

Dual Interpretations and Duality Applications

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(LY, Chapters 4.1-4.2, 4.5)

Production Problem I

$$\max \mathbf{p}^T \mathbf{x} \quad \text{s.t.} \quad A\mathbf{x} \leq \mathbf{r}, \quad \mathbf{x} \geq \mathbf{0}$$

where

- \mathbf{p} : profit margin vector
- A : resource consumption rate matrix
- \mathbf{r} : available resource vector
- \mathbf{x} : production level decision vector

Production Problem II: Liquidation Pricing

- \mathbf{y} : the fair price vector
- $A^T \mathbf{y} \geq \mathbf{p}$: competitiveness
- $\mathbf{y} \geq 0$: positivity
- $\min \mathbf{r}^T \mathbf{y}$: minimize the total liquidation cost

Primal :

$$\begin{array}{llll} \text{maximize} & x_1 & +2x_2 & \\ \text{subject to} & x_1 & & \leq 1 \\ & & x_2 & \leq 1 \\ & x_1 & +x_2 & \leq 1.5 \\ & x_1, & x_2 & \geq 0. \end{array}$$

Dual :

$$\begin{array}{llll} \text{minimize} & y_1 & +y_2 & +1.5y_3 \\ \text{subject to} & y_1 & & +y_3 \geq 1 \\ & & y_2 & +y_3 \geq 2 \\ & y_1, & y_2, & y_3 \geq 0. \end{array}$$

Optimal Value Function

For a fixed matrix A and an objective coefficient vector c , the optimal value is a function of right-hand-side vector b :

$$\begin{aligned} z(b) = \quad & \text{minimize} \quad c^T x \\ & \text{subject to} \quad Ax = b, \\ & \quad \quad \quad x \geq 0. \end{aligned}$$

Theorem: $z(b)$ is a convex function in b , that is, for any $0 \leq \alpha \leq 1$ we have

$$z(\alpha b^1 + (1 - \alpha)b^2) \leq \alpha z(b^1) + (1 - \alpha)z(b^2).$$

Shadow Prices of the Optimal Value

Define a new right-hand-vector \mathbf{b}^+ as

$$b_k^+ := b_k + \delta \quad \text{and} \quad b_i^+ := b_i, \quad \forall i \neq k.$$

