# Complexity and global rates of trust-region methods based on probabilistic models

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**Abstract**

Trust-region algorithms have been proved to globally converge with probability one when the accuracy of the trust-region models is imposed with a certain probability conditioning on the iteration history. In this paper, we study their complexity, providing global rates and worst case complexity bounds on the number of iterations (with overwhelmingly high probability), for both first and second order measures of optimality. Such results are essentially the same as the ones known for trust-region methods based on deterministic models. The derivation of the global rates and worst case complexity bounds follows closely from a study of direct-search methods based on the companion notion of probabilistic descent.

## 1 Introduction

Trust-region methods form a well established and understood class of methods for the minimization of a nonlinear (possibly nonsmooth) function subject or not to constraints on its variables (see the book [7] and the recent survey [28]). They have also been comprehensively studied in the context of derivative-free optimization (DFO), where the derivatives of the objective or constraint functions cannot be computed or approximated (see the book [12] and the recent survey [14]). In this paper we focus on the unconstrained minimization of a smooth objective function $f : \mathbb{R}^n \to \mathbb{R}$ without using its derivatives.

In the derivative-free setting, trust-region algorithms use sampled points to build a model of the objective function around the current iterate, typically by quadratic interpolation. The quality of these models is measured by the accuracy they provide relatively to a Taylor expansion in a ball $B(x, \delta)$ of center $x$ and radius $\delta$. Models that are as accurate as first-order Taylor ones are called fully linear [9, 12].

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**Definition 1.1** *Given a function $f \in \mathcal{C}^1$ and constants $\kappa_{ef}, \kappa_{eg} > 0$, a $\mathcal{C}^1$ function $m : \mathbb{R}^n \to \mathbb{R}$ is called a* $(\kappa_{eg}, \kappa_{ef})$-fully linear model *of $f$ on $B(x, \delta)$ if, for all $s \in B(0, \delta)$,*

$$\begin{array}{rcl} |m(s) - f(x+s)| & \leq & \kappa_{ef}\delta^2, \\ \|\nabla m(s) - \nabla f(x+s)\| & \leq & \kappa_{eg}\delta. \end{array}$$

Fully linear models are not necessarily linear or affine functions. Models that are as accurate as second-order Taylor ones are called fully quadratic [9, 12]. Similarly, such models are not necessarily quadratic functions.

**Definition 1.2** *Given a function $f \in \mathcal{C}^2$ and constants $\kappa_{ef}, \kappa_{eg}, \kappa_{eh} > 0$, a $\mathcal{C}^2$ function $m : \mathbb{R}^n \to \mathbb{R}$ is called a* $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic model *of $f$ on $B(x, \delta)$ if, for all $s \in B(0, \delta)$,*

$$\begin{array}{rcl} |m(s) - f(x+s)| & \leq & \kappa_{ef}\delta^3, \\ \|\nabla m(s) - \nabla f(x+s)\| & \leq & \kappa_{eg}\delta^2, \\ \|\nabla^2 m(s) - \nabla^2 f(x+s)\| & \leq & \kappa_{eh}\delta. \end{array}$$

The construction of fully linear/quadratic models based on sampled sets raises a number of geometrical questions. Conn, Scheinberg, and Vicente [9, 10, 12] provided a systematic approach to the subject of deterministic sampling geometry in DFO, establishing error bounds for polynomial interpolation and regression models in terms of a constant measuring the quality or well poisedness of the corresponding sample set (ensuring then the fully linear/quadratic properties). They also showed how to deterministically build or update such sets to ensure that such a constant remains moderate in size. Some numerical studies pioneered by [15] have however shown that trust-region methods can tolerate the use of models updated without strict geometry requirements, although it is also known [25] that convergence cannot be ensured to first-order critical points without appealing to fully linear models when the size of the model gradient becomes small (a procedure known as the criticality step).

A DFO context of expensive function evaluations often makes it unaffordable to construct a deterministic model that is guaranteed to be fully quadratic, as such a process requires $(n+1)(n+2)/2$ function evaluations. Practical approaches rely on considerably less points (but at least $n+1$ to preserve fully linearity), and use the remaining degrees of freedom to minimize the norm of the model Hessian or its distance to the previous one. The most studied examples use minimum Frobenius type norms [8, 23], yet in [1] it was proposed to apply the theory of sparse $\ell_1$-recovery to build quadratic models based on random sampling. Such models were proved to be fully quadratic with high probability even when considerably less than $(n+1)(n+2)/2$ points were used, depending on the sparsity of the Hessian of the objective.

Such findings have then called for a probabilistic analysis of derivative-free trust-region algorithms [2], where the accuracy of the models is only guaranteed with a certain probability. It was shown in [2] that the resulting trust-region methods converge with probability one to first and second order critical points. The main purpose of this paper is to establish (with overwhelmingly high probability) the rate under which these methods drive to zero the corresponding criticality measures: the norm of the gradient $\|\nabla f(x_k)\|$ (in the first-order case) and the minimum $\sigma(x_k) = \min\{\|\nabla f(x_k)\|, -\lambda_{\min}(\nabla^2 f(x_k))\}$ between the gradient and the symmetric of the smallest eigenvalue of the Hessian (in the second-order case). We will see that these results match the convergence rates known for deterministic trust-region algorithms. The proofs rely heavily on the technique developed in [19] for establishing global rates and worst

case complexity bounds for randomized algorithms in which the new iterate depends on some object (directions in [19], models here) and the quality of the object is favorable with a certain probability. The technique is based on counting the number of iterations for which the quality is favorable and examining the probabilistic behavior of this number. Although the road map for our paper was described in [19, Section 6], its actual concretization poses a few delicate issues and, in addition, we go beyond [19, Section 6] in other aspects (bounds in expectation, coverage of the second-order case).

