Short-step Methods Are Not Strongly Polynomial-Time

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Abstract

Short-step methods are an important class of algorithms for solving convex constrained optimization problems. In this short paper, we show that under very mild assumptions on the self-concordant barrier and the width of the ℓ_2 -neighbourhood, any short-step interior-point method is not strongly polynomial-time.

1 Introduction

An algorithm for solving linear programming problems is said to be strongly polynomial-time if the required number of arithmetic operations is a polynomial in the numbers of variables and constraints, independent of the bit-length for encoding the problem instance. A major open problem in optimization and computer science is whether there exists a strongly polynomial-time algorithm for solving linear programming problems. The purpose of this short note is to prove that short-step methods are not strongly polynomial-time.¹

2 Preliminaries

Consider the linear programming problem

minimize
$$c^{\top}x$$

subject to $Ax \le b$, (P)

where $c \in \mathbb{R}^n$, $b \in \mathbb{R}^m$ and $A \in \mathbb{R}^{m \times n}$. Denote the feasible region of problem (P) and its interior by \mathcal{F} and \mathcal{F}° , respectively. We assume that \mathcal{F} is bounded and that \mathcal{F}° is non-empty. For simplicity, we denote the optimality gap of a feasible point $x \in \mathcal{F}$ by

$$\operatorname{\mathsf{gap}}(x) = c^{\top} x - \min_{x' \in \mathcal{F}} c^{\top} x'.$$

The notion of self-concordant barriers plays vital role in the study of interior-point methods. Let $\mathcal{K} \subseteq \mathbb{R}^n$ be a proper convex domain, *i.e.*, a convex set with non-empty

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¹After we finished this work, we were informed that a similar result has been obtained independently by another group [2] around the same time, via a different approach.

interior and containing no 1-dimensional affine subspace. A function $\phi: \operatorname{int}(\mathcal{K}) \to \mathbb{R}$ is said to be a barrier on \mathcal{K} if $\phi(x) \to +\infty$ as $x \to \partial \mathcal{K}$. A three times continuously differentiable convex function ϕ is said to be self-concordant on \mathcal{K} if for any $x \in \operatorname{int}(\mathcal{K})$ and $h \in \mathbb{R}^n$,

$$|D^3\phi(x)[h, h, h]| \le 2(D^2\phi(x)[h, h])^{\frac{3}{2}}.$$

If ϕ additionally satisfies that for any $x \in \text{int}(\mathcal{K})$ and $h \in \mathbb{R}^n$,

$$|\mathrm{D}\phi(x)[h]| \le \left(\nu \,\mathrm{D}^2\phi(x)[h,h]\right)^{\frac{1}{2}},$$

then ϕ is said to be ν -self-concordant on \mathcal{K} . This paper focuses on the proper convex domain $\mathcal{K} = \mathcal{F}$, which is a polytope defined by the linear inequalities $Ax \leq b$. A standard self-concordant barrier on \mathcal{F} is the logarithmic barrier

$$\phi_{\ln}(x) = -\sum_{i=1}^{m} \ln(b - Ax)_i.$$

Given a self-concordant barrier ϕ on \mathcal{F} , we consider the problem

minimize
$$c^{\top}x + \mu \phi(x)$$

subject to $Ax < b$. (P_{μ})

From [3, Section 5.3.4], for any $\mu > 0$, there exists a unique minimizer $x^{\phi}(\mu)$ to problem (P_{μ}) . We call $x^{\phi}(\mu)$ the μ -analytic center of problem (P) associated with the self-concordant barrier ϕ . The central path of problem (P) associated with ϕ is then defined as (the image of) the curve $\mu \mapsto x^{\phi}(\mu)$ for $\mu > 0$. By [3, Theorem 5.3.10], $x^{\phi}(\mu)$ converges to an optimal solution to problem (P) as $\mu \to 0$.

By [3, Theorem 5.1.6], $\nabla^2 \phi(x)$ is positive definite for any $x \in \mathcal{F}^{\circ}$. This allows us to define a norm

$$||h||_x = \sqrt{h^\top \nabla^2 \phi(x) h}, \quad h \in \mathbb{R}^n,$$

and its dual norm

$$||h||_x^* = \sqrt{h^\top (\nabla^2 \phi(x))^{-1} h}, \quad h \in \mathbb{R}^n.$$

For any $\theta \in (0,1)$ and $\mu > 0$, the ℓ_2 -neighbourhood of problem (P) is defined as

$$\mathcal{N}_{\theta}^{\phi}(\mu) = \left\{ x \in \mathcal{F}^{\circ} : \|c + \mu \nabla \phi(x)\|_{x}^{*} \le \theta \mu \right\}.$$

Note that $c + \mu \nabla \phi(x)$ is the gradient of the objective function of problem (P_{μ}) . The ℓ_2 -neighbourhood is important and a natural choice for the design of path-following interior-point methods since the Newton's method applied to problem (P_{μ}) converges quadratically to the optimal solution $x^{\phi}(\mu)$ [3, Theorem 5.2.2]. We write

$$\mathcal{N}_{\theta}^{\phi} = \bigcup_{\mu > 0} \mathcal{N}_{\theta}^{\phi}(\mu),$$

which is also called the ℓ_2 -neighbourhood of problem (P). By the optimality condition of problem (P_{\mu}), we can see that $x^{\phi}(\mu) \in \mathcal{N}^{\phi}_{\theta}(\mu)$ for any $\theta \in (0,1)$ and $\mu > 0$.

