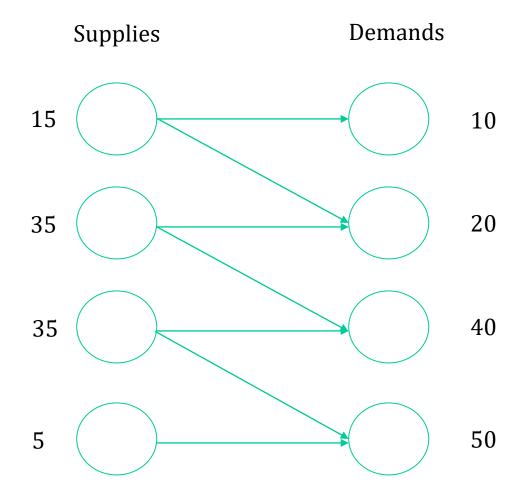
LEC011 Maximum Flow and Linear Program

VG441 SS2021

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Max Flow Applications



Linear Programming

Comparison to systems of linear equations

$$a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1$$

$$a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2$$

$$\vdots$$

$$a_{m1}x_1 + a_{m2}x_2 + \dots + a_{mn}x_n = b_m$$

Linear Programming

Ingredients of a Linear Program

- 1. Decision variables $x_1, \ldots, x_n \in \mathbb{R}$
- 2. Linear constraints, each of the form

$$\sum_{j=1}^{n} a_{ij} x_j \quad (*) \quad b_i$$

where (*) could be \leq, \geq , or =

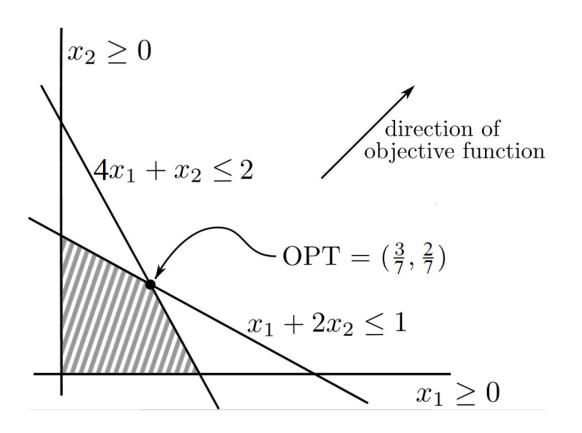
3. A linear objective function, of the form

$$\max \sum_{j=1}^{n} c_j x_j \qquad \text{or} \qquad \min \sum_{j=1}^{n} c_j x_j$$

A Simple Example

max
$$x_1 + x_2$$

s.t. $4x_1 + x_2 \le 2$
 $x_1 + 2x_2 \le 1$
 $x_1, x_2 \ge 0$



Python + Gurobi Time!





MaxFlow is a LP

Decision variables

$$\{f_e\}_{e\in E}$$

• Constraints (2m + n - 2)

$$\underbrace{\sum_{e \in \delta^{-}(v)} f_e - \sum_{e \in \delta^{-}(v)} f_e}_{\text{flow in}} = 0$$

$$f_e \le u_e$$

Objectives

$$f_e \ge 0$$

$$\max \sum_{e \in \delta^+(s)} f_e$$

Generalization of MaxFlow

Min-Cost MaxFlow

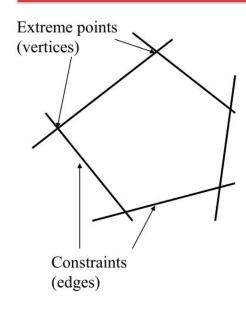
$$\min \sum_{e \in E} c_e f_e$$

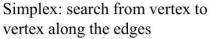
Easy to change the LP formulation!

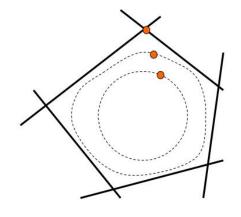
Solution Approaches

- Simplex methods
- Interior point methods

Interior point methods







Interior-point methods: go through the inside of the feasible space

LP Duality

• Question: given a feasible solution, how can we know whether it is optimal or close to optimal?

max
$$x_1 + x_2$$

s.t. $4x_1 + x_2 \le 2$
 $x_1 + 2x_2 \le 1$
 $x_1, x_2 \ge 0$

$$\underbrace{x_1 + x_2}_{\text{objective}} \le 4x_1 + x_2 \le \underbrace{2}_{\text{upper bound}}$$

$$\underbrace{x_1 + x_2}_{\text{objective}} \le x_1 + 2x_2 \le \underbrace{1}_{\text{upper bound}}$$

Can we get an even better upper bound?

$$x_1 + x_2 \le \frac{1}{7} \underbrace{(4x_1 + x_2)}_{\le 2 \text{ by (2)}} + \frac{3}{7} \underbrace{(x_1 + 2x_2)}_{\le 1 \text{ by (3)}} \le \frac{1}{7} \cdot 2 + \frac{3}{7} \cdot 1 = \frac{5}{7}$$

Deriving the Dual LP

Compact form

 $\mathbf{c}^T \mathbf{x}$ max s.t. $\mathbf{A}\mathbf{x} \leq \mathbf{b}$

$$\mathbf{x} \ge 0$$

 $\sum c_j x_j$ max

"Multipliers"

