Projected Gradient Descent Solves the Trust Region Problem

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Introduction

Trust region methods are sequential programming procedures which formulate and solve many instances of the following **trust region problem**

$$\begin{array}{ll}\text{minimize} & (1/2)x^TAx + b^Tx \\ \text{subject to} & \|x\| \le R\end{array} \qquad (1)$$

with variable x. Do **not** assume A is definite.

Recall... If $A \in \mathbf{R}^{n\times n}$ is symmetric then for Λ, orthonormal U,

$$A = U\Lambda U^T \quad \Lambda = \mathbf{diag}(\lambda) \quad \lambda_1 \le \cdots \le \lambda_n \quad U = [u_1 \mid \cdots \mid u_n]$$

Also have for $f : \mathbf{R}^n \to \mathbf{R}$ with L-Lipschitz gradient

$$f(x) - f(y) \le \nabla f(y)^T(x-y) + \frac{L}{2}\|x-y\|^2$$

Projected Gradient Descent

We investigate the behavior of **projected gradient descent** (PGD) which begins at an initialization $x^{(0)} \in \mathbf{R}^n$ and generates iterates

$$\begin{aligned} y^{(k+1)} &= x^{(k)} - \eta\nabla f(x^{(k)}) \\ x^{(k+1)} &= \Pi_{\mathcal{B}(R)}(y^{(k+1)}). \end{aligned}$$

We make the following assumptions about this procedure:

- step size satisfies $0 < \eta < 1/\|A\|_{\mathrm{op}}$
- initialize at $x^{(0)} = 0 \in \mathbf{R}^n$.

Variational interpretation

Complete the square to verify that PGD iterates satisfy (cf. Nesterov)

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

(Essentially) immediately implies that PGD is a descent method:

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

Optimality criterion

The following result provides a useful optimality condition.

Theorem 1 ([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 iff $A + zI \succ 0$. In this case, we write $x = x^\star$.

We show (and make use of) the following weaker statement.

Corollary 2. *Suppose that $b^Tu_1 \ne 0$. Then if at $\tilde{x} \in \mathcal{B}(R)$, $z \ge 0$, have*

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

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

Asymptotic result

Under mild assumptions we obtain the following result.

Proposition 3 (Asymptotic convergence). *Let the step-size and initialization assumptions hold, and assume further that suppose $b^Tu_1 \ne 0$. Then as $k \to \infty$, the iterates of projected gradient descent satisfy $x^{(k)} \to x^\star$ and $f(x^{(k)}) \downarrow f(x^\star)$, where $x^\star$ is the unique global minimizer to f over $\mathcal{B}(R)$.*

- In English, unless you have a pretty sick trust region problem, PGD eventually gets to the global minimizer of f.
- *Disclaimer:* this statement (nor its proof) admit an obvious convergence rate. This means, you could get to opt quite slowly (though not in practice, ...)

Convergence proof

Idea: Show that $\|x^{(k+1)} - x^{(k)}\|_2^2 \to 0$ and hope that's enough.

- Use descent method inequality to show that
  $$x^{(k+1)} - x^{(k)} \to \infty. \qquad (2)$$
- Introduce continuous map $g : \mathcal{B}(R) \to \mathbf{R}^n$,
  $$x \mapsto \Pi_{\mathcal{B}(R)}(x - \eta\nabla f(x)) - x$$
  - this is just a single PGD step
  - can rewrite Eq. (2) as $g(x^{(k)}) \to 0$
- Consider a subsequential limit (one exists since $x^{(k)}$ lie in compact set) L
  - Use continuity to conclude that limits satisfy $g(L) = 0$
  - Use the optimality criterion, projection map, and case work to analyze $\ker g$
  - Conclude that $L = x^\star$
- The analysis above applies to any limit point, so we're done (here we use the fact that $\{x^{(k)}\} \subset K = \mathcal{B}(R)$)

Numerical example

Example below has $A \in \mathbf{R}^{2\times 2}$ with $\lambda_1(A) = -8$, $\lambda_2(A) = 3$. We took $R = 1$, $\eta = 1/16$. Note that $b^Tu_1 = 0.790857$ and $\|x^\star\| = 1$.