A short-step method associated with ϕ is defined as an algorithm that generates a sequence of iterates $\{x^k\}_{k\geq 0}$ such that the polygonal (i.e., continuous piecewise linear) curve formed using the sequence $\{x^k\}_{k\geq 0}$ is contained in the ℓ_2 -neighbourhood $\mathcal{N}^{\phi}_{\theta}$ of problem (P) for some $\theta \in (0,1)$, where k is the iteration counter, or more precisely,

$$\bigcup_{k>0} [x^k, x^{k+1}] \subseteq \mathcal{N}_{\theta}^{\phi}.$$

Another popular choice of the neighbourhood for path-following algorithms for solving linear programming problems is the so-called wide neighbourhood [4]:

$$\mathcal{W}_{\theta}(\mu) = \left\{ x \in \mathcal{F}^{\circ} : \exists y \in \mathbb{R}_{+}^{m} \text{ such that } A^{\top}y = -c, \ y^{\top}(b - Ax) = m\mu, \right.$$

and $y_{i}(b - Ax)_{i} \geq (1 - \theta)\mu, \ i = 1, \dots, m \right\}.$

Similarly to the ℓ_2 -neighbourhood, we write

$$\mathcal{W}_{\theta} = \bigcup_{\mu > 0} \mathcal{W}_{\theta}(\mu).$$

3 Main Results

Our non-strong polynomiality result is based on the following family of linear programs introduced in [1]:

minimize
$$x_1$$

subject to $x_1 \le t^2$,
 $x_2 \le t$,
 $x_{2j+1} \le t x_{2j-1}, \quad j = 1, \dots, r-1,$
 $x_{2j+1} \le t x_{2j}, \quad j = 1, \dots, r-1,$
 $x_{2j+2} \le t^{1-1/2^j} (x_{2j-1} + x_{2j}), \quad j = 1, \dots, r-1,$
 $x_{2r-1}, x_{2r} \ge 0$,

where t > 1 is a real number and $r \ge 1$ is an integer. The notation $\mathbf{LW}_r(t)$ follows from [1] and signifies that the central path of this linear program is long and winding.

To distinguish the properties of problem $\mathbf{LW}_r(t)$ from those of a general linear program, we introduce an extra subscript t to the notations. For instance, the feasible region, the μ -analytic center associated with a self-concordant barrier ϕ and the wide neighbourhood of problem $\mathbf{LW}_r(t)$ are denoted as \mathcal{F}_t , $x_t^{\phi}(\mu)$ and $\mathcal{W}_{\theta,t}$, respectively.

We can now present the main results of this paper, whose proofs are deferred to Section 4. The main contribution of this paper is the non-strong polynomiality of short-step methods.

Theorem 1 (Non-strong Polynomiality of Short-step Methods). Consider $\mathbf{LW}_r(t)$ for a sufficiently large t > 1. Let $\theta \in (0, (\sqrt{69} - 3)/10)$, ϕ be a ν -self-concordant barrier on \mathcal{F}_t

with ν independent of t and $\{x^k\}_{k\geq 0}$ be a sequence of iterates generated by a short-step method associated with ϕ . Suppose that

$$\mathrm{gap}(x^0) \geq \frac{(1+\beta_{\theta})(3r+1)(1+\nu+2\sqrt{\nu})\sqrt{t}}{1-\beta_{\theta}} \quad and \quad \mathrm{gap}(x^K) \leq \frac{1-\beta_{\theta}}{2(1+\beta_{\theta})(1+C_{3r+1})},$$

where $\beta_{\theta} \in (0,1)$ is a constant depending only on θ defined in (8). Then, $K \geq 2^{r-3}$.

We should emphasize that although the self-concordance parameter ν in Theorem 1 is assumed to be independent of t, it could possibly depend on the numbers of variables and constraints of problem $\mathbf{LW}_r(t)$. This subsumes almost all known barriers. Furthermore, we note that the requirement on the initial optimality gap is only very mild. Indeed, it is customary for interior-point methods to start at the ∞ -analytic center $x^{\phi}(\infty)$. Using Lemma 2, we can check that $\mathsf{gap}(x^{\phi}(\infty)) = \Omega(\frac{t}{\nu})$, see also the proof of Lemma 4.

The cruxes of the proof of Theorem 1 are the following lemmas. The first shows a certain equivalence among the central paths of all self-concordant barriers. Geometrically speaking, it guarantees that when restricted to a constant-cost slice, all central paths are approximately equally close to (or away from) the boundary of the feasible region.