Let us now review what is known about the complexity of trust-region methods in the deterministic unconstrained case[1]. Using first-order Taylor models, trust-region methods are known [20] to take at most $\mathcal{O}(\epsilon^{-2})$ iterations to reduce the $\|\nabla f(\cdot)\|$ below $\epsilon \in (0,1)$ (see also [18] for the corresponding bounds under convexity $\mathcal{O}(\epsilon^{-1})$ and strong convexity $\mathcal{O}(-\log(\epsilon))$). Using second-order Taylor models, it has been proved [4] that at most $\mathcal{O}(\max\{\epsilon_g^{-2}\epsilon_h^{-1}, \epsilon_h^{-3}\})$ iterations are needed to reduce simultaneously $\|\nabla f(\cdot)\|$ below $\epsilon_g \in (0,1)$ and $-\lambda_{\min}(\nabla^2 f(\cdot))$ below $\epsilon_h \in (0,1)$. Later in [17] it was also proved a complexity bound of the type $\mathcal{O}(\max\{\epsilon_g^{-3}, \epsilon_h^{-3}\})$. In a recent paper [13] it was suggested a modification to the classical trust-region approach to make it achieving the first-order $\mathcal{O}(\epsilon^{-1.5})$ bound of cubic regularization methods.

In the derivative-free case, we are also interested in counting function evaluations and to understand the dependence of the complexity bounds in terms of the dimension $n$ of the problem. Using fully linear models instead, the first-order bound [16] is then of the form $\mathcal{O}(\kappa_{eg}^{-2}\epsilon^{-2})$, and since interpolation techniques can ensure $\kappa_{eg} = \mathcal{O}(\sqrt{n})$ with at most $\mathcal{O}(\sqrt{n})$ evaluations per iteration, one recovers the bounds $\mathcal{O}(n\epsilon^{-2})$ for iterations and $\mathcal{O}(n^2\epsilon^{-2})$ for function evaluations, also known for direct search [27]. Using fully quadratic models, the second-order complexity bounds [16, 21] do not entirely match the derivative-based case as a single tolerance $\epsilon$ must be used, being of the form $\mathcal{O}(n^3\epsilon^{-3})$ (resp. $\mathcal{O}(n^5\epsilon^{-3})$) for measuring the number of iterations (resp. function evaluations) needed to drive $\sigma(\cdot)$ below $\epsilon$.

We are ready to start presenting our ideas on how to derive global rates and complexity bounds for trust-region methods based on probabilistic models. We will do so in Section 2 for first-order stationarity and in Section 3 for the second-order counterpart. In Section 4 we comment on the extension of our work to other settings.

## 2 Complexity of first-order trust-region methods based on probabilistic models

We consider now the scenario analyzed in [2] where the models used in a trust-region method are randomly generated at each iteration. As a result, the iterates and trust-region radii produced by the algorithm will also be random. Upper case letters will be then used to designate random variables and lower case their realizations. Hence, $m_k, x_k, \delta_k$ will denote respectively the realizations of the random model, iterate, and trust-region radius $M_k, X_k, \Delta_k$ at iteration $k$. The random models are then asked to be fully linear with a certain favorable property regardless of the past iteration history. The following definition was proposed in [2] to analyze global convergence of the corresponding trust-region methods to first-order critical points.

[1]The notation $\mathcal{O}(A)$ will stand for a scalar times $A$, with this scalar depending solely on the problem considered or constants from the algorithm. The dependence on the problem dimension $n$ will explicitly appear in $A$ when considered appropriate.

**Definition 2.1** *We say that a sequence of random models $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eg}, \kappa_{ef})$-fully linear for a corresponding sequence $\{B(X_k, \Delta_k)\}$ if the events*

$$S_k \;=\; \{M_k \text{ is a } (\kappa_{eg}, \kappa_{ef})\text{-fully linear model of } f \text{ on } B(X_k, \Delta_k)\}$$

*satisfy $\mathbb{P}(S_0) \geq p$ and, for each $k \geq 1$, the following submartingale-like condition*

$$\mathbb{P}\left(S_k | M_0, \ldots, M_{k-1}\right) \;\geq\; p.$$

An example is given in [2] where, using random matrix theory, it was shown that linear interpolation based on Gaussian sample sets of cardinality $n+1$ (with a fixed point and the remaining $n$ points being generated randomly from a standard Gaussian distribution) gives rise to fully linear models with a favorable probability (say $p > 1/2$). By using increasingly more sample points and building the models by linear regression it is possible to reach a probability as high as desired ([12, Chapter 4]; see also [22]).

## 2.1 Algorithm and assumptions

To simplify the presentation, we describe the trust-region methods under consideration (later given in Algorithm 2.1) for each realization of the model randomness. A few components of these methods are classical, with or without derivatives. At each iteration $k$, one minimizes a quadratic model

$$m_k(x_k + s) \;=\; f(x_k) + g_k^\top s + \frac{1}{2} s^\top H_k s$$

in a trust region of the form $B(x_k, \delta_k)$. For global convergence to first-order criticality, the Hessian models are assumed uniformly bounded and the step $s_k$ is asked to satisfy a fraction of the model decrease given by the negative model gradient within the trust region. These two assumptions are formalized next.

**Assumption 2.1** *There exists a positive constant $\kappa_{bhm}$ such that, for every $k$, the Hessians $H_k$ of all realizations $m_k$ of $M_k$ satisfy*

$$\|H_k\| \;\leq\; \kappa_{bhm}.$$

**Assumption 2.2** *For every $k$, and for all realizations $m_k$ of $M_k$ (and of $X_k$ and $\Delta_k$), we are able to compute a step $s_k$ so that it satisfies a* fraction of Cauchy decrease*, i.e.,*

$$m(x_k) - m(x_k + s_k) \;\geq\; \frac{\kappa_{fcd}}{2} \|g_k\| \min\left\{ \frac{\|g_k\|}{\|H_k\|}, \delta_k \right\}, \tag{2.1}$$

*for some constant $\kappa_{fcd} \in (0, 1]$, and with the convention that $\frac{\|g_k\|}{\|H_k\|} = \infty$ if $\|H_k\| = 0$.*

Finally, the step acceptance and trust-region radius update are based on the ratio between the actual decrease in the objective function and the one predicted by the model, namely

$$\rho_k \;=\; \frac{f(x_k) - f(x_k + s_k)}{m_k(x_k) - m_k(x_k + s_k)}.$$

What is different now from the classical derivative-based case is that some form of criticality step has to be taken into account, where models are recomputed in regions small enough compared to the size of the model gradient. Following [2], the presentation and the analysis can be

