



Linear Program

$$\begin{array}{ll} \min & C^T x \\ \text{s.t.} & Ax = b \\ & x \geq 0 \end{array}$$

$$\begin{aligned} L(x, \lambda, v) &= C^T x - \lambda^T (Ax - b) - v^T (Ax - b) \\ &= (C - \lambda - A^T v)^T x + b^T v \\ &= \begin{cases} -\infty & C - \lambda - A^T v \neq 0 \\ b^T v & C - \lambda - A^T v = 0 \end{cases} \end{aligned}$$

$$\begin{array}{ll} \max_{\lambda, v} & b^T v \\ \text{s.t.} & C - \lambda - A^T v = 0 \\ & \lambda \geq 0 \end{array}$$

Weak duality: if x is primal feasible and λ, v are dual feasible

$$C^T x \geq b^T v$$

$$C^T x - b^T v = C^T x - (Ax)^T v = x^T (C - A^T v) = x^T \lambda \geq 0$$

$$\begin{aligned} p^* &= g(A^*, v^*) = \inf_x L(x, \lambda^*, v^*) \\ &= \inf_x C^T x - \lambda^{*T} x - v^{*T} (Ax - b) \\ &\leq C^T x^* - \lambda^{*T} x^* - v^{*T} (Ax^* - b) \\ &\leq p^* \end{aligned}$$

optimality condition

primal feasible: $x \geq 0, Ax = b$

dual feasible: $\lambda \geq 0$

complementary slackness: $\lambda_i x_i = 0$

gradient vanishes: $A^T v + \lambda = C$

Simplex method: maintain equality conditions and aim for $x \geq 0, \lambda \geq 0$

Interior point method: maintain linear conditions and aim for complementary

Barrier of primal and dual

$$\begin{array}{ll} \min & C^T x \\ \text{s.t.} & Ax = b \\ & x > 0 \end{array}$$

↓

$$\begin{array}{ll} \min_x & C^T x - \frac{1}{\epsilon} \sum \log(x_i) \\ \text{s.t.} & Ax = b \end{array}$$

$$\begin{array}{ll} \min_{\lambda, v} & -b^T v \\ \text{s.t.} & A^T v + \lambda = C \\ & \lambda > 0 \end{array}$$

↓

$$\begin{array}{ll} \min_{\lambda, v} & -b^T v - \frac{1}{\epsilon} \sum \log(\lambda_i) \\ \text{s.t.} & A^T v + \lambda = C \end{array}$$

→ dual ←

the primal barrier problem and dual barrier problem are dual of each other

$$\min_x c^T x - \frac{1}{\epsilon} \sum \log(x) \quad \text{primal barrier}$$

$$\begin{aligned} \mathcal{L}(x, \lambda) &= c^T x - \frac{1}{\epsilon} \sum \log(x) - \lambda^T (Ax - b) \\ &= (c - A^T \lambda)^T x - \frac{1}{\epsilon} \sum \log(x) + b^T \lambda \\ \nabla_x \mathcal{L} &= c - A^T \lambda - \frac{1}{\epsilon} \frac{1}{x} = 0 \quad x = \frac{1}{\epsilon} (c - A^T \lambda) \end{aligned}$$

$$\begin{aligned} g(\lambda) &= \inf_x \mathcal{L}(x, \lambda) \\ &= \begin{cases} -\infty & (c - A^T \lambda)_i \leq 0 \text{ for some } i \\ \eta/\epsilon - \frac{1}{\epsilon} \sum \log\left(\frac{1}{\epsilon} (c - A^T \lambda)_i\right) + b^T \lambda & \text{otherwise} \end{cases} \end{aligned}$$

$$\begin{aligned} \max_{\lambda} \quad & \eta/\epsilon - \frac{1}{\epsilon} \sum \log\left(\frac{1}{\epsilon} (c - A^T \lambda)_i\right) + b^T \lambda \\ \text{s.t.} \quad & c - A^T \lambda > 0 \end{aligned} \Rightarrow$$

dual barrier

$$\begin{aligned} \max_{\lambda} \quad & \frac{1}{\epsilon} \sum \log(\lambda) + b^T \lambda \\ \text{s.t.} \quad & c - A^T \lambda = \lambda \\ & \lambda > 0 \end{aligned}$$