Lemma 1 (Equivalence of Central Paths). Consider the linear program (P). Let ϕ and ψ be ν_{ϕ} - and ν_{ψ} -self-concordant barriers on the feasible region \mathcal{F} . Let $\mu, \eta > 0$ be such that $c^{\top}x^{\phi}(\mu) = c^{\top}x^{\psi}(\eta)$. Then, for any $i = 1, \ldots, m$,

$$(1 + \nu_{\phi} + 2\sqrt{\nu_{\phi}})^{-1} \le \frac{(b - Ax^{\phi}(\mu))_i}{(b - Ax^{\psi}(\eta))_i} \le (1 + \nu_{\psi} + 2\sqrt{\nu_{\psi}}).$$

The second one bounds the optimality gap of analytic centers.

Lemma 2 (Optimality Gap of Analytic Center). Consider the linear program (P). Let ϕ be a ν -self-concordant barrier on the feasible region \mathcal{F} . Then, for any $\mu > 0$,

$$\min\left\{\frac{\mu}{2}, \frac{\rho\|c\|_2}{2\nu + 4\sqrt{\nu}}\right\} \le \operatorname{\mathsf{gap}}(x^{\phi}(\mu)) \le \mu\nu,$$

where $\rho > 0$ is the radius of the largest ball contained in \mathcal{F} .

It should be pointed out that the upper bound in Lemma 2 is not new and can be found in [3, Theorem 5.3.10]. The novelty of the lemma lies in the lower bound.

4 Proofs

Throughout this section, given a vector $\bar{x} \in \mathbb{R}^n$ and a positive definite matrix Q, we let $\mathcal{E}(Q,\bar{x}) = \{x \in \mathbb{R}^n : (x-\bar{x})^\top Q(x-\bar{x}) \leq 1\}$. Also, for any $\nu > 0$, we let $C_{\nu} = \nu + 2\sqrt{\nu}$. We first collect a simple lemma about linear optimization over ellipsoids.

Lemma 3. Let $\bar{x} \in \mathbb{R}^n$, $a \in \mathbb{R}^n$ and $Q \in \mathbb{R}^{n \times n}$ be a positive definite matrix. Then,

$$\max_{x \in \mathcal{E}(Q, \bar{x})} a^\top x = a^\top \bar{x} + \sqrt{a^\top Q^{-1} a} \quad and \quad \min_{x \in \mathcal{E}(Q, \bar{x})} a^\top x = a^\top \bar{x} - \sqrt{a^\top Q^{-1} a}.$$

The proof of Lemma 3 uses only elementary optimality arguments and is thus omitted.

Proof of Lemma 1. Let $\mathcal{H} = \{x \in \mathbb{R}^n : c^{\top}x = c^{\top}x^{\phi}(\mu)\}$. By [3, Theorem 5.1.5], we have

$$\mathcal{E}(\nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \subseteq \mathcal{F}$$
 and $\mathcal{E}(\nabla^2 \psi(x^{\psi}(\eta)), x^{\psi}(\eta)) \subseteq \mathcal{F}$.

Combining [3, Theorem 5.3.8] with these inclusions yields

$$\mathcal{E}(\nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \cap \mathcal{H} \subseteq \mathcal{F} \cap \mathcal{H} \subseteq \mathcal{E}(C_{\nu_{\phi}}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \cap \mathcal{H},$$

and

$$\mathcal{E}(\nabla^2 \psi(x^{\psi}(\eta)), x^{\psi}(\eta)) \cap \mathcal{H} \subseteq \mathcal{F} \cap \mathcal{H} \subseteq \mathcal{E}(C_{\nu_{\eta_0}}^{-2} \nabla^2 \psi(x^{\psi}(\eta)), x^{\psi}(\eta)) \cap \mathcal{H},$$

which implies, respectively,

$$x^{\psi}(\eta) \in \mathcal{E}(C_{\nu_{\phi}}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \cap \mathcal{H} \quad \text{and} \quad x^{\phi}(\mu) \in \mathcal{E}(C_{\nu_{\psi}}^{-2} \nabla^2 \psi(x^{\psi}(\eta)), x^{\psi}(\eta)) \cap \mathcal{H}.$$

Using Lemma 3, for any i = 1, ..., m,

$$\max_{x' \in \mathcal{E}(C_{\nu_{\phi}}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu))} (b - Ax')_i = (b - Ax^{\phi}(\mu))_i + C_{\nu_{\phi}} \sqrt{a_i^{\top} (\nabla^2 \phi(x^{\phi}(\mu)))^{-1} a_i}, \quad (1)$$

and

$$\min_{x' \in \mathcal{E}(C_{\nu_{\phi}}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu))} (b - Ax')_i = (b - Ax^{\phi}(\mu))_i - C_{\nu_{\phi}} \sqrt{a_i^{\top} (\nabla^2 \phi(x^{\phi}(\mu)))^{-1} a_i}, \quad (2)$$

where a_i^{\top} is the *i*-row of A. Also, since $Ax' \leq b$ for any $x' \in \mathcal{E}(\nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \subseteq \mathcal{F}$, Lemma 3 implies that

$$0 \le \min_{x' \in \mathcal{E}(\nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu))} (b - Ax')_i = (b - Ax^{\phi}(\mu))_i - \sqrt{a_i^{\top} (\nabla^2 \phi(x^{\phi}(\mu)))^{-1} a_i}.$$