• $y_1 \ge 0$

s.t.
$$\sum_{i=1}^{n} a_{1j} x_j \le b_1$$

$$\sum_{j=1}^{n} a_{2j} x_j \le b_2 \qquad \longrightarrow \qquad y_2 \ge 0$$

$$\vdots \leq \vdots$$

$$\sum_{j=1}^{n} a_{mj} x_j \le b_m \quad \longrightarrow \quad y_m \ge 0$$

$$x_1, \ldots, x_n \ge 0$$

The idea is to "dominates the objective coefficients": $\sum_{i=1} y_i a_{ij} \geq c_j$

$$\sum_{i=1}^{m} y_i a_{ij} \ge c_j$$

More compactly,

Find $\mathbf{y} \geq 0$ such that $\mathbf{A}^T \mathbf{y} \geq \mathbf{c}$

Deriving the Dual LP

 $\begin{array}{ll}
\max & \mathbf{c}^T \mathbf{x} \\
\text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b} \\
\mathbf{x} \geq 0
\end{array}$

Find $\mathbf{y} \ge 0$ such that $\mathbf{A}^T \mathbf{y} \ge \mathbf{c}$

$$\sum_{j=1}^{n} c_j x_j \leq \sum_{j=1}^{n} \left(\sum_{i=1}^{m} y_i a_{ij}\right) x_j$$
x's obj fn

$$= \sum_{i=1}^{m} y_i \cdot \left(\sum_{j=1}^{n} a_{ij} x_j\right)$$

$$\leq \sum_{i=1}^{m} y_i b_i$$
upper bound

More compactly,

$$\mathbf{c}^T \mathbf{x} \leq \left(\mathbf{A}^T \mathbf{y} \right)^T \mathbf{x} = \mathbf{y}^T (\mathbf{A} \mathbf{x}) \leq \mathbf{y}^t \mathbf{b}$$

Deriving the Dual LP

$$\begin{array}{ll}
\max & \mathbf{c}^T \mathbf{x} \\
\text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b} \\
\mathbf{x} \geq 0
\end{array}$$

Find $\mathbf{y} \geq 0$ such that $\mathbf{A}^T \mathbf{y} \geq \mathbf{c}$

$$\mathbf{c}^T \mathbf{x} \le \left(\mathbf{A}^T \mathbf{y} \right)^T \mathbf{x} = \mathbf{y}^T (\mathbf{A} \mathbf{x}) \le \mathbf{y}^t \mathbf{b}$$

min
$$\mathbf{b}^T \mathbf{y}$$
s.t. $\mathbf{A}^T \mathbf{y} \ge \mathbf{c}$
 $\mathbf{y} \ge 0$

A Simple Example

$$\begin{array}{ll}
\max & \mathbf{c}^T \mathbf{x} \\
\text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b} \\
\mathbf{x} \geq 0
\end{array}$$

min
$$\mathbf{b}^T \mathbf{y}$$
s.t. $\mathbf{A}^T \mathbf{y} \ge \mathbf{c}$
 $\mathbf{y} \ge 0$

max
$$x_1 + x_2$$

s.t. $4x_1 + x_2 \le 2$
 $x_1 + 2x_2 \le 1$
 $x_1, x_2 \ge 0$

min
$$2y_1 + y_2$$

s.t. $4y_1 + y_2 \ge 1$
 $y_1 + 2y_2 \ge 1$
 $y_1, y_2 \ge 0$

$$x_1^* = 3/7, x_2^* = 2/7$$

$$y_1^* = 1/7, y_2^* = 3/7$$

Optimal objectives are the same!

Weak and Strong Duality

$$\begin{array}{ll}
\max & \mathbf{c}^T \mathbf{x} \\
\text{s.t.} & \mathbf{A} \mathbf{x} \leq \mathbf{b} \\
\mathbf{x} \geq 0
\end{array}$$

min
$$\mathbf{b}^T \mathbf{y}$$
s.t. $\mathbf{A}^T \mathbf{y} \ge \mathbf{c}$
 $\mathbf{y} \ge 0$

We have

- Weak Duality $\mathbf{c}^T \mathbf{x} \leq \mathbf{b}^T \mathbf{y}$ for any feasible solutions \mathbf{x} and \mathbf{y}
- Strong Dualiy $\mathbf{c}^T \mathbf{x}^* = \mathbf{b}^T \mathbf{y}^*$ at optimality

Proof = Separating hyperplance theorem + Farkas's Lemma

More General Form

Primal	Dual
variables x_1, \ldots, x_n	n constraints
m constraints	variables y_1, \ldots, y_m
objective function ${f c}$	right-hand side ${f c}$
right-hand side \mathbf{b}	objective function \mathbf{b}
$\max \mathbf{c}^T \mathbf{x}$	$\min \mathbf{b}^T \mathbf{y}$
constraint matrix ${f A}$	constraint matrix \mathbf{A}^T
i-th constraint is " \leq "	$y_i \ge 0$
i-th constraint is " \geq "	$y_i \le 0$
i-th constraint is "="	$y_i \in \mathbb{R}$
$x_j \ge 0$	j-th constraint is " \geq "
$x_j \leq 0$	j-th constraint is " \leq "
$x_j \in \mathbb{R}$	j-th constraint is " $=$ "

Back to MaxFlow

Let the decision variable be flow on an s-t path

max
$$\sum_{P \in \mathcal{P}} f_P$$
s.t.
$$\sum_{P \in \mathcal{P}: e \in P} f_P \le u_e \text{ for all } e \in E$$
total flow on e

$$f_P \ge 0 \text{ for all } P \in \mathcal{P}$$

Question: how to write its dual and what is its interpretation?