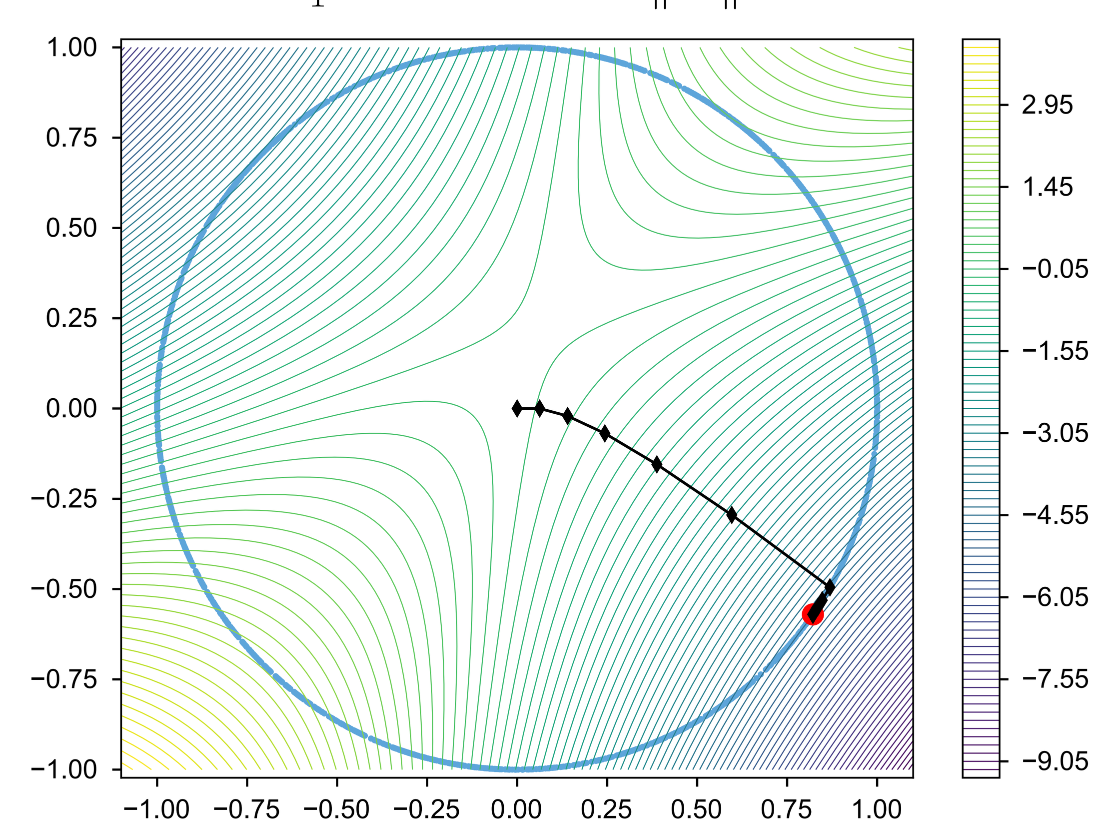

Figure 1: Trust region problem. Black diamonds are $x^{(k)}$, red dot is $x^\star$, blue circle is $\partial\mathcal{B}(R)$.

Ideas for non-asymptotics

Basically, it looks like a non-asymptotic proof of convergence could follow the following lines (roughly)

1. Show that there is a τ^{bd} such that when $t \ge \tau^{\mathrm{bd}}$, we can guarantee that you've used projection at least once (*i.e.*, you've hit the boundary)
   $$\|y^{(t)}\|^2 = \eta^2\left\|\sum_{k=0}^{t-1}(I - \eta A)b\right\|^2 = \sum_{i=1}^n\left(\frac{b^Tu_i}{\lambda_i}\right)^2(1 - (1 - \eta\lambda_i)^t)^2 > R^2$$
2. Show that once the boundary is reached, successive iterates remain on the boundary. In other words, $\|y^{(t+1)}\| > R$ for all $t \ge \tau^{\mathrm{bd}}$.