**Algorithm 2.1:** A simple first-order derivative-free trust-region framework

Fix parameters $\eta_1, \eta_2, \delta_{\max} > 0$ and $0 < \gamma_1 < 1 < \gamma_2$. Select initial $x_0$ and $\delta_0 \in (0, \delta_{\max})$.
**for** $k = 0, 1, \ldots$ **do**
Build a quadratic model $m_k(x_k + s)$ of $f$, and compute $s_k$ by approximately minimizing $m_k$ in $B(x_k, \delta_k)$ so that it satisfies (2.1). If $\rho_k \geq \eta_1$, set $x_{k+1} = x_k + s_k$ and

$$\delta_{k+1} = \begin{cases} \min\{\gamma_2 \delta_k, \delta_{\max}\} & \text{if } \|g_k\| \geq \eta_2 \delta_k, \\ \gamma_1 \delta_k & \text{otherwise.} \end{cases}$$

Otherwise, set $x_{k+1} = x_k$ and $\delta_{k+1} = \gamma_1 \delta_k$.
**end**

significantly simplified if this requirement is mitigated at each iteration. So, in Algorithm 2.1, the trust-region radius is reduced (at iterations where $\rho_k$ is large enough and the step is taken) provided $\delta_k$ is too large compared to $\|g_k\|$.

Note that we have slightly extended the framework in [2] by using two different parameters (namely $\gamma_1$ and $\gamma_2$) to update the trust-region radius, instead of using a single one and its inverse. As we will see, these parameters are intimately connected to the minimum probability with which the models are required to be fully linear. Also, the safeguard $\delta_{\max}$ is not used in the analysis of the first-order methods and is only there for coherence with the second-order case (where it appears in the analysis) as well as with [2].

The algorithm will be analyzed under the following two assumptions on $f$. As in [2] it would be enough to assume continuously differentiability in an enlarged initial level set, but we skip this detail for keeping the presentation simple.

**Assumption 2.3** *The function $f$ is continuously differentiable on $\mathbb{R}^n$, and its gradient is Lipschitz continuous.*

**Assumption 2.4** *The objective function $f$ is bounded from below on $\mathbb{R}^n$, and we denote by $f_{\text{low}}$ a lower bound.*

At this point we can state a fundamental result for establishing the complexity of trust-region methods based on probabilistic models. As in the classical setting of trust-region methods, it ensures that the step is taken if the trust-region radius is small enough compared to the size of the true gradient. There are two differences compared to [2, Lemma 3.2]: first, the result is stated for the true gradient, in alignment to what is needed to establish complexity bounds; second, it is inferred additionally that the trust-region radius is increased under the same condition.

**Lemma 2.1** *If $m_k$ is $(\kappa_{eg}, \kappa_{ef})$-fully linear on $B(x_k, \delta_k)$ and*

$$\delta_k < \left( \kappa_{eg} + \max\left\{ \eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}}{\kappa_{fcd}(1 - \eta_1)} \right\} \right)^{-1} \|\nabla f(x_k)\|, \tag{2.2}$$

*then at the $k$-th iteration the step is taken ($x_{k+1} = x_k + s_k$) and $\delta_k$ is increased.*

**Proof.** From (2.2), one has

$$\kappa_{eg}\delta_k + \max\left\{\eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}}{\kappa_{fcd}(1-\eta_1)}\right\}\delta_k \;<\; \|\nabla f(x_k)\|,$$

and from this and Definition 1.1,

$$\max\left\{\eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}}{\kappa_{fcd}(1-\eta_1)}\right\}\delta_k \;<\; \|\nabla f(x_k)\| - \|g_k - \nabla f(x_k)\| \;\leq\; \|g_k\|.$$

Hence,

$$\delta_k \;<\; \min\left\{\frac{1}{\eta_2}, \frac{1}{\kappa_{bhm}}, \frac{\kappa_{fcd}(1-\eta_1)}{4\kappa_{ef}}\right\}\|g_k\|,$$

and from [12, Proof of Lemma 10.6] we obtain $\rho_k \geq \eta_1$. Since the first term in the minimum gives $\eta_2\delta_k < \|g_k\|$, the trust-region radius is increased. □

## 2.2 Behavior of the trust-region radius

We will now prove that the sequence of the trust-region radii is square summable and establish an explicit upper bound for the sum. The proof makes use of the set of indices corresponding to iterations where the trust-region radius is increased, that is

$$\mathcal{K} \;=\; \{k \in \mathbb{N} : \rho_k \geq \eta_1 \text{ and } \|g_k\| \geq \eta_2\delta_k\}. \tag{2.3}$$

**Remark 2.1** *In context of direct search based on probabilistic descent [19, Lemma 4.1], it was proved a similar result for the sequence of the step size $\alpha_k$. There, an iteration attains a decrease of the order of $\alpha_k^2$ whenever the step is taken, in which case such direct-search algorithms always increase the step size. In the trust-region context, as we will see in the proof below, a decrease of the order of $\delta_k^2$ corresponds only to the iterations where the trust-region radius is increased. There are iterations where the step is taken and the trust-region is decreased, in which case the decrease obtained is not necessarily of this order.*

**Lemma 2.2** *For any realization of Algorithm 2.1,*

$$\sum_{k=0}^{\infty}\delta_k^2 \;\leq\; \beta \;:=\; \frac{\gamma_2^2}{1-\gamma_1^2}\left[\frac{\delta_0^2}{\gamma_2^2} + \frac{f_0 - f_{\text{low}}}{\eta}\right],$$

*where $f_0 = f(x_0)$ and*

$$\eta \;=\; \eta_1\eta_2\frac{\kappa_{fcd}}{2}\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}.$$

**Proof.** We only need to address the case where there are infinitely many iterations at which the trust-region radius is increased (i.e., $|\mathcal{K}| = \infty$). For any $k \in \mathcal{K}$, from (2.1),

$$\begin{aligned} f(x_k) - f(x_k + s_k) \;&\geq\; \eta_1\left(m_k(x_k) - m_k(x_k + s_k)\right) \\ &\geq\; \eta_1\frac{\kappa_{fcd}}{2}\eta_2\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}\delta_k^2 \;=\; \eta\delta_k^2. \end{aligned}$$

