

Interior point method

History of interior method

The simplex method:

- invented by George Dantzig in 1947
- "walks" the edge of the polyhedral feasible set
- worst-case complexity is exponential (may need to visit every vertex)
- experience (and some analysis) suggest average polynomial complexity

Interior point methods (IPM) are a radical departure from the simplex method:

- IPMs traverses the interior of the polyhedral set
- (impractical) polynomial algorithm for LP first proposed by Karmarkar (1979)
- Karmarkar (1984) offered first "practical" polynomial LP algorithm.

Big idea

- Constraints are hard to deal with
- Let's turn them into penalties
- We know how to deal with smooth unconstrained problem.

Penalty function

$$\underset{x}{\text{minimize}} \quad f(x) \quad \text{subject to} \quad h_i(x) \geq 0 \quad i=1, \dots, m \\ Ax = b$$

- $f, h_i : \mathbb{R}^n \rightarrow \mathbb{R}$ are convex and twice differentiable
- $A \in \mathbb{R}^{m \times n}$ with $\text{rank}(A) < n$.

Reformulate as

$$\underset{x}{\min} \quad f(x) + \sum_{i=1}^m \phi_t(h_i(x)) \quad \text{s.t. } Ax = b$$

Conditions

- $\phi_t(s) \rightarrow \infty$ as $s \rightarrow 0$ → avoid boundary
- $\phi_t(s) \rightarrow \infty$ for all $s \geq 0$ as $t \rightarrow \infty$ → penalty parameter

Indicator function

First pass example:

$$I_S(x) = \begin{cases} 0 & \text{if } x \in S \\ \infty & \text{if } x \notin S \end{cases}$$

Then, we can reformulate

$$\min_x f(x) \quad \text{as} \quad \min_x f(x) + I_S(x)$$

s.t. $x \in S$

However, this problem is not easy to solve. The objective is not (in general) differentiable.

Eliminating non-negative constraints

Apply to the primal problem in standard form:

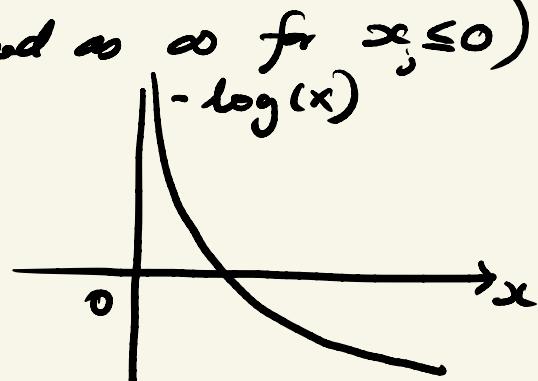
$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} \quad \text{subject to } \mathbf{A}\mathbf{x} = \mathbf{b}, \quad \mathbf{x} \geq \mathbf{0}$$

The core difficulty in LP is the presence of $\mathbf{x} \geq \mathbf{0}$.

Eliminate non-negative constraint via barrier function:

$$B_t(\mathbf{x}) = \mathbf{c}^T \mathbf{x} - t \sum_j \log(x_j)$$

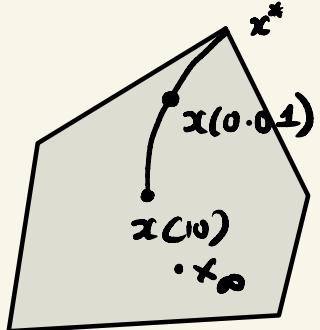
- $\log(x_j) \rightarrow \infty$ as $x_j \rightarrow 0^+$ (defined as ∞ for $x_j \leq 0$)
- $t \sum_j \log(x_j) \rightarrow \infty$ as $x_j \rightarrow 0^+$



BARRIER function

$$(P_t) \underset{x}{\text{minimize}} \quad B_t(x) \quad \text{s.t.} \quad Ax = b$$

- minimizer of the barrier problem depends on t :
- x_t solves P_t
- minimizer of P_t is unique for each t because of convexity of B_t



$$x_0 = \arg \min - \sum_j \log(x_j)$$
$$Ax = b$$

Example

minimize x subject to $x \geq 0$

x

$$B_t(x) = x - t \log(x)$$

$$\frac{d}{dx} B_t(x) = 1 - \frac{t}{x} = 0 \Rightarrow x_t = t$$

$$\Rightarrow \lim_{t \rightarrow 0^+} x_t = 0$$

Example

maximize x_2 subject to $x_1 + x_2 + x_3 = 1, x \geq 0$
 x_1, x_2, x_3

$$B_t(x) = x_2 - t \log(x_1) - t \log(x_2) - t \log(1-x_1-x_2)$$

$$\begin{array}{l} \uparrow \\ \text{min } x_2 - t \log(x_1) - t \log(x_2) - t \log(1-x_1-x_2) =: B_t^2 \\ x_1, x_2 \end{array}$$

$$\Rightarrow x_2(t) = \frac{1 - x_2(t)}{2} \rightarrow \frac{1}{2}$$

$$x_2(t) = \frac{1 - 2t - \sqrt{1 + 9t^2 + 2t}}{2} \rightarrow 0$$

$$x_3(t) = \frac{1 - x_2(t)}{2} \rightarrow \frac{1}{2}$$

$$X^* = \{(x_1, 0, x_3) \mid \begin{cases} x_1 + x_3 = 1 \\ x \geq 0 \end{cases}\}$$

This problem has infinitely many solutions:

Example

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} \quad \text{subject to } \mathbf{A}\mathbf{x} \leq \mathbf{b}$$

Reformulate as

$$\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} - t \underbrace{\sum_{i=1}^m \log(b_i - \mathbf{a}_i^T \mathbf{x})}_{:= \phi_t(\mathbf{x})}$$

Gradient $\nabla \phi_t(\mathbf{x}) = t \cdot \mathbf{A}^T \mathbf{z}, \quad \mathbf{z} = \frac{1}{b_i - \mathbf{a}_i^T \mathbf{x}}$

Hessian $\nabla^2 \phi_t(\mathbf{x}) = t \cdot \mathbf{A}^T \text{diag}(\mathbf{z})^2 \mathbf{A}$

- pick some t to start
- solve approximately $\min_{\mathbf{x}} \mathbf{c}^T \mathbf{x} + \phi_t(\mathbf{x})$
- decrease t

Primal barrier method

solve a sequence of linearly constrained nonlinear functions:

choose $x_0 > 0$, $t_0 > 0 (\approx 1)$, $\gamma < 1$

repeat

$x_{k+1} \underset{x}{\operatorname{arg\,min}} B_t(x)$ subject to $Ax = b$

$$t_{k+1} \leftarrow \gamma t_k$$

until t_k is "small"

under mild conditions $x_k \rightarrow x^*$.