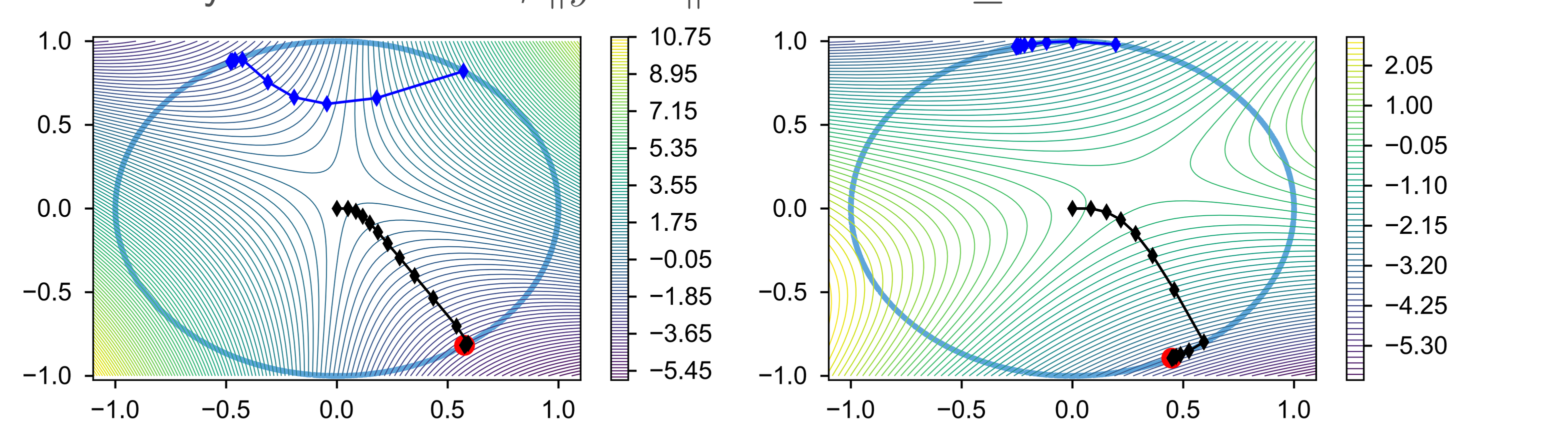

Figure 2: Initializing randomly on the boundary of $\mathcal{B}(R)$ doesn't always work!

- Importantly, property of remaining on boundary for all successive iterates is not true of all points $x \in \partial\mathcal{B}(R)$, ...

3. Show a contraction inequality like (for $k \ge \tau^{\mathrm{bd}}$)
   $$\|x^{(k+1)} - x^\star\| \le (1 - \epsilon)\|x^{(k)} - x^\star\| \qquad (\epsilon > 0)$$

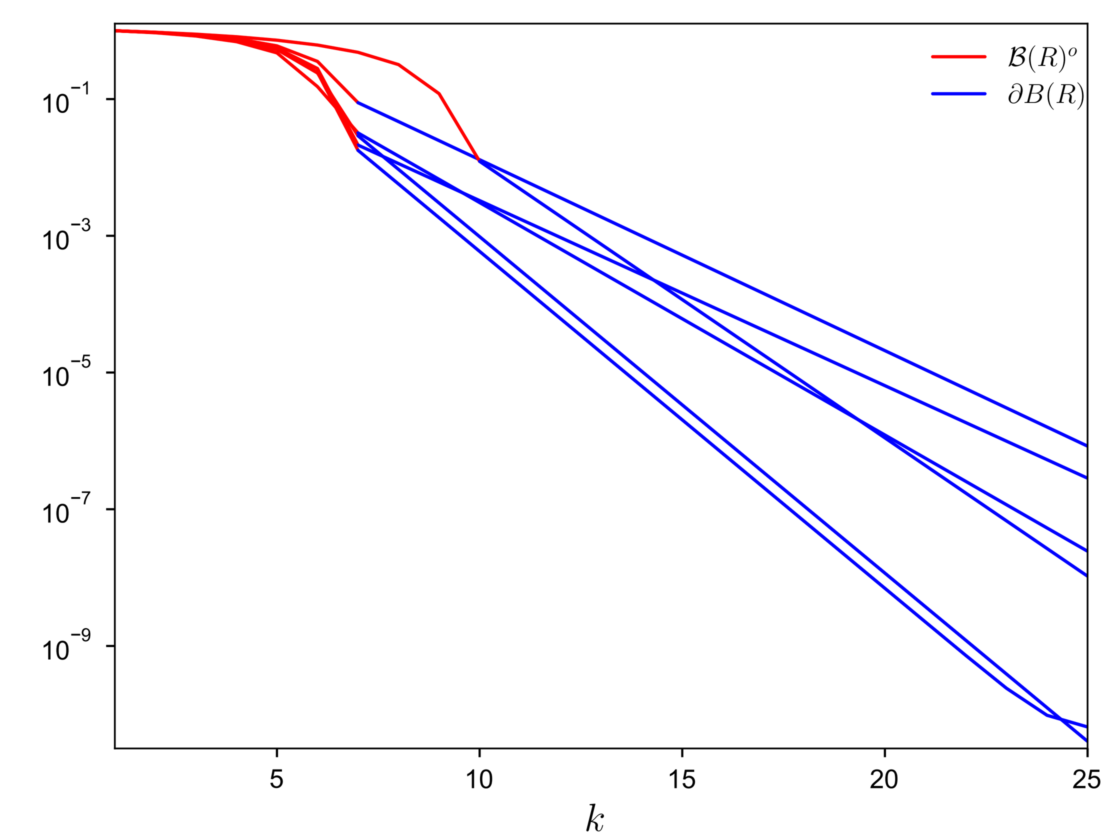

Figure 3: Two regimes of convergence

4. Conclude via smoothness, standard GD analysis for smooth problems.

References & Acknowledgements

[CD16] Yair Carmon and John C. Duchi. Gradient descent efficiently finds the cubic-regularized non-convex Newton step. *CoRR*, abs/1612.00547, 2016.

[CGT00] Andrew R. Conn, Nicholas I. M. Gould, and Philippe L. Toint. *Trust-region methods*. Society for Industrial and Applied Mathematics, Philadelphia, PA, USA, 2000.

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