KKT for primal barrier

primal feasible: $Ax = b, x > 0$

dual feasible: $\lambda + A^T \lambda = c, \lambda > 0$

gradient vanishes: $c - A^T \lambda = \frac{1}{\epsilon} \frac{1}{x} \Rightarrow \lambda_i x_i = \frac{1}{\epsilon}$

$$\begin{aligned} \min_{\lambda, x} \quad & -b^T \lambda - \frac{1}{\epsilon} \sum \log \lambda \\ \text{s.t.} \quad & A^T \lambda + \lambda = c \end{aligned} \quad \left. \vphantom{\min_{\lambda, x}} \right\} \text{dual barrier}$$

$$\begin{aligned} \mathcal{L}(\lambda, x) &= -b^T \lambda - \frac{1}{\epsilon} \sum \log \lambda + x^T (A^T \lambda + \lambda - c) \\ &= (Ax - b)^T \lambda - \frac{1}{\epsilon} \sum \log \lambda + x^T \lambda - c^T x \\ \nabla_{\lambda} \mathcal{L} &= -\frac{1}{\epsilon} \frac{1}{\lambda} + x = 0 \quad \lambda = \frac{1}{\epsilon x} \end{aligned}$$

$$\begin{aligned} g(x) &= \inf_{\lambda} \mathcal{L} \\ &= \begin{cases} -\infty & \text{if } Ax - b \neq 0 \\ -\infty & x_i \leq 0 \text{ for some } i \\ -\frac{1}{\epsilon} \sum \log \frac{1}{\epsilon x} + \eta/\epsilon - c^T x & \text{otherwise} \end{cases} \end{aligned}$$

$$\begin{aligned} \max_{\lambda} \quad & -c^T x - \frac{1}{\epsilon} \sum \log \frac{1}{\epsilon x} \\ \text{s.t.} \quad & Ax = b \\ & x > 0 \end{aligned} \Rightarrow \begin{aligned} \min_{\lambda} \quad & c^T x - \frac{1}{\epsilon} \sum \log x \\ \text{s.t.} \quad & Ax = b \\ & x > 0 \end{aligned} \quad \left. \vphantom{\min_{\lambda}} \right\} \text{primal barrier}$$

KKT for dual barrier:

primal feasible: $\lambda > 0, A^T \lambda + \lambda = c$

dual feasible: $x > 0, Ax = b$

gradient vanishes: $\lambda_i x_i = \frac{1}{\epsilon}$

primal barrier and dual barrier have the same optimality condition

assume primal problem and dual problem are strictly feasible,

→ the primal dual central path is $\{(x(t), v(t), \lambda(t))\}$

s.t. $x(t)$ solves the primal barrier
 $\lambda(t), v(t)$ solve the dual barrier

↕

$$A^T x(t) > b, x(t) > 0$$

$$A^T v(t) + \lambda(t) = c, \lambda(t) > 0$$

$$x_i(t) \lambda_i(t) = \frac{1}{\epsilon}$$

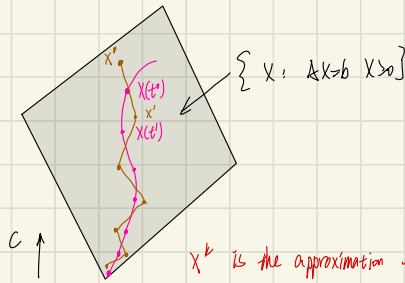
for the primal barrier, obj is strictly convex
for the dual barrier, obj is strictly convex,
 A is full-rank

∴ $(x(t), \lambda(t), v(t))$ is unique

Path-following Interior-point method

generate $(X^k, \lambda^k, V^k) \approx (X(t^k), \lambda(t^k), V(t^k))$

key details $\left\{ \begin{array}{l} \cdot \text{proximity to central path} \\ \cdot \text{increase } t \\ \cdot \text{update } (X^k, \lambda^k, V^k) \end{array} \right.$



X^k is the approximation of $X(t^k)$ as $t^k \rightarrow \infty$
Solutions to the primal-barrier

Neighborhoods of central path

let $\mathcal{F}^0 = \{ (X, \lambda, V) : AX=b, X \geq 0, X \leq 0 \}$ be the feasible set

