point can be computed in at most $O(\epsilon^{-(p+1)/p})$ evaluations of the problem's objective function and its derivatives. This generalizes and subsumes results known for $p = 1$ and $p = 2$.

1 Introduction

Recent years have seen a surge of interest in the analysis of worst-case evaluation complexity of optimization algorithms for nonconvex problems (see, for instance, Vavasis [15], Nesterov and Polyak [14], Nesterov [12, 13], Gratton, Sartenaer and Toint [11], Cartis, Gould and Toint [3, 4, 5, 8], Bian, Chen and Ye [2], Bellavia, Cartis, Gould, Morini and Toint [1], Grapiglia, Yuan and Yuan [10], Vicente [16]). In particular the paper [14] was the first to show that a method using second derivatives can find an ϵ-approximate first-order critical point for an unconstrained problem with Lipschitz Hessians in at most $O(\epsilon^{-3/2})$ evaluations of the objective function (and its derivatives), in contrast with methods using first-derivatives only, whose evaluation complexity was known [12] to be $O(\epsilon^{-2})$ for problems with Lipschitz continuous gradients. The purpose of the present short paper is to show that, if one is willing to use derivatives up to order p (for $p \geq 1$) and to assume Lipschitz continuity of the p-th derivative, then an ϵ-approximate first-order critical point can be computed in at most $O(\epsilon^{-(p+1)/p})$ evaluations of the objective function and its derivatives. This is achieved by the use of a regularization method very much in the spirit of the first- and second-order ARC methods described in [4, 5].

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2 A $(p+1)$-rst order model and algorithm

For $p \geq 1$, p integer, consider the problem

$$\min_{x \in \mathbb{R}^n} f(x), \tag{2.1}$$

where we assume that f from $\mathbb{R}^n$ to $\mathbb{R}$ is bounded below and p-times continuously differentiable. We also assume that its p-th derivative tensor is Lipschitz continuous, i.e. that there exists a constant $L \geq 0$ such that, for all $x, y \in \mathbb{R}^n$,

$$\|\nabla^p f(x) - \nabla^p f(y)\|_T \leq (p-1)!\, L \|x - y\| \tag{2.2}$$

where $\nabla^p f(x)$ is the p-th order derivative tensor of f at x, and where $\|\cdot\|_T$ is the tensor norm recursively induced by the Euclidean norm $\|\cdot\|$ on the space of p-th order tensors. Let $T_p(x,s)$ be the Taylor series of the function $f(x+s)$ at x truncated at order p. Then Taylor's theorem, the identity

$$\int_0^1 (1-\xi)^{p-1}\, d\xi = \frac{1}{p},$$

the induced nature of $\|\cdot\|_T$ and (2.2) imply that, for all $x, s \in \mathbb{R}^n$,

$$\begin{aligned}
f(x+s) &= T_{p-1}(x,s) + \frac{1}{(p-1)!}\int_0^1 (1-\xi)^{p-1} \nabla^p f(x+\xi s, \underbrace{s, \ldots, s}_{p \text{ times}})\, d\xi \\
&\leq T_p(x,s) + \frac{1}{(p-1)!}\left| \int_0^1 (1-\xi)^{p-1} [\nabla^p f(x+\xi s, \underbrace{s, \ldots, s}_{p \text{ times}}) - \nabla^p f(x, \underbrace{s, \ldots, s}_{p \text{ times}})]\, d\xi \right| \\
&\leq T_p(x,s) + \frac{1}{(p-1)!}\int_0^1 (1-\xi)^{p-1} |\nabla^p f(x+\xi s, \underbrace{s, \ldots, s}_{p \text{ times}}) - \nabla^p f(x, \underbrace{s, \ldots, s}_{p \text{ times}})|\, d\xi \\
&\leq T_p(x,s) + \left[\int_0^1 \frac{(1-\xi)^{p-1}}{(p-1)!}\, d\xi\right] \max_{\xi \in [0,1]} |\nabla^p f(x+\xi s, \underbrace{s, \ldots, s}_{p \text{ times}}) - \nabla^p f(x, \underbrace{s, \ldots, s}_{p \text{ times}})| \\
&\leq T_p(x,s) + \frac{1}{p!}\, \|s\|^p \max_{\xi \in [0,1]} \|\nabla^p f(x+\xi) - \nabla^p f(x)\|_T \\
&= T_p(x,s) + \frac{L}{p}\, \|s\|^{p+1}
\end{aligned} \tag{2.3}$$