Consequently, if we sum a finite number of consecutive iterations in $\mathcal{K}$, we obtain

$$\eta \sum_{\substack{j\in\mathcal{K}\\ j\leq k}} \delta_j^2 \;\leq\; \sum_{\substack{j\in\mathcal{K}\\ j\leq k}} [f(x_j) - f(x_{j+1})] \;\leq\; \sum_{j\leq k} [f(x_j) - f(x_{j+1})] \;\leq\; f_0 - f(x_{k+1}) \;\leq\; f_0 - f_{\rm low},$$

leading to

$$\sum_{k\in\mathcal{K}} \delta_k^2 \;\leq\; \frac{f_0 - f_{\rm low}}{\eta}.$$

From now on the proof is as in the proof of [19, Lemma 4.1]. Let $\mathcal{K} = \{k_1, k_2, \ldots\}$ and, for auxiliary reasons, $k_0 = -1$ and $\delta_{-1} = \delta_0/\gamma_2$. The sum $\sum_{k=0}^{\infty} \delta_k^2$ can thus be rewritten as

$$\sum_{k=0}^{\infty} \delta_k^2 \;=\; \sum_{i=0}^{\infty} \sum_{k=k_i+1}^{k_{i+1}} \delta_k^2.$$

Besides, one has for each index $i$, $\delta_k \leq \gamma_2(\gamma_1)^{k-k_i-1}\delta_{k_i}$ for $k = k_i + 1, \ldots, k_{i+1}$. Hence,

$$\sum_{k=k_i+1}^{k_{i+1}} \delta_k^2 \;\leq\; \frac{\gamma_2^2}{1-\gamma_1^2}\delta_{k_i}^2,$$

and we finally obtain the desired result:

$$\sum_{k=0}^{\infty} \delta_k^2 \;\leq\; \frac{\gamma_2^2}{1-\gamma_1^2} \sum_{i=0}^{\infty} \delta_{k_i}^2 \;\leq\; \frac{\gamma_2^2}{1-\gamma_1^2}\left[\frac{\delta_0^2}{\gamma_2^2} + \frac{f_0 - f_{\rm low}}{\eta}\right].$$

□

This is a stronger version of the result $\lim_{k\to\infty} \delta_k = 0$ proved in [2] for the purpose of global convergence.

### 2.3 Number of iterations with fully linear models

Recall the set of indices (2.3) corresponding to iterations where the step is taken and the trust-region radius is increased, and let $y_k$ denote the corresponding indicator ($y_k = 1$ if $k \in \mathcal{K}$, $y_k = 0$ otherwise). One sees that $\delta_k$ and $\mathcal{K}$ play the same roles as the step size $\alpha_k$ and the set of successful iterations for the analysis of the direct search based on probabilistic descent [19].

Let now $\nabla f(\tilde{x}_k)$, with $\tilde{x}_k \in \{x_0, \ldots, x_k\}$, represent a minimum norm gradient among $\nabla f(x_0), \ldots, \nabla f(x_k)$. Let us also consider the minimum probability

$$p_0 \;=\; \frac{\ln(\gamma_1)}{\ln(\gamma_1/\gamma_2)} \tag{2.4}$$

that will be assumed when applying Definition 2.1. When $\gamma_1 = 1/2$ and $\gamma_2 = 2$, one has $p_0 = 1/2$.

The next step in the analysis is to show, similarly to [19, Lemma 4.2], that if $\|\nabla f(\tilde{x}_k)\|$ is too large then necessarily not too many iterations benefited from a fully linear model[2]. The binary variable $z_k$ below indicates whether $m_k$ is $(\kappa_{eg}, \kappa_{ef})$-fully linear or not.

[2] As opposed to Lemma 2.2 this result follows more directly from the theory in [19], given that the discrepancy mentioned in Remark 2.1 does not need special treatment.

**Lemma 2.3** *Given a realization of Algorithm 2.1 and a positive integer $k$,*

$$\sum_{l=0}^{k-1} z_l \;\leq\; \frac{\beta}{(\min\{\delta_0/\gamma_2, \kappa\|\nabla f(\tilde{x}_k)\|\})^2} + p_0 k,$$

*where*

$$\kappa \;=\; \left(\kappa_{eg} + \max\left\{\eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}}{\kappa_{fcd}(1-\eta_1)}\right\}\right)^{-1}.$$

**Proof.** For each $l \in \{0, 1, \ldots, k-1\}$, define

$$v_l \;=\; \begin{cases} 1 & \text{if } \delta_l \;<\; \min\{\gamma_2^{-1}\delta_0, \kappa\|\nabla f(\tilde{x}_k)\|\}, \\ 0 & \text{otherwise.} \end{cases} \tag{2.5}$$

The proof relies then on $z_l \leq (1 - v_l) + v_l y_l$, which is true because, when $v_l = 1$, Lemma 2.1 implies that $y_l \geq z_l$ (since $\|\nabla f(\tilde{x}_k)\| \leq \|\nabla f(\tilde{x}_{k-1})\| \leq \|\nabla f(\tilde{x}_l)\|$). It suffices then to separately prove

$$\sum_{l=0}^{k-1}(1 - v_l) \;\leq\; \frac{\beta}{(\min\{\delta_0/\gamma_2, \kappa\|\nabla f(\tilde{x}_k)\|\})^2} \tag{2.6}$$

and

$$\sum_{l=0}^{k-1} v_l y_l \;\leq\; p_0 k. \tag{2.7}$$

Inequality (2.6) is justified by Lemma 2.2 and the fact that (2.5) implies

$$1 - v_l \;\leq\; \frac{\delta_l^2}{(\min\{\delta_0/\gamma_2, \kappa\|\nabla f(\tilde{x}_k)\|\})^2}.$$

The proof of inequality (2.7) is verbatim as in the proof of [19, Lemma 4.2]. It is in here that the particular choice (2.4) for $p_0$ comes into a play. □

## 2.4 Worst case complexity and global rate

From Lemma 2.3, one then has the following inclusion of events

$$\left\{\|\nabla f(\tilde{X}_k)\| \geq \epsilon\right\} \;\subset\; \left\{\sum_{l=0}^{k-1} Z_l \leq \frac{\beta}{\kappa^2\epsilon^2} + p_0 k\right\}, \tag{2.8}$$

for any $\epsilon$ satisfying

$$0 \;<\; \epsilon \;<\; \frac{\delta_0}{\kappa\gamma_2}. \tag{2.9}$$

On the other hand the probabilistic behavior of the event on the right-hand side is known from the application of the Chernoff bound to the lower tail of $\sum_{l=0}^{k-1} Z_l$ (see, e.g., [19, Lemma 4.4]), and here is where the conditioning on the past in Assumption 2.1 comes to play a role.