Then the optimal dual solution \mathbf{y}^* satisfies

$$y_k^* = \frac{z(\mathbf{b}^+) - z(\mathbf{b})}{\delta}$$

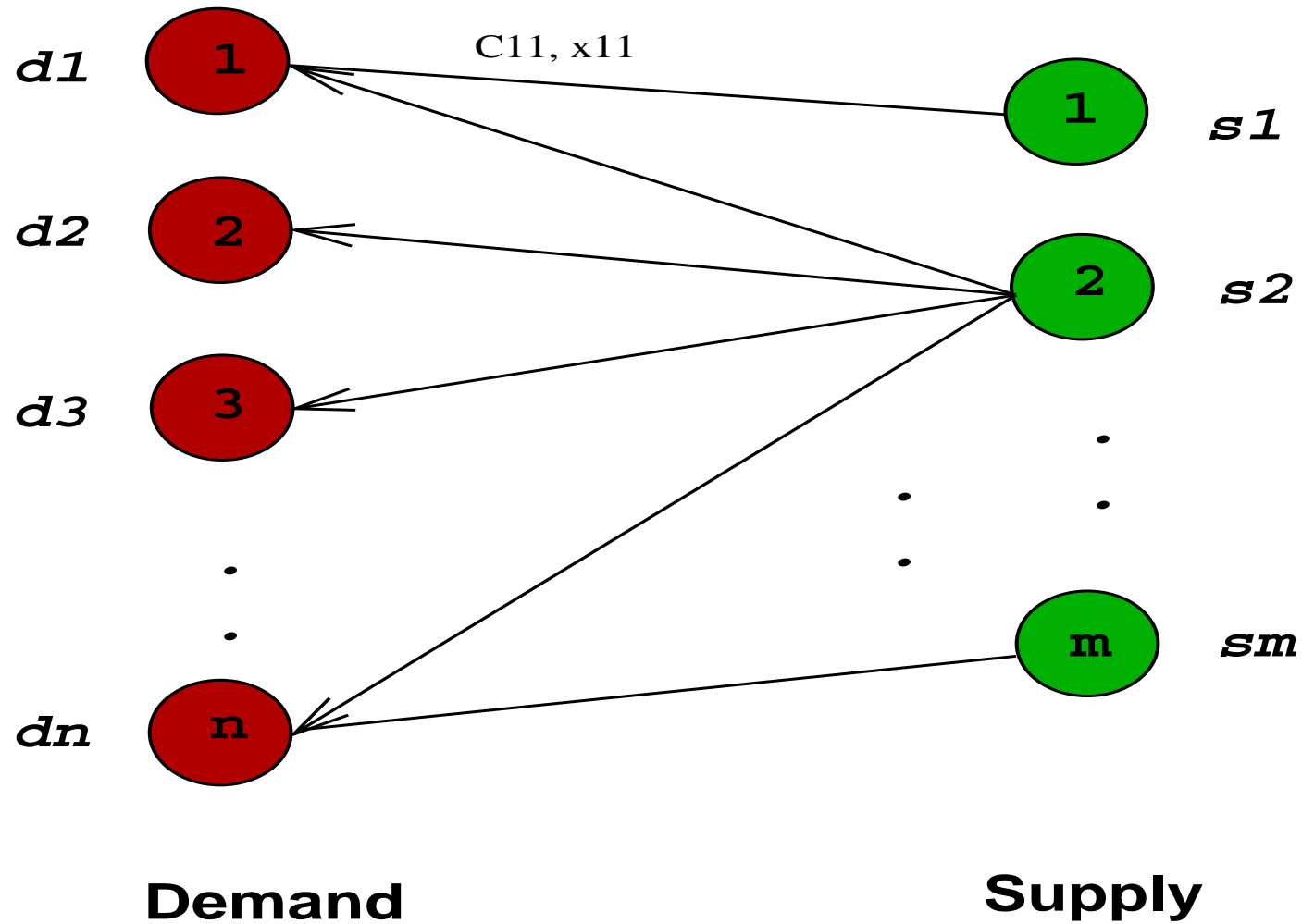
as long as \mathbf{y}^* is the dual optimal solution for \mathbf{b}^+ , since

$$z(\mathbf{b}^+) = (\mathbf{b}^+)^T \mathbf{y}^* = z(\mathbf{b}) + \delta y_k^*.$$

Thus, the optimal dual solution is the **shadow price** vector of the right-hand-vector, or the **rate** of the net change of the optimal objective value over the net change of an entry of the right-hand-vector.

Transportation Problem

$$\begin{array}{ll} \min & \sum_{i=1}^m \sum_{j=1}^n c_{ij} x_{ij} \\ \text{s.t.} & \sum_{j=1}^n x_{ij} = s_i, \quad \forall i = 1, \dots, m \\ & \sum_{i=1}^m x_{ij} = d_j, \quad \forall j = 1, \dots, n \\ & x_{ij} \geq 0, \quad \forall i, j. \end{array}$$



Transportation Dual

$$\begin{array}{ll}\max & \sum_{i=1}^m s_i u_i + \sum_{j=1}^n d_j v_j \\ \text{s.t.} & u_i + v_j \leq c_{ij}, \forall i, j.\end{array}$$