It follows from (1), (2) and $x^{\psi}(\eta) \in \mathcal{E}(C_{\nu_{\phi}}^{-2}\nabla^{2}\phi(x^{\phi}(\mu)), x^{\phi}(\mu))$ that

$$\left| (b - Ax^{\phi}(\mu))_i - (b - Ax^{\psi}(\eta))_i \right| \le C_{\nu_{\phi}} \sqrt{a_i^{\top} (\nabla^2 \phi(x^{\phi}(\mu)))^{-1} a_i} \le C_{\nu_{\phi}} (b - Ax^{\phi}(\mu))_i.$$

Using the same arguments, we also obtain

$$\left| (b - Ax^{\phi}(\mu))_i - (b - Ax^{\psi}(\eta))_i \right| \le C_{\nu_{\psi}} \sqrt{a_i^{\top} (\nabla^2 \psi(x^{\psi}(\eta)))^{-1} a_i} \le C_{\nu_{\psi}} (b - Ax^{\psi}(\eta))_i.$$

Thus, for any $i = 1, \ldots, m$,

$$(b - Ax^{\psi}(\eta))_i \le (1 + C_{\nu_{\phi}})(b - Ax^{\phi}(\mu))_i$$
 and $(b - Ax^{\phi}(\mu))_i \le (1 + C_{\nu_{\psi}})(b - Ax^{\psi}(\eta))_i$,

which completes the proof.

Proof of Lemma 2. The upper bound follows directly from [3, Theorem 5.3.10]. Therefore, we prove only the lower bound. Two cases are discussed separately:

$$\begin{split} \nabla \phi(x^{\phi}(\mu)))^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu))\right)^{-1} \nabla \phi(x^{\phi}(\mu))) &\leq \frac{1}{4} \\ \text{and} \quad \nabla \phi(x^{\phi}(\mu)))^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu))\right)^{-1} \nabla \phi(x^{\phi}(\mu))) &> \frac{1}{4}. \end{split}$$

We first consider the case of

$$\nabla \phi(x^{\phi}(\mu)))^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu))\right)^{-1} \nabla \phi(x^{\phi}(\mu))) \le \frac{1}{4}.$$

By [3, Lemma 5.1.5 and Theorem 5.2.1], we have

$$\frac{\|x^{\phi}(\mu) - x^{\phi}(\infty)\|_{x^{\phi}(\infty)}^2}{1 + \frac{2}{3} \|x^{\phi}(\mu) - x^{\phi}(\infty)\|_{x^{\phi}(\infty)}} \le \frac{(\frac{1}{4})^2}{1 - \frac{1}{4}} = \frac{1}{12},$$

where $x^{\phi}(\infty)$ is the ∞ -analytic center, *i.e.*, the unique optimal solution to the problem

minimize
$$\phi(x)$$

subject to $Ax < b$.

Solving the quadratic inequality, we get

$$||x^{\phi}(\mu) - x^{\phi}(\infty)||_{x^{\phi}(\infty)} \le \frac{1}{2}.$$
 (3)

Using Lemma 3 and inequality (3), we have that

$$\begin{split} \operatorname{gap}(x^{\phi}(\mu)) &\geq \min_{x \in \mathcal{E}(16\nabla^2 \phi(x^{\phi}(\infty)), x^{\phi}(\infty))} \operatorname{gap}(x) \\ &= \operatorname{gap}(x^{\phi}(\infty)) - \frac{1}{2} \sqrt{c^{\top} \left(\nabla^2 \phi(x^{\phi}(\infty))\right)^{-1} c}. \end{split} \tag{4}$$

Next, since $\mathcal{E}(\nabla^2 \phi(x^{\phi}(\infty)), x^{\phi}(\infty)) \subseteq \mathcal{F}$, Lemma 3 implies

$$0 \le \min_{x \in \mathcal{E}(\nabla^2 \phi(x^{\phi}(\infty)), x^{\phi}(\infty))} \operatorname{\mathsf{gap}}(x) = \operatorname{\mathsf{gap}}(x^{\phi}(\infty)) - \sqrt{c^{\top} \left(\nabla^2 \phi(x^{\phi}(\infty))\right)^{-1} c}. \tag{5}$$

Combining the inequalities (4) and (5), we obtain

$$\operatorname{gap}(x^{\phi}(\mu)) \ge \frac{1}{2} \sqrt{c^{\top} \left(\nabla^{2} \phi(x^{\phi}(\infty))\right)^{-1} c}. \tag{6}$$