**Lemma 2.4** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eg}, \kappa_{ef})$-fully linear and $\lambda \in (0, p)$. Then*

$$\pi_k(\lambda) \;:=\; \mathbb{P}\left(\sum_{l=0}^{k-1} Z_l \leq \lambda k\right) \;\leq\; \exp\left[-\frac{(p-\lambda)^2}{2p}k\right].$$

Thus, when $\epsilon < \delta_0/(\kappa\gamma_2)$ and

$$k \;\geq\; \frac{2\beta}{(p-p_0)\kappa^2\epsilon^2}, \tag{2.10}$$

the inclusion (2.8) and the monotonicity of $\pi_k(\cdot)$ will give us (setting $\lambda = (p+p_0)/2$ in Lemma 2.4)

$$\begin{aligned}
\mathbb{P}\left(\|\nabla f(\tilde{X}_k)\| \leq \epsilon\right) &\geq \mathbb{P}\left(\|\nabla f(\tilde{X}_k)\| < \epsilon\right) \\
&\geq 1 - \pi_k\left(\frac{\beta}{k\kappa^2\epsilon^2} + p_0\right) \\
&\geq 1 - \pi_k\left(\frac{p-p_0}{2} + p_0\right) \\
&\geq 1 - \exp\left[-\frac{(p-p_0)^2}{8p}k\right],
\end{aligned} \tag{2.11}$$

leading to the following global rate result.

**Theorem 2.1** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eg}, \kappa_{ef})$-fully linear with $p > p_0$ and*

$$k \;\geq\; \frac{2\beta\gamma_2^2}{(p-p_0)\delta_0^2}. \tag{2.12}$$

*Then, the minimum gradient norm $\|\nabla f(\tilde{X}_k)\|$ satisfies*

$$\mathbb{P}\left(\|\nabla f(\tilde{X}_k)\| \;\leq\; \frac{\sqrt{2}\beta^{\frac{1}{2}}(p-p_0)^{\frac{1}{2}}}{\kappa^{\frac{1}{2}}}\frac{1}{\sqrt{k}}\right) \;\geq\; 1 - \exp\left[-\frac{(p-p_0)^2}{8p}k\right].$$

**Proof.** Let

$$\epsilon \;=\; \frac{\sqrt{2}\beta^{\frac{1}{2}}(p-p_0)^{\frac{1}{2}}}{\kappa^{\frac{1}{2}}}\frac{1}{\sqrt{k}}.$$

Then (2.10) holds with equality, and $\epsilon < \delta_0/(\kappa\gamma_2)$ is guaranteed by (2.12). Hence (2.11) gives us the bound. □

We have thus proved a global rate of $1/\sqrt{k}$ for the norm of the gradient with overwhelmingly high probability.

Similarly, one can prove a worst-case bound of the order of $\mathcal{O}(\epsilon^{-2})$ for the first iteration index $K_\epsilon$ for which $\|\nabla f(\tilde{X}_{K_\epsilon})\| \leq \epsilon$, also with overwhelmingly high probability (and we note that $K_\epsilon$ is a random variable due to the randomness of the models). The proof relies on again applying (2.11), on the observation that $\mathbb{P}(K_\epsilon \leq k) = \mathbb{P}(\|\nabla f(\tilde{X}_k)\| \leq \epsilon)$, and on taking $k$ as

$$k \;=\; \left\lceil \frac{2\beta}{(p-p_0)\kappa^2\epsilon^2} \right\rceil.$$

**Theorem 2.2** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eg}, \kappa_{ef})$-fully linear with $p > p_0$ and that $\epsilon$ satisfies (2.9). Then, $K_\epsilon$ satisfies*

$$\mathbb{P}\left(K_\epsilon \;\leq\; \left\lceil \frac{2\beta}{(p-p_0)\kappa^2\epsilon^2} \right\rceil\right) \;\geq\; 1 - \exp\left[-\frac{\beta(p-p_0)\delta^2}{4p\kappa^2\epsilon^2}\right].$$

Results in expectation are a natural byproduct of our analysis. It can be shown that $\mathbb{E}(\|\nabla f(\tilde{X}_k)\|)$ is bounded by a function of the order of $k^{-\frac{1}{2}} + \exp(-k)$ up to multiplicative constants (see [19, Proposition 5.2]). It is also possible to bound the expected value of $K_\epsilon$ [24].

**Theorem 2.3** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eg}, \kappa_{ef})$-fully linear with $p > p_0$ and that $\epsilon$ satisfies (2.9). Then,*

$$\mathbb{E}\left(K_\epsilon\right) \;\leq\; c_1\epsilon^{-2} + \frac{1}{1-\exp(-c_2)},$$

*where*

$$c_1 \;=\; \frac{2\beta}{(p-p_0)\kappa^2}, \quad c_2 \;=\; \frac{(p-p_0)^2}{8p}.$$

**Proof.** Since $K_\epsilon$ only takes non-negative integer values, the expected value of $K_\epsilon$ satisfies:

$$\mathbb{E}\left(K_\epsilon\right) = \sum_{j=0}^{\infty} j\mathbb{P}\left(K_\epsilon = j\right) = \sum_{j\geq 0}\sum_{\substack{k\geq 0\\ k<j}} \mathbb{P}\left(K_\epsilon = j\right) = \sum_{k\geq 0}\sum_{\substack{j\geq 0\\ k<j}} \mathbb{P}\left(K_\epsilon = j\right) = \sum_{k\geq 0} \mathbb{P}\left(K_\epsilon > k\right).$$