where $\nabla^p f(x, \underbrace{s, \ldots, s}_{p \text{ times}})$ is $\nabla^p f(x)$ applied p times to s. Similarly, we have that

$$\begin{aligned}
&\|\nabla f(x+s) - \nabla_s T_p(x,s)\| \\
&\quad \leq \frac{p}{(p-1)!}\left\| \int_0^1 (1-\xi)^{p-1} [\nabla^p f(x+\xi s, \underbrace{s, \ldots, s}_{p-1 \text{ times}}) - \nabla^p f(x, \underbrace{s, \ldots, s}_{p-1 \text{ times}})]\, d\xi \right\| \\
&\quad \leq \frac{1}{(p-1)!}\, \|s\|^{p-1} \max_{\xi \in [0,1]} \|\nabla^p f(x+\xi s) - \nabla^p f(x)\|_T \\
&\quad \leq L\, \|s\|^p
\end{aligned} \tag{2.4}$$

In order to describe our algorithm, we also define the regularized Taylor series

$$m(x,s,\sigma) = T_p(x,s) + \frac{\sigma}{p+1}\|s\|^{p+1}, \tag{2.5}$$

whose gradient is

$$\nabla_s m(x,s,\sigma) = \nabla_s T_p(x,s) + \sigma\|s\|^p \frac{s}{\|s\|}. \tag{2.6}$$

Note that

$$m(x,0,\sigma) = T_p(x,0) = f(x). \tag{2.7}$$

The minimization algorithm we consider is now detailed as Algorithm 2.1.

Algorithm 2.1: ARp

Step 0: Initialization. An initial point x_0 and an initial regularization parameter $\sigma_0 > 0$ are given, as well as an accuracy level ϵ. The constants θ, η_1, η_2, γ_1, γ_2, γ_3 and $\sigma_{\min}$ are also given and satisfy

$$\theta > 0, \quad \sigma_{\min} \in (0,\sigma_0], \quad 0 < \eta_1 \leq \eta_2 < 1 \text{ and } 0 < \gamma_1 < 1 < \gamma_2 < \gamma_3. \tag{2.8}$$

Compute $f(x_0)$ and set $k = 0$.

Step 1: Test for termination. Evaluate $\nabla f(x_k)$. If $\|\nabla f(x_k)\| \leq \epsilon$, terminate with the approximate solution $x_\epsilon = x_k$. Otherwise compute derivatives of f from order 2 to p at x_k.

Step 2: Step calculation. Compute the step s_k by approximately minimizing the model $m(x_k,s,\sigma_k)$ with respect to s in the sense that the conditions

$$m(x_k,s_k,\sigma_k) < m(x_k,0,\sigma_k) \tag{2.9}$$

and

$$\|\nabla_s m(x_k,s_k,\sigma_k)\| \leq \theta\|s_k\|^p \tag{2.10}$$

hold.

Step 3: Acceptance of the trial point. Compute $f(x_k+s_k)$ and define

$$\rho_k = \frac{f(x_k) - f(x_k+s_k)}{T_p(x_k,0) - T_p(x_k,s_k)}. \tag{2.11}$$

If $\rho_k \geq \eta_1$, then define $x_{k+1} = x_k + s_k$; otherwise define $x_{k+1} = x_k$.