On the other hand, by supposition, the feasible region \mathcal{F} contains a ball of radius ρ . By [3, Theorem 5.3.9], it is contained in the ellipsoid $\mathcal{E}(C_{\nu}^{-2}\nabla^{2}\phi(x^{\phi}(\infty)), x^{\phi}(\infty))$. Hence,

$$\mathcal{E}(\rho^{-2}I,x^\phi(\infty))\subseteq\mathcal{E}(C_\nu^{-2}\nabla^2\phi(x^\phi(\infty)),x^\phi(\infty)),$$

where the left-hand side is a ball with center $x^{\phi}(\infty)$ of radius ρ . Using Lemma 3, we get

$$\begin{split} & \operatorname{gap}(x^{\phi}(\infty)) + \rho \|c\|_2 = \max_{x \in \mathcal{E}(\rho^{-2}I, x^{\phi}(\infty))} \operatorname{gap}(x) \leq \max_{x \in \mathcal{E}(C_{\nu}^{-2}\nabla^2\phi(x^{\phi}(\infty)), x^{\phi}(\infty))} \operatorname{gap}(x) \\ & = \operatorname{gap}(x^{\phi}(\infty)) + (\nu + 2\sqrt{\nu}) \sqrt{c^{\top} \left(\nabla^2\phi(x^{\phi}(\infty))\right)^{-1} c}, \end{split}$$

which, upon substitution into (6), yields

$$\operatorname{\mathsf{gap}}(x^\phi(\mu)) \geq \frac{\rho \|c\|_2}{2(\nu + 2\sqrt{\nu})}.$$

Then, we consider the case of

$$\nabla \phi(x^{\phi}(\mu)))^{\top} \nabla^2 \phi(x^{\phi}(\mu)) \nabla \phi(x^{\phi}(\mu))) > \frac{1}{4}.$$

Using the optimality condition of problem (P_{μ}) , we get $c + \mu \nabla \phi(x^{\phi}(\mu)) = 0$. Therefore,

$$c^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu)) \right)^{-1} c > \frac{1}{4} \mu^2. \tag{7}$$

Since $\mathcal{E}(\nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \subseteq \mathcal{F}$, by Lemma 3,

$$0 \leq \min_{x \in \mathcal{E}(\nabla^2 \phi(x^\phi(\mu)), x^\phi(\mu))} = \operatorname{gap}(x^\phi(\mu)) - \sqrt{c^\top \left(\nabla^2 \phi(x^\phi(\mu))\right)^{-1} c},$$

which, together with (7), yields

$$\operatorname{gap}(x^{\phi}(\mu)) > \frac{\mu}{2}.$$

This completes the proof.

We then prove a proposition that compares the slack of the μ -analytic center with that of any point in its ℓ_2 -neighbourhood.

Proposition 1. Consider the linear program (P). Let $\theta \in (0, (\sqrt{69} - 3)/10)$, $\mu > 0$, ϕ be a self-concordant function on \mathcal{F} and $x \in \mathcal{N}^{\phi}_{\theta}(\mu)$. Then, for any $i = 1, \ldots, m$,

$$(1 - \beta_{\theta})(b - Ax^{\phi}(\mu))_i \le (b - Ax)_i \le (1 + \beta_{\theta})(b - Ax^{\phi}(\mu))_i,$$

where $\beta_{\theta} \in (0,1)$ is a constant depending only on θ defined in (8).

Proof. Let $x \in \mathcal{N}^{\phi}_{\theta}(\mu)$. By [3, Lemma 5.1.5 and Theorem 5.2.1] and the definition of ℓ_2 -neighbourhood,

$$\frac{\|x - x^{\phi}(\mu)\|_{x^{\phi}(\mu)}^2}{1 + \frac{2}{3} \|x - x^{\phi}(\mu)\|_{x^{\phi}(\mu)}} \le \frac{\theta^2}{1 - \theta}.$$

Solving the quadratic inequality yields $||x - x^{\phi}(\mu)||_{x^{\phi}(\mu)} \leq \beta_{\theta}$, where

$$\beta_{\theta} = \frac{1}{3} \left(\frac{\theta^2}{1 - \theta} + \sqrt{\frac{\theta^4}{(1 - \theta)^2} + \frac{9\theta^2}{1 - \theta}} \right). \tag{8}$$

We note that $\beta_{\theta} < 1$ whenever $\theta \in (0, (\sqrt{69} - 3)/10)$. Using Lemma 3, we get

$$\max_{x' \in \mathcal{E}(\beta_{\theta}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu))} (b - Ax')_i = (b - Ax^{\phi}(\mu))_i + \beta_{\theta} \sqrt{a_i^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu))\right)^{-1} a_i},$$

and

$$\min_{x' \in \mathcal{E}(\beta_{\theta}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu))} (b - Ax')_i = (b - Ax^{\phi}(\mu))_i - \beta_{\theta} \sqrt{a_i^{\top} (\nabla^2 \phi(x^{\phi}(\mu)))^{-1} a_i} \ge 0,$$

where the inequality follows from that $Ax' \leq b$ for any $x' \in \mathcal{E}(\beta_{\theta}^{-2} \nabla^2 \phi(x^{\phi}(\mu)), x^{\phi}(\mu)) \subseteq \mathcal{F}$. Therefore, we have

$$\left| (b - Ax)_i - (b - Ax^{\phi}(\mu))_i \right| \le \beta_{\theta} \sqrt{a_i^{\top} \left(\nabla^2 \phi(x^{\phi}(\mu)) \right)^{-1} a_i} \le \beta_{\theta} (b - Ax^{\phi}(\mu))_i.$$

This completes the proof.