Hence,

$$\begin{aligned}
\mathbb{E}\left(K_\epsilon\right) &= \sum_{0\leq k<c_1\epsilon^{-2}} \mathbb{P}\left(K_\epsilon > k\right) + \sum_{k\geq c_1\epsilon^{-2}} \mathbb{P}\left(K_\epsilon > k\right) \\
&\leq c_1\epsilon^{-2} + 1 + \sum_{k\geq c_1\epsilon^{-2}} \mathbb{P}\left(K_\epsilon > k\right) \\
&= c_1\epsilon^{-2} + 1 + \sum_{k\geq c_1\epsilon^{-2}} \mathbb{P}\left(\|\nabla f(\tilde{X}_k)\| > \epsilon\right).
\end{aligned}$$

For any index $k \geq c_1\epsilon^{-2}$, similar to (2.11), we have

$$\mathbb{P}\left(\|\nabla f(\tilde{X}_k)\| > \epsilon\right) \;\leq\; \exp(-c_2 k).$$

As a result,

$$\mathbb{E}\left(K_\epsilon\right) \;\leq\; c_1\epsilon^{-2} + 1 + \sum_{k\geq c_1\epsilon^{-2}} \exp(-c_2 k) \;\leq\; c_1\epsilon^{-2} + \sum_{k\geq 0} \exp(-c_2 k) \;\leq\; c_1\epsilon^{-2} + \frac{1}{1-\exp(-c_2)},$$

which proves the desired result. □

The obtained bound is thus

$$\mathcal{O}\left(\frac{\kappa^{-2}\epsilon^{-2}}{p-p_0}\right) + \mathcal{O}(1),$$

which matches the results of [5] for line-search methods based on probabilistic models (where $p_0$ is taken as $1/2$). We also emphasize that these expectation bounds exhibit a dependence on the inverse of $p - p_0$.

### 2.5 A note on global convergence

Our complexity theory implies (see [19, Proposition 5.1])

$$\mathbb{P}\left(\inf_{k\geq 0} \|\nabla f(X_k)\| = 0\right) \;=\; 1.$$

If we assume for all realizations of Algorithm 2.1 that the iterates never arrive at a stationary point in a finite number of iterations, then the events $\{\liminf_{k\to\infty} \|\nabla f(X_k)\| = 0\}$ and $\{\inf_{k\geq 0} \|\nabla f(X_k)\| = 0\}$ are identical and we recover the liminf result in probability one of [2, Theorem 4.2]. Note also that such a result could be derived even more directly by using the argument of [19, Lemma 3.2 and Theorem 3.1]. The paper [2] takes it one step further, establishing also a lim-type result.

## 3 Complexity of second-order trust-region methods based on probabilistic models

The same proof technology enables us to derive a similar complexity study for the class of trust-region algorithms under consideration but now with the goal of approaching or converging to second-order critical points. To do so, additional assumptions need to be enforced regarding both the quality of the models and the properties of the step resulting from the approximate solution of the trust-region subproblem. We start by the probabilistic counterpart to the concept of fully quadratic models of Definition 1.2.

**Definition 3.1** *We say that a sequence of random models $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic for a corresponding sequence $\{B(X_k, \Delta_k)\}$ if the events*

$$S_k \;=\; \{M_k \text{ is a } (\kappa_{eh}, \kappa_{eg}, \kappa_{ef})\text{-fully quadratic model of } f \text{ on } B(X_k, \Delta_k)\}$$

*satisfy $\mathbb{P}(S_0) \geq p$ and, for each $k \geq 1$, the following submartingale-like condition*

$$\mathbb{P}\left(S_k | M_0, \ldots, M_{k-1}\right) \;\geq\; p.$$

It was shown in [1] how to build fully quadratic models with high probability from quadratic interpolation and uniformly generated sample sets. It is also proved there that such a procedure may recover such models with considerably less than $(n+1)(n+2)/2$ function evaluations when the Hessian of the function is sparse.

### 3.1 Algorithm and assumptions

As before, we consider quadratic models around the iterate $x_k$, with the same definitions for $m_k$, $g_k$, and $H_k$ (and the imposition of Assumption 2.1). As curvature is now present in our analysis, we will make use of the notation $\tau_k = \lambda_{\min}(H_k)$. The solution of the trust-region subproblem has now to be second-order accurate.

**Assumption 3.1** *For every $k$, and for all realizations $m_k$ of $M_k$ (and of $X_k$ and $\Delta_k$), we are able to compute a step $s_k$ so that it satisfies both a* fraction of Cauchy decrease *and a* fraction of eigendecrease*, i.e.,*

$$m(x_k) - m(x_k + s_k) \;\geq\; \frac{\kappa_{fod}}{2} \max\left\{\|g_k\| \min\left\{\frac{\|g_k\|}{\|H_k\|}, \delta_k\right\}, -\tau_k \delta_k^2\right\}. \tag{3.1}$$

*for some constant* $\kappa_{fod} \in (0, 1]$.

The first part of (3.1) can be satisfied by a Cauchy step, while considering a step of norm $\delta_k$ along an eigenvector of the model Hessian associated with the eigenvalue $\tau_k$ yields the second-order decrease in $\delta_k^2$. A step satisfying (3.1) can be obtained by taking the one corresponding to the largest decrease caused in the model value.

Such considerations lead us from Algorithm 2.1 to Algorithm 3.1, preserving the overall structure of the method (and, in particular, the updating rules for the trust-region radius). As mentioned in the Introduction we make use of the second-order criticality measure

$$\sigma(x) \;=\; \max\left\{\|\nabla f(x)\|, -\lambda_{\min}(\nabla^2 f(x))\right\},$$

for which a natural estimator at $x_k$ is

$$\sigma^m(x_k) \;:=\; \max\left\{\|g_k\|, -\tau_k\right\}.$$

In the case of a fully quadratic model, the two quantities are related as follows.