Step 4: Regularization parameter update. Set

$$\sigma_{k+1} \in \begin{cases} [\max(\sigma_{\min}, \gamma_1\sigma_k), \sigma_k] & \text{if } \rho_k \geq \eta_2, \\ [\sigma_k, \gamma_2\sigma_k] & \text{if } \rho_k \in [\eta_1,\eta_2), \\ [\gamma_2\sigma_k, \gamma_3\sigma_k] & \text{if } \rho_k < \eta_1. \end{cases} \tag{2.12}$$

Increment k by one and go to Step 1 if $\rho_k \geq \eta_1$ or to Step 2 otherwise.

Each iteration of this algorithm requires the approximate minimization of $m(x_k,s,\sigma_k)$, but we may note that conditions (2.9) and (2.10) are relatively weak, in that they only

require a decrease of the $(p+1)$-rst order model and an approximate first-order stationary point: no global optimization of this possibly nonconvex model is needed. Fortunately, this approximate minimization does not involve computing f nor its derivatives, and therefore the exact method used and the resulting effort spent in Step 2 have no impact on the evaluation complexity. Also note that the numerator and denominator in (2.11) are strictly comparable, the latter being Taylor's approximation of the former, without the regularization parameter playing any role.

Iterations for which $\rho_k \geq \eta_1$ (and hence $x_{k+1} = x_k + s_k$) are called "successful" and we denote by $\mathcal{S}_k \stackrel{\rm def}{=} \{0 \leq j \leq k \mid \rho_j \geq \eta_1\}$ the index set of all successful iterations between 0 and k. We also denote by $\mathcal{U}_k$ its complement in $\{1, \ldots, k\}$, which corresponds to the index set of "unsuccessful" iterations between 0 and k. Note that, before termination, each successful iteration requires the evaluation of f and its first p derivatives, while only the evaluation of f is needed at unsuccessful ones.

We first derive a very simple result on the model decrease obtained under condition (2.9).

Lemma 2.1

$$T_p(x_k, 0) - T_p(x_k, s_k) \geq \frac{\sigma_k}{p+1}\|s_k\|^{p+1}. \tag{2.13}$$

Proof. Observe that, because of (2.9) and (2.5),

$$0 \leq m(x_k, 0, \sigma_k) - m(x_k, s_k, \sigma_k) = T_p(x_k, 0) - T_p(x_k, s_k) - \frac{\sigma_k}{p+1}\|s_k\|^{p+1}$$

which implies the desired bound. □

As a result, we obtain that (2.11) is well-defined for all $k \geq 0$. We next deduce a simple upper bound on the regularization parameter σ_k.

Lemma 2.2 For all $k \geq 0$,

$$\sigma_k \leq \sigma_{\max} \stackrel{\rm def}{=} \max\left[\sigma_0, \frac{\gamma_3 L(p+1)}{p\,(1-\eta_2)}\right]. \tag{2.14}$$

Proof. Assume that

$$\sigma_k \geq \frac{L(p+1)}{p\,(1-\eta_2)}. \tag{2.15}$$

Using (2.3) and (2.13), we may then deduce that

$$|\rho_k - 1| \leq \frac{|f(x_k + s_k) - T_p(x_k, s_k)|}{|T_p(x_k, 0) - T_p(x_k, s_k)|} \leq \frac{L(p+1)}{p\,\sigma_k} \leq 1 - \eta_2$$

and thus that $\rho_k \geq \eta_2$. Then iteration k is very successful in that $\rho_k \geq \eta_2$ and $\sigma_{k+1} \leq \sigma_k$. As a consequence, the mechanism of the algorithm ensures that (2.14) holds. □

Our next step, very much in the line of the theory proposed in [5], is to show that the steplength cannot be arbitrarily small compared with the gradient of the objective function at the trial point $x_k + s_k$.

