LPMS Note

1 General Linear Programming Problem

General LP Problem: **Decision Variables**: x_i **parameters**: a_{ij}, b_i, c_i **Objective Function**: f **Constraints**: subject to 后边的部分

LP problem can be written as:

$$\begin{aligned} \text{maximize} \quad & f = c_1x_1 + c_2x_2 + \cdots + c_nx_n \\ \text{subject to} \quad & a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n \le b_1 \\ & a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n \le b_2 \\ & \vdots \\ & a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n \le b_m \\ & x_1 \ge 0, x_2 \ge 0, \cdots, x_n \ge 0 \end{aligned}$$

We can also write the LP problem in matrix form:

$$A = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ \vdots & \ddots & \vdots \\ a_{m1} & \cdots & a_{mn} \end{pmatrix}, \mathbf{b} = \begin{pmatrix} b_1 \\ \vdots \\ b_m \end{pmatrix}, \mathbf{c} = \begin{pmatrix} c_1 \\ \vdots \\ c_n \end{pmatrix}, \mathbf{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$$

$$\begin{aligned} \text{maximize} \quad & f = \mathbf{c}^T\mathbf{x} \\ \text{subject to} \quad & A\mathbf{x} \le \mathbf{b} \qquad \mathbf{x} \ge 0 \end{aligned}$$

Feasible Solution: If $\mathbf{x}$ satisfies all constraints (i.e. $A\mathbf{x} \le \mathbf{b}$), then $\mathbf{x}$ is a feasible solution. (可行解) **Optimal Sol**: (最优解) (可多个)

Find Optimal Solution: **Graphical Method**: 略. **Vertex Enumeration**: 所有顶点检查, 找出最优解. **Simplex Method**: 后面详述.

Slack Variables: For each inequality constraint, we introduce a slack variable x_i $(i > n)$ to convert it to an equation. (松弛变量)

LP problem can be written as: ps: $x_i \ge 0$ $(i > n)$.

$$\begin{aligned} \text{maximize} \quad & f = c_1x_1 + c_2x_2 + \cdots + c_nx_n \\ \text{subject to} \quad & a_{11}x_1 + a_{12}x_2 + \cdots + a_{1n}x_n + x_{n+1} = b_1 \\ & a_{21}x_1 + a_{22}x_2 + \cdots + a_{2n}x_n + x_{n+2} = b_2 \\ & \vdots \\ & a_{m1}x_1 + a_{m2}x_2 + \cdots + a_{mn}x_n + x_{n+m} = b_m \\ & x_1 \ge 0, x_2 \ge 0, \cdots, x_{n+m} \ge 0 \end{aligned}$$

We can also write the LP problem in matrix form:

$$\overline{A} = [\ A \ \ I_m\ ], \mathbf{b} = \mathbf{b}, \overline{\mathbf{c}} = \begin{pmatrix} \mathbf{c} \\ \mathbf{0}_{m\times 1} \end{pmatrix}, \mathbf{x} = \begin{pmatrix} \mathbf{x} \\ \vdots \\ x_{n+m} \end{pmatrix}$$

$$\begin{aligned} \text{maximize} \quad & f = \overline{\mathbf{c}}^T\mathbf{x} \\ \text{subject to} \quad & \overline{A}\mathbf{x} = \mathbf{b} \qquad \mathbf{x} \ge 0 \end{aligned}$$

Solving: $\mathbf{x} = \mathbf{x}_b + \mathbf{v}$ where $\overline{A}\mathbf{v} = 0$ and $\mathbf{x}_b = [\mathbf{0}\ \mathbf{b}]^T$

Feasible Region: It's the set K of the solutions to $\overline{A}\mathbf{x} = \mathbf{b}$ **Convex Set**: The set K is convex if $\forall \mathbf{x}, \mathbf{x}' \in K, \forall \theta \in [0,1], \mathbf{x}_\theta = (1-\theta)\mathbf{x} + \theta\mathbf{x}' \in K$.

Vertex on Convex Set: A vertex of the convex set K is a point $\mathbf{x} \in K$ which doesn't lie strictly inside any line segment connecting two points in K.

· **Theorem**: If LP has a unique optimal solution is a vertex. **Theorem**: If LP has a non-unique solution, ∃ optimal solution at vertex

Solve LP Problem: Assume $f = \overline{\mathbf{c}}^T\mathbf{x}$ with $\overline{A}\mathbf{x} = \mathbf{b}$ and $\mathbf{x} \ge 0$.

1. 修改 x_i/列顺序,A 中换顺序后得到可逆的 $B_{m\times m}$ $\Rightarrow$ $\overline{A}\mathbf{x} = \mathbf{b} \Leftrightarrow B\mathbf{x}_B + N\mathbf{x}_N = \mathbf{b}$ $\mathbf{c} \to [\mathbf{c}_B\ \mathbf{c}_N]^T$ $\overline{A} \to [B\ N]$ $\mathbf{x} \to [\mathbf{x}_B\ \mathbf{x}_N]^T$ Let $\hat{\mathbf{b}} = B^{-1}\mathbf{b}$ $\hat{N} = B^{-1}N$
2. **Basic Solution**: $\mathbf{x}_B = \hat{\mathbf{b}}, \mathbf{x}_N = \mathbf{0}$ $\Rightarrow$ If $\hat{\mathbf{b}} \ge 0$. Corresponding $\mathbf{x}$ is: [1] vertex of K; [2] **Basic Feasible Solution (BFS)**
3. **Basic Costs**: $\mathbf{c}_B^T$ **Nonbasic Costs**:$\mathbf{c}_N^T$ **Reduced Costs**: $\hat{\mathbf{c}}_N = \mathbf{c}_N - \hat{N}^T\mathbf{c}_B = \mathbf{c}_N - N^TB^{-T}\mathbf{c}_B$ $\hat{f} = \mathbf{c}_B^T\hat{\mathbf{b}}$ $\mathbf{x}_B, \mathbf{x}_N \ge 0$
4. **Objective Value**: $f = \overline{\mathbf{c}}^T\mathbf{x} = \mathbf{c}_B^T\mathbf{x}_B + \mathbf{c}_N^T\mathbf{x}_N = \hat{f} + \hat{\mathbf{c}}_N^T\mathbf{x}_N$ If $\hat{\mathbf{c}}_N \le 0$, then $f \le \hat{f}$ $\Rightarrow$ Corresponding $\mathbf{x}$ is optimal.
5. If $\hat{\mathbf{c}}_N \le 0$ doesn't hold, we using **Simplex Algorithm.**