

Formula:

- When using the simplex method for solving linear programming problems, we have

$$\begin{array}{c}
 x_B \\
 f
 \end{array}
 \begin{array}{|c|c|}
 \hline
 & \begin{array}{c} x_N \\ 1 \end{array} \\
 \hline
 & \begin{array}{c} -A_B^{-1}A_N \\ A_B^{-1}b \end{array} \\
 \hline
 & \begin{array}{c} p_N^t - p_B^t A_B^{-1}A_N \\ p_B^t A_B^{-1}b \end{array} \\
 \hline
 \end{array}$$

- Given a vector  $\mathbf{v}$  and a matrix  $A$ , we have

$$proj_{null(A)}\mathbf{v} = (I - A^T(AA^T)^{-1}A)\mathbf{v}$$

- (PAS algorithm) Given the  $k$ -th interior point  $\mathbf{x}^k$ , compute the affine transformation  $\mathbf{x}^k = T^k\mathbf{y}^k$ , where  $\mathbf{y}^k = (1, \dots, 1)^t$ . Use this affine transformation to rewrite the linear programming problem into *minimize*  $f = \mathbf{p}^k\mathbf{y}$ , *subject to*  $A^k\mathbf{y} = \mathbf{b}$ ,  $\mathbf{y} \geq 0$ . For the transformed problem, compute the direction vector  $\mathbf{d}^k = proj_{null(A^k)}(-\nabla f)$  and the step length  $\alpha^k$ . Use these to calculate  $\mathbf{y}^{k+1} = \mathbf{y}^k + \beta\alpha^k\mathbf{d}^k$ . Finally, transform it back to the original problem by using  $\mathbf{x}^{k+1} = T^k\mathbf{y}^{k+1}$ .
- (Primal-dual interior point method) Given  $\mathbf{x}^k, \mathbf{s}^k, \mathbf{u}^k$ , compute  $\mu^k = \frac{\mathbf{x}^k \cdot \mathbf{s}^k}{n(k+1)}$ ,  $D = XS^{-1}$ ,  $\mathbf{r}_a = -A\mathbf{x}^k + \mathbf{b}$ ,  $\mathbf{r}_b = -A^t\mathbf{u}^k - \mathbf{s}^k + \mathbf{p}$ ,  $\mathbf{r}_c = -XSe + \mu\mathbf{e}$ . Then compute  $\mathbf{d}_u = (ADA^T)^{-1}(\mathbf{r}_a + AD\mathbf{r}_b - AS^{-1}\mathbf{r}_c)$ ,  $\mathbf{d}_s = \mathbf{r}_b - A^t\mathbf{d}_u$ ,  $\mathbf{d}_x = S^{-1}\mathbf{r}_c - D\mathbf{d}_s$ . Use the ratio test to compute  $\alpha_x, \alpha_s$ , and  $\alpha_u$ . Finally,  $\mathbf{x}^{k+1} = \mathbf{x}^k + \alpha_x\mathbf{d}_x$ ,  $\mathbf{s}^{k+1} = \mathbf{s}^k + \alpha_s\mathbf{d}_s$ ,  $\mathbf{u}^{k+1} = \mathbf{u}^k + \alpha_u\mathbf{d}_u$ .
- The Lagrange function for problem

$$\begin{array}{ll}
 \min & f(\mathbf{x}) \\
 \text{subject to} & g_1(\mathbf{x}) \geq b_1 \\
 & \dots \\
 & g_m(\mathbf{x}) \geq b_m
 \end{array}$$

is

$$L(\mathbf{x}, \mathbf{u}) = f(\mathbf{x}) - u_1(g_1(\mathbf{x}) - b_1) - \dots - u_m(g_m(\mathbf{x}) - b_m)$$

where  $\mathbf{u} \geq 0$ .

- (Active set algorithm) Given  $\mathbf{x}^k$ , use the Lagrange function to check whether it is an optimal solution or not. If  $\mathbf{x}^k$  is not an optimal solution, remove the constraint that corresponds to the most negative Lagrange multiplier from the active set. Then, compute  $\mathbf{y}_k$  satisfying

$$\begin{array}{ll}
 \min & f(\mathbf{x}^k + \mathbf{y}^k) \\
 \text{subject to} & (\mathbf{x}^k + \mathbf{y}^k \text{ satisfies all the rest of active constrains})
 \end{array}$$

Set  $\mathbf{d}_k = \mathbf{y}_k$ . Next, compute  $\alpha^k = \min(1, \bar{\alpha})$ , where  $\bar{\alpha}$  is the largest number which guarantees that  $\mathbf{x}^k + \bar{\alpha}\mathbf{d}^k$  satisfies all inactive constraints. Set  $\mathbf{x}^{k+1} = \mathbf{x}^k + \alpha^k\mathbf{d}^k$ .