Lemma 2.3

$$\|s_k\| \geq \left(\frac{\|\nabla f(x_k + s_k)\|}{L + \theta + \sigma_k} \right)^{\frac{1}{p}}. \tag{2.16}$$

Proof. Using the triangle inequality, (2.4) and (2.6) and (2.10), we obtain that

$$\begin{aligned} \|\nabla f(x_k + s_k)\| &\leq \|\nabla f(x_k + s_k) - \nabla_s T_p(x_k, s_k)\| + \left\| \nabla_s T_p(x_k, s_k) + \sigma_k \|s_k\|^p \frac{s_k}{\|s_k\|} \right\| \\ &\quad + \sigma_k \|s_k\|^p \\ &\leq L\|s_k\|^p + \|\nabla_s m(x_k, s_k, \sigma_k)\| + \sigma_k \|s_k\|^p \\ &\leq [L + \theta + \sigma_k] \, \|s_k\|^p \end{aligned}$$

and (2.16) follows. □

We now bound the number of unsuccessful iterations as a function of the number of successful ones.

Lemma 2.4 The mechanism of Algorithm 2.1 then guarantees that, if

$$\sigma_k \leq \sigma_{\max}, \tag{2.17}$$

for some $\sigma_{\max} > 0$, then

$$k \leq |\mathcal{S}_k| \left(1 + \frac{|\log \gamma_1|}{\log \gamma_2} \right) + \frac{1}{\log \gamma_2} \log \left(\frac{\sigma_{\max}}{\sigma_0} \right). \tag{2.18}$$

Proof. (See [5, Theorem 2.1].) The regularization parameter update (2.12) gives that, for each k,

$$\gamma_1 \sigma_j \leq \max[\gamma_1 \sigma_j, \sigma_{\min}] \leq \sigma_{j+1}, \quad j \in \mathcal{S}_k, \quad \text{and} \quad \gamma_2 \sigma_j \leq \sigma_{j+1}, \quad j \in \mathcal{U}_k.$$

Thus we deduce inductively that

$$\sigma_0 \gamma_1^{|\mathcal{S}_k|} \gamma_2^{|\mathcal{U}_k|} \leq \sigma_k.$$

We therefore obtain, using (2.17), that

$$|\mathcal{S}_k| \log \gamma_1 + |\mathcal{U}_k| \log \gamma_2 \leq \log \left(\frac{\sigma_{\max}}{\sigma_0} \right),$$

which then implies that

$$|\mathcal{U}_k| \leq -|\mathcal{S}_k| \frac{\log \gamma_1}{\log \gamma_2} + \frac{1}{\log \gamma_2} \log \left(\frac{\sigma_{\max}}{\sigma_0} \right),$$

since $\gamma_2 > 1$. The desired result (2.18) then follows from the equality $k = |\mathcal{S}_k| + |\mathcal{U}_k|$ and the inequality $\gamma_1 < 1$ given by (2.8). □

Using all the above results, we are now in position to state our main evaluation complexity result.

Theorem 2.5 Let $f_{\rm low}$ be a lower bound on f. Then, given $\epsilon > 0$, Algorithm 2.1 needs at most

$$\left\lfloor \kappa_s \, \frac{f(x_0) - f_{\rm low}}{\epsilon^{\frac{p+1}{p}}} \right\rfloor$$

successful iterations (each involving one evaluation of f and its p first derivatives) and at most

$$\left\lfloor \kappa_s \, \frac{f(x_0) - f_{\rm low}}{\epsilon^{\frac{p+1}{p}}} \right\rfloor \left(1 + \frac{|\log \gamma_1|}{\log \gamma_2} \right) + \frac{1}{\log \gamma_2} \log \left(\frac{\sigma_{\max}}{\sigma_0} \right)$$

iterations in total to produce an iterate x_ϵ such that $\|\nabla f(x_\epsilon)\| \leq \epsilon$, where $\sigma_{\max}$ is given by (2.14) and where

$$\kappa_s \stackrel{\rm def}{=} \frac{p+1}{\eta_1 \sigma_{\min}} \left(L + \theta + \sigma_{\max} \right)^{\frac{p+1}{p}}.$$

