

Primal-Dual Interior Point Algorithm (Path-Following Algorithm) for Linear Programming



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Consider the primal/dual pair of LPs:

Primal

Minimize $c^t x$
subject to $Ax = b$
 $x \geq 0$

Dual

Maximize $y b$
subject to $yA \leq c^t$

i.e.,

Maximize $b^t y$
subject to $A^t y \leq c$

Convert dual constraints to equalities:

Primal

$$\begin{aligned} &\text{Minimize } c^t x \\ &\text{subject to } Ax = b \\ &\quad x \geq 0 \end{aligned}$$

Dual

$$\begin{aligned} &\text{Maximize } b^t y \\ &\text{subject to } A^t y + z = c^t \\ &\quad z \geq 0 \end{aligned}$$

Use barrier functions to relax the non-negativity conditions:

Primal

$$\begin{aligned} &\text{Minimize } c^t x - \mu \sum_{j=1}^n \ln(x_j) \\ &\text{subject to } Ax = b \end{aligned}$$

$$\begin{aligned} &\text{as } x \rightarrow 0, \\ &-\mu \ln(x) \rightarrow \infty \end{aligned}$$

Dual

$$\begin{aligned} &\text{Maximize } b^t y + \mu \sum_{j=1}^n \ln(z_j) \\ &\text{subject to } A^t y + z = c^t \end{aligned}$$

Use Lagrange multipliers to relax the equality constraints:

Lagrangian Functions

$$L_P(x, y) = c^t x - \mu \sum_{j=1}^n \ln(x_j) + y^t (A x - b)$$

$$L_D(x, y, z) = b^t y + \mu \sum_{j=1}^n \ln(x_j) - x^t (A^t y + z - c)$$

The optimality conditions may be written

$$\frac{\partial L_P(x, y)}{\partial x} = 0, \quad \frac{\partial L_P(x, y)}{\partial y} = 0$$

and

$$\frac{\partial L_D(x, y, z)}{\partial x} = 0, \quad \frac{\partial L_D(x, y, z)}{\partial y} = 0, \quad \frac{\partial L_D(x, y, z)}{\partial z} = 0$$

These reduce to the following
optimality conditions

$$\begin{array}{l}
 Ax = b \\
 A^t y + z = c \\
 x_j z_j = \mu, j=1,2, \dots, n
 \end{array}
 \left. \begin{array}{l}
 \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{linear} \\
 \left. \begin{array}{l} \\ \\ \end{array} \right\} \text{equations} \\
 \leftarrow \text{nonlinear} \\
 \leftarrow \text{equations}
 \end{array} \right.$$

To solve the nonlinear system of equations, we might use the *Newton-Raphson* method:

Given an initial approximate solution (x^0, y^0, z^0) :
an improved approximate solution is given
by

$$\begin{cases}
 x^1 = x^0 + \delta_x \\
 y^1 = y^0 + \delta_y \\
 z^1 = z^0 + \delta_z
 \end{cases}$$

where δ_x , δ_y , and δ_z are found by solving a linear system.

Notation

$$X = \text{diag}\{x_1, x_2, \dots, x_n\}$$

$$Z = \text{diag}\{z_1, z_2, \dots, z_n\}$$

$$e = [1, 1, \dots, 1]$$

Then the constraints

$$x_j z_j = \mu, \quad j=1, 2, \dots, n$$

may be written

$$X Z e = \mu e$$

We wish to solve the *nonlinear* system

$$\begin{cases} A x - b = 0 \\ A^t y + z - c = 0 \\ X Z e - \mu e = 0 \end{cases}$$

Newton-Raphson Method: given (x^0, y^0, z^0) , solve the *linear* system

$$\begin{cases} A \delta_x & & = -[A x^0 - b] \\ & A^t \delta_y + \delta_z & = -[A^t y^0 + z^0 - c] \\ Z \delta_x & + X \delta_z & = -[X Z e - \mu e] \end{cases}$$

That is, solve

$$\text{Jacobian matrix} \rightarrow \begin{bmatrix} A & 0 & 0 \\ 0 & A^t & I \\ Z & 0 & X \end{bmatrix} \begin{bmatrix} \delta_x \\ \delta_y \\ \delta_z \end{bmatrix} = \begin{bmatrix} d_p \\ -d_D \\ \mu e - XZ e \end{bmatrix}$$

where $d_p = b - Ax^0 \leftarrow \text{primal infeasibility}$

$d_D = A^t y^0 + z^0 - c \leftarrow \text{dual infeasibility}$

and then compute the improved approximation

$$\begin{cases} x^1 = x^0 + \delta_x \\ y^1 = y^0 + \delta_y \\ z^1 = z^0 + \delta_z \end{cases}$$

Solving the linear system:

$$\delta_x = Z^{-1} [\mu e - XZ e - X \delta_z]$$

$$\delta_z = -d_D - A^t \delta_y$$

$$\Rightarrow [A Z^{-1} X A^t] \delta_y = b - \mu A Z^{-1} e - A Z^{-1} X d_D$$

$$\text{or } \delta_y = [A Z^{-1} X A^t]^{-1} (b - \mu A Z^{-1} e - A Z^{-1} X d_D)$$

Computing

$$\delta_y = [A Z^{-1} X A^t]^{-1} (b - \mu A Z^{-1} e - A Z^{-1} X d_D)$$

by using matrix inversion is computationally costly for large problems...

other methods for solving the linear system for δ_y are preferred.

After computing the step $(\delta_x, \delta_y, \delta_z)$,

$$\begin{cases} x^1 = x^0 + \delta_x \\ y^1 = y^0 + \delta_y \\ z^1 = z^0 + \delta_z \end{cases}$$

An alternative would be to go (almost) as far as possible in the x direction and the (y,z) direction:

$$\begin{cases} x^1 = x^0 + \alpha_P \delta_x \\ y^1 = y^0 + \alpha_D \delta_y \\ z^1 = z^0 + \alpha_D \delta_z \end{cases}$$

for stepsizes α_P and α_D , respectively.

$$\alpha_P = \tau \min_j \left\{ \frac{-x_j^0}{\delta_{xj}} : \delta_{xj} < 0 \right\}$$

$$\alpha_D = \tau \min_j \left\{ \frac{-z_j^0}{\delta_{zj}} : \delta_{zj} < 0 \right\}$$

for $0 < \tau < 1$ *e.g., $\tau = 0,995$*
 ($\tau = 1$ will result in one of the x and z variables
 reaching zero!)

Generally, only one Newton-Raphson step is used, so that the nonlinear system is only approximately solved.

This completes one iteration. As $\mu \rightarrow 0$, the values of x,y, and z will converge to the optimal primal and dual solutions.

The path followed by (x,y,z) is referred to as the *central path* and the algorithm as a *path-following* algorithm.

Reduction of μ :

$$\mu = \frac{c^t x^1 - b^t y^1}{\theta(n)}$$

suggested value of parameter θ :

$$\theta(n) = \begin{cases} n^2 & \text{if } n \leq 5,000 \\ n \sqrt{n} & \text{if } n > 5,000 \end{cases}$$

Termination criterion:

$$\frac{c^t x^k - b^t y^k}{1 + |b^t y^k|} < \epsilon$$

The number of iterations required is rather insensitive to the size n of the problem, and is usually between 20 and 80 for most problems.