Interior Point Methods for Linear Programming Problems

Lecture 1

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Brief historical comments

- Klee and Minty (1972): How good is the simplex algorithm?
- Khachiyan (1979): Ellipsoid method
- Karmarkar (1984): Projective method

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- ⊳ For a list of pioneering articles and legends of IPM until 2001, visit
 www.mcs.anl.gov/research/projects/otc/InteriorPoint/

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Given LPP

$$\text{(P)} \quad \begin{cases} \min & c^T x \\ \text{subject to} & b - Ax = 0, x \geq 0. \end{cases}$$

KKT system for (P) is

$$\begin{cases} (\mathsf{PF}) & Ax = b, x \geq 0 \\ (\mathsf{St} \ \& \ \mathsf{DF}) & c - A^T \mu - \lambda = 0, \lambda \geq 0 \\ (\mathsf{CS}) & \lambda^T x = 0 \end{cases}$$

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Given LPP

(P)
$$\begin{cases} \min & c^T x \\ \text{subject to} & b-Ax=0, x\geq 0. \end{cases}$$

Denoting $s = \lambda$ and $y = \mu$, the KKT system for (P) is

$$\text{(KKT P)} \left\{ \begin{array}{l} Ax = b, \\ A^Ty + s = c, \\ \\ x \geq 0, s \geq 0, \\ \\ s^Tx = 0. \end{array} \right.$$

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Denoting $s = \lambda$ and $y = \mu$, the KKT system for (P) is

$$(\mathsf{KKT}\;\mathsf{P})\left\{\begin{array}{l} Ax=b,\\ A^Ty+s=c,\\ x\geq 0, s\geq 0,\\ s^Tx=0. \end{array}\right.$$

(H.W.) KKT system of the dual of (P) is also (KKT P).

KKT system for (P) is

(KKT P)
$$\begin{cases} Ax = b, & (1) \\ A^{T}y + s = c, & (2) \\ s^{T}x = 0, & (3) \\ x \ge 0, s \ge 0. & (4) \end{cases}$$

Note

- (3) is the only nonlinear equation in (KKT P)
- Simplex method maintains (1), (2) & (3) and aims for (4).
- Interior-point methods maintain (1), (2) & (4) and aim for (3).

Given LPP

(P)
$$\begin{cases} \min & c^T x \\ \text{subject to} & Ax = b, x \ge 0. \end{cases}$$

Denoting $\mathcal{X} = \{x \in \mathbb{R}^n : x \geq 0\}$, (P) can be equivalently written as follows:

(I)
$$\begin{cases} \min & c^T x + I_{\mathcal{X}}(x) \\ \text{subject to} & Ax = b, \end{cases}$$

where

$$I_{\mathcal{X}}(x) = \begin{cases} 0, & \text{if } x \in \mathcal{X} \\ +\infty, & \text{if } x \notin \mathcal{X}. \end{cases}$$

Approximate (I) by

(BP)
$$\begin{cases} \min & c^T x + \frac{1}{t} \phi(x) \\ \text{subject to} & Ax = b, \end{cases}$$

where $\frac{1}{t}\phi$ is a continuous approximation of $I_{\mathcal{X}}$.

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By writing $\mu = \frac{1}{t}$, (BP) can be equivalently written as follows:

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(BP)
$$\begin{cases} \min & \frac{c^T x}{\mu} + \phi(x) \\ \text{subject to} & Ax = b, \end{cases}$$

The function $\phi_B(x;\mu)=\frac{e^Tx}{\mu}+\phi(x)$ is called a barrier function of the problem (P).

Given LPP

$$\text{(P)} \quad \begin{cases} \min & c^T x \\ \text{subject to} & Ax = b, x \geq 0. \end{cases}$$

The log-barrier formulation of (P) is

(LBP)
$$\begin{cases} \min & \phi_B(x;\mu) \equiv \frac{c^T x}{\mu} - \sum_{i=1}^n \ln(x_i) \\ \text{subject to} & Ax = b. \end{cases}$$

The first order necessary and sufficient optimality conditions for (LBP) is

(LBP OC)
$$\begin{cases} \nabla \phi_B(x;\mu) + \sum_{i=1}^m \lambda_i \nabla h_j(x) = 0 \\ Ax = b \end{cases}$$