Proof. At each successful iteration, we have that

$$\begin{aligned} f(x_k) - f(x_k + s_k) &\geq \eta_1 (T_p(x_k, 0) - T_p(x_k, s_k)) \\ &\geq \frac{\eta_1 \sigma_{\min}}{p+1} \, \|s_k\|^{p+1} \\ &\geq \frac{\eta_1 \sigma_{\min}}{(p+1)(L + \theta + \sigma_k)^{\frac{p+1}{p}}} \, \|\nabla f(x_k + s_k)\|^{\frac{p+1}{p}} \\ &\geq \frac{\eta_1 \sigma_{\min}}{(p+1)(L + \theta + \sigma_{\max})^{\frac{p+1}{p}}} \, \epsilon^{\frac{p+1}{p}}, \end{aligned}$$

where we used (2.11), (2.13), (2.12), (2.16), (2.14) and the fact that $\|\nabla f(x_k + s_k)\| \geq \epsilon$ before termination. Thus we deduce that, as long as termination does not occur,

$$f(x_0) - f(x_{k+1}) = \sum_{j \in \mathcal{S}_k} [f(x_j) - f(x_j + s_j)] \geq \frac{|\mathcal{S}_k|}{\kappa_s} \, \epsilon^{\frac{p+1}{p}},$$

from which the desired bound on the number of successful iterations follows. Lemma 2.4 is then invoked to compute the upper bound on the total number of iterations. □

3 Final comments

We have shown that, under suitable smoothness assumptions, an ϵ-approximate stationary point must be found by Algorithm 2.1 in at most $O(\epsilon^{-(p+1)/p})$ iterations and function evaluations. This extension of results known for $p = 1$ and $p = 2$ to arbitrary $p \geq 1$ is made possible by the introduction of two main innovations: weaker termination conditions on the model minimization subproblem (no global optimization is required at all) and a reformulation of the ratio of achieved versus predicted decreases where the model is limited to the Taylor's approximation. Of course, each iteration of the proposed algorithm requires the approximate minimization of a typically nonconvex regularized $(p+1)$-rst order model but this minimization does not involve computing the objective function of the original problem nor its derivatives, and therefore its cost does not affect the evaluation complexity of Algorithm 2.1. Which numerical procedure is best for this task is beyond the scope of the present note (for instance, one might think of applying an efficient first-order method on the model).

We observe that, for p tending to infinity, the evaluation complexity order tends to $O(\epsilon^{-1})$, which is the known bound for several algorithms (including a first-order variant of the ARC method) to produce an iterate x_ϵ such that $f(x_\epsilon) - f_* \leq \epsilon$ when applied on a convex problem with optimal value f_* (see [12] or [9]).

It is of course interesting to consider if the extensions of the theories developed for the first- and second-order ARC methods for second-order optimality [8] or convexly constrained problems [7] can be extended to higher-order regularization approaches. We also note that Cartis *et al.* showed in [6] that a worst-case evaluation complexity of order $O(\epsilon^{-3/2})$ is optimal for a large class of second-order methods applied on twice continuously differentiable problems with Hölder continuous Hessians. The generalization of this optimality result for $p > 2$ is also an open question.

Whether the approach presented here has practical implications remains to be seen, since the approximate model minimization could be costly even if computation of f is avoided, and computing p derivatives for $p > 2$ may often be out of reach.

We conclude this paper by mentioning a simple extension which we anticipate could be useful in other contexts. We may, instead of minimizing $f(x)$, split the objective function into two parts and consider minimizing $\Phi(x) = h(x) + f(x)$ where h is bounded below and continuously differentiable. In this case, we then replace the model defined by (2.5) by $m(x, s, \sigma) = h(x + s) + T_p(x, s) + \sigma\|s\|^{p+1}/(p + 1)$ and, provided we are ready to (approximately) minimize this augmented model in Step 2 of the algorithm, the above analysis remains unchanged. There are many possible interesting choices for $h(x)$: in the context of optimization with non-negative variables, a possibility is, for example, to choose $h(x) = [\max(x, 0)]^2$. Which part of the objective function is "easy" enough to be included in the model $m(x, s, \sigma)$ explicitly and which part is better included using a Taylor series approximation may depend on the problem at hand, but it is interesting to note that the evaluation-complexity bound presented in Theorem 2.5 is unaffected.

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