u_i : supply site unit price

v_j : demand site unit price

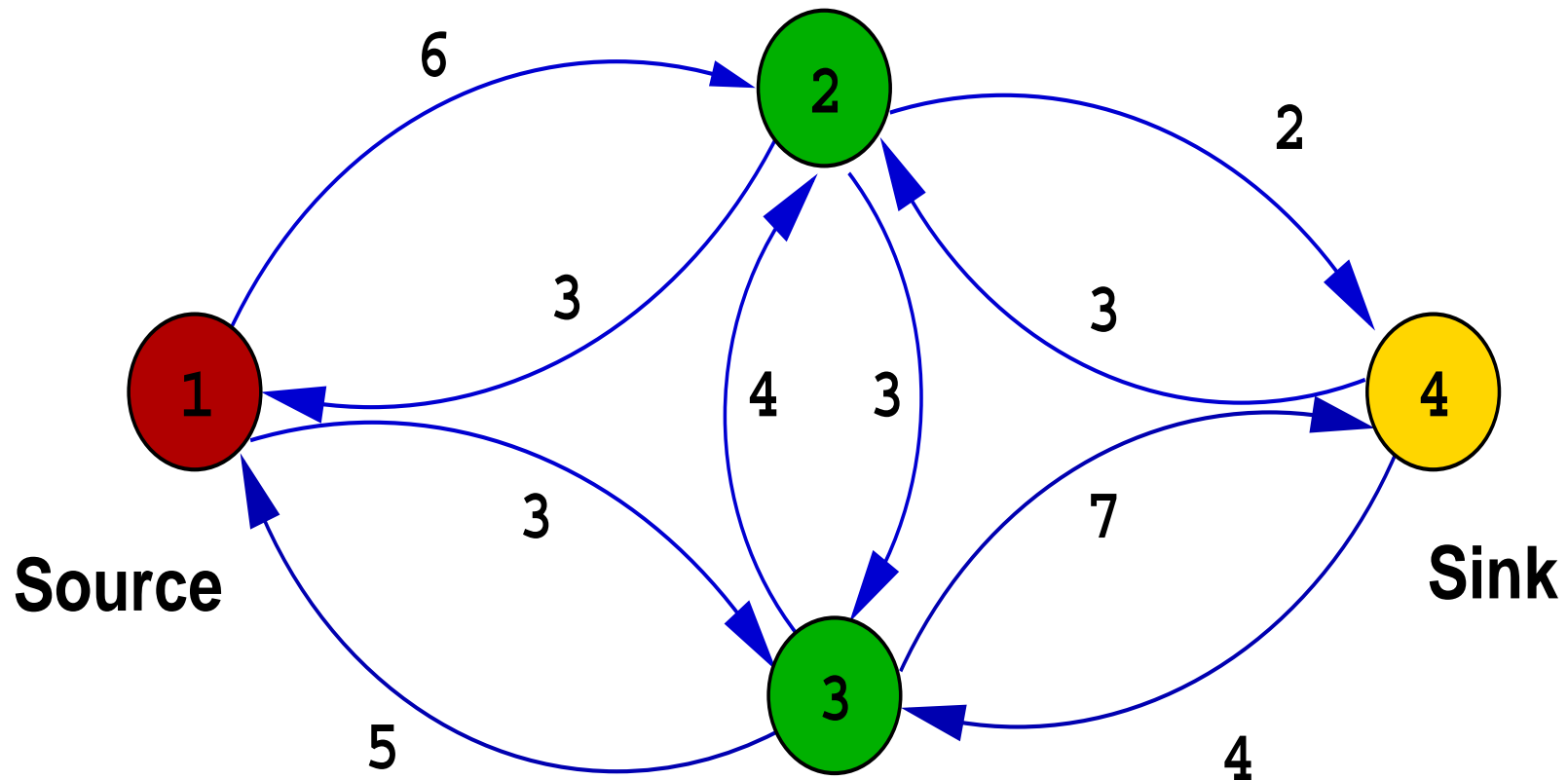
$u_i + v_j \leq c_{ij}$: competitiveness

Max-Flow and Min-Cut

Given a **directed graph** with nodes $1, \dots, m$ and edges \mathcal{A} , where node 1 is called the **source** and node m is called the **sink**, and each edge (i, j) has a flow rate **capacity** k_{ij} . The **Max-Flow** problem is to find the largest possible flow rate from source to sink.