**Lemma 3.1** *[12, Lemma 10.15] If $m_k$ is $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic on $B(x_k, \delta_k)$, then*

$$|\sigma(x_k) - \sigma^m(x_k)| \;\leq\; \kappa_\sigma \delta_k, \tag{3.2}$$

*where $\kappa_\sigma = \max\{\kappa_{eg}\delta_{\max}, \kappa_{eh}\}$.*

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**Algorithm 3.1:** A simple second-order derivative-free trust-region framework

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Fix parameters $\eta_1, \eta_2, \delta_{\max} > 0$ and $0 < \gamma_1 < 1 < \gamma_2$. Select initial $x_0$ and $\delta_0 \in (0, \delta_{\max})$.
**for** $k = 0, 1, 2, \ldots$ **do**

Build a quadratic model $m_k(x_k + s)$ of $f$, and compute $s_k$ by approximately minimizing $m_k$ in $B(x_k, \delta_k)$ so that it satisfies (3.1). If $\rho_k \geq \eta_1$, set $x_{k+1} = x_k + s_k$ and

$$\delta_{k+1} \;=\; \begin{cases} \min\{\gamma_2\delta_k, \delta_{\max}\} & \text{if } \sigma^m(x_k) \geq \eta_2\delta_k, \\ \gamma_1\delta_k & \text{otherwise.} \end{cases}$$

Otherwise, set $x_{k+1} = x_k$ and $\delta_{k+1} = \gamma_1\delta_k$.
**end**

---

**Lemma 3.2** *If $m_k$ is $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic on $B(x_k, \delta_k)$ and*

$$\delta_k \;<\; \left(\kappa_\sigma + \max\left\{\eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}\delta_{\max}}{\kappa_{fod}(1-\eta_1)}, \frac{4\kappa_{ef}}{\kappa_{fod}(1-\eta_1)}\right\}\right)^{-1} \sigma(x_k),$$

*then at the $k$-th iteration the step is taken ($x_{k+1} = x_k + s_k$) and $\delta_k$ is increased.*

**Proof.** The proof is similar to the one of Lemma 2.1. Combining (3.2) with the error bound of Lemma 3.1 yields

$$\delta_k \;<\; \min\left\{\frac{1}{\eta_2}, \frac{1}{\kappa_{bhm}}, \frac{\kappa_{fod}(1-\eta_1)}{4\kappa_{ef}}, \frac{\kappa_{fod}(1-\eta_1)}{4\kappa_{ef}\delta_{\max}}\right\} \sigma^m(x_k).$$

This allows to directly conclude that $\rho_k \geq \eta_1$ (see [12, Lemma 10.17]). Also, since the first term in the minimum gives $\eta_2\delta_k \leq \sigma^m(x_k)$, the trust-region radius is increased.

### 3.2 Behavior of the trust-region radius

Given the decrease properties now enforced by the algorithm, similar to Lemma 2.2, we can prove that the sequence of the trust-region radii is cube summable. Let $\mathcal{K}_{2nd}$ be the set of indexes corresponding to iterations where the step is taken and the trust-region radius is increased, i.e.,

$$\mathcal{K}_{2nd} \;=\; \{k \in \mathbb{N} : \rho_k \geq \eta_1 \text{ and } \sigma^m(x_k) \geq \eta_2 \delta_k\}\,.$$

**Lemma 3.3** *For any realization of Algorithm 3.1,*

$$\sum_{k=0}^{\infty} \delta_k^3 \;\leq\; \beta_{2nd} \;:=\; \frac{\gamma_2^3}{1-\gamma_1^3}\left[\frac{\delta_0^3}{\gamma_2^3} + \frac{f_0 - f_{\text{low}}}{\eta_{2nd}}\right],$$

*where*

$$\eta_{2nd} \;=\; \eta_1\eta_2\frac{\kappa_{fod}}{2}\min\left\{\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}\frac{1}{\delta_{\max}}, 1\right\}.$$

**Proof.** Similar to the proof of Lemma 2.2, we only need to consider the case where $|\mathcal{K}_{2nd}| = \infty$. For any $k \in \mathcal{K}_{2nd}$, if $\sigma^m(x_k) = \|g_k\|$, we have by Assumption 3.1 that

$$\begin{aligned} f(x_k) - f(x_{k+1}) &\geq \eta_1\left[m_k(x_k) - m_k(x_k + s_k)\right] \\ &= \eta_1\frac{\kappa_{fod}}{2}\|g_k\|\min\left\{\frac{\|g_k\|}{\|H_k\|}, \delta_k\right\} \\ &\geq \eta_1\eta_2\frac{\kappa_{fod}}{2}\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}\delta_k^2 \\ &\geq \eta_1\eta_2\frac{\kappa_{fod}}{2}\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}\frac{1}{\delta_{\max}}\delta_k^3. \end{aligned}$$

Meanwhile, if $\sigma^m(x_k) = -\tau_k$, a similar reasoning leads to:

$$f(x_k) - f(x_{k+1}) \;\geq\; \eta_1\eta_2\frac{\kappa_{fod}}{2}\delta_k^3.$$

As a result, for any index $k \in \mathcal{K}_{2nd}$, one has

$$f(x_k) - f(x_{k+1}) \;\geq\; \eta_1\eta_2\frac{\kappa_{fod}}{2}\min\left\{\min\left\{\frac{\eta_2}{\kappa_{bhm}}, 1\right\}\frac{1}{\delta_{\max}}, 1\right\}\delta_k^3 \;=\; \eta_{2nd}\delta_k^3.$$

The rest of the proof follows the lines of Lemma 3.3 replacing the squares of the trust-region radii by cubes. □

### 3.3 Number of iterations with fully quadratic models

An upper bound on the number of iterations where the models are fully quadratic is derived similarly as in the first-order case, and all that is required is to define $\tilde{x}_k \in \{x_0, \ldots, x_k\}$ such that $\sigma(\tilde{x}_k)$ is a minimum value among $\{\sigma(x_0), \ldots, \sigma(x_k)\}$ and $z_k$ as the binary variable indicating if $m_k$ is $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic or not.