The next proposition compares the optimality gap of the μ -analytic center with that of any point in its ℓ_2 -neighbourhood.

Proposition 2. Consider the linear program (P). Let $\theta \in (0, (\sqrt{69} - 3)/10)$, $\mu > 0$, ϕ be a self-concordant function on \mathcal{F} and $x \in \mathcal{N}^{\phi}_{\theta}(\mu)$. Then,

$$(1 - \beta_{\theta})\operatorname{gap}(x^{\phi}(\mu)) \le \operatorname{gap}(x) \le (1 + \beta_{\theta})\operatorname{gap}(x^{\phi}(\mu)).$$

The proof of Proposition 2 uses the same arguments as in the proof of Proposition 1 and is therefore omitted.

We will need to compare the μ -analytic center associated with ϕ and the η -analytic center associated with the logarithmic barrier ϕ_{ln} along the constant-cost slices of \mathcal{F}_t .

Lemma 4. Consider the linear program $\mathbf{LW}_r(t)$. For any self-concordant barrier ϕ on \mathcal{F}_t and $\mu > 0$ satisfying

$$gap(x^{\phi}(\mu)) < \frac{t}{4(3r+1) + 8\sqrt{3r+1}},$$

there exists a unique $\eta(\mu) > 0$ such that

$$\frac{\eta(\mu)}{2} \leq \operatorname{gap}(x^{\phi}(\mu)) = \operatorname{gap}(x^{\phi_{\ln}}(\eta(\mu))) \leq (3r+1)\eta(\mu).$$

Proof. We first prove the existence of $\eta(\mu)$ satisfying $\mathsf{gap}(x^{\phi}(\mu)) = \mathsf{gap}(x^{\phi_{\ln}}(\eta(\mu)))$. Since $\mu \mapsto \mathsf{gap}(x^{\phi}(\mu))$ and $\eta \mapsto \mathsf{gap}(x^{\phi_{\ln}}(\eta(\mu)))$ are both continuous and strictly increasing functions attaining the minimum value 0 at 0, it suffices to show that for any $\mu > 0$ with

$$gap(x^{\phi}(\mu)) < \frac{t}{4(3r+1) + 8\sqrt{3r+1}},$$

there exists $\eta > 0$ such that $gap(x^{\phi}(\mu)) \leq gap(x^{\phi_{ln}}(\eta))$. To show this, we note that the feasible region \mathcal{F}_t contains a hypercube of side length t, which in turn contains a

ball of radius $\frac{t}{2}$. Also, the cost vector of problem $\mathbf{LW}_r(t)$ is $c_t = (1, 0, \dots, 0)^{\top}$ and hence $||c_t||_2 = 1$. Furthermore, by [3, Section 5.3], ϕ_{ln} is (3r+1)-self-concordant on \mathcal{F}_t . Lemma 2 then implies that for a large enough $\eta > 0$,

$$\operatorname{\mathsf{gap}}(x^\phi(\mu)) < \min\left\{\frac{t}{4(3r+1) + 8\sqrt{3r+1}}, \frac{\eta}{2}\right\} \leq \operatorname{\mathsf{gap}}(x^{\phi_{\ln}}(\eta)).$$

Therefore, there exists a unique $\eta(\mu) > 0$ with $gap(x^{\phi}(\mu)) = gap(x^{\phi_{ln}}(\eta(\mu)))$. It remains to prove the inequalities for $gap(x^{\phi}(\mu)) = gap(x^{\phi_{ln}}(\eta(\mu)))$. By Lemma 2,

$$\min\left\{\frac{t}{4(3r+1)+8\sqrt{3r+1}},\frac{\eta(\mu)}{2}\right\} \leq \operatorname{\mathsf{gap}}(x^{\phi_{\ln}}(\eta(\mu))) \leq \eta(\mu)(3r+1).$$

Since

$$\mathrm{gap}(x^{\phi}(\mu)) = \mathrm{gap}(x^{\phi_{\ln}}(\eta(\mu))) < \frac{t}{4(3r+1) + 8\sqrt{3r+1}},$$

we get

$$\frac{\eta(\mu)}{2} \leq \operatorname{gap}(x^\phi(\mu)) = \operatorname{gap}(x^{\phi_{\ln}}(\eta(\mu))) \leq \eta(\mu)(3r+1).$$

This completes the proof.

