Projected Gradient Descent Efficiently* Solves the Trust Region Subproblem

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Abstract

We show that projected gradient descent asymptotically converges to a global minimizer of the trust region subproblem. We remark on next steps in this project at the end.

1 Introduction

Trust region methods are sequential programming procedures in which heuristics are used to approximately solve a general optimization problem through multiple constrained quadratic programs. As a subroutine, these methods formulate and solve many instances of the following optimization problem

$$\begin{array}{ll} \text{minimize} & (1/2)x^T Ax + b^T x \\ \text{subject to} & \|x\| \leq R \end{array} \tag{1}$$

with variable $x \in \mathbf{R}^n$. The problem data are a symmetric matrix $A \in \mathbf{R}^{n \times n}$, a vector $b \in \mathbf{R}^n$, and a radius parameter $R > 0$. Crucially, the matrix A is possibly indefinite. Problem (1) is referred to as the *trust region subproblem*. Here, we are interested in procedures that provably return a (ε-suboptimal) global minimizer $x \in \mathbf{R}^n$.

1.1 Previous works

The trust region subproblem is well-studied, and thus there many previous works worth mentioning. In earlier papers, the problem was solved either via subspace methods such as Steihaug-Toint, where no global convergence guarantees to our knowledge have proven, or using fast eigenvector and eigenvalue computation procedures like the Lanczos method [CGT00, EG09, GLRT99, GRT10]. More recently, however, some authors have provided convergence guarantees for this problem. For example, by reducing the trust region subproblem to a sequence of approximate eigenvector computations, Hazan and Koren [HK16] demonstrate that $\tilde{O}(1/\sqrt{\varepsilon})$[1] matrix-vector multiplies are enough to guarantee an ε-suboptimal point. In [HK17], Nguyen and Kilinç-Karzan reduce the trust region problem to a convex QCQP using eigenvector calculations, where first-order methods apply.

However, perhaps the most obvious algorithm to solve (1), is the *projected gradient method*, which we study in this paper. To our knowledge, the only previous work that analyzes the convergence properties of this procedure on (1) is [TA98], where Tao and An augment this procedure

*Technically, a conjecture.

[1] We use the $\tilde{O}(\cdot)$ notation to hide logarithmic factors.

by a restarting scheme, requiring possibly $O(d)$ restarts, which could scale poorly for large-scale problems. We also mention a recent work by Carmon and Duchi [CD16], studying the closely related problem

$$\text{minimize } (1/2)x^T Ax + b^T x + (\rho/3)\|x\|_2^3, \tag{2}$$

in variable $x \in \mathbf{R}^n$, again with A symmetric, possibly indefinite, and parameter $\rho > 0$. The authors analyze gradient descent, proving that $\tilde{O}(1/\varepsilon)$ gradient steps are enough to output an ε-suboptimal point.

In this paper we demonstrate that the projected gradient method on (1) asymptotically converges to a global minimizer on the trust region subproblem. In §2 we prove that projected gradient descent is a descent method, in particular, converging to the global minimizer of the objective in problem (1).

1.2 Notation and classical results

In the sequel, we refer to the objective function as $f : \mathbf{R}^n \to \mathbf{R}$, given by $f(x) = (1/2)x^T Ax + 2b^T x$. Additionally, the constraint set is the closed ball $\mathcal{B}(R) \triangleq \{x \in \mathbf{R}^n \mid \|x\| \leq R\}$, where $\|\cdot\|$ denotes the Euclidean norm. We use the notation $x^\star$ to denote the global minimum of f when it is unique, so that $x^\star = \operatorname{argmin}_{x \in \mathcal{B}(R)} f(x)$. We use $f^\star$ to denote the optimal value of f, so that $f^\star = \inf_{x \in \mathcal{B}(R)} f(x)$. Hence, when $x^\star$ exists, $f^\star = f(x^\star)$.

We fix the eigendecomposition of $A = UDU^T$, where $D = \mathbf{diag}(\lambda_1, \dots, \lambda_n)$, and U has orthonormal columns u_i. We impose without loss that $\lambda_1 \leq \lambda_2 \leq \cdots \leq \lambda_n$. By $\|\cdot\|_{\text{op}}$, we denote the ℓ_2-operator norm $\|M\|_{\text{op}} = \sup_{\|x\|=1} \|Mx\|$, for any $M \in \mathbf{R}^{n \times n}$. A useful identity is that $\|M\|_{\text{op}} = \max_i |\lambda_i(M)|$ when M is a symmetric $n \times n$ matrix. We will put $\beta \triangleq \|A\|_{\text{op}}$.