Let x_{ij} be the flow rate from node i to node j . Then the problem can be formulated as

$$\begin{aligned}
 &\text{maximize} && x_{m1} \\
 &\text{subject to} && \sum_{j:(j,1) \in \mathcal{A}} x_{j1} - \sum_{j:(1,j) \in \mathcal{A}} x_{1j} + x_{m1} = 0, \\
 & && \sum_{j:(j,i) \in \mathcal{A}} x_{ji} - \sum_{j:(i,j) \in \mathcal{A}} x_{ij} = 0, \forall i = 2, \dots, m-1, \\
 & && \sum_{j:(j,m) \in \mathcal{A}} x_{jm} - \sum_{j:(m,j) \in \mathcal{A}} x_{mj} - x_{m1} = 0, \\
 & && 0 \leq x_{ij} \leq k_{ij}, \forall (i, j) \in \mathcal{A}.
 \end{aligned}$$



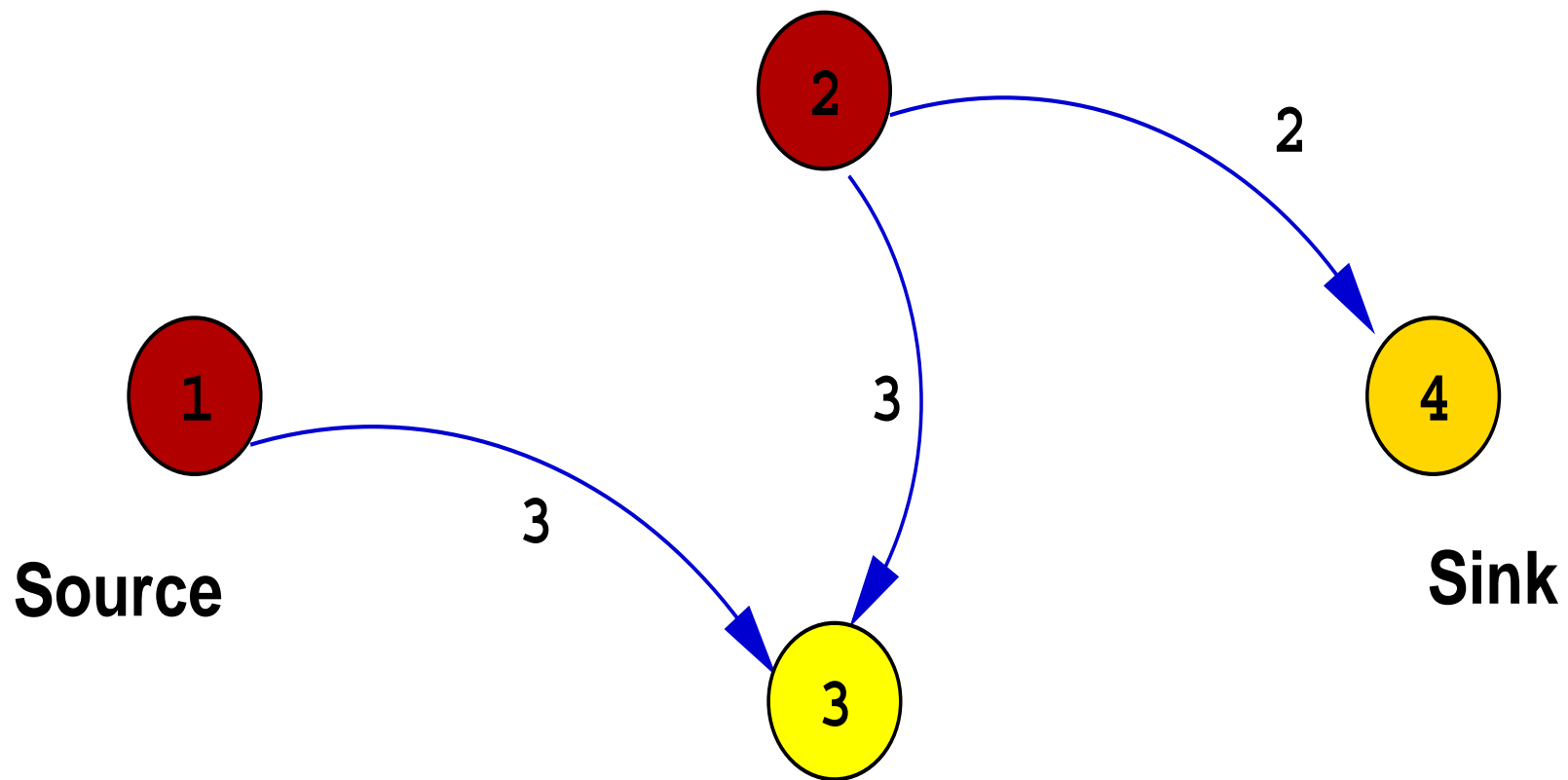
The Dual of the Max-Flow Problem

$$\begin{aligned} &\text{minimize} && \sum_{(i,j) \in \mathcal{A}} k_{ij} z_{ij} \\ &\text{subject to} && -y_i + y_j + z_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A}, \\ &&& y_1 - y_m = 1, \\ &&& z_{ij} \geq 0, \quad \forall (i,j) \in \mathcal{A}. \end{aligned}$$

y_i : **node potential value**. At an optimal solution, it has the following property.
 $y_1 = 1$, $y_m = 0$ and for all other i :

$$y_i = \begin{cases} 1 & \text{if } i \in S \\ 0 & \text{if } i \notin S \end{cases}$$

This problem is called the **Min-Cut** problem.



Application: Combinatorial Auction Pricing I

Given the m different **states** that are mutually exclusive and exactly one of them will be **true at the maturity**. A **contract** on a state is a paper agreement so that on maturity it is worth a notional **\$1** if it is on the **winning** state and worth **\$0** if is not on the winning state. There are n **orders** betting on one or a combination of states, with a **price limit** and a **quantity limit**.