We will also need the following remarkable result from [1, Theorem 29].

Theorem 2. Let $\omega \in (0,1)$. Consider the linear program $\mathbf{LW}_r(t)$ for

$$t > \left(\frac{2(5r-1)(10r-1)^4((10r-2)!)^8}{1-\omega}\right)^{2^{r+2}}.$$

Suppose that

$$[x^0, x^1] \cup [x^1, x^2] \cup \cdots \cup [x^{K-1}, x^K] \subseteq \mathcal{W}_{\omega,t},$$

with $x^0 \in \mathcal{W}_{\omega,t}(\eta_0)$ and $x^K \in \mathcal{W}_{\omega,t}(\eta_K)$ for some $\eta_0 \geq \sqrt{t}$ and $\eta_K \leq 1$. Then, $K \geq 2^{r-3}$.

Some remarks are in order. First, the original statement of [1, Theorem 29] concerns iterates of a longer vector consisting of primal, dual and slack variables. But Theorem 2 concerns only the primal variables and hence is seemingly stronger than [1, Theorem 29], because, for a polygonal curve in \mathbb{R}^N with K pieces, its projection to a lower dimensional space could possibly have less than K pieces in general. However, upon a close inspection of the proof of [1, Theorem 29] and [1, Section 6.2], we find that Theorem 2 holds for the linear program $\mathbf{LW}_r(t)$. Using the language of [1], the reason is that for the tropical central path of the linear program $\mathbf{LW}_r(t)$, even the projection onto the primal variables is already a polygonal curve with a huge number of pieces. Second, in the original statement of [1, Theorem 29], the requirement on η_0 is that $\eta_0 \geq t^2$, and the conclusion is that $K \geq 2^{r-1}$. By considering a shorter part of the tropical central path of $\mathbf{LW}_r(t)$, we find that replacing the requirement on η_0 with the weaker bound of $\eta_0 \geq \sqrt{t}$ leads the weaker conclusion of $K \geq 2^{r-3}$, see [1, Section 4.3].

Proof of Theorem 1. Let

$$\omega = 1 - \frac{(1 - \beta_{\theta})}{(1 + \beta_{\theta})(1 + C_{\nu})(1 + C_{3r+1})}$$

and

$$t > \left(\frac{2(5r-1)(10r-1)^4((10r-2)!)^8}{1-\omega}\right)^{2^{r+2}}.$$

Note that $\omega \in (0,1)$.

Reduction

Without loss of generality, we can assume that for any $x \in [x^0, x^1] \cup \cdots \cup [x^{K-1}, x^K]$,

$$\operatorname{gap}(x^0) = \frac{(1+\beta_{\theta})(3r+1)(1+C_{\nu})\sqrt{t}}{1-\beta_{\theta}} \ge \operatorname{gap}(x) = \frac{1-\beta_{\theta}}{2(1+\beta_{\theta})(1+C_{3r+1})} = \operatorname{gap}(x^K). \tag{9}$$

Indeed, if this is not the case, because of the continuity of gap and the assumption that

$$\operatorname{\mathsf{gap}}(x^0) \ge \frac{(1+\beta_{\theta})(3r+1)(1+C_{\nu})\sqrt{t}}{1-\beta_{\theta}} \quad \text{and} \quad \operatorname{\mathsf{gap}}(x^K) \le \frac{1-\beta_{\theta}}{2(1+\beta_{\theta})(1+C_{3r+1})},$$

we can choose a sub-curve (connected subset) of $[x^0, x^1] \cup \cdots \cup [x^{K-1}, x^K]$ that satisfies all the assumptions of Theorem 1 as well as assumption (9).

Our goal is to show that $[x^0, x^1] \cup \cdots \cup [x^{K-1}, x^K] \subseteq \mathcal{W}_{\omega,t}$ and that $x^0 \in \mathcal{W}_{\omega,t}(\eta_0)$ and $x^K \in \mathcal{W}_{\omega,t}(\eta_K)$, for some $\eta_0 \geq \sqrt{t}$ and $\eta_K \leq 1$. If this can be proved, the desired conclusion would then follow from Theorem 2.

Proving
$$[x^0, x^1] \cup \cdots \cup [x^{K-1}, x^K] \subseteq \mathcal{W}_{\omega,t}$$

Let $x \in [x^0, x^1] \cup \cdots \cup [x^{K-1}, x^K]$. Then, $x \in \mathcal{N}_{\theta,t}^{\phi}(\mu)$ for some $\mu > 0$. By assumption (9) and Proposition 2, we have

$$\operatorname{gap}(x^{\phi}(\mu)) \le \frac{(1+\beta_{\theta})^2 (3r+1)(1+C_{\nu})\sqrt{t}}{1-\beta_{\theta}} < \frac{t}{4(3r+1)+8\sqrt{3r+1}}.$$

Using Lemma 4, there exists a unique $\eta(\mu) > 0$ such that

$$c_t^{\mathsf{T}} x_t^{\phi}(\mu) = c_t^{\mathsf{T}} x_t^{\phi_{\text{ln}}}(\eta(\mu)).$$