Additionally, say a differentiable function $g : \mathbf{R}^n \to \mathbf{R}$ is L-smooth on convex set $C \subset \mathbf{R}^n$, provided that

$$\|\nabla g(x) - \nabla g(y)\| \leq L\|x - y\| \qquad \text{for any } x, y \in C.$$

It is well known that this implies

$$g(x) - g(y) \leq \nabla g(y)^T (x - y) + \frac{L}{2}\|x - y\|^2 \qquad \text{for any } x, y \in C. \tag{3}$$

Equivalently, $\|g(x)\|_{\text{op}} \leq L$, for Lebesgue almost every $x \in C$. For nonempty, closed, convex sets $C \subset \mathbf{R}^n$, associate the projection operator $\Pi_C : \mathbf{R}^n \to C$ given by

$$\Pi_C(x) = \operatorname*{argmin}_{y \in C} \left(\frac{1}{2}\|x - y\|^2 \right),$$

for any $x \in \mathbf{R}^n$. In the sequel we denote by $I : \mathbf{R}^n \to \mathbf{R}^n$ the identity operator on $\mathbf{R}^n$.

2 Asymptotic convergence to a global minimizer

2.1 Projected gradient descent

Projected gradient descent (PGD) begins at an initialization $x^{(0)} \in \mathbf{R}^n$ and generates iterates

$$y^{(k+1)} = x^{(k)} - \eta \nabla f(x^{(k)}) \tag{4}$$

$$x^{(k+1)} = \Pi_{\mathcal{B}(R)}(y^{(k+1)}), \tag{5}$$

for nonnegative integer k and step size η. We make the following assumptions about this procedure.

Assumption 2.1. In (4), the step size η satisfies $0 < \eta < \frac{1}{\beta}$.

Assumption 2.2. The initial point satisfies $x^{(0)} = 0$.

2.2 Asymptotic convergence to a global minimizer

We begin by providing a few results characterizing the iterates of projected gradient descent.

Lemma 2.3. *Let Assumptions 2.1 and 2.2 hold. Then the iterates of gradient descent satisfy* $(u_i^T x^{(k)})(u_i^T b) \leq 0$ *for all* $i = 1, \dots, n$ *and every* $k \geq 0$. *0*

Proof. Evidently, the claim holds due to Assumption 2.2 when $k = 0$. Thus, inductively assume that for some k

$$(u_i^T x^{(k)})(u_i^T b) \leq 0 \qquad \text{for all } i = 1, \dots, n. \tag{6}$$

By definition, $x^{(k+1)} = cy^{(k+1)}$ for some $c \in (0, 1]$, so it suffices to ensure $(u_i^T y^{(k+1)})(u_i^T b) \leq 0$. Using (6) along with Assumption 2.1,

$$(u_i^T y^{(k+1)})(u_i^T b) = (1 - \eta\lambda_i)(u_i^T x^{(k)})(u_i^T b) - \eta(u_i^T b)^2 \leq 0,$$

since $\eta < \beta^{-1} < \lambda_i^{-1}$, for all $i = 1, \dots, n$. This proves the result. $\square$

It will be useful to have the following variational characterization of these iterates.

Lemma 2.4. *Let Assumption 2.1 hold. Then, for all* $k > 0$, *iterates of projected gradient descent satisfy*

$$x^{(k+1)} = \operatorname*{argmin}_{x \in \mathcal{B}(R)} \left(\nabla f(x^{(k)})^T (x - x^{(k)}) + \frac{1}{2\eta} \|x - x^{(k)}\|^2 \right). \tag{7}$$

Proof. Basic manipulations imply

$$\nabla f(x^{(k)})^T (x - x^{(k)}) + \frac{1}{2\eta} \|x - x^{(k)}\|^2 = \frac{1}{2\eta} \|x - (x^{(k)} - \eta \nabla f(x^{(k)}))\|^2 - \frac{\eta}{2} \|\nabla f(x^{(k)})\|^2.$$