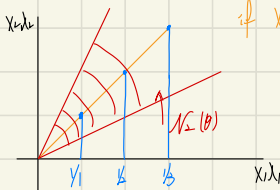
$\mathcal{F}^0 \xrightarrow{\quad} \mathbb{R}^n_{++}$
 $(X, \lambda, V) \mapsto \begin{pmatrix} X, \lambda \\ X, \lambda, V \end{pmatrix}$

given $X, \lambda \in \mathbb{R}^n_+$ $U(X, \lambda) = \frac{X \lambda}{n}$

if X is primal feasible and λ, V is dual feasible $c^T X - b^T V = X \lambda$ $U(X, \lambda)$ is the duality gap.

the norm neighborhood: for $\theta \in (0, 1)$

$$N_\theta(\theta) = \left\{ (X, \lambda, V) : (X, \lambda, V) \in \mathcal{F}^0, \|X \lambda - U(X, \lambda)\|_2 \leq \theta U(X, \lambda) \right\}$$



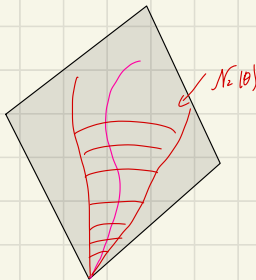
if X, λ is on the central path
 $X, \lambda = \frac{1}{t} X^0, \lambda^0$

let $X = \frac{1}{t} X^0$
 $\lambda = \frac{1}{t} \lambda^0$

$$K = \{ (X, \lambda) : \left\| \begin{pmatrix} X \\ \lambda \end{pmatrix} - \begin{pmatrix} \frac{X \lambda}{n} \\ \frac{X \lambda}{n} \end{pmatrix} \right\|_2 \leq \theta \frac{X \lambda}{n} \}$$

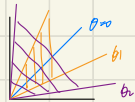
if $(X, \lambda) \in K$ $(X, \lambda) \in K$

$$a(X, \lambda) + b(X, \lambda) = (a(X, \lambda), b(X, \lambda)) \in K$$



if $\theta \rightarrow 0$ $X, \lambda = U(X, \lambda) = \frac{X \lambda}{n}$

then $X, \lambda = \frac{1}{t} X^0, \lambda^0$ for some t , X, λ is on the central path
the larger θ is the bigger neighborhood is



one-sided infinity-norm neighborhood for $f \in [0,1]$

$$N_{\infty}(f) = \{ (x, \lambda, \nu) : (x, \lambda, \nu) \in f^0, x_{iL} > f(u(x, \lambda)) \}$$



if $f \approx 0$ then $N_{\infty}(f) \approx f^0$

Newton Step

$$\begin{bmatrix} A^T \nu + \lambda - c \\ Ax - b \\ \text{diag}(x) \text{diag}(\nu) \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\epsilon} L - x \cdot \lambda \end{bmatrix} \quad x \gg \lambda \gg 0$$

$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ \text{diag}(\nu) & 0 & \text{diag}(x) \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta \nu \\ \Delta \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\epsilon} L - x \cdot \lambda \end{bmatrix}$$

Short-step Path-Following Algorithm (2-norm neighborhood, small)

choose $\theta, \delta \in (0,1)$ s.t. $\frac{\theta^2 + \delta^2}{2\theta(1-\theta)} \leq (1 - \frac{\delta}{n})\theta$ (can choose $\theta = \delta = 0.4$)

let $(x^0, \lambda^0, \nu^0) \in N(\theta)$

for $k=0,1,\dots$

$$\text{let } \frac{1}{\epsilon} = (1 - \frac{\delta}{n}) u(x, \lambda)$$

$$\text{compute newton step } \begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & x \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta \nu \\ \Delta \lambda \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\epsilon} L - x \cdot \lambda \end{bmatrix}$$

$$(x^{k+1}, \lambda^{k+1}, \nu^{k+1}) = (x^k, \lambda^k, \nu^k) + (\Delta x, \Delta \lambda, \Delta \nu)$$

the sequence generated by STP satisfies

$$(x^k, \lambda^k, \nu^k) \in N(\theta)$$

$$u(x^{k+1}, \lambda^{k+1}) = (1 - \frac{\delta}{n}) u(x^k, \lambda^k)$$

$$\begin{aligned} x^{k+1} \cdot \lambda^{k+1} &= (x^k + \Delta x)(\lambda^k + \Delta \lambda) = x^k \lambda^k + x^k \Delta \lambda + \lambda^k \Delta x + \Delta x \Delta \lambda \\ &= x^k \lambda^k + \frac{1}{\epsilon} L - x^k \lambda^k + o(x \Delta \lambda) \\ &= \frac{1}{\epsilon} L + o(x \Delta \lambda) \end{aligned}$$