By Proposition 1 and Lemma 1, for any i = 1, ..., 3r + 1,

$$\frac{(b_t - A_t x)_i}{(b_t - A_t x_t^{\phi_{\ln}}(\eta(\mu)))_i} = \frac{(b_t - A_t x_t^{\phi})_i}{(b_t - A_t x_t^{\phi}(\mu))_i} \cdot \frac{(b_t - A_t x_t^{\phi}(\mu))_i}{(b_t - A_t x_t^{\phi_{\ln}}(\eta(\mu)))_i} \ge \frac{(1 - \beta_{\theta})}{(1 + C_{\nu})},\tag{10}$$

From the definition of the logarithmic barrier ϕ_{ln} and the optimality conditions of problem (P_{μ}) , there exists $y \in \mathbb{R}_{+}^{3r+1}$ such that $A_{t}^{\top}y = -c_{t}$ and

$$y_i(b_t - A_t x_t^{\phi_{\text{ln}}}(\eta(\mu)))_i = \eta(\mu), \quad i = 1, \dots, 3r + 1.$$

Averaging these 3r + 1 equalities and then using Proposition 1, Lemma 1 and the fact that ϕ_{ln} is (3r + 1)-self-concordant on \mathcal{F}_t , we get

$$\eta(\mu) = \frac{1}{3r+1} \sum_{i=1}^{3r+1} y_i (b_t - A_t x_t^{\phi_{\ln}}(\eta(\mu)))_i
\geq \frac{(1+C_{3r+1})^{-1}}{3r+1} \sum_{i=1}^{3r+1} y_i (b_t - A_t x_t^{\phi}(\mu))_i
\geq (1+C_{3r+1})^{-1} (1+\beta_{\theta})^{-1} \frac{y^{\top}(b_t - A_t x)}{3r+1}.$$
(11)

Hence, using (10) and (11), for any i = 1, ..., 3r + 1,

$$y_{i}(b_{t} - A_{t}x)_{i} \geq \frac{(1 - \beta_{\theta})}{(1 + C_{\nu})} \cdot y_{i}(b_{t} - A_{t}x_{t}^{\phi_{\ln}}(\eta(\mu))_{i} = \frac{(1 - \beta_{\theta})}{(1 + C_{\nu})} \cdot \eta(\mu)$$

$$\geq \frac{(1 - \beta_{\theta})}{(1 + \beta_{\theta})(1 + C_{\nu})(1 + C_{3r+1})} \cdot \frac{y^{\top}(b_{t} - A_{t}x)}{3r + 1},$$

$$(12)$$

which implies that $x \in \mathcal{W}_{\omega,t}(\eta_x)$ with

$$\eta_x = \frac{y^\top (b_t - A_t x)}{3r + 1}.\tag{13}$$

Proving $x^0 \in \mathcal{W}_{\omega,t}(\eta_0)$ and $x^K \in \mathcal{W}_{\omega,t}(\eta_K)$ for some $\eta_0 \ge \sqrt{t}$ and $\eta_K \le 1$

Using definition (13), inequality (11), Lemma 4 and Proposition 2, we get

$$\begin{split} \eta_{x^K} &= \frac{y^\top (b_t - A_t x^K)}{3r + 1} \leq (1 + \beta_\theta) (1 + C_{3r + 1}) \eta(\mu_K) \leq 2 (1 + \beta_\theta) (1 + C_{3r + 1}) \mathrm{gap}(x^\phi(\mu_K)) \\ &\leq \frac{2 (1 + \beta_\theta) (1 + C_{3r + 1})}{1 - \beta_\theta} \mathrm{gap}(x^K) \leq 1, \end{split}$$

where $x^K \in \mathcal{N}_{\theta,t}^{\phi}(\mu_K)$. Similarly, using definition (13), inequality (12), Lemma 4 and Proposition 2, we get

$$\begin{split} \eta_{x^0} &= \frac{y^\top (b_t - A_t x^0)}{3r + 1} \geq \frac{1 - \beta_\theta}{1 + C_\nu} \eta(\mu^0) \geq \frac{1 - \beta_\theta}{(3r + 1)(1 + C_\nu)} \mathsf{gap}(x^\phi(\mu_0)) \\ &\geq \frac{1 - \beta_\theta}{(1 + \beta_\theta)(3r + 1)(1 + C_\nu)} \mathsf{gap}(x^0) \geq \sqrt{t}, \end{split}$$

where $x^0 \in \mathcal{N}_{\theta,t}^{\phi}(\mu_0)$ Taking $\eta_0 = \eta_{x^0}$ and $\eta_K = \eta_{x^0}$, the proof is completed.

Acknowledgments

The authors thank Defeng Sun, Kim-Chuan Toh and Stephen Wright for their helpful discussions.

Statements and Declarations

The authors have no competing interests to declare that are relevant to the content of this article.

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