Since $\eta > 0$ and $\nabla f(x^{(k)})$ is constant with respect to the minimization in (7),

$$\operatorname*{argmin}_{x \in \mathcal{B}(R)} \left(\nabla f(x^{(k)})^T (x - x^{(k)}) + \frac{1}{2\eta} \|x - x^{(k)}\|^2 \right) = \operatorname*{argmin}_{x \in \mathcal{B}(R)} \left(\frac{1}{2} \|x - (x^{(k)} - \eta \nabla f(x^{(k)}))\|^2 \right).$$

The claim now immediately follows from the projected gradient descent iteration, (4) and (5). $\square$

Lemma 2.5 (PGD is a descent method)**.** *Let Assumption 2.1 hold. Then for any* $k > 0$,

$$f(x^{(k+1)}) - f(x^{(k)}) \leq \left(\frac{\beta}{2} - \frac{1}{2\eta} \right) \|x^{(k+1)} - x^{(k)}\|^2.$$

Proof. As $x^{(k)} \in \mathcal{B}(R)$, Lemma 2.4 yields

$$\nabla f(x^{(k)})^T (x^{(k+1)} - x^{(k)}) \leq -\frac{1}{2\eta} \|x^{(k+1)} - x^{(k)}\|^2.$$

Since f is β-smooth, the smoothness inequality (3) implies

$$f(x^{(k+1)}) - f(x^{(k)}) \leq \nabla f(x^{(k)})^T (x^{(k+1)} - x^{(k)}) + \frac{\beta}{2} \|x^{(k+1)} - x^{(k)}\|^2 \leq \left(\frac{\beta}{2} - \frac{1}{2\eta} \right) \|x^{(k+1)} - x^{(k)}\|^2,$$

as needed. $\square$

The following result provides a useful optimality criterion for the trust region subproblem (1).

Theorem 2.6 ([CGT00], Corollary 7.2.2.)**.** *A point $x \in \mathcal{B}(R)$ is a global minimizer of f subject to $\|x\| \le R$ if and only if for some $z \ge 0$,*

$$(A + zI)x = -b \qquad A + zI \succeq 0 \qquad z(\|x\| - R) = 0.$$

Furthermore, x is unique if and only if $A + zI \succ 0$. In this case, we write $x = x^\star$.

An important special case from Theorem 2.6 is that when $\|x^\star\| < R$, then $\nabla f(x^\star) = 0$. Furthermore, with a simplifying assumption, we can provide a set of simpler optimality criterion.

Corollary 2.7. *Suppose that $b^T u_1 \neq 0$. Then if for some $\tilde{x} \in \mathcal{B}(R)$, it holds that*

$$(A + zI)\tilde{x} = -b \qquad z(\|\tilde{x}\| - R) = 0 \qquad (u_1^T \tilde{x})(u_1^T b) \le 0 \tag{8}$$

then $\tilde{x}$ is the unique global minimizer to f over $\mathcal{B}(R)$, i.e., $\tilde{x} = x^\star$.

Proof. Focusing on the first condition, $b^T u_1 = -(z + \lambda_1)(u_1^T \tilde{x})$. Thus, $b^T u_1 \neq 0$ implies that $(u_1^T \tilde{x}) \neq 0$ and $z + \lambda_1 \neq 0$, strengthing the third condition to $(u_1^T \tilde{x})(u_1^T b) < 0$. But this implies that $z + \lambda_1 = -(u_1^T b)(u_1^T \tilde{x})/(u_1^T \tilde{x})^2 > 0$, which implies that $z > \lambda_i$ for all i, whence $A + zI \succ 0$, establishing the result. □

Proposition 2.8 (Asymptotic convergence)**.** *Let Assumption 2.1 and 2.2 hold. Furthermore, suppose $b^T u_1 \neq 0$. Then, the iterates of projected gradient descent satisfy $x^{(k)} \to x^\star$ and $f(x^{(k)}) \downarrow f(x^\star)$, as $k \to \infty$.*

Proof. Lemma 2.5 and Assumption 2.1 yield the following bound for any integer $T \ge 1$,

$$\left(\frac{1}{2\eta} - \frac{\beta}{2}\right) \sum_{k=0}^{T-1} \|x^{(k+1)} - x^{(k)}\|^2 \le f(x^{(0)}) - f(x^{(T)}) \le f(x^{(0)}) - f^\star. \tag{9}$$

We demonstrate shortly that the display in (9) implies that $x^{(k)} \to x^\star$. Conditional on this fact, the result $f(x^{(k)}) \downarrow f(x^\star)$ immediately follows from continuity and Lemma 2.5.