$$\begin{aligned} u(x^{k+1}, \lambda^{k+1}) &= \frac{1}{n} (x^{k+1})^T (\lambda^{k+1}) = \frac{1}{n} \left(\frac{1}{\epsilon} + \Delta x^T \Delta \lambda \right) \\ &= \frac{1}{\epsilon} + u(\Delta x, \Delta \lambda) \\ &= \left(1 - \frac{\delta}{n}\right) u(x^k, \lambda^k) + \underbrace{u(\Delta x, \Delta \lambda)}_0 \end{aligned}$$

$$\begin{aligned} \Delta x^T \Delta \lambda + \Delta \lambda^T \Delta x &\approx 0 \\ \Delta x^T \Delta \lambda + \Delta \lambda^T \Delta x &\approx 0 \\ \therefore \Delta x^T \Delta \lambda &\approx 0 \end{aligned}$$

theoretically fast, practically slow

Long-step path Following Algorithm (inf-norm neighborhood, large)

choose $\tau \in (0,1)$ $0 < \delta_{\min} < \delta_{\max} < 1$

let $(x^0, \lambda^0, v^0) \in \mathcal{N}_{\text{inf}}(\tau)$

for $k=0,1,\dots$

choose $\theta \in [\delta_{\min}, \delta_{\max}]$, $\frac{1}{\theta} = \theta U(x^k, \lambda^k)$

compute newton step
$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & X \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta \lambda \\ \Delta v \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\theta} (I - X)v \end{bmatrix}$$

choose $\alpha_k \in [0,1]$ s.t.

$$(x^k, \lambda^k, v^k) + \alpha_k (\Delta x, \Delta \lambda, \Delta v) \in \mathcal{N}_{\text{inf}}(\tau)$$

$$(x^{k+1}, \lambda^{k+1}, v^{k+1}) = (x^k, \lambda^k, v^k) + \alpha_k (\Delta x, \Delta \lambda, \Delta v)$$

the sequence generated by LPT satisfies

$$(x^k, \lambda^k, v^k) \in \mathcal{N}_{\text{inf}}(\tau)$$

$$U(x^{k+1}, \lambda^{k+1}) \leq (1 - \frac{\theta}{2}) U(x^k, \lambda^k) \quad \delta \text{ depends on } \tau, \delta_{\min} \text{ and } \delta_{\max}$$

LPT is practically faster than SPF

Infeasible Interior-point Algorithm

given $x^0 > 0$, $\lambda^0 > 0$

given $\tau \in (0,1)$, $\beta \geq 1$

$$\begin{bmatrix} Xu + \lambda - c \\ Ax - b \\ \lambda x \end{bmatrix} = \begin{bmatrix} rd \\ rp \\ rc \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \frac{1}{\theta} \end{bmatrix}$$

$$\mathcal{N}_{\text{inf}}(\tau) = \left\{ (x, \lambda, v) : \|(rp, rc)\| \leq \frac{\beta U}{\theta} \|r_p, r_c\|, x > 0, \lambda > 0, x_i v_i \geq \tau u_i \right\}$$

choose $\tau \in (0,1)$ $0 < \delta_{\min} < \delta_{\max} < 0.5$ and $\beta \geq 1$

choose (x^0, λ^0, v^0) with $x^0, \lambda^0 > 0$

For $k=0,1,\dots$

choose $\theta \in [\delta_{\min}, \delta_{\max}]$

$$\frac{1}{\theta} = \theta \cdot U(x^k, \lambda^k)$$

solve newton step
$$\begin{bmatrix} 0 & A^T & I \\ A & 0 & 0 \\ S & 0 & X \end{bmatrix} \begin{bmatrix} \Delta x \\ \Delta \lambda \\ \Delta v \end{bmatrix} = \begin{bmatrix} -rd \\ -rp \\ \frac{1}{\theta} (I - X)v \end{bmatrix}$$

choose $\alpha \in [0,1]$ s.t.

$$(x^k, \lambda^k, v^k) + \alpha (\Delta x, \Delta \lambda, \Delta v) \in \mathcal{N}_{\text{inf}}(\tau, \beta)$$

$$U(x^k + \alpha \Delta x, \lambda^k + \alpha \Delta \lambda) \leq (1 - \alpha \theta) U(x^k, \lambda^k)$$