**Lemma 3.4** *Given a realization of Algorithm 3.1 and a positive integer $k$,*

$$\sum_{l=0}^{k-1} z_l \;\leq\; \frac{\beta_{2nd}}{(\min\{\delta_0/\gamma_2, \kappa_{2nd}\sigma(\tilde{x}_k)\})^3} + p_0 k,$$

*where*

$$\kappa_{2nd} \;=\; \left(\kappa_\sigma + \max\left\{\eta_2, \kappa_{bhm}, \frac{4\kappa_{ef}\delta_{\max}}{\kappa_{fod}(1-\eta_1)}, \frac{4\kappa_{ef}}{\kappa_{fod}(1-\eta_1)}\right\}\right)^{-1}.$$

### 3.4 Worst case complexity and global rate

The derivation of the second-order complexity theory is based on observing that Lemma 3.4 implies now

$$\left\{\|\sigma(\tilde{X}_k)\| \geq \epsilon\right\} \;\subset\; \left\{\sum_{l=0}^{k-1} Z_l \leq \frac{\beta_{2nd}}{\kappa_{2nd}^3\epsilon^3} + p_0 k\right\},$$

for any $\epsilon$ satisfying

$$0 \;<\; \epsilon \;<\; \frac{\delta_0}{\kappa_{2nd}\gamma_2}. \tag{3.3}$$

Then a result identical to Lemma 2.4 can be ensured considering the definition of $Z_l$ based on fully quadratic models and replacing the probabilistic fully linear assumption by the probabilistic fully quadratic one. The rest of the analysis proceeds similarly with minor changes in constants. The global rate is now $1/\sqrt[3]{k}$, as shown below.

**Theorem 3.1** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic with $p > p_0$ and*

$$k \;\geq\; \frac{2\beta_{2nd}\gamma_2^3}{(p-p_0)\delta_0^3}.$$

*Then, the minimum second-order criticality measure $\sigma(\tilde{X}_k)$ satisfies*

$$\mathbb{P}\left(\sigma(\tilde{X}_k) \;\leq\; \frac{\sqrt[3]{2}\beta_{2nd}^{\frac{1}{3}}(p-p_0)^{\frac{1}{3}}}{\kappa_{2nd}^{\frac{1}{3}}}\frac{1}{\sqrt[3]{k}}\right) \;\geq\; 1 - \exp\left[-\frac{(p-p_0)^2}{8p}k\right].$$

Similar conclusions as those of Subsection 2.5 can be drawn here regarding global convergence results of the inf and liminf type that can be deduced from the above result, and regarding their interplay with the second-order convergence theory of [2]. The only difference from the first-order case is the difficulty in obtaining a lim-type result [2].

A worst-case complexity bound of the order of $\epsilon^{-3}$ is established similarly with overwhelmingly high probability.

**Theorem 3.2** *Suppose that $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic with $p > p_0$ and that $\epsilon$ satisfies (3.3). Let $K_\epsilon$ be the first iteration index for which $\sigma(\tilde{X}_{K_\epsilon}) \leq \epsilon$. Then, $K_\epsilon$ satisfies*

$$\mathbb{P}\left(K_\epsilon \;\leq\; \left\lceil\frac{2\beta_{2nd}}{(p-p_0)\kappa_{2nd}^3\epsilon^3}\right\rceil\right) \;\geq\; 1 - \exp\left[-\frac{\beta_{2nd}(p-p_0)}{4p\kappa_{2nd}^3\epsilon^3}\right].$$

As in Theorem 2.3, we can also bound the expected number of iterations needed to reach the desired accuracy.

**Theorem 3.3** *Suppose at $\{M_k\}$ is $(p)$–probabilistically $(\kappa_{eh}, \kappa_{eg}, \kappa_{ef})$-fully quadratic with $p > p_0$ and that $\epsilon$ satisfies (3.3). Then,*

$$\mathbb{E}\,(K_\epsilon) \;\leq\; c_3\epsilon^{-3} + \frac{1}{1-\exp(-c_2)},$$

*where*

$$c_3 \;=\; \frac{2\beta_{2nd}}{(p-p_0)\kappa_{2nd}^3},$$

*and $c_2$ is defined as in Theorem 2.3.*

# 4 Remarks on open questions

Recently a number of papers have appeared proposing and analyzing derivative-free trust-region methods for the unconstrained optimization of a stochastic function. In this setting, what is observable is $\tilde{f}(x, \varepsilon(\omega))$, where $\varepsilon$ is a random variable. The objective function $f(x)$ may be given by $\mathbb{E}(\tilde{f}(x, \varepsilon))$. One approach [26] extended the framework [11] using Sample-Average Approximation (SAA). The number of observations in each Monte Carlo oracle may be up to $\mathcal{O}(\delta_k^{-4})$. First-order global convergence was proved with probability one but for algorithmic parameters that depend on unknown problem constants. Another approach [6] extended trust-region methods based on probabilistic models [2] to cover also probabilistic estimates of the objective function. In the non-biased case with $f(x) = \mathbb{E}(\tilde{f}(x, \varepsilon))$, the probabilistic assumptions can be ensured by SAA within $\mathcal{O}(\delta_k^{-4})$ observations. This approach can also handle biased cases like failures in function evaluations or even processor failures (thus accommodating gradient failures when using finite differences). First-order global convergence was also proved with probability one but again for algorithmic parameters that depend on unknown problem constants. A similar approach [22] led to first-order global convergence in probability (weaker than with probability one), but under more practical assumptions. Very recently, a paper [3] developed a complexity analysis for the approach in [6] showing a complexity bound of $\mathcal{O}(\epsilon^{-2})$ on the expected number of iterations needed to satisfy $\|\nabla f(X_k)\| \leq \epsilon$ (again under unverifiable assumptions on algorithmic parameters).

It is an open question whether our proof technology can improve upon these stochastic optimization approaches in the sense of establishing global convergence with probability one and global rates and complexity bounds with overwhelmingly high probability without unverifiable assumptions on algorithmic parameters. Another challenging prospect for future work is to develop better rates and bounds for the convex and strongly cases for either deterministic or stochastic functions.

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