Define $\phi : \mathcal{B}(R) \to \mathbf{R}^n$ by $\phi(x) = \Pi_{\mathcal{B}(R)}(x - \eta \nabla f(x)) - x$, for points $x \in \mathcal{B}(R)$. The bound in (9) implies that the displayed series is convergent as $T \to \infty$ and thus $\phi(x^{(k)}) \to 0$. Note also that the map ϕ is evidently continuous, as ∇f is β-Lipschitz and $\Pi_{\mathcal{B}(R)}$ is non-expansive, thus 1-Lipschitz.

Suppose now that $\tilde{x} \in \mathcal{B}(R)$ is a subsequential limit of $(x^{(k)})$ (indeed, one exists since this sequence is bounded), and observe by continuity $\phi(\tilde{x}) = 0$. To show that $\tilde{x} = x^\star$, by Corollary 2.7, it suffices to establish the first two conditions of (8), as the latter immediately holds by Lemma 2.3. Observe first that $\phi(\tilde{x}) = 0$ implies that for some $c \ge 1$,

$$\tilde{x} - \eta \nabla f(\tilde{x}) = c\tilde{x}. \tag{10}$$

Indeed, setting $z = (c - 1)\eta^{-1}$, this implies that $(A + zI)\tilde{x} = -b$. If $\tilde{x}$ lies on the boundary of $\mathcal{B}(R)$, so that $\|\tilde{x}\| = R$, then as $z \ge 0$, this establishes (8) and hence $\tilde{x} = x^\star$. On the other hand, if $\tilde{x}$ is in the interior of $\mathcal{B}(R)$, so that $\|\tilde{x}\| < R$, then $\phi(\tilde{x}) = 0$ implies that $c = 1$ in (10), and thus $z = 0$, once again establishing (8), hence also that $\tilde{x} = x^\star$. As this analysis applies to any such subsequential limit $\tilde{x}$ of the bounded sequence $(x^{(k)})$, the claim is now proven. □

We provide some numerical evidence demonstrating the effect of Proposition 2.8 in Figure 1.

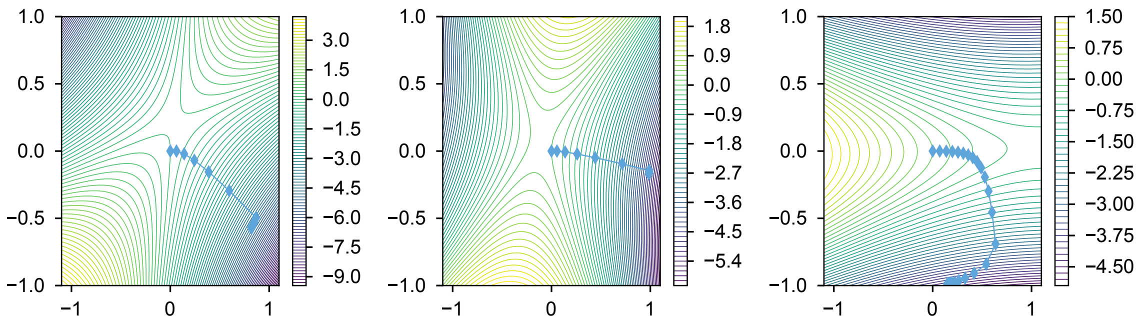

Figure 1: Three random indefinite instances of the the trust region subproblem (1), with $\eta = 1/(2\|A\|_{\text{op}})$ and $x^{(0)} = 0$. From left to right, the eigenvalues are $\lambda = (-8, 3)$, $\lambda = (-9, 3)$, and $\lambda = (-7, 1)$. The dots indicate iterates of projected gradient descent and the lines indicate the process $\dot{x} = -\nabla f(x)$.

3 Non-asymptotic convergence guarantees

We plan to continue this work by providing convergence rates for this problem. In particular, the goal now is to prove the equivalent of Theorem 3.1, [CD16].

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