Combinatorial Auction Pricing II: Order

The j -th **order** is given as $(\mathbf{a}_j \in R_+^m, \pi_j \in R_+, q_j \in R_+)$: \mathbf{a}_j is the combination betting vector where each component is either 1 or 0

$$\mathbf{a}_j = \begin{pmatrix} a_{1j} \\ a_{2j} \\ \dots \\ a_{mj} \end{pmatrix},$$

where 1 is winning and 0 is non-winning; π_j is the **price limit** for one such a contract, and q_j is the **maximum number** of contracts the better like to buy.

World Cup Information Market

Order	#1	#2	#3	#4	#5
Argentina	1	0	1	1	0
Brazil	1	0	0	1	1
Italy	1	0	1	1	0
Germany	0	1	0	1	1
France	0	0	1	0	0
Bidding Prize: π	0.75	0.35	0.4	0.95	0.75
Quantity Limit: q	10	5	10	10	5
Order Fill: x	x_1	x_2	x_3	x_4	x_5

Combinatorial Auction Pricing III: Pricing Each State

Let x_j be the number of contracts **awarded** to the j th order. Then, the j th better will pay the amount

$$\pi_j \cdot x_j$$

and the total collected amount is

$$\sum_{j=1}^n \pi_j \cdot x_j = \pi^T \mathbf{x}$$

If the i th state is the winning state, then the **auction organizer** need to pay back

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

The question is, how to decide $\mathbf{x} \in R^n$.

Combinatorial Auction Pricing IV: LP model

$$\begin{aligned} \max \quad & \pi^T \mathbf{x} - z \\ \text{s.t.} \quad & A\mathbf{x} - \mathbf{e} \cdot z \leq \mathbf{0}, \\ & \mathbf{x} \leq \mathbf{q}, \\ & \mathbf{x} \geq \mathbf{0}. \end{aligned}$$

$\pi^T \mathbf{x}$: the **optimistic** amount can be collected.

z : the **worst-case** amount need to pay back.