The gradient and Hessian of ϕ_B is given by

$$\nabla \phi_B(x;\mu) = \frac{c}{\mu} - X^{-1}e \text{ and } \nabla^2 \phi_B(x;\mu) = X^{-2}$$

 $\nabla\phi_B(x;\mu)=\frac{c}{\mu}-X^{-1}e \ \ \text{and} \ \ \nabla^2\phi_B(x;\mu)=X^{-2},$ where $X=\operatorname{diag}(x_1,x_2,\ldots,x_n)$ and e is the n-vector $(1,1,\ldots,1)^T.$

(LBP OC) is given by

(LBP OC)
$$\begin{cases} \frac{c}{\mu} - X^{-1}e + A^T\lambda = 0 \\ Ax = b. \end{cases}$$

(LBP OC) reduces to the following system by putting $y=-\lambda\mu$ and $s=\mu X^{-1}e$:

(PD OCS)
$$\begin{cases} A^T y + s = c, \\ Ax = b, \\ Sx = \mu e, \end{cases}$$

where $S = \operatorname{diag}(s) = \operatorname{diag}(s_1, s_2, \dots, s_n)$.

(H.W.) The log-barrier formulation of the dual of (P) is

$$\min -\frac{b^T y}{\mu} - \sum_{i=1}^n \ln(s_i)$$

subject to $A^Ty + s = c$.

Show that the first order necessary and sufficient optimality conditions this problem is also (PD OCS).

Note

Log-barrier problem to the following problem does not have a solution:

$$\min 0$$
 subject to $x \ge 0$.

Notations

$$\overset{\circ}{\mathcal{F}}(P) = \{ x \in \mathbb{R}^n : Ax = b, x > 0 \}$$

$$\label{eq:final_condition} \begin{split} & \stackrel{\circ}{\mathcal{F}}(P) = \{x \in \mathbb{R}^n : Ax = b, x > 0\} \\ & \stackrel{\circ}{\mathcal{F}}(D) = \{(y,s) \in \mathbb{R}^m \times \mathbb{R}^n : A^Ty + s = c, s > 0\} \end{split}$$

Notations

$$\label{eq:final_equation} \begin{split} & \stackrel{\circ}{\mathcal{F}}(P) = \{x \in \mathbb{R}^n : Ax = b, x > 0\} \\ & \stackrel{\circ}{\mathcal{F}}(D) = \{(y,s) \in \mathbb{R}^m \times \mathbb{R}^n : A^Ty + s = c, s > 0\} \end{split}$$

Existence of a minimizer of $\phi_B(x;\mu)$

A necessary and sufficient condition for the existence of a minimizer $\phi_B(x;\mu)$ in $\overset{\circ}{\mathcal{F}}(P)$ is ' $\overset{\circ}{\mathcal{F}}(P)$ and $\overset{\circ}{\mathcal{F}}(D)$ nonempty'.

For a given $\mu > 0$, let $(x(\mu), y(\mu), s(\mu))$ be the solution to (PD OCS)

Central path

- $\{x(\mu): \mu>0\}$ is called the primal central path.
- $\{(x(\mu),y(\mu),s(\mu):\mu>0\}$ is called primal-dual central path.

Analytic center

If the feasible region of (P) is bounded, then the central path starts (i.e., when $\mu \to \infty$) from the unique point

$$\operatorname{argmin} \sum_{i=1}^{n} -\ln(x_i),$$

which is called the analytic center of the feasible region.

Central path

If μ decreases, then $c^Tx(\mu)$ decreases and $b^Ty(\mu)$ increases.

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On the central path, $c^T x(\mu) - b^T y(\mu) = n\mu$.

Hence, as $\mu \to 0+$, duality gap becomes zero and we will reach at an optimum solution of both primal and dual.

References

- 1. D. den Hertog (2012). Interior point approach to linear, quadratic and convex programming: algorithms and complexity, Springer.
- W. Forst and D. Hoffmann (2010). Optimization—theory and practice.
 Springer.
- A. V. Fiacco and G. P. McCormick (1987). Nonlinear programming: sequential unconstrained minimization techniques, Classics in applied mathematics, Vol. 4, Society for Industrial and Applied Mathematics.
- R. J. Vanderbei (2020). Linear programming: foundations and extensions. Vol. 285. Springer Nature, 2020.
- Wright, M. (2005). The interior-point revolution in optimization: history, recent developments, and lasting consequences, *Bulletin of the American mathematical society* 42(1), 39–56.