Combinatorial Auction V: The Dual

$$\begin{array}{ll}\min & \mathbf{q}^T \mathbf{y} \\ \text{s.t.} & A^T \mathbf{p} + \mathbf{y} \geq \pi, \\ & \mathbf{e}^T \mathbf{p} = 1, \\ & (\mathbf{p}, \mathbf{y}) \geq 0.\end{array}$$

\mathbf{p} represents the **state price**. What is \mathbf{y} ?

Combinatorial Auction V: Strict Complementarity

$x_j > 0$	$\mathbf{a}_j^T \mathbf{p} + y_j = \pi_j$ and $y_j \geq 0$ so that $\mathbf{a}_j^T \mathbf{p} \leq \pi_j$
$0 < x_j < q_j$	$y_j = 0$ so that $\mathbf{a}_j^T \mathbf{p} = \pi_j$
$x_j = q_j$	$y_j > 0$ so that $\mathbf{a}_j^T \mathbf{p} < \pi_j$
$x_j = 0$	$\mathbf{a}_j^T \mathbf{p} + y_j > \pi_j$ and $y_j = 0$ so that $\mathbf{a}_j^T \mathbf{p} > \pi_j$

The price is **Fair**:

$$\mathbf{p}^T (A\mathbf{x} - \mathbf{e} \cdot z) = 0 \quad \text{implies} \quad \mathbf{p}^T A\mathbf{x} = \mathbf{p}^T \mathbf{e} \cdot z = z;$$

that is, the worst case cost equals the worth of total shares. Moreover, if a lower bid wins the auction, so does the higher bid on any same type of bids.

World Cup Information Market Result

Order	#1	#2	#3	#4	#5	State Price
Argentina	1	0	1	1	0	0.2
Brazil	1	0	0	1	1	0.35
Italy	1	0	1	1	0	0.2
Germany	0	1	0	1	1	0.25
France	0	0	1	0	0	0
Bidding Price: π	0.75	0.35	0.4	0.95	0.75	
Quantity Limit: q	10	5	10	10	5	
Order Fill: x^*	5	5	5	0	5	

Combinatorial Auction Pricing VI: Convex Programming Model

$$\begin{aligned} \max \quad & \pi^T \mathbf{x} - z + u(\mathbf{s}) \\ \text{s.t.} \quad & A\mathbf{x} - \mathbf{e} \cdot z + \mathbf{s} = \mathbf{0}, \\ & \mathbf{x} \leq \mathbf{q}, \\ & \mathbf{x}, \mathbf{s} \geq 0. \end{aligned}$$

$u(\mathbf{s})$: a **value function** for the market organizer on slack shares.

If $u(\cdot)$ is a strictly concave function, then the state price vector is **unique**.

Constructing the Dual

Obj Coef Vector RHS A	RHS Obj Coef Vector A^T
Max Model $x_j \geq 0$ $x_j \leq 0$ x_j : free i -th constraint \leq i -th constraint \geq i -th constraint $=$	Min Model j -th constraint \geq j -th constraint \leq j -th constraint $=$ $y_i \geq 0$ $y_i \leq 0$ y_i : free

$$\begin{array}{ll}
 \text{maximize} & x_1 + 2x_2 \\
 \text{subject to} & x_1 \leq 1 \\
 & x_2 \leq 1 \\
 & x_1 + x_2 \leq 1.5 \\
 & x_1, x_2 \geq 0.
 \end{array}$$

Primal :

$$\begin{array}{ll}
 \text{minimize} & y_1 + y_2 + 1.5y_3 \\
 \text{subject to} & y_1 + y_3 \geq 1 \\
 & y_2 + y_3 \geq 2 \\
 & y_1, y_2, y_3 \geq 0.
 \end{array}$$

Dual :